

PePe: Personalized Post-editing Model utilizing User-generated Post-edits

Jihyeon Lee^{*†}

gina.lee@kakaobrain.com

Taehee Kim^{*}

taehee.kim@letsur.ai

Yunwon Tae^{*‡}

yunwon.tae@vuno.co

taeheekim@kaist.ac.kr

Cheonbok Park

cbok.park@navercorp.com

Jaegul Choo

jchoo@kaist.ac.kr

Abstract

Incorporating personal preference is crucial in advanced machine translation tasks. Despite the recent advancement of machine translation, it remains a demanding task to properly reflect personal style. In this paper, we introduce a personalized automatic post-editing framework to address this challenge, which effectively generates sentences considering distinct personal behaviors. To build this framework, we first collect post-editing data that connotes the user preference from a live machine translation system. Specifically, real-world users enter source sentences for translation and edit the machine-translated outputs according to the user's preferred style. We then propose a model that combines a discriminator module and user-specific parameters on the APE framework. Experimental results show that the proposed method outperforms other baseline models on four different metrics (*i.e.*, BLEU, TER, YiSi-1, and human evaluation).

1 Introduction

Language usage is strongly influenced by the state of the individual, which can be considered by multiple attributes such as age, gender, socioeconomic status, and occupation (Tannen et al., 1991; Pennebaker et al., 2003). Taking these aspects into account in the machine translation task, we need personalized translations to reflect individual characteristics that vary from person to person; thus, the translation system should consider not only fluency and content preservation, but also personal style.

However, most existing neural machine translation (NMT) models ignore personal style (Mirkin et al., 2015). Previous studies attempt to address this problem by personalizing the NMT models, but in these studies the definition of personal style

* Indicates equal contribution.

†Work done at Korea Advanced Institute of Science and Technology, correspondence to jihyeonlee@kaist.ac.kr.

‡Work done at Korea University, correspondence to tyj204@korea.ac.kr.

<i>src:</i>	This is a <i>primary contribution</i> of our research.				
<i>mt:</i>	이것은	우리	연구의	주로	공헌이다.
	(This is a)	(of our)	(research)	(<i>primarily</i>)	(contribution)
				grammar error	
<i>pe:</i>	이것은	우리	research의	주된	기여이다.
	(This is a)	(of our)	(<i>research</i>)	(primary)	(<i>contribution</i>)
			src language		synonym

Figure 1: Example of a *personal post-editing* triplet (*i.e.*, source (*src*), machine translation (*mt*), and post-edit (*pe*)) given the source text in English and the translated text in Korean. A post-edited sentence does not only contain error correction of an initial machine translation result but also reflects individual preference. For instance, a human post-editor modifies the word "primarily" to "primary," but also change "공헌" to its synonym "기여" while keeping the rest as it is (*e.g.*, "research").

is often over-simplified (Rabinovich et al., 2017; Sennrich et al., 2016; Si et al., 2019). For example, Rabinovich et al. (2017) and Sennrich et al. (2016) define the personal style as politeness and gender respectively, which is not sufficient to tackle the multifarious character of an individual. Namely, previous works defined the personal style in a constrained form.

In contrast with previous studies, we propose a method based on an APE framework and newly utilize post-editing data to capture diverse personal traits in translation. Originally, the need for post-editing data is to improve the quality of machine-translated sentences in an APE task (Simard et al., 2007; Pal et al., 2016; Correia and Martins, 2019). However, we suggest that the post-editing data can also be adequate references for personalized translation if various users post-edit sentences according to their preferences. In this respect, we collect a **user-generated post-editing** dataset called USP through a live translation system. After the system translates a source sentence (*src*) to a target sentence, *i.e.*, machine-translated sentence (*mt*), each

user edits the translated result according to their purpose or preferences, *i.e.*, post-edited sentence (*pe*). We collect (*src*, *mt*, *pe*) triplets called *personalized post-editing* triplets for each user and an example is depicted in Fig 1.

Along with the personalized post-editing data, we develop a model which utilizes user parameter and a discriminator module. The user-specific parameters allow the model to adapt to each user in that the model can consider inter-personal variations. These parameters are aggregated with the output word probability such that the generation word probability distribution differs by each particular user. Moreover, since the prevalence of pre-trained language models encourages significant performance improvements on various natural language generation tasks (Song et al., 2019; Lewis et al., 2019; Correia and Martins, 2019), we exploit the pre-trained language model (LM) but do not fully lean on it. We assume that not all the features from the pre-trained LM contribute to capturing the distinct taste of users that are departing from the neutral and standardized patterns. Thus, our discriminator module, inspired by adversarial training (Goodfellow et al., 2014), attempts to dismantle the unnecessary features from a pre-trained LM, while tuning the model to incorporate a personal style. The details will discuss in Section 3.

Experiments on our dataset and speaker annotated TED talks dataset (Michel and Neubig, 2018) (SATED) demonstrate that the proposed approach generates diverse translations for different users.

In summary, our contributions include the following:

- To the best of our knowledge, this is the first work that leverages the APE framework to a personalized translation task.
- We propose a personalized post-editing model based on user-generated post-edits, which is able to capture the inter-personal variations that consist of multiple attributes.
- Extensive experimental results show that the proposed method robustly reflects personal traits and consistently outperforms baselines in three different quantitative metrics and human evaluation results.

2 Related Work

Our work is closely related to the recent work on personalized neural machine translation and auto-

matic post-editing.

Personalized neural machine translation.

Standard NMT systems are not able to consider the personal preference in a machine-translated output (Mirkin et al., 2015). Mima et al. (1997) is the early paper that proposes a concept of reflecting an author’s properties, such as gender, dialog domain, and role in the translation. However, including Mima et al. (1997), most studies conduct a limited range of personalized translations, which address only a single attribute (*e.g.*, politeness) (Sennrich et al., 2016; Rabinovich et al., 2017).

Turchi et al. (2017) and Karimova et al. (2018) fine-tune the model on the human post-edits to improve the NMT quality, which can be viewed as a naive approach to handle the personalized translation without attribute labels. Wuebker et al. (2018) extend this approach to adjust only a small number of parameters, but still requires extensive training resources. Meanwhile, Michel and Neubig (2018) and Huan et al. (2021) propose a generalized form of a personalized translation method, which are closely related work with ours. Michel and Neubig (2018) cast this problem as an extreme form of domain adaptation, while Huan et al. (2021) introduce cache module and contrastive learning to increase the diversity on dissimilar users. However, the reference sentences for personalized translation were constructed by a few professional translators, not by a variety of people with diverse characteristics; personal preferences reflected in the dataset are limited. Our user-generated post-edits are edited by a large number of people who provide the original sentences.

Automatic post-editing. Prior to the emergence of the transformer (Vaswani et al., 2017), RNN based APE models (Pal et al., 2016; Junczys-Dowmunt et al., 2016; Junczys-Dowmunt and Grundkiewicz, 2017) are actively studied. Subsequently, as self-attention based models show significant improvements on various downstream tasks, transformer based models also prevail in the APE task. Specifically, a popular approach is to set a separate encoder for the source and machine-translated (MT) output. Separately encoded representations are joined in the following encoder (Pal et al., 2018) or fused in the decoder (Tebbifakhr et al., 2018; Junczys-Dowmunt and Grundkiewicz, 2018). More recently, Correia and Martins (2019) improve the performance of APE tasks by leveraging a

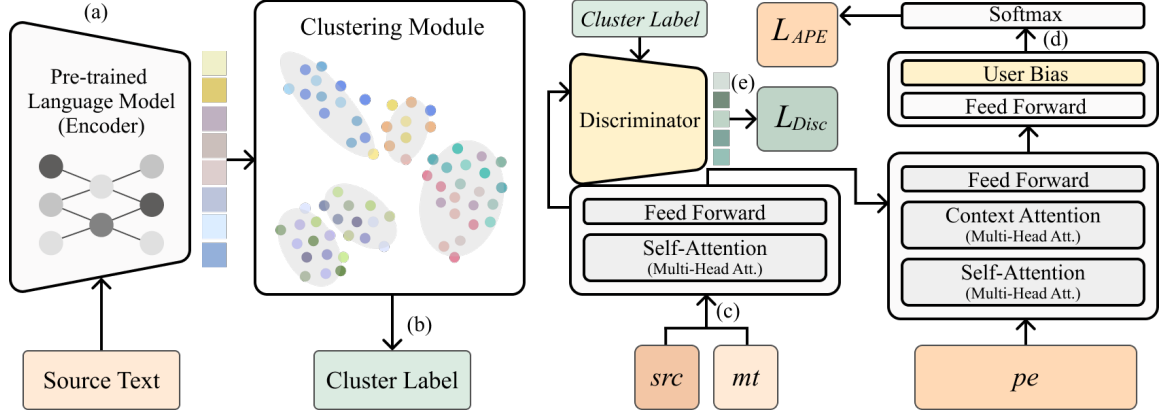


Figure 2: An overview of our proposed method. PePe consists of two parts: 1) Clustering module that relies on pre-trained LM encoder and Gaussian mixture model. 2) APE architecture that includes an auxiliary discriminator and user-specific parameters.

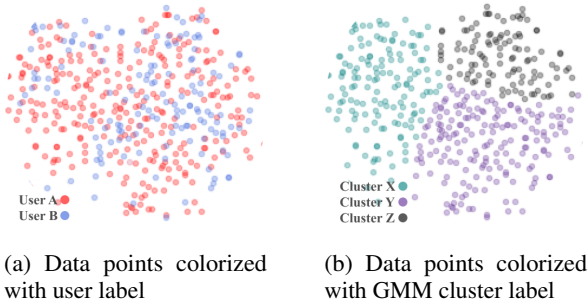


Figure 3: Source sentences of USP embedded with the pre-trained LM. (a) and (b) shows the discrepancy between the user data distribution and the contextual similarity-based data distribution.

pre-trained LM. Compared to these studies, our work is the first attempt to examine the neural network based APE model for personalized translation. There is a study where they use an APE module for domain adaptation (Isabelle et al., 2007), but the explored one is based on a statistical machine translation system.

3 Proposed Method

Overview: It is challenging to generate appropriate translations that impose personal variations. To address such a demanding problem, we take a detour by applying an APE framework. We propose PePe, a personalized post-editing model utilizing user-generated post-edits. PePe includes a discriminator module to allow the model to dismantle the pre-trained LM features. Specifically, we maximize the discriminator loss to encourage the encoder to throw away irrelevant pre-trained LM features, while minimizing the APE loss to guide the model

to utilize the pre-trained LM features that are useful for personalization. In addition, PePe utilizes user-specific parameters to capture the personal style. User-specific parameters are combined at the end of the decoder layer to adjust the prediction of the word probability, i.e., the word choice based on a user preference. Our strategy does not require expensive supervision on the personal style, such as explicit attribute labeling or an attribute-tailored model architecture.

The overall architecture of PePe is illustrated in Fig. 2. The two following subsections will describe the modules shown in Fig. 2-(a), (b), (c), (d), and (e), respectively.

3.1 Contextual Similarity vs. User-specific Style

The pre-trained LM is well known for capturing the contextual similarity that is useful to define the label for in-domain data (e.g., sports, IT, and economy). However, the user-specific style is far from those domains; it does not coincide with contextual similarity yet involves somewhat arbitrary traits (i.e., user preferences). Hence, we argue that some of the features from a pre-trained LM distract personalized translation, which rather requires generating biased results to meet the individuals’ needs. Fig. 3 demonstrates the discrepancy between the user data distribution and the contextual similarity-based data distribution.

We map the sampled sentences from USP to the embedding space of the pre-trained LM. Each sentence is encoded with RoBERTa (Liu et al., 2019) and visualized using t-SNE (van der Maaten and Hinton, 2008). The data on both sides show the same embedding representations obtained from the

same set of sentences, but labeling is different. The data items in Fig. 3a are color-coded by the users, whereas those in Fig. 3b are color-coded by the semantic cluster labels obtained from the Gaussian mixture model (GMM) (Rasmussen, 2000), which allocates the similar sentences to the same label based on the RoBERTa embedding of each.

In Fig. 3b, semantically similar points, which are close in embedding space, belong to the same clusters. However, the red and blue points in Fig. 3a, which indicate sentence representations from two different users, are distributed unruly instead of being grouped by semantic similarity. In other words, the fine-grained style differences of each user are somewhat distant from the contextual similarity of the sentences; thus it is hard to distinguish user-specific preferences when the model is highly oriented to learning the contextual similarity.

3.2 Generating Cluster Labels based on Pre-trained LM

Inspired by the finding in Section 3.1, we devise a discriminator module that uses the semantic cluster labels to unlearn the features from the pre-trained LM that are unnecessary to reflect the personal styles. Before introducing the details about PePe, we describe how to generate the semantic cluster labels from a pre-trained LM in an unsupervised manner. We first encode *src* into encoded vectors using a pre-trained LM¹ as shown in Fig 2-(a). Based on these encoded vectors, semantic cluster labels are generated by GMM (Rasmussen, 2000) as illustrated in Fig 2-(b). A Gaussian mixture is a function made up of the k number of Gaussian components, where k is the number of clusters² and is a hyperparameter. Specifically, in GMM, $\sum_{i=1}^k \pi_i p_i(\mathbf{h}|\theta_i)$ represents the distribution of data point \mathbf{h} , where \mathbf{h} is an encoded vector of the first token of *src*, *i.e.*, [CLS] token, π_i is the probability of each Gaussian fitting the data, and p_i is the Gaussian density function parameterized by θ_i . We assign each sentence to a Gaussian that best describes the data, and the Gaussian corresponds to the semantic cluster label. The label, *i.e.*, $T = t_1, \dots, t_k$, is then used as a classification label for our discriminator, which is described in the following subsection.

¹Though we use RoBERTa as a pre-trained LM to generate cluster labels, other pre-trained LMs can also be used in our approach.

²Ten clusters are used for all the experiments in the main paper.

3.3 PePe: Personalized Post-editing Model utilizing User-generated Post-edits

We adopt BERT-based Encoder-Decoder APE model (Correia and Martins, 2019) called Dual-Source BERT (DS-BERT) as our backbone, which is based on transformer (Vaswani et al., 2017) with pre-trained multilingual BERT (Devlin et al., 2019). DS-BERT uses a single encoder which is used to encode both the *src* and the *mt* by concatenating them with the specialized token [SEP] as described in Fig 2-(c).

Our model also learns to generate $y = [y_1, \dots, y_n]$, *i.e.*, *pe*, from x , *i.e.*, *src*, and $\tilde{y} = [\tilde{y}_1, \dots, \tilde{y}_m]$, *i.e.*, *mt*, by maximizing the likelihood,

$$P(y|x, \tilde{y}; \theta_{APE}) = \prod_{i=1}^n P(y_i|x, \tilde{y}, y_{<i}; \theta_{APE}),$$

where y_i is the i -th target word and $y_{<i} = y_1 \dots y_{i-1}$ is the partial translation result. θ_{APE} represents the parameters for translating source sentence into post-edited sentence with machine-translated result \tilde{y} .

In order to adapt user-specific linguistic styles, we add user-specific parameters before the softmax layer in the decoder as shown in Fig 2-(d), *i.e.*,

$$P(y_i|x, \tilde{y}, y_{<i}; \theta_{APE}, \theta_{user}) = f(FFN(o_i) + \theta_{user}),$$

where FFN and f are a feed-forward network and softmax function, respectively. o_i is the output for the i -th target word from the decoder. $\theta_{user} \in \mathbb{R}^V$ is a user-specific embedding vector from a set of trainable user embedding matrix $U \in \mathbb{R}^{N \times V}$ where N is the number of users and V is the size of vocabulary.

The model is then optimized by minimizing \mathcal{L}_{APE} defined as

$$\mathcal{L}_{APE} = - \sum_{i=1}^n \log P(y_i|x, \tilde{y}; \theta_{APE}, \theta_{user}).$$

Furthermore, as shown in Fig 2-(e), we introduce a discriminator module to unlearn the contextual similarity feature learned from a pre-trained LM. To train the discriminator, we compute the discriminator loss \mathcal{L}_{Disc} defined as

$$\mathcal{L}_{Disc} = \sum_i^k t_i \log(\tilde{t}_i),$$

where k is the number of classes (*i.e.*, the number of Gaussians we pre-defined) and t_i is the ground-truth label of the semantic cluster. \tilde{t}_i represents the

output from the discriminator which is a single-layer feed-forward network for the classification of semantic cluster labels. We use the first token of a source sentence to extract a sentence representation from the encoder and pass it to the discriminator as an input. Note that we use the gradient ascent method to prevent the encoder from classifying the clusters. In this way, we diminish the unnecessary feature from pre-trained LM, while our APE loss function incorporated with user-specific parameters leads the model to capture the user-specific style.

Finally, PePe optimizes a combination of two losses, \mathcal{L}_{Disc} and \mathcal{L}_{APE} , with an adjustment rate β , *i.e.*,

$$\mathcal{L}_{Train} = \beta \cdot \mathcal{L}_{Disc} + (1 - \beta) \cdot \mathcal{L}_{APE}.$$

4 Experiments

In this section, we qualitatively and quantitatively demonstrate the effectiveness of our proposed method. We validate PePe, described in Section 3, against other baseline methods using a real-world user dataset USP. We also provide a detailed explanation for the dataset. Moreover, through extensive experiments and analyses, we show that PePe can incorporate inter-personal variations into a target sentence. We provide training details in Appendix A.

4.1 Dataset

We collect the user-generated post-editing dataset, USP, from a publicly available online translation system³ (*e.g.*, Google Translate). Fig 4 illustrates the user experience flow. The users enter the sentences they want to translate, and the system provides the corresponding outputs that are generated by the high-quality commercialized machine translator. From the machine-translated outputs, users can start to edit the translated sentences according to their preference by clicking the “post-edit” button. Consequently, when the users click the “Finish” button after completing the changes, a triplet of the source sentence, machine-translated output, and personalized post-edit is sent to our database. Note that the origin of post-edited sentences is each particular user, which makes USP contains inter-personal variation, unlike existing APE datasets.

³We collected data only from users who consent to the data collection for research purposes. In addition, there is no privacy issue because de-identification had taken for the collected data.

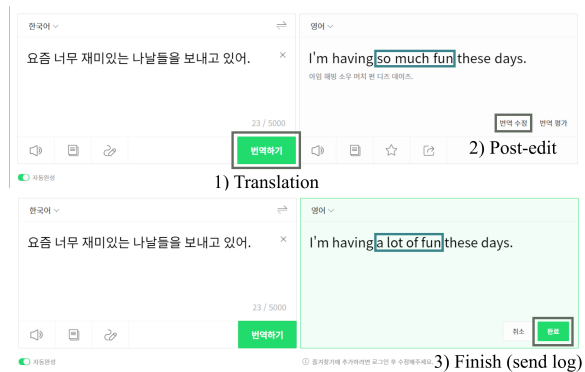


Figure 4: Illustration of the user experience flow for post-edit log generation.

Since we collect USP from the real-world users’ inputs that contain various noises (*e.g.*, unedited, duplicated, or meaningless examples), we preprocess the data to eliminate these noises. Furthermore, most users only edited few examples, which are not sufficient to represent their style. Therefore, we select the users who left more than 100 samples, *i.e.*, 30 users with 7K sentences and 70 users with 9K sentences for $en \rightarrow ko$ and $ko \rightarrow en$ USP dataset, respectively. For users who left less than 100 samples, we aggregate the samples (*i.e.*, 0.12M sentences) and utilize them as training data for the task-adaptive pre-training (Gururangan et al., 2020). The discriminator module and user-specific parameters are not used in the task-adaptive pre-training and only the parameters for DS-BERT are utilized for the pre-training stage. Details of data preprocessing are in Appendix A.

Additionally, we adopt a Speaker Annotated TED (SATED) dataset (Michel and Neubig, 2018) containing more than 2,000 sets of speaker style-contained source sentences, which is publicly available. We select the dataset to show the robustness of our model regarding different datasets and languages.

4.2 Experimental Setup

Evaluation metric. We use three different metrics to evaluate how well our proposed model preserves the content and incorporates the personal preferences. BLEU (Papineni et al., 2002) and TER (Snover et al., 2006) scores are considered to assess the translated sentence where the ground-truth sentence is a *pe* sentence. We also leverage YiSi-1 (Lo, 2019) that computes the semantic similarity of phrases between the model output and *pe*, which can be sensitive to detailed styles. We

Methods	<i>en</i> → <i>ko</i>			<i>ko</i> → <i>en</i>		
	BLEU↑	TER↓	YiSi-1↑	BLEU↑	TER↓	YiSi-1↑
(1) Uncorrected	64.9 (-5.6)	21.1 (+1.2)	87.3 (-1.1)	75.1 (-3.5)	17.7 (+1.4)	88.9 (-0.8)
(2) DS-BERT	68.4 (-2.1)	21.1 (+1.2)	87.6 (-0.8)	77.1 (-1.5)	17.6 (+1.3)	89.1 (-0.6)
(3) DS-BERT + Full Bias	68.6 (-1.9)	20.9 (+1.0)	88.0 (-0.4)	78.0 (-0.6)	16.9 (+0.6)	89.6* (-0.1)
(4) DS-BERT + Factor Cell	67.5 (-3.0)	22.1 (+2.2)	88.0 (-0.4)	76.5 (-2.1)	18.4 (+2.1)	89.2 (-0.5)
(5) DS-BERT + User CLS	69.0 (-1.5)	20.9 (+1.0)	87.1 (-1.3)	78.1 (-0.5)	16.5 (+0.2)	89.4 (-0.3)
(6) DS-BERT + User Token	68.8 (-1.7)	20.5 (+0.6)	87.0 (-1.4)	74.3 (-4.3)	21.6 (+5.3)	88.5 (-1.2)
(7) PePe	70.5	19.9	88.4	78.6	16.3	89.7
(8) -discriminator	68.6 (-1.9)	20.9 (+1.0)	88.0 (-0.4)	78.0 (-0.6)	16.9 (+0.6)	89.6* (-0.1)
(9) -(8) & user bias	68.4 (-2.1)	21.1 (+1.2)	87.6 (-0.8)	77.1 (-1.5)	17.6 (+1.3)	89.1 (-0.6)
(10) -(9) & pre-training	60.2 (-10.3)	31.9 (+12.0)	86.3 (-2.1)	67.6 (-11.0)	28.7 (+12.4)	87.6 (-2.1)

Table 1: Quantitative comparison with the baselines on the USP dataset that contains *en*→*ko* language pairs and vice versa. (8) to (10) denotes the ablation results. The ablation study is designed to verify each module in PePe. User bias in (9) denotes the user-specific parameters located at the end of the decoder, and pre-training in (10) denotes the task-adaptive pre-training stage. The bold represents the significant difference ($p < 0.05$) against other baselines. We conduct the t-test with five runs and report the average score of it. * means that there is no significant difference in the scores between the model and PePe.

also conduct a human evaluation, which will be described in the following section.

Baseline Methods. We compare the performance of our method with the following baselines. Since this is the first attempt to personalize the translation using post-edits, we newly adjust existing personalized translation methods onto the APE framework for comparisons.

1) Uncorrected is the same as *mt* in personalized post-editing data, which is generated from the online MT system. No correction was made on it. **2) DS-BERT** is a transformer based post-editing model (Correia and Martins, 2019) that we adopt as our backbone in the method section. DS-BERT is a general approach in the recent APE task. To our knowledge, the recently proposed state-of-the-art APE models (Yang et al., 2020; Oh et al., 2021) are either based on the Dual-Source Transformer (Junczys-Dowmunt and Grundkiewicz, 2018) or DS-BERT. We believe that demonstrating the feasibility of personalized post-editing using a fundamental APE model is more suitable than models that use APE task-specific techniques. **3) DS-BERT + Full bias** (Michel and Neubig, 2018) utilizes additional user bias vectors on the decoder’s output. **4) DS-BERT + Factor bias** (Michel and Neubig, 2018) uses factorized user bias on the output of the decoder. User-independent biases are shared with all users. However, the user-specific vector can adjust each user-independent vector’s magnitude. **5) DS-BERT +**

User CLS is a multi-task composed of a user classification and APE task. The first token of an encoder input is used to stand for user identity. The corresponding output vector is used to classify a ground-truth user label. A single layer of a feed-forward neural network is used for the classifier. **6) DS-BERT + User Token** (Senrich et al., 2016) adds a token at the start of each post-edited sentence to indicate the user for each sentence. We train the model in a teacher-forcing manner.

4.3 Quantitative Evaluation

Results using automatic metrics and human evaluation are presented in this section. PePe consistently outperforms the baselines on all datasets we considered. We also show the robustness of PePe regarding the different number of users, data distributions, and language pairs.

Performance of PePe against other baselines.

(1) to (7) in Table 1 shows the personalized translation results of varied baselines. Our proposed method outperforms the six baselines with the non-trivial margin both on *en*→*ko* and *ko*→*en* USP dataset. For instance, BLEU score increased in the range of 1.7 to 5.6, YiSi-1 increased in the range of 0.4 to 1.4, and TER decreased in the range of 0.6 to 2.2 over baselines, in *en*→*ko* dataset. Consistent results from these three different metrics verify that PePe easily figure out distinct taste of users while preserving source contents. Especially, experiments in *en*→*ko* dataset show the most out-

Metrics	PePe	DS-BERT	Uncorr.
Style - 1st	59.6	18.1	22.2
Style - 2nd	21.0	39.1	39.9
Style - 3rd	19.5	42.6	37.9
Non-Style	3.94(1.08)	3.60(1.19)	3.82(1.16)

Table 2: Human evaluation on $en \rightarrow ko$ USP dataset. Style and non-style factors are both surveyed. For the style factor, each score represents the proportion. For instance, 59.6% of evaluators choose PePe as the first place among other models. For the non-style factor, a Likert scale from 1 to 5 evaluates fluency and source contents preservation. We report the average score and the standard deviation.

Model	$en \rightarrow de$	$en \rightarrow fr$
	BLEU \uparrow	BLEU \uparrow
Michel and Neubig (2018)	27.2	38.5
DS-BERT	30.4	42.2
PePe	31.2	43.7

Table 3: Experiments on the SATED dataset. PePe outperforms DS-BERT on different language pairs even for a synthetic post-editing dataset. The bold represents the best score among the baselines and significantly ($p < 0.05$) outperforms DS-BERT.

standing performance gains since the data mostly come from the users whose first language is Korean; the users can reflect the linguistic preference more naturally on this dataset.

Ablation study. The comparison between PePe and (8) in Table 1 shows the importance of the discriminator module. When we exclude the discriminator module, the BLEU and TER scores are decreased on both $en \rightarrow ko$ and $ko \rightarrow en$. The results of the vanilla APE model (*i.e.*, (9) in Table 1) show that the user-specific parameters are also significant for personalized translation. Moreover, when we do not adopt the APE task-adaptive pre-training (*i.e.*, (10) in Table 1), the performance of the model drops even further. Overall, our ablation study demonstrates that each component is essential for the task.

Human evaluation. To validate the advantage of our approach, we conduct human evaluations. Human evaluation can be a reasonable measurement choice to evaluate the personalization task because even sophisticated evaluation metrics can fail to capture the abstract (*i.e.*, high-level) user behavior

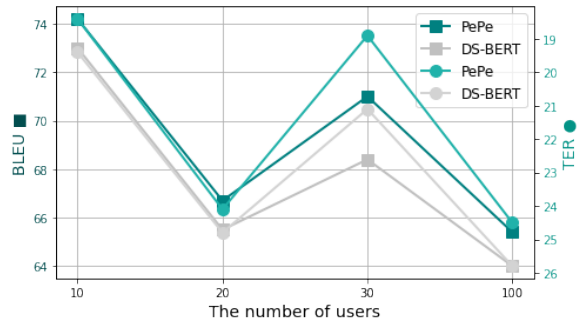


Figure 5: Robustness on the number of users. The dark squares denote the BLEU score, and the light circles denote the TER score. The number of clusters is equally adopted as ten for all cases. The users are randomly selected from the USP dataset.

reflected in the pe sentence. We hired 20 Korean-English who are bilingual and engaged in the fields of linguistics and machine learning for human evaluation. We randomly select 30 source sentences and generate corresponding target sentences from Uncorrected, DS-BERT, and PePe before carrying out two types of questions to compare different metrics. 1) We ask participants to annotate generated sentences along with fluency and content preservation. Sentences are measured on a Likert scale from 1 to 5. 2) We take three sentences generated from three different models. Participants rank these sentences from first to third, *i.e.*, asking which sentence is most similar to the ground-truth pe that contains distinct writing styles.

As reported in Table 2, PePe is ranked 1st by most evaluators. PePe not only achieved the best score on style evaluation but also on non-style factors (*i.e.*, fluency and contents preservation), which is essential for the translation task. DS-BERT achieves the lowest score on both measures, indicating that the ambiguous reflection of style is worse than none. The human evaluation results are consistent with our quantitative results measured by automatic metrics.

Robustness of our model. Table 3 shows the personalized translation results on $en \rightarrow de$ and $en \rightarrow fr$ SATED dataset. Since the dataset is initially constructed for the machine translation task where post-edited sentences do not exist, we utilize target sentence (*i.e.*, mt) in the place of pe and independently generate mt from a particular translation model (*i.e.*, pre-trained transformer based NMT model). Regardless of the language, the results demonstrate that PePe and DS-BERT, which leverages triplets (src, mt, pe), outperform Michel and Neubig (2018)

<i>en</i> → <i>ko</i>	
<i>src</i>	<u>Immediately</u> provide non-monetary <u>benefits</u> as required.
<i>mt</i>	필요에 따라 즉시 비화폐성 편익을 제공하십시오.
PePe	요구된대로 비화폐성 혜택을 즉시 제공한다.
<i>pe</i>	요구되어진 비화폐성 혜택을 즉시 제공한다.
<i>src</i>	Choose this option to make the current preset load whenever a new multi Instrument is created.
<i>mt</i>	새 멀티 계측기가 생성될 때마다 현재 사전 설정된 로드를 만들려면 이 옵션을 선택하십시오.
PePe	새 multi instrument 가 생성될 때마다 현재 preset 을 만들려면 이 옵션을 선택하십시오.
<i>pe</i>	새 multi instrument 가 생성될 때마다 현재 preset load 를 만들려면 이 옵션을 선택하십시오.
<i>ko</i> → <i>en</i>	
<i>src</i>	겨울왕국 2 속에 나오는 장면이 있다.
<i>mt</i>	there is a scene in winter kingdom 2 .
PePe	there is a scene in frozen 2 .
<i>pe</i>	there is a scene in frozen 2 .
<i>src</i>	관사 아래에 있는 모음코드가 이렇게 바뀌어진다.
<i>mt</i>	the vowel code under the official building changes like this.
PePe	the vowel code under the article changes like this.
<i>pe</i>	the vowel code under the article changes like this.

Table 4: Qualitative examples of post-edited sentences generated from PePe. User-specific parts in *pe* and corresponding parts in *mt* are colored. We highlight the post-edited words in PePe with bold if the words are identical to *pe*. Corresponding parts in *src* are underlined. Our model finds an appropriate combination of attributes in accordance with sentences and users.

that relies on paired sentences (*src*, *mt*). In addition, the results also show that even if *pe* is not edited from the *mt*, PePe translates the source sentence close to the ground-truth target sentence that connotes the speaker’s characteristics.

Fig. 5 shows that our model works well regardless of the number of users. Grey-colored lines are the performance of the baseline model, and colored lines are the performance of PePe. TER axis is reversed on the graph to make consistency with the BLEU score. Note that the higher points denote a better score than the lower points.

Furthermore, we conduct additional experiments that show the robustness of our approach regarding the number of clusters and adjustment rates, which are hyperparameters. We represent the results in Appendix B.

4.4 Qualitative Analysis

To understand how user-specific preferences are incorporated into the sentences, we qualitatively analyze the post-edited results of our model as shown in Table 4. A typical example of the multi-attribute correction appears in the first row, which changes the sentence structure and the preferred word choices. Our model tends to retain the overall meaning of the source sentence while precisely treating an abstractive personal behavior. The output of PePe in the second row tends to keep loanwords in English instead of translating them into Korean (*i.e.*, “*multi instrument*”, “*preset load*”),

while *mt* suffers from generating sentences that consider those preferences. An example of changing a homonym to a suitable word is shown in the last row. Since “*official building*” and “*article*” are homonyms in Korean, PePe chooses the word that is appropriate for the semantic meaning of the sentence. We further provide several examples that consider the multidimensional attributes in Appendix C. In either a single attribute or a multi attributes case, our model properly reflects distinct preferences.

5 Conclusion

In this work, we propose a personalized post-editing method, PePe, utilizing user-generated post-edits. Based on the APE framework, PePe leverages two modules, 1) user-specific parameters and 2) a semantic cluster-based discriminator module. These modules lead to reflect the multifarious interpersonal variations, where the former allows the model to learn user-dependent probabilities for each word while the latter unlearns the detrimental features in a pre-trained language model and maintains advantageous effects of the transfer learning. We empirically demonstrate that PePe reflects fine-grained user preference in a variety of settings. To the best of our knowledge, this work is the first attempt to utilize the APE framework with the user-generated post-edits for personalized translation. We believe that our work can draw more attention toward personalized translation, which is the ul-

timate direction that the neural translation model should go forward.

6 Limitations

Promising future work is analyzing the pattern of personalization depending on language pairs. Depending on the nationality of users, the pattern of personalization may appear differently due to cultural differences, and extensive experiments on various language pairs are required to analyze this. In addition, if anyone can access the personalized model, there is a potential risk that the model can be abused to disguise itself as a specific individual. Therefore, there is a need for a strategy of limiting the authority to access the personalized model or verifying a person who uses the personalized model.

Acknowledgement

This work was supported by the Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korean government(MSIT) (No. 2019-0-00075, Artificial Intelligence Graduate School Program(KAIST)). This work was supported by Papago, NAVER Corp. The authors appreciate Hyoung-Gyu Lee, Eunjeong Lucy Park, and Papago MT researchers in NAVER. We also thank the anonymous reviewers for their valuable feedback.

References

- Gonalo M. Correia and Andr e F. T. Martins. 2019. A simple and effective approach to automatic post-editing with transfer learning. In *Proc. the Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 3050–3056.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proc. of The Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, pages 4171–4186.
- Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial networks. In *Proc. the Advances in Neural Information Processing Systems (NeurIPS)*, pages 2672–2680.
- Suchin Gururangan, Ana Marasovi c, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A Smith. 2020. Don’t stop pretraining: Adapt language models to domains and tasks. *arXiv preprint arXiv:2004.10964*.
- Lin Huan, Yao Liang, Yang Baosong, Liu Dayiheng, Zhang Haibo, Luo Weihua, Huang Degen, and Su Jin-song. 2021. Towards user-driven neural machine translation. In *Proc. the Annual Meeting of the Association for Computational Linguistics (ACL)*.
- P. Isabelle, Cyril Goutte, and Michel Simard. 2007. Domain adaptation of mt systems through automatic postediting. *Proc. of Machine Translation Summit*.
- Marcin Junczys-Dowmunt, Tomasz Dwojak, and Rico Sennrich. 2016. The amu-uedin submission to the wmt16 news translation task: Attention-based nmt models as feature functions in phrase-based smt. In *Proc. of the Conference on Machine Translation (WMT)*, pages 319–325.
- Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2017. An exploration of neural sequence-to-sequence architectures for automatic post-editing. In *Proc. of the International Joint Conference on Natural Language Processing (IJCNLP)*, pages 120–129.
- Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2018. Ms-uedin submission to the wmt2018 ape shared task: Dual-source transformer for automatic post-editing. In *Proc. of the Conference on Machine Translation (WMT)*, pages 822–826.
- Sariya Karimova, Patrick Simianer, and Stefan Riezler. 2018. A user-study on online adaptation of neural machine translation to human post-edits. *Machine Translation*, 32:309–324.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *Proc. the International Conference on Learning Representations (ICLR)*.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *Computing Research Repository (CoRR)*, abs/1907.11692.
- Chi-kiu Lo. 2019. Yisi-a unified semantic mt quality evaluation and estimation metric for languages with different levels of available resources. In *Proc. of the Conference on Machine Translation (WMT)*, pages 507–513.
- Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *Proc. the International Conference on Learning Representations (ICLR)*.

- Paul Michel and Graham Neubig. 2018. Extreme adaptation for personalized neural machine translation. In *Proc. the Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 312–318.
- Hideki Mima, Osamu Furuse, and Hitoshi Iida. 1997. Improving performance of transfer-driven machine translation with extra-linguistic information from context, situation and environment. In *Proc. the International Joint Conference on Artificial Intelligence (IJCAI)*, pages 983–989.
- Shachar Mirkin, Scott Nowson, Caroline Brun, and Julien Perez. 2015. Motivating personality-aware machine translation. In *Proc. of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1102–1108.
- Shinhyeok Oh, Sion Jang, Hu Xu, Shounan An, and Insoo Oh. 2021. Netmarble ai center’s wmt21 automatic post-editing shared task submission. *arXiv preprint arXiv:2109.06515*.
- Santanu Pal, Nico Herbig, Antonio Krüger, and Josef van Genabith. 2018. A transformer-based multi-source automatic post-editing system. In *Proc. of the Conference on Machine Translation (WMT)*, pages 827–835.
- Santanu Pal, Sudip Kumar Naskar, Mihaela Vela, and Josef van Genabith. 2016. A neural network based approach to automatic post-editing. In *Proc. the Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 281–286.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proc. the Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 311–318.
- James W Pennebaker, Matthias R Mehl, and Kate G Niederhoffer. 2003. Psychological aspects of natural language use: Our words, our selves. *Annual review of psychology*, 54(1):547–577.
- Ella Rabinovich, Raj Nath Patel, Shachar Mirkin, Lucia Specia, and Shuly Wintner. 2017. Personalized machine translation: Preserving original author traits. In *Proc. of the Annual Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 1074–1084.
- Carl Edward Rasmussen. 2000. The infinite gaussian mixture model. In *Proc. the Advances in Neural Information Processing Systems (NeurIPS)*, pages 554–560.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Controlling politeness in neural machine translation via side constraints. In *Proc. of The Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, pages 35–40.
- Chenglei Si, Kui Wu, Ai Ti Aw, and Min-Yen Kan. 2019. Sentiment aware neural machine translation. In *Proceedings of the 6th Workshop on Asian Translation*.
- Michel Simard, Nicola Ueffing, Pierre Isabelle, and Roland Kuhn. 2007. Rule-based translation with statistical phrase-based post-editing. In *Proc. of the Workshop on Statistical Machine Translation (WMT)*, pages 203–206.
- Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In *Proc. of the association for machine translation in the Americas (AMTA)*, pages 223–231.
- Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. Mass: Masked sequence to sequence pre-training for language generation. *arXiv preprint arXiv:1905.02450*.
- Deborah Tannen et al. 1991. *You just don’t understand: Women and men in conversation*. Virago London.
- Amirhossein Tebbifakhr, Ruchit Agrawal, Matteo Negri, and Marco Turchi. 2018. Multi-source transformer with combined losses for automatic post editing. In *Proc. of the Conference on Machine Translation (WMT)*, pages 846–852.
- Marco Turchi, Matteo Negri, M Amin Farajian, and Marcello Federico. 2017. Continuous learning from human post-edits for neural machine translation. *The Prague Bulletin of Mathematical Linguistics (PBML)*, 108:233–244.
- Laurens van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-sne. *Journal of Machine Learning Research (JMLR)*, 9:2579–2605.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Proc. the Advances in Neural Information Processing Systems (NeurIPS)*, pages 5998–6008.
- Joern Wuebker, Patrick Simianer, and John DeNero. 2018. Compact personalized models for neural machine translation. In *Proc. of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 881–886.
- Hao Yang, Minghan Wang, Daimeng Wei, Hengchao Shang, Jiaxin Guo, Zongyao Li, Lizhi Lei, Ying Qin, Shimin Tao, Shiliang Sun, and Yimeng Chen. 2020. Hw-tsc’s participation at wmt 2020 automatic post editing shared task. In *Proc. of the Conference on Machine Translation (WMT)*.

Supplementary Material

This material complements our paper with additional experimental results and miscellaneous details. Section A provides the implementation details. Section B addresses the additional experiments that show the robustness of our model against a varied number of clusters and adjustment rates. In Section C, we demonstrate the variety of qualitative examples of post-edited sentences generated from PePe.

A Training details

Data Preprocessing. For the data preprocessing, we first filter out the duplicate lines and normalize the data such that each line represents a single sentence. Also, we exclude sentence that is longer than 100 words. Then, we utilize term frequency inverse document frequency (TF-IDF) to compute the user similarity score and filter out the noisy users. To be specific, we form a document for each user by aggregating *src*. If a particular user has a lower than 0.1 similarity score, we exclude those users. We assume that if a user has a lower similarity score with others, then those users may contain noisy sentences. After preprocessing noisy data for USP, we divide the dataset into train/valid/test, which results in 5,207, 1,001, and 1,125 samples for Korean to English language pair, and 6,330, 1,360, and 1,357 samples for English to Korean. Since we split into train/valid/test for each user, the user appearing in the train dataset guarantees to appear in the test dataset.

Training and Inference Procedures. The main difference between training and inference procedures is the existence of a discriminator module. In other words, the clustering module and the discriminator are not utilized during the inference procedure. However, similar to the training procedure, we utilize the trained user-specific bias vector that corresponds to the user ID of each input sentence while generating a post-edited sentence.

Evaluation and HyperParameter Details. We evaluate all experiments based on SacreBLEU⁴, TER⁵, and YiSi-1⁶ scores. Since YiSi-1 requires pre-trained word embedding vectors, we utilize fastText⁷ to pretrain word embeddings. For the

⁴<https://github.com/mjpost/sacrebleu>

⁵<https://www.statmt.org/wmt18/ape-task.html>

⁶<https://github.com/chikiulo/yisi>

⁷<https://github.com/facebookresearch/fastText>

Hyperparameters	Value
Pre-trained LM	BERT-base-multilingual
Learning rate	0.00005
Batch size	512
Accumulation step	2
Optimizer	AdamW
Dropout	0.1
Label smoothing	0.1
Random seed	42, 101, 1215, 1129, 909
Decoding strategy	Beam search
Beam size	3

Table 5: Hyperparameter settings. AdamW (Loshchilov and Hutter, 2019) is the Adam (Kingma and Ba, 2015) optimizer with weight decay.

hyper-parameter settings, we use 10 clusters with 0.3 adjustment rates for all the experiments in the main paper. We select the combination of hyperparameters by manual tuning, which achieves the highest performance in the validation set based on the TER metric. Conditions for early-stopping and decoding are equally applied to the baselines. We follow the settings of hyperparameters in Correia and Martins (2019) except sharing the weight of the encoder and the decoder. We conducted all the experiments five times, and the random seeds used were 42, 1215, 101, 909, and 1129. We selected the highest performance learning rate value between 0.00005 and 0.0001. We report the configuration of our best model in Table 5.

Environment Details. All experiments in Table 1 is examined with CentOS Linux release 7.8.2003, Tesla P40 GPU, and Intel Xeon CPU E5-2630. Results in Table 3 are examined with Ubuntu 16.04.6, Intel Xeon processor, and Tesla V100-PCIE-32GB GPU. The versions of the libraries we used in all experiments are 3.7.6 for Python and 1.4.0 for Pytorch.

B Robustness to the number of cluster and hyperparameter

In the main paper, we conduct all experiments with 10 cluster labels. However, to be useful for the varied settings, it is crucial to demonstrate the model’s robustness to the number of clusters and adjustment rate. Here we provide the results trained on 30 cluster labels with various adjustment rates from 0.1 to 0.5. Identical with Table 1, we utilize *en*→*ko* dataset of 30 users. Table 6 indicates that PePe

Models	BLEU \uparrow	TER \downarrow
Uncorrected	64.9	21.1
DS-BERT	68.5	21.1
PePe (k30, m0.1)	70.2	20.2
PePe (k30, m0.2)	69.7	20.3
PePe (k30, m0.3)	69.9	19.9
PePe (k30, m0.4)	69.0	20.8
PePe (k30, m0.5)	70.2	20.3

Table 6: Experiments on various hyperparameter settings on a USP dataset. k denotes the number of clusters and m denotes the adjustment rate.

consistently generates high-quality sentences, regardless of the hyperparameters.

C Additional qualitative examples

This section provides additional qualitative examples from PePe. We choose the samples from the inference results of USP dataset, and both $ko \rightarrow en$ and $en \rightarrow ko$ language pairs are reported. As shown in Table 7, Table 8, Table 9, Table 10, Table 11, and Table 12, the tables are organized according to the typical personalization cases (*i.e.*, error correction, word choice, politeness, and multiple attributes). **Red color** represents error correction case, **Yellow color** represents word choice case, and **Green color** represents politeness case. Each case also accompanies the insertion and deletion of the words (*i.e.*, tokens). Sentences inferred from PePe show that it well reflects the personal traits of each user and the characteristics of each language.

D Importance of personalized translation

The importance of stylized translation can stand out in certain scenarios, such as the translation of everyday conversations. For example, when an English speaker uses a translator to talk to a German speaker, he or she may wish to communicate with a translation result that includes an individual’s personality rather than a normal translation of a neutral tone (e.g., replacing with a word that the user likes to use). At this time, our personalized translation methodology can be used to deliver translation results containing the user’s personality to the German speaker without post-processing. We believe that in order for a translation model to be utilized in the everyday conversation of various users, it is ultimately important to consider the individuality of each user beyond fluency.

Error Correction (<i>en</i> → <i>ko</i>)	
<i>src</i>	Begin the stroke by moving the hand , while the elbow remains still and high.
<i>mt</i>	팔꿈치가 가만히 있고 높게 유지되는 동안 손을 움직이면서 뇌졸중을 시작한다.
PePe	팔꿈치가 가만히 있고 높게 유지되는 동안 손을 움직이면서 팔동작을 시작한다.
<i>pe</i>	팔꿈치가 가만히 있고 높게 유지되는 동안 손을 움직이면서 팔동작을 시작한다.
<i>src</i>	Periodically check on her progress.
<i>mt</i>	정기적으로 진행 상황을 확인합니다.
PePe	정기적으로 그녀의 진행 상황을 확인합니다.
<i>pe</i>	정기적으로 그녀의 진행 상황을 확인합니다.
<i>src</i>	All manual checks unclaimed for more than 6 months shall be canceled.
<i>mt</i>	6개월 이상 청구되지 않은 모든 수동 점검은 취소된다.
PePe	6개월 이상 청구되지 않은 모든 수동 수표는 취소된다.
<i>pe</i>	6개월 이상 청구되지 않은 모든 수동 수표는 취소된다.
<i>src</i>	If a signal has finite power its energy will be infinite.
<i>mt</i>	만약 어떤 신호가 한정된 힘을 가지고 있다면 그 에너지는 무한할 것이다.
PePe	만약 어떤 신호가 한정된 전력을 가지고 있다면 그 에너지는 무한할 것이다.
<i>pe</i>	만약 어떤 신호가 한정된 전력을 가지고 있다면 그 에너지는 무한할 것이다.
<i>src</i>	The historical cost of the intangible fixed assets transferred shall be the historical cost recorded in the accounting records of the receiver.
<i>mt</i>	이전하는 무형고정자산의 역사적원가는 수취인의 회계기록에 기록된 역사적원가를 말한다.
PePe	이전하는 무형고정자산의 취득원가는 수취인의 회계기록에 기록된 취득원가를 말한다.
<i>pe</i>	이전하는 무형고정자산의 취득원가는 수취인의 회계기록에 기록된 취득원가를 말한다.
<i>src</i>	Emotional exhaustion is the central quality and the most obvious manifestation of burnout.
<i>mt</i>	감정 기진맥진은 중심적인 질이고 가장 명백한 소진 증상이다.
PePe	정서적 소진은 중심적인 질이고 가장 명백한 번아웃 증상이다.
<i>pe</i>	정서적 소진은 번아웃의 중심특성이자 가장 명백한 징후이다.

Table 7: PePe generates post-edited sentences that corrects the grammar errors from the machine-translated outputs.

Word Choice (<i>en</i> → <i>ko</i>)	
<i>src</i>	Hide the layer containing the cutting lines.
<i>mt</i>	절단선이 들어 있는 레이어를 숨긴다.
PePe	커팅 라인이 들어 있는 레이어를 숨긴다.
<i>pe</i>	커팅 라인이 들어 있는 레이어를 숨긴다.
<i>src</i>	The worker explores cultural diversity factors that may be a part of the problem or situation.
<i>mt</i>	노동자는 문제나 상황의 일부일 수도 있는 문화적 다양성 요소를 탐구한다.
PePe	사회복지사는 문제나 상황의 일부일 수도 있는 문화적 다양성 요소를 탐구한다.
<i>pe</i>	사회복지사는 문제나 상황의 일부일 수도 있는 문화적 다양성 요소를 탐구한다.
<i>src</i>	Exemestane is one of the most potent aromatase inhibitors presently available.
<i>mt</i>	exemestane은 현재 사용 가능한 가장 강력한 방향족 억제제 중 하나이다.
PePe	exemestane은 현재 사용 가능한 가장 강력한 aromatase 억제제 중 하나이다.
<i>pe</i>	exemestane은 현재 사용 가능한 가장 강력한 aromatase 억제제 중 하나이다.
<i>src</i>	You do not want them drunk and lazy.
<i>mt</i>	너는 그들이 술에 취해서 게을러지는 것을 원하지 않는다.
PePe	당신은 그들이 술에 취해서 게을러지는 것을 원하지 않는다.
<i>pe</i>	당신은 그들이 술에 취해서 게을러지는 것을 원하지 않는다.
<i>src</i>	By combining the two outputs without the external phase shift, a sum signal is provided for range tracking.
<i>mt</i>	외부 위상 이동 없이 두 출력을 결합함으로써 범위 추적을 위한 합계 신호가 제공된다.
PePe	외부 위상 이동 없이 두 출력을 결합함으로써 거리 추적을 위한 합계 신호가 제공된다.
<i>pe</i>	외부 위상 이동 없이 두 출력을 결합함으로써 거리 추적을 위한 합계 신호가 제공된다.
<i>src</i>	What are my needs for developing my capacity and potentiality?
<i>mt</i>	내 능력과 잠재력을 개발하기 위한 나의 필요성은 무엇인가?
PePe	내 능력과 잠재력을 개발하기 위한 나의 needs는 무엇인가?
<i>pe</i>	내 능력과 잠재력을 개발하기 위한 나의 needs는 무엇인가?

Table 8: PePe changes the words that are not suitable for personal style but are grammatically correct to other candidates, such as synonyms and loanwords.

Politeness (<i>en</i> → <i>ko</i>)	
<i>src</i>	Spend some time looking over the meeting agenda in advance and think about some of the key topics.
<i>mt</i>	회의 안건을 미리 살펴보고 몇 가지 주요 주제에 대해 생각해 보십시오.
PePe	회의 안건을 미리 살펴보고 몇 가지 주요 주제에 대해 생각해 보라.
<i>pe</i>	회의 안건을 미리 살펴보고, 몇 가지 주요 주제에 대해 생각해 보라.
<i>src</i>	She wants the assignment.
<i>mt</i>	그녀는 그 과제를 원한다.
PePe	그녀는 그 과제를 원합니다.
<i>pe</i>	그녀는 그 과제를 원합니다.
<i>src</i>	<u>Watch</u> this video for directions on how to complete the S1 Conversations challenge.
<i>mt</i>	대화 과제를 완료하는 방법은 이 비디오를 참조하십시오.
PePe	대화 과제를 완료하는 방법은 이 비디오를 참조하세요.
<i>pe</i>	대화 과제를 완료하는 방법은 이 비디오를 참조하세요.
<i>src</i>	According to the U.S. Bureau of Census, there are approximately 90 million households in the United States.
<i>mt</i>	미국 인구조사국에 따르면, 미국에는 약 9천만 가구가 살고 있다고 합니다.
PePe	미국 인구조사국에 따르면, 미국에는 약 9천만 가구가 살고 있다고 한다.
<i>pe</i>	미국 인구 조사국에 따르면, 미국에는 약 9천만 가정이 살고 있다고 한다.
<i>src</i>	The store is located inside the Terminal 1.
<i>mt</i>	그 상점은 터미널 1 안에 있다.
PePe	지점은 터미널 1 안에 있습니다.
<i>pe</i>	지점은 터미널 1 내에 있습니다.
<i>src</i>	Maps are also available that show the tract boundaries, making the data readily discernible.
<i>mt</i>	트랙 경계가 표시된 지도도 사용할 수 있어 데이터를 쉽게 식별할 수 있습니다.
PePe	트랙 경계가 표시된 지도도 사용할 수 있어 데이터를 쉽게 식별할 수 있다.
<i>pe</i>	통로 경계를 보여주는지도도 제공되므로 데이터를 쉽게 식별 할 수 있다.

Table 9: PePe controls the level of politeness. The usage of the honorifics varies from language to language.

Multiple Attributes (<i>en</i> → <i>ko</i>)	
<i>src</i>	Our staff will send you back to the airport.
<i>mt</i>	우리 직원이 너를 공항으로 돌려보낼 것이다.
PePe	저희 직원이 공항으로 돌려보낼 것입니다.
<i>pe</i>	저희 직원이 고객님을 공항으로 데려다 줄 것입니다.
<i>src</i>	When the <u>machine</u> receives the data, it automatically reads the crop marks using a sensor, and then starts cutting .
<i>mt</i>	기계가 데이터를 받으면 자동으로 센서를 이용해 자르기 표시 를 읽은 뒤 절단 을 시작한다.
PePe	장비 가 데이터를 받으면 자동으로 센서를 이용해 crop mark 를 읽은 뒤 커팅 을 시작한다.
<i>pe</i>	장비 가 데이터를 받으면 자동으로 센서를 이용해 crop mark 를 읽은 뒤 커팅 을 시작한다.
<i>src</i>	When transferring major repairs of fixed assets for non-business activities, <u>the following accounts shall be recorded</u> .
<i>mt</i>	비사업활동용 고정자산의 주요수리를 이전할 때에는 다음 사항을 기재하여야 한다.
PePe	비영리활동용 고정자산의 주요수리를 이전할 때에는 다음과 같이 회계처리 하여야 한다.
<i>pe</i>	비영리활동용 고정자산의 주요수리를 이전할 때에는 다음과 같이 회계처리 하여야 한다.
<i>src</i>	The free shuttle bus will come to pick you up around 10 minutes.
<i>mt</i>	무료 셔틀버스가 약 10분 정도 당신 을 데리러 올 것이다.
PePe	무료 셔틀버스가 약 10분 정도 고객님 을 데리러 올 것입니다.
<i>pe</i>	무료 셔틀버스가 약 10분 정도 고객님 을 데리러 올 것입니다.
<i>src</i>	If using 3 crop marks, select 3-point start.
<i>mt</i>	3개의 자르기 표시 를 사용하는 경우 3-point start를 선택하십시오.
PePe	3개의 crop mark 를 사용하는 경우 3-point start를 선택한다.
<i>pe</i>	3개의 crop mark 를 사용하는 경우 3-point start를 선택한다.
<i>src</i>	The following parameters control the display of points-clouds (right).
<i>mt</i>	다음 매개 변수 는 점 구름 (오른쪽) 의 표시를 제어합니다.
PePe	다음 파라미터 는 포인트 클라우드 (오른쪽) 의 표시를 제어합니다.
<i>pe</i>	다음 파라미터 는 포인트 클라우드 (오른쪽) 의 표시를 제어합니다.

Table 10: PePe not only tackles a single attribute but also generates high-quality sentences with multiple attributes revised. Each attribute is colored with a corresponding color.

Error Correction (<i>ko</i> → <i>en</i>)	
<i>src</i>	그래서 전치사 ‘reo’는 ‘to’와 ‘for’의 의미가 있다.
<i>mt</i>	so the prepositions ‘reo’ have the meaning of ‘to’ and ‘for’.
PePe	so the preposition ‘reo’ has the meaning of ‘to’ and ‘for’.
<i>pe</i>	so the preposition ‘reo’ has the meaning of ‘to’ and ‘for’.
<i>src</i>	관사 아래에 있는 모음코드가 이렇게 바뀌어진다.
<i>mt</i>	the vowel code under the official building changes like this.
PePe	the vowel code under the article changes like this.
<i>pe</i>	the vowel code under the article changes like this.
<i>src</i>	professor는 단일한 관리통제 기구보다 상업적 차원, 정부 차원 등 다차원적 모델의 시도를 결합하는 노력이 필요하다고 지적한다.
<i>mt</i>	the processor points out that efforts need to be made to combine attempts by multi-dimensional models such as commercial and government levels rather than single management and control organizations.
PePe	the professor points out that efforts need to be made to combine attempts by multi-dimensional models such as commercial and government levels rather than single management and control organizations.
<i>pe</i>	the professor gasser points out that efforts need to be made to combine attempts by multi-dimensional models such as commercial and government levels rather than single management and control organizations.
<i>src</i>	‘dagesh’가 놓일 수 없다.
<i>mt</i>	‘dagesh’ can’t be let go .
PePe	‘dagesh’ can’t be placed .
<i>pe</i>	‘dagesh’ can’t be placed .

Table 11: PePe generates post-edited sentences that corrects the grammar errors from the machine-translated outputs.

Word Choice (<i>ko</i> → <i>en</i>)	
<i>src</i>	내부배선의 색상은 아래와 같이 구분하여 사용하여야 한다.
<i>mt</i>	the colour of the inner wiring shall be used separately as follows.
PePe	the color of the inner wiring shall be used separately as follows.
<i>pe</i>	the color of the inner wiring shall be used separately as follows.
<i>src</i>	추정 공시가격이 올해 거래된 urgent sale price를 앞서고 있다.
<i>mt</i>	the estimated official price is ahead of the current sales price traded this year.
PePe	the estimated official price is ahead of the urgent sale price traded this year.
<i>pe</i>	the estimated official price is ahead of the urgent sales price traded this year.
<i>src</i>	12월 싱가포르, 말레이시아지역 패키지 상품 판매 확대
<i>mt</i>	expanding sales of package products in singapore and malaysia in december.
PePe	expanding sales of pkg products in singapore and malaysia in december.
<i>pe</i>	expanding sales of pkg products in singapore and malaysia in december.
<i>src</i>	한해 전에 쓰고 남은 돈이 1억2천만원 정도였다.
<i>mt</i>	the remaining money was about 120 million won a year ago.
PePe	the remaining money was about krw 120 million a year ago.
<i>pe</i>	the remaining money was about krw 120 million a year ago.

Table 12: PePe changes the words that are not suitable for personal style but are grammatically correct to other candidates, such as synonyms and loanwords.