Exploring Back Translation with Typo Noise for Enhanced Inquiry Understanding in Task-Oriented Dialogue

Jihyun Lee[1*], **Junseok Kim**[2*], **Gary Geunbae Lee**[1,2]
[1]Graduate School of Artificial Intelligence, POSTECH, Republic of Korea
[2]Department of Computer Science and Engineering, POSTECH, Republic of Korea
{jihyunlee, junseokkim00, gblee}@postech.ac.kr

Abstract

This paper presents our approach to the DSTC11 Track 5 selection task, which focuses on retrieving appropriate natural language knowledge sources for task-oriented dialogue. We propose typologically diverse back-translation method with typo noise, which could generate various structured user inquries. Through our noised back translation, we augmented inquiries by combining three different typologies of language sources with five different typo noise injections. Our experiments demonstrate that typological variety and typo noise aids the model in generalizing to diverse user inquiries in dialogue. In the competition, where 14 teams participated, our approach achieved the 5th rank for exact matching metric.

1 Introduction

Task-oriented dialogue (TOD) systems have been developed to offer information and perform specific tasks such as making reservations. In general, TOD systems depend on domain-specific APIs and pre-defined databases (DB), limiting their ability to handle a wide range of scenarios. (Eric et al., 2019; Rastogi et al., 2020). In order to enhance their capabilities and offer more valuable assistance, recent studies have incorporated unstructured textual information from the web into a dialogue system (Dimitrakis et al., 2018; Kim et al., 2020; Majumder et al., 2022).

However, in order to effectively integrate unstructured information, a more advanced comprehension of the user's utterances is needed. For example, when a user mentions having a backache and asks for hotel recommendations, the model should accurately comprehend the user's core intentions (e.g., "need a *comfortable* bed") and extract relevant information from the hotel review set rather than rely only on a pre-defined DB. By precisely understanding the user's question and leveraging others' comments, the model can respond with up-to-date information and diverse perspectives. Unfortunately, precise methods for effectively utilizing these knowledge sources have not been thoroughly researched yet in TOD systems.

DSTC11-track 5 selection task (Zhao et al., 2023) was introduced to address this challenge. Unlike previous TOD approaches that rely on a pre-defined DB, this task offers an external natural language form knowledge source that contains reviews and Q&As. Participants are required to devise approaches that select the relevant information from the provided knowledge source. This track's objective is to improve the system's capacity to accurately address user inquiries by integrating external sources, going beyond the structured information.

Even if a user is asking a commonly asked question, the inquiry form can vary in their words or sentence structure, highlighting the importance of comprehending the core intent behind the user's utterance. To address this, a larger training dataset is essential to ensure robustness and generalize to a diverse form of inquiries. To tackle this challenge, we augment user inquiries by leveraging the back translation, which has been widely used for low-resource problems (Hoang et al., 2018a; Burlot and Yvon, 2019; Caswell et al., 2019; Marie et al., 2020). However, previous studies have shown that machine translations may lack diversity compared to a human-generated dataset (Gimpel et al., 2013; Ott et al., 2018; Vanmassenhove et al., 2019; Soto et al., 2020). To overcome this limitation, we conducted back translation across various typological languages, including fusional, isolating, and agglutinative languages. In total, we carefully selected 12 distinct languages for the back translation.

Another effective approach to generating diverse back-translated sentences involves introduc-

[*]These authors contributed equally to this work.

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September 11, 2023

ing noise into the translated data (Edunov et al., 2018). Moreover, applying typo errors to human-written datasets has been improve robustness across various tasks (Martins and Silva, 2004; Zhang et al., 2020; Zhuang and Zuccon, 2021). Building on these previous achievements, we propose adopting typo noises to the back-translated dataset to enhance the stability and performance when dealing with user-written inquiries.

During the experiment, we compared our performance to the baseline and achieved an exact matching score of 0.448 using our augmentation methods, which surpassed the average score for this task. Furthermore, in our analysis, we extensively examined the impact of typological diversity and typo noise in the back translation process. In the competition, our method achieved the 5th position in the exact matching score among the 14 participating teams.

2 Related Work

Back translation was initially introduced to enhance neural machine translation performance through augmented monolingual datasets (Sennrich et al., 2016) and has proven effective when language resources are limited. Subsequently, various methods have been developed to enhance the augmented dataset. For the training method, iterative back translation method leverages two translation models and continues the training of each model with an augmented dataset until no further improvement is observed in both directions (Hoang et al., 2018b; Artetxe et al., 2020). Alternatively, some researchers (Wang et al., 2019) focus on selecting among the translated datasets based on model confidence scores to ensure dataset quality. similarly, distinguishing between back-translated and original datasets by adding tags to the training set (Caswell et al., 2019; Ranathunga et al., 2023) and assigning weights based on the quality of translated sentences (Dou et al., 2020; Khatri and Bhattacharyya, 2020) also helps in using the back translation method with the original dataset.

In the context of our study, Edunov et al. (2018) is particularly relevant. They enhanced back translation by incorporating noise during decoding with beam search, improving the machine translation performance. We, too, introduce noise to our back-translated data, but in our case, we adopted a typo as the injecting noise method.

Many natural language applications such as retriever (Martins and Silva, 2004; Gao et al., 2010), optical character recognition (OCR) (Soper et al., 2021), and language model pre-training (Liu et al., 2021; Zhang et al., 2021) have dealt with typos to impart robustness to a human-generated dataset. By injecting typo noise into the user inquiries, we also aim to be more stable to some erroneous conversation inquiries.

3 DSTC11-Track5

In the DSTC11-Track5 selection task, participants are required to retrieve relevant knowledge from a provided review dataset in response to a user's utterance. The dialogue dataset consists of 32,604 dialogue data instances and 244,032 turns, which contain the system and user's utterances. The dialogue dataset is a revised version of MultiWoZ 2.1 (Eric et al., 2019), by specifically modifying several turns to be necessary subjective and factual knowledge.

The knowledge data comprises 143 entities, representing individual hotels or restaurants. In total, there are 4,299 reviews and Q&As available for these entities. It is worth noting that this knowledge data exhibits several unique characteristics compared to previous challenges. First, a single review can encompass multiple aspects. Second, there are multiple review posts from diverse individuals, which may include conflicting opinions.

During the training and testing of the selection model, participants are provided with user and system dialogue that includes the entity relevant index. Participants can use this entity index when retrieving the knowledge set. For additional guidance, participants can access the baseline and evaluation scripts on the website. [1].

4 Method

We now introduce our back translation method with typo noise. We denote the conversation dataset as D, and i-th dialgoue in D is denoted as d_i = (u_1^i, s_1^i, u_2^i, s_3^i, ..., u_t^i) where u_t^i is a user utterance and s_t^i is a system utterance at turn t. Here, the last user turn u_{last}^i is the utterance that requires seeking information from external sources in order to provide a response. The knowledge source consists of n number of entities $K = \{e_1, e_2, e_3 \ldots , e_n \}$, and for the j-th entity, e_j consists of k number of reviews and Q&A data, denoted as $e_j = \{r_1, r_2, r_3, \ldots ,r_k\}$. In the training as well as test phases,

[1]https://github.com/alexa/dstc11-track5

Table 1: Typology and languages used for back translation. Language codes follow ISO 639-1.

Typology	Example
Fusional	da, de, es, hi, ine
Agglutinative	fi, hu, ko, tr
Isolating	id, zh,tl

Table 2: Examples of each typo injection method.

Method	Example
Random Delete	"typo technique" → "typo tecnique"
Swap Adjacent	"typo technique" → "typp technique"
Swap Char	"typo technique" → "typo techinque"
Rand Insert	"typo technique" → "typio technique"
Rand Substitute	"typo technique" → "type technique"

the conversation-relevant entity index j is given for each dialogue d_i, and participants should retrieve relevant reviews in the given entity e_j.

4.1 Back Translation

In order to ensure a robust system that can handle various inquiry sentences, we first employed the back translation method for data augmentation. For each dialogue d_i, we obtained the last user turn u^i_{last}, translated the utterances into targeted languages, and then translated them back into English. In translation, to enhance the diversity of augmented utterances, we leveraged various typology languages, including fusional, isolating and agglutinative. We utilized the open source translation model, available in Tiedemann and Thottingal (2020) for translation. The languages we used are in Table 1, and in total, we generated 12 different augmented datasets. We combined 12 different back-translated datasets with original dialogue dataset D, and denoted augmented dataset as $\bar{D}$, which is 13 times larger than D.

4.2 Typos

To enhance the robustness to user's inquiry, we augmented the data by injecting typos into the back-translated inquiry dataset. We employed the following types of typos at random: (1) Random Delete - randomly deleting a character, (2) Swap Adjacent - randomly swapping adjacent characters, (3) Swap Char - randomly swapping a single character with one of its neighbor, (4) Rand Insert - randomly inserting a character, and (5) Rand Substitute - randomly substituting a character. These types of typos were selected based on the errors commonly found in actual human-written sentences. We added these noises randomly to $\bar{D}$ and denoted this noised dataset as $\check{D}$. Examples of each methods are in Table 2.

4.3 Back Translation with Typo

The overall process of data augmentation is depicted in Figure 1. Initially, we perform back-translation using typologically diverse languages. Subsequently, we introduce five distinct typos randomly into the translated data. For the submission, we utilized all back-translation languages and typo methods together with the original dataset, resulting in a dataset that is 13 times larger than the originally provided dataset. Augmented examples are presented in Appendix A.1

4.4 Model Description

To retrieve plausible candidates from the subjective knowledge and return a relevant review list, we leveraged the pre-trained transformer encoder model DeBERTa (He et al., 2020). DeBERta is the enhanced version of BERT (Devlin et al., 2019), with an disentangled attention mechanism and decoding reflecting absolute position. In the given scenario, the input consists of the latest user and system utterance, denoted as s_{last-1} and u_{last}, respectively. Then, this context input is concatenated with the review from the knowledge source, using separate tokens. The model structure and input example is shown in Figure 2. If a review is required to answer the user's inquiry, the corresponding label is assigned as 1; otherwise, it is assigned as 0. Binary cross-entropy loss is calculated between the predicted probabilities and the true labels as in Equation 1,

$$\begin{aligned} L = -\frac{1}{NM}\sum_{i=0}^{N}\sum_{j=0}^{M}[y\log(P(\hat{y}|s^i_{last-1}, u^i_{last}, r_j)) \\ + (1-y)\log(P(1-\hat{y}|s^i_{last-1}, u^i_{last}, r_j))] \end{aligned} \tag{1}$$

Here, N is the number of dialogue numbers in $\check{D}$ and M is the number of reviews and Q&As for a given entity index.

5 Experiments

5.1 Evaluation Metrics

For evaluating our methods, we used precision, recall, F1 and exact matching (EM) as a metrics. Precision measures the proportion of retrieved data

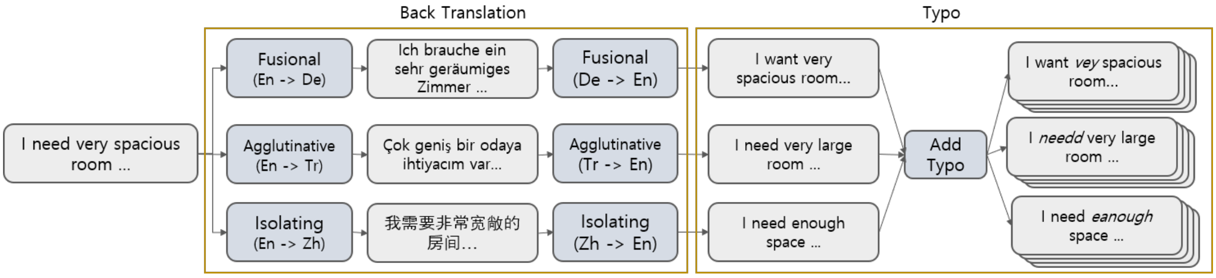

Figure 1: Overview of back translation with typo noise method.

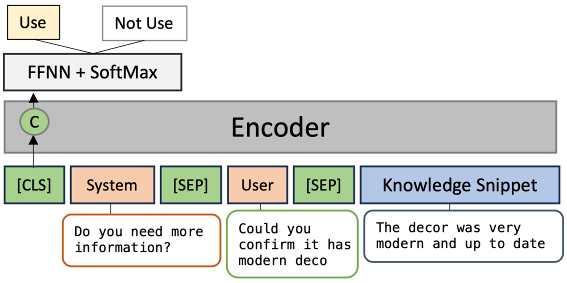

Figure 2: Overview of the model and input example.

that is relevant to the user query. Recall computes the proportion of retrieved relevant knowledge from the total amount of relevant knowledge. F1 computes the harmonic mean of precision and recall. EM computes the proportion of accurate knowledge among the total knowledge entity set.

5.2 Main Result

Table 3: Main result and ablation study of back translation and typo noise. Here, back translation is denoted as BT.

Model	Prec	Recall	F1	EM
	Dev data			
DeBERTa	0.795	0.884	0.837	0.405
+BT	**0.782**	0.906	**0.840**	0.440
+BT+Typo (Ours)	0.751	**0.912**	0.823	**0.498**
	Test data			
Average	0.794	0.800	0.784	0.449
Ours	0.774	0.856	0.813	0.468
Best (Team 13)	**0.834**	**0.871**	**0.855**	**0.657**

To show the effectiveness of our back translation and typo noise methods, we conduct an ablation study by adding them to the backbone model (Table 3). The result indicates that the back translation helps to improve the score in EM (0.440), and injecting the typo could achieve additional progress in performance (0.498). It shows that incorporating the typo noise reduces over fitting and is more robust to written-form dialogue inquiries. Eventually, through our submission we were able to achieve the fifth-highest score of EM among other participants [2]. However, when noise is added to the back-translated dataset, the Precision and F1 scores decrease. This suggests that introducing noise makes the model more likely to predict information that is not necessarily relevant or accurate.

5.3 Analysis of Typology in Back Translation

To assess the impact of utilizing different typologies in back translation, we conducted an analysis of each typology's effect on language pairs, as summarized in Table 4 [3]. The results revealed that the effect varies based on language typology. Fusional languages contribute to improving precision, agglutinative languages encourage recall, and isolating languages enhance the EM score. These findings demonstrate that various language typologies generate distinct sentence structures. We can infer that incorporating diverse typologies leads to a variety of augmented sentences, addressing the monotony problem observed in previous back-translation researches.

5.4 Effect of Typo Noise in Back Translation

In this experiment, we conducted a detailed analysis of the effects of typo noise by individually applying each method to the back-translated data (Table 5). The findings indicated that incorporating most of the noise methods resulted in improved EM scores when compared to using back translation alone. Notably, the random-deletion and character-swapping noise methods exhibited more promising performance. Furthermore, when the five noise methods were combined together, their synergistic effect further enhanced the EM score.

[2]Compared the best submission score of each participant.

[3]We chose 9 languages out of 12 that achieved a BLEU score exceeding 25 by referencing Tiedemann and Thottingal (2020).

Table 4: Result from data augmented by each language on dev data. Fus. means fusional, Agg. means agglutinative, and Iso. means isolating.

Typology	Language	Prec	Recall	F1	EM
Fus.	da	0.762	0.882	0.818	0.390
	de	0.800	0.878	0.837	0.429
	es	0.784	0.869	0.824	0.409
	Avg	**0.782**	0.876	**0.826**	0.409
Agg.	fi	0.758	0.876	0.812	0.369
	hu	0.745	0.891	0.811	0.370
	tr	0.783	0.886	0.831	0.403
	Avg	0.762	**0.884**	0.818	0.381
Iso.	id	0.819	0.870	0.844	0.429
	tl	0.758	0.887	0.817	0.408
	zh	0.767	0.864	0.813	0.404
	Avg	0.781	0.874	0.825	**0.414**

Table 5: Effect of typo noise methods with back translation on dev data.

Model	Prec	Recall	F1	EM
DeBERTa	0.795	0.884	0.837	0.405
DeBERTa +BT	0.782	0.906	0.840	0.440
+ RandDelete	**0.816**	0.892	**0.853**	0.460
+ SwapAdjacent	0.800	0.899	0.847	0.457
+ SwapChar	0.815	0.893	0.852	**0.465**
+ RandInsert	0.795	0.905	0.846	0.438
+ RandSubstitute	0.814	0.893	0.852	0.453
+ ALL	0.751	**0.912**	0.823	**0.498**

5.5 Analysis of Typo Noise

In the experiment in Table 6, we focused solely on the effects of typo noise itself, without using back translation. The results revealed that random insertion and character swapping were effective in enhancing the EM score. However, other types of typo noise either demonstrated similar results or even worse performance. This suggests that introducing noise without augmenting the dataset does not contribute to stable training.

5.6 Conclusion

In this study, we present an effective augmentation method that incorporates typo noise into back translation. In addition, to further enhance the diversity of the augmented text, we employed a range of typologically diverse languages in the back-translation process. Through our experiments, we observed that the noised back translation could improve retrieving accuracy on diverse user inquiries. In the competition, our methods for back translation with typo noise achieved a 5th ranking in terms of EM score, out of a total of 14 participants.

Table 6: Effect of typo noise methods on dev data.

Typo	Prec	Recall	F1	EM
DeBERTa	0.795	0.884	**0.837**	0.405
+ randDelete	0.768	0.887	0.823	0.360
+ swapAdjacent	**0.794**	0.874	0.832	0.392
+ swapChar	0.763	**0.889**	0.821	0.410
+ randInsert	0.791	0.888	**0.837**	**0.434**
+ randSubstitute	0.784	0.875	0.827	0.399

Acknowledgements: This work was supported by Institute of Information & communications Technology Planning & Evaluation(IITP) grant funded by the Korea government(MSIT) (No.2021-0-00575, Development of Voicepishing Prevention Technology Based on Speech and Text Deep Learning) and MSIT under the ITRC (Information Technology Research Center) support program (IITP-2023-2020-0-01789) supervised by the IITP.

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A Appendix

A.1 Augmented Dataset Example

Table 7: Examples of augmented dataset. RI: Random insertion, RD : Random delete, RS : Random substitution, SC : Swap character, SA : swap adjacent

Method	Example
Original	A : I have back issues. Does this place have comfortable beds? B : Do they have nice outdoor dining area? C : Do you know if the Bridge Guest House has cozy beds? D : Is the staff friendly, polite, and responsive? E : Are they easy to get to and in a convenient location?
Fusional	A : I have back problems. Does this place have comfortable beds? B : Do you have a nice outdoor dining area? C : Do you know if Bridge Guest House has comfortable beds? D : Is the staff friendly, courteous and receptive? E : Are they easy to reach and in a convenient location?
Fusional + Typo	A :I have **bacJk** problems. Does this place have comfortable beds? (RI) B :Do you have a nice outdoor dining **ara**? (RD) C :Do **yBu** know if Bridge Guest House has comfortable beds? (RS) D :Is the staff **rfiendly**, courteous and receptive? (SC) E :Are they easy to reach and in a **donvenient** location? (SA)
Agglutinative	A : Are there any nice beds here? B : Do they have a nice walkroom? C : Do you know if there's any nice beds in Bridge Guest House? D : Are the staff friendly, polite and receptive? E : Are they easily accessible and comfortable?
Agglutinative + Typo	A :Are there **anAy** nice beds here? (RI) B :Do **hey** have a nice walkroom? (RD) C :Do you know if **there'H** any nice beds in Bridge Guest House? (RS) D :Are **hte** staff friendly, polite and receptive? (SC) E :**Sre** they easily accessible and comfortable? (SA)
Isolating	A : Have I ever had a comfortable bed in this area? B : Do they have a beautiful dining place outside the house? C : Do you know if there's a comfortable bed in the bridge guest room? D : Are staff friendly, polite and responsive? E : Is it easy to go and put in a convenient place?
Isolating + Typo	A :Have I ever had a comfortable bed in **Nthis** area? (RI) B :Do they have a beautiful **dinng** place outside the house? (RD) C :Do you know if **thMre's** a comfortable bed in the bridge guest room? (RS) D :Are staff friendly, **ploite** and responsive? (SC) E :Is it easy to go and put in a **conveniebt** place? (SA)