From LMS to LXP: Extending Moodle with AI-based Recommendations for Learning

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Abstract. We propose a Moodle-based LXP (Learning Experience Platform) architecture that extends the classical Moodle LMS (Learning Management System) into LXP. The extension of the Moodle LMS to an LXP is developed to improve the learner's motivation and to enable personalized learning. The first component in our architecture of the Moodle - based LXP is a recommender component based on Artificial Intelligence (AI). It helps learners by proposing appropriate learning resources based on the content they are currently studying. These recommendations are derived from metadata of the learning resources, such as predefined descriptions, number of views, ratings, and comments on the resources.

Keywords: Learning Management System; Learning Experience Platform; recommender component.

1 Introduction

In the last decades, Learning Management Systems (LMS) have been deployed in various educational institutions [1], [2]. An LMS is mainly used to organize and support online learning and includes learning content presentation, communication tools such as forums, tools for tests and exercises, and administrative functions [1], [3]. In practice, the teacher-centric LMS is mainly used for administrative purposes such as course announcements and content distribution, while the effective support of the learning process is not considered [1]. In addition, an LMS provides an identical service to all learners rather than a personalized learning, which would result in an environment that learners perceive as more relevant and motivating [4]. Advanced learning platforms, called Learning Experience Platforms (LXP), are designed to help learners to experience personalized learning by curating content from various sources and recommending it to other learners individually based on their current learning level and personal learning preferences [5]. The content of each particular course can be enhanced through Open Educational Resources (OER) created by other educators and shared by the public to support learning and knowledge sharing in society [6]. In addition to AI-supported content curation and AI-based recommendation, other features of an LXP include an attractive, social media like user interface (user experience), support for social interaction by integrating feedback and content rating features, and search for specific content [7]. Additionally, in many cases, gamification and reward systems are incorporated into LXPs to promote motivation.

In this paper, we present an architecture that extends Moodle [16], an open source LMS widely used in higher education [17], into an LXP. We identified the main components of our approach and designed the core architectures consisting of a recommender component, recommender plugins, and a feature to rate and provide feedback for learning resources. Recommendation systems in the educational domain are approaches for retrieving and filtering learning resources and similar profiles to provide suggestions for learning resources that are most likely to be of interest to learners and thus support personal learning [18], [8]. The interaction between learners and learning resources can be analyzed and evaluated for aggregating learning resources into a list of personalized recommendations for the learners [4]. In general, recommendation systems can be categorized into content-based recommendations and collaborative recommendations [20], [9]. A hybrid approach can also be applied by combining both content-based and collaborative recommendations [9].

The proposed recommender component in this paper is based on course data and anonymous user data. It supports each learner with appropriate internal or OER learning resources to enable personalized learning. The rating system of a recommender component for learning resources within Moodle gives students the opportunity to rate and review all kinds of learning resources. In addition, the recommender component also contains content-based recommendations that recommend a list of learning resources that are similar to the queried learning resource. The description of the learning resource is compared with the description of other learning resources in the course. We have also designed a collaborative recommendation system component which implements trends in learning resources based on the number of views on the learning resource.

To the best of our knowledge there is an approach to extend Moodle with recommendations proposed by Vera et al. They proposed an educational resource recommendation system based on user preferences and needs that focuses on the knowledge level of students using Python and Moodle [15]. The input data for the recommendation system algorithm are survey data and students' academic grades [15]. In the paper [15], the education resource recommendation system is a collaborative recommendation system, which is different to the content-based recommendation system for similar learning resources and the collaborative recommendation for trending learning resources that we have designed. They used totally different data without an LXP.

2 Enhancing Moodle to an LXP

For many years, at Offenburg University of Applied Sciences the Moodle LMS has been used to provide students with learning resources for their courses. Teachers and students are used to the system. A lot of Moodle content was created, and many features were implemented in the courses, e.g. tests or gamification elements. Hence, replacing the Moodle LMS with a completely new LXP system was not an option. Instead, we decided to gradually expand Moodle into an LXP with AI-based recommendations for learning, so that the existing features of the original Moodle will remain available.

In the summer semester of 2023, we conducted an explorative survey at our faculty in various courses to understand which components of an LXP are important from students' point of view. Ninety-eight students provided their anonymous opinions on AI-based learning recommendations in an online questionnaire. By learning recommendations, we mean suggestions for a learner which learning content could or should be learned next. Examples could be: "Read chapter x in book y" or "Open the following link and attempt the corresponding quiz."

First, we wanted to know if and how students use external learning content. The survey results indicated that many students make use of external learning contents. For example, more than 80% of the participants often pursue external resources to clarify

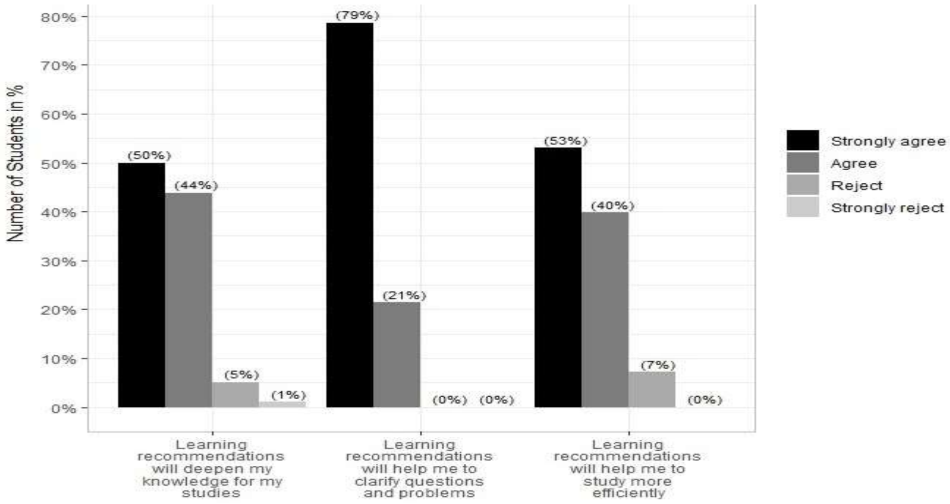

Fig. 1. Expected effect of learning recommendations (n=98).

open questions. And more than 60% utilize external learning contents to prepare for the examination. There are more options for using external content, such as repeating the learning content, exercising, or learning more about the topic. But here, the frequency of usage is lower, which means between 20% and 30% of the participants answered with "often." Regarding the learning recommendations (see Fig. 1), more than 90% of the participants stated that they would use them to deepen their knowledge for their studies (50% strongly agreed, 44% agreed). Similarly, more than 90% of the participants expected that learning recommendations will help them to study more efficiently (53% strongly agreed, 40% agreed). And 100% of the participants believed that learning recommendations will help them to clarify questions and problems (79% strongly agreed, 21% agreed). In addition, 80% (31% strongly agreed, 49% agreed) indicated that they agreed to make their anonymized data available for learning recommendations. However, only 40% of the participants would possibly provide non-anonymized data for personal learning recommendations (10% strongly agreed, 30% agreed). Many students are also willing to support a recommendation system through ratings and tags. 86% of participants would rate learning resources with 1 to 5 stars (agreed and strongly agreed), and 59% would tag learning resources to support content recommendations. In contrast, only 31% of the students are willing to write content summaries for learning resources. Although, more than 85% of the participating students prefer to select learning resources based on summaries. Although our study has limitations, especially due to the selection of students at the faculty of media, we consider for the Moodle LXP:

- In the group surveyed, the demand for learning recommendations is very high.
- Recommendations based only on anonymous data should be provided. Also, recommendations based on personal data could be available for those students who are willing to provide their personal data. Hence, we need one pool for personal and another for anonymous data.
- External learning content seems to be helpful for many students. As the collection of high-quality external learning resources is time-consuming, a component for content curation will be very important for Moodle LXP.
- It could be helpful if students evaluate and rate the contents when a new external content is integrated into a course, and best of all, provide short summaries for other students. In general, a component for ratings is mandatory so that rating data of external and internal learning resources for later recommendations can be collected.

3 Architecture of the Moodle-based LXP

According to the results of the survey, we designed a detailed architecture of the Moodle LMS and the recommender component. Fig. 2 depicts the relationship between the recommender component and the Moodle LMS. The recommender component is designed separately from the LMS, because hardware separation between the component and the original LMS can reduce the load of processing on the LMS. In general, loose coupling of recommender components and Moodle LMS helps to keep Moodle independent. The productive Moodle system (software and hardware) of the university is used for numerous courses from various teachers and students for the learning processes. Moodle is indispensable for the university. The proposed recommender component makes use of anonymized data such as descriptions and user-specific data such as ratings and number of views. The recommender component which is shown in Fig. 2, gathers and retains both anonymous and individual learner data.

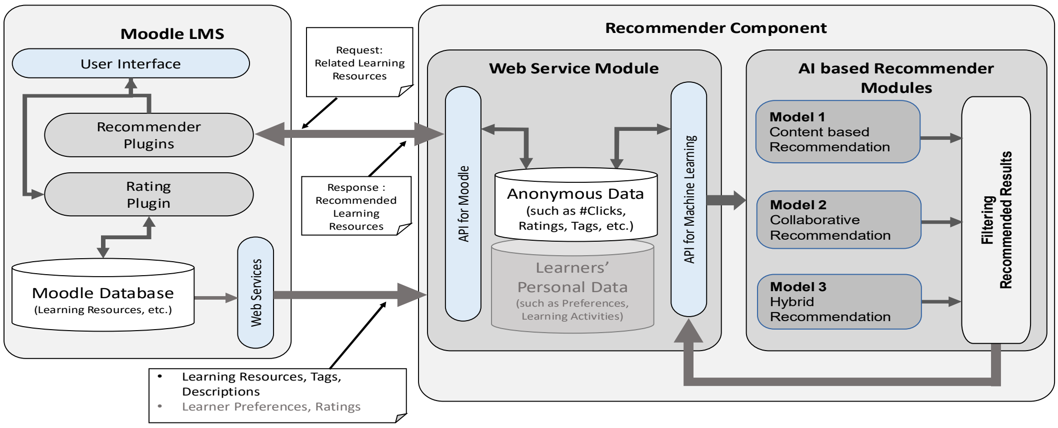

Fig. 2. The architecture of the Moodle LMS and the recommender component.

The main task of the recommender component is to use AI algorithms to examine the most appropriate learning resources and then to provide the results to the recommender plugin. In the current phase of the project only anonymous data is used for providing recommended resources. However, in later versions, we will also collect personal data from students, if they agree to provide their data. The personal data will include learning preferences and information about their learning activities. The data that describes the learning resources and learning behavior can be used for the recommendation process. When a learner in the Moodle system accesses a learning resource, the request to the recommender component is sent. The component then creates a corresponding list of recommended resources. The resulting list is sent to Moodle and presented to the learner in near real-time.

In Fig. 2 we can see that the recommender component is composed of web service module and AI-based recommender Module. Web service module's primary function is to store/transfer data between Moodle LMS and itself. There are two API definitions in the module: one which faces towards Moodle LMS (i.e. provides access to stored data to Moodle plugins) and the other which provides/stores data to/from various machine learning algorithm contained in the AI based recommender module.

4 Moodle LXP Implementation

For the specified architecture, a few Moodle plugins have already been implemented and integrated in our productive Moodle system. These include similar learning resources, rating systems, trending learning resources. In the current phase of the project, we have implemented several block plugins for Moodle LXP that display a list of relevant resources based on the selected content and the user interaction to the courses. When a learner chooses a learning resource (by clicking at it or by hovering the mouse to it for at least two seconds), the ID of the resource is sent to the recommender component, which in succession, computes recommendations by using TF-IDF and returns the recommended learning resources to the plugin, effectively a bidirectional communication. In addition, trending resources listed in Moodle are processed using Z-Score. Learners will now see a list of resources relevant to the resource in question and a list of trending resources as shown in Fig. 3.

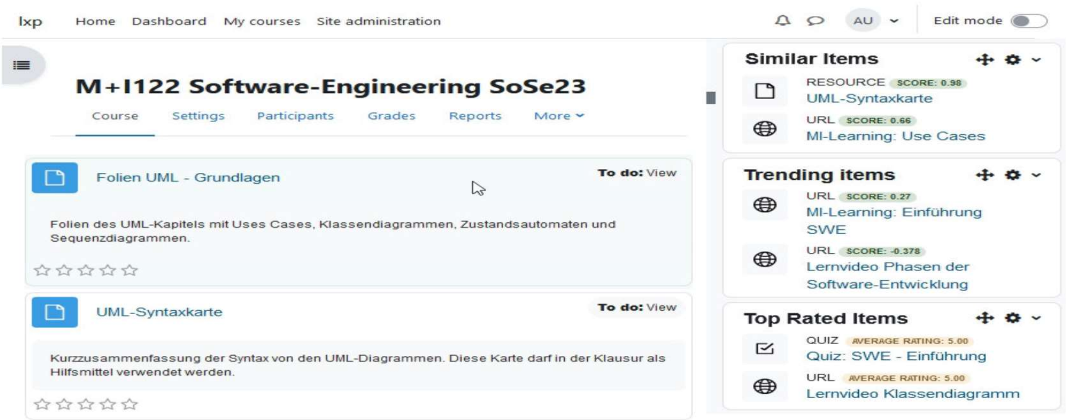

Fig. 3. The similar items, trending items and top-rated plugins for Moodle LXP.

4.1 Content based recommendation

In content based recommendations, the similarity between several content resources can be compared by using metadata that describes these resources. Metadata of resources can be tags, keywords, or descriptions. The content based recommendation uses various methods to analyze the similarity between metadata of learning resources. It uses Natural Language Processing (NLP) which is a subfield of AI that enables machines to understand information created by humans [11]. The Term Frequency and Inverse Document Frequency (TF-IDF) is one of the text processing approaches used in machine learning methods for NLP [12], [13]. TF-IDF is one of the most popular methods for measuring how important description words are to a learning resource document in information retrieval [9], [10], [11]. It is a weighting approach to describe resources in the vector space model so that resources with similar metadata will be rated similarly [23]. Metadata that describe resources can be created, assigned, and collected as input for the recommendation process to generate resource recommendations to users [22]. Metadata such as descriptions for resources or products can affect the quality of recommendations offered by recommendation systems [21]. TF-IDF implemented with SpringBoot framework has been used to recommend learning resources and courses [29]. In our project, we use TF-IDF to model the similarity between different learning resources in a course module. We utilize the `sklearn` [25], a Python API with libraries, to extract TF-IDF features and calculate cosine similarity.

Information of a course such as course ID, resource ID, resource name, resource type, and description retrieved from the moodle database are stored in the LXP server database. Learning resource types can be URL, resource, folder, quiz, etc. In content based recommendation, resource descriptions, course IDs, and resource IDs are inputs for the recommendation algorithm that analyzes the similarity between learning resources in a course. The result of the algorithm is a list of learning resources that are similar and relevant to a queried learning resource as indicated by the Cosine similarity score. Fig. 4 shows the sequence diagram for the request and response process of Moodle's similar items plugin and web service module of the recommender component. The list of similar learning resources is sent from the AI-based recommender module to the web service module of the recommender component in the form of JavaScript Object Notation (JSON) with the format schema as shown in Fig. 4. In the JSON response, `coursemodules` are the list of similar resources returned from the recommender component. The `cmid` provides the ID of the learning resource and `courseid` is the course the learners are currently viewing.

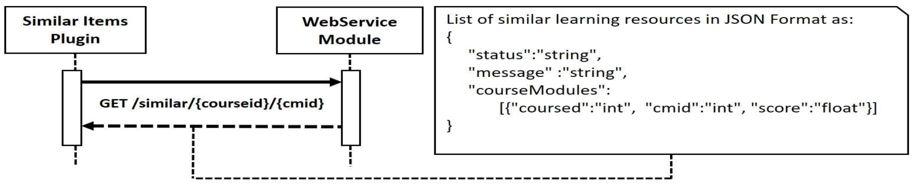

Fig. 4. The sequence diagram of similar items plugin and web service module of recommender component with response in JSON.

4.2 Collaborative recommendation

Collaborative recommendation systems, as the name suggests, takes into consideration what other users interacted with in the past and makes recommendations based on these conditions. Schafer, et. al. thus recommended this type of recommendation system as "people-to-people" [26]. It is also considered a popular and widely implemented system. The system evaluates learners' previous behavior, expressed in the form of ratings, feedback, number of clicks given by learners, to generate recommendations for other learners [24]. New learners can utilize this information to find resources that fit their needs. This process also facilitates finding a good learning path, as a new learner is following the successful steps performed by the other learners.

4.2.1 Rating system Collaborative systems make use of rating and comment features to know how likely a learning resource is recommended to other users. Originally, a rating system in the Moodle LMS is only available for forum topics, database items, and glossary items. Moodle does not provide an overall rating system for learning resources. In order to cover all learning resources in Moodle, we implemented a rating plugin. The new rating plugin allows learners to rate all kinds of learning resources in Moodle like book, wiki, quiz, page, file, URL, etc. Users can rate learning resources with one to five stars, and they can assign a short review to the resource, such as "The video explains the topic excellently". We calculate the average rating given by all the learners and present it on the Moodle LXP. But the ratings are always presented anonymously.

The result of the assessment for each resource is displayed in the top-rated resources block. The top-rated and displayed resources become a recommendation for other learners to choose. Learners can easily visit resources based on ratings given by other learners.

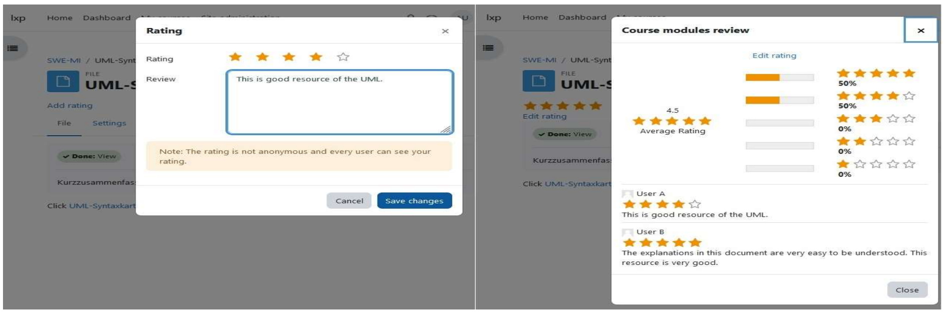

Fig. 5. The window popup of course modules for adding and reviewing ratings.

As a first step, the course Software Engineering was extended with various OER, including learning videos, chapters of e-books from our library, and websites from the internet. When learners select one of the internal or external resources, such as a file or a video, they will see the page of the resource they have selected. They can rate it in two different ways. Fig. 5 shows the user interface when they click the add rating link and the review rating link. The rating data will be stored in the Moodle LMS database. Learners and teachers can view the rating results of each resource.

4.2.2 Trending Items Trending (or Fad) generally refers to describing topics, hashtags, or keywords that are currently popular or gaining a lot of attention. Items that are trending follows a positively skewed, escalating slope, unsteady asymptote and a rapid declining slope [27]. Understanding popular resources can help us identify relevant or significant learning materials. With that knowledge it becomes easier to make effective decisions.

There are some things to consider while populating trending items such as number of clicks, rate of clicks (number of clicks per time period) and the baseline level of clicks. Since, the trending items will only be displayed in a few courses at the moment, the baseline level of clicks is considered zero. That means, there is no minimum number of clicks that an item should have before it is even considered for calculating the score. There are various methods which we can use to calculate trending items such as Slope analysis (Mann-Kendall and Sen's slope analysis), standard score (z-score) [14] and chi squared tests [28]. However, at the moment, the standard score is selected to calculate the trending items.

Trending items are displayed by a Moodle's block plug-in and currently all the data and calculations are stored in the Moodle's database. In the future, the recommender component will store the data and the calculations also will be performed by the recommender module. The plug-in's architecture is based on strategy pattern used in software development to make it flexible. Having this flexibility to Moodle's plug-in brings us ease in further research and testing of various algorithms in the future. Fig. 6 shows such a design.

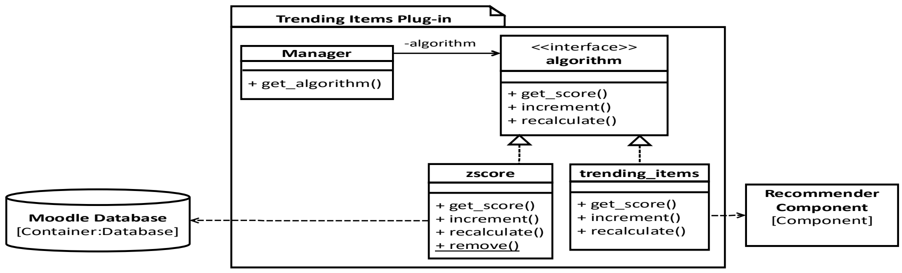

Fig. 6. Design of trending items plug-in and its interaction with recommender component.

The plug-in records the number of clicks for a certain time period. For instance, seven days. These seven days are called a window. The window is divided into seven panes each of width of one day. The window then slides each day, removing the last pane and adding a new pane corresponding to the current day, effectively becoming a sliding window.

Standard score (z-score) indicates how many standard deviations a datum (number of clicks) is above/below a standard deviation. So by definition, we calculate mean and standard deviation on the data. We calculate average number of clicks (mean) and standard deviation by using the data from history panes. Then we calculate the average z-score of the current panes. This is further illustrated in Fig. 7. Calculating average and z-scores for all activities/resources of a course takes time. So there is a scheduler task in the plug-in which is run daily.

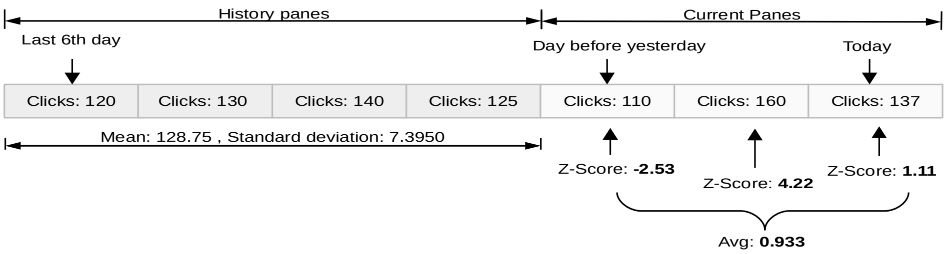

Fig. 7. Window panes with calculated z-score.

5 Conclusion and Future Work

In this paper we presented an architecture for an LXP built on top of a classic Moodle LMS. We designed and implemented initial parts of the recommender component and the initial plugins: a content based recommender plugin for similar learning resources, a collaborative recommender plugin for trending learning resources, and a rating plugin for all types of learning resources in the Moodle LMS. Based on the architecture presented, a separate server was set up for the recommender component and the interfaces to the productive Moodle server were defined.

For recommending learning materials, we have curated a variety of open educational resources and extended several courses in Moodle with these resources. We have already integrated the rating plugin in few courses in summer semester of 2023, and now we are in the process of collecting feedbacks from the students. Additionally, we are planning to deploy similar items plugin, trending items plugin in the following winter semester and gather response and feedbacks from the students to further evaluate Moodle as an LXP platform.

In the next steps, we will implement of various components including hybrid recommendation systems and filtering modules. Furthermore we plan deeper investigations of various AI methods and different AI-based recommendation algorithms to support tailored and personalized learning.

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