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Αναζητώντας τον “έμπειρο άλλο” μέσω της ανάλυσης εκπαιδευτικών δεδομένων

Looking for the “More Knowledgeable Other” through Learning Analytics

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Abstract

Long-tested pedagogical theories can provide the basis to analyze and interpret students' interactions in distance learning environments. Through this lens, useful conclusions can be drawn from students' data that could help to improve the teaching and learning process. In this paper, a number of forum posts were analyzed and the role of tutors and students was scrutinized through the use of network visualization. It was found that certain students have a central positive role in the discussion forum although tutors have the main burden of answering and keeping the interaction alive. These students can act as the *more knowledgeable other* and support their peers. Further research in order to gain insight into students' interaction and promote collaboration, is proposed.

Keywords: *learning analytics, students' discussion fora, interaction, distance learning, network*

Περίληψη

Παιδαγωγικές θεωρίες, δοκιμασμένες επί μακρόν, μπορούν να αποτελέσουν τη βάση για την ανάλυση και την ερμηνεία των αλληλεπιδράσεων οι οποίες πραγματοποιούνται μεταξύ των φοιτητών σε εξ αποστάσεως εκπαιδευτικά περιβάλλοντα. Τα δεδομένα που αντλούνται από την δράση των φοιτητών, όταν μελετώνται υπό το πρίσμα των αντίστοιχων θεωριών, μπορούν να προφέρουν σημαντικές πληροφορίες για την βελτίωση της διδασκαλίας και της μάθησης. Στην παρούσα εργασία αναλύονται οι αναρτήσεις των φοιτητών και των καθηγητών-συμβούλων τους στα forum των μαθημάτων τους μέσω της οπτικοποίησης των σχηματιζόμενων δικτύων. Από τη μελέτη προέκυψε ότι μερικοί φοιτητές κατέχουν κεντρικό και θετικό ρόλο, παρόλο που το μεγαλύτερο μέρος της ευθύνης για την επίλυση αποριών και την διατήρηση της επικοινωνίας βαρύνει τους καθηγητές-συμβούλους. Οι φοιτητές αυτοί θα μπορούσαν να δράσουν ως *έμπειρος άλλος* και να ενισχύσουν την προσπάθεια των συμφοιτητών τους. Προτείνεται περαιτέρω έρευνα προκειμένου να αναδυθούν χρήσιμες πτυχές της αλληλεπίδρασης των φοιτητών για τη βελτίωση της μεταξύ τους συνεργασίας.

Λέξεις κλειδιά: *ανάλυση εκπαιδευτικών δεδομένων, forum συζήτησης φοιτητών, αλληλεπίδραση, εξ Αποστάσεως Εκπαίδευση, δίκτυα*

Introduction

Lately, Learning Analytics has shifted focus from accountability to providing tools for educational improvement. The goal is to optimize learning outcomes by upgrading the learning experience by enhancing the interactions, updating the learning material, and improving the learning environment. However, learning analytics has not received enough focus from national and European level bodies (Nouri et al. 2019) to successfully create a wide-range strategy towards data-driven development of education. In an era of continuous change in the educational setting, even the curriculum is constantly on the spotlight for updating and adjusting to the new demands of transferable skills. Under these circumstances, the ability to have a clear picture of the learning process in real-time is of utmost importance. The appropriate indices that will provide useful information for upgrading educational planning need to be identified. The implication of Learning Analytics and the evaluation of its impact on learning is one of the key challenges of the educational field (Tan, & Koh, 2017).

Furthermore, educational success and failure have been related to the quality of learners' educational dialogue (Ferguson, & Shum, 2012). Obviously, there are different kinds of dialogues taking place in an educational environment: disputational, cumulative and explanatory dialogue. In any case, the context of the discussion is indicative of the students' concerns. In distance education, the discussion forum is the most common way to communicate and in addition a place for collaboration. Monitoring and analyzing students' interaction can lead to the production of methods that can strengthen the positive results of the collaboration. Some features of collaborative work such as Heterogeneous Grouping, Peers Interaction, Individual Accountability, Positive Interdependence and Cooperative Skills (Jagadish, 2014) can be enhanced provided that the behavior of students is clear to their tutors and the course designers. Schaffer et al., (2016) suggest that forum networks should be visually monitored in order to ensure the inclusiveness of all students and their overall effectiveness. Also, the interaction monitoring can be linked with the creation of an early dropout prediction system. However, it is important to combine quantitative methods with the necessary theoretical basis in order to produce meaningful and actionable results. For example, Fincham, Gašević, & Pardo (2018) highlighted the influence of the different definitions used to describe the concept "social tie" on the results of the analysis in order to raise awareness of the consequences that such methodological choices may have and to promote transparency in future research. Educational theories can provide a solid basis for research planning and effective data processing.

Theoretical framework

Vygotsky's sociocultural theory is based on the assumption that intellectual development is a process that concerns human communities, rather than individuals (Vygotsky, 1978). Communication and cultural activity take place in the field of the social environment that acts as a facilitator of development and learning (Tudge & Scrimsher, 2003). Consequently, students transform their experiences based on their knowledge and their characteristics and reorganize their mental structures (Shunk, 2010). The concepts of guidance, collaboration and encouragement are very important in this theory, as well as the role of the "More Knowledgeable Other" (MKO). The MKO can provide guidance and encouragement to the students. Most of the time, the role of the MKO is undertaken by the teacher. However, peer-to-peer collaboration can be just as effective. In a group of students, the MKO usually emerges among his or her peers as an important leading member (Sweet, & Michaelsen, 2007). On the other hand, Connectivism (Siemens, 2005) as a more recent learning theory that is based on

networks and interactions, has a common epistemological base and it is considered to be an evolution of the Vygotskian model that incorporates the social aspect of learning that emerges through the new web-based learning technologies. The influence of Vygotsky's theory and in particular of the Zone of Proximal Development is obvious in the theory of Connectivism (Kop, & Hill, 2008). The social aspect of learning is emphasized in both theories. Learning is not a personal, isolated process. The influence of Vygotsky's theory is also present in a series of upgraded learning tools. An impressive example is the Squirrel AI Learning (Cui, Xue, & Thai, 2019). It is a highly advanced platform of personalized learning with AI intergraded technology that contains learning objects divided into small "proportions of knowledge" just to fit practically in any student's skill level. This way, the digital learning material is adjusted according to the student's Zone of Proximal Development.

It is obvious that the combination of Humanities, Social Sciences and Data Science in an interdisciplinary approach, can contribute significantly to the educational field. Data science effectiveness has to go beyond algorithms, visualization, and predictive models. Domain expertise is required to understand and interpret data into actionable information. Consequently, the results of educational data analysis could make a significant impact only inside a domain-specific framework and only as long as they are embedded in an organized, holistic institutional approach (Tsoni, Stavropoulos & Verykios, 2019). A field of research that takes advantage of the synergy between the above scientific fields is Social Learning Analytics. *"Social learning analytics make use of data generated by learners' online activity in order to identify behaviors and patterns within the learning environment that signify an effective process."* (Buckingham Shum & Ferguson, 2012). Along with methods that can reveal facts that are not so obvious, especially as they apply to large populations, there are other methods which are essential for the viability of Distance Learning Systems. Sentiment analysis is also a technique that can provide this kind of information and keep tutor on track with the acceptability of his or her teaching. *"Sentiment analysis is the process of categorizing opinions and statements as positive and negative according to the sentiment that they express"* (Wilson, Wiebe & Hoffmann, 2005). In this paper, we were based on the abovementioned theoretical approach in order to apply data analysis aiming to create an image of students' and tutors' interaction in the educational fora of a distance learning program at the Hellenic Open University. Hopefully, the conclusions should provoke decisions for teaching and learning improvement.

Related work

Relevant studies have been focused on the behavior of forum participants. Sentiment analysis of students' fora and emotion classification was held by Gkontzis et al., (2017a) in postgraduate students of the School of Science and Technology in HOU. The study revealed that positive polarity was dominant in students' posts. At the same time, the visualization of the results allows tutors to instantly leverage data analysis results. Learning Analytics dashboards have been successfully used, enabling tutors with no previous learning analytics training to detect students' trends in order to provide personalized assistance (Gontzis, et al., 2017b). Forum activity has also been used to predict students' performance. Chiu & Hew, (2018) investigated the predictive strength not only of forum posts but also of viewing and commenting. They found that viewing was the best predictive action rather than commenting although we have to stress the difference of learner's behavior in the MOOCs audiences from a traditional Distance Learning course due to open entry and diverse learner backgrounds.

In a relevant study, a significant predictor for students' success was the overall contribution to the forum. There was a statistically significant difference between those

students who had contributed with an on-topic, larger than 50 words post at least (Crossley, et al., 2017). In a more computational approach Chiru, Rebedea & Erbaru, (2014) proposed a model for computing connections between the debated topics and the chat participants and between each of the debated topics in the conversation, called the participant-topic and the topic-topic attraction. Sun, B., Wang, M., & Guo, W. (2018) studied students' interactions in the course's forum and compared their behavior depending on whether they had been placed in a previously formed group or not. They found a significant difference in the degree and the type of communication bonds between the students of these two groups, indicating that the approach followed when designing the course is affecting the type of the interaction that would take place during the course.

Going deeper into the dialogue that takes place inside the forum community Joksimovic et al., (2019) used multiple regression models to show that the combined use of measures derived from discourse analysis and social ties predicted learning outcomes. Sundararajan, (2010) proposed a model called the PI-Matrix (Participation-Interaction Matrix) that can be used to help lurkers and shirkers, become workers and take an active role in their learning by incorporating content analysis in their research. More recently, by a literature review Cela, Sicilia, & Sánchez, (2015) revealed that the most common indices used in Social Network Analysis is centrality and density and concluded that Social Network Analysis, particularly when combined with content analysis, can provide a detailed understanding of the nature and the type of interactions between the members of the network, allowing the optimization of the course design, the composition of learner groups and the identification of learners in danger of dropping out. In a similar approach, Hernández-García, et al., (2016) analyzed data from a cross-curricular course with Gephi software to prove that each learning system requires to focus on tailored tools for advanced and in-depth analysis in order to create useful results that they will shed light to the core of the problems that need solving and will significantly support distance learning.

Methodology

Research goal

The aim of this study is to investigate interactions taking place in discussion fora and finally to identify the positive role of certain students through their forum participation. The social aspect of students' behavior is highly important for the learning outcome. Thus, it is very important to recognize and reinforce the impact of the persons that could act as "the more knowledgeable other" and facilitate learning. Apart from the tutors, peer's interaction can be a key element for learning especially in Distance Learning. Forum posts can provide us significant insight into the interaction, the behavior, and the course flow during the academic year.

Data

This paper examines data from students' fora at the School of Science and Technology of the Hellenic Open University in the academic year 2013-2014. Totally 166 students of the postgraduate program: "Master's in Information System" participated in the program's fora. There was a different forum community for each of the five modules of the study program (PLS50, PLS51, PLS60, PLS61 and PLS62). In these modules, 15 tutors are facilitating learners. Tutors are also participating in the discussion forum communities. Data management techniques were used to draw data from the discussion fora. Anonymization process is highly important for both reasons of compliance with the newly established General Data Protection Regulation and ethical reasons as well.

Privacy protection applies in all stages of data processing: data preprocessing, data analysis and data publishing (Kyritsi, Zorkadis, Stavropoulos, & Verykios, 2018). Thus, data went through the process of anonymization and a reference number was assigned to each student. Consequently, from now on we will refer to st1, st2 and so on. In advance, students' posts have been characterized as positive, negative or neutral depending on the emotion that they indicate. The polarity has been attributed "manually" by the researchers and no automated tools have been used. The main characteristics of the sample used in this analysis are presented in table 1.

Participants:	15 tutors
	166 students
Number of messages:	1505
Program duration:	One academic year
Courses:	PLS50-Fundamental Specialization in Theory and Software (first year)
	PLS51-Fundamental Specialization in Computer Architecture and Computer Networks (first year)
	PLS60-Specialization in Software Engineering (second year)
	PLS61-Software Design and Management (second year)
	PLS62-Specialization in Networks and Communications (second year)
Mean number of messages per participant:	5 messages per student (max=39, min=1)
	43 messages per tutor (max=127, min=4)
Messages' polarity:	729 positive messages
	418 negative messages
	358 neutral messages

Table 1: Sample's main characteristics

Tools

In this research, Cognos Analytics Software was used to create networks and visualize the interactions between forum participants. Cognos Analytics is a cloud-based platform provided by IBM that offers an easy way to gain insight into business-related data but also it can be used for educational purposes as well. Useful visualizations can be created revealing relations between the variables. There is also the possibility to prepare presentations, infographics, and data storytelling dashboards. One of the optimal visualizations for forum-related data is Network visualization since it can illustrate the social interaction between the participants. Network visualization comes with interesting additional features that allow filtering certain values of the variables used in the analysis. Thus, it is possible to investigate the impact of each variable in the network's characteristics. This key feature along with the simplicity and the effectiveness of the tool was the main reason for our decision to use it in our research.

Results and discussion

We used the Network visualization tool to create two-node networks. Each node represents a variable count. Blue nodes represent the variable "Post" and green nodes

represent the variable “ID” (figure 1). This way it becomes visible who is participating in the discussion and the topic that he or she is involved in. Information about the gender, the age of the participants and other personal characteristics are not included in the research. This study is focusing on the form of the networks created by tutor students’ participation and interaction and also on identifying students who facilitate the learning process thus they could act as the MKO. The first graph (figure 1) illustrates the complete picture of the interaction for all of the participants during the whole academic year. In this graph, the role of the tutor as communication facilitator is clearly shown.

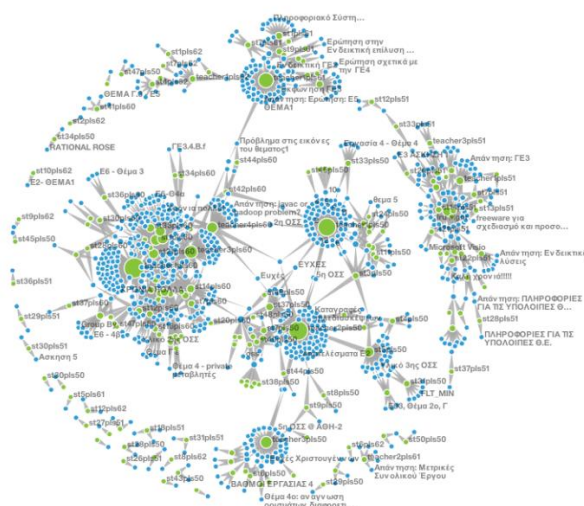


Figure 1: ID to Post, all year long

Tutors are playing a centric role since they are involved in the majority of the subjects discussed. In the perimeter, some isolated posts are taking place with a low degree of interaction. This means that in some cases, the posts have a unique answer. By thoroughly sampling a number of these posts it was found that typically there was a straight question for a practical issue that was directly answered by the tutor in most cases. That means that short discussion threads do not always signify a low level of interaction. They could possibly indicate a problem directly solved.

For each different module, a different concentration can be found in the graph. In some modules (for example in PLS60) some smaller concentrations can be detected. This is due to the different geographical groups (sections) that the participants of the course are divided in. Apart from that, the course PLS60 presents a very concrete network and the levels of interaction seem to be very high. Examples of the network’s form for each course separately are shown in figures 2 and 3.

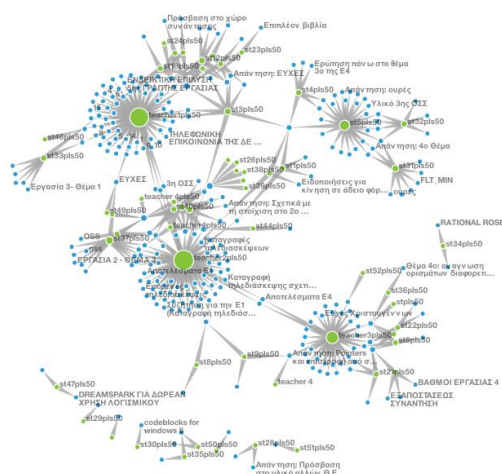


Figure 2: ID to post in PLS50 all year long

In figure 2 the “ID to Post” network of PLS50 module is illustrated for all participants. In this case as well, tutors are in the center of interaction. Some smaller individual networks of students are also created. Moreover, there is a small number of peripheral non-connected posts.

It is interesting to investigate whether the characteristics of the network change in a second year’s posts where students become more familiarized with the learning process. In figure 3 it is shown the “ID to Post” network for PLS60 module.



Figure 3: ID to post in PLS60 all year long

This network includes concentrations where students play the central role. This is better shown in the next figure (figure 4) where the participation of the tutors has been excluded from the graph. Students’ central role becomes more visible and “star” students can be easier identified.

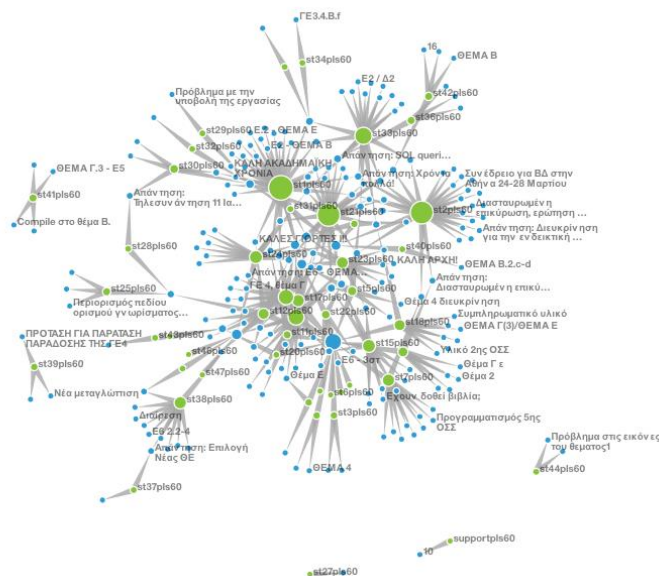


Figure 4: ID to Post all year (students only) PLS60

In figure 5 the network, without tutors, for all courses, all year long, is presented. The fact that the clusters are concentrated around certain students and not around certain subjects proves that no major issues have arisen during the academic year.



Figure 5: ID to post, all year long students only

Furthermore, the network in figure 5 can reveal the most active students. There are two different types: those who are involved in many discussions (green dots that concentrate a lot of blue dots around them) and those who concentrate a lot of other students around them (green dots connected with a lot of other green dots in a central place). The second type of activity indicates better collaboration and a possible “more knowledgeable other”.

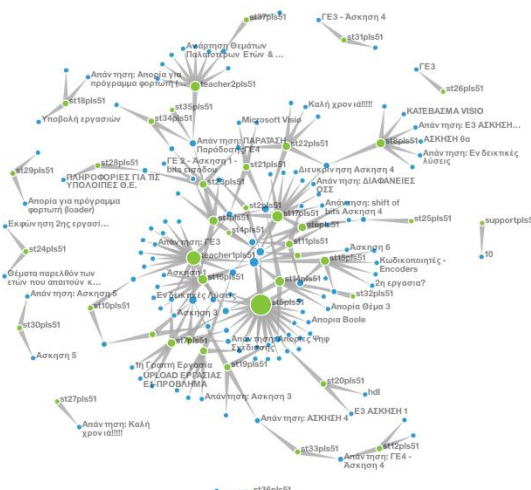


Figure 6: ID to post PLS51

In some cases a very active student can have a more central role from the tutor. For example, in PLS51 course the student st5 is bonded with more students and has contributed in more posts that the most active tutor (teacher1). Although PLS51 is an entry module it seems that there is a strong collaborative system between peers. To investigate further the case of PLS51 we visualized the “ID to Post” network without the tutors. Seeing this network without the participation of tutors it is easier to recognize the collaboration groups. In figure 7 the action of st5 is more obvious but also the contribution of other students like st1, st14, st7, and st8 is now clearly shown.

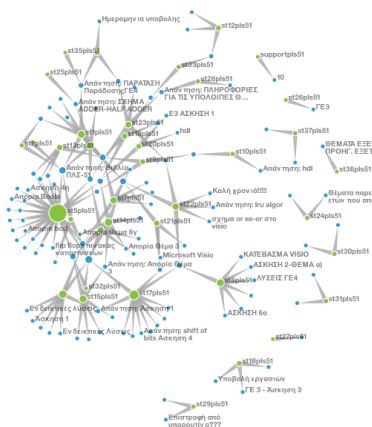


Figure 7: ID to post all year (students only) PLS51

As it was previously mentioned the content of the messages influences the type and the effectiveness of the communication and interaction between students and tutors and also among peers. Thus, sentiment analysis of the messages combined with network visualization is useful for providing a more thorough view to each participant's contribution. As it is presented in figure 11, in neutral posts, there are some clustering centers in which instructors lead. Interestingly, positive posts have a large inclusive center where students are shown to play a central role creating a positive climate in conversations. Negative posts do not cluster around a particular topic, which indicates that students did not negatively deal with a major or unresolved issue.

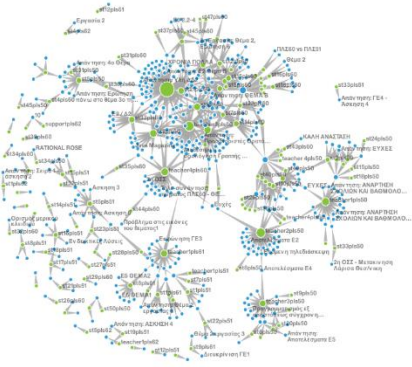


Figure 8: ID to post positive



Figure 9: ID to post negative

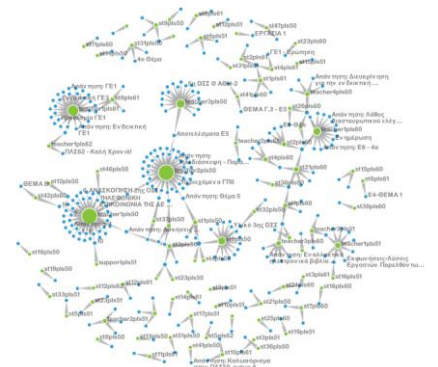


Figure 10: ID to post neutral

Using the same type of visualization, we created a two-node network where blue dots represent the polarity of the message and the green dots represent the participants' ID (figure 12).

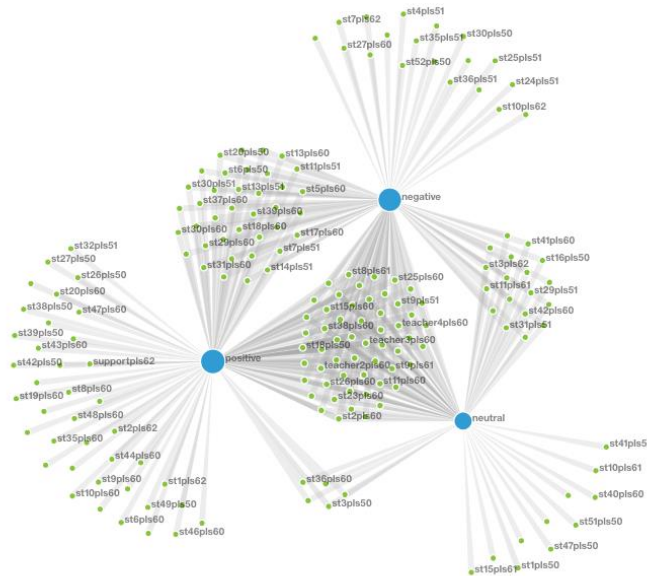


Figure 11: ID to polarity sized by post counts (all fora)

There are seven groups of participants depending on the sentiments they express:

- All sentiments
- Positive and negative
- Negative and neutral
- Neutral and positive
- Only positive
- Only negative
- Only neutral

It is obvious that there are students of all possible combinations of sentiments expressions. But, most commonly, participants' messages include all the three types of sentiments during the academic year. There is also a large group of participants whose contribution does not contain negative messages, followed by a group of only positive contributions. To identify students who could act in a positive, motivating or facilitating way in the forum community we searched for the most active students amongst the polarity groups. Student st2pls60 and student st21pls60 are very active and have a

central role in their forum activity and at the same time they had expressed all the types of sentiment during the academic year. Therefore, they may be considered as the “average voice” that reflects the students’ general feeling. In addition, there are some very active students that seem to have a positive impact on the forum community. Students st3pls50, st46pls60 and st47pls60 have not expressed any negative sentiment during the whole year. This positive attitude from a highly active student can empower his or her peers and provide motivation and support. Consequently, students st3pls50, st46pls60 and st47pls60 could easily act as the MKO in the course’s community. This information could be useful to the tutor in order to encourage this helpful behavior and boost confidence amongst the group of peers. On the other hand, there are some very active students that express exclusively negative feelings. For example, student st2pls50 although he/she posted a lot of times in the course’s forum, all of his/her messages were either negative or neutral. In this case, the tutor should seek personal communication with the student to discover the reasons for his/her general dissatisfaction or his/her negative attitude.

Conclusions and future work

There is a “de facto” power in the impact of tutors since all the previous years of formal education have consolidated the hierarchical structure of pedagogical relationships (Bliss et al., 2001). Students trust their tutor to answer their questions. That does not apply in the case of active students that have to earn their colleagues trust. However, our analysis showed that there are some students that can act positively and strengthen the communication and the interaction in a discussion forum. Although the main role of learning facilitator belongs to the tutors, it is important to strengthen peer interaction. It is beneficial for learners, especially in distance learning modules and courses, to feel that they belong to a community and to create bonds of trust and collaboration. Apparently, the way students interact in a discussion forum can be indicative of their academic performance, even though it is not as obvious as just counting logins or posts. A thorough network analysis combined with methods like context and sentiment analysis can reveal hidden relations and characteristics.

Metrics can be important for drawing conclusions. Traxler, Gavrin, & Lindell, (2018) found in their research that central network positions are positively linked with course success and highlighted that centrality is a more reliable indicator of grade than non-network measures such as post counts. In addition, Crossley et al., (2017) propose the use of Network Analysis indices to develop more actionable automated signals of student success. We aim in a similar approach that would also incorporate automated sentiment analysis. This would be possible if students’ data are made available in real-time through a system offering data stream capabilities. PRIME-EDU software can send educational data to a cloud database making them available for processing and analysis in real time (Tsoni et al., 2019). Modern techniques could simplify the way we approach this knowledge even in the case of massive or complex networks (Vu, Pattison, & Robins, 2015) and help us identify critical events that demand attention and immediate intervention.

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