

# GENERATIVE AI & LLMs

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## ABSTRACT

This study presents a method for implementing generative AI services by utilizing the Large Language Models (LLM) application architecture. With recent advancements in generative AI technology, LLMs have gained prominence across various domains. In this context, the research addresses the challenge of information scarcity and proposes specific remedies by harnessing LLM capabilities. The investigation delves into strategies for mitigating the issue of inadequate data, offering tailored solutions. The study delves into the efficacy of employing fine-tuning techniques and direct document integration to alleviate data insufficiency. A significant contribution of this work is the development of a Retrieval-Augmented Generation (RAG) model, which tackles the aforementioned challenges. The RAG model is carefully designed to enhance information storage and retrieval processes, ensuring improved content generation. The research elucidates the key phases of the information storage and retrieval methodology underpinned by the RAG model. A comprehensive analysis of these steps is undertaken, emphasizing their significance in addressing the scarcity of data. The study highlights the efficacy of the proposed method, showcasing its applicability through illustrative instances.

By implementing the RAG model for information storage and retrieval, the research not only contributes to a deeper comprehension of generative AI technology but also facilitates its practical usability within enterprises utilizing LLMs. This work holds substantial value in advancing the field of generative AI, offering insights into enhancing data-driven content generation and fostering active utilization of LLM-based services within corporate settings.

**Keywords:** Generative AI, LLM, RAG, LangChain, LLM framework, Embedding, Vector Store.

## I. INTRODUCTION

This Recent developments in generative AI, catalyzed by ChatGPT, have become a focal point of discussion. Generative AI possesses the potential to contribute across a myriad of domains, encompassing natural language generation, translation, and the generation of diverse imaginative content. A notable indication of global anticipation for generative AI is underscored by the '2023

Within the realm of 'Emergent AI,' which denotes burgeoning artificial intelligence, the category of 'Generative AI' is marked as being at the 'Peak of Inflated Expectations.' The report forecasts that within 2 to 5 years, the field of generative AI will achieve transformative accomplishments, heralding a new era of enhanced human productivity and machine creativity. Of particular significance, Large Language Models (LLM) such as OpenAI's GPT series have demonstrated groundbreaking outcomes in the realm of natural language comprehension and generation. The wave of generative AI, instigated by ChatGPT, has extended its influence to encompass visual mediums, including Stable Diffusion and Midjourney, capturing the attention of the general populace. In light of these advancements, LLM are being extensively harnessed across diverse domains. Leveraging extensive training on copious volumes of textual data, LLM exhibit the ability to comprehend and generate natural language. Building upon this prowess, LLMs find application in various domains,

including customer interactions, creative content creation, and question answering. However, generative AI still faces various limitations. LLM require extensive amounts of data for training, which incurs substantial costs and time investment. Furthermore, LLMs exhibit limited adaptability to new data, making it challenging to provide accurate responses to questions unrelated to the data they were trained on. Notably, ChatGPT, provided by OpenAI, tends to exhibit a phenomenon known as "hallucination." This entails fabricating information when faced with queries about unfamiliar facts. Consequently, while responses may appear plausible on the surface, they often contain incorrect information. In efforts to mitigate this, approaches to minimize hallucination and elicit responses that align with actual data are being pursued. Strategies include appending context to prompts, employing Chain-Of Thought (Cot) techniques, enhancing self-consistency, and requesting concise answers from the model. Another constraint arises from the limited answer capacity of LLMs due to information gaps. For instance, the GPT 3.5 model lacks data beyond.

September 2021, rendering it incapable of furnishing responses pertaining to recent news events. Moreover, since external information is utilized for generating answers, there is a growing demand for methods to address inquiries related to sensitive business insider information. As a primary solution to address these challenges, fine-tuning of LLM with new data is proposed. This approach involves additional training on specific domains using fresh datasets. For ultra-

large AIs, updating all parameters can be arduous. Consequently, strategies such as LoRA and P-tuning are employed, focusing on training only a subset of parameters. In pursuit of overcoming such limitations, OpenAI introduced the capability to fine-tune the GPT-3.5 Turbo model, a significant advancement unveiled in August 2023. Furthermore, plans are in place to offer fine-tuning capabilities for the GPT-4 model by the autumn of 2023. This update empowers developers to customize models according to their use cases, harnessing enhanced performance. These tailored models can subsequently be deployed at scale. Initial tests have demonstrated that the fine-tuned GPT-3.5 Turbo version exhibits comparable, and in some cases even superior, performance to the base GPT-4 model across specific narrow tasks. Notably, similar to all APIs, data transmitted through the finetuning API is owned by the customers, and OpenAI or any other organization is precluded from employing this data for training alternative models, as officially stated. However, this approach entails significant costs. Currently, the fine-tuning expenses for the GPT-3.5 Turbo model are categorized into two primary buckets: initial training costs and usage costs. For instance, the anticipated cost for a gpt-3.5-turbo finetuning task involving a training file containing 100,000 tokens trained over three epochs is approximately \$2.40. An alternative strategy involves directly incorporating user-desired information, encapsulated within documents, into the prompt context. Nonetheless, the practicality of manually embedding all information into the context is unfeasible. GPT-3.5 has the capacity to store information equivalent to roughly 8,000 words or around 5 pages of text, while GPT-4's processing capabilities are restricted to inputs of up to approximately 50 pages. In such scenarios, it is more efficient for users or businesses to store their information in databases. Subsequently, when user queries arise—such as inquiries regarding company dress codes through a chatbot—pertinent information can be retrieved and presented to the LLM through prompts, proving to be a more practical and efficient approach. For instance, the approach involves uploading a PDF document and posing a question, whereby the system searches for relevant information within the PDF to provide an answer. This methodology represents the second approach, termed Retrieval Augmented Generation (RAG) service architecture. In this manner, RAG informs the LLM of pertinent queries and associated reference materials in advance, mitigating hallucination tendencies and enabling more accurate response generation. The RAG architecture thus addresses the information scarcity issue within LLM, possessing the potential to furnish high-quality responses without necessitating new data training. The RAG models offer a means to supply users with more precise and fitting answers to their inquiries, making it a valuable technology for real-world business contexts. This versatility renders it applicable across various business domains, enhancing LLM performance. Efforts to enhance language model performance through leveraging

search techniques have long been underway. Notably, in 2021, DeepMind introduced RETRO, utilizing its internal database for information retrieval, while OpenAI unveiled WebGPT with Bing-based searching capabilities in the same year. However, the current prominence of the RAG architecture in the industry stems from its remarkable improvement in in-context learning abilities and the convenience of not requiring separate model training effort.

## **II. METHODOLOGY**

We employed an exploratory methodology to understand the potential benefit of ChatGPT in Education. The purpose of this methodology is to systematically review and explore (a) how interactive ChatGPT is, (b) the benefits of ChatGPT and related generative AI in advancing teaching and learning, (c) the possible drawbacks of using ChatGPT and related generative AI in education, reflections and implications for practice. The study was guided by these research questions –(a) How interactive is ChatGPT? (b) What are the potential benefits of ChatGPT and related generative AI in advancing teaching and learning? (c) what are the possible drawbacks of using ChatGPT and related generative ai in education? The study focused on publicly available resources on ChatGPT from November 2022-March 2023. Specifically, we focused on articles published in a peer-reviewed journal.

## **III. WHAT IS CHAT GPT?**

To begin, we asked ChatGPT to explain itself. The prompt we started with was “What is ChatGPT?”. ChatGPT generated this response. ii. “ChatGPT is a large language model trained by OpenAI. It is designed to generate human-like text based on a given prompt or context. It can be used for a variety of natural language processing tasks, such as text completion, conversation generation, and language translation”. (By ChatGPT January 23, 2023). As a follow-up, we used another prompt “How does it work?” To know how conversational it is, we intentionally wrote “How does it work?” instead of “How does ChatGPT work?”. It returned with the response below. iii.

“ChatGPT is based on a transformer architecture, a type of neural network that has been shown to be very effective for natural language processing tasks. It is trained on a large dataset of text, such as books and articles, and learns to generate text that is similar to the text it was trained on. When given a prompt or context, the model processes the input and generates a response. The response is generated one word at a time, with the model predicting the next word based on the input and the words it has generated so far. iv. The model uses attention mechanisms to focus on the most relevant parts of the input and generate a response that is coherent and appropriate for the given context. After the training, the model can be

fine-tuned on a specific task such as question answering or dialogue generation by providing it with task-specific examples and fine-tuning the model on this data. It can also generate text in multiple languages by finetuning the model on the multilingual dataset or by providing the model with the language code” (By ChatGPT January 23, 2023). Then the topic of conversation was changed to discuss COVID-19 and impacts on educational deliveries using the prompt “Now discuss how COVID-19 has changed educational pedagogies.” Within seconds, it wrote the passage below. v. The COVID-19 pandemic has had a significant impact on the way education is delivered, with many schools and universities shifting to online or remote learning in order to comply with social distancing guidelines. This has resulted in a rapid shift to digital and online pedagogy, as educators have had to quickly adapt to this new mode of instruction. One of the major changes that has occurred is the increased use of technology for teaching and learning. This has included the use of online learning platforms, such as Zoom, Google Classroom, and other video conferencing tools, as well as the use of digital materials, such as e-books, videos, and interactive activities. This has allowed for increased flexibility and accessibility in the delivery of education, as students can now access materials and participate in classes from anywhere with internet access. vi. Additionally, there has been a shift towards more self-directed and asynchronous learning, where students are given more autonomy in their learning and are able to complete coursework at their own pace. This approach allows students to work at a time that is convenient for them, and it can be beneficial for students who may have other responsibilities or who may have difficulty attending live classes. vii. However, the shift to online learning has also highlighted the digital divide, where students in low-income or rural areas may not have access to the technology or internet connectivity needed to fully participate in remote learning. And it also brought challenges such as lack of interaction, lack of motivation, and lack of accountability. viii. Overall, COVID-19 has accelerated the adoption of technology and digital pedagogy in education, but it has also highlighted the need for equity and

#### **IV. GENERATIVE AI & LARGE LANGUAGE MODEL**

In recent years, the rapid pace of AI development and public release tools such as ChatGPT, GitHub Copilot, and DALL-E have attracted widespread attention, optimism, and alarm (The White House, 2022). These technologies are all examples of “generative AI,” a class of machine learning technologies that can generate new content—such as text, images, music, or video—by analyzing patterns in existing data. In this section, we provide

background on generative AI as a technology and discuss its potential economic implications.

##### *Some Common Advantage*

1. *Creative Content Generation:* Generative AI can create content autonomously, ranging from text, images, music, to even videos. This is advantageous for creative industries like advertising, entertainment, and marketing where fresh and diverse content is constantly in demand.
2. *Data Augmentation:* In fields like computer vision and natural language processing, generative AI can be used to augment datasets. This helps in training robust machine learning models, improving their performance and generalization on unseen data.
3. *Personalization:* Generative AI can tailor content or recommendations to individual preferences. This is particularly useful in e-commerce, content streaming platforms, and personalized advertising, where understanding and catering to individual tastes can significantly enhance user experience and engagement.
4. *Simulation and Synthesis:* Generative models can simulate scenarios or synthesize data that might be difficult, costly, or dangerous to obtain in real life. For instance, in medicine, generative models can simulate the effects of drugs on the human body, aiding in drug discovery and development.
5. *Anomaly Detection:* Generative models can learn the underlying distribution of normal data, enabling them to identify anomalies or outliers. This is useful in various applications such as fraud detection, cybersecurity, and predictive maintenance in industrial settings.
6. *Reduced Dependency on Human Labor:* Generative AI can automate the generation of content, reducing the need for human involvement in repetitive or mundane tasks. This allows human workers to focus on more strategic and creative aspects of their work.
7. *Adaptability and Flexibility:* Generative models can adapt to new data distributions or tasks with minimal retraining. This flexibility makes them suitable for dynamic environments where the data distribution may change over time.

8. *Personal Assistants and Chatbots:* Generative AI powers conversational agents and virtual assistants that can understand and generate human-like responses. These assistants can handle customer queries, provide recommendations, and even engage in personalized conversations, enhancing customer service and user interaction

#### **LARGE LANGUAGE MODEL**

After For the purpose of this study, an extensive investigation into recent significant research papers, journals, articles, and books related to generative AI and LLM has been conducted. This chapter delves into a comprehensive exploration of both LLM and generative AI as a whole. It commences by delving into the concept and diverse application domains of generative AI. Furthermore, it examines the intricate elements, technological components, and frameworks pertinent to LLM, as well as demarcates the realm of RAG that is the focus of this paper. In this chapter, an exhaustive review of pertinent literature has been undertaken to contextualize the research within the contemporary landscape of generative AI and LLM. The chapter unfolds by providing a detailed understanding of the concepts and applications of generative AI, followed by a meticulous breakdown of the technical components and frameworks underlying LLM, and concludes by delineating the RAG domain. Through this literature review, we aim to establish a comprehensive understanding of the theoretical foundations and recent advancements in the field, setting the stage for the subsequent chapters that delve

#### **V. BACKGROUND FOR GENERATIVE AI**

In the context of AI, IDC positions generative AI as illustrated in Fig 1., encompassing unsupervised and semi-supervised algorithms that enable computers to respond to short A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author sequence that will be used in future citations and by indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

prompts and create new content using previously generated content such as text, audio, video, images, and code [1]. Over the past few years, generative AI technology has undergone rapid advancement, ushering in novel opportunities across various industries. Unlike traditional methods that merely process or analyze existing data, generative AI employs a novel approach to generate fresh and inventive content. These models learn patterns and are trained on extensive datasets to generate new

outputs resembling the training data Generative AI types and application Generative AI technology has the remarkable ability to create a wide range of data forms, including text, code, Fig 2., showcases representative models within generative AI technology based on different data formats and the application domains they serve [2, 3].

#### **VI. RESULTS: HOW DID CHATGPT RESPOND?**

1. **Academic Integrity:** With the ability to generate human-like responses, ChatGPT raises concerns about academic integrity. Students could potentially misuse the model to generate plagiarized content or cheat on assignments and assessments. This poses a challenge for educators and institutions in ensuring fair evaluation and maintaining academic standards.

2. **Quality Control:** ChatGPT generates responses based on the data it has been trained on, which includes a vast amount of information available on the internet. While the model strives to provide accurate and helpful information, there is still a possibility of generating incorrect or misleading responses. Institutions need to carefully assess and validate the information provided by ChatGPT to ensure its accuracy and reliability.

3. **Personalized Learning:** While ChatGPT can provide personalized responses to individual queries, it might not fully capture the nuanced needs of each learner. Higher education institutions often focus on tailoring education to meet the specific requirements of students. Relying solely on ChatGPT for personalized learning experiences may overlook certain aspects of individual student needs, such as their learning style, preferences, and unique challenges.

4. **Expertise and Authority:** ChatGPT lacks the domain-specific expertise that specialized instructors and professors possess. Higher education institutions emphasize the role of subject matter experts in providing deep insights, critical analysis, and guidance in specific fields. Relying solely on ChatGPT might not fully meet the expectations and needs of students seeking expertise from highly qualified professionals.

5. **Communication and Collaboration:** Effective communication and collaboration are integral parts of the higher education experience. ChatGPT, being an AI language model, might not possess the same level of human interaction and interpersonal skills as an instructor or peers. This can limit its effectiveness in supporting group work, discussions, and other collaborative activities that are crucial for a well-rounded educational experience.

It is important to note that these challenges are not insurmountable, and institutions can develop strategies to address them effectively. With careful implementation and integration, ChatGPT can still

offer significant benefits and opportunities for higher education.

Interviewer: What significant benefits or opportunities for higher education can ChatGPT offer?

ChatGPT: ChatGPT indeed presents several significant benefits and opportunities for higher education. Here are some of them

## VII. FOUNDATION OF MODEL

Transformer. Transformer is the backbone architecture for many state-of-the-art models, such as GPT-3, DALL-E-2, Codex, and Gopher. It was first proposed to solve the limitations of traditional models such as RNNs in handling variable-length sequences and context awareness. Transformer architecture is mainly based on a self-attention mechanism that allows the model to attend to different parts in a input sequence. Transformer consists of an encoder and a decoder. The encoder takes in the input sequence and generates hidden representations, while the decoder takes in the hidden representation and generates output sequence. Each layer of the encoder and decoder consists of a multi-head attention and a feed-forward neural network. The multi-head attention is the core component of Transformer, which learns to assign different weights to tokens according their relevance. This information routing method allows the model to be better at handling long term dependency, hence, improving the performance in a wide range of NLP tasks. Another advantage of transformer is that its architecture makes it highly parallelizable, and allows data to trump inductive biases [40]. This property makes transformer well-suited for large-scale pre-training, enabling transformer-

based models to become adaptable to different downstream tasks.

### 1. Pre-trained Language Models

Since the introduction of the Transformer architecture, it has become the dominant choice in natural language processing due to its parallelism and learning capabilities. Generally, these transformers based pre-trained language models can be commonly classified into two types based on their training tasks: autoregressive language modeling and masked language modeling. Given a sentence, which is composed of several tokens, the objective of masked language modeling, e.g., BERT and RoBERTa refers to predicting the probability of a masked token given context information. The most notable example of masked language modeling is BERT which includes masked language modeling and next sentence prediction tasks. RoBERTa, which uses the same architecture as BERT, improves its performance by increasing the amount of pre-training data and incorporating more challenging pre-training objectives. XL-Net, which is also based on BERT,

incorporates permutation operations to change the prediction order for each training iteration, allowing the model to learn more information across tokens. While autoregressive language modeling, e.g., GPT-3 and OPT, is to model the probability of the next token given previous tokens, hence, left-to-right language modeling. Different from masked language models, autoregressive models are more suitable for generative tasks. We will introduce more about autoregressive models in Section

Categories of pre-trained LLMs. Black line represents information flow in bidirectional models, while gray line represents left-to-right information flow. Encoder models, e.g. BERT, are trained with context-aware objectives. Decoder models, e.g. GPT, are trained with autoregressive objectives. Encoder-decoder models, e.g. T5 and BART, combines the two, which use context-aware structures as encoders and left-to-right structures as decoders.

### 2. REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

Despite being trained on large-scale data, the AIGC may not always produce output that aligns with the user's intent, which includes considerations of usefulness and truthfulness. In order to better align AIGC output with human preferences, reinforcement learning from human feedback (RLHF) has been applied to fine-tune models in various applications such as Sparrow, Instruct, and ChatGPT. Typically, the whole pipeline of RLHF includes the following three steps: pre-training, reward learning, and fine-tuning with reinforcement learning. First, a language model  $\theta_0$  is pre-trained on large-scale datasets as an initial language model. Since the (prompt-answer) pair given by  $\theta_0$  might not align with human purposes, in the second step we train a reward model to encode the diversified and complex human preference. Specifically, given the same prompt  $x$ , different generated answers  $\{y_1, y_2, \dots, y_3\}$  are evaluated by humans in a pairwise manner. The pairwise comparison relationships are later transferred to pointwise reward scalars,  $\{r_1, r_2, \dots, r_3\}$ ,

using an algorithm such as ELO. In the final step, the language model  $\theta$  is fine-tuned to maximize the learned reward function using reinforcement learning. To stabilize the RL training, Proximal Policy Optimization (PPO) is often used as the RL algorithm. In each episode of RL training, an empirically-estimated KL penalty term is considered to prevent the model from outputting something peculiar to trick the reward model. Specifically, the total reward  $r_{total}$  at each step is given by  $r_{total}(x, y) = r_{RM}(x, y) - \lambda \text{DKL} \pi_{\theta} \pi_{\theta_0}$ , where  $r_{RM}$  is the learned reward model,  $\text{DKL}$  is the KL penalty

term, and  $\pi$  is the trained policy. For more details on RLHF, please refer to

## VIII. INTEGRATING CHATGPT IN HIGHER EDUCATION

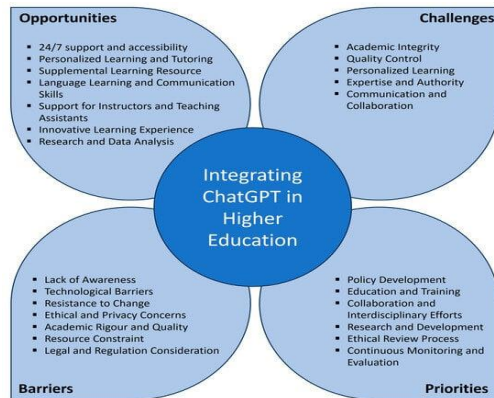


Fig (CHATGPT FEATURES)

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