Linux Command Assistant (RAG task)

1. Objective

The objective of this project was to design and implement a Retrieval-Augmented Generation (RAG) system for Linux commands and related documentation.
The system enables semantic search and contextual answering over a structured dataset containing Linux commands, installation guides, fundamentals, troubleshooting steps, common scenarios, and package managers.
The project evolved from a pure embedding-based semantic search (Phase-1) into a fully developed RAG pipeline using a vector database (Phase-2).

2. Dataset Description

The dataset is stored in a structured JSON file named **"linux.json"**, containing the following sections:

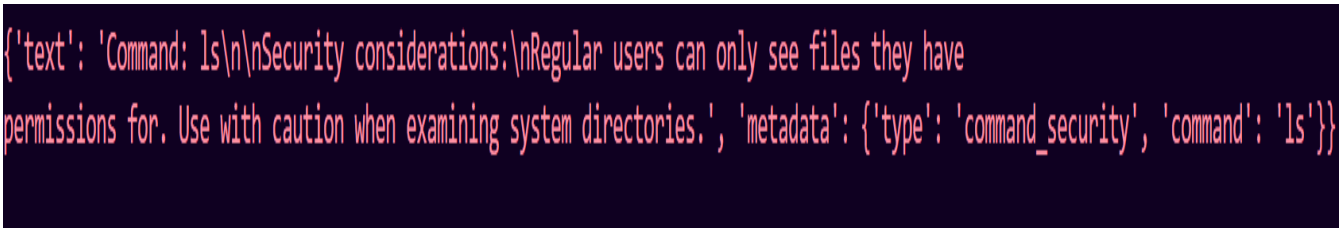
i. commands
ii. installation_guides
iii. linux_fundamentals
iv. troubleshooting_guides
v. common_scenarios
vi. package_managers

3. Chunking Strategy

Each logical unit is converted into self-contained text chunks, including:

- Command core information (syntax, description, explanation)
- Command options
- Examples
- Permission modes
- Installation guide sections (overview, steps, troubleshooting, security)
- Linux fundamentals (directories, permissions, processes, operators)
- Troubleshooting workflows
- Common scenarios
- Package manager commands

Chunking example:



Outcome:

i. Chunking ensures contextual completeness
ii. Improves retrieval precision
iii. Enables multi-section answers in RAG

4. Embedding Model Selection

Models Evaluated	Model Characteristics
BAAI/bge-m3	High-quality, multilingual, best semantic understanding
all-MiniLM-L6-v2	Lightweight, fast, lower semantic depth
all-MiniLM-L12-v2	Balanced speed and quality
all-mpnet-base-v2	Strong semantic similarity, moderate size

Final Choice: BAAI/bge-m3
Reason for choosing BAAI/bge-m3 as embedding model:

i. Best semantic alignment for technical documentation
ii. Performs well for both short and complex queries
iii. Suitable for RAG systems despite higher initial download cost

5. Embedding Generation and Caching

Phase-1 Approach

i. All chunk embeddings were generated once
ii. Stored locally as embeddings.npy
iii. Avoided recomputation during query time

Phase-2 Improvement

i. Migration to ChromaDB vector store
ii. Embeddings are now:
- Generated once
- Persisted inside the vector database
- Automatically loaded on subsequent runs

Key Change:
Locally stored embeddings as **embeddings.npy** is no longer required**,** Vector DB persistence replaces manual embedding storage.

6. ChromaDB Integration (Vector database)

Reason why chroma database was choosen as vector database :

i. Persistent storage
ii. Fast similarity search
iii. Metadata filtering
iv. Easy to create collections
v. Scales beyond in-memory embeddings

Implementation Details

i. Chunks are embedded using SentenceTransformers “BAAI/bge-m3” model
ii. Stored in a persistent Chroma collection linuxDB
iii. Collection is reused across runs
iv. Embeddings are not recomputed if data already exists

Benefits

i. Faster startup after first run
ii. Clean separation of concerns
iii. Production-ready retrieval layer

7. Retrieval Process

i. **Query Encoding:** User queries are encoded using BGE-M3 embeddings, optimized for multilingual retrieval with enhanced performance
ii. **Vector Search:** Query embeddings are searched against ChromaDB vector store using cosine similarity
iii. **Top-K Retrieval:** Top 3 most relevant chunks are retrieved based on semantic similarity
iv. **Context Assembly:** Retrieved chunks are assembled into a unified context for LLM processing
v. **Response Generation:** Context is passed to Groq LLM for grounded response generation

8. LLM Integration in RAG pipeline

- **Provider:** Groq (Cloud API)
- **Model:** llama-3.3-70b-versatile

Why Groq for This Implementation:

i. Extreme Low Latency: Sub-second response times for real-time Linux assistance
ii. High-Quality Instruction Following: Excellent at adhering to strict context usage rules
iii. 70B Parameter Model: Sufficient capacity for detailed technical explanations
iv. Cost-Effective: Competitive pricing for production deployment
v. Reliable API: High uptime and consistent performance

LLM Configuration:

i. Temperature: 0.2 (Low for factual accuracy)
ii. Max Tokens: 1024 (Adequate for comprehensive Linux explanations)
iii. Retries: 2 automatic retries on failure
iv. Timeout: 20 seconds per request

LLM Role in RAG Pipeline:

i. Context-Only Responses: Answers derived exclusively from retrieved documents
ii. No External Knowledge: Prevents information leakage beyond documentation
iii. Structured Responses: Maintains technical accuracy with proper formatting
iv. Error Handling: Graceful fallback when context is insufficient

Conversation Memory:

i. Implementation: ConversationBufferMemory from LangChain
ii. Memory Key: "chat_history" tracks complete conversation flow
iii. Context Retention: Enables follow-up questions and multi-turn dialogues
iv. Session Management: Memory persists throughout user session

9. Prompt Engineering

Key Prompt Rules:

- Use ONLY provided context
- If information is missing say: “I couldn't find relevant information in the knowledge base.”
- Do not use external knowledge
- Do not explain beyond what is documented

Impact

- Prevents hallucinations
- Ensures answers reflect the dataset only
- Makes system behavior predictable and auditable

10. User Interface & Deployment Architecture

FastAPI with integrated HTML/CSS/JavaScript

API endpoints:

- GET /
- POST /ask
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12. Results and Observations

i. Vector database mase the system performance efficient
ii. User queries returned expected answer, no hallucibations at all
iii. Fast API user interface was working smoothly

13. Conclusion

This project successfully demonstrates a production ready RAG system specialized for Linux documentation. The implementation achieves the critical balance between retrieval accuracy, response quality, and system efficiency.

By combining:

- Structured chunking
- High-quality embeddings
- Persistent vector storage
- Controlled answer generation

The system delivers accurate, contextual, and trustworthy responses while remaining efficient and extensible.

OUTPUT: