A CONTACT RECOMMENDER SYSTEM FOR A MEDIATED SOCIAL MEDIA

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Abstract: Within corporate intranet or on the WWW, a global search engine is the main service used to discover and sort information. Nevertheless, even the most "intelligent" ones have great difficulties to select those targeted to each user specific needs and preferences. We have built a mediated social media named SoMeONe, which helps people to control their information exchanges through trusted relationships. A key component of this system is a contact recommender, which helps people to open their relationship networks by exchanging targeted information with qualified new users. Instead of using only matching between interests of users, this "socially aware" recommender system also takes into account existing relationships in the social network of the system. In this paper, we describe the computations of those recommendations based on a social network analysis.

1. A NEW MEDIA FOR PERSONALIZED ACCESS TO INFORMATION

A large part of companies' knowledge is embedded in each employee's documents. Web technologies are now being used to make those numerous documents easily accessible through a decentralized intranet or extranet. The WWW also provides access to many interesting resources to any employees but they are lost through the huge quantity of available pages. Those information networks are becoming essential for being correctly informed. However, in such a web environment, information is distributed throughout the company or through the WWW. This makes it difficult to find information which is useful and relevant to each user's needs.

One of the great challenges of search engine tools, mainly based on an artificial (computer-based) centralized intelligence, is to be able to select relevant answers according to user's preferences, background, or current activity. In order to face this personalization challenge, we are developing a complementary approach based on users' distributed intelligence where the relevancy of a resource for a user is based on the existing references to this resource from other users and the trustworthiness of relationships between those users. This is based on our assumption that some users might prefer to trust other users than machine to obtain good advice about information resources. We are thus introducing a user-centric approach as opposed to a computer-centric one to develop a new intelligent interface for accessing the WWW.

This approach is supported by our collaborative system named SoMeONe (Social Media using Opinions through a trust Network) (Agosto, 2003). This system is particularly adapted to users preferring to access information which already has a certain approval, for instance, information coming from appreciated or skilled people in corresponding domains.

Key issues in this system are motivating users to exchange information and helping them to manage and optimise their relationship network. To deal with those problems we have integrated in SoMeOne a contact recommender system, which suggests that some users exchange information with new users. We make the assumption that users will be motivated to produce and exchange good information in order to be recommended by the recommender. Those recommendations are not only based on the common interests of users but also on social qualities of each user. This "socially aware recommender system" is the focus of this paper.

2. SOCIAL MEDIA

The idea of using communication networks as a support tool to find "focused" people is not new. Newsgroups and mailing lists are the most famous examples of such collaborative systems. By using them, people are acquiring a new, social, cyber-behaviour that asks them to adopt new habits in working and even in thinking schemas. They form online communities in the sense of J. Preece (Preece, 2000). We call "social media" systems capable of relating persons to establish relationships. We call "mediated social network" the social network of a social media.

Using information technology can help to improve the flow of pertinent information between people and the global efficiency of the system by analysing the structure of a mediated social network. Such a mediated social network can be used to receive very personalized recommendations of information resources carefully selected by trusted users. By doing this, we develop a new vision where information navigates from users to users instead of having users navigating through information. We named this vision the "web of people" (Plu, 2003). The ultimate goal is to help people to get in contact with appropriate persons according to the diversity of their needs to find and filter suitable information.

Let's now look more deeply into one of the key issues presented before: the user motivation to share information. We assume this requirement to be true. Indeed, we believe that in our information society, and more particularly in a competitive and dynamic business environment, this collaborative behaviour is crucial for an awareness of new information and in order to receive support or credits from others. Bourdieu and others have also largely demonstrated the value of social capital not only as being the knowledge of individual workers but also the relations between them (Bourdieu, 1986). Consequently, it is sensible for companies that want to develop their social capital to develop and support cooperative behaviour in the everyday practice of their employees.

But even if this collaborative behaviour is supposed to be natural for our users, it has to be applied to our system. To deal with this requirement, one can imagine having a regulation component, which organizes the behaviour of users and applies a user management policy (Durand, 2003). An alternative approach is to integrate some components in the system to influence such users' behaviour in order to have them following the required behaviour rules. To illustrate how a technology can influence user's behaviour, one can look to how indexing technologies used by major Internet search engines have transformed the way web authors are designing their web pages.

The contact recommender system we are presenting is such a component. Within the SoMeONe system, a user has to be recommended to be able to receive information from new users. Thus, the recommender can recommend users with the required social behavior. However, having interesting information might not be sufficient for being recommended. The recommender has also to analyse the defined social qualities of the users' participation into the mediated social network. These social qualities of a user can depend for example on the credits s/he receives from others or the originality of his/her contribution (which means that no user could replace his/her contribution). One can imagine many other social qualities to qualify the user willingness to collaborate and the value or his/her participation to the community. Those social qualities can be computed using social network analysis techniques (Wasserman, 1994).

We call "**socially aware recommender system**" a recommender system that takes into account those social qualities to compute and rank its recommendations.

3. SOMEONE: A COOPERATIVE SYSTEM FOR PERSONALIZED INFORMATION EXCHANGE

To experiment those ideas, we have integrated such a recommender in our SoMeONE system (Agosto, 2003). The main goal of this system is to support the creation and management of mediated social networks. It helps users to exchange recommendations about good contents available through an information network like the WWW or corporate intranet. It is supposed to help people to improve and to optimise their mediated social network in order to discover and find information resources, which are adapted to their needs, taste, background, culture or any other personal features which make humans so different.

The way to share personal information in SoMeONe is described as follows:

– Each user manages a personal taxonomy, in order to annotate and to index their documents.

Each element in that taxonomy is called a topic. A document could be for instance an email, an image, a video, or a report. In fact, it is anything that can be identified with an URL.
- When displayed, all information associated with a document (also called meta-information) is aggregated. For that, we introduce the concept of review. Reviews are created by associating topic(s) and other information (like a text annotation) on documents.
- The accessibility of reviewed information, and thus the exchange of information between users, depends on the accessibility of topics in the reviews. The accessibility of a topic is defined according to a list managed by the topic owner; this list is called a topic distribution list (TDL for short). It groups the users allowed to access all information having a review with the topic.
- We call a user's contacts, the set of users belonging to the distribution list of at least one of his/her topics. Those contacts could be friends, colleagues, family members, or any others.

Information is exchanged between users when they access the system using their personal home page. This page lets the user navigates through all information s/he is allowed to access, and let him/her to create new reviews for personal indexing purposes. However, creating a new review to a document discovered from a received review on that document makes it accessible to all the new users in the TDL of the topics associated to the new review. In consequence, personal indexing is automatically associated to information forwarding. As a result, information in the reviews, including document references, flow through the network of users according to the topic's TDL. We called "semantic addressing", this information routing process based on the indexing of information. This is the basic principle of the "web of people" where information navigates from users to users instead of having users navigating through information (Plu, 2003).

4. A "SOCIALLY AWARE" RECOMMENDER SYSTEM

The recommender we have developed and integrated in SoMeONe lets people have new contacts. It suggests to a user to add some users to the distribution list of some topics.

For this, the recommender needs first to identify topics which show the similar interests of two users. Like many others do, our recommender system is also using a collaborative filtering approach (Resnick, 1997). The originality of our work lies in the fact that we complement this approach with the computation of new ranking features based on social network analysis (Wasserman, 1994). The goal is to filter the recommendations obtained from the collaborative filtering process according to a personal information requirement and users social qualities corresponding to it. We qualify such a recommender as "socially aware".

In a **social network analysis**, people, groups or organizations that are members of social systems are treated as "sets of nodes" (linked by edges) –forming networks. They represent social structures. Given a set of nodes, there are several strategies for deciding how to collect measurements on the relations among them. Matrices or vectors can be used to represent information, and algebraic computations are done to identify specific patterns of ties among social nodes (Wasserman, 1994).

Differences in how users are connected can be a key indicator of the efficiency and "complexity" of the global social organization supported by the mediated social network. Individual users may have many or few ties. Individuals may be "sources" of ties, "sinks" (actors that receive ties, but don't send them), or both. The analysis of the relations between users can indicates a degree of "reciprocity" and "transitivity" which can be interpreted, for instance, as important indicators of stability.

The graph structure analysis of a mediated social network can be used for many purposes. It might be used to show users' roles, their position, their global appreciation, their dependency to communities to which they belong. It is also useful in order to qualify the exchanged information. Further in this paper, we present how we use these analysis techniques to propose new contacts.

Furthermore, social network analysis has also been largely used in a sub-field of classical information retrieval called biblio-metrics to analyse citations in scientific papers (Garfield, 1972). It has also led to the development of new algorithms for information retrieval algorithms for hypertext like PageRank (Brin, 1998). They are mainly based on the computation of a centrality measure of the nodes in a graph formed by web pages. The assumption is that a link provides some credit to the linked page

The social network we extract from the mediated social network supported by SoMeONe, is a directed graph consisting of a set of nodes with directed edges between pairs of nodes. Nodes are the topics of users and edges are their relations. Those relations between two topics are computed according to reviews being associated within those two topics. Thus, in this social network, there is an edge i from a topic v to a topic u, if the owner of topic u is receiving and taking information associated to topic v. In other words, the owner of topic u is in the distribution list of the topic v and takes at least one review containing the topic v and creates a new review on the same document with his/her topic u. Consequently, the graph representation will show the relation v → u.

The relation v → u indicates the flow of appreciated information through the network. It means that the owner of topic u is receiving and appreciates information from the owner of topic v.

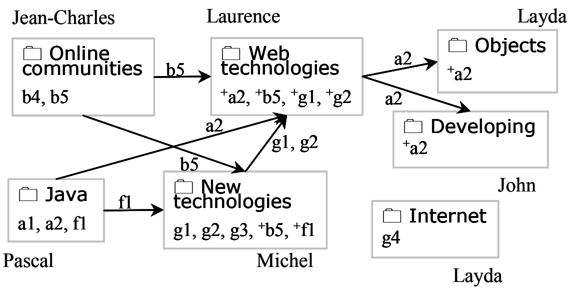

Figure 1: Mediated social network example

Figure 1 shows a graphical representation of a small part of such a network. In this example, there is six users. Each box shown as folders represents some of the topics of these users. Each relation v → u between topics is presented by a directed lattice. Reviewed information resources are noted with a lower case letter and a number. A label on a lattice means that a resource has been discovered from a review in the source topic.

Our **socially aware recommender system** first takes into account the interest of users and then takes into account the state of the users topics in the social networks.

In the first step, it finds the relationships of users with approximate interests (not only commons ones). This means that for instance, we avoid giving only recommendations directly obtained from intersections of appreciated items in the users' profiles, which is generally the strategy of existing systems. This first feature is obtained by our collaborative filtering techniques using repositories of already classified items (Plu, 2003). Second, the user can control the type of contact recommendations s/he is going to receive. This means that a user can define the strategy to rank computed recommendations. This last feature is accomplished by our SocialRank algorithm, which completes our collaborative filtering algorithm.

The SocialRank algorithm uses some social properties to filter topics which are candidates for recommendations (those topics initially computed with the collaborative filtering algorithm). The social properties used depend on the information strategy chosen by the users. They are computed by using the SoMeONe's social network described above.

By using those social properties as filters, two users with the same interest would not receive the same recommendations of contacts. Thus, this should avoid the traditional problem of "preferential attachment" in network based communication systems (Adar, 2000). The preferential attachment problem rises when most of users communicate with the same very small group of users. Recommending only experts to everyone could lead to this situation. We will see below (see section 5.3.4) how SoMeONe prevents such a situation by letting users choose another information strategy than the "Looking for Experts" strategy. More generally, different "social properties" computed from the social network analysis can be used to choose the contact recommendations in order to influence the way the social network will evolve! Thus, a socially aware recommender system can help to give the social network some interesting global properties depending on the global criteria the designer of a social media wants to optimise. Such interesting properties can be, for instance: a good clustering factor, a small diameter, a good global reciprocity or/and transitivity factor.

We assume that some users will be seeking to be recommended to others. Therefore, by using some specific social properties in the recommendation process, we think the recommender system can influence the motivation and participation of the users. In other words, if users know the strategy used by the recommender system, we can assume that some users will try to adapt their behaviour according to it.

To be able to test this idea, we have first implemented the computation of some social properties and we have implemented some information strategies using those properties in order to select appropriate contact recommendations.

In order to let users to select one of the implemented strategies which best fit their needs we have ascribed “names” and descriptions to them. Here are the three we have already implemented and experimented:

– "**Looking for Experts**". The user only trust credited experts who filter information for him.
– "**Gathering all**". The user want to have the widest coverage of a topic, thus gathering as much information as possible,
– "**Going to the sources**". The user wants to obtain the newest information rapidly, avoiding users who are acting as intermediaries.

We have started with these three strategies but our goal is to look for new ones or improving the existing ones. By default, the "Going to the source" strategy is selected, but users can change it by editing her/his personal profile. This choice can be refined for each personal topic.

The formulae related to the computation of the social properties used by each "strategy" are explained in the SocialRank section.

5. COMPUTING CONTACT RECOMMENDATIONS

In this section we are going to present the three steps of our recommendation process. *Firstly*, we describe the collaborative filtering algorithm used to compute potential contact recommendations based on topic similarities using an existing classification of a large amount of URLs. *Secondly*, we specify the computation of social properties of each topic in the SoMeONe's social network. *Finally*, we show how we filter the potential contact recommendations obtained in the first step according to the topic similarities, the social properties of the recommended topics, and the information strategy chosen by users.

5.1 Collaborative filtering

The bases of the collaborative filtering algorithm that we have built are presented in (Plu, 2003). It uses URL co-citations analysis. Co-citation is established when two users associate personal reviews to the same documents or to different documents referenced within the same category of a WWW directory. The recommendations of contacts are computed using one or more specialized directories. By directories, we mean repositories of web sites categorized by subject. For our tests we have started with the one provided by the Open Directory Project (http://www.dmoz.org).

The collaborative filtering algorithm (CFA) computes similarity between topics. It has to detect the case of two topics having reviews with URLs equal or similar to the URLs classified in the same ODP category. The CFA computes a similarity measure between each topic and each ODP category. Like others do, this similarity measure is based on URLs co-citation analysis. (the URLs to which the reviews inside topics make reference). This similarity measure is computed according to the formula given in (Plu, 2003).

The CFA only computes the similarity between topics that do not belong to the same user. Pairs of similar topics noted (t1, t2) for topics labelled t1 and t2, are sorted according to the similarity measure S. Contact recommendations are then computed from those similar topics.

5.2 SocialRank

The SocialRank algorithm filters the topic recommendations according to some of their social properties.

Having the topics' taxonomy of users, and the distribution list of the topics defined, we are able to extract the social network explained above. We model this directed graph as an adjacent matrix. Each matrix element represents the relationship between two topics. As introduced above, a relationship is established when a user creates new reviews from other reviews received from other users. They thus establish relationships between their topics within the created reviews and the topics of others within the received reviews. To take into account the importance of each relation, each vertex is weighted with a measure W(e,f) representing the number of documents received from topic f and then reviewed with a topic e. We compute a matrix W with each element noted W(e, f), topic e being in the row and topic f in the column of the matrix, for the vertex from f . W(e,f) is computed with the formula:

$$W(e,f)=\frac{Card^*(e,f)}{card(e)} \quad \textbf{(1)} \qquad \text{or } W(e, f) = 0 \text{ if } card(e)=0$$

Card*(e,f) counts all the documents having a review with the topic e and a review with the topic f, the review with topic f being older than the review with topic e; card (e) is the total number of reviews with topic e.

Using this W matrix, the SocialRank algorithm also computes one square matrix and two vectors of topics:

- A vector of experts E, in order to obtain the expert topics.
- A redundancy matrix R, in order to obtain redundant topics.
- A vector of originals O, in order to obtain original topics.

The computation of these matrix and vectors could be obtained by different methods, as clearly explained in (Wasserman, 1994).

To identify topics as "**experts**" we use a common centrality measure of a topic defined recursively according to the centrality of the topics receiving information from it. Each element E(e) of the expert vector is defined according to the recursive formula:

$$E(e)=\sum_{h\in H} W(h,e)*E(h) \qquad \textbf{(2)}$$

For the computation of vector E we use the algorithm named PageRank and used for WWW pages (Brin, 1998). But the matrix used has to reflect a reputation relation ("e is giving reputation to f", f←e). We consider that this relation is the invert of the relation modelled in our matrix W, which reflects the flow of information through the topics (f→e). Indeed, if a user reviews documents received with topic f with his topic e, then topic e is giving reputation (credit) to topic f. That is why we use the weight W(h, e) instead of W(e, h) to compute E(e).

The PageRank algorithm requires that the weights of the adjacent matrix W(e, f) have to be modified in W*(e, f) in order to have the following needed convergence properties (see (Brin, 1998) for more details). This is partly achieved because the new weights W*(e, f), once normalized, represent the probability for a document being reviewed with topic f to be reviewed with a topic e. Thus, our matrix W corresponds to a stochastic matrix. Following the PageRank algorithm, we also complete the graph with new connections in order to have all nodes connected.

To compute **redundancy and originality**, we first define vectors G(e) as the set of all topics g connected to topic e. Second, we define P(e, f) as the proportion of the relation between topic e and f among all the relations with topic e. P(e, f) is computed with the formula:

If $f \in G(e)$ $P(e,f)=\frac{W(e,f)}{\sum_{g \in G(e)} w(e,g)}$ else P(e,f)=0 **(3)**

The evaluation of redundancy between topics is computed in a matrix R. We define that a topic e is redundant with f if both are the same type of information sources because they have the same information obtained from the same sources. Explicitly, the redundancy between e and f depends on:

– If f is connected with e. This means that e is receiving information from f.
– If topics connected to e are also connected to f. This means that topics sending information to e are also sending it to f.

We compute R(e, f) according to the following formula:

$$R(e,f) = p(e,f) + \sum_{g \in G(e)} p(e,g)p(f,g) \qquad \textbf{(4)}$$

Finally we compute the vector O to represent original topics. The originality of a topic is measured according to the novelty of URLs in the topic compared to the URLs received from connected topics. A topic e is original if it contains more URLs discovered by the owner of the topic than received from other topics. It also depends on the number of URLs in the topic. We compute the vector O according to the following formula:

$$O(e)=1-\sum_{h \in G(e)} W(e,h) \qquad \textbf{(5)}$$

5.3 Applying SocialRank

Now we illustrate these calculations with our social network example presented in figure 1 where there are six actors, seven topics shown as folders, and reviews noted with a lower case letter and a number. The URLs of the reviews belong to 4 ODP categories noted A,B,F,G. For example we note "a1" a review having an URL referenced in the category A of the ODP directory. A label on a lattice means that a URL has been discovered from a review in the source topic.

In this example, we suppose that the user Layda wants to obtain recommendations about her topic Internet. The CFA similarities computation produces the following recommendations: (Internet → New technologies) and (Internet → Web technologies) because those three topics have reviews on URLs referenced in the category G of the ODP category (even if their intersection is empty). A recommendation noted (t1→t2) means that owner of the topic t2 should be in the distribution list of the topic t1 if it is not the case.

Those initial recommendations are going to be analysed by our SocialRank algorithm. One issue of the analysis is which topic the system will recommend to Layda related to her topic Internet, Web technologies or New technologies (or both)? R is an important matrix because it helps to decide if two topics are redundant to each other. If so, which of them are more relevant to recommend according to the user specific needs? This decision is going to be applied to the topics Web technologies (noted WT) and New technologies (Noted NT).

Before the computation of R, we first have to compute W and P. From (1) we compute W(WT, NT). Then, we have:

$$\text{W(WT, NT)}=\frac{Card^*(WT,NT)}{card(WT)}=\frac{3}{4}=0.75$$

(*we assume that b5 were reviewed by WT before being reviewed by NT*).

This means that the average of information received by Web technologies from New technologies is 0.75, which is high (meaning that their relation is important).

Here are the matrix W and P for our example:

W	**NT**	**WT**	**Java**	**OC**
NT			0.2	0.2
WT	0.75		0.25	0.25

P	NT	WT	Java	OC
NT			0.5	0.5
WT	0.6		0.2	0.2

With matrix P, we obtain the proportion of the relation between WT and NT among all the relations with WT. The value 0,6 indicates an important relation between both topics.

5.3.1 Evaluating redundant topics

As we explained above, matrix R helps to decide if two topics are redundant to each other. From (4), R(WT, NT) can be computed as

$$\mathrm{R(WT,NT)} = \left[\mathrm{p}(WT,NT) + \left(\begin{array}{l} \mathrm{p}(WT,OC)\mathrm{p}(NT,OC) + \\ \mathrm{p}(WT,Java)\mathrm{p}(NT,Java) + \\ \mathrm{p}(WT,NT)\mathrm{p}(NT,NT) \end{array} \right) \right] = 0.8$$

This value indicates a redundancy between WT and NT, which reveals that WT could be a similar information source to NT; therefore, it is relevant to recommend only one of them.

The same computation gives R(NT,WT) = 0,2.Notice that R(WT,NT) > R(NT,WT) ! This is an important result because it helps the system to decide which topics to recommend according to the user's strategy. We will develop this in a later section.

5.3.2 Evaluating experts

Let's now compute the expert property. If we follow (2), we will obtain E(WT) =0.095879; E(NT)= 0.080576 for topics WT and NT. This result is interpreted as follows:

– Web technologies is the more expert topic. We can notice (figure 1) that even if it does not have its own reviews, it has collected different reviews from two topics having a good level of expertise. Web technologies is supplying with its information two other topics, Objects and Developing, who are giving to it a kind of credibility or reputation.
– New technologies is at second level of expertise From figure 1, we can see that it has collected different reviews from two topics with a good level of expertise but it is supplying only one topic with its information! Remember that the computation of E is based on a centrality measure indicating a reputation degree (Brin, 1998). However, its level of expertise being higher than a defined threshold this topic is kept as candidate for being recommended.

5.3.3 Evaluating original topics

By applying (5), we obtain the next O vector values:

Topic	O(e)
Internet	1.0
Java	1.0
Online Communities	1.0
New technologies	0.6
Web technologies	-0.25
Developing	0.0
Objects	0.0

The result is interpreted as follows:

– Internet is the more original topic. The originality of Internet is evident because it is isolated, because it is not redundant with the others and because it can bring new information. Java and Online communities are also original topics because URLs have been reviewed with them before the other topics (see figure 1).
– However, comparing their place in the vector O, NT is more original than WT.

5.3.4 Applying users' strategies

Because WT and NT have been identified as redundant, only one will be chosen according to Layda's information strategy. If she has selected:

1. **Looking for experts**: This leads to the selection of a topic with the highest Expert property; the answer of the recommender would be WT.
2. **Gatherint all**: The answer with this strategy is the topic having the highest value for R, therefore it would be WT because R(WT,NT) > R(NT,WT) (*reinforcing the global approval of WT over NT*).
3. **Going to the sources**: the selected topic would be NT, because the strategy gives priority to the most originals among topics with a sufficient level of expertise.

What happens if Layda does not define an initial strategy? We explained that one of the priorities of our mediated system is avoiding the preferential attachment problem (Jin, 2001). Therefore, the default strategy is "Going to the sources", because it should improve the reactivity of the social networks by minimizing intermediaries. Another important situation to encourage is the connection of independent components.

In order to protect user's information privacy, no user can add his identifier to the topic access list of any other user's private topics. Thus, recommendations displayed only suggest sending information to new users. In our example, the system will recommend to Layda to add Michel owner of NT or Laurence, owner of WT to the distribution list of her topic Internet. But we assume that a user receiving new information will also send back new information. To encourage such reciprocal relationships the recommender needs also to check if the topic Internet satisfies Michel's or Laurence's information strategy for their topic NT or WT. Thus finally the recommender will try to choose the topic that will stratify the best the strategy of the two users involved in the suggested relationship.

6. CONCLUSION

In this paper, we've proposed to improve an original information exchange system, SoMeONe, which facilitates the creation of relationships between users, in order to cover each user's information need. We've included a contact recommendation module that helps users to open their closed relational network and thus discover new sources of information.

We had proposed in (Plu, 2003) to use a collaborative filtering algorithm. This algorithm suggests that a user exchanges reviews on information source that they have already evaluated or produced. But these recommendations have to be carefully chosen in order to not let him/her having a too big relational network and for the global efficiency of the social media. Thus, our SocialRank algorithm presented in this article filters those recommendations using the computation of one matrix and two vectors. This lets the system propose to users several information strategies to establish new relationships.

Many recommender systems have already been studied and some of them are operational like online bookshops (Resnick, 1997). However, our system recommends *users* instead of recommending *contents*. Thus it is more similar to McDonald's expertise recommender (McDonald, 1998). But as far as we know, none of the recommender systems integrate a traditional collaborative filtering algorithm with social properties resulting from social network analysis. The use of social network analysis to improve information retrieval in enterprise is also recommended in (Raghavan, 2002). But this paper does not present any recommender system in order to establish exchange relationships between users. Our work was partly inspired by the ReferalWeb system (Kautz, 1997) but in our system, we've introduced social properties and the social network is manually controlled by users, and evolves according to users accepting contact recommendations.

In order to test our ideas, we've introduced the system in the Intranet of France Telecom R&D and in the portal of the University of Savoie, inside the project called "Cartable Electronique"®. The usage of our system in these different contexts should allow us to validate our initial hypothesis: a recommendation process of carefully selected contacts should incite users to produce interesting information and develop collaborative behaviour.

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