Development of Fuzzy Cognitive Map for Optimizing E-learning Course

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Abstract. Learning management system (LMS) optimization has been one of the core issues in the face of increasing learning content supply and the rising number of online-course participants. This optimization is mostly based on LMS logs data analysis and revealing the users' behavior patterns linked to the content. This article focuses on the approach to LMS users' behavior pattern simulation that stems from the fuzzy cognitive maps-featuring approach. The proposed model describes the user-content interaction within the system and can be applied to predict users' reactions to its learning, testing and practical elements. The obtained cognitive map has been tested with the INFOMEPHIST system data. This system has been used to assist leaning process in a number of National Research Nuclear University MEPhI departments for more than nine years. The current and further research is supported by the NRNU MEPhI development program.

Keywords: Fuzzy cognitive maps · Moodle-based LMS · Users' Behavior Simulation · E-learning

1 Introduction

As of today e-learning has been gaining increasing attention both in the corporate sector (with the Corporate University concept being massively introduced) and among classic educational institutions [4]. Some MOOC platforms such as Coursera, EdX etc. should surely be noted as well. This pattern helps to boost learning process and to lower organization and production costs, as well as to make knowledge transmission automatic and to obtain additional sources of the information on education quality and students' behavior. There exist corporate and open source LMS. Among the latter, Moodle is the most popular. It is implemented in many universities as a framework for their own software. Moodle LMS is an object-oriented module-consisting dynamic learning platform. The system records student behavior data to a file and stores it in the database. This data is represented as a table that features the information on Course, Time, Student's Name, Action and Section. The latest years have seen e-learning accumulating more data which makes it relevant for the E-learning data mining. This is why boosting education process with the help of learning content optimization seems essential. This information can be used for making up a sufficient and detailed student behavior model.

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The data on his behavior can reveal his behavior pattern, which will then enable us to classify it (to relate it to a previously obtained student behavior pattern). Using this classification we can build up recommendations concerning course-related materials and boost the academic performance level on the course.

This work is an extension of [13]. Comparing with the previous work in this paper a modification of developed cognitive map is introduced. Additional simulations results with different initial conditions are presented and discussed.

2 Modern Views on the Problem

Most of the approaches to web-content and LMS optimization lie in revealing users' behavior patterns after analyzing the way they use the system (Web Mining) [2, 3]. The current analysis in mostly conducted through clustering and classification. Besides we use association rules mining, sequential and content analyses (see Fig. 1).

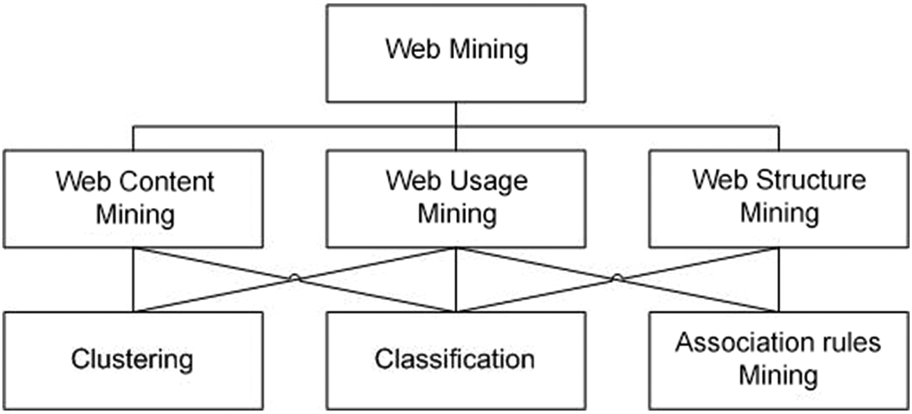

Fig. 1. Web mining today

The latest years have also seen cognitive visualization development [10], which enables us to describe users' studying trends with the LMS logs. All the methods listed above help to reveal local characteristics of users' behavior, although it is still quite rare when we can apply the obtained results to the whole user-LMS interaction process [5]. Thus, revealing the weak points of the system content calls for additional (mostly time-consuming) research.

Due to various reasons a course author does not always has the opportunity to conduct such a research, and the existing data remains unclaimed. Thus, meeting fundamental content requirements is also essential. These requirements should be laid down at the first stage of a course designing process to result into better quality content. To reach this goal we embark on making a generalized model that will allow us to define the optimal-quantity and optimal-quality forms of the educational content.

One of the new Decision Support System theory trend is cognitive modeling with semi-structured data and semi-structured cases management analysis. Cognitive structuring includes defining prospective targets of the object in control, as well as undesirable conditions and valuable environment factors that affect the transition of the object to its current state. It also includes revealing cause-effect relations, taking into account the mutual influence factor.

3 Fuzzy Cognitive Maps

Cognitive maps are one of the tools to represent ideas in weakly-formalized fields such as economics, politics and the military sphere. This approach was introduced in 1976 by Robert Axelrod in his book, dedicated to cognitive maps in politics [7]. A cognitive map is a symbolic directed graph that features vertices that represent entities, concepts, factors, targets and events, and arcs that show the influence of one vertex to another. A concept of a situation suggests that this situation develops in time and under changing environment that is reflected in changing factor values. A concept map enables us to set a problem of prediction (which is a direct task) and to explore possible ways to manage the situation, i.e. to find out what effects lead the desired (targeted) condition (which is an inverse task). The effect is characterized by a threshold function which can be defined in a variety of ways. The function includes an expert valuation, which is initially set in a natural language. Bart Kosko extended the paradigm by introducing fuzziness [1]. This reflects the dispersion of the experts opinions on the mutual influence of different factors. Fuzzy numbers are usually represented by triangular numbers.

On the whole the objective to define the vertices (concepts) state can be reduced to the following calculations (see Formula 1):

$$A_i(k+1) = f\left(A_i(k) + \sum_{j \neq i, j=1}^{N} A_j(k) W_{ji}\right) \tag{1}$$

The calculating process is iterative, which means that after you set the initial vertices states their values are recalculated until the difference between the current states and the previous states is less that an ε value.

As of today, managing complex systems often implies using differently-formalized cognitive maps [6] on different stages of decision-making in semi-structured problem fields, especially in the social and economic spheres. Cognitive maps serve as the basis for map generation and map verification methods, which support the formation of a situation common knowledge bank. At this stage designing cognitive maps aims at visual representation of a problem [11, 12] to help explain a subject's actions, with his point of view analysis serving as the starting point. In this case whether the map is adequate or not can be confirmed by the subject. Different interpretations of edges, weights, vertices and various functions that define lines-factors influence make up diverse cognitive map modifications and ways to examine them.

The interpretations can differ both contently and mathematically. Due to the fact that cognitive maps have a great number of modifications, we can consider different types of models based on these maps. One of the modern trends in cognitive map development is frame-based cognitive maps [9].

4 The Proposed Approach

We suggest a fuzzy cognitive map as a user-LMS interaction model. It describes the way a set of concepts that characterize the content from the didactic and systematic point of view influence the student academic efficiency (Course Competence) [13]. The course in particular represents a set of modules (Module Competence), the acquisition level of which affects the Course Competence concept. A separate module includes a set of static and interactive content. Static learning content (Learning Competence) includes abstracts and lecture-related presentations, additional teaching materials, etc. Interactive content includes a solely controlling component of tests (Tests Competence) and a practically-oriented learning component (Practice Competence) of lab assignments and simulators that students run via the system (e.g. SCORM packages). Generally speaking, this kind of content depends on accomplishment time: it could formally be the same as Moodle Task component, but we include it into Practice only when the maximum accomplishment time does not exceed the standard 4-hours learning maximum.

Other entities include: the user-system interaction (LMS Interaction), the number of the user's log-ins (Entry Attempts), the Time, spent in the system (LMS Time), the Feedback Quality, the Number of new topics created by the user (Topics Number), the Number of messages sent by the user (Messages Number), the Results of other students (Listeners Results), the Final grade for the course (Course Mark), the Trajectory, which stands for the time the user accesses the modules and the content within them, corresponding to the natural sequence of learning course (FOR), the Recommended Sources, the Learning Materials, the Number of tests, the Number of attempts for passing a test (KP), the Time spent for the tests (Tests Time), etc. Initially proposed cognitive map was modified. Thus, there have been added 4 new concepts to obtain a more balanced result. The new map was created with the help of an open source Mental Modeller application [14] (see Fig. 2).

These concepts to some extent oppose the already existing elements, such as Exercises Number, Tests Number, Tasks Number, Materials Number, i.e. the High Tests Number concept positively influence the Tests Competence, but if number of tests is small or equals zero, it negatively tells on the Competence. To represent such a case there has been introduced a new Low Tests Number concept that has the negative weight connection with the Tests Competence. As far as a low and a high number cannot exist at the same time, these concepts were connected by the negative feedback edges (See Fig. 3).

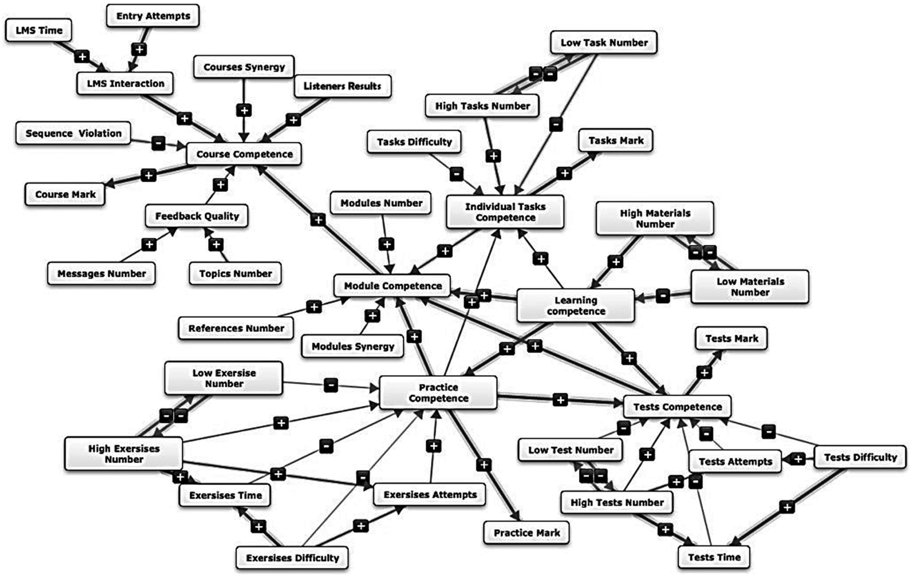

Fig. 2. A user-LMS interaction cognitive map (created with Mental Modeller)

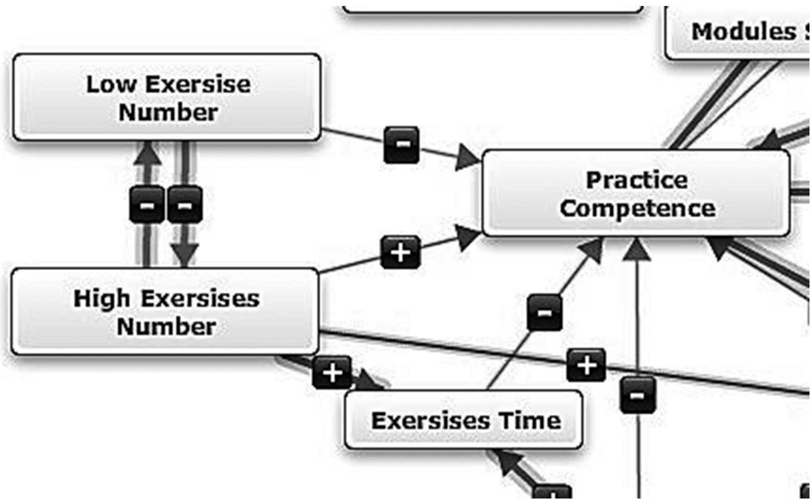

Fig. 3. The added concept

After consulting 5 e-learning course making experts, we have defined the weights of the arcs. We used simple linguistic 5-point scales, where 1 point stands for the lowest influence level and 5 points stand for the highest influence level. The experts grades were adjusted with the help of the AHP technique and fuzzificated. We used the unit step function as a threshold function for the states of the concepts (see Formula 2):

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x \leq 0 \end{cases} \tag{2}$$

Under these conditions were have conducted several simulations to determine the sensitivity and adequacy of the model. Figure 4 shows that if the values of the highly practical concepts, filled with practical tasks, home assignments and other related content is high, it slightly increases the Module Competence, but shows no effect on the Course Competence.

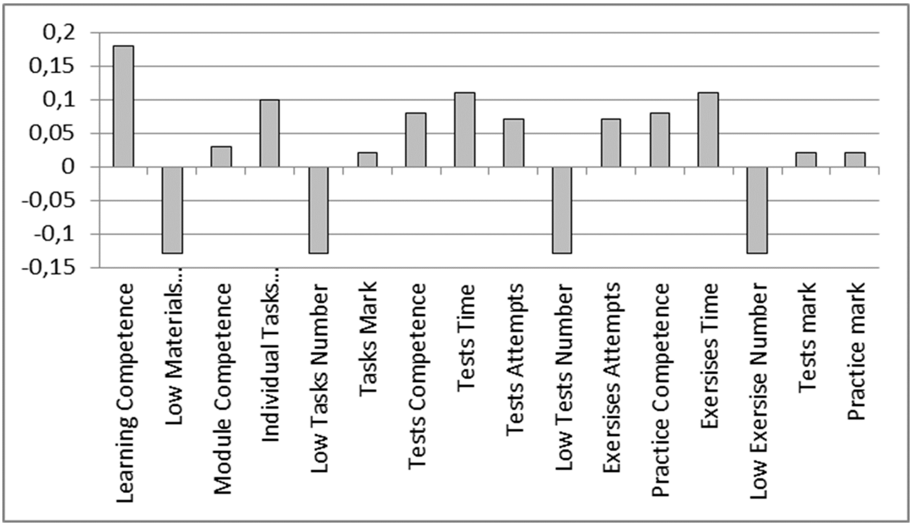

Fig. 4. The results of the simulation featuring a great number of tests, practical tasks and home assignments (created with Mental Modeller)

When diverse difficulty is increased (tests difficulty, etc.), it negatively affects the Module Competence (see Fig. 5) and the time required to accomplish these educational elements.

The proposed model has been tested with a free Fcmapper application. The test included several complexity level scenarios that featured different amount of practical, independent and testing components (see Fig. 6).

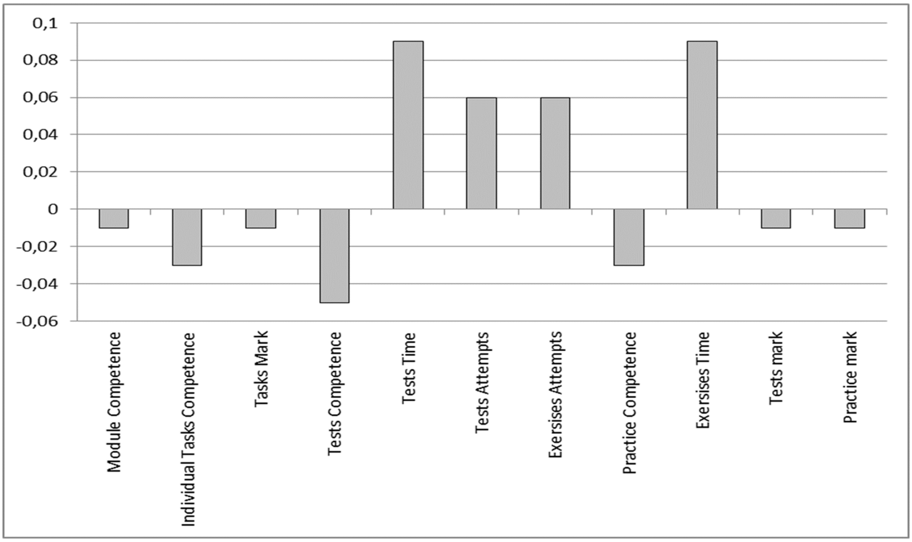

Fig. 5. The results of the simulation featuring high complexity level of of tests, practical tasks and home assignments (created with Mental Modeller)

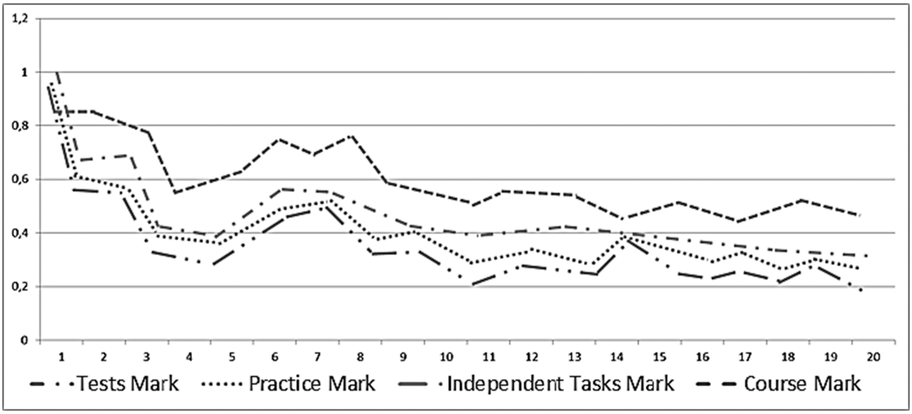

Fig. 6. The results of the low complexity level scenario

The line graph shows the main concepts, including the Course Competence, and we can see that the low complexity level lets the Course Competence value reach the acceptable number of 0,6. The display indicators (or course components marks) also fit within the normative values, including those of the ECTS system.

Table 1 represents a part of the simulation results, which show that increasing learning elements number and their difficulty does not lead to increasing Course Competence.

Table 1. The results of the FCM simulation

Factor	Competence			
	Tests	Practice	Independent Tasks	Course
The Number of tests, exercises and tasks is the Highest	Increases	Increases	Increases	No effect
The Difficulty of tests, exercises and tasks is the Highest	Decreases	Decreases	Decreases	No effect
The Modules Number, the Modules Synergy, the Materials Number and the References Number are the Highest	Increases	Increases	Increases	Increases
The Number of tests, exercises and tasks, the Difficulty of tests and exercises, the Modules Number, the Modules Synergy, the Materials Number and the References Number are the Highest	Increases	Increases	Increases	Increases

5 The Proposed Model Testing

Cognitive map verification is a nontrivial task which is usually solved in two different ways [8]: (1) checking the obtained vertices values or the whole model with the help of alternative patterns and methods, such as Monte Carlo methods, simulation modeling etc.; (2) checking each edge conclusion on the real historical data. The model was tested on the real data, provided by the INFOMEPHIST system (see Fig. 7), which supports the learning process at the NRNU MEPhI Economics and Management department and the Cybernetics and Information security department since 2007, and at the NRNU MEPhI Business school since 2015. During this time there have been more than 100 different courses introduced in the system. Over 15 thousands students took these

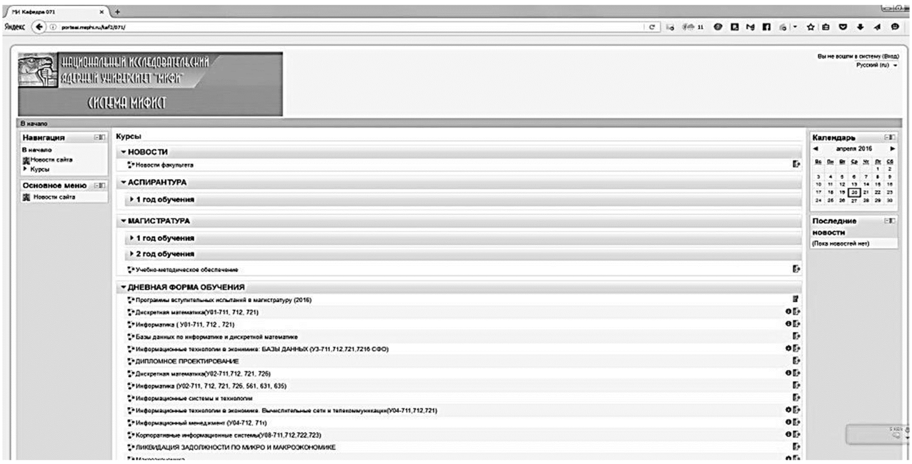

Fig. 7. The INFOMEPHIST home page

courses. The INFOMEPHIST system is based on the open source Moodle LMS, which enables us to manage the content and the users, and to monitor their activity. Thus, there has been accumulated much information about users behavior that was later analyzed to make the proposed cognitive map parameters more clear. The system register includes more than 3 million records.

The analysis used the system data corresponding to the curriculum of the master's program in Economics. With the help of correlation and regression approach there have been estimated several proposed entities, such as the indicator elements (practical component marks and other marks) against the second order entities, such as the SCORM laboratory works number (EN), the number of attempts taken (AN), the total time (ET), etc. (see Formula 3):

$$Y_{TM}^{i} = F\left(X_{EN}^{i}, X_{AN}^{i}, X_{ED}^{i}, X_{ET}^{i}\right) + \varepsilon_i \qquad (3)$$

We used a quadratic function as the model regression function. The source data for each component included aggregated indicators of each student. For example: if we take the practical component, we deal with the sum of all the SCORM tasks marks, the time spent for all the tasks, the sum of the attempts to each task, the total number of the tasks. There have been calculated residuals for each of the regression factors, with help of a standard Excel Data Analysis module.

The obtained results (see Fig. 8) show experts' compliance in assessing the weights of the model edges and the constructed regression. Still some of the weights values need further consideration (for example, the time spent for a test). Besides, to make the model work more accurately there will be allocated additional entities and factors, that represent the course and the learning content more precisely.

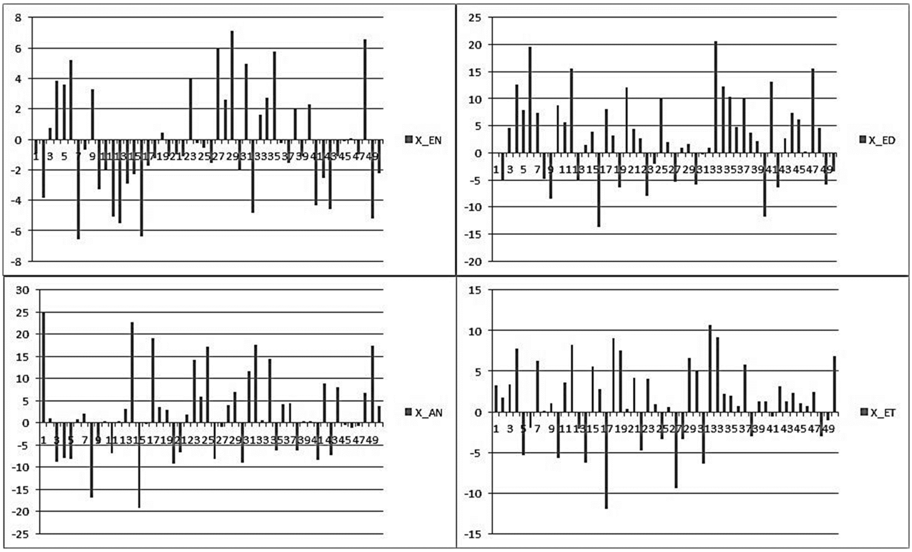

Fig. 8. The correlation and regression analysis results of an innovation marketing course.

6 Conclusion

Cognitive maps enable us to simulate weakly-formalized fields to improve prognosis quality and make up different scenarios of a situation. The article focuses on the possible ways to use fuzzy cognitive maps as a basis for modeling users' behavior patterns in the process of LMS e-learning. Further research will be focused on defining the proposed cognitive map parameters in terms of fuzzy functions that describe the map entities mutual influence, as well as the edges weights values.

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