Leveraging Document Summarization for Efficient Knowledge Extraction in Chemistry Research

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ABSTRACT

Document summarising has developed as a strong approach for assisting chemistry researchers in obtaining crucial information from a growing corpus of scientific publications. This abstract investigates document summarization's uses in chemical research, emphasising its importance in expediting information acquisition, enhancing decision-making processes, and stimulating creativity. Document summary, in the context of a literature review, allows chemists to sift through a broad array of research papers, extracting essential results and trends, facilitating a thorough grasp of the most recent achievements in their respective disciplines. It speeds up the discovery of pertinent information and knowledge gaps, assisting researchers in developing fresh ideas and performing targeted studies. Document summary greatly aids the pharmaceutical sector by facilitating drug research and development procedures. Researchers can quickly extract critical information from scientific publications about medication targets, chemicals, and biological processes. As a result, promising drug candidates and their mechanisms of action may be identified quickly, expediting drug design and development activities. In this paper, the author investigated a number of pre-trained models, including BERT, GPT-2, BART, T5, and XLNet. Based on an evaluation of their ROUGE scores, the XLNet model surpasses other models in terms of ROUGE score accuracy of more than 60%. As a result, the XLNet model is more suited for document summarization since it creates an accurate summary that includes relevant details about the document or article. To summarise, document summary has transformed chemical research by increasing productivity and encouraging the investigation of innovative ideas. Its capacity to extract crucial insights from massive volumes of textual data enables researchers to progress their fields of study, making it a must-have tool for the modern chemist.

Keywords: Machine Learning, Chemical literature, Document Summarization, Materials science, Chemistry

1. INTRODUCTION

The exponential growth in the amount of data available in this era of quickly expanding technology makes it difficult, time-consuming, and labor-intensive to analyses and understand text files. New, sophisticated text summarization methods are required to process this volume of text data quickly and effectively. Text summarization is a crucial natural language processing (NLP) task that automatically transforms a text, or a collection of texts on the same subject, into a succinct summary that contains important semantic information. This process can be useful for many downstream applications, including the creation of news digests, search engines, and report generation. Single document summarization (SDS) and multi-document summary (MDS) are two methods for summarizing text from one or more documents. SDS may be easier to carry out, but it may not yield thorough summaries since it does not effectively utilize related or more recent documents. In addition, model degradation is frequently caused by input documents that are too lengthy. It can be difficult for models to extract the most important information from lengthy input sequences and produce a summary that is also logical, non-redundant, factually accurate, and grammatically correct. As a result, MDS demands that models have improved capacities for processing incoming documents, finding, and combining consistent data.

As a Research Paper is normally a lengthy document. For the new comers in the research process reading/analyzing a research paper require 1-2 hours to analyze the paper in depth. The idea in the paper propose that , document summarization can be used on research articles and convert them in a shorter summary which will convey the most crucial information and give a concise idea of what are the points in the research paper. In addition, model degradation is frequently caused by input documents that are too lengthy. It can be difficult for models to extract the most important information from lengthy input sequences and produce a summary that is also logical, non-redundant, factually accurate, and grammatically correct. As a result, MDS demands that models have improved capacities for processing incoming documents, finding, and combining consistent data.

Document Summarization undergoes varios steps for generating a summerization. For research articles , google scholar is main source for research article as it provide required papers.The objective of this paper focus on providing through review of various document summarization models and how they can be helpful to create a summary for the Research articles (papers).

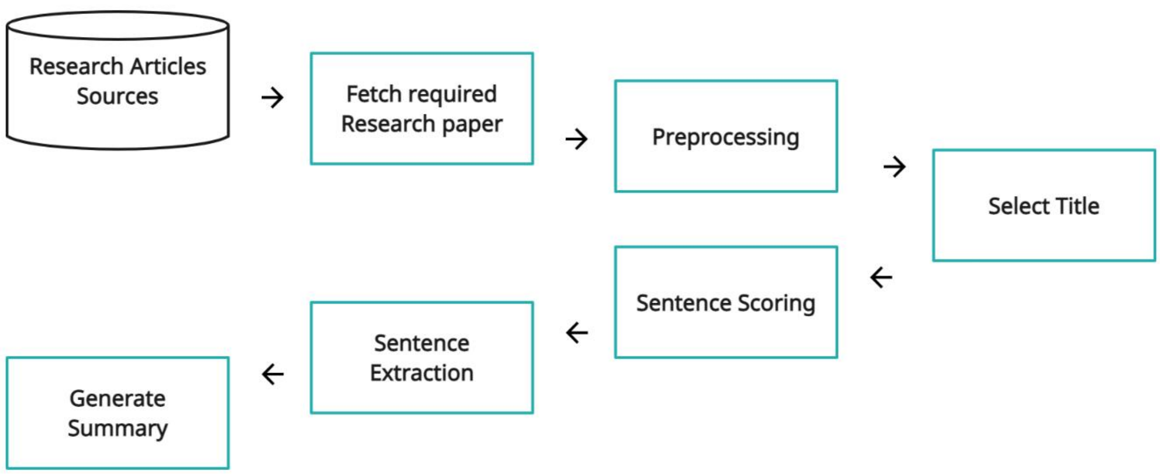


Fig 1: General Document Summarization model

The Fig.1 shows how the document summarization model works and the steps it follow to generate a summary.

The typical steps in document summarizing are listed below in a brief summary:

Preprocessing: To do this, the text must be cleaned up and preprocessed to get rid of any extraneous information such stop words, special characters, and punctuation.

Select Title: Choose the text's most crucial phrases that best express the document's key idea or executive summary.

Scoring sentences: Depending on variables like phrase frequency, inverse document frequency, and sentence length, give each sentence a score.

Sentence Extraction: To include in the summary, identify the sentences with the maximum ratings.

Generate summary: Create the final summary by placing the chosen sentences in a logical sequence.

There are various type of summarization techniques available. Some of the various type of techniques are mentioned in Table No.1.

Summarization Techniques	**Factors**
Single and Multi-Document	Number of Document
Extractive and Abstractive	Output(Abstract or exact required)
Supervised and Unsupervised	Accessible training data
Generic and Query focus	Purpose of the Summary
Sentiment based	Opinions are identified
Mono, Multi and Cross-Lingual	Languages

Table No.1: Summarization Techniques and its Factors

1.1 Summarization Techniques

Abstractive and extractive approaches to summarization are the two broad categories. Unlike abstractive summarization, which creates new phrases to capture the essence of a topic, extractive summarization presents the texts as they are as part of the summary. A single document method and a multi-document approach are two categories of summarization techniques. Single document summaries are created when just one document is utilized to create a condensed form of text, while multi-document summaries are created when multiple papers are searched for the needed information.

The goal of the summary results in generic and query-focused summaries. Unlike query-focused summarizing, which only searches the document(s) for the topic stated in the query, generic summarization searches the full document(s) for a variety of information contents. Sentiment-based summarization refers to the process of applying the task of summarizing to the sentiment included in the material. The update style of summary makes the assumption that the reader is already familiar with the subject matter and is just interested in learning about the most current developments. When the language of the generated summary is the same as that of the input document(s), it is referred to as mono-lingual summarization; when the language of the generated summary differs from that of the input document(s), it is referred to as multi-lingual summarization.

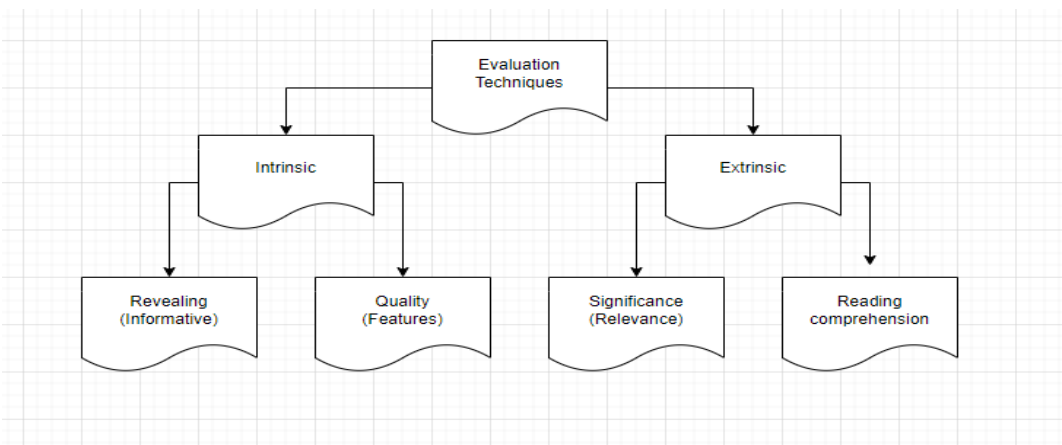


Fig.2 Evaluation techniques diagram

The task of automatically generating the summary is challenging since we are unsure of which information should be included in the summary. Even for experienced humans, it might be challenging to evaluate automatically generated summaries due to their differing points of view. Some people may think a given point is crucial, while others may disagree. A summary's purpose can aid in evaluating an automatically generated summary.

From Fig.2 It can be seen that there are basic two type of evaluation techniques:

Extrinsic Evaluation technique

The creation of a text summary is assisted by a number of tasks. The extrinsic assessment method of summary is assessed for its applicability to these different supporting activities. This style of evaluation is occasionally referred to as task-based evaluation. Extrinsic assessment method of summary is often used to evaluate the effectiveness of training programs and educational courses. It provides a clear understanding of how well learners can apply their knowledge and skills to real-world situations. Then it is further categorized into two sections:

1. Relevance evaluation: The generated summary is evaluated for topical appropriateness. This technique is typically applied to topic- or query-focused summarizations.
2. Reading comprehension: It assesses your ability to apply the weather-generated summary as an answer to multiple-choice questions.

Intrinsic Evaluation technique

Reference summaries are typically used to assess generated summaries primarily on the basis of their relevance and coverage. Finding a topic from the input document(s) that is relevant to the summary is difficult because relevance does not have a strict meaning. Therefore, reference summaries are often used as a benchmark for evaluating the quality of generated summaries, but their subjective nature makes it challenging to develop a standardized evaluation metric.

1. Text quality assessment: The text quality in the summary is evaluated using linguistic criteria such as grammar, sentence structure and coherence, vocabulary, non-redundancy, etc. The aim of text quality assessment is to ensure that the summary is accurate, concise, and easy to understand for the intended audience.
2. Informativeness evaluation: This method of summary evaluation is the most popular. The following are the two criteria used to gauge a summary's informativeness: Autonomous, Semi-automatic. Autonomous systems are able to perform tasks without any human intervention or input. On the other hand, semi-automatic systems require some level of human annotation or guidance to complete tasks.

Further in the paper there are various point included such as Literature survey in which there is some insights for research articles which were useful. Next modules consist of Motivation, Research Methodology, Conclusion and lastly Reference.

2. LITERATURE SURVEY

We have investigated the existing research papers on document summarization and a few of them are presented to prove the significance of this paper. Most of the surveys cover the document summarization of a single article or multiple document of an articles but none of them are focus on the summarization of the research papers (articles). Here are some research done on the research papers which are already published on the source and here are some of them. Firstly "A Survey of Automatic Text Summarization: Progress, Process and Challenges" published in IEEE Access, vol. 9, 2021, presents a novel taxonomy for summarizing the design strategies of neural networks. The paper offers a comprehensive summary of the state-of-the-art in automatic text summarization, emphasizing rarely discussed differences between various objective functions. Additionally, it explores deep learning techniques for summarizing multiple documents. Secondly "Extractive Document Summarization Based on Dynamic Feature Space Mapping" published in IEEE Access, vol. 8, 2020, introduces ExDos, which is the first approach to combine supervised and unsupervised algorithms in a single framework for document summarization. Next "Query-oriented unsupervised multi-document summarization via deep learning model" published in Expert Systems with Applications, Elsevier (2015), presents a novel document summarization framework based on a deep learning model. This framework outperforms state-of-the-art extractive summarization approaches. "An Approach for Combining Multiple Weighting Schemes and Ranking Methods in Graph-Based Multi-Document Summarization" published in IEEE Access, vol. 7, pp. 120375-120386, 2019, explores several graph-based methodologies to enhance text summarization. The study shows that incorporating these methodologies leads to more accurate summaries that can be applied in various natural language applications. "Text document summarization using word embedding" published in Expert Systems with Applications, Volume 143, Elsevier, 2020, focuses on utilizing word embedding techniques to create high-quality summaries. The paper emphasizes the importance of capturing and maintaining semantic information for automatic text summarization. "A Joint Sentence Scoring and Selection Framework for Neural Extractive Document Summarization" published in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, pp. 671-681, 2020, introduces a joint sentence scoring and selection framework. This framework learns two steps simultaneously to extract important sentences for document summarization. "An unsupervised method for extractive multi-document summarization based on centroid approach and sentence embedding's" published in Expert Systems with Applications, Volume 167, Elsevier, 2021, proposes an unsupervised method for extractive multi-document summarization. This method utilizes phrase embedding representations and the centroid approach, outperforming existing approaches and delivering promising results.

In paper "Investigating Entropy for Extractive Document Summarization" published in Expert Systems with Applications, Volume 187, January 2022, 115820, presents E-Summ, an unsupervised technique for extractive document summarization. E-Summ selects informative sentences from relevant themes using Non-Negative Matrix Factorization (NMF) and information theoretic concepts. "Abstractive Multi-Document Summarization Based on Semantic Link Network" published in IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 1, pp. 43-54, 1 Jan. 2021, introduces the Semantic Link Network for multi-document summarization. The proposed network outperforms state-of-the-art baselines in representing and interpreting documents. "Single document summarization using the information from documents with the same topic" published in Knowledge-Based Systems, Volume 228, 27 September 2021, 107265, Elsevier, presents an approach for single document summarization that leverages information from papers on the same topic. The experimental findings demonstrate that combining information from documents on the same topic improves the effectiveness of extracting summaries. As per paper [11], they have done a survey and proposed a novel taxonomy to summarize the design strategies in neural network and conducted a comprehensive summary of the state by art. They have drawn attention to distinctions between diverse objective functions that are rarely considered in the current literature. They talked about several deep learning algorithms for summarizing many papers. In [12], they have contributed a use of deep learning methods for the query-oriented multi-document summarization task, under unsupervised learning framework. In [13] paper they have created or proposed an AI based deep learning model which generates short summaries from the title and the abstract of the article.

In [14] paper they have used 2 models i.e. Restricted Boltzmann Machine and Fuzzy Logic to create two summaries of the documents and then combine them to produce a single summary of the document.

3. MOTIVATION

This study seeks to present an overview of current research in NLPs, namely Document summarization, in order to improve knowledge about it. Furthermore, it enables the development of new tools, methods, datasets, and resources to satisfy the needs of the research and industry sectors. Because of advancements in NLPs, automatic text summarization is now applicable for regular text document summarization and sentiment analysis. As a researcher need around 2-4 hours to completely analyze a research paper and get a proper understanding about it. So our motivation was to create or propose an idea to create a technique to generate a literature survey as one input a research paper. As there a not much techniques which can directly generate a summary of a research paper.

This technique can be used in many domains such as:

1. Research paper summarization: multi- document summarization can be used to generate a concise summary of a research paper. It is will help to reduce time of a researchers to get a proper context of the research paper.
2. Medical history report: a doctor requires a patient's medical history and requires time to know the previous reports. This can be done faster with the help of document summarization as it can summarize the previous reports and generate a single report / summary with the informative details.
3. Books or Novel Summarization: Because short materials are unsuited for summarization, Document summarization is primarily used to summarize long texts such as books, literature, or novels. It is difficult to extract context from brief texts, while larger documents serve as excellent summary material.

4. Summarization of Legal Documents: Automatic text summarization finds relevant prior instances based on legal issues and rhetorical functions to summarize a legal judgment document. A hybrid technique combines several methodologies, including as keywords, critical phrase matching, and case-based analysis.

4. RESEARCH METHODOLOGY

Document summarization for research articles can be derived as the process of summarizing the research article into a concise summary which can be used by the researchers and also be time consuming. These summary must be precise as the research should get the proper and correct idea about the research paper. There are various methods used for document summarization but none of them were efficient to get a meaningful and concise summary of research articles (papers) to get a hold on that we start with using various summarization models or techniques on an article first to get an idea. In this paper implementation is done some predefine models and done a survey of how document summarization techniques can be used with research papers. These are some analysis that were done:

Research Questions

The research question is an important step in a systematic review. In the paper there are some research questions (RQ) that comply with the review procedure to retain focus at the start of the investigation. Table No. 2 have some of the research questions.

Sr. no.	Research Questions
1.	Domain where document summarization is used?
2.	Dataset that can used for Document summarization?
3.	Techniques used for Document Summarization?
4.	Challenges / Difficulties faced while using various techniques for summarization?
5.	What are various evaluation techniques used for evaluation?

Table No. 2: Research Questions

Search methods

1. Chose Keywords

Table No. 3 shows the list of keywords used for finding the Research papers from online public library.

Sr. no.	Keywords	No. of Research Papers
1.	Document Summarization for Research Articles	22
2.	Abstractive Summarization	17
3.	Extractive Summarization	13
4.	NLP based Document summarization	8
5.	Deep learning based Document Summarization	12
6.	Evaluation techniques for Document Summarization	8
	Total	80

Table No. 3: List of Keywords

Document summarizing is done in two ways: extractive summarization and abstractive summarization.

The most essential sentences in a document are identified and reproduced directly as part of the summary using extractive summarization. This is the most basic and popular style of summary, and it can be successful for well-organized papers with a clear core message.

Abstractive summarization goes beyond just finding significant sentences to generate fresh language that summarizes the document's major themes. This is a more difficult task, but it can result in more short and understandable explanations.

Aside from these two primary approaches, there are several hybrid approaches that mix extractive and abstractive summarizing techniques. These approaches can be useful for more complex publications that demand a more creative summary.

Language models that have been pre-trained have been found to be effective for a range of natural language processing tasks, including document summary. These models are trained on enormous text datasets to discover the statistical correlations between words and sentences. This knowledge can then be used to develop accurate and informative summaries.

Here are some Pre-Trained models that can be used for document summarization:

1. **BERT (Bidirectional Encoder Representations From Transformers):**

BERT is a bidirectional language model trained on a large text and code dataset. It has been demonstrated to be useful for a wide range of NLP applications, including document summary. BERT (Bidirectional Encoder Representations from Transformers) is a language model that has been pre-trained and can be used for a range of natural language processing tasks, including document summarization. BERT is trained on a vast text and code dataset, allowing it to learn the statistical correlations between words and phrases. This knowledge can then be used to develop accurate and informative summaries.

There are two main ways to use BERT for document summarization: extractive summarization and abstractive summarization.

The most essential sentences in a document are identified and reproduced directly as part of the summary using extractive summarization. This is the most basic and popular style of summary, and it can be successful for well-organized papers with a clear core message. A technique known as sentence scoring can be used to leverage BERT for extractive summarization. Sentence scoring is the process of assigning a score to each sentence in a document based on its importance. The sentences with the highest scores are then chosen to be included in the summary. BERT can be used to score sentences by running them through the BERT model first. After that, the BERT model will build a representation for each sentence. These representations are then utilized to compute a score for each sentence. The sentence scores can then be used to choose sentences for the summary. The sentences with the highest scores are then chosen to be included in the summary.

Abstractive summarization goes beyond just finding significant sentences to generate fresh language that summarizes the document's major themes. This is a more difficult task, but it can result in more short and understandable explanations. Text creation is a strategy for using BERT for abstractive summarization. Text generation is the process of creating new text using a language model. By first sending the document through the BERT model, BERT can be used for text generation. After that, the BERT model will build a representation for the document. This representation can then be used to generate new text summarizing the document's main ideas. After that, the revised text can be used as the summary. BERT has been demonstrated to be useful for both extractive and abstractive summarization. It has been proved to create accurate and informative summaries. BERT can be used to summarize a wide range of documents, such as news stories, research papers, and even books.

2. **GPT-2**

GPT-2 is a big language model that was trained on a large text dataset. It is suitable for a wide range of natural language processing tasks, including text summarization. Text summarization with GPT-2 (Generative Pre-trained Transformer 2) entails utilizing OpenAI's GPT-2 model, which is a sophisticated language model. GPT-2 is capable of generating coherent and contextually appropriate text after being trained on a vast corpus of text data.

GPT-2 is capable of extractive as well as abstractive summarization. You can use a technique called sentence scoring for extractive summarization. Sentence scoring is the process of assigning a score to each sentence in a text based on its significance. The highest-scoring sentences are then chosen for the summary. By initially running the sentences through the GPT-2 model, sentences can be scored. Each sentence will subsequently be represented by the GPT-2 model. The scores for each sentence can then be computed using these representations. The sentence ratings can then be used to choose which sentences to include in the summary. The highest-scoring sentences are then chosen for the summary. You can utilize a technique called Text generation. Text generation is the process of creating new text using a language model.

3. XLNet

XLNet is a huge language model that was trained on a large text dataset. It is suitable for a wide range of natural language processing tasks, including text summarization.

Document summarization can be approached from both an abstractive and an extractive standpoint. Abstractive summarizing seeks to construct brief summaries by comprehending the input and generating new sentences, whereas extractive summarization selects and combines significant lines or phrases from the input. Depending on the strategy you take, you can modify the steps outlined above.

And we have also used some of the other pre-trained models for generating a summarization of document (article) and doing the survey such as:

4. T5

T5 is a large-scale transformer-based language model developed by Google researchers that has achieved state-of-the-art performance on numerous NLP tasks, including text summarization.

T5 is a multi-task encoder-decoder model that has been pre-trained on a variety of unsupervised and supervised tasks. They turned each assignment into a text-to-text format, allowing T5 to work effectively on a wide range of activities right out of the box. The model accomplishes this by appending a distinct prefix to the input for each task. T5's capacity to do numerous NLP jobs by just altering the input prefix is a huge advantage. Furthermore, its performance on a variety of tasks has established it as one of the most promising techniques for NLP applications. The model has the ability to generalize well to new tasks because it was pre-trained on a combination of unsupervised and supervised activities.

Text summarization is one of T5's most exciting applications. Summarizing lengthy documents while retaining the most important information is a difficult undertaking, but T5 has produced outstanding success in this area. T5 may generate a succinct summary that captures the substance of the original document by inputting the text to be summarized with the prefix "summarize".

This is excellent for news stories, research studies, and legal documents, among other things. The encoder-decoder variation of the T5 paradigm unifies both NLU and NLG jobs by converting them into sequence-to-sequence tasks. This means that they used text as the encoder input for the text classification problem, and the decoder must generate the label as normal text rather than a class.

5. BART

BART (Bidirectional and Autoregressive Transformers) is a Facebook AI-developed generative pre-trained transformer model. It is trained on a vast text and code dataset and can do a range of tasks such as summarization, translation, and question answering.

BART is a sequence-to-sequence model, which means it can take a set of input tokens (for example, a document) and generate a set of output tokens (for example, a summary). BART is taught to predict missing tokens in a sequence using a masked language modelling (MLM) objective. This training goal assists BART in learning the links between words and sentences, which is necessary for summarization.

It has been demonstrated that BART is successful for document summarization. On a range of datasets, BART was demonstrated to outperform state-of-the-art summarization methods in a recent study. BART can also produce summaries that are both informative and fluent.

BART employs the fundamental sequence-to-sequence Transformer architecture from, with the exception of changing the activation functions for ReLUs to GeLUs and the initialization settings to N, as per GPT (0, 0.02). It uses 6 layers in the encoder and decoder for our basic model, and 12 layers in each for our large model. The architecture is similar to BERT's, with a few exceptions: (1) In the transformer sequence-to-sequence model, each decoder layer performs cross-attention across the encoder's final hidden layer; and (2) BERT employs an additional feed-forward network before word prediction, whereas BART does not; and BART has approximately 10% more parameters than a comparable BERT model.

6. Pegasus

Pegasus (Pre-training with Extracted Gap-sentences for Abstractive Summarization Sequence-to-sequence) is a Google AI-developed generative pre-trained transformer model. It is specifically built for abstractive summarization and is trained on a vast dataset of text and code.

Abstractive summarization is a sort of summarizing in which a new summary is created that is not merely a rewording of the original material. Instead, the summary should rephrase and condense the essential themes of the original text.

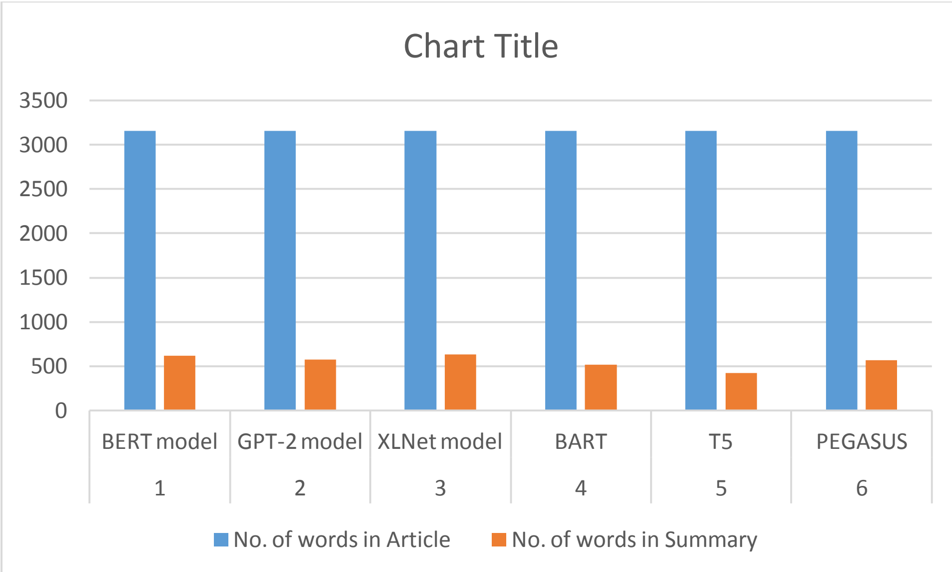
Pegasus can do abstractive summarization using a technique known as "gap-sentence generation." Pegasus is trained to generate a sequence of tokens that fills in the gaps in a sequence of tokens in gap-sentence generation. The gaps are made by randomly blocking out some of the pixels.

For sequence-to-sequence learning, PEGASUS employs an encoder-decoder paradigm. In such a model, the encoder will first examine the context of the entire input text before encoding it into something called a context vector, which is just a numerical representation of the input text. This numerical representation will then be sent to the decoder, whose function it is to decode the context vector in order to generate the summary.

Table No. 4 shows the comparison between the models and Graph No.1 shows the graphical representation of the table.

Sr. no	Model	No. of words in Article	No. of words in Summary
1.	BERT model	3160	619
2.	GPT-2 model	3160	574
3.	XLNet model	3160	629
4.	BART	3160	516
5.	T5	3160	420
6.	PEGASUS	3160	567

Table No.4: Evaluation of the Pre-trained models.



Graph No.1: No. of words in Article W.R.T No. of words in Summary

5. RESULT

ROUGE Evaluation

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is a collection of measures used to assess the quality of automatic summaries. ROUGE compares the summary to a reference summary, which is a human-generated summary of the same document. ROUGE is a recall-oriented metric, which means it looks for overlap between the summary and the reference summary even if the words aren't in the same order.

Each of the ROUGE metrics assesses a different component of the overlap between the summary and the reference summary. The following are the most frequent ROUGE metrics:

- ROUGE-N: Calculates the n-gram overlap between the summary and the reference summary.
- ROUGE-1, for example, measures overlap at the unigram level (that is, overlap between individual words).
- ROUGE-L is a tool that calculates the overlap between the summary and the reference summary at the longest common subsequence (LCS) level. The LCS is the longest sequence of words that appear in the same order in both the summary and the reference summary.

In ROUGE scores are commonly presented as:

F1, which is the harmonic mean of precision and recall.

$$F1\ Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (1)$$

Precision is the percentage of terms in the summary that occur in the reference summary.

$$Precision = \frac{No.of\ matching\ N-Grams}{No.of\ N-Grams\ in\ Candidate} \quad (2)$$

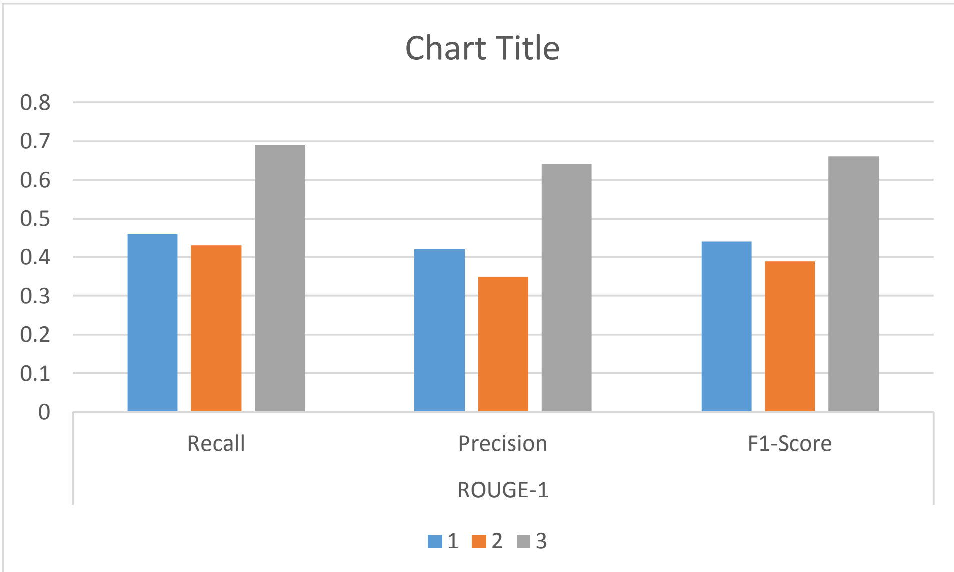
Recall is the percentage of words in the reference summary that appear in the summary.

$$Recall = \frac{No.of\ matching\ N-Grams}{No.of\ N-Grams\ in\ Reference} \quad (3)$$

So for the above pre-trained models the following ROUGE score comes as following tables.

Sr.no	Model	ROUGE-1		
		Recall	Precision	F1-Score
1.	BERT model	0.46	0.42	0.44
2.	GPT-2 model	0.43	0.35	0.39
3.	XLNet model	0.69	0.64	0.66

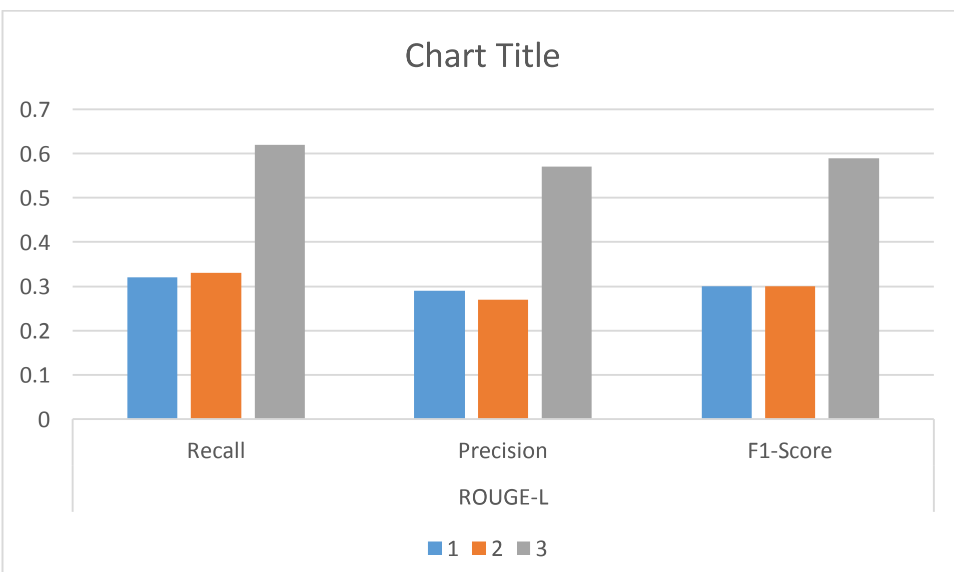
Table No. 5: ROUGE-1 score



Graph No.2 ROUGE-1 score

Sr.no	Model	ROUGE-L		
		Recall	Precision	F1-Score
1.	BERT model	0.32	0.29	0.30
2.	GPT-2 model	0.33	0.27	0.30
3.	XLNet model	0.62	0.57	0.59

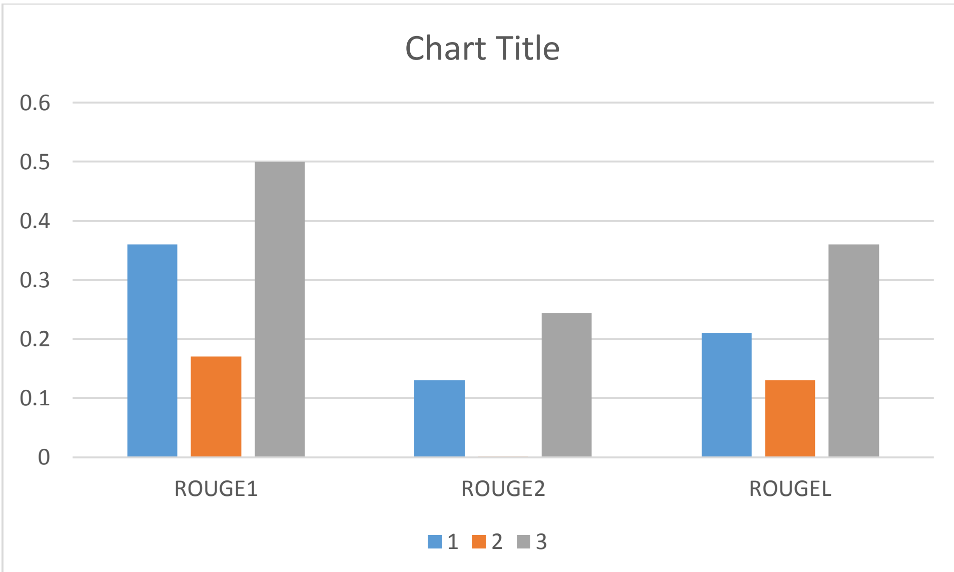
Table No. 6: ROUGE-L score



Graph No.3 ROUGE-L score

Sr. no	Model	ROUGE1	ROUGE2	ROUGEL
1.	BART	0.36	0.13	0.21
2.	T5	0.17	0.001	0.13
3.	Pegasus	0.500	0.244	0.36

Table No. 7: ROUGE evaluation



Graph No.4 ROUGE Evaluation

As from the above table and Graph it can come to a conclusion that the Pre-trained model of XLNet is well suited and has a better accuracy based on the comparison with the expert summary generated.

There are several different deep learning models that may be implemented to increase the accuracy or the output summary. In the Sequence 2 sequence model, we can work on the Pointer generator model due to the fact it has the greatest potential for summarizing documents and can be applied on research papers. We also have the option of using a hybrid strategy in conjunction with the Pointer Generator model to generate a noteworthy concise summary for research papers.

6. Conclusion

In this survey, it divides summarization methods into three categories: classic approaches, machine learning-based approaches, and emerging approaches that leverage the concept of deep neural networks to generate summaries.

The paper also discussed many types of summarization, such as abstractive-extractive, multi-lingual monolingual, supervised-unsupervised, and so on. Several summary evaluation measures include intrinsic and extrinsic measurements, as well as the estimated ROUGE score for several pre-trained modes are also described.

The testing on these pre-trained models shows that the XLNet model gives a more accurate summary.

In future, further work on document summarization on research papers can be performed out, and this paper suggests some future scopes where researchers can use various hybrid deep learning models such as the Pointer

Generator model, which can generate a summary based on topics in research papers and which researchers can use to understand the paper more efficiently and quickly.

After delving this deeply, the survey can conclude that Text Summarization is a widely researched topic in the field of AI-NLP, and research is currently ongoing to achieve human-level excellence in producing summaries. Because there is no exact metric for determining whether a summary is worthy or dreadful, and because readers' perceptions differ depending on domain knowledge, the topic of text summarizing remains a work in progress for researchers.

7. Reference

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