

# Intelligent Composition of Test Papers based on MOOC Learning Data\*

Lin Ma

Department of Computer Science and  
Technology, Tsinghua University  
Beijing, China 100084  
ml16@mails.tsinghua.edu.cn

Yuchun Ma

Department of Computer Science and  
Technology, Tsinghua University  
Beijing, China 100084  
myc@mail.tsinghua.edu.cn

## ABSTRACT

In recent years, most of the studies related to MOOC are mainly about prediction and data analysis, while how to evaluate the learning performance is still based on the experience of teachers. Especially, how to compose a proper exam paper is still a tedious work. In this paper, we use genetic algorithm to compose test papers with the support of MOOC learning data considering various constraints and objectives. The experimental results based on a MOOC course show that the mean absolute error of prediction model is roughly around 12 points on 100 points scale and we can successfully achieve the intelligent composition of test papers with various objectives optimized.

## Keywords

MOOC(Massive Open Online Course); Machine Learning; Performance Prediction; Genetic Algorithm; Automatic Composition of Test Paper

## 1. INTRODUCTION

In this paper, we focus on how to evaluate MOOC learners' learning performance. Traditional written test's high dependence on the teacher and neglect of the learners make it ineffective in the MOOC learning environment. So in this paper, we provide a novel approach that the final exam papers could be automatically composed with the support of MOOC learning data considering various constraints and objectives. In our approach, different machine learning techniques are employed to construct a prediction model of learning performance based on MOOC learning data. With the prediction model of the learning performance, an intelligent composition approach is proposed with various objectives and constraints considered.

## 2. RELATED WORK

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From 2012 to now, more and more people start to study MOOC, such as [2, 1]. Common algorithms of automatically generating test papers mainly include stochastic selection with approximate matching[6], backtracking and genetic algorithm[4, 5].

## 3. MODEL AND OVERALL FRAMEWORK

### 3.1 Model

Figure 1 shows the whole process of using MOOC learning data to intelligently auto-generate test paper. The input is MOOC learners' learning data, and the output is a test paper. Here we use the scores of usual quiz and homeworks as learning data, and use the score of final exam to represent learning performance. The whole process is composed of two important phases, performance prediction and test paper's composition. In the first phase, we use machine learning techniques to train the performance prediction model. And in the second phase, we use genetic algorithm to generate test paper.

### 3.2 Classified Performance Prediction Model for Different Levels of Learners

Performance prediction is a very common and simple regression problem. However, if model is constructed simply for all learners, the prediction results are always not very satisfactory because of the complexity and diversity of learners. Intuitively, we know that students with different learning levels will have different learning patterns [2]. Therefore, the features which are useful and contribute to the prediction results are obviously different for different levels of learners. Hence, the performance prediction of massive learners should be based on the level of learners, rather than treating them as a whole. Different levels of learners should have different prediction model.

### 3.3 Intelligent Composition of Test Papers Based on Genetic Algorithm

The goal of this section is to generate a test paper that meets all constraints as much as possible. The constraints include total score, difficulty, question types and knowledge points. We need to format all constraints to a argument matrix as the input of the composition of test papers[6]. For question types and knowledge points, it can be obtained by multiplying distribution matrix by total scores. For difficulty, most of the statistical analysis show that a good test has a normal distribution of scores, so we can generate it according to the

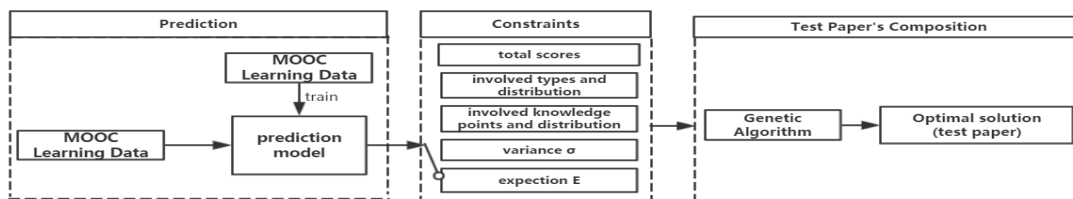


Figure 1: The model framework of intelligent composition of test paper based on MOOC learning data

Table 1: Prediction Error of Machine Learning Algorithms

Model	M5rules	SMOreg	LWR	LR	BP
Overall	21.103	21.423	21.657	21.132	34.006
Classified	12.069	12.82	11.127	13.026	15.058

expected scores  $E$  and variance  $\sigma$ . The expected score is exactly our predicted results in the last phase. The proportion of a certain difficulty level can be derived from the proportion of students in the corresponding scores. For instance, the proportion of "easy" level is equal to the proportion of students in scores 80-100 if there are a total of 5 levels. The design of the genetic algorithm can be obtained from [4] and [6].

## 4. EXPERIMENTAL RESULTS

### 4.1 Data Description

Our data comes from *Combinatorial Mathematics*, a math class opened for graduates majored in computer science and technology, Tsinghua University. It has been opened in both EdX and xuetangX. We can get a total of 35 features, including 25 quiz scores, 8 homework scores and 1 final exam score. And the feature need to be predicted is final exam score since we use it to represent learner's learning performance.

### 4.2 Prediction Experiment and Results

This experiment is a comparative experiment of the classified prediction model and the overall prediction model. We adopt machine learning algorithms used in [3]. In classified model, we divided the learners into two groups according to their academic performance, passing the exam as a group and the rest as a group. The final prediction results are shown in table 1. Note that here we adopt mean absolute error as our prediction error and all of the scores appearing in this paper are converted to percentile scores. From the results, we find classified model for different levels of learners can greatly reduce the prediction error by around 10 points.

### 4.3 The Composition of Test Paper Based on MOOC Learning Data

This experiment is conducted to verify the performance of the composition algorithm. In this experiment, we first randomly select  $n$  testers from 17 testers. And then generating a test paper according to the average performance of all selected testers to test them. From the experimental results shown in table 2, we find that predicted scores(performance)

Table 2: Examination Results

number of testers	predicted scores (performance)	real exam scores
17	77.59	75.08
16	79.75	71.37
13	73.91	69.23
12	75.94	61.14
6	82.48	69.63

are very close to their real exam scores and the error decreases as the number of testers increases, which indicates that our model is effective for evaluation of a group of MOOC learners' learning performance.

## 5. CONCLUSION

The general idea of this paper is automatically generating personalized papers under the guidance of MOOC learners' usual performance, so as to guide their further study. But there are still many details need to be further refined, such as prediction accuracy, efficiency of the composition algorithm, and so on. Therefore, it's just a first step in integrating machine learning, MOOCs, and test development. Our future work will continue to focus on these details to make it better.

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