# Movie Chatbot Development Process

Git Link: https://github.com/maheshsai252/movies-rag

## Demo:


### 1. Domain Selection

**Application:** Movie Chatbot

**Scope and Data Type:**

- The application will handle data related to movies, including movie overview, genres, release dates, and ratings.
- The chatbot will respond to user queries about movies, provide recommendations, and offer information about movie details.

### 2. Data Collection and Preprocessing

**Data Source:** Kaggle dataset on movies, Prompt Engineering to get mock data

**Steps:**

1. **Acquire Data:** Download the movie dataset from Kaggle.

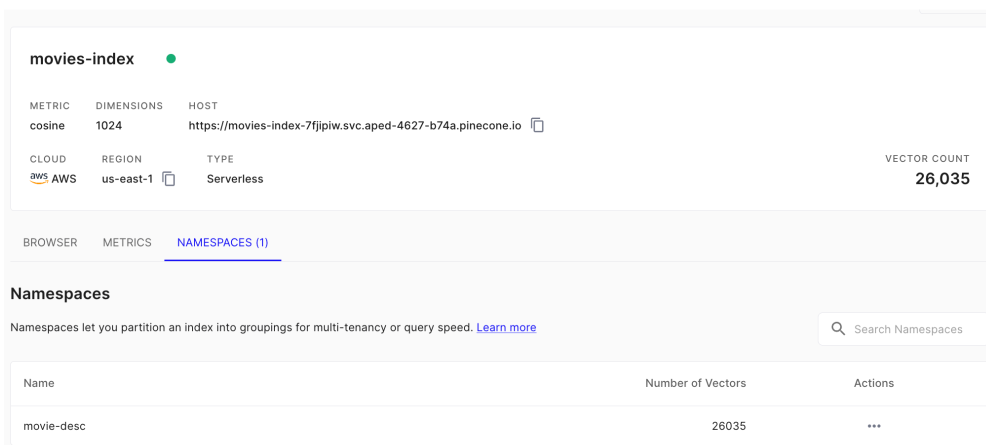
2. **Data Cleaning:**
   - Remove any irrelevant columns or information not needed for the chatbot.
   - Handle missing data by filling in defaults or removing incomplete entries.
   - Generate missing plots of movies using LLM.
3. **Text Preparation:**
   - Remove special characters and unnecessary whitespace.
   - Address missing by prompt - engineering.

## 3. Vector Database Implementation

**Chosen Database: Pinecone**

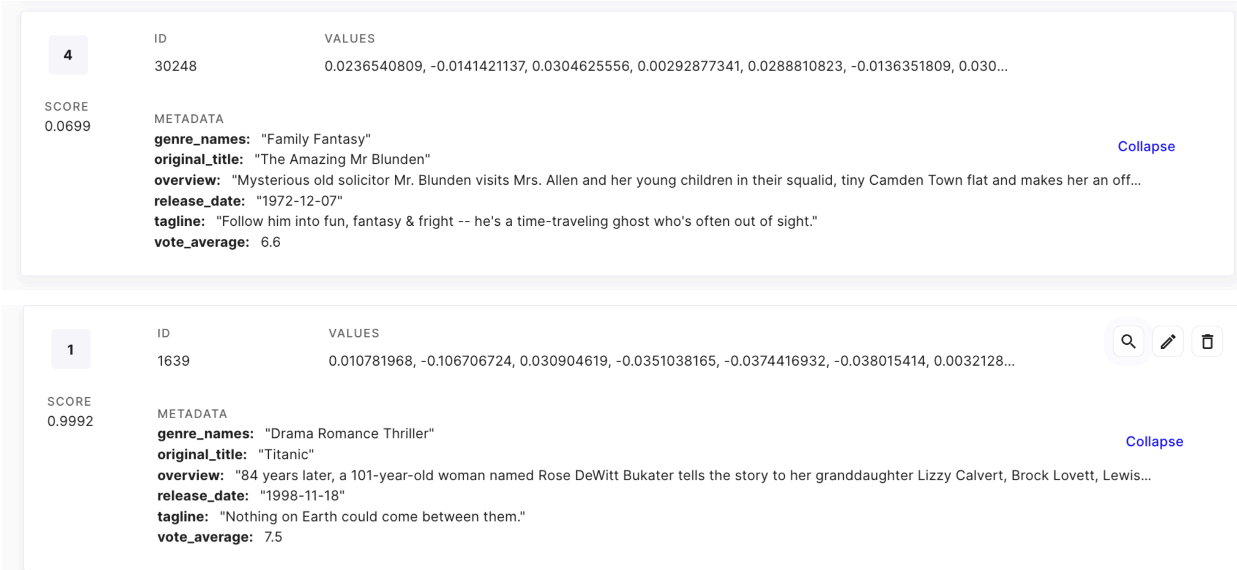
**Steps:**

1. **Setup Pinecone:**
   - Create an account and set up an index in Pinecone.
2. **Data Indexing:**
   - Use sentence transformer to Transform movie descriptions and relevant textual data into embedded vectors.
   - Store these vectors in Pinecone, ensuring efficient indexing for quick retrieval.
3. **Configuration:**
   - Configure the index to support semantic similarity searches, which will allow the chatbot to retrieve relevant movie data based on user queries.




## 4. Upload Data to Vector DB

Upload cleaned data into pinecone vector db. We uploaded around 26k movies




## 5. Application Development

### Frameworks Used: FastAPI for backend, Streamlit for frontend

### Steps:

1. **User Interface:**
   - Designed a simple, user-friendly interface in Streamlit where users can input natural language queries.
2. **Backend Logic:**
   - Implemented a FastAPI backend to handle incoming queries
   - Based on chat history, refine latest user question to standalone question based on chat history. Use a GPT-3.5 instruct to understand user intent and extract relevant information.
   - Use the Pinecone vector database to retrieve the most relevant movie data based on the processed query
   - Embed the retrieved context and refined query into prompt in langchain and send the content to user.
3. **Orchestration**: orchestrated frontend and backend using docker-compose.

## 5. Evaluation and Testing

- Conduct extensive testing with a variety of queries to ensure the chatbot understands and responds accurately.
- Include edge cases and unusual queries to evaluate robustness.

### Testing whether bot can chat without losing context:

**Queries**: Recommend Animated Movies, Should have Sci-FI as well, Add drama

**Hallucination test:**

**Queries**: what is plot of movie 'ksk', changed release year of titanic in vector db and tested asking year

**Complex queries:**

**Queries**: any movies you know involving gang dramas story origin from india

I am going to India for holidays, i want to watch movies on the way that shows the country heritage

I am going to Florida for vacation, show me some movies involving catastrophic situations that can happen there

**Confusing Queries:**

any bollywood movies where good wins over bad
any bollywood movies where good wins over bad

Refer to Demov Video for results from our chatbot

## Steps to Run Application :

- CD to Web-Service
- Place your pinecone_api_key and openai_key.
- "docker-compose build" build requirements
- "docker-compose up" to start the app.

## Challenges Faced

### Data Quality:

**Challenge:** The Kaggle dataset contained incomplete or inconsistent entries.

**Solution:** Implemented robust data cleaning procedures, including filling missing values and removing irrelevant information.

### Vector Database Configuration:

**Challenge:** Ensuring efficient and accurate indexing in Pinecone.

**Solution:** Experimented with different indexing parameters and configurations to optimize performance for semantic similarity searches.

## Query Understanding:

**Challenge:** Ensuring the LLM accurately understands and processes diverse natural language queries.

**Solution:** Tuned prompt of LLM using a variety of techniques learnt in class to improve understanding and accuracy.

## Performance Optimization:

**Challenge:** Maintaining fast response times while handling complex queries.

**Solution:** Tested latency against different retreival mechanisms cosine, dot product and euclidian for latency