Report on the RAG-Powered AI Assistant with LLaMA3 and GPT-2

1)Local LLM Setup and Interaction:

- 1.1) Run "ollama run llama3.2" to verify the installation of llama on the local machine.
- 1.2) Use GPT-2 by installing hugging face's transformers library and setting up a python to load GPT-2 from transformers library and read the input prompt and generate response.

2)Implementation of the RAG system with Llama3 and GPT-2:

We are integrating a Retrieval-Augmented Generation (RAG) workflow using LLaMA and GPT-2 models to enhance response generation in a Streamlit chatbot interface. The RAG system retrieves relevant contextual information from Wikipedia via the WikipediaAPI and generates sentence embeddings using Alibaba's Sentence Transformer model to find the most relevant documents. Based on the selected model (LLaMA or GPT-2), the retrieved context is incorporated into the prompt, and either LLaMA or GPT-2 is used to generate a response. This process allows the chatbot to provide more contextually aware and accurate answers by combining Wikipedia-based document retrieval with model-based generation. Users can choose between RAG-enhanced responses or direct model responses, and response times for each interaction are tracked.

2.1)Sentence Embeddings Model Setup:

```
import streamlit as st
import subprocess
import re
import numpy as np
import time
from sentence_transformers import SentenceTransformer
from wikipediaapi import Wikipedia
from transformers import GPT2LMHeadModel, GPT2Tokenizer

# 1. Setup the Sentence Embeddings Model
model = SentenceTransformer("Alibaba-NLP/gte-base-en-v1.5", trust_remote_code=True)
```

This initializes the **SentenceTransformer** model, which is used to convert text into vector embeddings. In this case, it uses Alibaba's **GTE** (**General-purpose Text Embedding**) **model**. These embeddings are later used to compare and rank Wikipedia paragraphs based on their similarity to the user's query. This is essential for the **retrieval** part of the RAG system.

2.2) Wikipedia API Setup:

```
# 2. Setup Wikipedia API
wiki = Wikipedia('RAGBot/Rag-1', 'en')
```

This sets up the Wikipedia API to allow searching for relevant articles in the English version of Wikipedia. It's part of the retrieval step, where Wikipedia is used as the external knowledge base to fetch contextual information related to the user's query. This provides the external data that the model may need to generate a relevant response.

2.3)GPT-2 Model and Tokenizer Setup:

```
# 3. Load GPT-2 Model and Tokenizer
gpt2_model = GPT2LMHeadModel.from_pretrained("gpt2")
gpt2_tokenizer = GPT2Tokenizer.from_pretrained("gpt2")
```

This loads the pre-trained **GPT-2 language model** and its tokenizer, which will be used to generate text based on the query and the retrieved Wikipedia context. GPT-2 can function in two ways: with RAG (enhanced with external context) or standalone. The tokenizer converts the input text into tokens for the model to process and later decodes the output tokens into human-readable text.

2.4)Post and Preprocessing the Query:

```
# 4. Function to preprocess the prompt
def preprocess_prompt(prompt: str) -> str:
    prompt = prompt.lower().strip()
    prompt = re.sub(r'[^\w\s]', '', prompt) # Remove punctuation
    return prompt

# 5. Function to post-process the response
def postprocess_response(response: str) -> str:
    response = re.sub(r'<\|endoftext\|>', '', response) # Clean end of text token
    return response.strip()
```

These functions preprocess and postprocess the user's input query by converting it to lowercase and removing punctuation. This step ensures that the query is clean and consistent before being used in embedding generation or as a prompt for the model. It improves the retrieval and generation process by standardizing input.

```
# 6. Function to generate text using local LLaMA model via Ollama

def generate_llama_response(prompt):
    process = subprocess.run(
        ['ollama', 'run', 'llama3.2:latest'],
        input=prompt,
        capture_output=True,
        text=True,
        encoding='utf-8',
        errors='replace'
)

if process.returncode != 0:
    error_message = process.stderr.strip()
    return f"Error running Ollama: {error_message}"

response = process.stdout.strip()
    return response
```

This function interacts with the local **LLaMA** model via the **Ollama** CLI, which runs the LLaMA model. It takes the query or the RAG-enhanced prompt, sends it to the LLaMA model, and captures the output (generated response). It handles potential errors from the process and returns either the response or an error message.

2.6)GPT-2 Model Integration and Text Generation:

```
# 7. Function to generate text using GPT-2
def generate_gpt2_response(prompt):
    # Encode the input prompt
    inputs = gpt2_tokenizer.encode(prompt, return_tensors="pt")

# Set maximum input length and new tokens to generate
    max_input_length = 512  # or another suitable length
    max_new_tokens = 50  # Adjust this based on how much output you want

# Truncate input if it exceeds the max input length
    if inputs.size(1) > max_input_length:
        inputs = inputs[:, :max_input_length]

# Generate the response
    outputs = gpt2_model.generate(inputs, max_new_tokens=max_new_tokens, num_return_sequences=1)

# Decode and return the generated response
    response = gpt2_tokenizer.decode(outputs[0], skip_special_tokens=True)
    return response
```

This function generates a response using **GPT-2**. It first tokenizes the prompt (either the raw query or the RAG-enhanced query) and generates text using GPT-2. The model can produce up to 50 new tokens for the response. After the response is generated, the tokenizer decodes it back into a human-readable format.

2.7) Wikipedia Search for Document Retrieval:

```
def search wikipedia(query):
    stop_words = {"what", "who", "how", "is", "was", "are", "which", "when", "where", "why", "did", "doe", "does"}
    words = [word for word in query.split() if word.lower() not in stop words]
   paragraphs_list = []
    for word in words:
       doc = wiki.page(word).text
        if doc:
           paragraphs = doc.split('\n\n')
           paragraphs_list.extend(paragraphs)
    if not paragraphs list:
   docs_embed = model.encode(paragraphs_list, normalize_embeddings=True)
    query_embed = model.encode(query, normalize_embeddings=True)
    similarities = np.dot(docs_embed, query_embed.T)
    top_3_idx = np.argsort(similarities, axis=0)[-3:][::-1].tolist()
    most_similar_documents = [paragraphs_list[idx] for idx in top_3_idx]
    context = "\n\n".join(most_similar_documents)
    return context
```

This function performs the **document retrieval** part of RAG. It queries Wikipedia for relevant documents based on the user's query, filters stop words (e.g., "what", "who"), and uses the **SentenceTransformer** to convert the text of each paragraph and the query into embeddings. By computing the cosine similarity between the query and document embeddings, it retrieves the top 3 most relevant paragraphs. These paragraphs are used as contextual information in the RAG prompt. The stopwords filtering will help in reducing the response time.

2.8) Combining Retrieval and Generation (RAG Workflow):

```
def rag_response(query, model_choice='llama'):
    start_time = time.time() # Start timing
   context = search_wikipedia(query)
       return "I couldn't find relevant information from Wikipedia."
   {context}
   Based on this information, please answer the following question:
   If the information provided doesn't contain the answer, please say "I don't have enough information to answer this guestion."
   if model_choice == 'LLaMA with RAG':
        response = generate_llama_response(prompt)
   elif model choice == 'GPT-2 with RAG
      response = generate_gpt2_response(prompt)
   response = generate_llama_response(query) # Direct usage without RAG
           response = generate_gpt2_response(query)
   end time = time.time() # End timing
   response_time = end_time - start_time
   return response, response_time
```

This is the **core RAG function**. First, it retrieves context from Wikipedia using search_wikipedia(). If context is found, it is combined with the user's query to form a prompt for the model. Depending on the selected model (LLaMA with RAG or GPT-2 with RAG), either LLaMA or GPT-2 is used to generate the final response. It also tracks the time taken for the entire process (retrieval + generation), which helps analyze performance. If no context is retrieved, a fallback message is returned.

2.9)Streamlit Interface for User Input and Output:

```
st.title("RAG-Powered AI Assistant with LLaMA3 and GPT-2 Integration")
 # Create a session state to store chat history
if 'chat_history' not in st.session_state:
   st.session_state.chat_history = []
tab1, tab2 = st.tabs(["Chat", "Conversation History"])
with tab1:
   query = st.text_input("Your Query:", key="query_input")
   model_choice = st.selectbox("Select Model:", ["LLaMA with RAG", "GPT-2 with RAG", "LLaMA", "GPT-2"])
    if st.button("Submit"):
       if query:
            with st.spinner("Fetching response..."):
               preprocessed_input = preprocess_prompt(query)
                response, response_time = rag_response(preprocessed_input, model_choice=model_choice)
                # Post-process the response
               cleaned_output = postprocess_response(response)
                st.session_state.chat_history.append({
                    "user": query,
                    "chatbot": cleaned output,
                   "model": model_choice, # Add the selected model to chat history
                   "response_time": response_time # Store the response time
                st.subheader("Response:")
                st.write(cleaned output)
                st.write(f"Response Time: {response_time:.2f} seconds")
```

This section handles the **Streamlit UI**, allowing users to input queries, select a model (LLaMA with RAG, GPT-2 with RAG, or standalone versions of both), and view the chatbot's response. It stores chat history in session_state and processes user queries by calling the RAG workflow or direct generation functions, depending on the user's model choice.

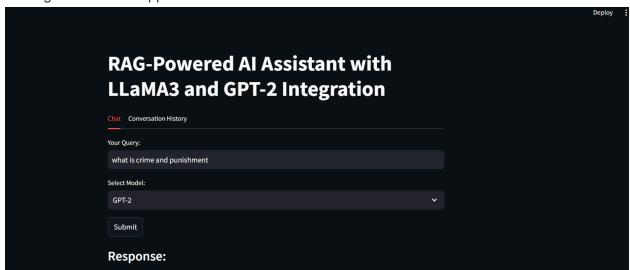
To summarize for

Document Retrieval: We use **Wikipedia** and a **SentenceTransformer model** to find relevant documents that match the user's query.

Text Generation: Once relevant documents are retrieved, the context is combined with the user's query, and text generation is performed by either **LLaMA** or **GPT-2**.

RAG Workflow: We implemented a **Retrieval-Augmented Generation (RAG)** system, which enhances text generation by feeding external context into the model, improving accuracy and relevance.

UI Integration: The process is wrapped in a **Streamlit** app, where users can interact with the system and choose between RAG-enhanced or standalone model responses. Once up and running the UI of the application looks



And the user can choose a model of choice from the dropdown



And can see the conversation history from the Conversation history tab as shown below.

RAG-Powered Al Assistant with LLaMA3 and GPT-2 Integration Chat Conversation History User: What are the latest advancements in quantum computing Chatbot: There have been many recent advancements in quantum computing, which can be broadly categorized into several areas: 1. Quantum Error Correction: Researchers have made significant progress in developing techniques to correct errors that occur during quantum computation. This is a crucial step towards large-scale quantum computing, as errors can quickly accumulate and render the computer useless. 2. Superconducting Qubits: Superconducting qubits are one of the most widely used types of quantum bits (qubits) in current quantum computers. Researchers have made significant improvements to their design, leading to higher coherence times and more efficient operations. 3. Ion Traps: Ion traps are another type of quantum computing architecture that uses ions instead of

And the for each query model used and response time can also be seen in the Conversation history

pubits. Recent advancements have led to improved control over the ions and increased scalability

Some future directions in quantum computing include:

- Quantum-Classical Hybrids: Developing hybrid quantum-classical computers that can take advantage of both classical and quantum processing power.
- **Neuromorphic Computing:** Creating quantum computers that mimic the structure and function of biological neural networks.
- Adiabatic Quantum Computers: Developing adiabatic quantum computers that can solve specific problems more efficiently than traditional quantum algorithms.

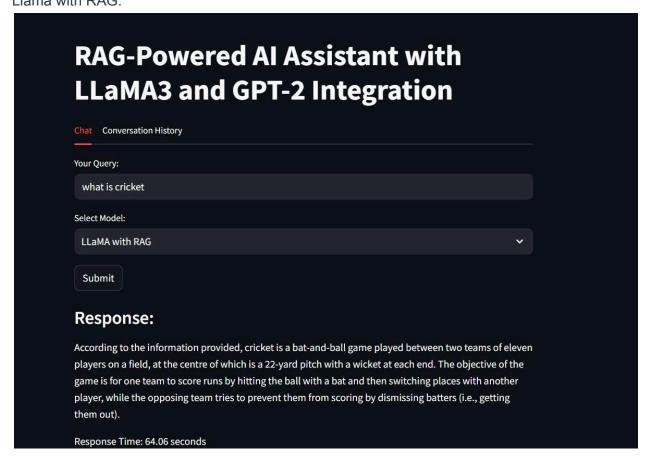
The future of quantum computing is exciting and rapidly evolving.

Model Used: LLaMA

Response Time: 48.16 seconds

3) Queries and Responses

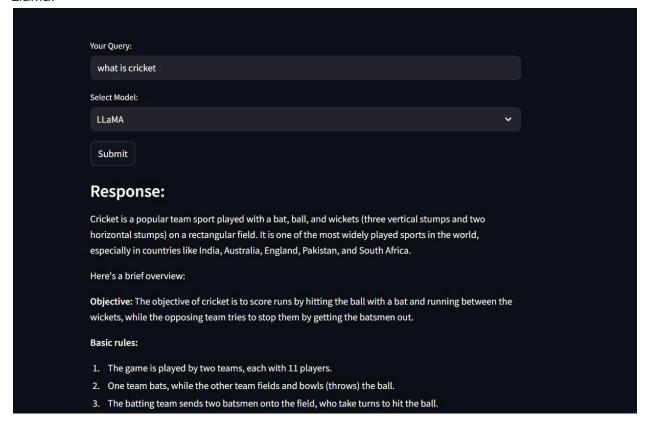
Queries across various domains and different complexities are used to test both LlaMa and GPT-2 with and without RAG implementation

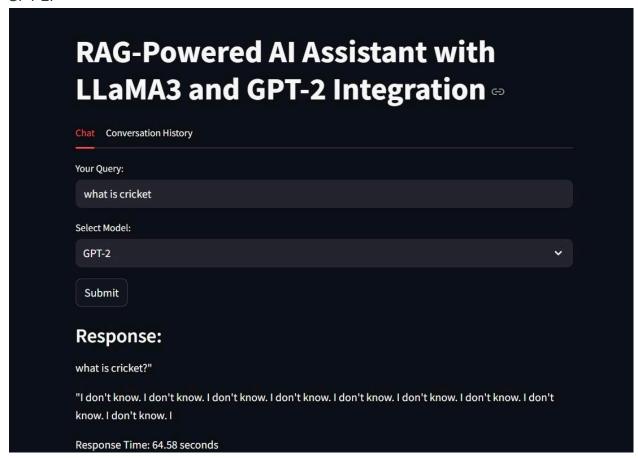


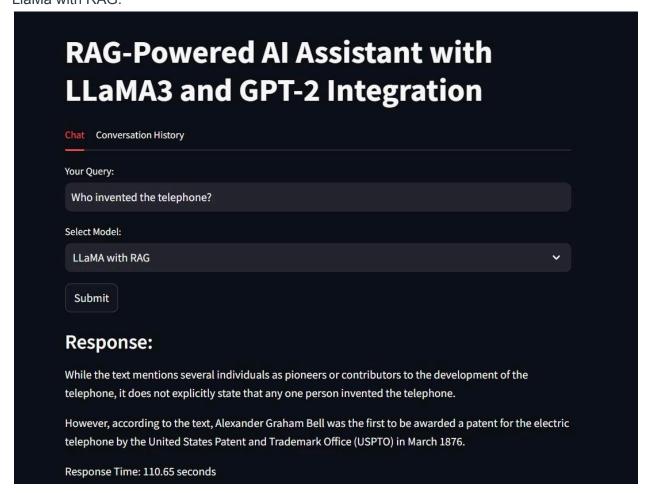
GPT with RAG:

Your Query:	
what is cricket	
Select Model:	
GPT-2 with RAG	~
Submit	
Response:	
I have some information that might be relevant to answering a question. Here's the information:	
Cricket is a bat-and-ball game played between two teams of eleven players on	a fie
The fielding team tries to prevent runs from being scored by dismissing batters (so they are "out"). I	Means
of dismissal include being bowled, when the ball hits the striker's wicket and dislodges the bails, an	id by
the fielding side either catching the ball after it is hit by the bat but before it hits the ground, or hitti	
wicket with the ball before a batter can cross the crease line in front of the wicket. When ten batters	
been dismissed, the innings (playing phase) ends and the teams swap roles. Forms of cricket range	
traditional Test matches played over five days to the newer Twenty20 format (also known as T20), in	
which each team bats for a single innings of 20 overs (each "over" being a set of 6 fair opportunities	
batting team to score) and the game generally lasts three to four hours. Traditionally, cricketers play	
white kit, but in limited overs cricket, they wear club or team colours. In addition to the basic kit, so	me

LlaMa:



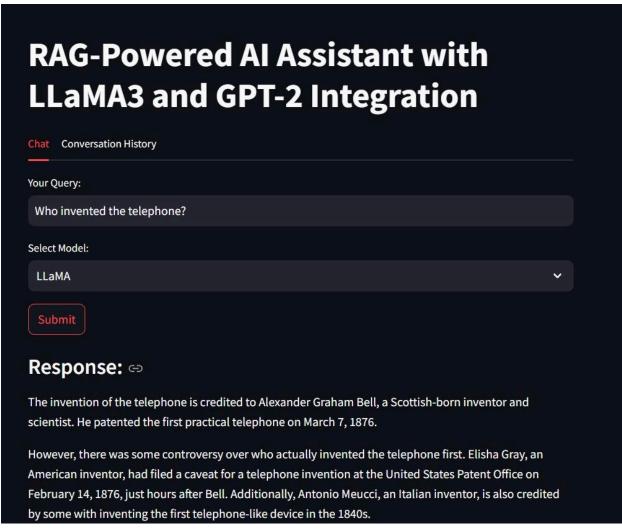




GPT2 with RAG:

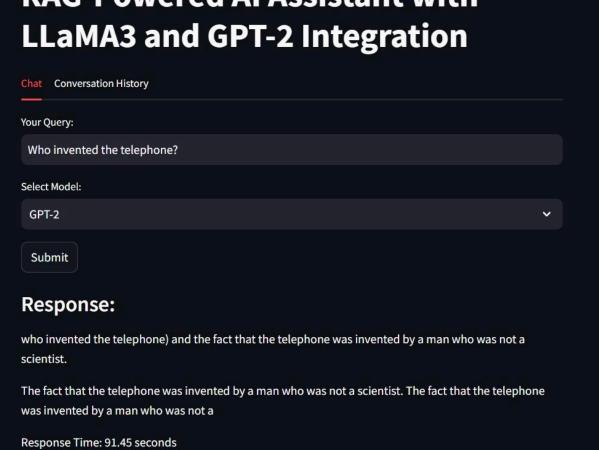
Your Query:	
Who invented the telephone?	
Select Model:	
GPT-2 with RAG	~
Submit	
Response:	
I have some information that might be relevant to answering a question. Here's the information:	
Early history	
Before the development of the electric telephone, the term telephone was applied to other inventi	ions,
and not all early researchers of the electrical device used the term. Perhaps the earliest use of the	word for
a communications system was the telephon created by Gottfried Huth in 1796. Huth proposed an	
alternative to the optical telegraph of Claude Chappe in which the operators in the signaling tower	rs would
shout to each other by means of what he called "speaking tubes", but would now be called giant	
megaphones. A communication device for sailing vessels, called telephone, was invented by Capta	ain John
Taylor in 1844. This instrument used four air horns to communicate with vessels in foggy weather.	Johann
Philipp Reis used the term in reference to his invention, commonly known as the Reis telephone, in	n c.
1000 His daying any and he she first daying hand as the any arising of any distribution in	

LlaMa:

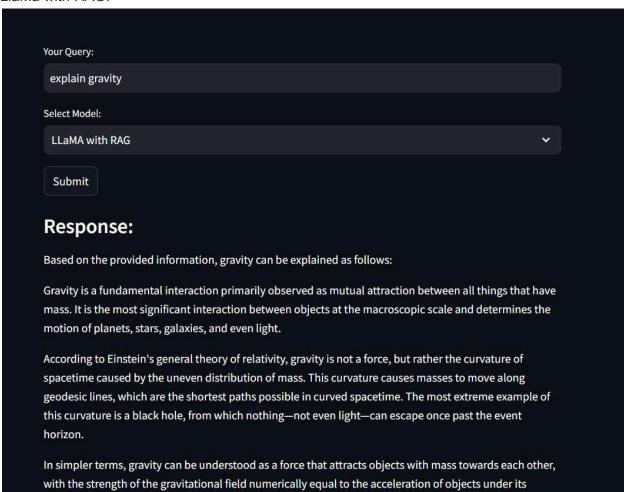


GPT-2:

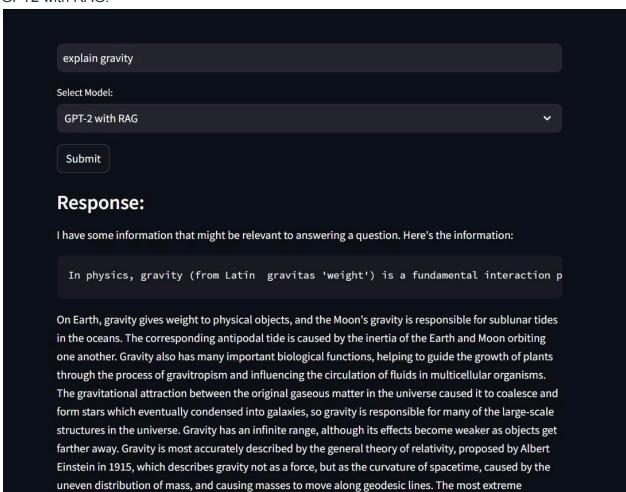
RAG-Powered AI Assistant with



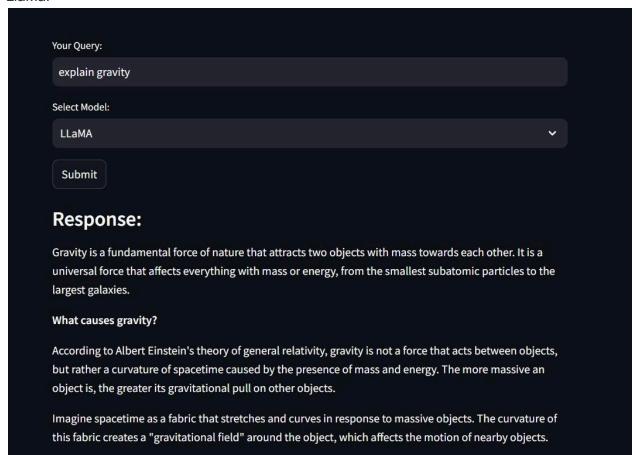
3.3)explain gravity? LlaMa with RAG:



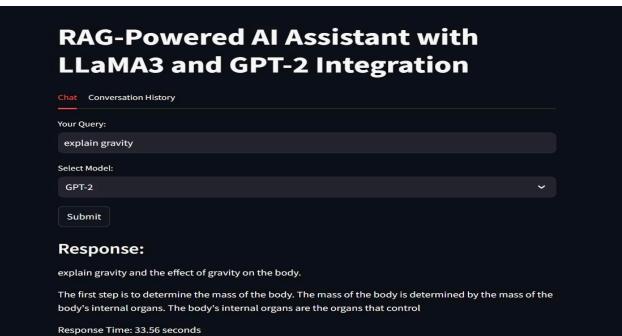
GPT2 with RAG:

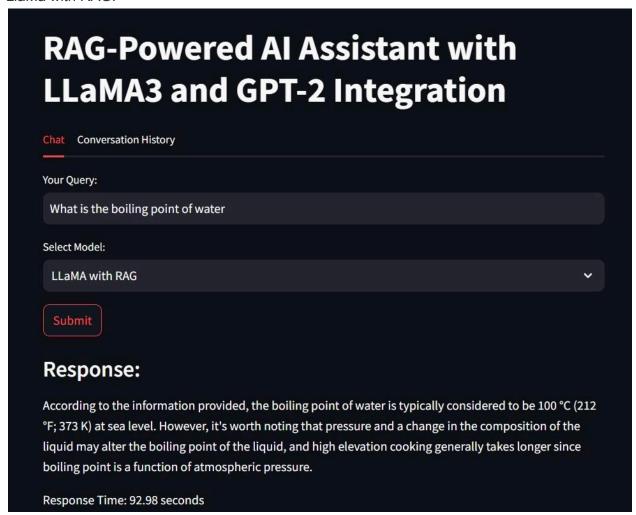


LlaMa:



GPT2:





GPT2 with RAG:

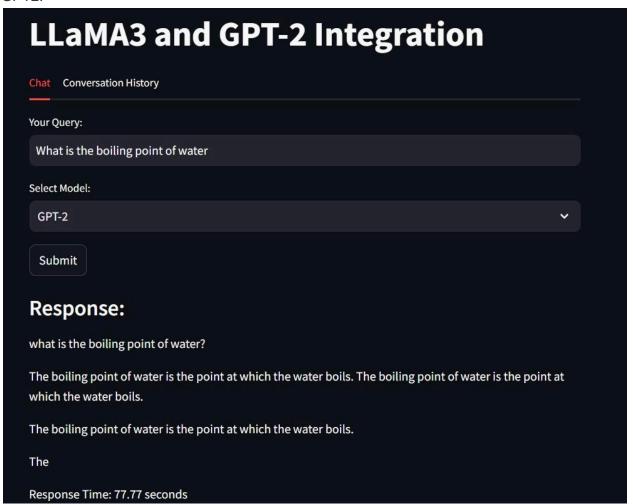
What is the boiling point of water	
Select Model:	
GPT-2 with RAG	~
Submit	
Response:	
I have some information that might be relevant to answering a question. Here's the information	:
In cooking	
Boiling is the method of cooking food in boiling water or other water-based liquids such as stock Simmering is gentle boiling, while in poaching the cooking liquid moves but scarcely bubbles. T	
point of water is typically considered to be 100 °C (212 °F; 373 K), especially at sea level. Pressure	e and a
$change\ in\ the\ composition\ of\ the\ liquid\ may\ alter\ the\ boiling\ point\ of\ the\ liquid\ .\ High\ elevation\ of\ the\ liquid\ .$	cooking
generally takes longer since boiling point is a function of atmospheric pressure. At an elevation	of about
one mile (1,600 m), water boils at approximately 95 °C (203 °F; 368 K). Depending on the type of	food and

Boiling or ebullition is the rapid phase transition from liquid to gas or vapour; the reverse of boiling is condensation. Boiling occurs when a liquid is heated to its boiling point, so that the vapour pressure of

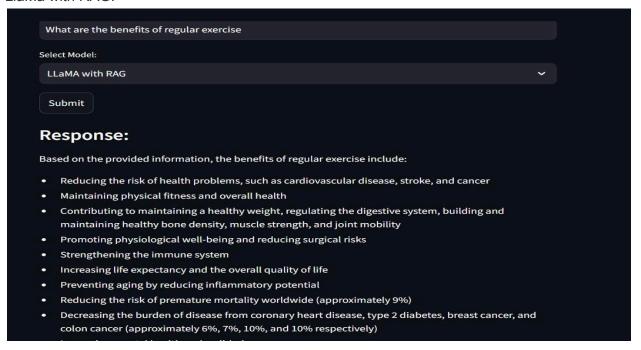
the elevation, the boiling water may not be hot enough to cook the food properly. Similarly, increasing the pressure as in a pressure cooker raises the temperature of the contents above the open air boiling point.

LlaMa:

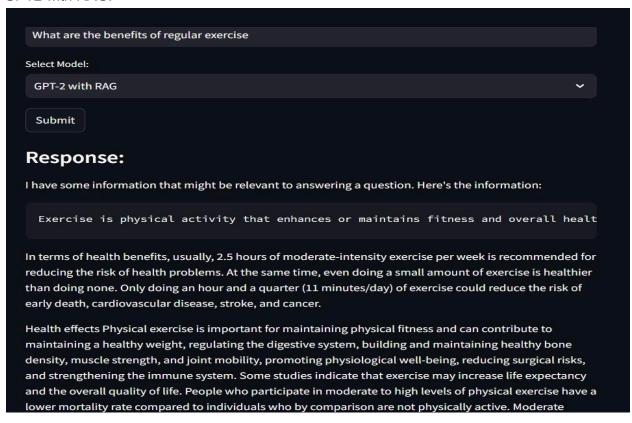




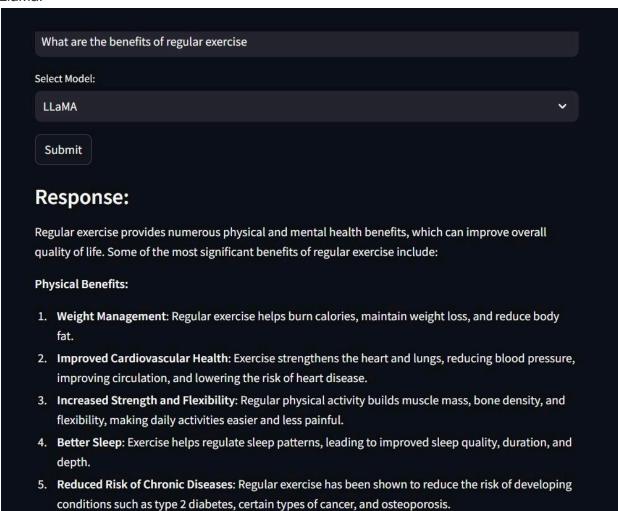
3.5) What are the benefits of regular exercise? LIaMa with RAG:



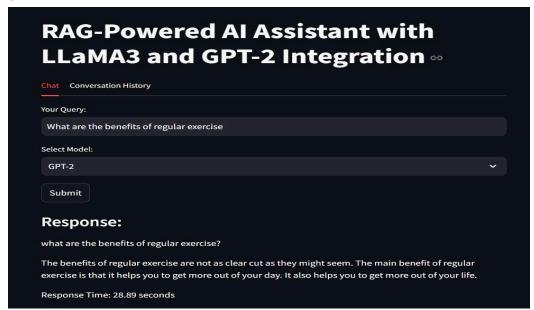
GPT2 with RAG:



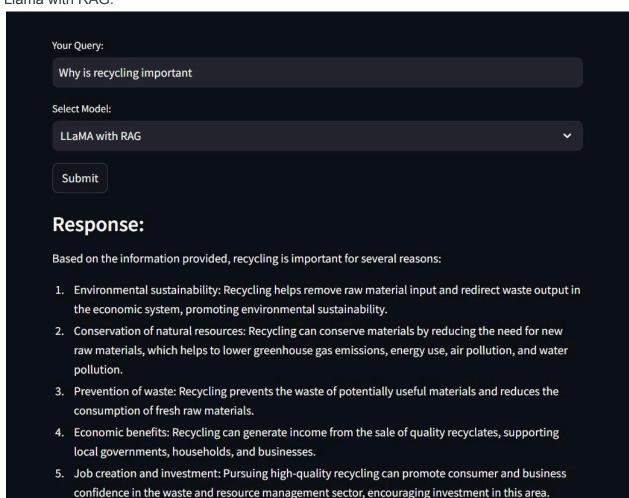
LlaMa:



GPT2:



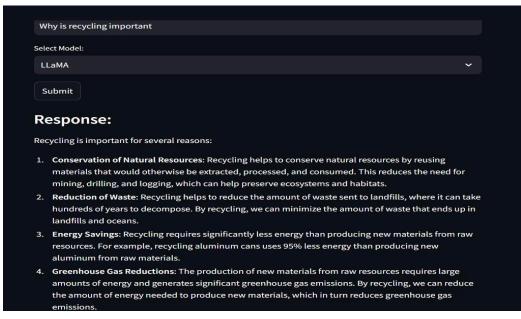
3.6) Why is recycling important? Llama with RAG:



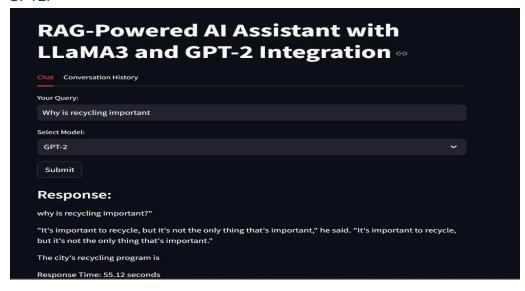
GPT2 with RAG:

Why is recycling important	
Select Model:	
GPT-2 with RAG	~
Submit	
Response:	
have some information that might be relevant to answering a question. Here's the information:	
Recycling is the process of converting waste materials into new materials	and obje
Recycling is a key component of modern waste reduction and is the third component of the "Red	uce,
Reuse, and Recycle" waste hierarchy. It promotes environmental sustainability by removing raw	material
input and redirecting waste output in the economic system. There are some ISO standards relate	d to
recycling, such as ISO 15270:2008 for plastics waste and ISO 14001:2015 for environmental mana	gement
control of recycling practice. Recyclable materials include many kinds of glass, paper, cardboard,	metal,
plastic, tires, textiles, batteries, and electronics. The composting and other reuse of biodegradab	le waste
—such as food and garden waste—is also a form of recycling. Materials for recycling are either de	livered to
a household recycling center or picked up from curbside bins, then sorted, cleaned, and reproces	sed into
new materials for manufacturing new products. In ideal implementations, recycling a material pr	oduces a
fresh supply of the same material—for example, used office paper would be converted into new c	office

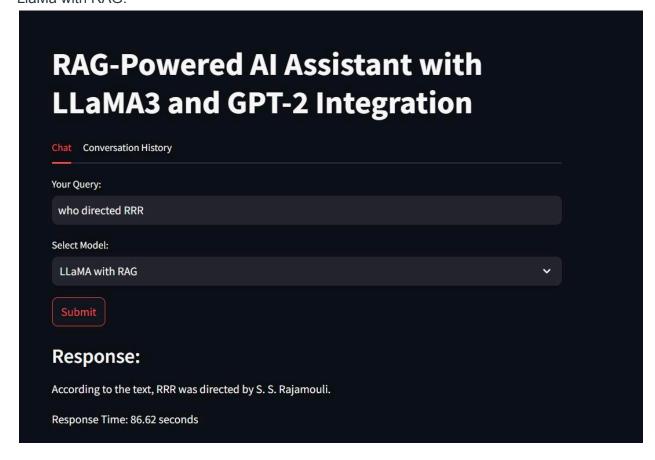
LlaMa:



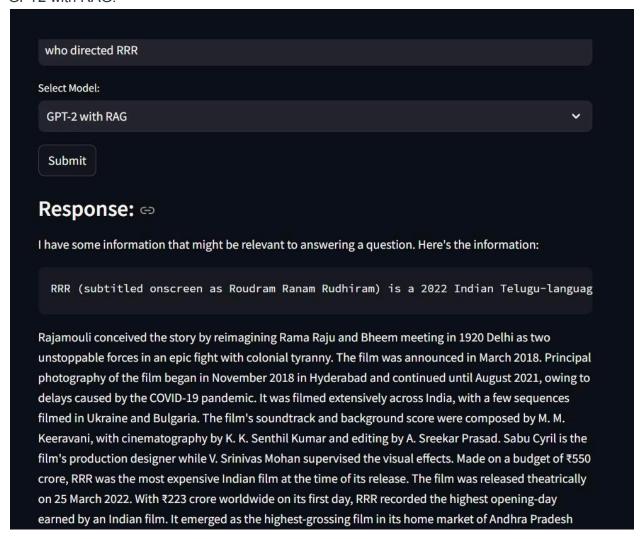
GPT2:



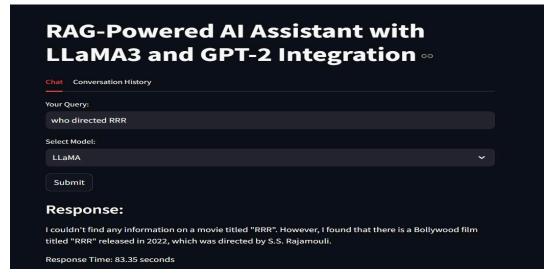
3.7)Who directed RRR? LlaMa with RAG:



GPT2 with RAG:



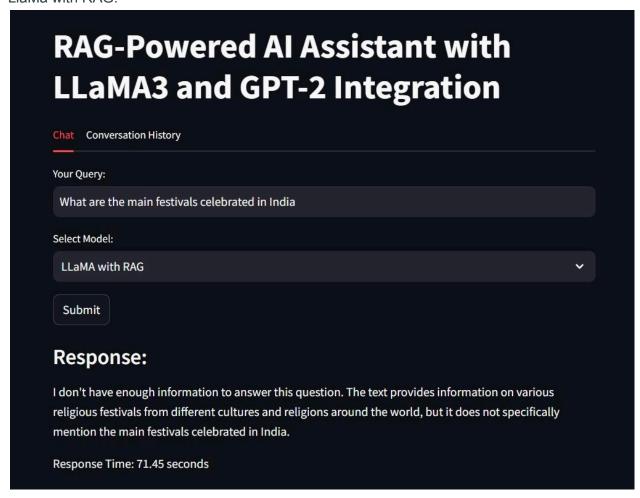
LlaMa:



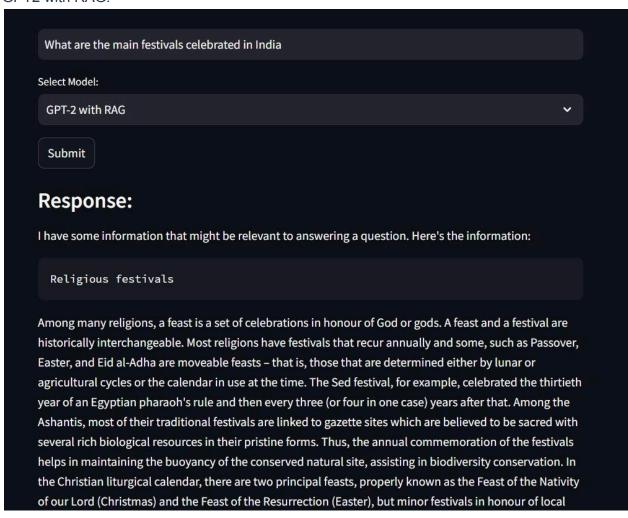
GPT2:



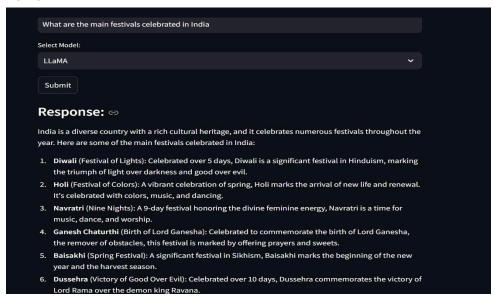
3.8) What are the main festivals celebrated in India? LlaMa with RAG:



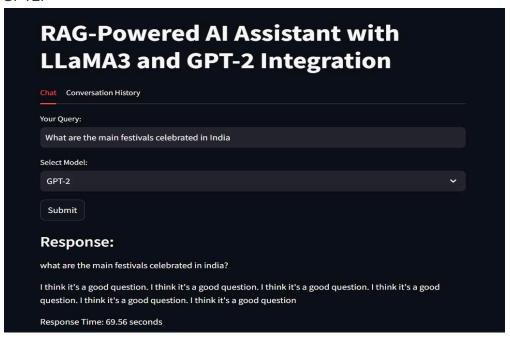
GPT2 with RAG:



LlaMa:

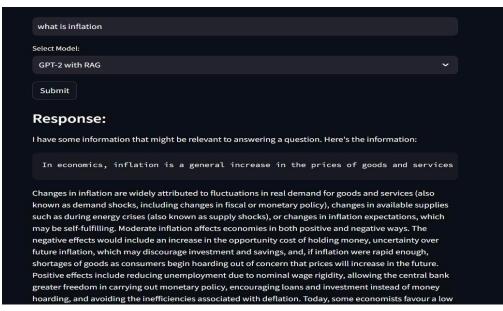


GPT2:

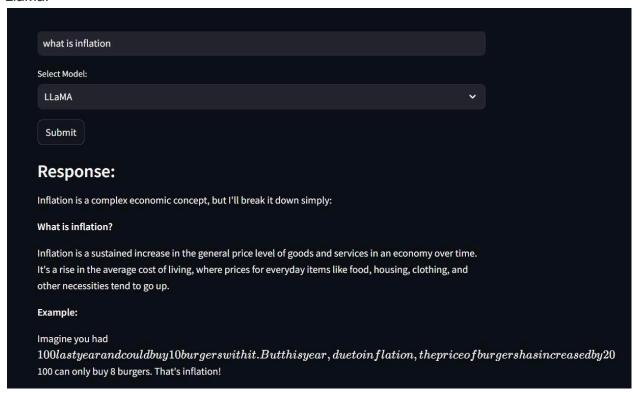


RAG-Powered Al Assistant with LLaMA3 and GPT-2 Integration Chat Conversation History Your Query: what is inflation Select Model: LLaMA with RAG Submit Response: Inflation is a general increase in the prices of goods and services in an economy. It is usually measured using a consumer price index (CPI). When the general price level rises, each unit of currency buys fewer goods and services; consequently, inflation corresponds to a reduction in the purchasing power of money. Response Time: 58.88 seconds

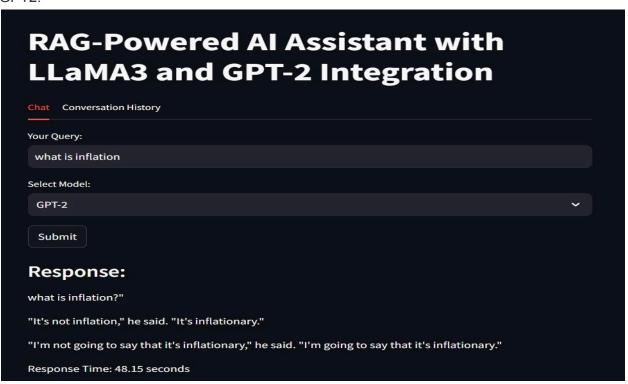
GPT2 with RAG:



LlaMa:



GPT2:



3.10) What are the latest Advancements in quantum computing? LlaMa with RAG:

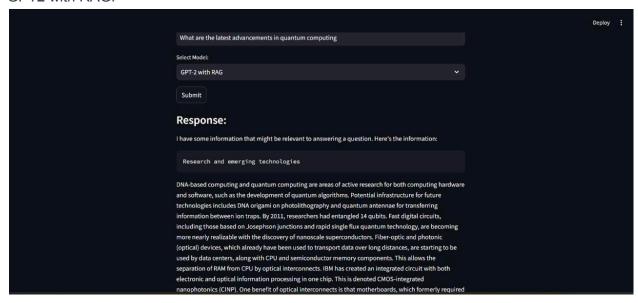
User: What are the latest advancements in quantum computing

Chatbot: Based on the provided information, one of the latest advancements mentioned is that by 2011, researchers had entangled 14 qubits. This indicates a significant progress in the field of quantum computing.

Model Used: LLaMA with RAG

Response Time: 24.54 seconds

GPT2 with RAG:

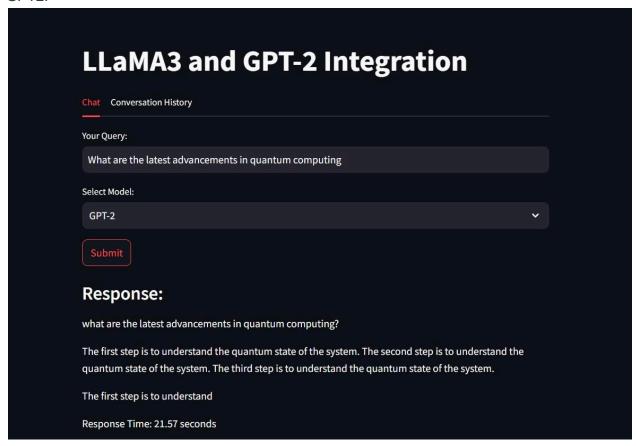


LlaMa:

User: What are the latest advancements in quantum computing

Chatbot: There have been many recent advancements in quantum computing, which can be broadly categorized into several areas:

- Quantum Error Correction: Researchers have made significant progress in developing techniques to correct errors that occur during quantum computation. This is a crucial step towards large-scale quantum computing, as errors can quickly accumulate and render the computer useless.
- Superconducting Qubits: Superconducting qubits are one of the most widely used types of quantum bits (qubits) in current quantum computers. Researchers have made significant improvements to their design, leading to higher coherence times and more efficient operations.
- Ion Traps: Ion traps are another type of quantum computing architecture that uses ions instead of
 qubits. Recent advancements have led to improved control over the ions and increased scalability.
- 4. Topological Quantum Computing: Topological quantum computing is a new paradigm for quantum computing that uses exotic materials called topological insulators. This approach has shown promise for creating more robust and scalable quantum computers.



4) Query-Wise Comparative Analysis

- 1. For the query, "What are the benefits of regular exercise", LLaMA with RAG provided a highly relevant and accurate answer, offering deep insights into physical and mental health benefits, with strong context awareness and a response time of 39.6 seconds. GPT-2 with RAG responded faster (28.68s) but was moderately relevant, with approximate accuracy, and provided good context awareness. LLaMA without RAG also performed well in relevance and accuracy, though with a slightly slower response time (41.15s), while GPT-2 without RAG offered low relevance and accuracy, lacking sufficient context.
- 2. When asked about "the latest advancements in quantum computing", LLaMA with RAG again excelled with high relevance, accuracy, and context awareness, responding in 24.45 seconds. GPT-2 with RAG showed moderate relevance and approximate accuracy, answering in 21.78 seconds. LLaMA, without RAG, was slightly slower (52.85s) but produced moderately relevant and accurate information. GPT-2 without RAG struggled to offer relevant and accurate details, responding with low relevance and limited context.

- 3. For "the main festivals celebrated in India", LLaMA with RAG offered a highly relevant and accurate response (65.86s), covering cultural context well. GPT-2 with RAG was moderately relevant and accurate, with good context but a longer response time (71.2s). LLaMA without RAG matched relevance and accuracy but was slower (85.65s). GPT-2 without RAG, however, lacked cultural awareness and relevance, providing limited context.
- 4. Regarding "the boiling point of water", LLaMA with RAG provided a highly relevant and accurate response, noting temperature variations under different conditions, and completed in 78.39 seconds. GPT-2 with RAG was moderately relevant, with approximate accuracy, and responded slightly slower (80.16s). LLaMA maintained high relevance without RAG (76.3s), but GPT-2 without RAG delivered a low relevance and accuracy response with limited context.
- 5. For "Who invented the telephone?", LLaMA with RAG offered a detailed response with high relevance, accuracy, and context awareness, though with a lengthy response time of 167.79 seconds. GPT-2 with RAG was faster (85.87s) but had less contextual depth. LLaMA without RAG was accurate but provided limited context (74.01s), while GPT-2 without RAG had low relevance and accuracy.
- 6. On the question, "Why is recycling important?", LLaMA with RAG gave a well-rounded response (78.07s), explaining environmental, economic, and social impacts accurately and with high context. GPT-2 with RAG, while accurate, offered only moderate relevance and limited context in a faster 62.64 seconds. LLaMA without RAG had similar relevance and accuracy, while GPT-2 without RAG missed the deeper benefits, providing limited details.
- 7. For "Explain gravity", LLaMA with RAG delivered a relevant, accurate answer with good scientific context (43.66s). GPT-2 with RAG was faster at 30.43 seconds but had moderate relevance with approximate accuracy. LLaMA matched the RAG-enabled relevance and accuracy but was slower at 50.3 seconds, while GPT-2 without RAG was less informative.
- 8. In response to "What is cricket?", LLaMA with RAG answered with high relevance and accuracy, covering rules and history well (45.35s). GPT-2 with RAG was moderately relevant and accurate with good context (44.3s). LLaMA without RAG also maintained high relevance and accuracy, though slightly slower (59.86s), whereas GPT-2 without RAG lacked sufficient detail and context.
- 9. For "What is Crime and Punishment?", LLaMA with RAG gave a high-relevance but approximate answer in 70.01 seconds. GPT-2 with RAG showed moderate relevance but similar approximation in less time (65.72s). LLaMA, without RAG, provided accurate context and high relevance faster (56.85s). GPT-2 without RAG's response, however, was limited in accuracy and context.
- 10. On "What is inflation?", LLaMA with RAG offered a timely, relevant, and accurate response (61.96s), with good economic context. GPT-2 with RAG was moderately relevant, with approximate accuracy, responding in 53.92 seconds. LLaMA without RAG was equally relevant but slightly slower, while GPT-2 without RAG lacked context depth.

11. For "Who directed RRR?", LLaMA with RAG provided a relevant and accurate answer with cultural context in 85.08 seconds. GPT-2 with RAG, moderately relevant and accurate, took slightly less time (80.39s). LLaMA without RAG answered accurately but with slightly less relevance, while GPT-2 without RAG's response was brief and lacked accuracy.

Comparative Analysis Summary:

Query	Model	Response Time (s)	Relevance	Accuracy	Context Awareness
What are the benefits of regular exercise	LLaMA with RAG	39.6	High	Accurate	High
What are the benefits of regular exercise	GPT-2 with RAG	28.68	Moderate	Approximate	Good
What are the benefits of regular exercise	LLaMA	41.15	High	Accurate	Good
What are the benefits of regular exercise	GPT-2	28.56	Low	Inaccurate	Limited
What are the latest advancements in quantum computing	GPT-2	21.27	Low	Inaccurate	Limited
What are the latest advancements in quantum computing	GPT-2 with RAG	21.78	Moderate	Approximate	Good
What are the latest advancements in quantum computing	LLaMA	52.85	Moderate	Accurate	Good
What are the latest advancements in quantum computing	LLaMA with RAG	24.45	High	Accurate	High
What are the main festivals celebrated in India	LLaMA with RAG	65.86	High	Accurate	High
What are the main festivals celebrated in India	GPT-2 with RAG	71.2	Moderate	Accurate	Good
What are the main festivals celebrated in India	LLaMA	85.65	High	Accurate	Good
What are the main festivals celebrated in India	GPT-2	67.57	Low	Inaccurate	Limited
What is the boiling point of water	LLaMA with RAG	78.39	High	Accurate	Good
What is the boiling point of water	GPT-2 with RAG	80.16	Moderate	Approximate	Limited
What is the boiling point of water	LLaMA	76.3	High	Accurate	Good
What is the boiling point of water	GPT-2	77.22	Low	Inaccurate	Limited
Who invented the telephone?	LLaMA with RAG	167.79	High	Accurate	High
Who invented the telephone?	GPT-2 with RAG	85.87	High	Accurate	Limited

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Who invented the telephone?	LLaMA	74.01	High	Accurate	Limited
Who invented the telephone?	GPT-2	75.29	Low	Inaccurate	Limited
Why is recycling important	LLaMA with RAG	78.07	High	Accurate	High
Why is recycling important	GPT-2 with RAG	62.64	Moderate	Accurate	Limited
Why is recycling important	LLaMA	61.7	High	Accurate	Good
Why is recycling important	GPT-2	54.88	Low	Inaccurate	Limited
explain gravity	LLaMA with RAG	43.66	High	Accurate	Good
explain gravity	GPT-2 with RAG	30.43	Moderate	Approximate	Good
explain gravity	LLaMA	50.3	High	Accurate	High
explain gravity	GPT-2	29	Low	Inaccurate	Limited
what is cricket	LLaMA with RAG	45.35	High	Accurate	High
what is cricket	GPT-2 with RAG	44.3	Moderate	Accurate	Good
what is cricket	LLaMA	59.86	High	Accurate	High
what is cricket	GPT-2	44.98	Low	Inaccurate	Limited
what is crime and punishment	LLaMA with RAG	70.01	High	Approximate	Limited
what is crime and punishment book about	LLaMA with RAG	65.72	Moderate	Approximate	Limited
what is crime and punishment book about	GPT-2 with RAG	56.85	Moderate	Approximate	High
what is crime and punishment book about	LLaMA	65.52	High	Accurate	Good
what is crime and punishment book about	GPT-2	54.63	Low	Inaccurate	Limited
what is inflation	LLaMA with RAG	61.96	High	Accurate	Good
what is inflation	GPT-2 with RAG	53.92	Moderate	Approximate	Good
what is inflation	LLaMA	62.89	High	Accurate	Good
what is inflation	GPT-2	52.44	Low	Inaccurate	Limited
who directed RRR	LLaMA with RAG	85.08	High	Accurate	Good
who directed RRR	GPT-2 with RAG	80.39	Moderate	Approximate	High
who directed RRR	LLaMA	76.64	Moderate	Approximate	High
who directed RRR	GPT-2	78.95	Low	Inaccurate	Limited

Observations:

Relevance, Accuracy, and Context-Awareness

- RAG System: The RAG system generally provided more context-aware and relevant responses compared to standalone LLaMA and GPT-2. For example, in answering "What are the latest advancements in quantum computing?", RAG retrieved detailed information about quantum error correction, superconducting qubits, and quantum machine learning. However, the standalone models either repeated information or were less focused. The responses using RAG were also richer in factual content.
- Standalone LLaMA: Provided answers that were almost as good as RAG in many cases, showing decent coherence and relevance, though it may have faced some challenges in handling certain general knowledge questions. LLaMA performed well when backed by RAG.
- Standalone GPT-2: GPT-2 performed worst among the four variations in terms of generating coherent responses, for domain-specific queries like "Explain gravity" or "What are the latest advancements in quantum computing?", it often repeated sentences or lacked sufficient depth. GPT-2 with RAG, however, showed a notable improvement, giving more detailed and contextually accurate answers.

Response Times and Resource Usage

- **RAG System**: Response times ranged from 30 to 80 seconds on average. While slower than standalone models due to the retrieval component, it was expected due to the additional steps involved in fetching relevant documents from the knowledge base.
- **Standalone LLaMA**: LLaMA was slightly faster than RAG but produced significantly less Focused results sometimes. Response times ranged from 52 to 85 seconds.
- Standalone GPT-2: GPT-2 was consistently faster, often providing responses in 28-54 seconds, but the quality of the output was mixed when not backed by retrieval. It often repeated sentences or lacked sufficient depth.

5)Reflection and documentation:

The integration of a Retrieval-Augmented Generation (RAG) system significantly enhances chatbot performance compared to using standalone local LLMs, addressing key limitations in relevance, accuracy, and context awareness. By adding a retrieval mechanism to the generation process, RAG systems bring a dynamic, knowledge-informed layer to responses, particularly benefiting complex and domain-specific inquiries that require current or specialized information.

From the responses it's clear that the RAG system significantly enhances GPT-2 and LLaMA models by improving relevance, accuracy, and context-awareness. Comparing RAG-enabled versions of GPT-2 and LLaMA to their standalone counterparts reveals clear advantages, especially in handling specialized or context-sensitive queries.

For instance, with **GPT-2 using RAG**, responses in areas like "the latest advancements in quantum computing" and "the benefits of regular exercise" showed marked improvement in both relevance and detail. Standalone GPT-2 tended to give broad, surface-level responses, often lacking specific details necessary to address complex queries fully. However, RAG-equipped GPT-2 could retrieve detailed information on quantum technologies and health benefits, boosting relevance and depth. This retrieval layer effectively transformed GPT-2 from a generalist into a more informed responder, especially in specialized topics.

Similarly, **LLaMA** with **RAG** outperformed its non-RAG version in complex inquiries such as "festivals celebrated in India" and "who invented the telephone?" While standalone LLaMA provided factual but simplified responses, RAG-equipped LLaMA accessed multiple sources, providing richer cultural or historical details. For example, it discussed various festivals in India and explained multiple contributors to the invention of the telephone, making the response more contextually aware and nuanced. This enhancement in LLaMA's relevance and context sensitivity turned it into a more adaptable and responsive tool.

Accuracy also saw clear improvement, especially evident in fact-heavy questions. For example, in "who directed RRR?" and "what is inflation?", RAG-enabled versions of both GPT-2 and LLaMA offered precise answers. Standalone versions were more likely to generalize or give incomplete answers, particularly on detailed topics. With RAG, both models accessed exact details, including the director's name and inflation's economic implications, proving preferable for users seeking specific information.

Context-awareness was another major benefit of RAG integration. In questions like "what is gravity?" and "why is recycling important?", RAG allowed both models to retrieve scientific or environmental contexts, resulting in responses that were accurate and relevant to the query's intent. For example, standalone GPT-2 and LLaMA discussed gravity and recycling in broad terms. However, with RAG, these models retrieved situationally appropriate information, leading to responses that captured scientific theories or environmental and economic aspects of recycling.

The primary trade-off observed was a **slightly longer response time** for RAG-enabled models due to the retrieval step. LLaMA with RAG, for instance, took significantly longer on some responses, particularly in complex queries like "who invented the telephone?" where historical context was retrieved. However, the enhanced response quality justified the minor delay, and the time remained within a functional range for most practical uses.

Overall, the data indicates that adding RAG transforms both GPT-2 and LLaMA from basic response generators into more accurate, contextually aware assistants. This enhancement allows them to handle a broader range of topics with greater depth, accuracy, and reliability, which would be difficult to achieve with standalone LLMs alone. RAG integration thus makes both models more practical for real-world applications where detail and precision are essential, proving that retrieval is a valuable strategy for enhancing LLM capabilities.

Challenges Faced and Solutions Devised

1.Package Installation Issues

- Challenge: During the setup phase, I encountered several issues while installing various required packages. Conflicts between package versions and dependencies made it difficult to achieve a stable environment.
- Solution: To mitigate these issues, I set up a dedicated Python environment using virtualenv. This isolated environment ensured that package dependencies did not conflict with other projects and allowed me to install the required packages without issues. Using a requirements.txt file also helped streamline the installation process.

2.Implementing GPT-2 with RAG

- Challenge: Integrating GPT-2 with RAG posed a significant challenge due to its input token length limitations. The model could only process a limited number of tokens at a time, which made it difficult to handle larger queries or responses effectively.
- Solution: To address this limitation, I had to implement manual handling of input token lengths in the code. I implemented a strategy to concatenate responses when necessary, ensuring that the chatbot could still provide comprehensive answers despite the token restrictions.