Sentence Simplification from Non-Parallel Corpus with Adversarial Learning

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ABSTRACT

In this study, we propose sentence simplification from a non-parallel corpus with adversarial learning. In recent years, sentence simplification based on a statistical machine translation framework and neural networks have been actively studied. However, most methods require a large parallel corpus, which is expensive to build. In this paper, our purpose is sentence simplification with a non-parallel corpus in open data en-Wikipedia and Simple-Wikipedia articles. We use a style transfer framework with adversarial learning for learning by non-parallel corpus and adapted a prior work [by Barzilay et al.] to sentence simplification as a base framework. Furthermore, from the perspective of improving retention of sentence meaning, we add pretraining reconstruction loss and cycle consistency loss to the base framework. We also improve the sentence quality output from the proposed model as a result of the expansion.

CCS CONCEPTS

• Computing methodologies → Natural language generation.

KEYWORDS

sentence simplification, adversarial learning, non-parallel corpus

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1 INTRODUCTION

The main purpose of sentence simplification is to reduce the linguistic complexity of the sentence while preserving the information and meaning of the original sentence. Sentence simplification supports many readers who are learning a language (including children) and is essential in NLP because sentence simplification is sometimes used for improving the performance of parsers [5]

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and summary task [17]. There are two linguistic aspects of operation for the sentence simplification: (a) the lexical aspect, which is to replace complex words in a sentence with simple words or idioms [2][3][4][10][13][15][40], and (b) the syntactic aspect, which is to compress complex sentence structures and delete original elements [4][8][26]. Earlier work focused on these individual aspects of the simplification problem. From the perspective of sentence construction, sentence simplification can be considered a form of text-transformation that has three main operations: (a) splitting [22], (b) deletion/compression [8][28], and (c) paraphrasing [33].

There are two main approaches to sentence simplification. The first approach is a method that generates a simple sentence from an input sentence by a statistical machine translation framework that interprets monolingual machine translation [22][36][34][35][46]. The second approach is a method using a neural network [29][32][43]. In other NLP tasks (e.g., QA task, word embedding), the neural network method has had excellent results and is being actively researched. However, most of these techniques require a large parallel corpus for the training model. It is difficult to obtain sufficient data volume about a simplification parallel corpus because the construction of the monolingual parallel corpus necessary for training a sentence simplification model is expensive, unlike machine translation to a different language. Moreover, the machine translation task [1] has an unsupervised model with data-driven generation.

To avoid the expense of creating a large parallel corpus about sentence simplification, we simplify sentences from a non-parallel corpus with adversarial learning in the framework of unsupervised style transfer in NLP. The style transfer task is being actively researched in the fields of NLP and image processing. In particular, style transfer in NLP has sentiment modification, word substitution decipherment, and so on. The style transfer task is frequently taken with adversarial learning not requiring a parallel corpus because it is difficult to obtain a large parallel corpus. Generative Adversarial Nets (GAN) learn by means of an adversarial generator and discriminator. The generator tries to generate real data, and the discriminator distinguishes between the generator's output and real data. GAN developed rapidly from the proposal in [11] in the field of image generation. We adapt [30] with adversarial learning to sentence simplification from a non-parallel corpus. Furthermore, to improve the retention of sentence meaning, we add pretraining reconstruction loss and cycle consistency loss to the base model [30]. The pretraining teaches the generator to output the same sentence as the input sentence. The cycle consistency loss compares the difference of input sentence and output sentence by transferring twice (i.e., complex → simple → complex). We compare [30] as a Base

model, Base+Pretrain model, and Base+Pretrain+Cycle model. We use FRE difference, BLEU, and SARI for the quantitative evaluation. The results show that our proposed model (Base+Pretrain+Cycle) had a better performance for BLEU and SARI than the other models, and the comparison in the output sentence was a more effective simplification than the other models.

2 RELATED WORK

2.1 Sentence Simplification

Sentence simplification has often been discussed from the psychological and linguistic point of view. Recently it has become a mainstream research topic in computational linguistics since [26] proposed a model to automatically extract a simplification rule from an annotated corpus. [42] proposed a sentence simplification method that uses a morphological analyzer and part-of-speech tagger from both lexical and syntactical aspects. However, these methods cannot paraphrase phrase-base because most of them only perform operations such as word substitution and sentence separation or deletion. As mentioned above, there are two main approaches to sentence simplification. The first is a method that generates simple sentences from an input sentence by a statistical machine translation framework that interprets monolingual machine translation. The second approach is a method that uses a neural network. It is now possible to create paraphrase-based sentence simplification since data-driven sentence simplification has appeared.

In the case of statistical methods, [46] proposed a tree-based model inspired by statistical machine translation. [34] formulated simplification in the framework of quasi-synchronous grammar and used integer linear programming to score sentence simplification rules. [35] proposed a PBMT-R with two stages. PBMT-R trains a phrase-based machine translation model from normal-simple aligned sentence pairs and reranks the generated sentences by comparing them with a normal sentence by dissimilarity. [22] also proposed a model with two stages: deep semantic analysis and machine translation. [36] adapted syntax-based machine translation with a large parallel corpus to sentence simplification. [23] proposed an unsupervised model to replace complex words with simple words.

In the case of neural network methods, [43] enabled sentence simplification by deep reinforcement learning in which simplicity, relevance, and fluency are considered in the reward. [32] adapted a sequence-to-sequence model with a Neural Semantic Encoder [31] for the purpose of sentence simplification. [29] is a simple sequence-to-sequence model that can be efficiently used for in-domain and cross-domain sentence simplification.

2.2 Generative Adversarial Nets

In the General Adversarial Nets (GAN) proposed by [11], the discriminator learns to distinguish between the generator's output and real data and the generator learns to mislead the discriminator by generating data that seems real. This approach has many applications in the field of image processing. [27] generated images from detailed textual descriptions. [20] utilized weight-sharing between networks for learning cross-domain representation and enabled style transfer of images. [45] proposed CycleGAN, which

enables image-to-image transfer from an unsupervised framework by removing pair restriction of train data.

In contrast to GAN in NLP, [41] proposed a model that extends GAN to sequential data. In recent years, GAN in NLP is being actively studied. Regarding text generation, [44] proposed TextGAN using RNN that performs optimization in a high-dimensional latent space. [7] proposed MaskGAN masking encode so that it can be recovered from unknown input at decoding. In the field of dialogue, [19] evaluated whether the generated utterance can be distinguished from human beings (like Turing testing) and used reinforcement learning to give rewards for each generated word. [37] proposed a model not using reinforcement learning but rather an approximate layer. This model doesn't need sampling. In the field of machine translation, [38] is a conventional model that applies GAN to neural machine translation and a discriminator to determine whether it is a system translation or manual. In [6], a discriminator identifies the presence or absence of noise and improves the robustness of neural machine translation.

2.3 Style Transfer in Natural Language

The style transfer task in the parallel corpus is often regarded as a monolingual machine translation task. At this time, many sequence-to-sequence models have been adapted and achieved good results. For example, [14] proposed a sequence-to-sequence model to convert modern standard English to Shakespearean English. [25] used the framework of back translation for style transfer.

On the other hand, because of the lack of a parallel corpus, research on the style transfer model in a non-parallel corpus that does not require a parallel corpus is also popular in recent years. [12] used a variational autoencoder that has a discriminator to generate sentences with controllable attributes. [30] used an encoder that maps the original sentence to style-independent variables and a decoder that converts it to the specified style. [39] applied the language model of the target domain in a discriminator to convert more fluency. [18] proposed deleting words related with the source style, retrieving similar sentences, and replacing them with similar phrases related with the target style.

3 MODEL DESCRIPTION

In this paper, based on the method of [30] adapted to style transfer, we propose sentence simplification with GAN. We define two corpora of different styles as $X_0 = \{x_1^0, \dots, x_m^0\}$, $X_1 = \{x_1^1, \dots, x_n^1\}$. Neither corpus has to be parallel and has style values s_0, s_1 (e.g., complex and simple). K -th sentence in corpus X_i with style s_i writes x_k^i to generalize. In 3.1, we formulate the base model. In 3.2 and 3.3, we formulate the extension by introducing the proposed model pretraining and cycle consistency loss to the base model.

3.1 Base Model

3.1.1 Generator. The generator includes two mechanisms: encoder E and decoder G . We denote latent variable output z_k^i regarding E as $E(x_k^i, s_i) = z_k^i$ when sentence x_k^i and style s_i are input. We denote the sequence of latent variable output $H_k^{i \rightarrow j}$ regarding G as $G(\tilde{h}_{i,k}^0) = H_k^{i \rightarrow j}$ when latent variable z_k^i and style s_j are input ($\tilde{h}_{i,k}^0 = [z_k^i, s_j]$) and $H_k^{i \rightarrow j} = \{\tilde{h}_{i,k}^1, \dots, \tilde{h}_{i,k}^T\}$. We add a tilde to the h

Figure 1: Discriminator overview about D_j .

if the style has changed. T is the number of G 's latent variant output. E and G use GRU. In contrast, we denote a teacher-forced process (upper part of Fig. 1) when we write $G(h_{i,k}^0, x_k^i)$ (add x_k^i to G). Let $\hat{x}_k^{i \rightarrow j}$ be generated with $H_k^{i \rightarrow j}$ and logit vector $v_{i,k}^t$ be calculated with $\tilde{h}_{i,k}^t$ at t step. Decoder's input is $\text{softmax}(v_{i,k}^t / \gamma)$ (lower part of Fig. 1) and $\gamma \in (0, 1)$ is the temperature parameter. $X_{i \rightarrow j}$ is the sentence set that includes input sentence x_k^i (style s_i) converted into sentence $\hat{x}_k^{i \rightarrow j}$ (style $s_i \rightarrow s_j$). If $j = i$, let $H_k^{i \rightarrow i} = \{h_{i,k}^1, \dots, h_{i,k}^T\}$ be the decoder's latent variant and sequence of output and $\hat{x}_k^{i \rightarrow i}$ be the output sentence. Also, the generator output sentence is converted from the style of the input sentence to the target style in order to mislead the discriminator.

3.1.2 Discriminator. Next, we explain the discriminator for adversarial learning, as shown in Fig. 1. This discriminator uses CNN, the same as [30]. The discriminator includes D_i, D_j and identifies whether the style of the input sentence has been converted or not. In the following, we explain D_j , but the same applies to D_i . The ideal discriminator D_j 's output is probability value. The probability is close to 1 if the input is what style of the sentence doesn't change ($s_j \rightarrow s_j$) and close to 0 if it does change ($s_i \rightarrow s_j$). We denote $D_j(\tilde{h}_{i,k}^0, H_k^{i \rightarrow j}) = p_{D_j}(s_j | \tilde{h}_{i,k}^0, H_k^{i \rightarrow j})$ if D_j 's input is $\tilde{h}_{i,k}^0, H_k^{i \rightarrow j}$ and $D_j(h_{j,k}^0, H_k^{j \rightarrow j}) = p_{D_j}(s_j | h_{j,k}^0, H_k^{j \rightarrow j})$ in the case of $s_j \rightarrow s_j$.

3.1.3 Loss Function. In the following, we explain reconstruction loss and adversarial loss. Reconstruction loss $\mathcal{L}_{rec}$ is the difference between sentence input and output (like autoencoder) and is calculated using input sentence x_k^i, x_k^j and output $\hat{x}_k^{i \rightarrow i}, \hat{x}_k^{j \rightarrow j}$:

$$\mathcal{L}_{rec} = \mathbb{E}_{x_k^i \sim X_i} \left[-\log p_G \left(x_k^i | E \left(x_k^i, s_i \right), s_i \right) \right] + \mathbb{E}_{x_k^j \sim X_j} \left[-\log p_G \left(x_k^j | E \left(x_k^j, s_j \right), s_j \right) \right] \quad (1)$$

Adversarial loss $\mathcal{L}_{adv}$ is low value if the discriminator's performance is good and high value if the generator's performance is good. Adversarial loss $\mathcal{L}_{adv_i}$ regarding s_i is calculated as

$$\mathcal{L}_{adv_i} = \mathbb{E}_{x_k^i \sim X_i} \left[-\log D_i \left(\left[E \left(x_k^i, s_i \right), s_i \right], G \left(h_{i,k}^0, x_i \right) \right) \right] + \mathbb{E}_{x_k^j \sim X_j} \left[-\log \left(1 - D_i \left(\left[E \left(x_k^j, s_j \right), s_i \right], G \left(h_{j,k}^0, x_j \right) \right) \right) \right], \quad (2)$$

and adversarial loss $\mathcal{L}_{adv_j}$ regarding s_j is calculated as

$$\mathcal{L}_{adv_j} = \mathbb{E}_{x_k^j \sim X_j} \left[-\log D_j \left(\left[E \left(x_k^j, s_j \right), s_j \right], G \left(h_{j,k}^0, x_j \right) \right) \right] + \mathbb{E}_{x_k^i \sim X_i} \left[-\log \left(1 - D_j \left(\left[E \left(x_k^i, s_i \right), s_j \right], G \left(h_{i,k}^0, x_i \right) \right) \right) \right], \quad (3)$$

During training, E, G , and D aim to minimize or maximize losses as follows:

$$\mathcal{L}(\theta_E, \theta_G, \theta_D) = \min_{E, G} \max_D \mathcal{L}_{rec} - \lambda \left(\mathcal{L}_{adv_i} + \mathcal{L}_{adv_j} \right), \quad (4)$$

where $\theta_E, \theta_G, \theta_D$ are parameters of E, G, D , respectively.

3.2 Model Pretrain

As one element of the proposed model, we expand the base model to learn how to minimize $\mathcal{L}_{rec}$ before adversarial learning. To

Figure 2: Generator overview.

minimize $\mathcal{L}_{rec}$, decrease the difference between input and output (as explained in 3.1.3). Therefore, this process improves retention of sentence content.

3.3 Cycle Consistency Model

3.1 cannot calculate the loss regarding the sentence transferred style ($X_{i \rightarrow j}$, $X_{j \rightarrow i}$). We introduce cycle consistency loss to the model of 3.2 to resolve this problem. This process improves retention of sentence content by imposing the constraints on the generated sentences. An overview of the generator used in the proposed model is shown in Fig. 2. We denote the latent variable output $z_k^{i \rightarrow j}$ regarding E as $E(\hat{x}_k^{i \rightarrow j}, s_j) = z_k^{i \rightarrow j}$ when sentence $\hat{x}_k^{i \rightarrow j}$ and style s_j are input. We denote the sequence of latent variable output $H_k^{i \rightarrow j \rightarrow i}$ regarding G as $G(\tilde{h}_{i \rightarrow j, k}^0) = H_k^{i \rightarrow j \rightarrow i}$ when latent variable $z_k^{i \rightarrow j}$ and style s_i are input ($\tilde{h}_{i \rightarrow j, k}^0 = [z_k^{i \rightarrow j}, s_i]$). Let $\hat{x}_k^{i \rightarrow j \rightarrow i}$ be the sentence generated by $H_k^{i \rightarrow j \rightarrow i}$. Cycle consistency loss $\mathcal{L}_{cyc}$ is calculated by

$$\mathcal{L}_{cyc} = \mathbb{E}_{x_k^i \sim X_i} \left[-\log p_G \left(x_k^i | E \left(\hat{x}_k^{i \rightarrow j}, s_j \right), s_i \right) \right] + \mathbb{E}_{x_k^j \sim X_j} \left[-\log p_G \left(x_k^j | E \left(\hat{x}_k^{j \rightarrow i}, s_i \right), s_j \right) \right] \quad (5)$$

Adversarial loss $\mathcal{L}_{cyc_adv_i}$ regarding $\hat{x}_k^{i \rightarrow j \rightarrow i}$ is calculated by

$$\mathcal{L}_{cyc_adv_i} = \mathbb{E}_{\hat{x}_k^{i \rightarrow j} \sim X_{i \rightarrow j}} \left[-\log \left(1 - D_i \left(\left[E \left(\hat{x}_k^{i \rightarrow j}, s_j \right), s_i \right], G \left(\tilde{h}_{i \rightarrow j, k}^0 \right) \right) \right) \right], \quad (6)$$

and adversarial loss $\mathcal{L}_{cyc_adv_j}$ regarding $\hat{x}_k^{j \rightarrow i \rightarrow j}$ is calculated by

$$\mathcal{L}_{cyc_adv_j} = \mathbb{E}_{\hat{x}_k^{j \rightarrow i} \sim X_{j \rightarrow i}} \left[-\log \left(1 - D_j \left(\left[E \left(\hat{x}_k^{j \rightarrow i}, s_i \right), s_j \right], G \left(\tilde{h}_{j \rightarrow i, k}^0 \right) \right) \right) \right] \quad (7)$$

Therefore, our proposed model (Base+Pretrain+Cycle model) is optimized by

$$\mathcal{L}(\theta_E, \theta_G, \theta_D) = \min_{E, G} \max_D \mathcal{L}_{rec} + \mathcal{L}_{cyc} - \lambda \left(\mathcal{L}_{adv_i} + \mathcal{L}_{adv_j} + \mathcal{L}_{cyc_adv_i} + \mathcal{L}_{cyc_adv_j} \right) \quad (8)$$

4 TRAINING ALGORITHM

The algorithm of our proposed model (Base+Pretrain+Cycle model) is Algorithm 1.

Algorithm 1 Unsupervised simplification algorithm by cycle consistency model. The hyper-parameters are set as $\lambda = 0.05$, $\gamma = 0.001$ and learning rate is 0.0001 for all experiments.

Input: Two corpora of different styles X_0, X_1 (e.g., complex and simple). Initialize $\theta_E, \theta_G, \theta_{D_0}, \theta_{D_1}$

Pretrain:

Train embedding model using X_0, X_1

Train E, G using $\mathcal{L}_{rec}$

Adversarial Learning:

repeat

Train D_0 using $\mathcal{L}_{adv_0}, \mathcal{L}_{cyc_adv_0}$

Train D_1 using $\mathcal{L}_{adv_1}, \mathcal{L}_{cyc_adv_1}$

Train E, G using $\mathcal{L}_{rec}, \mathcal{L}_{cyc}$

until specified number of epochs are finished or convergence

Let input sentence x_k be word sequence $x_k = \{w_k^1, \dots, w_k^T\}$ (w_k^t is word at t step). We introduce word2vec [21] to w_k^t for embedding pretrain. Word2vec can be considered the similarity of the meaning of the word. Therefore, it is effective for style transfer that maintains the meaning of the sentence. The data for embedding pretrain is a combined corpus of s_i and s_j .

$\mathcal{L}_{rec}, \mathcal{L}_{cyc}$ are the difference between input and output. This input to E is a random word sequence while the model is training. This process, called denoising, changes the word sequence to E and compares true input and output while calculating loss. Therefore, denoising improves the grammaticality.

λ in Eqs. (4) and (8) is a hyperparameter to control adversarial loss. λ of high value emphasizes adversarial loss while λ of low value emphasizes $\mathcal{L}_{rec}$, $\mathcal{L}_{cyc}$. [30]’s default value is $\lambda = 1$, but our value is $\lambda = 0.05$, as we prioritize maintaining sentence meaning.

5 EXPERIMENT

5.1 Dataset

5.1.1 Train Data. In order to train the model for sentence simplification, we made a non-parallel corpus of simple-Wikipedia and en-Wikipedia articles. The following conditions were added to simplify the problem when extracting sentences:

- (1) Exclude sentences that contain symbols other than the period (.) and comma (,).
- (2) The number of words in the sentence is more than four or less than 15.

When processing the corpus, processing was performed under the following conditions:

- (1) Convert numbers to `_num_`.
- (2) Unify all words into lower case.
- (3) If a word occurs in both corpora five times or less, change to `<unk>`.

We used Flesch Readability Ease (FRE) [9] to separate complex sentences and simple sentences more clearly. FRE is a metric in which the higher the numerical value, the easier it is to read a sentence. The sentences in the en-Wikipedia corpus, which have an FRE of 25 or less, are the complex corpus, and the sentences in the simple-Wikipedia corpus, which have an FRE of 75 or more, are the simple corpus. These corpora were each divided into training data and development data. As training data, the complex corpus has 181,095 sentences, and the simple corpus has 147,882 sentences. As development data, there were 22,637 sentences in the complex corpus and 18,485 sentences in the simple corpus.

5.1.2 Evaluation Data. For evaluation data, we need a parallel corpus to calculate the metrics described in 5.2. We used the WikiLarge corpus, the same as [43]. The WikiLarge corpus is a collection of [16] alignment sentence pairs, [46] alignment sentence pairs and revision sentences, and [34] WikiSmall. This parallel corpus is used as evaluation data by extracting only sentences that meet the above conditions. The evaluation data was a parallel corpus of 13,905 sentences.

5.2 Evaluation

We use three models with three evaluation metrics for comparison. The first is the Base model (3.1) and the second and third are the proposed model, specifically, Base+Pretrain model (base model plus the model in 3.2) and Base+Pretrain+Cycle model (base model plus the models in 3.2 and 3.3). For quantitative evaluation, we used three metrics: (a) FRE difference, (b) BLEU, and (c) SARI. These are explained below.

5.2.1 FRE difference. FRE [9]¹ is a metric for evaluating the readability of a sentence based on the number of words and the number of syllables. The larger the value, the more readable the sentence.

¹<https://github.com/mmautner/readability>

Table 1: Evaluation scores.

	FRE difference	BLEU	SARI
Base	+19.92	0.445	0.312
Base+Pretrain	+15.52	0.445	0.321
Base+Pretrain+Cycle	+9.98	0.453	0.322

$$FRE = 206.835 - 1.015 \left(\frac{\text{total words}}{\text{total sentences}} \right) - 84.6 \left(\frac{\text{total syllables}}{\text{total words}} \right) \quad (9)$$

The FRE difference is an average value of FRE differences between input and output sentences. In other words, it can measure how simple it is compared to the input sentence.

5.2.2 BLEU. BLEU [24] is used to measure the meaning of the output and the correctness of its grammar by measuring the overlap between generated sentences and references. BLEU is defined by

$$BLEU = e^{(1-\frac{r}{c})} \exp \left(\sum_{n=1}^N w_n \log p_n \right), \quad (10)$$

where r is the reference sentence length, c is the output sentence length, $w_n = 1/N$, and p_n is the modified n-gram precisions. In the experiment, calculation is performed in 4-gram.

5.2.3 SARI. SARI [36]² is a metric that measures the simplicity of output sentences. Evaluation of SARI requires a pair of three types of sentences, an input, a reference, and an output, and calculates the arithmetic mean of the precision and recall of the three rewrite operations (add, copy, delete) in n-gram.

5.3 Model Parameters

In all models, the embedding dimension is 100, the style s dimension is 200, dimension of z is 500, and the dropout rate is 0.5. The discriminator uses filters from 1 to 5 in size for the convolution layer, and has 128 filters each.

6 RESULTS

Table 1 shows the results of three models: FRE difference, BLEU, and SARI. As shown, the Base+Pretrain+Cycle model had the best performance in the evaluation with BLEU and SARI. By introducing pretrain reconstruction loss and cycle consistency loss, we can see that sentences with high grammaticality were generated closer to human sentence simplification. For the FRE difference, the Base model had the best performance. Next, we consider the FRE difference. Table 2 shows a part of the output of the actual model in order to qualitatively determine why the Base+Pretrain+Cycle model was inferior to the Base model.

Looking at the Base model output of Transfer Example 1 in Table 2, the value of FRE difference is large, as the number of words apparently decreased and simpler words were used, but the meaning of the whole sentence was not maintained. Furthermore, as *price* $\rightarrow$ *process*, the meaning at the word level could not be

²<https://github.com/cocoxu/simplification>

Table 2: Example outputs from models.

Transfer Example	Model	Sentence
1	Input Reference Base Base+Pretrain Base+Pretrain+Cycle	the equilibrium price for a certain type of labor is the wage . the balanced price for any kind of labor is called a wage . the process for a source of one is the us wage . the price of aerobic is a type of the labor wage . the equilibrium factor for any type of the labor is wage .
2	Input Reference Base Base+Pretrain Base+Pretrain+Cycle	he was diagnosed with inoperable abdominal cancer in april _num_ . he was diagnosed with abdominal cancer in april _num_ . he was diagnosed with donna brown in april _num_ . he was diagnosed with dead cancer in april _num_ . he was diagnosed with persistent cancer in april _num_ .
3	Input Reference Base Base+Pretrain Base+Pretrain+Cycle	finland rejected territorial demands and was invaded by the soviet union in november _num_ . finland rejected the soviets , so it was attacked in november _num_ . it was welcomed threat , and invaded the soviet union in november _num_ . finland did control and trade was fought by the soviet union in _num_ . finland was rejected libya and pushed by the soviet union in november _num_ .

maintained. On the other hand, in the Base+Pretrain+Cycle model, the sentence length was long and conversion to simple words was less, but the retention of the sentence meaning and the correctness of the grammar were higher than that of the Base model.

In Transfer Example 2, the Base model performed a conversion (*inoperable abdominal cancer* → *donna brown*) whose meaning was not kept. However, in the Base+Pretrain+Cycle model, the conversion was *inoerale* → *persistent*, and thus the retention of the meaning was high.

Similarly, Transfer Example 3 was converted to *finland rejected* → *it was welcomed* in the Base model, and its meaning could not be maintained. On the other hand, in the Base+Pretrain+Cycle model, it was converted into *invaded* → *pushed*, and the retention of meaning was high.

In other words, each output of the Base model had a reduced number of words and many simple words. Although a high FRE difference was obtained, the FRE difference being inferior is not a big problem; the bigger problem is regarding grammaticality and the retention of meaning. From the above, we can see that the Base model had a reduced number of words and many simple words, but its retention of meaning and grammar was not preserved. In contrast, the proposed model (Base+Pretrain+Cycle) reduced the number of words within the range while retaining the meaning and grammar, and used simple words within it; thus, we can assume that the proposed model is better.

Also, in the output of development data in which there was no reference, there were a few transformations such as from “*the faculty offers a broad range of academic programs and other training opportunities*.” to “*the faculty offers a wide range of training and other training opportunities*.”. Word substitution of the transfer (*broad* → *wide*, *academic programmes* → *training*) showed excellent results.

7 CONCLUSION

In this paper, we simplified sentences from a non-parallel corpus with adversarial learning in the framework of unsupervised style transfer in NLP. We collected sentences from simple-Wikipedia and en-Wikipedia articles and created a non-parallel corpus to create a model for sentence simplification. The proposed model

(Base+Pretrain+Cycle model), which introduces pretraining for reconstruction loss and cycle consistency loss, had a better performance in terms of BLEU and SARI than the base model. Moreover, the comparison in the output sentences showed more effective simplification and content retention in our model than in the base model. In the future, we plan to modify the generator’s model structure for problem complication (e.g., to remove the word limit).

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