Conceptualization of an Algorithm for Social Learning Management Systems to Promote Learning Interactions

Orven E. Llantos[1],*

[1]Mindanao State University-Iligan Insitute of Technology (MSU-IIT), Tibanga Hi-way, Iligan City, 9200

Abstract

A **dropout** is a situation where a user lacks the motivation to continue the learning interactions, thereby losing the engagement and eventually stopping the utilization of the Social Learning Management System (sLMS). The term was originally defined for students losing interest in using a sLMS but is generalized in this paper so the term can be applied to all users of sLMS. Several approaches involves artificial intelligence technique like fuzzy cognitive maps are used in conceptualizing feedback mechanisms that improved the students' situation awareness. Another approach might be based on actual user interactions and the computation of centrality scores from social network algorithms. This paper introduces the algorithm, which uses centrality measures to drive automated decision-making so an intervention can be selected when dropout is detected. The conceptualization of the algorithm is helpful in the adaption efforts of schools that are newly acquainted with learning technologies like the sLMS, to eliminate the dropout of the administrator, teachers, students, and parents.

Keywords

Centrality, Social Network, Learning Interactions, Social Learning Management System, dropout

1. Introduction

A **social learning management system** (sLMS) is an application that provides functionalities for the conduct of online distance learning with features for social interactions (i.e., video conference, chat, etc.) in one platform. sLMS can be considered as the environment providing the information and the users as the one that interprets and consequently use the information for present or future actions. Engagement in sLMS soared high especially during the time of the pandemic where many of the world's leading institutions adopted the platform for delivering learning. Some studies have even pointed out that both the student and instructor stay late at night to continue accessing the platform for learning interactions [1]. Reason points to the enhanced outcomes of learning while using the platform and having teachers and quality content enhances platform engagement [2]. However, despite of the mentioned beneficial factors associated with utilizing sLMS, user dropout still occurs.

A **dropout** is a situation where a user lacks the motivation to continue the learning interactions, thereby losing engagement and eventually stopping utilization of the sLMS. The term was initially defined for students losing interest in using a sLMS but is generalized in this paper so the term can be applied to all users of sLMS.

The intention of this paper is to present an algorithm that utilizes centrality measures to perform tasks that encourages learning interactions from *principal, faculty members, students,* and *parents.* The contribution of this paper is on the utilization of centrality measures in coming up the algorithm to engage the user encouraging learning interactions.

2. User Dropout and Interventions

Accordingly, infrastructure factors, cultural factors, digital inequality, and the threat to digital privacy were cited for causing student dropout [2]. However, there are environments that have overcome the mentioned factors but still dropouts are eminent. Reasons like frustration and boredom are among the factors affecting learning interactions that can lead to dropout [3]. The literature is rich in enumerating approaches utilizing artificial intelligence to avoid dropouts. One such piece of literature is the implementation of Fuzzy Cognitive Maps used in conceptualizing feedback mechanisms that improved the students' situation awareness. The deployed and tested system indicated promising results addressing dropout [4].

3. Centrality Measures for Automated Intervention

On the other hand, Social Network Analysis (SNA) can serve as another method for developing automated feedback mechanism. SNA requires representing social networks as a mathematical entity called **graph** into which associated algorithms describe the properties of the network. A graph G is composed of nodes V (i.e., indi-

Joint Proceedings of the ACM IUI Workshops 2023, March 2023, Sydney, Australia

*Corresponding author.
orven.llantos@g.msuiit.edu.ph (O. E. Llantos)
0000-0002-0787-0282 (O. E. Llantos)

viduals in the networks) and edges E (connections of nodes), $G = (V, E)$. The graph which resulted from the learning interactions of the users is expressed in the equation $G^p_{school_i} = G^p_{advisory_{i,j}} \cup G^p_{admin_{i,k}}$, where p is the period the graph is formed at $school_i$. $G^p_{school_i}$ is composed of the learning interactions between the k administrators to the teachers $G^p_{admin_{i,k}}$, and teachers of advisory class j to the students and parents $G^p_{advisory_{i,j}}$ [5]. It is also possible to understand the node contribution in the network by computing its centrality scores. Different algorithms calculate different centrality scores like influence and betweenness, among others [6].

3.1. Social Network for Two Schools

In 2018, the Department of Education, Iligan City permitted research in the adoption of **my.eskwela**, a sLMS, on any school willing to participate. The duration of the activity was from September 2018 up to March 2019, in which two schools participated. The resulting social network is the accumulated interactions of school i over period p as expressed in Equation, $\bigcup_{p=1}^{m} \bigcup_{i=1}^{2} G^p_{school_i}$.

Calculating influence and betweenness centralities in the graph produces two graphs for each centrality which lead to the discovery of Equation 1.

$$\Phi^p_{A_{i,k}} > \Phi^p_{T_{i,j}} > \Phi^p_{SP_{i,j}} \tag{1}$$

where $\Phi^p_{A_{i,k}}$ is the centrality score of administrator A_k in school i, and $\Phi^p_{T_{i,j}}$ is the centrality score of teacher T in school i and advisory section j, and $\Phi^p_{SP_{i,j}}$ is the centrality score of students S and parents P under advisory section j in school i.

The centrality measures identify the important figure in the social network and how their interactions affect the ties and flow of information.

3.2. Conceptualization of the Algorithm

Equation 1 will be the basis of the algorithm to send out reminders to concerned users once the requirement is not satisfied. Further data experimentation using social network analysis with interactions from 2019-2022 will help verify Equation 1 using two-column proofs as one of the preferred methods. User evaluation grounded on the technology acceptance model will follow once Equation 1 is integrated into the system.

4. Final Remarks

The conceptualization of the algorithm is helpful in the adaption efforts of schools that are newly acquainted with learning technologies like the sLMS, to eliminate the dropout of the administrator, teachers, students, and parents. The effects of such an algorithm still needs further investigation.

Acknowledgments

The author would like to thank DepEd Iligan for supporting this study, Ateneo Social Computing Science Laboratory for sharing resources, DOST-ERDT for the financial support during the conduct of previous researches, DOST-X for the research grant, and MSU-IIT for continually supporting the efforts of my.eskwela throughout the years.

References

[1] A. Abdullah, A. Kamaludin, A. Romli, Uncovered user engagement pattern in lms during covid-19 pandemic using temporal visualization matrix, in: 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE), 2020, pp. 1–5. doi:10.1109/ETCCE51779.2020.9350899.

[2] S. S. K. B. Khlaif, Zuheir N., Emergency remote learning during covid-19 crisis: Students' engagement, Education and Information Technologies 26 (2021). doi:10.1007/s10639-021-10566-4.

[3] R. S. Baker, S. K. D'Mello, M. T. Rodrigo, A. C. Graesser, Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments, International Journal of Human-Computer Studies 68 (2010) 223–241. URL: https://www.sciencedirect.com/science/article/pii/S1071581909001797. doi:https://doi.org/10.1016/j.ijhcs.2009.12.003.

[4] G. D'Aniello, M. De Falco, M. Gaeta, M. Lepore, A situation-aware learning system based on fuzzy cognitive maps to increase learner motivation and engagement, in: 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2020, pp. 1–8. doi:10.1109/FUZZ48607.2020.9177590.

[5] O. E. Llantos, M. R. J. E. Estuar, Learning interactions as it evolves in a social learning management system, in: 2021 Eighth International Conference on Social Network Analysis, Management and Security (SNAMS), 2021, pp. 1–8. doi:10.1109/SNAMS53716.2021.9732106.

[6] S. P. Borgatti, M. G. Everett, J. C. Johnson, Analyzing Social Networks, 2 ed., SAGE Publications Ltd., London, 2018.