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Research on the Development of a Personalized Learning Assessment Model: Building Connections Between Knowledge Components and Cognitive Levels

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Abstract: Assignment and examination are typical formative and summative assessment strategies in K-12 education. A large number of assessment data generated by learners offers an opportunity for personalized assessment. The research on assessment data has centered on large-scale reporting on aggregate level results, fewer studies have focused on student-level features. In this study, we tried to align Bloom's taxonomy of educational objectives with learning assessment, and construct a personalized assessment model using the assignment and examination data based on the cognitive diagnostic assessment approach. The model includes three assessment dimensions including the achievement of educational objectives, the mastery level of knowledge components and risk detection. The model was validated using 2,600 online learning data from 50 senior high school students. The testing content includes one topic from algebra and another one from trigonometry. The results indicate that the model can help students make timely and targeted remedies of their learning gaps. There is a positive correlation between students' cognitive level and their mastery of knowledge components, and students with the same scores have different cognitive structures and knowledge structures, although they are at the same level in the traditional sense, they can find out the complementary intervals and increase the effective interaction. Assessment data is an explicit form of students' internal cognitive level, compared with a total score, teachers are more concerned about students' cognitive level and their mastery of specific knowledge, especially knowledge components with risks.

Keywords: Personalized assessment, assessment data, taxonomy of educational objectives, knowledge components

1. Introduction

Learning analytics (LA) is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Gasevic, 2012). Presently educational institutions compile and store huge volumes of data, such as student attendance records and behavioral data, as well as their examination results. Mining such data yields better understanding of student performance. However, traditional learning assessment is limited to the statistical analysis of students' scores, class average scores, percentile ranks, etc., and ignore the details of test content and answering data (Liu, You, Wang, Ding, & Chang, 2013; Roberts & Gierl, 2010), resulting in data information cannot be effectively recorded, mined and used. While data-driven learning evaluation gradually becomes intelligent (Dutti, Ismaili, & Herawani, 2017), and the research of assessment model tends to be personalized, comprehensive and self-adaptive. There are still some deficiencies, including lack of personalized assessment from the perspective of knowledge and cognition, and basic education practice is difficult to achieve to promote learning by assessment. In view of the above problems, this study constructed the personalized assessment model from the perspective of evaluation process based on student learning assessment data. This model analyzes the learning assessment data of students from the micro and fundamental level, and evaluates learners' performance by connecting cognition and knowledge, and detects students' learning gaps and learning risks.

2. Conceptual Framework

2.1 Bloom's Taxonomy of Educational Objectives

The taxonomy of educational objectives is a framework for classifying statements of what we expect or intend students to learn as a result of instruction. In the revision of Bloom's taxonomy, Anderson et al. (2005) used the research results of cognitive psychology for reference, and distinguished the objectives from the two-dimensions of knowledge and cognitive process. The knowledge dimension includes *Factual Knowledge, Conceptual Knowledge, Procedural Knowledge* and *Metacognitive Knowledge,* mainly to help teachers distinguish what to teach. The cognitive process dimension is divided into six categories: *Remember, Understand, Apply, Analyze, Evaluate* and *Create*, which help teachers to clearly promote the stage process of students' mastering and applying knowledge. Any objective would be presented in two-dimensions table, which termed the *Taxonomy Table*. Using the *Taxonomy Table* to classify objectives, activities, and assessments provides a concise, visual representation. In this study, the guiding significance of Bloom's taxonomy of educational objectives includes item classification, attribute classification and result elaboration.

2.2 Cognitively Diagnostic Theory

The increasing demand of researchers and educational stakeholders for more formative information from educational test has fueled research efforts in CDT (Nichols & Joldersma, 2008). In contrast to classical test theory and item response theory conceptualize learners' competence as a unidimensional latent construct, cognitive diagnosis models (CDMs) assume multiple, discrete skills or attributes, thus allowing CDMs to provide a finer-grained assessment of learners' tests performance. It is designed to measure students' specific knowledge structures and processing skills so as to provide information about their cognitive strengths and weakness (Leighton & Gierl, 2007). This study uses the attribute mastery probability cognitive diagnostic model based on Q matrix (Zhu, Zhang, & Xin, 2009). By specifying a number of skills/attributes required to solve the test items, attribute profiles are reported for any specific response pattern (Rupp, Templin, & Henson, 2010). Q-matrix is a common component of CDMs for specifying the attributes required for each item (Tatsuoka, 1983). This theory, by determining the non-observable cognitive attributes, and transforming them into observable question answering modes, links the non-observable cognitive structures with observable answering responses on items, and provides a basis for understanding students' cognitive structures.

3. Personalized Assessment Modeling Based on Learning Assessment Data

3.1 Classification of Test Questions

The analysis of mainstream online test software, such as *Onion Math*, *Zuoyebang*, *Geek Big data*, shows that software covers multiple types of data. In this study, test questions and test result data are the core data. Test questions data includes test number, content, educational objectives involved, knowledge components covered, etc. Test result data includes right or wrong answers, problem solving process, etc. Bloom's taxonomy of educational objectives is used in this study to support learners' internal cognitive dimension, which provides a basis for the classification of cognitive objective attributes.

The classification of test questions is the basis of composing test papers, analyzing test papers and evaluating students. In this study, the test questions were classified from Bloom's objectives classification and knowledge components classification. The specific contents are as follows: (1) classification of teaching objectives. When using Bloom's taxonomy of educational objectives, we only need to correspond the relationship between nouns and verbs in objectives and each level in two dimensions. For example, in the objective of "using sine theorem solve an authentic problem", the verb "using" corresponds to the “Apply” in the cognitive process category of the Taxonomy Table, and the noun "sine theorem" corresponds to the “Conceptual Knowledge” in the knowledge category, which belongs to “apply conceptual knowledge”. (2) classification of knowledge components. Analyzed the content of the textbook, and then the question data is divided into each interrelated knowledge component.

3.2 Data analysis process based on Q matrix theory

In this study, the attribute mastery probability model based on Q matrix is used to calculate the learning assessment data. The feasibility and effectiveness of the model have been verified to meet the practical needs of teachers in the transformation process from assessment data to effective evaluation. The calculation steps are as follows:

1. Suppose that in a certain test, there are *m* questions and *n* students, and the correct answer is marked as 1 and the wrong answer is marked as 0. The project response matrix, i.e., R matrix, for all students to answer right or wrong on all questions can be obtained.

2. Assume that all the test questions only involve *l* attributes. Through the analysis of the test questions, if the test questions involve this attribute, it will be denoted as 1; if not, it will be denoted as 0. Thus, a Q matrix describing the relationship between test questions and measured attributes is formed:

$$R_{n\times m}=\begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix}, Q_{m\times l}=\begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1l} \\ q_{21} & q_{22} & \cdots & q_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ q_{m1} & q_{m2} & \cdots & q_{ml} \end{pmatrix}, r_{ij}, q_{jk} \in \{0,1\}$$

3. According to the Q matrix and R matrix obtained above, using matrix multiplication $\mathrm{N}_{\mathrm{n}\times\mathrm{l}} = \mathrm{R}_{\mathrm{n}\times\mathrm{m}}\mathrm{Q}_{\mathrm{m}\times\mathrm{l}}$, the number of correct responses of each student on each attribute can be obtained by N_{ik}, that is, the number of correct responses of student *i* to the test questions involving attribute *k*:

$$N_{n\times l}=\begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix}\begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1l} \\ q_{21} & q_{22} & \cdots & q_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ q_{m1} & q_{m2} & \cdots & q_{ml} \end{pmatrix}=\begin{pmatrix} n_{11} & n_{12} & \cdots & n_{1l} \\ n_{21} & n_{22} & \cdots & n_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ n_{n1} & n_{n2} & \cdots & n_{nl} \end{pmatrix}$$

4. The probability that student *i* correctly answered question *j* is estimated as the product of the correct frequency of all the attributes involved in the question. If question 1 involves attribute 2 and attribute 3, the probability that student 1 correctly answered question 1 is $g\_{11}=f\_{12} * f\_{13}$. Thus, the probability that student *i* correctly answered question *j* can be obtained:

$$g_{ij}=\prod_{k=1}^{l}\left(f_{ik}\vee(1-q_{jk})\right), x\vee y=\max(x,y)$$

5. Finally, the probability of student *i*'s mastery of attribute *k* = the sum of the correct answer probabilities of all items involving attribute *k* and correctly answered by student *i* / the sum of the correct answer probabilities of all items involving attribute *k*. At this point, the estimated probability of all students' mastery of all the attributes involved in this exam can be obtained:

$$p_{ik}=\frac{\sum_{j=1}^{m} min(r_{ij},q_{jk})\times g_{ij}}{\sum_{j=1}^{m} q_{jk}\times g_{ij}}, x\wedge y=\min(x,y), \text{if } \sum_{j=1}^{m} q_{ik}\times g_{ij}=0, \text{then } p_{ik}=0.$$

On the basis of determining data sources and research methods, we have sorted out and divided the dimensions and contents of personalized assessment, and built a personalized assessment model (Figure 1). In the model, we use bloom's two-dimensional educational objectives to evaluate the students' internal cognitive level. It takes the mastery of attributes as the quantitative form, the probability method of attribute mastery as the algorithm support. The left round wheel of the personalized assessment model takes iPadagogy wheel(Cochrane, Narayan, & Oldfield, 2010) as the source of the design idea, so as to show the data basis and the division of the assessment dimension. With the accumulation of assessment data, personalized assessment and the authentic learning situation of individual students tend to be consistent, and gradually play the role of personalized assessment, problem diagnosis, prediction and warning.

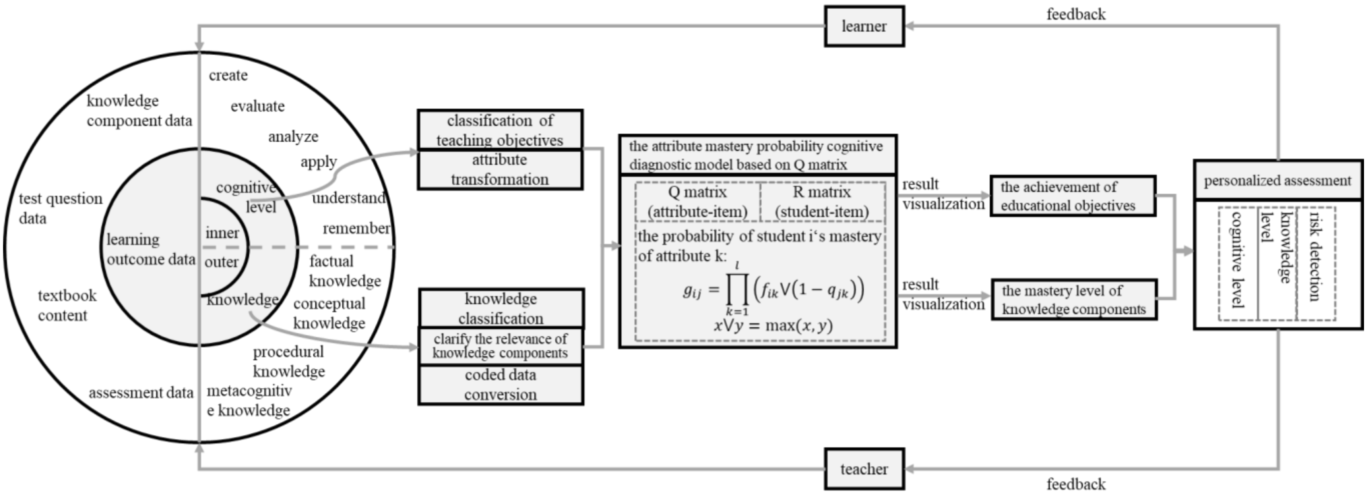

Figure 1. The personalized assessment model based on learning assessment data

4. Data Validation of the Personalized Assessment Model

4.1 Participants and Data Collection

In this study, 50 senior high school students in a class of a high school in Jiangsu province, China were selected as research participants, among which 28 were male students and 22 were female students. Three examination information of the participants on a data analysis platform was taken as data source to test the model. After collaborative screening with the teacher, 21 questions that were not included in the teaching content and incomplete data of students' answers were excluded. A total of 52 test questions were selected as data sources. The types of questions involved include choice question, fill-in-the-blank questions and calculation questions, among which the teaching contents involved in the test questions are the compulsory high school mathematics course 5 chapter 11 "solving triangles" and chapter 12 "sequence of numbers". On this basis, the tested knowledge components can be divided into six knowledge components: the sine theorem, the cosine theorem, the application of the sine theorem and the cosine theorem, the arithmetic sequence, the geometric sequence, and the comprehensive application of the sequence.

4.2 Data Analysis

Firstly, the data are collected and the item response matrix R50x52 of students and test questions is obtained. Secondly, by analyzing the test questions, we get the correlation matrix Q52 x 12 of 52 questions and 12 Bloom educational goal attributes involved. Finally, the probability estimates of students' mastery of target attributes are calculated, and the cognitive level is explicit with specific numerical values. Similarly, through the above data analysis method, we calculated the probability estimates of 50 students' mastery of knowledge attributes in the class.

4.3 Results

This paper makes statistical analysis from two aspects: average situation of class and individual situation of students. The results show that the average achievement of Bloom's educational objectives in the whole class decrease as the increase of the objective level. Students generally have the best command of "remember" and "factual knowledge". As the cognitive process from lower order thinking skills to higher order thinking skills and knowledge ranging from concrete to abstract, students' objective achievement degree decreases successively. In terms of the individual situation of the students, student A is similar to the average level of the class in terms of remembrance and understanding, but lower than the average level of the class in terms of application, evaluation and analysis. Therefore, the student should focus on strengthening the training of high-level cognition. In terms of knowledge dimension, this student has not reached the average level of the class, especially the factual knowledge and procedural knowledge, which are far from the average level of the class(figure 2a). The reason may be that this student is not good at mastering a lot of factual knowledge and thus falls behind other students. To sum up, the student should strengthen the learning of factual knowledge and gradually improve his high-level cognitive level. In addition, by comparing students with the same score in different grades, it is found that students with the same score also have different cognitive distribution, as shown in figure 2 (b). Student B has the same score as student C, and both of them are behind the class average. Student C is superior to student B in low level cognition, factual knowledge and conceptual knowledge. Therefore, it is essential to quantify the cognitive attribute level, find out the complementary interval and increase the effective interaction between students.

The results knowledge components are as follows: (1) The analysis of the average level of knowledge components in the class can help teachers identify weak knowledge components. The results show that students' overall mastery of knowledge components from high to low is Cosine Law, Sine Law, arithmetical progression, geometric progression, application of the sine-cosine law, application of the sequence. (2) In terms of the individual situation of students, we conducted a horizontal comparison of the mastery of each knowledge component of individual students, and found that the knowledge components with learning risks. For example, Student x has a good command of the concepts and principles of the sine theorem and the cosine theorem, but his application ability is lower than the average level of the class (Figure 2c), so as to put forward targeted guidance and suggestions. Secondly, student y and student z with the same score have different knowledge structure (Figure 2d), a longitudinal comparison of students' mastery of various knowledge components is conducted to find complementary components and find suitable learning partners.

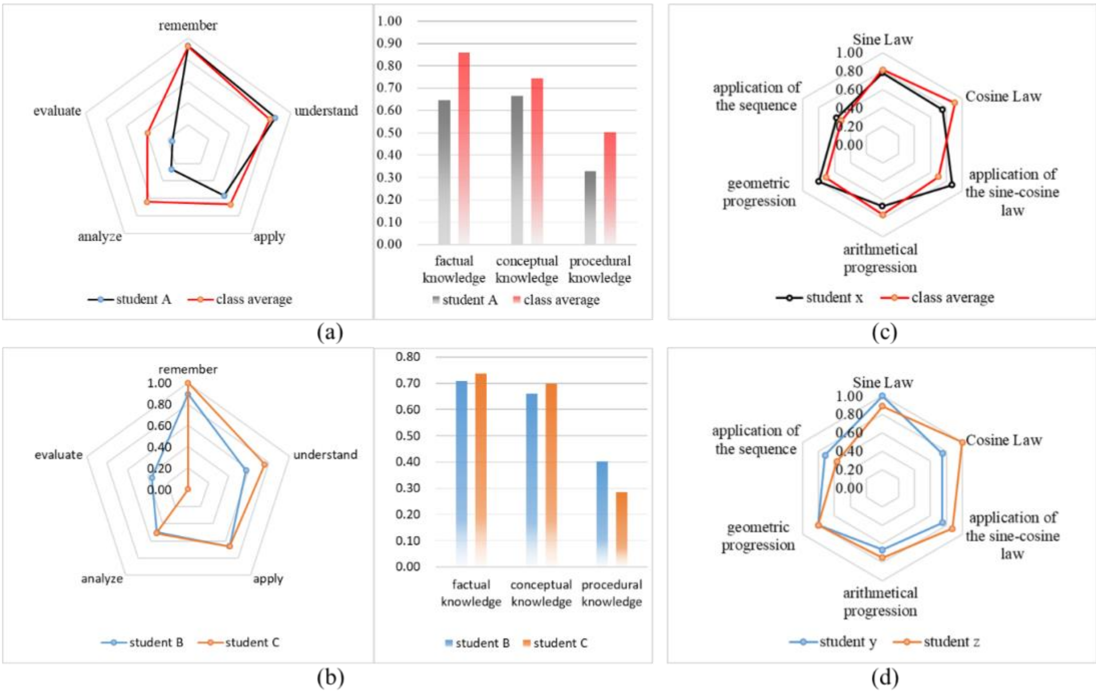

Figure 2. The achievement of educational objectives and the mastery level of knowledge components

5. Discussion and Conclusion

5.1 Discussion

Assessment analysis of cognitive goals links test scores provides an explanatory framework. Based on an examinee’s observed response pattern, detailed feedback about an examinee’s cognitive strengths and weaknesses can be provided through a score report. This diagnostic information can then be used to inform instruction tailored to the examinee, with the goals of improving or remediating specific cognitive skills. In the calculation results, the knowledge component with poor mastery level, namely the learning risk problem component, has attracted the common attention of teachers and students. Some teachers in the school believe that with the increase and improvement of assessment data, it is possible to discover learning risk knowledge components, solve learning problems, reduce teaching load and realize individualized teaching. This paper mainly reports the diagnosis results of students' knowledge structure and cognitive structure level, and is limited to the analysis of test data. Another limitation is that this study does not explore how the personalized assessment report of this study is used by teachers, parents and students to help teaching and learning, and does not track the evaluation data to explore the learning trajectory of students, which is also one of the author's future research directions.

5.2 Conclusion

The personalized assessment based on student assessment data provides the possibility for teachers to teach students in accordance with their aptitude, and satisfies the teachers' needs for understanding various mathematical and statistical knowledge in the educational measurement theory. This study analyzes the process of personalized evaluation and calculation, and constructs the personalized assessment model from two dimensions of cognition and knowledge, based on Bloom's taxonomy of educational objectives and cognitively diagnostic theory, and supported by the method of attribute mastery probability. At the same time, the assessment data of 50 senior high school students on a data analysis platform were used to verify the model. The model was iteratively optimized through effective feedback from teachers and students to improve its accuracy, and we investigate teachers' and students' view on the results of data analysis to ensure the feasibility and effectiveness of the model. In the follow-up research, the author hopes to design and develop a personalized assessment tool, which can be integrate into the existing learning platform, so as to conduct personalized process analysis and assessment for learners, help teachers to teach students in accordance with their aptitude, and ultimately help students to improve the learning effects.

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