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A LFCM APPROACH TO STUDENT PERFORMANCE PREDICTION BASED ON LEARNING FUZZY COGNITIVE MAP

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Abstract

Students' performance may be predicted using the Learning Fuzzy Cognitive Map (LFCM) technology in this study. Many academic sectors have been interested in predicting student academic success for a long time. Student outcomes may be predicted using several mathematical models. Although ANNs and regressions are excellent at predicting huge datasets, their practical use in real-world contexts is limited by their inability to handle small sample numbers. Learner's future success may now be predicted using the Learning Fuzzy Cognitive Map, a new and groundbreaking technique (LFCM). We discovered the most crucial aspects of student success, such as student involvement, using this method. An interrelationships model of the many factors affecting student performance is presented in the research. Results show that the model can accurately predict the incoming sequence when the sample size is small. Total online time and frequency of learning intervals in the LMS are also found to have a significant impact on overall performance. Participation by students is the most important factor in determining a student's overall success. This method might be tested in a variety of contexts to see if its usefulness has been shown. The suggested LFMC model might be improved by fine-tuning its components in future research.

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1. Introduction

In light of the increasing use of data and technology in education, educational data mining, artificial intelligence, and learning analytics (LA) have developed as new study subjects. E-learning, or computer-assisted learning, has experienced a tremendous increase in use in education. E-learning is presently being used by a number of educational institutions in order to meet their educational objectives. According to an open University study, designing and delivering online courses consumes 90% less energy and produces 85% less CO2 per participant than traditional classroom training. By 2025, the global eLearning business is expected to rise from $107 billion in 2015 to a projected $325 billion. As a result, educational institutions produce tremendous amounts of data. It is possible to analyses, simulate, and utilize this data to aid in decision-making. A new area of data analytics research, dubbed Learning Analysis (LA), emerged as a result (Papamitsiou and Economides, 2014). The measurement, preservation, analysis, interpretation, and reporting of student's knowledge and experiences are all part of the learner-centered assessment (LA) process. LA is using statistical analytic tools to make sense of the obtained data. Accurately predicting the outcomes of students (or learners) is an essential part of LA. Teachers must be able to accurately forecast student's academic performance when they take proactive measures to improve student learning (such as one-on-one tutoring and remedial sessions). To round things out, intelligent agents can use the output to initiate proactive support operations without the need for human intervention.

Our LFCM model was developed over the course of three semesters using data collected from 30 master's students enrolled in an online program. In addition, we utilize the LFCM technique to build a causal map demonstrating the links between factors that may be assessed and how those ties effect student accomplishment. The remainder of the paper is summarized in the following outline. E-learning scenario FCM implementations follow a literature review about student performance prediction and learning analytics. The technique is detailed in the next section. There follows a discussion of the report's findings and a conclusion.

2. Literature Review Student Performance Prediction and Learning Analytics

To better understand and improve learning, the word "LA" refers to the process of collecting, analyzing, and reporting data on students and their settings to various stakeholders. Academic analytics (AA) and electronic data management (EDM) share a number of aspects in the academic literature. Academic analytics, as the name implies, is the application of business intelligence to education, concentrating on institutions and the national level rather than individual students and courses. In the EDM's approach to educational data analysis, technology concerns are more essential than edagogical ones. According to this guy, education should be centered around Los Angeles. This may be used in a variety of ways.

These models can predict student's behavior, performance, retention, and dropout. Predicting the future status of pupils is tough since it requires looking at their prior behaviors or activities. Prior research in this field has been summarized in the following paragraphs, highlighting the most noteworthy findings.

Support vector machines are used to address the issue of class imbalance in student performance prediction. Linear support vector machines, feature engineering, and ensemble may all be used to make predictions about student performance. It's possible to make good use of these techniques if we have a lot of data about students and tasks. It used ordinal logistic regression to look for links between the topics of online questions and student's final grades. An integrated model is built to predict student test scores based on student effect, disengaged behavior, and performance in the classroom. Recent research shows that the amount of attention students pays to lectures, how effectively they take notes, and how much time they spend working independently are all important indicators of their class achievement.

Past research has employed a range of features and methodologies to model and predict student learning outcomes, as demonstrated in this brief synopsis. Linear models like linear and logistic regression were frequently used in early studies because of their simplicity and ability to account for precise linear connections between known input parameters and student achievement. ANNs, CNNs, Naive Bayes, and decision trees were eventually introduced into usage. Due to the varied levels of complexity of these methods, a recent study aimed to examine the accuracy of several models in anticipating student performance. There are a lot of parameters to modify and data to be sent through several conversion layers, therefore they only work well with huge datasets and have significant faults with small sample sizes.

3. Methodology

There are six distinct types of performance antecedents examined in this research: student characteristics, LMS features, student participation, student support, and institutional factors. Student happiness, knowledge construction level, and grade point average were all considered in determining how well the students performed. For four semesters, we collected longitudinal data on 30 postgraduate students and utilized the Learning Fuzzy Cognitive Map (LFCM) technique to analyses the findings.

3.1. Research method. The goal of this study is to apply the LFCM approach to predict student performance. Based on our findings from a literature review and analysis of historical data, we developed a study plan for identifying the factors that affect student achievement. At each of the significant milestones, the progress of the research is clearly visible.

4. FCM Learning

For example, fuzzy logic and neural networks are employed in FCMs. These networks are characterized by fuzzy weighted digraphs with a large number of nodes and arcs. The use of imprecise terms like "very high" and "very low" to express interactions in complex systems is common. Ci is the node or notion that represents the modelled problem and the arcs (Wij) that connect it (Wij). Wij signs are used to indicate the direction of causation between thoughts Ci and Cj, while the size of the Wij sign indicates the amount of the impact on those ideas. The concept values are in the $[0, +1]$ range and the weights are in the $[-1, +1]$ range. When N is the number of concepts in the system, and Ai is the value of Ci, then an $A = A1, \ldots, AN$ vector provides a snapshot of the system at each instant when $Ai = Ai$ is present in the data set. It is recommended by Salmeron et al. (2019) that in order to maintain Ai up to date at all times, the following guidelines be followed:

$$A_t^i = (A_i^{t-1} + \sum_{j=1,\ j=1}^{N} A_j^{t-1} Wij) \tag{1}$$

At represents the current value of concept Ci at t, $At1$ represents the current value of concept Ci at $t1$, and W represents the relationship between idea Ci and concept Cj. To map and confine the result in an interval, this study makes use of the unipolar sigmoid proposed by for the activation function f.

$$(x)\frac{1}{1 + \varepsilon - \alpha x} \tag{2}$$

A_n is a real positive integer that represents the slope of the function, x.

Static and dynamic studies may be performed in FCMs. Static analysis uses as many possible pathways from input ideas to output concepts to reveal the causal implications of concepts. A concept node Ci is linked to another concept node Cj via nodes such as $Ci\,Ck_1,\ Ck_1,\ \ldots,\ Ck_n,\ Ck_nC_j$ in the sequence of this study $(1,\ k_1,\ \ldots,\ k_n,\ j)$. I $k_1,\ \ldots,\ k_n,\ j)$ is a route via which Ci's indirect influence on Cj is transferred to Cj. In the end, Ci's total influence on Cj is the sum of all C's indirect impacts on Cj.

The t-norm and the s-norm are used to generate a basic fuzzy causal algebra by interpreting the indirect influence of the operator I on the partly ordered set P of causal values (so we simply call it as the maximum of minimums). Let's assume that there are m-many causal routes from Ci to $Cj : Ik \ldots k \ldots k \ldots j)$. It is known as $Ir\ (Ci,\ Cj)$ and $T(I\ Cj)$ is the total effect of Ci on the idea Cj along all m causal pathways. These operators are represented in Equations (3) and (4):

$$I \sim (Ci,\ Cj) = \min(w(Cp,\ Cp +) : (p,\ p + 1) \sim (i,\ k \sim \ldots k,\ \sim j)) \tag{3}$$

$$I \sim (Ci,\ Cj) = \max(Ir(Ci,\ Cj)),\ \text{where } 1 <\sim r <\sim m \tag{4}$$

Path indices p and $p + 1$ are continuous from left to right (Kosko, 1986).

Equations (1) and (2) are used to increase the values in a resultant vector, such as $A = A1, \ldots, AN$, until they reach their maximum value. Use experts and/or historical data to build an FCM. Although there are many advantages to relying solely on the opinions of experts, there are also significant drawbacks. The weighted matrix W is used as the core component of FCM learning systems that rely on expert interaction or historical data. The weight matrix of the FCM may be taught using ANNs, such as the Modified Asexual Reproduction Optimization (MARO) that we use in this work (2019).

MARO, an FCM-major, was invented in order to minimize the following error:

$$\text{in-sample-error} = \frac{1}{(k-1)N} \sum_{t=1}^{k} \sum_{n=1}^{N} | C_n(t) - C_n(t) | \tag{5}$$

Equations (1) and (2) are used to determine Cn(t) and Ccnn(tt), respectively, using the candidate FCM and Equations (1) and (2). N I signifies the sum of the number of input observations multiplied by the number of conceptions, which is K in this example. The pseudo code for the FCM-MARO algorithm is as follows.

$t = 1$ / Set the initial time.

loc = 1 / Initial setup of the local number

P = initialize(L,U)/A random weight matrix with lower and higher boundaries is created as the parent. Error

P = Cost(P) / Calculated in relation to Equation (5)

Do bud t = reproduce(P) / Generate a random mutant offspring from the parent when halting conditions (P)

Cost (bud t) - error bud t

If error bud t = error P, then P = bud t, loc =1; else, if error bud $t + t >$ error P, then P = bud t, loc =1; otherwise, clear (bud t), loc ++

The cost function for time t is defined by a random weight matrix and an equation. Locates indicate that the approach has not improved (5). To generate a random offspring from the pattern, the budding technique is employed. Then, the cost function is called on this random offspring. Once we have accepted the new solution's error, we remove the parent and construct a new parent with the new solution. Nevertheless, if the error in the solution is smaller than t times the parent error, we'll accept it. We must utilize Equation t in order to get to t (6). If the offspring fails to meet any one of these requirements, it is thrown away.

$$\Delta t = \frac{In(loc)}{\sqrt{t}} \tag{6}$$

The algorithm is done when it reaches the stopping condition. The end answer is the weight matrix of the targeted FCM.

5. The LFCM Model's Creation

The 37 antecedents were used as the first layer of the LFCM model, while three performance indicators were used as the second layer. The interdependencies were modelled using longitudinal data from three consecutive semesters.

6. Procedure for Collecting Data

The study model was based on a long-term collection of data. There were 45 students in the study who were registered at an online university in a four-semester master's degree program in Information Systems (only course-based enrollments). An open-source e-learning platform called Moodle is used at this university. When creating and distributing a questionnaire for Part A of the course, Moodle's "questionnaire" plugin was utilized, which allows students to link and follow their responses back to the questionnaire.

6.1. Findings student performance prediction. Student's FCMs were developed over the course of three semesters following the method indicated above in the section on Learning FCM (Pi). Recurrent neural networks were utilized to forecast each student's final semester performance using the FCM. MSE and standard deviations are shown in Table 1 for three distinct performance metrics. All three of these options are available. However, even with a small sample size, the prediction model was able to accurately anticipate outcomes.

Table 1. For performance variables, MSE and standard deviation are used.

Measure	OP1	OP2	OP3
MSE	0.07783908	0.07463091	0.05041522
StDev	0.05817604	0.08766665	0.05861402

What are the effects of pre-existing conditions on student achievement?

Use equations 1-4 to predict how the augmented adjacency matrix $(AiPj)$ between student performance antecedents (Ai) and overall performance (Pi) may be utilized to estimate the route effect $(AiPj)$. The computation results are displayed.

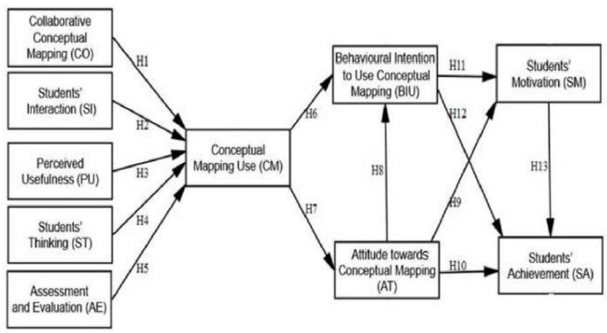

Figure 1. Partial and high-level cognitive maps of student performance and antecedents.

There are more indirect (maximum of minimums generated by equations 3) than direct (maximum of minimums formed by equations 4) repercussions for virtually all variables (blue lines). It is determined which path has the smallest graph value and which path has the largest graph value. Using this approach, it is feasible to record the indirect consequences of two notions.

6.2. Performance antecedent's causal interrelations. It also demonstrates how the antecedents of student success are interrelated. (see Appen-dix *B* for further details). In the X-axis, each variable's causal magnitude is represented by the number (rows in Appendix B). The Y-axis shows the impact's magnitude (columns in Appendix B). Accordingly, we've decided to categories elements into four separate groups. Quadrant 1's components appear to be "independent" and unconnected. These components, as far as I know, have no link to the entire system. As a result, there is no impact on the magnitude of other factors. The second quadrant has a number of "independent" components, each of which has a significant cause but little impact. The name of this cluster indicates that each factor functions independently and has a positive or negative impact on the magnitude of other variables.

7. Discussion

This study attempts to offer a new algorithm for forecasting student performance using LFCM. We used data from an online program that followed the development of 30 master's-level students over the course of three semesters to predict their performance in the fourth semester as part of our LFCM model study. We may also determine the relationship between observable factors and student performance using an LFCM approach. We'll go into further detail in the next paragraphs.

Student engagement has the greatest impact on a student's overall achievement, surprising to many. Because it focuses on the amount of time and effort students devote to educational activities, student engagement serves as a proxy for learning outcomes. This necessitated the development of approaches and strategies that encourage, support, and reward student participation. Technology-mediated learning also has a lower level of student engagement, which is a significant predictor of educational results. When it comes to e-learning platforms, this is an excellent statement because they often struggle to convey emotion or even engage students during class time. For this, the Learning Management System (LMS) must focus on increasing student involvement in class. In order to stimulate the attention of pupils, the learning process should be more dynamic and gamified. Users are also urged to do desired activities as a result of this type of marketing. Virtual items and tuition savings can be exchanged for badges or points. In order to get the most out of the app, students will be more engaged and motivated to earn more points.

Overall performance and other factors are greatly affected by student support. Because most of these items fall within the fourth quadrant, they are mostly self-sufficient. In other words, it is inevitable that enhancing student assistance will lead to advances in other areas. Study participants were surprised to see that SS7: subjective norm had the greatest impact on all other factors. According to a person's subjective norm, he or she believes that the majority of people in his or her life believe that he or she should participate in the activity at hand or not participate. Student perceptions have an enormous impact on overall performance and other aspects. User perceptions must be compared to their new perceptions in order for a user to meet the subjective norm. Having a large impact on other elements is not surprising given that student assistance has the potential to boost participation in class as well as student attitudes regarding utilizing the LMS. This discovery is in line with others from the same field of study.

Student support has a substantial influence on overall performance and other variables. Items in this category are primarily situated inside the fourth quadrant, which suggests they are largely autonomous. In other words, it is inevitable that enhancing student assistance will lead to advances in other areas. Study participants were surprised to see that SS7: subjective norm had the greatest impact on all other factors. According to a person's subjective norm, he or she believes that the majority of people in his or her life believe that he or she should participate in the activity at hand or not participate. Student perceptions have an enormous impact on overall performance and other aspects. User perceptions must be compared to their new perceptions in order for a user to meet the subjective norm. Having a large impact on other elements is not surprising given that student assistance has the potential to boost participation in class as well as student attitudes regarding utilizing the LMS. This discovery is in line with others from the same field of study.

Student performance improvement solutions should focus on the antecedents of student performance and their interrelationships. Decision-makers can benefit from 4's four-dimensional profile, which highlights the most significant categories and individual components, when there is a lack of funds available. Additionally, when developing improvement action plans, attention should be paid to variables in quadrants 2 and 4 of 5 (the ones that have the most impact), as these variables have the greatest impact even if no direct improvement plans are implemented.

8. Conclusion

Student's performance may now be predicted using the LFCM algorithm, which was created by academics. Small sample sizes impede the practical use of ANNs and logistic regression in real-world scenarios, despite their superior performance on big datasets. This limitation necessitates the development of a novel method for predicting student success. Future innovations like LFCM can aid in this endeavor. This concept has practical and management implications for e-learning. There is a clear correlation between student engagement and performance, as well as a strong correlation between student support and other factors. Even though our research has several limitations, the ramifications of our results are substantial. Starting with the fact that not all factors influencing student success are taken into consideration in this study, Due to the restricted number of indications that could be collected from Moodle, and the length of the questionnaire, we were forced to limit ourselves (particularly in long-term studies). Even though our research has several limitations, the ramifications of our results are substantial. Starting with the fact that not all factors influencing student success are taken into consideration in this study, Due to the restricted number of indications that could be collected from Moodle, and the length of the questionnaire, we were forced to limit ourselves (particularly in long-term studies). Not all master's programs or universities may benefit from our findings. This method may be used to find and understand connections between things. The suggested technique may be used to assess a potential future project in a variety of ways. It's critical to stress that LFCM model's predictive performance is far from perfect when compared to other approaches like ANN and regression, especially when it comes to LFCM. Small sample sizes are no problem for LFMC, though. An LFMC model's performance might be improved by tweaking the model's components in the future.

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