JobSelect: A custom Job Recommendation System

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KEYWORDS

 ${\it Job \, Recommendation \, System, \, Information \, Retrieval, \, Machine \, Learning, \, Natural \, Language \, Processing}$

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1 PROBLEM STATEMENT

This project aims to create a system that recommends suitable job opportunities to job seekers based on their skills and preferences. This will help job seekers find jobs that match their qualifications and career goals more quickly and easily while also helping employers find more qualified and motivated candidates. The system will use natural language processing and machine learning algorithms to analyze job seeker data, such as resumes and job applications, and suggest relevant job postings.

2 MOTIVATION

The process for job search is simplified for job seekers and the recruitment procedure is improved for employers using the Job recommendation system. Job seekers often have to go through a large number of job postings to find relevant opportunities, which can be time-consuming and overwhelming. It is time-consuming for prospective employees to find relevant opportunities, so they have to go through a large number of job openings on various platforms like Linkedin, Indeed, Naukri.com, etc. Candidates often want to build their resume according to a specific job role so they can tweak their profile until their recommended job profile matches their choice. Using machine learning and NLP techniques, a job recommendation system can provide personalized job profile recommendations to job seekers based on their skills, experience, and preferences, making it easier for them to find suitable jobs. At the same time, this system can help employers by matching them with more qualified and motivated candidates. Ultimately, the job recommendation system can benefit job seekers and employers by

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making the job search and recruitment processes more efficient and effective.

3 LITERATURE REVIEW

The research on job recommendation systems has gained significant attention in recent years.

3.1 Learning-Based Matched Representation System for Job Recommendation

Alsaif, S.A. and Sassi Hidri, M. developed a system that recommends the top-n jobs to the job seekers by analyzing and measuring the similarity between the job seeker's skills and explicit features of job listing using content-based filtering. The system used Natural Language Processing (NLP) to match skills between resumes and job descriptions. Finally, the job offer is recommended, similar to the users' skills on their resumes using Collaborative Filtering. [1]

3.2 A smart Geo-Location Job Recommender System Based on Social Media Posts

There was another study by A. Mughaid and I. Obeidat which aimed to match the best vacancy for the exact job seeker by way of mining social media networks, such as Facebook and twitter. This system involved intensive data mining techniques and used Natural Language Processing (NLP) classifiers such as Support Vector Machines, Naive Bayes, and Random Forest to locate the best job seekers and job locations based on their social media posts history. [5]

3.3 Investigating Natural Language Processing Techniques for a Recommendation System to Support Employers, Job Seekers and Educational Institutions

Koen Bothmer and Tim Schlippe built a Skill Scanner application that outputs the missed and covered skills for all three users,i.e., employers, job seekers, and educational institutions. In their prototype, they retrieved skills from the applicant's Resume, then compared the retrieved skills with the Market (Employers and Educational Institutions). The research focused on only one job type, i.e., data scientist, and scrapped the data from Kaggle and Indeed.com. They used Word2Vec, GloVe, and Sentence-BERT to represent the skills in vectorized form. They used a clustering-based approach for the recommendation to the three users. K-Means clustering was used with K equal to 31. [4]

3.4 NLP-Based Bi-Directional Recommendation System: Towards Recommending Jobs to Job Seekers and Resumes to Recruiters

Suleiman Ali Alsaif and Minyar Sassi Hidri built an NLP-based bi-directional Job recommendation system for job seekers and employers. They scrapped five job profile datasets from Indeed.com. The data extracted were preprocessed using Clean Tags, Tokenization, Lemmatization, and Stop words removal. Then the Bag of Words model converted the textual data into a vector representation. Further, Named Entity Recognition was used using spaCy to extract the named entities. Word2Vec model retrieves similar terms, and then cosine similarity is used to find the similarity. [2]

3.5 JobFit: Job Recommendation using Machine Learning and Recommendation Engine

The study intends to develop a job recommendation system, JobFit, which predicts the best candidates for a position using machine learning techniques, a recommender system, and previous data. The system generates a JobFit score indicating how well-suited a particular candidate is for a specific position depending on the applicant's profile and job requirements. The output is a ranked list of candidates best suited and most qualified for the position. This ensures that HR concentrates on interviewing a small group of top prospects, as recommended by the JobFit, without caring that the top candidates will be overlooked. The recommendation system developed in this study combines several different machine learning models with a collaborative filtering recommendation system, whose output is then fed to a final machine learning model through which an applicant's JobFit score is obtained for a specific job position. [3]

4 OUR APPROACH

We will create our database using web scraping from Job website like Linkedin. The database will be divided into test and train dataset. Train dataset will include job posting details like job ID, job title, company, job description, and job profile. On the other hand test data will contain user resume extracted from linkedIn profiles which will include details like name, about, experience, education, courses, skills, etc. thus; the aim would be to feed rich data to make the model highly robust. We will assign the top 3 job profile categories to every user resume according to their detail in the test dataset. Then we will incorporate various NLP techniques (preprocessing and word embeddings) to convert the textual job profile data into embeddings. Then various distance and similarity metrics will retrieve the relevant job profile. We will also inform the user to what extent his/her job profile matches our set of job profiles and what skillsets are missing from his job profile from his target job profile in a company. Hence, the use of rich data and information regarding expected and present skillset deviation will make the recommendation system more meaningful to the user.

5 TECHNIQUES TO BE USED

• Dataset Creation: Job postings and user resume data has been extracted from LinkedIn. Selenium has been used for

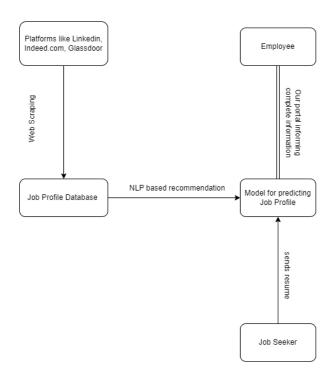


Figure 1: Flow Chart for NLP based Job Recommendation system

scraping the data from these websites. Job seekers are expected to provide the resume from which the information (skillset) will be extracted.

- Data cleanup: After data extraction all the redundant information will be removed from the data to make sure that only relevant data is present.
- Natural Language Processing: NLP techniques are used for the processing of the scrapped data like tokenization, stop words removal, lemmatization and stemming to retrieve the key terms/skills from resume and job profiles. Word Net and Porter algorithms are used for the lemmatization and stemming respectively.
- Job recommendation: BERT model will be used to learn the contextual relationship between words in a sentence. Thus, this pre-trained deep learning model is used to match the expected skill set for a job profile and skills present in candidate profile. Besides this we will also consider models like Word2Vec, GloVe that can learn static word embeddings. Classification techniques like Random Forest, Stacking Classifier will be used for recommendation of most suitable jobs based on matching between candidate and job profile.

6 BASELINE RESULTS

For the Baseline Results, we have used Count Vectorizer to create features or word embeddings of the training database i.e Job Profiles data scraped from various companies' websites. We have used a Random Forest classifier with n_estimators as 100 for predicting or recommending the job profiles of the resume of a candidate. To get the best 3 job recommendations, probabilities are used for each of the job classes and the highest 3 probabilities are then selected. Label encoding is done for both the training and testing set for probability prediction.

Following are the metrics which we considered for baseline evaluation:

- recall@2: Measures the fraction of relevant jobs (matches
 the ground truth values) that are retrieved by the system
 for the first 2 recommendations. For example, if the system
 returns 2 relevant recommendations out of 4 total relevant
 jobs then the recall@2 for that system would be 0.5 (50%),
 because it successfully retrieved half of the relevant recommendations within 2.
- precision@3: Measures how many of the 3 jobs recommended by the system are a good match for the user's interests or skills (matches the ground truth values). For instance, if the system suggests 3 jobs and 2 of them are relevant to the user's interests, then the precision@3 for that system would be 0.67 (67%), because it accurately identified 2 out of the 3 most relevant jobs for the user.
- Mean Average Precision (MAP): Measure that combines both recall@k and precision@k (where k is a particular number of recommended items) to provide an overall evaluation of a job recommender system's performance. For our evaluation we computed MAP for k=3.

Recall@3 and Precision@3 will be similar because of the fact that the denominator in both the formulas will result in the same value

This can be shown as:

Number of relevant documents = (No. of queries) x 3 (3 is the number of relevant documents in each query)

Number of retrieved documents = $(No. of queries) \times 3$ (3 is the number of retrieved documents in each query)

Since, number of documents is same in both the denominators of the formula, and numerator is same due to relevancy, the value of Precision@3 and Recall@3 results the same. However, this is not true for the case of Precision@2 and Recall@2 since the denominator of these formulas will be different.

7 EVALUATION

To evaluate the performance of our recommender system, we will use classification metrics like decision support metrics (precision and recall) and precision@k. These classification metrics will evaluate the decision making capacity of our recommender system without taking ranks/relevance of recommendations into account. We will also be using evaluation metrics that are used for rank based recommendation systems like Mean Average Precision (MAP).

Mean Average Precision: 0.6017025089605734

Recall@2: 0.7217741935483871 Precision@3: 0.6227598566308243

Figure 2: Result of the Baseline Model

CONTRIBUTIONS

- Data Webscraping : Rishita Chauhan
- Resume Information Extraction: Rishita Chauhan and Harshita Gupta
- Data cleanup : Harshita Gupta
- Natural Language Processing: Raghav Bhalla and Md.
 Zaid
- Classification Algorithms and Evaluation : Kartikey Gupta and Ansh Mittal

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