Representation of Chinese-Vietnamese Bilingual News Topics Based on Heterogeneous Graph

Zhilei He[1,2][0000−0002−5347−3384], Enchang Zhu[1,2][0000−0002−1340−4368], Zhengtao Yu[1,2][0000−0002−4012−461X], Shengxiang Gao[1,2][0000−0002−2980−8420]*, Yuxin Huang[1,2][0000−0003−1277−6212], and Linjie Xia[1,2][0000−0003−4532−3666]

[1] Kunming University of Science and Technology, Kunming 650504, China
[2] Key Laboratory of Artificial Intelligence in Yunnan Province, Kunming 650504, China gaoshengxiang.yn@foxmail.com

Abstract. The Chinese-Vietnamese bilingual news topic representations are generated from Chinese-Vietnamese bilingual news texts describing the same topic into concise Chinese sentences that can correctly describe the topic. However, there is a semantic gap between Chinese and Vietnamese, and the association relationship between multiple documents in multiple languages is complicated, which makes it challenging to generate concise and correct topic representations. In this paper, we propose a cross-language topic representation method based on heterogeneous graphs. The method first uses a heterogeneous graph containing sentences and entity nodes to represent bilingual Chinese-Vietnamese news texts and effectively models the complex association relationships between multiple texts in multiple languages through graph attention networks (GAT). The topic encoder is then used to encode topic words into cues for topic representation generation, and the decoder side constraints are incorporated to generate the correct topic representation. The experimental results show that the proposed method improves the ROUGE value by up to 3.5 compared with the baseline method.

Keywords: Chinese-Vietnamese Bilingual · Heterogeneous graph · topic representation · Cross-language · GAT

1 Introduction

In the context of "the Belt and Road", China and Vietnam are exchanging more and more closely, and there are more and more news topics of common interest between the two countries. The timely understanding of the news topics of common interest and the main contents of the two countries is of great value in promoting the exchange and cooperation between China and Vietnam. In order to cope with information overload, topic discovery technology [1][2] is used to organize the news by topic and help readers to get relevant information quickly. However, from the reader's perspective, organizing news texts by topic clusters only, there is a problem with multiple news headlines and texts with two language descriptions under one topic, and it is impossible to understand the general content of these topics in a short time. Therefore, topics need to be presented to readers in a concise form. For example, "Strictly implement all epidemic prevention and control measures," The reader can understand that the news text mainly describes the epidemic prevention and control measures through this topic. This allows readers to quickly understand these news texts and get the main content of the news quickly, which reduces time and energy consumption and facilitates analysis of the news by public opinion workers.

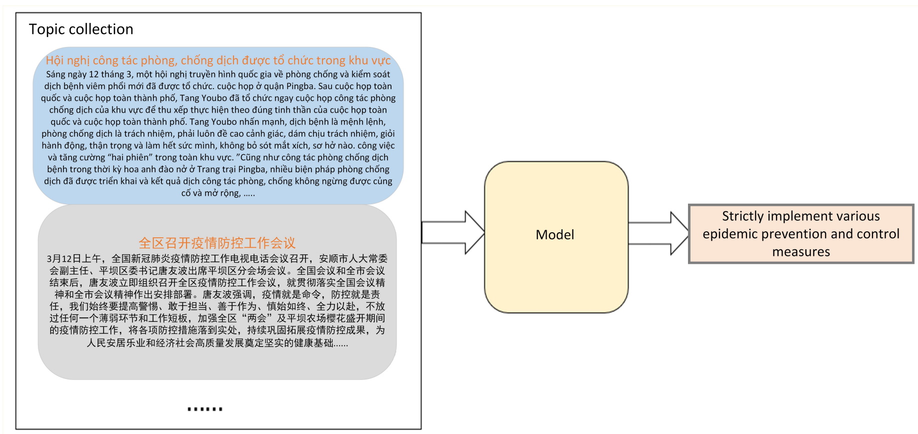

Fig. 1. Topic presentation task of Chinese Vietnamese Bilingual News

In this paper, as shown in Figure 1, we study how to automatically generate concise and correct Chinese topic representation for multiple Chinese and Vietnamese news texts under each topic. There are few studies on topic representation at home and abroad, and the traditional method uses keywords to represent topics in a monolingual environment [3]. The difficulty of this method is how to find keywords that contain key information and can be quickly understood by readers. For example, Zheng et al. [4] proposed to extract the 5W1H (when, where, who, what, whom, how) six-tuple feature of news text to represent the topic; Liu Tong [5] proposed to calculate the index of essential words in the text by constructing a word co-occurrence relationship network, to mine the topic keywords of the text. However, the method of keyword representation of topics has certain limitations, and the different order of keywords may lead to different semantics. Therefore, some scholars propose to use temporal information [6] and citation information [7] to smooth the connection between keywords. For example, Han [8] et al. proposed a concept bagging approach to represent documents by characterizing text as vector clusters on word2vec and using the frequency of clusters; other scholars proposed using extractive methods to represent documents, e.g., Weiyu Wang [9] et al. proposed an extractive topic representation method to extract common information from the headings of document sets and then fuse them to generate a short topic representation. Some scholars also use deep learning methods to represent texts, e.g., Jiang et al. [10] proposed a potential topic text representation model, which obtains a representation of text by measuring the distance between texts; Li et al. [11] proposed a neural network-based comment representation model, which classifies each sentence into a combination of text representations by calculating its weight.

Due to language differences, monolingual topic representation tasks cannot be directly applied to cross-lingual topic representation tasks. The topic representation task is similar to the topic summarization [12] task in that the cross-language summarization task is a process of inputting source language text and outputting a summary in the target language in a multilingual environment. The cross-language summarization task is more complex than the monolingual summarization task. It is challenging to solve the problem of linguistic variability and, at the same time to complete the text summarization task. For example, Ayana et al. [13] simulated the output of a pre-trained translation or title generation model to achieve the task of cross-language title generation; Zhu et al. [14] proposed a cross-language automatic summarization method incorporating translation patterns, which effectively solved the problems of large model capacity and long training time; Li et al. [15] combined multiple documents on the same topic, then pre-processed the combined documents by word separation, and finally used hLDA topic modeling to extract summary sentences; Steinberger et al. [16]built a sentence matrix based on a latent semantic analysis model, and selected some sentences as summaries by using singular value decomposition; Litvak et al. [17]proposed a language independent multilingual sentence extraction (Muse) algorithm based on the optimization of multiple sentence ranking methods using genetic algorithms; Conroy et al.[18] proposed three methods to assign weights to sentences using non-negative matrix decomposition, LSA, and LDA, and weighted the weights of the three methods to extract topic summaries; Abdelkrime et al. [19] used the fuzzy clustering algorithm to cluster the sentences according to the topic, score each sentence according to the degree of the topic covered by the sentence, and select the sentence with the highest score to construct the topic summary.

Although the above methods can effectively solve the task of monolingual multi-text topic representation, in the task of this paper, there are complex association relationships between multi-lingual multi-texts. The existing topic generation models are difficult to effectively model the association relationships between multi-lingual texts, resulting in deviations between the generated topic representation and the original text description of the topic. Therefore, this paper proposes a multi-lingual topic representation method that models the complex linguistic relationships between multi-lingual multi-texts through heterogeneous graphs and incorporates topic knowledge. The method first uses a heterogeneous graph containing sentences and entity nodes to characterize Chinese and Vietnamese bilingual news texts and effectively models the complex association relationships between multi-lingual multi-texts through GAT. Then the topic words are encoded into clues for topic representation generation by a topic encoder, which is incorporated into the decoder-side constraint to generate the correct topic representation. The experimental results show that the proposed approach of the text is effective.

2 Methodology

The model is illustrated in Figure 2. Here, we denote the number of words in the source language and the target language by V_s and V_t , respectively. Given multiple documents in different languages $D = (d_1, d_2, ..., d_n)$, d_i represents a sentence. First, we extract the subject word $T = \{t_1, t_2, ..., t_3\}$ from D, and t_i represents each subject word ($T \subseteq V_s$). Then, entity $E = (e_1, e_2, ..., e_n)$ and sentence $S = (s_1, s_2, ..., s_n)$ are extracted from D, e_i and s_i represent each entity and each sentence, respectively. Construct a heterogeneous graph $G = (V, E)$ with the obtained entities and sentences, where V is composed of e_i and s_i.Input the obtained T into the topic encoder and the obtained G into the graph encoder.Finally, the topic $S = \{w_1, w_2, ..., w_n\}$ is generated by the decoder,represents each topic word ($S \subseteq V_t$).

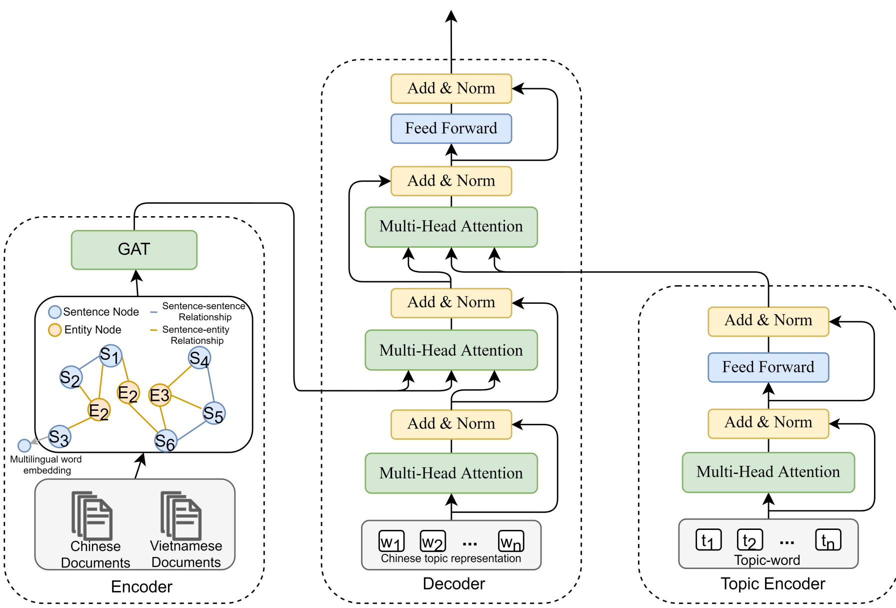

Fig. 2. Topic representation model of Chinese and Vietnamese news based on heterogeneous graph

2.1 Encoder

Construction of Graph This section describes how to build heterogeneous diagrams based on paragraphs and entities. Given a source document cluster D, we first divide it into smaller semantic units sentences S and entities E. Then construct the heterogeneous graph $G = (V, E)$, where V includes the sentence node V_{s} and the entity cluster node V_e. E represents an undirected edge between nodes. There is no undirected edge between the entity node and the entity node. However, there is an undirected edge between the entity and the paragraph and between the paragraph. We linked paragraphs and entities in different languages through the bilingual dictionary built by previous work. The sentence contains the entity if there is an edge between s_i and e_i. The weight of the edge is the number of times the sentence contains the entity. If there is an edge between s_i and s_i, there is a common entity between the two edges, and the weight of the edge is the number of entity repetitions. We delete vertices with a weight of 0 to reduce the impact of noise or useless sentences.

Graph Encoder Vertex embedding: as described above, the vertex is represented by the entity $E = \{e_1, e_2, ..., e_n\}$ and by the word sequence $S = \{\omega_1, \omega_2, ..., \omega_n\}$ make up sentences.In order to capture the position information of each word in an entity and a sentence, a position encoder needs to be used to obtain the position code. The final embedded representation of a sentence node is the sum of the word vector and the position of each word in the sentence. The embedded representation of an entity node is similar to that of a sentence node. Then the embedding of sentence and entity nodes is encoded to obtain the hidden states $\widetilde{h}_s$ and $\widetilde{h}_e$, respectively. The calculation method is as follows:

$$\widetilde{h}_s = SelfAttention\left(\|_{t=1}^{t}\left(\omega_i + PE\left(\omega_i\right)\right)\right) \tag{1}$$

$$\widetilde{h}_e = SelfAttention\left(s_i + PE\left(s_i\right)\right) \tag{2}$$

Graph embedding: After obtaining the hidden state representation of each node, use the Graph Attention Network to update the node representation. The design of the GAT layer is as follows:

$$z_{ij} = LeakyReLU\left(W_a\left[W_q h; W_k h_j\right]\right) \tag{3}$$

$$\widetilde{z}_{ij} = \widetilde{e}_{ij} \times z_{ij} \tag{4}$$

$$\alpha_{ij} = \frac{exp\left(\widetilde{z}_{ij}\right)}{\sum_{l \in N_i} exp\left(\widetilde{z}_{il}\right)} \tag{5}$$

$$\widetilde{u}_i = \sigma\left(\sum_{j \in N_i} \alpha_{ij} W_v h_j\right) \tag{6}$$

W_a, W_q, W_k, W_v denote the trainable weight matrix, σ represents sigmoid activation function, $\widetilde{e}_{ij}$ represents the weight of the edge. Following Wang et al.[20] iteratively update the node representation by discretizing real values into integers to follow the weights of the updated scalar edges $\widetilde{e}_{ij}$ and then learn the embedding of these integers. The weights are mapped to the multidimensional embedding space $\widetilde{e}_{ij} \in R^{de}$. Thus, the information contained in the value needs to be learned through a different embedding matrix.

Combining the GAT with a multi-headed attention mechanism, plus a residual connection to avoid gradient disappearance after multiple iterations:

$$\widetilde{h}_i = \widetilde{h}_i + \widetilde{u}_i \tag{7}$$

The node representation is then iteratively updated using the GAT layer above and the position feedforward layer. Each iteration contains a sentence-to-sentence and a sentence-to-entity update procedure. After t iterations, $\widetilde{H}_p$ is connected to each corresponding input representation vector to obtain the output $\widetilde{H}_{pw}$ of the graph encoder.

Topic Encoder Although the graphical encoder already captures the global article structure and sentence semantics, some important information is still omitted because vertices cannot represent different word meanings in a sentence. Therefore, we use Transformer's encoder as a topic encoder to capture the key topics in sentences. The Chinese and Vietnamese bilingual topics obtained from the above study are input to the pre-trained language model and mapped to the same semantic space, and then these key topics are stitched together as the input to the topic encoder. After encoding these topics, the resulting hidden vectors are fed into a multi-headed attention layer as q, k, and v:

$$MultiHead(Q, K, V) = [head_i; ...; head_h]W^O \tag{8}$$

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{9}$$

$$Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) = softmax\left(\frac{\left(QW_i^Q\right)\left(KW_i^K\right)^T}{\sqrt{d_k}}\right)\left(VW_i^V\right) \tag{10}$$

$$Q{=}K = V = \|_{i=1}^{n}\left(c_i\right) \tag{11}$$

Where W^O, W_i^Q, W_i^K, and W_i^V are learnable matrices, $\sqrt{d_k}$ is the dimension of the key value, and h is the number of heads.The results of multi-head attention are passed through the last layers of the topic encoder shown in Figure 2 to obtain the output z_i^C of the topic encoder.

2.2 Decoder

This decoder has the same structure as the topic encoder in the previous section, except that two additional multi-head attention layers are added to perform multi-head attention on the outputs of the graph encoder and the cue encoder.

Considering that some of the words in the generated topics are directly translated from the topic words, we use the Naive strategy proposed by Zhu et al. [21] to obtain the translation probabilities P_{trans} to decide which words are directly translated. The translation probabilities $P_{trans} \in [0, 1]$ are computed from the decoder hidden state H_{dec} through dynamic gates as follows:

$$P_{trans} = \sigma\left(W_2\left(W_1 H_{dec} + b_1\right) + b_2\right) \tag{12}$$

Where b_1 and b_2 are learnable offset vectors and W_1 and W_2 are learnable parameter matrices, σ Is the sigmoid activation function.

3 Experimental Results and Analysis

3.1 Evaluation Metric

This chapter conducts an experimental evaluation and comparative analysis of the Chinese-Vietnamese bilingual news topic representation model based on heterogeneous graphs. It mainly includes the selection and calculation of evaluation indicators and the experimental analysis of different parameter models. By reviewing domestic and foreign topic generation-related literature, we basically refer to the evaluation criteria of text abstract extraction for topic generation tasks, that is, the ROUGE (Recall-Oriented Understudy for Gistin Evaluation) [22] evaluation index is used. ROUGE is an automatic extraction task for evaluating text abstracts. And a set of indicators for machine translation tasks, mainly by comparing the text generated by the model with the standard text to compare the similarity of the two texts. The mathematical formula for ROUGE is as follows:

$$ROUGE - N = \frac{\sum_{s \in \{RefSum\}} \sum_{n-gram \in s} count_{match}\left(n - gram\right)}{\sum_{s \in \{RefSum\}} \sum_{n-gram \in s} count\left(n - gram\right)} \tag{13}$$

In the formula, n represents the length of $N - Gram$, and $Count_{match}(n - gram)$ is the number of $N - Gram$ contained in the generated topic representation and the labeled topic representation together. By using the ROUGE formula, we can find that the scoring system is mainly related to the recall rate of topics. In this thesis, the accuracy of the automated topic model is evaluated by considering the similarity from ROUGE-1, ROUGE-2, and ROUGE-3.

3.2 Datasets

In this paper, ten topics of Chinese and Vietnamese news, such as "epidemic prevention and control", "nuclear pollution", "China's anti-corruption" and "Civil Code" were crawled through the web crawler technology as the data set of the Chinese and Vietnamese news topic discovery experiment. Among them, 7664 news texts were crawled from Chinese news websites, and 3116 news texts were crawled from Vietnamese news websites. The specific distribution is shown in

Table 1. In order to verify the effectiveness of our method, this paper will use the Google translation engine to translate the Vietnamese extracted into Chinese. The texts with high translation errors are filtered by manual screening based on the translation.

Table 1. Chinese Vietnamese cross language news topic representation task dataset

News Topic	Chinese News Articles	Vietnamese News Articles
Epidemic prevention and control	1093	529
Nuclear pollution	532	143
Civil code	1097	283
The Belt and Road Initiative	972	498
Racial problem	482	277
War on terror	587	239
Anti corruption in China	865	244
Food Safety	753	368
2020 US general election	544	367
Explosion in Lebanese capital	423	168

3.3 Baseline Model

The topic representation task in this chapter is a generative method. To verify the effectiveness of this method, the following models are set in the same data set for comparison:

(1) STM-seq2seq[23]: The method first constructs a bilingual feature space with the help of a Chinese-Vietnamese bilingual dictionary and uses LSTM neural networks in both the encoder and decoder. A vector representation based on time series is obtained at the encoder side, and the sequence is extracted from the vector at the decoder side. It is often used as a baseline method in text generation tasks.

(2) NCLS[24]: The approach proposes to improve the end-to-end model (NCLS) for achieving cross-language summarization using the transform model, which is enhanced by jointly training the tasks MT and MS. Cross-language summarization is achieved by aligning different languages under the semantic space through an attention mechanism.

(3) hLDA[25]: The method extracts features from hLDA modeling for sentence scoring and selects sentences with high scoring results to generate summaries. First, the documents are modeled using the hLDA algorithm, and from the hLDA modeling results, a new feature is proposed that can reflect the semantic information to some extent. Then, this new feature is combined with other different features for sentence scoring. Based on the results of sentence scoring,

candidate summary sentences are extracted from the documents to generate summaries.

(4) MT-GAT: This method first translates the Vietnamese text into Chinese through the Google translation tool and then uses the method of this paper to construct a heterogeneous map for calculation.

3.4 Comparative Experimental Analysis

In this study, the heterogeneous graph-based bilingual Chinese and Vietnamese news topic representation model is compared with the four models introduced in the previous section on a self-constructed dataset, and the results are shown in Table 2.

Table 2. Topic representation comparison experiment

Way	**ROUGE-1**	**ROUGE-2**	**ROUGE-3**
LSTM-Seq2seq	23.4	16.6	11.3
NCLS	25.6	17.5	13.4
hLDA	26.2	19.8	15.8
MT-GAT	24.5	17.6	12.6
ours	**29.7**	**21.8**	**17.6**

The experimental results in Table 2 show that the heterogeneous map-based topic representation model for Chinese-Vietnamese bilingual news outperforms the other four methods in all three indexes, which indicates that the method in this paper can effectively generate the correct topic representation. Among them, the ROUGE value of this paper is improved by 3.5 on average compared with the traditional hLDA model, which indicates that it is difficult for the Chinese-Vietnamese bilingual dictionary to map two languages into the same semantic space under the low-resource scenario. the performance of the MT-GAT method is weaker, and it can be seen that the accuracy of machine translation has a more significant impact on the model.

3.5 Ablation Experiment

The topic representation model of Chinese Vietnamese Bilingual News Based on a heterogeneous graph generates concise sentences that can describe the topic correctly from the Chinese Vietnamese bilingual news texts that describe the same topic. In this method, the association between texts is modeled by heterogeneous graphs, encode topic words into clues generated by topic representation through topic encoder, and integrate into decoder-side constraints to generate the correct topic representation. Three ablation experiments were designed to verify the effectiveness of the heterogeneous graph and topic word coder in the topic generation task. Wherein Transformer means to change the heterogeneous graph coding into Transformer coding at the encoder stage; GCN indicates that the heterogeneous graph in the encoder stage is replaced by a graph convolutional network; W/OTE indicates that it is not integrated into the theme encoder. The experimental results are shown in Table 3.

Table 3. Ablation experiment results

Way	ROUGE-1	ROUGE-2	ROUGE-3
Transformer	22.3	16.4	11.5
GCN	26.6	18.6	15.3
W/OTE	24.7	16.0	12.7
ours	**29.7**	**21.8**	**17.6**

Table 3 shows that both the construction of the heterogram and the incorporation of the topic encoder have an impact on the model performance in the Chinese-Vietnamese bilingual news topic representation model proposed in this chapter. The reason is that the heterogram can effectively model the complex association relationship between multiple languages and multiple texts, while the topic encoder plays a certain constraining role in the model.The experimental results showed that the three ROUGE values decreased by an average of 5.25, 4.3, and 4.2 after replacing the heterogeneous map. In contrast, the ROUGE values of the model effect decreased by 5, 5.8 and 4.9 after not incorporating the topic encoder. It can be seen that the effect of both on the model is close, with the topic encoder having a slightly more significant effect on the model.

3.6 Case Analysis

Table 4 shows the samples generated by the Chinese-Vietnamese bilingual news topic representation model based on heterogeneous graphs. The topic number is only used as serial number identification, with no special meaning, and the sample generation process is shown in Figure 1. From this, we can see that the model can basically generate concise and concise topic representations for news texts describing the same topic. However, there are still some inaccurate descriptions; for example, topic two should be "food safety", but the generated example is "genetically modified food causing controversy", which is easily misunderstood. This is due in large part to the small size of the dataset used to train the model in this paper, which leads to weak model generalization.

4 Conclusions and Future Work

This paper first introduces the background and significance of bilingual Chinese and Vietnamese news topic representation research and briefly describes the

Table 4. Examples of generation results of Chinese Vietnamese Bilingual News Topic

Topic Number	**Generate Topic Representation**
0	Explosion in Lebanese capital
1	The US election was a complete success
2	Controversy over genetically modified food
3	Anti corruption in China
4	War on terror
5	Alleviation of racial problems in the United States
6	Implement the Belt and Road
7	Promulgation of civil code
8	Nuclear waste water discharge in Japan
9	Epidemic prevention and control in various places

task of topic representation under multilingual and multi-text. Then, we propose a heterogeneous graph-based bilingual Chinese and Vietnamese news topic representation model to generate concise and concise topic representations for multilingual and multi-text under the same topic and introduce the principles and framework of the model in detail. Comparative experiments are conducted with existing methods on a self-built news topic dataset, and the experiments show that the method in this paper outperforms the comparative model, and the results of topic generation are demonstrated.

For the problems in this paper, including the experiments are limited by the size of the dataset, resulting in a weak generalization of the model. And the constructed dataset is limited by the quality of the translation model, which is not accurate enough in the translation process, and the possibility of reducing the complexity of the model has not been carefully studied. The next work will consider incorporating multilingual external knowledge to solve the low resource problem.

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