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The Data Mine



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Future

Our project built an LLM-based chatbot to **reliably** answer maintenance questions related to the project dataset and a **user-focused application** for demonstration.

Our analogous dataset of Pan-AM manuals are a comprehensive set of scanned documents spanning approximately 13,000 images.

Dynamic Query Response **Context Handler** Processer Generator Ada ntegrate Query LaMA 3.2 11E User Query & Context Fetch Compute Conversationa Sentence Contextual Embeddings Segments Application User Interface Dynamic Loggin Programming Interface Effic

Feedback/Output

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Project uses Retrieval-Augmented Generation (RAG) system, which segments documents by sentence and stem uses embedding to match questions with correct sources. Sγ

Model (Llama 3.2)

• Combats hallucinations.

Retrieval-Augmente

Generation (Falcon

Reduces need for **model retraining** on new data.

Barnett, Scott, et al. "Fine-tuning or fine-failing? debunking performance myths in large language models." (2024).

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LLM Maintenance Chatbot

Sankhya Ganesh, Ptolemy Henson, Ashish Kashyap, Yassir Khalaf, Neelay Ranjan, Anuj Shah, Shreyas Sreenath, Fetume Teklu

Objective: Integrating Application with LLM enhances the User experience and functions as a fundamental aspect of the project.

Methodology: For portability and ease modifications to the codebase, the entire project is containerized in a Docker. Running a containerized Docker allows for the project to run, regardless of operating system or underlying hardware.

Feature	RAG	Fine-Tuning
aptability to Dynamic Information	Adapts well with access to latest information	May require updates to stay relevant
Customization and Linguistic Style	Limited customization based on retrieved data	High degree of personalization possible
Data Efficiency and Requirements	Leverages external datasets, less labeled data needed	Requires substantial, task- specific training data
ciency and Scalability	Cost-effective and scalable with external data	Higher initial resource investment required
Domain-Specific Performance	Broad topical coverage, versatile	Deep, precise domain expertise

Our vision remains centered on enhancing **performance**, transparency, and accessibility to build a more seamless and reliable system.

- Implement automated factchecking to ensure response accuracy and credibility.
- Optimize real-time processing to **reduce** latency in highdemand scenarios.
- Integrate multi-language support for broader accessibility and inclusivity.
- Return excerpts from the manual to give user option to learn more from the source

Incorporated Tools:

- Google Cloud
- Mongo DB
- React

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- NLTK
- Transformers
- Anvil
- PyTorch
- *Llama 3.2 3*B param, Text only model • *Llama 3.2* - 11B
 - param, Vision enabled model

Objective: Provide user-focused application to interface with LLM that emphasizes security, flexibility, and userfeedback capabilities.

Main Features:

- Multi-Format Communication
- Modifiable Conversation History
- Temporary Chats
- User Feedback Functionality

Methodology: Frontend and backend implementation was done using ReactJS and Express.JS. The conversation history utilizes a MongoDB database and Google Cloud Storage for saved media files.

The LLM Maintenance Chatbot integrates a large language model into a user-focused application to accurately respond to maintenance queries.

Our team improved efficiency and scalability by implementing a **RAG system**, an **API-driven** approach, and a unified frontend-backend structure.