Simple-QE: Better Automatic Quality Estimation for Text Simplification

Reno Kriz∗, Marianna Apidianaki△, and Chris Callison-Burch∗
∗ Computer and Information Science Department, University of Pennsylvania
△ CNRS, LLF, France and University of Helsinki, Finland
{rekriz,ccb}@seas.upenn.edu, marianna.apidianaki@helsinki.fi

Abstract

Text simplification systems generate versions of texts that are easier to understand for a broader audience. The quality of simplified texts is generally estimated using metrics that compare to human references, which can be difficult to obtain. We propose Simple-QE, a BERT-based quality estimation (QE) model adapted from prior summarization QE work, and show that it correlates well with human quality judgments. Simple-QE does not require human references, which makes the model useful in a practical setting where users would need to be informed about the quality of generated simplifications. We also show that we can adapt this approach to accurately predict the complexity of human-written texts.

1 Introduction

Simplification systems make texts easier to understand for people with reading disabilities and language learners, or for readers not yet familiar with a specific domain. They propose re-writings using simpler, meaning-preserving words and structures. For automatically-produced simplifications to be useful in practical settings, users should be able to easily assess their quality. Traditional evaluation metrics (Papineni et al., 2002; Xu et al., 2016) estimate the quality of generated texts by comparing them to human-written simplifications, which restricts their use to settings where such references are available. In addition, comparing simplifications to a single reference is often too restrictive, as most texts can be simplified in a variety of ways.

We propose a model for measuring the quality of automatically generated simplifications, which does not require human references. Our model, Simple-Quality Estimation (Simple-QE), adapts the BERT-based summary QE model Sum-QE (Xenouleas et al., 2019), to the simplification setting. As opposed to summaries – which contain specific pieces of information from the original text(s) and omit unimportant passages – simplified text typically expresses all the content present in the original text using simpler words and structures. Both types of text, however, need to fulfill some linguistic quality constraints in order to be useful, such as being grammatical and well-formed. We show that Simple-QE correlates well with human judgments of linguistic quality on system output produced by simplification systems. In addition, we adapt our model to make reasonable complexity predictions at both the sentence and document level. Our models can be used to optimize both simplification system development and the process of writing manual simplifications.

2 Related Work

Quality Estimation (QE) methods were first introduced in the field of machine translation to measure the quality of automatically translated text without need for reference translations (Bojar et al., 2017; Martins et al., 2017; Specia et al., 2018). In the most recent QE task, the best systems leveraged BERT via pre-training for specific language pairs and integrating a transfer learning approach (Fonseca et al., 2019).

Xenouleas et al. (2019) propose several extensions to the BERT fine-tuning process (Devlin et al., 2019) to estimate summary quality. Their proposed model, Sum-QE, predicts five linguistic qualities of generated summaries using multi-task training: Grammaticality, Non-redundancy, Referential Clarity, Focus, and Structure and Coherence. Similar to state-of-the-art results obtained by BERT on many classification tasks, Xenouleas et al. (2019) show that BERT can be successfully applied to QE. In our work, we adapt Sum-QE to simplification QE, estimating the Fluency, Adequacy and Complexity of simplified text.
Most recent simplification research uses both automatic metrics and human judgments during evaluation (Zhang and Lapata, 2017; Kriz et al., 2019; Mallinson and Lapata, 2019). The metrics commonly used are BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), and SARI (Xu et al., 2016). Contrary to Simple-QE, these metrics require a reference sentence. Furthermore, BLEU correlates poorly with deletion, a core aspect of simplification (Sulem et al., 2018). SARI correlates well with human simplification judgments at the lexical level, but this does not transfer to the sentence level, as shown in our experiments.

Alva-Manchego et al. (2019) recently created a toolkit to calculate various standard automatic simplification metrics, including SARI, word-level accuracy scores, and QE features such as compression ratio and average number of added/deleted words. Recent work that addresses QE for simplification experiment with a variety of features, including sentence length, average token length, and language model probabilities (ˇStajner et al., 2016; Martin et al., 2018). However, the best models from these works also use reference-reliant features such as BLEU and translation error rate, as these have been shown to correlate with Fluency and Adequacy. Note that these works were carried out before the rise of large-scale pre-trained models (Peters et al., 2018; Devlin et al., 2019). Sum-QE and our adaptation, Simple-QE, explicitly leverage the fine-tuning capabilities of BERT for assessing the quality of generated text.

3 Methodology

To estimate the quality of a simplification system output, we focus on three linguistic aspects: (a) **Fluency**: How well-formed it is. (b) **Adequacy**: How well it preserves the meaning of the original text. (c) **Complexity**: How much simpler it is than the original text. We adapt the architecture proposed by Xenouleas et al. (2019) in their Sum-QE model, which extends the BERT fine-tuning process (Devlin et al., 2019) to rate summaries with respect to five linguistic qualities. We expect Fluency, in our setting, to align well with Grammaticality as addressed by Sum-QE. In the case of Adequacy and Complexity, since judgments are relative (e.g. is the generated text simpler than the original text? does it convey the same meaning?), we need to also consider the original complex text.

Xenouleas et al. (2019) use BERT as the main encoder and fine-tune it in three ways, one single-task and two multi-task approaches:

- **Single Task (S-1)**: Train $k$ models on each annotation type, where $k$ is the number of linguistic qualities; here, $k = 3$.
- **Multi Task-1 (M-1)**: Train one model with a single regressor to predict $k$ annotations.
- **Multi Task-$k$ (M-3)**: Train one model with $k$ separate regressors.

To adapt Sum-QE to simplification, we extend the architecture to take into account the original complex sentence. We do so by passing the original complex sentence and simplification system output through the BERT architecture separately. We concatenate the resulting embedding representations, and pass them through a final dense linear regressor layer $R$ to predict each linguistic quality score. Our adaptation of the Sum-QE Multi Task-3 (M-3) approach is described on the left side of Figure 1.

To further adapt the QE model to our task, we also attempt to incorporate task-specific features: the average **Length** of content words in a sentence in characters and in Syllables, their **Unigram Frequency**, the **Sentence Length**, and the **Character Length**.
syntactic Parse Height. We pass these features extracted from the original complex sentence separately through a linear layer, before concatenating them with the BERT embeddings of the sentence. We do the same for the system output. The right side of Figure 1 describes this architecture.

4 QE Experiments on System Output

4.1 Data and Baselines

Our test data consists of human judgments collected by Kriz et al. (2019) on generated simplifications for 200 Newsela sentences (Xu et al., 2015). For each sentence, outputs from six simplification models were considered: vanilla Sequence-to-Sequence (Seq2Seq) (Nisioi et al., 2017), Seq2Seq with reinforcement learning (Zhang and Lapata, 2017), memory-augmented Transformer (Zhao et al., 2018), and three variations of Seq2Seq with post-training re-ranking Kriz et al. (2019). Annotators were asked to rate the Fluency, Adequacy, and Complexity of each system output on a 5-point Likert Scale.

We compare the Simple-QE model to baselines that use the simplification-specific features described in Section 3, quality estimates provided by BLEU (Papineni et al., 2002) and SARI (Xu et al., 2016), and three additional BERT-based baselines.

- **BERT as Language Model (BERT LM):** Given a sentence, we mask each token and predict the likelihood of the true word occurring in this context; this captures Fluency.

- **BERT embedding similarity (BERT Sim):** We convert the original and simplified texts into sentence-level BERT vector representations via mean pooling, and compute their cosine similarity; this estimates Adequacy.

- **Sum-QE:** We apply Sum-QE directly, fine-tuning only on annotated system output. For Sum-QE and Simple-QE, we perform 10-fold cross validation, combining the results to compute the overall correlation.

4.2 Results

The results are shown in Table 1. Simple-QE correlates better with human judgments than the baseline models tested. The correlation of BLEU and SARI with human judgments is particularly low, especially for Complexity. This is not surprising, given that SARI mainly addresses lexical simplification, while recent models approach simplification more holistically.

The three versions of Simple-QE perform similar to Sum-QE on Fluency, where the model does not need to access the original complex sentence. The difference between the two models is more noticeable for Adequacy and Complexity, where accessing the original sentence actually helps Simple-QE make more reasonable estimates. From the three versions of Simple-QE tested, the multi-task versions perform better than the single task on all three qualities tested. The BERT LM and BERT Sim baselines perform well on Fluency and Adequacy, as expected, but fall short on the other aspects of simplification.

As shown in Table 1, adding numeric features do not improve performance. This may be because the most predictive features, e.g. sentence length, are already implicitly learned by BERT.

5 Complexity Prediction on Human-written Text

5.1 Datasets

As seen in the previous section, Simple-QE makes reasonable estimates for Fluency and Adequacy.

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Table 1: Pearson correlation with human Fluency (F), Adequacy (A) and Complexity (C) judgments on simplification system output. The last three rows incorporate three numeric feature sets: Sentence Length (SL), Parse tree height (PH), and all features from Section 3.

| Model               | F     | A     | C     |
|---------------------|-------|-------|-------|
| BLEU                | 0.183 | 0.305 | 0.057 |
| SARI                | 0.133 | 0.207 | 0.013 |
| BERT LM             | 0.411 | 0.350 | 0.249 |
| BERT Sim            | 0.278 | 0.533 | 0.085 |
| Sum-QE S-1          | 0.619 | 0.489 | 0.388 |
| Sum-QE M-1          | 0.632 | 0.541 | 0.407 |
| Sum-QE M-3          | 0.638 | 0.518 | 0.418 |
| Simple-QE S-1       | 0.635 | 0.549 | 0.436 |
| Simple-QE M-1       | 0.643 | 0.630 | 0.433 |
| Simple-QE M-3       | 0.648 | 0.612 | 0.464 |
| Simple-QE M-3 SL PH | 0.649 | 0.538 | 0.443 |
| Simple-QE M-3 SL    | 0.650 | 0.541 | 0.432 |
| Simple-QE M-3 All   | 0.650 | 0.538 | 0.436 |

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Google n-gram corpus (Brants and Franz, 2006).

We do not use the QE dataset introduced by Štajner et al. (2016), as it focuses on small-scale lexical changes – similar to the Turk dataset (Xu et al., 2016) – while current neural models adopt a more holistic approach.

https://github.com/xu-song/bert-as-language-model

The syntax of a sentence can be extracted from contextual word embeddings with reasonable accuracy (Hewitt and Manning, 2019).
but scores lower on Complexity. To explore this further, we test Sum-QE's capability to predict the Complexity of hand-written text. Assuming this text is relatively well-formed, we can in this way focus on how the model deals with Complexity.

We perform this analysis on the entire Newsela Corpus (Xu et al., 2015), which contains 1,840 English news articles re-written at four complexity levels.\textsuperscript{5} We explore how well fine-tuning BERT performs, compared to incorporating features into a linear regression classifier (LinReg). Since we only address Complexity, we only consider the Single Task approach (Simple-QE S-1).

5.2 Sentence-level Complexity Prediction

We generate data by labelling sentences from Newsela articles with the complexity level of the corresponding document (0 to 4). When a sentence is found at different complexity levels, we label it with the level of the simplest article in which it appears; this results in 370,376 sentences. We measure the correlation between each feature and the sentence’s complexity level, and perform 10-fold cross-validation for LinReg and Simple-QE S-1. The results of this experiment are shown in the first column of Table 2. Sentence length is the most predictive feature, and combining all the features using a linear regression classifier improves correlation, but both are outperformed by our model.

5.3 Document-level Complexity Prediction

Most recent work has focused on sentence simplification, but document-level simplification might be more useful in practical settings. Given that BERT can only process 512 sub-word units at a time, we break a document down into sub-documents of up to 512 sub-word units. At test time, to get a single document-level complexity prediction, we take a length-based weighted average of the predictions for the sub-documents. The results of this experiment are shown in the second column of Table 2. We can see that, while sentence length and our linear regression classifier incorporating all features perform quite well, our model improves correlation even further.

5.4 Out-of-Domain Evaluation

Finally, we use PWKP (Zhu et al., 2010) to explore how well our complexity prediction model transfers to a different domain. We extract parallel texts from Simple and standard English Wikipedia dumps,\textsuperscript{6} aligning texts by their unique article ID. We label each Simple Wikipedia document with 0 (simpler) and each standard Wikipedia document with 1 (more complex). The alignment procedure results in 57,204 parallel documents. Similar to our document-level complexity prediction experiments, we combine the sentence and sub-document predictions into a single document-level prediction. In this experiment, our model reaches a Pearson correlation of 0.729. While this is lower than our in-domain Newsela experiments, it is still reasonably high, showing that our model can be applied for complexity prediction on other domains.

6 Conclusion

We present Simple-QE, a quality estimation model for simplification. We have shown that extending Sum-QE (Xenoulas et al., 2019) to include the reference complex sentence sensibly improves predictions on Adequacy and Complexity. QE systems can be useful for evaluating the overall quality of model output without requiring expensive human annotations or references. Future simplification systems can incorporate Simple-QE into the optimization process, similar to how SARI was incorporated into a Seq2Seq network (Zhang and Lapata, 2017). As shown, a fine-tuned BERT can also predict the complexity of human-written text, especially at the document level. This finding can be leveraged in future work as the simplification field moves towards simplifying entire documents.

\textsuperscript{5}https://newsela.com

\textsuperscript{6}The Wikipedia dumps used can be found at https://dumps.wikimedia.org/simplewiki/ and https://dumps.wikimedia.org/enwiki/

| Model          | Sentence | Document |
|----------------|----------|----------|
| Word Length    | 0.226    | 0.614    |
| Syllables      | 0.235    | 0.614    |
| Frequency      | 0.051    | 0.415    |
| Sentence Length| 0.548    | 0.907    |
| Parse Height   | 0.341    | 0.795    |
| LinReg         | 0.574    | 0.919    |
| Simple-QE S-1  | 0.726    | 0.964    |

Table 2: Pearson correlation of the fine-tuned BERT model and different feature-based baselines on the Complexity prediction task at the sentence and the document-level.
References

Fernando Alva-Manchego, Louis Martin, Carolina Scarton, and Lucia Specia. 2019. EASSE: Easier Automatic Sentence Simplification Evaluation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP): System Demonstrations, pages 49–54, Hong Kong, China. Association for Computational Linguistics.

Satyanjee Banerjee and Alon Lavie. 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 Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

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

Thorsten Brants and Alex Franz. 2006. Web IT 5-gram Version 1. In LDC2006T13, Philadelphia, Pennsylvania. Linguistic Data Consortium.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 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), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Erick Fonseca, Lisa Yankovskaya, André F. T. Martins, Mark Fishel, and Christian Federmann. 2019. Findings of the WMT 2019 shared tasks on quality estimation. In Proceedings of the Fourth Conference on Machine Translation (Volume 3: Shared Task Papers, Day 2), pages 1–10, Florence, Italy. Association for Computational Linguistics.

John Hewitt and Christopher D. Manning. 2019. A Structural Probe for Finding Syntax in Word Representations. 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), pages 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Reno Kriz, João Sedoc, Marianna Apidianaki, Carolina Zheng, Gaurav Kumar, Eleni Miltsakaki, and Chris Callison-Burch. 2019. Complexity-Weighted Loss and Diverse Reranking for Sentence Simplification. In Proceedings of NAACL 2019: Human Language Technologies, Volume 1, pages 3137–3147.

Jonathan Mallinson and Mirella Lapata. 2019. Controllable Sentence Simplification: Employing Syntactic and Lexical Constraints. arXiv.

Louis Martin, Samuel Humeau, Pierre-Emmanuel Mazaré, Éric de La Clergerie, Antoine Bordes, and Benoît Sagot. 2018. Reference-less Quality Estimation of Text Simplification Systems. In Proceedings of the 1st Workshop on Automatic Text Adaptation (ATA), pages 29–38, Tilburg, the Netherlands. Association for Computational Linguistics.

André F. T. Martins, Marcin Junczys-Dowmunt, Fabio N. Kepler, Ramón Astudillo, Chris Hokamp, and Roman Grundkiewicz. 2017. Pushing the Limits of Translation Quality Estimation. Transactions of the Association for Computational Linguistics, 5:205–218.

Sergiu Nisoi, Sanja Štajner, Simone Paolo Ponzetto, and Liviu P. Dinu. 2017. Exploring Neural Text Simplification Models. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 85–91, Vancouver, Canada. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: a Method for Automatic Evaluation of Machine Translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep Contextualized Word Representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.

Lucia Specia, Frédéric Blain, Varvara Logacheva, Ramón Astudillo, and André F. T. Martins. 2018. Findings of the WMT 2018 Shared Task on Quality Estimation. In Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pages 689–709, Belgium, Brussels. Association for Computational Linguistics.

Elior Sulem, Omri Abend, and Ari Rappoport. 2018. BLEU is not suitable for the evaluation of text simplification. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 738–744, Brussels, Belgium. Association for Computational Linguistics.
Stratos Xenouleas, Prodromos Malakasiotis, Marianna Apidianaki, and Ion Androutsopoulos. 2019. SUM-QE: a BERT-based Summary Quality Estimation Model. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6004–6010, Hong Kong, China. Association for Computational Linguistics.

Wei Xu, Chris Callison-Burch, and Courtney Napoles. 2015. Problems in Current Text Simplification Research: New Data Can Help. Transactions of the Association for Computational Linguistics, 3:283–297.

Wei Xu, Courtney Napoles, Ellie Pavlick, Quanze Chen, and Chris Callison-Burch. 2016. Optimizing Statistical Machine Translation for Text Simplification. Transactions of the Association for Computational Linguistics, 4:401–415.

Xingxing Zhang and Mirella Lapata. 2017. Sentence Simplification with Deep Reinforcement Learning. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 584–594, Copenhagen, Denmark. Association for Computational Linguistics.

Sanqiang Zhao, Rui Meng, Daqing He, Andi Saptono, and Bambang Parmanto. 2018. Integrating Transformer and Paraphrase Rules for Sentence Simplification. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3164–3173, Brussels, Belgium. Association for Computational Linguistics.

Zhemin Zhu, Delphine Bernhard, and Iryna Gurevych. 2010. A Monolingual Tree-based Translation Model for Sentence Simplification. In Proceedings of the 23rd International Conference on Computational Linguistics (Coling 2010), pages 1353–1361, Beijing, China. Coling 2010 Organizing Committee.

Sanja Štajner, Maja Popovic, and Hanna Béchara. 2016. Quality Estimation for Text Simplification. In Proceedings of the LREC Workshop on Quality Assessment for Text Simplification, pages 15–21, Portoroz, Slovenia.