International Journal of advanced studies in Computer Science and Engineering
IJASCSE Volume 4, Issue 5, 2015

Personalization in Educational Social Network Using a Heuristic Post Selection Method

Ahmad A. Kardan
Advanced E-Learning Technologies Laboratory,
Amirkabir University of Technology.
Tehran, Iran.

Omid R. B. Speily
Advanced E-Learning Technologies Laboratory,
Amirkabir University of Technology,
Tehran, Iran.

***Abstract*-Nowadays, social networks sites have become an important media in communication and propagation of information. By considering collaborative attribute of these networks, they could be used in different fields such as business, social interaction and entertainment. As the trend of applying collaborative learning is increased, Educational Social Networks (ESN) is one of the mediums which could facilitate this learning approach. Although in these ESNs huge amount of learning resources may seem desirable, often causes confusion for learners to find proper learning resource. So, there should be an approach to choose suitable educational resources based on desires of learners. In this paper a novel social filtering method is proposed which personalized learning resources in ESN environments. In this regard two parameters including trust and interest have been used. To evaluate this method an ESN is developed and 117 learners use it. The results indicate that proposed method increased the learners' satisfaction.**

***Keywords-Educational Social Networks,Social filtering, Trust, Interest Similarity, personalization*.**

I.INTRODUCTION

Development of information and communication technology has affected all aspects of human life such as learning. Recent researches indicate a great usage of e-learning which lead to a dramatic increase in the capacity of educational materials on the web. Although huge amount of learning resources may seem desirable, often causes confusion for learners to find proper resource. So, there should be an approach to distinguish suitable educational resource based on requirements and desires of learner from unrelated and inappropriate ones on the web. Indeed, educational contents should be personalized for learners.

Personalization means the adaptation of learning process according to requirements, experiences and characteristics of learner [1]. This information could gain explicitly from users or implicitly from their behaviours. In Contrast to explicit methodology that cost the learner's time and require the learner's willingness to participate, implicit methodologydoesn't not require any additional intervention by the learner [2]. Therefore, implicit methods are often usedfor personalization. This causes that e-learningsystems collect requirements of learners by analysing behaviours of learner in learning groups and characteristics of learner.

Nowadays, online social networks have become an important part of many users' life. So, these users spend amount of their times for social networking and making new electronically relationships in these sites. In these sites there are a lot of concepts including texts, links and multimedia that integrated [3].

The most important features of social networks are users being allowed to create contents, share them and interact with other users. These features caused increasing the growth rate of World Wide Web.

Social network sites provide useful applications which can be used to gain learners' attributes implicitly. Since the advent of Social Networks, they attract many users. Educational Social Networks are potential environments for personalized e-learning because of their flexibility, interactivity, and dynamicity.

In this paper a novel social filtering method is proposed for personalization of learning resources based on learners' desires and requirements in an ESN. This method applied two parameters including trust and interest to filter proper educational resources.

The rest of this paper is organized as follows. In the next section, some of the most important related works are reviewed. In section 3, the structure of proposed method for personalization of the educational resources in ESN is explained. The evaluation of this method is discussed in section 4. Finally, last section presents conclusion and directions for future works.

II.RELATED WORKS

As mentioned before, personalization is one of the most significant challenges in e-learning. So many research have been done in this field such as: Adaptive Systems [4] [5], Recommender Systems of educational contents [6] [7], Recommendation of learning paths [8]. Also many techniques and methods are used for personalization including: data mining and web mining, collaborative filtering methods, pattern recognition algorithms and machine learning.

Since 2001, with the general acceptance of social networks, and improvement of web 1.0 to web 2.0 and semantic web, successful systems such as Facebook, MySpace and YouTube have appeared. If the evolution of web-based-systems is studied, it could be seen that recently instead of spending time and energy creating more sophisticated algorithms for recognition of users' requirements and features; an interactive environment is provided for users to freely declare their needs by using tools such as like, comment, Share and so on. Using of social networks for educational proposes does not have long history.

In [1] utilized YouTube social network for children education. In [5] system made a primary model of learners with information gained via questionnaires. Then users can use educational contents after choosing a friend. Finally system provides a combined method for recommendation of the educational contents based on friends' model and expected content.

Also there are some works have been done in using social networks for learning purpose. In [9] developed a web-based tool among over 45000 European schools to enhance the cooperation and knowledge sharing. In [10] the role of social networks in computer science education is investigated. In [11] it is emphasized on potential of online social networks to enhance e-learning. The authors of this paper believe that social networks could help learning through making and environment for easier interaction and better collaboration.

III. The Architecture of Proposed Method

In this section the architecture of proposed social filtering method is described which is depicted in Fig.1.

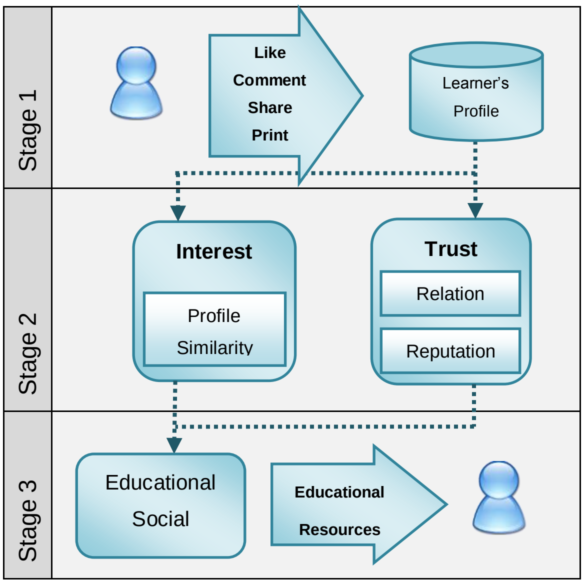

Figure1: The architecture of proposed social filtering method

As illustrated in Fig.1 the proposed method generally consists of three main stages: 1) Constructing learner's profile 2) Computing trust and interest similarity 3) Filtering educational resources. All of these stages will be explained in subsections A, B and C in order.

IV. Constructing Learner's Profile

At first stage learner's profile should be constructed. ESN consists of some groups which each of them has specific educational topic like "e-commerce", "Computer Networks" and "data structure". Learners could join different groups and friend with other members. Also, they can do social activities such as sharing, comment, like and printing. Now the profile of learners could be constructed based on their behaviors and activities in ESN groups. These profiles stored in a database named as "Learner Profile DB". In next stages when the learners' behaviors required, their profile should be retrieved from this database.

A. *Computing trust, interest and educational requirements*

In second stage, trust and interest should be determined. These two parameters computed based on learner's profile. Trust has different definitions but here it means how learners believe other members of ESN. In order to estimate trust two major factors are applied which includes Relation and Reputation. Another significant parameter is Interest. To find out this factor Profile Similarity is utilized. In following it will be explained how to compute these parameters.

B. *Trust*

In [12] trust between two persons was defined as" trust in a person is a commitment to an action based on a belief that the future actions of that person will lead to a good outcome ". As mentioned before Relation and Reputation are used to find out trust. Hence equation 1 is used.

$$T(A,B) = \frac{Relation(A,B) + Reputation(A,B)}{2} \qquad (1)$$

Relation and Reputation will be explained in following subsections. As will be mentioned later the values of these parameters are between 0 and 1. Consequently to normalize T from 0 to 1, the sum of them is divided by 2.

C. *Relation*

In ESN the learners have various interactions that some of them are strong and others are weak. If two learners have strong connectivity with each other, they will trust more to each other and vise versa. Therefore to measure the quality of two Learners A and B interactions, Relation is defined in equation 2.

$$\text{Relation (A , B)} = \frac{L_{AB} + SH_{AB} + C_{AB} + P_{AB}}{4 \times N_B} \quad (2)$$

TABLE I .PARAMETERS ARE USED IN EQUATION 2

parameters	The meaning of parameter
L_{AB}	How many times did A Like B's contents?
SH_{AB}	How many times did A share B's contents?
C_{AB}	How many times did A comment on B's contents?
P_{AB}	How many times did A print B's contents?
N_B	The number of B's contents

The parameters which are used in this equation are given in table 1. As the maximum value of each numerator's parameter could be equal NB, so at most numerator value will be 4NB. Therefore to normalize the value of relation, 4× NB in the denominator is applied. Therefore relation will be a value between 0 and 1.

For instance if learner A 17 times liked (NAB), 12 times shared (SHAB), 9 times commented (CAB) and 2 printed (PAB) B's contents in ESN which is equals 20, then Relation (A, B) equals to (17 + 12 + 9 + 2)/(20*4) = 0.25.

D. Reputation

Reputation in social network analysis is a measure to estimate how a user influences on other users [13]. The equation 3 is used to compute it. Also In the table 2 parameters which are used for computing the reputation are described.

$$\text{Reputation (B)} = \frac{N_L + N_{SH} + N_C + N_P}{N_B \times N_M} \quad (3)$$

TABLE II .PARAMETERS ARE USED IN EQUATION 3

parameters	The meaning of parameter
N_L	How many times did members Like B's contents?
N_{SH}	How many times did members share B's contents?
N_C	How many times did members comment on B's contents?
N_P	How many times did members printe B's contents?
N_B	The number of B's contents
N_m	The number of memberes visit B's content

In this equation NB and NM is used to normalize the reputation based on the number of B's contents and the learners who visited them. Therefore reputation will be a value between 0 and 1.

For instance if a learner posted 20 contents (NB) in the ESN and then these posts totally 100 times liked(NL), 16 times shared (NSH), 80 times commented (NC) and 4 printed(NP) by 14 learners, then the learner's reputation equals to (100 + 16 + 80 + 4) /(20 × 14) = 0.71.

E. Interest

Another influential factor in social filtering is Interest. According to [14] the objective of computing interest in ESN is to find the student's implicit requirement. The data sources for understanding interest come from learner's interactions in ESN. One of the common methods to determine learner's interest in forums and social networks is profile similarity [15]. The main idea of this method is identifying members who are more similar to learner. Then based on these members' interest some educational contents are offered to the learner.

Most significant part of this approach is determining the similarity between learners according to their profiles. Equation 4 shows how to measure the interest similarity of two learners.

$$IS(A,B)=\left(\frac{N_{CG}}{G_A+G_B}\right)+\left(\frac{N_{CF}}{F_A+F_B}\right) \quad (4)$$

The terms that are used in equation 4 are shown in table 3.

TABLE III . PARAMETERS ARE USED IN EQUATION 4

Parameters	The meaning of parameter
N_{CG}	How many mutual groups do learners A and B member?
N_{CF}	How many mutual friends do learners A and B have?
G_A	How many groups did learner A member?
G_B	How many groups did learner B member?
F_A	How many friends did learner A have?
F_B	How many friends did learner A have?

For instance if both of learners A and B member in 4 groups (NCG), have 40 mutual friends (NCF), learner A member in 7 groups (GA) and has 50 friends (FA), learner B member in 5 groups (GB) and has 110 friends (FB). Then the interest similarity between learners A and B equals 4/(7+5) + 40/(50+110) = 0/5.

V.FILTERING EDUCATIONAL RESOURCES

As mentioned before huge amount of educational resources in ESN lead to learner confusion. To overcome this problem in the last stage, educational resources are filtered based on combination of trust and interest similarity with equation 5.

$$R\ (A, B) = T\ (A, B) + IS\ (A, B) \quad (4)$$

Terms T and IS refer to trust and interest respectively which they are obtained in the previous stage. The parameter R indicates how much member B's posts are suitable for learner A. As mentioned before the values of T and IS are between 0 and 1. So R value is a number between 0 and 2.

In this stage the R value for all members are calculated. Then the posts of members who have more R value will be shown to Learner A sooner.

In the other words the educational contents that posted by members who have more trust and interest similarity are more accessible for a desired learner. To clarify this approach an example is given in table 4.

TABLE IV.AN EXAMPLE OF EDUCATIONAL SOCIAL FILTERING

	Trust (T)	Interest Similarity (IS)	R	Member's resources
(A, B_1)	0.60	0.45	1.05	7
(A, B_2)	0.46	0.41	0.87	15
(A, B_3)	0.51	0.17	0.68	12
(A, B_4)	0.31	0.13	0.44	8
(A, B_5)	0.13	0.08	0.21	14
(A, B_6)	0.09	0.05	0.14	17

In this table educational resources are filtered for learner A. Each row illustrated the values trust, interest similarity and R between learner A and another specific member Bi. The last column shows the number of resources that posted by Bi. The members are sorted based on their R value in the table. More R value between Learner A and Bi means more satisfaction will be obtained from Bi resources. For instance in this table educational resources which posted by learner B1 will be show to learner A at first because A and B1 have the highest R value. Also educational resources which posted by learner B6 will be show to learner A at last because A and B6 have the lowest R value. Hence in table 4 from up to down, the priority of educational resources according to R value for learner A is decreased.

Consequently with this educational social filtering method it is expected that learners couldaccess to more proper educational resources earlier.

VI.EVALUATION

In order to evaluate the proposed method, at Urmia University of Technology the ESN was developed. The specific learning domain of this system which called UUOTC was electronic commerce and 117 learners applied it. They could join in some research groups such as e-payment and security. Also Learners could share educational resources with each other and their feedbacks, which includes like, share, comment and print, are stored. These resources include news, contents, links and etc. Then educational resources were filtered with proposed method (was explained in previous section) and are shown to learners with other recourses. The learners could not distinguish between filtered resources and other contents. It is considerable that learners would be given extra mark for their contribution.

The statistical information of this experiment is depicted in table 5. All participants in this experiment are students of Information Technology department and none of them have passed the course of "e-commerce". English is second language of all participants however they are allowed to post English and Persian (first language of participants) contents.

As illustrated in table 5 each learner spent about 53 hours in the ESN. In should be noted that each learner was permitted to comment on a specific resources several times but all these comments are considered as one commenting in his profile.

To evaluate the method two kinds of feedbacks are obtained from learners:

- Explicit feedbacks: learners should rank each educational resource after reading it. This rank is a value between 0 and 5.
- Implicit feedbacks: Learners usage from social applications such as like, print, share and comment are collected.

The first month of using UUOTC is used to building learners profile after that for new resources the proposed social filtering method is used. For each learner top 10 posts from filtering method are assumed as filtered resources and the remained resources were named other resources.

TABLE V.THE STATISTICAL INFORMATION OF EXPERIMENT

Parameters name	Value of parameters
Number of students	117
Number of contents	1090
Number of groups	6
average number of like	3084
average number of Share	1853
average number of comment	2941
average number of print	327
Average number of memberships in groups	3.145
Average number of friends	22.71
Average visit time of ESN	53:17'

In Fig. 2 the comparison between implicit feedbacks of learners to filtered resources and other resources is illustrated. As could be seen in average the number of like and share on filtered resources are so higher than other ones. However the great difference in usage of print and comment applications between these resources are not observed. These results show that filtered resources cause more learners' satisfaction. In social networks applications the easiest and best ways to indicate agreement for users are like and sharing. So the more usage of these applications on filtered resources means more learners' satisfaction.

On the other hand in Fig. 3 the comparison between explicit feedbacks of learners to filtered resource and other resources is depicted.

Averagely learners give a higher rank to filtered resources comparing to other resources. To investigate with more detail, 21% of filtered resources got rank of 5 and 37% of them got rank of 4, meanwhile just 11% of others gained rank 5 and 20% got rank of 4. This result indicates that, the purposed method was successful in filtering proper educational resources for learners.

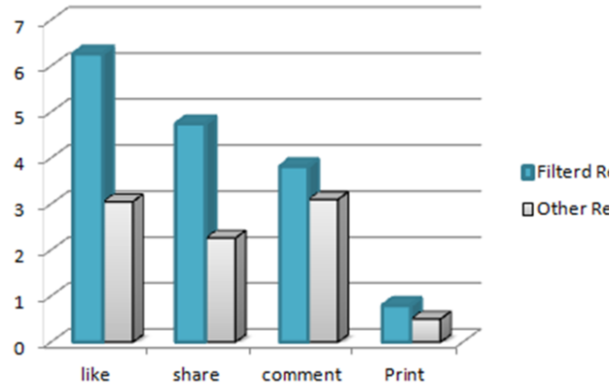

Figure2: Implicit feedback analysis

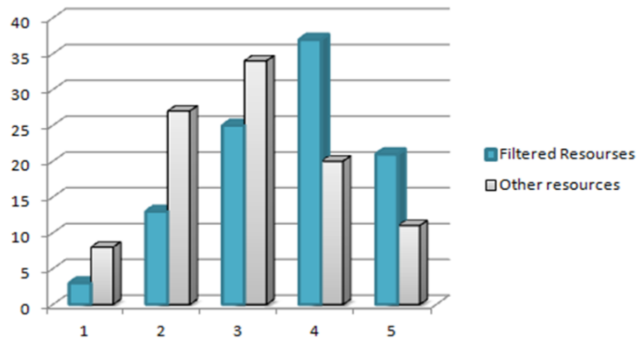

Figure3: Explicit feedback analysis

Ranks 4 and 5 show the satisfaction of learner, rank 3 is neutral and ranks 1 and 2 indicate that learner is not satisfied. So results of explicit feedbacks verify that filtered resources satisfied learners more than other resources.

VI.CONCLUSION AND DISCUSSION ABOUT FURTHER WORKS

Nowadays finding proper resource among the huge amount of learning resources in collaborative environments and ESNs is becoming an important problem for learners. To overcome this problem in this paper an educational social filtering method is proposed. This method works based on computing interest similarity and trust between learners. These parameters obtained from social behavior of learners in ESN such as likes, share, comment, etc. To evaluate this social filtering method an ESN was developed. Two kinds of feedbacks were collected from different 117 learners when using this ESN. These feedbacks indicate that the satisfaction of learners is higher when visiting filtered learning resources.

For further works it is expected that using other parameters such as knowledge level, goals, etc also could be effective in filtered suggests and personalization. Moreover, it is expected that using more accurate coefficients in computing trust and interest similarity could increased the performance of the method.

REFERENCES

[1] Chareen Snelson, Patt Elison-Bowers, Using YouTube videos to engage the affective domain in e-learning. Research, Reflections and Innovations in Integrating ICT in Education, 2008.

[2] Gauch, S., Speretta, M., Chandramouli, A. & Micarelli, A.:User Profiles for Personalized Information Access. In Brusilovsky, P., Kobsa, A. & Neid, W. (Ed.), The Adaptive Web: Methods and Strategies of Web, (PP. 3–53), PA: Berlin Heidelberg New York: Springer-Verlag, 2007.

[3] M. R.F. Sani, A. Omidvar, F. Farahmandnia, S. Shiry "WSOM: A novel method to people in social networks". WCIT, 2nd world conference on information Technology , Antalya 2011.

[4] Marengo, Agostino, Pagano, Alessandro, Barbone, Alessio; , "Adaptive learning: A new approach in student modeling",Information Technology Interfaces (ITI), Proceedings of the ITI 2012 34th International Conference on5-28 June 2012.

[5] Ahmad A. Kardan, Omid R.B Speily, Somayye Modaberi Recommender Systems for Smart Lifelong Learning Systems. ICVL09 International conferences on virtual learning, Bucharest, Romani 2009.

[6] T. Y. Tang, and G. Mccalla, "Smart Recommendation for an EvolvingE-Learning System", University of Saskatchewan, Department of Computer Science, 2005.

[7] S. Shishehchi, S. Y. Banihashem, and M. Zin, "A Proposed Semantic Recommendation System for E-Learning: A Rule and Ontology Based E-learningRecommendation System", IEEE, 2010.

[8] Karampiperis, P. and Sampson, D., “Adaptive Learning Resources Sequencing in Educational Hypermedia Systems” Educational Technology & Society, 8(4), pp 128-147, 2005.

[9] Breuer, R. & Klamma, R. & Cao, Y. & Vuorikari, R. Social Network Analysis of 45,000 Schools: A Case Study of Technology Enhanced Learning in Europe, in Cress, U., Dimitrova, V. and Specht, M. (Eds.) Learning in the Synergy of Multiple Disciplines, Proceedings of 4th European Conference on Technology Enhanced Learning, EC-TEL 2009, Nice, France, September/October 2009, LNCS 5794, Springer, pp. 166-180, 2009.

[10] Liccardi, I., Ounnas, A., Pau, R., Massey, E., Kinnunen, P.,Lewthwaite, S., et al, The role of social networks in students' learning experiences. ACM SIGCSE Bulletin , 39 (4), 224-237, 2007.

[11] Rodrigues,J.J.P.C. Inst. de Telecomun., Univ. of Beira Interior, Covilha, Portugal Sabino, F.M.R. ; Zhou, L. Enhancing e-learning experience with online social networks, Communications, IET, volume 5 , Issue: 8 , pages 1147 – 1154, 2011.

[12] Golbeck, J. Parsia, B. Trust network-based filtering of aggregated claims, Int. J. Metadata, Semantics and Ontologies, Vol. 1, No. 1, 2006.

[13] J.Sabater and C.Sierra. Reputation and social network analysis in multi-agent systems, In 1st International Joint Conference on Autonomuse Agents and Multiagent Systems, 2002.

[14] Gu, Rong; Zhu, Miaoliang; Zhao, Liying; Zhang, Ningning.Interest mining in virtual learning environments, Online Information Review vol. 32 issue 2 April 11, p. 133-146,, 2008.

[15] Trust and nuanced profile similarity in online social networks Golbeck, J. Trust and nuanced profile similarity in online social networks. In MINDSWAP Technical Report TR-MS1284,2006.