Applying Social Network Analysis in a Course Supported by a LMS: Report of a Case Study

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Abstract—**Social interactions, when analyzed, can provide several information to help intuitive understanding of individuals and their interactions. Social Network Analysis (SNA) is a study field that investigates people's interaction patterns. These patterns, when mapped, enable a detailed and in-depth view of individuals' groups. In the context of distance learning, this paper presents an analysis that uses SNA metrics for helping the teacher of a Learning Management System (LMS) to understand the social structure of students' interactions and more quickly identify active and inactive students within the class. The study was conducted in a discipline offered in a higher education institution. Four SNA metrics were used in the results. These metrics include: density, degree centrality, the relative centrality and global centrality. Through these metrics it became possible to measure the relationships between students and find out, for example, which students needed more attention from the teacher. In addition, it was possible to identify students who interact more and students who are relationship bridges on the network, among other information. Thus, the results showed that SNA helped the teacher in the understanding of the interaction structure between students.**

Keywords-social network analysis; learning management system; social interactions; students interactions; groups; student-centered education; SNA metrics; case study

I. INTRODUCTION

Learning Management Systems (LMSs) constitute important technological resources that enhance Distance Learning. They integrate from teaching materials to the relationship between teachers, students, methodologies and teaching strategies, for purposes of developing the knowledge construction of the student [1]. These environments are developed for the teaching-learning processes, facilitating the communication between students and teachers.

This way, the LMS constitutes a set of electronic tools aimed at the teaching-learning process. The main components include: systems for organizing contents, follow-up activities and providing students with an electronic communication and online support [2].

However, although these environments are beneficial, several difficulties have been identified by individuals that use them, such as, difficulties on the teacher's role to coordinate the social interactions that take place in the environment.

Another point that must be taken into consideration is that even these environments have a vast range of pedagogical benefits, teachers using these online environments do not receive any learning tips from the student. These tips are easily obtained from more traditional educational service provision means (face to face) [3]. For example, groups and subgroups formed in the classroom, identifying students who need more attention, the number of students succeeding or not to follow up the topic taught.

With the aim of minimizing the teacher's distance in relation to the interactions that occur in social network analysis and in order to help him to coordinate these social interactions, this paper investigates the interactions that occur between students in the distance learning environment.

In this paper two communication tools and the interaction of these environments are analyzed, which include: 1. Discussion forum tool, which is an asynchronous textual communication tool, mostly used for providing more depth a topic [4] and, 2. Messaging tool, also considered an asynchronous conversation, allowing message exchange between interlocutors.

Interactional information collected from these two tools are analyzed and some Social Networks Analysis metrics are applied to them. The interactional information was collected through a case study carried out in a distance learning course at the Federal University of Amazonas - Brazil, in which some sociograms were generated and made available to the teacher.

Therefore, the aim of this work is to aid the teacher in the identification of groups and subgroups within the course and identification of students who most and least participated. In other words, the teacher has at the information of the most predominant characteristics of the class, which helped him to adopt strategic decisions related to the real situation of the class.

This paper is organized as follows. Section II explains and exemplifies the sociogram term which is widely used in this paper. Section III conceptualizes and exemplifies the Social Network Analysis, explaining in details, measurements of density and centrality, which were the methods applied in this work. Section IV presents related research. Section V presents in details our case study. Section VI presents and analyzes the results obtained from the experiment applied in this work, and finally Section VII presents final considerations, as well as the limitations, contributions and future works.

II. SOCIOGRAM

In this work, several sociograms were generated which allowed the visual analysis by the teachers from interactions occurred between students of a distance learning course.

A sociogram is a graphical representation of relations, in the form of diagrams which allow the graphical exploration of the position that each individual occupies within the group.

Moreover, mounting a sociogram is not a simple process, because it requires a detailed study on interactions. According to Moreno [5], a sociogram is considered good when readable. For that, the number of lines that intersect must be reduced to the minimum, after the collection and tabulation of choices, and the sociogram is started by the most chosen people. We must put them in their natural formations – three people in a triangle, four in a square, five in a pentagon, well separated, and the existence of subgroups must be observable in the drawing.

The aim of the sociogram [6] is to make the reading of relations easier. This way, the sociogram must allow the visualization of the relations in the clearest possible way.

Figure 1 is an example of a sociogram that was elaborated according to social relations of a Facebook individual with his friendship network.

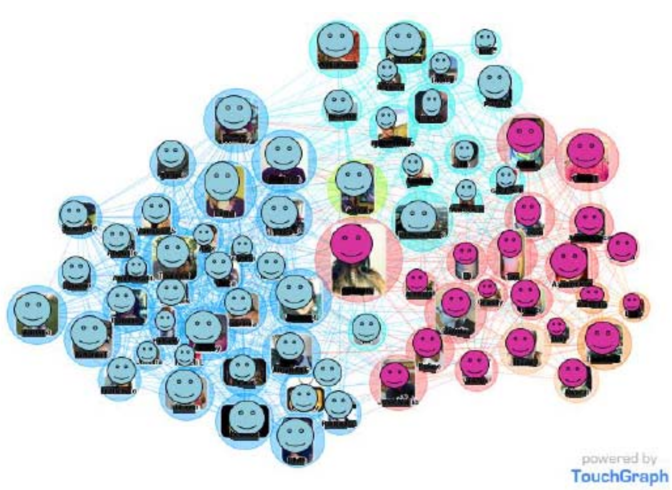

Figure 1. Example of a Sociogram [7].

The Sociogram presented in Fig. 1 was structured by means of the online tool called TouchGraph [8].

In order to develop sociograms there are three appropriate applications needed; these are: NetDraw [9], Weft QDA [10] and NodeXL [11].

In Fig. 1, it is possible to see the groups and subgroups highlighted by different colors. The circles are nodes that represent people.

The use of sociograms could aid teachers in SNA, having in mind that these environments do not have a mechanism that graphically shows the interactions and proportions a general and detailed view around social relations that are established throughout a course. This information is important, because the tutor is an influencer in the teaching-learning process [12] and that measurement is a key factor in distance learning.

In this paper, every time that a reference to a social relation is done, we are adopting the concept of [13] which states that social relations are related to actions of various people, or agents, equipped with mutually related meanings, in which, agents' conducts are oriented so that the meanings are shared by all.

III. SOCIAL NETWORK ANALYSIS

A Social Network, according to Newman [14] and Aggarwal [15], is a set of people (or entities) with some interaction pattern between them. Detailing even more this concept, it could be said that a Social Network is a social structure, made up of individuals or organizations called "nodes", linked by one or more types of relations [16]. In other words, the social network is formed by a set of actors that most often are called nodes, interconnected through one or more types of relationships [17], such as friendship, kinship, common interest, financial exchange, knowledge, prestige among others [18]. These links/relations found among the individuals are studied in SNA field.

In other words, Social Network Analysis can be considered a structural study of social relations [16], which is centered around the relations among individuals [19]. The analyses of these structures, in the conception of Scot [20], arose as a set of methods for social structural analyses and methods specifically focused on the investigation of aspects related to these structures.

According to Freeman [21], Social Network Analysis, apart from being focused on the investigation of interaction patterns of people, is also based on the intuitive notion that these patterns are important characteristics in the life of individuals. The way the individual lives, most of the time, is related to how the individual is related to a larger web of social connections. Therefore, the study involving SNA offers possibilities and profound observations in the analysis of groups of individuals.

Moreover, in the previous years, SNA has emerged as a popular method for studying the collaboration and organization of people working in software development in large teams [22].

Within the context of SNA, there are various metrics used for measuring existing relationships among social network authors. The use of these metrics varies according to the observation objective, being capable of be applied individually or collectively [23]. In the next section, some of the metrics used in the results of this work are described.

A. Density

Density, according to Garton *et al.* [24], is considered one of the most used measuring means in structural analysis of a social network. It is represented by the number of existing connections, divided by the number of possible connections [25], as shown in (1).

D = Density
L = number of existing lines
M = number Maximum connections
n = number of nodes

$$M = \frac{n(n-1)}{2};$$

$$D = \frac{L}{M}; \longrightarrow D \times 100\% \qquad (1)$$

Density, when calculated, presents a value in percentage of intensity of interactions in the center of the network, revealing if there exists a high or low connectivity in its interior [26]. From this, it is possible to classify the connections as strong or weak. These connections, from the viewpoint of Granovetter [27], are defined as: weak connections, those possessing a low density, in which there is the absence of many relationship possibilities, and strong connections, which are very close, representing a greater involvement among the actors.

In an overview, it is possible to state that density describes the level of connection between the points in a graph [28], revealing the percentage of the current relations in the network in reference to all the relationship possibilities [29].

Apart from density, Inclusivity was also calculated in this work, which is established by the proportion of actors and aim at establishing a connection, having in mind the total number of constituent elements in the network [28]. Equation (2) presents how Inclusivity is calculated.

I = Inclusiveness
n = total number of "nodes"
i = "nodes" isolated

$$I = \frac{(n-i)}{n}; \longrightarrow I \times 100\% \qquad (2)$$

The degree of Inclusivity is inversely proportional to the total number of excluded members, which are the isolated "nodes", that is, individuals who did not obtain any interaction registry [30].

B. Centrality

Calculating the centrality of an individual means identifying the position in which it is located in relation to exchange and communication within the network. Therefore, the more centralized an individual, the better positioned it will be in relation to exchange and communication [31].

This way, it can be stated that centrality is the position of an individual in relation to the rest, considered as a measure of the number of links placed between them [28]. These centrality metrics determine the relative importance of the graph vertex [14], hence, making it possible to discover the more centralized vertices, that is, those which possess more connections [32].

There are different ways of measuring the centrality of a vertex in a network, which are based on different graph characteristics [33]. In this work, two important centrality measurements are Local Centrality and Global Centrality.

Local centrality is composed of various metrics, for example, the degree centrality. Therefore, for purposes of this work, as concerns local centrality, the centrality degree was applied in the results. This centrality counts the number of incident edges to the graph vertex [34], that is, the number of ties that an actor possesses with respect to other actors in the network, taking into account only adjacent relationships [16].

To contextualize centrality, given G any graph (connected or not) with *n* vertices and given v_k, a vertex of G.; the centrality degree of v_k, denoted by d_k, is the number of incident edges to v_{ki}, *and* a_{kj} are elements in the adjacent matrix *A(G)* [34], represented in (3).

$$d_k = \sum_{j=1}^{n} a_{kj} \quad , \quad c_R(v_k) = \frac{d_k}{n-1} \qquad (3)$$

Apart from centrality degree, the Relative Centrality Degree was also calculated, having the normality function 1/(n-1). Equation 3 presents the calculation used to find the relative centrality, denoted by C_R.

Meanwhile, global centrality is the sum of the shortest path between the rest of the points (geodesic). Therefore, a point with the smallest sum of distances is closer than the rest. In literature, it is also known as *closeness*, defined as the size of the minimum path between all the pair of vertices [33], that is, it is based on the sum of distances of a vertex in relation to the other graph vertices [34], the higher the index, the closer is the actor to the others [35].

IV. Related Work

Some works analyze the individual interactions in a given environment, using Social Network Analysis, in order to extract predominant characteristics of these interactions and understand the social structure of the network. Below, some of these works are described which reinforce the purpose of this paper.

In the work of Saltz *et. al.* [19], a visualization tool is presented which uses social network centered on the student, in which instructors can identify active and inactive students within the classroom. With this, the instructors can provide guidance, help and incentivize the students. The work software was tested using data from various online students. Moreover, the work takes into account two SNA metrics related to the centrality degree, including: (1) *outdegree* – counting the number of messages sent by the student, and (2) *indegree* – counting the number of responses to the messages sent by the student. The aim of the work was to aid the instructor to try and understand how this information could be useful to improving the participation of students in the class. Furthermore, the work highlights the interest and importance of the use of other SNA metrics, such as density and closeness centrality.

Another relevant work is that of Gerry [36], which presents a study about group relations, understanding the nature of group cognition, and small groups. Therefore, the interactions of the individual and the unity of the group are analyzed, in order to understand the variety of groupware processes and suggest implications for groupware design.

Marisco *et. al.* [37] presented a study on certain social aspects of the CoP (Community of Practice) dynamics, carried out in the UnderstandIT European project scope, with basis on analyses and some evaluation metrics from the SNA research area. Using metrics such as *betweenness*, centrality and proximity, they aimed at obtaining relevant information. According to the authors, the application of the SNA methods and techniques in the case study allowed for the realization of a structural network analysis from the viewpoint of relations between all the members involved in the learning process. With the aid of the approach, it was possible to discover some unknown social structures and other important relationships, and hence reinforcing the validity of this work.

Meanwhile the work of Süβ and Billingsley [38] describes the first iteration of a course projected with the aim of resolving the problem of differences of software development practices carried out in the graduation of industrial practice. The course is designed around continuous integration and automated metrics, openly available to staff and students alike. Besides that, many of the features offered were deliberately designed to promote cooperation between groups.

Lima and Meirinhos [39] applied a social network analysis methodology in discussion forums carried out in a Virtual Environment, generating sociograms by mean of NETDRAW and UCINET software. The results of these analyses were a set of sociograms that enabled the visualization of dynamic interactions and the roles of various actors, enabling the teachers to adopt measures and decisions in advance.

In the work of Vargas *et. al.* [17], some information posted on the Twitter social network is extracted, through the use of linked data, which allows resource recovery and the linking with other sources, graphical databases and with social network analysis (SNA), with the aim of using the information which is published on Twitter to extract and recommend Open Educational Resources, in order to help in the learning process. The results obtained are a set of recommendations about users (identified as experts) and virtual communities (lists of Twitter users) and related events, according with the learning needs.

Finally, the work of Klamma *et. al.* [40] combines social network analysis with recommendation systems in scientific communities, in which a Social Network Analysis of corporations is carried out within 45.000 schools in Europe, with the aim of recommending the most relevant academic events to researchers.

V. Case Study

A case study was carried out in order to validate the proposal, in which various people, for example, teachers and students, were invited to participate in the experiment and all the participants signed the consent form, authorizing the disclosure of the case study results.

For the case study, a distance learning holiday course was elaborated which was made available on a server in the Laboratory for Educational Robotics of the Institute of Computing (IComp) of the Federal University of Amazonas (UFAM). The platform used was Moodle.

For being a holiday course, the course occurred in a three-weeks period, with 30 students and one teacher, totaling 31 participants. The students enrolled in the course were between 20 and 30 years of age, in addition were from different cities, most of them from the city of Itacoatiara, located in the state of Amazonas (Brazil). There were also students from Manaus, located in Amazonas (Brazil), students from Rome, located in Italy, as well as students from Perth, Australia. As shown in Fig. 2.

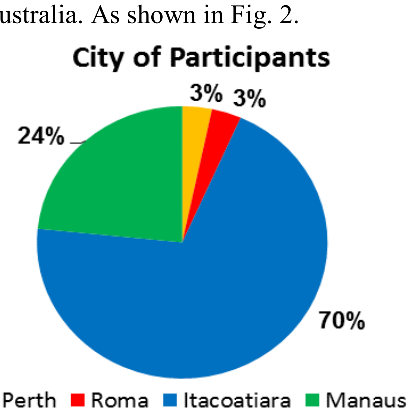

Figure 2. City that participants live.

Considering the different profiles of the cities in which the students lived, a course was designed in which students could exchange and share experiences of their cities with the other participants.

In addition, the students who took part in the holiday course already had experience with distance learning courses, but the vast majority of the students did not know each other.

During the course period, four sociograms were generated – social graphs/graphical representations of the existing relations in a group of individuals [6]; for each week of the course a new sociogram was generated as well as on the last day of the course, totalizing four sociograms as the results of this case study. Tables showing the interactions were also generated by the teacher of the distance learning course. The four sociograms can be seen in Fig. 3 which presents a timeline.

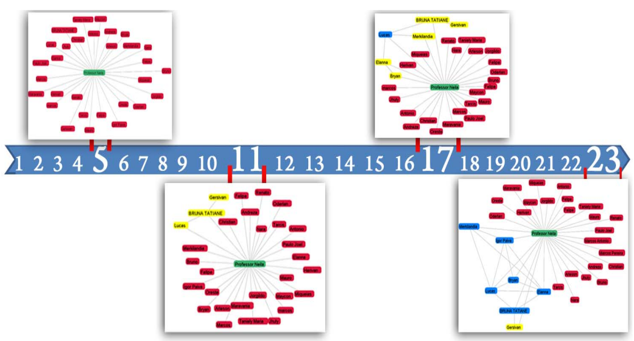

Figure 3. Sociograms Timeline.

The results obtained from the interactions of the students were structured in the form of sociograms in order to provide a better visualization of the interactions. Four SNA metrics were applied to these results, which helped to identify certain network characteristics. This way, it was possible to analyze the network evolution as well as its social structure.

The main contribution of this work consists of presenting the teacher with graphical interactions of his students and enable, by means of SNA metrics, the understanding and characterization of social interactions. This way, the case study carried out seeks to answer the following Research Questions (RQ):

- **RQ1:** Can the use of Social Network Analysis help the teacher to better organize and understand his class?
- **RQ2:** How can the Social Network Analysis metrics aid the distance learning environments?
- **RQ3:** What is/are SNA the metric/metrics which most helped the teacher?

VI. Results

The first week of this course was destined to the introductory activities of the course, as well as the teacher and students. By the end of the first week, the students had not yet interacted among themselves.

From the second week, the teacher began to motivate the students and the results of the interactions began to change. It was possible to identify the most participative students in the environment and those who interacted with other students, as shown in Fig. 4.

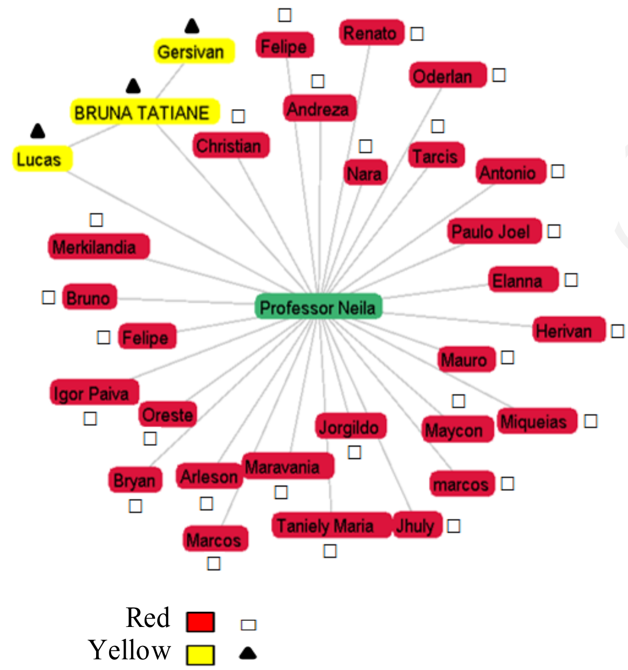

Figure 4. Sociogram second week [41].

At the center of the sociogram is the course teacher, represented by the green color; in red are students who did not interact and, in yellow, students who interacted. Applying the SNA metrics to the class, we have Table I.

TABLE I. SNA METRICS APPLIED IN SECOND WEEK

Taking into consideration the Social Graph full: 31 nodes, 27 isolates	
Number of nodes	31
Inclusiveness	0,12
Number of edges	4
Density	0,0086
Sum of degrees	8
Maximum geodesic distance	2

Analyzing Table I, we can observe the low density between the links, 0.86% (0.0086), a relatively low percentage due to the large number of isolated students within the network. Therefore, in a total of 31 students participating in the course, 27 were isolated.

Isolating the individuals who interacted in the class gives us the following structure presented by Fig. 5.

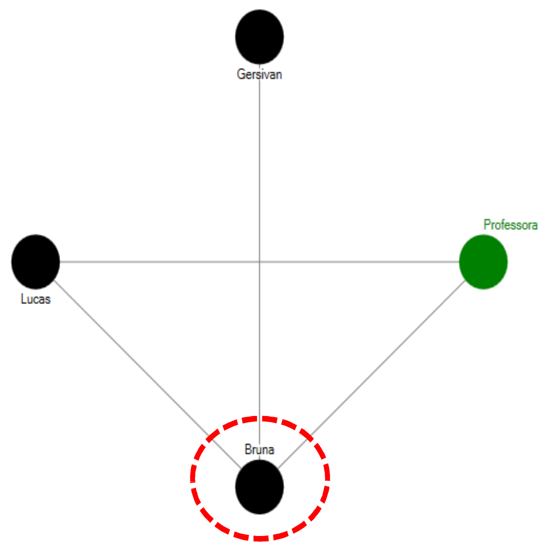

Figure 5. Sociogram of the interactions of second week.

Applying the metrics on students who interacted, we have Table II.

TABLE II. SNA METRIC APPLIED IN SECOND WEEK WITH THE STUDENT INTERATION

Taking into consideration the people who interacted				
	Prof	Bruna	Lucas	Gersivan
Degree Centrality	2	3	2	1
Relative Centrality	0,66	1,00	0,66	0,30
Global Centrality	4	3	4	5

Table II shows an analysis that takes into account only people who interacted. This is presented in Fig. 5 (a social graph with vertices with black and green colors).

According to the analysis, the student named Bruna was the vertex that obtained the least sum of distances, therefore affirming that at this stage of the course, she was the most centralized, that is, the closest to the other vertices.

Meanwhile Gersivan obtained a low relative centrality, therefore being classified as a peripheral point – points with low centrality and elements loosely connected to the network, in relation to the others (Bruna, Lucas and Teacher).

During the week, a context for each social interaction was evolved, although many students continued not to interact.

Based on the second week of tests, the teacher had the opportunity to act and adopt differential measures according to the context of each student.

This way, it is possible to visualize in the third week sociogram, the most participative students in the class. This is presented in Fig. 6.

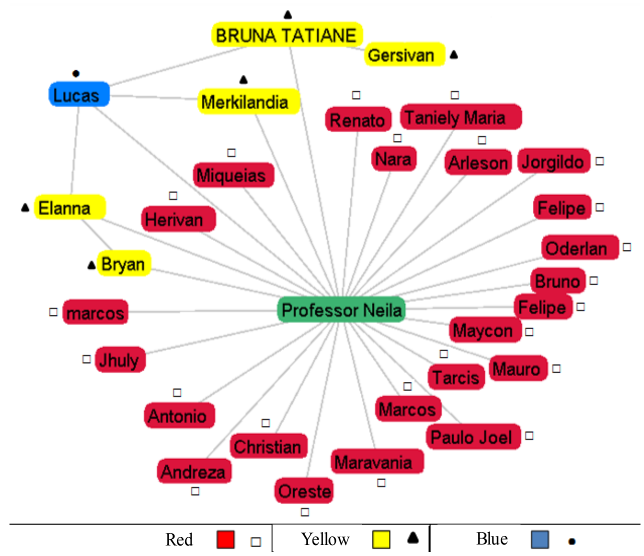

Figure 6. Sociogram third week [41].

Figure 6 presents a social graph of the third week, in which the participation of each individual is visible. In blue are the students with most interactions. Table III presents the SNA metrics applied based on the results of the third week.

TABLE III. SNA METRICS APPLIED IN THIRD WEEK

Taking into consideration the Social Graph full: 31 nodes, 23 isolates	
Number of nodes	31
Inclusiveness	0,23
Number of edges	10
Density	0,021
Sum of degrees	20
Maximum geodesic distance	3

Isolating individuals who interacted in the class gives us the following structure, presented in Fig. 7.

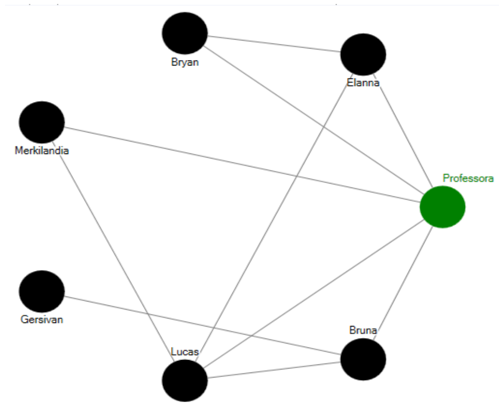

Figure 7. Sociogram of the interactions of third week.

Applying the metrics to the students who interacted, we obtained Table IV.

TABLE IV. SNA METRIC APPLIED IN THIRD WEEK WITH THE STUDENT INTERACTION

Taking into consideration the people who interacted							
	Prof	Bruna	Lucas	Gersivan	Bryan	Elanna	Merki
Degree Centrality	5	3	4	1	2	3	2
Relative Centrality	0,83	0,5	0,66	0,16	0,33	0,5	0,33
Global Centrality	7	9	8	14	11	10	11

According to Table IV it is possible to notice that the teacher already appears as the center of interactions, obtaining the least global centrality index. After the teacher, the student named Lucas is the second most active student in the class with a global centrality index of 8.

Finally, Fig. 8 presents the last sociogram generated in the course, in which it is possible to observe the increase in the number of participative students in the course as well as students with little interaction who became more active. Such results present a very different context as compared to the other generated sociograms.

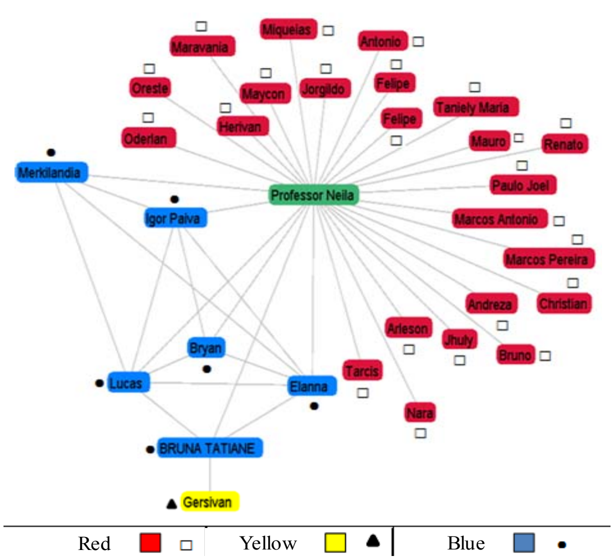

Figure 8. Sociogram of the last week [41].

Table V presents the SNA metrics applied based on the third week results.

TABLE V. SNA METRICS APPLIED IN PREVIOUS WEEK

Taking into consideration the Social Graph full: 31 nodes, 23 isolates	
Number of nodes	31
Inclusiveness	0,26
Number of edges	19
Density	0,04
Sum of degrees	38
Maximum geodesic distance	2

At the end of the course, the number of students who remained isolated was still large. In Table V, the 23 isolated students correspond to the percentage of 74.2% who are students who dropped out of the course. However, we can see that the density was 4%, a significant percentage compared to the density of the second week, which was 0.86%.

Isolating the individuals who interacted in class, we have the following structure presented in Fig. 9.

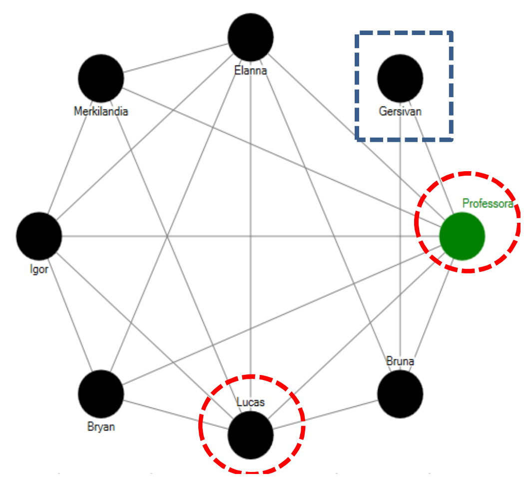

Figure 9. Sociogram of the interactions of last week.

Analyses from the previous result (Fig. 9) show a most active teacher. We can prove this through Table VI.

TABLE VI. SNA METRIC APPLIED IN LAST WEEK WITH THE STUDENT INTERACTION

Taking into consideration the people who interacted								
	Prof	Bruna	Lucas	Gersivan	Bryan	Elanna	Merki	Igor
Degree Centrality	7	4	6	2	4	6	4	5
Relative Centrality	1,00	0,57	0,85	0,28	0,57	0,85	0,57	0,71
Global Centrality	7	10	8	12	10	8	10	9

In Table VI, it is also possible to visualize some students who could help the teacher by being relationship bridges, for example, the student named Lucas, who obtained the second lowest global centrality index.

It is common, although not desirable, that the Distance Learning courses have a high dropout rate. Evasion in distance learning has been addressed as a problem that is very present in all educational institutions and at all levels of education in general [42]. According to the Censo EAD.br 2015 [43], the first semester is the main period of student dropout in the distance learning, one part does not adapt to the routine of individual studies that the modality demands and ends up giving up.

In the experiment course, it was not different. Many of the students came to enroll and did the first exercises, but still dropped out of the course, even with the teacher always encouraging them, sending messages and promoting pedagogical actions to resolve this issue.

Even having these difficulties, the results were satisfactory, because the SNA metrics helped in the identification of non-participating students, apart from providing information about the network, with its social characteristics, allowing the course mediator to adopt strategies according to the network social structure.

This way we can conclude by responding to the research questions, and for **RQ1: Can the use of Social Network Analysis metrics help the teacher to better organize and understand his class?**

It can be stated that the metrics positively helped the teacher of the distance learning course, once he was able to identify by means of metrics, the participative students, students who were not able to interact, which students were relationship bridges, that is, who interacted with more than one group. This way, the teacher could establish and elaborate pedagogical strategies according to the interactional situation of his class.

Answering the second research question – **RQ2: How can the SNA metrics aid the distance learning environments?**

The metrics helped in the identification of groups and subgroups and consequently in the identification of the most and least participative individuals. These information was valuable to the teacher, because once he had this information, he was able to adopt pedagogical strategies and obtain more performance information about his class.

Finally, third research question – **RQ3: What is/are the SNA metric/metrics that most helped the teacher?**

Several metrics can help, depending on the context of the metric used which could be better or not. In this context, we can affirm that the centrality degree metric stood out, because apart from identifying the most participative individual, it was also able to identify the "relationship bridge" individual, who is not necessarily the most popular in the network. However, he/she is the individual who interacts with individuals of other groups, and therefore connecting various groups, hence the name – relationship bridge.

VII. CONCLUSIONS AND FUTURE WORK

The work presented in this paper is a proposed solution to the problem of the teacher presented in the introduction of this paper. The use of the SNA metrics collaborates to the work performed by mediators, once they have at their disposition information about social structures of their online class.

Moreover, by means of these results, teachers can apply pedagogical studies to their classes and follow up the advances throughout the course. The results are provided by the course teacher, in order to help him or her identify social and group relations established by their students.

Also, it was verified that metrics like Density and Global and Local Centrality aid in the identification of these social relations, providing the teacher information that help to understand the interactions of individuals and adopt pedagogical measures according to their established interactions by the students, with the aim of improving teaching and learning of the distance learning course.

As future works, we aim to extend the SNA metrics used, besides from combining them with other existing techniques in the field of computing, such as grouping techniques in Data Mining, in order to more quickly identify groups and subgroups of the class and recommendation techniques, in order to recommend the groups to the teachers which can be mounted in the environment. Moreover, we intend to carry out more case studies, in order to identify new interactional characteristics.

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