# 🎬 Albert Query - Agentic Movie Intelligence System

> An intelligent conversational agent for querying movie and TV series data using Retrieval Augmented Generation (RAG), multi-tool orchestration, and semantic search.


## 📋 Table of Contents



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## 🎯 Overview

**Albert Query** is an agentic AI system we developed as part of our M1 project at **Albert School** in collaboration with **Mines Paris - PSL**. The system intelligently answers questions about movies and TV series by orchestrating multiple data sources and tools through a LangGraph-based workflow.

### What Makes It Special?

Unlike traditional chatbots, Albert Query:

- **Plans before acting** - Analyzes each question to determine which tools are needed
- **Multi-source intelligence** - Combines SQL databases, vector search, external APIs, and web search
- **Semantic understanding** - Uses OpenAI embeddings to find movies by plot similarity
- **Source attribution** - Always shows where information comes from
- **Context-aware** - Maintains conversation history for follow-up questions

### Use Cases

- 🔍 **Semantic Search**: "Find me movies about space exploration with AI themes"

- 📊 **Data Analysis**: "How many comedies were released on Netflix after 2020?"
- 🎭 **Movie Discovery**: "Show me films similar to Inception"
- 📈 **Trend Analysis**: "What are the top-rated action movies from the 2010s?"
- 🌐 **Latest Info**: "What's trending in movies this week?"

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# ✨ Features

## Core Capabilities

### 🧠 Intelligent Query Planning

- LLM-based planner analyzes questions and conversation history
- Automatically selects optimal tools (SQL, Semantic Search, OMDB, Web)
- Avoids unnecessary API calls for efficiency

### 🗄️ Multi-Database SQL Queries

- Comprehensive catalog of 8,000+ movies/shows from Netflix, Disney+, Amazon Prime
- Structured queries with filters (year, genre, rating, type)
- Automatic database schema understanding

### 🔍 Semantic Vector Search

- 114MB of OpenAI embeddings (text-embedding-3-small)
- Find movies by plot descriptions, themes, or similarity
- Natural language queries in English or French

### 🎬 OMDB API Integration

- Enriched movie metadata (actors, awards, ratings, posters)
- IMDb links for detailed information
- Full plot summaries

### 🌐 Web Search

- DuckDuckGo integration for trending topics
- Latest movie news and releases
- Current events in cinema

### 📚 Source Attribution

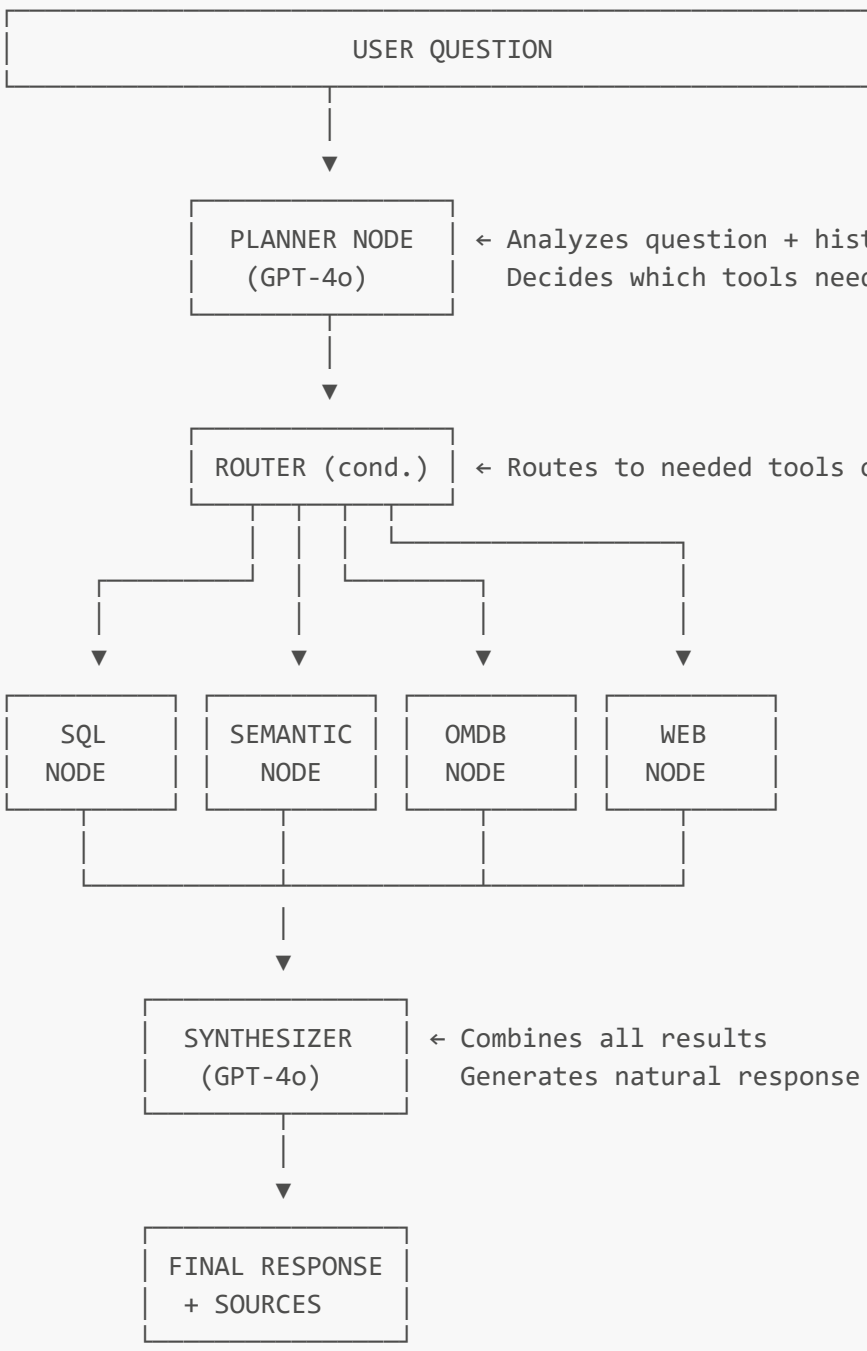
- Tracks all information sources
- Visual display of databases, APIs, and search results used
- Clickable links to IMDb and search results

### 💬 Conversational Memory

- LangGraph checkpointing with MemorySaver
- Full conversation history maintained
- Context resolution ("that movie" → actual movie name)

## Architecture

Our system follows an **agentic architecture** using LangGraph to create a stateful, multi-tool workflow:




## Project Structure

```
Agentic_Systems_with_RAG_Lamy-Waerniers/
│
├── code/                                    # Main source code
│   ├── albert_query_app.py                  # Main Streamlit application (1009
lines)
```

```
│   ├── embedding_manager.py                # Vector embedding management (418
lines)
│   ├── architecture.md                     # System architecture
documentation
│   ├── embeding.ipynb                      # Embedding pipeline notebook
│   ├── SQLdb_creator.ipynb                 # Database creation from CSVs
│   ├── testing.ipynb                       # API and integration tests
│   └── test_semantic_search.ipynb          # Semantic search validation
│
├── data/                                   # Data storage
│   ├── csv_db/                             # Source CSV files
│   │   ├── amazon_prime_titles.csv         # Amazon Prime catalog (3.9MB)
│   │   ├── netflix_titles.csv              # Netflix catalog (3.4MB)
│   │   └── disney_plus_titles.csv          # Disney+ catalog (385KB)
│   ├── databases/
│   │   └── movie.db                        # Consolidated SQLite DB (32.9MB)
│   ├── vector_database/                    # ChromaDB persistent storage
│   │   ├── chroma.sqlite3                  # Vector DB metadata (42.7MB)
│   │   └── 19c0759d-.../                   # Embedding data (114MB)
│   └── memory/                             # Conversation storage
│       ├── conversations/
│       └── user_profiles/
│
├── doc/                                    # Documentation
│   ├── graph_schema.png                    # LangGraph workflow diagram
│   ├── omdb_api_doc.json                   # OMDB API reference
│   └── OMDB_API_doc.txt
│
├── .env                                    # Environment configuration (git-
ignored)
├── .gitignore                              # Git ignore rules
├── requirements.txt                        # Python dependencies (223
packages)
└── README.md                               # This file
```

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## Components

### 1. Main Application (`albert_query_app.py`)

The core orchestrator built with **Streamlit** and **LangGraph**.

**Key Components:**

**Planner Node**

```python
def planner_node(state: AgentState) -> dict:
    """Analyzes question and plans tool usage"""
    # Uses GPT-4o-mini to decide which tools are needed
```

```
    # Returns: needs_sql, needs_semantic, needs_omdb, needs_web flags
    # Also prepares specific queries for each tool
```

**Decision Logic:**

- SQL: For structured data (titles, years, ratings, genres)
- Semantic: For plot-based searches and "movies like X"
- OMDB: For detailed metadata (actors, awards, posters)
- Web: For trending topics and recent news

**SQL Node**

```
def sql_node(state: AgentState) -> dict:
    """Generates and executes SQL queries"""
    # Analyzes database catalog
    # Generates SQL with proper table names, filters
    # Executes query and returns results
```

**Features:**

- Auto-detects correct table names
- Handles genre filtering (comma-separated values)
- Year ranges, type filtering (Movie vs TV Show)
- Result limiting and ordering

**Semantic Search Node**

```
def semantic_search_node(state: AgentState) -> dict:
    """Performs vector similarity search"""
    # Translates query to English if needed
    # Optimizes query for embeddings
    # Searches ChromaDB with OpenAI embeddings
    # Returns top-k similar movies
```

**Important Notes:**

- Movie descriptions are in **English** - queries are auto-translated
- Similarity scores may appear low (40-60%) but rankings are accurate
- Uses cosine similarity on text-embedding-3-small vectors

**OMDB Node**

```
def omdb_node(state: AgentState) -> dict:
    """Fetches enriched movie data from OMDB API"""
```

```
    # Extracts movie title from context
    # Queries OMDB API
    # Returns: plot, actors, awards, IMDb rating, poster URL
```

**Web Search Node**

```
def web_node(state: AgentState) -> dict:
    """Performs web search via DuckDuckGo"""
    # Executes search query
    # Returns recent results with URLs
```

**Synthesizer Node**

```
def synthesizer_node(state: AgentState) -> dict:
    """Combines all results into natural response"""
    # Takes SQL, semantic, OMDB, web results
    # Generates coherent natural language answer
    # Includes source attribution
```

### 2. Embedding Manager (`embedding_manager.py`)

Handles creation and management of vector embeddings for semantic search.

**Key Functions:**

```
def get_or_create_collection(chroma_path,
collection_name="movie_descriptions"):
    """Gets or creates ChromaDB collection with OpenAI embeddings"""

def embed_movies_if_not_exists(collection, movies, batch_size=100):
    """Embeds movies only if not already in collection"""
    # Checks existing IDs to avoid duplicates
    # Batches for efficiency
    # Tracks progress with tqdm

def query_movies(collection, query_text, n_results=5, where_filter=None):
    """Queries movies by semantic similarity"""
    # Embeds query with same model
    # Searches vector DB
    # Returns ranked results with similarity scores
```

**Embedding Structure:**

```
{
    "id": "net0042",                    # Unique ID (prefix + index)
    "document": "A sci-fi thriller...", # Movie description (embedded)
    "metadata": {
        "title": "The Matrix",
        "database": "movie.db",
        "table": "netflix_titles"
    }
}
```

### 3. Database Schema

**SQL Tables:**
Each table (netflix_titles, amazon_prime_titles, disney_plus_titles) contains:

| Column | Type | Description |
|---|---|---|
| show_id | TEXT | Unique identifier (e.g., "s1") |
| type | TEXT | "Movie" or "TV Show" |
| title | TEXT | Movie/show title |
| director | TEXT | Director name(s) |
| cast | TEXT | Comma-separated actors |
| country | TEXT | Production country |
| date_added | TEXT | Date added to platform |
| release_year | INTEGER | Year of release |
| rating | TEXT | Age rating (PG, R, etc.) |
| duration | TEXT | Runtime or seasons |
| listed_in | TEXT | Comma-separated genres |
| description | TEXT | Plot summary |

**Total Records:** ~8,800 movies/shows

### 4. Vector Database

**ChromaDB Collection:**

- Name: `movie_descriptions`
- Embedding Model: OpenAI text-embedding-3-small (1536 dimensions)
- Total Vectors: ~8,800 movie descriptions
- Storage: Persistent on disk (~156MB total)
- Metadata: title, database, table for filtering

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## Workflow

```
User Question
      │
      ▼
[Planner Node]
  Analyzes: question + history
  Decides: which tools needed
  Outputs: needs_sql, needs_semantic, needs_omdb, needs_web
      │
      ▼
[Conditional Router]
  Routes to first needed tool
      │
      ├─→ [SQL Node] ──────────┐
      ├─→ [Semantic Node] ─────┤
      ├─→ [OMDB Node] ─────────┤
      └─→ [Web Node] ──────────┤
                               │
                               ▼
                    [Synthesizer Node]
                    Combines all results
                    Generates response
                               │
                               ▼
                    [Final Response + Sources]
```

## Future Improvements

We've identified several areas for optimization and enhancement. Here's our roadmap:

### 1. **Catalog Caching System**

**Problem:**

- Database catalog is rebuilt on every app startup
- Slow initialization (~2-5 seconds)
- Redundant SQL queries for schema introspection

**Solution:**

```python
# Implement caching with invalidation detection
def get_or_build_catalog(db_path: str, cache_path: str) -> dict:
    """
    Cache database catalog as JSON
    - Compare file modification times to detect changes
    - Load from cache if DB unchanged
    - Rebuild only when necessary
    """
```

**Expected Impact:**

- ⚡ 10-50x faster startup time
- 💾 Reduced SQL queries
- 🔄 Auto-invalidation on schema changes

**Implementation:**

- Save catalog to `data/databases/catalog_cache.json`
- Include DB file mtime and size for change detection
- Add force-rebuild option for manual invalidation

### 2. 🧠 Persistent Long-Term Memory

**Current State:**

- Memory stored in LangGraph's MemorySaver (in-memory only)
- Lost on application restart
- No cross-session learning

**Proposed Architecture:**

```
# SQLite-based conversation storage
conversations/
  ├── user_123/
  │   ├── session_20250116_001.json    # Conversation history
  │   ├── session_20250116_002.json
  │   └── preferences.json              # Learned preferences
  └── user_456/
      └── ...

# Conversation schema
{
  "session_id": "20250116_001",
  "user_id": "user_123",
  "timestamp": "2025-01-16T10:30:00Z",
  "messages": [...],
  "topics": ["action movies", "2020s cinema"],
  "preferences_learned": {
    "favorite_genres": ["action", "sci-fi"],
    "preferred_platforms": ["netflix"]
  }
}
```

**Features to Add:**

- 💾 Persist conversations to disk (JSON or SQLite)
- 👤 User-specific history and preferences

- 🔍 Semantic search over past conversations
- 📊 Analytics on user interests
- 🎯 Personalized recommendations based on history

**Technical Implementation:**

- Replace MemorySaver with custom SQLiteCheckpointer
- Add user authentication (see #3)
- Implement conversation summarization for long histories
- Privacy controls (GDPR compliance)

### 3. 🔐 User Management & API Key Interface

**Current Limitation:**

- Single shared API keys in `.env`
- No multi-user support
- API costs not attributable to users

**Proposed UI:**

```
┌─────────────────────────────────────┐
│  ⚙️ Settings                        │
├─────────────────────────────────────┤
│  User ID: [user_123]                │
│                                     │
│  🔑 OpenAI API Key:                 │
│  [sk-proj-******************] [Save]  │
│                                     │
│  🎬 OMDB API Key:                   │
│  [8871ab87           ] [Save]       │
│                                     │
│  💰 Token Usage This Session: 1,234 │
│  💵 Estimated Cost: $0.05           │
│                                     │
│  [Clear History] [Export Data]      │
└─────────────────────────────────────┘
```

**Implementation:**

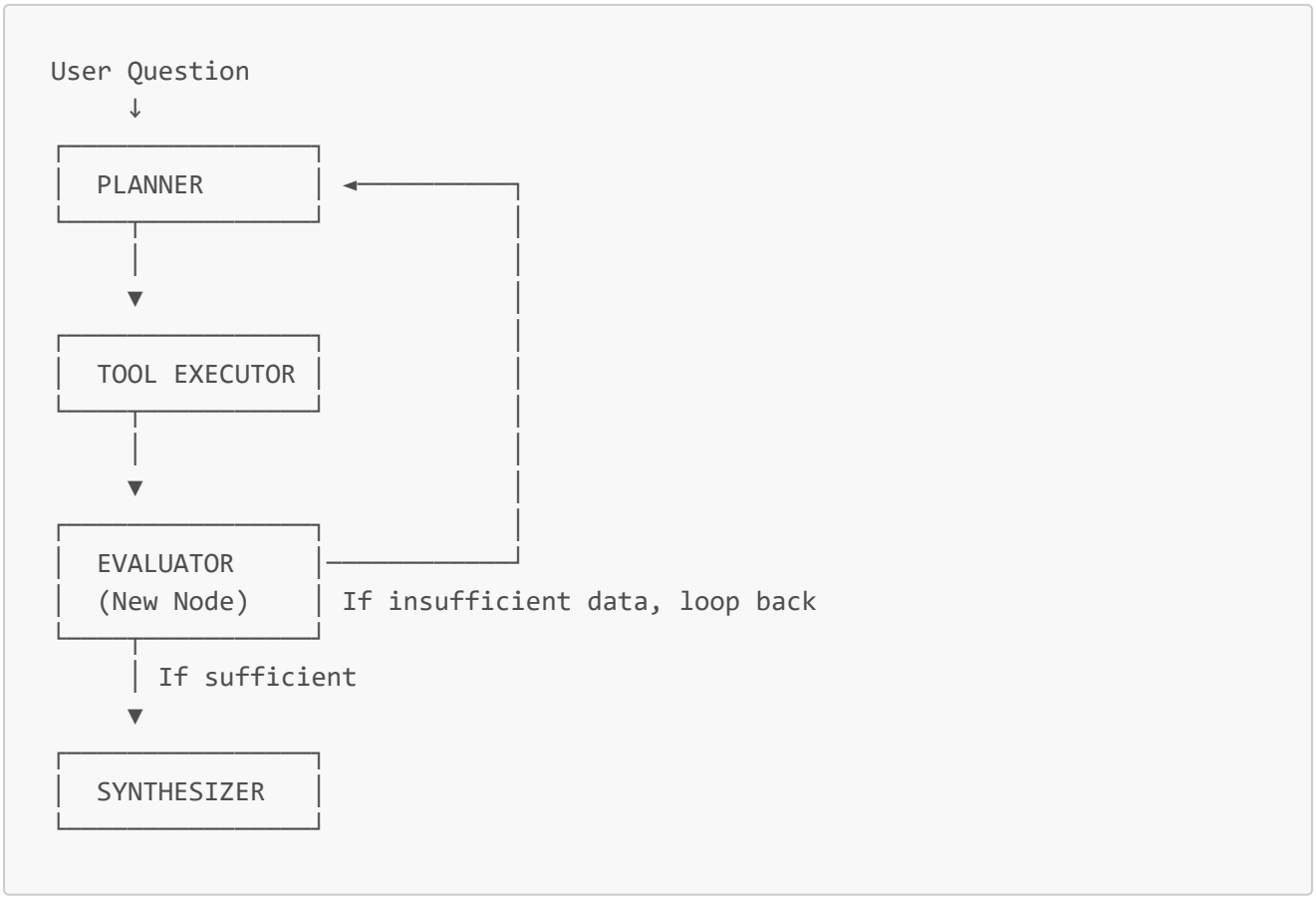
- Streamlit sidebar with settings panel
- Encrypted key storage per user (keyring library)
- Session-based authentication
- Token tracking and cost estimation
- Rate limiting per user

### 4. 🔄 Workflow Enhancement: Planner Loop

**Current Issue:**

- Linear workflow: Planner → Tools → Synthesizer → End
- No feedback loop if initial plan was insufficient
- Cannot self-correct or ask for more tools

**Proposed Architecture:**




**Evaluator Node Logic:**

```python
def evaluator_node(state: AgentState) -> dict:
    """
    Checks if gathered data is sufficient to answer question
    Returns: continue (to synthesizer) or replan (back to planner)
    """
    results_quality = assess_data_completeness(state)

    if results_quality["sufficient"]:
        return {"next": "synthesize"}
    else:
        # Request additional tools
        return {
            "next": "planner",
            "feedback": "Need more data: " + results_quality["missing"]
        }
```

**Benefits:**

- 🔁 Self-correcting behavior
- 🎯 More complete answers
- 🧠 Adaptive tool selection
- ⚡ Avoids premature responses

## 5. 📈 Embedding Quality Improvements

**Current Limitations:**

- Similarity scores often low (<50%)
- Movie descriptions are single sentences only
- No chunking strategy
- Basic embedding model (text-embedding-3-small)

**Improvement Strategies:**

**A. Enhance Movie Description Quality (Priority #1)**

Currently, we only embed the plot description field from databases (single sentence).

**Solution:**
Use APIs to enrich our database with way longer movie descritions.
Expected Impact:

- 🎯 More contextual embeddings
- 📈 Better similarity scores (10-20% improvement)
- 🔍 Genre/cast matching in semantic search

## 6. 📋 Structured Output Enforcement

**Problem:**

- JSON parsing errors possible in synthesizer
- Inconsistent response formats
- Difficult to extract structured data

**Solution - Pydantic Models:**

```
from pydantic import BaseModel, Field
from typing import List, Optional

class MovieResult(BaseModel):
    title: str
    year: int
    rating: Optional[str]
    genres: List[str]
    description: str
    source: str  # "sql", "semantic", "omdb"

class QueryResponse(BaseModel):
```

```
    answer: str = Field(..., description="Natural language answer")
    movies: List[MovieResult] = Field(default=[], description="Structured movie
data")
    sources: List[str] = Field(..., description="Sources used")
    confidence: float = Field(..., ge=0, le=1, description="Confidence score")
    follow_up_suggestions: List[str] = Field(default=[], description="Suggested
follow-up questions")

# Use in synthesizer
structured_llm = llm.with_structured_output(QueryResponse)
response = structured_llm.invoke(synthesis_prompt)
```

**Benefits:**

- ☑ Guaranteed valid JSON
- ☑ Type safety
- ☑ Easier frontend integration
- ☑ Better error messages

## 7. 🎯 Token Optimization

**Current Issues:**

- Prompts are verbose (500-800 tokens each)
- Full database catalog sent to planner (1000+ tokens)
- Conversation history grows unbounded

**Optimization Strategies:**

**A. Prompt Compression**

**B. Catalog Summarization**

**C. Conversation Summarization**

**D. Lazy Loading**

**Expected Savings:**

- 📉 60-70% reduction in prompt tokens
- 💰 ~$0.02 → $0.005 per query
- ⚡ Faster LLM responses

## 8. 🎨 UI/UX Enhancements

**Proposed Features:**

- 📊 **Results Table View** - Toggle between chat and table display
- 🎬 **Movie Cards** - Rich display with posters, ratings, cast
- 📈 **Query Statistics** - Show token usage, cost, response time

- **Dark Mode** - Theme switching
- **Export Results** - Download conversations as JSON/CSV
- **Voice Input** - Speech-to-text for queries
- **Multi-language Support** - Full i18n for French/English
- **Mobile Responsiveness** - Optimize for mobile devices
- **Keyboard Shortcuts** - Power user features

## 9. Testing & Quality Assurance

**Current Gap:** No automated tests

**Coverage Goals:**

- Unit tests for each node
- Integration tests for workflow
- Performance benchmarks
- Regression tests for common queries

## 10. Security & Privacy

**Enhancements Needed:**

- API key encryption at rest
- Input sanitization (SQL injection prevention)
- PII detection and redaction in conversations
- Audit logging for all queries
- Rate limiting and abuse prevention
- HTTPS enforcement in production
- Content filtering for inappropriate queries

## 11. Performance & Scalability

**Optimization Opportunities:**

- **Async Tool Execution** - Run SQL, Semantic, OMDB in parallel
- **Result Caching** - Cache common queries (Redis)
- **Vector Index Optimization** - Use HNSW parameters tuning
- **Database Indexing** - Add indexes on common query columns
- **Connection Pooling** - Reuse DB connections
- **Deployment** - Docker + cloud hosting (AWS/GCP)
- **CDN Integration** - Cache static assets

## 12. Analytics & Monitoring

**Tracking Metrics:**

- Query latency by tool type
- Cost per query (token usage)
- Tool selection accuracy (planner effectiveness)

- 👥 User engagement metrics
- ❌ Error rates and types
- 🔍 Most common queries and topics
- 📊 Semantic search quality metrics

## 👥 Contributors

This project was developed as part of our Master's degree at **Albert School X Mines Paris - PSL**.

**Team:**

- Vincent Lamy & Alexandre Waerniers

**Institution:**

- Albert School (Paris, France)
- Mines Paris - PSL

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## 📄 License



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