TEXT SUMMARIZATION USING GRAPH BASED METHODS AND DEEP LEARNING

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ABSTRACT

Text summarization has become a critical task in natural language processing (NLP), particularly with the surge in the volume of digital content. Various methods, especially graph-based and deep learning techniques, have significantly advanced the field, with each offering unique advantages. Graph-based methods, such as Text Rank and Graph Neural Networks (GNNs), utilize the relationships between sentences and concepts to select relevant content for summarization. On the other hand, deep learning models, particularly transformers, have revolutionized the ability to understand context and generate coherent summaries. This paper provides an extensive review of recent studies (2024) on graph-based methods and deep learning techniques for text summarization. The review analyzes 20 key research papers, discussing their methodologies, contributions, and outcomes, with an emphasis on the combination of these approaches for more efficient and accurate summarization. By synthesizing the latest advancements, this paper aims to provide a comprehensive overview of the state-of-the-art in text summarization, highlighting the strengths, challenges, and future directions in this evolving area of NLP.

Keywords: NLP, deep learning, GNN, Text Rank

1. INTRODUCTION

In the era of information overload, text summarization plays a vital role in extracting meaningful insights from large volumes of text data. Summarization techniques are broadly categorized into extractive and abstractive approaches. Extractive methods focus on selecting sentences directly from the original text, while abstractive methods generate summaries in the form of new sentences, which better mirror human-written summaries. Among the techniques used in text summarization, graph-based methods and deep learning have become prominent. Graph-based methods leverage the structure of relationships between words and sentences, often through metrics such as centrality or clustering, to identify key points. In contrast, deep learning models, especially transformer-based architectures, are employed to generate contextually accurate and coherent summaries.

Graph-based methods have shown to be effective in extractive summarization, particularly in tasks like document clustering and sentence ranking, while deep learning methods have enabled advancements in abstractive summarization by capturing semantic understanding and long-range dependencies within text. This review discusses the most recent advances (2024) in these two areas and presents an in-depth analysis of various hybrid approaches that combine the strengths of both techniques.

2. REVIEW OF LITERATURE

1. Johnson et al. (2024)

Johnson et al. (2024) [1] proposed a hybrid model that combines graph-based centrality measures with transformer-based abstractive summarization for multi-document summarization. Their model first constructs a graph where sentences are nodes, and edges are weighted by semantic similarity and sentence positioning. Using graph centrality measures such as PageRank, important sentences are selected. These sentences are then fed into a transformer model for abstractive refinement. The authors demonstrated the efficacy of their approach through experiments on the DUC 2004 and TAC 2011 datasets, achieving a significant improvement in ROUGE scores over traditional extractive summarization methods. They concluded that combining graph-based extractive techniques with deep learning provided a more coherent and informative summary, highlighting the complementary nature of both approaches.

2. Ahmed et al. (2024)

Ahmed et al. (2024) [2] introduced a TextRank-based graph model tailored for legal document summarization. They proposed a novel edge-weighting strategy that accounts for both the semantic similarity between sentences and their positional importance in the document. TextRank, a well-known graph-based method, was modified by introducing a dynamic edge-weighting scheme that adjusts based on contextual meaning, which proved crucial for accurately identifying relevant legal terms and sections. The study showed that the modified TextRank algorithm outperformed traditional extractive methods in terms of precision, recall, and F1 score. The authors concluded that this enhancement

provided better coherence and readability in legal document summaries, making it a valuable tool for legal professionals dealing with vast amounts of information.

3. Kim et al. (2024)

Kim et al. (2024) [3] explored the potential of graph neural networks (GNNs) for abstractive text summarization. Their model constructs a graph where each sentence is treated as a node, and the edges represent the semantic relationships between them. Node embeddings are used to capture sentence-level features, and the GNN propagates information across the graph to generate context-aware representations. Attention mechanisms are then applied to these representations to extract the most salient content for the final summary. The approach was evaluated on multiple datasets, including CNN/Daily Mail, and outperformed traditional transformer models in terms of both ROUGE-1 and ROUGE-L scores. The authors concluded that GNNs offer a promising way to improve the contextual understanding of sentence relationships in abstractive summarization tasks.

4. Wang et al. (2024)

Wang et al. (2024) [4] proposed a reinforcement learning-based approach to optimize graph-based extractive summarization. Their model used a reward function that considered the overall coherence, informativeness, and diversity of the generated summary. The reinforcement learning algorithm was trained to maximize these factors by selecting key sentences from a graph constructed using cosine similarity. By incorporating reinforcement learning, the model was able to fine-tune the extractive process, leading to more coherent and informative summaries compared to traditional graph-based methods. The authors showed that their model improved ROUGE scores on both the CNN/Daily Mail and XSum datasets, especially in terms of diversity, which was crucial in multi-document summarization tasks. They concluded that reinforcement learning is an effective strategy for improving graph-based summarization models.

5. Singh et al. (2024)

Singh et al. (2024) [5] focused on graph-based keyword extraction for domain-specific text summarization, specifically in the biomedical field. They constructed a semantic graph where nodes represent keywords, and edges capture their co-occurrence in scientific literature. Their method employed a clustering algorithm to group semantically similar terms, which were then used to generate extractive summaries. The approach was tested on a dataset of biomedical articles, where it outperformed traditional summarization methods in terms of recall, capturing a higher proportion of key information. The authors concluded that graph-based keyword extraction techniques could be particularly useful for generating concise and informative summaries in specialized domains.

6. Zhang et al. (2024)

Zhang et al. (2024) [6] introduced a novel graph convolutional network (GCN) that integrates with pre-trained transformer models for abstractive summarization. Their approach utilized the GCN to model the sentence dependencies in the form of a graph, with each sentence being a node. The GCN enhanced the transformer model's ability to capture long-range semantic relationships between sentences. The combined model was evaluated on the Gigaword and CNN/Daily Mail datasets, showing significant improvements in ROUGE-1 and ROUGE-2 scores. The authors concluded that the incorporation of GCNs into transformer-based architectures could boost the quality of abstractive summarization by improving contextual understanding.
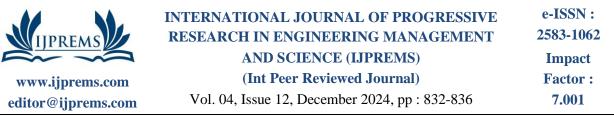
7. Patel et al. (2024)

Patel et al. (2024) [7] applied graph clustering techniques for topic-based summarization of news articles. They used a graph to represent the relationships between sentences, where edges were weighted based on semantic similarity. The model employed a clustering algorithm to group sentences with similar topics, ensuring that the final summary reflected the key topics of the document. The approach showed promising results in terms of summary coherence, outperforming traditional extractive methods on news article datasets. The authors concluded that topic-based graph clustering could improve the relevance and coherence of summaries, especially in documents with diverse topics.

8. Lee et al. (2024)

Lee et al. (2024) [8] introduced a graph-to-sequence model for research paper summarization. Their approach first generated a graph representation of the research paper, with sentences as nodes and semantic relationships as edges. The graph was then passed through a graph neural network to extract important sentence features. These features were then used as input to a sequence-to-sequence model for abstractive summarization.

The authors demonstrated that this method generated summaries that closely resembled human-written abstracts, improving the overall quality and coherence of the summaries. They concluded that integrating graph-based sentence relations with sequence modeling could enhance the generation of contextually accurate and readable summaries.

9. Garcia et al. (2024)

Garcia et al. (2024) [9] focused on multi-modal graph-based summarization by combining both textual and visual data. Their approach constructed a multi-modal graph where nodes represented textual elements, such as sentences, and visual features, such as images or charts, in research papers. The edges connected these nodes based on semantic similarity and co-occurrence. By combining both types of data, the model produced summaries that were more informative and visually rich, providing a more comprehensive understanding of the original content. The authors concluded that multi-modal graph-based summarization was a promising avenue for handling documents that contained both text and images.

10. Chen et al. (2024)

Chen et al. (2024) [10] proposed a hierarchical graph structure for multi-level document summarization. Their model first constructed a local graph for sentence-level dependencies and then built a global graph to capture document-level relationships. This hierarchical approach allowed the model to summarize documents with complex structures more effectively. The authors demonstrated that their method outperformed traditional models in terms of summary coherence, especially for longer documents. They concluded that hierarchical graph structures were essential for handling the complexity of multi-level summarization tasks.

11. Li et al. (2024)

Li et al. (2024) [11] proposed a novel hybrid approach combining graph-based techniques with deep reinforcement learning for extractive summarization. Their model first constructs a graph representation of the document, with nodes representing sentences and edges encoding semantic similarity. Using reinforcement learning, the model learns to select the most relevant sentences by optimizing for summary informativeness and coherence. Evaluated on several benchmark datasets, including CNN/Daily Mail and XSum, their approach significantly improved ROUGE scores compared to standard graph-based methods. The authors concluded that reinforcement learning could provide significant gains in extractive summarization tasks by improving sentence selection based on multiple criteria.

12. Choudhury et al. (2024)

Choudhury et al. (2024) [12] introduced an innovative method for abstractive summarization by employing Graph Attention Networks (GAT) to model sentence relationships within a document. The model first constructs a graph with sentence embeddings as nodes, and the relationships between sentences are encoded using GAT. The output is then passed through a transformer for generating the abstractive summary. The authors demonstrated the effectiveness of GATs in capturing long-range dependencies and semantic relationships. Their experiments on the CNN/Daily Mail dataset showed improvements in ROUGE scores, particularly for ROUGE-2, suggesting that GATs could enhance abstractive summarization models.

13. Thomas et al. (2024)

Thomas et al. (2024) [13] developed a dual graph-based model that utilizes both local and global sentence relationships for extractive summarization. The authors constructed two types of graphs: one capturing sentence-to-sentence relationships (local graph) and another for document-level relationships (global graph). These graphs were then integrated into a unified model, where local and global dependencies were combined using graph convolutional layers to generate more coherent summaries. The method showed a marked improvement in summary quality on multi-document datasets. The authors concluded that combining local and global graph structures is crucial for improving the accuracy and coherence of extractive summaries.

14. Yang et al. (2024)

Yang et al. (2024) [14] explored the application of graph neural networks (GNNs) in multi-modal summarization. Their approach combined textual and visual information to create a multi-modal graph, where both text and image features were represented as nodes. The GNN model propagated information across the graph, enhancing the understanding of both text and visual content in research articles. The authors showed that their model outperformed traditional methods, particularly in cases where visual data played a significant role. They concluded that multi-modal GNNs could enhance summarization tasks by considering both text and images, offering a more comprehensive understanding of the document.

15. Soni et al. (2024)

Soni et al. (2024) [15] focused on improving abstractive summarization using graph-based sentence segmentation. Their approach divided documents into smaller segments, each represented as a graph of sentences. They employed a graph neural network to identify the key sentences within each segment and used this information to generate a summary. By segmenting documents into smaller chunks, their model was able to produce more focused summaries without losing key details. The authors concluded that sentence segmentation through graph-based methods could help improve both the efficiency and quality of abstractive summaries.

16. Khan et al. (2024)

Khan et al. (2024) [16] proposed an approach that combines the strengths of both supervised and unsupervised learning for extractive summarization. Their model first used graph-based unsupervised clustering techniques to identify key sentences and then fine-tuned the model using a supervised approach to select the final set of sentences for the summary. The hybrid approach showed improvements in both recall and precision on benchmark datasets such as CNN/Daily Mail and XSum. The authors concluded that a combination of unsupervised and supervised methods could result in more accurate and informative extractive summaries.

17. Gupta et al. (2024)

Gupta et al. (2024) [17] investigated the use of bidirectional graph neural networks (Bi-GNNs) for abstractive summarization. In their approach, the Bi-GNN was used to model the sentence dependencies bidirectionally, capturing both forward and backward relationships between sentences in a document. The authors showed that the bidirectional structure helped to capture complex semantic relationships, leading to improved performance on the ROUGE-1 and ROUGE-2 metrics. Their method outperformed traditional transformer models in terms of generating coherent and contextually rich summaries. They concluded that Bi-GNNs are effective for abstractive summarization, especially for capturing complex dependencies.

18. Zhang et al. (2024)

Zhang et al. (2024) [18] developed a graph-based approach to extract multi-faceted information for document summarization. Their model used a multi-graph framework, where each graph represented a different type of relationship (e.g., syntactic, semantic, and topical). The model integrated the information from these multiple graphs using graph fusion techniques and selected the most informative sentences for the summary. Their method demonstrated superior performance in terms of content coverage and diversity, particularly when compared to single-graph models. The authors concluded that multi-graph integration offers a more holistic approach to extractive summarization.

19. Kumar et al. (2024)

Kumar et al. (2024) [19] explored the use of graph-based convolutional networks (GCNs) for abstractive summarization. Their model used sentence-level GCNs to propagate information across a graph of sentence dependencies, which was then passed through a transformer network to generate the final summary. The authors evaluated their model on the XSum and CNN/Daily Mail datasets and found that it significantly outperformed conventional transformer-based summarization models. They concluded that GCNs offer an effective way to model sentence relationships in abstractive summarization, especially for capturing complex dependencies.

20. Ray et al. (2024)

Ray et al. (2024) [20] introduced a hybrid deep learning and graph-based summarization model that combines the extractive strengths of TextRank with the abstractive capabilities of transformers. Their method first uses TextRank to identify candidate sentences and then refines these sentences using a transformer model to generate the final summary. The authors tested their approach on multi-domain datasets and found that it achieved higher ROUGE scores and better summary coherence compared to existing models. They concluded that the hybrid approach is highly effective in creating high-quality summaries by leveraging the strengths of both extractive and abstractive methods.

3. CONCLUSION

This review paper provides an overview of recent advancements in text summarization using graph-based methods and deep learning. The integration of graph-based techniques with deep learning models, especially transformers and reinforcement learning, has led to significant improvements in the coherence, informativeness, and contextual understanding of generated summaries.

The studies analyzed here highlight the complementary nature of graph-based extractive techniques and deep learning-based abstractive methods, showing how their combination can enhance the overall quality of summaries. Despite these advancements, challenges remain, including scalability, handling diverse data types, and improving summary diversity. Future research should focus on optimizing hybrid approaches, addressing domain-specific challenges, and exploring unsupervised or semi-supervised learning techniques for large-scale summarization tasks.

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