SoNARS: A Social Networks-Based Algorithm for Social Recommender Systems

Francesca Carmagnola, Fabiana Vernero, and Pierluigi Grillo

Dipartimento di Informatica, Università di Torino
Corso Svizzera 185; 10149 Torino, Italy
{carmagnola,vernerof,grillo}@di.unito.it

Abstract. User modeling systems have been influenced by the overspread of Web 2.0 and social networks. New systems aimed at helping people finding information of interest and including "social functions" like social networks, tagging, commenting, inserting content, arose. Such systems are the so-called "social recommender systems". The idea at the base of social recommender systems is that the recommendation of content should follow user's preferences while social network just represents a group of users joined by some kind of voluntary relation and does not reflect any preference. We claim that social network is a very important source of information to profile users. Moving from theories in social psychology which describe influence dynamics among individuals, we state that joining in a network with other people exposes individuals to social dynamics which can influence their attitudes, behaviours and preferences.

We present in this paper *SoNARS*, a new algorithm for recommending content in social recommender systems. SoNARS targets users as members of social networks, suggesting items that reflect the trend of the network itself, based on its structure and on the influence relationships among users.

1 Introduction

Users are finding it increasingly difficult to locate the right information at the right time. This is known as information overload problem. Recommender systems have emerged as an important response to this problem [13,1,14]. Recommender systems form a specific type of information filtering technique that attempts to predict and present items (movies, music, books, news, images, web pages) a user may be interested in.

Typically, a recommender system compares the user's profile to some reference characteristics which may be from the information item (content-based approach) or from the user's social environment (collaborative filtering approach). Collaborative filtering is the most widely used technique for recommender systems. In such systems the generation of high-quality recommendations for a target user is facilitated by leveraging the preferences of communities of similar users. Indeed, the collaborative filtering method takes advantage of the collaborative world moving from the idea that every user contributes with her ratings to the overall performance of the system. In such systems the only relation among users which is taken into account to produce recommendations is user similarity while no attention is given to the social relations among users [15].

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From about 2001 onwards, social relations have been included in many web sites. We have assisted at a wide revolution in recommender systems user experience. Recommender systems are no longer centered only on completing a finding task or making sales. With the deployment of social networking systems and the overspread of Web 2.0 the user is no more isolated but part of a *social context* meant as a *network of users*. Besides those systems that already considered the social relations of a user through group modeling, new systems arose. These can be defined as "social recommender systems", i.e. systems aimed at helping people finding information of interest (like recommenders do) and including "social functions" like social networks, tagging, commenting, inserting content. Some social recommender systems like LastFm, Findory, Memigo, del.icio.us, Tailrank, are even more "social" since the concept of social network as a network of users is crucial and most of their functions are related with it. Hence, in social recommender systems users are proposed, on the one hand, recommended content and, on the other hand, they can browse the content of the social network, e.g. in LastFm, users can access the playlist music of the users belonging to their social network.

However, in all such systems the starting idea is that the recommendation of content is performed simply on the basis of user's preferences/interests and the social network just represents a group of users joined by some kind of voluntary relation and does not reflect any preference. In terms of recommendations, in social recommender system (see Section 2) social networks are used, at most, to suggest content on the basis of the similarity among the users partaking the social network.

On the contrary, we claim that social networks are a very important source of information to profile users. Moving from theories in social psychology which describe influence dynamics among individuals, we state that joining in a network with other people exposes individuals to social dynamics which can influence their attitudes and behaviours. Therefore we assume that individuals become interested in topics or subjects that do not necessarily match their personal preferences and tastes, but that reflect those of their social network.

We propose a Social Networks-based Algorithm, which we called SoNARS, for recommending content in social recommender systems, both content-based and collaborative filtering. SoNARS targets users as members of social networks, suggesting items that reflect not only preference/interest, like in traditional recommender systems, but also the trend of the network itself, based on its structure and on the influence relationships among users.

The paper will first position our work in the relevant literature (Section 2), and will then give an overview of the social psychology theories we have referred to define our research (Section 3). Section 4 will present the Sonars algorithm in detail. In Section 5 we describe the evaluation of the algorithm, using Facebook as test bed social system. Finally Section 6 concludes the paper and points at future research directions.

2 Related Work

Since 2006 onwards, the rise of Web 2.0 and Social Web has brought people to interact with other users, their content and tags to find information and to connect with other people. In recommender systems some works have started to merge adaptation and Web 2.0. Dourish and Chalmers [4] and Farzan and Brusilovsky [5] use social annotation to provide social navigation support; Van Setten et al. [18] suggest that tags can become part of the user profile and Carmagnola et al. [3] exploit tagging in order to infer knowledge about the user.

Besides these works, systems that accompany the recommendation of content to social networks, namely *social recommender systems*, have become very popular (e.g. Pandora[1] LastFm[2], Findory[3], Memigo[4], and Tailrank[5]). Moreover, the KeepUp recommender system [19] applies an algorithm which exploits the *implicit social networks* based on shared interests which are created as a side-effect of recommendation processes; in this approach, users can "converse" with their peers and manually adjust their neighbors' influence in determining recommendations.

However, to the authors knowledge, none of the existing social recommender systems deeply investigate the behaviour of users in social networks for recommendations. All these systems use a collaborative filtering approach, more specifically a person-to-person approach, to create for each user a social network of unknown others who nevertheless have shared tastes, and through whose preferences information can be filtered on user's behalf. Like in conventional collaborative filtering approaches, that whilst they may list "people like you", they are generally aimed towards informing the user that "people like you also liked X". Indeed, recommendations are based on user's preferences and social networks are used just to assess user's preferences based on the similarity among the user and the other members of her social network.

In other words, social networks allow users to access new interesting information but they are not considered for their influence on user interests, which appear to be "given".

The work of Granovetter [7] highlighted how social networks can serve as a source of new information to which an individual may not otherwise have access.

Based on that, Health and Motta [8], following the principle that knowing who in the social network knows what, and who is the most trustworthy source of information on that topic is often the greatest challenge in seeking information or recommendations, propose an approach for generating trust profiles for members of a user's social network, in the context of word of mouth recommendation seeking.

Differently from our approach, they focus on investigating how to exploit social networks to judge the competence and trustworthiness of people the user knows, as she has greater background knowledge of their relevant traits in a particular domain.

On the contrary, we move from social network analysis [16] and social psychology theories [17] which describe influence dynamics among individuals (Section 3) to support the idea that the mere fact of taking part into social relationships may cause individuals to modify their attitudes and behaviours. Following the the principle of *homophily* [12] we state that we are likely to have more in common with members of our social networks than with other members of the population, and more likely to like what

1 www.pandora.com
2 www.last.fm
3 http://findory.com
4 http://memigo.org
5 http://tailrank.com

they like, independently by our preferences, and by the competence and trustworthiness in a particular domain of the network members.

Therefore, the algorithm we propose can be used by social recommender systems to suggest items not only on the basis of user's preference/interest, like in traditional social recommender systems, but also considering the trend of the user's social network, its structure and the influence relationships among users.

3 Social Background

Several theories in social psychology describe influence dynamics among individuals. Since we defined social networks based on social relationships, stating that such a relationship exists between individuals A and B if A performs an action which refers to or has an effect on user B [16] (e.g., A peruses B's user profile, as far as the domain of social websites is concerned), we can claim that joining in a network with other people exposes individuals to social dynamics which can influence their attitudes and behaviours. More specifically, we can therefore hypothesize that individuals become interested in topics or subjects that do not necessarily match their personal pre-existing preferences and tastes, but that reflect those of the network.

In the following, we briefly sketch three complementary theories of social influence [17] (*Social conformity* (3.1), *Social comparison* (3.2), and *Social facilitation*, (3.3)) which have been considered for the definition of our algorithm.

3.1 Social Conformity

The classical theory of social influence states that people belonging to a group usually experience a "pressure to conform", namely, they tend to change their attitudes and behaviours to match the expectations of the other members ($normative\ influence$). Conformity can be often limited to exterior, observable features and fail to alter the underlying principles. According to psychology literature, conformity, far from being an irrational process based on "suggestion", is a conscious and rational social dynamic aimed at allowing people to build an objective and shared vision of the world. Indeed, when they are required to make a decision or judgment, or to build a theory about some phenomenon, people take into consideration all the available information, regarding, on the one hand, their own perceptions and opinions and, on the other hand, social information coming from relevant others -that is, other members of the group.

In such a scenario, individuals who deviate from the vision advocated by the majority represent a sort of obstacle for the group to jointly achieve its goals and are therefore exposed to explicit or implicit pressure to conform; in case such pressure is not effective, they are usually excluded from the group itself.

As a consequence, people should be interested in topics which reflect the "shared vision of the world" of the groups they belong to, so that they can conform to it, at least superficially, and act as fully-integrated group members.

3.2 Social Comparison

People actively seek information about the opinions of others in order to evaluate how they compare and to correctly form their own attitudes and behaviours. In fact, after that social comparison has occurred, people usually act so that they minimize any differences they may have found. Social comparison most often occurs when people lack objective means for evaluation, being in a state of uncertainty about what they should be thinking or doing; in addition, the effects of social comparison are especially evident if people compare themselves to individuals who can be considered somehow similar to them (e.g., for their age or abilities), since these represent good comparison points.

In contrast with conformity, in social comparison processes the influenced individual plays an active role; moreover, in this case influence is not normative, but informative ($social\ proof$). As a consequence, people who are new to a certain context or are not expert of certain domain should be interested in topics which reflect the opinions of other individuals in their network, since these represent useful information for them to form their own attitudes.

3.3 Social Facilitation

Social facilitation occurs when people are encouraged in performing a certain target behaviour as a consequence of the physical or virtual company of other people; in other words, if they can observe others performing the same behaviour and are conscious that these people are also observing them.

In contrast with the previously exposed theories, social facilitation dynamics can influence the level of motivation, involvement, frequency and effectiveness, but do not refer to behaviours for which a certain individual had no pre-existing interest.

As a consequence, people who are interested in a certain topic, but lack strong motivation, should appreciate information showing that other people in their network share their interest, since this encourages and motivates them.

4 SoNARS: The Social Networks-Based Algorithm for Social Recommender Systems

Typically, the recommender module produces a ranked list of domain items tailored to the user preferences and interests, where such parameters can be estimated considering different approaches. More specifically, in collaborative recommenders interests and preferences are inferred on the basis of "person to person" similarity, while in content-based recommenders they are inferred on the basis of the match between the attributes of the item and the attributes of the user profile. Finally, hybrid recommenders use both user similarity and usage data [2,9].

On the contrary, the algorithm we propose exploits foremost social psychology theories (Section 3) to assess the interest of a target user x for an item to be recommended as a function i) of how much every user y in the target user's social network likes that item, *independently* of the similarity between the target user x and user y, and ii) of the strength of the relation among the target user x and user y. The idea at the basis of the algorithm is that the mere fact of taking part into social relationships may cause individuals to modify their attitudes and behaviours and they are more likely to be interested in what people belonging the their social network like, independently of their real preferences. Therefore, we consider that an item is likely to be recommended to a target user all the more another user in a deep relation with the target one in her social network likes the item.

The SoNARS algorithm takes into consideration the level of interest a certain item i has for each person y in the network of the target user x, balancing this value based on the strength of the relationship between x and y.

In particular, the total score ($Score_i$) is computed for item i and with respect to the target user x based on the following formula:

$$Score_i = \frac{\sum_{y=1}^{|users|} (Score_{iy} * R_{xy})}{\sum_{y=1}^{|users|} R_{xy}} \tag{1}$$

The formula sums up the results of the product of $Score_{iy}$ and R_{xy}, calculated for each user y. $Score_{iy}$ is the partial score indicating the level of interest item i has for user y and is determined considering the actions user y performed with respect to item i, such as clicking, posting, tagging, bookmarking and tagging. R_{xy} is the value indicating the strength of the relationship between the target user x and user y. The total sum is then divided by the term $\sum_{y=1}^{|users|} R_{xy}$, that is the total weight of all the relationships between the target user x and each user y in her network. $\sum_{y=1}^{|users|} R_{xy}$ represents therefore the *activism level* of user *x* in her social network.

It is clear from the formula that such a score need not be calculated for each item, since items for which no partial score $Score_{iy}$ exists relative to some user y for whom the value R_{xy} is positive can be automatically excluded. In other words, only the items on which at least one user y actually performed some actions (e.g., clicking, posting or tagging) can be taken into consideration by the SoNARS algorithm.

Notice that the measure of $Score_i$ as above defined, can be used by social recommender systems purely or such a value can be merged with the score of the actual interest of user x on item *i*, based on users' similarity or by monitoring user and usage data, as discussed in Section 6.

The following sections present how we estimate i) the strength of the relationship between x and y (Section 4.1) and ii) the level of interest a certain item i has for each person y in the network of the target user x (Section 4.2).

4.1 R_{xy}

R_{xy} represents the strength of the relation among the target user *x* and every user *y* of the target user's social network.

Before describing how we assess R_{xy}, let us explain how we conceive the network of the target user. According to network analysis, networks allow to represent relationships among people, which are usually heterogeneous and may vary according to several parameters such as their content, duration and frequency [16]. Moreover, they may or may not be mutual and they may be direct as well as indirect (e.g., actors A and B are directly connected if a tie exists between them; they are indirectly connected if A has some relationship with a third actor C and C is tied to B).

A social network can be effectively represented by means of a graph G = (V, E), where V is a set of nodes, corresponding to the actors, and E is a set of arcs, corresponding to the relationships which tie a couple of actors [16].

In our analysis, networks are defined as ego-centric networks where the target user *x* plays the role of focal node and the other nodes represent the users in relation with x[6]. In such a network, R_{xy} is the measure of the strength of the relation among the target user *x* and an actor *y* in her network. In the graph G representing the social network, R_{xy} is the length of every arc E joining *x* to other nodes. The higher is R_{xy}, the shortest is the path connecting *x* and *y*. But how can we measure the strength of the relation among a couple of users in a social recommender system? Since we define social networks based on social relationships, we claim that a relation between individuals *x* and *y* exists if *x* performs an action which refers to or has an effect on user *y*. Therefore, the more actions *x* performs on *y*, the higher R_{xy} will be. Thus, R_{xy} can be calculated by counting all the actions performed by *x* over *y*. In our case-study application (Section 5), as well as in many other social websites, a user is allowed to provide users of her social network with comments, messages, tags, invitations to take part to a virtual group, and so on.

Moreover, we considered that different actions may provide different pieces of evidence about the actual strength of the relation among *x* and *y*. The weights have been assigned based on the ideas expressed by Kobsa et al. [10] and our experience with iCITY [3].

R_{xy} is measured applying the following formula:

$$R_{xy} = \frac{\sum_{i=1}^{|actions|} (count_{xy}(i) * actionWeight(i))}{\sum_{i=1}^{|actions|} actionWeight(i)} \tag{2}$$

For each action type i, $(count_{xy}(i)$ is the total number of actions of type i performed by user *x* over user *y* and $actionWeight(i)$ is the weight of the action type i. The formula sums up the results of the product of $count_{xy}(i)$ and $actionWeight(i)$, calculated for each action type i; i ranges from 1 to $actions$ that is total number of action types we consider. Normalization is given dividing by $actionWeight(i)$ which represents the sum of the weights of all action types.

4.2 $Score_{iy}$

$Score_{iy}$ represents the level of interest a certain item i has for user y. This score is function of the actions user *y* performed on item *i*. Actions are considered in number and type, moving from the idea that actions reveal interest.

$Score_{iy}$ is derived by applying the following formula:

$$Score_{iy} = \frac{\sum_{a=1}^{actions} \frac{count(a_i) * AW(a)}{\sum_{j=1}^{items} count(a_j)}}{actions} \tag{3}$$

[6] For simplicity, we consider only direct relationships between the target user and the tied actors.

where, given the item *i* and the user *y*, (a_i) is action of type h that user y can perform over item *i*, while $AW(ah)$ is the weight associated to an action (a) accordingly to [3]. Finally, (a_j) is the action of type *h* related to item *j*. The obtained value is then divided by $actions$, that is the total number of action types.

A distinct value $Score_{iy}$ must be calculated for each item i on which a given user y has performed at least one action. In addition, such calculations must be repeated for all users y belonging to the network of the target user x.

5 Experimental Evaluation

Starting from our assumption that users are likely to be influenced by the network they belong to, the experimental evaluation we conducted aimed at assessing SoNARS algorithm with respect to its capacity to provide users with interesting contents. To this respect, we needed to understand if the recommended contents actually reflect the structure and influence dynamics in the social network of the target user or if we missed to consider some important parameters. Moreover, we were interested in understanding how relevant network recommendations actually are for users: this would be fundamental to assign a correct weight to this kind of recommendations if the network-based part of SoNARS algorithm were to be coupled with a traditional one, in order to provide users with contents which depend both on their own interests and on network dynamics.

Subjects. We selected a group of 45 subjects (20-50 years old, 21 females and 24 males) among the users of Facebook[7], according to an availability sampling strategy. Facebook was chosen as a test-bed since it is a very popular website where we could observe real social networks. All the selected subjects were considered target users.

Procedure. The experimental procedure consisted of two main steps: first, we identified the social networks of the target users and, after that, we generated recommendations for them with SoNARS algorithm. We opted for Facebook groups as items to recommend, for two reasons. First, Facebook groups can be compared to contents to be recommended in recommender systems; second, the huge number of groups per target user (approximately 210) suggests that users are probably pursued in subscribing to a group for other reasons besides their personal interests. Groups exist for very different subjects (from politics, to sport, to fun), organizations and geographical areas and consist in pages where users can post their contributions (e.g., comments and photos). Users can subscribe to groups in order to receive updates about their activities in their Facebook home page. We thought that groups are relevant contents with respect to social network dynamics since they actually aggregate people.

Social networks were constructed by parsing the target users' personal pages in order to identify i) all the persons with whom they interacted and ii) all the actions they performed which refer to or have an effect on another user. Each action was assigned a different weight based on the ideas expressed by Kobsa [10] and our past experience with iCITY DSA [3]. In particular, we considered the actions and the weights reported in the following in order to compute the value of R_{xy} for each person belonging to the network of the target users.

[7] http://www.facebook.com/

Comment: Weight = 0.6
Send Message: Weight = 0.9
Tag photo: Weight = 0.5
Group invitation: Weight = 0.6
Event invitation: Weight = 0.6

The complete list of the groups a certain user subscribed to was retrieved from the home page of all the people in the network of the target users and the corresponding partial score $Score_{iy}$ was computed for each group. For simplicity, as a special case of the formula we proposed, we only considered the action of subscribing, which was assigned a weight equal to 1. The total score $Score_i$ was then calculated for each group, considering each target user and her network separately from the others. Notice thet we kept trace of the users who had subscribed to the various groups. Recommendations for each taget user were generated by sorting the corresponding groups in descending order, according to their score.

Experimental task. Recommended groups were presented to the target users by means of a web interface in the style of Facebook pages, displaying the first thirty elements in the recommendation list (see Figure 1) and clearly indicating the names of the users who had already joined the various groups. Notice that the complete list of recommended groups could be retrieved by selecting the "Show all" link, as it normally happens in Facebook when long lists of groups have to be displayed. Target users were asked to indicate the groups they would like to subscribe to.

Performance measurement. We used *precision* and *recall*, which are popular performance measures in the domain of recommender systems [9], as well as *accuracy*, commonly used in machine learning. To evaluation purposes, we considered to be actually "recommended" only the first thirty groups in the recommendation list, since these are the items with the highest values for $Score_i$, that is, those which best reflect network dynamics. "Correctly recommended" groups are the recommended groups the target user would like to subscribe to. Groups "chosen by the user" (used in computing recall) are the groups the user would like to subscribe to, independently of the fact that they were actually recommended or not. As far as accuracy is concerned, true positives are represented by the correctly recommended groups, while true negatives are represented by the groups which were neither recommended (that is, the groups which were not displayed in the first page), nor chosen by users.

Performance results. The values we obtained were 0.67 for precision, 0.5 for recall and 0.8 for accuracy. In interpreting these results, notice that all the groups we propose are recommended, since they were all selected through SoNARS algorithm, according to the actions that users belonging to the social network of the target user performed on them; however, each group is assigned a specific score which reflects its esteemed relevance. When visualizing recommendations, we sort them in descending order according to their score and display 30 groups per page, so that the first 30 groups should be the most relevant to the target user. As explained in "Performance measurement", in computing precision, recall and accuracy we only considered the groups displayed in the first page as recommended.

facebook

Hi Anna,

in the following you can find the Facebook groups your friends have subscribed to. Every group shows your friends who joined it. Select the groups you would like to subscribe to by clicking on the corresponding checkbox.

Show all 264 groups

Groups	Your friends who joined in...	I'd like to join this group!
L' ALBERO GENEALOGICO	Giuseppe Cagno Valeria Carretto Lucia Cimmarusti Marco Cinquemui Dario Colavolpe Alessia D'Agostino Gian Francesco Rosso Kevin Imperiale Fabio La Viola Michele Marino Matteo Piseddu Bruno Rimedio Samuela Sculli	☐
Il gruppo di quelli nati tra il 1980 e il 1989	Valeria Carretto Elisa Chiabrando Lucia Cimmarusti Fabio La Viola Michele Marino Matteo Piseddu Paolo Sferlazza Enrico Zanirato	☐
L'EFFETTO PALLA DI NEVE	Elisa Chiabrando Dario Colavolpe Gian Francesco Rosso Fabio La Viola Michele Marino Matteo Piseddu	☐
Sostieni anche tu Belin su facebook...	Lucia Cimmarusti Emanuele Dabove Fabio La Viola Matteo Piseddu	☐
Facolta' di Scienze MFN - Corso di Informatica	Valeria Carretto Elisa Chiabrando Omar Cortassa Alessia D'Agostino Gian Francesco Rosso Fabio La Viola Elisa Marengo Paolo Sferlazza Alessia Visconti	☐
Torino	Roberto Barbaro Alessandra Boella Jurij Di Carlo Valeria Carretto Elisa Chiabrando Omar Cortassa Fabio La Viola Elisa Marengo Michele Marino Paolo Sferlazza Alessia Visconti	☐
Aboliamo CL	Valeria Carretto Matteo Piseddu	☐
NO al RITIRO PATENTE con tasso alcolico a 0.2%	Valeria Carretto Kevin Imperiale Matteo Piseddu Enrico Zanirato	☐
Nessuno tocchi Saviano!	Federica Cena Fabio La Viola	☐
JUVENTUS Or No Other	Lucia Cimmarusti Fabio La Viola	☐
TUTTO ESAURITO è il mio programma preferito!	Lucia Cimmarusti Gian Francesco Rosso Fabio La Viola Bruno Rimedio	☐

Fig. 1. The web interface used for the evaluation of SoNARS

Precision (0.67), which is probably the most interesting measure when evaluating recommending tasks, is quite satisfactory. This value suggests that network recommendations are actually interesting for users, so that they choose various groups among those displayed in the first page. Notice that the precision value could have been partially biased by the experimental task itself: as a matter of fact, users have been required to choose the Facebook groups they would like to subscribe to. This could have led users to provide *socially desiderable answers* [11], that is to choose those groups about significant and appreciable topics (like for the group "Say no to violence on children"), regardless of their social networks members subscriptions.

Accuracy (0.8) is definitely good, indicating that the algorithm tends to recommend groups that users actually choose and not to recommend groups that they do not choose. However, notice that target users selected on average 15 groups, consequently, the high value for accuracy is largely determined by the contribution of true negatives.

Notice that precision and accuracy are interdependent measures, since the number of correctly recommended groups is used to compute both. In examining the results for these measures, we must take into consideration the hypothesis that the relatively high number of correctly recommended groups is partially due to our visualization strategy, which presents the recommended groups in a prominent position. Users may have selected interesting groups in the first pages and then got tired and failed to carefully examine the whole list, therefore missing potentially interesting groups at the end.

The relatively low value for recall (0.5), which evaluates the capacity of providing a large number of correct recommendations, can be explained by the fact that the 30 recommended groups represented on average only one seventh of the complete list, which potentially contained many other relevant items (e.g., groups displayed in the second page probably had high values of $Score_i$ for most target users).

As a final remark, consider that our evaluation only considered network-based recommendations, while users' personal interests were not taken into account.

6 Conclusion and Future Work

The paper has proposed a new Social Networks-based Algorithm, called SoNARS, for recommending content in social recommender systems, both content-based and collaborative filtering. With respect to the related work, our algorithm estimates user's preferences and interests not only considering the actual user's preference/interest, like in traditional social recommender systems, but also considering the trend of the user's social network, its structure and the influence relationships among users.

The approach at the basis of SoNARS moves from social psychology theories which support the idea that the mere fact of taking part into social relationships may cause individuals to modify their attitudes and behaviours. In other words, we state that users are likely to have more in common with members of their social networks than with other individualsn, and more likely to like what they also like, independently of their real preferences and of the competences and trustworthiness of the network members.

In the immediate future work we plan to exploit SoNARS into iCITY [3], a social content-based recommender system we developed recently. Such an integration is aimed at investigating how network- and interest-based recommendations could be properly coupled in order to improve recommendations of relevant contents to users. Moreover, we will lead a further evaluation which integrates also a qualitative approach to collect explicit feedback from participants.

Regarding the algorithm, at the current stage it does not consider that a person's social network consists of acquaintances from different contexts. To improve SoNARS, we are working on modeling the relationship between two people by taking into account their shared context through FOAF [8].

As a final point, let us consider that in social recommender systems, and in social networks in general, calculating values of users trustworthiness and reputation is a very popular issue. In the social networks community several trust propagation mechanisms have been proposed. They are used to provide a trust value to a directly known user (e.g. [6]), as well as to all the users of the network. From this perspective, Heath and Motta [8] define a trust model by eliciting a set of dimensions typically used by people to determine the trustworthiness of recommendation sources, such as the user experience, expertise and affinity to her. At the current stage, SoNARS does not take into account trust. In the long run, we aim at investigating how trust and reputation can affect the strength of the relationships among users in her social network, how they both influence users preferences and interests, and how this can be estimated in SoNARS.

[8] http://www.foaf-project.org/

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