CUT: Controllable Unsupervised Text Simplification

Oleg Kariuk  
Ukrainian Catholic University  
ShipHawk  
olegkariuk@gmail.com

Dima Karamshuk  
Facebook  
karamshuk@fb.com

Abstract

In this paper, we focus on the challenge of learning controllable text simplifications in unsupervised settings. While this problem has been previously discussed for supervised learning algorithms, the literature on the analogies in unsupervised methods is scarce. We propose two unsupervised mechanisms for controlling the output complexity of the generated texts, namely, back translation with control tokens (a learning-based approach) and simplicity-aware beam search (decoding-based approach). We show that by nudging a back-translation algorithm to understand the relative simplicity of a text in comparison to its noisy translation, the algorithm self-supervises itself to produce the output of the desired complexity. This approach achieves competitive performance on well-established benchmarks: SARI score of 46.88% and FKGL of 3.65% on the Newsela dataset.

1 Introduction

Text simplification deals with the problem of rewriting complex texts into a language which is easier to read and understand while preserving its original information and meaning. Simplification techniques can improve reading comprehension for a broader range of users, ranging from foreign language learners (Allen, 2009; Petersen and Ostendorf, 2007) and non-experts (Elhadad and Sutaria, 2007; Siddharthan and Katsos, 2010) to people with disabilities (Canning et al., 2000; Carroll et al., 1999) or low-literacy (De Belder and Moens, 2010).

A variety of supervised and unsupervised approaches have been recently applied to the text simplification problem. On the supervised side, it has been considered as a monolingual machine translation exercise where a number of dedicated sequence-to-sequence models have been proposed (Kajiwara and Komachi, 2016; Scarton et al., 2018; Zhang and Lapata, 2017). Unfortunately, the scarcity of parallel datasets limits the scalability of these approaches in application to different languages, domains, and output styles. Moreover, the Parallel Wikipedia Simplification corpus, which has become the benchmark dataset for training and evaluating text simplification systems, is (a) prone to automatic sentence alignment errors, (b) contains a lot of inadequate simplifications and (c) poorly generalizes to other text styles (Xu et al., 2015).

Inspired by the recent success (Lample et al., 2018) of unsupervised machine translation, (Zhao et al., 2020) have applied unsupervised techniques of back-translation and noisy auto-encoders to the problem of text simplification. By adjusting these mechanisms to the particularities of mono-lingual translation, they managed to achieve performance results competitive with the supervised models. While this surprising effectiveness of unsupervised approaches and their ability to learn from vastly available non-parallel text corpora make them a significantly more attractive option than supervised text simplification, there yet remains many unsolved challenges. One of such is the challenge of controlling the complexity of the output produced by a text simplification algorithm. This problem has been solved for supervised approaches by learning on the characteristics of the output texts (Scarton and Specia, 2018; Martin et al., 2019), an idea that does not immediately apply to unsupervised settings.

In this work, we build on an idea of using dedicated tokens (Martin et al., 2019) to control the complexity of the produced output texts and apply it to unsupervised text simplification. We introduce this mechanism to the back translation algorithm, which allows the model to self-supervise the process of learning inter-relations between a control sequence and the complexity of the produced output. We compare this technique with simplicity-aware penalties for beam-search generation of the output texts, thus leveraging on both learning-based and decoding-based mechanisms for controlled text generation (Kikuchi et al., 2016). Together these contributions allow us to achieve and exceed the previously reported SARI and FKGL results on the Newsela dataset.
2 Methodology

We propose two different approaches for controlling the output complexity of unsupervised text simplification algorithms, namely, back-translation with control tokens (a learning-based approach) and beam search with simplicity-aware penalties (a decoding-based approach).

2.1 Back-translation with control tokens

For learning-based control, we get inspiration from (Martin et al., 2019) who introduced different types of dedicated tokens to control the output complexity of the supervised text simplification. We apply this idea to a self-supervised back-translation algorithm (Sennrich et al., 2016) as follows.

Firstly, we produce the noisy translation \( u^*(y) \) of the original phrase \( y \) and compute control tokens based on the original text \( y \) and its noisy translation, i.e., \( H(y, u^*(y)) \), where \( H \) is a sequence of four tokens which represent the compression ratio, Levenshtein similarity, word rank and the depth of dependency tree as defined in (Martin et al., 2019).

Then we concatenate the computed control tokens with the noisy translation \( H(y, u^*(y)) \sim u^*(y) \) and translate the resulting sequence back, aiming at reproducing the original text. We apply this procedure for both – simple \( (y \sim S) \) and complex sentences \( (x \sim C) \) – and train the algorithm to minimize the difference between the original and the output texts, i.e.,

\[
\mathcal{L} = \mathbb{E}_{y \sim S}[-\log P_{c \rightarrow s}(y|H(y, u^*(y)) \sim u^*(y))] + \mathbb{E}_{x \sim C}[-\log P_{c \rightarrow s}(x|H(x, v^*(x)) \sim v^*(x))]
\]

2.2 Simplicity-aware beam search

For a decoding-based control, we introduce the simplicit-aware penalties in the beam search when generating the output texts. Instead of decoding the most probable words in a greedy fashion, the beam search algorithm generates an output sentence by keeping a fixed number (specified by beam size parameter) of hypotheses with the highest log-probability at each step.

To manage the exact matches ratio, length and simplicity (FKGL-based) of each hypothesis in the beam search iterations, we added three types of score penalties:

- **Length penalty** (LP) favors shorter or longer hypothesis depending on \( \lambda_{\text{length}} \) parameter:
  \[
  LP = e^{\lambda_{\text{length}} \times \text{length(hypothesis)}}
  \]

- **Exact matches penalty** (EMP) uses cosine similarity between input and hypothesis to restrict the copying of input:
  \[
  EMP = e^{\lambda_{\text{exact matches}} \times \cos(input,hypothesis)}
  \]

- **FKGL penalty** (FKGLP) encourages hypothesis with lower FKGL score:
  \[
  FKGLP = e^{\lambda_{\text{FKGL}} \times FKGL(hypothesis)}
  \]

We find an optimal combination of different penalties by running a grid search on already trained models over a hold-out validation dataset and optimizing for the best trade-off between SARI and FKGL.\(^1\)

2.3 Pre-trained language models

We use the pre-trained language models from XLM library (Lample and Conneau, 2019) as the basis for our experiments. The XLM models were trained on a large Wikipedia + Toronto Book Corpus and already encapsulate powerful embeddings for English texts. We also use the implementation of the *noisy auto-encoders* (AE) and back-translation (BT) from the XLM library as the basis for our unsupervised approach and use supervised *machine translation* (MT) step for comparing the performance of the supervised and semi-supervised settings. We denote vanilla unsupervised and semi-supervised XLM models with \( XLM-U \) and \( XLM-S \); our approach to back-translation with control tokens with \( \text{CUT-U (t)} \) and \( \text{CUT-S (t)} \) and a variant with simplicity-aware penalties with \( \text{CUT-U (p)} \) and \( \text{CUT-S (p)} \), correspondingly.

3 Experiments

3.1 Dataset

We conducted our experiments on two different simplification datasets, the summary statistics of which are presented in Table 1.

*WikiLarge* has become a benchmark for training and evaluating text simplification models (Zhang and Lapata, 2017). Originally it had 296,402 sentence pairs, but we took 5,000 pairs for machine translation step during our model training. For validations and tests, we used TurkCorpus (Xu et al., 2016).

*Newsela* is a corpus of thousands of news articles professionally leveled to different reading

\(^1\)LP=0.1, EMP=0.4, LFGKLP=0.4 and LP=0.4, EMP=1.3, LFGKLP=1.0 have been identified as optimal for \( \text{CUT-S (p)} \) and \( \text{CUT-U (p)} \) in \( \text{range}(0.1, 1.3, 0.3) \), correspondingly.
complexities (Xu et al., 2015). We used the most contrast article versions. For the machine translation step, for the test, and for the validation datasets, we used parallel complex-simple pairs provided by (Xu et al., 2015).

3.2 Metrics
We use a variety of well established metrics from Easier Automatic Sentence Simplification Evaluation (EASSE) framework (Alva-Manchego et al., 2019) to analyze the quality of the produced text simplifications, including:

- **BLEU** (Bilingual Evaluation Understudy) - a precision-oriented metric that estimates the proportion of n-gram matches between a system’s output and a reference (Papineni et al., 2002).

- **SARI**, introduced by (Xu et al., 2016), compares system output against the references and against the input sentence. It measures how the simplicity of a sentence was improved based on the words added, deleted, and kept by the system.

- **FKGL** (Flesch-Kincaid Grade Level) estimates the readability of text using cognitively motivated features (Kincaid et al., 1975). Commonly reported as measures of simplicity, FKGL relies on average sentence lengths and the number of syllables per word.

We complement this set with (a) the proportion of **exact matches** between simplified and original sentences, (b) the average proportion of **added words** and (c) the average proportion of **deleted words** to gain additional insights on the nature of the transformations that a model is performing on the input texts.

3.3 Baselines
We benchmarked our model against several well-known baselines:

- **PBMT-R** is phrase-based machine translation system with a re-ranking post-processing step proposed by (Wubben et al., 2012)

- **Hybrid** is a simplification model that includes a probabilistic model for splitting and dropping and a PBMT-R model for substitution and reordering (Narayan and Gardent, 2014)

- **SBMT-SARI** is a syntax-based translation model trained on PPDB (Ganitkevitch et al., 2013) and trained with SARI (Zhang and Lapata, 2017)

- **EncDecA**, a basic attention-based encoder-decoder model, **DRESS**, a deep reinforcement learning model, DRESS-LS, a linear combination of DRESS and the lexical simplification model, all of them were introduced in (Zhang and Lapata, 2017). **DMASS+DCSS** is a combination of DMASS and DCSS models from (Zhao et al., 2018).

- **UNTS+10K** is an unsupervised model based on a shared encoder and two decoders with limited supervision of 10K labeled examples (Surya et al., 2019).

The BLEU, SARI, and FKGL results for the above-mentioned models were taken from (Zhang and Lapata, 2017) and (Zhao et al., 2018).

3.4 Results
In Table 2, we summarize the results of the experiments on the Newsela dataset. Both control mechanisms – penalties and tokens – achieve superior performance in comparison to the unsupervised baseline defined by the off the shelf XML-U model, however, a learning-based approach (CUT-U (t)) outperforms a decoding-based one (CUT-U (p)). This finding is in-line with the previous results achieved for supervised text summarization (Kikuchi et al., 2016). **CUT-U (t)** out-performs all baseline models from
We will be looking in understanding and improving the XLM model, we achieve the highest SARI score with extra supervision provided by the MT step in we combine our unsupervised control mechanisms.

In Table 3, we demonstrate an example of applying control tokens to an input sentence in the Newsela test set. A combination of different tokens provides flexibility to adjust the sentence’s output complexity, which is in line with the previous results in (Martin et al., 2019). What is remarkable, however, is that the model has managed to train itself in a completely unsupervised way by gradually learning from noisy outputs of the back-translation iterations.

Our results have been less striking on the other popular benchmark – the WikiLarge dataset Table 4. Although our models achieved significantly better results on SARI and FKGL than both XLM-U and XLM-S baselines, as well as significantly decreased the exact match ratio, we have not observed equivalent improvements in the BLEU score and in comparison to the state-of-the-art results. We attribute this to the fact that the WikiLarge dataset is a significantly noisier dataset (Xu et al., 2015). We will be looking in understanding and improving our performance in these settings in future work.

### Table 3: Results of applying control tokens to an example in a Newsela test set: NbChars for compression ratio, LevSim for Levenshtein similarity, WordRank as defined in (Martin et al., 2019).

| Input | Reference |
|-------|-----------|
| `NbChars_{1.0} + LevSim_{1.0}` | Back in 1950, Eiji Toyoda visited a Ford plant to learn how Americans made cars. |
| `NbChars_{1.0} + LevSim_{0.75}` | In 1950, Eiji Toyoda visited a Ford factory to learn how Americans made cars. |
| `NbChars_{1.0} + LevSim_{0.5}` | In 1950, Eiji Toyoda visited a Ford factory to learn how to make cars. |
| `NbChars_{1.0} + LevSim_{0.25}` | In 1950, Eiji Toyoda visited a Ford factory. |

### Table 4: Performance comparison of CUT models and baselines on Wikipedia Large.

| System                  | BLEU  | SARI  | FKGL  | Match | Add  | Del  |
|-------------------------|-------|-------|-------|-------|------|------|
| PBMT-R                  | 81.11 | 38.56 | 8.33  | -     | -    | -    |
| Hybrid                  | 48.97 | 31.40 | 4.56  | -     | -    | -    |
| SBMT-SARI               | 73.08 | 39.96 | 7.29  | -     | -    | -    |
| EncDecA                 | 88.85 | 35.66 | 8.41  | -     | -    | -    |
| DRESS                   | 77.18 | 37.08 | 6.58  | -     | -    | -    |
| DRESS-LS                | 80.12 | 37.27 | 6.62  | -     | -    | -    |
| DMASS+DCSS              | -     | 40.42 | 7.18  | -     | -    | -    |
| UNTS+10K                | 76.13 | 35.29 | -     | -     | -    | -    |
| XLM-S                   | 92.66 | 30.99 | 9.68  | 0.73  | 0.02 | 0.02 |
| CUT-S (t)               | 41.33 | 32.01 | 8.73  | 0.05  | 0.16 | 0.19 |
| CUT-S (t+p)             | 78.01 | 35.64 | 8.01  | 0.18  | 0.04 | 0.22 |
| XLM-U                   | 94.83 | 30.99 | 9.68  | 0.73  | 0.02 | 0.02 |
| CUT-U (t)               | 49.70 | 23.89 | 9.77  | 0.30  | 0.04 | 0.06 |
| Output = Input          | 97.41 | 27.32 | 9.90  | 1.00  | 0.00 | 0.00 |
| Output = Ref            | 68.87 | 40.83 | 8.33  | 0.00  | 0.19 | 0.21 |

In this paper, we looked at two unsupervised mechanisms – a learning-based and a decoding-based – to control the output complexity of text simplification algorithms. We built on an idea of adding complexity control tokens in the input text and applied it to the back-translation algorithm. By iterating the procedure of generating a noisy translation of a sentence and learning from its relative complexity compared to the original, the model self-supervised its ability to produce a controllable output and improved its simplification performance overall. An alternative – decoding-based mechanism – has also improved in comparison with the baseline but has demonstrated inferior performance on SARI and BLEU metrics.

While we find our models’ ability to self-supervise on noisy outputs rather striking, we think there is even more potential for improving the performance of this mechanism by providing more guidance in the trial-and-error process of applying control sequences and learning from them with reinforcement learning. We also plan to explore the generalizability of the unsupervised approaches by conducting a cross-corpora validation, i.e., validate the models on the corpora they have not seen during training. We believe that together these will help to establish unsupervised text simplification as a viable alternative to the supervised methods and remove the constraints imposed by the necessity of compiling parallel text corpora.

### References

David Allen. 2009. A study of the role of relative clauses in the simplification of new texts for learners of english. System, 37:585–599.

Fernando Alva-Manchego, Louis Martin, Carolina
Yvonne Canning, John Tait, Jackie Archibald, and Ros Crawley. 2000. Cohesive generation of syntactically simplified newspaper text. In Proceedings of the Third International Workshop on Text, Speech and Dialogue, TDS ’00, pages 145–150, London, UK, UK. Springer-Verlag.

Jan De Belder and Marie-Francine Moens. 2010. Text simplification for children.

Noemie Elhadad and Komal Sutaria. 2007. Mining a lexicon of technical terms and lay equivalents. In Proceedings of the Workshop on BioNLP 2007: Biological, Translational, and Clinical Language Processing, BioNLP ’07, pages 49–56, Stroudsburg, PA, USA. Association for Computational Linguistics.

Juri Ganitkevitch, Benjamin Van Durme, and Chris Callison-Burch. 2013. PPDB: The paraphrase database. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 758–764, Atlanta, Georgia. Association for Computational Linguistics.

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 COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pages 1147–1158, Osaka, Japan. The COLING 2016 Organizing Committee.

Yuta Kikuchi, Graham Neubig, Ryohei Sasano, Hiroya Takamura, and Manabu Okumura. 2016. Controlling output length in neural encoder-decoders. arXiv preprint arXiv:1609.09552.

J. Peter Kincaid, Robert P. Fishburne, Richard Lawrence Rogers, and Brad S. Chissom. 1975. Derivation of new readability formulas (automated readability index, fog count and flesch reading ease formula) for navy enlisted personnel.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. Advances in Neural Information Processing Systems (NeurIPS).

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2018. Unsupervised machine translation using monolingual corpora only. In International Conference on Learning Representations (ICLR).

Louis Martin, Benoît Sagot, Éric de la Clergerie, and Antoine Bordes. 2019. Controllable sentence simplification. arXiv preprint arXiv:1910.02677.

Shashi Narayan and Claire Gardent. 2014. Hybrid simplification using deep semantics and machine translation. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 435–445, Baltimore, Maryland. 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.

Sarah E. Petersen and Mari Ostendorf. 2007. Text simplification for language learners: a corpus analysis. In SLaTE.

Carolina Scarton, Gustavo Paetzold, and Lucia Specia. 2018. Text simplification from professionally produced corpora. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).

Carolina Scarton and Lucia Specia. 2018. Learning simplifications for specific target audiences. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 712–718.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96.

Advaith Siddharthan and Napoleon Katsos. 2010. Reformulating discourse connectives for non-expert readers. In Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, HLT ’10, pages 1002–1010, Stroudsburg, PA, USA. Association for Computational Linguistics.

Sai Surya, Abhijit Mishra, Anirban Laha, Parag Jain, and Karthik Sankaranarayanan. 2019. Unsupervised neural text simplification. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2058–2068, Florence, Italy. Association for Computational Linguistics.
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 (Volume 1: Long Papers)*, pages 1015–1024, Jeju Island, Korea. 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, Saptono Andi, and Parmanto Bambang. 2018. *Integrating transformer and paraphrase rules for sentence simplification*. *arXiv preprint arXiv:1810.11193*.

Yanbin Zhao, Lu Chen, Zhi Chen, and Kai Yu. 2020. *Semi-supervised text simplification with back-translation and asymmetric denoising autoencoders*. *arXiv preprint arXiv:2004.14693*.