Cooking Chatbot using Amazon Bedrock, RAG, S3, Langchain and Streamlit

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Abstract

The proliferation of digital content in PDF format presents challenges and opportunities for developing interactive applications, such as culinary assistance chatbots. These applications require robust solutions to effectively parse and respond to user queries from diverse PDF sources. This research focuses on the development and implementation of a chatbot application leveraging advanced technologies including Amazon Bedrock, the Retrieval-Augmented Generation (RAG) model, S3 storage, Langchain, and Streamlit. The system architecture integrates an administrative interface for PDF upload, segmentation, and vectorization, along with a user-facing interface for query processing and response generation.
This paper details the architectural design, implementation methodologies, and empirical findings, emphasizing improvements in document retrieval accuracy and chatbot interactivity. Additionally, it explores implications for advancing natural language processing and intelligent application frameworks.

Keywords: *chatbot, pdf, rag, aws-s3, langchain, streamlit*

1. Introduction

The proliferation of digital content in PDF format presents a formidable task in extracting and utilizing information effectively for interactive applications, such as culinary assistance chatbots. These applications require robust solutions to parse and respond to user queries from heterogeneous PDF sources.

This research endeavors to develop and implement a chatbot application leveraging advanced technologies including Amazon Bedrock, the Retrieval-Augmented Generation (RAG) model, S3 storage, Langchain, and Streamlit. The system architecture encompasses an administrative interface facilitating PDF upload, segmentation, and vectorization, alongside a user-facing interface for query processing and response generation.

This paper elucidates the architectural design, implementation methodologies, and empirical findings, emphasizing enhancements in document retrieval accuracy and chatbot interactivity. Furthermore, it explores implications for future advancements in natural language processing and intelligent application frameworks.

2. Literature Review

The extraction and utilization of information from PDF documents pose significant challenges in various domains, necessitating advanced solutions in natural language processing (NLP) and document management systems. This section reviews relevant literature focusing on methodologies and technologies employed in similar projects.

2.1. PDF Processing and NLP Techniques

Recent advancements in PDF processing techniques have explored methods for parsing and segmenting documents into meaningful chunks for further analysis. PyPDF2 is a Python library that provides tools to extract text, merge PDFs, and manipulate metadata. It is widely used for document manipulation tasks.

- **PyPDF2 Example**: The following code snippet demonstrates how to extract text from a PDF document using PyPDF2.

```
import PyPDF2
with open('document.pdf', 'rb') as file:
    reader = PyPDF2.PdfFileReader(file)
    text = ""
    for page in range(reader.numPages):
        text += reader.getPage(page).
    extractText()
```

Code 1. PyPDF2 Example.

Langchain is another library designed to facilitate text segmentation and vectorization. It helps in breaking down large text chunks into smaller, more manageable parts for further processing.

- **Langchain Example**: The following code snippet demonstrates how to use RecursiveCharacterTextSplitter from Langchain to segment text.

```
from langchain.text_splitter import
    RecursiveCharacterTextSplitter
text_splitter =
    RecursiveCharacterTextSplitter(
    chunk_size=1000, chunk_overlap=200)
chunks = text_splitter.split_text(text)
```

Code 2. Langchain Example.

2.2. Embeddings and Semantic Similarity

The utilization of embeddings for converting textual information into numerical representations has garnered attention due to its efficacy in semantic similarity tasks. Bedrock embeddings, specifically tailored for large-scale language models, offer robust solutions for semantic indexing and retrieval tasks.

- **Mathematical Concept**: Embeddings map words or text segments to high-dimensional vectors. The similarity between two text segments can be measured using cosine similarity:

$$\text{cosine\_similarity} = \frac{\mathbf{A} \cdot \mathbf{B}}{||\mathbf{A}||||\mathbf{B}||}$$

where $\mathbf{A}$ and $\mathbf{B}$ are embedding vectors.

- **Bedrock Embeddings Example**: The following code snippet demonstrates how to use Bedrock embeddings to convert text segments into numerical vectors.

```
from bedrock import BedrockEmbeddings
embedder = BedrockEmbeddings()
vectors = embedder.embed_text(chunks)
```

Code 3. Bedrock Embeddings Example.

2.3. Integration with Cloud Services

The integration of cloud storage solutions, such as Amazon S3, enhances scalability and accessibility in handling large datasets and model artifacts [4]. This integration not only facilitates efficient data management but also supports seamless deployment and scalability of applications across distributed environments.

- **Amazon S3 Example**: The following code snippet demonstrates how to upload a file to Amazon S3.

```
import boto3
s3 = boto3.client('s3')
s3.upload_file('document.pdf', 'bucket-name'
    , 'document.pdf')
```

Code 4. Amazon S3 Example.

2.4. Chatbot Systems and User Interaction

The implementation of retrieval-augmented generation (RAG) models in chatbot systems has revolutionized user interaction by augmenting queries with retrieved documents to enhance response generation [2]. This approach not only improves the relevance and accuracy of responses but also adapts to dynamic user queries effectively.

- **Mathematical Concept**: RAG models use a combination of retrieval and generation probabilities. The probability of generating an answer a given a query q and a set of documents D is:

$$P(a|q) = \sum_{d \in D} P(a|q,d) P(d|q)$$

  where $P(a|q,d)$ is the probability of generating a given q and d, and $P(d|q)$ is the probability of retrieving document d given query q.
- **RAG Model Example**: The following code snippet demonstrates how to use the RAG model to generate an answer based on user query and retrieved documents.

```
from rag import RAGModel
rag_model = RAGModel()
response = rag_model.generate_answer(query,
    documents)
```

Code 5. RAG Model Example.

2.5. Conclusion

The reviewed literature underscores the critical role of advanced NLP techniques, document processing methodologies, and cloud-based infrastructures in developing robust applications for information retrieval and user interaction. This framework informs the development of our Admin and User Web Apps, integrating these methodologies to streamline PDF handling and enhance user experience.

3. Methodology

This section details the steps involved in developing both the Admin and User Web Applications for processing PDF documents. We integrate natural language processing technologies and utilize cloud infrastructure to achieve our goals.

3.1. PDF Preprocessing

The preprocessing of PDF documents is the first and critical step in our system:

1. **PDF Analysis**: We use the PyPDF2 library to extract text from PDF documents. PyPDF2 is chosen for its robustness and wide adoption in the community, allowing for efficient extraction and manipulation of PDF content [7].

```
from PyPDF2 import PdfFileReader
with open('document.pdf', 'rb') as file:
    reader = PdfFileReader(file)
    text = ''
    for page in range(reader.numPages):
        text += reader.getPage(page).
    extract_text()
```

Code 6. Example code of PyPDF2.

2. **Text Segmentation**: We use the RecursiveCharacterTextSplitter from Langchain to segment large text chunks into smaller, manageable parts. Langchain is selected due to its ability to handle complex text segmentation tasks effectively, ensuring better processing and analysis in subsequent steps [6].

```
from langchain.utils.text_splitter import
    RecursiveCharacterTextSplitter
text_splitter =
    RecursiveCharacterTextSplitter()
chunks = text_splitter.split_text(text)
```

Code 7. Example code of RecursiveCharacterTextSplitter.

3.2. Text Embeddings

Once preprocessing is complete, the text segments are converted into numerical vectors:

1. **Vector Representation**: We use the Bedrock embeddings model to convert text segments into numerical vectors. Bedrock embeddings are chosen for their scalability and performance in large-scale language models, providing robust solutions for semantic indexing and retrieval tasks [5].

```
from langchain.community.embeddings import
    bedrock_embeddings
embeddings = bedrock_embeddings.EmbedText()
vectors = [embeddings.embed(text) for text
    in chunks]
```

Code 8. Example code of Bedrock embeddings.

2. **Mathematical Concept**: Embeddings map words or text segments to high-dimensional vectors. The similarity between two text segments can be measured using cosine similarity:

$$\text{cosine\_similarity} = \frac{\mathbf{A} \cdot \mathbf{B}}{||\mathbf{A}||||\mathbf{B}||}$$

   where **A** and **B** are embedding vectors **cosine-similarity**.
3. **Storing Embeddings**: The vector embeddings are stored in a FAISS Vector Store, a local vector storage known for its efficient similarity search and clustering of dense vectors [1].

```
import faiss
index = faiss.IndexFlatL2(768)  # Assuming
    768-dimensional vectors
index.add(vectors)
```

Code 9. Example code of FAISS Vector Store.

3.3. Cloud Integration

Cloud services, primarily AWS S3, are used to store both the original PDF documents and the vector embeddings:

1. **Cloud Storage**: The original PDF documents and vector embeddings are stored in Amazon S3. This ensures data security and availability for retrieval from anywhere in a secure and efficient manner [4].

```
import boto3
s3 = boto3.client('s3')
bucket_name = 'your-bucket-name'
s3.upload_file('document.pdf', bucket_name,
    'document.pdf')
s3.upload_file('vectors.pkl', bucket_name, '
    vectors.pkl')
```

Code 10. Example code of Amazone S3.

2. **Handling Large Data**: Using cloud services supports large data processing and easy deployment on a distributed system.

3.4. Retrieval-Augmented Generation (RAG)

Finally, the User Web Application employs the RAG model to enhance the relevance of answers:

1. **Query and Search**: When a user submits a query, the system uses FAISS to retrieve documents similar to the query based on vector embeddings. This process improves the search capability and suggestion of contextually rich answers [2].

```
import boto3
s3 = boto3.client('s3')
bucket_name = 'your-bucket-name'
s3.upload_file('document.pdf', bucket_name,
    'document.pdf')
s3.upload_file('vectors.pkl', bucket_name, '
    vectors.pkl')
```

Code 11. Example code of Query and Search.

2. **Contextual Augmentation**: The retrieved results from FAISS are used to augment the user's question with similar documents. This provides a rich context for the final answer generated by the RAG model [2].

```
context = ' '.join(similar_documents)
response = generate_response(user_query,
    context)
```

Code 12. Example code of Contextual Augmentation.

3. **Mathematical Concept**: RAG models use a combination of retrieval and generation probabilities. The probability of generating an answer a given a query q and a set of documents D is:

$$P(a|q) = \sum_{d \in D} P(a|q,d)P(d|q)$$

where $P(a|q,d)$ is the probability of generating a given q and d, and $P(d|q)$ is the probability of retrieving document d given query q [3].

This detailed methodology covers the entire process from preprocessing PDF documents, embedding text, storing data in the cloud, to retrieving and generating contextually relevant answers using the RAG model. Each step is designed to ensure efficient, secure, and scalable handling of PDF documents for enhanced user interactions.

4. Results

In this section, we present and analyze key observations and findings from the study, excluding specific quantitative measurements.

4.1. Key Findings

We conducted a series of experiments and detailed observations on the following aspects of the chatbot system:

- **Efficiency of PDF Processing and Analysis**: We found that the combination of Amazon Bedrock and the Retrieval-Augmented Generation (RAG) model significantly enhanced the system's capability to process and respond from complex PDF documents. The system accurately analyzed and extracted information from various PDF formats.
- **Enhanced Interaction and User Experience**: Implementing RAG improved the interaction between users and the system. Users could receive more detailed and contextually relevant answers to cooking-related queries.

5. Discussion

This Results section focuses on describing significant observations and findings from the study, excluding specific quantitative measurements. These insights provide an overview of the capabilities and performance of the chatbot system in real-world scenarios.

6. Conclusion

This study has proposed and implemented a cooking assistance chatbot application using advanced technologies such as Amazon Bedrock, the RAG (Retrieval-Augmented Generation) model, and cloud services for processing and responding to user queries from culinary PDF documents. The following are the key conclusions of the study:

- **Successful Technology Integration**: The integration of technologies like Amazon Bedrock and the RAG model has significantly enhanced the processing and responsiveness of the chatbot to user queries from complex PDF cooking documents.
- **Improved User Interaction and Experience**: The system has notably improved the interaction between users and the chatbot, providing detailed and relevant responses to cooking-related queries.
- **Future Directions**: The study also identifies limitations and challenges in scaling and optimizing the system. Future research could focus on enhancing scalability, improving performance, and increasing system availability.

In summary, the project has delivered positive outcomes and proposed future directions to enhance serving capabilities and user experience in cooking assistance applications. The technologies and research methods applied in this study can be widely applicable to other fields requiring processing of information from complex PDF documents.

References

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