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TEXT SUMMARIZATION

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***Abstract*- Today, information overload is a reality due to the rapid emergence and evolution of new technologies. Although readers can easily identify a text's readability by its abstract, most information is not written in an abstract. This project aims to simplify articles so that everyone can understand them. Text summarization is a process that can be used in web pages and social media applications to identify the trends in a given topic. In this project, we will use pre-trained Natural Language Processing models such as Pegasus, BERT, and Simple T5. These models can perform various tasks, and they can also be used to analyze the results of a study. The aim of the project is to fine-tune pre-trained models in order to increase their performance. Pegasus, Bert, and a simple T5 model have all been fine-tuned by us . These models were trained on a large corpus of text and fine-tuned on a samsum dataset. Evaluating the performance of different models can help determine which one is best at producing succinct, accurate summaries. The evaluation will be based on established metrics such ROUGE scores, and the findings will be examined to identify each model's advantages and disadvantages. The goal of this research is to improve text summarization's capabilities and to provide light on the efficiency of different models for this job.**

Keywords: Text Summarization, Abstractive Text Summarization, NLP, Pegasus, BERT, Simple T5, Rough Score.

Introduction

Natural Language Processing (NLP) is a field of AI in Computer Science[19]. NLP is used to extract information and organize or categorize the information from data. NLP is used in domains where there is the use of language understanding & generation, speech & text recognition, etc. Some popular examples of NLP we see in our day-to-day lives are Autocorrect and Autocomplete, Grammarly, (speech-to-text) Voice typing, Language translation, text summarization, Sentiment Analysis, Voice assistance, etc. Text Summarization enables NLP to summarize a large piece of information accurately into a small paragraph, ensuring that the meaning and original content is

preserved. Basically, it is a process where large text data is distilled and the most important information is fetched as a summary. Text Summarizers work by removing verbs and pronouns and extra unrequired grammar etc, extracting keywords and important segments, and calculating the frequency of repeated words. Text Summarization helps us to get the best information from the Data/content in a minimum amount of time [22]. Text summarization is becoming increasingly important in today's fast-growing world.

There are 4 types of Summarizations: Abstractive Summarization, Extractive Summarization, Indicative Summarization, and Informative Summarization. Here, we will know in depth abstractive text summarization. Extractive Text Summarization involves extracting certain keywords, important lines, sentences, and key phrases from the original content and combining and using them in the short Summary [25] .It can merge these extractive text summarization techniques with deep neural network-based models and can provide us with better performance. These models can be referred to as hybrid models (i.e. extractive and abstractive). Abstractive Text Summarization acts as a solution to all limitations faced by Extractive Text Summarization. It has the potential to make Text Summarization faster and improve text quality of generated text summaries. In abstractive text summarization, the original content is paraphrased and summarized in short, making sure that the meaning of the summarized content matches the original one. It doesn't use the same keyword from the original content but uses its own instead. The algorithm creates its own phrases and sentences which match the original content. It's similar to how the human brain works, it collects all semantic information, then picks up semantic based keywords, and uses that in the summarization. A variety of NLP-based pretrained models can be used to achieve abstract summarization..

A pre-trained model in NLP is a deep learning model that has been pre-trained on large datasets in order to learn the patterns and features of natural language. To adapt to the specific NLP task at hand, these models are then fine-tuned. Our approach to text summarization is abstractive summarization. In this approach, the pre-trained model generates a summary by synthesizing the input text and generating new sentences that capture the main points of the input text. Text Summarization models such as BERT, Pegasus, and T5 were used in this paper to generate coherent summary sentences that capture the essence of the input text.

Following is the structure of the rest of the paper: Section II outlines previous text summarization surveys, while Section III discusses widely used pre-trained models. Text summarization is illustrated in Section IV. The findings of the study are presented in Section V. The results of the study are presented in Section VI.

II. Literature Review

NLP and text summarization is a rapidly growing field with extensive research on various domains and topics. A wide range of approaches has been developed to achieve text summarization. These strategies include rule-based and machine learning-based methodologies, as well as extractive and abstractive summarization.

In 2011, Makbule Gulcin Ozsoy[1] suggested that semantic analysis is the newest way for text summarization. These cross and topic approaches can be applied in any language for summarization purposes, and the algorithms are assessed on Turkish and English documents, and their results are compared using their Rouge scores.

In 2020, Atif Khan[2] He also purposed text summarization using a semantic graph to abstractively sum up multiple documents. In another study, Achempong Francisca Adoma[3] compared the effectiveness of pre-trained transformer models, including BERT, RobertA, DistilBert, and Xlnet, for identifying emotions from the text. There was a high degree of recognition accuracy with RobertA in the study.

In 2021, Li Zhang[4] discussed fine-tuning approaches for pre-trained models. The study concluded that a conventional fine-tuning model should have minimal differences between the pre-trained and downstream architectures, as significant task-specific model changes can negatively impact the outcome. These studies contribute to the growing body of research on pre-trained models and their applications, providing valuable insights for further advancements in NLP and text summarization.

Sheng-Laun Hau[5] Paper that delves into the topic of automatic text summarization and its numerous applications. The paper provides insights into the approaches used in ATS, as well as highlights the current challenges and limitations of the methods and algorithms used in this field. It is hoped that this paper will inspire researchers to tackle these issues and address new challenges in ATS, ultimately advancing the field and improving the quality and effectiveness of automated text summarization techniques. Y. Chen[6] in 2021 show a method which suggested automatically creates a restaurant template with all relevant information, including specified subjects.

The new proposed T-BERT Sum[7] applies BERT in text summarization, which introduces rich semantic features, based on the modified transformer architecture that achieves efficient and paralleled computation. The background information is considered to be integrated into the encoding as additional knowledge, which is encoded to be an adjustable topic representation, aiming to guide the generation of summaries in an end-to-end manner.[23]

The advancements in the field of NLP have encouraged researchers to explore language-based summarization techniques. Several works have been proposed in the past, and a recent work by T. Islam[8] has focused on achieving text summarization in Bangla text documents.

III. Pretrained Models

Due to their exceptional performance on text summarization tasks, pre-trained models such as Pegasus, T5, BERT, and GPT-2 are commonly used. These models are carefully tuned to achieve the best possible results. Through deep learning, we can use these models to produce high-quality summaries of documents. The goal of this study is to develop a new text summarization algorithm that can provide high-quality summaries for various sources, such as academic papers and news articles.

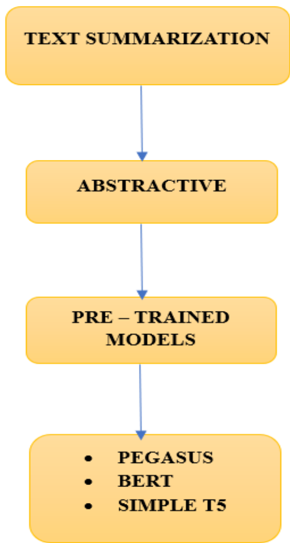

Fig 1 Structure of Text Summarization

PEGASUS

Google's pre-trained text summarization model, known as PEGASUS, is an advanced model that can extract gaps in the text and produce new summaries. It is based on a transformer architecture and is designed to be used on a large amount of data.[28]

Unlike other models, PEGASUS is not only trained on abstractive and extractive summarization tasks, but it also learns to summarize documents in a coherent manner. It has been shown that it performs better than state-of-the art models on various benchmark datasets[29].

SIMPLE T5

Google's T5 is a pre-built language model that can perform various NLP tasks. It's a text-based model that's been trained to map input data to output text, which makes it a powerful tool when it comes to summarization. T5's lighter sibling, Simple T5, can be tuned to perform various NLP tasks, such as text summarization. With a large corpus of text data, it can produce high-quality summaries.

BERT

The BERT model (Bidirectional Encoder Representations from Transformers) is one of the most popular deep learning models for NLP tasks, including text summarization[30]. This transformer-based model generates high-quality contextualized word embeddings, which are vector representations of words that describe their meaning and context. BERT is used for text summarization in an abstractive summarization approach by generating new sentences for each point in the input text. It is possible to develop highly effective text summarization models with BERT's pretrained model by leveraging its ability to generate contextualized embeddings and fine-tune it to specific NLP tasks. As a result of its high performance on a variety of NLP tasks, including text summarization, BERT is a popular choice among industry and academia for developing text summarization models.

IV. Methodology -

The steps needed for summarization are data collection, preprocessing, selecting an appropriate summarization algorithm, training the summarization model, evaluating the performance of the model, and deploying the model in a production environment to generate summaries for new input text. It is important to note that text summarization is a complex task, and the quality of the generated summaries depends on the quality of the data and the chosen algorithm. Therefore, careful attention should be paid to each step of the summarization process to ensure accurate and coherent summaries.

Step 1 Data Collection:: This stage entails loading the data set and performing preprocessing on it. For this research, we used the Samsum dataset, which comprises summaries for roughly 16k messenger-like chats. The chats may be informal, semi-formal, or formal, and they may also contain slang terms, emoticons, and typos. Then, summaries were added as annotations to the conversations. It was believed that summaries would offer a succinct summary of the topics covered in the third-person dialogue. Samsung R&D Institute Poland created the SAMSum dataset, which is made available for research. A dataset must go through a number of processes during preprocessing in order to get the input text ready for text summarizing.

id (string)	dialogue (string)	summary (string)
"13818513"	"Amanda: I baked cookies. Do you want some? Jerry: Sure! Amanda:…	"Amanda baked cookies and will bring Jerry…
"13728867"	"Olivia: Who are you voting for in this election? Oliver: Liberals as always. Olivia: Me too!! Oliver: Great"	"Olivia and Olivier are voting for liberals in this election. "
"13681000"	"Tim: Hi, what's up? Kim: Bad mood tbh, I was going to do lots of…	"Kim may try the pomodoro technique…
"13730747"	"Edward: Rachel, I think I'm in ove with Bella.. rachel: Dont say…	"Edward thinks he is in love with Bella. Rachel…
"13728094"	"Sam: hey overheard rick say something Sam: i don't know what t…	"Sam is confused, because he overheard…
"13716343"	"Neville: Hi there, does anyone remember what date I got married…	"Wyatt reminds Neville his wedding anniversary…

Fig 2 Dataset

Step 2Installation and Importing of Libraries: In this step, libraries are installed and imported. We have installed the necessary libraries for text summarization, including the transformers and ROUGE libraries, which also equipped our project with powerful tools for state-of-the-art natural language processing and evaluation. These libraries provide us with access to pre-trained models Pegasus, BERT, GPT as well as robust metrics like ROUGE, allowing us to develop and evaluate high-quality text summarization models.

Step 3Defining Model and Tokenizer: We defined the model and tokenizer in this phase. Selection of pretrained Models: Select a pre-trained language model that is effective for the purpose of text summarization. BERT, GPT-2, T5, and Pegasus are a few of the well-liked choices. Creating a tokenizer to convert the input text into a numerical representation, choosing a suitable model architecture, and training the model on a dataset of input text and related summaries are the steps in defining the model and tokenizer for text summarizing. In contrast to other models, the Pegasus model provides accurate and reliable results, thus we used it.

Step 4 Comparing Summary and Dialogue token: The comparison of different summaries is done in this step, along with dialogue token comparison.

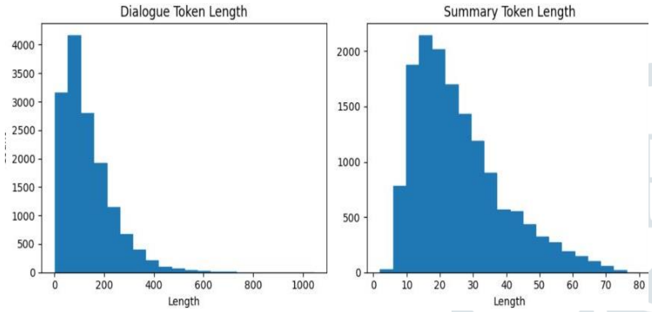

Fig 3 Comparison of dialogue tokens and summary tokens

Step 5 Fine-tuning the Model: The modelsneed to be fine-tuned for text summarization by being modified to perform the specific task of summarizing incoming material.

There are a number of methods that may be used to enhance the performance of the fine-tuned model, including layer addition, learning rate modification, and regularization methods like a dropout. Additionally, to produce more varied and fluid summaries during inference, you might employ strategies like beam search and nucleus sampling.

```
You're using a PegasusTokenizerFast tokenizer. Please note that with a fast toke
[920/920 29:39, Epoch 0/1]
```

Fig 5 Training Loss and Validation Loss for simple T5 model

Step	Training Loss	Validation Loss
500	1.704100	1.482772

```
TrainOutput(global_step=920, training_loss=1.8294374973877616, metrics=
{'train_runtime': 1784.6856, 'train_samples_per_second': 8.255,
'train_steps_per_second': 0.515, 'total_flos': 5526961323663360.0, 'train_loss':
1.8294374973877616, 'epoch': 1.0})
```

Fig 4 Training Loss and Validation Loss for Pegasus

```
You're using a T5TokenizerFast tokenizer. Please note that with a fast tokenize
[920/920 13:40, Epoch 0/1]
```

Step	Training Loss	Validation Loss
500	2.138500	1.906944

```
TrainOutput(global_step=920, training_loss=2.3123247063678245, metrics=
{'train_runtime': 824.5867, 'train_samples_per_second': 17.866,
'train_steps_per_second': 1.116, 'total_flos': 579616067813376.0, 'train_loss':
2.3123247063678245, 'epoch': 1.0})
```

Step 6 Evaluation Metrics: In this step, the quality of a text summary is evaluated using the rogue metric.

ROUGE(Recall-Oriented Understudy for Gisting Evaluation) is a tool used to evaluate the quality of automatic text summarization and machine translation. It measures the number of matching n-grams between the generated summary and the human-written reference. ROUGE-1, ROUGE-2 and ROUGE-3 measure the match rate of unigrams, bigrams, and trigrams respectively. ROUGE-L is based on the longest common subsequence between the generated summary and the reference, which measures the longest shared sequence of words between the two. We have

Fig 6 Training Loss and Validation Loss for BERT model

```
[920/920 42:34, Epoch 0/1]
```

Step	Training Loss	Validation Loss
500	5.914700	5.866799

```
TrainOutput(global_step=920, training_loss=6.378998196643332, metrics=
{'train_runtime': 2559.8917, 'train_samples_per_second': 5.755,
'train_steps_per_second': 0.359, 'total_flos': 8550245403433320.0, 'train_loss':
6.378998196643332, 'epoch': 1.0})
```

calculated ROUGE scores recall, precision, and F1-score to assess the quality of the summarization model.

Formulas for calculating Rouge values:

$$Recall = \frac{Number\ of\ n{-}grams\ found\ in\ model\ and\ reference}{number\ of\ n{-}grams\ in\ \boldsymbol{reference}} \ldots\ldots\ldots.(1)$$

$$= \frac{count_{match}(gram_n)}{count(gram_n)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$Precision = \frac{number\ of\ n - grams\ found\ in\ model\ and\ reference}{number\ of\ n - grams\ in\ \boldsymbol{model}} \ldots(3)$$

Table 1 Average rouge score comparison w.r.t different models

$$f - score = 2 * \frac{precision * recall}{precision + recall} \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Rouge values of the reference summary text w.r.t. original text has calculated before training the data set and later after fine-tuning and training of the data set the results for rouge scores are shown below:

	rouge1	rouge2	rougeL	rougeLsum
pegasus	0.296412	0.087722	0.229512	0.229311

Figure 7 Rough scores for Pegasus before fine

	rouge1	rouge2	rougeL	rougeLsum
pegasus	0.428706	0.198005	0.340192	0.339809

Figure 8 Rough scores for Pegasus after fine tuning

V. Result and Discussion

The study aimed to evaluate the performance of different text summarization models in generating coherent and informative summaries from long texts. To achieve this, three popular text summarization models were implemented and evaluated, including the Bert model, Pegasus model,and Simple T5 model. The models were tested on a samsum dataset collected fromonline sources. The evaluation of the models was based on the ROUGE metric, which is commonly used to measure the quality of summaries in text summarization tasks. The ROUGE scores were calculated for the generated summaries and compared with the reference summaries to assess the performance of each model[19].

Pre trained models	Rouge scores		
	R1	R2	RL
PEGASUS	0.4113712648	0.1943809429	0.3655917996
SIMPLE T5	0.1697108574	0.2101602842	0.3248705085
BERT	0.03051035991	0	0.09671560514

The results of the experiment show that the Pegasus model outperformed both the Bert and Simple T5 models in terms of ROUGE scores. The Pegasus model combines the strengths of both Bert and Simple T5 models, leading to more informative and coherent summaries.

The study shows how text summarizing models can produce insightful summaries from lengthy documents. The findings imply that the Pegasus model is the most successful. This result is in line with earlier studies that found Pegasus models to be superior to other models.

The study also emphasizes how crucial the ROUGE metric is for assessing the caliber of summaries. Due to its consistency and objectivity as a gauge of summary quality, the ROUGE metric is frequently employed in text summarizing studies. It's crucial to remember that the ROUGE measure only assesses how similar the generated and reference summaries are, and it ignores the coherence and readability of the created summaries[26]. One limitation of the study is that it only evaluated the models on a specific dataset. It remains unclear whether the results apply to other types of texts, such as scientific articles or social media posts.. Future studies could investigate the performance of text summarization models on different types of texts.

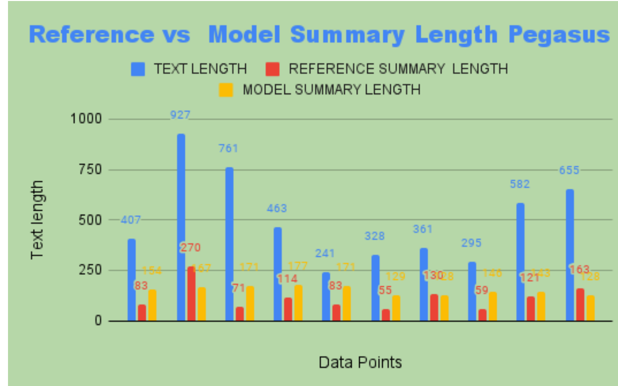

Fig 9Comparison of word length of Pegasus model w.r.t reference model[23]

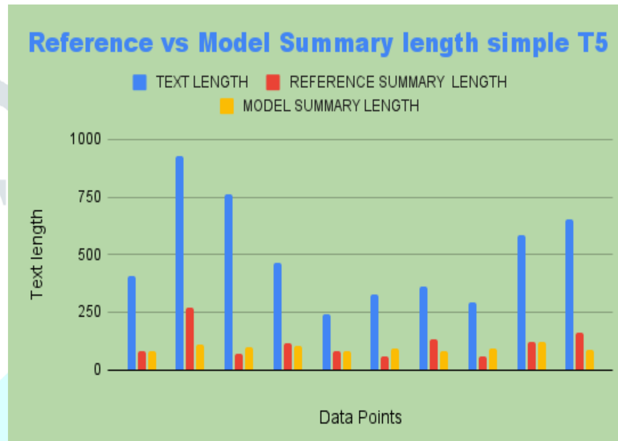

Fig 10Comparison of word length of Simple T5 model w.r.t reference model[23]

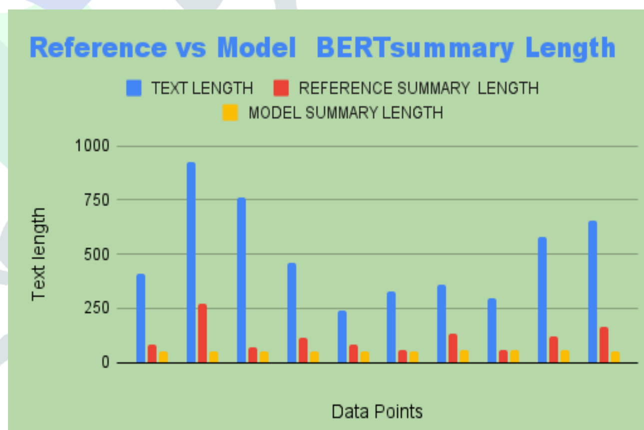

Fig 11Comparison of word length of BERT model w.r.t reference model[23]

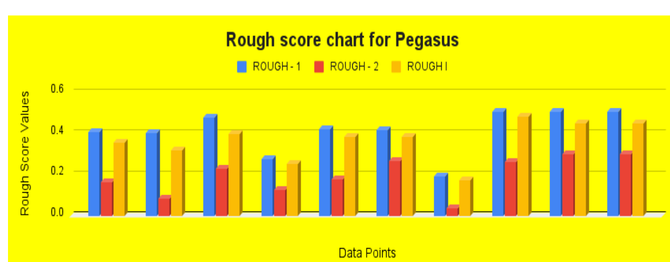

Fig 12 Rough score for Pegasus

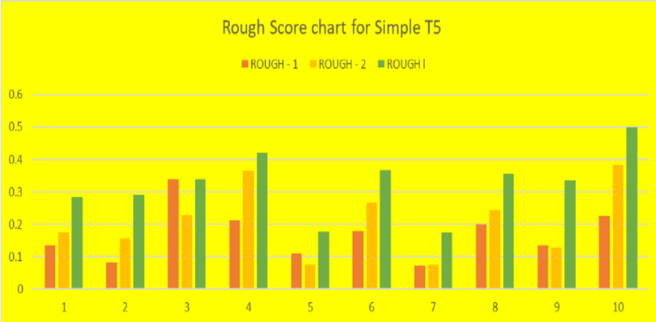

Fig 13 Rough score for Simple T5

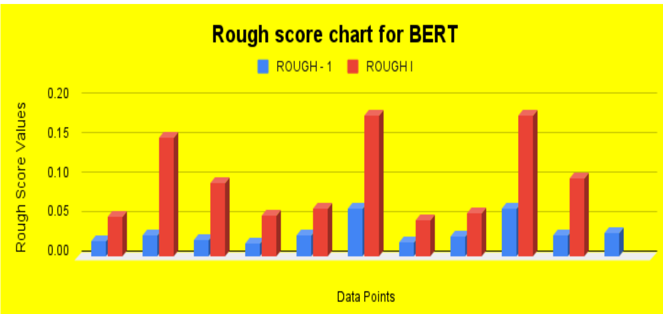

Fig 14 Rough score for BERT

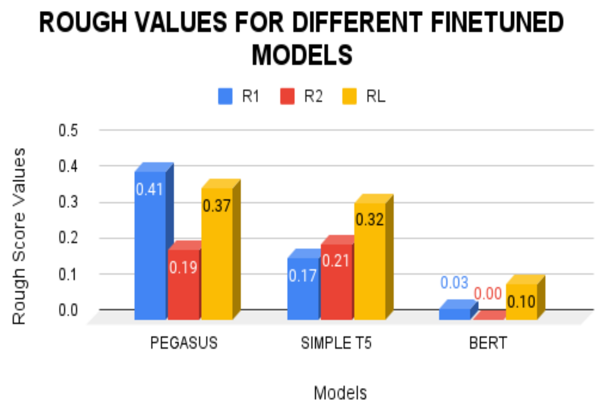

Figure 15 Rough values for different fine-tuned model

Conclusion - In summary, this study examines the effectiveness of various text summarization models and emphasizes the need for a reliable metric for assessment. For generating informative and coherent summaries from long texts, the Pegasus model appears to be the most effective approach. A ROUGE score of 4 was higher for Pegasus than Bert or Simple T5 according to the results of the experiment. The Pegasus model summarizes information in a more comprehensive and coherent manner that by combined results of Bert and Simple T5 models will not be able to achieve. Therefore, we are moving forward,to develop a text summary website based on the Pegasus model.

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