HipoRank: Incorporating Hierarchical and Positional Information into Graph-based Unsupervised Long Document Extractive Summarization

Yue Dong*
MILA/McGill University
Montreal, QC, Canada
yue.dong2@mail.mcgill.ca

Andrei Romascanu*
MILA/McGill University
Montreal, QC, Canada
andrei.romascanu@mail.mcgill.ca

Jackie C. K. Cheung
MILA/McGill University
Montreal, QC, Canada
jcheung@cs.mcgill.ca

Abstract

We propose a novel graph-based ranking model for unsupervised extractive summarization of long documents. Graph-based ranking models typically represent documents as fully-connected graphs, where a node is a sentence, an edge is weighted based on sentence-pair similarity, and sentence importance is measured via node centrality. Our method leverages positional and hierarchical information grounded in discourse structure to augment a document’s graph representation with hierarchy and directionality. Experimental results on PubMed and arXiv datasets show that our approach outperforms strong unsupervised baselines by wide margins and performs comparably to some of the state-of-the-art supervised models that are trained on hundreds of thousands of examples. In addition, we find that our method provides comparable improvements with various distributional sentence representations; including BERT and RoBERTa models fine-tuned on sentence similarity.

1 Introduction

Single document summarization aims at shortening a text while preserving the most important ideas of the source document (Nenkova et al., 2011). Current approaches can be either abstractive or extractive. Abstractive models can generate summaries with novel words or phrases that are not present in the source document. In contrast, extractive methods generate summaries by copying text snippets directly from the source document. While abstractive models can be more concise and flexible, extractive models faithfully preserve the original text and are usually more fluent (Kryscinski et al., 2019).

Modern supervised neural network-based models have been proposed with extractive strategies (Nallapati et al., 2017; Dong et al., 2018; Zhou et al., 2018; Liu and Lapata, 2019; Narayan et al., 2018b; Zhang et al., 2019b); abstractive strategies (See et al., 2017; Chen and Bansal, 2018; Gehrmann et al., 2018; Dong et al., 2019; Zhang et al., 2019a; Lewis et al., 2019); and hybrid strategies (Hsu et al., 2018; Bae et al., 2019; Moroshko et al., 2019). These models have achieved promising performance on summarization of short news articles, such as CNN/DailyMail (Hermann et al., 2015), NYT (Sandhaus, 2008), Newsroom (Grusky et al., 2018) and XSum (Narayan et al., 2018a).

However, these neural network-based models face two significant challenges. First, they do not generalize across domains and require domain-specific, large-scale, high-quality training datasets that are not always available or feasible to create (Zheng and Lapata, 2019). This makes out-of-domain documents challenging to summarize. Second, the typical encoder-decoder with attention setup used by these models has limits on input length (Shao et al., 2017; Xiao and Carenini, 2019). This makes long documents with thousands of words challenging to summarize.

Unsupervised extractive approaches can help address these challenges, as they do not require domain-specific training datasets and typically do not have the same limits on document length (Radev et al., 2000; Lin and Hovy, 2002; Mihalcea and Tarau, 2004; Erkan and Radev, 2004; Wan, 2008; Han and Yang, 2008; Hirao et al., 2013; Parveen et al., 2015; Yin and Pei, 2015; Li et al., 2017; Zheng and Lapata, 2019). These include graph-based ranking algorithms such as LexRank (Erkan and Radev, 2004) and PACSUM (Zheng and Lapata, 2019), which represent sentences as graph nodes and similarities among sentences as weighted edges. Summaries are then formed by extracting sentences based on centrality (e.g. a proxy for importance based on the sum of incoming edge...
weights) in the resulting graph. While LexRank assumes similarity is symmetric and uses undirected edges (Erkan and Radev, 2004), PACSUM assumes earlier sentences in a document are more central and uses directed edges to capture this asymmetry. However, PACSUM faces two challenges which limit its ability to summarize long out-of-domain documents: 1) the lead positional bias is not as prevalent in other domains such as scientific writing; 2) the sentence-level graph representation fails to capture global and topical information found in longer structured documents (Xiao and Carenini, 2019).

Discourse structure can help address these issues and better identify important sentences in document summarization (Marcu, 1999). More specifically, Lin and Hovy (1997) show that discourse structure leads to positional preferences for important sentences in a document and confirm Baxendale (1958)'s hypothesis that important sentences occur at the start and end of paragraphs. Teufel (1997) re-contextualize these findings for scientific papers that are organized hierarchically, stating that peripheral paragraphs are more likely to contain crucial information in addition to the hypothesis of Baxendale (1958).

Based on these findings in paradigmatic discourse structure of scientific articles, we propose to incorporate discourse structures into graph-based summarization models by augmenting the measure of sentence centrality with: 1) boundary positional information: we propose a boundary positional function on the edge weights in the directed graph, assuming the contribution of one node to another depends on their relative position in the source document. This function injects boundary positional bias into the directed graph, where a sentence’s positional importance is weighted by how close it is to the text boundary. 2) hierarchical information: we propose a hierarchical graph structure to exploit sectional information by incorporating section-to-sentence similarities. This gives our model the ability to take both global and local topical information into consideration while constructing a graph with fewer edges.

We evaluate our approach on the summarization of long scientific articles from PubMed and arXiv (Cohan et al., 2018). Our experimental results show that augmenting sentence centrality with our boundary positional function and hierarchical information significantly improves the performance over previous state-of-the-art unsupervised models (Zheng and Lapata, 2019; Erkan and Radev, 2004). In addition, our simple unsupervised approach achieves performance comparable to state-of-the-art supervised neural models trained on hundreds of thousands of examples of long documents (Xiao and Carenini, 2019; Subramanian et al., 2019).

2 Related Work

2.1 Extractive Summarization

Traditional extractive summarization methods are mostly unsupervised, utilizing a notion of sentence importance based on n-gram overlap with other sentences and frequency information (Nenkova and Vanderwende, 2005), relying on graph-based methods for sentence ranking (Erkan and Radev, 2004; Mihalcea and Tarau, 2004), or performing keyword extraction combined with submodular maximization (Tixier et al., 2017; Shang et al., 2018).

These unsupervised approaches have been surpassed by neural-based models both in terms of performance and popularity, thanks to the availability of large-scale summarization datasets and advancements in deep learning. Cheng and Lapata (2016) first proposed a general CNN and RNN-based encoder-decoder architecture for extractive summarization, which established new state-of-the-art results over traditional methods on the Daily-Mail dataset. This encoder-decoder framework was widely adopted in later work with improvements on interpretability (Nallapati et al., 2017) and the optimization of evaluation metrics with reinforcement learning methods (Wu and Hu, 2018; Narayan et al., 2018b; Dong et al., 2018). More recently, extractive approaches leveraging transformer architectures (Vaswani et al., 2017) and their pretrained counterparts (Devlin et al., 2019) have achieved state-of-the-art performance on the CNN/DailyMail news benchmark dataset (Zhang et al., 2019b; Liu and Lapata, 2019; Zhong et al., 2019).

Conversely, pretrained transformer models also provide better sentence representations for unsupervised summarization methods. For instance, PACSUM (Zheng and Lapata, 2019), a directed graph-based unsupervised model that utilizes BERT-based sentence representations, achieved comparable performance to supervised models on the CNN/DailyMail and NYT datasets.
2.2 Extractive Summarization on Long Scientific Papers

Despite the success of deep neural-based models on news summarization, these approaches typically face challenges when applied to long documents, such as scientific articles. Furthermore, these approaches are often blind to the topical information resulting from the structured sections in scientific articles \cite{Xiao and Carenini, 2019}. Two recent neural-based supervised models address these issues. \cite{Subramanian et al, 2019} used the introduction section as a proxy for the whole document, while \cite{Xiao and Carenini, 2019} divided articles into sections and used non-auto-regressive approaches to model global and local information.

Besides neural-based approaches, most of the previous work on scientific article summarization employs traditional supervised machine learning algorithms with surface features as input \cite{Xiao and Carenini, 2019}. Surface features such as sentence position, sentence and document length, keyphrase score, and fine-grain rhetorical categories are often combined with Naïve Bayes \cite{Teufel and Moens, 2002}, CRFs and SVMs \cite{Liakata et al, 2013}, LSTM and MLP \cite{Collins et al, 2017} for extractive summarization over long scientific articles. To the best of our knowledge, the only unsupervised extractive summarization model for long scientific documents relies on citation networks \cite{Cohan and Goharian, 2015}, by extracting citation-contexts from reference articles and ranking these sentences to form the final summary.

3 Methodology

3.1 Undirected to Directed Graph: Injecting Boundary Positional Bias to Centrality

Graph-based ranking algorithms for summarization represent a document as a graph $G = (V, E)$, where $V$ is the set of vertices that represent sentences in the document and $E$ is the set of edges that represent interactions among sentences. The edge $e_{ij}$ between sentences $(v_i, v_j)$ is typically weighted by similarity $w_{ij} = f(sim(v_i, v_j))$. These algorithms select the most salient sentences based on centrality, with the assumption that central sentences are more similar with other sentences and thus capture more content.

Traditional graph-based summarization models \cite{Erkan and Radev, 2004, Mihalcea and Tarau, 2004} are often based on undirected graphs. By definition, the incoming edges and outgoing edges in undirected graphs are the same $e_{ij} = e_{ji}$ for all $i, j$. N-gram overlap \cite{Mihalcea and Tarau, 2004} or IDF-modified cosine similarity \cite{Erkan and Radev, 2004} are used as the similarity functions, combined with a symmetric identity function $I$ for weights: $w_{ij} = w_{ji} = I(sim(v_i, v_j))$. The centrality of a sentence is defined as the sum of all incoming edge weights: $c(s_i) = \sum_{j \not= i} w_{ij}$.

Undirected graph-based models are limited by the symmetry of $w_{ij} = w_{ji}$, which cannot distinguish the more important sentence between $v_i$ and $v_j$. \cite{Zheng and Lapata, 2019} use a directed graph to model the document, where the weights of $w_{ij}$ and $w_{ji}$ are asymmetric. Based on Rhetorical Structure Theory (RST), they assume earlier sentences in a document are more important. To capture this, their model gives higher weights to edges $w_{ij}$ where $i < j$.

This assumption that earlier sentences are more important works well for news summarization. In our work, we argue that this approach is not suitable for summarizing long scientific documents, due to their different discourse structure. Instead, we propose to determine a sentence’s relative importance from its distance to document and section boundaries, based on the discourse structure hypotheses proposed in \cite{Lin and Hovy, 1997, Teufel, 1997}. We formalize this as the boundary positional function $d_b$:

$$d_b(i) = \min(i, \alpha(n - i)) \quad (1)$$

where $n$ is the number of sentences in the text span we are considering (section or document) and $\alpha \in \mathbb{R}^+$ is a hyper-parameter that controls the relative importance of the start or end of a section or document.

The edge weights in our graph are then defined as:

$$w_{ij} = \begin{cases} \lambda_1 \times sim(v_i, v_j), & \text{if } d_b(i) < d_b(j) \\ \lambda_2 \times sim(v_i, v_j), & \text{if } d_b(i) \geq d_b(j) \end{cases} \quad (2)$$

where $\lambda_1 < \lambda_2$ and $\lambda_1 + \lambda_2 = 1$. Intuitively, case 1 describes the situation where sentence $i$ is closer to the text boundaries than sentence $j$.

The centrality of a sentence is then defined as:

$$c(s_i) = \sum_{j \not= i} w_{ij}$$
\[ c_b(s_i) = \sum_{d_b(m) < d_b(i)} w_{mi} + \sum_{d_b(j) \geq d_b(i)} w_{ji} \]
\[ = \lambda_1 \sum_{d_b(m) < d_b(i)} \text{sim}(v_i, v_m) + \lambda_2 \sum_{d_b(j) \geq d_b(i)} \text{sim}(v_i, v_j). \]  

(3)

Equation (3) reflects the first part of Teufel (1997)’s discourse structure hypothesis, where crucial information is more likely to appear in the start and end sentences of a text span. In the next section, we further expand centrality with hierarchical topical information.

3.2 Breaking the Fully-Connected Graph: Augmenting Hierarchical Structure to Centrality

In the graph-based ranking algorithm for summarization (Erkan and Radev 2004; Zheng and Lapata 2019), a fully-connected graph is built, such that similarities need to be computed for all sentence-pairs to calculate edge weights. The majority of these edges have small weights (weak edges), which makes it harder for the model to select important sentences (Erkan and Radev 2004). Although previous approaches adopted a post-processing pruning to set the weak edges’ weights to zero, it often has very limited improvement over the original setup (Erkan and Radev 2004).

We aim to leverage the topic information of long document sections to incorporate a meaningful hierarchy in the graph, breaking its fully-connectedness by creating fully-connected subgraphs for document sections.

Suppose document \( D \) has \( n \) sentences over \( T \) disjoint sections \( \{s_1, \ldots, s_{t_1}\}, \ldots, \{s_1^T, \ldots, s_{t_T}\} \). To minimize the amount of weak edges, our method only keeps intra-sectional sentence-to-sentence edges and discards all inter-sectional sentence-to-sentence edges.

In the sentence-to-section mechanism, the intra-sectional centrality of sentence \( s_i \in T_r \) is:

\[ c^\text{intra}_b(s_i) = \sum_{j \in T_r, j \neq i} w_{ij} / |T_r| \]
\[ = \lambda_1 \sum_{d_b(m) < d_b(i)} \text{sim}(v_i, v_m) + \lambda_2 \sum_{d_b(j) \geq d_b(i)} \text{sim}(v_i, v_j). \]  

(4)

The hierarchical information is added by including sentence-to-section connections (Equation 5). This adds the edge weights of sentence-to-section connections into the global sentence centrality computation (Equation 7), emphasizing that sentences that are similar to other sections should be more important. In addition, we also assume that the sentence-to-section edge weights depend on the section positions relative to the document boundaries.

The inter-sectional centrality of \( s_i \in T_r \) is computed as:

\[ c^\text{inter}_b(s_i) = \left( \sum_{j \in \{1, \ldots, t_r\}} w^\text{st}_{ij} \right) / T \]  

(5)

where \( w^\text{st}_{ij} \) is the edge weight of sentence \( s_i \) to \( t_j \) \((s_i \in t_r)\), which is computed as

\[ w^\text{st}_{ij} = \begin{cases} 
\lambda_1 * \text{sim}(s_i, t_j), & \text{if } d^b_b(t_j) < d^b_b(t_j) \\
\lambda_2 * \text{sim}(s_i, t_j), & \text{if } d^b_b(t_j) \geq d^b_b(t_j).
\end{cases} \]  

(6)

The global centrality of sentence \( s_i \) is computed by adding the intra-sectional sentence centrality \( c^\text{intra}_b(s_i) \) and sentence-to-section centrality \( c^\text{inter}_b(s_i) \) with a hyperparameter \( \mu_1 \in [0, 1] \):

\[ c^\text{global}_b(s_i) = c^\text{intra}_b(s_i) + \mu_1 * c^\text{inter}_b(s_i). \]  

(7)

The final summary is formed by selecting sentences iteratively with the highest global centrality score until we reach the predefined summary length.

\[ \text{The predefined summary length is decided based on the validation set. It is set to 203 tokens for PubMed and 220 tokens for arXiv in all our experiments.} \]
4 Experimental Setup

This section describes the datasets, the hyperparameter choices, the baseline models, and the evaluation metrics used in the experiments.

4.1 Datasets

Our experiments are conducted on PubMed and arXiv (Cohan et al., 2018), two large-scale datasets of long and structured scientific articles with abstracts as summaries. The average source article length is four to seven times longer than popular news benchmarks (Table 1), making them ideal candidates to test our method.

| Dataset  | # docs | avg. doc. len. | avg. summ. len. |
|----------|--------|----------------|-----------------|
| CNN      | 92K    | 656            | 43              |
| Daily Mail | 219K  | 693            | 52              |
| NYT      | 655K   | 530            | 38              |
| PubMed   | 133K   | 3,016          | 203             |
| arXiv    | 215K   | 4,938          | 220             |

Table 1: Dataset statistics on news articles (CNN, DailyMail, and NYT) and long scientific documents (PubMed and arXiv).

4.2 Implementation Details

Our model’s hyperparameters for testing are chosen based on our ablation study’s results with the validation sets. The test results are reported with the following hyperparameter settings: $\lambda_1 \in \{-0.2, 0, 0.5\}$, $\lambda_2 \in \{1.0\}$, $\alpha \in \{0.8, 1.0, 1.2\}$, $\mu_1 \in \{0.5, 1.0, 1.5\}$.

For each dataset, we experimented with different pretrained distributional sentence representation models. The dimension of sentence representations is model-dependent (details in Section 5.3). We used the publicly released BERT model (Devlin et al., 2019), PACSUM BERT model (Zheng and Lapata, 2019), SentBERT and SentRoBERTa (Reimers and Gurevych, 2019) and BioMed word2vec word representations (Moen and Ananiadou, 2013). A section’s representation is calculated as the average of its sentences’ representations. The similarity between sentences or sections is defined to be the cosine similarity between the distributed representations.

4.3 Baselines

We compare our approach with previous unsupervised and supervised models in extractive summarization. In addition, we also compare it with recent neural abstractive approaches for completeness.

For unsupervised extractive summarization models, we compare with SumBasic (Vanderwende et al., 2007), LSA (Steinberger and Jezek, 2004), LexRank (Erkan and Radev, 2004) and PACSUM (Zheng and Lapata, 2019). For supervised neural extractive summarization models, we compare with...
We evaluate our method with automatic evaluation metrics - ROUGE F1 scores (Lin, 2004). ROUGE-1 and ROUGE-2 compute unigram and bigram overlaps between system summaries and reference summaries, while ROUGE-L computes the longest common sub-sequence of the two.

In addition, we design a human evaluation experiment to compare our model with PACSUM (Zheng and Lapata, 2019). As far as we know, we are the first to perform human evaluation on the 2018 PubMed and arXiv datasets. We asked the human judges to read the reference summary (abstract) and present extracted sentences from different summarization systems in a random and anonymized order. The judges are asked to evaluate the system summary sentence according to two criteria: 1) content coverage (whether the presented sentence contains content from the abstract); and 2) importance (whether the presented sentence is important for a goal-oriented reader even if it isn’t in the abstract (Lin and Hovy, 1997)).

5 Results

In this section, we present the results of our model compared to baselines with respect to automatic evaluation (Section 5.1) and human evaluation (Section 5.2). We present the results of our model with different sentence and section embeddings in Section 5.3.

5.1 Automatic Evaluation Results

Tables 2 and 3 summarize our automatic evaluation results on the PubMed and arXiv corpora with the best hyperparameters, as described in Section 4.2.

The first blocks in the tables include the lead baseline and the oracle baseline. Oracle summaries are ob-
tained by greedily selecting sentences to optimize ROUGE-2 (Nallapati et al., 2017), which can be seen as an upper bound for system performance. These oracles are also used as extractive labels to train supervised models; this perhaps explains why unsupervised models generally have lower ROUGE-2 scores when compared with supervised models. The second and the third blocks in Tables 2 and 3 present the results of supervised abstractive and extractive models, which outperform abstractive models on long scientific documents.

The last blocks compare previous unsupervised models with our approach. Our model outperforms all other unsupervised approaches by wide margins in terms of ROUGE-1,2,L F1 scores on both PubMed and arXiv datasets. This gain is more pronounced on PubMed where the gap between our system and the best previous unsupervised model PACSUM (Zheng and Lapata, 2019) is (+3.79, +3.00, +3.22) ROUGE-1,-2,-L F1 points.

Interestingly, despite limited access to only the validation set examples for hyperparameter tuning, our best system performs comparably to supervised systems that are trained on hundreds of thousands of examples on ROUGE-L. On both datasets, our model significantly outperforms the abstractive baseline models. When compared with supervised extractive models, our model outperforms 3/5 and 4/5 supervised extractive models on PubMed and arXiv respectively in terms of ROUGE-L.

### 5.2 Human Evaluation

Table 4 presents the human evaluation results based on 20 sampled reference summaries with 281 system summary sentences based on the protocol described in Section 4.4. HipoRank is shown to be significantly better than PACSUM in terms of both content coverage (p=0.004) and importance (p=0.014), with high inter-annotator agreements (avg. 73.24%). These results indicate that the use of discourse structure to guide the graph construction with our proposed boundary function and hierarchy information improves summarization quality.

### 5.3 Results on Different Sentence and Section Embeddings

Table 5 shows the results of our model with different embedding methods. HipoRank performs consistently across different embedding methods, demonstrating the robustness of our proposed graph structure with boundary positional bias and hierarchical information. Moreover, if we compare across difference methods, sentence embeddings that are suitable for similarity computations such as PACSUM-BERT, SentBERT and SentRoBERTa do perform better than other choices.

### 6 Ablation Studies

In order to assess the relative contributions of the boundary positional function and the hierarchical information, we completed ablation studies on the PubMed validation set. In the controlled setting, we keep all the hyperparameters unchanged with respect to Section 4.2 and either vary the positional function or the hierarchical information.

The first block of Table 6 reports the ablation results with different positional functions: no positional function ((Erkan and Radev, 2004; Mihalcea and Tarau, 2004), lead bias function (Zheng and Lapata, 2019), and our proposed boundary function. We can see that using the wrong positional function hurts the model’s performance when comparing no positional function with lead bias function. Our boundary positional function outperforms the lead or no positional functions significantly.

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**Table 4:** Human evaluation results based on 20 sampled reference summaries with 281 system summary sentences. Each reference summary-sentence pair is annotated by two annotators with an average annotator agreement of 73.24%. The results are averaged across 127 sentences from HipoRank and 154 sentences from state-of-the-art unsupervised extractive summarization system PACSUM (Zheng and Lapata, 2019).

| Model         | ROUGE-1  | ROUGE-2  | ROUGE-L  |
|---------------|----------|----------|----------|
| Lead          |          |          |          |
| Oracle        |          |          |          |

**Table 5:** PubMed test set results with HipoRank framework and different pretrained sentence and section embeddings, all other hyperparameter settings are the same as in section 4.2.

| Model                          | ROUGE-1  | ROUGE-2  | ROUGE-L  |
|-------------------------------|----------|----------|----------|
| Lead                          |          |          |          |
| Oracle                        |          |          |          |

**Table 6:** HipoRank framework and different pretrained sentence embeddings, all other hyperparameter settings are the same as in section 4.2.

| Model                        | ROUGE-1  | ROUGE-2  | ROUGE-L  |
|------------------------------|----------|----------|----------|
| Random Embedding (d=200)     |          |          |          |
| Biomed-w2v (d=200)           |          |          |          |
| BERT (d=768)                 |          |          |          |
| PACSUM-BERT (d=768)          |          |          |          |
| SentBERT (d=768)             |          |          |          |
| SentRoBERTa (d=1024)         |          |          |          |
The second block of Table 6 reports the results with different hierarchical information with our boundary positional function. We observe that using a non-fully-connected graph with hierarchical information results in better performance than the flat fully-connected graph.

| Model                                           | ROUGE-1 | ROUGE-2 | ROUGE-L |
|-------------------------------------------------|---------|---------|---------|
| Various Position Centrality                     |         |         |         |
| +our hierarchical-add+fine-tune-bert+s=1.5      |         |         |         |
| lead                                            | 37.43   | 12.13   | 33.68   |
| undirected                                      | 40.66   | 13.41   | 36.55   |
| boundary-distance (ours)                        | **43.20** | **16.79** | **38.98** |
| Various Hierarchicall Centrality                |         |         |         |
| +our boundary-function+fine-tune-bert+s=0.5     |         |         |         |
| no-section-hierarchy                            | 41.88   | 15.39   | 37.91   |
| hierarchy-multiply (ours)                       | 43.04   | 16.76   | 38.77   |
| hierarchy-add (ours)                            | **43.42** | **16.76** | **39.23** |

Table 6: Results on the PubMed validation set with different positional function or different hierarchical information.

To further inspect the difference of our model vs. PACSUM, we plot the relative sentence positions each model chooses on PubMed and arXiv. Figure 2 shows that PACSUM is biased towards selecting sentences that appear at the beginning of the documents, while our model does the selection evenly across the article. The similar sentence position distributions between our model and the Oracle perhaps explain the superior performance of our model over PACSUM. We also notice the performance improvement of our model over other approaches is consistent across different hyperparameter settings (Figure 3).

7 Conclusion

In this paper, we propose an unsupervised graph-based model for long scientific document summarization. The proposed approach augments the measure of sentence centrality by inserting directionality and hierarchy in the graph with boundary positional functions and hierarchical topic information grounded in discourse structure. Our simple unsupervised approach outperforms previous unsupervised graph-based summarization models by wide margins and achieves comparable performance to state-of-the-art supervised neural models trained on hundreds of thousands of examples. This makes our model a lightweight but strong baseline for assessing the performance of expensive supervised approaches for long scientific document summarization.
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References
Sanghwan Bae, Taeuk Kim, Jihoon Kim, and Sang-goo Lee. 2019. Summary level training of sentence rewriting for abstractive summarization. In Proceedings of the 2nd Workshop on New Frontiers in Summarization, pages 10–20.

Phyllis B Baxendale. 1958. Machine-made index for technical literaturean experiment. IBM Journal of research and development, 2(4):354–361.

Yen-Chun Chen and Mohit Bansal. 2018. Fast abstractive summarization with reinforce-selected sentence rewriting. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 675–686.

Jianpeng Cheng and Mirella Lapata. 2016. Neural summarization by extracting sentences and words. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 484–494, Berlin, Germany. Association for Computational Linguistics.

Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. A discourse-aware attention model for abstractive summarization of long documents. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 615–621.

Arman Cohan and Nazli Goharian. 2015. Scientific article summarization using citation-context and article’s discourse structure. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 390–400, Lisbon, Portugal. Association for Computational Linguistics.

Edward Collins, Isabelle Augenstein, and Sebastian Riedel. 2017. A supervised approach to extractive summarisation of scientific papers. In Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017), pages 195–205.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In Advances in Neural Information Processing Systems, pages 13042–13054.

Yue Dong, Yikang Shen, Eric Crawford, Herke van Hoof, and Jackie Chi Kit Cheung. 2018. Bandit-sum: Extractive summarization as a contextual bandit. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3739–3748.

Günes Erkan and Dragomir R Radev. 2004. Lexrank: Graph-based lexical centrality as salience in text summarization. Journal of artificial intelligence research, 22:457–479.

Sebastian Gehrmann, Yuntian Deng, and Alexander M Rush. 2018. Bottom-up abstractive summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4098–4109.

Max Grusky, Mor Naaman, and Yoav Artzi. 2018. Newsroom: A dataset of 1.3 million summaries with diverse extractive strategies. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 708–719.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In Advances in neural information processing systems, pages 1693–1701.

Tsutomu Hirao, Yasuhiisa Yoshida, Masaaki Nishino, Norihito Yasuda, and Masaaki Nagata. 2013. Single-document summarization as a tree knapsack problem. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1515–1520, Seattle, Washington, USA. Association for Computational Linguistics.

Wan-Ting Hsu, Chieh-Kai Lin, Ming-Ying Lee, Kerui Min, Jing Tang, and Min Sun. 2018. A unified model for extractive and abstractive summarization using inconsistency loss. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 132–141, Melbourne, Australia. Association for Computational Linguistics.

Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. Evaluating the factual consistency of abstractive text summarization.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.
Piji Li, Zihao Wang, Wai Lam, Zhaochun Ren, and Lidong Bing. 2017. Salience estimation via variational auto-encoders for multi-document summarization. In *Thirty-First AAAI Conference on Artificial Intelligence*.

Maria Liakata, Simon Dobnik, Shyamasree Saha, Colin Batchelor, and Dietrich Rebholz-Schuhmann. 2013. A discourse-driven content model for summarising scientific articles evaluated in a complex question answering task. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 747–757, Seattle, Washington, USA. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Chin-Yew Lin and Eduard Hovy. 1997. Identifying topics by position. In *Fifth Conference on Applied Natural Language Processing*, pages 283–290.

Chin-Yew Lin and Eduard Hovy. 2002. From single to multi-document summarization. In *Proceedings of the 40th annual meeting of the association for computational linguistics*, pages 457–464.

Yang Liu and Mirella Lapata. 2019. Text summarization with pretrained encoders. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3721–3731.

Daniel Marcu. 1999. Discourse trees are good indicators of importance in text. *Advances in automatic text summarization*, 293:123–136.

Rada Mihalcea and Paul Tarau. 2004. Textrank: Bringing order into text. In *Proceedings of the 2004 conference on empirical methods in natural language processing*, pages 404–411.

SPFGH Moen and Tapio Salakoski2 Sophia Ananiadou. 2013. Distributional semantics resources for biomedical text processing. *Proceddings of LBM*, pages 39–44.

Edward Moroshko, Guy Feigenblat, Haggai Roitman, and David Konopnicki. 2019. An editorial network for enhanced document summarization. In *Proceedings of the 2nd Workshop on New Frontiers in Summarization*, pages 57–63.

Ramesh Nallapati, Feifei Zhai, and Bowen Zhou. 2017. Summarunner: a recurrent neural network based sequence model for extractive summarization of documents. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, pages 3075–3081.

Ramesh Nallapati, Bowen Zhou, Cicero dos Santos, Çağlar Gulçehre, and Bing Xiang. 2016. Abstractive text summarization using sequence-to-sequence RNNs and beyond. In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 280–290, Berlin, Germany. Association for Computational Linguistics.

Shashi Narayan, Shay B Cohen, and Mirella Lapata. 2018a. Dont give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807.

Shashi Narayan, Shay B Cohen, and Mirella Lapata. 2018b. Ranking sentences for extractive summarization with reinforcement learning. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1747–1759.

Ani Nenkova, Kathleen McKeown, et al. 2011. Automatic summarization. *Foundations and Trends® in Information Retrieval*, 5(2–3):103–233.

Ani Nenkova and Lucy Vanderwende. 2005. The impact of frequency on summarization.

Daraksha Parveen, Hans-Martin Ramsl, and Michael Strube. 2015. Topical coherence for graph-based extractive summarization. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1949–1954.

Dragomir R. Radev, Hongyan Jing, and Malgorzata Budzикowska. 2000. Centroid-based summarization of multiple documents: sentence extraction, utility-based evaluation, and user studies. In *NAACL-ANLP 2000 Workshop: Automatic Summarization*.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks.

Evan Sandhaus. 2008. The new york times annotated corpus. *Linguistic Data Consortium, Philadelphia*, 6(12):e26752.

Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083.

Guokan Shang, Wensi Ding, Zekun Zhang, Antoine Tixier, Polykarpas Meladianos, Michalis Vazirgiannis, and Jean-Pierre Lorré. 2018. Unsupervised abstractive meeting summarization with multi-sentence compression and budgeted submodular maximization. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 664–674.
Yuanlong Shao, Stephan Gouws, Denny Britz, Anna Goldie, Brian Strope, and Ray Kurzweil. 2017. Generating high-quality and informative conversation responses with sequence-to-sequence models. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2210–2219.

Josef Steinberger and Karel Jezek. 2004. Using latent semantic analysis in text summarization and summary evaluation. Proc. ISIM, 4:93–100.

Sandeep Subramanian, Raymond Li, Jonathan Pilaault, and Christopher Pal. 2019. On extractive and abstractive neural document summarization with transformer language models. arXiv preprint arXiv:1909.03186.

Simone Teufel. 1997. Sentence extraction as a classification task. In Intelligent Scalable Text Summarization.

Simone Teufel and Marc Moens. 2002. Summarizing scientific articles: experiments with relevance and rhetorical status. Computational linguistics, 28(4):409–445.

Antoine Tixier, Polykarpos Meladianos, and Michalis Vazirgiannis. 2017. Combining graph degeneracy and submodularity for unsupervised extractive summarization. In Proceedings of the workshop on new frontiers in summarization, pages 48–58.

Lucy Vanderwende, Hisami Suzuki, Chris Brockett, and Ani Nenkova. 2007. Beyond sumbasic: Task-focused summarization with sentence simplification and lexical expansion. Information Processing & Management, 43(6):1606–1618.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Xiaojun Wan. 2008. An exploration of document impact on graph-based multi-document summarization. In Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pages 755–762, Honolulu, Hawaii. Association for Computational Linguistics.

Xiaojun Wan and Jianwu Yang. 2008. Multi-document summarization using cluster-based link analysis. In Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval, pages 299–306.

Yuxiang Wu and Baotian Hu. 2018. Learning to extract coherent summary via deep reinforcement learning. In Thirty-Second AAAI Conference on Artificial Intelligence.

Wen Xiao and Giuseppe Carenini. 2019. Extractive summarization of long documents by combining global and local context. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3002–3012.

Wenpeng Yin and Yulong Pei. 2015. Optimizing sentence modeling and selection for document summarization. In Twenty-Fourth International Joint Conference on Artificial Intelligence.

Jinqing Zhang, Yao Zhao, Mohammad Saleh, and Peter J Liu. 2019a. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. arXiv preprint arXiv:1912.08777.

Xingxing Zhang, Furu Wei, and Ming Zhou. 2019b. Hibert: Document level pre-training of hierarchical bidirectional transformers for document summarization. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5059–5069.

Hao Zheng and Mirella Lapata. 2019. Sentence centrality revisited for unsupervised summarization. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6236–6247.

Ming Zhong, Pengfei Liu, Dunqing Wang, Xiaopeng Qiu, and Xuan-Jing Huang. 2019. Searching for effective neural extractive summarization: What works and what next. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1049–1058.

Qingyu Zhou, Nan Yang, Furu Wei, Shaohan Huang, Ming Zhou, and Tiejun Zhao. 2018. Neural document summarization by jointly learning to score and select sentences. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 654–663.