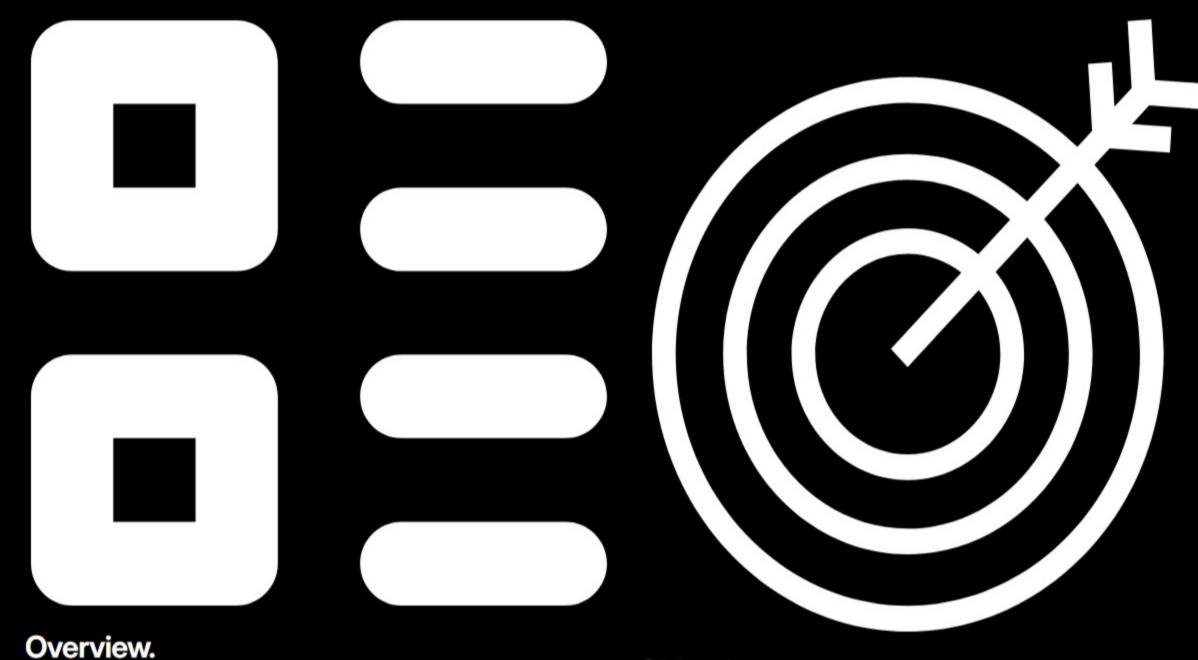
# PDF Chatbot with LLAMA2 & RAG



Al-powered assistant for querying PDF content using semantic search and language understanding.



This project implements an intelligent chatbot capable of answering user queries based on the content of uploaded PDF documents. It combines semantic retrieval with generative language modeling by using MiniLM2 for dense embeddings and LLAMA2 for natural language responses. The chatbot uses a RAG (Retrieval-Augmented Generation) pipeline, enabling accurate, context-aware answers grounded in the original PDF content.

Objective.

Build a domain-agnostic chatbot for querying PDFs in natural language. Use lightweight models to ensure fast embedding and inference. Provide relevant context to the LLM from retrieved document chunks. Maintain accuracy by grounding responses directly in source content.



## MiniLM2 (all-MiniLM-L6-v2)

- for generating dense vector embeddings of PDF chunks. • LLAMA2 (7B) – as the core language model
- for answer generation. LangChain / Haystack / Custom RAG - to connect retriever and generator
- in a modular pipeline. Chroma - vector store for fast semantic search. PyMuPDF / pdfminer /
- pdfplumber for extracting clean text from PDFs. Streamlit / Flask / FastAPI optional interfaces for
- interacting with the bot.

### Extracted raw text from PDF documents and chunked it using

Process.

- overlap strategies. Converted each chunk into an embedding using MiniLM2
- via SentenceTransformers. Stored embeddings in a vector index (e.g., FAISS or Chroma).
- On user query, embedded the question and retrieved top-k relevant chunks. Constructed a prompt
- by combining retrieved context with the question. Passed the prompt to LLAMA2 for a grounded, coherent response.

Retrieval-Augmented

Generation (RAG): Uses

semantic similarity to fetch

Methodologies.

- relevant context chunks from the document, which are then used to formulate a more accurate and source-grounded response. Embedding + Vector Search: Uses MiniLM2 for creating low-dimensional
- vector representations of text, allowing fast and memory-efficient retrieval with FAISS or Chroma. **Prompt Engineering:** Combined user query with top-k context snippets in a predefined prompt

template for optimal

generation quality.

• Lightweight Deployment: Leveraged quantized or low-memory variants of LLAMA2 and used efficient libraries for PDF parsing and search.

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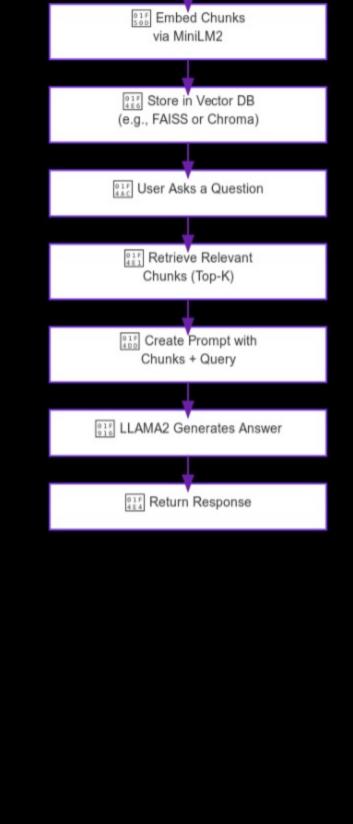
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## Chunk Granularity Trade-off: Smaller chunks led to incomplete context retrieval, while larger ones diluted relevance or exceeded token limits. • PDF Parsing Inconsistencies: Poorly formatted or scanned PDFs often

Challenges

- caused line breaks, headers, and footnotes to interfere with clean chunking. Embedding Speed vs. Accuracy: Using MiniLM2 ensured speed but sometimes sacrificed nuanced semantic matching, especially in technical domains. Context Injection Limitations: LLAMA2 occasionally hallucinated
- when the retrieved context lacked sufficient detail or clarity. Model Loading & Memory Constraints: Running LLAMA2 locally required careful resource management or quantized versions to prevent OOM errors.

**Flowchart** 



Upload PDF

Extract and Chunk PDF Text

## Enter your email Password

**Email** 

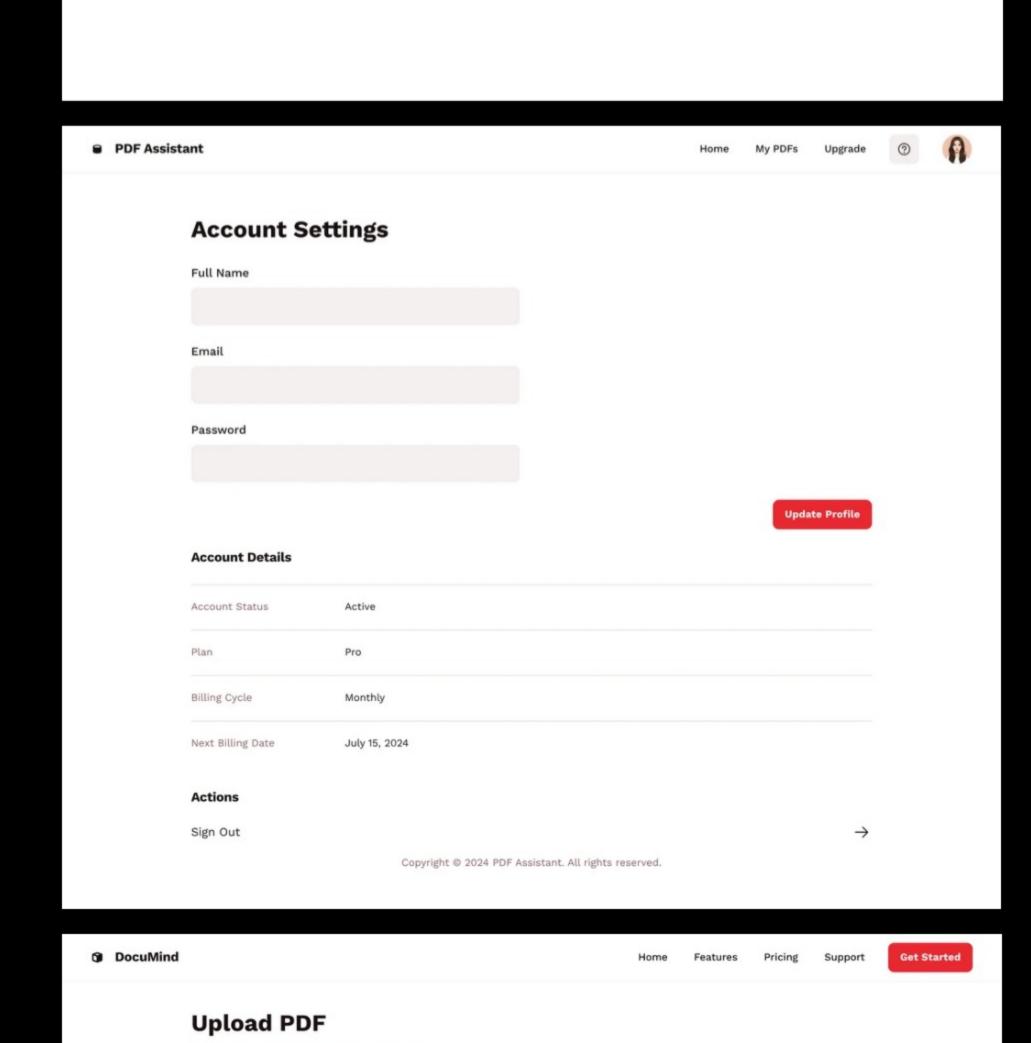
Interface & Usage Preview

**■** PDF Reader

Enter your password Forgot Password?

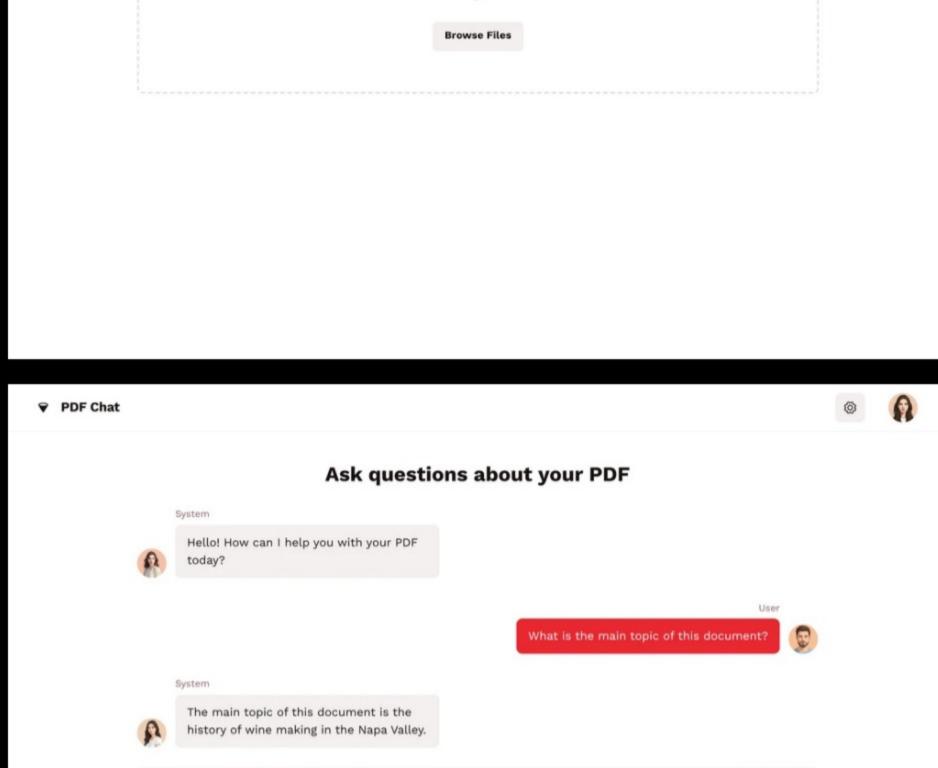
Drag and drop your PDF here or browse files

A glimpse of the chatbot in action with PDF inputs and responses

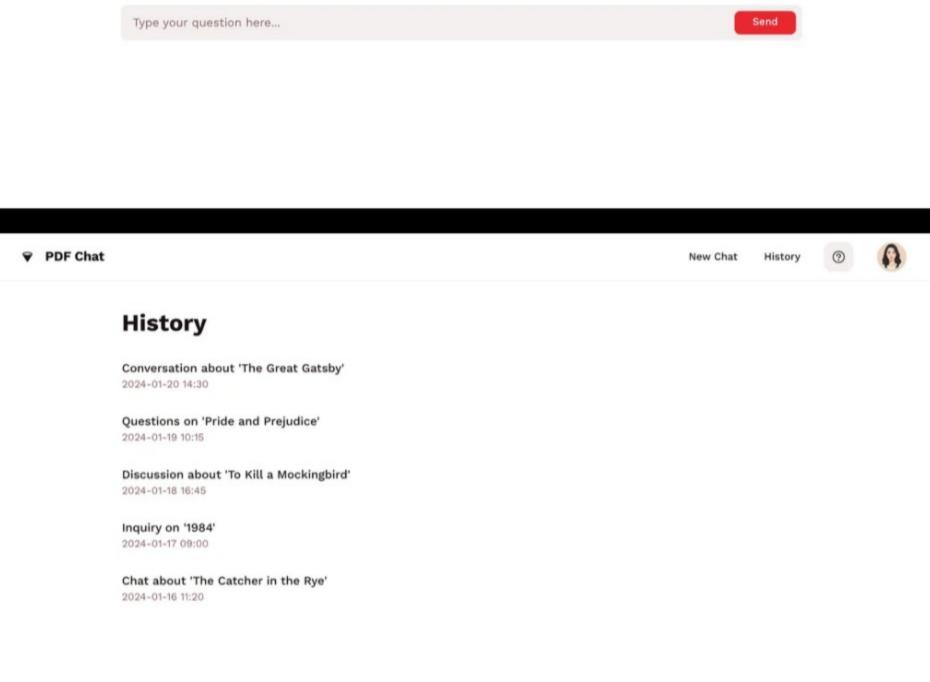


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# Results, Learnings, and Impact

chunking, prompt clarity, and the need for robust PDF text extraction pipelines.