ANALYSING STUDENTS' INTERACTIONS THROUGH SOCIAL PRESENCE AND SOCIAL NETWORK METRICS

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ABSTRACT

In online learning environments, tutors have several problems to carry out their activities, such as evaluating the student, knowing the right way to guide each student, promoting discussions, and knowing the right time to interact or let students build knowledge alone. We consider scenarios in which teaching and learning occurs in online social networks platforms and in order to support tutors' knowledge on the students' interactions, we propose an approach based on social presence and social network analysis. The solution consists on mapping profiles through the observation of interactions occurring in an online social network, then using automatic textual analyses of social presence based on the criteria of affection, interaction, cohesion and strength, as well as metrics for social network analysis to see the interactions and connections of members in the social network. We applied the approach in a case study and the students agreed their profile represented them correctly and the proposed solution had good acceptance.

KEYWORDS

Social Presence, Social Networks, Social Network Analysis, Learning Technologies, Technology Enhanced Learning

1. INTRODUCTION

The amount of users and the Internet usage rate has been increasing at an accelerated rate. Technologies are useful in different environments, whether in classrooms or outdoors, creating new spaces for communication and interaction on social networks. The social media is leading to the next generation of social learning innovation [Lytras et al., 2014].

Language is a social practice that organizes and structures the human relations [Vygotski, 2012]. Support and contact among students and teachers can be problematic in the distance learning, as the contacts happen mediated by machines. It is necessary to establish a network of relationships built between the participants and between them and the learning contents, in a scenario where the feelings and emotions should also be perceived [Bastos et al., 2013]. Therefore, an important activity for teachers and tutors is to observe and to support the participation of students in discursive interactions in order to maintain the sharing spirit of mutual trust and support among participants of a course [Marques et al., 2013] [Krejci and Siqueira, 2013].

The activity of observing and supporting students interactions is related to the notion of social presence (SP), which is an aspect considered relevant for establishing interpersonal relationships, particularly in text-based interaction resources [Garrison and Archer, 2000] [Mackey and Freyberg, 2010]. The SP is the degree to which a person is able to get herself attached to the course or study group, communicate effectively in an environment of trust and develop personal and affective relationships, designing her individual personality in computer mediated communication [Garrison, 2011].

In online discussions there are lots of messages shared between students and tutors, which express doubts, opinions and feelings. However, it is difficult to track the volume of online messages and understand the behaviour of students, making the role of tutors harder in supporting the development of students' knowledge. When analysing the interactions between the participants, one may also understand the underlying social network of the participants, which could also provide important information about the discussions. Therefore, we propose the extraction of social presence and an analysis of the interactions performed on an online social network platform. A prototype was developed to support a case study with students and tutors who used an online social network platform for performing communication activities in a course.

The remainder of this paper is organized as follows: the 2nd section presents a brief overview of the e Community of Inquiry (CoI) and the Social Presence (SP) concepts. Section 3 describes the face-Presence architecture proposed in this work, the 4th section shows how the case study was conducted, the 5th discusses the analysis of the results. Finally, the 6th and last section presents some final remarks.

2. COMMUNITY OF INQUIRY – COI, AND SOCIAL PRESENCE – SP

The Community of Inquiry (CoI) model was created in order to guide the use of asynchronous communication in written form, mediated by computer to support the development of critical thinking in higher education [Rourke et al., 2001] and prioritized into a space for discussion of academic subjects. The online collaborative constructivist experience is represented as an intersection of a function of three elements that interact dynamically: social presence, cognitive presence and teaching presence [Akyol et al., 2009].

The first element in the model is the development of cognitive presence, which is defined as "the extent that participants in any particular configuration of a research community are able to construct meaning through sustained communication" [Garrison and Archer, 2000]. The second element is the teaching presence, which includes designing and managing learning sequences, providing subject matter expertise, and facilitating active learning. The third element is the social presence (SP), defined as the ability of students to make themselves socially and emotionally noticeable in a community of inquiry. The social presence supports the cognitive goals through its ability to instigate and support critical thinking in a community of learners [Rourke et al., 2001]. It also supports the affective objectives, making attractive the interactions, engaging group, and therefore intrinsically rewarding, leading to increased academic, social and institutional integration and resulting in increased persistence and graduation [Tinto, 1987].

These three elements have a key role in the construction of meaningful learning by learners [Swan, 2010]. It is extremely important that students feel part of the group and there is empathy with the teacher and classmates for learning effectiveness. The cognitive presence, social presence and teaching presence must work together to reach the educational experience.

SP is the degree to which the other person is perceived as a "real person" in mediated communication technology [Lowenthal, 2000]. This concept is considered one of the most popular to describe and understand how people interact in virtual learning environments [Gunawardena and Zittle, 1997]. The level of awareness of each other in the virtual learning environment can be influenced both by personal characteristics of each (interest, dedication, initiative, etc.), as well as the resources offered by the environment to convey social and emotional information about the other [Tu, 2000].

[Bastos et al., 2013] set SP indicators (called clues, which were used to detect concepts belonging to SP. Then, the messages written on forums and chats bring important indications for the SP study in virtual learning environments, providing a measure for understanding the involvement of individuals.

The SP supports the emotional and cognitive learning objectives and contains three broad categories of communication responses: (i) affective, (ii) interactive and (iii) cohesive [Rourke et al., 2001]. These three categories are updated in the discourse of participants through observable indicators.

3. FACE-PRESENCE

The proposed approach maps students' profiles from teaching-learning activities in online social networking systems, by analysing their interactions. It also includes other properties related to the interactions that are common in social networks systems, as the amount of likes, shares, tags in the messages and comments. These properties provide more information about the behaviour of individuals in the group, and indicate their social presence as well as the network characteristics.

The first stage of mapping the profiles is the extraction of posts and comments. The second stage of our proposal is social network analysis (SNA), trying to verify the network characteristics according to its structure, making possible to observe the most influential members, the ones who interact more, those with more connections, among other features that may facilitate the planning of the tutors' actions.

For processing each message posted by users, along with the social networks properties, we built an architecture (Figure 1). We tried to reuse existing systems and adapt them, rather than building other ones.

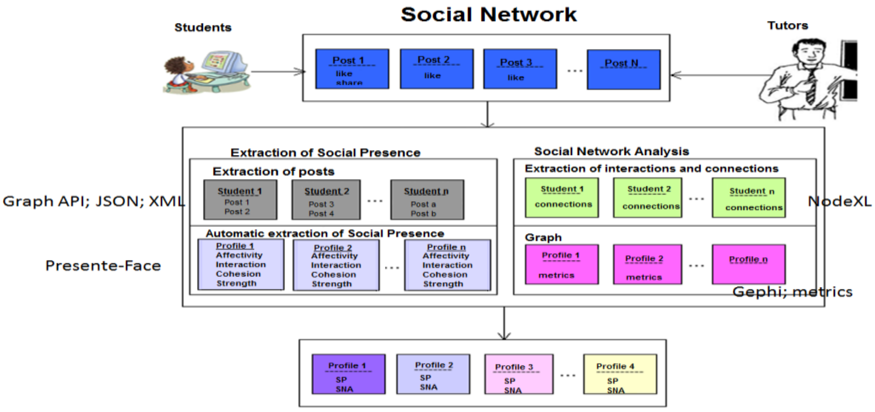

Figure 1. Proposed Architecture

The solution is organized in three main modules: extraction of social presence (in which the group's posts are extracted of the social network and the Social Presence’s indicators, subclasses and classes are identified), social network analysis (involving the extraction of interactions and group connections and the analysis of the interactions and connections with a social network analysis tool) and the creation of profiles.

For extraction of the posts from the social network we used the Facebook API that captures, through FQL queries (Facebook Query Language), the data entered by the group members. For the identification of Social Presence indicators we developed the Presente-Face, which consists of an adaptation of the Presente system [Bastos et al., 2013] to analyse the textual data and Facebook properties as like and share. For the other properties it was possible to use the tools that the system already had.

This tool analyses the file of postings based on the categories defined by the teacher or tutor. It takes as input a file with the names of the group members whose analyses are to be done. Then the Analyser returns three types of files: a set of files with the Social Presence detailed for each student; a file with the Social Presence related to the course; and a file with all students and their Social Presence values.

For extracting data from the social network group, in this case the Facebook, we used NodeXL, which is a pre-edited Microsoft Excel template specialized in creating graphs from social network data. The software makes the extraction of all public data made available by the group members as well as the interactions that occurred in the group. For more detailed analysis of graphs we used Gephi, a tool that allows the user to interact with the representation, manipulate the structures, shapes and colours to reveal hidden properties of each chosen graphic, helping to discover patterns, isolate singularities or failures during data supply.

4. CASE STUDY

During the period between February 19th, 2014 and May 19th, 2014, we performed a case study with 10 students and three tutors of the Computers and Education course, of the Bachelor of Information Systems program, at the Federal University of the State of Rio de Janeiro (UNIRIO). Throughout this period of time, students exchanged information through the group created on Facebook for supporting the course activities. The exchange of messages occurred in a natural and spontaneous way, which is an important factor so that it does not influence students to participate.

At the end of the course, the conversations were extracted from Facebook to generate a profile for each student, including the diagnosis of the Social Presence in the group, divided into 4 categories: Affection, Interactivity, Cohesion and Strength. All actions performed by students and tutors within the Facebook group were monitored and extracted. The group interactions were recorded through NodeXL software. As data collection process for qualitative analysis, individual interviews were scheduled with students after analyses of the profiles generated by research. The online interview method was the Underlying Discourse Explanation Method - MEDS [Barbosa et al., 2002]. Interviews were conducted through the Facebook chat with the students and tutors. The tutors were interviewed to analyse the profiles and verify if the obtained information assist them in tutoring activities.

In addition to the qualitative analysis of the interview data, the comments posted by the students during the activities of the subject were quantitatively analysed by checking the Social Presence clues. Together, all participants generated 205 messages, many of them with likes, reviews and tagging of group members. All participants in the case study have good knowledge of using technology in day-to-day and frequently use the Internet through smartphones, tablets, notebooks, etc. Most of the participants already use Facebook to communicate in day-to-day with friends and family. Students and tutors participants of this research are between 18-38 years old, and there were 6 men and 7 women.

The social presence degree (GRPs) is obtained by dividing the number of SP occurrences by the number of posts. Table 1 expresses the results of calculating the degree of Social Presence.

Table 1. Social Presence Degree

Name	Social Presence	Posts	GRPs
Student 1	**189**	47	4.02
Student 3	**122**	23	5.30
Student 2	**89**	18	4.94
Student 5	**53**	12	4.42
Student 4	**39**	16	2.45
Student 8	**35**	12	2.92
Student 7	**25**	7	3.57
Student 9	**10**	4	2.50
Student 6	**9**	4	2.25
Student 10	**2**	1	2.00

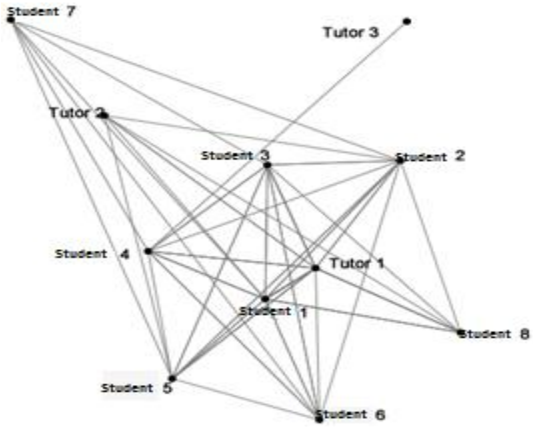

Figure 2. Group interactions graph

Thus, although the amount of messages may be important in the discussion, there is not direct correlation with the SP or GRP. Some Students post messages more focused on content and therefore containing less SP features. On the other hand, there are few students who post messages with interaction and emotion features and therefore more SP (or GRP). Although the Student 1 has a greater number of posted messages and has a larger value SP, the social Presence degree is not the highest, messages did not have many SP characteristics. Moreover, Student 5 posted about 26% of the number of messages that Student 1, about 30% of the total SP value of Student 1, but with a SP degree greater than Student 1. Thus, we noticed that the Student 1 had a higher volume of interaction, but did not promote more involvement of the group than the Student 5.

In addition, only 4 Students had moderate degree of Social Presence, which clearly reflects their participation in online interactions. This is partially justified because it was a face-to-face course and online interactions aimed to complement activities, besides the fact that the students have jobs and often have little study effort out of class hours. Figure 2 shows the graph of group interactions. The nodes or vertices represent the students and tutors and the edges represent the interactions between them. Social network analysis metrics allow a better understanding of the students (and tutors) activities and therefore of the course. Two students were not in the graph as they had no interactions.

The most connected students are Student 1 and Student 2, each one with 9 connections. An actor who has several relationships with other actors can, for example, quickly spread information. The degree centrality measures the degree of each node depending on its relationships and expresses the number of connections (or different people with whom the node is connected) in the network. In Table 2, the students are ranked in descending order according to the degree centrality value.

The students with greater proximity between the vertices are also the most connected (Student 1 and Student 2). And the student with lower proximity was one of the least connected - Student 8 with 0.063. Another actor with few relationships, but that is part of the shortest path between other actors, can exert a certain intervention in the communication between these actors. Through the closeness centrality metric is possible to analyse the students with greater proximity between the vertices with the most connected ones. Table 2 also shows the closeness centrality values displayed in descending order.

Table 2. Degree Centrality, Closeness Centrality, Betweenness Degree

Name	Degree centrality	Closeness centrality	Betweenness centrality
Student 1	**9**	0.091	2.733
Student 2	**9**	0.091	2.733
Student 3	**8**	0.083	1.450
Student 4	**8**	0.083	9.167
Student 5	**8**	0.083	1.450
Student 6	**7**	0.077	0.167
Student 7	**6**	0.071	0.000
Student 8	**5**	0.063	0.200

Table 3. Clustering Coefficient

Name	Clustering
Student 7	1.000
Student 6	0.952
Tutor 2	0.900
Student 8	0.900
Student 3	0.821
Student 5	0.821
Tutor 1	0.786
Student 1	0.750
Student 2	0.750
Student 4	0.714
Tutor 3	0.000

The student with highest betweenness degree was the Student 4, which had 8 connections on the network and betweenness degree 9,167 (i.e. he is not the student with more connections), while the students with more connections in the network has betweenness degree 2,733. It indicates that although the Student 4 has fewer connections, he has greater importance in mediating talks. There was a greater distribution of values, e.g., a student with 7 connections has betweenness degree (0.167), while other student with 5 connections has a higher betweenness degree (0.200), indicating that although he has a smaller number of connections exerts greater importance in mediating talks than the other.

A student with 6 connections present betweenness degree 0.000, while two students with 5 connections have betweenness degree 0.200, indicating that being connected with more people do not influence in facilitating conversation. Table 2 also shows the betweenness degree values.

Considering this group, the values of degree centrality follow the same order of the Eigenvector centrality values, indicating that the importance of a vertex according to its neighbours is bigger for the most connected ones. In Table 3, it is possible to see that the most connected people do not have higher clustering coefficient, which shows that these people have less tendency to cluster than the Student 7 which has degree centrality 6. Table 3 shows the clustering coefficient values displayed in descending order.

5. RESULTS AND DISCUSSION

We conducted qualitative analyses with data collected through interviews. The tutors know the students and interacted online during the period in order to be able to assess whether the received profiles effectively identify the students. The average of the rates for the tutors' confidence on the participants' profile provided by the proposed approach was 9.3, indicating that the tutors have a confidence level of 93% on the profiles.

Students analysed their participation in the Facebook group and the average of the rates obtained to the degree of correctness of their profile was 9.3, indicating that students attributed 93% degree of confidence to their profiles. Qualitative analysis was performed on data collected from interviews in online interviews.

5.1 Challenges to interact on Facebook

When asked about the challenges to interact on Facebook, many students cited the timidity and the difficulty of monitoring the conversations. Some answers illustrate this analysis:

"*I am a person who likes to talk a lot, but do not feel comfortable online. In person I'm not afraid of making mistakes, speaking wrong Portuguese and sometimes even knowing the right, but on the Internet I'm more cautions and it makes the process more bureaucratic.*"

"*My biggest challenge was to interact, especially when beginning a chat on some topic.*"

90% of students agreed that the profile helped to identify their characteristics in the group:

"*I fully agree with the description of this profile. Student with greater betweenness is not the one with most connections. For a person from the humanities, this metric is FASCINATING... !!!*"

"*Yes, with more information about the student one can know who has difficulties in this area and thus it helps you to continue at the same pace that others are.*"

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5.2 Challenges to interact Online with Students

When asked about the challenges to interact on Facebook, many students cited the timidity and the difficulty of monitoring the conversations. When asked about the challenges to interact online with students, tutors highlighted the difficulty of following the conversation, stimulating discussion and knowing the right tone for each student. The statements listed below underlie these conclusions:

"*Time to monitor and guide the discussions; know the right tone to guide each student and promote discussions; know the right time to interact or let the students build their own knowledge.*"

"*It was difficult to determine exactly what to say in posts, ask questions for promoting students to speak according to their minds, so I tried respond to posts and not initiate discussions.*"

5.3 Facebook Information supporting the Identification of Students' Difficulties

Tutors were asked about the information that could support the identification of students' difficulties in learning the content. They emphasized the lack of interaction might be indicative of difficulty, commented that questions also help them to understand the difficulties of the students and said that if the student does not interact is more difficult to identify his difficulties. The informality of a social network was mentioned as making it easier for students to express themselves more freely.

"*The questions and the lack of interactions are always a target; interactions on facebook can be simply like (or share), while discussions are important for knowledge construction; the questions are always indicative of doubts; the lack of interaction may be indicative of lack of interest, time problems or even misunderstanding something.*"

5.4 Relevant Information obtained from the Profile

When asked about the information on the profile they considered useful, tutors found that all the information was relevant and pertinent. The social network analysis was also cited as an important factor, which is a great advantage of this research, since only through the Social Presence is not possible to analyse the interactions of the members in the social network, making it impossible to analyse their connections and factors that can influence the participation of the student, such as friendship.

5.5 Profile as a Tool in Mentoring Activities

Tutors were asked if they thought the profile provided useful information of student participation in a social network group. All the tutors said the profile served as a supporting tool in mentoring activities.

"*Yes, with the profile I managed to get the activities on a more targeted manner, directly interact with the elements that can lead the group to develop and to learn better.*"

"*Yes. knowing the students' profile, according to the interactions, one can notice their participation.*"

5.6 Analysis of the Goals Set

All tutors agree that the profiles are useful and can be used to support activities in the course. 9 of 10 students said that the profile helped in identifying their characteristics in the course. The one who did not agreed with his profile didn't read the presentation that explained how the survey was conducted, a key factor to understanding how the profile was built:

"*I think that it does not identify me, because not all social indicators are directly proportional to the activity parameters in the social network, but I did not read the background of this work ...*"

In addition some students said that profile also helped in their self-analysis. If only the SP was examined in this work, some important issues would not be included in the profile, such as an actor having various relationships with other actors may, for example, spread information quickly.

The student with greater betweenness in the groups is not the most connected one, as the student 4 having 8 connections in the network, SP = 2.43 and 9.167 of betweenness degree, while the Students 1 and 2 have more connections in the network got betweenness degree equals to 2.733 and Student 1 has SP degree = 4.02 and the Student 2 has SP degree = 4.94. It indicates that although the Student 4 has fewer connections and low SP degree, he has a greater importance in mediating talks. This analysis brought a reflection for the evaluation of the work, as the Student 4 presents textual clues of vulnerability and said: "I am shy and I do not feel comfortable exposing ideas or thoughts here, especially in writing." SP analysis combined with SNA allowed the perception of the student importance in a group despite having low SP degree.

The Student 6 has 7 connections, betweenness degree of 0.167 and low SP degree = 2.25, while the Student 8 has 5 connections and has a slightly higher betweenness degree 0.200 and low SP degree = 2.91, indicating that although the student 8 has a smaller number of connections, he has a greater importance in mediating the other conversations, and provides more SP.

The Student 7 has 6 connections, shows the betweenness degree of 0.000 and low SP degree = 3.57, while the Student 8 has 5 connections, shows the betweenness degree of 0.200 and low SP degree = 2.91, indicating that although Student 7 is connected with more people and has a higher SP degree, he has no influence in facilitating conversation.

These characteristics support the analyses of the profiles. The SP alone would quantify the occurrence of textual clues of affection, interaction, cohesion and strength, but without the SNA it is impossible to understand the importance of the student in the network, understanding the connections and interactions. Therefore, analysing the objectives and the data obtained from interviews, the result of this work has the potential to be useful, since 90% of students mentioned that the profile represented them properly and all tutors said they helped in their mentoring activities. It was also demonstrated the importance of using both the SP and the SNA to compose profiles, as they together provide information so that tutors can analyse the behaviour of students in the social network and make inferences considering the profiles received as a source.

6. CONCLUSION

The support of the tutor throughout the course is very important to the success of each student. With the proposed approach it is possible to obtain data and issues for improving the teaching-learning process, the identification of individual and collective problems and greater flexibility in problem solving.

The previous proposals dealing with social presence, define the underlying concepts and present a questionnaire for getting information about it [Garrison and Archer, 2000], discuss the influence of social presence [Mackey and Freyberg, 2010] [Rourke et al., 2001] or propose indicators and tools for acquiring social presence from forums and chats [Bastos et al., 2013].

We proposed building students profiles that can be used by the teacher / tutor. Although there other works that capture users (or learners) profiles from their interactions in social networks (e.g., [Fernandes and Siqueira, 2013]), our proposal considers two main aspects: the SP and SNA metrics. With this diagnosis, the teacher/tutor is able to monitor and evaluate the students' interactions, to better understand the students and then make necessary interventions. One can use this information to aid the students' learning process.

This paper presents an approach for capturing the students' profile according to their participation in the courses. The profile is based on SP concepts and SNA metrics, motivated by the large number of data available in the learning environments. Therefore, tutors may use the profiles as a resource to assist in planning their mentoring activities to facilitate the student learning process. In their turn, the students may use this information to self-analysis (or self-assess) their participation in the group. Another contribution of this work is that in a given sample of students and tutors in a particular scenario, in which the students' profiles based on SP and SNA were presented, there was a 93% reliability rate and it showed the potential to help in tutoring. As a technical contribution it is possible to mention the construction of the prototype. In addition, the proposed architecture can be generalized and applied to other social networks.

As future work the profiles could be used in accordance to tutoring strategies to suggest actions to the tutor. It could be also interesting to develop a dashboard with the interactions and allow configuration of analysis metrics and tutoring strategies according to the approach or interest of teachers / tutors or students. In addition, it might be interesting to analyse the social network, partitioning its members in order to find groups that have common interests or characteristics, as proposed in [Guedes et al., 2014], and using educational data mining techniques as in [Gottardo et al., 2014]. Finally, the students' profiles could consider other pieces of information such as the learning styles.

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