Sparse modeling of test scores for estimating skills acquired by students
スパース符号化を用いた試験結果からスキル構造の抽出

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Tests provide a useful mean of knowing how well students understood the material taught in a class. It must be noted that students are usually required to know multiple elementary units of knowledge in order to solve each problem correctly. Such an elementary unit of knowledge is often called a "skill" in the field of educational data mining. Because each test problem relates to multiple skills, it is often difficult for an instructor to reconstruct from test results what skills each student has already acquired and what he hasn't.

To help instructors understand what skills are necessary to solve each of test problems, and also to know which skills are already acquired by each student, we propose an unsupervised data analysis method that factors a test result matrix into matrices representing skill-to-problem relationships and skill-to-student relationships. The method uses sparse modeling, also called dictionary learning. As is usual with matrix factorization, sparse modeling suffers from a model selection problem where the complexity of the model must be determined.

We propose a new rank selection method that splits the test result matrix into two, then carries out matrix factorization for each of the two parts, and compares them to measure stability of the dictionaries. We also conducted a model selection method based on information criterion. The dataset we used consists of test results from an actual course taken by college students. Using this data, we evaluated the effectiveness of the proposed method.

We also worked on feature analysis for predicting students' performance based on reading patterns in an e-learning system. The students' skills are indirectly represented in how they use e-learning systems. By identifying features that contribute to students' scores, the instructor can improve his teaching strategy.

In order to train machine learning models, features were designed heuristically, and various machine learning methods were trained and compared. The results showed that random forest and AutoML performed better than other methods. Analyzing trained random forest predictors revealed that time-related features contribute significantly to the performance of the regressor.

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