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A Review of System for Recommending Jobs Using Machine Learning

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Abstract: The purpose of this research is to conduct a literature assessment of job recommender systems (JRS) that have been published in the recent past. When compared to our prior evaluations of the relevant literature, we placed a greater amount of importance on contributions that took into account the temporal and reciprocal aspects of job recommendations. Previous research on JRS has shown that it may be possible to enhance model performance by taking different perspectives like these into consideration when designing JRS. Additionally, it may result in a more balanced distribution of applicants among a group of occupations that are comparable to one another. In addition to this, we look at the literature from the point of view of the fairness of algorithms. When we looked into this, we discovered that this topic is seldom brought up in the academic literature, and when it does, many writers make the incorrect assumption that deleting the discriminating characteristic would be enough. When referring to the kinds of models that are used in JRS, writers usually refer to their approach as being "hybrid." In doing so, however, they unfortunately conceal what exactly these procedures include. We divided this expansive class of hybrids into more manageable subclasses by making use of the recommender taxonomies that were already in existence. In addition, we come to the conclusion that the availability of data, and more specifically the availability of click data, has a significant bearing on the selection of a validation technique. Last but not least, despite the fact that the generalizability of JRS across various datasets is seldom taken into consideration, the findings imply that error scores may change across these datasets.

Keyword: Job Recommender Systems, Machine Learning , Businesses , Content Based Filtering , Gradient Boosting Regression Tree.

I. INTRODUCTION

Businesses that were impacted by a pandemic illness are making modest but steady progress toward regaining the momentum they lost while the rest of the globe was getting back on its feet. Now is the time for enterprises and corporations to look into making investments in their human resources, as this will enable them to regain the momentum that was lost during this time. In response to requests from governments throughout the globe for businesses to suspend operations as part of efforts to contain the epidemic, several firms have requested that their staff do their jobs from home. On the other hand, many other businesses began to cut their operating costs by firing personnel who were serving in permanent and contract capacities. People who were laid off as a direct result of the closure are now looking for new work and keeping an eye out for opportunities. Naturally, as humans, we make it our goal to persevere despite adversity so that we may fulfil the meaning behind our lives. An person receives a feeling of purpose from their day-to-day work [1], and as a consequence, they strive to do better at what they do, which leads to them quitting their present job and seeking for a new one; this is a continuous cycle that occurs throughout the hiring process.

In order to accommodate the endless recruitment process from the perspective of job seekers, a vast number of employment firms have devised solutions for the supply of job boards. A job seeker visits our website, looks for open positions [2] that may be of interest, and then applies for those positions. Jobseekers often go for the service that helps them the most, whether it's creating a CV, building a profile for potential employers, or being presented with fresh opportunities. Given the abundance of options, job seekers often choose for the board that best meets their needs.

Candidates seeking jobs are becoming more dogged and aggressive in their hunt for new possibilities that are a better match for their talents. However, businesses who are aiming their recruitment efforts towards these job searchers are having a difficult time determining the skills of the applicants and coming up with individualized suggestions for work.

1.1 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;

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nevertheless, very few organisations have attempted to integrate it in the employment process.

1.2 Why do we utilize 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 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.

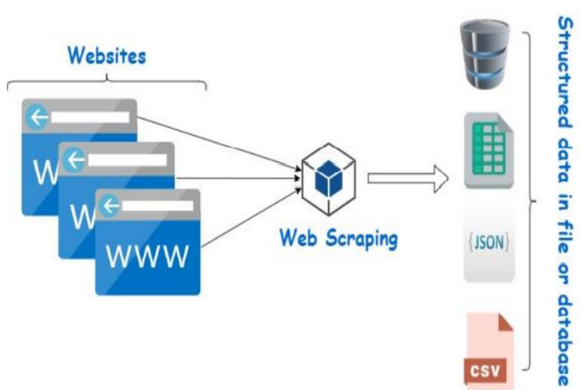

Fig. 1.1 Web Scrapping overview [5]

1.4 Content Based Filtering: As was previously mentioned, the collaborative filtering approach bases its recommenders on the history of a user's previous interactions with a certain item. The procedure begins with this history as its first point of entry. In contrast, content- or attribute-based recommenders take into consideration the specific characteristics of an item or the user, in addition to the user's history of interacting with the item, in order to provide the user with appropriate product recommendations. These types of recommenders are designed to help users find the best products for their needs. Because we have collected two separate data sets, one of which is a dataset of users and the other of which is a dataset of jobs taken from the internet, there has been no previous interaction between the user and the item. One of the data sets that we have collected is a dataset of users. As a consequence of this, as we are working on the implementation, we will be generating user profiles and item profiles based on the information, taking into mind the characteristics that are particular to persons and goods correspondingly. The operation of content-based recommenders is predicated on the notion that objects that have comparable features also share a similar degree of interest at the user level. Content-based recommendation engines will continue to recommend to a user things that are comparable to those products that the user has previously rated highly. It is possible that the user may get suggestions for jobs that need the same skills or are within the same work domain that the user has shown a preference for in the past. This behavior of the recommendation system is regarded as having reached its limit in the overwhelming majority of all feasible circumstances. Nevertheless, the user preference in the system does not change when it comes to the job domain. Because the user's choice to switch his job domain or focus on various skill sets does not vary often, and because job advertisements will be removed from the system after a position has been filled, the previously suggested job is not likely to be one of the available options. When it comes to making recommendations based on the content of a website, there are two different approaches:

1. Analysing the explicit properties of the material.

2. Creating a User Profile and an Item Profile Based on the Ratings Given by Other Users.

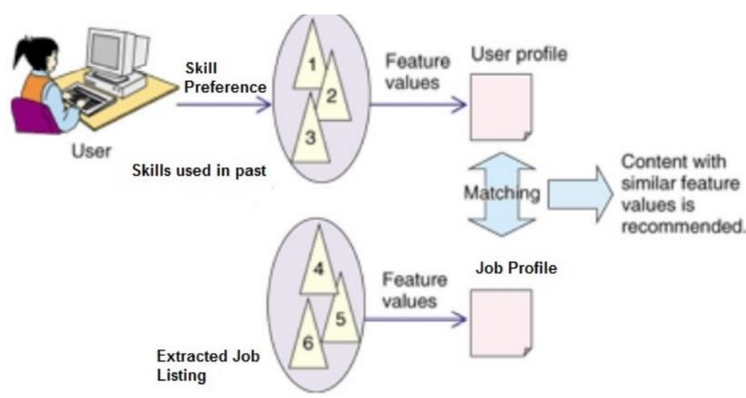

Fig. 1.2 Overview of Content-Based Recommender System [6]

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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 is made up of six primary components, each of which is in charge of independently collecting, integrating, and evaluating job adverts. In addition to this, it has three databases that hold data pertaining to jobs, the structure of each source, as well as gathered curriculum. At this time, users of VNJobSpace have access to over 700,000 job listings aggregated from 14 different job sites located in Vietnam. Users on the receiving end are able to explore the accumulated information, gain a prognosis for career prospects, and receive advice on necessary courses to achieve a desired job [7].

This system intends to assess the applicant performance and suggest candidates who are the best match for the position by utilising an algorithm known as Random Forest Regressor. This will help to optimise the placement probability of candidates, which in turn will make the recruiter's work easier. A number of decision trees are constructed by Random Forest, and then those trees are combined in order to provide a forecast that is both more accurate and more reliable. The process of recruiting will be made simpler and more effective by using this technique [8].

A growing number of companies are selecting individuals for further consideration based on the information included in their resumes; nevertheless, some job seekers embellish the skill sets shown on their resumes. Consequently, as an additional benefit, this approach also provides the recruiters with a thorough perspective through of the candidate's technical capabilities and domain knowledge. The organisation is able to take use of this fact in order to find the best possible candidate by ensuring that the appropriate individuals have access to the appropriate career opportunities [9].

The method of prediction is based on machine learning, deep learning, and ensemble learning models, and it is evaluated on large-sized and medium-sized simulated human resources datasets. After that, it is tested on a real small-sized dataset that has a total of 450 responses to be used as a benchmark. When contrasted with alternative methodologies, the accuracy of our technique is higher (0.96, 0.98, and 0.99 respectively) for each of the three datasets in question. According to the findings of our study, "business travel," a term that is less popular in the literature, is the primary motivation for workers and need to be taken into consideration within HR policy in order to retain [10] personnel. This is the case despite the fact that awards and compensation are often regarded as the most essential factors that contribute to employee retention, but our research shows that "business travel" is the most significant factor.

In this research study, we improved the algorithm by merging the information from job descriptions and resumes. In particular, the job choice prediction algorithm is enhanced by historical delivery weight calculated by position descriptions and similar user weight computed by resume information. Both of these factors contribute to improving the system. Both of these factors contribute to the optimization process. Our approaches have been found to significantly enhance job suggestion outcomes, according to the tests that were carried out on actual data sets and analysed [11].

The candidate's preferences as well as the application's content-based matching are taken into consideration when job proposals are sent to the target applicant. Either these preferences are saved in the form of mining rules or they are obtained from the candidate's own history of applying for jobs. When compared to other fundamental approaches to job suggestion, our strategy achieves a much higher degree of precision in terms of accuracy [12].

The purpose of this study is to develop a recommendation system for employment websites using a method called collaborative filtering. It is the purpose of the system to provide employment recommendations to the user based on his or her profile, as well as to compute a similarity index between two skill sets by determining the Euclidian distance between them, and then to rank those skill sets using the naive Bayes method. Python has been used as the language of implementation for the recommendation system [13].

After that, we will continue to show a job recommendation model that takes into consideration both the Gradient Boosting Regression Tree as well as the passage of time (T-GBRT). When attempting to predict individual preferences, the T-GBRT model incorporates time variables into the GBRT and also adds the weight of the time element to the topK ranks. In order to cut down on the amount of work that has to be done with the computer, this is achieved via the use of a technique called neighbor-based filtering. At the end of the research project, it is proven that the model obtains the best results in the experiment with four criteria, which suggests that the new model is more successful when compared to the other three models. [14].

We develop and merge SD-Predictor with a common scheduling framework known as YARN in order to enhance task scheduling and minimise the negative affects that may be caused by jobs that have been misconfigured. In addition, we investigate any connections that may exist between

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configurations and the termination status of tasks and provide some suggestions for the improvement of configuration settings. Our method achieves 78% precision, 52% recall, and 2% false positive rate in unsuccessful job prediction, which is significantly better recall and false positive rate than related works [15]. The results of the experiment show that our method performs at 78% precision, 52% recall, and 2% false positive rate.

It makes an accurate prediction of an item by making use of the feedback reward provided by prior users in the immediate context area. In addition to that, we provide a Monte-Carlo Tree Search (MCTS) approach for reducing the amount of work done by a computer in which things of a similar kind may be grouped together into a cluster. The level of regret and space complexity that our method may reach can be sublinear. Finally, several tests are carried out to evaluate our algorithm based on a huge database from Work4, which is the worldwide leader in social and mobile recruitment. These experiments may demonstrate that our algorithm has remarkable performance in comparison to other algorithms that already exist [16].

In the ideal situation, when there is a considerable amount of history associated with both a user and a repository in the system, we were able to obtain a precision of 0.886 by using a combination of well chosen lists of attributes and machine learning algorithms. Even though the suggested classifier has an issue with cold starting, it still achieves accuracy equal to 0.729, which is sufficient for the automated selection of notable projects for developers [17].

When trying to sift through the vast amounts of information available on the internet, job seekers often spend hours looking for relevant resources. We simplify the whole procedure by doing it in this way. The vast majority of the time, recommendation systems function by either capitalizing on linkages between known characteristics and material that is used to characterize services and items (content-based filtering) or by making use of the overlap of similar people who have interacted with or rated the target item (collaborative filtering). You may find a comparison that we give between collaboration based and content filtering in [18], which you can access here.

The process of reviewing a large number of jobs that have been posted on the internet, such as LinkedIn, fresherworld.com, naukri.com, and so on, on a regular basis becomes a tedious task; as a result, we have designed and implemented a recommendation system for people who are looking for work online. This system's goal is to attain an exceptionally high degree of accuracy while simultaneously providing the customer with rating predictions that are relevant to their needs. It is desirable to have job recommender systems so that one may get this degree of accuracy while also producing rating predictions that are essential to the customer. In spite of the fact that there are a great many job recommender systems on the market that make use of a variety of methods, an effort has been made in this article to create the job suggestions based on the applicants' profile coordination while also protecting the applicants' employment behavior or preferences. This article can be found here. The collaborative filtering includes a list of ratings that have previously been provided for an item by other users. The purpose of this study is to provide a short assessment of collaborative filtering rating prediction-based job recommender systems and their implementation using RapidMiner [19].

This article describes a recommender system with the intention of assisting job searchers in locating employment that are a good fit for them. After collecting job offers from job search websites, the next step is to prepare them so that significant characteristics can be extracted from them. These characteristics include job titles and technical abilities. Job opportunities that have certain characteristics are organised into clusters. If a job seeker finds success in one position that is part of a cluster, it is likely that he will also find success in other positions that are part of the same cluster. A list of the top n ideas is supplied once data from job clusters and job seeker behavior have been matched. Job seeker behavior is dependent on user behaviors such as rating, like, and applying for jobs [20]. The matching data served as the basis for the creation of this list.

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.
[23]	Implementation of Machine Learning Algorithms for Employee Recommendation	Logistic Regression Model, KNN, NAÏVE BAYES	LinkedIn and Facebook	KNN Classifier have give better accurac (88%) as compaire another method	Apply another classification for improved accuracy
[24]	JobFit: Job Recommendation using Machine Learning and Recommendation Engine	K Nearest Neighbors, Support Vector Machines, Random Forest Classifier, Decision Tree	National Longitudinal Survey o f Youth 1997 dataset	Random Forest Classifier have give better accurac (96%) as compaire another method	This would further enable the algorithm to understand the people better, and it would also increase the accuracy of the JobFit score.
[25]	Employment Recommendation System Using Machine Learning	Support Vector Machine algorithm	Different jobs	Got 94.31% accuracy using svm algorithm	Author will also add ratings feature at workers end so contractor can easily finalize workers based on the ratings and feedback.
[26]	User click prediction for personalized job recommendation	cluster users based	Current data and historical data	In order to rank models and show how successful it is, a new model that incorporates the most recent	The method that has been described is also applicable to other recommendation jobs in which the data shows

				advances in learning technology has been proposed.	multimodality behaviors.
[27]	Undergraduate engineering students employment prediction using hybrid approach in machine learning	Network and K-means based clustering method	300 students record	Predicting accuracy of 88.38%	Extended to be used for applications in different sorts of academic fields
[28]	Employability prediction: a survey of current approaches, research challenges and applications	Neural network, Logistic Regression, K Nearest Neighbors, Stochastic Gradient Decent, Support Vector Machines, Naïve Bayes, Multilayer Perceptron, AdaBoost, Random Forest Classifier	LinkedIn and Facebook	This survey offers a detailed road map, which enables data mining to be applied to employment opportunities.	It is recommended that diverse judgments be justified by referring to the specific aims and research questions in their respective contexts.

III. RESEARCH GAP

- There is a conceptual confusion about the definition of employee engagement, the labels of employee engagement, and the issue of whether or not employee engagement is a behavior or an attitude. Specifically, this misconception relates to the following.

- There are no theoretical reasons that point to a connection or relationship between the level of employee engagement and a person's religious beliefs.

- There are no theoretical reasons that suggest a tie or relationship between the level of employee engagement and an individual's character. It is clear from this that the influence of a person's personality on the level of involvement shown by workers has not been either theoretically argued for nor experimentally demonstrated.

- There is no empirical evidence to support the hypothesis that there is a connection between employee engagement and the financial success of organisations.

- There is no empirical evidence to imply that employee job performance functions as an intervening variable between employee engagement and the financial performance of a corporation. This is because there is a direct correlation between employee engagement and financial performance.

IV. CONCLUSION

Within the scope of this research, we looked at the existing research on job recommender systems also known as JRS from a variety of perspectives. These include the impact that data science contests have, the impact that the availability of data has on the technique and validation that is used, and the ethical concerns that need to be made while developing job recommender systems. In addition, in order to have a clearer picture of the ways in which hybrid recommender systems vary from one another, We created a subcategory within the larger group of hybrid recommender systems. Previous studies of job recommender systems did not address either this multi-perspective approach or the newly proposed taxonomy of hybrid job recommender systems. Neither of these topics was covered in this study. Despite the fact that application-oriented concerns in JRS were discussed in early JRS contributions, the vast bulk of the published work does not take these concerns into account. However, the contributions that do take alternative perspectives on the JRS issue indicate that such perspectives may have significant advantages. These advantages may include, but are not limited to, enhanced model performance (from a temporal viewpoint), improved distribution of applicants across a collection of homogenous openings (from a reciprocal perspective), or assurance that the method is fair (ethical perspective). In order to create job suggestions, the bulk of work that is being focused on right now is directed toward figuring out how to represent the considerable quantity of textual data that is obtained from applicant profiles as well as openings in order to fill them. In recent years, especially in-depth representations have shown very promising outcomes with relation to this. On the other hand, this focal point may also provide the impression that this is the only viewpoint that is significant. A singular viewpoint like that may be quite detrimental, particularly when it comes to issues of justice. An investigation of the applicant search engines of Indeed, Careerbuilder, and Monster revealed significant results for individual as well as group unfairness regarding gender. Audits of candidate search engines are something that we are familiar with, however algorithm audits of job recommender systems are not something that we are familiar with. The growing focus on algorithm fairness within the scientific community has, however, resulted in the development of algorithms and metrics that may be used to both assess and assure that algorithms are fair. Because of this, there is an opportunity for research to investigate how these may be adapted to work inside the job recommender system area.

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