The UMD Submission to the Explainable MT Quality Estimation Shared Task: Combining Explanation Models with Sequence Labeling

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Abstract

This paper describes the UMD submission to the Explainable Quality Estimation Shared Task at the Eval4NLP 2021 Workshop on “Evaluation & Comparison of NLP Systems”. We participated in the word-level and sentence-level MT Quality Estimation (QE) constrained tasks for all language pairs: Estonian-English, Romanian-English, German-Chinese, and Russian-German. Our approach combines the predictions of a word-level explainer model on top of a sentence-level QE model and a sequence labeler trained on synthetic data. These models are based on pre-trained multilingual language models and do not require any word-level annotations for training, making them well suited to zero-shot settings. Our best performing system improves over the best baseline across all metrics and language pairs, with an average gain of 0.1 in AUC, Average Precision, and Recall at Top-K score.

1 Introduction

Quality estimation (QE) is the task of predicting the quality of the machine translation (MT) output without reference translation. Predictions can be done at different levels of granularity, such as sentences or words. The explainable QE shared task (Fomicheva et al., 2021a) proposes to frame the identification of translation errors as an explainable QE task, where sentence-level quality judgments are explained by highlighting the words responsible for errors in the MT hypothesis. Given a source sentence and an MT hypothesis, systems are thus asked to provide word-level judgments of translation quality in addition to sentence-level judgments.

Our submission builds on state-of-the-art sentence-level QE models, MonoTransQuest (Ranasinghe et al., 2020a,b). As suggested by the organizers, we rely on the LIME explanation model (Ribeiro et al., 2016) to obtain word-level prediction from the MonoTransQuest model’s sentence-level score. We hypothesize that synthetic examples of translation errors can help improve word-level predictions. As a result, we combine the predictions of MonoTransQuest-LIME with those of the Divergent mBERT model which addresses the related task of detecting semantic divergences in bitext (Briakou and Carpuat, 2020). Divergent mBERT model can detect fine-grained differences in bitext by learning to rank synthetic divergence examples of varying granularity. As a result, our approach does not require any word-level labels at training time. Both models are based on multilingual language models and are therefore amenable to zero-shot transfer.

Our submitted system improves over its components and over the official baseline on all tracks and on all language pairs, based on all evaluation metrics (AUC, AP, Recall at Top-K, and Pearson’s correlation). Compared to the best baseline system for target languages, it improves AUC by 0.119 for Estonian-English (Et-En), 0.068 for Romanian-English (Ro-En), 0.085 for German-Chinese (De-Zh), and 0.128 for Russian-German (Ru-De). Similarly, for AP score, it has achieved an improvement of 0.095 for Et-En, 0.074 for Ro-En, 0.064 for De-Zh, and 0.13 for Ru-De. For Recall at Top-K score, it has achieved an improvement of 0.103 for Et-En, 0.071 for Ro-En, 0.045 for De-Zh, and 0.13 for Ru-De. For source language word-level scores, it achieves an average gain of 0.18 for AUC, 0.071 for AP and 0.12 for Recall at Top-K score over the average of all languages’ baseline scores. Finally, for sentence-level scores, it has achieved an improvement of 0.36 for Et-En, 0.359 for Ro-En, 0.271 for De-Zh, and 0.06 for Ru-De compared to the average of all baseline models for Pearson’s correlation.

2 Approach

We first describe the two components of our ensemble and then explain how they are combined.
2.1 MonoTransQuest-LIME Model

The first ensemble component is based on one of the baselines provided by the organizers. It uses MonoTransQuest, the state-of-the-art model in the WMT 2020 QE shared task (Ranasinghe et al., 2020a,b), including for mid-resource and high-resource language pairs. This model uses a single XLM-Roberta transformer model (Ranasinghe et al., 2020a,b) trained with data released in WMT quality estimation tasks in recent years. The input of the model is the concatenation of the original sentence \( x_{source} \) and its translation \( x_{target} \), separated by the \([SEP]\) token. Therefore, \( x = x_{source}, [SEP], x_{target} \) and the model used the embedding of the \([CLS]\) token as the input of a softmax layer, and this layer \( F \) predicts the sentence-level score \( F(x) \) of the translation at the sentence-level. Mean-squared-error loss is used as the objective function.

For generating word-level scores from the sentence-level scores, the toolkit LIME is suggested by the organizers. LIME explains the predictions of a black-box model by providing a local linear approximation of the model’s behavior. For generating an explanation for a prediction, LIME generates neighborhood data by randomly hiding features from the instance and then learns locally weighted linear models on this neighborhood data to explain each of the classes in an interpretable way. Here, LIME treats words in the input sequence as features and thus lets us generate word-level QE scores from the MonoTransQuest sentence-level QE predictions.

We use existing pre-trained MonoTransQuest models. Ranasinghe et al. (2020a,b) note that the QE task can be challenging in the practical environment where the systems have to work in a multilingual setting, so selecting appropriate models for each language pair is key. As summarized in Table 1, for the development languages (et-en, ro-en), we select existing MonoTransQuest models trained on the language pair tested. For the zero-shot test languages (de-zh, ru-de), we select existing MonoTransQuest models trained on language pairs that involve one of the two languages and English (en-zh and en-de, respectively).

2.2 Divergent mBERT

Briakou and Carpuat (2020) introduced the Divergent mBERT model which is a BERT-based model that can detect cross-lingual semantic divergences by ranking synthetic divergences of varying granularity without supervision. Cross-lingual semantic divergence refers to the difference in meaning between sentences written in different languages (Vyas et al., 2018) and therefore might correspond to some adequacy errors observed in MT output.

The Divergent mBERT model is designed to make both sentence-level and word-level predictions. The input of this model is a sequence \( x \) generated by concatenating an English sentence \( x_e \) and a French sentence \( x_f \) with helper delimiter tokens. Therefore, \( x = ([CLS], x_e, [SEP], x_f, [SEP]) \). Here, the \([CLS]\) token serves as the representative for the sentence-pair \( x \) which is passed through a feed-forward network \( F \) to get the score \( F(x) \) which is converted into the probability that \( x \) is equivalent.

For word-level prediction, the final hidden state \( h_t \) is passed through a feed-forward layer and a softmax layer for each token \( y_t \) in encoded sentence pair \( x \). This produces the probability that the token \( y_t \) belongs to the equivalent class. For sentence-level prediction, the model uses margin-loss and for token-level prediction, it uses cross-entropy loss of all tokens. The word-level evaluation on this model found that it outperforms Random Baseline across all metrics. Therefore, this model proves that we can benefit from training even with noisy word-level labels. We can map this task to identifying the error in the word-level QE by marking all divergences as errors.

We made a small change to the original Divergent mBERT model by fine-tuning XLM-Roberta (Conneau et al., 2020) rather than mBERT, and keeping the rest of the model architecture, loss definition, and training data unchanged. As a result, this model is trained on French-English sentence pairs, where positive examples of equivalence are drawn from bitext with a filtering step to ensure that they are not noisy, and negative samples are automatically generated by corrupting the positive samples to introduce meaning mismatches (e.g.,

### Table 1: MonoTransQuest models used for each task.

| Task      | Model and Training Data                                       |
|-----------|--------------------------------------------------------------|
| Et-En     | TransQuest/monotransquest-da_et_en_wiki                      |
| Ro-En     | TransQuest/monotransquest-da_ro_en_wiki                      |
| De-Zh     | TransQuest/monotransquest-da_en_zh-wiki                      |
| Ru-De     | TransQuest/monotransquest-da_en_de-wiki                      |

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1https://github.com/marcotcr/lime
by deleting dependency subtrees in one language, substituting words with near-synonyms, or phrases with other phrases that have the same syntactic structure). As a result, this model is used in zero-shot settings for all the test languages of the shared task and does not use any manual QE annotation.

2.3 Ensembling Method

We adopt the approach of Kepler et al. (2019) for building ensemble models for word-level quality estimation, which simply averages the predictions of the ensemble components. While their ensemble had five models, we average the predictions of the two models above, either at the sentence or word level. Given a source sentence (src) and the machine translation hypothesis (mt), Divergent mBERT and MonoTransQuest-LIME produce word-level scores for each word in the MT hypothesis. These are averaged to produce the final word-level score. The same process is used to combine sentence-level predictions. The overall system architecture is shown in Figure 1 for word-level predictions.

Figure 1: System architecture of the ensemble method. The input src-nt represents the language pair for which the sentence-level and the word-level score are being generated.

3 Datasets

In this section, we describe the data used for training, development, and evaluation.

3.1 Training Data

We use ensemble components that have been pre-trained on different datasets.

**MonoTransQuest** We use the original models that have been publicly released. They were trained on publicly available datasets from recent WMT sentence-level quality estimation tasks (Specia et al., 2018; Fonseca et al., 2019; Specia et al., 2020). These datasets were collected from Wikipedia and Reddit. In this setup, the Et-En and Ro-En are considered as medium resource language and En-Zh and En-De are considered as high resource language pairs. In Table 1, we can see the lists the training data used to train the original pre-trained MonoTransQuest models. We can note that as there were no De-Zh and Ru-De language pairs used, thus, this model supports prediction in a zero-shot setting.

**Divergent mBERT** We used the same training data as the original model by Briakou and Carpuat (2020). The training data was the English and French text from WikiMatrix which was normalized with Moses toolkit and tokenized. In our model, we have used “XLMRobertaTokenizer” where the original model used “BERTTokenizer”. Similar to the original model, the alignment of English and French bitext was done using Berkeley word aligner. After filtering the noisy samples, the top 5500 samples, ranked by LASER similarity score, were picked, and then the synthetic divergent examples were generated. The synthetic data was generated similar to the original model’s synthetic data generation process which is: subtree deletion by deleting a randomly selected subtree in the dependency parse of the English sentence, or French words aligned to English words in that subtree, Phrase Replacement by substituting random source or target sequences by another sequence of words with matching POS tags and lexical substitution by substituting English words with hypernyms or hyponyms from WordNet.

3.2 Development Data

We used the official shared task development data, which is drawn from the Multilingual Quality Estimation and Post-Editing (MLQE-PE) dataset (Fomicheva et al., 2020). There are two language pairs in the development set, with 1000 sentences each: Estonian-English (Et-En) and Romanian-English (Ro-En).

3.3 Test Data

The test data included four language pairs: Estonian-English (Et-En), Romanian-English (Ro-En), German-Chinese (De-Zh), and Russian-German (Ru-De). The first two language pairs are the same as the development set language pairs. German-English (De-Zh) and Russian-German (Ru-De) language pairs are zero-shot languages since they were not available in the development phase. Test set statistics are given in Table 2. Models are evaluated against human annotations by submitting to the official leaderboard.
| Language Pair | # of sentences |
|---------------|----------------|
| Et-En        | 1000           |
| Ro-En        | 1000           |
| De-Zh        | 1410           |
| Ru-De        | 1180           |

Table 2: Test data statistics.

4 System Configuration

We used the same set of system configurations for all the language pairs in our experiment to ensure consistency among all language pairs.

**MonoTransQuest** We have used pre-trained MonoTransQuest model on the HuggingFace Transformers library (Wolf et al., 2019). We used those pre-trained MonoTransQuest models. We have not changed any hyperparameter from those models.

**Divergent mBERT** For training Divergent mBERT we have used a batch size of 16, Adam optimizer with learning rate $2e^{-5}$ and a linear rate warmup. The model was trained with only training data. The model was trained for five epochs. We have varied the hyperparameter settings: epoch was varied from 3 to 15 epochs, the margin was varied from 5 to 10, the alpha value was varied from 0.2 to 1. Table 3 is the list of the final hyper-parameter settings we used for training in our experiments.

| Batch Size | 16 |
| Loss Function | Sentence-level: Margin Loss |
|             | Token-level: Cross Entropy |
| Optimizer   | AdamW |
| Learning Rate | $2e^{-5}$ |
| Scheduler   | Linear Schedule with Warmup |
| Epoch       | 3 |
| Margin      | 3 |
| Alpha       | 1 |

Table 3: Divergent mBERT hyperparameters.

5 Evaluation Metrics

This section describes the official evaluation metrics for the shared task. For sentence-level scores, Pearson’s correlation is used and for word-level scores, AUC, AP, and Recall at Top-K are used:

- **Pearson’s Correlation:** This measures the strength and direction of a linear relationship between the model predicted sentence-level score and human-annotated sentence-level score. Values always range between -1 (strong negative relationship) and +1 (strong positive relationship).
- **AUC Score:** In this shared task, the AUC score between the model predicted output and gold explanation MT score is computed using sklearn. Given a test set of $N$ sentences:

$$AUC = \frac{1}{N} \sum_{n} AUC_n(w_n, a^{x_T}_n)$$

Here, $w_n$ is a vector representing binary gold word-level labels for each sentence $n$ in the test set and $a^{x_T}_n$ is the vector for the model predicted word-level score for the target words $x^T$ in each target sentence in test set with length $T$. Equation 1 computes the AUC score to compare the model predicted word-level scores $a$ against binary gold labels (Fomicheva et al., 2021b). Here, $AUC_n$ is the area under the curve generated by plotting the true positive against false positive of the word-level scores of the $n^{th}$ sentence at different thresholds. AUC ranges in value from 0 to 1. A model whose predictions are 100% wrong has an AUC of 0.0; one whose predictions are 100% correct has an AUC of 1.0.

- **AP Score:** AP (Average Precision) evaluates word-level predictions and complements AUC scores which can be overly optimistic for imbalanced data (Fomicheva et al., 2021b). Average precision is defined as:

$$AP = \sum_{n} (R_n - R_{n-1}) P_n$$

where $P_n$ and $R_n$ are the precision and recall at the $n^{th}$ threshold, where words are assigned to the positive class if the model predicts a score for this word that is higher than the $n^{th}$ threshold.

- **Recall at Top-K:** This metric checks whether the highest predicted values have been assigned to the words corresponding to actual errors. For example, if the gold standard output is 1, 1, 0, 0, 0, 0, 0 then the recall value

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2https://huggingface.co/MonoTransQuest

3https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc

4https://scikit-learn.org/stable/modules/generated/sklearn.metrics.average_precision_score.html
checks whether in the model predicted output, the highest values have been assigned to the first and second word. Specifically this metric computes the proportion of words with the highest attribution corresponding to errors against the total number of errors in the MT output (Fomicheva et al., 2021b):

\[
\text{Recall at Top-K} = \frac{1}{k} \sum_{j \in e_{1:k}} w_j \quad (3)
\]

Here, \(k\) is the number of errors in the sentence and \(e = \text{argsort}(a^xT)\) is the sequence of highest to lowest sorted indexes of target words according to the attribution scores. The final score is the average over test instances, and ranges from 0 to 1.

6 Results

We describe the performance of our models on the development and test sets using the official shared task metrics.

6.1 Development Set Results

The results achieved by each of the organizers provided baseline systems, Divergent mBERT, and our ensemble method is described in Table 4. This table described the results on the Et-En and Ro-En language pairs of the validation set. Our ensemble model outperforms the baselines, as well as its components according to all metrics.

We can see a consistent improvement for all the language pairs in the development set. In comparison with the average of all baselines, for Et-En language pair, on target word-level scores, our ensemble method achieves an improvement of 0.15 in AUC score, 0.17 in AP score, and 0.17 in Recall at Top-K score. Similarly, for the source language, it achieves an improvement of 0.236 in the AUC score, 0.13 in AP score, and 0.208 in Recall at Top-K score over the average of all baselines.

6.2 Word-level Test Results

Table 6 summarizes model performance for all the language pairs in the test set. Consistent with the development set results, the ensemble improves over all the baselines, and outperforms each of its components.

Et-En For Et-En language pair, on target word-level scores, our ensemble method achieves an improvement of 0.164 in AUC score, 0.186 in AP score, and 0.181 in Recall at Top-K score over the average of all baselines. Similarly, for the source language, it achieves an improvement of 0.236 in the AUC score, 0.13 in AP score, and 0.208 in Recall at Top-K score over the average of all baselines.

Ro-En For Ro-En language pair, on target word-level scores, our ensemble method achieves an improvement of 0.129 in AUC score, 0.173 in AP score, and 0.135 in Recall at Top-K score over the average of all baselines. Similarly, for the source language, it achieves an improvement of 0.22 in the AUC score, 0.102 in AP score, and 0.193 in Recall at Top-K score over the average of all baselines.

De-Zh For De-Zh language pair, on target word-level scores, our ensemble method achieves an improvement of 0.13 in AUC score, 0.1 in AP score, and 0.09 in Recall at Top-K score over the average of all baselines. Similarly, for the source language, it achieves an improvement of 0.123 in the AUC score, 0.01 in AP score, and 0.08 in Recall at Top-K score over the average of all baselines.

Ru-De For Ru-De language pair, on target word-level scores, our ensemble method achieves an im-
Table 4: Word-level and sentence-level scores on development data. The baseline scores are taken from the leaderboard. Best results for each language by any method are marked in bold.

Table 5: Examples of word-level labels for different models.

Table 6: Word level results for all language pairs on the test set in terms of AUC, AP and Recall at Top-K. The baseline scores are taken from the leader-board. Best results for each language by any method are marked in bold.

**Discussion** Taken together, these results show that the ensemble method performs similarly for those language pairs that are used in the training phase (Et-En, Ro-En language pairs) and for the
zero-shot language pairs (De-Zh, Ru-De). It has an average improvement of 0.15 in AUC, 0.18 in AP, and 0.16 in Recall at Top-K score for those language pairs which is in its training data and an average improvement of 0.16 in AUC, 0.13 in AP, and 0.12 in Recall at Top-K score for those language pairs which it is not trained on. Therefore, we can see we can have a consistent gain for all language pairs with this method without including that particular language pair in the training data. The Divergent mBERT model is effective on all language pairs, even though it is trained on synthetic data generated from English-French bitext: this suggests that the word-level weak supervision provided by the synthetic samples is robust, although it would be interesting to investigate the impact of the choice of training languages further in future work. Secondly, a clear takeaway is that the ensembling of different systems can give large gains, even if some of the subsystems are weak individually and even in zero-shot settings.

6.3 Sentence-level Scores on Test Set

| Pair   | System                  | Pearson’s Correlation |
|--------|-------------------------|-----------------------|
| Et-En  | Random (Baseline 1)     | -0.029                |
|        | XMover-SHAP (Baseline 2)| 0.494                 |
|        | MonoTransQuest (Baseline 3)| 0.772               |
|        | Divergent mBERT         | 0.021                 |
|        | Ensemble                | 0.772                 |
| Ro-En  | Random (Baseline 1)     | 0.017                 |
|        | XMover-SHAP (Baseline 2)| 0.695                 |
|        | MonoTransQuest (Baseline 3)| 0.899              |
|        | Divergent mBERT         | 0.661                 |
|        | Ensemble                | 0.899                 |
| De-Zh  | Random (Baseline 1)     | 0.000                 |
|        | XMover-SHAP (Baseline 2)| 0.336                 |
|        | MonoTransQuest (Baseline 3)| 0.335             |
|        | Divergent mBERT         | 0.096                 |
|        | Ensemble                | 0.495                 |
| Ru-De  | Random (Baseline 1)     | -0.017                |
|        | XMover-SHAP (Baseline 2)| 0.252                 |
|        | MonoTransQuest (Baseline 3)| 0.498             |
|        | Divergent mBERT         | 0.449                 |
|        | Ensemble                | 0.303                 |

Table 7: Results of sentence-level submissions and their performance on the test set. The baseline scores are taken from the leaderboard. Best results for each language by any method are marked in bold.

Table 7 contains the results for the sentence-level submission on the test set. Evaluated on Pearson’s correlation, our ensemble method has a consistent improvement of 0.36 for Et-En, 0.359 for Ro-En, 0.271 for De-Zh, and 0.06 for Ru-De compared to the average of all baseline models. However, in a zero-shot setting, Pearson’s correlation varies significantly between different language pairs.

We observe that the MonoTransQuest baseline achieves better performance on test language pairs, which is not surprising since it was trained on all the language pairs of WMT. This impacts results on the zero-shot languages: for De-Zh MonoTransQuest outperforms Divergent mBERT by a large margin, but the ensemble still benefits from Divergent mBERT. For Ru-De, the MonoTransQuest achieve the strongest level correlation and Divergent mBERT does not improve over it when added to the ensemble, unlike for word-level predictions.

The Divergent mBERT model has unequal performance across languages. It achieves the highest Pearson Correlation for Ro-En, which is the closest language pair to the one it is trained on (English-French) but performs poorly for Estonian-English and German-Chinese.

7 Conclusion

We described the University of Maryland’s contribution to the Eval4NLP 2021 Shared Task on Quality Estimation. Our submission was based on ensembling existing models: (1) the state-of-the-art framework MonoTransQuest model followed by the LIME explanation model, and (2) an mBERT model trained to detect cross-lingual semantic divergences. We show that averaging the prediction of these models outperforms all the baselines and their individual predictions, even though none of the ensemble components are trained with word-level supervision.

Overall, our approach shows the benefits of leveraging pre-trained multilingual LMs to port to multiple language pairs, including in zero-shot settings: the Divergent mBERT component is even trained on a language pair that is not used for any of the test tasks. In the future, training Divergent mBERT with other language pairs can lead to more promising results. This work also shows the complementarity of explanation models and of sequence labelers trained on synthetic data for word-level predictions. In future work, controlled comparison of these approaches on the same languages and data conditions can lead to further insights on their respective strengths and weaknesses.

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