Topic-Aware Encoding for Extractive Summarization

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ABSTRACT

Document summarization provides an instrument for faster understanding the collection of text documents and has several real-life applications. With the growth of online text data, numerous summarization models have been proposed recently. The Sequence-to-Sequence (Seq2Seq) based neural summarization model is the most widely used in the summarization field due to its high performance. This is because semantic information and structure information in the text is adequately considered when encoding. However, the existing extractive summarization models pay little attention to and use the central topic information to assist the generation of summaries, which leads to models not ensuring the generated summary under the primary topic. A lengthy document can span several topics, and a single summary cannot do justice to all the topics. Therefore, the key to generating a high-quality summary is determining the central topic and building a summary based on it, especially for a long document. We propose a topic-aware encoding for document summarization to deal with this issue. This model effectively combines syntactic-level and topic-level information to build a comprehensive sentence representation. Specifically, a neural topic model is added in the neural-based sentence-level representation learning to adequately consider the central topic information for capturing the critical content in the original document. The experimental results on three public datasets show that our model outperforms the state-of-the-art models.

CCS CONCEPTS

• Computing methodologies → Information extraction; Natural language generation; • Information systems → Summarization.

KEYWORDS

Document Summarization, Neural Topic Model, Representation Learning

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1 INTRODUCTION

Automatic extractive summarization has drawn much attention in recent years, and it exhibits the practicability in document management and search systems, which is a fundamental task of information retrieval (IR) and the natural language process (NLP). It is of interest to generate concise and salient natural language summaries that are capable of retaining the main ideas of original documents. The critical challenges in automatic extractive summarization are correctly evaluating and selecting relevant information, which needs an encoding architecture to represent sentences effectively.

Recent successes of neural Seq2Seq models [1] enable the end-to-end framework for extractive summarization task, which allows constructing a neural network architecture for encoding text information sequentially. Then, many extractive models [11, 12] were proposed by an RNN-based encoder network to build representation for salient information extraction. However, RNN-based models are more prone to gradient vanishing due to their chain structure of non-linearities compared to the models equipped with attention mechanism Bahdanau et al. [1].

Later, several neural extractive summarization approaches have been proposed to encode the word-level information by various attention modules (e.g., hierarchical attention [4, 12]). However, most above methods adopted the discriminative encoding model [2, 4, 10, 15], which limits the representation ability on the latent structure information (e.g., topics) [6, 8]. Wang et al. [18] proposed a topic-aware encoding network via the traditional topic model and achieved better performance than the RNN-based, CNN-based, and mixtures models. However, the traditional topic model can not train end-to-end with the summarization model based on the neural networks, which leads a gap between two modules.

In this paper, we propose a novel topic-aware encoding architecture for extractive summarization model, which combines syntactic-level and topic-level information to build a comprehensive sentence representation for saliency extraction. Our extractive summarization model based on an actor-critic framework (policy-based reinforcement learning method) and jointly with a neural topic model. To the best of our knowledge, this is the first work for extractive summarization that incorporates the topic-level information in the encoding part by a neural topic model, which can provide themed and contextual alignment information into the encoding part of summarization model.

Extensive experimental results on three benchmark datasets demonstrate that by fully exploiting the power of the encoding architecture enhanced by word- and topic-level information, our proposed model yields high accuracy for extractive summarization, advancing the state-of-the-art baseline methods.
2 OUR MODEL

In this section, we describe our framework that leverages latent topics in document summarization. The overall architecture is consisting of two modules—a neural topic model for exploring potential topics and a policy-based extractive-abstractive model for document summarization. For the neural topic model, we exploit the recently proposed neural topic models [9] to infer latent topics of the given document, which facilitate end-to-end training with other neural models and do not require model-specific derivation. For the baseline reinforced summarization model [2], it consists of three parts: a hierarchical encoding network, and an extractor (pointer network [17]). To save space, for the details of the baseline model, please refer to Chen and Bansal [2]. Let’s begin with the problem definition.

Given a training set of document-summary pairs \( \{x_i, y_i\}_{i=1}^T \), where \( T \) denotes the total number of training pairs, and \( x_i \) and \( y_i \) are the document and reference summary of the \( i \)-th training pair. For a long text document \( x_i \) with a sequence \( \{x_{i,1}, ..., x_{i,n}, ..., x_{i,N}\} \) containing \( N \) sentences, summarization aims to output a readable multi-sentence summary. Each sentence \( x_{i,n} \) is made up of a sequence of \( M \) words \( \{w_{i,n,1}, ..., w_{i,n,m}, ..., w_{i,n,M}\} \). Additionally, we process each document \( x \) into bag-of-words (BoW) term vector \( x_{bow} \), which is a \( V \)-dim vector over the vocabulary \( V \) (being the vocabulary size). It is fed into the neural topic model following the BoW assumption [9].

2.1 Neural Topic Model

Our work is closely related to topic models that discover latent topics from word co-occurrence at the document level, and they are common in the fashion of latent Dirichlet allocation (LDA) based on Bayesian graphical models. In this paper, our neural topic model module is inspired by Miao et al. [9] based on variational autoencoder, which consists of an encoder and a decoder to resemble the data reconstruction process. Due to space limitation, for the training process of the neural topic model, please refer to [9] for details. In this paper, we only use the topic representation \( \theta \) and topic-word distribution \( W_{\phi_s} \).

2.2 Encoding Architectures

2.2.1 Syntactic-Aware Encoding Layer (Basic Encoder). To make the salient extraction process much more efficient, the original document is represented in sentence, which has been proven powerful to evaluate the saliency and further improve summarization performance [2, 4]. Thus, in this section, we propose a novel hierarchical encoding network to simultaneously capture syntactic-level information of the original document and recurrent dependencies among sentences. Specifically, the \( m \)-th word in the \( n \)-th sentence can be pre-embedded as a vector \( \hat{w}_{i,n,m} \in \mathbb{R}^{d_1} \). The global information \( \{x_{IP,n} \in \mathbb{R}^{d_2}\} \) of the \( n \)-th sentence can be modeled by:

\[
x_{IP,n} = \text{relu}(W_p \left( \frac{1}{M} \sum_{m=1}^{M} \hat{w}_{i,n,m} \right)),
\]

where \( W_p \) is a learnable mapping matrix. Meanwhile, the local information \( x_{IC,n} \in \mathbb{R}^{d_1} \) of this sentence can be computed by the temporal convolutional approach [5]. Then, the representation of the \( n \)-th input sentence (\( \hat{x}_{i,n} \in \mathbb{R}^{d_4} \)) can be obtained as:

\[
\hat{x}_{i,n} = \text{relu}(W_g [x_{IP,n}^T; x_{IC,n}^T]),
\]

where \( W_g \) is a learnable matrix to combine both local and global sentence information.

The second part tries to capture the recurrent and long-term dependencies among sentences. Thus, a Bi-LSTM layer is adopted to enhance the sentence representation, \( h_{i,n} = f_{bl}(\tilde{x}_{i,1}, ..., \tilde{x}_{i,n}, ..., \tilde{x}_{i,N}) \), where \( h_{i,n} = \{h_{i,n}\}_{n=1}^N \) and \( f_{bl} \) denotes the operation in the Bi-LSTM layer. \( h_{i,n} \in \mathbb{R}^{d_s} \) is the latent state of the \( n \)-th syntactic-aware sentence.

2.2.2 Topic-Aware Encoding Module. In this section, we introduce two different topic-aware encoding architectures and show how to combine syntactic- and topic-level information to build a novel comprehensive representation for extractive model.

TAE-TR: Topic-Aware Encoding via Topic Representation.

Topic information can effectively determine the core content of the article, to help summarizer model capture salient information from the original document [18].

Once having the topic representation \( \theta \), the sentence representation \( h_{i,n} \) can be enhanced as follows:

\[
\hat{h}_{i,n} = \text{relu}(W_f [h_{i,n}; \theta]).
\]

Here, \( \hat{h}_{i,n} \in \mathbb{R}^{d_s} \) and \( W_f \in \mathbb{R}^{d_s \times (d_s + k)} \) is a learnable mapping matrix.

TAE-TWD: Topic-Aware Encoding via Topic-Word Distribution.

Once having the topic-word distribution \( W_{\phi_s} \), the sentence representation \( h_{i,n} \) can be enhanced as follows:

\[
\hat{h}_{i,n} = \text{relu}(W_f [h_{i,n}; \phi_s h_{i,n}]).
\]

Here, \( \hat{h}_{i,n} \in \mathbb{R}^{d_s} \) and \( W_f \in \mathbb{R}^{d_s \times (d_s + k)} \) is a learnable mapping matrix.

Finally, to select the extracted sentences based on the above sentence representations, we follow the previous work [2] and add an LSTM-RNN to train a pointer network [17], to extract sentences recurrently.

3 EXPERIMENTS

3.1 Implementation Details

We implemented our model in PyTorch 0.4.0. All hyper-parameters are tuned on the validation set of the original text version of CNN/Daily Mail and BigPatent. For each dataset, the 30000 most frequently words are kept as the vocabulary. We used an embedding dimension of 128 for the word-level representation on both CNN/Daily Mail and BigPatent. Especially, \( d_1 = 128, d_2 = d_3 = d_4 = 300, d_5 = 512 \), and \( k = 50 \). The Adam optimizer with a learning rate of 1e-3 for reinforcement learning training. The extractor was trained similarly to [2] (including the same settings).

3.2 Experiment Settings

3.2.1 Three BenchMark Datasets. In this paper, we consider three datasets to evaluate the performance of the proposed model in the extractive summarization task. Therefore, we choose three benchmark summarization datasets (CNN/Daily Mail [3], DUC2004 and BigPatent [16]) with apparent differences in length and topic. A detailed description of each dataset is given below:

- **CNN/Daily Mail.** This corpus was proposed by Hermann et al. [3] for reading comprehension task, which includes news stories
As our work focuses on mining the indicative topic-level information in the single-document (especially for very long document) to achieve the multi-sentence extractive summarization task, which uses the topic as the auxiliary information to help extract salient content better. Our main results on the CNN/Daily Mail dataset are shown in Table 1, with the results of recent extractive models. Lead3 is a baseline which simply selects the first three sentences.

### 3.3 Results and Analysis

As our work focuses on mining the indicative topic-level information in the single-document (especially for very long document) to achieve the multi-sentence extractive summarization task, which uses the topic as the auxiliary information to help extract salient content better. Our main results on the CNN/Daily Mail dataset are shown in Table 1, with the results of recent extractive models. Lead3 is a baseline which simply selects the first three sentences.

| Baseline Models | ROUGE-1 | ROUGE-2 | ROUGE-L | R-AVG |
|-----------------|---------|---------|---------|-------|
| Lead-3[14]      | 40.34   | 17.70   | 36.57   | 31.54 |
| SummaRuNNer[11]| 39.60   | 16.20   | 35.30   | 30.37 |
| Refresh[13]     | 40.00   | 18.20   | 36.60   | 31.60 |
| rnn-ext + RL    | 41.47   | 18.72   | 37.76   | 32.65 |

**Basic Encoder**

| Basic Encoder   | ROUGE-1 | ROUGE-2 | ROUGE-L | R-AVG |
|-----------------|---------|---------|---------|-------|
| Lead3           | 41.61   | 19.00   | 37.88   | 32.83 |
| TAE-TWD         | 41.69   | 18.95   | 37.93   | 32.86 |
| TAE-TR          | 41.89   | 19.31   | 38.15   | 33.12 |

The neural extractive models are usually based on hierarchical encoders (SummaRuNNer; [11]). They have been extended with reinforcement learning (Refresh; [13] and rnn-ext + RL; [2]). Moreover, we adopt the ROUGE metric [7] for evaluation and summarize our experimental results in Table 1, Table 2, and Table 3 (the best results are in bold). Our experimental results show that the proposed TAE-TR achieves better performance on the three benchmark datasets.

3.3.1 Performance Comparison with Traditional Methods. Accurately, to verify the performance of our model on the ROUGE evaluation metric, we compared our method with several single-document based multi-sentence summarization systems that have reported results on the CNN/Daily Mail dataset. Overall, our model achieves strong improvements and the new state-of-the-art on the CNN/Daily Mail dataset.

3.3.2 Compared with Topic-Focused Methods. To verify the performance of our topic-aware encoding network, we compared it on the DUC2004 dataset with the most related method [18]. As can be seen from the Table 2, the result of our model is better than that of the baseline method RL-T-ConvS2S [18].

3.3.3 Effect Comparison on Different Length Documents. Many existing encoding networks of summarization models often show poor information capture ability when facing long documents. Therefore, to verify the coding capacity of this model for long documents, we compare the results on the BigPatent dataset of the reinforced summarization model with or without the neural topic model. By comparing the results on Table 1 and Table 3, the proposed model TAE-TR obtained higher improvement on the BigPatent dataset. Specifically, in terms of improvement gain, our model outperforms the reinforced baseline model rnn-ext+RL by 1.01%, 3.15%, 1.03%, 1.43% and 5.57%, 9.32%, 2.28%, 4.81% on CNN/Daily Mail and BigPatent, respectively. While considering the short and long documents simultaneously, TAE-TR can effectively capture the topic information for constructing sentences or document representations. As a result, TAE-TR achieves the highest performance on both CNN/Daily Mail and BigPatent datasets.

### 4 CONCLUSIONS

In this paper, to construct a comprehensive representation for salient extraction, we introduce a neural topic model to capture the indicative topic information adequately. The experimental results demonstrated that our model could better capture the essential information of documents and also achieve better performance than
the state-of-the-art baselines. In future work, we would like to extend our model on a multi-document summarization task.

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