



A Survey on Relationship Recommender System in a Business and Employment-Oriented Social Network

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Abstract: In the last ten years, social networks have had a great influence on peoples lifestyles. This is why, one of the main lines of research in the field of social networks focuses on finding the possible connections between users. The personalized recommender system is proposed to solve the problem of information overload and widely applied in many domains. The job recommender systems for job recruiting domain have emerged and enjoyed explosive growth in the last decades. User profiles and recommendation technologies in the job recommender system have gained attention and investigated in academia and implemented for some application cases in industries. In this paper, we introduce some basic concepts of user profile and some common recommendation technologies based on the existing research. Finally, we survey some typical job recommender systems which have been achieved and have a general comprehension of job recommender systems.

Keywords: Job Matching, Recommendation Technology, Job Recommender System

I. INTRODUCTION

With the rapid growth of the Internet technology, more and more job seekers release their own personal information whereas enterprises post the jobs on the Internet. The job recommender system, which is the online recruiting system with personalized recommendation, has been proposed to handle the aforementioned issue for job seekers and enterprises. Job seekers' personal information and enterprises' recruiting information for the job recruitment. As a recommender system, the job recommender system is capable of retrieving a list of job positions that satisfy a jobseeker's desire, or a list of talent candidates that meet the requirement of a recruiter by using the recommendation technology.

Based on the papers we have studied during our preliminary research, we have identified some issues that have been paid much attention in the job recommender system.

1. How to extract the information of jobs and people and contribute the user profile for matching jobs and people well?
2. Which recommendation technology is used in the job recommender system based on user profile?
3. How to build a job recommender system based on the real data with a certain application background?

Background: Three main technologies have been used in this work: Recommender Systems (RSs); their mechanism determines possible relationships between users and provides the system with suggestions. The use of text mining is crucial for the extraction of the different factors that can be contained in an un tagged or tagged text, these factors are necessary for detecting affinity. The third essential technology are Virtual Organizations (VOs) of agents which allow the system to obtain the best solution; their modular basis provides the system with great independence when applying all these methodologies. The rest of this section describes the role of these three technologies in similar studies found in the literature.



A. JOB AND PEOPLE MATCHING

Job seekers search the job positions whereas enterprises find candidates on the Internet, so the matching in the job recommender system is between jobs and people represented as information.

B. TARGET USER

Considering the diverse needs of users, a job recommender system can be designed for different target users, i.e. job seekers or recruiters. For job seekers, the job recommender system enables them to input their personal information or upload their resumes, and to receive their preferred job positions' information. For recruiters, they can post the recruiting job positions and the information of similarity candidates for their posted jobs can be provided in the job recommender system. A job recommender system generates different user profile and adopts the corresponding recommendation technology based on the characteristics of target users with the same goal of recommending the appropriate jobs or candidates to target users.

C. USER PROFILE

The taxonomy of user profiles in general and it's suitable for the job recommender domain. User profile is composed of initial profile and feedback relevance. Initial profile, which represents the target user's basic characteristics, contains some basic feature descriptions of job positions or candidates and the extracted information from the resumes or homepages. Feedback relevance is the user behavior or actions recorded in the system, including explicit feedback relevance and implicit feedback relevance, such as the numeric rating for items, a binary like/dislike button or textual comments. More information is integrated into user profile, more preferences and interests of target users can be obtained and better matching between jobs and people can be achieved.

The first step of user profiling is information extraction. Some structured or semi-structured data can be collected directly from the database, while unstructured information is stored in the textual form or other forms. So we need to extract the useful information for recommender systems from the textual files. To support automatic resume management and routing, design a cascaded Information Extraction(IE) framework to obtain the available feature from the jobseeker's resume. Figure 1 is the structure of the cascaded hybrid model. In the first stage, with Hidden Markov Modelling(HMM) model the entire resume is segmented into consecutive blocks to extract the general information. Based on the result, the detailed information in the certain block is extracted by different learning technology according to the feature characteristics. Sum up, the detailed information of job seekers which we want to know and be used for further similarity calculation is extracted from the resumes

1. SIMILARITY

An important step of achieving matching jobs and people is calculating the similarity or relevance based on their profiles. Several common similarity calculation measures, namely, Constrained Pearson Correlation, Pearson Correlation, Spearman Rank Correlation, Cosine and Mean Squared Differences in the recommender system. For example, with explicit rating information we can measure the similarity between two users or two jobs by Pearson coefficient which is defined as

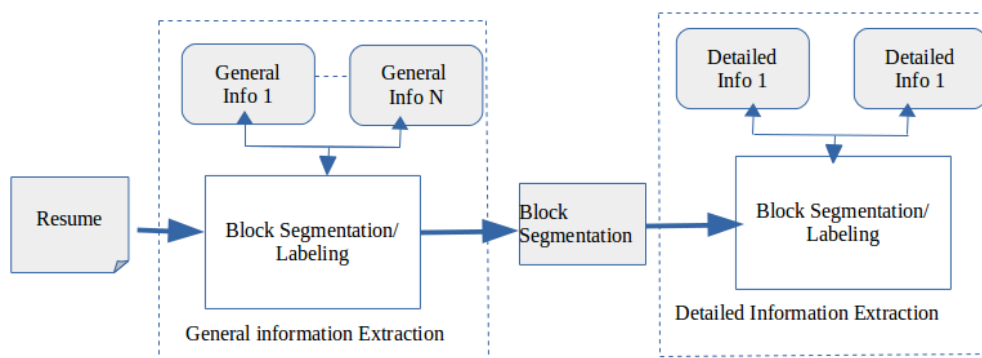


fig:1



$$PCSim_{u,v} = \frac{\sum_{\alpha \in O_{u,v}} (r_{u,\alpha} - \bar{r}_u)(r_{v,\alpha} - \bar{r}_v)}{\sqrt{\sum_{\alpha \in O_{u,v}} (r_{u,\alpha} - \bar{r}_u)^2} \sqrt{\sum_{\alpha \in O_{u,v}} (r_{v,\alpha} - \bar{r}_v)^2}}, \quad (1)$$

Where $R_{u\alpha}$ represents the user u rating for item D and r represents the average rating of user U . $O(u,v)$ indicates the set of objects rated by both u and v .

$$CosSim_{x,y} = \frac{r_x \cdot r_y}{|r_x| \cdot |r_y|} \quad (2)$$

where R_x and R_y are the rating vectors in the n -dimensional space for quantifying the similarity between users. Besides, it can be applied in the similarity of items while R_x and R_y represent the vectors consist of item features.

Different types of recommendation

1. Collaborative filtering
2. Content-Based Filtering
3. Hybrid Recommendation Systems

Collaborative filtering

Collaborative filtering recommender known as user-to-user correlation method, find similar users who have the same taste with the target user and recommend items based on what the similar user likes. The key step is computing the similarity among users. Collaborative filtering recommender algorithm includes user-based and memory-based and the input data is the division basis. For user-based, the content i.e. the basic information of users is used to search out the similar users like the similarity calculation in the content-based recommender. For memory based, the user-item rating matrix is used as input for recommender systems. Applied in the job recruiting domain, some user behavior or actions can generate the user-item rating matrix according to the predefined definitions and transition rules.

Content-Based Filtering

The principle of a content-based recommender is to suggest items that have similar content to ones the target user prefers. In the matching between people and jobs, the content is the personal information and their job desires for people while for jobs, it's the job description posted by recruiters, even including the background description of enterprises. The process of content-based recommender is selecting the same feature type and comparing them by calculating their similarity for people and jobs. The recommendatory result is a list of job positions or candidates sorted by the similarity index. In short, the two key components of content-based recommender are feature selection and similarity calculation. During selecting feature, not only it's need to select the common feature but also considering its influence on recommendation according to the target user's preferences or the scientific analysis in the job recruiting market. Then the selected features should be represented in an appropriate form, for instance vector space model and their similarity can be calculated.

Hybrid Recommendation Systems

Recent research has demonstrated that a hybrid approach, combining collaborative filtering and content-based filtering could be more effective in some cases. Hybrid approaches can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model. Several studies empirically compare the performance of the hybrid with the pure collaborative and content-based methods and demonstrate that the hybrid methods can provide more accurate recommendations than pure approaches. These methods can also be used to overcome some of the common problems in recommender systems such as cold start and the sparsity problem

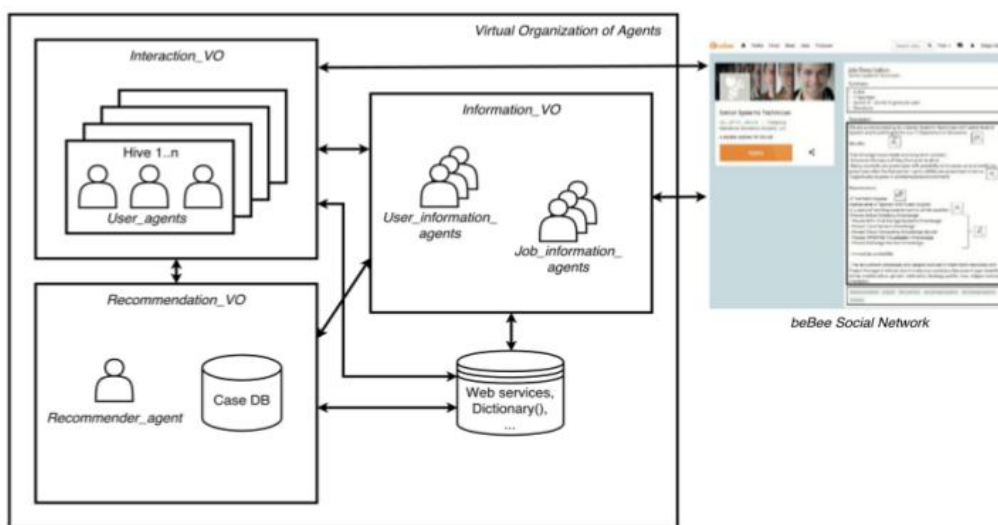


II. METHODOLOGY

In this section, we will introduce several job recommender systems which have been implemented under a certain application background with their architecture and mainly technology.

Methodology 1

This section describes the process that is carried out before a relationship is recommended (or not) to a user. To provide a recommendation, the system must detect a tie between two users or between a user and a job offer. According to the social tie proposals they are Strong ties, Weak ties, Absent ties. Addresses the endings and evaluations can be classified into 4 Virtual organizations, Information extraction, User-user relationships, User-job over relationships.



Interaction VO several User agent type agents interact with each other. A User agent is considered to be the interface between the user. This agent is in charge of generating and updating the user people. Information VO The Job information agent will be responsible for collecting information about a job over. User information agent will obtain information about users. Recommendation VO .The core of the system will be the sub organization responsible for carrying out the different recommendations. It will contain a Recommender agent responsible for performing all factor. It communicates with the User agent and Information agent types.

Methodology 2

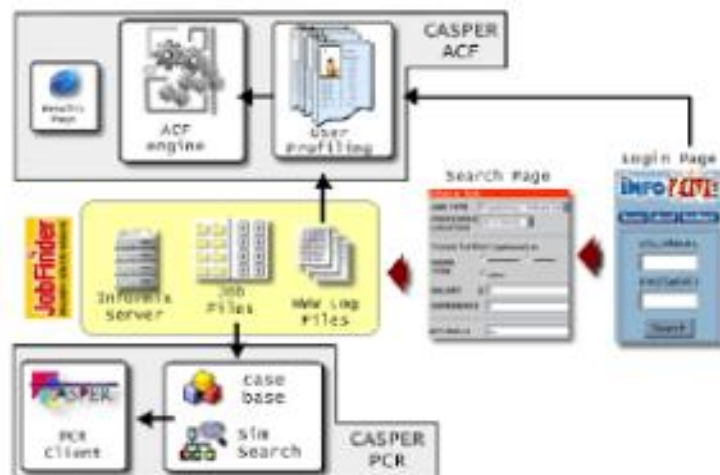


Fig 2.1: CASPER PCR System Architecture



CASPER is an intelligent online recruitment service which is designed for originally Job Finder search engine. we see, initial data are composed of the job database and the log files of the Job Finder website. Based on the different type of data, CASPER system takes two approaches, i.e. CASPER Automated Collaborative Filtering (ACF) and CASPER Personalized Case Retrieval (PCR), to generate personalized recommendation for job seekers. In CASPER ACF the first step is user profiling by collecting the users preferences such as revisit data, read time data and activity data from the log files since the moment that users login to the website. Then, according to the principle of collaborative filter in users and what they like, which could be recommended as the target users preferred jobs. g technology, the system uses the profile information to find out similar .

CASPER PCR uses a two stage personalization process to retrieval relevant results for job seeks and the workflow is shown in Figure 3. The first stage is to select similar jobs to a target query which provided by the user, in short, it is the similarity calculation between query and jobs. Then the job candidates are used for computing the relevance with a target users profile to update the user profile and sort the recommendation results. But before the two stages, there is the preparatory work for the nature and representation of case- base. No matter user profiles or job descriptions, even the query, contain several features such as salary, location, education background, etc and they are all represented in the form of case which is convenient to match the corresponding feature and calculate their similarity or relevance.

Methodology 3

A bilateral people-job recommender system is presented for recommending job positions to people as well as for recommending people to recruiter. Beginning with implementing a CV-recommender and a Job recommender respectively, the bi-lateral people-job recommender system shows the fusion results of the two separate recommenders to users.

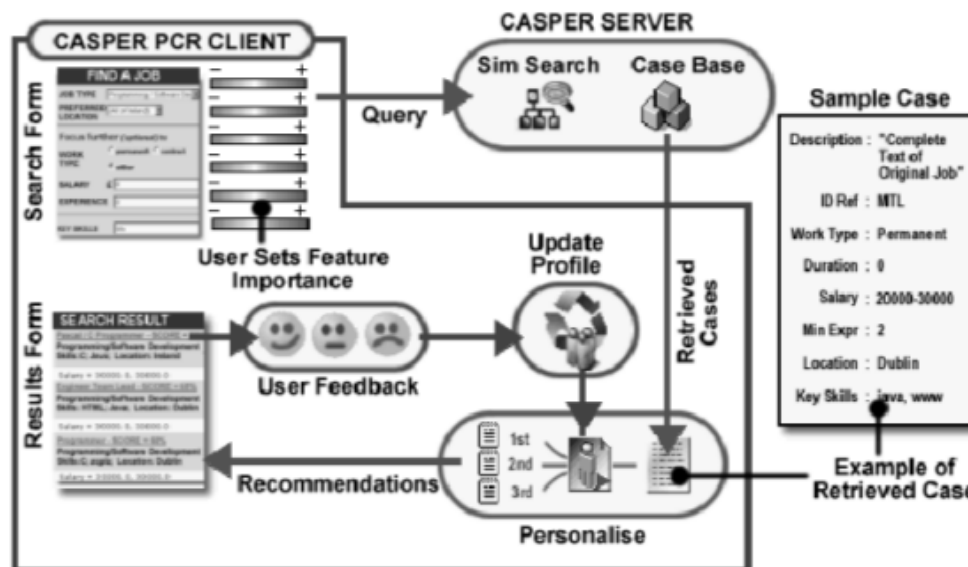


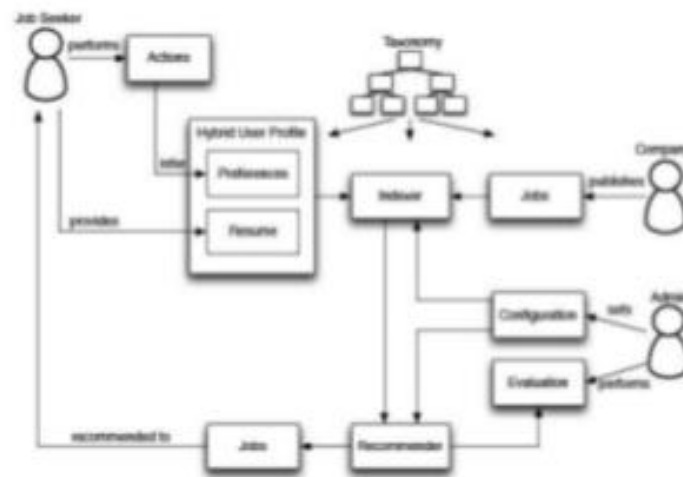
Fig 2.2: CASPER PCR System Architecture

The job description in the CV-Recommender is represented in a probabilistic latent aspect model as shown in Figure 2.3 as well the context of Job Recommender apply the similar model (Figure 2.5). From the observation, we know that not only the preferences of job seekers but also of recruiters need to be taken into considered while recommending jobs/candidates for job seekers/ recruiters. So the probabilistic CV-Recommender is built based on a convex combination of preference factors from the view of recruiters at first. Then the preferences of jobs seekers are used to contribute a probabilistic Job- Recommender with the help of Expectation Maximization algorithm. After that, a bilateral people-job recommender system is achieved by integrating both two recommenders into a single indicator representing its quality through two stages to improve the match between people and jobs.



Methodology 4

A job recommender for Absolvent en.at has been implemented. Its full architecting process is demonstrated in including requirements, architecture, user profiles and recommendation technique. The architecture for the job recommender system is shown in Figure To enhance the performance of the job recommender system, it focuses on the hybrid user profiling. Besides the initial profile extracted from users resumes, relevance feedbacks including explicit relevance feedback and implicit relevance feedback are integrated into user profile resulting in a hybrid user profile. So there are multiple different data sources for the job recommender system as input, for example the users personal information and their behavior or actions. The selecting and processing methods of user profile are another key step of enhancing the performance. In this job recommender system, it observes and records the user actions in real time, provides different weights for features or actions based on their influences. At the same time, it should be possible to either ignore outdated actions from the history or to appropriately weight actions according to their interaction date. With the help of the corresponding recommendation technique, the job recommender system will provide a list of job positions which satisfy the job seekers preferences or interests with more accuracy



III. CONCLUSION

Feature extraction plays a significant role in any of the Personalized recommender systems have gained much attentions by researchers and been widely used in many domains in the last decades. The job recommender system is proposed for job seekers who search job positions and recruiters who find candidates on the Internet by applying the concept of personalized recommender systems into the job recruiting domain. With the study by researchers, several job recommender systems which have a certain application background have been implemented and generate the satisfactory recommendation results. For a job recommender system, researchers focus on the user profile and recommendation technology at the aim of improving the accuracy and performance. User profile is the statistical foundation for the recommender system. For the user of a job recommender system, i.e. job seekers or recruiters, not only their personal information but also their behavior information are indicating their preferences and interests and can both be integrated into a hybrid user profile. The recommendation technology is the implement method of job recommender system. Besides the common recommendation technology, for example, collaborative filtering recommender, reciprocal recommender is an advanced recommendation technology and more and more attentions have been paid by researchers. Because of its advantages and effectiveness, reciprocal recommender will be mainly studied and applied in all kinds of domains, beyond the job recruiting domain.

IV. FUTURE RESEARCH DIRECTIONS

In the future, we attempt to investigate the useful information about job recruiting and extract as much as possible information to generate the enrich user profile. Then we will study the principle of reciprocal recommender and introduce it into the job recruiting domain to propose a reciprocal job recommender system with the better recommendation performance and accuracy



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