Unsupervised Neural Text Simplification

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Abstract

The paper presents a first attempt towards unsupervised neural text simplification that relies only on unlabeled text corpora. The core framework is composed of a shared encoder and a pair of attentional-decoders and gains knowledge of simplification through discrimination based-losses and denoising. The framework is trained using unlabeled text collected from en-Wikipedia dump. Our analysis (both quantitative and qualitative involving human evaluators) on a public test data shows that the proposed model can perform text-simplification at both lexical and syntactic levels, competitive to existing supervised methods. Addition of a few labelled pairs also improves the performance further. We open source our implementation for academic use.

1 Introduction

Text Simplification (TS) deals with transforming the original text into simplified variants to increase its readability and understandability. TS is an important task in computational linguistics, and has numerous use-cases in fields of education technology, targeted content creation, language learning, where producing variants of the text with varying degree of simplicity is desired. TS systems are typically designed to simplify from two different linguistic aspects (a) Lexical aspect, by replacing complex words in the input with simpler synonyms (Devlin, 1998; Candido Jr et al., 2009; Yatskar et al., 2010; Biran et al., 2011; Glavaš and Štajner, 2015), and (b) Syntactic aspect, by altering the inherent hierarchical structure of the sentences (Chandrasekar and Srinivasa, 1997; Canning and Tait, 1999; Siddharthan, 2006; Filippoiva and Strube, 2008; Brouwers et al.). From the perspective of sentence construction, sentence simplification can be thought to be a form of text transformation that involves three major operations such as (a) splitting (Siddharthan, 2006; Petersen and Ostendorf, 2007; Narayan and Gardent, 2014) (b) deletion/compression (Knight and Marcu, 2002; Clarke and Lapata, 2006; Filippova and Strube, 2008; Rush et al., 2015; Filippova et al., 2015) (c) paraphrasing (Specia, 2010; Coster and Kauchak, 2011; Wubben et al., 2012; Wang et al., 2016; Nisioi et al., 2017).

Most of the current TS systems require large-scale parallel corpora for training (except for systems like Glavaš and Štajner (2015) that performs only lexical-simplification), which is a major impediment in scaling to languages, use-cases, domains and output styles. In fact, one of the popular corpus for TS in English language, i.e., the Wikipedia-SimpleWikipedia aligned dataset has been prone to noise (badly aligned instances) and inadequacy (i.e., instances having non-simplified targets) (Xu et al., 2015; Štajner et al., 2015), leading to noisy supervised models (Wubben et al., 2012). While creation of better datasets (such as, Newsela by Xu et al. (2015)) can always help, we explore the unsupervised learning paradigm which can potentially work with unlabeled/weakly labeled datasets that are cheaper to obtain.

A supervised treatment of the TS task using parallel corpora seeks to learn both the language transformation (so that it preserves the semantics), and the style transformation, simultaneously for the task. However, since the preservation of language semantics is necessary for simplification, whereas only the style of the text needs to be changed, it should be possible to decouple these two aspects. From a neural-learning perspective, this necessitates a specially designed auto-encoder that also embodies additional capabilities of introducing variations so that the auto-encoded output is a simplified version of the input. Intuitively, both of these can be learned by looking at the structure and language patterns of a large
amount of non-aligned complex and simple sentences (which are much cheaper to obtain). These motivations form the basis of our work.

Our approach relies only on two unlabeled text corpora - one representing relative simple sentences than the other. Note again that these corpora need not be aligned. The crux of the framework is a shared encoder and a pair of decoders that gain knowledge of simplification through adversarial and classifier based losses. Additionally, we employ auto-encoding for preserving semantics, and denoising for enabling syntactic transformations. The framework is trained using unlabeled text collected from Wikipedia and Simple Wikipedia. The efficacy of our system is demonstrated through (a) quantitative analysis using automated evaluation metrics for natural language generation, and (b) qualitative analysis involving manual evaluation of the test outputs. We also show that by leveraging a small amount of labeled data, our systems performance can be improved further. We will release the code and a new dataset containing partitioned unlabeled sets of simple and complex sentences.

2 Related Work

Text simplification, often discussed from psychological and linguistic standpoints (L’Allier, 1980; McNamara et al., 1996; Linderholm et al., 2000), recently became a mainstream research in computational linguistics. To this end, a heuristic-based system was first introduced by Chandrasekar and Srinivas (1997) which induces rules for simplification automatically extracted from annotated corpora. Canning and Tait (1999) propose a modular system that uses NLP tools such as morphological analyzer, part-of-speech tagger along with heuristics to simplify the text both lexically and syntactically. A detailed review of the older systems are given by Siddharthan (2014). As discussed in the introduction, most of these systems are independently targeted towards lexical and syntactic simplification and often indulge in splitting and/or truncating sentences.

With the advent of data-driven machine translation paradigms, it became possible to perform paraphrasing based simplification. Some of the initial systems, based on the Statistical Machine Translation (SMT), rely on phrase base SMT (Specia, 2010; Štajner et al., 2015) or their variants (Coster and Kauchak, 2011; Xu et al., 2016a), that combine heuristic and optimization strategies for better TS. Some recently proposed TS systems are based on neural Seq2Seq architecture (Bahdanau et al., 2014) which is modified for TS specific operations (Wang et al., 2016; Nisioi et al., 2017). While these systems produce state of the art results on the popular Wikipedia dataset (Coster and Kauchak, 2011), they may not be generalizable because of the noise and bias in the dataset (Xu et al., 2015) and overfitting of supervised models on small scale labeled datasets. Towards this, tajner and Nisioi (2018) show that through improved datasets and minor model level changes (such as using reduced vocabulary and enabling copy mechanism) reasonable performance can be obtained for both in-domain and cross-domain TS.

In the unsupervised TS domain, a work that is close to ours is by Paetzold and Specia (2016) who propose an unsupervised lexical simplification technique that replaces complex words in the input with simpler synonyms; the synonyms are extracted and disambiguated using word embeddings. However, this work, unlike ours only addresses lexical simplification and can not be trivially extended for other forms of simplification such as simplification by splitting and rephrasing. As far as we know, ours is a first of its kind end-to-end solution for unsupervised TS. At this point, though supervised solutions perform superior to the unsupervised ones, we believe unsupervised paradigms should be further explored since they hold greater potential with regards to scalability to various tasks.

It is worth noting that in the absence of other end-to-end unsupervised baselines for TS, we train the unsupervised machine translation system by Artetxe et al. (2017) and consider it as a baseline.

3 Model Description

Our system is built based on the encode-attend-decode style architecture (Bahdanau et al., 2014) with both algorithmic and architectural changes applied to the standard model. An input sequence of word embeddings $X = \{x_1, x_2, \ldots, x_n\}$ (obtained after a standard look up operation on the embedding matrix), is passed through an encoder ($E$). The output representation from $E$ is fed to two decoders ($G_s, G_d$) empowered with attention mechanism. $G_s$ is meant to generate a simplified sentence, where as $G_d$ reconstructs the input sentence. A discriminator ($D$) and a classifier ($C$) are
also employed to distinguish between the encoded and decoded representations respectively. Figure 1 is a diagrammatic representation of our system. We describe the components below.

### 3.1 Encoder-Decoder Model

Encoder $E$ uses two layers of bi-directional GRUs (Cho et al., 2014b), and decoders $G_s$, $G_d$ have a two layers of GRUs each. $E$ extracts the hidden representations from an input sentence. The decoders output sentences sequentially, one word at a time. Each decoder-step involves using *global attention* to create attention-vector (weighted hidden representations) as an input for the next decoder-step. Attention mechanism enables the decoders to focus on different parts of the input sentence. For the input sentence $X$ with $n$ words, the encoder produces $n$ hidden representations, $H = \{h_1, h_2, \ldots, h_n\}$, the attended vectors extracted from $X$ by $G_s$ are represented as,

$$A_t(X) = \sum_{i=1}^{n} a_{it} h_i \quad (1)$$

where, $A_t(X)$ denotes the attention vector extracted by the decoder $G_s$ at step $t \in \{1 \ldots m\}$. $m$ denotes the total number of decoding steps performed. $a_{it}$ denote attention weights for the hidden representations, from $i^{th}$ input position and decoder-step $t$.

### 3.2 Discriminator and Classifier

The discriminator $D$ is employed to influence the way the decoder $G_s$ will attend to the hidden representations, which has to be different from the way $G_d$ attends. The input to $D$ is the attention vector sequence ($\{A_t\}_{t=1}^m$, where $m$ denotes the number of decoding steps) pertaining to $G_s$, and it produces a binary output, $\{1, 0\}$, 1 indicating the fact that the attended vector sequence is close to a typical attention vector sequence extracted from simple sentences seen in the dataset. $G_s$ and $D$ are indulged in an adversarial interplay through an adversarial loss function (see Section 4.2), analogous to GANs (Goodfellow et al., 2014), where the generator and discriminators, converge to a point where the distribution of the generations eventually resembles the distribution of the genuine samples. In our case, adversarial loss tunes the attention vector sequence extracted from a complex sentence by $G_s$ to resemble attention vector sequence of simple sentences in the corpora.

An auxiliary classifier ($C$) is introduced to distinguish between simple and complex (difficult) attention vector sequences. The job of the classifier is to predict whether an attended vector sequence represents complex or simple sentences. Refer Section 4.3 for more details.

Both $D$ and $C$ use CNN-based classifier proposed in Kim (2014). All layers are shared between $D$ and $C$ except the fully-connected layer preceeding the softmax function.

### 3.3 Special Purpose Word-Embeddings

Pre-trained word embeddings are often seen to have positive impact on sequence-to-sequence frameworks (Cho et al., 2014a; Qi et al., 2018). However, traditional embeddings are not good at capturing relations like synonymy (Tissier et al., 2017), which are essential for simplification. For this, our word-embeddings are trained using the *Dict2Vec* framework\(^1\). *Dict2Vec* fine-tunes the embeddings through the help of an external lexicon containing weak and strong synonymy relations. The system is trained on our whole unlabeled datasets and with seed synonymy dictionaries provided by Tissier et al. (2017). Our encoder and decoders share the same word embeddings. Moreover, the embeddings at the input side are kept static but the decoder embeddings are updated as training progresses. Details about hyper-parameters are given in Section 5.2.

### 4 Training Procedure

Let $S$ and $D$ be sets of simple and complex (difficult) sentences respectively from large scale unlabeled repositories of simple and complex sentences. Let $S_a$ and $D_a$ denote the set of simple and difficult attention vectors. $S_a$ and $D_a$ are extracted by decoders $G_s$ and $G_d$ respectively from $S$ and $D$ domains. Let $\theta_E$ denote the parameters of $E$ and $\theta_G$ denote the parameters of both $G_s$ and $G_d$. Let $A_S$ denote an attention vector sequence sampled from set $S_a$ and $A_D$ be an attention vector sequence sampled from the set $D_a$. Let $X_S$ denote a sentence sampled from the set of simple sentences $S$ and $X_D$ be a sentence sampled from the set of complex sentences. Training the model involves optimization with respect to the following losses and *denoising*, which are explained below.

\(^1\)https://github.com/tca19/dict2vec
Decoder $G_D$ (left) and $G_S$ (right) are trained to reconstruct input $X$ from $Y$. The discriminator $D$ is trained to distinguish between $G_S$ and $G_D$. The classifier $C$ is trained to distinguish between $G_S$ and $G_D$.

4.1 Reconstruction Loss

Reconstruction Loss is imposed on both $E - G_S$ and $E - G_D$. $E - G_S$ is trained to reconstruct sentences from $S$ and $E - G_D$ is trained to reconstruct sentences from $D$. Let $P_{E-G_S}(X)$ and $P_{E-G_D}(X)$ denote the reconstruction probabilities of an input sentence $X$ estimated by the $E - G_S$ and $E - G_D$ models respectively. Reconstruction loss for $E - G_S$ and $E - G_D$, denoted by $\mathcal{L}_{rec}$, is computed as follows.

$$\mathcal{L}_{rec}(\theta_E, \theta_C) = \mathbb{E}_{X \sim S} \left[ \log P_{E-G_S}(X_S) \right] + \mathbb{E}_{X \sim D} \left[ \log P_{E-G_D}(X_D) \right]$$  \hspace{1cm} (2)

4.2 Adversarial Loss

Adversarial Loss is imposed upon the attention vectors for $G_S$. The idea is that, attention vectors extracted even for a complex input sentence should resemble with the simple attention vectors in $S$. The discriminator $D$ is trained to distinguish the generated fake (non-simple) attention vectors from the real (simple) attention vectors. $E - G_S$ is trained to perplex the discriminator $D$, and eventually, at convergence, learns to generate simple real attention vectors from complex input sentences. In practice, we observe that adversarial loss indeed assists $E - G_S$ in simplification by encouraging sentence shortening. Let $A(\cdot)$ be a set of attention vectors defined in equation 1. Adversarial losses for $E - G_S$, denoted by $\mathcal{L}_{adv,G_S}$, and discriminator $D$, denoted by $\mathcal{L}_{adv,D}$ are as follows.

$$\mathcal{L}_{adv,D}(\theta_D) = \mathbb{E}_{A \sim S} \left[ \log (1 - D(A_S)) \right] + \mathbb{E}_{A \sim D} \left[ \log D(A_D) \right]$$  \hspace{1cm} (3)

$$\mathcal{L}_{adv,G_S}(\theta_E, \theta_G_S) = \mathbb{E}_{A \sim S} \left[ \log (1 - C(A_S)) \right] + \mathbb{E}_{A \sim D} \left[ \log C(A_D) \right]$$  \hspace{1cm} (4)

4.3 Classifier-Loss

Classifier-Loss is imposed by the classifier $C$ on attention vectors extracted by $G_S$ from complex input sentences. $C$ is trained to distinguish the simple attention vectors from the complex ones. $E - G_S$ learns to generate simple attention vectors distinguishable from complex attention vectors. Losses for classifier $C$, denoted by $\mathcal{L}_{classf,C}$ and model $E - G_S$ denoted by $\mathcal{L}_{classf,G_S}$ are computed as follows.

$$\mathcal{L}_{classf,C}(\theta_C) = \mathbb{E}_{A \sim S} \left[ \log C(A_S) \right] + \mathbb{E}_{A \sim D} \left[ \log (1 - C(A_D)) \right]$$  \hspace{1cm} (5)

$$\mathcal{L}_{classf,G_S}(\theta_E, \theta_G_S) = \mathbb{E}_{A \sim S} \left[ \log (1 - C(A_S)) \right] + \mathbb{E}_{A \sim D} \left[ \log C(A_D) \right]$$  \hspace{1cm} (6)

4.4 Denoising

Denoising has proven to be helpful to learn syntactic / structural transformation from the source side to the target side (Artetxe et al., 2017). Syntactic transformation often requires reordering the input, which denoising procedure aims to capture. Denoising involves arbitrarily reordering the inputs and reconstructing the original (unperturbed) input from such reordered inputs. In our implementation, the source sentence is reordered by swapping bigrams in the input sentences. The following loss function are used in denoising. Let $P_{E-G_S}(X|noise(X))$
Algorithm 1 Unsupervised simplification algorithm using denoising, reconstruction, adversarial and classifier losses.

**Input:** simple dataset $\mathcal{S}$, complex dataset $\mathcal{D}$

**Initialization phase:**
- Train $E, G_s, G_d$ using $L_{denoi}, L_{rec}$
- Train $D, C$ using $L_{adv,D}, L_{classf,C}$.

**Adversarial phase:**
- repeat
  - Train $E, G_s, G_d$ using $L_{denoi}, L_{rec}$
  - Train $E, G_s$ using $L_{adv,G_s}, L_{classf,G_s}$
  - Train $D, C$ using $L_{adv,D}, L_{classf,C}$.
- until specified number of epochs are completed or validation accuracy converges

and $P_{E-G_d}(X|\text{noise}(X))$ denote the probabilities that a perturbed input $X$ can be reconstructed by $E-G_s$ and $E-G_d$ respectively. Denoising loss for models $E-G_s$ and $E-G_d$, denoted by $L_{denoi}(\theta_E, \theta_G)$, is computed as follows.

$$L_{denoi}(\theta_E, \theta_G) = \mathbb{E}_{X \sim S}[\log P_{E-G_s}(X_s|\text{noise}(X_s))] + \mathbb{E}_{X \sim D}[\log P_{E-G_d}(X_D|\text{noise}(X_D))]$$

(7)

Figure 1 depicts the overall architecture and the losses described above; the training procedure is described in Algorithm 1. The initialization phase involves training the $E-G_s$, $E-G_d$, $D$, $C$ without using adversarial or classifier loss to update the generator. This gives the discriminator and generators time to learn. In the adversarial phase, adversarial and classifier losses are introduced along side denoising and reconstruction losses. Algorithm 1 is intended to produce the following results: i) $E-G_s$ should simplify its input, and ii) $E-G_d$ should act as an auto-encoder in complex sentence domain to extract the set of complex attention vectors $\mathcal{D}_a$, which is required in implementing the classifier loss.

A key requirement for a model like ours is that the dataset used has to be partitioned into two sets, containing relatively simple and complex sentences. The rationale behind having two decoders is that while $G_s$ will try to introduce simplified constructs (may be at the expense of loss of semantics), $G_d$ will help preserve the semantics. The idea behind using the discriminator and classifier is to retain signals related to language simplicity from which $G_s$ will construct simplified sentences. Finally, denoising will help tackle nuances related to syntactic transfer from complex to simple direction. We remind the readers that, TS, unlike machine translation, needs complex syntactic operations such as sentence splitting, rephrasing and paraphrasing, which can not be tackled by the losses and denoising alone. Bringing in additional explicit mechanisms to handle these in the pipeline is out of the scope of this paper since we seek a prima-facie judgement of our architecture based on how much simplification knowledge can be gained just from the data.

### 4.5 Training with Minimal Supervision

A system like ours, by design, is highly data-driven, and like any other sequence-to-sequence learning based system, can also leverage labelled data. We propose a semi-supervised variant of our system that could gain additional knowledge of simplification through the help of a small amount of labeled data (in the order of a few thousands). The system undergoes training following steps similar to Algorithm 1, except that it adds another step of optimizing the cross entropy loss for the $E-G_s$ part by using the reference texts available in the labelled dataset. This step is carried out in Algorithm 1 in both initialization and adversarial phases along with the other steps. Optimizing cross-entropy loss in sequence-to-sequence systems is a standard practice and the details are skipped here for brevity.

### 5 Experiment Setup

In this section we describe the dataset, architectural choices, and model hyperparameters.

#### 5.1 Dataset

For training our system, we created an unlabeled dataset of simple and difficult sentences by partitioning the standard en-wikipedia dump. Since partitioning requires a metric for measuring text simpleness we categorize sentences based on their readability scores. For this we use the Flesch Readability Ease (henceforth abbreviated as FE)
Sentences with lower FE values (up to 10) are categorized as complex and sentences with FE values greater than 70 are categorized as simple. The FE bounds are decided through trial and error through manual inspection of the categorized sentences. Table 1 shows dataset statistics. Even though the dataset was created with some level of human mediation, the manual effort is insignificant compared to that needed to create a labelled corpus.

To train the system with minimal supervision (Section 4.5), we extract 10,000 pairs of sentences from various datasets such as Wikipedia-SimpleWikipedia dataset introduced in Hwang et al. (2015) and the Split-Rephrase dataset by Narayan et al. (2017)\(^2\). The Wikipedia-SimpleWikipedia was filtered following Nisioi et al. (2017) and 4000 examples were randomly picked from the filtered set. From the Split-Rephrase dataset, examples containing one compound/complex sentence at the source side and two simple sentences at the target side were selected and 6000 examples were randomly picked from the selected set. The Split-Rephrase dataset is used to promote sentence splitting in the proposed semi-supervised system.

To select and evaluate our models, we use the test and development sets\(^3\) released by (Xu et al., 2016a). The test set (359 sentences) and development set (2000 sentences) have 8 simplified reference sentences for each source sentence.

### 5.2 Parameter Settings

For all the variants, we use a hidden state of size 600 and word-embedding size of 300. Classifier \(C\) and discriminator \(D\) use convolutional layers with filters sizes from 1 to 5. 128 filters of each size are used in the CNN-layers. Other training related hyper parameters include learning rate of 0.00012 for \(\theta_E, \theta_C\), 0.0005 for \(\theta_D, \theta_C\) and batch size of 36. For learning the word-embedding using \(\text{Dict2Vec}\) training, the window size is set to 5. Our experiments used at most 13 GB of GPU memory.

### 5.3 Evaluation Metrics

For automatic evaluation of our system on the test data, we used four metrics, (a) SARI (b) BLEU (c) FE Difference (d) Word Difference, which are briefly explained below.

SARI Xu et al. (2016a) is an automatic evaluation metric designed to measure the simplicity of the generated sentences. SARI requires access to source, predictions and references for evaluation. Computing SARI involves penalizing the n-gram additions to source which are inconsistent with the references. Similarly, deletions and keep operations are penalized. The overall score is a balanced sum of all the penalties. BLEU (Papineni et al., 2002), a popular metric to evaluate generations and translations is used to measure the correctness of the generations by measuring overlaps between the generated sentences and (multiple) references.

We also compute the average FE score difference between predictions and source in our evaluations. FE-difference measures whether the changes made by the model increases the readability ease of the generated sentence. Finally, Word Difference is the average difference between number of words in the source sentence and generation. It is a simple and approximate metric proposed to detect if sentence shortening is occurring or not. Generations with lesser number of changes can still have high SARI and BLEU. Models with such generations can be ruled out by imposing a threshold on the word-diff metric.

Models with high word-diff, SARI and BLEU are picked during model-selection (with validation data). Model selection also involved manually examining the quality and relevance of the generations.

### 5.4 Model Variants

Using our design, we propose two different variants for evaluation- (i) Unsupervised Neural TS (UNTS) with SARI as the criteria for model selection, (ii) UNTS with minimal supervision using 10000 labelled examples (abbreviated as ). Models selected using other selection criteria such as and similar hyper parameters resulted in similar and/or reduced performance (details skipped for brevity).

We carried out the following basic post-processing steps on the generated outputs. The OOV(out of vocabulary) words in the generations are replaced by the source words with high attention weights. Words repeated consecutively in the generated sentences are merged.

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\(^2\)https://github.com/shashiongithub/Split-and-Rephrase
\(^3\)We acknowledge that other recent datasets such as Newsela could have been used for development and evaluation. We could not get access to the dataset unfortunately.
5.5 Systems for Comparison

In the absence of any other direct baseline for end-to-end TS, we consider the Unsupervised NMT framework proposed by (Artetxe et al., 2017) as a baseline. It uses techniques such as backtranslation and denoising techniques to synthesize more training examples. To use this framework, we treated the set of simple and complex sentences as two different languages. Same model configuration as reported by Artetxe et al. (2017) is used. We use the term UNMT for this system.

We also compare our baselines with existing supervised and unsupervised lexical simplifications like LIGHTLS (Glavaš and Štajner, 2015), Neural Text Simplification or NTS (Nisioi et al., 2017), Syntax based Machine Translation or SBMT (Xu et al., 2016b), and Phrase based Machine Translation based simplification or PBSMT (Wubben et al., 2012). All the systems are trained using the Wikipedia-SimpleWikipedia dataset (Hwang et al., 2015). The test set is kept constant for all of these and our models.

6 Results

Table 2 shows evaluation results of our proposed baselines along with existing supervised and unsupervised alternatives. As expected, supervised systems such as SBMT and NTS achieve better content reduction as shown through SARI, BLEU and FE-diff scores. However, it is a good sign that the scores for the unsupervised system UNTS are not far from the supervised skylines. The higher word-diff scores for the unsupervised system also indicate that our system is able to perform content reduction (a form of syntactic simplification), which is crucial to TS. This is unlike the existing unsupervised LIGHTTS system which often replaces nouns with related non-synonymous nouns, which sometimes increases the complexity and affects the meaning. Finally, it is worth noting that aiding the system with a very small amount of labelled data can also benefit our unsupervised pipeline, as suggested by the scores for the UNTS+10K system.

We carry out a qualitative analysis of our system through human evaluation. For this the top 50 test samples were selected from the test data. Output of the seven systems reported in Table 2 along with the sources are presented to two linguists who would provide two ratings for each output: (a) Simplicity, a binary score [0-1] indicating whether the output is a simplified version of the input or not, (b) Grammaticality of the output in the range of [1-5], in the increasing order of fluency (c) Relatedness score in the range of [1-5] showing if the overall semantics of the input is preserved in the output or not. Table 3 presents the average values. The first column represent what fraction (in percentage) of output form that is a simplified version of the input. The second and third columns present the average fluency (grammatically) scores given by human evaluators and semantic relatedness with input scored through automatic means. Almost all systems are able to produce sentences that are somewhat grammatically correct and retain phrases from input. Supervised systems like PBSMT, as expected, simplify the sentences to a maximum extent. However, our unsupervised variants also have scores competitive to the supervised skylines, which is a positive sign.

Table 4 shows an anecdotal example, containing output from the seven systems. As it can be seen, the quality of output from our unsupervised variants, is far from that of the reference output. However, the attempts towards perform lexical simplifi-

| System        | FE-diff | SARI  | BLEU  | Word-diff |
|---------------|---------|-------|-------|-----------|
| UNTS+10K      | 10.4545 | 35.29 | 76.13 | 2.38      |
| UNTS          | 11.1516 | 33.8  | 74.24 | 3.55      |
| UNMT          | 6.60    | 33.72 | 70.84 | 0.74      |
| NTS-SARI      | 5.37    | 36.1  | 79.38 | 2.73      |
| SBMT          | 17.68   | 35.89 | 73.62 | -0.84     |
| PBSMT         | 9.14    | 34.07 | 67.79 | 2.26      |
| LIGHTLS       | 3.01    | 34.96 | 83.54 | -0.02     |

Table 3: Average Human evaluation scores for simplicity based ranking and grammatical correctness (fluency) and semantic relatedness between the output and input.
nevertheless, tagore emulated numerous styles, including craftwork from northern new ireland, haida carvings from the west coast of canada (british columbia), and woodcuts by max pechstein.

UNTS+10K
nevertheless, tagore replaced many styles, including craftwork from northern new ireland, haida carved from the west coast of canada (british columbia).

UNTS
however, tagore notably numerous styles, including craftwork from northern new ireland, haida carved from the west coast of canada (british).

UNMT
however, tagore featured numerous styles including craftwork from northern new ireland, haida from the west coast of Canada (british columbia) max by max pechstein.

NTS-SARI
however, tagore wrote many styles, including craftwork from northern new ireland, haida carvings from the west coast of canada (british columbia).

SBMT
however, tagore emulated many styles, such as craftwork in north new ireland, haida prints from the west coast of canada -lrb- british columbia -rrb-, and woodcuts by max pechstein.

PBSMT
nevertheless, he copied many styles, from new craftwork, haida carvings from the west coast of canada in british columbia and woodcuts by max pechstein.

LIGHTLS
however, tagore imitated numerous styles, including craftwork from northern new ireland, haida sculptures from the west coast of canada -lrb- british columbia -rrb-, and engravings by max pechstein.

| Type of Simplification | Source | Prediction |
|------------------------|--------|------------|
| Splitting              | Gumbasia was created in a style Vorkapich taught called Kinesthetic Film Principles. | Gumbasia was created in Vorkapich. Vorkapich is a style of Kinesthetic Principles. |
| Sentence Shortening    | During an interview, Edward Gorey mentioned that Bawden was one of his favorite artists, lamenting the fact that not many people remembered or knew about this fine artist. | During an interview, Edward Gorey mentioned that Bawden was one of his favorite artists. |
| Lexical Replacement    | In architectural decoration Small pieces of colored and iridescent shell have been used to create mosaics and inlays, which have been used to decorate walls, furniture and boxes. | In impressive decoration Small pieces of colored and reddish shell have been used to create statues and inlays, which have been used to decorate walls, furniture and boxes. |

Table 4: Example predictions from different systems

Table 5: Examples showing different types of simplifications performed by the best model UNTS+10k

7 Conclusion

In this paper, we made a novel attempt for unsupervised text simplification task. We gathered an unlabelled corpora containing simple and complex sentences and use them to train our system that is based on a shared encoder and two decoders. A novel training scheme is proposed which allows the model to perform content reduction and lexical simplification simultaneously through our losses and denoising. Experiments were conducted for multiple variants of our system as well as known unsupervised baselines and supervised systems. Both qualitative and quantitative analysis of the output for a publicly available test data reveals that our models, though unsupervised, can perform better than or competitive to the trivial unsupervised baseline systems and existing supervised methods. In future, we would like to improve the system further by incorporating better architectural designs and training schemes to tackle complex simplification operations. Applying our models for multi- and cross-lingual TS is is also on our agenda.
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