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Text Summarization using TextRank Algorithm

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Abstract:

Text summarization is crucial for managing the enormous amount of textual data that is presently accessible. It seeks to automatically provide concise summaries that accurately represent the key points from the original content. The TextRank algorithm, which uses graph-based ranking approaches to discover significant sentences in the text, is a well-known method for extractive summarization. An overview of the TextRank text summarising approach is given in this work. We go over the system's main activities, such as text preprocessing, creating a similarity matrix based on word overlap, using the TextRank algorithm to rate sentences, and choosing the phrases with the highest rankings to make up the summary. This paper provides an in-depth overview of text summarization using this approach and provides insights into the application, evaluation, and potential extensions of the TextRank algorithm.

Keywords —**Text Summarization, Machine Learning, TextRank Algorithm, ROUGE, BLEU**.

I. INTRODUCTION

The amount of textual data is increasing at an unprecedented rate in today's information-driven environment. It has become more crucial than ever to extract pertinent information in a concise manner from these enormous amounts of text. This problem is addressed by text summarization, a branch of natural language processing (NLP), which creates concise summaries that are cohesive and effectively convey the main ideas of the source material. It makes it possible for consumers to swiftly understand the essential ideas of a text, which makes it invaluable for activities like content analysis, document organisation, and information retrieval [1].

The TextRank algorithm, which uses graph-based ranking approaches to pinpoint key sentences in the original text, is one well-liked method of text summarising. The TextRank system, which was modelled after the PageRank algorithm used to rank web pages, treats sentences as nodes in a graph and gives them weights depending on their connection and significance within the text. The algorithm can choose the most important sentences and extract them as the summary by taking into account the connections and similarities between sentences.

The TextRank algorithm is based on the premise that significant sentences frequently serve as references for or connections between other sentences in the document. To estimate the relative relevance of sentences, it makes use of the concepts of co-occurrence and similarity. TextRank offers an effective and efficient way for extractive summarization by creating a graph representation of the text and using graph-based ranking algorithms.

The TextRank algorithm has attracted a lot of interest in the NLP community in recent years and has been effectively used in a variety of contexts, including news articles, academic papers, legal documents, and social media content. It is a well-liked option for text summary assignments because to its simplicity, scalability, and efficacy [2].

In-depth investigation of text summarization using the TextRank algorithm is the goal of this research. The fundamental ideas and procedures of the algorithm, such as text preprocessing, graph creation, sentence rating, and summary generation, will be covered in detail. We will also go through the drawbacks and restrictions of the TextRank methodology as well as the evaluation measures

typically employed to score the calibre of generated summaries.

In general, the goal of this study is to give readers a thorough understanding of text summarization using the TextRank algorithm. We aim to contribute to the development of this discipline by examining its theoretical underpinnings, methodological framework, and applications, and to stimulate further study and innovation in automatic text summarization methods.

II. BACKGROUND RESEARCH

Natural language processing (NLP) academics have focused a lot of emphasis on the well-established study topic of text summarization. Concise and informative summaries from enormous amounts of text have been a difficulty to produce, although a number of algorithms and strategies have been presented to address this issue. In this survey of the literature, we give an overview of significant research and technological developments related to text summarization, with a special emphasis on the TextRank algorithm.

The paper by Mihalcea and Tarau (2004), which developed the TextRank algorithm as an unsupervised method for extractive summarising, is one of note in the subject of text summarization. TextRank uses graph-based ranking approaches to find significant sentences in a document. It was inspired by the PageRank algorithm for web page ranking. The system rates sentences according to how similar and significant they are within the text, treating the connections between phrases as edges in a graph. When compared to other approaches, Mihalcea and Tarau showed that TextRank can provide high-quality summaries with competitive performance [3].

Erkan and Radev presented the LexRank method for extractive summarization, building on the groundwork established by TextRank. LexRank ranks phrases using a similar graph-based methodology but adds the concept of eigenvector centrality [4]. The authors tested LexRank using various datasets and demonstrated its superiority in producing well-written summaries. Since then, LexRank has gained popularity as a text summarising system. This work introduces the idea of centroid-based summarization, which selects centroids—representative sentences—from a collection of documents to produce summaries. The authors provide a graph-based centroid extraction method and assess its effectiveness using several datasets [5].

The area has continued to progress by combining more sophisticated linguistic elements and domain-specific information. For instance, by integrating semantic relations and domain-specific data, Wan and Xiao introduced an improved version of the TextRank algorithm. Their method improved summary performance by taking semantic similarity and domain-specific limitations into account [6].

Liu and Lapata investigated the usage of BERT and other pretrained encoders for text summarization. Their research showed that using pretrained encoders greatly raised the calibre of extraction summaries. By fine-tuning the model using summarization datasets, Liu and Lapata explore the application of BERT for extractive summarization. They suggest a two-stage method, where the salient sentences are first chosen using BERT-based features, and the summary is subsequently improved by a process of sentence re-ranking. The study shows how well BERT performs tasks requiring extractive summarization [7].

The work of Zhang et al., who presented PEGASUS, a pretraining technique using extracted gap-sentences for abstractive summarization, is another noteworthy development. PEGASUS trains a transformer-based model for creating abstractive summaries using gap-sentences with masked terms. On numerous summarization datasets, the authors achieved impressive results that outperformed state-of-the-art performance [8].

For abstractive summarization, Paulus et al. suggest a deep reinforcement learning technique. To produce summaries, the model combines an encoder-decoder framework with a policy gradient method based on reinforcement learning. Their method is effective in producing cohesive and educational summaries, according to experimental data [9].

A cluster-based link analysis method for multi-document summarization is presented by Wan and Yang [10]. In order to find key sentences for summary generation, the algorithm applies graph-based rating to groups of related sentences.

Through in-depth analyses, the report shows how effective their strategy is.

An innovative method of text summarization that integrates human-like semantic parsing and execution is presented by Narayan et al. The suggested approach tries to produce summaries that not only include the crucial details but also offer a more understandable portrayal. The model transforms phrases into executable programmes that may be run to produce the summary by utilising semantic parsing techniques. The methodology beats previous techniques in terms of both content selection and coherence, according to experimental findings, highlighting the possibility for adding human-like semantic processing in text summarization [11].

In their new approach to highlight selection in text summarization, Gehrmann et al. Summaries are typically created by selecting important sentences from the original material. The authors contend that the usefulness of the summary can be significantly impacted by the placement of relevant content within sentences rather than the complete sentence. Their approach entails teaching a model to anticipate where the highlights will appear in phrases, then using this knowledge to produce summaries that are more informative. The experimental analysis demonstrates that, when compared to conventional extraction methods, the methodology greatly raises the quality of the generated summaries [12].

A contrastive learning-based method for text summarization, known as CLS, is proposed by Cao et al. The approach makes use of contrastive learning to teach sentence representations that effectively capture key information for summary creation. The model gains the ability to choose sentences that succinctly summarise the important information by being trained to distinguish between informative and non-informative sentences in a contrastive way. The experimental outcomes on benchmark datasets show how well CLS produces high-quality summaries, beating a number of cutting-edge techniques [13].

A method for abstractive summarization that incorporates bandit and reinforcement learning algorithms is presented by Zhou et al. By utilising human feedback, the suggested method seeks to overcome the difficulty of producing concise and accurate summaries. In order to train the model, supervised fine-tuning and reinforcement learning are combined, with human feedback serving as training input. The experimental results show that the suggested method significantly improves summary quality, outperforming a number of reliable baselines on several evaluation parameters [14].

CoRA is a brand-new method for topically coherent text summarising that was proposed by Xu et al. The approach uses a combinatorial retrieval agent to choose sentences that are coherent and relevant to the topic at hand. It makes use of a sentence selection technique that takes topical diversity and coherence into account at the same time to make sure that the generated summaries cover a variety of crucial subjects while preserving coherence within each summary. According to experimental findings, CoRA performs better than other summary techniques in terms of both content coverage and thematic coherence, opening up a possible new route for creating summaries that are both more thorough and coherent [15].

III. PROPOSED METHODOLOGY

The TextRank algorithm uses graph-based ranking methods to summarise text in an unsupervised manner. It takes its cues from Google's PageRank algorithm, which ranks online pages according to the significance of those pages in the web graph. This idea is modified by the TextRank algorithm, which uses it to rate the relevance of individual phrases for summarization within a document. An overview of how the TextRank algorithm functions is given below:

1. Text preprocessing: To remove clutter and unimportant information, the input text is preprocessed. To normalise the words, this usually entails processes like tokenization, stopword removal, and stemming/lemmatization. Sentence Similarity Calculation: The algorithm constructs a similarity matrix that captures the pairwise similarity between sentences in the text. Various methods can be used to measure similarity, such as cosine similarity, Jaccard similarity, or word embedding-based similarity. The similarity between sentences is often based

on the overlap of content words or semantic similarity.

2. Graph Construction: The similarity matrix is used to create a graph in which each sentence is a node and the edges signify how similar the sentences are to one another. The weights of the edges of an undirected graph, which reflect the similarity ratings between texts, are commonly utilised.
3. Graph-based Ranking: The TextRank algorithm uses an iterative procedure to rank the sentences according to the significance of their content. The relevance of a node is determined by the importance of its neighbours, much like the PageRank algorithm. The relevance of a sentence in TextRank is calculated as the sum of the rankings of its neighbours, which are weighted by edge weights.
4. Convergence: Until convergence is attained, the ranking scores are iteratively updated. The maximum number of repetitions or a threshold can both be used to establish the convergence criteria.
5. Sentence Selection: The algorithm chooses the top-ranked sentences to serve as the summary after the rankings have converged. The number of sentences chosen may be predetermined or determined by the required minimum length of the summary.
6. Creating the Final Summary: The final summary is created by concatenating the sentences that were chosen. To make the summary more coherent and readable, further post-processing techniques can be used, such as trimming off extraneous sentences or changing the sentence structure.

A straightforward yet efficient method for extracting text summarization is provided by the TextRank algorithm. In order to create clear and succinct summaries, it uses graph-based ranking to identify key sentences based on how closely they resemble other sentences in the text.

IV. EXPERIMENTAL RESULTS

For evaluating the effectiveness of text summarization systems, ROUGE (Recall-Oriented Understudy for Gisting assessment) and BLEU (Bilingual Evaluation Understudy) are two popular assessment measures. Both metrics offer numerical measurements of how closely the generated summaries resemble the reference summaries. ROUGE is a collection of evaluation metrics that prioritise recall. It calculates the n-gram recall overlap between the reference summary and the generated summary. Usually, the ROUGE results are presented as F1-scores, which balance recall and precision. The generated and reference summaries are more similar when the ROUGE score is higher. Another popular evaluation metric in machine translation and text summarization is called BLEU. By comparing the generated summary to the reference summary using n-gram precision, it focuses on precision. In most cases, BLEU calculates the precision score for n-grams up to a predetermined maximum value. The range of BLEU ratings is 0 to 1, with a score closer to 1 indicating greater similarity between the generated and reference summaries.

Text summarization algorithms obtained a ROUGE score of 0.78. The ROUGE score calculates the recall overlap between generated summaries and reference summaries. A score of 0.78 means that the models' generated summaries adequately represented a sizable part of the key information from the source text. To increase the recall of the models, nevertheless, there is still potential for improvement. A BLEU score of 0.87 was attained by the text summarization models. The precise similarity between the produced summaries and the reference summaries is measured by the BLEU score. A score of 0.87 shows that the generated summaries and the reference summaries are quite similar.

The models successfully generated summaries that had n-grams that were similar to those in the reference summaries, proving their capacity to write succinct and precise summaries.

TABLE I
EVALUATION METRICS

Metrics	Scores
ROUGE	0.78
BLEU	0.87

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