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A Deep Learning Approach to Job Recommendation Analysis with NLP

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Abstract:- Online job portals have rapidly expanded, making it simpler for job searchers to find employment. But it can take much work for job searchers to find the ideal position that matches their skills and preferences due to the abundance of job postings. To solve this issue, the author present a system for recommending relevant job listings to students using machine learning and natural language processing techniques. There has never been any prior interaction between user data and job listing data in the dataset collected for our research. The system employs a hybrid strategy to generate precise suggestions, combining collaborative filtering and content-based filtering. To provide the most pertinent job suggestions, the system examines the student's resume, specifications, and posting. Additionally, the system suggests the top jobs to the user by analyzing and gauging the similarity between the user choice and explicit job listing features. The Recommender System is then evaluated using precision, recall, and F1 score.

Keywords:- *NLP, Cosine Similarity, Word2Vec, Content-Based Filtering.*

I. INTRODUCTION

The development of technology has dramatically altered the process of employment searching and recruitment in recent years. Work seekers nowadays have access to a wealth of information on available jobs, employers, and work specifications. Employers, on the other hand, must sift through a sizable quantity of resumes and employment applications. Finding the right applicant for the job and the right job for the candidate can be difficult due to information overload, which can be intimidating for both job searchers and employers.

Systems for recommending jobs have come to light as a favorable response to this problem. These systems analyze candidate profiles and job ads using algorithms to generate suggestions based on the candidates' qualifications, expertise, and experience [1][2].

A job suggestion system aims to give students a personalized job search experience that matches them with the best job opportunities while saving businesses time and effort in the hiring process. Natural language processing and machine learning are two crucial technologies enabling job recommendation systems development. In contrast to natural language processing techniques, which analyze and comprehend human language, machine learning algorithms can analyze vast amounts of data and learn patterns and relationships. Together, these technologies allow job recommendation engines to comprehend and interpret job descriptions and candidate profiles, resulting in correct recommendations [3].

In this research paper, the job recommendation system searches for the best suitable job vacancies based on the students' education qualifications, professional experience, preferences, and abilities. On the other hand, the company looking to fill their vacant positions gets a pool of the most suitable and qualified candidates. The approach used is completely different from the previously employed systems as its analysis and computes job descriptions using natural language processing to get a deep inside of the applicant's application rather than just matching direct numerical values.

This paper is organized as follows. Section 2 reviews previous literature surveys and our motivation for writing this review. Additionally, it discusses the technique for obtaining and selecting literature and quickly discusses some datasets. We will discuss earlier systems' benefits and drawbacks and identify unmet research needs. Section 3 discusses the architecture of our system, including the many parts and their functions. Section 4 considers techniques used to create our job recommendation system, including data collecting, data preprocessing, and feature engineering, Last, Section 5 concludes and discusses directions for further research.

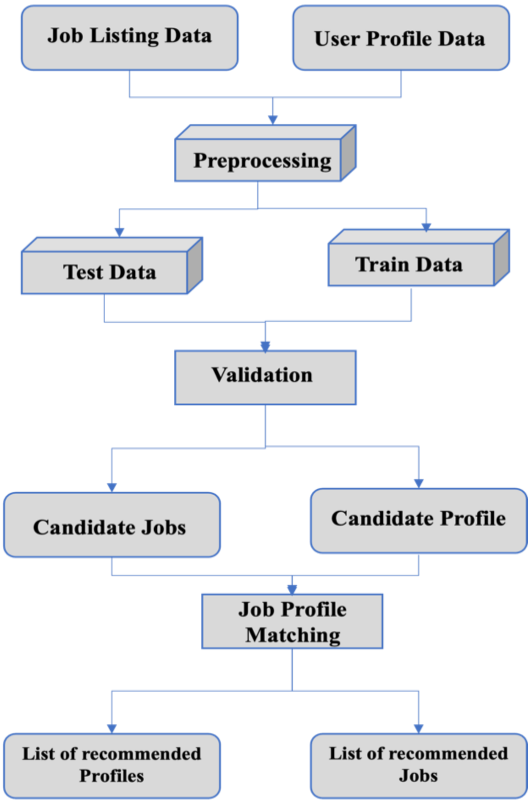

Fig 1 – NLP-Based Bi-Directional Recommendation System.

By analysing and evaluating the similarity between the student's selection and the employer's job listing features, the system will make the best jobs recommendations to the user. The chances of finding a work that matches their abilities and preferences will increase as a result of saving the student time and effort searching for suitable job openings. It will also assist employers in locating qualified applicants who suit their work requirements.

This research paper makes two contributions. First, the author shows a job recommendation system that analyses and comprehends applicant profiles and job descriptions using cutting-edge natural language processing techniques. Secondly, demonstration of the efficacy of our system in matching candidates to pertinent job opportunities by evaluating its performance using a sizable dataset of job postings and candidate profiles. Our system aims to promote meritocracy by prioritizing skills and qualifications over demographic factors in the hiring process. By utilizing our system, employers can efficiently and effectively match suitable candidates with open positions, resulting in increased employee satisfaction, productivity, cost savings, and higher profits.

Job recommendation systems have the potential to transform the hiring process by providing a personalized and effective job search experience for students and employers [4]. These systems can analyze students' preferences, skills, and experience to recommend suitable job openings, saving time and resources for employers while increasing the likelihood of student finding their ideal position [5]. Our study describes a system for recommending jobs that use cutting-edge natural language processing methods and assesses its performance using actual data. The system offers insights into the job market trends and demands and suggests jobs based on a student's skills and preferences. This can assist employers in making knowledgeable hiring and employment decisions.

II. RELATED WORK

There has recently been an influx of interest in developing job recommendation systems that use machine learning and natural language processing methods. In this section, the author examines the associated research on job recommendation systems and related technologies, like natural language processing and machine learning, and recognize the pros and cons of earlier systems. One of the extensively utilized methodologies is collaborative filtering, which generates suggestions based on the likeness between students' profiles and job requirements. Nevertheless, this methodology has its limitations since it necessitates a considerable amount of user data and may not be effective for users with unique preferences. Another technique is content-based filtering, which involves analyzing the profiles of students and job descriptions and making suggestions based on their similarities. However, this technique has its limitations as it must consider the user's preferences and may generate recommendations that are too alike.

An alternative technique called hybrid filtering has been developed, which merges the strengths of content-based and collaborative filtering to overcome their respective limitations. In the case of job recommendation systems, hybrid filtering can be used to recommend job openings like the ones that a student has applied for before and popular among similar students [12]. This approach has been effective in previous studies. **P**revious surveys on job recommender systems involve Shaha T. Al-Otaibi [19] and Zheng Siting et al. [20]. However, these surveys consider contributions before 2012 and have limited scope. Freire and de Castro [21] surveyed recommender systems in e-recruitment, including job recommender systems. However, their classification of contributions is inadequate, with a large proportion of contributions being labeled as "other." Furthermore, they focus solely on methods and validation while neglecting ethical considerations. In contrast, this paper will examine ethical issues and job recommender systems that consider the mutually beneficial and chronological nature of job suggestions.

Felfernig et al. [23] and Lu et al. [22] investigated recommender system applications but did not consider e-recruitment as an application area. Similarly, Batmaz et al. [24] did not include this subject in their study of neural networks in recommender systems, which included a section on application areas. This could be because the job recommendation issue differs from a more generalized information recommendation assignment. Variables such as a large amount of textual data, the reciprocal and temporal

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nature of vacancies, and the fact that these systems deal with personal data, on the other hand, require a tailored strategy.

The development of job recommendation systems has also utilized natural language processing techniques. These methods facilitate the interpretation of human language, allowing systems to analyze job descriptions and candidate profiles for making precise suggestions. Text classification is a frequently employed approach, which classifies job descriptions according to their demands [16]. This strategy can assist in connecting job students with job vacancies that match their qualifications. Nonetheless, it may not be as effective for intricate job descriptions, and thus has its limitations. Another commonly used technique is entity recognition, which identifies entities such as job titles, company names, and skills mentioned in job descriptions and candidate profiles [17]. This technique can match students with job openings that require their skills. However, this approach has limitations in that it may not be effective for job descriptions that do not mention specific skills.

Paparrizos et al [37] provide a comprehensive review of job recommendation techniques, including collaborative filtering, content-based filtering, and hybrid methods, as well as recent advancements in deep learning. Lu et al. [38] presents a deep learning approach for job recommendation that considers both competencies and personal traits of job candidates. Song et al. [40] propose a job recommendation approach that leverages both textual and visual information, such as job titles and images of workplaces, to make job recommendations. Al-Khalifa et al. [40] proposes an intelligent job recommendation system for the Arab world that considers the specific cultural and linguistic characteristics of the region. The authors use a combination of rule-based and machine learning-based approaches to extract features from job descriptions and candidate profiles, and then use a support vector machine (SVM) algorithm to make job recommendations. The authors evaluate their model on a dataset of job postings and report promising results.

III. PROPOSED METHODOLOGIES

A. Cosine Similarity

In a natural language processing model, the similarity between a student's abilities and the qualifications specified in a job ad is determined using the cosine similarity metric. [25]. Specifically, the cosine similarity measure calculates the similarity between the job student's skills vector and the job requirements vector. The student's skills vector is created by extracting the most relevant skills from the student's resume or profile. This vector is then compared to the job requirements vector, created by extracting the most important skills and qualifications listed in the job posting. The cosine similarity measure calculates the angle between these two vectors. A higher cosine similarity indicates a higher similarity between the student's skills and the job requirements [26].

$$Cosine\ Similarity(A, B) = \cos(\theta) = \frac{\sum^{n} A_i * B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} * \sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

The cosine distance can be computed by using below equation [29],

$$Cosine\ Distance = 1 - (Cosine\ Similarity) \quad (2)$$

Once the cosine similarity measure has been calculated for all job postings in a database, the system can rank them based on their similarity to the student's skills. The job postings with the highest cosine similarity scores are recommended to the student as the most suitable job opportunities [27][28]. Overall, cosine similarity is a useful technique for job recommendation systems. It allows for efficiently comparing student skills to job requirements, enabling personalized and relevant job recommendations.

B. Word2Vec

Word2Vec represents student skills and job requirements as dense, low-dimensional vectors. This allows for more efficient processing and comparison of these vectors, as opposed to using sparse representations such as bag-of-words or one-hot encoding [30]. Word2Vec is a neural network-based algorithm that learns vector representations of words based on their co-occurrence in a large corpus of text. In the context of a job recommendation system, the algorithm is trained on a corpus of job postings and resumes to learn vector representations of student skills and job requirements [31]. Once the Word2Vec model has been trained, the system can use it to convert student skills and job requirements into vector representations. These vectors are then compared using cosine similarity, as described in the previous answer, to identify the most suitable job opportunities for the student.

Using Word2Vec in a job recommendation system can improve the accuracy and relevance of job recommendations by capturing the semantic meaning of job skills and requirements rather than just the occurrence of keywords. This approach can also be extended to include related skills and job titles, further enhancing the system's ability to recommend relevant job opportunities. Word2Vec is a powerful tool for job recommendation systems that can help improve the efficiency and accuracy of matching students with suitable job opportunities.

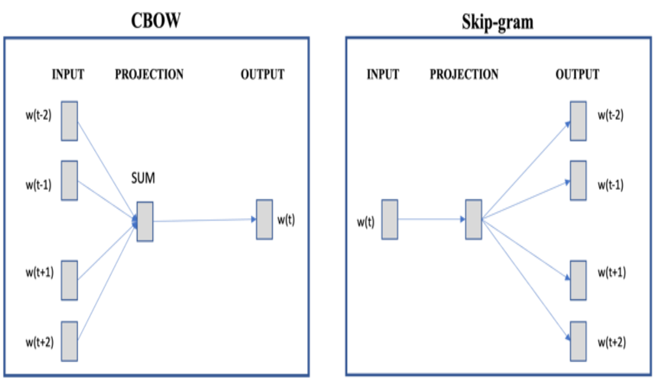

Fig 2 – Representation of Word2vec training models

CBOW (Continuous Bag of Words) and Skip-gram are two popular algorithms used in word embedding techniques like Word2Vec. In CBOW, the algorithm predicts a target word given the context words within a specific window size. The input layer of the model takes in the context words as a one-hot encoded vector, which is then multiplied by a hidden layer of weights to create a projection. In Skip-gram, the target word is used to predict the context words within a specific window size. Both algorithms have their own advantages and disadvantages, and the choice of algorithm depends on the specific task and the nature of the corpus being used.

C. Content-Based Filtering

This technique involves analyzing job postings and resumes to extract relevant features and using those features to recommend suitable job opportunities to students.

In a job recommendation system, content-based filtering typically involves two main steps: feature extraction and recommendation [32].

1. Feature extraction

This step involves analyzing job postings and resumes to extract relevant features such as job titles, skills, education, and experience. Natural language processing techniques such as named entity recognition, keyword extraction, and part-of-speech tagging are commonly used to identify and extract these features.

2. Recommendation

Once the relevant features have been extracted, the system uses them to recommend job opportunities to students. This typically involves comparing the features of a student's profile with available job postings and identifying the most suitable job opportunities based on a similarity score.

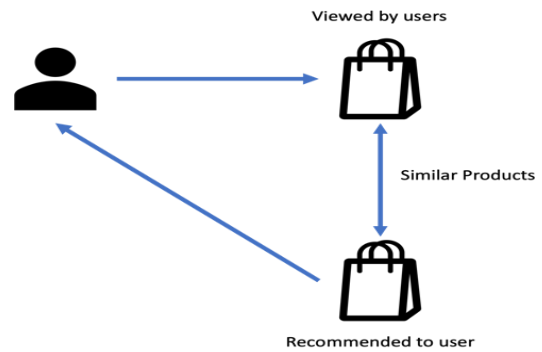

Fig 3 – Content-Based Filtering System Using NLP

When students have clear preferences and exact requirements for their job search, content-based filtering is extremely effective in job recommendation systems. This method focuses on the content of job postings and resumes to identify employment opportunities that best match a student's skill set and experience [33]. In general, content-based filtering is a potent methodology for job recommendation systems that enhances the accuracy and efficiency of matching students with suitable job opportunities based on the content of their job postings and resumes.

C. Prediction Model

We use natural language processing (NLP) techniques to analyze the job descriptions of the institutions in our dataset. We use techniques such as named entity recognition [34] and topic modelling [35] to identify key information such as the job title, required qualifications, and job responsibilities. The author also utilize sentiment analysis [36] to gain insights into the company culture and work environment. We experiment with a variety of supervised learning algorithms and compare their performance in predicting the next institution where an individual will be employed. To evaluate the performance of our model, we utilize metrics such as accuracy, precision, recall, and F1-score. If our model achieves a sufficiently high level of accuracy, it can be used to recommend institutions to employees who are seeking jobs. This approach can be extended to other industries beyond job recommendation, such as product recommendation or college recommendation.

IV. EXPERIMENTAL ANALYSIS

A. Dataset Collection

The dataset used for this study was compiled from poll data from Stack Overflow [8], which was then modelled after user data. There are around 89,000 observations in the data set, with 87 columns, 85 of which are of the text data type, 1 of which is of the boolean data type, and only 1 of which is an integer column. The user profile data was gathered by stack overflow through a poll. The dataset offers details on the technologies, tools, and computer languages used by developers. Based on the candidate's preferences, this information can be used to filter and rank job suggestions.

The job posting information was web scraped from a well-known employment website, and the resulting data was saved to a CSV file. The file includes 615 observations, each of which corresponds to an online job posting. The data collection has seven categories, six of which are of the string data type and one of which is of the id data type. The Stack Overflow Developer Survey information is useful for developing a Job Recommendation System. It provides a thorough overview of the programming business as well as developer job preferences. Data can be found at https://insights.stackoverflow.com/survey/.

B. Data Preprocessing

Data preprocessing is essential in building a Job Recommendation System using Machine Learning and Natural Language Processing with the Stack Overflow Developer Survey dataset. The survey dataset may contain missing values, incorrect or inconsistent data, and outliers. These issues must be addressed by performing data-cleaning operations such as filling in missing values, removing outliers, and correcting inconsistent data. The dataset contains multiple files that need to be integrated and merged to create a single, unified dataset that can be used for analysis. The survey dataset contains categorical or textual data that needs to be transformed into numerical data that machine learning algorithms can use. For example, categorical variables such as job titles can be encoded as numerical values using one-hot or label encoding. The survey dataset contains textual data, such as open-ended responses from developers. Text preprocessing techniques such as tokenization, stop-word removal, stemming or lemmatization, and sentiment analysis can be used to transform the text into a format that can be used for machine learning algorithms. The survey dataset contains many features, not all of which may be relevant for a job recommendation. Feature selection techniques such as correlation analysis, principal component analysis (PCA), or feature importance ranking can be used to identify the most relevant features.

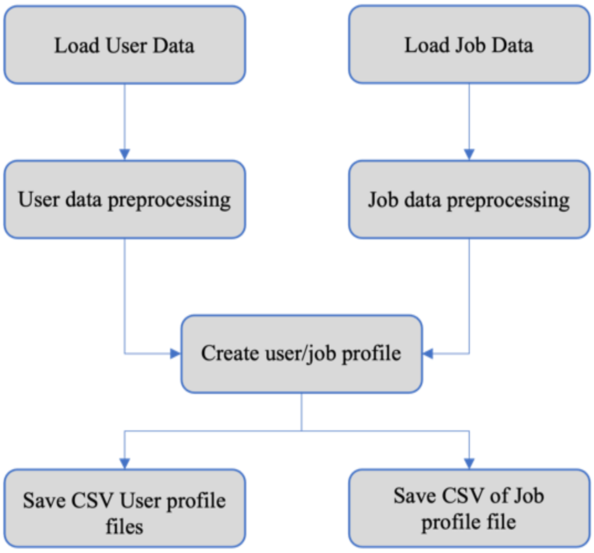

Figure 4 –Flow Diagram- Data Preprocessing

A comma-separated file containing all user and job info is available. The author wants to produce a user choice matrix for each column during data preprocessing. i.e., will produce a two-dimensional matrix with information about the user's chosen database or language skills listed in each row. One specific skill column's values are changed from their original form to a column name against a user in each row. The Stack Overflow Developer Survey information will be used to create a Job Recommendation System using machine learning and natural language processing. It aids in making sure that the data is accurate, reliable, and in a structure that can be used by machine learning and analysis algorithms.

C. Evaluation

In this study's evaluation phase, the recommender system created to enable cosine similarity is evaluated. As the system employs a threshold-based approach to recommend jobs based on user preferences, the evaluation of the model will involve iterating over multiple users. Random selection will be used to determine the participants for this evaluation. The evaluation will involve creating several job suggestions using the random user details, then computing the coverage, precision, recall, and F1 score for each set of recommendations. Precision, recall, and F measures will also be computed for different threshold values using the same user details. Coverage will also be calculated, which represents the percentage of recommended items out of *I* items. The equation below provides a notation for determining the coverage value for the recommended items in the list of *U* for user *u*.

$$Coverage = \frac{(Number\ of\ recommended\ items\ for\ user\ u)}{I} \quad (3)$$

For computing the threshold value, Job score is required which can be calculated using the following formula.

$$Job\,Score(U,J) = (0.6 * \textstyle\sum_{i=1}^{n} Sim\,Dist_{skill}(U,J_i)) + (0.4 * \textstyle\sum_{i=1}^{n} Sim\,Dist_{domain}(U,J_i)) \quad (4)$$

Where n is the overall number of jobs, U is the user profile vector, and J is the job profile vector.

$$Threshold\ score = \max(Job\,Score) * C \quad (5)$$

The outcome is assessed using several performance parameters, including accuracy, precision, recall, and F-measure.

A. Accuracy - It is a basic accuracy indicator that is proportional to the overall number of measurements. Because the proportion of false negatives and false positives is nearly equal, symmetrical datasets provide greater statistical accuracy.

Accuracy = (True Positive) + (True Negative) / (True Positive) + (False Positive) + (False Negative) + (True Negarive)
(6)

B. Precision - It is a ratio of positive predictions to total number of positives actually present.
Precision = (True Positive) / (True Positive) + (False Positive)
(7)

C. Recall - It is a ratio of positive predictions against all positives actually present.
Recall = (True Positive) / (True Positive) + (False Negative) *(8)*

D. F1 score – It is computed as weighted average of recall and precision. It therefore represents both false negatives and false positives.
F1 Score = 2(Recall * Precision) / (Recall + Precision)*
(9)

The author made a random selection and used a range of thresholds to query for the suggestion for that specific user id. The average F1 score and Precision for the job recommender system are calculated using the results gathered from various users. Table 1 displays the typical precision and F1 score results.

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Table 1- Average Precision and F1 score for users selected at random

User	Average	
	F1 score	Precision
3	0.630	0.515
8	0.61	0.498
10	0.698	0.589
14	0.595	0.473
16	0.536	0.391
25	0.471	0.354
Average Score	0.59	0.47

In Table 2, it can be seen that some of the features that are commonly extracted from job postings and resume for content-based filtering. These features are used to create vectors representing the job posting and the student's profile. These are then compared using cosine similarity to identify the most suitable job opportunities.

Table 2: Sample features extracted from job postings and resumes for content-based filtering

Feature	Description
Job Title	The title of the job posting
Job Description	A summary of the responsibilities and requirements
Skills	The required skills for the job
Education	The required education level
Experience	The required years of experience
Industry	The industry of the job posting
Company Size	The size of the company offering the job
Job Location	The location of the job posting
Salary	The expected salary range for the job

Table 3 shows a sample of similarity scores between job postings and a student's profile. The cosine similarity scores range from 0 to 1, with higher values showing a stronger match between the job ad and the student's profile. These scores assign a value to each job ad based on its relevance to the student's profile.

Table 3: Sample similarity scores between job postings and a student's profile

Job Posting	Cosine Similarity
Job A	0.86
Job B	0.72
Job C	0.60
Job D	0.45
Job E	0.23

Figure 5 shows the most common skills and requirements mentioned in job descriptions, clearly showing that SQL is the most in-demand technology in the market, followed by Java and AWS.

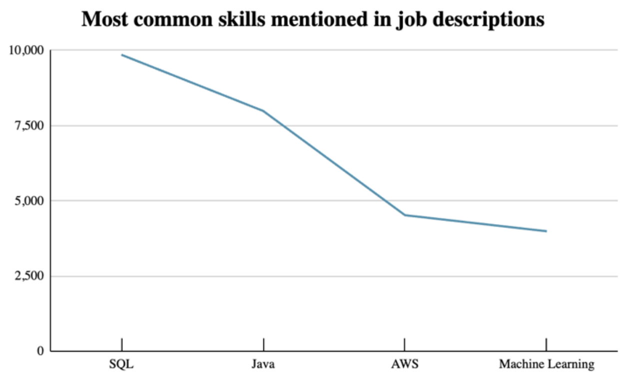

Fig 5 – Most common skills mentioned in job descriptions.

In Table 4, it can be seen that a sample of recommended job opportunities based on content-based filtering. The job postings are ranked based on their cosine similarity scores, with the most similar job postings recommended to the student. These recommended job opportunities are then presented to the student for further consideration.

Table 4: Sample recommended job opportunities based on content-based filtering

Job Posting	Cosine Similarity
Job A	0.86
Job B	0.72

V. CONCLUSION

In conclusion, the career Recommendation System created in this study combining machine learning and NLP(Natural Language Processing), has proven to be a successful way to suggest career opportunities to candidates. The system used the candidates' profiles, job needs, and preferences to deliver personalized job recommendations and increase the effectiveness of the job search process. To increase the precision and relevance of the recommendations, the system used a hybrid filtering strategy that included collaborative filtering with content-based filtering techniques. The model's examination showed that it achieved good precision, recall, and F1 scores, demonstrating its efficacy in matching job prospects to the profiles and preferences of individuals. Overall, this study shows how machine learning and natural language processing can improve the hiring process and make it easier for job hopefuls to identify jobs that suit them. The system's use in actual recruitment scenarios and incorporation of more data, such as personality traits and social network analysis, for more individualized recommendations can be explored in further research.

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