

Job–Applicant Recommendation System

Problem Statement

Recruiters struggle to efficiently match applicants with jobs because manual screening is **time-consuming, inconsistent, and error-prone**. This leads to missed talent, delayed hiring cycles, and poor candidate experience. An automated, intelligent recommendation system is needed.

Objectives

- Automate **job–applicant matching** using AI.
- Convert job and applicant **skills into vector embeddings** with SentenceTransformer (all-MiniLM-L6-v2).
- Compute **cosine similarity** for skills and align with **experience requirements**.
- Apply a **weighted scoring system** (70% skills, 30% experience).
- Provide **explainable feedback** (matched/missing skills, experience gaps).

Methodology

1. Skill Similarity (70%)

- Job and applicant skills → embeddings (384-dim vectors).
- Cosine similarity used to score overlap.

2. Experience Score (30%)

- Applicant's experience compared to job's min–max range.
- Full points if within range, scaled down if under/over.

3. Final Match %

$$\text{Score} = (0.7 \times \text{Skill Similarity}) + (0.3 \times \text{Experience Score})$$

4. Penalty System

- Missing required skills → reduce similarity score.
- Underqualified experience → stronger penalty than overqualified.
- Extra unrelated skills → ignored (no bonus).

Model Building at Startup

Steps:

1. Fetch Job Data

- The system queries the PostgreSQL database and retrieves all job postings, including job IDs, titles, required skills, and experience ranges.

2. Skill Embedding Conversion

- Required job skills are processed using the SentenceTransformer model (all-MiniLM-L6-v2).
- Each job's skills are converted into a 384-dimensional embedding vector.

3. Build Job Embedding Matrix

- All job vectors are stacked into a matrix (using NumPy/Pandas) for fast similarity calculations.
- This acts as the feature space for job–applicant matching.

4. Initialize Job Matching Model

- The JobMatchingModel class is initialized with:
 - Job metadata (ID, title, min/max experience).
 - Precomputed skill embeddings.

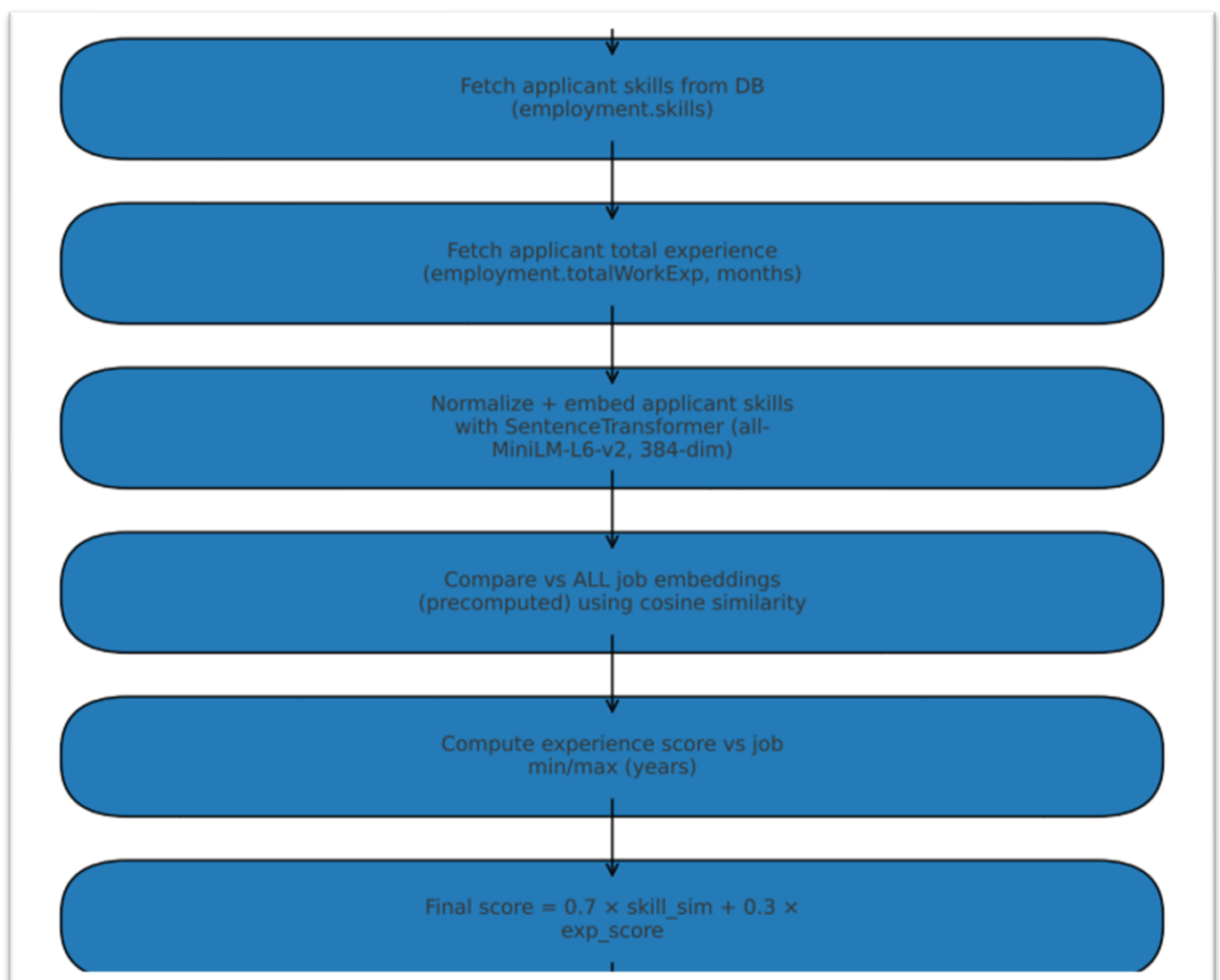
5. Persist Model (Caching)

- The trained model object is serialized and stored as job_matching_model.joblib using joblib.
- This allows quick loading on subsequent restarts without recomputing embeddings.

In this project, we have implemented 3 main flows:

Flow 1 (Jobs for an Applicant):

Recommends the top matching jobs for a given applicant based on skill similarity and experience alignment.



OUTPUT:

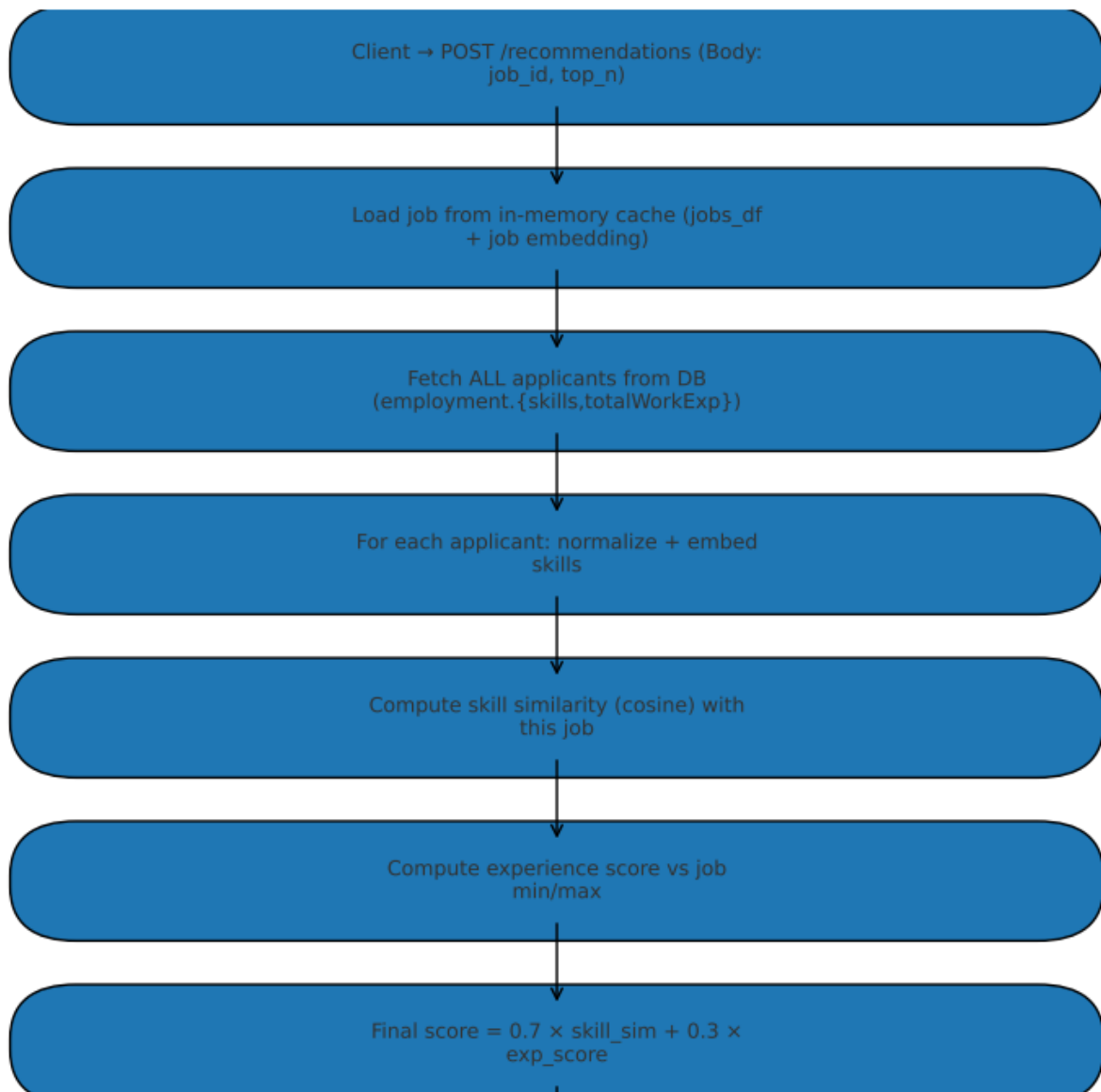
The screenshot shows a REST client interface with a POST request to `http://127.0.0.1:8080/recommendations/`. The request body is a JSON object: `{ "applicant_id": "AINN4500", "top_n": 5 }`. The response is a 200 OK status with a 1.50 s response time and 1.18 KB body size. The response is visualized as a table with 4 columns: Job ID, Job Title, Match Percentage, and Feedback.

Job ID	Job Title	Match Percentage	Feedback
JDAA7053	Backend Developer	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: -2.1 yrs Job Req: 1.0-2.0 yrs). Skills Score: 100.0%.
JDTS2269	Testing Soft	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: -2.1 yrs Job Req: 1.0-5.0 yrs). Skills Score: 100.0%.
JDJA4660	Java	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: -2.1 yrs Job Req: 1.0-2.0 yrs). Skills Score: 100.0%.
JDAD1961	Associate Developer	54.46	Skills: 0/1 matched. Missing: coding knowledge.... Exp Match: 100.0% (Applicant: -2.1 yrs Job Req: 0.0-8.0 yrs). Skills Score: 34.9%.
JDA7163	Associate	50.19	Skills: 0/1 matched. Missing: skill.... Exp Match: 100.0% (Applicant: -2.1 yrs Job Req: 0.0-10.0 yrs). Skills Score: 28.8%.

- Sort by score and select top N jobs.
- Generate readable feedback: matched skills, missing skills, and experience match.
- Return JSON response

Flow 2 (Applicants for a Job):

Finds the most suitable applicants for a specific job using precomputed job embeddings and scoring.



OUTPUT:

The screenshot shows a REST client interface with a POST request to `http://127.0.0.1:8080/recommendations/`. The request body is a JSON object: `{ "job_id": "JDTS2269", "top_n": 5 }`. The response is a 200 OK status with a 5.43 s response time and 1.04 KB of data. The response body is a JSON array of 5 objects, each containing an Applicant ID, Match Percentage, and Feedback.

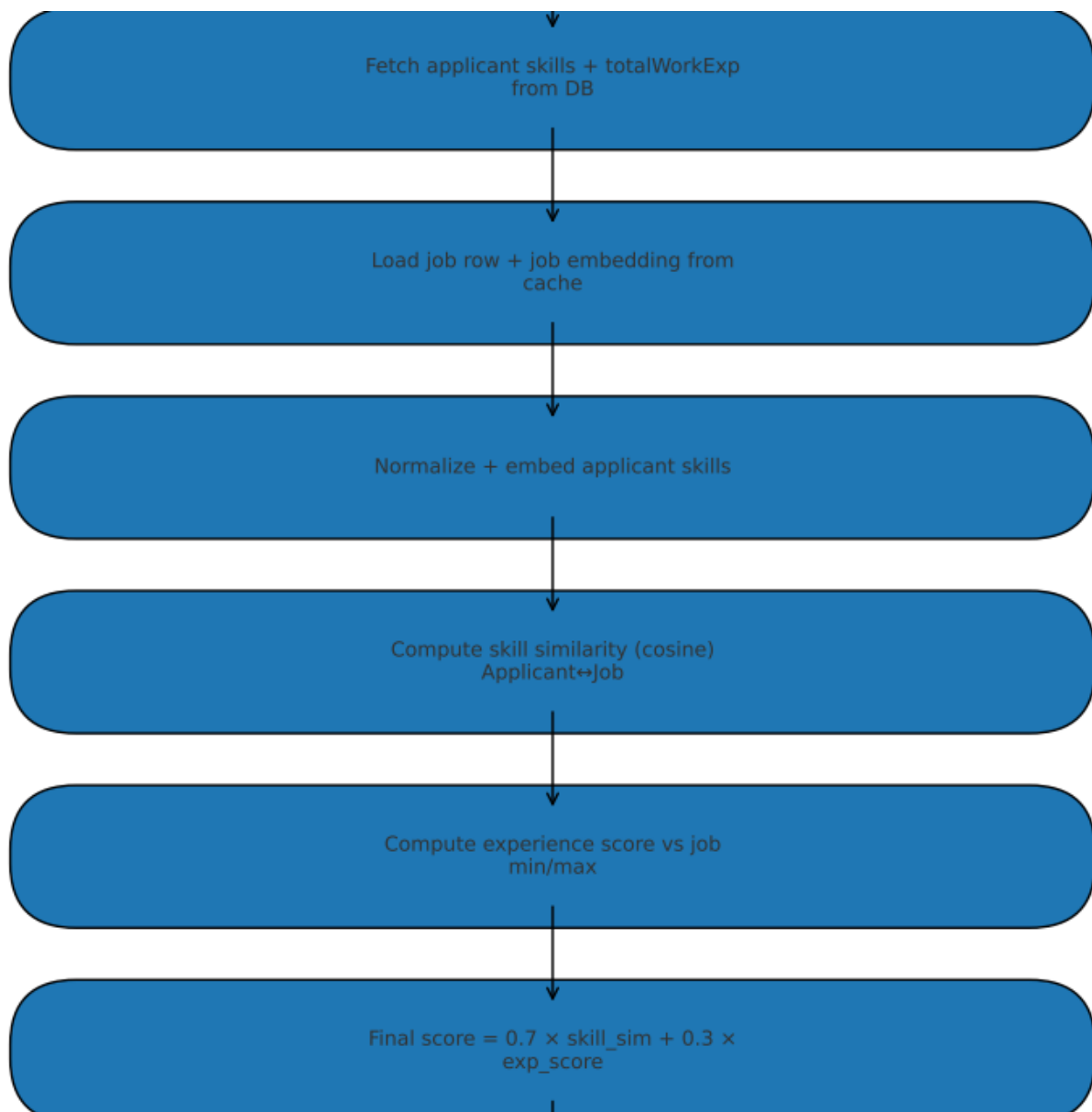
Applicant ID	Match Percentage	Feedback
AITC7852	100	Skills: 1/1 matched. Exp Match: 100.0% (Applicant: 2.2 yrs Job Req: 1.0-5.0 yrs). Skills Score: 100.0%.
AIDS2701	70.22	Skills: 1/1 matched. Exp Match: 100.0% (Applicant: 2.2 yrs Job Req: 1.0-5.0 yrs). Skills Score: 57.5%.
AIRK4969	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: 0.0 yrs Job Req: 1.0-5.0 yrs). Skills Score: 100.0%.
AITD4835	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: 0.0 yrs Job Req: 1.0-5.0 yrs). Skills Score: 100.0%.
AINN4500	70	Skills: 1/1 matched. Exp Match: 0.0% (Applicant: -2.1 yrs Job Req: 1.0-5.0 yrs). Skills Score: 100.0%.

- Sort by score and select top N applicants
- Generate feedback for each applicant
- Return JSON

Flow 3 (Applicant vs Job):

Provides a detailed compatibility score and feedback for a single applicant–job pair.

Evaluate One Applicant vs One Job



OUTPUT:

POST

http://127.0.0.1:8080/recommendations/

Send

ParamsAuthHeaders (8)BodyScriptsSettings

rawJSON

Cookies

Beautify

```
1 {
2   "applicant_id": "AIDS2701",
3   "job_id": "JDTS2269"
4 }
```

Body

200 OK • 1.90 s • 347 B •

{ } JSON

Preview

Visualization

Applicant ID	Job ID	Job Title	Match Percentage	Feedback
AIDS2701	JDTS2269	Testing Soft	70.22	Skills: 1/1 matched. Exp Match: 100.0% (Applicant: 2.2 yrs Job Req: 1.0-5.0 yrs). Skills Score: 57.5%.