Extending the Applicability of Recommender Systems: A Multilayer Framework for Matching Human Resources

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Abstract

Recommender Systems (RS) so far have been applied to many fields of e-commerce in order to assist users in finding the products that best meet their preferences. However, while the application of RS to the search for objects is well established, this is not the case for the search for subjects. This is astonishing as a growing number of people make personal and professional information digitally available to others by managing profiles in CV databases, social networking platforms and other online services. In order to address this new field of application for RS, we integrate own prior research into a unified multilayer framework supporting the matching of individuals for recruitment and team staffing processes. By this means we enhance RS research and make a next step towards the development of empirically and theoretically grounded decision support for the human resources function.

1. Introduction

Since Resnick and Varian in 1997 first defined the term "recommender system" as a system in which "people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients" [41] such methods have gained importance in both, research and e-commerce. While research in the past decade has been dealing with different ways to improve and measure the recommendation quality of content-based filtering, collaborative filtering and hybrid RS [33], many online applications such as book, CD and movie shops [46], restaurant guides [8] and others have integrated RS functionality in order to reduce customers' information overload, increase conversion and cross-selling rates and augment customer satisfaction and retention [45].

Likewise in the 1990s, the first internet job boards started to offer services such as the posting of online job ads and the searching of CV databases to companies seeking to fill their vacancies with qualified staff. Today, Monster.com as only one example counts a permanent number of hundreds of thousands of job ads posted on its different national websites and a total of over 40 million CVs stored in its resume databases [36]. Also, many employers nowadays start to establish such applicant databases on a corporate or internal level, too [26]. While such databases store individual information only, we currently observe a boom of so-called social networking platforms that allow users to link their profiles to each other and thus to complement individual profiles by relational information. Examples include platforms for the representation of private (e.g., MySpace, Friendster) and business (e.g., LinkedIn, OpenBC) networks and many of these platforms within only few months registered 7-digit numbers of users. But how would you identify suitable partners in such a vast amount of data?

Research shows that partner search processes are often based on browsing personal networks for recommendations and suitable candidates [16], [17], [28]. Therefore, as (i) partner search processes are highly driven by social recommendations and (ii) recommender systems "assist and augment this natural social process" [41], we argue that transferring RS to the search for persons is a challenging but promising goal. Thus, our research questions are:

- *How can we establish a theoretically and empirically grounded framework integrating the different requirements and dimensions needed when designing RS-based decision support for the matching of human resources?*

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In order to answer these questions, this paper is structured as follows: In Sections 2 and 3, we give a brief summary of the empirical and theoretical basis of our research. Section 4 then derives requirements for RS for collaboration scenarios and establishes a framework meeting these requirements. The framework builds on and integrates different modules of prior research that are sketched as part of Section 5 of this paper. The objective is to provide the reader with a comprehensive overview of the current state of our research in the field and to bring the overall concept down to a more concrete level of how RS can be applied to the matching of individuals. We conclude with an outlook on what our directions for future research are.

2. Research motivation

Our research in the field of HR decision support is motivated by own longitudinal quantitative and qualitative research with employers and job seekers in Germany. Since 2002, our Institute has questioned the Top 1,000 companies in Germany on their recruitment activities and on the adoption and diffusion of human resources information systems (HRIS) technology. One year later, we included small and medium-sized enterprises in our empirical research. The survey-based quantitative research within these four years was complemented by a total of over 20 case studies with 17 employers of different size and industry. Finally, also beginning in 2003 we started to question several thousand internet job seekers on their job search behavior (e.g., see [24] and [26] for detailed results).

The results from the surveys with the employer-side illustrate several fundamental changes in the ways (i) employers attract qualified staff and the ways (ii) they process incoming applications:

- The figures show that large employers in Germany increasingly attract qualified staff over the internet. In 2005, on average about three out of four vacancies within large employers are published on the corporate website. More than every second vacancy is posted on an external internet job board. The decline of print media over the years continues with only one out of four vacancies being published in this channel in 2005. Overall, both internet channels with 57 per cent of the new hires together account for more than every second vacancy filled in large enterprises [26].
- The increasing attraction of candidates over the internet has major implications for the ways by which applications enter the companies questioned. For example, large employers in Germany expect a complete shift in the ratio between paper-based and online applications within only eight years from 2002 on. In the employers' outlook, electronic applications in 2010 will represent 70 per cent of all incoming applications. Even more, employers anticipate a similar shift within electronic applications. They expect the ratio between e-mail and form-based applications to invert with the latter structured electronic applications accounting for 57 per cent of all incoming electronic applications in 2010 [26].
- Finally, with the amount of digital applications increasing, large employers tend to implement solutions for IS supported applicant management that store incoming applications in a company-wide database. Depending on the maturity of the diffusion process, all (and not only structured electronic) applications are stored in this database in order to give specialized departments access to it. Also, in some cases the external electronic labor market is complemented by a corporate or internal electronic labor market capturing applications by current employees [26].

From these considerations we conclude that from an IS adoption and diffusion perspective, the adoption of HRIS technology (i) increases over time and (ii) decreases with increasing progress of the overall recruitment process. Figure 1 summarizes these results from prior quantitative and qualitative research [25].

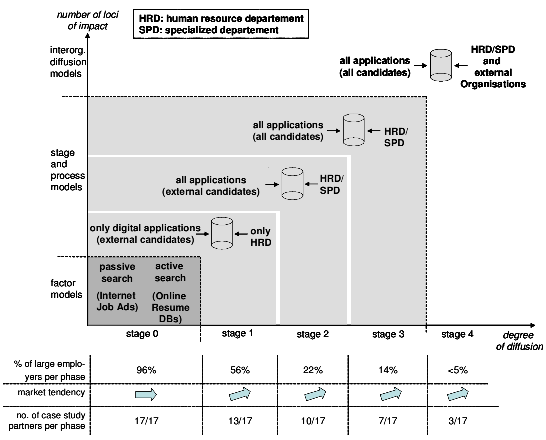

Figure 1. HRIS diffusion according to locus of impact (extending [25])

Further, the results document that (i) the attraction of qualified staff is increasingly carried out over the internet and that (ii) the amount of structured digital applicant data rises over time, too. This latter development in turn paves the way for the emergence of decision support for collaboration scenarios.

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3. Review of literature

The need to develop such decision support among others arises from the fact that information technology in the past decade has changed the ways people collaborate. Already in 1998, Malone and Laubacher presented their vision of an "e-lance economy" in which individuals supported by information technology collaborate in temporary and remote networks of experts in order to accomplish shared projects and achieve common objectives [32]. Also, many organizations today are pushed to implement flexible organizational and working structures such as team- or project-based working modes [3]. Both trends in turn will lead to a more frequent matching of individuals with projects and other individuals from within and outside their organizations. But what is the basis of the underlying collaboration partnerships and how can we build such decision support?

3.1. Perspectives on (virtual) collaboration

The various ways by which individuals identify new jobs and by which they collaborate has attracted the interest of many different researchers and disciplines. Granovetter, for example, already in 1974 showed that the recruitment of new staff is deeply rooted in social structures [17]. Also, it has been argued that the informal attraction of candidates over contact networks is highly effective compared to other personnel marketing channels such as job advertisements in print and online media [43]. One reason for this is that employee-referrals provide a low cost means of attracting candidates. Leicht and Marx suggest that employees show tendencies to attract candidates similar to their own type. As a consequence, not only attraction costs but also screening costs are lowered by means of employee referrals [35]. Even more importantly, from the candidates' perspective, information gained from an employer's current or former employees is highly reliable, thus leading to fewer frictions once the candidates are getting started on their new job [47], [37].

This fundamental character of informal relations, however, is not limited to the attraction of potential partners. Even more, research shows that once the team is set up informal relations serve to endorse the formal relations defined through organizational dependencies, roles and norms. Many theorists claim that trust is vital for maintaining such informal relations. Therefore, trust has been denoted as "sustaining a smooth-running of co-operative relations" [35].

While informal relations are important in face-to-face collaboration, this is even more true in virtual settings such as Malone's vision mentioned before. One argument in this context is that situations of virtual collaboration are characterized by ruptures of the temporal or geographic work location or of work group, organizational and cultural memberships [51] that prevent the formation of interpersonal trust. For example, it was stated that without a sufficient history of common interaction, sources of trust were limited thus inhibiting natural trust production. Therefore, in the following much research was carried out on how communication channels influence trust production in virtual collaboration and what mechanisms can enhance the formation of online trust. For examples of this research, see [5], [6], [15], [19], [27], [38] or [53].

While some authors researched the role of media richness in trust formation, others investigated they ways by which personal impressions transform with a partnership developing into cognitive estimations of the respective peers. The cognitive estimations, however, may not only emerge with regard to the peers, but also with regard to the situation the individuals find themselves in. Therefore, Dibben established a framework separating different *situational* trust types. His typology illustrates the dependency of trust formation on both, the knowledge of the other individual and of situational cues going beyond these former cues [10]. Looking at the specific environment of temporary systems, Meyerson further reduced the interpersonal character of trust by arguing that whenever time for trust production was scarce partners needed to act swiftly. This trust concept, referred to as *swift* trust, strengthens the cognitive and action-oriented aspects of trust while mutual adjustment is established [34]. As people do have only little time to get to know each other, they integrate existing personal or professional stereotypes into their trust considerations [9].

3.2. Review of literature on recommender systems

The above considerations show that face-to-face and virtual collaboration are highly dependent on social relations and the formation of different trust types. Also, identifying new jobs often relies on social structures and social recommendations. As RS were designed to automate such recommendation processes, we decided to build our decision support for HR partner matching on a RS-based approach.

Recommender systems are typically associated with the rise of the internet and with the amounts of information and products offered to users. As RS help users to overcome information overload and identify those products that best meet their preferences, RS can be considered as an information retrieval mechanism. Besides the reduction of information overload, other benefits expected from the application of RS are the higher conversion of users into customers, higher cross-selling rates and higher customer satisfaction [45]. The underlying mechanism of recommender engines is similar to the everyday life experience of exchanging recommendations with social peers when looking for a product to buy. In this way, RS explicitly or implicitly (e.g. from site visits and transaction data) capture users' preferences and based on the similarity of products or users automatically infer recommendations to the individual user [41], [44].

Recommender systems usually are separated into content-based filtering (CBF) and collaborative filtering (CF) approaches. While content-based methods recommend objects similar to those a user has preferred in the past, collaborative filtering approaches recommend unknown objects based on similarities between users and not objects [4], [7]. Hence, in the first case preference profiles of users have to be compared to object attributes and in the latter case the similarity of the users' preference profiles has to be determined. The model that we specify in the following section is built on a hybrid approach, i.e. both concepts, content-based filtering and collaborative filtering, are applied simultaneously. This helps to partially overcome the problem of rating data sparsity by leveraging synergies between the two approaches in a combined model. See for example [40], [44], [33] for a discussion of the advantages and drawbacks of CF and CBF. For a recent discussion of current RS and future directions in this field, please refer to [2].

4. A framework for decision support for collaboration scenarios

The above considerations show that the internet in recent years has transformed both: (i) the ways employers attract qualified staff or vice versa the ways people find work and (ii) the ways these people effectively collaborate together. Both processes are increasingly digitized and supported by information technology. However, we argue that both worlds have not yet been brought together. As qualified decision support for the intermediary step of partner selection still lacks, we think that there is a link missing. By creating such decision support for partner matching we aim to fill this gap. The interplay between these process stages, their current forms of IS support and the underlying research strands is depicted in Figure 2 below. The figure also illustrates that the different online platforms mentioned before currently do not offer such decision support, but rather rely on Boolean search techniques or on the additive combination of explicitly stated user preferences.

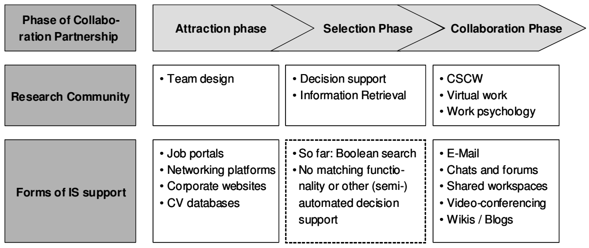

Figure 2. Stages, IS support and research strands in partner search for collaboration scenarios

In order to bridge IS supported attraction and collaboration, we are now going to derive requirements that need to be taken into account when adapting RS from the search for objects to the search for subjects. We then present a multilayer framework for partner matching and team staffing that meets the requirements previously identified.

4.1. Requirements for matching collaboration partners

So if partner search is highly driven by social recommendations and RS are designed to automate such processes why haven't we seen people recommender systems emerge earlier? - We argue that this is due to the specifics of partner matching that such systems have not been applied before. In this way, in order to successfully model partner matching one needs to consider the decision problem as a two dimensional problem in which [29]:

- Individuals need to be brought together with roles or jobs for which the actors possess the skills and abilities to perform these tasks.
- Individuals need to be matched to other individuals, i.e. their potential team members or collaboration partners with whom they need to actively collaborate.

Thus, any collaborative technology aiming at matching collaboration partners needs to consider (i) individual or unary attributes such as individual skills, mental abilities and personality attributes that determine the fit between the individual and the tasks to be accomplished as well as (ii) interpersonal or relational attributes that determine the fit between the individual and the upcoming team members. From this observation we derive the following major requirements when recommending candidates for collaborative partnership [29]:

- Recommending people is a bilateral process that needs to take into account the preferences not only of the active user or buyer (e.g. in our case the HR expert), but also of at least one other person (e.g. the candidate or other members of an already existing team).
- Recommendations cannot be based on the individual attributes tied to the persons in consideration only, but instead need to also consider the relational aspects that account for interpersonal fit.

An important additional requirement lies in the fact that in opposition to books or movies in online shops that typically are available several times, we need to consider every individual in our database as unique. Thus, we cannot select a single person several times which prevents the RS from learning user preferences. Instead, we need to combine the CF with content elements such as the attributes that constitute the individual's profile. Only in this case, successful learning of user preferences is possible when applying RS to the search for subjects. Also, a specific framework and distinct methods are necessary in order to successfully implement decision support for collaborative technologies.

4.2. A multilayer framework for matching collaboration partners

In order to meet the above requirements we developed a modular framework for decision support for collaborative technologies. As depicted in Figure 3, we separate three different layers. The first layer models and stores a set of different unary and binary attributes. The second layer provides various modules that act as filters to these data. For example, we implemented two distinct recommendation modules that assist recruiters or candidates in identifying relevant candidates or vacancies respectively. Thus, this approach refers to the bilateral dimension of our matching problem as identified before. For the binary attributes, we also implemented two different modules. While the descriptive trust module is supposed to provide users with the information and ways of representations needed to make qualified decisions on trusted relations, the predictive approach aims to go one step further and to actively recommend trusted relations with so far unknown individuals to the user. Within the descriptive module, we separate a historic or network-based trust module and a swift trust module. The former module captures existing trusted relations between users and on a general level can be compared to a sophisticated social networking platform. The swift trust module, in turn, in line with the considerations from our literature review is designed as an online interaction component that assists users in extracting situational or swift trust cues from their online interactions with other individuals so far unknown within the system. The basic idea is that this latter mechanism helps to overcome the typical illiquidity of one's own trusted personal network modeled within the first part of this module.

Finally, the aggregation layer as the third layer of our framework assumes the existence of a central instance for which the isolated recommendation results generated within the second layer are aggregated. For example, this is relevant in company-internal team staffing scenarios, e.g. in project-based organizations.

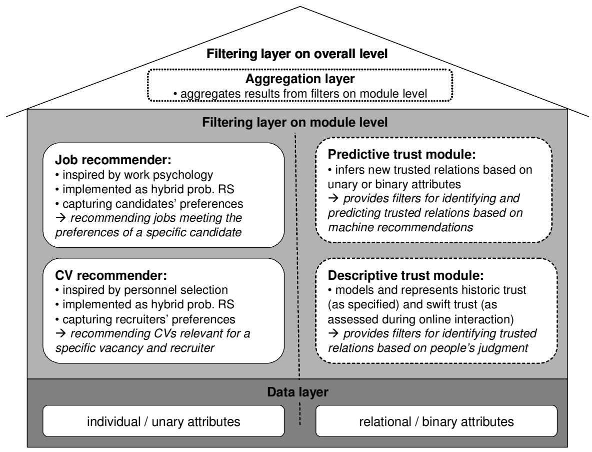

Figure 3. The multilayer framework for partner search (continuous lines represent implemented and validated modules, dashed lines stand for implemented and initially validated layers and the dotted line for the initial design phase of the aggregation mechanism)

5. A recommender-based approach to matching human resources

In order to further concretize the above framework, we implemented approaches for each of the different matching perspectives. The different modules together with selected validation results are going to be presented as part of Subsection 5.1 for the bilateral matching approaches and Subsection 5.2 for the relational matching approaches.

5.1. Bilateral decision support modules

5.1.1. The CV recommender. In a first step, we started in 2003 to build a system to support decisions from the recruiter's perspective. Therefore, we applied a RS originally used to recommend *objects* (such as movies or books) to a partner-matching scenario thus recommending *subjects* or concretely CVs. The probabilistic hybrid recommendation model is adapted from the probabilistic latent semantic analysis (PLSA) as described in [20] and [21]. The model interprets users' preferences as convex combination of underlying latent aspects.

Figure 4 shows a graphical representation of the latent aspect model applied to the context of partner matching. The model is composed of four variables with x representing the active user or in our case the recruiter together with the specific job description in consideration. Variable a in line with the prior considerations represents the attributes extracted from the candidate's CV. For example, each attribute a of the candidate y is composed of a quadruple such as a=("mathematical skills", "diploma grade", "1.0", "University of Frankfurt"). The latent aspect is represented in the model using the latent variable $z \in Z\{z_1,\ldots,z_k\}$.

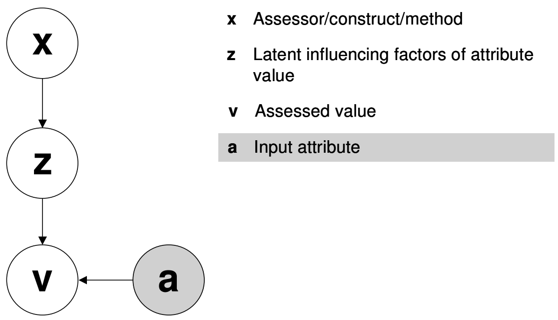

Figure 4. The Candidate Recommendation Model [14]

The model finally results in a rating matrix $R' = r'_{x,y,v}$ capturing the probability that recruiter x rates candidate y with value v. This latter value basically could be any value or just be defined as $v \in V = \{\text{"}qualified\text{"}, \text{"}not\ qualified\text{"}\}$. The model parameters are then estimated using the Expectation Maximization (EM) algorithm [11]. A detailed description of the approach can be found in prior research such as [14].

5.1.2. The job recommender. While the CV approach assists team staffing persons in finding candidates similar to other candidates they previously preferred for similar jobs, we complemented this module by an approach supporting job seekers' or team members' decision. In analogy to the above model, this module assists team members in finding jobs or roles within projects that might fit their preferences. A detailed description of the approach can be found in [30].

5.1.3. Bilateral modules: Validation results. To validate both approaches we conducted a multi-step student experiment with a group of 32 students. As part of the validation session students had to provide us with multiple unary and relational data and also with rating values in order to feed our RS. By this means, we assured to use real-life data such as existing student CVs and job ads from an internet job portal together with realistic rating values obtained from our students. In the following, we summarize parts of the results from tests with both approaches. For validation results including simple rankings, MAE, ROC and CROC, please see [31].

In order to validate the CV recommender, we matched the CV of 30 of our students with 10 job profiles taken from an internet job portal. After rating each of the CVs for the jobs, we separated our data set into the training and the testing data. We used three test runs and for each test run we separated the dataset into 250 ratings used to train the system and 50 ratings used to test its performance. To test the accuracy of the system, we applied a ROC curve analysis. Figure 5 below illustrates the true positive rate (Sensitivity) in function of the false positive rate (100-specificity) for different criterion values. Increasing the criterion value means that we include more results from the generated recommendations.

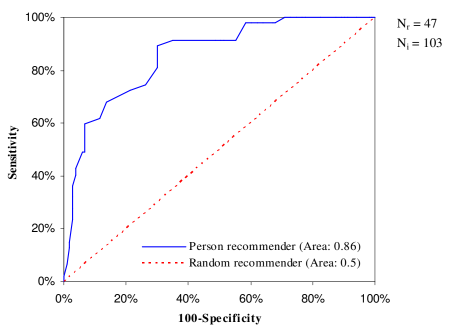

Figure 5: ROC curve for the CV or person recommender [31]

The area under the ROC curve for the testing set used is $A = 0.86$ (*SE: 0.04, 95% CI 0.79 to 0.91*). As a result, a randomly selected job-candidate rating pair from the group of relevant pairs has a predicted rating value that is larger than that from a randomly selected rating pair from the irrelevant group 86% of the time. The 95% confidence interval (CI) is the interval in which the true (population) area under the ROC curve lies. A comparison between the CV recommender and a random recommender reveals that the ROC generated by our approach is significantly different from a random prediction ($p=0.000$). Thus, our CV recommender is able to separate a relevant from an irrelevant job-candidate rating.

For the validation of the job recommender, we used 100 job profiles that almost entirely were rated by each of our students leading to a total of 2897 ratings. Again, we used three test runs and for each test run retained 50 ratings for testing issues. The area under the ROC curve for this recommender is $A = 0.88$ (*SE: 0.03, 95% CI 0.81 to 0.93*). Thus, the system is generally capable of correctly classifying relevant and irrelevant jobs in 88% of the time, with a 95% confidence interval of 0.81 to 0.93. Again, the ROC curve generated by our recommender is significantly different from the ROC curve for the random recommender on a $p=0.000$ level.

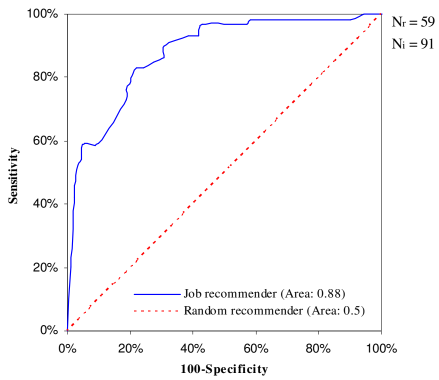

Figure 5: ROC curve for the job recommender [31]

5.2. Relational decision support module

The probabilistic approaches from the bilateral layer automatically recommend suited candidates to recruiters and vice versa jobs to candidates. However, both approaches lack a representation reflecting the importance of interpersonal attributes as previously identified as part of our literature review. None of the approaches considers relational information to evaluate interpersonal or person-team fit. Therefore, we extended these unary attribute based approaches by two modules incorporating interpersonal trust as a bilateral dimension.

5.2.1. The descriptive trust module. Within this module, we established a trust ontology capturing elements of network-based or historic as well as of situational and swift trust. The module aims at supporting users in making qualified decisions on whom to build up a trusted partnership with, but entirely leaves this decision to the user. Therefore, users in approach similar to current social networking platforms can specify people they know together with the levels of trust, the duration of the partnership and other information. The resulting network of users then can be searched and browsed by means of different tools and mechanisms. While this approach of browsing trusted networks and extending one's own social radius already was presented as a highly effective means of partner identification and selection and furthermore was characterized as transmitting "thick information" [16], it typically still limits the set of potential candidates to a small number [13]. In order to overcome this limitation, we integrated an online interaction based swift trust module into the system that provides the user with the functionality to assess candidates that are not yet members of his or her direct or indirect personal network. The peers participating in the session are members so far unknown to the person seeking the partnership. The online assessment is based on a real-time interaction with the candidate supported by a video-conferencing system. In parallel to the conference, the user is provided a list of questions that address multiple elements or attributes of trust. The user then for each of the candidates he is interacting with can score the candidate along these attributes. The trust ontology underlying the structured interview questionnaire was established based on a scenario-based design approach in order to assure the attributes measured meet the necessities of real-life partnering projects. This second online interaction mechanism represents a core element of the overall approach as it is highly adapted to the scenarios of virtual collaboration in which there is no common history and where users need to infer trust cues from the situation as well as from the candidates considered during the online interaction. Both approaches together, the network-based trust or the hindsight represented within these existing relations and the insight gained from the swift trust module are intended to guide the decision maker's foresight that is the estimation of the candidate's likely behavior within the specific project in consideration. A description of the overall approach can also be found in [23].

5.2.2. The predictive trust module. In order to further enhance trust formation in our framework, we implemented three different approaches that assist users in identifying trusted relations by actively recommending other users to them. The first approach within this module builds on existing social relations and analyzes how trust diffuses within network structures or how new relations can be recommended based on existing ones. Conforming to [42] we assume that trust can be expressed in a singular value even though it represents a quite complex and multidimensional phenomenon (see e.g. [1]). Furthermore, we assume trust to be a subjective impression thus differing from person to person. As a consequence, each member builds his personal web of trust ([18], [42]). We specify $t_{A,B}$ as the trust relation representing the trust user A holds for user B and constitute the values of $t_{A,B}$ to lie between 0 and 1 with 0 signaling distrust between user A and user B and a value of 1 indicating that B is fully trustworthy in the eyes of A. Based on these considerations, we still within the historic trust module of the bilateral layer consider three different ways of how trust propagates through the resulting network [18], [52]. As depicted in Figure 7 (a)-(c), we define three different scenarios of trust propagation. The first figure shows a propagation scenario where trust based on two given edges propagates along a third edge. While we consider this approach as a rather descriptive approach to trust propagation, we try to predict trust values based on given information in the scenarios 7(b) and (c). In these scenarios trust between users is inferred based on the similarity of relational or individual and relational attributes. Due to the calculation of these similarities between users, these approaches can be considered as related to recommender-based approaches. We refer to these latter approaches as collaborative trust prediction and similarity-based trust prediction. A detailed description of these trust approaches can be found in [29].

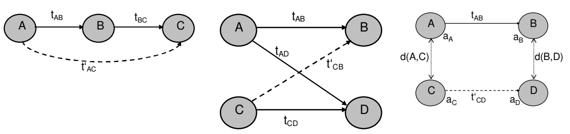

Figure 7(a). Direct Trust Propagation, (b) Collaborative Trust Prediction, (c) Similarity-based Trust Prediction

5.3. Outline of further research

While at the current state of implementation of our framework both bilateral modules already extend the applicability of RS and could easily fit into online applications such as state-of-the-art internet job portals, we see further potential in enhancing the relational modules and in better connecting them with the bilateral approaches. We expect that combined internet job boards and social networking platforms will emerge within the next years and that providing adequate search mechanisms for such mixed data structures will represent a crucial functionality for these platforms. Therefore, we will further investigate approaches to social matching such as investigated and proposed by [48]. Also, we will analyze methods of graph based mining (see e.g. [50] for an analysis of state-of-the-art methods in this field), and of relational mining such as presented by [49] or [22] for the integration in our relational layers. Domingos, for example, mined the social network structure of the EachMovie dataset and showed that the integration of the actor's network value construct can enhance viral marketing activities [12]. A similar mechanism could be applied in our scenario with the objective of enhancing team staffing decisions.

Furthermore, the four bilateral and relational modules of our framework so far provide four separate recommendation results. While this might be desirable in certain scenarios and even more a fully automated selection decision might not be desirable for ethical reasons, an aggregation of the different scores can be useful in decision situations in which teams are staffed and the preference functions of several current and potential team members need to be considered and aggregated. The complexity of such decisions can not be underestimated due to the fact that team members might have different preferences to collaborate with different candidates on different jobs. As one approach in this direction, Pennock et al., for example, undertook a formal analysis of the axiomatic foundations of RS and compared properties of Social Choice theory with collaborative filtering methods [39]. We argue that such an IS supported preference aggregation mechanism for the different layers might be desirable at least for those team staffing decisions in which a central actor is responsible for the allocation or matching of people to tasks and to collaboration partners. We think that when reaching such a stage, information systems could assist project managers in anticipating compatibility of personality types or complementarity of competencies thus leading to enhanced team design and performance.

6. Conclusion

In this paper, we argued that due to an increased availability of structured candidate data and due to a more frequent matching of collaboration partners in project-based work structures a necessity for qualified HR decision support will emerge. A literature review revealed that searching for partners is often driven by trusted, but illiquid contact networks and social recommendations. As recommender systems are designed to automate such processes of sharing recommendations based on similarities of users or objects, we argued that RS are highly adapted to support partner selection decisions. However, transferring RS from the search for objects to the search for subjects is a challenging task. In order to capture the bilateral and at the same time relational nature of such processes we elaborated an empirically motivated and theoretically grounded multilayer framework integrating different modules of prior research. As each of the modules to date was conceived as a stand-alone module and was able to serve independently e.g., as a recommender engine in an internet job portal, we were not able to represent team staffing processes in which a central actor makes the selection decision. Therefore, we integrated an aggregation layer into our framework that is supposed to aggregate the multiple preferences or recommendation results from the different layers. Further research is needed to conceive and validate this layer and thus to bridge the gap left in current online environments between the partner attraction stage and the effective collaboration phase.

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