Practical – 2

Retrieval-Augmented Generation (RAG) Application Using PDF READ+LANGCHAIN+ BEDROCK+LLAMA

Retrieval-Augmented Generation (RAG) is a technique that enhances large language models (LLMs) by retrieving relevant information from external knowledge sources before generating a response. Instead of relying solely on pre-trained knowledge, RAG enables the model to fetch real-time data from a vector database, improving accuracy and relevance, especially for domain-specific tasks.

In our project, we implement a **RAG-based system** using AWS Bedrock and LangChain. The code processes a **PDF document**, extracts its text using **PyPDF**, and converts it into vector embeddings using **Amazon Titan embeddings**. These embeddings are stored in a **FAISS vector database** for efficient similarity search. When a user asks a question, the system retrieves the most relevant document sections from the FAISS index and passes them to **Llama 3 (via AWS Bedrock)** to generate an informed response. This ensures that the model provides contextually relevant answers based on the uploaded PDF content.

Requirements.txt

boto3

botocore

awscli

pypdf

langchain

faiss-cpu

langchain-community

langchain-aws

Technologies and Libraries Used

- **AWS Services:** Amazon S3, AWS Bedrock, IAM Permissions
- **LangChain**

- LangChain is a framework designed to help build applications powered by large language models (LLMs).
- It simplifies working with AI models, vector stores (like FAISS), and retrieval-augmented generation (RAG) workflows.
- In your project, LangChain is used to manage embeddings, query processing, and interactions with AWS Bedrock.

- **PyPDF**
  - PyPDF is a Python library for reading, modifying, and extracting text from PDF files.
  - In your project, it is used to parse the uploaded PDF and convert it into text that can be embedded into a vector store.
- **FAISS (Facebook AI Similarity Search)**
  - FAISS is an open-source library for efficient similarity search and clustering of dense vectors.
  - It is used to store and retrieve document embeddings quickly based on user queries.
- **Boto3 (AWS SDK for Python)**
  - Boto3 is the official Amazon Web Services (AWS) SDK for Python.
  - It enables communication with AWS services, such as S3 (for storing PDFs) and Bedrock (for querying Llama 3).

Steps Followed

1. Setting Up the AWS Environment

- Created an **S3 bucket** to store the PDF documents.
- Configured an **AWS IAM role** with appropriate permissions for Bedrock and S3.
- Initialized AWS credentials using boto3.

2. Installing Required Libraries

- Installed langchain, langchain_community, langchain_aws, faiss-cpu, and boto3.
- Activated a **Conda virtual environment** and ensured dependencies were installed.

3. Loading and Processing the PDF Document

- Used pypdf to extract text from a local PDF file.
- Processed the extracted text into manageable chunks for embedding.

4. Generating Vector Embeddings with AWS Bedrock

- Used BedrockEmbeddings from langchain_aws to generate vector embeddings.

- Stored the vectors in **FAISS index** for efficient retrieval.

5. Querying the Document with Llama 3

- Loaded the FAISS index and retrieved relevant document chunks.
- Passed the retrieved text as context to the **Llama 3 8B Instruct v1** model.
- Displayed the response in the **VS Code terminal**.

2. Issues Encountered

1. ModuleNotFoundError for langchain_community

- The import statement for BedrockEmbeddings was outdated.
- Fixed by replacing from langchain.llms import Bedrock with from langchain_community.llms import Bedrock.

2. FAISS Index Not Found Error

- The script attempted to load a FAISS index that did not exist.
- Fixed by ensuring that the FAISS index was created before loading.

3. allow_dangerous_deserialization Warning in FAISS

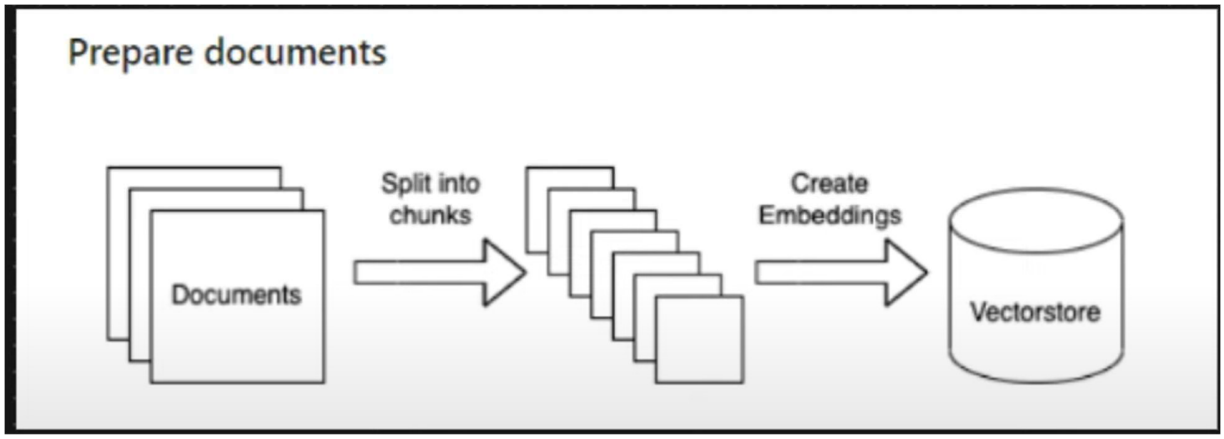
- FAISS requires explicit permission to deserialize pickle files.
- Fixed by setting allow_dangerous_deserialization=True in FAISS.load_local().

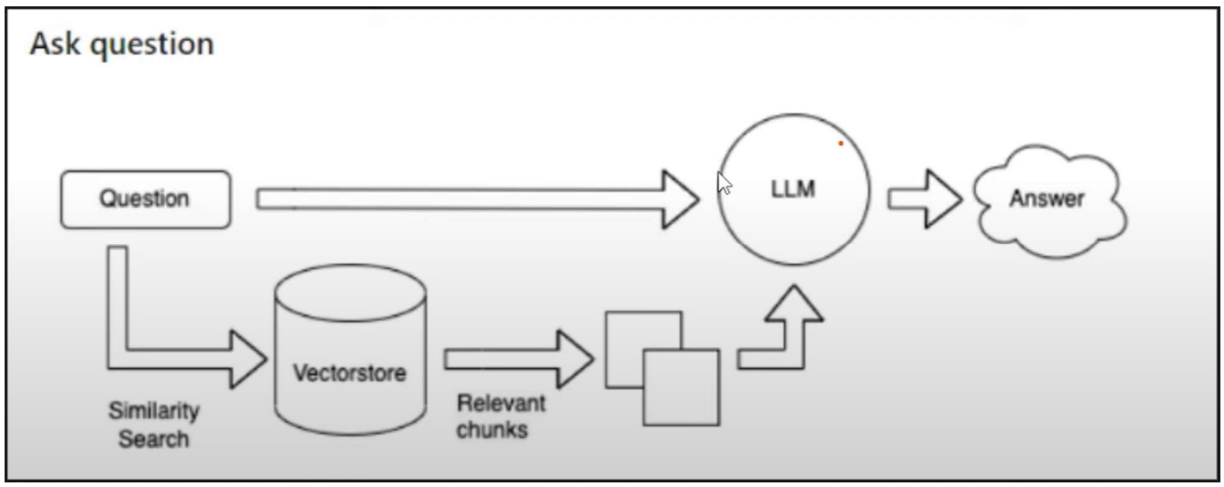
4. AccessDeniedException When Using AWS Bedrock

- The IAM role did not have permission to invoke the Llama 3 model.
- Fixed by adding bedrock:InvokeModel permissions in the IAM policy.

5. No PDF Found in Local Directory

- The script could not find the PDF file to process.
- Fixed by placing the PDF file in the correct directory before running the script.





Explanation of Data Flow

1. **User Uploads PDF → The document is uploaded to an S3 bucket for cloud storage.**
2. **PDF is Read → The text is extracted using PyPDF or similar libraries.**
3. **Convert Text to Embeddings → The text is converted into numerical representations using Amazon Titan Embeddings.**
4. **Store in FAISS → The embeddings are stored in a FAISS (Facebook AI Similarity Search) index for fast retrieval.**
5. **User Asks a Question → The user enters a query, which is processed by Llama 3.**
6. **Retrieve Similar Chunks → The system searches the FAISS index for the most relevant information.**
7. **Generate Response → The Llama 3 model uses the retrieved information to generate a final answer.**
8. **Response Sent to User → The generated answer is displayed to the user.**

Embedding and Vectorization Explained

Embedding and **vectorization** are techniques used to convert text (or other types of data) into a numerical format that machine learning models can understand. They are essential in **Natural Language Processing (NLP)**, **information retrieval**, and **AI-powered applications** like your RAG system.

1️⃣ What is Embedding?

- **Embedding** is the process of converting words, sentences, or entire documents into **dense numerical representations (vectors)** in a multi-dimensional space.
- These embeddings **capture semantic meaning**, so similar words or concepts are mapped **closer** together in this space.

Example of Word Embeddings:

Word	3D Embedding (Example)
Apple	[0.9, 0.1, 0.3]
Banana	[0.8, 0.2, 0.4]
Car	[0.1, 0.9, 0.7]

🔹 Here, **"Apple" and "Banana"** are closer in the vector space because they are both fruits, while **"Car"** is farther away.

🛠️ **Embedding Models Used in Your Project:**

- **Amazon Titan Embeddings** → Converts PDF text into embeddings.
- **FAISS (Facebook AI Similarity Search)** → Stores and retrieves these embeddings efficiently.

2️⃣ What is Vectorization?

- **Vectorization** is a broader term that refers to transforming any type of data (text, images, audio) into numerical vectors.
- It is the **step before embedding** in some cases.

Types of Vectorization in NLP:

1. **TF-IDF (Term Frequency-Inverse Document Frequency)** – Basic technique, weights words based on importance.
2. **Word2Vec / FastText** – Creates word embeddings based on context.
3. **Transformer-based Embeddings (like BERT, Titan, Llama 3)** – More advanced, understands entire sentences and context.

Difference Between Embedding and Vectorization

Feature	Embedding	Vectorization
Purpose	Capture meaning	Convert text into numbers
Output	Dense vector	Sparse/dense vector
Example Methods	Word2Vec, Titan, BERT	TF-IDF, One-hot encoding
Used in	NLP, AI, Search engines	Basic text processing

How It Works in Your Project

1. **PDF text is extracted and converted into embeddings** using **Amazon Titan**.
2. **FAISS stores these embeddings** and retrieves relevant vectors when a user asks a question.
3. **Llama 3 generates a response** using the retrieved embeddings, making the system efficient in answering queries based on PDF content.

🔹 **Conclusion:** Embeddings **understand meaning**, while vectorization is the **process of representing data numerically**. Your RAG system **relies on embeddings** to find relevant information before generating a response. 🚀

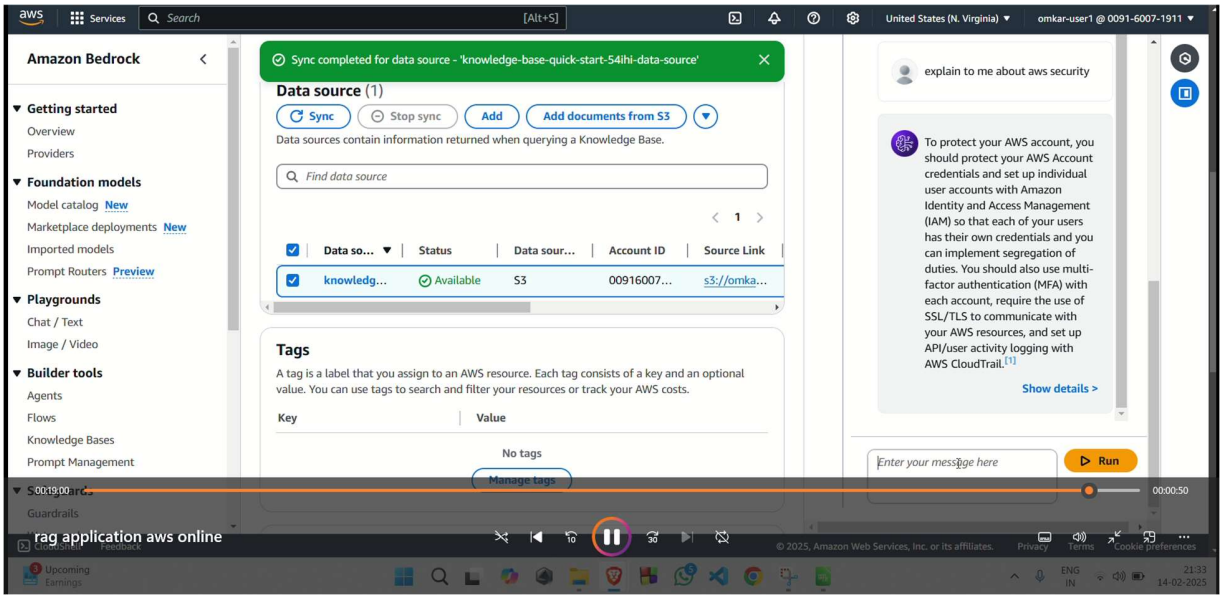
Python code :-

```
import json
import os
import boto3
from langchain_aws.embeddings import BedrockEmbeddings  # Requires `pip install langchain-aws`
from langchain_community.llms import Bedrock
from langchain.text_splitter import RecursiveCharacterTextSplitter
from langchain_community.document_loaders import PyPDFDirectoryLoader
from langchain_community.vectorstores import FAISS
from langchain.prompts import PromptTemplate
from langchain.chains import RetrievalQA

# Initialize AWS Bedrock client
bedrock = boto3.client(service_name="bedrock-runtime", region_name="us-east-1")

# Titan Embedding Model
bedrock_embeddings = BedrockEmbeddings(model_id="amazon.titan-embed-text-v2:0",
client=bedrock)

# Data ingestion function
def data_ingestion():
    print("Loading PDF documents...")
    loader = PyPDFDirectoryLoader("data")  # Ensure the PDF files are inside the 'data' folder
    documents = loader.load()

    text_splitter = RecursiveCharacterTextSplitter(chunk_size=10000, chunk_overlap=1000)
    docs = text_splitter.split_documents(documents)
    return docs
```

```
# Create and save FAISS vector store
def get_vector_store(docs):
    print("Creating vector embeddings...")
    vectorstore_faiss = FAISS.from_documents(docs, bedrock_embeddings)
    vectorstore_faiss.save_local("faiss_index")
    print("Vector store created successfully!")

# Initialize Llama 3 model
def get_llama3_llm():
    llm = Bedrock(
        model_id="meta.llama3-8b-instruct-v1:0",
        client=bedrock,
        model_kwargs={"max_gen_len": 512}
    )
    return llm

# Define prompt template
prompt_template = """
Human: Use the following context to answer the question.
Provide a concise yet detailed response of at least 250 words.
If you don't know the answer, say that you don't know.

<context>
{context}
</context>

Question: {question}

Assistant:
```

```
"""

PROMPT = PromptTemplate(template=prompt_template, input_variables=["context", "question"])

# Retrieve response from Llama 3
def get_response_llm(llm, vectorstore_faiss, query):
    qa = RetrievalQA.from_chain_type(
        llm=llm,
        chain_type="stuff",
        retriever=vectorstore_faiss.as_retriever(search_type="similarity", search_kwargs={"k": 3}),
        return_source_documents=True,
        chain_type_kwargs={"prompt": PROMPT}
    )
    answer = qa({"query": query})
    return answer['result']

def main():
    print("Chat with PDF using AWS Bedrock (Llama 3)")

    # Create vector store if needed
    if input("Do you want to create/update the vector store? (yes/no): ").strip().lower() == "yes":
        docs = data_ingestion()
        get_vector_store(docs)

    # Load FAISS index
    print("Loading vector store...")
    # error 1faiss_index = FAISS.load_local("faiss_index", bedrock_embeddings)
    # error 2faiss_index = FAISS.load_local("faiss_index", bedrock_embeddings,
allow_dangerous_deserialization=True)
```

```
    if not os.path.exists("faiss_index/index.faiss"):
        print("FAISS index not found! Creating new vector store...")
        docs = data_ingestion()  # Ingest data again
        get_vector_store(docs)  # Generate FAISS index

    # Now, load the FAISS index safely
    faiss_index = FAISS.load_local("faiss_index", bedrock_embeddings,
allow_dangerous_deserialization=True)

    # Initialize Llama 3
    llm = get_llama3_llm()

    while True:
        user_question = input("\nEnter your question (or type 'exit' to quit): ")
        if user_question.lower() == "exit":
            print("Exiting...")
            break

        print("\nProcessing your query...")
        response = get_response_llm(llm, faiss_index, user_question)
        print("\nLlama 3 Response:\n")
        print(response)

if __name__ == "__main__":
    main()
```


Amazon Bedrock
Sync completed for data source - 'knowledge-base-quick-start-54ihi-data-source'
Data source (1)
Sync
Stop sync
Add
Add documents from S3
Data sources contain information returned when querying a Knowledge Base.
Find data source
Data so...
Status
Data sour...
Account ID
Source Link
knowledg...
Available
S3
00916007...
s3://omka...
Tags
A tag is a label that you assign to an AWS resource. Each tag consists of a key and an optional value. You can use tags to search and filter your resources or track your AWS costs.
Key
Value
No tags
Manage tags
Getting started
Overview
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Marketplace deployments New
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Prompt Routers Preview
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Image / Video
Builder tools
Agents
Flows
Knowledge Bases
Prompt Management
Guardrails
explain to me about aws security
To protect your AWS account, you should protect your AWS Account credentials and set up individual user accounts with Amazon Identity and Access Management (IAM) so that each of your users has their own credentials and you can implement segregation of duties. You should also use multi-factor authentication (MFA) with each account, require the use of SSL/TLS to communicate with your AWS resources, and set up API/user activity logging with AWS CloudTrail.[1]
Show details >
Enter your message here
Run
00:19:00
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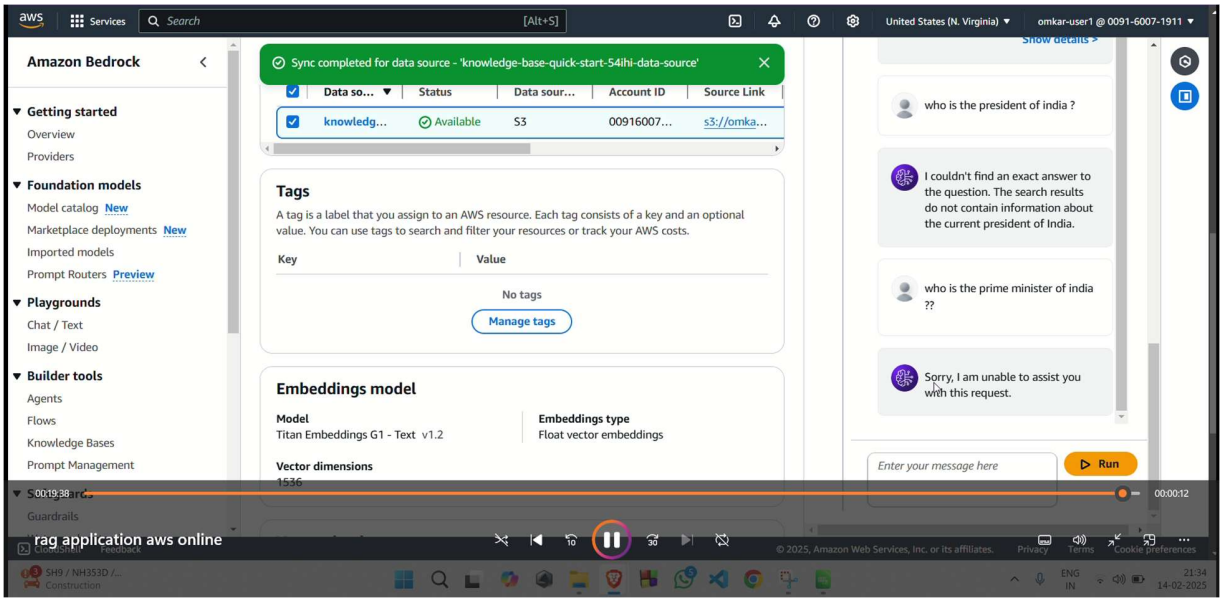
rag application aws online


Amazon Bedrock
Sync completed for data source - 'knowledge-base-quick-start-54ihi-data-source'
Data so...
Status
Data sour...
Account ID
Source Link
knowledg...
Available
S3
00916007...
s3://omka...
Tags
A tag is a label that you assign to an AWS resource. Each tag consists of a key and an optional value. You can use tags to search and filter your resources or track your AWS costs.
Key
Value
No tags
Manage tags
Embeddings model
Model
Titan Embeddings G1 - Text v1.2
Embeddings type
Float vector embeddings
Vector dimensions
1536
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Playgrounds
Chat / Text
Image / Video
Builder tools
Agents
Flows
Knowledge Bases
Prompt Management
Guardrails
who is the president of india ?
I couldn't find an exact answer to the question. The search results do not contain information about the current president of India.
who is the prime minister of india ??
Sorry, I am unable to assist you with this request.
Enter your message here
Run
00:19:38
00:00:12
rag application aws online