Rethinking the Word-level Quality Estimation for Machine Translation from Human Judgement

Anonymous ACL submission

Abstract

Word-level Quality Estimation (QE) of Machine Translation (MT) aims to detect potential translation errors in the translated sentence without reference. Typically, conventional works on word-level QE are designed to predict the quality of translated words in terms of the post-editing effort, where the word labels in the training and evaluation sets, i.e., `OK` or `BAD`, are automatically generated by comparing words between MT sentences and the post-edited sentences through a Translation Error Rate (TER) toolkit. While the post-editing effort can be used to measure the translation quality to some extent, we find it usually conflicts with the human judgement on whether the word is well or poorly translated. To overcome the limitation, we first create a golden benchmark dataset, namely *HJQE* (Human Judgement on Quality Estimation), where the expert translators directly annotate the poorly translated words on their judgements. Additionally, to further make use of the parallel corpus, we propose the self-supervised pre-training with two tag correcting strategies, namely tag refinement strategy and tree-based annotation strategy, to make the TER-based artificial QE corpus closer to *HJQE*. We conduct substantial experiments based on the publicly available WMT En-De and En-Zh corpora. The results not only show our proposed dataset is more consistent with human judgment but also confirm the effectiveness of the proposed tag correcting strategies.[1]

1 Introduction

Quality Estimation of Machine Translation aims to automatically estimate the translation quality of the MT systems with no reference available. Figure 1 shows an example of QE, where the sentence-level QE predicts a score indicating the overall translation quality, and the word-level QE needs to predict the quality of each translated word as

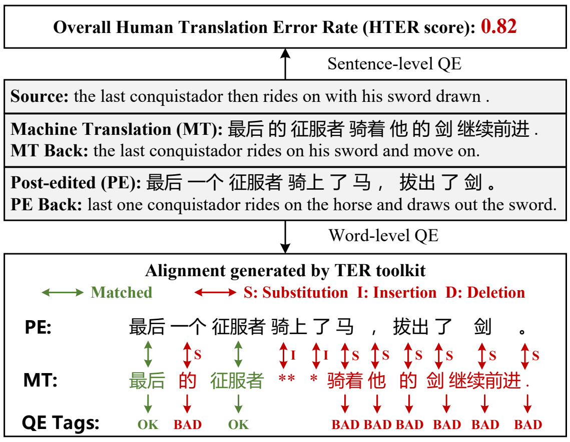


Figure 1: Illustration for word and sentence QE tasks.

`OK` or `BAD`. Recently, the word-level QE attracts more and more attentions for its potential abilities for directly detecting the poorly-translated words and alerting the user with concrete translation errors. Currently, the collection of the word-level QE datasets mainly relies on the Translation Error Rate (TER) toolkit (Snover et al., 2006). Specifically, given the machine translations and their corresponding post-edits (PE, generated by human translators or target sentences of parallel corpus as the pseudo-PE), the rule-based TER toolkit is used to generate the word-level alignment between the MT and the PE based on the principle of minimal editing (Tuan et al., 2021; Lee, 2020). All MT words not aligned to PE are annotated as `BAD` (shown in Figure 1). Such annotation is also referred as post-editing effort (Fomicheva et al., 2020a; Specia et al., 2020).

The post-editing effort measures the translation quality in terms of the efforts the translator need to spend to transform the MT sentence to the golden reference. However, in our previous experiments and real applications, we find it usually conflicts with human judgements on whether the word is well or poorly translated. Two examples in Figure 2 show the conflicts between the TER-based an-

[1] For reviewers, the corpora and codes can be found in the attached files.

Source: It is happy for me to be asked to speak here.

MT: 我 很 高兴 被 要求 在 这里 发言 。 **MT Back:** I am so happy to be asked to speak here.

PE: 被 邀请 在 这里 讲话 我 很 高兴 。 **PE Back:** Being invited to talk here makes me so happy.

TER-based: 我 很 高兴 被 要求 在 这里 发言 。
Human: 我 很 高兴 被 要求 在 这里 发言 。

a) Some words in MT are mistakenly annotated to **BAD** though the overall semantic is not changed.

Source: The Zaporizhian Hetman was then dispatched to Istanbul, and impaled on hooks.

MT: 扎 波罗 齐安海 特曼 号 随后 被 派 往 伊斯坦布尔 ，并 被 撞 在 钩 上 。
MT Back: The Zaporizhian Hetman was then dispatched to Istanbul, and was bumped on the hook.

PE: Zaporizhian Hetman 随后 被 派 往 伊斯坦布尔 ， 并 被 钉 在 钩子 上 。
PE Back: Zaporizhian Hetman was then dispatched to Istanbul, and was nailed on hooks.

TER-based: 扎 波罗 齐安海 特曼 号 随后 被 派 往 伊斯坦布尔 ，并 被 撞 在 钩 上 。
Human: 扎 波罗 齐安海 特曼 号 随后 被 派 往 伊斯坦布尔 ，并 被 撞 在 钩 上 。

b) Human annotate the clause “被撞在钩上” as a whole, while TER-based annotations are fragmented.

Figure 2: Two examples show the gap between the TER-based and human's direct annotation on detecting translation errors. The red color indicates BAD tags (text with translation errors), while the green color indicates OK tags.For readability, we also provide the back translation from Google Translate for the Chinese sentences.

notation and human judgement. In figure 2a, the translated words, namely “我", "很",“高兴" and “发言", are annotated as BAD by TER since they are not exactly in the same order with their counterparts in the PE sentence. However, from human judgement, the reordering of these words does not hurt the meaning of the translation and even makes the MT sentence polished. And the word “要求" is also regarded as a good translation by the human judgement as it is the synonym of the word “邀请". In figure 2b, the clause “扎波罗齐安海特曼号" in a very good translation for “The Zaporizhian Hetman " from human judgement. However, it is annotated as BAD by TER since it is not aligned with any words in the PE sentence. In many application scenarios and down-stream tasks, it is usually important even necessary to detect whether the word is well or poorly translated from the human judgement (Yang et al., 2021). However, most previous works still use the TER-based dataset for training and evaluation, which makes the models' predictions deviate from the human judgement.

To investigate this conflict and overcome the limitations stated above, for the first time, we rethink about the word-level quality estimation for the MT sentences from the human judgement. We first collect a high quality benchmark dataset, named *HJQE*, where human annotators directly annotate the text spans that lead to the translation errors in MT sentences. Then, to further make use of the large scale translation parallel corpus, we also propose two tag correcting strategies, namely tag refinement strategy and tree-based annotation strategy, which make the TER-based annotations more consistent with human judgment.

Our contributions can be summarized as follows: 1) We collect a new dataset called *HJQE* that directly annotates the word-level translation errors on MT sentences. We conduct detailed analyses and demonstrate the differences between *HJQE* and the previous TER-based dataset. 2) To make use of the large scale translation parallel corpus, we propose self-supervised pre-training approach with two automatic tag correcting strategies to make the TER-based artificial dataset more consistent with human judgment and then boost the performance by large-scale pre-training. 3) We conduct experiments on our collected *HJQE* dataset as well as the TER-based dataset MLQE-PE (Fomicheva et al., 2020a). Experimental results of the automatic and human evaluation show that our approach achieves higher consistency with human judgment.

2 Data Collection and Analysis

2.1 Data Collection

To make our collected dataset comparable to TER-generated ones, we directly take the source and MT texts from MLQE-PE (Fomicheva et al., 2020a), the widely used official dataset for WMT20 QE shared tasks. MLQE-PE provides the TER-generated annotations for English-German (En-De) and English-Chinese (En-Zh) translation directions. The source texts are sampled from Wikipedia documents and the translations are obtained from the Transformer-based MT systems (Vaswani et al., 2017).

Our data collection follows the following process. First, we hire a number of translator experts,

Dataset	Split	English-German				English-Chinese			
		samples	tokens	MT BAD tags	MT Gap BAD tags	samples	tokens	MT BAD tags	MT Gap BAD tags
MLQE-PE	train	7000	112342	31621 (28.15%)	5483 (4.59%)	7000	120015	65204 (54.33%)	10206 (8.04%)
	valid	1000	16160	4445 (27.51%)	716 (4.17%)	1000	17063	9022 (52.87%)	1157 (6.41%)
***HJQE* (ours)**	train	7000	112342	10804 (9.62%)	640 (0.54%)	7000	120015	19952 (16.62%)	348 (0.27%)
	valid	1000	16160	1375 (8.51%)	30 (0.17%)	1000	17063	2459 (14.41%)	8 (0.04%)
	test	1000	16154	993 (6.15%)	28 (0.16%)	1000	17230	2784 (16.16%)	11 (0.06%)

Table 1: The statistics of TER-based MLQE-PE dataset and the collected *HJQE*.

where 5 translators for En-Zh and 6 for En-De. They are all graduated students that major in the translation and have the professional ability on the corresponding translation direction. For En-Zh, the translations are tokenized as MLQE-PE. To make the annotation process as fair and unbiased as possible, each annotator is provided only the source sentence and its corresponding translation (the human annotators are not allowed to access the PE sentences in MLQE-PE). For each sample, we randomly distribute it to two annotators. After one sample has been annotated by two translators, we check whether the annotations are consistent. If they have annotation conflicts, we will re-assign the sample to other two annotators until we get the consistent annotations. For the annotation protocol, we ask human translators to find words, phrases, clauses or even the whole sentences that contain translation error in MT sentences, and annotate them as BAD tags. Here, the translation error means the translation distorts the meaning of the source sentence, but excluding minor mismatches such as synonyms and punctuation. Meanwhile, if the translation does not conform to the grammar of the target language, they should also find them and annotate as BAD. The annotation and distribution of samples are automatically conducted through the annotation system. After all samples are annotated, we ask another translator (1 for En-Zh and 1 for En-De, and they do not participant in the annotation process), sampling a small proportion (400 samples) of the full annotated dataset and ensure the accuracy is above 98%.

2.2 Statistics and Analysis

Overall Statistics. In Table 1, we show detailed statistics of the collected *HJQE*. For comparison, we also present the statistics of MLQE-PE. First, we see that the total number of BAD tags decreases heavily when human's annotations replaces the TER-based annotations (from 28.15% to 9.62% for En-De, and from 54.33% to 16.62% for En-Zh). It indicates that the human's annotations tends to annotate OK as long as the translation correctly expresses the meaning of the source sentence, but ignores the secondary issues like synonym substitutions and constituent reordering. Second, we find the number of BAD tags in the gap (indicating a few words are missing between two MT tokens) also greatly decreases. It's because that human's annotations tends to regard the missing translations (i.e., the BAD gaps) and the translation errors as a whole but only annotate BAD tags on MT tokens[2].

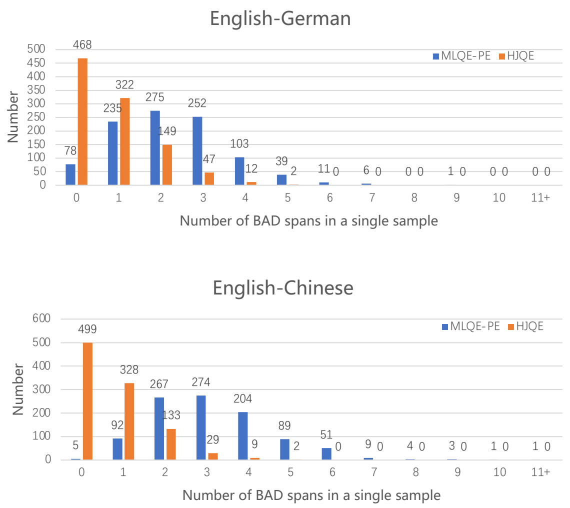
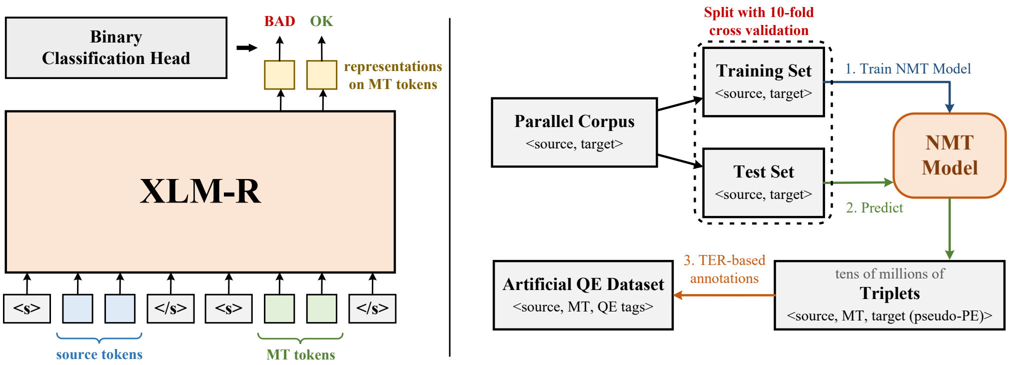


Figure 3: The distribution that reveals how many BAD spans in every single validation sample.

Unity of BAD Spans. To reveal the unity of the human's annotations, we group the samples according to the number of BAD spans in each single sample, and show the overall distribution. From Figure 3, we can find that the TER-based annotations follow the Gaussian distribution, where a large proportion of samples contain 2, 3, or even more BAD spans, indicating the TER-based annotations are fragmented. However, our collected annotations on translation errors are more unified, with only a small proportion of samples including more than 2 BAD spans. Besides, we find a large number of samples that are fully annotated as OK

[2]As a result, we do not include the sub-task of predicting gap tags in *HJQE*.



a) The overall architecture of our model. b) The construction steps of artificial QE dataset for pre-training.

Figure 4: The model architecture and the construction of artificial QE dataset.

in human's annotations. However, the number is extremely small for TER-based annotations (78 in English-German and 5 for English-Chinese). This shows a large proportion of `BAD` spans in TER-based annotations do not really destroy the semantic of translations and are thus regarded as `OK` by human annotators.

Based on the above statistics and the examples in Figure 2, we conclude the two main issues that result in the conflicts between the TER-based annotations and human judgement. First, the PE sentences often substitute some words with better synonyms and reorder some constituents for polish purposes. These operations do not destroy the meaning of the translated sentence, but make some words mistakenly annotated under the exact matching criterion of TER; Second, when a fatal error occurs, the human annotator typically takes the whole sentence or clause as `BAD`. However, the TER toolkit still tries to find trivial words that align with PE, resulting in fragmented and wrong annotations.

3 Approach

This section first introduces the model backbone and the self-supervised pre-training approach based on the large scale parallel corpus. Then, we propose two correcting strategies to make the TER-based artificial tags closer to the human judgment.

3.1 Model Architecture

Following (Ranasinghe et al., 2020; Lee, 2020; Moura et al., 2020; Ranasinghe et al., 2021), we select the XLM-RoBERTa (XLM-R) (Conneau et al., 2020) as the backbone of our model. XLM-R is a transformer-based masked language model pre-trained on large-scale multilingual corpus and demonstrates state-of-the-art performance on multiple cross-lingual downstream tasks. As shown in Figure 4a, we concatenate the source sentence and the MT sentence together to make an input sample: $\boldsymbol{x}_i = \texttt{<s>}w_1^{\text{src}}, \ldots, w_m^{\text{src}}\texttt{</s><s>}w_1^{\text{mt}}, \ldots, w_n^{\text{mt}}\texttt{</s>}$, where m is the length of the source sentence (src) and n is the length of the MT sentence (mt). `<s>` and `</s>` are two special tokens to annotate the start and the end of the sentence in XLM-R, respectively.

For the j-th token w_j^{mt} in the MT sentence, we take the corresponding representation from XLM-R for binary classification to determine whether w_j belongs to good translation (`OK`) or contains translation error (`BAD`) and use the binary classification loss to train the model:

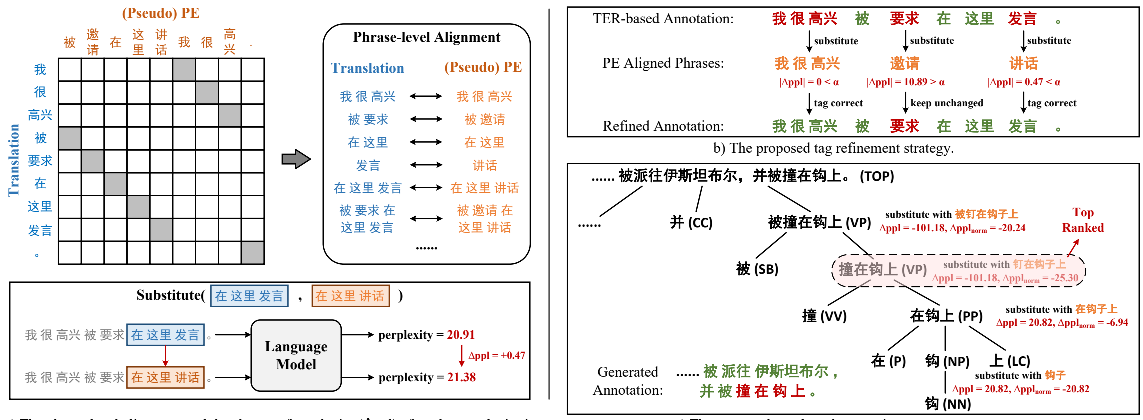
$$s_{ij} = \sigma(\boldsymbol{w}^{\top}\text{XLM-R}_j(\boldsymbol{x}_i)) \tag{1}$$

$$\mathcal{L}_{ij} = -(y \cdot \log s_{ij} + (1-y) \cdot \log(1 - s_{ij})) \tag{2}$$

where $\text{XLM-R}_j(\boldsymbol{x}_i) \in \mathbb{R}^d$ (d is the hidden size of XLM-R) indicates the representation output by XLM-R corresponding to the token w_j^{mt}, σ is the sigmoid function, $\boldsymbol{w} \in \mathbb{R}^{d \times 1}$ is the linear layer for binary classification and y is the ground truth label.

3.2 Self-Supervised Pre-training Approach

Since constructing the golden corpus is is expensive and label-consuming, automatically building the synthetic corpus based on the parallel corpus for pre-training is very promising and has widely been used by conventional works (Tuan et al., 2021; Zheng et al., 2021). As shown in Figure 4b, the conventional approaches firstly split the parallel corpus into the training and the test set. The NMT model is trained with the training split and then used to generate translations for all sentences in the test split. From this, a large number of triplets



a) The phrase-level alignment and the change of perplexity (Δppl) after phrase substitution.

b) The proposed tag refinement strategy.

c) The proposed tree-based annotation strategy.

Figure 5: The proposed two tag correcting strategies: Tag Refinement strategy and Tree-based Annotation strategy.

are obtained, each consisting of source, MT, and target sentences. Finally, the target sentence is regarded as the pseudo-PE from the MT sentence, and the TER toolkit is used to generate word-level annotations.

3.3 Tag Correcting Strategies

As we discussed above, the conflicts between the TER-based annotation and human judgement limits the performance of the conventional self-supervised pre-training approach on the proposed *HJQE*. In this section, we introduce two tag correcting strategies, namely tag refinement and tree-based annotation, that target these issues and make the TER-generated synthetic QE annotations more consistent with human judgment.

Tag Refinement Strategy. In response to the first issue (i.e., wrong annotations due to the synonym substitution or constituent reordering), we propose the tag refinement strategy, which corrects the false `BAD` tags to `OK`. Specifically, as shown in Figure 5a, we first generate the alignment between the MT sentence and the reference sentence (i.e., the pseudo-PE) using FastAlign[3] (Dyer et al., 2013). Then we extract the phrase-to-phrase alignment through running the phrase extraction algorithm of NLTK[4] (Bird, 2006). Once the phrase-level alignment is prepared, we substitute each `BAD` span with the corresponding aligned spans in the pseudo-PE and use the language model to calculate the change of the perplexity Δppl after this substitution. If $|\Delta ppl| < \alpha$, where α is a hyper-parameter indicating the threshold, we regard that the substitution has little impact on the semantic and thus correct the `BAD` tags to `OK`. Otherwise, we regard the span does contain translation errors and keep the `BAD` tags unchanged (Figure 5b).

Tree-based Annotation Strategy. Human's direct annotation tends to annotate the *smallest* constituent that causes fatal translation errors *as a whole* (e.g., the whole words, phrases, clauses, etc.). However, TER-based annotations are often fragmented, with the translation being split into multiple `BAD` spans. Besides, the `BAD` spans are often not well-formed in linguistics i.e., the words in the `BAD` spans from different linguistic constituents.

To address this issue, we propose the constituent tree-based annotation strategy. It can be regarded as an enhanced version of the tag refinement strategy that gets rid of the TER-based annotation. As shown in Figure 5c, we first generate the constituent tree for the MT sentences. Each internal node (i.e., the non-leaf node) in the constituent tree represents a well-formed phrase such as noun phrase (NP), verb phrase (VP), prepositional phrase (PP), etc. For each node, we substitute it with the corresponding aligned phrase in the pseudo-PE. Then we still use the change of the perplexity Δppl to indicate whether the substitution of this phrase improves the fluency of the whole translation. To only annotate the smallest constituents that exactly contain translation errors, we normalize Δppl by the number of words in the phrase and use this value to sort all internal nodes in the constituent tree: $\Delta ppl_{\text{norm}} = \frac{\Delta ppl}{r-l+1}$, where l and r indicates the left and right position of the phrase, respectively. The words of a constituent node are integrally labeled as `BAD` only if $|\Delta ppl_{\text{norm}}| < \beta$ as well as there is no overlap with nodes that are higher ranked. β is a hyper-parameter indicating the threshold.

[3] https://github.com/clab/fast_align

[4] https://github.com/nltk/nltk/blob/develop/nltk/translate/phrase_based.py

Model	English-German (En-De)				English-Chinese (En-Zh)			
	MCC	F-OK	F-BAD	F-BAD-Span	MCC	F-OK	F-BAD	F-BAD-Span
Baselines								
FT on *HJQE* only	26.29	**95.08**	31.09	20.97	38.56	90.76	47.56	26.66
PT (TER-based)	9.52	34.62	13.54	3.09	15.17	36.66	31.53	2.40
+ FT on *HJQE*	24.82	94.65	29.82	18.52	39.09	**91.29**	47.04	25.93
Pre-training only with tag correcting strategies (ours)								
PT w/ Tag Refinement	10.12*	49.33	14.32	3.62	19.36*	53.16	34.10	3.79
PT w/ Tree-based Annotation	8.94	84.50	15.84	6.94	21.53*	59.21	35.54	6.32
Pre-training with tag correcting strategies + fine-tuning on HJQE *(ours)*								
PT w/ Tag Refinement + FT	27.54*	94.21	**35.25**	21.13	40.35*	90.88	49.33	25.60
PT w/ Tree-based Annotation + FT	**27.67***	94.44	32.41	**21.38**	**41.33***	91.22	**49.82**	**27.21**

Table 2: Performance on the test set of *HJQE*. PT indicates pre-training and FT indicates fine-tuning. Results are all reported by $\times 100$. The numbers with * indicate the significant improvement over the corresponding baseline with p < 0.05 under t-test (Semenick, 1990). The results on the validation sets are presented in Appendix B.

4 Experiments

Datasets. To verify the effectiveness of the proposed corpus and approach, we conduct experiments on both *HJQE* and MLQE-PE (Fomicheva et al., 2020a). Note that MLQE-PE and *HJQE* share the same source and MT sentences, thus they have exactly the same number of samples. We show the detailed statistics in Table 1. For the pre-training, we use the parallel dataset provided in the WMT20 QE shared task to generate the artificial QE dataset.

Baselines. To confirm the effectiveness of our proposed self-supervised pre-training approach with tag correcting strategies, we mainly select two baselines for comparison. In the one, we do not use the pre-training, but only fine-tune XLM-R on the training set of *HJQE*. In the other, we pre-train the model on the TER-based artificial QE dataset and then fine-tune it on the training set of *HJQE*.

Implementation and Evaluation. The QE model is implemented based on an open-source framework, OpenKiwi[5]. We use the large-sized XLM-R model released by the hugging-face.[6] We use the KenLM[7] to train the language model on all target sentences in the parallel corpus. For the tree-based annotation strategy, we obtain the constituent tree through LTP[8] (Che et al., 2010) for Chinese and through Stanza[9] (Qi et al., 2020) for German. We set α to 1.0 and β to -3.0 based on the empirical results on the evaluation sets. [10] Following WMT20 QE shared task, we use Matthews Correlation Coefficient (MCC) as the main metric and also report the F1 score (F) for `OK`, `BAD` and `BAD` spans. We refer the readers to the Appendix A for implementation details.

4.1 Main Results

The results are shown in Table 2. We can observe that the TER-based pre-training only brings very limited performance gain or even degrade the performance when compared to the "FT on *HJQE* only" setting (-1.47 for En-De and +0.53 for En-Zh). It suggests that the inconsistency between TER-based and human's annotations leads to the limited effect of pre-training. However, when applying the tag correcting strategies to the pre-training dataset, the improvement is much more significant (+2.85 for En-De and +2.24 for En-Zh), indicating that the tag correcting strategies mitigate such inconsistency, improving the effect of pre-training. On the other hand, when only the pre-training is applied, the tag correcting strategies can also improve the performance. It shows our approach can also be applied to the unsupervised setting, where no human-annotated dataset is available for fine-tuning.

Tag Refinement v.s. Tree-based Annotation. When comparing two tag correcting strategies, we find the tree-based annotation strategy is generally superior to the tag refinement strategy, especially for En-Zh. The MCC improves from 19.36 to 21.53 under the *pre-training only* setting and improves from 40.35 to 41.33 under the *pre-training then fine-tuning* setting. This is probably because the

[5] https://github.com/Unbabel/OpenKiwi
[6] https://huggingface.co/xlm-roberta
[7] https://kheafield.com/code/kenlm.tar
[8] http://ltp.ai/index.html
[9] https://stanfordnlp.github.io/stanza
[10] We find that α and β is not so sensitive if they are set in the reasonable ranges, [0.8, 1.5] for α and [-2.0, -3.5] for β.

Evaluate on → Fine-tune on ↓	MLQE-PE			*HJQE*	
	MCC*	MCC	F-BAD	MCC	F-BAD
WMT20's best	59.28	-	-	-	-
No pre-training (fine-tuning only)					
MLQE-PE	**58.21**	**46.81**	**75.02**	22.49	34.34
HJQE	49.77	23.68	36.10	**45.76**	**53.77**
TER-based pre-training					
w/o fine-tune	56.51	33.58	73.85	11.38	27.41
MLQE-PE	**61.85**	**53.25**	**78.69**	21.93	33.75
HJQE	41.39	29.19	42.97	**47.34**	**55.43**
Pre-training with tag refinement					
w/o fine-tune	55.03	28.89	70.73	18.83	31.39
MLQE-PE	**61.35**	**48.24**	**77.17**	21.85	33.31
HJQE	39.56	25.06	67.40	**47.61**	**55.22**
Pre-training with tree-based annotation					
w/o fine-tune	55.21	26.79	68.11	20.98	32.84
MLQE-PE	**60.92**	**48.58**	**76.18**	22.34	34.13
HJQE	40.30	26.22	39.50	**48.14**	**56.02**

Table 3: Performance comparison for En-Zh with different fine-tuning and evaluation settings. Since the test labels of MLQE-PE are not publicly available, we report the results on the validation set of both datasets. MCC* indicates the MCC score considering both the target tokens and the target gaps.

Scores	En-De		En-Zh	
	TER	Ours	TER	Ours
1 (terrible)	3	1	5	0
2 (bad)	36	16	34	6
3 (neutral)	34	20	29	21
4 (good)	26	61	24	59
5 (excellent)	1	2	8	14
Average score:	2.86	3.47	2.96	3.81
% Ours ≥ TER:	89%		91%	

Table 4: The results of human evaluation. We select the best-performed model fine-tuned on MLQE-PE and *HJQE* respectively.

tag refinement strategy still requires the TER-based annotation and fixes based on it, while the tree-based annotation strategy actively selects the well-formed constituents to apply phrase substitution and gets rid of the TER-based annotation.

Span-level Metric. Through the span-level metric (F-BAD-Span), we want to measure the unity and consistency of the model's prediction against human judgment. From Table 2, we find our models with tag correcting strategies also show higher F1 score on `BAD` spans (from 26.66 to 27.21 for En-Zh), while TER-based pre-training even do harm to this metric (from 26.66 to 25.93 for En-Zh). This phenomenon also confirms the aforementioned fragmented issue of TER-based annotations, and our tag correcting strategies, instead, improve the span-level metric by alleviating this issue.

4.2 Analysis

Comparison with MLQE-PE. To demonstrate the difference between the MLQE-PE (TER-generated tags) and our *HJQE* datasets, and analyze how the pre-training and fine-tuning influence the results on both datasets, we compare the performance of different models on MLQE-PE and *HJQE* respectively. The results for En-Zh are shown in Table 3. When comparing results in each group, we find that fine-tuning on the training set identical to the evaluation set is necessary for achieving high performance. Otherwise, fine-tuning provides marginal improvement (e.g., fine-tuning on MLQE-PE and evaluating on *HJQE*) or even degrades the performance (e.g., fine-tuning on *HJQE* and evaluating on MLQE-PE). This reveals the difference in data distribution between *HJQE* and MLQE-PE. Besides, Our best model on MLQE-PE outperforms WMT20's best model (61.85 v.s. 59.28) using the same MCC* metric, showing that the modeling ability of our model is strong enough even under the TER-based setting.

On the other hand, we compare the performance gain of different pre-training strategies. When evaluating on MLQE-PE, the TER-based pre-training brings higher performance gain (+6.44) than pre-training with two proposed tag correcting strategies (+1.43 and +1.77). While when evaluating on *HJQE*, the case is opposite, with the TER-based pre-training bringing lower performance gain (+1.58) than tag refinement (+1.85) and tree-based annotation (+2.38) strategies. In conclusion, the pre-training always brings performance gain, no matter evaluated on MLQE-PE or *HJQE*. However, the optimal strategy depends on the consistency between the pre-training dataset and the downstream evaluation task.

Human Evaluation. To evaluate and compare the models pre-trained on TER-based tags and corrected tags more objectively, human evaluation is conducted for both models. For En-Zh and En-De, we randomly select 100 samples (the source and MT sentences) from the validation set and use two models to predict word-level `OK` or `BAD` tags for them. Then, we ask human translators to give a score for each prediction, between 1 and 5, where 1 indicates the predicted tags are fully wrong, and 5 indicates the tags are fully correct. Table 4 shows the results. We can see that the model pre-trained on corrected tags (Ours) achieves higher human evaluation scores than that pre-trained on TER-based tags on average. For about 90% of samples, the prediction of the model pre-trained on corrected dataset can outperform or tie with the prediction of the model pre-trained on TER-based dataset. The results of human evaluation show that *HJQE* is more consistent with human judgement. The case study is also presented in the Appendix C.

Limitation and Discussion We analyze some samples that are corrected by our tag correcting strategies and find a few bad cases. The main reasons are: 1) There is noise from the parallel corpus. 2) The alignment generated by FastAlign contains unexpected errors, making some entries in the phrase-level alignments are missing or misaligned. 3) The scores given by KenLM, i.e., the perplexity changes, are sometimes not sensitive enough. We propose some possible solutions to the above limitations as our future exploration direction. For the noise in the parallel corpus, we can use parallel corpus filtering methods that filter out samples with low confidence. We can also apply the data augmentation methods that expand the corpus based on the clean parallel corpus. For the alignment errors, we may use more accurate neural alignment models proposed recently (Jalili Sabet et al., 2020; Lai et al., 2022). For the scoring, we may introduce the neural-based phrase-level semantic matching model (Wang et al., 2021).

5 Related Work

Early approaches on QE, such as QuEst (Specia et al., 2013) and QuEst++ (Specia et al., 2015), mainly pay attention to the feature engineering. They aggregate various features and feed them to the machine learning algorithms for classification or regression. Kim et al. (2017) first propose the neural-based QE approach, called Predictor-Estimator. They first pre-train an RNN-based predictor on the large-scale parallel corpus that predicts the target word given its context and the source sentence. Then, they extract the features from the pre-trained predictor and use them to train the estimator for the QE task. This model achieves the best performance on the WMT17 QE shard task. After that, many variants of Predictor-Estimator are proposed (Fan et al., 2019; Moura et al., 2020; Cui et al., 2021). Among them, Bilingual Expert (Fan et al., 2019) replaces RNN with multi-layer transformers as the architecture of the predictor. It achieves the best performance on WMT18. Kepler et al. (2019) release an open-source framework for QE, called OpenKiwi, that implements the most popular QE models with configurable architecture.

Recently, with the development of pre-trained language models, many works select the cross-lingual language model as the backbone (Ranasinghe et al., 2020; Lee, 2020; Moura et al., 2020; Rubino and Sumita, 2020; Ranasinghe et al., 2021; Zhao et al., 2021). Many works also explore the joint learning or transfer learning of the multilingual QE task (Sun et al., 2020; Ranasinghe et al., 2020, 2021). Meanwhile, Fomicheva et al. (2021) propose a shared task with the new-collected dataset on explainable QE, aiming to provide word-level hints for sentence-level QE score. Freitag et al. (2021) also study multidimensional human evaluation for MT and collect a large-scale dataset. Additionally, Fomicheva et al. (2020b); Cambra and Nunziatini (2022) evaluate the translation quality from the features of the NMT systems directly.

The QE model can be applied to the Computer-Assisted Translation (CAT) system together with other models like translation suggestion (TS) or automatic post-edit (APE). Wang et al. (2020) and Lee et al. (2021) use the QE model to identify which parts of the machine translations need to be correct, and the TS (Yang et al., 2021) also needs the QE model to determine error spans before giving translation suggestions.

6 Conclusion

In this paper, we focus on the task of word-level QE in machine translation and target the inconsistency issues between the TER-based QE dataset and human judgment. We first collect and release a benchmark dataset called *HJQE* that reflects the human judgement on the translation errors in MT sentences. Besides, we propose the self-supervised pre-training approach with two tag correcting strategies, which makes the TER-based annotations closer to the human judgement and improves the final performance on the proposed benchmark dataset *HJQE*. We conduct thorough experiments and analyses, demonstrating the necessity of our proposed dataset and the effectiveness of our proposed approach. Our future directions include improving the performance of phrase-level alignment, introducing phrase-level semantic matching, and applying data augmentation. We hope our work will provide a new perspective for future researches on quality estimation.

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A Implementation Details

In the pre-processing phase, we filter out parallel samples that are too long or too short, and only reserve sentences with 10-100 tokens. We pre-train the model on 8 NVIDIA Tesla V100 (32GB) GPUs for two epochs, with the batch size set to 8 for each GPU. Then we fine-tune the model on a single NVIDIA Tesla V100 (32GB) GPU for up to 10 epochs, with the batch size set to 8 as well. Early stopping is used in the fine-tuning phase, with the patience set to 20. We evaluate the model every 10% steps in one epoch. The pre-training often takes more than 15 hours and the fine-tuning takes 1 or 2 hours. We use Adam (Kingma and Ba, 2014) to optimize the model with the learning rate set to 5e-6 in both the pre-training and fine-tuning phases. For all hyper-parameters in our experiments, we manually tune them on the validation set of *HJQE*.

B Main Results on the Validation Set

In Table 5, we also report the main results on the validation set of *HJQE*.

C Case Study

In Figure 6, we show some cases from the validation set of English-Chinese language pair. From the examples, we can see that the TER-based model (noted as PE Effort Prediction) often annotates wrong `BAD` spans and is far from human judgment. For the first example, the MT sentence correctly reflects the meaning of the source sentence, and the PE is just a paraphrase of the MT sentence. Our model correctly annotates all words as `OK`, while TER-based one still annotates many `BAD` words. For the second example, the key issue is the translation of "unifies" in Chinese. Though "统一" is the direct translation of "unifies" in Chinese, it can not express the meaning of winning two titles in Chinese context. And our model precisely annotated the "统一 了" in the MT sentence as `BAD`. For the third example, the MT model fails to translate the "parsley" and the "sumac" to "欧芹" and "盐肤木" in Chinese, since they are very rare words. While the TER-based model mistakenly predicts long `BAD` spans, our model precisely identities both mistranslated parts in the MT sentence.

Model	English-German (En-De)				English-Chinese (En-Zh)			
	MCC	**F-OK**	**F-BAD**	**F-BAD-Span**	**MCC**	**F-OK**	**F-BAD**	**F-BAD-Span**
Baselines								
FT on *HJQE* only	34.69	94.28	40.38	28.65	45.76	91.96	53.77	**29.84**
PT (TER-based)	13.13	37.30	18.80	4.72	11.38	25.91	27.41	2.16
+ FT on *HJQE*	35.02	94.00	40.86	26.68	47.34	91.30	55.43	28.53
With tag correcting strategies (ours)								
PT w/ Tag Refinement	13.26	52.43	19.78	6.42	18.83	53.29	31.39	3.48
+ FT on *HJQE*	37.70	94.08	43.32	30.83	47.61	**92.39**	55.22	28.33
PT w/ Tree-based Annotation	13.92	84.79	22.75	9.64	20.98	59.32	32.84	6.53
+ FT on *HJQE*	37.03	**94.46**	42.54	31.21	48.14	91.88	56.02	28.17
PT w/ Both	13.12	39.68	18.94	5.26	21.39	56.76	32.74	5.72
+ FT on *HJQE*	**38.90**	94.44	**44.35**	**32.21**	**48.71**	90.74	**56.47**	25.51

Table 5: The word-level QE performance on the validation set of *HJQE* for two language pairs, En-De and En-Zh. PT indicates pre-training and FT indicates fine-tuning.

Source: To win, a wrestler must strip their opponent's tuxedo off.
MT: 要 想 获胜 , 摔跤 运动员 必须 把 对手 的 礼服 脱下来 .
MT Back: To win, the wrestler had to take his opponent's dress off.
PE: 要 赢得 胜利 ， 摔跤 运动员 必须 脱掉 对手 的 燕尾服 。
PE Back: To win the victory, the wrestler had to remove his opponent's tuxedo.

TER-based: **要 想 获胜 , 摔跤 运动员 必须 把 对手 的 礼服 脱下来 .**
Ours: **要 想 获胜 , 摔跤 运动员 必须 把 对手 的 礼服 脱下来 .**

Source: April 28 Juan Díaz unifies the WBA and WBO Lightweight titles after defeating Acelino Freitas.
MT: 4 月 28 日 , 胡安 · 迪亚斯 在 击败 阿 切利 诺 · 弗雷 塔斯 后 统一 了 WBA 和 WBO 轻量级 冠军 .
MT Back: On April 28, Juan Díaz Unified the WBA and WBO lightweight titles after defeating Acelino Freitas.
PE: 4 月 28 日 ， Juan Díaz 在 击败 Acelino Freitas 之后 ， 将 W 世界 拳击 协会 和 世界 拳击 组织 的 轻量级 冠军 揽于 一身 。
PE Back: On April 28, Juan Díaz won both the WBA and WBO lightweight titles after defeating Acelino Freitas.

TER-based: **4 月 28 日 , 胡安 · 迪亚斯 在 击败 阿 切利 诺 · 弗雷 塔斯 后 统一 了 WBA 和 WBO 轻量级 冠军 .**
Ours: **4 月 28 日 , 胡安 · 迪亚斯 在 击败 阿 切利 诺 · 弗雷 塔斯 后 统一 了 WBA 和 WBO 轻量级 冠军 .**

Source: Fattoush is a combination of toasted bread pieces and parsley with chopped cucumbers, radishes, tomatoes and flavored by sumac.
MT: 法杜什是 烤面包片 和 帕斯 莱 与 切碎 的 黄瓜 、 萝卜 、 西红柿 、 和 洋葱 以及 香味 的 消耗品 的 组合 。
MT Back: Fadush is a combination of toast and pasai with chopped cucumbers, radishes, tomatoes and onions and scented consumables.
PE: Fattoush 是 烤面包片 和 欧芹 与 切碎 的 黄瓜 ， 萝卜 ， 西红柿 和 葱 的 组合 ， 并 以 盐肤木 调味 。
PE Back: Fattoush is a combination of toast and parsley with chopped cucumbers, radishes, tomatoes and scallions, seasoned with rhus salt.

TER-based: **法杜什是 烤面包片 和 帕斯 莱 与 切碎 的 黄瓜 、 萝卜 、 西红柿 、 和 洋葱 以及 香味 的 消耗品 的 组合 。**
Ours: **法杜什是 烤面包片 和 帕斯 莱 与 切碎 的 黄瓜 、 萝卜 、 西红柿 、 和 洋葱 以及 香味 的 消耗品 的 组合 。**

Figure 6: Examples of word-level QE from the validation set of English-Chinese language pair.