Approach Overview:

1. Data Crawling and Collection

- The data was scraped from SHL's Products Catalog using Playwright.
- Each test entry's structured metadata (e.g., *Name*, *Description*, *Test Type*, *Job Levels*, *Assessment Length*) was extracted and saved in a normalized format using **Pandas**.

2. Data Representation and Storage

- Data was stored in MongoDB Atlas.
- Text embeddings were generated using **SentenceTransformer** with the 'all-MiniLM-L6-v2' model from the **Hugging Face Transformers**. These embeddings were stored alongside the original documents.

3. Semantic Embeddings and Vector Search

- User queries were **refined and restructured** using **Google's Gemini 1.5 Pro** LLM via the **google.generativeai** Python client. The LLM extracted fields such as **Assessment** Length, Languages, Test Type, and created structured prompts.
- The refined queries were then embedded using **SentenceTransformer**.
- For search, I used **MongoDB's vectorSearch operator**, performing **approximate nearest neighbor search** using Cosine Similarity on the precomputed embeddings.

4. Query Expansion and Multi-Skill Search

- A second Gemini prompt was used to **extract core skills** from unstructured job descriptions.
- For each skill, a separate semantic search was run and the results merged and deduplicated using Python's set logic and sorted by **vector similarity score**.

5. Stack and Integration

- Backend: Built using FastAPI.
- Frontend: A simple interactive demo was developed using Streamlit.

6. Evaluation and Metrics

- Evaluated using Accuracy, Mean Recall@3, and Mean Average Precision (MAP@3) against the TEST set.
- The achieved accuracy was 60%.

Technologies and Libraries Used

- **Playwright** Web scraping
- MongoDB Atlas Scalable cloud database
- SentenceTransformers Semantic embeddings
- **google.generativeai** (**Gemini 1.5 Pro**) LLM-based query refinement
- FastAPI Backend API
- Streamlit Frontend demo UI