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If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.
We introduce EASSE, a Python package aiming to facilitate and standardise automatic evaluation and comparison of Sentence Simplification (SS) systems. EASSE provides a single access point to a broad range of evaluation resources: standard automatic metrics for assessing SS outputs (e.g. SARI), word-level accuracy scores for certain simplification transformations, reference-independent quality estimation features (e.g. compression ratio), and standard test data for SS evaluation (e.g. TurkCorpus). Finally, EASSE generates easy-to-visualise reports on the various metrics and features above and on how a particular SS output fares against reference simplifications. Through experiments, we show that these functionalities allow for better comparison and understanding of the performance of SS systems.

1 Introduction

Sentence Simplification (SS) consists of modifying the content and structure of a sentence to improve its readability while retaining its original meaning. For automatic evaluation of a simplification output, it is common practice to use machine translation (MT) metrics (e.g. BLEU (Papineni et al., 2002)), simplicity metrics (e.g. SARI (Xu et al., 2016)), and readability metrics (e.g. FKGL (Kincaid et al., 1975)).

Most of these metrics are available in individual code repositories, with particular software requirements that sometimes differ even in programming language (e.g. corpus-level SARI is implemented in Java, whilst sentence-level SARI is available in both Java and Python). Other metrics (e.g. SAMSA (Sulem et al., 2018b)) suffer from insufficient documentation or require executing multiple scripts with hard-coded paths, which prevents researchers from using them.

2 Package Overview

2.1 Automatic Corpus-level Metrics

Although human judgements on grammaticality, meaning preservation and simplicity are considered the most reliable method for evaluating a SS system’s output (Štajner et al., 2016), it is common practice to use automatic metrics. They are useful for either assessing systems at development stage, to compare different architectures, for model selection or as part of a training policy. EASSE implements works as a wrapper for the most common evaluation metrics in SS:

**BLEU** is a precision-oriented metric that relies on the proportion of n-gram matches between a system’s output and reference(s). Previous work (Xu et al., 2016) has shown that BLEU correlates fairly well with human judgements of grammaticality and meaning preservation. EASSE uses
SACREBLEU (Post, 2018)\(^1\) to calculate BLEU. This package was designed to standardise the process by which BLEU is calculated: it only expects a detokenised system’s output and the name of a test set. It ensures that the same pre-processing steps are used for the system output and reference sentences.

**SARI** measures how the simplicity of a sentence was improved based on the words added, deleted and kept by a system. The metric compares the system’s output to multiple simplification references and the original sentence. SARI has shown positive correlation with human judgements of simplicity gain. We re-implement SARI’s corpus-level version in Python (it was originally available in Java). In this version, for each operation \(\text{ope} \in \{\text{add, del, keep}\}\) and \(n\)-gram order, precision \(p_{\text{ope}}(n)\), recall \(r_{\text{ope}}(n)\) and F1 \(f_{\text{ope}}(n)\) scores are calculated. These are then averaged over the \(n\)-gram order to get the overall operation F1 score \(F_{\text{ope}}\):

\[
F_{\text{ope}} = \frac{1}{k} \sum_{n=1}^{k} f_{\text{ope}}(n)
\]

Although Xu et al. (2016) indicate that only precision should be considered for the deletion operation, we follow the Java implementation that uses F1 score for all operations in corpus-level SARI.

**SAMSA** measures structural simplicity (i.e. sentence splitting). This is in contrast to SARI, which is designed to evaluate simplifications involving paraphrasing. EASSE re-uses the original SAMSA implementation\(^2\) with some modifications: (1) an internal call to the TUPA parser (Hershcovich et al., 2017), which generates the semantic annotations for each original sentence; (2) a modified version of the monolingual word aligner (Sultan et al., 2014) that is compatible with Python 3, and uses Stanford CoreNLP (Manning et al., 2014)\(^3\) through their official Python interface, and (3) a single function call to get a SAMSA score instead of running a series of scripts.

**FKGL**. Readability metrics, such as Flesch-Kincaid Grade Level (FKGL), are commonly reported as measures of simplicity. They however only rely on average sentence lengths and number of syllables per word, so short sentences would get good scores even if they are ungrammatical, or do not preserve meaning (Wubben et al., 2012). Therefore, these scores should be interpreted with caution. EASSE re-implements FKGL by porting publicly available scripts\(^4\) to Python 3 and fixing some edge case inconsistencies (e.g. newlines incorrectly counted as words or bugs with memoization).

### 2.2 Word-level Analysis and QE Features

**Word-level Transformation Analysis** EASSE includes algorithms to determine which specific text transformations a SS system performs more effectively. This is done based on word-level alignment and analysis.

Since there is no available simplification dataset with manual annotations of the transformations performed, we re-use the annotation algorithms from MASSAlign (Paetzold et al., 2017). Given a pair of sentences (e.g. original and system output), the algorithms use word alignments to identify deletions, movements, replacements and copies (see Fig. 1). This process is prone to some errors: when compared to manual labels produced by four annotators in 100 original-simplified pairs, the automatic algorithms achieved a micro-averaged F1 score of 0.61 (Alva-Manchego et al., 2017).

We generate two sets of automatic word-level annotations: (i) between the original sentences and their reference simplifications, and (ii) between the original sentences and their automatic simplifications produced by a SS system. Considering (i) as reference labels, we calculate the F1 score of each transformation in (ii) to estimate their correctness. When more than one reference simplification exists, we calculate the per-transformation F1 scores of the output against each reference, and then keep the highest one as the sentence-level score. The corpus-level scores are the average of sentence-level scores.

**Quality Estimation Features** Traditional automatic metrics used for SS rely on the existence and quality of references, and are often not enough to analyse the complex process of simplification. QE

\(^1\)https://github.com/mjpost/sacreBLEU  
\(^2\)https://github.com/eliorsulem/SAMSA  
\(^3\)https://stanfordnlp.github.io/standfordnlp/corenlp_client.html  
\(^4\)https://github.com/mmautner/readability
leverages both the source sentence and the output simplification to provide additional information on specific behaviours of simplification systems which are not reflected in metrics such as SARI. EASSE uses QE features from Martin et al. (2018)’s open-source repository. The QE scores that we currently use include the compression ratio of the simplification with respect to its source sentence, its Levenshtein similarity, the average number of sentence splits performed by the system, the proportion of exact matches (i.e. original sentences left untouched), average proportion of added words, deleted words and lexical complexity score.

### 2.3 Access to Test Datasets

EASSE provides access to three publicly available datasets for automatic SS evaluation (Table 1): PWKP (Zhu et al., 2010), TurkCorpus (Xu et al., 2016), and HSplit (Sulem et al., 2018a). All of them consist of the data from the original datasets, which are sentences extracted from English Wikipedia (EW) articles. It is important to highlight that EASSE can also evaluate system’s outputs in other datasets provided by the user.

#### PWKP

Zhu et al. (2010) automatically aligned sentences in 65,133 EW articles to their corresponding versions in Simple EW (SEW). Since the latter is aimed at English learners, its articles are expected to contain fewer words and simpler grammar structures than those in their EW counterpart. The test set split of PWKP contains 100 sentences, with 1-to-1 and 1-to-N alignments (resp. 93 and 7 instances). The latter correspond to instances of sentence splitting. Since this dataset has only one reference for each original sentence, it is not ideal for calculating automatic metrics that rely on multiple references, such as SARI.

#### TurkCorpus

Xu et al. (2016) asked crowdworkers to simplify 2,359 original sentences extracted from PWKP to collect eight simplification references for each one. This dataset was then randomly split into tuning (2,000 instances) and test (359 instances) sets. The test set only contains 1-to-1 alignments, mostly with instances of paraphrasing and deletion. Each original sentence in TurkCorpus has 8 simplified references produced through crowdsourcing. As such, it is better suited for computing SARI and multi-reference BLEU scores.

#### HSplit

Sulem et al. (2018a) recognised that existing EW-based datasets did not contain sufficient instances of sentence splitting. As such, they collected four reference simplifications of this transformation for the first 70 original sentences in the TurkCorpus test set. Even though SAMSA’s computation does not require access to references, this dataset can be used to compute an upperbound on the expected performance of SS systems that model this type of structural simplification.

### 2.4 HTML Report Generation

EASSE wraps all the aforementioned analyses in a simple comprehensive HTML report that can be generated with a single command. This report compares the system output with human
reference(s) using simplification metrics and QE features, and plots that illustrate the distribution of compression ratios or Levenshtein similarities between sources and simplifications over the test set. Moreover, the analysis is broken down by source sentence length in order to get insights on how the model handles short source sentence versus longer source sentences, e.g. does the model keep short sentences unmodified more often than long sentences? This report further facilitates qualitative analysis of system outputs by displaying source sentences with their respective simplifications. The modifications performed by the model are highlighted for faster and easier analysis. For visualisation, EASSE samples simplification instances to cover different behaviours of the systems. Instances that are sampled include simplifications with sentence splitting, simplifications that significantly modify the source sentence, output sentences with a high compression rate or that display lexical simplifications, among others. Each of these aspects is illustrated with 10 examples. An example of the report can be viewed at https://github.com/feralvam/easse/blob/master/demo/report.gif.

3 Experiments

We collected publicly available outputs of several SS systems (Sec. 3.1) to evaluate their performance using the functionalities available in EASSE. In particular, we compare them using automatic metrics, and provide some insights on the reasoning behind their results (Sec. 3.2).

3.1 Sentence Simplification Systems

EASSE provides access to various SS system outputs that follow different approaches for the task. For instance, we included those that rely on phrase-based statistical MT, either by itself (e.g. PBSMT-R (Wubben et al., 2012)), or coupled with semantic analysis, (e.g. Hybrid (Narayan and Gardent, 2014)). We also included SBSMT-SARI (Xu et al., 2016), which relies on syntax-based statistical MT; DRESS-LS (Zhang and Lapata, 2017), a neural model using the standard encoder-decoder architecture with attention combined with reinforcement learning; and DMASS-DCSS (Zhao et al., 2018), the current state-of-the-art in the TurkCorpus, which is based on the Transformer architecture (Vaswani et al., 2017).

3.2 Comparison and Analysis of Scores

Automatic Metrics For illustration purposes, we compare systems’ outputs using BLEU and SARI in TurkCorpus (with 8 manual simplification references), and SAMSA in HSplit. For calculating Reference values in Table 2, we sample one of the 8 human references for each instance as others have done (Zhang and Lapata, 2017).

When reporting SAMSA scores, we only use the 70 sentences of TurkCorpus that also appear in HSplit. This allows us to compute Reference scores for instances that contain structural simplifications (i.e. sentence splits). We calculate SAMSA scores for each of the four manual simplifications in HSplit, and choose the highest as an upper-bound Reference value. The results for all three metrics are shown in Table 2.

| System          | TurkCorpus SARI | TurkCorpus BLEU | HSplit SAMSA |
|-----------------|-----------------|-----------------|--------------|
| Reference       | 49.88           | 97.41           | 54.00        |
| PBSMT-R         | 38.56           | 81.11           | 47.59        |
| Hybrid          | 31.40           | 48.97           | 46.68        |
| SBSMT-SARI      | 39.96           | 73.08           | 41.41        |
| DRESS-LS        | 37.27           | 80.12           | 45.94        |
| DMASS-DCSS      | 40.42           | 73.29           | 35.45        |

Table 2: Comparison of systems’ performance based on automatic metrics.

DMASS-DCSS is the state-of-the-art in TurkCorpus according to SARI. However, it gets the lowest SAMSA score, and the third to last BLEU score. PBSMT-R is the best in terms of these two metrics. Finally, across all metrics, the Reference still gets the highest values, with significant differences from the top performing systems.

Word-level Transformations In order to better understand the previous results, we use the word-level annotations of text transformations (Table 3). Since SARI was design to evaluate mainly paraphrasing transformations, the fact that SBSMT-SARI is the best at performing replacements and second place in copying explains its high SARI score. DMASS-DCSS is second best in replacements, while PBSMT-R (which achieved the highest BLEU score) is the best at copying. Hybrid is the best at performing deletions, but is the worst at replacements, which SARI mainly measures. The origin of the TurkCorpus set itself could explain some of these observations. According to Xu et al. (2016), the annotators in TurkCorpus...
were instructed to mainly produce paraphrases, i.e. mostly replacements with virtually no deletions. As such, copying words is also a significant transformation, so systems that are good at performing it better mimic the characteristics of the human simplifications in this dataset.

| System          | Delete | Move | Replace | Copy  |
|-----------------|--------|------|---------|-------|
| PBSMT-R         | 34.18  | 2.64 | 23.65   | 93.50 |
| Hybrid          | 49.46  | 7.37 | 1.03    | 70.73 |
| SBSMT-SARI      | 28.42  | 1.26 | 37.21   | 92.89 |
| DRESS-LS        | 40.31  | 1.43 | 12.62   | 86.76 |
| DMASS-DCSS      | 38.03  | 5.10 | 34.79   | 86.70 |

Table 3: Transformation-based performance of the sentence simplification systems in the TurkCorpus test set.

**Quality Estimation Features** Table 4 displays a subset of QE scores that reveal other aspects of the simplification systems. For instance, the scores make it clear that Hybrid compresses the input way more than other systems (compression ratio of 0.57 vs. ≥0.78 for the other systems) but almost never adds new words (addition proportion of 0.01). This additional information explains the high Delete and low Replace performance of this system in Table 3. DRESS-LS keeps the source sentence unmodified 26% of the time, which does not show in the word-level analysis. This confirms that QE scores are complementary to automatic metrics and word-level analysis.

| System         | Compression ratio | Exact matches | Additions proportion | Deletions proportion |
|----------------|-------------------|---------------|----------------------|----------------------|
| PBSMT-R        | 0.95              | 0.1           | 0.1                  | 0.11                 |
| Hybrid         | 0.57              | 0.03          | 0.01                 | 0.41                 |
| SBSMT-SARI     | 0.94              | 0.11          | 0.16                 | 0.13                 |
| DRESS-LS       | 0.78              | 0.26          | 0.04                 | 0.26                 |
| DMASS-DCSS     | 0.89              | 0.05          | 0.15                 | 0.21                 |

Table 4: Quality estimation features, which give additional information on the output of different systems.

**Conclusion and Future Work**

EASSE provides easy access to commonly used automatic metrics as well as to more detailed word-level transformation analysis and QE scores which allows us to compare the quality of the generated outputs of different SS systems on public test datasets. We reported some experiments on the use of automatic metrics to obtain overall performance scores, followed by measurements of how effective the SS systems are at executing specific simplification transformations using word-level analysis and QE features. The former analysis provided insights about the simplification capabilities of each system, which help better explain the initial automatic scores.

In the future, we plan to continue developing the transformation-based analysis algorithms, so that more sophisticated transformations could be identified (e.g. splitting or subject-verb-object reordering). In addition, we expect to integrate more QE features to cover other aspects of the simplification process (e.g. depth of the dependency parse tree to measure syntactic complexity).

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