# Noisy Channel for Automatic Text Simplification

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#### Abstract

In this paper we present a simple re-ranking method for Automatic Sentence Simplification based on the noisy channel scheme. Instead of directly computing the best simplification given a complex text, the re-ranking method also considers the probability of the simple sentence to produce the complex counterpart, as well as the probability of the simple text itself, according to a language model. Our experiments show that combining these scores outperform the original system in three different English datasets, yielding the best known result in one of them. Adopting the noisy channel scheme opens new ways to infuse additional information into ATS systems, and thus to control important aspects of them, a known limitation of end-to-end neural seq2seq generative models.

#### **1** Introduction

Automatic Text Simplification (ATS) aims to rewrite text into a form that is easier to understand, while retaining the original meaning. Its is an active area of research with many interests in improving web accessibility (Alarcon et al., 2021), for cognitive disabled users (Kamran et al., 2022; Moreno et al., 2021), for scientific information access (Ermakova et al., 2021), and in general it is intended for social good (Štajner, 2021).

In the last years there has been a remarkable advance in ATS due to the advent of deep learning techniques and neural language models. This has lead to a variety of methods that follow the seq2seq architecture to build models that estimate p(y|x), the probability of producing a simple sentence y given the complex sentence x (Nisioi et al., 2017; Zhang and Lapata, 2017; Martin et al., 2020b; Lin and Wan, 2021; Omelianchuk et al., 2021). One of the main problems of this approach is the lack of control mechanisms to prevent the system to hallucinate or produce repetition when generating y, as well to infuse new information into the system. Previous works have tried to control the generation of simple sentences by using control codes that condition the system output with variables such as length, number paraphrases, lexical complexity, and syntactic complexity, etc (Martin et al., 2020a; Sheang and Saggion, 2021). Other works such as Clive et al. (2021) use control prefixes, including input-dependent conditional information pretrained models, incorporating learnable attributelevel representations at different layers of a transformer.

In this paper we propose an alternative method to control the generated simplifications of a seq2seq ATS model. Instead of controlling the simplifications at decoding time, we propose to re-rank the top candidates of an neural seq2seq model according to the noisy channel scheme (Brown et al., 1993; Yee et al., 2019; Yu et al., 2016). The noisy channel scheme decomposes p(y|x) into p(x|y), the probability of generating the complex sentence x given the simple sentence y, and p(y), the probability of the simple sentence y. We present a re-ranking method that considers all three probabilities using different models. Because each of the models is independently trained on different data, our method is able to infuse additional knowledge into a traditional seq2seq ATS system. The noisy channel method has been mainly applied in machine translation, but it was also applied for Document Compression (Daumé III and Marcu, 2002), exactly in the dropping word task (related to summarization). Dropping or deleting words is also one of the operations an ATS systems should carry our, but it is not limited to that: ATS systems should also split sentences, reorder words or sentences and add necessary words or phrases. Moreover, ATS systems's output should be coherent, and by only dropping words coherence can become deficient.

The contributions of this paper are the following:

• We propose a re-ranking method for seq2seq

ATS systems based on noisy channel.

- We show that our method outperforms the original system in three different English datasets, yielding the best known result in one of them.
- We show that the method is able to infuse new information in neural ATS systems, as the additional models in the noisy channel scheme can be trained on complementary data.

## 2 Noisy Channel based re-ranking for ATS

Given a complex text  $x = \{x_1, \ldots, x_M\}$  and its simplified version  $y = \{y_1, \ldots, y_N\}$ , a seq2seq ATS system builds a model that estimates p(y|x). At inference time, and given the input x, the model is used to select the simplification that maximizes this probability, e.g.,  $\arg \max_y p(y|x)$ . The noisy channel scheme is an alternative that has been widely used in machine translation, and which uses Baye's rule to parametrize p(y|x) as  $\frac{p(x|y)p(y)}{p(x)}$ . Because we are interested in finding y that maximizes the probability, the denominator p(x) is discarded.

In this paper we explore using the noisy channel scheme to re-rank the candidates generated by the seq2seq ATS model. Specifically, we propose to build three separate models to estimate p(y|x), p(x|y) and p(y). Following usual practice, will be henceforth refer to these models as the *direct model*, *channel model* and *language model*, respectively. Given x, our system first retrieve the list of top-k candidates given by the direct model, as well as the corresponding p(y|x) probabilities. Then, the channel and language models are used to compute p(x|y) and p(y) for each (x, y) pair. Finally, the top-k candidates are re-ranked according to a combination of the three probabilities, using the same score function as in (Yu et al., 2016)<sup>1</sup>:

$$\lambda_1 \log p(y|x) + \lambda_2 \log p(x|y) + \lambda_3 \log p(y) + \lambda_4 \cdot N$$
(1)

where N is the length of sentence y and  $\lambda_1, \lambda_2, \lambda_3, \lambda_4$  are hyper-parameters. As in (Yu et al., 2016), we use  $\lambda_4$  to penalize the model for generating simple sentences that are too short.

### **3** Experimental setup

This section describes the experiments we conducted to evaluate the effectiveness of the proposed noisy channel re-ranking method for English ATS. We describe the experimental setup, including the built models, datasets and evaluation metrics, as well as a description of the different systems and baselines.

#### **3.1** Building the models

The direct model p(y|x) is based on BART large, a encoder-decoder language model with 400M parameters that is pre-trained on English text (Lewis et al., 2020). The model is fine-tuned using the training splits of the respective datasets. We used default values for the learning rate ( $5 \times 10^{-5}$  with a linear schedule and a warmup of 500 steps). We trained the model for 10 epochs, and select the checkpoint with smallest loss on the respective validation sets. To generate the top-k candidates, we used beam search with a beam size of k, and set the maximum sentence length of 100.

The channel model p(x|y) is trained using the exact same settings as the direct model, but when fine-tuning the simple and complex sentences are swapped, so that the model learns to produce complex sentences given the simpler ones.

The language model p(y) is based on Bertlarge-uncased (Devlin et al., 2018). We continue to train the pre-trained model using the Simple Wikipedia, and the default language modeling objective. Again, we used default values: a weight decay of  $1 \times 10^{-2}$ , learning rate of  $2 \times 10^{-5}$ with warmup of 500 steps, and vocabulary size of 30, 522. Not being a generative model, BERT does not directly compute p(y) for any given y. Thus, we estimate this probability at inference time by consecutively masking each word in y and calculating the probability that BERT produced the correct word in the corresponding position. Specifically, we estimate  $\log p(y)$  using the following equation:

$$\log p(y) \sim \sum_{i}^{N} \log p_{\text{bert}}(y_i | y^{(i)})$$
 (2)

where  $y_i$  is the *i*th token,  $y^{(i)}$  is the original sentence with the *i*th token replaced by the MASK token, and N is the length of the sentence.

<sup>&</sup>lt;sup>1</sup>We tried alternative score functions such as the proposed in (Yee et al., 2019) with similar results.

#### 3.2 Datasets

We perform our experiments using three English ATS datasets: WikiSmall, WikiLarge/TurkCorpus, and Newsela. WikiLarge and WikiSmall were built by automatically aligning sentences belonging to the same article in English Wikipedia and Simple English Wikipedia. In both cases, we used the splits provided by Zhang and Lapata (2017). The WikiSmall dataset contains 88, 837 training instances, 205 validation instances, and 100 test instances. Regarding WikiLarge, the training set contains 296, 402 instances and the validation set 2,000. For evaluation, we used the TurkCorpus dataset (Xu et al., 2016), which comprises eight manually generated simplifications for each instance in the WikiLarge test set. Finally, the Newsela dataset consists more than 1k news articles that were rewritten four times at different complexity levels. We used the train/development/test splits from (Xu et al., 2015), containing 94, 208/1, 129/1, 076 sentences respectively.

### 3.3 Hyperparameter search

We perform a hyperparameter grid search on the respective development set to find the optimal values for  $\lambda_1, \lambda_2, \lambda_3, \lambda_4$  in Eq. (1). We tried all combinations ranging the value of each  $\lambda$  between 0 and 1, with 0.1 increments. The combination that obtains the best SARI score (see next section) in the development set is selected, and used in the respective test sets. We used k = 10 in our experiments.

#### 3.4 Evaluation Metrics and Systems

Following usual practice, we report the results using SARI (Xu et al., 2016) and Flesch-Kincaid Grade Level (FKLG) readability metric (Kincaid et al., 1975). We make the experiments with the original **BART** system, as well as our **NC-TS** system, the result of selecting the candidates after re-ranking based on the noisy channel scheme. We also test an **Oracle** system in the development test, which is the result of selecting the candidate that maximizes the SARI score wrt. the reference sentence in the gold standard, and represents an upperbound of the re-ranking process. Finally, we include a baseline (dubbed Cosine) that re-ranks the candidates according to their cosine similarity wrt. the complex sentence. Sentence embeddings are calculated using Sentence Transformers (Reimers

Dataset	System	SARI ↑	<b>FKLG</b> $\downarrow$		
Development Set					
Wikilarge/	Cosine	43.49	7.69		
TurkCorpus	BART	48.81	6.91		
	NC-TS	49.06 (+0.3)	6.23 (-0.7)		
	Oracle	58.09 (+9.3)	6.57 (-0.3)		
Wikismall	Cosine	40.99	8.58		
	BART	44.25	7.79		
	NC-TS	46.86 (+2.6)	7.20 (-0.6)		
	Oracle	54.30 (+10.0)	7.72 (-0.1)		
Newsela	Cosine	38.03	5.90		
	BART	41.24	4.92		
	NC-TS	43.63 (+2.4)	3.71 (-1.2)		
	Oracle	52.32 (+11.1)	4.43 (-0.5)		
Test Set					
Wikilarge/	Cosine	38.38	8.79		
TurkCorpus	BART	39.73	8.10		
	NC-TS	<b>40.24</b> (+0.5)	7.25 (-0.9)		
Wikismall	Cosine	39.00	11.04		
	BART	40.52	10.9		
	NC-TS	<b>44.46</b> (+3.9)	<b>9.63</b> (-1.3)		
Newsela	Cosine	38.12	5.64		
	BART	40.19	4.82		
	NC-TS	<b>41.67</b> (+1.5)	<b>3.65</b> (-1.2)		

Table 1: Results on the development dataset (top) and test set (bottom). Best results in test in bold. Numbers in parenthesis represent the gain wrt. BART.

## and Gurevych, $2019)^2$ .

### 4 Results

We start by showing the results for the development set in the upper part in Table 1. The oracle system reveals that selecting the first candidate from BART is not always the best strategy, and that there is ample room for improvement if we manage to correctly choose the best candidate among the top 10 alternatives. However, a straightforward baseline like Cosine does not improve BART results. The NC-TS system does improve BART results, but this is expected, as the hyperparameter search is performed in this development set. The  $\lambda$  values that yielded best results<sup>3</sup> show that p(y|x) is a reliable indicator, but that the contribution of p(x|y) is almost negligible. The language model p(y) barely helps in Turkcorpus and Wikismall, but this is expected as these datasets are based on simple Wikipedia, the same corpus p(y) is trained on. However, the system assigns a high score to p(y)in the Newsela dataset, showing that the additional information provided by simple Wikipedia helps improving the results.

<sup>&</sup>lt;sup>2</sup>We used the pre-trained paraphrase-albert-small-v2 model.

 $<sup>^{3}(\</sup>lambda_{1}, \lambda_{2}, \lambda_{3}, \lambda_{4})$ : TurkCorpus (0.5, 0.0, 0.1, 0.6), WikiSmall (0.5, 0.0, 0.1, 0.6), Newsela (0.9, 0.2, 0.7, 0.1).

Systems	<b>SARI</b> ↑	FKLG↓			
Wikilarge / Turkcorpus					
DRESS-LS (Zhang and Lapata, 2017)	37.27	6.62			
NSELSTM-S (Vu et al., 2018)	36.88	_			
DMASS (Zhao et al., 2018)	40.45	8.04			
EditNTS (Dong et al., 2019)	38.22	7.30			
ACCESS (Martin et al., 2020a)	41.87	7.22			
MUSS (Martin et al., 2020b)	42.53	7.60			
SDISS (Lin and Wan, 2021)	38.66	7.07			
Edit+synt (Cumbicus-Pineda et al., 2021b)	36.97	7.46			
TST (Omelianchuk et al., 2021)	41.46	7.87			
Control Prefixes (Clive et al., 2021)	42.32	7.74			
TS_T5 (Sheang and Saggion, 2021)	43.31	6.17			
T5+control (Štajner et al., 2022)	43.30	_			
NC-TS	40.24	7.25			
WikiSmall					
DRESS-LS (Zhang and Lapata, 2017)	27.24	7.55			
NSELSTM-S (Vu et al., 2018)	29.75	—			
EditNTS (Dong et al., 2019)	32.35	5.47			
SDISS (Lin and Wan, 2021)	34.06	4.58			
TST (Omelianchuk et al., 2021)	44.67	9.29			
NC-TS	44.46	9.63			
Newsela					
DRESS-LS (Zhang and Lapata, 2017)	26.63	4.21			
NSELSTM-S (Vu et al., 2018)	29.58	—			
DMASS (Zhao et al., 2018)	27.28	5.17			
EditNTS (Dong et al., 2019)	31.41	3.40			
MUSS (Martin et al., 2020b)	41.17	2.70			
SDISS (Lin and Wan, 2021)	32.30	2.38			
EditSynt (Cumbicus-Pineda et al., 2021b)	38.08	4.60			
NC-TS	41.67	3.65			

Table 2: Comparison of our system with state-of-theart neural systems, values have been obtained from the respective papers.

The main results on the test set are shown in the bottom part in Table 1. The NC-TS system obtains the best results on both metrics on all datasets, which confirms the previous results on development, and shows that the method is robust across datasets. In Table 2 we compare NC-TS with stateof-the-art systems. Our results are competitive with the state-of-the-art systems and in Newsela we obtain the best results in the SARI metric and a good score in FKLG.

## 5 Analysis

In this section we present the manual evaluation we have carried out to compare BART against the NC-TS system.

We first conducted a manual A/B test comparing the systems in the WikiSmall dataset, the one where the gain of NC-TS is the highest. We sampled 25 sentences from the output of each system, stratified according to the length of the original complex

Quartile	Q1	Q2	Q3	Q4	Total
BART	5	4	3	3	15
NC-TS	6	8	9	7	30
Equal	1	1	1	2	5

Table 3: Results of the manual evaluation. The Q columns correspond to the quartiles according to the sentence lengths.

sentences<sup>4</sup>. Two linguists with expertise in ATS have evaluated the sample. They were not English native speakers, but had advanced studies (one B.A. degree, the other a Phd.). They were presented the complex sentence and the outputs of both systems, and they had to choose one of them. They were allowed to evaluate both sentences as equal, but were instructed to do so only in very clear cases. When evaluating the sentences, they did not know which systems they belonged to, neither did they know the reference simplification in the gold standard. They followed the following criteria in the evaluation:

- Try always to always choose one system, and use equality only on extreme cases.
- Penalize hallucinations and misinformation, since they are known to cause harm (Cumbicus-Pineda et al., 2021a).
- All other criteria being equal, select the shortest sentence.
- Prioritise the meaning preservation and those sentences that keep the nuances.

In Table 3 we present the results of the manual evaluation, distributed in different sentence lengths. In total, the NC-TS system has obtained the best results (30 sentences) and the difference is higher on longest sentences (from quartile 2 on), which implies that the re-ranking is more beneficial on those cases.

We performed an additional analysis on the WikiLarge and Newsela datasets. We selected the 20 simplifications on each dataset where the SARI difference between Bart and NC-TS was highest (10 examples in BART favor, 10 examples on NC-TS favor)<sup>5</sup>. In the cases that NC-TS is better, we found out that the output of BART is mainly a

<sup>&</sup>lt;sup>4</sup>We grouped the sentences into four groups according to their length, and randomly sampled about 11-13 sentences on each group.

<sup>&</sup>lt;sup>5</sup>Examples of both systems can be found in appendix A

copy of the original sentence, that is, no simplification has been performed. This happens particularly in the WikiLarge dataset, but also in Newsela, although to a lesser extent. In Newsela, the NC-TS outputs clearly show a wider variety of operations (coreference changes, lexical simplification, person changes) compared to BART. On the other hand, when BART scores better, we found out that BART carries out slight changes with respect to the original and NC-TS tends to copy the original complex sentence. Again, this happens mostly in WikiLarge; in Newsela, the casuistry in the analysed dataset is bigger and no general conclusion can be obtained from the evaluated sample.

### 6 Conclusion and Future Work

In this paper we have presented simple re-ranking method to used the noisy channel in Automatic Text Simplification. We have compared our NC-TS system to a state-of-the-art seq2seq model (BART) and shown that the method obtains better results in terms of SARI and the readability metric FKLG in three well known ATS dataset (WikiSmall, WikiLarge/TurkCorpus and Newsela). Moreover, the NC-TS system obtains competitive results compared to state-of-the-art systems, and yields best results in the Newsela dataset. In this dataset, the system is able to leverage new information coming from the simple Wikipedia, which is not part of the dataset itself. We have conducted manual analysis in WikiSmall, where our NC-TS system has the most profit, and show that its outputs are better qualitatively, particularly on longer sentences.

In the future we plan to test the NC-TS system in ATS datasets in cross-lingual settings, where the models that compose the noisy channel schema can be trained using different datasets on several languages.

## 7 Limitations

Automatic text simplification is a subjective task: it highly depends on the target audience and experts do not agree on a perfect definition for simplification. Based on that, our manual evaluation can be biased towards the criteria explained in this paper of our experts and their experience. Moreover, all manual evaluations are subjective and difficult to reproduce.

This research has only been conducted for English due to the fact of the large data scarcity in other languages. Besides, Newsela, one of the datasets we have used is a proprietary dataset (data can be obtained in https://newsela.com/ data/). No examples can be shown unless explicitly allowed, therefore hindering the reproducibility of the results.

### References

- Rodrigo Alarcon, Lourdes Moreno, and Paloma Martínez. 2021. Lexical simplification system to improve web accessibility. *IEEE Access*, 9:58755–58767.
- Peter F. Brown, Vincent J. Della Pietra, Stephen A. Della Pietra, and Robert L. Mercer. 1993. The mathematics of statistical machine translation: Parameter estimation. *Comput. Linguist.*, 19(2):263–311.
- Jordan Clive, Kris Cao, and Marek Rei. 2021. Control prefixes for parameter-efficient text generation.
- Oscar M Cumbicus-Pineda, Itziar Gonzalez-Dios, and Aitor Soroa. 2021a. Linguistic Capabilities for a Checklist-based evaluation in Automatic Text Simplification. In *CTTS*@ *SEPLN*.
- Oscar M. Cumbicus-Pineda, Itziar Gonzalez-Dios, and Aitor Soroa. 2021b. A syntax-aware edit-based system for text simplification. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2021)*, pages 324– 334, Held Online. INCOMA Ltd.
- Hal Daumé III and Daniel Marcu. 2002. A noisychannel model for document compression. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 449–456.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding.
- Yue Dong, Zichao Li, Mehdi Rezagholizadeh, and Jackie Chi Kit Cheung. 2019. EditNTS: An neural programmer-interpreter model for sentence simplification through explicit editing. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3393–3402, Florence, Italy. Association for Computational Linguistics.
- Liana Ermakova, Patrice Bellot, Pavel Braslavski, Jaap Kamps, Josiane Mothe, Diana Nurbakova, Irina Ovchinnikova, and Eric SanJuan. 2021. Overview of simpletext 2021 - clef workshop on text simplification for scientific information access. In *Experimental IR Meets Multilinguality, Multimodality, and Interaction*, pages 432–449, Cham. Springer International Publishing.
- Maira Kamran, Marium Malik, Muhammad Waseem Iqbal, Muhammad Anwar, Muhammad Aqeel, and

Sana Ahmad. 2022. Web simplification prototype for cognitive disabled users. *Human Behavior and Emerging Technologies*, 2022.

- J Peter Kincaid, Robert P Fishburne Jr, Richard L 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. Technical report, Naval Technical Training Command Millington TN Research Branch.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. Bart: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880.
- Zhe Lin and Xiaojun Wan. 2021. Neural sentence simplification with semantic dependency information. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(15):13371–13379.
- Louis Martin, Éric de la Clergerie, Benoît Sagot, and Antoine Bordes. 2020a. Controllable sentence simplification. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 4689– 4698, Marseille, France. European Language Resources Association.
- Louis Martin, Angela Fan, Éric de la Clergerie, Antoine Bordes, and Benoît Sagot. 2020b. Multilingual unsupervised sentence simplification. *arXiv preprint arXiv:2005.00352*.
- Lourdes Moreno, Rodrigo Alarcon, and Paloma Martínez. 2021. Designing and evaluating a user interface for people with cognitive disabilities. In *Proceedings of the XXI International Conference on Human Computer Interaction*, pages 1–8.
- Sergiu Nisioi, 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.
- Kostiantyn Omelianchuk, Vipul Raheja, and Oleksandr Skurzhanskyi. 2021. Text simplification by tagging.
- Nils Reimers and Iryna Gurevych. 2019. Sentencebert: Sentence embeddings using siamese bertnetworks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.
- Kim Cheng Sheang and Horacio Saggion. 2021. Controllable sentence simplification with a unified textto-text transfer transformer. In *Proceedings of the 14th International Conference on Natural Language Generation*, pages 341–352, Aberdeen, Scotland, UK. Association for Computational Linguistics.

- Sanja Štajner. 2021. Automatic text simplification for social good: Progress and challenges. Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2637–2652.
- Tu Vu, Baotian Hu, Tsendsuren Munkhdalai, and Hong Yu. 2018. Sentence simplification with memoryaugmented neural networks. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 79–85, New Orleans, Louisiana. 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.
- Kyra Yee, Yann Dauphin, and Michael Auli. 2019. Simple and effective noisy channel modeling for neural machine translation. 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 5696–5701, Hong Kong, China. Association for Computational Linguistics.
- Lei Yu, Phil Blunsom, Chris Dyer, Edward Grefenstette, and Tomas Kocisky. 2016. The neural noisy channel.
- 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.
- Sanja Štajner, Kim Cheng Sheang, and Horacio Saggion. 2022. Sentence simplification capabilities of transfer-based models. In *Proceedings of the 36th* AAAI Conference on Artificial Intelligence.

### A Simplification examples

In this Appendix we show four simplification examples. The first two examples come from the WikiSmall dataset and the NC-TS outputs were evaluated as better. The third and forth examples come from WikiLarge and the NC-TS scored a higher SARI while in the fifth and sixth examples BART scored better. We cannot legally show examples from Newsela.

Dataset	Original	BART	NC-TS
WikiSmall	Being much more resistant to cold and moist weather condi- tions, brick enabled the con- struction of permanent build- ings in regions where the harsher climate precluded the use of mud bricks. It is therefore pointless to email our contact addresses asking for permission to reproduce articles or images, even if rules at your company or school or organiza- tion mandate that you ask web site operators before copying their content.	being much more resistant to cold and moist weather condi- tions, brick enabled the con- struction of permanent build- ings in regions where the harsher climate precluded the use of mud bricks. It is therefore pointless to email our contact addresses asking for permission to reproduce articles or images, even if rules at your company or school say that you ask web site operators before copying their content.	brick is much more resistant to cold and moist weather condi- tions. this made it possible to build permanent buildings in re- gions where the harsher climate meant that mud bricks were not suitable. do not email our contact ad- dresses asking for permission to reproduce articles or images, even if rules at your company or school say that you ask web site operators before copying their content.
WikiLarge (NC-TS better SARI)	He served as the prime minis- ter of Egypt between 1945 and 1946 and again from 1946 and 1948. a town may be correctly de- scribed as a market town or as having market rights even if it no longer holds a market , pro- vided the right to do so still ex- ists.	He served as the prime minis- ter of Egypt between 1945 and 1946 and again from 1946 and 1948. a town may be described as a market town or as having mar- ket rights even if it no longer holds a market, provided the right to do so still exists.	He was the prime minister of Egypt from 1945 to 1946 and again from 1946 to 1948. a town may be described as a market town even if it does not have a market anymore, as long as the right to hold a market still exists.
WikiLarge (BART better SARI)	Disney received a full-size Os- car statuette and seven minia- ture ones , presented to him by 10-year-old child actress Shirley Temple. Eugowra is said to be named after the indigenous Australian word meaning " the place where the sand washes down the hill "	Disney received a full-size Os- car statuette and seven minia- ture ones, presented to him by Shirley Temple, who was then 10 years old. Eugowra is said to be named af- ter the Australian word mean- ing "the place where the sand washes down the hill".	Disney received a full-size Os- car statuette and seven smaller ones, presented to him by 10- year-old child actress Shirley Temple. Eugowra is said to be named after the indigenous Australian word meaning "the place where the sand washes down the hill".

Table 4: Outputs of BART and the NC-TS systems