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**Section A:**

- 1) B
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- 16) B
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- 18) B
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## Section B

Link: [Click here](#)

1.

### 1. Chunking Strategy

To ensure high retrieval accuracy, we used a **Recursive Content-Aware** chunking strategy.

#### Implementation Details

- **Tool:** LangChain's `RecursiveCharacterTextSplitter`.
- **Chunk Size:** `500` characters. This provides a balance between sufficient context for the model and focused retrieval.
- **Chunk Overlap:** `50` characters. This ensures that information spanning across chunks maintains continuity.
- **Separators:** `["\n\n", "\n", " ", ""]`
  - **Priority 1 (`\n\n`):** We first attempt to split by double newlines to keep individual product entries as atomic units.
  - **Priority 2 (`\n`):** If a product entry is too long, we split by line breaks.
  - **Priority 3 ():** As a final resort, we split at word boundaries.

### 2. Embedding Configuration

Embeddings convert text into high-dimensional vectors that the chatbot uses to find relevant information.

#### Implementation Details

- **Model:** `models/embedding-001` via **Google Generative AI (Gemini)**.
- **Provider:** `langchain-google-genai`.
- **Vector Store:** **ChromaDB**.
- **Persistence:** Data is persisted locally in the `/home/labuser/assessment/chroma_db` directory.

### 3. Workflow Integration

During a query:

1. The user's question is embedded using the same `embedding-001` model.
2. A **Similarity Search** is performed against the ChromaDB vector store.
3. The top `k=3` most relevant chunks are retrieved and injected into the LLM prompt as context.

2.

### Walkthrough - Product Knowledge Base RAG

I have completed the end-to-end implementation of the Product Knowledge Base RAG system.

#### Changes Made

1. Knowledge Base Ingestion
  - Developed `ingest_data.py` to process product details.
  - Used `RecursiveCharacterTextSplitter` for chunking.
  - Stored embeddings in a persistent `ChromaDB` local instance.
2. RAG Inference Chain
  - Created `rag_chain.py` using LangChain Expression Language (LCEL).
  - **Model:** Configured `gemini-2.5-flash` as requested.
  - **Retriever:** Connected to the `ChromaDB` vector store.
  - **Prompting:** Implemented a system prompt that enforces answering strictly based on the provided context.

3.

1. LangGraph Workflow Structure

Developed `langgraph_workflow.py` which implements the following nodes:

  - **Node 1: Classifier:** Uses `gemini-2.5-flash` to categorize queries into `products`, `returns`, or `general`.
  - **Node 2: RAG Responder:** Reuses our RAG logic to answer product-specific questions when the classifier detects a product query.
  - **Node 3: Escalation:** Intercepts `returns` or `general` queries and provides a structured escalation response.
2. Conditional Routing

Implemented routing logic that directs the flow dynamically:

  - `products` → **RAG Responder**
  - `returns` or `general` → **Escalation**

4.

localhost:8000/docs#/

## Product Knowledge Base Chatbot 0.1.0 OAS 3.1

/openapi.json

### default

GET	/ Root
POST	/query Query Chatbot

### Schemas

[HTTPValidationError >](#) [Expand all](#) [object](#)

Code	Details
200	<p>Response body</p> <pre>{  "question": "what is the price of Smartwatch Pro X",  "category": "products",  "answer": "The price of SmartWatch Pro X is ₹15,999."}</pre>

## System Architecture

The system is built with a layered architecture for reliability and intelligence:

1. **Ingestion Layer:** Processes `product_details.txt` into high-quality vector embeddings stored in a local `ChromaDB`.
2. **Orchestration Layer:** A `LangGraph` workflow that classifies user intent and routes queries to either the RAG Responder or an Escalation handler.
3. **Service Layer:** A `FastAPI` application that provides a robust web interface for user interaction.

Outputs:



