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Recommending Learning Activities in Social Network Using Data Mining Algorithms

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ABSTRACT

In this paper, we show how data mining algorithms (e.g. Apriori Algorithm (AP) and Collaborative Filtering (CF)) is useful in New Social Network (NSN-AP-CF). "NSN-AP-CF" processes the clusters based on different learning styles. Next, it analyzes the habits and the interests of the users through mining the frequent episodes by the Apriori algorithm. Finally, it groups dynamically the users based on the collaborative filtering. The participants in this study consisted of 80 university students who were asked to analyze the differences in skill level when using various learning activities. Moreover, 40 students were included in this study in order to examine the effectiveness of NSN-AP-CF. The experiment results proved that the proposed algorithm, which considers the grouping dynamically the users and the discovery of all frequent episodes, generates better precisions compared with the other algorithms (F1 = 0.649).

Keywords

Social networks, Data mining, Apriori algorithm, Learning style, Collaborative filtering

Introduction

Social network has become one of the comfortable medium for user to share their knowledge (Zaidieh, 2012). Users pay more attention to share their knowledge spontaneously in a relaxed, informal environment more than the formal classroom environment. A teacher can easily understand user's learning from outside of the class and they can get full details about the learning system. It is very helpful for a teacher to understand the difficulties of the user he/she facing in the learning system.

Learning through social networking sites is limited when different users have different preferred ways to learn. Some may understand quickly through games and simulations, others may prefer problem solving. Some may deal well with theories, others may learn through projects and examples (Veletsianos & Navarrete, 2012).

In this way, most researches are based on using different characteristics to group users forgetting that these characteristics can change at any time. This change of the characteristics leads to the problem of the static grouping where the system does not edit the created groups automatically. In Mahnane and Touati (2015), the authors investigated the relationship between Traditional educational Social Networking (TSN) and learning styles.

Furthermore, information from social networks can present valuable data to report student problem. Examining such data, however, can be challenging task. The problem of student's behaviors reveal from social network site need human analysis. There are many traditional methods available such as questionnaires, surveys and interviews to analyze the student's behaviors in educational social networking sites (Chen, Vorvoreanu, & Krishna, 2014). But the main problem with these methods is these techniques cannot be performed efficiently with big data as the analysis has to be performed manually. For this, data mining techniques collect and analyze data generated in social networking sites.

The main objective of this research is to develop an educational social network site based on data mining techniques and learning styles. The rest of the paper is organized as follows. Section "Background and related scientific work" introduces the related work. The design of educational social network based on data mining methods and learning styles is described in Section "Research methods." Section "Analysis and Results" is reserved to present the tests and the obtained results. The conclusion and the future works are drawn in Section "Conclusion and future prospective."

Background and related scientific work

This section is organised in three subsections, firstly the general context of the educational social networks is briefly introduced. Secondly, we focus on the grouping of students based on learning style. We conclude with using data mining in educational social networks.

Educational social networks

The social networking sites brought about major change in how communication and participation between users and communities and information exchange (Allen, 2012; Greenhow, Gleason & Li, 2014). Advantages of using social network in education are:

- **Participation:** Social network encourages contributions and feedback from everyone who is interested.
- **Openness:** Most social networks are open to feedback and participation. They encourage voting, comments and the sharing of information.
- **Conversation:** Social network is better seen as a two way conversation.
- **Community:** Social network allows communities to form quickly and communicate effectively.
- **Communities:** Share common interests.
- **Connectedness**: Most kinds of social network thrive on their connectedness, making use of links to other sites, resources and users.

Thus, educational social network can provide the teacher and students a space in which they can discuss their experiences and their lessons. The Educational social network helps the teacher, student establish a long lasting relationship and powerful interactions with each other. These interactions help them determine educational needs. A general architecture of educational social networking inspired from (Valova, 2015), is shown in Figure 1.

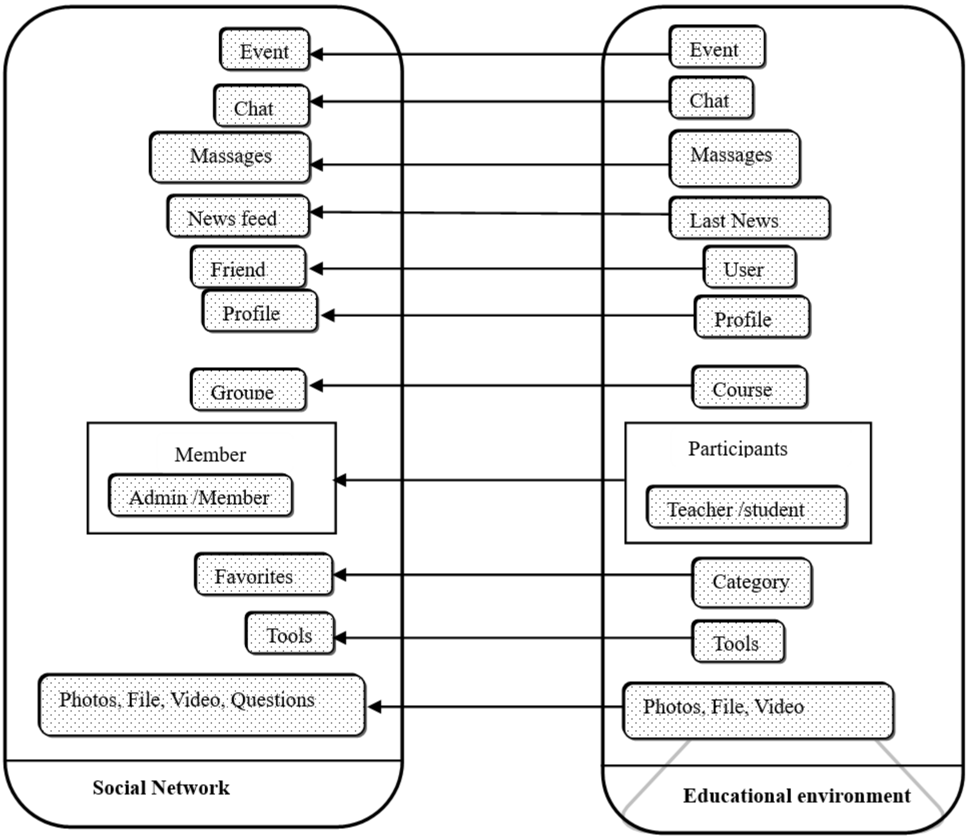

Figure 1. A general architecture of educational social networking inspired from (Valova, 2015)

The following is an explanation of the general components of educational social networking sites (Mahnane & Touati, 2015).

- **Events:** reminders of appointments and activities that we must implement. When the merger will always remember these dates because they will always be with us, both when you open the educational environments, or in times of entertainment across social networking sites.
- **Chat/Messages**: In the educational environment to be trapped between the student and the teacher only or between the student and the last in the means of social communication to be with a group of individuals, whether teachers or students are generic.
- **Latest News**: A list containing the news from people and groups on social network or educational environment, latest events include.
- **Profile**: through personal files can identify the name of the person, find out basic information about it, such as race, and date of birth, and the interests and personal images in addition to other information, is a profile entry gate to the world of the person, it is through the main page of the profile can be seen activity person recently, and find out who his friends are and what are the new images placed in addition to other activities.
- **Course**: the educational environment is set up course through the introduction of the name and the article is here from the field, but most important of these fields is the material name. And then it is handled through a set of tools that contribute to the educational process, including raising the files, images, video, questions, plus students and teachers of the material, and the distribution of the roles on them.

Moreover, the algorithm integrated educational environment and a social network (Mahnane & Touati, 2015) is summarized as follows:

Algorithm integration

Begin
Take the input of educational environment and social network.
Read the educational environment components from set of components collection.
For each content educational environment do
Begin
Compared the educational environment components with social network components
If components educational environment equal components social network, add content components educational environment to components social network.
End
End.

Here are some examples of the social networks that used in education:

- In Rožac, Pogačnik, Kos, Buendía, and Ballester (2012), the authors proposed an integration of e-learning systems with social networks and display its supporting software. The author solved the low level of interaction between users. Through direct relationship between learning content and communication between users and teachers in e-learning systems. Suggested use of social networks to increases the interaction between users in e-learning environments. The approach depends on the virtual classroom, integrating e-learning system COOM with Facebook.

- In Du, Fu, Zhao, Liu, and Liu (2012), the authors proposed an interactive and collaborative e-learning platform which integrates social software with a learning management system (LMS). This platform provides personalized space for users where they can interact and collaborate with others. The personalized space of users contains their course network, social network and knowledge network. This platform connects course network of users with his/her social network and knowledge network. Furthermore, users are able to build their personalized social network and knowledge network during the process of learning.

- In Meishar-Tal, Kurtz, and Pieterse (2012), the authors used a Facebook as an alternative to LMS. Their approach reviews the current research on the use of Facebook in academia and analyzed the differences between a Facebook group and a regular LMS. The authors used a Facebook group as a course website, serving as a platform for delivering content and maintaining interactions among the students and between the students and the lecturer.

- In Kurtz (2014), the author study the effect of integrating Facebook group and course website on participation and perceptions on learning. Such that use of two virtual platforms for learning. Show that Facebook, can be used for discussion and exchange of knowledge. Students reported that Facebook helps enhance the interaction and social learning processes with emphasis on the involvement of the user, and contribute effectively, and frequent interaction with peers and the instructor.

Finally, the differences between previous researches and our approach are as follows:

- Developing a model to enable creation, registration course student and teacher in educational environment.
- Developing a model of social networking site.
- Developing a model to enable creation, storing, publication and sharing of course materials from educational environment to social network.
- We will apply different learning methods to get an optimal teaching and learning strategy. This strategy based on learning style and data mining techniques depends on integrating of educational environments, and social networks.

Educational social networks and learning styles

Not all users can be assumed to benefit from social networks either due to their diverse backgrounds or due to their different learning styles, it may not be appropriate to suggest that social networks might be beneficial for every student, as students are generally from diverse backgrounds, and most importantly have different learning styles (García-Martín, & García-Sánchez, 2013; Lin, Hou, Wang, & Chang, 2013; Friesen & Lowe, 2012).

Felder and Solomon (2001) described learning styles across four dimensions answering following the questions: What type of information is emphasized by the instructor (SEnsing (SE)/ INtuiting (IN))? What mode of presentation is stressed (VIsual (VI)/VErbal (VE))? What mode of student participation is facilitated by the presentation (ACtive (AC)/REflective (RE))? What type of perspective is provided on the information presented (SeQuential (SQ)/GLobal (GL)).

In this way, Mahnane, and Touati (2015) used learning styles in order to provide interactive social network delivery by means of adaptable navigation and adaptive content selection. The most important contributions in this work are as follows: (1) Designing Traditional Social Network (TSN) based on user' learning style and user' skill level; (2) Supporting different types of educational content. In Mahane and Touati's (2015) study, the authors have shown that the use of TSN gives a good result compared to Facebook. Figure 2 shows an interface for TSN based on user' learning style (VI/SQ/IN/AC) and user' skill level (average).

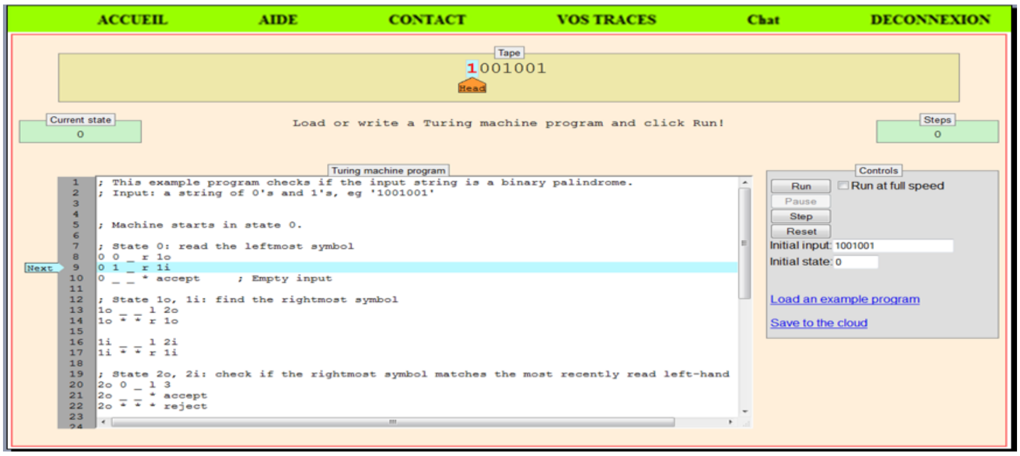

Figure 2. An integrated in TSN: domain (Mathematical logic), learning style (VI/SQ/IN/AC) and skill level (average)

Educational social networks and data mining

Nowadays social networks provide an important source of information. In addition to the common use, they are also used by researchers to extract information that is usually not visible to the naked eye. Analyzing such data, however, can be challenging. Within the most important educational social network from the fields of data mining we can found:

- In Gamila, Pavla, Jan, Katerina and Václav (2010), the authors were presented an application of spectral clustering method to find the patterns of behavior of groups of students enrolled in the e-learning system. For easier generation of the graphs described students' behavioral patterns in e-learning system, with requires setting of number of input variables for clustering method or setting of the dimensions (selection of the appropriate course or students' activities in the course provided in e-learning system), was developed specialized software. Moreover, authors attempted to find relations between the behavioral study patterns and the students' study performance in the selected course. The findings of the experiment did not show any relation between the similarity in students' behavior and their grades as well as relation between students' positions in generated network and their academic performance.

- In Ambrósio Gomes, Cavalcante Prudêncio, Azevedo Filho, Alves do Nascimento, and Alves de Oliveira (2013), the authors presented the evaluation of their strategy to group profiling applied to an educational social network called OJE. The OJE is a social network that connects students and teachers through games and enigmas. The OJE's platform provides an environment for conducting tournaments between teams and individual students (supervised by teachers) who engage in various disputes. In order to explain the group formation resulted from OJE educational social network, the authors present two differentiation-based group profiling methods: Wilcoxon rank-sum test and PART rules Algorithm.

- In Troussas, Espnosa, and Virvou (2016), the authors described the affect recognition for intelligent language learning using Rocchio Classifier. Furthermore, the authors presented important features for achieving a probabilistic approach of Rocchio classifier. The significance of using a more probabilistic approach of Rocchio algorithm for affect recognition is that the probabilistic methods are preferable from a theoretical viewpoint, since a probabilistic framework allows the clear statement and easier understanding of the simplifying assumptions made. The used data is a random sample of streaming Facebook states and were not collected by using specific queries. The size of hand-labeled data allows performing cross validation experiments and checking for the variance in performance of the classifier across folds. In this way, knowing the emotional state of each user, the authors used this characteristic as a value of the vector used for the group profiling, which can further ameliorate the educational experience through Facebook.

Discussion

From the Background and related scientific work, the following problems should be recognized:

- The majority of the traditional educational social network do not consider the adaptation according to the user's profile in their approaches (Troussas, Espnosa, & Virvou, 2016; Ambrósio Gomes et al., 2013; Gamila, Pavla, Jan, Katerina & Václav, 2010).
- Less attention was intended to study the application of machine learning techniques for generation of group profiling in educational social networks (Ambrósio Gomes et al., 2013).
- Several researches are made in the group formation where all these researches are vocalized on grouping users using different criteria: users' profiles, learning styles, etc. These previous works present some limitations where the grouping of users is static while the characteristics of users are dynamic (Mahnane & Touati, 2015). As result, groups are formed with the initial and the previous characteristics and not with the current ones.

A summary of the related scientific research is presented in Table 1.

Table 1. A summary of the related scientific research

Author (s)	Social network	Communities detection	Static/dynamic	Identification of learning activities	Recommendation process
(Ambrósio Gomes et al., 2013)	OJE	Explicit	Static	No	No
(Troussas, Espnosa, & Virvou, 2016)	Facebook	Explicit	Static	No	No
(Mahnane & Touati, 2015)	TSN	Implicit	Static	Pedagogical rules	Pedagogical rules
(Rožac et al., 2012)	Facebook	Explicit	Static	No	No
(Meishar-Tal et al., 2012)	Facebook	Explicit	Static	No	No
(Kurtz, 2014)	Facebook	Explicit	Static	No	No
Proposed approach	NSN-AP-AF	implicit	Dynamic	Apriori algorithm	Collaborative Filtering

Research methods

System framework

The operating principle of our model NSN-AP-CF as well as the input and output of each module is shown in Figure 3 and Table 2 respectively.

Furthermore, we describe in the following the different steps of our approach:
Step 1: The system gathers the users in different groups based on the learning styles of users.
Step 2: A pre-test questionnaire was given to the students for evaluates the users' skill level about the mathematical logic course.
Step 3: The users can access to their own lesson where they can access to the learning activities. Every lesson contains many activities such as: theory (A1), games and simulations (A2), problem solving (A3), discussion (A4), case study (A5), qustion/answer method (A6), project (A7) and practical work (A8). The system selects a frequent episodes by the Apriori algorithm.
Step 4: The system evaluates the user's skill level for each lesson
Step 5: The system updates groups of users based on collaborative filtering algorithm.

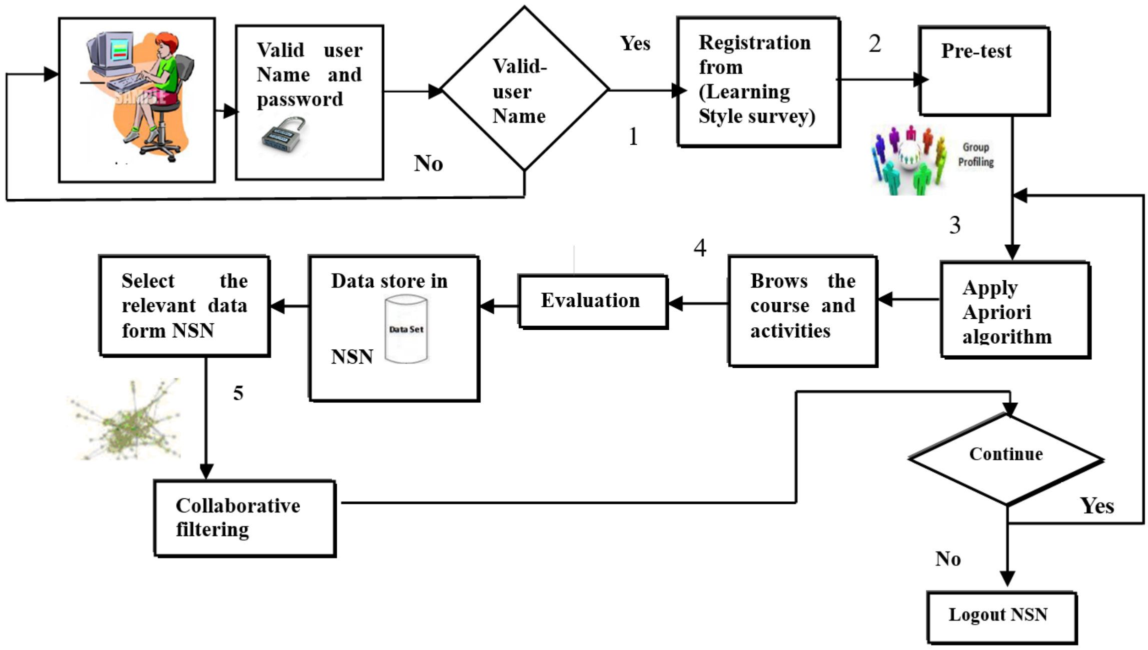

Figure 3. Framework for NSN-AP-CF using apriori algorithm and collaborative filtering

Table 2. The input and output of each module

Module	Input	Output
Learning style module	Questionnaire Index Learning Style.	Style in four dimensions
Mining sequential patterns module	• Style in four dimensions • Log file	The most probable activities
Evaluation module	Questions	Users' ratings
Recommendation process module	• Log file • users' ratings file	• 16 clusters. • Learning style based on skill level for user

The detail of each module in the proposed model **NSN-AP-CF** is presented as following.

Learning style identification

In our research, we employ the instrument inspired by Felder-Silverman's ILS to examine user's learning style by an online questionnaire, with the paraphrases on items. By literature review on learning styles and the experimental conclusion about Felder-Silverman's model (Felder & Solomon, 2001; Mahnane & Hafidi, 2016), the following general activities are provided for each pole of the 4 dimensions of our instruments (see Table 3).

Table 3. Learning styles and corresponding learning activities inspired from (Mahnane & Hafidi, 2016)

Learning style	Learning activities
ACtive (AC)	• Games and simulations • Problem solving • Discussion • Project
REflective (RE)	• Case study • Question/answer
SEnsing (SE)	• Problem solving • Question/answer
INtuitive (IN)	• Games and simulations • Discussion • Case study • Project
VIsual (VI)	• Games and simulations
VErbal (VE)	• Discussion • Question/answer
SeQuential (SQ)	• Question/answer
GLobal (GL)	• Case study • Project

Mining by Apriori algorithm

The mining by apriori algorithm establishes connection between episodes learning and the choice of activity. With this relationship, we can detect users' preference, as shown in Table 4.

Table 4. A small part of the database

User-id	Users' learning style	Users' rating	Gender	Units	Lessons	Access-time	Episode learning
1	VI/GL/AC/IN	2	Female	1	1	2015. January 10	{A2, A5, A1, A4}
1	VI/GL/AC/SE	3	Male	1	1	2015. January 11	{A2, A3, A8, A1}
1	VE/GL/AC/IN	4	Female	1	1	2015. January 12	{A7, A5, A1, A6}
2	VE/GL/RE/IN	2	Female	1	1	2015. January 20	{A5, A1, A3}
2	VE/SQ/RE/SE	3	Male	1	1	2015. January 21	{A1, A6, A8, A3}
2	VE/GL/RE/IN	3	Male	1	1	2015. January 22	{A5, A1, A3}
3	VI/GL/AC/IN	2	Female	1	1	2015. January 15	{A2, A4, A5, A1}
3	VI/GL/RE/IN	4	Female	1	1	2015. January 15	{A1, A5, A4, A3}

Table 5. The results of mining by Apriori algorithm (best rules)

Learning styles	Male	Female
VI/GL/AC/IN	{A3, , A2, A1}	{A7, A5, A1}
VI/GL/AC/SE	{A8, A2, A1}	{A8, A5, A1}
VI/GL/RE/IN	{A2, A1, A3}	{A5, A1, A7}
VI/GL/RE/SE	{A2, A1, A3}	{A5, A1, A8}
VI/SQ/AC/IN	{A3, A2, A1,A4}	{A3, A5, A6, A1}
VI/SQ/AC/SE	{A3, A2, A4, A1}	{A8, A5, A4, A1}
VI/SQ/RE/IN	{A2, A1, A3}	{A5, A1, A7}
VI/SQ/RE/SE	{A2, A4, A1, A3}	{A5, A4, A1, A8}
VE/GL/AC/IN	{A3, A2, A1}	{A7, A5, A1}
VE/GL/AC/SE	{A3, A2, A4, A1}	{A8, A5, A4, A1}
VE/GL/RE/IN	{A2, A4, A1, A3}	{A5, A4, A1, A7}
VE/GL/RE/SE	{A2, A4, A1, A3}	{A5, A4, A1, A8}
VE/SQ/AC/IN	{A7, A2, A1}	{A8, A5, A1}
VE/SQ/AC/SE	{A3, A2, A1}	{A7, A5, A1}
VE/SQ/RE/IN	{A2, A1, A3}	{A5, A1, A7}

VE/SQ/RE/SE	{A2, A4, A1, A3}	{A5, A4, A1, A8}

Afterward, with using this algorithm, we can predict the most probable episode learning and activities. The mining by Apriori algorithm is defined as follows:

***Algorithm**: Apriori Algorithm;*
Begin
C_1 = Itemsets of size one in I;
Determine all large itemsets of size 1, L_1;
i=1;
Repeat
i=i+1;
C_i= Apriori-Gen(L_{i-1});
Apriori-Gen(L_{i-1})
Generate candidates of size i+1 from large itemsets of size i.
Join large itemsets of size i if they agree on i-1.
Prune candidates who have subsets that not large
Count C_i to determine L_i;
Until no more large itemsets found;
End

In Table 5, we show the results of mining sequential patterns by Apriori algorithm with min-supp (α = 0.4) and min- conf (δ = 0.9).

Dynamic grouping of users

The objective of this work consists of forming groups of users with different learning styles. For this, we define the k-mean algorithm based on users learning style and users' skill level as follows:

Algorithm K-mean;
***Input** Maximum number of clusters k;*
Activity (unit, lesson, difficulty level, learning style, type of activity, time);
User (goal and preferences, learning style, skill level, gender);
Begin
1. *Choose k individuals randomly (as a center of initial classes);*
2. *Assign each individual to the nearest center; This gives a partition P into k classes P1={C1, C2,.., Ck};*
3. *The centers of gravity are calculated for each class P1, which provides k new cluster centers.*
4. *Repeating step (2) and (3) until two successive iterations yield the same partition.*

End.

In Table 6, we show the skill level had a significant relationship in the group G12. From this result, the users' learning styles (VI, RE, GL, and SE) had a better skill level in the episode {games and simulations, problem solving}.

Table 6. The centers of gravity in 16 clusters

	Centers of gravity															
	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16
VI	3	3	2	3	2	4	2	3	0	1	0	4	1	0	0	1
VE	0	0	1	0	1	0	1	1	4	3	2	2	4	3	2	3
AC	3	4	0	1	2	2	0	0	2	4	0	0	2	2	1	0
RE	0	1	2	2	0	0	2	2	0	0	2	3	0	0	4	2
SQ	0	0	0	0	3	3	3	3	0	0	0	2	3	4	2	2
GL	3	3	2	2	0	1	0	0	2	2	3	4	0	1	0	1
IN	3	0	2	0	2	0	2	0	4	0	4	1	4	0	3	0
SE	1	2	0	3	0	2	0	3	0	2	0	4	0	3	0	4

Several empirical findings have suggested that the sensitive style had a better skill level in the discussion (Huang, Lin, & Huang, 2012), and the global style had a high skill level in the learning based on problem solving (Carmo, Gomes, Pereira, & Mendes, 2006).

Methodology

In this experiment, we wished to ascertain if the use of an educational social network (NSN) was an effective way to improve student skill level and course satisfaction in "mathematical logic" course when compared to traditional social network (TSN).

Design of the study

The student skill level was measured by the pre/post-test instrument. Both the experimental and the control groups experienced similar learning activities. However, only the experimental group received access to the new educational social network (NSN). The performance pre-test served to determine the degree of homogeneity between the experimental and control groups. During the end of session the same performance post-test was administered to all participants. Additional data were also collected, in the form of post surveys (Brooke, 1996). The experimental groups post-survey explored the efficacy and the overall usefulness of NSN for learning.

Participants

To validate our approach, an experiment was conducted at the department of mathematic, university of Algeria, where the students learn the concepts of "Mathematical logic" subject. These students were divided into experimental and control groups. Each group consisted of 40 students. The NSN system was designated for the experimental group and the TSN system was designated for the control group. Figure 4 shows an interface for problem solving activity in new educational social network (NSN) based on Apriori algorithm and collaborative filtering (K-mean algorithm).

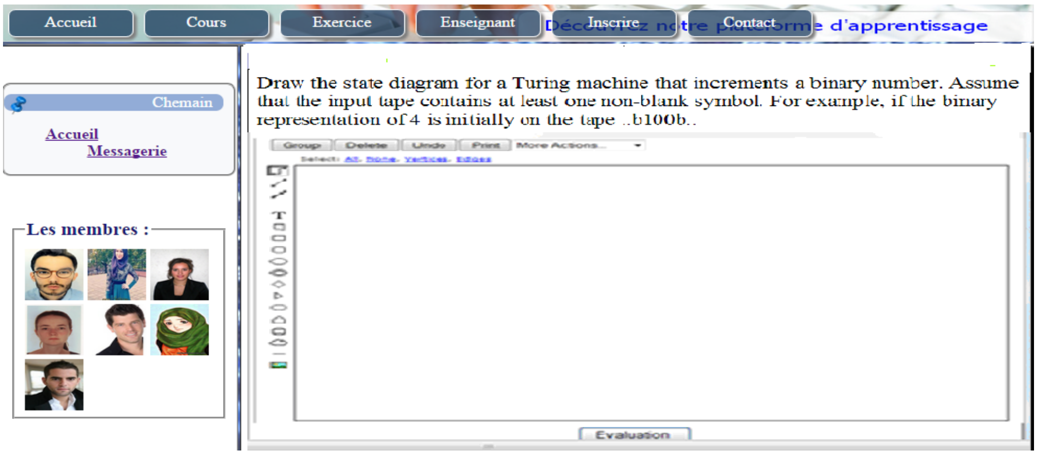

Figure 4. Problem solving activity in NSN-AP-CF

Analysis and results

Students' skill level

The first research question investigates whether differences between the experimental and control groups exists in terms of the students' skill level in the "mathematical logic" course between the students who used the NSN versus TSN, as measured by pre and post instrument. Table 7 presents the descriptive statistics for the pre-test and post-test data for both the experimental and control groups. A review of the descriptive statistics reveals that the pre-test scores appeared to be similar across groups; however, the post-test scores appeared to be different across groups with students in the experimental group outperforming students in the control group.

A *t*-test analysis was performed for both the pre-test and post-test scores function of the group type to determine the existence of differences between the two groups' means. For the pre-tests, the analysis concluded that there is not a statistically significant difference between the means of the pre-test scores of the control group and the experimental group ($p < .05$).

On the other hand, for the post-test scores, the analysis revealed that there is a statistically significant difference between the mean post-test scores for the two groups considered.

Based on the descriptive statistics generated in Table 7 and the conclusion of the t-test we can determine if indeed the utilization of the NSN had a positive impact over the post-test scores – the students in the experimental groups scored higher than the ones in the control group. The results of the hypothesis testing conducted states that indeed the mean of the post-test scores for the students included in the experimental group is statistically higher than the one of the students from the control group ($p < .05$). So, we can conclude that the NSN increased the students' skill level in their final session.

Table 7. Descriptive statistics for pre-test and post-test measure

	Control				Experimental			
	Pre-test		Post-test		Pre-test		Post-test	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Male (n = 14)	30.1	4.8	31.7	5.4	31.4	5.0	38.9	2.4
Female (n = 26)	35.2	3.6	34.4	3.2	35.7	3.3	40.8	2.8

We also calculate the difference between the post-test scores and pre-test scores, to determine if the students from the experimental group performed better than the ones assigned to the control group. The *t*-test concluded that indeed the students from the experimental group performed better than the ones in the control group ($p < .05$).

To support these findings, that indeed the students exposed to the NSN performed better than the ones not using the system, we conducted statistical testing on the learning activities for the two groups. Even though at the beginning of the course there was no statistical difference between the activities scores for the experimental versus the control group, by the last testing we were able to identify that the our approach is efficient. The analysis results are synthesized in Table 8.

Table 8. A comparison between the experimental and control groups

Activities	Group	Users	Mean	*SD*	*t*	*p*-value
Total score	Experimental	40	79.8	4.8	9.135	< .05
	Control	40	71.7	2.9		
Unit1/lesson1	Experimental	40	74.5	5.0	3.391	< .05
	Control	40	71.1	3.9		
Unit1/lesson2	Experimental	40	78.7	4.6	10.584	< .05
	Control	40	69.6	2.9		
Unit2/lesson1	Experimental	40	82.0	6.6	8.069	< .05
	Control	40	71.2	5.3		
Unit2/lesson2	Experimental	40	80.6	6.9	5.125	< .05
	Control	40	73.5	5.4		
Unit3/lesson1	Experimental	40	79.8	6.7	6.293	< .05
	Control	40	71.3	5.3		
Unit3/lesson2	Experimental	40	80.9	5.0	7.882	< .05
	Control	40	72.6	4.4		
Unit3/lesson3	Experimental	40	81.8	5.2	6.4	< .05
	Control	40	74.5	5.0		
Unit3/lesson4	Experimental	40	81.9	6.4	10.751	< .05
	Control	40	69.5	3.5		

These results have been supported by:

- Kunchala (2015) thought that student's posts on social network gives us a better concern to take decision about the particular education system's learning process of the system.
- Buzzetto-More (2012) Concluded that social networking have been shown to foster social learning while engaging students in a complex array of communicative and creative endeavors including new literacy practices.
- Shaqifah, Sani, Taib, Jusoff, and Shazi (2011) alleged that data mining discovered the patterns of students' participation in social networking. It is found that their participation relates with their personal behavior.

Students' perception

The second research question addresses the experimental groups' level of perceived satisfaction regarding the effectiveness of the NSN tools after the experiment; to what extent do students perceive access to the NSN contributed to their learning. The experimental groups' responses to the post-survey items referring to the usefulness of the NSN overall were used to answer this research question. The data for these 10 survey items were coded as 5 - Strongly Agree or 1 - Strongly Disagree. Descriptive statistics for the survey items 1-10 indicated that the perception scores appeared to be high, as displayed in Table 9. Table 9 shows that Q10, Q5 and Q1 provide the best score (Q10 = 64%, Q5 = 59.2%, Q1 = 70.7 %).

Table 9. Descriptive statistics for experimental - Survey response items

		Mean	*SD*	Strongly Disagree->Strongly Agree				
				1	2	3	4	5
Q1	I think that I would like to use this system frequently	3.94	1.028	5.3	3.1	25.3	38.7	32.0
Q2	I found the system unnecessarily complex	3.56	1.132	7.6	7.6	38.7	27.6	23.1
Q3	I needed to learn a lot of things before I could get going with this system	3.18	1.066	12.0	9.8	43.1	32.0	6.6*
Q4	I felt very confident using the system	3.49	1.050	5.3	14.2	32.0	36.5	16.5
Q5	I would imagine that most people would learn to use this system very quickly	3.65	1.019	5.3	7.6	32.0	39.3	19.9
Q6	I thought there was too much inconsistency in this system	3.52	0.835	3.1	3.1	54.2	32.0	12.0*
Q7	I found the various functions in this system were well integrated	3.67	0.972	3.1	9.8	34.2	36.5	19.1
Q8	I found the system very cumbersome to use	3.41	1.011	5.3	12.0	43.1	29.8	14.2*
Q9	I think that I would need the support of a technical person to be able to use this system	3.65	1.029	3.1	9.8	38.7	29.8	23.1*
Q10	I thought the system was easy to use	3.85	0.915	3.1	3.1	34.4	38.7	25.3

Note. *= [score of "Strongly Agree" and "Agree" is low]

Precision methods

The third research question addresses the precision of our proposed approach by a comparative study. Table 10 and Figure 5 presents a comparative study between the APriori algorithm (AP), Collaborative Filtering algorithm (CF), Traditional Social Network based on learning styles system (TSN), and APriori and Collaborative Filtering algorithm (AP-CF). For this, we can define the notions of precision, recall and F-measure (Aher & Lobo, 2012) as follow:

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$ With

$$Precision = \frac{TruePositive}{(TruePositive + FalseNegative)}$$ and

$$Recall = \frac{TruePositive}{(TruePositive + FalsePositive)}$$

As can be seen, the AP-CF algorithm that considers the grouping dynamically the users based on their learning styles and the discovery of all frequent episodes based on Apriori algorithm generates better precisions compared with the other algorithms.

Table 10. The comparison between TSN, NSN-AP, NSN- CF, and NSN-AP-CF algorithms

System	Recall	Precision	F1
TSN	0.297	0.598	0.396
NSN-AP	0.399	0.624	0.486
NSN-CF	0.497	0.646	0.561
NSN-AP-CF	0.566	0.758	0.649

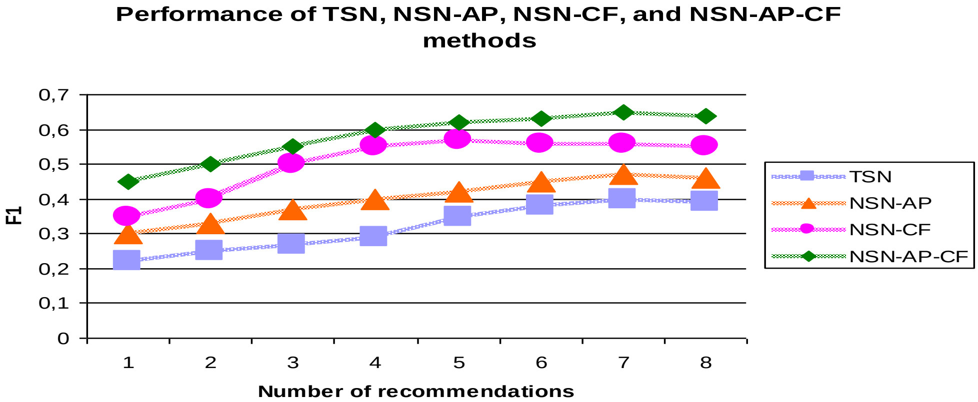

Figure 5. The performance of the TSN, NSN-AP, NSN- CF, and NSN-AP-CF systems

Conclusion and future prospective

Some researchers have shown that the users instead of educational environments and the social networks are more effective than users of educational environments (Veletsianos, & Navarrete, 2012; Troussas, Espnosa, & Virvou, 2016). Indeed, the social networks facilitate the involvement of the user process and make it in the heart of the educational process. Furthermore, social networks use several components that interact with the user more than others. Thus, the integration of educational environments with the social networks will have the ability to improve, support and build privileged system.

This paper describes a new educational social network based on Apriori and Collaborative Filtering algorithms (NSN-AP-CF) which can automatically adapt to the interests, learning styles and knowledge levels of users. Moreover, it aims at grouping dynamically the users based on user's learning style and user's skill level.

The experiment results confirm that a mining the frequent episodes by the Apriori algorithm in each learning style has the potential to improve the quality of NSN-AP-CF, as well as keep the recommendation up-to-date. Moreover, this study shows that our proposed approach can outperform the traditional recommendation algorithms significantly in precision and could be more suitable for personalization of educational environments. Different users can benefit from this study as follows:

- Motivate users by providing new and modern means of learning and teaching.
- Make it easy for users to access the information required in the fastest time.
- Flexibility and ease, students communicate with teachers and with peers material with enriches the learning process.

As a future work, we plan to conduct other tests in order to validate the proposed approach with a large sample of users. In addition, we envisage extracting the benefits of our approach by applying it to other domains. Finally, users can still use social networking tools for other purposes rather than learning.

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