Recommendation of Learning Resources based on Social Relations

Mohammed Tadlaoui[1,2], Karim Sehaba[3] and Sébastien George[4]
[1]*Université de Tlemcen, LRIT, Tlemcen, Algeria*
[2]*INSA de Lyon, LIRIS, UMR5205, F-69676, Lyon, France*
[3]*Université de Lyon, CNRS, Université Lyon 2, LIRIS, UMR5205, F-69676, Lyon, France*
[4]*LUNAM Université, Université du Maine, EA 4023, LIUM, 72085, Le Mans, France*

Keywords: Recommender Systems, Educational Resources, Social Networks, Social Influence.

Abstract: Recommender systems are able to estimate the interest for a user of a given resource from some information about similar users and resources properties. In our work, we focus on the recommendations of educational resources in the field of Technology Enhanced Learning (TEL) and more specifically the recommendations which are based on social information. Based on the results of research in recommender systems and TEL, we define an approach to recommend learning resources using social information present in social networks. We have developed a formal model for the calculation of similarity between users and the generation of three types of recommendation. We also developed a platform that implements our approach.

1 INTRODUCTION

Social media are increasingly used in education. They are either integrated into an LMS or used in standalone mode (Popescu, 2014). This type of media focuses on the interactions and mutual support between learners.

In social networks (Guy and Carmel, 2011), users suffer from information overload due to the multitude of resources and interactions related to the multitude of social relationships. To address this problem, we propose to recommend the users relevant resources based on existing social relationships.

Thus, the objective of our work is to propose an approach that allows customizing educational resources based on connections in social networks.

Our work is based on two principles identified by research in social science:

- the co-citation regularity (Bhagat et al., 2011) that stipulates that similar individuals tend to refer or to connect to the same resources;
- social influence (Sun and Tang, 2011) indicates that individuals tend to follow the behaviour of their friends.

The first principle is used in classical recommender systems. These systems are mainly based on the evaluation of similar users for a given user to predict her/his preferences. However, this kind of recommendation systems ignores the social influence connections between users. This type of connections can be used to increase the accuracy and relevance of recommendations.

According to the second principle, people who are socially connected can share the same interests or similar interests. So the users of a system can be easily influenced by their friends and be interested in their activities. This principle is used in social recommender systems.

In recent years, a particular research area of recommender systems has emerged. It concerns recommender systems for Technology Enhanced Learning (TEL). Drachsler (Drachsler, 2012) explains that this type of systems uses the experiences of a community of learners to help learners of this community to more effectively identify learning content or peers students from a set of potentially very wide choices.

Several recommendation systems dedicated to TEL were developed during the last decade. One of the first systems is Altered Vista (Recker and Walker, 2003). It collects assessments that users attribute to educational resources and propagates them in the form of "word-of-mouth" recommendations on the qualities of resources. RACOFI (Anderson et al., 2003) is a similar system; it incorporates an inference engine based on rules. LSRS (Huang et al., 2009) is a recommendation system which is based on sequencing rules and the analysis of learning groups. ReMashed (Drachsler et

Tadlaoui M., Sehaba K. and George S..
Recommendation of Learning Resources based on Social Relations.
DOI: 10.5220/0005452304250432
In *Proceedings of the 7th International Conference on Computer Supported Education* (CSEDU-2015), pages 425-432
ISBN: 978-989-758-108-3

al., 2009) asks learners to evaluate information from an informal learning network. This system uses these evaluations and tags associated with resources to make the recommendation.

The existing recommendation systems mainly use evaluations from users and their similarities to propose them resources adapted to their needs. However, they do not exploit the information contained in the profiles of similar users. Thus, in order to customize and make relevant the recommendation, we propose to use, in addition to the profile of the target user, the information present in the friends' profiles. It is mainly about the characteristics of friends' profiles, information on resources visualization, their utilities relative to learning fields and the results of exercises performed by a learner. Based on the co-citation regularity and the social influence theories, we hypothesize that the use of this information can help to make the recommendation richer, comprehensive and tailored to the needs of the user. The research question that we try to answer in this paper is "How to generate more specific recommendations, and therefore more relevant ones, basing on social relations and user evaluations? ".

Our approach is adapted to the traditional acquisition which is based on the sharing of resources. Nevertheless, being based on educational social network, the proposed approach can provide more interactions between users and so encourage collaborative learning.

The characteristics of a user's profile can be incomplete, outdated or inappropriate. In our approach, as the recommendation is based on user's characteristics, the quality of this recommendation is relative to the quality of these characteristics. In addition to the recommendation of learning resources, we think that social relationships can also help to enrich or correct the information stored in the learner profile based on the information present in the friends' profiles.

The paper is organized as follows: the first part presents the state of the art on recommendations in a social context and in the context of TEL. The second part presents the approach we propose to address the problem of information overload. Our approach identifies three types of recommendations of educational resources (recently viewed resources, popular resources and useful resources) and also a type of recommendation to help users to complete their profiles. The third part contains an illustration of our approach and the last part presents a conclusion and perspectives to our work.

2 RELATED WORK

Recommender systems have existed since the 90s (Resnick and Varian, 1997). The most commonly used methods in these systems are based on collaborative filtering (Goldberg et al., 1992) or are content-based systems (Pazzani and Billsus, 2007). The first method recommends resources from the similarity between user's preferences. The second method is based on the recommendation of resources that are similar to resources for which the user has expressed an interest in the past.

The algorithm of collaborative filtering was extended to be more scalable for large user bases. This extended method is called "item to item collaborative filtering" and it is one of the most widely deployed recommender methods today. For instance, this method is used by Amazon (Linden et al., 2003) for recommending products and LinkedIn (Wu et al., 2014) for recommending peoples, jobs, companies, groups, and other entities recommendations.

Since the last decade, recommender systems have increasingly used social information to improve the quality and relevance of the recommendation. Bellogína *et al.* (Bellogína et al., 2013a), (Bellogína et al., 2013b) divide the social recommender systems into four types:

1. Friend Based Recommender: this type of system uses collaborative filtering method but just by taking into account users that are explicitly declared as friends by a user.
2. Social Popularity Recommender: in this type of system, it is the most popular resources for the friends of a user that are recommended to her/him.
3. Personal Social Recommender: systems that are part of this type use the distance between users in the social graph to make the recommendation. The more users are far from a given user, the less the weight of evaluations of their resources is important in the formula for calculating the recommendation.
4. Hybrid Recommender: this type of system can use several methods of recommendation to take advantage of the benefits of each one.

Drachsler *et al.* (Drachsler et al., 2008) explain that recommender systems used in the educational field are different from those of other fields such as e-commerce. This difference is due to the fact that the objectives and user models in both types of systems are not the same. In (Drachsler et al., 2013), authors provide an analysis and comparison framework between recommender systems for TEL. These systems are classified according to several categories: supported tasks, user model, domain model, personalization, architecture, location and recommendation mode. In our work, we consider the first category that handles user tasks supported in a recommender system for TEL. The tasks that can be performed by the users of such systems are:

1. Find novel resources: recommendation of new resources in particular resources never viewed by the user.

2. Find interesting users: recommendation of other users for which a particular user may be interested, for example, offer an expert user in a domain or provide a user with similar interests.

3. Find good pathways: recommendation of learning path through educational resources, for example, propose a list of possible paths for the same resources to achieve a learning objective.

The approach that we propose fits into the first type of social recommender systems (friend-based recommender) and also in the first category of recommender systems for TEL (find novel resources).

3 SOCIAL RECOMMENDATION APPROACH

Since the context of our work concerns the social networks for learning, our approach (Tadlaoui, 2014) illustrated in Figure 1 is based on 1) data that describes users and stored in their profiles, 2) data on different types of links between users and between the groups to which they belong and 3) feedbacks on results of exercises made by learners. All these data will be used to make recommendations to learners.

Figure 2 illustrates the overall principle of our approach. Each user of the system is described with some information that characterizes her/his profile and is linked with friendships links with other system users. Users can view educational resources and they can also evaluate the quality and usefulness of the resources they have already seen.

In our approach, we define friendship as a link explicitly declared by a user of the system. Two types of friendship are supported, friends that the user knows in real life and has declared as friends on the social network and those she/he knows only on the social network. In both cases, following the principle of social influence, these friends may have the same interests, and following the principle of co-citation regularity, if these friends have some similarities in common, so they will be more likely to have the same interests.

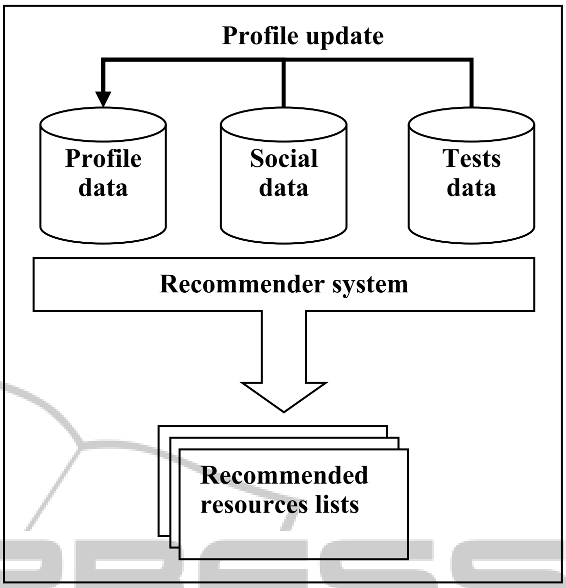

Figure 1: Overall architecture of the proposed approach.

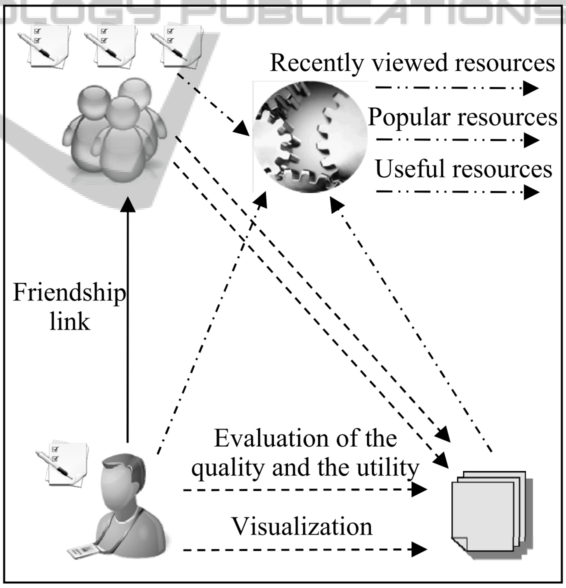

Figure 2: Overall principle of the proposed approach.

From the information that describes the users, resources, and links between them, the system generates lists of recommended resources for a given user. These lists are customized for each user of the system and are divided into three types, namely recently viewed resources, popular resources and useful resources.

The overall process of the recommendation system involves the following steps:

1. Select a type of recommendation;

2. Select users related to the current user by a friendship link;
3. Calculate the degree of similarity between the active user and her/his friends, following several criteria (explained in section 5);
4. Calculate the score of resources based on actions (visualization, evaluation and utility) performed by the active user's friends on resources;
5. Present the user with a list of resources ordered by score according to the selected type of recommendation.

4 FORMALIZATION

In this section we define the basic concepts for calculating scores for the recommendation of learning resources.

U is the set of all users of the system and B[u] = {v ∈ U: v friend with u} is the set of friends of the user u. IV_u, IE_u, IU_u represent respectively the sets of visualized resources, evaluated resources according to their qualities and evaluated resources in terms of utility by the user u.

D is the set of all teaching domains represented in the system and E[u] = {d ∈ D: d is a domain of u} represents areas of interest of the user u. For example, if the system is used in a research laboratory, domains can then be topics of research. If it is a university, domains can be specialties or course modules.

The user profile information are represented by the set C. Formally, C[u] is the set consisting of characteristic /value pairs that define the profile of the user u. C[u] = { (c, val) | c ∈ C , val is the value of the characteristic c of the user u} . The values of continuous type may be replaced by discrete values. For example, the value of age can be transformed into child, adolescent, adult …

Visu(u, i) is used to know the resources that are visualized by a given user. This function is equal to 1 if the user u viewed the resource i and 0 otherwise. t(u, i) represents the number of days since the date of the last visualization of the resource i by the user u.

Eval(u, i) is used to know the evaluation of the quality of a resource by a user. For example, the user u can evaluate the resource i from 1 to 5. If the resource has not been evaluated then this function is equal to 0. Eval(u, .) is the average rating of the user u for all the resources that she/he has evaluated .

In addition to the evaluation of the quality of a resource, a user can evaluate its utility according to a specific domain. Util(u, i, d) represents the evaluation of the usefulness of the resource i in the context of work d(domain) of the user u. Util(u, .) is the average evaluation of the user u of all the resources that she/he has evaluated .

Seval is the set of co-evaluated resources in terms of quality by users u and v: Seval = IEu ∩ IEv. Sutil represents the co-evaluated resources in terms of usefulness by users u and v: Sutil = IUu ∩ IUv.

5 SOCIAL SIMILARITY

The majority of works on recommendation use the Pearson correlation coefficient for calculating the similarity between two users of a system. These works are mainly interested in resource evaluation to calculate the similarity between users. Because our work takes place in the context of social networks for learning, we propose a new method for calculating the similarity which is based on 1) the similarity of the choice of users' visualizations and evaluations, 2) strength of the link between these users and 3) the similarity between users' profiles. This new formula, denoted SocialSim(u, v), represents the social similarity between users u and v:

We used the Pearson correlation coefficient to calculate the similarity in terms of evaluation EvalSim(u, v) and we adapted this coefficient to

$$SocialSim(u,v) = (EvalSim(u,v) + UtilSim(u,v) + VisuSim(u,v) + LinkS(u,v) + ProfilSim(u,v)) / 5 \tag{1}$$

$$EvalSim(u,v) = \frac{\sum_{i\in Seval}(Eval(u,i) - \overline{Eval}(u,.)) \,.\, (Eval(v,i) - \overline{Eval}(v,.))}{\sqrt{\sum_{i\in Seval}(Eval(u,i) - \overline{Eval}(u,.))^2} \,.\, \sqrt{\sum_{i\in S}(Eval(v,i) - \overline{Eval}(v,.))^2}} \tag{2}$$

$$UtilSim(u,v) = \sum_{d\in E[u]\cap E[v]} \frac{\sum_{i\in Sutil}(Util(u,i,d) - \overline{Util}(u,.,d)) \,.\, (Util(v,i,d) - \overline{Util}(v,.,d))}{\sqrt{\sum_{i\in Sutil}(Util(u,i,d) - \overline{Util}(u,.,d))^2} \,.\, \sqrt{\sum_{i\in S}(Util(v,i,d) - Util(v,.,d))^2}} \Big/ Card(E[u] \cap E[v]) \tag{3}$$

calculate the similarity in terms of utility UtilSim (u, v).

The formula for the similarity in terms of visualization is defined as follows:

$$VisuSim(u,v) = \frac{Card(IV_u \cap IV_v)}{Card(IV_u \cup IV_v)} \quad (4)$$

If both users have previewed no resources then the union is null. So in this case, we do not apply the rule and the visualization similarity is equal to 0.

In social networks (Sun and Tang, 2011), the link between two users is stronger if they have in common multiple neighbors. In our work, the strength of the relationship between two users is defined using the number of common friends and their total number of friends. The strength of the link between users u and v is defined by the following formula:

$$LinkS(u,v) = \frac{Card(B[u] \cap B[v]) + 2}{Card(B[u] \cup B[v])} \quad (5)$$

The last element that we have integrated into the formula of social similarity is the similarity related to characteristics present in users profiles. It will take into account the similarities between users in terms of preferences, knowledge, goals… This similarity is related to the number of common characteristics between the two users and the total number of characteristics. The formula that calculates such similarity between users u and v is:

$$ProfilSim(u,v) = \frac{Card(C[u] \cap C[v])}{Card(C)} \quad (6)$$

6 RECOMMENDATION TYPES

6.1 Recommendation of Recently Viewed Resources

The system can provide to a user a list of resources that have been recently viewed by similar users. This type of recommendation is useful for collaborative learning. Indeed, it allows users to follow courses at the same time as their friends to be able to collaborate and help each other on these different courses. Recommendation score of the resource i for the user u is determined by the following formula:

$$S_{visu}(u,i) = \sum_{v \in B[u]} e^{-\alpha t(v,i)}.Visu(v,i).SocialSim(u,v) \quad (7)$$

α is a decay factor. More a user has viewed a resource recently, the higher the score of this resource increases. We were inspired by the work of Guy *et al.* (Guy et al., 2009) and (Guy et al., 2010) to take into account the time in this formula.

6.2 Recommendation of Popular Resources

A user can also see a list of recommended resources highly rated by her/his friends. Recommendation score of resource i for user u is determined by the formula:

$$S_{eval}(u,i) = \mathrm{k} \sum_{v \in B_i[u]} Eval(v,i).SocialSim(u,v) \quad (8)$$

Only friends of user u who have evaluated item i can be used in the calculation of this score. This subset of B[u] is denoted by $B_i[u]$. k represents the normalizing factor. It is usually given as $\mathrm{k} = 1/\sum_{v \in B_i[u]} |\,\mathrm{SocialSim}(u,v)\,|$

The Seval formula uses the weighted sum approach (Adomavicius andTuzhilin, 2005).

6.3 Recommendation of Useful Resources

A list of resources can be recommended to a user based on their utilities according to learning domains of this user. Recommendation score of resource i for user u is determined by the formula:

$$S_{util}(u,i) = \mathrm{k} \sum_{v \in B_i[u]} SocialSim(u,v).\frac{\sum_{d \in E_{vi}[u]} Util(v,i,d)}{Card(E_{vi}[u])} \quad (9)$$

Only domains of interest of the user u which have been used to evaluate resource i by user v can be integrated in the calculation of this score. This subset of E[u] is denoted by $E_{vi}[u]$.

7 PRINCIPLE OF THE PROFILE UPDATE

The characteristics of a user can be partially filled, even outdated or inappropriate. As our approach is based in part on the characteristics of the user, it is necessary to update the user profile to be able to make a high quality recommendation.

The profile data can be filled manually by the user or/and set by the system based on her/his behavior. In addition to the two methods previously explained, the principle of social influence (Sun and Tang, 2011) leads us to enrich the user's profile with the information that characterizes the profiles of her/his influential friends, this by using one or the both of the following methods:

- Recommend to the user the most common characteristics present in the profiles of her/his friends. For example, the studies level the most common among her/his friends. The system will update the user profile if she/he validates this recommendation;
- Update directly the user's profile with the values of the most common friends' characteristics. This information may be exact or may be uncertain, so the system associates to them probabilities of accuracy (degree of reliability) and stores them in the user's profile.

8 EVALUATION

To evaluate our approach, we have wanted first to use datasets extracted from existing educational recommender systems. Among these datasets, we can mention Mendeley (Jack et al. 2010), MACE (Wolpers and Niemann 2010) and APOSDLE (Beham et al. 2010). After studying this type of datasets, we found it impossible to use them to evaluate our model. The data they provide do not contain all the data we need to conduct the evaluation, such as social relationships between users and resource evaluations in terms of utility.

We have considered the possibility to complete these datasets with missing information but the whole new modified dataset can be incoherent and it can make our simulation wrong.

To address this problem, we established a process for studying the feasibility of our approach, evaluate that it proposes relevant resources and compare it with other existing approaches. 1) The first step was to create a reduced dataset consisting of 10 users and 9 resources and evaluate the approach with it, 2) The second step was to develop a learning platform that implements our approach and test it with true users, 3) In parallel with this step we are trying to have a dataset from an existing platform named ACCEL (Delache et al., 2007) to run on it the evaluation.

8.1 Simulation on a Created Dataset

For the first step of the evaluation we have made a simulation on a dataset that we have created. This evaluation helped us, to test the algorithms related to our formulas to evaluate their effectiveness and to refine them. We have developed a prototype in Java that calculates the similarities between users and calculates and displays the three lists of recommendation that we propose in our approach.

The dataset that we have created contains all the information that our model needs. It uses the information about 10 users and 9 resources. This dataset contains mainly 1) user characteristics such as age, preferences ... 2) social relationships between users and 3) evaluation values that users attribute to educational resources.

8.2 Design and Test of the Platform of Icraa

To evaluate our approach with real users, we have developed a learning platform, named icraa (**I**craa is a so**C**ial lea**R**ning **A**nd **A**uthoring environment), which implements our formal models to recommend educational resources.

The effectiveness of our approach is measured by the users' evaluations on the recommendations that are proposed by the system.

The learning platform is currently used by 10 teachers from the University of Tlemcen (Algeria). The evaluation is conducted on 3 classes of 25, 28 and 40 students. The teachers are asked to upload educational resources related to their courses and we estimate that we will have more than 300 learning resources by the end of April 2015.

8.2.1 Platform Functionalities

Resources Upload: teachers who have rights can upload the resources of their courses into the platform and describe them by some metadata.

Resources Access: All resources are accessible to all system users (students and teachers).

Resource Download: all users can download all resources that have been added by their teachers.

Resource Evaluation: a user of the platform can evaluate the quality of a resource and its utility according to the user's domains. This functionality is illustrated in figure 3.

Resource Recommendation: the system provides the three types of recommendation of our approach namely recently viewed resources, popular resources and utile resources. When a user chooses one of these three types, the system displays a list of the 3 best rated recommended resources.

Social features: Icraa platform provides multiple social features that can be found in social networks as Facebook.

8.2.2 First Results

The platform was installed at the end of November 2014 and after 4 weeks of its usage 4 teachers started to upload their courses on the platform. They uploaded about 50 resources.

We are noticing that users have created about 340 friend relationships and there were 400 resources visualizations. Users were connecting frequently into the platform; there was an average of 33 users' connections by day. The resources of the system were visualized 875 times and there were 305 of resources evaluations by users.

As first results of this experimentation we noticed that 80% of the users found that the recommended resources were relevant. Also 82% of the users found the given recommendation useful.

The evaluation will be continued in the second semester of this academic year and it will finish by the end of April 2015.

8.2.3 Ongoing Evaluation

The first results that we have are interesting but not sufficient. Currently, we are working on the next step of the evaluation with icraa platform. We divided the set of the users of this system into 3 groups:

- G1: students of this group have recommend-dations that respect our approach;
- G2: students of this group have recommend-dation that respect the algorithm of Friend Based Recommender System (explained in section 2);
- G3: students of this control group have recom-mendation in a random order.

Once the results collected, it is necessary that the group G1 will be the most satisfied with the recommendations provided by the system and G2 will be more satisfied than G3.

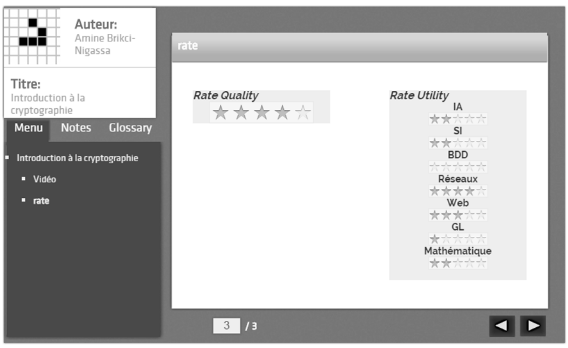

Figure 3: Interface for evaluating the quality and the utility of a resource.

8.3 Simulation on ACCEL Dataset

ACCEL is a distance learning platform developed and used by the University of Lille (France). It is an acronym of « Apprentissage Collaboratif et Communauté En Ligne » which means Collaborative Learning and Online Community.

ACCEL is used in life learning context with students which have different backgrounds when icraa is used with young students in university. All courses that are followed by students who use ACCEL are 100 % in distance learning but students who use icraa in the University of Tlemcen follow courses in blended learning mode.

The dataset extracted from the ACCEL platform can help us to evaluate our approach. It can give us a complementary evaluation compared to the icraa platform since the context of use and the type of users are not the same between these two systems.

The problem with this platform is that it does not contain the functionality of evaluating resources and the functionality of declaring friend relationships.

We are working with the ACCEL team to incorporate these functionalities on their platform. All their users will use these new functionalities and after some weeks of use we will extract a dataset which contains information that we need for our evaluation.

9 CONCLUSIONS

In this paper we have presented an approach to recommend educational resources based on social relationships. We have developed a formal model for the calculation of similarity between users and the generation of three types of recommendation of educational resources. We also presented an illustration and evaluation that we have followed to test, refine and validate our approach.

The platform icraa that we developed allowed us to have positive first results on the evaluation of our approach. More than 80% of users are satisfied with the recommendations made by the system. With the help of this platform, we continue in the next months to do a comparative evaluation between our approach and other recommendation approaches.

Our recommendation approach is based on collaborative filtering that uses evaluations of users. This approach can be enriched using a hybrid recommendation method that also uses a recommendation based on the content. Another perspective of our work can be the use of social information (profiles, relationships, affiliations ...)

present on public social networks such as Facebook or LinkedIn. This will help us to improve and enrich social information in the recommendation system.

REFERENCES

Adomavicius, G., Tuzhilin, A., 2005. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. Knowledge and Data Engineering, 17(6): 734-749.

Anderson, M., Ball, M., Boley, H., Greene, S., Howse, N., McGrath, S., and Lemire, D., 2003. Racofi: A rule-applying collaborative filtering system. In IEEE/WIC COLA 2003.

Beham, G., Stern, H., and Lindstaedt, S. N., 2010. APOSDLE-DS A Dataset from the APOSDLE Work integrated Learning System. In 1st Workshop on Recommender Systems for TEL.

Bellogína, A., Cantadora, I., Castellsa, P., and Díeza, F., 2013. Exploiting Social Networks in Recommendation: Multi-Domain Comparison. In DIR 2013.

Bellogína, A., Cantador, I., Díez, F., Castells, P., and Chavarriaga, E., 2013. An empirical comparison of social, collaborative filtering, and hybrid recommenders. ACM TIST, 4(1): 14.

Bhagat, S., Cormode, G., and Muthukrishnan, S., 2011. Node classification in social networks. In Social Network Data Analytics Springer US. 115-148.

Delache, D., D'Halluin C., Fichez, E., et al., 2007. Environnements numériques et pratiques collaboratives d'apprentissage.

Drachsler, H., 2012. Recommender systems for learning. http://fr.slideshare.net/Drachsler/recsystel-lecture-at-advanced-siks-course-nl. Visited 28/11/2014.

Drachsler, H., Hummel, H., and Koper, R., 2008. Identifying the Goal, User model and Conditions of Recommender Systems for Formal and Informal Learning. Journal of Digital Information, 10(2): 4-24.

Drachsler, H., Pecceu, D., Arts, T., Hutten, E., Rutledge, L., Van Rosmalen, P., Hummel, H., and Koper, R., 2009. ReMashed–recommendations for mash-up personal learning environments. In Learning in the synergy of multiple disciplines. Springer 788-793.

Drachsler, H., Verbert, K., and Duval, E., 2013. Recommender systems for learning. Springer.

Goldberg, D., Nichols, D., Oki, B. M., and Terry, D., 1992. Using Collaborative Filtering to Weave an Information Tapestry. Communications of the ACM.

Guy, I., and Carmel, D., 2011. Social recommender systems. In 20th international conference companion on World wide web. ACM. 283-284.

Guy, I., Zwerdling, N., Carmel, D., Ronen, I., Uziel, E., Yogev, S., and Ofek-Koifman, S., 2009. Personalized recommendation of social software items based on social relations. In Proceedings of the third ACM conference on Recommender systems. ACM. 53-60.

Guy, I., Zwerdling, N., Ronen, I., Carmel, D., and Uziel, E., 2010. Social media recommendation based on people and tags. In Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval. ACM. 194-201.

Huang, Y. M., Huang, T. C., Wang, K. T., Hwang, W. Y., 2009. A Markov-based Recommendation Model for Exploring the Transfer of Learning on the Web. Educational Technology & Society. 12(2): 144-162.

Jack, K., Hammerton, J., Harvey, D., Hoyt, J., Reichelt, J., and Henning, V., 2010. Mendeleys reply to the datatel challenge. Procedia Computer Science, 1(2): 1-3.

Linden, G., Smith, B. and York, J., 2003. Amazon. com recommendations: Item-to-item collaborative filtering. Internet Computing, IEEE, 7(1), 76-80.

Pazzani, M.J., and Billsus D., 2007. Content-based recommendation systems. In The adaptive web. Springer Berlin Heidelberg. 325-341.

Popescu, E., 2014. Providing collaborative learning support with social media in an integrated environment. World Wide Web. 17(2): 199-212.

Recker, M. M., and Walker, A., 2003. Supporting "Word-of-Mouth" Social Networks through Collaborative Information Filtering. Journal of Interactive Learning Research. 14(1): 79–99.

Resnick, P., and Varian, H. R., 1997. Recommender systems. Communications of the ACM. 40(3): 56-58.

Sun, J., and Tang, J., 2011. A survey of models and algorithms for social influence analysis. In Social network data analytics. Springer US. 177-214.

Tadlaoui, M., 2014. Recommandation de ressources pédagogiques basée sur les relations sociales. RJCEIAH 2014.

Wolpers, M. and Niemann, K., 2010. dataTEL challenge: CAM for MACE. In 1st Workshop on Recommender Systems for Technology Enhanced Learning.

Wu, L., Shah, S., Choi, S., Tiwari, M. and Posse, C., 2014, The Browsemaps: Collaborative Filtering at LinkedIn. In 6th Workshop on Recommender Systems and the Social Web, collocated with ACM RecSys 2014.