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Full Length Research Paper

A survey of job recommender systems

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The Internet-based recruiting platforms become a primary recruitment channel in most companies. While such platforms decrease the recruitment time and advertisement cost, they suffer from an inappropriateness of traditional information retrieval techniques like the Boolean search methods. Consequently, a vast amount of candidates missed the opportunity of recruiting. The recommender system technology aims to help users in finding items that match their personnel interests; it has a successful usage in e-commerce applications to deal with problems related to information overload efficiently. In order to improve the e-recruiting functionality, many recommender system approaches have been proposed. This article will present a survey of e-recruiting process and existing recommendation approaches for building personalized recommender systems for candidates/job matching.

Key words: Recommender systems, collaborative filtering, content-based filtering, hybrid approach, machine learning, e-recruiting, similarity measure.

INTRODUCTION

The fast growth of the Internet caused a matching growth of the amount of available online information that increased the need to expand the ability of users to manage all this information. This encourages a substantial interest in specific research fields and technologies that could benefit the managing of this information overload. The most important fields are Information retrieval and Information filtering. Information retrieval deals with automatically matching user's information and Information filtering aims to assist users eliminating unwanted information (Hanani et al., 2001).

The latest technology designed to fight information overload is the recommender systems that originated from cognitive science, approximation theory, information retrieval, forecasting theories and also related to management science and to consumer choice modeling in marketing (Adomavicius and Tuzhilin, 2005). The recommender systems used to determine the interested items for a specific user by employing a variety of information resources that is related to users and items.

In the mid-1990s, the term recommender system was published for the first time in information system literature (Resnick and Varian, 1997). Many researches in industry and academic areas have been known to develop new approaches for recommender systems in the last decade. The interest in this area still remains high because it is composed of a problem-rich research area and has a wealth of practical applications (Adomavicius and Tuzhilin, 2005).

Recommender systems are being broadly accepted in various applications to suggest products, services, and information items to latent customers. Many e-commerce applications join recommender systems in order to expand customer services, increase selling rates and decrease customers search time (Schafer et al., 1999). For example, a wide range of companies such as the online book retailer Amazon.com (Linden et al., 2003), books (Mooney and Roy, 2000), and news articles (Das et al., 2007). Additionally, Microsoft provides users many recommendations such as the free download products, bug fixes and so forth (Shani and Gunawardana, 2011). All these companies have successfully set up commercial recommender systems and have increased web sales and improved customer fidelity. Moreover, many software

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developers provide stand-alone generic recommendation technologies. The top providers include Net Perceptions, Epiphany, Art Technology Group, Broad Vision, and Blue Martini Software (Huang et al., 2007).

For many years, information system supports in human resource management have been mainly restricted in storing and tracking applicants' data through the applicant management systems. These systems support the internal workflows and communication processes between the human resource management department and the other departments. Recently, the increased amount of digital information and the emergence of e-business reform the way companies conduct business in different aspects. Initially, simple solutions are applied such as posting the job ads on the career unit of the corporate website. Then, based on the experiences gained from these first implementations, the opportunities are realized, establishing other changes and hence, implementing enhanced e-recruitment platforms.

The Internet-based online recruiting platform or e-recruitment platform is one of the most successful-business changes, which changed the way companies employ candidates. These platforms spread in the recent years because the recruiting of the appropriate person is a challenge faced by most companies, as well as the unavailability of certain candidates in some skill areas has long been identified as a major obstacle to companies success (Laumer and Eckhardt, 2010). The online channels like Internet job portal, social media applications or a firm's career website have driven this development. While the companies established job positions on these portals, job-seeker uses them to publish their profiles. For each posted job, thousands of resumes are received by companies. Consequently, a huge volume of job descriptions and candidate resumes are becoming available online. This vast volume of information gives a great opportunity for enhancing the matching quality; this potential is unused since search functionality in recruiting applications is mainly restricted to Boolean search method. The need increases for applying the recommender system technologies that can help recruiters to handle this information efficiently (Färber et al., 2003; Yi et al., 2007). Many researches have been conducted to discuss different issues related to the recruiting problem as well as, the application of recommender system technologies. However, job recommendation is still a challenging domain and a growing area of research. In order to support this research area, we conduct a comprehensive survey for job recommender systems. We will discuss the e-recruitment problem and present the state-of-art of solutions tailored to candidates/job matching.

MOTIVATION OF JOB RECOMMENDER SYSTEMS

The significance of Information System (IS) support in the recruitment process can be observed when considering the phases of the recruitment such as the handling of candidates' applications and the pre-selection of candidates. However, a best fit between job and candidates depends on underlying aspects that are hard to measure. These underlying aspects are a significant reason why information systems have not been extensively used in the area of personnel selection so far.

Mostly, IS technology is used to pre-select applicants based on Boolean search method. This method used queries contain a combination of key words that define skill requirements in order to determine those candidates that match with search criteria. Such type of skill matching is applied in numerous e-recruiting applications. However, as mentioned above, the simple filter techniques such as Boolean search method cannot be sufficient to realize the complexity of a person-job fit as selection decisions often depend on underlying attributes such as personal characteristics or social skills that cannot be put into an operational way easily (Malinowski et al., 2006). Additionally, the need to understand the job requirements, in terms of the skills that are mandatory and those that are optional but preferable, the experience criteria if any, preference for the location of the candidate etc. Consequently, the major challenge faced e-recruiting applications as identified by the literature analysis is the large number of low qualification of applicants that match the search criteria (Singh et al., 2010).

The recommender systems techniques can be used to address the problem of information overload by prioritize the delivery of information for individual users based on their learned preferences (Lee and Brusilovsky, 2007). Additionally, the success of personalization technologies depends critically on the existence of comprehensive user profiles that precisely capture users' interests (Rafter and Smyth, 2001) and the perfect matching method. Moreover, the recommender systems could use historical rating information to determine which type of job required which type of candidate characteristics in the past in order to be rated positively by the recruiter. This information could then be used to predict the match between job and previously not rated candidates. The need of applying the recommender system techniques for selection process can be motivated from different perspectives. While we interested in how people find an appropriate job, other researchers are interested in how change the ways people effectively collaborate once the candidate is recruited. This increases the requirements to select candidates that not only fit with the requirements of the job but also with the team members in terms of interpersonal compatibility (Malinowski et al., 2006).

THE RECRUITING PROCESS

Recruiting process is a core function of human resource management treating the labor as one of the important factors of production (Färber et al., 2003). The key

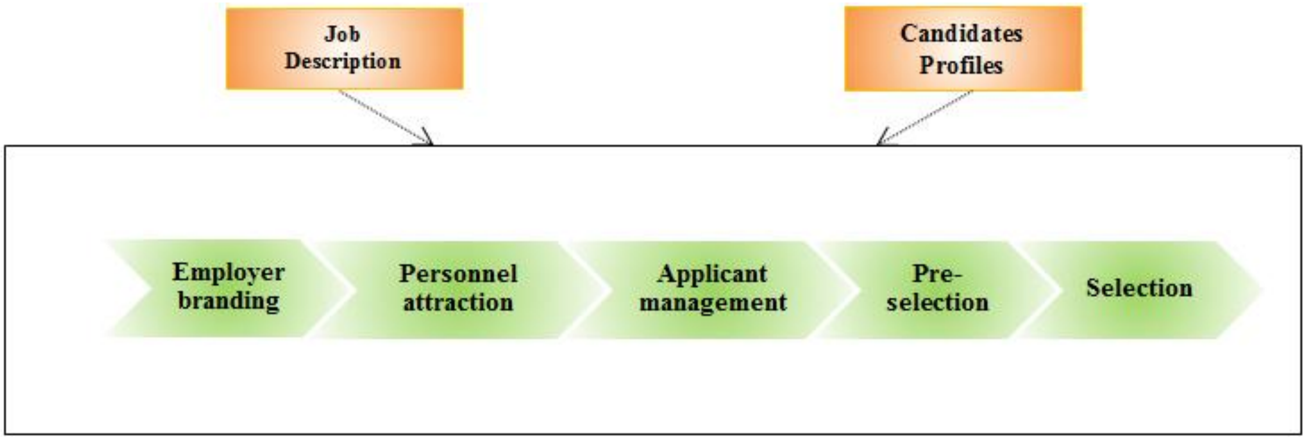

Figure 1. Recruiting process.

objective of the recruiting process is to hire candidates who are valuable for the company (Laumer and Eckhardt, 2009). Two viewpoints are distinguished: from recruiters' and job seekers. The recruiters generate the job description by determining the set of requirements and constraints on skills, expertise levels, and degrees. The job-seeker, on the other hand, generates his/her CV by specifying the academic background, previous work experience and skills (Fazel-Zarandi and Fox, 2010). The IT support for the recruiting activities is ranging from attracting and finding talent to choose and retain candidates (Laumer et al., 2010). The degree of process integration represents the complexity of using e-recruitment solutions (Malinowski et al., 2005).

Färber et al. (2003) demonstrated in their proposed model, the relationship between recruiting tasks and divided the recruiting process into two main phases: The attraction phase and the selection phase, both phases contain a planning and an execution part. The planning part determines the overall strategy and actual measures to attract valuable employees as well as, the explicit selection methods. The execution part comprises the employer branding activities that include all long-term marketing measures that attract qualified candidates. The attraction phase aims to generate a description for open job positions. The selection phase starts with the pre-screening of resumes and other submitted materials. Then, the final selection of candidates is conducted by comparing the remaining set of candidates that has not been filtered out in the screening phase. Finally, the applicant management serves as a secondary function; it consists of the contact of applicants, the management of applicant data and associated processes such as directing applications to organization's members involved in the selection decision. Figure 1 represents the recruiting process that is adapted from Lang et al. (2011). Additionally, Carroll et al. (1999) presented four phases of the recruiting process: an assessment of job position that needs to be filled, a description job profile, the construction of a job description and a candidate specification. Moreover, Breaugh and Starke (2000) composed the recruiting process into five main tasks: short-term and long-term candidate attraction, applicant management, pre-selection as well as the final selection of candidates. Short-term and long-term marketing measures are establishing the attractive employer image that intended to attract qualified candidates.

E-recruitment platforms

The e-recruitment is a system for quickly reaching a large set of potential job-seekers. E-recruiting has attractive growth since the late 1990s when the rapid economy changes produced a high demands for qualified candidates that the labor market could not fully satisfy. The e-recruiting platforms such as corporate homepages and job portals (for example monster.com) have driven this development. The International Association of Employment websites mention[1] that there are more than 40,000 employment sites helping job-seekers and recruiters worldwide (Fazel-Zarandi and Fox, 2010). While companies send open job positions on these portals, job-seekers use them to publish their profiles, this caused a vast amount of job descriptions and candidates' profiles are becoming available online. However, the adoption of these e-recruiting platforms accomplishing cost savings, effectiveness, and suitability for both recruiters and job-seekers (Lee, 2007). Many online recruiting platforms suffer from an inappropriateness of Boolean search methods for matching applicants with job requirements. Consequently, a large number of candidates missed the opportunity of recruiting (Lang et al., 2011). Actual practices and theoretical thoughts show that this search type is insufficient for achieving a good fit

[1]http://www.employmentwebsites.org/

between candidate aptitudes and job requirements (Färber et al., 2003). Researchers have identified different reasons why organizations implement e-recruiting platforms; they discussed several challenges that faced the organizations when implementing ITsupport for their recruiting activities. Lang et al. (2011) presented detailed information about drivers, challenges and consequences of e-recruiting platforms.

Categories of E-recruitment platforms

In order to give the reader a better understanding of the e-recruiting platforms, we present the six categories of e-recruiting sources that presented by (Lee, 2007): (1) General-purpose job boards (for example, Monster.com, HotJobs.com) that provide complete online recruiting functions. While job-seekers search jobs by category such as experience, location, education or any combination of these attributes, recruiters search applicants databases by skills, experience, preference, education, salary or any combination of key words; (2) Niche job boards (for example, Dice.com, Erexchange.com) serve the specialized markets such as a particular occupation, industry, education or any combination of specialties; (3) E-recruiting application service providers (for example, RecruitUSA, PeopleClick) present a collection of services such as recruitment software, recruitment process management, education and training; (4) Hybrid recruiting service providers (for example, magazines and Journals) are the traditional means that provide e-recruiting services; (5) E-recruiting consortium (for example; DirectEmployers.com; NACElink.com) is a search engine drives traffic directly to a member's career website; (6) Corporate career website is an employment source most commonly used by Fortune 500 companies where the use of the corporate career website is a regular extension of e-business applications.

REVIEW OF LITERATURE ON RECOMMENDER SYSTEMS TECHNIQUES

Background of recommender systems

The recommender system approaches are classified into the following main four categories: Collaborative filtering, Contend-based filtering, Knowledge-based and Hybrid approaches (Wei et al., 2007). The detailed descriptions of different techniques are presented in the following paragraphs.

Collaborative filtering approach

Collaborative filtering (CF) is one of the most successful approaches for building recommender systems. It applies the known preferences of a set of users to predicate the unknown preferences for new users. The fundamental assumption of CF is that if users x and y rate n items similarly, or have similar behaviors. Hence, they will rate other items similarly (Su and Khoshgoftaar, 2009). The ratings can either be explicit that refers to a user expressing his/her preference for an item using the numerical scale such 1–5, or implicit that refers to inferring the user behavior or selection to assign the user preference (Breese et al., 1998). CF approaches have the capability of working in domains where items contents are difficult to obtain or cannot be parsed automatically. However, CF techniques can provide unexpected recommendations, which are not similar to the items in the active user's profile, but interest him/her (Hu and Pu, 2011; Linden et al., 2003). Examples of recommender systems that based on CF techniques are presented by (Huang et al., 2007).

The CF approaches can be classified into two main types: Memory-based and Model-based methods (Breese et al., 1998; Adomavicius and Tuzhilin, 2005).

Memory-based CF methods

This makes use of a sample of user-item database to produce prediction. Each user is part of a group of users with similar interests. When identifying the neighbors of the active user, the user's prediction for preferences of new items can be produced (Breese et al., 1998). We compare users against each other directly using correlation or other measures (Burke, 2002). Additionally, The Memory-based CF methods include the user-based and item-based correlation/similarity measures. The user-based measures predict a target user's future preferences by aggregating the observed preferences of similar users. The algorithm first computes a user similarity score which is calculated based on the vector similarity function. A high similarity score indicates that the two users have similar preferences (Breese et al., 1998; Huang et al., 2007). On the other hand, the item-based measures are different from the user-based measures only in that item similarities are computed instead of user similarities. A high similarity score indicates that the two items are similar because they have been selected by many users (Huang et al., 2007).

Model-based CF methods

Is a method in which a model is produced from the historical rating and used to deduce the predictions (Breese et al., 1998). The development of models allows the system to learn and recognize complex patterns using the training data, and then produce predictions for test data. Model-based CF methods applied techniques such as Bayesian models, clustering models, and dependency network to solve the shortcomings of memory-based CF methods (Su and Khoshgoftaar,2009).

Characteristics and challenges of CF

The main characteristic of CF approaches is that they are fully independent of any machine-readable representation of the objects being recommended, and they work well for complex objects such as sounds and movies where variations in taste are affected the variation in preferences. On the other side, there are several major challenges suffered by CF such as cold-start problems that include data sparsity and ramp-up problems. In the data sparsity problem, there is lack of historical data. For example, in many real world applications, users' historical data, such as what they have viewed, purchased or rated, is sparse by nature because the website is in its initial operational stage. Therefore, it is highly possible that either the similarity between any two users is nearly zero or the measures are unreliable. In the ramp-up problem, while there is a large number of users whose preferences are known, the system cannot be useful for new users until a sufficient amount of items' rating has been collected (Burke, 1999). The second challenge is the scalability, when the number of available users and items rise extremely, the CF techniques will suffer serious scalability problems, with computational resources going beyond practical or acceptable levels (Su and Khoshgoftaar, 2009). Dimensionality reduction techniques such as Singular Value Decomposition (SVD) (Sarwar et al., 2002) can deal with the scalability problem and quickly produce good recommendations, but they have an expensive matrix factorization processing (Su and Khoshgoftaar, 2009).

Content-based filtering approach

Content-based filtering (CBF) is treated as information retrieval problem or machine learning problem. In information retrieval problem, the document representations have to be matched to user representations on textual similarity while, in machine learning problem, the textual content of the representations are combined as feature vectors, which are used for training a prediction algorithm (Wei et al., 2007). The CBF recommends items whose content is similar to the content that the user has previously viewed or selected (Mooney and Roy, 2000). CBR has been applied in various domains ranging from recommending web pages, news articles, television programs, restaurants, and items for sale (Pazzani and Billsus, 2007).

There are two main tasks related to CBF recommender systems, the User profiling and the Item representation. User profiling is one of most challenging tasks in CBF recommender systems that deal with acquiring, extracting and representing the features of users. User profile is often created automatically in response to user feedback on the interest of items that have been presented to the user. This profile may contain different types of information such as the selected items, ratings of items, and user's demographic data, etc. (Felfernig et al., 2010). However, the user interface can easily be created to assist users building their profiles. (Pazzani and Billsus, 2007) classified the profile information into two types: (1) the user's preferences such as item description that interest the user. There are many possible representtations of this description, but the common representation is using a function to predict the possibility of user is interested in that item. (2) The user's interactions history with the recommendation system that includes saving the items that a user has viewed with information about user's interaction. Item representation is also an important issue in CBF recommender systems. Items can be a structural data represented by the same set of attributes, and there are specific values that the attributes may have. Several approaches for learning a structural data used such as machine learning techniques. Additionally, unstructured data may occur in some applications such as unrestricted texts in news articles. In this type, there are no attribute names with well-defined values. A common approach to deal with free text fields is to exchange the text to a structured representation. Each word can be treated as an attribute, associated by Boolean value representing the availability of the word in the article with an integer value representing the number of occurrences of the word in the article (Pazzani and Billsus, 2007).

Characteristics and challenges of CBF

The clear characteristics of CBF approaches are that they are no domain knowledge required, and they are sufficient to collect implicit feedback from users about their item preferences. This make CBF the best algorithm in domains where acquiring explicit ratings from users is difficult or unwieldy, and where domain knowledge is hard to investigate. CBF techniques have a ramp-up problem in that they must collect enough ratings to construct a reliable classifier. Additionally, they are restricted by the features that are explicitly related to the objects that they recommend (Hu and Pu, 2011).

Knowledge-based approach

This type of recommender systems attempts to suggest objects based on inferences about user's needs and preferences (Burke, 2002). This approach assists users in the determination of suitable solutions from complex product and service assortments. These solutions based on exploiting deep knowledge about the product domain

Table 1. Characteristics and challenges in different recommender system approaches.

Recommendation approaches	Characteristics	Challenges
Collaborative filtering	Independent of any machine-readable representation of the recommended objects. Work well with complex objects such as sounds and movies. Domain knowledge not needed. Quality improves over time.	Ramp-up problems for new users and items. Performance decreased when user-item matrix become large. Limited scalability for large data. Model-based methods are expensive model building.
Content-based filtering	Domain knowledge not needed. Work well with implicit feedback when explicit rating is difficult. Quality improves over time.	Ramp-up problem for new user. Performance limited by the features that associated with recommended objects.
Knowledge-based	No need to gather information about a particular user because its judgments are independent of individual tastes. No ramp-up problem.	Need knowledge acquisition. Knowledge engineering difficulties.

to figure out the best wishes of the customer. In Knowledge-based recommendation techniques, the relationship between customer requirements and products can be explicitly modeled in an underlying knowledge base (Felfernig, 2005). They can use rules and patterns to recommend items based on functional knowledge of how a specific item meets a particular user need (Burke, 2002). Knowledge-based recommendations perform reasoning about what products meet the user's requirements by employing techniques such as a quantitative decision support tools (Bhargava and Sridhar, 1999).

Characteristics and challenges of knowledge-based approach

It does not need to collect information about a specific user because its judgments are independent of individual tastes. They do not have ramp-up problem because its recommendations do not subject to user ratings (Burke, 1999). These characteristics make knowledge-based recommenders valuable systems on their own, as well as, highly complementary to other types of recommender systems (Burke, 2000). The main challenges as all knowledge-based systems are they need knowledge acquisition and knowledge engineering with all of their attendant difficulties (Burke, 1999).

Hybrid approach

All recommendation approaches that mentioned above have characteristics and challenges summarized in Table 1. To get better performance and overcome challenges, these approaches have been combined. In general, collaborative filtering is integrated with other techniques in an attempt to avoid the previous mentioned challenges (Burke, 2002).

Burke (2002, 2007) presented different ways to integrate collaborative filtering, content-based filtering and knowledge-based approaches into a hybrid recommender system that classified as follows:

1. Weighted hybrid recommender: In which the score of item recommendation is calculated from the results of all of used recommendation techniques that are available in the system.
2. Switching hybrid recommender: The system uses some measure to switch between recommendation techniques.
3. Mixed: In which large number of recommendations are applied simultaneously.
4. Feature Combination uses the collaborative information as additional feature data for each example and use content-based techniques over this improved data set.
5. Cascade: It comprises a staged process. In this technique, one recommendation technique is used first to produce a rough ranking of candidates and a second technique refines the recommendation.
6. Feature augmentation: One technique is used to produce rating or classification of items and that information is then combined into the processing of the next recommendation technique.
7. Model: Where an output of one technique is used as an input for another.

These hybrid techniques are presented in details by Burke (2002, 2007).

Recent studies in recommendation techniques

Recently, many conferences and studies have been conducted to improve recommendation techniques and present new paradigms in this area of research. Some researches presented solutions to solve problems related to different recommendation approaches and other researches presented new applications for recommender systems. We will present some examples of these researches in the following paragraphs.

The CF recommendation framework was presented by Koren and Sill (2011) based on viewing user feedback on products as ordinal, rather than numerical view. Such an ordinal view frequently provides a more natural reflection of the user intention when providing qualitative ratings, allowing users to have different internal scoring scales. As mentioned in collaborative filtering approach, one key issue limits the success of collaborative filtering in certain application domains is the cold-start problem. Hu and Pu (2011) presented a framework to address the cold-start problem by incorporating human personality into the CF framework. They propose three approaches: the first is a recommendation method based on users' personality information alone; the second is based on a linear combination of both personality and rating information, and the third uses a cascade mechanism to leverage both resources. Additionally, the shared CF approach tries to leverage the data from contributor parties to improve beneficiary party's performance. Item neighborhood list was chosen as the shared data from the contributor party with considering different privacy (Zhao et al., 2011). Moreover, Hannon et al. (2010) focus on one of the key features of the social web, explicitly the construction of relationships between users. For a given user, other users might be recommended as followers. They try to join the real-time web as the basis for profiling and recommendation. They evaluate a range of different profiling and recommendation strategies, based on a large dataset of Twitter users and their tweets, to determine the potential for effective and efficient follower recommendation.

Hien and Haddawy (2007) presented an approach to develop a case-based retrieval method from the Bayesian network prediction model. The case-based component retrieves the past student most similar to the candidate being evaluated. Additionally, a Bayesian probabilistic model for explicit preference data was presented by Barbieri et al. (2011). Their model proposes a generative process, which takes into account both item selection and rating emission to bring into communities those users who experience the same items and tend to adopt the same rating pattern. Each user is modeled as a random mixture of topics, where each topic is characterized by a distribution modeling the popularity of items within the respective user-community. Moreover, the probabilistic model combines collaborative and content information in a coherent manner. They encode collaborative and content information as features, and then learn weights that reflect how well each feature predicts user actions (Gunawardana and Meek, 2009).

JOB RECOMMENDATION SYSTEMS

Recent researches show that the increasing demands of IS technologies for human resource management in general and recruiting processes in particular. Most companies put the focus on their own e-recruiting platforms as primary recruitment channels. Job ads are published automatically on the job portal as soon as they are entered into the system. On the other hand, the applicant creates a profile to apply it for one of the listed job positions. The user profile is stored in the system, letting the applicant reuse it for other job position. The last functionality gives the companies possibility to create the applicants pool. Thus, the companies achieved a uniform view for all applicants' data in one candidate pool. This pool is used by the recruitment department to find the applicant documents. Appropriate applicants' documents are directed to the human resource departments for more processing. In addition, the system supports all required communication processes as well as tracks applicant status inside the application process (Malinowski et al., 2005).

The e-recruiting platforms are usually based on Boolean search and filtering techniques that cannot sufficiently capture the complexity of a person-job fit as selection decisions (Malinowski et al., 2006). Many literatures have been applied the recommender system concept into the job problem. Malinowski et al. (2008) determined that, we must consider unary attributes such as individual skills, mental abilities and personality that control the fit between the individual and the tasks to be accomplished, as well as the relational attributes that determine the fit between the individual and the upcoming team members. In this context literatures usually distinguish between (1) person-job, (2) person-team and (3) person-organization fits (Sekiguchi, 2004). Thus, the recruitment approach must cover all this aspects. Keim (2007) argues that transferring recommender system approach to search for persons is a challenging but promising goal. Therefore, many recommendation approaches applied for matching candidates and jobs to overcome the previous challenges of holistic e-recruiting platforms (Laumer and Eckhardt, 2009).

System requirements for candidates/job recommendation

There are major requirements presented in literatures that should be derived when recommending candidates for a specific job (Malinowski et al., 2006, 2008; Keim, 2007).

1. The matching of individuals to job depends on skills and abilities that individuals should have.
2. Recommending people is a bidirectional process that

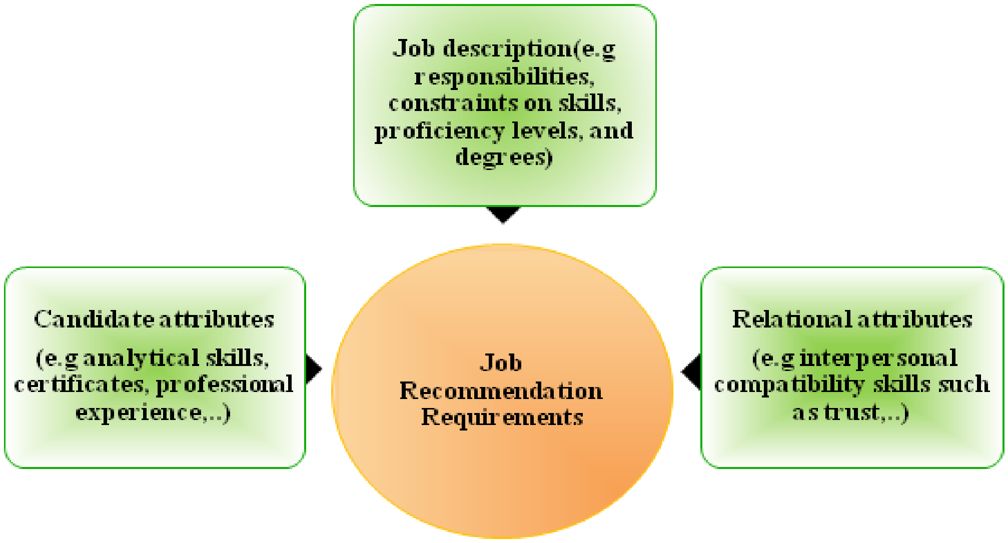

Figure 2. Model of system requirements for candidates/job recommendation.

needs to take into account the preferences not only of the recruiter but also of the candidate.
3. Recommendations should be based on the candidate attributes, as well as the relational aspects that determine the fit between the person and the team members with whom the person will be collaborated.
4. Individual is considered to be unique; we cannot choose a single person several times such as a movie or book.

Job recommendation problem is bidirectional recommendation between job-seeker and job. The recommendation process can be divided into two parts: job recommendation and job-seeker recommendation. The design idea of these two parts is the same roughly (Yu et al., 2011; Malinowski et al., 2006). For a job-seeker, the job with higher matching degree should be recommended to him. Similarly, for a job, the job-seeker with higher matching degree should be recommended to it (Yu et al., 2011). In general, the ranking items either are the top *n* candidates that best fit the job in consideration or the top *n* job profiles that best fit the candidates' preferences. Additionally, Fazel-Zarandi and Fox (2010) mentioned that skills requirements matching need to distinguish between must-have and nice-to-have requirements in the matching process. Must-have requirements are constraints that should be possessed by the applicant, whereas nice-to-have requirements are preferences that are taken into consideration when ranking applicants. Figure 2 summarizes the job recommendation requirements in a unified model.

Job recommendation information

Candidates and jobs should be matched based on certain criteria that used as indicators of performance on the job. In selection theory, the available information at a certain time of the decision selection is called predictor data which comprises the individual attributes. The actual selection method is called predictor. The prediction process is referred to the assessment of the criteria using the predictor data and a method-specific way of data combination (Färber et al., 2003).

However, to construct candidate profiles, the meta-data extracted from existing resumes. Rafter and Smyth (2001) proposed a system that builds user profile in recruitment environment directly from analyzing the behaviors of web users. In this system, user profiles are constructed by passively detecting the click-stream and read-time behavior of users. Malinowski et al. (2006) used an input data for their CV-recommender: demographic data, educational data, job experience, language skills and IT skills, awards, publications, others. In general, candidate's profile is composed of three sections.

1. Personal information about the employee, such as the first name, last name, and location.
2. Information about the current and past professional positions held by the candidate. This section may contain company names, positions, company descriptions, job start dates, and job finish dates. The company description field may further contain information about the company (for example the number of employees and industry).
3. Information about educational experiences, such as university names, degrees, fields of education, start and finish dates (Paparrizos et al., 2011).

Additionally, for collaboration measures, candidate may be asked to rate the job profiles using 5 point scale ranging from 1 to 5. Candidates were asked to evaluate whether the profiles interested to them with respect to their career perspectives and planning (Malinowski et al., 2006).From these meta-data, a number of features can be extracted to train and test recommendation (Paparrizos et al., 2011).On the other hand, the job profile should be constructed to describe the requirements and listing of all relevant skills that an employee for this job should have (Laumer and Eckhardt, 2009).

Moreover, the quality of the recommendation system can be assessed using statistical accuracy metrics such as the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) or Correlation calculations (Herlocker et al.,1999; Malinowski et al., 2006; Su and Khoshgoftaar, 2009).

Job recommendation architecture

Laumer and Eckhardt (2009) proposed system architecture that aligns recommender systems with the recruiting process based on the preceding holistic e-recruiting architecture provided by Lee (2007). They added new processes that supporting the development of job profiles and automated recommendation approaches. In his architecture proposal, Lee presented a work-flow management subsystem linked to a database management subsystem as the central component. All information related to recruiting activities is stored in the database. Any subsystem can have access to data stored by another subsystem and processes can include other processes or execute them. The integrated architecture for employee recruitment and recommender systems is built on the workflow management subsystem and database to manage the information flow and storage. For the integration of recommender systems, they added two important parts: First, a process to build job profiles that describes the job requirements and listing all related skills an employee for this profile should have. Second, they integrate a person-job recommender in the recruitment process as a process step in the selection phase. Finally, matching candidate and jobs can be managed by automated recommendation approaches. Figure 3 illustrates the integrated system architecture for job recommendation (Laumer and Eckhardt, 2009).

Case study: An example of recommending candidates for specific job

In order to understand the job recommendation problem, we present a simple and concrete example for matching candidate with job requirements. We focus on measurable skills possessed by human resources. This example applies a content-based recommendation approach that used the attributes related to both job and candidates. As mentioned before in content-based, we must construct a profile for each item, which is a record representing the important features of that item.

In job case, the candidate's profile consists of some features that are required for a specific job. Similarly, the job's profile consists of the job requirements that should be possessed by candidates. For simplicity, we consider only few features that might be relevant to a recommendation system.

The task of a job recommender system is to retrieve a list of candidates' CVs for a new job position. We conduct this example using one job description and list of 5 prospective candidates CVs. The job description was downloaded from Careers portal website[2]:

1. Job title: Computer system administrator.
2. Job description: The prospective employee will monitor, operate and supervise the internal computer systems of an organization.
3. Qualifications required: BSc certificate in Software Engineering, Computer Programming or IT and four years of experience in IT sector, especially as systems analyst or system programmer.
4. Skills: English language skill (1-low, 2-medium, 3-excellent) and Oracle developer skill.

The candidates' CVs were downloaded from BSR site[3]. As mentioned above, the first step to determine the best fit between candidates and job description is building the job profile and the prospective employees' profiles. We extract some features from employee resumes and job description to build both profiles. Then, we estimate the model parameters by creating a rating matrix *Rx,y,* where *x* represents the job and *y* represents the candidate CVs.

$$R_{x,y} \begin{cases} 1\ (\text{TRUE} = \text{"Exist"}) & \text{'If the target attribute is existed} \\ 0\ (\text{FALSE} = \text{"not Exist"}) & \text{'If the target attribute isn't existed} \\ \text{"Value"} & \text{'for quantity attributes} \end{cases}$$

The rating matrix $R_{x,y}$ transformed by treating the values of candidate's attributes as ratings of all the attributes extracted from the resumes using any similarity measures. That means the job profile as well as the candidates' profiles represented as vectors. We applied three measures in this example: Cosine Similarity, Euclidean Distance (Rajaraman et al., 2011) and New Jaccard Measure (Belkhirat et al., 2011).

The profiles vectors are constructed as the following: 0 (MSc not required), 1 (BSc required), 1(if one of these majors: Software Engineering, Computer Programming or IT), 1 (if he/she worked in IT sector), 1 (if the candidate's experience more than 4 years), 1-3 (for English skill levels), 1 (if the candidate has Oracle developer skill).

The resultant job's vector is [0 1 1 1 1 3 1] and the resultant candidates' vectors are:

[2]www.careersportal.ie
[3]www.bestsampleresume.

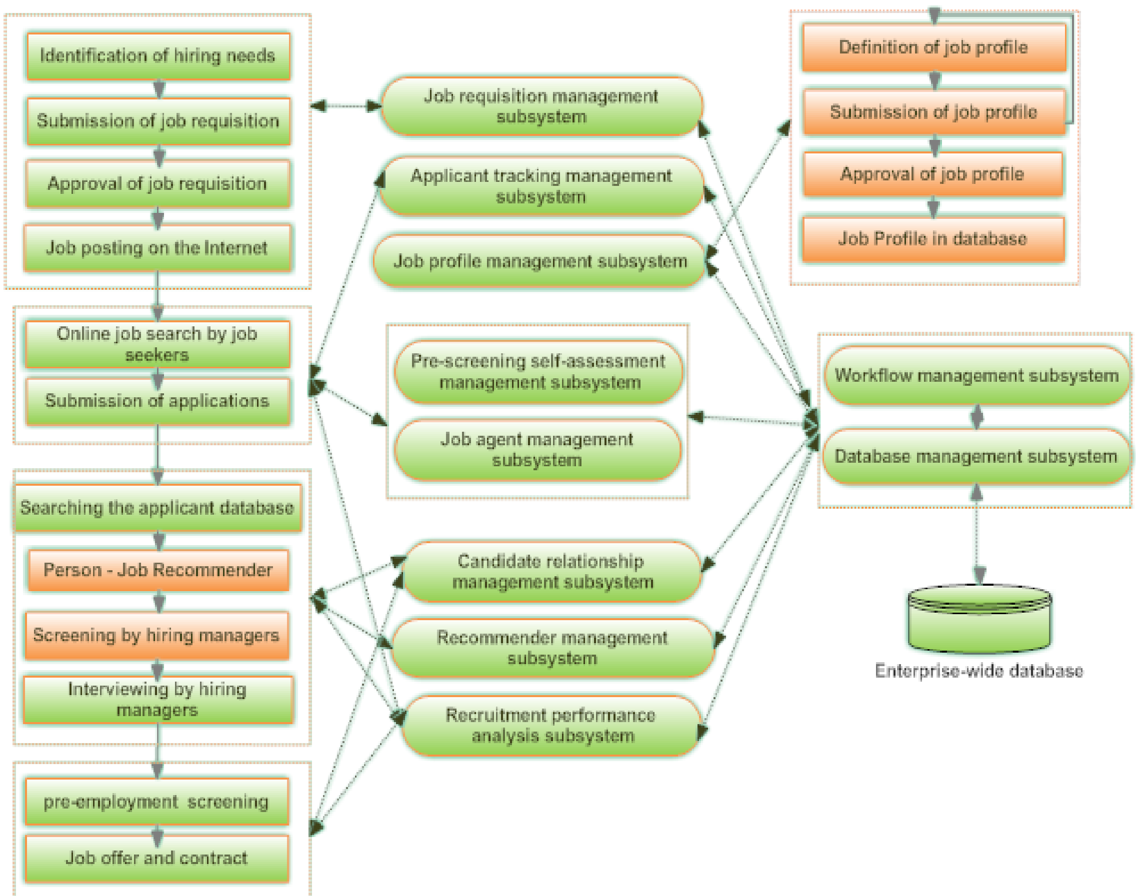

Figure 3. The integrated architecture for job recommender system.

Table 2. Ranking of candidates for the job position using three similarity measures.

Cosine similarity	Euclidean distance	New Jaccard measure
3^{rd} person 0.99	3^{rd} person 1.0	3^{rd} person 0.94
2^{nd} person 0.82	2^{nd}person1.41	2^{nd} person 0.83
4^{th} person 0.81	4^{th} person 1.7	4^{th} person 0.78
1^{st} person 0.70	1^{st} person 2.0	1^{st} person 0.61
5^{th} person 0.67	5^{th} person 2.65	5^{th} person 0.48

1^{st} person: [0 0 1 0 0 2 1], 2^{nd} person: [0 1 0 1 1 3 0], 3^{rd} person: [0 1 1 1 1 2 1], 4^{th} person: [0 1 0 1 1 2 0], and 5^{th} person:[1 1 0 1 1 1 0]. The candidates' ranking after applying the Cosine Similarity, Euclidean Distance and new Jaccard measure is presented in Table 2.

This example aims to find a candidate who best fits the requirements of job profile [0 1 1 1 1 3 1]. Based on the three similarity measures, 3^{rd} person is the best candidate who fits job requirements, followed by 2^{nd} person and 4^{th} person.

The 1^{st} person and 5^{th} person are the least appropriate candidates for the job requirements.

However, applying the Boolean search method for this problem will select candidates who have specific keywords in their profiles but will fail to take into account the level of precision in certain tasks. It will ignore the ratings of skills.

Job recommendation techniques

In recent years, several recommender system techniques applied in candidates/job matching problem, started by the personnel selection approach that proposed by

Table 3. Taxonomy of job recommender systems.

Recommendation approach	Techniques	References
Hybrid job recommender systems	Collaborative filtering, Content-based filtering, and Probabilistic latent semantic	(Färber et al., 2003) (Malinowski et al., 2006) (Keim, 2007) (Malinowski et al., 2008)
	Ontology-based and adaptive hypermedia.	(Lee and Brusilovsky, 2007)
	Logic-based and similarity-based	(Fazel-Zarandi and Fox, 2010)
	Fuzzy method based on information statistics and analytic hierarchy process	(Chen, 2009)
Content-based job recommender systems	Supervised machine learning model	(Paparrizos et al., 2011).
	Information retrieval techniques	(Singh et al., 2010)
	Preference function based on users' interaction history and a new similarity measurement.	(Yu et al., 2011)

Färber et al. (2003) who developed a probabilistic hybrid recommendation approach for candidates/job matching. Then, their model utilized and extended by Malinowski et al. (2006), Keim (2007) and Malinowski et al. (2008). Table 3 presents taxonomy of job recommender systems.

Hybrid job recommender systems

A probabilistic hybrid approach

Färber et al. (2003) applied a recommendation system initially used to recommend objects to users such as movies or books to matching partners. The recommendation approach used both concepts: content-based filtering and collaborative filtering simultaneously. This assists partially to overcome the problem of data sparsity. Another concept that they applied is the latent aspect model described by (Hofmann and Puzicha, 1999). It understands the individual preferences as a convex combination of preference factors. In a basic approach for collaborative filtering, we look at each value of user/ object pairs (x, y), where x is a set of users and y is a set of objects. The aspect model can then be represented as a variable z which is associated with each value of (x, y), assuming that x and y are independent conditioned on z. The model parameters are then estimated using the Expectation Maximization (EM) algorithm. This model produced a rating matrix that assigns assessed values to candidate's profile containing the probability that recruiter x rates candidate y with value v. Latter, they defined v = {"qualified", "not qualified"}. Then, they transformed the rating matrix by replacing variable y with a variable a to represent the attributes that was extracted from the candidate resumes. As many attributes are assigned to several profiles, we will see the attribute a several times with different values v. The entries of the transformed matrix are actually not either 0 or 1 but take values in the interval [0;1] depending on the relative frequency of value v being assigned to attribute a by recruiter x.

Based on the previous model proposed by Färber et al. (2003) and Malinowski et al. (2006) applying this model into two distinct recommendation systems in order to improve the match between people and jobs: a CV-recommender and a job recommender, separately. In the first step, they built a system recommending CVs that are similar to resumes previously selected by the recruiter for a specific job profile. In the second step, they developed a second recommendation system that recommends jobs to candidates based on their preference profiles which are in turn based on previous preference ratings. Moreover, Keim (2007) integrates these prior researches into a unified multilayer framework to support the matching of individuals for job and team member who will collaborate with them.

Later, Malinowski et al. (2008) utilized and extended a decision support system for team building using the probabilistic hybrid approach that presented above. They incorporate a trust into the recommender-based approach. They argue that a decision support system for team building needs to consider relational attributes such as trust in order to determine a fit between the candidate and existing team members.

A proactive job recommender system

The proactive recommender system is an adaptive system that attempted to integrate the idea of recommender systems (Schafer et al., 1999) and adaptive hypermedia (Brusilovsky, 2001). This system contains five components: web spider, ontology checker, profile analyzer, preference analyzer, and user interface generator. Web spider is a parser that periodically acquires job information from an exterior source. The ontology checker matches information with ontologies and performs the classification. Then, the job data is stored in a pre-designated form. The profile analyzer makes the recommendations, whenever the users modify the group of favorites by comparing the weight differences with current open jobs. Then, a list of recommended jobs is generated. Finally, the preference analyzer deduces the explicitly defined user's preferences and gives a recommendation for preferred jobs after calculating the similarity of jobs to user's preference (Lee and Brusilovsky, 2007).

Semantic matchmaking for job recruitment

Fazel-Zarandi and Fox (2010) tried to improve the matching process by providing an adaptive job offering and discovery environment. They combined different matchmaking strategies in a hybrid approach for matching job seekers and jobs using logic-based and similarity-based matching. First, they applied a deductive model to determine the match between individual and job, and then they used a similarity measure to rank the applicants with partial match.

A fuzzy multiple criteria method for recruitment

It is a model that tries to determine the suitable personality traits and key specialized skills through information statistics and Analytic Hierarchy Process (AHP). The AHP is a multi-objective decision making method that is applied in uncertainty of decision-making matters with other assessment criteria. Author performed a study started by questionnaire survey and criteria assessment. Then, the weight of relevant factors was determined based on AHP, and using fuzzy multiple criteria algorithm. This algorithm is based on triangular fuzzy number and linguistic variable, which is used to evaluate the importance and satisfactory level of certain criteria.

Finally, based on the comprehensive assessment the applicants' scores were computed as a basis of recruitment (Chen, 2009).

Content-based job recommender systems

Machine learned recommender system

The recommendation problem treated as a supervised machine learning problem. They build an automated system that can recommend jobs to applicants based on their past job histories, in order to facilitate the process of choosing a new job. An item in this learning model represents a person who is hired in an organization. Each item is characterized by set of features extracted from the candidates' resumes. Given a person who is currently working in an organization, they want to predict the next organization. If the accuracy of such predictions is sufficiently high, the model can be used to recommend organizations to employees who are seeking for jobs. This approach uses all past job transitions as well as the data of both employees and organizations to predict an employee's next job transition. They train a machine learning model using a large amount of job transitions extracted from person profiles available in the web (Paparrizos et al., 2011).

A system for screening candidates

Singh et al. (2010) have presented the PROSPECT system, which is a decision support tool assisting recruiters to shortlist candidate resumes list. It mines resumes to extract features of candidate profiles such as skills, education, and experience. It used information retrieval techniques to rank applicants for a given job position. For each job profile, the system ranks candidates based on the similarity between job profile and candidates resumes. The ranking can be refined by adding filtering criteria. These criteria based on the candidate meta-data, as well as on the information that is automatically extracted from the candidate resumes. This system consists of three main components: Batch processor, Query processor and Resume matcher. New applications are initially processed by the batch processor. It stores the candidate meta-data in the main database and extracts data from the candidate resumes, which in turn saved in extracted database. This information is used by the query processor and the resume matcher to provide the ranking candidate list for a given user query.

Reciprocal recommendation for recruitment

Yu et al. (2011) proposed a preference method based on user's interaction history and a new similarity measurement method. The recommendation process divided into two parts: job recommendation and job-seeker recommendation. For both parts, the recommendations should be the objects which are the most consistent with their preferences. The useful information is extracted from users' resumes. Then, they find the explicit preferences of users and acquire the implicit preferences indirectly depending on the condition of sending and receiving resumes. The similarity of different preferences is calculated using different methods. Finally, the complete similarity is calculated and the recommendation is generated. The steps of reciprocal recommendation are as follows: (1) users' preferences extracted from the content of users' resumes and then, the attribute is determined and converted to vector. (2) The similarity calculated between users in turn then calculates the reciprocal score. (3) Finally, the recommendation is generated by ranking the reciprocal scores to present the top-n recommendations.

DISCUSSION

The hybrid job recommendation approaches presented combined two or more techniques to overcome the problems that suffer from using each technique separately. For example, while the probability hybrid approaches in paragraph A realized a bidirectional recommendation and tried to cover different selection dimensions, they need to enhance by including more features for individuals and extending by various relational aspects other than trust. Additionally, they only adopted the binary representation with Yes and No when state user preferences, and it cannot measure the degree of users preferences for each index well, so the quality of recommendation is not high (Yu et al., 2011).

As for the content-based job recommender systems, it is presented some approaches and systems based on CBF techniques. As mentioned in the CBF, it is limited by the features that explicitly associated with recommended objects. Therefore, since the applicants' resumes are usually represented by their most important features using some key words, CBF systems cannot distinguish between different keywords meaning. In addition, the problem usually associated with the pure CBF systems; it cannot recommend jobs that are different from anything the user has seen before. Jobs will be recommended if they are similar to other jobs that the applicant has already interested. Thus, the applicants have to rate a sufficient number of jobs before a CBF recommender system can really understand the applicant's preferences and present reliable recommendations. For example, the machine learned recommender system in paragraph 0 builds an automated system to recommend jobs for applicants based on their past job histories. This system is used a classifier that makes a recommendation by training them on content information. It suffered from scalability and data sparsity problems (Ghazanfar and Pr¨ugel-Bennett, 2010). In addition to, this system performs the recommendation as a unary relation and ignores the person-team fit when matching candidates with jobs. Table 4 summarizes the advantages and disadvantages of these approaches and systems.

Finally, from our research and findings from existing literature, we showed the increasing importance of information technology for the recruitment process. Thus, the important challenge for most organizations as identified by the literature analysis is the low qualification of applicants, where skills of applicants do not fit with the job profile. Since, human attributes are usually pure content-based that would not work very well to produce recommendations. On the other hand, the candidates can rate previous seen job profiles to be integrated with content-based filtering. Thus, a method based on collaborative filtering would also fail due to a too sparsely filled matrix of comparable ratings. Additionally, in skills requirements matching, we are interested in determining whether or not an individual satisfies a set of requirements. We must distinguish between most important and preferable requirements when matching. Most important requirements are hard constraints whereas preferable requirements are soft constraints that are taken into account when ranking (Fazel-Zarandiand, 2010). Therefore, the selection of candidates to jobs needs to integrate unary candidate attributes as well as relational information and incorporate candidate ratings for already seen jobs' profiles to develop a computational model that suitable for these requirements.

This model can be benefited from successful recommender systems techniques that applied in e-commerce applications and produced good recommendations to users. We believe that this area of research has important practical implications in different levels of e-recruitment process that can support managers and recruiters. This is not aimed to replace completely traditional selection method but aims to support the human resource department by a list of candidates from which chose the suitable candidate.

CONCLUSION

In this article, we used a literature analysis of many journals and proceedings related to the recruiting process and the job recommendation researches. We have seen from our literature review and from the challenges that faced the holistic e-recruiting platforms, an increased need for enhancing the quality of candidates/job matching. The recommender system technologies accomplished significant success in a broad range of applications and potentially a powerful searching and recommending techniques. Consequently, there is a great opportunity for applying these technologies in recruitment environment to improve the matching quality. This survey shows that several approaches for job recommendation have been proposed, and many techniques combined in order to produce the best fit between jobs and candidates. We presented state of the art of job recommendation as well as, a comparative study for its approaches that proposed by literatures. Additionally, we reviewed typical recommender system techniques and the recruiting process related issues. We conclude that the field of job recommendations is still unripe and require further improvements.

As part of our ongoing research, we aim to build a new recommendation approach and test with real data for employee and staffing data from large companies. In

Table 4. Advantages and disadvantages of job recommendation approaches.

Recommendation approach	Techniques	Advantages	Disadvantages
Hybrid job recommender systems	Probabilistic hybrid approach.	Bidirectional recommendation. Relational aspects are included.	Binary representation only. Less attributes used. No perfect measures.
	Proactive job recommender system.	Adaptive system. Use many attributes. Use ontology to categorize jobs and as a knowledge base to define features (attenuate cold-start problem).	Key words search method. One way recommendation. Knowledge acquisition and knowledge engineering problems. No relational aspects are included.
	Semantic matchmaking for job recruitment	Bidirectional recommendation. Effective matching methods. Includes many attributes. Relational aspects are included. Qualitative and quantity representation (proficiency level for skills is included). Use two levels in skills matching (constrains and preferences).	Knowledge acquisition and Knowledge engineering problems. Tools and technologies skills excluded.
	Fuzzy multiple criteria method for recruitment.	Use many attributes. Relational aspects are included. Effective matching methods. Use linguistic variables to determine skill levels.	One way recommendation.
Content-based job recommender systems	Machine learned recommender system	Use many attributes. Transition history is included.	One way recommendation. No relational aspects are included. Scalability, ramp-up, and data sparsity problems.
	System for screening candidates	Use many attributes. Various information retrieval techniques are used. Constrains used to eliminate candidates before ranking.	Inefficient measures. One way recommendation. No relational aspects are included. Ramp-up and data sparsity.
	Reciprocal recommendation for recruitment	Bidirectional recommendation. Effective matching methods. Use integration-based similarity in skills matching (explicit and implicit preferences).	No relational aspects are included. Ramp-up and data sparsity.

addition to, we plan to enhance the similarity measures that suitable for this problem.

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