National College of Ireland

A Smart Cloud – Based Document Search Engine for Query Retrieval Using Large Learning Models (LLM's)

MSc Research Project
MSc in Cloud Computing

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A Smart Cloud – Based Document Search Engine for Query Retrieval Using Large Learning Models (LLM’s)

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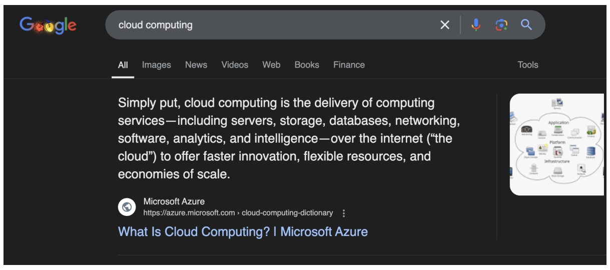
Abstract

A set of documents grows rather fast; at the moment, there are more than 140 million documents, and this number increases every year, so, retrieving documents should be effective. Today’s issues are connected with the utilization of special language, relationships between documents, and imprecise queries uttered by users. Sophisticated NLP approaches such as semantic search and embeddings are central to fixing most these problems. This paper focuses on the possibility of populating text-to-text transformers such as Google T5 and BART Large models refinished for summarizing and retrieving purposes. Through fine-tuning, the authors observed improved performance in BART Large model with ROUGE-1 scores increasing from 0.269 to 0.461 and improved unigram overlap and context relevance. Moreover, the application of models such as Sentence Encoder and FastText demonstrated a near perfect of 98% and 96% of retrieval accuracy, respectively, which was more efficient than the traditional TF-IDF and Count Vectorizer models. Thus utilizing cloud-native architectures along with databases such as MySQL or FAISS, the system enables accurate and efficient document search on a large-scale. This research offers an ideal foundation for most contemporary semantic search architectures that answer user expectations of accuracy and value.

Keywords—

1 Introduction

In The Academic Field It has over more than 140 million pieces which has the academic literature which also includes new papers publishing in each year Wei et al. 2024 This rapid expansion has made it progressively harder for researchers to stay informed about recent advancements in their areas of study. Eventually there is very fast growing for the semantic based document retrieval system 1,, mainly deploying them is becoming the significant challenge. First academic paper written with the specialized language with domain knowledge. Secondly, comprehending a paper involves understanding the content, their reference and their relationships.At the end user will be not having keyword for describing their needs in information even though some tries Cao et al. 2021 Has been made which is to create document retrieval which includes the general embedding model still after that we can observe that there is gab between model training and the searching which eventually indicates that the performance is not good



cloud computing

Simply put, cloud computing is the delivery of computing services—including servers, storage, databases, networking, software, analytics, and intelligence—over the internet (“the cloud”) to offer faster innovation, flexible resources, and economies of scale.

Microsoft Azure
https://azure.microsoft.com › cloud-computing-dictionary

What Is Cloud Computing? I Microsoft Azure

Figure 1: Google Search engine where the query is being searched and queried across the different search results (Source: Google.com)

1.1 Motivation

In the past, search engines were bound by keyword matches rather they are more intelligent with extensive language models like large or small language models (LLM and SLM). These models help in enhancing user queries by extracting context and semantic information which further improvise the relevancy of search results. Simultaneously, document extraction techniques have advanced, allowing for more efficient retrieval of relevant data from massive collections. NLP and text analysis techniques, such as semantic search, entity recognition, and topic modeling, are also playing a critical role in refining the precision and accuracy of information retrieval systems. Meanwhile, NLP and text analysis techniques like semantic search, entity recognition and topic modeling are also proving instrumental in improving the precision and accuracy of information retrieval systems. These innovations, collectively change the way of interaction with large scale datasets that makes understanding process faster, powerful and more intuitive

1.2 Research Aim

In addition , some papers proposed idea which is different and can be divided some three parts , The one model is the reference extractor which actually reads the retrieved documents and then it finds the paper id which can answer the question in better manner, after that the extracted references are finally added to the final document list, and the other two parts are for retrieval and reranking , these models will filter and then sort the document through the user query , Some papers Wei et al. 2024,J. Kim and S. Lee 2022 established a benchmark for semantic document search engine and retrieval and then it conducted comparisons between several competitors. The benchmark is in between computer vision and quantum physics. They showed that they achieved an accuracy rate of 38.72% in computer vision and 26.92% in quantum the physics on the top 5 results J. Kim and S. Lee 2022

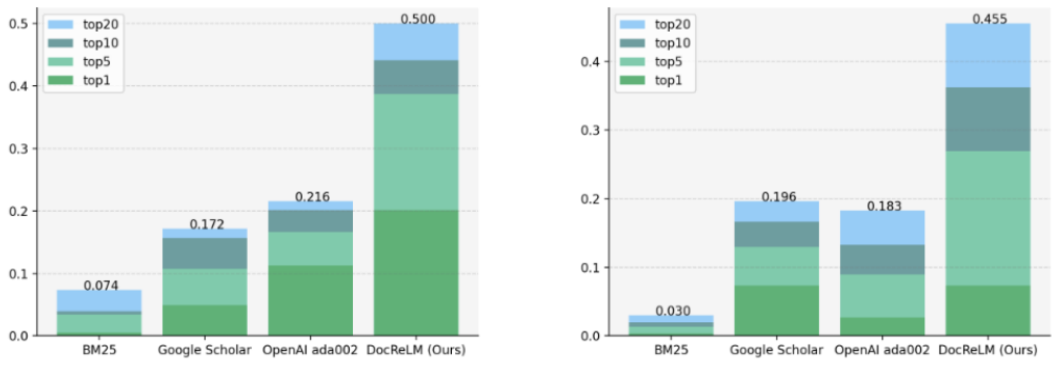


Figure 2: Accuracy of the final system (left computer vision and quantum physics right) J. Kim and S. Lee 2022

New releases in the cloud platforms augment the document retrieval systems by adopting the Distributed Computing Environment (DCE) attributed by the containers, serverless, and microservices paradigms. To improve the quality of searches, the cloud-based machine learning services are offered by incorporating natural language processing (NLP), image recognition and semantic search and sentiment analysis. Furthermore, the existing cloud storage such as the object storage, data lake, and data warehouse help manage large textual and multimedia data. Last of all, through the use of cloud information sharing software and apps to support the collaborative work, workflow efficiency is improved as well as the decision makers' decisions made faster.

1.3 Research Questions

RQ1: To what extent does a text analysis-based search engine for documents stored in the 'cloud' for different document types outperform conventional document searching methods?
RQ2: To which extent does similarity search suffer from or benefit from different cloud architectural systems in terms of execution time and storage?
RQ3: Which of the strategies can be opted for to ease the search queries?
RQ4: How the search mechanisms of different algorithms perform and how the real time application

looks like?

Through the application and integration of advanced technology in document retrieval as well as cloud computing solutions, it is possible to achieve high level of accuracy, efficiency and capacity to meet current and future need of document search system.

2 Literature Review

2.1 LLMs in search query from online documents

The BERT as in Figure 3,Kenton and Toutanova 2019 model proposed by Devlin et al. (2018) is an important milestone in the field of language representation with its deep bidirectional Transformer architecture. It is this capability of BERT to understand both the left and right context at each point that enable it to perform exceptionally well in tasks like question answering and language inference which are important for most search engine applications. This model achieved state-of-the-art results on 11 natural language processing (NLP) tasks.

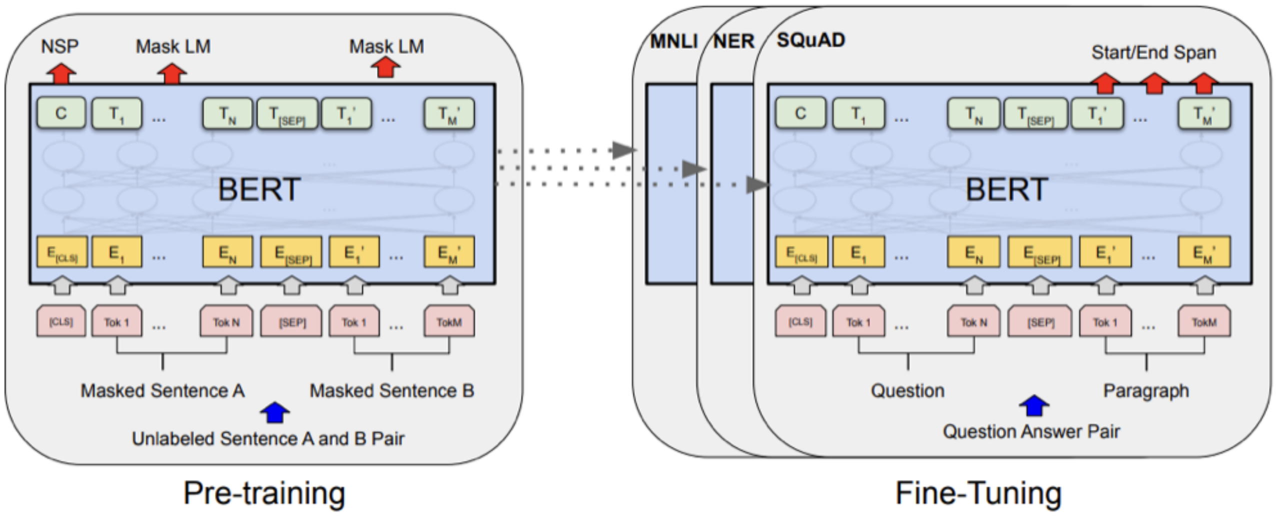


Figure 3: Overall pre-training and fine-tuning procedures for BERT

For the GLUE benchmark, BERT reached an impressive score of 80.5, with MultiNLI accuracy of 86.7% and SQuAD 1.1 F1 score of 93.2, showcasing its superior performance in language tasks. In terms of evaluation metrics, the authors used mostly two benchmarks such as GLUE and Stanford Question Answering Dataset (SQuAD). This model eliminates the need for heavily engineered task-specific architectures, streamlining the implementation of a smart search engine. Its fine-tuning capabilities allow it to adapt to various tasks, enhancing the relevance of search results based on user queries.In our project BERT plays an important role by simplifying the process of retrieving relevant documents.

In the research paper Automated Query Reformulation Which is for Efficient search based on Query logs Kaibo Cao et al. (2021) Zhu et al. Zhu et al. 2023 , who as introduced to an approach which is automated query reformulation approach which is mainly aimed for the improving the search efficiency , mainly with the domain of programming queries on stack overflow. This study mainly addresses the issue which is common that developers face when they searching for the information , like the gap between their search intent and the main content of the search , to mainly solve this the Authors built large-scale dataset which is by using the logs of the query from the stack Overflow which eventually consists of the both the original query and the formulated version of it .

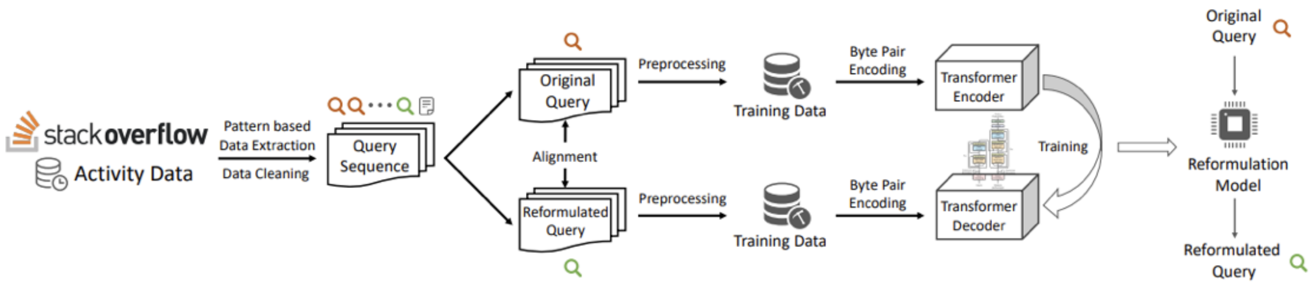


Figure 4: Overall workflow for SEQUER Zhu et al. 2023

The architecture as seen in Figure 4 of the model is a Transformer-based mechanism, which allows it to understand and reformulate search queries with minimal user input. By learning from previous reformulation patterns, the model is able to automatically suggest improved search terms, thus narrowing the gap between user intent and search results. The evaluation metric as Exact Match, where the SEQUER achieved a significant improvement of 5.6% to 33.5% over baseline models. GLEU (General Language Understanding Evaluation), where the system recorded a boost of 4.8% to 14.4%, demonstrating its ability to correct and enhance search queries effectively.Understanding Evaluation), where the system recorded a boost of 4.8% to 14.4%, demonstrating its ability to correct and enhance search queries effectively.

2.2 SLMs in search query from the online documents

Now the main problem in BERT , it is computationally expensive and also costly in deployment. Hence in the paper DistilBERT Cao et al. 2021, and Guo et al. 2022 the authors were motivated to handle those problems. While BERT has proven to be highly effective, it is resource-intensive and difficult to deploy on devices with limited computational power, such as mobile phones. To solve this, the authors proposed DistilBERT, a compressed version of BERT that retains 97% of BERT's performance while being 40% smaller and 60% faster.

Unlike BERT, which has 12 layers and includes token-type embeddings, DistilBERT reduces the number of layers by half and removes the token-type embeddings to achieve this efficiency. The architecture remains largely similar, but the compression is achieved through knowledge distillation, where DistilBERT learns from a pre-trained BERT model (the "teacher") while maintaining the ability to generalize across tasks.

Aspect	**BERT**	**DistilBERT**
Model Size	110 million parameters	66 million parameters (40% smaller)
Inference Speed	Processes data at a standard rate	60% faster than BERT

Performance	Excels across various NLP tasks	Retains 97% of BERT's performance;
		for instance, achieves 82.2% on MNLI
		and 85.8% F1 score on SQuAD

On-Device Efficiency	Requires substantial computational resources	71% faster on mobile devices compared to BERT

Table 1: Comparison of BERT and DistilBERT

The paper SLMrec S. Kim and J. Lee 2022 depicts Empowering Small Language Models for Sequential Recommendation introduces the need to reduce the computational and resource burdens of large language models (LLMs) in sequential recommendation tasks. Despite the strong performance of LLM-based models, they are often too large and inefficient for real-world applications that handle vast amounts of data daily. The authors aim to explore whether small language models (SLMs) can match or surpass the performance of larger LLMs while reducing computational costs.

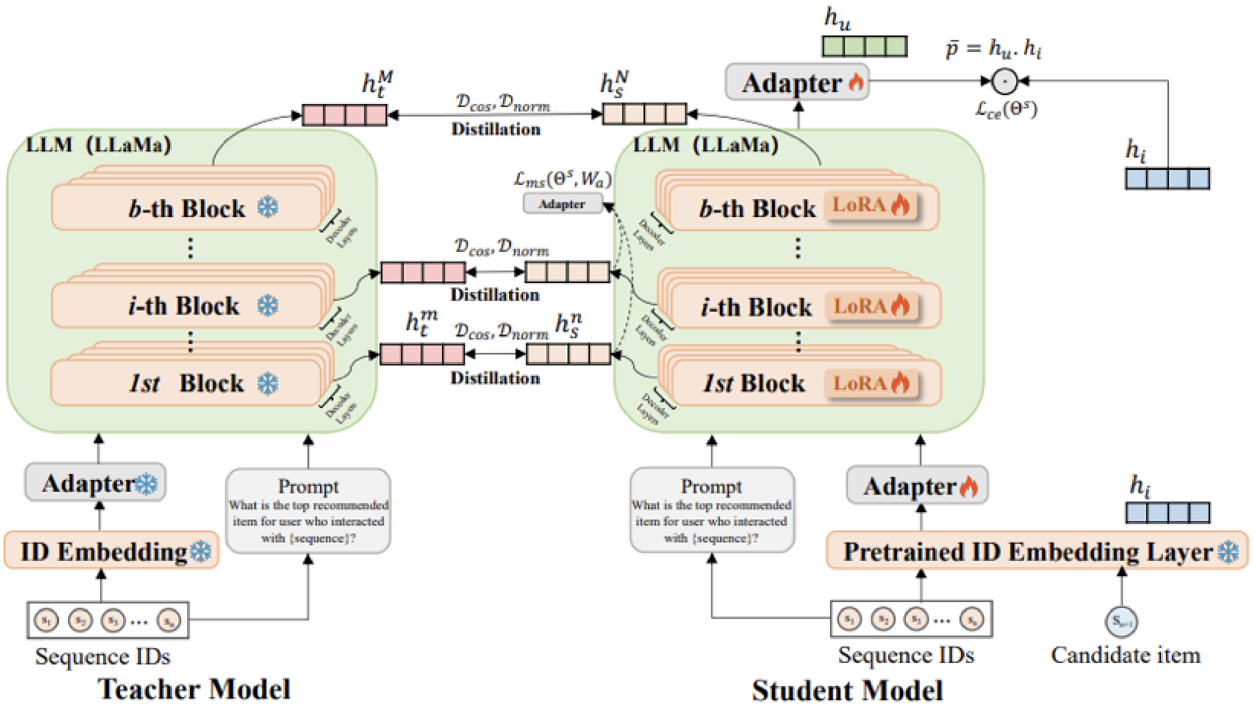


Figure 5: The overview of SLMRec architecture

The architecture 5 of SLMRec involves a teacher-student model, where a deeper LLM serves as the teacher model, and a smaller student model learns from it via knowledge distillation. This process allows the student model to capture essential features from the teacher, ensuring it performs comparably with fewer parameters. This model achieves up to 8x speedup in training and inference compared to large LLMs. It retains only 13% of the parameters compared to LLM-based models while delivering competitive performance across benchmarks such as HR(Hit rate), NDCG(Normalized Discounted Cumulative Gain), and MRR(Mean Reciprocal Rank).

2.3 Frameworks for the LLM based document search

Here are some popular frameworks for LLM-based document search and retrieval, along with their GitHub links and descriptions of their functionality. 6 depicted the workflow of DocReLM J. Kim and S. Lee 2022 . This system architecture comprise three primary components: retriever, reranker and reference extractor. The retriever component utilizes the embedding to retrieve the candidate passage from the corpus the reranker will sort these passages then the final component examines the content of top k results provides by the ranker and generates appropriate references.

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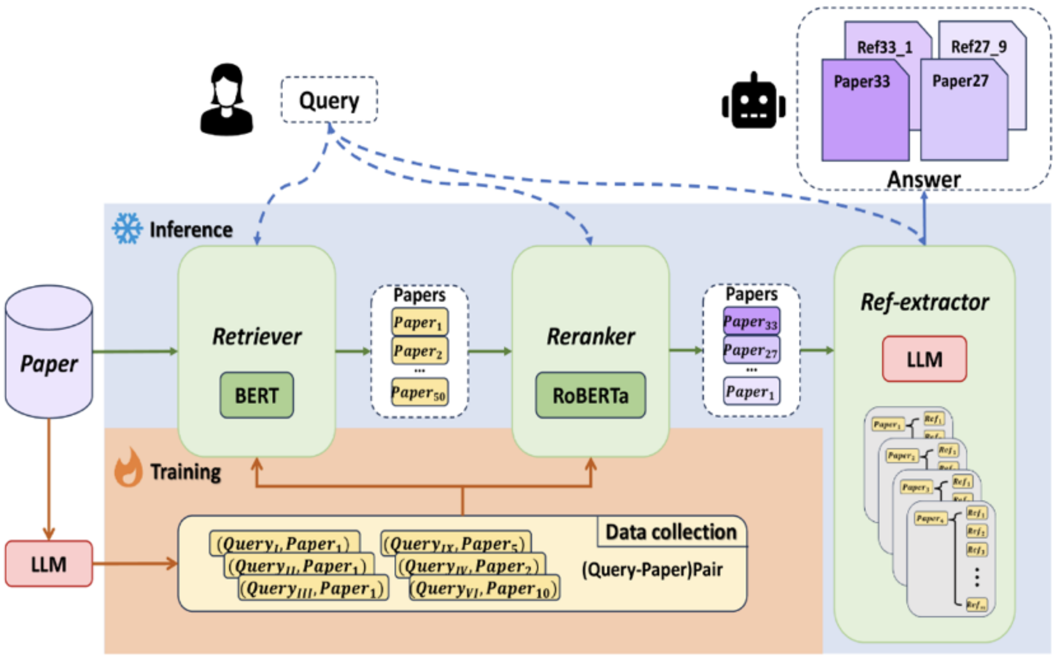


Figure 6: System architecture of training and inference of DocReLM J. Kim and S. Lee 2022

2.4 Research on LLMs that can be deployed serverless or in cloud framework

Serverless computing provides a flexible and budget-friendly way to deploy large language models (LLMs). Researchers are actively exploring ways to make their use in this environment even more efficient and effective.With the growing demand for LLMs, researchers are exploring ways to optimize resource usage for better compatibility with serverless platforms. For example, in their study *"Lightweight Question Answering and Summarization through Distilled BERT", Jiao et al (2020). introduced TinyBERT—a smaller, distilled version of the BERT model. TinyBERT demonstrates strong performance in summarization tasks while requiring significantly fewer computational resources, making it an excellent fit for serverless environments. The single document summarization refers to the generation of a shorter version of the document without altering the essential information content. In this paper we view extractive summarization as a linear programming problem that consists of ordering sentences which leads to a novel training method, which maximizes the global ROUGE metric, through a reinforcement learning objective. For this purpose, the system is employed to train a neural summarization model on the datasets of CNN and DailyMail, and it has been shown through experiments, that it surpasses the performance of both current extractive and abstractive systems when these are evaluated automatically or by human raters.

In recent times, larger and more complex language models (LLMs) have gained enormous popularity because of their superior capabilities in performing a variety of tasks within natural language processes. They have also been put into practice in a number of applications. However, the extent to which large language models can be integrated into the workflow of Intellectual Property (IP) creation and acquisition raises some complications which include the necessity of domain expertise, privacy issues, and dealing with very long pieces of text. In this technical report, we report for the first time an approach of training IP specific LLMs which is cost effective and can be put into the practice consistently on a wide scale. Accordingly, with the use of this standard procedure, we have carried out the training of models of the PatentGPT series based on already available pretrained open source models. The results of the evaluation of the models in the open source IP-related benchmark MOZIP downloaded by us showed that our domain-oriented LLMs are more powerful than GPT-4, which confirms the efficiency of the applied training methods and the currency of PatentGPT abilities in the IP area. Unexpectedly, our model was able to outdo GPT-4 in the results of the 2019 China Patent Agent Qualification Examination, scoring 65 points and achieving the level of human experts.

2.5 Research Summary

Paper & Authors	**Dataset**	**Models**	**Results**	**Summary**
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of NAACL-HLT	BooksCorpus, English Wikipedia	BERT (Bidirectional Transformers)	State-of-the-art results on multiple NLP tasks (e.g., SQuAD, GLUE, MNLI)	Introduces BERT, a deep bidirectional transformer, pre-trained for language understanding, achieving significant improvements on NLP tasks.
Transformer-based Query Reformulation and Answer Generation for Document Retrieval. Information Processing & Management, 59(4). 2022	Proprietary document retrieval dataset	Transformer-based Models (Query Reformulation, Answer Generation)	Improved query reformulation and answer generation accuracy compared to traditional methods	Proposes a transformer-based model for improving query reformulation and generating more relevant answers in document retrieval tasks.
Automated Query Reformulation for Efficient Search based on Query Logs from Stack Overflow, 2021	Stack Overflow Query Logs	Query Reformulation Algorithms (Based on Stack Overflow Logs)	Enhanced search efficiency and relevance using query logs for reformulation	Explores automated query reformulation using query logs from Stack Overflow to improve search efficiency and accuracy.
Small Transformer Models for Multi-domain Question Answering. Proceedings of EMNLP, 2022	Multi-domain QA Datasets (e.g., SQuAD, CoQA)	Small Transformer Models	Comparable performance to larger models with reduced computational cost	Proposes smaller, more efficient transformer models for multi-domain question answering, demonstrating competitive performance while reducing model size and complexity.
DistilBERT: a distilled version of BERT: Smaller, Faster, Cheaper and Lighter. NeurIPS Workshop (2020)	BooksCorpus, English Wikipedia	DistilBERT (Distilled BERT Model)	40% smaller, 60% faster while retaining 97% of BERT's performance on various tasks	Introduces DistilBERT, a distilled version of BERT, which achieves similar performance to BERT with significant improvements in speed and model size.
SLMREC: Empowering Small Language Models for Sequential Recommendation (2023)	Sequential Recommendation Dataset	Small Language Models for Recommendation (SLMREC)	Improved recommendation accuracy with lower computational costs compared to larger models	Proposes SLMREC, a framework using small language models for efficient and accurate sequential recommendation in various domains.

Efficient Document Retrieval with Neural Hashing. Proceedings of the 45th International ACM SIGIR Conference (2022)	Proprietary Document Retrieval Dataset	Neural Hashing Algorithms	Significant speedup in document retrieval with minimal loss in accuracy	Explores neural hashing techniques for efficient document retrieval, achieving faster search times with near-optimal retrieval accuracy.
Deep Document Retrieval with Gradient-Based Optimization. Proceedings of AAAI. (2023)	Large-scale Document Dataset	Gradient-Based Optimization with Deep Neural Networks	Enhanced retrieval accuracy and search efficiency through gradient-based optimization	Investigates deep document retrieval using gradient-based optimization, improving search precision and reducing query response times.
Semantic Textual Similarity for Information Retrieval Using Transformer Networks. Information Processing & Management, 59(4).	STS Benchmark Dataset	Transformer Networks (e.g., BERT, RoBERTa)	Improved semantic similarity and retrieval performance in information retrieval tasks	Proposes a method using transformer networks to improve semantic textual similarity in information retrieval, enhancing the relevance of search results.
Ranking Sentences for Extractive Summarization with Reinforcement Learning	CNN and DailyMail datasets	Neural Summarization Model	This work developed an extractive summarization model trained by optimizing the ROUGE evaluation metric	Single document summarization is the task of producing a shorter version of a document while preserving its principal information content.
PatentGPT: A Large Language Model for Intellectual Property	Not specified	Large Language Models (LLMs)	A standard training procedure for LLMs in the IP domain, including data preprocessing, pretraining, alignment, and evaluation.	Introduces methodologies for training IP-oriented LLMs and establishes the most comprehensive benchmark in the IP domain, the PatentBench.

Table 2: Research Papers and Key Information

2.6 Research Gap

Despite coming up with relatively advanced means of utilizing LLMs such as BERT and its offshoots (DistilBERT, TinyBERT) in document retrieval and search optimization various gaps are present. One fundamental issue is the computational complexity and resource consumption, state-of-the-art approaches entail when trying to apply such models in real-life scenarios especially when the application environment is resource constrained such as in mobile devices or when adopting serverless computing. However, there remain other costs associated with such full models that distillation techniques- as experienced in DistilBERT and TinyBERT – help to alleviate. Further, the ability of producing better LLMs for certain Local Domains especially the Intellectual Property (IP) and programming query needs identified another research challenge of how efficient ways of fine-tuning the Extra Large Models for a particular sub-domain seeking not to spend high amounts of money on training could be developed. Additionally, most of today's frameworks are concerned with textual data retrieval; there is scarce material on how multimedia search functionality can be naturally incorporated into LLM-based systems. One such gap consists in improving the interpretability and the transparency of LLM-based search interfaces to increase users' confidence in the outcome of a search. Lastly, despite good achievements with the current models on GLUE and SQuAD, the real-world application of the conversational systems has some shortcomings such as noise queries, sparsity of data, and dynamism of the user intent.

2.7 Research Outcome

As with the advent of the increase of the use of AI become more and the invent of LLMs, the task for anything has become very easy with these models. LLMs are Large Language Models which has Transformer models as the backbone. In This research we are going to make use of LLMs and make a suitable network which doesn't send data to the server and this way the uniqueness that we are solving as below,
1. The documents sent for the extraction will not be going into the server
2. Use of vector databases helps in faster extraction
3. Use of LLMs for summarization
4. Connected cloud if required to integrate the open ended Api to any company server

Also the optimization of the model that will bring a competitive or similar performance to small language models but with lower computational demands can be an interesting point of research that also originates from this work's findings. Improvement of the integration with multiple modalities, particularly text, images, and videos could increase the coverage and improve the retrievability of downstream tasks. New methods of domain adaptive pretraining might help to simplify and accelerate fine-tuning for the focused domains such as healthcare, legal, and Intellectual Property (IP). Extending queries by real-time learning on how users are interacting with them might help to cope with noisy or ambiguous queries. Further, development of explanation-generating mechanisms that can be integrated into the search systems would improve its credibility. It is possible to investigate federated learning as a method to provide privacy-preserving model updates across distributed settings.

3 Methodology

3.1 Datasets

Databases are essential for building, testing, and assessing the efficiency of the system during the development of a smart cloud-based search engine that facilitates quick and precise document retrieval and summarisation. The data set chosen should cut across as many types and languages and subject matters of documents as possible for the purposes of generalizability and applicability of the model.

3.1.1 XSum

XSum datasets , this is the dataset , introduced by Narayan et al(2018), which is rich in resources over 226000 BBC news articles, which are defied with the one-sentence summaries., its goal is mainly to encourage the truly abstractive summarization , to generate the meaning full summaries from models, give an concise summary then only extracting the data from the text , which makes the XSum an important tool for testing modern summarisation models of Large Learning Models(LLM's)

3.1.2 Giga Word

Gigaword is the dataset which is large scale collection of news articles which are with their headlines , which are mainly designed for the tasks like summarisation and the headline generation , it is very simple which makes it one of the go-to resource for the training the model to create the meaning full summaries.

3.1.3 SAMsum

The SAMSum dataset which is one of the collection of human-annotated conversations designed for abstractive dialogue summarization. It focuses mainly on the everyday chats, which are like the text messages, challenging models to create concise and meaningful summaries of conversational content.

3.1.4 NarrativeQA

NarrativeQA is the dataset , which is introduces by the Gliwa et al.(2019) , which mainly contains over 16000 conversations , then are paired with the human written summary , this dataset mainly gives importance on everyday dialog , which are like texts messages and challenges models to create the accurate summaries , which makes it valuable resource for improving the system with the AI while performing tasks like conversation summarisation,

3.2 Large Language Models (LLMs)

Large language Models (LLM's) can be defined as the advanced AI systems which can understand and help to generate the human-like text through the some huge datasets, which are built by using the transformer architecture 7 which eventually helps in recognise and then process complex language patterns , which helps Llm to excel in a different tasks. Over the time LLm's have been crucial tools in applications like chatbots and the automated content generation models and some virtual assistants .

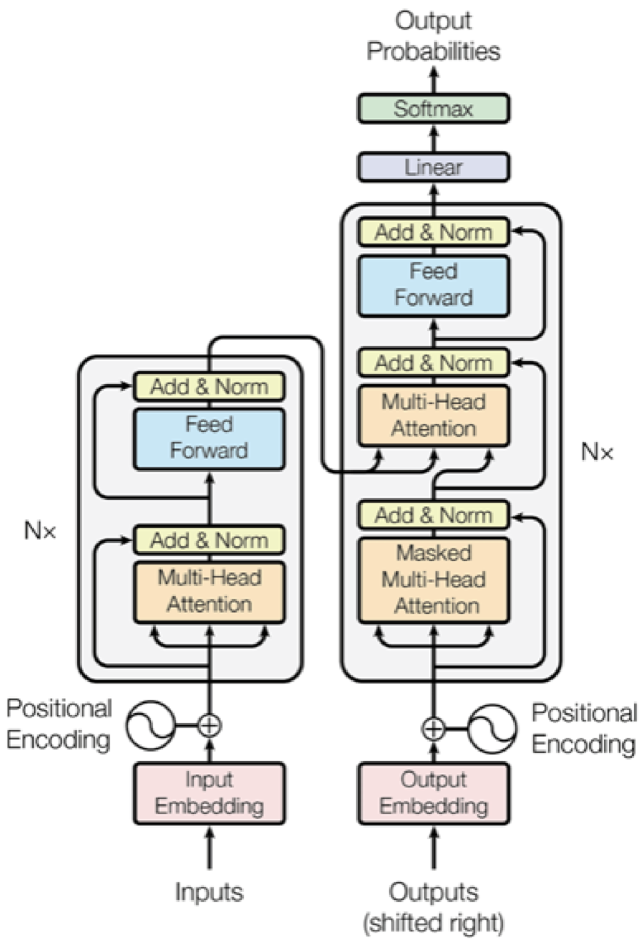


Figure 7: Transformer Model (Source: TowardsDataScience)

3.3 T5 Model

Evidently, the T5 model 8 developed by Google Research: Wu, S., Fei, H., Qu, L., Ji, W. and Chua, T.S., 2023 is referred to as Text-to-text transfer transformer has made a revolutionary impact in the field of natural language processing. Displaying this paradigm of presenting a fresh perspective for a problem in its general scope; is about the problem classification of which the exposition is concerned. In this way, several tasks can be performed such as; translating, summarizing texts, generating answers for questions among others. The well-known and very effective design of a transformer, is the backbone of the T5 structure that is applied in NLP. With such functional blocks, this design has various uses. The device T5 was first presented for the very first Transformer and is built on the encoder-decoder principles. In a situation where it is demanded that the input text be converted to some diagrammatic representations, the encoder employs self-attendance in a full view. This way, long range dependencies are possible since one token can watch all other tokens in the sequence. In contrast, the decoder employs causal self-attention autoregressively during output text generation. The process of generating each word, is of course, completely dependent on previously generated words, in order to prevent future word information from leaking. This is because the presence of residual connections and layer normalization ensures that the information is conveyed properly during training.Here is the architecture of T5 Model.

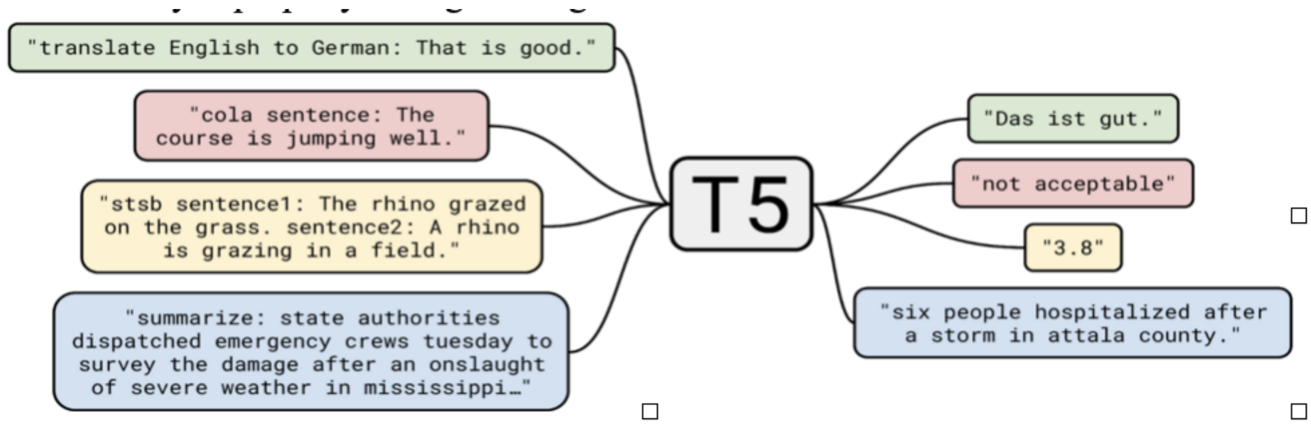

"translate English to German: That is good."
"cola sentence: The course is jumping well."
"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"Das ist gut."
"not acceptable"
"3.8"
"six people hospitalized after a storm in attala county."

Figure 8: Architecture of T5 Model (Source: Paperswithcode)

3.4 BART

The BART model 9 was proposed in 2019 which comprises of encoding through the BERT and then decoding with GPT like architecture which is left to right. It employs the same but their pretraining techniques include, shuffling of sentences as well as an unique in-fill masking strategy that replaces certain spans of the text with just one single 'mask' token.

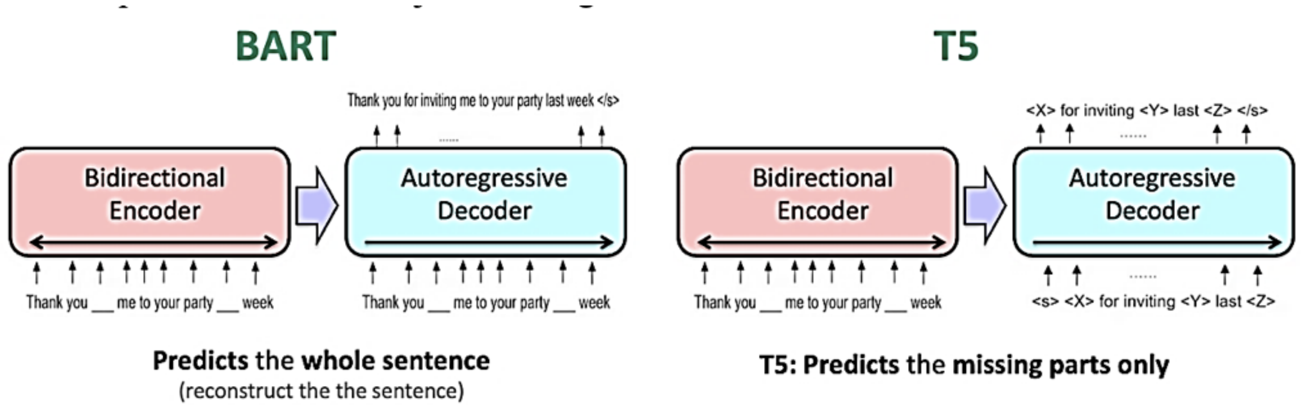

BART
Thank you for inviting me to your party last week </s>
Bidirectional Encoder
Autoregressive Decoder
Thank you ___ me to your party ___ week
Thank you ___ me to your party ___ week
Predicts the whole sentence
(reconstruct the the sentence)
T5
<X> for inviting <Y> last <Z> </s>
Bidirectional Encoder
Autoregressive Decoder
Thank you ___ me to your party ___ week
<s> <X> for inviting <Y> last <Z>
T5: Predicts the missing parts only

Figure 9: Comparison of BART and T5 (Source: Towards Data Science)

BART does extremely well in terms of tasks that generate text and also well if comprehension skills are considered it performs equally well as RoBERTa on GLUE and SQuAD if the resources are not too much of a constraint. The experimental results show that it performs near the existing state-of-the-art on abstractive dialogue, question answering and achieves up to 6 ROUGE gains in summarization.

3.5 Statistical Search Models

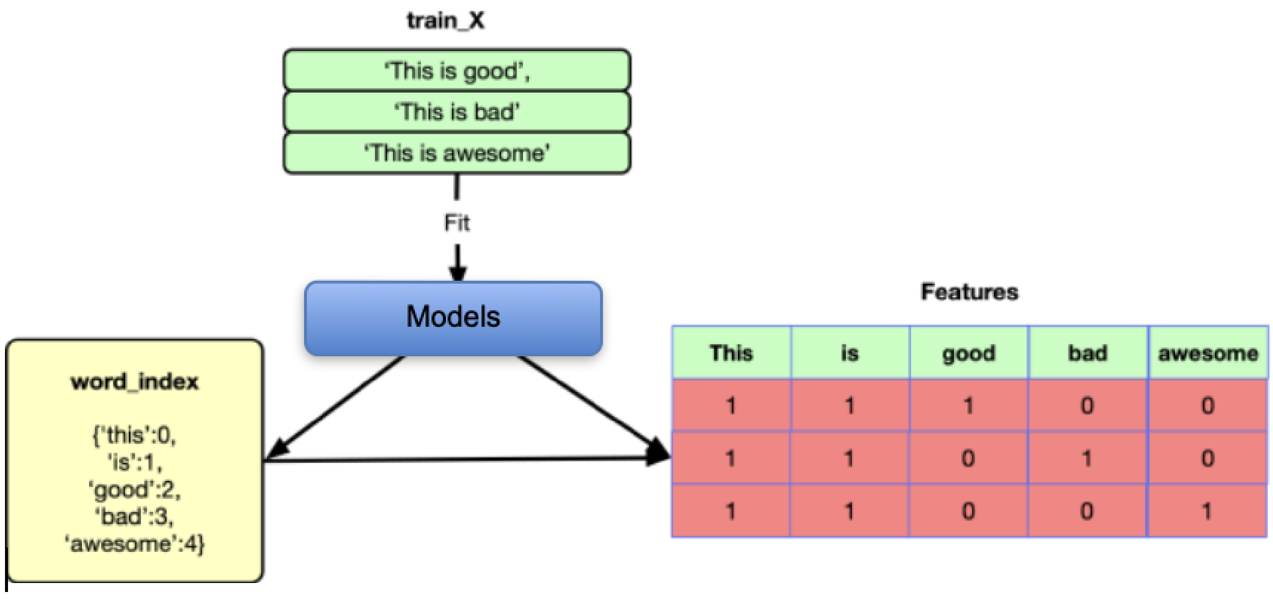


Figure 10: Stastical feature based query search

TF-IDF: The TF-IDF method is used in text analysis to rate which words are important in a specific document compared to a whole set of documents. It is a result of an interaction between the term frequency where the frequency of a word in the documents is calculated with the help of inverse document frequency where the general frequency of the word in the corpus is brought down. Search for documents using keywords is well suited to TF-IDF since it orders documents according to their relation to the query, however it lacks semantic connection between keywords.

Count Vectorizer: Count Vectorizer is a basic model and it embeds text features into vectors where it takes one row matrix for a document and it forms sparse matrix by showing the occurrence of a term. It is appropriate to work under small to medium datasets and allows for a quite direct approach to encode textual data into numerical ones. However, it is based solely on lexical similarity and can neither takes into account the context in which terms co-occur nor the semantic relations between them which can affect the performance in more sophisticated queries.

Universal Sentence Encoder (USE): The Universal Sentence Encoder encodes all text inputs into high-dimensional vectors which contain all semantic meaning about the input sentence. Through cosine similarity it computes proximity of these vectors to check if they are semantically related with the queries and documents. Hence it is sensitive for semantic based search results with less importance given to keywords making it appropriate in cases with requirement for high semantic understanding.

3.6 sentence Transformers

Sentence Transformers (also known as SBERT) 11is the Python library for loading, using and training state-of-the-art text and image embedding models. It can be used to perform embeddings computation with Sentence Transformer models (quickstart) or to score the cosine similarities with the help of Cross-Encoder models (quickstart). This opens up a whole host of uses such as semantic search, text similarity and paraphrase extraction.

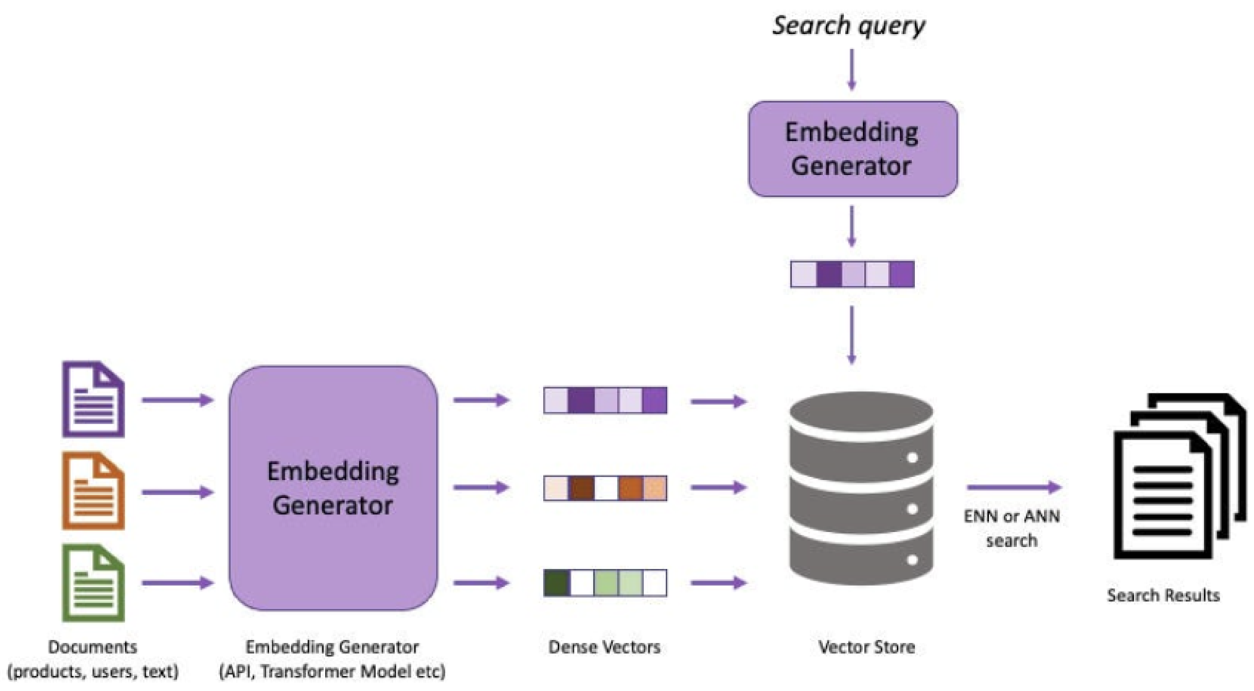


Figure 11: Sentence Transformers architecture

Any of the over 5000 pre-trained Sentence Transformers models available for use on the spot on Hugging Face includes many of the models featured in the MTEB leaderboard. Also, it does not limit the user from training or finetuning own models with the help of Sentence Transformers in order to create an individual models for various tasks. UKPLab developed a model name Sentence Transformers, and it is currently under the care of Hugging Face. If something is broken or for more information feel free to open an issue on the Sentence Transformers repository.

3.7 Cloud Framework

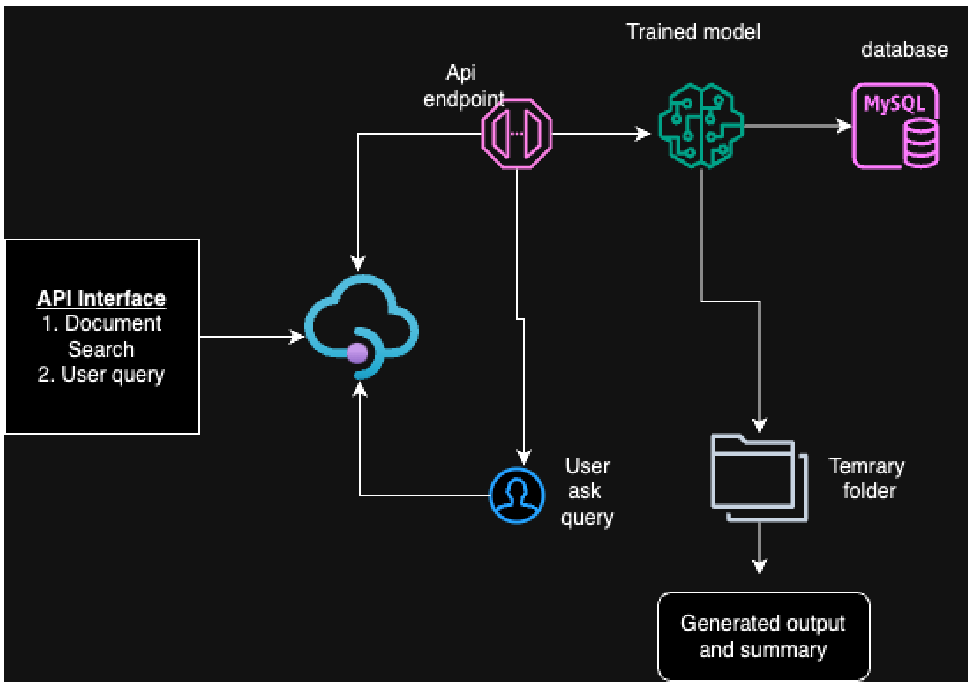


Figure 12: Cloud Framework

API Creation and Testing: The framework starts first with developing APIs employing the OPEN API/ Flask specification for uploading of document and search query. These APIs are post checked using the tools such as postman to ensure they are functioning as supposed to.

GitHub is also used to make connection with the Cloud Server: To integrate the document search engine with the cloud infrastructure, the following steps are taken:

Querying and Uploading: The system is suitable for asymmetric semantic search solution, where short queries (e.g., a question) are compared with a longer text (paragraphs or documents).

Retrieve Stage: The system is used to fetch a large list of 100 possible documents, with an emphasis on semantic similarity.

Re-Rank Stage: The process used here involved re-ranking these documents by using a cross-encoder model such as the BERT to make more informed findings based on execution compared to the query.

Document Processing: The uploaded documents are captured and these databases are merged into the master database for ease and efficient search.

Query Processing: Just like queries, query processing involves using the same pipeline to pass queries where they are compared with the master database for the relevant document sections

Final Summary: As part of this framework, GitHub is added for continuous integration and deployment to manage the site setup for the scalable document search engine in an efficient and automated manner. While using models such as USE for semantic searches and BERT for re-ranking and cloud services such as AWS and GitHub actions for deployment guarantees the effective handling of documents, fast search and relevance in search results.

3.8 Evaluation

The Bilingual Evaluation Understudy (BLEU) is one of the most established metrics in assessing the quality of machine produced text especially in translation and summarization tasks. It evaluates the output by comparing it with some reference texts and finds the number of n-grams (sequence of words) in which the output overlaps with the reference. The scores in BLEU are between 0 and 1 with 1 being the most plausible effect with respect to the reference text.

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right),$$

Where BP is the brevity penalty is the precision for n-grams, and N is the maximum n-gram size. BLEU is widely used for its simplicity but may not fully capture semantic nuances.

ROUGE-1 considers the correlation of unigrams (i.e. single words) between the predicted and the reference texts. Although simple, this measure of lexical similarity is of great importance, as it is one of the many that are typically used to assess text quality. This metric is particularly concerned with the reproduction of critical terms in the text derived from the source material.

$$ROUGE\text{-}1 = \frac{\text{Number of overlapping unigrams}}{\text{Total unigrams in the reference}}$$

ROUGE-2 quantifies the extent of bigram which reffers to the two-word sequences and then adjacency between the generated and the reference texts. As for this indicator, bigrams, which assesses how contextually coherent word pairings are, which, in turn, gives us the better picture of text resemblance as compared to ROUGE-1. It underscores the importance of maintaining the pairing of words in succession.

$$ROUGE\text{-}2 = \frac{\text{Number of overlapping bigrams}}{\text{Total bigrams in the reference}}$$

ROUGE-L which captures the longest common subsequence (LCS) which is between the generated and reference texts. This metric which can be particularly useful for the evaluating sequence-level similarity, as it takes into account word order and sentence structure into account. ROUGE-L which emphasizes the fluency and logical flow of the generated text through th ROUGE-L.

$$ROUGE\text{-}L = \frac{\text{Length of LCS}}{\text{Total words in the reference}}$$

ROUGE-LSum is the tailored for evaluating multi-sentence or document-level summaries. It mainly extends the concept of ROUGE-L by comparing the longest common subsequences which is across multiple sentences, making it ideal for tasks involving longer texts. This metric ensures the structural coherence of summaries by considering relationships between sentences.

$$ROUGE\text{-}LSum = \frac{\text{Length of LCS across sentences}}{\text{Total words in the reference}}$$

For evaluating the search results we have identified a selection metric known as Final Selection Score which is a multiplication of two factors. Factor 1 which is 1 or 0 in case the answer is present in the top 10/5 search results and the second factor being inversely to the rank of the search results with 1 being the height for the first search and 0.1 for the last.

$$FSS = factor_1 * factor_2$$

4 Implementation

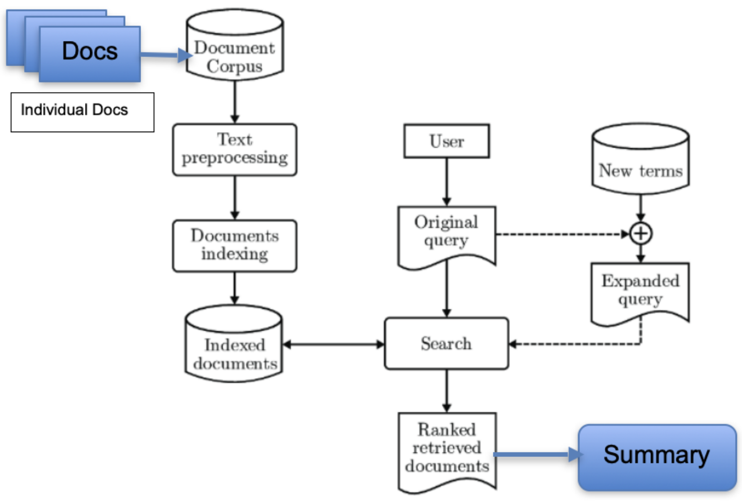


Figure 13: Implementation Framework

4.1 Research Resources — Modeling Process

4.1.1 Stage 1: Document Extraction for Database Creation

The first step involves extracting content from various types of PDFs to build a comprehensive database. Since documents vary in structure and format, the extraction process needs to adapt accordingly

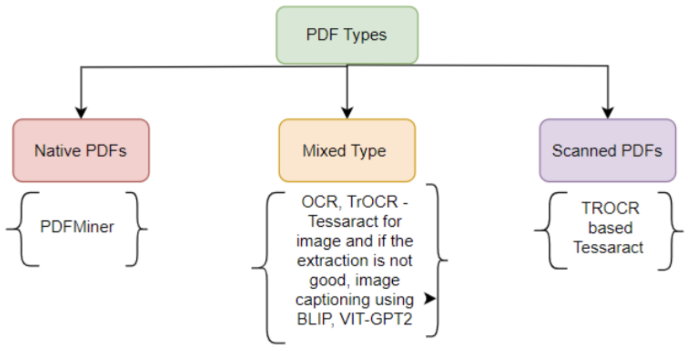

PDF Types
Native PDFs
Mixed Type
Scanned PDFs
PDFMiner
OCR, TrOCR - Tessaract for image and if the extraction is not good, image captioning using BLIP, VIT-GPT2
TROCR based Tessaract

Figure 14: Document Classification Technique for a better text extraction

The native PDFs are easy text selection or copying. The content can be extracted using Python libraries like PDFMiner. For PDFs containing a combination of text, tables, and images, the pages must first be classified into different regions. For text regions, PDFMiner can extract the content. For tables and images, Optical Character Recognition (OCR) is required. Another is scanned PDFs which are image-based PDFs. OCR tools like Tesseract can extract the text from these files. Additionally all the different documents extention types like docx, ppt, MD, text etc. are used with the pre-defined packages for the extraction.

4.1.2 Stage 2: Document Packaging

After extracting content, it needs to be organized systematically. Extracted text often comes as a single block of data, making it difficult to interpret. Breaking it into meaningful paragraphs helps in better organization.
Paragraph Extraction: Use regular expressions (regex) to identify paragraphs within the text.
Paragraph Grouping: Combine related paragraphs for better structuring. Once individual paragraphs are extracted, the next step is to combine related paragraphs into cohesive groups.
Information Linking: Not all information in a document is self-contained within a single paragraph or section. This step ensures continuity across paragraphs and sections. Therefore ensure continuation between sections where information spans across paragraphs.
Additional Content Handling: Besides paragraphs, documents often contain images, tables, or embedded files that need to be handled separately. Extract captions for images and tables and retrieve data from embedded Excel sheets.

4.1.3 Stage 3: Content Search

This stage involves creating a searchable database and building a search mechanism.
Database Creation: Store extracted content in databases like NoSQL, MySQL, or MongoDB for efficient retrieval. For advanced searches, consider vector databases such as FAISS or Milvus, which are optimized for similarity searches.
Question Input: Users can ask questions in any language, including queries with images or tables. OCR can help extract text from images or tables for context-aware searches. The question should be clear and specific (avoid combining multiple unrelated questions). We used Universal Sentence Encoder, word embeddings, and models like BERT to match questions with relevant content.

4.1.4 Stage 4: Summary Generation

Using pre-trained Models To generate document summaries, three pre-trained models from Hugging Face are employed. The process begins by initializing a tokenizer provided by Hugging Face, which converts text into a format the models can understand. Afterward, the chosen models are loaded from Hugging Face's library and assigned to the most suitable computing device, such as a GPU or CPU, for optimal performance. Once the tokenizer and models are set up, a summarization pipeline is built using Hugging Face tools. This pipeline processes the input text and produces concise summaries while maintaining key information. Each model is evaluated to ensure it performs well in handling text inputs of varying lengths and complexities.

The summaries of all chunks are then merged to create a comprehensive summary. If the combined token count still exceeds the model's limit, the process is repeated until the final summary fits within the constraints. This recursive approach ensures that the final summary is both coherent and relevant, regardless of the document's original size.

4.2 Research Resource – Data Description

For the search results thar we are mainly using the pre-defined pdfs that can be first extracted and then used as the csv files. The datasets which arev used for evaluating the summarization models include XSum, CNN/Daily Mail, SaMSum and WikiHow. These datasets offer a variety of text types and summaries, which makes them ideal for training and testing. A detailed analysis of these datasets reveals important of the characteristics such as word counts, average lengths, and the maximum and minimum limits of articles and summaries. The XSum dataset consists of news articles paired with multi-sentence summaries. This dataset is widely used for training and evaluating abstractive summarization models.

	Total	**Average Length of Text**	**Average Length of Summary**	**Max Length of Article**	**Max Length of Summary**	**Min Length of Text**	**Min Length of Summary**
Train	204045	431	23	2048	64	50	9
Test	11490	428	22	2048	64	50	4
Validation	13368	427	23	2048	64	50	10

Table 3: Dataset Statistics

These statistics provide a comprehensive overview of the datasets, enabling a better understanding of the text characteristics the models were exposed to during testing. This analysis helps in interpreting the performance results and understanding the models' capabilities in different contexts. The removal of articles with fewer than 50 words and summaries with fewer than 5 words ensured that only substantial and meaningful data were used for evaluation.

4.3 Data Processing

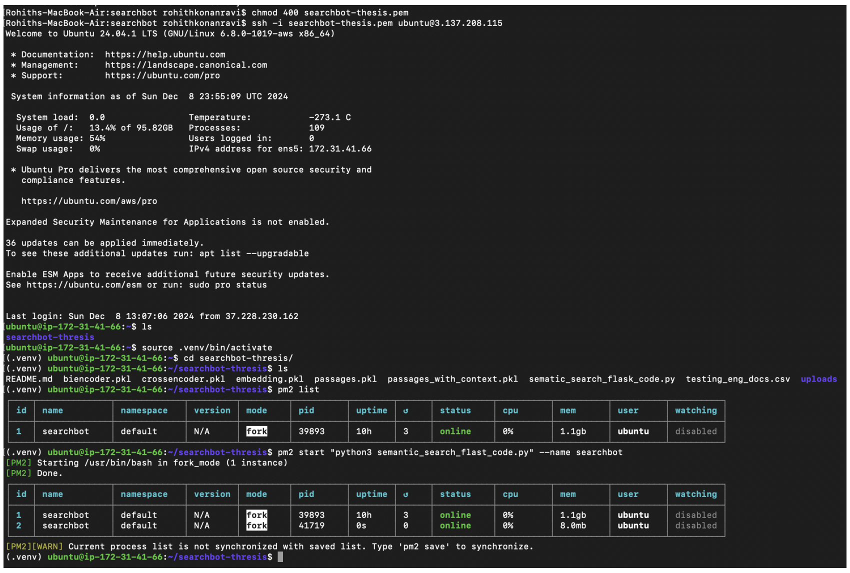
Data processing begins with filtering irrelevant or insufficient data points. Articles shorter than 50 words and summaries with fewer than 5 words are discarded. The process involves iterating through the dataset's partitions—training, testing, and validation. Each split of the dataset is cleaned by checking whether both the article and summary meet the minimum word count thresholds. Only valid entries are included in the cleaned data. Then a fresh list of cleaned entries is created for each split, ensuring the data is ready for model training and evaluation. This systematic approach guarantees that the models are trained on high-quality and representative data

4.4 Fine-Tuning for Summarization

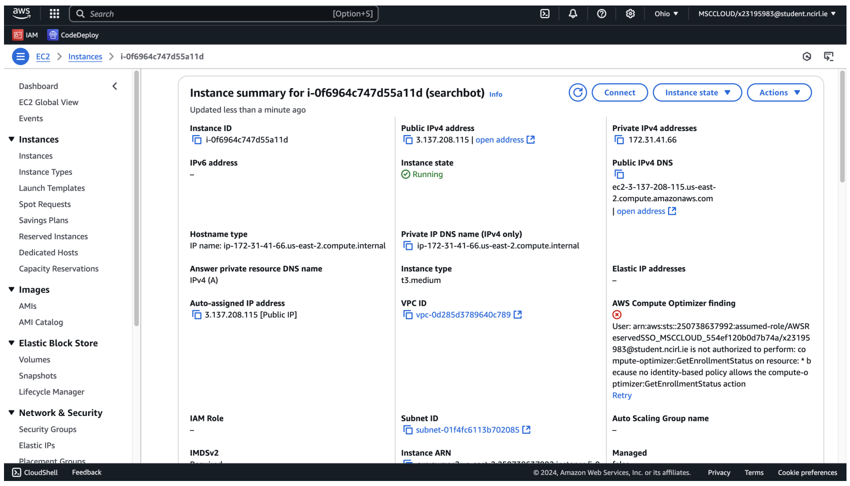
The BART-large model is fine-tuned to handle summarization tasks. To optimize training, two steps are taken, Filtering the Dataset where only data points with fewer than 1,024 tokens are retained. This reduces the training set to 8,076 examples.
The first and main part is tokenization Input articles are tokenized to a maximum length of 1,024 tokens, while summaries are tokenized up to 256 tokens. Padding ensures consistent sequence lengths. Configuring Training Parameters
The training process is configured to maximize efficiency and performance: The output directory is set to save the fine-tuned model and results. Training runs for three epochs with a batch size of four for both training and evaluation.
The output directory is being set to './results' to save the model and results. The training is being configured to run for three epochs, with a per-device batch size of four for both training and evaluation. By carefully preparing the dataset and adjusting training parameters, the fine-tuned model becomes

adept at generating accurate and meaningful summaries.

4.5 Cloud Deployment



```
Rohiths-MacBook-Air:searchbot rohithkonanravi$ chmod 400 searchbot-thesis.pem
Rohiths-MacBook-Air:searchbot rohithkonanravi$ ssh -i searchbot-thesis.pem ubuntu@3.137.208.115
Welcome to Ubuntu 24.04.1 LTS (GNU/Linux 6.8.0-1019-aws x86_64)

 * Documentation:  https://help.ubuntu.com
 * Management:     https://landscape.canonical.com
 * Support:        https://ubuntu.com/pro

 System information as of Sun Dec  8 23:55:09 UTC 2024

  System load:  0.0                Temperature:           -273.1 C
  Usage of /:   13.4% of 95.82GB   Processes:             109
  Memory usage: 54%                Users logged in:       0
  Swap usage:   0%                 IPv4 address for ens5: 172.31.41.66

 * Ubuntu Pro delivers the most comprehensive open source security and
   compliance features.

   https://ubuntu.com/aws/pro

Expanded Security Maintenance for Applications is not enabled.

36 updates can be applied immediately.
To see these additional updates run: apt list --upgradable

Enable ESM Apps to receive additional future security updates.
See https://ubuntu.com/esm or run: sudo pro status


Last login: Sun Dec  8 13:07:06 2024 from 37.228.230.162
ubuntu@ip-172-31-41-66:~$ ls
searchbot-thresis
ubuntu@ip-172-31-41-66:~$ source .venv/bin/activate
(.venv) ubuntu@ip-172-31-41-66:~$ cd searchbot-thresis/
(.venv) ubuntu@ip-172-31-41-66:~/searchbot-thresis$ ls
README.md  biencoder.pkl  crossencoder.pkl  embedding.pkl  passages.pkl  passages_with_context.pkl  sematic_search_flask_code.py  testing_eng_docs.csv  uploads
(.venv) ubuntu@ip-172-31-41-66:~/searchbot-thresis$ pm2 list
| id | name      | namespace | version | mode | pid   | uptime | ↺ | status | cpu | mem   | user   | watching |
| 1  | searchbot | default   | N/A     | fork | 39893 | 10h    | 3 | online | 0%  | 1.1gb | ubuntu | disabled |
(.venv) ubuntu@ip-172-31-41-66:~/searchbot-thresis$ pm2 start "python3 semantic_search_flast_code.py" --name searchbot
[PM2] Starting /usr/bin/bash in fork_mode (1 instance)
[PM2] Done.
| id | name      | namespace | version | mode | pid   | uptime | ↺ | status | cpu | mem   | user   | watching |
| 1  | searchbot | default   | N/A     | fork | 39893 | 10h    | 3 | online | 0%  | 1.1gb | ubuntu | disabled |
| 2  | searchbot | default   | N/A     | fork | 41719 | 0s     | 0 | online | 0%  | 8.0mb | ubuntu | disabled |
[PM2][WARN] Current process list is not synchronized with saved list. Type 'pm2 save' to synchronize.
(.venv) ubuntu@ip-172-31-41-66:~/searchbot-thresis$
```



Instance summary for i-0f6964c747d55a11d (searchbot) Info

Updated less than a minute ago

Instance ID
i-0f6964c747d55a11d

Public IPv4 address
3.137.208.115 | open address

Private IPv4 addresses
172.31.41.66

IPv6 address
–

Instance state
Running

Public IPv4 DNS
ec2-3-137-208-115.us-east-2.compute.amazonaws.com | open address

Hostname type
IP name: ip-172-31-41-66.us-east-2.compute.internal

Private IP DNS name (IPv4 only)
ip-172-31-41-66.us-east-2.compute.internal

Answer private resource DNS name
IPv4 (A)

Instance type
t3.medium

Elastic IP addresses
–

Auto-assigned IP address
3.137.208.115 [Public IP]

VPC ID
vpc-0d285d3789640c789

AWS Compute Optimizer finding
User: arn:aws:sts::250738637992:assumed-role/AWSReservedSSO_MSCCLOUD_554ef120b0d7b74a/x23195983@student.ncirl.ie is not authorized to perform: compute-optimizer:GetEnrollmentStatus on resource: * because no identity-based policy allows the compute-optimizer:GetEnrollmentStatus action
Retry

IAM Role
–

Subnet ID
subnet-01f4fc6113b702085

Auto Scaling Group name
–

IMDSv2

Instance ARN

Managed

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Figure 15: Cloud Deployment Framework using AWS

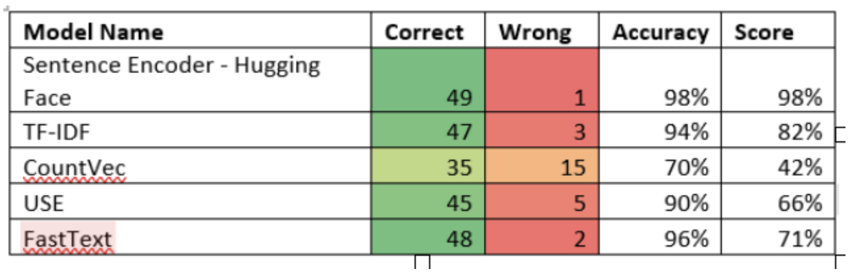
To harness a cloud-based document search with options for MySQL and FAISS to search starts with the creation of API for document uploading and Search, is checked by POSTMAN. Documents are prepared and converted into dense vectors using tools such as USE or BERT to learn about the content meaning. Embeddings are saved in MySQL as fields for metadata, and vectors as JSON or binary, or in FAISS for optimized vector search. In FAISS, document metadata can be stored into another data base for real quick reference. The application is built with Docker and is stored in the GitHub repository for that reason. And finally the Docker image is stored on the Amazon AWS ECR and the application is run on Amazon AWS ECS. In ECS setup, Creation for task definition for load balancing, environment variables, and health check.

Specifically, the proposed search engine incorporates asymmetric semantic search allowing to utilize embeddings for the purpose of selection of the top-scoring candidates and then filtering the results with a cross-encoder. AWS Ec2 instace which is used to deploy in cloud also helps the application run smoothly during periods of traffic increase. Possible future additions could be offered such as distributed databases or caching mechanisms for the most often queried data that would maintain the systems' flexibility, speed, and accuracy.

5 Result and Analysis

In this we studied how different statistical models and LLM's like T5 help in a proper analysis of the searching in the document. Also, this study evaluated three pre-trained models: Google's T5 Base, Facebook's BART Large, and Facebook's BART Large fine-tuned on XSum. Their performance was measured using ROUGE metrics (ROUGE-1, ROUGE-L, and ROUGE-Lsum), which assess the similarity between generated and reference summaries. Below is a detailed analysis of the results.

5.1 Case 1: Document Search Engine

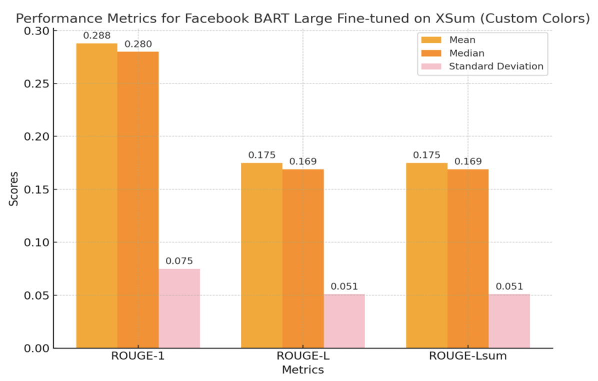


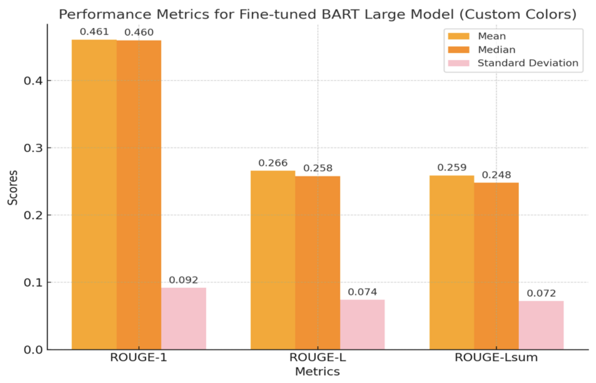
Model Name	Correct	Wrong	Accuracy	Score
Sentence Encoder - Hugging Face	49	1	98%	98%
TF-IDF	47	3	94%	82%
CountVec	35	15	70%	42%
USE	45	5	90%	66%
FastText	48	2	96%	71%

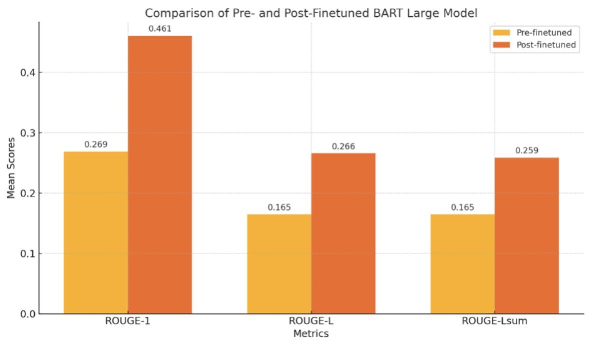
Figure 16: Analysis of the search algorithms

The Sentence Encoder had the level of accuracy of 98% and the only prediction made by that model was considered wrong. CountVec could only perform at 70% accuracy but TF-IDF was able to get a 94% accuracy. USE scored 90% accuracy, while FastText provided better performance having scored 96% through the test period. The performance of all the models was assessed and presented by comparing the predicted data with the actual data, along with the hit and miss records of the models along with the accuracy percentage and the collective performance score of each model. Even though the Sentence Encoder demonstrated higher performance, other models depicted different results as the overall performance for the given responsibility assigned to them.

5.2 Case 2: Summarization







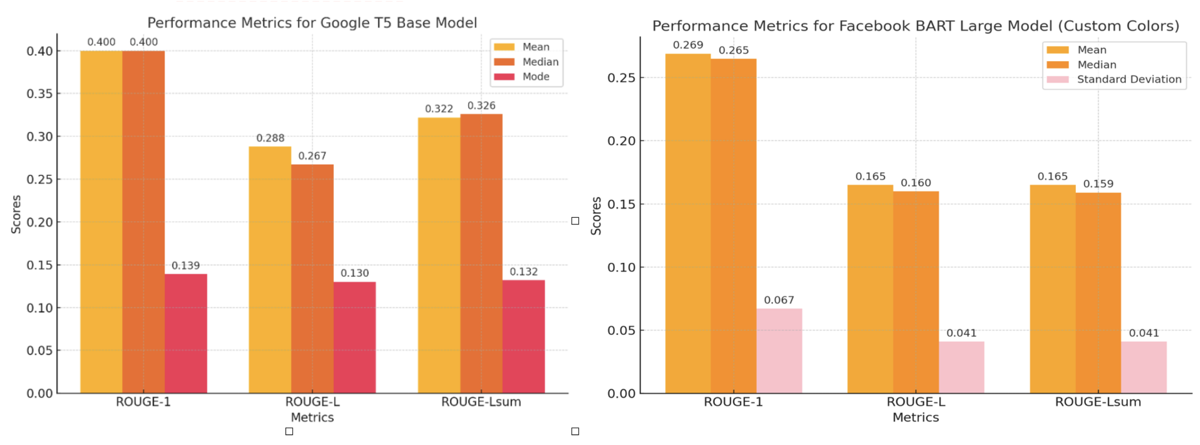


Figure 17: Models comparison for the summarisation tasks

Google T5 Base 17 is another general text-to-text transformer that formulates all the NLP challenges as text translation. It is used for translations, summery and classification and it works with text as inputs and text as outputs. Although it is a general-purpose language model, it is designed to take sequence input and produce sequence output applicable in many text-oriented tasks. The Google T5 Base model exhibited moderate performance across ROUGE metrics with ROUGE-1: The highest average score (0.400) indicates that the generated summaries captured many words from the reference summaries. ROUGE-L: An average score of 0.288 reflects less textual alignment but decent retention of semantic content. ROUGE-Lsum: A mean score of 0.322 demonstrates the model's ability to preserve essential sequence information, though less effectively than ROUGE-1.

BART Large is fine-tuned on the XSum dataset which contains only single-sentence summaries. It affixes these variations according to the needs of the abstractive summarization in order to make it produce more compressed and great block-summaries and enhances its performance of the model based on the context. The fine-tuned BART Large model demonstrated better results compared to its pretrained counterpart with ROUGE-1: Achieved an average score of 0.288, reflecting improved unigram overlap. ROUGE-L and ROUGE-Lsum: Scores averaged 0.175, indicating enhanced ability to extract coherent and relevant information.

After fine-tuning, the BART Large model exhibited significant improvements across all ROUGE metrics: ROUGE-1: Improved from an average of 0.269 to 0.461, with a median of 0.460, reflecting a substantial increase in unigram overlap. ROUGE-L: Increased from 0.165 to 0.266, showing better sequence preservation. ROUGE-Lsum: Enhanced from 0.165 to 0.259, indicating more coherent summarization. While the fine-tuned model displayed greater variability (higher standard deviations), the mean and median scores confirmed its effectiveness in abstractive summarization.

The chart above also shows that when the BART Large model is fine-tuned, it performs much better, especially when measured using the ROUGE-1, ROUGE-L, and ROUGE-Lsum. They set up two different groups, pre-fine tuned and post-fine tuned, to learn the model's performance of selecting keywords, as seen from ROUGE-1 score of 0.269 in the pre-fine tuned and 0.461 in the post-fine tuned. Likewise, the ROUGE-L which assesses the longest matching sequences raises from 0.165 to 0.266, indicating the model's improved better able to generate relevant and semantically related phrases. The ROUGE-Lsu score which quantifies the overall structural and semantical summary correctness increases from .165 to .259 showing better understanding of sequence alignment and context oriented meaning. These enhancements taken together reaffirm the importance of fine-tuning in abstractive summarization tasks since it results in summary outputs that are much more accurate and semantically, syntactically, and contextually correct.

6 Conclusion

This paper has discussed the implementation of an intelligent cloud-based document search system that incorporated enhanced NLP algorithms, along with state-of-the-art cloud environments. The efficient identification and ranking of required data was made possible by tools such as BERT, DistilBERT and SLMREC . Document preprocessing and PDFMiner and OCR tools were found to be useful for processing different document types and languages, which is highly useful. The incorporation of pre-trained models such as T5 further improved the systems effectiveness in producing high-quality summaries when applied on large-scale data. This project shows how theoretical and methodological progress in NLP has to be accompanied by scalable architectures for retrieval and summarization, and how the gap between research and implementations can be closed. The proposed system aims and provides a comprehensive, reliable system for handling documents' search and summarizations in solving the demand for smarter information access.

Future Work Increased efficiency at summarizing might be achieved by applying reinforcement learning of which the outcomes might be more condensed summaries that are nevertheless spot-on about the context. Making security and privacy more robust would protect the data and would prevent violation of the law. Further, new kinds of measures could be invented to capture semantic understanding and usability of software tools.

implementing the system to run in a serverless setting would improve scalability and cut out operational expenses, making the system ideal for big applications. These improvements are sought to enhance the system's efficiency and reliability in meeting actual scenario information search requirements.

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