

Graphs and Key Players in an Educational Social Network

Fernando Calle-Alonso¹, Vicente Botón-Fernández², Dimas de la Fuente², Carlos J. Pérez⁴,

Miguel A. Vega-Rodríguez³ and Daniel de la Mata¹

¹Research & Development Department, ASPgems SL, Spain

²Cátedra ASPgems, University of Extremadura, Spain

³Department of Technologies of Computers & Communications, University of Extremadura, Spain

⁴Department of Mathematics, University of Extremadura, Spain

Keywords: E-learning, Social Graph, Cooperative Learning, Key Player, Engagement, Dropout, NeuroK, Social Learning Analytics.

Abstract: A new social learning graph tool has been proposed and implemented in NeuroK. This is an interactive visualization of the relationships among students, based on their comments, favorites, mentions and rates in a course or a learning unit. Some illustrative examples are provided showing its possibilities, challenges and future potential of using the social graph tool. Social graph can help teachers and students to have an easy visual image of their relationships, discovering the key players in the network and also the isolated students in risk of dropping out. The teacher can use this information to reach the students “in risk” and try to retain them with some motivating and engaging actions. The social graph and the indices that can be obtained from it show up to be also a very good tool to analyse the development of the course and to help the teacher to evaluate the students.

1 INTRODUCTION

E-learning is a current formative strategy that can solve many problems from the traditional education environment. But it can also have some regrets too depending on the platform used, such as the isolation of the students, the high dropout rate, or the dependence on technology/internet. Depending on the kind of learning process, the student can be more or less involved and motivated, and the pros and cons are different than with the traditional approach.

The learning process can be individual, collaborative or cooperative. Online education technology can support these three perspectives (Schoor et al., 2015), but which kind of learning is more effective? Technology may support both individual learning and access to social networks to allow the individual development, engagement, and motivation within social relationships. McInnerney and Roberts (2004) point out that there is a certain overlap and inter-concept usage between cooperative and collaborative learning and they have provided definitions and a deep analysis. A way to distinguish the three concepts is focusing on how the learning is taking place. Individual learning is conducted *alone*,

collaborative learning depends on *groups* and cooperative learning takes place in *networks* (Panitz, 1999).

Online cooperative learning (Paulsen, 2017) tries to give the students a space for individual development, and also the freedom to participate in networks or communities to improve their knowledge together.

This article presents a new tool showing a social interactive graph, which is implemented in an innovative e-learning platform called NeuroK (Calle-Alonso et al., 2017). This platform is based on the principles of neurodidactics, and on cooperative learning. The relationships among students (and also with the teacher) are shown with some illustrative examples. A great number of visual interactive features have been implemented and shown in this paper, and the way to calculate the graph is explained. This kind of social graph analysis is demonstrated to be a good way to measure collaborative or cooperative distance learning (Reffay and Chanier, 2003). Some e-learning platforms have tried to use social networks to develop their learning process, but most of them have taken advantage of the most common applications, such as Facebook or Twitter,

instead of developing and using their own. The experiences in many cases have not been satisfactory, and almost none of them have performed a social analysis of the interactions among students.

In online education, it is very important to boost the motivation and the engagement with the purpose to reduce the dropouts (Willging and Johnson, 2009). With the social graph it can be observed which students are isolated or disconnected from the others, and which are the key players (Zhou and Chen, 2015) that act as influencers. The role of this influencers is very important because they can spread information in the network and reaching a lot of students. In this paper an example of how to identify this kind of student is also presented.

According to this information from the graph and the role of the student in the network, the teacher could grab one disconnected student and try to regain his motivation. Also, the teacher could use this easy to understand visual information as one of the factors contributing to assess students, in this case according to their participation in a course, or a lesson.

2 SOCIAL GRAPHS

Nowadays, the popularity of social networks has led teachers to use them as a motivating factor (Rennie and Morrison, 2013). Social learning networks analytics are beginning to play an important role in e-learning platforms (Buckingham Shum and Ferguson, 2012). The relationships among students of a social network hide a lot of important information that can be extracted with the right tools. This information can be used to measure the participation and the cohesion of a group of students. In addition, social networks provide social learning graphs to capture and represent the interactions and relationships that take place among multiple entities in a learning environment (Pardo, 2013).

Some teachers have tried to use some of the most popular social networks (such as Facebook, Twitter or LinkedIn) for educational purposes (Bosch, 2009). However, most e-learning platforms do not have any kind of social graph analysis or valuable measures to properly evaluate the participants' relationships.

In this section we present the analysis of social networks that is being applied to the cooperative e-learning platform, NeuroK.

2.1 Implementation

Social graphs are considered as a global mapping of the members within a social network and how they

relate to each other. In our case, the graph focuses on an e-learning social environment. Nodes represent students from a certain course or topic and the lines linking the nodes represent a relationship between them. In our social graph representation, the thicker is the linking line between two nodes, the greater is the number of communications between the two students represented by the nodes. Due to the different types of communications that may exist between two students, each of them has been assigned a different weight that affects the thickness of the line, as we will see below.

The data obtained from NeuroK to build the social graph and to calculate the social measures are mainly:

- Comments: these are the replies that students make of a content published by another student, creating a direct communication between them.
- Mentions: a student can be mentioned in comments or tasks evaluations, creating a social bond between the student mentioned and the one who mentions.
- Favorites: sometimes a student can set as favourite another student's comment, pointing out that they like its content.
- Rates: students can rate a content proposed by another student as long as they justify their assessment.

Each type of communication provides a different score for the student who receives it. This score is the one used as a weight when establishing the thickness of the lines in the social graph, as it was mentioned before.

For the representation of the graph, *d3.js* library has been used. This library has some advantages such as:

- It lets you make your visualizations in the way you want (e.g. you can use avatars as node representations).
- It allows you to add many other DOM (Document Object Model) functions, like zoom or pan functions for any graph you want.
- It supports a large amount of data.
- It has tools that make the connection between data and graphics easy.
- It is as flexible as the client side web technology stack.
- It allows you to build a graph based on social gravity. This representation follows some rules according to this gravity, such as the length of a line or the attraction between nodes.
- It is easy to debug using the browser's built-in element inspector.

The teacher and students can interact with the social graph by doing any of the following actions (see Fig. 1):

- Choosing the course or topic they want to be represented in the graph.
- Filtering data by user: students and teacher/s or only students.
- Filtering data by event type: comments, mentions, favourites, rates or all events.
- Selecting the number of influencers: from 1 to 5 or no influencers.
- Displaying a tooltip when the mouse is over any node.
- Moving the graph structure by dragging a node.
- Highlighting all the relationships of a node when the mouse is over it.
- Displaying the neighbourhood of a node by double clicking that node.
- Zooming in or out the entire social graph using the mouse wheel.



Figure 1: Social graph filters.

The social graph represents the relative importance of each student in NeuroK based on their activity (comments, mentions, likes or ratings) providing great information about the structure of the network and how the students are related, as we will see in the next subsection.

2.2 Study Case

Here a typical scenario that covers the concepts mentioned above has been described in order to better understand the system operation. We have tested NeuroK through an existing topic called “Machine Learning” to obtain a real dataset. There are five students enrolled in the course and two teachers. In order to build the social graph, all the information from comments, mentions, favorites and rates has been saved into the NeuroK database. That information has been registered during a period of one month. Once the dataset is ready, it is time to navigate to the “Social Graph” view and set up the filters. In this case, we establish the following settings: Machine Learning topic, all users, all events and no influencers.

After running our social graph approach over the previous dataset, it generates the social graph that appears in Fig. 2. It shows a global mapping of students and teachers enrolled in the Machine Learning topic and how they are related.

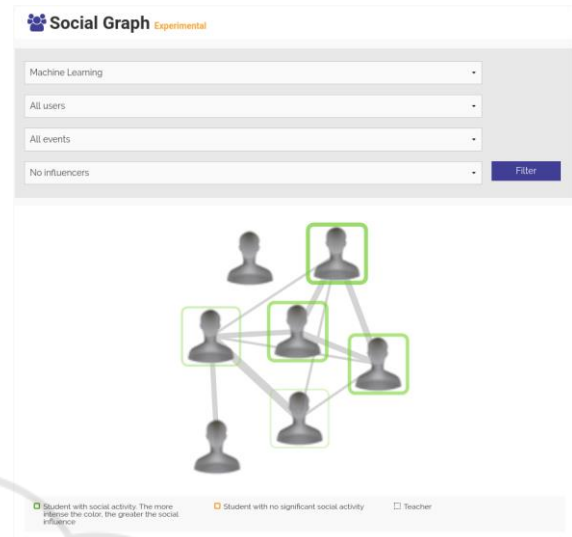


Figure 2: Social graph for Machine learning topic.

The nodes include the avatars of each student profile (in this case we use the default avatar to maintain their anonymity). They also have different border colors depending on their role and how they relate to each other. The students with social activity have a green border. A student is considered to have social activity when they send/receive comments, mentions, favorites, and rates to/from other students. The greater the social influence, the thicker and more intense the green border. The metrics used to measure this social influence will be discussed in the next section. On the other hand, the isolated students with no social activity have an orange border. Finally, teacher nodes have no borders, since their activity will not be evaluated.

The lines linking the nodes also highlight the intensity of the relationship between two nodes. The thickness of the line defines the intensity of the relationship. With the proposed graph, a teacher can have an overview of the participation in a course or topic with a single chart. Some of the students may be isolated, indicating that they are not participating in the course or topic. The teacher should try to find out why they are not using the platform. This is a simple and effective way to identify students who may leave the course before completing it.

3 KEY PLAYERS IN E-LEARNING

The information of the social network provided by the graph would help in the identification of influencers or key players, who may be good knowledge brokers. Identification of a set of key players in a given social network is of great interest in this context. Up to now, most of the used algorithms for this task are based on a single characteristic, however, in this case, it is necessary to find a set of key players which can perform well with respect to several characteristics of interest. Within a social graph, students are distributed into clusters. These clusters can be analysed to find out what they are talking about and what learning contents they are sharing and commenting on. Clusters should not be isolated from each other. The teacher's goal should be for all groups to be connected, share information and collaborate with each other. Some students will be related to different groups. These students are often selected as influencers or key players, as they can provide information between groups and have different views on the proposed materials and discussions. These key players are very interesting to analyse, and teachers could propose a specific line of action to help the rest of the students thanks to their broad influence.

Different metrics have been used when assessing the influence or social activity of a particular student: betweenness centrality, global activity and Dijkstra's distance. The mean value of these three metrics represents the influence of a node. With these three metrics we manage to assess three fundamental aspects of an influencer: direct communication with the largest number of students (Dijkstra's distance), largest number of communications received or sent (global activity) and communication between different groups (betweenness centrality).

Let us go back to the study case from Subsection 2.2. Taking the same filter settings, but showing only students and modifying the number of influencers to 1 as shown in Fig. 3, we can display the key player of that topic.

4 CONCLUSIONS AND FUTURE WORK

A new social graph tool has been proposed and implemented in the e-learning platform NeuroK. It has many visual customizations and possibilities to let the teacher observe the participation of the students in a course. With this tool the teacher is able to discover

the main relationships among the students and the intensity of the relationships, which of them are key players and who is disconnected and is a candidate to drop out. Teachers can then try to re-engage isolated students. Also they can use the social participation of the students as part of their evaluation at the end of the course.

In addition, groups of students can stand out showing different behaviors and in the future, we classification

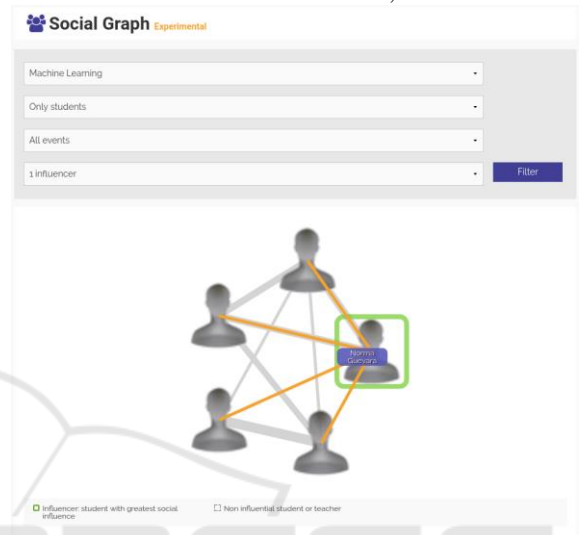


Figure 3: Social graph and key player for Machine learning topic.

Fig. 4 shows the direct relationships of the influencer by placing the mouse cursor over it.

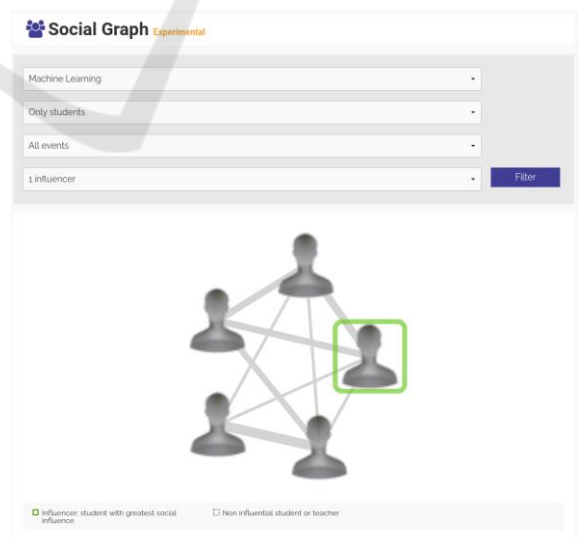


Figure 4: Key player relationships.

models to discover the main characteristics of each group to deliver personalized recommendations.

Finally, the main indices obtained from the social graph will be included in an evaluation book, available for the teachers to help them to evaluate students, and also, as a future work, an automatic marking will be suggested.

ACKNOWLEDGEMENTS

This research has been supported by Ministerio de Economía y Competitividad (Centro para el Desarrollo Tecnológico Industrial, Contract IDI-20161039), Junta de Extremadura (Contract AA-16-0017-1, and projects GR15106 and GR15011), Cátedra ASPgems, and European Union (European Regional Development Funds).

REFERENCES

- Bosch, T.E. 2009. Using online social networking for teaching and learning: Facebook use at the University of Cape Town. *South African Journal for Communication Theory and Research*, 35(2), 185–200.
- Buckingham Shum, S., & Ferguson, R. 2012. Social Learning Analytics. *Educational Technology & Society*, 15(3), 3–26.
- Calle-Alonso, F., Cuenca-Guevara, A., de la Mata Lara, D., Sánchez-Gómez, J. M., Vega-Rodríguez, M. A., & Sánchez, C. P. (2017). NeuroK: A Collaborative e-Learning Platform based on Pedagogical Principles from Neuroscience. In *Proceedings of the 9th International Conference on Computer Supported Education (CSEDU 2017)-Volume Vol. 1*, pp. 550-555.
- McInnerney, J. M., & Roberts, T. S. 2004. Collaborative or cooperative learning? *Online collaborative learning: Theory and practice*, 203-214.
- Panitz, T. 1999. Collaborative versus Cooperative Learning: A Comparison of the Two Concepts Which Will Help Us Understand the Underlying Nature of Interactive Learning.
- Pardo, A. 2013. Social learning graphs: combining social network graphs and analytics to represent learning experiences. *International Journal of Social Media and Interactive Learning Environments*, 1(1), 43–58.
- Paulsen, M. F. 2017. Cooperative online education. In *Seminar.net* (Vol. 4, No. 2).
- Reffay, C., & Chanier, T. (2003). How social network analysis can help to measure cohesion in collaborative distance-learning. In *Designing for change in networked learning environments* (pp. 343-352). Springer Netherlands.
- Rennie, F., & Morrison, T. 2013. E-learning and social networking handbook: Resources for higher education. *Routledge*.
- Schoor, C., Narciss, S., & Kördle, H. 2015. Regulation during cooperative and collaborative learning: A theory-based review of terms and concepts. *Educational Psychologist*, 50(2), 97-119.
- Willing, P. A., & Johnson, S. D. (2009). Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Networks*, 13(3), 115-127.
- Zhou, J., & Chen, Y. J. (2015). Key leaders in social networks. *Journal of Economic Theory*, 157, 212-235.