An Approach Based on Social Network Analysis Applied to a Collaborative Learning Experience

Iván Claros, Ruth Cobos, and César A. Collazos

Abstract—The Social Network Analysis (SNA) techniques allow modelling and analysing the interaction among individuals based on their attributes and relationships. This approach has been used by several researchers in order to measure the social processes in collaborative learning experiences. But oftentimes such measures were calculated at the final state of experiences, what may be hardly representative of students' behaviours during the learning processes. Therefore, a temporal dimension in SNA metrics may extend and improve the understanding about students' interactions in a collaborative scenario. In this respect, this paper presents a systematic review about SNA metrics used for analysing CSCL scenarios and proposes to trace the behaviour of such metrics during experiences through the inclusion of a temporal dimension. In order to expose this approach, a real collaborative learning experience, supported by a platform called SMLearning System, was analysed. We found that social relationships among students tend to be symmetric, i.e., there was a proportional distribution of efforts and contributions of students, which is an expected condition in a collaborative scenario. Such observations are based on the temporal behaviour of the reciprocity metric and the correlation between in- and out-degree centrality metrics measured in time.

Index Terms—Asynchronous interaction, collaborative learning, evaluation/methodology, web-based interaction

1 Introduction

THEORETICAL and empirical evidences show that there is a close relation between social interaction and learning processes [1], [2]. Social interaction enables groups become aware of their environment and shared goals while the members of a group build the knowledge required to solve the tasks [3], [4], [5]. Students encourage each other to: ask questions, explain and justify their opinions and reasoning, elaborate and reflect upon their knowledge, which fosters motivation and improves the learning process [6]. Also, the quality of interaction is reflected on communication processes and the actions on shared workspaces; i.e., it influences the learner experience and his/her achievements [7]. In consequence, social interaction requires communication and negotiation mechanisms [3], [4] and also skills for inquiring, sharing ideas and fostering the motivation among teammates [7], [8].

In this sense, social interaction is one of the most important aspects in the collaborative learning theory [2]. Several successful experiences show that students learn from peers as much as they do from an instructor or a textbook [9], [10], [11]. In this context, the research field of CSCL (Computer-Supported Collaborative Learning) aims to understand the conditions in which collaborative learning is more effective than individual learning [3]. Some of such conditions include [12]: individual accountability and attitude toward collaboration [13]; the positive interdependence among peers [14]; mechanisms for coordination, communication [15] and awareness [5], [16]; and establishment of strategies toward a common goal [3], [17]. These conditions suggest that social processes in CSCL scenarios are highly dynamic and complex. In consequence, a better understanding about such processes may improve the learning experiences through more effective feedback channels among learners and instructors [18], [19], [20] and a better sense of community [21]

There are several approaches for analysing interaction, mainly: content analysis methods [7], [22], [23], [24]; collaborative indicators [17], [25]; mixed-evaluation methodologies [26], [27], [28], [29]; and social network analysis (SNA) [28], [30], [31].

Content analysis is a messages-based approach which systematically characterizes each analysis unit into a set of categories. An analysis unit is a sentence, paragraph, or idea shared by learners during the learning activities. These categories may be used as metrics of the learning process on aspects such as: cognitive skills [22], motivation [23], critical thinking [24], and teaching presence, among others [22]. Chen et al. have applied data mining techniques to students' informal conversations on Twitter in order to explore the social and emotional aspects [32]. In this case, the messages categories were the major worries and issues that engineering students encountered in their studies and personal life.

On the other hand, some indicators have been proposed as measuring of success or performance in a collaborative learning experience. For instance, Index of Collaboration [25] has been redefined through five indicators [17]: the use of strategies, an intra-group cooperation measure, the checking out of success goals, the monitoring and performance of the group. These indicators combine content analysis methods and system-based measures, for instance, log of students' access.

Moreover, the mixed-evaluation methodologies [29], propose to combine several methods and data sources, such as: log files, surveys, content analysis, social network analysis, among others, in order to obtain a whole perspective about the learning scenario [26], [27], [28] and enhance the confidence of findings [29].

Finally, SNA defines different methods based on the structure of students' social interaction [28], [31], [33].This approach is supported on the graph theories which define several metrics related to features in a network model [33]. Such metrics allow detecting social patterns such as: leaders, bridges or isolated individuals [30], [34], [35] . Meanwhile, some authors claim that the evolution of social structure seems to offer an early cue of success in learning experiences [31]. However, the interpretation of SNA metrics depends of the modelled features in the network, so they are hardly comparable among different scenarios [28].

According with several authors, mostly of research reports about SNA metrics applied to collaborative scenarios are measured at the final stage of experience. This suppose that any temporal fluctuation of the measures is discarded, which in consequence, makes to lose useful information about the social dynamics [36]. Laat et al. compare the value of several metrics in three stages of the experiences in order to analyse such dynamic [28]. On the other hand, Marcos-Garcia et al. propose a semi-automatic role detection method, used for monitoring CSCL scenarios in order to provide support adapted to participants in a collaborative experience [37]. Molenaar [38] and Reimann [36] claim the relevance of temporal analysis on learning sceneries. Molenaar illustrates her ideas with a content analysis method applied to a face-to-face collaborative experience [38]; while, Reimann proposes an event-centred analysis and suggests the Markov modelling as method [36]. A more complete and formal approach for facing this requirement is the Dynamic network analysis (DNA) based on theory of complex systems [39]. In this case, the network's attributes are modelled as stochastic variables. However, there are not previous experiences which relate that approach with social interaction analysis and its complexity is outside of the scope of this paper.

According with the literature reviewed, a great part of the methods employed in interaction analysis for a collaborative learning experience neglect aspects related to time and order [36]. Additionally, SNA seems to describe in a better way the social interaction

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processes among members group rather than approaches based on individual performance [20]. In consequence, a temporal dimension in SNA metrics could improve the understanding about learners' interactions and the collaborative phenomenon.

In this respect, this paper offers: first, a review of research works about SNA in CSCL context in order to identify SNA metrics which empirically have been useful to analyse such scenarios; and second, a case study where a subset of such metrics were applied in an experience carried out with students at Cauca University (Colombia) and supported by a CSCL platform called Social Media Learning (SMLearning) System [40]. These metrics have been calculated as time function, in order to offer a better representation of the dynamic group rather than an analysis based on the final stage of experience.

The following section presents a brief description about several concepts and metrics proposed in SNA. Section 3 describes the scenario used as a case study and the SMLearning system is presented. Section 4 shows the main results and findings of this experience. Finally, the section 5 proposes some conclusions and future work.

2 Social Network Analysis Applied to CSCL Contexts

SNA is defined as a set of methods which allow analysing network structures represented through graphs composed by nodes and ties [41]. These nodes may have arbitrary attributes, whilst the ties may have directions and weights. The distance between two nodes is defined by the length of the shortest path. The mode in a network is the number different node types, i.e., if a graph contains two types of nodes, for instance, resources and learners, is a two-mode network. Commonly, the analysed models are simplified to one-mode networks.

The ties among nodes may be represented through an adjacency matrix with many rows and columns as nodes there are in the network. If the ties are non-directed, then such matrix is symmetric. If the ties do not have weights, then the model is called dichotomous network and the adjacency matrix is formed by ones and zeros which indicate connection or isolation among nodes. Frequently, non-directed networks are used in the data analysis; those are created from non-symmetrical directed graphs using an operator as min-, max-, mean- or sum- which replaces the original matrix [35].

SNA metrics may be divided in three scopes: global, individual, and related to clusters. The global metrics measure a single value for the whole network; individual metrics measure a value by each node; and metrics related to clusters allow to identify patterns or sub-groups into the graph.

Usually, the studied reports have used one-mode symmetric networks; in consequence, several assumptions were applied by their authors, for instance: the symmetry of ties. In this context, we propose that the symmetry seems to be a feature related to collaborative phenomenon. However, we consider that it is not an assumption in all interaction processes.

According with the reviewed literature, the SNA metrics which have been used for analysing CSCL experiences are: global metrics: Density, Centralization; Inclusiveness; individual metrics: Centrality (Degree, Betweenness and Closeness); cluster metrics: Cliques; Change propensity. Also, we have included the global metric called Reciprocity in order to analyse the symmetry of ties. At following, brief descriptions about these metrics are presented; a more formal and detailed definition about them and their measures can be found in Ref. [31].

2.1 Density

This aspect indicates how connected nodes are in the network. It is measured as the proportion of ties in a network relative to the total number possible, without to consider the distribution of connections among nodes [33]. Its value seems to be associated with the speed of dissemination of information and the attitude toward collaboration in the group [20]. Density values are reported by Refs. [20], [26], [28], [34] and [42].

2.2 Centralization

This aspects indicates how centred the network is around its most valuable points [33]. It is measured from the centrality value of the most valuable node in relation with the other nodes' centrality. The centrality metric is introduced after. A high value indicates that information or interaction is focused in few nodes, i.e., there is a high dependency toward nodes with social roles usually associated with instructors or moderators [26], [42]. In contrast, a low value indicates a more regular distribution of efforts, thus, a better attitude toward collaboration [28]. Centralization values are reported by Refs. [26], [28], and [42].

2.3 Inclusiveness

This concept specifies the proportion of nodes which have interacted in the network. It is measured as the total number of nodes minus the number of isolated nodes [34]. Its value may help to understand the attitude of learners toward not mandatory activities, reported by Ref. [34].

2.4 Reciprocity

This metric is also named Mutuality, and it indicates the symmetry in the social relationships. It is measured as a percent of how reciprocated ties are in the network [33], i.e., how a directed-graph is similar to its non-directed version.

2.5 Centrality

It is the measure of the value of a node within the network. This metric allows studying the homogeneity of the social structure [26]. Its value is associated with the node's visibility or power to control information in the network. It is measured by several approaches, mainly: Degree, Betweenness and Closeness. Valente et al. [43] analysed the correlation among Centrality values calculated by several approaches; their results show that such approaches seem to be different measures of a same conceptually related concept. Thus, a mixed approach may be the best strategy.

Degree centrality value is based on the direct connections with a node. Betweenness centrality value is based on how many times the node is part of the shortest path between two other nodes [43]. The Closeness centrality value is based on the distance among the node and all other ones, such that the highest value is given to node with the lowest distance with others [43]. Degree and Closeness centralities may be calculated taking account in-, out-, or ties in both directions.

According with Cho et al. [27], Degree centrality is positively associated with individual performance, team outcomes, and satisfaction with the learning process. Also, often high values of Degree centrality coincide with social roles of teaching presence, such as: instructors and moderator [28], [34], [42], .

The Betweenness centrality seems to be an indicator of information control [43]: Nodes with higher values may play roles of brokers or bridges with branches of nodes in the network [33]. Usually, such positions correspond with teaching presence roles because they tend to interact with all nodes and connect learners' ideas in order to foster interaction [20], [34] among them.

On the other hand, Closeness centrality can be associated with features of efficiency and autonomy: Nodes with higher values are able to transmit information more efficiently; also, they do not need to seek information from other more peripheral nodes [43]. Degree and Closeness centralities seem to relate closer with learners' performance than Betweenness centrality [27].

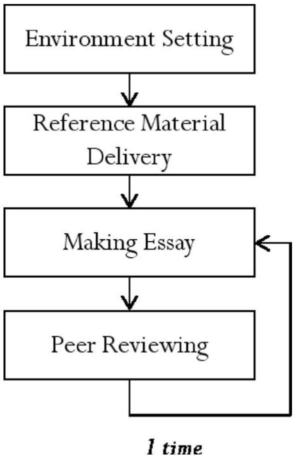

Fig. 1. Schema which represents the collaborative learning script proposed for the case study.

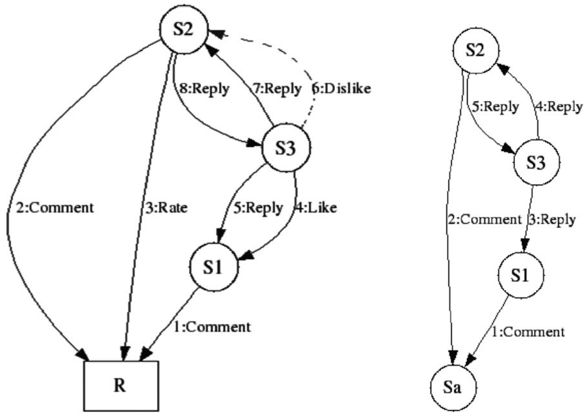

Fig. 2. On left: a realistic interaction model expected in the learning activity. On right: the summarized interaction model used in the analysis process; the resource entities was replaced by its authors (Sa) and ties were created by comments and replies.

These metrics have been reported by the following authors: Degree centrality [20], [26], [27], [28], [34], [42]; Betweenness centrality [20], [27], [34], [42]; and Closeness centrality [27], [34], [42].

2.6 Cliques

This concept allows to identify sub-structures in the network. A Clique is created from a sub-set of nodes intensely linked each other, which is defined by a minimal number of tied nodes and a minimum weight on their connections [33]. There are several measures associated with this concept, for instance: size, strength or the total number of cliques. Commonly, researches aim to explain why such clusters are created and identify patterns on them [35]; besides, to compare empirical and hypothetical structure. Some experiences show that learners tend to interact within small groups, because fewer connections are easier to maintain and coordinate than a lot of them [34], [44].

2.7 Change Propensity

This aspect allows to view how individuals explore new social links [27]. It is measured comparing status of ties in different periods of time during the experience [28]. The use of a survey has been reported by Martinez et al. [26] in order to estimate the impact of the CSCL experience over social relationships among learners.

3 Case Study

In order to consolidate a strategy for analysing interaction processes in a collaborative learning scenario based on SNA metrics, this section describes a case study carried out at Universidad del Cauca (Colombia), with 18 undergraduate students (four females, 14 males), who were between 19 and 21 years old. This experience was performed in the context of the "Computer-supported Collaborative Learning" course in 2012 academic year. The proposed learning activities are based on peer-assessment and asynchronous social interaction processes through comments. This experience was supported by CSCL platform called SMLearning [40].

The learning script is described as follows. Before experience, the instructor selected a topic related to the course which was divided in three subtopics. Reference resources were chosen for each subtopic. Freely, the students were divided into six teams of three members. The whole experience was planned to seven days, however, even after assessment process had finished, some students continued interacting with the system until ninth day, as result of motivation fostered by the experience. The collaborative learning script designed to the case study is presented in the Fig. 1. Such script includes the following steps:

- Step 1: Environment Settings. In 10 minutes, students created their teams and selected a Coordinator per team which had the responsibility to foster the achievement of goals and the social interaction among peers.
- Step 2: Reference Material Delivery. The reference resources prepared by the instructor are delivered to teams through SMLearning system which supports the resources visualization and some asynchronous social interaction mechanisms, such as comments.
- Step 3: Making Essay, first version. Freely, each team applied a collaborative technique for visualizing and writing an essay about the topics proposed by the instructor. The document just had three pages as maximum with the aim to achievement an abstract view of concepts and a quick review. The essays were shared through the document manager service provided by SMLearning system.
- Step 4: Peer Reviewing. The essays are reviewed by the team assigned by the following rule: The team (n) assesses the essay (n + 1); except the last team which assesses the first team's essay. Such assessment includes a rating over a five-point Likert scale and at least three comments.
- Step 5: Making Essay, second version. The outcomes of peer-assessment process were used by each team to improve their essays. Also, the teams could reply and assess the usefulness of the comments made by their peers.
- Step 6: Peer Reviewing. The new versions of essays were reviewed by all teams. The assessment process was repeated; however, writing new comments was not mandatory.

As example, a realistic interaction model expected according with proposed tasks is presented on left in the Fig. 2. There, some students are represented by circles (S1, S2, and S3) and a resource by a square (R); students have commented and rated the resource. Also, a comment was replied and marked with like/dislike. However, in order to simplify such interaction model, on right in the same figure, the resource entity was replaced by its owner (Sa) and ties were created by comments and replies because were considered the most representative action of social interaction. This last type of model was used in the analysis process.

3.1 Environment

The whole experience was supported by a CSCL environment called Social Media Learning System (SMLearning System) [40], [45], which was developed at University Autonoma of Madrid. SMLearning system allows the management of multimedia resources and provides services for designing interactive objects based on the combination of objects such as: videos; images; texts; and

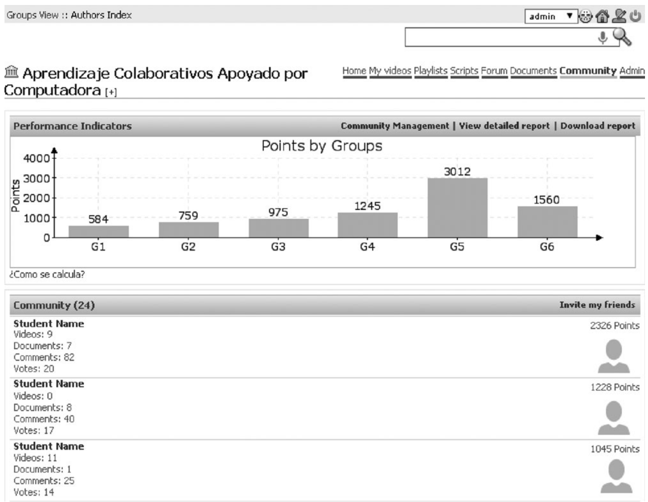

Fig. 3. Awareness mechanisms presented in Community View of SMLearning System.

interactive mechanisms, namely: questionnaires, navigation controls and user dialogs.

In the context of this case study, SMLearning supported to visualize, comment, rate, and share resources. Such resources initially were video lectures proposed by the instructor as reference material; after, learners shared their essays and other resources, in video or text format. Additionally, the system offered several awareness information views. For instance, Fig. 3 shows the Community View which presents graphs and summary tables of learners' actions. A global performance indicator is calculated as the sum of weighted actions. The learners were ranked according with such indicator which seems fostering user interaction as consequence of a competitive attitude among learners. In order to influence positively to collaborative phenomenon, cooperative actions receive better rewards than individualistic action.

The whole experience was scheduled by seven days. In the first day, the instructor exposed the activities and enables the access to reference resources through the platform. The third day was the deadline for delivering the essays by teams. The seventh day, a face-to-face session was carried out to discuss the experience and treated topics. During the assessment process of students, several aspects were considered, namely: individual interaction with the platform, quality of essays, auto-assessment and team-assessment. Those aspects offered partial scores which were combined with instructor's observations in order to calculate the final student's score.

4 Results

Some students interacted with the platform by nine days, even when the assessment process was done on seventh day. Such behaviour was explained by the students as the result of a high motivation level with the activity. The Table 1 presents a summary of actions registered during the experience. In the assessment process, the final score reached by the students in this activity was 4.17 (SD 0.70) in a scale 0 to 5 (5 is the maximum value). The data shows that resources in video format have had more interactions than

TABLE 1
Summary of Main Learners' Actions with the System

Action	Textual Resources	Multimedia Resources	Total
Adding	30	22	52
Commenting	108	201	309
Rating	74	131	205

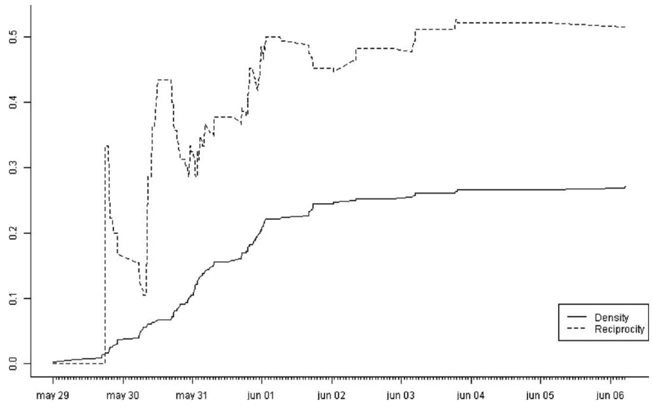

Fig. 4. Density and Reciprocity metrics calculated during the experience.

ones with text format. This observation is coherent with multimedia learning theory which claims that the multimedia is an attractive and versatile way to present content in a learning context [46].

The model network reached at the final stage presents notorious differences with the structure expected for the case study in correspondence to the learning script proposed. Students claim that they understood that the script was aimed to reduce overload in the review tasks. However, boosted by their own motivation, they commented and rated as many resources as they could. That new strategy was still valid for learning goals, thus, was allowed that it continued.

The data analysis process was implemented with R scripts and the *igraph* package [47]. An adjacency matrix which represents the current stage of scenario is created by each social event in the system. In this case study, the social interaction processes were analysed through the following SNA metrics: Density, Reciprocity, Inclusiveness, Centralization, Degree centrality, Betweenness centrality and Closeness centrality. Metrics related to clusters, such as, Clique and Change Propensity, have not been calculated in this case.

Fig. 4 shows the behaviour of Density and Reciprocity metrics calculated during the experience. The Density tends a non-linear accumulative increasing function with a max value of 0.27. This behaviour expected for groups with a limited number of members, however, is a low final value and more or less stable after the fourth day. It is a cue of the tendency of interactions in small groups [44]. On the other hand, the Reciprocity metric presents peaks and valleys, but it tends to increase until a max value of 0.53 in the last day. A high value means that the social interactions among students are symmetric. In this case, the experience show a moderated value, which corresponds with the observation of a set of highly motivated students which shared a lot of resources.

The symmetry evidences were complemented by a strong correlation between in- and out- Degree centrality measures for each node. We calculated the Pearson's correlation between the contributions of an individual (represented by out-Degree centrality) and interaction received by him from the community through comments and replies (represented by in-Degree centrality). We found that such values fall in the range of [0.71; 0.87] (p-value < 0.01). These results suggest that the social interaction processes among learners tend to be symmetric, i.e., students correspond with the interest showed by others in their resources through replies and comments to resources of mates. Similar behaviour has been observed in another scenario [48], and authors in social networks context [49]. Such symmetry is related to a uniform distribution of efforts and contributions by learners, which is a feature expected in a collaborative environment [3].

The inclusiveness metric has not been relevant, in this case. The highest value was reached at the end of the second day, 19, as the total number of participants.

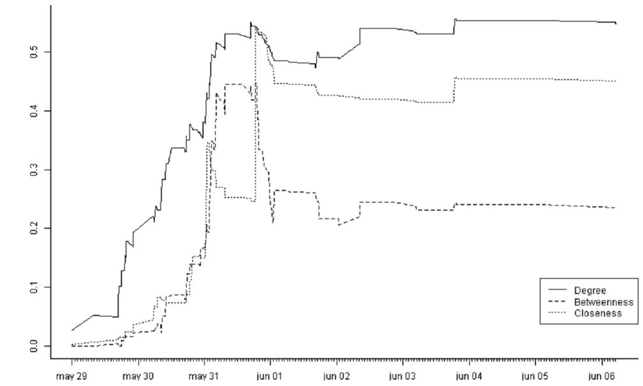

Fig. 5. Centralization metric, calculated by Degree, Betweenness, and Closeness.

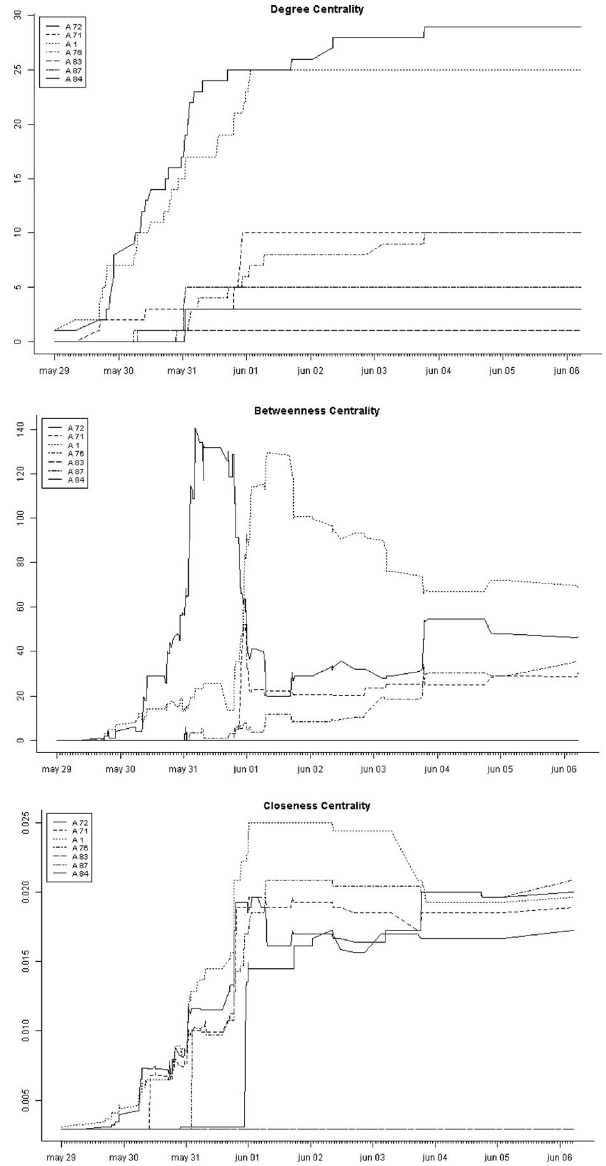

Fig. 6. Degree, Betweenness, and Closeness centrality metrics by the instructor (A1), and students with the best (A72, A71, A76) and the worst (A84, A83, A87) scores.

Centralization metrics by Degree, Betweenness and Closeness are shown in Fig. 5. Around the third day, students had to present the first version of essays, which is reflected in a peak on the registered interaction by the system. Such milestone seems to be reflected in the Centralization metric by Degree and Betweenness, which have increased at morning in the day, but later have decreased. In contrast, the Centralization metric by Closeness presents an opposite behaviour, with a valley around such event. After that, these metrics tend to be more stable values with a low variation. The data suggest a low Centralization of power, which reinforces the symmetry evidences.

The Fig. 6 presents the Centrality metrics by Degree, Betweenness and Closeness. In order to facilitate the visualization of these measures, this graph presents values for the instructor (A1) and the students with the three best and the three worst scores. The best performances were obtained by A72 (score 4.88), A71 (score 4.87) and A76 (score 4.80); while, the worst scores were obtained by A84 (score 2.9), A83 (score 3.19) and A87 (score 3.21). According with the graph, the Degree centrality seems an accumulation function which is related directly with learners' interactions; A72 and A1 played central roles during the experience. Their contributions were better distributed in the time, in contrast with users with lower scores, which interact by peaks around the milestones of experience. Also, the instructor stopped his social interaction around the middle of experience; A72 was an active participant until the end of it.

On the other hand, Betweenness centrality seems to be more sensible to social behaviours. Around of the first delivering (3th day), A72 represented the main connector among his mates, however, A1 started to meditate among students and took such role. Around the second delivering (7th day) A72 increased again his position, but this time with less strength. According with SNA theories, the Betweenness centrality is associated with sources of information. The results seem to correspond with the fact that on third, sixth and seventh day, the focus of discussions was on the essays, while the other days, it was on reference resources, mainly contributed by the instructor.

Finally, the Closeness centrality value presented very low, around 0.025. This is associated with a network weakly connected, also reflected in the low value of Density. Also, The Closeness centrality show a behaviour highly similar for every node, with higher peaks around the fourth to sixth days for A1, A76 and A71.This peaks represents a more efficient or opportunistic connections as consequence to interact with the most popular resources [43].

5 Conclusions and Further Work

This article has presented an approach for analysing social interaction processes in collaborative learning scenarios based on social network analysis metrics calculated in time. According with the reviewed literature, a set of metrics has been identified as useful for describe behaviours in a collaborative experience, namely: Density; Centralization; Inclusiveness; Reciprocity; Centrality; Cliques; and Change propensity. In order to prove our approach, a successful collaborative learning experience was analysed using some of this approach.

Among findings, we found that: (1) social interaction processes tend to be symmetric, i.e., students seem to correspond with the interest showed by others in their resources through replies and comments to resources of pairs; such conclusion is based on the temporal behaviour of Reciprocity metric and a strong correlation between in- and out- Degree Centrality metrics. (2) The Betweenness centrality seems to reflect the sources of resources where the interaction takes place, in this case, represented by essays and reference material. Finally, (3) the behaviours observed in SNA metrics show measuring the final state of the interaction on a CSCL experience is inconclusive about the group dynamic as consequence of high variation of data observed during time. Thus, a temporal dimension on SNA metrics seems to provide valuable information in order to analyse CSCL scenarios, however, the SNA theories require to be brought closer to the concepts of such scenarios.

Finally, the literature reviewed suggests that content analysis methods have been applied as a relevant part of social interaction analysis processes; however, such results are treated independently of the SNA approach. We believe that the messages categories can enrich or create alternative networks which may represent in a better way the interaction processes. As future work, we are going to apply this approach to other experience and scenarios, and include metrics related to clusters and interaction patterns.

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