Design of a Conceptual Knowledge Extraction Framework for a Social Learning Environment based on Social Network Analysis Methods

Alex Becheru, Elvira Popescu
Department of Computers and Information Technology
University of Craiova
Craiova, Romania
becheru@gmail.com, popescu_elvira@software.ucv.ro

***Abstract*—The advent of social media in education has the potential to foster collaborative learning. Exploring students' interactions on the social media tools is an important research direction, which could bring an insight into the collaborative learning process. Therefore, our aim is to propose a conceptual framework for knowledge extraction and visualization from a social media-based learning environment. In particular, we focus on our in-house platform, called eMUSE, which has been successfully used in a project-based learning scenario. The paper addresses the construction of a social graph starting from students' interactions on the social media tools; the objective is to identify appropriate social network analysis techniques that can answer specific educational needs and integrate them in a conceptual knowledge extraction framework. The basis, rationale and analysis levels of the framework are discussed in the paper.**

Keywords*—social media; social learning environment; knowledge extraction and visualization; social network analysis

I. Introduction

According to social learning theory [3], people can learn by observing and modeling the behavior and attitudes of others. Understanding is socially constructed by means of conversations and interactions around specific problems and activities. Learning is seen as a product of participation in a community, rather than an independent, individual process with social aspects [1]. With the advent of social media, learning by observing the activities, productions and discussions of experts and peers is made possible on a new level [2, 24].

Therefore, in recent years, social media tools have found their way into the educational landscape, being used to foster communication and collaboration between learners, help build communities and encourage positive interactions [12]. Practical usage scenarios for various categories of social media tools are well summarized in [8, 23]. For example, *wikis* can be used to co-create content, collaboratively edit a document, incrementally accumulate and organize knowledge and integrate resources from different web sources. *Blogs* can provide support for writing a group learning diary, for creating an e-portfolio, for asking and receiving help from peers. *Social bookmarking tools* can help students discover relevant educational resources, which may be further tagged, organized and shared with peers [24, 26].

In addition, dedicated social learning spaces have started to be created, which add educational support features to general-purpose social media tools [24]. Investigating students' interactions and the collaborative learning processes taking place in these social learning environments is an important research direction, which could bring valuable insight to the instructor. Hence, what we propose in this paper is a *conceptual framework for knowledge extraction and visualization from a social media-based learning environment*. In particular, we will focus on our in-house platform, called eMUSE, that we have proposed in [25]; the platform integrates several social media tools (blog, wiki, microblogging tool, social bookmarking tool, media sharing tools) and provides value added services both for the students and the instructor; more details about eMUSE are provided in section 3. Since eMUSE supports the creation of learning networks, which can be modeled as social graphs, the knowledge extraction process can be performed by applying *social network analysis (SNA)* methods [29]. Hence, the objective of this paper is to identify appropriate SNA techniques and integrate them in a *conceptual knowledge extraction framework*.

The rest of the paper is structured as follows: some related works on previous uses of SNA techniques in online learning environments are included in section 2. The basis, rationale and development guidelines of our framework are described in section 3. The analysis levels of the proposed framework together with the selected knowledge extraction methods are discussed in section 4. The paper ends with some conclusions and future research directions.

II. Related Work

Social Network Analysis is part of a greater cross-disciplinary research domain, called either Complex Networks Analysis (CNA) or Network Science (NS). NS has as main

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building blocks the following research fields: *graph theory, computer science, physics* and *social sciences/sociology*. NS has the scope of investigating non-trivial features of graph problems, that are not explained by lattice theory or random graphs theory. SNA addresses problems that appear in social environments that can be modeled as graphs [4].

SNA has started to be used also in technology-enhanced learning area, as summarized in [28]. The paper focuses especially on the use of *collaborative filtering* techniques, which can generate personalized recommendations for students; learning objects, relevant links, relevant courses or most appropriate study partners can be the subject of these recommendations. Various communication aspects, patterns of academic collaboration and the structure of online learning communities have also been investigated, according to [28].

More recently, Maglajlic and Gutl [20] also used SNA in an educational environment in order to observe, measure, enhance collaboration and as an early detection method of potential weak trainees. Also, they proposed a social engineering algorithm with the purpose of placing a trainee in the appropriate tutored group. The authors employed SNA techniques such as *cliques, centrality* and *density*. Furthermore, the authors brought evidence that the efficiency of digital learning environments can be monitored through SNA.

Crespo and Antunes [9] focused their attention on the representation and analysis of teamwork in an educational context. They found that SNA can be used with success in representing, exploring and predicting teamwork results. As SNA techniques, the authors used diverse variants of the *PageRank* algorithm for ranking learners.

Haythornthwaite [14] also investigated SNA methods and metrics for e-learning, based on specific educational needs. The following SNA methods were selected for use: *number of ties, density, centrality* and *cliques*. The authors further discussed the perspectives of SNA for understanding social learning in [15]. In addition to an overview on the use of SNA techniques in learning networks, the paper includes a discussion on how to create/interpret a social graph. In designing our framework, we tried to answer some of the questions raised by the authors, e.g., *What metrics matter for networked learning?* [15].

Our framework proposal builds on the previous papers and aims to cover SNA methods that have the potential to answer specific instructional needs and have been proven useful in similar scenarios; in addition, the particularities of the social learning environment and instructional scenario are taken into consideration.

III. FRAMEWORK BASIS AND RATIONALE

The proposed conceptual knowledge extraction framework is designed around eMUSE [25] social learning environment. Hence, we will select only SNA methods that could be used on the data provided by eMUSE. Furthermore, the analysis methods have to address certain *knowledge needs* defined by instructors working with eMUSE.

A. eMUSE Social Learning Environment

eMUSE is an educational platform which provides integrated access to several social media tools: blog (Blogger), wiki (MediaWiki), social bookmarking tool (Delicious), microblogging tool (Twitter), media sharing tools (YouTube, SlideShare); learner tracking functionality is also provided, i.e., all student actions on the social media tools are retrieved and stored in a local database. In addition, the platform offers a summary of each student's activity, including graphical visualization, evolution over time and comparisons with peers; a simple way for instructors to keep track of the class activity as well as quickly monitor, visualize and grade each student's contributions is also included [25].

The platform has been used in the instructional process since 2010, in the context of a collaborative project-based learning (PBL) scenario [11, 25]. A large amount of student interaction data has been collected from the social media tools, therefore a knowledge extraction approach could provide valuable insight into the collaborative learning process. Student interactions and message exchanges performed on the social media tools (retrieved by eMUSE platform) are a marker of communication and collaboration; they could be represented as a social graph, which could be subsequently analyzed with SNA methods, as discussed next.

B. Knowledge Needs

The general purpose of our framework is to provide useful knowledge from the instructors' point of view. Hence, we asked the teachers working with eMUSE to define their *knowledge needs* (KN). Next, we filtered the KNs by keeping only those that we could partially/totally quantify and satisfy through the use of SNA methods/techniques. Then, a series of refinement and clustering stages were conducted based on instructors' continuous feedback. The compiled list of extracted knowledge needs is included in Table 1.

TABLE I. EXTRACTED SET OF KNOWLEDGE NEEDS

ID	**Short description**
KN 1	Determine the collaboration network
KN 2	Determine methods to quantify collaboration over various time intervals and various network granularities
KN 3	Determine salient students or communities of students
KN 4	Determine if the course environment adequately supports collaboration
KN 5	Determine external factors that influence the evolution of collaboration
KN 6	Determine the impact of instructors' actions on collaboration
KN 7	Determine clear and comprehensive methods of presenting the information extracted

KN 1 is an obvious need as there cannot be any analysis without building the collaboration network. This need will be treated in the next subsection.

KN 2 implies the use of current SNA methods and possible development/adaptation of new techniques to capture collaboration. The development/adaptation of new methods is justified by their use in a new context, the digital learning context.

Salient students or communities are those that are usually at the high end of the collaboration spectrum. By satisfying KN 3, instructors should be able to pinpoint students / communities that mostly support collaboration. Also, instructors could be presented with early warnings for students / communities that do not engage in collaboration, those with possibly low learning outcomes.

By course environment we refer both to the platform used in the course (in our case, eMUSE in conjunction with several social media tools), and to the pedagogical scenario set by the course instructor (in our case, group project-based learning). The environment is an important factor in the evolution of any collaboration network. Hence, knowing if the course environment adequately supports collaboration (KN 4) is a valuable affordance.

KN 5 addresses the discovery of external factors that influence the evolution of the collaboration network. We define external factors as those which are not controlled by the instructor, e.g., social phenomena or students' habits [21, 30]. Having an insight on the presence of such phenomena/habits would give the instructor additional leverage. For example, the presence of *preferential attachment*[1] phenomenon could explain a high rate of collaboration among some learners.

By satisfying KN 6, teachers would get the means of evaluating their actions based on the impact on the collaboration network.

Instructors should be presented with extracted knowledge in a clear manner, that is easy to understand (KN 7). Thus, the framework adoption effort would be reduced and the focus would shift to the benefits it provides.

C. Constructing the Social Graph

As already mentioned, the objects of study of our framework are *social graphs*. A *social graph* is a graph where persons are depicted through vertices/nodes. Relations among vertices are an abstraction of an interaction manner. In our context, vertices represent learners and interactions represent messages exchanged through the social media tools integrated in eMUSE.

Graph theory defines two manners of representing relations among vertices: oriented links (*arcs*) and non-oriented links (*links*). We argue that human communication usually implies bidirectional relations; thus, the use of *arcs* may lead to an oversimplification, as opposed to the use of *links*. However, by using *arcs* we can extract knowledge on *leadership* and *pro-activity*. Hence, we are advocating the use of both methods for representing social relations, as we can capture diverse facets of inter-human communication.

Since eMUSE provides a data collection mechanism which records student interactions on social media, we can easily develop software tools to extract social graphs. We can enrich these social graphs by incorporating the time of message exchanges as an attribute of the arcs/links. Thus, we will be able to develop time-series analyses as requested by KN 2. Furthermore, we can add weights to the arcs/links in order to capture the number of messages exchanged between two students. In addition, the weight can be coupled with the length of the messages (number of characters), to better capture the quantitative aspect of communication.

Qualitative aspects of communication are harder to extract through computing methods. However, as reported in previous papers [11, 27], we were able to successfully apply textual complexity indices to analyze students' contributions. By using these metrics to compute arc/link weights, we can balance the quantitative aspects with qualitative aspects.

We aim to create as many relevant social graphs as possible, from various facets of communication. We define a facet as a unique way of communication based on the type, digital tool, purpose, etc. Also, graphs can be obtained through aggregation of various other graphs. In our case, we could aggregate the social graphs for each social media tool present in eMUSE, thus obtaining a social graph capturing all communication established through the platform.

We consider that the above discussion fully addresses KN 1 (*Determine the collaboration network)* for our scenario; hence, in what follows we will only focus on the other KNs.

D. Software Tools

The majority of the SNA methods mentioned in this framework can be computed and used via open source software, like *Gephi*[2], *Pajek*[3], *NetworkX*[4] and *GraphViz*[5].

Gephi is a visualization and exploration software for graphs. *Pajek* is a software tool for large graph analysis; although it lacks *Gephi's* ease of use, it comprises many more SNA methods. *NetworkX* and *GraphViz* represent mature programming libraries oriented on the study of graphs.

IV. Conceptual Framework Design

Based on the previously mentioned knowledge needs and on our experience in using SNA, we identified some methods of knowledge extraction. We consider these methods adequate for our analysis scenario, with a high probability of being useful in similar scenarios; however, we do not imply that the selection is exhaustive. For each method, we will mention the knowledge need(s) that it is able to partially/totally satisfy and give short examples of their respective affordances for an instructor.

The proposed conceptual framework is structured to address three levels of graph granularity. The first level investigates the social *graph as a whole*. The second level addresses *communities* that appear inside the graph. *Individual vertices* in the graph are studied through the framework's third level. Hence, we will be able to explain general traits through

[1] Process in which some type of credit/trait/wealth is distributed among a number of individuals/objects according to how much they already have.

[2] https://gephi.org/
[3] http://vlado.fmf.uni-lj.si/pub/networks/pajek/
[4] https://networkx.github.io/
[5] http://www.graphviz.org/

individual/group particularities and vice versa. Last but not least, time series analysis perspective will be discussed.

Due to space restrictions, we cannot possibly present each SNA method in detail, however we refer the reader to fundamental works such as [4, 6, 10, 29].

A. Whole Graph Perspective

From the perspective of the whole graph, we selected the set of SNA methods included in Table 2.

TABLE II. SNA METHODS FOR THE GRAPH AS A WHOLE PERSPECTIVE

Method	KN Addressed
Graph connectivity *No. of connected components, Line connectivity*	KN 2, KN 4, KN 6
Information diffusion *Diameter, Average shortest path*	KN 2, KN 4, KN 6
Graph clustering *Global average clustering coefficient, No. of K-cliques*	KN 2, KN 4, KN 6
Graph ability to support information exchange	KN 4, KN 6
Models of network growth	KN 5
Visualization *Force-directed: Force Atlas 2, Fruchterman-Reingold* *Bow-tie structure*	KN 7

In our scenario, *graph connectivity* refers to the paths of communication between learners. The *number of connected components* is inversely correlated with the ability of the graph to support communication between learners. A *connected component* can be considered a communication silo; no communication is possible with members that are not part of the component. Thus, the *number of connected components* could be seen as a marker for collaboration. In the case of only one *strong connected component,* we can use *line connectivity* as another marker for collaboration. *Line connectivity* is defined as the minimum number of edges whose deletion from a graph would lead to an increase in the *number of connected components.* The higher the value of *line connectivity* the more communication paths exist; hence, the higher probability of successful collaboration.

In addition, we define *information diffusion* as the number of steps it takes for information to spread out in the entire graph, if it is passed from one learner to another. Hence, in our graph representation of *information diffusion* is related with paths in the graph. The *diameter* of a graph is the longest shortest path between any pair of vertices. The *average shortest path* is computed as the average value of all shortest paths in the graph. The lower the value of the above mentioned metrics, the more direct communication there is, hence increasing the chances of successful collaborations. Therefore, *information diffusion* methods are yet another way to capture and evaluate collaboration.

In the real world, people tend to bond together and communities of people arise. Hence, it is obvious that the more bonding there is the more paths of communication emerge. The *global clustering coefficient* represents an overall graph measure of the degree to which vertices in a graph tend to cluster together. Another measure to capture the clustering effect is determining the *number of K-cliques.* A clique represents a complete subgraph of K vertices. Since in our PBL scenario learners using eMUSE generally form teams of 4 members, we would expect the *number of 4-cliques* to be at least equal to the number of teams. Otherwise, it would mean that there are teams where not all members communicate directly, leading to potentially low collaboration and poor course outcomes.

The ability of a social graph to *support knowledge / information exchange* is essential in our scenario, as it affects learners' capability to receive and transmit knowledge. An instructor possessing such an insight can act to modify the social graph to better support knowledge exchange, e.g., encourage active learners to share knowledge among each other. More details on how to determine a graph's ability to support information exchange can be found in [5].

In addition to the traits which can be influenced by the instructor, the graph could exhibit also other traits that appear due to social phenomena or peculiar habits present among the community of learners. Determining the evolutionary mechanism of the network through the *model of network growth* [22], could lead to identifying external factors that impact the collaboration network.

Finally, in order to satisfy *knowledge need* 7, we will introduce graph drawing methods in our framework. We consider graph visualizations as an easy way to evaluate communication. *Force-directed* drawing algorithms (e.g., *Force Atlas 2* [16] and *Fruchterman-Reingold* [13]) present graphs in an aesthetically pleasant way, with no additional requirements from the instructor, e.g.: as few crossings of links as possible; positioning of learners in a gradient way, with most active learners in the center; learners belonging to the same community plotted in close vicinity etc.

B. Communities' Perspective

From the perspective of the learning communities that appear inside a graph, we selected the set of SNA methods included in Table 3.

TABLE III. SNA METHODS FOR THE COMMUNITIES' PERSPECTIVE

Method	KN Addressed
Community detection *Graph clustering, Modularity*	KN 1-7
Important parts discovery *Strong component detection, Island detection, K-cores detection*	KN 1-7
Transformation & Visualization *Reduction, Context, Dendrogram*	KN 1-7

We use the term *community* for a group of learners that communicate/collaborate together significantly more than with other learners. A number of methods can be used for *community detection. Graph clustering* [19] is the task of grouping the vertices of a graph into communities taking into consideration the arcs/links. For an easy visualization of the arrangement of clusters we can use *dendrograms*. *Modularity* [18] measures the strength and division of the network in communities. Hence, it can be used as a method to determine communities.

Important parts discovery refers to identifying subgraphs with peculiar attributes for further analysis. A *strongly connected component* of a directed graph is a maximal subgraph where there is a path between all vertices. *Island detection* represents a method to identify relevant parts of a network usually by inspecting the distribution of vertices or arcs'/links' values. A *K-core* [18] is a maximal subgraph with the property that all vertices in the subgraph have a degree equal or higher than K. Thus, we consider *K-core* detection as a method of discovering important parts.

Having identified the learning communities, we can further analyze each one. Considering that a part or a community is a subgraph, which in turn is a graph, we can analyze it with all the methods present in our proposed framework; thus all knowledge needs can be covered.

A *reduction* of a graph represents the merging of constituent parts (e.g., communities) into a vertex for each part (Vpart). Links/arcs between initial vertices of the same constituent part are suppressed. Initial links/arcs between vertices of different constituent parts become links/arcs between their respective Vparts. A *context* transformation is similar to a reduction, with the exception that one initial part is preserved as it is. A graphical illustration of the above mentioned transformations for our learning scenario can be seen in Fig. 1.

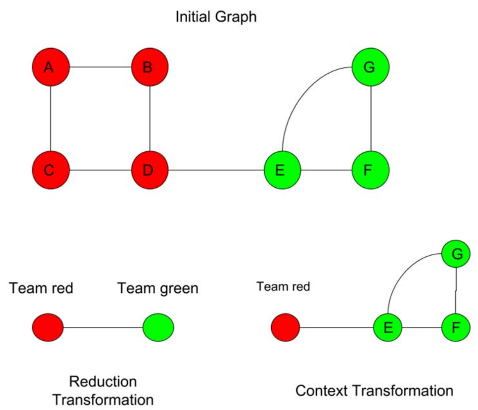

Fig. 1. Graph transformation example; the color of each vertex defines team membership: students A-D belong to Team "red" and students E-G belong to Team "green"

Visualizing communities/parts and their respective bridges of communication exchange represents a quick and intuitive manner of informing instructors on the general knowledge exchange status. Hence, teachers can easily identify communities that require additional attention. For example, reduction transformation could be used to evaluate inter-team communication. In our scenario, this type of communication is neither restricted nor endorsed by the instructors; thus, it is of interest to see if learners break the team boundary and engage in communication with other fellow learners. Context transformation could be further used to pinpoint the students, from a specific team, who are engaging in inter-team communication (e.g., student *E* from Fig. 1).

C. Individual Perspective

From the perspective of the individual learners inside the graph, we selected the set of SNA methods included in Table 4.

TABLE IV. SNA METHODS FOR THE INDIVIDUAL PERSPECTIVE

Method	KN addressed
Measures of centrality *Degree, PageRank, Katz*	KN 2, KN 3, KN 6
Information cycle *Hubs, Authorities*	KN 2, KN 3
Positioning *Closeness coefficient, Local clustering coefficient, Betweenness*	KN 2, KN 3
Visualization *Vertex/link scaling, coloring & shaping* *Bow-tie structure*	KN 7

Centrality measures quantify vertices' importance from a graph theory perspective [10]. In our scenario, these methods try to assess each learner's collaboration activity. One of the most popular centrality measures is the *degree* of the vertex. This metric could be used to easily determine the learners that are the most/least active. However, this is a quantitative measure, which gives no indication regarding the quality of the interactions between the students. Hence, a more suitable centrality measure could be *PageRank* or *Katz,* as both take into consideration qualitative aspects of communication. Salient learners (i.e., those with particularly high or low activity), could be determined by ordering students based on the above centrality measures.

Through the *information cycle* methods, we are trying to assess which learners are the sources of information (*hubs*) and which learners are the sinks for information (*authorities*) [17].

In a graph, a vertex's positioning is of great importance as it may be a critical point in maintaining certain graph traits, e.g., *connectivity*. Hence, learners represented through such vertices are salient. Through *betweenness* an instructor can determine the learners that bridge community silos, those learners that facilitate the exchange of knowledge between communities. The *local clustering coefficient* is similar with the *global clustering coefficient* (introduced in subsection A), with the difference that it measures a vertex's tendency to communicate with others. The *closeness* metric is computed as the sum of the lengths of the shortest paths between a vertex and all other vertices in the graph. Hence, learners with low *closeness* values are positioned on various communication paths, playing an important role in knowledge diffusion.

By using the above mentioned methods, instructors should be able to determine the status of each learner involvement and their recognition by other learners. These insights can be included in the grading methodology, harnessing and encouraging valuable learners.

A *bow-tie* [7] graphical representation of the social graph is able to categorize learners in four categories: sharing information, sharing and acquiring, only acquiring and inactive students. Such a method provides useful information in an easy to understand manner. Through *scaling, coloring &*

shaping of links and vertices we can present various attributes in graph drawings, hence making it easy for instructors to visualize multiple facets of communication in a graph representation.

D. Time-Series Perspective

The *time series perspective* is a valuable complementary method for all the three graph granularity perspectives. It represents a recurrent application of the above mentioned SNA methods at certain points in time or for certain timeframes. Hence, the evolution of the social network can be visualized throughout time. In addition, the instructor can investigate inflection points and correlate them with learning activities; thus, important affordances can be extracted and harnessed. The *time series perspective* was introduced to satisfy KN 2.

V. Conclusion

In this paper, we introduced a conceptual knowledge extraction framework to explore the collaborative learning process supported by eMUSE environment and the integrated social media tools. A set of knowledge extraction methods based on SNA techniques were proposed, starting from specific educational needs identified by the instructor. The social graph built from student interactions on the social media tools was analyzed at several levels of granularity (whole graph, communities and individual perspective). While we acknowledge that our framework is not exhaustive, we believe that the selected methods could prove useful in similar social learning scenarios.

As future work, we plan to experimentally validate the proposed conceptual knowledge extraction framework on eMUSE platform. In addition, we will investigate the possibility of developing / adapting SNA inspired methods dedicated for our social learning environment context.

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