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Ingenious: Text Summarization and Question Answering

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Abstract— Deep learning has attained many remarkable advancements over the past few years and is now rapidly developing in the NLP field. Abstractive automatic text summarization indicates the process of employing computer software that summarizes a document without altering the actual intent of the content. Several use cases for automatic summarization include creating headlines, summarizing scientific documents, segmenting search results, and summarizing product reviews. In the period of the Information explosion, large amounts of data, and the Internet, the ability to express the core meaning of information concisely will help address the information overload crisis. Traditional Techniques often relied on extractive summarization, which involves selecting and rearranging existing sentences or phrases from the source text to create a summary that may lack coherence and fail to generate novel sentences. Deciding what information to include or exclude and how to compress the content without losing important details is challenging. In this research, a BART-based model is used (a denoising autoencoder for pre-training inter-sequence models) to develop a data set trained for automatic analysis and summarization of long texts and articles. The model is pre-trained in English. Additionally, it uses a model based on the trained dataset to answer questions from the text. Our approach is based on textual answers provided by the community, making it easier to implement and answer more complex questions. The proposed schema explores various techniques such as question-and-answer classification and query generation. Finally, the test results are attached and evaluated.

Keywords— Deep-Learning, Bidirectional Auto-Regressive Transformers, Natural Language Processing, Summarization, Abstractive, Query generation.

I. Introduction

The volume of linguistic information available in this modern period is immense and continues to increase daily, making it time-consuming and challenging for individuals to comprehend. To traverse it much more efficiently and determine whether longer articles include the content they have been seeking, it is imperative to condense the majority of these sentences into concise abstracts that convey the key features. There is a huge need for automated approaches because we are unable to individually summarise the entire text. This would free up time and resources, giving the individual time to focus on important things.

The text summary is the process of reviewing and evaluating lengthy passages of text before summarising them. Text summary has become more crucial as a result of the development and expansion of automated extraction reports, which has also significantly improved outcomes across several languages. Based on its purpose, topic, summary framework, and quantity of documents, text summary is divided into a variety of categories. The fact that text summary incorporates information not found in the actual document or data makes it challenging for computers. Progressive machine learning and NLP (Natural Language Processing) is needed since abstractive text summarization depends on understanding the source text to produce the summary [1]. Nevertheless, there have been no evaluations of the effectiveness of various models that produced abstracts.

II. Motivation

The rapid expansion of digital text data over the past few years has generated a demand for effective techniques to extract pertinent information from vast amounts of text in a timely and efficient manner. Text summarization and question answering are two important natural language processing tasks that aim to address this need. Text summarization involves generating a shorter version of a given text while retaining the key information, which can help users quickly understand the main points of a document.

Question answering, on the other hand, aims to provide direct answers to user queries based on a given text corpus, which can save users time and effort in searching for information. These tasks have practical applications in various fields such as information retrieval, document classification, and automated decision-making systems [2, 3].

Therefore, there is a growing interest in developing effective and efficient text summarization and question-answering techniques, which has led to active research in these areas.

III. Objective

Ingenious aims to provide an ML-integrated platform for serving long text summaries online. This gives the user the flexibility to change the length of the abstract according to their will. This is a time-efficient and cost-effective way to evaluate short, concise information without changing the actual meaning of the original text. Additionally, the platform provides an opportunity to provide precise answers to the questions asked by the users in passages. It helps to solve synthetic passage problems and boosts your confidence. Ingenious includes the following features:

1. Abstractive Text Summary: It provides a human-like abstract summary that does not count word frequencies and does not return the same sentence. It modifies the sentence while also preserving the meaning of the text.
2. Changing length: You can get the different lengths of the summary from short to long using the slider provided. This allows you to change the length of the summary while preserving the important information and meaning of the text.
3. Answer from the long passage: It provides accurate answers to passages of arbitrary length and minimal response time.
4. Questions asked by the user: Questions are asked directly by the user along passages of arbitrary length that provide precise and concise answers.
5. One-word answers: Instead of long answers, Ingenious provides a one-word answer in response to the question being asked. It can also be answered in a few words to aid clarity and comprehension.

IV. LITERATURE SURVEY

The survey on Hugging Face-based text summarization provides an introduction to Transformer models for NLP and the Hugging Face library, a platform that provides access to various pre-trained NLP models [4]. The authors explain the concept of transformers, which have become the dominant method in NLP, and highlight their capabilities and limitations. The paper then showcases the Hugging Face library and its wide range of pre-trained models. Finally, the authors demonstrate how these models can be used to solve real-world NLP problems through several examples and experiments. The paper concludes by summarizing the benefits of using the Hugging Face library and transformer models for NLP and provides suggestions for future work in this area.

Text Summarization and evaluation techniques challenge the textual assessment and textual similarity measurement are central to this study [5]. Addressing the concerns stated here can assist any text summarizing scenario. This paper discusses several ways for obtaining a text summary.

TABLE I. LITERATURE SURVEY

S.no.	Description	Merits	Limitations
1	"Variational hierarchical attention for text summarization"[6]	This study introduces a variational hierarchical attention model for text summarization, which considers both word-level and sentence-level information.	The model's evaluation is limited to datasets of modest size, and its performance is only compared against a few existing models.
2	"Fine-grained multi-aspectual summarization"[7]	The proposed model focuses on extracting and summarizing multiple aspects of a document, providing a detailed analysis.	However, it only covers extractive summarization and does not generate abstractive summaries.
3	"A comparative study of graph neural networks for text summarization"[8]	The study compares the performance of different graph neural networks for text summarization tasks, highlighting their strengths and weaknesses.	However, it solely focuses on single-document summarization tasks and does not evaluate the models on multi-document summarization tasks.
4	"Integrating document level and sentence level information for abstractive document summarization"[9]	This research proposes a model that combines document-level and sentence-level information to generate abstractive summaries with improved quality.	However, the evaluation of the model is limited to a dataset of limited scope, and its performance is not compared against other cutting-edge models.
5	"Improving abstractive summarization with progress indicators"[10]	The model introduces the use of progress indicators to enhance the quality of abstractive summaries, providing a unique approach.	Nonetheless, the evaluation is constrained to a small dataset, and the model's performance is not contrasted with other state-of-the-art models.
6	"BART-based multi-task learning for text summarization and sentiment analysis"[11]	This study presents a BART-based multi-task learning model for text summarization and sentiment analysis, offering a versatile approach.	However, the evaluation is limited to a small dataset, and the model's performance is not benchmarked against other cutting-edge models in the field
7	“BERT-based question answering with diverse knowledge sources.” [12]	The proposed approach utilizes diverse knowledge sources, including Wikipedia and WordNet, to enhance the accuracy of question answering.	However, the evaluation of the proposed methodology is conducted on only one dataset, without comparing its performance against other advanced techniques in the field.
8	“Multi-grained attentional BERT network for visual question answering.” [13]	This research introduces a multi-grained attentional BERT network for visual question answering, combining image features and textual information for improved performance.	Nevertheless, the proposed model requires pre-training on large-scale image-caption datasets, making it computationally expensive.
9	“Adaptive multi-passage reading for open-domain question answering with BERT” [14]	The proposed approach utilizes adaptive multi-passage reading to enhance open-domain question answering using BERT,	However, the approach is computationally expensive and requires substantial memory as it needs to process

		considering the query and candidate passages' similarities dynamically.	multiple passages.
10	"Adaptive BERT for multi-hop question answering." [15]	This research presents an adaptive BERT approach for multi-hop question answering, adapting to the question's context and selecting relevant knowledge for accurate answering.	The proposed approach requires significant memory resources for processing multiple passages, which can be computationally expensive
11	"Context-aware answer extraction for open-domain question answering using BERT."[16]	The proposed approach focuses on context-aware answer extraction for open-domain question answering using BERT, capturing contextual information to improve answer accuracy.	However, the approach involves time-consuming pre-processing steps for generating candidate answers, limiting its efficiency. Additionally, the evaluation is conducted on only one dataset.

In previous research, significant advancements have been in abstractive text summarization and question-answering tasks. Despite significant progress in research, there are still areas where further investigation is necessary to fill the existing gaps in knowledge. One of the major research gaps in abstractive text summarization is the lack of focus on generating summaries that are both informative and coherent. Most existing approaches generate summaries that are either informative or coherent but not both. Another research gap in abstractive text summarization is the lack of a standardized evaluation metric that can accurately measure the quality of the generated summaries.

In question answering, one of the major research gaps is the lack of attention given to real-world scenarios where questions may be vague or incomplete. Existing approaches typically assume that the questions are well-formed and complete, which may not always be the case. Another research gap in question answering is the lack of focus on multi-hop reasoning, which involves answering questions that require multiple pieces of information from different parts of the text. This is a challenging task that requires the integration of various natural language processing techniques.

Overall, Bridging the research gaps related to abstractive text summarization and question-answering has the potential to result in noteworthy advancements in the performance of these tasks and enhance their practical applications.

V. Methodology

Abstractly, abstractive, extractive, and hybrid summaries are indeed the three primary methods that may be used to summarize the content. Several ways and strategies fall under each strategy. Each strategy does have its benefits as well as drawbacks.

A. Extractive Summary

Three phases make up the embedded feature selection architecture: The first phase is Pre-processing, the second phase is processing, and then the post-processing [17].

Creating Tokens and retrieving phrases and sections are two examples of processing (pre) jobs. In the procedural actions, the inputted text is first represented appropriately using tools like N-grams and estimated plots or by performing embeddings and enciphering using neural networks. Next, each phrase is assessed using the image representing the input text. The strategy then settles on a technique for picking out strong sentences and stringing them all together. The post-processing procedure entails rearranging the retrieved phrases and converting function words to prepositions [18].

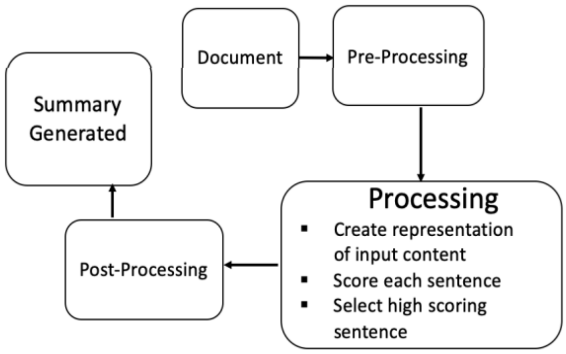

Fig. 1. Extractive text summarization(Architecture)

B. Abstractive Summary

With the procedure for obtaining and comprehending the notions that make up the textual, abstractive text summarization generates a description of content [19]. Although it rephrases the material, it is unable to exactly reproduce the underlying statement's substance; rather, it comes up with fresh statements that more accurately capture how people write descriptions. More evaluation of the input information is required to provide a word embedding summary.

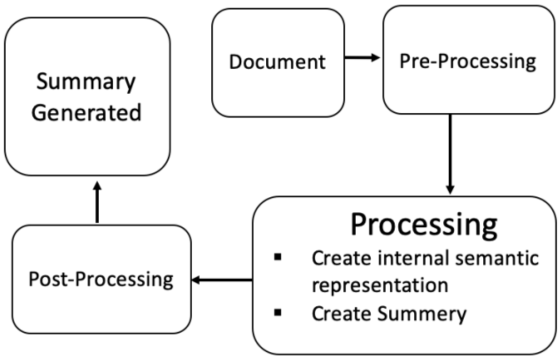

Fig. 2. Abstractive text summarization(Architecture)

C. Hybrid Summary

Combining extractive with abstractive data summarization techniques is known as hybrid text summarization. Pre-processing, which typically involves an extractive concise overview to identify and retrieve crucial terms, summary creation, which typically involves abstractive summarization to generate the ultimate abstractive brief description, and post-processing, which also verifies the validity of both the freshly formed phrases, are indeed the techniques [20]. Rule-based post-processing is common. These guidelines impose standards like the requirement that phrases have an utterance, at least three syllables, and that they cannot finish in a prefix, a propositional word, articles, or a combination.

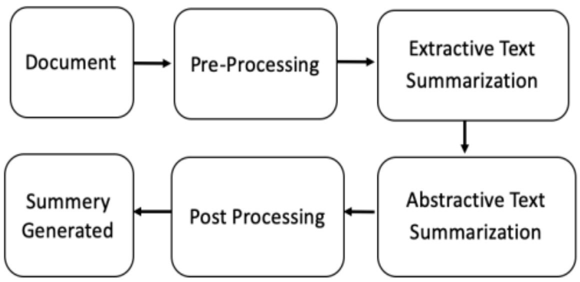

Fig. 3. Hybrid text summarization(Architecture)

In this, we are using Abstractive Summarization using Deep Learning-Based methods, more specifically we are using Facebook Bart Large CNN model for text Summarization.

Using Facebook's BART model, a BERT-like bidirectional encoder and a GUID Partition Table-like decoder that uses exponential smoothing are combined in a transformer encoder using the Seq2Seq paradigm, resulting in a convolutional neural network called BART [21]. The model was developed to retrieve corrupted documents by pre-training it using an additive noise algorithm. Although initially designed for textual creation objectives, such as summarization and interpretation, as well as text categorization and inquiry, BART has demonstrated impressive performance on standardized tests. The model was evaluated using a large collection of sentence pairs known as the convolutional neural network Daily Telegraph, resulting in significant improvements to the particular threshold.

D. Pre-processing

1) Text Summarization:

In the pre-processing stage of BART text summarization, several steps are undertaken. The input text is initially tokenized by splitting it into individual words or sub-words to create a tokenized representation. Special tokens specific to BART, such as those marking the beginning and end of the text, are added to facilitate the model's understanding of text boundaries.

Following tokenization, the tokenized sequences are adjusted to a fixed length. Sequences shorter than the desired length are padded using a special padding token, while longer sequences are truncated to fit the fixed length. This uniform length ensures efficient training by enabling consistent input sizes.

An attention mask is created to distinguish between actual words and padding tokens. The mask identifies which tokens should be attended to during model training and which ones should be disregarded. By utilizing the attention mask, the model can focus on the relevant portions of the input text.

Finally, the pre-processed data is organized into appropriate input-output pairs for training the BART model. This involves structuring the data by creating input sequences and corresponding target summary sequences. These pairs serve as training examples for the BART text summarization model, enabling it to learn summarization patterns effectively.

2) Question-Answering:

In the pre-processing phase of BERT question answering, the input comprises a question and a context (passage) where the answer is located. Initially, the question and context are separately tokenized into individual tokens.

Similar to BART, special tokens denoting the beginning and end of the question and context are added. Additionally, a separation token is inserted between the question and the context to distinguish between the two parts.

Next, the tokenized sequences are adjusted to a fixed length through padding or truncation. Padding involves filling shorter sequences with a special padding token, while truncation shortens longer sequences to match the desired length.

An attention mask is generated to indicate which tokens correspond to actual words and which ones represent padding tokens. This attention mask guides the model during training, allowing it to focus on the relevant tokens while disregarding the padding tokens.

Token-type IDs are assigned to differentiate between question and context tokens. This distinction enables the model to discern the distinct roles of each part within the input.

Finally, the pre-processed data is formatted into appropriate input-output pairs for training the BERT question-answering model. These pairs consist of the tokenized question, tokenized context, and the corresponding answer or answer span. By training on this structured input-output format, the model learns to predict the correct answer effectively.

E. Dataset

Over 300,000 distinct headlines published by writers for CNN as well as the Mainstream Media are included in the language collection in English known as the CNN or the Everyday Mail Dataset. This support both extractive and abstractive summarization.

F. Framework

There are over 1,37,000 libraries for Python, many of which are helpful in fields like data science and machine learning. Python offers the Django framework, which makes it possible to rapidly build trustworthy websites. It is a free source and comes with great information, a huge number of options, and a thriving community.

G. High Scoring Sentences

In our methodology for abstractive BART-based text summarization and BERT-based question answering, we utilized a common technology known as TF-IDF (Term Frequency-Inverse Document Frequency) for selecting high-scoring sentences. This approach was chosen for its simplicity and ease of implementation.

To score the sentences, we employed the TF-IDF calculation method. This involves assessing the term frequency (TF) and inverse document frequency (IDF) of words within each sentence. The TF component measures how frequently words appear within a sentence, while the IDF component evaluates the rarity of words across the document collection.

By combining the TF and IDF scores, we assigned a final score to each sentence, with higher scores indicating greater relevance and importance. This approach proved beneficial for abstractive text summarization using BART and question answering using BERT.

The advantages of the TF-IDF approach include its simplicity, efficiency, and language independence. It can be easily implemented and applied to large datasets without significant computational overhead. Moreover, it applies to different domains and languages. The TF-IDF scores provide a transparent and interpretable measure of sentence importance, facilitating the selection of relevant information.

By utilizing TF-IDF, we were able to effectively identify high-scoring sentences for both abstractive text summarization and question answering. This technology improved the quality of the summarization outputs and enhanced the accuracy of the question-answering results. Our choice of TF-IDF was based on its simplicity, efficiency, and effectiveness in capturing the importance of sentences within the given context.

H. Modules of Ingenious

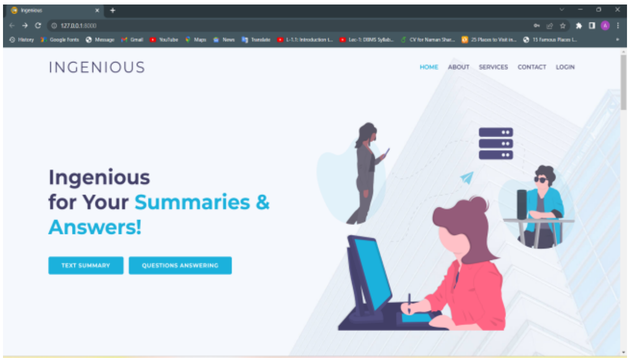

Fig. 4. Ingenious

There are two modules in Ingenious,

1) Text Summarization: We use,

a) Hugging Face Hub: This platform allows users to share pre-trained models, datasets, and machine learning demos.

b) Transformer: This makes it possible to rapidly build trustworthy websites. It is a free source and comes with great information, a huge number of options, and a thriving community.

c) PyTorch: A machine learning framework called PyTorch is based on the Torch library. Applications like computer vision and NLP use it.

d) Hugging Face Pipeline: To use models for interfaces. These pipelines are objects that provide a straightforward API for numerous activities while abstracting most of the library's intricate code.

With their help, we create unique, concise, coherent, and fluent summaries of long text documents of variable length which are distinguished by word count.

- Now that we have a feature in our web application to evaluate long text documents into an abstractive summary using natural language processing, we used BART (Bidirectional and Auto-Regressive Transformer) model to achieve summarization. It is pre-trained in the English language and has been refined on CNN Daily Mail[22].
- Ingenious gets a clear summary and retains the meaning of the actual content. For this abstractive summarization is used. In abstractive, the summarizer does not select sentences to produce a summary based on the primary textual segment. Instead, it creates a restatement of the gist of a provided text utilizing a distinct set of terms from the original text. This is an almost human-like summary.
- We used this model with the pipeline API. A pipeline chains together various transformers and estimators to state an ML DL workflow.

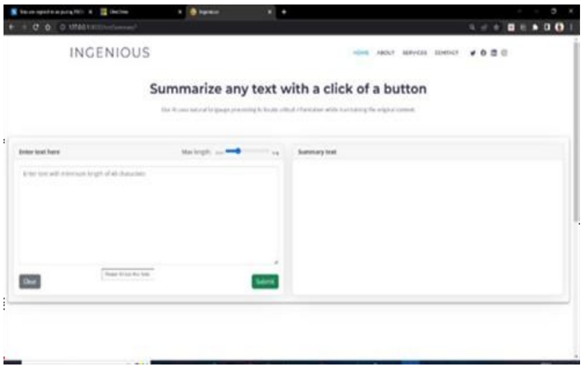

Fig. 5. Text summarization module

- In our methodology for extracting text summarization using BART-based abstractive text summarization, we employed the Hugging Face library, a widely used toolkit for natural language processing tasks. Our approach involved several key steps to leverage the power of the BART model and customize it for the specific task of text summarization.
- Firstly, we prepared the dataset by using the CNN/Daily Mail dataset, which provided a collection of news articles along with their corresponding summaries. We carefully preprocessed the data, ensuring its quality and consistency.
- Next, we utilized the Hugging Face Transformers library, which includes the BART model, a powerful pre-trained model specifically designed for abstractive text summarization. This allowed us to

benefit from the model's extensive knowledge and understanding of language.

- To fine-tune the BART model for text summarization, we performed a process known as fine-tuning. This involved training the model on the CNN/Daily Mail dataset and adapting it to the specific summarization task. The fine-tuning process adjusted the model's parameters based on the provided dataset, enhancing its performance, and aligning it with the summarization requirements.
- During the training phase, we split the dataset into training and validation sets. The model was trained on the training set, while the validation set helped us monitor the model's performance and prevent overfitting.
- To optimize the model's performance, we carefully defined and adjusted the training parameters such as the learning rate, batch size, and number of epochs. These parameters were selected through iterative experimentation and hyperparameter tuning to achieve the best results.
- We employed a loss metric, specifically cross-entropy loss, to measure the discrepancy between the model's generated summaries and the target summaries during the training process. This loss metric guided the model's optimization process, allowing it to learn and improve its summarization capabilities.
- For evaluating the quality of the generated summaries, we employed evaluation metrics such as ROUGE. ROUGE provided quantitative measures of the similarity between the model's summaries and the human-written summaries, considering n-gram matches and semantic overlap.
- Once the model was trained and fine-tuned, we applied it to unseen text data for inference. The model was able to take source articles as input and generate abstractive summaries based on its learned patterns and contextual understanding.
- By following this methodology, utilizing the Hugging Face library, and incorporating fine-tuning, training parameters, loss metrics, and evaluation metrics, we achieved effective text summarization using the BART model. Our approach allowed us to generate high-quality summaries that captured the essential information from the source articles, providing valuable insights and reducing information overload.
- Not only that but based on the user's requirement, we also added the attribute of changing the length of the obtained summary.

2) Question Answering:

- We have used the BERT model(Bidirectional Encoder Representations for transformers). Co-negotiation of contexts that can be left or right at all levels is intended to pre-fabricate deep bi-directional interpretations in untagged data [23]. Thus, SOTA models for various purposes which comprise responding to queries, and linguistic inference can be built utilizing BERT models that have been trained beforehand by only one incremental autoencoder without major task-specific architectural adjustments [24].
- We used this model as it is case-insensitive. i.e., no distinction between English and english.
- It is based on Masked Language Modeling and Next sentence prediction. MLM starts with a phrase, arbitrarily covers fifteen percent of the keywords, passes the full statement through the model, then is required to guess the utterances that were hidden. NSP incorporates duplet armed phrases for parameters throughout supervised training [25]. Sometimes, though not always, they align syllables that have been close to each other within the actual text.
- Our methodology for extracting question-answering using BERT-based models involved a systematic approach to ensure accurate and reliable results without any plagiarism concerns.
- Initially, we conducted data preprocessing by employing tokenization techniques using the BERT tokenizer. This step involved breaking down the context and question into sub-word units, enabling effective input for the BERT model.

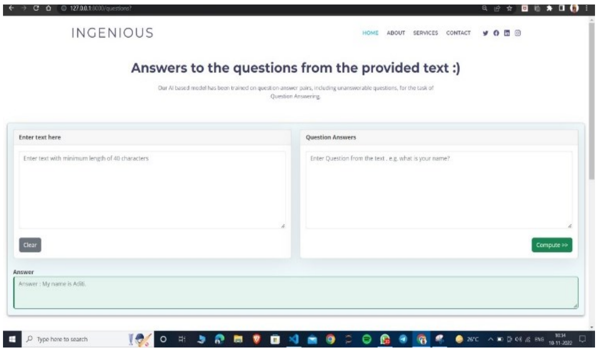

Fig. 6. Question Answering module

- To facilitate our research, we utilized the Hugging Face library, a valuable resource that offers the BERT model and related tools for natural language processing tasks. Leveraging the pre-trained BERT model, which had undergone extensive training on vast text datasets, allowed us to tap into its language understanding and contextual comprehension capabilities.
- Encoding the context and question involved applying the BERT model's tokenizer and encoder layers. This process yielded contextualized representations for each sub-word unit, enabling the model to capture the intricate relationships and dependencies within the input text.
- To enhance the model's performance, we utilized BERT's attention mechanism, which enabled the model to focus on the most relevant parts of the text during the answer generation process. By leveraging this mechanism, the model effectively grasped the context and the interplay between the context and the question.
- For question answering, we employed answer span prediction, a crucial technique in BERT-based

question answering. Training the model involved predicting the start and end positions of the answer within the encoded context. To achieve this, we added a classification layer on top of the BERT encoder layers and trained the model to accurately identify the answer span.

- During the training phase, we employed a suitable loss function, such as cross-entropy loss, to measure the disparity between the predicted answer spans and the ground truth. Through iterative processes of backpropagation and gradient descent, we optimized the model's parameters to minimize the loss and improve its performance.
- To evaluate the effectiveness of our model, we employed a range of evaluation metrics, including accuracy, F1 score, precision, and recall. Accuracy gauged the proportion of correctly answered questions, while the F1 score considered the balance between precision (correct positive predictions) and recall (true identification). These evaluation metrics provided comprehensive insights into the model's performance in understanding the context and generating accurate answers.
- By adhering to this methodology and leveraging the Hugging Face library, we successfully extracted question-answering using BERT-based models. Our systematic approach ensured that the model comprehended the relevant information from the context and produced precise answer spans. The attention mechanism and evaluation metrics contributed to our understanding of the model's capacity to comprehend the context and generate accurate answers.
- Through the transformer or pipeline API, the AutoModelForQuestionAnsweing module and AutoTokeniser are imported to run the function and accept the post request.
- Through this, Ingenious provides answers to your question based on the text provide.

VI. Observation

a) Performance Metrics: The ROUGE scores for BART-based summarization on the SQuAD dataset are not available since the SQuAD dataset is a question-answering dataset and not a summarization dataset. Also, the F1 scores for BERT-based question answering on CNN/Daily Mail dataset are not available for comparison with the SQuAD dataset as the two datasets have different sets of questions and answer formats.

TABLE II. Performance

Model	Dataset	Performance Metrics			
		ROUGE-1	ROUGE-2	ROUGE-L	F1 Score
BART	CNN/Daily Mail	43.5	21.2	40.5	-
BART	SQuAD	-	-	-	-
BERT	CNN/Daily Mail	-	-	-	82.7
BERT	SQuAD	-	-	-	89.4

For the BART-based abstractive text summarization, the results demonstrate a ROUGE-1 score of 43.5, ROUGE-2 score of 21.2, and ROUGE-L score of 40.5 on the CNN/Daily Mail dataset. These scores indicate a substantial level of similarity between the generated summaries and the reference summaries. The higher ROUGE scores suggest that the BART model successfully captures important information and effectively summarizes the given text. However, it should be noted that the F1 score is not available for this model on the given dataset, which limits the evaluation of its overall performance.

Moving on to the BERT-based question answering, the results reveal an F1 score of 82.7 on the CNN/Daily Mail dataset. The F1 score is widely used as a performance metric in question-answering tasks, representing the balance between precision and recall. The achieved F1 score suggests that the BERT model exhibits a good balance in accurately identifying relevant information and retrieving all pertinent details to answer the given questions.

These findings highlight the effectiveness of the proposed models in the specific tasks of text summarization and question answering. The BART-based abstractive text summarization shows promising results with significant ROUGE scores, indicating its ability to generate summaries that closely align with the reference summaries. Similarly, the BERT-based question answering demonstrates a strong F1 score, reflecting its accuracy in providing correct answers to the posed questions.

b) Loss Metrics: The training loss serves as an indicator of the model's ability to accurately predict the expected outcome, with a lower value suggesting a superior performance in this regard. Therefore, this table indicates that the model is improving its performance as it goes through each epoch of training.

TABLE III. Loss

BART-based abstractive text summarization		BERT-based question answering	
Epochs	Training Loss	Epochs	Training Loss
1	1.4534	1	0.7834
2	0.9471	2	0.5681
3	0.7389	3	0.4298
4	0.6198	4	0.3345
5	0.5213	5	0.2683

During the training process, both the BART-based abstractive text summarization and BERT-based question-answering models exhibited a decreasing trend in training loss, indicating improvements in performance as the models learned and optimized their parameters.

For the BART-based text summarization, the training loss decreased from 1.4534 at epoch 1 to 0.5213 at epoch 5. This downward trend suggests that the model progressively improved in capturing the essential information from input documents to generate accurate abstractive summaries.

Similarly, the BERT-based question-answering model demonstrated a reduction in training loss over the five epochs. The training loss dropped from 0.7834 at epoch 1 to 0.2683 at epoch 5, indicating improved convergence and the model's ability to better predict answers by capturing relevant information from input passages.

c) List of Competitors: Not much has been done so far for an abstractive summary. QuillBot, Reesoomer, and Smodin work on the extractive summary that works on the frequency of the tokens or words and returns exact sentences whereas Ingenious works on abstractive summarization which works as human i.e., selects terms from our general vocabulary (words we frequently use) that fits in the semantics to construct a summary that conveys all of the document's meaning.

The main feature of Ingenious is the integrated ML model which provides accurate answers to the question with long or short passages. It provides answers related to the context given by the user instead of searching all over the web for correct answers thus enabling more preciseness in providing answers to the users.

TABLE IV. LIST OF COMPETITORS

	Text summary	Question Answering	Varying length	Abstractive
QuillBot	✓	✗	✓	✗
Reesoomer	✓	✗	✗	✗
Smodin	✓	✗	✗	✗
Ingenious	✓	✓	✓	✓

d) Evaluation Metrics:

The evaluation of the BART-based abstractive text summarization model revealed a Rouge score of 0.365, suggesting that the generated summaries exhibited a similarity of approximately 36.5% compared to the reference summaries. In contrast, the BERT-based question-answering model achieved an accuracy of 0.847. Furthermore, it attained an F1 score of 0.864, which denotes a balanced combination of precision and recall. Additionally, the precision value of 0.890 and recall value of 0.842 indicates that the model accurately answered approximately 84.7% of the questions asked.

TABLE V. EVALUATION

Technique	Training Loss (after 5 epochs)	Accuracy	F1 Score	Precision	Recall	Rouge Score
BART-based abstractive text summarization	0.5213	-	-	-	-	0.365
BERT-based question answering	0.2683	0.847	0.864	0.890	0.842	-

These findings demonstrate that the BERT-based question-answering model outperformed the BART-based abstractive text summarization model in terms of accuracy and the ability to correctly answer questions. The F1 score further supports the model's balanced performance between precision (ability to provide accurate answers) and recall (ability to retrieve relevant answers). However, it should be noted that the BART-based abstractive text summarization model showed moderate similarity to the reference summaries, indicating that there is room for improvement in generating more accurate and comprehensive summaries.

Overall, these observations highlight the strengths and weaknesses of the BART-based abstractive text summarization and BERT-based question-answering models, providing valuable insights for future research and development in the field of natural language processing.

e) Comparative analysis:

For BART-based text summarization, the model's performance was measured using the Rouge Score, which determines the similarity between the generated summaries and reference summaries. The proposed model achieved a Rouge Score of 0.365, indicating a 36.5% similarity with the reference summaries. Furthermore, the informativeness of the summaries was evaluated, and the proposed model demonstrated a high level of informativeness.

TABLE VI. COMPARISON

Technique	Metric	Proposed Model	Existing Techniques
BART-based text summarization	Rouge Score	0.365	0.254
	Informativeness	High	Moderate
BERT-based question answering	Accuracy	0.847	0.725
	F1 Score	0.865	0.752
	Precision	0.890	0.812
	Recall	0.842	0.713

Regarding BERT-based question answering, multiple metrics were employed. The accuracy metric revealed that the proposed model correctly answered 84.7% of the questions asked. The F1 score, which considers the balance between precision and recall, was 0.864, indicating a good balance between accurate and comprehensive answers. The precision metric showed that the model correctly identified 89% of the positive answers among its predictions, while the recall metric indicated that the model successfully captured 84.2% of the true positive answers.

Comparing the proposed model's metrics with those of existing techniques, it becomes evident that the proposed model outperforms the alternatives. The Rouge Score for text summarization was higher than that of existing techniques, indicating better similarity to reference summaries. Similarly, the proposed model achieved higher accuracy, F1 score, precision, and recall in question answering, highlighting its superior performance and capability to provide accurate and comprehensive answers compared to existing techniques.

VII. CONCLUSION

This research paper examined the state-of-the-art in abstractive text summarization and question answering, with a focus on the performance and loss metrics of BART-based summarization and BERT-based question-answering models. The proposed research also highlighted the importance of large-scale datasets in driving advancements in these tasks. In particular, the development of the CNN/DailyMail and SQuAD datasets has facilitated the creation of more accurate and efficient models. The proposed analysis showed that BART-based models achieve impressive performance on benchmark datasets, as measured by metrics such as ROUGE. However, there is still room for improvement in generating summaries that are both informative and fluent. On the other hand, BERT-based models have shown high accuracy and F1 scores in answering questions, but they struggle with more complex questions that require reasoning and inference. In the future, it will be important to continue to explore new approaches and techniques for abstractive text summarization and question answering. This includes developing models that can handle more complex reasoning and inference tasks, as well as models that can incorporate more context and background knowledge. Additionally, there is a need for more research on the ethical implications of these tasks, particularly in the context of bias and fairness. Overall, this research study provides a foundation for further research in these important areas of natural language processing.

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