Problem Statement:

Development of a Retrieval-Augmented Generation (RAG) System with User Access Control for Knowledge-Based Question Answering

In many organizations, information is stored in the form of documents such as reports, manuals, and research papers in PDF ,text format. These documents often contain valuable insights that employees or stakeholders need to access for informed decision-making. However, retrieving specific information from large collections of documents is time-consuming and inefficient without an intelligent system.

Goal

The goal is to develop a Retrieval-Augmented Generation (RAG) system that can provide precise answers to user queries by retrieving and generating responses based on the knowledge contained in uploaded documents. Additionally, user access control must be implemented to restrict access to specific documents and functionalities based on user roles, enhancing data protection and ensuring that sensitive information is not accessed by unauthorized users.

Steps

Document Upload and Management:

Enable users to upload multiple PDF documents through an interactive user interface. Extract and process the text from the uploaded documents for use in the RAG system. Document Chunking and Embedding:

Chunking

Split documents into manageable chunks for efficient processing and retrieval.

Vector embeddings

Create vector embeddings for document chunks and store them in a vector database for fast and accurate search capabilities.

Retrieval

Retrive the information based on the documents uploaded and access provided

User Access Control

Implement role-based access control (RBAC) to ensure users have different levels of access (e.g., admin, researcher, end-user). Authenticate and authorize users through secure methods to restrict or allow access to specific files and system features. Retrieval-Augmented Generation:

Use OpenAi LLM via API

Integrate a large language model (LLM) to generate responses using retrieved document chunks. Refine user queries before sending them to the LLM for more relevant and accurate answers. Experiment with and without Maximal Marginal Relevance (MMR) to optimize the retrieval process. User-Friendly Interface:

User Interface

Create a web-based interface using tools such as Gradio or Streamlit to allow users to upload files, input queries, and receive responses in an intuitive way.

Install Dependencies and import libraries

```
%%capture
!pip -q install faiss-cpu
!pip -q install langchain_community
!pip -q install langchain pyjwt bcrypt PyPDFLoader
!pip -q install openai
!pip -q install langchain-openai
!pip -q install langchain-core
!pip -q install langchain-community
!pip -q install sentence-transformers
!pip -q install langchain-huggingface
!pip -q install langchain-chroma
!pip -q install chromadb
!pip -q install PyPDF2
!pip -q install tiktoken
!pip -q install gradio
```

```
from langchain_community.document_loaders import TextLoader
import faiss
import numpy as np
from langchain.text_splitter import RecursiveCharacterTextSplitter
from langchain.schema import Document
from langchain.chains import create_retrieval_chain
from langchain_core.prompts import ChatPromptTemplate
from sklearn.metrics.pairwise import cosine_similarity
import gradio as gr
import jwt
import datetime
```

```
import bcrypt
from langchain.vectorstores import Chroma
from langchain.embeddings.openai import OpenAIEmbeddings
from langchain.chains import RetrievalQA
from langchain.docstore.document import Document
from io import BytesIO
from PyPDF2 import PdfReader
```

Loads Documents:

The code begins by loading text files into a list called docs. It uses the TextLoader class from langchain for this purpose.

Combines and Splits:

1.Combines all the loaded documents and splits them into smaller chunks using the RecursiveCharacterTextSplitter. 2.For efficient processing and to allow for more targeted retrieval of information later.

Chunk Size and Overlap:

This overlap helps to ensure that context is preserved between chunks.

Stores as Documents:

The resulting chunks are stored in a list called documents, where each chunk is represented as a Document object. These Document objects are a standard way to represent text in langchain and contain the text content as well as metadata about the source of the text.

```
docs = []
loader = TextLoader("HR.txt")
docs.extend(loader.load())
loader = TextLoader("Sales.txt")
docs.extend(loader.load())
loader = TextLoader("Tech.txt")
docs.extend(loader.load())
loader = TextLoader("Marketing.txt")
docs.extend(loader.load())

text_splitter = RecursiveCharacterTextSplitter(chunk_size=1000, chunk_overlap=300)
documents = text_splitter.split_documents(docs)
```

The below code associates each document chunk with a specific role (HR, Sales, Tech, Marketing) based on the source file name. It stores this role information in the document's metadata for access control.

```
text_files = {
    "HR.txt": ["HR"],
    "Sales.txt": ["Sales"],
    "Tech.txt": ["Tech"],
    "Marketing.txt": ["Marketing"],
}

for doc in documents:
    doc.metadata["role"] = text_files[doc.metadata["source"]]


# Read OpenAI key from Colab Secrets

from google.colab import userdata
import openai # Import the openai module
import chromadb
import os  # Import the os module

api_key = userdata.get('OA_API')           # <-- change this as per your secret's name
os.environ['OPENAI_API_KEY'] = api_key
openai.api_key = os.getenv('OPENAI_API_KEY')
```

Initializes OpenAI Embeddings:

embeddings_model = OpenAIEmbeddings() creates an instance of the OpenAIEmbeddings class, which is used to generate embeddings (numerical representations) of text using OpenAI's models.

Generates and Extends Embeddings:

The code iterates through each document (doc in documents). For each document, it generates an embedding using embeddings_model.embed_query(). Then, it calculates a numerical value (role_value) based on the document's role (HR, Sales, Tech, Marketing), and extends the embedding vector by adding this role_value.

Creates Embedding Array:

Finally, embedding_array = np.array(embedding_vectors) converts the list of extended embedding vectors (embedding_vectors) into a NumPy array for efficient storage and further processing. This array now holds the numerical representations of your documents, enriched with role information.

```
import numpy as np

embeddings_model = OpenAIEmbeddings()  # OpenAIEmbeddings is assigned to embeddings_model
embedding_vectors = []

for doc in documents:
```

```
    embedding = embeddings_model.embed_query(doc.page_content)
    role_value = 0
    if "HR" in doc.metadata["role"]:
        role_value += 1
    if "Sales" in doc.metadata["role"]:
        role_value += 2
    if "Tech" in doc.metadata["role"]:
        role_value += 3
    if "Marketing" in doc.metadata["role"]:
        role_value += 4

    extended_vector = np.concatenate([embedding, [role_value]])
    embedding_vectors.append(extended_vector)

embedding_array = np.array(embedding_vectors)
```

```
<ipython-input-11-b3bbb87deeb2>:3: LangChainDeprecationWarning: The class `OpenAIEmbe
  embeddings_model = OpenAIEmbeddings()  # OpenAIEmbeddings is assigned to embeddings
```

In essence, below lines prepare your data for efficient similarity search using FAISS. The code determines the dimensions of your embedding vectors, creates a suitable index, and adds your data to it. This setup enables fast retrieval of relevant documents based on user queries and their roles.

```
embedding_dim = len(embedding_vectors[0]) - 1
index = faiss.IndexFlatL2(embedding_dim + 1)
index.add(embedding_array)
```

Custom Retriever:

Defines a class MetadataFAISSRetriever to manage document retrieval based on content and user role.

Initialization:

Stores FAISS index, embedding model, and documents within the retriever object. Role-Based Query: retrieve function converts user role into a numerical value, adding it to the query's embedding. FAISS Search: Uses FAISS index to find the top k (here, 5) nearest document embeddings to the query embedding.

Access Control:

Filters retrieved documents, only returning those accessible to the user's role.

```
class MetadataFAISSRetriever:
    def __init__(self, index, embedding_model, documents):
```

```
        self.index = index
        self.embedding_model = embedding_model
        self.documents = documents

    def retrieve(self, query, user_role):
        query_embedding = self.embedding_model.embed_query(query)

        if user_role == "HR":
            query_role_value = int(format(1, '016b'), 2)
        elif user_role == "Sales":
            query_role_value = int(format(2, '016b'), 2)
        elif user_role == "Tech":
            query_role_value = int(format(3, '016b'), 2)
        elif user_role == "Marketing":
            query_role_value = int(format(4, '016b'), 2)
        else:
            query_role_value = int(format(5, '016b'), 2)

        query_vector = np.concatenate([query_embedding, [query_role_value]])
        distances, indices = self.index.search(query_vector.reshape(1, embedding_dim + 1)

        retrieved_docs = []
        for i in indices[0]:
            if i < len(self.documents):
                doc_role_value = 0
                if "HR" in self.documents[i].metadata["role"]:
                    doc_role_value += int(format(1, '016b'), 2)
                if "Sales" in self.documents[i].metadata["role"]:
                    doc_role_value += int(format(2, '016b'), 2)
                if "Tech" in self.documents[i].metadata["role"]:
                    doc_role_value += int(format(3, '016b'), 2)
                if "Marketing" in self.documents[i].metadata["role"]:
                    doc_role_value += int(format(4, '016b'), 2)
                if query_role_value & doc_role_value:
                    retrieved_docs.append(self.documents[i])

        return retrieved_docs

    # Ensure this function has the same indentation level as the __init__ and retrieve me
    def score_documents(self, query, retrieved_docs):
        query_embedding = np.array(self.embedding_model.embed_query(query)).reshape(1, -1

        doc_embeddings = []
        for doc in retrieved_docs:
            doc_embedding = np.array(self.embedding_model.embed_query(doc.page_content))
            doc_embeddings.append(doc_embedding)
        doc_embeddings = np.array(doc_embeddings)

        similarities = cosine_similarity(query_embedding, doc_embeddings).flatten()
        scored_docs = [(doc, similarity) for doc, similarity in zip(retrieved_docs, simil
        scored_docs.sort(key=lambda x: x[1], reverse=True)


        top_docs = [doc for doc, _ in scored_docs[:10]]
        return top_docs
```

Below creates a retriever object using FAISS index, embeddings, and documents for role-based retrieval.

```
retriever = MetadataFAISSRetriever(index, embeddings_model, documents)
```

Define the user roles and input the current role for response

Change the role and rerun the code for other roles and quesries

```
user_role = 'HR'  # Current user's role
query = "What does the labour laws in India cover?"

if user_role == 'HR':
    role_str = "Role: ['HR'], so you are in HR."
if user_role == 'Sales':
    role_str = "Role: ['Sales'], so you are in Sales."
elif user_role == 'Tech':
    role_str = "Role: ['Tech'], so you are in Tech."
elif user_role == 'Marketing':
    role_str = "Role: ['Marketing'], so you are in Marketing."
```

Below code prepares the system to use a large language model (gpt-4o) to generate answers to user queries, incorporating document context and user roles to guide the model and enforce access restrictions.

Installs & Imports:

Installs the langchain package and imports necessary modules for working with LLMs

Defines Prompt:

Creates a prompt template instructing the LLM to answer questions based on provided documents and user roles, ensuring access control.

Assembles Prompt:

Combines prompt components into a finalPrompt, preparing it for use in the retrieval chain.

```
#!pip install langchain --upgrade
from langchain.llms import OpenAI
from langchain.prompts import ChatPromptTemplate
from langchain.chat_models import ChatOpenAI
```

```
# Update the llm instantiation to use ChatOpenAI:
llm = ChatOpenAI(model_name="gpt-4o", temperature=0.5)

promptList = []
promptPart1 = """
You are a system designed to provide information based on documents available to either t
"""
promptPart2 = """
Ensure that:
1. If the relevant document(s) are accessible to the user's role, provide only the inform
2. If the relevant document(s) are not accessible to the user's role, strictly state: 'So
3. Avoid adding any extra details, speculative information, prior content, or context bey
4. If the document is accessible by multiple roles, validate access accordingly, but do n

**Important**
- Provide a response that is solely based on the document content relevant to the query.
- Exclude any information that is not present in the document(s) provided.
<context>
{context}
</context>
Question: {input}
"""
promptList.append (promptPart1)
promptList.append (role_str)
promptList.append (promptPart2)
finalPrompt = "".join (promptList)
prompt = ChatPromptTemplate.from_template (finalPrompt)


from langchain.chains.combine_documents import create_stuff_documents_chain
document_chain = create_stuff_documents_chain(llm, prompt)


retrieved_docs = retriever.retrieve(query, user_role)
most_relevant_docs = retriever.score_documents(query, retrieved_docs)

response = document_chain.invoke({"input": query, "context": most_relevant_docs})

print(response)
```

```
The Labour Laws in India cover a broad spectrum of aspects, including minimum wages,
```

```
# User database with hashed passwords (for demonstration purposes)
users_db = {
    "hr": {
        "password": bcrypt.hashpw("hr123".encode('utf-8'), bcrypt.gensalt()),
        "roles": ["admin"]
    },
    "sales": {
        "password": bcrypt.hashpw("sales123".encode('utf-8'), bcrypt.gensalt()),
        "roles": ["user1"]
    },
    "marketing": {
        "password": bcrypt.hashpw("marketing123".encode('utf-8'), bcrypt.gensalt()),
```

```
            "roles": ["user2"]
        },
        "tech": {
            "password": bcrypt.hashpw("tech123".encode('utf-8'), bcrypt.gensalt()),
            "roles": ["user3"]
        }
    }
```

Code for creating Gradio Interface

```
import gradio as gr
import bcrypt  # Make sure bcrypt is imported

def predict(query, user_role):
    # Assuming retriever, document_chain, and other necessary variables are defined in th

    if user_role == 'HR':
        role_str = "Role: ['HR'], so you are in HR."
    elif user_role == 'Sales':
        role_str = "Role: ['Sales'], so you are in Sales."
    elif user_role == 'Tech':
        role_str = "Role: ['Tech'], so you are in Tech."
    elif user_role == 'Marketing':
        role_str = "Role: ['Marketing'], so you are in Marketing."
    else:
        role_str = "Invalid Role"

    promptList = []
    promptPart1 = """
    You are a system designed to provide information based on documents available to eith
    """
    promptPart2 = """
    Ensure that:
    1. If the relevant document(s) are accessible to the user's role, provide only the in
    2. If the relevant document(s) are not accessible to the user's role, strictly state:
    3. Avoid adding any extra details, speculative information, prior content, or context
    4. If the document is accessible by multiple roles, validate access accordingly, but

    **Important**
    - Provide a response that is solely based on the document content relevant to the que
    - Exclude any information that is not present in the document(s) provided.
    <context>
    {context}
    </context>
    Question: {input}
    """
    promptList.append(promptPart1)
    promptList.append(role_str)
    promptList.append(promptPart2)
    finalPrompt = "".join(promptList)
    prompt = ChatPromptTemplate.from_template(finalPrompt)
```

```
    retrieved_docs = retriever.retrieve(query, user_role)
    most_relevant_docs = retriever.score_documents(query, retrieved_docs)

    # Update the chain invocation using the new prompt
    response = document_chain.invoke({"input": query, "context": most_relevant_docs})
    return response

def login_fn(username, password):
    """Validates user credentials against the users_db."""
    user = users_db.get(username)
    if user and bcrypt.checkpw(password.encode('utf-8'), user["password"]):
        # Successful login
        return True, "Login successful!", ""  # Return True for success, message, and cle
    else:
        # Invalid login
        return False, "", "Invalid username or password."  # Return False for failure, cl


# Define the main Gradio Blocks
with gr.Blocks() as demo:
    # Input components for login
    with gr.Row():
        username_input = gr.Textbox(label="Username", placeholder="Enter your username")
        password_input = gr.Textbox(label="Password", placeholder="Enter your password",

    # Button for login
    login_button = gr.Button("Login")

    # Initially hide the main interface
    iface = gr.Interface(
        fn=predict,
        inputs=[
            gr.Textbox(label="Enter your query"),
            gr.Radio(["HR", "Sales", "Tech", "Marketing"], label="Select your role", valu
        ],
        outputs=gr.Textbox(label="Response"),
        title="Document QA System",
        description="Ask questions related to the provided documents.",
        visible=False  # Hide initially
    )

    # Display message for invalid login
    invalid_login_message = gr.Textbox(label="Login Status", value="Please log in.", visi

    # Define outputs for the login button click
    login_button.click(
        login_fn,
        inputs=[username_input, password_input],
        outputs=[iface, invalid_login_message, gr.Textbox(label="Login Status", visible=F
    )

demo.launch(share=True, debug=True) # Added debug=True
```

```
Colab notebook detected. This cell will run indefinitely so that you can see errors a
* Running on public URL: https://472b6b7406b5b988a5.gradio.live

This share link expires in 72 hours. For free permanent hosting and GPU upgrades, rur
```

Enter your username

Enter your password

Login

Document QA System

Ask questions related to the provided documents.

Enter your query

What does the policy say about Termination and Resignation

Select your role

HR Sales Tech Marketing

Clear Submit

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/gradio/queueing.py", line 624, in prc
    response = await route_utils.call_process_api(
  File "/usr/local/lib/python3.10/dist-packages/gradio/route_utils.py", line 323, in
    output = await app.get_blocks().process_api(
  File "/usr/local/lib/python3.10/dist-packages/gradio/blocks.py", line 2025, in proc
    data = await self.postprocess_data(block_fn, result["prediction"], state)
  File "/usr/local/lib/python3.10/dist-packages/gradio/blocks.py", line 1826, in post
    raise InvalidComponentError(
gradio.exceptions.InvalidComponentError: <class 'gradio.interface.Interface'> Compone
```

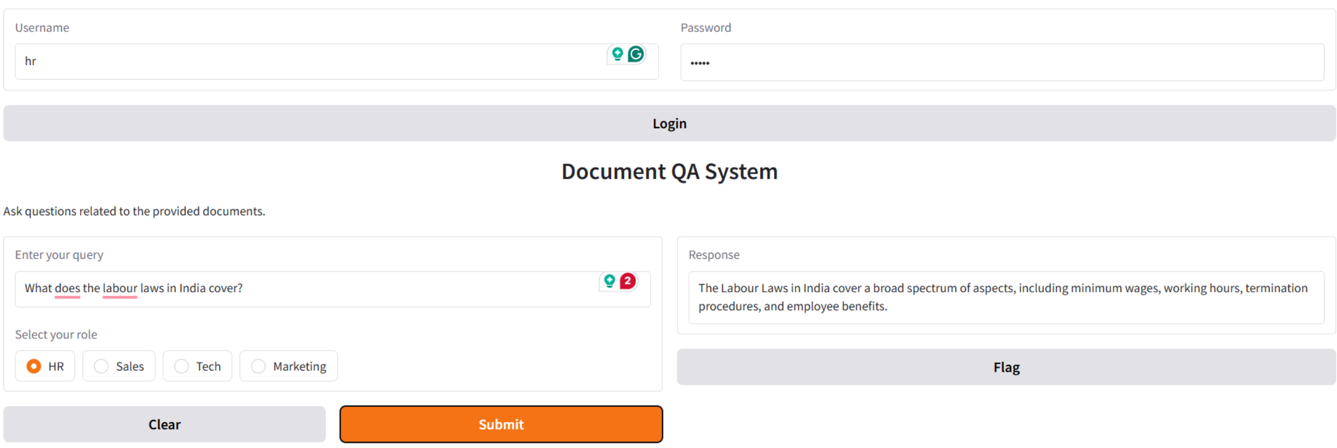
The code is designed to update the embeddings and FAISS index if there are changes in the original documents or their associated roles. This ensures the RAG system stays up-to-date with the latest information.

```
for i, doc in enumerate(documents):
```

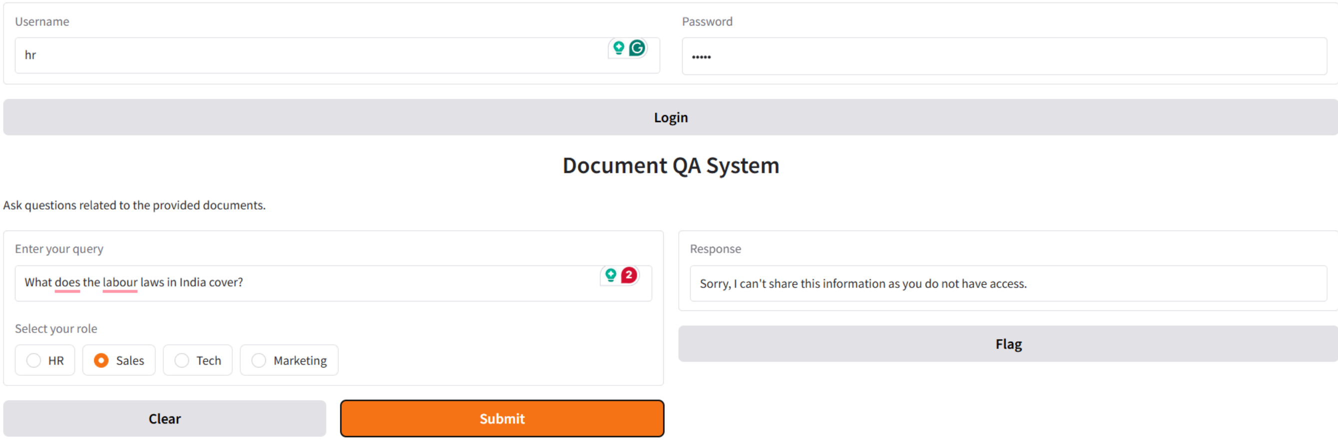
```
    file_name = doc.metadata['source']

    # Reload the document using TextLoader
    loader = TextLoader(file_name)
    new_documents = loader.load()
    new_content = new_documents[0].page_content

    # Determine the new role value
    new_role_value = 0
    roles = text_files.get(file_name, '')
    if "E" in roles:
        new_role_value += 1
    if "S" in roles:
        new_role_value += 2

    # Check if the content or role has changed compared to the existing state
    embedding_model = OpenAIEmbeddings() # Using OpenAI embeddings
    current_embedding = embedding_model.embed_query(new_content)
    extended_vector = np.concatenate([current_embedding, [new_role_value]])
    extended_vector = np.array(extended_vector, dtype=np.float32)

    if (i < len(embedding_vectors) and
        not np.array_equal(embedding_vectors[i], extended_vector)):
        # Update the embedding in the list
        if i < len(embedding_vectors):
            embedding_vectors[i] = extended_vector
        else:
            embedding_vectors.append(extended_vector)
        # Rebuild the entire index
        index.reset()
        index.add(np.array(embedding_vectors, dtype=np.float32))
    else:
        print(f"No changes detected for document chunk {i}.")
```

Show hidden output

The below screen shot shows user based access dislaying the results for HR RBAC



When The RBAC is changed to sales it says , I canbot share the information



Example query to generate the email for compensation benifits query