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Text Summarization using GPT-3

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ABSTRACT: The amount of information on the internet is enormous, making it incredibly challenging to keep up with the expanding quantity of articles. Since data in this era is digital, it is difficult to manually summarize the same for various purposes. Automatic Text Summarization (ATS), a component of Natural Language Processing (NLP), compresses information and delivers it to users in a clear and concise manner. It utilizes two strategies: extractive summarization which extracts significant text units from the input content; and abstractive summarization that produces new sentences not present in the original document. The words which occur frequently help to ease summarizing the text and are then organized to provide a synopsis that retains the meaning of the original text. The most important and first step in the summarizing plan is to choose the most effective method. There are large language models, a part of neural network-based models that can take into account the context of the article to make more accurate predictions of the next word in the sequence. This paper presents a simulated model that aims to achieve improved results by combining abstractive and extractive summarization with the Generative Pre-trained Transformer(GPT-3).GPT-3 is capable of producing anything with a text structure, not just text in human languages. This technology is easy to use and delivers fast output. Another advantage of GPT-3 is that it customizes base models for specific use cases with finetuning for text summarization. Thus, this approach enhances the overall meaning of the phrase and with further refinement through fine-tuning the model on summarizing texts, GPT-3 can be used to generate text summaries of superior quality.

KEYWORDS: Automatic Text Summarization, NLP, synopsis, language models, GPT-3, fine-tuning

I.INTRODUCTION

Several domains are beginning to adopt software, as technological resources develop, and employ it in ways that make specific features of access to knowledge in each area more efficient. Massive amounts of digital data have invaded our modern world. Automatic text summary (ATS) techniques can be useful in this situation since people in the field would be able to analyze report texts and other relevant documents to derive thorough conclusions. This can be achieved by using Large Language Models. Large Language model (LLM) is the neural network model which understands the context of words to make them more accurate. The size and capacity of LLM continue to grow, along with its potential applications. It will soon become an invaluable tool in a variety of industries and fields. Examples of LLM models are GPT3. In recent years, there has been a growing trend in Natural Language Processing systems towards utilizing pre-trained language representations. These representations have become increasingly versatile and task-agnostic, allowing for effective transfer to downstream applications. Initially, NLP systems made use of single-layer word vector representations, which were then passed to task-specific architectures. Subsequently, systems began utilizing recurrent neural networks (RNNs) with multiple layers of representations and contextual states to form more robust representations, though they were still applied to task-specific architectures. Recently, pre-trained transformer or recurrent language models have been directly fine-tuned, thus eliminating the need for task-specific architectures altogether.

Generative Pre-trained Transformer enables the creation of high-quality summaries by extracting and generating new text that captures the most important information from the input text. This makes GPT-3 a valuable tool for various applications in industries such as journalism, content creation, and research. The objectives of this study include:

1. Compress information: The primary objective of text summarization is to compress large amounts of



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information into a shorter form while retaining the most important information.

- 2. **Improve readability:** By summarizing the text, the GPT-3 model can help to make the content more accessible and easier to read, especially for those who may not have the time or ability to read lengthy documents.
- 3. Enhance efficiency: Summarizing text with the GPT-3 model can help people to quickly identify key points and important information in a large body of text, which can save time and improve efficiency.
- 4. **Facilitate decision-making:** By summarizing important information, the GPT-3 model can help individuals and organizations make better-informed decisions.

Overall, the GPT-3 text summarization model aims to provide a more efficient and effective way of extracting essential, meaningful information from large volumes of text, ultimately leading to improved comprehension, decision-making, and productivity.

II. MOTIVATION AND APPLICATIONS OF ATS

The study's aim is to give a general overview of GPT-3 text summarization abilities while analyzing the various documents.

Generative Deep learning is used by the autoregressive language model known as Pre-trained Transformer 3 (GPT-3) to generate text that emulates human speech. By providing a preliminary text as input, it can generate text that follows the given prompt. This model was chosen mostly because of its forerunners, and it continues to be one of the most important language models in use today. ATS encompasses advanced research and promising future prospects in this exceptional domain by utilizing diverse information sources.

This research was motivated by these general conclusions. Reading research papers and long articles for studying purposes consumed a significant amount of our time. As a result, we required a system which can give a clear and concise overall view of the required document, thus saving our time. ATS has found widespread application in areas such as information retrieval, information extraction, question-answering, text mining, and analytics. Its implementation has greatly improved the functionality of search engines, enabling the development of applications such as news summaries, email summaries, and domain-specific summaries. Below are some examples of domain-specific applications of ATS:

- 1. Financial research: Maintaining financial records like earnings statements and financial news is made easier by using the summary tool.
- 2. Social Media Marketing: Businesses who create long-form content, such as blogs and e-books, utilize summarizing technologies to reduce it to small chunks that can be shared on various social media platforms such as Instagram, LinkedIn, Twitter, and more. It enables numerous businesses to reuse the existing information.
- **3.** Literature and books: The majority of Google's projects are around literature and books and try to comprehend novels. In view of this use case, summarization enables customers to rapidly comprehend any writing or book and how it effectively influences their purchasing decision.
- 4. Legal contract analysis: Summarization can be used to examine legal documents in a legal contract analysis. The best value in critical clauses is summarization, which also allows you to compare various agreements.
- 5. Media Surveillance: Content shock and information overload are hot topics in the media. In this situation, an algorithmic summary can be utilized to break down the detailed material into more manageable and insightful chunks.

III. LITERATURE REVIEW

"A Survey of Automatic Text Summarization: Progress, Process and Challenges" published in IEEE Xplore, tells us the importance of the evolution of automatic text summarization. Text summarization is of 3 types: (i) Abstractive (ii) Extractive and (iii) A Combination of both Abstractive and Extractive. Abstractive text summarization is characterized by a vocabulary that extends beyond the original text being summarized, thereby making it more similar to human



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summarization. It outlines important ideas and is typically shorter in length. This method is extremely desired and has been the focus of numerous case studies as it mimics how humans condense information. However, automatically synthesizing abstractive text summarization poses a significant challenge, as it demands numerous GPUs to train for deep learning, or complex algorithms and rules with limited generalizability for standard NLP approaches, which can take several days. As an alternative, the extractive text summarization technique can be employed. Extractive text summary uses the original text's basic sentence structures, clauses, or phrases to generate a summary that only uses the information found in the original source. While extractive text summarization can be a useful technique, it also has its limitations. For instance, it may lack training data that cover diverse scenarios, struggle with the complexities of human language and how emotions are expressed, particularly in written materials, face the challenge of the anaphora problem (frequently substituting the subject with synonyms or pronouns), and may struggle to maintain the quality of the original text, among other potential issues. Although a combination of abstractive and extractive and extractive summarization techniques, it may still have some limitations. For instance, this approach may not adequately consider important words, address the anaphora problem, or fully account for the nuances of human language. Furthermore, building the necessary big data manually may require significant human effort.



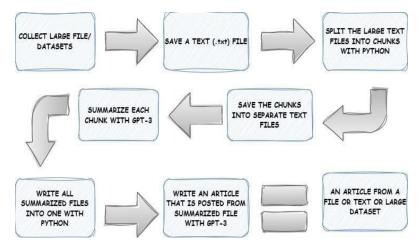


Fig. 1: Structure of proposed model

GPT-3 is a state-of-the-art language generation model developed by OpenAI platform. Although GPT-3 was not specifically designed for summarization tasks, it can be used to generate the same. It uses deep learning methods to produce text that mirrors human-like text. Here is a brief explanation of how GPT-3 functions:

• Pre-training: Using a transformer-based neural network architecture, GPT-3 is pre-trained on a significant amount of text data. For the model to produce cohesive and intelligible text, pre-training entails learning the statistical patterns in the text input.

• Fine-tuning: By giving GPT-3 a modest quantity of task-specific data, it can be adjusted for a particular task or domain. The model performs better and adapts to the task's unique requirements thanks to this process of fine-tuning.

• Inference: After the model has been trained and optimized, it can generate text when given a prompt. The model then creates a string of words based on the patterns it discovered during training that are likely to follow after the prompt.

• Iteration: To enhance its text production, GPT-3 can also be improved iteratively by leveraging human feedback. Human judges evaluate the model's output in this process, and their ratings are utilized to adjust the model and enhance its text generating abilities.

In general, GPT-3's capacity to generate text that resembles that of a person is the result of its capacity to recognize



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statistical patterns in vast volumes of text data, which enables it to produce language that is coherent and intelligible in response to a given prompt.

V. IMPLEMENTATION AND RESULTS

This paper mainly focuses on the way to produce a text summarization model that is correct and efficient. The primary reason for carrying out such a project is to create a quick and effective summary tool that is user-friendly for everyone. Our project entails developing this model utilizing many technologies like GPT-3, Jupyter notebook, Kaggle dataset, and Python.

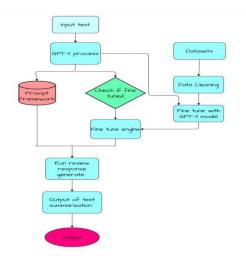


Fig. 2: Process Flow Diagram

The following steps explain how GPT-3 model performs text summarizing using the language generation feature:

• Processing of Input Dataset: The processing of the input text begins by separating it into distinct words or tokens. Tokenization is the term for this technique. After that, a pre-trained embedding layer is used to encode the tokens into numerical vectors.

• Language Generation: GPT-3 creates text by anticipating the word or series of words that will occur next in a given input sequence. The model uses the input text as a prompt and creates a summary based on that prompt when used for summarizing tasks.

During the language creation process, a new text sequence is created that highlights the most crucial details from the original input text.



Fig. 3: Token Embeddings

•Abstractive and Extractive Summarization: GPT-3 employs a blend of abstractive and extractive summarization strategies to provide a summary that catches the most crucial details while preserving the main points and themes of the original text. Extractive summarization entails picking out the key clauses or phrases from the source material and using them to build a summary. The language generation capability of GPT-3 can



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be used to extract the key phrases or sentences from the input text and use them in the summary. Abstractive summarization entails writing new text that ummarizes the main concepts of the source material. With the help of its language generating feature, GPT-3 may create brand-new sentences or phrases that effectively summarize the content of an input text.

• Fine-Tuning: GPT-3's performance can be enhanced by fine-tuning it for certain summarization tasks on a given domain or dataset. During fine-tuning, the model is trained using a smaller collection of data that is unique to the current summarizing task. By going through this process, the model is better able to grasp the subtleties of the language and produce high-quality synopsis.

- 1. Selecting a dataset
- 2. Pre-processing the dataset
- 3. Fine-tuning the model
- 4. Saving the model

• Output: GPT-3 produces a summary of the text after the model has analyzed the input text. The user has the option to specify the summary's length. The output summary is a brand-new text sequence that gathers the most crucial details from the first input text.

• Output generation time: Our web application also displays the time required for generating the output text or summary from the original text.





Fig. 5: Summarized Result

Fig. 4: Original text paragraph



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The metrics of the generated summary are evaluated as follows :

Evaluation Metric	Score	
F score	1.7278018950603865e-231	
METEOR score	0.5308426314343475	
BLEU score	8.639009475301933e-232	

Fig. 4: Evaluated metrics

Rouge Metric	Recall	Precision	F score
Rouge-1	0.7032967032967034	0.5614035087719298	0.6243902389653777
Rouge-2	0.537878787878787878	0.4382716049382716	0.48299319233097326
Rouge-l	0.6703296703296703	0.5350877192982456	0.595121946282451

Fig. 4: Calculated rouge scores

VII. LIMITATIONS AND CHALLENGES

There exist several limitations and constraints on GPT-3 and its examination, owing to the fact that any machine learning (ML) model that interacts with people using natural language has intrinsic restrictions. Open-ended systems have a high potential for risk, ML components lack robustness, they are biased, and safety is a shifting target for ML systems. Furthermore, GPT-3 has a tendency to produce text that confidently asserts falsehoods, just like any model with ML components. Thus, it is only expected to produce reasonable results when presented with inputs that are similar to those in its training data. In addition to these fundamental limits, there are several technical constraints examined in the paper, some of which are highlighted below:

- Repetition: GPT-3 samples can occasionally lose coherence over long stretches, contradict one another, and contain non sequitur words or paragraphs. At times, they may even repeat themselves semantically at the document level.
- Lack of world grounding: Since it is not anchored in other modalities of experience, such as video, real-world physical interaction, or human input, GPT-3, like other big pretrained language models, lacks a substantial amount of world context.
- Predominantly English: GPT-3 is most suited for categorizing, finding, summarizing, or creating texts in the English language since it was primarily trained on English-language text. GPT-3 will automatically perform poorly on inputs that differ from the distribution of training data, such as non-English languages and certain English dialects that are underrepresented in training data. There is a need for improvement in multilingual summarization.
- Interpretability and predictability: GPT-3 has very low interpretability and predictability, which is a drawback shared by most deep learning systems, particularly in models of this size.



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VIII. FUTURE SCOPE

Text summarisation has a huge scope when it comes to text summarization as its models and algorithms are continuously evolving. It can be further carried out using GPT-4 version and can be fine tuned to their unique domain suitably.

Features, such as speech to text, and then summarizing can be added for blind people or people who are unable to type their text manually, or just provide ease of task.

GPT-3 can also be used to summarize the text in languages other than English. It needs to be trained on a huge number of the required language dataset for providing rich summarization. Thus, GPT-3 can be used for multilingual summarization in the future.

IX. CONCLUSION

A text summarizing web application has thus been developed and tested using deep learning and natural language processing through the newly created GPT-3 model. The front end of the system has been designed using the Streamlit framework. Although this summarization model cannot replace the entire process of actually reading a paper or document, it can serve as a tool to explore a wider range of interesting articles in less time and by saving the reader's energy.

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