Sociograms: An Effective Tool For Decision Making in Social Learning

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Abstract

In the last few years, social learning, i.e., learning based on the analysis and discussion of topics by means of social collaborative systems, mainly social network services such as Facebook or Twitter, has acquired a great importance and led many instructors and institutions to deploy courses that include activities to be performed in them. For effective learning, both teachers and learners are required to gain insight into how the interaction takes place and how the learning process evolves over the time. Given that the nature of this kind of learning is inherently social, the Social Network Analysis (SNA) theory is perfectly suitable for this purpose. Therefore, this paper proposes the use of sociograms, SNA representations, to answer many of the questions that both learners and teachers need to know to make the best decisions and act accordingly. Furthermore, several network settings are suggested and the interpretation of the most relevant centrality measures when applied to online social learning is provided. Finally, the usefulness of sociograms is shown by means of the analysis of the activity performed in a MOOC course hosted in OpenMOOC platform.

1 Introduction

Currently, the use of computer-based collaborative tools in the learning arena is fully generalised. In particular, we refer to those tools used for the interaction and communication among actors who are involved in a learning process. For instance, forums for communication and topic discussion (Joubert and Wishart 2012; Tobarra et al. 2014), blogs or services such as Google Docs for the development of collaborative writing activities (McNely

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et al. 2012), or social networks as Facebook (Weber and Vincent 2014) or Twitter for commenting on and spreading topics with the aim of building a community interested in them as well as for boosting and fostering student communication for team work activities (Magogwe et al. 2014), among others (Wilson et al. 2012).

Collaborative tools are being used in all ranges of teaching levels, from primary education to higher education, being extensively utilised in Massive Online Open Courses (MOOCs). This is the case of the ECO project[1], a European commission funded project whose aim was to train teachers so that they could create their own educational resources and MOOC courses. The courses hosted at this platform were designed following a connectivist, heutagogical approach where educators and learners created, shaped and evolved knowledge together, deepening their skills and understanding as they went along. Learners become the authors, drivers and assessors of their experiences and educators become a guide-on-the-side, coach, resource-suggester and cheerleader who encourages learners to create their own learning journey (Gerstein 2014) and knowledge.

Social networks services, particularly, are one of the essential instructional tools of this new educational pedagogy where teachers design learning activities that involve learners in being connected and in interacting with others (Brinton et al. 2014). Furthermore, their use in MOOCs is well appreciated by students (no Garrido et al. 2015). These social activities allow learners to develop new skills and ideas which are not solely individual achievements, but are also developed, extended and approved through interaction and collaboration. The ease of publishing, searching and tracking user-generated information in these services as well as their ubiquity lead to an increasingly greater use as collaboration spaces for learning.

In order to achieve effective learning and promote awareness, reflection, and sense-making, learners must be motivated, encouraged and informed about how the learning process is taking place. Likewise, teachers also require metrics and patterns for verifying hypotheses, drawing conclusions and making decisions (Gómez Aguilar et al. 2014). Thus, it is particularly important to supply both teachers and learners with a tool which helps them to meet their needs.

As the activity performed in social network services is logged, this can be read and managed to answer relevant questions such as: for teachers: what kind and degree of participation is taking place in each service?, how does each learner community rise and evolve over the time?, who are the most influential learners?, who fosters communication?, who is a good candidate for spreading information across the whole network?; and for students: who are my peers?, who can I ask about a topic or what is my social reputation?.

The answer to these questions requires the use of data management and analysis tools which include, among others, techniques from statistics, data mining and social network analysis fields so as to measure, identify patterns and establish relationships between data. These are not exclusive to the field of education but are applicable to any context, business or organization in order to gain greater insight into what is happening and take more informed actions. The application of these techniques to the learning field is known as Learning Analytics (LA) (Siemens and Long 2011).

Learning analytics seeks thus to enhance the learning processes through systematic measurements of learning related data and to provide informative feedback to learners and

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[1] http://ecolearning.eu/

teachers. Dashboards have been proved to be the most friendly, meaningful and under-standable tools for displaying the current status of these metrics (Keim et al. 2010).

In the last few years, different kinds of dashboards have been developed to support some of the different methods of learning: traditional face-to-face lectures (Barr and Gunawardena 2012), face-to-face group work (Martínez Maldonado et al. 2012), blending or virtual learning (Arnold and Pistilli 2012; Dyckhoff et al. 2012), etc. But, according to Verbert et al.'s review (Verbert et al. 2014), most dashboards have been addressed to meet teachers' needs so that they could make instructional decisions, for instance, identifying relevant actors and at-risk students, or driving the thread of a discussion. But in a social learning context where the role of teacher and learner changes towards a multi-actor setting where knowledge is exchanged and where actors learn by interaction and co-create new knowledge in on-going interaction (Sol et al. 2013), every participant should be able to know his peers, which the assessment of his contribution is or which participants are more active or have a great prestige so that participants make decisions about how to act and progress in the course.

Therefore, we propose the use of a graphical representation which helps all users involved to identify and know their peers by their contribution in the community created. Given the inherently social nature of this relationship, we rely on techniques from social learning analytics for its study (Ferguson and Shum 2012). According to Hernández-García et al. (2015), this refers to the application of Social Network Analysis (SNA) theory to learning processes with the purpose of understanding, explaining and improving them.

In literature, there are a still few tools developed for visualising the social interaction and collaboration, for instance, SNAPP (Bakharia and Dawson 2011), TUT Circle Dashboard (Silius et al. 2010), Meerkat-ED (Rabbany et al. 2011) or Social Map (Longhi et al. 2018). Authors of these tools point out the importance of social network analysis for mining structural data and its applicability in the domain of education with different case uses. These were not designed with a social and global perspective for all participants but exclusively to help teachers as claimed (Kitto et al. 2017; Teasley and Whitmer 2017). Furthermore, these tools only make use of a small subset of centrality measures available in SNA and thus they are not taking advantage of all the informational power of these metrics.

The research contribution of this paper is twofold: First, in Sect. 2, we provide you with a brief introduction to the social network analytics field, how SNA has been applied and used for different educational targets and next, give an interpretation of the most relevant centrality measures when applied to online social learning and how these can be used for decision making. Second, in Sect. 3, we point out the need for including sociograms in social learning dashboards as a suitable tool for decision making and describe a set of network settings that visualises metrics that could be used to estimate social affiliation, recognition and responsibility via graphs. Likewise, the opportunities to make decisions that these sociograms offer to both learners and teachers are pointed out. This explanation is supported on several real cases of study and the teachers' conclusions about its power to discover hidden behaviours and patterns. Unfortunately, learners' opinion could not be gathered since at the time of this study the course had already concluded, therefore their opinion on the matter could not be verified. Finally, Sect. 4 draws the conclusions and enumerates some works to be performed in the near future.

2 Social Learning Analytics

Social learning is a broad term used to describe the learning that takes place through devices that allow you to interact with other learners and build and develop new contents socially through grounded interactions around problems and actions, especially with others (Brown and Adler 2008). This now includes learning through using information provided by social networks (Facebook, Twitter, etc.) and engaging in online collaboration with the use of these and other resources. The advantages that social learning provides can be summarised in: on the one hand, participants can meet and learn from one another (the role of teacher changes into moderator or inclusive learner) and, on the other hand, the discussion space is accessible from anywhere. According to Buckingham Shum and Ferguson (2012), online social learning can take place when people are able to: clarify their intention concerning learning rather than browsing; ground their learning - by defining their question/problem and experimenting; and engage in learning conversations by increasing their understanding.

The fact of supporting learners during their learning process with the aim of guiding their acquisition of knowledge and providing them with tools that allow them to reflect and redirect their learning is highly important. Likewise, teachers and course designers should be reported on issues arising and areas of the course that need to be updated. In this context, learning analytics emerges as a set of tools addressed to this target. Learning analytics, according to Siemens and Long (2011) can be defined as "the measurement, collection, analysis and reporting of data on learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs". When data is analysed by means of techniques from the social network analysis field, the adjective "social" is added.

Shum and Ferguson [23] defined five levels of social learning analytics: social network analytics, discourse analytics, content analytics, disposition analytics, and context analytics. The two first categories are inherently social, while the others are classified as "socialized analytics", that means that they have a social dimension. This work focuses on the former, and particularly, on social network analytics, i.e., the analysis of the interpersonal relationships that arise when social platforms are used and how this uncovered information can help both teachers and learners to improve the learning process and their level of engagement and satisfaction.

2.1 Social Network Analysis and Its Application on Educational Contexts

Social network analysis (SNA) has its origins in the social science field. Georg Simmel and Emile Durkheim were its precursors, i.e., who wrote about the importance of studying patterns of relationships that connect social actors for the first time. SNA thus is not focused on the individuals and their attributes, but on the relationships between them. In 1934, Jacob Moreno became interested in the dynamics of social interactions and introduced the first analytical methods (Moreno 1934) establishing the foundations of *sociometry*, a field of study that later became SNA.

SNA represents both actors and relationships in terms of the network theory, depicting them as a *graph* or *network*, where each *node* corresponds to an individual actor within the network, e.g., a person, a group or an organization, and each *link* symbolizes some form of social interaction between two of those actors, e.g., friendship or kinship. This representation is called *sociogram*. SNA draws on various concepts from the graph theory in order to

evaluate network properties such as density, centrality, degree, betweenness and closeness, among others. For the sake of easy understanding, we avoid using the mathematical formulation (see Freeman 1977) in this paper and focus on their interpretation for the educational setting with the aim of enabling teachers and students to extract useful and interesting knowledge and make better-informed decisions.

Apart from centrality measures, there is an extraordinary variety of techniques that have been and are being currently developed in this field, such as algorithms for community detection (Fortunato 2010), computational tools for studying dynamics and evolution patterns of large networks (Leskovec 2008) or new approaches for visualising dynamic networks (Federico et al. 2011) due to the usefulness and power for knowledge extraction that SNA offers.

SNA techniques have been applied on data from very different contexts for allowing researchers to model different types of interactions, e.g., movie actors (Watts and Strogatz 1998) or sexual contact networks (Klovdahl et al. 1994), and giving solutions to very diverse problems, e.g., detection of criminal and terrorist patterns (Krebs 2002) or identification of important actors in social networks (Palazuelos and Zorrilla 2011). In the last few years, SNA has also been used for extracting relevant information that can be used in educational settings. For example, Brewe et al. Brewe et al. (2012) used a multiple regression analysis of the Bonacich centrality measure (Bonacich 1972) for evaluating the factors that influence participation in learning communities, e.g., students' age or gender. Crespo and Antunes Crespo and Antunes (2012) proposed a strategy for quantifying the global contribution of each student in a team-work through adaptations of the PageRank algorithm. Tobarra et al. Tobarra et al. (2014) propose a set of algorithms for detection and tracking of relevant topics. Dawson et al. used SNA to monitor the learners' creative capacity (Dawson et al. 2011) and to detect and encourage "at risk" students (Dawson 2010). Bayer et al. Bayer et al. (2012) used several centrality measures for the prediction of dropouts and Romero et al. Romero et al. (2013) and Hernández et al. Hernández-García et al. (2015) for the prediction of final students' performance. A similar work was performed by Palazuelos et al. Palazuelos et al. (2013), but in this case, the goal was to evaluate whether SNA attributes along with student's activity data (e.g. time spent on the course, quizzes performed, etc.) helped to build more accurate students' performance and dropout mining models. Cuellar et al. Cuéllar et al. (2011) proposed a method based on an ontology for the formulation and interpretation of learning management platforms as social networks with the aim of making further studies about the social structure between learners, teachers, and learning resources, and discovering useful relationships to improve the learning process.

More recently, centrality measures have been applied for comprehending how learners engage with one another in peer-feedback provision interactions inherent in an ongoing process of communities of Learning Practice building (Dingyloudi and Strijbos 2018), concluding that the examination of social network structures constitutes a prerequisite for this purpose. Kitto et al. (2017) presented two partially successful learning design patterns which included student-facing learning analytics with the aim of assessing their usefulness as enablers for encouraging sense-making, metacognition, and reflection. From a theoretical point of view, Jan and Vlachopoulos (2018) have proposed an Integrated Methodological Framework grounds SNA for structurally identifying communities of practice and communities of inquiry in higher education online learning and demonstrated its effectively in a case study on an online blogging network.

2.2 Understanding Measures of Centrality in Educational Networks

Most of the works previously mentioned in the educational field make use of centrality measures, generally applied on data sets from forums in e-learning systems, to perform their research. The social graph is frequently implemented from the interaction between all the students who posted a message(s) on the discussion forum (García-Saiz et al. 2014; Rabbany et al. 2014; Romero et al. 2013; Dawson et al. 2011). Other works have proposed the building of a network of the terms used in threads (Rabbany et al. 2014), or the analysis by means of SNA of chat and bulletin board conversations in a CSCL (Computer-Supported Collaborative Learning) system (Sundararajan 2010).

In a MOOC environment, apart from forums, the new social network services such as Twitter and Facebook are being widely used for developing collaborative tasks oriented to discuss and spread knowledge and find new people interested in topics developed in the course (social learning).

The analysis of the relationships that arise in these networks are highly useful and informative. Participants can discover and better understand each other's role is, who fosters conversation, which the most interesting topic is, who adopts the role of leader, how strong the community is and how it grows and evolves over the time. In de Lima and Zorrilla (2017), the authors demonstrated how SNA metrics and sociograms help to answer research questions such as What Types of Networks Emerge in a social MOOC? And Do Social Network Based Activities Enable the Creation of Learning Communities that Endure Over Time?

The centrality measures can be grouped in measures at an individual level and at a network level (Wasserman and Faust 1994). The former aim at identifying participants who have a prominent behaviour in the network, whereas the latter inform us about the structure and cohesion of the network. Next, it is given an interpretation of these measures when applied to a network built between participants in a forum. These measures are easily adapted to Facebook or any other collaboration tools used in a course. The formal definition of all of them is gathered in one of the most cited review papers, the one written by Santo Fortunato Fortunato (2010).

The *degree* measures the immediate influence: which participants are more active, i.e., those whose involvement in the activity is deeper, either ask or respond. If we take into account the direction of the links, the *indegree* reveals those participants who receive the most responses from other learners, because of their reputation or the question itself, i.e., it may be an interesting or controversial question. On the other hand, the *outdegree* recovers those participants who respond the most, i.e., those who contribute to the activity by adding a new content, by proposing new approaches to the discussion, or by asking for further explanations.

In directed networks, *hubs* are those participants who answer the questions of others that have already received a considerable number of answers, whereas they are called *authorities* if they are responded by participants that often answer questions(authorities act as a definitive source of information). Hubs are participants that point to a relatively large number of authorities. Authorities are essentially the mutually reinforcing analogues to hubs. Hubs and authorities reinforce one another. Those participants with high hub values seem to be very collaborative: they do not open new threads but help others. However, they happen to answer only those questions they consider to be helpful for the debate. They can be seen either as *shy* people or individuals who just intervene

when the discussion reaches a certain level. Those participants with high authority values seem to have some sort of reputation, because what they ask is usually worthy of a response.

The *betweenness* detects those participants who discuss the most and make others discuss, either by asking questions or answering in such a way that the others are encouraged to intervene, i.e, they act as the vehicle of communication. On the other hand, *clique count* visualises those participants who, by means of messages, are connected to more participants and thus can receive more information.

The *Bonacich* centrality (Bonacich 1972) measures how powerful the participant is, that means, how important his participation is as a consequence of being connected to people that have fewer connections in their neighbourhood and thus they depend on him. The *closeness* discovers those participants who act as a "reference point" since their contribution is followed by a larger number of people. Finally, the *local clustering coefficient* can be helpful to identify those participants to whom the information goes through.

At a network level, the most relevant measure from an educational point of view is *density*, that is, how cohesive a network is. A higher density means a participants' community strongly tied and well-related ones to each other. And the *network diameter* that measures how compact it is, that is, if many or few steps are necessary to get from one side to the other. For instance, it could help to discover how information flows between teachers and students or to study homogeneity in people that discuss a topic among others. Social networks with a small diameter are supposed to have high homogeneity, connectivity and communication between nodes.

In a collaborative setting, there are two general and interesting kinds of networks to be modelled, *participant x participant* and *participant x topic*, that means, a network that gathers the interaction arisen between peers and another one that shows the participants' interest with relation to each topic discussed in the course. We can mention several networks that might be analysed in this context when social collaborative network services such as Twitter or Facebook are used.

Facebook, similar to forums, is useful to build a network which collects the interaction between all the participants who wrote comments on posts. If each post was linked to a specific topic, a two-mode network between participants and topics could be also analysed and then one can discover which topics are more relevant, how many participants are involved in several topics and how topics are connected via participants and, viceversa how participants are linked via topics.

On the other hand, a participants' network that mentions a hashtag allows teachers to know how the digital word of mouth spreads all over the net and fosters more people to contribute to social learning (in particular, it is interesting to discover people who are not enrolled in the MOOC). Of course, the building of a network of hashtags that co-occurs within the same tweet is also interesting in order to uncover terms that have some relationship between them. This allows participants to open new discussions and deepen in how near these terms are.

Likewise, in social network services such as Twitter, it can be useful to construct a retweet network, with the aim of discovering how information flows from one participant to another through their followers. Another interesting network is that one created from *mentions*, that is, a network built from the participants who send messages explicitly directed to other participants. This enables us to measure the real network of participants interested in the course (each course is supposed to have its own Twitter account).

3 Social Dashboard

Over the last few years, dashboards have shown to be one of the most effective, friendly, understandable and thus, actionable tools (Keim et al. 2010). These generally display a graphical presentation of the current status (snapshot) and also historical trends of a set of indicators from the observed processes in order that instantaneous and informed decisions can be made at a glance. Bar charts, donuts charts, scatter plot, gauge charts, histograms and radar charts are frequently used in dashboards to display progress, performance, effort or time of dedication to name a few metrics related to the educational settings. But, sociograms have been barely used, and even more, where they were shown, a very reduced number of centrality measures were displayed, essentially degree and betweeness. This is the case of SNAPP (Bakharia and Dawson 2011) that visualizes the evolution of social interactions among learners in online forums; TUT Circle Dashboard (Silius et al. 2010) that shows his activity to every user and the one performed by his neighbourhood; Meerkat-ED (Rabbany et al. 2011) that allows teachers to assess the students' participation in asynchronous discussion forums of online courses, and ElWM (Palazuelos et al. 2013), a web application which generates mining patterns and social graphs for analysing collaboration and discovering communities in virtual courses hosted in e-learning platforms through forums and blogs.

The informative power of the analysis of social networks and its perfect adequation for the analysis of human relations arising in social networks has been scientifically proved by different authors (Fortunato 2010; Zhu et al. 2010), therefore we propose its use to analyse the social perspective of the learning process.

3.1 Learning Social Graphs: Design Criteria

In a social learning environment, there are two perspectives that must be considered: the academic one and social (Dowson and McInerney 2003) one. The former is mainly addressed to measure progress and performance as in any other teaching method, whereas the latter aims to collect and show metrics that estimate social affiliation, recognition and responsibility. In this paper, we mainly focus on the social dimension.

First of all, we have written our interpretation of these three terms in the paper. We adopted the definition of social affiliation popularised by David McClelland McClelland (2009). This describes a person's need to feel a sense of involvement and "belonging" within a social group. In other words, "to feel loved" and "accepted" by others. Our definition of social recognition underlies the statement claimed more than 150 years ago by the Harvard psychologist and author William James, "the deepest human need is the need to be appreciated". That means, the need of recognising that the individual's contribution has led to the fulfilment of personal or communal goals. Finally, social responsibility aims to measure the degree of commitment to perform the tasks assigned with quality and on time.

In our opinion, the best way to represent and assess the social affiliation in a learning setting is by means of a social graph where the participant can observe his position with respect to the group according to the communication and collaboration that have taken place in the course. Centrality measures such as degree, betweeness and Bonacich are suitable to measure social affiliation because they give a rough indication of the social power of a node based on how well they connect the network. This graph can be also enriched with demographic data available in public profiles of social network services or others such

as marks, number of tasks performed, etc. that the learning platforms gather enable teachers to better know learners' profile and their behaviour.

In regard to the social recognition, centrality measures such as indegree, authority or hub can be used since they allow ranking individuals according to the level of their interaction. There are also other external metrics that can be considered and extracted from social networks such as number of likes or the rating achieved by students' contributions, which can assess their quality to a certain degree. Regarding social responsibility, it can be similarly measured but only considering students' participation in the assessable collaborative activities during the period defined, that means, calculating hub or indegree of each participant but only considering data from assessable activities with a strict deadline.

As dashboards, with the aim of being effective, must be simple and easy for any individual to interact with, we propose the inclusion of social graphs that collect the relationship between people involved in learning tasks in a MOOC, for example, commenting on a post, re-sending messages or writing tweets including a hashtag, to assess learners' interaction. Once sociograms are defined, by means of the use of graphical elements such as color, size or shape of nodes and thickness of edges, the end user tool that integrates them will highlight those features that allow participants to easily validate their hypotheses. These features can be demographic data (gender, nationality, age, etc) or the other type such as mark or the number of likes that his comments received as well as centrality measures extracted from the network. If the network is very big and dense, the user will be able to zoom the graphs in and out and interactively filter the sociogram by the strength of relationship or the value of attributes in order to observe the details of a community, a set of nodes or a particular node.

3.2 A Proposal of Visualizations of Sociograms Based on a Real Case Study

In this section, we show the visualization of several graphs built and analysed by the instructors of a MOOC course hosted in OpenMOOC entitled "Educational innovation and teacher professional development. Possibilities and limits of ICT" and taught in Spanish in the spring of 2015 with a length of eight weeks. This course aimed at preparing students to understand how to develop educational projects which included the use of information and communication technologies. The course designed through a student-centered approach, sought to provide students with the autonomy to select activities and contents that interested them. The course included individual and P2P tasks which were combined with debates in forums and social networks with the goal of promoting the exchange of experiences and creating communities which had the same interests and goals, taking into account the Wenger's words, "communities of practice develop around things that matter to people" (Wenger 2010). In particular, some collaborative activities proposed were developed on Facebook and Twitter. These tasks were optional, not mandatory to finish the course or to get certification. These tasks were designed to promote interaction between students in order to build a community of practice and learning, one of the principal goals of ECO Project.

The teachers in charge of the course opened an account on Facebook named "Innovación Educativa y Desarrollo Profesional" and wrote five posts (linked with course's modules and subjects), one for each topic that had to be discussed by the participants (see Table 1). On the other hand, they also created the account @*ecoinnovatic* in Twitter and

Table 1 Facebook posts proposed as collaborative activity in the MOOC course

Title: URL

Repensando la idea de innovación en educación:

https://www.facebook.com/permalink.php?story_fbid=1587186584868043&id=1497219020531467

El papel de los docentes en los procesos de innovación:

https://www.facebook.com/permalink.php?story_fbid=1589338177986217&id=1497219020531467

Profundizando en la dimensión curricular:

https://www.facebook.com/1497219020531467/photos/a.1519055971681105.1073741828.1497219020531467/1591531201100248/?type=1

Liderazgo en los proyectos de innovación:

https://www.facebook.com/permalink.php?story_fbid=1597287347191300&id=1497219020531467

Compartiendo redes de innovación:

https://www.facebook.com/1497219020531467/photos/a.1519055971681105.1073741828.1497219020531467/1597287813857920/?type=1
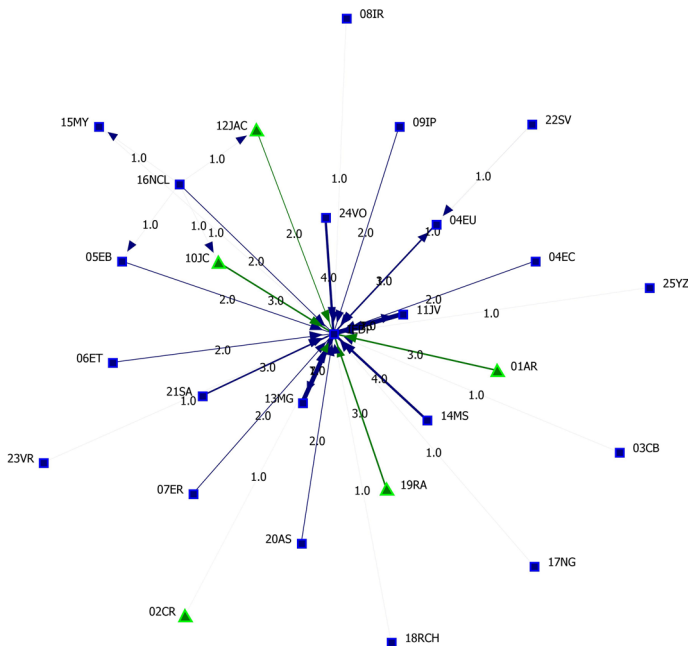
Fig. 1 Social network built from comments wrote on Facebook. The nodes represent participants (triangles for males and squares for females), the edges, the interactions, and the thickness of the edges corresponds to the volume of the interaction, also depicted numerically

the hashtag *#ecoinnovatic* with the aim of disseminating events and references of interest for course participants.

Next, we display several graphs built ad-hoc and discuss the conclusions that can be drawn and how these can help participants to make decisions. In this study, we focused our conclusions on teachers' perceptions and opinions. Due to the fact that the course had
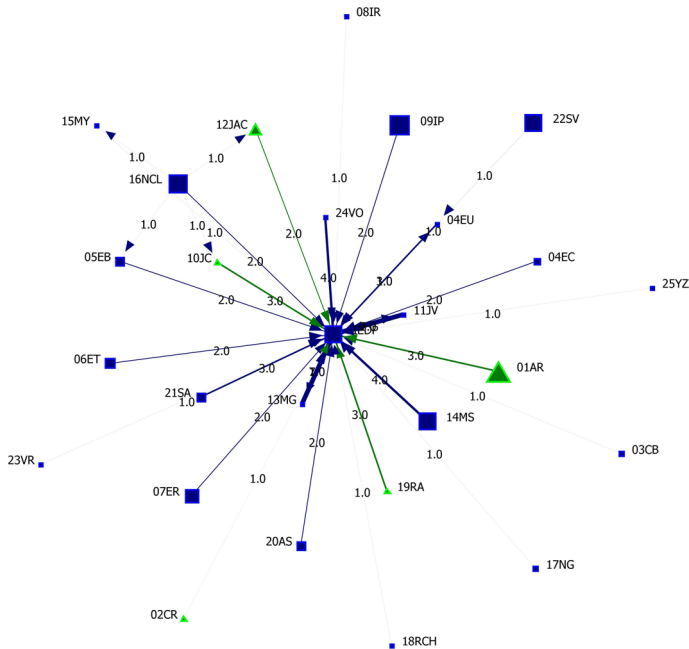
Fig. 2 Graph that displays the uncorrelated relationship between performance and participation in Facebook activities of this course. The nodes are scaled according to the mark achieved in the course

already finished at the moment that this study was performed; it was not possible to ask students about the usability and the effectiveness of these social graphs. In any case, along this section, we emphasize how sociograms could also be useful for the students, providing them with information that could guide their learning decisions during the course.

First, we show the network communication built by people who sent a comment to, at least, one of posts opened on Facebook in Fig. 1. The nodes represent people and the weight in edges gathers the number of messages sent from one node to another in the sense of the arrow (directed network). As can be observed, at a glance, both teachers and learners can check that the degree of participation is very low, barely 27 out of 372 people enrolled, being males represented by triangles and females by squares. Furthermore, the network presents a radial structure which means that communication has been mainly established between "Innovación"(IEDP) and each individual, except for 16NCL and 22SV who answered to other people, and thus showed to be more collaborative. The thickness of the edges allows us to highlight who were more active (larger degree) and more influential (larger outdegree, see the arrows of the edges), in this case 13MG and 11JV and were the ones who adopted this role, although they only communicated with teachers (IEDP). Teachers observing these plots, should urgently seek for strategies to encourage the learners' participation in such a way that these students themselves should be the ones who moderate and modulate the discussion. For instance, teachers could write a message that mentions the contribution of these more active participants or click on the 'like' button of the message written by them. Students, by observing Fig. 1, could awaken their interest to read the messages sent by the most active peers and continue deepening in the topic with new comments.
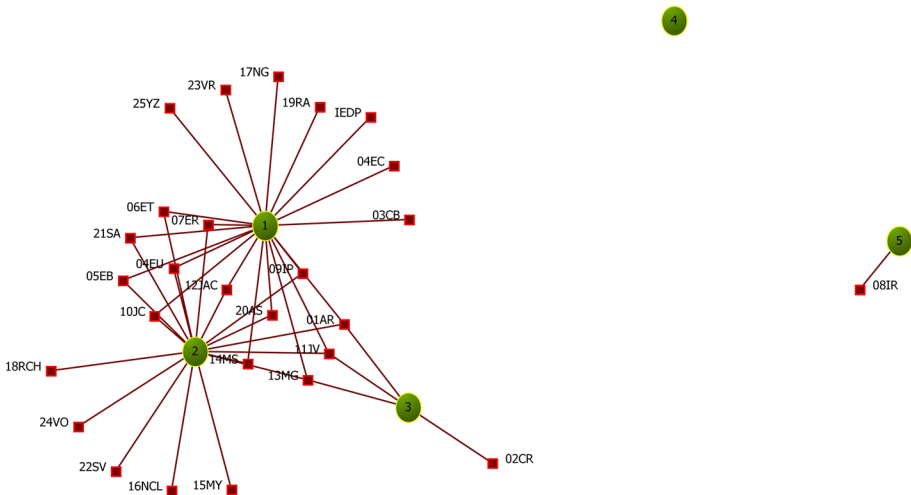
Fig. 3 Graph that displays participation in different topics. The nodes are scaled according to the number of likes that their comments received

Figure 2 depicts the same graph but scales the size of the node according to the mark achieved in the course. One can quickly guess that performance and participation are not correlated in this kind of courses and method of teaching. This is the case of 13MG and 11JV who, despite being the most active, they were not interested in certification. Teachers, when observing this image could have better understood their students' behaviour in the course and have asked to those active students with underperformance if they had found problems in the course.

Figure 3 reflects the level of discussion generated in each topic. This shows that the course opened five topics (identified with a pentagon in green colour) and that except for the number one and two, the rest did not have audience, which responds to the pattern of participants' profiles observed by Alario-Hoyos et al. (2014). In this sense, the two first tasks generated more participation (week 1 and 2) and, from then on, participants got dispersed, looking for the nuggets, contents or materials that generated more interest for each one, or just dropped out of the course.

In addition, it can be observed that 13MG, 11JV and 01AR contributed in three topics whereas the rest only in one or two. Teachers and learners, when observing a graph like this, could uncover who is interested in each topic and to what extent, by observing the number of messages sent (value in the edge). Teachers could try to activate discussion about topics with a few or no messages or redirect their target; and students could check activities where they have not yet participated. Furthermore, if it also shows the rating achieved by each participant as in this case, based on the number of likes that their comments received, learners could also discover who provides interesting information according to the community's opinion. Likewise, those well-assessed participants would see their work recognised, achieving thus a very positive feedback (social recognition) and competitive learners would try to gain relevance and they would probably dynamize the activity to achieve a significant position.

Given that this activity had low participation, in order to show how other centrality measures can be used and which its expressive power is, next we show some
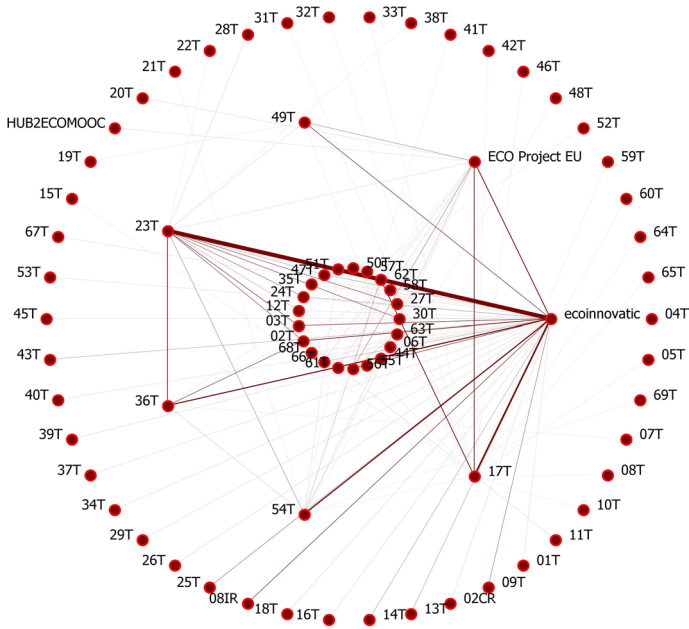
Fig. 4 Graph that depicts the network of participants who mentioned ecoinnovatic. The thickness of the edges corresponds to the number of tweets sent
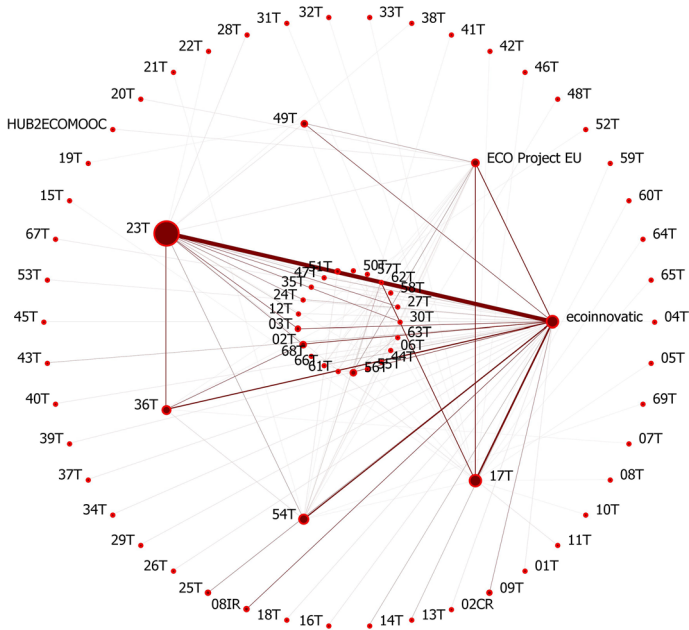

Fig. 5 Graph that depicts the network of participants who mentioned ecoinnovatic. The nodes are scaled according to their hub and edges according to the tweets sent
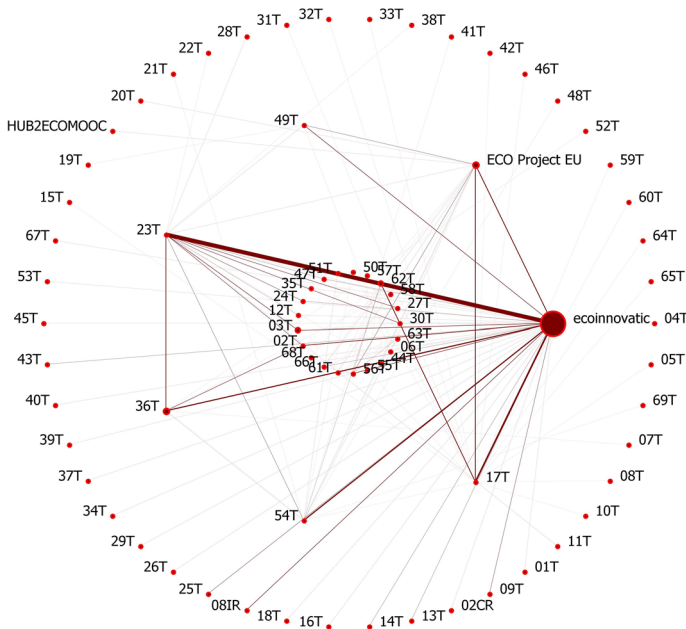
Fig. 6 Graph that depicts the network of participants who mentioned ecoinnovatic. The nodes are scaled according to their authority and edges according to the tweets sent

visualizations built from the network of participants who mentioned ecoinnovatic in their Twitter messages. As it can be observed, Fig. 4 is a bit more complex than the previous ones, with 74 nodes and 141 edges which leads thus to a very low density (0.00062) as it is usual in this type of networks. It can be easily observed that four participants stood out for their participation (see the thickness of the edges), 23T, 17T and in lesser degree, 54T and 36T. It must be highlighted that 17T and 36T did not contribute on Facebook and, even more, these were people who had not enrolled in the course and thus, they were attracted by the use of social networks.

Figure 5 shows that 23T is the individual with the highest hub since he sent messages to many who had already received messages, thus he can be considered a participant interested in the course who only retweets what may have a certain level of interest, whereas Ecoinnovatic is the authority in the network (see Fig. 6) as expected because all twitter messages mention @*ecoinnovatic*.

This figure, also allows us to discover that 36T and ECO project EU contributed to disseminate information of interest for those enrolled in the course since what they sent was worth being resent. In general, hubs are nodes with high degree and betweeness centrality. Teachers could take advantage of their relevant position in the network to disseminate information or to name them as assistant students. Learners, for instance, would identify who are influencers and, those with the largest hub value would feel motivated and would probably contribute more.

Figure 7 highlights nodes with the highest betweeness, where a bigger size of the node means a higher value of betweeness. Here 23T and 54T are those people who can be considered as mediators, who act as the vehicle of communication. Thus, their recognition would contribute to increase their motivation and engagement in the course.
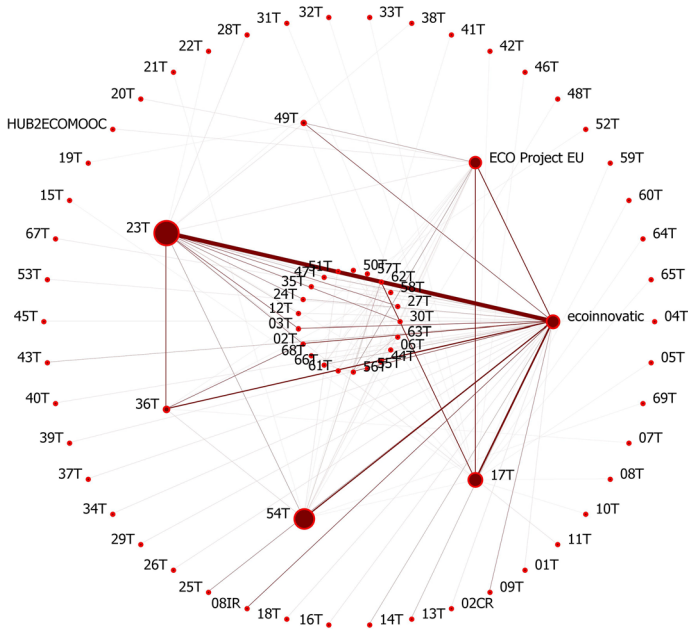
Fig. 7 Graph that depicts the network of participants who mentioned ecoinnovatic. The nodes are scaled according to their betweeness and the edges according to the tweets sent

Furthermore, teachers could rely on them to keep the network active. It is worth mentioning that 23T and 54T, although they followed the course, they did not participate on Facebook activities, but profusely did it on Twitter.

Considering that external social networks tasks were not mandatory, the information offered in the sociograms could have clarified some aspects and given clues to teachers and course designers as to which participants were more interested in one network or other, linking this information with the subjects of interest and the profile of those students. This strategy could have helped to keep the forums of discussion active, deriving in communities of practice or forums of interest points beyond the length of the course.

In addition, this reinforces the fact that the preferences and likes of the participants are different and thus, in social learning whose goal is to learn by sharing knowledge and discussing topics with others, the larger the number of different social networks are used, the higher the likelihood of fulfilling the goal is, as demonstrated in de Lima and Zorrilla (2017).

When observing the graph in Fig. 8 that points out those people with high Bonacich, three new people appear as relevant, apart from those just mentioned in previous figures, 68T, 55T and 56T because of their participation in the community (social affiliation) since they got to send messages to poorly connected people. Thus, their contribution is also valuable in order to expand the network. Teachers could recognize their role and motivate them to participate more actively, whereas learners would feel they are important members of the community and get a positive reinforcement.

Finally, another interesting metrics is the number of cliques, see Fig. 9. This allows us to discover people who are connected to others of many of the groupings, and serves to keep them connected, that means, they act as connectors in the community. As expected,

Fig. 8 Graph that depicts the network of participants who mentioned ecoinnovatic. The nodes are scaled according to their Bonacich

Fig. 9 Graph that depicts the network of participants who mentioned ecoinnovatic. The nodes are scaled according to the number of cliques in which they participate

Table 2 Survey performed to teachers in order to assess the usefulness of sociograms

Question

1. As a MOOC teacher, do you think that it is important to have information about the participation, interaction, performance, etc., of the participants during the course?

Yes

No

2. During the time you have been teaching ECOLearning, have you had access to this type of information?

Yes, how?

No

3. Do you consider that sociograms presented here are an accessible tool to know / understand the information about the interactions of students in certain activities / forums?

Yes

No. What difficulties do you find to understand these graphs?

4. Do you think that these graphs could have helped you in your role as a teacher during the course?

Yes, how?

No

5. If you had had this tool, would you have proposed activities or a methodology different from those used during the course?

Yes

No

6. What information would you like to know / know about the participation, interaction and activity of the students that these graphs do not provide?

7. Open comments

Ecoproject and Ecoinnovatic adopted this role mainly as a consequence of the fact that the network is very small and teachers involved in the course and in the ECO project were deeply engaged. The information that provides this graph could be used for both, learners and teachers, to define teams or work groups, for instance.

3.3 Participants' Opinion

With the aim of evaluating our proposal, these graphs were shown to the teachers of this course along with a short survey whose questions are gathered in Table 2. Four out of eight teachers answered.

All of them confirmed that these charts had helped them enormously to prove their hypotheses at the time that the course was being taught. ECO platform lacked a monitor tool and the social networks did not provide it either. Thus, they had to write down by hand those who participated in each task something which was tedious and error prone, and consequently, many times the actions taken during the course were made by "feelings" about the high or low participation when teachers logged into the Facebook or Twitter account of the course, more than in response to real facts or evidence.

Teachers found our social graphs very useful and they could draw conclusions once they understood the definition of each metrics. From a pedagogical point of view, they stated that these graphs had allowed them to analyse their students' behaviour in social networks in real time and extract patterns with which they had planned and designed more engaging learning activities. For instance, due to the fact that the participation was not very high on

Facebook, just one message per post on average, teachers indicated that if they had known this information, they would have acted by responding to students' comments with motivating messages and even writing their names in the text in order to increase their feeling of belonging and social recognition. Likewise, they could have added gamification in their Facebook activities using the number of likes that learners' comments had received and their hub value.

Two teachers answered that sociograms had also helped them to discover those learners who actively participated and who could have been good candidates for spreading news, events or writing controversial statements contributing thus to foster discussion as well as to help build a solid community in some issues, for example, inviting them to offer support as facilitators in the next edition of the course. Only 50% of teachers confirmed that if they had had this tool during the course, they would have changed, to a certain extent, the methodology and activities proposed.

Regarding the sixth question about what other information teachers would like to know and that these graphs do not provide, three teachers said that a plot summary should be included where the most relevant, socially speaking, people were highlighted. For instance, showing the name and if available, the photo of the top 5 most active people in a week as well as the number of new peers who joined with the aim of reinforcing the social affiliation. Since social recognition is also important, the top 5 people with the largest hub and betweeness should be also pointed out. Finally, in order to visualise participants' commitment with the course, those who participated in a higher number of collaborative activities should be on the spotlight. Some teachers advocated the need for an intermediary, a data wrangler (Clow 2014), between data analysis and intervention who can help them understand what the analysis means and the best way to act accordingly.

At the time of writing this paper, the course had already finished and therefore this proposal could not be shown to learners. Nevertheless, we foresee that these sociograms will provide them with the following advantages: they will be able to easily find people with the same interests and/or profile, to measure one's contribution and influence in comparison with their peers and to get social recognition according to their participation, something which will stimulate them to continue and progress in their learning process. Our forecast is supported on (1) the previous results extracted from literature, which show that SNA contributes positively to understand, explain and improve learning processes designed from a social perspective; (2) the little evidence found with regard to learners' interest in having a learning dashboard and, (3) the effectiveness of including student-facing learning analytics in teaching practice (see Sect. 2.1).

3.4 Privacy and Ethical Issues

According to Pardo and Siemens (2014), privacy is defined as the regulation of how personal digital information is observed in itself or distributed to other observers. Nowadays privacy is being threatened as a consequence of the fact that more and more technologies collect data about people's whereabouts, behaviour, and feelings. Learning analytic services and dashboards make an extensive use of personal data of learners and staff such as teachers and tutors, including tracking their behaviour and actions in the platforms. Consequently, these platforms and services have to be designed and operated in a legally compliant manner, that means, according to Data Protection Directives. All users must be informed about the fact that data is being collected, and what purpose and goal. Furthermore, people whose data is being gathered,

must give their consent. Moreover, individuals have the right to request that all their data be removed at any time. An exception can be made for data that an institution is obliged to keep for other reasons (e.g. names, dates of birth, final grades). In the context of learning analytic applications that transgress the boundaries of the institutional learning or MOOC environment, consent must be obtained for the collection of all data from all non-institutional sources (e.g. Twitter).

Regarding the data shown in this paper, all participants of this study freely accepted to create a public profile on the social networks used with the aim of gaining visibility and audience while the course went on.

3.5 Tools Used for the Development of Proposed Sociograms

Several software tools were used to develop these sociograms. On the one hand, Facebook Graph API and Twitter API were needed to extract data from these social network services. These APIs presented some limitations that had to be taken into account, for example Twitter API frequently requires reading data since only the latest two hundreds tweets are available and Facebook does not allow to extract comments on comments directly, therefore an external module based on regular expressions had to be programmed.

Data extracted from social sites were next stored in a MySQL database to be later processed and next flat files be created according to ORA Software requirements. ORA Software (Carley 2014) was the tool chosen to measure and visualise the social networks which arose from the participants' interaction. Two types of files were built, agent x agent and agent x knowledge. The first one gathered who answered to whom and the number of times that this fact happened in the course or the learning task. The second one collected who wrote comments on a certain post and how many times he or she did it. Both files were complemented with a file which contained several columns of attributes (profile and centrality measures) per each node (participant). Then, graphs with different layouts and showing distinct features were built.

4 Conclusions

The widespread use of information technologies, in particular social network services, has allowed learning designers to use the social learning theory in order to create new and attractive learning environments that move away from the traditional teacher/student approach (Pandey 2016). Technologies enable participants to learn from each other and discuss, develop contents and solve doubts collaboratively and ubiquitously, which makes social learning adoption easier. This method for learning is being more and more used in non-traditional teaching such as MOOCs and is pretty suitable for distance and blended learning.

The interaction data generated and available in social network services is a wealthy information source that, if adequately managed (accurate data), can be well used by teachers and learners for improving the teaching-learning process from different perspectives: motivation, engagement, feedback, recognition, reflection, etc. To this end, Social Network Analysis is a useful and effective tool to be included in the teaching practice thanks to the informative power of its graphic representation (Sobieski and Dell'Angelo 2016), the

sociogram. Likewise the centrality measures that can be computed on interaction data and that allow identifying the participants' behaviour in collaborative activities reinforce the use of these social graphics tools.

Therefore, this work proposes the inclusion of social graphs based on the theory of Social Network Analysis in educational dashboards since its objective is to analyze and measure the strength of the relationships that arise between individuals, giving them tools to evaluate and redirect their participation during the course. Furthermore, if these tools are used within a social recognition system (Karma system), they could help people to keep more engaged. Beyond that, with the information provided by sociograms, teachers can redirect activities, adjust content, keep the discussion forums that cause the most interest active, as well as take actions to encourage those who participate less, etc. On the other hand, students can use the information provided by this tool to guide their learning interests, increase their participation, act as peer tutor, as well as establish connection with other participants who share their same interests. Finally, this could also help achieve the objectives related to building a community of practice and allow both teachers and students to try new roles in the online learning process.

Additionally, this work suggests how to build different types of social graphs for the most known and used social network services in education such as Facebook and Twitter (but not limited to them) and provides an explanation of the main centrality measures when these are applied to analyse the interaction in an educational environment. Through a case study, the usefulness and feasibility of our proposal and the advantages that this offers for both students and teachers are highlighted. Therefore, we emphasize the importance of the inclusion of social graphs for making educational decisions in social learning activities.

As future work, we point out that it is necessary to advance in the analysis of causality among teaching methodologies and the use of a SNA-based track engagement system. Another open issue is the design of graphical representations which helps to visualise the temporal evolution of the community (Beck et al. 2014) since currently this evolution is shown as a series of static network snapshots and its analysis is not very direct. Finally, another interesting research area is the network settings focused on analysis of discourse (Wagner and González-Howard 2018).

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