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A Conceptual Framework of Career Move Recommendation System

Zhou Zou[1,*], Sharin Hazlin Huspi[2], Ahmad Najmi Amerhaider Nuar[2], Kebiao Zhu[3]

[1] School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310, Malaysia
[2] Department of Applied Computing and Artificial Intelligence, School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Johor 81310, Malaysia
[3] School of Computer and Information Science, Hubei Engineering University, Xiaogan 432000, China

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ABSTRACT

Nowadays, job recommendation systems are becoming more and more popular for job seekers to generate personalized job recommendations, but it is increasingly challenging as the techniques used are changing rapidly. Most of the existing job recommendation systems only consider the user's interests, without consideration of the user's skills, which can help them to make a career move. In this paper, the problem was addressed by applying the Design Science Research Methodology to propose an artefact. The proposed conceptual framework generates personalized job and skill recommendations for a career move. This framework consists of five main components: Data Collection and Processing, Skill Identification and Mapping, Recommendation Engines, Job Recommendation, and Skill Recommendation. The data collection component retrieves job descriptions and online courses, while the skill identification component categorizes and maps skills to different job titles. The recommendation engines utilize content-based and collaborative filtering techniques to generate personalized job and skill recommendations based on user profiles, preferences, and skills. The proposed framework aims to enhance job-matching efficiency and assist users in identifying the required skills for career moves. Future research directions include evaluating the framework's effectiveness and incorporating the user's skill proficiency weighting to determine reskilling and upskilling needs.

1. Introduction

As the labor market becomes increasingly complex and dynamic, both job seekers and employers face significant challenges in identifying suitable matches. Job recommendation systems have gained significant attention in recent years as a valuable tool for facilitating job matching in the ever-evolving job market [1]. These systems leverage data analytics and machine learning algorithms to provide personalized job recommendations based on the profiles, preferences, and past behavior of job seekers. By analyzing a huge mass of data, such as job descriptions, candidate profiles, and user

* *Corresponding author.*
E-mail address: zouzhou@graduate.utm.my

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interactions, these systems aim to enhance the efficiency of the hiring process and improve job satisfaction for both candidates and employers [2].

Traditional methods of job searching, such as online job boards and resume submission, often need to provide personalized recommendations that accurately align with individual preferences and qualifications. Most traditional job recommendation systems only focus on providing generic jobs based on the user's preferences without considering the specific skills and career goals [3]. Under the circumstances, it is an opportunity for personalized job recommendation systems to provide career move recommendations, identify the needs of the company, and serve required skills to users.

In this paper, a conceptual framework is presented to address the aforementioned problems. It combines text mining techniques and hybrid filtering algorithms to generate job recommendations and skill recommendations separately. In this way, users not only find a job but identify the skills that are desired for the career move.

The structure of this paper is presented as follows: Section 2 provides a brief overview of the related research in job recommendation systems. Section 3 provides a succinct description and rationale for the research design decisions made. Section 4 presents a brief overview of the proposed conceptual framework and each of the components is discussed. Finally, Section 5 concludes the paper by summarizing the key findings and outlining potential directions for future research.

2. Related Work

2.1 Job Recommendation Systems

Current job recommendation systems aim to help job seekers to achieve their career goals. In this way, this paper presents state-of-the-art job recommendation systems available nowadays.

LinkedIn is a widely used professional social network that serves as a platform for connecting professionals, sharing industry insights, and building professional networks. LinkedIn utilizes content-based and collaborative filtering techniques to suggest relevant job opportunities to users [4]. Content-based filtering considers the characteristics of a particular job, such as job descriptions and required skills, and then matches them with the preferences of users. On the other hand, collaborative filtering analyzes the job preferences and activities of similar users to recommend jobs. However, the current LinkedIn system cannot provide skill recommendations [5].

Glassdoor is a famous job posting and job search portal that utilizes content-based filtering techniques to provide job recommendations to users. The techniques entail generating recommendations based on the jobs that the user has browsed previously, taking into account similarities between those jobs [6]. The same as LinkedIn, Glassdoor cannot provide skill recommendations to users either.

Wellfound is an application dedicated to job postings and job searches, with a particular focus on startups and tech companies. The advantage of this website is highlighting the user's skills and preferences when creating the profiles. However, it does not provide the capability of skill recommendations [5].

JobFit is proposed to utilize machine learning models for diverse input characteristics to solve the disadvantages of conventional memory-based recommendation systems [7]. It also utilizes natural language processing and relevance to map the skills of users and requirements of jobs and describes relevant skills. The system finally provides a sorted list of all job seekers to HR professionals and first recommends the more suitable candidates for the job position.

2.2 Recommendation Techniques

Content-based Filtering (CBF) is a prediction technique that utilizes the characteristics of items and their historical data to recommend similar content to users based on their preferences. This technique has shown significant success in recommending web pages and news recommendations [8]. The process involves selecting items with similar features and calculating their similarity to make recommendations based on content similarity [9]. CBF contains user profiling and job profiling methods. User profiling involves acquiring, extracting, and representing user features, while job profiling focuses on identifying job skills and skill levels from users. Usually, CBF techniques are used to match users with relevant jobs based on their skills and preferences in job recommendation systems [10].

Another technique for recommendation systems is Collaborative Filtering (CF), which recommends items to specific users based on ratings provided by other users [11]. It has been proven to be highly successful in recommendation systems. CF works by creating a database of user preferences for items and calculating similarities between user profiles based on their similar preferences. It can generate recommendations that may not be similar to the items in the active user's profile but are still interesting to the user [12]. CF techniques can be categorized into two main types: memory-based techniques and model-based techniques. Memory-based techniques can generate accurate results for users with limited past ratings, while model-based techniques perform better in handling cold-start problems by generating recommendations for users and items [13].

2.3 Skill Recommendation Systems

A skill recommendation system is a technology-driven solution that suggests relevant skills to individuals based on their specific needs, interests, and goals. One example, CaPaR (Career Path Recommendation) is designed to provide users with relevant career recommendations by analyzing their profiles and skills [5]. By employing text mining and CF techniques, the system scans the user's resume and profile, identifies their key skills, and generates personalized recommendations. Additionally, CaPaR utilizes a skill recommendation engine to recommend additional skills that match the requirements of related job openings. Figure 1 demonstrates the entire process of the Skill Recommendation submodule. In this way, it is capable of performing job and skill recommendations to not only match suitable jobs but also identify the desired skills in the job portal.

Whilst SkillRec is a Skill Recommendation system that recommends relevant job skills to a given job based on its title [14]. SkillRec gathers and identifies the skill set needed for a job by analyzing job descriptions provided by hiring companies. Along with its data collection and pre-processing capabilities, SkillRec employs word/sentence embedding techniques to represent job titles and utilizes a feed-forward neural network to recommend job skills based on the job title representations.

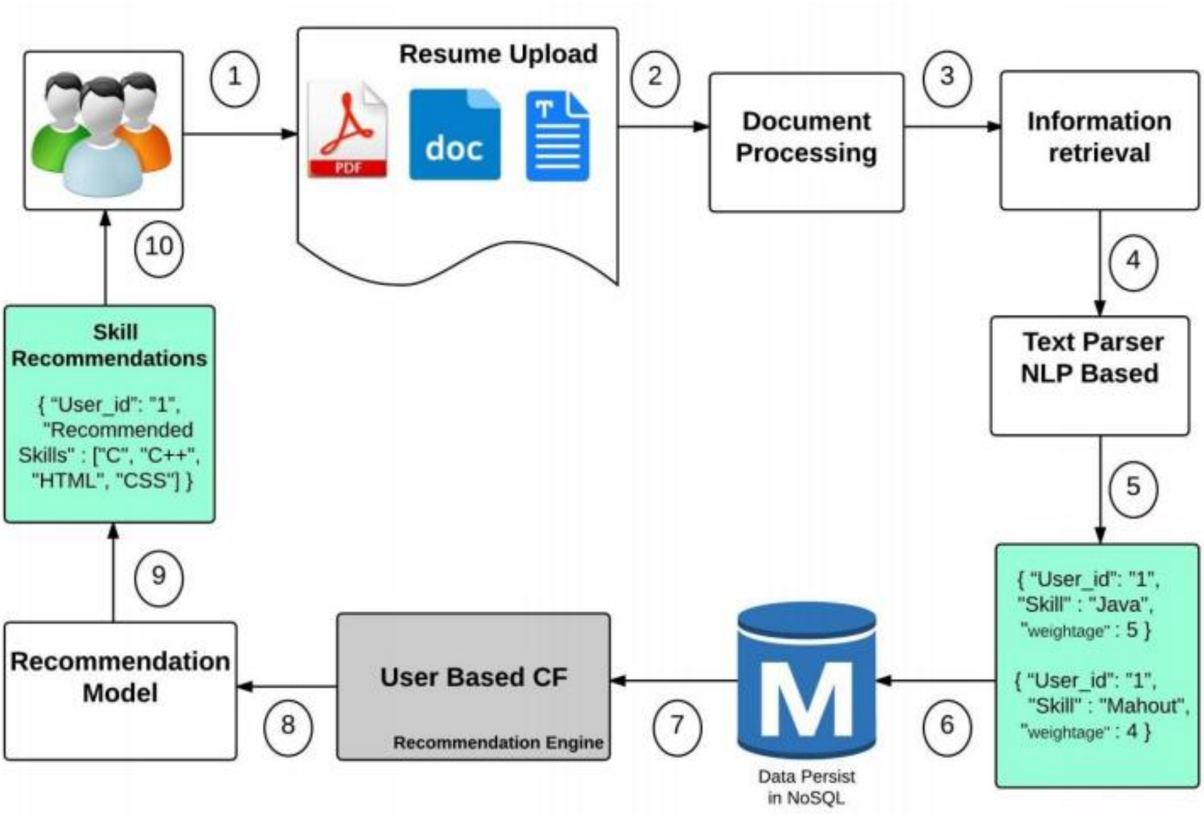

Fig. 1. The skill recommendation module of CaPaR [5]

3. Methodology

In this paper, the Design Science Research Methodology (DSRM) was used to develop the process [15]. The objectives of DSRM are (a) to provide a conceptual framework for conducting DS research; (b) to draw on prior DS literature in information systems and related fields; and (c) to provide an academic conceptual representation for the research [16]. The DSRM is structured around six steps: problem identification and motivation, definition of the objectives for solution, design and development, demonstration, evaluation, and communication [16,17]. For the search, we plan to develop an artefact (framework) that refers to sets of steps used to perform tasks. However, the DSR output will be a conceptual framework due to some reasons. Table 1 shows the design science research approach process.

Table 1
Design science research approach process

Research step	Concern	Approach
Problem Identification and Motivation	Define the problem and show the importance	Problem Identification: Job seekers look for career move recommendations in JRS Motivation: Improve the JRS
Objectives of a Solution	Understand the definition of the problem	Create a method to achieve career move recommendation
Design and Development	Identify the appropriate methods for conducting the search to improve the framework	Based on interview and questionnaire results, improve the skill recommendation component and integrate it with career move recommendation

Demonstration	Use artefact to solve the problem	Demonstrate the artefact
Evaluation	Observe if artefact is effective, efficient	Evaluate the artefact by experts
Communication	Publications	Present the findings at conference presentations and apply them in research

4. Results

The proposed conceptual framework comprises five core components, including data collection and processing component, skill identification and mapping component, recommendation engines component, job recommendation component and skill recommendation component. Figure 2 shows the details of the proposed conceptual framework. Then, we give a short introduction for each component to describe the function throughout the entire system.

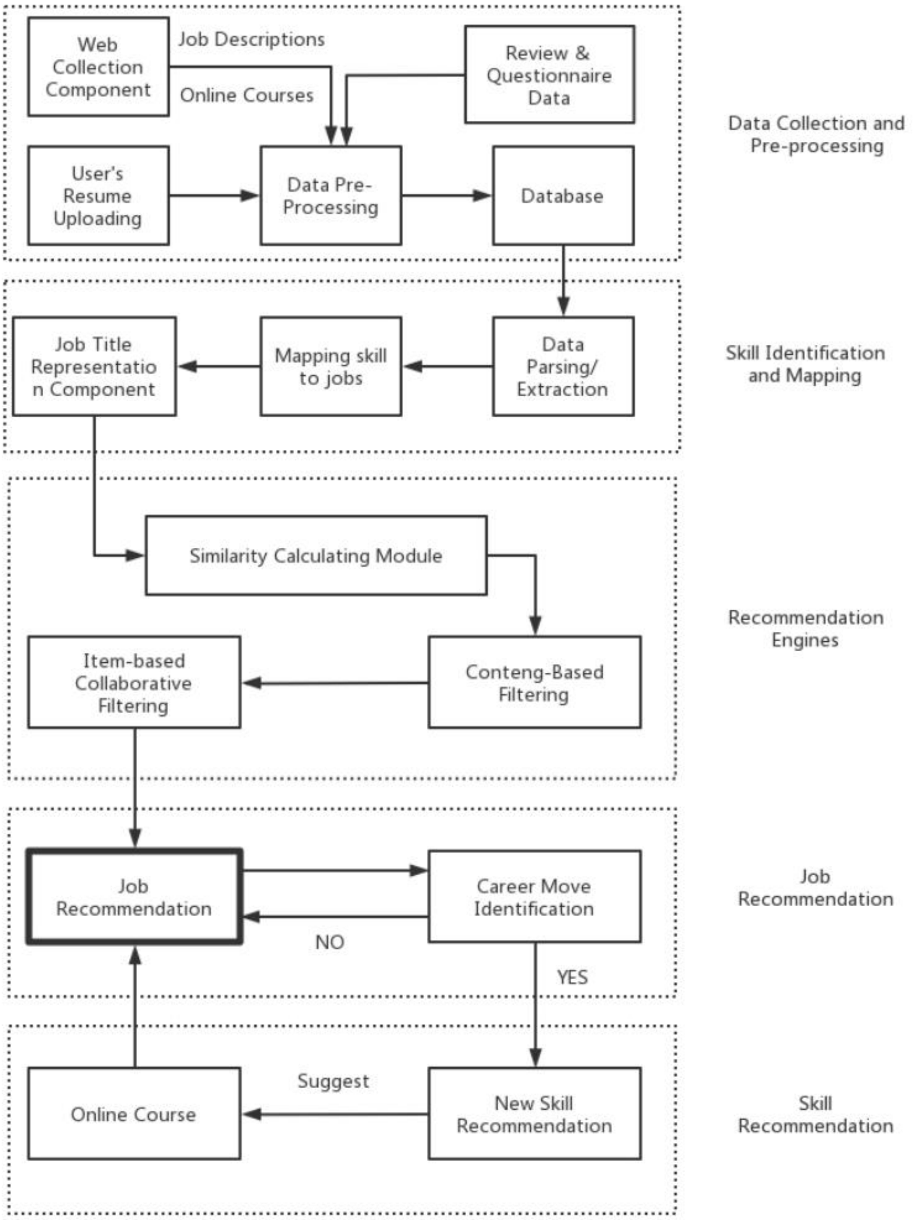

Fig. 2. The conceptual framework of career move recommendation system

4.1 Data Collection and Processing Component

The data collection and processing component retrieves job descriptions and online courses from various web sources, such as job market portals and public online course websites. On the other hand, it collects data from interviews and questionnaires with reliability test [18]. Then, it performs the data pre-processing and stores data in the database.

4.2 Skill Identification and Mapping Component

In skill identification and mapping component, the data extraction module fetches job announcements posted from job market websites and extracts some basic information as well as the required skills. Meanwhile, the resumes are uploaded into the parsing module to be processed. The extracted skills are categorized based on their nature and domain so that the skills can be mapped to different job titles. Then, the job title representation component utilizes word embedding techniques to model job titles in terms of their vector representation.

4.3 Recommendation Engines Component

The recommendation engines component consists of many sub-engines, backed up by a two-level hybrid recommendation engine that combines content-based filtering and collaborative filtering. It assists in solving cold start and scalability problems effectively [13]. The modules take as input the profile, preferences, and skills from users, and output into job and skill recommendations.

4.4 Job Recommendation Component

The job recommendation component employs CBF and CF techniques to match the most similar ranked jobs to the requirements of users. The system utilizes the K-Nearest Neighbors (K-NN) algorithm and Euclidean distance between the user's profile vectors and all jobs to calculate the similarities [19-21]. In the next step, the job recommendations are generated to the career move identification module. If the recommended job is not in the same field as the existing job, it is considered to be a career move.

4.5 Skill Recommendation Component

The skill recommendation component generates new skill recommendations to users for each job they desire. As skills are mapped to the relevant job titles in the previous step. The system runs a simple binary comparison of the user's skill to the job's required skills, and then recommends skills that are required for the job. Thanks to the online courses collected by the data collection component, users can find and learn the required skills directly. Afterward, the job recommendation system will recommend jobs based on the user's improved skills.

5. Conclusions

In this paper, we have addressed the current problems in the job recommendation system by proposing an artefact of framework. We presented the conceptual framework for personalized job recommendations, but also skill recommendations for career move. The architecture of the framework was presented as well as the core components were discussed. Although it was a proposed conceptual framework, the DSRM was implemented to state the problems after obtaining enough data from interviews and questionnaires.

For future research, we plan to focus on evaluating the effectiveness of the framework. The artefact would be evaluated by experts later. Another direction is to weight the user's proficiency in skills to determine if the user needs reskilling or upskilling.

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