An Empirical Study of Automatic Post-Editing

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Abstract

Automatic post-editing (APE) aims to reduce manual post-editing efforts by automatically correcting errors in machine-translated output. Due to the limited amount of human-annotated training data, data scarcity is one of the main challenges faced by all APE systems. To alleviate the lack of genuine training data, most of the current APE systems employ data augmentation methods to generate large-scale artificial corpora. In view of the importance of data augmentation in APE, we separately study the impact of the construction method of artificial corpora and artificial data domain on the performance of APE models. Moreover, the difficulty of APE varies between different machine translation (MT) systems. We study the outputs of the state-of-art APE model on a difficult APE dataset to analyze the problems in existing APE systems. Primarily, we find that 1) Artificial corpora with high-quality source text and machine-translated text more effectively improve the performance of APE models; 2) In-domain artificial training data can better improve the performance of APE models, while irrelevant out-of-domain data actually interfere with the model; 3) Existing APE model struggles with cases containing long source text or high-quality machine-translated text; 4) The state-of-art APE model works well on grammatical and semantic addition problems, but the output is prone to entity and semantic omission errors.

1 Introduction

The goal of automatic post-editing (APE; Simard et al., 2007) is to correct errors in machine-translated outputs that cannot be processed in the decoding stage (Bojar et al., 2017), thereby reducing human post-editing effort. APE systems learn knowledge from human post-edits, and apply it to the output of machine translation systems to improve the quality of translation.

Human-annotated APE datasets are composed of triplets including source text (src), machine-translated text (mt), and human post-edits (pe). APE models take src and mt as input and generate post-edited text with pe as the target. During human post-editing, pe is generated with reference to mt, which means that different machine-translated outputs correspond to different human post-edits. Parallel corpora, which comprise pairs of source text (src) and reference text (ref), were utilized in a number of works (Negri et al., 2018; Lee et al., 2021, 2022). Lee et al. (2021, 2022) have presented the edit distance between mt and its target (pe or ref) in detail to prove that pe is closer to mt.

In recent years, several studies have come to the conclusion that existing neural APE systems do not perform as well on strong in-domain neural machine translation (NMT) systems as on statistical machine translation (SMT) systems (Chatterjee et al., 2018, 2019). As opposed to this view, one previous study (Chollampatt et al., 2020) pointed out that existing APE systems would still be able to improve the translation quality of strong NMT systems, given sufficient in-domain human-annotated APE triplets. However, we suppose it impractical to build different human post-edited datasets for different domains on all language pairs. Therefore, constructing large-scale APE datasets by manual post-editing is not the final resort for APE.

However, due to the scarcity of human post-edits (pe), the quantity of genuine APE triplets in most APE datasets is heavily insufficient to train a Transformer-based Seq2Seq APE model. A number of studies (Junczys-Dowmunt and Grundkiewicz, 2016; Negri et al., 2018; Lee et al., 2022) circumvent the data scarcity problem by adopting data augmentation methods to generate artificial training data. We believe that the construction of artificial training data has a great impact on the performance of APE systems and higher-quality synthetic data can help improve APE system performance. To study data augmentation on APE
task, we vary construction method of the artificial training data and domain of our synthetic data, and compare the final performance on multiple APE datasets. Empirically, we find that: 1) Construction methods that generate high-quality src and mt work best on APE models. 2) In-domain artificial training data are more beneficial to APE systems, while irrelevant out-of-domain synthetic data will hurt the performance of APE models.

In addition, considering the fact that existing APE systems perform poorly on the output of strong NMT systems, we bring in an APE dataset constructed on the basis of the state-of-art NMT system, MLQE-PE (Fomicheva et al., 2020). We compare the output of the state-of-art APE model on MLQE-PE test set with those on test sets of other APE datasets. In general, we find that despite the APE model performs quite differently on these datasets, it always struggles when dealing with triplets containing long src or high-quality mt. Moreover, we conduct human evaluation to analyze error type in mt, the APE output and pe. The experimental results demonstrate that the APE model works well on correcting grammatical and semantic addition problems in mt, but fails on semantic omission and entity errors. We believe that these phenomena indicate the existence of some common problems in existing APE systems which need to be solved in future works. The code and data will be released to the community.

2 Related Work

In contrast to Pal et al. (2016) formalizing APE as a monolingual MT problem in the target language, Vu and Haffari (2018) has applied the Seq2Seq model to APE with conditioning on src. Early-stage neural APE models implemented a bidirectional RNN architecture (Pal et al., 2016) to improve the translation output of SMT systems. On the basis of this model framework, a number of studies have separately imported alignment information (Pal et al., 2017), self-attention module (Junczys-Dowmunt and Grundkiewicz, 2017), attention query mechanism (Grangier and Auli, 2018) and some other methods to improve the performance of APE models.

Data scarcity has always been a tough issue for APE task because of the high cost of manual construction. Researchers have built several public artificial corpora to handle data scarcity, which have been widely used. Junczys-Dowmunt and Grundkiewicz (2016) and Negri et al. (2018) proposed two public large-scale artificial APE datasets constructed by round-trip translation and direct translation respectively. Inspired by back translation (Sennrich et al., 2016) from MT task, Lee et al. (2021) adopted forward generation and backward generation to optimize the eScape (Negri et al., 2018) corpus.

Transformer-based (Vaswani et al., 2017) architecture has shown superiority on APE task. Dual-Source Transformer (Junczys-Dowmunt and Grundkiewicz, 2018) implemented two encoders to extract semantic information from src and mt respectively. Huang et al. (2019) added copy mechanism to the Transformer architecture to help retain correctly translated parts in mt. Correia and Martins (2019) proposed BERT Enc.+BERT Dec. model, which innovatively applied BERT (Devlin et al., 2018) to decoder and added parameter sharing (Sachan and Neubig, 2018) between encoder and decoder.

Although these Transformer-based APE models work well in many cases, they underperform on the output of some strong NMT systems (Ive et al., 2020). Recent WMT APE task has focused on NMT systems, and the performance of existing models is not as good.

3 Experimental Setup

Considering the fact that more en-de APE datasets are available, we mainly focus on APE from English to German in our experiments. Two representative Transformer-based APE models are used to investigate the effect of different artificial training data. Two widely-used artificial corpora are utilized in our study as well.

3.1 Datasets

APE datasets are divided into SMT APE datasets and NMT APE datasets according to the type of the MT system that generates mt. The datasets we use for testing in our experiments include WMT’18 SMT, SubEdits and MLQE-PE. Since triplets in MLQE-PE are collected from Wikipedia containing various domains, it is not convenient to study data domain on this dataset. Therefore, we conduct comparative experiments on WMT’18 SMT and SubEdits. In addition, constructed with a strong in-domain NMT system, MLQE-PE is more difficult for APE models than the other two datasets. We use MLQE-PE to analyze the problems of the APE
Table 1: Summary of APE datasets used in this study, datasets marked with * are artificial APE data

| Dataset          | Domain       | Translation System | Train. size | Dev. size | Test. size |
|------------------|--------------|--------------------|-------------|-----------|------------|
| WMT'18 SMT       | IT           | SMT                | 23,000      | 1,000     | 2,000      |
| SubEdits         | Subtitles    | NMT                | 141,413     | 10,000    | 10,000     |
| MLQE-PE          | Wikipedia    | NMT                | 7,000       | 1,000     | 1,000      |
| eSCAPE*          | Mixed        | NMT                | 7,258,533   |           | /          |
| SubEscape*       | Subtitles    | NMT                | 5,633,518   |           | /          |

Model that achieves the best results on WMT’18 SMT and SubEdits. We also make use of two artificial APE datasets, eSCAPE (Negri et al., 2018) and SubEscape (Chollampatt et al., 2020), to help build different synthetic training data. The summary of these APE datasets is shown in Table 1.

WMT’18 SMT  WMT’18 SMT (Chatterjee et al., 2018) is the data from the WMT 2018 APE shared task (en-de SMT), which consists of 23,000 triplets for training, 1,000 for validation, and 2,000 for testing.

SubEdits  SubEdits (Chollampatt et al., 2020) is collected from Rakuten Viki, a popular video streaming platform. Subtitle segments are clipped from videos, translated by a proprietary NMT system and post-edited by volunteers from the community when necessary. SubEdits is a large human-annotated APE dataset containing 161K subtitle domain triplets in total.

MLQE-PE  Source texts in MLQE-PE (Fomicheva et al., 2020) are selected from Wikipedia and translated by an in-domain state-of-art NMT model. Human post-edges in MLQE-PE are generated by paid editors from the Unbabel community. MLQE-PE has been used in WMT 2021 APE shared task.

eSCAPE  eSCAPE corpus (Negri et al., 2018) is a large-scale artificial APE dataset constructed by direct translation. Parallel corpora from different domains are collected and merged to train a NMT model. Output of the NMT model is used as mt and ref in parallel corpora is used directly as pe to compose a triplet.

SubEscape  SubEscape (Chollampatt et al., 2020) is an artificial corpus that is constructed by the same method as eSCAPE but only contains subtitles domain triplets.

3.2 Models
Transformer-based models are proved to be advantageous in processing outputs from both SMT and NMT systems. Most competitors in WMT 2020 APE task (Lee, 2020; Lee et al., 2020a,b; Wang et al., 2020; Yang et al., 2020) and WMT 2021 APE task (Sharma et al., 2021; Oh et al., 2021) adopt models based on the Transformer architecture. Therefore, we choose two typical Transformer-based models, Transformer and BERT Enc.+BERT Dec., to conduct comparative experiments on. Both models are used in the comparison of construction methods, and we choose BERT-APE for domain study.

Transformer  Transformer (Vaswani et al., 2017) employs multi-head attention to extract features from the input sequence. It is widely used in natural language processing and has achieved relatively excellent performance on APE task.

BERT Enc.+BERT Dec. (BERT-APE)  BERT Enc.+BERT Dec. (Correia and Martins, 2019), (simplified as BERT-APE), initializes decoder with parameters of BERT and shares the self-attention module in encoder and decoder. Since there is no context attention layer in BERT, BERT-APE initializes context attention layers in decoder with the parameters of self-attention layer in BERT. BERT-APE is now the state-of-art model on WMT’18 SMT and SubEdits.

We report our model configurations and their hyperparameters in Appendix A. In all our experiments, APE models are firstly pre-trained with artificial triplets and then fine-tuned on genuine data.

3.3 Evaluation
Following previous research on APE, we evaluate the output of APE systems with three different automatic metrics, BLEU (Papineni et al., 2002), ChrF (Popović, 2015) and TER (Snover et al., 2006). We compute BLEU and ChrF with SacreBLEU (Post,
4 Comparison of Construction Methods

Considering the importance of data augmentation in APE, different construction methods of artificial triplets have been proposed. In this section, we mainly study three representative methods for creating artificial triplets to examine the importance of src, mt and pe in synthetic data.

4.1 Construction Methods

Direct-Trans Negri et al. (2018) created a widely-used artificial corpus, eSCAPE, by training a MT system to translate the source text (src) of parallel corpora to obtain mt and using ref of parallel corpora as pe. The strength of this method is that mt, which is generated in the same way as genuine data, can reflect errors in real MT outputs. However, since the edit distance between mt and the created pe is larger than real human-edits, the correlation between mt and pe will be weaken. Overall, Direct-Trans constructs artificial triplets with high-quality src and mt but low-quality pe.

Round-Trans A competitor of the WMT 2016 APE task constructed a large artificial APE dataset with Round-Trans method (Junczys-Dowmunt and Grundkiewicz, 2016). During the process, two MT models need to be trained, one from English to German and the other from German to English. Monolingual sentences are directly used as pe and then translated by the two MT systems to obtain src and mt. Round-Trans ensures the quality of pe, but the quality of src and mt generated by trained MT models are unstable.

Noising Applying editing operations to smooth texts is a common data augmentation method in grammatical error correction (Awasthi et al., 2019). Lee et al. (2020b) creates artificial triplets by adding noise to ref of parallel corpora to generate mt. In our experiments, we randomly perform edit operations, including Random Insertion, Random Swap and Random Deletion (Wei and Zou, 2019) to ref. The probability of adding noise to each word is denoted by p. We set p to 0.05 and 0.1 respectively to study the influence of p value.

4.2 Experimental Results

We use eSCAPE corpus as a representative of Direct-Trans. Edit operations are performed to pe in eSCAPE to construct the Noising artificial data. We take pe in eSCAPE as monolingual corpus to implement Round-Trans method. Experimental results are shown in Table 2.

Seen from the table, artificial data constructed by Direct-Trans method help APE models achieve the best performance on both SubEdits and WMT’18 SMT. This result demonstrates that with src and mt closer to real outputs of MT systems, APE models are more likely to work better. Besides, when employing Noising method, changing the p value from 0.05 to 0.1 actually improves the performance of both models. We suppose that the number of errors in mt has nothing to do with the training of APE models. In this case, more noise in mt does not result in a decrease in model performance, but actually benefits it. One possible reason for the slightly poorer performance of Noising than Direct-Trans is that artificial triplets created by Noising can only cover limited error types. Besides, taking semantic features into account is difficult when corrupting ref. Translation errors in relation to semantics are hard to be artificially constructed in this way. In general, constructed artificial triplets are supposed to help APE models learn how to correct errors in mt. Triplets constructed by Direct-Trans are able to cover more error types in mt, thus closer to the distribution of genuine data.

5 Comparison of Data Domain

In view of the fact that NMT performance is particularly domain-dependant (Chu and Wang, 2018), Chollampatt et al. (2020) empirically demonstrated that in-domain human post-edited data are more helpful to APE models than out-of-domain human post-edited triplets. However, no previous research has studied the influence of artificial data domain. In order to investigate it, we pre-train BERT-APE with artificial data from different domains, and assess the model performance on WMT’18 SMT and SubEdits.

5.1 In-domain v.s. Out-of-domain

To compare in-domain and out-of-domain artificial triplets, we split the eSCAPE dataset into several small corpora that contain single-domain data from IT, Medic, Legal and News. To deal with the imbalance between domains, we control the amount of data from each domain equal, containing 200K training examples. The same amount of data are sampled from SubEscape to obtain single-domain data from subtitles. The results are reported in
Table 2: Performance of APE models pre-trained with artificial corpora constructed by Direct-Trans, Round-Trans and Noising.

| Model    | Method    | SubEdits   | WMT'18 SMT   |
|----------|-----------|------------|--------------|
|          |           | BLEU↑  | ChrF↑  | TER↓  | BLEU↑  | ChrF↑  | TER↓  |
| Without APE |           | 61.9   | 71.3   | 27.3   | 63.4   | 82.5   | 23.6   |
| BERT-APE  | Direct-Trans | **65.7** | **75.6** | **23.1** | **72.2** | **86.0** | **17.5** |
|          | Round-Trans | 63.4   | 73.4   | 24.2   | 70.7   | 85.2   | 18.6   |
|          | Noising(p=0.05) | 63.8   | 73.8   | 23.8   | 69.7   | 84.6   | 19.4   |
|          | Noising(p=0.1) | 64.1   | 74.2   | 23.6   | 70.4   | 85.2   | 18.6   |
| Transformer | Direct-Trans | 64.1   | 74.2   | 23.4   | 71.0   | 85.4   | 18.6   |
|          | Round-Trans | 64.0   | 74.2   | 23.8   | 70.5   | 84.9   | 18.6   |
|          | Noising(p=0.05) | 63.1   | 73.1   | 24.6   | 68.5   | 83.9   | 19.9   |
|          | Noising(p=0.1) | 64.1   | 74.1   | 23.5   | 69.3   | 84.5   | 19.6   |

Table 3: APE performance on SubEdits and WMT'18 SMT pre-trained with synthetic data from different domains. Values marked with † are results pre-trained with in-domain data.

Table 3.

In-domain artificial data help the APE model achieve better results than out-domain synthetic data on both SubEdits and WMT'18 SMT. It can be found that performance of the APE model has declined when pre-trained with some single-domain data. For example, pre-training with IT and Medic data reduces the BLEU score on SubEdits. We speculate that out-of-domain artificial data from relevant domains can improve APE performance, while others may interfere with the training of the APE model.

5.2 What Can Out-of-domain Data Do?

In practical applications, there might be a serious imbalance between artificial triplets from different domains. The amount of parallel datasets collected by eSCAPE corpus varies across domains. The amount of data from IT domain is only about one tenth of those from Medic domain. Therefore, considering the difficulty constructing large-scale artificial in-domain triplets, out-of-domain data is necessary when implementing APE on translation outputs. In addition, artificial data from similar domains can possibly help APE system learn more useful knowledge. We keep the in-domain subset unchanged with 200K training examples, and incorporate out-of-domain data into it to observe the effect of out-of-domain triplets. The trend is illustrated in Figure 1 and complete experimental results are available in Appendix B.

As is shown in Figure 1b, contrary to expectations, incorporating data from Medic and IT domains does not improve the performance of the APE model, but results in a decrease in BLEU score. The experimental results indicate that synthetic triplets from irrelevant domains are not helpful to our APE model. A large-scale artificial APE datasets of mixed domains are likely to contain some triplets from irrelevant domains, which are harmful to the performance of our model.

5.3 Rethinking of Synthetic Data Domain

Our experiments illustrate that artificial triplets from inappropriate domains are harmful to the performance of the APE model. Some researches (Lee et al., 2020b, 2021) that work from the data perspective, have proposed that low-quality training data can interfere on APE models. We have found that in addition to low-quality artificial triplets, data
Table 4: The performance of BERT-APE model pre-trained with eSCAPE corpus unfiltered and filtered out Medic data.

|                | SubEdits | WMT’18 SMT |
|----------------|----------|-------------|
|                | BLEU↑    | ChrF↑       | TER↓   | BLEU↑    | ChrF↑       | TER↓   |
| Unfiltered     | 65.7     | 75.6        | 23.1   | 72.2     | 86.0        | 17.5   |
| Filtered       | 65.9     | 75.5        | 22.8   | 72.8     | 86.4        | 17.1   |

Motivated by this idea, we filter out Medic data from eSCAPE and pre-train the BERT-APE model with the rest artificial triplets. The experimental results are shown in Table 4. The APE model has done a better job on both SubEdits and WMT’18 SMT. From this point of view, when applying large-scale artificial datasets like eSCAPE, domain filtering might be a common way to help improve model outputs.

6 Problem Analysis

Although existing APE models work well on some APE datasets, they fail to achieve the same improvement on outputs of strong NMT systems. Our method of pre-training BERT-APE model on filtered eSCAPE corpus and then fine-tuning on genuine data has achieved an improvement of +4.0 BLEU and -4.5 TER on SubEdits, and +9.4 BLEU and -5.5 TER on WMT’18 SMT, but results in a decrease of -0.9 BLEU and +0.8 TER on MLQE-PE. In WMT 2021 APE shared task, the best result of the contestants has achieved an improvement of +0.46 BLEU and -0.77 TER, which is much worse than the performance on SubEdits and WMT’18 SMT. Therefore, in this section, we aim to analyze the reasons for the poor performance on MLQE-PE and explore the problems of current APE systems. Although MLQE-PE is a mixed-domain dataset, examples from Medic domain are only a very small part of it. Consequently, we filter out the Medic data from eSCAPE as well. We conduct research on the output of BERT-APE pre-trained on filtered eSCAPE, which achieves the best results in our experiments.

6.1 Impact of Text Length

It is known that large language models tend to generate incoherent long texts (Wang et al., 2022). In order to study the impact of this problem on the
performance of APE systems, we split the test set of WMT'18 SMT, SubEdits and MLQE-PE into 4 subsets according to the length of \( src \). We use \( \Delta \text{BLEU} \), the improvement of BLEU score from \( mt \) to APE output, to measure the effect of APE.

As is shown in Figure 2, as the text length increases, the performance of the APE model declines in WMT'18 SMT, and has a declining trend in the other datasets. Considering BERT is applied in the APE model, we speculate that the problem of long text generation might also exist in this APE system. Detailed statistics can be found in Appendix C.

6.2 Impact of Translation Quality

To study the impact of APE with varying quality of MT output, we conduct analysis on test sets of the three APE datasets (Figure 3). We split the dataset into 5 subsets by aggregating triplets with \( mt\text{-pe} \) sentence BLEU in \([0,20] \), \((20,40]\), \((40,60]\), \((60,80]\) and \((80,100]\), respectively. Whether for SMT or NMT output, the APE system performs poorly on high-quality \( mt \), while it does a good job on low-quality \( mt \). For translation results with sentence BLEU exceeding 80, the APE model will reduce the translation quality on all three datasets. We suppose there are only some subtle errors in these high-quality MT outputs, but the APE system modifies some correctly translated-texts, resulting in poor performance on these data. Nearly half of \( mt \) in MLQE-PE have sentence BLEU score over 80, which can be one of the reasons why the APE model performs the worst on this dataset. Therefore, we believe that APE models need to learn more about which translation outputs need modifying and which ones are already correct. When employing post-editing on \( mt \), the APE model is supposed to estimate the quality of \( mt \) and vary its cautiousness.

6.3 Human Annotation

There are different translation problems in MT outputs. We believe that it is necessary to analyze what problems Transformer-based Seq2Seq models can solve and what they cannot. Most of the existing APE models adopt the traditional Seq2Seq paradigm without dealing with specific types of problems. Understanding the problems of the APE models not only allows for better tuning of the model structure, but also helps the APE system assist humans in post-editing MT outputs. We classify errors in translation results into 7 categories and conduct human annotation on error types of \( mt \), \( pe \) and APE output. Our human annotators are all college students majoring in German and they have passed English proficiency examinations. They know common English and German words well and are familiar with the grammatical requirements of English and German. Before formal annotation, an instruction document with examples of different error types is provided to help them understand various error types clearly. We select 100 triplets from MLQE-PE test set, and ask annotators to respectively evaluate \( mt \), APE output, and \( pe \) as a German translation of \( src \) (Table 5). They need to point out types of errors in the translation according to \( src \). Since one translated-text may contain various kinds of errors, annotators can note multiple error types for one translation. Each text is annotated by...
two annotators independently. If their results differ, a third annotator is responsible for determining the final result. The errors we define include the following types:

**Omission** The translated-text misses some semantic information in the source text.

**Addition** The translated-text contains semantic information not found in the source text.

**Entity error** Incorrect translation of name entities in the source text.

**Polysemy error** Some word in the source text has multiple meanings and a wrong meaning is chosen in the translated text.

**Word Order** Improper word order in translated-text.

**Grammatical error** Problems with tense, word form and some other grammatical errors in the translated-text.

**Translation word error** Although the meaning of the source text is translated correctly, the translated-text is not fluent due to the problem of word selection in translation.

Through comparing the results of APE output and pe on Omission and Addition, we can see that as opposed to human post-editing, the APE system has an noticeable effect on solving Addition problems, but fails on Omission. APE output is not likely to contain semantic information not appearing in src, but some important information that have been translated in mt might get lost. Moreover, the APE model has a relatively good effect on solving grammatical errors in mt. The output of the model correctly revises grammatical problems in half of the examples without generating new grammatical errors. However, the APE system works extremely terrible at handling entity errors. Not only does the APE model fail to correct the translation errors of name entities in most mt, it rather generates more mistranslations of name entities. This may be related to the lack of corresponding information between name entities in src and mt during the training process. The model does not learn how to recognize name entities in src and mt, or how to translate entities into target language. Therefore, we suppose that adding entity information in the training process can help the model perform better.

It is not easy to obtain a fluent translation by correcting errors in the output of MT system, as there are some problems in the text structure and word selection of mt that are hard to address by text-editing. Even human post-editing cannot resolve translation word error well. Nevertheless, entity error and omission that will affect the semantics of the APE output, are more worthy of attention.

### 7 Conclusion

We empirically compare construction methods of artificial training data and data domain of synthetic data on Transformer-based APE models. We draw several conclusions to help construct better artificial training triplets in the future, for example, domain filtering can be helpful. We also analyze the problems of the state-of-art APE model on MLQE-PE dataset. Our work shows that although the APE model has achieved good results on some MT outputs, it fails on addition and entity error, which is worth exploring in the future.

### 8 Limitations

We find that some out-of-domain artificial data will negatively affect the automatic post-editing systems. However, we fail to give a strict answer to the question that what kinds of domains can help
improve the performance. Further research and experiments are needed to find a more accurate and effective data filtering method to exclude artificial triplets that are making interference. Besides, our experiments only focus on APE in en-de. Multilingual APE task is also worthy of future research.

References

Abhijeet Awasthi, Sunita Sarawagi, Rasna Goyal, Sabyasachi Ghosh, and Vihari Piratla. 2019. Parallel iterative edit models for local sequence transduction. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4260–4270, Hong Kong, China. Association for Computational Linguistics.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Shujian Huang, Matthias Huck, Philipp Koehn, Qin Liu, Varvara Logacheva, Christof Monz, Matteo Negri, Matt Post, Raphael Rubino, Lucia Specia, and Marco Turchi. 2017. Findings of the 2017 conference on machine translation (WMT17). In Proceedings of the Second Conference on Machine Translation, pages 169–214, Copenhagen, Denmark. Association for Computational Linguistics.

Rajen Chatterjee, Christian Federmann, Matteo Negri, and Marco Turchi. 2019. Findings of the WMT 2019 shared task on automatic post-editing. In Proceedings of the Fourth Conference on Machine Translation (Volume 3: Shared Task Papers, Day 2), pages 11–28, Florence, Italy. Association for Computational Linguistics.

Rajen Chatterjee, Matteo Negri, Raphael Rubino, and Marco Turchi. 2018. Findings of the WMT 2018 shared task on automatic post-editing. In Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pages 710–725, Belgium, Brussels. Association for Computational Linguistics.

Shamil Chollampatt, Raymond Hendy Susanto, Liling Tan, and Ewa Szymanska. 2020. Can automatic post-editing improve NMT? In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2736–2746, Online. Association for Computational Linguistics.

Chenhui Chu and Rui Wang. 2018. A survey of domain adaptation for neural machine translation. In Proceedings of the 27th International Conference on Computational Linguistics, pages 1304–1319, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Gonçalo M. Correia and André F. T. Martins. 2019. A simple and effective approach to automatic post-editing with transfer learning.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding.

Marina Fomicheva, Shuo Sun, Erick Fonseca, Chrysoula Zerva, Frédéric Blain, Vishrav Chaudhary, Francisco Guzmán, Nina Lopatina, Lucia Specia, and André F. T. Martins. 2020. Mlqe-pe: A multilingual quality estimation and post-editing dataset.

David Grangier and Michael Auli. 2018. QuickEdit: Editing text & translations by crossing words out. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6122–6132, Hong Kong, China. Association for Computational Linguistics.

Xuancheng Huang, Yang Liu, Huanbo Luan, Jinfang Xu, and Maosong Sun. 2019. Learning to copy for automatic post-editing. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6122–6132, Hong Kong, China. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding.

Marina Fomicheva, Shuo Sun, Erick Fonseca, Chrysoula Zerva, Frédéric Blain, Vishrav Chaudhary, Francisco Guzmán, Nina Lopatina, Lucia Specia, and André F. T. Martins. 2020. Mlqe-pe: A multilingual quality estimation and post-editing dataset.

David Grangier and Michael Auli. 2018. QuickEdit: Editing text & translations by crossing words out. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6122–6132, Hong Kong, China. Association for Computational Linguistics.

Julia Ive, Lucia Specia, Sara Szoc, Tom Vanallemeersch, Joachim Van den Bogaert, Eduardo Farah, Christine Maroti, Artur Ventura, and Maxim Khalilov. 2020. A post-editing dataset in the legal domain: Do we underestimate neural machine translation quality? In Proceedings of the 12th Language Resources and Evaluation Conference, pages 3692–3697, Marseille, France. European Language Resources Association.

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2016. Log-linear combinations of monolingual and bilingual neural machine translation models for automatic post-editing.

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2017. An exploration of neural sequence-to-sequence architectures for automatic post-editing. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 120–129, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2018. Ms-uedin submission to the wmt2018 ape shared task: Dual-source transformer for automatic post-editing.

Dongjun Lee. 2020. Cross-lingual transformers for neural automatic post-editing. In Proceedings of the Fifth Conference on Machine Translation, pages 772–776, Online. Association for Computational Linguistics.
Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Santanu Pal, Sudip Kumar Naskar, Mihaela Vela, and Shinhyeok Oh, Sion Jang, Hu Xu, Shounan An, and Matteo Negri, Marco Turchi, Rajen Chatterjee, and WonKee Lee, Jaehun Shin, Baikjin Jung, Young-Kil Kim, and Jong-Hyeok Lee. 2020a. POSTECH-ETRI’s submission to the WMT2020 APE shared task: Automatic post-editing with cross-lingual language model. In Proceedings of the Fifth Conference on Machine Translation, pages 777–782, Online. Association for Computational Linguistics.

WonKee Lee, Seong-Hwan Heo, Baikjin Jung, and Jong-Hyeok Lee. 2022. Towards semi-supervised learning of automatic post-editing: Data-synthesis by infilling mask with erroneous tokens.

WonKee Lee, Jaehun Shin, Baikjin Jung, and Jong-Hyeok Lee. 2021. Adaptation of back-translation to automatic post-editing for synthetic data generation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 3685–3691, Online. Association for Computational Linguistics.

WonKee Lee, Jaehun Shin, Baikjin Jung, Jihyung Lee, and Jong-Hyeok Lee. 2020b. Noising scheme for data augmentation in automatic post-editing. In Proceedings of the Fifth Conference on Machine Translation, pages 783–788, Online. Association for Computational Linguistics.

Matteo Negri, Marco Turchi, Rajen Chatterjee, and Nicola Bertoldi. 2018. escape: a large-scale synthetic corpus for automatic post-editing.

Shinhyeok Oh, Sion Jang, Hu Xu, Shounan An, and Insoo Oh. 2021. Netmarble AI center’s WMT2020 automatic post-editing shared task submission. In Proceedings of the Sixth Conference on Machine Translation, pages 307–314, Online. Association for Computational Linguistics.

Santanu Pal, Sudip Kumar Naskar, Mihaela Vela, Qun Liu, and Josef van Genabith. 2017. Neural automatic post-editing using prior alignment and reranking. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 349–355, Valencia, Spain. Association for Computational Linguistics.

Santanu Pal, Sudip Kumar Naskar, Mihaela Vela, and Josef van Genabith. 2016. A neural network based approach to automatic post-editing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 281–286, Berlin, Germany. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Weijing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In Proceedings of the Tenth Workshop on Statistical Machine Translation, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Devendra Sachan and Graham Neubig. 2018. Parameter sharing methods for multilingual self-attentional translation models. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 261–271, Brussels, Belgium. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96, Berlin, Germany. Association for Computational Linguistics.

Abhishek Sharma, Prabhakar Gupta, and Anil Nelakanti. 2021. Adapting neural machine translation for automatic post-editing. In Proceedings of the Sixth Conference on Machine Translation, pages 315–319, Online. Association for Computational Linguistics.

Michel Simard, Nicola Ueffing, Pierre Isabelle, and Roland Kuhn. 2007. Rule-based translation with statistical phrase-based post-editing. In Proceedings of the Second Workshop on Statistical Machine Translation, pages 203–206, Prague, Czech Republic. Association for Computational Linguistics.

Matthew Snover, Bonnie Dorr, Rich Schwartz, Linnea Micciulla, and John Mahkoul. 2006. A study of translation edit rate with targeted human annotation. In Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers, pages 223–231, Cambridge, Massachusetts, USA. Association for Machine Translation in the Americas.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need.

Thuy-Trang Vu and Gholamreza Haffari. 2018. Automatic post-editing of machine translation: A neural programmer-interpreter approach. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3048–3053, Brussels, Belgium. Association for Computational Linguistics.

Jiayi Wang, Ke Wang, Kai Fan, Yuqi Zhang, Jun Lu, Xin Ge, Yangbin Shi, and Yu Zhao. 2020. Alibaba’s submission for the WMT 2020 APE shared
task: Improving automatic post-editing with pre-trained conditional cross-lingual BERT. In Proceedings of the Fifth Conference on Machine Translation, pages 789–796, Online. Association for Computational Linguistics.

Rose E Wang, Esin Durmus, Noah Goodman, and Tat-sunori Hashimoto. 2022. Language modeling via stochastic processes.

Jason Wei and Kai Zou. 2019. EDA: Easy data augmentation techniques for boosting performance on text classification tasks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6382–6388, Hong Kong, China. Association for Computational Linguistics.

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 Proceedings of the Fifth Conference on Machine Translation, pages 797–802, Online. Association for Computational Linguistics.
A Model Configuration

Our model configurations are shown in Table 6.

| Settings       | Transformer | BERT-APE |
|----------------|-------------|----------|
| Optimizer      | Adam        | AdamW    |
| Layers         | 6           | 12       |
| Heads          | 8           | 12       |
| Hidden-size    | 512         | 768      |
| Feed-forward   | 2048        | 3072     |
| Batch-size     | 4096        | 512      |
| Activation     | RELU        | GELU     |
| Warmup steps   | 5000        | 5000     |
| Decay function | Noam        | Noam     |
| Training steps | 200K        | 200K     |
| Training times | 50 hours    | 100 hours|
| GPUs           | 1080Ti*1    | 1080Ti*1 |
| Parameters     | 55.3M       | 262.5M   |

Table 6: Model configurations

B Complete Data of Different Domains

We incorporate different amount of out-of-domain data into in-domain artificial triplets. In our experiment, artificial data from IT domain are in-domain when dealing with WMT'18 SMT, while data from Subtitles domain are in-domain when working on SubEdits. Complete data on SubEdits and WMT'18 SMT are shown respectively in 7 and 8.

| Out-of-Domain Data | Data Amount | BLEU↑ | ChrF↑ | TER↓ |
|--------------------|-------------|-------|-------|------|
| Only In-Domain Data|             | 64.1  | 74.1  | 24.0 |
| Medic              | 50K         | 63.2  | 73.3  | 24.2 |
|                    | 100K        | 63.6  | 73.7  | 23.9 |
|                    | 150K        | 63.7  | 73.9  | 23.8 |
|                    | 200K        | 63.9  | 73.9  | 23.7 |
| Legal              | 50K         | 64.2  | 73.8  | 23.4 |
|                    | 100K        | 64.5  | 73.7  | 23.4 |
|                    | 150K        | 64.5  | 73.9  | 23.3 |
|                    | 200K        | 64.7  | 74.3  | 23.1 |
| News               | 50K         | 63.9  | 74.1  | 23.6 |
|                    | 100K        | 63.6  | 73.7  | 23.8 |
|                    | 150K        | 63.9  | 74.1  | 23.7 |
|                    | 200K        | 64.2  | 74.4  | 23.5 |
| IT                 | 50K         | 63.2  | 73.5  | 24.2 |
|                    | 100K        | 63.6  | 73.7  | 23.9 |
|                    | 150K        | 63.6  | 73.6  | 24.1 |
|                    | 200K        | 63.5  | 73.6  | 24.0 |

Table 7: The experimental results of incorporating different amount of out-of-domain data into in-domain data on SubEdits.
| Out-of-Domain Data | Data Amount | BLEU↑ | ChrF↑ | TER↓ |
|--------------------|-------------|-------|-------|------|
| Only In-domain Data | 68.9        | 84.6  | 19.7  |
| Medic              | 50K         | 67.8  | 83.3  | 20.9 |
|                    | 100K        | 67.9  | 83.4  | 20.9 |
|                    | 150K        | 68.1  | 83.6  | 20.7 |
|                    | 200K        | 68.3  | 83.8  | 20.0 |
| Legal              | 50K         | 68.7  | 83.8  | 20.1 |
|                    | 100K        | 69.5  | 84.4  | 19.7 |
|                    | 150K        | 69.7  | 84.5  | 19.5 |
|                    | 200K        | 69.7  | 84.5  | 19.5 |
| News               | 50K         | 69.7  | 84.5  | 19.5 |
|                    | 100K        | 69.7  | 84.5  | 19.4 |
|                    | 150K        | 69.6  | 84.4  | 19.4 |
|                    | 200K        | 70.5  | 84.9  | 18.9 |
| Subtitles          | 50K         | 69.5  | 84.3  | 19.4 |
|                    | 100K        | 69.4  | 84.2  | 19.7 |
|                    | 150K        | 70.1  | 84.6  | 19.1 |
|                    | 200K        | 69.5  | 84.3  | 19.7 |

Table 8: The experimental results of incorporating different amount of out-of-domain data into in-domain data on WMT’18 SMT.

C Statistics of Datasets

We split SubEdits, WMT’18 SMT and MLQE-PE into several groups according to the length of src and sentence BLEU of mt. To analyze the performance of our APE model on different groups, we calculate the corpus BLEU score as a measurement. The positive value of APE improvement indicates that APE system improves translation quality, whereas APE causes translation quality decline.

| Length of src | Num | Before APE | After APE | APE improvement |
|---------------|-----|------------|-----------|-----------------|
| 0-10          | 392 | 65.81      | 78.15     | +12.34          |
| 11-20         | 1066| 62.82      | 73.86     | +11.04          |
| 21-30         | 498 | 63.36      | 70.86     | +7.50           |
| >30           | 44  | 64.19      | 70.59     | +6.40           |

Table 9: APE performance on different lengths of src on WMT’18 SMT.

| Length of src | Num | Before APE | After APE | APE improvement |
|---------------|-----|------------|-----------|-----------------|
| 0-10          | 4957| 67.48      | 70.46     | +2.98           |
| 11-20         | 4412| 60.24      | 63.96     | +3.72           |
| 21-30         | 591 | 57.93      | 58.99     | +1.06           |
| >30           | 40  | 44.09      | 45.59     | +1.50           |

Table 10: APE performance on different lengths of src on SubEdits.
### Table 11: APE performance on different lengths of src on MLQE-PE.

| Length of src | Num  | Before APE | After APE | APE improvement |
|---------------|------|------------|-----------|-----------------|
| 0-10          | 124  | 72.17      | 72.21     | +0.04           |
| 11-20         | 624  | 73.17      | 72.75     | -0.42           |
| 21-30         | 225  | 72.01      | 70.48     | -1.53           |
| >30           | 7    | 63.57      | 62.32     | -1.25           |

### Table 12: APE performance on different quality of mt on WMT’18 SMT.

| Sentence BLEU Score of mt | Num  | Before APE | After APE | APE improvement |
|---------------------------|------|------------|-----------|-----------------|
| 0-20                      | 154  | 11.26      | 34.11     | +22.85          |
| 21-40                     | 334  | 33.52      | 51.01     | +17.49          |
| 41-60                     | 474  | 52.61      | 66.98     | +14.37          |
| 61-80                     | 512  | 72.00      | 79.25     | +7.25           |
| 81-100                    | 526  | 92.64      | 91.64     | -1.00           |

### Table 13: APE performance on different quality of mt on SubEdits.

| Sentence BLEU Score of mt | Num  | Before APE | After APE | APE improvement |
|---------------------------|------|------------|-----------|-----------------|
| 0-20                      | 62   | 10.31      | 18.84     | +8.53           |
| 21-40                     | 114  | 31.48      | 36.50     | +5.02           |
| 41-60                     | 159  | 52.28      | 53.43     | +1.15           |
| 61-80                     | 190  | 71.29      | 69.18     | -2.11           |
| 81-100                    | 475  | 96.18      | 91.15     | -5.03           |

### Table 14: APE performance on different quality of mt on MLQE-PE.

| Sentence BLEU Score of mt | Num  | Before APE | After APE | APE improvement |
|---------------------------|------|------------|-----------|-----------------|
| 0-20                      | 62   | 10.31      | 18.84     | +8.53           |
| 21-40                     | 114  | 31.48      | 36.50     | +5.02           |
| 41-60                     | 159  | 52.28      | 53.43     | +1.15           |
| 61-80                     | 190  | 71.29      | 69.18     | -2.11           |
| 81-100                    | 475  | 96.18      | 91.15     | -5.03           |