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A Review of Job Recommendation Systems Using Machine Learning

M. Tech Scholer Reena Tiwari, Assistant Professor Mrs.Vaishali Upadhyay
Department of computer science & engineering
Swami Vivekanand college of engineering, Indore

Abstract- This research aims to assess recent literature on job recommender systems (JRS), placing particular emphasis on studies that consider temporal and reciprocal aspects in job recommendations. Unlike previous reviews, we highlight how incorporating these perspectives can improve model performance and lead to a more balanced distribution of applicants across similar jobs. Additionally, we examine the literature on algorithmic fairness, finding that it is rarely addressed, and when it is, authors often mistakenly assume that simply removing discriminatory features is sufficient. Many studies label their models as "hybrid" but fail to clarify what these methods entail, so we used existing recommender taxonomies to categorize these hybrids into more specific subclasses. We also found that data availability, particularly click data, significantly influences the choice of validation techniques. Finally, the research shows that generalizability across different datasets is rarely considered, though error scores can vary between datasets.

Index Terms- Job Recommender Systems (JRS), Temporal and Reciprocal Aspects, Algorithmic Fairness, Hybrid Recommender Models ,Data Validation Techniques.

I. INTRODUCTION

Businesses affected by the pandemic are gradually regaining the momentum they lost, as the world returns to normal. Now is an opportune time for companies to invest in their human resources to recover fully. During the pandemic, many governments urged businesses to halt operations to contain the outbreak, leading to widespread remote work arrangements. However, some companies reduced costs by laying off permanent and contract employees. Those laid off are now actively seeking new job opportunities. As humans, we naturally strive to overcome challenges, seeking purpose in our work, which drives individuals to improve, leave their current jobs, and look for better opportunities—a cycle that repeats during the hiring process.

To meet the continuous demand for recruitment from job seekers, numerous employment firms have developed job boards. Job seekers visit these sites to search for open positions and apply to jobs of interest. They gravitate towards services that offer the most value, whether it's building a CV, creating an employer-attractive profile, or accessing new job listings. With so many options available, job seekers often choose the platform that best fits their needs.

At the same time, job seekers have become more determined and proactive in finding opportunities that better align with their skills. However, companies targeting these candidates face challenges in assessing their qualifications and providing personalized job recommendations.

1. Can you explain the Recommender system to me?
When we make a purchase online, these are the mechanisms that assist us in weeding out items that are comparable to the one we want. A recommender system is a term that refers to the process of recognising a user's preference based on the user's online behaviour, prior purchases, or experience inside the system. The use of a recommender system [3] has become more important over recent years. At first, sectors related to entertainment made the most of the advantages offered by these technologies. Then, recommender systems were applied in e-commerce enterprises as well as online news websites; nevertheless, very few organisations have attempted to integrate it in the employment process.

2. Why do we utilise a system that recommends things?
Businesses always look for new methods to expand their income streams. When a salesperson attempts to sell an additional item to a customer based [4] on other goods the client is going to buy, this kind of transaction is referred to as "upselling" in traditional business models. Customers revealed their preferences by engaging with the company or buying the product it was offering to them as businesses began to incorporate technology in an effort to boost the amount of time users spent interacting with the company's products and services. The company has made use of the large amounts of data that it has acquired in order to provide a more tailored

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advice to its clientele. Netflix is a streaming service that derives its income from the subscription fees paid by users for access to its library of films and television shows.

Web scraping (or rvest) is a technique used to collect data useful to a research endeavor. Conventional data collection procedures would be time-consuming and difficult if the information was already available online in HTML format on a particular website. As a result, gathering the necessary information might be challenging. Online information will be shown in HTML components including forms, tables, comments, articles, and job postings. Considering the sheer amount of information, compiling this information would not be a simple process. As a result, we depend on methods such as scraping websites. This method first came into existence about the same time that the internet was made available to people all over the globe.

Fig. 1 Web Scrapping overview [5]

4. Content Based Filtering

As previously mentioned, the collaborative filtering approach makes recommendations based on a user's past interactions with specific items, starting with this history as the foundation. In contrast, content- or attribute-based recommenders consider both the item's specific attributes and the user's interaction history to offer relevant product recommendations. These systems aim to help users discover the best-suited products for their needs. Since we are working with two separate datasets—one for users and one for jobs collected from the internet—there has been no prior interaction between the user and the items in question. Therefore, as part of our implementation, we will generate user and item profiles based on their respective characteristics.

Content-based recommenders operate on the premise that items with similar attributes will likely appeal to users who have shown interest in similar items. Thus, these recommenders suggest items similar to those the user has previously rated highly. For example, a user may receive job suggestions that require similar skills or fall within the same work domain they have shown interest in before. However, this approach has its limitations. User preferences in terms of job domains tend to remain stable, as users rarely switch domains or focus on entirely new skill sets. Moreover, job listings are removed from the system once a position is filled, so previously recommended jobs may no longer be available.

- In content-based recommendation systems, there are two key approaches:
- Analyzing the explicit properties of the material.

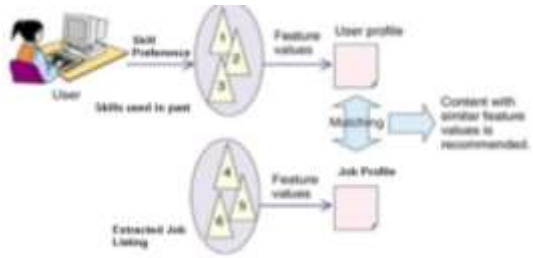

Fig. 2 Overview of Content-Based Recommender System [6]

The following outline provides an outline of the structure of the paper. The second section contains the materials and research that are relevant to the topic. Section IV is where we draw our conclusions and discuss what comes next.

II. LITERATURE STUDIES

VNJobSpace consists of six core components that independently collect, integrate, and analyze job advertisements. It includes three databases that store job-related data, the structure of each source, and collected curricula. Currently, VNJobSpace users can access over 700,000 job listings from 14 different job sites in Vietnam. Users can explore this aggregated data, receive career forecasts, and get advice on courses needed to achieve their desired jobs [7].

The system uses a Random Forest Regressor algorithm to assess applicant performance and recommend the best candidates for a position, optimizing placement probability and easing the recruiter's task. Random Forest builds multiple decision trees and combines them to provide more accurate and reliable forecasts, simplifying and enhancing the recruitment process [8].

Increasingly, companies are selecting candidates based on resume information, though some candidates exaggerate their skills. This system also provides recruiters with a thorough view of a candidate's technical skills and domain knowledge, helping organizations ensure the right candidates access the right career opportunities [9].

The prediction method is based on machine learning, deep learning, and ensemble models, tested on large, medium, and small datasets. Our method outperforms alternative approaches, achieving high accuracy (0.96, 0.98, and 0.99, respectively). Surprisingly, "business travel" was identified as

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a key factor for employee retention, more significant than traditional factors like awards or compensation [10].

In this study, we enhanced a job prediction algorithm by combining job descriptions and resumes. Historical delivery weights and user similarity weights, calculated from job descriptions and resume data, optimize the system. Tests on real datasets show that our methods significantly improve job suggestion accuracy [11].

Job proposals consider both the candidate's preferences and content-based matching. Preferences are either mined from rules or extracted from the candidate's job application history. Our approach achieves much higher accuracy compared to basic job suggestion methods [12].

This study develops a job recommendation system using collaborative filtering. The system suggests jobs based on user profiles and calculates a similarity index between skill sets using Euclidean distance, then ranks them using the naive Bayes method. The recommendation system is implemented in Python [13].

We present a job recommendation model incorporating Gradient Boosting Regression Tree (GBRT) with time (T-GBRT). The T-GBRT model adds time variables and weights to improve prediction accuracy while reducing computational complexity through neighbor-based filtering. Experimental results show that our model performs best across four criteria compared to other models [14].

We integrate SD-Predictor with YARN to improve task scheduling and minimize the impact of misconfigured jobs. Our method achieves 78% precision, 52% recall, and a 2% false positive rate in predicting job failures, showing better recall and false positive rates than related approaches [15].

Our algorithm accurately predicts outcomes using feedback from previous users. We also propose a Monte-Carlo Tree Search (MCTS) method to reduce computational complexity by clustering similar items. Testing on a large database from Work4 demonstrates our algorithm's superior performance compared to existing methods [16].

In ideal conditions with significant user and repository history, we achieved a precision of 0.886 using machine learning and selected attributes. Despite issues with cold starts, the classifier still reached an accuracy of 0.729, sufficient for automatically selecting prominent projects for developers [17].

Job seekers often spend hours sifting through vast amounts of online job listings. We simplify this process by comparing content-based and collaborative filtering methods. Our system provides highly accurate job recommendations based on applicants' profiles while protecting their preferences and behaviors [18].

This paper describes a job recommender system aimed at helping job seekers find suitable positions. Job offers are collected, processed, and clustered by characteristics such as titles and technical skills. Job seeker behavior, including ratings and applications, is matched with job clusters to generate a top-n list of recommendations based on user preferences[19][20].

Table 1: Comparative Study of Job Prediction and Job Recommendation techniques

Reference	Title	Method	Dataset	Result	Future work
[21]	Prediction of recommendations for employment utilizing machine learning procedures and geo-area based recommender framework	Logistic Regression, K Nearest Neighbors, Stochastic Gradient Decent, Support Vector Machines, Naïve Bayes, Multilayer Perceptron, AdaBoost, Random Forest Classifier	LinkedIn and Facebook, LinkedIn dataset consists of 39,538 candidates with 26 job features	Random Forest Classifier have give better accurac (99.03%) as compaire another method	To designe model for geo-area based recommender
[22]	Job Prediction: From Deep Neural Network Models to Applications	TextCNN, Bi-GRU-LSTM-CNN, and Bi-GRU-CNN	10,000 distinct job descriptions collected from the online finding job sites	With an F1 score of 72.71%, the proposed ensemble model came out on top as having the best outcome.	As a result of this study's findings, the author plans to investigate the LSTM variations.

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[25]	[24]	[23]
Employment Recommendation System Using Machine Learning	JobFit: Job Recommendation using Machine Learning and Recommendation Engine	Implementation of Machine Learning Algorithms for Employee Recommendation
Support Vector Machine algorithm	K Nearest Neighbors, Support Vector Machines, Random Forest Classifier, Decision Tree	Logistic Regression Model, KNN, NAÏVE BAYES
Different jobs	National Longitudinal Survey o f Youth 1997 dataset	LinkedIn and Facebook
Got 94.31% accuracy using svm algorithm	Random Forest Classifier have give better accurac (96%) as compaire another method	KNN Classifier have give better accurac (88%) as compaire another method
Author will also add ratings feature at workers end so contractor can easily finalize workers based on the ratings and feedback.	This would further enable the algorithm to understand the people better, and it would also increase the accuracy of the JobFit score.	Apply another classification for improved accuracy

[28]	[27]	[26]
Employability prediction: a survey of current approaches, research challenges and applications	Undergraduate engineering students employment prediction using hybrid approach in machine learning	User click prediction for personalized job recommendation
Neural network, Logistic Regression, K Nearest Neighbors, Stochastic Gradient Decent, Support Vector Machines, Naïve Bayes, Multilayer Perceptron, AdaBoost, Random	Network and K-means based clustering method	cluster users based
LinkedIn and Facebook	300 students record	Current data and historical data
This survey offers a detailed road map, which enables data mining to be applied to employment opportunities.	Predicting accuracy of 88.38%	In order to rank models and show how successful it is, a new model that incorporates the most recent advances in learning technology has been proposed.
It is recommended that diverse judgments be justified by referring to the specific aims and research questions in their respective contexts.	Extended to be used for applications in different sorts of academic fields	The method that has been described is also applicable to other recommendation jobs in which the data shows multimodality behaviors.

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III. RESEARCH GAP

There is conceptual confusion regarding the definition of employee engagement, including whether it is a behavior or attitude. No theoretical reasons suggest a link between employee engagement and religious beliefs or personal character, and the influence of personality on engagement has not been proven. Additionally, there is no empirical evidence supporting a connection between employee engagement and an organization's financial success, nor that job performance mediates the relationship between engagement and financial performance.

IV. CONCLUSION

In this research, we reviewed existing studies on job recommender systems (JRS) from various perspectives, including the influence of data science contests, data availability on techniques and validation, and ethical concerns. We also introduced a new subcategory for hybrid JRS to clarify differences between them, which previous studies had not explored. Most work on JRS overlooks these multi-perspective approaches, though they can offer benefits like improved model performance, better applicant distribution, and fairness. Current research mainly focuses on representing large amounts of textual data from profiles and job openings, with deep representations showing promising results. However, focusing solely on this can obscure other important aspects like fairness, which has been shown to be an issue in applicant search engines like Indeed and Careerbuilder. While audits exist for candidate search engines, job recommender systems lack algorithmic fairness audits, presenting a research opportunity to adapt fairness metrics to JRS.

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