Building Test Recommender Systems for e-Learning Systems

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ABSTRACT

Modern e-Learning systems offer a wide variety of functionalities, from basic ones like accessing courses or online communication to more advanced ones like providing personalized feedback or assets. The learning environment can benefit from recommendations by providing students with tailored learning pathways, or assessment materials, thus ensuring the personalization and adaptation of the e-Learning platform to the student's individual needs. It can also allow for tracking and evaluation of the learner's progress, showing potential for improving the user experience for both students and professors. This research aims to investigate how a recommendation system can be used for building personalized tests in the context of education. The system's main goal is to improve the efficiency of the overall testing activity of learners by recommending questions relative to their knowledge level. It extracts input data based on past test results and uses learning analytics to provide a personal ranking of questions for each student based on their personal and their peers' experience with the studied concepts in a course. Contributions are foreseen on four different levels. First is the design and implementation of the recommendation algorithm. Second, raw data needs to be pre-processed by defining and extracting the features that can be used as input for the recommendation algorithm. Third, a post-processing step is needed for applying data analytics, rules and constraints to the resulted model in order to obtain proper recommendations. Last but not least, the presentation layer must be updated by providing a user interface for students and professors.

Keywords

e-learning; recommender system; user customization

1. INTRODUCTION

Most recommenders aim at providing recommendations to users based on their personal likes and dislikes. These systems use a specific type of information filtering technique that attempt to recommend information items to the user. In an e-learning environment, both personal and collective information should be taken into account, as well as the links/relationships between the concepts covered in a chapter, as these could provide an insight into the level of knowledge of the student and uncover the missing gaps in the learning process a student is going through for each course.

Using a recommender system, in the context of e-assessments (i.e. online tests), enables the personalization and adaptation of the e-learning platform to the student's individual needs. The information it provides also allows for the tracking and evaluation of a student's progress by both learner and professor. By further analysing it, the information can provide a better understanding and structuring of the material which follows in subsequent chapters, thus providing a more logical chaining of concepts covered for a specific course.

Question recommendations in a test can provide a useful tool in the learning process of students for both the student (through tailored learning paths) and professor (by employing the means of defining and refining learning materials to a more logical and easy-to-understand chain of topics) with a direct impact in the application domain of e-Learning.

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2. RELATED RESEARCH

Basic techniques for recommender systems (collaborative, content-based, knowledge-based, and demographic techniques) have known shortcomings such as the well known cold-start problem for collaborative and content-based systems (what to do with new users with few ratings) and the knowledge engineering bottleneck [7] in knowledge-based approaches, as Wikipedia states in [8].

According to an MIT tutorial for SVD (Singular Value Decomposition) [3], calculating the SVD for a matrix M (i.e. finding U and V such that $M = U \times \Sigma \times V$) reduces to finding the eigenvalues and eigenvectors of MM^T and M^TM. The eigenvectors of MM^T make up the columns of U, while the eigenvectors of M^TM make up the columns of V. Also, the singular values in Σ are the square roots of eigenvalues from MM^T or M^TM. These singular values represent the diagonal entries of the Σ matrix and are arranged in descending order. They are always real numbers. If matrix M is a real matrix, then U and V will also be real.

Recommender systems for e-Learning platforms are based on many approaches like web mining and information retrieval [4], recommender systems based on the context [13] or even using intelligent agents [14]. One interesting approach of using collaborative filtering in e-Learning systems [2] was to assign greater weights for users with higher knowledge than users with lower knowledge and the authors propose some new equations in the nucleus of the memory-based collaborative filtering. Another interesting paper, presenting clear results regarding recommender systems in smart e-Learning environments shows their approach [9] along with their encouraging results and their aim to extend the system for more faculties.

A concept map or conceptual diagram is a diagram that depicts suggested relationships between concepts, which are defined as "perceived regularities or patterns in events or objects, or records of events or objects, designated by a label" and are depicted as shapes in the diagram [10]. It is a graphical tool that instructional designers, engineers, technical writers, and others use to organize and structure knowledge [6].

3. RESEARCH QUESTIONS

Research questions that need to be addressed are primarily related to the area of recommender systems and selecting the proper recommendations in the context of e-Learning. The main focus is on the actors, which are both learners and professors using the system. The following questions arise:

Q1. How can a recommender system be efficiently used in the context of e-Learning?
A recommender system can give the student personalized tests, find learning gaps and suggest areas of improvement or concept revisions.

What data can a recommender system use as input?
Data from previous usage of the system by the student and his/her peers is required for a good output of the recommender system.

Q2. Are all types of recommender systems "recommended" in e-Learning?
There are majorly six types of recommender systems which work primarily in the Media and Entertainment industry: Collaborative, Content-based, Demographic based, Utility based, Knowledge based and Hybrid recommender system. Which type is better suited for the e-Learning system or how can these types be merged to obtain the most of the recommender for specific target (students of a specific group age, area of study etc.)? This is one of the questions that the research aims to answer.

Q3. How can the recommender system help the student in his/her learning process?
For a student, the recommender system can potentially help the student see his/her current level of knowledge, provide ways of revision and improvement, provide a general indication of the final results before a potential test and assess accumulated knowledge over time.

Q4. How can the recommender system help the professor in the learning process of his/her students?
For a professor, the recommender system can potentially show a student's progress, point out the difficulties each student has at certain areas of a course and moments when he/she might need a tutor's help, provide hints on how a student is expected to perform at a test/exam, provide insight on how well the students acquire new concepts based on past ones, identify out-of-order topics or missing information from the course materials.

4. PROPOSED CONTRIBUTIONS

4.1 Research Context

Classical on-line learning environments aim to create a support for learners to get their learning resources and take exams or to be evaluated by the professors; the next learning environments should be more personalized, analyzing each users' needs and adapting the interface to their concerns and needs. If we consider a usual learning platform, we can say that the learning progress should be considered to be good by the professor for every student, but not all the students have the same needs, nor do they have the same performances at school. A tool that employs a recommender system can create intelligent interfaces capable to adapt to the users' specific needs, to aggregate learning materials in order to provide the content necessary for the user at that moment and to create an order ranking over the learning materials and among students.

4.2 Research Activities

The main goal of this research proposal is to enhance the effectiveness of the e-Learning environments. In order to achieve this goal, three prerequisites need to be accomplished.

4.2.1 Prerequisites

P1. Analysis and formalization of recommender system's usage in e-Learning An in-depth study should be conducted in order to assess the way recommender systems are currently used in the e Learning environment. Furthermore, an investigation on new ways to integrate them, along with other information retrieval algorithms for the definition and refinement of the input and output data of the recommended items, into existing e-Learning tools should be made.

P2. Adaptation and definition of data analysis pipelines for input data provided by e-Learning systems A data analysis must be performed on data available for processing in the e-Learning environment in order to filter out unnecessary data, fill in missing information and/or transform it into input data which can be then used by the recommender system. The format of the input data for the recommender system's algorithm must be defined and updated as the internal processes of the algorithm itself are also updated.

P3. Application and validation of recommender system in student's and professor's activity on e-Learning system The aim of the recommender system is to prove itself useful in the context of an e-Learning environment. For this, the recommender system must be integrated in tools that have real application in e-Learning. Upon using and refining its process, a validation must be performed in order to ensure that it provides an increase in productivity of the learning process of the students and the objective evaluation of the professors. For this, certain evaluation methodologies or metrics have to be devised for a reliable evaluation of the improvements and benefits the new system offers when using the recommender system.

4.2.2 Methodology

Figure 1 presents a generic workflow with 3 main layers and 4 general steps for designing, implementing and validating a recommender system in the context of e-Learning. The division of the system into four steps is inspired by [1] in which the authors propose a framework for an adaptive learning of MOOCs. We identify 3 actors that influence the system: learners (i.e.: students), professors and data analysts.

Data Representation Layer. From this layer, data needs to be gathered. Most systems use a database or log files to keep raw data about users and their activity. The data is taken from this layer and transformed as needed for the recommendation process. This is a layer responsible for providing data input for the Learning Analytics layer. The steps that manipulate data from this layer are the Data gathering and Pre-processing steps. The actors involved in this layer and the associated steps are the data analysts.

Learning Analytics Layer. This layer is responsible for data processing and data analytics, transforming data, defining rules and constraints, preparing data for the algorithms used and applying the final recommendation engine. It communicates with the Data Representation layer for data input and Presentation layer for data output. The specific steps for this layer are the Pre-processing step (for transforming data to the needed format and building data models) and Recommendation step (for employing needed rules, constraints, custom logic and algorithms needed for the recommendation engine). The actors involved in this layer are both data analysts (for building the data model, defining pre-processing logic, rules and constraints, defining and refining the recommendation engine based on experimental results) and users interested in the system (learners and professors) as they are the ones that enforce the domain-level constraints.

Presentation Layer. This layer is responsible with defining the graphical user interface of the system and providing services to the users, such as learner self-testing and online communication (a key feature in modern e-Learning platforms). It communicates with the Learning Analytics layer for data input. The Presentation step is specific to this layer and handles the user interface aspects of the end-user application. The actors involved in this layer are learners and professors which actively use the features of the system.

5. CURRENT STATUS

As research status, three papers have been written so far and an incremental approach is being used to actively improve the recommendation engine based on past results.

In paper [5], which I have co-authored, a custom recommender system based on SVD has been implemented in the context of extending an existing e-learning platform used for distance-education students enrolled in our local university. The recommender has been subsequently tested on students from our university in collaboration with professors for defining the pool of questions and concept maps in the system, with small adjustments being applied after each year of study. The initial implementation of the recommender, presented in [5], was relying on a collaborative SVD algorithm applied on aggregated test results from all students enrolled in a course. The algorithm selected the proper questions from the available pool of questions, with the only constraints on question repetition and unknown question exploration in case of no questions in the initial aggregation matrix. This approach suffered from the cold-start problem, since it first resulted in generating random recommendation vectors and gradually getting to the desired recommendation mechanism.

Data visualization was implemented in the second paper [11] by building a concept map for the course and assigning concepts to each question in the system. This way, a concept map status could be generated for each student after each test, in which the concept would be colored in red/orange/green to highlight the progress of the student. Greener nodes would indicate that a student is starting to answer most questions in the concept correctly, while redder nodes would indicate that the student answered most questions in the concept incorrectly. Orange nodes were the middle point of the representation, signaling a half-correct distribution of the answers for that concept.

After the first experiment, a custom validation mechanism was implemented, as part of the third paper [12], in which a special function called Correctly Recommended Concepts (CRC) function was implemented. The CRC function was defined as a set of CRC values, plottable for each individual student. A concepts for revision functionality was implemented, which enabled the professor to mark which concepts should be recommended next based on a previous test result of a student. The CRC value was then computed for each test of a student (except the first, for which no revision concept would be defined) as the accuracy of matched concepts by the recommender system relative to the revision concepts, marked by the professor, on a scale of 0 to 1. More specifically, it was computed by dividing the number of matched concepts to the total number of concepts in the test. These values were then plotted for the student on a timeline having the test number on the X axis and CRC value on the Y axis. By observing the slope between tests, the relative performance could be computed by distinguishing 2 main categories of situations: *negative slope* for learners with a lower performance for the student in the next test and *zero or positive slope* for improvements in the performance of the student in the next test.

A second experiment has been conducted, with results to be analysed comparatively for students in a subsequent year of study as part of an incremental approach of improving the system based on results from previous work. The recommendation engine has been refined to consider the order defined in the concept map when choosing questions from the concepts. Also, the cold-start problem has been eliminated by using the old model alongside the new one, as previous test results from the former year have not been deleted from the database and will be used when aggregating input matrix data for the recommender system.

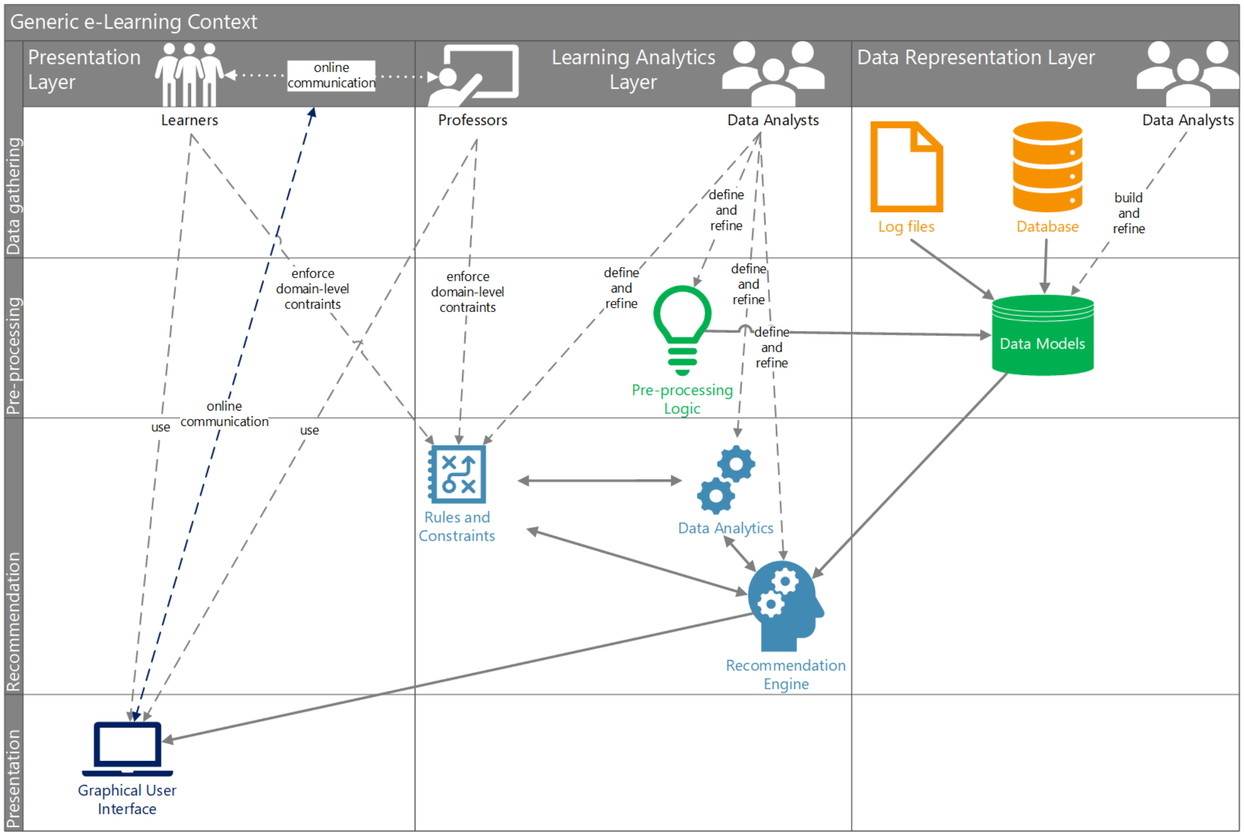

Figure 1: Generic layers and steps for defining a recommendation engine in the context of e-Learning

6. CONCLUSIONS

The main goal of the recommender system is to provide a personalized set of questions depending on both their current status and the status of their peers that have previously taken tests. Visual analytics of the experimental results in terms of knowledge coverage of the concept map show promising initial results.

Future work may regard not only the correctness by which the recommender manages to assign questions from right concepts, but also checking if recommended questions improve the student's learning rate or knowledge level. More work needs to be performed in terms of defining and integrating appropriate quantitative and qualitative metrics for measuring accumulated knowledge with and without the usage of the recommender system. Another future plan is providing the recommender as a software package such that integration into other e-Learning platforms can also be achieved.

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