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RESEARCH ARTICLE

A hierarchical similarity based job recommendation service framework for university students

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Abstract When people want to move to a new job, it is often difficult since there is too much job information available. To select an appropriate job and then submit a resume is tedious. It is particularly difficult for university students since they normally do not have any work experience and also are unfamiliar with the job market. To deal with the information overload for students during their transition into work, a job recommendation system can be very valuable. In this research, after fully investigating the pros and cons of current job recommendation systems for university students, we propose a student profiling based re-ranking framework. In this system, the students are recommended a list of potential jobs based on those who have graduated and obtained job offers over the past few years. Furthermore, recommended employers are also used as input for job recommendation result re-ranking. Our experimental study on real recruitment data over the past four years has shown this method's potential.

Keywords job recommendation, students, similarity, time, re-ranking

1 Introduction

The job market has become highly competitive and as such it becomes harder and harder for people when they wish to move to a new job [1]. The situation is even more fierce for new professionals, particularly for newly graduated university students, since the requirement of potential employers continuously changes [2]. Therefore, how to help university students find satisfactory jobs, in the "school-to-work" transition [3], has become an essential task.

To face fierce job market competition, a lot of efforts have been applied by university students. For example, some students obtain help from their family in hunting jobs [4]. Some students prefer to take part-time jobs to accumulate necessary work experience [5]. Some students rely on mentors or supervisors to obtain job seeking guidance and suggestions [3]. With the development of social networks, students also refer to their network of friends to get job information [6,7]. Though there are multiple channels through which a student can seek jobs, a vast number of students obtain potential job information from university offices [8], particularly in China, since every Chinese university has an employment office, which helps organise "employment fairs" [9] for students and potential employers.

Though the advantage of university's support for connecting student job hunters and employers is well documented, an essential difficulty is revealed that both the students and employers face the problem of information overload [10]: so many job choices for students and so many resumes for employers. Therefore, it is becoming a necessity to design a suitable mechanism for students and employers to filter the information and get quicker and better matches.

To overcome this difficulty, several mechanisms have been

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proposed. For example, early employment systems can filter resumes of candidates based on keyword matching. Though these methods are simple and robust, they cannot measure the match rate of latent factors between job hunters and the job itself [11], thereby calling for advanced recommendation methods to overcome this challenge.

In the past decades, with the development of information technology, selecting needed information from massive data has become an important issue to academia and industry. In the 1990s, personalised recommendation systems were proposed for the first time. Due to their capability of evaluating matching degree of similar users and similar items [12], they have been gradually developed and widely applied to many application domains, e.g., e-commence [13], and also job seeking areas [14,15].

As one of the most important and interesting applications of recommendation technology, job recommendation can composite all kinds of data from a user profile to discover the user's potential interests, thereby providing an individual recommendation list to match the user and potential job positions. In job recommendation systems, user profile information can contain both basic information and behaviour history [16]. The basic information consists of the user's individual background, e.g., demographic information, education background, and skill. Behaviour information normally includes the user's activity in using the job recommender systems, e.g., browsing archives, resume delivery, and grading. Recently, time information such as job occupation duration [17,18], social network behaviour [19] and other external information has also attracted extensive interest in job recommender systems.

Though the job recommender systems have proven their success in different applications, to properly recommend university students to appropriate employers is still a major challenge since the students usually lack work experience and sometime have ambiguous career objectives [20]. To better solve this problem, an advanced method is necessary to help students find satisfactory jobs. In constructing such systems, certain specific information can be considered. Normally, universities collect an enormous amount of employment data and student training data over a number of years. Such data contains a lot of useful information such as student personal profiles, employer background, and student training activities. It is then interesting to ask: is it feasible to create proper recommendation based on such historical data?

In this paper, we focus on recommending potential jobs to students by considering the accumulated employment history reports and student profiles of a university. We design a similarly pattern between jobs and students and then analyse various recommendation strategies. Finally, in order to improve the accuracy of recommendation, a re-ranking method is proposed using historic employer recruitment information of students. The major steps of this framework can be summarised as: 1) constructing a student interest model and calculating similarities between students and those who have received job offers over the past years according to their property and training information; 2) ranking the potential employers from the history and recommending to students who will soon graduate.

The rest of the paper is structured as follows. In Section 2, we will introduce the related work about job recommendation. Section 3 will present the proposed university student job recommendation framework in detail. Our experimental study based on real employment data will be described in Section 4, and Section 5 will conclude this paper and outline potential future work.

2 Related work

2.1 Recommendation systems

With the development of the Internet, more and more products and services have become available online [21] and a huge number of opinions and comments have also publicly posted [22]. As a result, it is now a great challenge for people to find the needed information from such massive data set when making a decision. Accordingly, recommender systems have been proposed to deal with this challenge [23], and can be roughly divided into three categories, i.e., content based methods, collaborative based methods, and hybrid methods [12].

Since their development in the 1990s, recommender systems have been widely lauded as an innovative approach for people to make appropriate choices [24], and many advanced recommendation technologies have been successfully applied to real applications. For example, Amazon provides recommendation for books and products to different users through personalised recommendation technology [13]. Microsoft has also proven success in supplying service recommendation of product downloads and bug fixes to different users [25].

2.2 Job recommendation

Recommender systems have been proven their potential in many applications. They have also been adopted in the employment market to help bridge the gap between applicants and employers [26], since sometimes the employers do not present their requirements clearly, and also the job hunters are not capable of presenting their needs appropriately [27]. Employment recommendation is a powerful mechanism to solve this challenge and much importance has been attached to it. Currently, there are many employment recommender systems in the literature. They can be classified similarly to general recommender systems [12], i.e., content based job recommendation, collaborative based job recommendation, and hybrid approach for job recommendation.

2.2.1 Content based job recommendation

The main idea of content-based recommendation systems is to match items with user preference profiles [28]. In the job recommendation area, the content based approaches employ the job description and/or job title [29], and also the user profile to decide if the targeted job matches a user's needs [30]. The first task in content based job recommendation is to properly model the user's profile and the job description. Therefore some researchers focus on proposing advanced models to better describe the profile. An example is the structured relevance model proposed in [31] to describe the semi-structured profile documents of jobs and users.

Some other researchers put emphasis on modelling user skills and then matching potential jobs. For example, Almalis et al. took into consideration employer needs and the job seeker skills to examine the suitability of a user for a specific position [32]. Some scholars proposed further approaches to model the skills and an example is the work by Bastian et al. [33], which presents a topic extraction model to constitute a folksonomy of user expertise by which the matching process can be more effectively conducted.

Though content based job recommendation is easy to implement, it has several challenges. Particularly, unclear career intention and stagnant profile are typical problem areas [30]. Furthermore, content based job recommendation utilises only a user's own profile, but sometimes considering group of employers and users will provide a better recommendation result [34]. To this end, a collaborative based job recommender can be an alternative solution.

2.2.2 Collaborative based job recommendation

Collaborative based recommender systems are based on group knowledge to make recommendations. One of the major techniques used is collaborative filtering, which locates and then recommends similar users that have similar interests via a user-item score matrix [12].

In a job recommender system, collaborative recommendation uses the user-job matrix in terms of employment information graded by job hunters. An example of behaviour includes user revisits, visit duration and activity in using job recommender systems [27]. Similarly, Zhang et al. designed and implemented an item-based collaborative recommender system based on user application records for online job-hunting [35]. Collaborative based recommendation has shown its potential in job market and a lot of applications have been implemented to prove its capability.

2.2.3 Hybrid job recommendation

As mentioned in [12], it could be promising to combine different individual recommendation mechanisms to create a hybrid system to serve recommendation needs. In job recommendation applications, the advantages of hybrid approaches have been thoroughly studied. For example, Fazel-Zarandi and Fox proposed a hybrid mechanism integrating description logic matchmaking and a similarity based ranking model [36]. Some other methods utilised user profiles to initialise the job recommendation and subsequently provide dynamic mechanisms to polish the recommendation list [30,37], in which it is argued that when different methods are combined together, it is feasible to deal with dynamic features of user profiling and also job requirements.

2.2.4 Other approaches

As well as the above mentioned three categories of job recommender systems, there are some additional groups suggested in the literature, e.g., knowledge based job recommendation and reciprocal job recommendation [38]. The main idea beneath knowledge based job recommendation is to find some rules or patterns from user activities in finding jobs. For example, Bradley et al. developed a domain knowledge to present job skills, thereby making job matching more effective [39]. Similarly, Chien and Chen proposed a data mining oriented method using decision trees and association rules for job candidate selection [40].

Different from traditional recommendation systems, the job recommenders aim to satisfy both job hunters and employers at the same time, similar to typical win-win requirements of dating services [41]. This is a reciprocal requirement [42]. For example, Malinowski et al. proposed a bilateral approach ensuring both job applicants and employers are satisfied [26]. This kind of system is particularly important and useful, since precise matching will reduce the needed effort and required resources for both applicants and employers.

3 BH-JRS framework

3.1 Framework overview

According to the above discussion, the requirement, research direction and application of job recommendation technology has been clearly elaborated. However, when narrowing down the problem of supporting university graduate students' job seeking, there are several specific challenges. For example, the students normally do not have work experience, and have very little work training. Sometimes, they are also unclear on their own career direction [43]. Therefore, they are likely to feel anxious in selecting potential employers. To better serve the university student to find a potential employer, the job recommendation framework, BH-JRS, is proposed in this paper, as shown in Fig. 1.

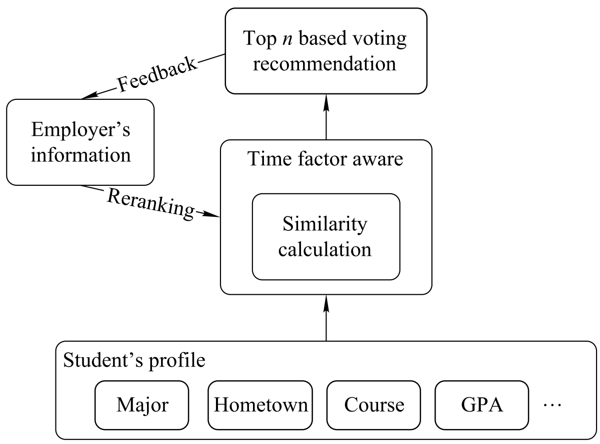

Fig. 1 BH-JRS job recommendation framework

In this framework, the most fundamental task is to properly model university students. Since most fresh graduate students do not have much work experience, in this research, their demographic information and also training achievements are employed to constitute their profiles, which include major, course, home town, etc. Afterwards, a similarity mechanism is designed to determine similar students. The motivation behind this step is that similar students may have similar job seeking preferences. In this step, we not only use basic information to calculate similarity, but also utilise time information for further extension. Inspired by the findings in [17], where the authors argued that job duration time is an essential factor for people in considering to move to a new job, it is feasible to assume that different graduate times in the history will have sensitive effect on job recommendations of newly graduated students.

After finding similar students, the next step is to recommend potential employers to submit resumes. In this research, we propose a top n based voting mechanism to retrieve a potential employers list. Afterwards, we further study the employers that students have obtained offer from the past and feed the employer information back into the student similarity calculation. Using this re-ranking mechanism, the overall recommendation performance can be improved to some extent.

3.2 Student profiling

First, we need to model students before appropriate job recommendation. In this research, a student profile is composed of two main attributes, i.e., basic attributes and achievement attributes. The basic attributes include the student's individual background and also his educational background, such as home town, gender, university, department, major and courses taken. In contrast to this kind of static information, achievement attributes mainly reflect this student's academic outcomes such as grades, scholarships, awards, grants, etc. Therefore, in this paper, a student profile can be formally defined as below:

$$u = \{a_1, a_2, \ldots, a_n\}, \tag{1}$$

where u is the student and a_i represents the users ith attribute.

For a graduate student who has obtained an offer from an employer in the past, we can further define that student as:

$$g = \{u, e\} = \{a_1, a_2, \ldots, a_n, e\}, \tag{2}$$

where g is the graduate student with a job offer and e is his/her employer.

3.3 Student similarity calculation

The proper job recommendation relies on how we evaluate the similarity of students and graduates. In this research, we employ a similarity degree representation mechanism by calculating the similarity of attributes between different students with different weights. The similarity calculation process can be defined as:

$$S(u, g) = \sum_{i=1}^{n} w_i \cdot sim(u_{a_i}, g_{a_i}), \tag{3}$$

where u and g are the students who are looking for a job and a graduate who has an offer, respectively, and w_i is the ith attribute weight in the similarity calculation, while a_i is the ith attribute.

A student's attributes can be divided into two types, i.e., bool and discrete. An example of the bool type is the home town (in this research province is employed as the granularity). If the students come from the same place, the similarity on this attribute will be 1, otherwise 0. Accordingly, similarity for bool types can be defined as:

$$sim(u_{a_i}, g_{a_i}) = \begin{cases} 1, & u_{a_i} = g_{a_i}; \\ 0, & u_{a_i} \neq g_{a_i}. \end{cases} \quad (4)$$

For discrete attributes including the grade which ranges from 0 to 100, similarity is defined as:

$$sim(u_{a_i}, g_{a_i}) = 1 - \frac{|u_{a_i} - g_{a_i}|}{a_{imax} - a_{imin}}, \quad (5)$$

where *max* and *min* define the value range. An example is the student's grade where the similarity in this perspective can be defined as the grade difference divided by the whole grade range, i.e., 100.

Looking at the similarity of student major subject, defining similarity as bool type is inappropriate, because 1) the granularity is too coarse for two different majors since they can include similar courses to some extent, for example computer science and electronic engineering; 2) students can also select slightly different courses even within the same major. To solve this problem, in this paper we use courses taken instead of major name to calculate any two students' similarity in terms of their majors, which can be defined as below:

$$sim_{course}(u, g) = \frac{|C(u) \cap C(g)|}{|C(u) \cup C(g)|}, \quad (6)$$

where $C(x)$ is the set of all courses that student x has taken.

3.4 Job recommendation

By means of the above presented similarity mechanism, we can now obtain all students' similarity with regard to those who have obtained job offers. Based on this information, an intuitive method is proposed for student job recommendations. The main idea is to first rank all graduates according to the similarity to a particular student. Afterwards, the employers that offered graduates jobs will be recommended to students. For duplicate employers by different graduates, only one is returned in the recommendation list. The whole sequence is listed in Algorithm 1.

Though pure similarity based recommendation is simple to implement, inspired by the classification algorithm KNN [44], we argue that the most similar graduates will have more influence on the student's job seeking process. Based on this hypothesis, we further propose a voting based recommendation based on the top n similar graduates to form the potential employers list. The steps are quite similar to Algorithm 1 while the main difference occurs in the list formation. After similar graduates with regard to the student are calculated, the top n graduates are recorded and accordingly all employers relating to those graduate can be retrieved. Consequently, a list of potential employers will be returned based on the number of all employers in the employer set. The detailed process is described in Algorithm 2.

Algorithm 1 Similarity based recommendation

Input: G, u
Output: E
1: **for** each graduate g_i in G **do**
2: Calculate similarity with the student $s_{u,g_i} = S(u, g_i)$
3: **end for**
4: Sort s_{u,g_i} in descending order
5: Obtain each employer e from very g_i to form a employer set E
6: Remove duplicate employer from E
7: return E

Algorithm 2 Top n voting based recommendation

Input: G, u
Output: E'
1: **for** each graduate g_i in G **do**
2: Calculate similarity with the student $s_{u,g_i} = S(u, g_i)$
3: **end for**
4: Sort s_{u,g_i} in descending order
5: Obtain Top n graduates to form G_k graduate set
6: Obtain all employers to form employer set E' related to G_k
7: **for** each employer e in E' **do**
8: Obtain employer number $number_e$ in G_k
9: **end for**
10: Sort E' in descending order of $number_e$
11: return E'

3.5 Time factor aware job recommendation

In the job market, the position duration time has been identified as an important factor in relation to people's behaviour in seeking new job [18]. Therefore, in university students job recommendation, it is not inappropriate to assume that the employers recruitment and students job seeking intention will be gradually changed over time [45]. In this research, we also want to thoroughly investigate the effect of time when job offers were issued. In this paper, we use a time factor α, which is a constant variable and smaller than 1, into the similarity calculation process. Therefore the original similarity degree defined in Eq. (3) can be redefined as:

$$S'(u, g) = (1 - (|t(u) - t(g)| - 1) \cdot \alpha) \cdot \sum_{i=1}^{n} w_i \cdot sim(u_{a_i}, g_{a_i}), \quad (7)$$

where $t(u)$ is year when student u is looking for jobs, and $t(g)$ is the time when graduate g obtained the offer. By using this revised similarity, we can test if the graduate time can truly reflect the difference in the job market.

3.6 Employer based re-ranking for job recommendation

From the above process, a list of potential employers will be recommended to the student. Considering we have a great deal of employer information, it raise the question: can this employer information be fully utilised to further improve job recommendation?

This idea is based on an important feature called re-ranking, which has been widely adopted in recommender systems and has proven success in improving overall recommendation performance [46]. Re-ranking may polish the recommendation list and also is convenient, since this re-ranking component can be easily added, removed, changed, without affecting the original job recommendation framework.

In fully utilised re-ranking model, the first step is to identify the employer's attributes, such as properties, business category, and location, which can be defined as

$$e = \{b_1, b_2, \ldots, b_n\}, \tag{8}$$

where e is an individual employer and b_i is the employer's ith attribute.

In this research, the top t employers returned to student u will be used as the re-ranking model input, which is called a virtual employer for that student and can be defined as:

$$e_u = \{b_{11}, b_{12}, \ldots, b_{1n}, \ldots, b_{t1}, b_{t2}, \ldots, b_{tn}\}, \tag{9}$$

where e_u is the student u's virtual employer attributes.

Afterwards, we can further compare a student's virtual employer attributes against the graduate students in E. Each graduate's virtual employer's attributes can simply repeat its own attributes t times and can be defined as:

$$e_g = \underbrace{\{b_1, b_2, \ldots, b_n, \ldots, b_1, b_2, \ldots, b_n\}}_{t}. \tag{10}$$

Now we can revise the students and graduates similarity in terms of employer's virtual attributes as defined below:

$$sim_{employer}(u, g) = \frac{|e_g \cap e_u|}{t \times n}. \tag{11}$$

Based on the newly added employer's virtual attributes, the similarity between students and graduates indicated in Eq. (7) can be further revised as below:

$$S''(u, g) = (1 - (|t(u) - t(g)| - 1) \cdot \alpha) \cdot \sum_{i=1}^{n} w_i \cdot sim(u_{a_i}, g_{a_i}) + \beta \cdot sim_{employer}(u, g). \tag{12}$$

4 Experimental study

In this paper, to validate and evaluate the proposed framework, we conduct experimental analysis on real job recruitment data obtained in the last four years in Beihang University, which is a top university in China with 28 schools and departments and around 30 000 enrolled students including undergraduate, postgraduate, and oversea students. In this experimental study, we will use the postgraduate students as case study to test the proposed framework.

4.1 Dataset and configuration

In this research, a total of 129 employers that have frequently recruited postgraduate students from 2012 to 2015 are included in this experimental study. These employers include governments, state-owned companies, joint ventures, private companies, universities, institutes, etc, which well represent the employer distribution in China. The student distribution in this research is listed in Table 1, in which all students graduated from 2012 to 2014 are considered as the training set and the students graduated in 2015 are used as the test set.

Table 1 Students distribution

Year	Student number	Male/%	Female/%
2012	737	71.2	28.8
2013	731	72.0	28.0
2014	637	70.8	29.2
2015	532	72.4	27.6

4.2 Evaluation metric

Inspired by the evaluation metric of $P@n$ in the field of information retrieval [47], which emphasizes the top n items in the return list based on the assumption that people will probably not be interested in the items beyond top n candidates [48], in this paper, we constitute a metric called $S@n$, which is defined as below:

$$S@n = \sum_{i=1}^{n} hit(u_i), \tag{13}$$

where $hit(u_i)$ represents a real employer of the student in the test set has been correctly included in the recommended list with the k employers. As such the $hit(u)$ is defined as:

$$hit(u_i) = \begin{cases} 1, & e_{u_i} \in E'; \\ 0, & \text{otherwise}, \end{cases} \tag{14}$$

where E' is the returned list defined in Algorithm 2.

From the above equation, it is found that setting an appropriate k value is essential for the proposed framework. In this research, we will test the variance of different k values and this parameter will be set to 1, 3, 5, and 10, respectively. Furthermore, we will mainly study the performance when k equals to 10, since we need to balance the effectiveness and efficiency of the propose framework, and a too small list size will have a risk of missing potential employers while too large a list may cost too much effort for the students to find really useful information.

4.3 Experimental results

In this research, we have comprehensively studied the effect of different attributes a student has in the job seeking process. However, since the students are all from Beihang University, we will ignore the attributes of university background and education level since they are all the same. Meanwhile, we also remove the gender information since the majority of students are male. Finally the major, home town, and grade point average (GPA) are selected in this experiment to evaluate the proposed job recommendation service.

1) Experiment 1

Firstly, we will empirically investigate the different weights of the attributes in student's profile on the final job recommendation. In this research, the major, home town and GPA are investigated. During the process of identifying the effect of different weights of these three variables, we firstly randomly set the weight of one variable to zero and set 50 % for the rest two variables. The results are listed in Table 2, from which it is found that the most important factor is the student's major, which is consistent to our experience. For a postgraduate student, the major is of great importance indeed. Another interesting finding is that as the weight of major increases when the rest two variables keep balanced, the overall performance does not increase accordingly. This is partly because the inappropriate usage of discrete major information. Therefore, we need to test if using course to replace major will result in improvement.

Table 2 Effect of student's personal profile in job seeking

Major	Home town	GPA	$S@n$			
			1	3	5	10
0.5	0	0.5	21	49	72	112
0	0.5	0.5	13	40	54	104
0.5	0.5	0	19	65	93	147
0.4	0.3	0.3	29	73	96	148
0.5	0.25	0.25	29	73	96	148

2) Experiment 2

In this experiment, we replace similar degrees of major with courses and the result is shown in Table 3. From the result it is observed that the hit rate of $S@10$ is improved indeed along with the increase of weights of courses.

3) Experiment 3

As elaborated in Section 3, it is argued that top n voting based recommendation mechanism will have advantage over a pure similarity based method. To test this hypothesis, we implement top n voting based method and keep the student's profile unchanged with weights set as 0.9, 0.05, 0.05, respectively, as shown in Table 3. The performance result is shown in Table 4, where it is found that the hypothesis does work well as the overall performance is improved. Furthermore, the $S@10$ achieves the best results when K is 100.

Table 3 Course vs major in job seeking

Course	Home town	GPA	$S@n$			
			1	3	5	10
0.5	0.25	0.25	39	79	95	146
0.6	0.2	0.2	39	80	98	148
0.7	0.15	0.15	41	87	102	146
0.8	0.1	0.1	34	86	110	151
0.9	0.05	0.05	26	74	103	167

Table 4 Top n voting based job recommendation

Top n voting	$S@n$			
	1	3	5	10
60	47	107	148	207
80	47	114	150	212
100	47	106	155	219
120	52	111	139	215
140	52	111	146	214

4) Experiment 4

In the job market, time employed is argued as an important factor. Therefore, in this research, we also test this hypothesis by using individual year's employment history to predict the employment result in 2015. The parameters are the same as in Table 4 and the top n recommendation method are employed. The result is displayed in Table 5, from which it is observed that the more recent the history data used, the better the prediction results are.

Table 5 Job recommendation according to individual year's history data

Year	$S@n$			
	1	3	5	10
2012	31	73	109	154
2013	37	98	134	181
2014	42	88	129	186

5) Experiment 5

This experiment will test Eq. (7) as to whether it will help improve overall performance if different year's history data are combined together. The experimental result is depicted in Table 6, where we can find that the prediction is improved indeed. Particularly when α equals 0.025, the framework can achieve the best result.

6) Experiment 6

The final experimental study is to validate the usefulness of the re-ranking strategy. Following the same settings in previous experiments, we implement the re-ranking component by using the employer's virtual attributes. Furthermore, we also test the different effect on weights of β and t. From the result in Table 7, it is found that the re-ranking method does improve the overall hit rate, it significantly improves $S@1$, $S@2$, and $S@3$, while maintaining the $S@10$ at the same time. This result is very efficient for the students since we will provide precise prediction instead of sacrificing their opportunities.

Table 6 History data combination strategy for job recommendation

α	$S@n$			
	1	3	5	10
0.010	51	109	151	218
0.015	52	110	151	220
0.020	51	109	152	219
0.025	53	109	150	220
0.030	52	107	149	216

Table 7 Re-ranking based job recommendation

β	t	$S@n$			
		1	3	5	10
0.05	60	55	110	154	219
0.05	40	50	113	152	216
0.05	20	51	110	146	211
0.04	60	56	114	155	222
0.03	60	57	112	156	219

4.4 Analysis and discussion

To better illustrate the different mechanism's influence on the proposed framework, we compare the different approaches and the result is presented in Fig. 2.

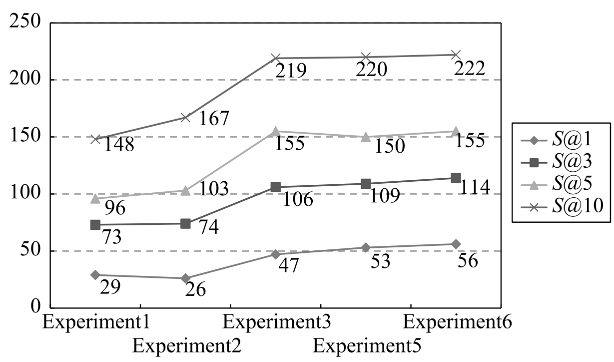

Fig. 2 Overall performance comparison

In this research, we propose a university students oriented job recommendation, which is based on the idea of finding similar graduates to help new students in finding a job. History data based recommendation is not a trivial task as such in the experimental study we have tested the different hypotheses proposed in the framework. Some interesting findings and conclusions are revealed:

1) The student's course similarity does have a strong influence in recommending potential jobs. Currently, more and more universities provide flexible curricula. With the development and popularity, massive open online courses (MOOCs) also come to us for individual study. It is expected that different students will have different capabilities even under the umbrella of the same major. As such the tested hypothesis will provide an insight for future research in this area.

2) From the performance, study of top n voting mechanism follows the hypothesis. Similarity combined with job information itself makes more sense since the student personal profile can just describe static and clear features, it cannot model people's intrinsic motivation, however. It is expected that providing a mechanism to bridge student and job will provide more useful suggestions.

3) In the job market, the intention and practical selection changes over time. From this study, it is found that the students will likely refer to more closed history data in finding jobs. However, when all history data are combined together, we can balance the long term goals and short term goals.

4) The re-ranking model is effective in this framework and it is also replaceable and removable, which makes the framework adaptive to future applications.

Though this research has reported promising results, there are some limitations of this work.

1) This case study only involve students from one university, i.e., Beihang University. As a result, some features in student profiles are not used, e.g., education level. Therefore, it will be more convincing if more students with diverse background information can join the study. Furthermore, in this research, training achievements are not studied since modelling such capability is a bit difficult, which calls for more thorough study in the future work.

2) The employers, information is also useful. This phenomenon reflects the idea of a "reciprocal" feature. Therefore how to reduce the employer's effort while maintaining students satisfied deserves more study.

5 Conclusion and future work

In the job market, recommending university students appropriate jobs has become an important task. Many challenges are identified in this kind of applications, not only from job recommender systems themselves, but also implied from the situations of the student community. In this research, we have thoroughly analysed the currently widely-used job recommendation techniques. Based on the investigation, we propose a university student oriented job recommender framework.

In this paper, we employ similarity to predict whether a student will find interest in certain employers that have given an offer to other graduate students who have similar backgrounds and behaviours. We have proposed several mechanisms to calculate the similarity of students and tested their performance in the experimental study. Afterwards we have also developed a top *n* voting recommendation method to predict student preference over different employers. Based on this work, we have further investigated the time issue in the job recommender systems and provided a combination strategy for different historical data. Finally, a flexible re-ranking module is introduced to further polish the recommendation result. The experimental study on real data from Beihang University over the past four years has shown the framework's capability and effectiveness.

As a future work, we intend to conduct a more comprehensive study using students from more than one university to increase the diversity of student background. We also intend to study employer satisfaction while maintaining student expectations since job recommendation is reciprocal, which deserves deep investigation in the future work.

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