Semantic Features Based on Word Alignments for Estimating Quality of Text Simplification

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Abstract

This paper examines the usefulness of semantic features based on word alignments for estimating the quality of text simplification. Specifically, we introduce seven types of alignment-based features computed on the basis of word embeddings and paraphrase lexicons. Through an empirical experiment using the QATS dataset (Štajner et al., 2016b), we confirm that we can achieve the state-of-the-art performance only with these features.

1 Introduction

Text simplification is the task of rewriting complex text into a simpler form while preserving its meaning. Systems that automatically pursue this task can potentially be used for assisting reading comprehension of less language-competent people, such as learners (Petersen and Ostendorf, 2007) and children (Belder and Moens, 2010). Such systems would also improve the performance of other natural language processing tasks, such as information extraction (Evans, 2011) and machine translation (MT) (Štajner and Popović, 2016).

Similarly to other text-to-text generation tasks, such as MT and summarization, the outputs of text simplification systems have been evaluated subjectively by humans (Wubben et al., 2012; Štajner et al., 2014) or automatically by comparing with handcrafted reference texts (Specia, 2010; Coster and Kauchak, 2011; Xu et al., 2016). However, the former is costly and not replicable, and the latter has achieved only a low correlation with human evaluation.

On the basis of this backdrop, Quality Estimation (QE) (Specia et al., 2010), i.e., automatic evaluation without reference, has been drawing much attention in the research community. In the shared task on quality assessment for text simplification (QATS),† two tasks have been addressed (Štajner et al., 2016b). One is to estimate a real-value quality score for given sentence pair, while the other is to classify given sentence pair into one of the three classes (good, ok, and bad). In the classification task of the QATS workshop, systems based on deep neural networks (Paetzold and Specia, 2016a) and MT metrics (Štajner et al., 2016a) have achieved the best performance. However, deep neural networks are rather unstable because of the difficulty of training on a limited amount of data; for instance, the QATS dataset offers only 505 sentence pairs for training. MT metrics are incapable of properly capturing deletions that are prevalent in text simplification (Coster and Kauchak, 2011), as they are originally designed to gauge semantic equivalence. In fact, as shown in Table 1, well-known MT metrics are strongly biased by the length difference between original and simple sentences (r_length), while they are less correlated with the manually-labeled quality (r_label).

Table 1: The QATS training data shows that typical MT metrics are strongly biased by the length difference between original and simple sentences (r_length), while they are less correlated with the manually-labeled quality (r_label).

| Metrics | r_length | r_label |
|---------|----------|---------|
| BLEU    | -0.765   | 0.245   |
| METEOR  | -0.617   | 0.257   |
| TER     | 0.741    | -0.233  |
| WER     | 0.757    | -0.230  |

†http://qats2016.github.io/shared.html
spondences using two pre-compiled external resources: (a) word embeddings learned from large-scale monolingual data and (b) a large-scale paraphrase lexicon. Using the QATS dataset, we empirically demonstrate that a supervised classifier trained upon such features achieves good performance in the classification task.

2 Semantic Features Based on Word Alignments

We bring a total of seven types of features that are proven useful for the similar task, i.e., finding corresponding sentence pairs within English Wikipedia and Simple English Wikipedia (Hwang et al., 2015; Kajiwara and Komachi, 2016). Specifically, we assume that some of these features are useful to capture inequivalency between original sentence and its simplified version introduced during simplification, such as lexical paraphrases and deletion of words and phrases.

Throughout this section, original sentence and its simplified version are referred to as \(x\) and \(y\), respectively.

2.1 AES: Additive Embeddings Similarity
Given two sentences, \(x\) and \(y\), AES between them is computed as follows.

\[
AES(x, y) = \cos \left( \sum_{i=1}^{\|x\|} \frac{x_i}{\|x\|} \sum_{j=1}^{\|y\|} \frac{y_j}{\|y\|} \right)
\]  

(1)

where each sentence is vectorized with the sum of the word embeddings of its component words, \(\vec{x}_i\) and \(\vec{y}_j\), assuming the additive compositionality (Mikolov et al., 2013).

2.2 AAS: Average Alignment Similarity
AAS (Song and Roth, 2015) averages the cosine similarities between all pairs of words within given two sentences, \(x\) and \(y\), calculated over their embeddings.

\[
AAS(x, y) = \frac{1}{\|x\|\|y\|} \sum_{i=1}^{\|x\|} \sum_{j=1}^{\|y\|} \cos(\vec{x}_i, \vec{y}_j)
\]  

(2)

2.3 MAS: Maximum Alignment Similarity
AAS inevitably involves noise, as many word pairs are semantically irrelevant to each other. MAS (Song and Roth, 2015) reduces this kind of noise by considering only the best word alignment for each word in one sentence as follows.

\[
MAS(x, y) = \frac{1}{\|x\|} \sum_{i=1}^{\|x\|} \max_{j} \cos(\vec{x}_i, \vec{y}_j)
\]  

(3)

As MAS is asymmetric, we calculate it for each direction, i.e., \(MAS(x, y)\) and \(MAS(y, x)\), unlike Kajiwara and Komachi (2016) who has averaged these two values.

2.4 HAS: Hungarian Alignment Similarity
AAS and MAS deal with many-to-many and one-to-many word alignments, respectively. On the other hand, HAS (Song and Roth, 2015) is based on one-to-one word alignments.

The task of identifying the best one-to-one word alignments \(\mathcal{H}\) is regarded as a problem of bipartite graph matching, where the two sets of vertices respectively comprise words within each sentence \(x\) and \(y\), and the weight of an edge between \(x_i\) and \(y_j\) is given by the cosine similarity calculated over their word embeddings. Given \(\mathcal{H}\) identified using the Hungarian algorithm (Kuhn, 1955), HAS is computed by averaging the similarities between embeddings of the aligned pairs of words.

\[
HAS(x, y) = \frac{1}{|\mathcal{H}|} \sum_{(i,j) \in \mathcal{H}} \cos(\vec{x}_i, \vec{y}_j)
\]  

(4)

where \(|\mathcal{H}| = \min(|x|, |y|)\), as \(\mathcal{H}\) contains only one-to-one word alignments.

2.5 WMD: Word Mover’s Distance
WMD (Kusner et al., 2015) is a special case of the Earth Mover’s Distance (Rubner et al., 1998), which solves the transportation problem of words between two sentences represented by a bipartite graph.\(^2\) Let \(n\) be the vocabulary size of the language, WMD is computed as follows.

\[
WMD(x, y) = \min \sum_{u=1}^{n} \sum_{v=1}^{n} A_{uv} \text{emd}(\vec{x}_u, \vec{y}_v)
\]  

subject to:

\[
\sum_{u=1}^{n} A_{uv} = \frac{1}{|x|} \text{freq}(x_u, x)
\]

\[
\sum_{u=1}^{n} A_{uv} = \frac{1}{|y|} \text{freq}(y_v, y)
\]

\(^2\)Note that the vertices in the graph represent the word types, unlike the token-based graph for HAS.
where $A_{uv}$ is a nonnegative weight matrix representing the flow from a word $x_u$ in $x$ to a word $y_v$ in $y$, $\text{euclid}(\cdot, \cdot)$ the Euclidean distance between two word embeddings, and $freq(\cdot, \cdot)$ the frequency of a word in a sentence.

### 2.6 DWE: Difference of Word Embeddings

We also introduce the difference between sentence embeddings so as to gauge their differences in terms of meaning and simplicity. As the representation of a sentence, we used the averaged word embeddings (Adi et al., 2017).

$$\text{DWE}(x, y) = \frac{1}{|x|} \sum_{i=1}^{|x|} \vec{x}_i - \frac{1}{|y|} \sum_{j=1}^{|y|} \vec{y}_j \quad (6)$$

### 2.7 PAS: Paraphrase Alignment Similarity

PAS (Sultan et al., 2014, 2015) is computed based on lexical paraphrases. This feature has been proven useful in the semantic textual similarity task of SemEval-2015 (Agirre et al., 2015).

$$\text{PAS}(x, y) = \frac{\text{PA}(x, y) + \text{PA}(y, x)}{|x| + |y|} \quad (7)$$

$$\text{PA}(x, y) = \sum_{i=1}^{|x|} \left\{ \begin{array}{ll} 1 & \exists j : x_i \leftrightarrow y_j \in y \\ 0 & \text{otherwise} \end{array} \right. \quad (6)$$

where $x_i \leftrightarrow y_j$ holds if and only if the word pair $(x_i, y_j)$ is included in a given paraphrase lexicon.

### 3 Experiment

The usefulness of the above features was evaluated through an empirical experiment using the QATS dataset (Štajner et al., 2016b).

#### 3.1 Data

The QATS dataset consists of 505 and 126 sentence pairs for training and test, respectively, where each pair is evaluated from four different aspects: Grammaticality, Meaning preservation, Simplicity, and Overall quality. Evaluations are given by one of the three classes: good, ok, and bad.

We used two pre-compiled external resources to compute our features. One is the pre-trained 300-dimensional CBOW model\(^3\) to compute the features based on word embeddings, while the other is PPDB 2.0 (Pavlick et al., 2015)\(^4\) for PAS.

### 3.2 Evaluation Metrics

Each system is evaluated by the three metrics as in the QATS classification task (Štajner et al., 2016b): Accuracy (A), Mean Absolute Error (E) and Weighted F-score (F). To compute Mean Absolute Error, class labels were converted into three equally distant numeric scores retaining their relation, i.e., $\text{good} = 1$, $\text{ok} = 0.5$, and $\text{bad} = 0$.

#### 3.3 Baseline Systems

As the baseline, we employed four types of systems from the QATS workshop (Štajner et al., 2016b): two typical baselines and two top-ranked systems. “Majority-class” labels all the sentence pairs with the most frequent class in the training data. “MT-baseline” combines BLEU (Papineni et al., 2002), METEOR (Lavie and Denkowski, 2009), TER (Snover et al., 2006), and WER (Levenshtein, 1966), using a support vector machine (SVM) classifier.

SimpleNets (Paetzold and Specia, 2016a) has two different forms of deep neural network architectures: multi-layer perceptron (SimpleNets-MLP) and recurrent neural network (SimpleNets-RNN). SimpleNets-MLP uses seven features of each sentence: the number of characters, tokens, and word types, 5-gram language model probabilities estimated on the basis of either SUBTLEX (Brysbaert and New, 2009), SubIMDB (Paetzold and Specia, 2016b), Wikipedia, and Simple Wikipedia (Kauchak, 2013). SimpleNets-RNN, which does not require such feature engineering, uses embeddings of word $N$-grams.

SMH (Štajner et al., 2016a) has two types of classifiers: logistic classifier (SMH-IBk/Logistic) and random forest classifier (SMH-RandForest, SMH-RandForest-b). Both are trained relying on the automatic evaluation metrics for MT, such as BLEU, METEOR, and TER, in combination with the QE features for MT (Specia et al., 2013).

Instead of reimplementing the above baseline systems, we excerpted their performance scores from (Štajner et al., 2016b).

#### 3.4 Systems with Proposed Features

We evaluated our proposed features in the supervised classification fashion as previous work. Specifically, we compared three types of supervised classifiers that had been also used in the above baseline systems: SVM, MLP, and RandForest. Hyper-parameters of each system were de-
Table 2: Results on QATS classification task. The best scores of each metric are highlighted in bold. Scores other than ours are excerpted from Stajner et al. (2016b).

| System                        | Grammaticality | Meaning | Simplicity | Overall |
|-------------------------------|----------------|---------|------------|---------|
| Majority-class               | 76.2           | 18.3    | 65.9       | 57.9    |
| MT-baseline                  | 76.2           | 18.3    | 65.9       | 57.9    |
| SimpleNets-MLP               | 74.6           | 17.1    | 68.8       | 53.2    |
| SimpleNets-RNN (N = 2)       | 75.4           | 18.7    | 65.5       | 50.0    |
| SimpleNets-RNN (N = 3)       | 74.6           | 19.1    | 65.1       | 52.4    |
| SMH-IBk/Logistic             | 70.6           | 19.4    | 71.6       | 50.0    |
| SMH-RandForest               | 75.4           | 17.5    | 71.8       | 52.4    |
| SMH-RandForest-b             | 75.4           | 18.3    | 70.0       | 57.1    |

| Best score among the above   | 76.2           | 17.1    | 71.8       | 57.1    |
| Our SVM                      | 76.2           | 18.3    | 65.9       | 57.9    |
| Our MLP                      | 68.3           | 24.6    | 66.9       | 59.5    |
| Our RandForest               | 76.2           | 18.3    | 65.9       | 63.5    |
| Our SVM w/ MT-baseline       | 76.2           | 18.3    | 65.9       | 63.5    |
| Our MLP w/ MT-baseline       | 63.5           | 26.6    | 63.8       | 64.3    |
| Our RandForest w/ MT-baseline| 76.2           | 18.3    | 65.9       | 61.9    |

| Feature set                  | C   | γ   | Grammaticality | Meaning | Simplicity | Overall |
|-------------------------------|-----|-----|----------------|---------|------------|---------|
| ALL                           | 1.0 | 0.1 | 76.2           | 65.1    | 57.1       | 57.9    |
| -AES                          | 1.0 | 0.1 | 76.2           | 65.1    | 57.1       | 57.9    |
| -MAS(original, simple)        | 0.1 | 0.1 | 76.2           | 57.9    | 55.6       | 56.4    |
| -MAS(simple, original)        | 1.0 | 0.1 | 76.2           | 64.3    | 57.1       | 54.8    |
| -PAS                          | 0.1 | 0.1 | 76.2           | 57.9    | 55.6       | 53.2    |
| -DWE                          | 0.01| 1.0 | 76.2           | 57.9    | 55.6       | 51.6    |
| -WMD                          | 0.01| 0.1 | 76.2           | 57.9    | 55.6       | 46.8    |
| -AAS                          | 0.1 | 0.1 | 76.2           | 57.9    | 55.6       | 45.2    |
| -HAS                          | 0.01| 0.01| 76.2           | 57.9    | 55.6       | 38.7    |

Table 3: Ablation analysis on accuracy. Features are in descending order of overall accuracy.

3.5 Results

Experimental results are shown in Table 2. The SVM classifier based on our features greatly outperformed the state-of-the-art methods in terms of overall quality. The RandForest classifier somehow achieved the best simplicity scores ever, even though we had optimized the system with respect to the accuracy of overall quality. As we expected, MLP did not beat the other two classifiers, presumably due to the scarcity of the training data. The bottom three rows reveal that the performance in terms of overall quality was deteriorated when MT-baseline features were incorporated on top of our feature set. This suggests that word embeddings are superior to surface-level processing in finding corresponding words within sentence pairs.

Focusing on the overall quality, we conducted an ablation analysis of the SVM classifier. The analysis revealed, as shown in Table 3, that HAS, AAS, and WMD were the most important features. This can be explained by the role of word alignments during the computation. Since MT metrics, such as BLEU, rely only on surface-level matches, they are insensitive to meaning-
While historians *concur* that the result itself was *not manipulated*, the voting process was neither free nor secret.

**Simple**

*Most* historians *agree* that the result was *not fixed*, but the voting process was neither free nor secret.

**Hungarian Alignment**

(while, but), (concur, agree), (itself, most), (manipulated, fixed), and identical word pairs.

Table 4: An example of word alignment. Differences between the original and simplified versions are presented in bold. This is a sentence pair from *good* class on overall quality. HAS using word-level similarity reaches 0.85, while BLEU is 0.54.

| Feature   | $r_{\text{length}}$ | $r_{\text{label}}$ |
|-----------|----------------------|---------------------|
| AES       | -0.661               | 0.185               |
| AAS       | -0.335               | 0.318               |
| MAS(original, simple) | -0.817 | 0.226 |
| MAS(simple, original) | 0.092 | -0.090 |
| HAS       | 0.061                | -0.050              |
| WMD       | 0.788                | -0.215              |
| PAS       | -0.120               | -0.039              |

Table 5: Correlation between each feature and the difference of sentence length and the manually-labeled quality. Note that DWE cannot be included, as it is not a scalar value but the differential vector between original and simplified sentences.

The contribution of WMD was expected as it was proven effective in the sentence alignment task of English Wikipedia and Simple English Wikipedia (Kajiwara and Komachi, 2016).

Table 5 shows that some of our semantic similarity features are also strongly biased by the length difference between original and simple sentences, as MT metrics (cf. Table 1). Nonetheless, HAS was not biased by the length difference almost at all, and AAS and WMD highly correlated with the manually-labeled quality.

### 4 Conclusions

We presented seven types of semantic similarity features based on word alignments for quality estimation of text simplification. Unlike existing MT metrics, our features can flexibly deal with word alignments, taking deletions and paraphrases into account. Our SVM classifier based on these features achieved the best performance on the QATS dataset.

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### References

Adi, Yossi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. 2017. Fine-grained Analysis of Sentence Embeddings Using Auxiliary Prediction Tasks. In *International Conference on Learning Representations*.

Agirre, Eneko, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Inigo Lopez-Gazpio, Montse Maritxalar, Rada Mihalcea, German Rigau, Larraitz Uria, and Janice Wiebe. 2015. SemEval-2015 Task 2: Semantic Textual Similarity, English, Spanish and Pilot on Interpretability. In *Proceedings of the 9th International Workshop on Semantic Evaluation*. pages 252–263.

Apidianaki, Marianna. 2016. Vector-space models for PPDB paraphrase ranking in context. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. pages 2028–2034.

Belderr, Jan De, and Marie-Francine Moens. 2010. Text Simplification for Children. In *Proceedings of the SIGIR Workshop on Accessible Search Systems*. pages 19–26.

Biran, Or, Samuel Brody, and Noemie Elhadad. 2011. Putting it Simply: a Context-Aware Approach to Lexical Simplification. In *Proceedings of the 49th
Annual Meeting of the Association for Computational Linguistics: Human Language Technologies. pages 496–501.

Marc Brysbaert and Boris New. 2009. Moving beyond Kučera and Francis: A Critical Evaluation of Current Word Frequency Norms and the Introduction of a New and Improved Word Frequency Measure for American English. Behavior Research Methods 41(4):977–990.

William Coster and David Kauchak. 2011. Simple English Wikipedia: A New Text Simplification Task. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies. pages 665–669.

Richard J. Evans. 2011. Comparing methods for the syntactic simplification of sentences in information extraction. Literary and Linguistic Computing 26(4):371–388.

William Hwang, Hannaneh Hajishirzi, Mari Ostendorf, and Wei Wu. 2015. Aligning Sentences from Standard Wikipedia to Simple Wikipedia. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. pages 211–217.

Tomoyuki Kajiwara and Mamoru Komachi. 2016. Building a Monolingual Parallel Corpus for Text Simplification Using Sentence Similarity Based on Alignment between Word Embeddings. In Proceedings of the 26th International Conference on Computational Linguistics. pages 1147–1158.

David Kauchak. 2013. Improving Text Simplification Language Modeling Using Unsimplified Text Data. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics. pages 1537–1546.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In Proceedings of the 3rd International Conference on Learning Representations.

Harold W. Kuhn. 1955. The Hungarian Method for the Assignment Problem. Naval Research Logistics Quarterly 2:83–97.

Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From Word Embeddings To Document Distances. In Proceedings of The 32nd International Conference on Machine Learning. pages 957–966.

Alon Lavie and Michael Denkowski. 2009. The ME-TETOR Metric for Automatic Evaluation of Machine Translation. Machine Translation 23(2-3):105–115.

Vladimir Isosovich Levenshtein. 1966. Binary Codes Capable of Correcting Deletions, Insertions and Reversals. Soviet Physics Doklady 10(8):707–710.

Oren Melamud, Omer Levy, and Ido Dagan. 2015. A Simple Word Embedding Model for Lexical Substitution. In Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing. pages 1–7.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed Representations of Words and Phrases and Their Compositionality. In Advances in Neural Information Processing Systems. pages 3111–3119.

Gustavo H. Paetzold and Lucia Specia. 2016a. SimpleNets: Evaluating Simplifiers with Resource-Light Neural Networks. In LREC 2016 Workshop & Shared Task on Quality Assessment for Text Simplification. pages 42–46.

Gustavo H. Paetzold and Lucia Specia. 2016b. Unsupervised Lexical Simplification for Non-Native Speakers. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence. pages 3761–3767.

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

Ellie Pavlick, Pushpendre Rastogi, Juri Ganitkevitch, Benjamin Van Durme, and Chris Callison-Burch. 2015. PPDB 2.0: Better paraphrase ranking, fine-grained entailment relations, word embeddings, and style classification. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing. pages 425–430.

Sarah E. Petersen and Mari Ostendorf. 2007. Text Simplification for Language Learners: A Corpus Analysis. In Proceedings of the Speech and Language Technology in Education Workshop. pages 69–72.

Stephen Roller and Katrin Erk. 2016. PIC a Different Word: A Simple Model for Lexical Substitution in Context. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. pages 1121–1126.

Yossi Rubner, Carlo Tomasi, and Leonidas J. Guibas. 1998. A Metric for Distributions with Applications to Image Databases. In Proceedings of the Sixth International Conference on Computer Vision. pages 59–66.

Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Muccilwa, and John Makhoul. 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. pages 1–9.
Yangqiu Song and Dan Roth. 2015. Unsupervised Sparse Vector Densification for Short Text Similarity. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. pages 1275–1280.

Lucia Specia. 2010. Translating from Complex to Simplified Sentences. In Proceedings of the 9th International Conference on Computational Processing of the Portuguese Language. pages 30–39.

Lucia Specia, Dhwaj Raj, and Marco Turchi. 2010. Machine Translation Evaluation versus Quality Estimation. Machine Translation 24(1):39–50.

Lucia Specia, Kashif Shah, Jose G.C. de Souza, and Trevor Cohn. 2013. QuEst - A translation quality estimation framework. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics. pages 79–84.

Md Arafat Sultan, Steven Bethard, and Tamara Sumner. 2014. Back to Basics for Monolingual Alignment: Exploiting Word Similarity and Contextual Evidence. Transactions of the Association for Computational Linguistics 2:219–230.

Md Arafat Sultan, Steven Bethard, and Tamara Sumner. 2015. DLS@CU: Sentence Similarity from Word Alignment and Semantic Vector Composition. In Proceedings of the 9th International Workshop on Semantic Evaluation. pages 148–153.

Sanja Štajner, Ruslan Mitkov, and Horacio Saggion. 2014. One Step Closer to Automatic Evaluation of Text Simplification Systems. In Proceedings of the 3rd Workshop on Predicting and Improving Text Readability for Target Reader Populations. pages 1–10.

Sanja Štajner and Maja Popović. 2016. Can Text Simplification Help Machine Translation? Baltic Journal of Modern Computing 4(2):230–242.

Sanja Štajner, Maja Popović, and Hanna Béchara. 2016a. Quality Estimation for Text Simplification. In LREC 2016 Workshop & Shared Task on Quality Assessment for Text Simplification. pages 15–21.

Sanja Štajner, Maja Popović, Horacio Saggion, Lucia Specia, and Mark Fishel. 2016b. Shared Task on Quality Assessment for Text Simplification. In LREC 2016 Workshop & Shared Task on Quality Assessment for Text Simplification. pages 22–31.

Sander Wubben, Antal van den Bosch, and Emiel Krahmer. 2012. Sentence Simplification by Monolingual Machine Translation. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics. pages 1015–1024.

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.