Abstract

Encoder-decoder models have achieved remarkable success in abstractive text summarization, which aims to compress one or more documents into a shorter version without the loss of the essential content. Unfortunately, these models mostly suffer a discrepancy between training and inference, i.e., the exposure bias problem. During the training stage, with teacher forcing these models are optimized to maximize the likelihood of the gold summary given the gold summary tokens as input to the decoder, while at inference the given tokens are replaced by the generated tokens. Consequently, low-quality summaries are very likely to be generated. To remedy this problem, we propose to leverage contrastive learning to decrease the likelihood of these low-quality summaries, and meanwhile increase the likelihood of the gold summary. Since our solution expands the states that the model perceives during training, we expect that the exposure bias problem can be alleviated. We experimentally demonstrate that our method effectively improves the performance of the state-of-the-art model on different datasets.

1 Introduction

Abstractive text summarization is a task to create a short text according to one or several related documents, while at the same time preserving salient information. Recently, encoder-decoder models with pre-training such as BART (Lewis et al., 2020) and PEGASUS (Zhang et al., 2020) have achieved state-of-the-art (SOTA) performance in this task. The architectures of these models are commonly based on Transformer (Vaswani et al., 2017) inspired by its great success in many Natural Language Generation (NLG) tasks. Essentially, their impressive achievements derive from pre-training. During this stage, models learn knowledge from massive unlabeled data through elaborate self-supervised objectives. After pre-training, these models are fine-tuned with teacher forcing in downstream NLG tasks, like abstractive text summarization.

However, as a result of teacher forcing, these models mostly suffer a gap between training and inference (Bengio et al., 2015), like most of the vanilla sequence-to-sequence (seq2seq) models (Sutskever et al., 2014). Their training objectives are to maximize the likelihood of each token in the gold summary given its previous tokens. At inference, however, the tokens of the gold summary are unavailable and they have to be replaced by the generated tokens. It means that a model is often optimized under a limited part of the state space at the training time, so its performance is very likely to suffer degradation. This problem is well known as the exposure bias (Ranzato et al., 2016). It may lead to the serious errors that accumulate quickly along the generated tokens. As a result, these models are peculiarly prone to producing the unexpected summary, which we term as “silver summary” in contrast to gold summary. What is worse, because of this problem, the silver summaries often contain fake facts (Cao et al., 2018; Yuan et al., 2020), which may look similar to the text in its surface form but actually contrary to its original meaning.

To alleviate the exposure bias, we propose to leverage the contrastive learning method to expand the states that the model perceives during training. We expect not only to increase the likelihood of the gold summary via Maximum Likelihood Estimation (MLE) but also to decrease the likelihood of the silver summary via Contrastive Learning (CL) during the training process. It helps to prevent the model from generating the silver summary to a certain degree. This method can also be regarded as a special data augmentation strategy, which enables the model to learn from both the positive sample
With teacher forcing, their learning objective is to

\[
L_{\text{nll}} = -\sum_{i=1}^{n} f(y_i|X, y_{<i})
\]

where \( f(y_i|X, y_{<i}) \) is the log-likelihood of the \( i \)th token of the gold summary \( Y \). At inference, the models have to use the generated tokens \( \hat{y}_{<i} \) instead to predict the token \( \hat{y}_i \). Typically, the beam search algorithm is used to maintain multiple alternatives at each timestep based on the beam search score \( S \). The models then produce the candidate summaries token by token via beam search and choose the one with the highest beam search score as the output summary. The beam search score of one alternative sequence \( \hat{Y} \) with \( m \) tokens associated to the input text \( X \) is calculated as follows:

\[
S(\hat{Y}|X) = \frac{1}{m^\beta} \sum_{i=1}^{m} f(\hat{y}_i|X, \hat{y}_{<i})
\]

where \( f(\hat{y}_i|X, \hat{y}_{<i}) \) is the predicted log-likelihood of the \( i \)th token of the generated sequence \( \hat{Y} \), \( \hat{y}_{<i} \) represents the tokens generated earlier than the token \( \hat{y}_i \), and \( \beta \) is an additional exponential penalty associated to the sequence length. As for the task of text summarization, \( \beta \) is smaller than 1.0 in order to avoid generating redundant information.

When training on the dataset via the NLL loss \( L_{\text{nll}} \), the score \( S \) of the gold summary is expected to rise so that it becomes more likely to produce the gold summary as one of the candidate summaries and consequently chooses the gold summary as the final output among the generated candidate summaries. However, there might exist a low-quality candidate that gets a higher score \( S \). It is termed as “silver summary” when it is picked up as the output summary. The silver summary can be attributed to the discrepancy problem since the seq2seq model is only able to observe the gold summary at the time of training while the model needs to assess a large number of unseen alternatives at the time of inference. This problem is well-known as “exposure bias”.

2 Method

2.1 Problem Definition

The existing abstractive text summarization models mostly follow the seq2seq framework. They accept a long text as the input sequence and produce the output sequence as the corresponding summary. As for the task of text summarization, \( \beta \) is an additional exponential penalty associated to the sequence length. As for the task of text summarization, \( \beta \) is smaller than 1.0 in order to avoid generating redundant information.

2.2 Contrastive Learning

To mitigate the above-mentioned problem, we propose to explicitly decrease the score \( S \) of the silver summary during training via contrastive learning, which is inspired by the success of a similar contrastive learning method used in extractive summarization (Zhong et al., 2020).

Specifically, in our method, the seq2seq model is optimized to ensure that the “pos score” is higher than the “neg score”. For the identical text \( X \), the pos score \( S(Y|X) \) is calculated via Equation (2) using the gold summary, while the neg score \( S(\hat{Y}|X) \) is computed in the same way but using the silver summary. A margin ranking loss is defined to increase the pos score and meanwhile decrease the neg score as follows:

\[
L_{\text{con}} = \max(0, S(\hat{Y}|X) - S(Y|X) + \gamma)
\]

where \( \gamma \) is a margin value.

Note that the model cannot be optimized if the pos score is higher than the neg score over the margin value \( \gamma \), because when the value of \( L_{\text{con}} \) is zero, the gradient is also zero. To make the most efficient use of training data and prevent the model from underfitting, we also include the NLL loss in the overall loss function, i.e.,

\[
L = L_{\text{con}} + L_{\text{nll}}
\]

2.3 Model Training

The working flow of training the seq2seq model via contrastive learning is illustrated in Figure 1. Both the pos score and the neg score are computed and calculated based on the identical seq2seq model.
with the encoder-decoder architecture. Our method is not restricted to the vanilla seq2seq model, so the seq2seq model can also contain the copy mechanism and the coverage mechanism (See et al., 2017). While they share the encoder output for an input document, the two scores are respectively calculated by using the gold summary and the silver summary as the decoder input. It means that our method mainly imposes an effect on the decoder side.

3 Experiment

We evaluate our method by testing whether it can improve the latest SOTA abstractive text summarization model called PEGASUS considering our method can be applied to almost any seq2seq model. We utilize the same encoder-decoder architecture as PEGASUS and initialize the parameters by the fine-tuned PEGASUS model. We freeze the encoder parameters to save computational resources and time as our method focuses on adjusting the decoder. We train the model via our contrastive learning method.

Our code is implemented based on the Transformers\(^2\) from Hugging Face, which well replicates PEGASUS model and provides the fine-tuned models for the evaluation purpose. More details of replication can be found in Appendix.

3.1 Dataset

We evaluate our method on three datasets, i.e., XSum, CNNDM and Multi-News, since they represent different kinds of text summarization tasks: (1) XSum contains news articles each associated with a summary. It is designed for single-document summarization and each summary contains one single sentence. (2) CNNDM is a collection of news articles accompanied with several highlights as their summaries. It is also used for single-document summarization but the summaries often contain more than one sentence. (3) Multi-News is a multi-document summarization dataset, which consists of news articles and human-written summaries. In general, Multi-News summaries are longer than CNNDM summaries.

3.2 Baselines

To comparatively evaluate our method, we choose four SOTA models and one baseline method. BERTSUMABS (Liu and Lapata, 2019) enhances sentence-level BERT (Devlin et al., 2019) to be the document-level encoder. MASS (Song et al., 2019), BART (Lewis et al., 2020) and PEGASUS (Zhang et al., 2020) are pre-trained models based on Transformers and they have obtained impressive performance. Hi-MAP (Fabbri et al., 2019) incorporates MMR into a pointer-generator network for multi-document summarization. Scheduled Sampling (Bengio et al., 2015) (abbreviated to SS) is a conventional method to alleviate the exposure bias problem. We implement its two variants as baselines, where the decoder input (i.e., gold summary) is randomly replaced by the silver summary at either the summary level (denoted as sum) or the token level (denoted as token) with the probability of 0.5.

4 Results and Analysis

4.1 Automatic Evaluation

We automatically evaluate summary quality using Rouge (Lin, 2004)\(^3\). The Rouge scores of single-document summarization and multi-document summarization are presented in Tables 1 and 2, respectively. The first block shows the results reported in their original papers. The second block shows the results of our implementation. ConSum is the abbreviation of our method, which stands for Contrastive Summarization. There is a very small gap between the results of our implementation of PEGASUS and its reported results. This results from the fact that the beam search logic is different from the original implementation\(^4\).

\(^2\)https://github.com/huggingface/transformers

\(^3\)https://github.com/google-research/google-research/tree/master/rouge

\(^4\)One possible reason from the Transformers contributor (https://github.com/huggingface/transformers/issues/6844)
As shown in Tables 1 and 2, our method can commonly obtain the rise of Rouge-1, Rouge-2 and Rouge-L on all datasets except a slight drop of Rouge-2 on Multi-News. Maybe this drop is because the summaries on Multi-News are longer. With the rise of Rouge-1, more information can be contained in summaries. Besides, our method also outperforms scheduled sampling on Xsum and CNNDM, while it obtains competitive results on Multi-News. It shows that our method is likely to obtain a bigger improvement than scheduled sampling. These results can reflect that our method is an effective way to boost PEGASUS.

### 4.2 Ablation Study

The ablation study is conducted on CNNDM to evaluate the contribution of the NLL loss and the contrastive loss (Con loss), and the results are given in Table 3. It tells that the NLL loss and the Con loss are complementary since we can achieve better results by using both of them. Besides, without the NLL loss, the model degrades a lot (0.33) but a suitable margin value (γ = 0.0) can reduce the margin to 0.09. This is because the model optimizes more slowly and avoids overfitting when more document-summary pairs obtain the gradient 0 with the smaller margin value.

### 4.3 Results on Different Margin Value

A suitable margin value can balance the NLL loss and the Con loss to obtain better performance. The performance is heavily influenced by the margin value, so we test the influence of margin γ in the range {0.0, 0.5, 1.0, 1.5, 2.0}. The results in Figure 2 show that our method can achieve the best result on CNNDM when γ = 1.5. These results indicate that a small margin value is usually helpful to obtain competitive performance while the method is sensitive to the margin value.

### 5 Conclusion

In this paper, we propose to incorporate contrastive learning to train the abstractive summarization model as a means to alleviate the exposure bias resulting from teacher forcing. Experiments on three benchmark datasets indicate that our method...
improves the performance of the SOTA model and outperforms the scheduled sampling method. In the future, we would like to further explore whether this method can boost the performance of the SOTA models in other generation tasks such as question answer and response generation.

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A Appendix

A.1 Implementation Details

We download the processed datasets from the websites\footnote{Xsum: https://cdn-datasets.huggingface.co/summarization/xsum.tar.gz; CNNDM: https://cdn-datasets.huggingface.co/summarization/pegasus_data/cnn_dailymail.tar.gz; Multi-News: https://cdn-datasets.huggingface.co/summarization/pegasus_data/multi_news.tar.gz.}, where the three datasets have been well pre-processed for training and evaluation, especially for the PEGASUS model that we use as the baseline to evaluate our method.

The hyperparameters used for the different datasets are shown in Table 4. The other hyperparameters are shared among all datasets. The dropout rate is 0.1 for all Transformer and attention layers. The learning rate is set to 1e-6 and weight-decay is set to 1e-8. We also use a learning rate schedule based on the cosine function along with linear warming-up. For fast validation, we only use 1000 random samples from the validation set instead of all validation data, and we validate the performance with a frequency of 0.01. The parameters of our model are optimized by Adafactor\footnote{https://huggingface.co/google/pegasus-large/blob/main/config.json} (Shazeer and Stern, 2018). We use an early-stopping strategy to obtain the best performance and reduce training time, where we monitor the Rouge-2 values and stop training when no improvement for 4 validation results is observed.

We conduct experiments on Xsum dataset by using 1 GTX1080Ti-12G GPU and spend at most 20 hours obtaining the model. And we train and evaluate my method on CNNDM and Multi-News datasets by using 1 RTX3090-24G GPU and spend no more than 30 hours obtaining the results.

| Dataset | Xsum | CNNDM | M-News |
|---------|------|-------|--------|
| batch size | 8 | 8 | 4 |
| length penalty | 0.6 | 0.8 | 0.8 |
| doc length | 512 | 1024 | 1024 |
| sum length | 64 | 128 | 256 |
| margin value | 0.0 | 1.5 | 1.0 |

Table 4: The hyperparameters related to datasets. M-News stands for Multi-News.

A.2 Replication

We can replicate the experiments on the same computer, but our results become unstable when we use the different computer although we use the same hyperparameters. This is because our method is trained based on the generated silver summary, which can be altered as the rounding of different GPU varies.

We usually need to adjust the hyperparameters to obtain a great improvement for different datasets or computer configurations. We empirically adjust the margin value or add scaling factor to NLL loss, while other hyperparameters mostly come from the PEGASUS fine-tuning configurations file\footnote{https://huggingface.co/google/pegasus-large/blob/main/config.json} and keep fixed. The margin value or scaling factor is usually set to a small value from 0.0 to 2.0. If the model overfits quickly, we usually reduce the learning rate with a decay rate 0.1 or 0.5, and simultaneously decrease the weight-decay using the same rate. In most cases, we can get a competitive result within 10 trials.