Defining Dimensions in Expertise Recommender Systems for Enhancing Open Collaborative Innovation

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Abstract. In open innovation a firm's R&D crosses not only internal boundaries but disciplines. It is an interactive process of knowledge generation and transfer between internal and external firms. However, the search for an external partner can be time consuming and costly. Open innovation marketplaces broker relationships between seekers and solvers of challenges. Seekers have a problem which they need to solve and solvers are a community of people with the right skills to discover innovative ideas to address them. Despite the assistance of open innovation marketplaces, the process of matching seekers and solvers remains a challenge. It will be argued in this article that expertise recommender systems in an open innovation marketplace can facilitate finding the "right partner" leading to benefits not only for the seeker and the solver but also for the marketplace. With this aim, a list of appropriated dimensions to be considered for the expertise recommender system are defined. An illustrative example is also provided.

Keywords. open innovation, recommender system, expertise

Introduction

In the past, a corporation's internal research and development organization was a strategic asset which acted as a barrier to entry to competitors. Closed innovation environments where firms managed the development of a product from conception to distribution required heavy investment in Research and Development (R&D) resources. Towards the end of the 20th century, the closed innovation model began to erode due to the increased mobility of workers who transported their ideas and expertise with them. An open innovation model emerged where innovation could easily move between a firm and its surroundings. Organizations recognized they could profit from research developed externally and from licensing the use of their intellectual property [1].

In an open innovation model firms can commercialize ideas which they purchased externally and commercialize internally generated ideas through external channels. Open innovation marketplaces enable companies to transfer their R&D outside of the organi-

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zation enabling them to remain competitive, agile, and cost effective. For firms to benefit from transferring this effort to external parties, the cost of the transaction needs to be less than the cost of internal development. In other words, economic activity will move outside the firm whenever the costs of using the market are lower than those of using the firm [2].

Open innovation marketplaces, such as InnoCentive[2], consist of a network of scientist, professionals, retirees, and students who solve a wide variety of challenges presented by seeker companies [3]. However, due to the unsystematic nature of partner identification, realizing transactions presents a managerial challenge [4]. In this context, recommender systems may be able to facilitate the technology brokering.

Recommender systems are able to filter the range of available choices [5] to content of interest to individuals of a community [6] or to users with similar profiles. In turn, expertise recommender systems are a specific type of recommender system, which help find people who have some expertise with a problem. They allow organisations to expand and foster the interaction among users with different backgrounds, opinions and levels of expertise, ultimately leading to higher creativity and inspiration.

The aim of this paper is to show how expertise recommender systems can help seeker firms find the right solver. Accordingly, firms will be able to better engage in a collaborative open innovation environment given the right fit with their innovation partner (the solver).

The rest of the paper is organised as follows. First, the role, benefits and existing challenges of open innovation intermediaries is highlighted. In the next section, the properties of existing expertise recommender systems are explained. Then expertise recommender systems are proposed to be integrated into open innovation marketplaces in order to address current challenges that these intermediaries are facing. Finally, a number of specific selected dimensions are listed for an expertise recommender system in an open innovation markplace. Future research in this line is also explained.

1. Open Innovation Platforms

Open innovation, a widely researched area in the last decade, is defined as the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively [1]. Intermediaries in open innovation play a key role in facilitating the transfer of this knowledge by connecting firms to unknown resources.

1.1. Literature Review

Open innovation marketplaces are a type of intermediary. They serve the interests of two communities: seekers and solvers. Seeker firms may post challenges to introduce problems which need innovative solutions. Solvers are individuals, institutions or firms which create innovative solutions in response to these problems or post innovative ideas that need to be marketed. Intermediaries are platforms which facilitate the search of highly scattered solvers for companies in search of solutions. In this paper, innovation intermediaries are referred as “platform providers in two-sided innovation markets created

[2] www.innocentive.com

to co-ordinate the flow of innovation requests and solutions across distinct, distant and previously unknown innovation actors" [7].

Innovation intermediaries create value for both the seekers and solvers. By stimulating growth in the number of challenges, they attract a larger community of solvers. In growing the solver community, they offer a greater diversity of solvers drawing more seekers. This exchange increases the value of the intermediary. Intermediaries capture value from seekers by applying fees for posting challenges, commissions on successful solutions, and consulting services. In addition, some platforms charge solvers for membership and commission on their awards [7]. Therefore, establishing a match between seekers and solvers is extremely relevant and needs further development. We consider a match to occur when two parties agree to work together regardless of whether or not they arrive at a solution.

The process of finding a partner through these marketplaces follows five steps. First, a seeker firm posts a challenge which includes details of the problem, deadline for the proposal, and monetary rewards. The research problem is then broadcasted to a diverse intellectual background of solvers. Second, solvers review the challenges and self-select to develop a solution. Third, solvers select the challenge they want to attempt and agree to transfer intellectual property to the seeker firm. Forth, solvers obtain a project room in which they can communicate with the seeker firms. Fifth, the seeker firm selects and rewards the winner in exchange for intellectual property rights to the solution [8,9].

One of the most well known open innovation marketplaces is InnoCentive which was created by Eli Lilly in 2001 to connect companies and communities of experts together. It follows a challenge-based model which defines the problem in a manner which is universally understood to invite diverse participation [10].

As of 2008, InnoCentive's aim was to increase the productivity of problem-solving through faster and richer solutions. One proposal to allow collaboration would enable solvers to find each other, request help, and share knowledge [11]. Today, InnoCentive has 300,000 registered solvers and 1,650 challenges posted across 9 disciplines[3]. A current solve rate was not posted to the website. These studies suggest a growing need to connect seekers to solvers and solvers to other solvers with applicable skills across diverse fields.

1.2. Existing Challenges

As stressed in [12], with the use of these Internet platforms the cost of linking seekers with potential solvers has decreased dramatically. However, there are still very important challenges for improving these best practices.

Firstly, as already mentioned open innovation intermediaries create value by matching seekers and solvers. However, today intermediaries face difficulties finding solvers that fulfill the requirements of the seeker in a timely manner. Studies have shown that people in the boundaries of disciplines create innovative solutions [8,13]. Identifying these solvers for each solution will increase the pool of potential solvers and the diversity and quality of the solutions. Thus, efficient matching benefits both partners, and ultimately will enable intermediaries to scale-up their business model.

Secondly, intermediaries' main goal is to make the process of bringing in ideas efficient and to reduce the cost of the knowledge transaction. However, this efficiency ap-

[3]Retrieved from InnoCentive, Inc. website, http://www.innocentive.com/about-innocentive/facts-stats.

proach makes the nature of the ties that are formed between the solver and the seeker very weak [12]. According to weak-tie theory [14,15], weak ties, such as the ties formed by using open innovation intermediaries' channel, are regarded as good at bringing in ideas but they are also seen as problematic for transferring knowledge. Especially relevant is the effect of these weak ties on the transfer of tacit knowledge, which is revealed through its application [16] and is sticky by its nature [17]. Tie strength can be enhanced by reducing the distance and the frequency of the transaction between both parties [15].

2. Expertise Recommender Systems

In this era of information, people struggle to filter vast quantity of data. Recommender systems have sought to fulfill this need. Since their appearance in the mid-1990s, there have been many advances in the development of new approaches to recommender systems. However, information is not always stored in systems or databases. Rather, information can be processed and embodied in people. Expertise recommender systems address this issue by identifying people with specific information and knowledge.

2.1. Literature Review

Up to date, several expertise recommender (ER) systems have been developed. In the following, a list of existing expertise recommender systems that come as standard is provided, as well as a description of their main characteristics:

Who Knows [18] finds people with appropriate expertise by doing latent semantic indexing of their work products. In a nutshell, when a user enters search text, Who Knows returns a list of people whose profiles match this text.

Yenta [19] analyses people's email archives, communications, news postings, and other types of documents to create a user profile. When the user enters a query, Yenta searches for individuals with profiles that match the query. One of Yenta's weaknesses is that it matches people with similar interests without taking into account their expertise.

Expertise Recommender (ER) [20] uses locally meaningful data to recommend sets of potential answerers for queries. ER recommends expertise based on both the best expertise in a particular area and on the best context fit with the seeker. One important characteristic of this system is that it rates experts based on their work products, which are mined by ER, rather than on their areas of interest or on peer ratings.

MITRE's Expert Finder [21] was created within the MITRE Corporation to identify experts within topic domains. The system ranks the expert by the number of times his/her name is associated with specific terms found in corporate documents, newsletters, communications and so forth. The user enters a key word search and the system returns the top ranked experts [22].

Expert Finder [23] creates user profiles based upon their work. When a user queries for a skill set, the system searches other users' profiles for those skills. The system returns experts whose skills are slightly more advanced than the user's.

Expertise Recommender using Web Mining [24] obtains a person's expertise by dynamically extracting data from semi-structured web documents. It consists of the following five main components: web crawler, expertise extractor, referral chain builder, knowledge base, and web interface.

APOSDLE's People Recommender Service [25] is a service integrated into APOSDLE's platform[4] that delivers a list of people based on the user's current context. It retrieves candidates that are relevant for a particular topic. To perform this recommendation, the system automatically detects the user's current work task and relevant domain concept taking into account both the candidate and the user's profile.

2.2. Existing challenges

ER systems should recommend people based on an appropriate mixing and an optimal matching of the characteristics of the candidates and the preferences of the user. Currently, recommender systems focus on finding the person with the "right level of expertise" rather than "the right person". According to [9], intermediaries aim to find the "uniquely prepared mind" to solve the problem. However, as explained above, the main challenge of intermediary networks is that seeker firms need to identify the "right" partner to build strong ties in order to make knowledge transfer efficient.

3. Improving Open Innovation Platforms with ER Systems

Expert recommender systems can address two of the main challenges that open innovation platforms are currently facing. First, the need to match seekers and solvers efficiently and effectively. Second, the need to strengthen the tie between the seekers and the solvers.

Match. Expertise recommender systems filter the number of capable solvers to the most suitable. Filtering allows seekers to arrive at a solution faster. Moreover, by limiting the number of solutions proposed, the number of resources required for firms to review, select and test solutions is reduced.

Tie strength. According to [16], firms need to integrate specialized knowledge. However, this knowledge integration and transfer is not efficient across markets due to the sticky nature of knowledge. In this regard, it is suggested in [17] that the more closely related are two people, the more likely it is that tacit knowledge is transferred. For this reason, finding the "right person" is of paramount importance to forging the gap of weak ties. Advanced recommender systems can play an important role by incorporating specific dimensions to find the best match for both parties. This facilitation requires assessing not only the level of knowledge (expertise) but the collaborative behavior of and distance between both parties. Taking these dimensions into account recommender systems enable open innovation platform users to initiate relationships which can lead to strong ties.

[4] APOSDLE (Advanced Process-Oriented Self-Directed Learning Environment) is partially funded under the 6th framework programme (FP6) for R&D of the European Commission within the Information Society Technologies (IST) work program 2004 under contract no. IST-027023. See http://www.aposdle.org.

3.1. Proposed Dimensions Needed in this Environment

In this paper, the following dimensions for expertise recommender systems in an open innovation marketplace are proposed: expertise, qualifications, proximity and availability.

The *expertise dimension* represents the areas of knowledge of each candidate to solve a problem. They reflect in which topics the candidate has a certain degree of expertise. This information can be analyzed in both explicit and implicit way. On the one hand, collecting explicit expertise is related to the manual selection of topics that the candidate knows best. It can also be obtained by analyzing ratings specified by other people about the expertise of the candidate in such topics. On the other hand, obtaining implicit expertise implies the automatic processing of documents from different sources, such as forums, papers or presentations, in order to find keywords which will reflect the candidate's level of expertise in a specific topic.

The *qualification variables* capture the behavior of the solver. The solver can directly state explicit information by choosing the qualification topics that best define herself. But in this case implicit information would be more important due to its objective nature. This implicit information must be collected by analyzing the interaction between the solver and the intermediary platform. It will mainly consist on analyzing available information like quantity of selected solutions, speed in the responses or quantity of proposed solutions to problems.

The *proximity information* is used to measure the distance between the solver and the seeker. This information will be extracted by analyzing the connections between the solver's and the seeker's social network.

Finally, it is proposed to incorporate the *dimension of availability*, which informs about the current availability of each solver. Each solver in the platform should state her own availability at any time. This dimension will complement and allow for the perfect match between solvers and seekers.

3.2. Illustrative Example of an Expertise Recommender

This subsection details an illustrative example of an expertise recommender prototype that is being developed. Leo (seeker), Technical Director of the ACME enterprise, is starting the design and development of a new product and would like fresh ideas from outside of his R&D team. He decides to look for external solutions. However, he is concerned with the lead time required to find a innovation partner (solver). Once a partner has been identified and the solutions presented, Leo is worried about incorporating the external solution into his firm. As explained before, because of its sticky nature, knowledge is difficult to transfer. As a consequence, Leo learns about an open innovation intermediary which has an innovative tool which helps seekers find the right solver.

On the website of the intermediary, Leo goes to the screen where he can enter his requirements for the desired solver (Figure 1). In the skills and expertise section he selects the required skills for the desired solver and picks "development" as his first requirement and specifies a high level of expertise. Next, Leo values a person who is able to communicate his design in great detail, so he adds the "presentation" skill to his list and chooses a medium level of expertise. In order ensure that the new design is up to date with the current state of the art, he adds the requirement of expertise in "research" skill and picks a low level of expertise. Finally, Leo includes the "brainstorming" requirement because he desires a high level of creative and innovative design.

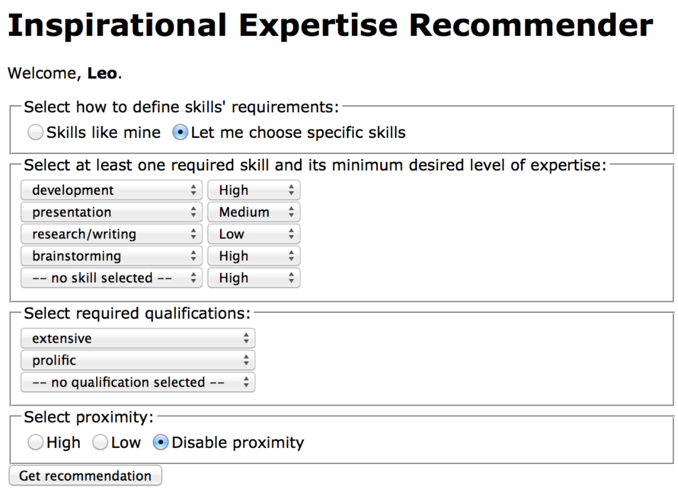

Figure 1. Selection of requirements

Because Leo is concerned with the transfer of knowledge he looks for qualifications of communication skills. In this direction, he picks "extensive" and "prolific" from the qualification section with the intent of obtaining complete and accurate documentation of the innovation. Lastly, Leo is not interested in the proximity of the solvers, so he disables this dimension.

The ER automatically adds "high availability" to the list of requirements and gets back to Leo the recommended solvers detailed in Figure 2.

The recommendations' table includes the solver candidates by rows and the requirements taken into account by columns. The best candidate is Kevyn (0.845), a prolific developer with medium expertise in research and presentation, mainly due to his almost perfect match with the required skills (three out of four). Anselma is not too far (0.815) because she just meets two out of four of the required skills with the maximum level.

Leo analyzes the recommended solvers and decides to contact Kevyn for the developer position, although he does not discard the profile of Anselma because he thinks she can complement the skills of Kevyn.

4. Conclusions and Future Work

Expert recommender systems can address two of the main challenges that open innovation platforms are currently facing, matching and building strong ties between firms and experts. If resolved, they will contribute directly to intermediaries' value creation. It has been proposed that ER systems can help to fill this need by applying specific dimensions. Furthermore, ER systems will transfer the ownership of search from the solver to the seeker providing greater control over when partners will be matched. By accelerating the

Candidate	Skills				Qualifications		Availability	Assessment
	"Development" (high)	"Presentation" (medium)	"Research/writing" (low)	"Brainstorming" (high)	"Extensive"	"Prolific"	High	
1. Kevyn Parker (UK) • *Skills*: **presentation** (medium), **research/writing** (medium), **development** (high). • *Qualifications*: quick response, **prolific**. • *Availability*: fully available	1	1	1	0	0	1	1	**0.845**
2. Anselma Ariella (Spain) • *Skills*: marketing (low), **brainstorming** (medium), **presentation** (high), **research/writing** (high). • *Qualifications*: **extensive**. • *Availability*: fully available	0	1	1	0.667	1	0	1	**0.815**
3. Dinah Linnet (UK) • *Skills*: marketing (low), **research/writing** (high). • *Qualifications*: **prolific**, **extensive**. • *Availability*: fully available	0	0	1	0	1	1	1	**0.756**
4. Alton Jeffery (Ireland) • *Skills*: marketing (medium), **brainstorming** (medium), **research/writing** (medium). • *Qualifications*: quick response, **extensive**. • *Availability*: fully available	0	0	1	0.667	1	0	1	**0.722**
5. Roger Julio (Spain) • *Skills*: conceptual design (high), **development** (high). • *Qualifications*: **prolific**. • *Availability*: fully available	1	0	0	0	0	1	1	**0.655**

Figure 2. Recommended solvers

process of finding the right solver for a challenge, ER systems reduce the costs of partner identification and innovation lead time for the seeker, and increase the community of participants for the intermediary while growing their revenue stream.

The proposed dimensions for an ER are derived from literature on open innovation intermediaries and expertise recommender systems. However, it should be recognized that there may be additional dimensions specific to open innovation marketplaces which can further enhance matching and strong ties. Future research may include studies across different intermediaries to support the dimensions we proposed and elicit new ones. Finally, our proposal was developed to place an ER system in an open innovation marketplace, independent of the quality of the content it would reference for its recommendation. In other words, the recommendation is limited by the content that the seekers and solvers provide.

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