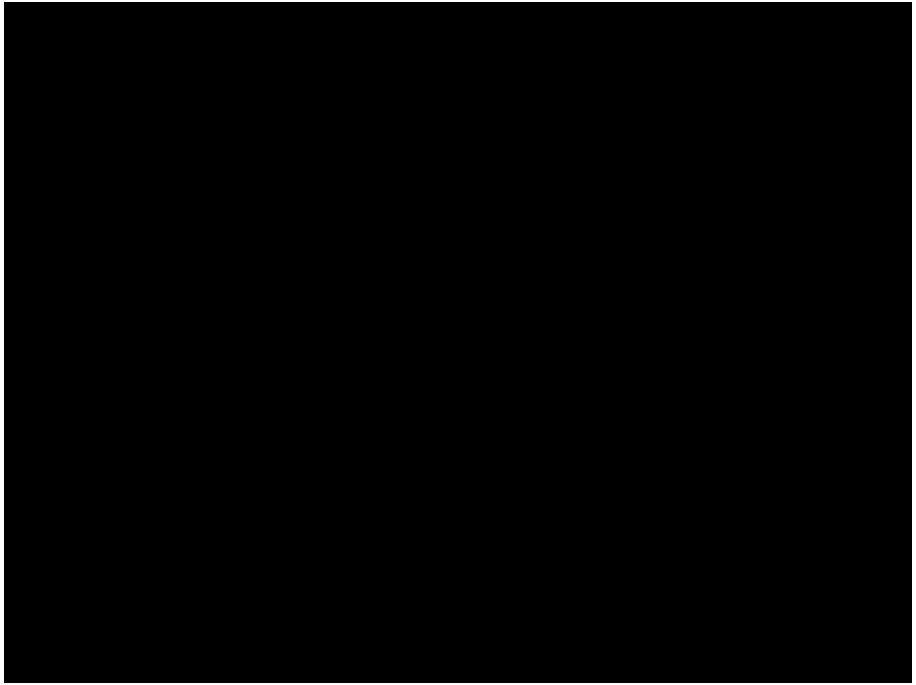
# Generative AI COE

Technical Assessment
Job Candidate Generative AI Application

# Demo



*Click to be redirected to video in Google Drive*

# 1.1 Application / Logic Flow Diagram

1, **User asks question** via Streamlit UI.

2. Langchain's conversational retrieval chain **checks** if there is any **chat history** in the same session.

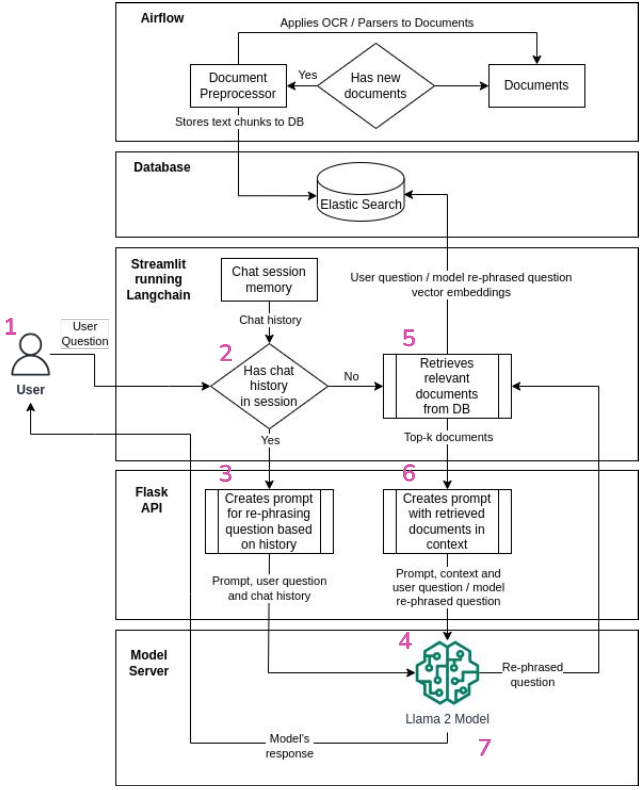
3. If **yes, user question is augmented** to prompt the LLM to re-phrase the question based on the chat history.

4. **LLM re-phrases** the original user question, responds to Flask API which streams the response to Langchain.

5. Langchain **retrieves relevant documents** based on the original user question / model re-phrased question from the Elasticsearch data store.

6. **Final prompt** is created for LLM to respond to.

7. **LLM's response is streamed to the user** via Flask API and Streamlit application running Langchain



Airflow
Applies OCR / Parsers to Documents
Document Preprocessor
Yes
Has new documents
Documents
Stores text chunks to DB
Database
Elastic Search
Streamlit running Langchain
Chat session memory
User question / model re-phrased question vector embeddings
Chat history
1
User Question
User
2
Has chat history in session
No
5
Retrieves relevant documents from DB
Yes
Top-k documents
Flask API
3
Creates prompt for re-phrasing question based on history
6
Creates prompt with retrieved documents in context
Prompt, user question and chat history
Prompt, context and user question / model re-phrased question
Model Server
4
Re-phrased question
Llama 2 Model
Model's response
7

# 1.2 Application / Logic Flow Insights

1. How to chunk documents?

- All LLMs have limited input context length -> must chuck input documents and retrieve only most relevant documents.
- But chunking process can lead to loss of contextual information of chunks.
- Possible workarounds: Use metadata, summarise first then chunk or chunk depending on use-case (e.g. overlap, chunk size etc).

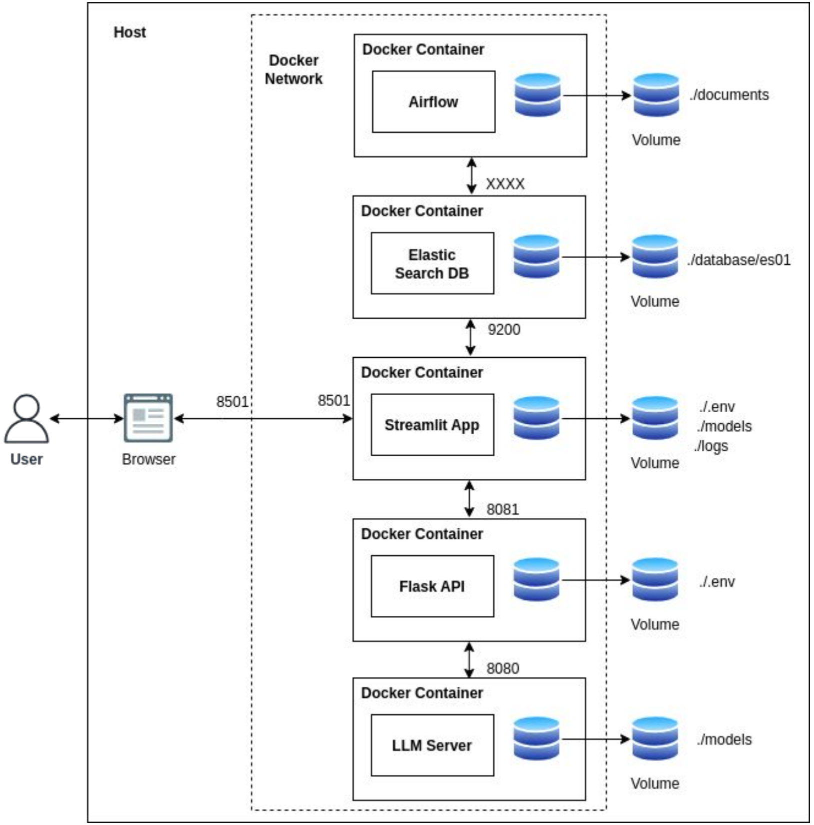
2. Which documents are more relevant?

- Some organisations have lots of documents with same information / conflicting information -> which is more accurate?
- Possible workarounds: Up-weigh based on metadata (recency, author's seniority or user interactions), provide source document or cluster during retrieval.

3. Prompting

- Must engineer prompts: ensures that LLM does not answer irrelevant questions, LMM does not hallucinate and LLMs received the system prompt in the right format for model.

# 2.1 Architecture Diagram



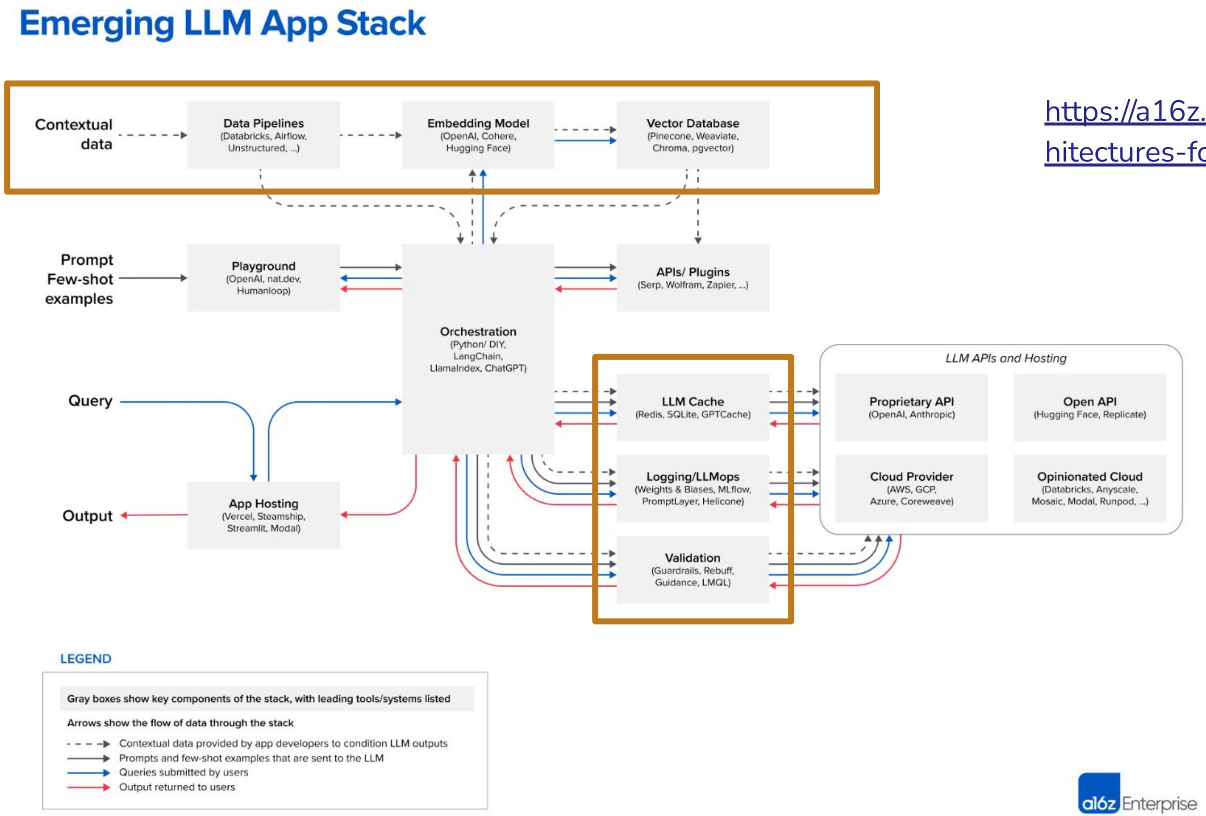
**Start containers with:**
*docker compose up*

# 2.2 Architecture Insights

Overall deployment considerations

- Differentiation of services by frontend, backend and LLM server based on purpose.
  - Frontend Streamlit: Serves UI to users and for defining the chat application interaction logic using Langchain.
  - Backend Flask API: Pre-processes user inputs into prompts specific to the task (e.g. chatbot for job candidates based on documents) and specific prompt templates used by the LLM.
  - Model Server: Hosts the LLM - LLama 2 Chat model.
  - **Advantages**:
    - Ability to change components easily. For example, change the model server to a different model, change the UI or change the database vector store independently.
    - Ability to add new components easily. For example, using different models for rephrasing questions and responding to final questions.
    - Ability to scale vertically or horizontally depending on the load requirements. For example, to use more powerful machines for model server.
    - Ability to re-purpose stack for other tasks. For example, instead of a chatbot for a job candidate can easily change the prompts in the API to do document answering for enterprise search.
    - Allows LLM server to be shared with other applications and not specifically for one application.

# Improvements - Reference Architecture



Emerging LLM App Stack
Contextual data
Data Pipelines (Databricks, Airflow, Unstructured, ...)
Embedding Model (OpenAI, Cohere, Hugging Face)
Vector Database (Pinecone, Weaviate, Chroma, pgvector)
Prompt Few-shot examples
Playground (OpenAI, nat.dev, Humanloop)
Orchestration (Python/ DIY, LangChain, LlamaIndex, ChatGPT)
APIs/ Plugins (Serp, Wolfram, Zapier, ...)
Query
Output
App Hosting (Vercel, Steamship, Streamlit, Modal)
LLM Cache (Redis, SQLite, GPTCache)
Logging/LLMops (Weights & Biases, MLflow, PromptLayer, Helicone)
Validation (Guardrails, Rebuff, Guidance, LMQL)
LLM APIs and Hosting
Proprietary API (OpenAI, Anthropic)
Open API (Hugging Face, Replicate)
Cloud Provider (AWS, GCP, Azure, Coreweave)
Opinionated Cloud (Databricks, Anyscale, Mosaic, Modal, Runpod, ...)
LEGEND
Gray boxes show key components of the stack, with leading tools/systems listed
Arrows show the flow of data through the stack
Contextual data provided by app developers to condition LLM outputs
Prompts and few-shot examples that are sent to the LLM
Queries submitted by users
Output returned to users
a16z Enterprise

https://a16z.com/emerging-architectures-for-llm-applications/

# Enhancements

1) **Text Pre-processing**
   - Orchestrator (Airflow)
   - Documents to Text Parser (PDF, Images, HTML, Markdown etc)
   - Pre-processing methods (Entities, meta-data etc)

2) **Operational Considerations**
   - Database at Scale (ElasticSearch)
   - LLM Cache (GPTCache)
   - LLM Logging (User query, Prompts, Model Responses, User Feedback etc.)
   - LLM Response Guard Rails (Safety LLM, filters (PIIs, Bias) etc.)

# Thank you!