Matching People and Jobs: A Bilateral Recommendation Approach

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Abstract

Recommendation systems are widely used on the Internet to assist customers in finding the products or services that best fit with their individual preferences. While current implementations successfully reduce information overload by generating personalized suggestions when searching for objects such as books or movies, recommendation systems so far cannot be found in another potential field of application: the personalized search for subjects such as applicants in a recruitment scenario. Theory shows that a good match between persons and jobs needs to consider both, the preferences of the recruiter and the preferences of the candidate. Based on this requirement for modeling bilateral selection decisions, we present an approach applying two distinct recommendation systems to the field in order to improve the match between people and jobs. Finally, we present first validation test runs from a student experiment showing promising results.

1. Introduction

Personalization systems such as recommender engines in recent years attracted the interest of many researchers and practitioners. Since Resnick and Varian first established the term “recommender system” in 1997 [23], researchers have been improving recommendation quality and scalability of such systems by various means. While some researchers merged content-based with collaborative filtering in order to overcome sparsity problems and combine the advantages of both approaches [19], [26], others focused on how to reduce the dimensionality of the user-item-matrix underlying collaborative filtering approaches [27], [31]. Today, recommendation systems successfully assist consumers on the Internet in finding products or objects based on items similar to the ones the customer himself previously liked or based on items that other customers similar to him liked in the past. However, personalization systems are not yet applied when searching for subjects. Thus our research question is: How can the selection of individuals be supported or improved with IS support? We argue that a match between a candidate and a job needs to be bilateral as it requires considering the preferences of the recruiter and the preferences of the candidate.

The remainder of the paper is organized as follows. Based on our research motivation and building on existing theory and own prior research, we derive concrete requirements for a bilateral recommender that can be used to match people and jobs in a recruiting scenario. We then present first validation results from a student experiment and outline further research.

2. Research motivation

Information technology in recent years has transformed (1) the ways people find work as well as (2) the ways they effectively work together. With regard to the first aspect, we conducted a longitudinal empirical research with the Top-1.000-companies in Germany as well as with over 11.000 job seekers shows that the Internet has replaced print media as the most important recruitment channel [12], [13]. With 78% of all vacancies being published within the

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career section of the corporate website and 49% of open jobs being posted on Internet job-portals, IT-supported channels dominate print media (30%) as a way to attract candidates. Also, over the years the ratio of actual hires generated through job ads on the Internet rises reaching 58% in 2004 [13]. When considering the later stages of the recruitment process such as the treatment of incoming applications and the (pre-)selection of candidates, a diminished importance of IS-support can be observed. However, as digital applications lower application costs, the number of incoming (electronic) applications increases. Thus, companies seek adapted IS-support for the selection stage in order to process the masses of incoming applications efficiently.

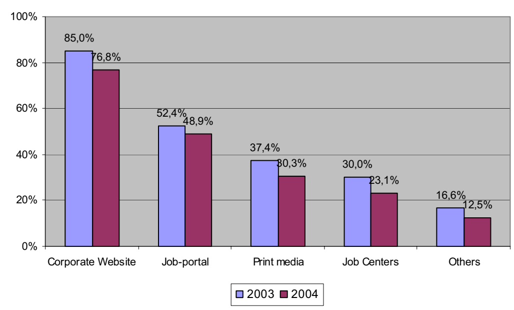

Figure 1. Ratio of vacancies published

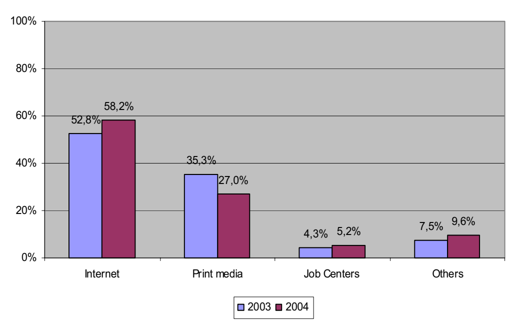

Figure 2. Ratio of jobs filled

However, a good fit between candidate and job often depends on underlying aspects that are usually hard to measure [10]. Autor sees these underlying aspects as one important reason why information systems have not been extensively used in the area of personnel selection so far [1], [33]. In practice, IS technology is mainly used to pre-select candidates based on standard database queries. Such queries define concrete skill requirements for a specific job profile in order to identify those individuals that match with the criteria. This requires employee and job profiles to be captured and stored based on a common skill-based ontology as this is a prerequisite for executing a skill matching algorithm to calculate the fit between person and job. Such kind of skill searching and matching is applied in numerous Human Resource information systems such as SP-Expert from Astrum or SAP R/3 Human Resources.

However, as pointed out, simple keyword-based search and filter techniques cannot be sufficient to capture the complexity of a person-job fit as selection decisions often depend on underlying attributes such as personal characteristics or social skills [10] that cannot be operationalized easily. Theoretical consideration let us draw an analogy to problems in the area of information retrieval. In this area automated recommendation systems are used to address the problem of information overload such as already mentioned above.

Applied to the context of pre-selecting candidates in a recruitment scenario, recommender systems could use past rating information to determine which kind of job required which kind of individual characteristics in the past in order to be rated positively by the recruiter. This information could then be used to predict a match between a job and previously not rated candidates.

The need for an improved IS support for selection processes can also be motivated from a different perspective. While our empirical research deals with how people find work, other research strands are concerned with how information systems change the ways people effectively work together once the candidate is recruited. Starting from Malone and Laubacher's vision of the "e-lance economy" [18], special attention was paid to the ways communication channels and "discontinuities" of space, time and organizational boundaries characteristic of virtual work influence collaboration patterns [2], [32]. Thus, as work in changing projects and organizational settings gains importance, individuals are more frequently matched to new colleagues within their lifetime which 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.

3. The personalized search for persons

From these considerations that (1) matching situations within a person's work history will increase and (2) decision support for the matching of collaboration partners will emerge, we started to develop a system for the personalized search for individuals. In the following, we present requirements for such a person-recommender when applied to a recruitment scenario.

3.1. Requirements for recommending persons

The challenge of finding a good match between person and job has been analyzed by a variety of disciplines. Typically, such problems are considered under the perspectives of task-related and social aspects [10], human and social capital or person-environment fit [28]. Building up on these theories, an IS-supported approach for the selection of candidates needs to consider two dimensions:

- The matching of individuals to tasks for which the candidate possesses the skills and abilities to carry them out.
- The matching of individuals to other individuals with whom the person is able to collaborate successfully.

In a first step of our overall research approach we concentrate on the first aspect – fitness of the candidate in relation to the job – which is usually discussed in the literature termed as person-job (P-J) fit. P-J fit has been the traditional approach in recruitment and selection literature for matching individuals and jobs. The construct belongs to the overarching concept of person-environment (P-E) fit which – besides P-J fit – additionally consists of person-organization (P-O), person-vocation or occupation (P-V) and person-group (P-G) or person-team fit [4], [14].

Various research fields such as vocational psychology, recruitment and selection research and management research have dealt with the P-E fit framework [4], [14], [29], [30]. The concept of P-E fit is based on the interactionist theory of behavior [21] which is grounded on research done by Lewin [17] who argued that behavior is a function of the person and the environment that surrounds that person [29]. It is not the person or the environment alone that determines the variance in behavioral and attitudinal variables but the interaction between their characteristics. Thus P-E fit defines the degree of congruence between the characteristics of an individual and the characteristics of the environment in which the individual has to act [29]. In general it is assumed that a high level of fit leads to positive outcomes for the individual (e.g. satisfaction and performance) as well as for the team he or she works in and finally for the organization as a whole [30], [14].

One can basically distinguish three different perspectives how P-E fit can be conceptualized [14], [29]. As P-E fit is the overarching concept for all the mentioned different types of fit, these perspectives apply to each of them.

The first perspective distinguishes between supplementary versus complementary fit. Supplementary fit exists when an individual “supplements, embellishes, or possesses characteristics which are similar to other individuals” in an environment [21]. On the other hand, complementary fit exists when a person’s characteristics make whole the environment or add to it what is missing [21]. It is essential to note, that the definition of environment is different for the supplementary and the complementary model. In the case of supplementary fit, the environment is described according to the people who inhabit it. In the case of complementary fit, the environment is defined apart from its inhabitants (see also [29]).

The second perspective to conceptualize P-E fit is the needs-supplies and the demands-abilities distinction [21]. Needs-supplies comprises the fit between the individual’s needs, desires or preferences and the environmental supplies. Demands-abilities is concerned with the fit between the environmental demands and the individual’s abilities (see also [4], [14]). As Kristof [14] notes, these two distinctions basically extend the conceptualization of complementary fit.

The third perspective is the perceived (subjective) versus actual (objective) distinction. Perceived fit is based on human judgment whether a fit exists or not. Usually, direct measures are used to assess the perceived fit by for example asking to what degree a person believes a fit exists [14]. However, Edwards discusses various issues related to direct measures (for details regarding those issues please see [4]). On the other hand, the actual fit refers to an explicit comparison between individual and environmental characteristics. Usually indirect measures such as interactions, difference scores or polynomial regressions are used to asses this kind of fit [4].

While many researchers have discussed these three perspectives and the distinctions within each of them separately, some authors recently note the importance of combining all perspectives into an integrated fit approach [14].

Figure 3 shows the relation between the different conceptualizations.

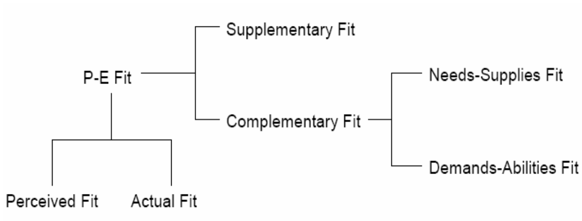

Figure 3. Relationship among different conceptualizations of P-E fit [29]

Despite the fact that recently some authors stressed the importance of all of the mentioned types of fit for recruitment, we restrict ourselves in the following to the concept of P-J fit.

Edwards [4] defines P-J fit to consist of two classes of corresponding person and job constructs, the fit between employees' desires and job supplies and the fit between the job demands and the employees' abilities which matches with the above described conceptualization of the person-environment framework.

This concept has major implications for our person-recommender as we cannot consider a good match between the candidate and the job as being based on a unilateral decision. While the customer chooses the movie he wishes to watch and not vice versa, this is not the case when recommending people. Selecting a candidate or partner is a bilateral selection decision in which not only the preferences and demands of the recruiter (representing the job) needs to be considered, but also the preferences and requirements of the candidate.

Thus, we retain the following key requirements when matching people and jobs:

- Recommending people for jobs is a bilateral process that needs to take into account the preferences not only of the recruiter but also of the candidate.
- Finally, as every individual is considered to be unique, we cannot recommend a single item or person several times such as in the case of a movie or book. As every person can only be selected once, we need to consider the rating of a person as rating for all his characteristics. This allows the recommendation system to predict ratings based on the predicted compatibility between candidate attributes.

3.2. Matching people and jobs

On our way towards a bilateral person-job recommendation system, we started with implementing a CV-recommender and a Job-recommender separately. Those two models are outlined hereunder before we discuss how the results could be integrated into a bilateral person-job recommendation system.

3.2.1. The CV-recommender. In a first step, we built a system recommending CVs that are similar to resumes previously selected by the same recruiter for a specific job-profile considered. The probabilistic hybrid recommendation engine is based on a latent aspect model that understands individual preferences as a convex combination of preference factors [9], [22]. As depicted in Figure 4, the recruiter together with the job description is represented in variable x, the preference factors being modeled in variable z. In coherence with our prior considerations, the recruiter – by rating a candidate profile or CV with variable v = {"qualified", "not qualified"} – does not rate the person itself, but the sum of its attributes. These "content"-elements, taken from the candidate's resume are composed of a quadruple such as a=("mathematical skills", "diploma grade", "1.0", "University of Frankfurt"). Thus, the rating value v depends indirectly on the position considered x and directly on the candidate's attributes a. With a set of observed values v for an attribute assessed by x and assigned to a, we are able to estimate the model parameters using an Expectation Maximization (EM) algorithm. A detailed description of the approach together with validation results can be found in [5].

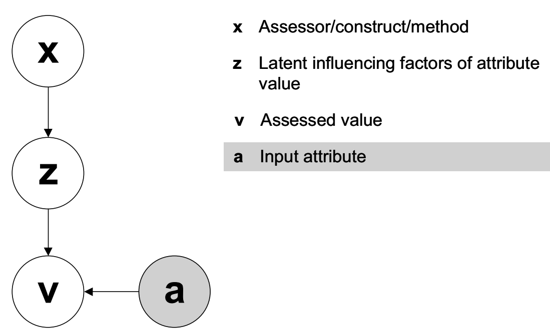

Figure 4. The probabilistic CV-Recommender

3.2.2. The Job-recommender. Based on the person-job fit conceptualizations as described above, a match between person and job also needs to consider the demands-supplies perspective by considering the preferences of the candidate for a specific kind of job. We therefore developed a second recommendation system that recommends jobs to candidates based on their preference profiles which are in turn based on previous preference ratings.

Thus the underlying conceptual requirements for the job recommendation are pretty similar to the ones for the CV recommendation which was described in the previous section. We therefore apply a similar probabilistic latent aspect model additionally to the context of job recommendation (Figure 5).

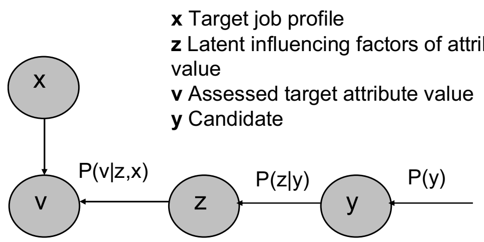

Figure 5. The probabilistic Job-Recommender

In this case, the candidate is represented in variable y, the job profile in variable x, and the latent aspect is modeled in variable z.

Using the Expectation Maximization algorithm as described earlier we can calculate the probability that candidate y rates job profile x with value v = ["fits to my preferences" | "does not fit to my preferences"].

4. First validation results

In order to validate our bilateral recommendation approach we conducted a multi-step experiment with a group of 32 students (N=32). The participants in the experiment were members of a seminar carried out as a joint project between two German universities. Students' background ranged from Economics over Business Administration and Industrial Engineering to Economics and Business Education. All students were about one year from their final degree.

The experiment was separated into two different phases. In a first step, students were asked to provide their resumes. We therefore implemented a web-interface by which we were able to capture students' CV data in a structured digital format. The data gathering was organized in a similar way to the registration procedures of many online job-portals. In addition to using this web form, students also were able to upload their CV as an entire document as this was supposed to facilitate the human judgment needed in later stages. The following data was collected within this phase of the experiment and used as input data for the CV-recommender:

- Demographic data (e.g. date of birth, contact information)
- Educational data (e.g. school courses, grades, university, type of degree, intermediate and final university examinations, postgraduate studies)
- Job experience (e.g. name of the company, type of employment, industry group, occupational field)
- Language skills (e.g. language, level of knowledge)
- IT skills (e.g. type of skill, level of knowledge)
- Awards, scholarships, publications, others

In a second stage, students were provided with 100 real life job profiles that prior to the experiment were randomly selected and downloaded from a large German job-portal (www.jobpilot.de). In order to ensure a certain level of diversity between the job profiles selected, we queried the job portal's database for jobs within 11 different occupational fields. Among those were job profiles in fields such as accounting, finance, controlling and banking, marketing and public relations, distribution and sales, organization, administration and legislation, engineering, consulting, top management, logistics and materials management, human resources and information and communication technologies. We only selected fulltime jobs available in any region within Germany. No further restrictions were made to this search for job ads.

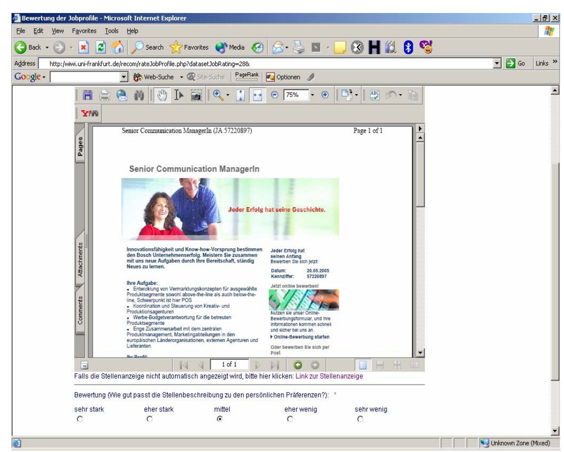

Figure 6. Screenshot of the job rating functionality

Still within this stage of the experiment, students were asked to rate the job profiles presented on a 5 point scale ranging from 1 (does not fit my preferences at all) to 5 (perfectly fits my preferences) (Figure 6). Within this process, students were asked not to consider criteria mentioned in the job ads that they were not yet able to meet e.g., x years of job experience being required or the person being obliged to move to another German region. Instead, students were asked to evaluate whether the profiles appealed to them with regard to their mid- or long-term career perspectives and plannings. The job ratings gathered from students were then used as input data for the job recommender described above.

4.1. Results from student experiment

Based on the above data and ratings, we started first test runs and validation activities with both systems. In order to evaluate the quality of the recommendations generated by the system, we considered the list of recommendations as a list of top n items. In our case these 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. The result list is based on calculated predictions whether or not the user will "like" an item (i.e. job or candidate profile). The quality of the recommendation system can therefore be assessed in terms of the quality of the predictions generated. This in turn can be evaluated using statistical accuracy metrics such as the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) or Correlation calculations (for details on these measures, see e.g., [7]). In our case, we retained the Mean Absolute Error (MAE) – sometimes also termed as average absolute deviate – in order to assess the overall prediction quality of the recommendation system.

If P_a is the set of predicted ratings, $p_{a,j}$ the predicted value for item j, $v_{a,j}$ the actual rating value and m_a the number of predicted votes in the test, the MAE is defined as [7]:

$$MAE = \frac{1}{m_a} \sum_{j \in P_a} | p_{a,j} - v_{a,j} |$$

4.1.1. Test runs with the CV-recommender system.

We tested the CV-recommender with a subset of 10 job-profiles. One person assessed the match between the abilities of all 32 student profiles available and the specific requirements of the job-profiles. Thus, this person emulated the pre-selection decision as normally carried out by a recruiter in a company. As the person possesses a personal track record in the HR field and has been involved in selection decisions before, he was familiar with such kind of evaluations.

In order to train the recommendation model, we removed the ratings of 10 randomly chosen candidates for job-profiles 001-005 from the original rating set. After the model was trained with the remaining subset of the original rating data, the assessments were predicted by the recommender system.

Figure 7 shows the results of the test run. The recommender system generated a top 10 candidate list in which candidates were ranked based on their predicted probability to fit the job-profile. These predicted ratings represented in the ranking list need to be compared to the original assessments marked by the (+) and (-) signs behind each of the candidate IDs indicating whether or not the original assessment was positive or negative. Despite the very small rating set, the results are quite promising. For job-profiles Job001, Job002 and Job004 the system recommends all candidates that were selected based on human judgment as the top results in the ranking list. For job profiles Job003 and Job005, where a relatively large number of candidates was relevant for the job in consideration, the system shows less precision, but results still are very close to the original ratings as for both profiles the top two candidates would also have been selected based on human judgment.

Recommendations on Candidate profiles 001 - 010

	Job001		Job002		Job003	
1.	006	(+)	009	(+)	004	(+)
2.	007	(+)	008	(–)	009	(+)
3.	010	(–)	006	(–)	008	(–)
4.	002	(–)	004	(–)	006	(+)
5.	005	(–)	002	(–)	001	(+)
6.	008	(–)	010	(–)	005	(+)
7.	009	(–)	007	(–)	010	(–)
8.	004	(–)	005	(–)	007	(–)
9.	001	(–)	001	(–)	002	(–)
10.	003	(–)	003	(–)	003	(–)

	Job004		Job005	
1.	008	(+)	004	(+)
2.	006	(–)	009	(+)
3.	009	(–)	008	(–)
4.	004	(–)	006	(+)
5.	007	(–)	005	(+)
6.	005	(–)	007	(–)
7.	002	(–)	001	(+)
8.	010	(–)	010	(–)
9.	001	(–)	002	(–)
10.	003	(–)	003	(–)

Figure 7. CV-Recommender: Results from the test run

In order to measure the overall precision of the model we additionally assessed the Mean Absolute Error in relation to the sparsity level. As figure 8 shows, the MAE decreases as sparsity reduces thus indicating the increasing prediction accuracy.

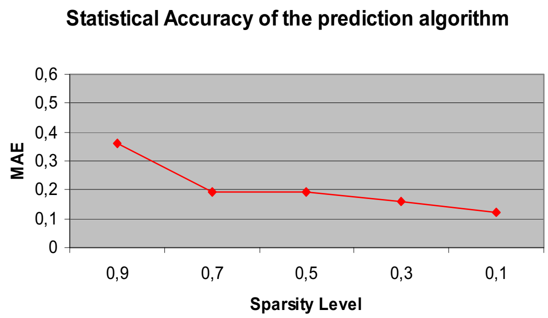

Figure 8. MAE of the CV-Recommender

4.1.2. Test runs with the job-recommender system. The job-recommender was tested in a similar kind of way. From the original rating set, which consisted of 32 candidates and their ratings of 100 job-profiles, we removed 5 randomly chosen candidates and their ratings for the first ten job-profiles. The reduced rating set was then used to train the model in order to evaluate its prediction quality. The system generated a ranked list of job-profiles based on their predicted fit with the candidates' preferences (Figure 9). Again, the (+) and (-) sign stand for the original assessments of the students. Hereby we interpreted a rating value of 4 and 5 as indicating that the job profile in general fits to the candidate's preferences (+) and lower ratings as indicating a 'non-fit' (-).

Recommendations on Job profiles 001 - 010

	Student001			Student002			Student003	
1.	008	(+)	1.	008	(+)	1.	008	(+)
2.	007	(+)	2.	009	(+)	2.	010	(+)
3.	010	(+)	3.	004	(+)	3.	005	(+)
4.	005	(+)	4.	003	(–)	4.	003	(+)
5.	003	(+)	5.	010	(+)	5.	002	(+)
6.	002	(+)	6.	005	(+)	6.	007	(+)
7.	009	(+)	7.	001	(+)	7.	001	(–)
8.	001	(+)	8.	006	(–)	8.	004	(–)
9.	006	(–)	9.	002	(+)	9.	009	(–)
10.	004	(–)	10.	007	(–)	10.	006	(–)

	Student004			Student005	
1.	008	(+)	1.	008	(+)
2.	010	(–)	2.	005	(+)
3.	009	(–)	3.	010	(+)
4.	005	(–)	4.	004	(+)
5.	004	(–)	5.	003	(+)
6.	003	(–)	6.	001	(+)
7.	002	(–)	7.	009	(–)
8.	001	(–)	8.	002	(–)
9.	007	(+)	9.	007	(–)
10.	006	(–)	10.	006	(–)

Figure 9. Job-Recommender: Results from the test run

Figure 9 illustrates that for students Student001, Student003 and Student005 the system ranks exactly those job profiles as the top jobs that were originally evaluated by the same students as the profiles that highly matched their preferences. For students Student002 and Student004 the system shows less accuracy but still predicts at least one highly relevant job as the highest ranked job profile. Figure 10 additionally shows the Mean Absolute Error of the whole prediction model in relation to the sparsity level.

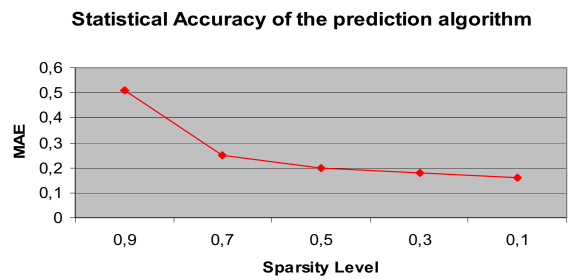

Figure 10. MAE of the Job-Recommender

4.2. The bilateral matching problem

In general the results can be interpreted as quite promising for both recommender systems separately. However, as a good person-job fit needs to consider both, the needs-supplies and the demands-abilities perspective, a challenging question remains unsolved: the integration of both recommendations into a single indicator representing not the individual, but the bilateral matching quality. Thus, we need to somehow aggregate the recommendations generated independently from each other into a single recommendation or value integrating the recruiters' and the job seekers' preference. In order to address this interesting question, in a first step we formalized this problem. This can be done as follows:

Given a set of agents X and a set of $|X|$ preference orders P_x over X, the bilateral matching problem (BMP) is generally defined by finding a pareto-optimal binary matching relation $M \subset XxX$ so that no agent x occurs in more that one tupel in M and there is no other matching relation M' in which no agent x is matched to an inferior agent according to its preference relation P_x and at least one agent x is matched to an agent y' rated superior to y.

A BMP is called bipartite (BBMP) when the set of agents X is composed by two disjoint sets, the set of recruiters (or jobs) R and the set of candidates C and the matching relation M is restricted to contain pairs composed by one element from each of these two sets only (i.e. no candidate is matched with a candidate and no recruiter with a recruiter). The domain of preference relations P_x may therefore be restricted to

$C \; \forall x \notin R$ and to $R \; \forall x \notin C$ (i.e. candidates only rank recruiters and vice versa). The marriage partner matching problem is only a BBMP as long as women are restricted to marry men and vice versa!

Due to the multi-agent nature of the problem and the bounded availability of partners (candidates may eventually only be recruited for one position) we first have to decide about the stakeholder(s), i.e. whose problem we are going to solve.

- Option a): We model bilateral social recommendation as a social welfare maximization problem, arising all problems of social aggregation of individual utility function or preference relations.
- Option b): We decline the recommender system's responsibility for finding a pareto-optimal matching and always assume it to act for a single stakeholder whose utility has to be maximized, thereby totally ignoring the fact that other users might do the same, resulting in situations where recommended candidates are not available when finally selected.
- Option c): We take the decentralized perspective trying to design a decentralized mechanism aiming to approximate a pareto-optimal solution to the matching problem.

Option b) would be a very fast solution as it simply gives priority to the preferences of the recruiter. This option selects a number of top n candidates and then in a second step ranks those candidates by their own preferences. This however unfortunately implies the inter-subjective comparability of preferences in the sense that recruiter *x's* rank by candidate y has to be compared with the preferences of candidate y' for recruiter x. As part of our research we therefore will further evaluate the possibilities to integrate both recommendation approaches.

5. Conclusion

In this paper we argued that recommendation systems so far personalize only the search for objects, but not for subjects. Also, we discussed our goal to not only personalize the search for persons, but we aim to bring people together with jobs. This however is a bilateral selection decision. While the candidate selects a vacancy he or she wishes to fill and the recruiter selects a candidate possessing the skills needed to accomplish this same job, a match between person and job needs to model a bilateral recommendation process. We therefore implemented and validated two different recommendation systems personalizing the search for jobs and for candidates. Test runs with data from a student experiment showed promising results.

Also, we formally described different ways to integrate both recommendations into a single indicator representing the quality of the match between candidate and job profiles. In addition to this question, our future research will include additional test runs and validation activities. Also, we aim to extend the system to the field of interpersonal relations thus building a relational recommender that would be applicable not only to recruiting but also to team configuration scenarios.

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