GoSum: Extractive Summarization of Long Documents by Reinforcement Learning and Graph Organized discourse state

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Abstract

Extracting summaries from long documents can be regarded as sentence classification using the structural information of the documents. How to use such structural information to summarize a document is challenging. In this paper, we propose GoSum, a novel graph and reinforcement learning based extractive model for long-paper summarization. In particular, GoSum encodes sentence states in reinforcement learning by building a heterogeneous graph for each input document at different discourse levels. An edge in the graph reflects the discourse hierarchy of a document for restraining the semantic drifts across section boundaries. We evaluate GoSum on two datasets of scientific articles summarization: PubMed and arXiv. The experimental results have demonstrated that GoSum achieve state-of-the-art results compared with strong baselines of both extractive and abstractive models. The ablation studies further validate that the performance of our GoSum benefits from the use of discourse information.

1 Introduction

Document summarization refers to generating short and conductive summaries over given texts, which can help readers rapidly acquire essential knowledge from documents. There are two main categories of approaches to summarization: the extractive approach and the abstractive approach. The extractive approaches score and filter out the sentences of a given document to ensure the semantic and grammatical correctness of the selected sentences in the summary. Abstractive approaches mostly read an input text, comprehend it, and output its summary within the seq2seq framework. This procedure is similar to humans’ summarising articles. The theoretical upper bound on the performance of the seq2seq model is higher than what extractive approaches can achieve. However, abstractive approaches have the drawback of producing some meaningless and unfaithful summaries (Kryściński et al., 2020). The generated summaries read smoothly with a high ROUGE score, but there is a significant gap in semantic information between them and the gold summaries.

In this paper, we focus on the use of extractive models for summarizing scientific literature. Extractive summarization (Zhong et al., 2020; Zhou et al., 2018a) has been extensively studied in short summarization datasets such as CNN/DailyMail (Hermann et al., 2015). However, studies on long texts have lagged relatively behind because long document summarization is more challenging due to the following two reasons: 1) An increase in the input length expands the memory cost of the model; and 2) The complex discourse structural information about long-form documents should be taken into account. Reading a long text, especially scientific literature, one usually glances at the discourse structure of the whole text. Once reading a section title, one roughly should know on which this section focuses. Using this structural information of a text, one can better understand the meanings of its sentences. From the perspective of extractive summarization, it would be better to use this information for encoding sentences. The previous method encodes sentences and sections separately, making it difficult to capture the hier-
archival structure of the document. In this paper, we thereby propose to use a graph neural network (GNN) to well represent the structure information of documents. The additional benefit is that the computational complexity of GNNs is linear for long inputs.

Unlike abstractive approaches that are trained by using available gold summaries directly, the training labels of an extractive model need to be obtained by using a search algorithm (typically greedy search) based on the gold summary provided. This kind of label is not optimal and deterministic, i.e., the algorithm yields a single extracted label for each pair of document-abstract. In fact, there may be many valid labels that are very similar to these suboptimal labels. Insufficient such positive pairs may cause under-fitting (Narayan et al., 2018). These problems can be alleviated by increasing the number of samples and giving each training sample a reward from reinforcement learning (RL).

To address the above problems, we propose a novel model called GoSum that is trained by using reinforcement learning. Based on a given input and previously extracted sentences, GoSum generates the sentences of a summary sequentially. The process of scoring and selecting a sentence is regarded as an action in reinforcement learning. This action is taken after the agent (the GoSum model) takes the sentence state as input. For encoding sentence states, we leverage the structure of a document. Specifically, we use a graph neural network to encode the hierarchical structure of a document. In more detail, we treat each sentence and section as a node of a heterogeneous graph. A state contains 1) a local representation of a sentence with discourse awareness, 2) the global context of a sentence within the document, and 3) information about the extraction history. As such, we seamlessly integrate RL with GNN in GoSum. To summarize, our main contributions of this paper are: 1) We propose an approach called GoSum \footnote{Source code is available on Supplementary Files} as a novel graph-based discourse-aware extractive summarization model. GoSum can generate a concise and informative summary operating on a subsentential discourse unit level. 2) We effectively integrate reinforcement learning with GNN under GoSum. With obtaining sufficient samples in reinforcement learning, GoSum relies on GNN to capture discourse information about documents, particularly for the discourse hierarchy, to extract compact summaries. 3) We have conducted comprehensive experiments to validate the performance of GoSum. GoSum has achieved state-of-the-art performance compared with strong baselines on two benchmark datasets: PubMed and arXiv.

2 Related work

2.1 Long Document Summarization

Unlike the short-input summarization that BERT-based models (Liu and Lapata, 2019) have been successfully used, studies on long document summarization struggle with long-input sequences. Research on abstractive models (Zaheer et al., 2020; Huang et al., 2021) mainly exploring different architectures of Transformer to cope with excessively long inputs. However, the study of extractive models focus on other perspectives. For example, long documents follow a standard discourse structure, i.e. scientific papers are written section by section to describe the background, methodology, experiment etc. Several methods (Xiao and Carenini, 2019; Collins et al., 2017; Zhu et al., 2021) leverage such section information to guide the generation of summaries. Reinforcement learning has also successfully been applied to long document extractive summarization. LG+RdLoss (Xiao and Carenini, 2020) is an improved version of LG (Xiao and Carenini, 2019) that constrains sentence redundancy with reinforcement learning. Differing from LG-RdLoss, MemSum (Gu et al., 2022) uses extraction history (Zhou et al., 2018b), and treat extractive summarization as a multi-step episodic Markov decision process.

2.2 Graph-based Extractive Summarization

Early summarization solutions are graph-based unsupervised methods (Erkan and Radev, 2004), relying on explicit surface features. They construct a similarity graph between sentences and formulate extractive summarization as a task of ranking nodes. Recently, researchers use graph neural network on supervised summarization. HSG (Wang et al., 2020) was the first to construct a heterogeneous graph neural network for extractive document summarization. HahSum (Jia et al., 2020) considers inter-sentence redundancy in graph construction. HEROS (Zhu et al., 2021) applies graph-based to the long text field and uses the information about input article discourse. All these methods treat sentences and words as nodes in a graph. Based on the RST tree, DiscoSum(Xu et al., 2020) uses
a graph to capture the long-range dependencies among discourse units, with Elementary Discourse Units as the nodes in a graph. To some extent, the graph-based approach solves the quadratic computational and memory complexities encoded using Transformer and works well with the structural information of the input. Therefore, we choose to use GNNs for GoSum.

3 GoSum

Figure 1 shows the architecture of GoSum. With the input of a structural text, GoSum starts with constructing a graph of the text and then generates an embedding for the current state by using three sub-encoders: 1) The Graph-based Discourse Awareness Encoder, 2) The Global Context Encoder, and 3) The Extraction History Encoder. After this, the extractor decides whether to stop or continue the extraction based on the current embedding.

3.1 Task Definition

Extractive summarization is regarded as a sequence labeling task. Denote $D = \{s_1, s_2, ..., s_n\}$ as a document that consists of $n$ sentences. Extractive summarizer produces a sequence of indexes $\hat{Y} = \{\hat{y}_1, \hat{y}_2, ..., \hat{y}_T\}$ to determine which sentences should be included in the summaries. \(\hat{y}_i\) denotes the index of the sentence. Since the datasets only contain document-abstract pairs, we use beam search and automatic metric ROUGE to sample a set of oracle labels \(\{Y^1, Y^2, ...\}\). Then, we keep the ROUGE score of each oracle label’s corresponding summary against the abstract as a reward for reinforcement learning.

3.2 GoSum via Policy Gradient

From the perspective of RL for extractive summarization, we can view our GoSum model as an agent, parameters of the network as a policy \(\pi_{\theta}\), and extracting at each step as an action. Given an oracle label $Y = \{y_1, y_2, ..., y_T\}$, $R = \{r_1, r_2, ..., r_T\}$ is a reward list, $r_t$ is the reward of an action to select sentence $y_t$ after the set of $\{y_1, y_2, ..., y_{t-1}\}$ are already selected. The goal of policy gradient in GoSum is to maximize objective function $\mathcal{L}(\theta) = E_{\pi_{\theta}}(R)$. The reward value $r_t$ is the same as the ROUGE (Lin, 2004) score $r$ between the oracle summary and gold abstract.

$$r = \frac{1}{3} \left( \text{ROUGE-1}_f + \text{ROUGE-2}_f + \text{ROUGE-L}_f \right)$$

(1)

In reinforcement learning (Williams, 1992), the policy gradient is defined as:

$$\nabla \mathcal{L}(\theta) = -E_{\pi_{\theta}} \left[ r \sum_{t=1}^{T} \nabla_{\theta} \log \pi_{\theta}(A_t|S_t, \theta) \right]$$

(2)

where $\pi_{\theta}(A_t|S_t, \theta)$ represents the likelihood of action $A_t$ from policy net $\pi_{\theta}$ when a state is $S_t$ and the time step is $t$. Usually, the extractive method
extracts a fixed number of sentences. However, GoSum uses a stop mechanism, which determines the point at which to stop extracting itself. So the policy likelihood can be written in the following form:

$$\pi(A_t|S_t, \theta) = p(\text{stop}|S_t, \theta)p(A_t|\text{stop}, S_t, \theta)$$ (3)

In each step, the policy net first outputs a probability $p_{\text{stop}}$. If $p_{\text{stop}}$ is greater than a pre-defined threshold, then the model will stop extracting, otherwise, the model continues to find the next sentence.

### 3.3 State Encoder

#### 3.3.1 Graph-based Discourse Awareness Encoder

**Graph Construction:** GoSum constructs a heterogeneous graph that represents sections and sentences of a document at the discourse level. There are only two kinds of nodes in the graph: sentence nodes and section nodes. The way we build the graph is slightly different from the previous graph-based approach (Zhu et al., 2021; Wang et al., 2020; Jia et al., 2020) in that we discard the word nodes. As reinforcement learning is time-consuming, removing word nodes can significantly improve the running time of GoSum. In addition, the information transferred from word nodes to sentence nodes is essentially about the representation of the sentence’s local content. Therefore, the use of a simple encoder is sufficient, such as LSTM. We connect edges between each sentence and the section containing the sentence. Also, a fully-connected subgraph is built among each section.

**Graph Initialization:** After the graph is constructed, we give each node an initial representation. Suppose that a sentence in a document consists of $s$ words: $(sw_1, sw_2, ..., sw_s)$, and the text of a section (e.g. "Related work") is composed of $c$ words: $(cw_1, cw_2, ..., cw_c)$. We first employ Glove (Pennington et al., 2014) word embeddings to embed these words, then use BiLSTM (Hochreiter and Schmidhuber, 1997) with Multi-head pooling (MHP) to produce sentence representation $h^0_s$ and section representation $h^0_c$:

- $h^0_c = \text{MHP}(\text{LSTM}(\text{Glove}(cw_1, cw_2, ..., cw_c)))$ (4)
- $h^0_s = \text{MHP}(\text{LSTM}(\text{Glove}(sw_1, sw_2, ..., sw_s)))$ (5)

**Graph Attention Networks:** With the available graph $G$ and its node features, we use a graph attention layer (GAT) (Veličković et al., 2017) to update our semantic nodes. The expressions of GAT are as follows:

$$e_{ij} = \text{LeakyRELU}(W_u [W_q h_i; W_k h_j])$$ (6)

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})}$$ (7)

$$h'_i = \sigma\left( \sum_{j \in \mathcal{N}_i} \alpha_{ij} W_q h_j \right) + h_i$$ (8)

where $W_u, W_q, W_k$, and $W_v$ are trainable weights, and $h_i$ is the node representation of the $i$-th node in the graph. $\mathcal{N}_i$ is the neighbor nodes of node $i$.

**Message Passing:** We first update section nodes with their neighbor sentence nodes via the GAT and Feed Forward Net (FFN) layers:

$$U_{s \rightarrow c} = \text{GAT}(H^0_c, H^0_s, H^0_s)$$ (9)

$$H^1_c = \text{FFN}(U_{s \rightarrow c} + H^0_c)$$ (10)

where $H^0_s$ is the initialized representation of sentence nodes, and $H^0_c$ is for section nodes. GAT($H^0_c, H^0_s, H^0_s$) denotes $H^0_s$ as an attention query, and $H^0_s$ as a key and value. We continue to update section nodes by section to section edges:

$$U_{c \rightarrow c} = \text{GAT}(H^1_c, H^1_s, H^1_s)$$ (11)

$$H^2_c = \text{FFN}(U_{c \rightarrow c} + H^1_c)$$ (12)

After a section node is updated, it already has section-level discourse information. We then pass this discourse information to each corresponding sentence node:

$$U_{c \rightarrow s} = \text{GAT}(H^0_c, H^2_c, H^2_s)$$ (13)

$$H^3_s = \text{FFN}(U_{c \rightarrow s} + H^0_s)$$ (14)

Since GoSum uses only one-layer GAT, the output is $H^3_s$.

#### 3.3.2 Global Context Encoder

After that, a Bi-LSTM takes $H^1_s$ as input to produce sentence embeddings $H^2_s$ that encodes global contextual information. This module encodes global contextual information such as the sentence’s position in the document and information on neighboring sentences.
3.3.3 Extraction History Encoder

In extractive summarization, extracting sentences by an extraction history encoder is first used in NeuSum (Zhou et al., 2018b), in order to avoid redundancy. Comparing the extracted sentences and the remaining unextracted sentences, an extraction history encoder (EHE) generates the embedding for each of the remaining sentences. The result is used to guide the scoring of those unextracted sentences. Our design of the extraction history encoder (EHE) in GoSum follows (Gu et al., 2022). It consists of a series of $N_h$ identical layers. Each layer first performs a multi-head self-attention between the remaining sentences, followed by another multi-head self-attention performed on the sentences that have been extracted. Two attention sublayers capture the information of both extracted and remaining sentences. For those sentences that have not been extracted yet in time step $t$, an extraction history embedding $H_{te}^t$ is obtained.

3.4 Extractor

As shown in Eq(3), the extractor decides whether to stop extraction or generate the score of each remaining sentence according to the state. The state $S_t$ is described by concatenating three types of vectors: sentence representation from discourse graph $H^1_s$, sentence global content representation $H^g_s$, and extraction history embedding $H^t_e$ as:

$$S_t = [H^1_s; H^g_s; H^t_e]$$ (15)

A multi-head pooling followed by a multi-layer perceptrons (MLP) is used to compute stop signal of extraction. Another MLP decides to extract which sentence.

3.5 Training

Usually, the training samples of reinforcement learning algorithms are obtained by sampling the policy net that is currently being trained. Since the golden standard is already known at the time of training for extractive summarization, we can obtain high-quality training samples by performing beam search sampling in advance. This saves the time spent on sampling and allows the model to converge more quickly. The flow of the training process in GoSum is shown in Algorithm 1.

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### Algorithm 1 Training procedure in one iteration

**Input:** Document-Summary pair $<D, S>$

**Parameters:** Learning rate: $l$, and model parameters: $\theta$

1. A label sequence $Y = \{y_1, y_2, \ldots, y_T\}$ is sampled using beam search, with corresponding summaries having ROUGE scores $r$ against $S$.

2. Obtain discourse-aware sentence embedding $H^1_s$.

3. Initialize Graph $H^0_s, H^0_c$.

4. Message passing $(H^0_s, H^0_c) \rightarrow H^1_c$.

5. Message passing $(H^1_c, H^1_e) \rightarrow H^2_c$.

6. Message passing $(H^2_c, H^0_s) \rightarrow H^1_s$.

7. Obtain global-content sentence embedding $H^g_s$.

8. Let $t = 1$.

9. while $t$ is no larger than $T$ do

10. Produce extraction history embedding $H^t_e$ for the remaining sentences.

11. Output the probability of the sentence from the Extractor to select $y_t$ and $p_{stop}$ by using state $S_t = [H^1_s, H^g_s, H^t_e]$.

12. Update policy gradient: $\theta \leftarrow \theta + l \cdot r \nabla \pi(A_t|S_t, \theta)$

13. $t \leftarrow t + 1$

14. end while

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4 Experiments

4.1 Summarization Datasets

We evaluate our model on the two scientific paper datasets: PubMed and arXiv (Cohan et al., 2018). Both datasets provide information about the structures of the papers. The inputs of these datasets are the full text of scientific papers except for the abstract, and the gold summaries are the corresponding abstracts. As can be seen from Table 1, both datasets are relatively large in size, especially the arXiv dataset.

4.2 Experimental Setup

4.2.1 Evaluation Metrics

ROUGE score (Lin, 2004) is used to evaluate the model performance. We report the F1 score of unigram, bigram overlap (ROUGE-1, ROUGE-2), and the longest common subsequence (ROUGE-L).
4.2.2 Training data Sampling

The original PubMed and arXiv datasets do not provide extractive training labels. We use beam search to obtain extractive oracle summaries. For each document-abstract pair, the algorithm generates at most 15 different summaries with the largest ROUGE score. For the PubMed and arXiv datasets, we set the maximum sequence length of extracted summaries to 7 and 8, respectively.

4.2.3 Implementation Details

Our model is trained using adam (Kingma and Ba, 2015) optimizer with the learning rate $1e^{-4}$, $\beta_1 = 0.9$, and $\beta_2 = 0.999$. GoSum and its variants are trained from 20 epochs on the both pubmed and arxiv dataset. In each iteration, for each input document, we randomly sample one pre-prepare label for training. Model checkpoints are saved and evaluated every 10,000 steps. During the testing phase, the threshold of $p_{stop}$ for PubMed and arXiv is set to 0.6, and 0.45, respectively. GoSum and its variants are all trained on four TITAN XP GPUs.

4.2.4 Baselines

We compare GoSum with state-of-the-art extractive methods and abstractive methods on the two datasets mentioned above. In particular, the extractive baselines are Local-Global (2019) that incorporates local and global contexts to extract summaries, and Local-Global+RdLoss (2020), that further adds a redundancy reinforcement learning loss. HEROS (Zhu et al., 2021) use heterogeneous graph-based with nodes from different discourse levels. To ensures that the input is consistent with other baseline, we also record its results without content ranking module. NeuSum (2018b) is a model that considers the extraction history. MemSum (2022) is a reinforcement-learning-based extractive summarizer. Sent-CLF and Sent-PTR (Pilault et al., 2020) are a LSTM based sentence classifier and a hierarchical seq2seq sentence pointer.

For the abstractive methods, we compare GoSum with the following methods: PEGASUS (Zhang et al., 2020) is a pre-trained language model for summarization. Dancer (Gidiotis and Tsoumakas, 2020) is a divide-and-conquer method. BigBird (2020) uses sparse and windowed attentions to handle long input sequences. Hepos (Huang et al., 2021) uses the efficient encoder-decoder attention with head-wise positional strides to effectively pinpoint salient information from the source. HAT (Rohde et al., 2021) adds hierarchical attention layers to an encoder-decoder model to summarize long documents.

5 Results

5.1 Performance Comparisons

Tables 2 and 3 report the results of our model on arXiv and PubMed datasets, respectively. On both datasets, GoSum outperforms state-of-the-art extractive and abstractive baselines. RL-based meth-
| Models                      | R-1   | R-2   | R-L   |
|----------------------------|-------|-------|-------|
| Oracle                     | 61.99 | 34.95 | 56.76 |
| **Extractive models**      |       |       |       |
| Lead-10                    | 37.45 | 14.19 | 34.07 |
| Local-Global               | 45.18 | 20.20 | 40.72 |
| + RdLoss                   | 45.30 | 20.42 | 40.95 |
| Sent-CLF                   | 45.01 | 19.91 | 41.16 |
| Sent-PTF                   | 43.30 | 17.92 | 39.47 |
| HEROS                      | 48.18 | 21.82 | 43.33 |
| w/o content ranking        | 46.63 | 20.63 | 42.01 |
| Topic-GraphSum             | 48.85 | 21.76 | 35.19 |
| NeuSum                     | 47.46 | 21.92 | 42.87 |
| MemSum                     | 49.25 | 22.94 | 44.42 |
| **GoSum (ours)**           | 49.83 | 23.56 | 45.10 |
| **Abstractive models**     |       |       |       |
| PEGASUS                    | 45.97 | 20.15 | 41.34 |
| BigBird-base               | 43.70 | 19.32 | 39.99 |
| BigBird-large              | 46.32 | 20.65 | 42.33 |
| Dancer                     | 46.34 | 19.97 | 42.42 |
| HAT                        | 48.36 | 21.43 | 37.00 |
| Hepos-Sinkhorn             | 47.93 | 20.74 | 42.58 |
| Hepos-LSH                  | 48.12 | 21.06 | 42.72 |

Table 3: Results on PubMed Dataset.

Table 4: Abaltion studies on PubMed dataset.

Methods like GoSum, MemSum and LG-RdLoss show substantial performance gain, demonstrating the effectiveness of the reinforcement learning. Compared with MemSum, GoSum has better performance. The results depend on two factors: 1) the use of the structural information from the input articles; and 2) the use of graphs to model sentences and sections. In this way, sentences can obtain more abundant information from sections, and sections can share and propagate their topical information. GoSum has more performance improvement on PubMed dataset compared to arXiv dataset. One reason for this may be that the section information provided by the pubmed dataset is more accurate, as explained in more detail in section 5.3.

5.2 Ablation Studies

In table 4, we conduct ablation studies by comparing GoSum with its variants.

To validate the performance of the graph structure, we set the following GoSum variants: **GoSum w/o sec2sec edges** remove section-to-section edges in graph construction, and take \( H_c^1 \) as a key input in Eq(13). **GoSum w/o graph** has no graph modeling. In particular, the global contextual embedding \( H_g^s \) is obtained directly using \( H_c^0 \). State representation \( S_t \) in Eq(15) includes one more embedding \( H_c^0 \) to capture section information. **GoSum w/o sec & graph** does not use document structural information and graph modeling.

Improvements from **GoSum w/o graph** to **GoSum w/o sec2sec edges** demonstrate that the addition of paper structure information can slightly improve GoSum. The performance of GoSum has a greater improvement if using graphs to model the relationships between sentences and sections.

Next, we examine the effects of different embeddings on the performance of GoSum. For **GoSum w SecE**, the extractor takes additional section representation \( H_c^2 \) in Eq(12). **GoSum w/o GCE**, **GoSum w/o DLE**, and **GoSum w/o EHE** remove Global Context Embedding \( H_c^2 \), Discourse aware Local sentence Embedding \( H_c^1 \), and Extraction History Embedding \( H_e^s \) in Eq(12), respectively.

Although **GoSum w SecE** adds an extra embedding, the resulting scores instead slightly decrease. This indicates that the information about section nodes has been incorporated into the local content embedding during the graph update process so that adding section embedding will be redundant with possible over-fitting. If the other three embeddings are removed, the performance drops. **GoSum w/o DLE** with removing \( H_c^1 \) results in the most decrease. This also indicates that the discourse-aware local sentence embedding contains more useful information.

5.3 What exactly enhances GoSum?

Aspects of graph-organized discourse states: With the use of reinforcement learning and graph neural networks, GoSum has achieved a significant
Table 5: Comparisons between GoSum trained with the complete datasets and those without the section titles.

|         | R-1  | R-2  | R-L  |
|---------|------|------|------|
| PubMed  |      |      |      |
| GoSum   | 49.83| 23.56| 45.10|
| w/o SecTitle | ↓ 0.20 | ↓ 0.11 | ↓ 0.12 |
| arXiv   |      |      |      |
| GoSum   | 48.61| 20.53| 42.80|
| w/o SecTitle | ↓ 0.08 | ↓ 0.03 | ↓ 0.06 |

Figure 2: GoSum performance varies as section information is corrupted at a rate (x-axis). Y-axis is the average ROUGE score. The green dots show the scores of GoSum on the PubMed dataset, while the blue dots show the results of GoSum on the arXiv dataset.

For the above reasons, we disrupt the section attribution of the input sentences proportionally, with an increment of 10% in each experiment. Since experimenting with the full data set is too time-consuming, we select 10,000 samples from each PubMed and arXiv datasets for training. As seen from Fig 2, the performance of GoSum decreases rapidly with the declining amount of discourse information. Because of the small number of training samples and the instability of reinforcement learning, the performance of GoSum fluctuates slightly from dataset to dataset but shows a slow decreasing trend overall. The performance of GoSum decreases significantly at the beginning, which indicates that GoSum is sensitive to the accuracy of section information. It also confirms that accurate discourse information is required to improve the performance of GoSum.

In addition to the discourse information of the literature, which divides the sentences into different sections, there are also section-specific names, such as “introduction”, “methodology” etc. These specific text title contexts contain semantic information, which helps to improve the performance of GoSum. First, we set up a control model of GoSum w/o SecTitle, which has the same architecture as GoSum, but the section title in the training data is replaced with a meaningless text “section #id”. The experimental results in Table 5 show that the performance of GoSum w/o SecTitle is slightly worse than that of GoSum. This indicates that the semantic information about section title text is useful but not essential. The key to performance improvement is the discourse hierarchies of documents. Moreover, GoSum w/o SecTitle drops more significantly on the PubMed dataset. The difference in the performance between GoSum w/o SecTitle and GoSum on the arXiv dataset is not significant, probably because the title quality of the documents in the arXiv dataset is not satisfied.

Aspects of reinforcement learning: There are two factors that can improve the performance of GoSum by using reinforcement learning: First, more sampling is performed, which is equivalent to data augmentation; and second, the model gives a feedback reward to different samples during training which helps to distinguish between good and bad samples. The experimental results on investigating the impact of these two factors on the GoSum performance are reported in Table 6.

w/o reward: sets rewards of all samples to 1, and the experimental results are slightly lower than those of the complete RL model. Complete RL samples an average of 6.52 label sequences per document-abstract pair. The sample top-k indicates that GoSum is trained with only the k highest sampled label sequences of an input document. As
|                  | R-1   | R-2   | R-L   |
|------------------|-------|-------|-------|
| Complete RL      | 49.83 | 23.56 | 45.10 |
| w/o reward       | 49.64 | 23.37 | 44.96 |
| sample top-1     | 49.10 | 23.00 | 44.42 |
| sample top-2     | 49.27 | 23.07 | 44.61 |
| sample top-4     | 49.64 | 23.33 | 44.96 |

Table 6: GoSum performance by reinforcement learning with different settings on PubMed dataset.

the number of samples increases, the performance of GoSum improves significantly. In conclusion, the experimental results on RL verified our conjecture.

6 Conclusion

In this paper, we have presented a novel approach called GoSum for extracting summaries from long documents. It effectively integrates reinforcement learning with a graph neural network. In particular, we have shown how graph-organized discourse information can be applied in reinforcement learning-based extractive summarization. Experimental results on the arXiv and PubMed datasets have demonstrated that GoSum achieves state-of-the-art performance. The ablation experiments examine the effect of discourse information on GoSum. The results show that the performance of GoSum comes from the use of the hierarchical attribution of sentences and the semantic information about section titles of documents. With achieving satisfactory results in scientific literature, GoSum requires hierarchical discourse information about long texts as its inputs. In the future, we will attempt to automatically generate discourse information from documents.

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