Controllable Sentence Simplification: Employing Syntactic and Lexical Constraints

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Abstract
Sentence simplification aims to make sentences easier to read and understand. Recent approaches have shown promising results with sequence-to-sequence models which have been developed assuming homogeneous target audiences. In this paper, we argue that different users have different simplification needs (e.g., dyslexics vs. non-native speakers), and propose CROSS, a ContROllable Sentence Simplification model, which allows to control both the level of simplicity and the type of the simplification. We achieve this by enriching a Transformer-based architecture with syntactic and lexical constraints (which can be set or learned from data). Empirical results on two benchmark datasets show that constraints are key to successful simplification, offering flexible generation output.

Introduction
Sentence simplification aims to reduce the linguistic complexity of a text whilst retaining most of its meaning. It has been the subject of several modeling efforts in recent years due to its relevance to various applications. Examples include the development of reading aids for individuals with autism (Evans, Orasan, and Dornescu 2014), aphasia (Carroll et al. 1999), dyslexia (Rello et al. 2013a), and population groups with low-literacy skills (Watanabe et al. 2009), such as children and non-native speakers.

Modern approaches (Zhang and Lapata 2017; Vu et al. 2018; Guo, Pasunuru, and Bansal 2018; Zhao et al. 2018) view the simplification task as monolingual text-to-text rewriting and employ the very successful encoder-decoder neural architecture (Bahdanau, Cho, and Bengio 2015; Sutskever, Vinyals, and Le 2014). In contrast to traditional methods which target individual aspects of the simplification task such as sentence splitting (Carroll et al. 1999); Chandrasekar, Doran, and Srinivas 1996, inter alia) or the substitution of complex words with simpler ones (Devlin 1999; Kaj et al. 2002), neural models have no special-purpose mechanisms for ensuring how to best simplify text. They rely on representation learning to implicitly learn simplification rewrites from data, i.e., examples of complex-simple sentence pairs.

In this paper, we propose a user-centric simplification model which draws on the advantages of the encoder-decoder architecture but can also explicitly model rewrite operations, such as lexical and syntactic simplifications, and as a result generate output according to specifications. Although many simplification systems (Zhu, Bernhard, and Gurevych 2010; Kauchak 2013; Zhang and Lapata 2017) are intended as general purpose, different target populations may have different needs (Siddharthan 2014). For instance, whether or not the syntax should be simplified depends on the reader: those affected by aphasia benefit from simpler syntax, while dyslexics have trouble processing long and infrequent words (Rello et al. 2013a); Shewan and Canter 1971). It is therefore beneficial to have a model which can be easily adapted for particular users or user populations without being redesigned every time from scratch.

Our simplification model adopts the Transformer architecture (Vaswani et al. 2017) which has become state-of-the-art in machine translation (Bojar et al. 2018) and relies entirely on self-attention to compute representations of its input and output without using recurrent or convolutional neural networks. Our innovation is to enrich a Transformer-based sequence-to-sequence model with syntactic and lexical constraints which allow the user to control both the level of simplicity and the type of simplification. Importantly, this requires no additional annotation (e.g., for grade levels) and the constraints are applied post training, allowing one model to be used across datasets and tasks. We enable the model to make decisions about which words or syntactic structures to replace by enriching the training data with explicit information pertaining to lexical substitution and syntactic simplification. For example, we can mark words as to keep or substitute, or append a high-level level syntactic description (a template) to the source and target sentence. At test time, the user provides their constraints and the decoder must first decode the syntax of the target sentence before decoding the lexical tokens.

We evaluate our system on two publicly available datasets collected automatically from Wikipedia (Woodsend and Lapata 2011); Kauchak 2013; Zhu, Bernhard, and Gurevych 2010) and human-authored
news articles Xu, Callison-Burch, and Napoles (2015) and report results using automatic and human evaluation. By comparing our constrained model against non-constrained variants we show that constraints are key to successful simplification, offering generation flexibility and controllable output. Our contributions in this paper are three-fold: (1) we show that adding lexical and syntactic constraints to a Transformer produces state-of-the-art simplification results; (2) these constraints allow users to adapt the model to their personal needs; and (3) we conduct a comprehensive evaluation and comparison study which highlights the merits and shortcomings of various recently proposed simplification models on two datasets.

Related work

Our model resonates the recent trend of developing simplification models using neural architectures based on the encoder-decoder paradigm. It also agrees with previous work in acknowledging that both lexical and syntactic information is important in creating simplified text.

One of the first neural network approaches to simplification was presented by Zhang and Lapata (2017) who use an encoder-decoder LSTM, trained using reinforcement learning, to optimize for grammaticality, simplicity, and adequacy. They also propose an extension which ensembles their basic model with a lexical simplification component. Vu et al. (2018) augment an encoder-decoder model with the Neural Semantic Encoder Munkhdalai and Yu (2017): a variable sized memory that updates over time through the use of read, compose, and write operations. This increased capacity allows for better tracking of long range dependencies encountered within sentence simplification.

Guo, Pasunuru, and Bansal (2018) use multi-task learning to augment the limited amount of simplification training data. In addition to training on complex-sentence pairs, their model employs paraphrases, created automatically using machine translation, and entailment pairs. Zhao et al. (2018) are closest to our work: they augment a Transformer-based simplification model with lexical rules obtained from simple PPDB. Ganitkevitch, Van Durme, and Callison-Burch (2013), a subset of PPDB which has been automatically annotated with a simplicity score. A memory unit is added to the model which holds the applicable PPDB rules and a new loss rewards the model using rules from simple PPDB. Although the backbone of our model is also a Transformer, our aim is to develop a simplification system capable of adapting to the individual needs of specific users.

In recent years there has been increased interest in controlling the output of sequence-to-sequence models. Previous work has focused on controlling the length and content of summaries (Kikuchi et al. 2016; Fan, Grangier, and Auli 2018). politeness in machine translation Sennrich, Haddow, and Birch (2016), and style Ficler and Goldberg (2017). Scarton and Specia (2018) develop a text simplification model that controls the grade level of the output. They train a text sequence-to-sequence model on Newsela, attaching tags which specify the output sentences’ grade level. Nishihara, Kajiwara, and Arase (2019) expand upon this work by weighting the loss function to favor the generation of certain words. In this way, they can train different models with different output lexical preferences. As both approaches require explicit grade level annotations, they cannot be used with Wikipedia based simplification datasets.

In contrast, our work requires no grade level annotation, and user control is applied at test time, allowing us to train only one model. Our work draws inspiration from Grangier and Auli (2018) who post-edit the output of a machine translation under the assumption that a human modifies a sentence by marking tokens they would like the system to change. Our model also controls simplification by taking as input both the sentence and change markers for it. However, we allow for a wider spectrum of rewrite operations than Grangier and Auli (2018) who focus solely on deletion and do not take syntax into account. Bingel, Paetzold, and Sogaard (2018) notably acknowledge the fact that there is no one-size-fits-all solution to text simplification and develop a tool which can be personalized to user needs and adapt over time. Their system decides whether a word (in context) poses difficulty to the reader and suggests lexical substitutions.

Earlier approaches to simplification rely heavily on syntax, either by developing rule-based components Chandrasekar, Doran, and Srinivas (1996) or models which operate over parse trees and learn a mapping from complex to simpler structures Xu et al. (2016); Woodsend and Lapata (2011). Our model is informed by syntax, however, only indirectly since generation proceeds sequentially token-by-token. Lyver et al. (2018) learn how to generate paraphrases subject to a syntactic template. We adapt their template extraction method to the simplification task and incorporate it in our model.

Model Description

In this paper, we devise a model that adapts to the user’s simplification needs. The main idea is to equip a neural encoder-decoder model with constraints. The model still learns how to simplify from data, i.e., pairs of source (complex) and target (simple) sentences which are additionally annotated with change markers (e.g., indicating which words to replace, which syntactic constructs to delete) and takes these into account while generating simplifications.

Transformer

We will first define a basic encoder-decoder model for sentence simplification and then explain how to add constraints. Given a complex sentence \( X = (x_1, x_2, ..., x_{|X|}) \), our model learns to predict its simplified target \( Y = (y_1, y_2, ..., y_{|Y|}) \). Inferring the target \( Y \) given source \( X \) can be modeled as a sequence-to-sequence learning problem. We adopt Transformer’s multi-layer and multi-head attention architecture Vaswani et al. (2017).

The hidden state \( h_i \) at time step \( i \) in layer \( l \) in the Transformer encoder is calculated from all hidden states of the previous layer, as seen below:

\[
h_i^l = h_i^{l-1} + f(\text{self-attention}(h_i^{l-1}))
\]
where \( f \) is a feed-forward network using ReLU and layer normalization \cite{Ba2016}. In the input layer, \( h_0^l \) is calculated as:

\[
h_0^l = E_{x_i} + e_{pos,i}
\]

(2)

where \( E \) is the word embedding matrix and \( e_{pos,i} \) are positional embeddings.

Analogously, the decoder also consists of multiple layers, which apply self-attention. However, the decoder has an additional attention network, inserted after the self-attention network, which attends over the source sentence hidden states. Each hidden state \( h_i^{l} \) in the final layer \( L \), is fed through a softmax ranging over the target word vocabulary.

### Lexical Constraints

Lexical substitution, the replacement of complex words with simpler alternatives, is an integral part of sentence simplification and has been the subject of much previous work \cite{Specia2012,Paetzold2017,Lee2018,Yatskar2010,Devlin2017,Inui2003,Kai2002}. We enrich the encoder of the Transformer with lexical constraints, by adding indicator features to each word embedding, specifying if the token should be kept. We employ three indicator types:

1. The token should be replaced; during training this is set if the token does not appear in the target sentence;
2. The token should be kept; during training this is set if the token is in the target sentence;
3. There is no preference for the token to be kept or replaced; during training half of all tokens are randomly assigned this value.

Unlike \cite{Grangier2018}, we do not require tokens in the source and target to constitute an exact match. Instead, we apply constraints more flexibly, and mark tokens (to be replaced or kept) as long as their stems match. Indicator features are added to the word embedding and positional encoding, as seen in the equation below:

\[
h_0^i = E_{x_i} + e_{pos,i} + cw_i
\]

(3)

where \( cw_i \) are indicator features learnt during training. We also restrict the generation of complex words; during decoding we use constrained beam search, where complex words are given zero probability \cite{Post2018}.

At test time, the user can control the model’s output simply by (1) striking out tokens they wish to discard; (2) marking tokens they want to keep; or (3) leaving tokens unmarked. These could be words that an aphasic reader has trouble understanding, or a second language learner is not familiar with. For example in the sentence “Dextromethorphan occurs as a white powder”, occurs should be replaced and white powder should be preserved. Lists of complex words can be provided to the model in two formats: as a dictionary of complex and corresponding simple words or as a list of complex words. When a dictionary is available, we mark for replacement all complex words and during decoding we constrain the output to include only words which appear as simplifications. When a list is provided, we again mark for replacement complex words and leave it up to the model to decide what to simplify.

In experiments we used the simplification dictionary provided by the Wikipedia editor “SpencerK” (Spencer Kelly). Due to the limited size of this dictionary, we combine it with an automatically created simplification dictionary, learnt from the training data. Word alignments, produced using GIZA++ \cite{Och2003}, were used to create phrase tables, which we treat as a simplification dictionary (abandon \( \rightarrow \) leave, replenished \( \rightarrow \) filled, fraudulent \( \rightarrow \) fake; see the supplementary material for more examples).

In addition we use a fairly inexpensive approach to learn a list of complex words from training data. We calculate the relative probability that a word appears in the simple and complex corpora:

\[
\text{Complexity}(\text{word}) = \frac{P(\text{word}|\text{complex})}{P(\text{word}|\text{simple})}
\]

(4)

Using Equation (4), we order all words in the training set with \( \text{Complexity}(\text{word}) > 1 \) and take the first \( N \) words to produce the complex list (e.g., cavalier, offbeat, insofar; see the supplementary for more examples).

### Syntactic Constraints

Syntactic simplification aims to reduce the syntactic complexity of a text while preserving its meaning and information content. Although the bulk of previous work has focused on sentence splitting, namely rewriting a complex sentence into multiple simpler sentences \cite{Carroll1999}, Chandrasekhar, Doran, and Srinivas (1996), other operations which reduce syntactic complexity involve rendering passive voice into active, simplifying relative clauses and coordinating, as well reordering constituents or deleting them.

Syntax is introduced to our model by annotating the complex source and simplified target with high level syntactic descriptions (aka templates). Templates are induced from the training corpus by parsing source and target sentences with a universal dependencies parser \cite{Straka2018}. An example of a parse can be seen in Table 1. Dependency parses are further linearized and we extract a template corresponding to the top two levels of the parse. Templates are appended to the front of the source and target sentences. Once the model is trained on this template-enriched corpus, the decoder must first generate a target template and then decode the string.

The annotation process described above renders the model syntax-aware. Analogously to the lexical constraints, a globally constraint variant of beam search is used at test time and syntactic indicator features (i.e., replace, keep, don’t care) are added to the encoder. To reduce sparsity, a Markovian assumption is applied to the templates. Each constraint consists of one parent and its children as found within the template (see Table 1 for examples). Unlike lexical constraints, which are applied at the token level, syntactic constraints are applied at the rule level. At test time, the user provides a list of constraints the system must adhere to.

\[^{1}\text{http://www.spencerwaterbed.com/soft/simple/about.html}\]
The list is used to mark the input syntax and to constrain the decoder’s output. For example, applying the constraint Root(nsubj nmod nmod advcl) \rightarrow Root(nsubj nmod advcl) to the source sentence “She remained in the United States until 1927 when she and her husband returned to France.” produces the simplification “She remained in the USA until she returned to France with her husband in 1927.” As with lexical constraints, we provide syntactic simplifications in two formats. As a list of synchronous grammar rules (see Table 2) or a list of complex rules which the output must avoid (see Table 3) Newsela and WikiLarge are benchmark datasets we experimented with; see next section for details.

We should point out that lexical and syntactic constraints can be easily combined by merging the two sets of constraints provided by the user. In this case six indicator features are used, three for the lexical constrains and three for the syntactic constrains.

### Experimental Setup

**Datasets** We experimented with two simplification datasets: (1) Newsela [Xu, Callison-Burch, and Napoles (2015)], a simplification corpus of news articles created by Newsela’s professional editors. Each news article is written at four different simplicity levels. It consists of 1,130 articles, 30 of which are reserved as test set; and (2) WikiLarge [Zhang and Lapata (2017)], a large (296,402 sentence pairs) corpus which consists of a mixture of three Wikipedia simplification datasets collated by [Zhu, Bernhard, and Gurevych (2010), Woodsend and Lapata (2011) and Kauchak (2013)]. The test set for WikiLarge was created by [Xu et al. (2016)] and consists of 359 sentences, taken from Wikipedia, and then simplified using Amazon Mechanical Turkers to create eight references per source sentence.

**Model Configuration** For both datasets we used the Transformer as implemented within OpenNMT-py [Klein et al. (2017)]. The encoder and decoder consist of 8 layers with a hidden dimension of size 500. Word embeddings, size 500, were initialized randomly and shared between the encoder and decoder. We used ten attentional heads and a copy mechanism [See, Liu, and Manning (2017)]. The network was optimized using Adam [Kingma and Ba (2014) and SARI [Xu et al. (2016)] was used for early stopping. The vocabulary size was limited to the 50,000 most frequent tokens, the remaining tokens were replaced with an UNK token.

**Constraint Configuration** Table 4 presents statistics of the dictionaries used in our experiments. At test time, we explored two approaches to applying the constraints to the encoder. For WikiLarge, simple tokens were marked with keep and complex tokens were marked with replace. When using the complex list, we included ∼12,000 most complex words. For Newsela, simple tokens were marked with indifference and complex tokens were marked with replace. When using the complex list, we included ∼7,000 most complex words. In both approaches, all functions words were marked with indifference.

At test time, complex syntactic rules were marked with the replace indicator and all other rules were always marked with the keep indicator. For Newsela, when using the
complex list, we include approximately 29% of the rules. Whereas for WikiLarge we include approximately 13% of the rules.

**Evaluation Metrics** As there is no single agreed-upon metric for simplification, we evaluated model output using the combination of five automatically generated scores:

- **BLEU** (Papineni et al., 2002) assesses the degree to which generated simplifications differ from gold standard references; unlike Zhang and Lapata (2017), we use multi-bleu.perl as the test sets are already tokenized.
- **SARI** (Xu et al., 2016) is calculated using the average of three rewrite operation scores: addition, copying, and deletion. It rewards addition operations when the system’s output is not in the input but occurs in the references; analogously, it rewards words deleted/retained if they are in both the system output and the references; our SARI implementation differs from previous versions as we use the precision of the delete operation when calculating SARI, as recommended in Xu et al. (2016). Previous approaches used the F1 of all three rewrite operations.
- **FKGL** the Flesch-Kincaid Grade Level index measures the readability of the output (lower FKGL implies simpler output). We modified FKGL such that a newline indicates the end of sentence, so as to prevent unrelated lines being calculated as one continuous sentence.
- **S-BLEU** is a shorthand for self-BLEU and computes the BLEU score between the output and the source. This metric allows us to examine whether the models are making trivial changes to the input.
- **Copy** measures the percentage of sentences copied (with no changes made) from the source to the output as a way of quantifying the extent to which a model performs any rewriting at all.

We also evaluated system output by eliciting human judgments via Amazon’s Mechanical Turk. Native English speakers (self reported) were asked to rate simplifications on three dimensions: Grammaticality (is the output grammatical and fluent?), Meaning Adequacy (to what extent is the meaning expressed in the original sentence preserved in the output, with no additional information added?), and Simplicity (is the output a simpler version of the input?). The ratings were obtained using a five point Likert scale. 100 sentences were randomly sampled from the test set. Each sample received five ratings, resulting in 500 judgments per test set.

| WikiLarge | SARI | BLEU | FKGL | S-BLEU | Copy |
|-----------|------|------|------|--------|------|
| Reference | N/A  | N/A  | 8.24 | 63.92  | 16.2%|
| Source    | 26.31| 99.37| 9.54 | 100.00 | 100% |
| Truncate  | 35.62| 99.32| 9.54 | 95.48  | 0%   |
| PBMT-R    | 40.30| 81.02| 8.40 | 74.95  | 09.7%|
| Hybrid    | 27.59| 48.69| 4.72 | 30.57  | 03.1%|
| SBMT-SARI | 40.75| 73.01| 7.53 | 67.93  | 10.6%|
| EncDecA   | 39.58| 89.00| 8.61 | 83.81  | 40.7%|
| DRESS     | 35.45| 77.32| 6.76 | 56.96  | 21.5%|
| DRESS-Ls  | 36.08| 80.35| 6.90 | 60.21  | 26.2%|
| Transformer| 36.21| 81.51| 8.73 | 76.33  | 36.2%|
| DMass     | 40.35| 79.68| 7.45 | 70.82  | 15.6%|
| CROSS-Lex | 38.82| 70.70| 7.92 | 65.62  | 10.6%|
| CROSS-Syn | 33.89| 64.98| 7.98 | 68.88  | 19.9%|
| CROSS     | 36.07| 64.64| 7.46 | 56.11  | 15.6%|

| Newsela  | SARI | BLEU | FKGL | S-BLEU | Copy |
|-----------|------|------|------|--------|------|
| Reference | N/A  | N/A  | 3.43 | 17.81  | 0%   |
| Source    | 11.97| 20.79| 8.61 | 100.00 | 100% |
| Truncate  | 36.92| 21.54| 5.57 | 62.54  | 0%   |
| PB MT-R   | 41.23| 17.62| 7.96 | 75.29  | 05.9%|
| Hybrid    | 35.37| 10.87| 4.14 | 19.96  | 03.3%|
| EncDecA   | 42.98| 21.17| 5.48 | 52.54  | 15.7%|
| DRESS     | 42.85| 22.65| 4.20 | 39.69  | 11.3%|
| DRESS-Ls  | 43.26| 23.66| 4.36 | 42.72  | 14.5%|
| Transformer| 42.21| 19.90| 4.77 | 40.05  | 11.6%|
| DMass     | 37.36| 07.51| 3.84 | 11.15  | 01.1%|
| CROSS-Lex | 41.56| 18.88| 3.81 | 33.98  | 06.8%|
| CROSS-Syn | 38.12| 14.30| 3.48 | 21.35  | 05.1%|
| CROSS     | 37.57| 12.68| 3.51 | 26.55  | 05.6%|

Table 5: Automatic evaluation on WikiLarge and Newsela test set. We also report the average FKGL, S-BLEU, and Copy of all references (Reference).

**Results**

Our first suite of experiments compares our approach against the state-of-the-art aiming to show that our model can also function as a general-purpose simplification system. There is no point having a controllable model if it cannot generate adequate simplifications on its own. Our second suite of experiments examines how the simplicity level can be manipulated.

**Automatic Evaluation** Table 5 summarizes our automatic evaluation results on WikiLarge and Newsela. We compared our model against three well-established non-neural models: PBMT-R Wubben, Van Den Bosch, and Krahmer (2012), a phrase-based machine translation model, SBMT-SARI Xu et al. (2016), a syntax-based translation model trained on PPDB and which is then tuned using SARI, and Hybrid Narayan and Gardent (2014), a model which performs sentence splitting and deletions and then simplifies with PBMT-R. We also compare against various neural simplification models: (a) the three LSTM-based models reported in Zhang and Lapata (2017), namely EncDecA,

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2. Our evaluation procedure can be found at https://github.com/Jmallins/CROSS
3. Zhang and Lapata (2017) use mtevalv13a.pl which is intended for untokenized text.
4. Further fixes were applied to cases where a single reference was provided.
5. We used the same samples as Zhang and Lapata (2017).
6. As our automatic metrics differ from previous papers we re-calculate all scores for all available simplification models.
Table 6: Human evaluation on WikiLarge and Newsela. Models significantly different from CROSS are marked with * (p < 0.05) and ** (p < 0.01). Significance tests were performed using a student t-test.

|         | WikiLarge | Gram | Mean | Simp | AVG | Min |
|---------|-----------|------|------|------|-----|-----|
| Reference | 4.01*    | 4.13** | 3.56** | 3.90** | 3.16* |
| DRESS-Ls | 4.32**   | 3.97** | 3.14  | 3.81** | 2.80 |
| D MASS  | 3.69      | 3.21  | 2.57** | 3.16  | 2.29** |
| Transformer | 3.91    | 3.63  | 3.04** | 3.53  | 2.72** |
| CROSS-Lex | 3.72     | 3.41  | 3.18  | 3.43  | 2.80 |
| CROSS-Syn | 3.54      | 2.22  | 2.46** | 3.07** | 2.15** |
| CROSS   | 3.61     | 3.37  | 3.13  | 3.37  | 2.84 |

|         | Newsela   | Gram | Mean | Simp | AVG | Min |
|---------|-----------|------|------|------|-----|-----|
| Reference | 4.11**   | 3.75** | 3.88** | 3.91** | 3.47** |
| DRESS-Ls | 3.33**   | 2.98** | 2.93  | 3.08** | 2.45 |
| D MASS  | 2.05**   | 1.55** | 1.74** | 1.78** | 1.39** |
| Transformer | 2.88**   | 2.47** | 2.70  | 2.68** | 2.00** |
| CROSS-Lex | 3.07**   | 2.89** | 2.95  | 2.97** | 2.45 |
| CROSS-Syn | 3.60     | 3.37  | 2.89  | 3.27  | 2.31 |
| CROSS   | 3.54     | 3.41  | 2.91  | 3.28  | 2.29 |

Human Evaluation  The results of our human evaluation are presented in Table 6. We follow previous approaches and report Grammaticality, Meaning Adequacy, and Simplicity individually and combined (AVG is the average of the three dimensions). In addition, we include a new metric Minimum, which is the (average) minimum value of Grammaticality, Meaning Adequacy, and Simplicity per sentence. We include Minimum because we argue that a simplification is only as good as its weakest dimension. We note that it is trivial to produce a sentence that is perfectly adequate and fluent, by simply repeating the source sentence. It is also easy to produce a simple sentence if we do not care about adequacy. We evaluated CROSS and CROSS-Lex, CROSS-Syn variants against the two state-of-the-art models DMASS and DRESS-Ls as well as a Transformer baseline. We also elicited judgments on the gold standard Reference as an upper bound.

Human evaluation on WikiLarge (top half in Table 6) shows that both DRESS-Ls and CROSS achieve highest scores for Minimum. CROSS significantly outperforms all other models for both Min and Simplicity. Transformer achieves a higher score for both Grammaticality and Meaning compared to CROSS. However, this can be explained due to the high Copy score, which therefore guarantees high Grammaticality and Adequacy scores. This can also in part explain the high Grammaticality and Meaning Adequacy scores for DRESS-Ls. CROSS-Syn achieves lower scores compared to CROSS-Lex, suggesting that syntactic changes are not as important for WikiLarge.

Human evaluation on Newsela (second half of Table 6) shows that all CROSS variants are better than related Transformer and DMASS models across all metrics. CROSS and DRESS-Ls both achieve the highest Minimum scores. For all other metrics, CROSS is better or the same than all other models. CROSS and CROSS-Syn achieve similar results, both outperforming CROSS-Lex. This suggests that syntactic simplifications are more prominent in Newsela compared to WikiLarge.
were performed using a student t-test. Similar simplifications to the references, and substantially
model, and the references. As can be seen, CROSS performs
these phenomena for CROSS, the baseline Transformer
and sentence splitting (Split). Table 7 shows a breakdown
into two categories, namely lexical (Lex) or syntactic (Syn).
(50 from each test set) and classified the simplifications
of simplifications it generates. We sampled 100 sentences
plifications produced by CROSS to gain insight on the types
of simplifications CROSS can be adapted to user needs. We test this claim,
Analysis of Model Output We further analyzed the simplifications produced by CROSS to gain insight on the types of simplifications it generates. We sampled 100 sentences (50 from each test set) and classified the simplifications into two categories, namely lexical (Lex) or syntactic (Syn). For syntactic simplifications we further marked whether these pertained to common changes, i.e., passive to active voice (Voice), past tense to present or past perfect (Tense), and sentence splitting (Split). Table 2 shows a breakdown of these phenomena for CROSS, the baseline Transformer model, and the references. As can be seen, CROSS performs similar simplifications to the references, and substantially more syntactic changes compared to the Transformer.
Controllability A central claim of this paper is that CROSS can be adapted to user needs. We test this claim, by experimenting with varying the simplicity level of the output. Specifically, we sampled 100 complex source sentences (with FKGL score of 11 or higher) from the WikiLarge and Newsela test sets and produced two sets of outputs, one with our general-purpose system which produces a moderate amount of simplification (Simple), and another one where we forced the model to simplify more drastically, extra simple (XSimple). This was achieved by increasing the number of lexical and syntactic constraints the model must adhere to. Specifically, we included the 12,000 most complex words for Newsela, and the 18,000 most complex tokens for Wikilarge. We also increased the number of complex syntactic constraints to approximately 40% for Newsela and 25% for Wikilarge.

Results in Table 2 show that CROSS is able successfully to alter the simplicity level of the output. For both datasets we see that participants perceive differences between the output of the simple and XSimple models (this is also reflected in the FKGL which is lower for XSimple). For Wikilarge, all scores apart from simplification do not differ significantly. For Newsela, we see that XSimple sentences are significantly less adequate and grammatical. However, on average Simple and XSimple sentences do not significantly differ, showing a trade-off between simplicity and adequacy/grammaticality. Examples of system output are shown in Table 9 (and in the supplementary).

Table 7: Proportion of simplifications on a 100 sentence sample from the WikiLarge and Newsela test sets.

|       | Lex   | Syn   | Voice | Tense | Split | All   |
|-------|-------|-------|-------|-------|-------|-------|
| Reference | 35%   | 10%   | 7%    | 5%    | 6%    | 41%   |
| Transformer | 9%    | 1%    | 1%    | 0%    | 0%    | 9%    |
| CROSS   | 29%   | 8%    | 8%    | 2%    | 8%    | 35%   |

Table 8: Human evaluation on varying simplicity of model output. Ratings that are significantly different are marked with * (p < 0.05) and ** (p < 0.01). Significance tests were performed using a student t-test.

|       | Lex | Syn | Voice | Tense | Split | AVG | Min | FKGL |
|-------|-----|-----|-------|-------|-------|-----|-----|------|
| WikiLarge Gram | Mean | Simp | AVG | Min | FKGL |
| XSimple | 3.30 | 3.09 | 3.06* | 3.15 | 2.84 | 6.96 |
| Simple | 3.24 | 3.11 | 2.87 | 3.08 | 2.77 | 7.46 |
| Newsela Gram | Mean | Simp | AVG | Min | FKGL |
| XSimple | 3.46** | 3.11** | 3.15 | 2.33** | 2.91 |
| Simple | 3.89 | 3.59 | 2.53 | 3.34 | 2.10 | 3.51 |

Table 9: Output of Simple and XSimple systems based on CROSS. We also show the output of DRESS-Ls, the source complex sentence, and the reference simplification.

Complex The United States is about to spend billions of dollars to build a top-secret warplane.
Reference Mission to build the secret warplane.
DRESS-Ls The United States is about to spend billions to build a new drone.
Simple The United States is about to spend billions to build a top-secret warplane.
XSimple It could also bring hundreds of jobs.

Conclusions

We developed a simplification model, which is able to jointly or individually control the syntax and lexical choice of its output. Experiments showed that our constraint-aware model produces state-of-the-art simplification results, receiving the best Minimum score on WikiLarge. We further showed that by adjusting these constraints we are able to control the level of simplification of the output. In the future we plan to incorporate more explicit controls, e.g., allowing the user to determine if the sentence should be split or not, or the readability level of the output.

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Appendix

Table 10 presents examples of the lists of complex words and dictionaries used in our experiments. We also show simplification examples created by our model and comparison systems on Wiki-Large and Newsela (see Tables 11–14).

| List       | Dictionary       |
|------------|------------------|
| Wikilarge  | Newsela          |
| kunaič     | expans           |
| official   | personnel        |
| insofar    | epidem           |
| silkmoth   | array            |
| lagerphonist | deploy       |
| conduc     | swath            |
| offbeat    | perspect         |
| cavalier   | dispar           |
| midfield   | crucial          |
| straddl    | prototyp         |
|            | Complex          |
| abandon    | leave            |
| assembled  | built            |
| cherishing | loving           |
| customary  | normal           |
| educating  | teaching         |
| fraudulent | fake             |
| initiated  | started          |
| iterated   | repeated         |
| replenished| refilled         |
| shove      | push             |

Table 10: Examples of (stemmed) complex words and complex-simple dictionary.
Complex: It is situated at the coast of the Baltic Sea, where it encloses the city of Stralsund.
Reference: It is located at the coast of the Baltic Sea where it surrounds the city of Stralsund.
DRESS-Ls: It is situated at the coast of the Baltic Sea.
Transformer: It is situated at the coast of the Baltic Sea, where it encloses the city of Stralsund.
DMASS: It is located at the shore of the Baltic Sea, where it is located at the shore of the borough of Stralsund.
CROSS-Lex: It is at the coast of the Baltic Sea, where it encloses the city of Stralsund.
CROSS-Syn: It is located at the coast of the Baltic Sea.
CROSS: It is found at the coast of the Baltic Sea, near the city of Stralsund.

Table 11: System output on WikiLarge. We show the source Complex sentence, the Reference, and output from DRESS-Ls, a Transformer, DMASS, and three CROSS variants; the full system (CROSS), and with on lexical (CROSS-Lex) and syntactic (CROSS-Syn) constraints. Items signalled for replacement are marked with a strike-out and substitutions are in bold.

Complex: In its pure form, Dextromethorphan occurs as a white powder.
Reference: Dextromethorphan is a white powder in its pure form.
DRESS-Ls: In its pure form, Dextromethorphan occurs as a white powder.
Simple: In its pure form, Dextromethorphan is like a white powder.
XSimple: Dextromethorphan can be found as white powder.

Table 12: System output on WikiLarge for varying simplicity levels. We show the source Complex sentence and the Reference as well as output from DRESS-Ls, and two variants of our model Simple and XSimple. Substitutions are shown in bold.
He thinks the new stealth bomber program would ultimately cost $90 billion.

Reference He thinks the new stealth bomber program would actually cost $90 billion.

DRESS-Ls He thinks the new combat number would cost $90 billion.

Transformer He thinks the new bomber program would cost $90 billion.

DMASS The new $ sinkhole program would be used this year.

CROSS-Lex He thinks the program would cost $90 billion for the new stealth bomber.

CROSS He thinks the program would cost $90 billion for the new bomber.

But then he heard the radio: A massive glacier had crashed down the mountain.

A huge glacier of ice had just crashed down the mountain.

But then he heard the radio: A massive glacier had crashed down the mountain.

Then he heard the radio even though a huge piece had crashed down the mountain.

But then he heard the radio: A huge glacier had crashed down the mountain.

But then he heard a glacier crash down the mountain.

But then he heard a glacier crash down the mountain.

The Pentagon is poised to spend billions to build a new stealth bomber, a top secret project that could bring hundreds of jobs to the wind-swept desert communities in Los Angeles County’s northern reaches.

Mission to build the secret warplane.

The Pentagon is trying to spend billions to build a new drone.

The Pentagon secret project that could bring hundreds of jobs to the desert-swept communities in Los Angeles County.

It could also bring hundreds of jobs.

The United States is about to spend billions of dollars to build a top-secret warplane.

Mission to build the secret warplane.

The United States is about to spend billions of dollars to build a secret bomb.

The United States is about spend dollars to build a top-secret warplane.

The United States is about to build a warplane.