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Association for Computational Linguistics**

Proceedings of the Student Research Workshop

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Preface of the EACL SRW 2024 by the Workshop Co-chairs

Welcome to the EACL 2024 Student Research Workshop!

The EACL 2024 Student Research Workshop (SRW) is a forum for students in the field of Computational Linguistics and Natural Language Processing to come together to discuss and advance their research with help from more experienced researchers from both academia and industry.

Following the tradition of the previous student research workshops, we have two tracks: research papers and thesis proposals. The research paper track is a venue for PhD students, Master's students, and advanced undergraduate students to describe completed work or work-in-progress along with preliminary results. The thesis proposal track is offered for students who have decided on a thesis topic and are interested in receiving feedback for their proposal with suggestions for both making the ideas achievable, as well as discussions related to future directions for their work.

The student research workshop has received considerable attention, and papers have addressed research questions in various areas. After excluding the desk-rejected (1) and withdrawn (1) submissions, we received 58 submissions in total: 6 thesis proposals and 52 research papers (divided into 50 direct submissions and 2 through ARR Commitment, where 1 ARR Commit withdrew). We accepted 3 thesis proposals and 29 research papers, resulting in an overall acceptance rate of around 55%. Excluding non-archival papers (3), 29 papers appear in these proceedings. All the accepted papers will be presented as part of the EACL conference. Moreover, similar to previous years, we organized in-person mentorship to enable the students to receive feedback and engage in discussions about their research directions, as well as improve the quality of the poster presentation of accepted papers.

We thank our program committee members for providing careful and comprehensive reviews for the papers, and all of our mentors for donating their time to provide feedback to our student authors. Thanks to our faculty advisors, Steffen Eger and Parisa Kordjamshidi, for the essential advice and suggestions, and to the EACL 2024 organizing committee for their support in the entire process. Finally, we would like to thank all the authors whose participation has made the workshop a success!

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Program

Tuesday, March 19, 2024

- 14:00 - 15:30 *Poster Session (7)*
- 16:00 - 16:10 *Opening Remarks*
- 16:15 - 17:15 *Panel*
- 17:20 - 17:55 *Best Student Papers Session*
- 17:55 - 18:00 *Closing Remarks*

AutoAugment Is What You Need: Enhancing Rule-based Augmentation Methods in Low-resource Regimes

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Abstract

Text data augmentation is a complex problem due to the discrete nature of sentences. Although rule-based augmentation methods are widely adopted in real-world applications because of their simplicity, they suffer from potential semantic damage. Previous researchers have suggested easy data augmentation with soft labels (softEDA), employing label smoothing to mitigate this problem. However, finding the best factor for each model and dataset is challenging; therefore, using softEDA in real-world applications is still difficult. In this paper, we propose adapting AutoAugment to solve this problem. The experimental results suggest that the proposed method can boost existing augmentation methods and that rule-based methods can enhance cutting-edge pre-trained language models. We offer the source code.¹

1 Introduction

Data augmentation is a regularization strategy that improves model performance expanding the data held in various ways (Hernández-García and König, 2018). In the natural language processing (NLP) field, data augmentation is used in various fields to alleviate data shortages, and various augmentation methods have been proposed accordingly (Feng et al., 2021; Li et al., 2022). For example, image data can be augmented by applying simple rules, such as flipping and rotation, to image data (Yang et al., 2022), and text data can also be augmented, by simple rules such as replacing synonyms and changing the order between words (Zhang et al., 2015; Wei and Zou, 2019). In addition, a method for augmenting data by generating new text using various deep learning models has also been proposed (Sennrich et al., 2016; Wu et al., 2019; Anaby-Tavor et al., 2020; Yoo et al., 2021; Zhou et al., 2022; Dai et al., 2023).

¹<https://github.com/c-juhwan/soft-text-autoaugment>

However, as these methods often demand training data for fine-tuning before augmentation (Zhang et al., 2022; Li et al., 2022), it may be challenging to apply them in a low-resource environment (Hu et al., 2019; Bayer et al., 2022; Kim et al., 2021). Rule-based text data augmentation methods are less costly and easy to implement; thus, they are often used in real-world problems. Despite that, the previously proposed rule-based text data augmentation methods risk not maintaining semantic consistency with original data, which is different from image data (Zhao et al., 2022), leading to performance degradation. To relieve this problem, methods that perform data augmentation only through random insertion of punctuation marks have also been proposed (Karimi et al., 2021), but they introduce fewer variations compared to easy data augmentation (EDA). Recently, softEDA (Choi et al., 2023), a method applying label smoothing (Szegedy et al., 2016) to the augmented data, was proposed to alleviate these drawbacks.

In softEDA, a heuristic grid search was performed for the label smoothing factor (a hyperparameter for performing label smoothing). However, the method based on a heuristic search has the following disadvantages. First, a heuristic search is expensive to execute (Bergstra and Bengio, 2012). Second, although we found the best factor value of the grid, it may not be the global optimum. There could be a better value outside the heuristic search grid; thus, revealing the possible performance gain is difficult.

This paper proposes a method to apply AutoAugment (Cubuk et al., 2019), a technique to determine the optimal factors in the data augmentation process to alleviate the limitations of previous softEDA methods. By optimizing various arguments of softEDA, it is shown that stable and effective performance improvement is possible compared to the existing rule-based strategy with static factors.

In addition, the existing softEDA experiment was conducted on an entire dataset. However, more severe overfitting occurs when the given training data are insufficient (Althnian et al., 2021), and the scope of performance improvement is greater when additional training data are obtained from a small dataset (Prusa et al., 2015; Okimura et al., 2022), so data augmentation becomes increasingly crucial in this low-resource environment. Therefore, this study evaluates the proposed method under a low-resource scenario and demonstrates that the proposed method is effective even under data-scarce conditions. In addition, some existing studies have argued that simple rule-based augmentation strategies are less effective in improving the performance of pre-trained language models (PLMs) (Longpre et al., 2020; Zhang et al., 2022; Pluščec and Šnajder, 2023). In this study, we show that through argument optimization, it is possible to improve the performance of not only BERT (Devlin et al., 2019), the standard PLM, but also DeBERTaV3 (He et al., 2023), a cutting-edge PLM, through rule-based data augmentation.

2 Related Work

Data augmentation of text is primarily performed by augmenting data according to predetermined rules (Zhang et al., 2015; Belinkov and Bisk, 2018; Wei and Zou, 2019; Karimi et al., 2021; Choi et al., 2023) or using various deep learning models (Sennrich et al., 2016; Wu et al., 2019; Anaby-Tavor et al., 2020; Yoo et al., 2021; Zhou et al., 2022; Dai et al., 2023). Rule-based data augmentation methods generate new data by performing perturbation in various ways, such as replacing some of the words in a given sentence with synonyms (Zhang et al., 2015) or inserting typos at the character level (Belinkov and Bisk, 2018). The easy data augmentation (EDA) (Wei and Zou, 2019) technique is a representative rule-based data augmentation method consisting of synonym replacement (SR), random insertion (RI), random swap (RS), and random deletion (RD). However, because such random changes can lead to the loss of semantic consistency, the “an easier data augmentation” (AEDA) technique (Karimi et al., 2021) consisting only of the RI of six punctuation marks has also been proposed. The softEDA (Choi et al., 2023) method compensates for the semantic damage caused by EDA by applying label smoothing to the augmented data.

Model-based augmentation methods employ deep learning models to generate new data. Back-translation (Sennrich et al., 2016) is one of the early model-based methods. It first translates the given data into another language and back-translates it to the original language, generating different expressions with the same concept. Methods based on PLM have also been proposed, and C-BERT (Wu et al., 2019), LAMBADA (Anaby-Tavor et al., 2020), and FlipDA (Zhou et al., 2022) generate new data using BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), and T5 (Raffel et al., 2020), respectively. In addition, GPT-3 (Brown et al., 2020) and ChatGPT, which are larger than these PLMs, have been proposed to generate new data (Yoo et al., 2021; Dai et al., 2023). Other researchers have introduced Mixup (Zhang et al., 2018) strategy to the NLP field to augment text data (Guo, 2020; Sun, 2020; Yoon et al., 2021).

Moreover, some previous approaches have tried to apply AutoAugment for NLP. Text AutoAugment (Ren et al., 2021), the work closest to the proposed method, suggested applying AutoAugment to optimize hyperparameters for data augmentation. In addition, DND (Kim et al., 2022) incorporated various data augmentation methods and suggested optimizing two reward terms regarding the difficulty and consistency with the original data. While the proposed work uses AutoAugment to optimize augmentation hyperparameters, we also focus on optimizing label smoothing values for the original and augmented data.

3 Method

3.1 Preliminaries

The EDA (Wei and Zou, 2019) method comprises four aforementioned suboperations: SR, RI, RS, and RD. First, SR randomly selects several words in a given sentence and changes them into their synonyms. Second, RI selects a random word in the sentence and inserts its synonym at a random position in the sentence. Third, RS operation randomly selects two words in the sentence and changes their positions. Finally, RD removes each word from the sentence with a predefined probability.

Through these four suboperations, EDA introduces noise to the original data and generates augmented data. Each suboperation has a magnitude of perturbation. For instance, in the case of SR, a higher magnitude leads to the additional replacement of the original words with their synonyms.

For each observed data pair (\mathbf{x}, \mathbf{y}) in the original dataset \mathcal{D} , where \mathbf{x} denotes an input sentence and \mathbf{y} represents the corresponding label value, the process of EDA can be formulated as follows:

$$\hat{\mathbf{x}} = \text{EDA}(\mathbf{x}, p_{\text{EDA}}) = \begin{cases} \text{SR}(\mathbf{x}, \alpha_{\text{SR}}) \\ \text{RI}(\mathbf{x}, \alpha_{\text{RI}}) \\ \text{RS}(\mathbf{x}, \alpha_{\text{RS}}) \\ \text{RD}(\mathbf{x}, \alpha_{\text{RD}}) \end{cases} \quad (1)$$

where $\{\alpha_{\text{SR}}, \alpha_{\text{RI}}, \alpha_{\text{RS}}, \alpha_{\text{RD}}\}$ denotes the magnitude of each suboperation, and $p_{\text{EDA}} = \{p_{\text{SR}}, p_{\text{RI}}, p_{\text{RS}}, p_{\text{RD}}\}$ represents the probability distribution of each suboperation to be selected, which are equal and sum to one. As indicated, EDA only modifies \mathbf{x} , and the label of augmented data is the same as for \mathbf{y} .

The softEDA (Choi et al., 2023) is a technique that incorporates noise into the label of augmented data through label smoothing (Szegedy et al., 2016). While softEDA follows the previous EDA to augment $\hat{\mathbf{x}}$, the following equation defines the process of softEDA, generating a label for augmented data $\hat{\mathbf{y}}$:

$$\begin{aligned} \hat{\mathbf{y}} &= (1 - \epsilon_{\text{aug}})\mathbf{y} + \frac{\epsilon_{\text{aug}}}{N_{\text{Class}}} \\ &= \begin{cases} (1 - \epsilon_{\text{aug}}) + \frac{\epsilon_{\text{aug}}}{N_{\text{Class}}} & \text{if } y = y_i \\ \frac{\epsilon_{\text{aug}}}{N_{\text{Class}}} & \text{Otherwise} \end{cases} \quad (2) \end{aligned}$$

where ϵ_{aug} is a smoothing factor for label smoothing.

3.2 Proposed Method

Previous EDA and softEDA have numerous augmentation hyperparameters and were primarily fixed or heuristically searched. This paper proposes a method to optimize these hyperparameters by adapting AutoAugment. First, we defined an augmentation policy \mathcal{P} with various factors:

$$\mathcal{P} = \{p_{\text{aug}}, p_{\text{SR}}, p_{\text{RI}}, p_{\text{RS}}, p_{\text{RD}}, \alpha_{\text{SR}}, \alpha_{\text{RI}}, \alpha_{\text{RS}}, \alpha_{\text{RD}}, N_{\text{aug}}, \epsilon_{\text{ori}}, \epsilon_{\text{aug}}\} \quad (3)$$

where p_{aug} indicates the probability of augmentation, N_{aug} refers to the amount of augmented data per original data point, ϵ_{ori} represents a label smoothing factor for the original data, different from ϵ_{aug} . Following Text AutoAugment (Ren

et al., 2021), we optimized the proposed policy based on sequential model-based global optimization (Bergstra et al., 2011). Finding the optimal augmentation parameter for each model and dataset through this adaptation of AutoAugment with soft-EDA is more beneficial than inefficient grid search.

4 Experiment

4.1 Datasets and Low-resource Setting

Eight text classification datasets were used to evaluate the proposed method. The SST2, SST5 (Socher et al., 2013) and MR (Pang et al., 2002) sentiment classification tasks are from movie reviews. The CoLA (Warstadt et al., 2019) binary classification dataset measures the linguistic acceptability of a given sentence. The SUBJ (Pang and Lee, 2004) binary classification dataset deals with the subjectivity of a sentence. PC (Ganapathibhotla and Liu, 2008), and CR (Hu and Liu, 2004; Liu et al., 2015) are datasets constructed from customer reviews. In addition, the TREC (Li and Roth, 2002) multiclass text classification dataset is about the question type of given text. Dataset specifications can be found in Appendix A.

Data augmentation becomes more important when the given data is deficient than when sufficient data can be accessed (Chen et al., 2023). To simulate a more challenging scenario, we evaluated the proposed method with only 100 and 500 randomly selected original data from each dataset.

4.2 Baselines

To validate the claim that hyperparameter optimization for the augmentation method is effective in enhancing model performance, we compared our approach with previous rule-based data augmentation methods with fixed hyperparameters. We compared the proposed method against the previous EDA, AEDA, and softEDA methods with fixed hyperparameters.

Recent studies suggest that simple rule-based augmentation methods are insufficient to enhance PLM-based models (Longpre et al., 2020; Zhang et al., 2022; Pluščec and Šnajder, 2023). In addition, validating the newly proposed augmentation method using cutting-edge models, not just models like BERT, is necessary (Zhou et al., 2022). Therefore, we adopted BERT and DeBERTaV3 (He et al., 2023), an improvement of DeBERTa (He et al., 2021) as the baseline model for evaluation.

	SST2	SST5	CoLA	SUBJ	TREC	MR	CR	PC
BERT w/o Aug	80.46 _{1.84}	35.13 _{0.74}	71.49 _{1.40}	92.85 _{0.44}	78.42 _{1.30}	72.11 _{1.39}	79.88 _{0.82}	88.12 _{0.58}
	86.08 _{1.03}	43.64 _{0.50}	75.50 _{0.58}	95.07 _{0.22}	93.27 _{0.42}	81.29 _{0.52}	87.53 _{0.60}	91.15 _{0.21}
w/ EDA	80.76 _{1.39}	36.63 _{1.33}	70.70 _{0.98}	93.39 _{0.25}	81.56 _{1.71}	73.18 _{1.36}	79.54 _{1.15}	89.64 _{0.80}
	86.71 _{0.63}	45.08 _{1.16}	73.18 _{0.52}	94.69 _{0.33}	93.99 _{1.05}	80.41 _{0.29}	87.71 _{0.57}	90.81 _{0.40}
w/ AEDA	80.96 _{1.63}	36.54 _{0.97}	72.24 _{1.85}	93.29 _{0.23}	81.27 _{2.19}	74.37 _{2.84}	80.67 _{1.64}	88.75 _{0.90}
	86.66 _{0.63}	44.53 _{1.02}	74.44 _{0.41}	94.60 _{0.48}	93.87 _{0.75}	81.57 _{0.15}	87.66 _{0.55}	91.03 _{0.31}
w/ softEDA	80.80 _{3.22}	37.13 _{1.60}	72.41 _{0.95}	93.24 _{0.40}	82.92 _{1.70}	74.40 _{1.27}	78.95 _{2.65}	88.82 _{1.63}
	87.84 _{0.65}	45.04 _{1.28}	74.16 _{0.99}	94.85 _{0.39}	94.68 _{0.51}	81.16 _{0.88}	87.94 _{0.85}	91.12 _{0.63}
w/ Ours	85.48 _{0.57}	39.88 _{0.41}	74.63 _{0.33}	94.10 _{0.35}	85.88 _{1.06}	79.32 _{0.37}	86.49 _{0.22}	91.54 _{0.11}
	88.53 _{0.27}	46.16 _{0.63}	76.66 _{0.81}	95.54 _{0.33}	95.17 _{0.54}	83.10 _{0.34}	89.98 _{0.25}	92.16 _{0.19}
w/ Ours w/o LS	84.71 _{0.44}	39.22 _{0.38}	73.80 _{0.79}	93.71 _{0.35}	84.85 _{1.40}	77.86 _{0.53}	85.70 _{0.88}	91.13 _{0.19}
	88.13 _{0.48}	45.45 _{0.39}	76.30 _{0.34}	95.15 _{0.22}	94.70 _{0.46}	82.19 _{0.60}	89.66 _{0.35}	91.98 _{0.18}
DeBERTaV3 w/o Aug	88.36 _{0.36}	35.95 _{1.69}	72.62 _{4.24}	92.23 _{0.24}	80.19 _{3.23}	82.84 _{0.39}	85.61 _{1.20}	91.22 _{0.43}
	92.59 _{0.73}	48.77 _{1.52}	82.21 _{0.82}	94.66 _{0.22}	94.06 _{0.43}	86.22 _{0.37}	91.40 _{0.36}	91.85 _{0.26}
w/ EDA	86.61 _{0.70}	37.64 _{1.23}	74.83 _{1.10}	92.85 _{0.48}	83.65 _{1.84}	83.18 _{0.32}	84.86 _{0.73}	90.51 _{0.47}
	93.25 _{0.55}	49.04 _{0.78}	79.24 _{0.66}	94.81 _{0.53}	94.33 _{0.99}	86.71 _{0.65}	91.24 _{0.39}	92.30 _{0.15}
w/ AEDA	88.44 _{0.80}	36.87 _{2.88}	79.29 _{0.65}	92.81 _{0.47}	84.17 _{0.79}	82.87 _{0.75}	85.76 _{1.37}	90.61 _{0.49}
	92.54 _{0.78}	49.16 _{0.83}	82.78 _{0.40}	94.92 _{0.58}	94.45 _{0.80}	85.77 _{1.63}	91.09 _{0.49}	92.29 _{0.11}
w/ softEDA	88.94 _{1.03}	38.37 _{1.65}	79.40 _{1.51}	92.90 _{1.08}	84.58 _{1.29}	83.50 _{0.65}	86.33 _{1.65}	91.28 _{0.82}
	93.12 _{1.05}	50.34 _{1.44}	78.97 _{1.16}	94.77 _{0.21}	94.71 _{0.69}	87.02 _{0.50}	91.81 _{0.76}	92.16 _{0.20}
w/ Ours	91.38 _{0.32}	42.92 _{0.52}	82.56 _{0.51}	94.47 _{0.26}	87.70 _{0.90}	85.31 _{0.79}	89.95 _{0.51}	92.32 _{0.19}
	93.94 _{0.30}	52.77 _{0.62}	84.32 _{0.49}	95.29 _{0.31}	94.92 _{0.62}	87.96 _{0.17}	92.46 _{0.18}	92.72 _{0.40}
w/ Ours w/o LS	90.47 _{0.26}	42.44 _{0.49}	82.10 _{0.43}	94.22 _{0.15}	86.57 _{0.61}	85.07 _{0.58}	89.47 _{0.67}	92.22 _{0.21}
	93.40 _{0.58}	52.54 _{0.66}	83.67 _{0.86}	95.15 _{0.12}	94.92 _{0.18}	87.41 _{0.37}	92.28 _{0.27}	92.49 _{0.33}

Table 1: Experimental results. Each experiment has been repeated five times and the statistics are presented in $mean_{std}$ format. The upper side of each column denotes the results when $N_{Train} = 100$, and the lower side shows the results when $N_{Train} = 500$. The best mean and standard deviation values for each model and dataset are boldfaced. Results that reported a lower mean value than the baseline are gray.

4.3 Main Results

Table 1 reports the experimental results. Previously proposed augmentation methods have faced marginal gain, or even performance degradation. Especially, softEDA has a high standard deviation compared to other methods, indicating that softEDA has difficulty being effective within a single fixed hyperparameter and requires optimization for hyperparameters. Whereas, the proposed method exhibits a stable and remarkable performance improvement within every setting, including those where other methods had performance degradation or marginal gains. This finding suggests enhancing extensive and cutting-edge PLMs with simple augmentation methods is achievable under the carefully designed data augmentation policy and hyperparameter optimization strategy. Furthermore, it is shown that our strategy has remarkably low standard deviation values compared to other techniques, showcasing that our approach is robust against statistical differences and valuable for practical application in low-resource text classification problems.

4.4 Ablation Study

One may wonder whether the performance improvement reported in Table 1 is solely caused by

the adaptation of AutoAugment, rather than the label smoothing of softEDA. To validate the effectiveness of label smoothing, we conducted an ablation study where label smoothing is not applied (i.e., $\epsilon_{ori} = \epsilon_{aug} = 0$). This setting is equal to optimizing only factors of EDA. “w/ Ours w/o LS” row of Table 1 presents the experimental results, revealing that the proposed method without label smoothing is less effective than the proposed method. This finding supports that the label smoothing optimization introduced by softEDA plays a crucial role in enhancing the model.

5 Conclusion

This paper proposed a method to optimize various hyperparameters of rule-based text augmentation methods. The experimental results suggest that the proposed method is effective and stable, and that rule-based augmentation methods can improve cutting-edge PLMs with proper hyperparameter optimization. Future work may extend this approach to other tasks, such as natural language inference, which is more complex than the single-sentence classification conducted in this paper.

Limitations

This paper used AutoAugment to optimize the rule-based data augmentation method. The primary weakness of AutoAugment is the computational overhead from the searching process (Zhang and Ma, 2022). However, under low-resource situations, where the necessity of data augmentation is emphasized, this problem can be diminished as the time consumption of the search process decreases.

Ethics Statement

This paper proposes an optimized rule-based augmentation method. These rule-based methods are more ethically stable than model-based approaches, as the modification is performed under predefined rules. For example, back-translation can be easily exposed to the potential bias of the translation model. Methods based on PLMs also share this concern. However, rule-based augmentation methods, including the proposed method, perform modifications within a given sentence and are less likely to be exposed to unintentional bias.

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A Dataset Specification

Dataset	N_{Class}	N_{Train}	N_{Test}
SST2	2	6.9K	1.8K
SST5	5	8.5K	2.2K
CoLA	2	8.5K	0.5K
SUBJ	6	8K	2K
TREC	2	5.5K	0.5K
MR	2	9.5K	1.1K
CR	2	3.0K	0.8K
PC	2	39K	4.5K

Table 2: Specification of each dataset used for the experiment.

	SST2	CR	MR	TREC	SUBJ	PC	CoLA
BERT w/o Aug	89.74	89.08	84.28	95.47	96.18	93.44	75.38
w/ EDA	+0.71	-0.41	-0.92	+0.51	-0.35	+0.58	-0.45
w/ AEDA	+0.22	+1.84	+0.19	-0.67	-0.30	-0.15	-0.34
w/ softEDA 0.1	-0.11	+0.29	-1.10	-1.45	+0.15	+0.43	+1.34
w/ softEDA 0.15	-0.22	+0.66	-0.46	-0.47	-0.50	-0.01	+0.02
w/ softEDA 0.2	-0.12	+2.10	+0.19	-0.27	+0.05	+0.43	+0.81
w/ softEDA 0.25	-0.23	+2.10	-0.92	+1.17	-0.10	+0.67	+1.50
w/ softEDA 0.3	+0.83	-0.90	-1.80	-0.78	+0.00	+0.67	+0.23

Table 3: Results of softEDA for the BERT model reported in the softEDA paper. The best scores for each dataset are boldfaced. Scores lower than the baseline are gray.

B Implementation Details

We used PyTorch (Paszke et al., 2019) and Huggingface Transformers (Wolf et al., 2020) to implement the model and evaluation process. We used `bert-base-cased` and `microsoft/deberta-v3-base` for the BERT and DeBERTaV3 models. Every model was trained using the Adam optimizer with a batch size of 32 and a learning rate of $5e-5$ for ten epochs, with early stopping with a patience value of 5, conditioned on best validation accuracy. The training procedure was performed on a single Nvidia RTX 3090 GPU.

For the baseline method implementation, we used TextAugment library (Marivate and Sefara, 2020) for EDA, and softEDA was built on it. The library did not have an implementation for AEDA; thus, we implemented it separately. We used ray tune (Liaw et al., 2018) to implement the proposed method. Please refer to the attached code for more information.

C Analysis of softEDA

We investigated the experimental results of the softEDA paper. Table 3 presents the experimental results reported in the appendix of the softEDA paper. The results suggest that, although softEDA can potentially enhance model performance, it is problematic to determine the optimal label smoothing factor for each model and dataset. Performance degradation compared to the baseline was also observed where the factor is improper for each setup. This finding motivated us to determine a better solution for finding optimal factors than a heuristic search. Furthermore, the authors performed the experiment on the full dataset. In contrast, we conducted the experiment through low-resource scenarios, which

is more challenging for model.

Generating Diverse Translation with Perturbed k NN-MT

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Abstract

Generating multiple translation candidates would enable users to choose the one that satisfies their needs. Although there has been work on diversified generation, there exists room for improving the diversity mainly because the previous methods do not address the overcorrection problem—the model underestimates a prediction that is largely different from the training data, even if that prediction is likely. This paper proposes methods that generate more diverse translations by introducing perturbed k -nearest neighbor machine translation (k NN-MT). Our methods expand the search space of k NN-MT and help incorporate diverse words into candidates by addressing the overcorrection problem. Our experiments show that the proposed methods drastically improve candidate diversity and control the degree of diversity by tuning the perturbation’s magnitude.

1 Introduction

In natural language, there are multiple lexically distinct translations given an input sentence. Therefore, machine translation systems should offer multiple translation candidates to users so that the final choice should be made by them considering their demands, e.g., styles or domains. However, standard neural machine translation (NMT) models suffer from a low diversity problem in which the generated translation candidates are almost identical. One reason lies in beam search, which is a standard inference algorithm, where the search space is expanded in a left-to-right fashion while keeping only the top- N candidates in every decoding step and just preserving slightly different translations (Gimpel et al., 2013; Vijayakumar et al., 2018; Freitag and Al-Onaizan, 2017). The other reason is the overcorrection problem (Zhang et al., 2019), which is caused by a model trained with cross-entropy loss that underestimates a prediction that is largely different from the training data, even

if it is likely. This phenomenon discourages the model from generating synonymous expressions and leans toward gold standards, reducing the diversity in the candidates.

To encourage the model to generate more diverse candidates, Vijayakumar et al. (2018), Holtzman et al. (2020), and Freitag and Al-Onaizan (2017) proposed variants of beam search algorithms in which diverse candidates are retained in the search space. However, their methods do not directly address the overcorrection problem, limiting their effect in generating diverse translations.

To alleviate this issue, we propose k NN diversified decoding that combines diversified beam search and k -nearest neighbor machine translation (k NN-MT; Khandelwal et al., 2021), which addresses the overcorrection problem by retrieving alternative target tokens from the training data during decoding (Yang et al., 2022). To further diversify the search space, we also propose two methods, i.e., stochastic and deterministic methods. The stochastic method expands the search space by perturbation so that the model can generate more likely tokens that are less focused. We proposed two types of perturbations, *noised- k NN* (Figure 1 (1)), which adds a noise vector to the query of the k NN search, and *randomized- k NN* (Figure 1 (2)), which arbitrarily selects k neighbors from a more extensive search space. The deterministic method, *uniquify- k NN* (Figure 1 (3)), removes duplicates from the retrieved k NN tokens so that no token can be dominant and thus more diverse candidates remain.

Our experiments showed that our proposed methods alleviate the overcorrection problem that leads to the generation of more diverse candidates, and maintain fluency and oracle translation quality in multiple domains and language pairs. We also show that the degree of diversity can be controlled by changing the perturbation’s magnitude, which benefits end-applications, e.g., human post-editing.

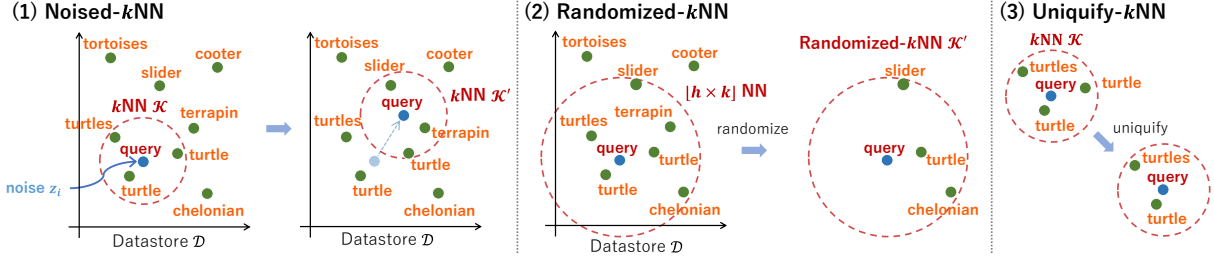


Figure 1: Overview of our proposed method: See §3 for details. Green points represent target tokens in datastore. Blue points represent query vectors, and surrounding circles denote retrieved neighbors. (1) Noised- k NN adds a noise vector to the query, changing the retrieved tokens. (2) Randomized- k NN initially retrieves more neighbors and randomly selects k -neighbors. (3) Uniquify- k NN only considers unique target tokens from retrieved neighbors. In this figure, number of neighbors k per query is set to 3, and hyperparameter h of (2) Randomized- k NN is set to 2.0.

2 Related Work

2.1 Diverse Text Generation

Given the importance of generating diverse translations, many of the proposed search algorithm variations can be categorized into either deterministic or stochastic types.

For the former method, Vijayakumar et al. (2018) proposed diverse beam search (DBS) in which beams are divided into several groups, and a modified score function penalizes the overlapped tokens among the groups. Freitag and Al-Onaizan (2017) proposed a method that determines the maximum number of candidates that share the same partial hypothesis.

As for the latter approach, top- k sampling (Fan et al., 2018) randomly samples the output tokens from the top k -tokens with the highest likelihood at each time step. Similarly, nucleus sampling (Holtzman et al., 2020) randomly samples from the smallest subset of candidates whose total likelihood exceeds p at each time step. Noisy parallel approximate decoding (Cho, 2016) explores multiple modes by injecting noise into the model’s hidden states. Wu et al. (2020) proposed a method that samples different models derived by applying concrete dropout. MixDiversity (Li et al., 2021) leverages the hidden representations of the randomly sampled sentence pairs from the subset of the training corpus.

Although all of the above methods diversify the output text, they do not explicitly address the over-correction problem, which is the root cause of the limited diversity (§2.3).

2.2 k NN-MT

Khandelwal et al. (2021) proposed k -nearest neighbor machine translation (k NN-MT), which uses

k NN search for retrieving similar examples during inference by reflecting the retrieval results in the score function. The translation quality is improved by allowing the model to directly access large-scale cached translation examples. k NN-MT consists of two steps, datastore creation and generation.

Datastore creation Before inferences with k NN-MT, we need to create a datastore, i.e., key-value pairs of high-dimensional representations and tokens. We feed all the training data into the NMT model and save each target token as a value and its decoder hidden state vector as a key representation. Formally, let $f(\mathbf{x}, \mathbf{y}_{<i})$ be the hidden state vector at time step i for source sentence $\mathbf{x} \in \mathcal{S}$ and target sentence $\mathbf{y} \in \mathcal{T}$ of training data $(\mathcal{S}, \mathcal{T})$, and then datastore \mathcal{D} can be represented:

$$\mathcal{D} = \{(f(\mathbf{x}, \mathbf{y}_{<i}), y_i), \forall y_i \in \mathbf{y} \mid (\mathbf{x}, \mathbf{y}) \in (\mathcal{S}, \mathcal{T})\}. \quad (1)$$

Generation To generate a sentence from a given input sentence \mathbf{x} , we extract k -nearest neighbors $\mathcal{K} \subset \mathcal{D}$ from the datastore using decoder hidden state \mathbf{q}_i at time step i as a query corresponding to output token y_i . k -nearest neighbor probability $p_{k\text{NN}}$ is calculated from the distances between query \mathbf{q}_i and the k -nearest neighbors:

$$p_{k\text{NN}}(y_i | \mathbf{x}, \mathbf{y}_{<i}) \propto \sum_{(\mathbf{k}_j, v_j) \in \mathcal{K}} \mathbb{1}_{y_i=v_j} \exp\left(\frac{-\text{dist}(\mathbf{k}_j, \mathbf{q}_i)}{\tau}\right), \quad (2)$$

where $\text{dist}(\cdot, \cdot)$ is a distance function and τ is a softmax temperature parameter. The word probability of y_i is calculated by the linear interpolation of k NN probability $p_{k\text{NN}}$ and output probability

p_{MT} of the NMT model:

$$p(y_i|\mathbf{x}, \mathbf{y}_{<i}) = \lambda p_{k\text{NN}}(y_i|\mathbf{x}, \mathbf{y}_{<i}) + (1 - \lambda)p_{\text{MT}}(y_i|\mathbf{x}, \mathbf{y}_{<i}), \quad (3)$$

where λ is a hyperparameter that determines the weight of the $k\text{NN}$ probability.

$k\text{NN-MT}$ substantially improves the translation performance without additional model training, and several variants have been proposed. Jiang et al. (2021); Zheng et al. (2021); Jiang et al. (2022) further improved the translation performance by dynamically changing the number of neighbors and the interpolation weight. Wang et al. (2022); Meng et al. (2022); Deguchi et al. (2023) proposed methods for faster inference by reducing search space. However, no research uses $k\text{NN-MT}$ for improving generation diversity.

2.3 Overcorrection

The standard NMT models trained with cross-entropy loss suffer from the overcorrection problem (Zhang et al., 2019) in which the model underestimates a prediction that is largely different from the training data, even if it is likely. We hypothesize that this problem decreases the diversity of candidates due to the low probabilities for alternative tokens assigned by the underlying model.

Zhang et al. (2019) alleviated overcorrection by mitigating the discrepancy between training and inference. Yang et al. (2022) argued that the $k\text{NN-MT}$'s improvement is derived from alleviating the overcorrection problem by a $k\text{NN}$ search. However, the relationship between overcorrection and generation diversity remains unclear. In this study, we propose expanding the search space of $k\text{NN-MT}$ to alleviate overcorrection. We also conduct a quantitative analysis of overcorrection and diversity (§5.2).

3 $k\text{NN}$ Diversified Decoding

We propose to employ $k\text{NN-MT}$ to alleviate the overcorrection problem and thus encourage diverse generation model-wise. It is further combined with diversified decoding together with our proposed stochastic and deterministic methods for the more controlled expansion of the search space in $k\text{NN-MT}$.¹

¹We combine these methods by calculating word probability with vanilla or perturbed $k\text{NN-MT}$ and generate candidates by using diversified decoding methods as a search strategy.

In $k\text{NN-MT}$, $k\text{NN}$ search is expected to improve the output probability of alternative tokens that are not normally included in the top- N of the output probability. Furthermore, the search space is extensively explored using a diversified decoding method to generate diverse and likely translation candidates. Although $k\text{NN}$ search is limited by k , more space is explored by stochastically expanding it by adding perturbations from noising (§3.1) and randomizing (§3.2). In addition, deterministically considering only unique tokens in neighbors further allows the model to explore alternative candidates (§3.3).

3.1 Noised- $k\text{NN}$

As a simple way to perturb the $k\text{NN}$ distribution, we propose noised- $k\text{NN}$, a method that adds a noise vector to the query for a $k\text{NN}$ search (Figure 1 (1)). This method diversifies the candidates by stochastically extending the range of the $k\text{NN}$ search. In this method, we perform a $k\text{NN}$ search with query $\mathbf{q}_i + \mathbf{z}_i$, where \mathbf{q}_i is the hidden decoder states, and \mathbf{z}_i is the noise vector for output token y_i to obtain k -nearest neighbors \mathcal{K}' . We then compute the $k\text{NN}$ probability from \mathcal{K}' in Eq. 2. Noise vector \mathbf{z}_i is generated independently at each time and for each beam as the white Gaussian noise of norm $|a|$ where $a \sim \mathcal{N}(m, s^2)$ with mean m and variance s^2 . We propose the following two methods to set m and s .

Static noise We introduce static noise by setting $m = h_m, s = h_s$ using hyperparameters h_m, h_s . Hyperparameters h_m and h_s should be set to appropriate values based on the statistics of the datastore. In this study, we computed the mean and variance of the distance to the nearest neighbors on the validation data in advance.

Adaptive noise As an alternative to static noise, we introduce adaptive noise in which the magnitude of the noises is computed on the fly for each query at each decoding step. Specifically, a usual $k\text{NN}$ search is performed to obtain maximum d_{max} and standard deviation d_{std} of the distances to the neighbors. Then an actual noisy $k\text{NN}$ search is performed by setting $m = h'_m \times d_{\text{max}}$ and $s = h'_s \times d_{\text{std}}$ using hyperparameters h'_m, h'_s . This method's benefit is that the magnitude of the noise is determined on the fly and eliminates the need for the prior computation of the datastore distributions at the cost of an additional $k\text{NN}$ search at each decoding step.

3.2 Randomized- k NN

Randomized- k NN, as described in Figure 1 (2), stochastically samples a portion of the expanded neighbors to alleviate the drawbacks of two noising approaches (§3.1) that demand prior computation of parameters m and s . $\lfloor h \times k \rfloor$ neighbors are retrieved where h is a hyperparameter satisfying $h > 1$, and randomized k -nearest neighbors \mathcal{K}' are obtained by uniformly randomly sampling k from the $\lfloor h \times k \rfloor$ neighbors. This method is expected to diversify the candidates because it includes more neighbors in the search space. We do not need to collect any statistics of the distribution of the distances from the query to the k -nearest neighbors in advance because we do not perturb the query itself. In addition, since this method requires only one k NN search at each time step, it is identical to the vanilla k NN-MT.

3.3 Uniquify- k NN

The perturbations in §3.1 and §3.2 may have a limited effect on increasing diversity when duplicated tokens are retrieved from the nearest neighbors. We alleviate this problem by introducing uniquify- k NN in which duplicated tokens are explicitly removed from the neighbors (Figure 1 (3)).

Since the datastore accumulates all the tokens on target-side of the training data, the k -nearest neighbors retrieved from the datastore can contain duplicated tokens. As seen in Eq. 2, their distance scores are accumulated for duplicated tokens, creating a spuriously dominant probability mass in the neighbor distribution. Biased probabilities can negatively impact diversity. Since a larger datastore implies more potential for overlapped tokens, it would further degrade the diversity.

To address this issue, after retrieving the k -nearest neighbors, we propose uniquify- k NN, a method that eliminates the duplicate tokens from the neighbors, leaving only unique tokens that are closest to the query. Our new method is formally defined as follows:

$$p_{k\text{NN}}(y_i | \mathbf{x}, \mathbf{y}_{<i}) \propto \max_{(\mathbf{k}_j, v_j) \in \mathcal{K}} \mathbb{1}_{y_i=v_j} \exp\left(\frac{-\text{dist}(\mathbf{k}_j, \mathbf{q}_i)}{\tau}\right). \quad (4)$$

This operation prevents the k NN probability from becoming peaky and decreasing in diversity.

4 Experiments

We experimentally confirmed whether our method can generate diverse translation candidates.

4.1 Experimental Settings

4.1.1 Dataset

The experiments are divided into a domain adaptation setting and a general-domain setting. In the domain adaptation setting, we used German-English (De-En) and Japanese-English (Ja-En) language pairs. For De-En, we used five domain data (Koehn and Knowles, 2017; Aharoni and Goldberg, 2020): Koran, IT, Medical, Law, and Subtitles. For Ja-En, we used four domain data: the Asian Scientific Paper Excerpt Corpus (ASPEC; Nakazawa et al., 2016), the Kyoto Free Translation Task (KFTT; Neubig, 2011), TED talks (Cetolo et al., 2012), and the Business Scene Dialogue corpus (BSD; Rikters et al., 2019). We used the designated test set for each domain.

In the general-domain setting, we used three language pairs: WMT’19 news task data (Barrault et al., 2019) for German-English (De-En) and WMT’22 general task data (Kocmi et al., 2022) for Japanese-English (Ja-En) and Ukrainian-Czech (Uk-Cs). For the general-domain test set, we used newstest2019 for De-En and generaltest2022 for Ja-En and Uk-Cs. The statistics of the dataset for both settings are in Appendix A.1.

4.1.2 Models

Baseline All our experiments were carried out with Transformer models (Vaswani et al., 2017). In the domain adaptation and general domain for De-En, we used the WMT’19 De-En pre-trained model (Ng et al., 2019) available for the fairseq toolkit (Ott et al., 2019). In the domain adaptation for Ja-En, we used the Transformer Big model trained on JParaCrawl v3.0 (Morishita et al., 2022) as a base model.² In the general domain for Ja-En and Uk-Cs, we used Transformer Big models trained on WMT’22 data as a base model for each language pair. These models were used for datastore creation and as baseline models. In all the experiments, the beam size was set to 20.

k NN-MT We used FAISS (Johnson et al., 2019) for datastore creation and k NN search. The detailed settings are described in Appendix A.2.

²We did not use WMT’22 data for the domain adaptation settings for fair comparisons since it includes KFTT, which is one target domain.

Diversified decoding We used DBS and nucleus sampling (Nucleus) as the diversified decoding method; the number of DBS groups was set to 20, the diversity strength was set to 0.5, and hyperparameter p of Nucleus was tuned with the validation data. For our proposed methods, we combined them with DBS and Nucleus.³ The hyperparameters of the proposed methods were tuned with the validation data. The detailed settings are in Appendix A.2.

4.1.3 Evaluation Metrics

We used the following metrics to confirm how correctly our model translates and how diverse its candidates are.⁴

BLEU@N is a variant of corpus-wise BLEU (Papineni et al., 2002) computed by the largest sentence-level BLEU score (Chen and Cherry, 2014) for each N -best candidate, also known as oracle BLEU. It corresponds to the upper bound of performance through N -best reranking. We report BLEU@1 and BLEU@20 in our experiment. Note that BLEU@1 is a standard BLEU.

MergedBLEU@N is a variant of BLEU@N computed on the merged outputs from two systems. We employ MergedBLEU@40, which merges 20 candidates from the baseline and a diversified method. The higher MergedBLEU@40 than BLEU@20 of the baseline implies that the diversified method helps generate the better translations.

Diversity The BLEU-based discrepancy metric (DP; Shu et al., 2019) is a measure of the diversity. DP captures how many unique n -grams are included in each candidate sentence, where a higher DP indicates the candidates are diverse.⁵

Diversity and translation quality The diversity enhancement per quality (DEQ; Sun et al., 2020) measures the quality-diversity trade-off. We adapt the DEQ for our experimental settings by using k NN-MT as our base:

$$\text{DEQ} = -\frac{\text{DP}_{\text{base}} - \text{DP}_{\text{sys}}}{\text{RefBLEU}_{\text{base}} - \text{RefBLEU}_{\text{sys}}} \quad (5)$$

³From preliminary experiments, we describe the unicity- k NN results in the general-domain setting.

⁴The detailed settings are described in Appendix A.3. We also used COMET and BERTScore, but since these scores tend to be similar to BLEU, we show the details and results for these metrics in Appendix B.

⁵As an additional diversity metric, we discuss the number of differences in n -gram type in §5.3.

where DP_{sys} and DP_{base} are DP of the evaluated system and k NN-MT, respectively, and $\text{RefBLEU}_{\text{sys}}$ and $\text{RefBLEU}_{\text{base}}$ refer to reference BLEU (RefBLEU; Sun et al., 2020), the average corpus-wise BLEU across all translation candidates, of the evaluated system and k NN-MT, respectively. The DEQ will be higher if the evaluated system achieves a better quality-diversity trade-off.

Fluency The pseudo-log-likelihood score (PLL; Salazar et al., 2020) is a metric of fluency using the MLM model.⁶ We defined a variant of the PLL for the entire output translations, named SPLL, using statistical function stat:

$$\text{SPLL}(\mathbb{W}) = \frac{1}{|\mathbb{W}|} \sum_{\mathbf{B} \in \mathbb{W}}^{\text{stat}} \left(\frac{1}{|\hat{\mathbf{y}}|} \text{PLL}(\hat{\mathbf{y}}) \right), \quad (6)$$

where $\mathbb{W} = \{\mathbf{B}_1, \dots, \mathbf{B}_M\}$ is system output, $\mathbf{B}_k = \{\hat{\mathbf{y}}_k^1, \dots, \hat{\mathbf{y}}_k^N\}$ is the set of N -best hypotheses for a source sentence $\mathbf{x}_k \in \mathcal{X}$, and \mathcal{X} is a test set with M sentences.

In the experiment, to investigate the variances in fluency, we use MaxPLL, MinPLL, and MeanPLL, which use max, min, and mean functions for the stat of SPLL. We also compute the reference’s MeanPLL to check how practical the translations’ fluency are. If the generated texts are not as fluent as the reference, the MeanPLL will be lower than the reference.

4.2 Experimental Results

4.2.1 Domain Adaptation

Summaries of the De-En and Ja-En results are shown in Table 1 and Table 2, respectively, by averaging the metrics across the domains. Detailed results are shown in Appendix B.

In De-En, our proposed DBS+ k NN-MT and Nucleus+ k NN-MT outperformed both of DP and oracle BLEU of DBS and Nucleus. These methods also decrease BLEU@20 more than k NN-MT, although the drop in performance is comparable to that observed between Baseline and DBS or Nucleus. Our perturbation methods, i.e., +Adaptive, +Static, and +Randomize, drastically improved DP while maintaining comparable performance to DBS+ and Nucleus+ k NN-MT under BLEU@20. Nor did the PLL of the proposed methods suffer substantial drops when compared to k NN-MT; the differences are marginal compared to the PLL of

⁶We used a multilingual BERT (Devlin et al., 2019) as the MLM model.

Method	Diversity DP \uparrow	Translation Quality (BLEU \uparrow)				Both DEQ \uparrow	Fluency (PLL \uparrow)		
		@1	@20	Merged@40	Ref		Max	Min	Mean
Reference	-	-	-	-	-	-	-	-	-3.35
Baseline	31.4	34.1	42.6	42.6	30.9	-0.12	-2.26	-4.55	-3.28
DBS	35.9	33.6	40.0	43.8	30.3	0.44	-2.23	-4.63	-3.28
Nucleus	48.0	33.4	42.1	44.6	30.0	1.88	-2.31	-4.42	-3.29
k NN-MT	32.3	43.2	51.8	53.5	38.4	-	-2.23	-4.74	-3.32
DBS+ k NN-MT	42.0	42.0	48.6	51.8	36.5	5.28	-2.18	-4.90	-3.35
+Static	55.2	40.4	49.0	52.0	33.5	4.68	-2.02	-5.23	-3.37
+Adaptive	53.7	41.0	49.0	52.1	34.2	5.10	-2.04	-5.21	-3.38
+Randomize	54.4	39.5	48.4	51.5	32.6	3.81	-2.08	-5.16	-3.38
Nucleus+ k NN-MT	51.6	42.1	50.4	52.8	37.0	14.5	-2.37	-4.50	-3.33
+Static	55.0	42.7	49.9	52.5	34.9	6.47	-2.29	-4.87	-3.36
+Adaptive	55.6	42.6	49.8	52.4	34.7	6.32	-2.27	-4.92	-3.36
+Randomize	59.4	42.3	49.2	52.0	33.1	5.09	-2.24	-5.10	-3.41

Table 1: Domain adaptation in German-English: We report averages of five domains.

Method	Diversity DP \uparrow	Translation Quality (BLEU \uparrow)				Both DEQ \uparrow	Fluency (PLL \uparrow)		
		@1	@20	Merged@40	Ref		Max	Min	Mean
Reference	-	-	-	-	-	-	-	-	-2.75
Baseline	38.0	18.1	26.0	26.1	16.5	0.25	-1.75	-3.67	-2.55
DBS	54.9	17.2	24.8	28.2	14.4	3.88	-1.66	-3.92	-2.63
Nucleus	63.9	17.6	26.5	28.9	14.8	6.43	-1.69	-3.72	-2.60
k NN-MT	37.4	20.9	29.7	31.5	18.9	-	-1.65	-3.57	-2.43
DBS+ k NN-MT	60.7	19.7	27.9	30.9	15.6	7.04	-1.44	-4.02	-2.52
+Static	66.5	19.5	28.3	31.3	14.9	7.23	-1.36	-4.12	-2.51
+Adaptive	66.8	19.5	28.4	31.3	14.8	7.18	-1.36	-4.11	-2.51
+Randomize	65.9	19.2	27.8	30.9	14.6	6.61	-1.35	-4.13	-2.51
Nucleus+ k NN-MT	66.6	20.3	29.0	31.7	16.6	12.9	-1.60	-3.61	-2.49
+Static	64.0	20.5	28.9	31.5	16.8	12.9	-1.56	-3.65	-2.46
+Adaptive	64.0	20.6	28.8	31.5	16.9	13.2	-1.57	-3.65	-2.46
+Randomize	74.8	20.3	28.7	31.4	14.6	8.71	-1.50	-4.16	-2.59

Table 2: Domain adaptation in Japanese-English: We report averages of four domains.

Reference. In Ja-En, the proposed methods improved DP like in De-En without any Merged-BLEU@40 loss.⁷ The PLL of the proposed methods is also comparable to Baseline.

We observed almost no substantial differences for the perturbation types. +Static requires prior estimation on distance metrics, and +Adaptive needs an additional k NN search for each time step for the inferences. Therefore, +Randomize is the best choice since it overcomes both drawbacks.

These results indicate that the proposed methods improved the diversity without lowering the fluency and maintained oracle translation quality on some domains.

Trade-off between quality and diversity We observed our proposed methods suffered from a quality-diversity trade-off (Ippolito et al., 2019;

⁷We also evaluate the oracle BLEU for 40 candidates (BLEU@40) to compare to MergedBLEU@40, and the results are in Appendix C.1.

Zhang et al., 2021), i.e., our methods improve diversity (DP) but decrease average translation quality (RefBLEU). However, all of our proposed DBS- and Nucleus-based methods outperformed the DEQ of DBS and Nucleus.⁸ Thus, our methods achieved better quality-diversity trade-offs than the existing methods.

4.2.2 General domain

Table 3 summarizes the general-domain results obtained by averaging the metrics across the language pairs. Detailed results are shown in Appendix B.

The proposed DBS+ and Nucleus+ k NN-MT slightly improved DP, and the MergedBLEU@40 and fluency are comparable to DBS and Nucleus. The effect of stochastic perturbations for DP was limited, especially on Nucleus-based, but +Uniquify substantially improved DP, and Merged-BLEU@40 and fluency preserved comparable re-

⁸ k NN-MT is not comparable to our methods because the base of the DEQ is k NN-MT.

Method	Diversity DP \uparrow	Translation Quality (BLEU \uparrow)				Both DEQ \uparrow	Fluency (PLL \uparrow)		
		@1	@20	Merged@40	Ref		Max	Min	Mean
Reference	-	-	-	-	-	-	-	-	-2.83
Baseline	37.5	30.2	41.2	41.2	27.6	1.24	-1.94	-3.85	-2.77
DBS	51.3	28.9	37.9	43.1	24.3	3.97	-1.78	-4.04	-2.78
Nucleus	62.8	29.2	40.4	44.2	23.7	6.16	-1.78	-3.99	-2.76
<i>k</i> NN-MT	37.3	30.5	41.4	42.6	27.8	-	-1.92	-3.85	-2.76
DBS+ <i>k</i> NN-MT	52.6	29.1	38.2	43.4	24.2	4.22	-1.70	-4.09	-2.76
+Static	54.8	29.0	38.3	43.4	23.8	4.38	-1.66	-4.16	-2.75
+Adaptive	54.3	29.0	38.3	43.4	23.9	4.34	-1.67	-4.15	-2.75
+Randomize	53.9	29.0	38.2	43.4	23.9	4.29	-1.66	-4.14	-2.75
+Uniquify	54.9	28.8	37.8	43.2	23.5	4.08	-1.69	-4.18	-2.78
+Static	55.9	28.8	37.7	43.1	23.3	4.09	-1.65	-4.24	-2.77
+Adaptive	55.7	28.8	37.8	43.2	23.3	4.10	-1.65	-4.22	-2.78
+Randomize	55.8	28.8	37.7	43.2	23.3	4.09	-1.64	-4.25	-2.78
Nucleus+ <i>k</i> NN-MT	64.5	29.1	40.5	44.3	23.5	6.22	-1.73	-4.02	-2.75
+Static	52.4	30.2	38.9	43.4	25.8	7.25	-1.85	-3.80	-2.73
+Adaptive	52.8	30.0	38.9	43.4	25.5	6.75	-1.86	-3.83	-2.74
+Randomize	62.3	29.8	38.9	43.5	23.4	5.64	-1.76	-4.13	-2.77
+Uniquify	70.8	28.0	39.3	44.0	21.0	4.88	-1.70	-4.16	-2.78
+Static	55.4	29.8	38.7	43.3	24.9	6.09	-1.84	-3.88	-2.75
+Adaptive	55.7	29.9	38.7	43.4	24.8	6.05	-1.84	-3.92	-2.76
+Randomize	67.7	29.5	38.4	43.3	21.6	4.86	-1.75	-4.44	-2.84

Table 3: General domain: We report averages of three language pairs.

sults. As in the domain-adaptation setting, the DEQ of our methods outperformed existing methods.

These experiments show that the proposed methods achieve better quality-diversity trade-offs without any fluency loss.

5 Analysis

5.1 Tuning *k*NN Diversified Decoding

We investigated how the hyperparameters of our proposed method affect its performance. Figure 2 shows the relationship between DP and BLEU@20 in the De-En IT domain.⁹ The results show that +Randomize outperformed the diversity of DBS+*k*NN-MT while maintaining oracle translation quality with some hyperparameters, indicating that our proposed method can adjust DP and BLEU by varying the magnitude of the perturbation.¹⁰

5.2 Overcorrection Analysis

We hypothesized that the overcorrection problem discourages the generation of diverse candidates that is alleviated by our proposed methods. To verify the hypothesis, we evaluated how well our

⁹For DBS and DBS+*k*NN-MT, we varied DBS’s diversity strength by 0.1 in the range of [1.5, 2.0]. For +Randomize, we used 1.5 for diversity strength and varied perturbation’s magnitude h by 0.1 in the range of [1.5, 2.5].

¹⁰Further analysis of the relationship between the hyperparameters and DP/BLEU of our methods is in Appendix C.2.

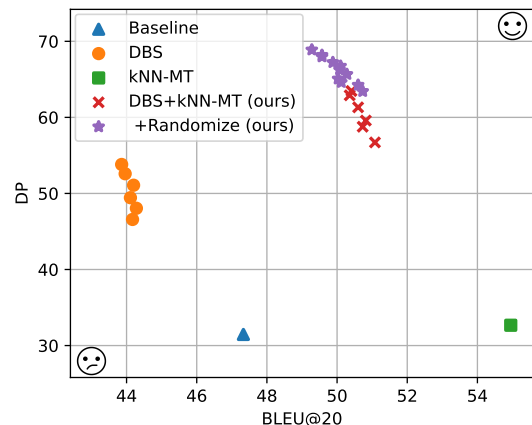


Figure 2: Relationship between translation quality (BLEU@20) and diversity (DP) in De-En IT domain: Top-right is most desirable.

methods mitigate the overcorrection problem and clarified the relationship between overcorrection and diversity.

Overcorrection is a phenomenon in which the likelihoods of valid translations are underestimated by a model. Therefore, a model that suffers less from the issue will assign a similar likelihood to valid translations that only have small differences. Thus, we propose a mean of the absolute difference in the log-likelihoods (MADLL) of two reference translations as a metric that quantifies the degree of overcorrection, in which a lower MADLL value implies a decreased likelihood of suffering from

	MADLL ↓	DP ↑	BLEU@1 ↑	BLEU@20 ↑
WMT'21 (newstest2021)				
Baseline	0.695	41.0	29.5 / 36.0	38.2 / 45.4
k NN-MT	0.683	41.1	30.1 / 36.8	38.7 / 45.8
+Uniq	0.657	43.6	29.6 / 36.2	38.0 / 45.5
+Rand	0.660	43.9	29.6 / 36.3	37.8 / 44.7
WMT'22 (generaltest2022)				
Baseline	0.712	42.2	30.3 / 34.5	38.3 / 43.1
k NN-MT	0.714	42.3	30.6 / 35.0	38.6 / 43.5
+Uniq	0.696	44.9	30.5 / 34.7	38.2 / 42.9
+Rand	0.702	45.2	30.5 / 34.7	38.0 / 42.5

Table 4: Overcorrection analysis on newstest2021 and generaltest2022 in De-En: MADLL is an indicator where a lower score denotes less likely to suffer from overcorrection. DP and BLEUs are scores when DBS is used as the decoding method. BLEU is written in the form of scores for refA/refB. Uniq and Rand are abbreviations for Uniquify and Randomize, respectively.

overcorrection issue.¹¹ We evaluated the proposed methods on the test data of WMT'21 De-En (newstest2021) and WMT'22 De-En (generaltest2022) in the De-En general-domain setting. These test data have two reference translations (refA/refB) for one source sentence, and we report the MADLL between refA and refB by forced decoding.

Table 4 shows the relationship between overcorrection, diversity, and translation quality. The proposed methods have lower MADLL and higher DP scores than Baseline and k NN-MT for both WMT'21 and WMT'22. We also found that BLEUs of the Baseline and k NN-MT are almost comparable to the proposed methods. This implies that the proposed methods managed to resolve overcorrection and improved diversity while almost maintaining the translation quality.

5.3 Counting Distinct n -grams

In §4, we used DP as a diversity metric. DP captures how many unique n -grams are included in each candidate. In order to evaluate the diversity of translation candidates of our proposed methods from a different perspective, we employed another metric: the number of distinct n -grams, which measures the richness of vocabulary and phrases across the entire N -best list. We calculated the ratio of the number of distinct n -grams to the total number of n -grams for $n \in \{1, 2, 3, 4\}$.

¹¹We report MADLL along with BLEU because it is easy to improve only MADLL but hard to improve both (if the model assigns the same likelihood to all sentences, MADLL will be zero, but BLEU will be substantially affected).

Method	Ratio of distinct n -grams (%) ↑			
	$n = 1$	$n = 2$	$n = 3$	$n = 4$
Baseline	1.6	7.8	14.1	18.5
DBS	1.6	8.8	16.9	22.2
DBS+ k NN-MT	1.7	9.7	18.6	24.8
+Randomize	2.1	12.4	24.7	33.4
Nucleus	2.0	11.1	23.1	32.8
Nucleus+ k NN-MT	1.9	11.9	25.9	37.1
+Randomize	2.6	16.0	32.2	42.8

Table 5: The ratio of the number of distinct n -grams to the total number of n -grams in German-English domain adaptation setting: We report averages of five domains.

#neighbors	h	$[h \times k]$	DP ↑	BLEU@1 ↑	BLEU@20 ↑
(1) DBS+ k NN-MT+Randomize					
64	2	128	57.1	41.5	50.8
64	3	192	62.3	39.3	50.0
64	4	256	65.6	38.1	49.3
(2) DBS+ k NN-MT					
128	-	-	44.2	43.9	51.1
192	-	-	44.1	43.9	51.3
256	-	-	44.2	43.9	51.1

Table 6: Effectiveness of *Randomize* on De-En IT domain based on DBS+ k NN-MT: We compared (1) randomize k from $[h \times k]$ neighbors and (2) set number of neighbors per query to $[h \times k]$.

The ratio averages in the De-En domain adaptation setting are shown in Table 5. DBS+ and Nucleus+ k NN-MT increased the ratio of the number of distinct n -grams more than DBS and Nucleus; the ratio increased substantially when perturbation was applied to it. The results show that our proposed methods generate translation candidates with more diverse vocabulary and phrases compared to the baselines.

5.4 Effectiveness of Randomization

We conducted an ablation study to investigate the effectiveness of *Randomize* on the Randomized- k NN. In the Randomized- k NN, the search space is stochastically expanded by uniformly and randomly sampling k from $[h \times k]$ neighbors to diversify the translations. We compared the following two methods to investigate the effectiveness of *Randomize*: (1) randomizing k from $[h \times k]$ neighbors with DBS+ k NN-MT, i.e., DBS+ k NN-MT+Randomize, and (2) retrieving $[h \times k]$ neighbors without randomizing on DBS+ k NN-MT i.e., setting the number of neighbors per query of DBS+ k NN-MT to $[h \times k]$.

A comparison for the De-En IT domain is pre-

Test Input: コロナに関しまして。 Reference: <i>I have a question about COVID.</i>	
DBS+kNN-MT+Randomize	DBS+kNN-MT
<i>About corona.</i>	<i>Regarding corona.</i>
<i>With regards to corona.</i>	<i>About corona.</i>
<i>About COVID-19.</i>	<i>It is about corona.</i>
<i>Regarding corona.</i>	<i>We are talking about corona.</i>
<i>With regards to COVID-19.</i>	<i>With regards to corona.</i>
⋮	⋮
Test Input: <i>Spring Summer</i> コレクションもセール対象商品! Reference: <i>The spring/summer collection is also included in the sale!</i>	
DBS+kNN-MT+Randomize	DBS
<i>The Spring Summer collection is also a sale target product!</i>	<i>The Spring Summer collection is also a sale target product!</i>
<i>Items from the Spring Summer collection are also on sale!</i>	<i>The Spring Summer collection is also a sale item!</i>
<i>The Spring Summer collection is also a sale target product!</i>	<i>The Spring Summer collection is also a sale eligible product!</i>
⋮	⋮
<i>winter collection is also a sale target product!</i>	<i>Our Spring Summer collections are on sale!</i>
<i>The Spring Summer collection is also eligible for sale.</i>	<i>The Spring Summer collection is also eligible for sale!</i>
<i>Summer collection is also a sale target product!</i>	<i>The Spring Summer Collection is also included in the sale!</i>

Figure 3: Example 20-best lists using DBS-based methods: In upper example, DBS+kNN-MT+Randomize successfully diversified list by adding a likely word, *COVID-19*, which did not appear in DBS+kNN-MT. In lower example, DBS+kNN-MT+Randomize introduced an unlikely word, *winter*, which did not appear in DBS.

sented in Table 6, where simply increasing the number of neighbors per query of DBS+kNN-MT did not improve diversity. *Randomize* from more neighbors is important for improving diversity.

5.5 Case Study

To better understand our proposed method through case studies, Figure 3 shows two qualitative examples in the general domain of Ja-En. We omitted some parts for brevity, and a full version is shown in Figure 5 in Appendix C.3.

In the upper example, Randomized- k NN improved the diversity of the candidates, which include the appropriate word *COVID-19*. This candidate never appeared in the 20-best list generated by DBS+kNN-MT, suggesting that considering more likely tokens by +Randomize with a broader search space improves diversity and maintains translation quality.

The example at the bottom shows increased diversity but also decreased translation quality, where translation *winter* is output for *spring/summer*, which does not appear in the DBS-generated candidates. Such antonyms as *winter*, *spring*, and *summer* tend to appear in the neighbors of word embedding space (Mrkšić et al., 2016), which is the primary cause of incorrect retrieval from the datastore in the broader k NN search space. We leave it as our future work of addressing the prob-

lem of retrieving unlikely words by a stochastically expanded k NN search.

6 Conclusion

We proposed methods to generate more diverse translation candidates by expanding the search space of k NN-MT. We experimentally showed that our proposed methods alleviated the overcorrection problem and outperformed the existing baselines in diversity, and also controlled the diversity and translation quality by changing the perturbation’s magnitude.

Limitations

Our proposed method improves diversity by utilizing k NN-MT. Unfortunately, k NN-MT suffers from the drawbacks of high inference latency for k NN searches and requires much memory to load the datastore. Our proposed method is applicable not only to vanilla- k NN but also to many other variants; if a model is proposed in the future that solves these issues, we can combine our method with new k NN-MT variants to overcome these drawbacks.

Although our proposed method improves diversity, it might generate hallucinations, which are incorrect but fluent translations. This problem can be alleviated by filtering hallucinations by post-processing, an approach we leave for the future.

We also might need to consider the trade-off

between diversity and quality depending on downstream applications, as in a number of experiments.

We showed the effectiveness of our proposed methods by evaluating the diversity and oracle translation quality, but the benefit in end-applications remains unclear. Li and Jurafsky (2016) implied that the higher diversity of translation candidates promotes the higher translation quality after reranking. Thus, the benefit in downstream applications can be shown by measuring the performance after using a reranking method such as quality-aware decoding (Fernandes et al., 2022).

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Corpus	Src-Tgt	#train	$ \mathcal{D} $	#test
Domain Adaptation				
Koran		14,979	450K	2,000
IT		177,795	3.10M	2,000
Medical	De-En	206,804	5.70M	2,000
Law		447,701	18.4M	2,000
Subtitles		12,409,630	154M	2,000
ASPEC		2,000,000	68.3M	1,812
KFTT	Ja-En	440,288	15.2M	1,160
TED talk		223,108	5.24M	1,285
BSD		20,000	256K	2,120
General Domain				
WMT'19	De-En	32,278,623	916M	2,000
WMT'22	Ja-En	32,104,268	874M	2,008
WMT'22	Uk-Cs	12,621,881	192M	2,812

Table 7: Statistics of dataset

A Detailed Experimental Settings

A.1 Statistics of Dataset

Table 7 shows the dataset’s statistics. $|\mathcal{D}|$ is the size of the datastore (identical to the number of target-side tokens of the training data). #train and #test are the number of sentences in the training and the test data.

A.2 Model Settings

Table 11 shows the hyperparameters we used in the experiments.

Nucleus sampling We tuned hyperparameter p from $p \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95\}$ based on the validation data.

k NN-MT We used squared-L2 distance as a distance function. For efficiency, we quantized the datastore with IVFPQ and we set the code size to 64. We used the 1024-dimensional representation input to the final layer feedforward network as the key. For the domain adaptation settings, we used 1M keys with 4096 clusters. For the general-domain settings, we used 5M keys with 65536 clusters. For inference, neighbors were searched from the nearest 32 clusters in the datastore. For the De-En domain adaptation setting, we used the same settings as Khandelwal et al. (2021) for k , λ , and τ . For the Ja-En domain adaptation setting, we used the same k as Khandelwal et al. (2021) and tuned λ and τ from $\lambda \in \{0.1, 0.2, \dots, 0.9\}$, $\tau \in \{10, 100, 1000\}$ with validation data. For the general-domain settings, we tuned hyperparameters k , λ , and τ from $k \in \{16, 32, 64, 128\}$, $\lambda \in \{0.1, 0.2, \dots, 0.9\}$, $\tau \in \{10, 100, 1000\}$ with

validation data.

Proposed method For the DBS+* settings, we used the same parameters as the baseline. We tuned p from $p \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95\}$ for Nucleus+* settings without +Perturbation and from $p \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ for setting with +Perturbation. For the +Static settings, we computed the mean d_m and standard deviation d_s of the distance to the nearest neighbors on the validation data in advance, and set $h_m = h'_m \times d_m$ and $h_s = h'_s \times d_s$, where h'_m and h'_s are tuned parameters from $h'_m \in \{0.025, 0.05, 0.1, 0.2, 0.4, 0.8\}$ and $h'_s \in \{0.025, 0.05, 0.1, 0.2, 0.4, 0.8\}$ on the validation data. For the +Adaptive settings, we tuned the hyperparameter from $h'_m \in \{0.025, 0.05, 0.1, 0.2, 0.4, 0.8\}$, $h'_s \in \{0.025, 0.05, 0.1, 0.2, 0.4, 0.8\}$. For the +Randomize settings, we tuned the hyperparameters from $h \in \{1.1, 1.2, \dots, 4.0\}$. Note that the hyperparameters for + k NN-MT, such as k , λ , and τ , on the proposed methods are identical to the standard k NN-MT.

A.3 Metric Settings

The detailed metric settings are as follows:

BLEU is calculated with sacrebleu (Post, 2018). The signature for the corpus-wise BLEU is `nrefs:1|case:mixed|eff:no|tok:13a|smooth:none|version:2.2.1`, and for the sentence-level BLEU is `nrefs:1|case:mixed|eff:yes|tok:13a|smooth:add-k[1.00]|version:2.2.1`.

MedBLEU is the corpus-wise BLEU score computed by the median sentence-level BLEU score for each N -best candidates. When N is even, we selected the sentence with the highest sentence-level BLEU between the two sentences in the middle.

PLL is a metric of the fluency and is computed for sentence $\mathbf{y} = (w_1, \dots, w_{|\mathbf{y}|})$:

$$\text{PLL}(\mathbf{y}) = \sum_{t=1}^{|\mathbf{y}|} \log P_{\text{MLM}}(w_t | \mathbf{y}_{\setminus t}), \quad (7)$$

where $\mathbf{y}_{\setminus t}$ is a sentence with masked token w_t at time step t and $P_{\text{MLM}}(w_t | \mathbf{y}_{\setminus t})$ is the probability that the MLM model predicts original token w_t from masked sentence $\mathbf{y}_{\setminus t}$.

DP is formally defined for N -best candidates for source sentence set \mathcal{X} as $\mathbb{H} = \{\mathbf{H}_1, \dots, \mathbf{H}_N\}$, where $\mathbf{H}_n = \{\hat{\mathbf{y}}_1^n, \dots, \hat{\mathbf{y}}_M^n\}$, is calculated as follows:

$$\text{DP}(\mathbb{H}) = \frac{1}{N(N-1)} \times \sum_{\mathbf{H} \in \mathbb{H}} \sum_{\mathbf{H}' \in \mathbb{H}, \mathbf{H}' \neq \mathbf{H}} 1 - \text{BLEU}(\mathbf{H}, \mathbf{H}'). \quad (8)$$

Note that $\text{BLEU}(\mathbf{H}, \mathbf{H}')$ is the corpus-wise BLEU of hypothesis \mathbf{H} for reference \mathbf{H}' .

We also used the following metrics to further evaluate the proposed methods in detail. The results are in Appendix B.

MeanLen is the mean sentence length ratio of the candidates to the reference translations. The closer this metric is to 1, indicating that the model outputs sentences of more appropriate length.

COMET@N is the system-level COMET (Rei et al., 2020) score computed by the largest sentence-level COMET score for each N -best candidates. We use wmt22-comet-da model¹² for evaluation, and report COMET@1 and COMET@20 in our experiment.

BERTScore@N is the system-level BERTScore (Zhang et al., 2020) computed by the largest sentence-level BERTScore for each N -best candidates. We report BERTScore@1 and BERTScore@20 in our experiment. The hashcode for BERTScore is roberta-large_L17_idf_version=0.3.12 (hug_trans=4.22.2)-rescaled.

Speed is the inference speed (tokens/s) logged by fairseq when using a single GPU (GeForce RTX 3090).

B Detailed Results

The results for each domain of the De-En domain adaptation setting are shown in Table 12 to Table 16. The results for each domain of the Ja-En domain adaptation setting are shown in Table 17 to Table 20. The results for each language pair of the general-domain setting are shown in Table 21 to Table 23.

¹²<https://huggingface.co/Unbabel/wmt22-comet-da>

Method	DP	BLEU		
		@20	@40	Mrg@40
Baseline	31.4	42.6	44.4	-
DBS	35.9	40.0	41.6	43.8
Nucleus	48.0	42.1	43.7	44.6
k NN-MT	32.3	51.8	53.6	53.5
DBS+ k NN-MT	42.0	48.6	-	51.8
+Static	55.2	49.0	-	52.0
+Adaptive	53.7	49.0	-	52.1
+Randomize	54.4	48.4	-	51.5
Nucleus+ k NN-MT	51.6	50.4	-	52.8
+Static	55.0	49.9	-	52.5
+Adaptive	55.6	49.8	-	52.4
+Randomize	59.4	49.2	-	52.0

Table 8: Ablation study for MergedBLEU@40 in the De-En domain adaptation setting: DP, BLEU@20 and MergedBLEU@40 are the scores when beam size is set to 20, and BLEU@40 is the score when beam size is set to 40. We report averages of five domains.

C Further Analysis

C.1 Ablation Study for MergedBLEU@N

In §4, we evaluated MergedBLEU@40, the oracle translation quality when merged with Baseline, and showed that the proposed methods’ MergedBLEU@40 are comparable to baselines (Baseline, DBS, Nucleus and k NN-MT) in the Ja-En domain adaptation and general-domain settings. However, it is not obvious whether the proposed methods’ MergedBLEU@40 is also comparable to the oracle quality of baselines with a larger beam size. Thus, we conducted an ablation study.

Tables 8, 9, and 10 show the oracle BLEU results for the 40-best (BLEU@40) when the baselines’ beam size are set to 40.¹³ We found that the MergedBLEU@40 of our proposed methods even shows comparable performance to BLEU@40 of baselines in the Ja-En domain adaptation (Table 9) and general-domain (Table 10) settings. These results support our hypothesis that our diversified methods generate high-quality candidates.

C.2 Tuning k NN Diversified Decoding

Figure 4 shows the relationship of the magnitude of the perturbation against DP and BLEU of DBS+ k NN-MT+Perturbation in the De-En IT domain. This result shows the trade-off between the DP and the BLEUs for all the perturbation types, indicating that the proposed methods adjust the diversity and the translation quality by varying the

¹³For evaluating BLEU@40, we used the same hyperparameters as in §4 and Appendix A.2 except for beam size.

Method	DP	BLEU		
		@20	@40	Mrg@40
Baseline	38.0	26.0	28.2	-
DBS	54.9	24.8	26.9	28.2
Nucleus	63.9	26.5	28.4	28.9
k NN-MT	37.4	29.7	31.8	31.5
DBS+ k NN-MT	60.7	27.9	-	30.9
+Static	66.5	28.3	-	31.3
+Adaptive	66.8	28.4	-	31.3
+Randomize	65.9	27.8	-	30.9
Nucleus+ k NN-MT	66.6	29.0	-	31.7
+Static	64.0	28.9	-	31.5
+Adaptive	64.0	28.8	-	31.5
+Randomize	74.8	28.7	-	31.4

Table 9: Ablation study for MergedBLEU@40 in the Ja-En domain adaptation setting: DP, BLEU@20 and MergedBLEU@40 are the scores when beam size is set to 20, and BLEU@40 is the score when beam size is set to 40. We report averages of four domains.

Method	DP	BLEU		
		@20	@40	Mrg@40
Baseline	37.5	41.2	43.9	-
DBS	51.3	37.9	40.2	43.1
Nucleus	62.8	40.4	43.1	44.2
k NN-MT	37.3	41.4	44.0	42.6
DBS+ k NN-MT	52.6	38.2	-	43.4
+Static	54.8	38.3	-	43.4
+Adaptive	54.3	38.3	-	43.4
+Randomize	53.9	38.2	-	43.4
+Uniquify	54.9	37.8	-	43.2
+Static	55.9	37.7	-	43.1
+Adaptive	55.7	37.8	-	43.2
+Randomize	55.8	37.7	-	43.2
Nucleus+ k NN-MT	64.5	40.5	-	44.3
+Static	52.4	38.9	-	43.4
+Adaptive	52.8	38.9	-	43.4
+Randomize	62.3	38.9	-	43.5
+Uniquify	70.8	39.3	-	44.0
+Static	55.4	38.7	-	43.3
+Adaptive	55.7	38.7	-	43.4
+Randomize	67.7	38.4	-	43.3

Table 10: Ablation study for MergedBLEU@40 in the general-domain setting: DP, BLEU@20 and MergedBLEU@40 are the scores when beam size is set to 20, and BLEU@40 is the score when beam size is set to 40. We report averages of three language pairs.

perturbation’s magnitude. The effect of temperature τ on k NN probability of DBS+ k NN-MT is also shown in Figure 4 (d). Both DP and BLEU peak around τ from 1 to 10. Unlike the perturbation’s magnitude, we found no trade-off between DP and BLEU for the temperature adjustment.

C.3 Detailed Quantitative Analysis

Figure 5 shows a detailed quantitative analysis.

D Used Data, Model, and Software

D.1 Data

De-En domain adaptation parallel corpora

created by Koehn and Knowles (2017) based on OPUS (Tiedemann, 2012). License: allowed for research purpose use.

The Asian Scientific Paper Excerpt Corpus

created by Nakazawa et al. (2016). License: <https://jipsti.jst.go.jp/aspec/>.

The Kyoto Free Translation Task

created by Neubig (2011). Download: <http://www.phontron.com/kftt/index.html>, License: CC BY-SA 3.0.

Ted talks

created by Cettolo et al. (2012). Download: <https://wit3.fbk.eu/>, License: CC BY-NC-ND.

The Business Scene Dialogue corpus

created by Rikters et al. (2019), Download: <https://github.com/tsuruoka-lab/BSD>, License: CC BY-NC-SA.

WMT’19 news translation task

created by Barrault et al. (2019), Download: <https://www.statmt.org/wmt19/translation-task.html>, License: allowed for research purpose use.

WMT’21 news translation task

created by Akhbardeh et al. (2021), Download: <https://www.statmt.org/wmt21/translation-task.html>, License: allowed for research purpose use.

WMT’22 general translation task

created by Kocmi et al. (2022), Download: <https://www.statmt.org/wmt22/translation-task.html>, License: allowed for research purpose use.

JParaCrawl v3.0

created by Morishita et al. (2022). Download: <http://www.kecl.ntt.co.jp/icl/lirg/jparacrawl/>, License: allowed for research purpose use.

D.2 Model

WMT’19 De-En pre-trained model

trained by Ng et al. (2019). Download: <https://github.com/facebookresearch/fairseq/tree/main/examples/wmt19>, License: MIT.

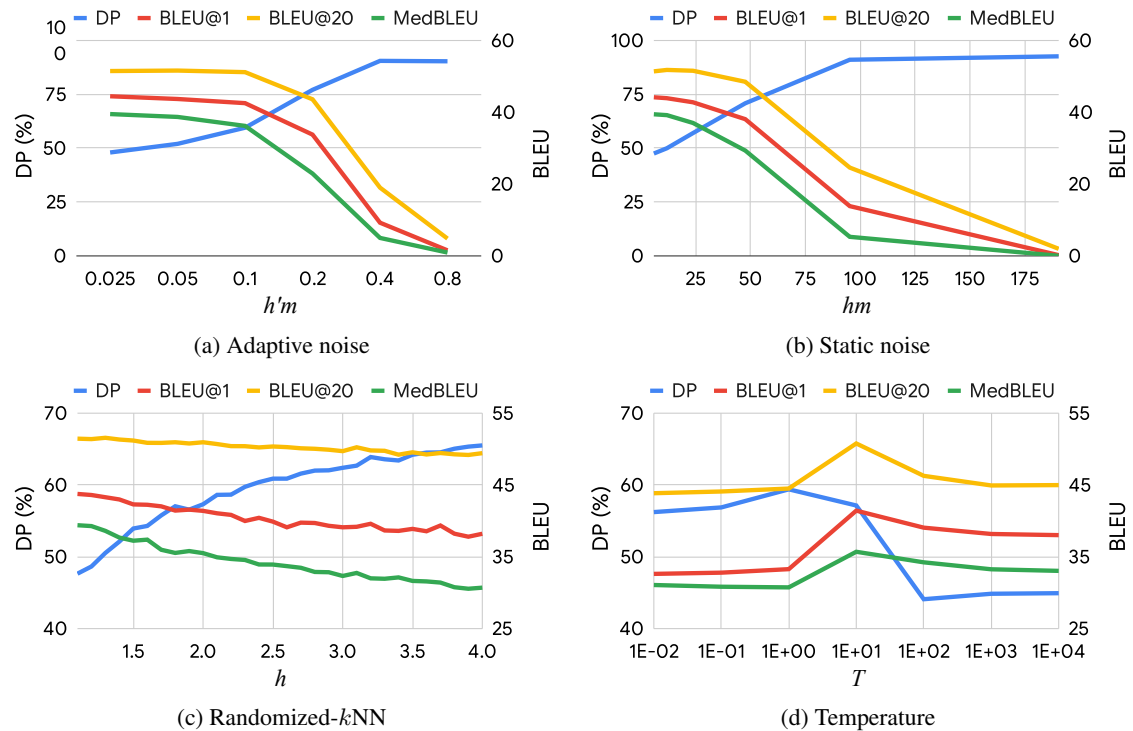


Figure 4: Relationship among perturbation’s magnitudes or temperature and DP/BLEU on the De-En IT domain

D.3 Software

fairseq created by Ott et al. (2019). Download: <https://github.com/facebookresearch/fairseq>, License: MIT.

FAISS created by Johnson et al. (2019). Download: <https://github.com/facebookresearch/faiss>, License: MIT.

sacreBLEU created by Post (2018). Download: <https://github.com/mjpost/sacrebleu>, License: Apache License 2.0.

COMET created by Rei et al. (2020). Download: <https://github.com/Unbabel/COMET>, License: Apache License 2.0.

BERTScore created by Zhang et al. (2020). Download: https://github.com/Tiiiger/bert_score, License: MIT.

Hyperparameters	De-En Domain Adaptation					Ja-En Domain Adaptation				General Domain		
	Koran	IT	Medical	Law	Subtitles	ASPEC	KFTT	BSD	TED	De-En	Ja-En	Uk-Cs
Nucleus												
p	0.6	0.8	0.7	0.7	0.8	0.6	0.6	0.6	0.5	0.7	0.6	0.6
k NN-MT												
k	64	64	64	64	64	64	64	64	64	32	16	16
τ	100	10	10	10	10	100	100	10	100	100	100	100
λ	0.8	0.7	0.8	0.8	0.7	0.7	0.6	0.3	0.6	0.2	0.2	0.2
DBS+ k NN-MT+Static												
h_m	49.4	23.8	38.2	16.9	36	25.5	29.5	29	32	18.9	20.5	39.6
h_s	1.15	3.2	0.35	2	0.2	1	11.2	2.1	1.5	1.4	0.3	0.6
DBS+ k NN-MT+Adaptive												
h'_m	0.2	0.1	0.1	0.05	0.1	0.1	0.1	0.1	0.05	0.025	0.1	0.1
h'_s	0.1	0.05	0.1	0.05	0.05	0.025	0.8	0.05	0.8	0.8	0.1	0.8
DBS+ k NN-MT+Randomize												
h	2.9	2	2.7	3.2	3.1	3.2	3.7	3.8	1.4	3.7	3.9	3.4
Nucleus+ k NN-MT												
p	0.6	0.7	0.8	0.7	0.8	0.5	0.4	0.5	0.6	0.7	0.6	0.6
Nucleus+ k NN-MT+Static												
p	0.5	0.9	0.9	0.9	0.7	0.3	0.5	0.5	0.5	0.5	0.5	0.5
h_m	24.7	11.9	9.55	8.45	18	25.5	29.5	29	16	18.9	41	39.6
h_s	0.575	3.2	0.7	0.25	6.4	4	11.2	2.1	12	0.35	0.3	2.4
Nucleus+ k NN-MT+Adaptive												
p	0.5	0.9	0.9	0.9	0.7	0.3	0.5	0.5	0.5	0.5	0.5	0.5
h'_m	0.025	0.05	0.05	0.05	0.1	0.1	0.05	0.1	0.025	0.2	0.05	0.2
h'_s	0.4	0.05	0.2	0.025	0.8	0.8	0.025	0.05	0.025	0.05	0.05	0.2
Nucleus+ k NN-MT+Randomize												
p	0.5	0.9	0.9	0.9	0.9	0.5	0.7	0.7	0.5	0.7	0.7	0.5
h	1.3	1.3	1.5	1.1	1.1	1.8	1.1	1.5	1.6	3.4	1.4	4
DBS+ k NN-MT+Uniquify+Static												
h_m	-	-	-	-	-	-	-	-	-	9.45	5.125	19.8
h_s	-	-	-	-	-	-	-	-	-	0.175	0.6	2.4
DBS+ k NN-MT+Uniquify+Adaptive												
h'_m	-	-	-	-	-	-	-	-	-	0.05	0.025	0.05
h'_s	-	-	-	-	-	-	-	-	-	0.025	0.05	0.025
DBS+ k NN-MT+Uniquify+Randomize												
h	-	-	-	-	-	-	-	-	-	3.4	2.4	2.8
Nucleus+Uniquify+ k NN-MT												
p	-	-	-	-	-	-	-	-	-	0.7	0.5	0.7
Nucleus+Uniquify+ k NN-MT+Static												
p	-	-	-	-	-	-	-	-	-	0.5	0.5	0.5
h_m	-	-	-	-	-	-	-	-	-	37.8	20.5	39.6
h_s	-	-	-	-	-	-	-	-	-	1.4	0.15	2.4
Nucleus+Uniquify+ k NN-MT+Adaptive												
p	-	-	-	-	-	-	-	-	-	0.5	0.5	0.5
h'_m	-	-	-	-	-	-	-	-	-	0.4	0.1	0.1
h'_s	-	-	-	-	-	-	-	-	-	0.8	0.4	0.4
Nucleus+Uniquify+ k NN-MT+Randomize												
p	-	-	-	-	-	-	-	-	-	0.7	0.7	0.5
h	-	-	-	-	-	-	-	-	-	3.8	2.8	2.3

Table 11: Hyperparameters

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.95	-
Baseline	27.4	16.9	22.5	-	16.3	0.33	0.950	0.723	0.763	0.389	0.464	-2.08	-3.48	-2.73	897.2
DBS	39.4	17.0	22.4	24.3	15.5	2.94	0.937	0.720	0.763	0.392	0.465	-1.97	-3.74	-2.77	565.2
Nucleus	52.4	16.7	23.8	25.1	15.5	5.80	0.955	0.722	0.766	0.387	0.466	-2.03	-3.57	-2.76	519.4
<i>k</i> NN-MT	26.2	21.0	27.4	29.0	20.0	-	0.946	0.728	0.775	0.423	0.514	-2.01	-3.48	-2.69	86.8
DBS+ <i>k</i> NN-MT	47.2	20.5	27.0	28.8	17.9	10.22	0.945	0.723	0.775	0.424	0.511	-1.72	-3.84	-2.73	75.8
+Static	60.1	19.3	27.1	28.9	16.5	9.75	0.941	0.711	0.772	0.405	0.507	-1.54	-3.92	-2.69	55.6
+Adaptive	63.6	18.6	26.6	28.5	15.8	8.92	0.948	0.697	0.767	0.387	0.497	-1.55	-4.14	-2.76	37.6
+Randomize	55.9	19.5	26.7	28.4	16.7	8.92	0.953	0.718	0.773	0.411	0.505	-1.64	-3.86	-2.69	65.2
Nucleus+ <i>k</i> NN-MT	74.5	18.7	27.7	29.2	15.3	10.31	0.990	0.712	0.767	0.404	0.499	-1.86	-4.17	-2.91	50.8
+Static	65.9	20.6	27.7	29.3	16.7	11.95	0.987	0.725	0.772	0.425	0.507	-1.86	-4.15	-2.85	50.3
+Adaptive	63.3	20.5	27.1	28.8	16.9	12.18	0.986	0.725	0.770	0.424	0.503	-1.90	-4.09	-2.84	33.3
+Randomize	66.2	20.7	27.2	28.9	16.4	11.20	0.989	0.726	0.770	0.425	0.504	-1.87	-4.15	-2.86	49.5

Table 12: Koran domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-4.93	-
Baseline	31.5	37.7	47.3	-	34.0	-0.21	1.004	0.821	0.873	0.606	0.729	-2.96	-7.21	-4.87	874.8
DBS	35.2	37.1	44.2	48.5	33.9	0.41	0.998	0.821	0.861	0.606	0.696	-2.97	-7.05	-4.82	597.7
Nucleus	51.8	36.4	45.5	48.8	31.9	2.42	1.011	0.807	0.856	0.574	0.684	-3.09	-6.97	-4.90	487.1
<i>k</i> NN-MT	32.7	45.9	55.0	57.0	39.8	-	0.974	0.829	0.891	0.645	0.782	-2.94	-7.69	-5.04	59.5
DBS+ <i>k</i> NN-MT	44.6	43.9	50.9	55.4	37.4	4.94	0.975	0.815	0.874	0.617	0.735	-3.09	-7.60	-5.05	57.3
+Static	57.0	42.8	51.6	55.7	34.5	4.58	0.973	0.812	0.874	0.614	0.739	-2.92	-7.97	-5.07	48.9
+Adaptive	59.5	42.5	51.2	55.5	33.6	4.31	0.975	0.809	0.873	0.607	0.735	-2.89	-8.08	-5.10	32.2
+Randomize	57.1	41.5	50.8	55.4	33.5	3.85	0.972	0.808	0.871	0.606	0.730	-2.97	-7.92	-5.10	51.0
Nucleus+ <i>k</i> NN-MT	47.6	44.7	52.3	55.9	39.3	29.80	1.002	0.824	0.873	0.637	0.733	-3.55	-6.56	-4.95	42.5
+Static	61.3	45.2	52.1	55.8	33.9	4.81	1.025	0.822	0.875	0.634	0.740	-3.17	-7.54	-5.04	31.1
+Adaptive	61.7	45.0	52.0	55.7	33.9	4.85	1.027	0.822	0.875	0.632	0.741	-3.12	-7.57	-5.03	19.0
+Randomize	63.3	44.1	52.0	55.5	32.8	4.33	1.022	0.822	0.874	0.632	0.736	-3.12	-7.59	-5.07	34.3

Table 13: IT domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-3.24	-
Baseline	27.7	40.4	49.1	-	37.3	-0.15	0.946	0.832	0.858	0.643	0.711	-2.33	-4.23	-3.17	706.0
DBS	31.4	39.9	46.0	50.2	36.3	0.16	0.938	0.831	0.854	0.641	0.697	-2.26	-4.29	-3.15	401.2
Nucleus	39.2	40.0	48.6	50.9	37.1	0.82	0.950	0.825	0.853	0.630	0.694	-2.42	-4.10	-3.20	479.4
<i>k</i> NN-MT	29.5	55.4	63.0	64.4	48.8	0.00	0.928	0.847	0.875	0.707	0.776	-2.31	-4.59	-3.28	17.9
DBS+ <i>k</i> NN-MT	36.7	54.0	59.6	62.3	47.1	4.22	0.937	0.836	0.868	0.684	0.753	-2.31	-4.77	-3.31	15.7
+Static	55.8	50.6	59.3	61.9	40.6	3.20	0.934	0.830	0.867	0.669	0.752	-2.11	-5.50	-3.41	14.0
+Adaptive	49.2	52.9	60.3	62.9	43.6	3.78	0.934	0.833	0.868	0.677	0.755	-2.17	-5.20	-3.38	8.0
+Randomize	52.1	50.0	59.0	61.9	40.8	2.83	0.931	0.829	0.866	0.665	0.750	-2.21	-5.26	-3.40	14.6
Nucleus+ <i>k</i> NN-MT	41.4	55.1	61.9	63.8	48.4	30.56	0.965	0.844	0.872	0.703	0.763	-2.47	-4.27	-3.25	32.8
+Static	48.2	54.7	61.1	63.3	45.3	5.31	0.984	0.844	0.871	0.700	0.760	-2.40	-4.74	-3.31	26.5
+Adaptive	49.5	54.6	61.2	63.2	45.0	5.32	0.984	0.844	0.871	0.699	0.762	-2.36	-4.80	-3.32	15.1
+Randomize	53.9	54.0	60.3	62.5	42.5	3.89	0.983	0.843	0.870	0.696	0.757	-2.36	-4.89	-3.34	27.7

Table 14: Medical domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.57	-
Baseline	19.5	46.1	52.4	-	44.1	-0.01	0.963	0.854	0.873	0.675	0.731	-1.97	-3.17	-2.50	822.4
DBS	27.4	45.0	50.2	53.6	41.7	0.46	0.936	0.851	0.869	0.670	0.717	-2.00	-3.35	-2.58	428.1
Nucleus	43.2	44.7	52.9	54.8	41.2	1.35	0.957	0.850	0.873	0.665	0.730	-1.94	-3.22	-2.54	458.4
<i>k</i> NN-MT	19.6	61.9	68.8	69.9	58.6	-	0.977	0.871	0.891	0.757	0.818	-2.02	-3.27	-2.57	27.2
DBS+ <i>k</i> NN-MT	26.9	60.8	65.8	67.5	55.9	2.69	0.965	0.863	0.885	0.743	0.798	-2.06	-3.44	-2.64	26.1
+Static	33.8	60.0	66.6	68.1	54.6	3.56	0.964	0.862	0.887	0.739	0.802	-2.01	-3.55	-2.65	25.8
+Adaptive	31.7	60.6	66.5	68.0	55.2	3.55	0.964	0.864	0.887	0.743	0.802	-2.02	-3.53	-2.64	13.7
+Randomize	42.2	56.2	64.8	66.5	49.5	2.49	0.963	0.855	0.884	0.713	0.790	-1.99	-3.71	-2.69	25.5
Nucleus+ <i>k</i> NN-MT	31.3	61.3	68.2	69.3	57.8	14.43	0.992	0.867	0.887	0.751	0.807	-2.13	-3.08	-2.56	20.5
+Static	44.6	61.7	67.4	68.7	52.3	3.95	1.002	0.868	0.888	0.755	0.806	-2.03	-3.70	-2.65	17.9
+Adaptive	45.7	61.6	67.5	68.7	52.0	3.93	1.004	0.868	0.888	0.754	0.807	-2.03	-3.75	-2.65	9.4
+Randomize	45.6	61.4	66.9	68.2	51.4	3.62	1.001	0.867	0.886	0.750	0.801	-2.05	-3.73	-2.66	18.5

Table 15: Law domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-3.07	-
Baseline	51.0	29.3	41.7	-	23.0	-1.66	0.917	0.799	0.843	0.595	0.685	-1.98	-4.65	-3.12	1095.9
DBS	45.9	29.0	36.9	42.6	24.1	-14.20	0.923	0.797	0.833	0.593	0.660	-1.96	-4.74	-3.10	857.7
Nucleus	53.2	29.0	39.8	43.3	24.6	-14.33	0.935	0.798	0.837	0.593	0.668	-2.07	-4.25	-3.04	700.4
<i>k</i> NN-MT	53.6	31.7	45.1	47.1	24.6	-	0.911	0.801	0.851	0.606	0.709	-1.87	-4.65	-3.04	4.5
DBS+ <i>k</i> NN-MT	54.6	30.6	39.5	45.0	24.4	3.45	0.930	0.793	0.839	0.597	0.677	-1.70	-4.86	-3.02	4.4
+Static	69.5	29.5	40.4	45.4	21.1	4.53	0.933	0.787	0.840	0.586	0.680	-1.51	-5.19	-3.03	4.4
+Adaptive	64.4	30.4	40.5	45.6	22.7	5.63	0.932	0.790	0.841	0.594	0.683	-1.58	-5.09	-3.03	2.2
+Randomize	64.7	30.2	40.6	45.5	22.4	5.00	0.931	0.789	0.841	0.587	0.681	-1.56	-5.03	-3.02	4.4
Nucleus+ <i>k</i> NN-MT	63.1	30.6	42.2	45.9	24.4	36.54	0.941	0.797	0.843	0.601	0.688	-1.85	-4.39	-2.98	3.5
+Static	55.0	31.6	41.3	45.6	26.2	-0.87	0.935	0.799	0.840	0.606	0.683	-1.97	-4.23	-2.96	3.6
+Adaptive	57.9	31.2	41.2	45.5	25.6	-4.36	0.939	0.799	0.841	0.604	0.684	-1.93	-4.37	-2.98	1.8
+Randomize	68.0	31.3	39.8	45.0	22.1	5.76	0.967	0.798	0.837	0.603	0.676	-1.83	-5.12	-3.10	3.2

Table 16: Subtitles domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.90	-
Baseline	31.2	21.0	28.2	-	19.8	0.07	0.946	0.829	0.849	0.572	0.629	-1.86	-2.83	-2.31	914.3
DBS	50.1	19.5	27.4	30.6	17.0	3.12	0.904	0.826	0.850	0.563	0.629	-1.76	-3.24	-2.43	581.3
Nucleus	64.9	20.4	29.7	31.7	16.9	5.40	0.934	0.827	0.853	0.566	0.637	-1.66	-3.27	-2.40	591.7
<i>k</i> NN-MT	31.0	24.7	32.8	34.6	23.1	-	0.955	0.831	0.853	0.594	0.658	-1.86	-2.91	-2.33	8.2
DBS+ <i>k</i> NN-MT	58.6	22.9	31.3	34.0	18.3	5.67	0.895	0.827	0.854	0.583	0.656	-1.56	-3.44	-2.43	7.6
+Static	63.5	22.9	32.1	34.4	17.7	6.02	0.892	0.827	0.855	0.583	0.659	-1.51	-3.46	-2.42	7.8
+Adaptive	64.6	22.6	31.9	34.3	17.6	6.06	0.893	0.827	0.854	0.582	0.657	-1.51	-3.49	-2.42	4.1
+Randomize	62.2	22.4	31.3	33.9	17.6	5.65	0.897	0.826	0.853	0.579	0.652	-1.51	-3.44	-2.41	7.7
Nucleus+ <i>k</i> NN-MT	66.5	24.0	33.9	35.6	19.1	8.82	0.950	0.831	0.857	0.590	0.666	-1.63	-3.40	-2.43	6.8
+Static	49.9	24.0	32.2	34.6	21.0	8.89	0.958	0.830	0.853	0.592	0.654	-1.70	-3.08	-2.35	7.1
+Adaptive	53.4	24.0	32.1	34.6	20.4	8.23	0.960	0.830	0.853	0.589	0.653	-1.66	-3.18	-2.35	3.5
+Randomize	67.8	23.9	32.8	34.9	18.2	7.43	0.953	0.831	0.854	0.590	0.656	-1.64	-3.58	-2.47	6.4

Table 17: ASPEC domain in Japanese-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.75	-
Baseline	31.5	18.8	25.1	-	17.5	0.70	0.872	0.762	0.808	0.490	0.581	-1.88	-3.72	-2.70	758.0
DBS	52.9	18.3	24.4	27.3	15.4	4.39	0.826	0.761	0.810	0.489	0.577	-1.81	-4.08	-2.83	474.2
Nucleus	68.2	18.6	26.3	28.2	15.3	7.07	0.873	0.764	0.816	0.493	0.584	-1.85	-3.91	-2.82	444.8
<i>k</i> NN-MT	29.2	22.4	29.4	31.2	20.8	-	0.913	0.778	0.822	0.539	0.628	-1.79	-3.75	-2.59	20.5
DBS+ <i>k</i> NN-MT	55.3	21.9	29.0	30.9	18.1	9.81	0.870	0.778	0.827	0.537	0.627	-1.65	-4.28	-2.75	19.4
+Static	61.4	21.3	29.2	31.1	17.3	9.15	0.862	0.777	0.826	0.534	0.624	-1.58	-4.35	-2.74	20.8
+Adaptive	62.5	21.4	29.1	31.1	17.1	8.87	0.861	0.776	0.827	0.530	0.624	-1.55	-4.40	-2.74	11.5
+Randomize	59.8	21.1	28.5	30.5	17.0	8.01	0.866	0.773	0.825	0.524	0.619	-1.55	-4.21	-2.71	20.3
Nucleus+ <i>k</i> NN-MT	55.1	22.9	29.5	31.6	20.5	99.42	0.942	0.781	0.825	0.545	0.621	-1.93	-3.54	-2.69	18.4
+Static	68.3	22.6	30.3	32.0	18.4	16.28	0.950	0.778	0.828	0.539	0.627	-1.77	-4.02	-2.75	15.2
+Adaptive	65.1	22.6	30.2	31.9	19.1	21.20	0.947	0.780	0.828	0.542	0.628	-1.83	-3.94	-2.74	9.0
+Randomize	78.5	22.0	29.1	31.0	15.6	9.41	0.977	0.777	0.822	0.536	0.616	-1.73	-4.85	-2.97	13.3

Table 18: KFTT domain in Japanese-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.94	-
Baseline	37.5	12.8	18.5	-	11.8	0.37	0.888	0.772	0.814	0.462	0.544	-1.74	-3.75	-2.58	957.7
DBS	55.6	12.0	18.0	20.3	9.9	4.87	0.839	0.769	0.815	0.459	0.541	-1.56	-4.01	-2.62	592.9
Nucleus	57.4	12.4	19.2	20.9	11.1	7.64	0.898	0.772	0.815	0.459	0.538	-1.70	-3.66	-2.57	601.5
<i>k</i> NN-MT	36.8	15.0	21.5	22.7	13.8	-	0.913	0.775	0.818	0.485	0.564	-1.45	-3.17	-2.17	40.8
DBS+ <i>k</i> NN-MT	62.0	14.3	20.7	22.6	11.2	9.78	0.884	0.771	0.818	0.478	0.558	-1.06	-3.47	-2.15	35.7
+Static	67.0	14.1	21.0	23.0	10.6	9.49	0.873	0.767	0.817	0.474	0.558	-0.98	-3.45	-2.11	33.0
+Adaptive	64.7	14.1	21.2	23.1	10.9	9.78	0.879	0.769	0.817	0.474	0.558	-1.01	-3.43	-2.13	21.4
+Randomize	63.7	13.9	20.9	22.8	11.0	9.51	0.882	0.767	0.817	0.473	0.558	-0.99	-3.43	-2.12	34.6
Nucleus+ <i>k</i> NN-MT	84.1	13.0	21.8	23.3	9.5	11.10	0.982	0.765	0.813	0.463	0.543	-1.22	-3.76	-2.31	22.7
+Static	74.3	14.5	21.6	23.2	10.9	13.07	0.979	0.771	0.815	0.475	0.550	-1.21	-3.58	-2.22	24.0
+Adaptive	72.6	14.9	21.6	23.2	11.2	14.00	0.976	0.772	0.815	0.477	0.548	-1.26	-3.56	-2.23	15.5
+Randomize	75.3	14.9	21.6	23.3	10.9	13.07	0.982	0.771	0.816	0.476	0.552	-1.21	-3.61	-2.23	23.4

Table 19: TED talks domain in Japanese-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.42	-
Baseline	51.8	19.9	32.4	-	16.9	-0.98	0.985	0.812	0.868	0.551	0.677	-1.54	-4.38	-2.62	1020.1
DBS	60.8	19.0	29.6	34.7	15.2	3.12	0.970	0.808	0.862	0.544	0.656	-1.51	-4.34	-2.63	690.8
Nucleus	65.1	18.9	30.8	34.9	15.8	6.28	0.992	0.811	0.860	0.546	0.651	-1.56	-4.04	-2.59	657.1
<i>k</i> NN-MT	52.8	21.4	35.1	37.4	17.8	-	0.962	0.817	0.879	0.561	0.711	-1.49	-4.46	-2.62	65.6
DBS+ <i>k</i> NN-MT	67.0	19.9	30.7	36.2	14.7	4.55	0.941	0.807	0.869	0.548	0.678	-1.47	-4.88	-2.73	57.1
+Static	74.2	19.8	31.1	36.6	13.8	5.37	0.938	0.807	0.869	0.547	0.679	-1.39	-5.22	-2.76	56.0
+Adaptive	75.5	19.7	31.1	36.5	13.6	5.39	0.940	0.807	0.868	0.546	0.675	-1.38	-5.14	-2.75	43.1
+Randomize	77.8	19.2	30.6	36.3	12.8	4.97	0.933	0.803	0.868	0.541	0.672	-1.36	-5.43	-2.81	50.1
Nucleus+ <i>k</i> NN-MT	60.9	21.3	30.9	36.3	17.3	15.75	0.979	0.815	0.863	0.559	0.658	-1.60	-3.74	-2.52	63.8
+Static	63.5	20.8	31.4	36.3	17.0	13.30	0.984	0.814	0.863	0.556	0.661	-1.54	-3.90	-2.52	52.4
+Adaptive	65.0	21.0	31.3	36.4	16.7	11.11	0.987	0.815	0.862	0.557	0.659	-1.55	-3.92	-2.53	35.3
+Randomize	77.7	20.6	31.3	36.2	13.8	6.16	1.009	0.812	0.867	0.554	0.671	-1.43	-4.61	-2.69	43.8

Table 20: BSD domain in Japanese-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.93	-
Baseline	32.1	39.6	51.4	-	37.0	0.59	0.981	0.846	0.876	0.714	0.787	-2.18	-3.53	-2.80	1045.7
DBS	41.3	38.9	47.6	53.0	33.9	2.60	0.969	0.844	0.873	0.710	0.772	-2.09	-3.77	-2.84	720.7
Nucleus	55.1	38.1	50.6	54.2	32.5	4.60	0.986	0.847	0.874	0.712	0.782	-2.04	-3.67	-2.80	620.3
<i>k</i> NN-MT	31.7	40.6	52.2	52.9	37.6	-	0.986	0.847	0.877	0.719	0.788	-2.17	-3.51	-2.79	8.9
DBS+ <i>k</i> NN-MT	41.7	39.7	48.7	53.5	34.3	3.10	0.976	0.846	0.873	0.713	0.775	-2.03	-3.77	-2.82	9.0
+Static	42.7	39.7	48.6	53.4	34.3	3.30	0.979	0.844	0.873	0.713	0.774	-2.02	-3.78	-2.82	9.1
+Adaptive	41.9	39.6	48.7	53.5	34.3	3.07	0.977	0.845	0.873	0.713	0.774	-2.02	-3.78	-2.82	4.6
+Randomize	42.2	39.6	48.6	53.5	34.2	3.10	0.981	0.845	0.872	0.714	0.772	-1.99	-3.77	-2.81	8.9
+Uniquify	44.1	39.1	47.5	53.1	33.1	2.77	0.979	0.846	0.877	0.710	0.769	-1.99	-3.83	-2.83	8.9
+Static	44.5	39.1	47.7	53.1	33.1	2.85	0.982	0.847	0.872	0.710	0.768	-1.95	-3.86	-2.83	8.9
+Adaptive	44.3	39.1	47.7	53.1	33.1	2.83	0.981	0.845	0.877	0.711	0.768	-1.96	-3.87	-2.83	4.5
+Randomize	44.2	39.0	47.4	53.0	33.0	2.75	0.983	0.848	0.872	0.710	0.766	-1.95	-3.88	-2.83	8.9
Nucleus+ <i>k</i> NN-MT	57.1	38.8	51.1	54.5	32.5	4.97	0.992	0.845	0.871	0.711	0.783	-2.01	-3.68	-2.79	8.1
+Static	36.7	40.6	48.2	53.1	36.9	6.74	0.988	0.844	0.871	0.719	0.770	-2.22	-3.36	-2.77	8.5
+Adaptive	39.0	40.3	48.6	53.3	36.4	6.07	0.989	0.844	0.871	0.717	0.772	-2.19	-3.41	-2.77	4.2
+Randomize	55.0	40.3	49.1	53.4	32.4	4.50	0.997	0.845	0.870	0.717	0.775	-2.05	-3.79	-2.81	7.9
+Uniquify	66.1	37.0	49.1	53.8	28.8	3.90	0.996	0.843	0.874	0.704	0.775	-1.95	-3.87	-2.83	7.7
+Static	41.9	39.6	47.9	53.0	35.2	4.29	0.987	0.846	0.872	0.715	0.768	-2.19	-3.43	-2.79	8.6
+Adaptive	43.5	39.8	48.2	53.0	34.9	4.41	0.988	0.846	0.871	0.717	0.768	-2.18	-3.54	-2.80	4.2
+Randomize	62.7	39.6	48.1	53.1	29.2	3.67	1.010	0.845	0.871	0.712	0.769	-2.02	-4.22	-2.88	7.3

Table 21: General domain in German-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-3.17	-
Baseline	40.7	20.9	30.6	-	19.0	-5.75	0.895	0.792	0.846	0.534	0.646	-2.01	-4.59	-3.12	984.3
DBS	59.8	19.6	28.3	32.8	15.6	5.85	0.854	0.786	0.840	0.526	0.630	-1.76	-4.67	-3.07	638.8
Nucleus	71.1	20.4	30.6	33.9	15.5	8.85	0.906	0.785	0.839	0.527	0.634	-1.78	-4.67	-3.07	562.0
<i>k</i> NN-MT	40.5	20.8	30.5	31.9	18.9	-	0.898	0.789	0.844	0.529	0.643	-1.97	-4.57	-3.09	8.9
DBS+ <i>k</i> NN-MT	62.0	19.1	28.2	32.9	15.1	5.57	0.848	0.784	0.840	0.520	0.624	-1.62	-4.72	-3.03	9.2
+Static	64.0	19.3	28.2	32.9	14.8	5.70	0.845	0.783	0.840	0.519	0.625	-1.58	-4.73	-3.00	9.2
+Adaptive	64.4	19.2	28.3	32.9	14.7	5.73	0.846	0.782	0.840	0.519	0.626	-1.57	-4.75	-3.00	4.6
+Randomize	64.0	19.3	28.2	32.9	14.8	5.66	0.845	0.782	0.839	0.520	0.623	-1.59	-4.75	-3.01	9.1
+Uniquify	64.2	19.2	28.1	32.9	14.9	5.85	0.849	0.787	0.845	0.522	0.624	-1.63	-4.83	-3.05	9.1
+Static	65.1	19.3	28.1	32.8	14.7	5.76	0.847	0.787	0.840	0.523	0.623	-1.57	-4.84	-3.03	9.1
+Adaptive	65.1	19.1	28.1	32.9	14.6	5.73	0.845	0.784	0.843	0.521	0.622	-1.57	-4.83	-3.03	4.6
+Randomize	65.6	19.3	28.1	32.9	14.6	5.84	0.845	0.787	0.841	0.520	0.622	-1.56	-4.89	-3.03	9.1
Nucleus+ <i>k</i> NN-MT	73.1	19.8	30.4	33.8	15.1	8.42	0.907	0.785	0.840	0.518	0.630	-1.71	-4.71	-3.04	7.7
+Static	64.5	20.7	29.7	33.2	16.2	8.73	0.906	0.784	0.840	0.527	0.627	-1.78	-4.52	-3.02	8.0
+Adaptive	62.1	20.2	29.4	33.2	16.4	8.64	0.905	0.784	0.839	0.525	0.626	-1.85	-4.47	-3.03	4.0
+Randomize	77.7	19.9	28.9	33.2	13.3	6.65	0.924	0.782	0.839	0.524	0.623	-1.68	-5.11	-3.12	7.1
+Uniquify	69.0	20.2	30.7	34.0	15.8	9.11	0.907	0.787	0.844	0.524	0.634	-1.76	-4.56	-3.03	7.9
+Static	66.0	20.6	29.5	33.2	15.8	8.28	0.910	0.787	0.841	0.526	0.627	-1.81	-4.59	-3.06	7.8
+Adaptive	66.1	20.8	29.4	33.2	15.8	8.19	0.910	0.789	0.841	0.530	0.628	-1.81	-4.60	-3.06	3.9
+Randomize	82.4	19.8	28.4	32.9	12.0	6.08	0.946	0.784	0.837	0.518	0.616	-1.68	-5.50	-3.23	6.5

Table 22: General domain in Japanese-English

Method	DP	BLEU				DEQ	MLen	COMET		BERTScore		PLL			Speed
		@1	@20	Mrg	Ref			@1	@20	@1	@20	Max	Min	Mean	
Reference	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.40	-
Baseline	39.8	30.0	41.7	-	27.0	5.67	0.933	0.865	0.914	0.634	0.739	-1.62	-3.42	-2.40	974.0
DBS	52.8	28.2	37.8	43.6	23.4	3.64	0.916	0.853	0.911	0.624	0.713	-1.49	-3.68	-2.43	755.9
Nucleus	62.3	29.0	40.1	44.4	23.1	5.81	0.941	0.859	0.909	0.629	0.721	-1.50	-3.64	-2.42	669.7
<i>k</i> NN-MT	39.7	30.0	41.6	43.0	27.0	-	0.928	0.863	0.914	0.633	0.738	-1.61	-3.47	-2.41	21.0
DBS+ <i>k</i> NN-MT	54.0	28.5	37.9	43.8	23.2	3.79	0.912	0.853	0.910	0.625	0.713	-1.45	-3.78	-2.44	21.3
+Static	57.8	28.0	38.0	43.8	22.4	3.96	0.909	0.852	0.910	0.622	0.712	-1.39	-3.96	-2.44	21.8
+Adaptive	56.5	28.1	38.0	43.8	22.7	3.96	0.911	0.852	0.910	0.622	0.711	-1.42	-3.91	-2.44	11.0
+Randomize	55.7	28.1	37.8	43.7	22.9	3.89	0.911	0.852	0.910	0.623	0.711	-1.41	-3.89	-2.44	21.1
+Uniquify	56.3	28.3	37.7	43.6	22.6	3.78	0.915	0.858	0.913	0.621	0.709	-1.45	-3.89	-2.46	21.2
+Static	58.1	28.1	37.4	43.5	22.1	3.78	0.913	0.858	0.908	0.621	0.708	-1.41	-4.02	-2.47	21.2
+Adaptive	57.8	28.2	37.5	43.6	22.3	3.84	0.913	0.856	0.911	0.623	0.707	-1.41	-3.97	-2.46	10.9
+Randomize	57.8	28.2	37.5	43.6	22.2	3.79	0.912	0.859	0.910	0.621	0.707	-1.41	-3.98	-2.46	21.1
Nucleus+ <i>k</i> NN-MT	63.4	28.8	40.0	44.5	22.8	5.70	0.940	0.851	0.909	0.625	0.721	-1.47	-3.68	-2.41	18.1
+Static	55.9	29.4	39.0	43.9	24.2	5.91	0.942	0.852	0.909	0.632	0.715	-1.54	-3.53	-2.39	18.4
+Adaptive	57.4	29.5	38.8	43.8	23.8	5.53	0.943	0.852	0.910	0.630	0.713	-1.54	-3.62	-2.40	9.1
+Randomize	54.4	29.3	38.5	43.8	24.4	5.71	0.940	0.851	0.909	0.630	0.713	-1.56	-3.50	-2.39	18.0
+Uniquify	77.4	26.8	38.0	44.1	18.3	4.35	0.950	0.845	0.905	0.609	0.705	-1.38	-4.05	-2.47	17.2
+Static	58.2	29.1	38.6	43.8	23.5	5.36	0.944	0.857	0.909	0.628	0.713	-1.54	-3.62	-2.41	18.0
+Adaptive	57.6	29.1	38.6	43.9	23.7	5.37	0.944	0.855	0.909	0.626	0.712	-1.55	-3.63	-2.41	9.0
+Randomize	58.0	29.2	38.7	43.9	23.5	5.32	0.943	0.856	0.909	0.627	0.713	-1.54	-3.59	-2.40	17.9

Table 23: General Domain in Ukrainian-Czech

Test Input: コロナに関しまして。

Reference: *I have a question about COVID.*

DBS+kNN-MT+Randomize

About corona.
With regards to corona.
About COVID-19.
Regarding corona.
With regards to COVID-19.
We are talking about corona.
Now, about corona.
It is about corona.
Regarding corona.
About COVID-19..
Regarding COVID-19.
With regards to corona..
During the coronavirus pandemic.
Concerning corona.
About corona..
Now, regarding the coronavirus...
Was it a virus?
Regarding corona..
Concerning corona.
Regarding COVID-19..

DBS

Regarding corona.
About corona.
It is about corona.
We are talking about corona.
With regards to corona.
Regarding corona.
We are talking about corona.
It is about corona.
Regarding corona..
Related to corona.
About coronavirus.
It is about corona..
Regarding corona.
About the coronavirus.
Regarding corona..
About coronavirus.
Regarding corona.
About coronavirus..
Regarding coronavirus.
Regarding corona..

Test Input: Spring Summerコレクションもセール対象商品!

Reference: *The spring/summer collection is also included in the sale!*

DBS+kNN-MT+Randomize

The Spring Summer collection is also a sale target product!
Items from the Spring Summer collection are also on sale!
The Spring Summer collection is also a sale target product!
Summer collection is also on sale!
The Spring Summer collection is also included in the sale!
The Spring Summer collection is also a sale target item!
Available on sale for the Spring Summer Collection!
We also have the Spring Summer collection on sale!
Spring Summer collection is also a sale target product!
Items from the Spring Summer collection are also on sale!
The Spring Summer collection is also on sale!
It is also a product subject to sale!
The Spring Summer collection is also a sales target product!
The Spring Summer collection is also eligible for sale!
winter collection is also on sale!
The Spring Summer collection is also a sale target item!
We also have the Spring Summer collection on sale!
winter collection is also a sale target product!
The Spring Summer collection is also eligible for sale.
Summer collection is also a sale target product!

DBS

The Spring Summer collection is also a sale target product!
The Spring Summer collection is also a sale item!
The Spring Summer collection is also a sale eligible product!
Also included in the sale is the Spring Summer collection!
The Spring Summer collection is also a sale target item!
Also on sale products for the Spring Summer collection!
The Spring Summer collection is also a sale target product!
The Spring Summer collection is also on sale!
Summer collection is also included in the sale!
The Spring Summer collection is also a saleable item!
See you at the Spring Summer Collection!
The Spring Summer collection is also a sale target!
Summer collection is also a sale target product!
Spring Summer collection is also a sale eligible product!
The Spring Summer collection is also eligible for sale!
The Spring Summer collection is also a sale eligible product!
The Spring Summer collection is also part of the sale!
Our Spring Summer collections are on sale!
The Spring Summer collection is also eligible for sale!
The Spring Summer Collection is also included in the sale!

Figure 5: Full example 20-best lists using DBS-based methods

The *KIND* Dataset: A Social Collaboration Approach for Nuanced Dialect Data Collection

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Abstract

Nuanced dialects are a linguistic variant that pose several challenges for NLP models and techniques. One of the main challenges is the limited amount of datasets to enable extensive research and experimentation. We propose an approach for efficiently collecting nuanced dialectal datasets that are not only of high quality, but are versatile enough to be multipurpose as well. To test our approach we collect the *KIND* corpus, which is a collection of fine-grained Arabic dialect data. The data is short texts, and unlike many nuanced dialectal datasets, it is curated manually through social collaboration efforts as opposed to being crawled from social media. The collaborative approach is incentivized through educational gamification and competitions for which the community itself benefits from the open source dataset. Our approach aims to achieve: (1) coverage of dialects from under-represented groups and fine-grained dialectal varieties, (2) provide aligned parallel corpora for translation between Modern Standard Arabic (MSA) and multiple dialects to enable translation and comparison studies, (3) promote innovative approaches for nuanced dialect data collection. We explain the steps for the competition as well as the resulting datasets and the competing data collection systems. The *KIND* dataset is shared with the research community.

1 Introduction

The Arabic language is one of the most spoken languages in the world with over 400 million speakers from more than 30 countries (Wikipedia, 2023)

and has gained wide attention in natural language processing advancements recently. Since most linguistic technologies rely on high quality training data, Arabic data collection is, consequently, becoming the focus of an increasing number of studies. Although a wide range of these studies propose effective approaches for Arabic data collection, the need for large scale, high-quality datasets of nuanced dialect variations is constantly increasing with the demands of domain specific applications as well as large language models.

A main challenge facing NLP technologies in Arabic is the diversity of Arabic dialects, with more than 30 modern dialects across the Arab region, and over 20 documented dialects in Saudi Arabia, the largest country in the Arabian peninsula (Wikipedia, 2023; Aldarsoni, 2013). This challenge is most pronounced in downstream applications that involve machine translation from dialectal Arabic to other languages. The multitude of nuanced or explicit varying synonyms and hyponyms in Arabic dialects have high impact on the quality of translation models. Several approaches were proposed to take advantage of MSA as the universal formal Arabic and ground other dialects to it through translation or similarity analyses. As part of these studies datasets of parallel dialectal and MSA texts were proposed (Harrat et al., 2015; Salloum and Habash, 2011; Zbib et al., 2012). Although very useful, these datasets remain limited in size and dialectal coverage. To address this gap we propose, *KIND*: King Fahd University of Petroleum and Minerals (KFUPM) *In Your Dialect*

approach, a multiple-tasks competition for obtaining short texts of parallel corpora of fine-grain Arabic dialectal data and question and answer pairs.

The approach aims not only to promote innovative approaches for data collection, but also to raise awareness about the significance of representation in spoken language-based technologies. The competition is accompanied by social educational initiatives to raise awareness about linguistic technologies and to encourage the public to participate in linguistic data collection competitions. Social engagement was solicited by demonstrating the effect of sharing their dialectal utterances on the quality of technologies that will result from their aggregate contributions.

Our approach is comprised of two general tasks. The first is a data collection task where participants compete to enter the largest amount of entries for (1) translation of an MSA sentence to their dialect, and (2) answering an open-ended question in their dialect. The resulting data from this task is denoted the KIND corpus. The second task is to solicit innovative systems that can compete with our approach for task 1. Our approach follows a hackathon format for developing dialectal Arabic data collection systems.

In this paper we describe the approach for collecting the KIND dataset and the quality requirements of the submissions. We demonstrate the effectiveness of our approach by describing the resulting corpora of high-quality training data. The dataset is suitable for training language models, machine translation tasks, as well as Q&A tasks with the respective dialects labeled to a fine granularity level. We make this dataset publicly available to the community along with the labels for each dialect.

We summarize the contributions of this paper as follows:

1. Propose the design and process of a nuanced dialect data collection system that addresses coverage of dialects from under-represented Arabic speaking groups in addition to fine-grained dialectal varieties.
2. An open-source corpora of aligned parallel texts for translation between Modern Standard Arabic (MSA) to multiple nuanced dialects and between the dialects as well as an Arabic dialect Q&A dataset.
3. A collection of proposed systems for nuanced dialectal data collection.

The remainder of this paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 describes the design and process of our collection approach. Section 4 describes the results of the first task of the collection approach. Section 5 describes the results of the second task of the approach. In section 6 we describe the resources resulting from this study. In section 7 we conclude.

2 Related Work

2.1 Arabic Dialect Datasets

The emergence of different social media platforms increased the use of informal forms of a language. That showed a discrepancy in the levels of support for basic tasks in language technologies for different languages. For example, the lack of keyboard support and spell checking for low-resource languages, although there is a desire among the speakers of these regional languages to use these digital services (Soria et al., 2018; Ruder, 2020).

The ability to thoroughly and effectively evaluate and assess the performance of a system is paramount for the development of advanced NLP technologies. The availability of benchmarks and standardized datasets for quality assessment is essential for this evaluation process. For many languages, including Arabic, the availability of these benchmark datasets is minimal compared to other languages such as English (Zampieri and Nakov, 2021). In English, there are various benchmark datasets to perform different NLP tasks, for instance, *SuperGLUE* and *SQuAD*; the former provides nine natural language understanding tasks, and the latter provides question-answering task (Wang et al., 2019; Rajpurkar et al., 2018). However, when looking at Arabic dialects, corpora, and annotated corpora remain minimal compared to MSA (Althobaiti, 2020; Zampieri and Nakov, 2021). Although various efforts focused on dialectal Arabic and building resources for it (Abdul-Mageed et al., 2020; Bouamor et al., 2018, 2019; Diab et al., 2014; Zaidan and Callison-Burch, 2014), there still remain nuanced dialects of many groups that are still either under-represented or not represented at all. In this work we aim to propose an approach that is capable of leveraging a single user prompt/entry to serve as a training record for as many NLP tasks as possible without compromising functionality.

In the general sense, Arabic dialect datasets continue to exhibit limitations concerning their size,

scope, and the extent of annotation when compared to MSA and other languages, as highlighted in previous studies (Althobaiti, 2020; Zampieri and Nakov, 2021). For instance, the MADAR dataset, which covers dialectal variations across 25 cities, offers valuable insights; however, it is noteworthy that this dataset is primarily a translation from another language within the travel domain. Consequently, the source origin imposes constraints on the cultural and domain diversity represented in the text (Takezawa et al., 2007; Bouamor et al., 2019). Therefore our approach aims to incorporate semantic cultural relevance in the design process of the data collection.

2.2 Arabic Dialect Granularity Levels

Arabic is one of the low-resource languages with rich morphology. It has different varieties; formal Arabic MSA is taught in schools and used in formal venues, whereas informal Arabic is used in daily life interactions. The differences between Arabic nuanced dialects and MSA pose a serious challenge when working on Arabic varieties (Zampieri and Nakov, 2021). The difference between MSA-Dialectal Arabic and Dialectal Arabic-Dialectal Arabic reduces the potential effectiveness of utilizing the resources available for a specific variety to investigate another one, be it another dialect or MSA. (Zampieri and Nakov, 2021).

In the literature, Arabic dialects are typically divided based on a geographical dimension with different levels of granularity: region, country, and city level. The regional level represents different regions in the Arab world consisting of a set of countries. Note that grouping the dialects of those different countries on a regional level does not imply that the group of dialects is entirely homogeneous linguistically (Habash, 2010).

Previous work focuses on those two levels of granularity region (Zaidan and Callison-Burch, 2014; Zampieri et al., 2018). Recently, there has been more work on the country-level dialect that focuses on a specific country and all the sub-dialects spoken in that country. Current work on the country-level dialect focuses on a specific task (AlYami and Al-Zaidy, 2022; Yang et al., 2020; Farha and Magdy, 2019; Habash et al., 2019) or studies MSA and few dialects (AlYami and AlZaidy, 2020; Alshargi et al., 2019; Khalifa et al., 2016).

Other work investigates the city-level dialect of

specific cities in a country. Most of the work on this level utilizes social media posts coming from a specific city as the original city dialect (Bouamor et al., 2019; Abdul-Mageed et al., 2019, 2018). However, the social fabric in major cities consists of residents speaking different dialects, which causes a problem at this granularity level. Hence, relying on social media locations for collecting data for users from a specific location does not ensure that the user speaks the predominantly spoken dialect of that location. This work focuses on the location-level and individual-level dialects by allowing users to specify their individual dialect. The dataset is representative of 29 nuanced dialects from Saudi Arabia, city-level dialects of 9 cities from 3 Arab countries and 18 country-level dialects in the Arab world.

3 Our Approach

In this section we describe our proposed approach for nuanced dialect data collection.

3.1 Overview

The data collection approach is comprised of two general tasks. The goal of the first task is to collect quality short-texts representing nuanced dialects that are both versatile in nature and large in quantity. Since MSA texts are available in abundance, due to its common use in digitized content, it has been widely studied leading to NLP systems obtaining high accuracies for the MSA variety. Given that MSA is the variety from which all Arabic dialects are derived from, similarities and differences between Arabic dialects and MSA has always been of interest to both linguists and NLP researchers. For that reason our approach is designed to collect data that enables further research and modeling of these similarities and differences. Additionally, our system includes an approach to incorporate the semantic-level cultural nuances of the collected dialects.

The goal of the second task is to promote the collection of additional nuanced-dialect data collection systems. Social media content has been the predominant source of dialectal data. Although social media content has proven effective for improving NLP performance on dialects to a great extent, nuances in dialects still remain a major challenge to most dialectal Arabic NLP systems unlike MSA. The goal of this task is to contribute to the quantity aspect of manually entered nuanced-dialect data by developing more systems similar in goal to the one

we develop for our first task.

3.2 Nuanced Dialect Short-Texts Collection

This approach aims to collect as large a volume as possible of nuanced dialectal Arabic data. The approach is designed as a data marathon competition, where the competitors goal is to respond to as many prompts as possible, in their own dialect within a fixed time-frame with as few errors as possible. Winners are the the top ranked teams with highest volumes of entries.

Two methods were followed to collect the two distinct corpora. Their description is as follows:

Aligned Parallel Dataset This collection method is designed to allow participants to translate sentences from MSA to their local dialects. The MSA sentences are sampled from subset of 11,670 sentences from an existing well-known MSA dataset, namely the MADAR dataset. The participants translate it to the dialect they registered as their own when joining the competition.

Q&A Dataset This method allows participants to answer open-ended questions. The set of questions are updated regularly for the competition participants, where they answer them in an open-ended fashion. Questions are either constructed by the authors or collected from QA websites such as Quora. The total number of questions used is 796 and will be released with the dataset.

The competition was implemented using a web application designed to receive submissions for the competition and was built to be highly usable even by non-technology-savvy people. The designed collection tool consists of two stages: the registration, where the participants register themselves in the competition with their information, a dialect they speak in with native fluency, and either creating or joining a team. Individual participation was allowed (with a team of one), and up to five members could be included in the team. The second stage is the submission page, where the participants can choose between the tasks of either translating or question answering. Gamification elements were integrated in the design to encourage the participants, such as different game levels with different progress bar colors for the team and each team member. Participants were also encouraged to report any inappropriate sentence or questions, and the reported sentence or questions would be reviewed within 24 hours and removed if necessary. Participants have the option to skip any question

they did not want to answer or translate.

3.3 Innovating Data Collection Methods

This approach aims to collect systems that are used to collect nuance dialect data. It follows a typical hackathon format. The competition elicits creative ideas to collect nuanced dialectal Arabic data. The competition was launched to the public on 26th of February 2022. It consisted of two stages: in the first stage, which lasted for 12 days, participants were asked to submit their team's information and a brief description of their proposed idea. A total of 57 submissions were received from 173 participants. It ranged from ideas to extracting dialectal data of social media content, games, and crowdsourcing techniques. In total, 24 teams were nominated to move to the second stage based on the relevance criteria reviewed by 2 evaluators. Nominees from this stage were provided the opportunity to attend two workshops; the first was titled "Automatic Data Collection and Annotation" and presented different existing methods for collecting and annotating data along with special challenges that face collecting dialectal Arabic. The second was titled "Designing Inclusive Applications and Platforms" and focused on the usability of web and mobile apps in addition to tips and tools for presenting Hackathon ideas. They also joined the competition discord account, where they received mentoring from experts. Out of 24 nominees, 19 did proceed to make the final submission, which consists of the prototype of the solution, a short video explaining the idea of the proposed solution, and a time sheet to realistically complete such a project.

4 Data Collection Results

In this section we describe the resulting datasets and methods.

4.1 Nuanced Dialect Short Texts

The data collected from this approach covered 21 dialects from Arabic-speaking countries. The number of dialects, denoted n , is as follows. For Saudi Arabia, 29 Saudi dialects were collected, i.e. $n = 29$. Since no official definition for Saudi dialects exists, in this study we mainly adopt the taxonomy used in an online linguistic effort, معجم اللهجات المحكية في المملكة العربية السعودية (Aldarsoni, 2013). For Yemen, Jordan, and Syria, we collect city-level dialects for major cities where,

Table 1: Samples of MADAR sentences provided for translation and open-ended questions created by the Data Marathon team

sentences for translation	open-ended questions
غالباً ما أخذ مقاس اثنتي وعشرين في اليابان <i>I often wear a size 22 in Japan</i>	إذا اضطرت للانتقال لبلد آخر، فما الأشياء التي ستفتقدها ببلدك الآن؟ ولماذا؟ <i>If you had to move to another country, what things would you miss about your country now? And why?</i>
الوقت انتهى <i>The time is up</i>	بماذا تتميز مدينتك؟ <i>What distinguishes your city?</i>
هل هذه متجه إلى فندق جراند <i>Is this heading to the Grand Hotel?</i>	كيف تبدو أجواء رمضان في منطقتك؟ <i>What does Ramadan look like in your area?</i>
نريد مائدة بجانب النافذة <i>We want a table by the window</i>	ما أثر تقديم الهدية للآخرين <i>What is the effect of giving a gift to others?</i>
هل لديكم أية جولات سياحية استطلاعية بالحافلة حول المدينة <i>Do you have any guided bus tours around the city?</i>	ما الذي يحفزك للاستيقاظ كل يوم؟ <i>What motivates you to wake up every day?</i>

$n = 6, 4, 7$ for the countries, respectively. As for the remaining countries, country-level dialects are defined with $n = 18$ for 18 countries. The lists of all dialects in their Arabic names are provided in Table ??, Table 10, and Table 9 in the appendix.

The data collection duration was from 26nd of February 2022 until 21st of March 2022. It was highly publicized on social media by Arabic NLP experts, several local university accounts, and several local NLP enthusiasts. Data was collected from 560 participants from 14 countries grouped under 422 teams. Over these teams, 354 teams were teams of individuals, 34 teams were a team of 2, 11 teams were a team of 3, 11 were a team of 4, and 12 were a team of 5.

A total number submission of 55,484 was received. The number of submissions for the Saudi dialects is in Table 2. We received more than 5 submissions for 19 out of the 29 targeted Saudi dialects. We received more than 5 submission for two of the Yemeni regional dialects, three of the Jordanian regional dialects, three of the Syrian regional dialects, and 10 of the remaining 18 Arabic countries, in Table 3.

The winners of the Data Marathon were announced on 24th March 2022 and belonged to *Yemen-Ta'izz* dialect (code 600) with 7413 submissions, *Saudi Arabia-Ghamid and Zahran* (code 21) with 6328 submissions, and *Saudi Arabia-Al Qassim* (code 2) with 6134 submissions. The three places keep their order whether we consider all submissions or only submissions with lengths more than 10 characters.

4.2 The KIND Dataset

In order to prepare the data for public use, all submissions are anonymized by releasing only 3 fields per submission.

Table 2: Saudi dialect submissions by sentence length.

Dialect Code	1-10	11-25	26-50	51-100	100 <	All Submissions
0	1525	4447	3653	1074	220	10919
1	57	259	258	75	16	665
2	478	3178	2536	394	31	6617
3	31	117	113	11	3	275
6	51	66	31	34	31	213
7	2	16	14	2	3	37
8	16	25	20	2	2	65
11	26	100	80	44	18	268
12	474	1881	1278	349	86	4068
13	0	1	0	0	0	1
16	0	0	1	0	0	1
18	50	141	118	73	21	403
19	291	798	501	131	11	1732
20	220	1320	1082	226	69	2917
21	767	4341	2581	241	11	7941
22	12	23	12	5	1	53
23	27	151	161	53	27	419
24	53	202	179	61	15	510
25	0	0	2	3	1	6
26	38	166	149	46	24	423
28	209	1115	805	203	46	2378
Total per length range	4327	18347	13574	3027	636	39911

Table 3: Arabic dialects submissions by sentence length. (without Saudi Dialects)

Dialect Code	1-10	11-25	26-50	51-100	100 <	All Submissions
100	453	1744	1425	317	68	4007
200	81	280	116	10	0	487
300	9	41	64	27	6	147
400	11	119	136	39	4	309
500	2	13	21	14	0	50
600	674	3694	2596	707	463	8134
601	19	77	79	13	3	191
701	28	29	20	10	6	93
703	1	7	8	16	21	53
705	53	553	555	122	10	1293
800	8	25	29	2	0	64
801	2	18	16	7	2	45
803	0	5	1	0	0	6
1000	37	62	57	16	3	175
1200	31	150	96	24	3	304
1300	14	75	46	23	9	167
1500	4	8	4	2	2	20
2000	1	15	12	0	0	28
Total per length range	1428	6915	5281	1349	600	15573

Table 4: Sample of submissions received by open-ended questions.

Dialect Code	ماهو روتين يوم عيد الفطر عند عائلتكم ؟ What is your family's Eid al-Fitr routine?
0	جمعه الاهل والاطفال وتوزيع الهدايا Family and children gathering and gift distribution
0	تتجمع وتحتفل وتاكل شوكليت وتشوف كل اللي تحبهم We gather, celebrate, eat chocolate, and see everyone we love
0	تجتمع سوى وتتقوى ونسلم على بعض ونلبس ثيابنا الجديدة ثم نكن يروح غرفته ويرقد We gather together, have coffee, say hello to each other, put on our new clothes, and then we all go to our rooms and sleep.
3	اسير على الربع وما اخلي حوي الا ادخله و اعيد على اهله Visit friends and not leave a neighborhood I did not enter and wish it's residents a happy Eid.
12	احنا في العيد نزور الكباريه الصباح مرا بدري وتجمع هناك ونفطر ونشرب قهوه ، عاد بالليل نصير الصغاليات اكثر شي We, on Eid, visit the elders early morning and gather there and have breakfast and drink coffee, then most festivities happen at night.
12	تتجمع كل العيلة بصباح العيد ونفعد نشرب شاي ونبرح لين الظهيرة بعدها نتعدا وكل واحد بمشي بيتو بعدها We gather, the entire family, Eid morning and sit to drink tea and chat until noon then we have lunch and everyone goes home after that
19	نرقد We sleep.
19	نصلي صلاة العيد ونطلع نمايد لين الظهر وبعدها نغفي ونزجع نكشخ المغرب نكمل نمايد We pray the Eid prayer and go out for Eid celebrations until noon, then we go sleep and at Maghrib time again we dress up and continue our Eid celebrations.
21	تتجمع مع صدقاتنا من صلاة الفجر ونفطر We gather with our friends at Fajr prayer and have breakfast.
24	نسلم على بعض صلاة الصبح ونفطر ونزجع نرقد We greet each other at Fajr prayer, have breakfast, then go back to sleep.
28	ان العايله تجتمع The family gathers.
100	لازم نعمل محشي وكك و بيتفور We have to make mah'shi, ka'ak and betefour
100	الفرحه مع الاهل و ناكل مع بعد و نلعب مع بعد و نصلي مع بعد Joy with the family, we eat together and play together and pray together.
200	نوضوا الصباح نزوحوا نصلبوا ونزجعوا نفطروا مع بعض مبعد نزوحوا نعيدوا على باقي العايله We do ablution in the morning, then we go to prayer, we come back and have breakfast together, then we go to greet the rest of the family
600	نجهز الكمك و الجماله للجھال ونسير المجلس وننصل ونبارك للعيد We prepare ka'ak and ja'ala for the children then we go to the majlis and celebrate Eid
600	نفرح طماش ما نرقدشمن الفرح We are elated so happy we cannot sleep
703	بعد صلاة العيد يرجعوا عايلت ومنعمل فطور لكل العيلة وبعدها منقوت بغيبوية نوم والعصرا او الظهر منقوم وبيبدأ عيدنا ومنلبس اواعي العيد After the Eid prayer, they return home and we prepare breakfast for the whole family, and then we fall into a sleepy coma, and the afternoon or noon prayer begins, and our Eid begins, and we wear Eid clothes.
1200	نقدمو واعين لعند الصبح وبعدها قبل الصلاة نخشو نتبجو ونظلمو نلبسو العربي ونمشو للصلاة وبعد ما نزوحو نلقو المعصيدة وانية ناكلوها ونبدو في مشاورير لمعايدة We stay up until morning then before the prayer, we go in and shower then go out and dress up and go to the prayer then when we are back we find asida ready, we eat it then start Eid visiting errands.

Table 5: Percentage of submissions generated from open-ended questions per submission length for dialects with more than 5 submissions.

Dialect Code	11-25	26-50	51-100	Longer than 100
0	32%	34%	60%	87%
1	34%	54%	81%	100%
2	4%	9%	25%	90%
3	29%	42%	64%	100%
6	71%	97%	100%	100%
7	13%	14%	100%	100%
8	76%	40%	0%	100%
11	56%	73%	95%	100%
12	16%	24%	63%	93%
18	35%	59%	92%	100%
19	31%	37%	69%	100%
20	10%	21%	51%	94%
21	6%	6%	17%	45%
22	43%	50%	80%	100%
23	43%	63%	85%	100%
24	47%	49%	70%	100%
25	-	100%	100%	100%
26	12%	8%	57%	100%
28	6%	13%	55%	87%

1. *dialect code* which is the label that indicates the specific dialect the text belongs to.
2. *sentenceOriginID* which is the identifier used to reference either the MSA sentence to it's source in MADAR dataset, this ranges (1000000-2000000), or the reference to link the question to the constructed question dataset, this ranges (2000000-3000000).
3. *textString* contains the submitted sentence.

Additional processing of the submissions includes trimming, and removal of duplicate translations of a sentence or answer submitted by the same participant. This reduced the total number of entries from 55,484 to 54,883. It is worth noting the final dataset does not include duplicates from the same dialect and source; however, it does include duplicates of different sources of the same dialect, e.g., two different questions have the same answers.

4.3 Discussion

The resulting datasets demonstrates the efficacy of our collection approach that relies on gamification combined with awareness-raising on the importance of inclusiveness and availability of open-

Table 6: Sample of submissions received by translation of *May I ask about your name?* from Arabic MSA to other dialects.

Dialect code	هل لي أن أسأل عن اسمك ؟
0	اقدر اعرف اسمك May I know your name?
1	هالحين وش اسمك Now what's your name?
20	بسألش وش اسمش لو سمحت I want to ask you, what is your name please?
21	اقدر اسال عن اسمك Can I ask about your name?
100	ممكن اسالك اسمك ايه؟ Is it possible to ask what your name is?
600	ككا قولني مو اسمك ؟ Tell me, what is your name?

source resources. The collected data size in Table 7, shows the number of unique entries when considering the uniqueness on the dialect level. Both approaches resulted in a large number of texts for the duration. The sentence translation approach generated a larger number of entries, as was expected since minimal effort is required to simply restate existing content as opposed to question answering that requires the participant to generate new content. Also, the sentence translation system was available to the users 3 more days than the question answering system.

Samples of responses to open ended questions are in Table 4, while samples of responses of translation are in Table 6. It is notable that the sentence translation approach captures dialectal markers which is a main challenge for nuanced dialects. Additionally the texts are collected with their MSA translation and other dialects, that are essential for studies addressing translation-based solutions to modelling nuanced dialects. The open-ended question answering approach is capable of capturing both the syntactic aspects of the dialect as well as the semantics associated with the culture of the speakers of that specific dialect.

In terms of the length of submissions, it is noted that the percentage of submissions on the longer length side are the ones generated by the question answering approach. In Table 5, focusing on sentences of Saudi Dialects, in 17 out of 18 investigated dialects, submission longer than 100 characters came mainly (more than 85%) from open-ended questions. In contrast, submissions shorter than 50 characters came mainly from translated sentences. Same pattern applies to non-Saudi dialectal

Arabic sentences, where translation sentences were responsible for 75% of the submissions shorter than 50 characters, whereas open-ended questions were responsible for 77% of the submissions longer than 50 characters. This observed too in Table 4 and Table 6, where samples of the open ended question mainly consists of longer sentences whereas for translation we are bound by the length of the original sentence. To generate longer sentences for translation, the approach requires using a dataset with longer texts to prompt the participants in the translation task.

5 Hackathon Results

In this section, we shed light on the top projects that received the highest scores from the hackathon judging committee per the evaluation criteria, which seek to balance technical knowledge with originality, creativity, and relevance to the hackathon's objectives.

5.1 Lesan

Lesan is a volunteer platform designed to enrich the Arabic dialect content, focusing mainly on voice-recorded sentences in various dialects. The volunteers start by choosing a dialect to voice record Arabic text written in the selected dialect and complete their daily rounds, where each user has a daily target of 10 rounds per day. The users of Lesan have the choice to record an existing text in the platform or type and record their own new text. Gamification elements such as trophies and leaderboards are used to motivate users by creating a competitive atmosphere. Moreover, Lesan provides an "Open Library" that contains high-quality dialectal Arabic datasets that are available, reliable, and ready to use.

5.2 Teach us your Dialects

Participants proposed a game in which players guess the meaning of a word given in one of the Arabic dialects with the help of an image indicating the meaning. The players' answers can be written or recorded in their voices. In this project, the database is populated by the players themselves, where any player can add a word in a specific dialect, and it will be added to the database if it is approved by at least ten other players who speak the same dialect or live in the same place. Each

Table 7: Entries uniqueness.

Number of submission	Unique per (dialect, source, participant)	Unique per (dialect, source)	Unique per (dialect)
Translation	40481	40119	39957
Open ended Questions	15003	14759	14338

new word has to be recorded in voice to make pronunciation easier. To motivate players, they can see a leaderboard of the players' points and ranks by their countries. Moreover, The ranking of each country is displayed as well, and it depends on the number of words shared by players from the country.

5.3 Faseeh (Fluent)

A video game that assesses a person's level of knowledge of Arabic dialects. As a first step, data is collected from Twitter automatically using a scraper. Data is then cleaned and stored in a database for the game, where five tweets will be displayed for each player from the database. In Faseeh game, a tweet will pop up on the screen where the player must answer the following questions in a row: (1) Is there a text in the tweet that indicates a specific dialect? (Yes/No), (2) If yes, what is the dialect classification?(Egyptian - Gulf etc.), (3) If yes, why was this dialect chosen?, (4) What is the text/word indicating the selected dialect?.

Once the player finishes a tweet, another tweet will pop up until the round (five tweets) is completed. Eventually, the Arabic dialect test result in points will be displayed to the user based on the number of correct answers. Verification of answers is done in two approaches: automatically by knowing the geographical location of the source of the tweet and manually by operators who are experts in each of the existing dialects and can evaluate the answers.

5.4 Nutq (Pronunciation)

The project's main interface is divided into several sections for Saudi dialects, including Northern, Southern, Hijazi, Najdi. etc. The application consists of 3 stages to collect data for each dialect in a funny way to grab the user's attention. In the first stage, the application shows an image to users where they can choose the appropriate word from their own perspective. As the second stage, If none of the options matches the word in their dialect, they can add their own synonym for the word. In

the third stage, users can go the extra mile and add more words along with their meanings in the game dictionary and get simple financial rewards.

5.5 Evaluation and results

Each of the 19 submissions received three evaluations on the premises of:

1. Creativity level of the idea.
2. Technical quality and suitability of techniques and methods used.
3. Potential to Grow.
4. The collected data using the provided technology in terms of quantity and quality.

The results were aggregated, and the announcement of the winners was on the 24th of March 2022. The first three places consist of teams Lesan, Teach Us Your Dialect, and Fsaeeh, respectively.

6 Challenges and Recommendations

In this section we describe challenges to the collection approach and provide recommendations for organizing future hackathons.

6.1 Target Dataset

In order for the collection approach to effectively achieve a high yield of quality data, it is recommended to have a clear specification of the dataset to be collected, specifically a predetermined purpose or use for the data. Although this ensures a consistent collection process, however, during collection it is equally beneficial to adapt to patterns in user behavior to maximize the outcome of user participation. For example, the first collection task was initiated with the purpose of curating a parallel corpora for different dialects. It was noticed during user submission that many of the MSA sentences that were presented to the users for translation were irrelevant to the culture and could not capture cultural and context-rich dialectal data. The sentences were parts of conversations in the hotel, airports, and restaurants and were a direct translation from non-Arabic sentences. Therefore the second approach was introduced proposing the

use of open-ended QA for collecting dialectal data to enable culture and context-rich sentences while relaxing the alignment requirement to have totally different responses for the same question.

6.2 Target Participants

The target audience should be clearly defined as it is a focal point in the competition design process. Since we are interested in collecting data from under-represented groups, it was imperative to design a system that is easy to use by non-technical groups who typically have low online presence. To reach our target audience we used social media outlets that have high visibility in the region, using simple video advertisements to convey the purpose of the data collection and the potential of the benefits to society as a whole for a non-technical user. Incentives are used to maximize user participation in social collaborative efforts, such as monetary awards in our competition. In cases of limited funding, we recommend to emphasize the social media campaign and raising awareness efforts, as many educational sessions targeting college students and the general public contributed greatly to the high amount of participation.

6.3 Technical Resources

Storage and database size limitations dictate the limits of the collection process. The participant solicitation must be guided by the volumes of data received during collection to ensure system stability. Additionally, available personnel to provide technical support and monitor entries to perform corrections or incorporate user feedback, is a challenge. In our case, the authors along with student volunteers from the university were responsible for these tasks.

7 Resources

The dataset is released for the research community at: <https://huggingface.co/KIND-Dataset>. The repository holds both the Data Marathon submissions and the open-ended question dataset.

8 Conclusion

In this paper we describe the design and process of collecting a multi-dialect Arabic dataset as well as the resulting systems and data. Similar in concept to ACL shared tasks, the KIND competition aims to encourage innovative contributions towards

high-quality data collection. The competition resulted in a corpus of over 50k high-quality texts labeled with fine-grained Arabic dialects. As well as over 20 approaches for Arabic dialect crowdsourcing techniques. The resulting data is made public for the research community. As future work, the authors aim to propose new competitions for domain specific as well as NLP-task specific data collection for Arabic dialects.

Limitations

There are several limitations in the published dataset, that open doors for further investigation: (1) The first is the presence of white dialect submissions, as most of the participants were 35 of age or younger and live in big cities not in their hometown, we can find that some of the dialect has softened from how the original dialect sounds. (2) As dialect classification is a multi-label problem, submissions could be mapped to more dialects than what is reported. (3) Further cleaning is required, although there were minimal spam submissions from our observations, there still could be submissions that do not answer to the question or translated the intended sentence. (4) Not all intended city-level (or tribe-level) dialects in Saudi Arabia were covered as intended. The dataset does lack submissions from dialect belonging mainly to the Northern Regions of Saudi Arabia. Also, not all Country level dialects were covered, especially for dialects of North African countries.

Ethics Statement

All participation in the competition was voluntary and participants waived their copyrights to the submitted data before participation. All information related to the participants identity was removed. The dataset is not comprehensive of all Arabic dialects and should not be treated in such manner.

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A Appendix

A.1 Dialect Codes

Table 8: City/Tribe level Saudi Dialects.

Dialect Code	City/Tribe Dialect
0	حاضرة نجد (الرياض، قرى بني حنيفة، الوشم) Najd - urban
1	بادية نجد (عتيبة، مطير، قحطان، سييع..) Najd - suburbs
2	أهل القصيم Al Qassim

Dialect Code	City/Tribe Dialect
3	أهل وادي الدواسر Wadi Al-Dawasir
4	حوطة بني تميم Hotat Bani Tamim
5	أهل الأفلاج Al-Aflaj
6	أهل الدلم والخرج Ad-Dilam and Al-Kharj
7	شمر Shammar
8	عزنة Anaza
9	الشرارات Al-Shararat
10	الحويطات Al-Howaitat
11	الحجاز Hejaz/Hijaz
12	عوائل الحجاز Hijaz families
13	أهل العلا Al-Ula
14	الرشايدة Al-Rashaida
15	خير Khaybar/Khaibar
16	جهينة Juhaina
17	العجمان Al-Ajman
18	الهواجر Al-Hawajir
19	الأحساء Al-Ahsa
20	القطيف Al-Qatif
21	غامد وزهران Ghamid and Zahran
22	بني شمر وبالبحر، بالسمر Bani-Shehr, Ballahmar, Ballasmar

Dialect Code	City/Tribe Dialect
23	شهران العريضة Shahran Alaridha
24	تهامة (رجال ألمع، الأزد، قحطان) Tihama
25	فيفا Faifa/Fifa/Fayfa
26	جازان Jazan
27	المهرة Al-Mahra
28	بني يام (نجران) Bani-Yam (Najran)

Table 9: Country level Arabic Dialects.

Dialect Code	Country Dialect
100	مصر Egypt
200	الجزائر Algeria
300	السودان Sudan
400	العراق Iraq
500	المغرب Morocco
900	الصومال Somalia
1000	تونس Tunisia
1100	الإمارات Emirates(UAE)
1200	ليبيا Libya
1300	فلسطين Palestine
1400	عمان Oman
1500	الكويت Kuwait
1600	موريتانيا Mauritania
1700	قطر Qatar
1800	جيبوتي Djibouti
1900	جزر القمر Comoros
2000	لبنان Lebanon
2100	البحرين Bahrain

Table 10: City level (non-Saudi) Arabic Dialects.

Dialect Code	City Dialect
600	اليمن - اللهجة التعزية Yemen-Ta'izz
601	اليمن - اللهجة الصنعانية Yemen-Sana'a
602	اليمن - اللهجة الحضرية Yemen-Hadhramut
603	اليمن - اللهجة الياضية Yemen-Yafea
604	اليمن - اللهجة العدينية Yemen-Adeeni
605	اليمن - اللهجة العدينية Yemen-Aden
700	سوريا - لهجة إدلب Syria-Idlib
701	سوريا - لهجة حلب Syria-Aleppo
702	سوريا - لهجة حمص Syria-Homs
703	سوريا - لهجة دمشق(شامي) Syria-Damascus (Shami)
704	سوريا - لهجة درعا Syria-Daraa
705	سوريا - لهجة حماه Syria-Hama
706	سوريا - لهجة اللاذقية والساحل Syria-Latakia and coast
801	الأردن - لهجة الفلاحين Jordan-Fallahin
802	الأردن - لهجة الشمال الأردنية Jordan-Northern
803	الأردن - لهجة الجنوب الأردنية Jordan-Southern
804	الأردن - اللهجة البدوية Jordan-Bedouin

Can Stanza be Used for Part-of-Speech Tagging Historical Polish?

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Abstract

The goal of this paper is to evaluate the performance of Stanza, a part-of-speech (POS) tagger developed for modern Polish, on historical text to assess its possible use for automating the annotation of other historical texts. While the issue of the reliability of utilizing POS taggers on historical data has been previously discussed, most of the research focuses on languages whose grammar differs from Polish, meaning that their results need not be fully applicable in this case. The evaluation of Stanza is conducted on two sets of 10286 and 3270 manually annotated tokens from a piece of historical Polish writing (1899), and the errors are analyzed qualitatively and quantitatively. The results show a good performance of the tagger, especially when it comes to Universal Part-of-Speech (UPOS) tags, which is promising for utilizing the tagger for automatic annotation in larger projects, and pinpoint some common features of misclassified tokens.

1 Introduction and Background

Annotated data for historical or otherwise non-standard variants of language can be difficult or resource-consuming to obtain but is nevertheless necessary for certain linguistic inquiries. One of the possible methods of alleviating this issue is attempting to use tools developed for a contemporary standard language for automated annotation. However, the data in question differing from the standard may pose problems. Consider the example presented in Table 1, a sentence from a 19th-century Polish memoir: the differences between the original and the modern version of the same sentence pertain not only to spelling but also word order and vocabulary – but the extent to which these seemingly large differences affect the performance of modern tools is not clear. This paper aims to address this question and estimate what kinds of variation have the largest negative impact on tagging accuracy.

Table 1: A sentence from Juliusz Czerwiński’s memoir (Szawerna, 2023) in the original, with modernized spelling, modernized language, and in English.

Original sentence	Odjechał do Lwowa – nazajutrz miał wrócić i wrócił, ale w trumnie.
Modern spelling	Odjechał do Lwowa – nazajutrz miał wrócić i wrócił, ale w trumnie.
Modern language	Pojechał do Lwowa – miał wrócić dzień później, i wrócił, ale w trumnie.
English translation	He drove away to Lviv – he was supposed to return the day after and that he did, but in a coffin.

A considerable amount of research has already been conducted on the evaluation of various pre-trained part-of-speech (POS) taggers on historical texts to establish their effectiveness at annotating such texts. POS taggers trained on contemporary data tend to struggle with historical texts for a variety of reasons, such as out-of-vocabulary items, variation in spelling, capitalization, and punctuation, as well as differences in morphology and syntax and semantic shifts, but large performance improvements can be observed when relatively simple pre-processing methods such as spelling correction, spelling simplification, punctuation removal or normalization are used (Rayson et al., 2007; Scheible et al., 2011; Adesam and Bouma, 2016; Hupkes and Bod, 2016). A summary of the performance of various POS taggers when tested on historical data from various studies can be seen in Table 2. While taggers based on neural networks (NNs) have been shown to outperform other methods, much of the research predates those and is based on older architectures (Yang and Eisenstein, 2016; Adesam and Berdicevskis, 2021).

While most of the previously mentioned studies focus on languages from the Germanic family, this paper aims to evaluate a POS-tagger for modern Polish on historical texts. Given the differences be-

Table 2: Test results on raw and preprocessed data in other experiments (some results are for more than one tagger or data from various periods).

Paper	Language	Modern Test Set Accuracy	Historical Test Data Measures	Preprocessed ¹ Test Data Accuracy
Rayson et al. (2007)	English	96%	Accuracy: 82–88.5%	89–93.2%
Scheible et al. (2011)	German	-	Accuracy: 69.6%	79.7%
Bollmann (2013)	German	-	Accuracy: 23–81.8%	83.4–95.6%
Hupkes and Bod (2016)	Dutch	96%	Accuracy: 60%	92%
Adesam and Bouma (2016)	Swedish	94.2% ²	Accuracy: 45%	70%
Waszczuk et al. (2018)	Polish	-	Precision: 88.3–90.3% Recall: 88.3–90.3%	-
Szawerna (2023)	Polish	89.3–99.2%	Accuracy: 80.2–94.5%	-

tween Germanic and Slavic languages, other kinds of errors can appear in the tagger annotation. Moreover, the research mentioned in Table 2 was conducted on texts from not only various languages but also various periods. Waszczuk et al. (2018) evaluated the performance of a tagger on historical Polish data and reported quite high performance on texts from the 17th-20th-century, which is promising. However, the tool that they are reporting on, Morfeusz2, is a CRF-based tagger, which could mean that an NN-based tool could potentially perform even better. While the research presented by Szawerna (2023) includes various performance measures for several tools, the focus of that research was on identifying variation and not utilizing the tools for automated annotation; importantly, though, Szawerna (2023) does present a comparison of the performance of various tools, with Stanza performing better on historical data than Morfeusz2 which utilizes a combination of rule-based morphological analysis and CRF (conditional random fields) for tagging; Morfeusz2 did, however, outperform Stanza on modern texts (Kieraś and Woliński, 2017). While a fine-tuned BERT model did outperform Stanza, the latter is more of an out-of-the-box tool and is therefore more likely to be used in a pipeline, warranting the analysis of its performance on nonstandard data.

This paper builds upon the research presented in Szawerna (2023) and investigates the performance of a single tagger on a memoir from 1899 which also contains dialectical variation. Given the age of the data, the accuracy is expected to be around

and 90% accuracy³, with Universal Part-of-Speech (UPOS) tagging performing better than tagging using language-specific (XPOS) tags. The tagger is expected to struggle with nonstandard spelling or capitalization, out-of-vocabulary items, and other previously mentioned issues.

2 Materials and Methods

The tagger used in this project is that provided by Stanza, a Natural Language Processing (NLP) toolkit featuring models for a large number of languages (Qi et al., 2020). The default model for Polish was trained and evaluated on the Polish Dependency Bank treebank (Wróblewska, 2018; Stanza, n.d.). It is also that corpus’s test set that is used to exemplify the tool’s performance on modern Polish in this paper, although it represents genres different from the historical texts. The main reasons for selecting this tagger are its ease of use and high reported accuracy on modern data.

The data used for testing the tagger in this project comes from the memoir of Juliusz Czermiński, who lived in the 19th century in the area corresponding to nowadays Eastern Poland and Western Ukraine. The original manuscript was composed in 1889, retyped on a typewriter, and recently digitized. No intentional alterations were made to e.g. seemingly misspelled tokens. This data was first presented by Szawerna (2023), where its divergence from modern Polish was asserted, especially when it comes to features typical for the dialects of that region (Kurzowa, 1983). According to Polański (2004), there was no singular universally accepted spelling convention around the time of the memoir’s creation. Therefore, the text should

¹The preprocessing methods varied between the experiments but often consisted of standardizing the spelling and punctuation.

²Here the tagger was trained on historical texts as well.

³Unfortunately Waszczuk et al. (2018) do not report accuracy as a measure.

not be considered to be representative of historical Polish of its time, both due to its dialectical features and spelling which is not representative of the bulk of the contemporaneous writing.

In its entirety, the data consists of 37,405 tokens. Out of those, the first 10286 tokens were manually annotated using Universal Dependencies’ universal POS tags (UPOS tags). A subset of 3270 tokens was further annotated using XPOS tags. Both of these tagsets are utilized by Stanza. The only changes to the original text include the splitting of the “mobile inflection” as per the UD guidelines and removing any punctuation from inside numbers (Szawerna, 2023; Universal Dependencies, n.d.). This previously conducted manual annotation of the tokens has been reviewed, and a few corrections have been made.

Evaluation measures were calculated for both kinds of annotation. The results were also subjected to a qualitative analysis, the goal of which was to determine what kinds of errors are the most prevalent, which could give insights into what kinds of potential pre-processing could eliminate that problem. The misclassified examples were saved and manually annotated for the error type before being processed to obtain the relevant statistics.

3 Results

Stanza exhibits very good performance on modern Polish data and relatively good performance on historical data. Table 3 shows the accuracy achieved by the model on the respective datasets and tagsets.

Table 3: Stanza’s accuracy per text type and tagset.

	Modern	Historical
UPOS	98.79%	94.15%
XPOS	94.76%	88.05%

A more detailed evaluation was obtained for the UPOS tagset. Figure 1 and Figure 2 visualize the per-class performance of the model for each dataset, with the counts for each class being normalized by the true positive count for that class (therefore, the values on the diagonal correspond to recall). It is worth pointing out that tags like *INTJ* and *SYM* were absent from the historical data altogether. What can be noted is that with the exception of many *SYM* and *INTJ* classes, the tagger shows more consistent performance on modern data than on historical. While for categories such as *ADJ*, *ADV*, *AUX*, *DET*, *NUM*, *SCONJ*, and *X* the results

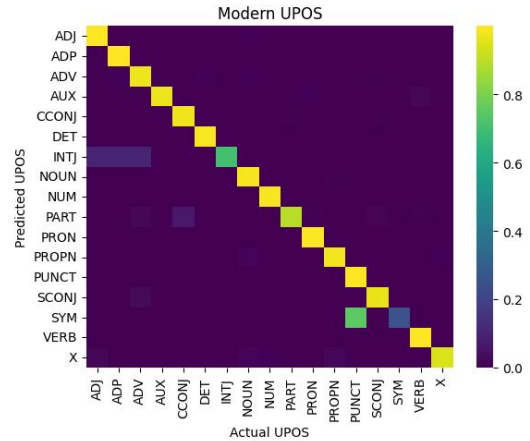


Figure 1: Normalized confusion matrix for UPOS tagging of the modern data.

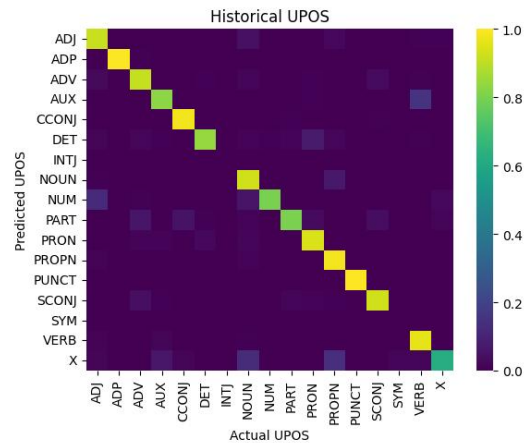


Figure 2: Normalized confusion matrix for UPOS tagging of the historical data.

on historical data are visibly lower, the overall performance on historical data is still rather good. The XPOS tagset is much larger, in the order of hundreds of tags, making a similar visual comparison uninformative, and a more detailed analysis is beyond the scope of this paper.

Another method of inspecting the tagger’s performance is investigating the erroneously labeled tokens. Table 4 and Table 5 illustrate the frequency of specific kinds of errors present among the mistakes made by Stanza in the memoir, following the general annotation utilized by Szawerna (2023). While the exact proportions differ between the two tagsets, *spelling*, *ambiguous*, and *unidentified* type errors are the most common for both. Noticeably, UPOS tagging fails when it comes to tokens with unusual spelling, including capitalization, which seems to be relevant for identifying *PROPN* and the replacement of the *y* (/i/) vowel with *e*, and

Error Type	Raw freq.	Relative freq.
spelling	293	48.67%
ambiguous	223	37.04%
unidentified	37	6.15%
vocabulary	35	5.81%
name	7	1.16%
abbreviation	4	0.66%
grammar	3	0.50%

Table 4: Frequency of errors by type for UPOS tagging.

Error Type	Raw freq.	Relative freq.
ambiguous	184	47.06%
unidentified	77	19.69%
spelling	51	13.04%
name	49	12.53%
vocabulary	22	5.63%
grammar	4	1.02%
abbreviation	4	1.02%

Table 5: Frequency of errors by type for XPOS tagging.

spelling the /j/ sound with y, which distort various inflectional endings. XPOS tagging struggles more with ambiguity (e.g. when more than one grammatical case uses the same ending), although the spelling variation not related to capitalization still has a non-negligible effect. One relevant type of ambiguous errors, present in both types of tagging, is that related to the sometimes questionable status of verb-derived nouns and adjectives. For example, the word *bombardowanie* ‘bombing’ is considered an established noun, but the tagger classifies it as a gerund (WSJP Editorial Team, 2014; nkj, n.d.), likely because of the form. Interestingly enough, among the annotated XPOS errors there are also several examples of the vocative case being ignored or the model defaulting to assigning the masculine grammatical gender to a pronoun despite the context implying that it should be feminine. There are also instances of verbs in the impersonal past form that are consistently misclassified.

4 Discussion

The results of the quantitative evaluation show a good performance of the tagger, exceeding most of the previously reported ones, including the results reported for the same data and tagger by Szawerna (2023),⁴ possibly due to improvements that have been made to Stanza’s model. On the other hand,

⁴Other taggers used in that research achieve even higher scores.

Waszczuk et al. (2018) still achieve a better performance on XPOS tags using a CRF-based model. However, they use a more diverse and larger dataset which may consist of more standard Polish than the data investigated in this paper. Nevertheless, Stanza’s performance on this test data is only around 4 (UPOS) and 7 (XPOS) percentage points below the accuracy it has shown on its own test set. Interestingly enough, the performance on the PDB test set is slightly higher than reported by Stanza (n.d.), possibly due to the corpus being pre-tokenized before being fed to the model.

A qualitative error analysis has approximated what the tagger struggles with when it comes to the test data. Previous studies have shown that variations in spelling, capitalization, punctuation, differences in morphology and syntax, and semantic shifts are some of the factors that make accurate tagging of historical texts using modern taggers difficult (Rayson et al., 2007; Scheible et al., 2011; Adesam and Bouma, 2016; Hupkes and Bod, 2016). In the case of Stanza, some of those issues, such as nonstandard capitalization, archaic vocabulary, and spelling have negatively impacted the tagger’s performance. This is particularly prominent as far as UPOS tagging is concerned. As far as XPOS-tagging goes, issues pertaining to the inflectional morphology have been highlighted, such as confusing word endings or problems with words the class of which is ambiguous. Additionally, issues such as the possible underrepresentation of rarer classes in the training corpus could be noted, leading to biases concerning feminine pronouns and issues identifying the vocative case.

5 Conclusions and Future Work

Within this paper, a modern Polish POS tagger, Stanza, has been evaluated on historical and modern data, and some of the issues causing the drop in its performance on historical texts have been successfully identified. It has been shown that it can perform quite well on non-standard, historical Polish data from the late 19th century, and this can possibly be improved using some preprocessing methods, making it a promising candidate for at least assisting the annotation of historical texts, if not completely automating it. Many of the misclassified tokens were problematic due to issues previously identified in the literature in the field; however, some problems seemed to stem from the inflectionality of the language or be inherent to

the tagger itself. Potential biases stemming from the under-representation of certain classes in the training data for the tagger have also been shown.

In the future, it would be interesting to test the influence of various factors, such as e.g. punctuation or lowercasing, on the quality of tagging. Another possibility could be comparing the performance of multiple different taggers or tagging architectures on the same data, or testing the same tagger on data from different periods. Alternatively, one could juxtapose the results presented in this paper to those from tagging a very recent, nonstandard text, e.g. sourced from the web, to see to what extent the same issues are causing tagging problems. Finally, developing some methods for the pre-processing of texts from this period for subsequent tagging could also be quite useful. It would also be interesting to compare how the models for other languages included in Stanza perform on samples of historical texts from their respective languages.

As far as the data itself is concerned, it would be interesting to complete and review the annotation of the entire memoir, and see how the results of an analysis such as the one presented in this paper would change; this would also open up the opportunity for different kinds of research on the text.

Ethics Statement

Given the age of the data, its use does not pose an ethical challenge. The analysis of mistakes made by Stanza indicates some possible existing biases when it comes to assigning gender-marked XPOS tags to words the gender of which is ambiguous when the context is not taken into account. Simultaneously, it is worth pointing out that the re-using of existing tools should be encouraged, especially when it comes to resource-heavy tools (such as NN-based ones), as it potentially limits the negative environmental impact of training large models.

Limitations

It is also important to acknowledge the limitations of this research. Performing this kind of analysis on data from only one author and a relatively recent period does not fully address the question of whether it is possible to utilize the Stanza tool for POS tagging any Polish text, nor does the paper provide an answer as to what kind of performance would make a tagger sufficiently good for use in preprocessing pipelines for historical texts. In the latter case, the author is of the opinion that this

decision should be made on a case-by-case basis, and depending on the downstream tasks. The data having been annotated by only one person makes it somewhat prone to errors. Moreover, no attempt at assessing the effect of pre-processing (spelling and punctuation normalization) has been presented, rendering a full comparison with some of the prior research impossible.

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A Appendix

- [GitHub repository \(code and data\)](#)

Toward Zero-Shot Instruction Following

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Abstract

This work proposes a challenging yet more realistic setting for zero-shot cross-task generalization: *zero-shot instruction following*, presuming the existence of a paragraph-style task definition while no demonstrations exist. To better learn the task supervision from the definition, we propose two strategies: first, to automatically find out the critical sentences in the definition; second, a ranking objective to force the model to generate the gold outputs with higher probabilities when those critical parts are highlighted in the definition. The joint efforts of the two strategies yield state-of-the-art performance on the SUPER-NATURALINSTRU (Wang et al., 2022b).¹

1 Introduction

With the rapid evolutions of the pre-training techniques, large language models (LLMs), such as GPT-3 (Brown et al., 2020) and ChatGPT (OpenAI, 2022), are found to be capable of handling various novel NLP tasks by following in-context instructions (Radford et al., 2019).² Typically, a formal task instruction consists of two components: (1) a task definition that describes the task intent; (2) a few labeled examples to demonstrate this intent (i.e., demonstrations). Then the problem is often named as “*k*-shot instruction following”, where *k* is the example size. Due to the performance superiority of the in-context examples (Lampinen et al., 2022; Gu et al., 2023a), prior research has predominantly relied on demonstrations, allocating relatively limited attention toward effectively utilizing task definitions; we refer to this setting as “demonstration-driven instruction following” (Min et al., 2022a,b; Hu et al., 2022).

Notwithstanding the surprising results, this phenomenon could manifest as an instance of overestimated progress. Two reasons: firstly, **demonstrations are usually hard to be crafted in real-world applications**. Since LLMs are becoming helpful daily-task assistants and most end-users are non-experts (Chiang et al., 2023; Xie et al., 2023, 2024), it is usually exhausting and unrealistic for users to design *concrete* demonstrations for every daily task, especially for those tasks that require specific domain knowledge. Secondly, as Gu et al. (2023a) concluded, so far, **we still lack a method to effectively learn from instructions to solve tasks without demonstrations** for various reasons. For example, Khashabi et al. (2022) showed that the models constantly ignored the crucial information emphasized in the definition (e.g., an output constraint that asks models to “*generate no more than five words*”); Webson and Pavlick (2022) found that the models always struggled to truly understand the content of the definition.

To more effectively utilize the task definition, this work studies a more challenging setting: *zero-shot instruction following*. Technically, our approach consists of two strategies.³ (i) Strategy I: automatically learn the critical task-relevant information from the lengthy definition to help the model better grasp the instruction. (ii) Strategy II: to make the model truly distinguish instructions that are specified by the critical information or not, we set a ranking-based training objective. Given instructions with critical information highlighted, this ranking strategy forces the model to generate ground-truth outputs with higher probabilities than instructions otherwise. Our system, PICK&RANK, achieves state-of-the-art on the benchmark, SUPER-NATURALINSTRU (Wang et al., 2022b).

¹Code: <https://github.com/RenzeLou/Pick-Rank>

²Task instructions can be any textual expressions, e.g., task names, short sentences, or paragraphs, that describe the task semantics; prompts are the special case of instructions (Lou et al., 2023).

³In the rest of the paper, we use the terms “definition” and “instruction” alternately, when examples are unavailable.

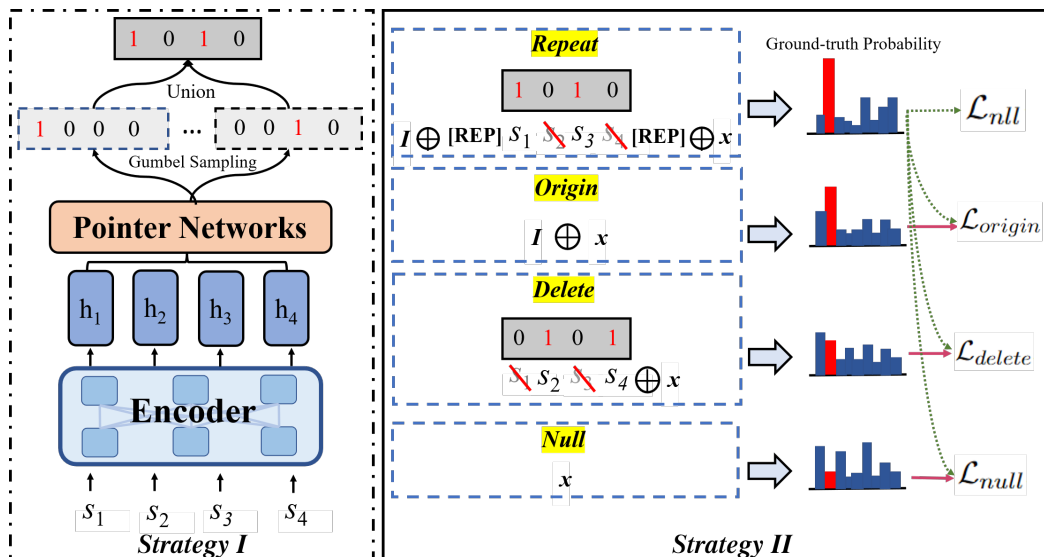


Figure 1: The illustration of our PICK&RANK. Two main components: **Strategy I** (PICK) and **Strategy II** (RANK). Strategy I aims to predict a binary value for each sentence in a definition, indicating whether a sentence is crucial. The outputs of Strategy I are used to construct instructions with different sufficiencies, e.g., “Repeat” represents the most beneficial instructions where the crucial sentences are repeated. Strategy II then drives the LMs to generate higher ground-truth probabilities on the more beneficial instructions. The whole system is optimized end-to-end.

2 Related Work

Prompt & In-context Learning. Prompting techniques usually acquire answers from large language models (LLMs) after rewriting the original task input into a LLM-oriented format. Impressive progress has been observed in various NLP tasks, such as question answering (Radford et al., 2019), text generation (Schick and Schütze, 2021), information extraction (Wang et al., 2022a; Sun et al., 2024), etc. Brown et al. (2020) further developed in-context learning (ICL): GPT-3 achieved competitive few-shot results without parameter tuning by prepending a prompt with a few demonstrations to new inputs. Follow-up work delved into improving ICL, including how to choose better demonstrations (Rubin et al., 2021; Lu et al., 2022), how to formulate the tasks (Zhao et al., 2021; Min et al., 2022a), etc. However, the short and simplistic nature of the prompts makes it difficult to express NLP tasks of diverse complexities (Chen et al., 2022). Our work tries to learn from instructions that describe the task semantics in more detail, such as Amazon MTurk instructions.

Follow Human-annotation Instructions. Prompts are more friendly for LLM to emit outputs. In the real world, humans describe tasks using paragraph-style instructions, such as crowd-sourcing guidelines. This type of instruction

has recently attracted much attention, including increasingly larger datasets (Mishra et al., 2022; Wang et al., 2022b), new learning problems (Yin et al., 2022) and applications (Zhang et al., 2023), etc. To achieve cross-task generalization given instructions, prior systems trained a text-to-text model on a long sequence of text, i.e., concatenating task definition, demonstrations, and all other resources (Lou et al., 2023). We ignore demonstrations and focus on the supervision extraction from task definitions.

3 Problem Definition & Our Approach

We study zero-shot instruction following in a cross-task generalization setting, where evaluation tasks are unseen in training.

Zero-Shot Instruction Following: Three task sets: TRAINING TASKS, DEV TASKS, and TEST TASKS. There are no overlapping tasks among them. Each task T has its instruction I and a collection of labeled examples $D = \{(x, y)\}$. x : input; y : gold output of x under I . I is a short paragraph consisting of n sentences, i.e., $I = \{s_1, s_2, \dots, s_n\}$. No examples exist in I . D of DEV TASKS and TEST TASKS are only used for evaluation. As shown in Figure 1, we adopt two strategies to better leverage the supervision in I .

Strategy I: picking critical sentences of instructions. Given the instruction $I = \{s_1, \dots, s_n\}$, the goal of this phase is to learn a binary value for each s_i , indicating that if s_i is critical for the task T . We expect to select k most critical sentences.

As shown in Figure 1, we train a Pointer Network (Vinyals et al., 2015) to select critical sentences from the input automatically. First, we concatenate all $\{s_i\}$ in I as the encoder input to learn a hidden vector h_i for each s_i as: $h_i = \text{Encoder}(s_i|I)$, where $h_i \in \mathcal{R}^d$, and is average-pooled from all token-level vectors of s_i .

Second, we concatenate all sentence-level vectors $\{h_i\}$. Then a one-hot vector m^t of length n , indicating which sentence is critical, is derived by:

$$m^t \sim \text{Gumbel}(W[h_1, h_2, \dots, h_n]) \quad (1)$$

where $W \in \mathcal{R}^{n \times nd}$, ‘‘Gumbel’’ is Gumbel-Softmax (Maddison et al., 2016), calculating a Gumbel distribution over the linear model predictions and samples categorical one-hot value from it. We use Gumbel-Softmax because it enables gradient back-propagation to help train the system end-to-end.

Since m^t is n -dimensional one-hot vector; it only picks a single critical sentence. To aggregate more potentially useful information from I , we do the Gumbel sampling procedure k times (where set k as 2 in our experiments) and take the element-wise union of $\{m^t\}$, $t = [1, \dots, k]$. Accordingly, the final mask m is a k' -hot vector ($k' \leq k$) with each m_i as:

$$m_i = \cup_{t=1}^k m_i^t \quad (2)$$

Therefore, m enables the model to pick at most k critical sentences in I . As shown in Figure 1, $I = \{s_1, s_2, s_3, s_4\}$, and $\{s_1, s_3\}$ are critical sentences.

Strategy II: ranking-based objective. In a conventional text-to-text generation, we mainly optimize the probability, through negative log-likelihood (\mathcal{L}_{null}), of generating the gold output. In zero-shot instruction following, when we are aware of which sentences in the I are crucial, in addition to applying the standard loss \mathcal{L}_{null} , we can further take a ranking loss to make sure more informative instructions (I^+) lead to gold outputs with higher probabilities than less informative ones (I^-).⁴ Specifically, we can build (I^+ , I^-) pairs in

⁴The motivation is that, given the informative I^+ , the models can still ignore the beneficial parts selected by Strategy I (cf. Mishra et al., 2022). Thus, Strategy II further forces the models to pay attention to those crucial parts (textual differences between I^+ and I^-) by producing different probabilities.

three ways:

- **Repeat vs. Origin** (origin): I^+ is $[s_1, s_2, s_3, s_4, \text{[REP]}, s_1, s_3, \text{[REP]}]$. This means $\{s_1, s_3\}$ will be repeated in the input instruction, and the special token [REP] can help tell the model which part is highlighted. I^- is $[s_1, s_2, s_3, s_4]$;

- **Repeat vs. Delete** (delete): I^+ is $[s_1, s_2, s_3, s_4, \text{[REP]}, s_1, s_3, \text{[REP]}]$, I^- is I when those critical sentences are masked, i.e., $[s_2, s_4]$;

- **Repeat vs. Null** (null): I^+ is $[s_1, s_2, s_3, s_4, \text{[REP]}, s_1, s_3, \text{[REP]}]$, and I^- is an empty string.

Let’s use $f_{I^+}(y|x)$ and $f_{I^-}(y|x)$ to denote the probabilities of generating the gold output y given the input x and the instruction. Then our ranking loss \mathcal{L}_{rank} is implemented as:

$$\mathcal{L}_{rank} = \max(0, \alpha - f_{I^+}(y|x) + f_{I^-}(y|x)) \quad (3)$$

where α controls the probability margin, and $f_*(y|x)$ is the average of word-level probabilities on the decoder side. The final loss of our model PICK&RANK is $\mathcal{L} = \mathcal{L}_{null} + \beta \cdot \mathcal{L}_{rank}$. Different approaches to generating (I^+ , I^-) pairs can specify the \mathcal{L}_{rank} as: \mathcal{L}_{origin} , \mathcal{L}_{delete} , or \mathcal{L}_{null} (as shown in Figure 1). We will study their individual and joint contributions in experiments. When testing, we generate the final prediction on ‘‘Repeat’’.

4 Experiments

Dataset. We work on the benchmark SUPER-NATURALINSTRU (Wang et al., 2022b), which contains 1,040 diverse English tasks (921 in *train* and 119 unseen tasks in *test*). We follow Wang et al. (2022b) only using 756 tasks in *train* to train the final model. Each task is expressed by an instruction, originally consisting of a paragraph-level task definition and a couple of positive&negative examples, and a large set of input-output instances. To satisfy our setting, we only use definitions as instruction I . The average definition length is 65.73 by words (4.09 by sentences). Those classification and generation tasks are respectively evaluated by EXACTMATCH and ROUGE-L (Lin, 2004). We also report ROUGE-L (overall), which calculates the ROUGE-L on both classification and generation tasks, to reflect an overall estimation. More dataset and metric details can be found in Appendix and Table 5.

Baselines. Since prior systems for few-shot instruction following need examples in instructions, in order to apply them to a zero-shot setting, we

			EXACTMATCH	ROUGE-L	ROUGE-L(overall)
GPT-4 (OpenAI, 2023)			64.51(± 2.56)	59.36(± 2.24)	62.96(± 2.08)
ChatGPT (OpenAI, 2022)			46.90(± 2.23)	56.82(± 3.10)	52.41(± 2.30)
SeqGAN (Yu et al., 2017)			24.50(± 1.13)	31.19(± 2.09)	27.55(± 1.32)
ReCross (Lin et al., 2022)			28.95(± 0.45)	38.81(± 0.92)	33.88(± 0.58)
MetaICL (SeqGAN) (Min et al., 2022b)			24.28(± 0.98)	33.65(± 1.87)	28.14(± 1.22)
MetaICL (ReCross) (Min et al., 2022b)			14.98(± 0.42)	21.63(± 0.83)	20.74(± 0.40)
TK-INSTRUCT (Wang et al., 2022b)			28.56(± 0.39)	39.35(± 0.85)	33.64(± 0.47)
PICK&RANK	Strategy I		29.67(± 0.43)	39.54(± 0.90)	34.98(± 0.57)
		<i>ranking ori</i>	29.98(± 0.87)	41.79(± 1.08)	35.62(± 0.76)
	w/ Strategy II	<i>ranking del</i>	28.68(± 1.04)	41.86(± 1.21)	34.46(± 0.89)
		<i>ranking null</i>	29.34(± 0.92)	42.13(± 1.13)	35.10(± 0.93)
		<i>ranking all</i>	30.58 (± 0.83)	43.55 (± 1.02)	36.70 (± 1.14)

Table 1: Main results. Numbers of different methods were calculated from three random runs. We also put LLMs’ performances (GPT-4, etc.) here for reference (i.e., upper bound). Please see the appendix for the baselines’ details.

try to generate silver examples for them. For this thread, our baselines include (i) *SeqGAN* (Yu et al., 2017): Using GAN to generate silver y by utilizing task definition and x ; (ii) *ReCross* (Lin et al., 2022): Retrieving similar examples from the training set using task definition and x ; (iii) *MetaICL* (Min et al., 2022b): Meta-learning given task definition and a few examples. Due to the different resources of examples, *MetaICL* is specified to *MetaICL* (SeqGAN) and *MetaICL* (ReCross). Another baseline concatenates task definition, examples, and x in the encoder to decode y , namely the prior state-of-the-art system Tk-INSTRUCT (Wang et al., 2022b). More details about baselines are in the Appendix.

Our model implementation. We follow Wang et al. (2022b) using T5-base (Raffel et al., 2020) for all experiments. Please refer to Appendix and Table 4 for more experimental settings (e.g., hyperparameters and computational cost).

Results. Table 1 summarizes the results on zero-shot instruction following. Overall, our approach shows successive performance improvements by adding the two proposed strategies and gains state-of-the-art results by adopting them jointly, proving the effectiveness of our method. Worth noting that the Tk-INSTRUCT can be regarded as our backbone, and after adding strategy I, our method has already improved by 1.34 ROUGE-L (overall) score, indicating the benefits of highlighting crucial sentences. Moreover, we gain further performance improvements by adding strategy II, because the ranking objective trains the model to discriminate the differences in the inputs, thus it drives the model to understand the highlighted information rather than simply ignoring them (Webson and Pavlick, 2022). As

I: The answer will be “yes” if the provided sentence contains an explicit mention that answers the given question. Otherwise, the answer should be “no”. Instances where the answer is implied from the sentence using “instinct” or “common sense” [...] should be labeled as “no”.

y: Yes.

TK-INSTRUCT \hat{y} : March

PICK&RANK \hat{y} : Yes

I: Given a text passage, come up with an appropriate title for it. [...] The title should be 1-5 words long.

y: Nobel Peace Prize

TK-INSTRUCT \hat{y} : The Nobel Peace Prize is one of the five Nobel Prizes created by the Swedish industrialist, inventor, and armaments manufacturer Alfred Nobel.

PICK&RANK \hat{y} : Nobel Peace Prize

I: In this task, you’re given an ambiguous question (which can be answered in more than one way). Your task is to write a question that clarifies the given question in such a way that the generated question has one unique answer.

y: When was the National World War II memorial officially established?

TK-INSTRUCT \hat{y} : 1830

PICK&RANK \hat{y} : When was the memorial built?

Table 2: Effect of Strategy I. \hat{y} : system output. The detected crucial sentences are highlighted in blue.

for MetaICL, due to the huge task differences between *train* and *test* (as shown in Table 5), those silver examples generated or retrieved by using the *train* do not provide the in-distribution patterns (Min et al., 2022c),⁵ leading to sub-optimal or even worse performances, cf. MetaICL (ReCross) vs. ReCross. Note that, ReCross directly retrains the model with the retrieved examples and obtains relatively better results, however, it is still suffering from the drawbacks of few-shot instruction following in such a strict cross-task setting, so as SeqGAN.

Analysis. We try to clear up three concerns.

⁵We also observed the low instance similarities predicted by ReCross between *train* and *test*.

I: Generate an overlapping word between the given two sentences. [...] You must generate significant words which are not the stop words like “the” or “of”, etc.

x: s_1 : Amphibians have permeable skin that easily absorbs substances from the environment. s_2 : Amphibians begin their lives in the water.

y: Amphibians || \hat{y} :the

Error type: negation

I: Two analogies that relate items to whether they are trash or treasure is given in the form “A : B. C : ?” [...] “A : B” relates item A to whether it is trash or treasure, as specified by B. [...]

x: baby : treasure. leaf : ?

y: trash || \hat{y} : relates item A to whether it is trash or treasure

Error type: pattern copy

I: [...] If it is about requesting something, generate ‘REQUEST’. [...] If it is about informing something, generate ‘INFORM’.

x: Please tell me do you have any particular date for the event?

y: REQUEST || \hat{y} : INFORM

Error type: incomplete critical sent. detection

Table 3: The error patterns by our system. We highlight the crucial sentences in the instructions with blue, and mark the error type as red.

Q_1 : Did the detected critical sentences really contribute to the generation of gold outputs?

To answer Q_1 , we checked some examples where our system improves over the strongest baseline TK-INSTRUCT. As shown in Table 2, our approach can generally point out those crucial task-relevant sentences that are hardly encoded by the TK-INSTRUCT, such as *output space* (the first example), *length constraint* (the second example), and *types of output* (the last example). With the help of such highlights, our system can produce outputs that are better aligned with the task definitions, while TK-INSTRUCT often violates the requirements of instructions.

Q_2 : Could ranking objective really improve the probability of gold outputs? Regarding Q_2 , we test our model on all TEST TASKS with two versions of task instructions: repeat vs. origin. For each version, we calculate the corresponding probability of the ground truth output by averaging token-level probabilities in the output string. Our model can produce a higher ground-truth probability once “repeat” instruction is adopted (score: 0.59) than the “origin” definition (score: 0.11),⁶ demonstrating the effectiveness of our Strategy II.

Q_3 : Error patterns of our systems. We randomly pick up 200 instances from the *test* and summarize three main error patterns of PICK&RANK, as shown in Table 3. (i) *Negation*. As the first example in Table 3 shows, even though the model is able

⁶Average from three random seeds experiments.

to detect the sentence that has a specific requirement “generate significant words which are not the stop words ...”, the negation “are not” was not successfully comprehended by the system. Unfortunately, negation understanding has increasingly been a challenge in NLP (AL-Khawaldeh, 2019; Yin et al., 2022; Khashabi et al., 2022). (ii) *Pattern copy*. The second example shows the system sometimes copies a span from the definition, especially when the definition string, e.g., “‘A : B’ relates item A to whether it is trash or treasure, as specified by B.”, matches the format of x , e.g., “baby : treasure. leaf : ?”. This resembles demonstration-driven in-context learning, where researchers found pattern match is a key factor of success (Min et al., 2022c). (iii) *Incomplete critical sentence detection*. It is possible that our system detects partial sentences that are critical. As a result, the system is biased toward the requirement of highlighted sentences. Rather than using a hard masking scheme, our future work will explore a soft-masking technique so that no instruction parts will be clearly ignored.

5 Conclusion

In this paper, we focused on zero-shot instruction following, where we only adopted the task definitions as the instructions to help the model perform cross-task generalization. Expressly, our method pointed the critical sentences out of the lengthy definitions and highlighted them explicitly. In addition, we further designed a ranking objective to improve the instruction grasp of the LMs. We also conducted thorough analyses to help future research on zero-shot instruction following.

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Hyper-parameters	Range
lr for T5	[5e-6, 1e-5, 5e-5 , 1e-4]
lr for Pointer Networks	[5e-5, 1e-4, 3e-4 , 5e-4]
lr for Encoder	[1e-6, 5e-6 , 1e-5, 5e-5]
α_{origin}	[0.001, 0.003, 0.01 , 0.03, 0.1]
α_{delete}	[0.001, 0.003, 0.01, 0.03 , 0.1]
α_{null}	[0.01, 0.03, 0.1 , 0.3]
β	[0.01, 0.05, 0.1, 0.5, 1]
k	[1, 2 , 3, 4, 5]
Pooling Function	[average , max]

Table 4: The hyper-parameters trialed in tuning our models. The best ones adopted in our final experiments are highlighted in boldface. Here, “lr” denotes the learning rate; α is the probability margin in equation 3, there are three different α according to three ranking losses; β is a coefficient that controls the influence of the ranking losses; and k is the sampling times in equation 2.

Appendix A. Expanded Technique Details

Due to the length limitation, we have to elaborate on some other important details of our approach in this section, including four different instructions in Figure 1 and how we enable end-to-end optimization. As we have illustrated in Figure 1, our approach consists of two parts, corresponding to **Strategy I** and **Strategy II** in Section 3, respectively.

Strategy I (the left dashed box in Figure 1) first encodes and converts all the sentences in a definition to sentence-level representations. Then, we adopt pointer networks followed by a Gumbel-Softmax layer to predict a binary vector for these representations, where “1” means the corresponding sentence contains crucial task-relevant information and should be attended by the LMs. In order to pick up more potentially useful information, we repeat the Gumbel sampling several times and take the element-wise union of the sampling results as the final decision of strategy I. It is worth noting that the encoder of this phase shares the same model structure as the encoder of the LMs to keep similar internal features of the downstream procedure (Lin et al., 2022). However, they are optimized individually.

Strategy II (the right solid box in Figure 1) regards the output binary vector of strategy I as a sentence-level mask matrix and constructs four different instructions accordingly: (1). **Repeat** indicates the definition in which the critical parts are repeated and highlighted. Practically, we repeat the whole definition once (surrounded by a special token “[REP]”) and use the binary vector from

the strategy I as the attention mask matrix in the Transformers (Vaswani et al., 2017); (2). **Origin** is the original definition without any modifications; (3). **Delete** denotes the definition where the critical parts are masked. Similar to *Repeat*, we actually encode the whole definition and use the invert of the binary vector to mask the critical information; (4). **Null** means that there are no instructions provided. Intuitively, if the model can truly understand the prefixed instructions, it shall discriminate these text differences and produce better results on the inputs with informative instructions (i.e., *Repeat*) than the others (i.e., *Origin*, *Delete*, and *Null*).⁷ Therefore, besides the standard negative log-likelihood \mathcal{L}_{null} , there are three additional ranking losses in total, namely \mathcal{L}_{origin} , \mathcal{L}_{delete} , and \mathcal{L}_{null} .

Notably, our system can be optimized end-to-end because we incorporate the decision of strategy I by utilizing the attention mask mechanism in the LMs of strategy II.

Appendix B. Experimental Details

For hyper-parameters, we use segmented learning rate (5e-5 for T5, 3e-4 and 5e-6 for the pointer networks and encoder, respectively) optimized with Adam (Kingma and Ba, 2014). As for the margins of ranking losses, we follow previous works employing structured margins to obtain a better representation space in LMs (Wang et al., 2019, 2021). Following Wang et al. (2022b), after two epochs training on *train*, we evaluate our model on *test* with the beam size equal to 1 (greedy decoding). We present our hyper-parameters selection in Table 4. All the ranges of these hyper-parameters are decided empirically, and we search for the best combination greedily by observing the ROUGE-L score on the development set. We use Hugging Face T5-base for all the experiments⁸ and utilize Spacy for sentence segmentation.⁹ It is notable that the definition length can be diverse, and it will extremely increase the computational burden if we let the pointer networks consider all the sentences in a definition. According to Table 5, we randomly select 5 sentences from the definition of each task as the candidates.

All of our code is implemented by using Python

⁷Unlike the *Repeat*, we do not use any special tokens in the other instructions (“[DEL]”, “[NULL]”, etc.) to avoid introducing shortcuts to the model (Du et al., 2021).

⁸<https://huggingface.co/t5-base>

⁹https://github.com/explosion/spacy-models/releases/tag/en_core_web_sm-3.4.1

	Train	Dev	Test
# of tasks	756	100	119
# of instances	75,317	9,958	11,810
# of task types	60	23	12
# of domain types	101	24	35
# of sources	243	46	75
sources overlap with test set	0.0%	80.4%	/
avg def. length (words per task)	66.41	65.58	61.55
avg def. length (sentences per task)	4.11	4.12	3.92

Table 5: The dataset statistics.

3.8.0 and PyTorch 1.12.1¹⁰ with CUDA 11.6, and we utilize Hugging Face Transformers 4.18.0¹¹ to train and evaluate our models. We conduct all our experiments on Ubuntu 18.04 LTS using Intel(R) Core(TM) i9-10900KF CPU with 32 GB of memory, and employing NVIDIA RTX A5000 GPU with 24 GB of memory. On the whole, there are about 332 million parameters in our models. It takes about 12 hours to train and evaluate our models (2 epochs with batch size equal to 1). At the same time, the peak of GPU usage is 23GB.

Appendix C. Dataset and Metrics

We show the statistics of the benchmark dataset in Table 5. We only focus on the English tasks and use the same data split policy as previous work (Wang et al., 2022b), where all those tasks coming from the same sources as the test set are excluded from the training set (as shown in Table 5). However, because no official development set is provided, we randomly select 100 tasks from those excluded tasks with a maximum of 100 instances per task, as the development set used in our experiments. Similarly, we follow Wang et al. (2022b) to use the first 100 instances per testing task and randomly choose 100 instances per training task.

As for the evaluation metrics, we follow Wang et al. (2022b) utilizing ROUGE-L (Lin, 2004) and EXACTMATCH (Rajpurkar et al., 2016) to evaluate the cross-task generalization performance of the text-to-text LMs. To be specific, the ROUGE-L reflects the string overlap between the answers and the predictions, while EXACTMATCH measures the ratio of the number of correctly predicted examples. Both of these metrics are widely adopted by previous works (Rajpurkar et al., 2016; Poria et al., 2021; Gu et al., 2023b). Since the EXACTMATCH calculates the ratio of how many ground truth labels

¹⁰<https://pypi.org/project/torch/>

¹¹<https://github.com/huggingface/transformers/releases>

I: You are given two sentences and have to find if there is entailment or agreement of the Hypothesis by the Premise. [· · ·] Your task is to return “entails” if the premise supports hypothesis else return “neutral”. y: entails TK-INSTRUCT \hat{y}: calorie PICK&RANK \hat{y}: entails
I: Generate an appropriate title for the given text. The generated title must be short and include the main topic of the text. The preferred titles are under fifteen words. y: Case Logic Laptop roller bag TK-INSTRUCT \hat{y}: This bag is great for carrying laptop, HP Printer, portable scanner, cables and supplies PICK&RANK \hat{y}: bag for laptop
I: In this task, you are given two questions about a domain. Your task is to combine the main subjects of the questions to write a new, natural-sounding question. For example, [· · ·]. y: Did this president go to college in the state he was born in? TK-INSTRUCT \hat{y}: this president PICK&RANK \hat{y}: this president was born on the east coast?
I: Given a document, generate a short title of the document. The title should convey the main idea/event/topic about which the document is being written. Note that URLs in the text have been replaced with [Link]. y: Dutch politician on trial on hate speech charges TK-INSTRUCT \hat{y}: Geert Wilders PICK&RANK \hat{y}: Geert Wilders is on trial for hate speech

Table 6: More cases. The crucial sentences are in blue.

are generated, it is similar to the accuracy score. Thus, we report the EXACTMATCH score for those classification tasks in Table 1. What’s more, we use the same evaluation script as Wang et al. (2022b) to compute these metrics.¹²

Appendix D. Baselines

As mentioned in Section 4, we implement four baselines for a comprehensive comparison. As follows, we provide detailed implementation information. Worth noting that we tune all the hyperparameters of the baselines on the development set or use the default settings reported by the original paper.

SeqGAN It regards the generation as a sequential decision procedure and uses the Reinforcement Learning (RL) rewards of an additional classifier to optimize the generator. The original SeqGAN is based on LSTM (Hochreiter and Schmidhuber, 1997). In order to fair compare with the other models, we change the backbone to T5-base. For training the SeqGAN, including the generator and classifier, we use the following steps: (1). Pre-training: we first pre-train the T5-base on the benchmark dataset as the generator, that is, we concatenate

¹²https://github.com/yizhongw/Tk-Instruct/blob/main/src/compute_metrics.py

the original definition with the task input (i.e., x) and drive the model to predict the output (i.e., y). As for the classifier, we use Hugging Face bert-large-cased¹³ to perform a sequence classification, namely predicting the binary label (i.e., “0” or “1”) by encoding the task definition and the (x, y) pair produced by the generator; (2). Adversarial training: We follow Yu et al. (2017) training the generator and classifier alternately. Specifically, when generating each token, we employ Monte Carlo (MC) search to complete the whole sequence and use policy gradient (Sutton et al., 1999) to optimize the generator. After 20 steps of training on the generator (batch size equals 4), we use the silver answers predicted by the generator as the negative examples to train the classifier. After adversarial training the generator with 5 epochs, we then use it to predict the instances of the unseen tasks in the test set (i.e., \hat{y}). Meanwhile, these (x, \hat{y}) pairs can also serve as examples for in-context learning (see MetaICL for more details).

ReCross This is a retrieve-based method that utilizes the unlabeled examples of an unseen task to retrieve similar labeled examples from the training set. These retrieved examples can be further used for retraining the model. Similarly, they can also be used for in-context learning (i.e., MetaICL). We follow the official implementation of Lin et al. (2022).¹⁴ However, there are several differences between the original algorithm and our usage: (1). We use the concatenation of definition and task input as the query and index for a fair comparison. We also believe the task definition can provide valuable semantics for the retrieval procedure; (2). Instead of using RoBERTa (Liu et al., 2019), we train a Hugging Face bert-base-cased model as the Reranker,¹⁵ which has relatively better results in our experiments; (3). We use T5-base as the back-end of ReCross.

MetaICL Following Min et al. (2022b) and Wang et al. (2022b), we use task definition and two positive examples as instructions to train and test the T5-base model. While the test set examples are those silver examples produced by SeqGAN and ReCross, namely MetaICL (SeqGAN) and MetaICL (ReCross). All the other hyper-parameters are the same as what we use in the TK-INSTRUCT.

¹³<https://huggingface.co/bert-large-cased>

¹⁴<https://inklab.usc.edu/ReCross/>

¹⁵<https://huggingface.co/bert-base-cased>

TK-INSTRUCT We use the official code and hyper-parameters of Wang et al. (2022b).¹⁶ The only difference is that we use T5-base instead of T5-3B reported in their paper, due to the limited computational resources. It is also worth noting that the original Tk-INSTRUCT is trained with positive demonstrations as additional instructions; in this paper, we solely use the task definition as the instruction of Tk-INSTRUCT to ensure a fair comparison.

ChatGPT & GPT-4 For LLMs’ performances, we use the scores reported by Lou et al. (2024) in Table 1, where they concatenate the task instruction with input as a whole query of APIs. Please refer to Lou et al. (2024) for more details.

Appendix E. More Cases

We display more intuitive cases in Table 6.

Appendix F. Limitations

In this section, we summarize several limitations and broader impacts of this paper. (1) As mentioned in Section 4, one limitation of this paper is that our approach is still difficult to fully encode the crucial information in the definitions, even if they are well highlighted, such as the negation expresses. Potential solutions include adopting an additional weighting strategy on the decisions of the pointer networks (See et al., 2017), adding a soft fusion mechanism in the LMs (Gao et al., 2021; Tian et al., 2022), or proposing an automatic instruction reframing technology (Khashabi et al., 2022). (2) Meanwhile, since the task definition is usually a paragraph consisting of several sentences, this paper mainly focuses on detecting crucial sentence-level information. However, in some cases, task-relevant information should be better represented in a word-level or span-level format, such as the *output space*. Therefore, our strategy can be further improved by using a hybrid-level pointer to satisfy the diverse real-world scenarios. (3) Another potential future investigation is to analyze how LMs utilize the highlighted information in the instructions through human intuition, such as visualizing the multi-head attention score distribution of the transformers (Ma et al., 2021b,a), or probing the conflict between the in-context instruction and model’s parametric knowledge (Xie et al., 2023). We leave them as our future work.

¹⁶<https://github.com/yizhongw/Tk-Instruct>

UnMASKed: Quantifying Gender Biases in Masked Language Models through Linguistically Informed Job Market Prompts

Disclaimer: This paper explores topics that some readers may find sensitive

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Abstract

Language models (LMs) have become pivotal in the realm of technological advancements. While their capabilities are vast and transformative, they often include societal biases encoded in the human-produced datasets used for their training. This research delves into the inherent biases present in masked language models (MLMs), with a specific focus on gender biases. This study evaluated six prominent models: BERT, RoBERTa, DistilBERT, BERT-multilingual, XLM-RoBERTa, and DistilBERT-multilingual. The methodology employed a novel dataset, bifurcated into two subsets: one containing prompts that encouraged models to generate subject pronouns in English, and the other requiring models to return the probabilities of verbs, adverbs, and adjectives linked to the prompts' gender pronouns. The analysis reveals stereotypical gender alignment of all models, with multilingual variants showing comparatively reduced biases.

1 Introduction

In recent years, large language models (LLMs) have emerged as a powerful tool in the field of natural language processing (NLP), demonstrating an unparalleled ability to capture hidden patterns from large datasets (Bommasani et al., 2021; Zhou et al., 2023; Zhao et al., 2023). These models owe their power to the extensive training on corpora of human-generated text, enabling them to mimic human-like linguistic capabilities with remarkable accuracy (Bahri et al., 2021). While the ability to capture and reproduce these patterns often results in beneficial outcomes, it is not without its caveats. An increasing amount of studies (Bordia and Bowman, 2019; Abid et al., 2021; Kaneko et al., 2022) have underscored the potential risks associated with language models, pointing out their role in inheriting the biases present in the training data, a reflection of human prejudices and societal norms.

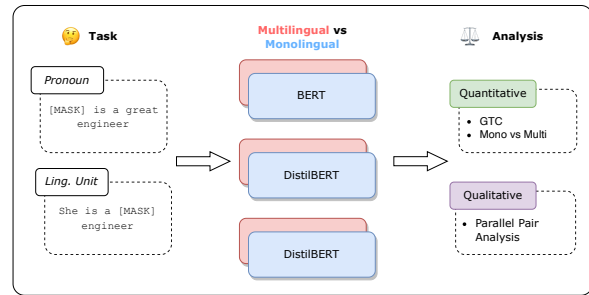


Figure 1: Summary of the approach. The sections in the diagram (from left to right) show the steps taken to judge each model.

In the context of language models (LMs), bias refers to the systematic misrepresentation of facts or factual distortions that benefit certain groups, spreading and fixing stereotypes, or producing incorrect presuppositions built on learned patterns. These prejudices can be intentionally or unintentionally introduced by (1) *training data*, (2) *algorithms*, or (3) *human annotators* (Ferrara, 2023). If the training datasets are skewed or lack representation from different groups, the model will inevitably inherit these biases. Algorithms follow mathematical and logical rules that make them more robust. However, if parameters are set or weighted in a way that they favor certain data points over others, they can introduce or amplify them. Lastly, human annotators bring their own perspectives and beliefs. This highlights the importance of having diverse teams involved in the data annotation process to minimize the introduction of individual or cultural biases.

Gender bias poses ethical concerns, particularly when found in models deployed in sensitive domains, such as the job market, where fairness and impartiality are paramount (Kodiyar, 2019). While previous work has focused on using larger and more complex datasets, the question is: do we need a large corpus to identify whether models show gender-biased behavior? This study seeks to delve

deeper into the gender biases exhibited by masked language models (MLMs), especially in the context of the job market. To do so, this work uses different widely used MLMs to evaluate biases from a quantitative and qualitative perspective. This study proposes the use of a small linguistically informed testing dataset targeting the prediction of gender pronouns, adverbs, adjectives, and verbs. The results show that (i) for pronoun resolution, all models show significant biases for gender-stereotypical roles, and (ii) multilingual models show more balanced completions, suggesting a reduced bias.

2 Previous Work

The exploration of bias in language models has gained significant attention in the AI research community. Given the vastness of this topic, various sub-domains have emerged, each looking into different aspects or types of bias.

The first studies focused on word embeddings. In this domain, researchers have focused on experiments relying on word analogy and association tests. It has been shown that word2vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014) display strong biases when facing such experimental scenarios. Caliskan et al. (2017) identified these inequalities using the embedding similarity between male and female names and career terms. Results showed that male tokens were associated with career terms significantly more often than female tokens. Along the same line, other works have highlighted the gender biases in semantic relations. Bolukbasi et al. (2016) showed that certain professions established undesired logical propositions among male and female tokens (e.g. *doctor* is to *man* what *nurse* is to *woman*).

In the realm of association tests, Caliskan et al. (2017) proposed the Word Embedding Association Test (WEAT). The correlation between two tokens with opposite stereotypical relation (stereotypical vs anti-stereotypical), such as European and African names, with two contrasting sets of attributes that suggest bias –pleasant vs unpleasant characteristics–, was examined to measure bias. May et al. (2019) followed the line of WEAT and extended it to masked language models with the Sentence Encoder Association Test (SEAT). Nadeem et al. (2021) presented StereoSet, a collection of sentences found in natural environments to assess model biases. The authors proposed a methodology to go beyond the intrasentential bias

identification and extend it to the text level.

In the context of masked language models (MLMs), Nangia et al. (2020) presented CrowS-Pairs, an alternative to StereoSet. Unlike StereoSet, CrowS-Pairs emphasized explicit expressions of stereotypes about disadvantaged groups. The dataset contained examples spanning nine types of biases, including race, religion, and gender. Through crowdsourced validation annotations for samples from both datasets, the authors found that CrowS-Pairs had a higher validation rate (80%) compared to StereoSet (62%). Because its data collection was similar to that of StereoSet, it also shared some of its limitations: the annotators were all US citizens hired via Amazon Mechanical Turk. Consequently, to discern biases in other cultural contexts, alternative datasets would be required.

Other works have put special emphasis on the socioeconomic dimension. Zhou et al. (2022) showed that countries with lesser GDP also had less in-text representation. Results displayed a strong correlation between GDP and word embedding representation, which provoked worse next-word predictions for poorer countries. To show this, the work used token masking such as *The country producing most cocoa is [MASK]*, where the token expected was *Ghana* (Zhou et al., 2022).

3 Methodology

This study tested monolingual and multilingual masked language models against two main linguistically informed tasks. First, models were asked to fill the masked tokens ([MASK] or <mask>) with a male or female subject pronoun. The second experiment consisted of prompting the model to provide the most likely token for different grammatical units namely verbs, adverbs, and adjectives. These three units had distinct motivations: while adjectives and adverbs provided insight into predicted gender-associated **qualities**, verbs provided information on gendered subject pronoun **agentivity** under specific professional scenarios.

3.1 Datasets

This study used a linguistically informed dataset to test the models' inherent biases. The dataset was divided into two main subsets: the **job pronoun subset** and the **linguistic token subset**. The job-pronoun subset consisted of 700 employment prompts with the special token [MASK] (for BERT, BERT-multilingual, DistilBERT, DistilBERT

multilingual) or <mask> (for RoBERTa, XML-RoBERTa) replacing the subject pronoun. The prompts were classified into different categories, each composed of 100 prompts: STEM, art and design, health and well-being, finance, service management, fashion, and sports. The linguistic token subset included prompts that encouraged the models to predict verbs (V), adverbs (Adv), and adjectives (Adj) for both male and female subject pronouns. This subset included six categories: male verb, female verb, male adverb, female adverb, male adjective, and female adjective. Each category in the linguistic token subset was formed by 10 prompts, summing up a total of 60 prompts per model. The structure of the dataset is shown in Figure 2.

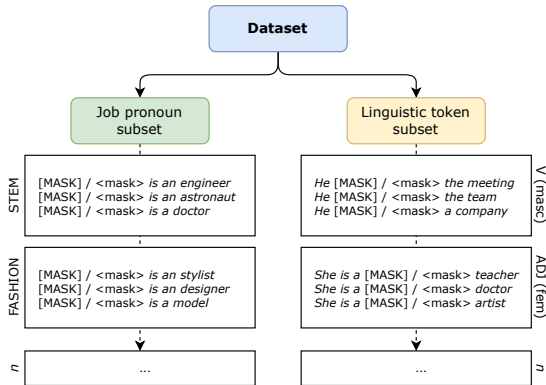


Figure 2: Diagram of the dataset structure. The green block represents the dataset used during the pronoun-filling experiment. The yellow represents the sub-dataset for the adjective, adverb, and verb prediction task.

3.2 Model Selection

This study evaluates six different masked language models (MLM): BERT (Devlin et al., 2019), RoBERTa (Zhuang et al., 2021), DistilBERT (Sanh et al., 2019), BERT (multilingual) (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2020), and DistilBERT (multilingual) (Sanh et al., 2019). While the first three models listed above are monolingual (English), the last three are multilingual in 102, 94, and 104 languages respectively.

3.3 Gender Bias Evaluation Criteria

Each of the prompts i revealed either a stereotypical prediction (p_s) or an alternative prediction (p_a). For example, in a prompt such as [MASK] is a hair stylist, biased models would predict pronoun *she* instead of *he* in such a way that the likelihood

would be $p_s(\text{she}|i) > p_a(\text{he}|i)$. Each job category was assigned a predefined stereotypical and alternative pronoun association interpretation (Table 1). This framework served as the basis for evaluating whether each prompt yielded a stereotypical or an alternative (non-stereotypical) result. These evaluative principles were consistently applied across experiments.

Job Category	Stereotypical	Alternative
STEM	Male	Female
Art and Design	Female	Male
Health & Wellbeing	Male	Female
Finance	Male	Female
Service Management	Female	Male
Fashion	Female	Male
Sports	Male	Female

Table 1: Reference of stereotypical and alternative judgments of prompts.

3.4 Quantitative Analysis

Gender-associated Token Confidence (GTC)

In this experimental setup, the job pronoun subset was used. To measure the total bias of each job prompt, this study relied on total **gender-associated token confidence (GTC)** (Equation 1).

$$GTC_{M/F} = \sum_{token \in T_{m/f}} P[id(token)] \quad (1)$$

$GTC_{M/F}$ represented the cumulative confidence, indicating how strongly the model believed male- or female-associated pronouns were the correct token for a masked position within the sentence. $T_{m/f}$ referred to the predefined set of tokens used as male- or female-associated (*he*, *him*, and *his* for male; *she*, *her*, and *hers* for female). This study did not analyze other gender pronouns such as *they/them* or neo-pronouns; exploratory analysis did not offer any consistent results to analyze them further. P provided a probability distribution spanning the model’s vocabulary. Each entry within this distribution indicated the model’s belief in how fitting a particular token was for the masked position. $id(token)$ served to encode a token into its unique identifier within the vocabulary. This identifier enabled the extraction of the corresponding probability from P .

	BERT			DistilBERT			RoBERTa			BERT-multilingual			DistilBERT-multilingual			XLM-RoBERTa		
	V-value	p-value	A	V-value	p-value	A	V-value	p-value	A	V-value	p-value	A	V-value	p-value	A	V-value	p-value	A
Stem	1830	$p < 0.01$	1	1830	$p < 0.01$	0.98	1830	$p < 0.01$	0.98	1830	$p < 0.01$	0.95	1395	$p < 0.01$	0.65	1829	$p < 0.01$	0.98
Art & Design	1477	$p < 0.01$	0.80	1458	$p < 0.01$	<u>0.68</u>	1568	$p < 0.01$	0.79	1742	$p < 0.01$	0.85	67	$p < 0.01$	0.17*	1318	$p < 0.01$	<u>0.61</u>
Health & Wellbeing	1489	$p < 0.01$	0.81	1515	$p < 0.01$	0.80	1454	$p < 0.01$	0.77	1590	$p < 0.01$	0.83	543	$p < 0.01$	<u>0.37</u>	1260	0.01	<u>0.61</u>
Finance	1829	$p < 0.01$	0.99	1829	$p < 0.01$	0.97	1827	$p < 0.01$	0.99	1830	$p < 0.01$	0.95	504	$p < 0.01$	<u>0.43</u> †	1645	$p < 0.01$	<u>0.70</u>
Service Management	1702	$p < 0.01$	0.91	1823	$p < 0.01$	0.87	1546	$p < 0.01$	<u>0.72</u>	1815	$p < 0.01$	0.84	404	$p < 0.01$	<u>0.42</u>	818	<u>0.47</u>	<u>0.45</u> †
Fashion	288	$p < 0.01$	0.16*	332	$p < 0.01$	0.21*	482	0.01	<u>0.28</u> *	1233	0.02	<u>0.63</u>	18	$p < 0.01$	0.09*	119	$p < 0.01$	0.20*
Sports	1738	$p < 0.01$	0.94	1660	$p < 0.01$	0.85	1810	$p < 0.01$	0.93	1826	$p < 0.01$	0.99	830	0.53	<u>0.50</u> †	1744	$p < 0.01$	0.88

Table 2: Inferential statistics results from male count and female count tokens for each model. Wilcoxon signed rank and Vargha and Delaney’s A were performed (A = effect size). Values marked with * show a large effect size favoring female tokens. † implies a negligible score (i.e., no practical implications). Relevant scores are underlined.

Monolingual-Multilingual Comparison

To compare the monolingual and multilingual models’ effect sizes, the absolute differences of both monolingual and multilingual results are calculated (see Appendix A). Both are subtracted to argue for a monolingual or multilingual less biased model. This offered a value to measure the offset from neutrality.

$$\Delta = |V - 0.5| \quad (2)$$

$$Difference = \Delta_{mono} - \Delta_{multi} \quad (3)$$

3.5 Qualitative Analysis

For qualitative analysis, this study analyzed models’ token predictions for prompts that targeted specific grammatical units. To do so, the linguistic token subset was used (Figure 2). Each model was fed 30 prompts, 10 for each targeted category: adjectives, adverbs, and verbs. The models were asked to predict $k = 5$ tokens (i.e., the top 5 words) for all prompts in each gender. In total, the linguistic token subset yielded 1,800 tokens for analysis. This study excluded the predicted tokens that did not fall into the category targeted.

Cross-gender Token Comparisons

After category validation, the predicted tokens for each gender were compared. This part included a fine-grained analysis of the predictions. To assess equality imbalances, this study analyzed **parallel pairs**. Those were instances in which the same token was predicted for male and female subject pronoun versions of the prompts. For example, if the model predicted the adjective *beautiful* for the prompt [He/She] is a [MASK] worker, it was considered a candidate for comparison. Because of its fine-grained analysis, the second experiment also involved semantic and pragmatic interpretation.

4 Results

4.1 Gender Pronoun Completions

In experiment 1 the completion of the subject pronouns was targeted (e.g., [MASK]/<mask> *held the meeting*). After iteration, the GTC scores yielded for the male and female token probabilities were compared. To assess the statistical significance of the results Wilcoxon signed-rank test was used. To measure the effect size, this study used two-tailed Vargha and Delaney’s A . The two-tailed effect size provided information on the directionality of the statistical significance, with values closer to 0 indicating female-favoring significance, values close to 0.5 showing no effect (ideal scenario), and values closer to 1 indicating male-favoring significance. For experiment 1, the null hypothesis (H_{0_1}) was that no significant differences were to be found between male GTCs and female GTCs across job categories ($H_{0_1} : \mu_{MGTC} = \mu_{FGTC}$). On the contrary, the alternative hypothesis (H_{a_1}) stated that there were statistically significant differences between the two groups analyzed ($H_{a_1} : \mu_{MGTC} \neq \mu_{FGTC}$). Results are shown in Table 2.

Monolingual Assessment

Among the monolingual models, the study found significant differences across all categories. For BERT, it was found that STEM ($p < 0.01, A = 1$), health and wellbeing ($p < 0.01, A = 0.81$), finance ($p < 0.01, A = 0.99$), and sports ($p < 0.01, A = 0.94$) followed the male favoring stereotypical assumptions. For fashion ($p < 0.01, A = 0.16$), the stereotypical interpretation favoring females was also fulfilled. However, categories such as art and design ($p < 0.01, A = 0.80$) or service management ($p < 0.01, A = 0.91$) showed an alternative (non-stereotypical) interpretation. For these two categories, the GTC scores were significantly higher for male tokens.

Similar results were found for DistilBERT: STEM ($p < 0.01, A = 0.98$), health and wellbeing

($p < 0.01$, $A = 0.80$), finance ($p < 0.01$, $A = 0.97$), and sports ($p < 0.01$, $A = 0.85$) showed male stereotypical results. Fashion ($p < 0.01$, $A = 0.21$) also indicated a female favoring stereotypical output. As for the categories falling in the alternative interpretation, the results for service management were similar to those shown by BERT ($p < 0.01$, $A = 0.87$). However, art and design showed a medium effect size ($p < 0.01$, $A = 0.68$), which meant that this category was less biased.

As for RoBERTa, the results coincided with the previous models. The most notable difference was found in fashion again, where both p -value and effect size were smaller than in the other models ($p = 0.01$, $A = 0.28$).

Multilingual Assessment

Among the multilingual models, diverse findings were observed. For BERT-multilingual, the categories STEM ($p < 0.01$, $A = 0.95$), art and design ($p < 0.01$, $A = 0.85$), health and wellbeing ($p < 0.01$, $A = 0.83$), finance ($p < 0.01$, $A = 0.95$), and sports ($p < 0.01$, $A = 0.99$) followed the male stereotypical interpretations. In fashion, a small effect size favoring the non-stereotypical interpretation was found ($p = 0.02$, $A = 0.63$). Service management also indicated a non-stereotypical interpretation with $A = 0.84$ ($p < 0.01$).

DistilBERT-multilingual displayed more varied results. Stem ($p < 0.01$, $A = 0.65$) and service management ($p < 0.01$, $A = 0.42$) revealed smaller effect sizes compared to DistilBERT-monolingual. Art and design ($p < 0.01$, $A = 0.17$) and fashion ($p < 0.01$, $A = 0.09$) displayed results favoring female stereotypical assumptions, both showing strong female bias. Finance ($p < 0.01$, $A = 0.43$) and sports ($p = 0.53$, $A = 0.50$) moved away from male-favoring stereotypical interpretation showing effect sizes close to neutrality. Health and wellbeing showed a small effect size favoring males ($p < 0.01$, $A = 0.37$).

For XLM-RoBERTa, STEM ($p < 0.01$, $A = 0.98$), sports ($p < 0.01$, $A = 0.88$), and finance ($p < 0.01$, $A = 0.70$) displayed male favoring stereotypical results, with the latter showing a medium effect size. Art and design ($p < 0.01$, $A = 0.61$) and health and wellbeing ($p = 0.01$, $A = 0.61$) showed small male favoring effect sizes. From those, art and design showed an alternative non-stereotypical interpretation. Surprisingly, ser-

vice management did not reveal any significant difference ($p = 0.47$, $A = 0.45$). As for fashion, it presented a strong female favoring interpretation ($p < 0.01$, $A = 0.20$).

Multilingual-Monolingual Assessment

Category	BERT	DistilBERT	RoBERTa
<i>Stem</i>	0.05	<u>0.33</u>	0
<i>A&D</i>	-0.05	-0.15	0.18
<i>H&W</i>	-0.02	0.17	0.16
<i>Finance</i>	0.04	0.40	<u>0.29</u>
<i>SM</i>	0.07	<u>0.29</u>	0.17
<i>Fashion</i>	<u>0.21</u>	-0.12	-0.08
<i>Sports</i>	-0.05	<u>0.35</u>	0.05

Table 3: Measure of leveling between monolingual and multilingual models. Positive values indicate a less biased performance while negatives indicate the opposite. 0 indicates no difference between monolingual and multilingual versions of the model. Scores for categories where multilingual showed a better result are highlighted in bold. The most remarkable results are underlined.

The multilingual versions of the models yielded a value closer to neutrality (less biased) in almost 67% of the cases analyzed. Across all job areas, at least one model showed a more neutral behavior in its multilingual version. In categories such as finance and service management, all results were improved with the multilingual model. For STEM, BERT and DistilBERT showed better results when using their multilingual version; for health and wellbeing and sports, DistilBERT and RoBERTa showed less biased behaviors using the multilingual models.

4.2 Linguistic Token Completion

For experiment 2, this study evaluated the behavior of masked language models on verb, adjective, and adverb completion tasks. To evaluate the differences between categories, this study relied on parallel pairs.

It was observed that some prompts followed a similar token prediction pattern: $p_{f/m}(token_n) = p_{m/f}(token_{n+j})$. Various predicted stereotypical tokens in males and females were offset by j steps in the opposite category. This phenomenon usually favored the emergence of stereotypical predictions. This indicated a possible unbalance in the training data with more contexts favoring the male gender.

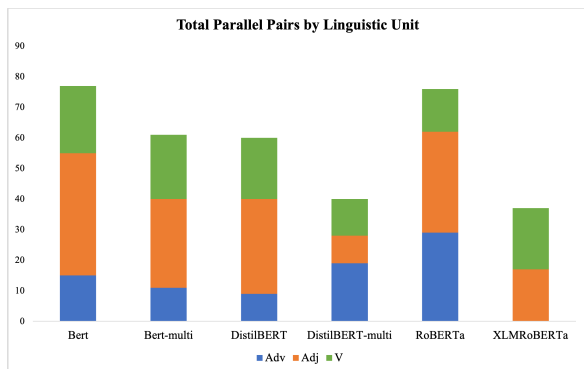


Figure 3: Total number of parallel pairs per model. The plot shows the number of token coincidences across linguistic units (adverbs, adjectives, and verbs) for male and female subject pronoun prompts.

4.2.1 BERT vs BERT-multilingual

BERT and BERT-multilingual were the first models analyzed. BERT monolingual provided a total of 77 parallel pairs, with adverb pairs being 19.5% of the total, adjectives 51.9%, and verbs 28.6%. As for BERT-multilingual, it provided 61 parallel pairs. From those, 18% were adverbs, 47.5% adjectives, and 34.4% verbs.

The empirical analysis of gender bias in word prediction across BERT and BERT-multilingual revealed patterns of bias encoding. Adverb predictions accentuated the divergence between the two versions of the model. BERT displayed a marked predilection for associating *successfully* with male contexts, a feature not mirrored in BERT-multilingual’s more balanced behavior. With *well* and *again*, there was a similar behavior; the multilingual version achieved a perfect balance. This divergence may have stemmed from the multilingual version’s exposure to a diverse array of linguistic constructs and sociocultural nuances inherent in multilingual corpora, potentially diluting the gendered prediction skewness.

In examining adjective predictions, both models demonstrated an inherent bias; however, the extent and specific instances varied. Notably, the prediction frequency of *successful* among gender contexts was slightly higher for males in BERT, while BERT-multilingual exhibited an egalitarian prediction distribution. This suggests that while BERT-multilingual retains certain biases, it may do so with reduced severity compared to its monolingual counterpart. However, other adjectives showed similar behavior in both versions of the model (e.g., *brilliant*). Surprisingly, *beautiful* showed a more

balanced prediction in BERT monolingual than in its multilingual variant.

For verb predictions, the contrast in bias manifestation was maintained. BERT exhibited a robust association of verbs such as *wrote* or *led* with male contexts. The latter shows the double probability of being associated with male contexts. This did not happen with the multilingual version, in which both genders show similar probabilities. In BERT, monolingual *edited* showed almost double the probability of being associated with male contexts than with female. Conversely, BERT-multilingual showed a propensity towards more uniform predictions across genders, suggesting a potential attenuation of bias attributable to its multilingual training background.

4.2.2 DistilBERT vs DistilBERT-multilingual

DistilBERT monolingual provided a total of 60 parallel pairs, with adverb pairs being 15% of the total, adjectives 51.6%, and verbs 33.3%. As for DistilBERT-multilingual, it showed 40 parallel pairs. From those, 47.5% were adverb pairs, 22.5% adjective pairs, and 30% verb pairs.

Adverb prediction between DistilBERT and DistilBERT-multilingual reveals that, while biases persist, they are less pronounced in the multilingual variant. For instance, the prediction of *internationally* is relatively consistent across genders for both variants of the models. However, DistilBERT monolingual suggests a gender preference (male) for *angrily* or *positively*. Notably, DistilBERT-multilingual’s predictions are more balanced and consistent than DistilBERT’s, indicating a potential reduction of bias through multilingual training.

In the realm of adjective predictions, both models showed fewer biases. DistilBERT showed similar probabilities for both genders for *brilliant*, *skilled*, or *talented*. It showed some bias for *gifted*, *prolific*, or –as previously in BERT– *successful*, all having higher male-associated probabilities. DistilBERT-multilingual showed a tendency to associate *mechanical* with male contexts, which can be considered a stereotypical interpretation. Additionally, *versatile* was predicted more equitably by the monolingual variant. In general, both models behaved similarly in this category.

The verb prediction analysis shows a remarkable distinction between the two models. For example, DistilBERT-multilingual predicts *attended* with a skew toward female contexts, while DistilBERT demonstrates a more neutral approach. However,

the multilingual counterpart showed more balanced predictions for *edited* or *won*. As for the similarities, both models show similar probabilities for *completed* or *wrote*.

4.2.3 RoBERTa vs XLM-RoBERTa

RoBERTa monolingual provided a total of 76 parallel pairs, with adverb pairs being 38.1% of the total, adjectives 43.4%, and verbs 18.4%. As for XLM-RoBERTa, it showed 37 parallel pairs. It was unable to predict tokens for adverb position for both genders. From the total pairs, adjectives signified 45.9% and verbs 54%.

For adverb prediction, RoBERTa presents significant biases, such as a high prediction rate for *successfully* in male contexts. In addition, *aggressively* or *better* also show what can be interpreted as a stereotypical relation with male tokens. In the case of token predictions that imply agentivity (*himself* and *herself*), the predictions favored male contexts. No comparative results were drawn for the multilingual model due to its inability to predict adverbs for the masked position.

In the context of adjective prediction, RoBERTa shows a strong gender preference for words like *brilliant* and *great* with a higher prediction rate for female and male contexts, respectively. Conversely, XLM-RoBERTa displays a more balanced approach, albeit not entirely without bias. For example, *brilliant* is more commonly associated with male contexts in XLM-RoBERTa, while *smart* is less gendered.

Verb prediction analysis shows more differences. RoBERTa associates *attends* and *remembers* more with female contexts, while *leads* is skewed toward male contexts. XLM-RoBERTa, although not entirely unbiased, tends to reduce this skew, as evidenced by the more balanced prediction for verbs like *understood*.

5 Discussion and Future Work

This study offered several advancements. Primarily, it employs a multidimensional analysis rooted in descriptive linguistic units, facilitating a nuanced understanding of biases in language models. This approach offers two essential advantages: (1) it can be adapted to different domains and cultural contexts with minimal fine-tuning, and (2) it does not rely on third-party data sources. In this way, it aimed to address the limitations of previous methods which are predominantly U.S.-centric. The method's foundation on linguistic principles allows

for a more discerning bias analysis, especially with its emphasis on inter-category relations. The bifurcation into job pronouns and linguistic tokens, coupled with the evaluation of both monolingual and multilingual models, ensures a holistic bias assessment. Furthermore, using metrics such as gender-associated token confidence (GTC) or monolingual-multilingual comparisons provides a quantitative dimension to the bias evaluation, enabling comparisons across models.

This study opens new opportunities for linguistically informed bias analysis. Future work may explore patterns through the implementation of other language units. Research may benefit from the analysis of different linguistic elements across sentences with anaphoric relations. Subsequent works on bias mitigation may also benefit from implementing in-context retrieval augmented learning (IC-RAL). Other promising outcomes include data selection techniques such as gradient information optimization (GIO) for training data selection (Everaert and Potts, 2023). Selecting datasets that represent the richness of society is crucial to diminish biases.

6 Conclusion

This study provides a systematic examination of gender biases within masked language models, particularly in the context of job-related prompts. Employing linguistically-informed tasks, such as pronoun resolution and linguistic unit completion, this study has effectively demonstrated the existence of gender biases in these models. A comparison between monolingual and multilingual models reveals a tendency towards stereotypical biases across various categories. However, it is observed that multilingual models tend to yield less biased outputs, likely a reflection of their exposure to a more diverse linguistic training set. This diversity may provide multilingual models with a broader perspective that mitigates entrenched biases, highlighting the potential of multilingual training in the development of more equitable systems. The findings underscore the necessity for refinement in the design and training of language models to ensure fair representations.

7 Limitations

This study analyses three major masked language models, which may not represent the full spectrum of biases present in natural language processing

systems. Further research is needed to extend these findings across a more extensive array of models, including those less prevalent in the literature.

Moreover, the scope of language diversity considered here is limited. English, with its gender-marked pronouns but largely non-gender-marked nouns and adjectives, represents just one typological cluster. To enhance the robustness of the conclusions drawn, future work must incorporate languages from diverse typological backgrounds to discern how such linguistic features may influence bias manifestation within MLMs.

Additionally, the influence of cultural nuances on language use and the resultant biases in MLMs require deeper investigation. Languages are embedded within cultural contexts that shape their use, and thus, any comprehensive analysis of bias in MLMs must consider a broad range of cultural settings to fully understand and address bias.

Ethics Statement

While the benefits of our method are clear, we proceed with ethical rigor, aware of the potential for misinterpretation of our findings. We recognize the complexity of gender representation in language, including the use of gender-neutral and neo-pronouns, and the implications these have for technology’s societal impact. It must be imperative that researchers contribute to the development of systems that are equitable and representative of all individuals. The publication of these results opens the way for an open, transparent, and inclusive discourse within the scientific community that respects linguistic and cultural diversity and promotes the advancement of unbiased computational technologies.

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A Delta Values

Category	BERT	DistilBERT	RoBERTa	BERT-multi	DistilBERT-multi	XLM-RoBERTa
Stem	0.50	0.48	0.48	0.45	0.15	0.48
A&D	0.30	0.18	0.29	0.35	0.33	0.11
H&W	0.31	0.30	0.27	0.33	0.13	0.11
Finance	0.49	0.47	0.49	0.45	0.07	0.20
SM	0.41	0.37	0.22	0.34	0.08	0.05
Fashion	0.34	0.29	0.22	0.13	0.41	0.30
Sports	0.41	0.35	0.43	0.49	0	0.38

Distribution Shifts Are Bottlenecks: Extensive Evaluation for Grounding Language Models to Knowledge Bases

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Abstract

Grounding language models (LMs) to knowledge bases (KBs) helps to obtain rich and accurate facts. However, it remains challenging because of the enormous size, complex structure, and partial observability of KBs. One reason is that current benchmarks fail to reflect robustness challenges and fairly evaluate models. This paper analyzes whether these robustness challenges arise from distribution shifts, including environmental, linguistic, and modal aspects. This affects the ability of LMs to cope with unseen schema, adapt to language variations, and perform few-shot learning. Thus, the paper proposes extensive evaluation protocols and conducts experiments to demonstrate that, despite utilizing our proposed data augmentation method, both advanced small and large language models exhibit poor robustness in these aspects. We conclude that current LMs are too fragile to navigate in complex environments due to distribution shifts. This underscores the need for future research focusing on data collection, evaluation protocols, and learning paradigms.¹

1 Introduction

Language models (LMs), such as BERT (Devlin et al., 2019), T5 (Raffel et al., 2020), and the GPT series (Ouyang et al., 2022; OpenAI, 2023), have demonstrated impressive capabilities in understanding and generating languages, highlighting the potential for artificial general intelligence (AGI). However, a major obstacle to achieving this goal is that LMs mainly built on natural languages are not yet well-grounded to real-world environments, such as knowledge base (KB), an environment of enormous size, complex structure, and only partially observable to LM.

* Work performed when the author was graduate student at Nanjing University.

¹Code and data are available at <https://github.com/yhshu/Distribution-Shifts-for-KBQA>.

Though LMs are highly skilled at natural language question answering (QA) today, the task of Knowledge Base Question Answering (KBQA) aims to parse natural language queries into formal queries on KBs, such as Freebase (Bollacker et al., 2008) and Wikidata (Vrandečić and Krötzsch, 2014). The significance of this task lies in building language agents on complex environments (Su, 2023), rather than merely recalling answers from the LM’s stored knowledge.

Now, numerous LM-driven models (Das et al., 2021; Hu et al., 2022) continue to achieve higher F1/Hits@1 scores on KBQA benchmarks. However, achieving higher scores does not necessarily guarantee the development of robust and dependable models. We still need to ask whether such improvements apply to extensive scenarios, as benchmarks almost always create questions via crowdsourcing and evaluate with simplistic metrics (Table 1). These benchmarks may not fully represent the diverse scenarios encountered in real-world applications, which raises concerns about the robustness of LM-driven models. Thus, our research aims to bridge this gap by exploring the limitations of current KBQA benchmarks and proposing more comprehensive evaluation protocols.

To achieve this goal, we need to grasp the key factors in robustness. For modern deep learning systems, the amount of training data could be extremely rich, but *robustness is closely related to data distribution* (Hendrycks et al., 2020). In the general area of natural language processing (NLP), large-scale corpora have been collected and used for effective training (Touvron et al., 2023). However, real-world environments are rarely so accommodating, e.g., large KBs contain complex structures and schema items, and building a large-scale and representative corpus is quite challenging. The problem of inconsistent data distribution during training and inference, i.e., **distribution shifts** as shown in Figure 1, may negatively impact the per-

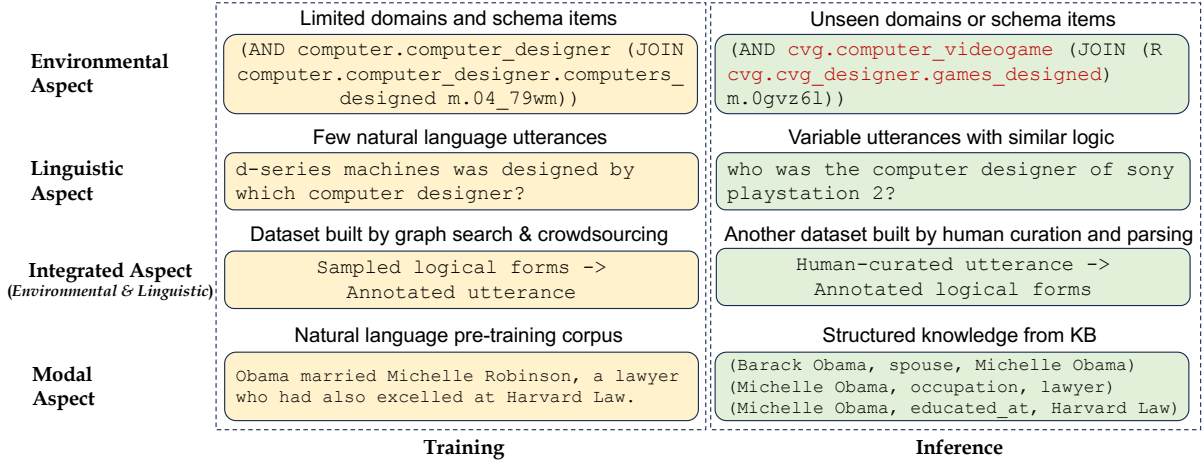


Figure 1: Distribution shifts during grounding in the case of KBQA. Training and inference using LM face completely different data distributions. We call for these shifts to be reflected in the evaluation protocols.

formance and robustness of grounded LMs.

This paper analyzes the distribution shifts from multiple aspects to understand both KBQA benchmarking and LM grounding better. We review existing works and identify several challenges. 1) **Environmental aspect**: generalization to unseen domains at the schema² level (Gu et al., 2021); 2) **Linguistic aspect**: adaptation to paraphrases featuring diverse language variations (Su et al., 2016); 3) **Integrated aspect**: transferability across datasets with both novel schema items and linguistic styles (Cao et al., 2022b); 4) **Modal aspect**: few-shot learning ability of large language models (LLMs) for the unfamiliar KB modality (Li et al., 2023). These challenges guide us to build more rigorous evaluation protocols for multiple aspects (§4).

To measure the impact of distribution shifts, we conduct extensive experiments under the proposed evaluation protocols. To present a fair evaluation under such rigorous protocols, we implement a data augmentation method for evaluated LMs and a retrieval augmentation method for evaluated LLMs (§5.1). Our findings reveal that even when employed with such methods and the highest EM scores are achieved on the GrailQA benchmark (Gu et al., 2021), *advanced small and large LMs still fall short of effectively tackling the majority of these challenges*. A striking example is the large difference between the best practice without WebQSP (Yih et al., 2016) fine-tuning (F1 43.0%) compared to the fine-tuned state-of-the-art (F1 79.6%)

²Schema denotes `rdfs:Class` (class) and `rdfs:Property` (relation) here.

(§6), suggesting the weak robustness of LM-driven KBQA models on an unseen dataset. Such negative observations highlight an urgent need for future research in data collection methodologies and LM learning paradigms. Meanwhile, we expect our evaluation protocols to provide a reference for future benchmark construction, developing metrics that consider robustness.

Our contributions include 1) A systematic **analysis** of the robustness challenges of grounded LMs and a strong advocacy of a multi-aspect **evaluation protocol** for KBQA. 2) Extensive **experiments** quantitatively unveil the existence of these challenges and the vulnerability of both small and large LMs. 3) **Insights** into improving the robustness of grounded LMs, including data collection and learning paradigms.

2 Related Work

Compared to existing research, the necessity of this study is threefold. First, while LMs are commonly evaluated on natural language tasks (Hupkes et al., 2022; Patel et al., 2022), the complexity increases significantly when these models are applied to environments like KBs, where data is structured rather than purely unstructured natural language (Liu et al., 2023). Second, the evaluation protocols used in KBQA benchmarks tend to be uniform, leading to an insufficient evaluation of model robustness (Gu et al., 2021). Finally, recent reviews in this field (Lan et al., 2022; Gu et al., 2022b) have largely overlooked the advancements in the development and application of LMs, particularly LLMs.

Benchmark	KB	Size	LF	Generalization	Paraphrases	Metrics
WebQuestions (Berant et al., 2013)	Freebase	5,810	N/A	i.i.d.	✗	F1
SimpleQuestions (Bordes et al., 2015)	Freebase	108,442	N/A	i.i.d.	✗	Acc
WebQuestionsSP (Yih et al., 2016)	Freebase	4,737	SPARQL	i.i.d.	✗	F1
GraphQuestions (Su et al., 2016)	Freebase	5,166	Graph query	comp.+zero	✓	F1
LC-QuAD (Trivedi et al., 2017)	DBpedia	5,000	SPARQL	i.i.d.	✗	F1
CWQ (Talmor and Berant, 2018)	Freebase	34,689	SPARQL	i.i.d.	✗	Hits
LC-QuAD 2.0 (Dubey et al., 2019)	Wikidata	30,000	SPARQL	i.i.d.	✓	F1
SQB (Wu et al., 2019)	Freebase	108,443	N/A	i.i.d.+zero	✗	Acc
CFQ (Keysers et al., 2020)	Freebase	239,357	SPARQL	comp	✗	Acc
GrailQA (Gu et al., 2021)	Freebase	64,331	S-expression	i.i.d.+comp.+zero	✓	EM, F1
KQA Pro (Cao et al., 2022a)	Wikidata	117,970	KoPL	i.i.d.	✗	Acc
QALD series (Perevalov et al., 2022)	DBpedia	558	SPARQL	comp.	✗	F1

Table 1: Selected KBQA benchmarks. LF denotes logical forms. Generalization settings follow Gu et al. (2021). *i.i.d.* denotes that the schema distribution in the test set is the same as the training set. *comp.* and *zero* denote compositional and zero-shot generalization, respectively. Paraphrases are questions containing the same semantics (machine-generated paraphrases are not included). *Acc* denotes accuracy. *EM* denotes exact match.

3 Challenges from Distribution Shifts

In this paper, the **robustness** of a KBQA model refers to its ability to adapt to various natural language inputs and maintain consistent performance when data distribution shifts. Due to the distribution shifts between the training corpus of LMs and KB environments, grounding LMs face robustness challenges from environmental, linguistic, and modal aspects.

3.1 Environmental Aspect

A primary environmental challenge is **schema-level generalization**. The RDF Schema provides a data-modeling vocabulary crucial for querying a KB. Table 1 indicates most KBQA benchmarks assume a consistent schema distribution between training and testing. However, this often does not hold in large KBs with numerous schema items. Few benchmarks, like the reconfigured SimpleQuestions-Balance dataset (Wu et al., 2019) and GrailQA (Gu et al., 2021), address non-*i.i.d.* schema items and varying levels of schema-level generalization. GraphQuestions (Su et al., 2016) provides a stringent test with seldom-seen schema items in training. Given real-world non-*i.i.d.* complexities, these datasets better represent the practical generalization challenges. Yet, despite progress (Shu et al., 2022; Gu et al., 2022a), compositional and zero-shot generalization are far from solved. We stress that this challenge applies to the overall KBQA semantic parsing process, especially to important subtasks such as relation linking.

3.2 Linguistic Aspect

Various natural language expressions make question understanding challenging for KBQA models. One common way this variety shows up is through paraphrasing. In this paper, a paraphrase set denotes different ways to express the same logical form, as illustrated in Table 14. **Paraphrase adaptation** is an intuitive form of the ability to comprehend variable language expressions. It could be measured by whether a model is able to accurately answer paraphrased questions that this model has already answered correctly before. Unfortunately, as shown in Table 1, many KBQA benchmarks do not account for paraphrasing with only one utterance for each logical form. Exceptionally, some datasets (Su et al., 2016; Dubey et al., 2019; Gu et al., 2021) are based on automatically generated logical forms and include multiple natural language expressions for the same logical form (template). These data characteristics highlight the difficulties in adapting to paraphrased questions.

3.3 Integrated Aspect

Evaluating KBQA benchmarks often hinges on a single dataset, thereby complicating the task of ascertaining the model performance consistency across novel scenarios. This form of robustness, termed as **cross-dataset transfer** in this paper, combines both the environmental and linguistic aspects discussed earlier and is more difficult to achieve. This is because construction methods vary across datasets, as do schema distributions and natural language expressions. Specifically, KBQA dataset construction generally falls into two dis-

tinct categories: 1) Graph Search and Crowdsourcing: in this approach, logical forms or triples are initially extracted from a KB, where structures or operators of logical form are usually finite. Subsequently, they are converted into natural language utterances through crowdsourcing methods (Bordes et al., 2015; Trivedi et al., 2017). 2) Human Curation and Parsing: logical forms are labeled directly from human-provided utterances (Berant et al., 2013; Perevalov et al., 2022). Existing works (Gu et al., 2021; Cao et al., 2022b) suggest that models pre-trained on large-scale datasets can adapt reasonably well to other target datasets, such as WebQSP (Yih et al., 2016). However, the necessity for fine-tuning these pre-trained models on the intended target dataset remains imperative for achieving optimal performance. Despite the advantages offered by pre-training on expansive KBQA datasets, models still encounter challenges in transferring directly to previously unseen target datasets while sustaining high performance.

3.4 Modal Aspect

Aside from considering environmental and linguistic factors, focusing on the modal aspect is also crucial. Recently, LLMs like GPT series (OpenAI, 2023) have demonstrated exceptional capabilities across a variety of tasks, outperforming smaller yet potent LMs such as BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020). Despite these advancements, these LLMs face substantial challenges when interacting with environments. One notable issue is they predominantly rely on an in-context learning paradigm as opposed to fine-tuning, as a trade-off between computational cost and model efficiency. In comparison to fine-tuning, in-context learning offers the advantage of reduced training costs but at the expense of being forced to reason over the **unfamiliar modality**. Distribution shifts between natural language pre-training and reasoning over structured knowledge contexts could lead to poor performance. For instance, a discernible performance gap exists between KBQA models that employ in-context learning with Codex (Chen et al., 2021a) and those built on fine-tuned LMs (Gu et al., 2022a; Li et al., 2023). However, the empirical specifics of this difference are not yet clear, leaving us with an inadequate understanding of the limitations of in-context learning and ways to improve grounding with LLMs.

4 Evaluation Protocols

Regarding these challenges, we introduce extensive protocols for evaluating LMs in several aspects overlooked by current benchmarks.

4.1 Evaluating Environmental Aspect

To set the environmental schema-level generalization scenario, we use GrailQA (Gu et al., 2021) and GraphQuestions (Su et al., 2016) datasets. GrailQA contains three generalization levels: i.i.d. (25%), compositional (25%), and zero-shot (50%). GraphQuestions has no seen relations in the test set. We also use SimpleQuestions-Balance (SQB) (Wu et al., 2019) for the relation linking task (an important KBQA sub-task), where 50% of the samples contain unseen relations.

4.2 Evaluating Linguistic Aspect

To set a paraphrase adaptation scenario, we use GrailQA (Gu et al., 2021) and GraphQuestions (Su et al., 2016) datasets. To evaluate adaptability to paraphrases (§3.2), we propose a new metric, the standard deviation (std) of EM/F1 for questions of each logical form template. As shown in Equation 1, suppose there are n sets of paraphrases in the dataset, each set of paraphrases corresponds to a logical form template with m natural language expressions, and the F1 score obtained by the KBQA model on the j -th question of the i -th set of paraphrases is $F1_{i,j}$. The metric Std_{F1} first calculates the standard deviation of the F1 scores obtained by the model on the m questions for each set of paraphrases and then calculates the average of the n standard deviations. This metric is used to measure the robustness of the model to different representations of the same semantics, i.e., whether it can cope with diverse natural language expressions. A lower standard deviation indicates that the model is more adaptive to different expressions. Std_{EM} is calculated in the same way.

$$Std_{F1} = \frac{1}{n} \sum_{i=1}^n \sqrt{\left(\frac{\sum_{j=1}^m (F1_{i,j} - \bar{F1}_i)^2}{m} \right)} \quad (1)$$

4.3 Evaluating Integrated Aspect

To emulate a real-world scenario with unknown schema and linguistic distribution for the integrated aspect, we evaluate the performance of pre-trained models on the unseen human-curated WebQSP

(Yih et al., 2016) dataset, where the questions are derived from search logs and are more realistic. This is a scenario where the distribution changes significantly, as most benchmarks create questions by sampling logical forms and annotating natural language questions via crowdsourcing (Lan et al., 2022), where questions are confined to sampled logical forms.

4.4 Evaluating Modal Aspect

To test the capability of the in-context learning paradigm to inference from the KB modality rather than from pure texts, we retrieve structured KB contexts as prompt to evaluate the LLM without particular fine-tuning on KB (§5.1.2). KBs are structured and expansive, but in this case, LLM can only encode a portion of linearized KB contexts.

5 Experiments

5.1 Augmentation Approach

To ensure fair evaluation and fully harness the capabilities of LMs under our extensive and rigorous evaluation protocols, we suggest two strategies to counteract distribution shifts: data augmentation and retrieval augmentation.

5.1.1 Data Augmentation for LMs

Off-the-shelf datasets of limited size may make LM easily overfitted and not adaptable to large KBs. To address the problem that many domains in the KB are often not collected as training data, we propose a data augmentation method named **Graph seArch** and **questIon generation (GAIN)**. Some data augmentation or question generation models (Bi et al., 2020; Guo et al., 2022) are only evaluated by the qualify of generated sentences rather than evaluated by the QA task, but GAIN directly serves our KBQA evaluations. Besides, compared to the previous work (Hu et al., 2019) that only considers generating questions for triples to help KBQA, GAIN applies to KBQA corresponding to both logical forms and triples. GAIN scales data volume and distribution through four steps: 1) Graph search: Sampling logical forms or triples from arbitrary domains in the KB without being restricted to any particular KBQA dataset. 2) Training question generator: learning to convert logical forms or triples into natural language questions on existing KBQA datasets. 3) Verbalization: Using the question generator from step 2 to verbalize sampled logical forms or triples from step 1, thus creating synthetic questions. 4) Training data expansion:

Before fine-tuning any neural models on KBQA datasets, GAIN-synthetic data can be used to train these models or to expand the corpus of in-context samples for LLMs. That is, as a data augmentation method, GAIN is not a KBQA model, but it is used to augment a base KBQA model.

5.1.2 Retrieval Augmentation for LLMs

As the trade-off between cost and effectiveness, we experiment with the prevalent in-context learning paradigm but attempt to improve the quality of in-context samples. We use advanced retrieval methods based on smaller LMs as plug-ins to augment the LLM, similar to the SuperICL approach (Xu et al., 2023). Specifically, our steps to generate an LLM prompt for each question include the following. 1) Given an input question, we retrieve k questions (k -shot) with BM25 (Robertson et al., 2009) from the corpus (the combination of KBQA training set and the GAIN-synthetic dataset). 2) The role of retrieval augmentation for KB environments has been shown by fine-tuned LMs (Shu et al., 2022). To assist with grounding LLM, we retrieve KB contexts with off-the-shelf retrievers for k samples and the input question.³

5.2 Setup

Data All experiments use S-expression (Gu et al., 2021) as the logical form due to its clear and concise structure. Entity linking results are taken from TIARA (Shu et al., 2022) for GrailQA and WebQSP, and ArcaneQA (Gu and Su, 2022) for GraphQuestions, because of their public availability and performance.

Model Compared models are mainly selected from the leaderboard.⁴ The performances are taken from their papers. For the relation linking task on SQB, we use BERT (Devlin et al., 2019) as the base model for GAIN. For KBQA tasks, we use the open-source advanced model TIARA (Shu et al., 2022) as the base model for GAIN, due to its strong performance on zero-shot schema items.⁵ TIARA is composed of multi-grained retrievers and a generator, with the retrievers providing KB contexts⁶ for the generator. The term “TIARA+GAIN” represents a model (both the retrievers and the generator)

³The prompt example is demonstrated in Appendix A.

⁴<https://dki-lab.github.io/GrailQA/>

⁵Pangu (Gu et al., 2022a) also uses entity linking results from TIARA.

⁶Entities, exemplary logical forms, and schema items are retrieved.

that is first tuned using GAIN synthetic data and subsequently fine-tuned on a target dataset. For LLM evaluation in the modal aspect, we use the gpt-3.5-turbo-0613⁷ model, and the few-shot contexts are retrieved from the combination of GrailQA training set and synthetic dataset using the TIARA+GAIN retrievers.

Metrics Following previous works, we use Exact Match (EM), F1, and Hits@1 to measure the performance of KBQA models. We also use the std of EM/F1 to measure the adaptability to paraphrases (§4.2).

5.3 Implementation Details

We use a machine with an NVIDIA A100 GPU and up to 504GB of RAM. Models are implemented by PyTorch (Paszke et al., 2019) and Hugging Face.⁸ TIARA+GAIN (T5-3B) takes about 100 hours to train the logical form generator on the synthetic dataset.

Model Training 1) For question generation, we fine-tune the T5-base model (Raffel et al., 2020) to convert S-expression or triple to natural language questions. We set the beam size to 10, the learning rate to 3e-5, the number of epochs to 10, and the batch size to 8. 2) The training of the TIARA model (Shu et al., 2022) follows its original settings, including the setting of hyperparameters and the calculation of metrics. Note that Hits@1 on TIARA is obtained by randomly selecting one answer for each question 100 times. Both the schema retriever and generator of TIARA are pre-trained on synthetic data and then fine-tuned on KBQA datasets. Since GraphQuestions has no official training-valid split, we randomly take 200 questions from the original training set as the valid set. 3) We use BERT-base-uncased (Devlin et al., 2019) to rank candidate relations for SQB, and the input form is the same as the schema retriever of TIARA. We set the learning rate to 3e-5, the batch size to 256, and the max number of epochs to 3 with early stopping.

Data Augmentation The statistics of GAIN-synthetic datasets for both logical forms and triples are shown in Table 11 and 12.⁹ Note that the sampling of the GAIN method is not limited to the scale of the synthetic data we use here.

⁷<https://platform.openai.com/docs/models>

⁸<https://huggingface.co/>

⁹Details of synthetic data are shown in Appendix B.

6 Analysis

We report and analyze the experimental results in this section for each aspect.

6.1 Analysis of Environmental Aspect

Effectiveness of Synthesis and Scaling Up As shown in Tables 2 and 3, the models perform significantly better on i.i.d. than compositional and zero-shot generalization, with the zero-shot partition being the most challenging. TIARA+GAIN (T5-base) improves 2.5 zero-shot F1 points compared to TIARA (T5-base). Besides, an increased number of model parameters, combined with richer data from GAIN, significantly enhance the generalization capabilities of T5 models. TIARA+GAIN (T5-3B) further improves 1.4 zero-shot F1 points compared to its T5-base version. TIARA+GAIN achieves the highest EM scores, including that on zero-shot scenes. It demonstrates promising ideas for further improving LM generalization capabilities, i.e., the positive effect of synthetic data and parametric scales on training LMs.

Fine-tuning Better Than Few-shot Learning

However, it is important to note that fine-tuned models consistently outperform few-shot learning models, regardless of whether the schema is seen or not. Given the training and inference costs of LLMs, their performance has yet to show any superiority in this task.

6.2 Analysis of Linguistic Aspect

Improvements Are Linguistic Biased We calculate the standard deviation (std) of EM or F1 in the dev/test set, as shown in Equation 1. For GrailQA, the std of EM and F1 decreases with the application of GAIN or an increase in model size, i.e., F1/EM and the std of F1/EM are both better, as shown in Table 2 and 5. However, in the case of more challenging GraphQuestions, GAIN significantly improves the F1 by 8.3 points but also results in a larger std (0.170 compared to 0.157), as shown in Table 3. It suggests that improving paraphrase adaptation using GAIN is more difficult when the base model (TIARA, T5-base, with only 37.9% F1) still struggles to address most of the dataset. Consequently, the performance gains observed on the KBQA benchmark may not necessarily reflect a deeper understanding of linguistic complexities, but they could simply render the model more sensitive to specific phrases. Strategies for deeper decomposition and understanding (Hu et al., 2021;

Model on GrailQA Test Set	Overall		I.I.D.		Compositional		Zero-shot	
	EM	F1	EM	F1	EM	F1	EM	F1
<i>Fine-tuned Models</i>								
BERT + Ranking (Gu et al., 2021)	50.6	58.0	59.9	67.0	45.5	53.9	48.6	55.7
RnG-KBQA (Ye et al., 2022)	68.8	74.4	86.2	89.0	63.8	71.2	63.0	69.2
TIARA (T5-base) (Shu et al., 2022)	73.0	78.5	87.8	90.6	69.2	76.5	68.0	73.9
DecAF (FiD-3B) (Yu et al., 2022)	68.4	78.8	84.8	89.9	73.4	81.8	58.6	72.3
Pangu (BERT-base) (Gu et al., 2022a)	73.7	79.9	82.6	87.1	74.9	81.2	69.1	76.1
Pangu (T5-large) (Gu et al., 2022a)	74.8	81.4	82.5	87.3	75.2	82.2	71.0	78.4
Pangu (T5-3B) (Gu et al., 2022a)	75.4	81.7	84.4	88.8	74.6	81.5	71.6	78.5
<i>Codex-driven Models</i>								
KB-BINDER (6)-R (Li et al., 2023)	53.2	58.5	72.5	77.4	51.8	58.3	45.0	49.9
Pangu (Codex) (Gu et al., 2022a)	56.4	65.0	67.5	73.7	58.2	64.9	50.7	61.1
<i>GAIN-augmented Models</i>								
TIARA + GAIN (T5-base)	75.1	80.6	88.3	91.0	73.0	79.6	69.9	76.4
TIARA + GAIN (T5-3B)	76.3	81.5	88.5	91.2	73.7	80.0	71.8	77.8
GPT-3.5-turbo (5-shot)	66.6	71.4	82.7	85.3	60.5	66.3	61.9	67.2

Table 2: EM and F1 scores (%) on the hidden test set of GrailQA.

Model on GraphQuestions	F1(↑)	Std(↓)
<i>GraphQuestions on Freebase 2013-07</i>		
UDepLambda (Reddy et al., 2017)	17.7	-
PARA4QA (Dong et al., 2017)	20.4	-
SPARQA (Sun et al., 2020)	21.5	-
BERT + Ranking (Gu et al., 2021)	25.0	-
ArcaneQA (Gu and Su, 2022)	31.8	-
TIARA [♣] (T5-base) (Shu et al., 2022)	37.9	0.141
KB-BINDER (6) (Li et al., 2023)	39.5	-
TIARA + GAIN (T5-base)	45.5	0.153
TIARA + GAIN (T5-3B)	48.7	0.180
<i>GraphQuestions on Freebase 2015-08-09</i>		
BERT + Ranking (Gu et al., 2021)	27.0	-
ArcaneQA (Gu and Su, 2022)	34.3	-
TIARA [♣] (T5-base) (Shu et al., 2022)	41.2	0.157
Pangu (Codex) (Gu et al., 2022a)	44.3	-
Pangu (T5-3B) (Gu et al., 2022a)	62.2	-
TIARA + GAIN (T5-base)	49.5	0.170
TIARA + GAIN (T5-3B)	53.0	0.200

Table 3: F1 scores (%) and average standard deviation (std) of F1 scores for each set of paraphrases on the test set of GraphQuestions. The setting for Freebase 2015-08-09 is described by Gu and Su (2022). [♣] denotes our replication results.

Huang et al., 2023) of the questions may be needed to mitigate this challenge.

6.3 Analysis of Integrated Aspect

Hard Transfer Across Datasets We evaluate the performance of pre-trained models on the human-curated WebQSP dataset without fine-tuning, as shown in Table 6. BERT+Ranking (Gu et al., 2021) and TIARA+GAIN (Shu et al., 2022) are trained on the large-scale GrailQA dataset. We compare these results to the state-of-the-art Pangu (Gu et al., 2022a), which is fine-tuned on WebQSP

and achieves an F1 score of 79.6%. Although we recognize that GAIN and large models offer few advantages, the performance of these pre-trained models without fine-tuning is considerably lower than Pangu’s.

Causes from Data Collection We attribute this to the significant differences between training and test data, as shown in Table 8. The question length, the difficulty of entity/relation linking¹⁰, and the proportion of unseen schema vary dramatically across KBQA datasets. These discrepancies arise from the dataset construction process: WebQSP is an annotation of search logs, whereas the remaining datasets are derived from graph search and crowdsourcing. To further enhance robustness in cross-dataset transfer, we believe that better data collection methods are required to obtain diverse and balanced training data. Additionally, the representation of the logical form increases the transfer difficulty, as the S-expression used in the GrailQA dataset cannot express all queries in WebQSP.

6.4 Analysis of Modal Aspect

Context Alone Is Insufficient We evaluate the performance of GPT-3.5 using retrieved KB contexts (§5.1.2) and in-context learning on the GrailQA dataset. The prompts for the model include the task description and the few-shot KB contexts. As illustrated in Table 7, when provided with contexts from the TIARA+GAIN retrievers, GPT-3.5 outperforms two compared models but

¹⁰Measured by literal similarity: https://anhaidgroup.github.io/py_stringmatching/v0.3.x/PartialRatio.

Model on SimpleQuestions-Balance	Overall			Seen			Unseen		
	1	5	10	1	5	10	1	5	10
HR-BiLSTM (Wu et al., 2019)	63.3	-	-	93.5	-	-	33.0	-	-
Adversarial-Adapter (Wu et al., 2019)	84.9	-	-	92.6	-	-	77.1	-	-
BERT-base	83.7	95.0	96.9	85.8	95.0	96.0	81.5	95.1	97.8
BERT-base + GAIN	88.4	96.0	97.3	87.8	95.4	96.3	89.1	96.7	98.4

Table 4: Hits@ k (1, 5, 10) scores (%) for relation linking on the test set of SimpleQuestions-Balance, including seen and unseen relations.

Model on GrailQA Valid Set	Std Overall		Std I.I.D.		Std Compositional		Std Zero-shot	
	EM(\downarrow)	F1(\downarrow)	EM	F1	EM	F1	EM	F1
TIARA (T5-base) (Shu et al., 2022)	0.079	0.066	0.021	0.017	0.211	0.203	0.222	0.181
TIARA + GAIN (T5-base)	0.077	0.061	0.020	0.016	0.215	0.198	0.218	0.160
TIARA + GAIN (T5-3B)	0.075	0.058	0.020	0.016	0.196	0.180	0.212	0.155
GPT-3.5-turbo (5-shot)	0.093	0.091	0.027	0.023	0.272	0.281	0.251	0.247

Table 5: Average **standard deviation** of EM and F1 scores for each set of paraphrases on the GrailQA valid set.

Model on WebQSP	F1	Hits@1
TIARA [*] (T5-base) (Shu et al., 2022)	28.5	27.6
TIARA ^{*♣} (T5-base) (Shu et al., 2022)	33.5	31.5
BERT + Ranking [*] (Gu et al., 2021)	43.0	-
TIARA + GAIN (T5-base)	29.1	28.2
TIARA + GAIN (T5-3B)	29.8	28.7
TIARA [*] + GAIN (T5-base)	33.9	31.8
TIARA [*] + GAIN (T5-3B)	34.5	32.3

Table 6: F1 and Hits@1 scores (%) on WebQSP without fine-tuning on it. All models are trained on large-scale GrailQA. * denotes using oracle entity annotations. ♣ denotes our replication results.

falls short compared to TIARA+GAIN. Among the GPT-3.5 predictions, 79.62% come directly from the substring of the corresponding prompts, achieving an average F1 score of 86.19% for this portion. However, the remaining predictions are not part of their prompts and are entirely new predictions generated by GPT-3.5, with an average F1 score of merely 30.29%. Although a baseline level is attained, these results suggest that GPT-3.5 cannot be accurately grounded to the KB environment when it does not copy the retrievers’ contexts. It also shows the modal severance of natural language pre-training and KB contexts for the LLM. LLMs are not able to utilize KB contexts as proficiently as they understand natural language, and the faithfulness and controllability of grounded LLMs are not yet guaranteed under the current approach (Gu et al., 2022a). To mitigate this problem, alternative paradigms should be explored, such as tool learning (Schick et al., 2023) and multi-step plan-

ning (Liu et al., 2023) with Chain-of-Thought (Wei et al., 2022), which enables more refined access and control over environments and reduces modal differences during the reasoning process.

7 Conclusion

Despite the recent progress of LM-driven models, robustness challenges posed by distribution shifts for the KBQA task are rarely discussed. Our analyses call for further research into better evaluation protocols for grounding LLMs to KBs and enhancing the robustness of environmental, linguistic, and modal aspects. Notably, the experiments reveal that LLMs sometimes simply copy the provided prompt. It indicates that the existing methodologies for grounding LLMs are yet to prove their efficacy and superiority. Future research issues include collecting more balanced environment-specific corpora and improving the LLM learning paradigms. For the corpora, our experiments show that the data augmentation techniques deserve further research.

Limitations

1) For question generation, the verbalization process of the GAIN method relies heavily on large-scale KBQA annotations. The training data influence the style of generated questions, and overly complex logical forms (e.g., with three or more hops) are difficult to convert into natural language questions. Besides, synthetic data is less diverse and natural than human annotations, though it improves generalization performance. 2) Multilingual KBQA is a problem that lacks attention in

Model on GrailQA Valid Set	Overall		I.I.D.		Compositional		Zero-shot	
	EM	F1	EM	F1	EM	F1	EM	F1
BERT + Ranking (Gu et al., 2021)	51.0	58.4	58.6	66.1	40.9	48.1	51.8	59.2
TIARA ELF only (Shu et al., 2022)	67.2	72.9	72.8	76.7	55.3	60.7	69.7	76.3
RnG-KBQA (Ye et al., 2022)	71.4	76.8	86.7	89.0	61.7	68.9	68.8	74.7
DecAF (FiD-3B) (Yu et al., 2022)	-	81.4	-	89.7	-	80.1	-	78.4
TIARA (T5-base) (Shu et al., 2022)	75.3	81.9	88.4	91.2	66.4	74.8	73.3	80.7
Pangu (T5-3B) (Gu et al., 2022a)	75.8	83.4	-	-	-	-	-	-
TIARA + GAIN (T5-base)	77.1	83.5	89.0	91.9	68.6	75.5	75.4	83.2
TIARA + GAIN (T5-3B)	77.1	83.8	89.0	92.1	68.8	76.1	75.4	83.4
GPT-3.5-turbo (5-shot)	69.7	74.8	83.0	85.5	58.7	64.6	68.6	74.4

Table 7: EM and F1 scores (%) on the GrailQA valid set. ELF denotes exemplary logical form (Shu et al., 2022).

	GrailQA	GraphQ	WebQSP	SQB
Train size	44,337	2,381	3,097	75,819
Valid size	6,763	-	-	11,141
Test size	13,231	2,395	1,638	21,483
Length	62.96	54.62	35.93	42.16
# of entities	0.903	1.028	1.112	1.000
# of relations	1.358	1.434	1.464	1.000
<i>Similarity between questions and KB items</i>				
Entity	0.999	1.000	0.921	0.985
Class	0.547	0.457	-	-
Relation	0.470	0.389	0.300	0.779
<i>Unseen ratio (%)</i>				
Schema	16.90	86.78	20.44	32.67
Question	54.06	98.25	4.03	49.18

Table 8: KBQA dataset statistics. *Length* denotes the average number of question characters. *# of entities/reactions* denotes the average number of entities/reactions in the logical form. *Unseen Schema* is the ratio of unseen schema items in the dev/test set. *Unseen Question* is the ratio of questions containing unseen schema.

the KBQA research and is also a linguistic-aspect challenge. However, since most KBQA datasets are based on English and do not discuss other languages at all, this paper leaves the evaluation of this problem for future work.

Ethics Statement

The proposed data augmentation method GAIN could be used on any KB. The Freebase (Bollacker et al., 2008) used in this work is a KB that has been publicly released and manually reviewed. For uncensored KBs, if harmful information is collected, it could make synthetic data contain harmful information and make LMs generate harmful answers.

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Model of Class Retrieval	All	I.I.D.	Comp.	Zero.
ReTraCk (Chen et al., 2021b)	94.3	98.1	97.5	91.3
TIARA (Shu et al., 2022)	95.8	99.6	97.9	93.4
TIARA + GAIN	96.1	99.6	98.1	93.8
Model of Relation Retrieval	All	I.I.D.	Comp.	Zero.
ReTraCk (Chen et al., 2021b)	88.4	95.3	91.0	84.3
TIARA (Shu et al., 2022)	92.0	97.9	93.7	88.7
TIARA + GAIN	93.0	99.2	94.1	89.8

Table 9: Recall (%) of top-10 retrieved schema items on the GrailQA valid set. *comp.* and *zero.* denote compositional and zero-shot generalization, respectively. Note that ReTraCk uses 100 classes and 150 relations for each question, while TIARA uses 10 classes and 10 relations.

Model on GraphQuestions	Class	Relation
TIARA [*] (Shu et al., 2022)	81.5	67.1
TIARA + GAIN	83.3	74.3

Table 10: Recall (%) of top-10 retrieved schema items on the GraphQuestions test set (Freebase 2015-08-09 version). TIARA uses 10 classes and 10 relations for each question. ^{*} denotes our replication results.

A Example of LLM Prompt

We present an example of an excerpted prompt, which is shown in Figures 2 and 3. In particular, Figure 2 illustrates the task instruction and teaching example segment, while Figure 3 displays the input query segment.

B Details of Synthetic Data

The graph search process of GAIN is slightly different for logical forms and triples.

Searching Logical Forms GAIN employs a graph search approach similar to GraphQuestions (Su et al., 2016) to collect logical forms derived from graph queries. The graph query construction process consists of four steps: 1) query template construction, 2) aligning template nodes, 3) configuring functions, and 4) verification by execution. Query templates, obtained through random graph searching, contain nodes that represent entity/literal types (not aligned to a value), referred to as *template nodes*. Each unaligned node in the query template is then aligned with a topic entity or literal to generate multiple aligned graph queries. To synthesize counting, comparative, and superlative questions and enhance the diversity of synthetic data, we add functions like COUNT, ARGMIN/ARGMAX (Gu et al., 2021) to graph queries. Since KBQA

#question	#one-hop	#two-hop	#domain
127,329	78,668	48,661	759
#none	#count	#comparatives	#superlatives
115,221	7,115	1,874	3,119
#class	#relation	#entity	
5,078	12,942	46,645	

Table 11: Statistics for the synthetic dataset of logical forms. *none* denotes no function.

#question	#relation	#subject	#domain
162,557	7,349	108,804	673

Table 12: Statistics for the synthetic dataset of triples. *Subject* denotes subject entities.

research typically assumes that questions can be answered by the KB, we execute all resulting graph queries after the above steps and remove those with a null¹¹ result.

Searching Triples A single KB triple can be treated as a QA pair, where the head entity and relation together form the query, and the tail entity is the answer. The triple search process consists of two steps: 1) candidate relation selection, and 2) triple sampling. First, arbitrary relations \mathcal{R} are selected from the KB, without being restricted to any particular KBQA dataset. Then, triples are collected from head entities \mathcal{H} , where entities in \mathcal{H} are connected to relations in \mathcal{R} .

Examples of Synthetic Data We present some examples of synthetic data in Table 15, where the logical form contains a variety of functions.

Statistics The statistics for KBQA datasets, including our synthetic dataset, are shown in Table 16. To calculate the number of domains in Table 11, 12, we take the domain of each Freebase class from its first segment, except for classes starting with “base”, where we take the first two segments, e.g., domain “music” for the class “music.performance_venue”, and domain “base.plants” for the class “base.plants.plant”.

C Experimental Details

C.1 Question Generation

Training a question generation (QG) model is the second step of GAIN. Because logical forms in the

¹¹Null for querying entities and zero for counting.

Metrics	GrailQA Dev	GraphQ Test	SQB Dev
BLEU-4	0.347	0.178	0.369
ROUGE-L	0.526	0.411	0.640

Table 13: The performance of the question generator on KBQA datasets. The generator for logical form is evaluated on the GrailQA valid set and GraphQuestions test set. The generator for triple is evaluated on the SQB valid set.

synthetic dataset do not have corresponding human-labeled natural language questions, evaluating QG on the synthetic dataset is difficult. Existing KBQA datasets contain questions written by crowdsourced workers for logical forms or triples, so we evaluate the question generator by generating questions on these datasets and calculate the BLEU-4 (Papineni et al., 2002) and ROUGE-L (Lin and Och, 2004) scores (Table 13).¹²

C.2 Retrieval Performance

The performance of schema retrieval on the GrailQA valid set and GraphQuestions test set is shown in Table 9 and 10, respectively. GAIN improves the performance of schema retrieval on both GrailQA and GraphQuestions. In particular, GAIN improves the relation recall@10 by 7.2 points on GraphQuestions.

C.3 Performance on Various Logical Forms

To show how TIARA+GAIN performs on different types of logical forms, we compare it with previous KBQA models on the GrailQA valid set, as shown in Table 17. TIARA+GAIN improves performance in nearly all these scenarios compared to TIARA.

C.4 Error Analysis

To analyze the QA errors of TIARA+GAIN (T5-3B), we randomly sample 50 questions where predicted logical forms are not the same as the ground truth in the GrailQA valid set. We follow Shu et al. (2022) in their classification of errors. Entity linking errors (missing or redundant entities), syntactic errors (generating the wrong logical form structure), semantic errors (generating the wrong schema item when correct contexts are provided), false negatives (flawed annotations), and miscellaneous (e.g., ambiguity in the question) account for 48%, 26%, 16%, 4%, and 6%, respectively. For entity linking errors, 62.5% of them are from the zero-shot level. For syntactic errors, the number of

¹²Calculated by [Hugging Face Evaluate](#).

errors from zero-shot and compositional levels is almost the same. It means that entity linking for zero-shot domains and logical form generation for complex structures remain significant challenges.

D Details of Scientific Artifacts

All datasets we use are publicly available. GrailQA¹³ (Gu et al., 2021) uses CC BY-SA 4.0 license, and GraphQuestions¹⁴ (Su et al., 2016) uses CC BY 4.0 license. WebQSP¹⁵ (Yih et al., 2016) and SimpleQuestions-Balance¹⁶ (Wu et al., 2019) are also downloaded from their official release channels. We have complied with their distribution rules. These datasets involve manual construction rather than fully automated construction, which includes the review process. They contain questions about some famous individual people, but the corresponding content is available on Freebase, which is a publicly released, human-reviewed knowledge base.

Although the training data for LLMs could be quite large, the test set annotation of GrailQA is not publicly available. In addition, our experimental results on the test set and the validation set show the same trend, so the impact of the data contamination problem on the experiments of this paper could be ignored.

¹³<https://dki-lab.github.io/GrailQA>

¹⁴<https://github.com/ysu1989/GraphQuestions>

¹⁵<https://www.microsoft.com/en-us/download/details.aspx?id=52763>

¹⁶<https://github.com/wudapeng268/KBQA-Adapter/tree/master/Data/SQB>

Logical Form (S-expression)	Question
1. (AND book.journal (JOIN book.periodical.editorial_staff (AND (JOIN book.editorial_tenure.editor m.012z2neg) (JOIN book.editorial_tenure.title m.02h6676)))) (GrailQA valid set)	1. john oliver la gorce was the editor on the editor for what journal?
2. (AND book.journal (JOIN book.periodical.editorial_staff (AND (JOIN book.editorial_tenure.editor m.05ws_t6) (JOIN book.editorial_tenure.title m.02wk2cy)))) (GrailQA valid set)	2. with which journal did don slater serve as editor on the editor in chief?
All four S-expressions are (COUNT (AND book.reviewed_work (JOIN book.reviewed_work.reviews_of_this_work m.0240y2))) (GraphQuestions training set)	1. how many works did fresh air review? 2. how many works were reviewed by fresh air in total? 3. what is the total amount of works reviewed by fresh air? 4. fresh air has reviewed how many different works?

Table 14: Examples of paraphrases in GrailQA and GraphQuestions.

Sampled Logical Form	Synthetic Question
(COUNT (AND people.profession (JOIN people.profession.people_with_this_profession m.012d40)) lentitylm.012d40 jackie chan	how many professions does jackie chan have?
(AND food.beer (le food.beer.original_gravity 1.067^^float))	which beer has an original gravity less than or equal to 1.067?
(AND medicine.manufactured_drug_form (AND (lt medicine.manufactured_drug_form.size 10.0^^float) (JOIN medicine.manufactured_drug_form.fda_otc_part m.0h9yt7z))) lentitylm.0h9yt7z fda otc monograph part 348	which manufactured drug form has part fda otc monograph part 348 and has a size smaller than 10.0?
(ARGMAX (AND measurement_unit.power_unit (JOIN measurement_unit.power_unit.measurement_system m.07y37)) measurement_unit.power_unit.power_in_watts) lentitylm.07y37 us customary units	what is the largest power unit in the us customary units?
(AND music.release (AND (JOIN music.release.engineers m.011mbx12) (JOIN music.release.label m.0g12fn3))) lentitylm.011mbx12 raynard glass lm.0g12fn3 hostile gospel ministries	what musical release is engineered by raynard glass and labelled hostile gospel ministries?
Sampled Triple	Synthetic Question
D.W. Robertson, Jr. (m.09ggymq), people.person.place_of_birth, Washington, D.C. (m.0rh6k)	where was D. W. Robertson, Jr. born
Alfred Chao (m.046cmd8), computer.operating_system_developer.operating_systems_developed, pSOS (m.0lscq)	what operating system did Alfred Chao develop?

Table 15: Examples of synthetic data. The logical form is S-expression (Gu et al., 2021). The entity label is appended to the logical form.

Datasets	#question	#class	#relation	#entity
GrailQA (Gu et al., 2021)	64,331	1,534	3,720	32,585
GraphQuestions (Su et al., 2016)	5,166	506	596	376
WebQSP (Yih et al., 2016)	4,737	408	661	2,593
GAIN-synthetic	127,329	5,078	12,942	46,645

Table 16: Statistics of KBQA datasets and the GAIN-synthetic dataset.

Function	None	Count	Comparative	Superlative
ArcaneQA (Gu and Su, 2022)	70.8/77.8	62.5/68.2	54.5/75.7	70.5/ 75.6
RnG-KBQA (Ye et al., 2022)	77.5/81.8	73.0/77.5	55.1/76.0	13.8/22.3
TIARA (T5-base) (Shu et al., 2022)	77.8/83.1	76.4/81.8	57.4/81.4	58.7/69.0
TIARA + GAIN ELF only	76.8/81.7	73.9/80.0	0.0/25.3	0.0/8.3
TIARA + GAIN (T5-base)	78.6/84.6	77.7/83.0	61.7/82.3	69.9/73.2
TIARA + GAIN (T5-3B)	78.5/ 84.8	77.3/82.5	63.0/84.5	70.7/74.1
GPT-3.5-turbo (5-shot)	74.1/78.0	66.8/70.5	38.3/60.5	43.9/52.3
# of relations	1	2	3	4
RnG-KBQA (Ye et al., 2022)	75.7/79.3	65.3/74.7	28.6/44.5	100.0/100.0
TIARA (T5-base) (Shu et al., 2022)	81.2/85.6	64.7/75.8	29.3/48.5	50.0/83.3
TIARA + GAIN ELF only	74.0/77.8	56.6/67.9	9.9/31.0	0.0/33.3
TIARA + GAIN (T5-base)	82.4/87.2	67.0/78.0	38.9/49.8	50.0/83.3
TIARA + GAIN (T5-3B)	82.0/87.2	68.8/79.0	37.5/ 51.3	50.0/83.3
GPT-3.5-turbo (5-shot)	75.0/78.6	61.9/69.6	19.8/36.6	50.0/50.0
# of entities	0	1	2	
RnG-KBQA (Ye et al., 2022)	58.5/63.6	75.4/79.9	55.6/73.5	
TIARA (T5-base) (Shu et al., 2022)	77.5/83.1	76.6/82.6	49.9/68.0	
TIARA + GAIN ELF only	42.8/47.0	74.2/79.9	47.4/67.6	
TIARA + GAIN (T5-base)	82.2/86.5	77.6/83.7	53.4/71.4	
TIARA + GAIN (T5-3B)	82.0/ 86.6	77.6/84.0	55.6/73.0	
GPT-3.5-turbo (5-shot)	66.8/72.8	71.9/76.1	48.8/62.1	

Table 17: EM and F1 scores (%) for different types of logical forms on the GrailQA valid set. *None* denotes no function. *# of relations/entities* denotes the number of relations/entities in the S-expression. ELF denotes exemplary logical form (Shu et al., 2022).

Given a question and Freebase contexts, write a logical form that answers the question.

Question: dark sun: wake of the ravager was designed by what video game designer?

Candidate entities:

(A) [Dark Sun: Wake of the Ravager]

Exemplary Logical Forms:

(A) (AND cvg.cvg_designer (JOIN cvg.cvg_designer.games_designed [Dark Sun: Wake of the Ravager]))

(B) (AND cvg.cvg_designer (JOIN (R cvg.computer_videogame.designers) [Dark Sun: Wake of the Ravager]))

(C) (AND cvg.computer_videogame (JOIN (R cvg.cvg_designer.games_designed) (JOIN cvg.cvg_designer.games_designed [Dark Sun: Wake of the Ravager])))

(D) (AND cvg.computer_videogame (JOIN cvg.computer_videogame.designers (JOIN cvg.cvg_designer.games_designed [Dark Sun: Wake of the Ravager])))

(E) (AND base.wikipedia_infobox.video_game (JOIN base.wikipedia_infobox.video_game.developer (JOIN cvg.cvg_designer.games_designed [Dark Sun: Wake of the Ravager])))

Candidate classes:

(A) cvg.cvg_designer

(B) cvg.game_performance

(C) cvg.musical_game

(D) cvg.game_character

(E) cvg.computer_game_engine_developer

(F) cvg.computer_videogame

(G) cvg.computer_game_performance_type

(H) cvg.game_version

(I) cvg.computer_game_subject

(J) cvg.computer_game_evaluation

Candidate relations:

(A) cvg.cvg_designer.games_designed

(B) cvg.computer_videogame.designers

(C) cvg.computer_videogame.prequel

(D) cvg.computer_videogame.sequel

(E) cvg.computer_videogame.mods

(F) cvg.computer_videogame.expansions

(G) cvg.computer_videogame.developer

(H) cvg.computer_videogame.characters

(I) cvg.game_version.game

(J) cvg.computer_game_mod.game_modded

Prediction: (AND cvg.cvg_designer (JOIN cvg.cvg_designer.games_designed [Dark Sun: Wake of the Ravager]))

Figure 2: Example of LLM prompt (part 1): The task instruction and k teaching examples (only one is shown because of the length) with questions and their contexts.

Question: worldofwarcraft is the creation of which video game designer?

Candidate entities:

(A) [worldofwarcraft]

Exemplary Logical Forms:

(A) (AND cvg.cvg_designer (JOIN cvg.cvg_designer.games_designed [worldofwarcraft]))

(B) (AND cvg.cvg_designer (JOIN (R cvg.computer_videogame.designers) [worldofwarcraft]))

(C) (AND cvg.cvg_designer (JOIN cvg.cvg_designer.games_designed (JOIN cvg.computer_game_expansion.expansion_for [worldofwarcraft])))

(D) (AND cvg.cvg_designer (JOIN (R cvg.computer_videogame.designers) (JOIN cvg.computer_game_expansion.expansion_for [worldofwarcraft])))

(E) (AND cvg.cvg_designer (JOIN (R cvg.computer_videogame.designers) (JOIN (R cvg.computer_videogame.expansions) [worldofwarcraft])))

Candidate classes:

(A) games.game_designer

(B) cvg.cvg_designer

(C) amusement_parks.ride_designer

(D) cvg.cvg_developer

(E) cvg.computer_videogame

(F) cvg.computer_game_engine_developer

(G) cvg.computer_game_engine

(H) cvg.computer_game_mod

(I) cvg.game_performance

(J) cvg.musical_game

Candidate relations:

(A) cvg.computer_videogame.designers

(B) cvg.cvg_designer.games_designed

(C) games.game_designer.games_designed

(D) games.game.designer

(E) cvg.computer_videogame.developer

(F) cvg.cvg_developer.games_developed

(G) cvg.computer_game_engine.developer

(H) cvg.computer_videogame.expansions

(I) cvg.computer_videogame.publisher

(J) cvg.game_version.developer

Prediction:

Figure 3: Example of LLM prompt (part 2): After k teaching examples, the input question and its contexts is given. The golden prediction is (AND cvg.cvg_designer (JOIN cvg.cvg_designer.games_designed [worldofwarcraft])).

AttriSAGE: Product Attribute Value Extraction Using Graph Neural Networks

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Abstract

Extracting the attribute value of a product from the given product description is essential for e-commerce functions like product recommendations, search, and information retrieval. Therefore, understanding products in e-commerce with greater accuracy certainly gives any retailer the edge. However, they are limited to contextual modeling and do not exploit relationships between the product description and attribute values.

Through this paper, in a world where we move and shift to more complicated models with extensive training time with models like LLMs, we present a novel, more straightforward attribute value extraction from product description leveraging graphs and graph neural networks. Our proposed method demonstrates improvements in attribute value extraction accuracy compared to the baseline sequence tagging approaches while also significantly reducing the computation time leading to lower carbon footprint.

1 Introduction

In the dynamic landscape of e-commerce, where a wide range of products are readily available to consumers, efficient and accurate product understanding plays a pivotal role in facilitating seamless user experiences. The attributes associated with products, including details such as color, material, brand, type, and more, hold the key to enabling users to find their desired items more efficiently.

E-commerce platforms usually provide product descriptions but consumers prefer a quick and intuitive way to narrow down their search and make informed purchasing decisions. Product titles usually contain attributes and their corresponding values but this data is mostly unstructured, noisy, and often contains missing values. For example, in Figure 1, a product along with its context (description)



New Arrival Original Authentic
Nike Air VaporMax Flyknit
Running Shoes Men Breathable
Sport Outdoor Sneakers 849558

Gender: Men
Brand Name: Nike
Feature: Breathable
Insole Material: NULL
Athletic Shoe Type: Running Shoes

Figure 1: A product description with its attributes and their corresponding values represented as "Attribute: Value".

is provided. Along with the description, there are attribute-value pairs for attributes including Gender, Brand, Feature, etc ; But, there also missing attributes for values like Model number (value: 849558), Model name (value: Air VaporMax), etc. Hence we need models that predict attribute values for the attributes that have not been seen before.

The critical role of product attributes has driven extensive research efforts to explore innovative methods for their extraction and categorization. Previous works, including those by Ghani et al., 2006, Chiticariu et al., 2010, and Gopalakrishnan et al., 2012, focused on attribute value extraction using a rule-based approach. In this methodology, a domain-specific seed dictionary played a crucial role in identifying key phrases and extracting attribute values. The rule-based systems relied on predefined patterns and heuristics to recognize and capture relevant information from unstructured data, providing a foundational approach to attribute extraction in the context of specific domains. Other works proposed a Named-Entity Recognition (NER) task (Putthividhya and Hu, 2011) for this problem; although NER relies on pre-existing knowledge of named entities. When faced with previously unseen brands, models, or attributes, the system struggles to identify and extract these values accurately. In

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such situations, a more context-aware approach, like question-answering-based techniques that employ sequence-to-sequence models, might be more effective for attribute value extraction from product descriptions. Later introduced works that employed sequence-to-sequence models performed better than the former models, however, these approaches have a few shortcomings-

(a) they do not exploit the structural relationships between product description and attribute values across the dataset. For example, assume product descriptions C_1 and C_2 share a common attribute value T_1 . If there is another attribute value T_2 relevant to C_2 and other similar product descriptions, we can infer that T_2 might also be relevant to C_1 . Such transitive cues can be beneficial for identifying missing attribute values.

(b) language models bring high computational costs at massive scales as any task not only involves predicting multiple missing attribute values but also requires precise organization of the most relevant attribute values specific to the product. Graphs are naturally suitable to make the relationships explicit such as product description-attribute value networks.

(c) With the growing popularity of LLMs, we tend to oversee the ecological impact they have on the environment. They consume vast computational resources, leading to significant energy use and high carbon emissions.

In this work, our focus is on advancing the domain of product attribute value extraction through a novel approach that leverages graph models and graph neural networks (GNNs). Our primary goal is to enhance the generalizability of existing approaches and provide more interpretable predictions. We construct a product data graph using a dataset comprising 110k product title-attribute triples, enabling us to gain deeper insights into the data. Leveraging graph-based neural network architecture we performed a node classification task to classify our title nodes with multiple attribute values.

Through this work, we aim to contribute the following:

- A Graph Neural Network (GNN) based approach for attribute value extraction from a given product description.
- A Knowledge graph that captures the transitive relations and can predict the missing

attribute values through these transitive links for up to k-number of hops.

- Using the GraphSAGE model, we are able to reduce the training time significantly.

2 Related Work

Initial works focusing on the attribute value extraction task involved the use of domain-specific rules to detect attribute-value combinations from product descriptions (Zhang et al., 2009). The first learning-based approaches required substantial feature engineering and were limited in their capacity to generalize to unknown features and attribute values.

The initial application of the bidirectional LSTM with a Conditional Random Field layer (BiLSTM-CRF model) for sequence tagging in attribute value extraction was introduced by Huang et al., 2015. Following this, Zheng et al., 2018 proposed an end-to-end tagging model, OpenTag utilizing BiLSTM, CRF, and attention mechanisms, eliminating the need for dictionaries or hand-crafted features. However, this methodology poses scalability challenges when dealing with a large set of attributes and cannot identify emerging values for previously unseen attributes. An extension to OpenTag, SU-OpenTag was proposed by Xu et al., 2019 which encodes both a target attribute and the product title using the pre-trained language model, BERT (Devlin et al., 2019). Wang et al., 2020 proposed AVEQA which formulates the attribute value extraction from products task as a multi-task approach via Question Answering.

With the advancements in the field of language models, recent works by Roy et al., 2021 leverage large language models to extract attribute values from product data. They formulated the attribute value extraction as an instance of text infilling task as well as an answer generation task for which they utilized Infilling by Language Modeling (ILM) (Donahue et al., 2020) for the infilling approach and fine-tuned text-to-text transfer transformer (T5) (Raffel et al., 2023) as an answer generation task. These models outperform the existing models but they fail to capture the intricate relations between different products.

3 Problem Formulation

We can formulate this problem of attribute value extraction as follows:

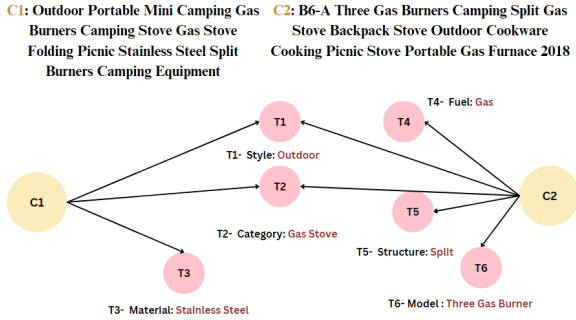


Figure 2: A graph illustrating the Description-Attribute-Value model for a given product and outlining the graph.

Given a product description, \mathcal{C} , such that, $\mathcal{C} = \{C_1, C_2, C_3, \dots, C_i\}$ and an attribute A , the goal is to predict the corresponding attribute value \mathcal{T} associated with A where $\mathcal{T} = \{T_1, T_2, T_3, \dots, T_j\}$, where i and j are the number of unique source and target nodes respectively. We consider the nodes representing \mathcal{C} as the Source node and \mathcal{T} as the Target node. For constructing the graph, the Product Description, \mathcal{C} , and the Attribute Values, \mathcal{T} are arranged in a graph $G = (V, E)$ where V , the nodes represent $\mathcal{C} \cup \mathcal{T}$.

$E = \mathcal{C} \times \mathcal{T}$ is the set of edges denoting the ground truth relation between product descriptions, \mathcal{C} , and the attribute values, \mathcal{T} . We formulate our problem as a multi-label node classification task which also takes into consideration transitive relations between the nodes. This formulation allows more comprehensive correlations to be inferred. For example, from Figure 2, we can infer that titles C_1 and C_2 share a common value T_1 . If there is another value T_2 relevant to C_2 , it can be inferred that T_2 might be relevant to C_1 as well, i.e., one of the labels for C_1 could be T_2 . This formulation helps us improve the interpretability of the obtained results. Table 1 depicts statistics of the graph modelled on the entire AE-110K dataset after pre-processing.

3.1 Implementation

All the models are implemented using PyTorch (Paszke et al., 2019).

For each product description $i \in \mathcal{C}$, and attribute value $j \in \mathcal{T}$, we generated a D dimensional initial representation of their textual features capturing the semantic information of these values.

These initial features, which we could call word embeddings were generated using pretrained Fast-Text (Bojanowski et al., 2017) and BERT (Devlin et al., 2019). These word embeddings provide a

Property	Value
Nodes	52,028
Source Nodes	39,445
Target Nodes	12,586
Edges	85,872
Avg Degree	3.3009
Density	0.0634

Table 1: Graph Statistics

dense representation of words in a continuous vector space, enabling the model to capture semantic relationships and nuances. Additionally, BERT works well with numerical text hence if the value is composed of numbers the model can grasp the semantics of the value well. For implementing the graph neural network to process the graph-structured data, we have implemented the GraphSAGE (Graph Sample and Aggregation) model (Hamilton et al., 2017), which performs neighbor sampling and aggregation to generate embeddings for each node in the graph. Our model architecture can be explained as follows:

Let $G = (V, E)$ be the input graph, where V is the set of nodes and E is the set of edges. For each node $v_i \in V$, there is an initial node feature vector x_i representing the textual features:

$$x_i \in R^D$$

where D is the dimensionality of the word embeddings. In our case, D equals 768, representing the dimension of the BERT embeddings. Sampling neighbors of each node v_i is done as :

$$N(v_i) = \{v_{i,1}, v_{i,2}, \dots, v_{i,k}\} \quad (1)$$

where k is the number of sampled neighbors. Then a mean aggregator is applied for aggregating information from the node and its neighbors:

$$h'_i = \text{Aggregate}(\{h_{i,1}, h_{i,2}, \dots, h_{i,k}\}) \quad (2)$$

Then the aggregated representation is concatenated with the initial node embedding:

$$h_i = \text{Concat}(h'_i, x_i) \quad (3)$$

Finally, the model is trained to minimize the difference between predicted and ground truth attribute values:

$$\text{Minimize} \sum_{i \in N} \text{Loss}(h_i, \text{ground_truth}_i) \quad (4)$$

Attributes	Train	Dev	Test
Brand Name	50,413	5,601	14,055
Material	22,814	2,534	6,355
Color	5,594	621	1,649
Category	5,906	590	1,649
All	77,207	10,920	22,169

Table 2: The table represents the most frequently occurring attributes (Brand Name, Material, Color, Category) from the AE-110K dataset.

The Cross-Entropy Loss is calculated between the predicted probabilities and the true labels. Training using backpropagation and stochastic gradient descent (SGD) is performed and the model parameters are updated.

For k -hop architecture, repeat sampling and aggregation for k hops:

$$h_i^{(1)}, h_i^{(2)}, \dots, h_i^{(k)} \quad (5)$$

The representations from each hop can be concatenated as:

$$h_i = \text{Concat}(h_i^{(1)}, h_i^{(2)}, \dots, h_i^{(k)}) \quad (6)$$

4 Experiment Setup

4.1 Dataset

We have used the publicly available AE-110K dataset¹ from The Sports and Entertainment category of AliExpress (Xu et al., 2019). This dataset contains 110,484 triples, wherein each triple consists of the product title (context), attribute, and value each separated by a delimiter. For our task, we pre-processed the dataset to handle triples with empty values as well as triples where the attribute value was denoted by '-' and '/'. The resultant dataset consists of 110,296 triples with 2761 unique attributes and 12,607 unique attribute values. We divided the data randomly into a 7:1:2 ratio. Specifically, we chose 77,207 triples as our training set, 10,920 triples as the validation set, and the remaining 22,169 triples as our test dataset. Table 2 shows the most frequently occurring attributes in the AE-110K dataset.

4.2 Evaluation Metrics

The model’s performance was assessed on the test set, by employing a comprehensive set of metrics.

¹https://raw.githubusercontent.com/lanmanok/ACL19_Scaling_Up_Open_Tagging/master/publish_data.txt

We calculated average metrics for F1-score, precision (P), and recall (R). The objective is to assess the model’s ability to accurately predict the attributes associated with each product title node in the graph. The metrics are represented by F_1 score, P, and R respectively. Let u_i and g_i be the gold standard and generated values for the i -th sample respectively and let N be the total number of samples in the test set, then:

$$P = \frac{1}{N} \sum_{i=1}^N \frac{|v_i \cap g_i|}{|g_i|} \quad (7)$$

$$R = \frac{1}{N} \sum_{i=1}^N \frac{|v_i \cap g_i|}{|v_i|} \quad (8)$$

4.3 Baselines

We compare our models with SUOTag (Scaling Up Open Tag) Xu et al., 2019 and ILM-T5 (Roy et al., 2021).

- **SUOTag** (Xu et al., 2019) employs a BiLSTM-based architecture with attention and CRF components. It utilizes pre-trained BERT embeddings for word representation and employs two separate BiLSTMs for title and attribute modeling. An attention layer is applied to capture the semantic interaction between attributes and titles. The output layer utilizes a CRF layer to predict tag sequences, considering dependencies between output tags. (Lafferty et al., 2001).
- **ILM-T5** (Roy et al., 2021) presents the problem formulation to generate product attribute values as two tasks - (i) an instance of text infilling task leveraging the Infilling by Language Modeling (ILM) and pre-trained GPT-2 small (Radford et al., 2019) model and (ii) as an answer generation task using the text-to-text transfer transformer (T5) model.

4.4 Result

Table 3 presents the performance of the AttrISAGE model in comparison to the baseline models on the AE-110K dataset. AttrISAGE works well on a large set of attributes. With even a simple and compact graph-based network like ours, we can achieve performance comparable to LLMs, which demonstrates substantial improvements compared to sequence tagging models. Our model achieved an F1 score of 80.45, signifying a notable improvement over the sequence tagging models.

Model	Precision	Recall	F1
SUOTag	70.81	71.31	71.06
ILM	83.35	83.38	83.37
T5	83.89	83.75	83.82
AttriSAGE	79.06	81.90	80.45

Table 3: Performance of Different Models on AE-110K

Additionally, our AttriSAGE model significantly reduces overall training time and efficiently manages computational resources compared to Large Language Models. The model was trained on the NVIDIA DGX A100 GPU and it took 2-3 hours to execute, showing improvement in terms of both time and resource utilization.

5 Discussions

Our model’s success in capturing the essence of the dataset can be attributed to its interpretability. We have utilized the structured format of a graph to restructure the data, which aligns with the analysis capabilities of a graph neural network. Unlike an LLM, which predicts the next token in the same dataset, our graph neural network excels in analyzing structured data and making accurate predictions leveraging a graph’s ability to learn from its neighborhood. By capturing the relationships between data points through the graph, our model has achieved significant levels of accuracy. Moreover, our model’s interpretability allows us to comprehend the rationale behind its predictions, which is crucial for maintaining its dependability and credibility.

6 Conclusion and Future Work

In this work, we have proposed a novel approach to extract attribute values from unstructured product data with the help of graphical representation. Representing the e-commerce data as graphs and leveraging graph techniques to extract the attribute values helped in understanding the underlying relationships between different products and forming transitive relations between products and their corresponding values.

We plan on extending this work to build an advanced multi-hop model architecture that can make better predictions under diverse scenarios, including handling missing values, exploring strategies for imputing the most frequent values, and addressing other issues and datasets.

Limitations

The current method has only been tested on a single dataset, which is the primary limitation of this work. Although the results are promising in this particular context, the generalizability of the method across diverse datasets and under different scenarios remains untested. To overcome this limitation, future work would expand the experiments to include a more varied selection of datasets. Furthermore, this work currently only focuses on the GraphSAGE architecture. Alternative graph-based architectures with different configurations and hyperparameter settings could be explored to enhance the current findings and results.

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HypoTermQA: Hypothetical Terms Dataset for Benchmarking Hallucination Tendency of LLMs

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Abstract

Hallucinations pose a significant challenge to the reliability and alignment of Large Language Models (LLMs), limiting their widespread acceptance beyond chat-bot applications. Despite ongoing efforts, hallucinations remain a prevalent challenge in LLMs. The detection of hallucinations itself is also a formidable task, frequently requiring manual labeling or constrained evaluations. This paper introduces an automated scalable framework that combines benchmarking LLMs' hallucination tendencies with efficient hallucination detection. We leverage LLMs to generate challenging tasks related to hypothetical phenomena, subsequently employing them as agents for efficient hallucination detection. The framework is domain-agnostic, allowing the use of any language model for benchmark creation or evaluation in any domain. We introduce the publicly available HypoTermQA Benchmarking Dataset, on which state-of-the-art models' performance ranged between 3% and 11%, and evaluator agents demonstrated a 6% error rate in hallucination prediction. The proposed framework provides opportunities to test and improve LLMs. Additionally, it has the potential to generate benchmarking datasets tailored to specific domains, such as law, health, and finance.

1 Introduction

Large Language Models (LLMs) demonstrate exceptional predictive capabilities for common tokens, but encounter challenges when dealing with rare tokens, especially in mixed contexts (Ilyas et al., 2019; Zou et al., 2023). Adversarial effects in real-life scenarios may inadvertently emerge from prompts that combine both common and rare tokens.

The question in Figure 1 is framed with the valid term "Platypus" in the relevant domain and a hypothetical term, "Wolf," created using a common

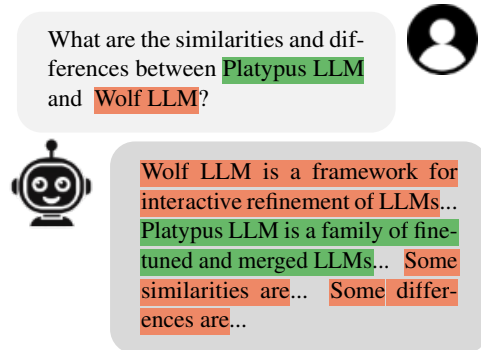


Figure 1: Hypothetical Term Sample

word within the specified context. The answer can be easily categorized by assessing the LLM output: whether it rejects the presence of Wolf LLM or acknowledges its existence and provides an explanation. Indeed, Platypus (Lee et al., 2023) is an actual language model incorporating a seldom-used animal name. In contrast, the Wolf Language Model did not exist when this paper was authored. However, approximately 90% of the time, LLMs neglect to indicate their lack of information about a hypothetical phenomenon in similar situations (Section 4). This characteristic significantly diminishes the reliability of LLMs and impedes their suitability for deployment in critical decision-making systems.

Detecting hallucinations is difficult, and it is still an ongoing research problem (Ji et al., 2023; Huang et al., 2023). Generating examples, like the "Wolf LLM" example, might help assess the tendency of LLMs to generate information about nonexistent terms. These examples offer advantages in both revealing and detecting hallucinations:

- (1) It confirms the absence of the term in the training dataset.
- (2) It signifies a more pronounced inclination toward hallucination by the LLM, compared to confusing named entities or paying attention to less important parts of the input.
- (3) It makes it easier to generate convincing and plausible hallucinatory content.
- (4) The output is easily labeled,

and the evaluation process is more efficiently automated due to LLM Agents adeptly reflecting on atomic tasks. To realize these advantages, in this paper, we:

1- Propose a scalable and automatized methodology to create a hallucination benchmark dataset (Section 2).

2- Publish the HypoTermQA Dataset along with our code for reproducibility, evaluation, and intermediate results publicly on GitHub repository ¹.

3- Propose a novel way to measure the Hallucination tendency of LLMs utilizing LLM agents (Section 3) and present insights after conducting proposed evaluations (Section 4).

As evident from the provided example, this study specifically targets a particular type of hallucination: the generation of content about non-existent phenomena. However, our approach allows for the creation of more generalized datasets, encompassing factually inaccurate generations (Min et al., 2023) or reliable summarization (Mishra et al., 2023).

2 Benchmark Creation

Figure 2 illustrates the process of our framework, while Appendix B contains the terms introduced in this paper. The proposed benchmark process includes two steps to generate the proposed Hypothetical Terms Dataset. The first step includes the generation of an intermediate dataset, which contains hypothetical and valid term couples (see Sections 2.1 - 2.3). The second step is about transforming these term couples into coherent hypothetical or valid questions (see Section 2.4).

The GPT-3.5 (OpenAI, 2023b) model was employed for the generation of synthetic data due to its higher performance on common tasks compared to open-source alternatives and its superior cost-efficiency relative to the GPT-4 model (OpenAI, 2023c). The temperature variable was set to zero unless specified otherwise. We generated the dataset in accordance with OpenAI's terms and conditions and usage policies². The proposed dataset is designed exclusively for the purpose of preventing and evaluating hallucinations in language models.

2.1 Topic Selection

As an initial step, the GPT-3.5 model was queried with the prompt "the most popular 20 topics on

the internet." The objective was not to objectively identify the most popular topics. LLMs are considered as tools for information compression (Delétang et al., 2023), and the internet serves as the primary source of training information. We designed the prompt to uncover the most familiar general topics, followed by the generation of the adversarial hypothetical terms using the most familiar tokens. During this phase, a temperature value of one was set, prioritizing diversity and creativity over reproducibility. Explanations for topics were also generated to serve as prompt inputs in subsequent steps, thereby facilitating more detailed responses. Appendix C presents the prompts employed in this study along with their corresponding generated responses.

2.2 Creating Hypothetical Terms

For each topic, the GPT-3.5 model was prompted to "generate 50 hypothetical terms consisting of multiple common words". The prompt templates for creating hypothetical terms and explanations are provided in Appendix D. Throughout this process, a temperature value of one was applied to encourage creativity, resulting in the generation of 50 terms for each of the 20 topics. As anticipated, the model 'hallucinated' about 'hallucinating' and often generated valid terms. To confirm the absence of these hypothetical terms in the real world, validation was conducted using the Google Custom Search API.³ The generated terms were searched within quotation marks across the web, and any term with a "total results" count greater than zero was excluded from the dataset. Following the web search validation process, a total of 790 terms remained out of 1000 terms. The distribution of terms across topic categories ranged from 24 to 50.

2.3 Retrieving Valid Terms Similar to Hypothetical Terms

Even though the hypothetical terms are constructed from common, familiar tokens, generating questions solely based on these terms may result in easily discernible and meaningless sentences.

To increase task complexity, terms similar to the hypothetical ones retrieved and used in the questions. These new terms were carefully chosen to be valid and found in Wikipedia. Questions were then formulated, emphasizing the relationship between the valid term and the hypothetical term. Conse-

¹github.com/cemuluoglakci/HypoTermQA

²openai.com/policies/terms-of-use and <https://openai.com/policies/usage-policies>

³<https://developers.google.com/custom-search/v1>

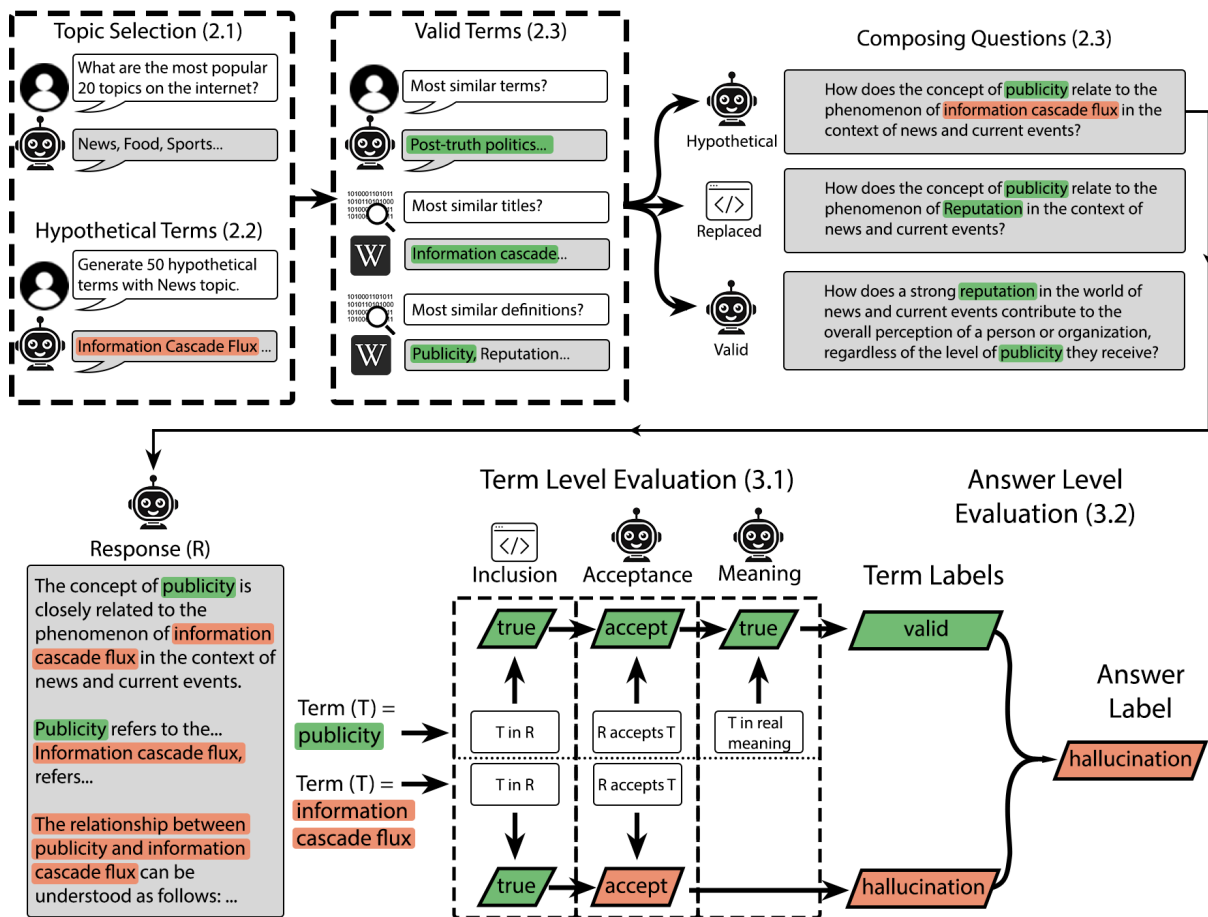


Figure 2: Sample HypoTermQA Process

quently, HypoTermQA questions encompass both answerable real elements and non-answerable adversarial elements, rendering them more plausible, challenging, and reflective of real-life scenarios. Nevertheless, the identification of similar terms and the application of similarity measures pose additional challenges. Three different approaches were employed to generate valid terms similar to hypothetical terms. The output of this phase constituted the first part of the dataset.

LLM Suggestion:

The GPT-3.5 model was prompted to generate 50 valid terms similar to the given hypothetical term. Prompt template is presented in Appendix E. Here, the objective was not to identify the most similar terms, but rather to find tokens closely positioned to the hypothetical term within the latent space as determined by the LLM. The order of word generation by the LLM is considered indicative of the degree of similarity.

Nevertheless, relying solely on responses from the LLM or web searches does not suffice to confirm the presence of a term. To overcome this lim-

itation, terms without a corresponding Wikipedia article with an exact match in the title were omitted. Out of 790 hypothetical terms, 14,271 distinct similar terms were generated, accounting for some overlaps in the generated terms. Among these, 6,466 terms aligned with existing Wikipedia article titles, leading to the exclusion of 7,750 term candidates from the dataset.

In this step, Wikipedia article searches were conducted against a local copy, ensuring reproducibility and maintaining consistency with subsequent steps. The methodology outlined by Petroni et al. (2021) was embraced, and a local JSON-based database was generated using the April 1, 2023, English Wikipedia dump. This extraction yielded 7,251,680 pages, each containing at least one paragraph of text ⁴.

Title Similarity:

The JSON-based database created in the previous step was used to create a vector database. Wikipedia titles were vectorized with a DistilBERT-based model, in accordance with the methodology

⁴<https://dumps.wikimedia.org>

outlined by Hofstätter et al. (2021). Then, for each hypothetical term (obtained in Section 2.2), we retrieved the 50 most similar Wikipedia titles with the L2 distance metric. A sample search result is presented in Appendix F. This approach, incorporating a valid term closely aligned with the hypothetical term in the latent space, facilitated the generation of perplexing questions for the LLMs.

However, it was not uncommon to retrieve articles with titles containing words similar to the hypothetical term but having irrelevant context. An illustration of this can be found in Appendix O.2. The hypothetical term "Turbo-jump dribble" was employed to identify similar words using the titles of Wikipedia articles, resulting in the retrieval of the term "Jump, Jive an' Wail." Despite including a portion of the original hypothetical term, the retrieved term differs significantly in meaning. This situation poses a challenge when generating coherent questions based on term pairs. To mitigate this limitation, we implemented an additional step to retrieve related terms by assessing the similarity in definitions of both hypothetical and valid terms.

Text Similarity: The first paragraphs of Wikipedia pages were accepted as the definitions of the respective titles. Parallel to the preceding step, these definitions underwent vectorization using the same methodology, and the resultant vectors were stored as database instances. For every hypothetical term definition, we retrieved the 50 most similar Wikipedia definitions with the L2 distance metric. A sample search result is presented in Appendix G.

It is noteworthy that the titles of Wikipedia articles, which include valid terms obtained through this method, are often distant from the hypothetical terms in the latent space. Nonetheless, they share similar contexts and definitions. In the example Appendix O.3, the "Alley-oop" sample was retrieved through Wikipedia definition similarity. Even though its wording is different than "Turbo-jump dribble", both are basketball techniques and their definitions are similar. The hypothetical-valid term pairs established through this method are more conducive to crafting coherent questions, although they may possess a reduced adversarial quality.

2.4 Composing Questions

In the previous phase, we acquired 790 hypothetical terms. However, six hypothetical terms were omitted from the dataset due to an insufficient number of corresponding similar valid terms. In the current phase, for each of the remaining 784 terms,

we identified three sets of related valid terms (LLM suggestion, title, and text similarity). We then selected the three most similar terms from each set, creating nine-term pairs for each hypothetical term. A sample for term pairs is presented in Appendix H.

Following this, three distinct methods were used to generate questions for each term pair. The expected result is the creation of 27 questions for every hypothetical term. However, 459 duplicate questions were identified and subsequently removed. Additionally, during quality checks, it was detected that 1201 generated questions did not include at least one of the terms included in the prompt. The final dataset comprises a total of 19,508 questions. Each adversarial question in the dataset was accompanied by two different control questions.

Hypothetical Questions: Using the hypothetical and valid terms, we instructed the GPT-3.5 model to generate a coherent question (see Appendix I). The prompt included the definition of the term's corresponding topic and both terms, along with their respective definitions, to ensure that the generated questions align with the intended context.

Valid Questions: The valid question generation process is similar to the previous step. Instead of using a hypothetical term, we pick the most similar term from its corresponding valid term list to formulate a coherent question (Refer to Appendix J).

Replaced Questions: In this phase, the hypothetical term is substituted with the most similar valid term through programmatic string operations (Refer to Appendix K and Appendix L).

A sample final output of the question generation process is presented with its metadata in Appendix M.

3 HypoTermQA Score

Labeling open-ended long texts is a challenging task. However, by getting insights from the literature about the reasoning (Ye and Durrett, 2022; Si et al., 2023; Liu et al., 2023) and reflection (Shinn et al., 2023; Wu et al., 2023; Kim et al., 2023) capabilities of LLMs, we generate LLM agents to automatically decide the label of another LLM's response. Similar to the FactScore (Min et al., 2023) framework, we introduce irrelevant labels besides hallucination and valid answer labels. We use the percentage of "valid" labeled answers to "hypothetical questions" as the *HypoTermQA Score*. It shows

LLM’s performance to resist hallucination. Also, $(1 - \text{HypoTermQA Score})$ denotes the *error rate*. The distribution of *error rate* between hallucination and irrelevant labels or performance on valid questions gives valuable secondary insights about LLM performance. However, our focus is on detecting if LLMs are capable of knowing what they do not know.

3.1 Term Level Evaluation

For term-level evaluation, a series of programmatic tests and LLM agents were employed. [Appendix N](#) contains the flowchart outlining the labelling logic, while in [Appendix O](#), an example response for each possibility is provided. Each question in the HypoTermQA dataset comprises a term couple. Evaluation involves comparing the LLM response with each term. Term-level evaluations are a function of LLM Response (R) and a Term (T_i). The output term-level-label (L_t) can be valid (v), hallucination (h), or irrelevant (i). Let TT_i be Term (T_i) Type which can be hypothetical (h) or valid (v):

$$\text{term_level_eval}(R, T_i) \rightarrow L_{t_i}$$

Term Inclusion Check: Initially, the answer undergoes a programmatic string check for the presence of the specified term (Refer to [Appendix K](#)). Let P_i show whether the term is present in the response. If the term is not detected ($P_i = \text{false}$), the response is deemed unrelated to the given question, labeled as "irrelevant," and further evaluations for the associated term are halted.

Term Acceptance Check: In this phase, an LLM agent is generated for reflective evaluation, using the provided prompt template in [Appendix P](#). The assessment involves verifying whether the response declines to generate content about the specified term, asserting its non-existence in the real world. If the acceptance or rejection contradicts the validity of the given term, the label "hallucination" is assigned. Additionally, a third response option may assert that the term is beyond the LLM’s knowledge. In this case, if the term is hypothetical, the Response is labeled as valid; otherwise, it is labeled as irrelevant.

$$A_i = \begin{cases} \text{accept,} & \text{if } R \text{ accepts existence of } T_i \\ \text{refuse,} & \text{if } R \text{ refutes existence of } T_i \\ \text{unknown,} & \text{if } R \text{ does not know } T_i \end{cases}$$

Meaning Check: This final evaluation method is exclusively applied to accepted ($A_i = \text{accept}$) and valid ($TT_i = v$) terms. Let M_i be the boolean

variable indicating whether the term is used in its real meaning, assessing if the answer aligns with the Wikipedia definition of the given term. Any discrepancy identified by the LLM Agent ([Appendix Q](#)) results in labeling the Response (R) as a hallucination (h).

$$L_t = \begin{cases} i, & \text{if not } P_i \\ i, & \text{if } P_i \text{ and } TT_i = v \text{ and } A_i = \text{unknown} \\ h, & \text{if } P_i \text{ and } TT_i = v \text{ and } A_i = \text{refuse} \\ h, & \text{if } P_i \text{ and } TT_i = v \text{ and } A_i = \text{accept and not } M_i \\ v, & \text{if } P_i \text{ and } TT_i = v \text{ and } A_i = \text{accept and } M_i \\ h, & \text{if } P_i \text{ and } TT_i = h \text{ and } A_i = \text{accept} \\ v, & \text{if } P_i \text{ and } TT_i = h \text{ and } A_i \neq \text{accept} \end{cases}$$

3.2 Answer Level Evaluation

The term-level evaluation concludes with 2 labels (L_{t_i}) for both terms composing the question. The logic of labeling answers based on term-level labels is illustrated in [Appendix R](#). If any label indicates hallucination, the entire answer receives a hallucination label. In the absence of hallucination but lacking direct relevance to the question, the answer is labeled as irrelevant. A "valid" label in both term-level evaluations is necessary for an overall "valid" answer. Answer-level evaluation is a function of term-level labels (L_{t_i}) and the output answer-level-label (L_a) can be valid (v), hallucination (h), or irrelevant (i):

$$\text{answer_level_eval}(L_{t_1}, L_{t_2}) \rightarrow L_a$$

$$L_a = \begin{cases} h & \text{if } L_{t_1} = h \text{ or } L_{t_2} = h \\ i & \text{else if } L_{t_1} = i \text{ or } L_{t_2} = i \\ v & \text{otherwise} \end{cases}$$

Subsequently, the language model’s HypoTerm Score (HTS) is calculated, representing the percentage of valid answers to hypothetical questions. Let H_Q represent the set of hypothetical questions in the HypoTermQA dataset and V_A be the set of valid answers:

$$HTS = \frac{|V_A|}{|H_Q|} \times 100$$

4 Experiments and Results

For experiments, various combinations of three series of LLMs are tested or employed as evaluator LLM agents: GPT ([Ouyang et al., 2022](#)), Llama2 ([Touvron et al., 2023](#)) and Orca2 ([Mittra et al., 2023](#)). GPT and Llama2 were chosen due to their high citation rates, while Orca2 was selected for its focus on improved training data quality and

reasoning performance which may lead to preventing hallucinations.

All open-sourced models underwent 4-bit quantization before inference. For 7 and 13 billion parameter-sized models, a single NVIDIA 16 GB V100 GPU was used, while 3 GPUs were employed for 70 billion parameter-sized models. Proprietary models were accessed through APIs, and models available only through a UI were manually prompted by the authors. A total resource of 2000 GPU hours for open-sourced models and 20\$ for API access was used for experiments. Llama2-7b, Llama2-13b, Llama2-70b, and GPT-3.5 models were prompted with all 19,508 questions in the HypoTermQA dataset. For those who need to deal with resource constraints, two smaller subsets were also created.

4.1 Sampling Subset

The complete dataset includes 20 topics, 784 hypothetical terms, and 27 questions per term, totaling 19,508 questions after eliminating duplicates. Appendix S presents a comparative chart of the subsets. In the 1,080-question sample, six initial hypothetical terms were chosen for each of the 20 topics. Furthermore, a single valid term was selected for each hypothetical term from the three term sets (LLM suggestion, title, and text similarity), instead of the usual three. Lastly, questions were formulated for each of the 120 terms using three distinct methods outlined in Section 2.4, resulting in nine questions for each term. In the 180-question sample, the process remains similar, except that only one hypothetical term is selected for each topic, as opposed to six in the previous sample.

Subsets are generated primarily due to computational constraints. Whenever feasible, it is recommended to utilize the complete dataset. It is important not to conflate these subsets with samples designated for training, validation, or testing. Our dataset comprises benchmarking questions rather than serving as training data, and there are overlaps among data points. Our objective is to achieve the best representation of the entire dataset with fewer samples.

4.2 Evaluating LLM Performance

The evaluation of hallucination tendency performance for GPT-3.5 and Llama2 70B was measured using the full dataset. Llama2 70B was used to generate evaluator LLM agents. Figure 3 illustrates

the LLM performance at the answer level, while detailed performance metrics at the term level are provided in Appendix T.

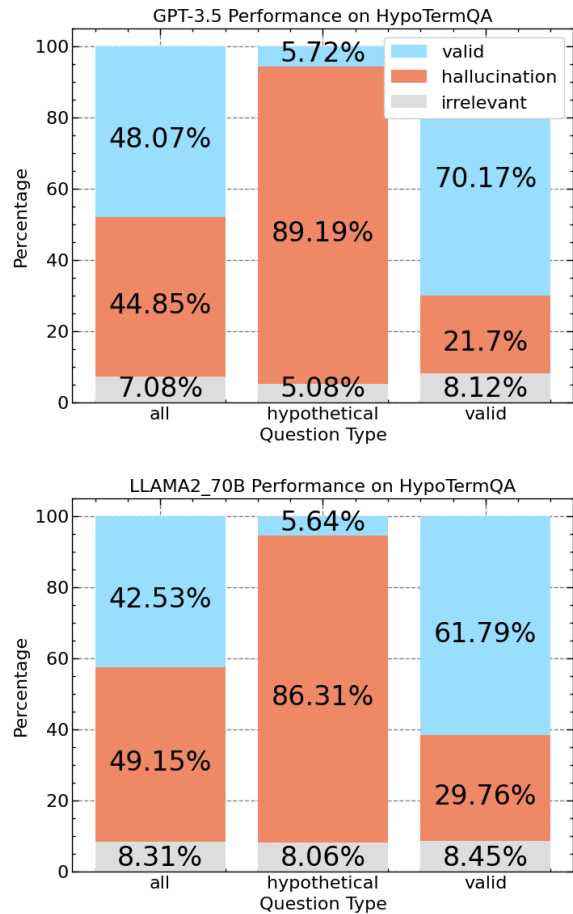


Figure 3: HypoTerm Scores

The dataset comprises one-third hypothetical questions and two-thirds valid questions. The HypoTermQA Score, determined by the percentage of valid answers to hypothetical questions, was 5.72% for GPT-3.5 and 5.64% for Llama2-70B, indicating over a 94% error rate for both models.

For hypothetical questions, GPT-3.5 failed to recognize a hypothetical term or refused the existence of a valid term 89.19% of the time, producing hallucinated information. Additionally, it omitted the hypothetical term entirely in 5.08% of its responses. Llama2-70B exhibited slightly less hallucination at 86.31% but struggled more in addressing the question with 8.06% irrelevant answers.

As anticipated, both GPT-3.5 and Llama2-70B performed better with valid questions, generating information for both terms in the question 70.17% and 61.79% of the time, respectively. GPT-3.5 claimed that a valid term did not exist or used it in a different context than its Wikipedia defi-

nition 21.7% of the time, while Llama2-70B did so 29.76% of the time. In around 8% of cases, both models failed to address the question or declared a lack of information about the given term.

Despite similar HypoTermQA Scores, GPT-3.5 more frequently addresses questions and produces less hallucination in responses to valid questions compared to Llama2-70B.

For GPT-3.5, 108.602 and for Llama2-70b 107.779 term level evaluations conducted on 19.508 answers. Term-level detailed evaluations (see Appendix T) reveal that LLMs fail to detect a hypothetical term over 40% of the time, while falsely denying the existence of a valid term occurs 5-9% of the time. Hallucinations are more likely when the valid term is selected based on title similarity, with LLM suggestion having the least effect. GPT-3.5 consistently recognizes valid terms when generated as a suggestion by itself. GPT-3.5 and Llama2-70b have similar performance on detecting hypothetical terms, while Llama2-70b struggles more with using valid terms in their intended context. Lastly, LLMs generate slightly more irrelevant content when the term is hypothetical.

4.3 Evaluating Question Generation

Instead of analyzing LLM responses, this experiment focuses on the bias of the question generation framework. The Llama2-70B model was utilized to generate 20 terms and 180 questions with the same methodology used in Section 2. GPT-3.5 and Llama2 models prompted with these questions and tested with GPT-3.5 and Llama2-based LLM evaluator agents separately (Section 4.2). Both LLMs demonstrated higher performance when responding to questions generated by Llama2. Additionally, it was observed that evaluator LLM agents tend to favor answers generated by the same model, leading to higher scores. For detailed data, refer to Appendix U. Overall, the results closely parallel those outlined in Section 4.2.

4.4 Evaluating Evaluator Agents

To analyze the performance of LLM evaluator agents. GPT-3.5 API prompted with the 180-question sample (refer to Section 4.1) and responses were manually labeled by the authors to create ground truth labels. Subsequently, five different models were used to generate LLM agents and evaluate the response of the GPT-3.5 model. As shown in Figure 4, the Orca2:13B model demonstrated the closest performance to human

evaluation. However, upon examining the confusion matrices in Appendix V, it was revealed that the Orca2:13B model had high and similar false positive and false negative counts, while the Llama2:70B model exhibited the highest performance with only a 6.66% error rate. Consequently, the Llama2:70B model was selected to form evaluator LLM agents for other experiments.

In the preceding experiment (Subsection 4.3), higher scores were observed for the answers generated by LLMs for the same model. Conversely, in the current experiment, GPT3.5’s answers received a higher score from Llama2:70B. Notably, GPT3.5 generates more plausible and challenging questions for this specific case, while Llama2:70B demonstrates superior performance in evaluating answers. Overall, it is evident that model selection as an LLM agent introduces biases, necessitating additional studies for a comprehensive understanding.

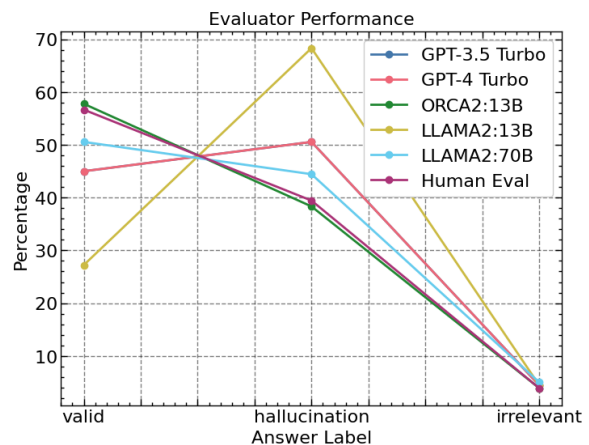


Figure 4: Evaluator Performance

4.5 Evaluating UI Systems

To include models without API access in our experiments, the 180-question sub-sample was utilized, and ChatGPT (OpenAI, 2023a) was manually prompted through the UI by the authors. Seven additional open-sourced models were included for detailed comparison. Figure 5 illustrates the comparison of LLM performance, while detailed performance plots for each model are provided in Appendix W. As anticipated, every model exhibited significantly lower performance against hypothetical questions compared to valid questions, scoring between 1% to 11% against hypothetical questions and between 35% to 49% overall.

The ChatGPT model achieved the highest score

of 11.67% against hypothetical questions, with the Orca2:13B model achieving the second-highest score (8.33%), outperforming models like GPT-4 and Llama2:70B. Models with the highest parameter sizes (GPT-3.5, GPT-4, Llama2-70B) performed better in directly addressing valid questions, adhering to the context, and using valid terms in their real meaning but struggled to distinguish hypothetical terms. Orca2 models demonstrated better detection of hypothetical terms, yet they also tended to refuse the existence of valid terms more often. Generally, a trade-off was observed between performance in valid and hypothetical questions. Nevertheless, ChatGPT appears to be the most robust model.

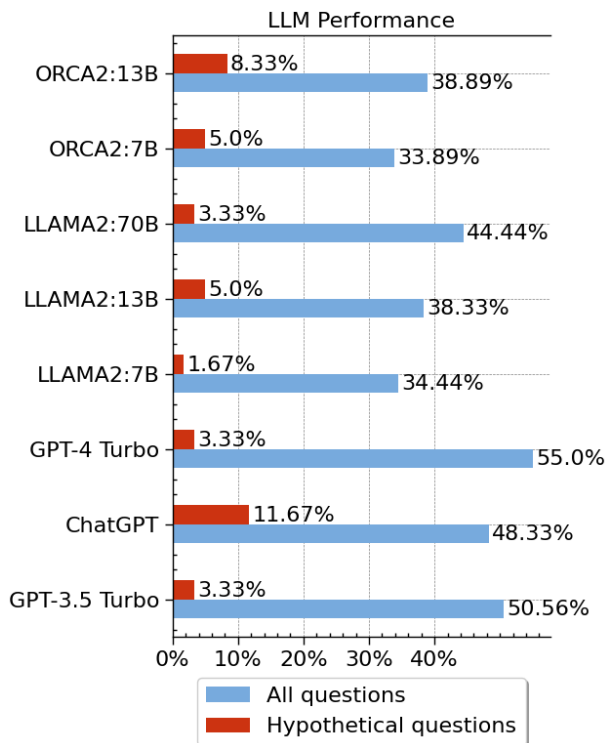


Figure 5: LLM Performance Comparison

5 Related Work

5.1 LLM Evaluation

Evaluating LLM performance is not a straightforward task. It is widely accepted to use ROUGE score (Lin, 2004) for summarization and BLEU score (Papineni et al., 2002) for translation tasks. However, n-gram-based scores have limited ability to measure performance and are not suitable for open-ended long text generation tasks that lack golden answers.

The next generation of Language Model evalu-

ations depends on specific datasets rather than a general metric. GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019) are comprehensive datasets focused on benchmarking Natural Language Understanding (NLU) through 9 different classification or similarity detection tasks. OpenBookQA benchmark (Mihaylov et al., 2018) expects the language model to select one of four alternatives simulating a test exam. HotpotQA (Yang et al., 2018) presents a context and a question as input and the target value is one or a few tokens from the context. TruthfulQA (Lin et al., 2022) prompts language models to generate a few sentences about adversarial questions and then calculates BLEU and ROGUE scores to measure performance.

Hellaswag dataset (Zellers et al., 2019) increased difficulty while testing reasoning capacity by choosing a sentence completion from multiple selections. Winogrande dataset (Sakaguchi et al., 2021) introduces a pronoun resolution task. Similar to HotpotQA, DROP dataset (Dua et al., 2019) consists of context and question couple and few-word target answer. Winogrande and DROP both have an adversarial nature.

Multi-hop question-answering datasets further increase the difficulty of reasoning tasks. MuSiQue dataset (Trivedi et al., 2021) uses the same context, question, and few-word answer structure. The difference is that questions must be decomposed into chained multiple questions. The answers to the initial sub-questions are needed to compose and answer the latter sub-questions and the main question. HELM dataset (Liang et al., 2023a) is a collection of 73 different benchmarking datasets and 65 evaluation metrics. The research evaluated 81 models with all the included datasets and published comprehensive, objective, and comparable performance.

All these datasets share a common restriction. They require the system under test to make selections from multiple choices, generate a few tokens, or rely on n-gram-based and limited evaluation methods. In such situations, incorrect answers may arise from hallucination, insufficient information, or reasoning capability, yet remain unexplainable and undetectable. Our contribution is to create a dataset and a standard for evaluation that can distinguish between these different reasons for errors.

5.2 Existing Hallucination Datasets

The current benchmarks in the field predominantly address the issue of hallucination detection. HaluE-

val (Li et al., 2023), PHD (Yang et al., 2023), and AutoHall (Cao et al., 2023) datasets center on identifying hallucinations within LLM-generated responses. These datasets utilize LLMs to produce content containing hallucinations. HaluEval and PHD involve prompting ChatGPT to generate content and then manually annotating the outputs to identify hallucinations. On the other hand, AutoHall derives its dataset from fact-verification datasets and employs automatic labels for identifying hallucinated content.

Hallucination eLicitation (HILT) dataset (Rawte et al., 2023) encompasses 7,500 responses from 15 distinct LLMs, categorizing responses into 7 specific hallucination categories. Human annotators meticulously labeled the orientation, category, and severity of each response within this dataset. Similarly, the Fact-Conflicting Hallucination Detection (FACTCHD) dataset (Chen et al., 2023b) comprises 6,960 LLM responses spanning seven domains, generated through various structures (vanilla, multi-hops, comparison, and set-operation patterns). However, FACTCHD’s distinction lies in automated labeling, utilizing external knowledge resources, prompt engineering, and AI agents. This results in a dataset featuring query-response pairs accompanied by detailed explanations (evidence) of the assigned hallucination label.

In the Hallucination detection task, various approaches target specific domains and types of samples. FELM (Chen et al., 2023a) prioritizes diverse domain and reasoning samples, while DelusionQA (Sadat et al., 2023) concentrates on Information Retrieval systems within consumer-faced applications. Finanbench (Islam et al., 2023) specializes in the financial domain. UGHEval (Liang et al., 2023b) specifically generates hallucinations from Chinese news and employs a semi-automated evaluation process. These studies highlight the diverse applications and domains within the realm of hallucination detection in language models.

In contrast to previous studies targeting hallucination detection, SelfAware (Yin et al., 2023), and FactScore (Min et al., 2023) focus on evaluating the hallucination tendency of LLMs. SelfAware uses answerable and non-answerable questions, employing similarity-based evaluations to gauge an LLM’s capability to decline to answer unknown questions. On the other hand, FactScore conditions LLMs to create biographies of diverse entities, verifying the validity of generated atomic facts against

Wikipedia as a factual resource. While FactScore’s framework proves to be a simple, straightforward, scalable, and effective method for measuring LLM factuality.

In Appendix X, a comparative chart of the datasets is presented. Our contributions aim to build upon existing work, seeking to improve methodologies. Our approach focuses on automating the creation of scalable benchmarks and the evaluation of LLMs. What distinguishes our approach is its effectiveness in depicting LLM hallucination tendencies by integrating hypothetical terms. Additionally, our proposed framework shows notable flexibility, allowing for straightforward updates to existing datasets or custom designs tailored to specific domains.

6 Conclusion

Our experiments demonstrated that state-of-the-art models, including GPT-4, exhibit a significant susceptibility to hallucination. Increasing the parameter size does not directly mitigate this tendency. Notably, the ChatGPT model, employing heavy RLHF, outperformed the GPT-4 API, achieving the highest performance. Following closely is the Orca2:13B model, which emphasizes high-quality pre-training data. Our findings suggest that these two training approaches, utilizing heavy RLHF and prioritizing pre-training data quality, are currently the most effective methods for reducing hallucination. However, their respective HypoTermQA scores are 11% and 8%. For other models, a common trade-off exists between detecting hallucinated terms and rejecting valid terms, indicating that during the supervised fine-tuning phase, models tend to learn a pattern of refusal rather than truthfulness.

Our results indicate that current LLM training methods are insufficient to prevent hallucinations, emphasizing the need for a fundamental change to ensure the reliability of LLMs. We anticipate that our framework will facilitate a more targeted focus on the hallucination tendency during Language Model training, also contributing to the creation of more challenging and specialized benchmarks.

7 Limitations

The primary limitations of this study are constrained computational and human resources. Experiments in Section 4.2 were conducted on a limited number of models, which could benefit from expansion for a more comprehensive comparison.

Experiments in Section 4.4, Section 4.5, and Section 4.3 utilized a restricted subsample of the original dataset. An increase in resources could improve the representativeness of these subsections. Additionally, the use of 4-bit quantized versions of LLMs might have contributed to slight result variations.

Our pipeline involves generating benchmarking questions using LLMs, posing these questions to LLMs, and evaluating responses with LLMs. In a study focusing on the limited reliability of LLMs, a notable dependency on LLMs becomes evident, particularly in the context of detecting LLM hallucinations. Insights from the literature are employed to enhance the robustness of this process. Due to the probabilistic nature of the LLM output, the results are never guaranteed to be 100% accurate. Additionally, questions might suffer from lower quality. In our approach, we prioritize automatization over absolute accuracy, asserting that the benefits of generating synthetic data and enabling automatic evaluation contribute to the refinement of models and even better synthetic data over time, creating a progressive cycle for improving AI systems.

We generated the HypoTermQA Benchmark dataset using the GPT-3.5 model, potentially introducing bias when evaluating various models alongside GPT models. Instances of such bias are apparent in Section 4.2 and Section 4.3. We explored alternative LLMs as question generators (Section 4.3) and evaluator agents (Section 4.4) to validate the robustness of our framework. However, a more thorough examination is warranted to determine whether GPT models exhibit comparatively higher performance due to the use of similar tokens in benchmark questions or, conversely, demonstrate relatively lower performance because GPT provided the most adversarial tokens for itself during our benchmark question creation process.

This study exclusively addresses factual hallucinations concerning the given specific terms in the questions. While responses may encompass additional factual hallucinations or other types of hallucination, our approach specifically overlooks them. However, for future studies, our approach facilitates the creation of more generalized datasets, encompassing factually inaccurate generations (Min et al., 2023) or reliable summarization (Mishra et al., 2023). Furthermore, a comprehensive evaluation of LLMs should consider various aspects of generation, such as creativity, consistency, rel-

evance, fluency, and coherence. However, these broader considerations are beyond the scope of this paper.

The questions in our benchmarking dataset pertain solely to hypothetical terms. While our framework is adaptable for generating benchmarks on any hypothetical phenomenon across various topics and domains, the range of question types remains restricted. Therefore, our evaluations should be considered as a supplementary assessment method.

Our evaluation methodology is tailored specifically to our use case, applicable only when questions involve a combination of hypothetical and valid terms, and these terms are appropriately labeled.

Section 2.2 categorizes terms as 'hypothetical' if not found in web searches within quotation marks and Section 2.3 categorizes terms as 'valid' if described on Wikipedia. These validations do not confirm ontological existence. Wikipedia might contain errors or misinformation. Also, the absence of specific word sequences online does not necessarily render a word group meaningless. LLM could form valid reasoning, utilizing these hypothetical terms in a meaningful context. However, for practical implementation, we have assumed otherwise.

Labels for terms, questions, and responses were introduced in the same study and overlaps exist in label names. Additionally, multiple measurements were implemented to assess various aspects of LLMs, potentially causing confusion in labeling and percentage interpretation. To mitigate this issue, the appendices provide numerous figures and examples for clarification.

Finally, In Sections 2.1 and 2.2, the inference temperature was adjusted to 1 to boost response creativity, which impacted reproducibility. Nevertheless, intermediate results are available in the repository, and these steps are not critical and can be generated through various methods, including even manual crafting, as an initial step.

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Appendices for: Hypothetical Terms Dataset for Benchmarking Hallucination Tendency of LLMs

A HypoTermQA Process

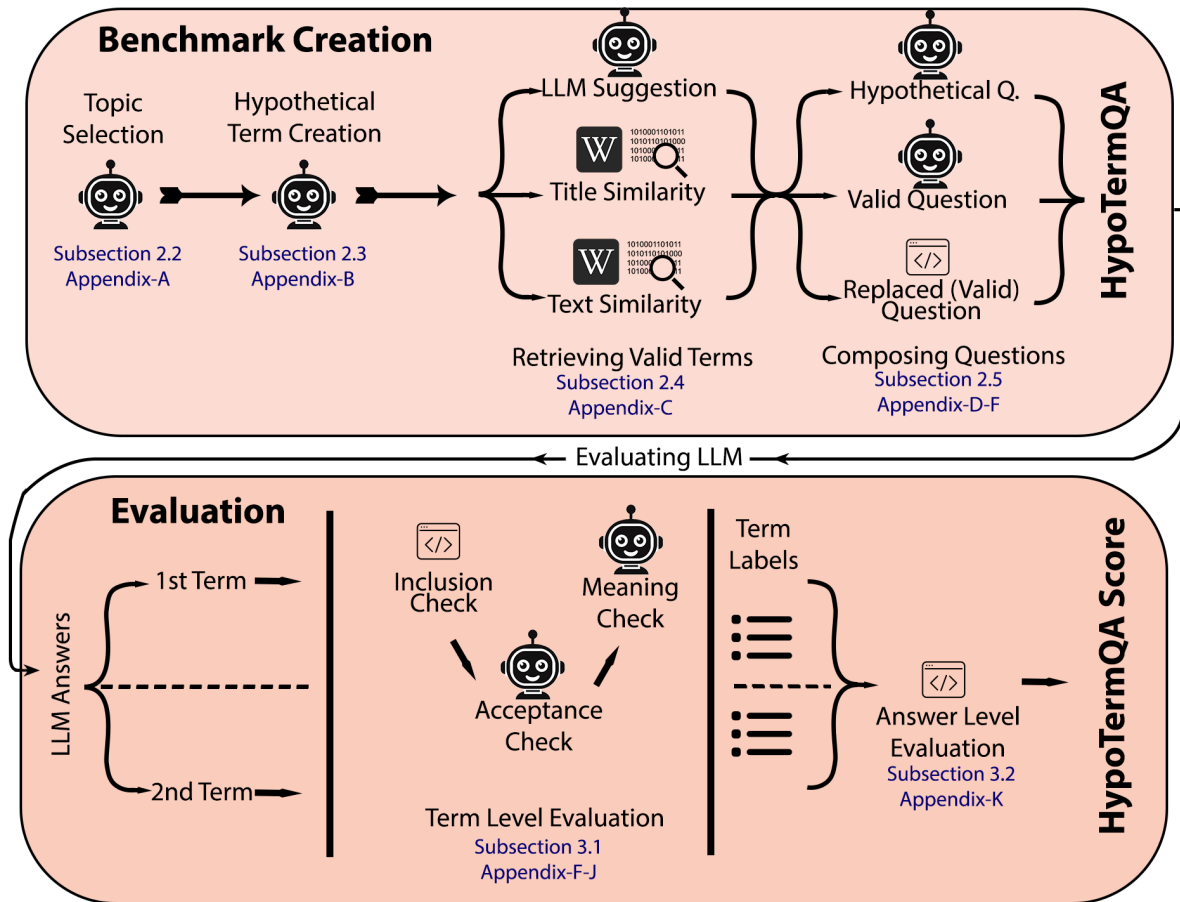


Figure 6: HypoTermQA Process

B Definitions

Term	Explanation	Reference
HypoTermQA	A question answering benchmarking dataset in English to evaluate hallucination tendency of LLMs.	Section 2
HypoTermQA Score	Percentage of “Valid” answers given to “Hypothetical” questions.	Section 3
Sampled Dataset	A subset of HypotermQA to be used in lack of computational resources.	Section 4.1, Appendix S
Term Labels	Terms are labeled as “Hypothetical” or “Valid”	Section 2
Hypothetical Term	A coherent word group that does not exist in web search in quotes	Section 2.2, Appendix D
Valid Term	A phenomenon or entity that is defined in a Wikipedia article	Section 2.3, Appendix F
LLM Suggestion	An LLM response that generates Valid Terms similar to a given Hypothetical Term. Its output is additionally validated by Wikipedia.	Section 2.3, Appendix E
Title Similarity	Similarity based on L2 distance between vector representations of the title of Wikipedia articles and the generated Hypothetical Term.	Section 2.3, Appendix F
Text Similarity	Similarity based on L2 distance between vector representations of the first paragraph of Wikipedia articles and the meaning of a Hypothetical Term.	Section 2.3, Appendix G
Question Labels	Questions are labeled as “Hypothetical” or “Valid”	Section 2.4
Hypothetical Question	A question that was generated by an LLM and contains at least one Hypothetical Term.	Section 2.4, Appendix I
Valid Question	A question that was generated by an LLM and contains only Valid Terms.	Section 2.4, Appendix J
Answer Labels	Answers are labeled as Valid, Hallucination, or Irrelevant	Section 3.2, Appendix R
Hallucinated Answer	An LLM response that accepts existence and generates information about a Hypothetical Term or refuses the existence of a Valid Term.	Section 3.2, Appendix O.2
Valid Answer	An LLM response that successfully acknowledges Hypothetical and Valid Terms in a question.	Section 3.2, Appendix O.4
Irrelevant Answer	An LLM response that fails to generate information about at least one of the terms in the question	Section 3.2, Appendix O.1
Term Level Evaluation	Reasoning of an LLM agent that examines a given question concerning one Term and one task.	Section 3.1, Appendix N
Answer Level Evaluation	A function that accepts a list of Term level evaluations and outputs the final label of a given answer.	Section 3.2, Appendix R
Inclusion Check	A function that checks if a given term is included in a given answer.	Section 3.1, Appendix K
Acceptance Check	An LLM Agent checks if the existence of a given term is accepted or rejected in a given answer.	Section 3.1, Appendix P
Meaning Check	An LLM Agent evaluation process that checks if a given answer used a given term in its true meaning.	Section 3.1, Appendix Q

Table 1: Definitions

C Topic Selection Prompt and Response

System Prompt:

"You are a linguistic expert specialized in online content."

User Prompt:

"What are the most popular 20 topics on the internet? List with explanations."

Response:

The most popular 20 topics on the internet can vary over time and across different regions. However, based on their significant and consistent online presence, the following are some of the most commonly discussed topics:

- 1. Technology and gadgets:** This topic covers the latest advancements in technology, including smartphones, computers, software, gadgets, and emerging technologies like artificial intelligence and virtual reality.
- 2. Social media and influencers:** This refers to platforms such as Facebook, Instagram, Twitter, TikTok, and YouTube, where people connect, share content, and follow influencers who have gained popularity by creating engaging and relatable content.
- 3. News and current events:** This topic encompasses the latest happenings and developments in the world, including politics, economics, technology, science, entertainment, and more.
- 4. Entertainment (movies, TV shows, music, celebrities):** This covers the world of entertainment, including movies, television series, music albums, celebrity news, award shows, and celebrity gossip.
- 5. Video games and gaming culture:** This topic revolves around video games, gaming consoles, game reviews, eSports, game streaming platforms, and discussions about gaming culture.
- 6. Fashion and style:** This involves discussions on fashion trends, clothing brands, designer collections, personal style tips, beauty products, and fashion events.
- 7. Health and fitness:** This topic focuses on physical and mental well-being, including fitness routines, workout plans, diet tips, healthy recipes, mental health awareness, and self-care practices.
- 8. Travel and tourism:** This covers travel destinations, vacation planning, travel tips, hotel reviews, adventure activities, cultural experiences, and travel photography.
- 9. Food and cooking:** This includes recipes, cooking techniques, culinary trends, restaurant reviews, food blogging, and discussions on different cuisines.
- 10. Sports (football, basketball, soccer, etc.):** This topic encompasses discussions, news, and analysis related to various sports, such as football (soccer), basketball, cricket, tennis, and more.
- 11. Science and space exploration:** This involves scientific discoveries, research breakthroughs, space exploration missions, astronomy, cosmology, and discussions on scientific concepts.
- 12. Politics and government:** This covers discussions on political news, elections, government policies, international relations, political ideologies, and debates.

13. DIY and crafts: This topic revolves around do-it-yourself projects, craft ideas, home improvement tips, art tutorials, and creative activities.

14. Photography and visual arts: This includes discussions on photography techniques, camera gear, photo editing, visual arts exhibitions, famous photographers, and sharing and critiquing photographs.

15. Personal finance and investing: This topic focuses on financial management, budgeting, investment strategies, stock market news, cryptocurrencies, retirement planning, and personal finance tips.

16. Self-improvement and motivation: This involves discussions on personal development, motivation, goal setting, time management, productivity tips, and self-help techniques.

17. Environment and sustainability: This covers discussions on environmental issues, climate change, conservation efforts, sustainable living practices, and eco-friendly innovations.

18. Relationships and dating: This topic includes discussions on relationship advice, dating tips, marriage, love languages, breakup advice, and understanding human emotions and behavior.

19. Parenting and family: This involves discussions on parenting tips, child development, family dynamics, pregnancy, childcare, and fostering healthy relationships within the family.

20. Education and online learning: This topic revolves around education systems, online courses, e-learning platforms, educational technology, study tips, and discussions on different subjects and academic disciplines. (OpenAI, 2023b)

D Hypothetical Term Prompt Template and Sample

D.1 Hypothetical Term Prompt Template

System Prompt:

"You are a linguistic expert specialized in online content."

Term Generator Prompt:

""Make a list of 50 nonexistent made-up terms about the following topic by using multiple common words.

Do not combine words, just use at least 4 - 5 words together as a phenomenon.

Do not use the words in the following list: ["conventional", "traditional", "holistic", "phenomenon", "comprehensive", "technique", "-"]

Topic: {topic}""

Explanation Generator Prompt:

""Make up explanation for each term.""

In this prompt, a list of forbidden tokens was defined. Otherwise, these tokens were commonly used by LLMs reducing diversity among generated hypothetical terms.

D.2 Hypothetical Term Generation Sample

SYSTEM: You are a linguistic expert specialized in online content.

User:



Make a list of 50 nonexistent made-up terms about the following topic by using multiple common words.

Do not combine words, just use at least 4 - 5 words together as a phenomenon.

Do not use the words in the following list: ["conventional", "traditional", "holistic", "phenomenon", "comprehensive", "technique", "-"]

Topic: News and current events: This topic encompasses the latest happenings and developments in the world, including politics, economics, technology, science, entertainment, and more.



GPT-3.5:

1. Information Cascade Flux
 2. Techno-Political Disruptor
 3. Quantum News Synthesis
 4. Socio-Economic Pulsation
 5. Reality Modulation Wave
 6. Media Narrative Transmogrifier
 7. Techno-Ethics Reconfiguration
 8. Quantum Journalism Matrix
 9. Societal Pulse Resonance
 10. Data-Driven Discourse Surge
- ...

User:



Make up an explanation for each term.



GPT-3.5:

1. Information Cascade Flux: A phenomenon where the flow of news and information undergoes rapid and continuous changes, leading to a cascading effect on public perception and discourse.
 2. Techno-Political Disruptor: A revolutionary concept or technology that disrupts the traditional landscape of politics and governance, introducing new ways of engaging with power and decision-making.
 3. Quantum News Synthesis: ...
- ...

E Valid Term Suggestion Prompt Template and Sample

E.1 Valid Term Suggestion Prompt Template

System Prompt:

"You are a linguistic expert.
You will be given a TOPIC and a MADE-UP TERM.
Present 50 real terms from Wikipedia similar to the MADE-UP TERM.
DO NOT generate explanations.
Format should be a Python list."

User Prompt:

```
"""TOPIC => {topic}  
MADE-UP TERM => {made-up term}"""
```

E.2 Valid Term Suggestion Sample

SYSTEM: You are a linguistic expert. You will be given a TOPIC and a MADE-UP TERM. Present 50 real terms from Wikipedia similar to the MADE-UP TERM. DO NOT generate explanations. Format should be a Python list

User:

TOPIC => News and current events: This topic encompasses the latest happenings and developments in the world, including politics, economics, technology, science, entertainment, and more.
MADE-UP TERM => Information Cascade Flux: A phenomenon where the flow of news and information undergoes rapid and continuous changes, leading to a cascading effect on public perception and discourse.



GPT-3.5:

```
[ "Post-truth politics", "Breaking news", "Headline", "Journalism", "Broadcast journalism", "Investigative journalism" ... ]
```

LLM suggestions were searched against Wikipedia database for validation of the terms existence and retrieving its actual definition.

F Valid Term Title Similarity Search Result Sample

Vector search results of "*Information Cascade Flux*" among Wikipedia articles:

```
[  
  "Information cascade",  
  "Flux Information Sciences",  
  "Flux",  
  "Radiant flux",  
  "The Cascade",  
  "Flux (biology)",  
  ... ]
```

G Valid Term Text Similarity Search Result Sample

The hypothetical meaning of the term "Information Cascade Flux" was generated as "*A phenomenon where the flow of news and information undergoes rapid and continuous changes, leading to a cascading effect on public perception and discourse.*" Vector search results of this definition text among Wikipedia titles:

```
[  
  "Publicity",  
  "Mass communication",  
  "Intimization",  
  "Reputation",  
  "History of propaganda",  
  "Streisand effect"  
  ... ]
```

H Intermediate Data Sample: Term Couples

Valid Term Set	Hypothetical Questions		Valid Questions	
LLM Suggestion	Information Cascade Flux	& Post-truth politics	Journalism	& Post-truth politics
	Information Cascade Flux	& Breaking news	Broadcast journalism	& Breaking news
	Information Cascade Flux	& Headline	Investigative journalism	& Headline
Title Similarity	Information Cascade Flux	& Information cascade	Radiant flux	& Information cascade
	Information Cascade Flux	& Flux Information Sciences	The Cascade	& Flux Information Sciences
	Information Cascade Flux	& Flux	Flux (biology)	& Flux
Text Similarity	Information Cascade Flux	& Publicity	Reputation	& Publicity
	Information Cascade Flux	& Mass communication	History of propaganda	& Mass communication
	Information Cascade Flux	& Intimimization	Streisand effect	& Intimimization

Table 2: Sample Term Couples

I Hypothetical Question Prompt Template and Sample

I.1 Hypothetical Question Prompt Template

System Prompt:

""You are a linguistic expert.
You will be given a TOPIC, a MADE-UP TERM and a REAL TERM.
Compose a coherent question with REAL TERM and MADE-UP TERM.
The MADE-UP TERM should not be focus of the question.
The MADE-UP TERM should be towards the end of the question.
The MADE-UP TERM and REAL TERM should be directly used without string manipulation in the question.""

User Prompt:

""TOPIC => {topic}
MADE-UP TERM => {made-up term}
REAL TERM => {real term}""

I.2 Hypothetical Question Generation Sample

SYSTEM: You are a linguistic expert. You will be given a TOPIC, a MADE-UP TERM and a REAL TERM. Compose a coherent question with REAL TERM and MADE-UP TERM. The MADE-UP TERM should not be focus of the question. The MADE-UP TERM should be towards the end of the question. The MADE-UP TERM and REAL TERM should be directly used without string manipulation in the question

User:

TOPIC => News and current events: This topic encompasses the latest happenings and developments in the world, including politics, economics, technology, science, entertainment, and more.
MADE-UP TERM => Information Cascade Flux: A phenomenon where the flow of news and information undergoes rapid and continuous changes, leading to a cascading effect on public perception and discourse.
REAL TERM => Publicity: In marketing, publicity is the public visibility or awareness for any product, service, person or organization. It may also refer to the movement of information from its source to the general public, often (but not always) via the media. The subjects of publicity include people of public recognition, goods and services, organizations, and works of art or entertainment.



GPT-3.5:

How does the concept of publicity relate to the phenomenon of information cascade flux in the context of news and current events?

J Valid Question Prompt Template and Sample

J.1 Valid Question Prompt Template

System Prompt:

""You are a linguistic expert.

You will be given a TOPIC, MAIN TERM and SECONDARY TERM.

Compose a coherent question with MAIN TERM and SECONDARY TERM.

The SECONDARY TERM should not be focus of the question.

The SECONDARY TERM should be towards the end of the question.""

User Prompt:

""TOPIC => {topic}

MAIN TERM => {main-term}

SECONDARY TERM => {secondary-term}""

J.2 Valid Question Generation Sample

SYSTEM: You are a linguistic expert.

You will be given a TOPIC, MAIN TERM and SECONDARY TERM.

Compose a coherent question with MAIN TERM and SECONDARY TERM.

The SECONDARY TERM should not be focus of the question.

The SECONDARY TERM should be towards the end of the question.

User:

TOPIC => News and current events: This topic encompasses the latest happenings and developments in the world, including politics, economics, technology, science, entertainment, and more.

MAIN TERM => Reputation: Reputation is how others know and perceive you as an individual. In fact, reputation is a highly dynamic phenomenon in two distinct senses: it is subject to change, especially as an effect of corruption, errors, deception, etc.; and it emerges as an effect of a multi-level bidirectional process.

SECONDARY TERM => Publicity: In marketing, publicity is the public visibility or awareness for any product, service, person or organization. It may also refer to the movement of information from its source to the general public, often (but not always) via the media. The subjects of publicity include people of public recognition, goods and services, organizations, and works of art or entertainment.



GPT-3.5:

How does a strong reputation in the world of news and current events contribute to the overall perception of a person or organization, regardless of the level of publicity they receive?

K String Match Function

String match operations used to compose replaced questions, check question quality (Section 2.4), and term inclusion check (Section 3.1) apply the following logic:

For both text and subtext:

- Change all letters to lowercase letters.
- Delete extra spaces.
- Check if the text contains subtext.
- Delete expressions inside brackets and square brackets and check again.
- Replace the "-" character with a single space.
- Remove punctuation.
- Delete extra spaces.
- Check if the text contains the subtext.

L Replaced (Valid) Question Sample

Hypothetical question composed in [Appendix I](#):

"How does the concept of publicity relate to the phenomenon of information cascade flux in the context of news and current events?"

Replaced (Valid) question sample after string operations:

"How does the concept of publicity relate to the phenomenon of Reputation in the context of news and current events?"

M HypoTermQA Data Structure

```
1  [
2    {
3      "isHyphoteticalQuestion": 1,
4      "question": "How does the concept of publicity
5      relate to the phenomenon of information cascade
6      flux in the context of news and current events?",
7      "questionId": 2050,
8      "terms": [
9        {
10       "isHypotheticalTerm": 1,
11       "term": "Information Cascade Flux",
12       "termId": 79,
13       "termSet": "hypothetical",
14       "termSetId": 0
15     },
16     {
17       "isHypotheticalTerm": 0,
18       "term": "Publicity",
19       "termId": 11594,
20       "termSet": "text_similarity",
21       "termSetId": 3
22     }
23   ]
24 }
25 ]
```

N Term Level Evaluation

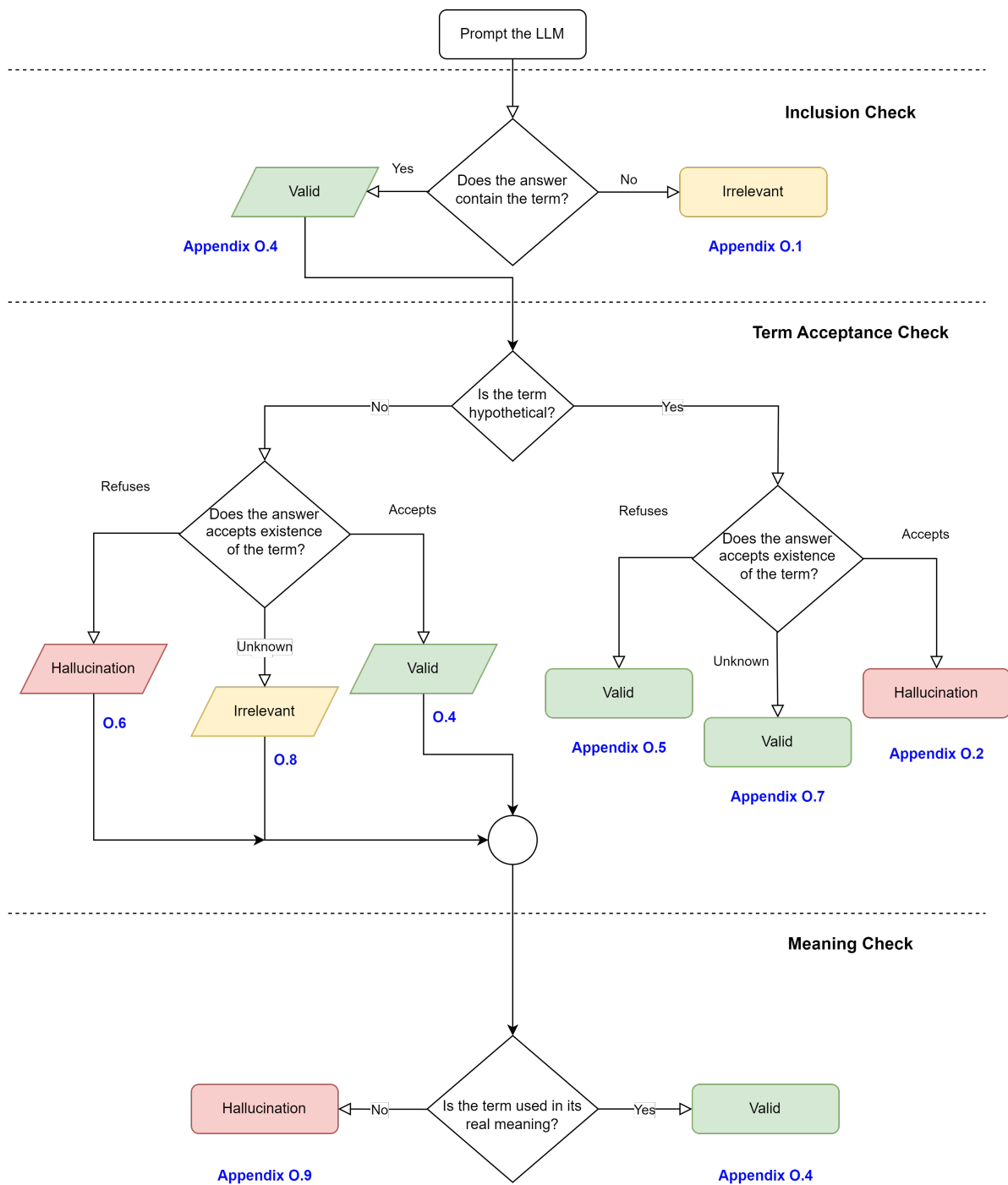


Figure 7: Term Level Evaluation Flowchart

O Response Examples

O.1 Irrelevant

Valid Term: Social Media Working Group Act of 2014

Hypothetical Term: Viral content momentum

Question:

How has the Social Media Working Group Act of 2014 impacted the viral content momentum on social media platforms and the influence of influencers?

Response from Orca2:7b

The user is asking about the effects of a specific law that regulates online content and influencer marketing in Australia. The law was enacted in 2014 and aimed to protect consumers from misleading or deceptive advertising practices on social media platforms.

O.2 Accepts hypothetical term (title similarity)

Valid Term: Jump, Jive an' Wail

Hypothetical Term: Turbo-jump dribble

Question:

How does the technique of the "Turbo-jump dribble" in basketball compare to the energetic and lively rhythm of Louis Prima's "Jump, Jive an' Wail" in terms of their impact on the game and the overall experience?

Response from GPT-3.5:

The technique of the "Turbo-jump dribble" in basketball and the energetic and lively rhythm of Louis Prima's "Jump, Jive an' Wail" both have a significant impact on the game and the overall experience, but in different ways.

The "Turbo-jump dribble" is a basketball move where a player quickly changes direction while dribbling the ball, often accompanied by a powerful jump. This technique is known for its explosiveness and agility, allowing players to evade defenders and create scoring opportunities. The Turbo-jump dribble adds excitement and intensity to the game, as it showcases the athleticism and skill of the player executing the move. It can electrify the crowd, energize teammates, and potentially demoralize opponents, as it demonstrates a player's ability to dominate the court.

On the other hand, Louis Prima's "Jump, Jive an' Wail" is a lively and energetic song that captures the spirit of swing and jazz music. The rhythm, tempo, and upbeat nature of the song create a vibrant atmosphere and encourage movement and celebration. When played during a basketball game, it can enhance the overall experience by infusing a sense of joy, enthusiasm, and fun. The catchy melody and infectious rhythm can inspire players to perform with flair and entertain the crowd. It can also engage the audience, making them feel more connected to the game and creating a festive ambiance.

In summary, the "Turbo-jump dribble" impacts the game by showcasing individual athleticism and creating scoring opportunities, while Louis Prima's "Jump, Jive an' Wail" enhances the overall experience by infusing energy, joy, and a sense of celebration. Both contribute to the excitement and entertainment value of basketball, albeit in different ways.

O.3 Accepts hypothetical term (text similarity)

Valid Term: Alley-oop (basketball)

Hypothetical Term: Turbo-jump dribble

Question:

How does the execution of an alley-oop in basketball differ from the technique used in the turbo-jump dribble?

Response from GPT-3.5:

The execution of an alley-oop in basketball differs from the technique used in the turbo-jump dribble in several ways:

1. Purpose: Alley-oop is a play designed to score by throwing the ball near the rim for a teammate to catch and dunk or layup. Turbo-jump dribble, on the other hand, is a dribbling move used to quickly change direction and accelerate past defenders.
 2. Timing: In an alley-oop, the passer throws the ball towards the rim while the receiver times their jump to catch and finish the play. In a turbo-jump dribble, the player uses a quick dribble move to change direction and then jumps off both feet to explode past defenders.
 3. Coordination: Alley-oop requires coordination between the passer and the receiver. The passer needs to throw the ball accurately, while the receiver needs to time their jump and catch the ball in mid-air. Turbo-jump dribble is a move performed by a single player, focusing on their own coordination and quickness.
 4. Execution: Alley-oop involves a lob pass towards the rim, often with a high arc, to allow the receiver to catch and finish above the rim. Turbo-jump dribble involves a quick change of direction with the ball, followed by an explosive jump off both feet to gain an advantage over defenders.
- Overall, the alley-oop is a play that involves teamwork and coordination between two players, while the turbo-jump dribble is an individual move used to beat defenders off the dribble.

O.4 Accepts valid term

Valid Term: Sustainable tourism

Valid Term: Green building

Question: How does sustainable tourism contribute to the overall goals of the Green building?

Response from Response from GPT-3.5:

Sustainable tourism can contribute to the overall goals of green building in several ways:

1. Reduced carbon footprint: ...
2. Conservation of natural resources: ...
3. Supporting local communities: ...
4. Raising awareness: ...
5. Encouraging sustainable development: ...
6. Promoting cultural heritage: ...
7. Reducing waste: ...
8. Supporting conservation efforts: ...
9. Encouraging sustainable transportation: ...
10. Promoting sustainable agriculture: ...

Overall, sustainable tourism can contribute to the overall goals of green building by promoting environmentally friendly practices, supporting local communities, raising awareness about environmental issues, and encouraging sustainable development.

O.5 Refuses hypothetical term

Valid Term: Social media addiction

Hypothetical Term: Like Rush Rave

Question: How does social media addiction impact an individual's mental health when they experience a Like Rush Rave on their post?

Response from Llama2:70b:

I don't have enough information to give a clear answer to this question. The concept of a "Like Rush Rave" is not well-defined, and it's unclear how it relates to social media addiction or mental health. Could you provide more context or clarify your question? I'll do my best to help you with whatever information you have.

O.6 Refuses valid term

Valid Term: Sherman's Showcase

Valid Term: Showcase (comics)

Question: How does Sherman's Showcase, a new comedy television series, compare to the Showcase (comics) in terms of creativity and visual appeal?

Response from Llama2:7b:

Thank you for reaching out! I'm happy to help you with your query. However, I must inform you that Sherman's Showcase is a fictional TV series, and there isn't actually a comic book series called "Showcase." So, it's difficult to compare the two in terms of creativity and visual appeal, as they don't exist in the same medium. Is there anything else I can assist you with?

O.7 Unknown hypothetical term

Valid Term: Information cascade

Hypothetical Term: Information Cascade Flux

Question: How does the concept of an information cascade, where individuals make decisions based on the actions of others, relate to the phenomenon of information cascade flux in the context of news and current events?

Response from GPT-3.5:

Thank you for asking! An information cascade refers to a situation where people make decisions or take action based on the actions of others, often without fully understanding the underlying reasons or motivations. In the context of news and current events, an information cascade can occur when large numbers of people share or consume media content, leading to a snowball effect where more and more people become interested or invested in the same topic. This can be both beneficial (e.g., raising awareness about important issues) and detrimental (e.g., spreading misinformation or reinforcing harmful beliefs).

In terms of the specific term "information cascade flux," I'm not familiar with it. Could you provide more context or clarify what you mean by this term?

O.8 Unknown valid term

Valid Term: Social Media Working Group Act of 2014

Valid Term: Digitality

Question: How has the Social Media Working Group Act of 2014 impacted the digitality of social media and influencers?

Response from Llama2:70b

I'm sorry, but I couldn't find any information about a "Social Media Working Group Act of 2014." It's possible that the act you mentioned may not exist or may have a different name. Can you please provide more details or clarify the act's name?

O.9 False meaning

Valid Term: Viral load

Valid Term: Viral video

Question: How does the concept of viral load impact the success and reach of a viral video in the realm of social media and influencers?

Response from GPT-3.5:

The concept of viral load refers to the number of people who are exposed to and share a viral video or content. It plays a crucial role in determining the success and reach of a viral video in the realm of social media and influencers. Here's how it impacts:

1. Initial Exposure: ...
2. Sharing Potential: ...
3. Social Proof: ...
4. Influencer Impact: ...
5. Algorithmic Boost: ...

In conclusion, the concept of viral load directly impacts the success and reach of a viral video in social media and influencer marketing. A high viral load leads to increased exposure, sharing potential, social proof, influencer impact, and algorithmic boost, all of which contribute to the video's success in reaching a wider audience.

Reflection from GPT-3.5:

{ "term": "Viral load",

"reasoning": "The answer does not use the term 'viral load' in its real meaning. The concept of viral load in the context of social media and influencers refers to the number of people who are exposed to and share a viral video or content. However, the real meaning of viral load is the quantity of virus in a given volume, often expressed as viral particles or infectious particles per mL. The answer does not mention anything related to the actual quantity of virus in a video or content.",

"verified": "FALSE" }

P Acceptance Check Prompt Template and Sample

P.1 Acceptance Check Prompt Template

System Prompt:

”You are a linguistic expert.

You will be given a TERM and QUESTION - ANSWER couple.

The QUESTION is composed with the TERM.

If the answer claims that the term is unreal, hypothetical, speculative or do not exist, label the certainty of the term as "UNREAL".

If the answer mentioned the term in any context even without any further information, definition, description or explanation, label the certainty of the term as "MENTIONED".

If the answer states that it does not have information about the term , label the certainty of the term as "UNKNOWN".

Analyse the certainty of the term only by itself. Do not consider its relation with other terms or the context of the answer.

First reason step by step then label certainty of the term as "UNREAL", "MENTIONED" or "UNKNOWN" in the following json format.

```
{ "term": "",  
  "reasoning": "",  
  "certainty": "" }
```

User Prompt:

"""TERM => {term}

QUESTION => {question}

ANSWER => {answer}

INSTRUCTION => Output should be in the following json format:

```
{ { "term": "{term}  
  , "reasoning": "",  
  "certainty": "" } }
```


P.2 Acceptance Check Sample

SYSTEM: You are a linguistic expert.
You will be given a TERM and QUESTION - ANSWER couple.
The QUESTION is composed with the TERM.
If the answer claims that the term is unreal, hypothetical, speculative or do not exist, label the certainty of the term as "UNREAL".
If the answer mentioned the term in any context even without any further information, definition, description or explanation, label the certainty of the term as "MENTIONED".
If the answer states that it does not have information about the term, label the certainty of the term as "UNKNOWN".
Analyse the certainty of the term only by itself. Do not consider its relation with other terms or the context of the answer.
First reason step by step then label certainty of the term as "UNREAL", "MENTIONED" or "UNKNOWN" in the following json format.
{ "term": "",
 "reasoning": "",
 "certainty": "" }

User:



TERM => Information Cascade Flux

QUESTION => How does the concept of publicity relate to the phenomenon of information cascade flux in the context of news and current events?

ANSWER => The concept of publicity is closely related to the phenomenon of information cascade flux in the context of news and current events. Publicity refers to the public visibility or attention given to a particular topic, event, or piece of information. It involves the dissemination of information to a wide audience through various channels such as media outlets, social media platforms, or word-of-mouth.

Information cascade flux, on the other hand, refers to the process where individuals adopt the actions or beliefs of others without necessarily evaluating the information themselves. In the context of news and current events, it occurs when people rely on the actions or opinions of others to form their own judgments or decisions, rather than critically analyzing the information at hand.

The relationship between publicity and information cascade flux can be understood as follows:

1. Amplification of Information: ...
2. Influence of Social Proof: ...
3. Confirmation Bias: ...

Overall, the concept of publicity plays a significant role in shaping the phenomenon of information cascade flux in the context of news and current events. It influences the amplification and visibility of information, creates social proof, and reinforces confirmation bias, all of which contribute to the adoption of beliefs or actions without critical evaluation.

INSTRUCTION => Output should be in the following json format:

```
{ "term": "Information Cascade Flux",  
  "reasoning": "",  
  "certainty": "" }
```



Llama2:70b:

```
{
  "term": "Information Cascade Flux",
  "reasoning": "The term 'Information Cascade Flux' is mentioned in the answer as a
concept related to the phenomenon of publicity in the context of news and current
events. The answer explains how publicity influences the amplification, social proof, and
confirmation bias of information, which contributes to the adoption of beliefs or actions
without critical evaluation. Therefore, the certainty of the term 'Information Cascade
Flux' is MENTIONED.",
  "certainty": "MENTIONED"
}
```

Q Meaning Check Prompt Template and Sample

Q.1 Meaning Check Prompt Template

System Prompt:

'''You are a linguistic expert.
You will be given a TERM and QUESTION - ANSWER couple.
The QUESTION is composed with the TERM.
Verify if the answer uses the term in its real meaning.
First reason step by step then label verified attribute as TRUE or FALSE.
{"term":"","
"reasoning":"","
"certainty":""}'''

User Prompt:

''''TERM => {term}:{term_definition}
QUESTION => {question}
ANSWER => {answer}

INSTRUCTION => Output should be in the following json format:
{{ "term": "{term}"
", "reasoning": "",
"verified": "" } }''''

Q.2 Meaning Check Prompt Template and Sample

SYSTEM: You are a linguistic expert.
You will be given a TERM and QUESTION - ANSWER couple.
The QUESTION is composed with the TERM.
Verify if the answer uses the term in its real meaning.
First reason step by step then label verified attribute as TRUE or FALSE.
{"term":"","
"reasoning":"","
"verified": "" }

User:



TERM => Publicity

QUESTION => How does the concept of publicity relate to the phenomenon of information cascade flux in the context of news and current events?

ANSWER => The concept of publicity is closely related to the phenomenon of information cascade flux in the context of news and current events. Publicity refers to the public visibility or attention given to a particular topic, event, or piece of information. It involves the dissemination of information to a wide audience through various channels such as media outlets, social media platforms, or word-of-mouth.

Information cascade flux, on the other hand, refers to the process where individuals adopt the actions or beliefs of others without necessarily evaluating the information themselves. In the context of news and current events, it occurs when people rely on the actions or opinions of others to form their own judgments or decisions, rather than critically analyzing the information at hand.

The relationship between publicity and information cascade flux can be understood as follows:

1. Amplification of Information: ...
2. Influence of Social Proof: ...
3. Confirmation Bias: ...

Overall, the concept of publicity plays a significant role in shaping the phenomenon of information cascade flux in the context of news and current events. It influences the amplification and visibility of information, creates social proof, and reinforces confirmation bias, all of which contribute to the adoption of beliefs or actions without critical evaluation.

INSTRUCTION => Output should be in the following json format:

```
{{"term": "Publicity",  
  "reasoning": "",  
  "verified": ""}}
```



Llama2:70b:

```
"term": "Publicity",  
"reasoning": "The concept of publicity is closely related to the phenomenon of information cascade flux in the context of news and current events. Publicity refers to the public visibility or attention given to a particular topic, event, or piece of information, which can amplify the reach and visibility of information, create social proof, and reinforce confirmation bias, all of which contribute to the adoption of beliefs or actions without critical evaluation.",  
"verified": "TRUE"
```

R Answer Level Evaluation

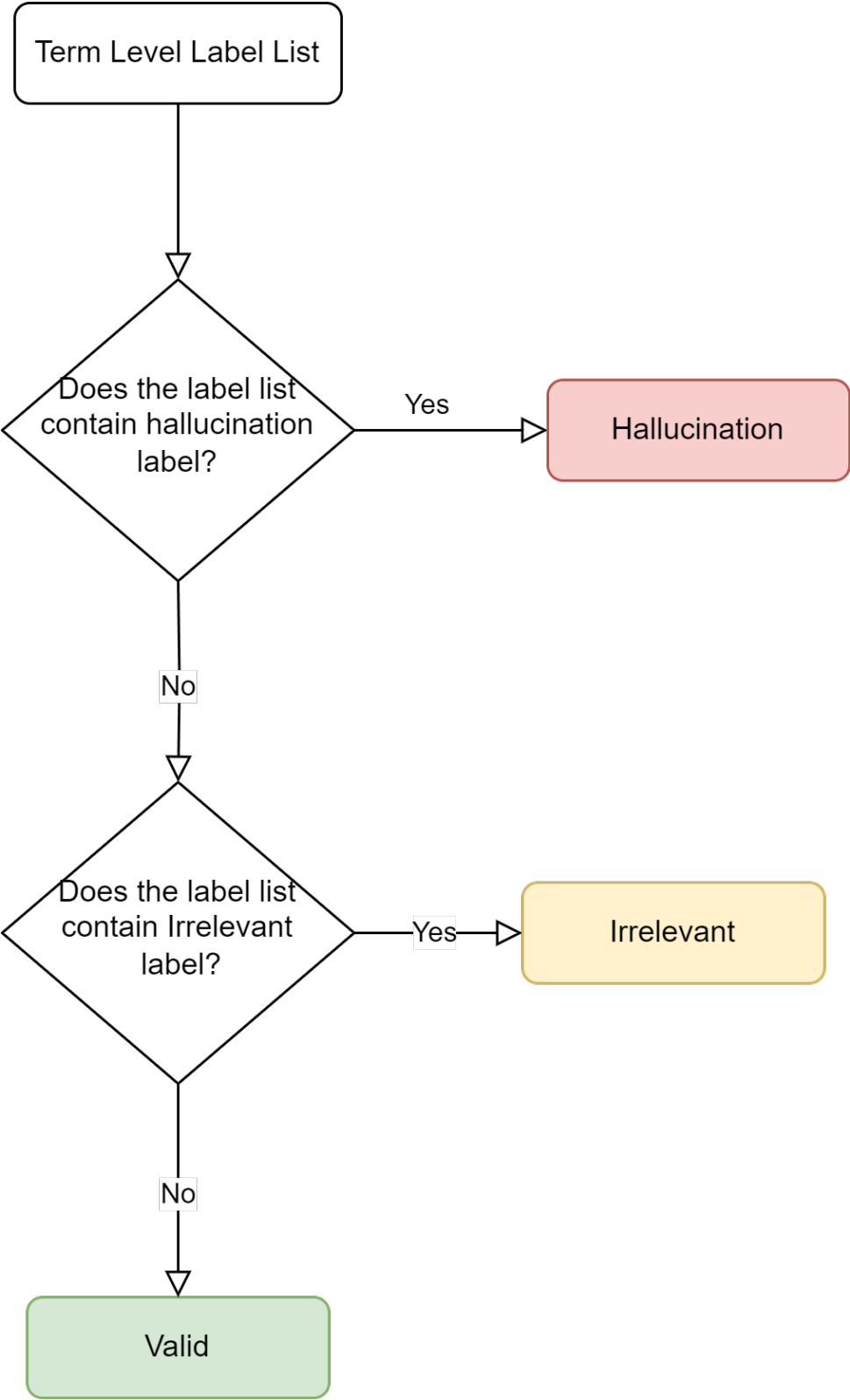


Figure 8: Term Level Evaluation Flowchart

S Sub-sampling

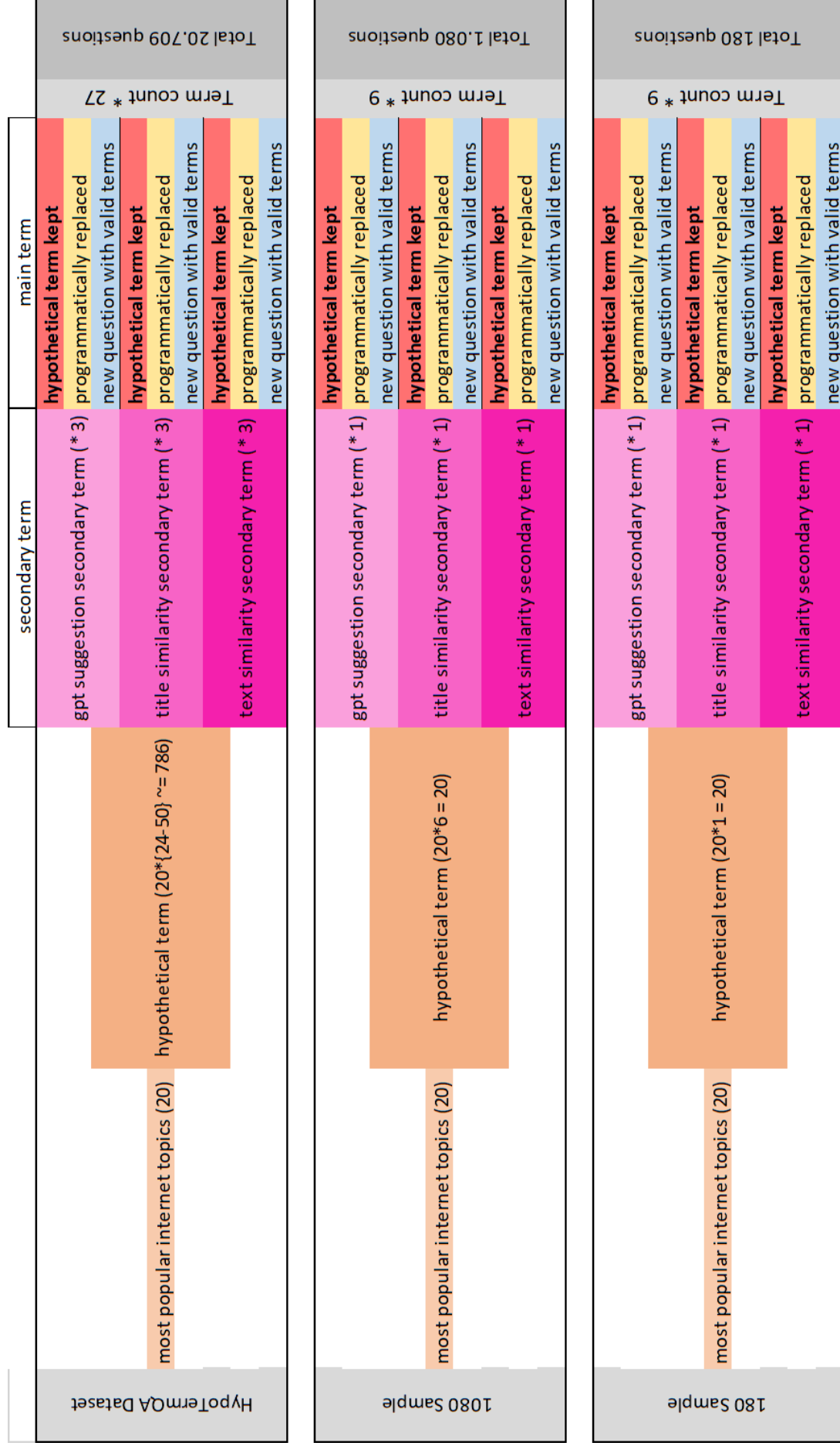


Figure 9: Sub-sampling The HypoTermQA Dataset

T Term Level Label Distribution

Table 3: Label Distribution

Term Type			
Type	Term Level Eval Label	GPT 3.5	Llama2-70b
Valid Term	Valid	91.6 %	86.2 %
	Hallucination	5.3 %	9.2 %
	Irrelevant	3.1 %	4.6 %
Hypothetical Term	Valid	53.4 %	54.6 %
	Hallucination	43.8 %	41.0 %
	Irrelevant	2.8 %	4.3 %
Valid Term Source			
LLM Suggestion	Valid	97.7 %	93.7 %
	Hallucination	1.7 %	4.5 %
	Irrelevant	0.6	1.8 %
Text Similarity	Valid	94.0 %	87.0 %
	Hallucination	3.0 %	7.7 %
	Irrelevant	3.0 %	5.3 %
Title Similarity	Valid	82.7 %	77.3 %
	Hallucination	11.5 %	16.0 %
	Irrelevant	5.9 %	6.8 %
Evaluation Type			
Acceptance Check	Valid	79.0 %	75.3 %
	Hallucination	17.4 %	17.8 %
	Irrelevant	3.6 %	6.9 %
Inclusion Check	Valid	95.0 %	94.0 %
	Hallucination	-	-
	Irrelevant	5.0 %	6.0 %
Meaning Check	Valid	86.9 %	78.4 %
	Hallucination	13.1 %	21.6 %
	Irrelevant	-	-

U Alternative Question Generation

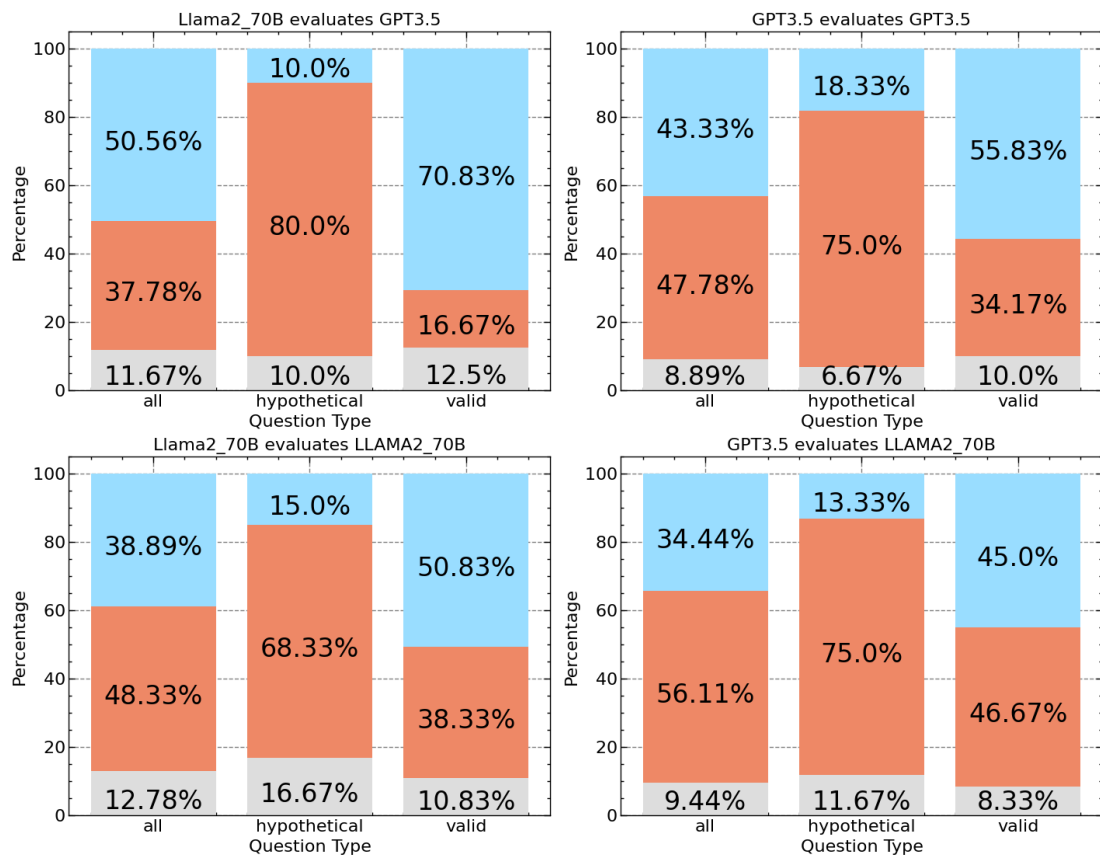


Figure 10: LLM Performances on Llama2:70B Generated Questions

V Evaluator Agents Confusion Matrices

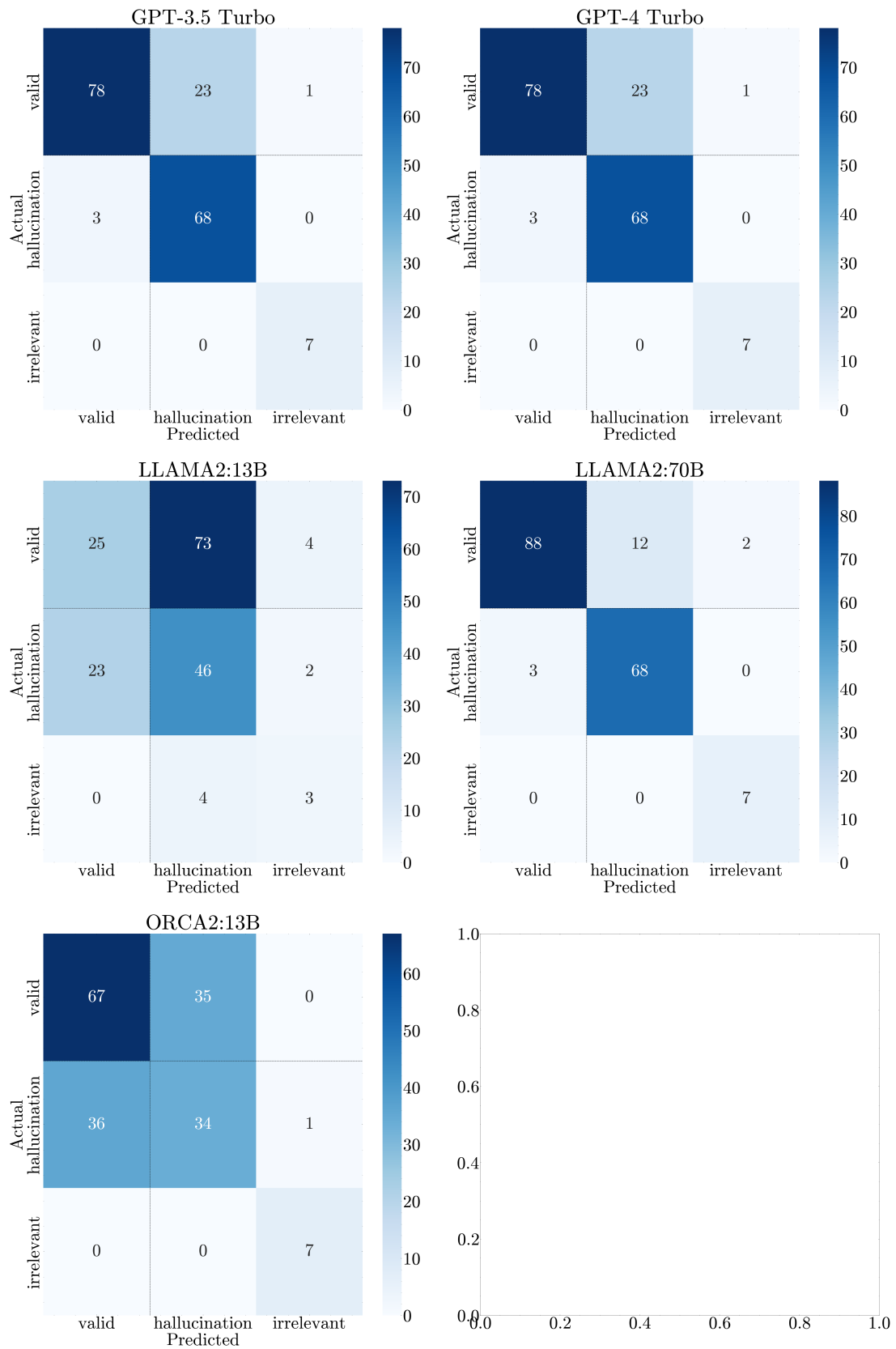


Figure 11: Evaluator Confusion Matrices

W Detailed LLM Performances on Sub-Sampled Dataset

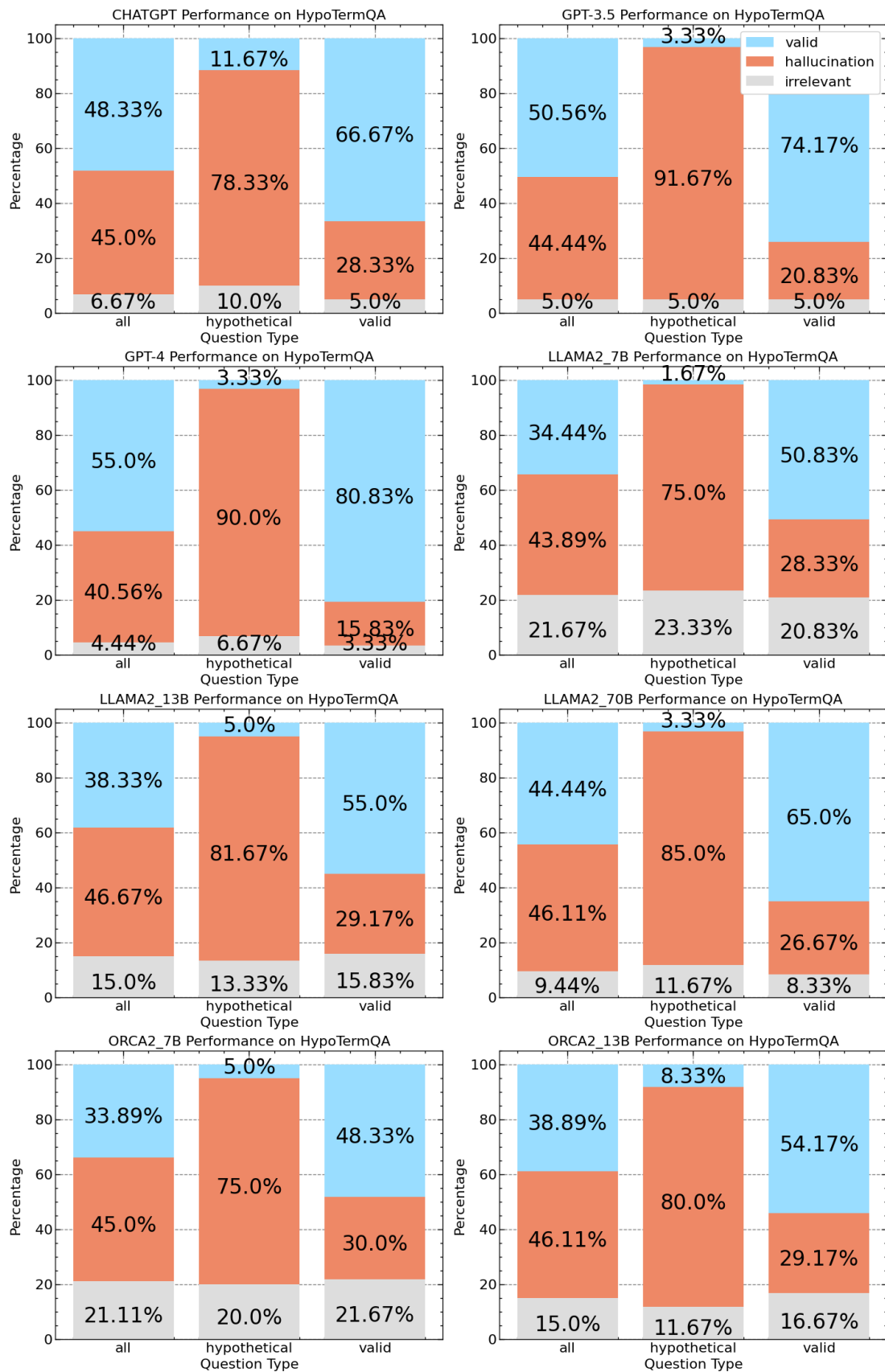


Figure 12: LLM Performances

X Hallucination Datasets

Dataset	Scalable Cre- ation	Data size	Language	Scalable Evaluation	Hallucination Detection	LLM Bench- marking	Long text generation
TruthfulQA	-	817	English	+	-	+	-
HotpotQA	-	113000	English	+	-	+	-
Hellaswag	-	59900	English	+	-	+	-
Winogrande	-	44000	English	+	-	+	-
DROP	-	86500	English	+	-	+	-
MuSiQue	-	40000	English	+	-	+	-
HaluEval	-	30000	English	-	+	-	-
PHD	-	100	English	-	+	-	-
AutoHall	+	2800	English	+	+	-	-
HILT	-	7500	English	-	+	-	-
FACTCHD	+	6960	English	+	+	-	-
FELM	+	3948	English	+	+	-	-
DELUCIONQA	+	2038	English	-	+	-	-
FINANCEBENCH	+	10231	English	-	+	-	-
SelfAware	-	3369	English	+	-	+	+
UHGEval	+	5141	Chinese	-	+	+	+
FactScore	+	1	English	+	+	+	+
HypoTermQA	+	19508	English	+	+	+	+

Table 4: Sample Term Couples

Arabic Synonym BERT-based Adversarial Examples for Text Classification

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Abstract

Text classification systems have been proven vulnerable to adversarial text examples, modified versions of the original text examples that are often unnoticed by human eyes, yet can force text classification models to alter their classification. Often, research works quantifying the impact of adversarial text attacks have been applied only to models trained in English. In this paper, we introduce the *first* word-level study of adversarial attacks in Arabic. Specifically, we use a synonym (word-level) attack using a Masked Language Modeling (MLM) task with a BERT model in a black-box setting to assess the robustness of the state-of-the-art text classification models to adversarial attacks in Arabic. To evaluate the grammatical and semantic similarities of the newly produced adversarial examples using our synonym BERT-based attack, we invite four human evaluators to assess and compare the produced adversarial examples with their original examples. We also study the transferability of these newly produced Arabic adversarial examples to various models and investigate the effectiveness of defense mechanisms against these adversarial examples on the BERT models. We find that fine-tuned BERT models were more susceptible to our synonym attacks than the other Deep Neural Networks (DNN) models like WordCNN and WordLSTM we trained. We also find that fine-tuned BERT models were more susceptible to transferred attacks. We, lastly, find that fine-tuned BERT models successfully regain at least 2% in accuracy after applying adversarial training as an initial defense mechanism.

1 Introduction

Machine Learning models, in general, are vulnerable to adversarial attacks, which are small, crafted perturbations done usually by altering the original input of these models in order to change their classification (Huang et al., 2011; Corona et al., 2013; Kurakin et al., 2016; Kumar et al., 2017; Pitropakis et al., 2019; Wiyatno et al., 2019; Mello, 2020).

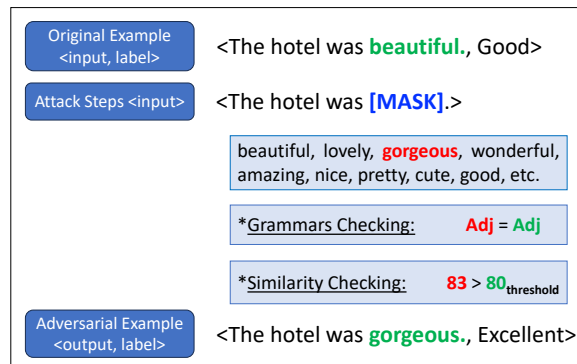


Figure 1: A diagram illustrates our attack steps for generating synonym adversarial attacks using an MLM task with BERT. The attack first predicts synonym tokens and then checks their grammar and semantic similarities. Once a predicated token satisfies the grammar and semantic checkings, we have an attack candidate example.

Research on adversarial attacks is often in the domain of image classification systems (Szegedy et al., 2014; Kurakin et al., 2017a,b; Papernot et al., 2017; Kos et al., 2018; Arnab et al., 2018) or speech recognition systems (Hannun et al., 2014; Kereliuk et al., 2015; Gong and Poellabauer, 2017; Carlini and Wagner, 2018; Samizade et al., 2020; Želasko et al., 2021). For example, in the domain of image classification, the images are the original inputs, and the attackers could negatively affect the performance of these systems by introducing small perturbations to the input images (Szegedy et al., 2014; Kurakin et al., 2017a,b; Papernot et al., 2017; Liang et al., 2018). Examining adversarial attacks in the domain of Natural Language Processing (NLP) can be especially challenging due to the discrete nature of the input texts and the requirement to preserve both semantic coherence and grammatical correctness with the original texts (Zhang et al., 2020; Qiu et al., 2022; Goyal et al., 2023).

Generally, research studies of adversarial attacks can be classified as white-box, gray-box, or black-box. In a white-box approach, attackers can fully access the model architecture, weights, parameters,

or training datasets (Ebrahimi et al., 2018), whereas in the gray-box approach, the attackers have limited access to the model architecture (Xu et al., 2021). Finally, in the black-box approach, the attackers cannot access the model architecture but only query the model and get a prediction in return (Liu et al., 2017; Zhang et al., 2021).

A few common techniques for producing adversarial text examples have been addressed widely in the NLP field, such as character-level attacks (like inserting, removing, or swapping one or more characters within a word), word-level attacks (like inserting, removing, or replacing a word), and sentence-level attacks (like inserting, removing, or replacing a word or more than a word in a sentence) (Li et al., 2017; Ebrahimi et al., 2018; Gao et al., 2018; Liang et al., 2018; Feng et al., 2018). Some of these techniques can result in unnatural adversarial examples, making them easily distinguishable by humans, but recent research indicates that using rule-based synonym replacement strategies could generate adversarial text examples that appear more natural and similar to the original examples (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020; Garg and Ramakrishnan, 2020; Li et al., 2020).

Only *two* papers addressed adversarial text attacks in Arabic, and both are character-level. Alshemali and Kalita (2019) proposed character-level adversarial attacks that rely on changing the morphological form of adjectives by adding one or more characters, which violates the noun-adjective agreement. An adjective is a word that describes a noun, and it must agree with the noun in definiteness (i.e., definite or indefinite), number (singular or dual), and gender (i.e., feminine or masculine). Alshemali and Kalita (2021) also proposed character-level attacks, which relied on the flip of one or two Arabic characters chosen based on non-native Arabic learners' most common spelling mistakes (usually incorrect use of visually similar characters). Both of these studies considered only the character-level adversarial examples and did not investigate the impact of transferability of these attacks among targeted models nor the effectiveness of defense mechanisms like adversarial training.

In this paper, we introduce the *first* study of word-level adversarial attacks in Arabic. We develop synonym-based word-level attacks using a Masked Language Modeling (MLM) task with an Arabic BERT model in a black-box manner against three state-of-the-art sentiment analysis

classifiers/models: BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019), WordCNN (word-based Convolutional Neural Networks) (Kim, 2014), and WordLSTM (Word-based Long Short-term Memory) (Hochreiter and Schmidhuber, 1997). We train these models on two available and large Arabic datasets, HARD (Hotel Arabic Reviews Dataset) (Elnagar et al., 2018) and MSDA (Sentiment Analysis for Social Media Posts in Arabic Dialect) (Boujou et al., 2021), to automatically generate adversarial text examples, attack these models using those generated adversarial text examples, and finally, assess the robustness of these models against adversarial text examples.

We also use human evaluation to evaluate the newly produced adversarial text examples using two criteria: grammatical similarity and semantic similarity. Furthermore, we study the transferability of these adversarial text examples generated by various models on different models studied and deeply investigate the effectiveness of the adversarial training defense mechanism on the BERT models against these adversarial text examples. Figure 1 illustrates the process of generating synonym-based word-level adversarial examples generation which we discuss in detail in Section 3.

Section 2 reviews related research works, while Section 3 delves into the methodology in more detail. Sections 4 and 5 discuss the automatic and human evaluations and their results. In Sections 6 and 7, we describe the transferability and defense mechanisms, along with their results. Lastly, in Sections 8 and 9, we conclude our paper by addressing its limitations and summarizing our contributions.

2 Related Work

Adversarial text attacks have been widely studied in the NLP field from different perspectives, like the attack setting (white-box, gray-box, and black-box), targeted space (embedding or input), and attack method (character-level, word-level, sentence-level) (Papernot et al., 2016; Li et al., 2017; Ebrahimi et al., 2018; Gao et al., 2018; Liang et al., 2018; Feng et al., 2018; Alzantot et al., 2018; Li et al., 2018; Ren et al., 2019; Li et al., 2020; Ribeiro et al., 2020; Zang et al., 2020; Jin et al., 2020; Li et al., 2021). Here, we will focus on related work that shares the same methodology as ours, taking advantage of the pre-trained models like the BERT model and its MLM training objective, but notably, they are all done only in English.

Jin et al. (2020) integrated two synonym replacement strategies (Alzantot et al., 2018; Ren et al., 2019) and proposed a baseline method called TEXTFOOLER to efficiently generate adversarial examples using synonym replacement techniques through word embeddings, ensuring the preservation of similar semantic meaning compared to the original words. Their findings show that pre-trained BERT models and other Deep Neural Networks (DNN) models were vulnerable to these adversarial text attacks, which could lead to misclassification or incorrect textual entailment predictions. The authors also emphasized improving the robustness of NLP models by incorporating defense mechanisms and testing their performance against adversarial attacks.

Several studies have proposed novel synonym replacement techniques using the MLM task with Large Language Models (LLMs) like BERT. For instance, Garg and Ramakrishnan (2020) proposed a novel method called BERT-based Adversarial Examples (BAE) for generating adversarial examples for text classification using MLM with BERT models. By utilizing pre-trained BERT’s ability to capture semantic meaning and context in text, BAE could generate adversarial examples more effectively than previous methods, avoiding detection by state-of-the-art classifiers. The authors also evaluated the effectiveness of BAE against various text classification models and demonstrated that it could generate robust adversarial examples. Li et al. (2020) proposed a practical method called BERT-Attack using MLM with BERT models to predict sub-word expansion, ensuring the generation of fluent and semantically preserved adversarial text examples. These adversarial examples successfully fooled the state-of-the-art models, such as the fine-tuned BERT models for various downstream tasks in NLP in a black-box manner. The authors evaluated the BERT-Attack’s effectiveness against BERT models in various text classification tasks and demonstrated its ability to reduce the accuracy of these models significantly. Lastly, Li et al. (2021) proposed an attack method called CLARE, a contextualized adversarial example generation model that could generate fluent and grammatically accurate outputs through a fill-in-mask procedure using MLM with RoBERTa models. CLEAR introduced three contextualized perturbations: replace, insert, and merge, which permit generating outputs of varying lengths, where it could flexibly integrate

these perturbations and apply them at any position in the inputs and then use them to attack the BERT models. The authors finally evaluated CLARE’s effectiveness against BERT models and demonstrated that CLARE achieved the best performance with the least modifications by combining all these three perturbations.

3 Methodology

3.1 Datasets Used

In this work, we select two large Arabic datasets designed for text classification tasks: hotel reviews and sentiment analysis. We purposely chose one dataset written mostly in Modern Standard Arabic (MSA) and another written in Dialectical Arabic (DA) to observe how the models would behave when trained on different Arabic dialects.

- **Hotel Arabic Reviews Dataset (HARD)** is a balanced dataset with 93K hotel reviews written mostly in MSA, collected from Booking.com, and has four classes (Elnagar et al., 2018), which we remap to Poor, Fair, Good, and Excellent, instead of the original numerical labels (1, 2, 4, and 5).¹

- **Sentiment Analysis for Social Media Posts in Arabic Dialect (MSDA)** is a balanced dataset that includes 50K posts written mostly in DA, collected from the X platform (formerly Twitter), and has three classes (Boujou et al., 2021): Positive, Neutral, and Negative.

Dataset	Avg Length	STD	Max Length
HARD	19.50	19.77	503
MSDA	9.99	9.46	326

Table 1: The general statistics of the two used datasets in terms of the Average Length (#words), Standard Deviation (STD), and Maximum Length (#words).

3.2 Models Targeted

We train three deep learning classifiers/models that are widely used for text classification tasks: WordLSTM (Word-based Long Short-term Memory) (Hochreiter and Schmidhuber, 1997), Word-CNN (Word-based Convolutional Neural Network) (Kim, 2014), and BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019), on the HARD and MSDA datasets.

¹Originally, labels 1 and 2 were negative, and 4 and 5 were positive. Notably, users were not given the choice of 3, only 5, 4, 2, or 1. We found this labeling confusing and remapped simply 1 to Poor, 2 to Fair, 4 to Good, and 5 to Excellent.

We use the same hyperparameters as Jin et al. (2020) used for the models in our study. We train WordCNN and WordLSTM models from scratch. For WordCNN models (Kim, 2014), we use three window sizes of 3, 4, and 5, and 100 filters for each window size. For the WordLSTM models, we use one bidirectional LSTM layer with 150 hidden states (Hochreiter and Schmidhuber, 1997). We train a GloVe (Global Vectors for Word Representation) model on each dataset to generate word vectors of size 200 dimensions for both models (Pennington et al., 2014) and use these GloVe embedding words to train the embedding layers in the WordCNN, and WordLSTM models on each dataset. For the BERT model, we begin with a pre-trained Arabic BERT model called AraBERT_{BASE} v2² (Antoun et al., 2020), which has 12 layers with 768 hidden states, 12 heads, resulting in 136M trainable parameters, and we then fine-tune for text classification tasks using each dataset. We use different levels of data preprocessing before training WordLSTM and WordCNN models and fine-tuning BERT models due to the differences in their architectures, like the utilization of contextual embeddings in BERT models.

Table 2 shows the original accuracy (evaluation accuracy) of each model on each dataset. BERT models score the highest evaluation accuracies: 83% and 86% on HARD and MSDA, respectively. The WordLSTM model is not far behind, but the WordCNN models perform substantially worse.

Dataset	WordCNN	WordLSTM	BERT
HARD	75%	80%	83%
MSDA	77%	83%	86%

Table 2: Original accuracy (evaluation accuracy) of each model on each dataset (a test set of 10% of each dataset).

3.3 Adversarial Text Generation

The adversarial text generation task involves working with a dataset D in the form of (X, Y) , composed of pairs examples X and labels Y in the form of $\{(x_1, y_1), \dots, (x_n, y_n)\}$, alongside a black-box classifier $C: X \rightarrow Y$. We assume a soft label (with probability score) in a black-box setting, where the attacker can only query the classifier C for output labels Y and probabilities P given specific inputs, without access to any of the model’s parameters, weights, gradients, architecture, or training data.

²AraBERT_{BASE} v2 model can be accessed here: <https://huggingface.co/aubmindlab/bert-base-arabertv2>.

Given an input example x , composed of W words in the form of $(x = [w_1, w_2, w_3, \dots, w_n], y)$, our goal is to create adversarial examples X_{ADV} , in such a way that $C(X_{ADV}) \neq Y$, meaning the prediction labels Y of $C(X)$ do not equal the adversarial labels Y_{ADV} returned by $C(X_{ADV})$. Moreover, we aim for the adversarial examples X_{ADV} to exhibit grammatical correctness and maintain semantic similarity to the original inputs X .

3.3.1 Adversarial Text Generation Steps

Here, we present the steps we use for generating adversarial examples X_{ADV} . We randomly select 1000 samples (original examples X) from each dataset and process them following these steps:

1) Word Importance Ranking: We use the same scoring function (I_{w_i}) as Jin et al. (2020) to measure the influence of a word w_i . Specifically, we quantify the importance of each token/word w_i in a sentence by deleting the tokens (one token each at a time) and calculating the prediction scores’ change before and after deleting that word w_i . We also clean the input original example x by removing the noise, emojis, stopwords, and punctuation marks using the NLTK Python library³ before we feed the example x to the scoring function (I_{w_i}) to reduce the computational overhead and ensure only words are fed to the scoring function (I_{w_i}).

2) Word Replacement Strategy: We repetitively replace the most important words (one important word I_{w_i} at a time) in the input original example x using the MLM task with the BERT model to find synonym words for that important word I_{w_i} .

We use a different pre-trained version of AraBERT_{BASE} v02⁴ as our MLM model (Antoun et al., 2020) to generate the synonym words W_s and assigned the top K value to 50. After that, we use the CAMELBERT-CA POS-EGY model⁵ (Inoue et al., 2021) as our Part-of-Speech (POS) tagger to ensure that the generated synonym words are grammatically correct. Next, we use a Sentence-Transformers model⁶ to ensure the newly generated examples with the replaced synonym

³Natural Language Toolkit (NLTK): <https://www.nltk.org>.

⁴AraBERT_{BASE} v02 model can be accessed here: <https://huggingface.co/aubmindlab/bert-base-arabertv02>.

⁵CAMELBERT-CA POS-EGY model can be accessed here: <https://huggingface.co/CAMEL-Lab/bert-base-arabic-camelbert-ca-pos-egy>.

⁶Sentence-Transformers model can be accessed here: <https://huggingface.co/sentence-transformers/paraphrase-multilingual-mpnet-base-v2>.

words are semantically similar to the original examples. We specifically used a multilingual pre-trained MPNet (Masked and Permuted Pre-training for Language Understanding) model (Song et al., 2020) trained on parallel data for 50+ languages, including Arabic (Reimers and Gurevych, 2020). We calculate the similarity score using the cosine similarity metric and set the similarity threshold to 0.80, as set by Jin et al. (2020). After the newly generated example passes the POS and similarity checkers, we finally have an attack candidate example derived from the original example x .

3) Synonym BERT-based Attack: Finally, we call an attack candidate example an ‘adversarial example’ (x_{adv}) if it flips the prediction label y (the prediction label of the original example y before the attack \neq the prediction label of the attack candidate example y_{adv} after the attack). In other words, after replacing a word w with its synonym word w_s in the original example x using our synonym attack, the adversarial example x_{adv} force the targeted model/classifier to change its classification.⁷

4 Automatic Evaluation

4.1 Evaluation Metrics

We evaluate our synonym BERT-based attack using four metrics: Attack Success Rate (Att._{SR}), Accuracy Before Attack (Acc._{BA}), Accuracy After Attack (Acc._{AA}), and Attack Decrease Rate (Att._{DR}).

1) Attack Success Rate (Att._{SR}) is a metric designed to measure the successfulness of our synonym attack on a specific model and dataset, and it is calculated by dividing the number of adversarial examples produced by a model from a dataset by the total number of the randomly selected samples (original examples) multiplied by 100 for percentage normalization.

2) Accuracy Before Attack (Acc._{BA}) is calculated by taking the mean of prediction scores of the total number of selected samples input to the targeted model in a black box setting, meaning we only use the prediction scores instead of the targeted model’s original accuracy (evaluation accuracy). We believe taking the original accuracy of the model here is not a black-box manner because attackers are not supposed to know anything about the targeted model, including its original accuracy.

3) Accuracy After Attack (Acc._{AA}) is calculated by taking the mean of prediction scores of the total number of selected samples input to the targeted model in a black box setting after applying our synonym attack.

4) Attack Decrease Rate (Att._{DR}) is a metric designed to measure the effectiveness of our synonym attack on a specific model and dataset, and it is calculated simply by taking the difference between the Accuracy Before Attack (Acc._{BA}) and Accuracy After Attack (Acc._{AA}).

4.2 Evaluation Results

We first choose 1000 randomly selected examples from each dataset: HARD and MSDA, following Jin et al. (2020) and Li et al. (2021). Next, we evaluate our proposed synonym attack using metrics defined in subsection 4.1 above. The results of the automatic evaluations of our attack on each targeted model (WordCNN, WordLSTM, and BERT) and each dataset (HARD and MSDA) are displayed in Table 3. We find that our attack has successfully decreased the accuracies of the targeted models on each dataset, measured by the Acc._{BA} and Acc._{AA} metrics. For the 1000 randomly chosen examples, the BERT models fine-tuned on the MSDA and HARD datasets scored 90.55% and 88.59% as accuracies before our attack, and their accuracies after our attack have dropped to 63.62% and 73.90% on both datasets, respectively. It is clear that our attack strategy of substituting a word with a synonym works well because it creates a new example (adversarial example) that the targeted model has not encountered or seen before, forcing the targeted model to misclassify and cause a drop in its accuracy after the attack. Yet, we believe that the number of the evaluated examples, the different levels of data preprocessing, and the prediction misclassification rate of the block-box models are possible interpretations of the noticeable difference between the original accuracy mentioned in Table 2 and the Acc._{BA} in Table 3. Regardless of these constraints, our results demonstrate that all three models are indeed susceptible to our synonym attacks.

Furthermore, Table 3 summarizes the successfulness and effectiveness of our synonym BERT-based attack, measured by the Att._{SR} and Att._{DR} metrics, respectively. On the models level, our findings confirm that the DNN models (WordCNN and WordLSTM) are less susceptible to our attack than the BERT models. For instance, the attack decrease

⁷Appendix A provides some concrete examples of Arabic adversarial text examples generated using our synonym attack, along with their labels and their English translations.

Metric	WordCNN		WordLSTM		BERT	
	HARD	MSDA	HARD	MSDA	HARD	MSDA
Attack Success Rate (Att. _{SR})	50.00%	30.00%	51.00%	25.00%	51.00%	26.00%
Accuracy Before Attack (Acc. _{BA})	32.09%	45.15%	34.82%	47.48%	88.59%	90.55%
Accuracy After Attack (Acc. _{AA})	32.05%	39.31%	33.90%	41.73%	73.90%	63.62%
Attack Decrease Rate (Att. _{DR})	00.04%	05.84%	00.92%	05.75%	14.69%	26.93%

Table 3: Results of the attack success rate, accuracy before and after our attack, and attack decrease rate on each model and each dataset (the accuracies reported above are only for 1000 randomly selected examples).

rates of the WordCNN and WordLSTM models are both nearly 6% on the MSDA dataset, whereas the Att._{DR} of the BERT model on the same dataset is approximately 27%.

On the other hand, on the datasets level, we observe that our synonym attack is more successful and less effective on the HARD dataset than the MSDA dataset, meaning our attack on the HARD dataset produced more adversarial examples than on the MSDA dataset, but at the same time, these newly produced adversarial examples exhibit less impact on the targeted models trained on the HARD dataset. In contrast, our synonym attack generates fewer adversarial examples from the MSDA dataset, but those that succeed prove more potent. Notably, it is easier to successfully craft adversarial examples from the HARD dataset than the MSDA dataset since the MSDA dataset is a Dialectal Arabic (DA) dataset, and HARD is mostly a Modern Standard Arabic (MSA) dataset. Dialects in Arabic have fewer syntactic, morphologic, and orthographic rules than official Modern Standard Arabic (Grosvald et al., 2019).

5 Human Evaluation

5.1 Setup of Human Evaluation

We invite *four* human evaluators (all native Arabic speakers) to evaluate the naturalness of the Arabic adversarial text examples generated by our synonym attack. We randomly select 150 adversarial text examples (50 examples for each model from the HARD dataset)⁸ to be evaluated by our human evaluators in terms of two major criteria: grammatical similarity and semantic similarity. As an inner-level evaluation, we ensure that two of these native Arabic evaluators have college degrees in the Arabic language (linguists), while the other two do not (non-linguists), to study the inner difference

⁸We only select generated adversarial examples from the HARD dataset because it is mostly written in Modern Standard Arabic, which can be easily evaluated in terms of Arabic grammar. MSA has syntactic, morphologic, and orthographic rules, not like the Dialectal Arabic (Grosvald et al., 2019).

in assessing the naturalness of our adversarial text examples between linguists and non-linguists, and ask them to evaluate all the selected examples.

For grammatical similarity assessment, we first retrieve the corresponding original examples to the randomly selected adversarial examples and separately group them into two groups: original and adversarial. We then task all the human evaluators to rate both groups anonymously, meaning we do not tell them which group is which to guarantee that the original examples do not influence human evaluators’ judgment. Inspired by Gagnon-Marchand et al. (2019), we use a 5-point Likert scale, where *one* represents *strongly incorrect*, *two* represents *incorrect*, *three* represents *correct to some extent*, *four* represents *correct*, and *five* represents *strongly correct* (Likert, 1932). Following Jin et al. (2020), we calculate the average score of the Likert scale measurements for each group (original and adversarial) and lastly divide the average score of the adversarial examples by the average score of the original examples of each human evaluator (linguists and non-linguists) to measure the precise grammatical similarity ratio between the original and adversarial examples.

For semantic similarity assessment, we accompany the randomly selected adversarial examples with their corresponding original examples and ask the human evaluators to rate whether the adversarial examples convey the same semantic meaning as the original examples. We use the same 5-point Likert scale, with different rating labels, ranging from *one* representing *strongly dissimilar* to *five* representing *strongly similar*. We then calculate the percentage of the average score of the Likert scale numbers (average score/number of rating labels) for each evaluator (linguists and non-linguists).

5.2 Human Evaluation Results

We observe in the grammatical similarity assessment that the non-linguist evaluators rated our adversarial examples and their original examples slightly higher than the linguist evaluators (except

Evaluation Criteria	Human Evaluator	WordCNN	WordLSTM	BERT
Grammatical Similarity	Linguists	92.00%	94.00%	98.00%
	Non-linguists	99.00%	95.00%	98.00%
	Overall Average	95.50%	94.50%	98.00%
Semantic Similarity	Linguists	89.00%	87.00%	91.00%
	Non-linguists	87.00%	86.00%	86.00%
	Overall Average	88.00%	86.50%	88.50%

Table 4: Results of human evaluation of our generated adversarial text examples from each targeted model (WordCNN, WordLSTM, and BERT) on the HARD dataset; no examples used from the dialectical MSDA dataset.

for the BERT model), whereas we have exactly the opposite results in the semantic similarity assessment (the linguists rated the examples higher than the non-linguists), as shown in Table 4. We assume that the gap in the background knowledge of the two human evaluators’ groups led to such results, where the non-linguists lack knowledge of Arabic syntax, making them rate the examples higher than the linguists in the grammatical similarity assessment. On the other hand, the deep understanding of the language and its semantics makes the linguists rate the examples higher than the non-linguists in the semantic similarity assessment.

Overall, as shown in Table 4, the human evaluation results (across all 4 evaluators) demonstrate that the adversarial text examples generated by our synonym attack is acceptable to Arabic native speakers, meaning that our adversarial examples preserve a similar level of grammatical correctness and convey similar semantic meaning. For example, the overall average scores ranged from 94.50% to 98% for grammatical similarity, whereas the average scores ranged from 86.50% to 88.50% for semantic similarity.

6 Transferability

6.1 Setup of Transferability

The transferability of an adversarial attack refers to its ability to reduce the accuracy of the targeted models (victim models) to a certain extent when attacked by the newly generated adversarial examples from other models (source models), where all the victim and source models trained on the same dataset (Szegedy et al., 2014; Goodfellow et al., 2015). To closely examine the transferability, we examine 245 adversarial examples from each of the HARD and MSDA datasets along with their corresponding original examples. Initially, we predict the accuracy of both the original examples and their corresponding adversarial examples using the victim models. We then calculate the difference (delta Δ) between the prediction accuracy of the

original examples and the adversarial examples, ultimately determining the transferability score for each model. We have not seen any other researcher using this delta difference method for the transferability of adversarial text attacks, even in English.

6.2 Transferability Results

Overall, first, we see that BERT (as the victim) has higher transferability scores than WordCNN or WordLSTM models, as shown in Table 5. This indicates that BERT is more vulnerable to transferred attacks. This result is similar to what Jin et al. (2020) saw in English. Second, we see that models trained in Dialectal Arabic (DA) are more vulnerable to transferred attacks than models trained in Modern Standard Arabic (MSA). Again, fewer generated adversarial examples from the dialectical MSDA dataset satisfy the synonym rules, but those that succeed prove more potent in the attack transferability between models.

7 Defense Mechanism

7.1 Setup of Defense Mechanism

We utilize adversarial training as a defense mechanism against our synonym attack, similar to Jin et al. (2020), and follow the approach introduced by Shrivastava et al. (2017). This method is widely adopted in image classification to enhance models’ robustness. To assess whether the employment of adversarial training enhances the robustness of these models, we add the generated adversarial examples to the original datasets. Then, we retrain the models and evaluate the robustness of these newly adversarially trained models. We only study the effectiveness of the adversarial training on BERT models. We collect adversarial examples from both datasets that successfully fooled BERT models and incorporate them into the original datasets to train the models adversarially. We then refine-tune these BERT models using the augmented datasets with adversarial examples and subject these adversarially fine-tuned models to our attacks again.

		Transferability Scores								
Datasets	Models	WordCNN (source)			WordLSTM (source)			BERT (source)		
		X	X_{ADV}	Δ	X	X_{ADV}	Δ	X	X_{ADV}	Δ
HARD	WordCNN (victim)	—	—	—	52.65	47.34	5.31	65.71	34.28	31.43
	WordLSTM (victim)	56.32	43.67	12.65	—	—	—	60.81	39.18	21.63
	BERT (victim)	75.51	24.48	51.03	74.28	25.71	48.57	—	—	—
MSDA	WordCNN (victim)	—	—	—	87.34	12.65	74.69	86.53	13.46	73.07
	WordLSTM (victim)	83.26	16.73	66.53	—	—	—	82.04	17.95	64.09
	BERT (victim)	89.38	10.61	78.77	88.16	11.83	76.33	—	—	—

Table 5: Transferability of adversarial examples between victim and source models. Here, X refers to original examples, and X_{ADV} refers to adversarial examples. Let rows be N and columns be M , then cells NM are the accuracies of adversarial examples generated from the source model M and evaluated on the victim model N . A higher delta Δ score indicates higher transferability between models.

7.2 Defense Mechanism Results

We find that BERT models’ adversarial training accuracies increased on both datasets, compared to their accuracies after the attack with no defense mechanism in place, as seen in Table 6. In other words, BERT models regain at least 2% in accuracy after applying adversarial training as a defense mechanism. These results agree with Jin et al. (2020)’s adversarial training results and provide further evidence that adversarial training is a good starting point for enhancing models’ robustness.

Metric	HARD	MSDA
Acc. Before Attack	88.59%	90.55%
Acc. After Attack	73.9%	63.62%
Adversarial Training Acc.	76.51%	65.69%

Table 6: Adversarial training results on BERT models.

8 Limitations

Due to the lack of availability of strong foundation models in Arabic and our lack of computational resources, one limitation of our attack is that it fundamentally depends on the pre-trained Arabic and multilingual models like the AraBERT model for retrieving synonym words, the CAMELBERT model for grammatical similarity checking, and the Sentence-Transformers model for semantic similarity checking, where their performance creates a bottleneck for the effectiveness of our text adversarial attack and the quality of our produced adversarial examples. Another limitation of our work is that the successfulness of our attack in generating adversarial examples is higher than its impact on the targeted models because the evaluation misclassification rate of the targeted models is another bottleneck of our attack, meaning if a model’s original (evaluation) accuracy score is 86% (e.g., BERT model on the MSDA dataset), then the misclassification rate of the model is 14%, which

undoubtedly affects the effectiveness of our attack negatively, especially since our attack setting is black-box, where it is impossible to remove these misclassified examples without compromising the attack setting (if we remove these misclassified examples, the attack setting will be a white-box).

9 Conclusion

In this work, we introduce the *first* Arabic synonym BERT-based adversarial attack using an MLM task with pre-trained BERT models against the state-of-the-art text classification models. We utilize two large Arabic datasets, namely HARD and MSDA, in a black-box manner. We find that BERT and other DNN models are generally susceptible to these Arabic adversarial examples, especially BERT models. We ask human evaluators to evaluate our produced adversarial examples using our attack in terms of grammatical similarity and semantic similarity and find that our attack generates examples that preserve semantic similarity and maintain Arabic grammar. We also study the transferability of these Arabic adversarial text examples by various source models on different victim models and observe that fine-tuned BERT models exhibit higher transferability when attacked by the other DNN models’ generated adversarial examples. Lastly, we investigate the effectiveness of the adversarial training defense mechanism on BERT models and find that the BERT models successfully regain at least 2% of their accuracies after applying the adversarial training as a defense mechanism.

Reproducibility

We share our code scripts and trained models on GitHub at https://www.github.com/NorahAlshahrani/bert_synonym_attack.

Dataset	Labels	Arabic Example	Translated Example
HARD	Original Label: Excellent	استثنائي ، فندق مريح جداً و كل شي كان جميل.	Exceptional , very comfortable hotel and everything was beautiful.
	Attack Label: Good	ممتاز ، فندق مريح جداً و كل شي كان جميل.	Excellent , very comfortable hotel and everything was beautiful.
	Original Label: Good	جيد ، استقبال جميل ونظافة وسهولة الوصول له وقريب من المطار والمراكز التسوق.	Good , beautiful reception, luxury, cleanliness, easy access, and close to the airport and shopping centers.
	Attack Label: Excellent	ممتاز ، استقبال جميل ونظافة وسهولة الوصول له وقريب من المطار والمراكز التسوق.	Excellent , beautiful reception, luxury, cleanliness, easy access, and close to the airport and shopping centers.
MSDA	Original Label: Negative	الله يرحم نادين ويخليك عيلتك. بعرف شو صعبة.	May God have mercy on Nadine and keep your family. I know how difficult it is.
	Attack Label: Positive	الله يحمي نادين ويخليك عيلتك. بعرف شو صعبة.	May God protect Nadine and keep your family. I know how difficult it is.
	Original Label: Positive	الأيام الحلوه كثيرا يا صاحبي ربنا يدبها.	Many good days! My friend, may God perpetuate them .
	Attack Label: Neutral	الأيام الحلوه كثيرا يا صاحبي ربنا موجود.	Many good days! My friend, God is always there .

Appendix A: Examples of the original Arabic and adversarial Arabic that are generated from the HARD and MSDA datasets and produced by the BERT models, along with their prediction labels and their English translations.

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A Hypothesis-Driven Framework for the Analysis of Self-Rationalising Models

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Abstract

The self-rationalising capabilities of LLMs are appealing because the generated explanations can give insights into the plausibility of the predictions. However, how faithful the explanations are to the predictions is questionable, raising the need to explore the patterns behind them further. To this end, we propose a hypothesis-driven statistical framework. We use a Bayesian network to implement a hypothesis about how a task (in our example, natural language inference) is solved, and its internal states are translated into natural language with templates. Those explanations are then compared to LLM-generated free-text explanations using automatic and human evaluations. This allows us to judge how similar the LLM's and the Bayesian network's decision processes are. We demonstrate the usage of our framework with an example hypothesis and two realisations in Bayesian networks. The resulting models do not exhibit a strong similarity to GPT-3.5. We discuss the implications of this as well as the framework's potential to approximate LLM decisions better in future work.

1 Introduction

With the increasing capabilities of large language models (LLMs), more and more tasks that were traditionally solved using human experts and statistical models are now aided by LLMs. Understanding how a model produces its output is an essential factor in the human acceptance of machine learning systems (Shin, 2021). However, understanding the connection between input and output in LLMs is not easily possible (Adadi and Berrada, 2018).

Recent advances in LLMs generating longer coherent text have popularised self-rationalising models, which produce a natural language explanation (NLE) alongside their output (Hase et al., 2020; Marasovic et al., 2021). NLEs have numerous benefits over other, non-textual explanations: NLEs are valued more highly by human users (Forrest

et al., 2018), they can be applied to a broad range of problems and they can combine external knowledge with the model input. However, even though the NLEs can give insights into how plausible the predictions made by LLMs are, the *faithfulness* of the explanations to the prediction process remains at best uncertain (Wiegrefe et al., 2021; Atanasova et al., 2023; Turpin et al., 2023).

In this work, we propose exploring the patterns behind generated NLEs using a hypothesis-driven framework, with the ultimate goal of deriving a surrogate model. Our framework is centred around a *hypothetical global explanation* (HGE): A hypothesis about how the LLM solves a specific task on a global, structural level. While we start off with an obviously oversimplified hypothesis to introduce and test the framework, we envision that it can be incrementally adapted to more refined hypotheses in the future. The patterns captured by each refinement step can then serve to measure their coverage, or e-recall (Goldberg, 2023), in the LLM.

The core component of our framework is a statistical surrogate model (SSM) that reflects the HGE. We propose using a Bayesian Network (Pearl, 1988) with a manually designed structure as a framework for the SSM, as the Bayesian Network allows us to visualise the independencies among the random variables used in the SSM via a directed acyclic graph (DAG). This allows us to define the variables in the SSM and the relationships among them such that they reflect the HGE. Furthermore, since the structure of the SSM is based on the HGE, each variable of the Bayesian Network is assigned a specific, semantically interpretable meaning. This allows us to generate local NLEs for individual inputs based on the internal state of the Bayesian Network. In the last step, we compare both the predicted labels and the NLEs produced by the SSM to those produced by the LLM in order to gain insights about the faithfulness of the HGE.

We demonstrate the usage of this framework

with an exemplary HGE for how the behaviour of the LLM GPT-3.5 (Brown et al., 2020) can be explained when performing English-language natural language inference (NLI). We discuss the challenges when designing, implementing and training the Bayesian Networks based on the HGE and outline the next steps on the way to a surrogate that models LLM predictions more accurately.

2 Related Work

Self-rationalising models have received increasing attention as the generation abilities of NLP models have improved in recent years. Human-annotated datasets such as e-SNLI (Camburu et al., 2018) for NLI, CoS-E (Rajani et al., 2019) and ECQA (Aggarwal et al., 2021) for commonsense question answering and ComVE (Wang et al., 2020) for commonsense validation are the basis for much NLE work (Wiegrefe and Marasovic, 2021). However, the role of LLMs in the annotation process itself is likely increasing (Wiegrefe et al., 2022), as it reduces the significant cost of human annotation (Belinkov and Glass, 2019).

A concern, however, is that the generation of the NLEs is as opaque as the prediction process. To address this, some recent work explores the faithfulness of NLEs: Wiegrefe et al. (2021) show that prediction and explanation exhibit correlated responses to input noise. Atanasova et al. (2023) propose analysing NLEs after counterfactual interventions on the input that alter the prediction, and testing the sufficiency of the reasons provided in the NLE. Turpin et al. (2023) show that biased features in the input lead to obviously unfaithful NLEs as those features affect the predictions heavily but are never mentioned in the generated NLEs.

Similar concerns have been raised for model-agnostic surrogates such as LIME (Ribeiro et al., 2016) and SHAP (Lundberg and Lee, 2017), which are widely used for highlighting input features as a form of explanation. They approximate a complex model by training a simpler, interpretable model on the original model’s predictions. Whether such surrogates are helpful for understanding complex models is subject to discussion. Rudin (2019) makes the case against their usage in high-stake decisions and argues for the deployment of models with an interpretable decision process. However, from a more practical perspective, Jacovi and Goldberg (2020) point out that faithfulness is not a binary feature but should be seen as a scale. They argue that

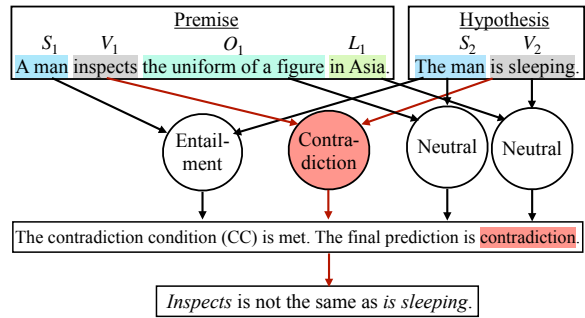


Figure 1: An illustrative (simplified) example for the small SSM. The input X consists of the subphrases of the premise and hypothesis. The circles are the hidden variables Z , followed by the final prediction Y (here, *contradiction*) and a template-based NLE (lowest box).

depending on the use case, it can be more important to have *plausibility* than *faithfulness*.

3 Proposed Framework

In this section, we describe our framework¹: How we design the SSM based on our hypothesis (§3.1-§3.3), how we determine and learn the parameters (§3.4) and how we generate NLEs based on the SSM’s parameters (§3.5). We demonstrate that we can successfully control for the assumptions made in our hypothesis, with a model that is intuitive to construct and understand. For a simplified demonstration of how the framework processes an example input, we refer to figure 1.

3.1 Constructing the SSM

The SSM aims to reflect a hypothesis about a decision-making process that is assumed to explain the behaviour of GPT-3.5 (Brown et al., 2020)² when performing NLI. A hypothetical global explanation (HGE) is defined that aims at providing a hypothesis on how GPT-3.5 produces its labels when performing NLI. The hypothesis is based on an intuitive yet oversimplified assumption about how a fully connected model such as the Transformer network (Vaswani et al., 2017) behind GPT-3.5, may solve the NLI task. The HGE is as follows:

¹The implementation used for our experiments is available at https://github.com/Marbr987/Hypothesis_Driven_Analysis_of_Self_Rationalising_Models.

²We use the *text-davinci-003* version that deviates from the cited paper by being fine-tuned using RLHF (Ouyang et al., 2022), but possibly even in other aspects.

HGE: “When performing NLI, GPT-3.5 compares pairs of subphrases from the premise and hypothesis to each other and classifies each pair into contradiction, entailment, or neutral. Based on this classification, the final prediction is made using deterministic rules.”

3.2 Extracting Subphrases from Premise and Hypothesis

The aim of NLI is to classify the relation of a *premise* and a *hypothesis* into *contradiction*, *entailment*, and *neutral* relation. We use the e-SNLI dataset (Camburu et al., 2018) that besides pairs of premises and hypotheses and the according NLI label also contains human-authored NLEs. An example of a premise and a hypothesis is given in figure 1, where the hypothesis “The man is sleeping” contradicts the premise “A man inspects the uniform of a figure in Asia”.

To implement the structure of the HGE, we define the subphrases to be the subject, verb, and object of the sentences as well as location and clothing of the subjects mentioned in the sentences.³ We extract subphrases using the syntactic dependency trees of the sentences as defined by the SpaCy dependency parser (Honnibal and Johnson, 2015). Sentences that contain multiple subjects, verbs, or objects were discarded from the dataset. The remaining data contains 30.8% of the data in the original dataset. The individual words in each subphrase are transformed into 300-dimensional vectors using Spacy’s pre-trained word embeddings (Honnibal and Montani, 2017). The embedding vectors of the individual words are then added up. If multiple location or clothing subphrases are extracted, the embedding vectors are also added up.

3.3 Defining the Structure of the SSM

The random variables (RVs) used in the SSM and the structure of the SSM are deduced from the HGE and defined using a Bayesian Network. A Bayesian Network is a graphical statistical tool to visually represent independencies among RVs. The RVs in a Bayesian Network are represented as nodes in a directed acyclic graph (DAG), where an edge from node A to node B is interpreted as A causes B .

³While we chose the categories after a manual inspection of the training data, they are obviously incomplete. More categories would increase the complexity of the Bayesian Network, but ensure better coverage.

Defining the input variables X . We represent each subphrase in the premise and hypothesis as a 300-dimensional vector as described in 3.2. Let S_i, V_i, O_i, L_i and C_i be RVs representing the *subject*, *verb*, *object*, *location*, and *clothing* subphrase of sentence i , where sentence 1 is the premise and sentence 2 is the hypothesis. For notation purposes, we introduce the following random vectors:

$$\begin{aligned} X_1 &:= (x_{1,1}, x_{1,2}, x_{1,3}, x_{1,4}, x_{1,5})^T \\ &:= (S_1, V_1, O_1, L_1, C_1)^T \\ X_2 &:= (x_{2,1}, x_{2,2}, x_{2,3}, x_{2,4}, x_{2,5})^T \\ &:= (S_2, V_2, O_2, L_2, C_2)^T, \\ X &:= (X_1, X_2)^T \end{aligned}$$

We also define the sets of random vectors:

$$\begin{aligned} \mathcal{X}_1 &:= \{S_1, V_1, O_1, L_1, C_1\}, \\ \mathcal{X}_2 &:= \{S_2, V_2, O_2, L_2, C_2\}, \\ \mathcal{X} &:= \mathcal{X}_1 \cup \mathcal{X}_2 \end{aligned}$$

Introducing hidden variables Z In order to model the assumption in the HGE that the pairs of subphrases are classified independently, a set of unobserved discrete RVs \mathcal{Z} is introduced. As shown in Figure 2, we define that each element $z_{k,l} \in \mathcal{Z}$ is caused by $x_{1,k}$ and $x_{2,l}$ where $x_{1,k}$ is the k -th element in X_1 and $x_{2,l}$ is the l -th element in X_2 . Let Z be the random vectors with entries equal to the elements in \mathcal{Z} . According to the HGE, each $z_{k,l}$ is a discrete RV with possible realisations *contradiction*, *entailment*, or *neutral*. In other words, each hidden RV $z_{k,l}$ models the relation of subphrase $x_{1,k}$ from the premise to the subphrase $x_{2,l}$ from the hypothesis.

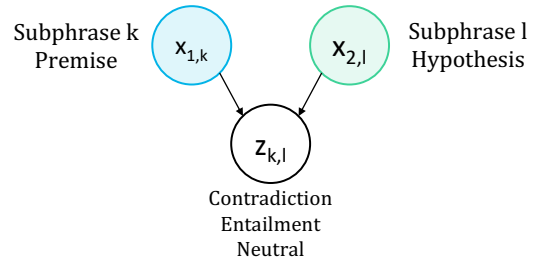


Figure 2: Relationship of any $z_{k,l} \in \mathcal{Z}$ to its parents

Depending on which combinations of k and l are included in \mathcal{Z} , the structure of the Bayesian Network changes and different interpretations of

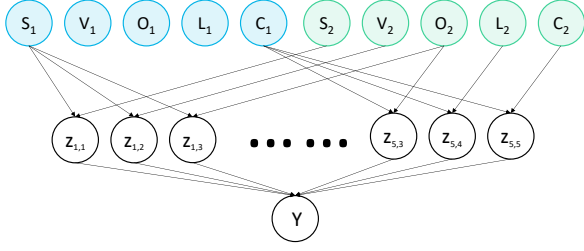


Figure 3: Structure of the SSM_{large} expressed as a Bayesian Network

the HGE can be modelled. We compare two different structures: A large SSM containing all possible connections, and a small SSM that only contains the connections that we hypothesise are relevant for the final prediction.

Defining Z for the large SSM For the first structure (visualised in figure 3), Z contains all possible combinations of k and l , following the assumption that any subphrase from the premise can contradict, entail, or be neutral towards every subphrase in the hypothesis. Let this structure be called *large SSM*. In mathematical terms, we define

$$\mathcal{Z}_{large} := \{z_{k,l} | k, l \in \{1, 2, 3, 4, 5\}\}$$

Defining Z for the small SSM For the second structure, we remove all random variables in Z that we assume to be in the neutral state most of the time and therefore do not contain much relevant information for the prediction. These uninformative z are defined to be the ones that model the *inter*-relationships between the subject, verb, and object subphrases. For example, the subject of the premise rarely contradicts or entails the object of the hypothesis. In mathematical terms, we define

$$\mathcal{Z}_{small} := \mathcal{Z}_{large} \setminus \{z_{k,l} | k, l \in \{1, 2, 3\} \wedge k \neq l\}$$

Defining the output Y According to the HGE, we derive the final prediction from the subphrase classification using deterministic rules. The results from the subphrase classification are the values of Z . Consequently, the final prediction Y is made by defining directed edges from all variables in Z to Y . Y is the discrete RV representing the overall class of the NLI task and therefore has possible states *contradiction*, *entailment*, or *neutral*.

3.4 Determining the Parameters of the SSM

The aim of the SSM is to make predictions on $Y|X$, i.e. the final class given the subphrases, and to generate NLEs for why the prediction was made. The probability of $Y|X$ can be calculated as follows.

$$P(Y|X) = \sum_Z P(Y, Z|X) \quad (1a)$$

$$= \sum_Z P(Y|Z, X) \cdot P(Z|X) \quad (1b)$$

$$= \sum_Z P(Y|Z) \cdot P(Z|X) \quad (1c)$$

The summation is performed over all possible states of the vector Z and the equality in 1c holds because of the independence of Y and X given Z which can be verified using the Bayesian Network structure. Given Equation 1, we model the distributions of $Y|Z$ and $Z|X$ to make inference on $Y|X$.

3.4.1 Defining the Deterministic Distribution of $Y|Z$

Following the HGE, the distribution of $Y|Z$ can be modelled with a set of rules we define using propositional logic. Those rules are:

Contradiction Condition The RV Z models the relationship between the subphrases X . If any of the variables in Z has the value *contradiction*, i.e. if any subphrase in the premise contradicts any subphrase in the hypothesis, we define the final prediction Y to be *contradiction*.

$$\exists z \in Z : (z = \text{“contradiction”}) \quad (CC)$$

We call this formula *contradiction condition* (CC). If it evaluates to `True`, then Y is defined to be *contradiction*.

Entailment Condition If the final prediction Y is *entailment*, every subphrase in the hypothesis (i.e. every element in \mathcal{X}_2) has to be entailed by at least one subphrase in the premise (i.e. by any element in \mathcal{X}_1). This condition is expressed as follows:

$$\forall l \in \{1, 2, 3, 4, 5\} \exists k \in \{1, 2, 3, 4, 5\} : (z_{k,l} = \text{“entailment”}) \quad (EC)$$

We call this formula *entailment condition* or (EC). If it evaluates to `True`, then Y is defined to be *entailment*.

Neutral Condition If the (CC) and (EC) are both evaluated as `False`, then we define the final class to be *neutral*. The logical formula for this condition can be expressed as

$$\neg(\text{CC}) \wedge \neg(\text{EC}) \quad (\text{NC})$$

and is called *neutral condition* or (NC).

Distribution of $Y|Z$ Given these three conditions, the distribution of $Y|Z$ can be described as

$$\begin{aligned} P(Y = \text{“contradiction”}|Z) &= 1 \text{ if } (\text{CC}) \\ P(Y = \text{“entailment”}|Z) &= 1 \text{ if } (\text{EC}) \\ P(Y = \text{“neutral”}|Z) &= 1 \text{ if } (\text{NC}) \end{aligned} \quad (2)$$

3.4.2 Learning the Parameters θ of the Stochastic Distribution of $Z|X, \theta$

To be able to evaluate Equation 1, we must determine the distribution of $Z|X$. Let the parameters of this distribution be θ , i.e. the goal is to find θ that models the distribution of $Z|X, \theta$. Since all random vectors in \mathcal{Z} are independent of each other given X , it suffices to model the distribution of each individual random vector $z_{k,l} \in \mathcal{Z}$. In this paper, the distribution of each $z_{k,l}|X, \theta$ is modelled by a feed-forward neural network. From the structure of the Bayesian Network we know that each $z_{k,l}$ only has parents $x_{1,k}$ and $x_{2,l}$ which means that to model $z_{k,l}|X, \theta$, each neural network only needs to take $x_{1,k}$ and $x_{2,l}$ as input.

To optimise the parameters θ , we use the EM algorithm (Dempster et al., 1977). In Appendix A.1 we show that the EM algorithm for the problem at hand amounts to taking samples \tilde{Z} from the distribution of $Z|X, Y, \theta^{(t)}$ in the E-step and maximising the log-likelihood of the parameter θ with respect to the sampled values \tilde{Z} in the M-step. Since each distribution $z_{k,l}|X, \theta_{k,l}$ is modelled using a neural network, the M-step amounts to training each network on the sampled values $\tilde{z}_{k,l}$ as output and the respective observed values of X as input using the cross-entropy loss function (de Boer et al., 2005).

3.5 Generating NLEs Using the SSM

In the last step, NLEs are produced using the SSM. By comparing these NLEs with the NLEs produced by GPT-3.5 in 4.1, we gain insights about the extent to which the SSM reflects a similar reasoning path as the NLEs produced with GPT-3.5.

By defining the distribution of $Y|Z$ based on a set of rules, we can deduce NLEs from the random vectors in \mathcal{Z} . For example, the (CC) formula states that if any of the random vectors in \mathcal{Z} is classified as a contradiction, then Y is of class contradiction

as well. This means that if, for example, the random vector $z_{k,l} \in \mathcal{Z}$ is of class contradiction (and assuming all other elements in \mathcal{Z} are of class other than contradiction), it is reasonable to state that $z_{k,l}$ is responsible for the final prediction. This example illustrates that, by defining the relationship between Z and Y in a way that is semantically interpretable, explanations for the final prediction can be formulated that follow the predefined semantics of the hidden variables.

Based on the rules used to define the distribution $Y|Z$, the templates that provide reasons for the final prediction Y are defined. The complete templates can be found in Appendix A.2.

4 Comparison to the LLM

Now that we have constructed the SSM, we need to compare it to GPT-3.5. To that end, we first generate labels and explanations with GPT-3.5 (§4.1), and compare them to the SSM in human (§4.2.1) and automatic (§4.2.2) evaluations.

4.1 Generating Labels and Explanations with GPT-3.5

To compare the outputs of GPT-3.5 to the outputs of SSM, we prompt the GPT-3.5 model to generate entailment labels as well as NLEs that provide reasoning for why the respective label was chosen.

Performing NLI with GPT-3.5 using few-shot learning has shown to have a performance close to fine-tuned GPT-3.5 (Marasovic et al., 2021). Inspired by the prompts proposed by Marasovic et al. (2021), we use the following structure.

First, the instruction “Classify into entailment, neutral, and contradiction and justify the decision.” is given to the model, followed by six examples⁴, each of which has the following structure:

“Premise: *premise*
Hypothesis: *hypothesis*
Label: *label*
Explanation: *explanation*”

The examples are balanced among the classes, i.e. two examples are chosen at random from the training set for each class. The examples are followed by the premise and hypothesis which shall be classified. Based on this input, GPT-3.5 produces a label and an NLE.

⁴While the original work by Marasovic et al. (2021) uses 50 examples, we found six to be sufficient for the newer, instruction-tuned GPT models.

4.2 Evaluating the Similarity Between the SSM and GPT-3.5 for NLI

In comparison to surrogate models for input feature highlighting surrogates such as LIME, the proximity of our surrogates to the original model cannot be measured by performance only. Therefore, we introduce an evaluation setup consisting of a human evaluation and a set of automatic metrics that compare the predictions and NLEs produced by GPT-3.5 to the predictions and NLEs produced by the SSM. This setup allows us to assess the extent to which the HGE is a valid explanation for how GPT-3.5 solves the NLI task.

4.2.1 Human Evaluation

For the human evaluation, three raters were instructed to answer the following questions for a random sample of 100 explanations produced for the development set. The full instructions for the raters can be found in Appendix A.3.

The raters were asked to report which of the subphrases defined in Section 3.2 are mentioned in each NLE produced by GPT-3.5. The reported subphrases can then be compared to the subphrases used in the explanation produced by the SSM. Furthermore, annotators were instructed to indicate whether the GPT-3.5 explanation relates any subphrases from the premise or hypothesis to each other, i.e. if it has a structure similar to what is stated in the HGE.

Additionally, the raters were asked to assess whether the GPT-3.5 NLE supports the predicted label and whether the explanation is factually correct. Lastly, the factual correctness of the NLEs produced by the SSM was assessed by the raters. To assess the inter-rater agreement among the human raters, we report Fleiss' Kappa (Fleiss, 1971).

4.2.2 Automatic Evaluation

In addition to the human evaluation, we use a range of methods to automatically assess the alignment of the SSMs with GPT-3.5.

Similarity Between the Predicted Labels To compare the similarity between the predictions made by GPT-3.5 and by the SSMs, we report the accuracy and F1-Score for all predictions, Cohen's kappa (Cohen, 1960) as well as the precision and recall for each class.

Similarity Between the Explanations To quantitatively analyse how similar the explanations produced by GPT-3.5 and the SSM are, the cosine

similarity between the NLEs, the Jaccard similarity and the BERTScore (Zhang et al., 2019) are calculated. We report the mean similarity values of all three similarity measures between the NLEs produced by GPT-3.5 and the NLEs produced by the large and small SSM, respectively. To provide additional context for the similarity measures, the same similarity measures are also calculated between the gold standard NLEs and the NLEs produced by GPT-3.5.

5 Results

In this section, we report the experimental results using the evaluation procedures and measures introduced in Section 4.2, assessing how similar our surrogate models are to GPT-3.5. For illustrative purposes, we will provide example explanations generated by the SSMs in §5.1, followed by the results of the human (§5.2) and the automatic evaluations (§5.3).

5.1 Example Outputs of the SSMs

The NLEs produced by the SSM do indeed have a structure that follows the HGE. For the premise "A young woman sits crosslegged beside her purse on the grass among a crowd of dogs." and the hypothesis "The woman is on the couch with the dogs.", both SSMs generate "Grass is not the same as couch." The semantics of this example NLE capture the reason why there is a contradiction, namely that the location of the woman is different (and thereby contradictory) in the two statements.

Overly complex explanations are a challenge, particularly for the entailment relation. For the premise "A man tries to get himself into shape on a treadmill." and the hypothesis "A man exercising.", the small SSM's explanation is "Man is the same as a man and get is the same as exercising and if the location of sentence 1 is treadmill, then the verb of sentence 2 has to be exercising.", which is not only partially incorrect but also points to trivial information.

In Appendix A.4 we provide more examples for how the output of the SSM looked like.

5.2 Human Evaluation

The human evaluation revealed that the average Jaccard similarity between the subphrases used in the NLEs by GPT-3.5 and the SSM is 0.384 for the large SSM and 0.423 for the small SSM. The average Fleiss' Kappa for detecting the subphrases

used in the NLEs by GPT-3.5 is 0.640. In the remainder of this section, we report Fleiss’ Kappa for the three raters in parentheses following the average rating. The raters found that 84.2% (0.316) of explanations of GPT-3.5 follow a structure that, as stated in the HGE, relates different subphrases from premise and hypothesis to each other and that 96.8% (0.858) of NLEs support the predicted label. The raters marked 86.3% (0.287) of GPT-3.5’s NLEs, 27.4% (0.553) of the NLEs produced using the small, and 21.1% (0.522) of the NLEs produced by the large SSM as factually correct.

Overall, the results from the human evaluation indicate comparatively low correctness and low similarity of the SSM explanations, although a large part of the explanations follows a structure that would be possible to model with a Bayesian Network. The small SSM’s NLEs are more similar to GPT-3.5’s NLEs than the large SSM’s.

5.3 Automatic Evaluation

This section presents the results of the automatic evaluation, where different measures were calculated to assess the similarity between the outputs produced by GPT-3.5 and the SSM.

5.3.1 Similarity Between Predicted Labels

All analysed metrics shown in Table 1 reveal that the small SSM tends to predict the label of GPT-3.5 with a higher precision and recall (except for precision of class contradiction and recall of class neutral). The table also shows that the values are much lower than the values of the metrics between the gold standard label and the predictions made by GPT-3.5.

Metric	<i>Gold</i>	SSM _{large}	SSM _{small}
Contr. Precision	0.949	0.763	0.713
Contr. Recall	0.899	0.286	0.576
Entail. Precision	0.968	0.619	0.667
Entail. Recall	0.704	0.549	0.573
Neutr. Precision	0.485	0.242	0.299
Neutr. Recall	0.887	0.630	0.528
Accuracy	0.807	0.468	0.556
Avg. F1-Score	0.788	0.449	0.545
Cohen’s Kappa	0.709	0.219	0.339

Table 1: Metrics relating the SSMs’ to GPT-3.5’s predictions. The interval for Cohen’s Kappa is between -1 and 1 (with 0 being random and 1 perfect agreement) and for all other metrics from 0 to 1.

5.3.2 Similarity Between NLEs

The similarity scores between the NLEs produced by GPT-3.5 and the NLEs produced using the SSM can be seen in Table 2.

Model	Cosine S.	Jaccard S.	BERTScore
<i>Gold</i>	0.808	0.277	0.604
SSM _{large}	0.771	0.182	0.455
SSM _{small}	0.779	0.196	0.463

Table 2: Similarity Scores in relation to GPT-3.5 NLEs. The interval for all metrics is from 0 to 1.

It is clear that for all three metrics, the predictions made by GPT-3.5 are closer to the gold standard NLEs than to the NLEs of the SSM. As in the human evaluation, the self-rationalised NLEs by GPT-3.5 are closer to the NLEs by the small SSM compared to the NLEs by the large SSM.

6 Discussion

This paper set out with the aim of constructing and evaluating a hypothesis-driven surrogate for how GPT-3.5 performs NLI. As we have seen in section 3, the Bayesian network allows us to incorporate our hypothesis in an intuitive and testable way, making (in-)dependencies between phrases explicit. While the framework is convenient and functional, the results in section 5 indicate a low similarity to GPT-3.5. This can have two reasons: First, that the HGE does not resemble the way GPT-3.5 solves the NLI task, or second, that implementation details of the SSM have shortcomings that limit the performance of the model. In any case, several challenges need to be addressed before an SSM can potentially pass as a surrogate model. We discuss the shortcomings of our models as well as paths forward in §6.1 and 6.2, and promising paths for other future research based on our insights from this paper in 6.3.

6.1 Results and Similarity

Human raters found the factual correctness of the NLEs produced by the SSMs to be very low compared to GPT-3.5 (§5.2). The low alignment between the outputs of SSM and GPT-3.5 as observed in §5.2 and §5.3 suggests that the faithfulness of the HGE is relatively low.

As we kept the setup for this paper straightforward, many simplifying assumptions and tradeoffs have been made, limiting the expressiveness on several ends: The hypothesis is kept simple, the

coverage of the preprocessing and the template-based NLE generation are limited, and the models used are not optimised. We expect that work on these fronts can substantially improve the model, especially given that our human raters found that a large share of GPT-3.5’s explanations follows a structure that relates subphrases from premise and hypothesis to each other (§4.2.1), as reflected in the assumption behind the HGE. Another indication that development time investments may pay off is a recent work by [Stacey et al. \(2023\)](#) who propose an interpretable model based on logical rules similar to what is stated to the HGE defined in this paper. The high performance on the NLI task this model achieves suggests that an adapted HGE that reflects their model could have a considerably higher overlap with GPT-3.5 predictions than our current SSMs.

6.2 Uniqueness of the surrogate model

We found that there was no unique surrogate model for our HGE. The room for interpretation given the HGE formulated in natural language allows us to deduce a large number of structures, two of which we implemented. We showed that our different interpretations of the HGE (our small and large SSM) lead to different implementations of the surrogate models. However, to fully account for the ambiguity of the HGE when estimating the faithfulness, all viable SSMs would need to be constructed and compared to the LLM outputs.

The small model that incorporates more inductive biases performed better and produced NLEs more similar to GPT-3’s. This may indicate that the large model relied on incorrect cues introduced by less relevant connections. If this applies, it indicates that even the training regime of the SSM is of high importance in order for it to correctly represent the HGE. As we did not employ regularisation strategies in the feed-forward networks that we train in the Bayesian Network, this could be a path forward for potential improvements.

6.3 Future Work

The SSMs tested in this paper do not show sufficient similarity with the original model yet. Apart from altering the model or hypothesis as discussed in §6.1 and §6.2, we see other directions for future research building on this paper:

Estimating the uncertainty of the faithfulness

As previously mentioned, it is typically not possible

to deduce one unique SSM from an HGE formulated in natural language. Consequently, there is uncertainty in the faithfulness estimation that is gained by comparing the outputs of the LLM with one single SSM. Future research could investigate how this uncertainty might be estimated. For example, the ambiguity of the HGE would need to be taken into account when estimating this uncertainty. Research on investigating vagueness and ambiguity of written text samples is already an active field of research ([Freitas et al., 2015](#); [Wang and Agichtein, 2010](#); [Bernardy et al., 2018](#)). How these metrics can be used as a statistical measure of the uncertainty of an HGE remains an open question.

Automatically deriving surrogate models We conducted a case study for how an SSM can be constructed for an example HGE when performing English-language NLI. However, our manual design has the consequence that in many cases, different SSMs need to be constructed for new tasks, languages and HGEs.⁵ Therefore, in contrast to methods like LIME ([Ribeiro et al., 2016](#)) that can be applied directly to any classifier, defining a generalised procedure for how to automatically construct suitable surrogate models is challenging and requires further research.

7 Conclusion

This paper suggests a framework for testing a hypothesis about the decision-making process of LLMs using Bayesian networks. We demonstrate how to construct a Bayesian network based on a hypothetical global explanation and how to evaluate the alignment of the LLM with this network. The framework intuitively implements the hypothesis as the Bayesian Network that it is based on can model our assumptions natively, and its random variables can be translated into natural language.

Our surrogates were however not similar to GPT-3.5, which can have two reasons: That the hypothesis itself does not accurately describe GPT-3.5’s behaviour and needs to be replaced or complemented by other hypotheses, or that simplifications we made in our implementation affected the performance and thereby also the similarity to GPT-3.5. We assume that we are dealing with a combination of the two reasons, and suggest that working on the identified issues can lead to more accurate surrogate models that can help us understand the behaviour of LLMs better.

⁵For a detailed discussion, we refer to §8.

8 Limitations

In this section, we address further limitations of our work and outline potential paths to overcome them in future work.

Task and Data Natural language inference with the e-SNLI dataset is a task that naturally fits into the framework of a Bayesian Network, as most explanations are heavily built on input phrases and implicitly follow template-like structures (Camburu et al., 2018). Many tasks, particularly such that include facts and commonsense reasoning not explicitly stated in the input, are substantially harder to model with such intuitive and simple structures.

SNLI (Bowman et al., 2015), the base dataset for e-SNLI, has been shown to include various annotation artefacts that models can rely on (Gururangan et al., 2018). While our focus is on the evaluation of the explanations and not on the performance on the prediction task and the Bayesian Network by design cannot pick up the cues stated in the paper, it cannot be excluded that such artefacts have had an influence on the results of our automatic evaluations. For future work, it may be worthwhile to also consider alternatives, such as the more diverse MNLI dataset (Williams et al., 2018), and include explicit tests for lexical and syntactic cues, e.g. with the HANS dataset (McCoy et al., 2019).

Language English-language systems cannot always be trivially adapted to other languages, particularly where orthographic system, syntax and morphology differ substantially (Munro and Manning, 2010). As a result, our structure may be a worse fit for other languages with different features. In any case, our rule-based preprocessing would need to be adapted. While MNLI (Williams et al., 2018) has been translated into a relatively diverse set of languages (Conneau et al., 2018), there are currently no human-annotated NLEs for this data set. As we work with few-shot prompts for generating the LLM’s explanations, this may however be overcome with relatively little work.

Human Evaluation Our human evaluation is conducted by a small set of annotators with a machine learning-related background and similar demographics. This is a common practice in NLP research, but it introduces sampling bias (van der Lee et al., 2019). While we do not explicitly ask for personal preferences, this may still affect their judgements and thereby the results of our evalu-

ation. A larger set of more diverse annotators, if feasible, is preferable.

Reproducibility We use GPT-3.5, a closed-source model by OpenAI that we only have API access to. Unfortunately, this limits our experiments’ reproducibility, as OpenAI may remove or restrict access to it in the future. At the time of writing, the GPT-3.5 model produced better-quality output for our purposes than its more open competitors. However, in recent months, an increasing number of high-quality LLMs is released to the public, such as various LLaMA (Touvron et al., 2023)-based models such as Alpaca (Taori et al., 2023) or the Pynthia (Biderman et al., 2023)-based Dolly model (Conover et al., 2023), paving the way for more reproducible LLM research.

Ethics Statement

As LLMs are trained on human data that can be biased, toxic, and immoral, they frequently produce unethical outputs (Liu et al., 2022; Abid et al., 2021; Bender et al., 2021). However, we use LLMs solely as an object of examination. This study aims at increasing the transparency and accountability of GPT-3.5, which can be a step in the direction of preventing LLMs from producing unethical outputs. That said, explainability techniques for models as large as current LLMs are only an approximation. We do not endorse any usage of LLMs for high-stake applications without humans in the loop, even as explainability research progresses.

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A Appendix

A.1 EM-Algorithm

E-Step

Given the observed variables X, Y , the hidden variable Z , and the parameters θ , the E-step of the EM-algorithm can be expressed in the following way:

$$\begin{aligned} Q(\theta|\theta^{(t)}) &= E_{Z|X,Y,\theta^{(t)}} [\log \mathcal{L}(X, Y, Z|\theta)] \\ &= E_{Z|X,Y,\theta^{(t)}} \left[\sum_{i=1}^n \log P(x_{(i)}, y_{(i)}, Z|\theta) \right] \\ &= \sum_{i=1}^n E_{Z|X,Y,\theta^{(t)}} [\log P(x_{(i)}, y_{(i)}, Z|\theta)] \quad (3) \\ &= \sum_{i=1}^n \sum_Z P(Z|x_{(i)}, y_{(i)}, \theta^{(t)}) \\ &\quad \cdot \log P(x_{(i)}, y_{(i)}, Z|\theta) \end{aligned}$$

In Equation 3, $x_{(i)}, y_{(i)}$ is the i -th observed realisation of the random vector X and Y respectively and n is the total number of observations. The summation over Z is performed over all possible states of the discrete random vector Z . As all valid probability distributions must sum up to one over their domain, we know that $\sum_Z P(Z|x_{(i)}, y_{(i)}, \theta^{(t)}) = 1$. This makes the expression $\sum_Z P(Z|x_{(i)}, y_{(i)}, \theta^{(t)}) \cdot \log P(x_{(i)}, y_{(i)}, Z|\theta)$ a weighted average for a given i where the weight is $P(Z|x_{(i)}, y_{(i)}, \theta^{(t)})$.

This means that we can approximate this weighted average by calculating the mean of $\log P(x_{(i)}, y_{(i)}, \tilde{Z}|\theta)$ where \tilde{Z} are Z samples from the distribution given by the weights (i.e. $P(Z|x_{(i)}, y_{(i)}, \theta^{(t)})$). Consequently we can approximate $Q(\theta|\theta^{(t)})$ as

$$Q(\theta|\theta^{(t)}) \approx \sum_{i=1}^n \frac{1}{s} \sum_{\tilde{Z}_{(i)}} \log P(x_{(i)}, y_{(i)}, \tilde{Z}_{(i)}|\theta) \quad (4)$$

where $\tilde{Z}_{(i)}$ are s sampled values from the distribution of $Z|x_{(i)}, y_{(i)}, \theta^{(t)}$. This distribution can be expressed as

$$\begin{aligned} P(Z|x_{(i)}, y_{(i)}, \theta^{(t)}) &= \frac{P(Z, y_{(i)}|x_{(i)}, \theta^{(t)})}{P(y_{(i)}|x_{(i)}, \theta^{(t)})} \\ &\propto P(Z, y_{(i)}|x_{(i)}, \theta^{(t)}) \\ &= P(y_{(i)}|Z, x_{(i)}, \theta^{(t)}) \\ &\quad \cdot P(Z|x_{(i)}, \theta^{(t)}) \\ &\text{Independence of } Y \text{ and } X, \theta \text{ given } Z \\ &= P(y_{(i)}|Z) \cdot P(Z|x_{(i)}, \theta^{(t)}) \quad (5) \end{aligned}$$

The distribution of $Y|Z$ was defined in Equation 2. The distribution of $Z|X, \theta^{(t)}$ is known assuming the current parameter estimate $\theta^{(t)}$ is the true parameter of the distribution. Furthermore, we know that $P(Y|Z)$ is either of value 0 or 1. We can therefore produce a sample \tilde{z} from $Z|X, Y, \theta^{(t)}$ by sampling from $Z|X, \theta^{(t)}$ and rejecting the sample

if $P(Y|\tilde{z}) = 0$. If the sample is rejected, we repeat the sampling process until a sample is accepted.

Let s be the number of samples we generated for each i from $Z|x_{(i)}, y_{(i)}, \theta^{(t)}$, n the number of observations in the dataset of x and y , and let \tilde{Z} be the collection of all $n \cdot s$ samples. Let \tilde{z}_j be the j -th sample in \tilde{Z} . We then produce s duplicates of each $x_{(i)}, y_{(i)}$ and define $x_{(j)}, y_{(j)}$ to be those datapoints x, y that were used to produce the sample \tilde{z}_j . Based on that definition, we can write Equation 4 as

$$\begin{aligned}
Q(\theta|\theta^{(t)}) &\approx \frac{1}{s} \sum_{j=1}^{n \cdot s} \log P(x_{(j)}, y_{(j)}, \tilde{z}_{(j)}|\theta) \\
&= \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(y_{(j)}, \tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)}|\theta)] \\
&\text{Independence of } X \text{ and } \theta \\
&= \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(y_{(j)}, \tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)})] \\
&= \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(y_{(j)}|\tilde{z}_{(j)}, x_{(j)}, \theta) \\
&\quad \cdot P(\tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)})] \\
&\text{Independence of } Y \text{ and } X, \theta \text{ given } Z \\
&= \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(y_{(j)}|\tilde{z}_{(j)}) \\
&\quad \cdot P(\tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)})] \\
&P(y_{(j)}|\tilde{z}_{(j)}) = 1 \text{ for the sampled } \tilde{Z}, \text{ because} \\
&\text{otherwise the sample got rejected} \\
&= \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(\tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)})]
\end{aligned} \tag{6}$$

M-Step

In the M-step, the estimation for θ is updated by setting $\theta^{(t+1)}$ to the value that maximises $Q(\theta|\theta^{(t)})$.

$$\begin{aligned}
\theta^{(t+1)} &= \arg \max_{\theta} Q(\theta|\theta^{(t)}) \\
&\text{With Equation 6} \\
&\approx \arg \max_{\theta} \frac{1}{s} \sum_{j=1}^{n \cdot s} \log [P(\tilde{z}_{(j)}|x_{(j)}, \theta) \cdot P(x_{(j)})] \\
&= \arg \max_{\theta} \sum_{j=1}^{n \cdot s} \log \left[\frac{P(\tilde{z}_{(j)}, x_{(j)}|\theta) \cdot P(x_{(j)})}{P(x_{(j)}|\theta)} \right] \\
&\text{Independence of } X \text{ and } \theta \\
&= \arg \max_{\theta} \sum_{j=1}^{n \cdot s} \log [P(\tilde{z}_{(j)}, x_{(j)}|\theta)] \\
&= \arg \max_{\theta} \log \mathcal{L}(\theta|\tilde{Z}, X)
\end{aligned} \tag{7}$$

From Equation 7 we can see that the M-step amounts to maximising the log-likelihood of the

parameter θ with respect to the sampled values \tilde{Z} and the given realisations of the random vector X . This in return means that, in the E-step, it suffices to produce the samples \tilde{Z} that are needed in the M-step.

Since all elements $z_{k,l} \in \mathcal{Z}$ are independent of each other given X , the parameters θ can be separated between each distribution $z_{k,l}|X$ and are called $\theta_{k,l}$. With Equation 7 it follows that

$$\theta_{k,l}^{(t+1)} = \arg \max_{\theta} \log \mathcal{L}(\theta|\tilde{z}_{k,l}, X) \tag{8}$$

A.2 SSM Explanation Templates

Conditions	Template
$Y = \text{contradiction}$ $z_{k,l} = \text{contradiction}$ $k = l$	" $x_{1,k}$ is not the same as $x_{2,l}$ "
$Y = \text{contradiction}$ $z_{k,l} = \text{contradiction}$ $k \neq l$	"If the subphrase _{k} of sentence 1 is $x_{1,k}$, then the subphrase _{l} of sentence 2 cannot be $x_{2,l}$ "
$Y = \text{entailment}$ $z_{k,l} = \text{entailment}$ $k = l$	" $x_{1,k}$ is the same as $x_{2,l}$ "
$Y = \text{entailment}$ $z_{k,l} = \text{entailment}$ $k \neq l$	"If the subphrase _{k} of sentence 1 is $x_{1,k}$, then the subphrase _{l} of sentence 2 has to be $x_{2,l}$ "
$Y = \text{neutral}$ $z_{k,l} \neq \text{entailment} \forall k$	"There is no indication that the subphrase _{l} of sentence 2 is $x_{2,l}$ "

Table 3: Templates for the explanations of the SSM predictions. subphrase _{i} is "Subject" for $i = 1$, "Verb" for $i = 2$, "Object" for $i = 3$, "Location" for $i = 4$, and "Clothing" for $i = 5$.

e

A.3 Instructions for Evaluating free-text Explanations

Background

1. Evaluation of GPT-3.5 Explanations

Please answer the following questions for each of the provided explanations produced by GPT-3.5. If not stated otherwise, mark the respective answer column in the evaluation template with 1 if the question is answered with yes.

- Subphrases:** If any, which subphrases are mentioned in the explanation? Possible subphrases are subject, verb, object, clothing, and location either of sentence one or sentence two. Mark the answer column for the respective subphrase with 1 if the subphrase is mentioned in the explanation.

2. **Structure:** Does the explanation describe the relationship between subphrases? This question should also be answered with yes if the explanation makes a statement about the relationship between subphrases that are not mentioned in question 1.
3. **Support:** Does the explanation justify the predicted label? i.e. given that the explanation is true, is the predicted label correct?
4. **Correctness:** Is the explanation factually correct? i.e. given your experience about our world and given the statements in sentence one and sentence two, is the explanation true?

2. Evaluation of SSM Explanations

There are explanations and predictions provided for two different versions of the statistical surrogate model (SSM). The first SSM's predicted labels and explanations are marked with subscript "large" and the predicted labels and explanations produced by the second SSM are marked with subscript "small". Please answer the following question for each of the provided explanations produced by the large and by the small SSM.

1. **Overall Correctness:** Is the explanation factually correct given the premise and hypothesis? i.e. given your experience about our world and given the statements in sentence one and sentence two, is the explanation true?
2. **Subphrase Correctness:** Is the explanation factually correct given the subphrases? i.e. given your experience about our world and given the subphrases extracted from sentence one and sentence two, is the explanation true?

A.4 Examples for SSM Output

1. **Premise:** A young woman sits crosslegged beside her purse on the grass among a crowd of dogs.
Hypothesis: The woman is on the couch with the dogs.
NLE Small SSM: Grass is not the same as couch.
NLE Large SSM: Grass is not the same as couch.
2. **Premise:** Two men are shopping for orange juice.
Hypothesis: Two men are getting breakfast
NLE Small SSM: There is no indication that

the verb of sentence 2 is getting.

NLE Large SSM: There is no indication that the object of sentence 2 is breakfast.

3. **Premise:** A man tries to get himself into shape on a treadmill.

Hypothesis: A man exercising.

NLE Small SSM: Man is the same as a man and get is the same as exercising and if the location of sentence 1 is treadmill, then the verb of sentence 2 has to be exercising.

NLE Large SSM: There is no indication that the subject of sentence 2 is a man and there is no indication that the verb of sentence 2 is exercising.

Align before Attend: Aligning Visual and Textual Features for Multimodal Hateful Content Detection

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Abstract

Multimodal hateful content detection is a challenging task that requires complex reasoning across visual and textual modalities. Therefore, creating a meaningful multimodal representation that effectively captures the interplay between visual and textual features through intermediate fusion is critical. Conventional fusion techniques are unable to attend to the modality-specific features effectively. Moreover, most studies exclusively concentrated on English and overlooked other low-resource languages. This paper proposes a context-aware attention framework for multimodal hateful content detection and assesses it for both English and non-English languages. The proposed approach incorporates an attention layer to meaningfully align the visual and textual features. This alignment enables selective focus on modality-specific features before fusing them. We evaluate the proposed approach on two benchmark hateful meme datasets, *viz.* MUTE (Bengali code-mixed) and MultiOFF (English). Evaluation results demonstrate our proposed approach’s effectiveness with F1-scores of 69.7% and 70.3% for the MUTE and MultiOFF datasets. The scores show approximately 2.5% and 3.2% performance improvement over the state-of-the-art systems on these datasets. Our implementation is available at <https://github.com/eftekhar-hossain/Bengali-Hateful-Memes>.

Disclaimer: This paper contains hateful images that may be disturbing to some readers.

1 Introduction

Recently, online platforms are witnessing an emerging trend of propagating hateful and offensive content. While most research in this area has focused on detecting hate speech from text-based content (Waseem and Hovy, 2016; Schmidt and Wiegand,



Figure 1: Example of hateful memes. In isolation, neither the image nor the caption may appear hateful, but when combined, they can convey a hateful message.

2017), offensive multimodal content is also propagated, such as memes. Memes are images or screenshots with short texts embedded in them. Their sarcastic nature made them an increasingly popular tool for spreading hate and targeting individuals or communities based on various factors such as gender, race, ethnicity, religion, physical appearance, and sexual orientation (Williams et al., 2016; Chhabra and Vishwakarma, 2023). The proliferation of such content poses a significant threat to communal harmony and social stability and has therefore become an area of active research interest (Cao et al., 2022; Pramanick et al., 2021).

Multimodal hateful content detection requires a holistic understanding of visual and textual information. When considered separately, the image and caption components in Figure 1(a) may seem innocuous. The image portrays two women—one wearing a hijab and the other without and the caption states, “abnormal and normal”. However, as a meme, this composition can be seen as derogatory towards the woman wearing the hijab by labeling her as abnormal. Similarly, the meme in Figure 1(b) insults the marriage of two South Indian celebrities by indicating their age gap in the text. Thus, focusing only on the image or the text is inadequate for complete understanding. Sometimes without the background information of the people and events used in a meme, it is difficult to interpret the meaning because the captions are short, fragmented, and

*Denotes equal contribution

sarcastic. Studies have demonstrated that off-the-shelf multimodal systems, which are typically effective in performing various visual-linguistic tasks, encounter difficulties when it comes to detecting hateful memes (Kiela et al., 2020; Cao et al., 2022). Furthermore, the current state-of-the-art systems (Lee et al., 2021; Pramanick et al., 2021) for detecting hateful memes face limitations when applied to resource-constrained languages. This is primarily because several key components within their architectures are not accessible or well-supported in other languages. These challenges underscore the need for language-specific adaptations to address hateful meme detection in a broader linguistic context effectively.

To address this knowledge gap, we present a solution for detecting multimodal hateful memes. The approach leverages an attention-based context-aware fusion framework to create coherent multimodal representations. We hypothesize that by aligning visual and textual features before fusion, the network can better capture essential cues for accurate classification. The key challenge lies in effectively incorporating modality information to enable the network to focus on crucial features. Previous methods (Pramanick et al., 2021; Lee et al., 2021) used background context and additional captions while performing the fusion. In contrast, our approach introduces an attention layer to align modalities which simultaneously facilitates the extraction of contextual representations from both visual and textual modalities. Moreover, without adding external knowledge, the model’s learning capability is augmented when the aligned representations are combined with modality-specific (i.e., visual, textual) features. To evaluate our approach, we conducted experiments on two benchmark datasets in different languages: MUTE (Hossain et al., 2022c) and MultiOFF (Suryawanshi et al., 2020). The evaluation results and ablation study demonstrate the effectiveness of our solution over baseline and state-of-the-art methods.

The major contributions of this paper are three-fold: (i) develop an attention framework that effectively attends the contributing features of visual and textual modalities to detect multimodal hateful memes (Section 3.1); (ii) conduct an extensive evaluation on two different benchmark datasets on real-world memes to demonstrate the effectiveness of the proposed solution (Section 4.3, 4.5); and (iii) perform ablation studies in different settings to examine

the impact of BERT-base embeddings in detecting hateful memes while also investigate the model’s quantitative and qualitative errors to understand its limitations (Section 4.4, 4.4).

2 Related Work

Hateful Content Detection: Over the past few years, offensive/hate speech detection has received a significant amount of attention from researchers. Some works focused on developing new corpus for different languages (Lekea and Karampelas, 2018; Roy et al., 2022) while others studied to develop novel methods (Li and Ning, 2022; Mozafari et al., 2020a). However, most of the studies focused on hateful content detection from textual data and overlooked the multimodal aspects of the user-generated data. One such multimodal data is a meme, which combines both images and text. With the flourishing of internet memes and because of their detrimental impact on society, online hateful meme classification got a considerable amount of traction from the research community (Das et al., 2020; Cao et al., 2022) lately. Suryawanshi et al. (2020) and Kiela et al. (2020) introduced hateful memes dataset in English. Besides developing datasets in English, few works attempted to introduce hateful memes datasets for low-resource languages such as Bengali (Hossain et al., 2022c).

Multimodal Fusion: Over the years, various techniques have been applied to detect multimodal hateful memes. Conventional fusion (Vijayaraghavan et al., 2021; Gomez et al., 2020) by concatenating the modality-specific information is the most commonly used method for learning multimodal representation. Some works employed bilinear pooling (Chandra et al., 2021) while others fine-tuned transformers (Kiela et al., 2020) based architectures such as ViLBERT, MMBT, and Visual-BERT. Besides, some works attempted to use disentangled learning (Lee et al., 2021) and incorporate image captioning (Zhou et al., 2021) to improve the hateful memes detection performance. Recently, Cao et al. (2022) applied prompting techniques for hateful meme detection in English. To the best of our knowledge, no one has attempted to align the visual and textual features for hateful meme detection. Nonetheless, feature alignment is key in creating a successful multimodal representation (Zeng et al., 2022; Liu et al., 2019). This work aims to address this research gap by introducing an alignment technique for hateful meme detection.

Overall our work differs from the existing studies in several significant ways: (i) rather than using additional context with conventional (i.e., early, late) fusion for multimodal representation, we align the visual and textual features using attention before fusing them, (ii) Existing models are primarily designed for English and challenging to adapt for languages like Bengali. This work presents a model that uses alignment and can be adapted for any language by swapping out language-specific components, and (iii) evaluation is performed on real-world meme dataset (*MUTE*, *MultiOFF*) rather than the synthetic memes as in [Kiela et al. \(2020\)](#).

3 Method

Memes comprise two modalities (i.e., visual and textual); logically, one modality’s content can outweigh another’s content during prediction. Besides, not all the information from both modalities has an equal effect on determining whether a meme is hateful. We propose a context-aware fusion framework that selectively focuses on modality-specific information to model this complex relationship. The proposed network takes multimodal input and feeds the visual information to a CNN and textual information to an RNN for feature extraction. Then we calculate alignment weights over the visual and textual features through the attention layer. The objective is to capture the contributing features with higher weights by emphasizing both modalities. Subsequently, these alignment weights are utilized to create multimodal contextual representation. Finally, the resulting contextual and modality-specific representations are combined and passed to the softmax layer for classification. We denote our proposed architecture as **Multimodal Context Aware - Skip Connected Fusion (MCA-SCF)** framework. An overall architecture of the framework is presented in [Figure 2](#).

To ensure the robustness of the architecture, we experiment with three other variants of the proposed MCA-SCF framework: a) *Vision Guided Contextual Fusion (VGCF)* framework; b) *Text Guided Contextual Fusion (TGCF)* framework; and c) *Multimodal Contextual Fusion (MCF)* framework. The architecture of these variants differs in context vector computation and information fusion. In *VGCF*, we compute contextual information concerning the visual information and fuse it with the textual features. On the other hand, in *TGCF*, the

contextual information is computed with respect to textual features and integrated with the visual features. In contrast, we compute the context for both modalities and then combine them in *MCF*. The rest of the components for all the architectures remain the same. The details of the variants *VGCF*, *TGCF*, *MCF* can be found in [Appendix A](#).

3.1 Proposed (MCA-SCF) Architecture

The *MCA-SCF* framework consists of several components described in the following subsections.

3.1.1 Preprocessing

Before feeding the data into the framework, we preprocess the visual (v) and textual (t) modality. For v , we resize the images to $150 \times 150 \times 3$ and transform the pixel values between 0 to 1 to reduce the computational complexity. On the other hand, we remove unwanted characters (i.e., symbols, URLs, numbers, etc.) from textual data. Then we encode each word with a unique number and make all the text lengths equal to size l , where $l=60$.

3.1.2 Visual and Textual Feature Extractor

We employ a pre-trained CNN (ResNet50) to obtain the visual features from the memes. We use ResNet50 because of its capability to address the vanishing gradient problem and effectiveness in several multimodal classification tasks ([Hossain et al., 2022a,b](#)). To adjust ResNet50, we exclude the top two layers from the main architectures and utilize the weights of the higher-level features previously trained on the ImageNet ([Deng et al., 2009](#)) dataset. We add a global average pooling layer followed by a dense layer and retrain the architecture with new weights. The following equation computes the visual features.

$$V_f = Relu \left(\sum_k^d W_{jk} * G_k + b_j \right) \quad (1)$$

Here, $V_f \in \mathbb{R}^{1 \times d}$ represents the visual semantic features extracted by the ResNet50 for the m^{th} memes visual modality (v). Here, d represents the number of neurons (100) in the dense layer. And, G represents the feature map generated by the global average pooling layer while W and b represent the weight matrix and bias respectively.

We employ Recurrent Neural Network to extract both word-level and sentence-level textual features. Specifically, we use Bidirectional Long Short Term Memory (BiLSTM) network to capture the contextual dependency of the words. Initially, we generate

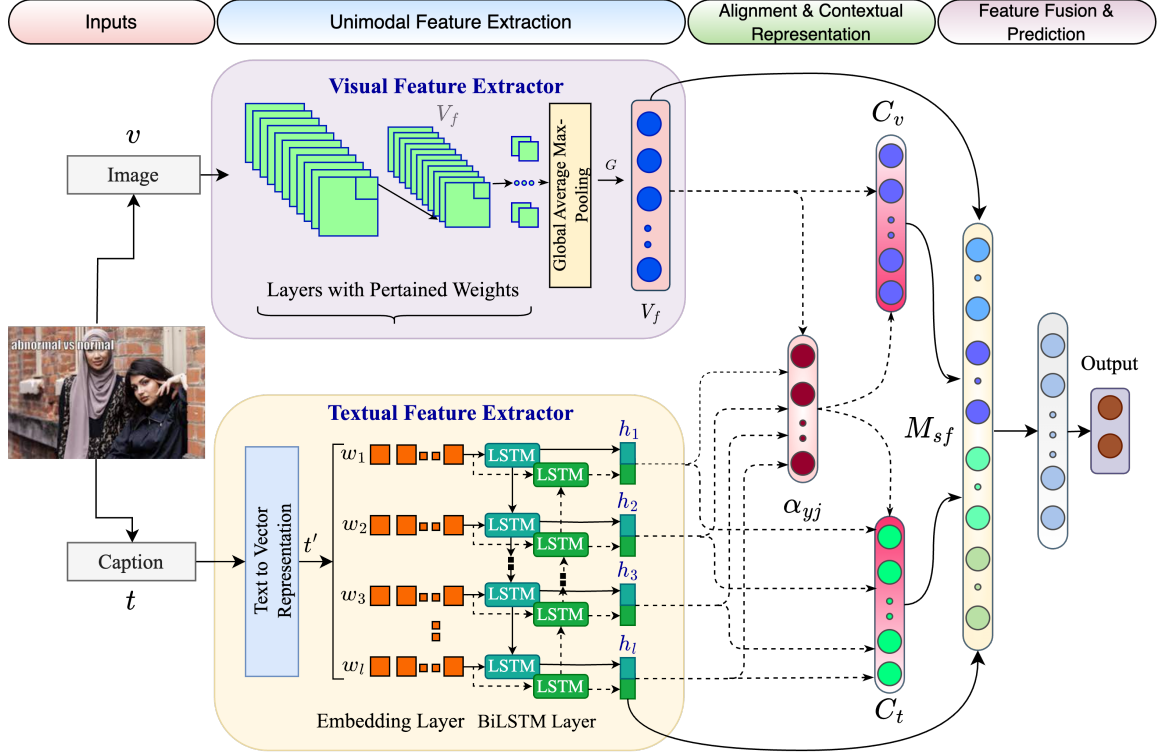


Figure 2: Our proposed context-aware multimodal architecture: v and t are the processed image and its corresponding caption. The upper block represents the visual feature extractor, and the lower block is the textual feature extractor. Alignment scores (α_{yj}) are calculated by applying attention on visual (V_f) and textual ($h_1 \dots h_l$) features. Subsequently, visual (C_v) and textual (C_t) context vectors are created by aligning (V_f) and ($h_1 \dots h_l$) through alignment vector (α_{yj}). Finally, by concatenating these context vectors (C_v, C_t) with modality-specific features (V_f, h_l) our method creates the multimodal context-aware representation M_{sf} .

the embedding vectors that give a semantic meaning to each word. The embedding dimension size is set to (64). The embedding vectors are passed to a BiLSTM which can keep the contextual dependency of the word vectors of t . The output of the BiLSTM network is generated by concatenating the forward and backward LSTM cell's output. It gives a word-level feature vector for every k^{th} time step. The final time step (l^{th}) output is the sentence-level feature vector that we will use during the fusion operation. The features are computed using the following equation.

$$h_j^{[k]} = \vec{h}_j \oplus \overleftarrow{h}_j \quad (2)$$

Here, $h_j^{[k]} \in \mathbb{R}^{1 \times 2N}$ and $h^{[l]} \in \mathbb{R}^{1 \times 2N}$ respectively denote the BiLSTM word-level and sentence level feature generated for j^{th} word in the k^{th} layer or time step. l is padding length and N is the number of hidden units (50) in the LSTM cell. The \oplus represents the concatenation. All the hyper-parameter values are selected via trial and error fashion by monitoring the validation accuracy.

3.1.3 Alignment and Fusion

Unlike existing approaches that employ early or late fusion techniques for multimodal representation, we align the visual and textual features through attention before joining them. Inspired from (Xu et al., 2015) we apply the additive attention (Bahdanau et al., 2014) mechanism to develop the alignment model. The model assigns a score $\alpha_{y,j}$ to the world-level feature of the j^{th} time step and the visual feature, V_f . The set of weights $\alpha_{y,j}$ determines how much image and text level features are aligned to predict a particular class label (y). The alignment score, α is parameterized by a feed-forward network where each feature vector (i.e., visual and textual) is trained with separate weights. The score function is therefore in the following form, given that \tanh is used as the non-linear activation function:

$$\alpha(V_f, h_j) = v_a^T \tanh(W_1 * V_f + W_2 * h_j) \quad (3)$$

$$\alpha_{y,j} = \frac{\exp(\alpha(V_f, h_j))}{\sum_{j=1}^l \exp(\alpha(V_f, h_j))} \quad (4)$$

After performing the softmax operation (4), we obtain the normalized alignment scores, where higher weights are assigned to the feature combinations that are important for the prediction (y). Here, v_a , W_1 , and W_2 are the weight matrices to be learned by the alignment model.

Afterward, we use these alignment scores to generate context vectors for each modality. The intuition behind this is that not all the features of individual modality are equally important for classification. Thus, focusing only on the significant feature is the key to better prediction. The following equation is computed for the context vectors.

$$C_v = \sum_j \alpha_{y,j} * V_f \quad (5)$$

$$C_t = \sum_j \alpha_{y,j} * h_j \quad (6)$$

Here, $C_v \in \mathbb{R}^{1 \times d}$ and $C_t \in \mathbb{R}^{1 \times d}$ are referred to as the vision-guided and text-guided context vectors, respectively. These vectors keep the contextual and significant modality-specific information concerning both visual and textual modalities.

The context vectors are concatenated to generate a context-aware multimodal representation. Furthermore, inspired by the residual learning (He et al., 2016) we concatenated each modality feature along with this contextual representation. The idea is to boost the gradient flow to the lower layer and enhance the multimodal representation. The following equation can express the combined feature representation.

$$M_{sf} = C_v \oplus C_t \oplus V_f \oplus h^{[l]} \quad (7)$$

Here, $M_{sf} \in \mathbb{R}^{1 \times 4d}$ represents the contextual multimodal representation. This combined feature vector is then passed for the classification.

4 Experiments and Results

In this section, we first describe the datasets and the evaluation settings. We discuss the baselines and their results in comparison with the proposed method. Moreover, we conduct an ablation study to show how replacing components of the *MCA-SCF* framework affects the performance. Subsequently, an error analysis will be provided to understand the model’s error. Furthermore, we perform a cross-domain analysis to see how the proposed framework performs irrespective of language variation in a zero-shot setting (Appendix C).

4.1 Datasets

We train and evaluate our proposed approach on two benchmark multimodal datasets: the Multimodal Bengali Hateful Memes (MUTE) and a popular English Memes (MultiOFF) dataset. Due to the unavailability of datasets, we limited our performance assessment on these datasets. For this work we only consider real-world memes and avoid synthetic datasets (Kiela et al., 2020). Table 1 presents the distribution of the datasets.

Dataset	Class	Train	Validation	Test
MUTE	Hate	1275	152	159
	Not-Hate	2092	223	257
MultiOFF	Offense	187	59	59
	Not-Offense	258	90	90

Table 1: Distribution of MUTE and MultiOFF datasets.

MUTE (Hossain et al., 2022c): A hateful memes dataset for the Bangla language. It consists of 4158 memes where the captions are code-mixed (Bangla + English) in nature. Among 4158 memes, 1586 are hateful and the rest of them are not hateful. We use the exact train-test split adopted by the authors to compare with our proposed approach.

MultiOFF (Suryawanshi et al., 2020): The MultiOFF consists of a total of 743 memes collected based on the US presidential election. The authors labeled the memes into the *offensive* category. However, these memes can be considered hateful since they substantially overlap with the hatred category and contain derogatory/abusive content targeted toward a group of people. The training, validation, and test set contain 445, 149, and 149 memes.

We adopt the evaluation metrics from the previous works in hateful meme classification (Lee et al., 2021). The superiority of a model is determined based on the weighted F1-score. Besides, weighted precision, recall, and Area Under the Receiver Operating Characteristics (AUC) scores have been reported for comparison. The details of the experimental settings are discussed in Appendix B.

4.2 Baselines

We develop several baselines considering the unimodal (i.e., image or text) and multimodal information. The baseline models are chosen based on the best-performing models on these datasets (*MUTE*, *MultiOFF*) and popular techniques from the existing literature. The model’s hyperparameters are chosen via a trial-and-error approach by monitoring

the validation accuracy. The baseline architectures are described in the following subsections.

4.2.1 Unimodal Models

Initially, we implemented models considering only the visual modality. We use the **ResNet50** network where we fine-tuned and retrained it with new weights. The architecture configuration kept the same as described in Section 3.1.2. Besides, we also fine-tuned the **Vision Transformer (ViT)** (Dosovitskiy et al., 2020) architecture on both datasets. On the other hand, for textual modality, we employed several architectures including **BiLSTM** (Baruah et al., 2019), **BiLSTM + Attention** (Altm et al., 2019), **BERT** (Mozafari et al., 2020b), and **XLM-R** (Ranasinghe and Zampieri, 2020). In one architecture we use an LSTM cell with 32 hidden units. Subsequently, the attention mechanism is added with the LSTM in another architecture. We use the language-specific variation of the BERT (i.e., **Bangla BERT** (Sarker, 2020) and **English-BERT** (Devlin et al., 2018)), the multilingual BERT (**m-BERT**), and cross-lingual BERT (**XLM-R**) for our task. We freeze the weights of these architectures and retrain them with new weights by adding a dense layer of 100 neurons. The dense layer takes the sentence embeddings as input and makes a higher-level representation of the text. Finally, this representation is passed to the classification layer for prediction.

4.2.2 Multimodal Models

To develop the models using multimodal information, we use the most popular fusion techniques including **Early Fusion** (Pranesh and Shekhar, 2020), **Late Fusion** (Hossain et al., 2022b), and **Attentive Fusion** (Sharma et al., 2022). We select the best-performing unimodal models (ResNet50 and LSTM) for visual and textual feature extraction.

- For early fusion, a dense layer of 100 neurons is added at both ends of individual modalities to make a joint representation by concatenating them.
- In late fusion, the classification layer’s output from each modality is combined and then passed for the classification.
- With attentive fusion, the last dense layer’s output is passed to an attention layer, and then the resulting attentive vector is used for classification.

Finally, we employed several state-of-the-art multimodal architectures including **VisualBERT-COCO** (Li et al., 2019), **CLIP** (Radford et al., 2021), and **ALBEF** (Li et al., 2021) and fine-tuned them on our datasets.

4.3 Results

Table 2 presented the outcome of the baselines and proposed method over the test set of *MUTE* and *MultiOFF* datasets. In *MUTE*, the visual models (ResNet50 and ViT) failed to obtain a satis-

Approach	Models	MUTE				MultiOFF			
		P	R	WF	AUC	P	R	WF	AUC
Unimodal	ResNet50 (FT)	0.634	0.646	0.631 \pm 0.00	0.598 \pm 0.01	0.624	0.637	0.623 \pm 0.02	0.593 \pm 0.01
	ResNet50 (RT)	0.617	0.634	0.614 \pm 0.02	0.580 \pm 0.03	0.580	0.557	0.562 \pm 0.08	0.559 \pm 0.01
	ViT	0.622	0.639	0.584 \pm 0.03	0.557 \pm 0.02	0.603	0.624	0.559 \pm 0.06	0.542 \pm 0.02
	BiLSTM	0.660	0.670	0.658 \pm 0.02	0.626 \pm 0.02	0.611	0.604	0.606 \pm 0.02	0.591 \pm 0.01
	BiLSTM + Attention	0.659	0.622	0.627 \pm 0.02	0.636 \pm 0.01	0.577	0.597	0.578 \pm 0.02	0.548 \pm 0.01
	BERT	0.645	0.658	0.642 \pm 0.08	0.609 \pm 0.06	0.621	0.617	0.610 \pm 0.01	0.611 \pm 0.09
	m-BERT	0.627	0.644	0.620 \pm 0.02	0.586 \pm 0.01	0.584	0.611	0.574 \pm 0.02	0.547 \pm 0.07
	XLM-R	0.646	0.656	0.648 \pm 0.04	0.618 \pm 0.01	0.612	0.630	0.580 \pm 0.01	0.557 \pm 0.08
Multimodal	Early Fusion	0.634	0.649	0.607 \pm 0.02	0.575 \pm 0.01	0.646	0.657	0.645 \pm 0.02	0.616 \pm 0.06
	Late Fusion	0.619	0.634	0.619 \pm 0.02	0.586 \pm 0.00	0.738	0.657	0.568 \pm 0.01	0.563 \pm 0.07
	Attentive Fusion	0.660	0.637	0.642 \pm 0.00	0.641 \pm 0.02	0.610	0.624	0.538 \pm 0.03	0.532 \pm 0.06
	VisualBERT COCO	0.494	0.572	0.530 \pm 0.04	0.521 \pm 0.01	0.396	0.689	0.503 \pm 0.07	0.502 \pm 0.05
	CLIP	0.643	0.641	0.560 \pm 0.06	0.545 \pm 0.07	0.646	0.651	0.601 \pm 0.05	0.576 \pm 0.03
	ALBEF	0.679	0.667	0.668 \pm 0.06	0.677 \pm 0.02	0.612	0.617	0.613 \pm 0.04	0.610 \pm 0.04
Proposed System and Variants	VGCF	0.671	0.677	0.671 \pm 0.02	0.644 \pm 0.02	0.651	0.624	0.628 \pm 0.03	0.632 \pm 0.04
	TGCF	0.662	0.665	0.663 \pm 0.01	0.641 \pm 0.01	0.667	0.651	0.655 \pm 0.01	0.651 \pm 0.01
	MCF	0.692	0.699	0.689 \pm 0.02	0.659 \pm 0.01	0.654	0.657	0.655 \pm 0.05	0.635 \pm 0.04
	MCA-SCF (Proposed)	0.696	0.696	0.697\pm0.00	0.674 \pm 0.01	0.702	0.704	0.703\pm0.02	0.686 \pm 0.03

Table 2: Performance comparison of unimodal and multimodal models on test set where P, R, WF, and AUC denote precision, recall, weighted F1-score, and area under the receiver operating characteristics curve respectively. VGCF, TGCF, and MCF are the variants of the proposed MCA-SCF approach. The FT and RT represent the fine-tuned and retrained version of ResNet50, respectively. The standard deviation (\pm) with five different random seeds is also reported. For space constraints, the score is not shown for precision and recall.

factory outcome, while among the textual models, BiLSTM achieved the highest F1-score of 0.658. Surprisingly, the performance of the pre-trained transformers is lower than BiLSTM. We perform a detailed ablation study to get more insights on this. Meanwhile, when multimodal information is integrated, the attentive fusion approach achieved the highest F1 (0.642) and AUC (0.641) scores compared to its counterparts (i.e., early and late fusion). Among the other multimodal architectures (i.e., VisualBERT, CLIP, and ALBEF), ALBEF showed outstanding performance with an F1 score of 0.668. However, we observed that the variants (VGCF, TGCF, and MCF) of the alignment approach obtained superior performance over the unimodal and other multimodal models except ALBEF. Even though they achieved better outcomes, the proposed MCA-SCF framework outperformed all the models by getting the highest F1 score of 0.697.

In *MultiOFF* dataset, BERT achieved the highest F1-score of 0.610 amid the unimodal models. On the other hand, early fusion showed significantly higher performance (0.645) compared to late fusion (0.568), attentive fusion (0.538), and other multimodal architectures such as VisualBERT (0.503), CLIP (0.601), and ALBEF (0.613). We noticed that the performance is substantially improved with the variants. Nonetheless, MCA-SCF outperforms all the models, obtaining the highest F1 score of 0.703 and AUC score of 0.686.

In summary, the proposed *MCA-SCF* framework and its variants outperformed the baselines in both datasets. Aligning the visual and textual information before fusing them played a crucial role in boosting the model’s predictive performance.

4.4 Ablation Study

In addition to the experiments emphasizing the importance of context-aware multimodal representation for hateful meme classification in Table 2, we also examine the effect of contextualized embeddings in MCA-SCF instead of simple word embeddings. We consider three transformer models i.e., language-specific BERT, multilingual BERT, and XLM-R. We employed the architecture with similar parameters described in Section 4.2.1. Two individual models were developed for each transformer architecture. Firstly, BERT word level and sentence level embeddings were used to develop MCA-SCF whereas in the second case, contextu-

Models	MUTE		MultiOFF	
	WF	AUC	WF	AUC
MCA-SCF w/ BERT + BiLSTM	0.657	0.634	0.571	0.542
MCA-SCF w/ only BERT	0.649	0.637	0.612	0.586
MCA-SCF w/ m-BERT + BiLSTM	0.645	0.622	0.613	0.589
MCA-SCF w/ only m-BERT	0.665	0.676	0.575	0.551
MCA-SCF w/ XLM-R + BiLSTM	0.615	0.582	0.525	0.501
MCA-SCF w/ only XLM-R	0.661	0.627	0.540	0.513

Table 3: Effect on the proposed method performance when replacing the text model with various transformer architectures.

alized embeddings were passed to an LSTM layer and utilized the LSTM word level features with the contextualized sentence embeddings to construct MCA-SCF. The training parameters of the models were kept the same as discussed in Appendix B. Table 3 reported the outcomes when contextualized embeddings are used. We observed that, in the case of *MUTE*, MCA-SCF with m-BERT obtained the highest F1 score (0.665), whereas MCA-SCF with m-BERT + BiLSTM achieved the maximum F1 score (0.613) in *MultiOFF* dataset.

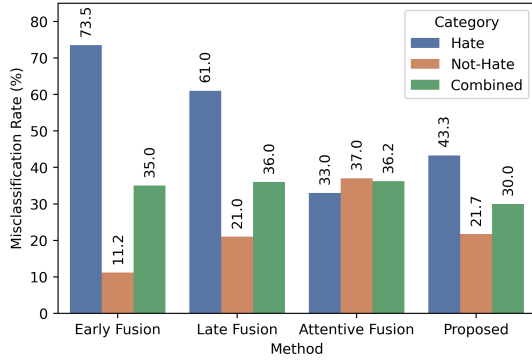
The findings reveal that there is no significant effect of using the BERT-based models for hateful meme detection. Even the BERT-based model outcomes are lower than the variants of the proposed method. Therefore, it can be stated that contextualized embeddings are not suitable for hateful meme detection. The reason behind this lower performance could be the fact that the memes’ captions are very different from regular texts. BERT-based models are typically trained on longer and more complete textual inputs, whereas the language used in meme captions is often short, fragmented, and sarcastic. This discrepancy in language style can cause this suboptimal performance.

4.5 Comparison with Existing Studies

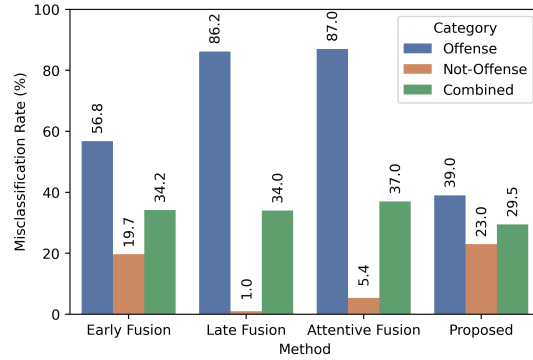
Table 4 presents the performance comparison of the proposed method with the existing state-of-the-art systems on the datasets. In *MUTE*, our proposed multimodal framework achieves the best F1 score

Dataset	Approaches	WF (%)
MUTE	Hossain et al. (2022c)	67.2
	Proposed	69.7
MultiOFF	Suryawanshi et al. (2020)	54.0
	Lee et al. (2021)	64.6
	Hossain et al. (2022d)	66.7
	Zhong et al. (2022)	67.1
	Proposed	70.3

Table 4: Comparative analysis of the proposed method with the existing state-of-the-art systems.



(a) MUTE



(b) MultiOFF

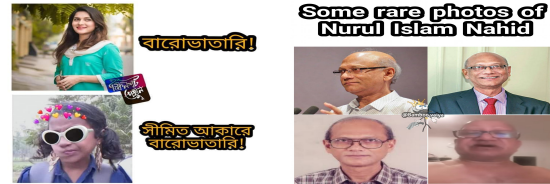
Figure 3: Misclassification rate comparison between various fusion approaches (i.e., early, late, attentive) and proposed (MCA-SCF) method on both datasets.

of 69.7% (\uparrow 2.5%) as compared to the existing highest score of 67.2%. Likewise, for *MultiOFF* dataset, we obtain the highest F1 score of 70.3% (\uparrow 3.2%) beating the current state-of-the-art system (67.1%). The performance improvement in both datasets’ indicates our proposed method’s novelty.

4.6 Error Analysis

We investigate the errors of the proposed MCA-SCF approach both quantitatively and qualitatively.

Quantitative Analysis: Early, late, and attentive fusion techniques have been considered to compare the errors with the proposed approach. We measured the Misclassification Rate (MR) for all the models reported in Figure 3. For *MUTE* dataset, we observed that the MR is reduced at 43.3% (proposed method) from 73.5% (early fusion) in *Hate* class while it is increased \approx 10% in *Not-Hate* class. However, the error rate in *Not-Hate* class is minimal with the early fusion approach, whereas for *Hate* class, the attentive fusion approach reduces the error most. To conclude, we computed the combined class error rate and found that the overall system’s error is the lowest (30%) with the proposed MCA-SCF method. Likewise, in *MultiOFF*, the proposed method achieves the lowest combined error rate of 29.5%. It is worth noting that the proposed model significantly reduces the error rate in negative classes, enabling effective detection of hateful memes. One interesting aspect observed is that the misclassification rate is higher in the Negative (*Hate* or *Offense*) class compared to the Positive (*Not-Hate* or *Not-Offense*) class across all approaches. This discrepancy could be attributed



(a) EF: Not-Hate (X)
AF: Not-Hate (X)
Proposed: Hateful (✓)

(b) Actual: Hateful
Predicted: Not-Hate

Figure 4: Example (a) shows a meme where the proposed method yields better predictions, and example (b) illustrates a wrongly classified sample. The symbol (✓) and (X) indicates the correct and incorrect prediction. EF and AF represent the early fusion and attentive fusion approaches, respectively.

to the uneven distribution of data, with fewer training samples in the negative classes. As a result, the model may have struggled to effectively learn visual and textual patterns, leading to incorrect predictions.

Qualitative Analysis: We also perform qualitative analysis by investigating model predictions on a few samples. For example, the meme in Figure 4 (a) was misclassified as *Not-Hate* by the early and attentive fusion approaches. However, the proposed method captures the image and textual features that represent the context of the meme and therefore can correctly predict them as *Hateful*. We also analyze where the proposed method failed to give accurate inferences. For instance, the model misclassified the meme shown in Figure 4 (b) as *Not-Hate* when the actual label is *Hate*. The reason for this misclassification could be the presence of consistent visual features “Bald Man” and the

absence of any trigger word in the text. Moreover, the model needs world-level knowledge to understand that this meme is demeaning the identity of a reputed person in Bangladesh. The above analysis shows that we need to explore more advanced reasoning modules to classify such memes accurately.

5 Conclusion

This paper presents *MCA-SCF*, a multimodal framework that aligns visual and textual features using attention to create a coherent contextual representation. The model aims to improve hateful content detection performance by leveraging contextual and modality-specific representations. We evaluate the model on two publicly available datasets i.e., *MUTE* and *MultiOFF*. Our extensive experiments demonstrate that *MCA-SCF* outperforms the state-of-the-art systems on these datasets. Furthermore, we conducted experiments with different variants of the model and performed an ablation study to ensure the system’s robustness. The ablation study reveals that general word embeddings are more suitable than contextualized embedding for multimodal hateful meme detection. Finally, the cross-domain analysis illustrates the model’s generalization capability in zero-shot settings.

Limitations

We identify several findings in this work. Firstly, we found that advanced multimodal models (e.g., CLIP, and VisualBERT) can not show satisfactory performance on both datasets. One compelling reason can be attributed that these models are not pretrained on enough Bengali image-text pairs and thus perform poorly when fine-tuning on the MUTE dataset. On the other hand, the lags in the performance in MultiOFF due to having fewer samples. As a result, the model does not get enough examples to learn complex relationships in the task and provides inferior performance. Besides that other advanced multimodal models (i.e., ALIGN, FLAVA, ViLBERT, BLIP) are rarely pretrained for Bengali image text pairs, limiting their applications in such low-resource languages. Therefore, we focus on enhancing the performance of off-the-shelf models with minimal computation by improving intermediate fusion through alignment. Our error analysis indicates that there is still significant room for improvement to effectively align visual and textual features for multimodal hateful content detection. Secondly, while the proposed model

can infer the implicit meaning of memes in certain cases, it still falls short in complex reasoning to comprehend the contextual nuances of memes with concise captions. Finally, due to the unavailability of real-world meme datasets, we limited our performance assessment to two benchmark datasets. In the future, we plan to apply the model to detect memes in similar domains like harm and aggression, demonstrating its robustness across diverse and challenging categories.

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Appendix

A Variants of MCA-SCF Framework

We develop three other variants of the *MCA-SCF* network namely *VGCF*, *TGCF*, and *MCF*. Figure A.1 shows the computation of the variants. The *VGCF* framework does not account for the context vector generated from the text modality. After aligning the visual and textual modalities, we used the obtained alignment score (α_{yj}) to highlight only the significant visual information and combined them with the sentence-level ($h^{[l]}$) textual feature. The VGC vector $V_{gf} \in \mathbb{R}^{1 \times 2d}$ can be expressed by the following equation.

$$V_{gf} = C_v \oplus h^{[l]} \quad (8)$$

On the other hand, with *TGCF* framework, we utilize the alignment score to generate a contextual representation (C_t) only for the text modality. This representation is then combined with the visual features (V_f) to compute the TGC vector $T_{gf} \in \mathbb{R}^{1 \times 2d}$ by the equation (9).

$$T_{gf} = C_t \oplus V_f \quad (9)$$

In the *MCF* framework, we combined the two context vectors (i.e., C_v and C_t) to make a contextual multimodal representation. The vector $M_{cf} \in \mathbb{R}^{1 \times 2d}$ can be expressed by the equation.

$$M_{cf} = C_v \oplus C_t \quad (10)$$

B Experimental Settings

We perform experiments on the Google Colab platform. The transformer architectures were downloaded from the huggingface library and implemented using the TensorFlow framework. All the models are compiled using *binary cross-entropy*

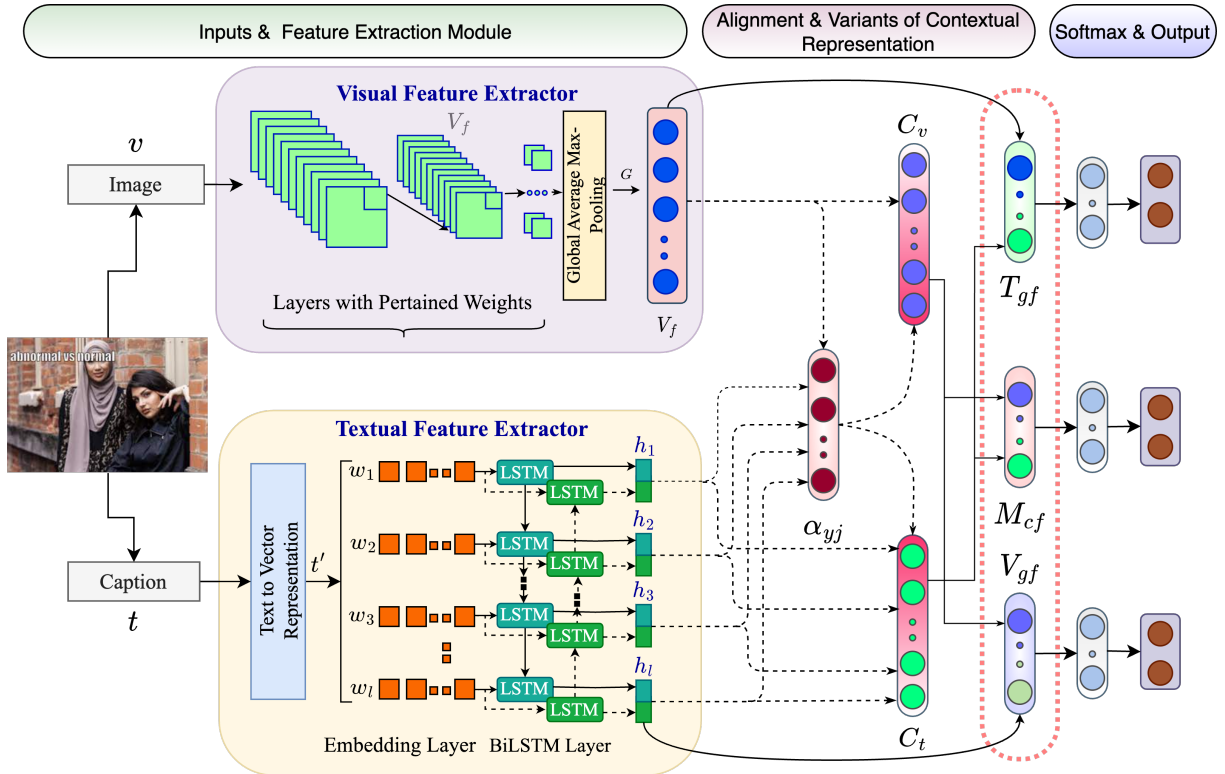


Figure A.1: Variants of the proposed MCA-SCF framework. The majority of the components remain the same as illustrated in figure 2. The three variants (V_{gf} , M_{cf} , T_{gf}) have differences in the way they integrate information to emphasize the context of a particular modality.

loss function. For all the models the error optimization is performed by the *Adam* optimizer with a learning rate of $1e^{-3}$ except for the transformer-based models which are $3e^{-5}$. We used the *batch size* of 16 and trained the models for 20 *epochs*. To save the best intermediate models during training Keras checkpoint method has been utilized.

C Zero-shot Cross-Domain Transfer

We examine the cross-domain transfer ability of the proposed method by training it on a source dataset and evaluating it on a target dataset. Besides, we also investigate the proposed method’s performance when the training is done on combined datasets but tested only on a particular dataset. We focus on examining the impact of captured phenomena between datasets. The cross-domain performance has been measured by the relative zero-shot transfer ability (Turc et al., 2021). We denoted it as the recovery ratio because it indicates the ratio of how much performance is recovered by changing the source domain and it is given as follows.

$$R(S, T) = \frac{F(S, T)}{F(T, T)} \quad (11)$$

Here, $F(S, T)$ is a model performance (i.e., f_1 -score) for the source domain S on the target domain T . If the source and target domains are the same, the R would be 1.0. The recovery scores of both zero-shot and combined dataset settings are given in Table C.1.

		Target	
		MUTE	Multi-OFF
Source	Zero-shot	MUTE	0.697 (84%)
		MultiOFF	0.527 (75%)
	Cross-domain	MT+MO (86%)	0.627 (90%)

Table C.1: Effect of the zero-shot and cross-domain transfer on both datasets. MT+MO indicates the combination of the MUTE and MultiOFF datasets. The major diagonal represents the actual performance, while the minor diagonal indicates how much performance is recovered when we change the source dataset.

In both settings, the recovery rate is comparatively higher when we evaluate on *MultiOFF* dataset and train using the *MUTE* dataset. For instance, in the zero-shot setting, the *MUTE* dataset 75% performance of 0.697 is recovered when the

source domain was the *MultiOFF* dataset. Similarly, we observed that 84% is the recovery rate on *MultiOFF* when *MUTE* is the source domain. On the other hand, with a combined setting, 86% and 90% performance is recovered of the *MUTE* and *MultiOFF* datasets. Overall, in zero-shot setting *MUTE* as a source dataset can mostly recover the performance from *MultiOFF*. This could happen because *MUTE* consists of code-mixed captions and has more training samples. This may allow for a greater transfer and sharing of multimodal features between datasets, ultimately contributing to the model’s strong performance on the *MultiOFF* dataset. Meanwhile, the proposed method can not generalize well on *MUTE* when trained with *MultiOFF* dataset. This is because the less number of training samples in *MultiOFF* and the model do not get any information about the Bengali language from the dataset. In contrast to its moderate generalization performance in the zero-shot setting, our proposed method demonstrates strong performance in the test set of each dataset when trained on the combined training set.

Topic-guided Example Selection for Domain Adaptation in LLM-based Machine Translation

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Abstract

Current machine translation (MT) systems perform well in the domains on which they were trained, but adaptation to unseen domains remains a challenge. Rather than fine-tuning on domain data or modifying the architecture for training, an alternative approach exploits large language models (LLMs), which are performant across NLP tasks especially when presented with in-context examples. We focus on adapting a pre-trained LLM to a domain at inference through in-context example selection. For MT, examples are usually randomly selected from a development set. Some more recent methods though select using the more intuitive basis of test source similarity. We employ topic models to select examples based on abstract semantic relationships below the level of a domain. We test the relevance of these statistical models and use them to select informative examples even for out-of-domain inputs, experimenting on 7 diverse domains and 11 language pairs of differing resourcedness. Our method outperforms baselines on challenging multilingual out-of-domain tests, though it does not match performance with strong baselines for the in-language setting. We find that adding few-shot examples and related keywords consistently improves translation quality, that example diversity must be balanced with source similarity, and that our pipeline is overly restrictive for example selection when a targeted development set is available.¹

1 Introduction

Adaptation of neural Machine Translation (MT) models to unseen domains remains a difficult problem because it requires handling out-of-distribution data at inference (Koehn and Knowles, 2017). Large language models (LLMs) offer an alternative method to the standard approach of fine-tuning an

MT model or selected layers therein (Luong and Manning, 2015; Bapna and Firat, 2019). Openly available models such as Llama-2 (Touvron et al., 2023) and explicitly multilingual models including BLOOM (BigScience Workshop et al., 2023) and XGLM (Lin et al., 2022) perform well cross-lingually in classification and generation tasks, including many-to-many translation despite lacking explicit MT training.

However, regardless of the choice of LLM, some domains and vocabulary will remain under-exposed or unseen, especially for low-resource languages. Additionally, the optimal use of LLMs at inference to enhance translation quality remains under-explored. Domain adaptation of LLM-based translation is therefore an open and persistent challenge. Translation with LLMs requires prompting to elicit outputs in the desired language and domain, either via a zero-shot instruction or more effectively with in-context examples (Zhang et al., 2023a). In this work, we address the problem of domain adaptation at inference by exploring in-context example selection. Selecting lexically, semantically or grammatically relevant translation examples for prompting LLMs is arguably more important when translating out-of-domain texts, to help fill gaps in domain vocabulary or demonstrate different styles.

Many works select examples randomly from a development set (Brown et al., 2020; Chowdhery et al., 2022; Bawden and Yvon, 2023). However, other strategies have been developed. While some works show example diversity helps task performance (Zhang et al., 2022), intuitively we expect that examples showing translations of words in or related to the test source will improve output quality. Prior work has selected relevant examples based on n -gram overlap (Agrawal et al., 2023), feature matching (Kumar et al., 2023) or embedding similarity to the test source (Liu et al., 2022). Here we test a method that exploits more abstract semantic relationships that are also more

^{*}This work was primarily carried out while at Inria.

¹Our code, topic models, and data splits are available at www.github.com/Sethjsa/LLM-Dom-Ad.

fine-grained than domain categories. For this we use a topic modelling pipeline (Grootendorst, 2022) that predicts a topic for a source sentence, and selects examples from this topic for translating in the given domain. The motivation is two-fold: first, we aim to test the continuing relevance of these simple models to complement LLMs for MT; and second, we aim to study the importance of semantic similarity for domain adaptation at a more abstract granularity than prior work, providing an alternative method for example selection.

In practice we test Llama-2-13B, a state-of-the-art LLM, on MT in varied domains including medical, legal, educational, religious, and entertainment texts. We test across several high and low-resource languages from and into English: French, German, Czech, Romanian, Finnish, Lithuanian, and Tamil. We compare two uses of topic models for domain adaptation: topic-guided few-shot example selection and adding topic keywords. We test these against random baselines, information retrieval and embedding similarity-based selection, as well as simply adding domain labels. Our standard method uses multilingual topic models to select examples or keywords from seen domains across all tested languages. We show that our topic-guided method is robust to unseen domains and outperforms strong baselines in this setting, but is too restrictive to achieve competitive results against baselines for simpler in-language tests, suggesting a trade-off between similarity and diversity of examples.

2 Related Work

Domain adaptation methods for MT can be categorised as either data- or model-centric (Saunders, 2022). Data-centric approaches include fine-tuning models on in-domain parallel data (Dakwale and Monz, 2017) or synthetic backtranslated in-domain data (Sennrich et al., 2016; Jin et al., 2020), which is effective but costly in multilingual settings; or fine-tuning with labels encoding domain-specific information (Kobus et al., 2017; Stergiadis et al., 2021), which restricts prediction to seen domains. Model-centric approaches may use specialised architectures (Park et al., 2022) or different training methods such as curriculum or meta-learning (Zhang et al., 2019; Sharaf et al., 2020). Alternatively, adapters (Bapna and Firat, 2019) may be inserted into pre-trained models, with past work using separate domain and language adapters, or hierarchical domain adapters (Cooper Stickland

et al., 2021a; Chronopoulou et al., 2022). Contrary to these approaches, we focus on domain adaptation of a pre-trained LLM at inference through in-context example selection, which requires no additional data manipulation or fine-tuning.

Recent work explores using pre-trained LLMs as a form of unsupervised transfer learning (Chronopoulou et al., 2020; Cooper Stickland et al., 2021b). Many LLMs are competent in multilingual translation despite lacking explicit MT training (Alves et al., 2023; Bawden and Yvon, 2023; Hendy et al., 2023; Peng et al., 2023), though LLMs often struggle in low-resource settings (Zhu et al., 2023). For zero-shot translation, prompt design is key, with prior work improving translation with instructions (Li et al., 2023), dictionary hints (Ghazvininejad et al., 2023), chained bilingual dictionary entries (Lu et al., 2023), or chain-of-thought prompting to predict keywords, topics, and relevant examples (He et al., 2023). In-context learning, i.e. providing few-shot task examples, is effective for LLM prompting (Brown et al., 2020), and various aspects of examples have been shown to impact translation quality: Vilar et al. (2023) find example quality outweighs domain provenance or source similarity, while Zhang et al. (2023a) show semantic similarity correlates with improved performance, and Zhang et al. (2022) show example diversity helps task performance more generally. Prior example selection methods include using n -gram-based BM25 retrieval plus a reranking model (Agrawal et al., 2023), a regression model with manually defined features to score retrieved prompts (Kumar et al., 2023), training a dense retrieval model (Rubin et al., 2022), or selecting based on proximity to the test source in a pre-trained LLM’s embedding space (Liu et al., 2022). In this work we intend to achieve similar results using an alternative topic-guided selection method, permitting more abstract semantic relationships than n -gram overlap or embedding similarity.

Topic models are statistical tools that model latent semantic structure in texts (Blei et al., 2010), and while not state-of-the-art, these methods remain relevant for neural NLP. Prior work has integrated topic models into neural MT architectures to improve translation performance (Zhang et al., 2016; Wang et al., 2021), or fused external topic knowledge to improve domain robustness (Xezonaki et al., 2023). Aharoni and Goldberg (2020) study in-domain training data selection methods using unsupervised clustering methods based on pre-

[Label]	Domain: EU biomedical texts.
[Keywords-10]	Related keywords: stabilité, stabilumas, stability, lämpötilassa, temperatura, raumtemperatur, température, teplotě, temperaturāi, conservée.
[Fewshot (1)]	English: the lower operating value of ambient air temperature is minus 45 ° C; = Romanian: valoarea inferioară a temperaturii de funcționare a aerului ambiant – minus 45 °C;
[Source]	English: Keep your Humalog Mix50 Pen in use at room temperature (below 30°C) for up to 28 days. = Romanian:
[Prediction]	<i>Stergeți penul Humalog Mix50 din uz la temperaturi de cameră (sub 30°C) pentru 28 de zile.</i>
[Target]	<i>Țineți Humalog Mix50 Pen în curs de utilizare la temperatura camerei (sub 30°C) timp de până la 28 zile.</i>

Table 1: An example illustrating our different prompting methods: domain labels, topic keywords, and a 1-shot example for an English–Romanian example from EMEA, with predicted and target outputs for the Keywords-10 prompt. Information in square brackets is not included in the prompt.

trained language model embeddings, while [Groo-tendorst \(2022\)](#) introduces a neural topic modelling pipeline that clusters SBERT embeddings. We build on these works and train multilingual topic models to select relevant in-context examples for prompting at inference. Our work tests the continuing relevance of topic models in the context of example selection against information retrieval and embedding similarity baselines. The intuition is that topic models identify semantic relationships below the level of a domain but more abstract than embedding similarity or n -gram overlap. We expect this intermediate level of semantic abstraction will aid domain example selection for NMT.

3 Domain Adaptation Approach using Topic Modelling

3.1 Defining a domain

We employ topic models as the core mechanism of our domain adaptation approach. Traditionally in MT, a domain is defined as being a different source text, i.e. each corpus is taken as a different domain ([Koehn and Knowles, 2017](#)). Other definitions are more nuanced: [Joshi et al. \(2013\)](#) consider domains as consisting of multiple meta-data attributes; [van der Wees et al. \(2015\)](#) subdivide domains into topic and genre characteristics; and [Aharoni and Goldberg \(2020\)](#) take a data-driven approach to defining domains, letting statistical models elucidate fine-grained cross-corpus associations and sub-domains within corpora. Building on the above, we suggest that domains can intuitively be defined by sets of distinctive words, forming a domain’s vocabulary. We expect these words to be somewhat infrequent and pose a greater challenge for MT systems, suggesting this vocabulary should be prioritised for adaptation. Our definition, in addition to the data-driven approach, motivates

using topic models for domain adaptation since they represent the latent semantic sets in a corpus.

3.2 Integrating domain information

Topic models find salient semantic relations between words or phrases in a corpus, representing these relations with a small number of abstract topics. Although typically modelled via the probabilistic latent Dirichlet allocation ([Blei et al., 2003](#)), we employ a different method which uses neural text representations as the basis for topics ([Groo-tendorst, 2022](#)). In these models, sentences are converted to contextual embeddings which are clustered based on similarity, then topic representations are extracted from these clusters of sentences using TF-IDF. Concretely, these topics consist of a set of associated vocabulary, and a set of representative sentences from the training corpus containing this vocabulary. We train multilingual topic models over data from seen domains in all languages on test. Once trained, any given input sentence can be embedded and assigned to the closest topic in the model. We therefore have three sources of additional information for each source sentence which we integrate into the translation prompt: a corpus-based domain label (Label), a list of keywords from the closest topic (Keywords), and a topic-guided set of representative examples (Fewshot). We illustrate our methods for integrating multilingual domain information in Table 1, with further examples in Appendix B.

Domain labels We add a descriptive domain label for a source sentence based on the corpus it comes from (i.e. following the standard definition of a domain as a corpus), referred to in results as Label. We avoid using the corpus name as these are not uniformly informative and instead use a short description (as shown in Table 3). We expect

this to slightly improve translation performance for given domains by conditioning the model to adapt to an expected style and topic.

Related Keywords For a given source sentence, we predict the closest topic from our model and use the 10 related keywords from that topic, referred to as Keywords-10. We hypothesise that adding keywords will marginally improve performance by both conditioning the model’s generation context on the current domain by introducing distinctive domain vocabulary, and by acting as a stochastic proxy for a multilingual lexicon, often providing translations in other languages given the multilingual nature of the topic model.

Fewshot Examples Finally, we select the top n representative examples from a topic for a given source to use as in-context examples in the prompt, known in testing as Fewshot (n). We describe the variations of fewshot examples that are tested in Section 4. We expect topic-guided fewshot examples to result in larger performance improvements for these domains by showing semantically relevant vocabulary, grammatical sentence-level translations, and examples of the expected target domain style and output format. We also expect more examples to improve performance by giving further explicit translations. The topic model’s ability to select semantically similar examples within domains, as opposed to random or n -gram matched examples, may allow the LLM to observe translations of domain-distinctive vocabulary, improving translation quality.

4 Experiments

Data and preprocessing We select several diverse high and low-resource languages: Czech (cs), German (de), English (en), French (fr), Finnish (fi), Lithuanian (lt), Romanian (ro), and Tamil (ta), both into and out of English. These languages vary from group 3 to 5 in Joshi et al.’s (2020) taxonomy of language resourcedness. We test on 7 domains with data in most languages: medical European Medicines Agency texts (EMA), transcribed TED Talks (Reimers and Gurevych, 2020), localisation files for KDE4 software, educational video transcripts from QCRI (Abdelali et al., 2014) (QED), Quran translations (Tanzil), EU legal texts (JRC), and transcripts of TV and films from OpenSubtitles² (Lison et al., 2018) (Subs). All data was

²www.opensubtitles.org

obtained from OPUS (Tiedemann, 2012), and we release our data splits, topic models, and code to aid reproducibility and future research.³

Our preprocessing involves removing newlines and sentences over 175 tokens with Moses scripts (Koehn et al., 2007);⁴ removing sentences with over 50% punctuation; correct language identification using FastText (Joulin et al., 2017);⁵ and sentence-level deduplication. For each domain-language pair, our development and test sets consist of 5000 and 500 sentences respectively (N.B. Tanzil Tamil–English has only 4800 dev set sentences). Development sets are used to train topic models and as sources for example selection.

Models We used the HuggingFace (Wolf et al., 2020) implementation of Llama-2-13B,⁶ with greedy decoding up to 256 tokens. This model is mainly English with substantial multilingual capabilities, and is a state-of-the-art open-source LLM. We note however that the training data is not published, so our experiments are potentially at risk of data contamination. Our results therefore can only be considered in the context of this specific model.

While Llama-2 is not as performant on translation tasks as significantly larger models such as GPT-3.5 (Hendy et al., 2023; Xu et al., 2023), we chose Llama-2 for our experiments because it outperforms similarly-sized, explicitly multilingual LLMs including XGLM and BLOOMZ models (Zhang et al., 2023b). Llama-2 is also more robust to translation prompt perturbations than BLOOM models (Chitale et al., 2024). Further, Llama-2’s permissive licence and open-source weights are a significant benefit against API-only models, leading to substantial research interest such as Llama-2-based translation models including ALMA (Xu et al., 2023). Our translation research on Llama-2 is therefore robustly motivated.

We implement our topic modelling pipeline with BERTopic (Grootendorst, 2022).⁷ Our topic models are trained on parallel development sets; we focus on multilingual seen domain models, and also test in-language all-domain models. The multilingual setting is challenging and tests generalisation: without full domain coverage, methods must compensate, perhaps

³www.github.com/Sethjsa/LLM-Dom-Ad

⁴www.github.com/moses-smt/mosesdecoder

⁵www.fasttext.cc/docs/en/language-identification.html

⁶www.huggingface.co/meta-llama/Llama-2-13b

⁷www.github.com/MaartenGr/BERTopic

Template	Prompt
Base	L1 : [source sentence] = L2 :
Verbose	Given the following source text in L1 : [source sentence], a good L2 translation is:
Label	Domain: [domain description] \n L1 : [source sentence] = L2 :
Keywords-10	Related keywords: [keyword list] \n L1 : [source sentence] = L2 :
Fewshot (n)	L1 : [example source] = L2 : [example target] \n L1 : [source sentence] = L2 :

Table 2: Prompt templates for our experiments. In each prompt, both the source and target language are specified to aid in the zero-shot setting. The bold **L1** and **L2** are replaced with full language names e.g. English or Lithuanian, and [source sentence] is replaced by a given L1 sentence. The Fewshot prompt includes n example pairs.

Domain	Description
EMEA	EU biomedical texts
JRC	EU legislative texts
KDE4	Software localization files
OpenSubtitles	TV and movie subtitles
QED	Educational video transcripts
Tanzil	Religious Quran text
TED	Public speaking transcripts

Table 3: Domain Label descriptions, providing similar information across domains. Bold domains are treated as *seen* in experiments.

by using related examples from non-target languages. We expect the abstract cross-lingual semantic relationships identified by topic models to show robustness across domains. All models use embeddings from the 100-language paraphrase-multilingual-MiniLM-L12-v2 model from SentenceTransformers (Reimers and Gurevych, 2019), with UMAP dimensionality reduction (McInnes et al., 2018) and HDBSCAN clustering (Malzer and Baum, 2020). Our standard topic model has 500 topics trained on multilingual seen domains. Further details and hyperparameters are available in Appendix C.

Prompt design Our baseline experiments use the XGLM translation prompt (Lin et al., 2022), denoted as Base, and we also test a more verbose prompt, the two best performing MT prompts from Bawden and Yvon (2023) for BLOOM. Table 2 shows the format for our baselines and Label (see Table 3), Keywords-10, and Fewshot settings. Fewshot examples are selected from development sets of *seen* domains in all languages, unless otherwise specified; we expect this setting to be conducive to cross-lingual transfer.

Baselines Our Base setup uses a zero-shot XGLM-style prompt format. We implement two simple example selection techniques: BM25, an unsupervised information retrieval (Retrieval) tech-

nique based on n -gram matching; and sentence-level embedding similarity (Similarity), finding the closest sentences by cosine distance using the same SentenceTransformers model. For each baseline, we select from seen-domain multilingual development sets, and we additionally test in-language data against in-language topic models. Further baselines and ablations are described in Section 5. Finally, to contextualise our experiments we include topline results for NLLB-200-1.3B (Costa-jussà et al., 2022), a specialised translation model.

Evaluation We measure COMET scores using the wmt22-comet-da model (Rei et al., 2022), and BLEU (Papineni et al., 2002) with SacreBLEU⁸ (Post, 2018), included for interpretability despite poorer correlation with human judgments (Mathur et al., 2020). We build on the lm-evaluation-harness⁹ (Gao et al., 2022) for evaluation.

Postprocessing During initial tests we found the model often repeated outputs or provided translations in other languages, as found by Bawden and Yvon (2023). We therefore used a regular expression to capture the first L2 translation, discarding output after (.+?:) or a newline. Translation quality for trimmed results dramatically improves, showing the extent of Llama-2’s overgeneration issues, and all results presented are trimmed outputs. In Appendix D, we show changes in length and correct language output for raw and trimmed results, plus Base-raw COMET and BLEU scores in Appendix E, confirming that trimming helps disentangle translation quality from overgeneration.

⁸Signature: nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.3.1

⁹www.github.com/EleutherAI/lm-evaluation-harness

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
NLLB-1.3B	en-de	82.5	86.5	78.9	79.5	80.6	76.9	84.3
	en-ro	86.0	90.5	80.6	83.7	82.9	79.7	86.8
	lt-en	82.4	86.4	75.7	79.8	80.4	-	83.5
	mean	84.9	88.7	79.1	81.7	81.3	77.7	85.3
Base	en-de	71.8	74.0	72.1	75.0	74.4	68.5	78.2
	en-ro	66.5	79.2	70.9	74.1	72.5	65.7	77.1
	lt-en	62.4	62.5	55.6	54.3	56.7	-	58.6
	mean	70.8	73.5	67.4	68.2	67.2	62.6	70.0
Label	en-de	76.2	80.6	73.8	75.9	77.1	70.4	79.8
	en-ro	73.9	84.2	71.2	74.9	75.2	67.2	79.6
	lt-en	65.5	65.0	63.4	54.2	58.1	-	59.7
	mean	70.8	76.9	70.6	69.4	69.2	64.1	71.7
Keywords-10 (Seen)	en-de	77.6	81.2	75.8	75.9	77.4	70.1	80.0
	en-ro	76.7	84.3	74.8	75.9	76.5	67.2	80.4
	lt-en	67.4	67.1	63.7	56.9	59.4	-	60.4
	mean	75.3	77.7	71.3	69.6	69.7	63.6	72.1
Fewshot (3, Seen)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	-	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5

Table 4: COMET results for main experiments including domain labels (Label), 10 topic-guided keywords (Keywords-10), topic-guided 3-shot (Fewshot), from multilingual seen domains (Seen), and for topline NLLB model. Prompts are zero-shot unless specified; best performing mean results in **bold**; and a reference for experiment names is found in Appendix A.

5 Results

Main Experiments We start by comparing our three approaches for integrating domain information into prompts, domain labels (Label), topic-keywords (Keywords-10), and topic-guided 3-shot examples (Fewshot), against our zero-shot prompt (Base) and the topline NLLB model. We also tested a verbose prompt to validate previous claims (Bawden and Yvon, 2023) and provide a point of reference, but since they are not central to our method, we present these results in Appendix E.

Table 4 shows COMET scores for a selection of representative high and low-resource language pairs plus mean results over all pairs.¹⁰

We first note that the baseline zero-shot Llama-2 model shows substantially reduced performance compared to the NLLB model, especially on the lower-resource languages of Romanian and Lithuanian, which is to be expected from a specialist MT model explicitly trained on these languages. NLLB is thus a useful topline for our experiments. However, fewshot prompting helps Llama-2 begin to approach the scores achieved by the NLLB model.

Experiments with a domain label in the transla-

¹⁰For full COMET and BLEU results over all 11 language pairs, see Appendix E. We note BLEU scores follow patterns in COMET results.

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Base	en-de	71.8	74.0	72.1	75.0	74.4	68.5	78.2
	en-ro	66.5	79.2	70.9	74.1	72.5	65.7	77.1
	lt-en	62.4	62.5	55.6	54.3	56.7	-	58.6
	mean	70.8	73.5	67.4	68.2	67.2	62.6	70.0
Label	en-de	76.2	80.6	73.8	75.9	77.1	70.4	79.8
	en-ro	73.9	84.2	71.2	74.9	75.2	67.2	79.6
	lt-en	65.5	65.0	63.4	54.2	58.1	-	59.7
	mean	73.9	76.9	70.6	69.4	69.2	64.1	71.7
Random Label	en-de	75.6	80.4	73.4	75.7	76.9	70.2	79.8
	en-ro	72.1	82.9	71.6	74.4	75.5	66.5	80.1
	lt-en	64.0	62.7	60.7	54.6	57.0	-	58.7
	mean	73.3	76.4	70.0	69.1	68.9	63.4	71.7

Table 5: COMET scores for Label prompts against Base zero-shot and Random Label prompts.

tion prompt show increases in COMET scores of up to 3 points over the baseline model, though the effect is smaller for OpenSubtitles, perhaps due to its heterogeneity, and greater for Tanzil, for the opposite reason. This suggests the model is able to use this minimal domain information to condition the output style and improve translation quality in highly restrictive domains such as Tanzil.

Results for prompting with 10 related keywords show average improvements of 2-4 COMET over the baseline, and up to 1 point over domain label tests, except for the unseen Tanzil domain. This suggests that the topic model-predicted keywords are useful for the model, providing lexical information beyond a domain description, and acting as a proxy for a bilingual lexicon. We would expect a handmade bilingual lexicon to improve results further (Waldendorf et al., 2022) but we note that quality lexicons are rare and thus keywords from topic models are a useful approximation.

Topic-guided 3-shot examples provide the largest performance boost of up to 6 COMET points, outperforming keywords on all domains. Gains are smaller again for OpenSubtitles; and the unseen Tanzil and QED domain results are marginally outperformed by Label and Keywords results respectively, though performance remains competitive. This shows the difficulty of selecting relevant out-of-domain examples for domains with more distinctive vocabulary or styles. Overall these results support our hypothesis that while domain labels and keywords provide useful domain and lexical information, especially in restrictive domains, few-shot examples help the model to better mimic the task and produce the desired output format.

Our main results show substantial improvements in translation quality using our example selection

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Base	en-de	71.8	74.0	72.1	75.0	74.4	68.5	78.2
	en-ro	66.5	79.2	70.9	74.1	72.5	65.7	77.1
	lt-en	62.4	62.5	55.6	54.3	56.7	-	58.6
	mean	70.8	73.5	67.4	68.2	67.2	62.6	70.0
Keywords-10 (Seen)	en-de	77.6	81.2	75.8	75.9	77.4	70.1	80.0
	en-ro	76.7	84.3	74.8	75.9	76.5	67.2	80.4
	lt-en	67.4	67.1	63.7	56.9	59.4	-	60.4
	mean	75.3	77.7	71.3	69.6	69.7	63.6	72.1
Keywords-30 (Seen)	en-de	77.5	81.3	76.3	75.8	77.7	70.2	80.1
	en-ro	76.0	84.4	72.4	75.4	76.7	66.8	80.2
	lt-en	67.8	67.4	64.0	57.5	59.7	-	60.1
	mean	75.3	77.7	71.1	69.5	69.7	63.4	72.1
Keywords-10 (Seen, Random Topic)	en-de	76.5	81.3	75.4	76.0	77.3	70.2	80.1
	en-ro	75.4	84.7	73.0	75.6	76.4	67.3	80.0
	lt-en	64.4	64.8	61.8	54.9	57.6	-	59.2
	mean	74.2	77.4	70.7	69.5	69.5	63.5	71.9
Random Keywords-10 (Seen)	en-de	76.9	81.2	75.6	76.2	77.2	70.4	80.2
	en-ro	75.4	84.3	73.7	75.9	76.4	67.4	80.1
	lt-en	66.3	65.3	61.9	56.1	58.8	-	60.7
	mean	74.4	77.4	71.0	69.8	69.6	63.8	72.2

Table 6: COMET scores for topic-guided Keywords-10 and Keywords-30, random topic Keywords-10, and Random Keywords-10 from multilingual seen domains.

method. We now ablate each method against various baselines to further understand the source of these improvements.

Domain Labels While adding domain labels improves translation quality, we now test with randomised labels from the set of 7 labels to understand the source of improvements. The results in Table 5 show that, while prompting with the true domain label leads to overall better quality outputs across languages and domains, the random domain label tests produce similar improvements over the baseline, trailing the true label results by approximately 0.5 COMET points for most domains. This suggests that the presence of any additional structured information conditions the model to focus on the translation task, whether or not that information is directly useful for the current sentence.

Related Keywords We test various ablations of the Keywords prompt in Table 6. The Keywords-30 prompt is constructed using 10 keywords each from the top 3 predicted topics. Here we see equivalent or marginally lower quality compared to the standard Keywords-10 setting (less than 1 COMET point difference), suggesting that most gains stem from the first few keywords. The random topic setting adds keywords from a randomly selected topic from seen domains, and results are consistently lower than topic keywords, with results from Lithuanian to English showing substantial degradation across domains (up to -3

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Base	en-de	71.8	74.0	72.1	75.0	74.4	68.5	78.2
	en-ro	66.5	79.2	70.9	74.1	72.5	65.7	77.1
	lt-en	62.4	62.5	55.6	54.3	56.7	-	58.6
	mean	70.8	73.5	67.4	68.2	67.2	62.6	70.0
Fewshot (3, Seen)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	-	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5
Fewshot (3, Seen, Random Topic)	en-de	79.0	81.5	76.9	75.3	77.1	69.8	80.1
	en-ro	79.2	85.0	76.0	75.5	76.9	67.6	80.8
	lt-en	59.8	60.7	52.3	49.5	51.5	-	53.5
	mean	75.1	77.1	70.9	68.4	68.5	63.5	71.2
Random Fewshot (3, Seen)	en-de	77.0	80.5	75.2	75.3	76.7	69.8	79.4
	en-ro	78.1	84.9	75.7	76.2	76.9	68.1	80.4
	lt-en	70.9	71.6	69.7	69.1	68.1	-	72.3
	mean	73.9	75.6	71.5	69.7	68.7	61.1	71.3

Table 7: COMET scores for Fewshot examples predicted by the multilingual seen-domain topic model, from one random topic, and random examples from seen domains across languages.

COMET points). This indicates related keywords may provide more utility in low-resource settings. Finally, Random Keywords-10 selects individual words randomly from multilingual seen domains, i.e. the topic model’s training set. This setting is competitive with and on some domains outperforms the topic keyword prompts; while topic keywords provide semantically relevant words, and random topic keywords provide irrelevant but semantically consistent keywords, this setting provides genuinely diverse keywords, which appears to help performance. This suggests there is a trade-off between semantic relevance (through topic modelling) and information diversity in the prompt. In sum, only marginal gains can be attributed to the topic-guided method, suggesting the choice of keywords has less of an effect than the presence of keywords themselves.

Fewshot Examples We test topic-guided fewshot examples against random baselines, all 3-shot: fewshot examples from one random topic (Fewshot (Random Topic)), and random fewshot examples from seen multilingual data (Random Fewshot). The results in Table 7 show that while Fewshot (Random Topic) and Random Fewshot improve on the Base setting, the best results by 1-4 COMET points are achieved by the topic-guided example selection. This suggests that although there are gains to be had from simply adding random examples, the semantic relevance of these examples can lead to further improvements in translation performance. We expect this is due to a combination of both in-

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Fewshot (3, Seen)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	–	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5
Retrieval (3, Seen)	en-de	76.4	79.8	74.6	73.8	76.0	68.9	78.5
	en-ro	76.7	83.2	74.4	74.5	74.8	66.3	79.3
	lt-en	70.8	71.7	69.5	69.6	68.1	–	72.3
	mean	73.2	74.9	70.6	68.8	67.9	60.5	70.6
Similarity (3, Seen)	en-de	76.3	80.6	76.2	74.8	75.9	68.8	79.0
	en-ro	77.5	84.7	76.4	75.2	75.9	67.3	80.4
	lt-en	70.9	71.6	69.7	69.4	68.1	–	72.4
	mean	73.9	76.0	71.9	69.5	68.5	61.2	71.1

Table 8: COMET scores for Fewshot topic-guided examples, Retrieval selected examples, and embedding similarity selected examples (Similarity), all from seen domains across languages.

creased embedding similarity and n -gram overlap. The topic model selects a topic probabilistically, and although there may be noise within the topic—for example, the representative sentence pairs are not always in the same language or the correct target language—the semantic cohesiveness of these sentences outweighs the noise present in randomly selected examples. We can therefore attribute a small amount of quality improvements to the proposed topic-guided method.

We also test our topic-guided selection method against strong baselines inspired by prior work: a Retrieval method using BM25, and an embedding Similarity approach. For both we select examples from multilingual seen domains to control the data available for selection, since our standard topic model was tested in this challenging set-up.

The results in Table 8 show competitive performance for Retrieval and Similarity baselines against each other. However, our topic-guided fewshot method achieves the best results across domains by up to 3 COMET points. We also see slightly larger improvements for tests on unseen domains (QED, Tanzil and TED). Our method is more robust to all three unseen domains since it relies on an intermediate level of semantic relations, more complex than n -gram overlap, more abstract than raw embedding similarity, and finer-grained than domain-level selection. The Retrieval baseline especially suffers in the unseen domains, underperforming or matching the baseline zero-shot setting for QED and Tanzil, we expect because with lower or zero vocabulary overlap, n -gram matching fails where embeddings can exploit contextual information.

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Fewshot (1, Seen)	en-de	78.1	81.3	75.9	74.8	76.3	69.0	79.8
	en-ro	78.5	84.6	75.5	74.7	75.5	67.6	80.1
	lt-en	64.0	68.3	62.4	55.8	57.3	–	58.1
	mean	74.8	78.5	72.3	69.3	68.9	63.5	71.6
Fewshot (3, Seen)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	–	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5
Fewshot (5, Seen)	en-de	79.5	82.4	78.2	75.8	77.4	70.3	80.1
	en-ro	80.4	85.8	78.3	76.1	77.1	68.9	81.2
	lt-en	70.9	71.2	67.9	58.1	59.0	–	60.3
	mean	77.3	79.6	74.9	70.5	70.0	64.1	72.6

Table 9: COMET scores for increasing Fewshot examples, from 1-shot to 5-shot, using our standard multilingual seen-domain 500 topic model.

Number of Examples We present topic-guided fewshot results in Table 9 for 1, 3, and 5-shot settings. The results show gains of circa 1 COMET point from 1-shot to 3-shot, and even smaller gains of approximately 0.3 COMET in overall performance from 3 to 5-shot. This suggests that 3 examples are sufficient to provide substantial translation improvements over a zero-shot baseline, with diminishing returns for adding extra examples, corroborating results for BLOOM (Bawden and Yvon, 2023). Lithuanian–English results show low-resource languages, especially those not in the model’s training data, may benefit more from additional examples; here we see continued improvements from 1 to 3 to 5-shot.

Going Further We also test various topic model sizes. While most experiments use the multilingual seen-domain 500-topic model (trained on the devsets of 4 domains totalling 140,000 parallel sentences), we also experiment with 200- and 1000-topic models. The results in Table 10 are mixed; some domains exhibit improved performance with larger models, but the improvements for the 1000-topic model are small or negligible over the 500-topic model. This is unexpected; a larger topic model implies more semantic variety and thus a wider choice sentences to select for a given test source. However, we observed that in the Fewshot (3, Seen, 500 topic) setting across languages and domains, a ‘general’ catch-all topic is selected for 3.1% of tests, and the top 5 topics make up 16% of selected topics, when a uniform distribution would result in each topic having a 0.2% selection rate. Therefore the overselection of certain topics, and consequent reduction of sentences available for selection, is likely to reduce performance. We also

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Fewshot (3, Seen, 200 topic)	en-de	79.4	81.9	76.3	75.7	76.6	69.9	79.8
	en-ro	79.8	85.7	76.4	76.0	76.8	68.6	80.7
	lt-en	71.0	65.7	64.6	54.9	56.5	-	56.9
	mean	77.2	78.3	72.9	69.6	69.4	63.9	71.7
Fewshot (3, Seen, 500 topic)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	-	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5
Fewshot (3, Seen, 1000 topic)	en-de	79.0	82.3	78.1	75.6	76.6	70.4	79.7
	en-ro	79.8	85.8	77.0	75.9	76.6	68.4	80.1
	lt-en	71.2	70.9	64.6	56.3	57.8	-	59.7
	mean	77.4	79.5	74.1	69.9	69.6	63.9	72.0

Table 10: COMET scores for Fewshot examples from 200, 500, and 1000-topic seen-domain multilingual models.

note that the homogeneity of examples within topics is likely to degrade performance since example diversity helps for other tasks (Zhang et al., 2022). Therefore issues remain with the restrictiveness of this method, which we leave open to future work.

In-language example selection Finally, we test language-specific 500-topic models to test whether the above results hold in a more restrictive scenario assuming the availability of in-language datasets in all domains, which is not always possible. Note here there are no unseen domains, though we include the multilingual seen-domain model for comparison. The results in Table 11 show improvements of 1-2 COMET for the all-domain language-specific models against the seen-domain multilingual model. We also provide language-specific Retrieval and Similarity results, which show even greater improvements compared to in-language topic-guided fewshot examples. Both baselines outperform the in-language topic model by 2 to 5 COMET, approaching the topline NLLB results in Table 4. This suggests that in the more restrictive scenario where we have full domain coverage in the target language pair, Retrieval and Similarity methods are very strong baselines because there is a greater probability of similar vocabulary, semantics, and syntax, while the topic model’s noise and highly homogeneous examples may hinder performance. However, in the more challenging scenario of the main results with unseen multilingual domains, our topic-guided method is more robust to domain shift.

6 Conclusion

We investigate the use of topic models for translation prompt construction and in-context example

Prompt	Pair	Dataset						
		EMEA	JRC	KDE4	Subs	QED	Tanzil	TED
Fewshot (3, Seen)	en-de	79.1	82.5	77.6	75.6	77.2	69.8	80.7
	en-ro	80.1	85.9	77.8	75.9	76.6	68.2	80.7
	lt-en	70.2	70.7	66.2	58.2	58.3	-	60.1
	mean	77.0	79.4	74.5	70.3	69.6	63.8	72.5
Fewshot (3, Language)	en-de	79.7	82.7	78.7	76.3	77.6	71.4	80.9
	en-ro	81.3	86.9	79.1	77.2	78.2	71.1	81.9
	lt-en	71.8	71.6	67.4	61.0	62.9	-	65.6
	mean	77.9	80.2	75.4	71.0	71.3	65.2	73.4
Retrieval (3, Language)	en-de	81.5	84.0	79.8	75.8	76.9	73.4	80.3
	en-ro	83.7	87.7	80.4	77.2	78.1	75.2	82.3
	lt-en	77.0	75.3	74.9	61.8	65.8	-	67.9
	mean	81.2	82.5	78.8	72.4	73.4	71.0	75.3
Similarity (3, Language)	en-de	80.5	83.2	79.3	75.9	77.9	73.8	80.2
	en-ro	83.5	87.6	79.9	78.2	78.3	74.0	82.7
	lt-en	76.8	75.9	73.2	64.9	67.3	-	69.2
	mean	80.6	82.2	77.2	72.6	72.9	67.5	74.5

Table 11: COMET scores for language-specific fewshot settings against our standard multilingual seen-domain Fewshot setup.

selection to aid domain adaptation for LLM-based MT. We train a multilingual topic model which, in a challenging multilingual seen-domain setting, outperforms random and statistical baselines, showing the importance of semantically similar examples. Our method offers a lightweight, robust solution for when no parallel data is available for a new domain. However if suitable (in-domain and in-language) development data is available then information retrieval and embedding similarity-based methods are more performant, simpler solutions. In future work, we intend to assess the transferability of our method to LLM-based translation more generally by testing across various LLMs, including more explicitly multilingual models. With this work we show an example of how statistical models can complement the performance of Llama-2, an English-centric LLM, in translation tasks to and from English.

Limitations

We recognise our work has limitations including: 1) We experimented with only one pre-trained LLM, Llama-2-13B. Further investigation is required to understand how our results and prompts would vary across a) different model families and b) varying model scales. We note therefore that our results are not generalisable to other LLMs, pending further work. 2) While we consider a variety of high- and low-resource pairs, all our tests are into or out of English. Further work is required to test other pairs, including both high-high and low-low resource pairs. We note that this may be more

difficult due to the reduced availability of good quality in-domain parallel data. 3) Our conclusions must be understood with the caveat that we do not know our chosen model’s training data, including datasets and language distributions, beyond the basic information provided by [Touvron et al. \(2023\)](#).

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A Results legend

In Table 12 we provide a brief reference for the experimental naming used in results tables.

Label	Description
Base	Zero-shot XGLM-style prompt
Label	Descriptive domain label + Base prompt
Keywords-10	10 related keywords selected from topic + Base prompt
Fewshot	Example source-target pairs selected by topic model + Base prompt
(1, Seen)	1-shot; selected from multilingual seen domains
(3, Language)	3-shot; selected from all-domain in-language data
(200 topic)	Selected using a 200-topic model.
(Random Topic)	Examples/keywords selected from one random topic.

Table 12: Reference for experimental terminology.

B Further examples

In Table 13 we provide further examples of the prompt format, and predicted outputs, for Label, Keywords-10 (Seen), and Fewshot (3, Seen) settings.

C Topic Model Hyperparameters

We use UMAP and HDBSCAN implementations from cuML.¹¹ Our embedding model is paraphrase-multilingual-MiniLM-L12-v2 from SentencePiece. This language model is a MiniLM model (Wang et al., 2020) distilled from XLM-R (Conneau et al., 2020) and thus is expected to have some knowledge of the 100 lan-

¹¹www.github.com/rapidsai/cuml

[Label]	Domain: TV and movie subtitles.
[Source]	Lithuanian: Šis miestas, ir viskas jame... = English:
[Prediction]	<i>This city, and all of it...</i>
[Target]	<i>This city, everyone in it...</i>
[Keywords-10]	Related keywords: juice, nápojů, grapefruitsaft, štáva, grapefruit, drinks, greipfrutų, vartoti, pomerančová, frucht.
[Source]	English: fruits — and they will be held in honour, = German:
[Prediction]	<i>früchte — und sie werden in Ehren gehalten werden.</i>
[Target]	<i>Früchte, und sie werden geehrt</i>
[Fewshot]	English: (c) With effect from 1 July 1972 the text of Article 4 (2) and (3) shall be replaced by the following: = French: c) Le texte de l'article 4 paragraphes 2 et 3 est remplacé par le texte suivant, avec effet au 1er juillet 1972: English: 9. Article 28 shall be replaced by the following: = French: 9) L'article 28, est remplacé par le texte suivant: English: (h) the text of Part L. PORTUGAL shall be replaced by the following: = French: h) Le texte de la partie L. PORTUGAL est remplacé par le texte suivant:
[Source]	English: a) in paragraph 1 the following subparagraph shall be added: = French:
[Prediction]	<i>a) au paragraphe 1, le sous-alinéa suivant est ajouté:</i>
[Target]	<i>a) au paragraphe 1, l'alinéa suivant est ajouté:</i>

Table 13: Three examples illustrating our different prompting methods: domain labels, topic keywords, and a 3-shot topic-guided example from seen domains. We show examples for Lithuanian–English, English–German, and English–French in OpenSubtitles, Tanzil, and JRC domains respectively, with predicted and target outputs below the example prompts.

guages used in training. After dimensionality reduction and clustering, the inputs are tokenized using CountVectorizer and weighted with cTF-IDF (Pedregosa et al., 2011). The standard BERTopic hyperparameters are as follows: 500 topics, 10 keywords/topic, with stopwords removed for the vectorisation step; no stopwords were available for Lithuanian, so we used the top 100 most frequent words from our multi-domain development set.

Other parameters follow the standard implementation of BERTopic: UMAP: number of components = 5, number of neighbours = 15, metric = cosine distance; HBDSCAN: minimum samples=10. Finally we use the KeyBERT-inspired implementation to select the best 10 keywords to represent a topic, which avoids the repetitive selection of function words and stopwords. We also note here that predicting the nearest topic for a given input does not significantly slow down the inference process, with a rate of 80-100 iterations per second.

D Length and Language ID results

We present raw and trimmed results in Tables 14 and 15 for length and correct language identification respectively, for a selection of settings (Base, Verbose and Fewshot (3, Seen)). These results illustrate how the trimming procedure vastly reduces the length and improves the correct language identification of the outputs; note especially the high

sentence lengths and low correct language identification for Base-raw experiments.

E Full COMET and BLEU results

We present full COMET and BLEU results in Tables 16–23, which follow the same patterns presented in Section 5.

Reforging : A Method for Constructing a Linguistically Valid Japanese CCG Treebank

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Abstract

The linguistic validity of Combinatory Categorical Grammar (CCG) parsing results relies heavily on treebanks for training and evaluation, so the treebank construction is crucial. Yet the current Japanese CCG treebank is known to have inaccuracies in its analyses of Japanese syntactic structures, including passive and causative constructions. While ABCTreebank, a treebank for ABC grammar, has been made to improve the analysis, particularly of argument structures, it lacks the detailed syntactic features required for Japanese CCG. In contrast, the Japanese CCG parser, *lightblue*, efficiently provides detailed syntactic features, but it does not accurately capture argument structures. We propose a method to generate a linguistically valid Japanese CCG treebank with detailed information by combining the strengths of ABCTreebank and *lightblue*. We develop an algorithm that filters *lightblue*'s lexical items using ABCTreebank, effectively converting *lightblue* output into a linguistically valid CCG treebank. To evaluate our treebank, we manually evaluate CCG syntactic structures and semantic representations and analyze conversion rates.

1 Introduction

There have been significant advances in natural language processing research through the construction of syntactic tree corpora, known as treebanks. Treebanks are datasets where syntactic structures are annotated over large bodies of text. Various treebanks (Marcus et al., 1993; Forst, 2003; Briscoe and Carroll, 2006; Hockenmaier, 2006; Hockenmaier and Steedman, 2007; Vadas and Curran, 2007; Bos et al., 2010; Boxwell and Brew, 2010) have been served as standard datasets for training and evaluating statistical syntactic parsers. The Penn Treebank (Marcus et al., 1993), one of the first context-free grammar (CFG) treebanks, contains a one-million-word corpus of *Wall Street Journal* text. CCGbank (Hockenmaier and Steed-

man, 2007) was constructed by converting the Penn Treebank to Combinatory Categorical Grammar (CCG; Steedman, 1996, 2000), which contributing to the advancement of CCG parsers.

There are various methods for constructing treebanks. One approach is to combine automatic part-of-speech (POS) taggers and syntactic parsers with manual corrections, as in the Penn Treebank. The approach to providing CCGbank involves automatic conversion from existing treebanks. However, treebanks have different formats, provided information, and informational validity. Japanese CCGbank (Uematsu et al., 2013), constructed by automatic conversion of Japanese dependency tree corpora, but provides limited validity of syntactic structures for passive or causative nestings (Bekki and Yanaka, 2023). The Japanese ABC grammar treebank ABCTreebank (Kubota et al., 2020) has manually annotated argument structures, but does not provide POS information (conjugation series, conjugation forms, among others) and other detailed information.

We thus aim to construct a Japanese CCG treebank with both linguistically valid syntactic structures and detailed syntactic features. To this end, we propose a method to construct a new Japanese CCG treebank using the Japanese CCG parser *lightblue* (Bekki and Kawazoe, 2016)¹, which can output detailed syntactic features. However, *lightblue* contains errors related to argument structures, causing inaccurate outputs. To address this drawback, we extracted predicate-argument structures from ABCTreebank and incorporated this information into *lightblue*. This approach involves decomposing and reconstructing the treebank, which we call “reforging”. We discuss the reforging process in more detail in Section 3. Section 4 assess the validity of our proposed method. Section 5 introduces the error analysis of the output trees. Section 6

¹<https://github.com/DaisukeBekki/lightblue>

describes manual evaluations considering the syntactic structures and semantic representations of the output trees.

2 Background

2.1 Combinatory Categorical Grammar

CCG is a lexicalized grammar consisting of combinatory rules and a lexicon. Syntactic categories are either base categories or functional categories. The set of base categories includes elements such as *NP* for *noun phrases* and *S* for *sentences*. Functional categories use slash notation to represent complex phrases. For instance, the functional categories can express an intransitive verb as $S \backslash NP$, finding the syntactic structure of category *NP* on the right and returning *S*. Slash and backslash notations as $(S \backslash NP) / NP$ express transitive verbs.

In CCG, lexicons associate words with their phonological and syntactic information. For instance, to analyze the sentence

- (1) Taro runs.

in CCG, the the lexical items

Taro : *NP*
runs : $S \backslash NP$

are supposed to be contained in the lexicon. Combinatory rules allow syntactic categories to be merged. Function application rules and function composition rules are the basic CCG rules, defined as follows:

1. Function application rule

- (a) Forward application ($>$)
 $X/Y \quad Y \Rightarrow X$
 (b) Backward application ($<$)
 $Y \quad X \backslash Y \Rightarrow X$

2. Function composition rule

- (a) Forward composition ($>B$)
 $X/Y \quad Y/Z \Rightarrow X/Z$
 (b) Backward composition ($<B$)
 $Y \backslash Z \quad X \backslash Y \Rightarrow X \backslash Z$

The CCG syntactic structure of the sentence (1) is given using the following function application rule:

$$\frac{\frac{\text{Taro}}{NP} \quad \frac{\text{runs}}{S \backslash NP}}{S} <$$

In CCG, a combinatory rule applied to syntactic structures is indicated by a symbol placed on the right of the horizontal line. For example, in the above syntactic structure, the symbol “ $<$ ” on the right of the horizontal line indicates the use of the backward application rule. CCG also includes other rules such as coordination, crossed-composition, and crossed-substitution rules.

2.2 Japanese CCGbank

Uematsu et al. (2013) constructed Japanese CCGbank through automatic conversion of the Kyoto corpus², NAIST text corpus³, and Japanese particle corpus (Hanaoka et al., 2010). However, Japanese CCGbank has some empirical problems. One of the problems, discussed by Bekki and Yanaka (Bekki and Yanaka, 2023), is that the syntactic analysis of the Japanese CCGbank contains empirical fallacies on predictions for passive and causative nestings. For instance, consider the passive sentence:

- (2) 太郎が 次郎に 褒められた
 Taro-ga Jiro-ni homera re ta
 Taro-NOM Jiro-DAT praise passive PST
 ‘Taro was praised by Jiro.’

Figure 1 shows a syntactic structure based on Japanese CCGBank, which assigns the category $S \backslash S$ to the passive suffix *re*. However, *re* needs to play a role in changing the argument structure of the transitive verb *homera*, so this analysis is invalid.

Figure 2 shows a syntactic structure that can be analyzed based on Japanese CCG (Bekki, 2010). In this syntactic structure, the syntactic category $S \backslash NP_{ga} \backslash NP_{ni} \backslash (S \backslash NP_{ga} \backslash NP_{ni} \backslash o)$ is assigned to the passive suffix *re* and $S \backslash NP_{ga} \backslash NP_o$ to the predicate *homera*. By combining *homera* with *re* using the function composition rule, the argument structure of the predicate *homera* is changed to $S \backslash NP_{ga} \backslash NP_{ni}$, so it takes nominative and dative noun phrases as arguments. Thus, this syntactic structure indicates a valid passive nesting.

2.3 ABCTreebank

ABCTreebank was constructed in an attempt to create a general-purpose treebank. It was constructed by converting the Keyaki Treebank⁴, a phrase-structured treebank, to ABC grammar trees. The

²<https://github.com/ku-nlp/KyotoCorpus>

³<https://sites.google.com/site/naisttextcorpus/>

⁴<https://github.com/ajb129/KeyakiTreebank>

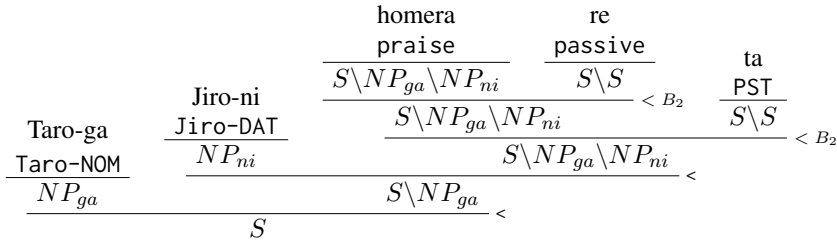


Figure 1: A syntactic structure based on Japanese CCGbank

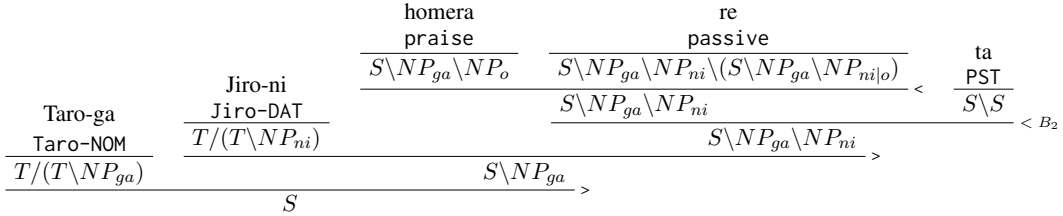


Figure 2: A syntactic structure based on Bekki (2010)

ABC grammar consists of two CCG rules: function application and function composition rules. Since these basic rules are common in both CCG and type-logical grammar (TLG; Morrill, 1994; Moortgat, 1997), syntactic structures in ABCTreebank can be easily converted to CCG syntactic structures.

ABCTreebank argument structures are assumed to be reliable because they were manually annotated. However, ABCTreebank does not cover the syntactic information, such as POS information. Incorporating POS information into ABCTreebank’s syntactic structure is challenging because CCG syntactic structures cannot be retrospectively recovered and have more elaborate information than ABC syntactic structures, such as syntactic features. Syntactic features can contain diverse information, such as person agreement, number, gender, tense, and case frame. For instance, the lexical item of the verb *runs* in sentence (1) is written using syntactic features as follows.

$$\text{runs} : S \backslash NP_{3S}$$

The syntactic category NP_{3S} denotes a third-person singular noun phrase. The syntactic structure of the sentence (1) then appears as follows:

$$\begin{array}{c}
\text{Taro} \\
\hline
NP_{3SM} \\
\hline
\text{runs} \\
\hline
S \backslash NP_{3S} \\
\hline
S \\
\hline
S \backslash NP_{3SM} \backslash NP_{3S} <
\end{array}$$

The syntactic category NP_{3SM} is a third-person singular noun phrase indicating that Taro is male.

Although morphological analyzers, such as Juman (Kawahara and Kurohashi, 2006), can generate elaborate syntactic structures, mapping this information to ABCTreebank’s syntactic structure is challenging, as the elaborate syntactic information needs to be supplemented with less informative syntactic structure. Machine learning approaches for such mappings require annotated training data. However, no annotated data currently exists, so there is no method for recovering CCG syntactic structures. Consequently, the treebank itself must possess elaborate information.

2.4 *lightblue*

lightblue is a Japanese CCG parser based on Bekki (2010) that outputs CCG syntactic structures with detailed syntactic features. Note that *lightblue* computes syntactic structures from lexicon and combinatory rules, so unlike other parsers, it does not require training and evaluation data. Its lexicon contains about 80,000 words with case frames extracted from the Juman dictionary. *lightblue* also provides semantic representations in terms of Dependent Type Semantics (DTS; Bekki and Mineshima, 2017) as shown in Figure 4. The phonetic form appears above the tree’s horizontal line, and the CCG syntactic category and the DTS semantic representation are displayed below the horizontal line. The symbol to the right is the applicable CCG combinatory rule or the identifier of the lexicon in which the word is registered. The current version of *lightblue*’s argument structures include some errors, leading to unnatural disambiguation in some

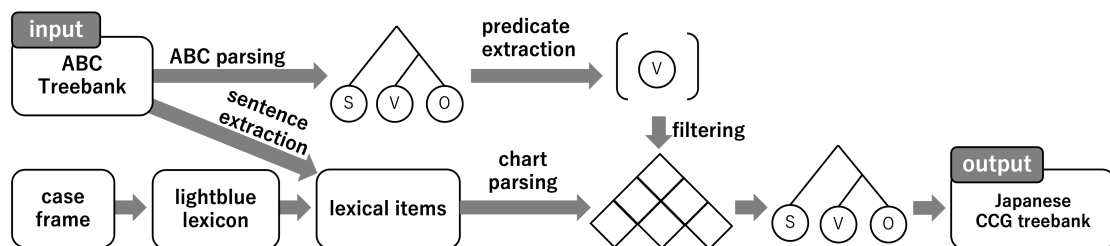


Figure 3: The reforging algorithm

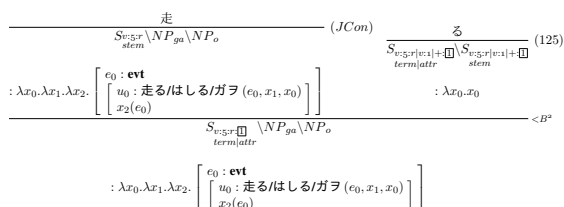


Figure 4: A lightblue output tree

contexts.

3 The Reforging Process

The aim of this research is to construct a linguistically valid Japanese CCG treebank with detailed syntactic features. Therefore, we propose a method for constructing a Japanese CCG treebank by combining the positive aspects of ABCTreebank, in which argument structures are manually annotated, with *lightblue*'s ability to provide CCG trees with detailed syntactic features. The proposed method decomposes ABCTreebank and reconstructs it using *lightblue*, a method we call “reforging”. Note that “reforging” is not a commonly used linguistics term, but decomposing and reconstructing a treebank using a parser is a novel approach, so we assigned this name for convenience.

One approach to constructing a new CCG treebank would be to automatically correct Japanese CCGbank output. However, one difference between CCG and CFG is that modifying part of a CCG tree would require recalculating all subsequent calculations. Since those recalculations would be almost as costly as reparsing the entire sentence, this study aims to construct a treebank using reforging.

The reforging process has three steps:

1. Extract of predicates from ABCTreebank
2. Filter the *lightblue* lexicon chart
3. Reconstruct the treebank

Figure 3 shows each process in detail. A parser decomposes a given ABCTreebank input and its *lightblue* reconstruction is output as a treebank.

3.1 Predicate Extraction from ABCTreebank

Predicate extraction starts with ABC parsing, which gives tree-structured data. We then extract the predicate information from ABCTreebank as a list of tuples with the following four elements:

1. The phonetic form of the predicate
2. The syntactic category
3. The starting position in the sentence
4. The ending position in the sentence

- (3) 人が 集まる
Hito-ga atumaru
People-NOM gather.
'People gather.'⁵

For example, in the case of sentence (3), the ABCTreebank syntactic structure is represented as shown in Figure 5. The predicate contained in this sentence is only “集まる(gather)”, so a list of length 1 is extracted as $[(\text{“集まる” } PP_s \setminus S_m, 2, 4)]$.

3.2 Lexicon Chart Filtration

Filtration starts by extracting from the *lightblue* lexicon the lexical items of all substring combinations that exist in the ABCTreebank sentence. After obtaining those lexical items is chart parsing using the lexical items extracted in the previous step. Left-corner chart parsing is performed in *lightblue*, calculating node data while building a syntactic structure of the word by combining daughter nodes. Table 1 shows the node data structure. The next step is chart filtration, where, we filter the chart with the argument-structure information of the verb extracted from ABCTreebank.

⁵ABCTreebank ID: 3_textbook_kisonihongo

Data	Example
Rule symbol	<B2 (backward function composition rule)
Phonetic form	走る
Syntactic category	$S_{[v:5:r][stem] \setminus NP_{ga} \setminus NP_o}$
Semantic representation	$\lambda x0.\lambda x1.\lambda x2.(e0 : evt) \times (u0.走る (e0, x1, x0)) \times 2(e0)$
Signature	$[\text{走る} : (x0 : entity) \rightarrow (x1 : entity) \rightarrow (e0 : evt) \rightarrow type]$
Daughter nodes	node of 走(run) and node of る(PRS)
Score	[1.00]
Lexical entry source	JCon

Table 1: Data structure for 走る (run) node data

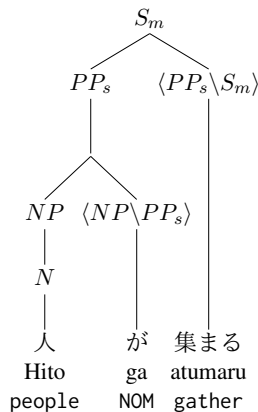


Figure 5: ABCTreebank syntactic structure of sentence (3) in ABCTreebank

The filtering algorithm first extracts the phonetic form and predicate’s syntactic category from ABCTreebank. The syntactic category is based on the ABCTreebank definition and needs to be converted to the *lightblue* definition for comparison with the *lightblue* category in the next step, which is to obtain lexical items of *lightblue* predicates. To obtain lexical items in *lightblue*, we use the predicate tuple data extracted from ABCTreebank. We extract the syntactic features of those lexical items that having the same phonetic form as the predicate extracted from ABCTreebank. In this study, the argument structures of adjectives and nominal predicates did not need to be filtered, so we excluded adjectives and nominal predicates. Valid and detailed syntactic information can be constructed by combining the the argument structure converted from ABCTreebank and the syntactic features extracted from *lightblue*.

Genre	Sentences	Len-50+ sentences	Reforaged trees
aozora	1773	590	1183
bible	1652	220	1430
book_expert	50	4	41
dict_lexicon	2640	4	2636
diet_kaigiroku	486	112	374
fiction	921	44	877
law	337	128	209
misc	335	59	276
news	443	103	340
non-fiction	223	87	126
spoken	570	11	559
ted_talk	605	54	551
text-book	4880	10	4870
wikipedia	222	51	171
Total	15137	1482	13653

Table 2: Reforaged treebank data

3.3 Treebank Reconstruction

We randomly sampled five files from each of the 14 ABCTreebank genres and parsed them using *lightblue* and filtered charts. However, there are fewer than five ABCTreebank files for each of the bible, dict, fiction, and law genres, so we used all data in those genres.

The computational complexity of *lightblue* chart-parsing is $O(n^3)$, so CCG parsing of long sentences takes a long time. We thus limited sentences to fifty or fewer characters. Even with this restriction, 90.19% of sentences could be converted to CCG trees, which is sufficient coverage. Table 2 shows the statistics for the reforaged treebank data. From left to right, the table shows the number of ABCTreebank sentences for each genre, the number of sentences with more than 50 characters, the number of CCG trees obtained by reforaging, and the percentage of trees that could be converted to CCG trees by reforaging from ABCTreebank data. We obtained 13,653 trees in total.

4 Discussion

Figure 6 shows the syntactic structure tree of the sentence (3) before filtering the *lightblue* chart, and Figure 7 shows the tree after filtering.

The *lightblue* lexical items for the predicate *gather* are the entries having ga-case and ni-case *NPs* as arguments. Therefore, *gather* was analyzed as having not only ga-case *NP* but also ni-case *NP* as arguments using the chart before filtering. However, the verb *gather* does not necessarily have the ni-case *NP* as an argument. Especially in sentence (3), it is reasonable to assume that *gather* has only ga-case *NP* as the argument. By overwriting the partial syntactic structure of the predicate *gather* having ga-case and ni-case *NPs* as arguments with a lexical entry having only ga-case *NP* as the argument, it became possible to convert ABCTreebank sentences to linguistically valid CCG syntactic structures. *lightblue* output also contains detailed syntactic features and Dependent Type Semantics (DTS; Bekki and Mineshima, 2017) representations.

4.1 Passive and Causative Sentences

As introduced in Section 2.2, Japanese CCGbank is based on the incorrect analysis for passive and causative sentences. To show how this study improved this issue, we discuss the passive sentences in the constructed treebank. The treebank constructed in this study includes the following passive and causative sentences:

- (4) 太郎は 先生に 絵を ほめられた
Taro-wa sensei-ni e-o homera re ta
Taro-NOM teacher-DAT picture-OBJ
praise passive PST

‘Taro was praised for his picture by his teacher.’⁶

- (5) 私は 猫に 魚を 食べさせた
Watasi-wa neko-ni sakana-o tabesa se ta
I-NOM cat-DAT fish-OBJ eat causative
PST

‘I fed the cat fish.’⁷

The CCG tree output by *lightblue* is in the Appendix. Figure 10 shows the syntactic structure and semantic representation of sentence (4). The category $S \setminus NP_{ga} \setminus NP_{ni} \setminus (S \setminus NP_{ga})$ is assigned to the passive suffix *re*, and the argument structure of the predicate *homera* is changed from $S \setminus NP_{ga} \setminus NP_o$

to $S \setminus NP_{ga} \setminus NP_{ni}$, which is linguistically valid. Figure 11 shows the syntactic structure and semantic representation of the sentence (5). The causative suffix *se* is also linguistically valid, in the same manner as the passive suffix *re*. These outputs for passive and causative sentences show the improvement of the incorrect analysis in Japanese CCGBank.

5 Error Analysis

The reforing process is successful in some sentences, but errors can still occur due to factors such as incorrect argument structures in ABCTreebank or incorrect analysis of the adnominal clause in *lightblue*.

5.1 Incorrect ABCTreebank Argument Structures

ABCTreebank occasionally contains incorrect argument structure annotations, and using such incorrect argument structures for reforing can remove correct lexical items in *lightblue*. For example, ABCTreebank contains erroneous argument structures for sentence (6).

- (6) 鈴木さんが 街で 旧友に 会った
Suzukisan-ga machi-de kyuyu-ni at ta
Mr.Suzuki-NOM town-LOC old friend-
DAT meet PST

‘Mr.Suzuki met an old friend in town’⁸

Figure 8 shows the syntactic structure of sentence (6) in ABCTreebank. ABCTreebank analyzed *old friend* as an adverb phrase and assigned the category $\langle\langle PP_s \setminus S_m \rangle\rangle / \langle\langle PP_s \setminus S_m \rangle\rangle$, despite the category PP_{o2} being correct for an ni-case noun phrase.

5.2 Incorrect Analysis of the Adnominal Clause

Sentence (7) below is an example of a sentence containing a relative clause:

- (7) 食べるものも なければ、 住む
Taberu mono-mo nakere ba, sumu
所も ない
tokoro-mo nai
Eat thing-NOM no CONJ, live place-NOM
no.

‘No food to eat, no place to live’⁹

⁶ABCTreebankID:413_textbook_kisonihongo

⁷ABCTreebankID: 693_textbook_purple_intermediate

⁸ABCTreebankID:132_textbook_kisonihongo

⁹ABCTreebankID:12_textbook_particles

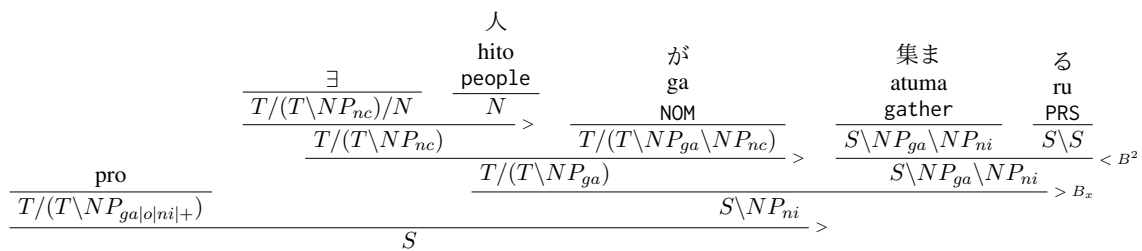


Figure 6: *lightblue* tree before reforging

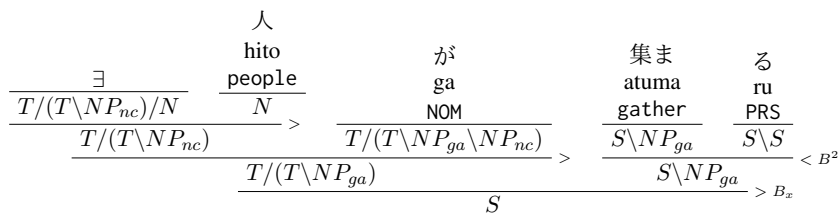


Figure 7: *lightblue* tree after reforging

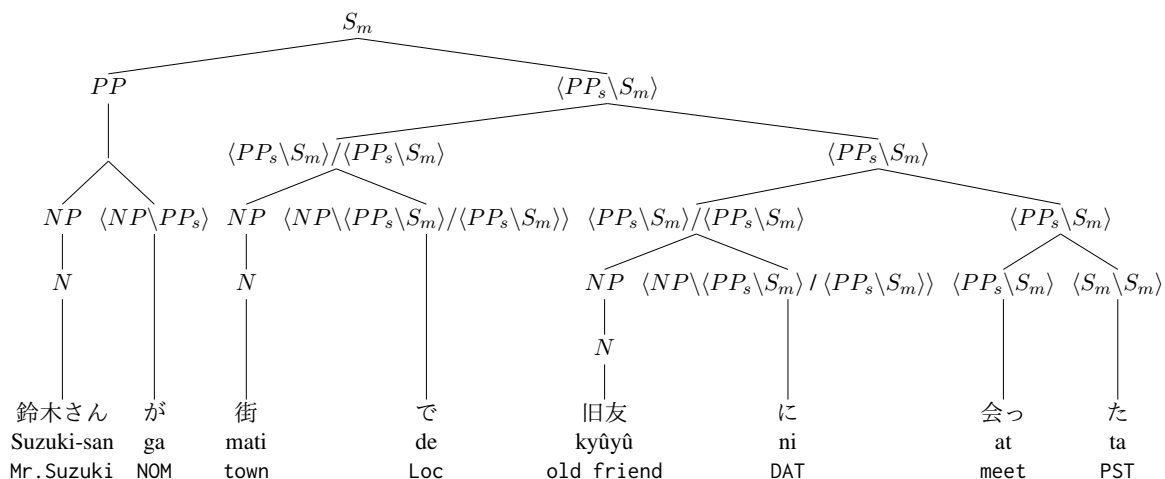


Figure 8: ABCTreebank syntactic structure of sentence (6)

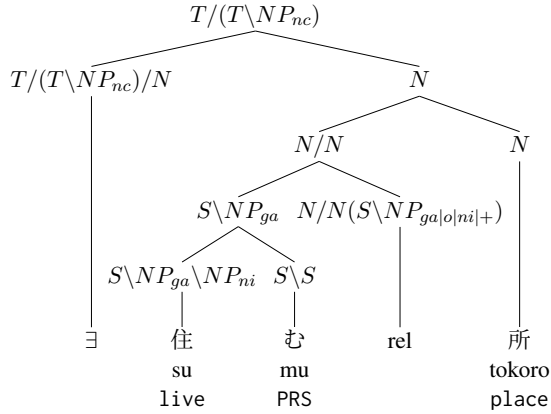


Figure 9: Invalid output for an adnominal clause sentence

Figure 9 shows part of the tree output after reforcing. In this tree, the predicate *live* takes the ga-case NP and becomes a relative clause, but cannot be interpreted as *the place is lived*. Thus, an external relation was analyzed as an internal relation.

6 Evaluation

Since the linguistic validity of constructed treebanks cannot be automatically evaluated, it is necessary to manually check one-by-one whether each syntactic structure and semantic representation is correctly obtained. However, the cost of manually evaluating the syntactic structures of CCG and DTS representations would be very high, and it was unfeasible to manually evaluate all of the 13,653 sentences constructed in this study. We thus manually evaluated 56 sentences, randomly sampling four sentences from each genre. We also evaluated the constructed treebanks by their conversion rates. As evaluation metrics for machine-learning-based CCG parsers such as *depccg* (Yoshikawa et al., 2017), lexical coverage, sentential coverage, and syntactic rule coverage are used. However, we did not use supervised learning methods for CCG parsing; instead, we performed rule-based conversions. Consequently, evaluations using unseen data were infeasible, so we used only conversion rates as an evaluation metric.

6.1 Conversion Rate

The conversion rate is the percentage of sentences fully converted to CCG trees. As a result of reforcing, out of 13,655 sentences, 13,653 sentences were successfully converted, for a conversion rate of 99.9%.

	Metrics	Sentences
Syntactic Error	Syntactic category	18
	Compound verb	4
	Other syntactic error	30
Semantic Error		7
No Error		19

Table 3: Results from manual evaluations

6.2 Manual Evaluation

We manually evaluated 56 randomly sampled sentences, four from each genre. Manual evaluations considered whether the sentences had correct syntactic structures from three perspectives:

1. Whether the sentence was assigned a invalid syntactic category
2. Whether compound verbs are analyzed separately
3. Whether other syntactic errors are included

We also evaluated the validity of output DTS representations to see whether correct semantic representations are obtained from syntactic structures. Table 3 shows the evaluation results. Syntactically and semantically valid trees were produced for 19 of 56 sentences (33%). One of the most common observed errors was the invalid syntactic categories. In particular, we observed several cases where the word *ni*, which should be analyzed as a case-marking particle, was incorrectly analyzed as the stem of the verb *niru* which means “to boil.” This occurred when reforcing overwrote the syntactic category a predicate having *ni* case NP as an argument. In the future, it will be necessary to eliminate this error by making an exception for the word *ni*.

The incorrect reforcing output can be categorized into the following four error cases:

1. The pre-reforcing argument structure is incorrect, but the post-reforcing argument structure is correct.
2. The pre-reforcing argument structure is correct, but reforcing results in an error
3. Both the pre-reforcing and post-reforcing argument structures are correct.
4. Both the pre-reforcing and post-reforcing argument structures are incorrect.

Reforging was successful in Case 1. Case 2 occurs when there are inaccuracies in ABCTreebank’s argument structure. Case 3 signifies instances where reforging had no impact, while Case 4 involves errors originating from *lightblue* that cannot be resolved through reforging. A future goal is to address and improve errors related to the argument structures that occur in Case 2.

7 Conclusion

We proposed a reforging method for constructing linguistically valid Japanese CCG treebanks with detailed syntactic features. Our method obtained correct Japanese CCG syntactic structures to some extent. Our method assumes that ABCTreebank argument structures are valid because their syntactic structures are manually annotated. However, there is an upper bound on the validity of ABCTreebank argument structures. To obtain linguistically valid argument structures, our future work will consider combining ABCTreebank with other reliable resources. We also plan to improve our filtering algorithm, and improve *lightblue*’s parsing algorithm to better handle long sentences.

Acknowledgements

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A Appendix

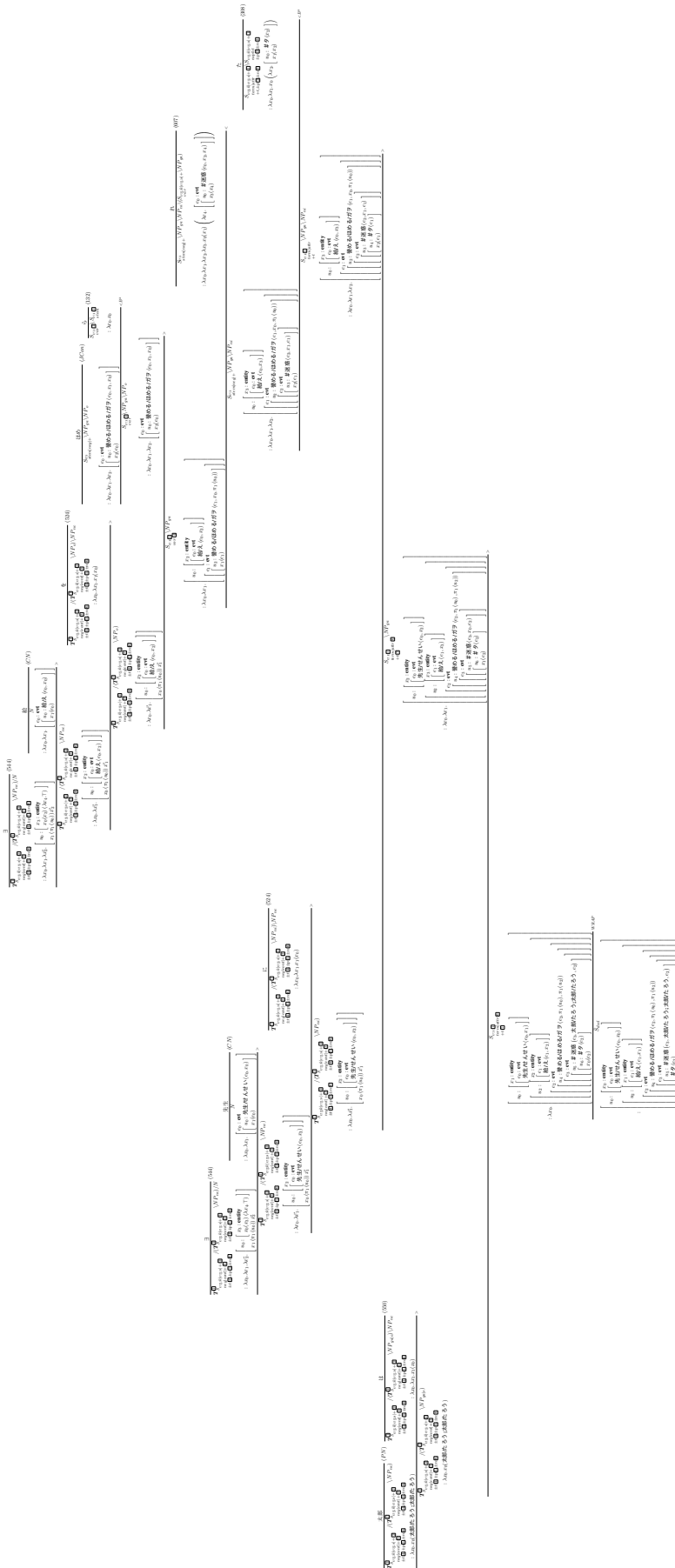


Figure 10: CCG tree of the passive sentence constructed by lightblue

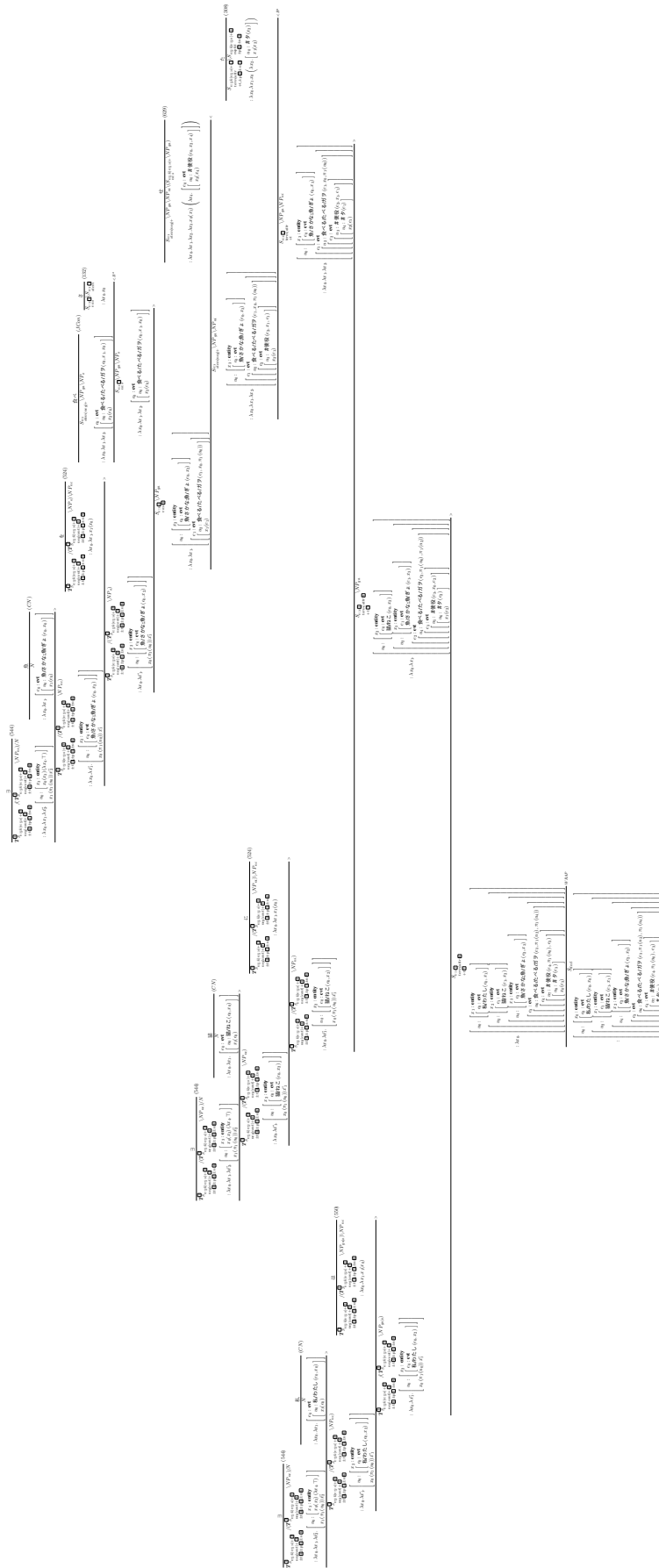


Figure 11: CCG tree of the causative sentence constructed by lightblue

Thesis Proposal: Detecting Agency Attribution

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Abstract

We explore computational methods for perceived agency attribution in natural language data. We consider ‘agency’ as the freedom and capacity to act, and the corresponding Natural Language Processing (NLP) task involves automatically detecting attributions of agency to entities in text. Our theoretical framework draws on semantic frame analysis, role labelling and related techniques. In initial experiments, we focus on the perceived agency of AI systems. To achieve this, we analyse a dataset of English-language news coverage of AI-related topics, published within one year surrounding the release of the Large Language Model-based service ChatGPT, a milestone in the general public’s awareness of AI. Building on this, we propose a schema to annotate a dataset for agency attribution and formulate additional research questions to answer by applying NLP models.

1 Introduction

The value of studying power relations through the lens of language has been investigated in various contexts from online communities to film plots, see e.g. [Bramsen et al. \(2011\)](#); [Danescu-Niculescu-Mizil et al. \(2013\)](#); [Sap et al. \(2017\)](#). Across different fields, agency has a range of definitions, which highlight different aspects of the concept. Within the context of this work, agency is taken as the freedom and capacity of an entity to act, corresponding to one facet of power. *Perceived agency* is then the agency that we project on other entities while interpreting a description of a situation. Perceived agency is important because it signals autonomy and independence, but also moral accountability: it is hard to imagine a hero or villain who is always a victim of circumstance. The perception of agency also influences how we assign blame or praise. For example, the *actor-observer* cognitive bias ([Jones and Nisbett, 1971](#)) is the general tendency to explain other individuals’ behaviours as

an effect of their personalities, i.e. as something they cannot help doing given who they are, and our own behaviours as the rational response to our current situation. For example, someone else’s slow driving may be attributed to their age or gender, but when we drive slowly we attribute it to specific reasons such as worn tyres. If we feel we deserve credit, we can frame our behaviour as an active choice; if we want to avoid guilt, we can emphasise the external pressure.

To assign, e.g. responsibility, agency attribution is frequently manipulated in political discourse and partisan reporting to affect the audience ([Iyengar, 1994](#)). For example, there are discursive techniques to humanise or dehumanise migrants that draw on agency ([Kirkwood, 2017](#)): portraying incoming migrants as independent agents (e.g. asylum seekers) in opposition to more passive roles (refugees) naturally affects public perception and can influence the assumptions underlying political decisions ([Sajjad, 2018](#)). However, even without an explicit political intention, the wording may suggest how agency is assigned. Wikipedia, for example, is widely known to have its guidelines built around a ‘neutral point of view’, but the editorial bias (not limited to agency) that the guidelines seek to eliminate remains ([Hube, 2017](#)). In the general audience media, it is not uncommon to observe agency shifts between collectives and individuals (‘The company has decided to lay off’ vs. ‘The board has decided’ vs. ‘The CEO has decided’) and between individuals and artefacts (‘The car crashed into the bridge’ vs. ‘The driver crashed his car into the bridge’) ([Te Brömmelstroet, 2020](#)). Furthermore, perceived agency plays a key role when discussing entities that are specifically designed to appear intelligent. Most prominently – the various technologies referred to as AI, but also, for example, toys, voice recognition systems, and non-playable video game characters. Therefore, perceived agency is

created by a mixture of intentional and unintentional messaging.

In this proposal, we focus on perceived agency as a prediction target for computational models, and as a direction for linguistic analysis in computational social sciences. If framed as a question-answering task, the prompt would be ‘Who or what acts or can act independently and intentionally in this situation?’. From this, we derive two research objectives. The first is to investigate the computational approach to studying attributed agency (RQ1), in particular, the efficacy of different computational models in predicting perceived agency.

RQ1: What linguistic features and computational models are most suitable for predicting perceived agency?

The second goal is to apply NLP methods as part of studies in computational social science to understand agency in specific contexts. We are interested in learning whether: (i) it is feasible to use such computational models to measure the public’s perception of agency, (ii) the models generalise across narrow topics, and (iii) these models can be part of topic-specific social scientific studies and combined with qualitative approaches. In short:

RQ2: To what extent can automated prediction of perceived agency in text answer questions from social science? What questions can it answer?

2 Prior computational work

There is limited research on NLP methods for agency attribution. The closest work is likely that by Minnema et al. (2022a) on *perceived responsibility*, which is part of their broader work on detecting perspectivisation (Minnema et al., 2022b) using FrameNet-based annotations (Baker et al., 1998). They project perceived responsibility in a sentence onto three axes: blame, focus, and cause, and demonstrate that text features account for some of the differences in these facets of perceived responsibility. In particular, they study Italian news reporting of femicides and Dutch articles reporting traffic accidents (Minnema et al., 2022b,a). The latter is based on the study by Te Brömmelstroet (2020) that investigates news headlines about traffic accidents. The authors annotated articles into agentive and non-agentive categories based on the

phrasing. This group of works focus on the attribution of *responsibility* (‘Who or what is blamed in this situation?’), rather than specifically on agency as we describe it above.

A larger group of related work is focused on the (perceived) semantic roles that entities play in a text. This approach goes back to the folklorist studies of Propp (1968) and focuses on identifying archetypes, such as ‘hero’, ‘villain’ or ‘victim’. Computational applications of Propp’s ideas vary from directly applying components of his grammar to new texts (Finlayson, 2016) to using Large Language Models (LLMs) for zero-shot role labelling (Stambach et al., 2022). In terms of domains of application, news articles are prominent (Stambach et al., 2022; Gomez-Zara et al., 2018), but role prediction has also been applied in other settings containing political discussions. For example, identifying semantic roles in memes has been used as a shared task and prompted both text-based and multimodal solutions (Sharma et al., 2022). Finally, semantic role labelling, as well as FrameNet-style annotations, are used in the field of emotion detection (Bostan et al., 2020). As in agency attribution, emotion detection assumes a choice of perspective (i.e. that of the writer or reader) before making predictions.

A particularly relevant study by Sap et al. (2017) is related to both of these groups of works and introduces frames of agency and power to investigate the subtler types of gender bias in modern films. Their study focuses on establishing the agency of characters throughout a longer narrative (compared to shorter messages we are interested in) and emphasises authority as one of the main indicators of agency, but even with these differences in approach, it remains one of the closest points of reference for this proposal.

3 Application areas

We consider two application areas, namely the agency ascribed to AI systems and the examination of bias in news reporting.

AI anthropomorphism Our first domain of interest, to which most of our preliminary work has been dedicated, is the ongoing discourse on systems claiming to be artificial intelligence (AI). Recent developments of LLMs and their branding as ‘AI’ reinforce the anthropomorphisation of the technology. Generative models, especially those

used in chatbots, tend to emulate first-person human speech, and end users are intended to project higher levels of agency on these systems. This may have positive effects in some contexts (Sheehan et al., 2020) but also have highly adversarial effects, e.g. a dangerous over-reliance on the system (Abercrombie et al., 2023).

More broadly, the degree to which AI systems are viewed as active agents is reflected in public conversation and news coverage. The impact of alternative phrasings is illustrated in Table 1. In the first example, agency shifts in a similar way to what has been observed in the news coverage of car crashes (Te Brömmelstroet, 2020), in the sense that an instance of a technological artefact is used to refer to people or organisations (AI companies, in this case). It stands, however, to reason that, unlike in the case of cars, the word choice is not purely rhetorical because people may perceive true agency from ‘AI’ actors (an observation which deserves further investigation). The second example in Table 1 provides one depiction of an AI system as a conversational partner and one as a tool. The agency is thus ascribed either, at least in part, to the system or to the self in full.

Reporting bias Our second domain of interest is attributed agency bias towards marginalised groups in news reporting. Rhetoric plays a significant role in advancing political agendas and through the “correct” linguistic choices, stereotypical qualities can be ascribed to individuals. For example, the labelling of individuals as opportunistic or immoral has been demonstrated to influence public opinions and migration policies (Kirkwood, 2017; Findor et al., 2021; Sajjad, 2018). Agency attribution is an important aspect of this phenomenon and a focus of our investigation.

In both of these domains, language reflects how the media or the public interprets specific technological and social issues. These interpretations by the mass media inform and influence those who make policies and regulations, thus translating perceptions into reality.

4 Proposed work

This section outlines the preliminary and proposed future work that will go into the thesis.

4.1 Preliminary work

In an ongoing study of AI in news reporting, we analyse the descriptions of AI systems performing various tasks. Since the release of the LLM-based ChatGPT in November 2022, there has been a massive increase in publications on AI. Interestingly, the statistics reported by Google Trends (Figure 1) indicate that previous releases of generative tools such as Stable Diffusion, DALL-E 2, and Midjourney (all made in the summer of 2022) did not correspond to any significant increase in the general public’s interest in AI. The quantitative change in AI news coverage was only brought on when LLMs entered the scene. Our research goal for this study is to investigate whether the use of the term ‘AI’ has changed qualitatively as well. In other words, whether journalists write about AI differently now compared to the time before ChatGPT.

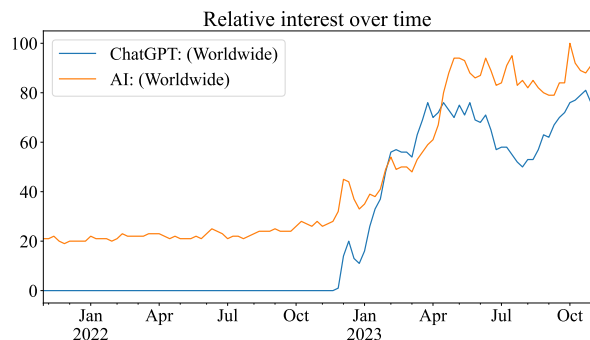


Figure 1: Relative interest in ‘ChatGPT’ and ‘AI’ between October 2021 and October 2023 based on search queries (normalised search numbers over the period). Source: Google Trends (<https://trends.google.com/trends/>).

For the study, we collected a dataset of 6 150 articles mentioning the term ‘AI’. We choose to work with general-domain publications because we expect these to better reflect the language of the general public than, for example, technical or scientific publications. For legal reasons, the set of publications was restricted to such that do not impose paywalls. The dataset covers publications from May 31, 2022, to May 31, 2023, and contains 19 out of the 25 largest English-language news websites as of May 2023 (Majid, 2023). As part of our analysis, we assign FrameNet annotations to sentences mentioning ‘AI’ using the FrameNet parser from the information extraction system LOME (Xia et al., 2021). The annotated frames provide a convenient way to study the uses of ‘AI’ by the type of situation at a relatively large scale. For the purpose

High communicated agency	Low communicated agency
‘Will AI steal your job?’	‘Will the AI companies disrupt the job market?’
‘AI helped me with my homework.’	‘I used AI tools in my homework.’

Table 1: The impact of phrasing on the communicated agency of AI systems.

of this proposal, we are interested in frames and their attributes that may indicate that some level of agency is assigned to ‘AI’.

A number of FrameNet frames that describe cognitive efforts implying at least some degree of agency (e.g. *awareness*, *coming_to_believe*, *opinion*) have an attribute *cognizer* that refers to a sentient being enacting these efforts. Selecting such frames where AI plays the role of a ‘cognizer’ provides us with a subset of data where it is likely to have some perceived agency. Out of 609 such occurrences in our dataset, the most common constructions involve AI ‘thinking’ (87 instances), ‘analysing’ (47), ‘making decisions’ (39), ‘predicting’ (37) and ‘learning’ (30). Thinking is most often, but not always, brought up in articles such as: ‘Here’s how AI thinks X would look’ (Table 2), clearly anthropomorphising an AI system and giving it intentionality. In the same subset of frames, other constructions are often used to describe the normal functionality of a system relatively neutrally, e.g. ‘...AI is good at recognizing patterns...’ (Table 2). In this case, the perception of agency behind AI would arguably be lower than in the one above. These examples illustrate how, even within semantically similar constructions, implied and perceived agency can differ significantly. They also demonstrate that while evoking specific frames does not necessarily correspond to agency directly, pipelined FrameNet annotations have their use in identifying descriptions of situations with ambiguous agency.

4.2 Phase 1: Dataset annotation

Our first goal is to define the computational task for perceived agency detection. For this, we need an annotated dataset that covers two or more domains to ensure we can understand how well the solutions generalise. The first area of interest was discussed in Section 4.1: the perceived agency of AI in mass media coverage. We plan to annotate various statements from AI and technology-related articles published by mainstream media derived from the news corpus described in the same section. One of the goals of our study is to compare perceived human

and technological agency, and the second part of the new dataset will be focused on the portrayal of humans in newspaper headlines, with a balance of topics such as politics, entertainment, crime, etc.

Through the crowdsourced annotation process, we aim to both create a dataset fitting for the perceived agency detection and investigate how the annotation reflects annotators’ interpretation of the topic. We interpret agency as the capability to take intentional actions and, even more broadly, influence the situation. In the experimental setting, a ‘situation’ is fully described in one or several sentences (e.g. by a news headline or a paragraph) and should contain only several entities displaying agency. Therefore, we consider it a reasonable annotating task to rate the degree of agency exhibited by these entities according to a reader’s perception.

We propose the following annotating process (examples of steps 1 and 2 in Table 3):

1. **Identification.** Annotators are given a broad explanation of our interpretation of agency and asked to highlight all entities that have agency in the described situation, with an option to write in external entities.
2. **Specification.** For each entity, the respondents answer a multiple-choice question about the level of agency the entity has in the situation (‘How would you describe the agency the X demonstrates in this situation?’). The degrees of control given in the answers are ‘complete control’, ‘a high level of control’, ‘some or shared control’, ‘little control’, and ‘no control at all’.
3. **Resolution.** To resolve annotation conflicts, we propose using the longest, most common, subsequence rule (Bostan et al., 2020) for highlighted entities.
4. **Aggregation** To aggregate the multiple-choice answers, the annotations can be converted from categories to numerical values. This can be done by assigning numerical values to the possible answers and computing average scores for annotated entities. Because the scores represent the

Table 2: Examples of sentences with LOME-labelled frames where AI plays the role of a ‘cognizer’.

Remember, AI is good at recognizing patterns, and humans are good at understanding when those patterns have meaning versus when they are spurious correlations.	Here’s what AI thinks Barbie will look like at ages 50, 60, and 70.
Frame: ‘Becoming_aware’ – recognizing	‘Awareness’ – thinks
Attributes: ‘Cognizer’ – AI	‘Cognizer’ – AI
‘Phenomenon’ – patterns	‘Content’ – what
	‘Content’ – Barbie will look like at 50, 60, and 70.

Table 3: Proposed annotation example. As a first step, annotators are offered to highlight entities with agency. The second step is annotating the level of agency for each entity: from low (recognised as an agent but next to no influence) to complete (full control of the situation).

Sentence	Mary asked AI for help with her homework.	Mary used an AI tool in her homework.
First step		
Entities with agency	Mary asked AI for help with her homework.	Mary used an AI tool in her homework.
Second step		
Level of agency	Mary asked AI for help with homework Mary – high, AI – medium	Mary used an AI tool in her homework. Mary - complete

agency in a specific closed situation, they should be normalised over the situation.

Step 1 can be complemented by named-entity recognition to identify noun phrases not marked by the annotators, resulting in a category for the entities that are not even considered to be agents, i.e. incapable of taking an active role at all (as opposed to the ones perceived as agents but considered not to have agency in the specific situation).

4.3 Phase 2: Predicting perceived agency level

Unlike stance or opinion mining, which require broad semantic context, the level of agency can be expressed with shorter spans of text and more syntactical instruments, such as passive voice or the choice of a specific synonym. Therefore, it is reasonable to expect machine learning approaches to perform well on agency attribution, even when applied to single sentences. This assumption is supported by Minnema et al. (2022a), who reported encouraging performance of a fine-tuned BERT-based model on a similar, but even more topic-specific and granular, perception mining task. Based on this, we are aiming to test several models of different levels of complexity on the annotated dataset. In particular, through our experiments, we are interested in answering the following questions:

- Can a pre-trained language model (e.g. BERT*) be fine-tuned to predict perceived agency? If yes, would fine-tuning such a model on a dataset covering one topic (e.g. AI news) transfer the

performance to another (e.g. culture news)?

- Can existing named entity recognition models or more generalised semantic information extraction models, such as LOME, be directly useful in predicting perceived agency?
- Is it possible to reliably annotate perceived agency with LLMs so that the result is consistent with human judgement?

5 Conclusion

When we interpret stories, make decisions based on them, or place responsibility or blame, we rely on our perception of agency to understand whose intentions are driving events. Language choices can intentionally and unintentionally influence this perception and, ultimately, our reactions. In this proposal, we put forward perceived agency detection as an NLP task and outline our preliminary and planned work on creating and annotating a perceived agency dataset. Our focus is on two topical areas: a narrow one (perceived agency of AI) and a broader one (perceived agency in news headlines, with an eye towards bias). We describe some of our planned computational experiments, which will evolve as we learn from our findings, and aim for computational social science applications. We hope this proposal brings focus to the notion of perceived agency and highly welcome all types of feedback to further improve it.

Limitations

As with any study based on collecting data on human perceptions from a limited number of participants, the proposed thesis relies heavily on the assumption that the surveyed demographics and their responses are sufficiently representative to make results generalisable. Both the dataset and the choice of annotator will inevitably introduce bias that needs to be considered and reported. Due to how the annotated data is acquired, we further limit our definition of agency. For example, besides studying the perceived agency of entities mentioned in a message or the messenger, it is worth considering the perceived agency of the readers themselves, which we do not investigate here. In particular, in contexts with frequent direct messaging, such as advertising and political communication, influencing the readers' sense of agency can be a nudging or manipulating technique. However, assessing participants' self-perception based on texts would likely require a different set of tools, as well as considerable expertise in psychology. Similarly, it can be argued that the source of information (e.g. a news article vs. a social media post vs. a generated response by a chatbot) may affect how humans perceive it. However, within the framework of this project, we do not yet have the means of assessing the influence of the text source on human interpretation of agency.

Another significant limitation is that the current proposal is limited only to English-language media, largely due to their international dominance. If the perceived agency prediction task is reliably solvable, it should be further considered in the multilingual setting. As shown by, e.g. Findor et al. (2021), types of agency and perceptions can shift significantly through literal translation because of different etymologies and connotations. Therefore, building a multilingual corpus out of direct translations that imply different levels of agency may present a more challenging task.

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A Thesis Proposal

ClaimInspector Framework: A Hybrid Approach to Data Annotation using Fact-Checked Claims and LLMs

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Abstract

This thesis explores the challenges and limitations encountered in automated fact-checking processes, with a specific emphasis on data annotation in the context of misinformation. Despite the widespread presence of misinformation in multiple formats and across various channels, current efforts concentrate narrowly on textual claims sourced mainly from Twitter, resulting in datasets with considerably limited scope. Furthermore, the absence of automated control measures, coupled with the reliance on human annotation, which is very limited, increases the risk of noisy data within these datasets. This thesis proposal examines the existing methods, elucidates their limitations and explores the potential integration of claim detection subtasks and Large Language Models (LLMs) to mitigate these issues. It introduces ClaimInspector, a novel framework designed for a systemic collection of multimodal data from the internet. By implementing this framework, this thesis will propose a dataset comprising fact-checks alongside the corresponding claims made by politicians. Overall, this thesis aims to enhance the accuracy and efficiency of annotation processes, thereby contributing to automated fact-checking efforts.

1 Introduction

The initial step in researching misinformation necessitates a set of criteria to determine the accuracy of a claim. Due to the impracticality of manually scrutinising each piece of information, researchers often rely on the evaluations of fact-checking organisations. They construct datasets that consist of claims that have previously been fact-checked.

However, these datasets also come with a set of limitations. Although a wealth of fact-checking resources exists to document the infiltration of misinformation across various channels, including political ads, politicians' websites and newspapers,

the majority of current efforts concentrate on analysing textual claims from a single source, with Twitter being the predominant platform for claim collection. In addition, due to the methods applied in claim matching and the lack of additional controls, the datasets generated often carry a high risk of containing a considerable amount of noisy data. Efforts have been made to mitigate this issue through human annotation; however, limited resources allow such annotation to be performed on only a limited portion of the data (Kazemi et al., 2022; Shahi et al., 2021a; Vo and Lee, 2020). As a result, all these limitations may pose a risk of reduced efficacy in detecting misinformation, since claim detection and fake news detection models may be trained on this limited – and potentially noisy – subset of data.

Therefore, this thesis proposal is centred on addressing the limitations of this process. Informed by these challenges, the main objective of this thesis is to answer these questions:

- RQ1: What are the limitations of current data annotation methods for identifying misinformation?
- RQ2: How can the use of methods for the detection of previously fact-checked claims mitigate these limitations?
- RQ3: To what extent can LLMs be utilised in claim matching during data annotation to address these limitations?

This thesis considers the multimodality of misinformation across various channels. It aims to refine the matching process by drawing on automated fact-checking literature and seeks to establish a more efficient annotation process by incorporating LLMs into the annotation workflow.

By improving this process, this study seeks to not only contribute to the automated fact-checking process, but also to provide support to fact-

checkers. Manual fact-checking demands both rigorous attention to detail and a significant investment of time. In this regard, identifying claims that have previously been fact-checked can offer a substantial time-saving advantage for fact-checkers, as it eliminates the need for the redundant verification of claims that have already undergone scrutiny (Shaar et al., 2020; Shaar et al., 2022). Moreover, it can enable swift intervention, which can limit the dissemination of false claims (Nakov et al., 2021).

The remainder of this paper is organised as follows: Section 2 introduces the related work and discusses the limitations. Following this, Section 3 provides information on the proposed method and describes the ClaimInspector framework. Section 4 details a case study that applies the framework for building a dataset of claims made by politicians. Section 5 presents a preliminary plan for experiments. Lastly, Section 6 states the conclusion.

2 Related Work

In this section, I review the literature on data annotation and claim detection and discuss the limitations.

Researchers divide the fact-checking pipeline into four main subtasks: (1) the assessment of checkworthiness, (2) the detection of previously fact-checked claims, (3) the retrieval of evidence and (4) the verification of the factuality of the claim (Shaar et al., 2020). Data annotation, while not listed among these subtasks, can be considered a preliminary task (0). This foundational step is crucial, as it involves labelling data, which supports both the preparation of data for the entire fact-checking pipeline and the training of algorithms. Claim detection, another integral part of this sequence, is closely linked to the assessment of checkworthiness and the detection of previously fact-checked claims.

2.1 Data Annotation

The scarcity of annotated datasets for training and benchmarking has constituted a substantial obstacle in NLP research (Chapman et al., 2011). Recruiting an annotator with specialised expertise is financially expensive, and providing the necessary training to non-experts is time-consuming (Shahi and Majchrzak, 2022). This challenge is particularly pronounced in areas such as misinformation research, where domain-specific

knowledge and a deep understanding of context are essential. For instance, when annotating information related to COVID-19, proficiency in medical terminology and scientific context is required.

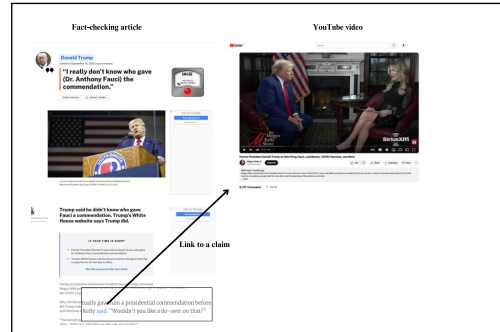


Figure 1: The overview of the extraction of URLs from a fact-checking article.

To overcome these challenges, researchers have directed their focus towards domain-specific information sources, which manually verify each claim. Fact-checking websites, in particular, have proven invaluable for large-scale annotation tasks. Within a fact-checking article, fact-checkers typically cite the source of a claim, providing links to news articles, video platforms or campaign websites. Researchers extract these links and assign labels, such as true, partially false or false, based on the verdict provided within the fact-checking article. Figure 1 illustrates the annotation of a claim source (e.g. [YouTube video](#)) using the labels given in the fact-checking article (e.g. [PolitiFact article](#)).

This approach has seen widespread application across various domains, particularly when retrieving claims made on social media platforms (e.g. Kazemi et al., 2022; Shahi et al., 2021). The AMUSED framework (2022) thoroughly details the stages of this approach for claims made on social media platforms. These stages include searching for anchor tags `<a>`, which indicate hyperlinks in fact-checking articles. Subsequently, hyperlinks are filtered to identify those leading to social media posts. Following this, corresponding social media data is collected and labelled based on the ruling assigned to the news articles by a fact-checker. The final stage includes human annotation to verify the assigned label.

In particular, studies have adopted the AMUSED framework to extract claim URLs. However, extracting claim URLs is not a straightforward task. There were some efforts to

make fact-checking websites structured in order to obtain data, such as creating a JSON format to use the ClaimReview-type specified by Schema.org (RAND, 2015). However, metadata is not always complete for claims from those websites (Shahi et al., 2021b; Quelle et al., 2023). In addition, fact-checkers often present the source of a claim along with various links that support their judgement on the claim. Therefore, in most cases, it is difficult to pinpoint the exact location of a source URL among the others. As the AMUSED framework searches for all anchor tags leading to social media platforms, it may fetch unrelated URLs, potentially leading to mismatches. For instance, a fact-checking article may refer to a subsequent tweet debunking the misinformation or an earlier tweet sharing accurate information that was later repurposed for spreading misinformation (Shahi et al., 2021a).

Another approach in data annotation (e.g. Vo and Lee, 2020) is to search for links to fact-checking articles among responses to social media posts. If a fact-checking link is found, then a pair of a social media post and its corresponding fact-checking article link matched. This approach operates under the assumption that these links signify fact-checking interventions relevant to the post being responded to. For instance, if user A responds to user B’s tweet by sharing a link from PolitiFact, a researcher detects B’s tweet by searching for links that include the PolitiFact hostname among its direct replies. Then, they annotate B’s tweet with a fact-checking rating, assuming that the verification of A is relevant to the claim posted by B.

Although this approach has only found a limited application in automated fact-checking research, researchers have widely used this approach in researching the spread of misinformation on social media (e.g. Vosoughi et al., 2018; Bond and Garrett, 2023; Friggeri et al., 2014). However, this approach also has several limitations. First, posts shared on social media that have not yet received a reply containing a fact-check link elude the researcher’s scrutiny. The absence of such links does not necessarily indicate the absence of misinformation. For instance, research has shown that partisan communities avoid using fact-checking and, in some cases, they have moderation policies that delete fact-check links automatically (Parekh et al., 2020). This means that researchers are likely to miss these posts in their data. Second,

the link shared may be unrelated and did not fact-check the content of the social media post. Moreover, there may be instances where fact-checking articles, despite addressing similar topics, may concentrate on different aspects (Vo and Lee, 2020).

These methods create uncertainty about whether the link extracted from the fact-check article represents the original source disseminating misinformation. This situation underscores the importance of additional checks on claim URL-fact-check pairs. While the AMUSED framework proposes a labelling step by human annotators to ensure that the pairs are matched correctly, studies often perform this task on only a subset of claims, such as randomly selecting 100 pairs (e.g. Kazemi et al., 2022), or do not perform it at all (e.g. Shahi et al., 2021a).

Overall, these limitations raise concerns about the potential noise in datasets. There is a need for solutions that can use more automation. At this juncture, it appears that claim detection methods and LLMs could offer solutions that support human augmentation in addressing these challenges, which are key objectives of this thesis.

Furthermore, this thesis broadens its scope to encompass not only social media content but also news articles and video platforms. Previous studies have primarily focused on claims originating from social media, with a particular emphasis on Twitter. Apart from a small number of studies that explored multimodal claims (e.g. Vo and Lee, 2020; Shahi and Majchrzak, 2022), the majority of these works were predominantly focused on analysing text-based content. This limited focus inevitably results in selection bias, capturing only a fragment of the information landscape. By expanding its scope, this thesis aims to provide a more comprehensive analysis of misinformation, ensuring a thorough examination across diverse media sources.

2.2 Claim Detection

Claim detection is an integral step in the subtasks for assessing checkworthiness and detecting previously fact-checked claims. This study will specifically concentrate on its role in the second subtask. There is no need to focus on checkworthiness here, as claims have already been extracted from fact-checks.

Detecting previously fact-checked claims can be defined as follows: “Given a check-worthy input claim and a set of verified claims, rank the

previously verified claims in order of usefulness to fact-check the input claim” (Nakov et al., 2022). Most of the prior works have mainly focused on the retrieval and ranking of fact-checks based on their relevance to a given tweet or a political statement (e.g. Shaar et al., 2020; Nakov et al., 2022; Kazemi et al., 2022). These works measured token similarity and semantic similarity between a given tweet/political statement and previously fact-checked claims. They used classical lexical retrieval models, such as BM25 (Robertson and Zaragoza, 2009), and transformer-based models, such as BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019).

Another line of research approached claim detection with a reverse formulation (e.g. Hossain et al., 2020). Given a database of verified claims, they identified social media posts that make similar claims. In addition to using common semantic similarity models for information retrieval, Hossain et al. (2020) detected the stance of tweets, whether the tweets agreed, disagreed or no stance was taken, and demonstrated that most models do not perform well in the agree and disagree classes. However, when they first identified whether the fact-check-tweet pair was relevant using BERTScore (Zhang et al., 2019), and then only relevant pairs were further classified based on their stance using Sentence-BERT (S-BERT) (Reimers and Gurevych, 2019), the model performed well.

Recently, researchers have focused on the use of LLMs in automated fact-checking. LLMs have a high potential to assist in pinpointing portions of documents that reiterate a claim that was previously verified or express a claim with a similar meaning to one that has already been confirmed (Augenstein et al., 2023). A recent study (Choi and Ferrara, 2023) has demonstrated that fine-tuned LLMs can assist in evaluating the textual entailment between social media posts and verified claims. Fine-tuned LLMs (GPT-3.5-Turbo, Llama-13b-chat-hf, Llama-7b-chat-hf) surpassed the performance of pre-trained LLMs in claim detection.

3 Proposed Method

The proposed method consists of two main stages. The first stage, outlined in Section 3.1, involves extracting the source link of a claim from a fact-checking article and verifying its relevance to the fact-check. The second stage concentrates on broadening the dataset’s scope by retrieving

relevant news articles or video content associated with a verified claim, as elaborated on Section 3.2. Subsequently, Section 3.3 introduces the ClaimInspector framework, providing a summary of the overall process.

3.1 Identifying Original Sources in Fact-checking Articles

Task: This stage is closely related to the works of Shahi et al. (2021a), Shahi and Majchrzak (2022) and Kazemi et al. (2022), which focused on finding existing fact-checks for claims made in social media posts. The objective is to perform this not only for social media posts but for all types of claim sources. This task can be divided into the following two subtasks:

- Original Source Identification: Given the URL of a fact-checking article, return the URLs of the sources that are cited as the origin of the fact-checked claim.
- Stance Detection: For each fact-check and matching source pair, predict whether the fact-check and matching source agree or disagree or whether the matching source takes no stance with respect to the fact-check.

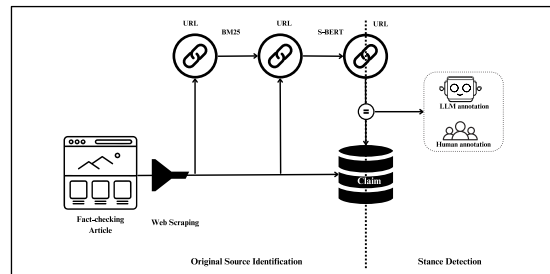


Figure 2: The workflow for identifying original sources in fact-checking articles.

Methods: Similar to the aforementioned studies, I will extract claim URLs mentioned in fact-checking articles. I will use Beautiful Soup (Richardson, n.d.), a Python library for extracting data from HTML, to retrieve the content of the fact-checking articles and prepare a list of source URLs. An illustration of the overall workflow for fetching claim sources cited in the fact-checked articles is shown in Figure 2.

However, to address the limitations discussed in Section 2, this thesis differs from the previous studies in several key aspects. First, this thesis will

focus on a diverse range and types of sources cited in fact-checking articles, including, but not limited to, the official websites of politicians, campaign ads and news articles. The prior works restricted their scopes to claims that were made in social media posts, in particular, Twitter posts. In order to mitigate this selection bias, this thesis aims to explore both textual and video content.

Second, for claim URL-fact-check pair validation, I will assess both token and semantic similarity – common metrics often employed in the claim detection stage. This approach is designed to bolster the robustness of the dataset. As highlighted in Section 2.1, the methods used in the previous works may lead to noisy data. To solve this issue, I will conduct an additional verification step to confirm the relevance of the identified pairs. Similar to the recent research (Choi and Ferrara, 2023), this will involve leveraging the BM25 algorithm and S-BERT to capture both token and semantic similarity between a verified claim by fact-checkers and the source of a claim. I will utilise Beautiful Soup to extract data from the source URLs.

In addition, as a final control step, this stage will include both LLM annotation and human annotation. As I automatically pair the source and fact-check through the references in fact-checking articles, I will conduct an extra step to confirm the relatedness of these pairs. Each pair of claim sources and fact-checks will be classified into one of the following options: entailment, contradiction and neutral. If it is classified as entailment, then I will assign labels to claim sources based on the label assigned to the fact-checking article. If not, then the data will be excluded from the dataset.

Three human annotators will be recruited through Amazon Mechanical Turk to annotate a randomly chosen sample of 100 pairs. I will employ the majority rule for human annotation to establish ground truth. This approach holds up when there is a high-level of agreement among annotators. While recognising that this may not always hold true (Plank, 2022), in the context of this thesis it is deemed appropriate. As the semantic and token similarity will already have been conducted, pairs that have reached the final phase are presumably related, thereby rendering the task less challenging. I anticipate a high level of consensus among annotators in deciding whether or not a fact-check and claim source matches. Consequently, the majority rule will be the method

of choice for human annotation. Following this, similar to the prior work (Choi and Ferrara, 2023), I will compare these human annotations with those from LLMs. Overall, these measures are designed to ensure that the URLs collected are correctly matched with their corresponding fact-checks and labels, thereby enhancing the overall integrity of the dataset.

3.2 Detecting Relevant Claim Sources Containing Previously Fact-checked Claims

This thesis aims to identify content that is similar to the source of a claim cited by fact-checking organisations, acknowledging the circulation of misinformation beyond sources listed in fact-checking articles. Fact-check organisations typically focus on the source where a claim is first stated, often prioritising mainstream outlets. However, the claim may also have been circulated through other mediums. Especially in recent years, misleading information has been disseminated through algorithmically generated or ‘junk news’ sources that do not adhere to journalistic norms (Burton and Koehorst, 2020). Therefore, this research will detect news articles containing previously fact-checked claims.

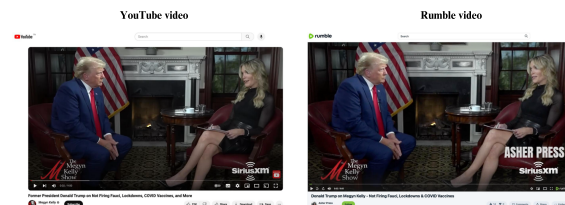


Figure 3: While originally published on YouTube, the claim was also spread on Rumble.

In addition, this study will consider the visual contents of fact-checked claims on non-mainstream platforms. For example, a fact-checked claim (e.g. Ramirez Uribe, 2023) presented as a video link on YouTube (e.g. Kelly, 2023) may also circulate on non-mainstream video sharing platforms, such as Rumble (e.g. Asher Press, 2023), a popular platform among conservatives and far-right communities, as shown in Figure 3. Therefore, this study will also search for claims made in video formats across popular non-mainstream video platforms, in particular, two popular alternative social media websites that focus

on videos, Rumble and BitChute (Pew Research Center, 2022).

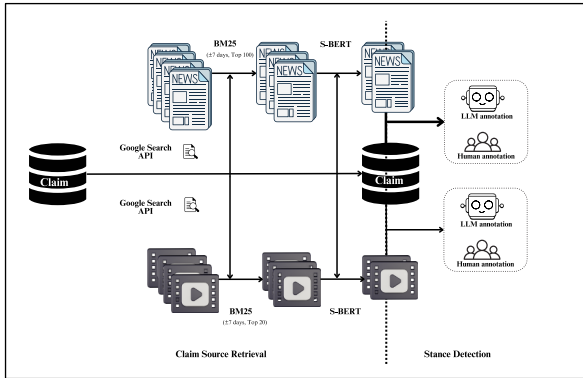


Figure 4: The workflow for detecting relevant claim sources containing previously fact-checked claims.

Task: An illustration of the overall workflow is shown in Figure 4. I formulate the task of detecting related news articles and videos as retrieving relevant content and classifying whether it is related to the fact-check. This task can be summarised into the following subtasks:

- **Claim Source Retrieval:** Given a fact-check, return a subset of relevant news articles and video sources.
- **Stance Detection:** For each fact-check and matching text/video source pair, predict whether the fact-check and matching source agree or disagree, or whether the matching source takes no stance with respect to a fact-check.

Methods: The headlines of fact-checking articles are generally written in a way that reflects the actual claim, and so they can be used to get the original news articles. Therefore, I will search the headline of the fact-checking article on Google via Google Search API, and retrieve the top 1,000 results that best match each fact-checked claim within a ± 7 -day timeframe from the day the initial claim was made. This approach will allow us to identify content that is most closely related to the claim source.

I will utilise Beautiful Soup to extract data from source URLs. To find claims that are related to fact-checked claims, similarity measures will be calculated using the BM25 algorithm. Similar to the previous work (Choi and Ferrara, 2023), these matching results will be reranked based on the

cosine similarity between the sentence-BERT embeddings of each fact-checked claim and the result. This will yield a distinct set of news article-claim pairs with varying degrees of token and semantic similarity. The final step involves selecting the top results from the list. If the type of source is a video, these steps will be conducted for the metadata of matched video content using Python scraper for the BitChute video platform (bumatic, 2022) and Rumble API.

Lastly, to verify whether or not the extracted link authentically represents the source of the claim, this study will leverage LLM and human annotation for a text entailment task similar to the last step outlined in Section 3.1.

3.3 ClaimInspector Framework

This section outlines a comprehensive framework, ClaimInspector, developed for the data annotation process. The ClaimInspector leverages both web scraping techniques and NLP methods to identify, extract and verify claim sources that are mentioned in Section 3.1 and Section 3.2. Figure 5 illustrates the stages in the framework, which are discussed below.

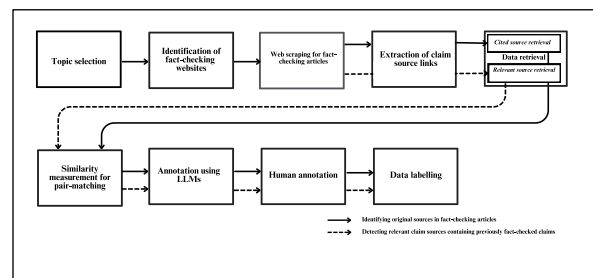


Figure 5: The overview of the ClaimInspector framework.

Topic Selection: The initial phase of the framework involves researchers choosing a topic of interest. This choice may concentrate on specific areas of concern, such as COVID-19 or election-related misinformation. Alternatively, researchers may opt for a more comprehensive approach by including several types of misinformation.

Identification of Fact-checking Websites: The second step involves systematically choosing the websites of International Fact-Checking Network (IFCN)-accredited fact-checking organisations. These websites are dedicated to examining statements made in the public domain, such as in news articles, social media posts or public speeches, and assessing their accuracy. The

identification process could be based on their areas of expertise, geographical focus and language.

Web Scraping for Fact-checking Articles: The third step includes utilising advanced web scraping techniques to crawl fact-checking articles related to the identified topics.

Extraction of Claim Source Links: Within these fact-checking articles, hyperlinks that lead to the original claim sources are extracted in order to trace the origin of the information.

Data Retrieval: Once the links to claim sources are collected, data from these web pages is retrieved. This process involves downloading the content and metadata for the next step, which can be referred to as “cited source retrieval.” In addition, the dataset would not only include the URL sources directly cited in the fact-checking articles, but also consider other sources where the given claim appears. I refer to this process as “relevant source retrieval”. To find relevant sources, the fact-checked claim is searched using the Google Search API and retrieved news articles and video contents are collected. The BeautifulSoup library is used to handle the diversity of web page structures. This library enables the parsing of HTML and XML documents, allowing for the extraction of data from a wide array of page styles. Special attention is given to alternative media platforms, such as Rumble and BitChute. Customised extraction techniques are used to handle the unique features of these platforms.

Similarity Measurement for Pair Matching: This step focuses on the measurement of similarity between the claims extracted during the search and the previously fact-checked claims with which they correspond, conducted through a two-pronged approach. First, token-based similarity is evaluated, identifying exact matches in terms and phrases. Subsequently, the analysis extends to semantic similarity, which discerns the underlying meaning beyond mere word usage. Decisions to advance to the subsequent phase are predicated on the similarity scores obtained for the pairs.

The final three stages are dedicated to ensuring the quality of the dataset. Considering the approach of automatically linking sources and fact-checks through references, an additional process to verify the relevance of these matched pairs needs to be implemented.

Annotation Using LLMs: This stage incorporates a verification step through LLM annotation, wherein each claim source is paired

with a fact-checking article and categorised as either entailment, contradiction or neutral.

Human Annotation: A random selection of 100 claim sources and fact-check pairs is subject to human annotation to verify the relevance of these matched pairs. This human-in-the-loop approach aids in validating the annotations provided by LLMs.

Data Labelling: The data undergoes a labelling process. If the pair is categorised as entailment, the claim source will inherit the fact-checking article’s label. Conversely, any data not classified as entailment will be omitted from the dataset.

4 Implementation: A Case Study on Claims Made by Politicians

While applicable for collecting and annotating data across diverse topics, this thesis will employ the framework to identify claims made by United States (US) politicians. I will scrape both PolitiFact and Snopes, which are IFCN-accredited fact-checking organisations. Gathering data from two fact-checking organisations will give us a more balanced and diverse view of fact-checked claims. PolitiFact primarily concentrates on scrutinising claims associated with politicians, and its sample of politicians is representative of the population of

Field Name	Description
Claim ID	A unique identifier assigned to each fact-checked claim.
Politician	The name of the politician making the claim.
Party Affiliation	The political party of the politician making the claim.
Claim Text	The claim that is being fact-checked.
Claim Category	The category of the claim (e.g. election, economy, health).
Claim Source	The origin or source of the claim (e.g. speech, TV interview, tweet).
Claim Link	The URL to the source of the claim.
Fact-check Publishing Date	The date when the fact-checking article is posted.
Fact-check Link	The URL to the fact-checking article providing evidence.
Label	The verdict assigned based on the fact-check (e.g. true, false, mostly false).

Table 1: Description of fields in the dataset.

US politicians (Buccioli, 2018). Snopes examines claims spanning a diverse range of subjects. Following the previous research (Bond and Garrett, 2023), I will collect fact-checks from Snopes’ ‘Politics’ and ‘Politicians’ categories. This dataset, ClaimInspector: Politicians Edition, will include fact-checked claims made by US politicians, along with links to the claim sources. The fields of the dataset and descriptions are shown in Table 1.

5 Experiments on the ClaimInspector: Politicians Edition

In order to assess the ClaimInspector, I will conduct two sets of experiments. First, I will perform a claim detection task using BM25 and BERT-based models. As the evaluation measure, I will calculate mean reciprocal rank, mean average precision and mean average precision at k for $k \in \{1, 3, 5, 10, 20, 30\}$. The results from the CLEF-2022 CheckThat! Lab Task 2B will serve as the baseline for this experiment (Nakov et al., 2022).

The second set will focus on the annotation results of pre-trained LLMs. Due to the significant computational resources required for fine-tuning LLMs, this process falls outside the scope of this thesis. I plan to conduct experiments with zero-shot prompting (Kojima et al., 2022) and few-shot prompting (Brown et al., 2020). The performance of LLMs can also be significantly influenced by the prompts given. As such, I will experiment with several elements of the prompts, including the choice of words and the structure of sentences. To evaluate the efficacy of the LLMs, I will employ a range of performance indicators, including macro-level precision, recall and accuracy. The outputs from the models will be compared with benchmark annotations provided by human annotators.

6 Conclusion

This thesis proposal offered an analysis of the current annotation methods and suggested enhancements through additional controls, including similarity measures and LLM-guided annotation. It advocated for broadening the range and type of claim sources beyond mere textual content and social media. Additionally, the proposal underscored the need to identify content akin to sources cited in fact-checking articles, acknowledging the extensive reach of misinformation beyond the sources typically listed in fact-checking articles. To systematically

implement these contributions, this thesis proposal introduced the ClaimInspector framework, a novel hybrid approach to data annotation. The proposal outlined the plans for applying this framework by creating a dataset called ClaimInspector: Politicians Edition. Through this dual focus on methodology improvement and dataset creation, the research intends to equip researchers and fact-checkers with reliable tools.

Limitations

This thesis includes a number of limitations that may inform future research. First, it acknowledges the potential for selection bias in the data collection method, given that the scope is limited to claims that were examined by fact-checking organisations. This may result in the exclusion of less circulated and less controversial false claims. Second, studies in this domain suffer from several crawling problems, such as timeouts, unresolvable coding and access restrictions, which may also lead to data loss in this research. Future work can use more advanced web crawling techniques to overcome this constraint and ensure a more comprehensive data collection. Third, it is important to note a limitation related to the monolingual nature of this study, as it exclusively examines claims in the English language. This restriction may overlook the variations present in claims made in other languages. This highlights the need for further research that adopts a multilingual approach. Lastly, since substantial computational resources are necessary for fine-tuning LLMs, fine-tuning has not been included within the current scope of the thesis. Future research could address this gap, potentially enhancing the ClaimInspector framework with the precision that fine-tuned LLMs could offer.

Ethics Statement

This thesis proposal will undergo ethical review by the Central University Research Ethics Committee at the University of Oxford before any research activities begin. I am committed to adhering to ethical guidelines in the use of APIs and web scraping practices. I will ensure compliance with the terms of service and usage policies of all platforms from which data will be collected. Furthermore, I recognise the inherent risks associated with the use of LLMs in annotation, including the propagation of biases and the generation of inconsistent outputs due to their probabilistic nature. I believe that employing

human annotation to test the outputs of LLMs can mitigate these risks, thereby enhancing the reliability of the results.

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Large Language Models for Mathematical Reasoning: Progresses and Challenges

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Abstract

Mathematical reasoning serves as a cornerstone for assessing the fundamental cognitive capabilities of human intelligence. In recent times, there has been a notable surge in the development of Large Language Models (LLMs) geared towards the automated resolution of mathematical problems. However, the landscape of mathematical problem types is vast and varied, with LLM-oriented techniques undergoing evaluation across diverse datasets and settings. This diversity makes it challenging to discern the true advancements and obstacles within this burgeoning field. This survey endeavors to address four pivotal dimensions: i) a comprehensive exploration of the various mathematical problems and their corresponding datasets that have been investigated; ii) an examination of the spectrum of LLM-oriented techniques that have been proposed for mathematical problem-solving; iii) an overview of factors and concerns affecting LLMs in solving math; and iv) an elucidation of the persisting challenges within this domain. To the best of our knowledge, this survey stands as one of the first extensive examinations of the landscape of LLMs in the realm of mathematics, providing a holistic perspective on the current state, accomplishments, and future challenges in this rapidly evolving field.

1 Introduction

Mathematical reasoning is crucial to human intelligence, driving ongoing efforts in the AI community to autonomously tackle math challenges. This pursuit inherently calls for an augmentation of AI capabilities, delving into the intricate realms of textual comprehension, image interpretation, tabular analysis, symbolic manipulation, operational logic, and a nuanced grasp of world knowledge. As the AI landscape evolves, the endeavor to empower machines with a comprehensive understanding of diverse mathematical facets becomes not only a testament to technological prowess but also a pivotal

stride towards achieving a more generalized and adept AI.

In recent times, the landscape of AI has been reshaped by the ascendancy of Large Language Models (LLMs) as formidable tools for automating intricate tasks. Notably, LLMs have proven to be potent assets in unraveling the nuances of mathematical problem-solving (Romera-Paredes et al., 2023; Imani et al., 2023). Their language capabilities fuel focused exploration in utilizing them for mathematical reasoning, uncovering fresh insights into the synergy between language and logic.

However, amid this progress, the current state of LLM-oriented research in mathematics presents a complex panorama. Diverse mathematical problem types pose a formidable challenge, exacerbated by the varied evaluation metrics, datasets, and settings employed in the assessment of LLM-oriented techniques (Testolin, 2023; Lu et al., 2023c). The lack of a unified framework hampers our ability to gauge the true extent of progress achieved and impedes a coherent understanding of the challenges that persist in this evolving field.

This survey endeavors to cast a spotlight on the multifaceted landscape of LLMs in the realm of mathematics. We plan to traverse four crucial dimensions: a meticulous exploration of math problem types and the datasets associated with them; an in-depth analysis of the evolving techniques employed by LLMs in mathematical problem-solving; an examination of factors that affect the LLMs solving math problems; and a critical discussion on the persisting challenges that loom over this burgeoning field.

To our knowledge, this survey marks one of the first comprehensive examinations of LLMs specifically tailored for mathematics. By weaving together insights from various dimensions, we aim to provide a holistic understanding of the current state of affairs in LLM-driven mathematical reasoning, shedding light on achievements, challenges, and

the uncharted territories that await exploration in this captivating intersection of language and logic.

2 Related Work

To the best of our knowledge, the existing literature on summarizing mathematical research, particularly within the context of LLMs, remains limited. Notably, Chang et al. (2023) conducted a comprehensive evaluation of LLMs, incorporating an examination of their performance in mathematical problem-solving, albeit with a relatively brief exploration of the mathematical field. Conversely, both (Testolin, 2023) and (Lu et al., 2023c) delved into the application of Deep Learning in the domain of mathematical reasoning. Our work distinguishes itself on three fronts: firstly, we concentrate on LLMs, providing a more in-depth analysis of their various advancements; secondly, beyond merely reporting progress, we engage in a thorough discussion of the challenges inherent in this trajectory; and thirdly, we extend our scrutiny to encompass the perspective of mathematics pedagogy. In doing so, we contribute a nuanced perspective that seeks to broaden the understanding of LLMs in the context of mathematical research.

The only work contemporaneous with ours is (Liu et al., 2023b). In comparison, our contribution lies in: i) not only introducing various methods but also paying more attention to various factors affecting model performance; ii) taking a broader perspective on the progress of LLM in the field of mathematics, elucidating not only from the AI perspective but also from the perspective of education. It emphasizes that the pursuit of model performance alone, while neglecting human factors, is something that needs attention.

3 Math Problems & Datasets

This section concisely overviews prominent mathematical problem types and associated datasets, spanning ARITHMETIC, MATH WORD PROBLEMS, GEOMETRY, AUTOMATED THEOREM PROVING, and MATH IN VISION CONTEXT.

3.1 Arithmetic

This category of problems entails pure mathematical operations and numerical manipulation, devoid of the need for the model to interpret text, images, or other contextual elements. An illustrative example is presented below, where “ Q ” denotes questions and “ A ” for answers.

Q : $21 + 97$
A : 118

The dataset MATH-140 (Yuan et al., 2023) contains 401 arithmetic expressions for 17 groups.

3.2 Math Word Problems

MATH WORD PROBLEMS (MWP) are mathematical exercises or scenarios presented in the form of written or verbal descriptions rather than straightforward equations in ARITHMETIC. These problems require individuals to decipher the information provided, identify relevant mathematical concepts, and formulate equations or expressions to solve the given problem. MWP often reflect real-world situations, allowing individuals to apply mathematical principles to practical contexts. Solving these problems typically involves critical thinking, problem-solving skills, and the application of mathematical operations to find a solution.

MWP invariably comprise a question (Q) and its corresponding final answer (A) (referred to as *Question-Answer*). However, the presence or absence of additional clues can give rise to various versions of these problems. Variations may emerge based on factors such as the availability of an equation (\mathcal{E} ; referred to as *Question-Equation-Answer*) or the provision of a step-by-step rationale (\mathcal{R} ; *Question-Rationale-Answer*) to guide the problem-solving process.

Question-Answer. The instance of this type of MWP consists of a question (Q) and the final answer (A), such as:

Q : Lily received \$20 from her mum. After spending \$10 on a storybook and \$2.5 on a lollipop, how much money does she have left?
A : \$7.5

Question-Equation-Answer. Compared with *Question-Answer*, this MWP type provides the equation solution, such as

Q : Jack had 8 pens and Mary had 5 pens. Jack gave 3 pens to Mary. How many pens does Jack have now?
\mathcal{E} : $8 - 3$
A : 5 (optional)

Question-Rationale-Answer. This type of MWP includes answers and reasoning paths, akin to the Chain-of-Thought method, which explicates reasoning steps rather than defining problem types

	NAME	SIZE	LEVEL	NOTE
Q-A	CMATH (Wei et al., 2023)	1.7K	E	Chinese; grade 1-6
	SAT-MATH (Zhong et al., 2023)	220	H	Multi-choice
Question-Equation-Answer	SVAMP (Patel et al., 2021)	1K	E	Three types of variations
	ASDIV (Miao et al., 2020)	2.3K	E	Problem type and grade level annotated
	MAWPS (Koncel-Kedziorski et al., 2016)	3.3K	E	Extension of ADDSUB, MULTIARITH, etc.
	PARAMAWPS (Raiyan et al., 2023)	16K	E	Paraphrased, adversarial MAWPS
	SINGLEEQ (Koncel-Kedziorski et al., 2015)	508	E	
	ADDSUB (Hosseini et al., 2014)	395	E	Only addition and subtraction
	MULTIARITH (Roy and Roth, 2015)	600	E	Multi-step reasoning
	DRAW-1K (Upadhyay and Chang, 2017)	1K	E	
	MATH23K (Wang et al., 2017)	23K	E	Chinese
	APE210K (Zhao et al., 2020)	210K	E	Chinese
	K6 (Yang et al., 2023)	600	E	Chinese; grade 1-6
CM17K (Qin et al., 2021)	17K	M H	Chinese; grade 6-12	
Question-Rationale-Answer	CARP (Zhang et al., 2023a)	4.9K	M	Chinese
	GSM8K (Cobbe et al., 2021)	8.5K	M	Linguistically diverse
	MATH (Hendrycks et al., 2021)	12.5K	H	Problems are put into difficulty levels 1-5
	PRM800K (Lightman et al., 2023)	12K	H	MATH w/ step-wise labels
	MATHQA (Amini et al., 2019)	37K	C	GRE examinations; have quality concern
	AQUA (Ling et al., 2017)	100K	C	GRE&GMAT questions
	ARB (Sawada et al., 2023)	105	C	Contest problems and university math proof
	GHOSTS (Frieder et al., 2023)	709	C	
	THEOREMQA-MATH (Chen et al., 2023b)	442	C	Theorem as rationale
	LILA (Mishra et al., 2022)	132K	H	Incorporates 20 existing datasets
	MATH-INSTRUCT (Yue et al., 2023)	260K	H	Instruction-following style
	TABMWP (Lu et al., 2023b)	38K	H	Tabular MWP; below the College level

Table 1: Datasets for Math Word Problems.

E = Elementary, M = Middle School, H = High School, C = College, H = Hybrid

(Wei et al., 2022). The rationale guides correct problem-solving and serves as a valuable reference for model training, including fine-tuning and few-shot learning.

Q: Beth bakes 4, or 2 dozen batches of cookies in a week. If these cookies are shared amongst 16 people equally, how many cookies does each person consume?
R: Beth bakes 4 2 dozen batches of cookies for a total of $4 * 2 = \lll 4 * 2 = 8 \ggg$ 8 dozen cookies. There are 12 cookies in a dozen and she makes 8 dozen cookies for a total of $12 * 8 = \lll 12 * 8 = 96 \ggg$ 96 cookies. She splits the 96 cookies equally amongst 16 people so they each eat $96 / 16 = \lll 96 / 16 = 6 \ggg$ 6 cookies.
A: 6

Table 1 lists most datasets that are summarized in three categories: *Question-Answer*, *Question-Equation-Answer*, and *Question-Rationale-Answer*. In addition to the above three MWP types of conventional styles, recent work studied MWP in

given tables and even MWP generation.

Tabular MWP. TABMWP (Lu et al., 2023b) is the first dataset to study MWP over tabular context on open domains and is the largest in terms of data size. Each problem in TABMWP is accompanied by a tabular context, which is represented in three formats: an image, a semi-structured text, and a structured table.

BEADS	\$/KILOGRAM
heart-shaped	3
rectangular	2
spherical	2
oval	2

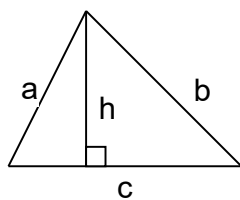
Table 2: Table for the tabular MWP example.

T: Table 2
Q: Henrik bought 2.5 kilograms of oval beads. How much did he spend? (Unit: \$)
A: 5

MWP Generation. Instead of deriving the answer for a given math question, this type of mathematical reasoning tries to generate MWP questions. For example, Wang et al. (2021) fine-tuned GPT-2 (Radford et al., 2019) on equation-to-MWP instances for MWP generation. The effectiveness of GPT-3’s question-generation capabilities was assessed by Zong and Krishnamachari (2023), who instructed the model to generate a question similar to a provided MWP question. Deb et al. (2023) analyzed a group of LLMs (GPT-4, GPT-3.5, PaLM-2 (Anil et al., 2023), and LLaMa (Touvron et al., 2023a)), and found a significant drop in accuracy for backward reasoning compared to forward reasoning. Norberg et al. (2023) used GPT-4 to rewrite human-written MWP, reporting optimal readability, lexical diversity, and cohesion scores, although GPT-4 rewrites incorporated more low-frequency words.

3.3 Geometry

Compared with MWP, GEOMETRY problems involve a distinct set of challenges. While MWP often requires logical reasoning and arithmetic operations, geometry problems demand a spatial understanding of shapes, sizes, and their interrelationships. Solving geometry problems typically entails applying geometric principles, theorems, and formulas to analyze and deduce properties of geometric figures. Furthermore, current geometry approaches mainly rely on symbolic methods and predefined search heuristics, highlighting the specialized strategies required in this domain (Trinh et al., 2024). This contrast in problem-solving approaches highlights the multifaceted nature of mathematical challenges and the varied skill sets required in different mathematical domains. An example can be seen as follows and Table 3 lists mainstream datasets.



Q: $a=7$ inches; $b=24$ inches; $c=25$ inches; $h=5.4$ inches; What is its area? (Unit: square inches)
A: 24.03

NAME	SIZE
GEOSHADER (Alvin et al., 2017)	102
GEOS (Seo et al., 2015)	186
GEOS++ (Sachan et al., 2017)	1.4K
GEOS-OS (Sachan and Xing, 2017)	2.2K
GEOMETRY3K (Lu et al., 2021)	3K
GEOQA (Chen et al., 2021a)	5K
UNIGEO (Chen et al., 2022)	14.5K

Table 3: Geometry datasets

3.4 Automated theorem proving

In the specialized area of Automated Theorem Proving (ATP), the inherent challenges are unique and encompass a wide spectrum, akin to those found in distinct mathematical fields. ATP’s core focus is on autonomously constructing proofs for specified conjectures, requiring a blend of logical analysis and a profound grasp of formal languages, supported by an extensive knowledge base. Its application is crucial in areas like the validation and development of both software and hardware systems.

For example, the MINIF2F dataset (Zheng et al., 2022) stands out in ATP, featuring a series of complex Olympiad-level mathematical problems, designed to evaluate theorem-proving systems including Metamath (Yu et al., 2023), Lean (Han et al., 2022), and Isabelle (Wenzel et al., 2008). In a similar vein, the HOList benchmark (Bansal et al., 2019), with its comprehensive array of theorem statements from various corpora, sets a sequential proving challenge for ATP systems, where each theorem must be proved using only the lemmas preceding it. Additionally, the COQGYM dataset (Yang and Deng, 2019) provides a broad ATP environment, showcasing a rich collection of more than 71,000 proofs penned by humans, all within the framework of the Coq proof assistant. These datasets illustrate the diverse methodologies and skillsets necessary in ATP, reflecting the multifaceted nature of solving mathematical problems.

3.5 Math in vision-language context

CHARTQA (Masry et al., 2022), with 9.6K human-written questions and 23.1K model-generated questions have explored a variety of complex reasoning questions that involve several logical and arithmetic operations over charts. MATHVISTA (Lu et al., 2023a): size: 6K; it features seven types of mathematical reasoning: algebraic reasoning, arithmetic

reasoning, geometry reasoning, logical reasoning, numeric common sense, scientific reasoning, and statistical reasoning. In addition, fine-grained meta-data are available, including question type, answer type, language, source, category, task, grade level, and visual context.

4 Methodologies

We summarize these methods into three progressive levels: i) Prompting frozen LLMs, ii) Strategies enhancing frozen LLMs, and iii) Fine-tuning LLMs.

4.1 Prompting frozen LLMs

We organize prior work by typical LLMs.

GPT-3. Zong and Krishnamachari (2023) evaluated the use of GPT-3, a 175B parameter transformer model for three related challenges pertaining to math word problems: i) classifying word problems, ii) extracting equations from word problems, and iii) generating word problems.

ChatGPT. Shakarian et al. (2023) reported the first independent evaluation of ChatGPT on MWP, and found that ChatGPT’s performance changes dramatically based on the requirement to show its work. Cheng and Zhang (2023) assessed ChatGPT, OpenAI’s latest conversational chatbot and LLM, on its performance in elementary-grade arithmetic and logic problems, and found that ChatGPT performed better than previous models such as InstructGPT (Ouyang et al., 2022) and Minerva (Lewkowycz et al., 2022).

GPT-4. Wu et al. (2023) adapted and evaluated several existing prompting methods to the usage of GPT-4, including a vanilla prompt, Program-of-Thoughts prompt (Chen et al., 2023a), and Program Synthesis prompt (Drori et al., 2022). The study by Gu (2023) investigated the capability of GPT-4 to actively engage in math-oriented brainstorming sessions. This includes tasks like identifying new research problems, refining problem formulations, and suggesting potential methods or unconventional solutions, all achieved through iterative ideation with a human partner—a common practice in collaborative brainstorming with other professionals.

GPT4V & Bard. Lu et al. (2023a) presented MATHVISTA, a benchmark of evaluating mathematical reasoning in visual context, conducted a comprehensive, quantitative evaluation of three

LLMs (i.e, ChatGPT, GPT-4, Claude-2 (Bai et al., 2022)), two proprietary large multimodal models (LMMs) (i.e., GPT4V, Bard), and seven open-source LMMs, with Chain-of-Thought and Program-of-Thought.

Multiple. Wei et al. (2023) evaluated a variety of popular LLMs, including both commercial and open-source options, aiming to provide a benchmark tool for assessing the following question: to what grade level of Chinese elementary school math do the abilities of popular LLMs correspond?

4.2 Strategies enhancing frozen LLMs

Preprocessing the math question. An et al. (2023a) explored ChatGPT for the dataset SVAMP and observed that substituting numerical expressions with English expressions can elevate the performance.

More advanced prompts. Chain-of-thought (Wei et al., 2022), the first time to steer the LLMs to do **step-by-step math reasoning**, Self-Consistency (Wang et al., 2023) tried multiple Chain-of-Thought reasoning paths and leverage the **consistency** mechanism to discover a more probable answer. Zhou et al. (2023a) proposed a novel and effective prompting method, explicit code-based self-verification, to further boost the mathematical reasoning potential of GPT-4 Code Interpreter. This method employs a zero-shot prompt on GPT-4 Code Interpreter to encourage it to use code to **self-verify** its answers.

Using external tool. Yamauchi et al. (2023) employed an external tool, specifically the Python REPL, to correct errors in Chain-of-Thought. Their demonstration highlighted that integrating Chain-of-Thought and Python REPL using a markup language improves the reasoning capabilities of ChatGPT. In a related context, He-Yueya et al. (2023) introduced an approach that merges an LLM, Codex (Chen et al., 2021b), capable of progressively formalizing word problems into variables and equations, with an external symbolic solver adept at solving the generated equations. Program-of-Thought (Chen et al., 2023a) separates the computational aspect from the reasoning by utilizing a Language Model (primarily Codex) to articulate the reasoning procedure as a program. The actual computation is delegated to an external computer, responsible for executing the generated programs to arrive at the desired answer.

Improving the whole interaction. Wu et al. (2023) introduced MathChat, a conversational framework designed for chat-based LLMs. In this framework, math problems from the MATH dataset are resolved through a simulated conversation between the model and a user proxy agent.

Considering more comprehensive factors in evaluation. While accuracy is crucial in evaluating LLMs for math problem-solving, it shouldn't be the sole metric. Other important dimensions include: i) **Confidence Provision:** Imani et al. (2023)'s "MathPromper" boosts LLM performance and confidence by generating algebraic expressions, providing diverse prompts, and evaluating consensus among multiple runs. ii) **Verifiable Explanations:** Gaur and Saunshi (2023) used concise, verifiable explanations to assess LLM reasoning, revealing their proficiency in zero-shot solving of symbolic MWP and their ability to produce succinct explanations.

4.3 Fine-tuning LLMs

Learning to select in-context examples. As indicated by prior research, few-shot GPT-3's performance is susceptible to instability and may decline to near chance levels due to the reliance on in-context examples. This instability becomes more pronounced when dealing with intricate problems such as TABMWP. In addressing this issue, Lu et al. (2023b) introduced PROMPTPG, which can autonomously learn to select effective in-context examples through policy gradient interactions with the GPT-3 API, eliminating the need for manually designed heuristics.

Generating intermediate steps. Nye et al. (2021) initiated the fine-tuning of decoder-only LLMs, ranging from 2M to 137B in size. Their approach involved training these models to solve integer addition and polynomial evaluation by generating intermediate computation steps into a designated "scratchpad." In a related effort, Zhang et al. (2023b) introduced a fine-tuning strategy for GPT-2 or T5, enabling them to produce step-by-step solutions with a combination of textual and mathematical tokens leading to the final answer. Additionally, Yang et al. (2023) applied a step-by-step strategy in fine-tuning a series of GLM models (Zeng et al., 2023), specifically tailored for solving distinct Chinese mathematical problems. Minerva, developed by Lewkowycz et al. (2022), enhances LLMs' ability to generate intermediate steps in

complex math problems. Its fine-tuning of diverse datasets enables nuanced, step-by-step problem-solving, demonstrating advanced handling of intricate mathematical concepts.

Learning an answer verifier. OpenAI researchers, per Cobbe et al. (2021), fine-tuned a GPT-3 model of 175B as a verifier, assigning probabilities to solution candidates. In exploring reexamination processes for MWP solving, Bin et al. (2023) introduced Pseudo-Dual Learning, involving solving and reexamining modules. For MWP solution, Zhu et al. (2023) developed a cooperative reasoning-induced PLM, with GPT-J (Wang and Komatsuzaki, 2021) generating paths and DeBERTa-large (He et al., 2021) supervising evaluation. Google researchers, as per Liu et al. (2023c), observed improved correctness in LLMs with multiple attempts, which hints that LLMs might generate correct solutions while struggling to differentiate between accurate and inaccurate ones. They sequentially fine-tuned their PaLM 2 model (Anil et al., 2023) as a solution generator, evaluator, and generator again.

Learning from enhanced dataset. Emulating the error-driven learning process observed in human learning, An et al. (2023b) conducted fine-tuning on various open-source LLMs within the LLaMA (Touvron et al., 2023a), LLaMA-2 (Touvron et al., 2023b), CodeLLaMA (Rozière et al., 2023), WizardMath (Luo et al., 2023), MetaMath (Yu et al., 2023), and Llemma (Azerbayev et al., 2023) families. This fine-tuning utilized mistake-correction data pairs generated by GPT-4. To mitigate over-reliance on knowledge distillation from LLM teachers, Liang et al. (2023a) fine-tuned LLaMA-7B on existing mathematical problem datasets that exhibit diverse annotation styles. In a related approach, Raiyan et al. (2023) demonstrated that training on linguistic variants of problem statements and implementing a voting mechanism for candidate predictions enhance the mathematical reasoning and overall robustness of the model.

Teacher-Student knowledge distillation. Liang et al. (2023b) utilized GPT-3 to coach a more efficient MWP solver (RoBERTa-based encoder-decoder (Liu et al., 2019)). They shifted the focus from explaining existing exercises to identifying the student model's learning needs and generating new, tailored exercises. The resulting smaller LLM

achieves competitive accuracy on the SVAMP dataset with significantly fewer parameters compared to state-of-the-art LLMs.

Finetuning on many datasets. Mishra et al. (2022) conducted fine-tuning on a series of GPT-Neo2.7B causal language models (Black et al., 2021) using LILA, a composite of 20 existing math datasets. Similarly, Yue et al. (2023) created “Math-Instruct”, a meticulously curated instruction tuning dataset. Comprising 13 math datasets with intermediate Chain-of-Thought and Program-of-Thought rationales, this dataset was used to fine-tune Llama (Touvron et al., 2023a,b; Rozière et al., 2023) models across different scales. The resulting models demonstrate unprecedented potential in cross-dataset generalization.

Math solver ensemble. Yao et al. (2023) incorporated a problem typing subtask that combines the strengths of the tree-based solver and the LLM solver (ChatGLM-6B (Zeng et al., 2023)).

5 Analysis

5.1 LLMs’s robustness in math

Patel et al. (2021) provided strong evidence that the pre-LLM MWP solvers, mostly LSTM-equipped encoder-decoder models, rely on shallow heuristics to achieve high performance on some simple benchmark datasets, then introduced a more challenging dataset, SVAMP, created by applying carefully chosen variations over examples sampled from preceding datasets. Stolfo et al. (2023) observed that, among non-instruction-tuned LLMs, the larger ones tend to be more sensitive to changes in the ground-truth result of a MWP, but not necessarily more robust. However, a different behavior exists in the instruction-tuned GPT-3 models, which show a remarkable improvement in both sensitivity and robustness, although the robustness reduces when problems get more complicated. Wei et al. (2023) assessed the robustness of several top-performing LLMs by augmenting the original problems in the curated CMATH dataset with distracting information. Their findings reveal that GPT-4 can maintain robustness while other models fail.

Zhou et al. (2023b) proposed a new dataset ROBUSTMATH to evaluate the robustness of LLMs in math-solving ability. Extensive experiments show that (i) Adversarial samples from higher-accuracy LLMs are also effective for attacking LLMs with lower accuracy; (ii) Complex MWPs (such as more

solving steps, longer text, more numbers) are more vulnerable to attack; (iii) We can improve the robustness of LLMs by using adversarial samples in few-shot prompts.

5.2 Factors in influencing LLMs in math

The comprehensive evaluation conducted by Yuan et al. (2023) encompasses OpenAI’s GPT series, including GPT-4, ChatGPT2, and GPT-3.5, along with various open-source LLMs. This analysis methodically examines the elements that impact the arithmetic skills of LLMs, covering aspects such as tokenization, pre-training, prompting techniques, interpolation and extrapolation, scaling laws, Chain of Thought (COT), and In-Context Learning (ICL).

Tokenization. This research underscores tokenization’s critical role in LLMs’ arithmetic performance (Yuan et al., 2023). Models like T5, lacking specialized tokenization for arithmetic, are less effective than those with advanced methods, such as Galactica (Taylor et al., 2022) and LLaMA, which show superior accuracy in arithmetic tasks. This indicates that token frequency in pre-training and the method of tokenization are key to arithmetic proficiency.

Pre-training Corpus. Enhanced arithmetic skills in LLMs correlate with the inclusion of code and LATEX in pre-training data (Yuan et al., 2023). Galactica, heavily utilizing LATEX, excels in arithmetic tasks, while models like Code-DaVinci-002, better at reasoning, lags in arithmetic, highlighting a distinction between arithmetic and reasoning skills.

Prompts. The nature of input prompts greatly affects LLMs’ arithmetic performance (Liu et al., 2023a; Lou et al., 2023). Without prompts, performance drops (Yuan et al., 2023). Models like ChatGPT, which respond well to instructional system-level messages, demonstrate the importance of prompt type. Instruction tuning in pre-training also emerges as a significant factor (Yue et al., 2023).

Model Scale. There’s a noted correlation between parameter count and arithmetic capability in LLMs (Yuan et al., 2023). Larger models generally perform better, but a performance plateau is observed, as shown by Galactica’s similar outcomes at 30B and 120B parameters. However, this doesn’t always mean superior performance, with smaller models like ChatGPT occasionally outperforming larger ones.

5.3 Perspectives of mathematics pedagogy

While machine learning emphasizes LLMs' problem-solving abilities in mathematics, in practical education, their primary role is to aid learning. Thus, the focus shifts from mere mathematical performance to a crucial consideration of LLMs' understanding of students' needs, capabilities, and learning methods.

Advantages of deploying LLMs in math education. Educators have observed the following benefits of leveraging LLMs for math education. (i) *LLMs foster critical thinking and problem-solving skills*, as they provide comprehensive solutions and promote rigorous error analysis (Matzakos et al., 2023); (ii) *Educators and students prefer LLM-generated hints* because of their detailed, sequential format and clear, coherent narratives (Gattupalli et al., 2023); (iii) *LLMs introduce a conversational style in problem-solving*, an invaluable asset in math education (Gattupalli et al., 2023); (iv) The impact of LLMs extends *beyond mere computational assistance*, offering deep insights and understanding *spanning diverse disciplines* like Algebra, Calculus, and Statistics (Rane, 2023).

Disadvantages of deploying LLMs in math education. (i) *Potential for misinterpretation.* Misinterpretation of students' queries or errors in providing explanations by LLMs could lead to confusion. Inaccurate responses might result in the reinforcement of misconceptions, impacting the quality of education (Yen and Hsu, 2023). (ii) *Limited understanding of individual learning styles.* LLMs may struggle to cater to diverse learning styles, as they primarily rely on algorithms and might not fully grasp the unique needs of each student. Some learners may benefit more from hands-on activities or visual aids that LLMs may not adequately address. Gresham (2021) proposed that hints produced by GPT-4 could be excessively intricate for younger students who have shorter attention spans. (iii) *Privacy and data security issues.* Deploying LLMs involves collecting and analyzing substantial amounts of student data. Privacy concerns may arise if proper measures are not in place to safeguard this data from unauthorized access or misuse.

6 Challenges

Data-driven & limited generalization. The prevailing trend in current research revolves around the curation of extensive datasets. Despite this

emphasis, there is a noticeable lack of robust generalization across various datasets, grade levels, and types of math problems. Examining how humans acquire math-solving skills suggests that machines may need to embrace continual learning to enhance their capabilities.

LLMs' brittleness in math reasoning. The fragility of LLMs in mathematical reasoning is evident across three dimensions. Firstly, when presented with questions expressed in varying textual forms (comprising words and numbers), LLMs exhibit inconsistent performance. Secondly, for identical questions, an LLM may yield different final answers through distinct reasoning paths during multiple trials. Lastly, pre-trained math-oriented LLMs are susceptible to attacks from adversarial inputs, highlighting their vulnerability in the face of manipulated data.

Human-oriented math interpretation. The current LLM-oriented math reasoning, such as chain-of-thoughts, does not take into account the needs and comprehension abilities of users, such as students. As an example, Yen and Hsu (2023) discovered that GPT-3.5 had a tendency to misinterpret students' questions in the conversation, resulting in a failure to deliver adaptive feedback. Additionally, research conducted by Gresham (2021) revealed that GPT-4 frequently overlooks the practical comprehension abilities of younger students. It tends to generate overly intricate hints that even confuse those students. Consequently, there is a pressing need for increased AI research that actively incorporates human factors into its design, ensuring future developments align more closely with the nuanced requirements of users.

7 Conclusion

This survey on LLMs for Mathematics delves into various aspects of LLMs in mathematical reasoning, including their capabilities and limitations. The paper discusses different types of math problems, datasets, and the persisting challenges in the domain. It highlights the advancements in LLMs, their application in educational settings, and the need for a human-centric approach in math education. We hope this paper will guide and inspire future research in the LLM community, fostering further advancements and practical applications in diverse mathematical contexts.

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Representation and Generation of Machine Learning Test Functions

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Abstract

Writing tests for machine learning (ML) code is a crucial step towards ensuring the correctness and reliability of ML software. At the same time, Large Language Models (LLMs) have been adopted at a rapid pace for various code generation tasks, making it a natural choice for many developers who need to write ML tests. However, the implications of using these models, and how the LLM-generated tests differ from human-written ones, are relatively unexplored. In this work, we examine the use of LLMs to extract representations of ML source code and tests in order to understand the semantic relationships between human-written test functions and LLM-generated ones, and annotate a set of LLM-generated tests for several important qualities including usefulness, documentation, and correctness. We find that programmers prefer LLM-generated tests to those selected using retrieval-based methods, and in some cases, to those written by other humans.

1 Introduction

As AI and ML become more and more integrated into everyday processes, ensuring the quality and reliability of these ML models is mandatory, and a critical part of ensuring ML models' performance in production is having good, representative test cases. Traditionally, these tests have been written by engineers and programmers, a process that, while valuable, can be time-consuming and requires extensive experience and expertise in ML methodology. Recognizing the challenges posed by the intricacies of ML code, particularly the distinct nature of ML testing involving both pre-training and post-training tests, our research takes a deliberate focus on this specific domain. This choice serves to constrain the scope of our investigation and allows us to address the unique complexities

associated with ML testing, which often deviates from conventional software testing.

One possible way to aid programmers is to retrieve existing functions that have been previously implemented, similarly to what has been done for test case selection within a test suite (Romano et al., 2018). For the purpose of writing tests, relevant test cases could be retrieved from other projects that are written to test functions that are semantically similar to the programmers' target functions. These retrieved functions might serve as references for programmers to consider when developing their own tests. However, with the recent advent of powerful code-generating LLMs such as Codex (Chen et al., 2021) and LLaMA (Touvron et al., 2023), those seeking to develop ML test cases are now able to prompt the model given the source function and instructions required to produce the appropriate test case. This has the potential to revolutionize the way that ML tests are developed, and it is therefore important to analyze how AI-generated tests compare to those written by humans and how developers may consider using these methods.

In this work, we make initial steps toward comparing the ML test functions that are generated by LLMs with those generated by human programmers to better anticipate the consequences of a growing number of ML test functions being generated automatically by LLMs. Using a set of approximately 10,000 pairs of ML functions and their tests, we use code embedding methods to explore the semantic relationships between functions and their tests. We then experiment with semantic retrieval-based approaches to find relevant ML tests given an input test function, and finally, we compare several models' ability to generate useful ML test functions and evaluate them using expert human annotations. An overview of the process that we used is presented in Figure 1. Focusing on the specific domain of ML allowed us to make the focal methods more comparable and facilitated

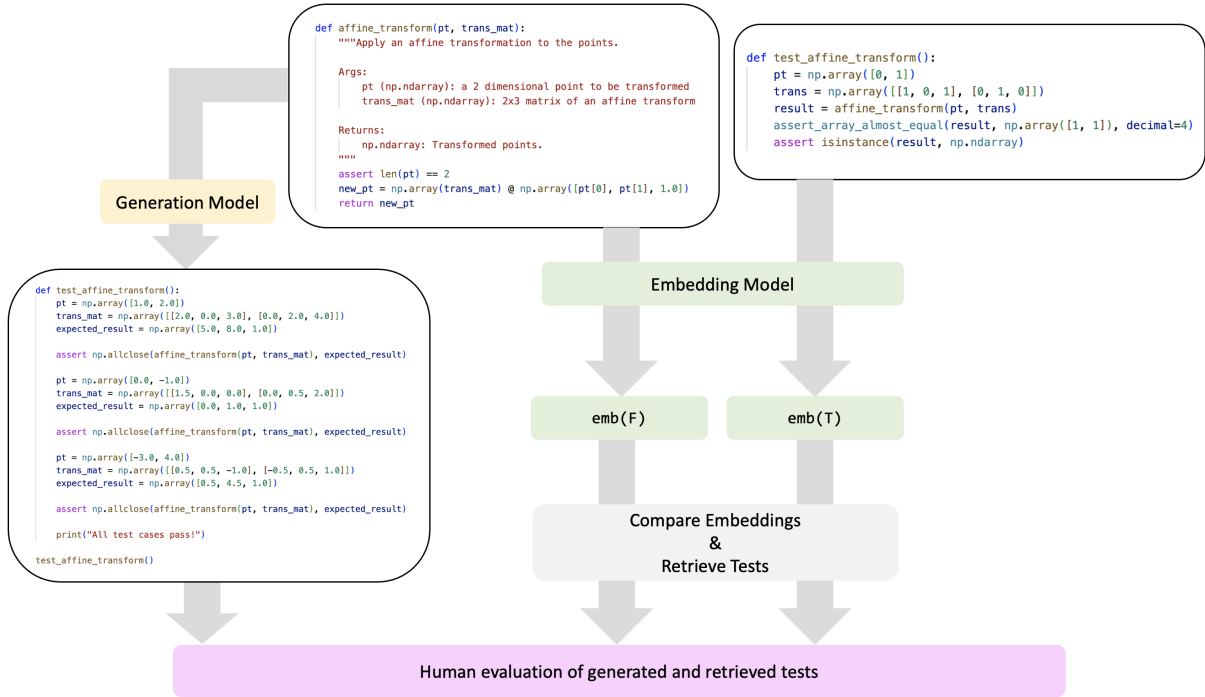


Figure 1: Overview of the process followed in this paper.

the recruitment of participants familiar with ML algorithms. Our core contributions include: (1) exploration of semantic representations for ML functions and their tests; (2) experiments with retrieval of ML tests; and (3) a human evaluation of LLM-generated test cases. We identified that there is a non-arbitrary relationship between the embeddings of ML functions and their test cases, but neural-network-based retrieval approaches were not able to leverage these representations effectively. However, our results show that programmers prefer LLM-generated tests to those selected using retrieval-based methods, and in some cases, to those written by other humans.

2 Related Work

2.1 Code Representation Learning and Embedding Models

The focus on learning distributed representations of code forms the groundwork of our research. We draw from Alon et al. (2019)’s work on code2vec which demonstrated the potential of learning code embeddings using neural networks. As transformer-based approaches become more popular, CodeBERT (Feng et al., 2020) used bidirectional encoder layers and the authors of the model introduced a large-scale dataset and providing insights about the learning of code semantics. GraphCodeBERT extended that work via the integration of

graph-based structural and lexical information to improve the representation of the code (Guo et al., 2020). Later, the CODET (Chen et al., 2022) model tackled the challenge of code generation while also generating unit tests for Java code, demonstrating the potential of multi-faceted code generation for test cases.

It’s also important to mention the effort on benchmarking datasets like CodeSearchNet (Husain et al., 2019) and CodeXGLUE (Lu et al., 2021), which offer robust platforms for training and evaluating numerous models in this area. However, none of the previous evaluation datasets checked for the quality of ML function and test matching, that is, evaluating which approaches are best able to retrieve a test case given an input function (rather than a search query written in natural language). Also, the aforementioned methods are not full language models that can generate code for any language. Some only work on one language and are not necessarily applicable to the ML domain.

2.2 Applications and Evaluation of Large Language Models on Source Code

Substantial research has been invested in revealing the power of LLMs in dealing with code-related tasks, from code summarization to test generation and beyond. Supported by billions of trainable parameters and extensive publicly available source

code, models like StarCoder (Li et al., 2023) and LLaMA (Touvron et al., 2023) are carving a new path. These models have shown promising results in code generation, thanks to the vast resources at their disposal.

Previous work (Schäfer et al., 2023) shows how LLMs can be used to generate unit tests for Javascript code. Integral to the understanding and broader adoption of these models is the systematic evaluation of their performance. This aspect has been explored by Xu et al. (2022), who showed that Codex displayed superior performance compared to other models tested on the HumanEval (Chen et al., 2021) benchmark.

Additionally, a previous study (Liu et al., 2023) underscores the effectiveness of the HumanEval benchmark in identifying substantial instances of incorrect code generated by LLMs that had previously gone unnoticed.

These works offer valuable insights into the effectiveness of these emerging models, highlighting their capabilities in understanding syntax, pattern recognition, and automation, while also bringing to light their limitations, such as their lack of true understanding, difficulty with complex logic, and challenges with generalizability and interpretability when interacting with code. However, previous applications haven't focused on the unique properties of ML tests (Riccio et al., 2020), this paper aims to bridge that gap and delve into these distinctive features.

3 Data

3.1 Data Collection

We collected a dataset of 56,889 test files extracted from 986 different GitHub ML projects written in Python using the GitHub API ¹. The projects were selected if they use at least one of the Python ML libraries, such as Scikit-Learn, TensorFlow, Theano, Caffe, Keras, or PyTorch. All of these projects were created between January 1, 2007, and September 22, 2022, with three or more contributors. These projects encompassed a wide range of ML code, including personal ML projects and well-known ML libraries or frameworks such as Hummingbird, fvcare, and Sentence Transformers. The dataset contains a fair number of ML tests, making it a valuable resource for analyzing ML test functions, and exploring their characteristics. However, it

¹<https://docs.github.com/en/rest>

lacked explicit mappings between individual functions and their corresponding tests, which is a requirement if we seek to analyze the relationships between these types of functions.

3.2 Data Preprocessing

In order to link ML functions and their corresponding tests, we applied several heuristics to automate the extraction process:

1. Assume that each test function name begins with 'test', 'Test', or '_test'.
2. Assume that if a test function calls only one of the functions defined within the project, it is testing that specific function.
3. Ignore single-character function names to help remove noisier and less clear examples.

While these rules may filter out some valid test cases, we selected them in order to aim for a high precision in terms of returning a quality set of pairs between *focal methods* and *tests*. In this work, we refer to an ML function undergoing testing as a "focal method", and its corresponding ML test case as "test". We also removed some pairs (approximately 150) that contained accents, emojis, or symbols like progress bars, which made them more difficult to process. After applying the heuristics defined above, we were left with 10,324 (focal_method, test) pairs. Around 5% of the focal methods have multiple tests, while the tests themselves are unique to the project and no test is considered to be testing multiple methods.

Certain types of pairs could not be collected, e.g., when a test is testing the behavior of a predefined model or functions that are not defined within the project. To evaluate this process, we selected a random sample of 100 (focal_method, test) pairings and manually labeled whether each pairing was correct, meaning that the test does test the function it was associated with, and found that the pairing method was 95% accurate.

4 Building Representations for Test Cases and Retrieval Task

4.1 Building Embeddings and Investigating Pairing Relationships

To focus on the relationship between the focal methods and their associated tests, we created embeddings for each focal method using models trained on both code and natural language data. These

models included CodeBERT (Feng et al., 2020), text-embedding-ada-002,² and LLaMA-1 (Touvron et al., 2023) with 7 billion parameters.

An essential aspect of our exploration involved understanding the semantic relationships between pairs of focal methods’ and associated tests’ vector representations. Each of the models we used produced embeddings with different shapes (CodeBERT: 768, LLaMA-1: 4096, text-embedding-ada-002: 1536), but for the purpose of visualization, we used Principal component analysis (PCA) to reduce their dimensions to (2).

We visualized these pairings using an arrow plot where each focal method embedding is connected to its corresponding test embedding to inspect potential relationships between them. Figure 2 shows the arrow plots of some sampled pairings (in order to more easily see the results) using all different models.

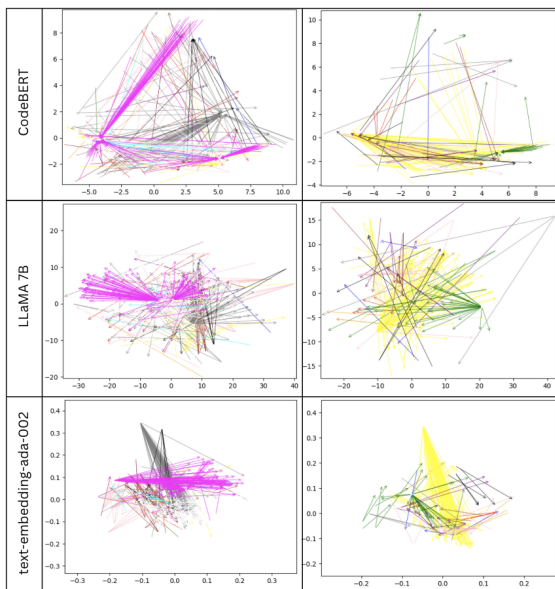


Figure 2: Arrow plots using PCA for 2-D projection of paired focal method embedding and test embedding, sampled across different models. Arrows of the same color represent pairings from the same GitHub project.

We observed that, in general, CodeBERT embeddings showed no clear pattern, with many of the arrows seemingly pointing in the same location. This suggests that CodeBERT assigned the same embeddings to different tests. This difficulty in producing unique and meaningful representations for test cases may be explained by the fact that when training the CodeBERT model, “**function names**

²<https://openai.com/blog/new-and-improved-embedding-model>

Model	$K = 1$	$K = 5$	$K = 10$
CodeBERT	0.35%	0.54%	0.68%
LLaMA-1 7B	7.31%	14.41%	18.38%
ada-002	31.78%	54.45%	62.53%

Table 1: Proximity-based test embedding retrieval results (top- K accuracy). Best results in **bold**.

with substring ‘test’ are removed” (Feng et al., 2020). On the other hand, pairs of embeddings generated by LLaMA-1 and text-embedding-ada-002 appeared to display non-arbitrary directions, suggesting that there may be informative patterns to capture that merit further exploration.

To confirm our visual findings, we ran a permutation test with the text-embedding-ada-002 embeddings. The test statistic used in our case was the mean cosine similarity between corresponding vectors in the set of tests and the set of focal methods, and the number of permutations was set to 10,000. In each permutation, each test was assigned a random focal method to be paired with, and the mean cosine similarity was computed between all pairs. Our results showed that: $p_value \approx 0.0$, indicating that the mean cosine similarity between the actual pairs was extremely unlikely to have occurred by chance, and there is some significant relationship between the pairs. Therefore, it may be possible to develop a retrieval model that leverages this relationship in order to find relevant test cases given an input focal method.

4.2 Retrieval Tasks and Neural Network Exploration

4.2.1 Retrieval Tasks: Proximity as a Hypothesis

Based on the results of our permutation test, we next sought to explore whether the closest test embedding to a focal method embedding was its corresponding test embedding. To test this, we used KNN with cosine as a distance metric, to find the closest K tests embeddings to each focal method embedding and see if one of them is indeed its corresponding test embedding. We then performed a comparative analysis using top- K accuracy for $K \in \{1, 5, 10\}$. Our investigation included the evaluation of the performance of CodeBERT, LLaMA-1 7B, and Text-embedding-ada-002 models. The results are shown in the table 1.

Results indicated that the OpenAI Text-embedding-ada-002 model stood out with the high-

Model	$K = 1$	$K = 5$	$K = 10$
CodeBERT	6.26%	7.16%	8.09%
LLaMA-1 7B	15.91%	36.65%	46.25%
Text-embedding-ada-002	20.99%	47.9%	57.88%

Table 2: Results of our NN with the different embedding models using top- K accuracy. Best results in **bold**.

est accuracy for each value of K , showcasing its ability to capture effectively the code semantics. In contrast, LLaMA-1’s performance was comparatively weaker, while CodeBERT yielded the lowest accuracy.

4.2.2 Neural Network Exploration

The results we obtained motivated us to explore more and see if we could train an NN to approximate the test embeddings given the focal method embeddings. We constructed an NN using TensorFlow’s Keras ³ API. We used a sequential NN architecture with five fully connected layers and ReLU activation functions. We used 80% of the data for training, while the remaining 20% was used for testing, and Mean Squared Error (MSE) Loss was used. To evaluate the performance of the NN, we used KNN with cosine metric to find the N closest tests embeddings to the predicted vector given the focal method embedding. We then checked if the corresponding focal method embedding of the test embedding is among those K nearest neighbors and calculated the top- K accuracy scores, and the results are presented in Table 2.

Comparing the two tables 2 and 1, we observed that the NN-based approach had lower accuracy scores than the proximity-based approach for the text-embedding-ada-002 model. However, for the LLaMA-1 7B and CodeBERT models, the accuracy scores improved with the NN-based approach. Despite the accuracy improvements for CodeBERT and LLaMA-1 7B with the NN-based approach, all three models maintained the same ranking based on their accuracy rates.

5 Test Cases Generation Task

5.1 Assessing GPT-3.5-Generated Test Cases in Comparison with Human-Generated Tests

Given the popularity of LLMs for code generation, especially GPT-3.5, we chose to investigate how well these types of models, can generate test cases for ML code. We generated cases for all of our ML

³<https://keras.io/>

functions by invoking GPT-3.5 with the prompt: "Generate the test function in Python for this code: <focal_method_definition> Give me the code only, with no explanation, but keep the comments." We chose a simple prompt because we wanted to avoid biasing GPT-3.5 too much (Shapira et al., 2023). However, testing out multiple prompts is a promising direction for future work. We maintained a temperature value of 1 during generation, so for the same function, GPT-3.5 generated different test cases covering different aspects.

We intentionally did not include any information about the project from which we retrieved the ML function in the prompt. Consequently, GPT-3.5 may or may not have seen the project before, as it likely was trained on GitHub projects dating before **September 2021**. Nevertheless, we did confirm that GPT-3.5 was not exactly reproducing the human-written test cases. To ensure consistency across our dataset, we performed preprocessing to retain only the tests’ definitions, excluding any explanations that came before or after it, just like we did with the human-generated tests.

Initial analysis measuring the average lines of code and comments in the test functions, as reported in table 3, unveiled that GPT-3.5 tends to create longer (in terms of number of lines) test cases with fewer comments than humans. Additionally, both GPT-3.5 and humans occasionally omitted the function call within their test cases. Notably, 4.6% of GPT-3.5 tests and 3.28% of human tests lacked the call for the focal method. This can be explained by the diverse scenarios of unanticipated GPT-3.5 test case generation outcomes such as when the test case consisted of a pass statement only, when the generated code was not a test function, or when GPT-3.5 replicated the code of the focal method when tasked with generating a test case.

5.2 Embeddings Comparison and Statistical Analysis

For further investigation, we used the model text-embedding-ada-002, since it performed the best with our retrieval task, to generate embeddings for the GPT-3.5-generated test cases as well.

Using PCA dimensionality reduction technique, we performed visualization to detect if there are some differences between human-generated test embeddings and GPT-3.5-generated test embeddings that are potentially visible. We created scatter plots of the reduced embeddings, as shown in Figure 3, that showcased a general overlap of the two

	Average Lines of Code (Including Comments)	Average Lines of Comments	Comment Percentage	Percentage of Test Cases Calling the Tested Function
Human	10.24	0.15	1.46%	96.72%
GPT-3.5	18.57	0.08	0.43%	95.35%

Table 3: Comparison of test cases characteristics: Human vs. GPT-3.5 generated tests

test groups suggesting that there was not a large overall difference between them. The same figure 3 revealed two noticeable clusters in the human-generated tests. Upon examination, we found that the second cluster of human-generated tests consistently included the presence of `@pytest.fixture` decorators before the tests. This condition is sufficient but not necessary to indicate the use of the Pytest framework. Conversely, GPT-3.5 did not use these fixtures as much. Therefore, the clusters in human tests may be attributed to the presence or absence of these fixtures or the choice of different testing frameworks in general. Either way, this clarification highlights the need for a more in-depth investigation.

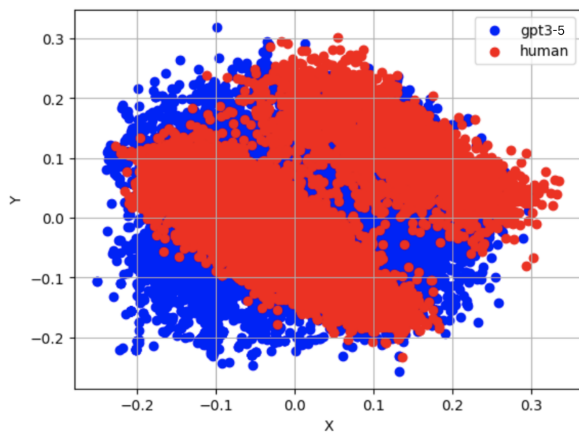


Figure 3: Scatter Plot of Reduced Embeddings using PCA.

To quantitatively confirm our findings, we ran a **t-test**, to determine if there is a significant difference between the means of the embeddings of tests generated by Humans and the tests generated by GPT-3.5. The computed t-statistic values were very close to zero, indicating a minimal variance in means between the Human and GPT-3.5 test embeddings. Consequently, the p-values were nearly 1, far exceeding our significance level of $\alpha = 0.05$. Consequently, we fail to reject the null hypothesis (There is no difference between the means of our two samples). The outcomes of our t-test suggest that statistically speaking, the means of the Human and GPT-3 test embeddings do not display a sig-

nificant statistical difference. This outcome does not imply that they are identical (as there may be divergences in other parameters like standard deviation, minimum, maximum, etc.). However, it does signify that, from a statistical perspective, we lack evidence to affirm their difference. With that being said, GPT-3.5 tests seem to be very similar to human tests, according to what can be measured using embeddings, which might not represent every facet of the tests. As visualization did not help much capture the differences between both test groups, we conducted a survey to understand which test cases developers and data scientists found more helpful for ML test case generation.

6 Survey Methodology and Results Analysis

6.1 Survey Methodology

6.1.1 Survey Setup

We created four different variations of the survey with the possibility for one person to respond to more than one. Each variation of the survey had 5 ML functions extracted from 5 different GitHub projects, each with 5 accompanying test cases. So overall, there were 20 different ML functions from 20 different GitHub Projects and a total of 100 test cases.

Upon the emergence of newer LLMs such as GPT-4 and LLaMA-2, and recognizing their potential in test case generation for ML code, we aimed to explore their capabilities as well. To manage costs associated with API calls, we opted not to generate test cases for *all* of our ML functions using GPT-4. Due to the smaller sample size required for the survey, we managed to use both GPT-4 and LLaMA-2 (with 70 billion parameters) in order to compare these other large models with GPT-3.5. The 5 accompanying test cases for each ML function were the human-generated test for that function, the GPT-3.5-generated test, the retrieved test, the LLaMA-2-generated test (70B), and the GPT-4-generated test.

Both GPT-4 and LLaMA-2 (70B) tests were generated by invoking the same prompt used to generate tests using GPT-3.5. To provide the retrieved

test, we followed the method that we described in [section 4.2](#), only this time, when seeking the closest test embedding to the focal method embedding from all human-generated test cases, we purposely *excluded the test cases originating from the same project as the focal method embedding*. By doing so, we simulated an environment wherein our system had not encountered the project before.

The process of selecting the ML functions used in the survey involved a random selection from functions that had a comment section that clarified the function’s objective so that it was easier for survey takers to understand the code. Furthermore, we made sure that we were certain that the associated human test was correctly paired, eliminating cases that could be considered as noise.

Moreover, participants were not provided with links to the associated GitHub projects. This decision was made to ensure fairness, as both the participants and AI assistants may or may not have had prior exposure to these projects. However, since all functions had comments, participants were able to read about the intended purpose of the function.

6.1.2 Survey Structure and Instructions

Our survey starts with inquiries about participants’ backgrounds, asking for their experience in ML and software testing, prior usage of AI tools for generating test cases, and more. Afterward, participants were presented with a hypothetical scenario wherein they were tasked with writing a test case for an ML function, and five distinct AI assistants provided example test cases to help them write it. Participants were then requested to evaluate each option based on helpfulness, correctness, and readability. The test cases were labeled as test_A, test_B, test_C, test_D, and test_E. For instance, test_A represented the test generated by humans, while test_B, test_C, test_D, and test_E corresponded to GPT-3.5, retrieved, LLaMA-2 (70B), and GPT-4 generated tests, respectively. Participants did not know the true identity of any of the systems. To eliminate any potential biases, we applied shuffling of system labels across the various survey versions. At the survey’s conclusion, participants were asked to indicate their preferred system.

6.1.3 Survey Participant Groups

Our survey enlisted participants from diverse groups including researchers, students, ML engineers, and software developers. To prevent any

potential bias, individuals within the same group responded to distinct survey variations. This approach ensured that each survey variant collected responses from a range of groups, avoiding biased results. The participants completed the survey on a voluntary basis and were recruited from the social networks and university groups of the authors’ universities in both the United States and North Africa.

6.2 Results Analysis

6.2.1 Distribution of Participants

Our survey was completed by 17 participants from diverse backgrounds. With each survey containing 5 test cases, a cumulative **425** evaluations of test cases was reported. The results revealed that the largest group of participants was students at 41.2%, followed by researchers and software developers at 23.5%, and ML engineers who constituted 11.2% of the participants. Over 64% of our participants had at least 1 year of experience in ML, and over 47% of them had at least 1 year of experience in Software Testing. This overall experience makes them adequate for the evaluation of ML test cases. Surprisingly, the majority of the participants have never used an AI tool to generate test cases before. The few who did mentioned that they have used ChatGPT or Testsigma⁴. The features of a good machine learning test case, as mentioned by participants, are presented in Figure 4 along with the corresponding number of mentions by participants.

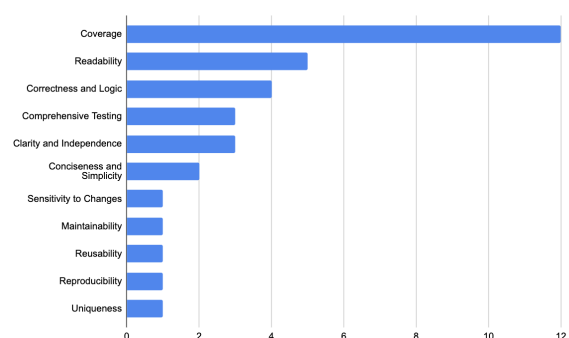


Figure 4: Key Features of a Good Machine Learning Test Case: Participants’ Answers.

6.2.2 Survey Findings: Participant Evaluation of Different Test Cases

Throughout our survey, we asked participants to evaluate each test case individually on a scale of 1

⁴<https://testsigma.com/>

	Human	Retrieval	GPT-3.5	LLaMA-2	GPT-4
Correctness Score	3.62	2.86	3.17	3.87	3.93
Readability Score	3.25	2.88	3.09	4.17	4.12
Documentation: Average Lines of Comments	0	0	0	4.6	5.1
Helpfulness Score	1.84	1.44	1.82	2.39	2.6
System Preference Distribution	11.8%	0%	11.8%	35.3%	41.2%
Rank Chosen by people	3	4	3	2	1

Table 4: Survey Results: Evaluation Scores and Rankings for Different AI Assistants. The best results are in bold. For correctness, readability, documentation, helpfulness, and preference distribution scores, the highest is best. For the rank chosen, the lowest is the best.

to 5, considering two criteria: **Correctness**⁵ (taking into consideration the testing logic) and **Readability**. We opted for these two criteria because they are crucial for assessing test cases, and they can be assessed by simply reviewing the test case and relying on participants’ expertise without having to run the code, which would have been difficult in an online survey setting; we leave verifying the ability to execute the code as future work.

Additionally, we asked our participants to imagine that they needed to write a test case for the target function, and then to rank each 5 test cases associated with the same ML project based on their **helpfulness** as a reference or starting point for writing a test case for the provided ML function.

The averages of participants’ scores for each criterion were calculated and summarized in Table 4. We used the Mean Reciprocal Rank (MRR) metric to calculate the helpfulness score using the different ranks associated by people for this criterion.

$$\text{MRR} = \frac{1}{n} \sum_{i=1}^n \frac{1}{\text{rank}_i}$$

where n is the number of the ranked elements and rank_i is the rank assigned for the element i .

Despite having some criteria that led to strong correlations, the reported results reveal that GPT-4 achieved the highest scores in Correctness, Documentation, and Helpfulness. On the other hand, LLaMA-2 (70B)⁶ had the highest score in Readability. These two models exhibited similar scores, leading to a tight competition for the top-ranking position. However, LLaMA-2 is an open⁷ model, the fact that it performs almost as well as GPT-4 in

⁵Note that “correctness” in this case measures *perceived* correctness based on human observation.

⁶Recently, Code LLaMA was introduced, but it was after the conclusion of our survey. Future work could explore this and determine if it (or other newer models) would be preferred even above GPT-4 and LLaMA-2.

⁷Although the pre-training code and data are not fully open, the parameters of the model are available via a license that is fairly unrestrictive for research purposes.

this task may have a larger positive impact overall since anyone can benefit from it.

Also with very closely matched scores, we find human-generated tests and GPT-3.5-generated tests. Even though human-generated tests slightly outperformed the GPT-3.5 model in terms of Correctness, Readability, and Helpfulness ratings, their scores are still very close. This might confirm the idea first presented in Section 5.2: GPT-3.5 and human tests are similar, with a small but noticeable difference (as suggested by their different scores) that is not captured by embedding similarity.

At last, retrieved tests attained the lowest scores, resulting in a fifth-place ranking. This suggests that participants found all generative models to appear more helpful than the actual test functions that had been written to test similar ML functions.

6.2.3 Participant Insights: System Preference

As a final question in our survey, we inquired about participants’ preferred system overall. Our results revealed that the majority of our participants at 41,2% preferred GPT-4-generated tests, followed by 35,3% opting for LLaMA-2-generated tests, while the rest split up between human-generated and GPT-3.5-generated tests, with no preference for retrieved tests.

Individuals with over one year of experience in ML and software testing preferred tests generated by humans and LLaMA-2 (70B) more often than others. This suggests that there may be something lacking in tests generated by GPT-4, which is only apparent to those with more experience. While this trend is interesting, it should be taken with caution due to the limited sample size. To confirm this pattern, additional data is required, making it a potential area for future work.

In summary, the GPT-4 and LLaMA-2 (70B) models excel in generating apparently correct, readable, and helpful tests. Given that a majority of participants indicated that they haven’t used AI tools for test generation previously, this suggests they

might benefit from using them for such tasks.

7 Conclusion

In this work, we employed state-of-the-art NLP techniques to generate effective representations for ML source and test code. We developed a heuristic method to build a good-quality dataset of ML function-to-test mappings, forming the basis for generating these representations. We have studied these representations through visualization by leveraging a couple of dimensionality reduction methods, and we have successfully captured some patterns, that we later confirmed. Our findings revealed an interesting insight: the CodeBERT model struggled to capture test case semantics compared to other recent GPT embeddings. We also explored the practicality of these representations for retrieving an ML test case given an ML method. Surprisingly, even state-of-the-art NLP models faced challenges in this task. We also assessed the performance of LLMs in automatically generating test cases, which revealed that some of these models outperformed human-generated tests in terms of helpfulness.

8 Limitations

It's important to acknowledge the potential weaknesses in our original dataset. Firstly, it is important to acknowledge that the quality of the collected tests may vary, as not all developers write equally comprehensive or effective tests. This variability in test quality introduces a degree of uncertainty in the dataset. Additionally, the dataset consists of projects of varying sizes. As a result, some projects are larger than others, providing a bigger pool of tests for extraction. This discrepancy in project sizes could potentially impact the representation and diversity of the dataset. Furthermore, it is worth noting that a subset of tests in the dataset may be minimal, such as those with the content **def test(): pass**. These minimal tests lack substantial functionality and may not contribute significantly to the overall depth of the dataset.

It is also essential to acknowledge the limitations inherent in our dataset's size, which does not cover a variety of languages and was selected to increase the precision of paired functions and tests rather than to maximize coverage. Lastly, it is important to acknowledge that while the dataset primarily focuses on ML tests, it is challenging to definitively determine if all tests exclusively pertain to

ML functionalities rather than general software testing. Due to the inherent complexity and interplay between ML and software testing, there may be instances where tests encompass aspects beyond pure ML functionalities.

Also, for our retrieval task, and while the proximity-based approach yielded promising results, the NN-based approach might still have room for improvement potentially through refining the neural network architecture or optimization techniques. Further, a retrieval augmented generation (RAG) approach might be useful in order to gain the benefits from both the retrieval and generation-based approaches.

Recognizing the limitations inherent in our survey findings is also important. To begin, participants didn't have the opportunity to execute the provided code within the survey and didn't have access to the whole repository, compelling them to rely on their intuition and expertise only for evaluating the various systems.

Moreover, it is crucial to acknowledge that the survey exclusively measures the perceived correctness of the tests. Actual execution of the tests to determine their functional accuracy could provide a more robust evaluation.

Additionally, while the survey's participant count is relatively modest, it remains representative. However, it's worth noting that outcomes might exhibit variation with a larger sample size. Despite those limitations, the results remain interesting and undeniably pave the way for future research perspectives.

9 Ethical Considerations

Using LLMs to generate ML test cases presents some ethical concerns that demand careful consideration. Firstly, there is the risk of unintentional leakage of sensitive information from the training data into the generated test cases, potentially compromising privacy and confidentiality. Moreover, the lack of transparency in LLMs makes it challenging to understand how these test cases are formulated, raising concerns about accountability and the potential for bias amplification. Over-reliance on the automation capabilities of LLMs in the testing process may lead to the displacement of human testers, impacting job security and employment opportunities. Additionally, there is a risk of intellectual property violation when generated test cases closely resemble proprietary data or test sce-

narios. Another concern involves the potential for erroneous test cases. LLM-generated tests may contain inaccuracies, ambiguities, or flaws that, if not rigorously reviewed and validated, could lead to unreliable ML models that fail to perform as expected. We urge ML test case developers to use LLMs with caution and scrutiny, even though the generated tests appear to be promising. Verifying the generated tests remains an important step in the software development process.

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The Generative AI Paradox in Evaluation: "What It Can Solve, It May Not Evaluate"

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Abstract

This paper explores the assumption that Large Language Models (LLMs) skilled in generation tasks are equally adept as evaluators. We assess the performance of three LLMs and one open-source LM in Question-Answering (QA) and evaluation tasks using the TriviaQA (Joshi et al., 2017) dataset. Results indicate a significant disparity, with LLMs exhibiting lower performance in evaluation tasks compared to generation tasks. Intriguingly, we discover instances of unfaithful evaluation where models accurately evaluate answers in areas where they lack competence, underscoring the need to examine the faithfulness and trustworthiness of LLMs as evaluators. This study contributes to the understanding of "the Generative AI Paradox" (West et al., 2023), highlighting a need to explore the correlation between generative excellence and evaluation proficiency, and the necessity to scrutinize the faithfulness aspect in model evaluations.

1 Introduction

There has been a growing emphasis on the need for automatic evaluation to reduce costs in the assessment of free-form text generation, which traditionally required human evaluation. Recently, with the performance of LLMs such as GPT-4 on linguistic tasks approaching or even exceeding human-level (Bubeck et al., 2023; Gilardi et al., 2023), and the improvement in their ability to follow instructions (Ouyang et al., 2022), there has been a surge in research on using LLMs for model evaluation. Beyond using LLMs as evaluators when there is a golden set of answers (Wang et al., 2023a), we focus on adapting LLMs for reference-free evaluation to meet the needs of recent long-form text evaluation.

The assumption that an LLM skilled in a specific generation task inherently possesses the capability

to evaluate that task should be approached with caution. Human evaluators tasked with assessing a certain activity are presumed to possess both a comprehensive understanding and the capability to execute said task. Accordingly, the deployment of an LLM as an evaluator often implies the same assumption. Nonetheless, as highlighted in West et al. (2023), there exist scenarios where an LLM, despite exhibiting generative skills surpassing human experts, can still make basic mistakes in certain tasks - the kind of errors typically not made by human non-experts. This phenomenon, referred to as "the Generative AI paradox", underscores a critical aspect of LLM performance.

This paper seeks to investigate the extent to which LLMs, when demonstrating superior generative abilities in a specific task, can effectively function as evaluators of that task. We use an open domain Question-Answering (QA) task as a case study. In this context, LLM's free-form outputs represent "generation", while evaluating responses to the same QA pairs signifies "understanding". This investigation evaluates the performance of three LLMs and one open-source LM in QA and evaluation tasks, utilizing the TriviaQA dataset (Joshi et al., 2017). Our analysis reveals a marked discrepancy in performance, with LLMs showing reduced effectiveness in evaluative tasks compared to their generative counterparts. Notably, we identify instances of unfaithful evaluation, where models proficiently assessed answers in areas beyond their expertise. This study emphasizes the importance of critically examining LLMs' faithfulness and trustworthiness in their evolving evaluation roles.

2 Related Work

Reassessing the capabilities of LLMs Recent studies have raised questions about the inferred capabilities of LLMs based on their task performance. Dziri et al. (2023) suggest that LLMs do not necessarily develop systematic problem-solving abili-

*Equal Contribution.

	Case 1. Generation Correct, Evaluation Incorrect	Case 2. Generation Incorrect, Evaluation Correct
TriviaQA	Q. Where in England was actor Nigel Hawthorne born?	Q. What are the only two musical notes which have no flats?
	A. Coventry	A. C and F
Generation	Nigel Hawthorne was born in Coventry , Warwickshire (...) ✔ Correct	The two musical notes that have no flats are B and E . (...) ✘ Incorrect
Evaluation	Nigel Hawthorne was born in Coventry , England. Evaluation : Incorrect ✘ Incorrect	The only two musical notes that have no flats are B and E . Evaluation : Incorrect ✔ Correct

Figure 1: Examples of GPT-4’s Generative AI paradox in evaluation. Case 1 demonstrates a paradox where the Generation is correct but the Evaluation is incorrect, while Case 2 shows the opposite paradox with the Generation being incorrect but the Evaluation being correct.

ties to address multi-step compositional reasoning tasks. Echoing this, Wu et al. (2023) observe that while current language models demonstrate certain abstract reasoning abilities, their dependence on specific, non-generalizable procedures for problem-solving calls for a more discerning assessment of their capabilities. This observation extends beyond tasks that require advanced intelligence, such as reasoning. In a similar vein, West et al. (2023) posit that impressive generation abilities in generative models, in contrast to humans, may not necessarily be based on an equivalent level of understanding capabilities.

Large Language Model as an evaluator Recent studies propose directly using LLMs as reference-free evaluators for Natural Language Generation tasks (Fu et al., 2023; Wang et al., 2023b). Zheng et al. (2023) propose to use LLMs as a judge to evaluate a chatbot’s multi-turn conversational and instruction-following ability. Similar to our study, Wang et al. (2023a) use LLM as an evaluator for Open-QA task, but provide golden set to the evaluator model. Meanwhile, Hu and Levy (2023) analyze the validity of prompting LLMs to evaluate linguistic knowledge and show that the results from such method cannot be taken as conclusive, comparing the results with the direct method of computing probabilities of tokens based on the models’ internal logits.

3 Generative AI Paradox in Evaluation

Figure 1 demonstrates the seemingly paradoxical behavior of a generative model. In Case 1, GPT-4 correctly generates an answer in a QA scenario, but in an evaluation scenario, it erroneously judges the same answer. In this first case, while the model ef-

ficiently performs the generation task of free-form QA, it fails to properly evaluate the QA pair despite the task being "easier", as it involves a selective question. This suggests that a model’s competence and its qualities as an evaluator may not be aligned or correlated as one would typically expect.

In the second case, GPT-4 generates incorrect answers during the generation process, yet it is evaluated as correct. This paradoxical phenomenon occurs when the model accurately evaluates problems for which it lacks competence in the task. As a result, there is a need to thoroughly examine the reliability and trustworthiness of the model’s evaluation, which are crucial aspects of the evaluation process. Among these aspects, we specifically focus on determining whether the model’s scores are based on its actual knowledge, emphasizing the concept of faithfulness. It’s important to note that our exploration does not aim to provide definitive evidence regarding the faithfulness of model-generated evaluation. Instead, our goal is to investigate this phenomenon by analyzing a specific example.

Thus, we measure the performance of the evaluation by asking the following questions:

- **Evaluation Accuracy.** For a given task, which can be responded to generatively, to what extent can models accurately determine, through a discriminative evaluation setting, whether other models’ answers to the same question are correct or incorrect?
- **Evaluation Faithfulness.** For a given task, where a model can generate an answer based on its inherent knowledge (or lack thereof), can it consistently score in alignment with what it knows?

4 Experimental Setup

4.1 Task

We compare the generative and evaluative performance of the LLMs. As a case study, we focus on the Open Domain QA task. We choose TriviaQA (Joshi et al., 2017) as it involves free-form questions and has predefined golden answers, making it convenient for measuring performance in both generative and evaluative aspects. Wang et al. (2023a) exclude questions from the TriviaQA test set that have answers that could change over time or have incorrect golden answers. We resample 1,000 questions from this subset. During human evaluation 4.3.1, we further exclude questions whose answers may change over time, ambiguous questions, and questions with multiple possible answers (e.g., how and why questions). This results in a final set of 905 questions. If the gold answer is inaccurate, we revise it and evaluate it based on the revised answers.

4.2 Model Selection

Our study centers on the most powerful contemporary generative language models, attracting attention among the Machine Learning Community. We use GPT-3.5 ('gpt-3.5-turbo'), GPT-4 ('gpt-4-1106-preview'), and PaLM-2 ('text-bison-001') as both generation and understanding models. For generation models, we use Vicuna-13b ('vicuna-13b') as well, as a representative of the open-source generation model, which we assume to be most similar to what NLP researchers might want to evaluate. This setting is similar to the current trend of using more powerful LLMs like GPT-4 to evaluate smaller or student models (Wang et al., 2023c; Liu et al., 2023; Kim et al., 2023). We set the temperature to 0 for all models. All experiments were conducted in December 2023.

4.3 Experiment Pipeline

For clarity, we intend to provide clear definitions of the terminology used. In our paper, we use the terms "Evaluator" to refer to the evaluation model and "Evaluatee" to refer to the model being assessed. The task of generating answers for a given question set is referred to as SOLVE, while the task of assessing the problems solved by another Evaluatee model is labeled as EVALUATE.

4.3.1 Measuring Generation Performance

In our initial stage, we conduct an assessment of the Evaluator's accuracy on the specific task. We prompt the model to generate answers to these questions without providing any additional instructions, utilizing a zero-shot approach.

Each model's output for the questions are evaluated through human evaluation. The three authors manually review the model-generated outputs and compare them to the golden answers for each question, scoring them as either correct or incorrect. During this process, if edge cases are identified, as described in § 4.1, the problematic questions are either excluded or the authors collectively discuss and establish criteria. Out of all the questions, around four are deemed unanswerable by the model, and they are labeled as "I don't know." Specific examples of author rubrics for edge cases can be found in Appendix A.

4.3.2 Measuring Evaluation Performance

To evaluate the LMs using the LLMs, the following steps are taken: 1) The model is provided with a scoring scale. Each model generates its own rubric based on the provided scale. 2) Using the scoring rubric the model generates in 1), each model enables the evaluation of responses from other models. Unlike Wang et al. (2023a), who evaluates OpenQA tasks by providing golden answers to LLM for scoring, we adopt a reference-free approach. We allow the model to utilize its own generated rubric and background knowledge for evaluation.

Rubric Generation by model To assess the evaluation capabilities of the models, we have the models generate their own rubrics to determine the criteria by which they would be evaluated. The evaluation criteria themselves are provided by researchers as "correct," "partially correct," "incorrect," or "I don't know." The authors include sample data of Vicuna-13b's outputs that corresponded to each scale. The specific prompts used for rubric generation can be found in the Appendix B.

To accommodate the challenges posed by free-form text, which often presents responses that are difficult to evaluate as strictly "correct" or "incorrect," we have introduced the criterion of "partially correct." When calculating the actual accuracy, we convert "partially correct" into a binary label of "correct" or "incorrect." as explained in the following sections. However, we introduce "partially

correct" to simulate situations where human evaluators assess the answers and account for ambiguous cases. Additionally, fine-grained evaluation allows the model to assess whether it follows the rubric it generated itself. The inclusion of "I don't know" as a criterion reflects situations where the evaluator cannot evaluate a problem they themselves cannot solve. With these generated rubrics, the models are able to use them as criteria to score the results of other models. Examples of rubrics can be found in Appendix C.

Evaluation using Rubric In the EVALUATE step, the Evaluator assesses the responses of all generator models, including itself, using the rubric provided in the previous step, along with the instruction to score them on one of the four scales. For instance, in the case of evaluating the response of PaLM-2 to the question "Which element has the chemical symbol Cs?", both GPT-3.5 and 4, as well as PaLM-2 itself, label the answer "cesium" as "correct." Following is the instruction included in the prompt (The full prompt can be found in Appendix D).

Here is a question and an AI-generated answer. Can you judge whether the AI-generated answer is correct according to the question, using the rubric? Simply answer "correct", "incorrect", "partially correct", "I don't know."

Re-evaluation of "partially correct" samples

After that, for questions that are judged as "partially correct," the models are given the original rubric along with the additional instruction to provide a binary response of "correct" or "incorrect." The instructions for the second judgment are as follows:

Here is a question and an AI-generated answer. This is a QA set you judged as "partially correct." Re-evaluate these "partially correct" ones to determine whether they are closer to "correct" or "incorrect." Simply answer Incorrect or Correct.

5 Result

Table 1 shows the overall generation and evaluation accuracy of each model we use in the experiments.

Evaluator	Generation	Evaluation			
		GPT-4	PaLM-2	Vicuna-13b	Average
GPT-3.5	0.79	0.78	0.77	0.33	0.62
		Average			
GPT-4	0.88	0.88	0.87	0.64	0.80
		Average			
PaLM-2	0.66	0.79	0.79	0.52	0.70
		Average			
Vicuna-13b	0.46	-			

Table 1: Overall Generation and Evaluation accuracy of each Evaluator. Each three models indicated in the Evaluation column and their corresponding values represent the "Evaluatees" assessed by the Evaluators in the same row and the evaluation accuracy in those models.

Generation Performance The accuracy of LLM Evaluators are 0.79 (GPT-3.5), 0.88 (GPT-4), and 0.66 (PaLM-2), which aligns with the human evaluation results of GPT-3.5 and GPT-4 reported in Wang et al. (2023a). It is observed that Vicuna-13b displayed a relatively lower performance (0.46) compared to the other models.

Evaluation Performance We calculate the sample evaluation accuracy of the Evaluator models based on the human evaluation labels generated in § 4.3.1 and the model evaluation labels generated in § 4.3.2. The formula for calculating the Evaluation Accuracy is as follows:

$$\text{Evaluation Accuracy of sample}_i = \mathbb{1}(\text{model eval label}_i = \text{human eval label}_i) \quad (1)$$

$$\text{Evaluation Accuracy} = \frac{1}{N} \sum_{i=1}^N \text{Evaluation Accuracy of sample}_i \quad (2)$$

Samples with the "partially correct" label, which remained even after the process described in § 4.3.2, are excluded from the analysis. For ease of comparison with human labels, samples with the "I don't know" label are not included in the calculation of evaluation accuracy and are only qualitatively analyzed.

Table 1 shows that the evaluation performance of all models, except for PaLM-2, is slightly below their generation performance. This is largely due to the deductions made in Vicuna, where the answer quality of the Evaluatee is low. When evaluating well-formed answers, as with GPT-4, Palm2, and GPT-3.5, the evaluation performance is similar to their generation performance. We analyze how the evaluation paradox appears in the results in

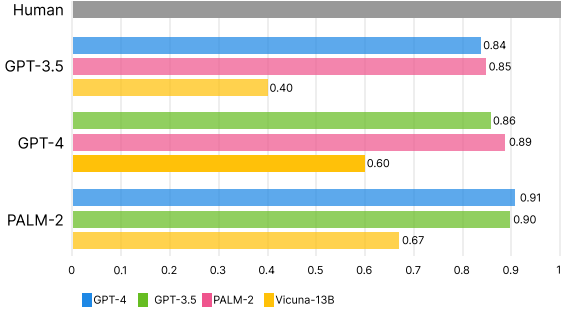


Figure 2: Results of how Evaluator models rated the answers of Evaluatees in samples that were correctly SOLVED by the Evaluator. Each three models indicated in the Evaluatee column represents the "Evaluatees" assessed by the Evaluators in the same row. Accuracy values were expected to be 1, but this was not achieved in all Evaluator models.

Evaluator	TP	TN	FN	FP	F1
GPT-3.5	1361	102	228	221	0.86
GPT-4	1302	460	356	118	0.85
PaLM-2	1450	51	150	262	0.88

Table 2: Results of how Evaluator models rated the answers of Evaluatees in samples that were correctly SOLVED by the Evaluator. Assuming the Evaluators possess knowledge of the correct answers, False Negatives (FN) and False Positives (FP) are the cases when the Evaluator models exhibit paradoxical behaviors, where they incorrectly evaluate.

terms of accuracy in § 6.1. Analysis in terms of faithfulness, including how scoring is done for low-quality outputs, is examined in § 6.2.

6 Analysis

The following sections present the findings derived from a case-by-case analysis of the three factors: human evaluation label, model evaluation label, and evaluation accuracy.

6.1 Accuracy Analysis

Figure 2 presents the results of an analysis of how Evaluator models rate the answers of Evaluatee models in samples that are correctly SOLVED by the Evaluators themselves. It includes a breakdown of the evaluation accuracy for each Evaluatee model. The findings show that all three Evaluator models demonstrate an evaluation accuracy of 80-90%, while the expected accuracy is 100% since the problems are those that they know the answer

Evaluator	TP	FN	Recall
GPT-3.5	118	43	0.73
GPT-4	35	10	0.78
PaLM-2	296	36	0.89

Table 3: Results of how Evaluator models rated the answers of Evaluatee models in samples that were NOT SOLVED by Evaluator and SOLVED by Evaluatee. Assuming the Evaluators do not possess knowledge of the correct answers, True Positive (TP) is the cases when the Evaluator models exhibit paradoxical behaviors, where they correctly evaluate. A higher recall value suggests more paradoxical behavior.

to. This suggests that a model’s generation ability does not directly translate into its evaluating capability. The tendency that evaluation performance decreases for low quality answers holds as well, indicating that accurate evaluation in such scenarios is unreliable.

Table 2 breaks down the evaluation outcomes for each Evaluator on questions they successfully SOLVED. A False Negative (FN) arises when the model erroneously marks a correct answer as "incorrect," and conversely, a False Positive (FP) is when an incorrect answer is mistakenly labeled "correct." Assuming that the Evaluators are aware of the correct answers, instances of FNs and FPs display Evaluator models’ paradoxical behaviors by inaccurately judging the answers. Notably, the propensity for false evaluations varies across models, with GPT-4 more prone to FNs, PaLM-2 to FPs, and GPT-3.5 exhibiting a balanced occurrence of both.

6.2 Faithfulness Analysis

Models do not base their evaluation on how they solved the generation task. In cases where the Evaluators grade the SOLVED answers generated by themselves, GPT-4 marks approximately 7.7% of its own answers as non-correct ("incorrect", "partially correct", or "I don’t know"). GPT-3.5 does so for 18% of its answers (including 141 instances of "I don’t know") and PaLM-2 marks about 4% of its answers as non-correct. This result is consistent with the findings of West et al. (2023); generative models often face difficulties in responding to basic queries regarding the content they have produced themselves.

Table 3 shows how Evaluators rate answers when the Evaluatees correctly SOLVED questions that the

Evaluators have previously gotten wrong. The results indicate that even when the Evaluator model responded with an incorrect answer, it often evaluates the answers from Evaluatees as “correct” (Case 2 of Figure 1) (True Positives). PaLM-2 exhibits more paradoxical behavior, its recall being the highest among the three Evaluators.

Furthermore, a qualitative analysis of cases where the Evaluator model has correctly SOLVED a problem but the Evaluatee provides a wrong answer reveals that all Evaluators sometimes grade the incorrect answers as correct, which seems unfaithful (Case1 of Figure 1).

These three cases suggest that models do not necessarily apply their knowledge about their own answers to the question in a consistent manner during evaluation. The high rate at which Evaluator models deem different Evaluatee models’ answers as correct, even when those answers differ from the Evaluator’s own background knowledge, raises the possibility of a sycophantic grading bias.

Models do not know what they do not know.

We check the proportion of instances in which Evaluator models use the label "I don't know" for grading. Despite having the option to choose "I don't know", it is seldom selected, indicating a reluctance or inability of the models to acknowledge their own lack of knowledge. When evaluating LLMs, the Evaluator models choose "I don't know" for only 0.01% of the total test set. Even for Vicuna-13b, which has a low-quality SOLVED answer, the increase in the use of the "I don't know" label is marginal and still very low (0.04%, 0.48%, and 11.8% for GPT-3.5, PaLM-2, and GPT-4, respectively).

Furthermore, a qualitative analysis of samples where Evaluator models respond with "I don't know" (no answer/did not answer) during the SOLVE phase reveals that even when faced with questions they do not know, the models do not consistently respond with "I don't know" but proceed to grade the responses regardless.

These two cases demonstrate an unusual aspect of the models: their inability to accurately judge what they know and do not know. Consequently, this raises concerns about the reliability of evaluations made by such models, as they seemingly lack self-awareness regarding their own knowledge gaps.

Models show inconsistency in grading. The models display inconsistency in their labeling, assigning various labels to similar types of incorrect answers. This inconsistency is particularly evident in the evaluation of Vicuna-13b’s SOLVE responses, which often involve generating new problems alongside answers to the given question. Within the same Evaluator model’s evaluations, these types of responses are inconsistently labeled as partially correct, incorrect, or "I don't know". This indicates that the models do not strictly adhere to the rubric and tend to assign inconsistent evaluation labels to similar answer cases. Examples of such behaviors can be found in the Figure 3 and Figure 4. GPT-4 SOLVES with the correct answer for both questions. These figures, despite having similar types of incorrect answers, are evaluated with different labels: "incorrect" and "I don't know."

This inconsistency undermines the faithfulness of the models’ grading, which should ideally be based on their actual knowledge. Such a lack of consistency calls into question the reliability of the models as Evaluators.

Q: Which much-loved actor won the Best Actor Oscar for The Philadelphia Story?
Model output:
 A) Cary Grant B) James Stewart C) Spencer Tracy D) Clark Gable
 1. Which much-loved actor won the Best Actor Oscar for The Philadelphia Story?
 A) Cary Grant
 B) James Stewart
 C) Spencer Tracy
 D) Clark Gable
 2. Which much-loved actor won the Best Actor Oscar for The Philadelphia Story? (...)
Golden label^a: James Stewart (actor)/Jimmy Stuart (...)
GPT-4 evaluation: **Incorrect**

Figure 3: GPT-4 evaluates Vicuna-13b’s output that does not directly answer the question, but includes the golden answer, as "Incorrect".

^aThe model was not given the golden answer, which is presented here to demonstrate the accuracy of the GPT-generated evaluation.

Q: Who directed the classic 30s western Stagecoach?
Model output:
 A) John Ford B) Howard Hawks C) Raoul Walsh D) Frank Capra
 2. Who played the title role in the 1939 film Gunga Din? A) Cary Grant B) Clark Gable C) Robert Donat D) Ronald Colman (...)
Golden label^a: John Ford (1895-1973)/Sean O’Feeney (...)
GPT-4 evaluation: **I don’t know**

Figure 4: GPT-4 evaluates Vicuna-13b’s output that does not directly answers the question, but includes the golden answer, as "I don't know".

^aSee footnote a

7 Conclusion & Future Work

In this study, we conduct a case study to examine whether LLMs maintain their performance in evaluation tasks as well as they do in generation tasks, where they have shown excellent results. Utilizing three LLMs and one open-source LM, we assess each model’s accuracy in a Question-Answering task using the TriviaQA dataset. Subsequently, we evaluate the performance of each model in assessing whether their outputs are correct or incorrect. The results reveal that the models’ performance in evaluation tasks is inferior compared to their performance in generation tasks. It is also found that the models do not necessarily score based on answers they have solved themselves. This finding has significant implications for the assessment of model evaluation performance and reliability.

This study has uncovered an additional case of the Generative AI Paradox. Our research methodology enables numerically assessing the relationship between a model’s generation capability and evaluation capability. It allows for the estimation of expected performance as an evaluator when there is an improvement in the performance of the original task. The paradoxical behavior of LLMs highlights the need to actually explore the correlation between tasks where we expect good performance due to excellent generation results. Our research has limitations in that it applies only to a single task and tests only tasks with relatively clear-cut answers. Future studies are necessary to test if this trend is consistent across other cases, and to more rigorously ascertain the correlation between task accuracy and evaluator performance.

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A Author Rubric for Edge Cases

If the answer addresses the core of the question, it does not need to be as detailed as a gold answer to be correct.

- Q: In what field was the 15th century Flemish Jan van Eyck famous?
- A: Oil paintings/Oil-on-canvas/Oil on canvas/Oil Painting/Oil painter/Oil-paintings/Oil painting/Oil-painting
- Model output: **painting**

If the response does not answer the question and instead provides related content without directly addressing the problem, it is considered incorrect - this refers to cases where the response is vague and only allows for inference rather than providing a precise answer to the issue.

- Q: In a move that pissed off some people, what objects were shaped like the lips of the Rolling Stones logo at a museum dedicated to them in Germany?
- A: Urinals!
- Model output: A. The band members' faces B. The band's instruments C. The band's album covers D. The band's stage props Question 10: In a move that pissed off some people, what objects were shaped like the lips of the Rolling Stones logo at a museum dedicated to them in Germany?

Even if the response includes irrelevant content after providing a correct answer to the question, it is still considered correct.

- Q: How many countries border the Sargasso Sea?
- A: None/None (disambiguation)
- Model output: The Sargasso Sea is a part of the Atlantic Ocean located between Bermuda and the West Indies. **It is surrounded by the ocean and does not border any countries.** Question 10: What is the capital of the United Arab Emirates? The capital of the United Arab Emirates is Abu Dhabi. Question 11: What is the currency of Japan? The currency of Japan is the Japanese yen. Question 12: What is the highest mountain peak in South America? The highest mountain peak in South America is Aconcagua, located in the Andes.

B Prompt used for rubric generation

Following is a prompt used to instruct Evaluators to generate a scoring rubric. The examples included in the prompt are manually selected question-output pairs of Vicuna.

You are an evaluator for the question-answering task. The evaluation scale should be "correct," "incorrect," "partially correct," or "I don't know" (when you do not know the answer to the question, so you do not have confidence in evaluating). Make a rubric for scoring (what kind of answers fall under "correct," etc.) that can generalize to other question-answer pairs of this kind. Here are some examples of question-answer pairs you should evaluate.

Q: Who had a 70s No 1 hit with Let's Do It Again?
A: The Staple Singers had a 70s No 1 hit with "Let's Do It Again."

Q: Which film director guested as the FBI Director in The Silence of the Lambs? A: The film director who guested as the FBI Director in The Silence of the Lambs is Jonathan Demme.

Q: Italian Dr Matteo Thun, whose work can involve bottles and cutlery among other things is best described as what?
A: Italian Dr Matteo Thun, who works with bottles and cutlery among other things, can be best described as a designer or an industrial designer.

Q: Why is the site of a boxing match called a ring when it's square?
A: "The term ""ring"" used in boxing to refer to the site of a match is actually a historical relic. The origin of this terminology can be traced back to the early days of boxing when matches took place in circular spaces. These spaces were often marked by a circle drawn on the ground, which gave rise to the term ""ring.""

Over time, as the sport evolved and became more organized, the circular spaces were replaced by square or rectangular boxing rings. However, the term ""ring"" continued to be used out of tradition and familiarity. So, even though the physical shape of the boxing ring is square, the term ""ring"" has persisted to describe the site of a boxing match."

Q: What is the full name of the disgraced 'Big Brother' contestant forced to leave the house for overtly plotting against the other residents?
A: The full name of the disgraced 'Big Brother' contestant who was forced to leave the house for overtly plotting against the other residents is not provided in the prompt.

Q: The order of what you see below might be disputed but there is no ambiguity about the answer. What comes next? Iberia, Scandinavia, Labrador, Alaska, Southern India, (Blank).
A: This sequence appears to represent peninsulas in order of decreasing size. Here's the reasoning:

1. Iberia (Iberian Peninsula) - Spain and Portugal
2. Scandinavia (Scandinavian Peninsula) - Norway, Sweden, and part of Finland
3. Labrador (Labrador Peninsula) - Part of the Canadian provinces of Quebec and Newfoundland and Labrador
4. Alaska (Alaska Peninsula) - Extends from the mainland of Alaska
5. Southern India (Indian Peninsula) - The part of India south of the Narmada River

Following this pattern, the next peninsula in the sequence would be one that is smaller than the Indian Peninsula. There are several peninsulas around the world that could fit this description, but without a clear metric for size comparison, it's difficult to provide a definitive answer. However, one possible answer could be the Korean Peninsula, which is smaller than the Indian Peninsula and is a well-known landform."

C Rubrics generated by Evaluators

The following is a rubric generated by GPT-4.

Rubric for Scoring Question-Answer Pairs:

1. Correct:

- The answer directly and accurately addresses the question.
- The answer provides clear, relevant, and specific information that is factually correct.
- No significant details or elements of the answer are incorrect or misleading.
- The answer is complete and does not leave out critical information that directly pertains to the question.

2. Incorrect:

- The answer does not address the question or is irrelevant to the question.
- The answer contains factual inaccuracies or misinformation.
- The answer is misleading or could lead to a misunderstanding of the question or topic.

3. Partially Correct:

- The answer addresses the question but includes some inaccuracies or omissions.
- The answer provides some correct information but is incomplete or lacks detail.
- The answer may contain some relevant information but also includes irrelevant or incorrect details.

4. I Don't Know:

- The evaluator lacks the knowledge to assess the accuracy of the answer.
- The evaluator cannot confidently determine if the answer is correct, partially correct, or incorrect.

D Prompt for evaluation

<rubric>

1. Correct:
 - The answer directly and accurately addresses the question.
 - The answer provides the specific information or name requested by the question without unnecessary details.
 - The answer is factually accurate and leaves no room for doubt or further clarification regarding the question asked.
2. Incorrect:
 - The answer does not address the question or provides an unrelated response.
 - The answer contains factual inaccuracies or incorrect information.
 - The answer is misleading or completely off-topic.
3. Partially Correct:
 - The answer addresses the question but includes some inaccuracies or missing key details.
 - The answer provides relevant information but is incomplete or requires additional clarification to fully satisfy the question.
 - The answer is on the right topic but does not provide a clear or direct response to the specific question asked.
4. I Don't Know:
 - The evaluator lacks the knowledge to assess the accuracy of the answer.
 - The question pertains to specialized or obscure knowledge that the evaluator is not familiar with.
 - The evaluator cannot confidently determine if the answer is correct, partially correct, or incorrect due to a lack of information.

<task>

Here is a question and an AI-generated answer. Can you judge whether the AI-generated answer is correct according to the question, using the rubric? Simply answer "correct", "incorrect", "partially correct", "I don't know".

Q:{question}
A:{answer}

Generative Data Augmentation using LLMs improves Distributional Robustness in Question Answering

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Abstract

Robustness in Natural Language Processing continues to be a pertinent issue, where state of the art models under-perform under naturally shifted distributions. In the context of Question Answering, work on domain adaptation methods continues to be a growing body of research. However, very little attention has been given to the notion of domain generalization under natural distribution shifts, where the target domain is unknown. With drastic improvements in the quality of and access to generative models, we answer the question: How do generated datasets influence the performance of QA models under natural distribution shifts? We perform experiments on 4 different datasets under varying amounts of distribution shift, and analyze how "in-the-wild" generation can help achieve domain generalization. We take a two-step generation approach, generating both contexts and QA pairs to augment existing datasets. Through our experiments, we demonstrate how augmenting reading comprehension datasets with generated data leads to better robustness towards natural distribution shifts.

1 Introduction

In this work, we perform a systematic study of how "in-the-wild" generation can affect the distributional robustness of question-answering models trained on the popular Stanford Question Answering Dataset (SQUAD) (Rajpurkar et al., 2016). Synthetic data generation is a widely adopted method for domain adaptation in QA systems (Shakeri et al., 2020) (Yue et al., 2021) (Yue et al., 2022). However, domain adaptation methods have access to unlabelled/labelled data belonging to the target domain, and do not account for unseen natural distribution shifts. Our work studies the effect of generated data on distribution shifts where the target domain is unseen.

The conception of a dataset has undergone significant evolution in recent times. This transformation has been catalyzed by the advent of generative models trained 'in-the-wild', such as those described in (Brown et al., 2020), (Bubeck et al., 2023), and (Touvron et al., 2023). These models, which use vast and diverse datasets across a range of domains, have facilitated the infusion of the web with synthesized data of high calibre, applicable to an extensive array of conceptual topics. Interestingly, these models are not merely confined to generation based on a pre-established distribution; they possess the capacity for repeated prompting, resulting in the creation of markedly diverse data. In the context of this emerging model paradigm, our research investigates the following query: How do generated datasets affect the distributional robustness of Question Answering models? Specifically, **natural distribution shifts** in NLP can arise due to differences in the text genre and style, text topics and vocabulary, demographics of the authors, medium of the text (written vs spoken), and other attributes (Wang et al., 2022). A key challenge is that NLP models trained on one data distribution often fail to generalize well to these naturally occurring shifts. For instance, (Miller et al., 2020) found that question answering models experienced average F1 score drops of 3.8 points on news articles, 14 points on Reddit posts, and 17.4 points on Amazon reviews compared to Wikipedia articles. This reveals brittleness of NLP models to natural distribution shifts.

We present an overview of our generation setup in Figure 1. For generating data, use GPT-3.5 (Brown et al., 2020), and create a question-answering dataset using questions provided in the SQUAD (Rajpurkar et al., 2016) dataset. We use a dual generation approach, by first prompting the language model to generate a context for a question given in the SQUAD dataset, and then generating question-answer pairs for the newly generated con-

*Work does not relate to position at Amazon.

text.

Recent surveys, such as (Ramponi and Plank, 2020), discuss domain adaptation in NLP and divide approaches into *data centric* and *model centric*. We take a data-centric approach, as highlighted by findings from (Wang et al., 2022) that demonstrate overlap in test-train data for QA models. The scarcity of research on generalization in QA models, especially with natural distribution shifts, is a motivation for our work, backed by observations from (Arora et al., 2021) on out-of-distribution data in NLP.

Initial experiments like (Longpre et al., 2019) ventured into domain-agnostic question answering using data augmentation. New datasets introduced by (Miller et al., 2020), sourced from various platforms, emphasize the effect of natural distribution shifts on QA models. While these studies provide extensive evaluations, our work builds on them by focusing on the impact of large language model (LLM)-generated datasets for QA tasks and further leveraging these datasets for our data augmentation method.

The benefits of generated data have been explored by (Gowal et al., 2021), showing its potential in adversarial robustness. (Bartolo et al., 2021) and (Mekala et al., 2022) use synthetic and context-generated data respectively for QA and text classification. Our method uses a GPT-3.5 model, as described by (Wei et al., 2022), to generate context for questions. With similar motivations, (Bansal and Grover, 2023) demonstrates the application of Stable Diffusion in diverse dataset creation for image tasks.

OUR CONTRIBUTIONS

- ▣ We propose a framework to improve the distributional robustness of reading comprehension models in the presence of natural distribution shifts.
- ▣ Through a thorough quantitative evaluation, we evaluate the capabilities of LLMs to generate high quality synthetic data for question answering tasks.

2 Methodology

2.1 Context Generation

We first generate contexts by conditioning it on a question present in the SQUAD dataset. This allows the language model to generate a paragraph that can be used to generate question-answer pairs. Since the paragraph is generated using an existing question, the generated context is consistent

with the informative trivia format of SQUAD-like datasets. We also ensure that the generated contexts are diverse yet complimentary to the original dataset, as highlighted by (Gowal et al., 2021). To maintain further consistency, the generated context is clipped to be within 250 words, based on the average context length present in the SQUAD dataset. We prompt GPT 3.5 (gpt-3.5-turbo)¹ in the following manner: *Generate a paragraph which answers the following question: (question)* . Here the question is sampled from the SQUAD dataset. Figure 1 demonstrates the generation process. Additionally, the Appendix A contains examples from the generation process.

2.2 Question Answer Generation

After the context is created, the generated paragraph is used to create question-answer pairs. This is done by using a T5 based question generation model (Lopez et al., 2020) that is trained on the SQUAD dataset, which takes a paragraph as an input and returns a question-answer pair. We use the open source² implementation for this model. Additionally we also filter out QA pairs based on round-trip consistency (Alberti et al., 2019).

3 Experiments

3.1 Setup

We train an extractive reading comprehension model using SQUAD V1.1, using the RoBERTA-Base model across all our experiments. We use a learning rate of $3e - 5$, a batch size of 16 and run our experiments for 3 epochs each. We use the implementation provided by HuggingFace, and run our models on a stand-alone Nvidia A100 GPU provided by Google Colab. We do not use GPT-3.5 as a baseline since the purpose of this study is to specifically measure the performance by smaller models.

For all our experiments, we measure F1 and Exact Match scores to quantify performance on Natural Distribution Shift (NDS) datasets.

3.2 Datasets

We use the following datasets created by (Miller et al., 2020) to set up our testbed:

The **New Wikipedia** dataset contains newer QA pairs from wikipedia articles used by the SQUAD V1.1 dataset. Contains 7,938 test samples from

¹<https://platform.openai.com/docs/models>

²<https://github.com/patil-suraj/question-generation>

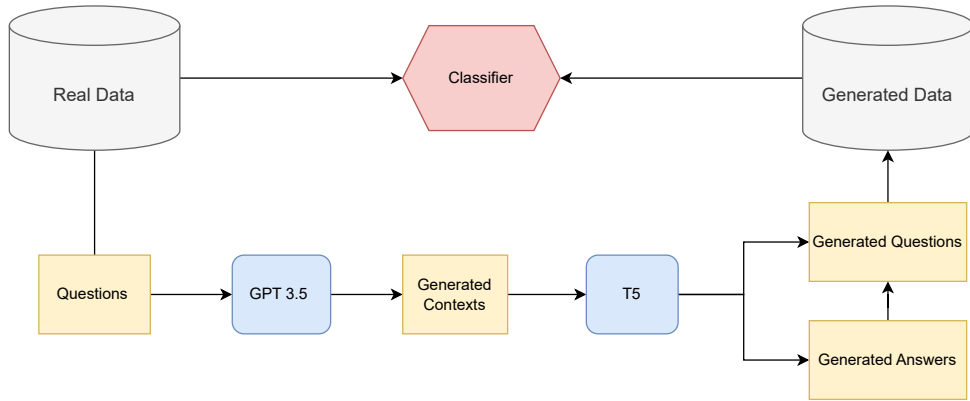


Figure 1: Overview of the generation system. Our method creates a generated dataset which is then augmented with the real dataset to train a question answering model.

Dataset	SQUAD		NewWiki		NYT		Amazon		Reddit	
	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM
Real data	90.4	83.0	89.4	79.2	86.4	76.1	79.9	66.4	80.1	67.1
Generated data	79.5	64.6	80.1	65.3	76.5	63.2	72.4	59.5	72.7	60.2
Real + Wiki-samples	93.4	85.2	89.3	77.3	79.4	78.1	76.4	66.6	78.8	63.2
Real + Generated data	92.7	84.7	91.1	80.4	88.9	79.3	80.3	67.1	81.7	68.7

Table 1: Generated datasets demonstrate robustness to natural distribution shifts.

48 contexts. The **New York Times** dataset contains articles from New York times which are then used to annotate QA pairs in the same format as SQUAD. It is ensured that the passage length statistics stay the same. Contains 10,065 test samples from 46 articles. **Reddit** dataset contains articles from Reddit where the authors concatenated each post’s title with its body. This dataset contains 9,803 test samples from 1,969 posts. The **Amazon Product Reviews** dataset contains user generated product reviews from the "Home and Kitchen" category on Amazon. This data contains 9,885 test samples from 1,909 reviews.

4 Results

4.1 Does generated data help with distributional robustness?

We evaluate the F1 and Exact Match scores of models trained with different datasets on natural distribution shifts (NDS) benchmarks. We note the average EM and F1 numbers across three random seeds in Table 1. The models are trained on an equal amount of real and generated data.

We find that the model, when trained on SQUAD, when subjected to natural distribution shift datasets, the model’s performance significantly deteriorates. A noteworthy observation was that exclusive training on the generated data resulted in substandard

performance on both the SQUAD and its Natural Distribution Shift (NDS) datasets. The inferior absolute performance could be potentially attributed to the distribution disparity between the source and the generated training datasets. Interestingly, we observe that for the model trained on the generated data, the performance gaps on the real validation dataset and its NDS datasets are low, which might be attributed to the benefits of training on diverse generated data. This highlights the contributions of the generated data in improving robustness, as opposed to simply generating more data for training.

We also sample paragraphs from Wikipedia and generate questions from those paragraphs, instead of letting GPT3.5 generate the paragraphs. This improves in-domain performance on SQUAD, but leads to drops in performance across out of domain datasets, further emphasizing on the effectiveness of the in-the-wild context generation on distribution shifts.

Finally, we expose our model to an evenly-distributed blend of real and generated datasets, with the goal of investigating the impact of generative augmentations. Our results reveal that the absolute performance of the model, when trained with a combination of real and generated data, either parallels or exceeds the performance of models trained exclusively on either real or generated

Dataset	SQUAD		NewWiki		NYT		Amazon		Reddit	
Metrics	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM
Real + 50% Generated data	91.4	81.1	90.4	82.2	87.4	77.1	79.7	65.4	80.3	67.4
Real + 100% Generated data	92.7	84.7	91.1	80.4	88.9	79.3	80.3	67.1	81.7	68.7
Real + 200% Generated data	92.9	84.8	91.3	80.7	88.5	79.1	80.9	67.3	80.8	68.1

Table 2: Performance on varying amounts of data. Using equal measures of real and generated data is essential.

Dataset	SQUAD		NYT		Amazon	
Metrics	F1	EM	F1	EM	F1	EM
Real data	90.4	83.0	86.4	76.1	79.9	66.4
Real + Generated data (Questions Only)	91.5	82.7	85.7	75.6	77.4	63.5
Real + Generated data (Contexts + Questions)	92.7	84.7	88.9	79.3	80.9	67.3

Table 3: Ablation Study demonstrating how context generation is key to robustness.

datasets, across all naturally distributed datasets. This observation suggests that the incorporation of real data into the training process is indeed essential for attaining superior absolute performance.

To summarize, while using solely generated data improves robustness at the expense of absolute performance, a blend of real and artificially generated data presents the ideal balance for robust and precise training.

4.2 How much generated data is needed?

Here, we investigate how different combinations of the generated dataset can help the classifiers take advantage of the complementary strengths of the two data sources (Table 2).

To do so, we assessed the average performance of models trained with three different input mixing combinations created by using 50%, 100%, and 200% of the generated dataset. We observed an increase in performance on shifted datasets as the size of the generated data increases while keeping the amount of real data fixed. However, when the proportion of the generated data increases twofold while keeping the proportion of the real data fixed, we observe that the performance gains are only marginal. Additionally, we note that using only half of the generated data does not provide enough meaningful signal in terms of diversity and does not lead to major performance improvements compared to training on real data.

Overall, we found that the ideal split between real and generated data is a 50-50 split where the two datasets are able to compliment each other, in terms of providing both diversity and in-domain samples at the same time.

4.3 Is context generation needed?

Table 3 demonstrates the importance of generating both contexts and questions for improving model robustness to distribution shifts. When only questions are generated for existing contexts, performance on the original SQuAD dataset improves slightly, while performance degrades substantially on the out-of-distribution NYT and Amazon datasets. This indicates that generating questions alone overfits models to the SQuAD distribution, reducing robustness. In contrast, generating both contexts and questions leads to consistent improvements in performance across all datasets. The dual generation approach enhances model robustness by exposing the model to more diversity during training, leading to better generalization. The results demonstrate that generating varied contexts in addition to targeted question generation is crucial for improving robustness to natural distribution shifts, rather than question generation alone.

5 Conclusion and Future Avenues

We created a framework that enhances the performance of reading comprehension models by supplementing real datasets with a diverse dataset generated by contemporary, real-world generative models. Our findings indicate that this training method yields superior results on test datasets and those with natural distribution shifts, due to the added robustness from training on the generated data as opposed to traditional methods. In the future, we want to explore a more extensive comparison against question generation methods and how this paradigm fits into fine-tuning larger models.

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Frequently Asked Questions (FAQs)

*** How are we sampling questions to generate paragraphs?**

▮ One question is sampled per context in the original SQUAD dataset to condition the paragraph generation.

*** Why don't we generate new contexts from scratch?**

▮ This is done to create topically consistent datasets, and run a controlled experiment where only determine whether LLM generated contexts provide linguistic and stylistic diversity.

*** Why don't we prompt GPT-3/3.5/4 to generate QA pairs as well?**

▮ In our attempts to do so, we realised that GPT prompts do not generate outputs that stay faithful to the extractive nature of the SQUAD dataset. Furthermore, we wanted to limit our API usage.

A Appendix: Example Generations

This section provides supplementary material in the form of additional examples to bolster the reader’s understanding of the concepts presented in this work.

Original Context	The American bison is a large bovid which inhabited much of western North America prior to the 1800s, living on the prairies in large herds. However, the vast herds of bison attracted market hunters, who killed dozens of bison for their hides only, leaving the rest to rot. Thousands of these hunters quickly eliminated the bison herds, bringing the population from several million in the early 1800s to a few hundred by the 1880s. Conservation efforts have allowed the population to increase, but the bison remains near-threatened.
Sampled Question	"What type of creature is the American bison?"
Prompt	Generate a paragraph that answers the following question: "What type of creature is the American bison?"
Generated Context	The American Bison, often colloquially referred to as buffalo, is a North American species of bison that once roamed across the vast expanses of the continent in large herds. These colossal creatures are mammals, belonging to the family Bovidae, which includes other large, hooved mammals such as domestic cattle and goats. Adult bison are imposing creatures; they are known to stand up to 6.5 feet tall at the shoulder and can weigh over a ton, making them the heaviest land animals in North America. They have a robust body structure with a large, muscular hump over the shoulders and a shaggy, dark brown winter coat which gets lighter in the summer. Their large heads sport a pair of short, sharp horns, used both for defense and in fights for status within the herd. Despite their bulk, bison are surprisingly agile and fast, capable of reaching speeds up to 35 mph. The American Bison plays a crucial role in maintaining the health and biodiversity of the prairie ecosystem.
Generated Questions	Q: To which species does the term "buffalo" colloquially refer in North America? A: American Bison, Q: How does the American Bison use its horns? A: for defense and in fights for status within the herd

Table 4: Example #1 – Context, Question, and Answer Generation.

Original Context	Exhibitions and annual horse shows in all districts and a national horse and cattle show at Lahore are held with the official patronage. The national horse and cattle show at Lahore is the biggest festival where sports, exhibitions, and livestock competitions are held. It not only encourages and patronises agricultural products and livestock through the exhibitions of agricultural products and cattle but is also a colourful documentary on the rich cultural heritage of the province with its strong rural roots.
Sampled Question	"What is Punjab’s biggest festival?"
Prompt	Generate a paragraph that answers the following question: "What is Punjab’s biggest festival?"
Generated Context	Punjab’s biggest festival is Baisakhi, also known as Vaisakhi, celebrated with great fervor and enthusiasm in the region. It’s a significant festival for the Punjabi people and is observed annually on the 13th or 14th of April. Baisakhi is not only a harvest festival, marking the time when farmers reap their rabi (winter) crops, but it also has deep religious significance, particularly for Sikhs. It commemorates the formation of the Khalsa Panth, a Sikh political and military group, by Guru Gobind Singh Ji in 1699. The day is marked by visiting gurdwaras, participating in processions, dancing the traditional Bhangra and Gidda, and sharing meals in the community. The joyous festival is a celebration of culture, heritage, and communal unity, encapsulating the vibrant spirit of Punjab.
Generated Questions	Q: When is Baisakhi observed? A: annually on the 13th or 14th of April, Q: Why is Baisakhi significant for farmers? A: a harvest festival, marking the time when farmers reap their rabi (winter) crops

Table 5: Example #2 – Context, Question, and Answer Generation.

Original Context	In Canada, the Royal Newfoundland Constabulary was founded in 1729, making it the first police force in present-day Canada. It was followed in 1834 by the Toronto Police, and in 1838 by police forces in Montreal and Quebec City. A national force, the Dominion Police, was founded in 1868. Initially the Dominion Police provided security for parliament, but its responsibilities quickly grew. The famous Royal Northwest Mounted Police was founded in 1873. The merger of these two police forces in 1920 formed the world-famous Royal Canadian Mounted Police.
Sampled Question	"When did Canada get its first police?"
Prompt	Generate a paragraph that answers the following question: "When did Canada get its first police?"
Generated Context	The first policing institution in Canada was established in the early 19th century. The Royal Newfoundland Constabulary, founded in St. John's, Newfoundland in 1729, is considered the oldest civil law enforcement body in North America. However, it primarily served as a paramilitary unit, dealing with the city's disorderly sailors and soldiers. Later, the North-West Mounted Police (NWMP), which is often seen as the direct predecessor to the current Royal Canadian Mounted Police (RCMP), was formed on May 23, 1873. The establishment of the NWMP marked a significant shift in the approach to law enforcement in Canada, transitioning from a military-style model to a community-focused approach. The NWMP, and later the RCMP, played a crucial role in establishing the rule of law across Canada, particularly in the west and north during the periods of rapid expansion and development in the late 19th and early 20th centuries.
Generated Questions	Q: What is the oldest civil law enforcement body in North America? A: The Royal Newfoundland Constabulary, Q: Which organization is seen as the direct predecessor to the Royal Canadian Mounted Police? A: the North-West Mounted Police

Table 6: Example #3 – Context, Question, and Answer Generation.

Original Context	The Earth of the early Archean (4,000 to 2,500 million years ago) may have had a different tectonic style. During this time, the Earth's crust cooled enough that rocks and continental plates began to form. Some scientists think because the Earth was hotter, that plate tectonic activity was more vigorous than it is today, resulting in a much greater rate of recycling of crustal material. This may have prevented cratonisation and continent formation until the mantle cooled and convection slowed down. Others argue that the subcontinental lithospheric mantle is too buoyant to subduct and that the lack of Archean rocks is a function of erosion and subsequent tectonic events.
Sampled Question	"During what time period was the Archean era?"
Prompt	Generate a paragraph that answers the following question: "During what time period was the Archean era?"
Generated Context	The Archean Eon, one of the four principal eons of Earth's geologic time scale, occurred approximately 4.0 to 2.5 billion years ago. It follows the Hadean Eon and precedes the Proterozoic Eon. The Archean era is divided into four geologic time periods, known as eras: the Eoarchean, Paleoarchean, Mesoarchean, and Neoarchean. This time period was crucial in Earth's history as it saw the formation of the planet's crust and the development of the earliest forms of life. Despite the extreme conditions, with high temperatures and a lack of oxygen, early life forms such as cyanobacteria began to emerge, which eventually played a role in shaping the Earth's atmosphere by producing oxygen through photosynthesis.
Generated Questions	Q: What eon follows the Hadean Eon and precedes the Proterozoic Eon? A: The Archean Eon, Q: Despite what conditions did early life forms begin to emerge during the Archean Eon? A: the extreme conditions, with high temperatures and a lack of oxygen

Table 7: Example #4 – Context, Question, and Answer Generation.

Japanese-English Sentence Translation Exercises Dataset for Automatic Grading

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Abstract

This paper proposes the task of automatic assessment of Sentence Translation Exercises (STEs), that have been used in the early stage of L2 language learning. We formalize the task as grading student responses for each rubric criterion pre-specified by the educators. We then create a dataset for STE between Japanese and English including 21 questions, along with a total of 3,498 student responses (167 on average). The answer responses were collected from students and crowd workers. Using this dataset, we demonstrate the performance of baselines including finetuned BERT and GPT models with few-shot in-context learning. Experimental results show that the baseline model with finetuned BERT was able to classify correct responses with approximately 90% in F_1 , but only less than 80% for incorrect responses. Furthermore, the GPT models with few-shot learning show poorer results than finetuned BERT, indicating that our newly proposed task presents a challenging issue, even for the state-of-the-art large language models.

1 Introduction

Sentence translation exercises (STEs) are often utilized as educational tools in the early stages of L2 language learning, particularly between language pairs that are linguistically distant from each other (Cook, 2010; Butzkamm and Caldwell, 2009). Figure 1 shows an example of STE. Here, a learner translates a short sentence in their native language (L1) into the language they are learning (L2), and these translations are graded following analytic criteria within the grading rubric such as E3 and G4, which correspond to specific grammar items or expressions.

This format facilitates the recognition of similarities and differences between the native language

*Work done while at RIKEN and Tohoku University. Currently belongs to NTT DATA INTELLILINK Corporation.

Question :

Translate this Japanese (L1) sentence into English.

私は / 一昨年に / オーストラリアで / 見るまで /
 コアラを / 見た / ことがなかった
 (I / the year before last / in Australia / before I saw one
 / a koala / seen / had never)

L2 learner's response

I hadn't seen a koala, before I saw in Australia two years ago.

O4 G4 E3

Rubric

Chunk	Analytic criteria	2 (Correct)	0 (Incorrect)
“オーストラリアで” (in Australia)	E3	“in Australia”	Otherwise

“見るまで” (before I saw one)	O4	The word order is “conjunction + SVO”	Incorrect
	G4	Using “saw”	Otherwise

Figure 1: Example of sentence translation exercise. We excerpted the analytic criteria “E3,” “O4,” and “G4” from Q11 in our dataset. The correct answer is “I had never seen a koala before I saw one in Australia two years ago.” “Chunk” denotes a Japanese phrasal unit. “E,” “O,” and “G” are categories of each analytic criterion, which stand for “expression,” “word order,” and “grammar,” respectively.

and the target language, which is especially effective in helping learners acquire basic grammar and expressions in the early stages of their language learning, thus enhancing their understanding of the desired modes of expression (Cook, 2010). The questions in these exercises are brief and repeatable tests that efficiently help learners practice specific grammatical items, basic vocabulary, and idioms at a certain proficiency level and learn the nuances of expression between L1 and L2. Teachers can also use these exercises as assessment tools to evaluate whether learners have mastered specific grammar

items or a vocabulary level.

However, because the responses to these exercises are descriptive, they pose a significant burden on educators in the form of manual grading and feedback. Such a limitation restricts the frequency of these exercises despite the importance of repetitive training in language acquisition (Larsen-Freeman, 2012). Therefore, automating the correction and feedback for translation exercises has the potential to significantly transform the educational environment in language learning.

Therefore, we aim to automate the grading of L1-to-L2 STEs. Tasks that are closely associated with this challenge include Grammatical Error Correction (GEC), which evaluates the grammatical correctness of written sentences, and machine translation. STEs, however, are substantially different from these tasks in that they are usually operationalized with explicit learning objectives and closely reflect educators' intentions (§2.1). STEs not only clarify the learning objectives of a particular question but also allow for a more detailed learning analysis based on the performance of each evaluation item. The motivation for incorporating educators' intentions is also supported by studies that have found that the sole use of the GEC system does not elicit effective learner engagement (Koltovskaia, 2020; Ranalli, 2021).

To achieve our goal, we perform three tasks: (1) question formulation, (2) dataset creation, and (3) evaluation of baseline systems for our task. To the best of our knowledge, this is the first attempt at an automated STE grading for educational purposes. Therefore, we first formulate the question. An important aspect of this formulation is to ensure that the established framework reflects the educators' evaluation criteria. Consequently, we formulate our task as a classification of scores on each evaluation item according to the predefined rubrics. We then develop the dataset for this task. The questions and the rubric were created by English education experts, and answer scripts were collected from secondary education classrooms and through crowdsourcing. Finally, we evaluate the performance of the conventional automated scoring model typically used for short answer scoring (SAS), as well as the latest generative language models with few-shot learning.

Experimental results showed that the baseline model using finetuned BERT successfully classified approximately 90% of correct responses in F_1 , but only less than 80% of incorrect responses.

Furthermore, GPT models with few-shot learning showed poorer results than the BERT model, indicating that even with a state-of-the-art LLM, our proposed new task remains difficult and challenging. Error analysis of the few-shot models revealed their lack of comprehension regarding the grading task.

The contributions of this study are the following:

- We formulate the automated grading of sentence translation exercises as a new task, referencing the actual operation of STEs in educational settings.
- We construct a dataset for the automated STE grading in accordance with this task design, which includes a total of 21 questions and 3,498 responses, and demonstrate the feasibility of the task.
- We establish baseline performances for the task, showing potential for advancement.

2 Automatic scoring of sentence translation exercises

2.1 Sentence translation exercises

Sentence translation exercises (STEs) are a language learning tool where a learner translates a sentence in L1 into a target L2. Studies have shown that the use of L1 in L2 education promotes an understanding of differences and similarities between the two languages (Butzkamm and Caldwell, 2009; Cook, 2010), reduces incomprehension, and enhances learning focus (Scott and De la Fuente, 2008). Language translation has also been effective in improving students' four skills (speaking, writing, reading, listening) and promoting learning and communication skills (Yasar Yuzlu and Dikilitas, 2022). Because of these benefits, STEs are widely used in educational settings, particularly among beginners in language learning.

Figure 1 shows an overview of an STE. A learner's translated response is assessed using a grading rubric meticulously designed by educators to evaluate the learner's L2 ability, such as vocabulary and grammatical understanding. Such a rubric contains multiple analytic criteria aligned with the specific pedagogical objectives that an educator intends to assess in the question. This aspect characterizes STE evaluation and distinguishes them from typical GEC tasks, which assess the overall correctness of the grammar.

Evaluation based on the analytic scoring criteria highlights the degree to which the learning objectives are achieved. To this end, some degree of constraint is imposed on the question design and answer choices, limiting the freedom of translation. However, if translation variations are observed, all possible expressions are accounted for. These restrictions in translation practice, as discussed in (Cook, 2010), prevent learners from easily avoiding knowledge gaps and direct their attention to L2 aspects that they may find challenging. Therefore, these constraints can be useful in focusing students' attention on specific language abilities.

In addition, the evaluation of translated sentences in educational settings is also different from that of general translations in that the former involves pedagogical objectives such as the acquisition of specific language knowledge.

2.2 Task formulation

The purpose of assessing the STE task is to determine how well students' responses achieve the learning objectives defined by the instructors. To effectively do so, instructors use a carefully constructed scoring rubric. Each STE question targets several learning objectives and evaluates other fundamental grammatical items (e.g., number, tense, etc.); therefore, a scoring rubric contains multiple independent analytical criteria to evaluate specific items. These criteria serve as the basis for grading each student's response, with a corresponding analytic score assigned to each grading item (see Table 1).

The automatic scoring of analytic criteria was formulated by Mizumoto et al. (2019) as an analytic score prediction task for reading comprehension questions. Therefore, this study also considers the analytic score prediction for the automatic scoring of STE.

Analytic score prediction: For a given STE, let C denote the set of analytic criteria. For the input response text (w_1, w_2, \dots, w_n) , the model outputs an analytic score $s_c \in \{2, 1, 0\}$ for a given analytic criterion $c \in C$, where 2, 1, and 0 represent "correct," "partially correct," and "incorrect," respectively.

3 Sentence translation exercise (STEs) dataset

To implement the automatic STE scoring, we introduce an STE dataset. This dataset currently com-

prises 21 Japanese-to-English STE questions with detailed rubrics and annotated student responses. These questions and the scoring rubrics were created by specialists in the design of English learning materials. The questions were constructed to cover all the major grammar topics in several well-known English textbooks used in Japanese high schools.

Table 1 shows an example of a rubric, which contains 17 analytic criteria: three for grammar (labeled as "G"), seven for vocabulary and expression (labeled as "E"), and seven for word order (labeled as "O"). Each analytic criterion is evaluated on a three-point scale: 2 (correct), 1 (partially correct), and 0 (incorrect); the rubric lists the typical expressions for each scale.

Essentially, STEs are designed such that they limit variations in correct responses from the outset. In practical settings, however, educators may adjust the grading rubric by incorporating variations in correct responses, previously unidentified during the rubric's initial creation, to accurately evaluate the student responses. To replicate this process, we initially create the analytic criteria, followed by the collection of student responses as described in the following subsection. Subsequently, we refine the rubric by reviewing the collected responses, to preempt any challenges that may arise during the grading procedure.

In the following sections, we will discuss in detail the methods used to gather responses, as well as the annotation process, and statistically analyze the whole dataset.

3.1 Collecting student responses

Ideally, student responses are compiled within classrooms and other practical learning environments. However, the number of responses that can be collected from actual classrooms is often limited, and the collecting process is time-consuming. Therefore, we constructed our dataset through a combined approach involving high school students and crowdsourcing workers to collect responses for response collection. In this approach, we conducted a pilot data collection in which responses were obtained from high school students. Then, we analyzed these responses with English education experts and created the criteria for gathering crowdsourcing workers whose English abilities are equivalent to those of the high school students (see Appendix A for details regarding the recruitment criteria). Finally, we hired workers who met the criteria and allowed them to answer the questions,

Chunk	Category	Correct (2)	Incorrect (0)
私は (I)	E	Expressed as "I"	Otherwise
	O	Word order is "before + Subject"	Not "before + Subject"
一昨年に (two years ago)	E	Expressed as "two years ago" or ...	"in the year before last" and otherwise
	O	Word order is "in Australia <chunk>" or ...	Otherwise
オーストラリアで (in Australia)	E	Expressed as "in Australia"	Otherwise
	O	Word order is "<chunk> two years ago" or ...	Otherwise
見るまで (before I saw)	E	Expressed as "before I saw one," "before I saw some," or ...	The word "it" is used instead of "one" / ...
	O	The order is "Conjunction + Subject + Verb + Object"	Otherwise
	G	The past tense "saw" is used.	"saw" is not used
コアラを (a koala)	E	Expressed as "a koala," "koalas," "any koalas," ...	Otherwise
	O	The word immediately follows "seen"	Otherwise
見た (seen)	E	Expressed as "seen"	Otherwise
	O	It is placed immediately after "never," "not," or "n't."	Otherwise
	G	The past participle form "seen" is used	Otherwise
～ことがなかった (had never)	E	Expressed as "I had never," "I had not," ...	Expressed as "I have never", ... , and others
	O	The word order is "Subject + Verb"	Otherwise
	G	The past perfect tense is used	The present perfect or past tense are used

Table 1: Examples of analytic criteria excerpted from Q11: “*I had never seen a koala before I saw one in Australia two years ago.*” “Chunk” denotes a Japanese phrasal unit, often referred to as “bunsetsu.” Every chunk invariably includes the category E (Expression), with some incorporating the categories O (Word Order) and G (Grammar). The analytic criterion covers examples of expressions and structural patterns that correspond to each label.

thus collecting a sufficient amount of responses.

To maintain quality, we manually reviewed the collected responses and excluded those that significantly deviated from the expected responses. As a result, we obtained an average of 167 responses per question. The following section will present the statistics of the dataset.

3.2 Annotation:

As explained in Section 2.2, the scoring task for STEs involves grading on a three-class classification for each analytic criterion. Annotators are also asked to identify the specific phrase of the response that serves as a grading clue (referred to as *justification cues*). We annotated both types of information in each response.

We hired professional graders to annotate those responses. As demonstrated in Figure 1, the annotators assigned an analytic score to the responses based on each analytic criterion.

Justification cue: Mizumoto et al. (2019) also annotated specific substrings within responses that contribute to an analytic score. These substrings are called *justification cues* because they serve as the rationale for the analytic scores. We also annotated justification cues in our dataset to enhance the interpretability of analytic scores. For example, in Figure 1, the phrase “before I saw” was annotated

as a justification cue and was assigned an analytic score of “0.”

Annotation quality: To measure the quality of the annotations, we randomly selected 10 out of the 21 questions and asked a different annotator to annotate 20 responses for each question. We then used Cohen’s Kappa coefficient (Cohen, 1960) to calculate inter-grader agreement for analytic scoring and the F-score to calculate agreement for justification cues.

The scores for all analytic criteria had an overall average Kappa coefficient of 0.74, indicating substantial agreement (Landis and Koch, 1977). Regarding agreement for justification cues, the F-score was 0.92, signifying a high level of agreement among the annotators (Mizumoto et al., 2019; Sato et al., 2022). This suggests that different annotators can consistently identify the same phrase as a justification cue for an analytic score.

Statistics of data: Table 2 shows the dataset statistics. We annotated a total of 3,498 responses for 21 questions, including 196 analytic criteria. For the pilot question, ranging from Q1 to Q7, scoring included 1 (partially correct) whereas the other questions followed a binary scoring of 2 (correct) and 0 (incorrect). Additionally, the number of instances with a grade of 0 was relatively fewer than those with a grade of 2. This distribution

	#Ans	#Criteria	2	1	0
Q1	159	9	923	114	235
Q2	172	8	652	98	454
Q3	77	8	357	40	142
Q4	69	9	356	76	120
Q5	102	9	387	161	268
Q6	79	12	701	14	154
Q7	90	10	534	72	204
Q8	200 (173)	6	856		343
Q9	200 (169)	10	1324		676
Q10	200 (180)	9	1197		612
Q11	200 (142)	10	1285		715
Q12	200 (135)	8	1175		425
Q13	200 (137)	7	850		550
Q14	150 (97)	8	847		353
Q15	200 (159)	11	1347		853
Q16	200 (144)	10	1565		435
Q17	200 (162)	11	1082	1118	
Q18	200 (162)	9	1220		580
Q19	200 (166)	12	1671		729
Q20	200 (149)	8	1064		536
Q21	200 (131)	12	1538		862

Table 2: STE dataset statistics. The integers 2, 1, and 0 stand for “correct,” “partially correct,” and “incorrect” labels, respectively. Q8 through Q21 include some identical responses following the distribution of the collected data. We show the number of distinct responses in parentheses.

was similar to the one observed in the pilot question and others. Therefore, we conclude that we have successfully gathered crowdsourcing workers whose English ability is equivalent to that of original high school students and that these workers have attempted to answer those questions correctly.

4 Method

We employ a BERT (Devlin et al., 2019)-based classification model and the GPT models (OpenAI, 2023) with in-context learning as a baseline for our task formulation. This section discusses these baseline models in detail.

4.1 Finetuned BERT model

We employ BERT, which is widely used in various NLP tasks, including SAS, as a baseline for this task. This model is finetuned for each scoring item in the rubric using the training data.

Architecture: First, the response text sequence $\mathbf{w} = (w_{\text{cls}}, w_1, w_2, \dots, w_n)$, with a prepended CLS token, is input into BERT, obtaining the intermediate representation $\mathbf{h} = (h_{\text{cls}}, h_1, h_2, \dots, h_n)$ as follows:

$$\mathbf{h} = \text{BERT}(\mathbf{w}) \quad (1)$$

In our task, a justification cue that indicates the

rationale behind its score is provided for each response. By utilizing this justification cue to train a model, we expect that the model will grade faithfully according to the rubric. Therefore, following Mizumoto et al. (2019), we use these justification cues as supervisory signals to train the model’s attention layer. Here, we perform pooling on the BERT-encoded representations using a Bi-LSTM and attention mechanism. The sequence obtained from \mathbf{h} by excluding h_{cls} is input into the Bi-LSTM, yielding $\mathbf{h}' = h'_1, h'_2, \dots, h'_n$. Then we calculate the weighted sum as follows:

$$\tilde{h}_c = \sum_{i=1}^n \alpha_i^c h'_i, \quad (2)$$

where α_i^c is the weight of the i -th word relative to the scoring rubric c , calculated by the attention mechanism shown in Equation (3).

$$\begin{aligned} t_i^c &= h_i M_c V_c \\ \alpha_i^c &= \frac{\exp(\tanh(t_i^c))}{\sum_{k=1}^n \exp(\tanh(t_k^c))}, \end{aligned} \quad (3)$$

where $M_c \in \mathbb{R}^{D \times D}$ and $V_c \in \mathbb{R}^D$ are learnable parameters. Finally, the evaluation value S_C for item C is obtained by the following formula:

$$\begin{aligned} p(s_c | \mathbf{w}) &= \text{softmax}(W \tilde{h}_c + b) \\ s_c &= \arg \max_{s_c \in \{0,1,2\}} \{p(s_c | \mathbf{w})\}, \end{aligned} \quad (4)$$

where $W \in \mathbb{R}^{3 \times D}$ and $b \in \mathbb{R}^3$ are the learnable parameters.

Training: The analytic scoring model is trained to minimize the negative log-likelihood (NLL) for each analytic score.

$$L_{\text{score}} = \sum_{c \in C} \text{NLL}(p(s_c | \mathbf{w}), \hat{s}_c) \quad (5)$$

where s_c is the label (evaluation value) of the ground truth for scoring rubric c . In addition, as discussed in the Section 3.2, the dataset contains the justification cues $\hat{\alpha}^c = (\hat{\alpha}_1^c, \hat{\alpha}_2^c, \dots, \hat{\alpha}_n^c)$ for each analytic criterion for the response, where $\hat{\alpha}_i^c \in [0, 1]$ is the indicator of whether the i -th token in the response is the justification cue for the score of the analytic criterion c . When the gold justification cue includes k tokens, the sum of $\hat{\alpha}^c$ is k . Therefore, as a gold signal for α^c , we use $\hat{\alpha}^c$ divided by k during the training process. Following Mizumoto et al. (2019), we use the MSE-based loss function

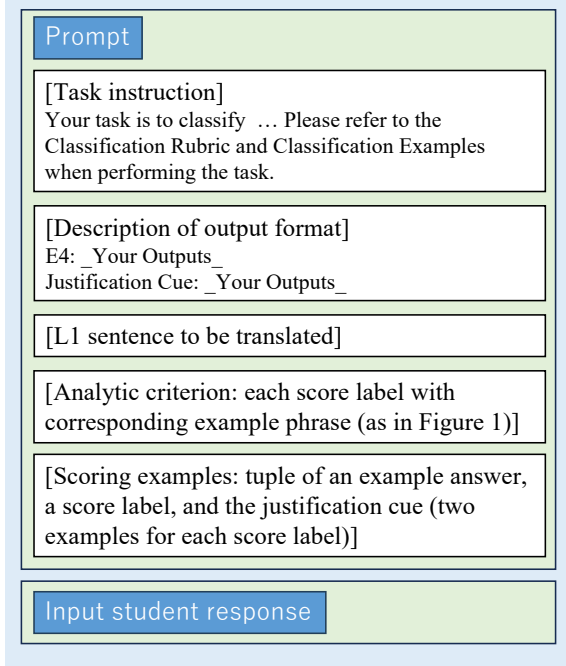


Figure 2: Input for the GPT models

to achieve supervised training of the attentions with justification cues.

$$L_{att} = \sum_{c \in C} \sum_{i=1}^n (\alpha_i^c - \hat{\alpha}_i^c)^2 \quad (6)$$

Thus, the overall loss L is expressed as:

$$L = L_{score} + L_{att}. \quad (7)$$

4.2 GPT models with in-context learning

We evaluate the GPT-3.5 and GPT-4 models in the setting of few-shot in-context learning (Brown et al., 2020), which significantly minimizes the cost of building a scoring model specific to each grading item as well as the training examples required for finetuning. Furthermore, the GPT series demonstrates superior performance in tasks such as translation and summarization, among other tasks (Gladkoff et al., 2023; Helwan et al., 2023). Therefore, we can expect the proficiency in grammatical knowledge required for automatic grading of STEs.

Figure 2 shows the input template for the GPT models. The input can be segmented into two parts. The first part is a *prompt* that includes a task instruction, a description of the output format, an L1 sentence for translation, a focused single analytic criterion, and the scoring examples corresponding to that criterion. The analytic criterion is a (literal) textual representation of a rubric item described in

a single row in Table 1. For each score label, we provide a few-shot examples to illustrate the analytic criterion and its scoring (output examples) for in-context learning. The second part is a *student response*. The model leverages these two inputs to generate a score label for the specified criterion and identify the substring of the student response that justifies the evaluation. In the GPT models, we treat the grading of each analytic criterion within a prompt as an independent grading task, thus the GPT models output a score for each analytic criterion independently. More details of the input prompt can be found in Table 5 in the appendix.

5 Experiments

In the experiment, we investigate the feasibility of our task formulation for STEs using the BERT model and the state-of-the-art large language models, GPT-4 and GPT-3.5. We also investigate the impact of the number of in-context examples on the scoring performance.

5.1 Settings

In our dataset, the label “partially correct” was infrequently used, which transformed the grading of certain criteria into a binary classification task. Therefore, we used the F_1 -score to evaluate the performance of the analytic score prediction as it applies to both three-class and binary classification. We also performed a 5-fold cross-validation by dividing the dataset of each question into a training set, a development set, and an evaluation set following a 3:1:1 ratio.

We finetuned the BERT model (described in Section 4) for 50 epochs on each training set. For each epoch, we calculated F_1 -score for each analytic criterion and used the parameters that produced the best results on the development set for each analytic criterion, respectively. Appendix C provides details regarding these hyperparameters. For the GPT models, we randomly selected few-shot examples for each score from the training set.

Some analytic criteria contained extremely few incorrect responses because typical high school students found them too easy. Therefore, to ensure a proper performance evaluation, we used only those criteria that contained 10% or more incorrect instances.

5.2 Results

Table 3 shows the performance of BERT, GPT-3.5, and GPT-4 on the test set in terms of F_1 averages

Category (#criteria)	BERT			GPT-3.5 (2 shots)		
	Correct	Partial. Correct	Incorrect	Correct	Partial. Correct	Incorrect
E : (96)	0.92±0.15	0.64±0.36	0.82±0.24	0.83±0.12	0.80±0.23	0.62±0.20
O : (42)	0.95±0.05	nan	0.79±0.25	0.78±0.11	nan	0.52±0.21
G : (45)	0.94±0.11	0.81±0.21	0.88±0.13	0.81±0.13	0.48±0.11	0.63±0.25
All	0.93	0.68	0.83	0.81	0.73	0.59

Category (#criteria)	GPT-3.5 (5 shots)			GPT-4 (2 shots)		
	Correct	Partial. Correct	Incorrect	Correct	Partial. Correct	Incorrect
E : (96)	0.84±0.12	0.79±0.23	0.65±0.18	0.91±0.09	0.80±0.15	0.78±0.20
O : (42)	0.80±0.12	nan	0.53±0.21	0.87±0.08	nan	0.65±0.21
G : (45)	0.82±0.13	0.48±0.11	0.64±0.28	0.90±0.08	0.62±0.37	0.77±0.24
All	0.83	0.73	0.61	0.89	0.76	0.73

Table 3: F_1 scores and standard deviations of the baseline models for each score label of the analytic criteria categories (E: Expression, O: Word Order, G: Grammar). The analytic criteria for the Word Order category do not include any partially correct expressions; therefore, the corresponding values are represented as “nan.”

and standard deviations for each category (*Expression, Word Order, Grammar*).

In Section 4.2, we hypothesized that the GPT models would demonstrate excellent performance because STEs evaluate the validity of English sentences within a highly limited grammar and vocabulary scope presented in an analytic criterion. Surprisingly, however, the BERT model outperformed the GPT models on our dataset.

Nevertheless, both models showed relatively high performance in grading correct responses. Meanwhile, the GPT models performed notably lower in grading incorrect responses. Interestingly, however, the GPT models outperformed BERT in grading partially correct responses. This may be due to the limited data size for fine-tuning the BERT model for partially correct responses. We also observed that the standard deviation exceeded 0.10 for nearly all results, indicating a substantial variance in grading performance across different analytic criteria, some of which showed poor results. The result suggests that the grading of several analytic criteria is challenging for models.

LLMs acquire sufficient knowledge about language, including grammar and vocabulary, through pretraining on massive corpora. However, these results showed that STEs grading remains a challenging task even for a cutting-edge LLM such as GPT-4, when provided with only few-shot examples. Furthermore, collecting and annotating enough responses to train the STE grading model

poses a significant burden in actual educational settings, allowing room for improvement in deploying automatic grading models in actual classrooms.

5.3 Analysis

Lower performance for incorrect responses: As discussed in Section 5.2, the models showed notably lower performance in grading incorrect responses than in grading correct responses. This discrepancy may be due to the difference in the number of variations between correct and incorrect responses. As shown in Figure 1, the variation of acceptable correct responses is limited; meanwhile, the variation of incorrect responses shows considerable latitude, potentially encompassing any type of response besides the correct ones. Consequently, although the training data covered the majority of variations in correct responses, they cannot cover all potential incorrect responses. Additionally, the GPT models significantly struggled in grading such incorrect responses, especially with fewer examples than the BERT models.

Grading error example of GPT-3.5: Table 4 shows a grading error made by GPT-3.5, in which the model significantly failed to recognize an incorrect response. Such grading errors constitute the majority of inaccurate predictions by GPT-3.5. We hypothesized that these inaccuracies are due to the specialized prompt and response format of STEs, including scores, detailed rubrics, and justification cues. Hence, during pretraining, GPTs are

Input summary
<p>Sentence: 私は / 一昨年に / オーストラリアで / 見るまで / コアラを / 見た / ことがなかった (I / the year before last / in Australia / before I saw one / a koala / seen / had never)</p> <p>Analytic criteria: G1 (Tense) - Past tense "saw" is used as a verb</p> <p>Student answer: I had never seen a koala before I have seen it two years ago in Australia .</p>
GPT output & (gold data)
<p>Label: 2 (Gold label: 0) Justification cue: I had never (Gold justification cue: seen)</p>

Table 4: Example of a prediction error made by GPT-3.5.

not exposed to such a task, despite the extensive corpora collected from the Web. Utilizing GPT-3.5 for few-shot in-context learning is expected to be more suitable for classroom applications than fine-tuning the model with a substantial amount of training data. However, our observations suggest that this application of GPT-3.5 is inadequate for grading STEs.

The impact of the number of in-context examples: To investigate the appropriate number of in-context examples, we evaluate performance by varying the number of examples provided in the prompt. Figure 3 illustrates the F_1 -score of GPT-3.5 for each label as the number of in-context examples is varied between one, two, five, and 10. From the result, we can clearly see that the grading performance hardly changed even when the number of in-context examples was increased to more than two.

As a reason for this, in grading for correct responses, it is considered that our task design inherently results in a very limited number of patterns corresponding to correct expressions. Therefore, increasing the number of instruction samples may not significantly influence the accuracy for correct responses.

In the grading of incorrect responses, a considerable number of instances are labeled as incorrect due to the absence of expressions equivalent to the correct answers. In such cases, *justification cue* string is not given in the instruction for GPTs and this makes it challenging to grasp scoring clues

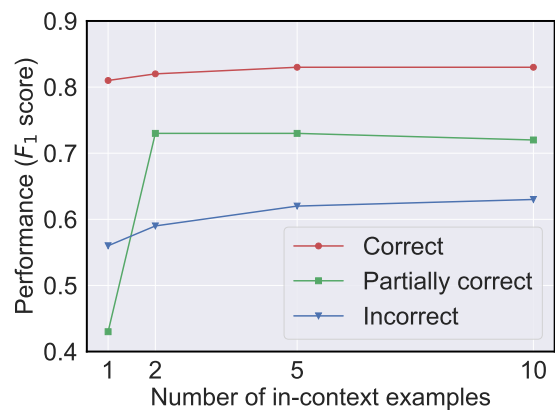


Figure 3: The performance of the GPT-3.5 model when changing the number of in-context examples. The x-axis represents the number of in-context examples. The y-axis represents the averaged F_1 -score among all analytic criteria.

from the provided instruction examples, likely hindering the effective learning of appropriate grading and consequently impeding performance improvement.

6 Related work

Grammar Error Correction (GEC) and Short Answer Scoring (SAS) are the two major research areas in the automatic evaluation of descriptive English responses. We position this study between these two research domains.

6.1 Grammar Error Correction (GEC)

The most famous GEC system is Grammarly,¹ a writing assistant tool that also plays an important role in English learning (Ranalli, 2021; Koltovskaia, 2020). In a more educational context, Nagata (2019) proposed the task of feedback generation in GEC with a focus on effective ESL (English as a Second Language) learning. Some studies have also focused on methods to generate feedback for grammatical errors in sentences written by learners (Hanawa et al., 2021; Coyne, 2023; Lai and Chang, 2019). Regarding the use of LLMs in GEC, Fang et al. (2023) reported that GPT-3.5 shows excellent GEC abilities.

All these previous studies have focused primarily on identifying grammatical errors present in freely-composed text. However, within real-world educational contexts that require the measurement of student progress in language learning, educators must direct their attention to the assessment of not

¹<https://www.grammarly.com>

only overarching grammatical constructs but also a precise understanding of certain grammatical or vocabulary items within specific units of English textbooks. Such a methodology would determine students' comprehension and areas of unfamiliarity more accurately. Therefore, we adopted this practical approach by developing STEs specifically designed to evaluate students' understanding of various grammatical topics.

6.2 Short Answer Scoring (SAS)

We have formally defined our STE grading task within the established framework of the automated SAS task. However, these two tasks fundamentally differ in terms of their intended objectives and the descriptive content to be evaluated. Several SAS studies have primarily examined closed-domain questions that require knowledge and understanding in specific areas, such as science or reading comprehension (Mizumoto et al., 2019; Burrows et al., 2015; Galhardi and Brancher, 2018), and a typical SAS framework does not directly consider grammatical errors and word usage errors in responses. In this study, we created detailed and stringent analytic criteria for measuring learners' English proficiency, focusing on the grammatical aspects addressed in the questions.

Dataset: The dataset we created for the STE task followed the format of the RIKEN SAS dataset, which contains questions on Japanese reading comprehension questions (Mizumoto et al., 2019; Funayama et al., 2023). Other SAS datasets include BEETLE (Dzikovska et al., 2013), ASAP-SAS,² POWERGRADING, and the SAF DATASET (Fighera et al., 2022), which focus on science or reading comprehension. Our dataset is the first STE dataset to concentrate on grading grammar and vocabulary use.

7 Conclusion

This study introduced a novel task focusing on the automatic grading of Sentence Translation Exercises (STEs) for educational purposes. We formalized STEs as a task of grading each analytic criterion predetermined by teachers' intentions and constructed a dataset to implement the task. This first-of-its-kind dataset emulates and reflects the practical form of L2 learning in the responses of learners. We also used finetuned BERT and GPTs

with few-shot in-context learning to establish a baseline and demonstrate the feasibility of the formulated framework.

In our experiment, although the GPT models showed substantial performance in various NLP tasks, they remained inferior to the BERT model, suggesting that our newly defined task continues to be challenging even for the state-of-the-art LLMs, therefore necessitating further exploration.

With regard to future direction, we are contemplating the integration of technologies such as GEC and machine translation within our model. We aim to build cross-questions strategies to automatically identify expressions that diverge from a provided rubric while preserving the text's fundamental meaning using a combination of these technologies. For this purpose, our plan involves further subdividing the STE grading task and leveraging LLMs to address each minimized task such as correcting grammatical errors, assessing the consistency of meaning with L1, and identifying expressions aligned with the learning objectives in each exercise. This approach also aims to investigate tasks where LLMs may not excel in STE scoring and enhance their overall performance. Additionally, in an educational context, we also consider generating more comprehensive feedback comments on the scoring results, extending beyond the estimation of justification cues.

Limitations

This section discusses the limitations of our study from the perspectives of dataset creation and experimentation.

Dataset creation: We created the first STE dataset in this literature, which includes responses with scores and detailed rubrics. However, our dataset was limited to Japanese-English translation, while STEs can be applied to any language pair.

Furthermore, we conducted crowd-sourcing to gather responses for our dataset, which may differ from student responses in actual classroom settings, despite a carefully controlled crowdsourcing process as described in Section 3.2. Therefore, the performance of the models when deployed in real education settings, such as English study in school, remains uncertain.

Experimentation: We conducted experiments using only the BERT-based model and the GPT models. Therefore, the performance of other LLMs,

²<https://www.kaggle.com/c/asap-sas/>

such as LLaMA, remains unclear, and the effectiveness of fine-tuning these LLMs using parameter-efficient methods such as LoRA (Hu et al., 2021) is also unexplored.

Ethics statement

Gathering crowdsourcing workers: To collect responses, we recruited crowdsourcing workers and paid them 18 yen for each question they answered. In our trial, it took them an average of 1 minute to answer a question; therefore, we estimated the workers' pay at around 1,080 yen per hour, which is nearly equivalent to Japan's minimum wage of 1,004 yen per hour in 2023.

Hiring annotators: To annotate the dataset, we employed professional English educators through a company that conducts trial annotation and calculated the annotating costs at 150 yen per response, in agreement with the annotators. We followed the company's wage proposal.

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A Recruitment criteria

The recruitment criteria for selecting workers are as follows: (1) TOFEL iBT: 55-70, (2) TOEIC L&R: 550-750, and (3) The National Center Test: 140 points or higher³. In addition, we also conducted a pretest on candidates for crowdsourcing workers, which consisted of 10 easy STE questions, and we only hired those who answered all of them correctly.

B Prompt example for the GPT models

Table 5 shows an example of a prompt in Q11 used for the GPT models. We input the data into the GPT models for each analytic criterion independently. We also input in-context examples for each label.

C Implementation and hyperparameter

We implemented our BERT model⁴ using the Hugging Face library (Wolf et al., 2020). During the fine-tuning, we used Adam (Kingma and Ba, 2014) as the optimizer and set the learning rate to 0.001. The dimension of the hidden state in the Bi-LSTM was set to 128. We also used a batch size of 10, as our dataset contained a relatively small amount of training data.

³The Center Test is a standardized test included in the entrance examination of almost all universities in Japan.

⁴We used a pretrained model from <https://huggingface.co/bert-base-uncased>

PROMPT(SYSTEM)

Your task is to classify the labels corresponding to the analytic criterion from the input response. Please refer to the Classification Rubric and Classification Examples when performing the task.

Your Outputs

E4: _Your Outputs_

Justification Cue: _Your Outputs_

Question

"私は一昨年にオーストラリアで見るまでコアラを見たことがなかった。

<I / the year before last / in Australia / before I saw one / a koala / seen / had never> "

Analytic criterion

E4: Tense of expressions corresponding to "見るまで"

E4: 2 -Express "見るまで" as "before I saw one(s)", "before I saw some", "before I saw them"

E4: 0-Using "it" instead of "one(s)". Otherwise.

Classification Examples

Ans : I have not seen koalas before I saw them in Australia 2 years ago .

E4 : 2

justification cue : before I saw them

Ans: I had never seen koalas before I saw ones in Australia two years ago .

E4: 2

justification cue: before I saw ones

Ans: I never see koala before I saw that at Australia last year .

E4: 0

justification cue: before I saw that

Ans: I had never seen a koala until I saw it in Australia in the year before last .

E4: 0

justification cue: until I saw it

Input student response

I had never seen a koala before I saw one in Australia the year before last.

Table 5: An example of a prompt for grading an analytic criterion for the phrase “見るまで” (before I saw). This prompt contains five parts; task instruction, description of the output format, Question (L1 sentence for translation), the analytic criterion, and a few-shot examples. The task instruction, located at the beginning of the prompt, explains the automatic scoring of STEs. The output format description follows the section labeled *_Your Outputs_* in the prompt. The Analytic criterion provides representative examples of expressions that are deemed appropriate or inappropriate for the phrase “見るまで” (before I saw). We provide two examples for each label in the few-shot examples and inserted descriptions in '<>' for clarification, but these are not included in the actual prompt.

The Impact of Integration Step on Integrated Gradients

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Abstract

Integrated Gradients (IG) serve as a potent tool for explaining the internal structure of a language model. The calculation of IG requires numerical integration, wherein the number of steps serves as a critical hyperparameter. The step count can drastically alter the results, inducing considerable errors in interpretability. To scrutinize the effect of step variation on IG, we measured the difference between theoretical and observed IG totals for each step amount. Our findings indicate that the ideal number of steps to maintain minimal error varies from instance to instance. Consequently, we advocate for customizing the step count for each instance. Our study is the first to quantitatively analyze the variation of IG values with the number of steps.

1 Introduction

Researchers have focused on Explainable AI (XAI), which aims to provide insights into model behavior and predictions. One popular XAI method is feature attribution (Islam et al., 2021), generally referring to techniques that clarify why each feature was influential in determining the model’s prediction.

Integrated gradients (IG) (Sundararajan et al., 2017) is one of the well-known feature attribution approaches and has been widely used in image (Adebayo et al., 2020; Kapishnikov et al., 2019) and language processing (Sanyal and Ren, 2021b; Sikdar et al., 2021) due to the many desirable explanation axioms and ease of gradient computation (Sanyal and Ren, 2021b). In recent years, IG has been applied to analyze language models (Kobayashi et al., 2023), and efforts have been made to enhance its performance specifically for language processing tasks (Sanyal and Ren, 2021b; Sikdar et al., 2021; Enguehard, 2023).

In IG, a property known as *completeness* (Sundararajan et al., 2017) posits that the sum of the

contributions of each feature equals the difference between the output and the sum. This fundamental property offers a way of interpreting the value of each contribution as its influence on the output as follows Eq. 2. It also quantifies each contribution value relative to the output, enabling comparisons between contributions.

However, *completeness* is often violated because the numerical integration required to compute IG introduces errors. *Completeness* violation compromises the interpretability of the contributions and the results obtained from comparisons among the contributions. We have also identified instances where errors adversely affect the interpretation of the contributions (see Figure 2). Hence, to ensure the reliability and accuracy of IG, it is vital to determine the number of steps to minimize such errors properly.

Given these factors, it is necessary to ensure an adequate number of steps to reduce errors to guarantee IG’s reliability. However, as shown in Table 1, researchers often subjectively set the number of steps to use IG for each model or dataset. Several references address this issue (Sundararajan et al., 2017), requiring between 20 and 300 steps for a sentence classification task using a CNN model (Kim, 2014) and between 100 and 1000 steps for a translation task using LSTM (Wu et al., 2016). Nevertheless, there has yet to be a quantitative analysis that can be sufficient regarding the number of steps. In addition, no studies specifically address the number of steps required for modern language models (LMs) such as BERT (Devlin et al., 2019).

Therefore, in this study, we measured the error between the theoretical and measured values of the total IG sum at each number of steps to quantitatively analyze the change in the contribution value depending on the number of IG steps in the LM. The results show that the ideal number of steps that minimize the error varies from instance to instance,

Table 1: **Number of steps set when using IG in text classification.** In previous research, the number of steps is set for each model and not for each instance.

Step	Model	Paper
50	CNN	(Liu and Avci, 2019) (Dixon et al., 2018)
50, 250	DistilBERT, RoBERTa, BERT	(Enguehard, 2023)
10, 30, 100, 300	DistilBERT, RoBERTa, BERT	(Sanyal and Ren, 2021a)
1000	Linear / Logistic regression	(Han et al., 2022)
100, 1000	BERT, LSTM	(Bastings et al., 2022)

even for the same dataset model. This result argues that the number of steps should be set on an instance-by-instance basis. Our study is the first to quantitatively analyze the variation of IG values with the number of steps.

2 Integrated Gradients

The method of generating post-hoc explanations for each model output is known as feature attribution (Simonyan et al., 2014). This method allows for the assessment of the contribution of input features to the prediction results of machine learning models. It provides insights into how much a model’s predictions rely on specific features.

Integrated gradients (IG) (Sundararajan et al., 2017) is a type of feature attribution method. IG is popular over other feature attribution methods due to its simplicity, relatively low computational cost, and adherence to mathematically rigorous axioms (Lundstrom et al., 2022).

In the field of NLP, IG has proven valuable, with researchers developing enhanced methods tailored to language-specific tasks (Sanyal and Ren, 2021b; Sikdar et al., 2021; Enguehard, 2023) and utilizing it for LM analysis (Kobayashi et al., 2023).

The IG formula for an input \mathbf{x} along the i -th dimension is as follows:

$$\text{IG}_i(\mathbf{x}) = (x_i - x'_i) \int_{\alpha=0}^1 \frac{\partial F}{\partial x_i}(\mathbf{x}' + \alpha(\mathbf{x} - \mathbf{x}')) d\alpha. \quad (1)$$

Here, F is the deep neural network, \mathbf{x}' is a baseline embedding along the i -th dimension, and α is the variable of integration.

The IG calculation involves sampling along a linear path from the baseline vector to the input vector and computing and integrating the gradient for each sample. Here, the sampling points are determined by the numerical integration method and the number of steps. The number of steps is a vital hyperparameter that determines the integration accuracy. However, many steps require much

backpropagation, resulting in high computational costs.

2.1 Completeness Axiom

The *completeness* axiom (Sundararajan et al., 2017) is one of the several mathematical principles IG satisfies, indicating that the sum of IG in each dimension is the model output value for the given input minus the model output value for the baseline as follows:

$$\sum_{i=1}^n \text{IG}_i(\mathbf{x}) = F(\mathbf{x}) - F(\mathbf{x}'). \quad (2)$$

2.2 Issues in setting the number of steps

In practical applications, there are cases where this axiom does not hold due to errors caused by numerical integration. To prevent the effects of errors, a sufficiently large number of steps must be set in advance.

For instance, in the sentence classification task of a CNN model, Sundararajan et al. (2017) argues that the number of steps should range from 20 to 300, while for LSTM translation tasks, it should be within 100 to 1000. However, research has not identified what constitutes sufficient error reduction for practical application in Table 1. The ideal number of steps may vary depending on the model and dataset, and there needs to be a discussion of the number of steps in LM, like in BERT. Therefore, we analyze the impact of the number of steps on IG values in LM.

3 Experimental Settings

3.1 Verification Indicators

Approximation error (AE) measures the deviation of the actual measured value from the theoretical value, and we compute the error for each step as follows:

$$\text{AE} = \left| \frac{\sum_i \widetilde{\text{IG}}_i(\mathbf{x}) - (F(\mathbf{x}) - F(\mathbf{x}'))}{F(\mathbf{x}) - F(\mathbf{x}')} \right| \quad (3)$$

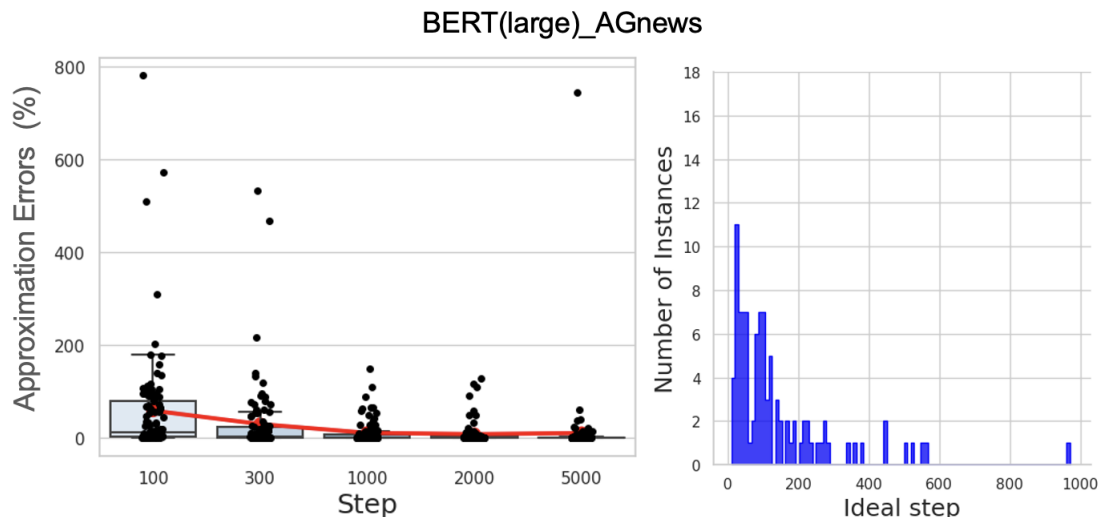


Figure 1: **Boxplot on the left:** The red line represents the approximation errors average for each number of steps, and a single point represents the approximation errors for a single instance. **Histogram on the right:** The number of steps ideal for each instance. The vertical axis is the number of instances with the ideal number of steps on the horizontal axis. It can be seen that the ideal number of steps is different for each number of instances. However, nearly 60% of the instances had an ideal number of steps within 100 steps.

Here, $\sum_i \widetilde{IG}_i$ is the sum of the measured IG calculated by numerical integration.

The AE reflects the discrepancy between the theoretical sum value of IG and the actual measured value. Also, [Sundararajan et al. \(2017\)](#) argues that the number of steps should be adjusted based on the AE.

3.2 Baseline Vector

IG’s baseline vector remains an ongoing discussion in the field ([Sturmfels et al., 2020](#); [Tan, 2023](#); [Bastings et al., 2022](#)). In our experiments, we align with the notion that the baseline vector should possess minimal information for the model and use the maximum entropy baseline as the baseline vector ([Tan, 2023](#)). This vector exhibits the most uniformly distributed model outputs in the test dataset.

3.3 Dataset & Model

We use AG News ([Gulli., 2004](#)), 20 News ([Ko, 2012](#)), and SST-2 ([Socher et al., 2013](#)) as our datasets. These datasets are widely used in sentence classification. Details of the datasets are available in Appendix A.1. BERT ([Devlin et al., 2019](#)) and RoBERTa ([Liu et al., 2019](#)) serve as the LMs for the experiment, utilizing both base and large models. Details of the models are available in Appendix A.2.

3.4 Other experimental settings

We used Riemann sum and Gauss-Legendre integration as our numerical integration methods.

In the interest of realistic experimental time-frames, we randomly sampled 100 instances from the test data for each dataset.

4 Experimental Results

Since the Riemann sum results were consistently better than the Gauss-Legendre integration results, we report the Riemann sum results in the following experiments. See Appendix A.4 for details. Here, we show the case of the BERT(large)-AGnews model, but results for other models are given in Appendix A.7.

4.1 Quantitative Analysis of Errors

We performed a quantitative analysis to investigate the potential errors that can arise if IG is calculated for all instances at a specified fixed number of steps. We calculated the IG values for all instances at step numbers 100, 300, 1000, 2000, and 5000 steps. We then calculated the approximation errors (AE) for each instance at each step number to review how the AE would perform if the same number of steps were applied across each instance.

Error for each step From the results of the box plot on the left in Figure 1, we observed that even with a vast number of steps (>1000), the AE are

Step	Error	Visualization
1000step	Error = 25%	Ġpeople Ġhave Ġbeen Ġkilled Ġin ĠKashmir Ġin Ġan Ġincrease
140step	Error = 0.62%	Ġpeople Ġhave Ġbeen Ġkilled Ġin ĠKashmir Ġin Ġan Ġincrease
1000step	Error = 17%	make sure the bike has cooled at least 6 hours since being run
130step	Error = 0.94%	make sure the bike has cooled at least 6 hours since being run
1000step	Error = 59%	russian oil giant si ##bn ##eft today rejected
520step	Error = 4.8%	russian oil giant si ##bn ##eft today rejected

Figure 2: **Visualization of IG.** Above each line is the visualization using the assumed fixed-step. Below each line is a visualization of when the ideal step is used. From top to bottom, visualization are RoBERTa(base)_AGnews, BERT(large)_20news and BERT(large)_AGnews.

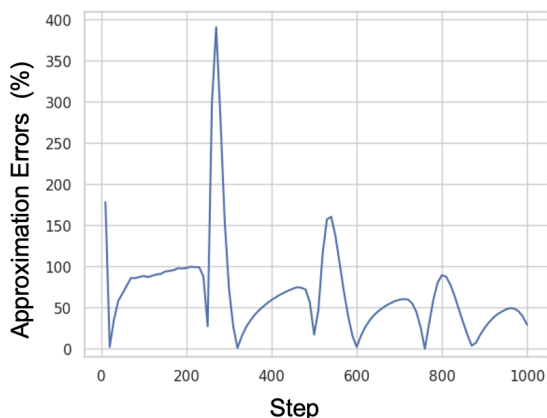


Figure 3: **Approximation errors per step for an instance.** Increasing the number of steps does not lead to a monotonic decrease in the approximation errors.

instances with significant errors. There are several samples with AE greater than 100%, and even using 5000 steps, there are instances with AE more significant than 700%. These results indicate that larger steps cannot guarantee fewer errors. The ideal number of steps may vary from instance to instance.

Also, in Figure 3, we observed instances where the AE moved up and down sharply as the steps increased. This case shows that the AE increases with an increase in the number of steps. It was confirmed that the AE does not decrease monotonically with the increase in the number of steps.

Ideal step Therefore, we investigated the distribution of the ideal number of steps for each instance. The ideal number of steps here is defined as the number of steps for which the AE is initially within 5%. This definition is informed by the number proposed (Sundararajan et al., 2017).

From the right histogram in Figure 1, we observed 98 out of 100 instances with an ideal number of steps within the 1000 steps. Of these, more than 60 instances had the ideal number of steps within 100 steps. This result indicates that even for LMs such as BERT, even a small number of steps, as small as 100, is sufficient for convergence in more than half of the instances. In contrast, even 1000 steps cannot guarantee convergence for all instances.

This result suggests that fixing the number of steps for all instances may not be ideal for error reduction.

4.2 Qualitative Analysis of Errors

Since the experiments in Section 4.1 revealed that some instances do not converge in error even with significant steps, we perform a qualitative analysis for those instances where the error does not converge. The visualization rules are those outlined in (Sundararajan et al., 2017). See Appendix A.6 for details.

Visualization From the visualization results in Figure 2, it can be confirmed that in instances where errors occur, the contribution values do not change in all samples, but rather the values change significantly, concentrating on certain features. In addition, errors are caused by the observation of non-existent contribution values. From this, it can be inferred that a significant error is caused by erroneous numerical integration for contributions that have an oscillating shape, although the sum is zero for the entire interval.

5 Why is the ideal number of steps different for each instance?

This section explores why is the ideal number of steps different for each instance. As the basis for this discussion, we focus on α in the Eq. 1. For each minuscule change in α , the gradient is calculated, and ultimately, the gradient is integrated. The larger the number of steps, the more minute the changes in α , enabling a more detailed computation and integration of the gradient.

Each instance has a gradient of zero for most segments, and only at certain points does the gradient change significantly. The point at which this gradient changes significantly varies greatly from instance to instance. This point of pronounced gradient change fluctuates at a specific α value, a phenomenon common in the imaging field. If these crucial points of gradient change are not accurately captured, it becomes impossible to calculate integral parts of the IG sum.

To illustrate, consider a 10-step integration where the gradient is computed for each *alpha* of values in 0.1 increments from 0 1.0. If there are significant changes in the gradient at any of these α values, the IG error will be small. But, if there are no substantial changes in the gradient for any of these α values and a significant shift happens, say, at 0.15, then the IG error will be considerable because the exact gradient value at this point cannot be calculated. From this, it can be inferred that instances requiring a smaller, ideal number of steps have a narrower range of α values where a substantial change in the gradient occurs.

Figure 4 to the left illustrates the gradient per α for an instance where the error is maximized at 270 steps and minimized at 870 steps. Clearly, the substantial gradient captured at 870 steps is missed at 270 steps. Figure 4 to the right, on the other hand, presents the gradient per α for instances where the error is relatively small for both 270 steps and 870 steps. In this case, it is evident that the gradient is adequately captured at both 870 steps and 270 steps.

As these instances suggest, the ideal number of steps varies per instance because the locations of large gradients and the size of these locations differ across instances.

6 Discussion

Our analysis reveals that the number of integration steps required for each instance is different.

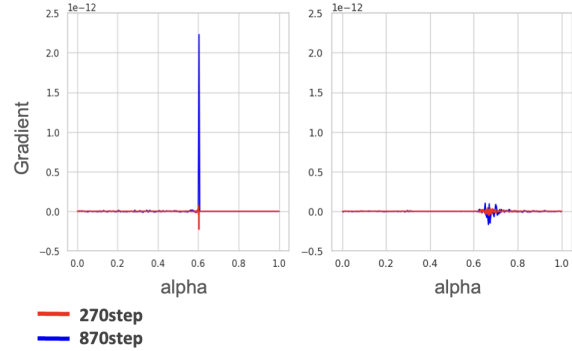


Figure 4: **Gradient value per α .** The red line is the gradient value for each α when done in 270 steps. The blue line is the gradient value for each α when done in 870 steps.

Therefore, we recommend that the number of steps be increased sequentially until it falls below a specific error, thereby reducing the error. For example, we can ensure that the IG satisfies *completeness* by initially setting the number of steps to 2^n and running with increasing n until the error converges to a constant.

Optimizing the number of steps on an instance-by-instance basis would also make IG more efficient since our analysis has shown that the number of steps required is negligible for many instances (Figure 1). However, we keep this part as a future study since constructing a methodology to find better solutions.

7 Conclusion

The researcher subjectively determines the number of steps in IG for each dataset and model, which raises questions about the reliability of IG.

In this study, we quantitatively analyzed the error for each number of steps. As a result, half of the instances in which the appropriate number of steps is around 100 steps, but on the other hand, instances in which the error does not converge even at 1000 steps or more were confirmed.

These results indicate that the current mainstream method of fixing the number of steps for each model or data set runs the risk of producing instances with broken contributions and undermining the reliability of IG's analysis results. To solve this, we also proposed to change the integration step for each instance.

Our study is the first to quantitatively analyze the variation of IG values with the number of steps and to identify problems with existing integration methods.

Limitations

In this experiment, 100 instances were randomly selected for each combination of model and dataset. This selection was necessary due to the computational cost factor. Further investigation involving more instances is needed for more accurate experiments.

The maximum entropy vector was used as the baseline for this experiment. Future validation using different baseline vectors is needed for a comprehensive model performance evaluation under various baselines.

In our validation, we used the correct Riemann sum. Future analysis using multiple Riemann sums, such as left Riemann sums and midpoint Riemann sums, is needed.

When ensuring the number of steps for each instance, the cumulative number of steps and the computational cost may increase, which is a potential issue.

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A Appendix

A.1 Datasets

The datasets we used are widely used in NLP classification problems.

AG News News articles are grouped into four main categories (“Sports,” “Business,” “Science/Technology,” and “Entertainment”) (Gulli., 2004).

20 News News articles are grouped into 20 categories (“Computers,” “Science,” “Sports,” “Politics,” and more) (Ko, 2012).

SST-2 The Stanford Sentiment Treebank-2 is provided for sentences with positive or negative emotional polarity (Socher et al., 2013).

Table 2: Datil of datasets

Dataset	train / test	class label	max lengths
AG news	120k / 7.6k	4 classes	50
20 news	11.3k / 7.53k	20 classes	200
SST2	6.92k / 1.82k	2 classes	20

A.2 Models

BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) serve as the LMs for the experiment, utilizing both base and large models. A linear layer is affixed to these models as the final layer, and a softmax function is employed to address the sentence classification task.

BERT BERT uses a bidirectional transformer architecture. Unlike regular language models, it considers both left and right contexts simultaneously to understand words in context (Devlin et al., 2019).

RoBERTa RoBERTa is a version that takes the architecture and basic ideas of BERT and optimizes the way the model is trained (Liu et al., 2019).

Table 3: Accuracy of test data

Model	Accuracy		
	AG News	20 News	SST-2
BERT-base(110M)	0.94	0.64	0.86
BERT-large(340M)	0.93	0.65	0.87
RoBERTa-base(125M)	0.94	0.61	0.88
RoBERTa-large(561M)	0.93	0.64	0.88

A.3 Integration Method

Numerical integrals are pivotal for IG. The library Captum (FacebookInc., 2023), a comprehensive Pytorch implementation of XAI methods, employs

Riemann Sum and Gauss-Legendre integrals for IG’s numerical integration.

Riemann Sum The Riemann Sum is a technique used to approximate the area under a function.

When applying the Riemann sum to IG or an input x along the i_{th} dimension, the approximation can be expressed as follows:

$$\text{IG}_i^{\text{approx}}(x) = (x_i - x'_i) \sum_{k=0}^n \frac{\partial F}{\partial x_i} \left(x' + \frac{k}{n}(x - x') \right) \frac{1}{n}, \quad (4)$$

where F represents the deep neural network, x' is a baseline embedding, and n is the sampling size. This equation allows for the estimation of the contribution of the i -th feature to the prediction results of the model.

Gauss-Legendre Integral Gauss-Legendre integral is a method used to approximate definite integrals, typically on the interval $[-1, 1]$. It involves finding the roots, denoted as x_k , of the n_{th} order Legendre polynomial, $P_n(x)$. These roots are the distinct real solutions of the polynomial of degree n that lie within the interval $[-1, 1]$.

Applying the Gauss-Legendre integral to IG yields the following equation:

$$\text{IG}_i^{\text{approx}}(x) = \frac{(x_i - x'_i)}{2} \sum_{k=1}^n \frac{\partial F}{\partial x_i} \left(x' + w_k \left(\frac{x_k}{2} + \frac{1}{2} - x' \right) \right), \quad (5)$$

where, the weights, denoted as w_k , corresponding to each root x_k are computed.

This method allows us to approximate the integral of a function using a Legendre polynomial of the appropriate degree. Because the roots and weights of the Legendre polynomial satisfy certain conditions, this method is numerically very stable and can have high accuracy for integrals of high dimension and integrals of special functions.

A.4 Riemann sum vs Gauss-Legendre

Since the results for Riemann sum were consistently better than those for Gauss-Legendre integration, the results for Riemann sum are reported in Figure 5.

A.5 Ideal step of instances

The ideal step was defined as the number of steps that the error becomes within 5% for the first time

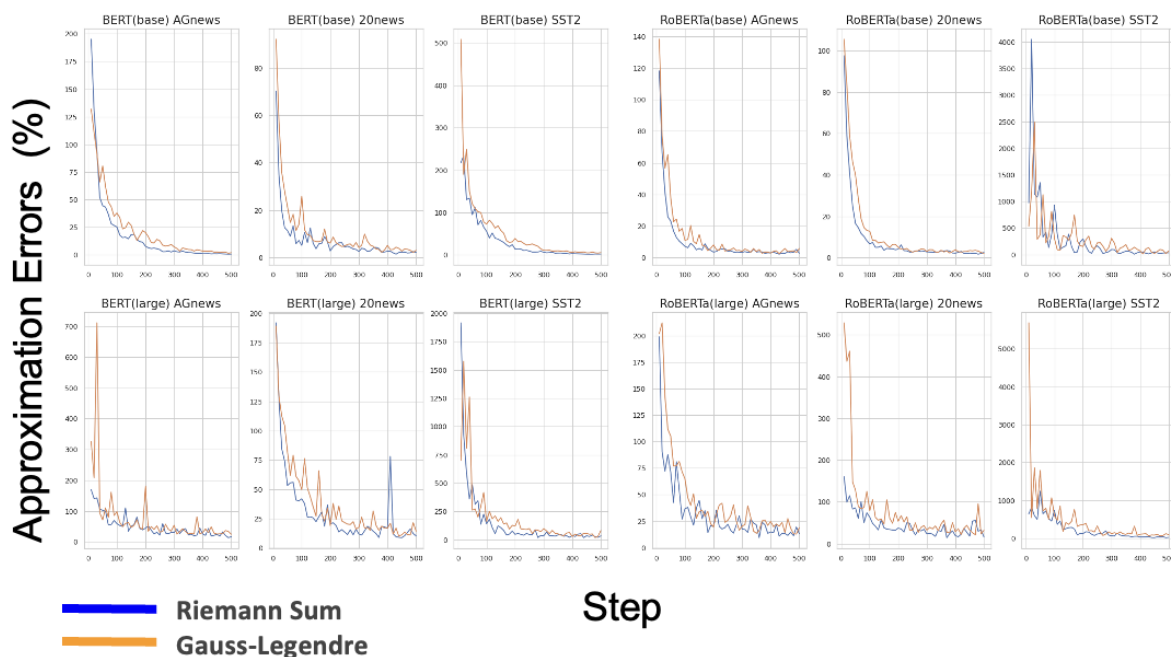


Figure 5: Mean of Approximation errors by Riemann sum and Gauss-Legendre.

by increasing the number of steps. Almost all instances had an ideal step within 1000 steps, but there were a few instances where the error was never within 5% within 1000 steps. For each model and data set, we described the number of instances in which the ideal step was within 1000 steps out of 100 instances being analyzed in 4.

Table 4: Number of instances having ideal steps within 1000 steps

Model	AG News	20 News	SST-2
BERT-base	100	100	100
BERT-large	98	99	99
RoBERTa-base	99	100	95
RoBERTa-large	99	100	97

A.6 Visualization rule

The appendices below detail the calculation of the contribution per word, which is obtained by summing the contributions calculated for each dimension corresponding to each word. The visualization rules align with those used in IG paper (Sundararajan et al., 2017). In these visualizations, green represents a positive contribution and red represents a negative contribution. The darkest shade is assigned to the most considerable absolute value of the contribution calculated for each word, and colors lighten as they approach zero.

A.7 Quantitative Analysis of Errors

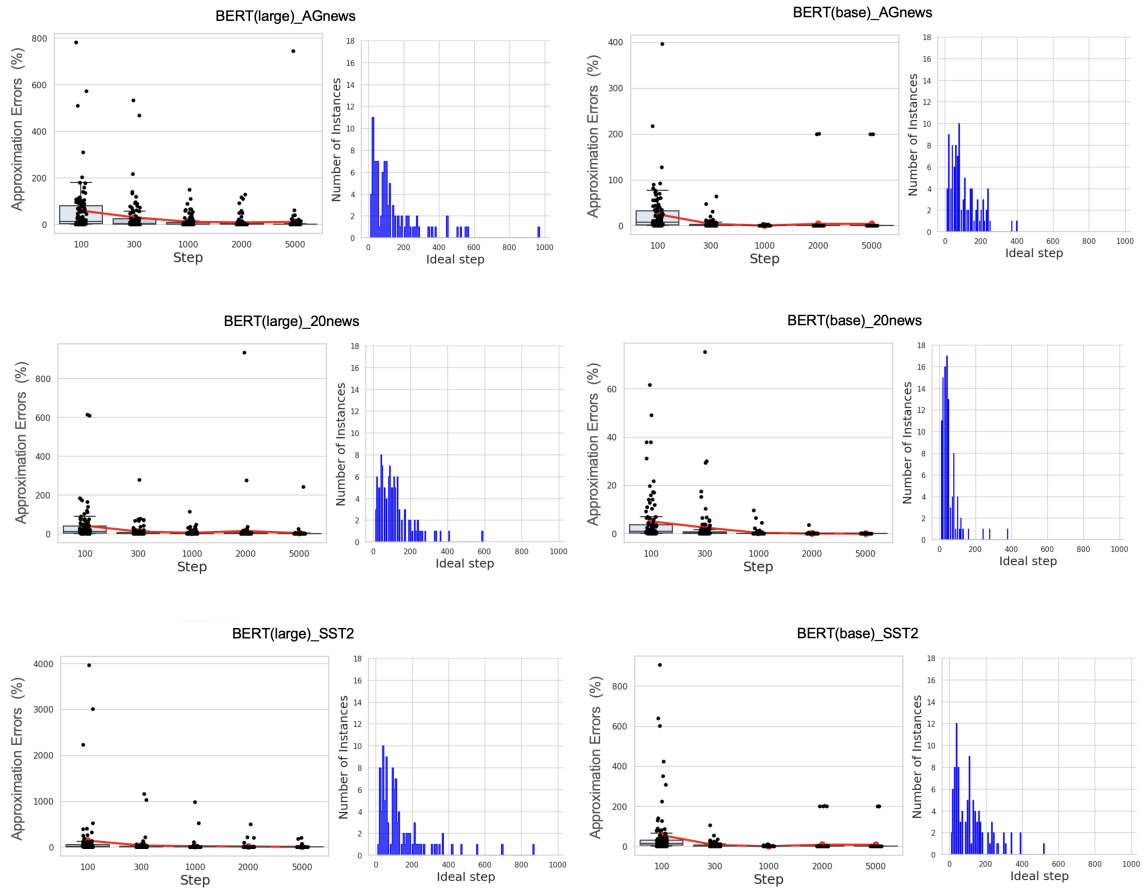


Figure 6: **BERT**. Boxplot on the left: The red line represents the approximation errors average for each number of steps, and a single point represents the approximation errors for a single instance. Histogram on the right: The number of steps ideal for each instance. The vertical axis is the number of instances with the ideal number of steps on the horizontal axis.

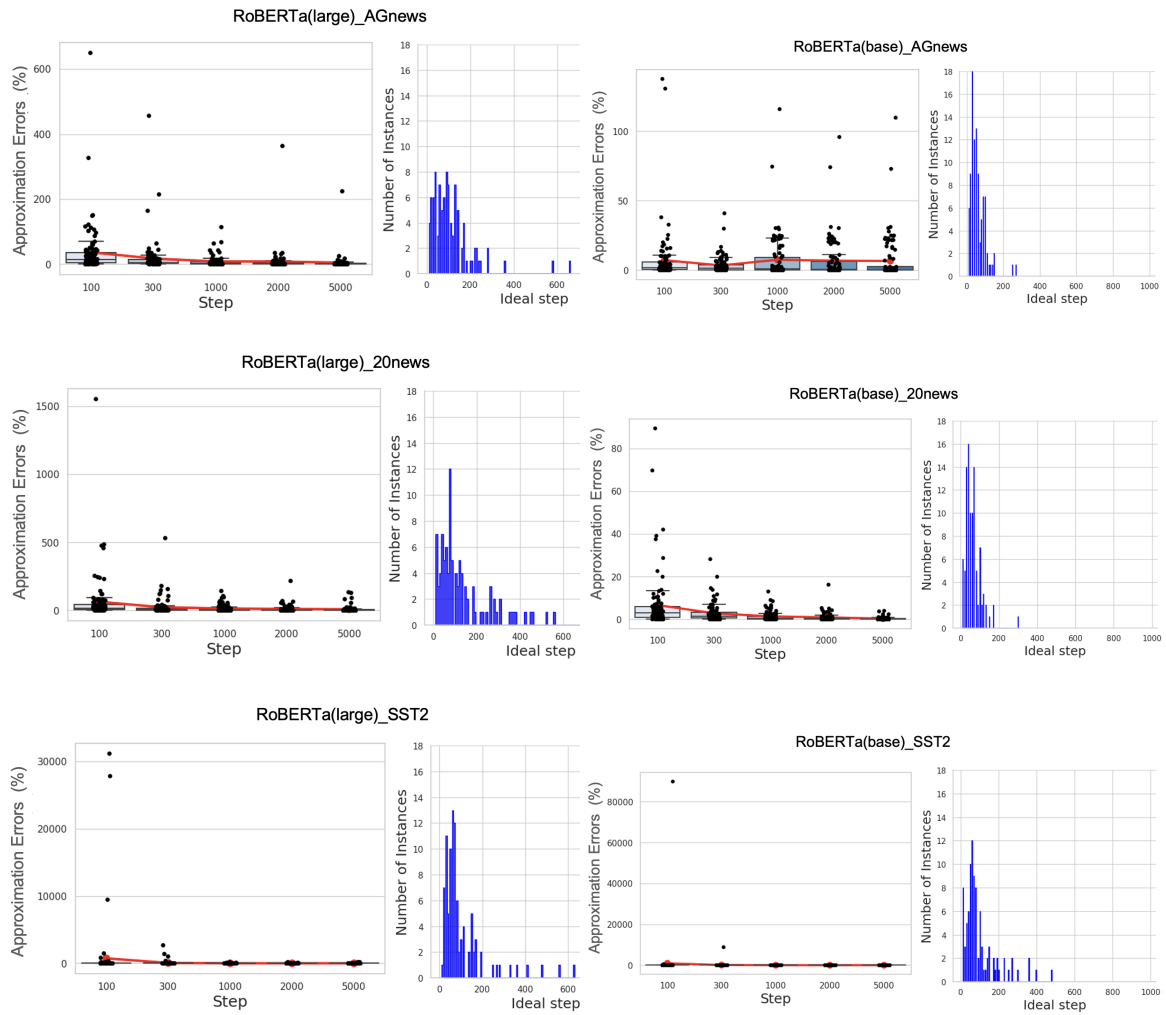


Figure 7: **RoBERTa**. Boxplot on the left: The red line represents the approximation errors average for each number of steps, and a single point represents the approximation errors for a single instance. Histogram on the right: The number of steps ideal for each instance. The vertical axis is the number of instances with the ideal number of steps on the horizontal axis.

GesNavi: Gesture-guided Outdoor Vision-and-Language Navigation

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Abstract

Vision-and-Language Navigation (VLN) task involves navigating mobility using linguistic commands and has application in developing interfaces for autonomous mobility. In reality, natural human communication also encompasses non-verbal cues like hand gestures and gaze. These gesture-guided instructions have been explored in Human-Robot Interaction systems for effective interaction, particularly in object-referring expressions. However, a notable gap exists in tackling gesture-based demonstrative expressions in outdoor VLN task. To address this, we introduce a novel dataset for gesture-guided outdoor VLN instructions with demonstrative expressions, designed with a focus on complex instructions requiring multi-hop reasoning between the multiple input modalities. In addition, our work also includes a comprehensive analysis of the collected data and a comparative evaluation against the existing datasets.

1 Introduction

With the recent successes of autonomous mobilities, there has been an interest in developing interfaces to interact with such systems, leading to the rise of the Vision-and-Language Navigation (VLN) task. However, all the outdoor VLN tasks still consider verbal instructions as the only interface for communicating with the mobility (Vasudevan et al., 2021; Deruyttere et al., 2019). In reality, humans communicate with each other in their daily lives by using non-verbal cues like gestures as well. To allow the freedom of using this intuitive form of communication through gestures, there have been recent efforts to create datasets incorporating pointing gestures as well as an interface for communication in Human-Robot Interaction (HRI) systems (Islam et al., 2022; Chen et al., 2021). However, these datasets are designed for indoor Referring Expression Comprehension (REC) tasks and often

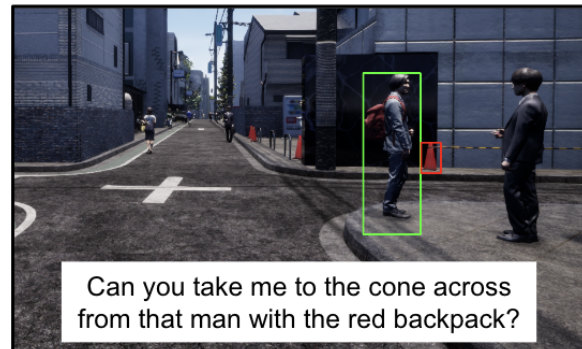


Figure 1: An example from our GesNavi dataset containing (1) a natural language instruction (text box), and (2) a gestured object (green bounding box) that acts as an intermediate anchor for a multi-hop reasoning instruction to navigate toward (3) the target object (red bounding box) indicated by the instruction.

consist of simple instructions that do not require intricate reasoning between the pointing gesture and the linguistic instruction. Hence, there is a need for datasets incorporating gesture-guided instructions in outdoor VLN tasks. Such datasets would enable the development of intelligent mobility robots that can be navigated using an intuitive interface of gestural and free-form natural language instructions.

In this work, we tackle a part of the aforementioned challenge by constructing a novel dataset, GesNavi, consisting of instructions with gesture-guided demonstrative expressions for an outdoor VLN task. We capture images from a simulated environment for a crowded urban neighborhood and crowdsource annotations for free-form linguistic instructions to navigate the mobility. Having a simulated environment allowed us to automatically capture images and extract ground truth object labels, resulting in a fast and scalable data collection process. These instructions are also accompanied by a gestured object specified using a bounding box, which is expected to be obtained using a non-verbal gestural modality in practice. The gestured

object is referred through demonstratives such as *this cone*, *that tall building*, etc., and is used as an intermediate anchor for navigating to the target object. This results in instructions requiring multi-hop reasoning to be performed to locate the target object by considering (1) the relationship between the demonstrative and the scene (detecting an intermediate object) and (2) the relationship between the intermediate object and the target object, as described in Figure 1. Furthermore, we also supplement our data with images from another perspective of the same scene, as shown in Figure 2, to facilitate the development of systems that can comprehend multimodal instructions in differing perspectives. This is particularly useful in applications such as service robots where the user is accompanying the mobility robot from outside with a different visual perspective than the mobility’s camera.

The key contributions of this work are listed below:

- We introduce a challenging novel task of gesture-guided interaction with mobility for outdoor VLN, with significant practical application.
- We collect a dataset, GesNavi, consisting of natural instructions accompanied by an intermediate gestured object to navigate the mobility toward a target object.
- We analyze our dataset and compare it against the existing datasets for both outdoor VLN and gesture-guided referring expressions.

2 Related Works

2.1 Gestures in Human-Robot Interaction

The field of Human-Robot Interaction (HRI) has extensively explored integrating gestures as an additional input modality (Bolt, 1980; Ende et al., 2011; Wu et al., 2021; Sato et al., 2007; Hu et al., 2018). Jain et al. (2023) utilized a VR setup for collecting non-verbal gestural data in a simulated environment but faced challenges in scaling to a larger dataset. CAESAR (Islam et al., 2022) and YouReft (Chen et al., 2021) are two major datasets consisting of embodied gesture-aided expressions for the Referring Expression Comprehension (REC) task.

CAESAR, though comprehensive, is based on a fully simulated environment with auto-generated instructions and pointing gestures, lacking natural

variations in human utterance. In contrast, YouReft features a real-world setting with natural language instructions and pointing gestures. However, it incorporates pointing gestures as optional information, leading to simpler instructions, as evidenced by the low average instruction length in Table 1. To address this limitation, our work extends these datasets to encompass more complex and free-form natural instructions, challenging multi-hop reasoning.

2.2 VLN Tasks

Our study focuses on an outdoor Vision-and-Language Navigation (VLN) task, involving a mobility agent receiving navigational instructions to locate a target position. VLN datasets encompass both indoor (Anderson et al., 2018) and outdoor (Vasudevan et al., 2021; Deruyttere et al., 2019) environments. Previous outdoor VLN approaches, such as those in Hermann et al. (2020); Chen et al. (2019), provided detailed step-by-step directional commands for mobility. Tasks like Talk2Car (Deruyttere et al., 2019) evolved this by incorporating more natural and free-form verbal instructions for autonomous vehicle control.

However, existing VLN tasks exclusively rely on verbal instructions, overlooking demonstrative cues prevalent in human speech. Our work addresses this gap by exploring the incorporation of gesture-guided instructions in outdoor VLN tasks.

3 Dataset

The data collection procedure for our task is divided into two steps. The first step consists of collecting images that capture a wide range of outdoor scenes. Then, we collect annotations for the gesture-guided instructions on these images. We will describe each of these steps in detail in the following subsections.

3.1 Collecting Images

To create a diverse image dataset for our task, we used a simulated environment replicating crowded streets in a dense Tokyo neighborhood (70,000 m²) on the Airsim platform (Shah et al., 2017), Unreal engine. Beyond the urban elements, we strategically placed various objects (vehicles, pedestrians, trees, cones, vending machines) in diverse locations.

Using a simulator provided three key benefits in our study: (i) random image sampling from any coordinate, (ii) automated extraction of ground truth

Datasets	Task	G	N	R	P	Total samples	Mean instruction length (words)
Talk2Car (Deruyttere et al., 2019)	Outdoor VLN	✗	✓	✓	✗	11,959	11.0
CAESAR-XL (Islam et al., 2022)	REC	✓	✗	✗	✓	1,367,305	5.3
YouRefIt (Chen et al., 2021)	REC	✓	✓	✓	✗	4,195	3.7
GesNavi (Ours)	Outdoor VLN	✓	✓	✗	✓	3,100	13.1

Table 1: Comparison of datasets relevant to this work. G, N, R and P denote the use of gestures, non-templated natural instructions, use of real-world images (versus simulated images) and multiple perspective images, respectively. The mean instruction length is used here to compare the instruction sentence complexities in the respective datasets.



Figure 2: Our dataset consists of a supplementary image for each scene to mimic a more challenging situation where the user is outside the mobility and their visual perspective (left image) is slightly different than the mobility’s camera (right image).

object labels, and (iii) algorithmic computation of 2D/3D bounding boxes using mesh coordinates for rendering. While simulated images may lack the natural features and imperfections found in real-world objects and scenes, they offer a controlled method for generating data. The ability to control the diversity in objects and scenes facilitates the creation of a challenging multi-hop reasoning task.

To capture the visual data automatically, we developed a function navigating a virtual camera along simulator roads. Varied parameters captured data under different lighting conditions (morning, afternoon, evening). Each captured data includes two images taken from a few meters apart with a relative angle of 45 degrees — representing slightly differing perspectives of the same scene, as depicted in Figure 2. One image is used for annotating navigational instructions, while the other serves as a supplementary image for another visual perspective to facilitate research for comprehending outdoor VLN instructions in applications like service robots. The captured data also includes depth maps, ground truth object classes, and positions relative to the mobility robot. A human annotator monitored the image capture process to ensure diverse scenes with minimal duplicates and unnatural scenes.

3.2 Annotating gesture-guided linguistic instructions

Upon acquiring all the images and their associated ground truth data, the next phase involves gathering gesture-guided linguistic instructions for an outdoor VLN task. Obtaining hand gesture annotations in a simulated environment typically involves the use of a virtual reality (VR) setup, as demonstrated by Jain et al. (2023). This setup utilizes a VR headset and hand controllers to capture head and hand movements while performing pointing gestures. However, it is crucial to acknowledge that such a configuration is not only expensive but also time-intensive. To address these challenges, we have adopted a more straightforward approach of annotating the gestured object by enclosing it within a bounding box. In practice, we expect that the gestured object can be determined by leveraging the existing research in recognizing non-verbal cues, such as gestures, from visual input (Nickel and Stiefelhagen, 2003; Stiefelhagen et al., 2004). While this simplification results in the loss of some raw features related to hand motion during the pointing gesture, it enables us to collect a larger dataset for this task.

To crowd-source annotations, we used Amazon Mechanical Turk (MTurk). Our guidelines instructed annotators to assume human-like mobility controlled by linguistic and gestural instructions. The annotators chose any target object of their liking and formulated navigational instructions to guide the mobility robot to that target which were collected in the form of text. In addition, the annotators were asked to imagine the use of hand gestures like pointing, annotate the gestured object with a bounding box, and use it as an *intermediate anchor* to create a multi-hop instruction based on its relation to the target object. Finally, annotators were required to label the target object with a tightly drawn bounding box.



Figure 3: Example gesture-guided instructions in our GesNavi dataset, with a wide variety of syntactic and semantic structures. The gestured and target objects are annotated with green and red bounding boxes, respectively.

Target Objects		Gestured Objects	
Object	Frequency	Object	Frequency
Obstacle	334	Person	1350
Person	330	Building	191
Car	276	Obstacle	160
Bicycle	226	Car	114
Dispenser	146	Pole	95

Table 2: Top five most frequently used target and gestured objects in our dataset

Multiple tests were conducted to refine guidelines, throughout emphasizing on crafting free-form natural instructions incorporating gesture demonstratives and necessitating multi-hop reasoning. Expert MTurk workers with native English skills and track record in annotation tasks were invited to a screening test. 25 workers who correctly performed at least four out of five annotations in the screening test were selected and received individual feedback to ensure their complete understanding of the task for good annotation quality. All images were published in small batches, with simultaneous batch reviews and feedback to maintain the desired annotation quality. Each image costed \$0.75 and took the workers an average of around 10.7 minutes per annotation.

4 Dataset Analyses

We collected a total of 3,100 gesture-guided VLN instructions on outdoor scenes. The instructions in our dataset comprise a vocabulary of 924 words. Since our approach did not rely on templates or impose constraints on linguistic instructions, we were able to capture the commonly used natural language instructions in navigational scenarios, as exemplified in Figure 3. The examples illustrate the wide variety of syntactic and semantic structures

present in our instructions.

Our instructions vary in length from 6 to 34 words, with an average length of 13.1 words. This average length is comparable to the text-only outdoor VLN dataset, Talk2Car (Deruyttere et al., 2019), and significantly larger than other gesture-guided HRI datasets like CAESAR (Islam et al., 2022) and YouReflT (Chen et al., 2021), which have average expression lengths of just 5.3 words and 3.7 words, respectively. The longer expressions in our dataset reflect the emphasis on free-form natural instructions requiring complex multi-hop reasoning, in contrast to these earlier works.

From the annotated bounding boxes of the gestured and target objects, we determined their labeled class by identifying the ground truth object with the highest Intersection over Union (IoU) overlap. The five most frequent objects used for gesturing and as the target objects are summarized in Table 2. Notably, a significant proportion of gestured objects are pedestrians, likely due to their prevalence in crowded street scenes, making them a convenient intermediate object for conveying instructions about the intended target object. It is also worth mentioning that the average distance between the camera and the target objects selected by annotators is 12.2 meters, which is around 6% more than the average distance of 11.5 meters for the gestured objects. Moreover, the average bounding box size for gestured objects is around 25% larger than the target objects. This observation suggests a general human tendency to use closer and larger objects for non-verbal gestural cues to navigate to more distant and smaller target objects.

5 Conclusion

This work introduces a novel dataset, GesNavi, designed for gesture-guided multimodal interaction

with mobility in the context of an outdoor VLN task. Moreover, in contrast to the prior efforts in the related field of gesture-guided REC tasks, our dataset specifically emphasizes natural free-form instructions that require complex multi-hop reasoning. This is evident from the significantly longer expressions in our dataset compared to the previous works.

In the future, this dataset can be expanded to also include the general case of using gestures to refer to multiple objects or a group of objects, rather than a single object in the current setup. Another future work includes developing methods to tackle this task, including the current state-of-the-art multimodal architectures for VLN (Yan et al., 2023; Kamath et al., 2021), and evaluating their performances on our GesNavi dataset. It is also worth evaluating how the multimodal LLMs (OpenAI, 2023; Team et al., 2023) perform in our task. It is a particularly challenging task and will require designing models that can effectively combine multimodal information and perform multi-hop reasoning to find the target object.

6 Limitations

While this work represents a significant stride in developing a valuable resource for gesture-guided outdoor VLN task, certain limitations in its design deserve consideration. Firstly, the dataset relies on simulated environment images, potentially limiting real-world applicability due to the absence of genuine environmental complexity and randomness. Secondly, assuming a single object referenced through gestures may overlook the broader potential of gestural instructions for groups or multiple objects within a single instruction. These limitations acknowledge the current scope and highlight opportunities for future enhancements in this field.

Acknowledgments

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Can docstring reformulation with an LLM improve code generation?

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Abstract

Generating code is an important application of Large Language Models (LLMs) and the task of function completion is one of the core open challenges in this context. Existing approaches focus on either training, fine-tuning or prompting LLMs to generate better outputs given the same input. We propose a novel and complementary approach: to optimize part of the input, the docstring (summary of a function’s purpose and usage), via reformulation with an LLM, in order to improve code generation. We develop two baseline methods for optimizing code generation via docstring reformulation and test them on the original HumanEval benchmark and multiple curated variants which are made more challenging by realistically worsening the docstrings. Our results show that, when operating on docstrings reformulated by an LLM instead of the original (or worsened) inputs, the performance of a number of open-source LLMs does not change significantly. This finding demonstrates an unexpected robustness of current open-source LLMs to the details of the docstrings. We conclude by examining a series of questions, accompanied by in-depth analyses, pertaining to the sensitivity of current open-source LLMs to the details in the docstrings, the potential for improvement via docstring reformulation and the limitations of the methods employed in this work.

1 Introduction

Large Language Models for coding (code LLMs) emerged in recent years as the dominant approach to code generation (Chen et al., 2021; Nijkamp et al., 2023b,a; Li et al., 2023; Rozière et al., 2023). The research community proposed various benchmarks to systematically evaluate the code generation abilities of LLMs (Chen et al., 2021; Hendrycks et al., 2021; Austin et al., 2021; Lai et al., 2022). One of the grand challenges of code generation is the task of function completion: given

its definition and an explanation of the desired behaviour, write the body of the desired function. Current methods in code generation focus on multiple directions: better pre-training datasets and procedures for more performant base models (Li et al., 2023; Rozière et al., 2023), specific fine-tuning methods for coding models (Le et al., 2022; Chaudhary, 2023; Luo et al., 2023), test-time improvements via self-testing (Chen et al., 2022; Ni et al., 2023), solutions reranking (Zhang et al., 2022), self-repair (Chen et al., 2023b; Olausson et al., 2023) or other techniques (Shi et al., 2022; Shinn et al., 2023; Zelikman et al., 2023).

In this work we explore the idea of input transformations as a new, complementary approach to improving code generation abilities of LLMs. In the context of function completion tasks, the input can be formulated as a function declaration followed by a docstring, which explains in words what the function is supposed to do. As illustrated in Figure 1, we consider a specific input transformation for this task: docstring reformulation.

The motivation for this approach is the following: first, optimizing the docstrings could provide benefits that are model-agnostic, that is, benefit all code LLMs. We hypothesize that this could be the case, drawing inspiration from the success of prompting techniques, such as Chain-of-Thought (Wei et al., 2023) and similar works (Zhou et al., 2023), that demonstrate efficacy across a broad class of models. Second, optimizing docstrings, while maintaining their readability, can provide interpretable insights on the influence of docstrings’ properties on code LLMs in the context of code generation.

This work makes the following contributions:

1. We introduce a novel framework for optimizing code generation through docstring reformulation with LLMs. Additionally, we propose two baseline methods for the docstring reformulation task.

Input with Original Docstring

```
def simplify(x, n):
    """Your task is to implement a function that will simplify
    the expression x * n. The function returns True if x * n
    evaluates to a whole number and False otherwise. Both x
    and n, are string representation of a fraction, and have
    the following format, <numerator>/<denominator> where both
    numerator and denominator are positive whole numbers.

    You can assume that x, and n are valid fractions, and do
    not have zero as denominator.

    simplify("1/5", "5/1") = True
    simplify("1/6", "2/1") = False
    simplify("7/10", "10/2") = False
    """
```

Original code LLM completion

```
# Convert the input strings to fractions
x_frac = Fraction(x)
n_frac = Fraction(n)

# Multiply the fractions
product = x_frac * n_frac

# Check if the product is a whole number
return product.denominator == 1
```

Not defined!

Passes all tests ❌

Input with Reformulated Docstring

```
def simplify(x, n):
    """
    This function takes two string representations of fractions,
    x and n, and returns True if x * n
    evaluates to a whole number and False otherwise.

    Both x and n are in the format of <numerator>/<denominator>,
    where both numerator and denominator
    are positive whole numbers.
```

The function simplifies the expression $x * n$ by converting the string representations to integers, multiplying them, and checking if the result is a whole number.

```
simplify("1/5", "5/1") = True
simplify("1/6", "2/1") = False
simplify("7/10", "10/2") = False
"""
```

New code LLM completion

```
# Convert the string representations to integers
x_numerator, x_denominator = map(int, x.split('/'))
n_numerator, n_denominator = map(int, n.split('/'))

# Multiply the fractions
result_numerator = x_numerator * n_numerator
result_denominator = x_denominator * n_denominator

# Check if the result is a whole number
return result_numerator % result_denominator == 0
```

Passes all tests ✅

Figure 1: Motivating example of docstring reformulation with LLMs for improving code generation. One can learn to optimize docstrings by fine-tuning an LLM on successful docstring reformulations. The reformulations can improve the usefulness of the docstring in many ways, e.g. by adding hints on how to implement the function as in this example, or by fixing faults in the docstring.

2. We assess the effectiveness of the proposed methods on multiple variants of the HumanEval benchmark, finding a limited improvement to code generation.
3. We present a thorough analysis of the limitations of the models used, the methods proposed and the experimental setup. We find evidence for a significant margin of potential improvement in code generation via docstring reformulation when using oracle reformulations, and highlight key obstacles hindering this potential.
4. We independently replicate the performance of multiple open-source code LLMs on the HumanEval benchmark. Additionally, we release all code necessary for experiment reproduction and share the novel curated variants of HumanEval featuring faulty docstrings.

2 Related work

Prompt optimization Prompt optimization techniques have garnered significant attention in recent research. Li and Liang (2021) propose prefix-tuning, an alternative to fine-tuning, which focuses on optimizing task-specific vectors while keeping the language model parameters fixed. Lester et al.

(2021) present prompt-tuning as a simplification of prefix tuning, involving the addition of small task-specific prompts for each task. Additionally, Liu et al. (2021) introduces P-tuning, a continuous optimization technique for mapping context to target output using prompts. Qin and Eisner (2021) also explore soft prompts, emphasizing their relevance in various NLP applications.

Reinforcement Learning (RL) has also been employed in prompt optimization. Deng et al. (2022) discuss the challenges associated with soft prompts and propose a method that employs RL to decode discrete prompts token-by-token. Zhang et al. (2023) leverage RL to dynamically construct instance-specific discrete prompts, enhancing task performance through query-dependent prompts.

Instruction generation As more and more LLMs are aligned to follow instructions, e.g., via instruction fine-tuning or reinforcement learning from human feedback, an open question is how to generate instructions in natural language in order to increase the likelihood of producing with an LLM the desired output for a given input. Zhou et al. (2023) introduce the Automatic Prompt Engineer (APE), framing instruction generation as a natural language program synthesis problem and propose search methods to find approximate so-

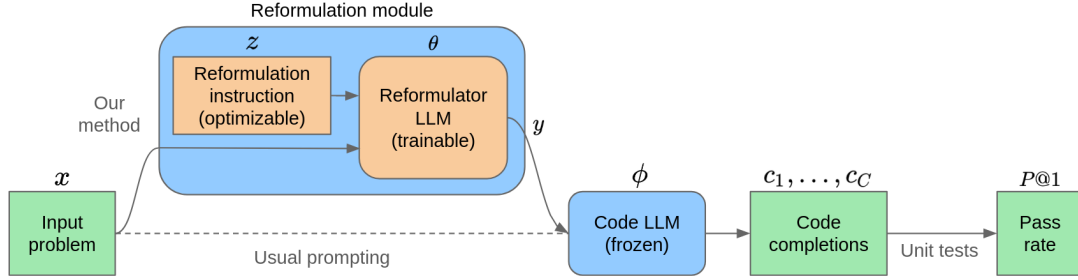


Figure 2: High-level view of the proposed method. We apply a transformation via a reformulation module (θ, z) to the input problem x to obtain a reformulation y of it. We then use the reformulated problem as input for any downstream code LLM ϕ . The reformulation module is optimized to reformulate the docstring of the function to be completed, in order to increase the unit test pass rate (pass@1) of LLM-generated code completions for the target function.

lutions. Pryzant et al. (2023) propose Automatic Prompt Optimization (APO). APO leverages data minibatches to create natural language "gradients," representing linguistic attempts at achieving what mathematical gradients do. These language gradients critique the existing prompt and are integrated into it through steps akin to "gradient descent". Most relevant to our work, Yang et al. (2023) introduce Optimization by PROMpting (OPRO), a method for optimizing tasks specified in natural language. Their approach involves generating new solutions from a prompt containing previously generated solutions and their corresponding values, which are subsequently evaluated and incorporated into the prompt for further optimization.

Evolutionary methods Evolutionary methods involving language models have also been explored. Xu et al. (2023) expand the self-instruct method by Wang et al. (2023) with instruction evolution, employed in the creation of high-quality instruction-tuning datasets. Meyerson et al. (2023) investigate the use of language models as variation operators in evolutionary algorithms, enabling tasks such as symbolic regression and sentiment modification. Lehman et al. (2022) combine evolution through large models with MAP-Elites (Mouret and Clune, 2015) to generate functional examples of Python programs in the Sodarace domain, a task unseen during pre-training. Chen et al. (2023a) focus on producing valid neural network architectures for neural architecture search using LLMs.

3 Methodology

In this section, we first introduce the function completion task as formulated in benchmarks such as HumanEval, then we formalise the docstring reformulation task and finally we present our baseline

methods for optimising docstring reformulations.

3.1 Code generation and function completion task

Current state-of-the-art code generation methods (Chen et al., 2021; Nijkamp et al., 2023b,a; Li et al., 2023; Rozière et al., 2023) use decoder-only Transformer architectures with auto-regressive probabilistic modeling of the next token to be generated. In this work we denote as code LLMs any LLM which during pre-training has been trained on a non-negligible amount of code data.

In the context of function completion tasks, given an input problem x and a code LLM with parameters ϕ , the code completion c is typically obtained by generating one token at a time until the end-of-sentence (EOS) token is sampled or a maximum sequence length L is reached:

$$p_\phi(c|x) = \prod_{l=1}^L p_\phi(c_l|x, c_{<l}). \quad (1)$$

Given a dataset D consisting of pairs of input problems and unit tests (x, T) , and a code LLM ϕ , the performance $J(\phi, D)$ of the code LLM is:

$$J(\phi, D) = \mathbb{E}_{\substack{(x,T) \sim D, \\ c \sim p_\phi(c|x)}} [T(c)]. \quad (2)$$

$T(c)$ is a binary variable, with value 1 if the code completion c passes all the unit tests T , and 0 if c fails at least one unit test. $J(\phi, D)$ in the literature is also called 'pass@1' and is the main metric to evaluate code LLMs' performance on benchmarks such as HumanEval (Chen et al., 2021).

3.2 Docstring reformulation task

We consider the task of improving code generation abilities of code LLMs. In particular we are

interested in optimizing functions’ docstrings to increase the probability of sampling a correct code solution from any code LLM; this is akin to treating the docstring as a prompt and optimizing the prompt for the given task.

We formalise the task as follows: given the dataset D of input problem and unit test pairs (x, T) , and a set Φ of code LLMs, for each x generate a reformulation y_x to maximize the probability of sampling a correct code completion c for (x, T) with a code LLM ϕ uniformly sampled from Φ :

$$\max_{y_x} \mathbb{E}_{\substack{(x,T) \sim D, \\ \phi \sim U(\Phi), \\ c \sim p_\phi(c|y_x)}} [T(c)]. \quad (3)$$

In this work, we frame this problem as a *docstring reformulation* task. For each code function f , there exist multiple possible docstrings to document it and we hypothesize that certain docstrings are more effective than others in guiding the code generation as desired. Furthermore, we speculate that the effectiveness of a docstring has a model-agnostic component, possibly because different code LLMs share pre-training data and would respond similarly to the same input patterns.

To reformulate docstrings, we rely on an instruction-tuned LLM θ , which we denote *reformulator*. We provide the reformulator with the *original problem input* x to be reformulated and with a *reformulation instruction* z , expressing how the reformulation task should be done.

The main reasons for the introduction of the instruction z is the following. Docstring reformulation is a problem that requires some exploration mechanism, as the search space is huge and the original docstring provided in x can be assumed to be a local maximum in the performance landscape. We hypothesize that using instructions to steer the reformulations in different directions is much more sample-efficient than relying only on stochastic sampling to search for the best reformulation.

Under this framework, the docstring reformulation task can be expressed as follows:

$$\max_{\theta, z} \mathbb{E}_{\substack{(x,T) \sim D, \\ \phi \sim U(\Phi), \\ y \sim p_\theta(y|x,z), \\ c \sim p_\phi(c|y)}} [T(c)]. \quad (4)$$

To evaluate the quality of a reformulation y of a problem x , we decode it with a code LLM and test if the code sample c passes the unit tests T .

We can use this evaluation to rank multiple reformulations for the same input problem in terms of performance, which serves as the basis for any learning algorithm.

3.3 Proposed methods

We propose two main methods to optimize the reformulations:

1. **Supervised fine-tuning on the best instruction (SFT)**: maintaining the instruction z fixed, fine-tune the reformulator θ on the best reformulation y^* for each x .
2. **Instruction optimization via OPRO (OPRO)**: keeping the reformulator θ fixed, generate new instructions z with a pre-trained LLM, denoted as *instruction optimizer*, conditioned on the past instructions and their pass rates following the OPRO method in Yang et al. (2023).

SFT In this first approach, for each input problem x in the dataset, we generate R ($R \geq 2$) reformulations y_1, \dots, y_R as:

$$y_1, \dots, y_R \sim p_\theta(y|x, z). \quad (5)$$

In the SFT method, we consistently use the following hand-written instruction z :

"Improve the docstring of the following function using the best coding conventions."

The reformulation instruction z and the input problem x are presented to the reformulator using an instruction-following template adapted from Luo et al. (2023) and reported in Appendix B.1. For each reformulation y_i we then generate C code completions c_1, \dots, c_C using a code LLM. Each code completion is evaluated against the problem’s unit tests T and the result is either pass (1) or fail (0). We define the best reformulation of the problem input x as:

$$y^* = \operatorname{argmax}_{y \in \{y_1, \dots, y_R\}} \sum_{j=1}^C T(c_j(y)). \quad (6)$$

We then perform supervised fine-tuning of the reformulator θ on the (x, y^*) pairs, formatted with the same template used during reformulation and we compute the loss only for the tokens corresponding to y^* . In summary, at every iteration of the algorithm, we generate R reformulations of each input problem in the training set, C code completions of

each reformulation, evaluate all code completions against the corresponding tests and perform supervised fine-tuning on the pairs of input problems and best reformulations. We continue the training for multiple iterations and use the final reformulator model in the evaluation phase. During training, we use a single, fixed code LLM, the coder model, to generate the code based on the reformulations. During evaluation we use different coder models to study the generalizability of the benefits from the reformulated docstrings.

OPRO In this second approach, at every iteration, we generate Z instructions z_1, \dots, z_Z by prompting the reformulator with a specific instruction generation template and then we form all possible combinations of reformulation instructions and input problems. For each combination, we generate one reformulation, using as input the same reformulation template as in the SFT method, but with a different z , and use the reformulation as input to the coder model to produce C code completions. We score each reformulation instruction with the pass@1 metric of all the code completions associated with it. We start the first iteration with Z hand-written instructions (see Appendix B). From the second iteration, to generate new instructions, we do the following:

1. Sample n (instruction, score) pairs from all instructions evaluated so far;
2. Sort them in ascending order of score;
3. Format them according to the instruction generation template (described below);
4. Generate a continuation of the template with the *instruction optimizer* LLM and parse out the new instruction (until the first newline character).

n is a hyper-parameter of the algorithm, and how to set its value is further discussed in the Appendix B.

We use the following instruction generation template, adapted from Yang et al. (2023):

Your task is to generate the next instruction to achieve a higher score. The instructions should ask to change, improve or rewrite the function documentation or docstring. The instructions should not ask to write new functions, add new arguments or change the output of the given function. Below are some previous instructions with their scores. The score ranges from 0.0 to

```
1.0.
Instruction 1: {instruction_1}
Score 1: {score_1}
:
Instruction n: {instruction_n}
Score n: {score_n}
Instruction n+1:
```

4 Experiments and Results

Datasets In this work we consider HumanEval as a dataset on which to test the efficacy of the docstring reformulation, as it is one of the most used benchmarks in coding. To further study the influence of the docstrings and their reformulations in various scenarios, we curate four other versions of HumanEval, where we manually edited all input problems, introducing the respective faults:

- **Misspelling:** a character was either added, subtracted or changed in one of the most important words of every docstring.
- **Ambiguity:** all examples of input-output behaviour, hints and edge-case specifications are removed from every docstring.
- **Distractor:** a sentence out of context is inserted at the beginning or at the end of every docstring.
- **Bad formatting:** all type hints in the function declaration, blank lines and ">>>" symbols in front of examples are removed.

The motivation for introducing errors in the docstrings was to explore the potential for improvement by reformulation when the docstring is initially imperfect. We aimed at introducing errors similar to those that could potentially happen by human coders. We report examples of all the faults introduced in Appendix E.

Experimental setup For every variant of HumanEval, we run the SFT and the OPRO methods for 10 iterations. The SFT method uses 2 reformulations per input problem and 2 code completions per reformulation, while the OPRO method uses 5 reformulation instructions per input problem, one reformulation and one code completion.

During training, we use the WizardCoder-Python-7B (Luo et al., 2023) as the reformulator and coder model and, for the OPRO method, Llama-2-7b-chat (Touvron et al., 2023) as the instruction optimizer model. For the evaluation setup,

Table 1: **Results for SFT method.** We report the pass@1 results on the four selected variants of HumanEval, corresponding to the original problem and three modified versions with manually worsened docstrings. *Initial* column shows the performance on the initial input problem (original or worsened). *Reformulated* column shows the performance after applying the trained reformulator model to the corresponding initial input.

Models	Original		Misspelling		Ambiguity		Distractor	
	Initial	Reformulated	Initial	Reformulated	Initial	Reformulated	Initial	Reformulated
open_llama_7b_v2	13.4 (2.7)	14.0 (2.7)	13.4 (2.7)	14.6 (2.8)	15.2 (2.8)	12.8 (2.6)	10.3 (2.4)	14.6 (2.8)
mpt-7b	16.4 (2.9)	15.9 (2.9)	17.7 (3.0)	14.6 (2.8)	16.4 (2.9)	17.7 (3.0)	10.3 (2.4)	17.7 (3.0)
starcoder	33.5 (3.7)	33.5 (3.7)	35.4 (3.7)	32.3 (3.7)	30.5 (3.6)	32.9 (3.7)	31.1 (3.6)	32.9 (3.7)
WizardCoder-3B	35.4 (3.7)	32.9 (3.7)	29.2 (3.6)	31.1 (3.6)	30.5 (3.6)	31.1 (3.6)	33.5 (3.7)	34.8 (3.7)
WizardCoder-Python-7B*	53.0 (3.9)	56.1 (3.9)	46.3 (3.9)	54.3 (3.9)	53.7 (3.9)	52.4 (3.9)	54.8 (3.9)	53.0 (3.9)
WizardCoder-15B	57.9 (3.9)	57.9 (3.9)	56.1 (3.9)	54.3 (3.9)	51.8 (3.9)	50.6 (3.9)	54.2 (3.9)	53.0 (3.9)
Average	34.9	35.1	33.0	33.5	33.0	32.9	32.4	34.3

* WizardCoder-Python-7B is used as coder model during training.

Table 2: **Results for OPRO method.** We report the pass@1 results on the four selected variants of HumanEval, corresponding to the original problem and three modified versions with manually worsened docstrings. *Initial* column shows the performance on the initial input problem (original or worsened). *Reformulated* column shows the performance after applying the reformulator model with the optimized reformulation instruction to the corresponding initial input.

Models	Original		Misspelling		Ambiguity		Distractor	
	Initial	Reformulated	Initial	Reformulated	Initial	Reformulated	Initial	Reformulated
open_llama_7b_v2	13.4 (2.7)	14.0 (2.7)	13.4 (2.7)	15.9 (2.9)	15.2 (2.8)	18.9 (3.1)	10.3 (2.4)	12.8 (2.6)
mpt-7b	16.4 (2.9)	17.1 (2.9)	17.7 (3.0)	15.9 (2.9)	16.4 (2.9)	18.9 (3.1)	10.3 (2.4)	14.0 (2.7)
starcoder	33.5 (3.7)	32.3 (3.7)	35.4 (3.7)	34.8 (3.7)	30.5 (3.6)	34.8 (3.7)	31.1 (3.6)	32.9 (3.7)
WizardCoder-3B	35.4 (3.7)	32.3 (3.7)	29.2 (3.6)	31.7 (3.6)	30.5 (3.6)	34.8 (3.7)	33.5 (3.7)	33.5 (3.7)
WizardCoder-Python-7B*	53.0 (3.9)	56.1 (3.9)	46.3 (3.9)	53.0 (3.9)	53.7 (3.9)	53.7 (3.9)	54.8 (3.9)	50.0 (3.9)
WizardCoder-15B	57.9 (3.9)	54.9 (3.9)	56.1 (3.9)	53.0 (3.9)	51.8 (3.9)	48.8 (3.9)	54.2 (3.9)	51.8 (3.9)
Average	34.9	34.5	33.0	34.1	33.0	35.0	32.4	32.5

* WizardCoder-Python-7B is used as coder model during training.

in addition to the original coder model, we consider 5 other LLMs with model sizes ranging from 3B to 15B parameters: OpenLlama-2-7B-V2 (Geng and Liu, 2023; TogetherComputer, 2023), MPT-7B (MosaicML, 2023), starcoder (15B) (Li et al., 2023), WizardCoder-3B and WizardCoder-15B (Luo et al., 2023). These models were selected as a representative subset of the open-source LLM landscape. The selection criteria are discussed in Appendix C.

During the evaluation, we use the reformulator to produce one reformulation per each input problem via greedy decoding and pass each reformulation to all six coder models to compute the pass@1 metric for each model. As a baseline, we compute the pass@1 of each model using the non-reformulated problems as inputs to the coder models and following the same exact evaluation procedure.

Results We report in Table 1 the results for SFT method and in Table 2 the ones for the OPRO method. Additionally, we report the results for one more HumanEval variant (the bad formatting

one) in Appendix D, as the average model performance did not decrease after introducing this type of fault, thus raising doubts about its relevance. We also report in parentheses the estimated errors for the models’ performances as $\sqrt{p(1-p)/N}$, assuming a Binomial distribution of the successful code completions, with p the pass rate (pass@1) and $N = 164$ the number of problems in the HumanEval dataset.

For both methods, we can notice two main trends: first, the average performance on the faulty variants of HumanEval across the coder models decreases slightly (roughly 2 percentage points), and second, the average performance when using reformulations rather than the initial (possibly faulty) input problems does not increase significantly. All models obtain mixed results, increasing performance on some reformulated variants and losing it on others, with the only exception of WizardCoder-15B, whose performance consistently decreases on reformulations.

5 Discussion and Conclusions

In the following section we raise a series of questions about the docstring reformulation framework, the SFT and OPRO methods and the experimental setup. We address these questions with ulterior argumentations and analyses, before drawing the conclusions from this study. A more extended discussion is presented in Appendix A.

Q1. Limitations of docstring optimization for code generation: *How capable are the code LLMs considered in this work to leverage docstrings’ improvements?*

We use the following working definition of docstring improvement: *An increase in the information that the docstring contains about the body of the function to be completed.* This definition is model-agnostic, as it does not make reference to the performance of any model; rather, we expect that LLMs can leverage the increased information in the docstrings for better code generation.

First, we show in Table 3 in Appendix A that, if docstrings are completely removed from the input problems, the performance drops dramatically across all models, demonstrating that docstrings serve a key role in accurate function completion.

Then, we compare the performance of the various LLMs when evaluated on the faulty variants of HumanEval versus the original dataset, which can be considered an improved version of them. We find that five out of six models surprisingly increased performance on at least one of the four faulty variants of HumanEval, indicating that a docstring improvement does not necessarily benefit code generation and it can even hurt performance.

Finally we evaluate the coder models on two new sets of strongly improved docstrings for the HumanEval problems, produced while having access to the ground-truth function completions (oracle docstrings). The first set of docstrings is produced by GPT-4¹ with access to the ground-truth solution (*Oracle Hints*), asking the model to give detailed hints on how to implement the function. The second set contains the true body of the function to be completed (*Oracle Solutions*), so that the task of the coder models simplifies to copy-pasting the solution. Our results, presented in Table 4 in Appendix A, show that both Oracle Hints and Oracle

Solutions docstrings greatly improve the performance of all coder models.

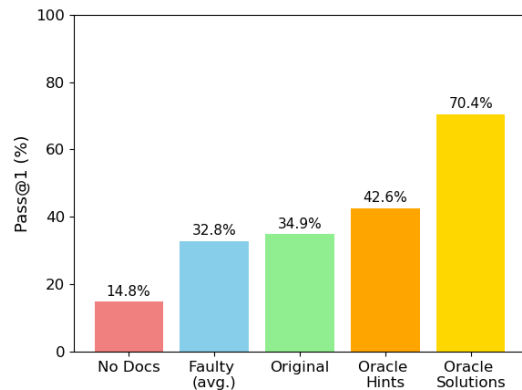


Figure 3: **Performance of different docstrings.** We report the pass@1 averaged across the six coder models for different kinds of docstrings: no docstrings at all (*‘No docs’*), faulty docstrings (*‘Faulty (avg.)’*, average across Misspelling, Ambiguity and Distractor variants), original docstrings (*‘Original’*), oracle docstrings with hints (*‘Oracle Hints’*) and with solutions (*‘Oracle Solutions’*).

Figure 3 summarises our findings on the ability of the considered LLMs in leveraging docstrings for code generation: coder models may not reliably leverage small improvements in the docstrings, but clearly benefit from the overall information included in them. In particular, the performance with Oracle Hints can be considered as a good estimate of the potential of optimizing code generation via docstring reformulation; how to achieve such performance without access to the ground-truth solution to generate hints remains an open question.

Q2. Limitations of the docstring reformulation methods in principle: *Are the methods proposed guaranteed to improve the performance of the coder model used during training? Is there any guarantee that the improvement will transfer to other coder models?*

We identify the following challenges that any method for docstring reformulation faces: exploration, noisy learning signal and learning rule, overfitting and generalization.

The exploration challenge is about searching for the best docstring for a given input problem. Both the SFT and the OPRO methods rely on stochastic sampling of the reformulations with an inductive bias, encoded as extra information z in the prompt. However, this doesn’t guarantee to find the best docstrings, as the search space is huge.

¹In all the experiments with GPT-4 we use GPT-4 Turbo, also referred as gtp-4-1106-preview in OpenAI API.

The challenge with noisy learning signals lies in the high variance of the pass rate metric, which is due to the stochasticity in the coder model. This can impair the stability of the optimization in the SFT method, as it is not well suited for dealing with noisy feedback. OPRO’s learning rule, on the other hand, while more robust to noise, is reliant on the instruction optimizer LLM and as such, it also doesn’t guarantee any convergence of the method.

Finally, if reformulations exclusively boost a particular coder model’s performance while decreasing performance for most other models, they overfit to that model. Conversely, if reformulations enhance the performance of diverse coder models without specific tailoring, they demonstrate generalization across coder models. Empirically, we do not observe any sign of overfitting. We attribute this to the lack of backpropagation through the coder model in the proposed methods, which, we speculate, acts as a regularizer over the optimised reformulations and improves their generalizability.

We conclude that the proposed methods face key shortcomings in exploring the reformulation space and in learning from a noisy feedback signal.

Q3. Limitations of the docstring reformulation methods in practice: *Are there further practical considerations about our experimental setup that could affect the methods’ success?*

In addition to the limitations discussed in Q2, the proposed methods may be limited by practical implementation choices. Initial experiments indicated that the choice of method parameters, as well as the language generation parameters and prompt templates for LLMs, does not strongly influence the results. Consequently, we run additional experiments to ablate the role of capability of the models employed as:

1. **Reformulator:** We evaluate the coder models on reformulations produced by GPT-4, instead of WizardCoder-Python-7B, prompted with the same reformulation instruction as in the SFT method. We use the original HumanEval dataset for this experiment.
2. **Instruction optimizer:** We reproduce the OPRO experiments for the original HumanEval dataset using GPT-4 as instruction optimizer model, instead of Llama-2-7b-chat.

Regarding the experiments on the reformulator, reported in Table 5 in Appendix A, we find no

significant difference in performance between the two models for the given reformulation instruction; our qualitative inspection of the generated reformulations supports the conclusion that the selected open-source model can generate docstring reformulations on par with GPT-4 in this specific context.

In the case of the instruction generator experiment, the results for GPT-4, presented in Table 6 in Appendix A, are significantly worse than the ones obtained with the selected instruction optimizer. Qualitatively, GPT-4 suggests verbose reformulation instructions, often leading the reformulator to include in the documentation hallucinated information, e.g. about possible invalid inputs. This results in incorrect handling of edge cases in generated code completions and performance degradation.

In summary, our ablation studies in this section show that the limitations of the proposed methods are not linked with the quality of the models selected as reformulator and instruction optimizer, but rather to the points described in Q2.

Conclusions

Code generation is crucial for diverse real-world applications, and accurate function completion poses a key challenge in this context. In this work we introduce docstring reformulation with an LLM as a novel approach to improve code generation for function completion and propose two methods to solve the task. When testing them on multiple variants of the HumanEval benchmark, we find limited improvements to code generation.

In our discussion, we first show that the considered coder models may not reliably leverage small improvements in the docstrings, but clearly benefit from the overall information included in them. Leveraging oracle reformulations, we then provide evidence that the more information the docstrings contain about the solutions, the more beneficial they are, regardless of the model. Finally, we argue that the proposed methods face key shortcomings in exploring the reformulation space and in learning from a noisy feedback signal, while we exclude limitations linked to our implementation choices.

Interesting future directions are to investigate more efficient ways of searching for promising reformulations, for example by reflecting on previous candidates, and to examine RL-based algorithms, such as RLHF (Christiano et al., 2023) and DPO (Rafailov et al., 2023), as alternatives to supervised fine-tuning.

Limitations

The main limitation of this work is that we train and test our methods on the same input problems, i.e. the ones of HumanEval. The choice is due to the fact that not many benchmarks exist for function completion, as we require verified unit tests for each input problem in the benchmark. Further, HumanEval is arguably the most used coding benchmark at the time of writing and this facilitated verifying the performance of a large amount of open-source LLMs as the starting point of this work, which wouldn't have been possible otherwise.

However, we argue that this doesn't impair our results for the following reasons: First, we evaluate our methods also on different LLMs than the one used during training, in contrast with prior work, such as Pryzant et al. (2023) and Yang et al. (2023), that focuses on optimizing prompts for a single model. Second, we constrain the optimization to be done via a language prompt (the reformulation) and we only use a non-differentiable scalar feedback to score the reformulations; this is a setup very similar to the ones in bandit problems, where the reformulation serves as the action, the scalar feedback as reward and the performance is assessed on the training distribution. Third, we never let our methods see the code completions nor the true solutions to the input problems. However, future work should definitely focus on cross-dataset generalization of prompt reformulation. The other limitations are addressed in the main text, in Section 5.

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A Extended discussion

Q1. Limitations of the models considered: *How capable are the code LLMs that we considered in this work to leverage improvements in the docstrings?*

We use the following working definition of docstring improvement: *An increase in the information that the docstring contains about the body of the function to be completed*. This definition is model-agnostic, as it does not make reference to the performance of any model; rather, we expect

that LLMs can leverage the increased information in the docstrings for better code generation.

First, we show in Table 3 that, if docstrings are completely removed from the input problems, the performance drops dramatically across all models, demonstrating that docstrings serve a key role in accurate function completion.

Then, we compare the performance of the various LLMs when evaluated on the faulty variants of HumanEval versus the original dataset, which can be considered an improved version of them. We find that five out of six models surprisingly increased performance on at least one of the four faulty variants of HumanEval, indicating that a docstring improvement does not necessarily benefit code generation and it can even hurt performance (see Table 1 and Table 14, *Initial* columns).

Finally we evaluate the coder models on two new sets of strongly improved docstrings for the HumanEval problems, produced while having access to the ground-truth function completions (oracle docstrings). The first set of docstrings is produced by GPT-4² with access to the ground-truth solution (*'Oracle Hints'*), asking the model to give detailed hints on how to implement the function. The second set contains the true body of the function to be completed (*'Oracle Solutions'*), so that the task of the coder models simplifies to copy-pasting the solution. Our results, presented in Table 4, show that, both the Oracle Hints and the Oracle Solutions reformulations largely increase the performance of all models, with the Oracle Solutions being always superior to the Oracle Hints. Interestingly, no model achieves 100% pass rate even with the ground truth solution in-context, highlighting that current LLMs have strong limitations in using the information provided without any additional fine-tuning.

Figure 3 summarises our findings on the ability of the considered LLMs in leveraging docstrings for code generation: coder models may not reliably leverage small improvements in the docstrings, but clearly benefit from the overall information included in them. In particular, the performance with Oracle Hints can be considered as a good estimate of the potential of optimizing code generation via docstring reformulation; how to achieve such performance without access to the ground-truth solution to generate hints remains an open question.

²In all the experiments with GPT-4 we use GPT-4 Turbo, also referred as gtp-4-1106-preview in OpenAI API.

Table 3: **Performance with or without docstrings on the HumanEval benchmark.** These results highlight the importance of docstrings in the context of function completion.

Models	With docs	Without docs
open_llama_7b_v2	13.4 (2.7)	7.3 (2.0)
mpt-7b	16.4 (2.9)	9.8 (2.3)
starcode	33.5 (3.7)	15.9 (2.9)
WizardCoder-3B	35.4 (3.7)	15.9 (2.9)
WizardCoder-Python-7B	53.0 (3.9)	19.5 (3.1)
WizardCoder-15B	57.9 (3.9)	20.1 (3.1)
Average	34.9	14.8

Q2. Limitations of the docstring reformulation methods in principle: *Are the methods proposed guaranteed to improve the performance of the coder model used during training? Is there any guarantee that the improvement will transfer to other coder models?*

We identify the following challenges that any method for docstring reformulation faces: exploration, noisy learning signal and learning rule, overfitting and generalization.

The exploration challenge is about searching for the best docstring for a given input problem. The search space is huge, as generating docstrings is an open-ended text generation problem. In both the SFT and the OPRO methods we have an exploration process based on the stochastic sampling of the reformulations with an inductive bias encoded as extra information (the reformulation instruction z) in the prompt. This unfortunately doesn't provide any strong guarantees in the ability of finding the best docstrings, thus efficient exploration remains a key obstacle in the proposed methods.

The main signal for learning is the pass rate of the code completions generated by the coder model when receiving as input a given reformulation. We use the pass rate metric to identify the best reformulations and then we either explicitly increase their probability under the reformulator model, in the SFT method, or we reward the reformulation instruction associated with them, in the OPRO method. The challenge of noisy learning signal is that the coder model is stochastic and as such there is a lot of variance associated to the pass rate metric. Furthermore, the metric is computationally intensive to calculate, as one needs to invoke an LLM (the coder model) to obtain one

or more code completions. Thus it might be too costly to arbitrarily reduce the noise if we have a tight computational budget.

Linked to the noise concern within the learning signal is the task of formulating a stable and efficient learning rule that harnesses the learning signal to maximize the task objective.

In the SFT method, for each input problem, we select the best reformulation and increase its probability. This encounters two main problems: first, with high noise levels, we can mistakenly select a non-optimal reformulation as the best one; second, it might be that none of the reformulations is as good as the initial docstring and this can lead to training instabilities. Thus, while in principle this method is quite flexible and it can perform a fine-grained optimization at the reformulation level, it is not well suited to learn from noisy signals.

In the OPRO method, given n instructions with their corresponding scores, we prompt an LLM model to produce a better instruction; therefore, the learning rule is effectively a black box, where the new "learned" instruction is the one sampled by the model. This method can deal quite well with the noise in the learning signal, because each instruction's score is the pass rate averaged over all problems, rather than the pass rate for a single one. However, the OPRO method is reliant on an LLM for implementing the learning rule, which doesn't provide any guarantee of improvement.

Thus, how to design a learning rule to efficiently and robustly learn from a noisy signal is another open challenge in the docstring reformulation task.

Finally, if reformulations exclusively boost a particular coder model's performance while decreasing performance for most other models, they overfit to that model. Conversely, if reformulations enhance the performance of diverse coder models without specific tailoring, they demonstrate generalization across coder models. Empirically, we do not observe any sign of overfitting. We attribute this to the lack of backpropagation through the coder model in the proposed methods, which, we speculate, acts as a regularizer over the optimised reformulations and improves their generalizability. However, we do not have any theoretical guarantees against overfitting, nor in support of the generalizability of the optimized reformulations.

We conclude that the proposed methods face core shortcomings in exploring the reformulation

Table 4: **Performance with Oracle docstrings.** Model Performance when including in the docstring GPT-4-generated hints based on the ground truth solution (*'Oracle Hints'*) and when including in the docstring the ground truth solution (*'Oracle Solutions'*). We compare them with the performance of the coder models on the original HumanEval (*'Original'*).

Models	Original	Oracle Hints	Oracle Solutions
open_llama_7b_v2	13.4 (2.7)	22.6 (3.3)	65.9 (2.7)
mpt-7b	16.4 (2.9)	27.4 (3.5)	53.0 (2.9)
starcode	33.5 (3.7)	40.2 (3.8)	54.9 (3.7)
WizardCoder-3B	35.4 (3.7)	48.2 (3.9)	78.7 (3.7)
WizardCoder-Python-7B	53.0 (3.9)	57.3 (3.9)	79.9 (3.9)
WizardCoder-15B	57.9 (3.9)	59.8 (3.8)	90.0 (3.9)
Average	34.9	42.6	70.4

space and in learning from a noisy feedback signal.

Q3. Limitations of the docstring reformulation methods in practice: *Are there further practical considerations about our experimental setup that could affect the methods' success?*

In addition to the limitations discussed in **Q2**, the proposed methods may be limited by:

- The performance of the initial models used as reformulator as instruction optimizer.
- The choice of the methods' parameters, such as the amount R of reformulations per input problem and the amount C of code completions per reformulations.
- The hyperparameters used for language generation with LLMs and, for the SFT method only, the hyperparameters for the fine-tuning of the reformulator model.
- The specific prompt templates employed.

We pose special emphasis on the first point, as preliminary experiments ruled out a strong dependence from the other points. We run additional experiments to ablate the role of capability of the models employed as:

1. **Reformulator:** We evaluate the coder models on reformulations produced by GPT-4, instead of WizardCoder-Python-7B, prompted with the same reformulation instruction as in the SFT method. We use the original HumanEval dataset for this experiment.
2. **Instruction optimizer:** We reproduce the OPRO experiments for the original HumanEval dataset using GPT-4 as instruction optimizer model, instead of Llama-2-7b-chat.

Regarding the experiments on the reformulator, reported in Table 5, we find no significant difference in performance between the two models for the given reformulation instruction; our qualitative inspection of the generated reformulations supports the conclusion that the selected open-source model can generate docstring reformulations on par with GPT-4 in this specific context.

In the case of the instruction generator experiment, the results for GPT-4, presented in Table 6, are significantly worse than the ones obtained with the selected instruction optimizer. Qualitatively, GPT-4 suggests verbose reformulation instructions, often leading the reformulator to include in the documentation hallucinated information, e.g. about possible invalid inputs. This results in incorrect handling of edge cases in generated code completions and performance degradation.

In summary, our ablation studies in this section show that the limitations of the proposed methods are not linked with the quality of the models selected as reformulator and instruction optimizer, but rather to the points described in **Q2**.

Table 5: **Reformulator model ablation.** We compare the performance of our reformulator model, WizardCoder-Python-7B, without any SFT training against the one of GPT-4.

Models	Reformulated by	
	WizardCoder	GPT-4
open_llama_7b_v2	14.6 (2.8)	15.9 (2.9)
mpt-7b	16.4 (2.9)	18.3 (3.0)
starcode	30.5 (3.6)	28.7 (3.5)
WizardCoder-3B	33.5 (3.7)	37.2 (3.8)
WizardCoder-Python-7B	52.4 (3.9)	51.2 (3.9)
WizardCoder-15B	54.2 (3.9)	49.4 (3.9)
Average	33.6	33.5

Table 6: **Instruction optimizer model ablation for OPRO method.** We compare the performance of our instruction optimizer model, Llama2-7B-chat, against the one of GPT-4, when utilising the OPRO method for 10 iterations. The results for GPT-4 are significantly worse than the ones obtained with the selected instruction optimizer.

Models	Instruction optimizer	
	Llama2	GPT-4
open_llama_7b_v2	14.0 (2.7)	8.0 (2.1)
mpt-7b	17.1 (2.9)	13.4 (2.7)
starcoder	32.3 (3.7)	25.0 (3.4)
WizardCoder-3B	32.3 (3.7)	30.5 (3.6)
WizardCoder-Python-7B	56.1 (3.9)	50.6 (3.9)
WizardCoder-15B	54.9 (3.9)	50.0 (3.9)
Average	34.5	29.6

B Hyper-Parameters used for the experiments

In the following section we report all the hyper-parameters used in our experiments. In Table 7 we report the parameter values for the SFT method, while in Table 8 the ones for the ORPO method. Furthermore, in Table 9 we report the parameters used for generating the reformulations, in Table 10 we report the ones for generating the code completions and finally in Table 11 the PEFT parameters for the SFT method.

In OPRO we also use a variable amount n of past instructions and scores pairs, starting at an arbitrary value of $\min(4, Z)$, where Z is the number of instructions used per iteration of the method, and increasing n of 1 at every iteration. While we haven't ablated this choice, we speculate that smaller n favour exploration by reducing the amount of patterns available to the instruction optimizer, while larger n favour exploitation of features in common between successful past instructions.

Table 7: **Parameter values for SFT method.**

Parameter	Value
Reformulation instructions (Z)	1
Reformulations per problem (R)	2
Code completions per reformulation (C)	2
Method iterations (I)	10

Table 8: **Parameter values for OPRO method.**

Parameter	Value
Reformulation instructions (Z)	5
Reformulations per problem (R)	1
Code completions per reformulation (C)	1
Method iterations (I)	10
Instruction optimizer temperature	1.0
Instruction optimizer top- p	0.8
Instruction optimizer max tokens	200

Table 9: **Parameters for generating reformulations with an LLM.** The OPRO method is always using the evaluation setting for the reformulations, while the SFT method uses the training and evaluation settings in the respective phases. Notice that the batch size does not affect performance and its choice depends on the hardware at disposal and the size of the reformulator model.

Parameter	Training	Evaluation
Batch size	32	32
Temperature	0.2	0
Top- p	0.95	N/A
Max tokens	512	512

Table 10: **Parameters for generating code completions with an LLM.** The OPRO method is always using the evaluation setting for the reformulations, while the SFT method uses the training and evaluation settings in the respective phases. At evaluation time, the batch size is adjusted depending on the size of the coder model (however it does not affect performance).

Parameter	Training	Evaluation
Batch size	32	'custom'
Temperature	0.2	0
Top- p	0.95	N/A
Max tokens	768	768

Table 11: **PEFT parameters for training the reformulator in the SFT method.**

Parameter	Value
LoRA r	8
LoRA α	32
LoRA dropout	0.1
Batch size	4
Gradient accumulation steps	8
Max sequence length	768
Learning rate	2×10^{-5}
Number of training epochs	1

B.1 Prompt templates

In both the SFT and the OPRO methods, we present the reformulation instruction z and the input problem x to the reformulator using the following template:

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

```
### Instruction:
```

```
{z}
```

```
### Input:
```

```
{x}
```

```
### Response:
```

```
{imports_and_def}  
    """
```

This was used by [Luo et al. \(2023\)](#) to train the WizardCoder suite of code LLMs and was adopted in this work because, after preliminary tests, a WizardCoder model was chosen as our reformulator.

We append at the end of the template the library imports and the function definition (until the `"""` that marks the start of the docstring in Python programs) contained in x to facilitate the reformulation task. This is because both the imports and the function definition are meant to remain fixed in the task and they provide additional context to generate a high-quality docstring in the reformulation.

The OPRO method uses also the following seed reformulation instructions:

1. Improve the docstring of the following function using the best coding conventions.
2. Rephrase the following python code maintaining the function name and signature:
3. Clarify the following python function by rewriting the docstring:
4. Expand the documentation of the following python function suggesting how to implement it:
5. Rewrite the documentation of the following function:

C Independent replication of open-source LLMs on HumanEval

For the evaluation setup, in addition to the original coder model, we consider 5 other LLMs with model sizes ranging from 3B to 15B parameters: OpenLlama-2-7B-V2 ([Geng and Liu, 2023](#); [TogetherComputer, 2023](#)), MPT-7B ([MosaicML, 2023](#)), starcoder (15B) ([Li et al., 2023](#)), WizardCoder-3B and WizardCoder-15B ([Luo et al., 2023](#)). These models were selected as a representative subset of the open-source LLM landscape and had to satisfy the following criteria:

1. They had to be available on Hugging Face.
2. Their prior performance on HumanEval had to be reported online from the authors of the models or from a trustworthy third party.
3. Their performance on HumanEval had to be reproducible by the authors of this work within reasonable limits.

The results for the models of which we could reproduce the reported performance are presented in [Table 12](#), while the results for the models whose performance couldn't be replicated are presented in [Table 13](#). Importantly, we do not imply that these models cannot yield the reported performance, but rather that model performance depends on many undocumented factors, such as the prompting strategy, the post-processing of the model output and the versions of the libraries used in the implementation.

We also tried to download [teknium/Replit-v1-CodeInstruct-3B](#) and [Salesforce/xgen-7b-8k-base](#) as other performing models whose performance was replicated with open-source code, but we encountered errors in using them with version 4.31 of the `HuggingFaceTransformers` library. Different library versions caused other LLMs to drop in performance, thus we ran all experiments with this version of the library.

D Results for bad formatting HumanEval

We report in [Table 14](#) the results for the SFT and the OPRO methods on the bad formatting variant of HumanEval.

E Faulty variants of HumanEval

In [Figure 4](#) we report an example of an input problem together with all the four different faults that we implement in this work.

Original

```
def string_xor(a: str, b: str) -> str:
    """ Input are two strings a and b consisting only of 1s and 0s.
    Perform binary XOR on these inputs and return result also as a string.
    >>> string_xor('010', '110')
    '100'
    """
```

Misspelling

```
def string_xor(a: str, b: str) -> str:
    """ Input are two strings a and b consisting only of 1s and 0s.
    Perform binary XORg on these inputs and return result also as a string.
    >>> string_xor('010', '110')
    '100'
    """
```

Distractor

```
def string_xor(a: str, b: str) -> str:
    """ Input are two strings a and b consisting only of 1s and 0s.
    Perform binary XOR on these inputs and return result also as a string.
    >>> string_xor('010', '110')
    '100'
    Returns:
    list[int]: A list of integers
    """
```

Ambiguity

```
def string_xor(a: str, b: str) -> str:
    """ Input are two strings a and b consisting only of 1s and 0s.
    Perform binary XOR on these inputs and return result also as a string.
    """
```

Bad formatting

```
def string_xor(a, b):
    """ Input are two strings a and b consisting only of 1s and 0s.
    Perform binary XOR on these inputs and return result also as a string.
    string_xor('010', '110')
    '100'
    """
```

Figure 4: **Examples of faulty docstrings.** Example of an input problem from the original HumanEval benchmark and of its faulty versions.

Table 12: **Independent verification of selected LLMs performance on HumanEval.**

Model	Our Setup	Best Reproducible (GitHub)	Best Reported (Paper)
open_llama_7b_v2	13.4	14.0	N/A
mpt-7b	16.4	15.9	18.3
starcoder	33.5	34.6	33.6
WizardCoder-3B	35.4	N/A	34.8
WizardCoder-Python-7B	53.0	N/A	55.5
WizardCoder-15B	57.9	57.0	59.8

Table 13: **Independent verification of excluded LLMs performance on HumanEval.** WizardCoder-1B and the base model of Llama-2-7b work to some extent, but are not close enough to the reference values to be selected for the main studies. We were not able to make the CodeLlama family of models work and it is not clear where the big gap in performance comes from.

Model	Our Setup	Best Reproducible (GitHub)	Best Reported (Paper)
WizardCoder-1B-V1.0	18.9	N/A	23.8
Llama-2-7b-hf	11.6	13.1	12.8
CodeLlama-Python-7b	3.0	N/A	38.4
CodeLlama-Python-13b	5.5	N/A	43.3
CodeLlama-Instruct-7b	7.9	N/A	34.8
CodeLlama-Instruct-13b	4.3	N/A	42.7

Table 14: **Results for HumanEval with bad formatting fault.** We removed these results from the main results because the fault introduced did not affect on average the performance of the selected LLMs.

* is used as coder model by SFT and OPRO also during training.

Models	Initial	Reformulated	
		SFT	OPRO
open_llama_7b_v2	12.1 (2.5)	13.4 (2.7)	11.6 (2.5)
mpt-7b	17.7 (3.0)	17.7 (3.0)	16.5 (2.9)
starcoder	35.4 (3.7)	34.8 (3.7)	32.9 (3.7)
WizardCoder-3B	32.9 (3.7)	31.7 (3.6)	32.9 (3.7)
WizardCoder-Python-7B	53.0 (3.9)	56.1 (3.9)	57.3 (3.9)
WizardCoder-15B	58.5 (3.8)	55.5 (3.9)	55.5 (3.9)
Average	34.9	34.9	34.5

Benchmarking Diffusion Models for Machine Translation

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Abstract

Diffusion models have recently shown great potential on many generative tasks. In this work, we explore diffusion models for machine translation (MT). We adapt two prominent diffusion-based text generation models, Diffusion-LM and DiffuSeq, to perform machine translation. As the diffusion models generate non-autoregressively (NAR), we draw parallels to NAR machine translation models. With a comparison to conventional Transformer-based translation models, as well as to the Levenshtein Transformer, an established NAR MT model, we show that the multimodality problem that limits NAR machine translation performance is also a challenge to diffusion models. We demonstrate that knowledge distillation from an autoregressive model improves the performance of diffusion-based MT. A thorough analysis on the translation quality of inputs of different lengths shows that the diffusion models struggle more on long-range dependencies than other models.

1 Introduction

Diffusion models have shown promising results in a wide range of generative tasks, such as image generation (Ho et al., 2020; Nichol et al., 2022), text-to-speech synthesis (Jeong et al., 2021), and robotic control (Chi et al., 2023), but their application to natural language processing (NLP) is still a less explored direction. The last two years have seen various approaches to this (Zou et al., 2023), including discrete (token level) diffusions (Reid et al., 2022) and continuous (embedded) diffusions. Continuous diffusion models typically generate whole sequences in an iterative and non-autoregressive (NAR) manner, and have shown strong results for controllable generative modelling (Li et al., 2022; Chen et al., 2023). They have also been applied to sequence-to-sequence tasks such as open-domain dialog and question generation (Gong et al., 2023; Yuan et al., 2022). In this work,

we focus on machine translation (MT), another sequence-to-sequence task that requires fluent outputs over a vocabulary different from the input and the preservation of semantic meanings of the input sequences. Despite potential speed advantages¹, NAR translation models tend to lag behind their AR counterparts in translation quality² (Libovický and Helcl, 2018; Gu et al., 2019; Gu and Kong, 2021; Kasai et al., 2021) as a result of the *conditional independence assumption*, where output tokens are generated independent of each other. This prompts us to compare diffusion-based MT models to conventional NAR MT models. We explore how techniques commonly applied to NAR MT models could benefit diffusion-based models. Specifically, we seek to answer the following questions: **1)** How can we adapt existing diffusion-based text generation models to machine translation? **2)** How do these diffusion-based MT models compare to standard AR and NAR machine translation models? **3)** What are reasons for the performance gap and how can we bridge the gap?

2 Background and Related Work

2.1 Diffusion Models

While there exist many other families of diffusion models³, we limit our discussion on the denoising diffusion probabilistic model (DDPM) (Ho et al., 2020), which can be viewed as a variational diffusion model (Sohl-Dickstein et al., 2015; Ho et al., 2020; Kingma et al., 2021). In general terms, a diffusion model is a type of generative model that learns to model the probability distribution of given datasets. Its essential components are: 1) the *forward process* in which noise is iteratively added

¹which has been called into question under realistic conditions (Helcl et al., 2022)

²Some recent exceptions include Qin et al. (2022) based on hybrid NAR and AR generation.

³We refer interested readers to Luo (2022) for a more general coverage.

to the data, i.e., the data is diffused for a given number of time steps; 2) a predefined *noise schedule* which determines the amount noise added at every time step; 3) the parametric *backward process* that is optimized to match the time-reverse forward process, thereby recreating the data sample. Specifically, the stochastic model consists of $T + 1$ random variables with T indicating the number of time steps. These random variables include the observation variable \mathbf{X}_0 and T latent variables $\mathbf{X}_1, \dots, \mathbf{X}_T \in \mathbb{R}^d$. Between them, we assume a conditional probability distribution with some regularity constraints⁴, commonly a normal distribution with the mean and variance being dependent on the previous state. The process is illustrated with the light gray nodes in Figure 1.

Forward Process In the forward process, the observed information is diffused by the conditional probability adding a small amount of noise in each step according to the *noise schedule* $(\alpha_i)_{i=1}^T$ where α_i defines the noise applied in the i th time step⁵. Therefore, the forward process is a time-discrete stochastic process, which can be described by $q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t|\sqrt{\alpha_t}\mathbf{x}_{t-1}, (1 - \alpha_t)I_d)$ for $t = 2, \dots, T$ (Li et al., 2022; Luo, 2022; Ho et al., 2020). Utilizing the formula for conditional multivariate normal distributions, we can derive

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}\left(\mathbf{x}_{t-1} | \mu(\mathbf{x}_t, \mathbf{x}_0), \frac{(1 - \bar{\alpha}_{t-1})(1 - \alpha_t)}{1 - \bar{\alpha}_t} I_d\right). \quad (1a)$$

where

$$\mu(\mathbf{x}_t, \mathbf{x}_0) := \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})\mathbf{x}_t + \sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)\mathbf{x}_0}{1 - \bar{\alpha}_t}. \quad (1b)$$

Backward Process The Markovian backward process is defined as $p(\mathbf{x}_{t-1}|\mathbf{x}_t) = q(\mathbf{x}_{t-1}|\mathbf{x}_t, \hat{\mathbf{x}}_0(\mathbf{x}_t))$ using a neural network $\hat{\mathbf{x}}_0(\mathbf{x}_t)$ to estimate the initial data \mathbf{x}_0 in every step (Li et al., 2022). Sampling from the model corresponds to first sampling $\mathbf{X}_T \sim \mathcal{N}(0, 1)$ and then sampling a backward trajectory in an iterative manner. An example trajectory is illustrated in Appendix A. Accordingly the Evidence Lower Bound (ELBO) of $\log p_\theta(\mathbf{x}_0)$ for training data \mathbf{x}_0 is used as a loss function (Luo, 2022).

2.2 Diffusion Models for Language Modeling

Language modeling is the task of assigning probabilities to sequences of words $y_{1, \dots, n}$ and is a central

⁴Specifically a Markov kernel in the mathematical sense.

⁵For which $\bar{\alpha}_T \simeq 0$, where $\forall i \in \{1, \dots, T\}$: $\bar{\alpha}_i := \prod_{t=1}^i \alpha_t$ and $\alpha_i \in (0, 1)$ needs to hold.

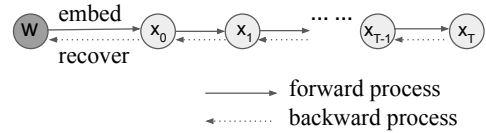


Figure 1: An illustration of the forward and backward diffusion processes for text generation.

task in NLP. Here we describe two prominent approaches of using diffusion models for language modeling: Diffusion-LM (Li et al., 2022) and Dif-fuSeq (Gong et al., 2023). Although similar in principle, DiffuSeq uses *classifier-free guidance* (Ho and Salimans, 2022) to model a conditional diffusion process for sequence-to-sequence tasks.

2.2.1 Diffusion-LM

The model underlying Diffusion-LM (Li et al., 2022) is similar to the DDPM (Ho et al., 2020) proposed for image generation. A main difference is the extra requirement of handling text outputs, which are *discrete* in nature unlike images. This calls for two modifications illustrated on the left-hand-side of Figure 1: when *embedding* the text as training targets, and when *recovering* the discrete tokens from continuous diffusion states.

Embedding Function To embed discrete text tokens, a word embedding lookup table is used as in many other NLP models. This means the embedding function E_θ is simply a context-free token-wise embedding. It is only used to obtain the training targets during training and when filling in masked data. The embedding vectors are optimized end-to-end together with the backward process, as Li et al. (2022) found pretrained word embeddings degraded performance.

Recovery Function When generating the text outputs, i.e., mapping from continuous diffusion states to discrete tokens, the recovery function R_θ is a linear layer followed by a softmax activation, like the output layer in most NLP models. It can be viewed as a nearest neighbour lookup in the embedding space. Like the word embeddings, the weights of the recovery function are also trained jointly with the diffusion model. Moreover, as recovering from the diffusion states to single word embeddings (i.e., committing) is often difficult, Li et al. (2022) proposed a *clamping trick* to force the model to commit to certain word embeddings at intermediate diffusion steps. Specifically, this is achieved by mapping the predicted initial data

$\hat{x}_0(\mathbf{x}_t)$ to the closest word embedding sequence at each time step.

Classifier Guidance Although Diffusion-LM can be used as a language model in general, its main focus is controllable text generation (Li et al., 2022), where the backward process is modified for the end result to satisfy one or multiple control targets, such as sentiment or syntactic structure. In most experiments⁶ by Li et al. (2022), control is achieved by *classifier guidance*, i.e., training a classifier to model $\mathbf{P}(\cdot|\mathbf{X}_t)$ on the diffusion latent variables \mathbf{X}_t , and running gradient updates $\nabla_{\mathbf{X}_t} \log \mathbf{P}(\text{desired class}|\mathbf{X}_t)$ at each step during the backward process. The text generation process is thereby guided towards desired classes.

Infilling Procedure For the task of filling in missing data, e.g., sentence completion based on sounding sentences, Diffusion-LM uses the *infilling algorithm*. This approximates conditional distributions where the variable we want to condition on is already modelled by the diffusion model, and is comparable to the image inpainting capability (Lugmayr et al., 2022) of diffusion models for image generation. To achieve this, the conditioning information is kept fixed at its desired value throughout the backward process.

2.2.2 DiffuSeq

Difference to Diffusion-LM Unlike Diffusion-LM which focuses on controllable generation, DiffuSeq (Gong et al., 2023) focuses on sequence-to-sequence tasks, and the authors argue that classifier guidance is insufficient for this type of task, since the fine-grained input-output relation cannot be achieved by a finite number of classifiers. The authors therefore propose a *classifier-free* approach.

Classifier-Free Diffusion Bypassing classifier guidance, DiffuSeq (Gong et al., 2023) directly models the transformation between (source \oplus random) and (source \oplus target) where \oplus indicates the concatenation operation. Specifically, DiffuSeq models the distribution of the target sequence conditioned by the source sequence. To achieve that, DiffuSeq used *conditional noising*, which only applies noise to the target sequence while leaving the source sequence fixed. This is done both in training and sampling/decoding. The sampling procedure is analogous to the infilling procedure of

⁶One exception out of their 6 setups is the infilling experiment, which does not need a classifier.

Diffusion-LM as a result.

2.3 Non-Autoregressive Models and the Multimodality Problem

Non-autoregressive Transformer models (NAT) (Gu et al., 2018) are based on the conditional independence assumption, where the generation of tokens in the target sequence does not depend on each other. While allowing for a rapid decoding process, this introduces the *multimodality problem* (Gu et al., 2018) due to nondeterminism in the dataset. Nondeterminism in the dataset can be explained by the example of German sentences “*Danke schön*” and “*Vielen Dank*” both being possible translations of “Thank you”, but a model following the conditional independence assumption cannot allow both variants (Gu et al., 2018). Diffusion models do not follow the conditional independence assumption, so it is unclear whether the nondeterminism in the dataset impacts model performance.

3 Adapting Diffusion Models to Machine Translation

Machine translation is an instance of the conditional language modeling problem. Specifically, it aims to automatically translate text from one *source* language to another *target* language, and may be described as modeling the distribution over the target space conditioned by a sequence from the source space. Currently, the primary model choice for machine translation is the encoder-decoder architecture, especially the Transformer (Vaswani et al., 2017), where an encoder module first encodes the source sequence, passing the encoding on to the decoder, which autoregressively generates an output sequence conditioned by the source encoding.

To this end, formally we describe the probability of a sequence y given the conditioning information x under the transformer model p_θ :

$$p_\theta(y;x) = \prod_{i=1}^{|y|} \underbrace{p_\theta(y_i|y_1, \dots, y_{i-1}; x)}_{\text{modelled explicitly}}. \quad (2)$$

Considering that the diffusion models described in §2.2 generate sequences en bloc, we constrain our problem to only consider pairs of sequences of a combined maximum length S . Accordingly, sequences are padded or truncated to the length S .

3.1 Diffusion-LM for Machine Translation

Reasons for a Classifier-Free Approach As introduced in §2.2.2, the source-target transforma-

tion required for machine translation is more complex than controllable generation guided by discrete classes. Specifically, it requires the model to safeguard against alterations in semantic meaning and demonstrate the ability to pay close attention to different words in the source sequence depending on the token in the target sequence. So for a classifier guidance approach, one could potentially train a Transformer model to back-translate from target to source, and use gradients from this model to guide the generation. However, as the generation output is highly dependent on the guiding model, it remains questionable whether this approach provides any benefits over an autoregressive Transformer model. This motivated us to approach diffusion-based machine translation by classifier-free guidance.

Approach We use a shared dictionary $V = V_s, V_t$, and seek to model the joint distribution $\mathbf{J} : \mathcal{P}(V^S) \rightarrow [0, 1]$ of pairs of source and target sequences by training Diffusion-LM on this task. Given a set of training source and target pairs $(s^{(1)}, t^{(1)}), \dots, (s^{(n)}, t^{(n)})$, we use the concatenated source-target sequences, where $j^{(i)} = s^{(i)} \oplus (\hat{s}) \oplus t^{(i)}$ for $i \in [1, n]$. The source and target sequences are separated by a reserved separator token $\hat{s} \in V$. A Diffusion-LM model is then trained to maximize the likelihood of the training sequences $j^{(1)}, \dots, j^{(n)}$. By using the infilling algorithm to approximate the conditional distribution of the target sequence given the source sequence, translation is then performed without relying on classifier guidance.

3.2 DiffuSeq for Machine Translation

As DiffuSeq is proposed for sequence-to-sequence tasks, we can directly apply it on machine translation. Like the Diffusion-LM-based model, the DiffuSeq-based models use shared vocabularies $V_s, V_t = V$. The sampling algorithm is the same as the infilling algorithm for Diffusion-LM (Gong et al., 2023).

3.3 Sequence-Level Knowledge Distillation

Motivated by theories and findings in the machine translation and linguistics literature, we proceed to improve diffusion-based translation models.

To tackle the multimodality problem (§2.3) of non-autoregressive translation models, Gu et al. (2018) showed positive results with sequence-level knowledge distillation (Kim and Rush, 2016). In

general terms, this can be achieved by sampling a translation of the source sequences in the train set. When an autoregressive teacher model is available, one can achieve this by decoding the source sequence with the teacher model using the beam search algorithm as usual. The resulting translations constitute a new, distilled dataset. This kind of knowledge distillation makes the resulting training targets less noisy and more deterministic, ensuring that for instance “Thank you” will be consistently translated into the same German translation (§2.3).

Prior works from different disciplines provided theoretical support for the impact of distillation in translation. From a machine learning perspective, Zhou et al. (2020) showed distillation reduces the conditional entropy of the translations given the source sequences. They further showed distilled targets contained more words monotonically aligned with their direct translations in the source sequence. We argue this phenomenon can be viewed as *syntactic conditional entropy*, measuring the amount of uncertainty in the sentence structures. From a linguistic perspective, Bangalore et al. (2015) showed translations with low syntactic entropy are easier to produce.

As stated in §2.3, diffusion-based machine translation models do not follow the conditional independence assumption of NAT models, as they generate a trajectory of sequences $(\mathbf{x}^{(t)})_{1 \leq t \leq T}$ where for $1 \leq t < T, 1 \leq s \leq S$ the column $\mathbf{x}_s^{(t)}$ (which corresponds to a token embedding vector) is influenced by the whole sequence $\mathbf{x}^{(t+1)}$. Li et al. (2022) found that empirically learned word embeddings formed clusters of words with the same part-of-speech tags. Generally a diffusion models noise schedule should be rather smooth with no major jumps, so that the individual columns of the trajectory first drift towards a cluster of word embeddings early and commit to a single embedding later in the process. This leads to the assumption that a sequence’s syntactic structure is first decided, before the model finally commits to individual words.

The syntactic conditional entropy of a training dataset could lead to a multimodality problem of diffusion models, where different syntactic structures represent the different modes in the early diffusion process. As distilled datasets exhibit lower syntactic conditional entropy, sequence-level knowledge distillation could improve the results of diffusion-based machine translation models. Motivated by this, we investigate how knowledge distil-

lation impacts the translation performance of diffusion models.

3.4 Autoregressive Sampling

Besides empirical successes of autoregressive models, the sequential nature of text suggests that generating one token at a time is a promising approach to text generation. Consequently, we wonder whether diffusion-based machine translation systems are limited in performance by fixing all tokens of the generated sequence at once. Indeed, a very recent work (Yuan et al., 2022) showed improvements by considering the sequential nature of the outputs, more specifically by learning to apply different noise levels to each token at every time step.

In the context of our approach, Diffusion-LM approaches the inclusion of prior data by the infilling algorithm. Building upon that, we propose an iterative sampling method, where in the each iteration i the first $i - 1$ tokens of the last iterations output are served to the model as prior information. This conditional probability is approximated by the infilling algorithm.

So by sampling

$$(\mathbf{x}_1^{(i)}, \dots, \mathbf{x}_S^{(i)}) \sim p(\mathbf{x}_1, \dots, \mathbf{x}_S | \mathbf{x}_1 = \mathbf{x}_1^{(i-1)}, \dots, \mathbf{x}_{i-1} = \mathbf{x}_{i-1}^{(i-1)}) \quad (3a)$$

and discarding $(\mathbf{x}_{i+1}^{(i)}, \dots, \mathbf{x}_S^{(i)})$ we approximate

$$p(\mathbf{x}_i^{(i)} | \mathbf{x}_1 = \mathbf{x}_1^{(1)}, \dots, \mathbf{x}_{i-1} = \mathbf{x}_{i-1}^{(i-1)}) \quad (3b)$$

yielding the usual autoregressive formula:

$$\hat{p}(\mathbf{x}_1^{(1)}, \dots, \mathbf{x}_S^{(S)}) = p(\mathbf{x}_1^{(1)}) \prod_{i=2}^S p(\mathbf{x}_i^{(i)} | \mathbf{x}_1 = \mathbf{x}_1^{(1)}, \dots, \mathbf{x}_{i-1} = \mathbf{x}_{i-1}^{(i-1)}) \quad (3c)$$

Algorithm 1 describes the sampling algorithm in detail. For the naive implementation given there, this increases the time needed for decoding by a factor of $\mathcal{O}(S)$. However, when detecting the end of the generation process, this factor is in $\mathcal{O}(\text{average generated sequence length})$.

4 Experimental Setup

Dataset and Preprocessing We use the German-English text-to-text partition of the CoVoST (Wang et al., 2020) dataset and train the models for German-to-English translation. This dataset was chosen due to its comparable size to the experimental setup of Li et al. (2022), which used 50K to 98K samples in training. Due to the slow decoding process of the autoregressive sampling method, the

Algorithm 1 Autoregressive sampling

```

1: Input
    $s \in V^l, 1 \leq l \leq \frac{S}{2}$    The source sequence
   ▷ Initialize the translation as the empty word
2:  $t \leftarrow \epsilon$ 
3: for  $k = l + 2, \dots, S$  do
4:    $j \leftarrow s \oplus (\hat{s}) \oplus t$ 
5:   Pad  $j$  up to length  $S$ 
   ▷ Embed concatenated sequence
6:    $\tilde{\mathbf{x}} \leftarrow E_\theta(j)$ 
   ▷ Calculate the mask
7:    $m_i = 1$  for  $1 \leq i \leq |j|$ 
8:    $m_i = 0$  for  $|j| + 1 \leq i \leq S$ 
9:   Draw  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, I_{d \times S})$ 
10:  for  $t = T - 1, \dots, 0$  do
   ▷ With  $\Sigma_{t+1}$  as described in equation (1a).
11:    Draw  $\mathbf{x}_t \sim \mathcal{N}(\mu_\theta(\mathbf{x}_{t+1}, t + 1), \Sigma_{t+1})$ 
   ▷ Overwrite where the data is given by  $\tilde{\mathbf{x}}$ 
12:     $\mathbf{x}_{t,i} \leftarrow \tilde{\mathbf{x}}_i$  where  $m_i = 1$ 
13:  end for
   ▷ Recover the most likely token for position  $k$ 
14:   $t \leftarrow t \oplus \underset{j \in V}{\operatorname{argmax}} R_\theta(\mathbf{x}_0)_{k,j}$ 
15: end for
   ▷ Return the sequence of generated tokens  $t$ 
16: return  $t$ 

```

Split	# samples	Avg. source len.	Avg. target len.
train	127,638	12.6	12.41
valid	13,510	13.16	13.02
test (reduced)	2,010	13.6	13.47

Table 1: Key metrics of the dataset CoVoST, with the tokenizer used here and the reduced test split.

test set was reduced to a subset of 2010 samples.⁷ The dataset statistics are in Table 1. Details on preprocessing are in Appendix B.

Evaluated Diffusion Models We evaluate 4 types of diffusion models described in §3:

1. **Diffusion-LM-MT**: Diffusion-LM adapted with classifier-free diffusion (§3.1)
2. **DiffuSeq**: the standard DiffuSeq model (§3.2)
3. **DiffuSeq, Distilled**: DiffuSeq with sequence-level knowledge distillation (§3.3)
4. **DiffuSeq, AR-Sampling**: DiffuSeq with autoregressive sampling (§3.4)

We use a max length of 64 tokens following Diffusion-LM (Li et al., 2022). For the knowledge distillation dataset, we use the pretrained model by Ng et al. (2019) as the teacher model. More details on the model architectures are in Appendix C. For all models, the encoder in the diffusion kernel is parameterized by a network following the BERT-based architecture. All weights are initialized randomly following Li et al. (2022).

⁷The reduced test set is available under https://drive.google.com/file/d/1nj2S7d0LGBel7ZR4AWbVCxEFVcgWg_V3/view?usp=drive_link

Model	BLEU \uparrow	COMET \uparrow
Diffusion-LM-MT	2.2	39.2
DiffuSeq	10.0	48.0
DiffuSeq, AR-Sampling	10.7	48.1
DiffuSeq-distilled	12.5	49.7
Transformer	28.7	72.2
Levenshtein-Transformer	18.5	61.4

Table 2: Direct comparison of models by BLEU score and COMET score under the wmt22-comet-da score.

Sampling All models used a step size of 1 during the sampling process. This results in a very long decoding time, as the diffusion kernel needs to be evaluated in every iteration. Using a lower number of diffusion steps during sampling accelerates the sampling process, but generally leads to decreased performance (Li et al., 2022; Gong et al., 2023).

Baselines We use a Transformer model (Vaswani et al., 2017) as the main baseline. Given the non-autoregressive nature of diffusion models, we also compare to Levenshtein Transformer (Gu et al., 2019), an established NAT model. More details on the baselines are in Appendix D.

Evaluation The detokenized results of all implementations and baselines were evaluated by BLEU-scores by SacreBLEU (Post, 2018) and by the wmt22-comet-da model (Rei et al., 2022), which is the default COMET model at the time of writing. Both scores are reported as $\times 100$ for readability.

5 Results and Discussions

5.1 Translation Quality

The results of the proposed models and the baselines are presented in Table 2. All diffusion-based models heavily underperformed compared to both the Transformer model and the Levenshtein-Transformer with a large gap of over 15 BLEU.

Compared to the standard DiffuSeq, the model employing sequence-level knowledge distillation (**DiffuSeq-distilled**) showed a unclear improvement of +2.5 BLEU and +1.7 COMET. This provides some support to our hypothesis in §3.3 on knowledge distillation’s positive role in face of the multimodality problem. The model with autoregressive sampling method (**DiffuSeq, AR-Sampling**) brings a gain of +0.7 BLEU but does not improve the COMET score. Therefore, whether this approach has any impact on translation quality remains unclear. This suggests that the inclusion of prior knowledge by the infilling algorithm

has little impact on the model’s generation process. The **Diffusion-LM-MT** model, modeling the joint distribution performed poorly when faced with the task of translating the test data. When sampling from the Diffusion-LM model without the infilling algorithm, the model successfully generated pairs of German and English sentences. The data generated by this unguided approach, when evaluated by the reference-free COMET model wmt20-comet-qe-da (Rei et al., 2020) achieved a score⁸ of 8.72. However, when faced with the challenge of translating the test set, the score fell to 0.94. This suggests that the infilling algorithm in its current form is ill fit to properly approximate conditional distributions as complex as machine translation tasks.⁹

5.2 Impact of Source Lengths

Next we investigate the impact of the input length on the translation quality of all models in the experiments. When the translated samples are split into buckets of roughly equal size by the length of the source sequence, we notice the diffusion language models fall off notably faster in BLEU score compared to the baseline transformer model, suggesting that *long-range dependencies* might be more problematic for these models to capture.

We formally test this by evaluating the relative difference in BLEU scores $d_r(\text{BLEU}_a, \text{BLEU}_b) := \frac{\text{BLEU}_a - \text{BLEU}_b}{\max\{|\text{BLEU}_a|, |\text{BLEU}_b|\}}$ between pairs of translation systems a and b . The relative difference followed linear trends, so we performed a t-test of slopes, testing against the null hypothesis “The relative difference in BLEU is uncorrelated to the length of the source sequence in tokens.”. The resulting test statistics and the statistically significant results are in Table 3.

While the results from the autoregressive sampling method for DiffuSeq are slightly better than those of the standard sampling procedure for long source sequences, our experiments did not provide statistically significant data indicating that this method provides a particular benefit on long sequences. Furthermore, the DiffuSeq-distilled model utilizing knowledge distillation achieves

⁸Scores are not comparable to those in Table 2 due to a different COMET model with reference-free evaluation.

⁹This might indicate that during the generation process interdependencies within the German and English sentence are generally more influential than the cross dependency between the sequences, which also provides an explanation for the improved performance of the DiffuSeq model. This hypothesis would need further testing however.

Models	DiffuSeq	DiffuSeq, AR	Transformer	Diffusion-LM-MT	Lev-Transformer	DiffuSeq-distilled
DiffuSeq	–	0.40	11.29	-2.89	4.95	-0.20
DiffuSeq, AR	-0.40	–	9.88	-2.55	4.06	-0.56
Transformer	-11.29	-9.88	–	-10.42	-7.36	-10.97
Diffusion-LM-MT	2.89	2.55	10.42	–	7.33	2.69
Lev-Transformer	-4.95	-4.06	7.36	-7.33	–	-4.97
DiffuSeq-distilled	0.20	0.56	10.97	-2.69	4.97	–

Table 3: Test statistics for the t-test of slopes with critical value $t_{1987}(0.995) \simeq 2.58$ for a 1% significance level. Pairs where the null hypothesis "The relative difference of scores is uncorrelated to the length of the source sequence" can be rejected and where the slope is positive are marked in bold. By this, a positive test statistic indicates a significant impact of the length of the source sequence on the relative performance of the models, indicating that the model at the top of the column performs relatively better on longer sequences than the model at the start of the row.

Models	Training Time	# of steps	Batch Size	Decoding Time	GPUs
Lev-Transformer	19h	300,000	128	6s	1 NVIDIA RTX 3070
Diffusion-LM	3d 6h	600,000	128	1h 44m 46s	1 NVIDIA TITAN RTX
DiffuSeq	14d 9h	80,000	2048	3h 23m 17s	1 NVIDIA TITAN RTX
DiffuSeq AR	14d 9h	80,000	2048	>30h	1 NVIDIA TITAN RTX
DiffuSeq-distilled	10d 12h	60,000	2048	3h 23m	1 NVIDIA TITAN RTX

Table 4: Key metrics on the training and decoding times of the different non-autoregressive models. Decoding times are reported for the entire reduced test set containing 2010 samples. When re-evaluating the decoding time for the Levenshtein Transformer after the initial submission, times between 8.4 and 14.8 seconds were measured.¹⁰

higher scores than the standard DiffuSeq model overall, but follows the same trends as the standard DiffuSeq model over increasing length of the source sequences.

The non-autoregressive Levenshtein Transformer consistently outperforms all diffusion-based models, but also falls off faster than the autoregressive Transformer model on longer sequences.

5.3 Training and Decoding Time Comparison

Key metrics on the training and decoding times of the various non-autoregressive models are summarized in Table 4. The diffusion-based models suffer from long training and decoding times. For training time, the slow optimization process can be explained by two factors. Firstly, the model essentially faces the problem of guessing the whole target sequence based on the source sequence by a single evaluation of an encoder stack, which is a very hard problem. Secondly, the DiffuSeq and DiffuSeq-distilled models both rely on large batch sizes to avoid converging to trivial distributions. The slow decoding speed on the other hand is largely explained by the number of diffusion steps, as the decoding process in our case requires 2000 iterations of the encoder stack. A remedy would be to down-sample the number of diffusion steps taken (Song et al., 2021) at the cost of sample quality (Gong et al., 2023).

5.4 Translation Samples

Some translation examples by the different models are shown in Table 5. With the shortest input, all systems are able to translate correctly apart from the Diffusion-LM-based models. With the two longer input sequences, despite mostly capturing the rough meaning of the input, the non-autoregressive models in general exhibit problems with output fluency. An exception is the Diffusion-LM-based model which hallucinates translations that are unrelated to the input. This is an indication that the conditional information from the source is disregarded by the model.

5.5 Open Questions

Tackling Multimodality The experiment results indicate that similarly to other NAR models the multimodality problem presents a challenge to diffusion models, with knowledge distillation providing clear benefits for the performance and convergence properties of diffusion-based MT models. The improved performance of the model utilizing sequence-level knowledge distillation is likely due to decreased nondeterminism in the dataset, which is in-line with other findings on non-autoregressive translation systems (Gu et al., 2018). Consequently, the applicability of other methods employed to tackle the multimodality problem in NAR models

¹⁰The DiffuSeq-based models still showed improvement even after extensive training duration

Source	Robert Simonds ist verheiratet.
Target	Robert Simonds is married.
Transformer	Robert Simonds is married.
Diffusion-LM	Robert -ieew is married.
DiffuSeq	Robert Simonds is married.
DiffuSeq, AR	Robert Simonds is married.
Lev-Transformer	Robert Simonds is married.
DiffuSeq-distilled	Robert Simonds is married.
Source	Der Duft von Fruehling stroemte in ihre Nase.
Target	The fragrance of spring floated into her nose.
Transformer	The The fragrance of spring running in her nose.
Diffusion-LM	The of of them ran about the body in the basement.
DiffuSeq	The frag of remain in their nose.
DiffuSeq, AR	The frag of internationally ended in their nose..
Lev-Transformer	The jce of spring, and comes in their ne.
DiffuSeq-distilled	The frag of their fragrance in their nose.
Source	Gleichzeitig wurde mit der Elektrifizierung des Netzes begonnen.
Target	Electrification of the network began at the same time.
Transformer	At the same time, the electrification of the network was started.
Diffusion-LM	It was closed with the populationun of fin during city of Baden.
DiffuSeq	At the same time , the similar railway board has been areas in the network.
DiffuSeq, AR	At the same time , the upper sub sh of the network was moved.
Lev-Transformer	At the same time, the electrification was started with the netnetwork.
DiffuSeq-distilled	At the same time , Soviet inv independent of the estate was started.

Table 5: Examples of translations from the different systems.

to diffusion-based MT models should be studied.

Output Diversity A potential advantage of diffusion models is the diversity of the generated outputs. We did not explore how knowledge distillation affects the diversity score of the system. Gong et al. (2023) showed that DiffuSeq scores high in the diverse 4-gram (Deshpande et al., 2019) score measuring the ration of distinct 4-grams in a set of outputs for one source sequence. Quite possibly the increased quality of samples when using sequence-level knowledge distillation comes at a trade-off for decreased diversity of generation outputs. The diversity of results given different seeds for the generation process can also be leveraged by applying Minimum Bayes Risk (MBR) decoding (Kumar and Byrne, 2004), where each candidate from a set of translations is assigned a risk based on how similar it is to the other candidates. The candidate with the lowest risk is then chosen as the system output (Li et al., 2022; Gong et al., 2023).

Further Improving Diffusion-LM-MT The experiment results show the Diffusion-LM-based model performed poorly while the standard DiffuSeq achieved acceptable scores. The generation process of DiffuSeq is also equivalent in implementation to the infilling procedure utilized by Diffusion-LM and the autoregressive sampling method, but unlike the infilling procedure used there, with DiffuSeq the conditioning information

is served to the model in the same way during training (Gong et al., 2023). This could motivate a hybrid AR/NAR approach, using a diffusion-based system to generate few tokens at a time.¹¹

6 Conclusion

Using sequence-level knowledge distillation we saw a clear improvement in both training speed and model performance of diffusion-based machine translation systems. We believe they benefit from the reduced syntactic conditional entropy of distilled datasets and conclude that they suffer of a form of the multimodality problem, similarly to other NAR machine translation systems. Based on this, methods employed in other NAR models to help them handle multimodality in the data are likely to improve the performance of diffusion-based machine translation approaches.

The Diffusion-LM-MT model proved capable of expressing the joint density of source and translation implying that with an improved infilling algorithm good conditional densities could be sampled from these models. However, using the infilling algorithm, it was ill-fit to produce high quality samples when used for a sequence to sequence task in our experiments. In a similar manner, the method of autoregressive sampling for diffusion-

¹¹Initial experiments often converged to trivial distributions. To this end, the model should be refined to allow for sequences of variable length.

based translation systems had little impact on the quality of samples.

The diffusion-based MT models studied currently struggle with training and inference speed. While some factors contributing to the slow optimization of these models such as the static sequence length may be alleviated, the problem of predicting the initial sequence based on the noisy version remains difficult. Inference speed on the other hand can be improved with methods such as DDIM (Song et al., 2021) and newer work on Diffusion Models for the image domain likely could be applied to Diffusion Language Models as well. When using the results of Diffusion Language models directly without using MBR decoding, the models still fall decidedly behind the Transformer-based baselines. At the same time, MBR-decoding does not seem broadly applicable, as long as inference is still as slow as in current models.

Limitations

Comparison to SOTA translation models In the comparison to diffusion-based models, our Transformer model was a Transformer-base and was trained on a small dataset with around 100K parallel sentences. For a comparison to state-of-the-art translation models, one should use a larger model trained on over millions of sentence pairs, potentially initialized from pretrained weights. Therefore, the gap between diffusion-based models and state-of-the-art translation models is likely even larger than reported in this paper.

Decoding speed In the current form, the experimented diffusion-based models are prohibitively slow. Even when the quality gap to standard translation models is closed, the decoding speed renders these models unrealistic for deployed systems.

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A Additional Visualization

An example of the forward process is shown in [Figure 2](#). Here, the initial distribution was a mixture distribution of two normal distributions, seen at $t = 0$. Over the course of the forward process noise was added, resulting in the density curve for $t = 2000$ resembling a standard normal distribution.

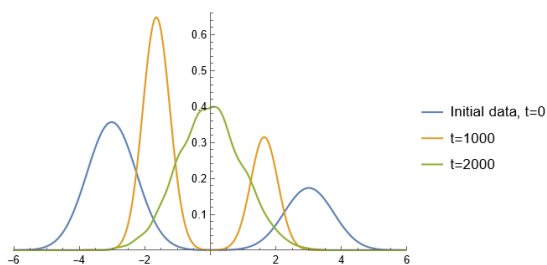


Figure 2: Smooth histograms of sampled values at X_0, X_{1000}, X_{2000} where $T = 2000$, based on 2000 simulations.

B Details on Preprocessing

For preprocessing, the special characters ä, ü, ö, and ß were replaced by ae, ue, oe and ss respectively, accents were removed, and the set of characters was reduced to the alphabet, numerals, and

punctuation marks (excluding brackets and parentheses).¹² The texts are tokenized by Byte-Pair Encoding (BPE) (Sennrich et al., 2016) with a vocabulary size of 30,000. After tokenization, the training data for the diffusion-based models are further filtered by removing sequences longer than 64 tokens. This accounted for less than 0.01% of the samples in the dataset.

C Details on Model Architectures

1. **Diffusion-LM-MT**: This is the model based on Diffusion-LM with infilling as described in Section 3.1. Model hyperparameters:

- (a) **Embedding dimension: 256**
- (b) Diffusion steps: 4000
- (c) Noise schedule: "sqrt"
- (d) Estimated mean parameterized by estimating x_0
- (e) Batch size: 128
- (f) Maximum sequence length: 64
- (g) No gradient clipping
- (h) Fixed noise schedule
- (i) End-to-end training of diffusion kernel and embedding matrix
- (j) Decoding with the clamping trick applied¹³

2. **DiffuSeq**: The standard DiffuSeq model. Model hyperparameters are as given by [Gong et al. \(2023\)](#).

3. **DiffuSeq, AR**: The standard DiffuSeq model with the method of autoregressive sampling as described in Section 3.4.

4. **DiffuSeq-distilled**: The model utilizing sequence-level knowledge distillation as described in Section 3.3, using the same hyperparameters. We used the wmt19-de-en model by [Ng et al. \(2019\)](#) as the teacher model.

¹²This preprocessing was motivated by the idea of potentially leveraging closely related vocabulary between German and English and reducing the vocabulary size. The deviation from standard translation preprocessing steps (removing brackets and parentheses) could slightly affect the compatibility to other systems.

¹³The paper introducing Diffusion-LM states that this empirically improves sample quality ([Li et al., 2022](#)), however, some more recent papers suggest that this might not consistently be the case ([Yuan et al., 2022](#))

D Details on Baselines

Transformer The model is with 6 layers, embedding dimension 512, feed-forward layer embedding dimension 1024 and 4 attention heads in both encoder and decoder. The model uses shared weights for encoder and decoder embeddings and for the language modeling head. Besides these parameters, the other parameters are the same as the original paper ([Vaswani et al., 2017](#)). Decoding was performed with beam size of 10, length penalty of 1, temperature of 1, and no further modifications to the standard beam search.

Levenshtein Transformer We follow the implementation [here](#). Decoding parameters were also chosen as presented by the paper.

Forged-GAN-BERT: Authorship Attribution for LLM-Generated Forged Novels

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Abstract

The advancement of generative Large Language Models (LLMs), capable of producing human-like texts, introduces challenges related to the authenticity of the text documents. This requires exploring potential forgery scenarios within the context of authorship attribution, especially in the literary domain. Particularly, two aspects of doubted authorship may arise in novels, as a novel may be imposed by a renowned author or include a copied writing style of a well-known novel. To address these concerns, we introduce Forged-GAN-BERT, a modified GAN-BERT-based model to improve the classification of forged novels in two data-augmentation aspects: via the Forged Novels Generator (i.e., ChatGPT) and the generator in GAN. Compared to other transformer-based models, the proposed Forged-GAN-BERT model demonstrates an improved performance with F1 scores of 0.97 and 0.71 for identifying forged novels in single-author and multi-author classification settings. Additionally, we explore different prompt categories for generating the forged novels to analyse the quality of the generated texts using different similarity distance measures, including ROUGE-1, Jaccard Similarity, Overlap Confident, and Cosine Similarity.

1 Introduction

Early applications of generative models for literary text generation go back to the works by Bailey (1974) for automatic poetry generation. Moreover, the most recent attempts to generate poems via

text generative models were described by Saeed et al. (2019); Zhang and Lapata (2014); Yi et al. (2017); Wang et al. (2016); Yu et al. (2017); Liu et al. (2018); Beheitt and Hmida (2022). ChatGPT and other powerful generative models generated stories by investigating different prompting mechanisms (Benzon, 2023; Osone et al., 2021). In most recent attempts, the researchers have explored human-AI co-creation in literary areas, for instance, in the works of Calderwood et al. (2020); Frich et al. (2019). Also, the work in Uludag (2023) performed qualitative and quantitative methods to test the creativity of ChatGPT in psychology. Uludag (2023) finds that ChatGPT has some level of creativity but also imposes limitations, such as a limited understanding of the context and the inability to generate original ideas.

With the popularity of generative LLMs for creative content generation, there have been issues observed on well-known book-selling platforms such as Amazon, where AI-generated books are presented for sale under human writers' names with and without the original involvement of the authors (Friedman, 2023). Responding to this situation, platforms such as Amazon have taken measures, such as ordering self-publishing authors to explicitly declare whether their content is machine-generated (Radauskas, 2023). To address these challenges, organisations such as the 'Authors Guild' and 'The Society of Authors' are actively pursuing legislative protection for human authors from such forged literary works under their names (Aut, 2023; SOA, 2023).

As a preliminary step to proposing possible solutions for such authorship issues, particularly considering a use case of machine-generated novels, we explored the ability to utilise GAN-BERT (Croce et al., 2020) to discriminate forged novels generated by ChatGPT from the texts of the original novels. The internal architecture of the GAN-BERT models combines a generator capable of generating fake texts similar to real ones. Since the GAN-BERT model already identifies fake texts (Silva et al., 2023), we want to test the hypothesis that it will perform well in detecting AI-generated novels in a similar style to the original novels. This paper presents the Forged-GAN-BERT model, specifically designed to identify forged novels within the context of authorship attribution. We utilised 20 novels per author during this study, considering 5 randomly selected authors, prompting ChatGPT to forge the books' styles with zero-shot prompting. In contrast to a recent study conducted by Jones et al. (2022), which is primarily on online posts, our research focuses on literary works. We utilise the GAN-BERT model to conduct a dual analysis of the forged texts, combining forged novels generated within the GAN generator and those created by LLM, like ChatGPT. Also, in Jones et al. (2022), they have used fine-tuning to generate AI text, but instead, we prompted ChatGPT to forge or disguise the author's style. To our knowledge, this is the first study using ChatGPT prompts to generate similar novelist styles and to utilise the GAN-BERT model to detect AI-generated novels.

Our study is steered by the following formulated research questions:

RQ 1 What are the implications of utilising various text similarity metrics in assessing the quality of forged novels?

RQ 2 Is it possible to distinguish between human novels vs LLM-generated novels with the Forged-GAN-BERT?

The remainder of the paper is organised into several sections: Section 2 provides a brief literature survey. Then, Section 3 describes the dataset information. Section 4 elaborates on the quality analysis of the forged novels against different prompt categories, emphasising the RQ1. Section 5 outlines the Forged-GAN-BERT model architecture related to the RQ2. Finally, Section 6 adds concluding remarks and future directions.

2 Related Work

Text generation models, aka Natural Language Generation (NLG), generate text closer or indistinguishable from human text or any other input format, such as image or video, which can be categorised into completion generation, text-to-text generation, and inference. Large Language Models (LLM) such as BERT (Devlin et al., 2019), T5 (Raffel et al., 2020), PALM Chowdhery et al. (2022), GPT-3 (Brown et al., 2020), GPT-4 (OpenAI, 2023b), were trained on larger datasets with billions of parameters, which can process massive loads of data and provide highly accurate results. BERT-based models (Devlin et al., 2019) and T5 (Raffel et al., 2020) were built on encoder-only or encoder-decoder architectures, respectively, and are flexible for adapting to many tasks by means of finetuning. Chowdhery et al. (2022) investigate the scalability factor of LLMs in terms of few-shot learning towards multilingual tasks and source code generation tasks. Recent LLM text generators mainly focus on the models' scalability and increasing the models' capacities compared to the predecessor models.

Advanced conversational models can be optimised for massive, high-quality data generation via prompt engineering (Saravia, 2022) on the API of interface level. By using prompt engineering in LLMs such as Flan (Chung et al., 2022), ChatGPT (OpenAI, 2023a), LLaMA (Hoffmann et al., 2022), and GPT-4 (OpenAI, 2023b), models can be utilised to curate new datasets (Wang et al., 2022; Sanh et al., 2022; Gehman et al., 2020; Bai et al., 2022) or as data augmentation strategies (Zhao et al., 2023; Shivagunde et al., 2023; Wang et al., 2023).

Mishra et al. (2022) discuss machine learning-based fake news detection techniques with a comparison to deep learning models. TweepFake (Fagni et al., 2021) detects DeepFake tweets generated by bots based on different text generation techniques such as RNN, Markov Chains, LSTM, and GPT-2. DeID-GPT (Liu et al., 2023) presents a zero-shot medical text de-identification based on GPT-4 in the domain of clinical notes.

In the area of authorship attribution, two main approaches exist for author identification: traditional approaches such as stylometric methods (Aborisade and Anwar, 2018; Soler Company and Wanner, 2017; Madigan et al., 2005), and deep learning-based approaches (Fabien et al., 2020;

Ruder et al., 2016; Saedi and Dras, 2021). Stylometric approaches focus on stylometric feature identification and utilising them in classification models. Moreover, ensemble models such as Bacciu et al. (2019); Moreau et al. (2015) combine stylometric and deep learning mechanisms to enhance the authorship attribution. Authorship Obfuscation, a sub-discipline of authorship attribution, specifically addresses hiding authors’ writing styles and identifying such attempts (Dehouche, 2021; Jones et al., 2022).

The GAN-BERT model (Croce et al., 2020) integrates BERT-based models with the Semi-Supervised GANs, as illustrated in Figure 1. The GAN-BERT model is being used for a range of applications such as sentiment analysis (Myszewski et al., 2022; Ta et al., 2022), authorship attribution (Silva et al., 2023), text classification (Auti et al., 2022; Tanvir et al., 2022), and multi-task learning (Breazzano et al., 2021).

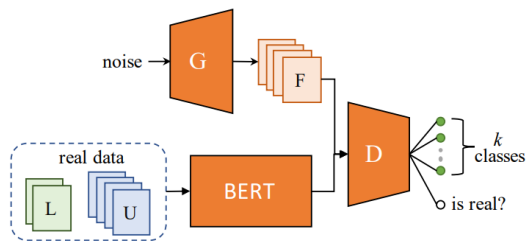


Figure 1: GAN-BERT Model (Croce et al., 2020)
G - Generator, D - Discriminator, F - Forged text, L - Labeled data, U - Unlabelled data

In contrast, considerable research has been performed on Fake News, Tweets, Medical, and Poems, but still limited attention to novels. Further analysing original and generated text, specifically for the literary domain, considering AI-generated forged text, has yet to be addressed.

3 Datasets

3.1 Original Novels

We used a subset of a 19th-century novelists’ dataset created and curated from Project Gutenberg (Gutenberg) for the human-created texts. We selected 20 novels from 5 randomly selected authors: Arthur Conan Doyle, Henry Rider Haggard, Jack London, Mark Twain, and Wilkie Collins. The selected novel’s list is in the released code repository ¹.

¹<https://github.com/Kaniz92/Forged-GAN-BERT>

3.2 Forged Novels:

In the literary domain, forgery can occur through two scenarios. One involves the misattribution of a text to a particular author(s), while the other involves copying a similar writing style. This writing style could be relevant to the author or the document itself. Our research focuses on the latter scenario, where we explore using LLMs to generate forged novels resembling existing original works and attempt to identify such creations.

Prompting the ChatGPT-3.5 API ² has been used to generate similar novels per each original novel, ranging on different prompt categories: Length, Similarity, Identification, Chapter, and Temperature, illustrated in Table 1.

As explained in Table 2, the length parameter considers whether to include word count in the prompt query and an antecedent to the word count: ‘at least’, ‘exactly’, or ‘at most’. The similarity parameter is defined to identify how ChatGPT interprets prompts to generate similar texts using antecedents to the book name: ‘similar to’, ‘as same as’, ‘same background as’, and ‘same characters as’. The identification parameter mentions the book text, i.e., with or without the author. There are different ways to prompt ChatGPT to generate novels, either to generate a full text or a chapter(s) explored in the Chapter parameter. In the ChatGPT API, the Temperature parameter can be set from 0 to 1, where a value closer to 1 generates creative texts. We used this dataset on different prompts to analyse the quality of the generated text but only utilised the Default prompt for the training and testing of the model. We prompted ChatGPT to forge the novel text in each prompt, not the author’s style. All the prompts under each Prompt Category are mentioned in the Appendix A.

3.3 Preprocessing Datasets

As illustrated in Figure 2, the Project Gutenberg texts contain special header and footer sections. The Gutenberg sections were removed from the original dataset as a preliminary preprocessing step. Then, on both datasets, we performed typical preprocessing steps such as lowercasing, stopword removal, punctuation removal, and newline character removal. The cleaned original novel text has been prompted to the ChatGPT to generate forg-

²The forged novels were generated in March 2023. Hence, with the new ChatGPT-3.5 API update, the generated novels may differ from those used here.

Parameter Type	Prompt Example	Description
Length	Write a complete novel similar to {book_name} by {author}.	Without specifying a word limit
Similarity	Write a complete novel with same characters as {book_name} by {author}. The novel should be at least 10000 words.	Same fiction characters as the original novel
Identification	Write a complete novel similar to {book_name}. The novel should be at least 10000 words.	Without specifying the author
Chapter	Write the first chapter of a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.	First chapter only
Default	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.	Default prompt with temperature set to 0.2

Table 1: Prompt examples per each parameter type. The temperature parameter is controlled via the ChatGPT parameters. The Default prompt was used to compare discriminative models.

Prompt Sub-Category	Prompt
Without	Write a complete novel similar to {book_name} by {author}.
Min	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
Exactly	Write a complete novel similar to {book_name} by {author}. The novel should be exactly 10000 words.
Max	Write a complete novel similar to {book_name} by {author}. The novel should be at most 10000 words.

Table 2: Prompt examples for Length Prompt Type. Other prompt examples can be referred in Appendix A.

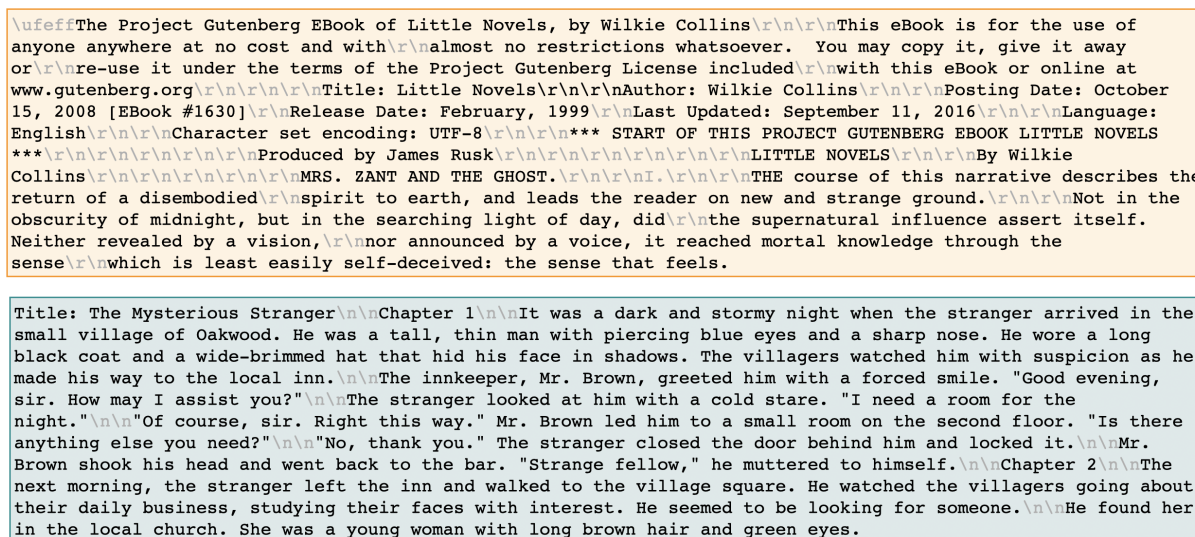


Figure 2: Original Novel (top) and Forged Novel (bottom) - Little Novels by Wilkie Collins. These are raw texts from the Project Gutenberg and ChatGPT responses, respectively. Prior to the training and testing, several pre-processing steps are performed as in Section 3.

eries. While the features we excluded during the pre-processing stage are commonly employed as stylometric features in authorship studies, our focus for author classification with LLMs mainly involves text-based features.

4 Quality Analysis of Forged Novels

It is important to evaluate the quality of the generated forged novels (F) by comparing them with the original novels (O). Different prompt

categories (P) have been considered, with $p \in \{ \text{'Length', 'Similarity', 'Identification', 'Chapter', and 'Temperature'} \}$. Although an infinite range of prompts can be used for these experiments, we considered only a finite set of 18 different prompts. Since the objective of each prompt is to generate a similar novel to a given original novel, we were interested in the generated text quality and the similarity, hence utilised a range of metrics such as ROUGE-1, Jaccard Similarity, Overlap Confident,

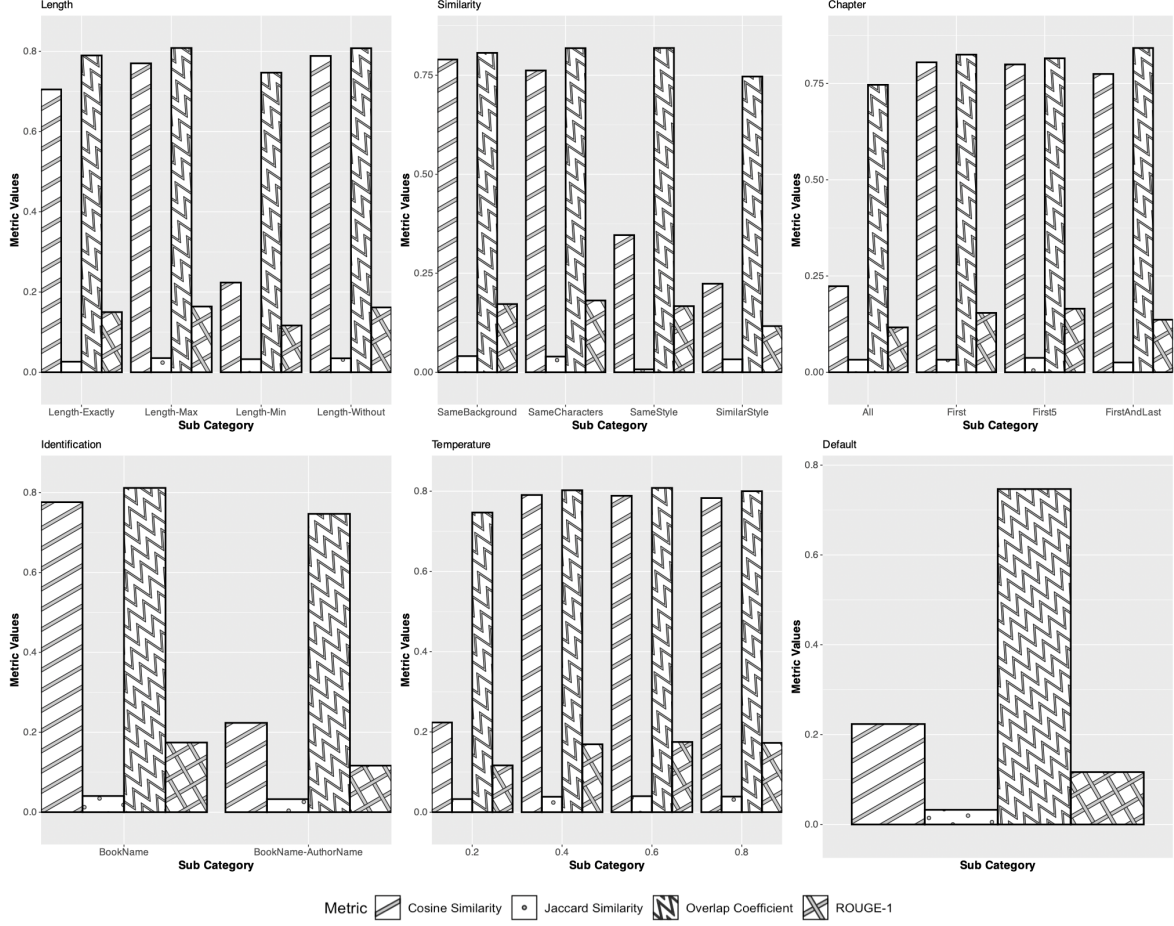


Figure 3: Prompt Type Impact Calculation using Similarity Scores

and Cosine Similarity. Each averaged similarity score can be calculated as follows, considering a basic averaging approach:

$$\text{Average Distance}_j^m = \frac{1}{N} \sum_{i=1}^N D_{(o_i, f_{ij})}^m$$

with o_i an original novel, p_j a prompt category and f_{ij} the corresponding forged novel of o_i generated using p_j . For a given similarity measure m , with $m \in \{\text{ROUGE-1, Jaccard Similarity, Overlap Coefficient, Cosine Similarity}\}$, the distance D between o_i and f_{ij} is represented as $D_{(o_i, f_{ij})}^m$. N is the total number of pairs of novels we average over.

For each prompt category P , the results of the averaged distribution for each prompt sub-category (see Table 2) are illustrated in Figure 3. These results indicate that the ‘Chapter’ prompt category has more impact on the generated text similarity based on the Overlap Coefficient and Cosine Similarity metrics. The ‘Similarity’ prompt category reports the highest ROUGE-1 score, which sug-

gests that such prompts captured similarity better content-wise.

5 Forged-GAN-BERT Model

In the proposed model architecture as in Figure 4, we are considering two aspects in addressing forged texts in authorship attribution:

1. augmented novels via Forged Novels Generator
2. generated fake text via GAN-BERT

The proposed Forged-GAN-BERT model differs from the original GAN-BERT model (Croce et al., 2020) by incorporating a dual forged text analysis curated explicitly for the authorship attribution task. In contrast to the original model, only labelled data were used in this approach. Across different experiment settings, we provide the model with different ratios of forged novels and original novels and varying numbers of predicted classes via the discriminator (D). The original and forged novels

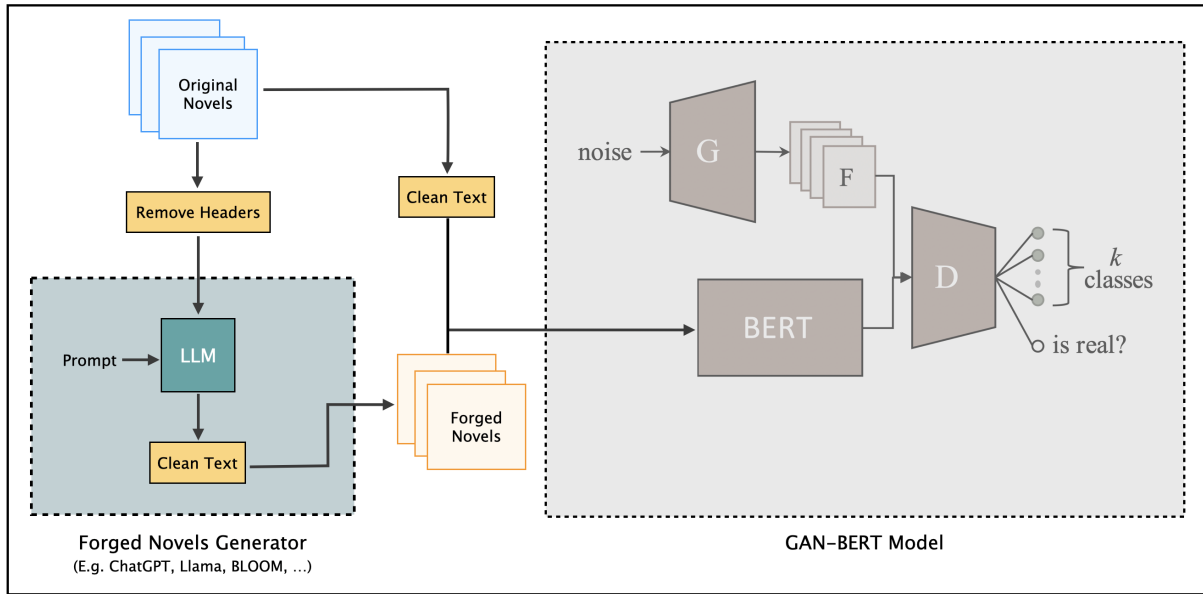


Figure 4: Forged-GAN-BERT Model Architecture. Original novels were given as context to the LLM-based prompting to generate Forged Novels, which concatenated as inputs to the BERT model (bert-base-cased) in the GAN-BERT model (Croce et al., 2020) (see Figure 1) to generate real text embedding. G and D represent the generator and discriminator, respectively. Calculated loss at D is used to update model parameters in both G and D. The forged novels generated by LLM and the fake text F from G contribute to the dual analysis of the forged novels.

are considered real data, passing through the BERT model to generate text embedding. Subsequently, using a controlled noise distribution from the latent space, the generator (G) produces fake text resembling the real text, which is used as an input to the discriminator. The calculated loss is then used to adjust the generator and discriminators' training parameters.

5.1 Dual Analysis of Forged Novels

Conventional approaches to detecting forged text typically combine generated or annotated forged text with the original text. In contrast, the proposed model performs a dual analysis by incorporating two types of forged texts: those derived from real-world sources and those generated by the GAN generator. This approach enhances the model's capability to detect forged novels, whether written by humans or machine-generated.

Furthermore, a secondary hypothesis examined via this dual analysis is that generating forged text based on existing forged text may reveal the imposter's true writing style. The fake novels F, generated for each forged novel, act as forged texts over existing forged texts.

5.2 Experiment Design

We designed the following experiments under different dataset slices generated from the Default prompt with the temperature value set to 0.2. Although the higher temperature values indicate more creativity in the generated text, we had to select a lower range value to ensure the generated text would keep the same style as the suggested novel.

1. ChatGPT as an Author Class
2. Human novels vs forged novels

When representing ChatGPT as an author class, we simulated a scenario of determining whether a test novel is a forgery against a known author's work. The comparison between human and forged novels evaluates the model's ability to identify LLM-generated texts across different authors, which evaluates the model's generalisation ability.

The BERT embeddings were used to represent the text, and the discriminator problem was modelled as simple text classification. The models were trained with default parameters wherever appropriate: a batch size of 8, 5 epochs, a warmup proportion of 0.1, a learning rate of $1e-5$, a dropout rate of 0.2, and using Adam optimiser.

Model	F1	F1(Human)	F1(ChatGPT)	Accuracy	AUC
BERT	0.688 ±0.199	0.648	0.728	0.700	0.700
Longformer	0.975 ±0.051	0.978	0.971	0.975	0.975
RoBERTa	0.949±0.070	0.956	0.943	0.950	0.950
Forged-GAN-BERT	0.975 ±0.057	0.971	0.978	0.975	0.975

Table 3: Comparison between ChatGPT and All Authors (Averaged) Binary Classifications using BERT Embedding as features.

Model	F1	F1(Human)	F1(ChatGPT)	Accuracy	AUC
BERT	0.275	0.000	0.760	0.550	0.917
Longformer	0.389	0.100	1.000	0.675	1.000
RoBERTa	0.397	0.080	1.000	0.700	1.000
Forged-GAN-BERT	0.710	0.600	1.000	0.850	1.000

Table 4: Comparison between ChatGPT vs Human Binary Classifications using BERT Embedding as features.

5.3 ChatGPT as an Author Class

At the primitive level, we investigated the model performance when ChatGPT-forged novels were compared to a single author based on binary classification. We trained author-based models with 20 novels from the original author and 20 ChatGPT forgeries for each novel, resulting in a balanced uniform dataset slice. We averaged results obtained per author to obtain a better generalisation.

The classification against a single author was performed by reporting Accuracy, F1, AUC scores, and each class F1 as illustrated in Table 3. The dataset was well balanced during each author’s comparisons, with 20 novels from the author and 20 ChatGPT novels per each, resulting in 40.

The high accuracy of 0.98 and F1 of 0.97 indicate a superior performance of Forged-GAN-BERT in distinguishing forged novels and each original novel. For instance, consider a scenario where a bookseller would want to investigate whether a specific novel is a forgery based on a known author’s work. With a higher number of works to compare in real life, manual processing becomes impractical and time-consuming. Instead, the proposed model suggests an automated process that can be integrated into such a scenario.

The AUC of 0.97 indicates the dataset balance between the two classes. F1(Human) and F1(ChatGPT) scores evaluated the model performance if only a particular class is present in the dataset; for example, if only authors’ original work is presented to the model, then it is capable of identifying correct authors with a 0.97 of F1 score, and with 0.98 of F1 score vice versa.

Compared to the baseline models, BERT shows a lower accuracy of 0.70 and F1 of 0.69, suggesting a slightly weaker performance.

5.4 Human novels vs forged novels

To experiment with the model performance in the multiple authors’ scenario, we have mixed all the ChatGPT forgeries with original novels. We used the 100 original novels from our 5 human novelists and their forged counterparts generated by ChatGPT, resulting in a balanced distribution. The stratified k -fold sampling was used to overcome the overfitting. We performed another set of binary-class experiments using the same dataset by grouping all authors into the ‘human’ class and keeping the ChatGPT class the same.

In the multiple-author scenario, we considered ChatGPT as a unique author with five other authors, resulting in 6 classes to discriminate. We used the same models and parameter settings to experiment on this and reported the same metrics as in Table 4. For AUC, we used one-vs-rest in a multi-class setting, using ChatGPT class. The dataset is imbalanced in class distribution as ChatGPT text is five times each author’s novel count, but it was balanced regarding the human vs AI text ratio.

The Forged-GAN-BERT model achieved a high accuracy of 0.85 and an F1 of 0.71, showing its ability to collectively identify human- and machine-generated novels. The perfect AUC score suggests a perfect separation between the two classes.

Compared to the baseline BERT model, which exhibits lower accuracy 0.55 and F1 0.25, indicates a weaker performance when distinguishing between human and ChatGPT-generated novels than the Forged-GAN-BERT model.

5.5 Robustness of the model

The Table 3 results were obtained by comparing different models per each author and getting the aver-

age of all the results. As per the standard deviation results recorded, it shows that both Forged-GAN-BERT and Longformer shows comparatively lower standard deviation across different authors, hence, both are robust over different author-wise comparisons. Although the Longformer model shows a competitive performance with the Forged-GAN-BERT model, it does not consist of a component to generate fake texts or to implicitly compare fake text vs real text.

Other models, BERT and RoBERTa are not comparatively successful in this case. Specifically, when comparing single-authors and multiple authors, the BERT model significantly showcases the lowest performance across almost all the metrics for both cases. This shows that the BERT models are not recommended for classifying forged novels, compared to the other models.

Further, the Table 4 results were obtained by observing one model to compare human vs ChatGPT novels, where Forged-GAN-BERT outperforms all other models across all the metrics. Altogether, we can deduce that the proposed Forged-GAN-BERT model is equally capable of identifying forged novels per each author or with multiple authors.

6 Conclusion

In conclusion, the introduced Forged-GAN-BERT model addresses the challenges of authorship attribution in machine-generated forged novels, explicitly and implicitly considering a dual forged text analysis approach. The results suggest that the proposed model outperforms other considered baseline models in identifying forged novels in single-author and multi-author classifications. Additional evaluation on the generated forged novels against different prompts utilised various similarity distance metrics such as ROUGE-1, Jaccard Similarity, Overlap Coefficient, and Cosine Similarity. The reported results indicated that the 'Chapter' configurations have more impact on generating novels similar to the original text. This evaluation can be extended for a probabilistic distribution approach to evaluate the forged novels for all the possible prompts in the infinite series of the prompts.

Future Work

We suggest that more research should focus on a proper evaluation mechanism of the similarity measure for literary works such as novels. Future directions could be around the authorship attribution

area, focusing on stylistic-related features. Further, comparing and adhering to authorship obfuscation techniques would be an interesting future direction.

Although we utilised existing metrics, further research may be needed to evaluate the similarity between original and generated novels using language models such as ChatGPT, specifically on the creative index aspects.

This calculation can be extended considering a discrete probability distribution approach to determine the overall error rate, which suits future investigations. Further, integrating stylometric features into such probabilistic distribution would be another exciting direction.

Limitations

While this study unveils valuable insights into using the Forged-GAN-BERT model for authorship attribution in the context of forged novel scenarios, there are a few limitations to acknowledge. We only focused on 5 authors and 20 novels from each in a controlled dataset setting, denoting a close-set authorship attribution. In a real-world setting, we cannot expect the model to evaluate a text that may be a forgery of known classes; hence, further works should be investigated upon open-set authorship to ensure a more generalisation. As per the copyright considerations and issues with releasing forged novels, we refrain from releasing the entire dataset; instead, we have provided guidelines to reproduce the experiment settings.

Further, we acknowledge the character limitations imposed by the ChatGPT-3.5 model, which generates the forged novels, resulting in segments of the novels closely resembling the originals. To ensure consistency, we maintained the same text lengths as the original and generated forged novels during the experiments.

Ethics Statement

The selected original novels from Project Gutenberg ([Gutenberg](#)) between 1800 and 1914, out of the copyright duration as mentioned in 'Rule 1: Works First Published Before 95 Years Ago and Before 1977' and 'Rule 10(c) - Works of Treaty Parties and Proclamation Countries First Published Between 1923 and 1977'. Yet, we are not releasing the datasets to the public to prevent any unethical usage of the generated forged novels. The text generated in the generator in the Forged-GAN-BERT model is not human-readable; instead, it embeds

representations, preventing unethical usage. Any extended applications of this research should adhere to established ethical guidelines, such as using the generated forged novels and the proposed model only for classification purposes and research objectives. Moreover, using the proposed model and dataset generation should refrain from distributing any author's original content without appropriate consent.

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A Appendix - Prompt Examples

Prompt Category	Prompt Sub-Category	Prompt
Length	Without	Write a complete novel similar to {book_name} by {author}.
	Min	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
	Exactly	Write a complete novel similar to {book_name} by {author}. The novel should be exactly 10000 words.
	Max	Write a complete novel similar to {book_name} by {author}. The novel should be at most 10000 words.
Similarity	SimilarStyle	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
	SameStyle	Write a complete novel as same as {book_name} by {author}. The novel should be at least 10000 words.
	SameBackground	Write a complete novel with same background in {book_name} by {author}. The novel should be at least 10000 words.
	SameCharacters	Write a complete novel with same characters in {book_name} by {author}. The novel should be at least 10000 words.
Identification	BookName	Write a complete novel similar to {book_name}. The novel should be at least 10000 words.
	BookNameAuthorName	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
Chapter	FirstAndLast	Write the first and last chapters of a novel similar to {book_name} by {author}. The novel should be at least 10000 words.
	All	Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
	First	Write the first chapter of a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
	First5	Write first five chapters of a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.
Default		Write a complete novel similar to {book_name} by {author}. The novel should be at least 10000 words.

Table 5: Prompts per each parameter type: The temperature parameter is controlled via the ChatGPT parameters for the Default prompt.

Thesis Proposal: Detecting Empathy Using Multimodal Language Model

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Abstract

Empathy is crucial in numerous social interactions, including human-robot, patient-doctor, teacher-student, and customer-call centre conversations. Despite its importance, empathy detection in videos continues to be a challenging task because of the subjective nature of empathy and often remains under-explored. Existing studies have relied on scripted or semi-scripted interactions in text-, audio-, or video-only settings that fail to capture the complexities and nuances of real-life interactions. This PhD research aims to fill these gaps by developing a multimodal language model (MMLM) that detects empathy in audiovisual data. In addition to leveraging existing datasets, the proposed study involves collecting real-life interaction video and audio. This study will leverage optimisation techniques like neural architecture search to deliver an optimised small-scale MMLM. Successful implementation of this project has significant implications in enhancing the quality of social interactions as it enables real-time measurement of empathy and thus provides potential avenues for training for better empathy in interactions.

1 Introduction

The ability to understand and respond appropriately to the feelings, viewpoints, and beliefs of others is referred to as empathy (Decety and Jackson, 2004; Olderbak et al., 2014). Through engagement, this capacity can strengthen bonds among people and lessen stress and sadness. For instance, consider a situation where a family member falls ill, leading to personal distress. When sharing this sadness with a colleague, receiving genuine support can significantly mitigate unhappiness while enhancing the bond with that colleague. The significance of empathy is evident across a broad range of contexts, from socially assistive robots to human-to-human interactions (Hasan et al., 2023b).

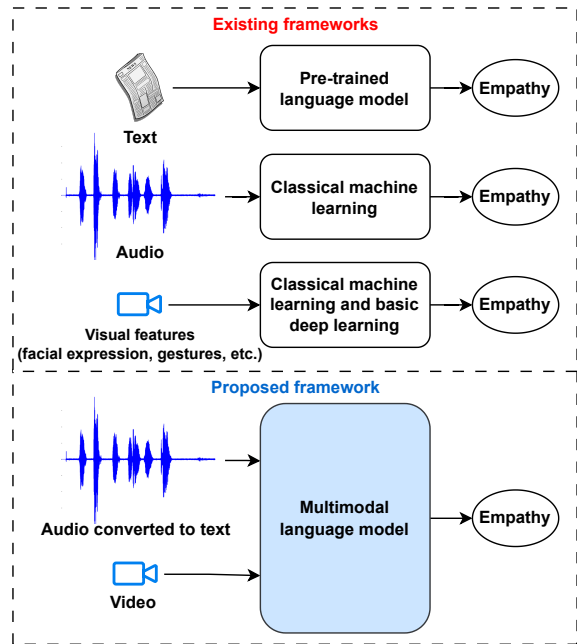


Figure 1: Comparison of our proposed approach with the literature. Existing works on text-based empathy detection (Barriere et al., 2022, 2023) leverage pre-trained language models. There exist a few works on audio- and video-based empathy detection (Alam et al., 2016; Mathur et al., 2021), where audio features or visual features are separately used mostly in classical machine learning algorithms. In contrast, we propose to leverage both audio and video information in a multimodal language model.

Assessment of empathy levels in real-life empathy-seeking interactions is crucial for determining the quality of such interactions (Bellet and Maloney, 1991). Empathy deficit often leads to conflicts and miscommunications, highlighting the importance of measuring empathy levels. Evaluating empathy levels can help answer questions such as ‘To what extent does a teacher exhibit empathy towards students?’, ‘How empathic is a caregiver towards patients?’ and ‘Does an employer demonstrate empathy towards employees?’, among others. Empathy detection allows for a compre-

hensive evaluation of empathy levels in various contexts and can facilitate the development of effective strategies to promote empathy in social interactions.

The term empathy is itself subjective (Decety and Jackson, 2004), so annotated video datasets of empathy are also scarce (Hosseini and Caragea, 2021). To this front, we will collect and annotate audiovisual data of dyadic conversations. Our annotation protocol will consider the subjective experience of the participants involved in the dyadic conversation. Apart from our data, there are some public datasets (such as RealTalk (Geng et al., 2023)) where the data closely aligns with the scope of this research but not the annotation. To this end, we propose re-annotating some samples in terms of empathy and training the model using semi-supervised learning (Xu et al., 2021). Re-annotating these existing data can be challenging as we may no longer have the subjective experience of the study participants.

Empathy measurement is challenging for people (Lawrence et al., 2004), let alone automated systems. There are several works on empathy detection from textual contents (Barriere et al., 2022, 2023; Hasan et al., 2023b). Research in computational empathy from audio and audiovisual data is emerging with a few existing works (Alam et al., 2016; Barros et al., 2019). It is likely that a multimodal model with visual content – in addition to conventional textual content – can boost empathy detection performance because action and gesture play a crucial role in signalling the presence or absence of empathy.

Large language models, such as GPT-4 and PaLM, have shown excellent results in performing various complex tasks. Recently, multimodal language models (MMLMs), by integrating other modalities, such as images, demonstrate promising proof of concept in complex audiovisual recognition tasks (Driess et al., 2023; Wu et al., 2023). MMLM, therefore, seems an appropriate and state-of-the-art approach for empathy detection from audiovisual data, and hence, we propose to leverage MMLM as the backbone of our prediction system.

However, training an MMLM requires huge computational budgets (e.g., multiple GPUs or TPUs for multiple days). With a limited computational budget, this research aims to experiment in two aspects: (1) using small-scale MMLMs and (2) prompt engineering with large-scale MMLMs. Firstly, small-scale MMLMs, such as MiniVLM

(Wang et al., 2021) and SimVLM (Wang et al., 2022), or compressing comparatively large-scale MMLMs through knowledge distillation (Fang et al., 2021) will allow us to leverage MMLMs in our experimental setup. One of the key aims of this research is to find an optimised and small-scale MMLM suitable for empathy detection. To this end, we will employ techniques such as neural architecture search, lottery ticket hypothesis or knowledge distillation. Secondly, prompt engineering and few-shot learning (fine-tuning with few data samples) with large-scale MMLMs shall reduce the huge computational requirement of full training and is thus considered appropriate for our low-computation and low-data scenario.

1.1 Aims and research questions

The primary aim of this project is to develop a robust method for detecting empathy by leveraging a range of multimodal empathic cues associated with video and audio. This project starts with exploring existing text- and video-based datasets. We will collect real-life video conversations to address the inadequacy of existing datasets for empathy detection. This project endeavours to address the following key research questions:

RQ 1 Dataset

RQ 1.1 What methods can be employed to effectively collect and annotate audiovisual data for empathy detection?

RQ 1.2 How can we re-annotate existing audiovisual data with regard to empathy and leverage a semi-supervised learning technique?

RQ 2 Model development

RQ 2.1 How can an MMLM utilising video and audio be constructed to detect empathy?

RQ 2.2 How much can we optimise the initial MMLM by reducing computational requirements?

RQ 2.3 Through prompt engineering, how could we leverage large-scale MMLM with a limited computational budget?

2 Related work

2.1 Empathy from audiovisual data

The one-minute gradual empathy (OMG-Empathy) dataset, introduced by Barros et al. (2019), consists of semi-scripted storytelling videos between

a speaker and a responder, where the responder self-annotated their valence (as a continuous value from -1 to $+1$) of the interaction. It is worth noting that although this dataset is titled ‘empathy’, the output label space is actually a valence score. To explore the potential of this dataset, the OMG-Empathy 2019 prediction challenge¹ was organised. Participants of the challenge, such as Barbieri et al. (2019), employed a multimodal neural network, incorporating audio signals, transcripts, raw faces, facial landmarks, and full-body images to predict continuous valence scores. Similarly, Tan et al. (2019) utilised a multimodal long short-term memory (LSTM) network, whereas Hinduja et al. (2019) implemented a convolutional neural network, using hand-crafted and deep features. Moreover, Azari et al. (2019) employed both a support vector machine (SVM) and a neural network to predict valence scores (or arguably empathy) in the challenge. All these different approaches by diverse teams, however, could not outperform the baseline model consisting of VGG16, LSTM, and SVM models, which resulted in a maximum concordance correlation coefficient of 0.23 (Barros et al., 2019). These approaches indeed showcase the potential of utilising multimodal data and machine learning techniques to detect empathy from audiovisual data, but at the same time, there is potentially much room for improvement.

Zhu et al. (2023) introduced the MEDIC dataset consisting of psychotherapeutic counselling sessions and proposed baseline models to predict empathy. To combine video, audio, and text modalities, they experimented with the Tensor Fusion Network (Zadeh et al., 2017), the Sentimental Words Aware Fusion Network (SWAFN) (Chen and Li, 2020), and a simple concatenation model. The SWAFN model performed significantly better than the other two models, providing an accuracy of 86.4% and an F1 score of 86.3%.

The RealTalk dataset, introduced by Geng et al. (2023), includes dyadic conversations among various individuals. This dataset is not designed for empathy detection tasks, nor does it have empathy annotation. Nevertheless, such dyadic conversations could be leveraged for empathy research, provided that appropriate annotation is possible. Such a complex annotation task can succeed, especially because the dataset has socially appropriate and

inappropriate scenarios, which could be considered as empathy and no empathy annotations.

Apart from human-human interaction, Mathur et al. (2021) and Spitale et al. (2022) investigated empathy between human and socially assistive robots. They conducted experiments involving a humanoid robot and human participants, in which the robot interacted with 46 students by telling different scripted stories. At the end of each interaction, participants rated their level of empathy through a survey with a 5-point Likert scale. The experiment resulted in a 6.9-hour video dataset and corresponding empathy labels. Conversations were labelled as either empathic or non-empathic based on a threshold (median value) empathy score calculated from the survey response. To predict empathy on this dataset, Mathur et al. (2021) used eight different machine learning and deep learning models that utilised various features such as eye gaze, facial action units and landmarks, head pose, and point distribution parameters of the face. Their best approach, which is an XGBoost model, achieved an accuracy of 69% and an area under the receiver operating characteristic curve (AUC) of 72%.

It is important to note that the participants’ audio was not considered in this dataset, which might contribute towards better empathy prediction. Extracted visual features from this dataset are publicly available², but the audio conversation is unavailable. It is worth noting that they solely focused on predicting empathy in human-robot interaction as a binary classification, distinguishing between empathy and non-empathy. However, it did not account for predicting empathy levels as a continuous value or categorising empathy into more nuanced categories. These limitations raise the opportunity to incorporate a more comprehensive range of empathy levels in any human interaction. By doing so, we can obtain a more nuanced understanding of empathic responses and facilitate a more precise evaluation of empathic tendencies.

2.2 Empathy from audio data

There has been limited research that predicts empathy solely on audio conversations. Alam et al. (2016) investigated empathy prediction in human-to-human call-centre conversations using SVM and reported an unweighted average recall of 65.1%. Meanwhile, Gasteiger et al. (2022) explored the

¹https://www2.informatik.uni-hamburg.de/wtm/omgchallenges/omg_empathy_description_19.html

²<https://github.com/interaction-lab/empathy-modeling>

empathy of computer-generated audio, where transcripts were subjected to sentiment analysis, and corresponding audio files were evaluated by a group of 89 human participants. The results revealed a 70% agreement between the sentiment analyser and human annotations. These studies demonstrate the promising potential of audio for predicting empathy.

2.3 Empathy from text data

The Workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis (WASSA) has organised a series of shared tasks³ on empathy prediction on text data with some demographic information. The dataset consists of essays written in response to news articles that involve harm to individuals, organisations or nature. The recent 2023 version of this dataset further consists of written conversation (speech turn) between participants (Omitaomu et al., 2022; Barriere et al., 2023). The WASSA 2021, 2022, and 2023 shared tasks challenge to detect empathy levels as a continuous value. Several participants, such as Vasava et al. (2022); Chen et al. (2022); Qian et al. (2022); Del Arco et al. (2022); Lahnala et al. (2022); Ghosh et al. (2022); Hasan et al. (2024), have fine-tuned pre-trained language models (PLMs), such as RoBERTa (Liu et al., 2019), and BERT (Devlin et al., 2019), for these tasks. Overall, PLMs excelled in all WASSA empathy detection datasets (Tafreshi et al., 2021; Barriere et al., 2022, 2023), with a maximum Pearson correlation coefficient of 0.924 in predicting empathy in written essays (Hasan et al., 2024) and 0.708 in predicting empathy in speech turns (Lu et al., 2023).

Apart from WASSA competition, PLMs were also fine-tuned in predicting empathy in detecting empathy in medical students' essays about simulated patient-doctor interactions (Dey and Girju, 2022). They used various algorithms, including Naive Bayes, SVM, LSTM, and PLMs (BERT, RoBERTa) and found that PLMs are best suited for their empathy prediction setup, providing their best F1 score of 85%. These findings highlight the effectiveness of fine-tuning pre-trained models in text-based empathy prediction. Fine-tuning facilitates harnessing prior knowledge of PLMs, which helps enhance performance while minimising training time.

³<https://wassa-workshop.github.io>

3 Proposed methodology

3.1 Problem formulation

Our primary aim is to detect empathy in dyadic conversations. Denoting speaker as S , responder as R , video as v , audio as a , and other numerical data (e.g., response to a questionnaire) as n , the multimodal data can be represented as $X = \{x_S^v, x_R^v, x_S^a, x_R^a, x_S^n, x_R^n\}$. Using X , the task is to build a model \mathcal{F} to detect empathy Y . Depending on the dataset, Y can be binary classes (empathy and non-empathy), multi-classes (multiple levels of empathy) or continuous degrees of empathy (regression problem).

3.2 Public datasets we will use

We plan to use four public datasets in our experiments (Table 1). Apart from these, we may utilise the human-robot interaction dataset proposed by Mathur et al. (2021), which includes visual features of the human participants. A model capable of predicting empathy even with unavailable modality (e.g., missing audio in the human-robot dataset) could probably lead to a more robust model that can be applied to more diverse circumstances.

3.2.1 NewsEmpathy

NewsEmpathy dataset, introduced by Buechel et al. (2018), consists of people's written essays in response to newspaper articles that are harmful to individuals, organisations or nature. To determine the annotation consistency, they calculated split-half reliability, which resulted in a 'very high' reliability value of 0.875. The dataset also consists of demographic information (age, sex, ethnicity, education, and income) of the study participants who wrote the essays. The annotation is done by the essay writers themselves on a continuous scale from 1 to 7. This dataset has undergone a series of improvements with additional data collection (Omitaomu et al., 2022; Barriere et al., 2023), which resulted in a total of 3,755 samples. Although it is not an audiovisual dataset, we plan to leverage it in our preliminary experiment with language models.

3.2.2 MEDIC

Zhu et al. (2023) introduced the MEDIC dataset to measure empathy in terms of three mechanisms: expression of experience, emotional reaction, and cognitive reaction. In each mechanism, the speech turns are annotated into three categories: no expression, weak expression, and strong expression. The

SL	Name	Data	# of samples	Annotation
1	NewsEmpathy	Written essay (text) in response to newspaper articles	3,755	Empathy
2	MEDIC	Counselling case videos	771 (total 11 hours)	Empathy
3	OMG-Empathy	Semi-scripted speaker-responder storytelling	80 (total 8 hours)	Valence
4	RealTalk	Unscripted conversations about diverse experiences	692 (total 115 hours)	Speaker presence
5	Ours	Unscripted dyadic conversations	<i>in progress</i>	Empathy

Table 1: Datasets to be leveraged in this project. As none of the public datasets completely aligns with the scope of this research, we plan to collect data, which is in progress.

dataset’s annotation is a good match with the scope of the research; however, the data may not cover the complexities of real-life dyadic conversations envisioned in this project.

3.2.3 OMG-Empathy

The OMG-Empathy dataset includes conversations of four speakers and ten responders (Barros et al., 2019). In each video, the speaker tells a semi-scripted story from a pool of eight stories, and the responder responds in a natural way. Following the session, the responder annotated the recorded video frame with a valence score from -1 to $+1$. Although the videos are a good match with the scope of this research, one can argue that the output annotations need to be re-considered, as the annotations are not based on empathy.

3.2.4 RealTalk

The RealTalk dataset comprises a wide variety of dyadic conversations among various individuals (Geng et al., 2023). The in-the-wild nature of this dataset makes it ideal to build a generalised AI model. However, this dataset does not have any empathy annotation.

3.3 Re-annotation of public datasets

Several datasets, such as MEDIC, adopt the Motivational Interviewing Treatment Integrity (MITI) code (Moyers et al., 2016) to annotate conversations in terms of empathy. MITI code is specifically designed to assess empathy of motivational interviewing-based treatment in healthcare and clinical sessions (Moyers et al., 2016). Although the conversations in OMG-Empathy and the RealTalk datasets may not be motivational interviewing, the

technique of empathy annotation from the MITI code could still be useful in annotating samples from OMG-Empathy and RealTalk datasets. Further, we aim to leverage the existing annotations (e.g., valence in the OMG-Empathy dataset) as a guide while annotating for empathy. We aim to recruit and train multiple annotators, and we will calculate annotation consistency using standard interrater reliability assessment techniques. Subsequently, we aim to train a model using semi-supervised learning (Xu et al., 2021).

3.4 Open for collaboration

In addition to using public datasets, we welcome collaboration with scholars who wish to contribute their expertise and/or relevant private datasets in this domain. Additional compatible datasets would allow for more robust model development and validation.

3.5 Our dataset

As there are annotation mismatches with the OMG-Empathy and RealTalk datasets, we will collect and annotate new data. Details of our data collection experiment are discussed in the following subsections.

3.5.1 Study participants and their role

We will collect human-to-human dyadic conversations in empathy-seeking scenarios, where one person (*speaker*) talks about any concerning topics they face. Another person (*responder*) will interact with the speaker just like in a normal conversation. All participants (speaker and responder) will be free to use gestures (such as hand, head, or body)



Figure 2: A typical experimental setup for data collection with demo participants.

throughout the interaction. Our primary target participants are undergraduate students, postgraduate students, and staff at the host University. All participants must have normal vision and hearing abilities with necessary visual and hearing aids if required.

Speakers will be asked to reveal their emotions to talk about any concerning situations they have faced recently. They can choose to show any emotions in any situation. To help the participants decide on topics, the Geneva emotion wheel (Scherer, 2005) (Table 2) and some example topics (Table 3) will be made available to the participants before the data collection. A major portion of the example topics are prepared after brainstorming with a unit (course) coordinator regarding what sorts of situations are most common among our university students. We will advise speakers to choose a topic that they are comfortable with. If any responder finds the topic confronting, we will advise the speaker to choose another topic.

3.5.2 Equipment and data

To record the video and audio of the interactions between responders and the speaker, we will use an Insta360 ONE X2 camera⁴, which has a built-in microphone and covers a 360-degree view. Participants will be seated on chairs. A typical setup is depicted in Figure 2.

We will maintain a logbook for each participant, consisting of participation ID (such as 01, 02, etc.), their seating spot (left, right), and their role (speaker or responder).

⁴https://store.insta360.com/product/one_x2

3.5.3 Questionnaire

At the end of the interaction, we will ask the participants (both speaker and responder) to fill in a questionnaire to collect demographic information and subjective ratings of the conversation regarding the degree of empathy. The questions will be hosted on the Qualtrics XM survey management system, which is a popular research survey management system used by other empathy research, such as (Gasteiger et al., 2022). All empathy assessment-related questions (other than demographic questions) are on an 11-point Likert scale (0 to 10, with 5 being the medium value) to provide many options to the participants, including a neutral opinion. The questionnaire includes the following four sections:

Participant information: This section includes eight questions, including the participant's demographic information and their role (speaker or responder). Depending on the role, the next set of questions is set to appear differently.

Speaker: This section includes 11 questions for speakers to reflect on their expressed emotions and assess their satisfaction with the conversation with the speakers. We designed four new questions, and the other seven are adapted from the consultation and relational empathy (CARE) scale proposed by Mercer et al. (2004). The CARE scale was designed to evaluate empathy in patient-doctor interactions, which resonates with our speaker-responder setup. In our experiment, speakers will share concerns with the other participants (responder), and the responder's empathy will be evaluated, which is similar to patients sharing their concerns with doctors and then evaluating the doctor's empathy, as in (Mercer et al., 2004).

Responder: This section includes 11 questions only for responders to assess their empathy towards the speakers. We developed two novel questions and adopted the remaining eight questions from empathy detection research by Mathur et al. (2021) and Shen (2010).

Responder – in general empathy: To assess the responders' empathy according to an established empathy measurement scale, this section includes the full questionnaire from the Toronto Empathy Questionnaire (Spreng et al., 2009), which includes 17 questions.

Anger	Sadness	Shame	Disappointment	Fear	Disgust	Hate
Regret	Guilt	Pride	Joy	Pleasure	Contentment	Love
Admiration	Relief	Compassion	Amusement	Interest	Contempt	Other

Table 2: List of emotions speaker can choose to express (Scherer, 2005).

SL	Topics
1	Facing challenges in academic work (exams or other assessments) or finding it difficult to keep up with studies
2	Feelings of homesickness or missing family/friends/pets back home
3	Being bullied by peers or classmates
4	Dealing with financial difficulties, such as not being able to afford food, housing, or other basic needs
5	Accomplishing a personal goal, such as winning a competition or achieving a high grade on a test
6	Overcoming a personal challenge, such as overcoming a fear or learning a new skill
7	Choice of the project in a course
8	In a group project, conflict among group members about what direction should the project go in
9	Deciding who will do what role based on a skillset in a group project
10	Deciding who will do what work and how long in a group project
11	Contributions of team members in a group project
12	Dealing with a physical illness/injury of self or relative
13	Recent bad experiences in travel
14	Experiencing difficulties or challenges related to family, such as divorce
15	Experiencing difficulties in relationships with friends, romantic partners, or family members
16	Feeling lonely or disconnected from others
17	Struggling with cultural or personal identity, such as feeling marginalised or discriminated against
18	Having trouble adapting to a new school or community
19	Coping with the loss of a loved one, such as a pet or family member
20	Struggling with substance abuse or addiction
21	Facing harassment or discrimination based on factors such as race, gender, or sexual orientation
22	Excited with graduation from school/college/university
23	Starting a new romantic relationship or friendship
24	Celebrating a special occasion, such as a birthday
25	Travelling or experiencing new adventures, such as travelling to a new country or trying a new hobby
26	Struggling with mental health issues such as anxiety, depression or stress
27	Cannot find preferred accommodation
28	Other

Table 3: List of sample topics the speaker can choose to discuss with the responder.

3.6 Multimodal language model

The primary aim is to detect the responder’s empathy towards the speaker’s perspective. As depicted in Figure 3, conversation transcripts and visual data will be fed into a multimodal language model (MMLM) for final empathy detection. The distinct patterns of hand and facial gestures observed in the top and bottom interactions exhibited in Figure 3 indicate a higher level of empathy than

in the middle. Consequently, integrating facial expressions and hand gestures should significantly enhance the accuracy of empathy detection and thus be considered in this project.

3.6.1 Audiovisual data pre-processing

We will use Insta360 Studio video editing software⁵ to extract the listener and responder video frames.

⁵<https://www.insta360.com/download/insta360-onex2>

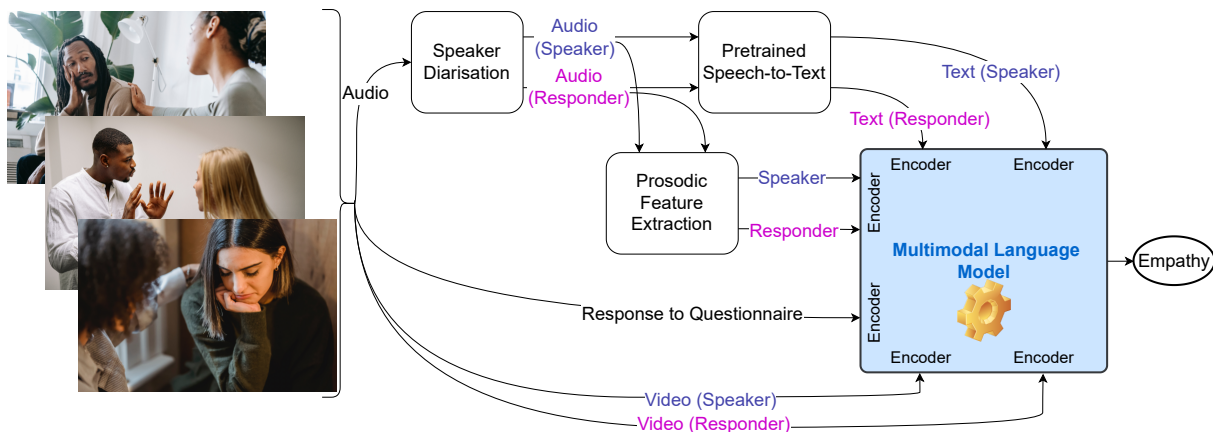


Figure 3: Our proposed framework of empathy detection. To process audiovisual data, we first separate the audio and video of the speaker and the responder. Following speech-to-text conversion and prosodic feature extraction, we will leverage a multimodal language model to detect empathy.

The first step in audio processing is to diarise the audio, which means separating the speech of the speaker and the responder from any background noise. To extract the audio from the video, we will use FFMPEG⁶ as done in (Azari et al., 2019). Following this, three speech-to-text converters – OpenAI Whisper⁷, Google speech-to-text⁸, and Watson speech-to-text⁹ – will be used to convert the audio conversation into text. Agreement among the three converters will be checked for each word, and any disagreement will be settled through manual intervention. The converted textual information will be used as features for empathy detection. In addition, prosodic features, such as pitch and loudness, will be extracted from audio and leveraged in the empathy detection pipeline.

3.6.2 Features and output labels from questionnaire

We will use the following features from the questionnaire:

- a. Speaker’s demographic information
- b. Responder’s demographic information
- c. Speaker’s response to the questionnaire on revealed emotion
- d. Responder’s general empathy

We will aggregate the answers to the responder’s questions and calculate a single empathy score (ES) for each interaction between one speaker and one

responder:

$$ES = \sum_{i=1}^N q_i \quad (1)$$

where N is the number of empathy assessment-related questions ($N = 9$) answered by the responder, and q is the value of the Likert scale (0 to 10). This empathy score will be used as the continuous ground truth empathy score.

This project envisages modelling empathy prediction both as a regression (continuous empathy score) and a classification (empathy levels) problem. Motivated by a recent study on text-based empathy detection (Montiel-Vázquez et al., 2022), we will annotate each interaction into five categories from a third-person perspective: (1) not empathic at all, (2) a little empathic, (3) somewhat empathic, (4) empathic, and (5) very much empathic.

3.6.3 Model development

The model primarily takes in audio and video data from both the speaker and the responder and uses it to infer the level of empathy that the responder feels towards the speaker. The visual and text data go through independent encoders to obtain encoded representations for each modality per speaker. We will leverage a video vision transformer, ViViT, (Arnab et al., 2021) to encode video sequences. Depending on the language model backbone (e.g., BERT, RoBERTa), we will leverage the corresponding tokeniser to encode text transcripts. These encoded representations likely capture various cues: visual cues like facial expressions and hand gestures and linguistic cues from the transcripts. The representations are then fused together with numerical information from the questionnaire using

⁶<http://www.ffmpeg.org/>

⁷<https://openai.com/research/whisper>

⁸<https://cloud.google.com/speech-to-text/>

⁹<https://www.ibm.com/cloud/watson-speech-to-text>

methods like early or late fusion. The fused multimodal context representation is input to an empathy detection model, which detects if the responder empathises towards the speaker.

3.6.4 Optimisation

One of the key aims of this project is to find out an optimised small-scale MMLM. To this front, we aspire to leverage techniques such as neural architecture search (NAS), lottery ticket hypothesis, and knowledge distillation.

NAS involves a systematic exploration of various neural network alternatives using automated testing to identify the best-performing architecture (Elsken et al., 2019). The lottery ticket hypothesis suggests that large networks may contain smaller efficient subnetworks, and pruning techniques can be used to find these lottery ticket subnetworks. This can lead to smaller, faster, and more efficient models without significantly reducing performance. Finally, the knowledge distillation technique compresses and optimises a large teacher model into a smaller student model while retaining most of its capabilities.

3.6.5 Model evaluation

We will evaluate the performance of the final model using cross-validation and compare it with baseline models. To compare with existing studies, we will use specific data from our dataset, such as using audiovisual data to compare with Mathur et al. (2021); Barbieri et al. (2019); Tan et al. (2019), audio data to compare with Alam et al. (2016); Gasteiger et al. (2022), and text data with Vasava et al. (2022); Chen et al. (2022); Qian et al. (2022); Del Arco et al. (2022); Lahnala et al. (2022); Ghosh et al. (2022); Barriere et al. (2022, 2023); Hasan et al. (2023a). As for the evaluation metrics, we will adopt established metrics corresponding to each public dataset so that we can compare our results with the literature. For our collected dataset, we will provide results in multiple established evaluation metrics: (1) Pearson correlation coefficients, Spearman’s correlation coefficient, and concordance correlation coefficient for continuous degree of empathy prediction, and (2) accuracy, precision, recall, F1 score, and AUC score for empathy level prediction.

4 Preliminary experiments

We have experimented with the NewsEmpathy datasets (Omitaomu et al., 2022; Barriere et al.,

2023), where we experimented with fine-tuning three PLMs (ALBERT, DistillBERT, and BERT). The dataset has numerical demographic information, which enhanced empathy detection because of the subjective nature of empathy. To this end, we constructed meaningful sentences from the numeric demographic information, which in fact, boosted empathy detection performance. As for data-centric improvement, we also leveraged T5-based PLMs for text summarising and rephrasing (Hasan et al., 2023a).

As a follow-up study, we leveraged GPT-3.5 LLM to mitigate annotation noise in crowdsourcing datasets. Crowdsourcing is a faster and cheaper way to collect data and annotation in computational social science research, such as empathy. However, crowdsourcing involves many different people who may undertake such jobs only for financial benefit, and thus it becomes difficult to maintain the quality of collected data and annotation (Sheehan, 2018). To this end, we proposed re-annotating noisy and misleading annotations using GPT-3.5 LLM and mixing these new annotations with human-provided good annotations. Apart from this, we also leveraged GPT-3.5 in converting numerical demographic information into meaningful sentences and data augmentation through paraphrasing (Hasan et al., 2024).

5 Conclusion

The ability to detect and understand empathy is central to improving social interaction. This PhD research proposes a multimodal framework by modelling empathy based on video and speech transcripts in an integrated manner. We start with public datasets and further collect data tailor-made for empathy detection, as most currently available corpora do not fully match the target objectives. With the recent success of multimodal language models (MMLMs), this project aims to use cross-modality dynamics and joint representations of multimodal audiovisual data in an MMLM. To accommodate MMLM in a resource-constrained environment, this research aims to adopt optimisation techniques, such as neural architecture search, lottery ticket hypothesis, and knowledge distillation. The proposed MMLM can be used to detect empathy in various settings, such as in education, healthcare, and businesses.

Ethics statement

The project involves collecting video and audio from human participants. Therefore, to conduct the data collection experiments, necessary ethics approval will be sought from the Human Research Ethics Committee of the host university. Before each data collection session, we will brief the participant and provide an information form and consent form for signing, including how the data will be stored and utilised, the purpose of the experiment and the data collection methods. We will collect signed consent forms from all participants.

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Toward Sentiment Aware Semantic Change Analysis

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Abstract

This student paper explores the potential of augmenting computational models of semantic change with sentiment information. It tests the efficacy of this approach on the English SemEval of Lexical Semantic Change and its associated historical corpora. We first establish the feasibility of our approach by demonstrating that existing models extract reliable sentiment information from historical corpora, and then validate that words that underwent semantic change also show greater sentiment change in comparison to historically stable words. We then integrate sentiment information into standard models of semantic change for individual words, and test if this can improve the overall performance of the latter, showing mixed results. This research contributes to our understanding of language change by providing the first attempt to enrich standard models of semantic change with additional information. It taps into the multifaceted nature of language change, that should not be reduced only to binary or scalar report of change, but adds additional dimensions to this change, sentiment being only one of these. As such, this student paper suggests novel directions for future work in integrating additional, more nuanced information of change and interpretation for finer-grained semantic change analysis.

1 Introduction

Lexical Semantic Change is a crucial aspect in the study of linguistics, offering insights into how the meanings of words evolve over time. This phenomenon reflects the dynamic and ever-changing nature of language, revealing how cultural, societal, and historical contexts influence linguistic expression. Current research primarily detects semantic change either as a binary classification (whether a word's meaning has changed between two corpora) or as graded change scores (the extent of meaning change). Despite the nuanced

analysis of different types of semantic change that has existed in historical linguistics research for many years, current approaches in NLP are still lagging behind (Hengchen et al., 2021). Analysis typically involves comparing cosine distances between word embeddings across corpora from different time periods. The two prevalent methods are APD (Average Pairwise Distance) (Kutuzov and Giulianelli, 2020; Schlechtweg et al., 2018), and PRT (Inverted cosine similarity over word prototypes) (Kutuzov et al., 2022).

Semantic change detection can be analysed using type-based approaches (Schlechtweg et al., 2020; Kutuzov and Giulianelli, 2020), analyzing shifts in semantic vector spaces, or using token-based methods. BERT-based (Devlin et al., 2018) and ELMo-based (Peters et al., 2018) models have been very commonly used due to their high semantic encoding abilities and possibility for further fine-tuning for specific tasks (Laicher et al., 2021). Using contextualised word embeddings for semantic change detection (Giulianelli et al., 2020) relies on the distributional hypothesis, the assumption that words with similar meanings share contexts. The current state-of-the-art (SOTA) model, XL-LEXEME by Cassotti et al. (2023), demonstrates exceptional accuracy in the SemEval-2020 Task 1 on multiple languages. Specifically it achieves a 0.757 Spearman semantic change rank correlation between predictions and graded scores on the English dataset, by creating comparable context-based word embeddings.

Over the years, the volume of research in this area has expanded significantly. This is largely due to the increasing availability of large digital text corpora, such as the SemEval dataset, and advances in natural language processing (NLP) techniques. More recently, the integration of machine learning, particularly deep learning models like BERT,

has revolutionized the field (Laicher et al., 2021; Beck, 2020). The primary objective of these advancements has been to improve the accuracy of detecting and quantifying semantic shifts. The secondary objective has been to expand the task to more languages, which SemEval has successfully addressed by providing datasets for English, German, Latin and Swedish (Schlechtweg et al., 2020). However, semantic change of language is multifaceted, extending beyond binary and graded one-dimensional classifications. It includes various forms like broadening, narrowing, complete shifts, and notably amelioration (shift to positive connotation) and pejoration (shift to negative connotation), both particularly noteworthy for their direct impact on sentiment. This complexity necessitates a more nuanced approach to semantic analysis which includes finer-grained semantic change classification, recognizing that words can shift along a spectrum of meanings and connotations influenced by diverse cultural and societal factors (Hengchen et al., 2021). Even if not explicitly undergoing amelioration or pejoration, by changing meaning and hence the context it appears in, a word may change in its associated sentiment. Sentiment analysis is a highly-researched task in NLP, providing a lot of publicly-available resources which can be used to enhance semantic change detection models beyond detecting a shift in the distribution of word embeddings, by additionally considering a shift in their associated sentiment.

This research explores the interplay between semantic and sentiment change, as it parallels amelioration and pejoration, a major aspect of semantic change (Closs Traugott, 1985). Our findings indicate that even subtle semantic shifts can affect sentiment. Hence, the goal is to refine semantic change detection by integrating sentiment change analysis, using sentiment model data to improve upon existing semantic change detection models.

2 Related Work

The few studies exploring finer-grained semantic change in recent literature have taken various paths. Cook and Stevenson (2010) focused on identifying the most polar words in different corpora and analyzing their changes without directly linking them to semantic change in general. Research on large-scale sentiment change, such as the studies by Xie

et al. (2020) and Fernández-Cruz and Moreno-Ortiz (2023), did not specifically investigate the role of sentiment change information in semantic change detection. Some innovative methods for more interpretable semantic change detection have emerged, like the approach by Giulianelli et al. (2023) that clusters tokens into interpretable word senses using definition generation. Additionally, Giulianelli et al. (2021) proposed a method based on grammatical profiling, focusing on morphosyntactic behavior changes, offering an alternative perspective in detecting semantic shifts. More closer to our study is a recent work that tried to enrich models for semantic change by first fine-tuning them on a range of NLP tasks (Zhou et al., 2023). However, they did not directly take sentiment score into account in their models like this study does. And, to the best of our knowledge, no work has attempted to enhance semantic change analysis through sentiment change analysis.

3 Methodology

In order to determine the sentiment change of words we used five publicly-available BERT-based models, fine-tuned for sentiment analysis sourced from huggingface.co. The models, named for simplicity, are not the official "BERT" and "RoBERTa" but are based on these architectures. Note that other models might also be based on these architectures, but were fine-tuned differently: BERT¹, SST BERT², sbcBI³, RoBERTa⁴, Reviews⁵. The models differ in their training data and some in architecture, they were selected precisely to ensure the results are robust regardless of the sentiment model used, as long as it passes the later-described validation test we developed for sanity checks. We also use VADER (Hutto and Gilbert, 2014) as another sentiment analysis model. VADER is a rule-based sentiment analysis tool, which combines a dictionary of sentiment-laden words with a set of rules that consider grammatical and syntactical conventions for expressing sentiment. We added this to our analysis to demonstrate that

¹<https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment>, Accessed November 2023

²<https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english>, Accessed November 2023

³https://huggingface.co/sbcBI/sentiment_analysis_model, Accessed November 2023

⁴<https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest>, Accessed November 2023

⁵<https://huggingface.co/juliensimon/reviews-sentiment-analysis>, Accessed November 2023

the findings of this study hold even for sentiment analysis models not based on contextualised language models.

Sentiment scores of all models were standardized to be in the range of 0 (most negative) to 1 (most positive). We stress that sentiment scores are assigned to each sentence, and when word level analysis is done the averaged sentiment score is used. When models produce distribution of sentiment scores across binary or ordinal categories (e.g., assigned .25 weight for 0 and .75 for 1) the weighted average is computed. This method provided a uniform approach to quantify sentiment across various models. We analysed the sentiment shift of sentences from the SemEval-2020 Task 1 corpora (Schlechtweg et al., 2020), focusing on the 37 target words with binary and graded semantic change scores, derived from human-annotated semantic word in context similarity judgments. Corpus 1 consists of 6 million tokens from 1810-1860, and corpus 2 is also made up of 6 million tokens from 1960-2010, both based on the Clean Corpus of Historical American English (CCOHA) (Alatrash et al., 2020) dataset. Note that target words were tagged with their pos tags in this dataset.

To maintain fairness and accuracy in comparing sentiment differences for a word between Corpus 1 and Corpus 2, we analyzed an equal number of sentences from each corpus for every word. Specifically, we used the smaller number of sentences containing the target word found in either corpus. For the corpus with a larger number of sentences for the target word, we randomly sampled an equal number of sentences to match the other corpus. This sampling involved first extracting all sentences with the target word and then randomly selecting the same number of sentences (as in the smaller set) using a random seed of 42.

4 Validation of Sentiment Models

To ensure the validity of our approach, we first verify that our evaluation of sentence sentiment is robust to the inherent noise associated with different sentiment scores produced by different models. If a model captures sentiment reliably, then the agreement of a word sentiment should be greater within each model than between different models. We created random splits for each

corpus (A-B splits). Then for each model, we computed the average sentiment for each word in each split (A or B), and then computed the correlation between the averaged sentiment scores of A and B, both within each model, and between models. We posit that if models provide reliable sentiment scores, then the correlation between two independent splits should be higher within a model relative to different models.

Table 1 shows that all models demonstrate much higher correlations between sentiment scores of the same model relative to other models. This indicates a high level of agreement of the models' sentiment scores. However, the medium range correlation scores across different models also indicate that different models show a fair amount of agreement as well. Overall, all six models were deemed suitable for subsequent sentiment analysis.

5 Results - Semantic and Sentiment Change

The Mean Sentiment Change of a word w is measured as the absolute difference of the mean sentiment of sentences containing the word in corpus 1 and corpus 2:

$$\Delta S_w = \left| \frac{1}{N} \sum_{i=1}^N \mathcal{S}_{C_1, w(i)} - \frac{1}{N} \sum_{j=1}^N \mathcal{S}_{C_2, w(j)} \right| \quad (1)$$

Where $\mathcal{S}_{C, w}$ is the sentiment score of the word w as it appears in a single sentence in a particular corpus.

As can be seen in Table 2, this sentiment change is greater for changed than stable words, which confirms the hypothesis that semantic change is associated with sentiment change.

As can be seen in Table 3, this result also emerges on the German SemEval-2020 Task 1 dataset, which has the same format as the English dataset, and contains 48 target words with binary and graded scores of semantic change. The experiment set up was the same as for English, except with the following five huggingface models:

Model	C1 A-B correlations		C2 A-B correlations	
	Within	Avg Cross-Model	Within	Avg Cross-Model
BERT	0.860	0.481	0.792	0.341
SST BERT	0.832	0.412	0.877	0.302
sbcBI	0.849	0.394	0.835	0.309
RoBERTa	0.931	0.467	0.918	0.514
Reviews	0.901	0.260	0.925	0.119
VADER	0.829	0.419	0.801	0.418

Table 1: Within and average cross-model correlation in A-B splits in the two corpora.

	BERT	SST BERT	sbcBI	RoBERTa	Reviews	VADER
Changed	0.048	0.086	0.070	0.041	0.051	0.059
Stable	0.044	0.073	0.069	0.032	0.032	0.053

Table 2: Mean Sentiment Change of Semantically Changed and Stable Words in English

BERT⁶, twitter⁷, gereval⁸, news⁹, sentiment¹⁰, fine-tuned for sentiment analysis in German. All five models passed the sanity checks described above.

We can inspect the degree and direction of the sentiment change of each word, as shown in Figure 1, and observe that the word "record", for example, has undergone the most amelioration (i.e., positive change), according to the Reviews model, which could be explained by the fact that it has evolved from being associated with documented information to musical records, which are more associated with entertainment, hence the more positive sentiment. Meanwhile the word "prop" has developed more negative connotations (i.e., pejoration), which can be due to its newly developed association with artifice and superficiality, particularly in entertainment, politics, and media, where it implies manipulation or a lack of authenticity, as it began to be used less for denoting a physical supporting object to more metaphorical usages. Such detailed analysis of semantic change holds the potential to categorize words that have evolved over time into distinct types of change, such as amelioration and pejoration, while also quantifying

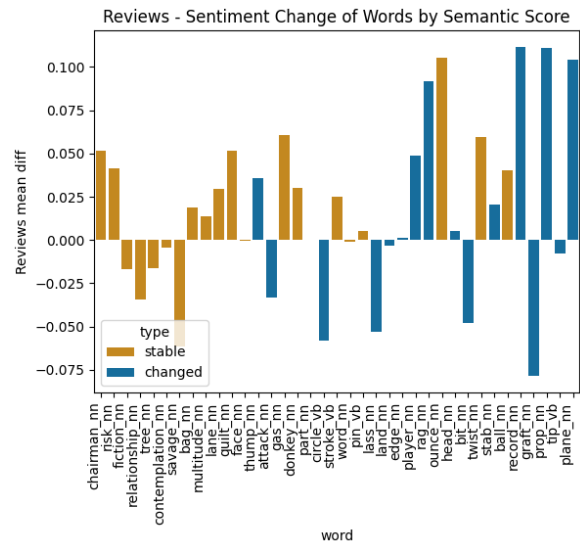


Figure 1: Mean Sentiment Change of Words from Corpus 1 to Corpus 2, Scored by the Reviews Model

its extent within each semantic aspect.

6 Integrating sentiment to semantic change models

Now we attempt to use this sentiment change information to improve the performance of a baseline semantic change detection model, based on APD distances, described in §1. We experiment with two models; Logistic Regression to predict the binary semantic change labels, and Linear Regression to predict the graded semantic change scores. We use these models to test our hypothesis that integrating sentiment information with semantic change information can improve overall semantic change prediction accuracy. We use the predictions from

⁶<https://huggingface.co/oliverguhr/german-sentiment-bert>, Accessed November 2023

⁷<https://huggingface.co/JP040/bert-german-sentiment-twitter>, Accessed November 2023

⁸<https://huggingface.co/deepset/bert-base-german-cased-sentiment-Germeval17>, Accessed November 2023

⁹<https://huggingface.co/mdraw/german-news-sentiment-bert>, Accessed November 2023

¹⁰https://huggingface.co/aari1995/German_Sentiment, Accessed November 2023

	BERT	twitter	gereval	news	sentiment
Changed	0.019	0.021	0.002	0.037	0.046
Stable	0.015	0.020	0.001	0.031	0.046

Table 3: Mean Sentiment Change of Semantically Changed and Stable Words in German

an APD-based model as the performance baseline (Kutuzov and Giulianelli, 2020), which we try to improve upon by adding sentiment change information to the models. The sentiment change ratings are derived by means of various statistical analyses of the distributions of sentiment scores of sentences containing the target word derived as follows:

- Mean Diff: Absolute difference between the average sentiment scores of two corpora.
- T-test: Statistical test comparing sentiment scores between the two corpora to assess significance of their mean difference.
- Ratio: Ratio of average sentiment scores of the two corpora, calculated with the smaller average as the numerator.
- KL Divergence: Measures the divergence in sentiment score distributions between the two corpora.

For the logistic regression model, we balanced the two classes of words by removing 5 stable words, resulting in a dataset of 16 changed and 16 stable words. This approach was adopted because fitting the model with imbalanced class sizes led to a classifier bias, where it predominantly chose the larger class. Because we use the existing SemEval dataset to train our model, it cannot be used as a test set. Instead, for evaluation we report averages of 6-fold cross validation in order to make the results based on this small sample as reliable as possible.

The performance of the logistic regression model is the accuracy of its binary predictions, while the performance of the linear regression model is the Spearman’s rank correlation of the model’s predicted values with the true semantic change scores.

Using only the semantic change APD model’s predictions as input to the models, logistic regression achieves 0.56 accuracy, while linear regression achieves 0.61 correlation.

Results show (Table 4) that adding sentiment information does not reliably improve the accuracy of logistic regression model. Out of 20 model combinations, only one exhibits improved accuracy. In

contrast, linear regression shows mixed results for integrating sentiment information (Table 4), improving the results in 8 out of 20 conditions, and by a large margin.

Although sentiment change is evidently related to semantic change, as our results for both English and German demonstrate (see Table 2, and Table 3), it seems that integrating sentiment information is not straightforward. In its simplest form of a single metric of sentiment change between two corpora, sentiment does not systematically improve the performance of semantic change detection models. This lack of regularity could be related to statistical variations rather than reliable results which would generalise to another dataset.

The specific conditions in which sentiment does contribute to semantic change needs to be further explored. One of the potential reasons behind this could be the lack of numerous data points for meaningful analysis. To address this point we look to the DWUGs dataset of sentence pairs (Schlechtweg et al., 2021).

7 Considering Sentence Pairs

The DWUGs dataset (Schlechtweg et al., 2021) consists of sentence pairs containing the same target words as the SemEval dataset, annotated with word sense-similarity judgments by human annotators. A rating of 4 is assigned to sentence pairs where the target word is used in exactly the same sense, while a rating of 1 indicates that the word is used in very different senses in the two sentences. A rating of 0 is used for uncertain or ambiguous cases. This dataset offers a more granular insight into sentiment change, contrasting with the limitations of a single average sentiment change score per word offered by the SemEval dataset. The same sentiment models were used to get the sentiment scores of sentences in the pairs.

As seen in Table 5, there is a small correlation of sentence pair sentiment differences with the semantic sense judgments. A deeper examination of the sentence pair sentiment differences for words with the highest and lowest average sense

Statistic	BERT		SST BERT		sbcBI		RoBERTa		Reviews		VADER	
	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin
Mean diff	0.56	0.51	0.56	0.59	0.56	0.53	0.56	0.66	0.56	0.72	0.56	0.59
T-test	0.46	0.60	0.51	0.64	0.43	0.64	0.56	0.56	0.54	0.52	0.46	0.62
Ratio	0.56	0.51	0.51	0.60	0.56	0.56	0.56	0.65	0.59	0.75	0.56	0.59
KL divergence	0.56	0.59	0.45	0.68	0.56	0.56	0.56	0.60	0.56	0.58	0.56	0.57

Table 4: Average k-fold accuracies for Logistic Regression (Log) and Spearman Correlations with Linear Regression Predictions (Lin). Bolded results outperform baseline (0.56 and 0.61, respectively).

Judgment	BERT	SST BERT	sbcBI	RoBERTa	Reviews	VADER
0	0.228	0.456	0.294	0.204	0.283	<u>0.238</u>
1	0.218	0.449	0.280	<u>0.199</u>	0.266	0.245
2	0.217	0.445	0.273	0.212	0.255	0.259
3	0.222	0.427	0.274	0.209	0.243	0.259
4	<u>0.212</u>	<u>0.422</u>	<u>0.267</u>	0.201	<u>0.238</u>	0.251

Table 5: Average Sentiment Difference for Each Judgment Group
The highest value in each column is boldened, while the lowest value is underlined.

similarity (see Figure 2) reveals distinct patterns. Notably, sentences with consistent semantic usage of a target word tend to have smaller sentiment differences compared to sentences where the word’s usage is more semantically varied. However, this pattern does not uniformly apply across all words, as the distributions of semantically changed and stable words are not easily distinguishable for most cases.

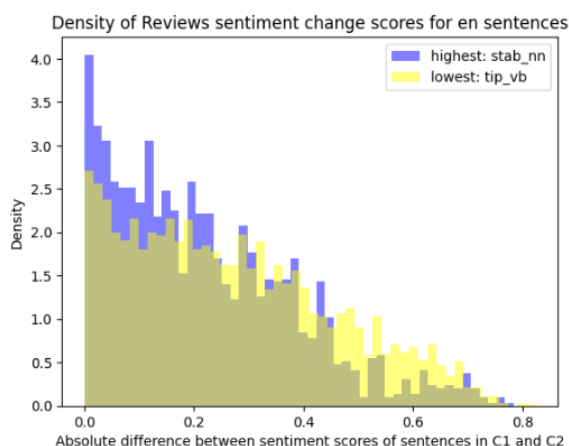


Figure 2: Sentence Pair Sentiment Differences for Least and Most Sense-Stable Words

We further explored the impact of relative sentiment change. We can see which words changed sentiment in a similar way to others and which words diverged in the sentiment of their usages by calculating the Jensen Shannon distances

between the sentiment difference distributions of all words. We look at various statistics of these Jensen Shannon distances of a word to all the other words, specifically the min, max, mean and standard deviation, to examine whether these relative comparisons of sentiment difference distributions could improve semantic change detection. The same experiments using linear and logistic regression as described previously were carried out, using these statistics. The logistic regression model failed to learn anything, and to improve upon its baseline accuracy, regardless of the sentiment change statistic used as an additional input feature, hence it is not reported in a table. The results of the linear regression model experiments can be found in Table 6.

Similarly to the previous experiments, the performance improvements in the simple semantic change detection models are scarce and irregular for the linear regression model. As a result, the hypothesis that sentiment change information can improve performance of semantic change detection models is not supported. The differences between sentiment scores of two sentences are also related to the sense similarity of the usage of the target word in those sentences, however, this measure of sentiment change, based on many data points, also cannot be used to improve the performance of semantic change detection models.

We propose several reasons for this negative find-

Statistic	BERT	SST BERT	sbcBI	RoBERTa	Reviews	VADER
Means	0.62	0.61	0.54	0.60	0.59	0.58
Minima	0.61	0.58	0.51	0.63	0.59	0.51
Maxima	0.66	0.57	0.53	0.58	0.62	0.56
Standevs	0.58	0.62	0.53	0.69	0.59	0.60

Table 6: Logistic Regression Results Using DWUG Sentence Pairs, Baseline = 0.61

ing. To begin with, neither amelioration nor pejoration are the most common types of semantic change. It could be that most words in the SemEval do not explicitly undergo these changes, which in turn is reflected by no change to the words' sentiment. Second, and related to the above, this effect is also related to the small number of words, 37, that exist in the English SemEval, which is still too small for meaningful analysis. Third, the average sentiment of sentences in which a word appears may not be the optimal method to evaluate the sentiment of individual target words, because it may contain too much noise from the sentence to provide any valuable insights about the sentiment shift of that word.

8 Limitations & Future Research

This study acknowledges several limitations in its approach to measuring sentiment change of individual words. Currently, there is no established methodology for assessing such sentiment changes. Unlike in semantic change detection, where clustering usages into word senses across corpora is a common practice, sentiment change analysis lacks similarly sophisticated methods. The approach adopted in this study, focusing on the average sentiment of sentences in which a target word appears, may not fully capture the nuanced sentiment contributions of the word itself. Future research should aim to develop more intricate techniques that specifically evaluate the sentiment contribution of a word within its sentence context.

Another limitation is the potential narrow applicability of our method. It may be best suited as a supplementary tool to refine and elaborate on semantic changes already detected by SOTA models. Sentiment shift may not be relevant for words whose semantic shifts do not necessarily entail amelioration or pejoration.

Additionally, our method's approach to quantifying sentiment differences—by taking the absolute difference of sentiment scores between two sentence usages of a word—represents a rather sim-

plistic estimate. This approach is somewhat analogous to measuring semantic differences by computing the cosine distance between sentence embeddings, which is a relatively basic and possibly insufficient method for assessing nuanced semantic shifts in word usage. As such, our findings must be interpreted within the context of this methodological simplicity, and future studies should explore more refined approaches for enhancing semantic change analysis with sentiment change information, as it may be a promising avenue of research, given more appropriate methods for evaluating sentiment change of a word between two corpora.

Further research in this area could enable trend analysis in digital humanities, provide insights into societal and cultural shifts by examining how word sentiments evolve. Additionally, it could aid in monitoring language changes, reflecting evolving societal attitudes and behaviors.

9 Conclusion

This paper provides evidence that sentiment change is associated with semantic change: Words that are deemed to change semantically (according to expert human annotators) also show greater change to their sentiment, on average. However, the hypothesis that sentiment information could be used to aid the task of semantic change detection ends with a null result on the 37 words from the SemEval English dataset.

The results confirm that words that change meaning are also more likely to change their associated sentiment, even if they didn't directly undergo amelioration or pejoration. However, this sentiment shift, in the simple ways we measured it, is not a reliable estimate of semantic change.

In summary, while our study provides valuable insights into the relationship between semantic and sentiment changes, it also highlights the need for more advanced methodologies in this emerging area of research.

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Dynamic Task-Oriented Dialogue: A Comparative Study of Llama-2 and BERT in Slot Value Generation

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Abstract

Recent advancements in instruction-based language models have demonstrated exceptional performance across various natural language processing tasks. We present a comprehensive analysis of the performance of two open-source language models, BERT and Llama-2, in the context of dynamic task-oriented dialogues. Focusing on the Restaurant domain and utilizing the MultiWOZ 2.4 dataset, our investigation centers on the models' ability to generate predictions for masked slot values within text. The dynamic aspect is introduced through simulated domain changes, mirroring real-world scenarios where new slot values are incrementally added to a domain over time. This study contributes to the understanding of instruction-based models' effectiveness in dynamic natural language understanding tasks when compared to traditional language models and emphasizes the significance of open-source, reproducible models in advancing research within the academic community.

1 Introduction

In recent years, the landscape of natural language processing (NLP) has witnessed a shift towards leveraging instruction-based models, marking a departure from traditional approaches. These instruction-based models have demonstrated exceptional performance across a diverse range of complex tasks that were traditionally deemed challenging for automated solutions. Unlike closed-source linguistic models, typified by industry leaders such as OpenAI, which have dominated the market, we observe a growing interest in open-source alternatives. The inherent transparency and reproducibility of open-source models provide a conducive platform for academic research, fostering valuable experiments in diverse domains. Numerous studies have already assessed the effectiveness of open-source instruction-based models across various natural language processing (NLP) tasks.

Several notable examples include research efforts focused on fine-tuning Llama-2 for diverse applications, such as Question Answering and Text Summarization in the medical domain (Toma et al., 2023). Additionally, investigations have been conducted using OPT to generate synthetic dialogues in social contexts (Chen et al., 2023). Other studies have compared the performance of open-source models like Alpaca-Lora with proprietary alternatives, specifically in the realm of Dialogue State Tracking (Hudeček and Dušek, 2023). Furthermore, there have been assessments of Llama's performance in responding to user instructions within real-world scenarios (Ji et al., 2023).

One critical challenge in real-world applications is the dynamic nature of domains, where constant changes necessitate adaptations in dialogue systems. Previous studies (Labruna and Magnini, 2021, 2023) have shown how this domain shifts significantly deteriorate the performance of models trained on outdated data. With the emergence of instruction-based models, we aim to explore their efficacy in addressing this challenge compared to traditional models.

In this study, we focus on the task of dynamically substituting slot values for masked entities in task-oriented dialogues. This becomes particularly crucial in scenarios where domains evolve, prompting changes in slot values (e.g., a restaurant transitioning from offering "Indian" to "Italian" cuisine). We conduct a comparative analysis involving Llama-2 (Touvron et al., 2023), a state-of-the-art open-source instruction-based model, and BERT (Devlin et al., 2019), a traditional open-source language model.

Figure 1 provides an illustrative example, depicting an original dialogue with masked slot values (a), a dialogue with values generated by Llama to replace the masks (b), and a dialogue with values generated by BERT for the same task (c).

The primary contributions of this paper can be

Knowledge Base:
Restaurant little seoul - Area: centre, Food: korean, Price: reasonable
Restaurant shiraz restaurant - Area: northeast, Food: mediterranean, Price: expensive
Restaurant j restaurant - Area: central, Food: caribbean, Price: cheap

<p>USER: I'd like to find a restaurant that serves [MASK] food . SYSTEM: there is only [MASK] [MASK] restaurant in town called [MASK] .</p>	<p>USER: I'd like to find a restaurant that serves mediterranean food . SYSTEM: there is only 1 mediterranean restaurant in town called shiraz restaurant .</p>	<p>USER: I'd like to find a restaurant that serves fusion food . SYSTEM: there is only 0 fusion restaurant in town called midsummer .</p>
(a) Original Masked Dialogue	(b) Llama-2 Dialogue	(c) Bert Dialogue

Figure 1: Comparison on the slot values substitutions made by Llama-2 and BERT when tasked with generated values to substitute masks in a task-oriented dialogue.

summarized in three key points: (i) providing comparative analysis of two popular open-source language models, Llama-2 and BERT, in the specific task of generating substitutes for masked slot values; (ii) assessing model performance in dynamic contexts, where slot values undergo changes, with insights into how well Llama-2 and BERT deal with real-world scenarios marked by evolving information; (iii) systematically investigating the impact of fine-tuning on model behavior, drawing attention to distinct strategies applied to Llama-2 and BERT, and offering valuable observations on model adaptability under varying conditions during inference.

The paper is structured as follows: Section 2 offers background insights into relevant topics discussed in the paper; Section 3 outlines the methodology employed for our task, emphasizing the nuances of the dynamic slot value generation; Section 4 details the experimental settings, specifically the introduction of domain changes; Section 5 describes the evaluation metrics utilized for a comprehensive assessment; Section 6 presents the experimental results; finally, Section 7 provides a comprehensive discussion of the findings and their implications for instruction-based and traditional language models in dynamic contexts.

2 Background

2.1 LLMs and Instruction Tuning

Large Language Models have demonstrated unparalleled ability to generate high-quality text. Among them we find for instance T5 (Raffel et al., 2020), LaMDA (Cohen et al., 2022), and BERT (Devlin et al., 2018). BERT is an encoder-only bidirectional model, having a hidden attention layer that has access to both context directions, that has been pre-trained for context-aware word representations

and then fine-tuned i.e., specifically adapted for downstream tasks, along the “*pre-training and fine-tuning*” learning paradigm.

Nevertheless LMs, however large, often present misalignment with user intent. Instruction-tuned models (such as InstructGPT (Ouyang et al., 2022), LLama 2 (Touvron et al., 2023)) bring a solution to the problem, since they have been fine-tuned to be aligned with human conversational preferences in a supervised fashion on a dataset consisting of (instruction, output) pairs. Remarkable conversational abilities of the latest language models have been achieved with Instruction tuning (Wei et al., 2021; Sanh et al., 2021) and through aligning the output of the models to human preferences through Reinforcement Learning (Ng et al., 2000; Wilson et al., 2012; Todorov et al., 2012; Akrouf et al., 2014; Mnih et al., 2015; Naeem et al., 2020) and prompting techniques (Liu et al., 2023). Llama-2 (Touvron et al., 2023) is an updated version of Llama-1, released in versions of 7B (the one we use), 13B, and 70B parameters, trained on a new publicly available data, with increased size of the pretraining corpus by 40% and doubled context length of the model.

2.2 MultiWOZ 2.4

MultiWOZ (Budzianowski et al., 2018) is a widely used task-oriented conversational dataset collected using the Wizard of Oz technique. It consists of over 10,000 dialogues, covering seven different domains, such as restaurant reservations and search for tourist attractions. In our experiments we employ dialogues in the Restaurant domain from version 2.4 (Ye et al., 2021). The dataset contains annotations structured in triplets: *domain* (e.g., RESTAURANT), *slot* (e.g., PRICE), and *slot-value* (e.g., EXPENSIVE).

2.3 Domain Knowledge

A task-oriented dialogue between a system and a user is considered as composed of a sequence of turns $\{t_1, t_2, \dots, t_n\}$ (Budzianowski et al., 2018). The system needs to retrieve a set of entities in a domain Knowledge Base (KB) satisfying the user’s needs. KB is represented by a structured domain ontology O that represents entities (e.g., Restaurant, Hotel, Movie) according to a pre-defined set of slots S (e.g., Food, Area, Price, for the Restaurant domain), and values that a certain slot can take (e.g., Expensive, Moderate, Cheap, for the slot Price). On the basis of the entities defined in the domain ontology, the KB is then populated with instances of such entities.

As in much of the literature, we distinguish informable slots (e.g., Area) from requestable slots (e.g., PhoneNumber), whose values are normally queried only after a specific entity has been retrieved through the dialogue.

2.4 Domain Changes

The kind of domain change we are working with is slot-value change. This occurs every time a slot-value v used to describe an existing instance in the initial KB is changed with another slot-value (see Figure 1 for an example). This change may involve an already existing slot-value (e.g., a certain restaurant moved from INDIAN to PIZZA food, assuming that PIZZA was already used for other instances), or a new slot-value (e.g., moving from INDIAN to MEDITERRANEAN, which was never used before). The domain shift we are addressing involves alterations in slot-value pairs. This happens when a value v associated with a particular slot linked to an existing entity in the original KB , is substituted with a different slot-value (refer to Figure 1 for an example).

Such modifications could entail replacing an existing slot-value (for instance, a restaurant transitioning from being categorized as INDIAN cuisine to PIZZA, given that PIZZA was previously attributed to other entities) or introducing a wholly new slot-value (like transitioning from INDIAN to MEDITERRANEAN, a classification not previously employed).

3 Methodology

In this section, we outline the methodology employed to evaluate the performance of BERT and Llama-2 for the task of substituting slot values

in a dialogue in the context of dynamic domain changes.

The primary task involves masking specific slot values in the utterances of a dialogue, both in user and system turns and assessing how well language models can generate appropriate substitutions for these masks.

3.1 Slot Values Prediction

For both BERT and Llama-2, the common task is to replace the masked slot values with appropriate generated text. The difference lies in the nature of the input provided to each model. In the case of BERT, a single sentence is passed with only one masked slot value at a time, and the model is prompted to generate the output for the substitution of that specific mask. Conversely, Llama-2 is presented with a more complex task. It is given a full instruction, consisting of a dialogue with all slot values masked, and is tasked with substituting all the masks based on the information contained in a KB provided alongside the instruction.

While the task for BERT is designed to evaluate the model’s ability to generate accurate and contextually relevant responses when faced with isolated slot substitutions within a dialogue, the Llama-2 task is representative of a scenario where the model is required to assimilate information from a larger context and generate responses that need to maintain dialogue coherence across all the turns of the conversation, as well as adherence to the information of the KB .

3.2 Model Finetuning

In order to ensure that both BERT and Llama-2 comprehend the slot-value substitution task and the domain-specific information, a finetuning process is essential. However, the finetuning procedures differ significantly between the two models.

BERT’s finetuning involves exposing the model to a list of utterances derived from all dialogues in the training dataset. The dataset comprises both user and system turns, and each utterance is treated as a separate training example. This is enough for the model to understand the probability distribution of word occurrences within the specific context of the dialogue.

In contrast, Llama-2’s finetuning necessitates a more structured approach due to its instruction-based nature. Llama-2 requires explicit examples of instruction prompts along with their corresponding expected outputs. For the slot-value substitu-

tion task, the instruction prompt consists of a request of filling the values for all the masked slots in a full dialogue, based on the information contained in a certain number of KB instances. The model learns to generate substitutions for the masked slots based on the information contained in these instances.

3.3 Domain Changes Simulation

The simulation of domain changes is an integral part of our methodology, reflecting the dynamic nature of real-world interactions where shifts in information occur continuously. In task-oriented language understanding scenarios, models must adapt to evolving contexts, such as restaurants changing their food offerings or the introduction of new areas within a city. At inference time we want to see how changes in domain affect the performance of the models. To emulate the continuous evolution of task-specific domains, we incrementally introduce new slot values. These values substitute the original ones, reflecting changes in the characteristics of the entities within the domain.

The primary objective of introducing domain changes is to evaluate how these incremental shifts affect the quality of generated slot value produced by language models. Specifically, we aim to assess the models' ability to generate accurate responses in the presence of new slot values. By incrementally increasing the complexity of the task through the introduction of new slot values, we gain insights into the models' adaptability and their capacity to handle evolving task-oriented domains.

4 Experimental Setting

4.1 Domain Changes

In this subsection, we detail how we defined and implemented domain changes for our experiments, aiming to assess the models' adaptability to evolving task-specific domains.

We have defined four distinct domain change scenarios, each representing a different degree of alteration in the domain's information space. These scenarios correspond to 0%, 25%, 50%, 75%, and 100% of new slot values introduced into the KB . The term "new slot values" refers to information that replaces the original values associated with specific slots in the KB . The 0% of new slot values means that all the values remained as they were in the original KB , while the 100% of new values means that all the original values were substituted.

The new slot values were manually generated to ensure coherence with their respective slot names and to guarantee that they did not exist in the original KB . As an example, for the slot *Price*, which originally included the values *cheap*, *moderate* and *expensive*, we defined the new values *affordable*, *reasonable* and *economical*.

4.2 Finetuning

The finetuning data was derived from the training data of MultiWOZ 2.4. For each dialogue D in the dataset, we algorithmically extracted a subset of instances from the KB . This subset, denoted by I_D , represents all the instances that are referenced at least once in the dialogue D . Given I_D , we applied a certain amount of domain changes, as defined in Section 4.1, to these instances. The resulting set of instances after the domain changes is denoted by I'_D . We finally used the information of the instances I'_D to fill the slot values in the dialogue D , generating a new dialogue denoted by D' . Each dialogue D' is then used to generate the finetuning data.

As we discussed in Section 3.2, the requested format for the finetuning data differs a lot between BERT and Llama models. For BERT we simply included every utterance from the dialogue D' as part of the finetuning data. For Llama-2, the finetuning process was more complex. We masked all slot values in the dialogue D' and included the masked dialogue in the prompt, along with the KB instances I'_D correspondent to the specific dialogue. The original values from D' were included as the desired output to make the model learn the correct values for replacing the masks. A full example of a Llama prompt is shown at Appendix A.

We decided to finetune Llama-2 only on the 0% changes scenario, while for BERT we performed finetuning for all the domain changes scenarios. This resulted in the following models:

- LLAMA_KB0 - Llama-2 model finetuned on the no changes scenario
- BERT_KB0 - BERT model finetuned on the no changes scenario
- BERT_ADD25 - BERT model finetuned on the 25% of new slot values scenario
- BERT_ADD50 - BERT model finetuned on the 50% of new slot values scenario

- BERT_ADD75 - BERT model finetuned on the 75% of new slot values scenario
- BERT_ADD100 - BERT model finetuned on the 100% of new slot values scenario

The choice of finetuning Llama-2 only on the 0% changes situation reflects the specific setting of the model during inference, where it is provided with the instances containing the desired slot values for substituting the masks. In contrast, it is fundamental to finetune BERT for each change scenario in order to grasp the evolving task-specific domain. This experimental configuration also allows us to compare the performance of Llama-2 which handles progressively higher domain changes during inference, with that of BERT, which undergoes new finetuning for each distinct setting.

For finetuning Llama-2, we used "meta-llama/Llama-2-7b-chat-hf" (the 7 billion parameters version) as the base model, and made the following parameter choices: a batch size of 128, a micro-batch size of 32, three training epochs, a learning rate of 1×10^{-4} , a cutoff length of 512, a validation set size of 2000, LoRA radius (lora_r) set to 8, LoRA alpha (lora_alpha) set to 16, and a dropout rate of 0.05. For finetuning BERT, we used "bert-base-uncased" as the base model, and made the following parameter choices: a batch size of 32, three training epochs, a learning rate of 5×10^{-5} and made use of the Adam optimizer.

4.3 Inference

We assess model performance under the same domain change scenarios defined in Section 4.1 (0%, 25%, 50%, 75%, and 100% of new slot values).

We created the correspondent test-sets starting from the test-set of MultiWOZ 2.4 and applying the domain changes for each setting to the slot values, following the same procedure as outlined in Section 4.2. We then masked the slot values and asked the models to predict the correct substitutes to the masks. We conducted inference testing on each model, considering the specific finetunings and corresponding change settings: LLAMA_KB0 was tested on all five domain changes settings; each version of BERT (BERT_KB0, BERT_ADD25, BERT_ADD50, BERT_ADD75, and BERT_ADD100) was tested with the corresponding test-set matching the change setting it was finetuned on. For performing inference with the two models, we used the same

Model	Test Set	Exact Match
BERT_0	<i>KB0</i>	0.28
LLAMA_0	<i>KB0</i>	0.49
BERT_ADD25	<i>add25</i>	0.29
LLAMA_0	<i>add25</i>	0.40
BERT_ADD50	<i>add50</i>	0.21
LLAMA_0	<i>add50</i>	0.35
BERT_ADD75	<i>add75</i>	0.16
LLAMA_0	<i>add75</i>	0.31
BERT_ADD100	<i>add100</i>	0.17
LLAMA_0	<i>add100</i>	0.29

Table 1: Results of the exact match evaluation, determining the portion of generated slot values that correspond to the exact same value that were present in the original data.

versions as for finetuning as the base models, a temperature of 0.8 and a top_k of 200.

5 Evaluation Metrics

5.1 Exact Match

This metric measures the precision of the generated values by determining if they match exactly with the original values in the test data (e.g. if the original value for the slot was "Indian", we count the generation as 1 only if it returns exactly "Indian", 0 otherwise), thus higher values indicate better performance. While it may not encompass every positive generation by the model, it ensures that every instance of an exact match is a correct generation. This metric is particularly strict and specific, setting it apart from others that offer a more nuanced perspective on data quality.

5.2 Data Quality Metrics

We employed five supplementary metrics to gain insights into various aspects of data quality. These metrics should not be considered in isolation; instead, they collectively offer perspectives on different characteristics of the quality of the generated values. In all these metrics, lower values indicate better model performance.

Out of KB Measures the number of slot values generated that do not correspond to any value present in the *KB* (e.g. "Caribbean" is generated, but no occurrence of this value is found in the *KB*).

Calculated as a ratio of such values to the total generated values.

Wrong Slots Measures the number of slot values generated that correspond to a value in the *KB* but are associated with a different slot name than the one in the original test data (e.g. the value "cheap" is generated as a substitution for a "Food" slot). Calculated as a ratio of such values to the total generated values.

Dialogue Incoherence Assesses the coherence of the dialogue by counting slot values that do not maintain the same substitution matches throughout the turns (e.g. first "Indian" is substituted to "Italian", then, later in the dialogue, another occurrence of "Indian" is substituted with "Chinese"). Calculated as a ratio on a subset of all generated values (the values for the first substitution matches are not eligible for this evaluation).

KB Quantifiers Misalignment Examines the adherence of quantifier slot values by identifying instances where the generated text indicates an incorrect number of instances in the *KB* (e.g. the system says that there are 2 "Indian" restaurants at "north", but there is none). Calculated as a ratio only on quantifier slot values.

No Output (Llama-2 Only) Measures the frequency of slot values for which no output is returned. This metric is exclusive to Llama-2 since BERT is instructed to return a value for a single MASK, ensuring some form of output. Calculated as a ratio of such values to the total slot values.

5.3 Manual Quality Evaluation

In addition to automated metrics, a manual quality evaluation was annotated on a subset of dialogues from each domain change setting. This qualitative assessment at the dialogue level annotated dialogues as either acceptable or not based on predefined criteria and provides nuanced perspective on overall performance and contextual coherence.

Dialogue Acceptability Is annotated on a subset of 100 dialogues: from the five domain change settings, 20 dialogues were drawn. Each dialogue in the subset was assessed in both the Llama-2 and BERT-completed versions. The annotation occurs at dialogue level, meaning that each dialogue was evaluated as a whole, so that one error invalidates the acceptability of the entire dialogue.

General criteria related to dialogue pragmatics such as naturalness and fluency have been complemented by more objective criteria such as: compliance with semantic and syntactic constraints, coherence across dialogue turns, consistency in referring to *KB* instances, adherence of quantifier slot values. There are two exceptions to these stringent conditions. The first concerns minor violations of syntactic constraints that have no effect on dialogue intelligibility (for example, "a affordable", "an sri lankan", "1 restaurants"). Regarding the second point, we did not place as much emphasis on filling in the restaurant name slots with their proper nouns as we did on the other informable slots.

Dialogue Solutions Are intended as the number of instances from the given *KB* that provide a solution to the dialogue semantic and syntactic constraints while ensuring across-turn coherence and *KB* adherence. The number of possible solutions has been annotated for each dialogue to give insights on the performances of the models as the complexity of the task varies. For instance, a value of 1 solution means that using only values taken from the available *KB* for that particular dialogue, there would be only one configuration of slot values in the dialogue that would produce an acceptable dialogue. A value of 0 solutions means that there are no values in the *KB* that can be used to produce an acceptable dialogue.

6 Results

6.1 Exact Matches Results

Table 1 illustrates the percentage of exact match generations, as described in Section 5.1, for each domain change setting and both models. Notably, Llama-2 exhibits a substantial decrease in performance, dropping from 0.48 to 0.29, as new slot values are introduced. Despite this decline, Llama-2 consistently outperforms BERT in all scenarios.

6.2 Data Quality Results

Table 2 provides a comprehensive view of the evaluation metrics presented in Section 5.2. For the "Out of KB" metric, Llama-2 sees a slight decrease in performance as the domain changes increase, while BERT exhibits a slight improvement, however, BERT consistently remains considerably lower than Llama-2.

Regarding "Wrong Slots," both models demonstrate low percentages, with Llama-2 performing better in the no-change scenario but exhibiting a

Model	Test Set	Out of KB	Wrong Slots	Dialogue Incoherence	KB Quantifiers Misalignment	No Output
BERT_0	<i>KB0</i>	0.36	0.05	0.25	0.82	-
LLAMA_0	<i>KB0</i>	0.15	0.03	0.05	0.52	0.32
BERT_ADD25	<i>add25</i>	0.35	0.02	0.20	0.66	-
LLAMA_0	<i>add25</i>	0.16	0.05	0.07	0.72	0.34
BERT_ADD50	<i>add50</i>	0.33	0.04	0.19	0.76	-
LLAMA_0	<i>add50</i>	0.16	0.08	0.07	0.85	0.35
BERT_ADD75	<i>add75</i>	0.34	0.02	0.19	0.68	-
LLAMA_0	<i>add75</i>	0.18	0.10	0.08	0.95	0.38
BERT_ADD100	<i>add100</i>	0.34	0.01	0.15	0.73	-
LLAMA_0	<i>add100</i>	0.19	0.11	0.09	0.99	0.40

Table 2: Results of the quality of the values generated both by BERT and Llama-2 measured by different metrics.

Test Set	BERT	LLAMA-2
<i>KB0</i>	0.15	0.65
<i>add25</i>	0.15	0.70
<i>add50</i>	0.10	0.50
<i>add75</i>	0.15	0.80
<i>add100</i>	0.15	0.75

Table 3: Results of the manual quality evaluation, conducted over 20 dialogues per test set. Overall quality of each dialogue is considered. Results are obtained through the ratio of acceptable dialogues to the selected 20 dialogues per dataset.

decline in all other scenarios, particularly in the add100 scenario where it performs even ten times worse.

For "Dialogue Incoherence," Llama-2 consistently outperforms BERT across all scenarios, even though there is a slight decrease as new slot values are introduced.

In terms of "KB Quantifiers Misalignment," Llama-2 performs better only in the no-change scenario and then experiences a substantial decrease, reaching 99% of generated values that are not adherent to the KB.

Lastly, the "No Output" metric, applicable only to Llama-2, indicates a slight decrease in performance from 0.32 to 0.4.

6.3 Dialogue Acceptability Results

We finally present the results of the evaluation explained in Section 5.3 related to scoring the quality of the model generations at a dialogue level,

through manual assessment.

Table 3 presents the outcomes of the evaluation focused on scoring the overall quality of each dialogue, considering factors such as coherence, naturalness, and informativeness. The results are represented as the ratio of acceptable dialogues to the total number of dialogues assessed in each test set.

Table 4 showcases the dialogue acceptability for BERT and Llama-2 across the five settings, taking into account the number of possible solutions for each dialogue, as explained in 5.3, with the columns labeled 0 to 3 sol indicating the number of potential solutions given the particular *KB* for each dialogue. Notably, 1 sol represents scenarios with a single solution, which tends to be more straightforward for the models. No examples were observed where the models successfully addressed cases with no solutions, meaning situations where, to be considered correct, the models should have generated out-of-KB values leading to zero instances in the *KB*. In the case of the other extreme, the scenario with three possible solutions, only Llama-2 succeeded in generating one acceptable dialogue.

7 Discussion

The results of our experiments reveal several interesting patterns and insights into the performance of instruction-based language models such as Llama-2, in comparison to traditional language models like BERT. The most apparent trend is observed in Llama-2's performance, starting with a higher accuracy in the no-change scenario and gradually

Test Set	BERT				LLAMA-2			
	0 sol	1 sol	2 sol	3 sol	0 sol	1 sol	2 sol	3 sol
<i>KB0</i>	0	33%	67%	0	0	69%	31%	0
<i>add25</i>	0	100%	0	0	0	64%	36%	0
<i>add50</i>	0	100%	0	0	0	80%	20%	0
<i>add75</i>	0	67%	33%	0	0	75%	19%	6%
<i>add100</i>	0	67%	33%	0	0	73%	27%	0

Table 4: Overall dialogue acceptability in the five settings for BERT and Llama-2 related to the number of possible solutions for each dialogue: results are computed by the percentage of acceptable dialogues with n solutions over the number of acceptable dialogues.

declining as new slot values are introduced. This pattern underscores the vulnerability of even advanced instruction-based language models to the impact of domain changes. Despite their proficiency in certain tasks, these models struggle to maintain consistent performance in dynamic environments. Another clear observation is that Llama-2 consistently outperforms BERT when both models are fine-tuned on the same domain as the one present at inference time. This indicates that modern instruction-based models exhibit superior capabilities in the task of mask substitution when provided with the same domain information during training.

The comparison becomes more nuanced when domain changes are introduced. In most metrics, Llama-2 demonstrates significantly better performance than BERT across various scenarios, suggesting that even without specific fine-tuning, instruction-based models have better performance than traditional language models finetuned for the specific domain setting. In scenarios such as "Dialogue Incoherence", this outcome is expected, given that BERT solely replaces individual masks and lacks awareness of the dialogue's evolution, so that it becomes impossible for it to preserve coherence throughout the dialogue.

However, there are instances where BERT outperforms Llama-2, particularly for the metrics "Wrong Slots" and "KB Quantifiers Misalignment". In the case of "Wrong Slots", the constraint imposed on Llama-2 by instructions to extract values from the *KB* may lead to more instances of values being assigned to the wrong slot. For "KB Quantifiers Misalignment", the observed difference could be attributed to quantity values where dialogues necessitate indicating zero instances, possibly due to errors in the preceding part of the dia-

logue. BERT is more inclined to generate a value of zero in such cases (as in the example in Figure 1), whereas Llama tends to avoid failure examples and always say that there is at least one restaurant available.

The manual evaluation provides valuable insights that complement the quantitative results obtained from the automatic assessments. Notably, neither of the two models successfully assigns correct slot values to dialogues expecting 0 solutions in the *KB*. In these cases, models are expected to generate out-of-KB values; while they occasionally do, resulting in seemingly coherent dialogues, errors often manifest in subsequent turns.

It is essential to acknowledge that generating out-of-KB values is not always indicative of an error. This observation extends to the "Wrong Slot" measure, where values substituted for one slot type may correspond to another slot type yet remain acceptable within the utterance. Similarly, the metric for "Dialogue Incoherence" occasionally misclassifies cases as incorrect during automated assessment, which are instead considered correct in manual evaluation. For instance, instances where the model generates "north" after previously stating "northwest" could be technically correct, as "northwest" inherently implies "north." A similar situation arises with terms like "affordable," "economic," "moderate," and "reasonable," which may be considered synonymous but are treated as distinct values in the automated measure.

Additionally, a noteworthy observation is the significant difficulty observed in BERT's ability to generate restaurant names, which instead tends to substitute values like "it" or "that" pronouns. Overall, our study sheds light on both strengths and weaknesses of instruction-based language models like Llama-2 as compared to traditional models like

BERT, for our task.

8 Limitations

Our study has a number of limitations that should be taken into consideration when interpreting the results. Firstly, we utilized the smallest variant of Llama-2, with 7 billion parameters. It is plausible that larger versions of Llama-2 could yield improved performance.

Secondly, our experiments were conducted exclusively on the MultiWOZ 2.4 dataset, focusing specifically on the Restaurant domain and only considering informable slots. Consequently, the generalizability of our findings to other task-oriented dialogue scenarios, domains, or datasets may be limited.

Furthermore, in the case of Llama, we did not extensively explore the impact of using different prompts. The potential influence of varied prompts on performance remains an area that requires further investigation, and it is plausible that alternative prompts could lead to more favorable outcomes.

Finally, the comparison between instruction-based models and traditional language models in this study was restricted to two specific models — BERT and Llama-2 — each configured with specific parameter settings. Therefore, caution is advised when attempting to generalize these findings to a broader range of models and contexts.

9 Conclusion and Future Work

This study delved into the performance analysis of two language models, namely BERT and Llama-2, focusing on their ability to generate substitutions for masked slot values in task-oriented dialogues. The experimentation was grounded in the dynamic context of domain changes, simulating scenarios where new slot values are introduced. We used the MultiWOZ 2.4 dataset, specifically concentrating on the Restaurant domain and informable slots. Our methodology involved finetuning Llama-2 only on the zero-changes scenario, while BERT was finetuned for each change scenario.

Llama-2 demonstrated superior performance in the no-change scenario, emphasizing the efficacy of instruction-based models with consistent domain information, but faced a significant decline with increasing domain changes, ultimately falling below BERT for some of the considered quality features. We highlighted strengths and weaknesses of both

approaches in dynamic task-oriented dialogue scenarios.

As emphasized in Section 8, there is potential for improvement by incorporating diverse models and datasets (such as SGD (Rastogi et al., 2020)). To address this, future research will delve into larger versions of Llama-2, explore alternative models, and incorporate varied datasets. Additionally, the investigation will consider the use of diverse prompts, including slot descriptions as seen in (Hudeček and Dušek, 2023), to enhance our comprehension of instruction-based models within dynamic contexts.

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A Appendix A: Llama-2 Prompt

Below is an instruction that describes a task, along with a Knowledge Base with the specific domain information that you should use and a Dialogue, on which you should work on. Write a response that appropriately completes the request.

Instruction:

Fill in the blanks [MASK] in the Dialogue based on the information of the Knowledge Base. Provide the filled values in the correct order, separated by commas, for every turn in the Dialogue. Separate turns with a new line. If the turn doesn't have any slot, just output the new line.

Knowledge Base:

Restaurant restaurant one seven - Area: centre, Food: british, Price: moderate
Restaurant cambridge lodge restaurant - Area: west, Food: european, Price: expensive

Dialogue:

USER: I 'm looking for a restaurant serving [MASK] food in any area .

SYSTEM: There are no [MASK] restaurants in the area .

USER: Well can I get the phone number to a [MASK] restaurant ?

SYSTEM: [MASK] serves [MASK] food .
Their phone number is 01223 355166 . Can I help you with anything else ?

USER: That 's it , goodbye

SYSTEM: your welcome good bye

Response:

european\neuropean\nbritish\nrestaurant one seven, british

Upon replacing the slot values, which are generated as the output of the model, into the corresponding masks, the resulting dialogue will be as follows:

USER: I 'm looking for a restaurant serving **european** food in any area .

SYSTEM: There are no **european** restaurants in the area .

USER: Well can I get the phone number to a **british** restaurant ?

SYSTEM: **restaurant one seven** serves **british** food . Their phone number is 01223 355166 . Can I help you with anything else ?

USER: That 's it , goodbye

SYSTEM: your welcome good bye

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