Visualization of sentiment spread on social networked content:

Learning analytics for integrated learning environments

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***Abstract*— Social Media has been disrupting traditional technology mediated learning, providing students and educators with unsupervised and informal tools and spaces where authentic learning occurs. Still, the traditional LMS persists as the core element in this context, while lacking additional management, monitoring and analysis tools to handle informal learning and content. In this paper, we present an integrated methodology that combines social network analytics, sentiment analysis and topic categorization to perform social content visualizations and analysis aimed at integrated learning environments. Results provide insights on networked content dimension, type of structure, degree of popularity and degree of controversy, as well as on their educational and functional potential in the field of learning analytics.**

Keywords—sentiment analysis, learning analytics, social network analysis, popularity, controversy, Moodle, Facebook.

I. INTRODUCTION

Social networks have been entering educational contexts as privileged spaces for social interactions, information exchange, collaborative knowledge building, immediate communication and persistent attention retaining, among others.

Together with current Learning Management Systems (LMS), social networks have been providing teachers with knowledge and data on students' performance and pedagogy, both of formal and informal nature. In fact, learning analytics have become a hot topic since unparalleled volumes of digital data about learners' activities, learning processes and interests have become available. This opens up possibilities to significantly increase the potential to make use of this data to improve learning outcomes and to provide instructors with informed decision making tools that can benefit teaching-learning contexts [1, 2].

In order to address the current needs of teachers and organizations to access, collect, organize, display and translate educational data we have been conducting research and have presented results concerning the Social Student Relationship Management (Social SRM) [3] and the development of the EduBridge Social system [4]. The second, the EduBridge Social system, consists on a system that integrates Learning LMS and Social Networks.

Therefore, our main aim consists on capacitating the LMS, (namely Moodle) with features that, not only provide the appropriate integration of social networks' interactions and data inside the LMS, but also to provide teachers, organizations and students with integrated learning analytics obtained by collecting, organizing and visually displaying formal and informal data.

Currently, this integration is essentially based on linking Moodle with Facebook Groups [5], thus EduBridge Social dynamically incorporates and displays, in Moodle, the analytics gathered from the interactions developed in a predefined Facebook group or set of groups. This configuration aims at providing educators with the necessary convenience and usability in the management of intrinsically disconnected learning environments, by integrating them in a complementary functional relationship.

As a result of the above mentioned research and development we were able to provide learning analytics based on the integration of these systems. We believe, however, that research on the social network's content needs to be further analyzed, particularly concerning its (1) development, relevance and structure and (2) how processes relate to the sentiment spread on the network.

The paper is structured as follows: in section II we present the methodology and the characteristics of the dataset used to provide the intend visualizations and analysis, which we describe in Section III. This third section is dived in two main subsections: the representation and analysis of the social graph of the community and the representation and analysis of the content subnets that emerged in that same community. In this latter section we provide insights on the dimension, type of structure, degree of popularity and degree of controversy for the identified content subnets.

II. METHODOLOGY

Social Network Analysis (SNA) has been integrated into learning analytics for identifying, relating and visualizing the set of interactions and intrapersonal relationships carried out by learners and teachers in learning communities or contexts [6].

Social network analysis considers networks to be made up of nodes and ties. Nodes consist of the individuals within the network and ties are the relationships between those individuals. Social networks can provide insights on several domains, such as: the dimension of the network (number of individuals), the relevance or participation level of an individual within the network (the node dimension), the closeness between individuals (for example, given by the thickness of the ties), etc.

Given that social learning is intrinsically linked to: (1) user-generated content (UGC) or repurposed content, (2) the learning that is generated through intrapersonal interactions within the network, we propose the use of the SNA theory, together with topic categorization of the Social Student Relationship Management (Social SRM) theory [3], and sentiment analysis as an integrated methodology to unveil which topics emerge, how they are developed on the network and how the individuals relate to those topics.

A. Networked content in Facebook Groups

In Facebook groups, networked content is obtained by the relations (ties) among the messages (nodes) posted by the individuals (A, B, C) inside that community. Typically, an emergent topic is inserted into the network through a Facebook 'post'. This consists on the main node to which several ties are established by other nodes in the form of Facebook 'comments' and 'replies', as illustrated in Fig. 1.

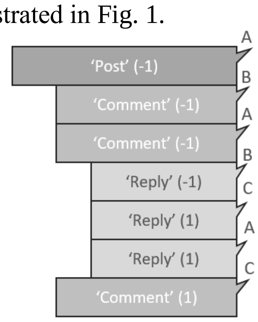


Fig. 1: Ties between Facebook 'posts', 'comments' and 'replies'

Using the SNA theory to display networked content in Facebook groups may result in the development of several more or less dense nets, according to the number of nodes generated around the topic(s) of the 'post', 'comment' and / or 'reply', which may fade more or less rapidly (or not fade at all). This provides insights on how relevant the topic may be for that community.

B. Sentiment spread in networked content

Applying sentiment analysis, one of the techniques associated to learning analytics [7], to the networked messages will allow to observe how the community relates to the topics of each node and how discussions / arguments and even new content that is added to the thread might influence the sentiment associated to the topics.

In this case, analyzing sentiment in networked content can result on individuals agreeing on issues related to the identified topics, disagreeing and arguing against those issues, raising additional issues, etc., thus allowing to infer the level of involvement that those individuals have towards that / those topics, their possible level of expertise and / or their commitment to aid the community in finding answers to complex problems.

Considering Figure 1, an example of a visualization of the sentiment spread on that networked content (subnet), would consist of seven nodes, where '-1' represents negative sentiment and '1' represents positive sentiment, among three of the individuals of the network (A, B and C) regarding a topic (or one set of topics), as illustrated in Fig. 2:

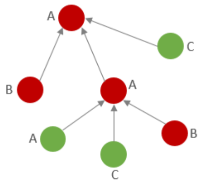


Fig. 2: Example of visualization sentiment spread in a content subnet

Through the visualization of the sentiment spread in each of the formed content subnets in the community it is also possible to analyze which individuals, with which sentiment polarity contribute to the formation of the content subnet, and how controversial it is.

C. The case context and dataset

The aforementioned methodological procedures were applied to real-world settings through the analysis of a Facebook group composed by 42 participants (41 students and 1 teacher). The group was introduced to students as a complementary support environment, to which every member could contribute and / or require interaction about any useful / interesting topic. The Facebook group was used during an entire semester (winter semester), i.e., during about five months.

The dataset collected through the Facebook API consisted on the following fields:

- user_id;
- user_name;
- post_id;
- post_message;
- post_createdtime;
- comment_id;
- comment_createdtime
- comment_message;
- reply_id;
- reply_createdtime
- reply_message.

A total of 697 messages ('posts', 'comments' and 'replies') were collected. All messages containing text were processed for sentiment analysis.

Also, the established connections between participants (social graph) and messages (content subnets) were computed, in order to provide the basis for the analysis presented in the following sections.

III. SOCIAL NETWORK ANALYTICS: PEOPLE AND CONTENT

In this section we present visualizations and analysis for both the interactions generated among participants and for the content nets that emerged in the community.

A. Characteriztion of the social graph

In order to better understand how messages (content) emerged on the network, it is necessary to analyze the structure of network in itself primarily. In fact, the traces of activity left by participants can facilitate the perception on their individual behavior, the social relationships it has established and the community efficiency [8]. Tools and processes to analyze social traces are essential for enabling educators to study and nurture meaningful and sustainable interactions occurring in learning communities.

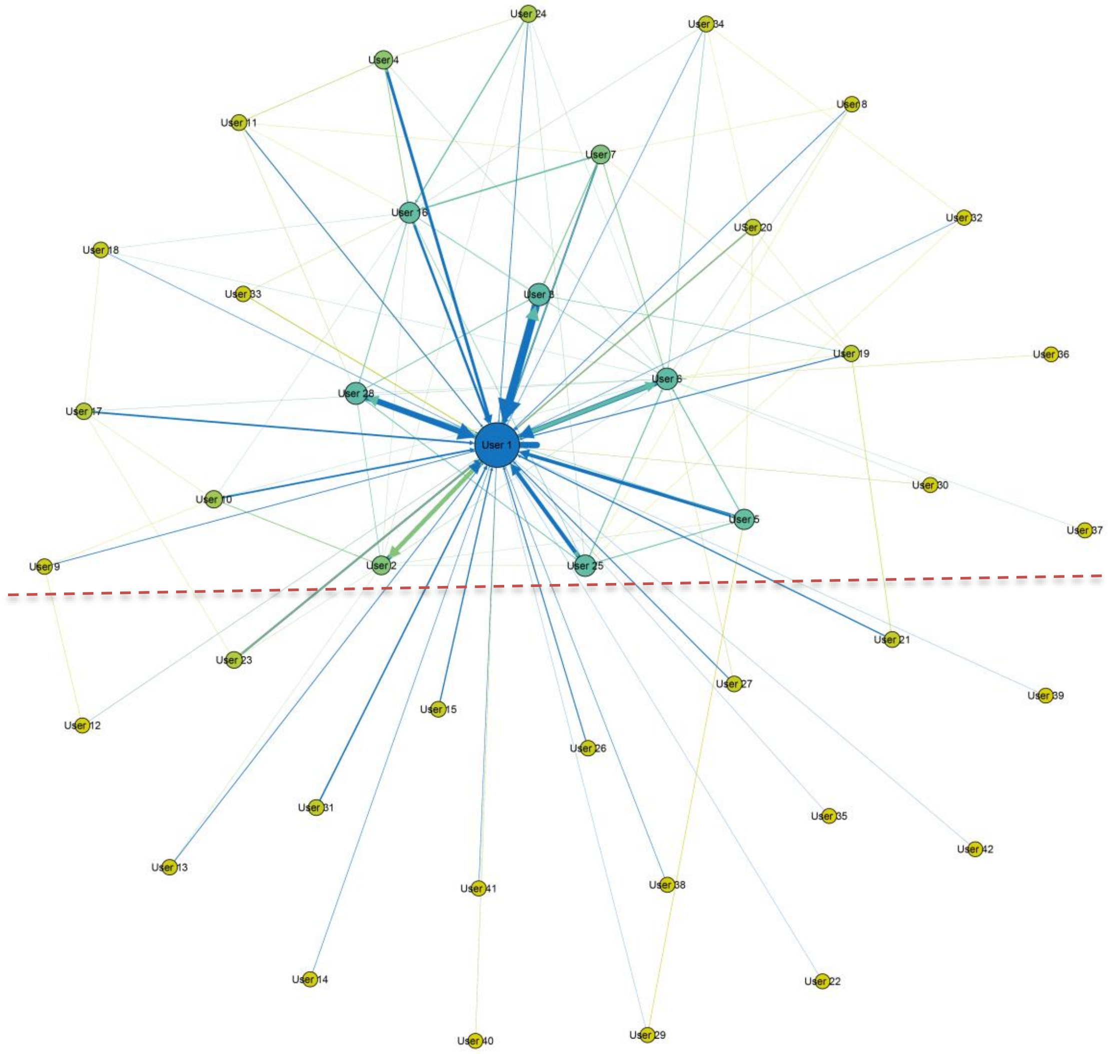


Fig. 3: Social graph

In the case under analysis, the Facebook group with 42 participants makes up a social graph with 42 nodes, each node being a person, as illustrated in Fig. 3. The identities of the participants have been anonymized in order to assure confidentiality, thus user's identification was replaced for research purposes The connections established between the participants may assume the form of a 'comment-to' or a 'reply-to' a post. In this case, there were 553 established connections during the five-month period, which represent the edges of the social graph. (Fig. 3).

The representation of the network adheres to the Fruchteram-Reingold algorithm, which is a force-directed layout algorithm. The purpose of this type of representation is to position the nodes of the graph in the two-dimensional space so that all the edges are of more or less equal length and there are as few crossing edges as possible, by assigning forces among the set of edges and the set of nodes, based on their relative positions [9]. Using this type of representation usually provides good quality, simple and intuitive visualizations, that enable a quicker and accurate analysis of the network and of the relations established among participants.

As it is possible to observe in Fig. 3 some nodes are bigger than the others. This happens because we set the size of each node to be proportional to its out-degree, i.e., the number of messages (interactions) that the participant has posted on the community. Therefore, the biggest the node size, the largest is its out-degree The nodes are also colored according to this metric, in order to provide an easier visualization of the relation of the node's proportion in relation to the others.

In the presented social graph some edges are thicker than others to depict a repeated connection, that is, the amount of messages sent / received between nodes (participants) Also the edges of the graph have been colored according to the target node, i.e., who are the messages targeted to.

With these metrics and corresponding visual representations, it becomes easy to identify the most active participants in the community. In this case, 'User 1' (the teacher) is the most active participant (bigger node) and also the node who bridges most of all other nodes in the network. It is also possible to observe that only a minority of nodes (apart from the teacher) are connected to other nodes, i.e., students do not frequently engage in each other conversations or are not very solicited. However, there are about eleven exceptions to this rule.

In fact, observing the upper section of the social graph, it is possible observe a higher density area and to locate nodes that, despite having a strong connection to the teacher, are also strongly connected to other nodes on the network, such as nodes of users: 28, 26, 16, 8, 6, 5, 7, 4, 2, 24 and 10. These nodes, (students) allow the information to propagate fast, and make the network more responsive to posts. Conversely, the lower section of the graph (below the red dashed line) is characterized by a lower density in connections among nodes, and a few almost isolated participants (nodes), which are only connected to the teacher, can be located.

The previous analysis also led us to identify a graph density of about 3%. This levels to a poorly connected network, which is a characteristic of Ego-Networks or high-centralized networks. On the other hand, the maximum geodesic distance is 4, while the average geodesic distance reduces to 1.9, which means that it is possible to, on average, to reach any other node in about two hops. Therefore, despite not being a dense network, it is a well-connected one, because of the high centralization index.

Educational insights on graph interaction analysis provide teachers with knowledge on which type of community has developed or is being developed. Many considerations could be built on this topic: weather the interactions should be teacher or student centered, which are not our main purpose. We can however stress that knowledge on this aspect is both relevant for teachers and for students, namely: to identify the type of community, its main intervenient, the origin of interactions and how oneself relates to the others in that network.

In the following section we deepen the network analysis by identifying the types and structure of the connections that were created among participants.

B. Networked content analysis

As previously explained, we applied the SNA theory, together with sentiment analysis and topic domain to the messages that emerged on the community: 'posts', 'comments' and 'replies'. For this purpose, we only considered:

- Messages containing text, because it we did not use image or other media recognition to perform sentiment analysis, thus messages only containing media / multimedia elements were discarded;
- Facebook 'posts' with at least one comment, otherwise we would obtain isolated / unconnected nodes, which we considered as not relevant because there was no discussion developed around those topics.

As a result, we obtained 104 content subnets which correspond to the number of unique discussion threads that emerged on the network. The content subnets can be characterized by dimension, type of structure, degree of popularity, and degree of controversy.

The dimension of the content subnet is measured by the number of nodes that compose it, given that each node consists on a message. The type of structure of the subnet is determined by the relations among the messages of that same subnet. The degree of popularity is obtained by the ratio between the number of active participants and the number of messages of a subnet. Finally, the degree of controversy results from the convergence / divergence of sentiment expressed in the messages of the subnet.

Each one of these features is further analyzed in the following subsections.

1) Dimension of the content subnets

Concerning the dimension of the content subnets, there is a variation between 2 (min.) to 26 (max.) messages per subnet, as depicted in Fig. 4.

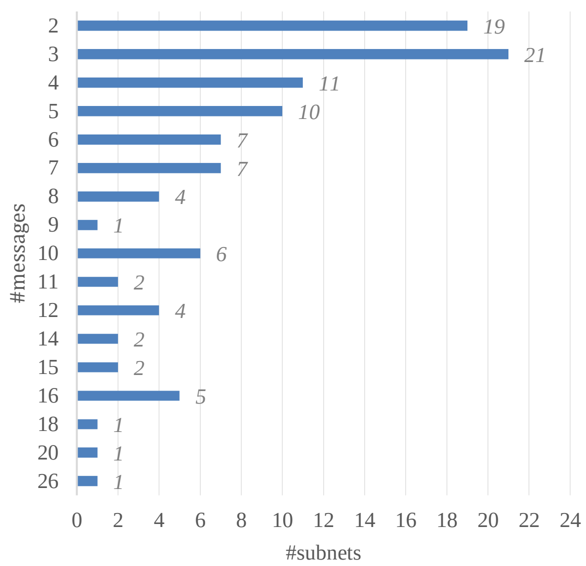


Fig. 4: Number of messages (nodes) per subnet

The great majority of the obtained subnets are composed by a small number of messages (nodes): around 50% of the subnets are composed by 2 to 4 nodes. In Fig. 4 it is also possible to detect that only 3 subnets (10%) are composed by more than 16 nodes, and that the remaining 40% of the subnets are composed by 10 to 15 messages.

From this analysis it is possible to conclude that, in this community, topics tend not to produce very large discussions /

conversations. Considering that the community is composed by 42 participants, only 12 of the 104 nets gather up a minimum of 1/3 of the total maximum number of possible unique interactions, which would consist of 14 unique users producing one message each.

2) Structure of the content subnets

Considering the structure of the content subnets it is possible to identify several types that result in distinct visualizations:

- Stellar type subnets, in which all content nodes are linked to one central node (Fig. 5). In this type of subnet all of the 'comments' are targeted to the same 'post', thus the topic of discussion may consist on a question posed to participants or on a subject that does not promote additional (concurrent) discussion amongst the participants.

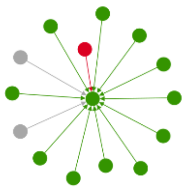


Fig. 5: Stellar type content subnet

- Stellar-branched type subnets, in which most of the content nodes are linked to one central node, but one or more of the linked nodes expands into an autonomous discussion (Fig. 6).

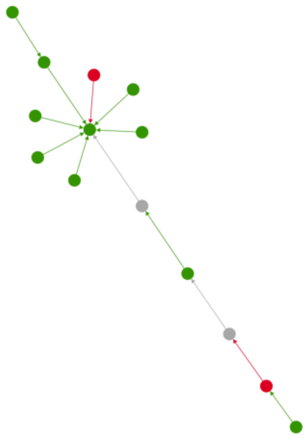


Fig. 6: Stellar-branched type content subnet

- Path type subnets, in which nodes are consecutively linked and none of the nodes has more than one connection (Fig. 7). This type of subnet may correspond to a conversation between two or more participants, in which each 'comment' / 'reply' is targeted at the last message that was posted.

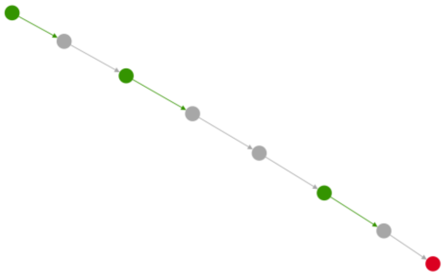


Fig. 7: Path type content subnet

- Branched type subnets, which link together a set of path type branches (Fig. 8). In this type of subnet, the central node ('post') instigates several concurrent discussions that reveal the spread of conversations around different aspects related to the main subject.

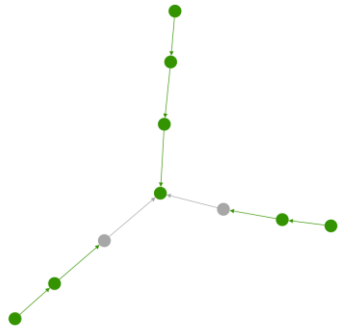


Fig. 8: Branched type content subnet

- Hybrid type content subnets, in which there is two or more central nodes with approximate in-degrees, and some of those nodes branch into path type conversations (Fig. 9).

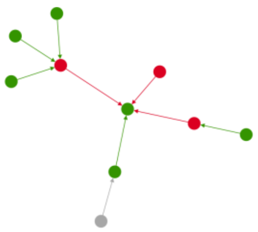


Fig. 9: Branched type content subnet

The visualization of the size and type of structure of the content subnets is a good indicator of the complexity of the interactions generated around a subject ('post'). For instance, in a stellar-branched type subnet the node that is expanded into an autonomous conversation may be of particular relevance for analyzing which aspects of the subject under discussion have been given more relevance.

The size and type of structure of the content subnets also adds to the analysis conducted on the social graph (Fig. 3). Despite the fact that it consists of an Ego-Network there are only 2 stellar and 6 stellar-branched type content subnets. The most common subnet structure is the path type, which represents about 50% of the detected content subnets. This characteristic is coherent with the lack of density in the social graph, since the path type content structures tend to denote dialogues between two (or other very low number of) participants instead of complex discussions around a subject, particularly when they are small.

From this analysis it is also possible to conclude that there is a direct relationship between the subnet size and the complexity of its type of structure. Assuming that stellar and path type subnet structures (Figs. 5 and 7) are less complex than the other aforementioned types (Figs. 6, 8 and 9), the great majority of the detected subnets are, in fact, path type subnets composed by 2 to 7 nodes (messages), which is coherent with the data illustrated in Fig. 4.

3) Degree of popularity

Having analyzed the dimension of the content subnets it becomes possible to determine their degree of popularity among the topics that emerged in the community. For this purpose, we use a ratio between two criteria to determine how popular a content subnet is, when compared to the other subnets on the network: (1) the size of the subnet, and (2) the number of unique users involved in the discussion of that subnet, as explained below.

$$Degree\ of\ Popularity = \frac{\#subnet\_unique\_users}{\#subnet\_messages}$$

We base the degree of popularity under the premise that bigger subnets are more likely to be more relevant and that, among the bigger subnets, the ones with higher number of unique users are considered to be more popular / relevant in the context of the community.

Content subnets have been sequentially numbered according to the moment they emerged on the network. Table 1 details the number of messages, unique users and degree of popularity for the top ten content subnets:

Table 1: Top ten most popular content subnets (ranking)

SubnetId	#msgs	#Uusers	Pop.
31	18	16	89%
30	15	9	60%
42	15	9	60%
6	16	8	50%
40	16	7	44%
14	26	11	42%
22	16	6	38%
56	16	6	38%
91	16	5	31%
36	20	6	30%

As it is possible to observe, the biggest subnet, composed by 26 messages, is not the most popular subnet, ranking 6^{th}. Similarly, the second bigger subnet, composed by 20 messages, is ranked 10^{th}, because the ratio of unique users is the lowest among the set (6 users).

According to these principles, we believe that it is relevant to further analyze the top ten most popular content namely in providing insights on which is their type of structure and subject of conversation. The visualization of some of the top ten content subnets is depicted in the following Figs, in which each subnet is represented by the connections between the messages it is composed by, the nodes are colored according to the sentiment expressed in that message (green for positive, grey for neutral and red for negative) and each node is labelled with the anonymized ID of the author of the message. The top four most popular subnets are represented in Fig. 10.

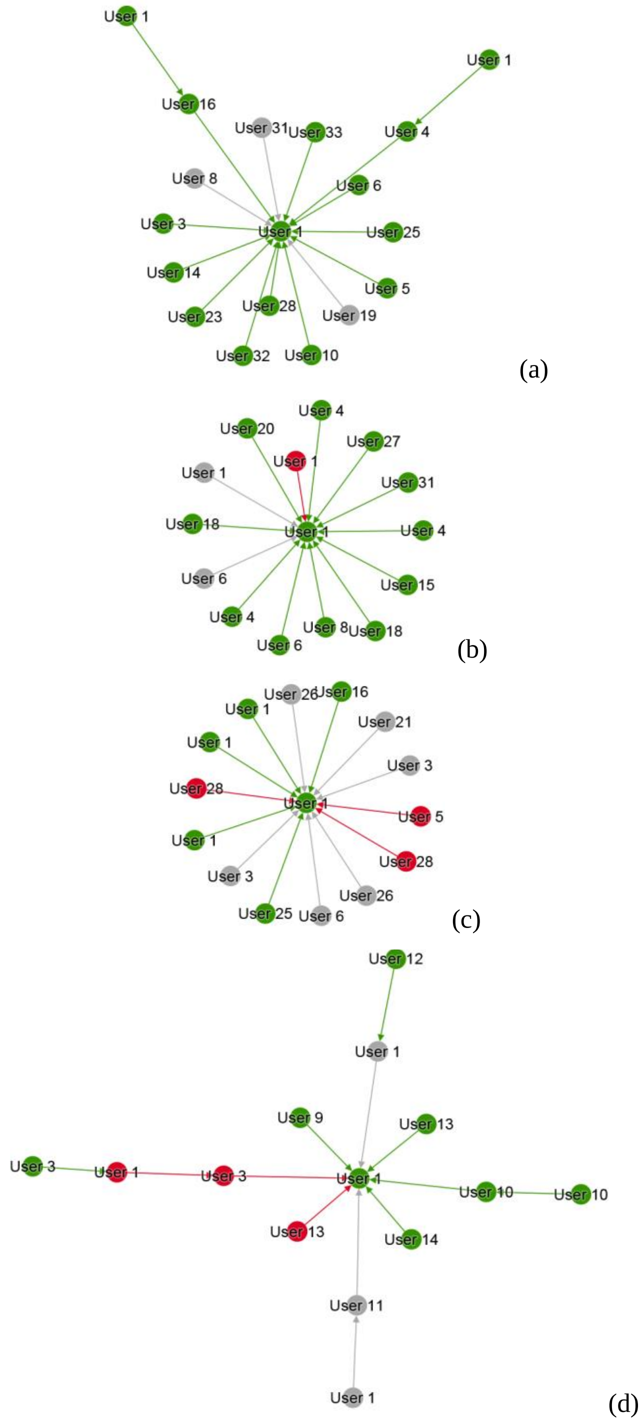


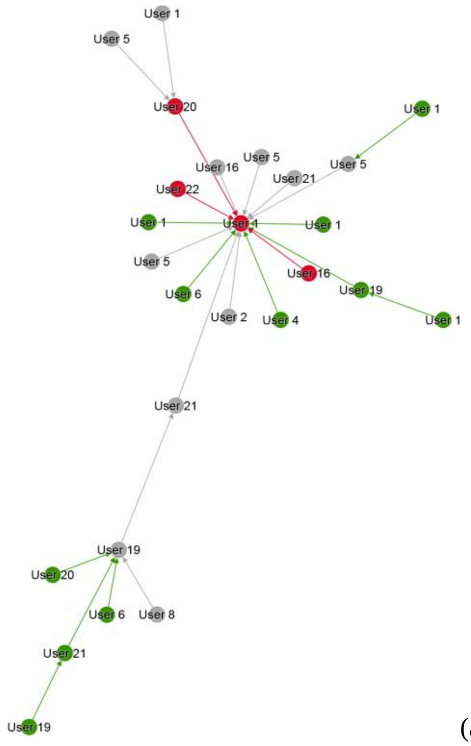
Fig. 10: Top four most popular content subnets: (a) subnet 31, (b) subnet 30, (c) subnet 42 and (d) subnet 6.

Considering the top four most popular content subnets it is curious to notice that all of them consist of stellar (branched or not) type subnets. For the top three most popular the topic of discussion was introduced by the same user: User 1 (the teacher). This user is also the central node in the social graph presented in Fig. 3, thus the popularity of these subnets might be under the influence of some sense of authority usually linked to the teacher.

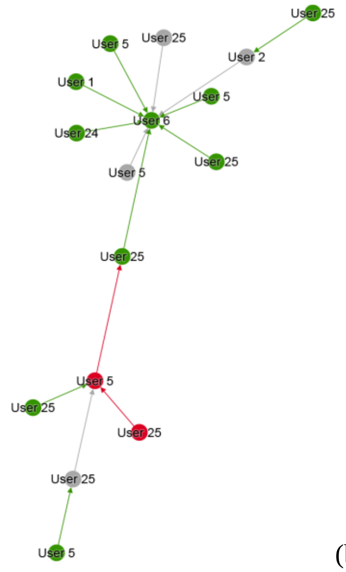
As previously explained about these types of subnet structures they are more representative one-time conversations and not discussions or debates. Looking at the subject of the conversations in more detail, using the categorization of ‘posts’ proposed under the concept of Social SRM [3], it is possible to conclude that these four content subnets are essentially aimed at serving functional purposes. Except for subnet 31 (Fig. 10 (a)), which fall under the category “course unrelated personal interests / projects” (it consists of a request / invitation for cooperation in research), the remaining three content subnets fall under the category “classroom administration”, and are related to: attendance issues (subnet 30, Fig. 10 (b)), ensuring access to learning tools and resources (subnet 42, Fig. 10 (c)) and assessment guidelines (subnet 6, Fig. 10 (d)).

Considering the remaining most popular content subnets it’s possible to observe that they are not as centralized as the top four. However, there appears to be a relationship between the subject category and the subnet content type.

Among the remaining six subnets two other stellar type based subnets have emerged under the Social SRM category “classroom administration”, as illustrated in Fig. 11.



(a)



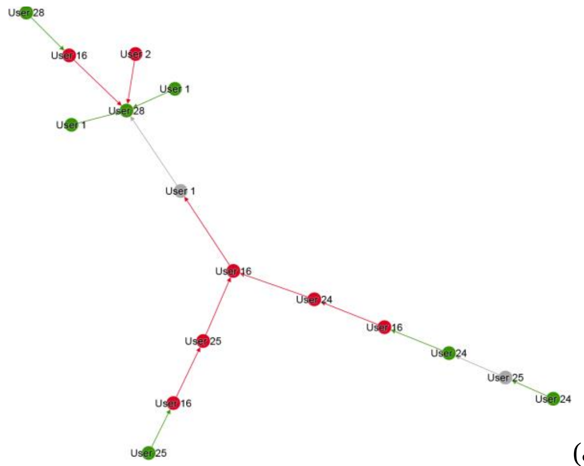
(b)

Fig. 11: Other stellar based type subnets among the top ten set: (a) subnet 14, (b) and subnet 56.

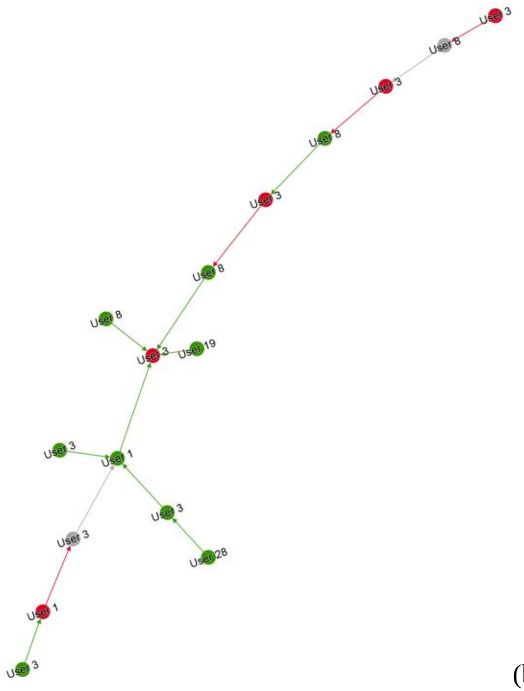
Although not the most popular, the content subnet 14 (Fig. 11 (a)), is the bigger net on the network, in number of messages, and the second bigger in total unique number of users.

Overall, the stellar type structure appears to be typical of small functional conversations, posing questions or posting social messages. In this case, subnet 14 (Fig. 11 (a)) is related to assessment issues and subnet 56 (Fig. (b)) consists of a social greetings message.

Contrariwise, path type content subnets are more typical for actual discussions about subjects related “course contents / curriculum” (according to de Social SRM categories), such as represented in Fig. 12.



(a)



(b)

Fig. 12: Path type most popular content subnets, among the top ten: (a) subnet 22 and (b) subnet 91

Though, among the top ten most popular, these two subnets are the one with less unique participants they consist on the representations of the discussions in which actual informal learning occurs. In both subnets, the topic of discussion is brought up by a student who is requiring opinions or posing questions to peers, regarding the curriculum topics or class projects.

In these types of subnet structures the sentiment polarity also appears to vary more than on stellar type structures. This aspect is further discussed in the next subsection.

4) Degree of controversy

Combining sentiment analysis and the SNA theory we have been able to provide visualizations of how the sentiment is spread around a certain topic ('post'). Going back to Figs. 10 to 12 it is possible to observe variations of sentiment polarity among the messages of each of the content subnets.

The visualization of sentiment spread and variation is of high interest for determining the degree of controversy in a certain subnet, or in other words, the degree of disagreement expressed in the messages around a certain subject in a community. In terms of learning analytics, the degree of controversy may indicate which subjects of discussion are of higher interest / relevance for that community, particularly in the cases where the discussions are bigger, i.e., the content subnets are composed by a higher number of messages.

Therefore, in order to determine which are the most controversial subnets we used two criteria: the dimension of the content subnet and the pattern deviation of the sentiment score of each message that composes it. For this purpose, we used the same set of top ten bigger subnets, which we have previously identified, and computed the corresponding pattern deviation. We consider higher standard deviation to be an indicator of higher controversy, since there is higher variation in sentiment polarity. Results are depicted in Table 2.

Table 2: Pattern Deviation of the top ten most popular subnets

SubnetId	#msgs	#Uusers	Pop.	PD
31	18	16	89%	0,305129665
30	15	9	60%	0,449128166
42	15	9	60%	0,343700954
6	16	8	50%	0,42083765
40	16	7	44%	**0,471144733**
14	26	11	42%	0,377346634
22	16	6	38%	**0,492161858**
56	16	6	38%	0,431340319
91	16	5	31%	**0,554509561**
36	20	6	30%	0,331856996

As it is possible to observe, the higher standard deviation among the bigger subnets rounds about 0,55 in the content subnet 91. There are two other subnets with approximate higher values (greyed lines in Table 2): subnets 22 and 40.

Also, analyzing the data on Table 2, there doesn't appear to be a correlation between the subnet size and the degree of controversy (given by the standard deviation). In fact, the bigger subnets in the top ten set (subnets 36 and 14) have relatively lower standard deviations, meaning they are not as controversial. The same applies to the degree of popularity: there is not direct correlation between the popularity of the subnet and its degree of controversy, although one would expect otherwise. In common sense, one would believe that a subnet formed by a higher number of unique users would be more prone to be controversial. It is not the case in the dataset that characterizes this network.

There appears, however, to be a correlation between the subnet type of structure and the degree of controversy. The two subnets with higher standard deviations (subnets 91 and 22) are visually represented in Fig. 12, where both were identified as path type content subnets, which typically represent discussions about subjects that, in this case, were related "course contents / curriculum". The same applies to subnet 40, which also consists of a path type content subnet that falls under de Social SRM category "course contents / curriculum", more specifically consisting on a student requiring peers to validate his work.

According to the visualizations we have provided in the above mentioned Figs., each colored node is not only linked to other node(s) but also to the author of the message (in the node label). The relation between the polarity of the sentiment expressed in a message and its author is of high interest concerning the domain of learning analytics, since it allows to profile the community users / students. For instance, note that student 25 has introduced messages with negative polarity in both the subnets 56 (Fig. 11 (b)) and 22 (Fig. 12 (a)). The same applies to student 16 in subnets 14 (Fig. 11 (a)) and 22 (Fig. 12 (a)). These students also consist on two of the bigger nodes in the social graph illustrated in Fig. 3.

The identification of the participants in the visual representations of the content nets where the expressed sentiment is specified provides participants with an overview of the role they play in discussions or conversations, and in terms of utility in the domain of learning analytics are of high interest both in the perspective of the teacher and of the student.

IV. Conclusions and future work

We have presented an integrated methodology that combines the application of several theories and techniques for social and content analysis, which include SNA, sentiment analysis and topic classification according to Social SRM. In what topic classification is concerned, we have considered including the *Tf-Idf* (*term frequency* × *inverse document frequency*) in the methodology, which consists of a text mining method to perform topic detection in documents, by determining the most frequent terms (words) in each message. However, this method did not prove to add any valid or valuable input to the proposed methodology, mainly because of the structure of each message that was collected from the network. The *Tf-Idf* method has proven to be very helpful in revealing the most important terms in large texts (such as essays or news), but the messages posted on the Facebook group, in this case (and in general), are more similar to instant messages than to long structured texts.

We have also presented a set of visualizations and analysis aimed at characterizing the social interactions among participants and the dimension, structure, degree of popularity and degree of controversy for the topics that emerged, which is given by the sentiment spread on the networked content. We have identified five types of content subnet structures, which we have related to the degree of popularity and degree of controversy of the 'posts' introduced by the participants.

In the case presented in the paper we found no direct relation between the popularity and controversy of the content subnets. However, the we have identified a relation between the visual representations of the content subnets and their degree of controversy. Content nets with a path type structure appear to be more prone to controversy (higher standard deviation in sentiment polarity) and more characteristic of actual debates, rather than dialogs.

As we have initially stated, our main goal was to provide methods and features in the domain of social content representation and analysis, aimed at improving the EduBridge Social system, that integrates Facebook's social learning analytics in the Moodle environment. We believe we have brought forward relevant techniques, visualizations and analytics with great added value to the system.

This work is, however, far from being complete. Once added to the system one of the essential required features for content emergence and sentiment spread visualization is an interactive timeline where a graph is created for each conversation and all graphs that emerged through time are stored and accessible.

The interactive timeline should allow to visualize which content nets have emerged, how big / small they are, how lasting and how controversial they are / were and to preview the message behind the node. Considering this temporal evolution feature it should also be possible to verify if (and which) content nets are resumed, and when, by community individuals and also to analyze their continuous development.

Finally, and in order to increase the consistency of the proposed methods and analysis, other datasets need to be included in future research, since they may lead to the detection of new relevant features in social content analysis.

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