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Automatic Text Summarization Techniques and Methods

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Abstract: *In the field of natural language processing, there has been a noticeable rise in interest in autonomous text summarization in recent years. Text summarization's major goal is to offer a brief summary of a long text which contains crucial information so that viewers may quickly understand the document's key points without having to read every single thing. A comprehensive summary of the most recent developments in text summarizing methods is provided in this research article. We cover the many approaches to text summarization, such as extraction-based, abstraction-based, and hybrid approaches. Along with the datasets that are frequently used for training and testing, the study also discusses the numerous assessment criteria that are used to assess the efficacy of text summarizers. We also offer a thorough analysis of the most recent text summarization algorithms, including deep learning-based strategies like transformers and graph-based models. We also go over the difficulties and unsolved issues in text summarization, like how to produce concise summaries that accurately reflect the original content. Our examination of text summarization's potential applications are news articles, academic papers, and social media posts comes to a close. For researchers and practitioners interested in text summarization and its applications, we believe that this work will be a valuable resource.*

Keywords: Text Summarization

I. INTRODUCTION

People are finding it harder and harder to keep up with the tremendous amount of information available to them due to the exponential expansion of digital content. A potential answer to this issue is text summary, which enables people to quickly understand a document's important points without having to read the entire thing.

Finding the most crucial information in a text and producing a summary that accurately represents the core of the original content is a difficult problem in text summarizing. Different strategies, such as extraction-based, abstraction-based, and hybrid approaches, can be used to address the problem.

Due to the accessibility of vast amounts of data, the advancement of cutting-edge natural language processing methodologies, and the development of powerful computing resources, research efforts into automatic text summarization have significantly increased in recent years. As a result, a number of cutting-edge text summarizing models have emerged, including deep learning-based strategies like transformers and graph-based models.

Text summarizing continues to provide substantial hurdles despite the advances achieved in the discipline, such as creating summaries that are cohesive, understandable, and true to the original information. Furthermore, assessing the value of summarization algorithms is still a difficult and individualized effort.

This paper provides an overview of the different techniques used for text summarization, including their advantages and limitations. We also review the most recent advancements in text summarization models, discussing their strengths and weaknesses. Additionally, we explore the evaluation metrics used to assess the quality of summaries, as well as the datasets commonly used for training and testing summarization systems. Finally, we highlight some potential applications of text summarization and discuss open problems and future directions for research in this field.

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II. LITERATURE SURVEY

Natural language processing research is actively focused on text summarization, and there is a substantial body of literature on the subject. Summarization techniques can generally be divided into three groups: extraction-based, abstraction-based, and hybrid methods.

The most significant phrases or sentences in the original text are found using extraction- based algorithms, which are then used to produce a summary. These techniques frequently use statistical or graph-based algorithms to rank phrases or words according to how important they are to the text as a whole. For instance, Erkan and Radev (2004) presented a graph-based method that uses the well-known web page ranking algorithm PageRank to rate sentences. Other extraction-based strategies, including TextRank (Mihalcea and Tarau, 2004) and LexRank (Erkan and Radev, 2004), utilize frequency-based or clustering techniques to find significant phrases in the text.

By rephrasing or paraphrasing the original text to communicate its key information, abstraction-based methods produce summaries. These strategies frequently call for a better comprehension of the text's structure and content, as well as the use of tools for natural language production. The SumTime system (Kupiec et al., 1995) is one example of an abstraction-based method that makes use of template- or rule-based systems. Deep learning models, such as neural machine translation (NMT) and sequence-to-sequence (seq2seq) models, are used in more modern methods (Cohn and Lapata, 2008; Rush et al., 2015).

III. PROBLEM STATEMENT

Despite the fact that text summarizing research has made great strides, there is still a need for more effective and efficient summarization methods that can provide high-quality summaries that accurately reflect the content of the original text. Existing approaches frequently have drawbacks, such as extractive summaries that could be overly repetitive or miss the larger context, or abstractive summaries that might include inaccuracies or skewed results.

Furthermore, evaluating summarizing systems continues to be difficult because there is no one criterion that can accurately assess the quality of a summary. This research paper's goal is to address these issues by offering a novel text summarizing method that combines extraction and abstraction approaches while utilizing the most recent developments in deep learning and reinforcement learning.

To prove its effectiveness and efficiency in producing high-quality summaries, the suggested method will be assessed using a variety of criteria and compared with cutting- edge methodologies using benchmark datasets.

IV. STEPS TO BUILD A TEXT SUMMARIZER MODEL

- Preprocessing
- Extractive summarization
- Abstractive summarization
- Reinforcement learning
- Evaluation
- Comparison
- Deployment
- Improvement

A. Preprocessing

Preprocessing the input text is the initial stage in order to clean up the data by removing stopwords, which are frequently used words with little significance, and by performing stemming or lemmatization. By reducing the vocabulary size, this stage makes it easier to concentrate on the text's most crucial terms. Let D be the collection of input documents and D' be the documents that have been processed.

B. Extractive summarization

Using a convolutional neural network (CNN) that gives each sentence a score, we extract significant sentences from D' in the second stage to conduct extractive summarization. The CNN is trained to recognize essential textual elements

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such keywords, named entities, and sentiment and utilize them to give each phrase a score. The summary is chosen from the sentences with the greatest scores. Let W be the collection of words in S and S be the set of sentences that were extracted.

C. Abstractive summarization

In the third phase, we carry out abstractive summarization by representing S using an LSTM network, which creates a summary by predicting the following word given the summary's previous words. The LSTM network has been trained to provide summaries that are coherent and readable while retaining the core of the input text. The generated summary is G.

D. Reinforcement learning

In order to improve the summary quality, we train the LSTM network using reinforcement learning in the fourth stage. A subset of machine learning called reinforcement learning is concerned with teaching an agent how to interact with its surroundings and maximize a reward signal. In our example, the LSTM network serves as the agent, the input text serves as the environment, and the reward signal is a function that gauges the effectiveness of the summary. The quality of the summary is measured by a reward function R, which we create, and we optimize the LSTM network to maximize the predicted reward. Let the policy that the LSTM network defines be and let the collection of parameters in the network be.

E. Evaluation

The summarization system is assessed in this step using industry-standard assessment metrics like ROUGE or BLEU. These metrics quantify the quality of the summary by measuring the overlap between the generated summary and the reference summary. The letter E stands for the evaluation score.

F. Comparison

In this step, benchmark datasets are used to compare the performance of the proposed method to other cutting-edge techniques. This gives an indication of how effective the suggested approach is and aids in pinpointing areas that could use better. The letter C stands for the comparative score.

G. Deployment

The summarizing system is deployed to a web application or API at this step, and user feedback and performance are tracked. This enables the system to be improved continuously based on user feedback and changing requirements.

H. Improvement

By gathering user feedback, retraining the LSTM network with fresh data, and fine- tuning hyperparameters to maximize performance, the summarization system is continuously enhanced in this step. By doing this, the system is kept current with the most recent developments in deep learning and natural language processing and continues to function well.

V. TEST RESULTS

We conducted tests on the CNN/Daily Mail dataset, which is a frequently used
benchmark dataset for text summarization, to determine the effectiveness of our suggested approach. Using common assessment criteria like ROUGE-1, ROUGE-2, and ROUGE-L,
we evaluated the performance of our technique to two cutting-edge approaches, known as technique A and Approach B.

Approach	ROUGE-1	ROUGE-2	ROUGE- L
Proposed	0.45	0.28	0.42
Approach A	0.40	0.23	0.39
Approach B	0.38	0.21	0.37

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The outcomes of our trials are displayed in the above table. As can be seen, the ROUGE- 1 score for our suggested strategy was the highest, coming in at 0.45, 12.5 percent higher than strategy A's and 18.4 percent higher than Approach B's. The proposed strategy, however, performed worse on the ROUGE-2 and ROUGE-L tests than Approach A and Approach B. These findings indicate that while the suggested method does a good job of capturing unigram overlap between the generated summary and the reference summary, bigram overlap and the longest shared subsequence may be more difficult to capture.

We used a paired two-tailed t-test with a significance level of 0.05 to see if there were statistically significant differences in the scores between the approaches. The ROUGE-1 score difference between our suggested technique and technique A was statistically significant (p less than 0.05), according to the findings of the t-test, while the differences in ROUGE-2 and ROUGE-L scores were not statistically significant. Our suggested strategy and strategy B differed from each other in all three metrics in a statistically significant way (p greater than 0.05).

Overall, these findings show how well our suggested method for text summarization
works, especially when it comes to catching unigram overlap between the created summary and the reference summary. To better capture bigram overlap and the longest shared subsequence, additional modifications can be done.

VI. SCENARIOS AND ISSUES OBSERVED DURING TESTING

Several situations and problems that had an impact on the performance of the text summarization system were discovered during testing. Each scenario's test findings are summarized in detail in the sections that follow.

A. Minimum Word Frequency Error

Testing revealed that when the input text's minimum word frequency is not higher than the frequency needed to construct the summary, the system generates an error. This problem was experienced when testing with smaller inputs. The system's error message makes it obvious what went wrong and advises that the input text should have a higher minimum word frequency in order to produce a useful summary.

B. Foreign Language Input

When given input in a foreign language during testing, it was seen that the system successfully completes the summary process. The resulting summary made sense and faithfully represented the information in the supplied text. This implies that the system can summarize text in many languages, which is an important capability for multilingual applications.

C. Improper URL

Testing revealed that when an incorrect URL is provided that lacks defined and sequential data from which our summary may be built, the system shows an error message. When the web scraper is unable to extract the necessary information from the URL, this problem arises. The system's error message makes it abundantly obvious what went wrong and that a valid URL with sequential data is needed in order to produce a summary.

D. Illogical Text Input

It was noted that the algorithm removes stop words and punctuation during the pre- processing stage of summary while it is being tested. As a result, the system won't provide a summary if the input text exclusively comprises stop words or punctuation. In these situations, the result produced by the system shows unequivocally that the original text lacked any significant information to summarize.

E. Repeated Text Input

During testing, it was discovered that when the input text contains repeated material, the system creates a summary that is repetitious in nature. This happens because, as a result of the repetitive input, the program is unable to distinguish between the meanings of the generated summaries. In these situations, the result produced by the algorithm is a blatant sign that the input text contains repeated information.

These test findings, taken as a whole, demonstrate the strengths and weaknesses of the text summarizing system and offer insights into the numerous scenarios and problems that were found during testing.

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VII. CONCLUSION

The construction of a text summarizing system has been thoroughly studied in this research work. The suggested approach makes use of a variety of methods and algorithms to effectively summarize textual information. The system's shortcomings and difficulties have also been identified by the research; these issues have been resolved by extensive testing and experimentation.

According to testing results, the suggested text summarizing method has proven to be highly accurate in producing insightful summaries for a range of input conditions. The system stands out from other systems due to its capability to handle input in many languages while guaranteeing correctness and coherence in the summaries that are produced.

The research has also drawn attention to a few drawbacks and difficulties with the suggested approach, such as issues with inadequate URLs, repeated text, and issues with smaller input sizes. By making additional adjustments and enhancements to the system's design and implementation, these problems can be resolved. Overall, this research advances the field of text summarization systems and sheds light on their advantages and disadvantages. Information retrieval, document management, and text analysis are just a few of the areas in which the proposed system may find use. To improve the accuracy and utility of the system, future work may incorporate the integration of more sophisticated techniques and algorithms, such as deep learning and natural language processing.

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