Coreference Graph Guidance for Mind-Map Generation

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Abstract

Mind-map generation aims to process a document into a hierarchical structure to show its central idea and branches. Such a manner is more conducive to understanding the logic and semantics of the document than plain text. Recently, a state-of-the-art method encodes the sentences of a document sequentially and converts them to a relation graph via sequence-to-graph. Though this method is efficient to generate mind-maps in parallel, its mechanism focuses more on sequential features while hardly capturing structural information. Moreover, it's difficult to model long-range semantic relations. In this work, we propose a coreference-guided mind-map generation network (CMGN) to incorporate external structure knowledge. Specifically, we construct a coreference graph based on the coreference semantic relationship to introduce the graph structure information. Then we employ a coreference graph encoder to mine the potential governing relations between sentences. In order to exclude noise and better utilize the information of the coreference graph, we adopt a graph enhancement module in a contrastive learning manner. Experimental results demonstrate that our model outperforms all the existing methods. The case study further proves that our model can more accurately and concisely reveal the structure and semantics of a document. Code and data are available at https://github.com/Cyno2232/CMGN.

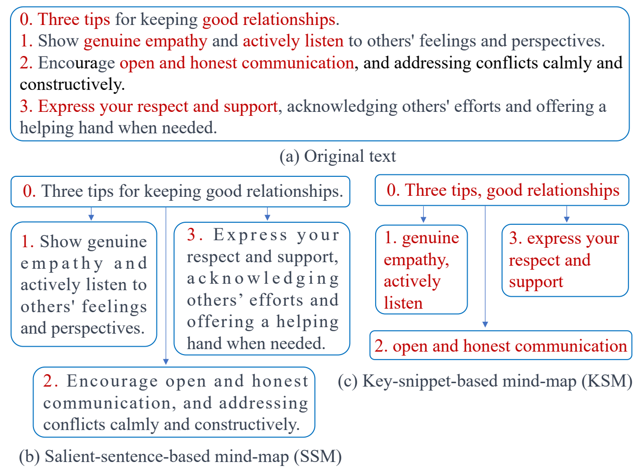

Figure 1: A document (a) and two forms of mind-map derived from the document, namely salient-sentence-based mind-map (SSM) and key-snippet-based mind-map (KSM), constructed by sentences (b) or keywords (c).

Introduction

A mind-map generally consists of a series of hierarchical nodes, including central nodes and branches, which are conceptually connected and visually linked with lines (Kudelić, Konecki, and Maleković 2011; Wei et al. 2019; Hu et al. 2021). Mind-map is designed to describe core concepts and to guide the text through a cognitive structure, which makes it easier to understand than reading the original text directly (Dhindsa and Roger Anderson 2011). Figure 1 provides an example of a mind-map. As depicted, a node represents the idea of a single sentence, and an edge represents the governing relationships between sentences. There are generally two kinds of mind-map, namely salient-sentence-based mind-map (SSM) and key-snippet-based mind-map (KSM). The difference between them is that the nodes of SSM are constructed using whole sentences, while the nodes of KSM are constructed using keywords (Dhindsa and Roger Anderson 2011).

Many softwares have been invented to assist *manual mind-map construction*, such as FreeMind, MindMapper, Visual Mind, etc (Kudelić, Konecki, and Maleković 2011). Afterward, various approaches have been proposed to *automatically generate mind-maps* from input texts. Some aim to identify the semantic relationship within one single sentence by using pre-established rules (Brucks and Schommer 2008; Rothenberger et al. 2008) or syntactic parser (Elhoseiny and Elgammal 2012). Recent works (Wei et al. 2019; Hu et al. 2021) generate mind-maps by detecting the semantic relations between different sentences in a document.

Concretely, the generation process is divided into two phases, as shown in Figure 2. Assume a document has N sentences, the first phase aims to build a graph $\mathbf{G}$ for all pairs of sentences. Each element in $\mathbf{G}$ indicates the governing relationship between two sentences. Then, since the graph is redundant, the second phase prunes the extra edges to obtain the mind-map. Yet the number of sentence pairs increases exponentially with the length of the document, which raises

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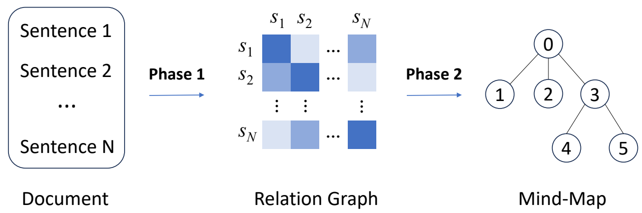


Figure 2: Two-phases mind-map generation process. Phase 1 builds a relation graph for a given document. Phase 2 discards extra edges to yield the final mind-map.

the computational complexity. Recently, Hu et al. (2021) propose to improve the efficiency of the first phase by encoding sentences sequentially and feeding them into a sequence-to-graph module to obtain the relation graph. Although sequential encoding can raise efficiency, its perception of graph structure is limited. Additionally, as document length increases, it becomes more difficult for sequential encoders to capture semantic relationships over long distances.

To address the above issues, we propose a coreference-guided mind-map generation network (CMGN). Specifically, a coreference graph is first constructed to explicitly introduce prior graph structure information. The coreference graph contains the coreference semantic relationships, which imply the governing relation of the sentence at various positions in the document. Based on this graph, we employ a coreference graph encoder based on graph convolutional network (GCN) to further mine the potential semantic relationships between sentences, especially for long-distance sentence pairs.

However, the semantic relations in coreference graphs are not always reliable. For instance, some coreference entities are unrelated to the subject of the document. To address the issue, we introduce the graph enhancement module, which is based on graph contrastive learning (GCL). Concretely, we utilize dual graph neural network (GNN) encoders with the same architecture, one of which is obtained by applying perturbations to all the parameters of the other. Then, we take original graph data as input and dual GNN encoders as counterparts to obtain two correlated views. With the encoder perturbation as noise, we can obtain two different embeddings for the same input as positive pairs, and take other graph data as negative pairs. We maximize the agreement of the positive pairs.

In summary, the main contributions of this paper are as follows.

- We propose a novel mind-map generation method that constructs the coreference graph to involve graph structure information. Then we employ a graph encoder to capture long-range semantic relations.
- Since the information of the coreference graph is not always reliable, we employ a graph enhancement module to sufficiently utilize the information of the coreference graph.
- Extensive experimental results demonstrate that the proposed method outperforms the state-of-the-art method. Further analysis proves that the proposed method can generate more meaningful and concise mind-maps while maintaining efficiency.

Related Works

A mind-map is a diagram with a hierarchical structure, which can disclose the logical structure of a document (Buzan and Buzan 2006). Of the two kinds of mind-map, SSM is similar to extractive text summarization (Zhong et al. 2020), which involves selecting and combining essential sentences or phrases from a given document to create a concise summary. Mind-map, by contrast, aims at not only the general idea of a document but also the relation of succession between paragraphs.

There are a number of works that use sentence-based graphs to generate text summarization. A previous study LexRank (Erkan and Radev 2004) employs a graph-based approach to compute an adjacency matrix for sentence representation. This method relies on intra-sentence cosine similarity. However, generating a meaningful mind-map from this graph representation becomes challenging, as specific sentence pairs with semantic relations may possess zero lexical similarity. Additionally, several extractive summarization studies have utilized graph techniques. For instance, to enhance the ranking of sentences within a document, several methods have been proposed, including the utilization of bipartite graphs for sentence and entity nodes (Parveen and Strube 2015), and weighted graphs featuring topic nodes (Parveen, Ramsl, and Strube 2015). Recently, Wang et al. (2020) utilize a heterogeneous graph for the purpose of capturing the relations between words and sentences. Liu, Hughes, and Yang (2021) construct sentence graphs based on both the similarities and relative distances in the neighborhood of each sentence. However, these attempts of involving graph knowledge can hardly acquire governing relations between sentences, and thus can not reveal the logical structure of a document.

Graph contrastive learning (GCL) is a self-supervised learning algorithm for graph data. It learns to capture meaningful patterns and relationships within the graph by encouraging similar nodes or edges to be close in the embedding space while pushing dissimilar ones apart. Sun et al. (2022) construct heterogeneous graphs from texts and expand the heterogeneous graph neural network model (HGAT) with simple neighbor contrastive learning. The negative samples are created by corrupting the edges of the graphs. Hu et al. (2022) build the graph through the entities and dependency tree of the given document. The negative samples are constructed by masking keywords, while the positive samples are constructed by masking non-keywords. Xu et al. (2021) propose to construct a graph on top of the document passages to utilize multi-granularity information. Then they design a contrastive learning strategy where agreement among sub-document representations from the same document are maximized. In the case of the above work, their negative samples were obtained by modifying the text or graph structure. Different from them, we directly perturb the parameters of the encoder and generate the negative samples from the perturbed encoder.

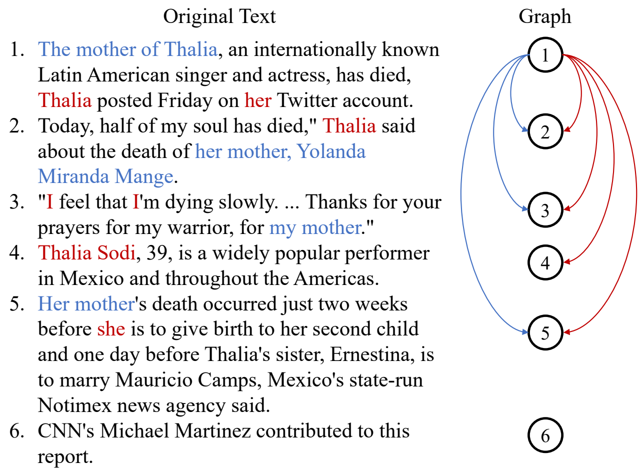


Figure 3: Illustration of coreference graph construction, with the mentions of *"Thalia"* and *"Thalia's mother"* highlighted as examples.

Methodology

Problem Definition

We define that a document D consists of the sentences $\{s_1, s_2, ..., s_N\}$, and a sentence s_i consists of the words $\{w_i^1, w_i^2, ..., w_i^L\}$, where N and L are the number of the sentences and the words respectively. The mind-map generation task can be defined as:

$$D \rightarrow \mathbf{G} \rightarrow M \tag{1}$$

where the input document D is firstly converted to a relation graph $\mathbf{G}$. Then the final mind-map M is generated by removing unrelated nodes and edges.

Our work focuses on the former phase $D \rightarrow \mathbf{G}$. In the following sections, we construct the coreference graph to model the long-range relationships in a document. Then, based on the coreference graph, we employ a coreference graph encoder and a graph enhancement module to extract better representations, which can help optimize the relation graph. For the latter phase $\mathbf{G} \rightarrow M$, two types of mind-maps are generated from the graph $\mathbf{G}$ by pruning the extra edges. The strategy works recursively to determine the governing relationship of sentences. Please refer to Hu et al. (2021) for details of phase 2.

Coreference Graph

Hu et al. (2021) propose a sequence-to-graph method to generate graphs from sequentially encoded sentences. Although this approach contributes to preserving the sequential semantic information within articles, it shows a restricted capability to perceive the structural information. In addition, the model is less effective in modeling long-range semantic relationships. In order to address these two issues, we employ the coreference graph (Xu et al. 2020) to model the documents. This approach introduces explicit graph structures to incorporate additional structural information and improves the perception of long-distance semantic relations.

Algorithm 1: Coreference Graph Generation

Input: Coreference clusters $\mathcal{C} = \{c_i\}_{i=1}^{|\mathcal{C}|}$
Initial coreference graph $\mathcal{G} \leftarrow \mathbf{0}$
for $i = 1$ to $|\mathcal{C}|$ **do**
  Match each mention $\{M_1^i, M_2^i, ..., M_m^i\} \in c_i$ to its origin sentences and obtain the index set $\mathcal{I}$.
  for $j = 2$ to $|\mathcal{I}|$ **do**
    Create an edge $\mathcal{G}_{\mathcal{I}[1],\mathcal{I}[j]} = 1$
  end for
end for
return the final coreference graph $\mathcal{G}$

Algorithm 1 describes the construction process of the coreference graph. In this work, we treat a sentence as the minimal unit. We first use Allennlp (Lee, He, and Zettlemoyer 2018) to find all mentions that refer to the same entity in a document and obtain the coreference clusters $\mathcal{C} = \{c_i\}_{i=1}^{|\mathcal{C}|}$. Each cluster c_i contains a number of mentions $\{M_1^i, M_2^i, ..., M_m^i\} \in c_i$. Next, for each cluster $c_i \in \mathcal{C}$, we match the mentions to the sentences sequentially in which they are located. Then, for each cluster, we select the sentence containing the first occurring mention as the root node and create an edge from the root node to the other sentence where the mention is located. The edges indicate the potential governing relation. Following this process of iterating through all the clusters can complete the construction of the final coreference graph.

Figure 3 provides an example, where *"Thalia"* and *"Thalia's mother"* are two entities to which various mentions refer. Edges are constructed from the first sentence node to the others. Note that the final graph does not contain duplicate edges.

Coreference-Guided Relation Graph Generation

Document Encoder In order to obtain the representations for each node, we firstly map the given sentence s_i into an embedding sequence $\{\boldsymbol{e_i^1}, \boldsymbol{e_i^2}, ..., \boldsymbol{e_i^L}\}$ through a pre-trained embedding matrix GloVE (Pennington, Socher, and Manning 2014). Then we exploit a Bi-directional LSTM (BiLSTM) (Graves, Mohamed, and Hinton 2013) to encode the embedding sequence into the hidden states $\{\boldsymbol{h_i^1}, \boldsymbol{h_i^2}, ..., \boldsymbol{h_i^L}\}$. The vector representation for each sentence is computed by a max-pooling operation over the hidden states.

$$\boldsymbol{s_k} = \max(\boldsymbol{h_i^1}, ..., \boldsymbol{h_i^L}) \tag{2}$$

Additionally, to model the sentence-level context, we encode the vector representations of all sentences $\{\boldsymbol{s_i}\}_{i=1}^N$ with another BiLSTM. We take the output $\mathbf{H} = \{\boldsymbol{h_1}, \boldsymbol{h_2}, ..., \boldsymbol{h_N}\}$ as the final representations.

Coreference Graph Encoder In the coreference graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, nodes $\mathcal{V}$ represent all sentences from the document and edges $\mathcal{E}$ represent the coreferential relationships between sentences. We utilize a GCN encoder to update the representations of all sentences (Xu et al. 2020). Figure 4 depicts the architecture design of the GCN network, which contains multiple layers of the same structure.

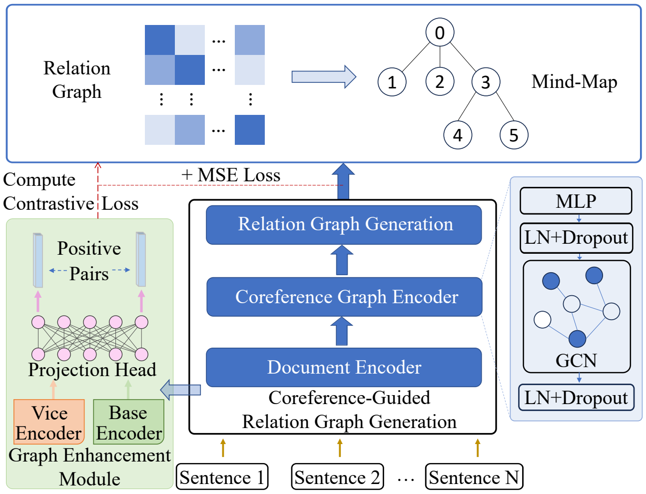


Figure 4: The network architecture of the proposed approach, where the document D is processed to obtain the relation graph, with the assistance of graph enhancement.

First, we define $\mathbf{H}^{(k)} = \{\boldsymbol{h}_1^{(k)}, ..., \boldsymbol{h}_N^{(k)}\}$ as the input of the k-th layer in the model, which is also the output of the former layer (except the first layer). $\mathbf{H}^{(1)} = \mathbf{H}$, which is the output from the document encoder. The k-th layer is designed as follows:

$$\boldsymbol{u}_i^{(k)} = \mathbf{W}_2^{(k)}\mathrm{ReLU}(\mathbf{W}_1^{(k)}\boldsymbol{h}_i^{(k)} + \boldsymbol{b}_1^{(k)}) + \boldsymbol{b}_2^{(k)} \quad (3)$$

$$\boldsymbol{v}_i^{(k)} = \mathrm{LN}(\boldsymbol{h}_i^{(k)} + \mathrm{Dropout}(\boldsymbol{u}_i^{(k)})) \quad (4)$$

$$\boldsymbol{w}_i^{(k)} = \mathrm{ReLU}(\sum_{j\in N_i} \frac{1}{|N_i|}\mathbf{W}_3^{(k)}\boldsymbol{v}_i^{(k)} + \boldsymbol{b}_3^{(k)}) \quad (5)$$

$$\boldsymbol{h}_i^{(k+1)} = \mathrm{LN}(\mathrm{Dropout}(\boldsymbol{w}_i^{(k)}) + \boldsymbol{v}_i^{(k)}) \quad (6)$$

where $\mathrm{LN}(\cdot)$ is layer normalization, N_i is the neighbourhood of the i-th node, and $\boldsymbol{h}_i^{(k+1)}$ is the output of the i-th node in the k-th layer.

After multi-layer message propagation, we obtain the output of the last layer $\mathbf{R} = \{\boldsymbol{r}_1, \boldsymbol{r}_2, ..., \boldsymbol{r}_N\}$ as the final representation of all the sentences in the document.

Relation Graph Generation We employ sequence-to-graph (Dozat and Manning 2016; Zhang et al. 2019)to process the final representations into a relation graph. Concretely, we first compute the representations of all sentences when they are regarded as the start or end nodes in the edges separately. Then we calculate the governing scores with a bilinear operation. The process can be described as follows:

$$\boldsymbol{r}_i^{start} = \mathrm{MLP}_1(\boldsymbol{r}_i) \quad (7)$$

$$\boldsymbol{r}_j^{end} = \mathrm{MLP}_2(\boldsymbol{r}_j) \quad (8)$$

$$\mathbf{G}_{i,j} = \sigma(\boldsymbol{r}_i^{start}\mathbf{W}_4\boldsymbol{r}_j^{end} + \boldsymbol{b}_4) \quad (9)$$

where MLP_1 and MLP_2 are two linear transformations, $\mathbf{W}_4$ is the parameter matrix, and $\boldsymbol{b}_4$ is the bias. σ is the sigmoid operation, guaranteeing that each governing score is between 0 and 1. By calculating the scores for all pairs of sentences, we get the relation graph $\mathbf{G}$.

Graph Enhancement Module

The graph structure information introduced in the previous section is not always reliable. Following Xia et al. (2022), we employ a graph enhancement module based on GCL to address this issue, which consists of the following three major components.

Encoder Perturbation We first define a GNN encoder $f(\cdot;\boldsymbol{\theta})$ as the base encoder, and its perturbed version $f(\cdot;\boldsymbol{\theta'})$ as the vice encoder for contrasting. The method to perturb the encoder $f(\cdot;\boldsymbol{\theta})$ can be described mathematically as:

$$\boldsymbol{\theta}_l' = \boldsymbol{\theta}_l + \eta \cdot \boldsymbol{\Delta\theta}_l \quad (10)$$

$$\boldsymbol{\Delta\theta}_l \sim \mathcal{N}(0, \sigma_l^2) \quad (11)$$

where $\boldsymbol{\theta}_l$ and $\boldsymbol{\theta}_l'$ are the weight tensors of the l-th layer of the GNN encoder and its perturbed version respectively. η is the hyperparameter used to regulate the perturbation. $\boldsymbol{\Delta\theta}_l$ is the perturbation term which samples from Gaussian distribution with zero mean and variance σ_l^2.

Then, we use the same coreference graph $\mathcal{G}$ and the output of document encoder $\mathbf{H} = \{\boldsymbol{h}_1, \boldsymbol{h}_2, ..., \boldsymbol{h}_N\}$ as the input of both GNN encoders, and obtain extracted representation:

$$\boldsymbol{h} = f(\mathcal{G};\boldsymbol{\theta}) \quad (12)$$

$$\boldsymbol{h'} = f(\mathcal{G};\boldsymbol{\theta'}) \quad (13)$$

Projection Head A projection head is a non-linear transformation that can map representations to another linear space. This is beneficial in defining contrastive loss (Chen et al. 2020). We employ a two-layer MLP to obtain:

$$\boldsymbol{z} = g(\boldsymbol{h}) = \mathbf{W}_6\mathrm{ReLU}(\mathbf{W}_5\boldsymbol{h}) \quad (14)$$

$$\boldsymbol{z'} = g(\boldsymbol{h'}) = \mathbf{W}_6\mathrm{ReLU}(\mathbf{W}_5\boldsymbol{h'}) \quad (15)$$

Contrastive Loss Following previous works (Oord, Li, and Vinyals 2018; Sohn 2016; Wu et al. 2018; You et al. 2020; Xia et al. 2022), we use the normalized temperature-scaled cross-entropy loss (NT-Xent) as loss function, which benefits agreement between positive pairs. Concretely, we randomly sample a minibatch of N examples and then feed them to the base encoder $f(\cdot;\boldsymbol{\theta})$ and its perturbed version $f(\cdot;\boldsymbol{\theta'})$. We can obtain a total of $2N$ examples as output. We select negative examples from the other $N-1$ perturbed representations for each positive pair. Finally, for the i-th representation, the contrastive loss is defined as:

$$l_i = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_i')/\tau)}{\sum_{i'=1, i'\neq i}^{N} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_{i'}')/\tau)} \quad (16)$$

where $\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_i') = \boldsymbol{z}^\top\boldsymbol{z'}/\|\boldsymbol{z}\|\|\boldsymbol{z'}\|$ is the cosine similarity function, and τ is the temperature parameter. The final loss is computed across all positive pairs:

$$\mathcal{L}_c = \sum_{i=1}^{N} l_i \quad (17)$$

Models		SSM				KSM			
		R-1	R-2	R-L	Avg	R-1	R-2	R-L	Avg
Baseline Methods	Random	32.71	23.51	30.08	28.77	29.73	26.50	29.67	28.63
	LexRank	34.53	25.04	31.79	30.45	31.04	27.75	31.00	29.93
	MRDMF	38.19	29.51	35.72	34.47	33.18	30.26	33.08	32.18
	DistilBERT	42.15	33.34	39.66	38.38	40.00	36.92	39.92	38.95
	EMGN	46.14	38.21	43.84	42.73	43.33	40.67	43.28	42.43
Model Variants	w/o CGE	26.44	15.51	23.26	21.74	26.11	21.63	26.05	24.60
	w/o GEM	45.88	37.60	43.44	42.31	43.03	40.07	43.10	42.08
	w/o CGE&GEM	44.99	37.02	42.71	41.57	42.56	39.58	42.50	41.55
Full Model	CMGN	**47.73**	**39.75**	**45.33**	**44.27**	**44.65**	**41.77**	**44.59**	**43.67**

Table 1: Evaluation results of SSM and KSM in terms of R-1 (%), R-2 (%), R-L (%) and the average score (%). Model variants are further described in the ablation study section.

Training Objective

In the coreference graph encoder module, our training goal is to fit the relation graph **G** to the pseudo graph annotated by DistilBERT (Sanh et al. 2019). The DistilBERT model is fine-tuned to automatically annotate a large number of relation labels rapidly[1]. The graph encoder module fits the pseudo graph **Y** by a mean square error (MSE) loss.

$$\mathcal{L}_g = \frac{1}{N^2}\sum_i\sum_j(\mathbf{G}_{i,j} - \mathbf{Y}_{i,j})^2 \tag{18}$$

Then we combine the final loss $\mathcal{L}_c$ and the training loss of coreference graph encoder $\mathcal{L}_g$ as an overall training objective to optimize the parameters θ.

$$\mathcal{L} = \mathcal{L}_g + \lambda\mathcal{L}_c \tag{19}$$

where λ is the hyperparameter adjusting the influence of the graph enhancement module.

Experiments

Dataset

We use a human-annotated evaluation benchmark with 135 articles[2], 98,181 words, which are selected from CNN news articles (Hermann et al. 2015; Cheng and Lapata 2016) randomly. The benchmark consists of a testing set $\mathcal{D}_t$ and a validation set $\mathcal{D}_v$, with 120 and 15 articles respectively. We select 5000 articles from CNN news, where both the length and the number of sentences are no more than 50. We utilize the fine-tuned DistilBERT to annotate their pseudo graphs, which are then used for model training.

Implementation Details

Software and Hardware We compare all the models in the same software and hardware environments, as follows:

- System: Ubuntu 22.04.2; Python 3.7; PyTorch 1.12.1; DGL 1.0.2+cu116 (For the implementation of GNNs)
- CPU: Intel(R) Xeon(R) Gold 5218 CPU @ 2.30GHz
- GPU: NVIDIA Tesla V100S PCIe 32 GB

[1]For details on fine-tuning, please refer to Hu et al. (2021).

[2]https://github.com/hmt2014/MindMap

Hyperparameter Settings We initialize the word embeddings with 50-dimension GloVE. We initialize all other parameters by sampling from a normal distribution with $\mathcal{N}$(0, 0.02). The hidden size of BiLSTM is set to be 25×2. The models are optimized by Adam (Kingma and Ba 2015) with a learning rate of 1e-4. The batch size is 64. An early stop strategy is utilized during training if there is no performance improvement on the validation set $\mathcal{D}_v$ in 3 epochs, and the best model is saved for evaluating testing set $\mathcal{D}_t$. All the reported results are the average score of 5 runs.

For the coreference graph encoder, we employ a 2-layer model for training. For the graph enhancement module, we employ a 5-layer GIN (Xu et al. 2018) model as the base encoder. We set η to 0.2, which adjusts the magnitude of the perturbation of the base encoder, and λ to 0.001, which adjusts the impact of contrastive loss.

Compared Methods

Baselines Methods We validate our method by comparing its effectiveness with the following baseline methods.

- **Random**: We randomly sample a graph **G** for a document. Each governing score $\mathbf{G}_{i,j}$ ranges from zero to one.
- **LexRank**: It computes the governing score of sentence pair by the cosine similarity of their TFIDF vectors.
- **MRDMF** (Wei et al. 2019): It employs multi-hop self-attention and gated recurrence network to reveal the semantic relations via sentences, and then select the most salient sentences recursively to constitute the hierarchy.
- **DistilBERT** (Sanh et al. 2019): It's a lighter version of BERT (Devlin et al. 2019) which helps annotate the pseudo graphs for training.
- **EMGN** (Hu et al. 2021): This is the state-of-the-art mind-map generation work. It converts a document into a graph via sequence-to-graph and designs a graph refinement module based on reinforcement learning.

Model Variants The proposed method is further analyzed by changing individual components.

- **w/o CGE**: The coreference graph encoder (CGE) is removed from the whole model.

Models	0-shot	1-shot	2-shot	3-shot
ChatGPT	42.36	40.38	45.87	39.96
ChatGPT w/ CoT	43.97	-	-	-
LLaMA2-70B	33.12	32.10	35.62	-
ErnieBot-4.0	36.59	38.29	35.13	-
CMGN	**52.41**			

Table 2: Evaluation results of LLMs in terms of SSM.

Models	0-shot	1-shot	2-shot	3-shot
ChatGPT	42.25	41.20	45.84	41.32
ChatGPT w/ CoT	42.48	-	-	-
LLaMA2-70B	33.57	33.94	36.27	-
ErnieBot-4.0	36.28	37.83	36.95	-
CMGN	**51.26**			

Table 3: Evaluation results of LLMs in terms of KSM.

- **w/o GEM**: The graph enhancement module (GEM) is removed from the whole model.
- **w/o CGE&GEM**: Both graph encoder and graph enhancement module are removed from the whole model.

Experimental Results

Overall Results The overall results are displayed in Table 1. It can be observed that CMGN achieves the best performance in both types of mind-map consistently, outperforming the state-of-the-art model EMGN by +1.54% and +1.24% on average of SSM and KSM, respectively. This indicates the effectiveness of CMGN. Moreover, though CMGN utilizes pseudo graph labels, it outperforms DistilBERT significantly. This observation highlights the successful utilization of pseudo labels by the proposed method, resulting in further enhancements in performance.

Ablation Study To validate the impact of individual components, several model variants are designed and the results are presented in Table 1. Firstly, it can be seen that w/o CGE causes performance to drop drastically. A possible reason is that w/o CGE and solely using contrastive learning may lead to negative effects on the representations of the document encoder. In this situation, the document encoder can not learn sequential information like EMGN but receive inaccurate graph representations from GEM. Secondly, we observe that w/o GEM leads to consistent degradation. This validates that our method can successfully enhance the graph representations. Moreover, the results of w/o CGE&GEM further demonstrate the effectiveness of CMGN.

Compared with LLMs The large language model (LLM) has proven its impressive skills in different language tasks. Thus, we try to test its potential in mind-map generation. However, using LLMs to generate a mind-map directly resulted in unstable outcomes, making automatic evaluation challenging. Thus, we make LLMs to generate a relation

Models	SSM Avg		KSM Avg	
	$\leq$25	>25	$\leq$25	>25
Random	31.94	26.63	32.53	26.22
LexRank	33.54	28.07	33.99	27.28
MRDMF	39.83	30.58	36.76	28.69
DistilBERT	44.36	34.34	44.27	34.89
EMGN	50.23	37.38	49.48	37.44
CMGN	**52.41**	**38.46**	**51.26**	**38.20**

Table 4: Evaluation results by splitting the testing set with the sentence number in a document. Among all 120 files in $\mathcal{D}_t$, there are 50 files with $\leq$ 25 sentences, and 70 files $>$ 25.

Models	SSM Avg	KSM Avg
CMGN(BERT)	39.22	38.82
CMGN(DistilBERT)	38.12	38.92
CMGN(RoBERTa)	38.27	39.54
CMGN(Sentence-BERT)	39.09	39.53
CMGN	**43.71**	**43.20**

Table 5: Evaluation results by different encoders.

graph (phase 1), which is further fed into phase 2 as other approaches for evaluation. The prompts are shown below.

Prompt: *Given a document which contains N sentences, you have to build an N*N relation graph G for all pairs of sentences. Each element in G is the governing relationship score between two sentence. For instance, the element in [2, 1] indicates the intensity of sentence 2 governing sentence 1. Here are several notes: 1. Guarantee that each governing score is between 0 and 1. 2. Output the relation graph in the format of Python list. 3. Don't provide me the code. Generate the relation graph directly. Now I'm giving you the document. Are you ready?*

We select ChatGPT, LLaMA2-70B (Touvron et al. 2023), and ErnieBot-4.0 for testing. In addition, we apply few-shot settings and the Chain-of-Thought strategy (Wei et al. 2022). Due to the context length limitation, we only evaluate documents with $\leq$25 sentences. The results are shown in Table 2 and 3. It can be observed that CMGN significantly outperforms all LLMs. This shows that LLMs are universal AI systems, which might lack specialty in particular tasks. Even though, LLMs are still powerful since it outperforms supervised methods, such as LexRank and MRDMF.

Effects of the Document Length To analyze performance across varying document lengths, the testing set $\mathcal{D}_t$ is split into two parts based on document length. Table 4 displays the evaluation results. Our model outperforms all baselines, especially on the dataset with longer documents. Since it's a more challenging task to generate accurate mind-map for longer documents, the results indicate the effectiveness of

Models	$\mathcal{D}_t$	$\mathcal{D}_v$
LexRank	349.21	95.24
MRDMF	467.07	62.49
DistilBERT	1219.51	201.04
EMGN	10.27	1.42
CMGN	**4.09**	**1.24**

Table 6: Inference time for each method (second).

our model in modeling long-range semantic relationships.

Effects of Transformer-based Encoders We try employing more transformer-based pretrained models, including BERT (Devlin et al. 2019), DistilBERT (Sanh et al. 2019), RoBERTa (Liu et al. 2019) and Sentence-BERT (Reimers and Gurevych 2019) to derive a sentence embedding. The results are shown in Table 5. It show that these embeddings do not contribute to the performances. A possible reason is that the self-attention mechanism in transformer architecture may make word representations difficult to distinguish. On the contrary, GloVe is trained using word co-occurrence statistics, relying on the concept that words frequently appearing together share semantic relationships. This approach captures global, long-range word relationships, making it useful for tasks like mind-map generation that demand understanding both sentence and keyword semantics.

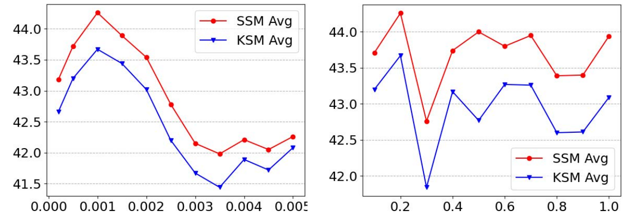
Further Analysis

Inference Time We compare the inference time of the validation set $\mathcal{D}_v$ and testing set $\mathcal{D}_t$ to verify the efficiency of our method. Table 6 demonstrates the time spent to convert a document to a relation graph (phase 1), while all the methods share the follow-up process (phase 2). The batch size of MRDMF is set to 256 sentence pairs, and the batch size of EMGN and CMGN-related methods is 32 documents. The result shows that our method is slightly more efficient than EMGN, while significantly reducing the computational complexity compared to other methods. This proves that our model improves performance without losing efficiency.

Hyperparameter Study In the graph enhancement module, η determines the extent of perturbation of the vice encoder, while λ balances the effect of the module. Figure 5 shows the performance curves of different η and λ values. We find a strong correlation between the performance of the model and λ, while it is not sensitive to variations in η.

Case Study Figure 6 depicts the mind-maps generated by different models, as well as the manually annotated mind-map[3]. Firstly, it can be observed that our model better demonstrates the governing relations of sentences 3-5 in general, which are the core of the document. In contrast, the mind-map by EMGN overlooks sentence 5, and the mind-map by DistilBERT places sentences 4-5 under the wrong governor. Furthermore, compared with other methods, ChatGPT selects an inaccurate root node, while other models

[3]The original text can be found at http://edition.cnn.com/2011/WORLD/asiapcf/08/10/koreas.unrest/index.html



(a) λ (b) η

Figure 5: Hyperparameter study for SSM and KSM.

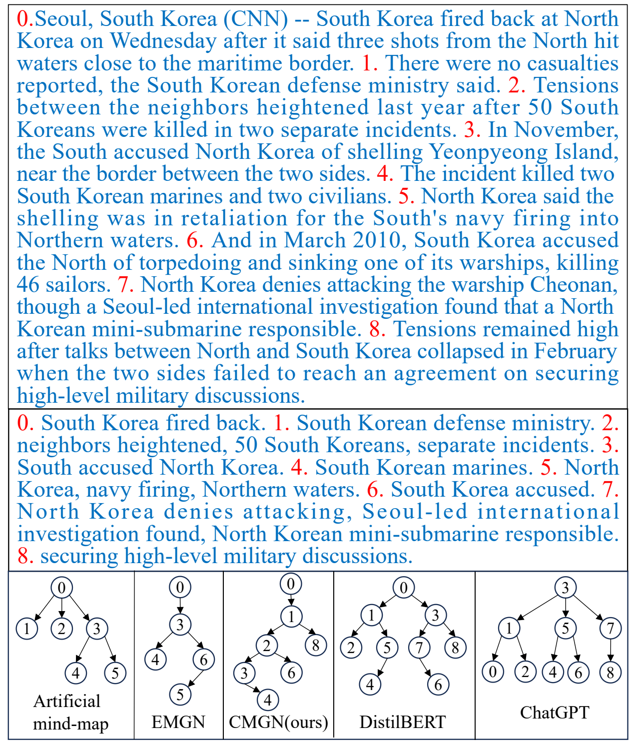


Figure 6: Case study for SSM and KSM.

commonly select sentence 0 as the root node. This reveals that LLMs like ChatGPT may have limitations on particular tasks. Small models are still essential in future research. In conclusion, the case study further illustrates that our model can reveal the hierarchical structure and semantic relationships of articles more accurately and concisely.

Conclusion

We propose an effective mind-map generation network based on coreference graph and coreference-guided relation graph generation. To better utilize the information of the coreference graph, we employ a graph enhancement module in a contrastive learning manner. The experiment results demonstrate the effectiveness of our method, while enjoying efficiency. The case study further proves that the mind-map of our method is better organized than other methods.

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