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In-Course Progressive Prediction and Recommendation for Supporting Personalized Learning

Young PARK
Dept. of Computer Science & Information Systems, Bradley University, U.S.A.
young@bradley.edu

Abstract: Personalized learning is known as an effective educational approach. Individual students' performance-based recommendations for learning improvement can be useful in supporting personalized learning. In this paper, we propose an in-course fine-grained progressive performance prediction and recommender system that provides recommendations of study topics, materials, and activities, and peers based on predicted grades to help guide individual students for personalized learning within a course. The performance prediction is based on collaborative filtering on the grades of courses and the grades of the course assessments in a course. This in-course prediction and recommendation can be a useful personalized learning supporting tool by continuously and progressively guiding individual students to prepare and do better in the course assessments throughout the entire course.

Keywords: Personalized learning, Personalized in-course prediction and recommendation, Learning activity recommendation, Peer recommendation, Grade and performance prediction, Collaborative filtering

1. Introduction

Personalized learning is recognized as an effective educational approach that focuses on individual student-centered learning (Grant, & Basye, 2014). It is important in both in-person and online learning environments. Personalized learning in the context of higher education is reviewed in Zhong (2022). A variety of technology-enhanced personalization and differentiation methods are used to support personalized learning. Current trends in learning path personalization and learning content recommendations in adaptive and personalized learning environments are summarized in Nabizadeh et al (2020) and Raj, and Renumol (2021). The Mastery Paths feature in the Canvas learning management system (LMS) is used in practice to design a personalized learning experiences for individual students through differentiated assignments based on students' actual performances in assignments (Paradiso, & Chen, 2021).

Peer learning is an essential educational practice that is based on student learning from and with other students in both formal and informal ways (Boud et al., 2014). Zhang, and Bayley (2019) reported peer learning in the context of higher education. Peer learning is often facilitated through group activities such as peer study group. Various peer recommendation methods have been proposed (Khosravi et al., 2017; Potts et al., 2018; Thanh et al., 2019).

Predicting individual student's performance in courses can be helpful for students to get better perspective and prepare better for the courses. There have been various course-level grade prediction methods (Hellas et al., 2020). A variety of educational prediction and recommender systems have been proposed and used in various educational subdomains including technology-enhanced learning (Drachsler et al., 2015). Collaborative filtering is a widely used and proven method for personalized predictions and recommendations (Aggarwal, 2016; Ricci et al, 2015).

In this paper, we propose an in-course fine-grained progressive prediction of personalized performances on graded course assessments using collaborative filtering, and based on the predicted performances, recommendation of personalized study topics, materials, activities, and various types of peers (classmates) for peer learning. Our goal is to help guide individual students achieve better actual performances in the graded assessments in a course through personalized learning activities based on the recommendations throughout the entire course.

2. Progressive Prediction and Recommendation

Given a course, we build an in-course prediction and recommender system called *myCourseMentor* for supporting personalized learning progressively within the course. Our personalized prediction and recommendation are based on collaborative filtering on the students' final course grades in all courses including the given course and students' performances in all course assessments in the given course. We maintain a student-course-letter-grade data and a student-course-assessment-performance data. Assume that course grades and course assessment performances are represented as numeric scores ranging from 0 to 100.

Each course has a set of measurable learning objectives (LO). Each learning objective is linked to a set of lesson topics (LT) to be covered, a set of learning materials (LM) to be used and a set of learning activities (LA) to be done by students and a set of graded learning assessments (GA) to be evaluated whether students achieve the learning objectives. Learning assessments are aligned with learning objectives through learning topics, material, and activities. A course C is viewed as follows:

$$C: LO \leftrightarrow \{LT\} \leftrightarrow \{LM\} \leftrightarrow \{LA\} \leftrightarrow \{GA\}$$

There are diverse types of graded assessments including quizzes, homework assignments, discussions, tests, exams, and projects. All graded assessments are also graded as numeric values ranging from 0 to 100. We also maintain a student-assessment-grade data.

Suppose that a course C consists of a sequence of *n* graded assessments GA_1, GA_2, …, GA_i, …, and GA_n, i.e.,

$$[GA_1, GA_2, \ldots, GA_{i-1}, GA_i, GA_{i+1}, \ldots, GA_n]$$

and let T_i be the learning time after GA_1, GA_2, …, GA_{i-1} have been completed and before GA_i begins, i.e.,

$$[T_1, GA_1, T_2, GA_2, \ldots, T_{i-1}, GA_{i-1}, T_i, GA_i, T_{i+1}, GA_{i+1}, \ldots, T_n, GA_n]$$

Given a target student S, a course C and a learning time T_i during a semester, our in-course prediction and recommender system predicts the student's expected grade in each graded assessment to be completed after T_i, and recommends the personalized study topics, materials, and activities as well as personalized peers for the target student to do better in each graded assessment. The prediction and recommendation process for GA_i is as follows:

1) Predict the grade of S in a graded assessment GA_i via the student-to-student-based collaborative filtering.
    - We compute the similarity values between S and all classmates based on the grades in the courses and the grades in the graded assessments GA_1, GA_2, …, GA_{i-1} that both S and all classmates have completed.
    - The predicted grade of S in GA_i is computed as a weighted average of the top k most similar students' grades in GA_i. Let PG_i be the S's predicted grade in GA_i.
    - Here, k can be tuned and other collaborative filtering techniques instead of the student-based collaborative filtering can be used.
2) Recommend personalized differentiated learning topics (LT), learning materials (LM), and learning activities (LA) for GA_i based on the PG_i range, i.e., 100-90 (A range), 90-80 (B range), 80-70 (C range) and 70-0 (D&F range).
3) Predict the grades of all classmates in course C in GA_i via the student-to-student-based collaborative filtering.
4) Recommend personalized three types of peers for GA_i based on the PGi range and all classmates' predicted grade ranges in GA_i,
    - As potentially more capable peers: Classmates whose predicted grade ranges are above (better than) the PG_i range,

- As potentially similar peers: Classmates whose predicted grade ranges are the same as the PG_i range, and
- As potentially less capable peers: Classmates whose predicted grade ranges are below (worse than) the PG_i range.

Starting from the beginning time of a semester T_1, the prediction and recommendation is done continuously and progressively throughout the semester for each learning time and learning assessment. The prediction and recommendation can be further fine-grained by refining a graded assessment GA_i into a set of sub-assessments and their corresponding sub-learning topics, materials, and activities and by incorporating fine-grained grades and predicting the sub-assessment grades.

3. Conclusion and Future Work

We present a collaborative filtering-based in-course fine-grained progressive performance prediction and predicted performance-based recommendation system for supporting personalized learning within a course. Throughout the entire course, this prediction and recommendation system progressively helps individual students prepare and do better in the course assessments such as homework assignments, quizzes and exams and eventually succeed in the course as a useful personalized learning supporting tool. Our recommendations are based on the predicted grades and thus can be used complementary with the actual grade-based Mastery Paths feature in Canvas.

As future work, we plan to conduct quantitative experimental evaluation using real course data for the efficacy of the proposed recommendations as a personalized in-course learning supporting tool. We will explore applying the proposed predicted performance-based recommendation to a learning management system like Canvas.

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