Enhancing Partner Matching with Recommendation Systems

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Abstract

Collaboration is vital for the survival of companies in today's fast moving economy and, therefore, finding and matching partners is an important task. This is true for many different scenarios ranging from companies building consortiums over organizations frequently staffing project teams to the recruitment of new employees. An empirical survey among the Top 1000 companies in Germany on state-of-the-art recruitment practices shows that the Internet is already heavily used to attract and identify large sets of potential partners or applicants. However, the selection of the most suitable candidates from this pool by predicting the quality of the resulting partnership is only merely supported by information technology. Building on existing research in the fields of team building and information systems, we first outline the enhanced information requirements for online partner matching compared to partner information currently available on the Internet. Based on this, we then delineate how recommendation systems can assist in improving matching quality by incorporating relational information when bringing partners together online.

Keywords

Partner matching, Recruiting, Recommendation systems

Introduction

Technological progress drives the importance of intangible assets, such as intellectual capital, for many organizations (Breese 2001). At the same time, the rapidly changing market environments oblige companies to keep their organizations flexible. This results in companies perpetually building new partnerships by setting up development co-operations, hiring new employees or changing their organizational structures.

However, these partners are often difficult to find due to limited knowledge of the existence as well as suitability of potential partners. Some portals on the Internet provide possible solutions by permitting companies and individuals to increase their visibility to others as well as to search for potential partners at low cost. However, keyword based Boolean search offers only limited support for the actual selection of potential partners.

Selecting and matching has long been subject to research conducted in information system sciences. With the rise of the Internet so-called recommender systems have proven their usefulness in matching different types of items, such as movies or research articles, with user preferences (Basu 1998, Sarwar 2000). The objective of this paper is to outline an approach to apply these methods to the field of partner matching and to delineate how obstacles can be overcome by considering different types of relations in a partner's network in order to increase matching quality when bringing partners together online.

Empirical Evidence

In order to identify instruments and functionalities associated with online partner matching, we conducted an empirical study in Germany on the e-recruitment practices of the 1.000 largest companies according to their revenues. 196 companies responded to the questionnaire-based survey, that was complemented by several case studies.

The survey results show that online recruitment already plays a major role in corporate recruitment practices. However, this is primarily true for the *attraction phase* of the recruitment process and not for the *selection phase*. 80% of the respondents state that they frequently use their corporate homepage to attract applicants, 48% frequently make use of Internet job portals, and 54% employ traditional print channels. The main reason companies indicate for the use of online channels for personnel marketing measures is cost savings.

89% of the companies do not limit themselves to job postings in online channels, but also offer the possibility to apply online for these vacancies. 42% of these companies offer an e-mail address as the sole electronic application channel. 5% of the participants offer only a web-form while 53% leave the choice to the applicant. Apparently candidates prefer e-mail applications to web-forms as 61% of all electronic applications are in fact received via e-mail. These as opposed to web-form applications are not provided in a structured format and as a consequence cannot be processed efficiently during the pre-selection phase.

The high percentage of e-mail applications is one reason why the actual selection of candidates is hardly supported by IS-based methods. Only 23% of the respondents state that IT-support in the selection phase significantly contributes to cost savings, shorter time-to-hire or increased matching quality. Nevertheless, particularly companies with large cost savings see a heavy contribution from filtering, administration and workflow support.[1] However, even among these companies sorting and filtering mechanisms are still based on standardized response types or keyword matches.

Relevant Research

Approaches from Team Building and Work Psychology

Partner matching in business contexts, such as team building or recruitment processes, can be considered as situations in which partners are brought together in order to fulfil a certain task

[1] This was confirmed by a Spearman-Rho correlation that was significant on the 0.01-level.

requiring a certain skill set. According to West (1994), teams differ from work groups in the way that subtasks usually are not additive, but interdependent. As a consequence, not only *task-related* aspects have to be considered when building successful teams, but also *social* factors. Similarly Guzzo (1996) and Bungard (1990) stated that tasks in teams do not require *co*-action between team members, but their *inter*-action and, thus, will make the sum be more than its parts.

While heterogeneity might be desired on the individual task level as far as the associated competences are *complementary* (Jackson 1996), this is rather not the case on the interpersonal level. For social aspects, team members' personalities should be *compatible*. According to Gabarro (1990) the respective importance of task-related or social aspects differs with the type of social interaction the partners are engaged in.

Some human attributes interfering on the task or social level are *readily detectable*. But the quality of a match often builds on *underlying attributes,* such as a person's attitudes, that are difficult to appraise (Jackson 1996). Nevertheless some of these underlying attributes can be derived by using trusted credentials such as university degrees or using assessments as proposed in personality theory. Examples are the Myers-Briggs Type Indicator (MBTI), based on Jungian personality theory, assuming four bipolar dimensions of personality (Bents 1997) and the assessment of a person's interests and values (Butler & Waldroop 2001).

Apart from these different categorisations and determination methods of attributes, the question arises how these attributes influence the quality or viability of a partnership in a certain context. Looking at a partner's qualification to fulfil tasks associated with a certain role in a team, we speak of competences denoting the relation between human skills and work tasks. Similarly, the different MBTI types have been subject to research with regard to their mutual compatibility and to their application in team building processes (Kummerow & McAllister 1988, Rideout & Richardson 1989).

Another approach aiming at establishing compatibility between team members is Belbin's team roles (West 1994) that were integrated by Lang & Pigneur (1999) into a taxonomy developed for company-internal staffing processes.

Relevant Research on Recommender Systems

Recommendation systems can generally be separated into content-based and collaborative filtering systems. Content-based recommendation systems give recommendations to a certain user based on the properties of items he likes. By detecting similarities between content of items that the user rated positively, these systems suggest other items that are unknown to this user, but share the same content. Collaborative filtering tools on the contrary give recommendations to users not on basis of their own preference profile, but based on similarities between the profiles of the active user and other users in the system (Pennock & Horvitz 1999).

Both content-based as well as collaborative filtering systems have different advantages and disadvantages. While content-based systems only require a user's own preferences, they are difficult to apply to domains in which items cannot be decomposed into content elements (Melville, Mooney & Nagarajan 2002). In contrast, collaborative filtering tools basically can deal with any type of content (Herlocker, Konstan & Riedl 2000), but suffer from the sparse data problem. In case there are lots of items rated by a small number of users or lots of users rating only a small number of items, recommendation quality will be poor as the suggestions generated will be based on a small number of base profiles possessing only low similarities with the target profile (Bradley 2000, Terveen & Hill 2001).

In order to overcome the shortcomings of both approaches, hybrid recommendation systems have been developed reducing the problem of sparseness in the user-ratings matrix. Melville creates pseudo user-rating vectors that then complement a user's actual ratings with content-based predictions for the items not rated (Melville et al. 2002).

Modelling a Partner Recommending System

Building on the presented research, we are developing a methodology to recommend partners in order to support the pre-selection and selection phase of partner matching processes. While the pre-selection phase aims at identifying those partners that are competent to fill a certain role, the final selection phase aims at verifying the predicted task-related aspects of potential partners as well as social factors.

Matching partners is very similar to areas in which recommender systems already have been successfully applied. However, instead of having a set of users $U = \{u_1, ..., u_n\}$ rating a set of items $I = \{i_1, ..., i_m\}$, there is only one single set of partners $P = \{p_1, ..., p_v\}$ rating each other. Thus, a partner can be both, a user providing ratings and an object that is rated. While this is not necessarily a problem, obstacles can be found elsewhere:

- Since attributes of human beings are usually too multi-faceted, pure content-based filtering would not work very well to produce recommendations.
- On the other hand, we have seen above that the importance of a certain attribute depends on the task to be carried out and on the types of partners engaged in the interaction. In order to make ratings comparable, these elements have to be considered. Thus, a method solely based on collaborative filtering would also fail due to a too sparsely filled matrix of comparable ratings.

In order to overcome these structural obstacles, we incorporate relational information in addition to non-relational partner attributes. Relational information refers to personal or professional networks as well as other trusted relationships that usually can be attributed to each partner. By exploiting this information we are able to generate new ratings that are trusted by the active user.

As an analogy one might consider the example of executive search where head-hunters and recruiters heavily take advantage of personal and professional networks to put their recommendations on a solid base of opinions. In another example, recruiters might evaluate the reputation of educational degrees and former employers or jobs.

We also pursue hybrid recommending approaches. In particular probabilistic aspect models such as those proposed by Hofmann and Puzicha (1999) and Popescul, Ungar, Pennock and Lawrence (2001) provide characteristics that address the complexity of reasons for selecting partners by modelling convex combinations of different aspects.

Conclusions and Further Research

In this paper we outlined a partner recommender system combining hybrid recommender systems with the relational information typically existing among human beings, groups of human beings or different types of institutions. The objective is to develop a novel methodology assisting decision makers in the selection of partners for multiple partner matching scenarios such as HR-responsibles seeking suitable candidates for job vacancies. We believe that this approach will bear significant improvements to existing Web-based applications as the pre-selection of potential partners will use more relevant information from the existing data than traditional methods such as Boolean search. Thus, the pre-selection process will be more streamlined and HR-responsibles will be able to spend more time on strategic issues or on personnel development. By doing so, we hope to improve the effectiveness and longevity of the partnerships and teams resulting from these matching processes. Our next steps include the development of an algorithm for the example given as well as its validation with real candidate data.

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