Regulation mechanisms in an open social media using a contact recommender system

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Abstract. This paper presents how an information exchange network can be improved by users' collaboration. This social media is based on content recommendation. Instead of using an automated content recommender system, we suggest an alternative approach where the information comes from trusted users. In order to overcome traditional problems of an open social media, we propose some regulation mechanisms. First each user manually controls her/his contacts network. Second we have introduced a contact recommender system to help users to carefully open their closed relationship network. This recommender system selects the recommended relationships in such a way it should optimize some global qualities of the social media. This paper details the algorithms of this recommendation process.

Objectives

Our main goal is to build an information exchange network on the Web, optimized by collaboration. This new service should allow users to better access and discover web resources. The purpose is to provide them with enriching features through the ability to interact and exchange with others. We propose a social media integrating regulation mechanisms in order to decrease information overload, influence of gurus and inefficiency of information spreading. Moreover, users normally have an individual behavior. Those mechanisms are expected to motivate and incite people to exchange information. It results in trustable "web of people" (Plu et al. 2003).

The underlying problematic is similar to other tools like search engines. One of the great challenges of search engines, mainly based on an artificial (computer-based) centralized intelligence, is to be able to select relevant answers according to users' preferences, background, or current activity. In order to face this personalization challenge, many recommender systems have already been proposed and some of them are operational for example inside online bookshops (Resnick and Varian, 1997). Those systems traditionally recommend *contents* to users, trying to match users' interests with contents selected by other users having interests calculated as similar. However, many problems have been identified with such systems using traditional collaborative filtering algorithms (Herlocker et al. 2004), (Resnick and Varian, 1997). We focus our attention on the following ones. First of all, the quality of the information provided depends on the quantity of people using the system: we need a great number of users if we want valuable results. Secondly, the users must be altruistic, as the information centralized by the system has to be annotated. Thirdly, most of the time, these systems rely on a small number of people ("gurus") who provide the relevant information to many other users (Adar and Huberman, 2000). This phenomenon leads to a huge influence of very few people on the nature of information sent to many.

Users prefer recommendation from users

In order to improve recommendation systems, we are developing a complementary approach where:

- **Recommended information is relevant according to user's preferences, background, or current activity**. We take advantage of the synergy of classical collaborative filtering algorithms (Resnick and Varian, 1997) combined with well-known resource classifications.
- **Information is trustable**. The resource relevancy for a given user is also based on the trustworthiness of relationships between users. Indeed, users prefer to trust other users rather than a program to obtain good advice about information resources (Luhmann, 1998).
- **The dependence on "gurus" is reduced**. The relations between users based on the recommendation flow induce a network. Social properties resulting from the analysis of such a network (Waserman and Faust, 1994) guide future recommendations in order to equilibrate the information exchanges.
- **Users control their information exchanges**. They can filter information according to senders and associated metadata.

Our approach is supported by a collaborative system named SoMeOnE (Social Media using Opinions through a trust Network) (Agosto et al. 2003). This system offers access to information that has a certain approval, for instance, information coming from appreciated or skilled people in corresponding domains.

One key issue in our system is to motivate users to exchange information. We make the assumptions that this motivation is reinforced by:

- **Recommending users instead of contents**. We suppose users prefer users' advice to impersonal guidance and appreciate having enriching relationships with others.
- **Influencing users to get into touch with others**. In order to receive information from unknown users, a user must be recommended to them according to the quality of the information s/he has already provided.
- **Letting them control their visibility through an open network of people**. A user can control the list of users to whom s/he wants to provide information, and the list of users from whom s/he accepts to receive information. This helps to avoid spamming and to improve trust in the system.
- **Developing the value of information sharing based on users' cooperativeness**. The cost of searching for and producing a piece of information is balanced by the gain of receiving freely other ones induced by having shared this piece of information with others. Of course, "free riders" are supposed to be managed for example by isolating them from the network of cooperative users.
- **Combining personal information management and information sharing functionalities reduces the extra cost of cooperation**. It also let the system grows even without cooperation in order to reach the critical size for cooperation being valuable.

Those assumptions are founded on an analysis of a wide range of literature on cognitive economics and social psychology studies. A review of this abundant literature is outside of the scope of this article but the main publications which inspired our developments are Thibaut, J. W. & Kelley's initial work about groups (Thibaut and Kelly, 1959), P.Bourdieu's work on social capital (Bourdieu, 1986), Turner's work on social identity (Turner, 1982), Luhman's paper about trust (Luhmann, 1988), J.Preece's work on online communities (Preece, 2000).

We detail in the following sections the techniques we have developed to regulate the information exchanges.

Information exchange based on personal taxonomy and distribution lists

The main goal of our SOMEONE system (Agosto et al. 2003) is to help 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 optimize 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 (see also Figure 1):

- Each user manages a personal taxonomy, in order to annotate and to index their documents. Each element in that taxonomy is called a topic. In the following, we will call a topic owner the manager of the personal taxonomy in which the topic is included. Since users are free to choose the appropriate name of their topics, the system supports two topics with the same name belonging to two different personal taxonomies. A document could be for instance an email, an image, a video, or a report. In fact, it is anything that can be identified by a 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 define a user's contacts as the set of users belonging to the distribution list of at least one of her/his topics. These 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 navigate through all information s/he is allowed to access, and lets him/her 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, flows through the network of users according to the topic's TDL. We called this information routing process based on the indexing of information, "semantic addressing". 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 et al. 2003).

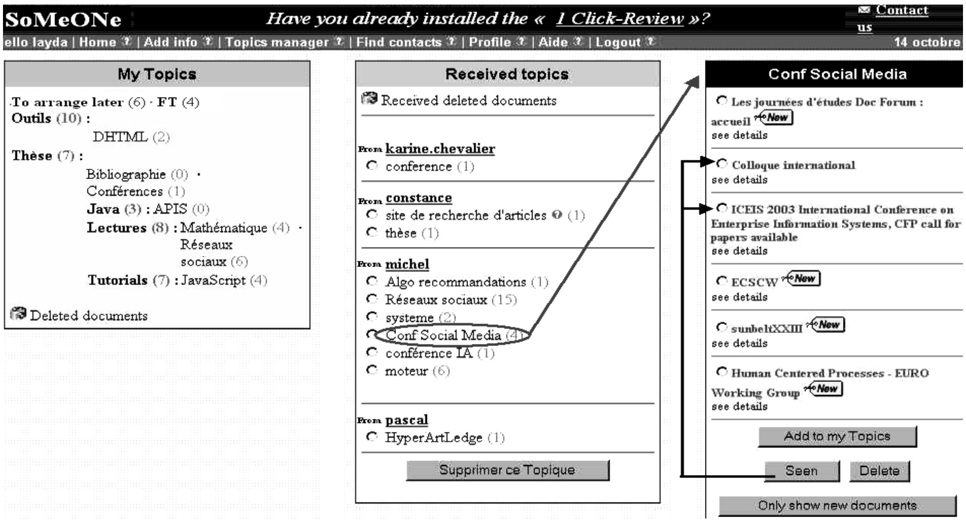

Figure 1. SOMEONE'S topic management interface

Recommendation of users instead of content using mediated social networks

Opening closed relationship network

The mains problems of open social media like mailing-list or newsgroup are information overload and spamming. They are avoided with SOMEONE since users can exchange information only if they already know each other. However, in order to open their relationship network, we have developed a contact recommender. It suggests to a user that s/he add some users to the distribution list of some of her/his topics.

For this, the recommender needs first to identify topics which show the similar interests of two users. As many others do, our recommender system uses a collaborative filtering approach (Resnick and Varian, 1997). Our collaborative filtering algorithm is presented in (Plu et al. 2003). It computes similarity between topics of different users, comparing their URLs to classes of URLs existing in recognized classification, like ODP (http://dmoz.org/). When it detects that two topics of different users have similarities, it could propose to each user to add the other to the distribution list of the corresponding topic.

A “socially aware” recommender system

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 and Faust, 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**". More precisely, in order to make contact recommendations, such a system not only takes into account the local profile of the users. It also considers all the existing relationships in the network. By this way, on the one hand, we want to reach individual goals, providing the user with contacts having the similar interests; on the other hand, we want to improve global properties of the social media. This last point is very important since it has been proved in the literature that communication networks having some specific structures (Jin et al. 2001), (Latora and Marchiori, 2003), (Phan, 2003), (Watts and Strigatz, 1998) can improve information spreading or users' cooperativeness.

Using social Network Analysis

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 and Faust, 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 indicate 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 has been largely used in a sub-field of classical information retrieval called biblio-metrics to analyze 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 and Page, 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.

In the next two sections we present the social network we extract from our SOMEONE system, and the social indicators we compute to qualify each nodes.

SOMEONE's social network

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 users' topics 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 her/his 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 2 shows a graphical representation of a small example of such a network. In this example, there are six users. Each box shown as a folder 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.

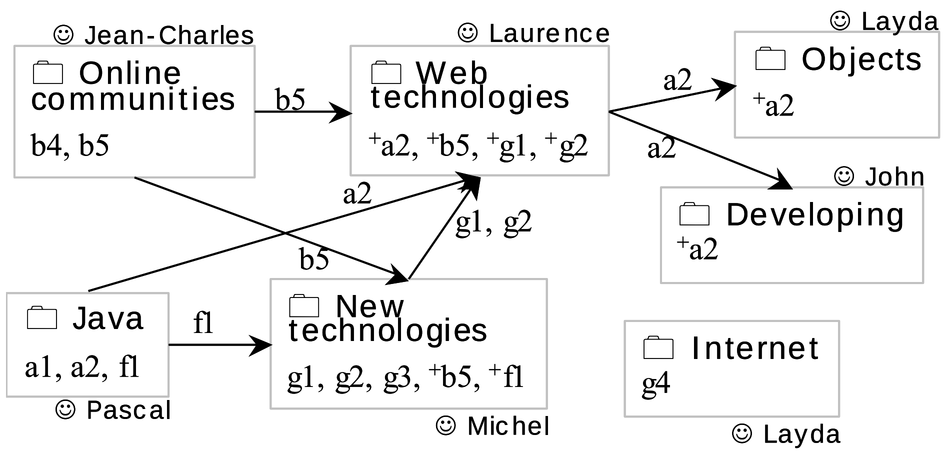

Figure 2. Graphical representation of a network

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.

Computing social indicators

In order to filter recommendation the nodes and the relations of the social network described above are qualified with social indicators. Three indicators are computed using the adjacent matrix: fame, coverage, and originality. These computations use indicators which we introduce first.

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. In other words, W(e, f) is the proportion of documents of topic e coming from topic f: the ones the owner of topic e found relevant. Thus, the range of W(e, f) is [0,1].

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:

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

Card*(e, f) includes 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.

Then, a famous topic is a topic appreciated by users who also have famous topics. Note that famous topics might be considered as expert topics if we first assume that users only appreciate the most expert topics, and second that they know all the topics about the domain of expertise in order to be able to identify the most expert. This indicator is managed as a vector of a value between 0 and 1 for each topic. A value next to 1 (respectively 0) indicates that the topic does (respectively does not) contain the most appreciated references of the corresponding domain.

To compute these values we use a common centrality measure of a topic defined recursively according to the centrality of the topics receiving information from it. Each element F(e) of the fame vector is defined according to the recursive formula:

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

For the computation of vector F we use the algorithm named PageRank and used for WWW pages (Brin and Page, 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 modeled 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 F(e).

The PageRank algorithm requires that the weights of the adjacent matrix W(e, f) be modified in W*(e, f) in order to have the following needed convergence properties (see (Brin and Page, 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 of being 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 **coverage 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:

$$\text{If } \mathrm{f} \in \mathrm{G(e)}:\ \mathrm{P}(e, f) = \frac{\mathrm{W}(e, f)}{\sum_{g \in \mathrm{G}(e)} \mathrm{W}(e, g)} \text{ else } \mathrm{P(e,f)} = 0 \qquad (3)$$

We define that a topic e covers a topic f if both collect the same type of information from the same sources. In some sense, the coverage indicator identifies topics which are redundant, not only according to their current content but also according to their capacity for aggregating future contents coming from other topics. Explicitly, the coverage between e and f depends on:

- f being connected to e. This means that e is having information from f.
- Topics connected to e being also connected to f. This means that topics sending information to e are also sending it to f.

The evaluation of coverage between topics is computed in a matrix R that computes the redundancy between topics. We compute R(e, f) according to the following formula:

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

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:

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

Example

Let's illustrate these calculations with our social network example presented in Figure 2 bringing together six actors, seven topics shown as folders, and reviews noted with a lower case letter and a number.

Before the computation of R, we first have to compute W and P. From (1) we compute W(WT, NT). Then, assuming that b5 were reviewed by WT after being reviewed by NT, we have:

$$\mathrm{W}(WT, NT) = \frac{Card*(WT, NT)}{card(WT)} = 0.75 \tag{6}$$

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 matrixes P (table I) and W (table II) for our example:

TABLE I

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

TABLE II

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

With matrix P, we are obtaining 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.

Evaluating famous topics

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

- Web-technologies is the most famous topic. We can note (Figure 2) that even if it does not have its own reviews, it has collected different reviews from three topics having a good level of fame. Web-technologies is supplying with its information two other topics, Objects and Developing, which are giving it a kind of credibility or reputation.
- New-technologies is at second level of fame. From Figure 2, we can see that it has collected different reviews from two topics with having a good level of fame but it is supplying only one topic, Web-technologies, with its information! Remember that the computation of F is based on a centrality measure indicating a reputation degree (Brin and Page, 1998). However, its

level of fame being higher than a defined threshold, this topic is kept as a candidate for being recommended.

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:

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. Matrix **R** values are presented as in the following table:

TABLE III

R	Developing	Objects	Internet	NT	WT	Java	OC
Developing		1.0			1.0		
Objects	1.0				1.0		
Internet							
NT					0.2	0.5	0.5
WT				0.8		0.2	0.2
Java							
OC							

The same computation gives R(NT,WT) = 0,2. Note that R(WT,NT) > R(NT,WT) ! This is an important result because it helps the system to decide

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

which topics to recommend according to the user's strategy. We will develop this in a later section.

Evaluating original topics

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

TABLE IV

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 results are interpreted as follows:

- Internet is the most 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 2).

- However, comparing their places in the vector O, NT is more original than WT. In the next section we describe how we use these social indicators to compute new contact recommendations.

The "socially aware" recommender system

We named SocialRank the algorithm in the socially aware recommender system we have developed.

SocialRank

The SocialRank algorithm uses the computed social indicators to filter contacts which are candidates for recommendations (those owning topics initially computed with the collaborative filtering algorithm). The social indicators effectively used depend on the information strategy chosen by the users.

By using those social indicators as filters, two users with the same interest would not receive the same contact recommendations. Different "social indicators" 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 optimize. Such interesting properties can be, for instance: a good clustering factor, a small diameter, a good global reciprocity or/and transitivity factor. This could help to decrease the dependence of the system on few "gurus", and to set "free riders" apart. In other words, those indicators are used to regulate the exchanges (Durand and Vignollet, 2003).

We assume that some users will be seeking to be recommended to others. Therefore, by using some specific social indicators 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 behavior accordingly to it. To be able to test this idea, we have first implemented the computation of some social indicators and we have implemented some information strategies using these properties in order to select appropriate contact recommendations. In order to let users to select one of the implemented strategies that best fits their needs we have ascribed “names” and descriptions to them. Here are the three we have already implemented and which are experimenting:

- "**Looking for Experts**". The user only trusts credited experts who filter information for her/him.
- "**Gathering all**". The user wants 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 to improve the existing ones. To avoid the preferential attachment problems (Jin et al. 2001), the "Going to the sources" strategy is selected by default. However, users can change it by editing their personal profile. This choice can be refined for each personal topic.

Applying users' strategies to our example

In our previous example (Figure 2), the URLs of the reviews belong to four ODP categories noted A, B, F, G. For example we note as "a1" a review having a 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 these 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 the owner of the topic t2 should be in the distribution list of the topic t1 if it is not already the case.
These initial recommendations are going to be analysed by our SocialRank algorithm. One issue of the analysis is which topic in relation to Layda's topic Internet the system will select, 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 is more relevant to select according to the user's specific needs? This decision is going to be applied to the topics Web-technologies (noted WT) and New-technologies (noted NT).

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

- **Looking for experts**: this leads to the selection of a topic with the highest fame indicator; the answer of the recommender would be Laurence, WT's owner.
- **Gathering all**: the answer with this strategy is the owner of the topic having the highest value for R, therefore it would be Laurence, WT's owner,

because R(WT,NT) > R(NT,WT) (reinforcing the global approval of WT over NT).

- **Going to the sources**: the selected topic would be NT, because the strategy gives priority to the most original among topics with a sufficient level of expertise. In that case, the recommendation would be Michel.

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 et al. 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 users' information privacy, no user can add her/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 that she adds 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 also needs 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 best satisfy the strategy of the two users involved in the suggested relationship.

Conclusion

Recommendation systems are principally used to reduce information overload and to improve information search and discovery. We propose a new kind of recommendation system, which recommends contacts instead of contents (that what we share with Mc Donald's expertise recommender (McDonald and Ackerman, 1998)). We make the assumptions that users prefer users' advice to impersonal guidance and appreciate having enriching relationships with others. This leads to the "Web of people" (Plu et al. 2003): information navigates from users to users instead of having users navigate through information.

Like many others, our recommender system uses a collaborative filtering approach (Herlocker et al. 2004), (Resnick and Varian, 1997). The value and originality of our work is to complement this approach with the computation of new ranking features based on social network analysis. The goal is to filter the recommendations obtained from the collaborative filtering process according to a particular information requirement and users' social qualities. The use of social network analysis to improve information retrieval in enterprise is also recommended by P. Raghavan in (Raghavan, 2002). However, this paper does not

present any recommender system in order to establish exchange relationships between users. Our work was partly inspired by Referral Web (Kautz zt al. 1997) but in our system, the "socially aware" recommender is included in SOMEONE, a personal information management system with information sharing facilities. We have introduced in this recommender the computation of social properties to carefully choose users to be connected to. Moreover, the social network is manually controlled by users and evolves according to users strategy. Those both features are the basis of our proposed regulation mechanism of a social media.
The main contribution of this proposition is to present an improvement to classical recommender systems essentially based on similarity of interests or of topicalities. A "socially aware" recommender system, as we propose in this paper, takes into account other selection factors. Those social factors are sensible to already existing relationships within a whole community and to the specificity of the contributions of each user. The computation of such social factors are defined and illustrated in an example, but of course many others can be defined. We argue that the choice of specific factors for recommending relationships between users can influence the connectivity and efficiency of a computer supported information exchange network.

In order to test our ideas, we have introduced the system in the Intranet of France Telecom R&D and in the portal of the University of Savoie, within the project called "Cartable Electronique" ("Electronic Schoolbag") . We would like to stress the fact that those portals are not an experimental testbed used by an artificial panel of users but ones already used by hundreds of people in their daily work.

The usage of our system in these different contexts should allow us to confirm our initial expectations based on theoretical works (Jin et al. 2001), (Latora and Marchiori, 2003), (Phan, 2003), (Watts and Strogatz, 1998): influencing the topology of the social network by using our "socially aware" contact recommender system improves the global efficiency of the system. Moreover, we also expect to verify that a recommendation process of carefully selected contacts should incite users to produce interesting information and develop collaborative behavior. We will also put particular attention on expected side effects of the use of the system: the motivation for a user to initiate new collaborations.

The analysis methodology of these experiments is described in (Chabert, 2001). But it takes a long time to have users to accept and to effectively use a new tool for their everyday needs. Thus this experimentation is a long time process in order to collect enough significant data.

We now enter a new cycle in the development of SOMEONE guided by the results of the current experimentations. We will also consider specific contexts of use where this social media should be particularly useful. The next section describes our research tracks in a near future.

Perspectives

Although the experiments still going on, first interviews with users state that a user expects:

- a better interface which should decrease cognitive overload; moreover, a non-adapted interface could really interfere with the experimentation results;
- informal communication features to let users express feelings and emotions. This would come up to the expectation of "face to face communication" identified by Dutton (Dutton, 1998);
- a suitable social awareness of the activity:
  - her/his role in her/his relationship network in order to know for example if the information s/he provides is appreciated?;
  - her/his expected/obtained benefits of her/his use of the system in order to improve trust in the value of the system.

We also have to focus our research developments to specific context of use. One environment is definitely enterprise. Intranet companies are getting bigger and bigger as companies grow. In addition, the biggest the company is, the more we find a large diversity of jobs, workers, and cultures. All this diversity hides differences in needs, backgrounds, and sensibilities. To face this diversity, only providing an access to information with some global indexing facilities is not always sufficient. To be efficient, collaborators need to access information relevant to their business and adapted to their personal capabilities and sensibilities. As an example, any industrial researcher knows that s/he will not present her/his work with the same slides to a scientific community or to marketers from a business unit. We believe that this level of adaptation can only come from people networks. These networks are open, flexible and dynamic. They cannot only rely on the enterprise organisation. Collaborators are increasingly working in teams belonging to multiple entities, inside or outside the company. Suppliers, technicians, engineers, marketers, even customers are getting closer relationships in information exchange networks.

For companies in the business of information society, communication is a key issue. In addition, the production of these companies is often based on the production of information and knowledge. The need of such companies is to build valuable social capital, made of the knowledge of their employees and their mutually enriching relationships (Bourdieu, 1986). Here again, SOMEONE is particularly adapted to support and develop these valuable relationships.

Finally, another application domain in enterprise is business intelligence. SOMEONE is a solution for distributing through the company the process of detecting important information and rapidly spreading it to appropriate audience with a validation and commenting process all along the chain that enriches the information.

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