Student Activity Recommender System

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Priporočilni sistem za aktivnosti študentov

V članku predstavljamo priporočilni sistem za aktivnosti študentov na podlagi vsebine poučevanja. Algoritem priporočilnega sistema temelji na avtomatskem generiranju konceptualnih zemljevidov (angl. Concept maps) učne snovi. Načrt algoritma omogoča optimizacijo glede na izbrane učne indikatorje. Kot testno področje algoritma smo izbrali generiranje testnih vprašanja za samoevalvacijo študentov na področju poučevanja matematike (matrični račun in linearna algebra). Okvir razvoja predlaganega priporočilnega sistema je mednarodni projekt iMath, v katerem sodelujemo kot partner.

Preliminarni rezultati kažejo, da obstoječi priporočilni sistema izboljša pravilnost odgovorov študentov v primerjavi z naključnim vrstnim redom vprašanj. Ker vzorec študentov, ki so sodelovali pri testiranju, ni representativen, rezultati niso posplošljivi.

1 Introduction

Regular and time-effective student activities and their outcome measurement are vital in any learning environment. Learning indicators as objective measures of these activities have been under development for several decades [1]. The possibility of self-assessment of current progress of learning outcomes in terms of selected learning indicators can improve student engagement in their learning path. Modern technologies can contribute to the time and outcome efficiency of student learning.

Any-time accessible self-assessment of student progress is important in any form of learning at the university level. We expect it to improve student engagement and also use student time invested into learning more efficiently. As it gets more and more critical, it also improves teachers' investment efficiency which can save time for improving the course and allow for more consultant time the teacher can afford.

The problem of measurement of learning outcomes in a wide context is set and discussed in [2]. Under the term educational indicators the learning outcome measurement definition and its relation to the educational system are presented and discussed in [1]. Learning performance prediction was studied in [3].

Recommender systems have been an active research and development topic for almost two decades now [4] and for more than ten years one of the cornerstones of personalization and user-adaptation of modern communication systems. Recommender systems to support learning were applied in online learning [5]. Full-learning path recommender was introduced in [6].

Concept maps of learning materials were studied by several researchers [7], [8]. An algorithmic approach based on wrongly and rightly answered questions was given in [9], [10]. Learning strategies based on concept maps were also studied in [11]. Concept maps in learning were applied and discussed by authors of [12]. A Concept Map-Based support for adaptive learning systems was presented in [13].

The goal of this research is to design, implement, and evaluate a student activity recommender system based on automatic concept map generation. The test domain is linear algebra and student activity is answering questions in a self-assessment test.

2 The iMath project

This work is largely connected to the activities of iMath project. The acronym iMath stands for An Intelligent System to Learn Mathematics. This Erasmus+ project [14] aims at:

- build up customized tools that facilitate students to learn Mathematics by offering a personalized path.
- Develop a one-to-one method to support and assist students in their study, relying on optimization techniques and learning algorithms.
- Foster debate among teachers, students, and researchers about how to teach and learn better using optimization and learning algorithms.

Main activities are

- aggregate articles, books, methods, algorithms, and codes into an online collaborative library about optimization and learning methods.
- Develop a framework to support students in their study by designing and suggesting a customized path through its resources.

Digital tools have the power to engage students more effectively, promoting a culture of collaboration, inclusion, and flexibility among students in the area of Mathematics.

Expected results are to diversify teaching approaches and pedagogical methodologies, to improve student's knowledge of subjects that require a strong mathematical background, and to contribute to support teachers and researchers on Optimization and Learning Algorithms.

Target Groups are college students, lecturers, researchers, and other teaching staff.

Project partners are Instituto Politécnico de Bragança (Portugal), Pixel (Italy), University of Genova (Italy), University of HAW Hamburg (Germany), University of Ljubljana (Slovenia), University of Malaga (Spain), and University of Peloponnese (Greece).

The role of the Slovenian partner (Lab Lucami at the Faculty of Electrical Engineering Universiti of Ljubljana, [15] is, among others, to develop and implement the student activity recommender system described in this paper.

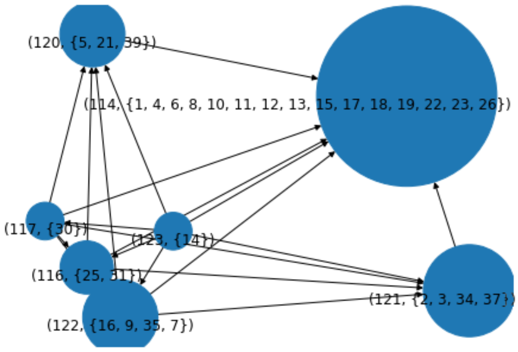

Figure 1: An example of a concept map where concepts are sets of questions and directed links indicate the order of answering them.

3 Concept map-based recommender system

We based our approach on automatic concept map generation and graph-based integration of different approaches.

We split the recommendation algorithm into 1. Concept map generation and manipulation, and 2. Question recommendation based on the concept map. First, we briefly introduce the concept as is used in learning (including its simplification to this research) and then present two components of the proposed algorithm.

3.1 What is a concept?

A definition of a concept is a complex matter and was developed more or less independently in different fields such as behavior science [16]. In the domain of learning, the concept is usually enframed in Concept Learning. Its development is traced back to the work of Bruner et. al. [7]. As summarized by Wikipedia [17], "concepts are the mental categories that help us classify objects, events, or ideas, building on the understanding that each object, event, or idea has a set of common relevant features."

We introduce concepts from the practical learning point of view as "knowledge entities linking learning terms into groups". In this research, concepts are simply considered as groups of questions from a given domain that should be considered and answered by students in single or adjacent sessions. Therefore, the proposed concept map generation is a question-grouping algorithm associating questions that students should link together to achieve better learning indicators.

3.2 Concept maps

A concept map is defined as a directed graph of concepts. In this research, concepts are groups of questions that should be associated together during the student's learning process. Directed links indicate a time ordering by which students should study the content (in this particular case, answering questions in self-assessment sessions). An example of a concept map generated by the proposed algorithm is given in Fig. 1.

Our approach to automatic concept map generation is based on the following components described in the sequel.

3.2.1 *Concepts maps from various perspectives*

We decided to address the concept map generation problem from several perspectives which are its dependence on (1) Available course data, (2) Teacher's (human expert) perspective, (3) Student group, and (4) This particular student. This led us to design Concept map generation algorithms by the following components:

1. Initial concept map: simple linear ordering of concepts
2. Content keywords-based concept map: keywords are the core of concepts.
3. Student history-based concept map: following the idea from Chen et al [9].
4. Concept map generated by the expert (teacher): The teacher can enter the structure of the content.

3.2.2 *Concept maps weighted merging*

A primary concept map is generated (for instance, from keywords) and additional concept maps are merged according to preselected weights. A concept map is improved by merging it with another concept map according to preselected weights.

3.2.3 *Concept map simplification*

Concept map generation and merging typically lead to complex weighted graphs which need to be simplified in order to provide better results.

3.3 Recommender system as a Concept map walk

The goal of the recommendation algorithm is to calculate a personalized learning path for a student, based on content structure, her learning history, and success. A learning path is an ordered sequence of tasks (problems) that a student is expected to successfully solve to master a topic of the course.

3.3.1 *Recommender system algorithm*

The recommendation algorithm simulates the natural learning path of a student, progressing from basic concepts and easier tasks toward more elaborate concepts and more difficult tasks. The hierarchical relation between concepts and related questions is given in a concept map. Further, we assume that there is a large pool of questions, possibly associated with multiple concepts. So each concept might have a large pool of associated questions, where some might be very similar. In order to master a concept, a student needs to correctly solve a subset of the questions, and then he/she is allowed to progress to the next concept.

In our basic scheme, we assume a fixed threshold of correctly answered questions of the concept, which indicates successful completion of the topic. However, more elaborate concept-dependent thresholds could be utilized.

3.3.2 *Learner success score*

For each concept of the course, a success score is calculated from previous answers, according to the criteria:

- completeness: % of correctly answered questions of the concept;
- correctness: % of correct answers (vs. all answered questions).

Then, all questions of the concept are sorted into three categories: unanswered questions, correctly and incorrectly answered.

Generation of the next question relies on parameters minimum correctness, and minimum completeness (to move to the next concept) following the rules:

- If the concept is not yet completed, then the next unanswered question is selected or incorrectly answered;
- If the concept is completed, we move to the next related concept from the concept map.

A more elaborate strategy can be used to select unanswered questions based on the difficulty level. The two criteria for estimating a learner's success in mastering a concept allow for adaptive strategies, so that the learning path is tailored to the capabilities and knowledge of the students. For example, if a concept is already well known to a student, she will solve a small number of questions correctly, and he will be allowed to progress with a low completeness score due to high correctness score.

4 Experimental results

Preliminary experimental results are given only. The proposed algorithm was tested as a part of the iMath [14] project activity where students were engaged to test the algorithm and to provide brief feedback.

4.1 Learning domain and test students

To test the proposed algorithm, the learning domain was focused on the subject of matrices and linear algebra. Student activity was solving questions with the aim of self-assessment during the course in order to monitor their own progress. Therefore, the recommendation item was a single question posed online and the answer was provided online.

Participant students were invited either by email or by in-person invitation during the course process. Students from different courses and universities were involved. After cleaning the participant list, 55 students responded to the invitation and solved a part or all of the 40 recommended questions from matrices and linear algebra once or several times. Students did not use any specific course material or attend any customized course on the related topic.

4.2 Recommender system portal

The evaluation system was a web-based application supporting user registration where the students' unique ID is her email and answering 5 questions from a selected domain in a single session. Questions are answered by selecting one option from the list of proposed ones. A typical user screen is given in Fig. 2. The system was designed and implemented by iMath [14] project partners and the proposed recommender algorithm was integrated into it.

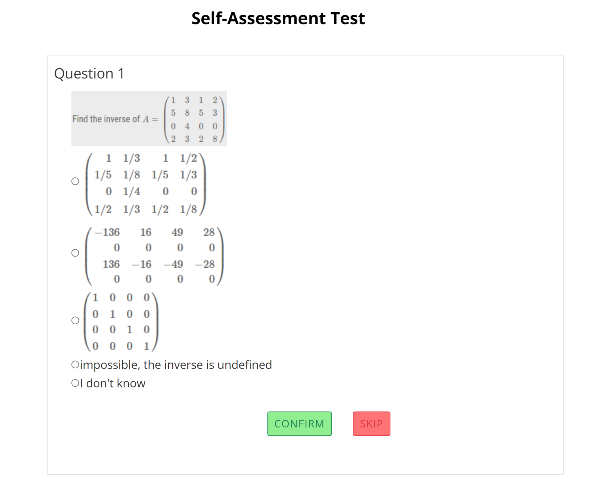

Figure 2: Recommender system screen seen by the student while answering questions

Students can decide on their self-assessment test anytime. She can take as much time as she needs to answer the question. A student is allowed to use any aid. The questions are structured in a way that the selection of the right option requires a solution to the given task or to consider theoretical aspects of the underlying theory.

4.3 Performance evaluation procedure and metrics

The proposed algorithm was evaluated by 55 students. Some students took one and some students took several sessions. Each student session includes the login to the test portal using its email as a unique ID, followed by answering 5 questions proposed by the system. An example of a question is depicted in Fig. 2.

The performance of the proposed Concept map-based recommender system for self-assessment questions was measured by the average correctness of answers achieved by test students using the proposed recommender. As can be seen from Subsec. 3.3, the recommender system was optimized according to several learning indicators which could also be used as performance metrics. However, at this stage, we decided on this simple metric in order to avoid the problem of using the same evaluation metrics as the optimization objective function.

These results are compared to the baseline which is the average correctness of answers achieved when question order is assigned randomly.

4.4 Results

Results show that student success slightly improves. The baseline performance (randomly assigned questions) in terms of average correctness of answers is 2.51 out of 5 (50.2%) questions. No correction for guessing answers [18] was applied. Results of the proposed algorithm are given in Tab. 1; the baseline was improved from 50.2% to 62.3%. Observe that students covered only 22.1% of all questions but they covered 58.9% concepts involved. This is in part due to the fact that students were not testing the system through the whole content, but just testing it in a few sessions (5 questions each session).

n	Cor. quest.	Cov. quest.	Cov. concepts
55	62.3%	22.1%	58.9%

Table 1: 55 students participated the test, they covered 22.1% of questions answering 22.1% correctly while covering 58.9% of involved concepts.

5 Discussion and conclussion

In this paper, a concept map-based recommender system for student activities was described. The evaluation used a test domain of matrices and linear algebra, and the recommendation items were questions posed to the students in an online session.

Results show a slight improvement in terms of correctly answered questions. The percentage of covered concepts is encouraging. Results are not generalizable since the student test group is very heterogeneous and not representative.

The main performance factor is estimated to be the automatic concept map generation algorithm. As shown by several studies, it is a challenging task for a fully automated procedure. As such, the main current effort aims at the improvement of this procedure including specific concept map generation (e.g. from keywords, from student past activities, etc. to concept map weighted merging and simplification procedure).

Future work will include improvements in Concept map generation together with more intensive testing. Also, the impact of the algorithm will be compared to a baseline selected as a linear ordering of questions as assigned by the course designer.

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