MDQE: A More Accurate Direct Pretraining for Machine Translation Quality Estimation

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Abstract

It is expensive to evaluate the results of Machine Translation (MT), which usually requires manual translation as a reference. Machine Translation Quality Estimation (QE) is a task of predicting the quality of machine translations without relying on any reference. Recently, the emergence of predictor-estimator framework which trains the predictor as a feature extractor and estimator as a QE predictor, and pre-trained language models (PLM) have achieved promising QE performance. However, we argue that there are still gaps between the predictor and the estimator in both data quality and training objectives, which preclude QE models from benefiting from a large number of parallel corpora more directly. Based on previous related work that have alleviated gaps to some extent, we propose a novel framework that provides a more accurate direct pretraining for QE tasks. In this framework, a generator is trained to produce pseudo data that is closer to the real QE data, and an estimator is pretrained on these data with novel objectives that are the same as the QE task. Experiments on widely used benchmarks show that our proposed framework outperforms existing methods, without using any pretraining models such as BERT.

1 Introduction

Machine Translation (MT) quality estimation (QE) aims to evaluate the translation quality of translation system without relying on any translation references (Specia et al., 2009). Given a source language translation X and a target language translation T = \{t_1, t_2, ..., t_n\} with n words, produced by an MT system, the QE system learns to word and sentence-level quality labels. More details can be found in the annual WMT quality estimation competitions outline\(^1\). An example is shown in Table 1.

| Source | remember that this code is called repeatedly, every 15 milliseconds |
|--------|----------------------------------------------------------------------|
| Target | beachten Sie, dass dieser Code alle 15 Millisekunden aufgerufen wird |
| HTER   | 0.083333                                                             |

Table 1: An example of QE. Word-level QE assigns labels to each token/word. For example, some tokens are tagged as ‘BAD’ (marked underline), and the rest are tagged as ‘OK’. Sentence-level QE labels the whole sentence with a single quality score, representing the effort to correct the translation manually.

Current state-of-the-art (SOTA) QE methods have switched from hand-crafted features to features automatically generated from neural-based models (Bojar et al., 2016). Here, we introduce two best performing QE approaches from the latest WMT QE shared task (Fonseca et al., 2019): predictor-estimator (Kim et al., 2017) and QE specific output layers on top of pretrained contextual embeddings (Kim et al., 2019), which we call this approach PLM-QE for convenience. Both approaches can make use of sentence encoder models, such as BERT (Devlin et al., 2018), XLM (Lample and Conneau, 2019) or XLM-R (Conneau et al., 2019).

Since the real QE data is limited in size because of the efforts of experts with bilingual knowledge and parallel data of the same translation direction is much more available, it is natural to transfer bilingual knowledge from parallel data to QE task. One common framework is the predictor-estimator framework (Kim et al., 2017) which achieves promising QE performance. It first trains a predictor on parallel data, which acts as a feature extractor. The training objective is to predict one target token given the source sentence

\(^1\) http://www.statmt.org/wmt19/qe-task.html
and the rest tokens in the reference. The estimator then uses the features generated from the predictor to make QE predictions. There are two different kinds of predictors in previous research, one is the NMT-based predictor which trains a Neural Machine Translation (NMT) model on parallel data (Fan et al., 2019; Kim et al., 2017), the other is PLM-based Predictor which use a Pretrained Language Model (PLM), e.g., BERT (Devlin et al., 2018).

Recently, due to the emergence of Pretrained Language Model and its strong performance in the most of downstream tasks, it is natural to use contextual knowledge extracted from parallel data to do QE predictions. The only difference between PLM-QE with predictor-estimator is it can allow for straightforward end-to-end learning and direct finetuning of the pretrained language model (Ranasinghe et al., 2020; Kim et al., 2019). This method has gradually become the mainstream of machine translation quality evaluation competition in WMT or CCMT during the last two years.

However, we suggest that both approaches have their limitations in some aspects. Firstly, the predictor and pretrained language model are both trained on well-translated parallel data. In contrast, the QE task deals with imperfect translations from MT systems as the input. The differences in data quality may lead to a degradation of QE performance (Pan and Yang, 2009). Secondly, for the predictor-estimator framework, because the training objectives of the predictor and the estimator are different, the features extracted from predictor may not be suitable to judge the translation qualities. Hence, it is hard for the predictor to learn QE-related features that the estimator can directly exploit. Thirdly, for the PLM-QE, finetuning pretrained models is highly unstable when the dataset is small (Devlin et al., 2018; Zhang et al., 2020), which annotated QE dataset are scarce. How to provide a smooth transition between pretraining and finetuning is crucial. One feasible method is using large scale labeled data relevant to the target task (Phang et al., 2018). This approach is nonetheless limited by its reliance on annotated data for supervised learning.

Recently, some works have focused on these limitations, and achieved promising performance. one well-known framework is DirectQE which consists of a generator that produce pseudo QE data and a detector that is pretrained on large pseudo QE data first and then finetuned on real QE data (Cui et al., 2021). It does provide a good solution to the above limitations. But the pseudo QE data is still different from the real QE data, especially the QE labels between pseudo QE data and real QE data. Another well-known approach is a self-supervised intermediate training approach to adapt a pretrained model to QE by modifying the popular masked LM objective (Rubino and Sumita, 2020). On the basis of the original simulation of target tokens replacement, insertion and deletion are introduced by this modified masked LM objective. But the features extracted from applying modified masked LM objective to the pretraining on the well-translated parallel pairs which may not be suitable to simulate errors occurred in translation. Hence, both approaches have corresponding limitations.

In this paper, we propose a novel framework called MDQE that provides a more accurate direct pretraining for QE tasks. In MDQE, a proposed generator is first trained on parallel data and then be used to produce a large amount of pseudo QE data. Our generator is based on the transformer with a novel modified masked LM objective which simulate all possible mistakes observed in translations. Therefore, pseudo QE data generated from the generator is more similar to the real QE data than the parallel data itself. Since the pseudo data generated by the generator is the same as the real data in format, the QE labels generation process of the pseudo data is the same as the real data. Then a proposed detector learns quality estimation by pretraining on the pseudo QE data and finetuning on real QE data. We well connect the pretraing and finetuning procedure due to almost the same data format and training objectives.

Unlike the previous estimator and PLM-QE, which could only be trained on limited QE data, the estimator in our framework enables a direct usage of a large amount of pseudo QE data. Besides, instead of relying on features from a QE-irrelevant predictor or PLM, our detector performs the quality predictions using features, learned through the direct pretraining, in its own way. With the same amount of the extra parallel dataset, MDQE achieves new SOTA results on EN-DE QE datasets.
Figure 1: The illustration of pur framework. The estimator is trained on the pseudo QE data generated from the generator. In this example, the source sentence is *Good night.* and the target sentence is *Gute Nacht.*

2 Approach

To bridge the gaps in the data quality and training objectives between the original predictor and estimator (Kim et al., 2017), we propose the MDQE framework that provides a more accurate direct pre-training for QE tasks. As shown in Figure 1, our framework includes a generator to generate pseudo QE data and an estimator pretrained with the same QE objectives on the generated pseudo parallel data.

2.1 Generator

The generator is trained on the parallel data to generate pseudo QE data. To achieve this goal, we randomly insert [mask] tokens into the target sentence, then randomly mask some tokens in the target sentence, and take the generator as a word rewriter. For the randomly inserted [mask] tokens, our goal is to recover them to [empty]. The generator is then used to produce pseudo translations with one-to-one correspondences with the references after inserted, from which labels could be generated just like the process of QE data labels generation.

Training the word rewriter on parallel corpus. The generator adopts an encoder-decoder architecture like transformer. (Waswani et al., 2017) However, we adopt a modified masked language model objective (Rubino and Sumita, 2020) at the target side. Given a parallel sentence pair \( <X, Y> \), we first randomly insert special tags [mask] into the target sentence, then finally generate a masked sentence \( \hat{Y} \) by randomly replacing some tokens in the reference with the same special tags [mask]. The generator is trained to recover the masked tokens given the source tokens and the other tokens at the target side. Suppose the masked token is \( y_i \), then the training objective is to maximize

\[
P(y_i | X, \hat{Y}_{<i}, [\text{mask}], \hat{Y}_{>i}; \theta). \tag{1}
\]

Following BERT, we insert [mask] tokens and mask tokens with a 15% ratio.

Generating pseudo QE translations. We use the trained generator as a word rewriter to produce pseudo translations \( Y' = \{y_1, y_2, ..., y_n\} \). Notice that the length of \( Y' \) is different from the reference \( Y \), but is the same as the reference after inserted \( \hat{Y} \), and the tokens in the reference after inserted \( \hat{Y} \) have one-to-one correspondences.

More specifically, we feed parallel data to the generator after inserted special tokens and masked some tokens at the target side. For each masked token, the generator will output a probability distribution over the whole vocabulary. In order to generate sentences with translation errors, we do not simply choose the best tokens with the highest probability like the usual practice.

To generate the pseudo QE translations that share a closer data quality with the real QE data, we choose to sample pseudo translations according to the probability distribution. Here, we introduce the following two commonly used strategies:

- **Temperature** To avoid either getting stuck in repetitive loops, we use Temperature strategy to sample tokens from a softmax with temperature \( \tau \) (Hinton et al., 2015).
- **Top-k** To improve sampling diversity, we alternatively randomly select tokens from those with the top \( k \) generation probability.

Generating QE labels. The generator produces a new translation \( \hat{Y}' \) for each parallel sentence pair. So we have a source sentence, a translation and an reference for each parallel sentence pair. Then, we generate QE labels on the translation like the process of real QE labels generation.

With the generated QE labels, we can now get a pseudo tuple \( <X, \hat{Y}, W, \text{HTER}> \), which \( W \) and \( \text{HTER} \) mean word label and sentence label.

2.2 Estimator

With the generated pseudo and real QE data, the estimator could be pretrained and finetuned, respectively, using the same data format and training objectives. That is why we named our method “more accurate direct” pretraining with respect to DirectQE framework (Cui et al., 2021).

Pretraining on generated pseudo QE data. The estimator uses the pseudo QE data generated by the generator. The pretraining task has word and
sentence-level predictions like finetuning task. The loss functions for word-level is to minimize
\[ \sum_{s \in D} \sum_{x \in s} - (p_{OK} \log p_{OK} + p_{BAD} \log p_{BAD}) \] (2)
where \( s \) denote each sentence in the dataset, \( p_{OK} \) and \( p_{BAD} \) denote the probability for each word to be classified as \text{OK}/\text{BAD}.

and that of sentence-level is to minimize
\[ \sum_{s \in D} \| \text{sigmoid}(W_s h(s)) - hter_s \| \] (3)
where \( x \) denote each word in the dataset, \( h(s) \) denotes the hidden representation for each sentence, and \( W_s \) denote the transformation matrices for sentence prediction, and \( hter_s \) denote the HTER\(^3\) measure for each sentence.

The estimator also uses the transformer architecture to capture the context semantics of source and target sentences as the generator does predict, and do word and sentence level prediction on the top of them.

Notice that, the \textit{Temperature} and \textit{Topk} strategies enable us to generate multiple pseudo target sentences given a parallel sentence pair. And the QE data has multiple target sentences given a parallel sentence pair. So in practice, we adopt the same procedure of sample as the official script does. Therefore, the estimator could possibly be exposed to diverse translation errors, leading to better QE performance.

In order to control the pretraining process for the estimator. We randomly cut 1% sentence pairs out of the parallel data and use the generator to produce pseudo QE data with the \textit{Sample} strategy. This dataset is used as the development set to monitor the pretraining process, and the performance on this dataset will be used for model selection.

\textbf{Finetuning on real QE data.} After pretraining on the pseudo parallel pairs, the estimator will be finetuned on real QE tasks directly. The loss functions for word and sentence level are the same as the pretraining above.

\section{Experiments}

\subsection{Experimental Settings}

\textbf{Dataset.} We carry out experiments on the WMT19 QE tasks for English-to-German(EN-DE) direction. The EN-DE parallel dataset is from the WMT19 Shared Task and contains 3.4M sentence pairs, which are far larger than the QE dataset(about 13k). These datasets are all officially released for the WMT QE shared Task.

\textbf{Models.} In our experiments, we reproduce the best previous models DirectQE as our baselines and compare it with the proposed MDQE.

- \textbf{DirectQE.} Using transformer(Waswani et al., 2017) as the generator to generate pseudo QE data with the \textit{Temperature} and \textit{Topk} strategies, and the same model as the detector for pretraining on the pseudo data, finetuning on the real QE data.

- \textbf{MDQE.} We implement the models described in the previous section with the \textit{Temperature} and \textit{Topk} strategies.

\textbf{Implementation Details.} For Direct QE, the detector is based on the transformer(Waswani et al., 2017), with one encoder and one decoder, also the same size as the NMT-based QE. The generator is based on a transformer of 6 layers but with hidden states dimension 256 for each layer(Clark et al., 2020). The total number of parameters is about 90M.

For MDQE, the generator is based on a transformer of 6 layers, with one encoder and one decoder with hidden states dimension 256 for each layer(Waswani et al., 2017). The estimator is based on three recent proposed pretrained models, Bert(Devlin et al., 2018), XLM(Lample and Conneau, 2019) and XLM-R(Conneau et al., 2019). Of course, the estimator is also based on transformer with the same configuration of DirectQE to get a better comparison.

We use BPE in our experiments and set BPE steps to 30,000. For the word-level task, if subtokens of a word have conflicting prediction results, we simply consider its word-level label as ‘BAD’.

\textbf{Metrics.} The evaluation of our experiments follows the WMT QE shared task. For the word-level task, the metric is the product of the F1-score for the ‘OK’ and ‘BAD’ tokens(F1-MULT). For the sentence-level task, the main metric is Pearson’s Correlation Coefficient. We also use mean absolute error (MAE), and root-mean-square error (RMSE).

\subsection{Main Results}

We use the same parallel data and QE data to train all the systems. The results are reported in Table 2 MDQE outperforms DirectQE on the test datasets at both the word-level and sentence-level. Both the two sampling strategies of MDQE achieve remarkable performance.

\footnote{https://github.com/jhclark/tercom}
Table 2: Main results of DirectQE and our MDQE on WMT19 EN-DE datasets. Temperature means we select tokens on the whole vocabulary according to the generation probability. Top-k means we randomly select one of the tokens with the top k generation probability.

4 Related Work

Our method has a similar training objective of generator with the approach (Rubino and Sumita, 2020). However we do not share the same motivation. Their work provides a smooth transition between pretraining and finetuning in PLM-QE. Our motivation is to generate more similar pseudo QE data for further pretraining.

We also share the same idea of using pseudo data with some automatic post-editing (APE) work, which tries to use different MT systems to produce pseudo APE data (Negri et al., 2018). It is similar to what we do that we train the generator on parallel data to produce pseudo data. The difference is that they directly use MT systems to generate machine translations, while we use MT systems to generate machine translations with mistakes. Then, we generate QE labels using tercom³.

Finally, our model has a similar architecture with the DirectQE (Cui et al., 2021). We both use a generator to produce pseudo sentences, a detector or an estimator for pretraining in the pseudo QE data first and then finetuning in the real QE data. However, the details of generating pseudo QE data and selected models for pretraining and finetuning are different. Our work can be seen as an improvement on DirectQE framework. Meanwhile, our estimator can be based on either transformer like DirectQE does or PLM, e.g. BERT.

5 Conclusion

We propose a novel architecture called MDQE that provides a more accurate direct pretraining for QE tasks. In our method, a generator is first trained on parallel data and will be used to produce the pseudo QE data. Then a estimator will be directly pretrained with quality estimation on these pseudo data and then finetuned on real QE data. Compare with previous methods, our method can bridge the gaps in the data quality and training objectives between the pretraining and finetuning, which enables our model to learn more suitable knowledge for QE tasks from parallel data. And our method can also provides a smoother transition between pretraining and finetuning in PLM-QE due to pretraining in the large amount of pseudo QE data. Extensive experiments show the effects of each part of our method.

In future work, is it interesting to combine modified mismatching features (Fan et al., 2019) into our framework.

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