Topic-Guided Abstractive Text Summarization: a Joint Learning Approach

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Abstract

We introduce a new approach for abstractive text summarization, Topic-Guided Abstractive Summarization, which calibrates long-range dependencies from topic-level features with globally salient content. The idea is to incorporate neural topic modeling with a Transformer-based sequence-to-sequence (seq2seq) model in a joint learning framework. This design can learn and preserve the global semantics of the document, which can provide additional contextual guidance for capturing important ideas of the document, thereby enhancing the generation of summary. We conduct extensive experiments on two datasets and the results show that our proposed model outperforms many extractive and abstractive systems in terms of both ROUGE measurements and human evaluation.

1 Introduction

Automatic summarization has made impressive success with the advance of large-scale language models. As one of the central problems in Natural Language Processing (NLP), summarization aims at generating an accurate text snippet to capture the key information of the input text. Comparing to extractive summarization which copies informative fragments from the input, abstractive summarization requires understanding the input document at first and subsequently generate a summary with novel and relevant words. A good abstractive summary is expected to cover principal information in the input, as well as being linguistically fluent.

In abstractive summarization, sequence-to-sequence (Seq2Seq) (Sutskever et al., 2014) has become a dominant framework using an encoder-decoder architecture based on RNNs (Chung et al., 2014) and more recently Transformers (Vaswani et al., 2017). This framework has often been utilized for language generation tasks, where two typical steps are involved: (1) defining the self-supervised pretraining objective for Transformer-based sequence-to-sequence models, and (2) fine-tuning it on the datasets for the downstream tasks. This framework has extended the success of text generation to summarization and achieved many promising results. Current state-of-the-art (SOTA) summarization models, including BART (Lewis et al., 2020), PEGASUS (Zhang et al., 2020) and ProphetNet (Qi et al., 2020), all adopted this Transformer-based architecture. Most transformer-based models are better at exploring the relationships among local tokens (Wang et al., 2020a). However, the performance of semantic understanding at a higher level (e.g, sentences, topics) is usually subpar (Reimers and Gurevych, 2019).

To better capture the global semantics of an input document for language generation tasks, researchers have made many attempts to improve current models. For example, topic-aware methods have been proposed to assist document summarization (Wang et al., 2018; Ailem et al., 2019; Narayan et al., 2018; Wang et al., 2020a; Fu et al., 2020). Topic models, such as LDA (Blei et al., 2003), PFA (Zhou et al., 2012) and prodLDA (Srivastava and Sutton, 2017), are able to provide additional signals for document understanding (Peinelt et al., 2020). They all consider topics as global variables to describe the distribution over all tokens in the vocabulary (Wang et al., 2020a). The topic is proven to be especially useful for dealing with domain-specific language since topic models have been exploited for domain adaption (Hu et al., 2014; Guo et al., 2009). For text summarization, by incorporating the topic-level features into the summarization model, we believe it can improve model performance since it encourages the model to focus on both local relationships and global semantics.

Despite the amount of literature in combing topic modeling into NLP tasks, we find that many prior studies use the topic model as a separate component for information extraction rather than jointly...
improve NLP tasks and topic modeling in a unified way. For example Bianchi et al. (2020a,b) developed a topic model where the input of an document is not traditional bag-of-words but representation learned via BERT (Devlin et al., 2019). Most cutting-edge topic models adopt the encoder-decoder network architecture where an input document is encoded into latent topic factors (i.e., coding) and these coding is then used to reconstruct the original input document during the decoding process. Such a design is very similar to seq2seq architecture where the input is also first converted to latent variables as input for decoder. Therefore, we believe embedding topic modeling into a seq2seq-based summarization model can improve performance.

In this paper, we design a topic-guided language generation framework for Transformer-based language models, by understanding the semantics learned via the topic model. We incorporate the topic model into a joint learning framework with the language generation and use the information provided by the topic model to guide the language generation. To demonstrate the effectiveness of our proposed method, we conduct extensive experiments on two real-world datasets. Both the quantitative results and the human evaluation feedback confirm that our model is more capable of capturing the key information for abstractive text summarization. Our key contributions are threefold:

- We propose a new framework for abstractive text summarization by incorporating topic modeling in a joint learning manner, which helps capture the global topic semantics for better summarization generation.
- We design a joint learning architecture to fuse neural topic modeling with transformer-based sequence-to-sequence model.
- We evaluate our topic-guided abstractive summarization model on two standard summarization datasets and demonstrate performance improvements over existing methods in both quantitative measurement and human evaluation.

2 Related Work

We now review the related literature grouped in three main categories and position our work in that context by indicating the respective issues (that are addressed by our contributions).

**Abstractive text summarization** has been widely explored over the past decades. Pre-trained encoder-decoder Transformers-based models have exhibited great success and become the first choice for many NLP tasks due to their long-term dependency modeling capability and scalability, particularly for text summarization tasks (Lewis et al., 2020; Zhang et al., 2020; Qi et al., 2020). Despite their outstanding performance on standard quantitative measurement, a common criticizing point is that higher-level global semantic structure in the text is usually ignored. For the summarization task, this can lead to the significantly inferior performance (Reimers and Gurevych, 2019).

**Topic model** explores the hidden semantic structures of text (Wang et al., 2020b). One basic assumption for the topic model is that a document is a mixture of topics and each topic is distributed over words in the vocabulary of the corpus. To learn these distributions, Latent Dirichlet Allocation (LDA) is introduced by imposing latent variables with Dirichlet prior (Griffiths et al., 2004). Recently, given the power of neural networks, topic models are improved and implemented through generic auto-encoder (Larochelle and Lauly, 2012; Salakhutdinov and Hinton, 2009) or neural variational auto-encoder (Miao et al., 2016, 2017; Röder et al., 2015; Srivastava and Sutton, 2017; Ding et al., 2018).

Topic model has been incorporated to different types of NLP tasks, including document classification (Wang et al., 2020b), translation (Zhang et al., 2016), and summarization (Ailem et al., 2019; Narayan et al., 2018; Wang et al., 2020a; Fu et al., 2020). Zhang et al. (2016) build a topic-informed RNN considering each word as a distribution over topics for machine translation. Ailem et al. (2019) develop a topic augmented decoder that generates a summary conditioned on both the input document and the latent topic for the document. Narayan et al. (2018) propose the topic-conditioned Seq2Seq model under the CNN framework. Wang et al. (2020a) introduce the friendly topic assistant for Transformer-based summarization models with the topic information explored by the separate topic component. Using the topic model to capture the global semantics has been proven to be an effective means for many NLP tasks. The topic model can be used as a separate component to provide additional information that can be used as an extra feature (Wang et al., 2020a; Zou et al., 2020; Fu et al., 2020). This topic-level feature has been applied
to the language generation process (Ailem et al., 2019; Wang et al., 2019), to guide text generation with designated topic guidance.

3 Methodology

3.1 Transformer-based Seq2Seq Model

Natural language generation tasks are best expressed as sequence-to-sequence (Seq2Seq) problems. They often assume that each word is encoded into a vector representation. Then a document \( d \) with \( n \) words can be represented as a sequence of \( n \) vectors: \( d = X_{1:n} = \{x_1, ..., x_n\} \). Consequently, the language generation problem can be defined as finding a function \( f \) mapping an input sequence \( X \) to a sequence \( s \) of \( m \) target vectors \( s = Y_{1:m} = \{y_1, ..., y_m\} \). A typical seq2seq model usually consists of three components: (1) An encoder, denoted as \( f_{\text{encoder}} \) that accepts an input sequence \( X_{1:n} \), and generates a corresponding sequence of contextualized representation \( h \). (2) A context vector, \( c \) that is a function of \( h \) conveying the essence of the input document to the decoder. (3) A decoder, \( f_{\text{decoder}} \) that uses \( c \) to generate an arbitrary length of sequence \( Y_{1:m} \) based on the task-specific requirement.

Transformer has become the most effective neural network architecture for natural language modeling (Vaswani et al., 2017). Comparing to Recurrent Neural Network (RNN), Transformers apply self-attention to compute in parallel every word from the input text an attention weight that gauges the influence each word has on others, thus allowing for parallelization than RNNs for large-scale model training (He et al., 2020). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Comparing to Recurrent Neural Network (RNN), Transformers apply self-attention to compute in parallel every word from the input text an attention weight that gauges the influence each word has on others, thus allowing for parallelization than RNNs for large-scale model training (He et al., 2020). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017). Transformer-based encoder-decoder models are introduced with scaled dot-product attention (Vaswani et al., 2017).

The transformer-based encoder encodes the input sequence \( X_{1:n} \) to a sequence of hidden states \( \bar{X}_{1:n} \) (a.k.a. \( h \)) by \( f_{\text{encoder}} : X_{1:n} \rightarrow \bar{X}_{1:n} \). The transformer-based decoder then models the conditional probability distribution of the target vector sequence \( Y_{1:m} \) given the sequence of encoded hidden states \( \bar{X}_{1:n} \) as \( p_{\text{decoder}}(Y_{1:m} | \bar{X}_{1:n}) \).

Transformer-based decoder is a stack of decoder blocks followed by a dense layer, the "LM head", which maps the learned sequence of target vectors \( Y_{0:t−1} \) to a sequence of logit vectors \( l_{1:m} = \{1, ..., l_m\} \). Transformer-based decoder defines the conditional probability distribution of a target sequence given the contextualized encoding sequence \( p_{\text{decoder}}(Y_{1:m} | \bar{X}_{1:n}) \), which by Bayes’ rule can be decomposed into a product of conditional distributions as Equation 1, where \( W_{\text{emb}}^T = [w_1, ..., w_{\text{vocab}}]^T \) refers to the transpose of the word embedding matrix, and the logit vector \( l_i \) represents the similarity score between the encoded output vector and each word embedding.

\[
P(s|d) = \prod_{i=1}^{m} p_{\text{decoder}}(y_i | y_{0:i−1}, \bar{X}_{1:n})
= \prod_{i=1}^{m} \text{softmax}(f_{\text{decoder}}(y_{0:i−1}, \bar{X}_{1:n}))
= \prod_{i=1}^{m} \text{softmax}(W_{\text{emb}}^T \cdot \text{LMHead}(y_{i−1}))
= \prod_{i=1}^{m} \text{softmax}(l_i)
\] (1)

3.2 Neural Topic Model

Topic model aims to extract the implicit topic representation as the short description for a document (Blei et al., 2003). Neural topic model (NTM) uses neural variational inference (Kingma and Welling, 2013; Rezende et al., 2014) as a flexible framework to accommodate more expressive topic models (Ding et al., 2018). Figure 1 is the fundamental model architecture of NTM. \( x \) is the representation of the input document and we depress it into a latent topic variable \( z \in \mathbb{R}^{|K|×1} \) where \( K \) is the number of topics. Usually, \( x \) is a bag-of-words representation for an input document for neural topic modeling. We define the structure of NTM following the notations from Ding et al. (2018):

- In the encoder \( q_\phi(h|x) \), it generates \( \mu(x) \) and \( \sigma(x) \) through neural networks to obtain \( h = \mu + \sigma \cdot \epsilon \) given the input \( x \). Then we learn the latent topic variable \( z = f'(h) \). NTM defines \( f \) as ReLU (Miao et al., 2016) and GSM uses softmax (Miao et al., 2017).
- The decoder network \( p_\theta(x|z) \) maps \( z \) to the predicted probability of each word in the vocabulary.
y through $W_{\text{topic}}$, which usually refers to the top frequent tokens after removing the stopwords.

Comparing to the procedure of the language generation of Seq2Seq model in Section 3.1, we find that the topic modeling task shares several similar features. They both use the encoder-decoder network. The language generation task uses the encoder to understand the input document and generates the task-specific sequence based on the hidden states learned from the encoder. Topic modeling uses the encoder to compress the input document to the latent topic variable, which is considered as the short descriptions of the input document while preserving the essential statistical relationships (Blei et al., 2003). The latent topic variable is then used to reconstruct the original document via the decoder.

Inspired by the similarity of NTM and Seq2Seq, in this study we incorporate the topic model component into the Seq2Seq model. Similar to Bianchi et al. (2020a,b), we use the latent representation from the pre-trained language model as the input for the topic model, which replaces the bag-of-words representation. Here we choose the last hidden state from the encoder as the latent representation for the input document. This contextualized context vector, which refers to the last hidden state in the Transformer-based Seq2Seq model, is expected to carry important information from the input document, on which the decoder relies to generate the output sequence. Using this as the input to the topic model allows us to keep both the valuable symbolic information as BoW and the structure information from the language sequence (Bianchi et al., 2020b). Another benefit of using the context vector is that it can help overcome some limitations from the BoW representation when inferring topics. The objective function of the topic model is to maximize the usual evidence lower bound (ELBO). The loss function of the topic model $L_{\text{tm}}$ can be written as the negative of the ELBO in Equation 2.

$$L_{\text{tm}} \approx D_{KL}(q_{\phi}(h|x)||p_{\theta}(h)) - \frac{1}{L} \sum_{l=1}^{L} \log p_{\theta}(x^{l} | z^{l})$$

### 3.3 TAS: Topic-Guided Abstractive Summarization

Incorporating the topic information into Seq2Seq model, we introduce our model TAS, Topic-Guided Abstractive Summarization, which learns and extracts the topic-level features to guide the language generation process. The key motivation for this topic-guided generation mechanism is to take the topic distribution as the prior knowledge which can guide the generation module to focus on important source words. To introduce the topic-level features into the language generation, we need to re-define the logit function (see Equation 3). Given a corpus, the topic model learns topics at a global level, which is usually represented as a topic-word matrix (also called topic embedding) $W_{\text{topic}} \in \mathbb{R}^{K \times V_{\text{topic}}}$, where $V_{\text{topic}}$ is the vocabulary size and $K$ is the number of topics. With this topic embedding, we re-write the language generation process as Equation 3. TMHead is the neural network which transforms the dimension for selecting a word from the vocabulary $W_{\text{emb}}$.

$$I_{i} = \text{softmax}(W_{\text{emb}}^{T} \cdot (\text{LMHead}(\bar{y}_{i-1}) + \bar{y}_{i-1} \cdot \text{TMHead}(W_{\text{topic}))))$$

We expect that the global semantic information can draw enough encoder-decoder attention, which provides guidance on the language generation process. We define the loss function as Equation 4. The loss for language generation $L_{\text{finetune}}$ uses the cross-entropy loss. $\alpha$ and $\beta$ are the hyper-parameters for balancing two losses.

$$L = \alpha L_{\text{tm}} + \beta L_{\text{finetune}}$$

Figure 2 is the framework for our proposed model. Comparing to the prior studies of applying topic-level features to the language generation process (see the discussion in literature (Fu et al., 2020)), our model is different in that:

- We embed the topic model component into the Seq2Seq model, by using the last hidden state from the encoder to infer the topic information.
We incorporate the topic-level features to the language generation process. By building a joint learning framework, our model is able to guide the generation process with the global semantics learned from topics.

4 Experiments

4.1 Experimental Setting

We evaluate our model using two summarization datasets: the CNN/Daily Mail dataset (CNN/DM) (Hermann et al., 2015) and the extreme summarization dataset (XSUM) (Narayan et al., 2018). Our experiments are conducted with 3 NVIDIA V100 GPUs. We adopt a 12 layer encoder and 6 layer decoder, and our model is warm started with the distilBART pre-trained model. We fine-tune our model for 20 epochs with a batch size of 64. We use Adam optimizer and fine-tune the model with the learning rate of $3 \times 10^{-5}$. For the topic model component, we choose the most frequent 2,000 words from the training set as the topic vocabulary for $W_{\text{topic}}$ and set the number of topics to $K = 1024$. Our code is available at: https://github.com/chz816/tas.

4.2 Experimental Results

We compare our proposed model with the following cutting-edge summarization models, including both extractive and abstractive models.

• **Lead-N** uses the first $N$ sentences of the article as its summary.
• **BERTSUM** (Liu and Lapata, 2019) proposes a novel document-level encoder based on BERT to generate summary.
• **MATCHSUM** (Zhong et al., 2020) formulates the task as a semantic text matching problem.
• **PGNet** (See et al., 2017) refers to the pointer-generator network. PGNet+Cov is with the coverage mechanism.
• **BART** (Lewis et al., 2020) employs the bidirectional encoder and the left-to-right decoder.

We adopt ROUGE (Lin, 2004) F1 score as the evaluation metric. We choose ROUGE-1, ROUGE-2, and ROUGE-L for performance measurement, which are the common choices in the literature. We report the performance of baseline models using the numbers from the original literature.

**Results on CNN/DM.** Table 1 summarizes the evaluation results on the CNN/DM dataset. We compare our model with different types of baselines, including strong extractive and abstractive state-of-the-art models. Our model achieves better performance in most cases. ROUGE-L score of our model is the highest among all models, which emphasizes the success of our model to capture the global semantics on this dataset. Comparing to rule-based baseline and extractive models, TAS achieves a comparable ROUGE-1 score with the extractive SOTA model MATCHSUM and improves the ROUGE-2 and ROUGE-L score by 1.6% and 1.9%. TAS also outperforms the pointer-generator network and the abstractive SOTA model BART on CNN/DM. The superior performance of TAS has emphasized the success of introducing the topic model component to help the Seq2Seq model capture the important information from the input document.

**Results on XSUM.** Table 2 shows our experimental results on the XSUM dataset. The summary of the XSUM dataset only contains one sentence, which requires the language model to compress 1We choose distilBART provided by HuggingFace due to fewer parameters. For CNN/DM, we use "sshleifer/distilbart-cnn-12-6". For XSUM, we use "sshleifer/distilbart-xsum-12-6". We record our detailed implementation in Appendix A.
the information and generate a precise sentence focusing on the key information. Our proposed model TAS outperforms extractive systems and has achieved comparable performance with BART.

![Table 1: ROUGE evaluation on CNN/DM dataset.](image)

| Model     | RG-1 | RG-2 | RG-L |
|-----------|------|------|------|
| Lead-3    | 40.07| 17.68| 36.33|
| BERTSUM   | 42.13| 19.60| 39.18|
| MATCHSUM  | 44.41| 20.86| 40.55|
| PGNet     | 36.44| 15.66| 33.42|
| PGNet+Cov | 39.53| 17.28| 36.38|
| BART      | 44.16| 21.28| 40.90|
| TAS       | 44.38| 21.19| 41.33|

To see whether our model is able to generate meaningful topics as NTM does, we show some topics learned by our model in Appendix B.

### 4.3 Human Evaluation

We also conduct a human evaluation to further examine the quality of the generated summaries by our model. We choose three metrics which are commonly used in prior studies (Huang et al., 2020; Xu et al., 2020): informativeness, fluency and succinctness. Informativeness measures whether the summary covers the important information from the input article, fluency focuses on if the generated summary is grammatically correct and succinctness measures whether the summary is concise and does not describe too many details. We randomly select 100 articles from the XSUM test set and hire 9 fluent English speakers as our annotators to rate summaries generated by distil-BART and our model TAS. They are required to give a comparison between the two generated summaries that are presented anonymously. Table 3 reports the human evaluation results. Overall, we find that our model is more capable of capturing the key information of a document and the global semantics. We provide two example summaries generated by our model TAS in Table 4.

![Table 3: Human evaluation results on XSUM dataset.](image)

| Win | Tie | Loss |
|-----|-----|------|
| 35.92% | 29.58% | 34.51% |
| 21.13% | 60.56% | 18.31% |
| 32.86% | 41.34% | 25.80% |

### 4.4 Model Analysis

To have a deeper understanding of why our model improves the summarization and the impacts of the topic model component, we conduct several additional experiments using the XSUM test set.

#### Impacts of the topic model.

Topic model is an important component in our model and provides semantic information. We repeat our experiments on XSUM using different types of topic models, including prodLDA (Srivastava and Sutton, 2017) and LDA (Blei et al., 2003). The main difference between these two models is prodLDA replaces the multinomial distribution over individual words in standard LDA with a product of experts. Table 5 records the results, and we can clearly see that prodLDA and LDA produce very similar results.

#### Impacts of the number of topics.

We fix the number of topics $K = 1024$ in our model. To test whether the number of topics affects the model performance, we need to add an additional neural network TMHead to adjust the dimension for the generation process in Equation 5. Table 6 records the performance. We can find that with an additional neural network, the model with $K = 1024$ *topics* perform the best and it achieves a similar ROUGE score with our proposed model which fixes the topic number. Considering the better performance of the proposed TAS model and fewer parameters, we report the performance of the model by fixing the topic numbers $K = 1024$.

\[
I_i = \text{softmax}(W^T_{emb} \cdot (\text{LMHead}(\tilde{y}_{i-1}) + \text{DimHead}(\tilde{y}_{i-1}) \cdot \text{TMHead}(W_{\text{topic}))))
\] (5)

Could we just fine-tune the original model in more epochs? Since our model is warmed up us-
The 32-year-old scored 25 points on Sunday to pass the milestone in his 10th season with the Cavaliers. He now has twice as many points as Zydrunas Ilgauskas, who is second on the team’s all-time list with 10,616. James, who also played for Miami Heat, is eighth on the NBA all-time list with 27,938 career points...

LeBron James has become the second highest scorer in NBA history after passing 10,000 points for the Cleveland Cavaliers.

The materials, which can sense pressure as sensitively and quickly as human skin, have been outlined by two groups reporting in Nature Materials. The skins are arrays of small pressure sensors that convert tiny changes in pressure into electrical signals...

Engineers have shown off two approaches to creating flexible "skin" that could be used in robotics and artificial limbs.

Table 4: Example summaries by our model on XSUM dataset.

Table 5: Performance for our model with different types of topic models, prodLDA and LDA. We use the same experimental settings with $\alpha = 0.1$ and $\beta = 1$.

Table 6: Performance for our model with different numbers of topics. * indicates the model with additional neural network.

(a) Performance on CNN/DM

(b) Performance on XSUM

Table 7: Performance of distil-BART and our model under the same experimental setting.

Table 8: Generated summaries from TAS and fine-tuned distil-BART.

Summary

Target "Artificial skin" that could bring a sensitive touch to robots and prosthetic limbs, has been shown off.

Our model Engineers have shown off two approaches to creating flexible "skin" that could be used in robotics and artificial limbs.

distil-BART Two approaches to developing flexible "skin" have been presented to scientists.
Ablation study. We perform ablation studies to test the effects of various hyper-parameters. As shown in Table 9, we report the performance under different values of $\alpha$. We fix $\beta = 1$ and find that our model achieves the best performance when $\alpha = 0.1$. In general, we find that different parameters, which balance the loss between two components, provide different performance, and smaller values on $\alpha$ usually perform better.

| $\alpha$ | RG-1  | RG-2  | RG-L  |
|---------|-------|-------|-------|
| 0       | 44.57 | 21.60 | 36.71 |
| 0.1     | 44.63 | 21.62 | 36.77 |
| 1       | 44.28 | 21.06 | 35.97 |

Table 9: Ablation studies on XSUM dataset, using different values for $\alpha$. We fix $\beta = 1$ and use prodLDA for the topic model component.

4.5 Robustness Check

In this section, we perform a robustness check for the proposed model. We use the heuristics used in Goel et al. (2021) to create sub-populations and perform experiments to check the performance of these sub-populations. We use the following metrics and first select the top 10% and bottom 10% examples in the test set of XSUM as two sub-populations.

- **Length** of the input document.
- **Position** is the average location in the source document of where information in the summary comes from.

Table 10 records the experimental results, using ROUGE-2 for evaluation. We find that TAS is more capable to handle different lengths of documents since the performance on the shortest and longest set is better. The design of TAS is aimed to add the topic model component to provide more topic-level information to guide the summary generation. The performance improvement on the longest document set especially encourages us, since we are motivated to find that TAS performs better when the input document is long which is harder to summarize. For position, we find that TAS performs better than the baseline in the latest position set, which is challenging. The latest position group requires our model to have a better understanding of the whole document. TAS achieves a higher ROUGE-2 score in this subpopulation than our baseline by 1.4%.

| Metric | Baseline | TAS  |
|--------|----------|------|
| Length | Shortest | 23.55| 23.71|
|        | Longest  | 15.48| 15.70|
| Position| Earliest | 22.50| 22.52|
|        | Latest   | 17.37| 17.61|

Table 10: Robustness Check on sub-populations defined by metrics. For Baseline model, we use the results from distil-BART. We report the performance using ROUGE-2 score.

5 Conclusion

In this paper, we propose to leverage the topic model incorporated into the Seq2Seq model to improve the performance of text summarization. We introduce the global semantic topic-level features into the language understanding to guide the generation process. Experiments on two datasets show that our model outperforms several strong baselines in both quantitative measurement and human evaluation, which demonstrates the effectiveness of our proposed model.

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3We report ROUGE-1, ROUGE-2 and ROUGE-L score for robustness check in Appendix C.
References

Melissa Ailem, Bowen Zhang, and Fei Sha. 2019. Topic augmented generator for abstractive summarization. arXiv preprint arXiv:1908.07026.

Federico Bianchi, Silvia Terragni, and Dirk Hovy. 2020a. Pre-training is a hot topic: Contextualized document embeddings improve topic coherence. arXiv preprint arXiv:2004.03974.

Federico Bianchi, Silvia Terragni, Dirk Hovy, Debora Nozza, and Elisabetta Fersini. 2020b. Cross-lingual contextualized topic models with zero-shot learning. arXiv preprint arXiv:2004.07737.

David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. the Journal of machine Learning research, 3:993–1022.

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186.

Ran Ding, Ramesh Nallapati, and Bing Xiang. 2018. Coherence-aware neural topic modeling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 830–836.

Xiyuan Fu, Jun Wang, Jinghan Zhang, Jinmao Wei, and Zhenglu Yang. 2020. Document summarization with vhtm: Variational hierarchical topic-aware mechanism. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 7740–7747.

Karan Goel, Nazneen Rajani, Jesse Vig, Samson Tan, Jason Wu, Steph an Zheng, Caiming Xiong, Mohit Bansal, and Christopher Ré. 2021. Robustness gym: Unifying the nlp evaluation landscape.

Thomas L Griffiths, Michael I Jordan, Joshua B Tenenbaum, and David M Blei. 2004. Hierarchical topic models and the nested chinese restaurant process. In Advances in neural information processing systems, pages 17–24.

Honglei Guo, Huijia Zhu, Zhi Li Guo, Xiaoxun Zhang, Xian Wu, and Zhong Su. 2009. Domain adaptation with latent semantic association for named entity recognition. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 281–289.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2020. Deberta: Decoding-enhanced bert with disentangled attention. arXiv preprint arXiv:2006.03654.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. Advances in neural information processing systems, 28:1693–1701.

Yuening Hu, Ke Zhai, Vladimir Eidelman, and Jordan Boyd-Graber. 2014. Polylingual tree-based topic models for translation domain adaptation. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1166–1176.

Luyang Huang, Lingfei Wu, and Lu Wang. 2020. Knowledge graph-augmented abstractive summarization with semantic-driven cloze reward. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5094–5107, Online. Association for Computational Linguistics.

Diederik P Kingma and Max Welling. 2013. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.

Hugo Larochelle and Stanislas Lauly. 2012. A neural autoregressive topic model. In Proceedings of the 25th International Conference on Information Processing Systems-Volume 2, pages 2708–2716.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. Bart: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In Text summarization branches out, pages 74–81.

Yang Liu and Mirella Lapata. 2019. Text summarization with pretrained encoders. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3721–3731.

Yishu Miao, Edward Grefenstette, and Phil Blunsom. 2017. Discovering discrete latent topics with neural variational inference. In International Conference on Machine Learning, pages 2410–2419. PMLR.

Yishu Miao, Lei Yu, and Phil Blunsom. 2016. Neural variational inference for text processing. In International conference on machine learning, pages 1727–1736. PMLR.
Shashi Narayan, Shay B Cohen, and Mirella Lapata. 2018. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1797–1807.

Nicole Peinelt, Dong Nguyen, and Maria Liakata. 2020. tbert: Topic models and bert joining forces for semantic similarity detection. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7047–7055.

Patrick von Platen. 2020. Transformers-based encoder-decoder models. https://huggingface.co/blog/encoder-decoder.

Weizhen Qi, Yu Yan, Yeyun Gong, Dayiheng Liu, Nan Duan, Jiusheng Chen, Ruofei Zhang, and Ming Zhou. 2020. Prophetnet: Predicting future n-gram for sequence-to-sequence pre-training. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 2401–2410.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3973–3983.

Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. 2014. Stochastic backpropagation and approximate inference in deep generative models. In International conference on machine learning, pages 1278–1286. PMLR.

Michael Röder, Andreas Both, and Alexander Hinneburg. 2015. Exploring the space of topic coherence measures. In Proceedings of the eighth ACM international conference on Web search and data mining, pages 399–408.

Ruslan Salakhutdinov and Geoffrey Hinton. 2009. Replicated softmax: an undirected topic model. In Proceedings of the 22nd International Conference on Neural Information Processing Systems, pages 1607–1614.

Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1073–1083.

Akash Srivastava and Charles Sutton. 2017. Autoencoding variational inference for topic models. arXiv preprint arXiv:1703.01488.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In Proceedings of the 27th International Conference on Neural Information Processing Systems-Volume 2, pages 3104–3112.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems, pages 6000–6010.

Li Wang, Junlin Yao, Yunze Tao, Li Zhong, Wei Liu, and Qiang Du. 2018. A reinforced topic-aware convolutional sequence-to-sequence model for abstractive text summarization. In Proceedings of the 27th International Joint Conference on Artificial Intelligence, pages 4453–4460.

Wenlin Wang, Zhe Gan, Hongteng Xu, Ruiyi Zhang, Guoyin Wang, Dinghan Shen, Changyou Chen, and Lawrence Carin. 2019. Topic-guided variational auto-encoder for text generation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 166–177.

Zhengjue Wang, Zhibin Duan, Hao Zhang, Chaojie Wang, Long Tian, Bo Chen, and Mingyuan Zhou. 2020a. Friendly topic assistant for transformer based abstractive summarization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 485–497.

Zhengjue Wang, Chaojie Wang, Hao Zhang, Zhibin Duan, Mingyuan Zhou, and Bo Chen. 2020b. Learning dynamic hierarchical topic graph with graph convolutional network for document classification. In International Conference on Artificial Intelligence and Statistics, pages 3959–3969. PMLR.

Song Xu, Haoran Li, Peng Yuan, Youzheng Wu, Xiaodong He, and Bowen Zhou. 2020. Self-attention guided copy mechanism for abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1355–1362, Online. Association for Computational Linguistics.

Jian Zhang, Liangyou Li, Andy Way, and Qun Liu. 2016. Topic-informed neural machine translation. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pages 1807–1817.

Jinqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In International Conference on Machine Learning, pages 11328–11339. PMLR.

Ming Zhong, Pengfei Liu, Yiran Chen, Danqing Wang, Xipeng Qiu, and Xuanjing Huang. 2020. Extractive summarization as text matching. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6197–6208, Online. Association for Computational Linguistics.
Mingyuan Zhou, Lauren Hannah, David Dunson, and Lawrence Carin. 2012. Beta-negative binomial process and poisson factor analysis. In Artificial Intelligence and Statistics, pages 1462–1471. PMLR.

Yicheng Zou, Lujun Zhao, Yangyang Kang, Jun Lin, Minlong Peng, Zhuoren Jiang, Changlong Sun, Qi Zhang, Xuanjing Huang, and Xiaozhong Liu. 2020. Topic-oriented spoken dialogue summarization for customer service with saliency-aware topic modeling. arXiv preprint arXiv:2012.07311.
A Implementation

For CNN/DM, we also add the post-processing step after the generation. We use the same post-processing program \(^4\) from SOTA model ProphetNet (Qi et al., 2020). We don’t perform post-processing for XSUM, considering the summary for XSUM only contains one sentence.

B Learned Topics

We show some learned topics in this section to check if the topic model component can generate meaningful topics as expected. Table 11 lists the example topics learned on CNN/DM and XSUM dataset. For each topic, we extract the top 10 words from the topic model vocabulary \(W_{\text{topic}}\). By analyzing the learned topics, we find that our topic model component has learned several topics which are explainable and meaningful.

\begin{table}[h]
\centering
\begin{tabular}{l}
\hline
\textbf{Top 10 words} \\
1 court, said, police, told, case, death, attorney, mr, judge, charges \\
2 family, told, life, mother, said, children, old, like, time, would \\
3 government, united, cnn, military, security, states, officials, international, al, forces \\
4 season, league, team, game, cup, win, match, club, goal, players \\
5 water, according, scientists, could, agency, earth, officials, government, per, region \\
\hline
\end{tabular}
\caption{(a) Example topics learned on CNN/DM.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{l}
\hline
\textbf{Top 10 words} \\
1 league, game, season, first, half, team, second, win, side, goal \\
2 police, family, court, found, old, heard, hospital, told, incident, died \\
3 health, service, site, work, company, use, help, children, patients, customers \\
4 first, game, league, win, season, team, club, side, second, players \\
5 mr, government, president, us, state, said, minister, security, country, un \\
\hline
\end{tabular}
\caption{(b) Example topics learned on XSUM.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{l}
\hline
\textbf{Metric} & \textbf{Baseline} & \textbf{TAS} \\
\hline
\textbf{Length} & \\
Shortest & 45.84 & 45.84 \\
Longest & 36.92 & 36.98 \\
\hline
\textbf{Position} & \\
Earliest & 45.35 & 45.31 \\
Latest & 39.46 & 39.81 \\
\hline
\end{tabular}
\caption{(a) Performance evaluated by ROUGE-1.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{l}
\hline
\textbf{Metric} & \textbf{Baseline} & \textbf{TAS} \\
\hline
\textbf{Length} & \\
Shortest & 23.55 & 23.71 \\
Longest & 15.48 & 15.70 \\
\hline
\textbf{Position} & \\
Earliest & 22.50 & 22.52 \\
Latest & 17.37 & 17.61 \\
\hline
\end{tabular}
\caption{(b) Performance evaluated by ROUGE-2.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{l}
\hline
\textbf{Metric} & \textbf{Baseline} & \textbf{TAS} \\
\hline
\textbf{Length} & \\
Shortest & 39.55 & 39.72 \\
Longest & 28.84 & 29.09 \\
\hline
\textbf{Position} & \\
Earliest & 37.72 & 37.8 \\
Latest & 31.51 & 31.81 \\
\hline
\end{tabular}
\caption{(c) Performance evaluated by ROUGE-L.}
\end{table}

Table 12: Robustness Check with ROUGE-1, ROUGE-2 and ROUGE-L.

C Robustness check

We report the ROUGE-1, ROUGE-2 and ROUGE-L score for robustness check to better understand our proposed model in Table 12.

\(^4\)https://github.com/microsoft/ProphetNet