Question Recommendation for Online Learning Recommendation Systems based on Rule-path in Knowledge Domain

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Abstract- This study aims to perfect the online learning recommendation system. Online learning recommendation system provides recommendations to learners in the form of material links, learning materials that can be learned by learners, learning activities and others. This study provides recommendations for questions that are tailored to learning outcomes and bloom taxonomy levels. Using knowledge-based and rule-path, recommendation questions are given to learners who are predicted to be of value and are unlikely to achieve in their learning. The results of this study were evaluated using root means square error and produced a question-based recommendation system model for online learning. Our contribution in this research is machine learning based questions which are processed based on learning outcome outcomes and refer to bloom taxonomy levels.

Keywords: Recommendation System, Online learning, Question recommendation system, Rule-path, Knowledge-base, Personalization, Question generator, Machine Learning.

I. INTRODUCTION

The recommendation system for online learning continues to develop and innovate for the perfection of the system being built. The recommendation system has proven to be an effective solution to the problem of information overload received by online learners. The recommendation system is also stated as an effective way of providing more personalized learning for learners. Using a variety of methods and approaches, various models of system recommendations for online learning continue to grow and produce greater accuracy with many evaluation models. The methods and approaches used are collaborative [1] context [2], knowledge-base [3], hybrid [4]. The resulting recommendation system also varies, the recommendation system based on student preferences [5], learning style [6], suggestion [7][8].

But until now, the online learning model still uses the same resources even though learners come from various circles with different characteristics. The focus of the research object of the previous research was the students themselves. But what about the teacher? We understand that the quality of the learner is also a determining factor for the success of the learning system. The quality of learning in online learning can be expressed as the quality of material delivered to learners. Based on that, this research was developed. Different characteristics and learning patterns of learners cannot be completely overcome by just giving one recommendation. What about the learning interests of learners? Based on the theory of Cognitivism, constructivism and behavioristic, it is known that there are many factors that influence the learning success of students. And, often learners repeat the material provided does not fully help their learning achievements.

Complementing our previous recommendation system (see Figure. 1) which produced a material link as a reference in providing recommendations for students based on predicted values, so in this Research we provide recommendations in the form of questions. The questions are given based on the results of the predicted values which are then mapped to the target learning outcomes. from learning outcomes 1 to 6. The questions given have been adjusted to the learning outcomes of each course and bloom taxonomy level. The list of recommended questions is generated using the question generator engine. (We have published research related to the question generator in another paper).
II. LITERATURE REVIEW

2.1. Recommender System

The recommendation system in education has a different focus area than the recommendation system in ecommerce, music and others. The recommendation system in education provides material recommendations, exercises and learning activities to students [9]. Recommendations are given based on the similarity of the student's profile [10] with previous learners, or based on the success of previous students in the same course [11]. Recommendations can also be given based on the similarity of student learning models in one subject with other subjects. A variety of recommendations are made with the aim of maximizing student learning outcomes and learning achievements.

2.2. Question Generator

[12] Concludes that there should not be an analysis of certain types of questions or how the relationship between questions and statements looks like, this needs to be done until we have a strong idea of the general question as well as a clear idea related to the ideal question. completeness of the question stated adequate and complete by examining wh-questions. Our previous research has produced questions with various phrases and has been tested to users regarding the results of questions created by the question generator [13]. The high percentage of the results of questions understood by humans makes this question generator engine used successfully. And, on the other hand, completing our research on the recommendation system, the question generator becomes one of the recommendations for student learning.

2.3. Rule Path

Several studies using rule mining have been successfully carried out [14][15][5]. With the same concept, this study uses a rule-based path based on assessments of student learning outcomes that have been outlined in the course outline of each course.

III. METHODOLOGY

3.1. Research Framework

The conceptual framework of the proposed recommender system in this study can be described in the following diagram. As can be seen from Figure 2, the framework comprises the main processes namely:

1) question prediction,
2) exam prediction,
3) exam references,
4) question recommendation system evaluation,
5) question recommendation system performance.

![Figure 2. The model of the question recommendation system](image)

### 3.2. Dataset

The dataset for this study can be categorized into two categories. First, secondary dataset collected from BINUS Online Learning repository comprises of student individual records from 2017 to 2018 (period 1711, 1712, 1721, 1722, 1811, 1812, 1821, 1822).

### 3.3. User-collaborative Filtering Model

Recommender system approach in this study is user-collaborative [16] filtering method whose inputs are:

1) students of BINUS Online Learning students as users;
2) mandatory courses as items;
3) student achievement.

### 3.4. Rule-path Material Suggestion

The aims of the learning material suggestion is to provide the targeted students additional material to improve the predicted learning outcome. The rules as basis for material suggestion in this study are as follows table 1:

<table>
<thead>
<tr>
<th>Boundary Values of predicted FIN ($\hat{F}$)</th>
<th>Set of Learning Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{F} &lt; 10$</td>
<td>LO1-The system analysis and information system development, LO1-Requirement determination, LO1-Use-case analysis, LO2-Process modeling, LO2-Data modeling, LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.</td>
</tr>
</tbody>
</table>
10 \leq \hat{F} < 20
LO1-Requirement determination, LO1-Use-case analysis, LO2-Process modeling, LO2-Data modeling, LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

20 \leq \hat{F} < 30
LO1-Use-case analysis, LO2-Process modeling, LO2-Data modeling, LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

30 \leq \hat{F} < 40
LO2-Process modeling, LO2-Data modeling, LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

40 \leq \hat{F} < 50
LO2-Data modeling, LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

50 \leq \hat{F} < 60
LO2-The design phase, design strategy, and architecture design, LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

60 \leq \hat{F} < 70
LO3-Program design, LO3-Data storage design, and LO3-Moving into implementation.

70 \leq \hat{F} < 80
LO3-Data storage design, and LO3-Moving into implementation.

80 \leq \hat{F} < 90
LO3-Moving into implementation.

### 3.5. Recommender System Evaluation

Performance of the proposed recommender system is used to measure deviation of predicted FIN score of the tested course from its actual FIN score using the following metrics: Mean Absolute Error (MAE) \[17\] and Root Mean Square Error (RMSE) \[18\]. MAE is the most commonly used and MAE is a measurement of the deviation of recommendations on the specific value of the user. Each metric is formulated as follows:

\[
\text{MAE} = \frac{1}{n} \sum_{u,i} (p_{u,i} - r_{u,i})^2 \tag{1}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{u,i} (p_{u,i} - r_{u,i})^2} \tag{2}
\]

### IV. RESULT AND DISCUSSION

#### 4.1. Knowledge-based
At this stage the questions are built with a level of difficulty based on the level of taxonomy bloom, learning objective and adjusted to the learning outcome. Questions are built based on the topics in each achievement towards the target learning outcome. These questions are given to learners and then rated. The rating is determined based on the highest percentage of questions with the correct answer. The results of mapping questions on taxonomy bloom, learning objective, learning outcomes to rating, we recap as shown in Figure 3.

4.2. Rule-path

The rule path that we use in this study refers to the evaluation based on the assessment of each course listed on the course outline (figure. 4). The intended assessment is given to students to determine the extent to which learning targets have been achieved by students based on the rule path in table 1.
4.3. Question generator

Figure 5 is a list of questions generated based on material links recommended to students. The learning material is used as an input engine for generating questions and generating questions based on the level of difficulty and refers to the level of taxonomy bloom.

The results of this study have been tested in a number of small cases using a small number of respondents. The results are quite optimal because most of the questions are in accordance with the material and the level of understanding of students based on the prediction results of their scores in our previous studies. But it cannot be denied that the questions generated by the question generator still have less than the phrases produced with an error rate of 0.1%. In our further research, a recommendation and question generator system is implemented to support a smart LMS system that can match student needs.

V. IMPLICATION, LIMITATION AND CONCLUSION

This research resulted in a recommendation system that combines the provision of material and the deepening of the material in the form of exercises and questions. This has proven to be effective as a step in personalizing student learning. Until we submit this paper, we are testing 4 classes of online learning students that we will evaluate for 10 weeks. And, in week 2 we have received a positive response with a fairly high level of interest from students in terms of their learning activities at LMS (Learning Management System).

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REFERENCE


