Assignment: Zocket

"Prototype: RAG Agent for Marketing Query Research"

Documentation

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Objective

The objective of this prototype is to build a lightweight AI agent that helps marketing teams quickly get actionable insights from existing marketing blog data by answering user queries using Retrieval-Augmented Generation (RAG).

Problem Statement

Marketing teams often need to extract insights for campaign planning from multiple blogs, resources, and notes, which is time-consuming. A lightweight AI agent can reduce manual search time and generate targeted, relevant marketing advice quickly.

Architecture and Tools Used

To design a lightweight AI agent for marketing-relevant research, we implemented a Retrieval-Augmented Generation (RAG) system using:

- FastAPI: To expose the agent as a REST API (POST /run-agent) for seamless Zocket integration.
- ChromaDB (PersistentClient): Used as a vector database to store and retrieve marketing blog chunks efficiently with metadata.
- SentenceTransformers (all-MiniLM-L6-v2): For embedding user queries and document chunks to enable semantic search.
- TinyLLaMA-1.1B-Chat-v1.0: A fast, open-source, lightweight LLM for coherent, marketing-focused response generation.
- Ngrok: To securely expose the FastAPI endpoint from Colab for demonstration and testing.

The pipeline:

- User sends a marketing-related query to the API.
- The query is embedded and used for semantic retrieval of top relevant blog chunks from ChromaDB.
- Retrieved context is compiled into a structured prompt.
- The LLM generates a clear, actionable marketing response.
- The response is returned to the user via the FastAPI endpoint.

Challenges Faced and Solutions

- 1. Environment Management: Ensuring GPU utilization for TinyLLaMA on Colab while managing VRAM constraints for stable generation.
- 2. ChromaDB Deprecation Issues: Migrated to the latest PersistentClient interface to resolve legacy configuration errors.
- 3. Ngrok Authentication: Integrated verified authtoken for stable, secure endpoint exposure.
- 4. Cutoff and Consistency: Adjusted max_new_tokens and eos_token_id to prevent incomplete responses and ensure prompt consistency.
- 5. LLM Selection: Extensively evaluated Mistral, OpenAI GPT, Phi-3, and other open models for balance between speed, quality, and cost before finalizing TinyLLaMA-1.1B-Chat-v1.0 for its fast, low-resource, high-quality generation suited for marketing RAG tasks.

These steps ensured the FastAPI endpoint remains stable, fast, and ready for production workflows.

Potential Improvements and Next Steps

- 1. Agentic RAG Expansion: Extend to multi-step reasoning by chaining sub-agents for query rephrasing or advanced reranking of retrieved documents.
- 2. Knowledge Graph Integration: Introduce a lightweight graph for ad platforms, user intents, and creative types to improve retrieval filtering and precision.
- 3. Evaluation Strategy:
- Relevance Scores: Manual checks on marketing queries.
- Hallucination Rate: Evaluate factual consistency in outputs.
- Latency: Ensure sub-3s response time for usability in real-time marketing workflows.
- Pattern Recognition and Improvement Loop: Integrate a feedback loop or memory nodes (via LangGraph) to refine retrieval and generation quality over time.

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1. Use of Graph RAG / Agentic RAG

- Currently, the agent uses standard RAG, retrieving relevant blog chunks and generating answers using an LLM. It does not yet use Graph-based RAG or Agentic RAG.
- However, in the future, adding Agentic RAG could allow the agent to handle multi-step reasoning, such as first rephrasing unclear queries before retrieval or refining results through re-ranking steps.
- This would improve recall and precision when answering complex marketing queries by structuring the retrieval and generation process in smaller, clear steps.

2. Knowledge Graph Integration

- Currently, the system retrieves data using vector embeddings without using a Knowledge Graph.
- In the future, integrating a Knowledge Graph could help structure domain knowledge like ad platforms, audience intents, or creative types.
- For example, it could map relationships such as "Facebook Ads → Video Ads → Engagement Metrics" to filter and retrieve more relevant content for user queries. This would improve response relevance and precision by providing the LLM with structured context during generation.

3. Evaluation Strategy

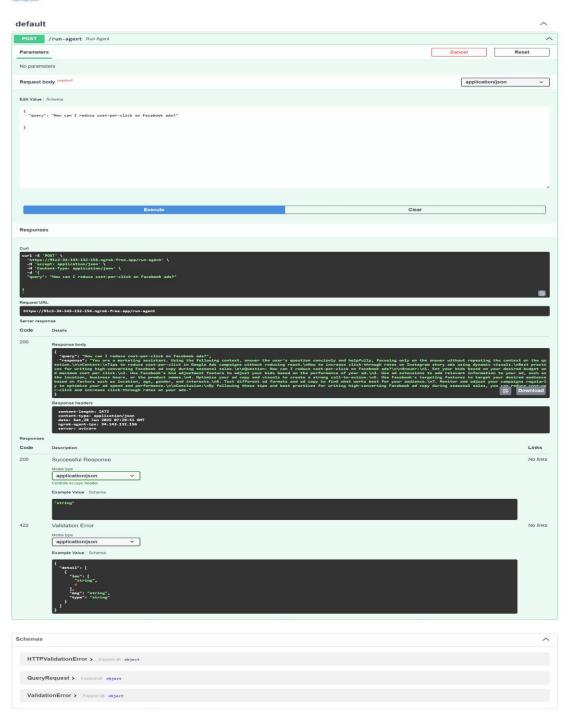
- The agent's performance can be evaluated using the following approach:
- Relevance: Manually check if the agent's answers accurately address the user's marketing questions.
- Hallucination Rate: Track how often the model generates incorrect or unrelated facts.
- Latency: Measure the time taken to generate responses, aiming for fast replies suitable for real-time workflows.
- In advanced stages, automated metrics like F1 score (for extraction accuracy) or ROUGE (for summarization quality) can be added. Initially, manual evaluation will ensure quality control before scaling automated tests.

4. Pattern Recognition and Improvement Loop

- The agent can improve over time by incorporating a feedback loop.
- User feedback (like thumbs up/down or relevance ratings) can be used to refine prompts and retrieval settings.
- Additionally, memory modules can be added to remember user preferences and common query patterns, helping the system adjust context and responses in future interactions. These steps will help the agent adapt, reduce repetitive errors, and improve the accuracy and quality of responses over time.

API Test Results

Zocket RAG Agent (510) (ASS)



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