Building a Social Recommender System by Harvesting Social Relationships and Trust Scores Between Users

Daniel Mican, Loredana Mocean, Nicolae Tomai

Babes-Bolyai University, Dept. of Business Information Systems, Str. Theodor Mihali 58-60, 400599, Cluj-Napoca, Romania
{Daniel.Mican,Loredana.Mocean,Nicolae.Tomai}@econ.ubbcluj.ro

Abstract. Recommender systems were created to guide the user in a personalized way to interesting resources and to help users cope with the problem of information overload. A system's ability to adapt to the users' needs is based on gathering user-generated collective intelligence. In this paper, we present WSNRS, the system proposed for recommending content within social networks. The main goal of the system is to identify and filter the recently published valuable resources while taking into account the interactions and the relationships the user has within social structures. The interactions are logged and aggregated in order to determine the trust scores between users. Using the scores obtained, one can identify the types of relationship established between users; the scores will then be integrated into an adaptive global model used for recommending resources. Our approach presents several advantages over classic CF-based approaches and content-based recommendations regarding cold start, scalability and serendipitous recommendations. We will illustrate this with a case study that we made using data provided by the implementation of the system in a real online social network.

Keywords: Recommender systems, Social networks, Trust in social networks, Social networks recommender system, Collective intelligence

1 Introduction

The new technologies and concepts that Web 2.0 brings to web applications and the ever-increasing expansion of the Internet have brought about the emergence of a large number of online communities and social networks based on shared interests. The fast rise in popularity of social media applications has drawn the attention of hundreds of millions of users worldwide. At the same time, it has created new challenges for the developers and researchers dealing with online social applications.

This paper presents the architecture of the social recommender system WSNRS (Wise Social Network Recommender System), the method used for implementing it and a case study. The proposed system logs, aggregates and uses the collective intelligence obtained as a result of the interaction of users with each other and with the content in order to determine the trust scores between users. Using these trust scores, one can identify the most trustworthy users in the social structures of a network. The trust one user has in another is an important piece of information that helps us to improve the recommendation algorithms by efficiently identifying the valuable resources, i.e. the resources that determined the user to get involved. In our system, the user's involvement requires making comments, adding the resource to favorites, rating it, clicking and recommending it on social media websites.

The proposed system fits into the Web 2.0 social applications where users publish, share and interact with the published content. The content is published at an amazing speed and it is very difficult for a user to read and stay up-to-date with all the resources. Therefore, WSNRS aims at identifying the quality of the user-generated content within a social network. If a resource is of low quality, it will receive a low rating. If the resource has a high quality, it will be promoted and recommended to users. Thus, users will stay up-to-date with all the new resources that are relevant and that have a high quality without wasting time.

The proposed recommender system aims to be a guiding service, to provide personalized content and to adapt to the users' needs within a social network. It recommends the most recently published resources taking into account the explicit and implicit relationships that the user has within social structures. The advantage of the proposed system is allowing quality resources to become visible without the risk of losing them for ever in a databank. Thus, the system we propose manages to filter and rank the recently published resources in a specified time period. The system also fulfills the task of moderating resources automatically. This is of ultimate importance because in a system where the number of resources generated by users is very high, manual moderation becomes virtually impossible.

Our approach presents several advantages over classic Collaborative Filtering (CF)-based approaches and content-based recommendation. As the saying goes, birds of a feather flock together and we believe that in a group of friends/sympathizers there are common tastes. In our opinion, this approach does not suffer from the "cold-start" problem due to the fact that the user doesn't have to rate the content in order to receive recommendations. To send recommendations, only the social structure to which the user belongs needs to be considered. Moreover, we don't have to take into account all the elements of the clusters of users and resources, which is a major advantage when considering the scalability problem. We will only consider the sub-clusters of friends and resources published/preferred by them. In order to find a solution to the problem of providing "serendipitous recommendations", a problem which occurs in content-based recommender systems, we will include not only the texts published by friends but also the texts that they rated favorably.

The recently published resources will be recommended within the social structure to which the author belongs. If the resource is liked, it can go through many social structures and go viral in a short time. The purpose of belonging to a social network is keeping in touch with friends, following various celebrities, interacting and meeting new people. This is accomplished by sharing resources within the network. Depending on the shared resources, preferences and interactions, people get to know each other better, discover something new and meet other people.

This paper is structured as follows: Section 2 presents the problem of content recommendation, the approaches and difficulties encountered. Section 3 presents WSNRS, the system proposed for recommending content in social networks. In

Section 4, we will present a case study that will illustrate the way in which the relationships between users that are based on trust can be used in recommending resources. Section 5 contains the related work. In the end, we will present our conclusions and future development directions.

2 Content recommendation in social networks considering the collective intelligence

Recommender systems were created to guide the user in a personalized way to interesting objects and to help users cope with the problem of information overload. A system's ability to adapt to the users' needs depending on how they navigate a website, to predict these needs and to provide a navigation path is particularly important in a web application. A social recommender system can accomplish this just by analyzing the data from collective intelligence extracted from the social network. According to Ramos [11], collective intelligence allows the capturing of the collective behavior of entities that interact with their environment in order to develop functional global patterns. All this data is captured and used to acquire knowledge and to create profiles, reputation models or recommender systems. In order to be efficient, the created models have to adapt to the collective dynamics of the environment in order to deal with possible unforeseen circumstances and changes.

According to [10], there are two approaches for recommending content: content-based approach and collaborative filtering (CF). The content-based recommendation system attempts to recommend resources similar to those a user expressed interest for in the past. The main flaw of this system is its inability to provide "serendipitous recommendations". Serendipitous recommendations are recommendations that are not in the context of users history of visited resources and have the ability to surprise in a positive and pleasant way. The collaborative filtering system takes into account reviews, ratings or explicit voting; its main role is to identify users with preferences similar to those of the current user in order to recommend resources that they prefer. Leaving its advantages aside, the collaborative filtering system faces problems [5], such as "cold start", sparsity, scalability and the malicious ratings. Cold start problem applies to new published resources that anyone in the community has not rated yet.

In social networks, the users are in the centre of the universe. This universe is based on technologies that allow the remodeling of applications with regard to structure, design and usefulness. In recent years, we have witnessed an online social revolution where the users started forming relationships, publishing, aggregating and storing content. These interactions have led to the building of online communities and social networks based on shared interests. Social networks [14] are being made of a finite group of people and the relationships they establish among them. The existence of information on the established relationships is a key feature of social networks. Analyzing the data generated by users within social networks has several practical applications that can be used to develop personalization and recommendation systems, and identification of trends within social systems.

Hogg [4] believes that users with similar preferences and characteristics tend to associate in social networks. This allows the improvement of collaborative filtering systems by considering users' preferences based on social distances and increased efficiency of the reputation mechanisms. The approach based on information provided by user communities recommends resources by taking into account their friends' preferences. This method is inspired by the proverbs: "Birds of a feather flock together" and "Tell me who your friends are and I'll tell you who you are".

3 Wise Social Network Recommender System (WSNRS)

In this chapter we will briefly describe the formal approach, the architecture and the way to implement WSNRS. On the one hand we will describe the method to calculate trust among users and on the other hand we will present the deduction of the follower's implicit status. In this article we define a follower as a user who is an enthusiastic supporter of another user in regard to his or her ideas or belief.

3.1 The formal approach

In our approach any existent relation between two users is represented by a vector that contains all interactions the users had over time.

Definition: A user-user relationship is represented by a vector: $V = (IdU_i \rightarrow IdU_j, LT, NF, NRw, NR, NC, NCk, TSt, T) \in M_{1x9}(R)$. In this formula, l represents the number of existing links among users and v_t the vector corresponding to each relationship for $t=1,l$. In what follows we will describe the vector attributes V:

- $IdU_i \rightarrow IdU_j$: represents the existing connection from user i to user j.
- LT: represents the type of the existing connection between user i and user j, $LT \in \{0,1,2\}$. The first element represents a connection of low intensity, namely below average. The second element represent an explicit connection, and the third one represents a connection of high intensity, above average.
- NF: is the number of favorite resources published by the user j, $NF \in [1, \infty)$.
- NRw: represents the number of positive reviews granted by user i to the user j or to the resources published by the user j, $NRw \in [1, \infty)$.
- NR: represents the number of user's recommendations or of the published resources within the social media sites, $NR \in [1, \infty)$.
- NC: represents the number of involvements resulted from the comments posted on the user's profile page or on the resource's pages published by the user j, $NC \in [1, \infty)$.
- NCk: represents the number of clicks to see the user j profile or the resources published by him, $NCk \in [1, \infty)$.
- TSt: represents the timestamp of last interaction initiated from user i to user j.
- T: represents the calculated trust score offered to user j by user i, $T \in [0,1]$.

We will use the same formal approach with regard to the relationships that are going to establish between users and content. The vectors containing the interactions among users are stored in tables of the form: *user_user*, whereas those containing the interactions among users and pages will be stored in a table of the form: *page_user*. The structure of the two tables is illustrated in Fig.1.

In order to calculate the trust score T_i for $IdU_i \rightarrow IdU_j$, we have normalized the following attributes of the vector v_i: *NF*, *NRw*, *NR*, *NC*, *NCk,* so that the attributes contain numeric values in the interval [0, 1].

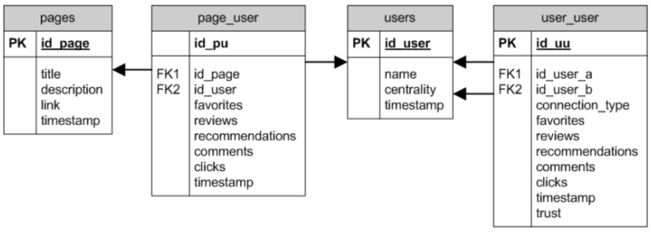

Fig. 1. Database structure for the proposed recommender system

The values have been normalized with the "min-max normalization" [2]. This is a method that performs a linear transformation of input data *v* to *v'* of an attribute *NF,* so that these data can be found in the interval [0, 1]. The formula adapted for the *NF* attribute of the vector *V,* is shown below:

$$v' \frac{v - \min(NF)}{\max(NF) - \min(NF)} * (1 - 0) + 0 \qquad \textbf{(1)}$$

The formula for the trust score T_i for $IdU_i \rightarrow IdU_j$, is illustrated below. The trust score is calculated for $\forall v_i$, $i = 1,l$.

$$T_i = \frac{1}{5}\left(\frac{vNF_i}{\max(NF)} + \frac{vNRw_i}{\max(NRw)} + \frac{vNR_i}{\max(NR)} + \frac{vNC_i}{\max(NC)} + \frac{vNCk_i}{\max(NCk)}\right) \qquad \textbf{(2)}$$

On the basis of T_i, that is calculated for all $IdU_i \rightarrow IdU_j$ links, all follower implicit links will be deducted. Where $T_i \geq \sum_1^l T_i / l$ all links $IdU_i \rightarrow IdU_j$ will have $LT = 2$. This means that the trust score is sufficiently high to transform the user in follower.

3.2 The architecture and the implementation of WSNRS

The main aim of the system is to identify and recommend the valuable resources that have been published recently. In order to achieve this goal, the system takes into account the collective intelligence resulted from the user's interaction within the network. Furthermore, the collective intelligence is collected and quantified with the "Data collection module". The interactions among users are managed with the "User-user interactions management module", whereas those among users and resources are managed with the "User-content interactions management module". The architecture of the system is illustrated in Fig.2.

The user-user interactions management module identifies all interactions that take place among users and among users and resources. All these interactions are managed by this module and then are stored in the *user_user* table. If two users interact for the first time, the system creates a new vector v_i that contains the link between $IdU_i \rightarrow IdU_j$. However, if the users have interacted in the past the corresponding vector will be updated. If the IdU_i user will add a positive review to IdU_j profile or to a published resource, NRw with a unity will be incremented, $NRw = NRw + 1$. The same happens with the NF, NC and NCk attributes.

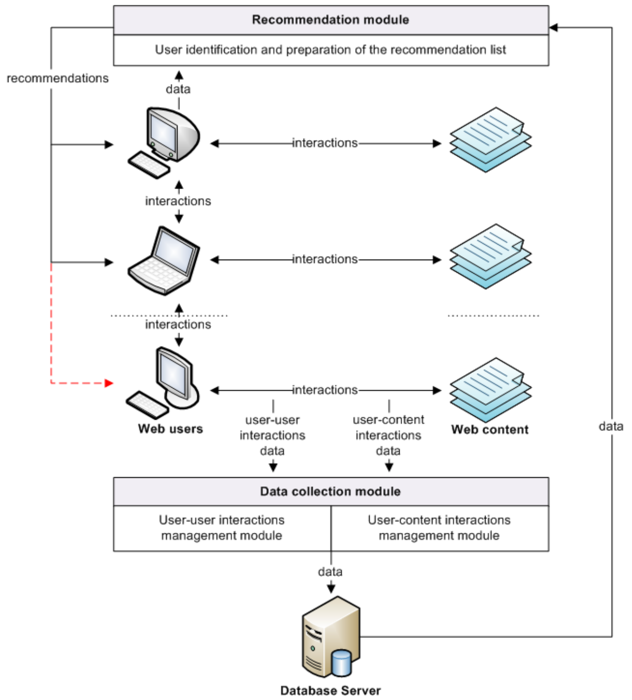

Fig. 2. WSNRS. The proposed architecture

With regard to the *NR's* attribute, the update is more complicated compared to the others. This is due to the fact that a user can give a "like" on the facebook button and recommend the text and after a period of time to withdraw the "like". The system succeeds in capturing not only the "like" action, in which case $NR = NR + 1$, but also the "dislike" action, in which case $NR = NR - 1$. The same is true for the module "User-user interactions management module".

Besides logging and updating the interactions, in this module we have integrated an algorithm that calculates the trust scores T_i, $\forall\, v_i$, $i = 1,l$, and updates the type of existing connection LT among users. If T_i is over average, results $LT = 2$, meaning that the user is an implicit follower, if not, than $LT = 0$. The time calculation of this algorithm increases with the number of existing links within the social network. Due to this fact it is recommended to run at predetermined periods of time depending on the number of interactions that have been realized in a certain period of time.

The recommendation module is designed to identify the current user on the basis of IdU_i and to prepare for this a recommendation's list. The recommended resources will include not only the texts published by the trusted users but also those that have been favorably rated. In order to achieve this goal, the algorithm will identify all connections that $IdU_i \rightarrow IdU_j$ has with $LT > 0$. Furthermore, the algorithm will extract user's IdU_j Ids and will return the most recent text published by this users. Likewise, it will also search for the most recent interactions of these users with the published texts and will return the texts list they have interacted with. The final recommendations represent an aggregation of the two lists mentioned above.

4 Case Study

As soon as a user accesses a website and until he/she closes the navigation, he/she performs a series of interactions. In the following section, we will present a case study in order to see how these interactions can be quantified and aggregated to create an adaptive global model. We will begin by presenting the framework used for the case study. Then, we will identify the relationships that users establish and we will determine the level of trust that one user has in another user. And finally, we will illustrate the way in which these relationships based on trust can be used in recommending resources within the network.

In order to achieve this goal, we implemented the proposed recommender system on the portal Intelepciune.ro. With an average number of 300,000 unique visitors for month, this portal is on the top list of Romanian cultural websites, being supported by a large community of users. In this portal, we created a section for a literary circle where any user can publish his own literary works. Due to the fact that Intelepciune.ro was built using Web 2.0 principles, it is possible for users to interact both with the published resources and with other users. Users can comment, rate, add to favorites or recommend any user profile and resource on social media channels.

For the purpose of creating this case study, we collected data provided by the social network that developed in the literary circle section on Intelepciune.ro. During the time period in which we collected data, 511 out of a total of 6,723 registered users established interactions. We quantified a total number of 16,620 direct interactions established among users and indirect interactions established through published resources. The number of interactions was calculated by taking into account the ratings, additions to favorites, recommendations, comments or clicks. After analyzing the interactions, 1,388 links between users were identified. 6.23% of these links are follower relationships expressed explicitly and 18.62% were inferred implicitly based on the proposed algorithm. The relationships established between users also reveal the structure of the social network and of the interest groups respectively. This structure can be subsequently analyzed.

The visual representation of the structure of the social network can be seen in the sociogram illustrated in Fig. 3. This is represented by an oriented graph that reveals the strongest links within the network. Due to the limited space and in order for the graph to be intelligible, we depicted only the first 50 links using arcs. 41 vertices were involved in these links. Thus, one can see the graphic representation of the links, the users involved in these links and the level of trust between the users. Also emphasized are the structures of the established groups that allow the identification of interest groups, leaders and isolated individuals.

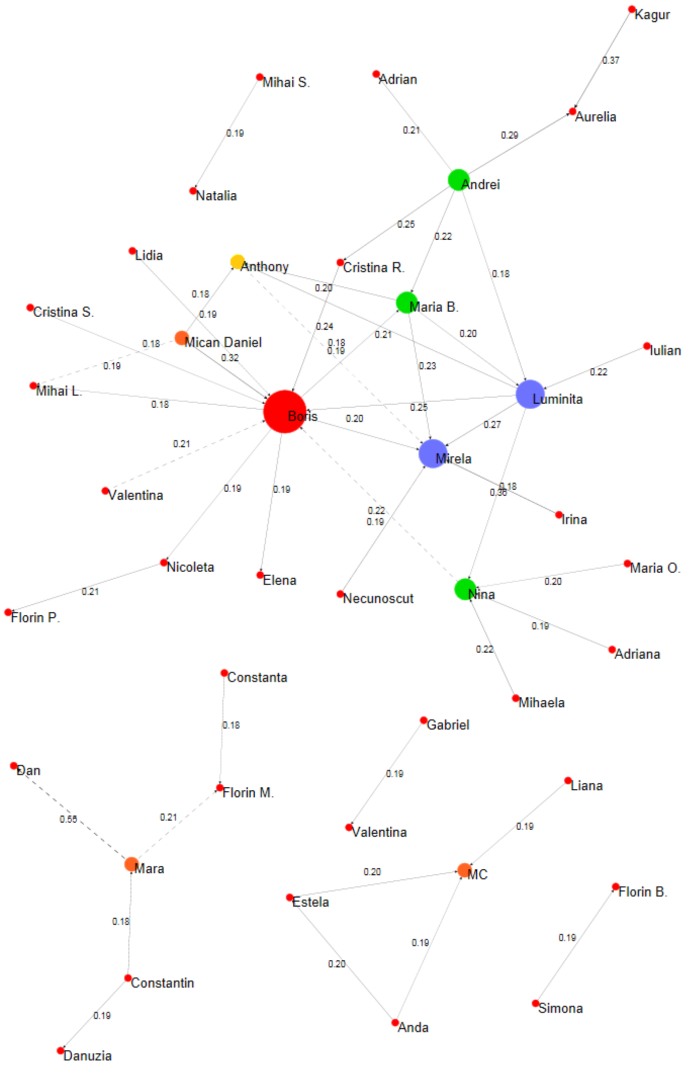

Fig. 3. The interest groups, types of relations and trust scores between users

In the graph, each vertex represents a user and the size of the vertex corresponds to its centrality within the network. The arcs between vertices represent the links that the users established and are labeled with a trust coefficient that was calculated by applying the suggested algorithm. The resulted values were normalized in order to be in the range [0.00, 1.00]. The links were ranked based on how close they were to the best result, which tended to reach value 1. If there is an explicit connection between two vertices, the arc is represented by a continuous arrow and if the connection is implicit, by a broken arrow.

Upon analyzing the graph, we notice that the vertex with the most central position within the network is Boris. This vertex has high levels of trust provided by the neighbouring vertices. The vertex Mican Daniel has the highest level of explicit trust in the vertex Boris and its value is 0.32. This is followed by the trust level of the vertex Luminita with a value of 0.25 and Cristina R.'s with a value of 0.24 respectively. As to the implicit trust, we can see that the vertex Nina provides a level of 0.22. The vertex Boris is that much more important considering that the neighbouring vertices also receive high centrality values and high trust levels.

Concerning the structure of the social network, we notice that three interest groups emerged at the top. The first group is created around Boris, the central vertex with the leading role. The vertices Mirela, Luminita, Nina and Maria B. are also noticeable within this group. In the second interest group, MC is the central vertex and in the third group, the vertex Mara plays an important role. Moreover, isolated links were identified between the vertices Natalia and Mihai S., Valentina and Gabriel, Simona and Florin B.

What comes as a surprise for us is the fact that the strongest connection within the network is represented by an implicit connection that was discovered using our algorithm. The connection has a trust level of 0.55 and is directed from the vertex Mara to the vertex Dan. This is followed by explicit connections with trust levels that are equal to 0.37, 0.36 and 0.32. The connections are directed from the vertex Kagur to Aurelia, from Luminita to Nina and from Mican Daniel to Boris, respectively.

Below, we will provide an example in order to see how the trust relationships established between users can be used to recommend resources within the network.

Fig. 4. List of recommendations for user Mican Daniel

In order to receive recommendations, a user must have the role of a follower, regardless of the fact that it was expressed explicitly or inferred implicitly. The newest resources will be recommended in the current version of the proposed recommendation algorithm. The recommended resources will be resources that have been published or positively rated by the users that the current user is following. In Fig. 4, one can see the list of recommended resources for the user Mican Daniel.

The list of recommendations contains ten resources arranged after the date when they were published. For the purpose of ensuring the transparency of the recommendation, the author of the resource is specified under the name of the resource along with the type of the relationship and the trust level that the current author has in the author of the resource. Concerning the fifth resource, we can see that it was published by Mihai L. The resource was recommended because the user Mican Daniel is an implicit fan of the user Mihai L. This is represented by the digit 2 enclosed in brackets and the level of trust in Mihai L. We can also see that resource number 5 was positively appreciated by Maria B. and Elena. Mican Daniel is an explicit fan of these users, which is evidenced by enclosing digit 1 in brackets. Resource number 6 was recommended due to the fact that it was liked by Boris and Mican Daniel is an explicit follower of Boris'.

The recommender system proposed was implemented and can be accessed online at the address: http://www.cenaclu.intelepciune.ro. The system can be accessed by creating a new user account or by logging into the account created by us for the purpose of testing the system. The user name and password for this account is WSNRS. The list of recommendations containing additional information on recommendations, the user who published/liked the resource, the type of follower and the trust level can be accessed at: www.cenaclu.intelepciune.ro/wsnrs.php?id=6731.

5 Related Work

As is well known, people usually ask their friends for recommendations when they want to see a film, read a book, listen to a song, find a place to spend their free time or consult any online resource. Therefore, we could assume that users place a higher degree of trust in recommendations made by their friends than in those made by people unknown to them who could share similar preferences. After studying the specialized literature, we reached the conclusion that the above-mentioned hypothesis tends to be true in most cases. The researches published in [12] include a study that drew comparisons between the recommendations made by six popular recommender systems and recommendations made by friends. Results showed that the user's friends constantly provided better recommendations than the analyzed recommender systems.

The use of existing links between users in social network to make recommendations surpasses the classic CF-based approach. This conclusion was reached after an extensive study was made in a social network of over one thousand participants and was published in [1]. Moreover, a collaborative recommender system was created in [6] that takes into account both ratings and social relationships illustrated using a tripartite graph involving users, resources and tags. These experiments also proved that the suggested social system performs better than the CF system based on determining similarity using the Pearson correlation coefficient.

A trust-based recommendation approach was suggested in [3]. This approach can recommend trustworthy agents in a social network. The initial premise was that an agent can be recommended as long as the agent's neighbors display a high level of trust in him/her. The system is modeled by using graphs and by defining similarity measures and determining trust values. To make recommendations, both the structure of the network and the trust values associated with the links are considered. A trust-based recommendation approach is suggested in [13] as well. In this system, agents use the social network to find resources and the established trust relationships to filter them. The system is self-organizing and takes into account the density of the network, the eclectic nature of the preferences and the knowledge sparseness. Furthermore, a study was conducted to examine how the dynamics of trust among agents influences the performance of the system by comparing it to a frequency-based system. Making recommendations based on what many individuals do was approached in [9]. This approach creates a Decision Data Model that depicts the data used and how it was derived by a large number of decision makers during the decision making process.

The consumers' preferences and interests can be identified on the basis of the knowledge extracted from the interests of their neighbours in the social network. Tad Hogg [4] identified the requirements for the network architecture and the correlation among preferences which contribute to the identification of large groups of users with similar interests. This knowledge improves the usefulness of deriving products from the social network. Based on the information gathered from a few users in the network, the consumers may be interested in these products. Therefore, the final estimations help design combined services for complementary products.

Conclusions

In this paper, we have illustrated and described the architecture of WSNRS which stands for the recommender system proposed for social networks. In order to accomplish our goal, we have shown the way in which the system logs and aggregates collective intelligence in order to calculate the trust scores between users. The trust among users is revealed by the information that helps to identify the types of relations established among users and define the social structures. Based on the scores and the types of relations established, we have developed an adaptive global model that enables recommendation and filtering of valuable resources recently published. On the one hand, the recommended resources take into account the relationships that the user has within social structures and on the other hand, they adapt themselves to the collective dynamics of the environment. Likewise, a very important aspect is that the system fulfills the task of moderating resources automatically, which is particularly important in the social network where manual moderation is impossible.

The results of the case study presented in this paper, coming from a real online WSNRS implementation, have revealed the way in which the computed trust scores allows to discover implicit connection between users that was not explicitly expressed and to define the interest groups. Furthermore, we have shown that on the basis of the aggregated trust scores, one can identify group leaders, isolated individuals and the most trustworthy existing users in social structure. Moreover, we have demonstrated that our approach brings a number of advantages over traditional CF-based approaches and content-based recommendation. Recommendations can be realized according to the user's social structure, without having to rate the content. According to our approach, the similarity with other users is revealed by the computed trust scores. This aspect, successfully solves both scalability and "cold start" problems.

Due to the fact that the provided recommendations include not only the text published by the friends but also the favorable rated texts, the user will be positively surprised by the resources and receive “serendipitous recommendations”.

In future works, we plan to study the way in which trust can be transferred from user to user and from user to resources. Further research with respect to [8] will focus on improving the model by integrating a recommender system with the help of tags. Thus, experts and trusted content identification in different categories of interest will be possible. Likewise, we aim to achieve hybridization through aggregating with the system that was proposed in [7] and that is based on extracting association rules from navigation sessions. Therefore, in future works, we will concentrate on developing a new hybrid system that aims to solve the problems encountered in traditional recommender systems.

References

1. Groh, G., Ehmig, C.: Recommendations in taste related domains: collaborative filtering vs.social filtering. In: GROUP ’07: Proceedings of the 2007 international ACM conference on Supporting group work, pp. 127-136. ACM, New York (2007)
2. Han, J., Kamber, M., Pei, J.: Data Mining: Concepts and Techniques (3rd ed.). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA (2011)
3. Hang, C.W., Singh, M.P.: Trust-Based Recommendation Based on Graph Similarity. In: The 13th AAMAS Workshop on Trust in Agent Societies (Trust) (2010)
4. Hogg, T.: Inferring preference correlations from social networks. J. Electronic Commerce Research and Applications, 9(1), 29-37 (2010)
5. Kim, H.N, Ji, A.T., Jo, G.S.: Enhanced Prediction Algorithm for Item-based Collaborative Filtering Recommendation. LNCS, Vol. 4082, pp. 41-50. Springer-Verlag, Berlin (2006)
6. Konstas, I., Stathopoulos, V., Jose, J.M.: On social networks and collaborative recommendation. In Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval, pp. 195-202. ACM, New York (2009)
7. Mican, D., Tomai, N.: Association-rules-based recommender system for personalization in adaptive web-based applications. In: Proceedings of the 10th international conference on Current trends in web engineering (ICWE'10), pp. 85-90. Springer-Verlag, Berlin, (2010)
8. Mican, D., Tomai, N.: Web 2.0 and Collaborative Tagging. In: Proceedings of the 2010 Fifth International Conference on Internet and Web Applications and Services (ICIW '10), pp. 519-524. IEEE Computer Society, Washington, DC, USA (2010)
9. Petrusel, R., Stanciu, P.L.: Making Recommendations for Decision Processes Based on Aggregated Decision Data Models. In Abramowicz, W. et al. (Eds.): BIS 2012, LNBIP 117, pp. 272–283. Springer-Verlag Berlin Heidelberg (2012)
10. Ramezani, M., Bergman, L., Thompson, R., Burke, R., Mobasher, B.: Selecting and Applying Recommendation Technology. In: Proceedings of International Workshop on Recommendation and Collaboration, in Conjunction with IUI 2008, Canaria, Spain (2008)
11. Ramos, V., Fernandes, C., Rosa, A.: Social Cognitive Maps, Swarm Collective Perception and Distributed Search on Dynamic Landscapes, J. of NMNCSE, Germany (2005)
12. Sinha, R.R., Swearingen, K.: Comparing recommendations made by online systems and friends. In: DELOS Workshop: Personalisation and Rec. Systems in Digital Libraries (2001)
13. Walter, F.E., Battiston, S., Schweitzer, F.: A model of a trust-based recommendation system on a social network. J. Autonomous Agents and Multi-Ag. Sys. 16, 1, 57-74 (2008)
14. Wasserman, S., Faust, K.: Social Network Analysis: Methods and Applications (Structural Analysis in the Social Sciences), Cambridge University Press, New York, USA (1994)