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Application of high-level fuzzy Petri nets to educational grading system

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ABSTRACT

For the purpose of understanding the students' learning achievement, the most direct way is to implement a test. Due to the rapid development of information technology, all kinds of combination of information technology with the adaptive test have been incessantly noted by many scholars. In general, the computerized adaptive test includes the item response theory that tests the students' learning ability of subjects. However, the results based only on the dichotomy of correct answers and wrong answers are not so comprehensive judgments. Situations of correct answers and wrong answers should be different in their degrees; for example, completely correct, partially correct, completely wrong, and partially wrong. But the partially correct or partially wrong is vague and difficult to define. Thus it is appropriate to use fuzzy theory to solve the vagueness problem. Therefore, this study presents a novel learning evaluation model which applies high-level fuzzy Petri net (HLFPN) and infers via a fuzzy reasoning method the different answering performances generated by different examinee's abilities corresponding to the test items in different degrees of difficulty. Finally, we synthesize the answering performance of every test item and make a reasonable evaluation.

1. Introduction

In the formal education, the evaluation model is very important and is designed to judge students' learning performance. It also represents the success or failure of teachers' teaching. Since the computer technology rapidly progresses with each passing day, the computerized adaptive test (Chen, Lai, & Mao, 2007; Chen, Ke, & Chang, 1990; Cheng & Xu, 2008; Cheng, Xu, & Yu, 2008; Cloete & Van Zyl, 2004; Du & He, 2006; Ju & Bork, 2005) and a combination of computerized adaptive testing with item response theory (Baker, 2001; Guzman & Conejo, 2005; Harris, 1989; Lord, 1980; Lord & Novick, 2008; Wang & Chen, 2008) use the computation ability to give each item which is selected by the computer according to the examinee's ability. In the process of a test, it can also immediately compute and assess the examinee's ability based on the situation of answering each item and properly adjust the degree of difficulty in each item to give the examinee the appropriate items to answer. The process of a test assesses the examinee's performance once the examinee answers each item until the examinee's ability is precisely assessed and stops the test when the test reaches the terminating conditions.

Based on the item response theory, the computerized adaptive test estimates the examinee's ability once the examinee answers each topic. Finally, the output ability value is the examinee's ability. But it computes ability value and adjusts the items according to the correct answer or wrong answer given by the examinee; that is, it only considers the correct answer or wrong answer. In fact, this judgment is somewhat unreasonable. If the testing items are all about mathematics or science, it is not appropriate to judge whether the examinee understands the teaching materials or not only by the correct or wrong answer. This is because it may be merely a miscalculation done by the examinee that results in the incorrect answer; that is, not because the examinee's ability is not good enough to answer the item with such a difficulty that it might lead the examinee to giving a wrong answer. Therefore, the judgment only based on the correct or wrong answer is not appropriate. It should take the examinee's answering performance into consideration. In the general evaluation of students' learning results, we will encounter the following problems:

1. When a teacher evaluates the student's learning performance, he/she may be affected by the prejudice of the students.

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2. One only considers student's scores in the test to judge but neglects the student's ability in answering the questions.
3. The information provided by the scores is not sufficient such that a teacher has difficulties in guiding the students to improve their learning performance on the basis of the scores.

Due to the above-mentioned problems, this study introduces a new approach in which the examinee's ability is coupling with items of the appropriate difficulty. The high-level fuzzy Petri nets (HLFPN) (Scarpelli, Gomide, & Yager, 1996; Shen, Chang, & Juang, 2010; Shen, 2006) is employed to conduct fuzzy reasoning and the answering performance is also evaluated. In addition, the integration of scores and answering performance will provide a more objective evaluation and compare the scores and answering performance with the known information. This can help teachers find the student's problems and guide the student to learn more about the course.

The remainder of this paper is organized as follows. Section 2 discusses some preliminary definitions, including a computerized adaptive test, item response theory, fuzzy theory-based learning evaluation, and HLFPN. In order to illustrate the modeling capabilities and concepts of HLFPN, the evaluation model is proposed in Section 3. Section 4 presents the implementation and experiments. Finally, concluding remarks are given in Section 5.

2. Preliminaries

This section presents a concise introduction to the related technologies in this study. The first part is the computerized adaptive test (Aybar & Iftar, 2006; Baker, 2001; Chen, Chen, & Liu, 2007; Chen et al., 2007). The second part is item response theory (Chen et al., 1990; Cheng & Xu, 2008; Cheng et al., 2008; Cloete & Van Zyl, 2004; Du & He, 2006; Echauz & Vachtsevanos, 1995; Foulloy, Boukezzoula, & Galichet, 2006; Guzman & Conejo, 2005; Harris, 1989). The third part is the application of fuzzy theory to the learning evaluation. The fourth part is the HLFPN (Shen et al., 2010; Shen, 2006).

2.1. Computerized adaptive test

In the computerized adaptive test, it can provide the examinees with the items that the degree of difficulty is in line with the examinee's ability. In the beginning of a test, it gives the examinee the items with moderate difficulty. According to the answering situation and the assessment method, it makes an assessment of the examinee's ability. Then based on the assessed value of the examinee's ability, it chooses an item that fits the examinee's ability value to continue answering the next item. After answering the next item, it re-computes the ability value, and it again chooses the next item based on the newly assessed ability value until the terminating conditions of a test is satisfied (Aybar & Iftar, 2006; Baker, 2001).

The examinee can answer the items that fit his/her ability without answering the items that are higher degree of difficulty or lower degree of difficulty than his/her ability in the computerized adaptive test. This way can meet the principle of individualized teaching and reduce the number of items such that it will save the testing time and obtain an efficient evaluation (Aybar & Iftar, 2006; Baker, 2001).

2.2. Item response theory

The computerized adaptive test is based on item response theory, which dominates the establishment of item database, parameter estimation, item selection, and scoring. In the computerized adaptive test, the item response theory plays a considerably important role (Cheng & Xu, 2008; Cheng et al., 2008).

(1) *Basic concepts*
There are two major concepts in item response theory (Baker, 2001; Lord, 1980; Lord & Novick, 2008). One is the examinee's performance on an item that can be forecasted or explained by a set of factors. This set of factors is called latent traits or abilities. The other concept is the relationship between the examinee's performance on an item and the latent traits that could be explained by a function of continuously progressive increases. This function is called item characteristic curve.
The item characteristic curve is used to express the relationship between the examinee's latent traits and the probability that he/she may make a correct reflection on an item. The higher degree the examinee's latent traits (or higher abilities) are, the higher probability the examinee making a correct reflection will be. On the contrary, it will be lower (Lord, 1980; Lord & Novick, 2008).

(2) *Item response model*
The single-parameter model of item response theory (Harris, 1989) is shown below

$$P(\theta) = \frac{1}{1 + e^{-D(\theta - b)}} \quad (1)$$

where $P(\theta)$ denotes the probability of correct response (given a correct answer) to an item from an examinee with θ ability, θ denotes the examinee's ability, b denotes the degree of difficulty in an item, e denotes the exponent with base 2.718, and D denotes a constant (usually set as 1.702).

According to the definition of a single parameter model, when the ability and the degree of difficulty in an item is equal; that is, $\theta - b = 0$, the probability of a correct answer given by the examinee is 50%; when the ability is greater than the degree of difficulty, that is, $\theta - b > 0$, the probability of a correct answer given by the examinee is greater than 50%; if the ability is smaller than the degree of difficulty, that is, $\theta - b < 0$, the probability of a correct answer given by the examinee is smaller than 50%. Thus we understand that when the degree of difficulty in an item is higher, the examinee has to own higher ability to give a correct answer.

2.3. Application of fuzzy theory to learning evaluation

Fuzzy theory introduced by Zadeh in 1965 was designed to express those vague concepts that could not be defined clearly. For example, the weather is hot, the height is high, etc. Fuzzy theory has been widely used in various fields including forecast, control, decision analysis, etc. There are many applications in learning evaluation, such as (Chen et al., 2007; Cloete & Van Zyl, 2004; Echauz & Vachtsevanos, 1995; Kwok, Ma, Vogel, & Zhou, 2001; Law, 1996; Weon & Kim, 2001; Zhou, Ma, Turban, & Bolloju, 2002).

Law (Law, 1996) introduced a five-grade (*A*, *B*, *C*, *D*, and *F*) evaluation model. First, set the percentage of each grade before obtaining the membership function of each grade with the percentage of each grade through Law's method. Now we can convert the score of each item and substitute it. Herein we can learn where the score of each item should locate. Then compile and reorganize the score of each item and calculate it. In the last step, substitute the compiled and reorganized values into the membership function. Pick up the grades that their degrees of membership are more than 0.5 as the student's final grade.

Assume that $\mu_A(x)$, $\mu_B(x)$, $\mu_C(x)$, $\mu_D(x)$, and $\mu_F(x)$ represent the membership function of grade *A*, *B*, *C*, *D*, *F*, respectively; where p_A, p_B, p_C, p_D, and p_F represent the percentage of *A*, *B*, *C*, *D*, *F*, respectively; and $E(A)$, $E(B)$, $E(C)$, $E(D)$, and $E(F)$represent the expectation value of *A*, *B*, *C*, *D*, *F*, respectively.