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A Review on Job Recommendation System

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ABSTRACT

With the rapid growth of artificial intelligence and machine learning technologies, the recommendation system aims to help users find items that match their preferences. In order to improve performance, many recommendation system techniques have been proposed. This paper presents a survey of some common recommendation techniques and related issues with advantages and disadvantages. At the same time, the different types of job recommendation systems are described in detail and compared with each other. The goal is to provide a comprehensive overview of the current state of job recommendation systems and to analyse the characteristics of each system. The results of the case studies can contribute to a better understanding of the strengths and weaknesses, as well as techniques used in different job recommendation systems. Through this review, insights are provided to guide the development of more effective recommendation systems. For future research, a system is proposed to generate career move recommendations with upskilling and reskilling suggestions.

1. Introduction

According to various studies, the volume of information has increased significantly due to the rapid development of network technology, leading to network overload and making it increasingly challenging for users to find relevant content [1,2]. Traditional search engines have limited capabilities to assist users in finding solutions to their problems, which has led to the development of personalized recommendation systems [3]. The fundamental goal of these systems is to identify individual user preferences and provide relevant resources [4]. Despite their potential benefits, personalized recommendation systems face several challenges, such as maintaining accuracy, overcoming cold start problems, addressing diversity, and adapting to changing user interests over time [1,5].

As Web 3.0 technology is coming, recommendation systems have evolved rapidly, consumer behavior has significant changed due to technological innovation [6]. Facebook, Twitter, Netflix, Amazon and LinkedIn are examples of recommendation systems that have gained popularity in recent years [7]. A recommendation system is a combination of data mining, prediction algorithms,

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machine learning, and other disciplines that help to filter information based on users' preferences and behavior [8]. Personalized recommendation technology has garnered attention from various sectors of society and has been successfully implemented on numerous websites, including news, film, music, and magazines [5,9]. In fact, recommendation systems have become a crucial means of business marketing, with approximately 30% of Amazon's revenue in the United States depending on recommendation systems [4]. Despite the successes achieved by recommendation systems in the fields of e-commerce, entertainment, healthcare, education and recruitment, there is still a need for further improvement and development to address issues such as security, sparsity, cold-start problem and so on [1].

The use of recommendation systems has rapidly increased in recent years, especially in the job market [5,10,11]. With the implementation of recommendation systems in job-hunting platforms, it is now possible to suggest job postings that match applicants' requirements, as well as recommend talent applicants that align with a company's needs [10]. The benefits of job recommendation systems are substantial, as they help both applicants and employers find the right match for their requirements, increasing the efficiency of the job search process. Moreover, job recommendation systems can also reduce the time and cost of recruiting by automating the process of filtering and recommending potential applicants [11].

This paper aims to provide a comprehensive overview of different job recommendation techniques and related issues, as well as present case studies of various systems. The structure of the paper is organized as follows: Section 2 presents the common techniques in the recommendation systems; Section 3 introduces related issues to address common challenges in job recommendation systems; An in-depth analysis of case studies of job recommendation systems which have been investigated in section 4. The final section contains some conclusions and discusses further research on career move recommendation systems.

2. Job Recommendation System Techniques

Based on how the recommendation is performed, job recommendation system techniques have been classified into six categories: Content-based Filtering (CBF), Collaborative Filtering (CF), Knowledge-based technique (KB), Utility-based technique (UB), Rule-based technique (RB) and Hybrid Filtering (HF) [12,13].

2.1 Content-based Filtering (CBF)

Content-based Filtering technique performs prediction based on characteristics of the item from their history, it aims to recommend items with similar content to ones the target user prefers. It is considered to be the most successful technique in web pages and news recommendation [14]. The process of CBF technique is to select the same feature type and calculating the similarity for items, then recommends items based on the similar content [7]. Content-based filtering can be classified into 2 tasks: user profiling and job profiling [15]. User profiling often deals with acquiring, extracting and representing the feature of users. Job profiling is a methodology that helps identifying the skills and skill level from users. It is a presentation of job details. Content-based filtering techniques can be used to match users with relevant jobs based on their skills and interests in job recommendation systems.

2.2 Collaborative Filtering (CF)

Collaborative filtering technique recommends items to particular users based on the ratings from other users [16]. This technique has achieved very huge success in recommendation systems. CF technique performs recommendation by building a database of preferences for items by the user. The system calculates similarities between the user profiles through the user's similar preferences. CF technique can give some recommendations which are not similar to the items in the active user's profile, but interesting to the user [17]. CF technique can be classified into two main categories: Memory-based technique and Model-based technique.

2.2.1 Memory-based Technique

Memory-based technique applies different similarity measures such as Pearson Correlation Coefficient, Jaccard Similarity, Cosine Similarity, Euclidean Distance and Manhattan Distance to identify the similarity between the particular user with other users. Then it selects users or jobs for active users [18,19]. There are two types of memory-based techniques: user-based and item-based technique. The difference between them is the process of getting neighbors is focused on finding similar users or similar items. The advantages of memory-based technique are that it can provide accurate recommendations for users with limited past ratings [10].

2.2.2 Model-based Technique

In the model-based technique, the available data and ratings are used to develop a model to represent the behavior of users. When the model is constructed, it can make prediction to the particular user. Algorithms in this category take a probabilistic technique and envision the CF technique as computing the expected value of a user prediction [20]. Model-based technique can handle the cold-start problem better than memory-based technique by generating recommendations for new users and items [10].

2.3 Knowledge-based Technique (KB)

Knowledge-based technique is proposed to generate predictions based on inferences on users' preferences [21]. It can ensure that recommendations are made consistently and without bias, as they are based on pre-defined rules and principles. It helps users to distinguish between the preference items without human intervention. In the field of job recommendation systems, knowledge-based technique is able to generate job recommendations by using deep knowledge to figure out desires of applicants more efficiently [22].

2.4 Utility-based Technique (UB)

Utility-based technique calculates the utility of each item for the user to generate recommendation. This technique elicits multi-attribute utility theory (MAUT) based on item ratings to describe user preferences, then applies the MAUT to calculate item utility [21]. However, utility-based technique requires remarkable burden of user-item interactions. Unlike CF technique, utility-based technique has no problem with cold start and sparsity problems [23].

2.5 Rule-based Technique (RB)

Apparently, a rule-based technique is a method of solving a problem or making a decision based on a set of pre-defined rules [24]. It mimics human intelligence to apply human-made rules to store, sort and manipulate data. In order to manipulate data, rule-based technique requires a set of facts and a set of rules to run. The rules are referred to as "if statements" as they tend to follow the line of "IF X happens THEN do Y". In addition, rule-based technique can be easily updated or modified by changing or add rules, it is flexible and adaptable to user's requirement [25].

2.6 Hybrid Filtering Technique (HF)

As any one of the techniques introduced above have the advantages and disadvantages, so Hybrid Filtering technique is proposed a combination of two or more techniques to improve performance [26]. CBF and CF are often integrated in different way to resolve the issues and challenges of other techniques. Hybrid Filtering technique has been categories into seven different types: Weighted, Switching, Mixed, Feature Combination, Feature Augmentation, Cascade, Meta-level. Each of these techniques has its own strengths and weaknesses, and the choice of which one to use depends on the specific application and the available data [15].

Comparison of each job recommendation system techniques is demonstrated in Table 1.

Table 1
Advantages and disadvantages of JRS techniques

Name of Technique	Advantages	Disadvantages
CBF	Easier for large numbers of users, No need data of other users, no sparse problem.	Limited ability to expand user's existing interest, characteristic data should be constructed well.
CF (Memory-based)	Simpler to use, no need to create items' profile.	Cold start, Scalability, sparsity problem.
CF (Model-based)	Scalable, useful in real time system, ignore sparse problem. Recommend fast.	Sensitive to data, cost too much in modelling, huge calculating workload.
KB	Recommend accurate and item to user effectively even data is limited.	Limited scope, difficulty in knowledge acquisition, limited adaptability.
UB	No cold start and sparsity problem. Sensitive to the change of user preference.	Need significant user effort, Recommendation is statical.
RB	Be able to find new interest for user, No need domain knowledge.	Synonym problem, less personalized recommendation.

3. Related Issues in Recommendation Techniques

This section discusses the common related issues in recommendation system techniques, these issues have a significant impact on the performance and effectiveness of recommendation system techniques. It is important to address them to ensure that recommendations are accurate, relevant and trustworthy.

3.1 Limited Content Analysis

Content-based filtering technique exists an obvious problem that it is restricted by the characteristic of recommended item. If the system obtains enough information of characteristic, the content must be parsed automatically or the characteristic can be assigned easily and manually [27]. In addition, when two items have the same characteristic, Content-based filtering technique is not capable to distinguish to the system [28].

3.2 Cold Start

Due to insufficient rating information or data, the system is incapable of identifying similarities between users and items, which results in inaccurate recommendations for both new users and items, and this is known as “Cold Start” [29]. In the field of job recommendation systems, the system needs enough information or interaction between applicants and jobs to produce high quality of recommendations. System cannot recommend accurate jobs to applicants if they interact little. This situation can be solved in two ways: (a) find the preferences of new applicants in advance and (b) ask applicants to input some ratings of jobs before running the systems [30].

3.3 Sparsity

Data sparsity problem means that if most users do not provide ratings of items consequently, it will lead to sparse in user-item matrix. In the field of job recommendation systems, Collaborative filtering technique uses user-job interactions such as ratings to make accurate predictions. It can calculate the similarity matrix between users and jobs with these ratings [27]. In a word, data sparsity problem exists in most of the cases and it might be generating wrong recommendations [22].

3.4 Scalability

Scalability is one of the significant issues in recommendation systems [31]. Memory-based techniques are very simple and it can handle in small algorithm. But when the data-set grows fast with the number of users and items, the system has to go through a great deal of the data-set to generate a single prediction. Under the pressure of huge computation, the memory-based techniques cannot run well in the real-time systems [32]. The solution of scalability can be (a) using Bayesian Network and dimensionality reduction and (b) using model-based techniques [33].

3.5 Security

As recommendation systems require sufficient data-set of users’ personalized information and ratings, it might cause issue on data security [34]. If the data get hacked or thieved by the malicious users, they can easily change or falsify the user-item ratings, as a result the system is unable to generate accurate recommendations. Thus, when designing a technique, the security should be considered in the first place, since recommendation system techniques have suffered from spam attacks from malicious users to mislead the recommendation [35].

3.6 Synonym

There are some similar items that have different names or entries in the system. Recommendation system techniques cannot distinguish the difference between those closely related items, so it is called “synonym problem” [34]. As synonym words affect the performance of collaborative filtering recommendations, A Thesaurus Generator, for example, is an effective way to generate synonyms using publicly available WordNet Lexicon [36].

3.7 Overspecialization

The system recommends preferences that are similar to active user’s content in CBF technique [22]. It means all the recommendations based on ratings by active users. Some suitable items which have not connection to the active users will not be suggested [32].

4. Case Study

In this section, some typical case studies of job recommendation systems are introduced with their features and technology. These case studies are frequently cited in the research on job recommendation systems because they represent innovative and successful approaches to job recommendation, and provide valuable insights into the design and implementation of effective job recommendation systems.

4.1 CASPER

Rafter *et al.,* [18] designed the CASPER (Cased-Based Profiling for Electronic Recruitment) project to build a more intelligent search engine for use in Job Finder website. The CASPER system contains two different approaches: CASPER Automated Collaborative Filtering (ACF) and CASPER Personalized Case Retrieval (PCR), as shown in Figure 1 below. CASPER ACF is a content free system that when the user login to the system then it starts to track. One of the server-side components is a User Profiling System, it gathers user’s preferences in order to construct a user profile. Another one component is a query less Automated Collaborative Filtering engine that generates personalized recommendations based on similar users’ preferred jobs. CAPSER PCR has two main stages to generate personalized job recommendations, the first stage is to provide an intelligent database query system by using a serve side similarity calculation between query and jobs. The second stage is a client-side content-based personalization engine, which calculates the relevance with a target user’s profile and classify the personalized job recommendations [37]. This approach makes retrievals not only match a user’s targeted query, but the potential preferences. The weakness of this system is facing sparsity and scalability problems. Besides, the system also needs some preparations to define and describe the case base [22]. To a certain extent, recommendation techniques based on mix of collaborative filtering and clustering might address the issues on sparsity and scalability [38].

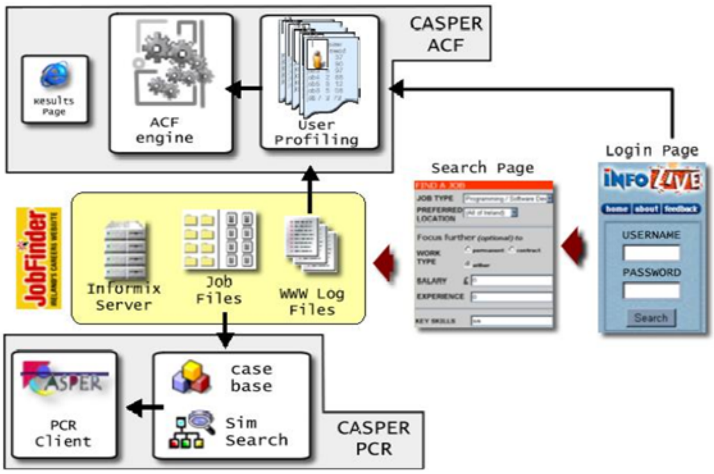

Fig. 1. The architecture of CASPER [18]

4.2 Bilateral People-JRS

A bilateral people-JRS has been proposed by Jochen Malinowski et al. [39] which not only recommends jobs to applicants but also recommends applicants to recruiters. This system represents the fusion result of two recommenders to users by implementing a CV-recommender and a Job-recommender separately. In CV-recommender the probabilistic hybrid recommendation engine is based on a latent aspect model. The preferences of both applicants and recruiter are taken into consideration for recommending jobs to applicants. The Job-recommender considers the demands-supplies perspective by considering the preferences of the applicants for the targeted job. So, the Job-recommender calculates the previous preferences ratings of applicants from their preference profiles to generate recommendations. Both the recommenders are represented as the convex mixture of preference factors from applicants and recruiters, the preferences of applicants are used to contribute a probabilistic Job-recommender by running Expectation Maximization algorithm. In the next step both two recommenders are integrated to a bilateral people-JRS to represent its high quality of recommendations between recruiters and applicants [37].

4.3 Proactive Job Recommender

A Proactive Job Recommender is proposed to assist applicants in different ways to find related positions [40]. Figure 2 shows the architecture of Proactive. When an applicant finds an interested job, the job can be assigned as a favorite job by the applicant. Personalized recommendations are generated based on the properties of favorite jobs. This system works on two groups of users, one group of users have broad range of interests and preferences but with no definite job description and career purpose. The other group has got a job and desire career move, and they have made clear career path. In order to meet various user's desire, the proactive recommender has implemented four different kinds of interfaces based on recommendation taxonomy: Most Recent Jobs, Recommender Jobs, Advanced Search and Most Recent Jobs. It helps applicants to access information and also makes a highly user-adaptive system [22]. Incomplete or inaccurate information provided by applicants results in negative suggestions, it is one the most significant shortages for Proactive Job Recommender. Collecting more comprehensive data about applicants such as not their skills, preferences, work history, education background and other relevant information could solve this problem [40].

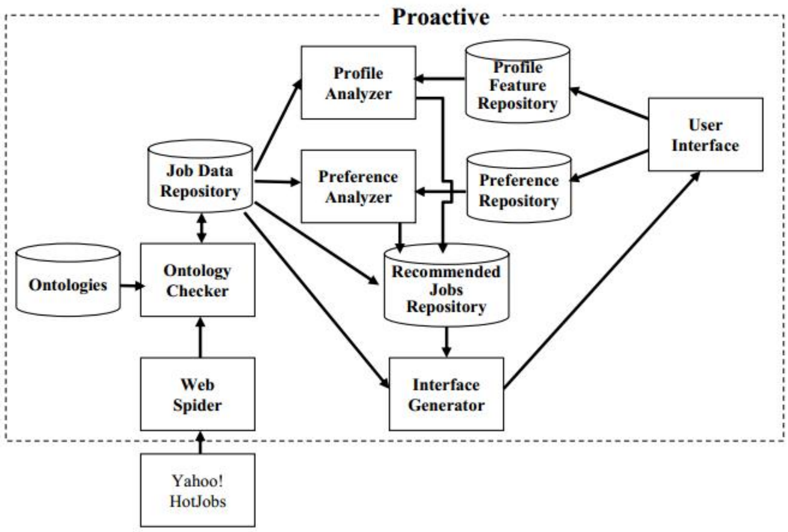

Fig. 2. The architecture of Proactive [40]

4.4 Absolventen.at

Absolventen.at is a website that focuses on hybrid user profiling in job recommendation systems [41]. The latest architecture of job recommender is a refinement of the existing one, which improves new components for the *Hybrid User Profile*, the *Configuration* and the *Evaluation*, as shown in Figure 3. This hybrid profile includes data extraction from resumes as well as some explicit and implicit relevant feedback. So, the input information of this job recommendation system contains multiple different data sources such as personal information and behavior or actions of users. In this recommender system, user actions are observed and recorded in real time, and features and actions are weighted. The weights in the applicant's user profile denote the skill level. In the meanwhile, outdated actions from history can be avoided and according to their interaction date, actions will be weighted appropriately. With the help of corresponding recommendation technique, it generates a list of job positions to match the applicant's preferences more accurately.

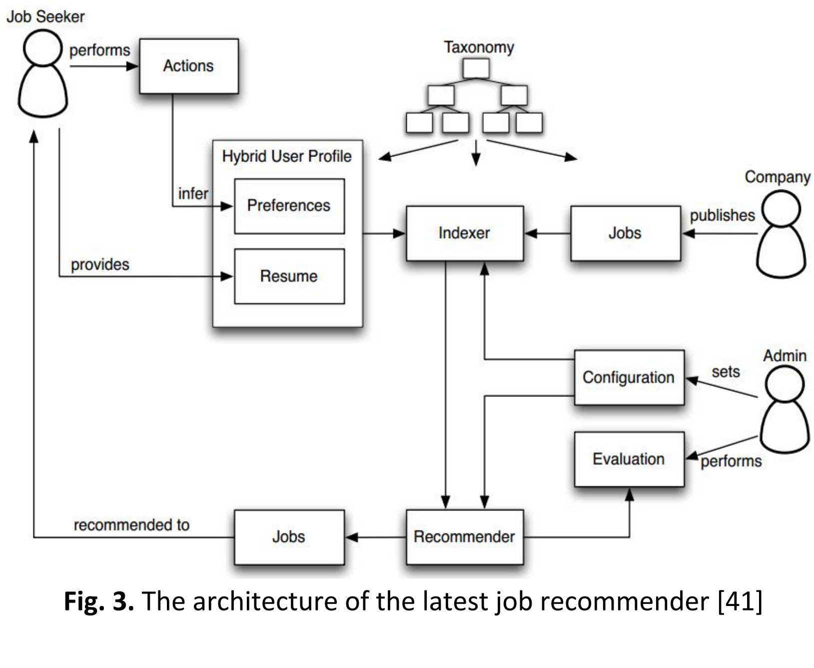

Fig. 3. The architecture of the latest job recommender [41]

4.5 Job-PI

Chen, Yi chen *et al.,* [42] proposed a job recommendation method called Job-PI which is aimed to generate effective job recommendation, the method is designed with a framework with applicant preference model and employer interest model. Job-PI is a job recommendation method that utilizes combination of content-based filtering (CBF) and collaborative filtering (CF) techniques to generate personalized job recommendations. The content-based filtering approach in Job-PI involves analysing the applicant's resume and job description to identify relevant job features, it then compares features with job listings to identify the most relevant job positions for the applicants. Collaborative filtering is used to identify similar applicants based on their profiles, behaviours and preferences, then it compares the profiles with similar applicants in order to recommend jobs that these similar applicants have applied for or shown interest in. Job-PI also incorporates a job ranking algorithm that assigns a score to each recommended job based on its relevance to the applicants' profile and preferences to improve the accuracy of job recommendations. The Job-PI method is designed with a framework composed of an applicant preference model and an employer interest model [40], as shown in Figure 4.

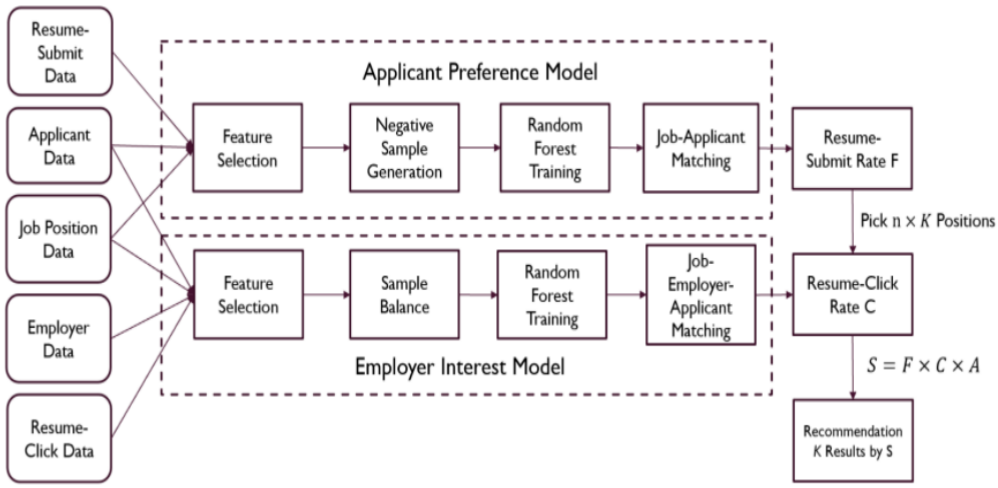

Fig. 4. The framework of *Job-PI* recommendation [42]

4.6 51Job

51Job is the top recruitment website in China, there are more than 5 million job positions online. It has developed a knowledge-based job recommendation system that utilizes machine learning algorithms and natural language processing to match applicants with relevant job opportunities. The platform collects data from applicants' resumes and job listings, and analyses this data using a knowledge graph to identify patterns and relationships between job titles, skills, and qualifications. The system also takes into account applicants' preferences and behaviour data to provide personalized job recommendations. It has been shown the advanced algorithms can provide accurate and relevant job recommendations to applicants [43].

The summary of each job recommendation system characteristics is shown in table 2. The table represents a better understanding of the strengths and weaknesses, as well as techniques used in different job recommendation systems.

Table 2
Summary of job recommendation system characteristics

JRS	Techniques	Strengths	Weaknesses
CASPER	CBF, CF	Its retrieval matches a user's query, and their implicit preferences.	Scalability and sparsity problem.
Bilateral people-JRS	CBF, CF	It improves the bilateral match between people and jobs.	Scalability problem.
Proactive JR	CBF, KB	It provides from the least personalized page to highly user-adaptive page.	Knowledge acquisition issues.
Absolventen.at	CBF, KB	Individual information and Behavior, it also collects implicit feedback.	Huge number of resumes are required.
Job-PI	CBF, CF	Shows high success matching ratio, benefit from its two-side matching and diversity enhancement treatment.	Lack of employer's feedback and fierce competition in hot positions.
51Job	CBF, KB	It provides personalized job recommendation, and career advice.	Sparsity and security problem.

5. Conclusion and Future Research

Overall, this paper is useful to researchers and practitioners working in the field of job recommendation systems by providing a clear understanding of different techniques and their potential applications. Job recommendation systems techniques were reviewed and evaluated with the related issues. It showed that job recommendation systems are different from other generic recommendation systems as it can also recommend job applicants to recruiters. A comparison was made to see the advantages and disadvantages of various job recommendation systems. It has been demonstrated that practically all popular Job Recommendation systems use hybrid approaches.

To increase accuracy and effectiveness of job recommendation systems, researchers concentrate on user profiles and recommendation technology. However, most of job recommendation systems does not recommend career move to applicants.

Concretely, if an applicant desires a higher position or a new career, the proposed system will initially analyze all the information provided by the applicant including educational background, professional experience, technical skills, then the proposed system will utilize techniques to crawl job data from recruitment websites, after data processing with collaborative filtering algorithms, the proposed system will make upskilling and reskilling recommendations for applicants to improve their competitiveness. The proposed system performs two different types of recommendations to applicants with jobs and skills. In this way, applicants can set about training to enhance their abilities. This paper could serve as a starting point for future research on career move recommendation.

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