Contextualized Rewriting for Text Summarization

Guangsheng Bao$^{1,2}$, Yue Zhang$^{1,2,*}$

$^1$ School of Engineering, Westlake University
$^2$ Institute of Advanced Technology, Westlake Institute for Advanced Study
{baoguangsheng, zhangyue}@westlake.edu.cn

Abstract

Extractive summarization suffers from irrelevance, redundancy and incoherence. Existing work shows that abstractive rewriting for extractive summaries can improve the conciseness and readability. These rewriting systems consider extracted summaries as the only input, which is relatively focused but can lose important background knowledge. In this paper, we investigate contextualized rewriting, which ingests the entire original document. We formalize contextualized rewriting as a seq2seq problem with group alignments, introducing group tag as a solution to model the alignments, identifying extracted summaries through content-based addressing. Results show that our approach significantly outperforms non-contextualized rewriting systems without requiring reinforcement learning, achieving strong improvements on ROUGE scores upon multiple extractive summarizers.

Introduction

Extractive text summarization systems (Nallapati, Zhai, and Zhou 2017; Narayan, Cohen, and Lapata 2018; Liu and Lapata 2019) work by identifying salient text segments (typically sentences) from an input document as its summary. They have been shown to outperform abstractive systems (Rush, Chopra, and Weston 2015; Nallapati et al. 2016; Chopra, Auli, and Rush 2016) in terms of content selection and faithfulness to the input. However, extractive summarizers exhibit several limitations. First, sentences extracted from the input document tend to contain irrelevant and redundant phrases (Durrett, Berg-Kirkpatrick, and Klein 2016; Chen and Bansal 2018; Gehrmann, Deng, and Rush 2018). Second, extracted sentences can be weak in their coherence with regard to discourse relations and cross-sentence anaphora (Dorr, Zajic, and Schwartz 2003; Cheng and Lapata 2016).

To address these issues, a line of work investigates post-editing of extractive summarizer outputs. While grammar tree trimming has been considered for reducing irrelevant content within sentences (Dorr, Zajic, and Schwartz 2003), rule-based methods have also been investigated for reducing redundancy and enhancing coherence (Durrett, Berg-Kirkpatrick, and Klein 2016). With the rise of neural networks, a more recent line of work considers using abstractive models for rewriting extracted outputs sentence by sentence (Chen and Bansal 2018; Bae et al. 2019; Wei, Huang, and Gao 2019; Xiao et al. 2020). Human evaluation shows that such rewriting systems effectively improve the conciseness and readability. Interestingly, existing rewriters do not improve the ROUGE scores compared with the extractive baselines.

Existing abstractive rewriting systems take extracted summaries as the only input. On the other hand, information from the original document can serve as useful background knowledge for inferring factual details. Take Figure 1 for example. A salient summary can be made by extracting the sentence “a biology teacher...weekend.” While a rewriter can simplify the sentence for making a better summary, it cannot provide additional details beyond the sentence unless the document context is also considered. For example, the name of the teacher is not given by the extractive summary, but we can infer that the teacher’s name is “karstein erstad” from the context sentences, thereby making the summary more informative.

We propose contextualized rewriting by using the full input document as a context for rewriting extractive summary sentences. Rather than encoding only the extractive summary, we use a neural representation model to encode...
the whole input document, representing extractive summary as a part of the document representation. To inform the rewrite of the current sentence being rewritten, we use content-based addressing (Graves, Wayne, and Danihelka 2014). Specifically, as Figure 2 shows, a unique group tag is used to index each extracted sentence in the source document, matching an increasing sentence index in the abstractive rerewriter as the rerewriter generates the output, where the group tags ① ② ③ are used to guide the first, second and third rewritten summary sentences, respectively.

We choose the BERT (Devlin et al. 2019) base model as the document encoder, building both the extractive summarizer and the abstractive rerewriter by following the basic models of Liu and Lapata (2019). Our models are evaluated on the CNN/DM dataset (Hermann et al. 2015). Results show that the contextualized rerewriter gives significantly improved ROUGE (Lin 2004) scores compared with a state-of-the-art extractive baseline, outperforming a traditional rerewriter baseline by a large margin. In addition, our method gives better compression, lower redundancy and better coherence. The contextualized rerewriter achieves strong and consistent improvements on multiple extractive summarizers. To our knowledge, we are the first to report improved ROUGE by rewriting extractive summaries. We release our code at https://github.com/baoguangsheng/ctx-rewriter-forsumm.git.

Related Work
Extractive summarizers have received constant research attention. Early approaches such as TextRank (Mihalcea and Tarau 2004) select sentences based on weighted similarities. Recently, Nallapati, Zhai, and Zhou (2017) use a neural classifier to choose sentences and a selector to rank them. Chen and Bansal (2018) use a Pointer Network (Vinyals, Fortunato, and Jaitly 2015) to extract sentences. Liu and Lapata (2019) use a linear classifier upon BERT. This method gives the current state-of-the-art result in extractive summarization, and we choose it for our baseline.

Rewriting systems manipulate extractive summaries for reducing irrelevance, redundancy and incoherence. Durrett, Berg-Kirkpatrick, and Klein (2016) use compression rules to reduce unimportant content within a sentence and make anaphoricity constraints to improve cross-sentence coherence. Dorr, Zajic, and Schwartz (2003) trim unnecessary phrases in a sentence without hurting grammar correctness by finding the syntactic structures of sentences. In contrast to their work, we consider neural abstractive rewriting, which can solve all the above issues more systematically.

Recently, neural rewriting has attracted much research attention. Chen and Bansal (2018) use a seq2seq model with the copy mechanism (See, Liu, and Manning 2017) to rewrite extractive summaries sentence by sentence. A reranking post-process is applied to avoid repetition, and the extractive model is also tuned by reinforcement learning with reward signals from each rewritten sentence. Bae et al. (2019) use a similar strategy but with a BERT document encoder and reward signals from the whole summary. Wei, Huang, and Gao (2019) use a binary classifier upon a BERT document encoder to select sentences, and a Transformer decoder (Vaswani et al. 2017) with the copy mechanism to generate the summary sentence. Xiao et al. (2020) build a hierarchical representation of the input document. A pointer network and a copy-or-rewrite mechanism are designed to choose sentences for copying or rewriting, followed by a vanilla seq2seq model as the rerewriter. The model decisions on sentence selecting, copying and rewriting are tuned by reinforcement learning. Compared with these methods, our method is computationally simpler thanks to the freedom from using reinforcement learning and the copy mechanism, as most of the methods above do. In addition, as mentioned earlier, in contrast to these methods, we consider rewriting by including a document-level context, and therefore can potentially improve details and factual faithfulness.

Some hybrid extractive and abstractive summarization models are also in line with our work. Cheng and Lapata (2016) use a hierarchical encoder for extracting words, constraining a conditioned language model for generating fluent summaries. Gehrmann, Deng, and Rush (2018) consider a bottom-up method, using a neural classifier to select important words from the input document, and informing an
abstractive summarizer by restricting the copy source in a pointer-generator network to the selected content. Similar to our work, they use extracted content for guiding the abstractive summary. However, different from their work, which focuses on the word level, we investigate sentence-level constraints for guiding abstractive rewriting.

Our method can also be regarded as using group tags to guide the reading context during abstractive summarization (Rush, Chopra, and Weston 2015; Nallapati et al. 2016; See, Liu, and Manning 2017), where group tags are obtained using an extractive summary. Compared with vanilla abstractive summarization, the advantages are three-fold. First, extractive summaries can guide the abstractive summarizer with more salient information. Second, the training difficulty of the abstractive model can be reduced when important contents are marked as inputs. Third, the summarization procedure is made more interpretable by associating a crucial source sentence with each target sentence.

**Seq2seq with Group Alignments**

As a key contribution of our method, we model contextualized rewriting as a seq2seq mapping problem with group alignments. For an input sequence X and an output sequence Y, a group set G describes a set of segment-wise alignments between X and Y. The mapping problem is defined as finding estimation

\[
\hat{Y} = \arg\max_{Y,G} P(Y, G|X),
\]

where

\[
X = \{w_i\}_{i=1}^{|X|}, Y = \{w_j\}_{j=1}^{|Y|}, G = \{G_k\}_{k=1}^{|G|},
\]

that |X| denotes the number of elements in X, |Y| the number of elements in Y, and |G| the number of groups. Each group \(G_k\) denotes a pair of text segments, one from X and one from Y, which belongs to the same group. Taking Figure 2 as an example, the first extractive sentence from the document and the first sentence from the summary form a group \(G_1\).

The problem can be simplified given the fact that for each group \(G_k\), the text segment from X is known, while the corresponding segment from Y is dynamically decided during the generation of Y. We thus separate G into two components \(G_X\) and \(G_Y\), and redefine the mapping problem as

\[
\hat{Y} = \arg\max_{Y,G} P(Y, G_Y|X, G_X),
\]

where

\[
G_X = \{g_i = k \text{ if } w_i \in G_k \text{ else } 0\}_{i=1}^{|X|},
\]

\[
G_Y = \{g_j = k \text{ if } w_j \in G_k \text{ else } 0\}_{j=1}^{|Y|},
\]

so that for each group \(G_k\), a group tag \(k\) is assigned, through which the text segment from X in group \(G_k\) is linked to the segment from Y in the same group. For the example in Figure 2, \(G_X = \{1, ..., 1, 0, ..., 0, 2, ..., 2, 3, ..., 3, 0, ..., 0\}\) and \(G_Y = \{1, ..., 1, 2, ..., 2, 3, ..., 3\}\).

In the encoder-decoder framework, we convert \(G_X\) and \(G_Y\) into vector representations through a shared embedding table, which is randomly initialized and jointly trained with the encoder and decoder. The vector representations of \(G_X\) and \(G_Y\) are used to enrich vector representations of X and Y, respectively. As a result, all the tokens tagged with \(k\) in both X and Y have the same vector component, through which a content-based addressing can be done by the attention mechanism (Garg et al. 2019). Here, the group tag serves as a mechanism to constrain the attention from Y to the corresponding part of X during decoding. Unlike approaches which modify a seq2seq model by using rules (Hsu et al. 2018; Gehrmann, Deng, and Rush 2018), group tag enables the modification to be flexible and trainable.

**Contextualized Rewriting System**

We take a three-step process in generating a summary. First, an extractive summarization model is used to select a set of sentences from the original document as a guiding source. Second, the guiding source text is matched with the original document, whereby a set of group tags are assigned to each token. Third, an abstractive rewriter is applied to the tagged document, where the group tags serve as a guidance for summary generation.

Formally, we use \(X = \{w_i\}_{i=1}^{|X|}\) to represent document X, which contains \(|X|\) tokens, and \(Y = \{w_j\}_{j=1}^{|Y|}\) to represent a final resulting summary Y, which contains \(|Y|\) tokens.

**Extractive Summarizer**

Following Liu and Lapata (2019), we use BERT to encode the input document, with a special [CLS] token being added to the beginning of each sentence, and interval segments being applied to distinguish successive sentence. On top of the BERT representation of [CLS] tokens, an extractor is stacked to select sentences. The extractor uses a Transformer (Vaswani et al. 2017) encoder to generate inter-sentence representations, on which, for extracting a summary, an output layer with the sigmoid activation is used to calculate the probability of each sentence being extracted.

**Encoder.** We use the BERT encoder BERTENC to convert source document X into a sequence of token embeddings \(H_X\), taking [CLS] embeddings as a representation of the source sentences, denoted as \(H_C\).

\[
H_X = \text{BERTENC}(X),
\]

\[
H_C = \{H_X^{(i)}|w_i = [\text{CLS}]\}_{i=1}^{|X|}.
\]

**Extractor.** We use a Transformer encoder TRANSENC to convert sentence embeddings \(H_C\) into final inter-sentence representations \(H_F\). and calculate the extraction probability on each sentence according to \(H_F\).

\[
H_F = \text{TRANSENC}(H_C),
\]

\[
P(\text{ext}_k|X) = \sigma(W \cdot H_F^{(k)} + b),
\]

where \(\text{ext}_k\) means the \(k\)-th sentence extracted, and W and b are model trainable parameters.

Given the sequence of extraction probabilities \(\{P(\text{ext}_k|X)|k=1\}^C\), where C denotes the number of sentences in X, we make decision on each sentence according to three hyper-parameters: the minimum number
of sentences to extract \( \text{min} \_ \text{sel} \), the maximum number of sentences to extract \( \text{max} \_ \text{sel} \), and a probability threshold. In particular, we sort the \( C \) sentences in descending order based on \( P(\text{ext}_i|X) \), where sentences that rank between 0 and \( \text{min} \_ \text{sel} \) are selected by default, while sentences that rank between \( \text{min} \_ \text{sel} \) and \( \text{max} \_ \text{sel} \) are decided by comparing the probability value with the threshold. Sentences with a probability above threshold are selected. We decide the hyper-parameter values using dev experiments.

Note that our method is slightly different from the extractive model of Liu and Lapata (2019), which extracts the 3 most probable sentences as the summary. For the purpose of rewriting with a strong compression, our method allows to extract more sentences as the summary for better recall.

**Source Group Tagging**

We match the extracted summary with the original document for group tagging, taking each sentence in the extracted summary as the summary. For the purpose of rewriting with a strong compression, our method allows to extract more sentences as the summary for better recall.

**Contextualized Rewriter**

The contextualized rewriter extends the abstractive summarizer of Liu and Lapata (2019), which is a standard Transformer sequence to sequence model with BERT as the encoder. As Figure 3 shows, to integrate group tag guidance, group tag embeddings are added to both the encoder and the decoder. Formally, for an extractive summary, group tags are shared by the encoder and the decoder.

**Encoder.** The original document is processed in the same way as for the extractive model, where a [CLS] token is added for each sentence and interval segments are used to distinguish successive sentences. After BERT encoding \( \text{BERTENC} \), the representation of each token is added to the group tag embedding for producing a final representation

\[
H_{X+G} = \text{BERTENC}(X) + \text{EMB}_{W_G}(G_X),
\]

where \( \text{EMB}_{W_G}(G_X) \) denotes the retrieved embeddings from the lookup table \( W_G \) for group tag sequence \( G_X \).

**Decoder.** Summary sentences are synthesized in a single sequence with special token [BOS] at the beginning, [SEP] between sentences, and [EOS] at the end. The decoder follows a standard Transformer architecture.

We treat each sentence in the summary as a group. Consequently, the group tag sequence \( G_Y \) is fully determined by the summary \( Y \). In particular, all the tokens in the \( k \)-th summary sentence \( Y_k (k \in [1, ..., K]) \) are assigned with a group tag \( k \). Therefore, Eq 5 is instantiated as

\[
G_Y = \{g_j = k \text{ if } w_j \in Y_k \text{ else } 0\}_{j=1}^{|Y|},
\]

where \( G_Y \) is the sequence of group tags for document \( Y \).

During decoding, the group tag is generated at each beam search step, starting with 1 after the special token [BOS] and increasing by 1 after each special token [SEP].

The embedding of group tag \( g_j \) is retrieved from the lookup table \( W_G \) by \( \text{EMB}_{W_G}(g_j) \), added to the token embedding \( \text{EMB}(w_j) \) and the position embedding.

\[
H_{Y+G} = \text{EMB}(Y) + \text{EMB}_{W_G}(G_Y)
\]

\[
P(w_j|w_{<j}, X, G_X) = \text{TRANSDEC}(H_{Y+G}^{<j}, H_{X+G}).
\]
Training
We train our extractive summarizer and abstractive rewriter separately on a pre-processed dataset labeled with gold-standard extractions. To generate gold-standard extraction, we match each sentence in human summary to each document sentence, choosing the sentence with the best matching score as the gold extraction for the summary sentence. Specifically, we use the average recall of ROUGE-1/2/L as the scoring function, which follows Wei, Huang, and Gao (2019). Differing from existing work (Liu and Lapata 2019), which aims to find a set of sentences that maximizes ROUGE matching with the human summary, we find the best match for each summary sentence. As a result, the number of extracted sentences is the same as the number of sentences in the human summary. This strategy is also adopted by Wei, Huang, and Gao (2019) and Bae et al. (2019).

After matching summary \( Y \) to document \( X \), we obtain a gold-standard extraction \( E = \{ E_k \}_{k=1}^K \). For training our extractive model, we convert gold-standard extraction \( E \) into a label \( l_k \) on each sentence \( X_k \) in \( X \). We set \( l_k = 1 \) if \( X_k \in E \), otherwise \( l_k = 0 \). We train the model with a binary cross-entropy loss function

\[
L_{ext} = \frac{1}{C} \sum_{k=1}^C \left[ -l_k \cdot \log P(\text{ext}_k|X) - (1-l_k) \cdot \log(1 - P(\text{ext}_k|X)) \right],
\]

where \( C \) denotes the number of sentences in \( X \).

For training our abstractive rewriter, we convert gold-standard extractions \( E \) into group tags \( G_X \) following Eq. 8, and train the model with a negative log-likelihood loss

\[
L_{wrt} = \frac{1}{|Y|} \sum_{j=1}^{|Y|} \log P(w_j|w_{<j}, X, G_X).
\]

Experimental Setup
We evaluate our model on the CNN/Daily Mail dataset (Hermann et al. 2015), which comprises online news articles with several human written highlights (on average 3.75 per article). There are 312,085 samples in total. We use the non-anonymized version and follow the standard splitting of Hermann et al. (2015), which includes 287,227 samples for training, 13,368 for dev testing, and 11,490 for testing. We preprocess the dataset following See, Liu, and Manning (2017) after splitting sentences with the Stanford CoreNLP (Manning et al. 2014). We tokenize sentences into subword tokens, and truncate documents to 512 tokens.

We evaluate our models automatically using ROUGE (Lin 2004), reporting the unigram overlap ROUGE-1 and the bigram overlap ROUGE-2 as metrics for informativeness, and the longest common subsequence ROUGE-L as an indicator of fluency. All scores are calculated using pyrouge.\(^1\)

Extractive Summarizer
The document encoder is initialized with pre-trained uncased BERT-base, which has 12 transformer layers and the output embedding size is 768. The Transformer extractor is set to 2 layers with an embedding size of 768 and randomly initialized. We use the Adam optimizer (Kingma and Ba 2015) with \( \beta_1 = 0.9 \) and \( \beta_2 = 0.999 \). The encoder and extractor are jointly trained for a total of 50,000 steps with a learning rate schedule (Vaswani et al. 2017).

\[
lr = 2e^{-3} \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}^{-1.5}),
\]

where \( \text{warmup} = 10,000 \). The model is trained with 2 v100 GPUs for about 9 hours.

For inference, we select sentences according to the hyper-parameters \( \text{min}\_\text{sel} = 3 \), \( \text{max}\_\text{sel} = 5 \) and \( \text{threshold} = 0.35 \), which are chosen by a grid search to find the best average score of ROUGE 1/2/L on the dev dataset.

Contextualized Rewriter
We initialize the document encoder with pre-trained uncased BERT-base model, and initialize the decoder randomly. The Transformer decoder has 6 layers with an embedding size of 768 and tied input-output embeddings (Press and Wolf 2017). We use the Adam optimizer and default setting \( \beta_1 = 0.9 \) and \( \beta_2 = 0.999 \). The model is trained for a total of 240,000 steps, with 20,000 steps for warming-up of the encoder and 10,000 steps for warming-up of the decoder:

\[
lr_{\text{Enc}} = 2e^{-3} \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_{\text{Enc}}^{-1.5})
\]

\[
lr_{\text{Dec}} = 0.2 \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_{\text{Dec}}^{-1.5}).
\]

We use a learning rate of 0.002 for the encoder, and 0.2 for the decoder, applying dropout with a probability of 0.2, label smoothing (Szegedy et al. 2016) with a factor of 0.1, and word dropout (Bowman et al. 2016) with a probability of 0.3 on the decoder. We train the model with 2 GPUS on a v100 machine for about 60 hours.

For inference, we constrain the decoding sequence to a minimum length of 50, a maximum length of 200, a length penalty (Wu et al. 2016) with \( \alpha = 0.95 \), and a beam size of 5. During beam search, we block the paths on which a repeated trigram is generated, namely Trigram Blocking (Paulus, Xiong, and Socher 2017).

Results and Analysis
We compare our models with existing summarization models before analysing the contextualized rewriter.

Automatic Evaluation
The results are shown in Table 1. The top section consists of extractive models. The middle section contains abstractive models and hybrid systems with a rewriter. The bottom section lists our models. In comparison with BERTSUMEXT, our extractive model BERT-Ext gives lower result due to differences in the extraction goal, as discussed earlier.

Compared with the extractive baseline BERT-Ext, our model BERT-Ext+ContextRewriter improves ROUGE-1/2/L by 2.48, 1.01 and 2.90, respectively. This shows the effectiveness of contextualized rewriting. To isolate the effect of the rewriter from the extractive summarizer, we also did an experiment using the Oracle extractive summary as the input to our contextualized

\(^1\)https://pypi.org/project/pyrouge/0.1.3/
rewriter, as Oracle+ContextRewriter shows. The gap between our BERT-Ext+ContextRewriter result and the Oracle+ContextRewriter result shows the room for further improvement when the extractive summarizer becomes stronger. The row BERT-Abs shows the result of the BERT based abstractive summarizer which copies the structure and settings of BERT-Ext-ContextRewriter excluding the components related to group tags in Figure 3. A contrast between our BERT-Ext+ContextRewriter model and BERT-Abs model shows the usefulness of the extractive summary for guiding abstractive rewriting.

Compared to the rewriting system BERT-Hybrid, our BERT-Ext+ContextRewriter increases ROUGE-1/2/L by 1.76, 1.26 and 1.7, respectively. It demonstrates the effectiveness of contextualized rewriting compared to non-contextualized rewriting. Although with the help of reinforcement learning, a better result can be achieved for the non-contextualized rewriting system, as the results of BERT-Ext+Abs+RL and BERT+Copy/Rewrite+HRL shows, the complexity of the algorithm is inevitably increased. Compared with the best rewriting system BERT+Copy/Rewrite+HRL, our contextualized rewriter BERT-Ext-ContextRewriter still shows a significant improvement by 0.6, 1.14 and 1.21 on ROUGE 1/2/L, respectively, despite that our model is purely generative without copying tokens from the source document.

Compared with the strong extractive model BERTSUMEXT, BERT-Ext-ContextRewriter gives a better score across three ROUGE metrics with a significant margin for 0.27, 0.33 and 0.93 on ROUGE-1/2/L, respectively. Considering the different length of extractive summaries and rewritten summaries, we normalize ROUGE scores following Sun et al. (2019). The relative improvement of our model after normalization is even larger, that it improves over BERTSUMEXT by 4% relatively (from 1.47 to 1.53) on normalized score, compared to the improvement by 0.6% relatively (from 43.25 to 43.52) on ROUGE-1. To our knowledge, we are the first to report improved ROUGE scores compared to a state-of-the-art extractive baseline by using abstractive rewriting. Human evaluation is given in the next section.

We did not include BART (Lewis et al. 2020) in the table, which reports ROUGE-1/2/L of 44.16, 21.28 and 40.90, respectively. Different pre-training method and data are used by BART as compared to the models in Table 1. First, we use BERT-base, while BART for summarization uses a large model. Second, models in Table 1 use only the first 512 tokens of the document, while BART uses 1024 tokens.

### Human Evaluation

Intuitively, our model can paraphrase extractive summaries instead of generating summaries from scratch, thereby improving the faithfulness. Furthermore, the abstractiveness of contextualized rewriter can enhance the readability, and the strong compression can improve the conciseness. To confirm these hypothesis, we conduct a human evaluation by randomly select 30 samples from the test set, scoring faithfulness, readability, informativeness, and conciseness from 1(worst) to 5(best) by 3 independent annotators. We report the final result by averaging across annotators.

The result is shown in Table 2. Compared with non-contextualized rewriter RNN-Ext+Abs+RL, our contextualized rewriter shows obvious advantage across the four aspects. Compared to the extractive baseline BERTSUMEXT, our rewriter enhances the readability, informativeness and

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>RNN-Ext+Abs+RL</td>
<td>4.71</td>
<td>3.62</td>
<td>3.22</td>
<td>3.35</td>
</tr>
<tr>
<td>BERTSUMEXT</td>
<td>5.00</td>
<td>3.45</td>
<td>3.90</td>
<td>3.55</td>
</tr>
<tr>
<td>BERTSUMEXTABS</td>
<td>4.86</td>
<td>4.22</td>
<td>3.78</td>
<td>3.85</td>
</tr>
<tr>
<td>BERT-Ext+ContextRewriter</td>
<td>5.00</td>
<td>4.15</td>
<td>4.01</td>
<td>3.80</td>
</tr>
</tbody>
</table>

Table 2: Human evaluation on faithfulness, readability, informativeness, and conciseness.
which is another proof that our rewriter is robust to input of.

...are applied with our rewriter, they give similar scores where

...trigram blocking” is much worse than BERTSUMEXT be-

...dicates a significant improvement on the fluency.

...improved by more than 1.4 points on ROUGE-L, which in-

...enhances the summary quality especially on ROUGE-L, with

...extractive summarizers including LEAD-3, BERT-

...models give lower ROUGE scores. BERTSUMEXT experi-

...when the trigram-blocking post-process is removed, all the

...with the work of Liu and Lapata (2019). As Figure 4 shows,

...automatic summarization. Here we study the impact of

...redundant extractive summaries.

**Analysis**

We further evaluate our rewriter on the ability to reduce ir-

...redundancy, improve abstractiveness, and enhance coherence.

**Redundancy** Redundancy has been a major problem for

...the model performance by comparing with the work of Liu and Lapata (2019). As Figure 4 shows,

...the abstractive model on average. However, by

...having more text, the rewriter obtains much improved infor-

**Universality of the Rewriter**

Our contextualized abstractive rewriter can serve as a gen-

...general summary rewriter. We evaluate the rewriter with four

...extractive summarizers including LEAD-3, BERT-

...extractive summarizers. In particular, using

...a basic extractive summarizer, the ROUGE

...scores improve by a large margin. Even with the best ex-

...extractive summarizer BERTSUMEXT, the rewriter still

...enhances the summary quality especially on ROUGE-L, with

...a 1.42 point improvement. All the extractive summaries are

...improved by more than 1.4 points on ROUGE-L, which

...indicates a significant improvement on the fluency.

In Table 3, the ROUGE scores for “BERTSUMEXT w/o

...trigram blocking” is much worse than BERTSUMEXT be-

...because there is redundant information. However, when they

...are applied with our rewriter, they give similar scores where

...the difference is less than 0.03 point across ROUGE-1/2/L,

...which is another proof that our rewriter is robust to input of

**Table 3:** Results of four extractive summarizers applied with contextualized rewriter. Tri-Bloc means Trigram Blocking.

<table>
<thead>
<tr>
<th>Method</th>
<th>ROUGE-1</th>
<th>ROUGE-2</th>
<th>ROUGE-L</th>
<th>Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oracle</td>
<td>46.77</td>
<td>26.78</td>
<td>43.32</td>
<td>112</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>52.57 (+5.80)</td>
<td>29.71 (+2.93)</td>
<td>49.69 (+6.37)</td>
<td>63</td>
</tr>
<tr>
<td>LEAD-3</td>
<td>40.34</td>
<td>17.70</td>
<td>36.57</td>
<td>85</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>41.09 (+0.75)</td>
<td>18.19 (+0.49)</td>
<td>38.06 (+1.49)</td>
<td>55</td>
</tr>
<tr>
<td>BERTSUMEXT w/o Tri-Bloc</td>
<td>42.50</td>
<td>19.88</td>
<td>38.91</td>
<td>80</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>43.31 (+0.81)</td>
<td>20.44 (+0.56)</td>
<td>40.33 (+1.42)</td>
<td>54</td>
</tr>
<tr>
<td>BERT-Ext (ours)</td>
<td>41.04</td>
<td>19.56</td>
<td>37.66</td>
<td>85</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>43.52 (+2.48)</td>
<td>20.57 (+1.01)</td>
<td>40.56 (+2.90)</td>
<td>66</td>
</tr>
</tbody>
</table>

**Figure 4:** Comparison of the ability to generate non-redundant summaries.

**Figure 5:** Proportion of rewritten, compressed, and unchanged sentences after rewriting.

**conciseness with a significant margin, while keeping the

...faithfulness. The enhancement of readability is mainly con-

...contributed by reduced redundancy and improved coherence.

...The improvement of conciseness confirms the strong com-

...pression of the rewriter. In comparison with the abstractive

...baseline BERTSUMEXTABS, our rewriter improves faith-

...fulness and informativeness, while keeping the readability

...and conciseness close. The conciseness of the rewriter is

...0.05 lower since it generates summaries for about one word

...longer than the abstractive model on average. However, by

...having more text, the rewriter obtains much improved infor-

...mativeness from 3.78 to 4.01.

**Universality of the Rewriter**

Our contextualized abstractive rewriter can serve as a gen-

...eral summary rewriter. We evaluate the rewriter with four

...different extractive summarizers including LEAD-3, BERT-

...SUMEXT, BERT-Ext and Oracle. As Table 3 shows, the

...contextualized rewriter improves the summaries generated

...by all four extractive summarizers. In particular, using

...LEAD-3 as a basic extractive summarizer, the ROUGE

...scores improve by a large margin. Even with the best ex-

...tractive summarizer BERTSUMEXT, the rewriter still

...enhances the summary quality especially on ROUGE-L, with

...a 1.42 point improvement. All the extractive summaries are

...improved by more than 1.4 points on ROUGE-L, which

...indicates a significant improvement on the fluency.

In Table 3, the ROUGE scores for “BERTSUMEXT w/o

...trigram blocking” is much worse than BERTSUMEXT be-

...cause there is redundant information. However, when they

...are applied with our rewriter, they give similar scores where

...the difference is less than 0.03 point across ROUGE-1/2/L,

...which is another proof that our rewriter is robust to input of

**Table 3:** Results of four extractive summarizers applied with contextualized rewriter. Tri-Bloc means Trigram Blocking.

<table>
<thead>
<tr>
<th>Method</th>
<th>ROUGE-1</th>
<th>ROUGE-2</th>
<th>ROUGE-L</th>
<th>Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oracle</td>
<td>46.77</td>
<td>26.78</td>
<td>43.32</td>
<td>112</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>52.57 (+5.80)</td>
<td>29.71 (+2.93)</td>
<td>49.69 (+6.37)</td>
<td>63</td>
</tr>
<tr>
<td>LEAD-3</td>
<td>40.34</td>
<td>17.70</td>
<td>36.57</td>
<td>85</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>41.09 (+0.75)</td>
<td>18.19 (+0.49)</td>
<td>38.06 (+1.49)</td>
<td>55</td>
</tr>
<tr>
<td>BERTSUMEXT w/o Tri-Bloc</td>
<td>42.50</td>
<td>19.88</td>
<td>38.91</td>
<td>80</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>43.31 (+0.81)</td>
<td>20.44 (+0.56)</td>
<td>40.33 (+1.42)</td>
<td>54</td>
</tr>
<tr>
<td>BERT-Ext (ours)</td>
<td>41.04</td>
<td>19.56</td>
<td>37.66</td>
<td>85</td>
</tr>
<tr>
<td>+ ContextRewriter (ours)</td>
<td>43.52 (+2.48)</td>
<td>20.57 (+1.01)</td>
<td>40.56 (+2.90)</td>
<td>66</td>
</tr>
</tbody>
</table>

**Analysis**

We further evaluate our rewriter on the ability to reduce ir-

...redundancy, improve abstractiveness, and enhance coherence.

**Redundancy** Redundancy has been a major problem for automatic summarization. Here we study the impact of trigram-blocking to the model performance by comparing with the work of Liu and Lapata (2019). As Figure 4 shows, when the trigram-blocking post-process is removed, all the models give lower ROUGE scores. BERTSUMEXT experiences the most significant drop, while BERTSUMEXTABS has a smaller drop because of less redundancy in an abstrac-

**Compression** As the column Avg Words in Table 3 shows, for all the four extractive summarizers, the contextualized rewriter can significantly compress the summaries. For Oracle extractive summaries, it compresses the size by almost a half. For the other models, it compresses the summaries to almost 2/3 of the original summaries on average.

Looking into the summaries generated by BERT-

...Ext+ContextRewriter, we find that, as Figure 5 shows,

...16% of extractive summary sentences are not changed by

...the rewriter, 39% are compressed, and 45% are rewritten.

We obtain these numbers on the test dataset, by adopting

...the edit-sequence-generation algorithm (Zhang and Litman 2014) to generate a sequence of word editing actions, mapping an extracted summary sentence to the rewritten one. We categorize a sentence as “Rewritten” if the sequence contains an action of adding or modifying, “Compressed” if it
Extractive Summary: oratilwe hlongwane , whose dj name is aj , is still learning to put together words but the toddler is already able to select and play music from a laptop and has become a phenomenon in south africa.\(^1\) two-year-old oratilwe hlongwane , from johannesburg , south africa , whose dj name is aj , is still learning to put together words but is already able to play music from a laptop , making him a worldwide phenomenon .\(^2\)

Rewritten Summary: oratilwe hlongwane , whose dj name is aj , is still learning to put together words .\(^1\) he is already able to play music from a laptop , making him a worldwide phenomenon .\(^2\)

Figure 6: Example of the ability to reduce redundancy.

<table>
<thead>
<tr>
<th>Method</th>
<th>1-grams</th>
<th>2-grams</th>
<th>3-grams</th>
</tr>
</thead>
<tbody>
<tr>
<td>GOLD</td>
<td>20.66</td>
<td>56.55</td>
<td>73.48</td>
</tr>
<tr>
<td>BERTSUMEXTABS</td>
<td>1.39</td>
<td>9.81</td>
<td>17.79</td>
</tr>
<tr>
<td>BERT-Ext+ContextRewriter</td>
<td>1.82</td>
<td>10.74</td>
<td>19.30</td>
</tr>
</tbody>
</table>

Table 4: Percentage of novel n-grams.

contains an action of deleting, and “Unchanged” otherwise.

According to 20 samples from the test dataset, all the compressions are on phrases instead of single words. Furthermore, most removed phrases are unimportant, given the fact that only 12% of the removed words are included in reference summaries. For instance, “they returned to find hargreaves and the girl, who has not been named, lying on top of each other.” is compressed into “they returned to find hargreaves and the girl lying on top of each other.”

Novel n-grams As a measure of abstractiveness, we calculate the percentage of novel n-grams as Table 4 shows the results of 1.82, 10.74 and 19.30. We can see that the contextualized rewriter generates summaries with more novel n-grams compared to BERTSUMEXTABS, which suggests better abstractiveness.

Coherence The text generation process of a contextualized rewriter can be controlled by the extractive input, through which we can observe the behavior of the rewriter. Figure 7 uses one output example to demonstrate how the rewriter maintains coherence. We can see that the student name is mentioned in the first summary sentence, while a pronoun is used in the second sentence. As the “Swap Group Tags” section shows, when we swap the group tags in the source document, the content of the two summary sentences swap their positions, but the student name is still presented in the first sentence and a pronoun is used in the second sentence. From this case, we can see that the cross-sentence anaphora is maintained correctly.

Source Document: a university of iowa student has died nearly three months after a fall ... andrew mogni , 20 , from glen ellyn , illinois , had only just arrived for ...\(^1\) he was flown back to chicago via ... but he died on sunday \(^2\) ...

Rewritten Summary: andrew mogni , 20 , from glen ellyn , illinois , had only just arrived for a semester program in italy when the incident happened in january \(^1\) he was flown back to chicago via air ambulance on march 20 , but he died on sunday \(^2\)

Swap Group Tags: andrew mogni , 20 , was flown back to chicago via air ambulance on march 20 , but he died on sunday \(^1\) he had only just arrived for a semester program in italy when the incident happened in january \(^2\)

Figure 7: Example of the ability to maintain coherence.

Conclusion

We investigate contextualized rewriting of extractive summaries using a neural abstractive rewriter, formalizing the task as a seq2seq problem with group alignments, using group tags to represent alignments, and constraining the attention to rewriting sentence through content-based addressing. Results on standard benchmarks show that using contextual information from the original document is highly beneficial for summary rewriting. Our model outperforms existing abstractive rewriters by a significant margin, achieving strong ROUGE improvements upon multiple extractive summarizers, for the first time. Our method of seq2seq with group alignments is general and can potentially be applied to other NLG tasks.

Acknowledgments

We would like to thank the anonymous reviewers for their valuable feedback and Wenyu Du for the inspiring discussion. We thank Westlake University High-Performance Computing Center for supporting on GPU resources. This work is supported by the Bright Dream Joint Institute for Intelligent Robotics.

References


Berlin, Germany: Association for Computational Linguistics.
Nallapati, R.; Zhou, B.; dos Santos, C.; Gulcehre, Ç.; and Xiang, B. 2016. Abstractive Text Summarization using Sequence-to-sequence RNNs and Beyond. In Proceedings of The 20th SIGNLL Conference on Computational Natu-


