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Orven E. Llantos

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Characterizing Instructional Leader Interactions in a Social Learning Management System using Social Network Analysis

Orven E. Llantos[a,b,*], Maria Regina Justina E. Estuar[a]

[a] *Ateneo de Manila University, Quezon City, Philippines*
[b] *Mindanao State University-Iligan Institue of Technology, Iligan City, Philippines*

Abstract

Online learning environments are designed with specific users and respective roles in mind. However, for social systems that thrive on the interaction between and among users, important features are developed based on relationships that evolve over time. Typical learning management systems are designed with the teacher and the student as primary users of the system. *my.eskwela* is a social learning management system that has been designed for use in public schools in the Philippines with the inclusion of an additional user, the school administrator. Although administrators influence on student learning through mediated effects of **instructional leadership**, pieces of literature are few that provide evidence of their presence in the learning environment, specifically in the implementation of sLMS. By applying Social Network Analysis in the interaction logs from a sLMS that includes instructional leaders in its implementation, this paper aims to answer the question: Can instructional leadership be manifested in social system interactions? Using measures of centrality in social network analysis, results show that administrators play a key role in the network as main drivers of the network information flow. The results affirm the explicit presence of instructional leadership in the implementation of my.eskwela. In addition, sLMS should provide a means for administrator to monitor activities in enforcing mediated learning to students. Contribution of this study is on the the method to verify the instructional leadership of administrators in its inclusion in the implementation of sLMS.

Keywords: Pattern Interaction Analysis; Social Network Analysis; Social Learning Management System; instructional leadership; centrality

1. Introduction

ICT enabled technologies are challenging traditional methods of managing relationships. Aside from empowering users to have full control over the data that is shared, digital footprints also serve as a way of understanding the evolu-

* Corresponding author.
E-mail address: orven.llantos@g.msuiit.edu.ph

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tion of social groups in this digital age. When it comes to education, learning management systems (LMS) is greatly challenged to integrate external social platforms that are now being used as part of the teaching and learning process in the hopes of achieving greater positive returns on student performance. Standard interaction features such chatrooms, forums, sharing of a common timeline, sharing of resources between and among users of the system provides the connection for collaborative work. However, these tools are usually moderated by the facilitator or instructor. External to the standard LMS, informal learning centered collaboration is being built because of the availability of semi-public conversation spaces found in messaging systems, social platforms and the like.

There are two approaches in viewing the collaborative environment in a learning management system. Using a social lens, a pure sLMS requires enhancement of an existing LMS to contain social features and to lessen the burden of faculty members in switching to multi-platforms[22, 20]. While combined implementation requires an existing LMS and another system to suffice for the social requirements. Effects of enabling social features enhances self-directed learning by collaboration through peers and faculty members.

An example implementation uses an open-source social platform called Elgg. With Elgg, social features are implemented and tailored to the specifications of the University. In the study, students are afforded some degree of freedom by giving control over their educational space. To participate in some discussions, students may choose who among the collaborators they wanted to interact with. The consequence of such implementation affected the view of administration and colleagues being wary of a **loss of centralized control**[2]. This outlook certainly has a point since administrators influence on student learning through mediated effects of **instructional leadership** through supervision and evaluation, use of technology, and use of data to guide instructional practices [13, 26]. Also, being an instructional leader is considered the primary task and regarded critical drivers for educational reforms in learning communities[8, 15, 24]. Such successful leadership, frequently underestimated, play a prominent role in enhancing student learning[15]. Administrator's impact on student learning depends on the choice of priorities and their leadership style, which influences the teachers[13].

By looking at how school leadership indirectly influences learning, pieces of literature are few that include school leaders in the implementation of sLMS[17]. Section 3 details pieces of literature whose discussion evolves around the teacher, student, and learning resources only to measure their impact on student's learning. An attempt to add the instructional leaders in the context of sLMS implementation should have the means to verify that the instructional leadership exists through latent relationships. One way to do this is by applying Social Network Analysis in the interaction logs from a sLMS that includes instructional leaders in its implementation. Thus, this paper aims to answer the question: Can instructional leadership be manifested in a sLMS, called my.eskwela[16], by studying their social system interactions?

2. Social System

A system is social if more than one individual are interacting[14]. These individuals have specific roles, tasks and goals that are achieved by using features designed for individual use and features designed for collective use. Most systems provide features for uploading and viewing content, managing tasks, and providing analytics that measure overall performance of individuals. This perspective sees the individuals as main actors and decision makers in the system. Social systems on the other hand show individuals as part of a system where there are other actors such that interaction is necessary to achieve explicit and implicit tasks. A system becomes a social system because of features that allow for collaborative tasks and therefore, social interaction to flourish.

2.1. Social Networks

Social Networks is a digital entity that arises out from the interaction between users of the system. Formally, these interactions can be represented by a graph $G = (V, E)$, where V is the set of vertices and E is the set of edges. The vertices represents the users in the system and the edges represents the interactions directed towards other users. For example, when a teacher in the sLMS post assignment to the students, a social network is formed that links the teacher to the students. Teacher and students now becomes part of set V and the interaction 'post assignment' is also in E. Similarly, student's interactions on the teacher's posted materials will add up to the set of interactions in E. With respect to social networks nomenclature, users are called agents.

2.2. Social Network Analysis

The main objective of this study is to discover the position of each agent in a social network. This can be extracted by computing the centrality measures. Simply put, centrality measures are metrics that determines the agent(s) that is/are the center of the social network. Through these measures, an agent's importance, prestige and information flow can be uncovered[21]. There are many techniques for computing centralities, this study is only interested on Influence and Betweenness measures.

2.2.1. Influence

Influence considers an agent neighbor connections. The agent is central if the agent's neighbors have more connections, more so strongly connected. Being influential requires neighbors to have fewer external connections because the fewer external connections they have the more it is that they will depend on the agent for information. All of these requirements are taken into consideration for computing influence by starting with approximations and improving on the approximations after examining the neighborhood, until finally the influence approximation value is derived and re-expressed by scaling constants. Influence can be computed using the eigenvector centrality. The centrality of a node is then computed using Equation 1.

$$\boldsymbol{Ax} = \boldsymbol{\lambda x} \tag{1}$$

Where λ is the largest eigenvalue derived from the eigenvector of adjacency matrix A needed to produce a unique and positive solution [3].

2.2.2. Betweenness

Betweenness centrality measures a node importance by counting the number of shortest-paths that passes through it. Nodes with high scores for this measure can be seen as those that can control the network information flow. As some literature point out, the node assumes the role of gatekeeping [4]. Equation 2 illustrates the computation of betweeness centrality of a node v.

$$c_B(v) = \sum_{s,t \epsilon V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{2}$$

Where s, t, v are nodes from the set of nodes V. The number of shortest-paths, (s, t), is expressed as $\sigma(s, t)$ and $\sigma(s, t|v)$ is the number of paths other than (s, t) that passes through node v [5].

2.3. Social Network Analysis Tool

Eigenvector and Betweenness Centrality are well implemented in the networkx add-on package available in Python programming language [10]. In addition, it also implements most of the common algorithms for doing SNA and provides visualization tools.

3. Social Network Analysis in Education

sLMS can provide abundant data that can be transformed into social network to be analyzed for various purposes. One motivation is to understand the detailed characteristics of the social network that can be used to enhance the learning environment[9]. Another motivation is to enhance course design, understand characteristics and interaction patterns of learner groups and identify at-risk learners for timely intervention[6].

A number of studies have looked at student collaboration networks and provided insights to better understand the dynamics and effects of the activities within the network. For one, these networks provide information on the different roles a student occupy while interacting with the course. These roles can determine the educational performance and can be used by the faculty members as feedback information to plan better strategies in promoting better learning experience[12]. It has been noted that students who interacted more and those that serve as relationship bridges can be identified[7].While student at the center of the network will achieve best results while those closer to the center will have better grades in comparison with those that are farther[19]. An attempt has been made to automate the detection of student leaders in the network in a form an index. Leaders are those that positively affect the dynamics of their network by engaging participants[27]. In a non-fully utilized network, interventions can be implemented to improve the student-student and faculty member-student collaborations[23].

On the other hand, students farther from the center of the network are consequently called at-risk students who are less engaged with accessing materials and are most likely to fail[11]. Since at-risk students cause problems learning institutions, an algorithm was developed called Good Fit Student to predict students that are most likely to succeed or fail. This is still an on-going study but the results are promising for adoption to provide information for better decision-making[25].

Most of the outlined studies have focused on the discovery of collaboration networks between students, faculty members and learning materials. The characteristics of the network interactions as well as the effect of student performance by merely looking at the placement of the student with respect to the central entity was used to detect the success or failure of a student in a course. However, having school administrators in the network and understanding their role on the usual faculty member-student-materials relationship is yet to be discovered. Once this is established the effect of their interactions in the student learning process can then be studied in detail.

4. Methodology

The data used in this study is derived from activity logs in my.eskwela software. The research has been given permission by the Department of Education (DepEd) Iligan City Division Office to proceed with any member schools willing to be part of the study. There were a total of four schools,two elementary schools and two high schools, that welcomed my.eskwela. A series of hands-on training were conducted to faculty members, students and parents. The training started last September 2018 and ended on October 2018.

4.1. Contextualizing my.eskwela Features

my.eskwela v3.0 is the third software iteration of a pure sLMS that includes administrators, teachers, parents and students for interactions. There are many features available in my.eskwela. This study limits the discussion to the commonly accessed features including: announcements, collaborate, enroll, grade and register. Announcements allow different user types post relevant information to their respective target audiences: principals for superintendent and supervisors, faculty members for principals, and students and parents for faculty members. The flow of interaction design was influenced by the specification of Philippine Republic Act 9155[18].

Collaborate is a feature that allows faculty members to share a subject load to co-faculty members so that they can encode grades for students. Enroll is a feature that assigns a student to a grade level and section. Grade is a feature that assigns a numeric value for the performance of a student with respect to enrolled subject. Finally, the register records student data in the system without assigning them to grade level and section.

The students and parents module are designed as read-only to the posts by teachers.

4.2. Data Source

All of the interaction activities are recorded in the *timeline* table. From September 2018 until March 21, 2019, a total of 3,643 anonymized datapoints were extracted. Another table was created to record user's *view* of different information propagated by the system. This table was updated every time the user access the timeline and load more of timeline items. This table consequently contains a total number of 3,214 records. These records came from the interactions of supervisors, principals, faculty members and students.

4.3. Data Transformation

The data from the *timeline* and *views* tables were converted to *weightedgraph* view. This view record the number of times an initiator performed a feature to a receiver. All the initators (i) and receivers (r) of the *weightedgraph* view are converted to vertices, $(i, r)\epsilon V$, while the performed features are converted to edges, $e\epsilon E$, of graph G^{W}_{DepEd}.

4.4. Pattern Interaction Analysis

Pattern Interaction Analysis (PIA) is a category of SNA that studies on the interaction patterns derived from the sLMS networks. There are two main approaches to study PIA that are inherent in SNA: mathematical analysis and visualization. The mathematical analysis includes computation for centrality measures, density, cliques, and clusters. Mathematical analysis is useful in discovering the structural properties of networks and communities. Visualization provides information on how the nodes in the networks relate to each other and their relative position and size in the network after applying the values which resulted from the mathematical analysis. PIA allows for the discovery of preferences for communication channels, participation levels, collaboration patterns, and members contributions. PIA is the primary approach used in this study to answer the research question.

4.5. Interactions in the Social Network

Consider the weighted graph G^{W}_{DepEd} with edges containing the weight of node interactions for the entire DepEd using the sLMS, and a tranformation function $f_T(G, v)$ that replaces all the corresponding node values of graph G with the values of set v respectively. Using this notion a transformed graph $G^{T}_{DepEd_k}$ is defined in Equation 3, where $cm_k(G)$ is a function that returns the centrality measures of each node in the graph G using k centrality measure algorithm in the set $\{influence, betweenness\}$. Thus, it is expected that there will be graph for each k.

$$G^{T}_{DepEd_k} = f_T(G^{W}_{DepEd}, cm_k(G^{W}_{DepEd})) \tag{3}$$

4.5.1. SNA for Python

Python networkx was used to generate the *weightedgraph* view in which the initiator and receiver fields become nodes and the interaction count is the weight of the edge from the initiator node to the receiver node. To give further information about the relationship between nodes, the edge is modified such that if the interaction is less than five, the edge is represented by a dashed line otherwise a solid line. The node's centrality measure is represented by its color and size, nodes with higher centrality measure is represented with bigger size compared to other nodes, and the color moves towards yellow as illustrated by the color bar. The code from Aksakalli was used in this exercise and was modified to accommodate additional specifications[1].

5. RESULTS AND DISCUSSION

5.1. Overview of the Social Network

An overview of the general social network can be seen in Figure 1 after conversion of all entries of *weightedgraph* into weighted graph as discussed in the previous section 4.3. This network provides a view of all the connections between and among users regardless of the interaction feature used.

The resulting social network is not fully connected because it contains isolates. These isolates are the interactions between teachers and students without the principal. Isolates represents independence of control, this means teachers perform tasks at their own pace without any form of monitoring from administrators. This might be the loss of control many administrators are wary of in some implementations of sLMS. Whereas, the presence of administrators in the sLMS unifies the network signifying authority and a sense of control.

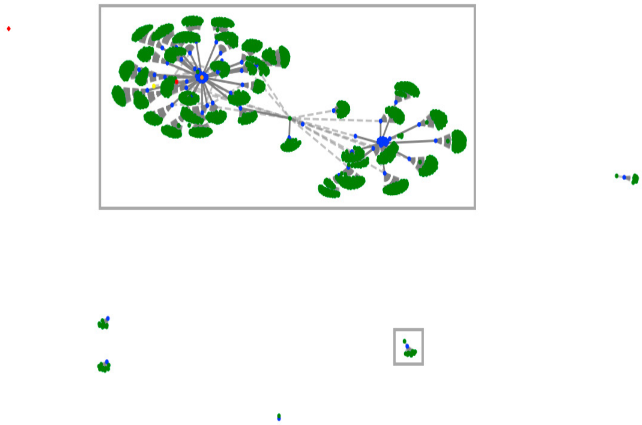

Fig. 1: Social Network Overview

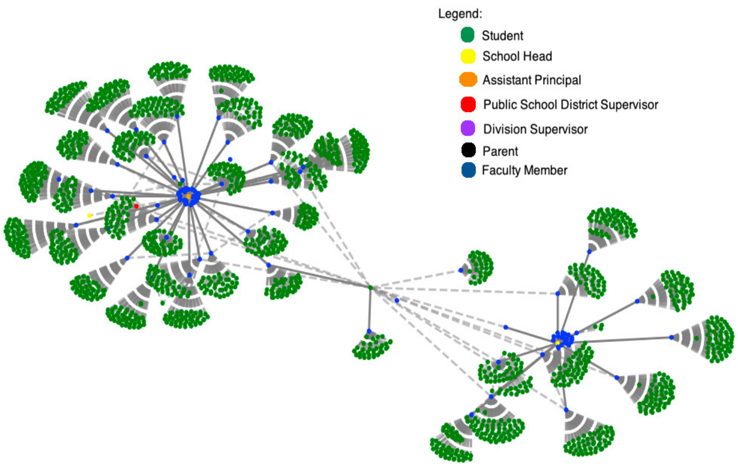

Fig. 2: Connected Cluster

The connected cluster graph describes the interaction between administrators (supervisors, principals, assistant principal), faculty members, students and parents. Most of the outer nodes are students, followed by faculty members and at the center of the graph are mostly administrators and some faculty members who did not interacted with the students through the sLMS. Connections between faculty members to students and to some faculty peers are usually observed to be weak. This observation holds true for supervisors. Only few faculty members and principals has strong connections to students and faculty respectively (see Figure 2). The weak connection is due to the fact that many of the users with differing roles are still getting to know the system, while those that exhibit strong connection indicates the early adopters.

In the succeeding sections, the realization of Equation 3 is computed and visualized using the concepts discussed in section 4.5.1.

5.1.1. Influence

Python networkx implementation of eigenvector centrality supports the algorithm discussed in section 2.2.1. The principal and assistant principal have the high influential scores of 0.446 and 0.443, respectively. It can be noted also that the nodes nearer to influential nodes also has higher influence compared to the other nodes, influence scores range from approximately 0.100 to 0.123. This score is significant since it represents the leadership of administrators which is a requirement to influence teachers that will impact student learning.

Taken into the Philippine context, the finding conforms to the section 5 of RA 9155 elaborating the *Principles of Shared Governance*. The law requires that administrators must be influential in order to direct improvements with the aim of delivering quality education. The result also suggests that in order to be influential one has to engage concerned individuals in order to propagate the improvement plans.

5.1.2. Betweenness

The algorithm discussed in 2.2.2 is implemented in Python networkx betweenness centrality. The nodes with the highest betweenness centrality measures are those of principals and assistant principals, with measures of 0.34 and 0.23 respectively. These results indicates that the administrators assumes the role of gatekeeper. Being the gatekeeper has the inherent characteristics of controlling the flow of information to the network. This affirms the administrators as drivers for educational reforms. For the reforms to take place, the administrators must be armed with the necessary information to drive the activities that supports the envisioned reform.

For example, the responsibility of making sure that the DepEd agenda is implemented in every classroom lies in the capacity of the principal in disseminating necessary information to the teachers through interactions. The principal could then receive feedback from the teachers then consolidated for submission to supervisors and/or superintendent.

6. CONCLUSIONS

The discovery of latent relationship has affirmed the significant presence of administrators as instructional leaders in a public school learning network. The centrality scores reveal that administrators are key drivers of the network information flow by being influential and gatekeeper.

In addition, this study provides evidence on the reason administrators are wary if they are not part of the sLMS as pointed out by previous study[2]. Being the central figure, they have the potential in influencing the direction of sLMS design aimed at improving learning as well as school management. Further, excluding the administrators in sLMS implementation might cause more isolates just like the smaller networks seen in Figure 1.

However, the long-term effect of having the administrators in the sLMS with respect to improved performance of students still needs to be tested. The centrality measures needs to be further evaluated if the communication between students will be enabled along with the involvement of parents in the network. These issues might be interesting to discover in future studies. Finally, this study hopes to lay the foundation into studying the influence of school leaders in the learning aspect. With the capability of technology to include more users in a social system, the understanding of the learning process can be expanded to include more actors that directly or indirectly affect the teaching and learning process.

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