Talent Recommendation Engine: Rank(IT)



Introduction



Motivation

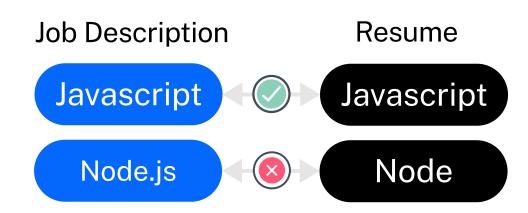
- Today, connecting the right candidates with the appropriate job position is more critical than ever.
- Manual screening is time-consuming and prone to errors and biases.
- Businesses are looking for more effective ways to match potential employees to opportunities.



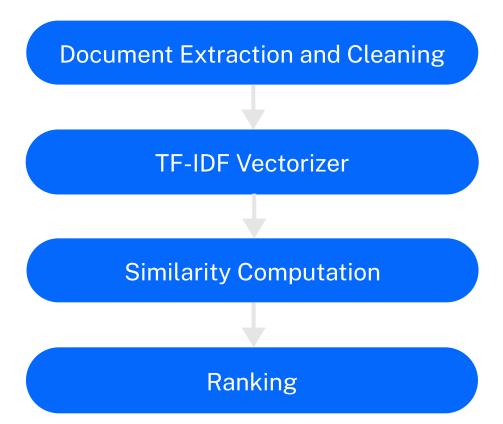


Previous Solutions

Keyword Matching



Early Machine Learning Approaches





Problem Definition

- Previous solutions are inefficient, time-consuming and prone to errors and biases.
- They fail to capture the nuanced connections of experience and skills leading to mismatches.





Objectives

- Automating the matching of candidates to job opportunities based on work experience, language and technical skills.
- Leveraging AI to achieve more accurate recommendations.





Experimental Setup



Dataset

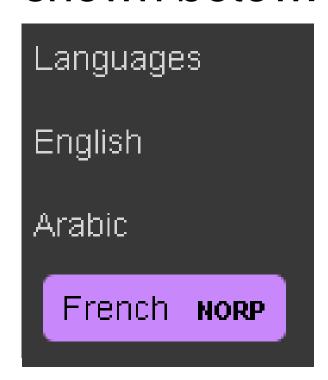
- 13 unique job descriptions.
- 126 unique resumes, of which 2 were corrupted.
- All documents in .pdf or .docx format.





Limitations of Old Parsers

 spaCy was not able to detect basic information such as languages as shown below:



While, widely known resume parsers, like PyResParser, failed to correctly extract most information.

```
"<mark>Content</mark>",
"Analysis".
                                                 "Research",
"Jsp",
                                                 "Unix".
                                                 "Hospital",
"Jira",
"Modeling",
                                                 "Htm15",
                                                 "Aws",
"Servers".
                                                 "<mark>Mobile</mark>",
"Php",
"Cms".
                                                 "Requests",
"<mark>Communication</mark>",
                                                 "Xml",
"Benchmarking",
                                                 "Oracle",
"<mark>Iphone</mark>",
                                                 "Presentation",
"Hotel",
                                                 "Javascript",
                                                 "Administration",
"Database",
                                                 "Coding",
"Technical",
"Apis",
                                                 "Github",
"Linux",
                                                 "Shell",
"Html",
                                                 "Ubuntu".
"<mark>Website</mark>",
                                                 "C++",
"Audit",
                                                 "Mysql"
"Rest",
                                            "college_name": null,
"Sql",
"English",
                                            "degree": null,
"Hotels",
                                            "designation": null,
                                            "experience": null,
"Programming",
                                            "company_names": null,
"Design",
"<mark>French</mark>",
                                            "no of pages": 4,
                                            "total experience": 0
"System",
```



Exploration of Large Language Models (LLMs)

Model	Computational Requirements	Accuracy	Cost	
Free Dolly	Low	Low	Free	
Llama 2	High	High	Free	
Falcon	High	High	Free	
Llama 2 (Small)	Low	Low	Free	
Falcon (Small)	Low	Low	Free	
ChatGPT	None (API)	High	\$0.005/CV	

 Given our limited computational resources, we chose OpenAI's ChatGPT for its superior performance at a relatively low cost.



Prompt Engineering

- Prompt Engineering played a vital role in accurately extracting data.
- LangChain allows us to specify a response schema to format the output. In our case, we went for the JSON format.
- For the job descriptions, we crafted a single prompt to extract all the necessary information.
- For resumes, we found that using one prompt led to inaccuracies. We opted for smaller distinct prompts to target the different sections of the resumes.



Choice of Embeddings

- Word2Vec and GloVe vocabulary is deficient in encompassing domainspecific terms such as "Kubernetes" and "Kotlin".
- They do not allow for words featuring punctuations like "C#," "C++,"
 "Node.js," and "React.js."
- They do not allow for terms such as "project management," "distributed systems design," and "relational database."
- OpenAI's text embeddings such as DaVinci and Curie are less accurate and costly.
- Our best option was OpenAI's ada-002 embedding which is accurate for semantic search and has a low cost of 0.0001\$/1,000 tokens.

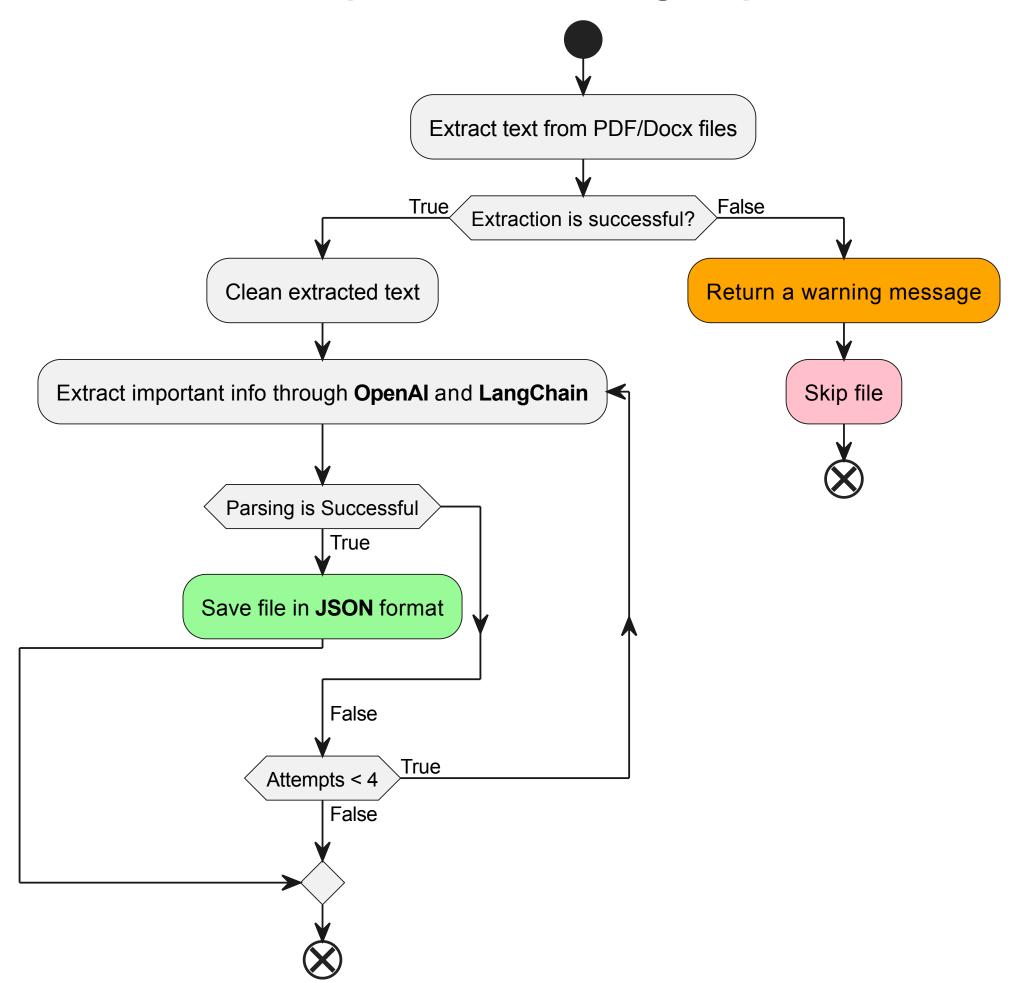


Final Proposed Approach



Job Description & CV Parsing Sequence

Parsing



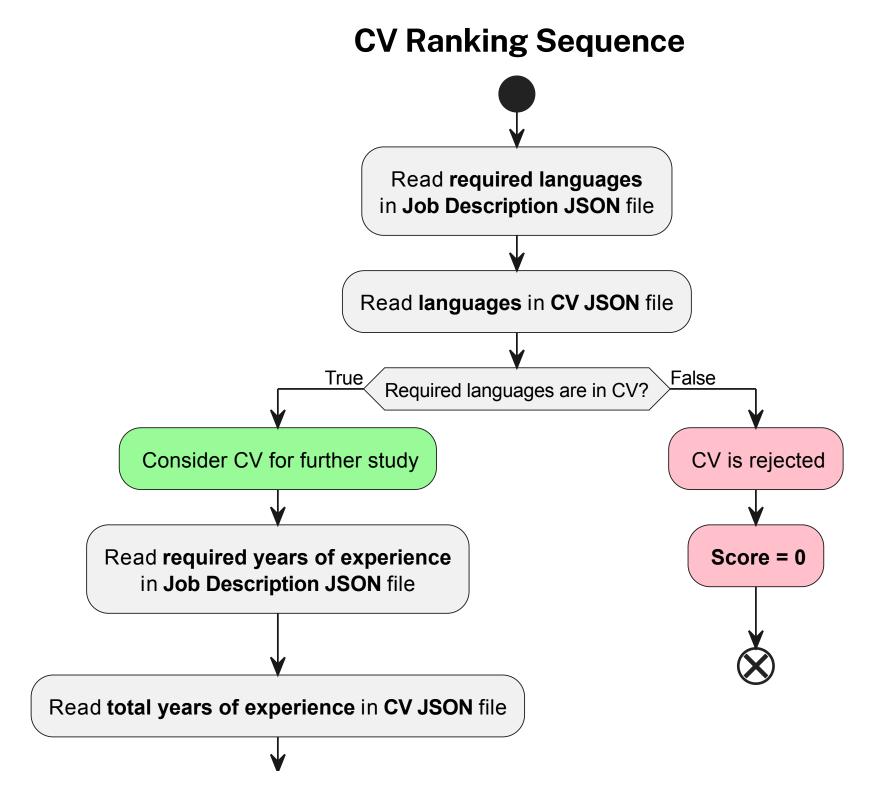


Parsing

- For job descriptions: information is extracted with one specific prompt.
- For resumes: we had to extract information in a step-wise manner using multiple prompts that target the different sections.
 - **Experience Breakdown:** simplifies the resumes, and then extracts job titles and durations.
 - Skills: extracts relevant skills from the entire resume.
 - Language Proficiency: Extract language skills and proficiencies.



Ranking Flowchart





Read total years of experience in CV JSON file **Ranking Flowchart** False True Required years of experience are met? CV is rejected Consider CV for further study Score = 0 Read job title and Read required skills in required years of experience in **Job Description** JSON **Job Description** JSON Read breakdown experience Read **skills** in {position: period} **CV** JSON in **CV** JSON Compute a skills score Compute a **experience score** Compute total score



Ranking Modes

- We developed 2 language assessment modes:
 - Strict: Candidate is proficient in all the required languages stated in the job description.
 - **Relaxed**: Candidate is proficient in at least two-thirds of the required languages stated in the job description.

- We developed 3 scoring modes:
 - Match: Uses keywords fuzzy matching.
 - ADA: Uses ada-002 context matching.
 - ADAMa: Uses a combination of ada-002 and fuzzy matching to prioritize certain desired job titles.



Results



Job Description Parsing

 Job description is parsed within a few seconds and a JSON is returned containing accurate important information.

```
DevOps Engineer - Infrastructure Focus
```

Focused Qualifications

- 1. Bachelor's Degree in Computer Science or related field
- 2. <mark>1-3</mark> years of professional cloud-based infrastructure (<mark>AWS</mark> Preferred).
- 3. 1+ years of experience with Java development
- 4. <mark>1+</mark> years of experience with <mark>SQL database design</mark> and development
- 5. <mark>1+</mark> years of experience working in an <mark>agile environment</mark>
- 6. Familiarity with web service design and development

```
"job_title": "DewOps Engineer",
"total_years_required": 1,
"languages": [
    "English"
```



CV Parsing

 Resume is parsed within 20 - 40 seconds and a JSON is returned containing accurate important information.

WORK EXPERIENCE

Software Engineer

PLUGIT Limited

07/2012 - Present

PLUGIT is a certified provider of trading support solutions and services to the global financial trading industry.

Achievements/Tasks

- Develop, test and implement new software programs.
- Clearly and regularly communicate with management and technical support colleagues.

LANGUAGES

Arabic

Native or Bilingual Proficiency

```
English
Full Professional Proficiency
```

```
"breakdown_experience": {
    "Software Engineer": 11.08
},

"languages": {
    "Arabic": 5,
    "English": 4
},
```



Ranking

- TF-IDF shows a very poor ranking accuracy.
- ADA shows a huge improvement from TF-IDF & ADAMa a slight improvement from ADA

			Rankings				
			Supportful	TF-IDF	ADA	ADAMa	
DevOps Engineer	er S	Elie Youssef	#1	#35	#7	#8	
	Hussein Hijazi	#2	#25	#1	#2		
	<u>а</u>	Charbel Nakad	#3	#41	#4	#7	
DotNet	Net	Bernard Estephan	#1	#61	#16	#7	
	Mohammad Darweech	#2	#78	#23	#3		
Quantitative Developer	Tony Mattar	#1	#75	#4	#10		
	Quant	Patricia Boulos	#2	#79	#29	#9	



Conclusion



Conclusion

- We developed a ranking engine with various language, work experience, and skills assessment modes.
- We used state of the art LLMs to accurately parse the job descriptions and resumes.
- We use state of the art ada-002 text embeddings and drastically improved the rankings as compared to old techniques.

Future suggestions

- Data gathering and data cleaning to build and train better models.
- LLM fine-tuning for faster parsing.
- Tokenizer and embeddings training for a higher ranking accuracy.

