Approaching English-Polish Machine Translation Quality Assessment with Neural-based Methods

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Abstract

This paper presents our contribution to the PolEval 2021 Task 2: Evaluation of translation quality assessment metrics. We describe experiments with pre-trained language models and state-of-the-art frameworks for translation quality assessment in both nonblind and blind versions of the task. Our solutions ranked second in the nonblind version and third in the blind version.

Keywords

machine translation quality estimation, machine translation evaluation, pre-trained language models, natural language processing

1. Introduction

Machine translation quality evaluation is the task of assessing translation quality based on a reference translation. In the past, traditional machine translation evaluation metrics such as BLEU (Papineni et al. 2002), METEOR (Banerjee and Lavie 2005), or CHRF (Popović 2015) relied on lexical-level features between the machine translation hypothesis and the reference translation. They remain popular to this day due to their computational speed and the fact that they can be applied to any translation direction.

The rise of Neural Machine Translation (NMT) in recent years has shown that high-quality NMT systems are often mistreated by lexical-level evaluation metrics, as such systems can generate correct translation that is lexically distant from a reference translation.

Recent advances in the field of neural language modeling (Devlin et al. 2019, Conneau et al. 2020) led to the creation of BERT cosine similarity-based metrics, such as BERTScore (Zhang et al. 2020), as well as metrics trained on human judgments, such as COMET (Rei et al. 2020) and BLEURT (Sellam et al. 2020). Human judgments include manually
assigned quality scores, such as *Direct Assessment* (DA) (Graham et al. 2013), but may also be derived from post-edited translation to calculate post-editing effort in the form of *Human-mediated Translation Edit Rate* (HTER) (Snover et al. 2006).

Machine translation quality estimation (QE) is a different task than evaluation, as the goal is to predict machine translation quality without access to a reference translation. Research on QE in recent years has shown that it is possible to achieve high levels of correlation with human judgments based only on a source segment and a machine translation hypothesis (Specia et al. 2020). Existing state-of-the-art frameworks for QE include *COMET* (Rei et al. 2020), which allows QE models to be trained in a reference-free mode and *TRANSQUEST* (Ranasinghe et al. 2020), which proposes two new architectures for QE: MONOTRANSQUEST and SIAMESETRANSQUEST.

### 2. Task description

The goal of Task 2 is to investigate metrics for automatic evaluation of machine translation in the English-Polish translation direction.

The organizers prepared distinct datasets for *nonblind* and *blind* versions of the task. The *nonblind* dataset consists of the following data: source segment, machine translation hypothesis, reference translation, and quality score. The *blind* dataset consists only of machine translation hypothesis and its quality score. The segment quality scores were created by averaging the scores assigned by six human annotators. Unlike most of the current human judgment-based QE tasks, where scores are assigned on a continuous scale (Graham et al. 2013), the task utilizes a standard Likert scale allowing ratings from 1 to 5. The evaluation metric used in both versions of the task is Pearson’s $r$ correlation score.

The datasets were split into a development set ("dev-0") and two test sets ("test-A" and "test-B"). The first of the test sets ("test-A") was the main test set during the initial testing phase of the competition and was converted to the development set with the release of the final test set ("test-B").

Table 1 presents statistics of the provided datasets: the number of segments, the average number of source tokens, the average number of MT hypothesis tokens, the minimum segment quality score, and the average segment quality score.

| Table 1: Statistics of datasets provided by organizers. |
|---------------------------------------------------------|
| **Nonblind** | **Dev-0** | **Test-A** | **Test-B** | **Blind** | **Test-A** | **Test-B** |
| Segments     | 485       | 500        | 1000       | 485       | 500        | 1000       |
| Avg. tokens (source) | 18.22  | 17.36      | 17.73      | -         | -          | -          |
| Avg. tokens (MT hypothesis) | 16.23 | 15.49      | 15.78      | 17.55     | 16.49      | 16.57      |
| Min. score   | 3.0       | 2.58       | 2.92       | 3.00      | 2.67       | 2.0        |
| Avg. score   | 4.30      | 4.37       | 4.38       | 4.33      | 4.31       | 4.40       |
3. Solutions

3.1. Nonblind task version solution

Our final solution to the nonblind version of the task is based on COMET. We used the "test-A" dataset as the training data and the "dev-0" dataset as the development data.

COMET uses pre-trained language model as the encoder for the source segment, the machine translation hypothesis, and the reference translation, which are independently encoded. Therefore, we decided to use HerBERT\textsubscript{LARGE} (Mroczkowski et al. 2021) as the pre-trained encoder model. We also experimented with XLM-RoBERTa (Conneau et al. 2020) (XLM-R) as the pre-trained encoder model, but the results were subpar. It is because HerBERT\textsubscript{LARGE} model was trained specifically for the Polish language and initialized with XLM-RoBERTa weights.

We applied gradual unfreezing and discriminative learning rates (Howard and Ruder 2018), meaning that we kept the encoder model frozen for 8 epochs while the feed-forward regressor was optimized with the learning rate of $3 \times 10^{-5}$. After 8 epochs, the entire model is fine-tuned but the learning rate is reduced to $1 \times 10^{-5}$ to avoid catastrophic forgetting. All hyperparameters used for training COMET models are presented in Table 4.

We experimented with other state-of-the-art methods for machine translation evaluation as well. We used BERTSCORE with contextual embeddings from the HerBERT\textsubscript{LARGE} model and found that it generates promising results given that it is based on cosine similarity and is not fine-tuned on the task data in any way.

Out of the trained metrics, we also experimented with BLEURT and TRANSQUEST with MONO-TRANSQUEST architecture. The BLEURT model was fine-tuned on the open-source bleurt-base-128 model\footnote{https://github.com/google-research/bleurt/blob/master/checkpoints.md} with default hyperparameters. The TRANSQUEST model was fine-tuned on the open-source English-to-Any model pre-trained on DA\footnote{https://tharindu.co.uk/TransQuest/models/sentence_level_pretrained} with default hyperparameters. TRANSQUEST is trained only on the source segment and the machine translation hypothesis and does not take into account the reference translation. The final results of all methods used in the nonblind version of the task are presented in Table 2.

Table 2: Results of the nonblind version of the task on the "test-B" dataset.

| Method            | Pearson's $r$ |
|-------------------|---------------|
| COMET (HerBERT)   | 57.28         |
| COMET (XLM-R)     | 53.84         |
| BLEURT            | 57.25         |
| TRANSQUEST        | 55.70         |
| BERTSCORE         | 48.74         |

3.2. Blind task version solution

Our final solution to the blind version of the task is based on COMET as well.
The provided dataset contains only machine translation hypotheses in this scenario. Therefore, we decided to create synthetic source segments by back-translating the provided machine translation hypotheses into English by using the open-source OPUS-MT (Tiedemann and Thottingal 2020) NMT model\(^3\), which is based on the Marian (Junczys-Dowmunt et al. 2018) framework.

We combined all the data from the nonblind dataset with the back-translated data from the blind dataset. Then, we randomly selected 100 segment pairs as the development set.

The model training procedure is the same as in the nonblind solution. The only difference is that the COMET model was trained in the reference-free mode in this scenario. Hyperparameters used for the blind model training are presented in Table 4.

In this version of the task, we also conducted experiments using TRANSQUEST. TRANSQUEST model architecture, hyperparameters, and used pre-trained model were the same as in the solution to the nonblind version of the task. The final results of all methods used in the blind version of the task are presented in Table 3.

Table 3: Results of the blind version of the task on the "test-B" dataset.

| Method        | Pearson's $r$ |
|---------------|---------------|
| COMET (HerBERT) | 47.93         |
| COMET (XLM-R)  | 43.52         |
| TRANSQUEST     | 41.71         |

Table 4: Hyperparameters used for training COMET models.

| Hyperparameter                        | Nonblind model                                      | Blind model                                         |
|---------------------------------------|-----------------------------------------------------|-----------------------------------------------------|
| Pre-trained encoder model             | HerBERT\text{\scriptsize LARGE}                     | HerBERT\text{\scriptsize LARGE}                    |
| Optimizer                             | Adam (default parameters)                           | AdamW (default parameters)                         |
| Learning rate                         | 3e$^{-5}$ and 1e$^{-5}$                             | 3.1e$^{-5}$ and 1e$^{-5}$                          |
| Layer-wise decay                      | -                                                   | 0.95                                               |
| Num. of frozen epochs                  | 8                                                   | 0.3                                                |
| Batch size                            | 4                                                   | 2                                                  |
| Accumulated gradient batches          | 2                                                   | 4                                                  |
| Loss function                         | MSE                                                 | MSE                                                |
| Dropout                               | 0.15                                                | 0.15                                               |
| Feed-forward hidden units             | 4096, 2048                                          | 2048, 1024                                          |
| Feed-forward activation function      | Tanh                                                | Tanh                                               |

4. Conclusions

We presented our contribution to the PolEval 2021 Task 2: *Evaluation of translation quality assessment metrics*.

\(^3\)https://huggingface.co/Helsinki-NLP/opus-mt-pl-en
The experiments consisted in comparing state-of-the-art methods for translation quality assessment in the English-Polish translation direction. The final solutions are based on the COMET framework. The solutions achieved second and third place in the nonblind and blind versions of the task, respectively. In the blind version of the task, we presented a procedure for creating a synthetic source segment input by back-translating machine translation hypothesis. All of the described methods are also worth further investigation in future experiments, as they generate competitive results.

The code and models used for creating the solutions are open-source and available on GitHub⁴.

References

Banerjee S. and Lavie A. (2005). METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarisation, pp. 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Conneau A., Khandelwal K., Goyal N., Chaudhary V., Wenzek G., Guzmán F., Grave E., Ott M., Zettlemoyer L. and Stoyanov V. (2020). Unsupervised cross-lingual representation learning at scale.

Devlin J., Chang M.-W., Lee K. and Toutanova K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Graham Y., Baldwin T., Moffat A. and Zobel J. (2013). Continuous measurement scales in human evaluation of machine translation. In Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse, pp. 33–41, Sofia, Bulgaria. Association for Computational Linguistics.

Howard J. and Ruder S. (2018). Universal language model fine-tuning for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 328–339, Melbourne, Australia. Association for Computational Linguistics.

Junczys-Dowmunt M., Grundkiewicz R., Dwojak T., Hoang H., Heafield K., Neckermann T., Seide F., Germann U., Fikri Aji A., Bogoychev N., Martins A. F. T. and Birch A. (2018). Marian: Fast neural machine translation in C++. In Proceedings of ACL 2018, System Demonstrations, pp. 116–121, Melbourne, Australia. Association for Computational Linguistics.

Mroczkowski R., Rybak P., Wróblewska A. and Gawlik I. (2021). HerBERT: Efficiently pre-trained transformer-based language model for Polish. In Proceedings of the 8th Workshop on

⁴https://github.com/arrurn/poleval2021-qe
Papineni K., Roukos S., Ward T. and Zhu W.-J. (2002). Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pp. 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

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

Ranasinghe T., Orasan C. and Mitkov R. (2020). Transquest: Translation quality estimation with cross-lingual transformers. In Proceedings of the 28th International Conference on Computational Linguistics.

Rei R., Stewart C., Farinha A. C. and Lavie A. (2020). COMET: A neural framework for MT evaluation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 2685–2702, Online. Association for Computational Linguistics.

Sellam T., Das D. and Parikh A. (2020). BLEURT: Learning robust metrics for text generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 7881–7892, Online. Association for Computational Linguistics.

Snover M., Dorr B., Schwartz R., Micciulla L. and Makhoul J. (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, pp. 223–231, Cambridge, Massachusetts, USA. Association for Machine Translation in the Americas.

Specia L., Blain F., Fomicheva M., Fonseca E., Chaudhary V., Guzmán F. and Martins A. F. T. (2020). Findings of the WMT 2020 shared task on quality estimation. In Proceedings of the Fifth Conference on Machine Translation, pp. 743–764, Online. Association for Computational Linguistics.

Tiedemann J. and Thottingal S. (2020). OPUS-MT — Building open translation services for the World. In Proceedings of the 22nd Annual Conference of the European Association for Machine Translation (EAMT), Lisbon, Portugal.

Zhang* T., Kishore* V., Wu* F., Weinberger K. Q. and Artzi Y. (2020). Bertscore: Evaluating text generation with bert. In International Conference on Learning Representations.