

CHATBOT BASED ON RETRIVEVAL AUGUMENT GENERATION

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CERTIFICATE

This is to certify that the thesis titled “CHATBOT BASED ON RETRIVEVAL AUGUMENT GENERATION” submitted by Vidipt Vashist (MA22M025) to the Indian Institute of Technology Madras, Chennai for the award of the degree of Master of Technology, is a bona fide record of the work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

The integration of Retrieval-Augmented Generation (RAG) technology into large language models (LLMs) has emerged as a noteworthy advancement in the realm of natural language processing. This integration effectively addresses the limitations of LLMs and enhances their performance in domain-specific tasks and applications that demand extensive knowledge. I will discuss specific concerns related to retrieving information from web search engines and extracting data from private PDF files in this abstract. It provides a thorough analysis of the development, importance, and practical uses of RAG technology. RAG technology was developed to address the challenges faced by LLMs, such as the tendency to produce inaccurate content or "hallucinations" when faced with queries that go beyond their training data or require up-to-date information. To enhance the accuracy and relevance of generated content, it is necessary to employ methods that effectively utilize external knowledge to overcome these limitations. The retrieval mechanism implemented in RAG improves LLMs by using semantic similarity calculations to find relevant document fragments from external knowledge bases. By incorporating RAG into LLMs, the occurrence of factual errors is greatly reduced, making them more useful and establishing them as a crucial technology in advancing language-based systems, such as chatbots. Since its beginning, which aligned with the rise of the Transformer architecture, the progress of RAG technology can be divided into distinct phases. With the goal of incorporating more knowledge into LLMs, RAG focused on improving pre-training techniques. There was a notable shift in RAG research's direction, with a newfound emphasis on improving the accuracy of information during the inference phase. This shift was demonstrated by the introduction of ChatGPT models and other subsequent advancements. Through extensive research and development, the field of RAG studies has made significant progress in enhancing the capabilities of LLMs to handle more intricate and information-rich tasks. Throughout the research process, RAG underwent additional refinement beyond the inference phase, which strengthened its integration within the broader domain of LLMs. The future of RAG technology and its overall development remain uncertain, even though it has gained significant attention and popularity. This initiative aims to address the deficiency by providing a comprehensive overview of RAG technology and its applications, with a particular focus on its integration with LLMs. It highlights the challenges that existing generative models face in maintaining current knowledge, incorporating less common knowledge, and protecting sensitive training data, underscoring the significance of information retrieval in the field of computer science. This abstract explores and analyzes two important applications of RAG technology. 1. Internal Document RAG System: Gathering data from confidential PDF files can pose significant challenges for organizations, hindering the efficient utilization of internal knowledge and leading to cumbersome data extraction processes. Our solution offers a comprehensive and effective method for extracting data from PDFs, allowing organizations to easily gain valuable insights from their closed documents. By integrating RAG technology, organizations can gain a competitive edge in the market. This technology enables strategic initiatives and enhances decision-making processes, leading to improved outcomes. II. RAG System for Web Search: Users often struggle to find accurate and relevant information from web search engines because current search engines don't always provide comprehensive context or additional details that would enhance the user's understanding of the retrieved data. To address this problem, a proposed conceptual framework aims to improve the retrieval of web search results by providing contextually relevant data and generating additional insights in response to user queries. By utilizing web extraction methods and RAG technology, the system can enhance the efficiency and effectiveness of information retrieval.

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While large language models have made impressive strides, they still have notable limitations, particularly when it comes to domain-specific or knowledge-intensive tasks. One issue that stands out is their tendency to generate inaccurate or irrelevant information when faced with queries outside their training data or when up-to-date information is needed. Retrieval-Augmented Generation (RAG) is a method that tackles challenges by improving LLMs. It does this by retrieving document chunks from an external knowledge base using semantic similarity calculation. With the use of external knowledge, RAG effectively addresses the issue of generating inaccurate content. Its incorporation into LLMs has led to extensive use, establishing RAG as a crucial technology in advancing chatbots and improving the applicability of LLMs in real-world scenarios. The technology of RAG has seen significant advancements in recent years, with the research in this field following a clear development trajectory. The era of large models has witnessed several distinct stages in the evolution of RAG technology. At the beginning, RAG was developed when the Transformer architecture gained popularity. The main goal was to improve language models by integrating extra knowledge using Pre-Training Models (PTM). During this initial phase, researchers focused on developing and improving pre-training techniques. The introduction of ChatGPT was a significant milestone, showcasing the impressive capabilities of LLM in context learning (ICL). Research on RAG has focused on enhancing the information available to LLMs, enabling them to tackle more intricate and knowledge-intensive tasks during the inference stage. This has resulted in significant advancements in RAG studies. As research advanced, the improvement of RAG expanded beyond just the inference stage and started to incorporate more with LLM fine-tuning techniques. The field of RAG has seen rapid growth, but there is a lack of a comprehensive synthesis to provide a clearer understanding of its overall direction. This survey aims to address the lack of information by examining the RAG process, its development over time, and its potential future directions, particularly in relation to its integration within LLMs. Information retrieval is a crucial application in the realm of computer science. Unlike generation, retrieval focuses on finding relevant existing objects from a large pool of resources. Document retrieval is a key focus of web search engines, as it is the most common application of retrieval. In today's age, highly effective information retrieval systems are capable of managing document collections that are on the scale of billions. In addition to documents, retrieval has also been used for other modalities. Despite the impressive advancements achieved by advanced generative models, there are still several well-known challenges that need to be addressed. These challenges include the difficulty of keeping knowledge up-to-date, the inability to incorporate less common knowledge, and the potential risk of exposing private training data. With the introduction of Retrieval-Augmented Generation (RAG), the challenges at hand can be effectively tackled thanks to its versatile data repository. The information stored for retrieval can be thought of as a non-parametric memory. This type of memory is highly adaptable, capable of storing a wide range of knowledge, and can also securely store sensitive information. Furthermore, utilizing retrieval methods can help minimize the expenses associated with generating content. In today's rapidly changing world of technology and business, the ability to effectively manage information is crucial for the success and longevity of organizations across the globe. Given the fast-paced nature of technology and the ever-changing demands of the market, organizations must constantly strive to innovate and improve their products in order to stay ahead of the competition and cater to the ever-evolving needs of their clients.

1.1. Problem Statement

The main goal of this project is to achieve two things: firstly, to create a reliable and open-source system that can efficiently extract information from private PDF files, and secondly, to develop a user-friendly web application that utilizes web scraping techniques to gather relevant data from online sources.

1. **Internal document RAG system:** Extracting information from private PDF files can pose significant challenges for organizations, leading to complexity and inefficiency in their data extraction processes. This challenge impedes their capacity to effectively utilize internal knowledge, resulting in missed chances for improved customer interactions and a competitive advantage in the market. To tackle this urgent problem, it is crucial to create a strong and effective solution for extracting data from PDFs. This will enable organizations to effortlessly extract valuable insights from their private PDF documents
2. **Web search RAG system:** Navigating the vast expanse of the internet can be quite the challenge when it comes to finding relevant and accurate information in a timely manner. While search engines have become essential for finding information, many users struggle to refine their search queries for more accurate results. In addition, current search engines often fail to offer a complete context or provide additional information to improve the user's comprehension of the retrieved data. To tackle these challenges, it is crucial to create a smart system that enhances web search retrieval by offering contextually relevant information and generating extra insights based on user queries.

CHAPTER 2: RETRIVEL AUGUMENT GENERATION (RAG)

Retrieval-Augmented Generation (RAG) is a groundbreaking paradigm in natural language processing that combines the strengths of retrieval-based and generation-based approaches. This innovative framework combines the best aspects of different methodologies to achieve impressive results in a wide range of NLP tasks, including question answering and text summarization, among others. The emergence of RAG represents a major breakthrough in the field, providing a flexible and effective solution to numerous longstanding obstacles. RAG combines the strengths of retrieval models, which are adept at accessing vast amounts of external knowledge, with generative models, known for their skill in producing coherent and contextually relevant text. This unique architecture enables RAG to surpass the inherent limitations of individual approaches, opening up new avenues for comprehending and generating natural language. The retrieval mechanism in RAG is crucial as it allows the model to tap into external knowledge sources like databases, websites, or pre-existing corpora. Through the integration of a vast repository of information, RAG is able to access a wealth of context and factual accuracy, which enhances its understanding of the task or query at hand. The retrieval process is usually guided by a similarity metric that assesses the relevance of retrieved documents by considering their semantic alignment with the input. After retrieving the necessary information, RAG utilizes its generative component to produce coherent responses or generate text that meets the desired task objective. Unlike conventional generative models, which work in isolation and may encounter difficulties with factual accuracy or coherence, RAG utilizes the retrieved knowledge to inform and direct its generation process. The combination of retrieval and generation in RAG allows for the production of top-notch outputs that are firmly based on contextually relevant information. One of the most impressive uses of RAG is in the field of question answering (QA).

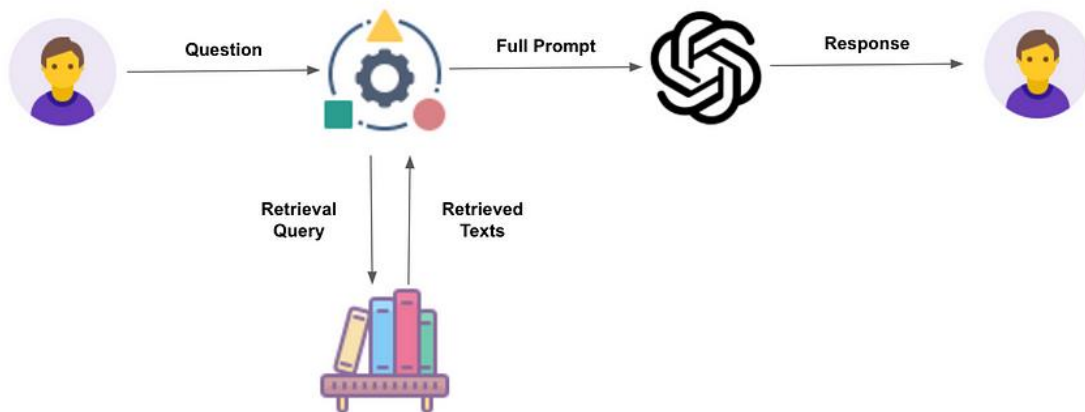


Figure 1 Overview of RAG System

Conventional QA systems frequently depend on pre-determined knowledge bases or manually crafted rules, which can restrict their effectiveness and scalability. On the other hand, RAG has the ability to retrieve and incorporate information from various sources, allowing it to provide more accurate and comprehensive answers to complex questions. With the combination of retrieval and generation techniques, RAG has the ability to offer detailed and contextually informed responses that demonstrate a profound comprehension of the query. In addition, RAG's capabilities go beyond just QA and can be applied to various NLP tasks like text summarization, dialogue generation, and content creation. For summarization tasks, RAG has the ability to retrieve passages or documents that are relevant and then generate concise summaries that capture the essential information. Similarly, in dialogue generation, RAG can utilize retrieved knowledge to ensure coherence and relevance throughout the conversation, resulting in more engaging and informative interactions. One of the

major benefits of RAG is its remarkable capacity to adapt and generalize across various domains and languages. Through the separation of the retrieval and generation processes, RAG has the ability to utilize pre-trained language models like BERT or GPT to effectively handle various inputs and tasks. This level of flexibility allows RAG to be easily implemented in a wide range of real-world applications, requiring little to no additional adjustments or customization. Although RAG has numerous strengths, it does come with its fair share of challenges and limitations. One of the main concerns revolves around the computational burden that arises when working with vast knowledge sources or tackling intricate tasks, especially in the context of retrieval and generation at a large scale. Resolving these scalability concerns is essential to fully harnessing the capabilities of RAG and facilitating its extensive use in real-world applications. In addition, the dependence of RAG on external knowledge sources brings up significant concerns about data privacy, bias, and reliability. It is crucial to meticulously choose and curate these knowledge bases to guarantee they encompass a wide range of perspectives and remain untainted by misinformation or propaganda. In addition, it is crucial to develop mechanisms that can effectively handle sensitive or proprietary information. This is necessary to safeguard user privacy and maintain compliance with legal and ethical standards.

Core Idea: Retriever + Generation

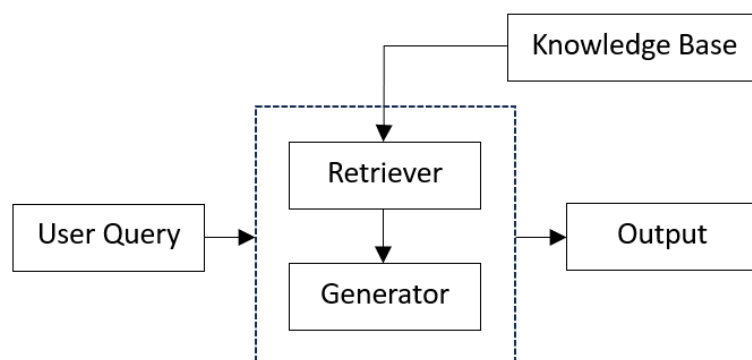


Figure 2 RAG-Based System

2.1. Key Components

1. **Retriever:** in Retrieval-Augmented Generation (RAG) is responsible for sourcing relevant information from external knowledge bases or corpora. Its main purpose is to access and retrieve documents, passages, or pieces of information that are contextually relevant to the given task or query. Using a similarity metric, the retriever assesses how relevant candidate documents are to the input query or context. This process typically involves organizing and indexing the knowledge base to make retrieval more efficient. Techniques like inverted indexing or neural retrieval models are often used. The retriever's unique capability to access external knowledge sources distinguishes RAG from conventional generative models, allowing it to enhance its comprehension and generate responses that are more informed and contextually relevant. Depending on the task requirements, the retriever can fetch either a single document or multiple documents. Each document adds its own unique perspectives or pieces of information to help with the subsequent generation process.
2. **Generator:** in Retrieval-Augmented Generation (RAG) is responsible for producing responses or text that are coherent and contextually relevant, using the retrieved information. Unlike conventional generative models, which work independently and may face challenges with factual accuracy or coherence, the generator in RAG utilizes retrieved knowledge to inform and direct its generation process. Various techniques are employed by the generator to produce text that fulfills the desired task objective. These techniques include autoregressive language models (e.g., GPT) or sequence-to-sequence models. It uses the retrieved information as context, utilizing it to shape the content, style, and coherence of the generated text. The combination of retrieval and generation in RAG

enables it to generate detailed and insightful outputs that demonstrate a thorough comprehension of the input query or context.

2.2. Benefits RAG

The benefits of Retrieval Augmented Generation (RAG) make it a transformative framework in Natural Language Processing, surpassing the limitations of traditional language models and enhancing the capabilities of AI-powered applications.

- 1. Enhanced LLM Memory:** RAG addresses the information capacity limitation of traditional Language Models (LLMs). Traditional LLMs have a limited memory called “Parametric memory.” RAG introduces a “non-parametric memory” by tapping into external knowledge sources. This significantly expands the knowledge base of LLMs, enabling them to provide more comprehensive and accurate responses.
- 2. Improved Contextualization:** RAG enhances the contextual understanding of LLMs by retrieving and integrating relevant contextual documents. This empowers the model to generate responses that align seamlessly with the specific context of the user’s input, resulting in accurate and contextually appropriate outputs.
- 3. Updatable Memory:** A standout advantage of RAG is its ability to accommodate real-time updates and fresh sources without extensive model retraining. This keeps the external knowledge base current and ensures that LLM-generated responses are always based on the latest and most relevant information.
- 4. Source Citations:** RAG-equipped models can provide sources for their responses, enhancing transparency and credibility. Users can access the sources that inform the LLM’s responses, promoting transparency and trust in AI-generated content.
- 5. Reduced Hallucinations:** Studies have shown that RAG models exhibit fewer hallucinations and higher response accuracy. They are also less likely to leak sensitive information. Reduced hallucinations and increased accuracy make RAG models more reliable in generating content.

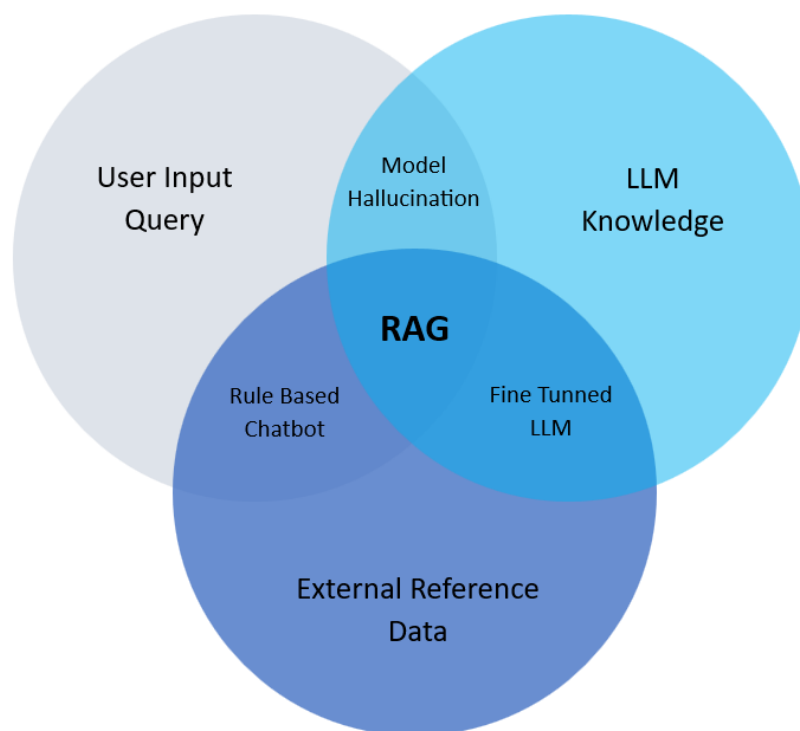


Figure 3 Benefits for RAG

2.3. Applications

RAG finds versatile applications across various domains, enhancing AI capabilities in different contexts. These applications highlight how RAG's integration of external knowledge sources empowers AI systems to excel in various domains, providing context-aware, accurate, and valuable insights and responses.

1. **Chatbots and AI Assistants:** RAG-powered systems excel in question-answering scenarios, providing context-aware and detailed answers from extensive knowledge bases. These systems enable more informative and engaging interactions with users.
2. **Education Tools:** RAG can significantly improve educational tools by offering students access to answers, explanations, and additional context based on textbooks and reference materials. This facilitates more effective learning and comprehension.
3. **Legal Research and Document Review:** Legal professionals can leverage RAG models to streamline document review processes and conduct efficient legal research. RAG assists in summarizing statutes, case law, and other legal documents, saving time and improving accuracy.
4. **Medical Diagnosis and Healthcare:** In the healthcare domain, RAG models serve as valuable tools for doctors and medical professionals. They provide access to the latest medical literature and clinical guidelines, aiding in accurate diagnosis and treatment recommendations.
5. **Language Translation with Context:** RAG enhances language translation tasks by considering the context in knowledge bases. This approach results in more accurate translations, accounting for specific terminology and domain knowledge, particularly valuable in technical or specialized fields.

Following is step by step detail explanation of various steps in methodology:

1. **Large Corpus Creation:** This involves gathering a massive amount of text data relevant to the chatbot's domain. This could include: Articles and manuals related to the topic, Website content and product , Code repositories and technical documentation. The more diverse and comprehensive the data, the better the chatbot will understand the nuances of the domain and provide accurate responses.
2. **Chunks Creation:** The large corpus is broken down into smaller units of text called chunks. These chunks are typically sentences or paragraphs that contain a single, focused idea. This process helps to manage the data and made to analyze and understand the meaning of each piece of information.
3. **Embedding:** Each text chunk is then converted into a numerical representation known as an embedding. This embedding captures the semantic meaning of the text, essentially translating the words into a mathematical code that represents their relationships and context in higher dimension.
4. **Vector Database (Indexed Embedding):** The generated embeddings are stored in a vector database. This database is indexed, like how a search engine indexes web pages. Indexing allows the chatbot to quickly search and retrieve relevant information based on the user query.
5. **User Query:** The user interacts with the chatbot by asking a question through text input.
6. **Similarity and Semantic Search:** The chatbot utilizes the indexed vector database to search for embeddings that are similar to the user query. This is done using semantic search algorithms that compare the mathematical representations of the query and the stored information. The goal is to identify the chunks of text that contain the most relevant information to the user's question.
7. **Context Injection:** The chatbot doesn't just rely on the exact match of the user query. It also injects context into the retrieved information. This context can include: Information about the user (e.g., their location, previous interactions), The current task or conversation flow & Additional knowledge about the domain. By considering context, the chatbot can provide more relevant and nuanced responses that go beyond simply matching keywords.
8. **LLM Response:** Finally, a large language model (LLM) is used to generate a response to the user query. LLMs are trained on massive amounts of text data and are adept at understanding and generating human-like text. Based on the retrieved information and injected context, the LLM formulates a response that addresses the user's question concisely. This could involve summarizing relevant information, providing instructions, or even generating creative text formats like poems or scripts.

3.1. Architecture

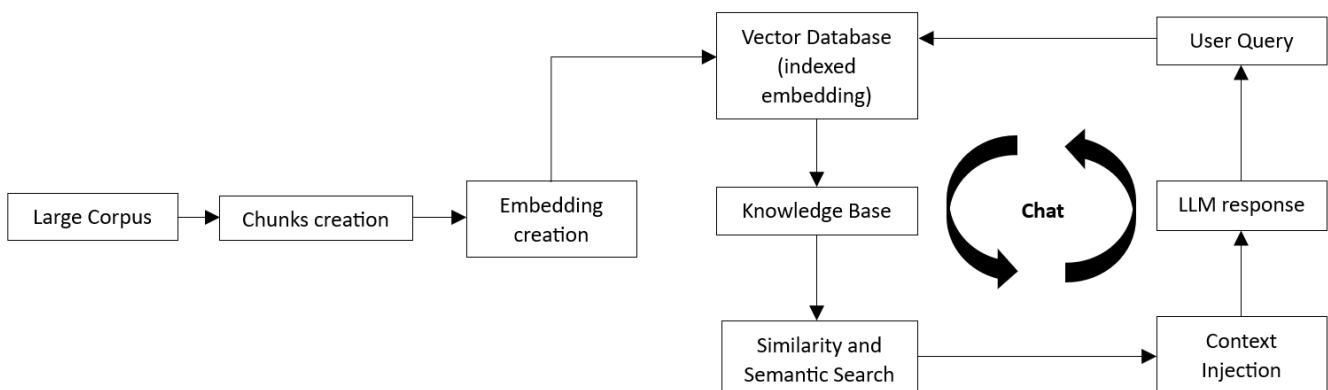


Figure 4 Custom Architecture of RAG System

3.2. High level technical view

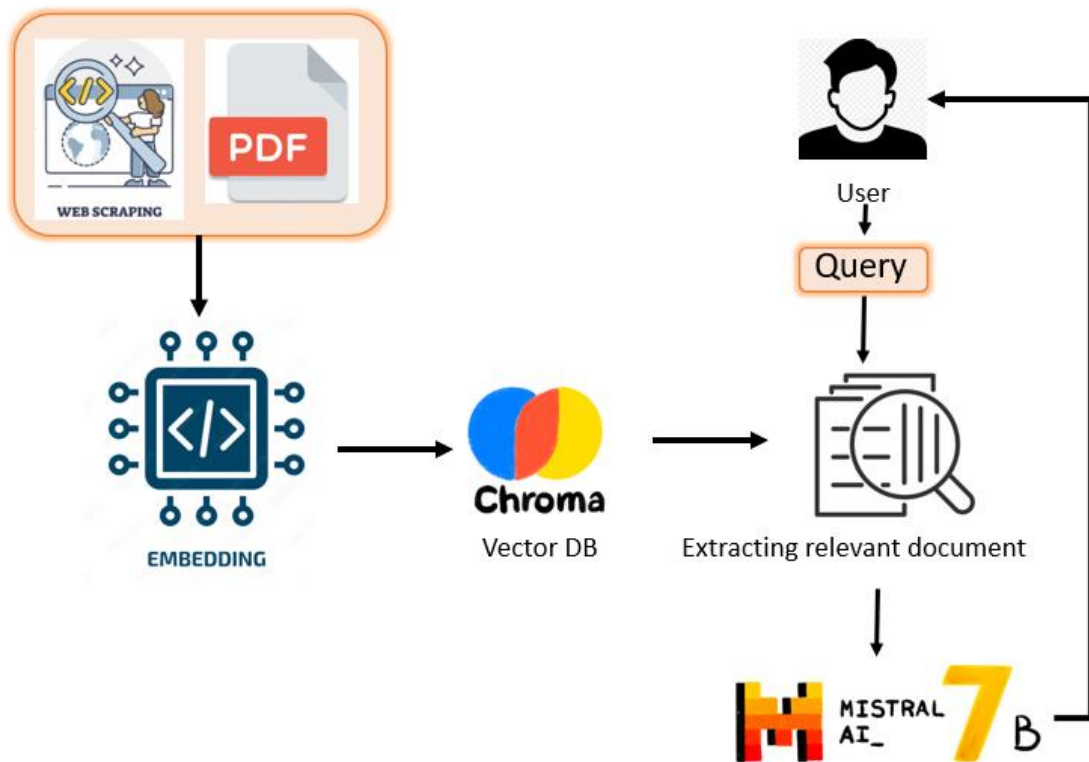


Figure 5 High level technical flow

3.3. Key Components in Architecture

These are key components in our custom architecture of RAG system supporting both PDF Question/Answer and Web search Question/Answer.

3.3.1. Vector Database

A vector database is a crucial component in various fields, including data science, machine learning, and information retrieval. It serves as a repository for storing and organizing high-dimensional data points, often represented as vectors. These vectors could denote features of objects, documents, images, or any other type of data.

Key Functions:

1. **Storage and Retrieval:** The primary function of a vector database is to efficiently store vectors and facilitate rapid retrieval based on similarity search queries. This is crucial for tasks like nearest neighbour search, where finding the most similar vectors to a given query is essential.
2. **Indexing:** To expedite search operations, vector databases often employ indexing techniques such as tree-based structures (e.g., KD-trees, Ball trees) or hashing methods (e.g., locality-sensitive hashing). These techniques enable faster search by reducing the search space.
3. **Scalability:** Scalability is a critical consideration for vector databases, especially with the ever-increasing volumes of data. Modern vector databases are designed to scale horizontally, allowing them to handle massive datasets distributed across multiple nodes or clusters.

4. **Support for High-dimensional Data:** Vector databases are optimized to handle high-dimensional data efficiently. Unlike traditional relational databases, which struggle with high-dimensional data due to the curse of dimensionality, vector databases are specifically tailored for such scenarios.

Chroma DB is an open-source vector storage system (vector database) designed for the storing and retrieving vector embeddings. Its primary function is to store embeddings with associated metadata for subsequent use by extensive language models. Moreover, it can serve as a foundation for semantic search engines that operate on textual data. Vector database offers an ideal solution for managing large volumes of unstructured and semi-structured data.

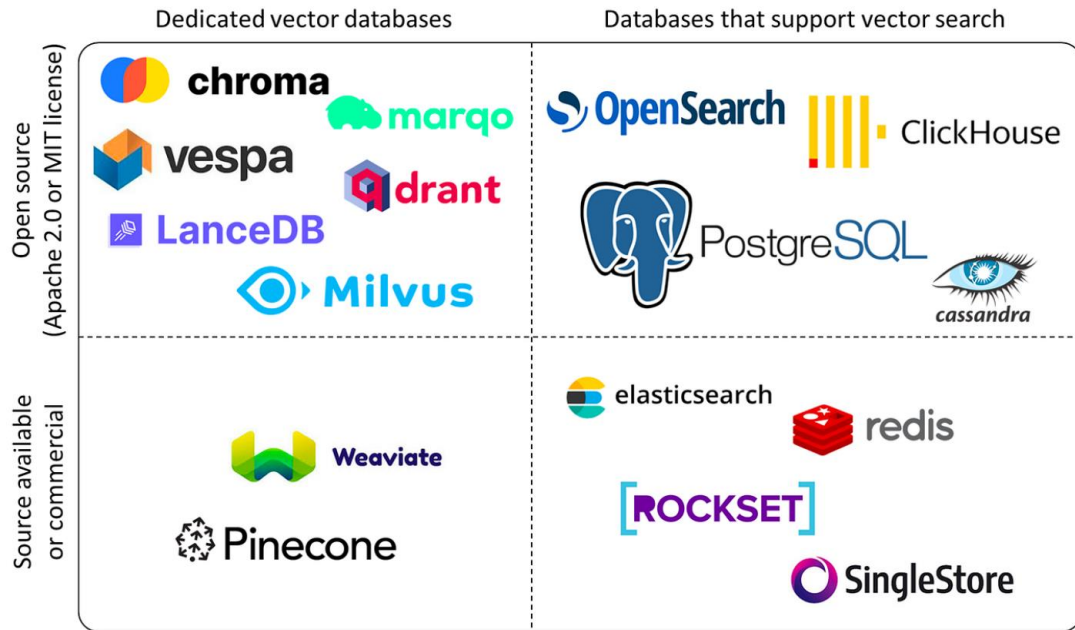


Figure 6 Available Vector Base in Industry.

3.3.2. Retriever

Retriever module plays a crucial role in the initial phase of the process. RAG is a framework primarily employed in natural language generation tasks, such as text summarization or question answering. The Retriever module focuses on sourcing relevant information from a knowledge base or corpus to feed into subsequent stages of the system. The primary purpose of the Retriever in the RAG system is to gather a set of candidate documents or passages that are likely to contain relevant information for the given task. These documents serve as the input data for downstream processing steps, such as aggregation and generation, to produce the final output.

Key Functions:

1. **Document Retrieval:** The Retriever module employs various retrieval techniques, such as keyword matching, semantic similarity, or neural retrieval models, to identify documents or passages that are potentially relevant to the input query or context.
2. **Scalability:** To handle large-scale knowledge bases or corpora efficiently, the Retriever is designed to be scalable. It may employ distributed computing techniques or indexing strategies to ensure fast and reliable retrieval even from massive datasets.
3. **Relevance Ranking:** In cases where multiple candidate documents are retrieved, the Retriever may rank them based on their relevance to the input query or context. This ranking helps prioritize the most promising sources of information for downstream processing.

4. **Query Expansion:** To improve retrieval accuracy, the Retriever may perform query expansion by augmenting the original query with additional terms or contextually related concepts. This helps capture a broader range of relevant documents that might otherwise be missed.

3.3.3. Transformers

Transformers are a groundbreaking type of deep learning architecture that has revolutionized various natural language processing (NLP) tasks. They've achieved state-of-the-art performance in tasks like language translation, text generation, sentiment analysis, and more. Introduced by Vaswani et al. in the paper "Attention is All You Need" in 2017, transformers have since become a cornerstone in the field of deep learning. Traditional sequence processing models, like recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have limitations in capturing long-range dependencies in sequential data due to their sequential nature or fixed-size receptive fields. Transformers address these limitations by introducing a novel mechanism called self-attention, which allows the model to weigh the importance of different input tokens when processing each token.

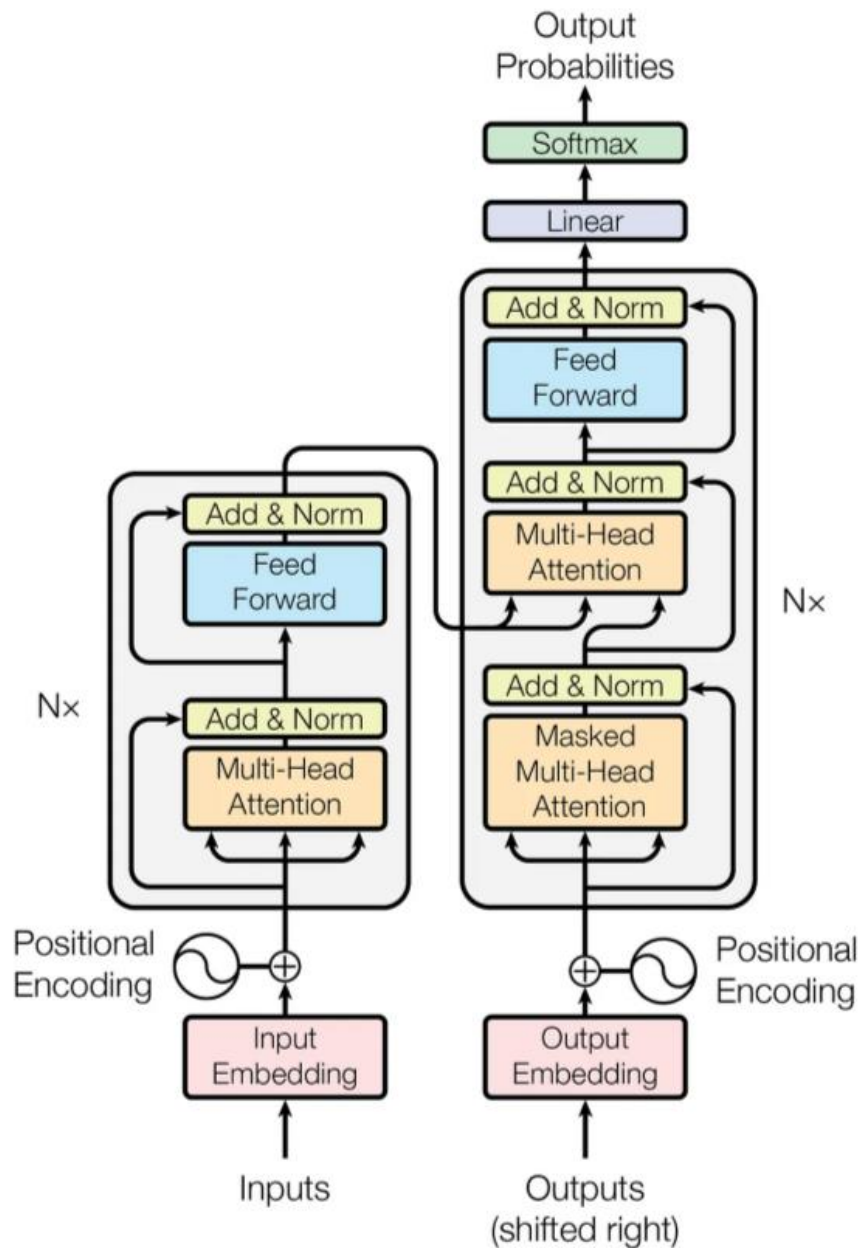


Figure 7 Transformer Architecture

Key Components:

1. **Self-Attention Mechanism:** At the heart of transformers is the self-attention mechanism, which enables the model to focus on different parts of the input sequence when processing each token. It computes attention scores between pairs of tokens and uses these scores to weigh the importance of each token's representation when computing the output.
2. **Multi-Head Attention:** Transformers typically employ multiple attention heads in parallel, allowing the model to learn different attention patterns. Each attention head computes its own set of attention scores, and the results are concatenated and linearly transformed to produce the final output.
3. **Positional Encoding:** Since transformers do not inherently maintain the order of tokens like RNNs, positional encoding is added to the input embeddings to provide the model with information about the position of each token in the sequence. This allows the model to leverage positional information when processing the input.
4. **Feedforward Neural Networks:** Transformers contain feedforward neural networks, typically with a simple architecture consisting of fully connected layers and activation functions like ReLU (Rectified Linear Unit). These networks are applied independently to each position in the sequence.
5. **Layer Normalization and Residual Connections:** Transformers commonly use layer normalization and residual connections around each sub-layer (attention and feedforward layers) to stabilize training and facilitate gradient flow.
6. **Transformer Encoder and Decoder:** Transformers are often composed of an encoder-decoder architecture. The encoder processes the input sequence to generate representations, while the decoder takes these representations and generates the output sequence step by step, attending to the encoder's outputs and previously generated tokens.

3.3.4. Huggingface

Hugging Face is a leading company and community in the field of natural language processing (NLP) and artificial intelligence (AI). It is renowned for its open-source library called "Transformers," which provides state-of-the-art pre-trained models for various NLP tasks, along with a comprehensive suite of tools and utilities for working with these models. Hugging Face was founded in 2016 with a mission to democratize AI and make NLP technology accessible to everyone. They believe in the power of open-source collaboration and community-driven development to advance the field of NLP and AI. The Transformers library, developed and maintained by Hugging Face, has become the go-to resource for researchers, developers, and practitioners working with transformer-based models. These models, such as BERT, GPT, RoBERTa, and many others, have achieved state-of-the-art results across a wide range of NLP tasks.

Key Features:

1. **Pre-trained Models:** The Transformers library provides access to a vast array of pre-trained transformer-based models, ranging from small and efficient models to large and powerful ones. These models are pre-trained on massive datasets and fine-tuned for specific downstream tasks, making them highly effective for various NLP applications.
2. **Model Hub:** Hugging Face offers a centralized Model Hub, where users can discover, share, and download pre-trained models and model checkpoints. This hub facilitates collaboration and knowledge sharing within the NLP community.

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3. **Easy-to-Use APIs:** The library provides intuitive APIs for loading, fine-tuning, and using pre-trained models in Python. Users can seamlessly integrate these models into their applications with just a few lines of code.
 4. **Pipeline Interface:** Hugging Face provides a convenient Pipeline interface that simplifies the process of performing common NLP tasks, such as text classification, named entity recognition, and text generation, using pre-trained models.
 5. **Tokenizers:** The library includes efficient tokenization tools for converting raw text into input tokens suitable for feeding into transformer-based models. These tokenizers support a variety of languages and tokenization strategies.
 6. **Model Training and Fine-tuning:** Users can leverage the library to train custom models or fine-tune pre-trained models on domain-specific datasets. This allows for customization and adaptation of models to specific tasks and domains.

3.3.5. Web Scrapping

Web scraping is the process of extracting data from websites. It involves retrieving, parsing, and extracting useful information from web pages to use for various purposes such as data analysis, research, or automation. Web scraping can be done manually by viewing the page source and extracting desired data, but it is more commonly automated using software tools or libraries.

Process:

1. **Fetching:** The first step in web scraping is fetching the HTML content of the target web page. This can be done using HTTP requests, typically with libraries like Requests in Python. The response contains the raw HTML code of the page.
2. **Parsing:** Once the HTML content is fetched, the next step is to parse it to extract the relevant data. Parsing involves analyzing the structure of the HTML code and identifying the elements that contain the desired information. Popular parsing libraries include BeautifulSoup and lxml in Python.
3. **Extracting Data:** After parsing the HTML, the data of interest is extracted from the identified elements. This may involve selecting specific HTML tags (e.g., <div>, <p>, <table>) or using CSS selectors to target elements with certain attributes or classes.
4. **Cleaning and Structuring:** In many cases, the extracted data may contain unwanted elements or formatting. Cleaning involves removing unnecessary tags, whitespace, or other noise from the extracted data. The cleaned data is then structured into a usable format, such as a CSV file, JSON object, or database.

Legal and Ethical Considerations: Web scraping raises legal and ethical considerations, as it involves accessing and extracting data from websites without permission. Website owners may have terms of service or robots.txt files that explicitly prohibit scraping their content. It's important to respect these rules and obtain permission from website owners before scraping their data. Additionally, scraping too aggressively can put strain on a website's servers and may be considered a form of denial-of-service attack

3.3.6. Sentence Transformer

Sentence Transformers are a type of transformer-based model specifically designed for encoding and embedding sentences or short text snippets into high-dimensional vector representations. These models leverage the power of transformer architectures, originally developed for tasks like language translation and text generation, to learn contextually rich representations of individual sentences.

The primary purpose of Sentence Transformers is to capture the semantic meaning and contextual information of sentences in a continuous vector space. These sentence embeddings can then be used for various downstream tasks, such as semantic similarity measurement, text classification, information retrieval, and clustering.

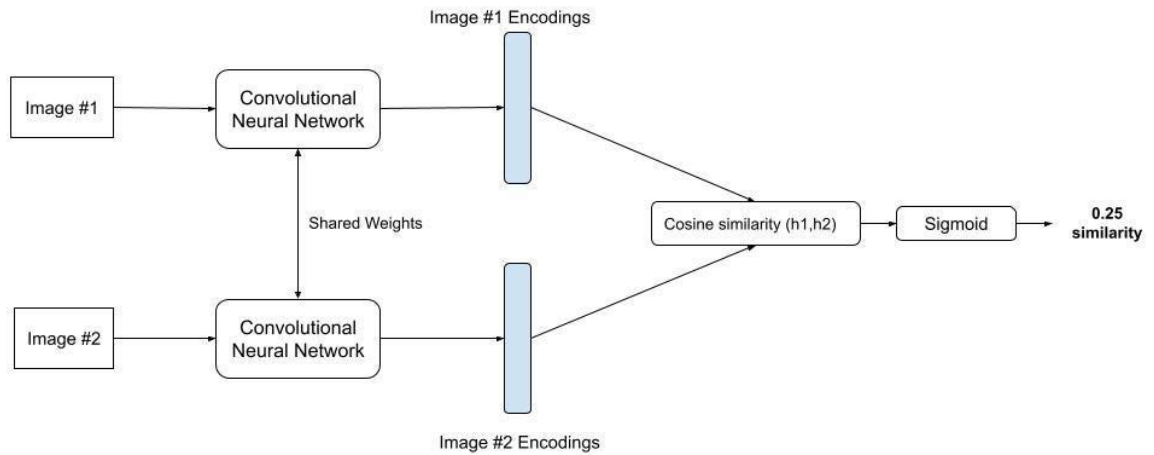


Figure 8 all-MiniLM-L6-v2 Architecture

Key Features:

1. **Transformer Architecture:** Sentence Transformers are based on transformer architectures, which have demonstrated exceptional performance in various natural language processing tasks. Transformers utilize self-attention mechanisms to capture dependencies between words and learn contextual representations of input sequences.
2. **Pre-trained Models:** Like other transformer-based models, Sentence Transformers are typically pre-trained on large text corpora using unsupervised learning objectives, such as masked language modelling or next sentence prediction. Pre-training allows the models to learn general-purpose sentence representations that capture semantic similarities and relationships.
3. **Fine-tuning:** Sentence Transformers can be fine-tuned on task-specific datasets to adapt the pre-trained representations to particular downstream tasks. Fine-tuning involves updating the model parameters using supervised learning objectives, such as classification or regression loss functions.
4. **Multi-task Learning:** Some Sentence Transformer models are trained using multi-task learning approaches, where the model is simultaneously trained on multiple tasks with shared parameters. This can lead to better generalization and improved performance across various tasks.
5. **Transfer Learning:** Sentence Transformers leverage transfer learning principles, where knowledge learned from pre-training on large text corpora is transferred to downstream tasks with limited annotated data. Transfer learning enables effective utilization of pre-trained models for a wide range of tasks without the need for extensive task-specific training data.

3.3.7. Langchain

Langchain is an open-source framework designed to simplify the development of applications powered by large language models (LLMs). It provides a set of tools and abstractions that make it easier to build, deploy, and manage LLM-based applications.

Key Features:

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1. **Purpose:** Streamlines the creation of LLM applications across various use cases, including document analysis, summarization, chatbots, code analysis, and more.
 2. **Open-source:** Freely available for anyone to use and contribute to.
 3. **Modular Design:** Offers a set of building blocks like chains, agents, and retrieval strategies that can be combined to construct complex applications.
 4. **Ease of Use:** Lowers the barrier to entry for developers, allowing them to build LLM applications without needing in-depth expertise in natural language processing (NLP).
 5. **Customization:** Enables developers to tailor LLM responses by providing context, integrating with external data sources, and refining prompts.
 6. **Production-ready:** Provides tools for monitoring, evaluating, and deploying LLM applications in production environments.

3.3.8. Google API

The Google Search API, also known as the Custom Search JSON API, is a service provided by Google that allows developers to retrieve search results programmatically from Google's search engine. It enables developers to integrate Google search functionality into their applications, websites, or services, providing users with access to relevant search results directly within their applications.

Key Features:

1. **Customizable Search Experience:** The Google Search API allows developers to create custom search engines tailored to specific topics, websites, or domains. Developers can define search engine specifications, including the sites to search, search queries, and result filtering criteria.
2. **Programmatic Access:** With the Google Search API, developers can query Google's search engine programmatically using HTTP requests. The API returns search results in JSON format, making it easy for developers to parse and integrate the data into their applications.
3. **Rich Search Results:** The API provides access to various types of search results, including web pages, images, videos, news articles, and more. Developers can specify the type of search results they want to retrieve and customize the presentation of search results in their applications.
4. **Usage Quotas and Billing:** Google imposes usage quotas and usage limits on the Google Search API to ensure fair access to resources and prevent abuse. While the API offers a free tier with limited usage, developers can also opt for paid plans to increase usage limits and access additional features.

CHAPTER 4: RESULT

Below is response generated by web search RAG System for various question, which usually Industry standard ChatGPT cannot answer due to knowledge cutoff.

Query	Response	URL
can you tell me about mathematics deparment of IIT Madras?	Yes, I can provide some information about the Mathematics Department at IIT Madras. It is one of the oldest and most reputed departments in the institute, with a rich history dating back to the late 1950s. The department offers undergraduate and postgraduate programs in mathematics, including a Bachelor of Science (BS) degree, a Master of Science (M.Sc) degree, and a Doctor of Philosophy (Ph.D) degree. The faculty members are renowned researchers and educators in various areas of pure and applied mathematics, including algebra, analysis, geometry, topology, number theory, statistics, and mathematical physics. The department also has strong collaborations with other research institutions and industries both in India and abroad. Additionally, the department organizes various seminars, workshops, and conferences throughout the year, providing opportunities for students to interact with leading mathematicians and researchers. Overall, the Mathematics Department at IIT Madras is known for its rigorous academic programs, cutting-edge research, and excellent faculty, making it a desirable destination for students pursuing advanced studies in mathematics.	'https://math.iitm.ac.in/' 'https://www.iitm.ac.in/academics/departments/departments-of-mathematics', 'https://math.iitm.ac.in/people/Faculty', 'https://www.quora.com/How-is-IIT-Madras-for-an-M-Sc-in-mathematics-and-then-for-pursuing-a-Ph-D-compared-to-all-the-other-IITs', 'https://joyofgiving.alumni.iitm.ac.in/endowments/institute-chair/institute-named-chair-professorship-in-mathematics-department-r-rama', 'https://www.linkedin.com/posts/dr-aradhana-narang-0249b44a_iitm-madras-phd-mathematics-activity-6954352903062966272-zytf?trk=public_profile_like_view', 'https://medium.com/@vidiptvashist', 'https://in.linkedin.com/in/vidiptvashist', 'https://twitter.com/vidipt_vashist?lang=en', 'https://www.researchgate.net/profile/Vidipt-Vashist', 'https://www.kaggle.com/vidiptvashist/competitions',
who is vidipt vashist	Vidipt Vashist is a contributor on Kaggle, a platform for predictive modelling and analytics competitions. He has also contributed to research on various platforms and has a presence on social media sites like LinkedIn, Twitter, and ResearchGate.	'https://medium.com/@vidiptvashist', 'https://in.linkedin.com/in/vidiptvashist', 'https://twitter.com/vidipt_vashist?lang=en', 'https://www.researchgate.net/profile/Vidipt-Vashist', 'https://www.kaggle.com/vidiptvashist/competitions',
who is Prof. kamakoti IIT Madras	Prof. V. Kamakoti is a faculty member in the Department of Computer Science and Engineering at IIT Madras. He is currently serving as the Associate Dean for Industrial Consultancy and Sponsored Research (ICSR). Prof. Kamakoti is also a member of the National Security Advisory Board, Government of India. He will be taking over as the next Director of IIT Madras.	'http://www.cse.iitm.ac.in/profile.php?arg=MTg=', 'https://rbcdsai.iitm.ac.in/people/kamakoti-veezhinathan/', 'https://www.iitm.ac.in/happenings/press-releases-and-coverages/prof-v-kamakoti-assumes-charge-today-new-director-iit', 'https://in.linkedin.com/in/kamakoti-veezhinathan-9a8528b',
how to fix Setting `pad_token_id` to `eos_token_id`:2 for open-end generation.	In order to fix the issue of setting `pad_token_id` to `eos_token_id`:2 for open-end generation, you should not set these values directly in the code. Instead, you should use the tokenizer provided by Hugging Face to handle the padding and ending tokens automatically. Here's an example of how to generate text using a Hugging Face model with open-end generation: <pre> python from transformers import AutoTokenizer, AutoModelForCausalLM # Load the tokenizer and model tokenizer = AutoTokenizer.from_pretrained("model name") </pre>	'https://stackoverflow.com/question/s/69609401/suppress-huggingface-logging-warning-setting-pad-token-id-to-eos-token-id', 'https://discuss.huggingface.co/t/setting-pad-token-id-to-eos-token-id-50256-for-open-end-generation/22247', 'https://github.com/huggingface/transformers/issues/12020', 'https://discuss.huggingface.co/t/strange-outputs-in-mixtral-model/73628', 'https://www.reddit.com/r/KoboldAI/comments/174k8ry/do_i_need_to_worry_about_this_e

	<pre> model = AutoModelForCausalLM.from_pretrained("model_name") # Preprocess the input text input_text = "Your input text here" inputs = tokenizer(input_text, return_tensors="pt", padding=True) attention_mask = inputs["attention_mask"] input_ids = inputs["input_ids"][:, :-1] # exclude the [CLS] token # Generate the output text output = model.generate(input_ids, max_length=100, num_beams=4, early_stopping=True, attention_mask=attention_mask) generated_text = tokenizer.decode(output[0], skip_special_tokens=True) print(generated_text) </pre> <p>In this example, the tokenizer handles the padding and ending tokens automatically, so you don't need to set 'pad_token_id' or 'eos_token_id' manually. This approach ensures that the model receives valid input and generates reliable outputs.</p>	<pre> rror_message and/', 'https://hugging face.co/meta-llama/Meta-Llama-3- 8B-Instruct/discussions/40', 'https://www.reddit.com/r/KoboldAI/ comments/nyqlqz/error_received_ when_entering_prompt/', 'https://jaketae.github.io/study/gpt2 /' </pre>
latest new in delhi?	<p>You can find the latest news headlines and live updates for Delhi on the Times of India website by visiting their Delhi News section at <https://www.hindustantimes.com/cities/delhi-news> and on NDTV by selecting "Delhi News" under the "Cities" category at <https://www.ndtv.com/cities/delhi-news>.</p>	<pre> <https://www.ndtv.com/cities/delhi-news>.', 'sources': ['https://indianexpress.com/section/cities/delhi/', 'https://timesofindia.in diatimes.com/city/delhi', 'https://www.hindustantimes.com/cities/delhi-news', 'https://www.ndtv.com/delhi-news', 'https://www.bbc.com/news/w orld/asia/india'], </pre>
latest python version?	<p>The latest stable version of Python as of March 7, 2023, is 3.11.2. However, it's important to note that using an older version like 3.4.4 is not recommended due to its lack of support and potential security vulnerabilities.</p>	<pre> 'https://www.python.org/downloads /', 'https://discuss.python.org/t/pytho n-latest-stable-version/24563', 'https://www.python.org/doc/versio ns/', 'https://devguide.python.org/ver sions/', </pre>
steps to create chatbot using llm"	<p>To create a chatbot using LangChain's LLM (Language Model), follow these steps:</p> <ol style="list-style-type: none"> 1. Import the necessary libraries, such as LangChain's LLMChain and OpenAI for language processing. 2. Create a chatbot template using a prompt template and ConversationBufferMemory. This will allow the chatbot to generate responses based on user input and store chat history for contextually relevant responses. 3. Set up the chatbot by instantiating the LLMChain class and utilizing its 'predict()' method to generate a response based on the user's input. 4. Customize the LLM chatbot using LangChain's finetuning capabilities to meet specific customer needs and preferences. 5. Test and deploy your chatbot for use in various applications. 	<pre> 'https://www.reddit.com/r/LocalLL aMA/comments/14jk0m3/what_is_ the_best_way_to_create_a_knowle dgebase/', 'https://medium.com/@ali sha3/build-your-first-llm-chatbot- 77456438f57b', 'https://datascienced ojo.com/blog/llm-chatbot/', 'https://mrmareshrajput.medium.co m/how-to-build-an-intelligent-qa- chatbot-on-your-data-with-llm-or- chatgpt-d0009d256dce', 'https://realpython.com/build-llm- rag-chatbot-with-langchain/', 'https://cobusgreyling.medium.com /bootstrapping-a-chatbot-with-a- large-language-model- 93fdf5540a1b', 'https://community.o penai.com/t/create-question-asking- chatbot-that-collects-user- information/657588', </pre>

This project represents a contribution to the understanding and advancement of RAG technology within the context of information management and retrieval. Through systematic exploration and innovation, RAG emerges as a transformative solution to the challenges faced by LLMs, offering unprecedented capabilities in leveraging external knowledge for enhanced decision-making and interaction. Large language models (LLMs) have undeniably marked a significant milestone in natural language processing (NLP), yet their inherent limitations, particularly in domain-specific tasks and knowledge-intensive queries, have propelled the development of innovative solutions. Retrieval-Augmented Generation (RAG) emerges as a key technology to address these challenges, enhancing LLMs by seamlessly integrating external knowledge sources through semantic similarity calculations. This project embarks on a comprehensive exploration of RAG technology, tracing its evolution, applications, challenges, and future directions within the landscape of information management and retrieval. The journey of RAG technology unfolds against the backdrop of rapid advancements in NLP, with its inception coinciding with the rise of the Transformer architecture. Early stages of RAG development were characterized by foundational work aimed at refining pre-training techniques, laying the groundwork for subsequent breakthroughs. The arrival of models like ChatGPT marked a pivotal moment, harnessing the power of in-context learning (ICL) and propelling RAG research towards addressing more complex and knowledge-intensive tasks during the inference stage. As research progressed, the integration of RAG with LLM fine-tuning techniques further enriched its capabilities, paving the way for widespread adoption and establishing RAG as a cornerstone technology in advancing chatbots and enhancing LLMs for real-world applications. A critical aspect of this project lies in mapping out the trajectory of RAG technology, providing a systematic synthesis of its evolution and anticipated future paths. Through this endeavor, the project aims to bridge existing gaps in understanding and clarify the broader implications of RAG within the realm of LLMs. Information retrieval emerges as a pivotal application, with RAG offering a solution to the challenges of maintaining up-to-date knowledge, incorporating long-tail information, and safeguarding against privacy risks. By leveraging its adaptable data repository, RAG transforms the landscape of information management, offering a non-parametric memory capable of accommodating diverse knowledge domains while ensuring data confidentiality. The project's primary objectives revolve around addressing pressing challenges in information extraction and retrieval. The development of an internal document RAG system aims to empower organizations with robust solutions for efficiently extracting insights from private PDF files. By overcoming the complexity and inefficiency inherent in traditional data extraction processes, this system unlocks valuable opportunities for organizations to leverage internal knowledge effectively, thereby enhancing customer interactions and maintaining a competitive edge in the market. Similarly, the creation of a web search RAG system responds to the need for accessing relevant and accurate information efficiently in the vast landscape of the internet. Existing search engines, while indispensable, often fall short in providing comprehensive context or augmentation to enhance user understanding. The web search RAG system addresses these shortcomings by augmenting traditional search retrieval with contextually relevant information and generating additional insights based on user queries, thereby enhancing the overall search experience. In the ever-evolving landscape of technology and business, effective information management products play a pivotal role in the success and sustainability of organizations worldwide. Rapid advancements in technology and changing market demands necessitate continuous innovation and refinement to remain competitive and meet evolving client needs. By embracing technologies like RAG, organizations can unlock new frontiers in information management, driving efficiency, insights, and value creation across diverse domains.

Exploring avenues for future work in the realm of Retrieval-Augmented Generation (RAG) opens up a myriad of exciting possibilities for advancing the field and pushing the boundaries of natural language processing (NLP). As technology continues to evolve and new challenges emerge, researchers and practitioners have an opportunity to innovate and refine existing approaches while exploring novel avenues for exploration. This section delves into potential directions for future work, ranging from the exploration of new large language models (LLMs) to the advancement of RAG architectures.

1. **Exploration of New LLM Architectures:** Future research could focus on exploring new LLM architectures that are specifically tailored to leverage the capabilities of RAG. While models like ChatGPT have demonstrated remarkable performance, there remains room for improvement and optimization. Investigating architectures that prioritize efficient retrieval and generation mechanisms could enhance the overall effectiveness of RAG systems. Additionally, exploring hybrid models that combine the strengths of different architectures, such as transformers and recurrent neural networks (RNNs), could lead to further advancements in RAG technology.
2. **Integration of Multimodal Information:** Incorporating multimodal information, including text, images, and audio, into RAG systems presents an exciting avenue for future research. By leveraging multimodal inputs, RAG models can provide more comprehensive and contextually rich responses to user queries. This integration could enhance the relevance and accuracy of generated content, particularly in tasks that require a deeper understanding of visual or auditory context. Exploring techniques for seamlessly integrating multimodal information retrieval with generation processes represents a promising direction for future work.
3. **Fine-Tuning Techniques and Optimization:** Refining fine-tuning techniques and optimization strategies for RAG models is another area ripe for exploration. Fine-tuning LLMs with retrieval-augmented data presents unique challenges, including balancing the trade-off between retrieval accuracy and generation fluency. Future research could focus on developing more efficient fine-tuning methods that optimize both retrieval and generation processes simultaneously. Additionally, exploring techniques for dynamic adaptation and re-ranking of retrieved information based on real-time feedback could further enhance the performance of RAG systems.
4. **Scalability and Efficiency:** As the scale of information continues to grow exponentially, ensuring the scalability and efficiency of RAG systems becomes increasingly important. Future work could focus on developing scalable architectures and algorithms that can handle large-scale knowledge bases efficiently. This includes exploring techniques for distributed retrieval and generation, as well as optimizing resource utilization to minimize computational overhead. Additionally, investigating strategies for incremental learning and adaptation could enable RAG systems to continuously improve and evolve over time.
5. **Addressing Privacy and Security Concerns:** Privacy and security considerations are paramount in the development of RAG systems, particularly when dealing with sensitive or confidential information. Future research could focus on developing robust privacy-preserving techniques that safeguard against data leaks and unauthorized access. This includes exploring encryption methods, differential privacy techniques, and secure multiparty computation approaches to protect user data during retrieval and generation processes. Additionally, investigating methods for auditing and verifying the integrity of RAG systems could enhance trust and transparency in their operation.

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