

Personalized Job Recommendation

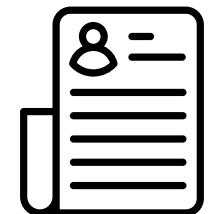
APAN 5430 - Group 4

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Business Background & Problem



In an **online job application portal and ATS** today, most recruitments are **relying on keyword-based search** and matching where recruiters enter skill keywords or technical skill, and candidates are ranked only by those texts overlap.

This approach overlooks:

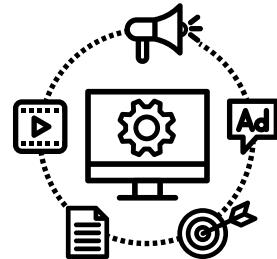
- 1. Candidate contextual relevance
- 2. Full story of candidate's background



System overlooks lead to:

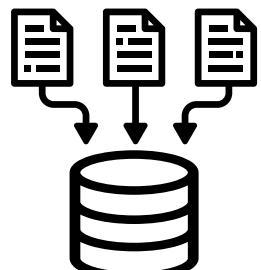
- 1. Missed the right candidate opportunity
- 2. Poor overall match quality

Project Goal and Use Case



The goal of this project is to **develop a personalized job recommendation system**:

- Calculates a **match score** between a candidate's resume & job descriptions
- **Rank job postings by compatibility**, showing the most relevant and well-aligned positions first, based on **both explicit qualifications and implicit signals**
- Provides **resume improvement recommendation** using LLM



Use case:

- **Candidate side:** Upload their resumes to receive a ranked list of job openings that best fit
- **Recruiter side:** Identify the most relevant candidates based on overall profile similarity.

Data source

Linkedin

The goal is to combine data from two sources:

- **LinkedIn Job Board:** Most up-to-date and realistic job postings
- **Hugging Face job dataset:** to ensure sufficient data volume and diversity of jobs listed



Web Scraping from Linkedin Job Board

- Scrapped ~30K LinkedIn job posts using linkedin_jobs_scraper
- 100 predefined titles (e.g., Digital Marketing Specialist)
- Extracted fields: Job Title, Company, Date, Link, Insights, Description
- Saved up to 10K records per JSON file (30K Total)



Job Description Data Set

The raw data source contained 22 columns with details about job opportunities. We adjusted the dataframe and filtered unnecessary columns. Finally, we have ~1GB data set filtered and includes only 10 important columns for the project

Source: https://huggingface.co/datasets/l0f223/job_description

Combined Dataset Size: 1.2GB

1. Job Title - The title of the job position
2. Company - The company name
3. Company Link - URL link to the company
4. Date - The date the job was posted
5. Date Text - Text representation of the date
6. Job Link - URL link to the job posting
7. Insights - Additional insights about the job
8. Description Length - The character count of the job description
9. Description - The full text of the job description

Hugging Face

A screenshot of a Jupyter Notebook cell showing the output of `df_all_jobs.info()`. The output provides a detailed summary of the DataFrame's structure, including the number of rows (1615940), the number of columns (11), and the data types for each column. The columns listed are Job Id, Experience, Salary Range, location, Country, Job Posting Date, Job Title, Company, Job Description, Benefits, and skills.

| # | Column | Non-Null Count | Dtype |
|----|------------------|----------------|-----------------|
| 0 | Job Id | 1615940 | non-null int64 |
| 1 | Experience | 1615940 | non-null object |
| 2 | Salary Range | 1615940 | non-null object |
| 3 | location | 1615940 | non-null object |
| 4 | Country | 1615940 | non-null object |
| 5 | Job Posting Date | 1615940 | non-null object |
| 6 | Job Title | 1615940 | non-null object |
| 7 | Company | 1615940 | non-null object |
| 8 | Job Description | 1615940 | non-null object |
| 9 | Benefits | 1615940 | non-null object |
| 10 | skills | 1615940 | non-null object |

dtypes: int64(1), object(10)
memory usage: 135.6+ MB

*Final columns in each data sources

Selected technologies & Rationale

01 Named Entity Recognition

Purpose:

To extract explicit, **factual entities** from resumes and job descriptions.

- Detects skills, company names, job titles, certifications, degrees, and other key entities.
- **Captures what the candidate knows or has done.**

NER: Skill Score

02 Word/Sentence Embedding

Purpose:

To measure **contextual similarity** between Resume and JD text.

- Computes similarity between the two embeddings to evaluate semantic closeness.
- **Captures what the candidate meant in the resume, even when the wording is different.**

Word Embedding: Semantic Score

03 Topic Modeling

Purpose:

To identify which **domain or industry topics** each document belongs to (e.g., Data Science, Finance).

- Trains an LSA model on JD text to learn latent topic distributions.
- **Captures whether both texts belong to the same industry or domain.**

Topic Modeling: Topic Score

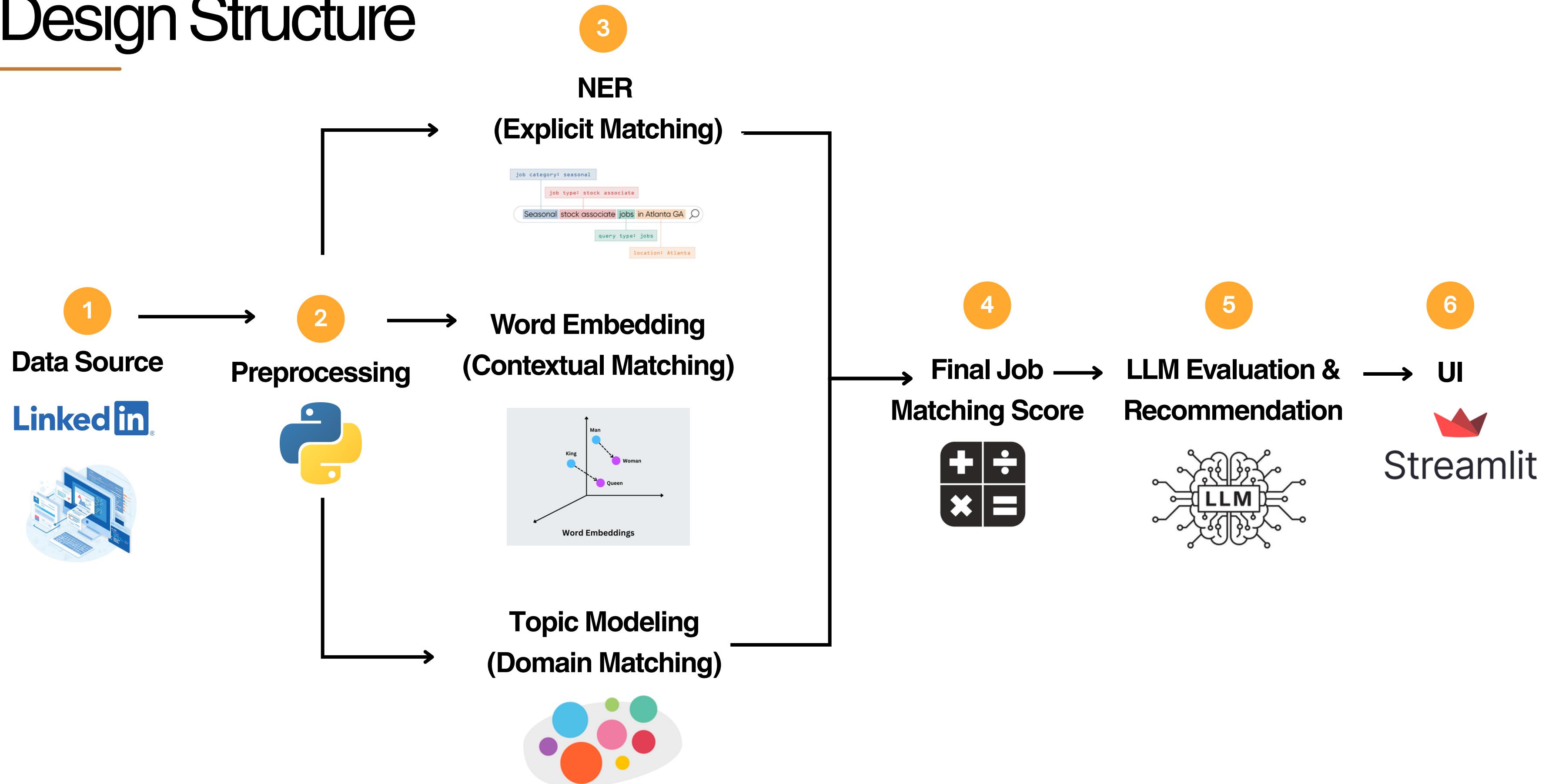
Integrated Scoring Engine - Job Recommendation

Candidate Matching Score Formula: $0.45 \times \text{SkillScore} + 0.35 \times \text{SemanticScore} + 0.20 \times \text{TopicScore}$

$\text{avg_topic_semantic} = (\text{topic_score} + \text{semantic_score}) / 2$

Selected Final Job Matching Score Formula = $\text{avg_topic_semantic} + (1 - \text{avg_topic_semantic}) * \text{skill_score}$

Design Structure



Development Process

Data Cleaning

Resume

- **Text extraction** using pymupdf package
- **Text Cleaning & Normalization**
 - Remove Invisible Characters
 - Remove Personal Identifiable Information sections (Name, Email, Address)
 - Strip HTML and Special Entities
 - Whitespace & Layout Cleaning
 - Reformat Bullet Points & Fix Typography
 - Keep Only Meaningful Resume Sections
- **Save final cleaned resume dataset**

Job Post

- **Unify required text fields** into a single column
- **Text Cleaning & Normalization**
 - Unicode normalize + remove zero-width characters
 - Remove emails, phone numbers, URLs
 - Remove names like: linkedin jobs, glassdoor jobs, etc.
 - Normalize bullet points
 - Whitespace & Layout Cleaning
- **Identify and remove duplicate** job descriptions
- **Save final cleaned job description dataset**

Data Cleaning - Result

Resume

===== CLEANED TEXT PREVIEW =====

SKILLS

- Programming & Analytics: Python, R – Version Control: Git,
- Databases & Data Management: PostgreSQL, MongoDB – Environment Contr (NoSQL), Navicat, SAP ERP – Microsoft: Excel, PowerPoint, Word, Outloo

PROFESSIONAL EXPERIENCE

CEF SOLUTIONS, INC. CONSULTING Seoul, South Korea

Business Enablement Associate Sep 2023 – Mar 2024

- Conducted market research and workflow analysis for a leading Asian synthesizing insights that informed strategic recommendations adopted
- Designed and delivered proposal decks and presentations for stakeholders stakeholder decision-making.
- Optimized and standardized process workflows for new initiatives res
- Managed project timelines and deliverables, leading structured meetings continuous progress.

SAMSUNG ELECTRONICS AMERICA Ridgefield Park, USA

Data Analyst Jul 2022 – Jul 2023

- Performed data validation and exploratory analysis for extensive vendor reducing transaction errors and ensuring data integrity.
- Conducted P&L analysis leveraging financial datasets to optimize priorities long-term operational sustainability.
- Analyzed large volumes of customer chargeback cases, investigating discrepancies and strengthen vendor compliance.
- Leveraged SAP ERP extractions and Power Query to create recurring reports efficiency and ensuring consistent accuracy.
- Monitored dashboard data accuracy, identified issues, and delivered timely resolutions.

Job Post

----- Last cleaned job text (wrapped, width=100) -----

Job Title: Business Development Consultant (Travel Partnerships)
CloudofGoods.com Role: Business Development Consultant (Part-Time)
Miami, Port Canaveral), Los Angeles, Anaheim, Las Vegas, Atlanta
hours/week About Cloud of Goods Cloud of Goods is the largest e-commerce company in the U.S., delivering mobility scooters, wheelchairs, strollers, cribs, and other travel essentials to U.S. cities and select international destinations. We make travel easier for elderly travelers, families with children, and those who need accessible destinations. Role Overview We are seeking part-time Business Development Consultants to establish partnerships with travel industry organizations, attractions, cruise lines, conference centers, travel agencies, and more, focused on outbound business development (cold calling, cold emails, etc.) with the goal of signing partnership agreements or MOUs. Consultants will招揽 local travel industry partners into our affiliate program, where customers who rent through CloudofGoods.com. Key Responsibilities and Approach Potential Partners: hotels, attractions, cruises, car rental companies, tour operators. Pitch Cloud of Goods' rental marketplace and explain its benefits to guests/customers. Negotiate and secure agreements, MOUs, or affiliate programs. Conduct cold calls, cold emails, and in-person site visits to generate leads and demos about Cloud of Goods services. Build strong local relationships with travel industry partners and contribute to the overall hospitality ecosystem. Affiliate Program Growth Sign up travel agents and tour operators to Cloud of Goods' affiliate program. Promote affiliate benefits, including discounts and commissions, to referring customers. Support affiliates with onboarding and marketing resources. Representation Represent Cloud of Goods in local travel industry events and trade shows. Provide feedback on market trends, competitive analysis, and opportunities for growth.

Named Entity Recognition - Skill Extraction

Modeling Pipeline

1

Custom Skill Dictionary

- Master Skill Dictionary combines 530 core technical and business skills with extended multi-industry

2

Identify technical skills and keywords

- Convert unstructured text into structured skill entities
 - Resumes
 - Job descriptions

3

Utilize pretrained NLP model - spaCy

- en_core_web_lg → (higher accuracy)
- Create a Skill Matcher using PhraseMatcher
 - Skill in skill list → mark them as “SKILL.”
- Tokenization: Splitting text into small pieces
- Name Entity Recognition: Labeling important entities in text.

4

Final Similarity Score

- Jaccard Similarity Score (Resume vs Job)

Extracted Skills - Resume

SKILLS

- Programming & Analytics: Python SKILL, R SKILL - Version Control: Git SKILL,
- Databases & Data Management: PostgreSQL SKILL, MongoDB SKILL - Environment Control: Docker SKILL
 - (NoSQL SKILL), Navicat, SAP SKILL SAP ERP SKILL - Microsoft: Excel SKILL, PowerPoint, Word, Outlook

PROFESSIONAL EXPERIENCE

CEF SOLUTIONS, INC. CONSULTING Seoul, South Korea

Business Enablement Associate Sep 2023 – Mar 2024

- Conducted market research SKILL and workflow analysis for a leading Asian financial institution's auto-loan initiative, synthesizing insights that informed strategic recommendations adopted by senior management.
- Designed and delivered proposal decks and presentations for stakeholders, enhancing project clarity and accelerating stakeholder decision-making.
- Optimized and standardized process workflows for new initiatives resulting in notable increases in operational efficiency SKILL.
- Managed project timelines and deliverables, leading structured meetings and documentation to ensure alignment and

Extracted Skills - Job Post

Event Manager

Specialize in conference and convention planning. Coordinate speaker sessions, exhibitors, and attendee experiences.

Oversee event registration and marketing.

A Conference Manager coordinates and manages conferences, meetings, and events. They plan logistics SKILL, handle budgeting SKILL, liaise with vendors, and ensure the smooth execution of events, catering to the needs and expectation of attendees.

Event planning SKILL Conference logistics SKILL Budget management Vendor coordination Marketing and promotion

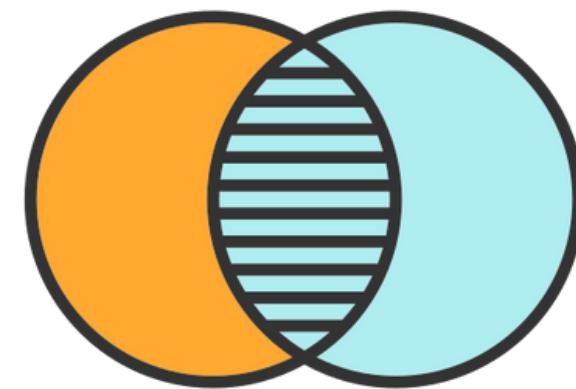
Client relations

Named Entity Recognition - Score and Result

Jaccard Similarity Score Calculation

Resume
Extracted
Skills

Job Description
Extracted Skills



What both sets share (overlap)

What they have in total (union)

$$\text{Jaccard} = |A \cap B| / |A \cup B|$$

Example

[A] Resume Skills

{python, sql, tableau, aws}

[B] Job Description Skills

{sql, python, excel, aws, communication}

Jaccard Similarity Score

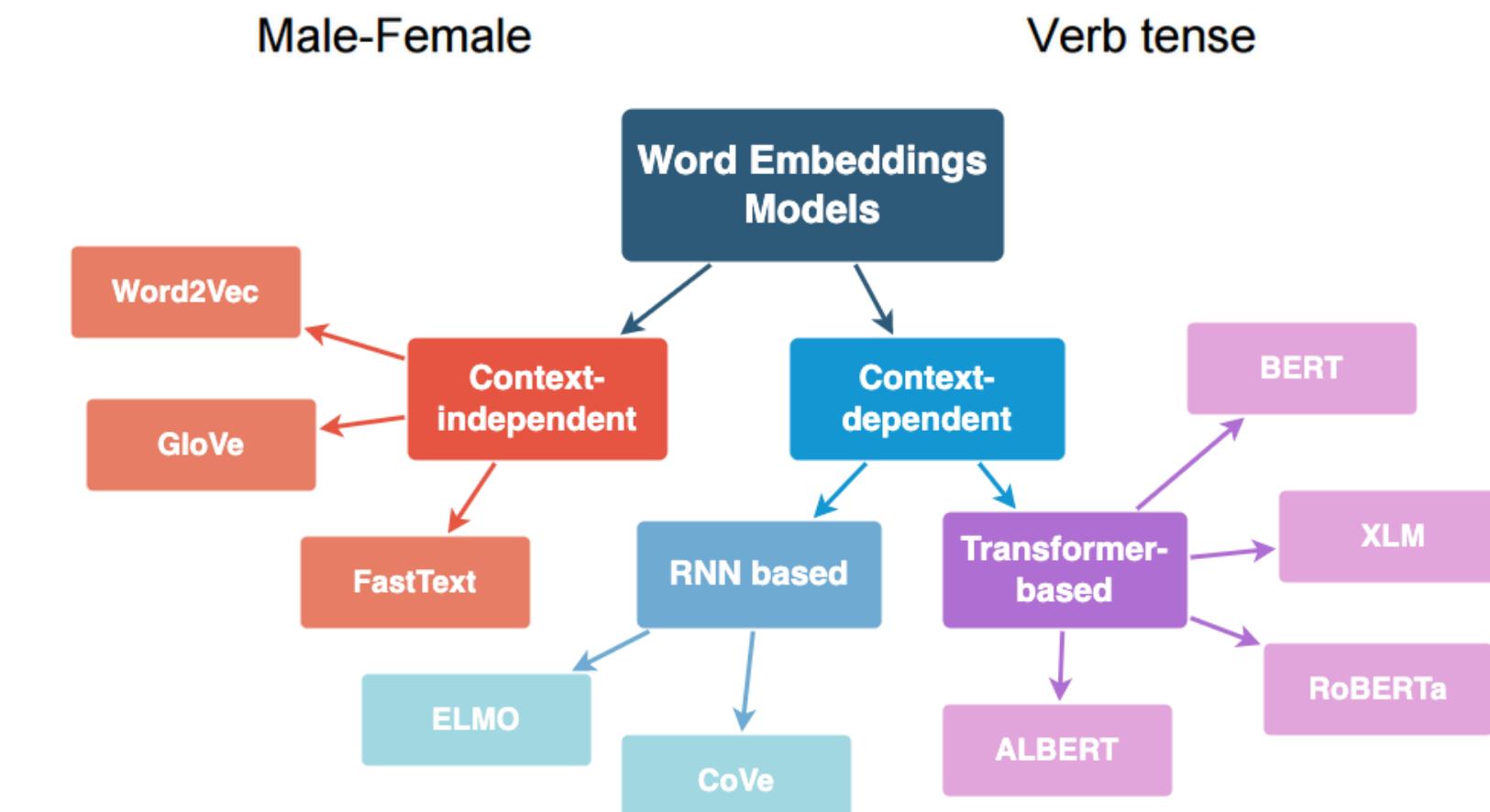
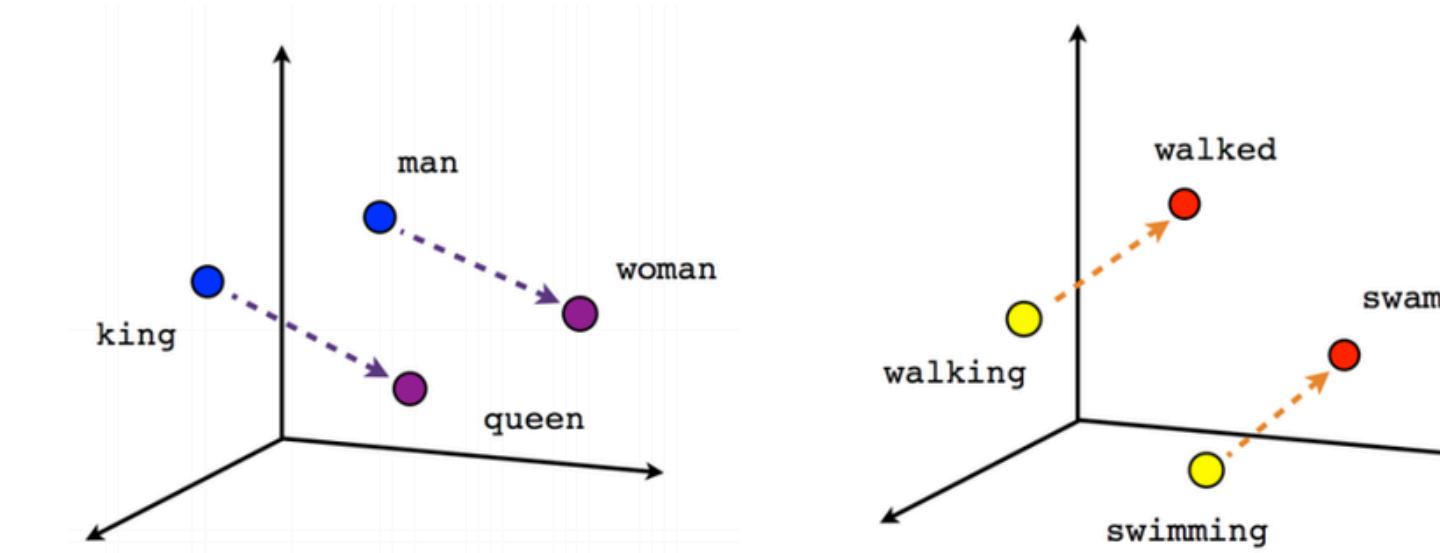
Overlap = {python, sql, aws} = 3

Union = {python, sql, tableau, aws, excel, communication} = 6

Jaccard = 3 / 6 = 0.50 → 50% matched

Word Embedding

- **How word embedding works?**
 - Core idea → “meaning” captured via geometric distance in vector space
 - Numerical vector representations of text where similar words/documents → similar vectors
- **Why we need word embeddings in job post-resume matching ?**
 - Enable semantic understanding beyond keyword matching
 - Word embeddings capture:
 - Role similarity
 - Skill relationships
 - Contextual meaning
- **World embeddings models can be divided based context dependency.**



Word Embedding Models Tested

01 Word2Vec (Skip-gram)

Description:

Neural embedding model using token co-occurrence to learn word vectors

- Captures basic semantic relations (e.g., “analyst” ~ “consultant”)
- However, no contextual understanding due to most word vectors loses sentence structure

02 SBERT (Sentence Bert)

Description:

Transformer-based model producing sentence- and document-level embeddings

- Strong contextual understanding
- Handles long job/resume text accurately
- Robust to synonyms & variation in writing style

03 CareerBERT (Pre-trained model)

Description:

Pre-trained model for career/job similarity.

- Tailored for occupation matching
- Domain-specific vocabulary understanding
- Less stable similarity output in our testing

Final Word Embedding Model: **SBERT (Sentence Bert)**

SBERT consistently produced more accurate and stable rankings compared to Word2Vec and CareerBERT, especially for resumes with varied experience levels.

- **Model version used: all-MiniLM-L6-v2**
- **Dimension tested : 300 , 384, 768, and 1536.**

Word Embedding

Modeling Pipeline

1

Cleaned Job/Resume Text

- Apply light cleaning (\n, unicode, tabs → space)
- Keep punctuation & wording to preserve context

2

Full-Text SBERT Embeddings

- Convert all cleaned texts to lists
- Encode using SBERT latest model
- Output: dimensional dense vectors

3

Cosine Similarity

- For each resume, compute similarity with all jobs
- $\text{semantic_score} = \cos(\text{resume_emb}, \text{job_emb})$
- Higher score → more semantically aligned roles

4

Ranked Results

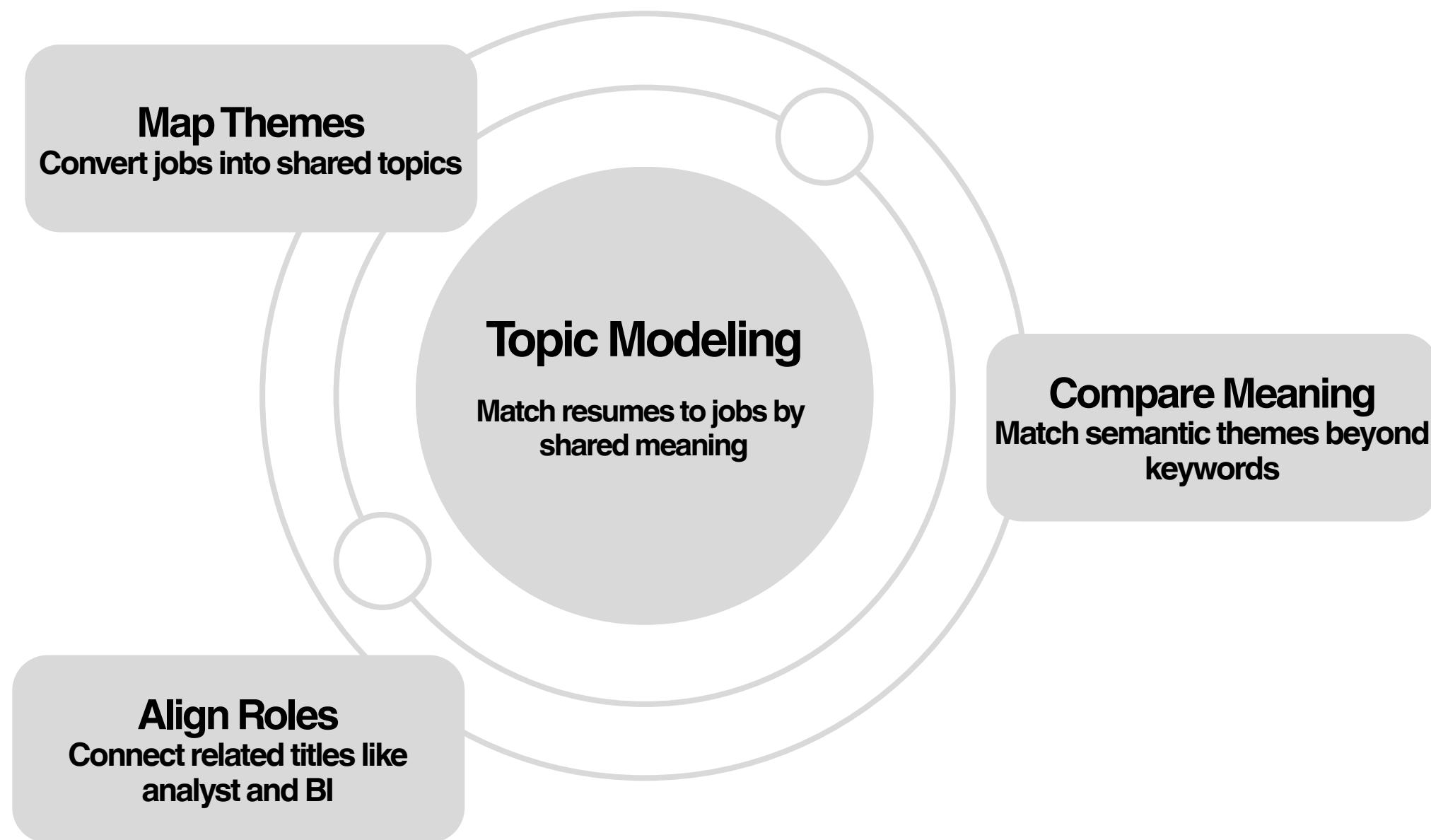
- Sort jobs by semantic score (descending)
- Stored the score for the final matching

Results

| Top Jobs | Score |
|------------------------|-------|
| Senior FP&A Analyst | 0.682 |
| Senior Data Management | 0.677 |
| Data Product Owner | 0.677 |
| Python Developer | 0.661 |
| Frontend Engineer | 0.654 |

Topic Modeling

Topic modeling compares meaning, not just keywords by mapping each resume into shared job themes



Technique Selection

LSA

- Works directly on TF-IDF vectors
- Uses SVD to reduce dimensions



Fast and Efficient for retrieval



Handles short/medium texts well



Reduces noises

*We also developed the model using “LDA” as alternative technique for result comparison

Topic Modeling

Modeling Pipeline

- 1 **Job/Resume Cleaned Text**
Cleaned input documents with job descriptions
- 2 **TF-IDF Vectorization**
Convert text to weighted term vectors (1–3 grams)
- 3 **TruncatedSVD**
Project into **120**-dimensional topic space
- 4 **Cosine Similarity**
Compute pairwise match scores
- 5 **Ranked Results**
Top-N recommendations per resume

Results

| Top Jobs | Score |
|--|-------|
| Delivery & Practice Head with verification | 0.997 |
| Database Operations Analyst | 0.995 |
| Application Engineer | 0.994 |
| Director Metals & Mining Consulting - Big4 | 0.993 |
| Research Analyst - Energy & Resources | 0.993 |

Results & Evaluation

Final Matching Score Calculation

Job Matching Score Formula = $\text{avg_topic_semantic} + (1 - \text{avg_topic_semantic}) * \text{skill_score}$



Detailed Results

| index | rank | resume_file | job_rar | job_title | job_company | Final Score | Skill Score | Semantic Score | Topic Score | resume_size | job_skills | matching | LLM Match |
|-------|------|-------------------------|---------|---------------------------------|-------------------|-------------|-------------|----------------|-------------|-------------|------------|----------|---|
| 90 | 1 | Minho_Kim_20251129_0 | 1 | Data Engineer AWS - Hybrid | TechTriad | 90.32 | 38.46 | 74.42 | 94.12 | 19 | 17 | 10 | X No |
| 93 | 2 | Nadia_Mahmoud_20251 | 1 | Sr. Analyst, Digital Initiative | Toast | 89.34 | 38.1 | 74.69 | 90.88 | 15 | 14 | 8 | ✓ Yes |
| 86 | 3 | Mia_Rodriguez_2025112 | 1 | Senior Data Engineer | Envision Employn | 88.7 | 36.67 | 71.17 | 93.15 | 20 | 21 | 11 | ✓ Yes |
| 12 | 4 | Ana_Martinez_20251129 | 1 | Data Analyst | Wyndham Hotels | 88.63 | 33.33 | 70.35 | 95.52 | 12 | 8 | 5 | ✓ Yes |
| 72 | 5 | Luca_Moretti_20251129_ | 1 | Data Analyst | Helic & Co. | 87.56 | 43.75 | 63.01 | 92.76 | 11 | 12 | 7 | ✓ Yes |
| 108 | 6 | Yin_Zhang_20251129_06 | 1 | Data Analyst | Helic & Co. | 86.27 | 31.82 | 68.37 | 91.37 | 17 | 12 | 7 | ✓ Yes |
| 36 | 7 | David_J_Frederickson.pd | 1 | Procurement Executive | Rockhill Asia | 86.17 | 26.32 | 77.69 | 84.77 | 13 | 11 | 5 | ✓ Yes |
| 98 | 8 | Resume Example 1.pdf | 1 | Procurement Executive | Rockhill Asia | 86.17 | 26.32 | 77.69 | 84.77 | 13 | 11 | 5 | ✓ Yes |
| 20 | 9 | Asha_Patel_20251129_00 | 1 | Data Engineer AWS - Hybrid | TechTriad | 85.94 | 24.24 | 73.73 | 89.14 | 24 | 17 | 8 | ✓ Yes |
| 8 | 10 | Amir_Boroumand.pdf | 1 | Sr. Full Stack Developer with | Motion Recruitme | 85.48 | 38.24 | 70.36 | 82.63 | 22 | 25 | 13 | ✓ Yes |
| 13 | 11 | Ari_Patel_20251129_063 | 1 | Data Engineer AWS - Hybrid | TechTriad | 85.28 | 18.52 | 75.13 | 88.74 | 15 | 17 | 5 | X No |
| 3 | 12 | Aisha_Thompson_20251 | 1 | Data Scientist, Watchlist | RemoteHunter | 84.98 | 33.33 | 59.66 | 95.3 | 17 | 11 | 7 | ✓ Yes |
| 47 | 13 | Jae_Kim_20251129_060 | 1 | Data Analyst | Sports Research | 84.62 | 15 | 74.38 | 89.43 | 13 | 10 | 3 | ✓ Yes |
| 69 | 14 | Lin_Wei_Chen_20251129 | 1 | Data Scientist, Watchlist | RemoteHunter | 84.44 | 28.57 | 64.51 | 91.93 | 16 | 11 | 6 | ✓ Yes |
| 107 | 15 | Steven_J_Vik_Incident_I | 1 | Cyber Defense Engineer | Confidential | 84.18 | 20 | 67.82 | 92.63 | 15 | 3 | 3 | X No |
| 65 | 16 | Leena_Patel_20251129_0 | 1 | Sr Data Analyst with verific | Horizontal Talent | 84.01 | 23.81 | 68.08 | 89.93 | 14 | 12 | 5 | ✓ Yes |

Our Resume-Job matching model **provides the final similarity score** for each resume and **identifies the best-matching job**

LLM Evaluation & Recommendation

*GPT-OSS:20B (DECODED ONLY MODEL) USED

Prompt Engineering

system_prompt

You are an expert recruiter evaluating resume-job matches. Job descriptions often list ideal candidates with all possible skills - this is unrealistic. Focus on ESSENTIAL qualifications needed to perform core job functions. Consider transferable skills, related experience, and learning ability. A 'Yes' means the candidate can reasonably do the job, not that they have every skill listed.

prompt_template

Evaluate if this resume matches this job posting. Be practical and realistic.

JOB POSTING:

Title: {title}

Description: {job_text}

RESUME:

{resume_text}

EVALUATION APPROACH:

1. Identify 3-5 CORE skills/requirements essential for this role (ignore nice-to-haves)
2. Check if candidate has these core skills OR transferable/equivalent experience
3. Assess if candidate's experience level aligns with role expectations
4. Consider: Can they reasonably perform the core job functions? If yes → "Yes"

DECISION RULES:

1. Answer "Yes" if: Candidate has essential qualifications OR strong transferable skills that indicate they can learn/adapt
2. Answer "No" only if: Missing critical core requirements that would prevent basic job performance

OUTPUT FORMAT:

Line 1: "Yes" or "No"

Line 2: One-sentence explanation

If "No", then:

Line 3: "RECOMMENDATIONS:" followed by 3-5 specific, actionable recommendations

Line 4: "LINKEDIN_KEYWORDS:" followed by 5-10 relevant job search keywords

Evaluation & Resume Improvement Recommendation

*LLM Evaluates “Yes matching”

LLM Evaluation:

- Match: Yes
- Reasoning: The candidate meets the essential qualifications—holding a bachelor's degree, possessing over 8 years of senior marketing experience, and demonstrating proficiency with HubSpot Marketing Hub, Salesforce, and marketing automation workflows, as well as analytics and reporting—which indicates they can effectively perform the core functions of the Marketing Operations Manager role.

*LLM Evaluates “Not matching”

LLM Evaluation:

- Match: No
- Reasoning: The candidate lacks the required Java expertise (and JavaScript experience) essential for the core backend role, which would impede immediate contribution.

Resume Improvement Recommendations:

- Develop proficiency in Java (e.g., build simple microservices with Spring Boot or Jakarta EE) through online courses or side projects.
- Gain working experience in JavaScript and Angular by contributing to front-end or full-stack tutorials, focusing on REST API integration.
- Highlight existing backend-like responsibilities (microservices, API design, CI/CD, Docker) and emphasize rapid learning of new languages.
- Seek certifications or short courses in Java and Angular to strengthen résumé credibility.
- Showcase transferable skills (Python, Docker, AWS, CI/CD, REST APIs, and ETL) that align with backend development tasks.

LinkedIn Job Search Keywords:

backend developer, data engineering, MLOps, Python, REST API, Docker, AWS, Azure, GCP, containerization, SQL, NoSQL, microservices, CI/CD, Java, JavaScript, Angular, Jakarta EE, FastAPI, Snowflake, Databricks.

backend developer, data engineering, MLOps, Python, REST API, Docker, AWS, Azure, GCP, containerization, SQL, NoSQL, microservices, CI/CD, Java, JavaScript, Angular, Jakarta EE, FastAPI, Snowflake, Databricks.

Evaluation Result

LLM as a Judge

- Collected 113 resumes (45 real and 68 synthetic) from peers representing a wide range of roles
- Each resume includes the user's actual current job title as ground truth for evaluation

Metrics

1. LLM-Verified Top-1 Match Rate

→ Percentage of resumes where the LLM answered "Yes" for the #1 recommended job.

2. LLM-Verified Top-3 Match Rate

→ Percentage of resumes where the LLM answered "Yes" for any job in the Top 3 recommendations.

| Metric | Usage | Evaluated Match % | Logic |
|---------------|-----------------|-------------------|--|
| Top-1 Match % | Strict Accuracy | 38.34% | Evaluates the model's ability to place the correct job at the very top of the ranking. |
| Top-3 Match % | Practical Usage | 41% | Evaluates overall recommendation quality and relevant alternative quality beyond the top choice. |

Findings & Conclusion

Findings

- The job-matching system that combines skill matching with semantic matching produced strong results
- From NER skill extraction reveal that job titles may vary, but the core responsibilities in the job description are usually consistent.
- LLM evaluation result always change every time we tested by nature
- SBERT's semantic score improved the relevance of Top-job matches. SBERT's also worked well to understand synonym and variation of writing style.
- Adding grams (1-3) and topics (120) helps improve the result in Topic modeling, and Using LSA runs much faster than LDA

Conclusion

- **Scalability**
 - Geographical Scale: job listings with multilingual support
 - Data Scale: Expand data collection across multiple job platforms and company sources
 - Enable real-time system integration for continuous job and resume processing.
- **Licensing**
 - Partner with job-posting platforms and companies for more diverse job descriptions.
- **Business Value**
 - This technique can be implemented in existing ATS systems for companies, not just as a tool for job seekers.

Limitations & Opportunities for Improvement

What We Could Have Improved With More Time

- Expand and refine the skill dictionary for higher coverage
- Automate normalization and tuning for SkillScore, SemanticScore, and TopicScore
- Incorporate experience years to better reflect seniority and adjust match quality
- Expand the job post dataset with a wider range of industries to improve model generalizability.

Where the Demo/App Breaks

- Fails when job descriptions contain missing fields or extremely short/empty text
- UI may freeze for very long job descriptions or large batch uploads
- LLMs have token limitations during evaluation, which can lead to reduced performance in cases where resumes or job descriptions contain long or complex text.
- The app currently supports only PDF-format resumes, which limits flexibility for users with other file types.

UI Demo

Thank You

APAN 5430 - Group 4

Reference

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