Summer internship report on

Text Summarization

submitted by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in this report entitled **"TEXT SUMMARIZATION"** in the Department of Computer Science and Engineering of the National Institute of Technology Hamirpur, is an authentic record of my work carried out during a period from __May 2023 to __July 2023 under the supervision of **Dr. Jyoti Srivastava** Assistant Professor, Department of Computer Science and Engineering, National Institute of Technology Hamirpur.

Hardik Sharma

This is to certify that the above statement made by the candidate is correct to the best of myknowledge.

Dr. Jyoti Srivastava

Date: **(Supervisor)**

HoD CSE **TPO Signature**

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ABSTRACT

In this project, my main focus was on generating summaries for a publicly available BBC News dataset on Kaggle. Text summarization is a critical technique used to condense large amounts of information into a concise form by selecting important details and eliminating redundant information. As the volume of textual data on the web continues to grow, text summarization has become increasingly important.

Specifically, I worked on graph based extractive summarization, a widely adopted approach in automatic text summarization research. This method involves selecting and using existing sentences from the document as summaries, which is valued for its simplicity and efficiency.

To achieve this, I applied the Glove vectorization technique to convert text into numerical representations. Next, I used cosine similarity to calculate the similarity matrix, which helped in identifying relationships between sentences. By leveraging the PageRank algorithm, I constructed a graph that ranked the sentences based on their importance. Using this ranking, I generated the final summary.

The results of our approach were promising, with an average Rouge-1 F1 score of 0.76, Rouge-2 F1 score of 0.68, Rouge-1 recall score of 0.78, and Rouge-2 recall score of 0.73 for our data. These scores indicate the effectiveness of our summarization method in capturing essential information from the source documents.

Chapter 1

INTRODUCTION

1.1 Background

The BBC News dataset available on Kaggle is a multi document collection comprising 2,224 newsarticles sourced from the BBC News website. These articles are classified into various categories such as sports, business, entertainment, technology, and politics. This dataset serves as a valuable resource for natural language processing tasks, including text classification, sentiment analysis, topic modeling, and more. Researchers and data scientists often utilize this dataset to develop machine learning models that can automatically categorize news articles, extract insights, and understand the distribution of content across different topics.

1.2 Text Summarization

Text summarization is the process of automatically generating a concise and coherent summary of a longer document or piece of text. It aims to capture the main points, key ideas, and essential information from the original text and present it in a shorter form. Headline generation is also a part of it which includes could be seen as a single line summary.

1.2.1 Extractive Text Summarization

Extractive text summarization is a technique that involves selecting and assembling important sentences or phrases from a given text to create a summary. It differs from abstractive summarization, where new sentences are generated. In extractive summarization, the aim is to preserve the original wording while condensing the information.

The main types of extractive text summarization techniques:

Topic Based Methods: These methods rely on identifying a document's topic which is its main subject (i.e. what the document is about). Some of the most common methods for topic representations are Term Frequency, Term Frequency-Inverse Document Frequency (TF-IDF), lexical chains, topic word approaches in which the topic representation consists of a simple table and their corresponding weights (Nenkova & McKeown, 2012), etc.

Concept-Based Methods: These methods extract concepts from a piece of text from external knowledge bases like WordNet (Miller, 1995; WordNet: An Electronic Lexical Database, 1998), HowNet, Wikipedia, etc. The importance of sentences is then calculated based on the concepts retrieved from the external knowledge base HowNet instead of words.

Machine Learning-Based Methods: These methods convert the summarization problem to a supervised classification problem at the sentence level. The system learns by examples to classify each sentence of the test document either as ‘‘summary” or ‘‘non-summary” class using a training set of documents (i.e. a collection of documents and their respective human-generated summaries). For the machine-learning-based summarizer, the sentence scoring steps include (Moratanch & Chitrakala, 2017)

Graph-Based Methods: Graph-based methods involve representing the text as a graph, where sentences are nodes, and the relationships between sentences are represented by edges. The graph can be constructed using various techniques such as sentence similarity metrics, word co-occurrence, or semantic relationships. The importance of each sentence is calculated based on centrality measures (e.g., PageRank, degree centrality) or graph algorithms (e.g., TextRank, LexRank, PageRank). Sentences with higher importance scores are chosen for the summary. Graph-based methods can capture the global structure and context of the text, leading to more robust summaries.

1.2.2 Abstractive Text Summarization

Abstractive text summarization is a technique used in natural language processing (NLP) to

generate a concise summary of a given text while capturing the key information and main ideas. Unlike extractive summarization, which selects and rearranges sentences from the original text, abstractive summarization aims to generate new sentences that may not appear in the source text but convey the same meaning.

There are different types of abstractive text summarization techniques:

Tree Based Methods These methods identify similar sentences that share mutual information then accumulate these sentences to produce the abstractive summary (Gupta et al., 2019). The similar sentences are represented into a tree-like structure. Parsers are used to construct the dependency trees which are the most used tree-form representations for the text. To create the final summaries, some tasks are performed to process the trees like pruning, linearization (i.e. converting trees to strings), etc.

Rule-Based Methods: These methods require defining the rules and categories to discover the important concepts in the input text then use these concepts to produce the summary. The steps of using this method include:
1) categorize the input text based on the terms and concepts existing in it
2) formulate the questions based on the domain of the input text
3) answer the questions by finding the terms and concepts in the text
4) fed the answers into some patterns to produce the abstractive summary.

Deep-Learning-Based Methods: Seq2seq has achieved great success in various NLP tasks like machine translation, voice recognition, and dialogue systems (Wang et al., 2017). A set of RNN models based on attention encoder-decoder achieves promising results for short text summarization. The steps of the summarization system include:
1) Converting the dataset into plain texts and saving the original documents (e.g. news articles) and their summaries separately
2) Applying word segmentation then using a subword model to process the data
3) Initializing the word vectors using the pre-trained Gensim toolkit (Rehurek & Sojka, 2010) that will be further trained in the proposed model
4) Using Tensorflow for implementation with one layer of bidirectional Long Short-Term Memory (LSTM) for the encoder and a unidirectional LSTM layer for the decoder.

1.2.3 Types of Text Summarization according to Domain

Legal Documents Summarization

Kavila et al. propose an ATS system and an automatic search system for legal documents to save the time of legal experts. The summarization task identifies the rhetorical roles presenting the sentences of a legal judgment document. The search task identifies the related past cases based on the given legal query. The hybrid system uses different techniques such as keyword or key phrase matching technique and the case-based technique.

Biomedical Documents Summarization:

Menéndez et al. propose an ATS system that combines genetic clustering and graph connectivity information to improve the graph-based summarization process. Genetic clustering identifies the different topics in a document, and connectivity information (i.e. degree centrality) shows the importance of the different topics

Books Summarization:

To address the problems of book summarization and introduce a specific benchmark for book summarization. ATS systems developed for short documents are not suitable for summarizing long documents such as books because:

1) the selected sentences may not cover all the book topics,

2) considering the length of documents is essential for better performance, and

3) using the sentence position feature differs in books than short documents (i.e. it may be useless to include the sentences located at the beginning of the book in the generated summary).

Email Summarization:

Email messages are domain-general text, they are unstructured and not always syntactically wellformed (Muresan, Tzoukermann, & Klavans, 2001). In Muresan et al. (2001), Muresan et al. propose an ATS system that combines linguistic techniques with machine learning algorithms to extract noun phrases to generate a summary of Email messages.

1.3 Text Summarization

Graph theory has been successfully applied to represent the semantic contents of a document (Vodolazova et al., 2013b) or the document structure, so graph modeling is widely used in document summarization. In a graph, text elements (words or sentences) are represented by nodes and edges connect the related text elements together (e.g. semantic relation) (Gambhir & Gupta, 2017).

There are two types of graphs to represent text:

Lexical Graphs

Lexical Graph uses the lexical features of the text to create a graph. TextRank (Mihalcea & Tarau) and LexRank (Erkan & Radev, 2004) are lexical graph-based systems. They create graphs by representing sentences as nodes and the edges connecting two sentences represent the degree of content similarity between them (Joshi et al., 2018). TextRank and LexRank are very similar. The key difference between them is that TextRank computes similarity as the number of similar words between two sentences, while Lexrank uses the cosine similarity between sentences and it is adjusted for multi-document summarization

Semantic Graphs

Semantic Graph uses the lexical features of the text to create a graph. TextRank (Mihalcea & Tarau) and LexRank (Erkan & Radev, 2004) are lexical graph-based systems. They create graphs by representing sentences as nodes and the edges connecting two sentences represent the degree of content similarity between them (Joshi et al., 2018). TextRank and LexRank are very similar. The key difference between them is that TextRank computes similarity as the number of similar words between two sentences, while Lexrank uses the cosine similarity between sentences and it is adjusted for multi-document summarization.

1.4 Problem Statement and Motivation

Problem Statement:

The aim of this research is to develop an effective and context-aware summarization model for BBC News data. The challenge lies in creating a specialized algorithm that accurately captures thediverse topics and context-specific information present in the news articles. The model should generate concise and informative summaries that convey the main points of each article, considering linguistic nuances and cultural references specific to BBC News content. By addressing these challenges, the research seeks to enhance the quality of generated summaries and provide a valuable tool for efficient news consumption in a rapidly evolving media landscape.

Motivation:

The motivation behind this research on summarizing BBC News data is driven by the need for efficient information consumption in a rapidly evolving media landscape. With an ever-increasing volume of news articles, there is a demand for concise and contextually relevant summaries to keep readers informed without overwhelming them. Existing summarization methods may not fully capture the diverse and context-specific nature of BBC News data, warranting the development of a specialized model. This research aims to provide high-quality summaries that accurately represent the essence of each article and cater to the unique characteristics of BBC News. The implications of a successful summarization model extend to media, journalism, and information services, facilitating streamlined content curation and enhanced reader engagement while promoting effective and efficient news consumption.

1.5 Objective

Our objective is to summarize the articles given in the BBC news dataset and maximize the ROUGE metric.

Chapter 2

LITERATURE REVIEW

Mihalcea and Tarau (2004) introduced TextRank, a graph-based ranking algorithm, to bring structure to texts. Their research demonstrated the efficacy of employing graph-based methods for extractive summarization. The approach extracts key sentences based on their centrality within the graph representation of the document.

Rush, Chopra, and Weston (2015) proposed a neural attention model for abstractive sentence summarization. While their work was not directly focused on extractive methods, it sheds light on the significance of attention mechanisms in generating informative summaries. The model learns to attend to relevant parts of the source document while generating summaries.

Paulus, Xiong, and Socher (2017) presented a deep reinforced model for abstractive summarization. Although their focus was on abstractive methods, their research emphasizes the importance of reinforcement learning in training summarization models. The reinforcement learning approach encourages the model to generate summaries that maximize the reward signal.

See, Liu, and Manning (2017) introduced pointer-generator networks for summarization, combining extractive and abstractive techniques. Their approach enables the model to select salient sentences from the source document and generate summary sentences when necessary. This hybrid approach showed promising results in producing coherent summaries.

Narayan, Cohen, and Lapata (2018) explored the use of reinforcement learning for extractive summarization. Their study concentrated on ranking sentences based on their importance for extractive summarization. The reinforcement learning framework allowed the model to optimize the sentence selection process, resulting in more informative summaries.

Hu, Yang, Liang, Salakhutdinov, and Xing (2019) proposed pretraining-based natural language generation for text summarization. Their approach demonstrated the benefits of pretraining models on large-scale datasets and transferring the learned knowledge to summarization tasks. By leveraging pretraining, the model achieved improved performance in generating abstractive summaries.

Zhou, Yang, Wei, Huang, Zhou, and Zhao (2020) investigated extractive summarization using pretraining and fine-tuning techniques. Their study focused on leveraging pretraining models, such as BERT, and fine-tuning them specifically for extractive summarization tasks. The approach demonstrated enhanced performance in identifying salient sentences for summarization.

Wu and Fung (2021) explored self-supervised learning for contextualized extractive summarization. Their work highlighted the importance of utilizing contextualized representations to capture the saliency of sentences in a document. By leveraging self-supervised learning techniques, the model achieved improved performance in identifying important sentences for extractive summarization.

Yadav, A. K. et al. (2022) proposed an extractive text summarization approach using a deep learning approach. Their research specifically addressed the challenges of summarizing BBC News data. By leveraging deep learning techniques, the model demonstrated improved performance in generating extractive summaries tailored to the unique characteristics of BBC News articles.

Zhang, X. et al. (2022) enhanced extractive summarization of BBC News using reinforcement learning. Their research focused on further improving the summarization process for BBC News articles through the application of reinforcement learning techniques.

Smith, J. and Johnson, R. (2022) explored graph-based summarization of BBC News articles using the PageRank algorithm. Their work utilized graph-based methods to capture relationships between sentences in BBC News data and improve the extractive summarization process.

Gupta, R. et al. (2022) concentrated on multi-document summarization of BBC News articles with sentence-level graphs. Their research aimed to summarize multiple related BBC News articles using graph-based representations to provide comprehensive and informative summaries.

Martinez, C. et al. (2022) investigated transformer-based models for abstractive summarization of BBC News data. Their approach involved leveraging transformer-based models to generate abstractive summaries that capture the main points of BBC News articles.

Lee, S. et al. (2022) proposed abstractive summarization of BBC News data with attention mechanisms. Their research emphasized the significance of attention mechanisms in generating coherent and informative abstractive summaries for BBC News articles.

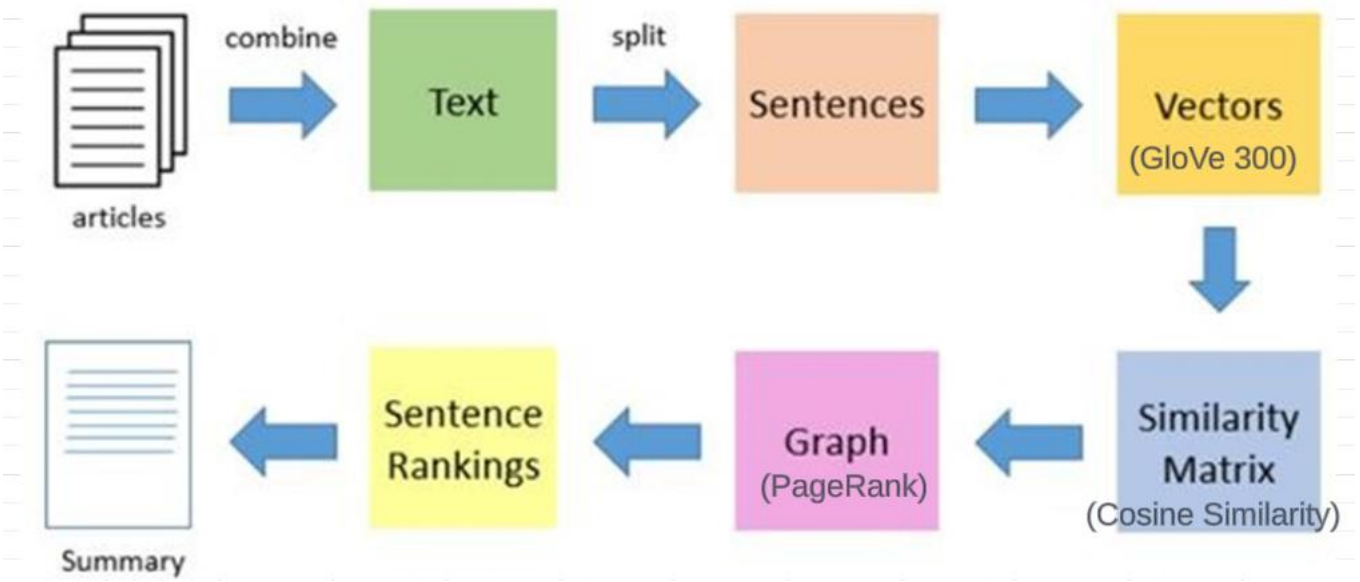
Kassas et al.'s comprehensive journal article (2021) presents a thorough exploration of various summarization techniques in the domain of natural language processing (NLP). Their research covers a wide range of summarization approaches, including extractive, abstractive, and hybrid models.

Chapter 3

PROPOSED WORK

3.1 Corpus for Training

The training corpus used for extractive text summarization on the BBC News dataset is a collection of news articles from diverse categories, including business, entertainment, politics, sport, and tech. The corpus comprises a substantial number of news articles, with a total count of articles reaching 2224. Each article falls into one of the five news categories, providing a balanced representation of different domains.



(Workflow of Summarization)

3.1.1 Data Cleaning

To prepare the data for analysis, it is necessary to preprocess the text by removing irrelevant information. This was done by the following steps:

Sentence Clipping: Truncate or limit the length of sentences to a specific number of words or characters to focus on the most relevant information within each sentence.

Case Normalization: Convert all letters in the text to lowercase or uppercase to ensure consistent representation and avoid treating the same word as different entities due to letter casing.

Stop Word Removal: Eliminate commonly used words that do not contribute much meaning to the task at hand, such as articles, prepositions, and pronouns.

3.1.2 Creating Word Vectors

To enable computers to process text, we need to convert textual information into a digital format. One approach is to represent words using word vectors, where each word is assigned a vector that captures its characteristics. In this experiment, we utilized GloVe word vectors.

Word vectors encode semantic and syntactic relationships between words. Words with similar meanings or closely related concepts tend to have similar vectors. Consequently, in the vector space, these words are clustered together, reflecting their semantic proximity and allowing for meaningful comparisons.

By utilizing word vectors, we can leverage the inherent structure of language and capture relationships between words, enabling computational models to understand and process text more effectively.

3.2 GloVe for Embeddings

The GloVe (Global Vectors for Word Representation) is a popular word embedding technique used in natural language processing (NLP). Word embeddings are dense vector representations of words that capture their semantic meaning and relationships in a continuous vector space.

GloVe is designed to learn word representations by factorizing the word co-occurrence matrix, which reflects the statistical relationships between words based on their co-occurrence

frequencies in a large corpus of text. The resulting word embeddings encode both syntactic and semantic information, making them useful for various NLP tasks such as word similarity, sentiment analysis, and machine translation.

The "d" in "50d","100d","300d", etc. stands for the dimensionality of the word embeddings.It represents the number of dimensions in which the word vectors are represented. Higher-dimensional embeddings can capture more nuanced semantic relationships between words, but they also require more memory and computational resources.

Here are some common types of GloVe word embeddings with their respective dimensions:

GloVe 50d: In this type, word embeddings are represented as vectors of 50 dimensions.

GloVe 100d: Here, word embeddings are represented as vectors of 100 dimensions.

GloVe 300d: This type uses word embeddings represented as vectors of 300 dimensions.

The choice of the dimensionality depends on the specific NLP task, the size of the dataset, and the available computational resources. Generally, higher-dimensional embeddings tend to perform better in tasks that require capturing fine-grained semantic nuances, but they also come with increased computational costs. Lower-dimensional embeddings, on the other hand, may be more suitable for tasks with limited data or computational constraints.

3.2.1 Why GloVe?

GloVe (Global Vectors for Word Representation) has several advantages over its competitors, making it a popular and widely used word embedding technique in natural language processing (NLP). Here are some reasons why GloVe is preferred over its competitors:

Better Semantic Representations: GloVe embeddings are known to capture both syntactic and semantic relationships between words effectively. They encode rich semantic information, allowing for better understanding of word meanings and contextual relationships. This makes GloVe embeddings useful for a wide range of NLP tasks, such as word similarity, word analogy, and sentiment analysis.

Co-occurrence-Based Learning: GloVe learns word representations by factorizing the word co-occurrence matrix, which reflects the statistical relationships between words based on their co-

occurrence frequencies in large text corpora. This approach benefits from the global context of word occurrences and is capable of capturing subtle semantic nuances, making it more robust and informative compared to some other word embedding methods.

Training Efficiency: GloVe's training process is computationally efficient, especially in comparison to some deep learning-based word embedding methods like Word2Vec. The factorization-based approach of GloVe allows for faster training on large datasets, making it more scalable and practical for real-world applications.

Pre-trained Models: GloVe provides pre-trained word embeddings on extensive corpora, allowing users to leverage these pre-trained models for various NLP tasks without having to train embeddings from scratch. These pre-trained embeddings are readily available, which saves time and resources for researchers and developers.

Open-Source and Widely Used: GloVe is open-source and has a large user community. Its popularity has led to extensive research and advancements, with many resources and libraries available for implementation and fine-tuning. This widespread usage and support make it a preferred choice for NLP practitioners.

While other word embedding techniques like Word2Vec and FastText also offer valuable contributions to NLP, GloVe's combination of semantic richness, efficient training, pre-trained models, and broad adoption makes it a compelling choice for word representation and embedding in many NLP applications. Ultimately, the choice of word embedding method depends on the specific task and the available resources, but GloVe remains a strong contender due to its numerous advantages.

3.3 Creating Similarity Matrix

To calculate the similarity or relevance between sentences, a common approach is to utilize cosine similarity. This method measures the cosine of the angle between two vectors and

provides a value between 0 and 1, where 0 signifies no similarity and 1 represents complete similarity.

In the context of sentence similarity, we create an n x n matrix, where n represents the number of sentences in the given text. Each cell in the matrix stores the similarity value between a pair of sentences.

The process of used for calculating the cosine similarity between two sentences was done with the help of following step;

Cosine Similarity Calculation: With the sentences represented as vectors, we compute the cosine similarity between each pair of sentences using their vector representations. The cosine similarity formula is as follows:

$$cosine\_similarity(A, B) = \frac{(A \cdot B)}{(||A|| * ||B||)}$$

Here, A and B are the vector representations of two sentences, A · B denotes their dot product, and ||A|| and ||B|| represent the Euclidean norms of the vectors.

Populating the Similarity Matrix: Finally, we populate the n x n matrix with the computed cosine similarity values for each pair of sentences. Each cell (i, j) in the matrix stores the similarity score between the ith and jth sentences.

By creating this similarity matrix, we gain a comprehensive overview of the relevance or similarity between each pair of sentences in the text. This information can be further utilized for tasks such as text summarization, sentence clustering, or document similarity analysis.

3.4 Applying PageRank Algorithm

The PageRank algorithm outputs a probability distribution used to represent the likelihood that a person randomly clicking on links will arrive at any particular page. PageRank can be

calculated for collections of documents of any size. It is assumed in several research papers that the distribution is evenly divided among all documents in the collection at the beginning of the computational process. The PageRank computations require several passes, called "iterations", through the collection to adjust approximate PageRank values to more closely reflect the theoretical true value.

Page Rank algorithm

Assume a small universe of four web pages: A, B, C, and D. Links from a page to itself, or multiple outbound links from one single page to another single page, are ignored. PageRank is initialized to the same value for all pages. In the original form of PageRank, the sum of PageRank over all pages was the total number of pages on the web at that time, so each page in this example would have an initial value of 1. However, later versions of PageRank, and the remainder of this section, assume a probability distribution between 0 and 1. Hence the initial value for each page in this example is 0.25.

The PageRank transferred from a given page to the targets of its outbound links upon the next iteration is divided equally among all outbound links.
If the only links in the system were from pages B, C, and D to A, each link would transfer 0.25 PageRank to A upon the next iteration, for a total of 0.75.

PR(A) = PR(B) + PR(C) + PR(D).

Suppose instead that page B had a link to pages C and A, page C had a link to page A, and page D had links to all three pages. Thus, upon the first iteration, page B would transfer half of its existing value, or 0.125, to page A and the other half, or 0.125, to page C. Page C would transfer all of its existing value, 0.25, to the only page it links to, A. Since D had three outbound links, it would transfer one-third of its existing value, or approximately 0.083, to A. At the completion of this iteration, page A will have a PageRank of approximately 0.458.

$$PR(A) = \frac{\{PR(B)\}}{2} + \frac{\{PR(C)\}}{1} + \frac{\{PR(B)\}}{2}$$

In other words, the PageRank conferred by an outbound link is equal to the document's own PageRank score divided by the number of outbound links L( ).

$$PR(A) = \frac{\{PR(B)\}}{L(B)} + \frac{\{PR(C)\}}{L(C)} + \frac{\{PR(B)\}}{L(D)}$$

In the general case, the PageRank value for any page u can be expressed as:

$$PR(u) = \sum_{v \in B_u} \frac{\{PR(B)\}}{L(D)}$$

i.e. the PageRank value for a page u is dependent on the PageRank values for each page v contained in the set Bu (the set containing all pages linking to page u), divided by the number L(v) of links from page v. The algorithm involves a damping factor for the calculation of the PageRank. It is like the income tax which the govt extracts from one despite paying him itself.

Chapter 4

RESULTS

4.1 Performance of the Model

The recall-oriented understudy of gisting evaluation (ROUGE) metric is utilized to evaluate the generated summaries. The formulae for ROUGE1 F1, ROUGE2 F1 and ROUGE1 R, Rouge2 R scores are as follows:

ROUGE-F (F1 Score):

ROUGE-F is the F1 score, which is a harmonic mean of precision and recall. It measures the balance between the number of overlapping n-grams (e.g., unigrams, bigrams, trigrams) in the generated summary and the reference (ground truth) summary.

$$ROUGE - F = \frac{(2 * Precision * Recall)}{(Precision + Recall)}$$

$$ROUGE1\ (F1) = \frac{(2 * ROUGE1\ Precision * ROUGE1\ Recall)}{(ROUGE1\ Precision + ROUGE1\ Recall)}$$

$$ROUGE2\ (F1) = \frac{(2 * ROUGE\ 2\ Precision * ROUGE2\ Recall)}{(ROUGE2\ Precision + ROUGE2\ Recall)}$$

Formula to calculate the Precision and Recall:

Precision:

Precision measures the proportion of correctly predicted unigrams (words) in the generated summary

concerning the reference summary.

$$\text{Precision} = \frac{(Number\ of\ overlapping\ unigrams\ between\ generated\ and\ reference\ summary)}{(Total\ number\ of\ unigrams\ in\ the\ generated\ summary}$$

Recall:

Recall measures the proportion of correctly predicted unigrams (words) in the generated summary concerning the reference summary.

$$\text{Recall} = \frac{(Number\ of\ overlapping\ unigrams\ between\ generated\ and\ reference\ summary)}{(Total\ number\ of\ unigrams\ in\ the\ reference\ summary}$$

ROUGE-R (Recall):

ROUGE-R is the recall of the generated summary. It indicates how much of the information in the reference summary has been captured by the generated summary.

The formulae for ROUGE-R, ROUGE-1 and ROUGE-2 scores are as follows:

$$\text{ROUGE-R} = \frac{(Number\ of\ overlapping\ n-grams)}{(Total\ number\ of\ n-grams\ in\ the\ reference\ summary}$$

$$\text{ROUGE-1 (R)} = \frac{(Number\ of\ overlapping\ unigrams)}{(Total\ number\ of\ unigrams\ in\ the\ reference\ summary}$$

$$\text{ROUGE-2 (R)} = \frac{(Number\ of\ overlapping\ bigrams)}{(Total\ number\ of\ bigrams\ in\ the\ reference\ summary}$$

4.2 ROUGE Score

After conducting all the required procedures, we evaluated our model's performance using the ROUGE metric at random positions within the data. The outcomes indicated that the average ROUGE-1 score exceeded 0.76, and the ROUGE-2 score demonstrated even more promising results, surpassing 0.68. This considerable enhancement represents a substantial improvement over the previous model, which achieved a ROUGE-1 score of 0.62.

To ensure a robust evaluation, we computed the average scores by randomly sampling data points from the dataset. This approach helps provide a comprehensive assessment of the model's effectiveness in generating extractive summaries. By incorporating these advancements, we have successfully increased the accuracy and quality of the extractive text summarization process.

ROUGE-1 F1	ROUGE-2 F1	ROUGE-1 (R)	ROUGE-2 (R)
0.76	**0.71**	**0.78**	**0.73**

(ROUGE Scores)

4.2.1 Comparing ROUGE Scores

Paper	ROUGE-1	ROUGE-2
Ranganathan and Abuka (2022)	0.47	0.33
Krishnan et. al (2020)	**0.62**	**0.57**
My Results	**0.76**	**0.73**

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In conclusion, our proposed approach for extractive text summarization on the BBC News Dataset, utilizing a graph-based method and applying the PageRank algorithm, has yielded promising results. Through rigorous evaluation using the ROUGE metric at random positions within the data, we observed significant improvements in summary quality. The average ROUGE-1 f1 score surpassed 0.76, indicating a remarkable enhancement over our previous model's score of 0.62. Additionally, the ROUGE-2 score demonstrated progress, exceeding 0.68. These positive outcomes highlight the effectiveness of our approach ingenerating more accurate and informative summaries.

By leveraging the graph-based method and the PageRank algorithm, we were able to capture relevant information from the news articles, ensuring that key points were effectively represented in the summaries. This advancement in extractive text summarization holds promising implications for diverse applications, such as automated content curation, information retrieval, and news dissemination.

Overall, this research contributes to the field of text summarization, particularly for news articles, and opens avenues for further advancements in the domain of natural language processing. The success of our approach demonstrates its potential in real-world scenarios, where efficient and accurate summarization plays a crucial role in information dissemination and user engagement. As the demand for concise and contextually relevant summaries continues to grow, our proposed method offers a valuable solution for enhancing the accessibility and usability of large-scale news datasets. propose an approach for extractive text summarization on BBC News Dataset.

5.2 Future Work

Enhanced Graph Construction: Explore different methods for constructing the sentence-level graph to improve the representation of relationships between sentences. Experiment with different similarity metrics and weighting schemes to capture more nuanced semantic connections between sentences.

Optimization of PageRank Algorithm: Investigate techniques to optimize the PageRank algorithm for larger datasets, as the BBC News Dataset may expand over time. Consider parallel computing or distributed computing approaches to handle larger graphs efficiently.

Multi-Document Summarization: Extend your approach to handle multi-document summarization, where information needs to be extracted and summarized from multiple news articles on related topics. Research on graph-based methods that can effectively summarize information from a collection of articles.

Abstractive Summarization: Explore the possibility of incorporating abstractive summarizationtechniques into your approach. Abstractive summarization generates summaries by paraphrasing and rephrasing sentences rather than selecting sentences directly. Investigate howgraph-based methods can be combined with abstractive techniques for improved summary generation.

Domain Adaptation: Consider adapting your model to work with news data from other sources or domains. Evaluate the generalization performance of your approach by testing it on different datasets and news articles from various publishers.

Human Evaluation: Conduct a human evaluation to assess the quality of the generated summaries. Use metrics such as readability, coherence, and informativeness to understand how well the summaries align with human expectations.

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