Centrality Meets Centroid: A Graph-based Approach for Unsupervised Document Summarization

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Abstract

Unsupervised document summarization has re-acquired lots of attention in recent years thanks to its simplicity and data independence. In this paper, we propose a graph-based unsupervised approach for extractive document summarization. Instead of ranking sentences by salience and extracting sentences one by one, our approach works at a summary-level by utilizing graph centrality and centroid. We first extract summary candidates as subgraphs based on centrality from the sentence graph and then select from the summary candidates by matching to the centroid. We perform extensive experiments on two benchmarked summarization datasets, and the results demonstrate the effectiveness of our model compared to state-of-the-art baselines.

1 Introduction

Extractive document summarization aims to extract relevant sentences from the original documents covering salient information. Remarkable success in single document summarization has been achieved in recent years with deep neural network (Nallapati et al., 2016a; Cheng and Lapata, 2016; See et al., 2017; Nallapati et al., 2016b; Narayan et al., 2018; Liu and Lapata, 2019). The success of these high-capacity supervised models heavily relies on large-scale annotated corpora containing hundreds of thousands of document-summary pairs. However, document summary reference writing and annotation can be both time-consuming and labor-intensive, making it extremely hard to obtain high-quality large-scale corpora. As a result, practical unsupervised summarization approaches requiring no annotated document-summary training data at all have received renewed attention recently (Chu and Liu, 2019; Zheng and Lapata, 2019).

Most of the existing unsupervised summarization methods are graph-based extractors. They utilize graph structure to model the relationship between sentences and then extract sentences to form a summary (Mihalcea and Tarau, 2004; Erkan and Radev, 2004; Wan and Yang, 2008; Zheng and Lapata, 2019). Specifically, a document (or a cluster of documents) is represented as a graph, with nodes representing sentences and edge weights representing sentence similarity. In order to decide which sentence to include in the summary, two critical graph properties, centrality and centroid, are widely used to score sentences (nodes). Centrality-based approaches (Mihalcea and Tarau, 2004; Zheng and Lapata, 2019) rely on edge connection information of the graph and rank sentences based on node centrality. On the other hand, centroid-based approaches (Radev et al., 2004; Rossiello et al., 2017) rely on node representation information, representing the whole document as a centroid of all sentence vectors and ranking sentences by their cosine similarity to the centroid vector. How to effectively utilize both node representation and edge information of the graph has not been investigated.

Moreover, previous approaches are all sentence-level extractors, which extract sentences one by one based on salience scores. Nevertheless, Zhong et al. (2020) recently argues that by considering the semantics of the entire summary, summary-level methods will select highly generalized sentences while ignoring the coupling of multiple sentences. Inspired by this, we propose Centrality Centroid Summarization (CCSUM), a summary-level graph-based extractive summarization model. Instead of ranking then extracting sentences, we treat extractive summarization as a subgraph selection problem by utilizing both centrality and centroid. We first generate summary candidates based on subgraph centrality, and then select from the candidates by matching subgraphs with the graph centroid vector after message passing. We also add a positional encoding to better model the sequence of the document. We perform extensive experiments...
on two benchmarked datasets: CNN/Daily Mail and NYTimes, and experimental results show that our approach outperforms state-of-the-art baselines on the board. We summarize our contributions as follows:

- Instead of ranking then selecting sentences one by one to form a summary, we propose a summary-level unsupervised extractive summarization model.
- Our model utilizes both edge information and node representation of the graph effectively by considering both centrality and centroid.
- We evaluate the proposed approach on two benchmarked summarization datasets, and experimental results prove the effectiveness of our proposed model.

2 Related Works

2.1 Extractive Summarization

Recent research works on extractive document summarization span a large range of approaches. One common model structure is the encoder-decoder framework. Different choices of encoders include recurrent neural networks (Cheng and Lapata, 2016; Nallapati et al., 2016a; Zhou et al., 2018) and Transformer (Vaswani et al., 2017; Zhong et al., 2019). Pre-trained language models, such as BERT (Devlin et al., 2018) are also widely applied in extractive summarization with its ability to model contextual word semantic representations (Zhong et al., 2019; Liu and Lapata, 2019; Lewis et al., 2019). All these models are essentially sentence-level extractors with various scoring methods.

Reinforcement Learning (RL) based methods (Narayan et al., 2018; Bae et al., 2019) provide a summary-level scoring and bring improvements. Recently, (Zhong et al., 2020) creates a new paradigm and formulate the extractive summarization task as a semantic text matching problem. They notice an inherent gap between summary-level and sentence-level approaches across different summarization datasets. The summary-level matching method further improves the performance of extractive summarization.

2.2 Graph-based Summarization

The core of extractive summarization is to model the relation between sentences in a document, which falls in graph models’ strength. In general, graph-based summarization models represent a document (or a cluster of documents) as a graph, with nodes representing sentences (or discourse) and edge weights representing sentence similarities.

Unsupervised graph summarization methods rely on graph connectivity (centrality) or node representations (centroid) (Radev et al., 2004; Rossiello et al., 2017) to score and rank sentences. Popular centrality-based methods include TextRank (Mihalcea and Tarau, 2004), LexRank (Erkan and Radev, 2004) and PACSUM (Zheng and Lapata, 2019). Details of centrality-based and centroid-based summarization will be discussed in Section 3.

Researchers also explore supervised graph neural network (GNN) on the task(Yasunaga et al., 2017; Xu et al., 2019; Wang et al., 2020). Our paper follows this line of works on developing novel unsupervised graph models for single document summarization.

3 Centrality vs. Centroid

Prior to talking about the proposed ccSUM model, we will first introduce the centrality and centroid properties, as well as their applications in document summarization, in this section. Formally, centrality and centroid are two important concepts in graph theory that are widely used in unsupervised extractive summarization for sentence ranking. For single-document summarization, let $D$ denote a document consisting of a sequence of sentences $\{s_1, s_2, ..., s_n\}$, and $e_{ij}$ denote the similarity score between sentence pair $(s_i, s_j)$. The document $D$ can be formulated as a graph, with those $n$ sentences as the nodes and pairwise sentence similarities as the weighted link among the nodes.

**Centrality** The centrality-based methods rank sentences by measuring the degree centrality for nodes. The degree centrality for a sentence $s_i$ is defined as:

$$\text{centrality}(s_i) = \sum_{j \in \{1, ..., i-1, i+1, ..., n\}} e_{ij}. \quad (1)$$

Then a summary is extracted by merely ranking sentences in reverse degree centrality order and de-queuing the ranked list of sentences until the desired summary length is reached.

**Centroid** The centroid-based methods rank sentences by measuring semantic similarity to the
whole document. It represents document $D$ by the centroid vector embedding $c$ as:

$$c = \text{centroid}(D) = \sum_{s_j \in D} e_j,$$  \hspace{1cm} (2)

where $e_j \in \mathbb{R}^{d_h}$ is the embedding vector of dimension $d_h$ about sentence $s_j$. The semantic similarity for a sentence $s_j$ to the document is defined as the cosine similarity between its vector representation and the centroid vector:

$$\text{sim}(c, e_j) = \frac{c^\top \cdot e_j}{\|c\| \cdot \|e_j\|}.$$ \hspace{1cm} (3)

A summary is then extracted by de-queuing the ranked list of sentences in a decreasing similarity order until the desired summary length is reached.

It should be noticed that centrality-based methods merely measure the connectivity information (edge) of the graph, while centroid-based methods merely rely on node representation of the graph. Effectively combining node representations and edge information would definitely help further improve graph-based summarization performance.

4 Method

To fully utilize sentence relation graph information and enable summary-level unsupervised summarization, we introduce our model Centrality Centroid Summarization (CCSUM). We first present how to construct a sentence relation graph for a given document and then introduce our centrality-based candidate summaries extraction method, which generates salient candidate summaries (subgraphs) from the sentence relation graph. These candidate summaries will be selected with our centroid-based matching method to get the best summary as output. Fig. 1 shows the overall architecture of our model.

4.1 Sentence Relation Graph Construction

We first present how to construct a sentence relation graph $G = (V, E)$ given a document $D = \{s_1, s_2, \ldots, s_n\}$. Each node $v_i \in V$ in the sentence relation graph represents a corresponding sentence $s_i$ in the document. The edge $e_{ij} \in E$ between node $v_i$ and node $v_j$ represents the semantic similarity between sentences $s_i$ and $s_j$. The node representations and edge weights are defined as follows:

**Node Representation** We use BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018) as sentence encoder to embed the semantic meanings of sentences as node representations. Compared to Convolutional Neural Networks (CNN) (LeCun et al., 1998) and Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), BERT is a general-purpose language model for text representation learning, which is pre-trained based on a large text corpus (like Wikipedia). The prior semantic knowledge it brings into the encoding helps generate more meaningful representations.

Specifically, we adopt the fine-tuned BERT encoder in (Zheng and Lapata, 2019), where the pub-
After obtaining the sentence relation graph \( \mathcal{G} \), we propose a summary-level centrality-based approach to generate candidate summaries. Instead of extracting sentences one by one, we generate candidate summaries by directly extracting subgraphs \( \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_m\} \) from graph \( \mathcal{G} \).

Specifically, for a subgraph \( \mathcal{C} \) of \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \), whose nodes \( \mathcal{V}_C \subset \mathcal{V} \), edges \( \mathcal{E}_C \subset \mathcal{E} \), we define its **subgraph centrality** \( \text{SC}(\mathcal{C}) \) as:

\[
\begin{align*}
\text{SC}(\mathcal{C}) &= \frac{1}{|\mathcal{V}_C|} \sum_{v_k \in \mathcal{V}_C} \text{cen}(v_k), \\
\text{cen}(v_k) &= \beta \sum_{j<k, e_{jk} \in \mathcal{E}_C} e_{jk} + (1-\beta) \sum_{j>k, e_{jk} \in \mathcal{E}_C} e_{jk}.
\end{align*}
\]

Here, \( \beta \) is a hyper-parameter measuring the influence of forward and backward-looking edges. The idea here is that backward-looking edges from previous sentences and forward-looking edges from succeeding sentences will have different influences on a sentence, so we distinguish the influence of forward and backward-looking edges here with \( \beta \). This follows the finding of (Zheng and Lapata, 2019) that similarity with previous content actually hurts the centrality of nodes. The influence of hyper-parameter \( \beta \) is also discussed in section 6.3.

Note that subgraph centrality is a term originally from graph theory to calculate a weighted sum of the numbers of all closed walks of different lengths in the network starting and ending at a node (Estrada and Rodriguez-Velazquez, 2005). We borrow the name and define subgraph centrality as the external edges directed degree centrality sum for a subgraph \( \mathcal{C} \). Here the idea is to treat the subgraph as a “super-node” in the graph and measures its external influence in the whole graph. The way that we treat and extract summary as a subgraph for the sentence relation graph naturally follows a summary-level manner.

Then for a given subgraph size \( q \), we simply calculate the subgraph centrality for \( q \)-node subgraphs and pick \( m \) subgraphs with largest centrality \( \mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_m\} \) as the candidate summaries for selection in next step. The subgraph size (summary size) \( q \) is up to the dataset and could be decided according to the length of gold summaries. Here \( m \) is another hyper-parameter, and obviously, when \( m \) is large enough, it will have little influence on the final result.

4.3 Centroid-based Subgraph Matching

After obtaining the candidate summaries (subgraphs) \( \mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_m\} \), we employ a centroid-based subgraph matching approach to select the best summary. The key idea is that the best summary should be semantically closest to the

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1[https://github.com/google-research/bert](https://github.com/google-research/bert)
Table 1: Statistics on CNN/Daily Mail and NYT dataset including average document length and reference summary length in terms of words and sentences, respectively.

| Dataset      | # Testset Doc | Document words | Document sentences | Summary words | Summary sentences |
|--------------|---------------|----------------|--------------------|---------------|------------------|
| CNN+DM       | 11,490        | 641.9          | 28.0              | 54.6          | 3.9              |
| NYT          | 3,452         | 800.04         | 35.55             | 45.54         | 2.44             |

document centroid, thus has the highest similarity among a set of candidate summaries.

In order to compare semantic similarity between candidate summaries and the document, we first embed the document $D$ and all candidates $\{C_1, C_2, \ldots, C_m\}$ into vector representations and then calculate their cosine similarities. We get the vector representation $e_c$ for a candidate summary $C$ by mean pooling over its nodes representations:

$$e_c = \frac{1}{|V_C|} \sum_{v_j \in V_C} e_j.$$  

Previous centroid-based methods (Radev et al., 2004; Rossiello et al., 2017) simply rely on the bag-of-words method and use the mean of sentence representations as document representation. We argue that this method could not fully utilize the sentence relation graph information since it ignores the graph connectivity. Instead, we use message passing architecture to update node representations and then transform it into a single feature vector with a readout function. All node embeddings from the sentence relation graph are grouped as the node feature matrix $E \in \mathbb{R}^{n \times d}$:

$$E = \begin{bmatrix}
- e_1 & - \\
- e_2 & - \\
\vdots & \vdots \\
- e_n & -
\end{bmatrix}$$  

Then we represent one-hop message passing on sentence relation graph $G$ by:

$$E^{(l)} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} E^{(l-1)},$$

where $A \in \mathbb{R}^{n \times n}$ is the adjacency matrix of the sentence relation graph, and $D$ is its corresponding diagonal matrix. $E^{(l)}$ represents the feature matrix after $l$ steps message passing, and the original feature matrix is $E^{(0)}$.

After $l$ rounds of message passing on the graph $G$, we get its representation $e_G$ with the following readout function:

$$e_G = \frac{1}{|V|} \sum_{v \in V} e_v + \alpha \cdot \max \left( e_1, \ldots, e_{|V|} \right),$$

where $\alpha$ is a hyper-parameter weighting the max-pooling term. The idea is to emphasize the key sentence updated representations in the document.

Finally, the semantic similarity between candidate summary $C_i$ and document $D$ is calculated by $\text{sim}(e_G, e_{C_i})$. We rank the summary candidates $C$ in reverse similarity order and select the candidate summary with highest similarity as the best summary. The corresponding sentences $\{s_1, s_2, \ldots, s_q\}$ of $C_{best}$ will be extracted as the final result.

### 4.4 Framework Pseudo-Code

Taken together, our two-staged approach operates in an unsupervised manner with no summary label requirement. Moreover, our approach treats summary as a whole and operates at a summary level, which naturally reduces the redundancy of the extracted summaries. The overall algorithm of ccSUM is described in Algorithm 1.

**Algorithm 1: ccSUM Algorithm**

```python
input : Sentence relation graph $G = (V, E)$
         its node feature matrix $E$
         its adjacency matrix $A$
         summary size $q$
output : Summary $O = \{s_1, s_2, \ldots, s_q\}$
1. Construct sentence relation graph $G = (V, E)$ based on document $D$;
2. for subgraph $C_i \subset G, |V_{C_i}| = q$ do
   3. calculate $SC(C_i)$
4. Rank subgraphs in descending $SC(C_i)$ order;
5. Select first $m$ subgraphs $C = \{C_1, C_2, \ldots, C_m\}$;
6. Update $E$: $E^{(l)} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} E^{(l-1)}$;
7. $e_G = \frac{1}{|V|} \sum_{v \in V} e_v + \alpha \cdot \max \left( e_1, \ldots, e_{|V|} \right)$;
8. for $C_i \in C$ do
   9. calculate $\text{sim}(e_G, e_{C_i})$
   10. if $\text{sim}(e_G, e_{C_i}) > \text{sim}(e_G, e_{C_{best}})$ then
       11. $C_{best} = C_i$
12. return corresponding sentences $\{s_1, s_2, \ldots, s_q\}$ of $C_{best}$
```
Table 2: ROUGE F1 results on CNN/DailyMail and NYT datasets (R1 and R2 are shorthands for unigram and bigram overlap; RL is the longest common subsequence).

| Method            | CNN/DM |       |       |       | NYT  |       |       |       |
|-------------------|--------|-------|-------|-------|------|-------|-------|-------|
|                   | R-1    | R-2   | R-L   |       | R-1  | R-2   | R-L   |       |
| ORACLE            | 52.6   | 32.2  | 48.9  |       | 64.0 | 43.5  | 60.70 |       |
| REFRESH           | 40.0   | 18.2  | 36.6  | 41.3  | 22.0 | 37.8  |       |       |
| POINTER-GENERATOR | 39.4   | 15.7  | 33.4  | 42.7  | 22.1 | 38.8  |       |       |
| LEAD-3            | 40.3   | 17.7  | 36.6  | 35.5  | 17.2 | 32.0  |       |       |
| CENTROID          | 34.1   | 12.4  | 30.2  | 33.8  | 13.4 | 29.7  |       |       |
| TEXT RANK         | 33.2   | 11.8  | 29.6  | 33.2  | 13.1 | 29.0  |       |       |
| PACSUM            | 40.7   | 17.8  | 36.9  | 41.4  | 21.7 | 37.5  |       |       |
| CC SUM            | 41.4   | 18.2  | 37.1  | 41.8  | 22.0 | 37.7  |       |       |

5 Experiment

In this section, we demonstrate our experimental setup to verify the effectiveness of our approach.

5.1 Datasets

We use two mainstream single-document summarization datasets CNN/Daily Mail and NYT for the experiment. Detailed statistics of these two datasets are shown in Table 1.

CNN/Daily Mail The CNN/Daily Mail question answering dataset (Hermann et al., 2015) is the most widely used benchmarked summarization dataset modified by (Nallapati et al., 2016b). It contains news articles sourced from both CNN and Daily Mail and uses the associated highlights as summaries. We followed the standard splits for training, validation, and testing splits used by supervised systems (90, 266/1, 220/1, 093 CNN documents and 196, 961/12, 148/10, 397 Daily Mail documents).

NYT NYT is another widely used single-document summarization dataset, which was collected from the New York Times Annotated Corpus (Sandhaus, 2008). It contains 110,540 news articles with abstractive summaries written by professional editors. Following (Durrett et al., 2016), we split the news articles into training, validation, and test with split (96, 834/4, 000/9, 706) and eliminate documents with summaries shorter than 50 words. The filtered test set (NYT50) includes 3, 452 examples.

5.2 Baseline Methods

We compare the performance of our model using ROUGE F1 scores (Lin and Hovy, 2003) with various baseline methods (supervised/unsupervised/extractive/abstractive):

LEAD3 LEAD3 (Narayan et al., 2018) is a simple but effective baseline in news summarization. It simply selects the first three sentences in each document as the summary.

ORACLE ORACLE is the oracle summary generated with a greedy algorithm (Nallapati et al., 2016a) to maximize the ROUGE score against the gold summary. It is the performance ceiling of extractive summarization methods and serves as an upper bound.

TEXT RANK TEXT RANK (Mihalcea and Tarau, 2004) is a popular centrality-based unsupervised summarization algorithm. It adopts PageRank (Brin and Page, 1998) to compute node centrality recursively based on a Markov chain model.

PAC SUM PAC SUM (Zheng and Lapata, 2019) is the state of the art unsupervised summarization model. It adopts BERT to encode sentence and build a directed text graph to model relative position of sentences in a document.

REFRESH REFRESH (Narayan et al., 2018) is an extractive summarization system that utilizes reinforcement learning (RL) to globally optimize the ROUGE metric. The application of RL provides a summary-level scoring and thus we can view REFRESH as a summary-level extractor.

POINTER-GENERATOR POINTER-GENERATOR (See et al., 2017) is an abstractive summarization system which can copy words from the source text with pointer network while producing novel words.
6 Results

6.1 Automatic Evaluation

We first evaluate summarization quality automatically using ROUGE F1 scores (Lin and Hovy, 2003). We evaluate summary informativeness with unigram and bigram overlap (ROUGE-1 and ROUGE-2) and summary fluency with the longest common subsequence (ROUGE-L).

Table 2 presents experimental results on both datasets. The results of baseline models are either adopted from the original papers or reported in (Zheng and Lapata, 2019). The first row shows the results of an extractive Oracle system as a performance upper bound. The following block in the table shows the results of supervised baselines, and the third block in the table shows the results of various unsupervised baselines and our method.

Table 3: Results of QA-based evaluation on CNN/Daily Mail and NYT datasets. Numbers in the table show the percentage of questions that participants answered correctly by reading system summaries.

| Method      | CNN/DM | NYT  |
|-------------|--------|------|
| ORACLE      | 53.9   | 64.2 |
| REFRESH     | 41.3   | 53.7 |
| LEAD-3      | 36.2   | 42.9 |
| CCSUM       | 40.7   | 51.4 |

The results of baseline models are either adopted from the original papers or reported in (Zheng and Lapata, 2019). The first row shows the results of an extractive Oracle system as a performance upper bound. The following block in the table shows the results of supervised baselines, and the third block in the table shows the results of various unsupervised baselines and our method.

Experimental results in the table prove the effectiveness of the proposed method. Specifically, our method outperforms all unsupervised baseline methods and achieves state-of-the-art performance in unsupervised extractive summarization. It can be noticed PACSUM is an extremely strong baseline, which outperforms other unsupervised methods by a huge margin with its directed text graph. We further improve its performance by transferring to a summary-level setting and matching with node representations.

As shown in the second block of the table, our method is even comparable to supervised methods trained on hundreds of thousands of document summary pairs (e.g., REFRESH and Pointer-Generator). This indicates that our graph model effectively captures the relation between sentences, which is significant and useful in the summarization task.

When comparing the results across datasets, it could be noticed that LEAD3 (Narayan et al., 2018) is extremely difficult to beat on CNN/DailyMail dataset but weaker on NYT dataset. This implies that CNN/DailyMail dataset is highly positional biased, and salient information is mostly concentrated at the beginning of a document. As shown in the table, our approach achieves state-of-the-art performance on both datasets, indicating our method effectively models both position features and semantic features of sentences in a document. This result agrees with the setting that the representation of a sentence $s_i$ in our method is $e_i = [r_i; p_i]$, the concatenation of its semantic representation from BERT and its positional information.

We also show the position (in the source document) of the sentences which were selected to appear in summary in Figure 2 on CNN/DailyMail dataset. From the distribution of ORACLE extraction summaries, we can further understand why textscLead-3 baseline performs so well on the dataset: over 36% of oracle sentences are extracted from the first three sentences. As a result, extractive summary systems can easily fall in positional bias and neglect the semantic meaning of sentences. Compared to ORACLE extractor, our method has a fairly similar distribution instead of mostly concentrating on the first few document sentences. This verifies that our method effectively models both position features and semantic features of sentences in a document.

6.2 Human Evaluation

In addition to automatic evaluation, we also evaluated system output by eliciting human judgments. Following previous works (Clarke and Lapata, 2010; Narayan et al., 2018; Liu and Lapata, 2019), evaluation experiments are performed under the same question answering (QA) paradigm, which quantifies the degree to which the output summaries retain key information from the document. A set of questions is created based on the gold summary, which highlights the most important document content. Participants will be asked to answer...
Table 4: ROUGE-1 F1 Score on NYT dataset with different hyper-parameter $\alpha$ values.

| $\alpha$ | ROUGE-1 F1 Score |
|----------|------------------|
| 0        | 40.5             |
| 0.1      | 40.8             |
| 0.2      | 41.4             |
| 0.4      | 41.3             |
| 1        | 40.4             |

these questions given only the output summaries of different models without access to the original article. We claim this QA-based paradigm is a summary-level evaluation of the informativeness of summaries.

We follow all the experimental settings from previous work (Clarke and Lapata, 2010; Narayan et al., 2018), so we omit the details here. For the CNN/DailyMail dataset, we used the same documents (20 in total) and questions (71 in total). For the NYT dataset, we did not find the questions in (Narayan et al., 2018) in public so we randomly selected 20 documents from the test set and created 63 questions in total. The human evaluation results (percentage of questions could be answered correctly given only summary) are shown in Table 3.

As shown in the table, even the ORACLE extractive system can only correctly (or partially correctly) answer about 50 percent of questions. This agrees with our claim that salient content needs to be captured in a summary-level since ORACLE is a sentence-level system that extracts sentences greedily by maximizing ROUGE score. Another interesting finding is that LEAD-3 has a relatively low score compared to its performance in ROUGE score. Our method ccSUM outperforms LEAD-3 by a large margin and achieves comparable scores with other baseline methods.

6.3 Hyper-parameter Analysis

We also study the influence of different hyper-parameters here. In our system, $\theta$ measures the threshold such that sentences with semantic similarity less than $\theta$ will be treated as unconnected nodes; $\beta$ measures the influence of forward and backward-looking edges, which distinguish the centrality contribution by previous sentences and succeeding sentences; $\alpha$ measures the influence of key sentence in the overall document representation.

As shown in Fig 3, $\theta$ has a large influence on the performance of our system. As $\theta$ increases from 0, performance improves as noisy edges are filtered from the graph. After $\theta$ reaches its optimal point, the model performance degrades dramatically if we keep increasing threshold $\theta$. This is due to the loss of informative edges and damage in graph connectivity. The results indicates the significance of sentence relation graph construction and extraction of valuable information from documents.

Regarding the edge influence factor $\beta$, it turns out that the optimal $\beta$ value is negative, which agrees with the conclusion in (Zheng and Lapata, 2019) that similarity with previous content actually hurts node centrality. We also empirically find hyper-parameter $\alpha$ has a slight influence on the output summary quality as shown in Table 4. The result shows that emphasizing the critical sentences also helps in generating more practical document-level presentation.

7 Conclusion

In this paper, we proposed a summary-level graph-based unsupervised document summarization system, ccSUM. Our method effectively utilizes both edge information (centrality) and node information (centroid) of the sentence relation graph. It first extracts the candidate summary as a subgraph and selects based on semantic similarity to the whole document. Experimental results on two benchmarked summarization datasets demonstrated the superiority of our approach against several strong baselines. Our method could be easily extended to multi-document summarization task and supervised setting with graph neural networks, which we would explore in future research.
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