Investigating Large Language Models for Complex Word Identification in Multilingual and Multidomain Setups

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Abstract

Complex Word Identification (CWI) is an essential step in the lexical simplification task and has recently become a task on its own. Some variations of this binary classification task have emerged, such as lexical complexity prediction (LCP) and complexity evaluation of multi-word expressions (MWE). Large language models (LLMs) recently became popular in the Natural Language Processing community because of their versatility and capability to solve unseen tasks in zero/few-shot settings. Our work investigates LLM usage, specifically open-source models such as Llama 2, Llama 3, and Vicuna v1.5, and closed-source, such as ChatGPT-3.5-turbo and GPT-4o, in the CWI, LCP, and MWE settings. We evaluate zero-shot, few-shot, and fine-tuning settings and show that LLMs struggle in certain conditions or achieve comparable results against existing methods. In addition, we provide some views on meta-learning combined with prompt learning. In the end, we conclude that the current state of LLMs cannot or barely outperform existing methods, which are usually much smaller.

1 Introduction

Complex word identification (CWI) aims to determine whether words or phrases are difficult for a target group of readers to understand. In the lexical simplification task, which targets replacing complex words and expressions with simplified alternatives (North et al., 2023a), CWI is the first step, and it was treated as part of this task until 2012 when it became a standalone task (Shardlow, 2013).

CWI was initially addressed as a binary classification task (Paetzold and Specia, 2016), identifying whether a word is complex in a given sentence. When the task became more popular (North et al., 2023b), it was extended to the continuous domain as Lexical Complexity Prediction (LCP, also referred to as the probabilistic classification for CWI) (Yimam et al., 2018), addressing multilingual and multidomain settings. Then, it was extended to multi-word expressions (Shardlow et al., 2021). Recently, new datasets started to emerge in various languages and domains (Ortiz Zambrano and Montejo-Ráez, 2021; Venugopal et al., 2022; Ilgen and Biemann, 2023; Zambrano et al., 2023). Previous approaches to CWI ranged from using Support Vector Machines (S.P et al., 2016) to deep neural networks based on Bidirectional Representation from Encoder Transformers (Pan et al., 2021), multi-task learning with domain adaptation (Zaharia et al., 2022), and sequence modeling (Gooding and Kochmar, 2019).

With the recent breakthrough in large language models (LLMs), particularly the work of OpenAI with Generative Pre-trained Transformer (GPT) models (Radford et al., 2019; Brown et al., 2020), natural language processing has seen a significant leap. These models have shown the potential to improve performances on various tasks as we scale up the model size and the amount of training data. The announcement of ChatGPT[1] and its conversational capabilities has sparked a race in developing and fine-tuning new models for general purpose and domain-specific applications using PaLM (Anil et al., 2023), LLaMA (Touvron et al., 2023; Dubey et al., 2024), Orca (Mitra et al., 2023), Mistral (Jiang et al., 2023), GPT-4 (OpenAI et al., 2023), GPT-4o[2], and many others.

Our work aims to provide the current state of LLMs in addressing CWI and LCP compared

[1]https://openai.com/blog/chatgpt

[2]https://openai.com/index/hello-gpt-4o/

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against state-of-the-art approaches. We focus on evaluating open-source (pre-trained Llama 2 (Touvron et al., 2023), Llama 3 (Dubey et al., 2024), Vicuna (Zheng et al., 2024)) and OpenAI's close-source ChatGPT-3.5-turbo and GPT-4o. We summarize the contributions as follows:

- We evaluate LLMs in binary (discrete set of labels) and probabilistic classification (continuous space labels) on multidomain and multilingual corpora.
- We employ various techniques for prompting and fine-tuning.
- We show that LLMs struggle to address CWI and LCP tasks; however, in limited instances, they can achieve similar results with other, more lightweight approaches.
- In the end, we analyze and provide an insight into where the models struggle.

2 Related Work

2.1 Complex Word Identification

CWI was previously addressed using straightforward baseline models based on feature engineering. For example, Aroyehun et al. (2018) compared CNN-based models with various feature engineering methods based on tree ensembles and features, such as inverse term frequency, parts-of-speech tagging, WordNet, and word2vec, achieving comparable results. Finnimore et al. (2019) proposed mono and cross-lingual models based on simple features and logistic regression, achieving similar results to more complex, language-specific state-of-the-art models. Zaharia et al. (2020) employed zero and few-shot learning techniques, along with Transformers and Recurrent Neural Networks, in a multilingual setting. Gooding and Kochmar (2019) considered CWI a sequential task, using a bidirectional LSTM with word embeddings, character-level representations, and a language modeling objective to learn the complexity of words given the context. Other methods improved performances, employing graph-based (Ehara, 2019), domain adaptation (Zaharia et al., 2022), and transformer-based models (Pan et al., 2021; Cheng Sheang et al., 2022).

2.2 Large Language Models

Recently, LLMs were successfully utilized in various generative tasks (Pu et al., 2023; Chen et al., 2021). The new paradigm in solving other non-generative tasks is based on prompting pre-trained language models to perform the prediction task (Liu et al., 2023a; Sun et al., 2023). Fine-tuning models on instructions showed improved results in zero-shot settings, especially on unseen tasks (Wei et al., 2022a). Prompt-based methods such as the use of demonstrations (Min et al., 2022), intermediate reasoning steps by breaking down complex tasks into simpler subtasks (also known as a chain of thought) (Wei et al., 2022b), and using LLMs to optimize their prompts (Zhou et al., 2023) made zero-shot inference much more appealing due to reduced costs and more efficient than fine-tuning LLMs.

2.3 Prompt Tuning and Meta-Learning

Fine-tuning usually requires high computational costs, especially in the context of LLMs, to achieve good performances. Therefore, there was the need to find alternatives. Prompt Tuning (Lester et al., 2021) is a soft-prompting technique for adapting a large language model for a custom task without training its parameters. While successful, prompt tuning falls short when applied in the few-shot learning regime, leading to a combination with meta-learning. MetaPrompting (Hou et al., 2022) utilizes the meta-learning algorithms FOMAML (Finn et al., 2017) and Reptile (Nichol et al., 2018) to obtain optimized initialization embeddings. One shortcoming of this approach is the requirement for supervised training data during meta-learning, which is alleviated in other works (Pan et al., 2023; Huang et al., 2023) by generating the meta-training tasks in an unsupervised or self-supervised manner. Additionally, other works explored the use of an adaptable gradient regulating function (Li et al., 2023) and domain-adversarial neural networks (Fang et al., 2023), both techniques used to increase model generalization.

3 Method

3.1 Problem Formulation in the Pre-LLM Era

Word complexity can be defined as absolute and relative (North et al., 2023b). Absolute complexity is determined by the objective linguistic properties (e.g., semantic, morphological, phonological). In contrast, relative complexity is related to the subjective speaker's point of view (e.g., familiarity with sound and meaning, culture, and context). In this work, we evaluate the relative complexity of words from non-native speakers' points of view. Considering an annotated dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ of N samples, the task can be viewed as a binary classification, CWI, where, given the pair $x_i = (C_i, w_i)$ of a sentence $C_i = (w_1, w_2, ...)$ and a word $w_i \in C_i$, the system outputs $y_i^{CWI} \in \{0, 1\}$ (i.e., complex or non-complex) (Paetzold and Specia, 2016). A variation of the CWI task is to evaluate the complexity $y_i^{MWE} \in \{0, 1\}$ of a multi-word expression $e_i = (w_1, w_2, ...)$ containing multiple words w_j, $j = 1 : |e|$, from a given context C_i (i.e., $x_i = (C_i, e_i)$) (Shardlow et al., 2021). Later, CWI was considered in the continuous domain known as LCP, indicating the degree of difficulty $y_i^{LCP} \in [0, 1]$ for the given word $w_i \in C_i$ in the context C_i (Yimam et al., 2018).

3.2 Problem Formulation in the LLM Era

Starting from the previous formulation, we derive the formalism in the context of LLMs.

Binary classification. Given an example $x_i = (C_i, w_i)$, the model predicts if a given phrase w_i from the sentence C_i is complex. Especially in closed-source models, the access to the tokens' logits is limited (e.g., OpenAI's ChatGPT or GPT-4o). Therefore, we consider having access to only the model's predicted text labels "true" or "false" (or any equivalent form) without a confidence estimation.

Probabilistic classification. The model produces a real value between 0 and 1 in the existing approaches, representing the degree of complexity for (C_i, w_i). LLMs are known to suffer from hallucinations (OpenAI et al., 2023), and reliably predicting real values is challenging. We abide by Liu et al. (2023b)'s solution for estimating the scoring function. In a nutshell, instead of letting the model predict the probability as a number, we let the model generate discrete signals, and then we estimate the score through averaging. Specifically, we prompt the model to predict on the 5-point Likert scale, in natural language, one of "very easy", "easy", "neutral", "difficult", or "very difficult". This scale is converted into a numerical representation using the following mapping: very easy - 0, easy - 0.25, neutral - 0.5, difficult - 0.75, and very difficult - 1. Since LLMs output tokens from a probability distribution, we set the temperature to a higher value (in our experiments, we use 0.8) to increase response variability. The numerical representation from LLM's output is denoted as $s_k \in S$ for a sampling step k, with $S = \{0, 0.25, 0.5, 0.75, 1\}$. The model's probability of outputting one 5-point Likert score is $p(s_k)$. The final score is:

$$score = \mathbb{E}_p[S] = \sum_{s \in S} p(s) \cdot s \qquad (1)$$

For experiments, we use the sample mean estimator $\overline{score} = \frac{1}{K} \sum_{k=1}^{K} s_k$ of K sampling steps.

In essence, we want to simulate the data annotation process involved. Instead of employing multiple human annotators, we use the same model that produces a more randomized output by setting a higher temperature. Note that randomized LLM outputs do not translate to randomized output labels. Variance in the results can be used as a confidence estimator, and we show (see §6.4) that models act more deterministically despite setting a high-temperature value. However, even for fine-tuned models, the variance is not 0; thus, it does not collapse to the multi-class classification setup (see §6.4).

3.3 Prompting LLMs

We set the system prompt of the model with the task and how to format the output. Then, we prompt it through the user prompt to predict the example label. Each example is prompted individually to avoid leaking knowledge from other examples.

All system prompts are listed in the Appendix A. These are obtained after prompt engineering, i.e., multiple trial-and-errors. Our focus was on optimizing the prompt length and the LLM's performance. Because performing prompt engineering on every LLM is time-consuming, we optimized the prompts on ChatGPT-3.5-turbo and LLama 2 7B models on LCP and CWI English, each as a whole task, respectively. The prompts for German and Spanish are translations of the English prompts.

We investigate prompting strategies for zero-shot and few-shot settings. In every setting, we evaluate with and without employing the chain of thoughts approach (Wei et al., 2022b) to reduce hallucination. Therefore, the model needs to reproduce the original sentence and the word and then, before the final answer, provide a short proof about the reason for the response.

A similar prompting procedure is applied for open-source and close-source models. The difference mainly lies in how we format the query using either the Chat Message API[3] for OpenAI's mod-

[3] https://platform.openai.com/docs/api-reference/chat/create

els or the chat template available in the HuggingFace tokenizer[4]. We provide details regarding the prompting format in Appendix A and the evaluation protocol in Appendix C.

3.4 Fine-tuning LLMs

For fine-tuned models, we prepare the dataset to include a minimal system prompt and the query with the answer. First, we discretize the probabilities similar to Shardlow et al. (2021): scores between 0 and 0.2 are very easy, between 0.2 and 0.4 are easy, between 0.4 and 0.6 are neutral, between 0.6 and 0.8 are difficult, and between 0.8 and 1 are very difficult. Next, we apply the prompt for open-source models using the template specific to the model available in the HuggingFace tokenizer. Fine-tuning OpenAI's ChatGPT models involves uploading the training and validation files and starting the training job. After finishing the fine-tuning step, we follow a procedure similar to §3.3. However, in this setting, the model does not generate a demonstration but directly generates the answer.

3.5 Meta-Learning

Meta-learning tries to adapt a model to a new task by acquiring knowledge from multiple learning tasks. Our approach involves training the model on various tasks using soft prompting methods. Therefore, we propose using FOMAML (Finn et al., 2017) in conjunction with Prompt tuning (Lester et al., 2021) and P-tuning v2 (Liu et al., 2022) to optimize the initial parameters of our adapters. In the prompt tuning setting, we prepend the input prompt with several virtual tokens learned during training. P-tuning v2 takes this idea to the next level by adding trainable prompts to different layers in the model. The model is only provided with the user prompt during input construction due to the system prompt's non-standardized nature and the variety of tasks it employs. We select 45 tasks from the BIG-bench suite, as detailed in §4.1 and Appendix G.

Most optimization-based meta-learning algorithms, including FOMAML, involve copying the model's parameters trained so far, sampling a random set of tasks, training the parameters for several steps, and then performing the optimization step. The inner training steps are task-dependent. In our case, we use the same causal loss as in fine-tuning. The algorithm is described in Algorithm 1. It is noteworthy that training requires more computational resources than fine-tuning.

[4] https://huggingface.co/docs/transformers/en/chat_templating

Algorithm 1: FOMAML algorithm

Data: α, β learning rates, n inner steps
Randomly initialize θ;
while *not converged* **do**
  `//Sample support and query sets`
  Sample task $\mathcal{T} = (\mathcal{T}_\mathrm{s}, \mathcal{T}_\mathrm{q})$;
  `//Inner training loop`
  $\theta'_0 \leftarrow \theta$;
  for $i = 0$ **to** n **do**
    $\theta'_{i+1} \leftarrow \theta'_i - \alpha \nabla_{\theta'_i} \mathcal{L}(\theta'_i, \mathcal{T}_\mathrm{s})$;
  end
  `//FOMAML optimization`
  $//\nabla_\theta \mathcal{L}(\theta'_n, \mathcal{T}_\mathrm{q}) \approx \nabla_{\theta'_n} \mathcal{L}(\theta'_n, \mathcal{T}_\mathrm{q})$
  $\theta \leftarrow \theta - \beta \nabla_{\theta'_n} \mathcal{L}(\theta'_n, \mathcal{T}_\mathrm{q})$; `//or Adam`
end

4 Experimental Setup

4.1 Datasets

CWI 2018 Shared Dataset. It was proposed at the CWI Shared Task in 2018 (Yimam et al., 2018) and addressed English multidomain and multilingual settings. The English split contains samples from three sources (News, WikiNews, and Wikipedia) totaling approx. 35,000 samples. In the multilingual setting, the dataset features German and Spanish with approx. 8,000 and 17,600 samples, respectively, and a French test set containing 2,251 samples. We present the split in train, validation, and test sets in Table 1. The dataset was developed to address binary and probabilistic classification tasks by assigning probabilities and labels such that samples with 0% probability are non-complex and others as complex. We consider only the binary classification tasks (see Limitations 8).

Dataset	Train	Valid.	Test
	CWI 2018		
English News	14,002	1,764	2,095
English WikiNews	7,746	870	1,287
English Wikipedia	5,551	694	870
German	6,151	795	959
Spanish	13,750	1,622	2,233
	CompLex LCP 2021		
Single-Word	7,662	421	917
Multi-Word	1,517	99	184

Table 1: Dataset splits in train/validation/test for CWI 2018 and CompLex LCP 2021 datasets.

CompLex LCP 2021. Proposed at SemEval 2021 Task 1 (Shardlow et al., 2021), CompLex LCP 2021 comprises around 10,000 sentences in English from three domains: European Parliament proceedings, the Bible, and biomedical literature. The data is split across two tasks: single-word (Single-Word) and multi-word expressions (Multi-Word). The complexity is provided as continuous values between 0 and 1, addressed as the probabilistic classification task. The average complexity is 0.3 for single and 0.42 for multi-word. The data splits are shown in Table 1.

BIG-bench. This recently proposed benchmark (Srivastava et al., 2023) contains over 200 tasks for evaluating large language models. We use this collection as part of the meta-learning stage in our pipeline. Since not all tasks are suitable for our use case, we select 45 tasks (detailed in Appendix G) and only pre-train on those. The unsuitable tasks include non-categorical responses, requirements for external knowledge, or might be too dissimilar to the target task. Our main task selection criteria were prompt length and similarity to the complex word identification task since we wanted as much intrinsic knowledge to be transferred on fine-tuning as possible.

4.2 Baselines

We compare against top-performing methods at CWI 2018 Shared task and LCP 2021. Camb (Gooding and Kochmar, 2018) employs heterogeneous features combined with an ensemble of AdaBoost classifiers. The TMU system (Kajiwara and Komachi, 2018) uses a random forest classifier with multiple hand-crafted features. ITEC (De Hertog and Tack, 2018) combines CNN and LSTM layers. SB@GU (Alfter and Pilán, 2018) employs Random Forest and Extra Tree on top of hand-crafted features. In addition, we include the XLM-RoBERTa-based approach combined with text simplification and domain adaptation (Zaharia et al., 2022), the MLP combined with Sent2Vec solution Almeida et al. (2021), and $RoBERTa_{LARGE}$ with an ensemble of RoBERTa-based models (LR-Ensemble) (Pan et al., 2021).

4.3 Models

We evaluate several open- and closed-source LLMs. Specifically, we choose Llama 2 (7B and 13B parameters) (Touvron et al., 2023), Vicuna (7B and 13B parameters) (Zheng et al., 2024), and Llama 3 8B (Dubey et al., 2024) for open-source models. For closed-source models, we employ OpenAI's ChatGPT-3.5-turbo and GPT-4o (OpenAI et al., 2023) specifically for their relatively lower prices than GPT-4 (see also Appendix D). The chat model is used in the zero- and few-shot settings, and the base or instruct model is used as the starting checkpoint for fine-tuning. Details regarding specific checkpoints for all models are listed in Appendix E.

4.4 Evaluation Metrics

We adopt the same evaluation methodology in Shardlow et al. (2021) for CompLex LCP 2021 and Yimam et al. (2018) for CWI 2018 datasets. Therefore, we employ Pearson correlation (P) and Mean Average Error (MAE) on the LCP task and F1-score (F1) and Accuracy (Acc.) for the CWI task. We report all results on a single run for CWI and multiple runs (described by K in §3.2) for LCP.

5 Results

5.1 English Multidomain Setup

We present the results in Table 2. The top-performing LLMs are ChatGPT-3.5-turbo and GPT-4o, which generally achieve higher scores than the open-source LLMs, especially in the zero- and few-shot settings. When fine-tuning, we notice that open-source models achieve competitive results with ChatGPT-3.5-tubo-ft. Meanwhile, all fine-tuned models match or outperform zero- and few-shot closed-source models. Fined-tuned ChatGPT-3.5-turbo-ft achieves over 80% F1-score, while the highest scores for English-News and English-Wikipedia are surpassed by Llama-3-8b-ft and Vicuna-v1.5-13b-ft, respectively, by 1-2%. However, LLMs fall behind baseline classifiers that are more lightweight and easier to run. On the Wikipedia domain, Vicuna-v1.5-13b-ft achieves the same F1-score as Camb. We found the main limitation is the task hallucination – the model does not reproduce the task it needs to solve (see §6.1).

5.2 Multilingual Setup

Like the multidomain setup, the fine-tuned LLMs achieve the highest score in German and Spanish datasets (see Table 2). Notably, Llama-2-7b-ft and ChatGPT-3.5-turbo-ft achieve higher scores than the submitted systems, but we cannot consider LLMs a good solution for this problem as these models achieve under 80% in F1-score. Because the models were trained with multilingual corpora, they perform similarly in German and

Model	CWI 2018										CompLex LCP 2021			
	EN-N		EN-WN		EN-W		DE		ES		Single-Word		Multi-Word	
	F1↑	Acc↑	F1↑	Acc↑	F1↑	Acc↑	F1↑	Acc↑	F1↑	Acc↑	P↑	MAE↓	P↑	MAE↓
Baseline														
Camb	**87.4**	-	**84.0**	-	**81.2**	-	-	-	-	-	-	-	-	-
ITEC	86.4	-	81.1	-	78.1	-	-	-	76.3	-	-	-	-	-
TMU	86.3	-	78.7	-	76.2	-	**74.5**	-	**77.0**	-	-	-	-	-
SB@GU	83.3	-	80.3	-	78.3	-	74.3	-	72.8	-	-	-	-	-
MLP+Sent2Vec	-	-	-	-	-	-	-	-	-	-	.4598	.0866	.3941	.1145
XLM-RoBERTa-based	-	-	-	-	-	-	-	-	-	-	.7744	.0652	.8285	.0708
RoBERTa_{LARGE}	-	-	-	-	-	-	-	-	-	-	**.7903**	**.0648**	.7900	.0753
LR-Ensemble	-	-	-	-	-	-	-	-	-	-	-	-	**.8612**	**.0616**
Zero-shot														
Llama-2-7b-chat	32.1	63.8	19.3	57.7	37.8	55.3	30.7	54.0	49.0	51.5	.3133	.3061	.5200	.2316
Llama-2-13b-chat	11.9	63.2	12.5	58.8	20.1	53.3	56.7	54.9	44.2	40.8	.2040	.2475	.3613	.1737
Vicuna-v1.5-7b	22.6	59.8	25.3	56.8	27.8	51.6	18.2	50.3	51.5	60.6	.3108	.3684	.4502	.2680
Vicuna-v1.5-13b	13.0	63.1	12.0	59.1	16.0	51.7	53.4	59.6	11.7	50.8	.2189	.1987	.4436	**.1425**
Llama-3-8b-chat	43.0	70.0	29.3	62.9	43.1	61.5	50.2	60.3	10.7	55.9	.3816	.1880	.6271	.1626
ChatGPT-3.5-turbo	40.1	69.5	37.0	64.6	45.6	62.0	53.3	60.1	35.3	63.3	.5352	**.1447**	.6284	.1529
GPT-4o	**65.9**	**76.8**	**64.2**	**73.2**	**66.8**	**71.0**	**63.3**	**73.0**	**68.9**	**75.8**	**.5953**	.2346	**.7753**	.2377
Zero-shot CoT														
Llama-2-7b-chat	56.5	56.2	61.1	59.1	62.8	57.2	57.2	45.7	56.7	46.0	.3617	.1698	.5040	.1632
Llama-2-13b-chat	54.9	61.6	49.1	56.5	57.8	54.7	55.5	53.2	57.7	49.7	.4335	.1393	.5905	.1118
Vicuna-v1.5-7b	38.1	60.3	38.5	58.7	52.4	56.9	20.6	50.0	55.4	58.3	.2558	.1504	.4916	.1310
Vicuna-v1.5-13b	32.9	66.8	27.9	61.8	33.3	55.9	42.1	58.9	29.8	58.7	.4664	**.0922**	.6357	**.1049**
Llama-3-8b-chat	50.5	66.9	45.7	63.0	61.0	64.4	49.3	59.9	34.9	55.5	.4617	.1507	.6923	.1167
ChatGPT-3.5-turbo	64.0	69.9	64.0	68.0	66.7	64.6	59.1	58.8	63.4	47.2	.5901	.2012	.6836	.1624
GPT-4o	**72.9**	**75.7**	**74.9**	**75.4**	**76.1**	**73.9**	**69.5**	**69.8**	**70.3**	**71.9**	**.6228**	.2145	**.7389**	.2586
Few-shot														
Llama-2-7b-chat	61.4	63.9	**63.2**	55.5	**70.6**	61.4	55.8	43.0	57.9	50.1	.1409	.2021	.5016	.1781
Llama-2-13b-chat	46.2	65.3	51.2	65.0	52.2	60.8	53.5	56.8	49.5	62.1	.2010	.2178	.4412	.2118
Vicuna-v1.5-7b	43.9	64.5	46.0	59.5	48.1	57.8	50.4	58.8	45.1	63.3	.1789	.1767	.4641	.1522
Vicuna-v1.5-13b	42.3	65.3	53.4	63.7	54.9	59.0	54.6	56.9	44.6	63.6	.2686	.1871	.4401	.2157
Llama-3-8b-chat	53.0	72.9	55.3	69.9	61.7	**67.6**	56.6	60.3	54.1	61.7	.3102	.1730	.5843	.1796
ChatGPT-3.5-turbo	52.1	72.3	44.5	66.4	53.8	65.1	55.4	65.5	42.5	72.7	.6385	**.0979**	.6742	**.1197**
GPT-4o	**63.8**	**76.6**	60.7	**71.8**	58.3	66.8	**60.2**	**75.9**	**66.0**	**75.7**	**.7111**	.1859	**.8284**	.2195
Few-shot CoT														
Llama-2-7b-chat	54.9	64.2	**60.7**	53.0	**67.5**	57.5	43.5	45.3	58.6	59.0	.4683	.1988	.5920	.2170
Llama-2-13b-chat	45.2	68.9	56.3	60.9	59.3	57.5	58.0	59.0	58.5	63.5	.5796	**.1289**	.6468	.1615
Vicuna-v1.5-7b	39.6	65.5	44.0	63.6	56.2	63.6	32.7	60.9	56.4	65.3	.5832	.1315	.6463	.1444
Vicuna-v1.5-13b	49.1	70.2	45.8	65.1	50.9	62.8	59.2	61.8	57.0	73.4	.5576	.1477	.6832	.1524
Llama-3-8b-chat	34.8	66.5	47.4	63.6	53.6	61.4	61.6	67.7	58.2	72.6	.2723	.2048	.7148	**.1146**
ChatGPT-3.5-turbo	58.3	72.4	51.4	66.0	55.5	65.2	**64.3**	72.9	**68.1**	**73.9**	.7175	.1421	.7568	.1707
GPT-4o	**66.1**	**77.2**	53.3	**68.9**	61.2	**68.5**	53.5	**73.8**	60.5	73.5	**.7594**	.1609	**.8211**	.1850
Fine-tuned														
Llama-2-7b-ft	78.0	82.9	78.2	81.1	77.4	76.7	70.5	75.7	74.6	79.4	.7734	**.0670**	.7919	.0767
Llama-2-13b-ft	77.6	83.3	77.7	81.3	73.1	74.6	**70.8**	76.6	**75.3**	**81.0**	**.7815**	.0798	**.8318**	**.0718**
Vicuna-v1.5-7b-ft	80.2	84.3	76.8	79.3	77.2	77.2	67.5	74.3	73.0	79.0	.7613	.0840	.7862	.0782
Vicuna-v1.5-13b-ft	81.2	85.2	77.4	80.3	**81.2**	**80.8**	70.0	75.4	72.1	76.7	.7530	.0914	.8000	.0763
Llama-3-8b-ft	**82.1**	**86.3**	79.6	82.9	76.8	77.5	**70.8**	76.9	72.2	78.1	.7497	.0909	.7800	.0834
ChatGPT-3.5-turbo-ft	80.7	83.9	**80.9**	**83.1**	80.2	79.4	66.6	**78.0**	74.4	78.1	.7397	.1372	.7537	.1815

Table 2: The results on the test sets from CWI 2018 and CompLex LCP 2021 datasets. Notation: EN - English, DE - German, and ES - Spanish; for English datasets, N - news domain, WN - WikiNews, W - Wikipedia. In bold, we denote the best scores.

Spanish. Zero-shot combined with the chain of thought performs better than other prompting techniques in most cases and falls behind fine-tuning by a small margin, especially in the case of the German split.

5.3 Lexical Complexity Prediction Setup

On the CompLex LCP 2021 dataset, Pan et al. (2021) achieved the best scores. Refer to Table 2 for the results. Fine-tuned LLM-based models outperform RoBERTa-based models on the Multi-Word task, the best-performing model being Llama-2-13b-ft. However, RoBERTa_{LARGE} has 355M parameters, while Llama 2 13B has 37 times more parameters, and the performance difference is only about 5% on the Pearson correlation. In addition, RoBERTa$_{\text{LARGE}}$ outperforms all models on the single-word expressions task. The few-shot method, combined with the chain of thought, usually performs better when considering the prompting techniques.

5.4 Meta-Learning Setup

Due to the high computational cost of our meta-learning algorithm, we only test on Llama 2 7B, both the chat and base versions. We also only test using data in English since changing the meta-training tasks requires a new suite that can be difficult to obtain in the multilingual setting. The reasons are low data availability and lack of knowledge in the other languages since Llama 2 was trained predominantly on English data.

The soft prompting techniques show results comparable to the zero-shot regime, as illustrated in Table 3. All combinations of methods and chat versus base versions of the LLMs show similar performances. In addition, we show the performance impact of varying the optimization steps our meta-learner goes through before the evaluation process in Table 4. The best number of steps is between 5 and 15 for the chat versions of Llama 2, as opposed to between 50 and 100 for the base model.

Model	News F1↑	News Acc↑	WikiNews F1↑	WikiNews Acc↑	Wikipedia F1↑	Wikipedia Acc↑
			P-tuning			
Llama-2-7b-chat	50.3	**46.7**	**66.8**	51.2	**65.3**	**51.9**
Llama-2-7b	**53.8**	41.2	65.4	**52.0**	61.2	49.8
			Prompt-tuning			
Llama-2-7b-chat	46.8	**53.0**	**66.1**	51.4	**61.9**	48.6
Llama-2-7b	**51.6**	43.8	64.0	**53.2**	61.3	**49.7**

Table 3: Results on the multi-domain English test set from CWI 2018 Shared Dataset in the few-shot learning regime, starting from the meta-learned models. In bold, we denote the best score.

6 Discussions

6.1 Task Hallucination

We investigate the hallucination effects of LLMs reproducing the task firsthand before outputting the prediction. Before providing the final answer, we check whether the model correctly copied the sentence and target word from the input query. We report the sentence error rate (S) and the word error rate (W). In this scenario, we mainly focus on the prompting settings. The results are presented in Table 5. In the CWI setting, we enforced the output structure using the Outlines library (Willard and Louf, 2023). We notice that the larger the model, the lower the error rates. The ChatGPT-3.5-turbo and GPT-4o models obtain the lowest error rates, while the Llama 2 7B model obtains the highest. The models usually struggle to recall the correct word to be evaluated. Investigating the outputs, we mostly see that the model considers more context than the target, for example, "America" (ground truth) vs "South America" (extracted by LLM). Other error cases we identified were extracting completely different words from the sentence. For example, the target “years” was replaced by Llama-2-13b-chat with “Aegyptosaurus”. Text locality is not always the main reason; in the first example, we have text locality; however, in the second example, the words were in different parts of the sentence. Additionally, we note that few-shot prompting also reduces the error rates because of the emerging pattern from the system prompt.

Model	Fine-tuning inner steps 5	10	15	25	50	100
			P-tuning			
Llama-2-7b-chat	**66.8**	66.3	66.7	64.2	65.7	59.7
Llama-2-7b	60.7	62.0	**65.4**	64.8	**65.4**	64.3
			Prompt-tuning			
Llama-2-7b-chat	64.8	65.7	**66.1**	65.4	62.4	61.8
Llama-2-7b	**64.2**	58.8	55.8	52.2	59.6	64.0

Table 4: The influence of the fine-tuning inner steps on the F1-score when evaluating on the CWI 2018 English WikiNews test set. In bold, we denote the best score.

In the LCP setting, we consider all the sampling runs, and thus, we report the average and standard deviation across those runs. We report lower error rates. Like the previous setting, employing few-shot prompting reduces the sentence and word error rates. In addition, ChatGPT-3.5-turbo and GPT-4o achieve error rates very close to 0, meaning that the models can produce better demonstrations for the results. In the zero-shot settings, the models struggle to recall the word and the sentence.

6.2 Generated Demonstrations

In the chain-of-thought settings, we prompt the model to provide a brief proof before generating the final label. The reasoning behind letting the model first produce a demonstration and then generate the answer is to enforce the model to “think before

Model	CWI Shared 2018										CompLex LCP 2021			
	EN-N		EN-WN		EN-W		ES		DE		Single-Word		Multi-Word	
	S↓	W↓	S↓	W↓	S↓	W↓	S↓	W↓	S↓	W↓	S↓	W↓	S↓	W↓
Zero-shot														
Llama-2-7b-chat	0.4	2.3	1.4	2.4	1.2	2.9	12.9	7.1	15.6	3.8	2.1$_{\pm 0.2}$	5.1$_{\pm 0.4}$	1.0$_{\pm 0.7}$	0.7$_{\pm 0.3}$
Llama-2-13b-chat	0.1	0.6	0.3	1.1	0.4	1.1	6.9	6.9	17.8	8.2	1.9$_{\pm 0.3}$	8.1$_{\pm 0.8}$	1.1$_{\pm 0.5}$	0$_{\pm 0}$
Vicuna-v1.5-7b	0.2	0.1	1.1	0.1	0.2	0.2	2.0	1.0	1.7	0.4	1.6$_{\pm 0.3}$	0.2$_{\pm 0.2}$	0.7$_{\pm 0.5}$	0$_{\pm 0}$
Vicuna-v1.5-13b	0	0.1	0.1	0	0.2	0.2	0.3	1.2	5.7	4.7	2.7$_{\pm 0.5}$	1.0$_{\pm 0.3}$	1.2$_{\pm 0.5}$	0.1$_{\pm 0.2}$
Llama-3-8b-chat	0	0.4	0.5	0.3	0.5	0.5	1.3	0.3	2.0	11.3	1.3$_{\pm 0.3}$	1.0$_{\pm 0.2}$	1.4$_{\pm 0.5}$	0.1$_{\pm 0.2}$
ChatGPT-3.5-turbo	0	0	0.1	0	0	0	0.1	0.2	4.6	6.1	0.6$_{\pm 0.2}$	0.1$_{\pm 0.1}$	0.9$_{\pm 0.4}$	0$_{\pm 0}$
GPT-4o	0	0	0.3	0	0	0	0	0.1	0	0	0$_{\pm 0}$	0$_{\pm 0}$	0$_{\pm 0}$	0$_{\pm 0}$
Zero-shot CoT														
Llama-2-7b-chat	1.0	3.7	6.0	4.9	1.0	2.8	16.8	4.0	34.4	6.8	6.4$_{\pm 0.5}$	5.3$_{\pm 0.4}$	5.6$_{\pm 1.0}$	0.9$_{\pm 0.5}$
Llama-2-13b-chat	1.1	3.6	1.1	5.0	4.1	3.0	8.1	8.4	15.0	7.5	3.4$_{\pm 0.2}$	1.7$_{\pm 0.5}$	2.4$_{\pm 1.1}$	0$_{\pm 0}$
Vicuna-v1.5-7b	0.4	0	1.5	0	0.5	0.3	2.2	0.8	1.4	0.6	2.2$_{\pm 0.4}$	0.7$_{\pm 0.3}$	1.9$_{\pm 0.8}$	0.1$_{\pm 0.2}$
Vicuna-v1.5-13b	0.2	0.1	0.7	0.1	0.7	1.0	0.6	2.1	5.0	4.1	1.3$_{\pm 0.3}$	0.8$_{\pm 0.2}$	0.9$_{\pm 0.5}$	0$_{\pm 0}$
Llama-3-8b-chat	0.5	1.2	1.7	1.1	3.2	1.2	1.2	0.2	2.6	6.2	3.9$_{\pm 0.6}$	0.9$_{\pm 0.2}$	3.0$_{\pm 0.9}$	0.2$_{\pm 0.3}$
ChatGPT-3.5-turbo	0.1	0	0.7	0.1	0.2	0	0.2	0.3	5.8	5.5	0.9$_{\pm 0.2}$	0$_{\pm 0}$	0.4$_{\pm 0.4}$	0$_{\pm 0}$
GPT-4o	0	0	1.3	0	0	0	0	0	0	0	0.1$_{\pm 0.1}$	0$_{\pm 0}$	0$_{\pm 0}$	0$_{\pm 0}$
Few-shot														
Llama-2-7b-chat	0.2	0	0.4	0.1	0.6	0	16.4	0.2	20.5	0.2	1.1$_{\pm 0.2}$	0.1$_{\pm 0.1}$	2.9$_{\pm 0.8}$	0$_{\pm 0}$
Llama-2-13b-chat	0.2	0.1	0.2	0	0	0	5.8	0.1	7.1	0	0.3$_{\pm 0.1}$	0.1$_{\pm 0.1}$	0.6$_{\pm 0}$	0$_{\pm 0}$
Vicuna-v1.5-7b	0.1	0	0.4	0	0.4	0	0.1	0	0.3	0	0.3$_{\pm 0.2}$	0$_{\pm 0}$	0.6$_{\pm 0.5}$	0$_{\pm 0}$
Vicuna-v1.5-13b	0	0	0	0	0.3	0	0.2	0	0	0	0.3$_{\pm 0.2}$	0.1$_{\pm 0.1}$	0.2$_{\pm 0.4}$	0$_{\pm 0}$
Llama-3-8b-chat	0.1	0	0	0	0.9	0	0.9	0	0.5	0	1.0$_{\pm 0.2}$	0.1$_{\pm 0.1}$	1.6$_{\pm 0.6}$	0$_{\pm 0}$
ChatGPT-3.5-turbo	0	0	0	0	0	0	0.1	0	0.5	0	0.1$_{\pm 0.1}$	0$_{\pm 0}$	0.4$_{\pm 0.3}$	0$_{\pm 0}$
GPT-4o	0.1	0	0	0	0	0	0	0	0	0	0$_{\pm 0}$	0$_{\pm 0}$	0.2$_{\pm 0.3}$	0$_{\pm 0}$
Few-shot CoT														
Llama-2-7b-chat	0.3	0	0.7	0.1	0.6	0	13.8	0.2	14.9	0	1.1$_{\pm 0.2}$	0.1$_{\pm 0.1}$	3.0$_{\pm 0.9}$	0$_{\pm 0}$
Llama-2-13b-chat	0.2	0	0.1	0.3	0	0.2	4.3	0.1	5.8	0	0.3$_{\pm 0.1}$	0$_{\pm 0}$	0.6$_{\pm 0.2}$	0$_{\pm 0}$
Vicuna-v1.5-7b	0	0	0.3	0	0.5	0	0.1	0	0	0	0.4$_{\pm 0.2}$	0$_{\pm 0}$	0.6$_{\pm 0.6}$	0$_{\pm 0}$
Vicuna-v1.5-13b	0.1	0	0	0	0.3	0	0.2	0	0	0	0.2$_{\pm 0.1}$	0.1$_{\pm 0.1}$	0.2$_{\pm 0.3}$	0$_{\pm 0}$
Llama-3-8b-chat	0.5	0	0	0	1.1	0	0.9	0.1	0.5	0	2.6$_{\pm 0.4}$	0.1$_{\pm 0.1}$	0.9$_{\pm 0.6}$	0$_{\pm 0}$
ChatGPT-3.5-turbo	0.1	0	0	0	0	0	0.3	0	0	0	0.6$_{\pm 0.3}$	0$_{\pm 0}$	1.7$_{\pm 0.9}$	0$_{\pm 0}$
GPT-4o	0	0	0	0	0	0	0	0	0	0	0$_{\pm 0}$	0$_{\pm 0}$	0$_{\pm 0}$	0$_{\pm 0}$

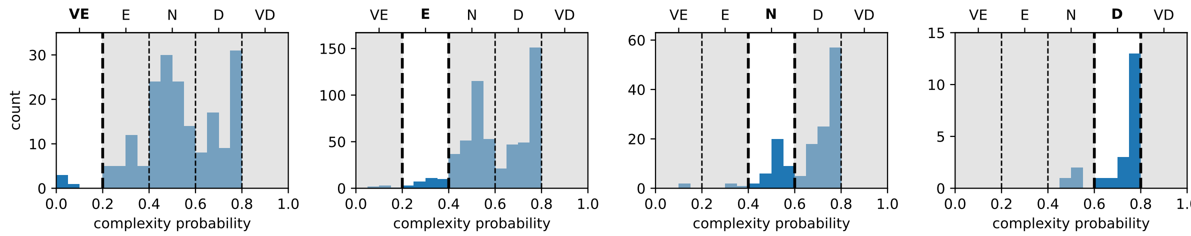
Table 5: LLMs hallucination rate on the CWI 2018 and CompLex LCP 2021 datasets. S indicates the percentage of wrong sentences, and W indicates the percentage of wrong target words in the LLMs' output.

answer", i.e., the generated proof guides the model to produce a better solution based on some reasons. If we let the model answer and then provide proof, the proof would have been influenced by the initial answer, altering the model's internal bias. In Table 15 from Appendix I, we show some examples of proofs regarding the answer provided by Llama-2-13b-chat on the CWI English dataset in the zero-shot setting. The generated proofs motivate the answers, but we notice some flaws in the reasoning. For example, the model says that "ft" (i.e., feet as a unit of measurement) is standard in English. Meanwhile, it tends to contradict that being an abbreviation makes it difficult to understand. We notice this pattern quite often in the outputs.

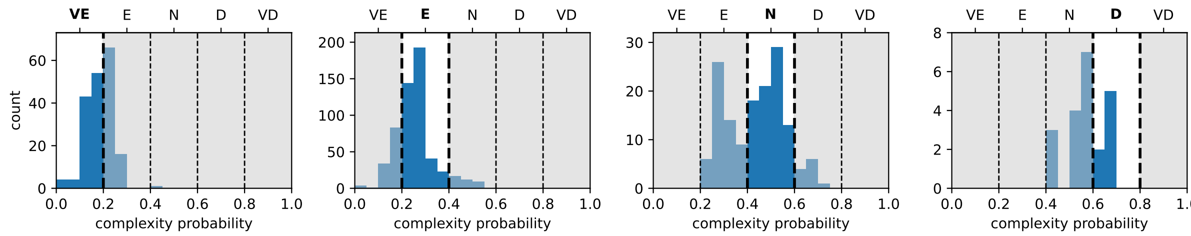
6.3 Confusion Matrices on CWI

We generate the confusion matrices to investigate how the predictions are affected by the domain, language, and model architecture. This section showcases the Llama 2 7B model on the CWI 2018 English WikiNews test set in Figure 2. More figures can be found in Appendix I.

The general tendency is that chat models have higher false-positive or false-negative rates. The same model checkpoints have the same bias towards one false positive and false negative rate in the multidomain setting. For example, Llama-2-7b-chat has a high false-positive rate, while Llama-2-13b-chat has a high false rate. Correlated with the proofs generated by the LLMs, this is motivated by the fact that LLMs tend to produce either overestimates or underestimates of the word difficulty. It is especially true if the model finds a synonym for the target word. Also, the errors correlate with the model's degree of hallucination. On the other hand, fine-tuned models show lower false-positive/negative rates, meaning that this approach reduces the hallucination, and the model learns latent instructions directly from the data.



(a) Zero-shot.



(b) Fine-tune.

Figure 1: Predictive probability distribution of Llama 2 7B on LCP 2021 Single Word dataset, zero-shot, and fine-tuned settings. The gray area indicates the outside of the expected label region (i.e., wrong labels); the white stripe indicates the correctly predicted labels. Neither model predicts in the very difficult interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.

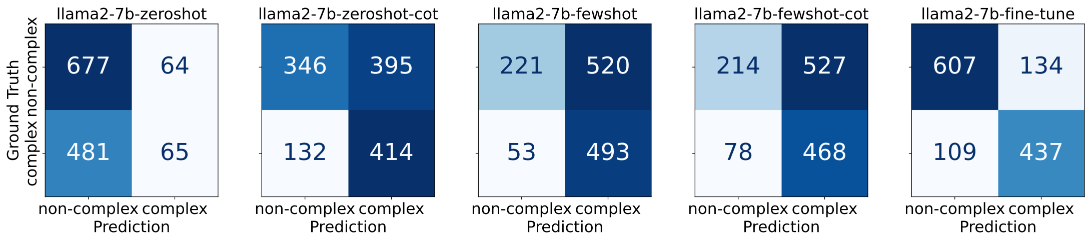


Figure 2: Confusion matrices computed on the CWI 2018 English WikiNews test set for Llama 2 7B.

6.4 Prediction Distribution on LCP

We analyze the complexity probability distribution outputted by the LLMs and present in Figure 1 the case for zero-shot and fine-tuned Llama 2 7B model. More figures across more settings, models, and datasets are shown in Appendix I. The analysis is constructed by binning the models' real-valued estimates (i.e., the x-axis) and generating a histogram (i.e., the y-axis). The discrete labels were mapped equidistantly in the range 0-1, as such: very easy (VE) in 0-0.2, easy (E) in 0.2-0.4, neutral (N) in 0.4-0.6, difficult (D) in 0.6-0.8, and very difficult (VE) in 0.8-1.

We notice a more uniform distribution among models' predictions, especially for the low-complexity words. The absolute error is more than one step in the difficulty scale. We notice that the models struggle to identify the very difficult label, regardless of whether the model was fine-tuned or not. There is a tendency to label very easy words as easy and misclassify neutral and complex words, generally considering the words easier. This yields a smoother distribution across the labels. However, in the case of ChatGPT-3.5 and GPT-4o, the outputs tend to be more deterministic – the majority of labels lie on the class scores.

7 Conclusions

In conclusion, we addressed CWI and LCP using LLMs, specifically Llama-based and OpenAI's GPT models. We observed that these models can determine the word difficulty level in multiple domains and languages, although with limited performances. Meanwhile, these models struggle to label very difficult phrases correctly. Future directions imply investigating multiple models in more languages. Also, the prompts and example selection greatly influence the models' performance. Thus, other future work should rely on reducing hallucination and determining which adversarial examples affect the model's capabilities the most.

8 Limitations

Our approach has some limitations regarding prompt design. During experiments, we noticed that prompt design can highly influence the results, especially in the case of zero-shot settings. Using the same prompt across all models is not optimal, but we tried to find those instructions that benefit all models. Providing the model with specific instructions helps reduce the hallucination. One way to mitigate hallucinations was to use a specific structured output like JSON format (see Appendix A), which required task validation through query reproduction.

Also, we know that random sampling is not the optimal solution for choosing fine-tuning examples for ChatGPT-3.5-turbo. The size and quality of data can significantly impact the prediction performance. To reduce this effect, we created a balanced dataset among label difficulties, such that the model is equally trained on easy and complex words. We also kept a uniform distribution among complexity probabilities strictly greater than zero for both tasks (CWI and LCP).

9 Ethical Considerations

Since we used pre-trained LLMs, all their limitations apply to our work. Developing CWI and LCP systems can benefit new language learners (e.g., chat-based applications in which LLMs help new language learners understand difficult words and even provide alternatives). However, because of the hallucinations and inaccuracies such models may provide, these systems can violate codes of ethics and harm or address attacks on such individuals. We are aware of the fast-paced development in the LLM area, and we think this area of research needs some attention. Therefore, we make the fine-tuned models publicly available for transparency and fair comparison with feature works[5]. These models should only be used for research. All the data we used is already publicly available, and the pre-trained Llama models are available on HuggingFace[6], under the Llama 2 License Agreement[7]. We did not use the resources for other purposes than the ones allowed.

[5] https://github.com/razvanalex-phd/cwi_llm

[6] https://huggingface.co/meta-llama

[7] https://github.com/facebookresearch/llama/blob/main/LICENSE

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A Prompts

A.1 Inference Prompts

A.1.1 LCP English Prompt

> You are a helpful, honest, and respectful assistant for identifying the word complexity for beginner English learners. You are given one sentence in English and a phrase from that sentence. Your task is to evaluate the complexity of the word. Answer with one of the following: very easy, easy, neutral, difficult, very difficult. Be concise. Please, answer using the following JSON format:

```
{
"sentence": "the sentence you were provided",
"word": "the word or words you have to analyze",
"proof": "explain your response in maximum 50 words",
"complex": "either very easy, easy, neutral, difficult, or very difficult"
}
```

> What is the difficulty of ‘`{token}`‘ from ‘`{sentence}`‘?

A.1.2 CWI English Prompt

> You are a helpful, honest, and respectful assistant for identifying the word complexity for beginner English learners. You are given one sentence in English and a phrase from that sentence. Your task is to say whether the phrase is complex. Assess the answer for the phrase, given the context from the sentence. Be concise. Please, use the following JSON schema:

```
{
"sentence": "the sentence you were provided",
"word": "the word or words you have to analyze",
"proof": "explain your response in maximum 50 words",
"complex": "either false (for simple) or true (for complex)",
}
```

> Is ‘`{token}`‘ complex in ‘`{sentence}`‘?

A.1.3 CWI German Prompt

> Sie sind ein hilfsbereiter, ehrlicher und respektvoller Assistent, um die Wortkomplexität für Anfänger im Deutschen zu identifizieren. Sie erhalten einen Satz auf Deutsch und eine Phrase aus diesem Satz. Ihre Aufgabe ist es zu sagen, ob die Phrase komplex ist. Bewerten Sie die Antwort für die Phrase, anhand des Kontexts aus dem Satz. Seien Sie kurz. Bitte verwenden Sie das folgende JSON-Schema:

```
{
"sentence": "der Satz, den Sie erhalten haben",
"word": "das Wort oder die Wörter, die Sie analysieren müssen",
"proof": "erklären Sie Ihre Antwort in maximal 50 Wörtern",
"complex": "entweder false (für einfach) oder true (für komplex)",
}
```

> Ist ‘`{token}`‘ von ‘`{sentence}`‘ complex?

A.1.4 CWI Spanish Prompt

> Eres un asistente útil, honesto y respetuoso para identificar la complejidad de las palabras para los principiantes que aprenden español. Se te da una oración en español y una frase de esa oración. Tu tarea es decir si la frase es compleja. Evalúa la respuesta para la frase, dada el contexto de la oración. Sé conciso. Por favor, usa el siguiente esquema JSON:

```
{
"sentence": "la oración que se te proporcionó",
"word": "la palabra o palabras que tienes que analizar",
"proof": "explica tu respuesta en máximo 50 palabras",
"complex": "false (para simple) o true (para complejo)"
}
```

> ¿Es ‘`{token}`‘ complejo en ‘`{sentence}`‘?

A.2 Fine-Tune Prompts

A.2.1 LCP English Prompt

> You are a helpful, honest, and respectful assistant for identifying the word difficulty for non-native English speakers. You are given one sentence in English and a word from that sentence. Your task is to evaluate the difficulty of the word. Answer only with one of the following: very easy, easy, neutral, difficult, very difficult.

```
sentence: `{sentence}`
word: `{token}`
```

A.2.2 CWI English Prompt

> You are a helpful, honest, and respectful assistant for identifying the word complexity for non-native English speakers. You are given one sentence in English and a word from that sentence. Your task is to say whether a word is complex or not. Answer only with one of the following: yes or no.

```
sentence: `{sentence}`
word: `{token}`
```

A.2.3 CWI German Prompt

> Du bist ein hilfsbereiter, ehrlicher und respektvoller Assistent für die Identifizierung der Wortkomplexität für nicht-deutsche Muttersprachler. Dir wird ein Satz auf Deutsch und ein Wort aus diesem Satz gegeben. Deine Aufgabe ist es zu sagen, ob ein Wort komplex ist oder nicht. Antworten nur mit einem der Folgenden: ja, nein.

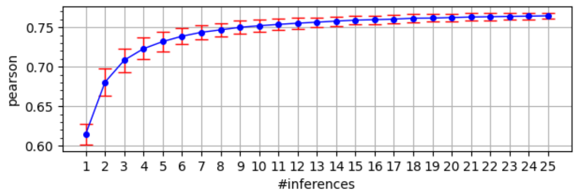
```
Satz: `{sentence}`
Wort: `{token}`
```

A.2.4 CWI Spanish Prompt

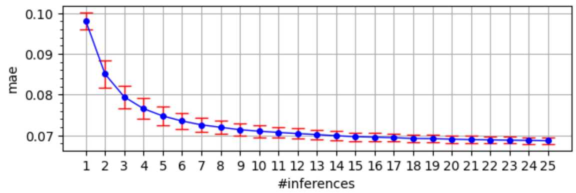
> Eres un asistente útil, honesto y respetuoso para identificar la complejidad de las palabras para hablantes no nativos de inglés. Se te da una oración en inglés y una palabra de esa oración. Tu tarea es decir si una palabra es compleja o no. Responde solo con una de las siguientes opciones: sí, no.

```
oracion: `{sentence}`
palabra: `{token}`
```

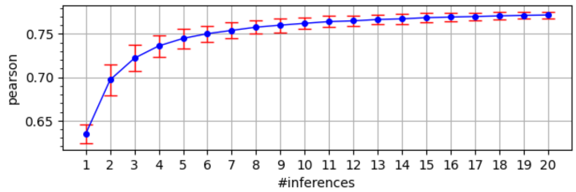
B Choice for Number of Inference Steps



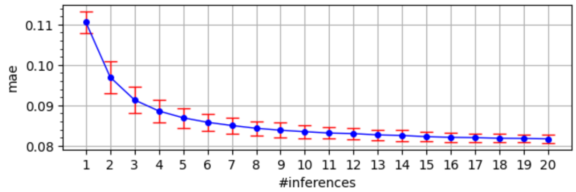
(a) Pearson score on Llama-2-7b-ft



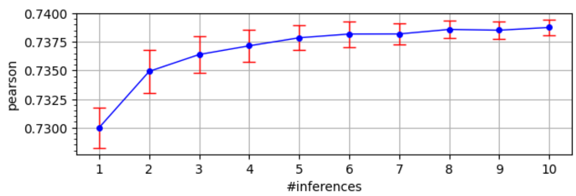
(b) MAE score on Llama-2-7b-ft



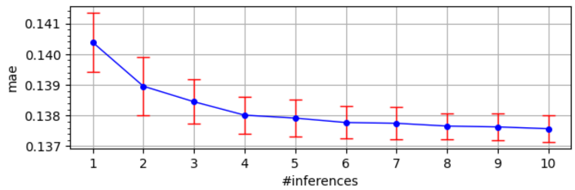
(c) Pearson score on Llama-2-13b-ft



(d) MAE score on Llama-2-13b-ft



(e) Pearson score on ChatGPT-3.5-turbo-ft



(f) MAE score on ChatGPT-3.5-turbo-ft

Figure 3: Estimated Pearson and MAE scores against the number of LLM inference steps.

As presented in §3, the estimated score in the LCP setting is an average of scores obtained after K inference steps. We wanted to know what is the minimum number of inference steps required until the results do not change significantly anymore.

Therefore, we set $K = 25$ for Llama-2-7b-ft, $K = 20$ for Llama-2-13b-ft, and $K = 10$ for ChatGPT-3.5-turbo-ft, and then estimated the average score per number of iterations using bootstrapping, with 100 samples. The plots are shown in Figure 3. We obtained that at least 10 to 15 runs are required, after which the scores do not change significantly.

C Evaluation Protocol

To evaluate the LLMs effectively, we employ an approach that uses optimized inference servers and a generic way to interface with the models. The overall protocol is showcased in Figure 4. First, we load the dataset, and for every example, we apply the system, user, and assistant prompt templates. We use the assistant prompt template for the few-shot examples only in the few-shot setting. The final prompt is sent to the server, which processes the input and returns the LLM's prediction. We send the queries in parallel to use batching and other optimizations, thus reducing the execution time. For local inference endpoints, we use HuggingFace Text Generation Inference (TGI)[8] for most LLMs available in HuggingFace and lmsys' FastChat[9] with vllm (Kwon et al., 2023) integration for improved inference throughput. OpenAI's models are evaluated using their endpoints. Ultimately, we aggregate and assess the results against the ground truth labels. We compute and report the metrics and perform analysis depending on the task.

During experiments, we noticed that some smaller LLMs struggle to output the response in the requested format, which makes it challenging to extract the prediction. To address this limitation, we employ guidance[10] and outlines (Willard and Louf, 2023), which force the model to follow our custom output structure by manipulating the output logits.

D Computational Costs and Hardware Infrastructure

Due to the number of experiments, available resources, and costs, we used hardware from multiple sources:

- A desktop PC with an Intel(R) Core i7-13700k CPU, 64GB RAM, 3TB NVMe SSD storage, and an Nvidia RTX 4080 16GB GPU.
- The cluster shared inside our organization through the SLURM cluster management[11]. The experiments were run on systems with Intel(R) Xeon(R) Gold 6326 CPU, 500GB RAM, NVIDIA A100-PCIE 40GB, and 250TB NFS storage.
- GPUs rented from the vast.ai[12] platform using NVIDIA RTX 4090 (approx. \$0.5/hr), A6000 (approx. \$0.9/hr), or H100 80GB-SXM (approx. \$3.2/hr), and the minimum required storage was 200GB.

We trained and ran inferences on NVIDIA RTX 4080 and 4090 (consumer-class GPUs) and NVIDIA RTX A6000, A100 40GB-PCIe, and H100 80GB-SXM (server-class GPUs), depending on the minimal requirements to run the model and execution time. The desktop PC could run most inference experiments regarding zero-shot settings. However, due to the limited VRAM of the RTX 4080, few-shot and fine-tuning experiments required at least 40GB of GPU VRAM because more input/output tokens result in higher video memory requirements. We rented H100 to speed up the experiments, with the observed speed-up of 2-6 times faster than the A100 40GB GPU. We decided to employ A6000 and A100 GPUs for training and inference in the meta-learning setting. The estimated costs for these experiments rise to about \$400.

For OpenAI's API, we used inference endpoints for ChatGPT-3.5-turbo and GPT-4o as well as training endpoints for ChatGPT-3.5-turbo, with the pricing at the time of writing this paper: \$0.0005 per 1k input tokens and \$0.0015 per 1k output tokens for ChatGPT-3.5-turbo; and \$0.0080 per training tokens, \$0.003 per 1k input tokens, and \$0.006 per 1k output tokens. For GPT-4o, we had access only to inference, with \$5 per 1M input tokens and \$15 per 1M output tokens. All experiments related to OpenAI's models totaled about \$300. Because of the high costs, we limited our experiments to only classification on large test sets.

E Model Checkpoints

In Table 6, we present the checkpoints used in this work, which are available on the Huggingface platform. We indicate with "ft" where we

[8] https://huggingface.co/docs/text-generation-inference/en/index
[9] https://github.com/lm-sys/FastChat
[10] https://github.com/guidance-ai/guidance
[11] https://slurm.schedmd.com/
[12] https://vast.ai

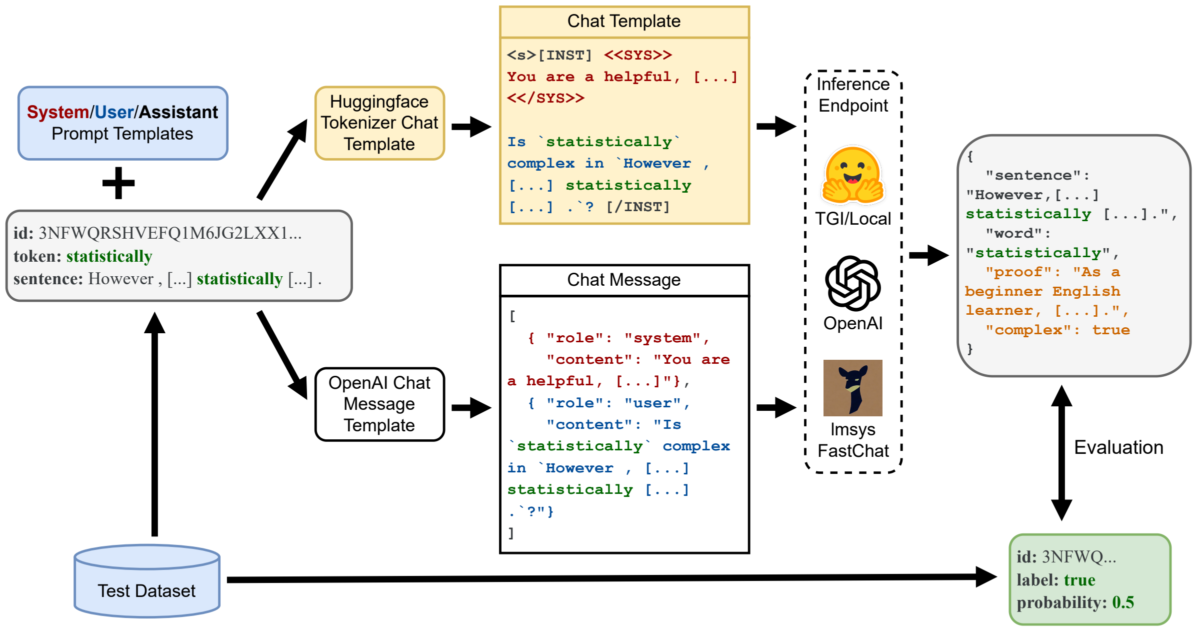


Figure 4: Evaluation protocol.

use a different checkpoint for fine-tuning. Fine-tuned models are available at https://github.com/razvanalex-phd/cwi_llm.

Model	Checkpoint
Llama 2 7B	meta-llama/Llama-2-7b-chat-hf
Llama 2 7B ft	meta-llama/Llama-2-7b-hf
Llama 2 13B	meta-llama/Llama-2-13b-chat-hf
Llama 2 13B ft	meta-llama/Llama-2-13b-hf
Vicuna 1.5 7B	lmsys/vicuna-7b-v1.5
Vicuna 1.5 7B ft	TheBloke/vicuna-7B-v1.5-AWQ
Vicuna 1.5 13B	lmsys/vicuna-13b-v1.5
Vicuna 1.5 13B ft	TheBloke/vicuna-13B-v1.5-AWQ
Llama 3 8B	meta-llama/Meta-Llama-3-8B-Instruct
Llama 3 8B ft	meta-llama/Meta-Llama-3-8B
ChatGPT-3.5-turbo	gpt-3.5-turbo-0125
GPT-4o	gpt-4o-2024-05-13

Table 6: Checkpoints used during experiments.

F Few-Shot Examples and Proofs

The few-shot examples for CWI datasets (see Tables 7, 8, 9, 10, and 11) were chosen such that we provide two samples for false complexity (probability is 0%) and one sample for every discrete label as presented in §3.2. This way, even if we are biased towards complex sentences, the distribution among discrete labels is uniform. The sentences were randomly chosen so that they fulfilled the previous criteria. We use GPT-4o to generate proofs for any given sentence and token regarding why the label is correct. Similarly, we also do this for LCP datasets (see Tables 12, 13) by sampling an example from every category. In both tasks, the few-shot samples were selected from the train set. When generating the prompt, we shuffle the few-shot examples to reduce the chances of a position bias; that is, the model would predict a specific label due to how the few-shot samples are ordered. Examples of generated outputs for Llama 2 13B on the CWI English Wikipedia test set are presented in Table 15.

G Meta-Learning Datasets

We select 45 tasks from the BIG-bench benchmark, all being classification tasks. Some tasks offer the choices in the original prompt, whereas others do not. For the ones that don't, we manually append them in the prompt. The tasks can be viewed in Table 14.

H Hyperparameters

Inference. During inference, we set the LLM to use a maximum of 4,096 tokens, the repetition penalty was set to 1.2, and the temperature to 0.8. We set the top-k parameter to 10 and the top-p to 0.95. The open-source models were loaded with quantized parameters using the nf4 format through `bitsandbytes` (Cannizzo, 2018). For LCP, we set

ID	Sentence	Token	Complex	Proof
7329	Northern Ireland's deputy first minister and Mid-Ulster MP, Martin McGuinness, said his heart went out to the family of the girl tragically killed.	MP	false	The abbreviation 'MP' for Member of Parliament is commonly understood in contexts involving government or politics, making it familiar and not complex.
7700	Activists said at least 30 people died on Sunday - mainly civilians - as violence surged at flashpoints across the country despite an increase of UN observers.	civilians	true	The word 'civilians' may be considered complex because it is specific to contexts involving military or emergency situations, and not everyone might be familiar with its precise meaning.
407	The regime is trying to punish these villages and to put an end to this revolution as quickly as it can, he said.	punish	false	The word 'punish' is a common verb used in everyday language to describe the act of imposing a penalty or suffering for an offense, making it familiar and not complex.
5182	The Philippines and Vietnam complained last year of increasingly aggressive acts by China in staking its claim to the South China Sea.	aggressive acts	true	The phrase 'aggressive acts' may be considered complex as it involves understanding both 'aggressive' and 'acts' together, implying a specific type of behavior which might not be immediately clear without context.
12472	Goodyear said police previously responded to the Florida 'Space Coast' home, about 15 miles south of Cape Canaveral, for domestic disturbance calls involving Jaxs Johnson.	domestic disturbance	true	The term 'domestic disturbance' can be complex as it combines 'domestic', related to the home or family, with 'disturbance', indicating trouble or conflict, requiring an understanding of both terms in context.
7131	Spain is set to intensify the clean-up of its banks on Friday after difficult last-minute talks between the government and lenders on details of planned financial system reforms.	Friday	false	The word 'Friday' is a basic term indicating a day of the week, universally understood and not complex.
10459	The country's leaders have to admit that there were numerous falsifications and rigging and the results do not reflect the will of the people, Gorbachev told Interfax, according to the AFP.	rigging	true	The word 'rigging' can be considered complex as it refers to the act of manipulating or tampering with something, often in a fraudulent way, which may not be a familiar concept to everyone.

Table 7: Few shot examples for CWI 2018 English - news domain.

the number of inference steps $K = 20$ for all open-source models, while for OpenAI models, we evaluate on $K = 10$ inferences (see also the discussion from Appendix B).

Fine-tuning open-source models. The open-source models are downloaded from HuggingFace. We employ QLoRA (Dettmers et al., 2023) with 4-bit quantization to reduce GPU memory usage for fine-tuning. We set R to 16, α to 32, and dropout to 0.05. The batch size varies between 10 and 32, and the learning rate uses a linear scheduler with a 10% warmup and a maximum value of $1e-4$. The LLM is limited to handling a maximum of 1,024 tokens. We trained the models for three epochs using the AdamW optimizer (Kingma and Ba, 2015).

Fine-tuning GPT models. We use OpenAI's platform with the default hyperparameters to fine-tune OpenAI models. We limit the training size to 250 samples uniformly sampled among labels from the train set specific to the dataset task and language.

Meta-Learning. For meta-learning, the inner learning rate is 0.1 and 0.03 for prompt learning and P-tuning, respectively, while the outer learning rates are 0.01 and 0.003. The batch size is set to 1, with the number of inner steps set to 5. We run each experiment for a total of 3,000 steps. During P-tuning, we also choose the LSTM (Hochreiter and Schmidhuber, 1997) model as our architecture. We use 16 virtual tokens, and the support and query sets contain six examples from the same task each.

I Results Discussions

LLMs can grasp word complexity, depending on the model's capabilities. We observed that performances across domains and language, and whether we deal with a word or a phrase, are similar if the model is fine-tuned. In the zero-shot setting, the input prompt and prediction temperature yield a high variance across the results. Also, we noticed that

ID	Sentence	Token	Complex	Proof
4055	#29-17 He joins 139 other Republican Party presidential candidates who have done likewise.	Party	false	The word 'Party' is common and widely understood in political contexts, making it familiar to both native and non-native speakers.
5461	#11-14 The experiments were funded by national research organizations in the United States and China and the government of Brazil.	national	false	The word 'national' is a basic adjective used to describe something related to a nation, and is commonly used in many contexts, making it easy for most speakers.
4911	#42-4 The team used Formica fusca, an ant species that can form thousand-strong colonies.	Formica fusca	true	The term 'Formica fusca' is a scientific name for a specific ant species, which is likely unfamiliar to most people outside of entomology or biological sciences.
3758	#22-5 According to doctors at Bethany Hospital, Kalam was dead by 7 p.m. but they waited for the arrival of Meghalaya chief minister V. Shanmuganathan, about an hour later, before announcing the death.	announcing	true	The word 'announcing' can be challenging due to its length, the presence of a silent letter, and the necessity to understand the appropriate context for its use.
2220	#36-16 Another had been to tether the nose cone to the car; Hunter-Reay mentioned renderings developed of a boomerang-like debris-deflector positioned in front of the driver.	tether	true	The word 'tether' is less commonly used and may not be familiar to many people, leading to difficulty in understanding its meaning and usage.
1951	#24-37 Furthermore, the data of radars at Maldives airports have also been analysed and shows no indication of the said flight", said Malaysian Transport Minister Hishamuddin Hussein.	analysed	true	The word 'analysed' can be difficult due to its British English spelling (with 's' instead of 'z'), which might confuse those more familiar with American English.
1498	#3-10 Pavlensky and Oksana were detained in December at Sheremetyevo airport for questioning, which went on for seven hours.	detained	true	The word 'detained' may be difficult due to its legal context and the less frequent use in everyday language, requiring a higher level of vocabulary knowledge.

Table 8: Few shot examples for CWI 2018 English - WikiNews domain.

sometimes the models (especially Llama-2-13b-chat, in the zero-shot setting) refused to predict some examples (especially in the Biblical domain) because of racial discrimination, despite that not being the case. Models tend to consider words easier than they are, mainly because if prompted to explain the choice, they could provide another synonym that is not necessarily simpler. Zero-shot prompting is achieved every time poor performances are detected, and the main effect is that models tend to have a high false positive rate in the CWI task. This can be changed during fine-tuning when we notice that imbalanced datasets towards a class lead to the model being biased and producing more often the predominant label from the fine-tuning set. We include supporting figures for confusion matrices on the CWI task in Figures 5, 6, 7, and 8 as well as the prediction distributions on the LCP task in Figures 9, 10, 11, 12, 13, 14, 15, and 16.

ID	Sentence	Token	Complex	Proof
3595	Once the series had received the backing of the FIA , a management structure including new executive directors Brian Menell and Tony Teixeira were appointed to oversee the sale of franchises for the operation of international teams .	Brian	false	The word 'Brian' is a common proper noun and a typical English name, which is familiar to both native and non-native speakers. Its presence in the sentence is straightforward and does not add complexity.
3400	The first recorded case of an actor performing took place in 534 BC (though the changes in calendar over the years make it hard to determine exactly) when the Greek performer Thespis stepped on to the stage at the Theatre Dionysus and became the first known person to speak words as a character in a play or story .	play	false	The word 'play' is a basic English word frequently used in both its noun and verb forms. It is easily understood by both native and non-native speakers, especially in the context of theater.
1048	Also , if the reviewing administrator concludes that the block was justified , you will not be unblocked unless the reviewing administrator is convinced that you understand what you are blocked for , and that you will not do it again .	administrator	true	The word 'administrator' is long and contains multiple syllables, which can make it challenging to pronounce and remember. Additionally, its specific meaning in the context of authority or management may not be immediately clear to non-native speakers.
3670	Two is the base of the simplest numeral system in which natural numbers can be written concisely , being the length of the number a logarithm of the value of the number (whereas in base 1 the length of the number is the value of the number itself) ; the binary system is used in computers .	numeral	true	The word 'numeral' is less commonly used in everyday language and pertains to a specific field (mathematics). This specialization can make it less familiar and harder to understand for some readers.
2767	The Angara rocket family is a family of space-launch vehicles being developed by the Moscow-based Khrunichev State Research and Production Space Center .	space-launch	true	The term 'space-launch' is a compound word that refers to a specific and technical concept related to aerospace. Its specialized nature and the combination of two words can make it more difficult to understand.
1155	Early references from the Vadstena Abbey show how the Swedish nuns were baking gingerbread to ease indigestion in 1444 .	indigestion	true	The word 'indigestion' is relatively long and describes a specific medical condition related to digestion, which might not be commonly known or used in daily conversation, making it harder for some readers.
919	The roof of the nave is composed of a pair and knuckle frame , coated inside by pieces of tracery .	tracery	true	The word 'tracery' is an architectural term that may not be widely recognized outside of specialized contexts. Its specific meaning and less frequent use contribute to its complexity.

Table 9: Few shot examples for CWI 2018 English - Wikipedia domain.

ID	Sentence	Token	Complex	Proof	Proof (En.)
4890	Unmittelbar nach den Anschlägen vom 11.	Unmittelbar	false	Das Wort 'Unmittelbar' ist nicht komplex, da es ein häufig verwendetes deutsches Adjektiv ist und weder selten noch schwierig zu verstehen ist.	The word 'Immediate' is not complex as it is a commonly used German adjective and is neither rare nor difficult to understand.
713	Janukowytsch findet dort die größte Unterstützung , während Juschtschenko das größte Wählerpotenzial sieht .	größte	false	Das Wort 'größte' ist ein Basisadjektiv in der deutschen Sprache und stellt keine besondere Schwierigkeit dar.	The word 'largest' is a basic adjective in the German language and does not pose any particular difficulty.
4106	Sie berichtete unter anderem über ihre derzeitige Tournee mit dem Thema Hitler-Tagebücher .	Tournee	true	Das Wort 'Tournee' stammt aus dem Französischen und wird in der deutschen Sprache seltener verwendet, was es für Nicht-Muttersprachler schwieriger macht.	The word 'tournee' comes from French and is used less frequently in the German language, making it more difficult for non-native speakers.
2738	Die Anwälte Berlusconis kündigten an , gegen die Verjährung einen Einspruch einzureichen , um einen Freispruch erster Klasse zu erreichen .	Freispruch	true	Das Wort 'Freispruch' kann komplex sein, da es ein spezifischer juristischer Begriff ist, der in alltäglichen Gesprächen selten vorkommt.	The word 'acquittal' can be complex because it is a specific legal term that rarely appears in everyday conversations.
3535	Der eineinhalbstündige feierliche Trauergottesdienst fand in der zu zwei Drittel gefüllten Friedenskirche im Nürnberger Stadtteil St. -Johannis statt .	Trauergottesdienst	true	Das Wort 'Trauergottesdienst' ist komplex, da es ein zusammengesetztes Substantiv ist und selten verwendet wird.	The word 'funeral service' is complex because it is a compound noun and is rarely used.
185	Konvergenz als Ursache der Fehleinordnung : Nach ihrer Analyse des Fibrinogen-Gens stellen etwa die äußerlich sehr ähnlichen Flamingos und Löffler zwei weit auseinanderliegende Gruppen auf den beiden Evolutionsästen dar .	Fibrinogen-Gens	true	Das Wort 'Fibrinogen-Gens' ist komplex, da es ein wissenschaftlicher Begriff ist, der in der allgemeinen Sprache nicht häufig vorkommt.	The word 'fibrinogen gene' is complex because it is a scientific term that is not commonly used in common language.
5726	Hauptgrund für die Verschlechterung des Zustandes sei der heiße und trockene Sommer 2003 mit hohen Ozonwerten .	Ozonwerten	true	Das Wort 'Ozonwerten' kann für Nicht-Muttersprachler schwierig sein, da es ein wissenschaftlicher Begriff ist und spezifisches Wissen über Luftqualität erfordert.	The word 'ozone levels' can be difficult for non-native speakers as it is a scientific term and requires specific knowledge of air quality.

Table 10: Few shot examples for CWI 2018 German. For proofs, we also provide the translation in English.

ID	Sentence	Token	Complex	Proof	Proof (En.)
11798	En 1911, escapó de su casa y se alistó en una expedición militar, organizada por Ricciotti Garibaldi, para liberar a Albania del control turco.	Garibaldi	false	El apellido 'Garibaldi' no es difícil porque es un nombre propio conocido, especialmente en el contexto de la historia y la cultura italiana.	The surname 'Garibaldi' is not difficult because it is a well-known proper name, especially in the context of Italian history and culture.
10963	Estos magos fueron, según la tradición, adorar al Mesías que acababa de nacer en Belén de Judea, el que posteriormente se llamaría Jesús de Nazaret.	adorar	true	La palabra 'adorar' puede considerarse difícil debido a su uso menos común y su connotación religiosa específica.	The word 'worship' may be considered difficult due to its less common use and its specific religious connotation.
8294	En marzo de 2011 firma con el BK Jimki dónde sustituirá a Meleschenko, entrenador interino desde la renuncia de Sergio Scariolo tras no conseguir el pase para el Top-16 de la Euroliga.	interino	true	La palabra 'interino' puede ser difícil debido a su uso en un contexto específico y profesional, lo que requiere un conocimiento preciso del término.	The word 'interim' can be difficult due to its use in a specific and professional context, which requires precise knowledge of the term.
6171	Linda con las poblaciones de Yepes, Huerta de Valdecarábanos y el término segregado de La Guardia, todas de Toledo.	Linda	true	La palabra 'Linda' es difícil porque se trata de un término geográfico específico que puede no ser conocido por todos los hablantes.	The word 'Linda' is difficult because it is a specific geographical term that may not be known to all speakers.
5911	Estuvieron presentes el presidente de Estados Unidos Bill Clinton y el presidente de la República de Corea Kim Young Sam, y se dedicó a los hombres y mujeres que sirvieron en la guerra.	Bill	false	El nombre 'Bill' no es difícil porque es un nombre propio común y fácil de reconocer, especialmente en el contexto de figuras públicas como Bill Clinton.	The name 'Bill' is not difficult because it is a common and easy to recognize proper name, especially in the context of public figures like Bill Clinton.
2673	Cada uno de los vectores columna de la matriz "A" se llama modo propio de vibración, y los "Ci" son las amplitudes relativas de cada modo propio.	amplitudes	true	La palabra 'amplitudes' es técnica y específica del campo de las matemáticas y la física, lo que puede hacerla difícil para quienes no están familiarizados con estos temas.	The word 'amplitudes' is technical and specific to the field of mathematics and physics, which can make it difficult for those unfamiliar with these topics.
1945	El Ducado de Prusia o Prusia Ducal (en alemán: "Herzogtum Preußen"; en polaco: "Prusy Książęce") fue un ducado entre 1525-1701 en la región más oriental de Prusia heredero del Estado monástico de los Caballeros Teutónicos.	monástico	true	La palabra 'monástico' es difícil porque es un término especializado que se refiere a la vida y organización de los monasterios, lo que puede no ser familiar para todos.	The word 'monastic' is difficult because it is a specialized term referring to the life and organization of monasteries, which may not be familiar to everyone.

Table 11: Few shot examples for CWI 2018 Spanish. For proofs, we also provide the translation in English.

ID	Sentence	Token	Complexity	Proof
6043	Containers lost at sea and compensation (debate)	Containers	Very Easy	The word 'Containers' is a common and easily understood term in English, referring to objects used for holding or transporting items.
4290	We have also shown that chondrogenesis can be initiated and chondrogenic differentiation will take place even in the absence of both BMP2 and BMP4 or BMP2 and BMP7.	differentiation	Easy	The word 'differentiation' is slightly technical and commonly used in biological contexts, making it easy but not very easy.
2143	Their scribes and the Pharisees murmured against his disciples, saying, "Why do you eat and drink with the tax collectors and sinners?"	scribes	Neutral	The term 'scribes' is not commonly used in everyday language and refers to a specific historical role, requiring some background knowledge to understand.
5144	Our data suggest that while recombination events destined to be resolved as COs can proceed normally in Trip13 mutants, DSBs that enter the NCO repair pathway are incompletely resolved or processed inefficiently.	COs	Difficult	The acronym 'COs' is specialized and requires specific knowledge in genetics to understand that it refers to 'crossovers' in the context of recombination events.
4873	In the mouse model of RA, small genetic contributions are also often observed.	RA	Very Difficult	The acronym 'RA' stands for 'rheumatoid arthritis,' a term that is highly specialized and not immediately clear without specific medical knowledge.

Table 12: Few shot examples for LCP 2021 single-word expressions.

ID	Sentence	Token	Complexity	Proof
526	Therefore, TGFβ and BMP signaling are playing distinct but necessary roles to maintain articular cartilage.	necessary roles	Very Easy	The phrase 'necessary roles' is straightforward, commonly used in English, and easily understood within the context of the sentence.
212	In this confidence, I was determined to come first to you, that you might have a second benefit;	second benefit	Easy	The phrase 'second benefit' is relatively simple, but the context may slightly challenge the reader, making it less immediate to understand.
1376	We will be very strict on enforcing this fundamental principle in this case as well.	fundamental principle	Neutral	The term 'fundamental principle' requires a moderate understanding of abstract concepts and formal language, making it neutral in difficulty.
503	neither to pay attention to myths and endless genealogies, which cause disputes, rather than God's stewardship, which is in faith–	endless genealogies	Difficult	The phrase 'endless genealogies' is less common and refers to complex and potentially obscure biblical or historical references, adding to its difficulty.
1008	Such polymorphisms should yield biomarkers suitable for more readily accessible samples, such as peripheral blood or buccal smears.	buccal smears	Very Difficult	The term 'buccal smears' is highly specialized and technical, typically known only to those with specific biomedical knowledge, making it very difficult.

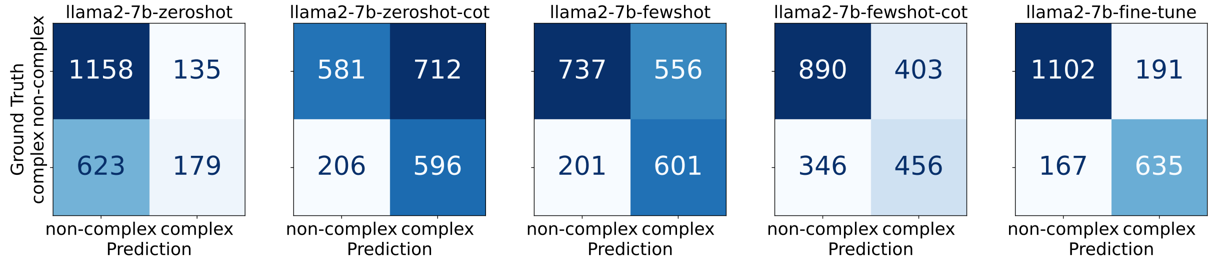
Table 13: Few shot examples for LCP 2021 multi-word expressions.

Tasks		
abstract_narrative_understanding	fantasy_reasoning	nonsense_words_grammar
analytic_entailment	figure_of_speech_detection	odd_one_out
bbq_lite_json	formal_fallacies_syllogisms_negation	penguins_in_a_table
causal_judgment	general_knowledge	phrase_relatedness
cause_and_effect	human_organs_senses	play_dialog_same_or_different
codenames	hyperbaton	presuppositions_as_nli
contextual_parametric_knowledge_conflicts	implicatures	question_selection
crash_blossom	implicit_relations	reasoning_about_colored_objects
crass_ai	intent_recognition	riddle_sense
dark_humor_detection	irony_identification	ruin_names
disambiguation_qa	logical_deduction	strange_stories
empirical_judgments	logical_fallacy_detection	temporal_sequences
entailed_polarity	metaphor_boolean	timedial
epistemic_reasoning	metaphor_understanding	tracking_shuffled_objects
evaluating_information_essentiality	movie_dialog_same_or_different	winowhy

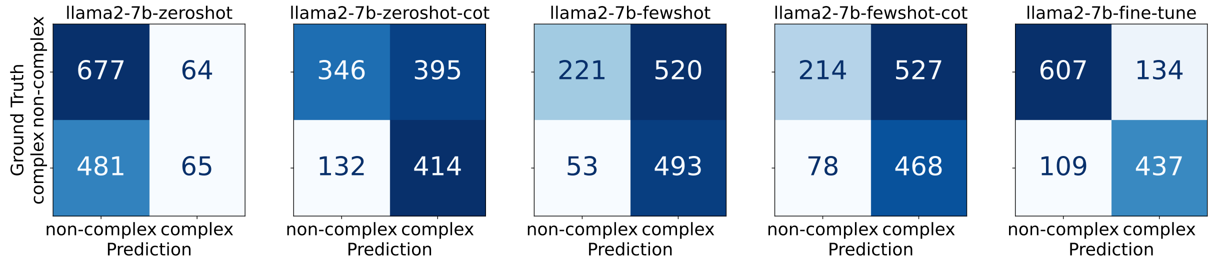
Table 14: All tasks selected from the BIG-bench benchmark that were used during the meta-learning process.

Sentence	Word	Answer	Proof	Ground Truth
Toronto traded Stewart to Chicago early in the 1947-48 season in a deal that brought Max Bentley to the Leafs.	brought	false	The verb 'brought' is not complex as it is a commonly used verb in everyday language with a straightforward meaning	true
His use of Russian language formed the basis of the style of novelists Ivan Turgenev, Ivan Goncharov, and Leo Tolstoy, as well as that of subsequent lyric poets such as Mikhail Lermontov.	basis	false	The word 'basis' is not particularly complex, but the concept it represents (i.e., the foundation or starting point of something) may be unfamiliar to some beginner English learners	true
Vertical distance measurements in the "down" direction are commonly referred to as depth.	depth	true	The word 'depth' has multiple meanings, including a vertical extent or height, making it potentially complex for beginning English learners to understand without proper context or explanation	true
The lack of oxygen above 2,400 meters (8,000 ft) can cause serious illnesses such as altitude sickness, high altitude pulmonary edema, and high altitude cerebral edema.	ft	true	The abbreviation 'ft' is commonly used in English to represent feet, which is a unit of measurement. However, in this context, it may be challenging for beginners to understand because they might not be familiar with the abbreviation.	false

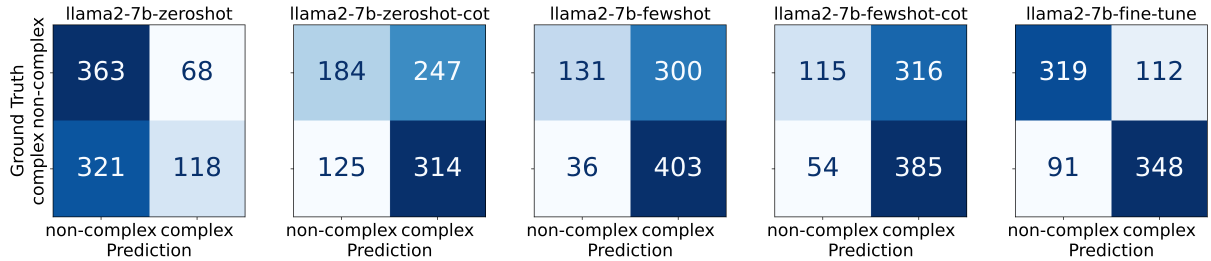
Table 15: Examples of predictions and proofs for the Llama-2-13b-chat model on the CWI English Wikipedia dataset in the zero-shot chain-of-thought setting.



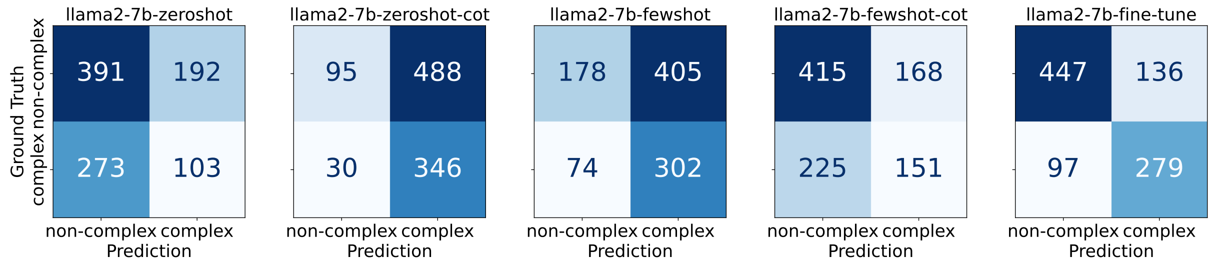
(a) CWI 2018 English News.



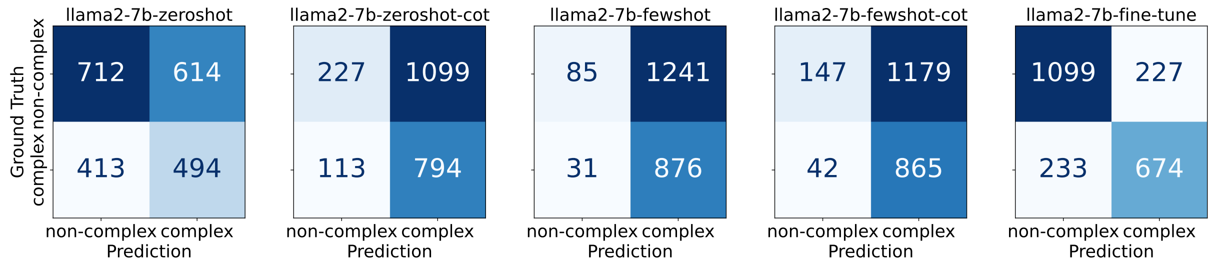
(b) CWI 2018 English WikiNews.



(c) CWI 2018 English Wikipedia.

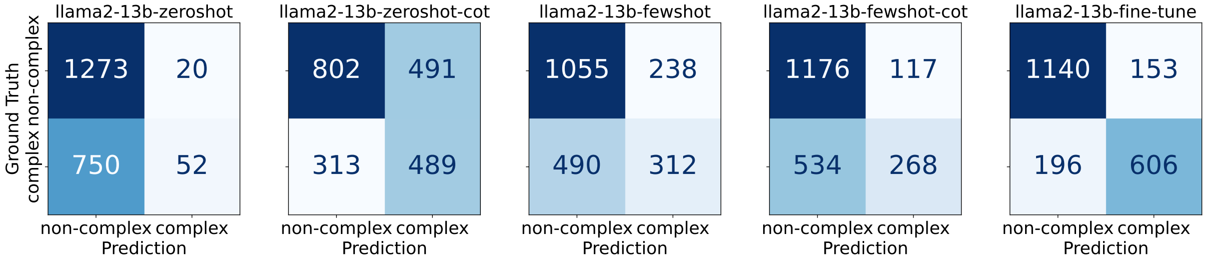


(d) CWI 2018 German.

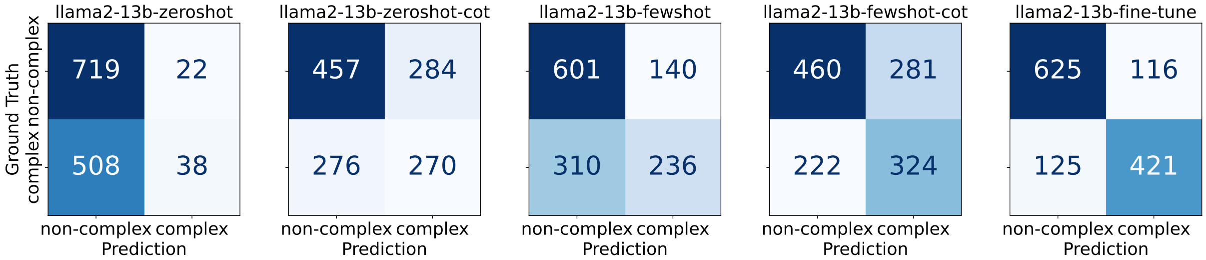


(e) CWI 2018 Spanish.

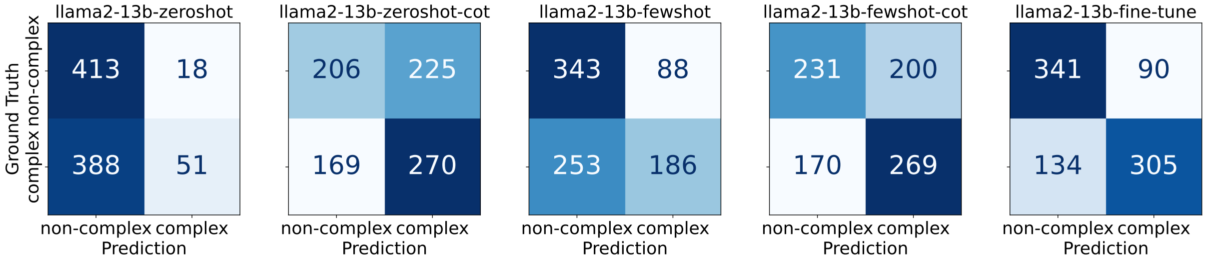
Figure 5: Confusion matrices computed on the CWI 2018 datasets for Llama2 7b.



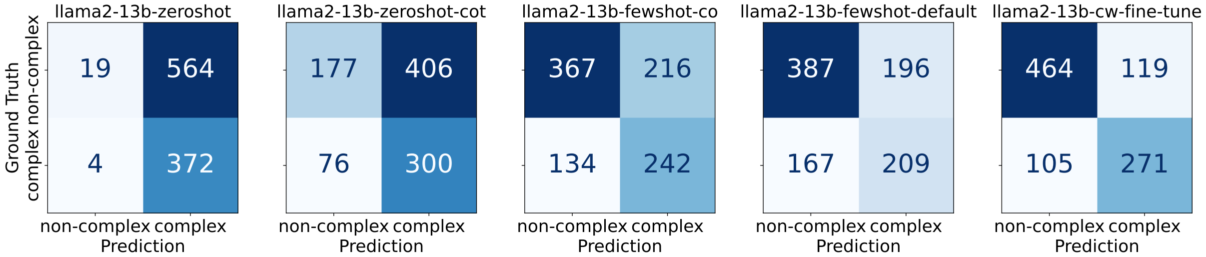
(a) CWI 2018 English News.



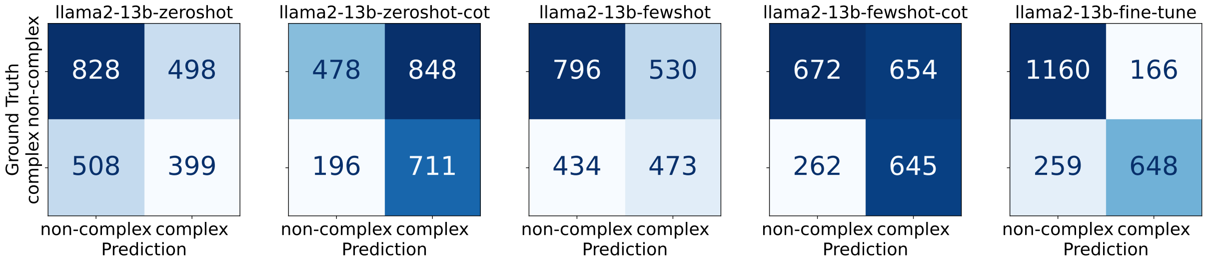
(b) CWI 2018 English WikiNews.



(c) CWI 2018 English Wikipedia.

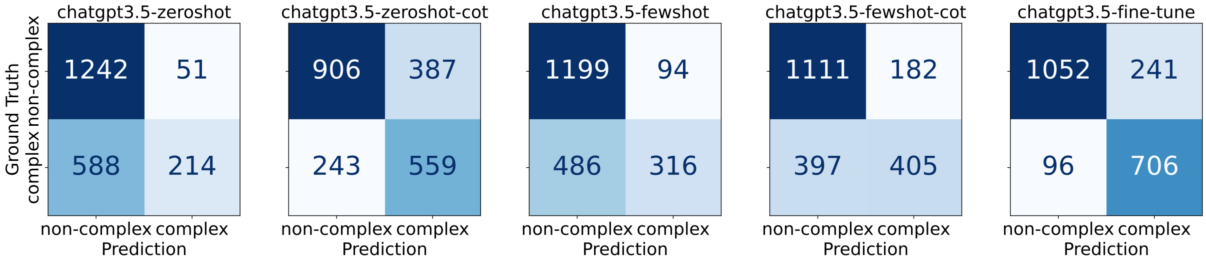


(d) CWI 2018 German.

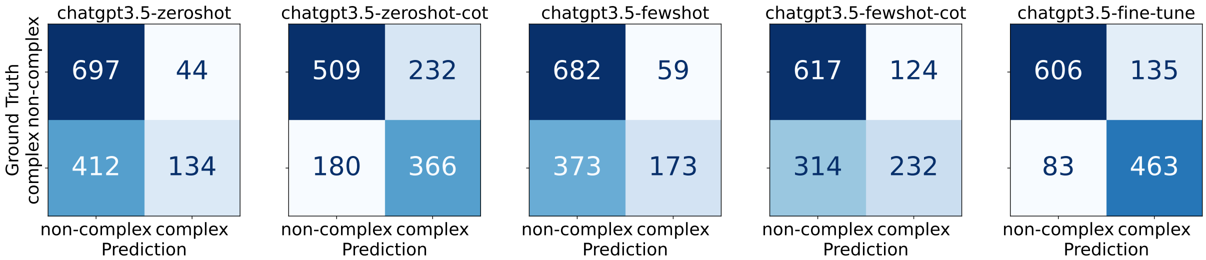


(e) CWI 2018 Spanish.

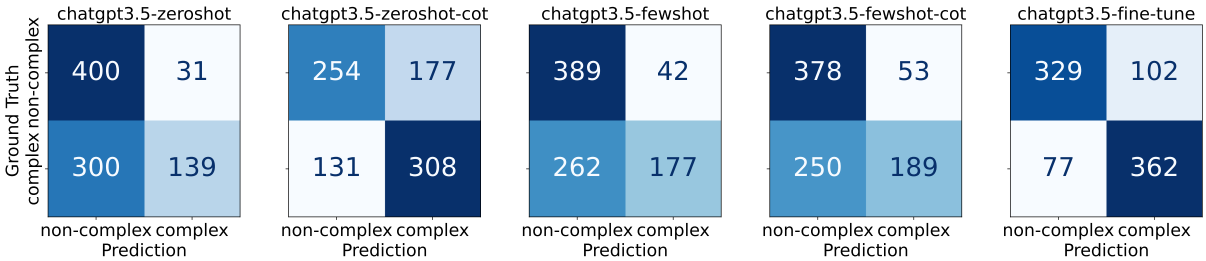
Figure 6: Confusion matrices computed on the CWI 2018 datasets for Llama2 13b.



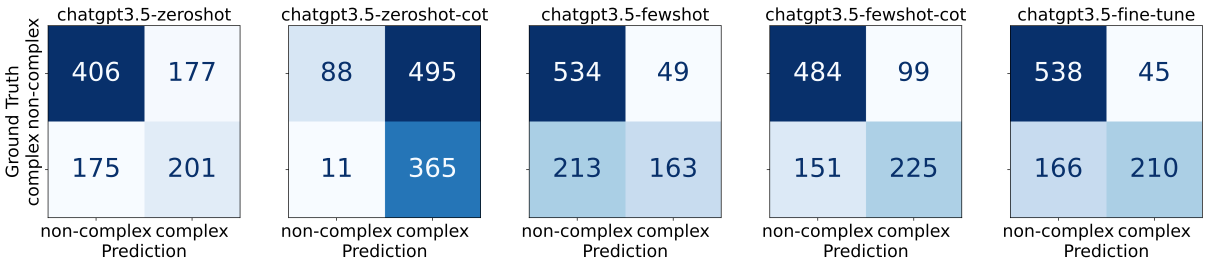
(a) CWI 2018 English News.



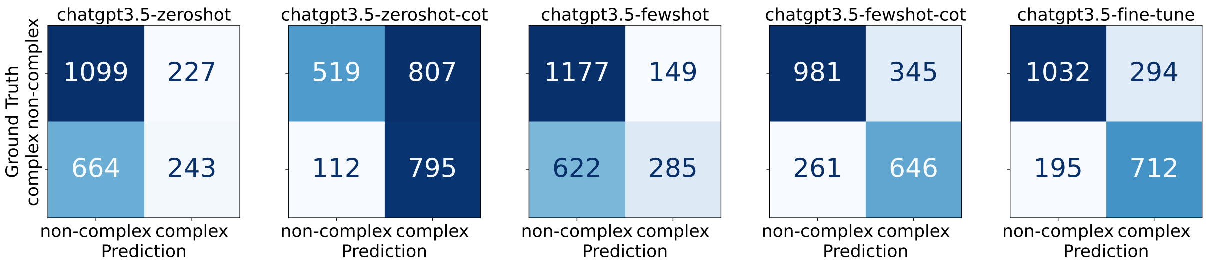
(b) CWI 2018 English WikiNews.



(c) CWI 2018 English Wikipedia.

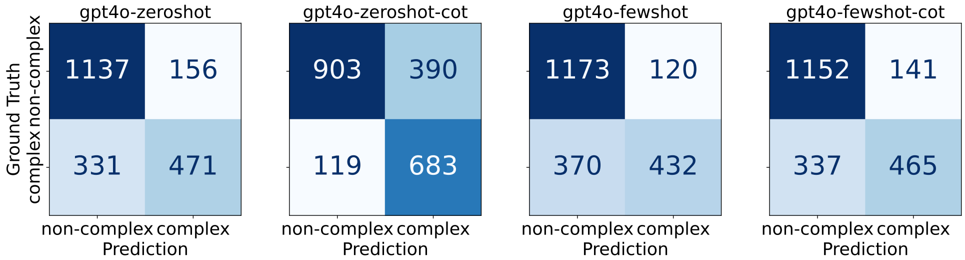


(d) CWI 2018 German.

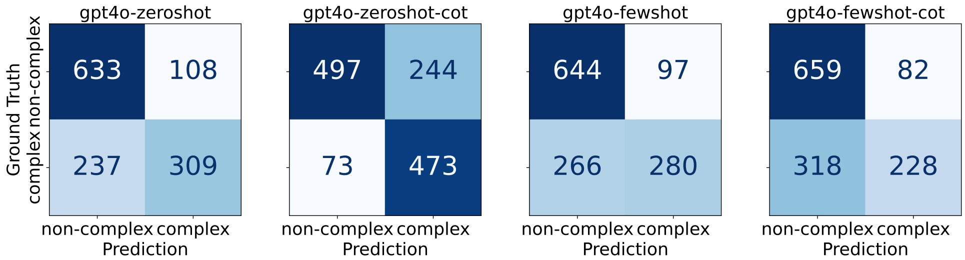


(e) CWI 2018 Spanish.

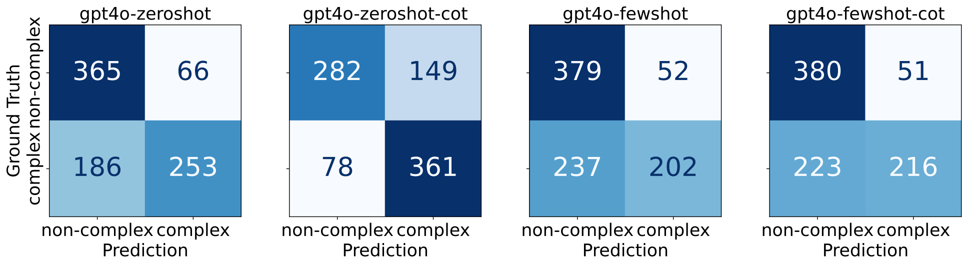
Figure 7: Confusion matrices computed on the CWI 2018 datasets for ChatGPT-3.5-turbo.



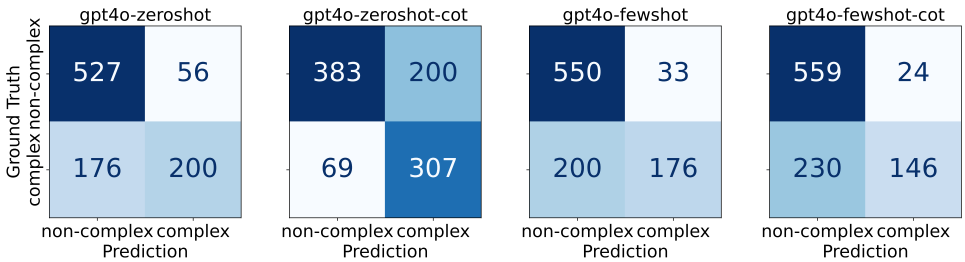
(a) CWI 2018 English News.



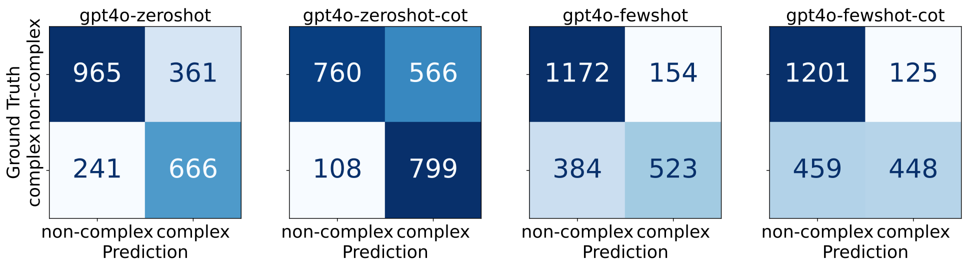
(b) CWI 2018 English WikiNews.



(c) CWI 2018 English Wikipedia.

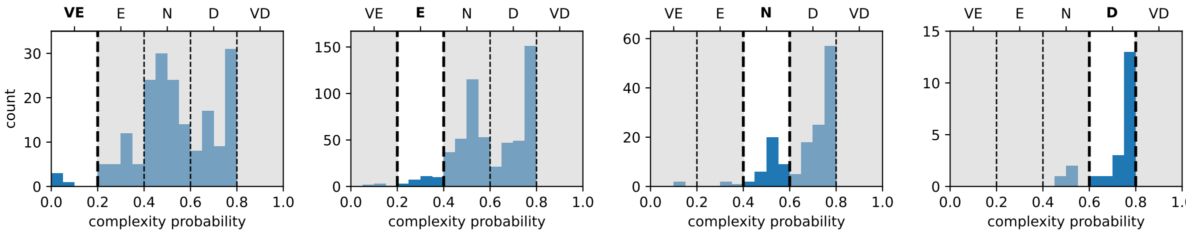


(d) CWI 2018 German.

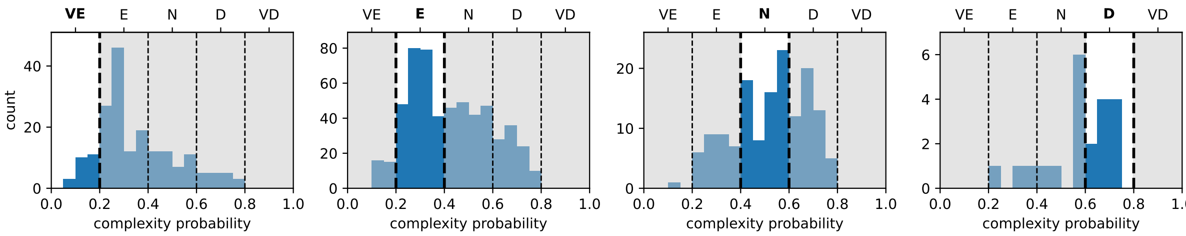


(e) CWI 2018 Spanish.

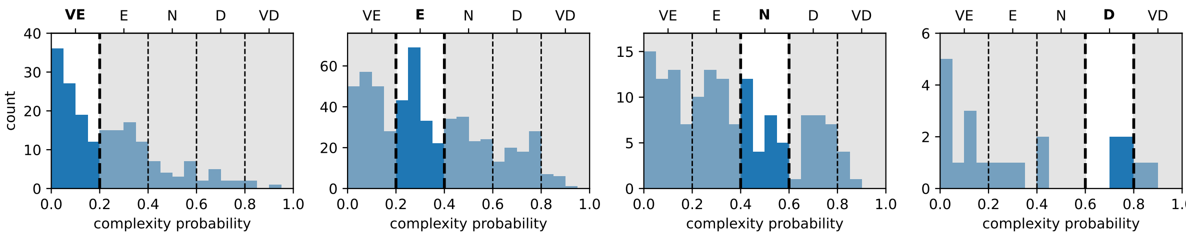
Figure 8: Confusion matrices computed on the CWI 2018 datasets for GPT-4o.



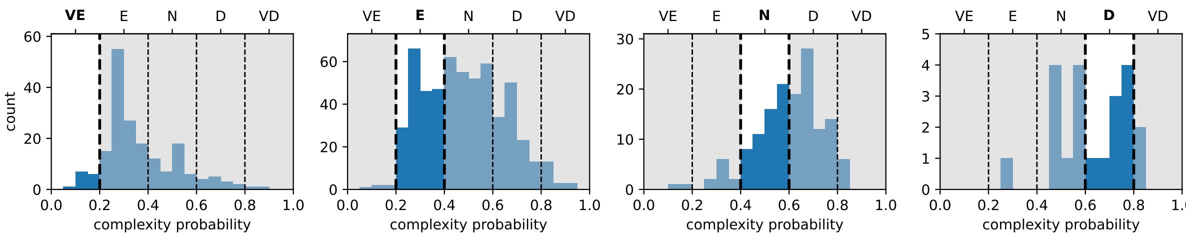
(a) Zero-shot.



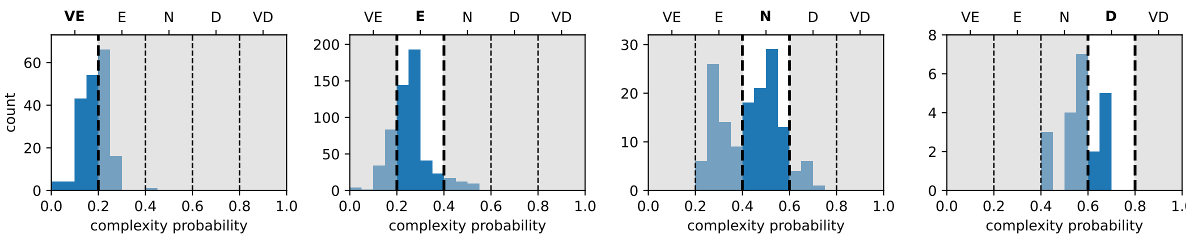
(b) Zero-shot CoT.



(c) Few-shot.

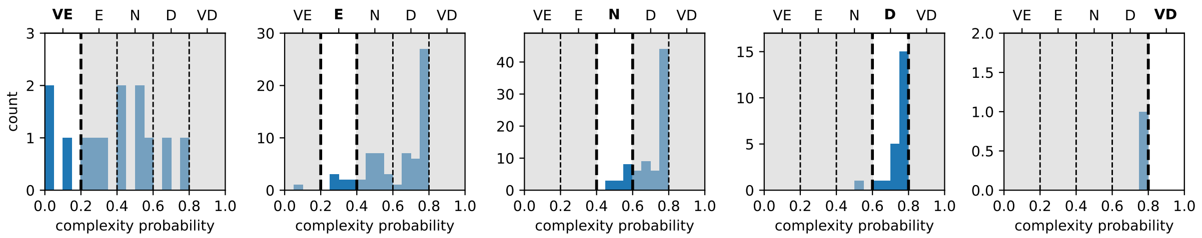


(d) Few-shot CoT.

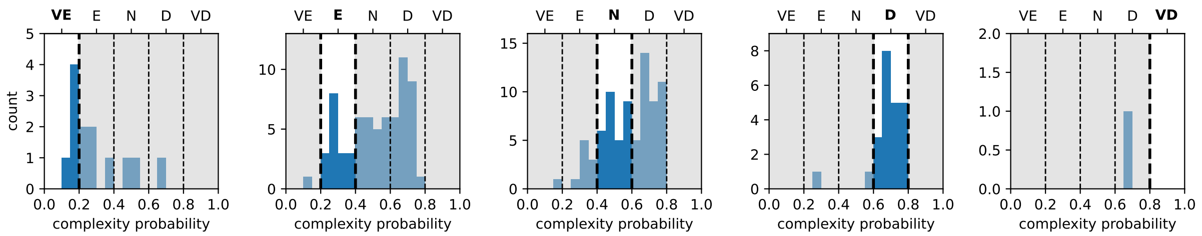


(e) Fine-tune.

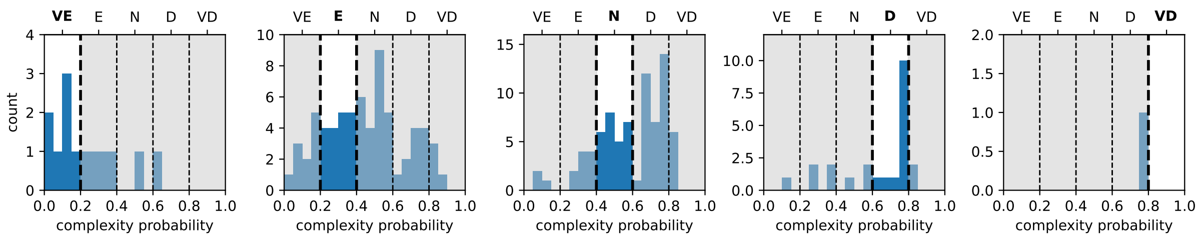
Figure 9: Predictive probability distribution of Llama2 7b on LCP 2021 Single Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



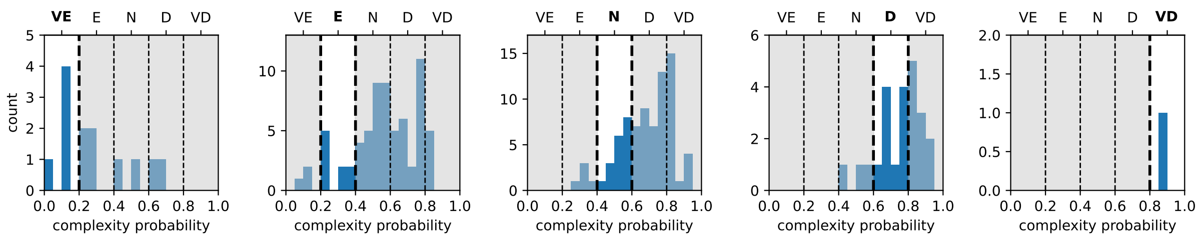
(a) Zero-shot.



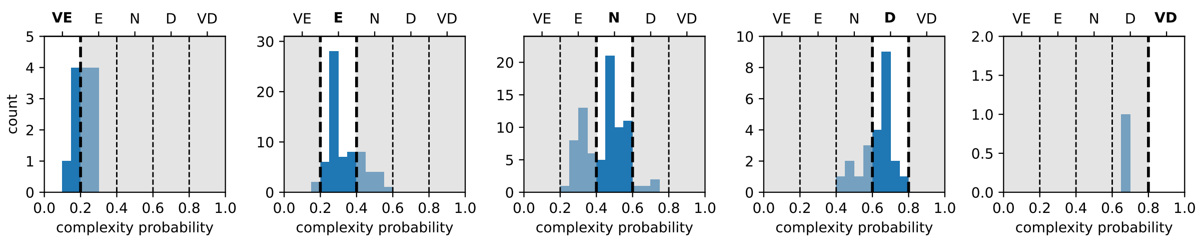
(b) Zero-shot CoT.



(c) Few-shot.

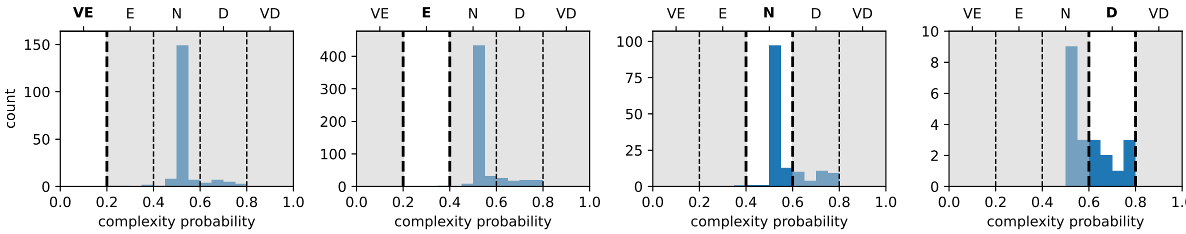


(d) Few-shot CoT.

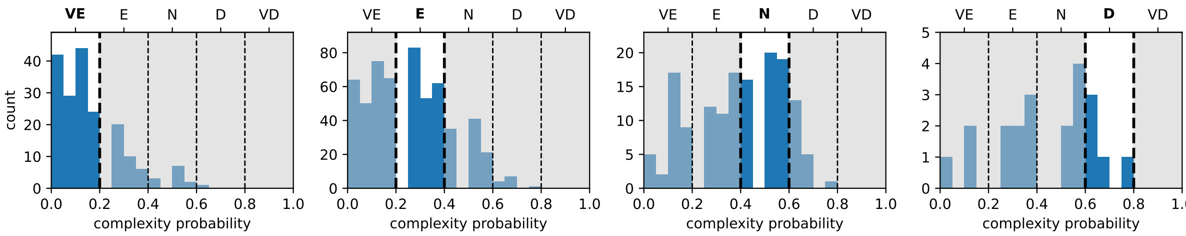


(e) Fine-tune.

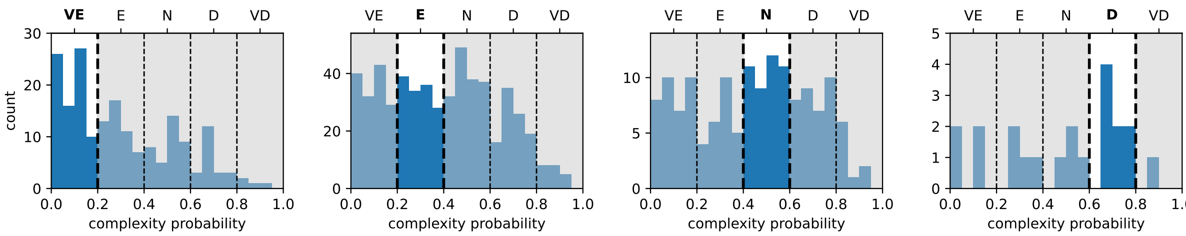
Figure 10: Predictive probability distribution of Llama2 7b on LCP 2021 Multi Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



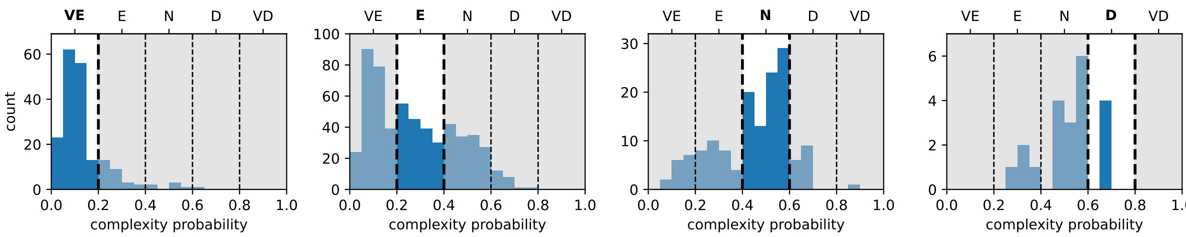
(a) Zero-shot.



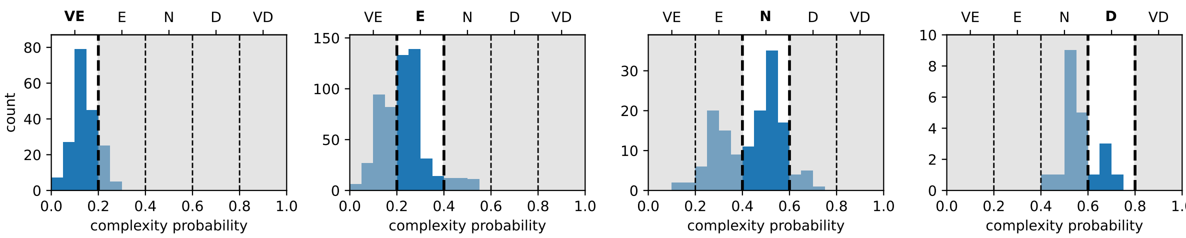
(b) Zero-shot CoT.



(c) Few-shot.

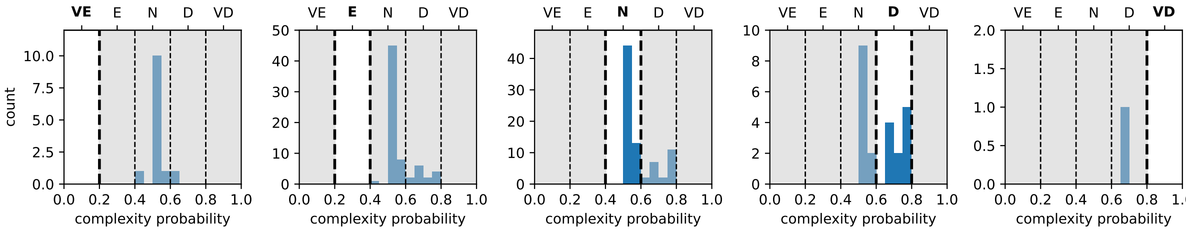


(d) Few-shot CoT.

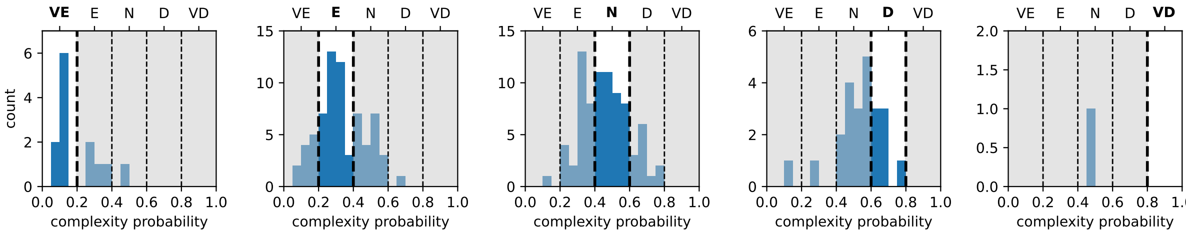


(e) Fine-tune.

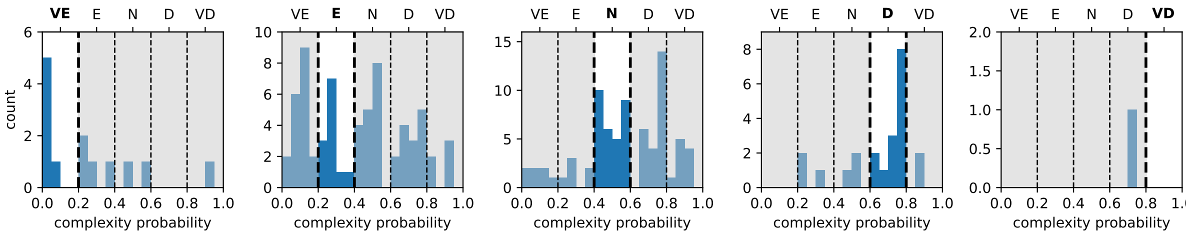
Figure 11: Predictive probability distribution of Llama2 13b on LCP 2021 Single Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



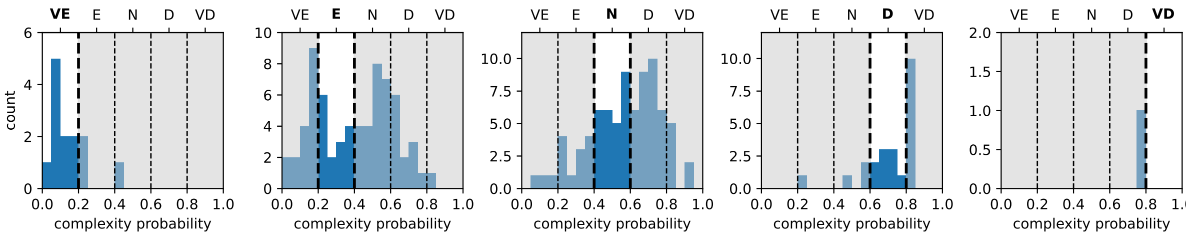
(a) Zero-shot.



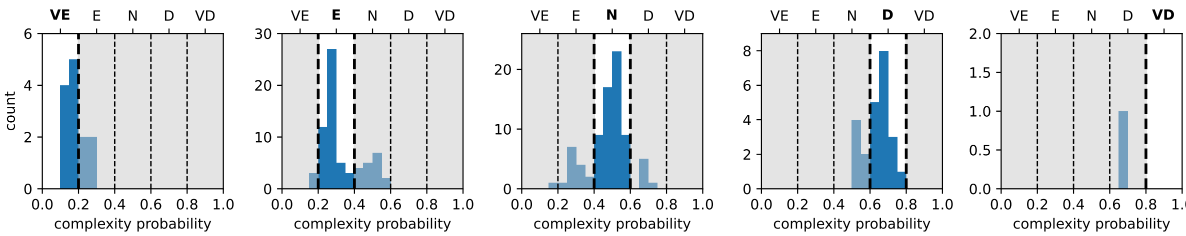
(b) Zero-shot CoT.



(c) Few-shot.

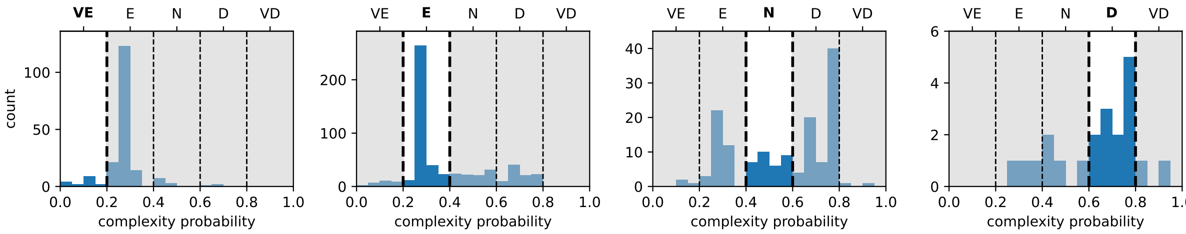


(d) Few-shot CoT.

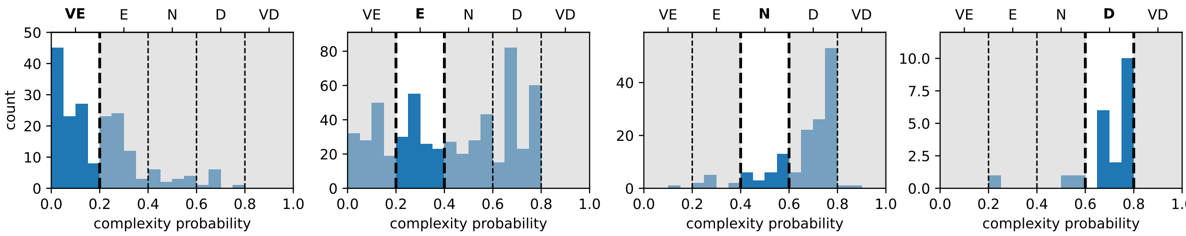


(e) Fine-tune.

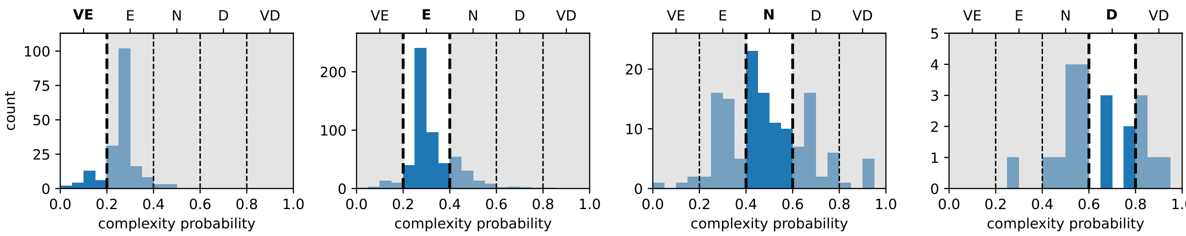
Figure 12: Predictive probability distribution of Llama2 13b on LCP 2021 Multi Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



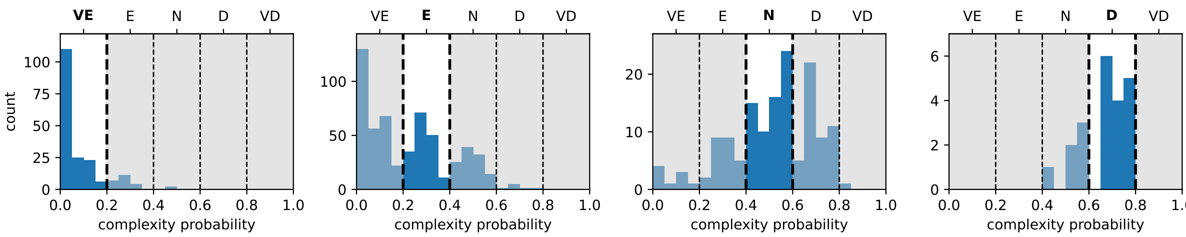
(a) Zero-shot.



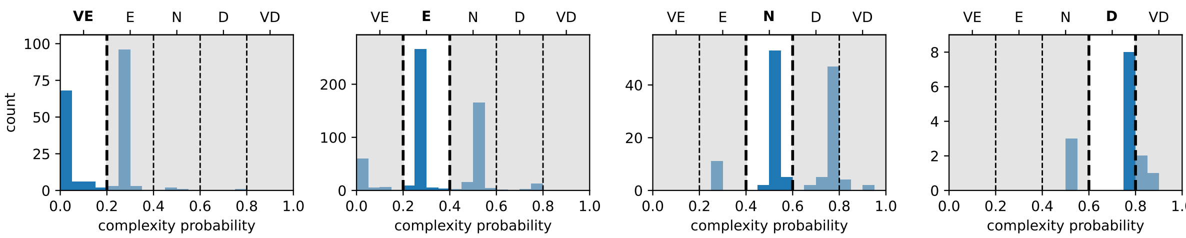
(b) Zero-shot CoT.



(c) Few-shot.

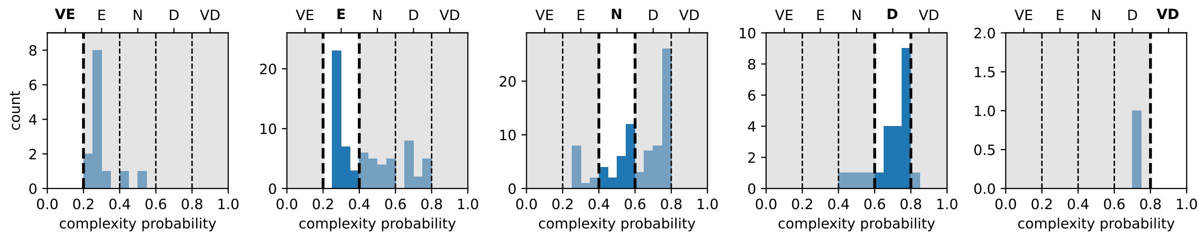


(d) Few-shot CoT.

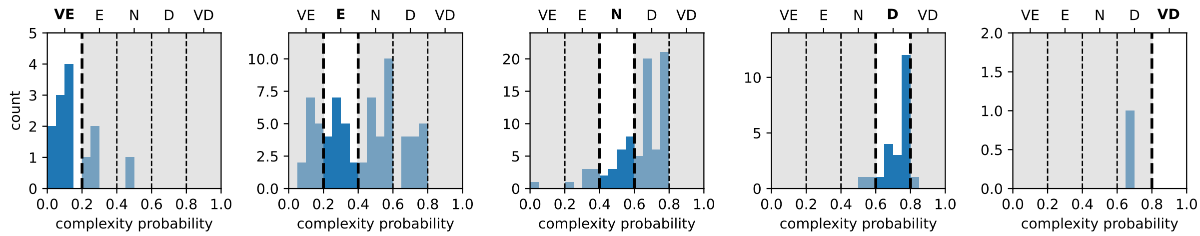


(e) Fine-tune.

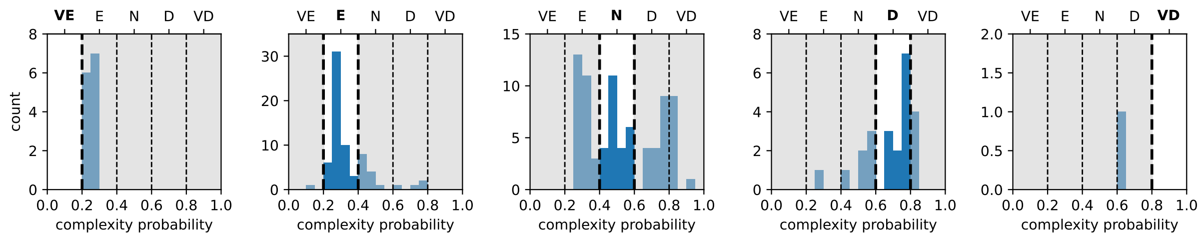
Figure 13: Predictive probability distribution of ChatGPT-3.5-turbo on LCP 2021 Single Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



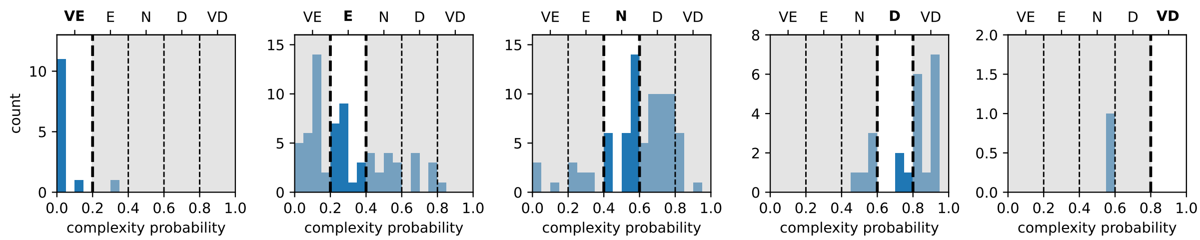
(a) Zero-shot.



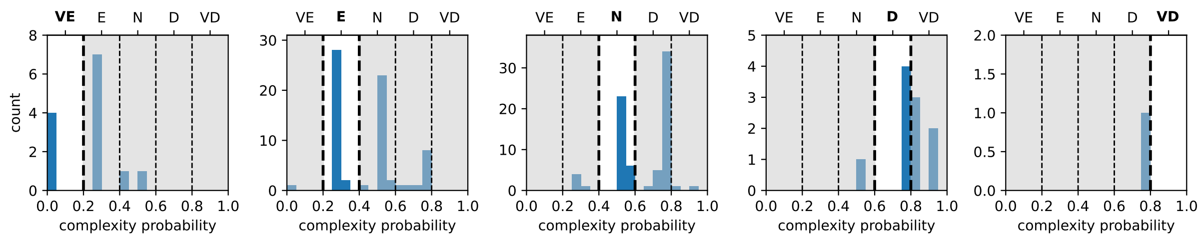
(b) Zero-shot CoT.



(c) Few-shot.

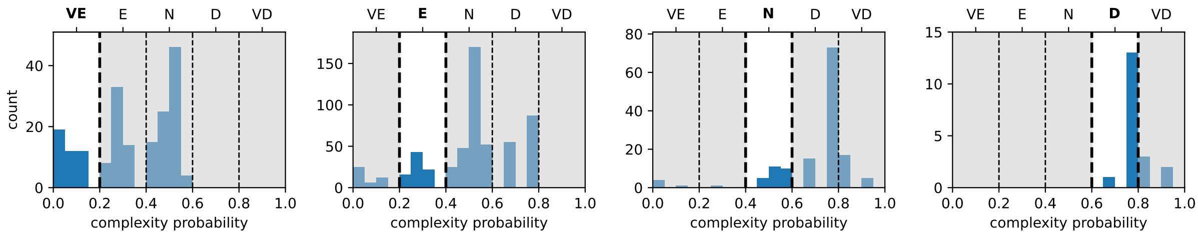


(d) Few-shot CoT.

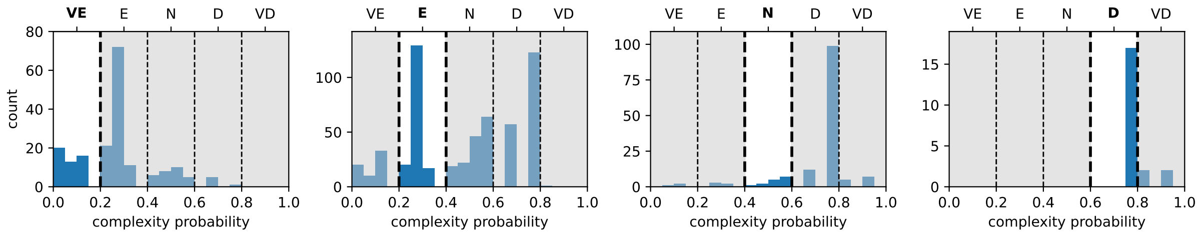


(e) Fine-tune.

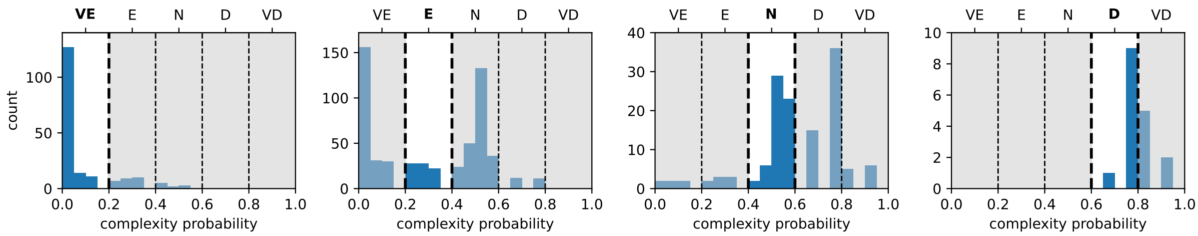
Figure 14: Predictive probability distribution of ChatGPT-3.5-turbo on LCP 2021 Multi Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



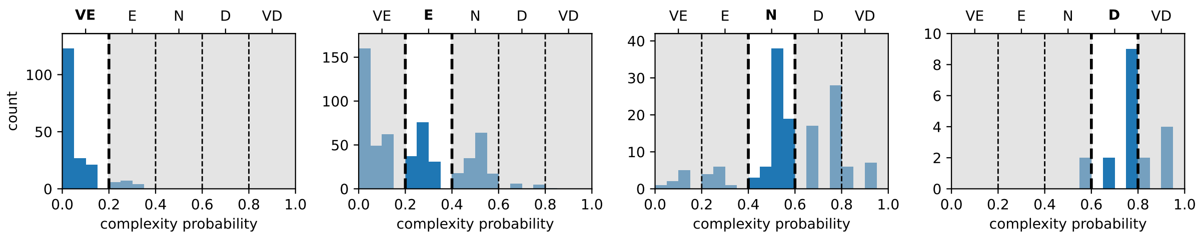
(a) Zero-shot.



(b) Zero-shot CoT.

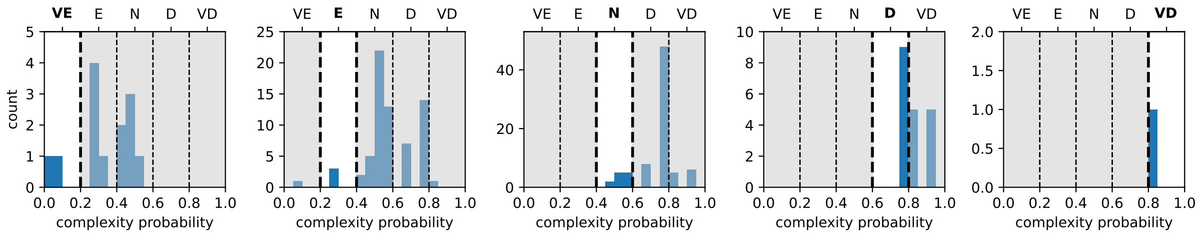


(c) Few-shot.

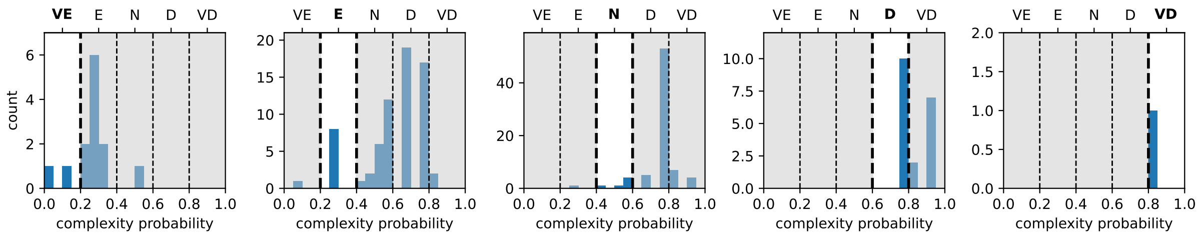


(d) Few-shot CoT.

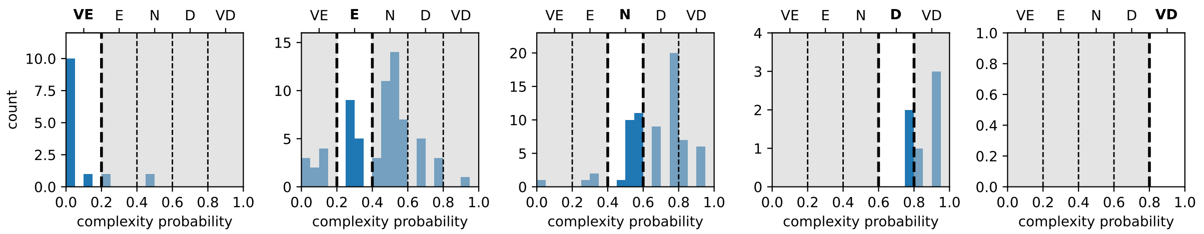
Figure 15: Predictive probability distribution of GPT-4o on LCP 2021 Single Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.



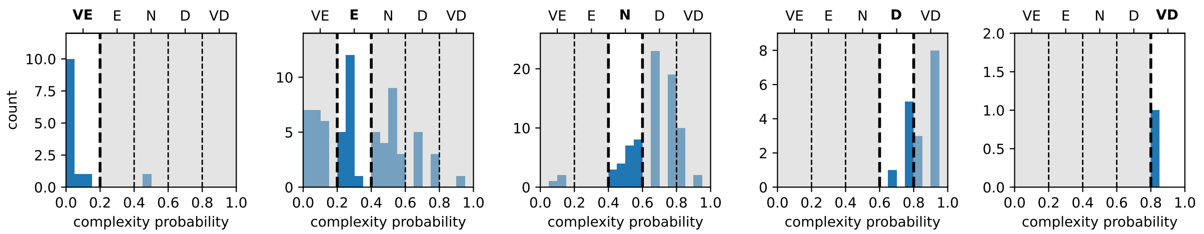
(a) Zero-shot.



(b) Zero-shot CoT.



(c) Few-shot.



(d) Few-shot CoT.

Figure 16: Predictive probability distribution of GPT-4o on LCP 2021 Multi Word dataset. Highlighted in white is the ground truth interval. Neither model predicts in the VD interval. Notation: VE - very easy, E - easy, N - neutral, D - difficult, VD - very difficult.