

Promptior Challenge

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1. Project Overview

The goal of this project is to develop a Retrieval-Augmented Generation (RAG) chatbot that answers questions about Promptior's services and founding date. The chatbot uses LangChain for the RAG pipeline, Ollama for running the llama2 model locally, and FastAPI for serving the application as an API.

Key Features

- Data Ingestion: Scrapes Promptior's website and parses the challenge PDF to create a combined dataset.
- RAG Pipeline: Uses LangChain to create a retrieval-augmented generation pipeline with open-source embeddings and the llama2 model.
- API Endpoint: Exposes the chatbot functionality via a FastAPI endpoint.
- Cloud Deployment: Deploys the FastAPI app to AWS ECS using AWS Copilot, with Ollama hosted on an EC2 instance.

2. Project Structure

The project is organized into three main folders:

data/

- Contains raw and processed data:
 - website_text.txt: Text scraped from Promptior's website.
 - pdf_text.txt: Text extracted from the challenge PDF.
 - combined_data.txt: Combined text used as context for the RAG pipeline.

src/

- Contains the application logic:
 - data_scraping.py: Scrapes Promptior's website and saves the text.
 - pdf_parser.py: Parses the challenge PDF into text.
 - data_combiner.py: Combines the website and PDF text into a single file.
 - my_rag_pipeline.py: Implements the RAG pipeline using LangChain.
 - app.py: Defines the FastAPI endpoint and starts the server.

doc/

- Contains project documentation (this pdf).

3. Implementation Details

Data Preparation:

I created 3 scripts to generate data about Promtior:

- `data_scraping.py` scrape Promtior's website and extract relevant text that then is saved in `data/website_text.txt`
- `pdf_parser.py` parse the challenge pdf to text and save it in `data/pdf_text.txt`
- `data_combiner.py` combines both .txt archives into one called `data/combined_data`. Which is the one I use to give context to the rag chain

RAG Pipeline:

After having that I created the file `my_rag_pipeline.py` that contains all the logic of the solution:

- Loads and splits into chunks the previously mentioned data
- Creates the Vector Store using an Open-source HuggingFace embeddings, then the embeddings are stored in a FAISS vector store for efficient similarity search.
- The llama2 model is initialized using Ollama and configured to run locally
- Defines the prompt template to guide the LLM in generating responses based on the retrieved context
- The retrieval and generation components are combined into a single RAG chain using LangChain

API Endpoint:

The `app.py` script defines a FastAPI endpoint (`/promtior-chatbot`) that accepts user queries and returns responses generated by the RAG pipeline. The API is served using Uvicorn.

4. Local Testing

1. Start the Ollama server and pull the llama2 model:

```
ollama serve
ollama pull llama2:7b
```

1. Start the FastAPI server:

```
uvicorn src.app:app --host 0.0.0.0 --port 8000
```

Test with Postman:

Send a POST request to `http://localhost:8000/promtior-chatbot/invoke` with a JSON payload:

The first screenshot shows a Postman interface for a POST request to `http://localhost:8000/promtior-chatbot/invoke`. The 'Body' tab is selected, and the 'Text' format is chosen. The JSON payload is:

```
{
  "input": "When was Promtior founded?"
}
```

The second screenshot shows the response of the same POST request. The 'Body' tab is selected, and the 'JSON' format is chosen. The response is a JSON object:

```
{
  "output": "Promtior was founded in May 2023.",
  "metadata": {
    "run_id": "f201b258-7ec7-4a4e-9ac9-7ea8e8ed93f6",
    "feedback_tokens": []
  }
}
```

Below the response, the status bar indicates: Status: 200 OK, Time: 4 m 16.98 s, Size: 1.09 KB. There is also a 'Save Response' button.

Now my application is correctly running on my local machine.

5. Cloud Deployment

First to ensure the application has access to Ollama, I deployed an instance of Ollama in EC2 making sure that the application has access to it through the url:

`http://ec2-3-85-233-72.compute-1.amazonaws.com:11434`

Then to deploy the API I created a Dockerfile and built a docker image with the fastAPI and then deploy it in ecs aws with the command: `copilot init --app [application-name] --name [service-name] --type 'Load Balanced Web Service' --dockerfile './Dockerfile' --deploy`

Configurations

Environment	Tasks	CPU (vCPU)	Memory (MiB)	Platform	Port
chatbot-env	1	0.25	512	LINUX/X86_64	8000

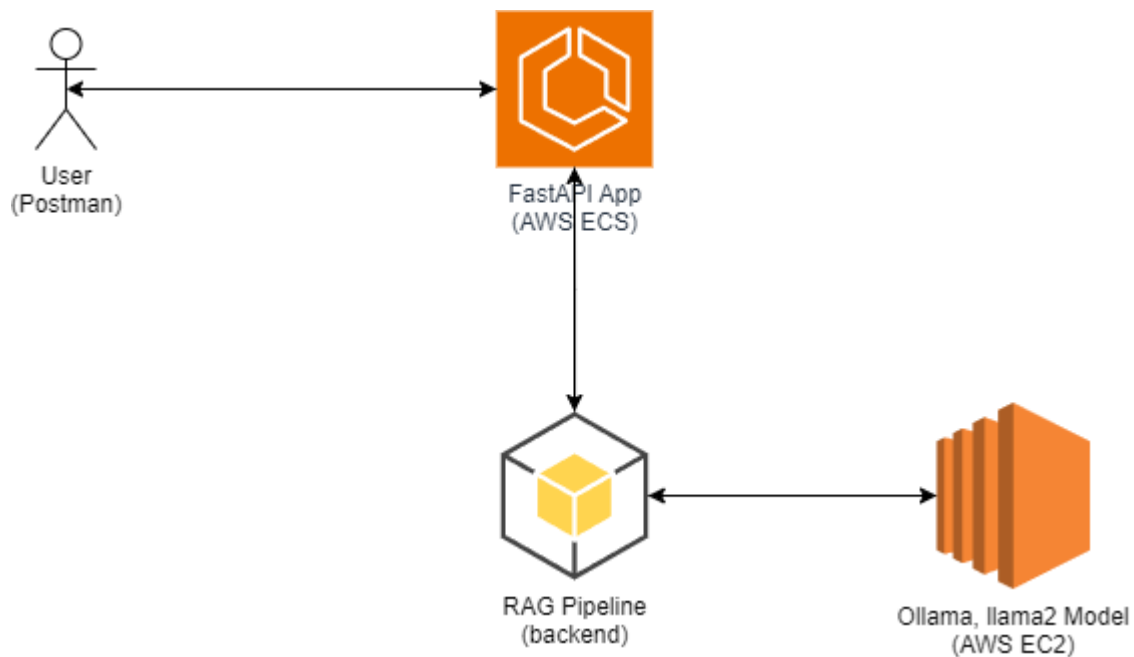
Routes

Environment	URL
chatbot-env	http://promti-Publi-o4wjzQual8Ev-516943211.us-east-1.elb.amazonaws.com

Internal Service Endpoints

Endpoint	Environment	Type
promptior-service:8000	chatbot-env	Service Connect
promptior-service.chatbot-env.promptior-chatbot.local:8000	chatbot-env	Service Discovery

6. Component Diagram



Explanation of Interactions

- User → FastAPI App:

The user sends a query (e.g., "What services does Promtior offer?") to the FastAPI endpoint.

- FastAPI App → RAG Pipeline:

The FastAPI app forwards the query to the RAG pipeline.

- RAG Pipeline → Ollama on EC2:

The RAG pipeline sends the query and retrieved context to the llama2 model hosted on Ollama (EC2).

- Ollama on EC2 → RAG Pipeline:

The llama2 model generates a response and sends it back to the RAG pipeline.

- RAG Pipeline → FastAPI App:

The RAG pipeline returns the generated response to the FastAPI app.

- FastAPI App → User:

The FastAPI app sends the response back to the user.

7. Challenges

The main challenge I encountered was deploying the application in the cloud because Ollama needed to be running and accessible to the FastAPI API. To solve this, I deployed Ollama on an EC2 instance, configured it to listen on all interfaces, and ensured the FastAPI app could connect to it by pointing to the EC2 instance's public IP. Additionally, I used AWS Copilot to automate the deployment of the FastAPI app to ECS, simplifying the process and ensuring scalability.