Study on Student Performance Estimation, Student Progress Analysis, and Student Potential Prediction based on Data Mining

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ABSTRACT

Student performance, student progress and student potential are critical for measuring learning results, selecting learning materials and learning activities. However, existing work doesn't provide enough analysis tools to analyze how students performed, which factors would affect their performance, in which way students can make progress, and whether students have potential to perform better. To solve those problems, we have provided multiple analysis tools to analyze student performance, student progress and student potentials in different ways. First, this paper formulates student model with performance related attributes and non-performance related attributes by Student Attribute Matrix (SAM), which quantifies student attributes, so that we can use it to make further analysis. Second, this paper provides a student performance estimation tools using Back Propagation Neural Network (BP-NN) based on classification, which can estimate student performance/attributes according to students' prior knowledge as well as the performance/attributes of other students who have similar characteristics. Third, this paper proposes student progress indicators and attribute causal relationship predicator based on BP-NN to comprehensively describe student progress on various aspects together with their causal relationships. Those indicators and predicator can tell how much a factor would affect student performance, so that we can train up students on purpose. Finally, this paper proposes a student potential function that evaluates student achievement and development of such attributes. We have illustrated our analysis tools by using real academic performance data collected from 60 high school students. Evaluation results show that the proposed tools can give correct and more accurate results, and also offer a better understanding on student progress.

1. Introduction

E-learning's main function is to support learning and teaching, and to transfer knowledge and skills through web and electronic devices with regard to curriculums or learning activities. E-learning is now well developed in the aspects of learning contents to guide learning, technologies to enhance learning, learning environment to make students engaged in learning, and learning platforms and tools to serve learning. Both teaching and learning have become flexible and adaptive. Teachers are required to provide students with various feedbacks, including scores and comments, description on what students are good at or bad at, and suggestions for further improvement. Most of this information can be expressed numerically and transferred to inputs to the e-learning systems [1] for generating adaptive courses. They may also generate meaningful feedbacks to teachers and students, and help them to make various enhancements. However, existing work has not developed such information very well. Our paper can solve this issue. We propose a student progress-monitoring model that forms a core component of e-Learning systems. The proposed model aims to generate comprehensive feedback indicators that allow students to understand their performance and how their performance can be improved, and allow teachers to change their teaching strategies based on students' performance, and allow both of them to identify main parameters that affect student progress and their development in different attributes. The proposed model based on students' performance related attributes (PAs) and non-performance related attributes (NPAs) to model students' learning performance, progresses, and their potential to make progresses. We also infer the causal relationships among those attributes to reflect how they affect the values of one another. They are useful to make teaching strategies to different groups of students. Hence, the proposed model contributes to the development of adaptive e-Learning technologies. The main contributions are:

1. First, this paper mathematically formulates student model with performance related attributes and non-performance related attributes by Student Attribute Matrix (SAM), which quantified student attributes, and sets the foundation to support student progress analysis.

2. Second, this paper provides a student performance estimation tool by using Back Propagation Neural Network (BP-NN) based on classification. We first group students on the basis of the proposed SAM, and use BP-NN model to estimate student performance according to the students' prior knowledge as well as the other students who have similar characteristics. Experiment approves that the estimation is fast and accurate.
3. Third, this paper proposes a set of student progress indicators and attribute causal relationship predicator based on BP-NN as well to comprehensively describe student progress on various aspects together with their causal relationships. Those indicators and predicator can tell which factor would affect student performance, so that we can train up students on purpose.
4. Finally, this paper proposes an improved student potential function [2] that better evaluates student achievement and development of such attributes.

The rest of this paper is organized as follows. Section 2 summarizes related work. Section 3 presents our modeling on student progress and development. Section 4 presents experimental results and discussions. Finally, Section 5 concludes this paper.

2. Background and Related Work

Student assessment measures the levels of student achievement in terms of knowledge and abilities. The methods of student assessment contains summative assessment and formative assessment [3]. Information about student progress is required to be collected before, during and after taking certain learning activities [3, 4]. Student progress can be expressed by growth rate [5, 6] and overall improvement [7]. Besides, prediction on student's future performance [8, 9] had been studied as well. Teachers could review and improve teaching strategies based on student progress [5, 10].

To model student learning states, both *subject specific* and *general attributes* should be considered. By considering subject specific attributes, [11] evaluated how much students can make progress on their understanding of some certain learning materials. The method used maximum likelihood estimation to estimate the level of students' understanding against difficulties of learning materials. [12] studied on self-assessment skills of students by identifying the reasons why a student gives up solving a problem and the ability of a student to find the way of solving problems. The method collected information of student progress mainly based on two kinds of attributes: the difficulty levels and the types of problem. [13] studied how to use self-assessment tests to improve students' examination performance; the examinations would generate questions adaptively based on students' answers to each previous answered question. The method adopted item response theory (IRT) to predict a student's probability of correctly answering questions based on the student's knowledge level. A student was evaluated based on the accuracy of answers and the distribution of probability, i.e., the probability of the corresponding knowledge levels in terms of concepts.

Apart from subject specific attributes, there are also non-subject related attributes affecting student learning progress, which are referred as general attributes. [14] investigated how students learn by peer assessment. Students were asked to qualitatively assess their peers about their feasibility, creativity and knowledge, where the first two attributes were general attributes, which respectively refer to the ability of choosing appropriate learning materials and the ability of coming up with original new ideas. [15] studied the minimal set of social behavior to be involved in the brief behavior rating scale (BBRS), and to form a compact progress monitoring tool in order to efficiently identify the changes of students' social behaviors. [16] presented that learning styles were critical to learning, which can be used to identify adaptive learning materials for students. Among others, learning styles could be changed over time. According to the above discussion, existing work modeled student learning states by a few specific types of attributes. They provided students feedbacks on certain aspects of attributes, but hardly provided students with a global view showing how improvement can be made after taking different subjects or learning activities, because they did not consider that student learning progress could be affected by students' performance and their developments in both subject specific and general attributes as well as the causal relationships among those attributes.

To estimate student performance, a lot of work relied on classification techniques, such as decision tree [17], artificial neural networks [18], support Vector machine [19], Regression [20], etc. For example, [17] applied naïve Bayes and a decision tree classifier to estimate the lost academic data, in order to best match a student's academic data with his classifier. While some other works focused on finding out specific student model for classification. For example, [20] collected student's online behavior from Learning Management System (LMS), and those behaviors were actually student performance on different types and degrees of LMS, which are considered as student model. And [21] also mentioned that individual differences should be considered for estimating student performance, so this work also focused on finding out the best variables to describe student characteristics, and building up effective student model, so that students can be classified into different groups according to their different levels of performance, engagement and behaviors. Considering that both representative student model (finding variables that best describe student characteristics) and correct classification method (grouping students to the group that closest to them) are the basic to make accurate estimation, the proposed method would not only involve effective student model and classification method, but also involve an estimator based on back propagation neural network to estimate student performance, in order to make the results more accurate and make the computation faster.

To evaluate students' learning progress, existing work had developed many methods to comprehensively model knowledge and skills of students. For instance, [22] applied attributed concept maps to express both knowledge obtained by a student after learning a learning activity and a teacher's prototypical knowledge. [10] proposed curriculum-based measurements to directly monitor students' learning progress. It frequently monitored student knowledge and skills and graphically depicted the results in order to present what progress a student had made globally over a period of time and locally each piece of knowledge/skill that a student had gained, and whether such progress could meet teacher's expectation. A fuzzy map matching process was then used to compare both global map and local map to determine how much progress a student has made in the learning. [4] proposed to use a fine-grained skill model to hierarchically present a set of skills. A generalized linear mixed effects model was used to generate statistic information in order to describe students' learning progress on different skills. [23] predicted student performance using the contextual estimation on the accuracy of student guessing and possibility of making errors, even though knowing the skill to construct the Bayesian Knowledge Tracing, in order to model student knowledge.

Existing work mainly identifies students' learning progress as a set of state-changes made by students regarding certain learning attributes and whether they meet with teacher's expectations. However, such learning progress information is quite primitive, which is not enough to form indicators helping both students and teachers to make improvement on learning and teaching. Otherwise, they have to pay extra cognitive effort to manually extract more comprehensive learning progress information from feedbacks. It is because learning attributes are not independent, while they may have certain complicate causal relationships among each other, which relationships can also be dynamically changed over time. In addition, at different learning stages, students' learning progress may be affected by different kinds of learning attributes. For example, a student is expected to mainly train up his ability of concept memorization at an initial stage rather than focusing on training the ability of applying knowledge. But the case would become different when the student stays at a mature learning stage. On the other side, a teacher may want a higher level of student progress information, for example, the performance distribution within a group of students, the portion of students that meets teacher's expectations, or whether a student or a group of students develop certain learning skills, to support adjustment of teaching strategies. Our work is carried out to provide a comprehensive solution to solve such complicated needs.

3. Student Progress and Development

Analyzing student progress is critical. Different subjects (or learning activities (LAs) [24]) have different assessment criteria, where some are subject specific, and some are shared among subjects. On the other side, learning styles and learning modes also play significant roles on how a student perform and make progress in different assessment criteria. We have developed student attribute descriptors to provide a more complete picture on student's progress, performance, and development.

3.1 Modeling of Student Attribute Descriptors

1) Student Attribute Matrix

We propose a student attribute model (SAM) (shown as Eqs. 1-2) to quantify both performance (PA) and non-performance (NPA) based learning attributes, which forms an unified expression to analyze student progress and their development. SAM is the foundation of student attribute descriptors. It comprises subject-related and generic outcome attributes according to Bloom's Taxonomy [25] (explained as Table 1), learning style attributes according to Felder-Silverman's model [26] and learning mode attributes which is to describe whether a LA is an individual one or a collaborative one [27] (explained as Table 2). We have applied these well-established models to describe student attributes as they have been widely used, classic and verified. In practice, teachers can just use a subset of attributes to model their teaching subjects (or LAs), forming a *local measurement*, and optionally interpret attributes with subject specific attributes if necessary. Teachers can also put together local measurements to show a bigger picture on the all attributes to analyze all-round performance and development of a student, and forming a *global measurement*.

SAM is modeled as a dot product of the attribute criteria matrix C, which is consisted of criteria for PAs (C_{PA}) and NPAs (C_{NPA}), and score matrix, which contains scores α_{ij}. As shown in Eq. 1, each criterion is modeled as a row vector A_i, which comprises a set of a_{ij} to model different aspects of an attribute. For subject-related and generic outcome attributes, each aspect corresponds to a level of complexity, while for attributes regarding learning styles and learning modes, each aspect is corresponding to a characteristic of each learning style or learning mode. An aspect is quantified by a real number between 0 and 1 to represent its importance degree in a subject (or LA), where an aspect is set to be 0 if it is not

Table 1
Attributes From Bloom's Taxonomy

Level of Complexity	Cognitive (Knowledge)	Affective (Attitude)	Psychomotor (Skill)
1	Knowledge	Receiving	Perception
2	Comprehension	Responding	Mind Set
3	Application	Valuing	Guided Response
4	Analysis	Organizing	Mechanism
5	Synthesis	Characterizing by value or value concept	Complex Overt Response
6	Evaluation	/	Adaptation
7	/	/	Origination

being assessed in the subject (or LA). To model student learning states and teacher expectations of a subject (or LA), as shown in Eq. 2, our work defines a score matrix that comprises scores α_{ij}, where each score indicates the level of achievement (or required effort) of an aspect of a PA (or NPA). Each subject (or LA) associates with a SAM to define teacher's expectation, while each student who studies the subject (or LA) will be assigned with a SAM that is constructed by the same attribute criteria matrix C to maintain his/her learning state.

$$C = \begin{bmatrix} C_{PA} \\ C_{NPA} \end{bmatrix} = [A_1, \cdots, A_i, \cdots, A_n]^T = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{nPA,1} & \cdots & a_{nPA,m} \\ a_{nPA+1,1} & \cdots & a_{nPA+1,m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \quad (1)$$

$$\mathrm{SAM} = \left\langle \begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} & \cdots & \alpha_{nm} \end{bmatrix}, \mathrm{C} \right\rangle = \begin{bmatrix} \alpha_{11} \cdot a_{11} & \cdots & \alpha_{1m} \cdot a_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} \cdot a_{n1} & \cdots & \alpha_{nm} \cdot a_{nm} \end{bmatrix} = \begin{bmatrix} sa_{11} & \cdots & sa_{1m} \\ \vdots & \ddots & \vdots \\ sa_{n1} & \cdots & sa_{nm} \end{bmatrix} \quad (2)$$

Because a student will perform independently among different aspects of the attributes, each aspect could then be considered as a random variable, which follows normal distribution $sa_{ij} \sim N(\theta, \sigma^2)$ shown as Eq. 3.

$$p(sa_{ij}; \theta) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(sa_{ij}-\theta)^2}{2\sigma^2}} \quad (3)$$

where $p(\cdot)$ is the probability distribution function of sa_{ij}; θ is the estimation value of sa_{ij}; σ^2 measures the width of the distribution. We apply *Maximum Likelihood Estimation* [28] to estimate θ, where the largest probability happens when sa_{ij} equals to θ, which has been proved as a correct expectation of the observed data of sa_{ij}. So *SAM* could be dynamically updated by the mean value of all previous SAMs (4).

$$SAM(t) = \frac{1}{t} \sum_{i=1}^{t} SAM_{\mathrm{i}} \quad (4)$$

where SAM_i only expresses the learning state for the i^{th} LA. $SAM(t)$ represents the overall learning state of a student after learning t LAs. Because the difference between $SAM(t)$ and $SAM(t\text{-}1)$ may be perturbed by some uncertain factors and may not reflect the real student performance, we consider the average of all previous student performance as the latest learning states of a student to reduce such an error.

2) Progress Potential Descriptor (PPD)

To analyze the potential of a student to make further progress, not just has better performance, but also develops better skills, we have proposed a progress potential descriptor (5-6).

$$P = f(L_{PAs}, L_{NPAs}) \quad (5)$$

$$L_{NPAs} = g(L_{NPAs1}, L_{NPAs2}) \quad (6)$$

where $f(\cdot)$ is the PPD, P is a student's learning progress, L_{PAs} (7) is the student's performance in higher-level attributes of *PAs*, and L_{NPAs} (6) contains two parts, L_{NPAs1} and L_{NPAs2} , shown in Eqs. 8-9, which are student performance in *NPAs*, and the balance degree of a student's development in *NPAs*, respectively. A student has a higher potential to achieve more if he/she can perform better in both higher-level attributes of *PAs* and *NPAs*, and has a more balanced development in *NPAs*.

$$L_{PAs} = \sum_{i=1}^{nPA} \sum_{j=1}^{m_i} sa_{ij} \quad (7)$$

$$L_{NPAs1} = \sum_{i=1}^{nNPA} \sum_{j=1}^{m_i} sa_{ij} \quad (8)$$

Table 2
Attributes Regarding Learning Styles And Learning Modes.

Learning Mode	Perception	Input	Organization	Processing	Understanding
Collaborative	Concrete	Visual	Inductive	Deductive	Sequential
Individual	Abstract	Verbal	Deductive	Passive	Global

$$L_{NPAs2} = \frac{1}{nNPA \times \sum_{i=1+nPA}^{n} m_i} \sum_{i=1+nPA}^{n} \sum_{j=1}^{m_i} \left(sa_{ij} - \frac{1}{m_i} \right)^2 \tag{9}$$

where m_i is the number of non-zero aspects for each attribute, N_{PA} is the number of *PAs*, N_{NPA} is the number of *NPAs*, and n is the number of attributes. $1/m_i$ is the perfect probability if *NPAs* can be developed evenly. Eq. 7 reflects that higher values of student ability will contribute to the overall student progress potential. Eq. 8 reflects that student ability in NPAs will contribute to the overall student progress potential as well. And Eq. 9 reflects that if the different aspects of *NPAs* tend to be developed evenly, then the student can have a more balanced development among the abilities in *NPAs*. We normalize the values of all L_{PAs}, L_{NPAs1} and L_{NPAs2} to be within [0, 1] to allow them to be processed in a unified way. In the end, $f(\cdot)$ is given by $P = L_{PAs} \cdot L_{NPAs1}/L_{NPAs2}$. We would evaluate the proposed function *P* in the evaluation section IV.

3.2 Student Performance Estimator

Given existing student SAM matrix, we can use it to estimate attribute values of new students using Back-Propagation neural network (BP-NN) model [29], and also we can apply the approach to estimate students' future performance with his previous performance. Assuming that we only know some attribute values of a student, but have no idea about the others. As long as we have some priority information of a student, and we have an existing SAM matrix, the unknown attribute values of a student can be estimated by Eq.10.

$$[sa_{n1} \dots sa_{no}] = BPNN(\begin{bmatrix} sa_{11} & \cdots & sa_{1o} \\ \vdots & \ddots & \vdots \\ sa_{n-1,1} & \cdots & sa_{n-1,o} \end{bmatrix}, \begin{bmatrix} sa_{1,o+1} & \cdots & sa_{1,i+o} \\ \vdots & \ddots & \vdots \\ sa_{n-1,o+1} & \cdots & sa_{n-1,i+o} \end{bmatrix}, [sa_{n,o+1} \dots sa_{n,i+o}]) \tag{10}$$

where $[sa_{n1} \dots sa_{no}]$ is the student attribute values to be estimated, BPNN(•)is the BP-NN function which is used to estimate, the first two inputs of the BPNN(•) function are the training data, and the last input of the BPNN(•) function is the priority data. *n* is the number of students, *i* is the number of input layer, and *o* is the number of output layer.

BP-NN can update network coefficient and threshold value to reduce errors along negative gradient direction and approaching expected outputs by training sample data. BP-NN is consisted of input layer, hidden layer, and output layer, while hidden layer can have one layer or multiple layers. Normally, BP-NN chooses Sigmoid differentiable function (11) as the excitation function for each neuron and uses BP error function to update network coefficient and threshold, in order to minimize the error function E (14). In Eq.11, $S(x)$is the S type transfer function. Eqs. 12-13 shows that the output of hidden layer (ho) is the Sigmoid function of hidden layer coefficient (wh) and input (x), while the output of output layer (yo) is the Sigmoid function of output layer coefficient (wo) and output of hidden layer (ho). In Eq.14, $d_o(k)$ is the expected output, and $yo_o(k)$ is the output of output layer.

$$S(x) = \frac{1}{1+e^{-x}} \tag{11}$$

$$ho = Sigmoid(wh \cdot x) \tag{12}$$

$$yo = Sigmoid(wo \cdot ho) \tag{13}$$

$$E = \frac{1}{2} \sum_{o=1}^{q} \left(d_o(k) - yo_o(k) \right)^2 \tag{14}$$

Similarly, based on different types of grouping, we can estimate a student performance according to the group of students that the student belongs to, rather than according to the data of all students, using the same BP-NN model. This way of estimation can provide more accurate values. For example, for the **subject group**, we can classify students into art students, and science students. And we can estimate an art student's performance according to all art students and his own priority knowledge rather than all students' performance. Similarly, for **performance group**, students are classified into best, good, satisfactory, below average, and disqualified students. And we can estimate a good student's performance according to students in "good" group and his own priority knowledge. The experiment and evaluation of estimation student performance will be given in experiment section.

3.3 Attribute Causal Relationship Predicator

Existing work evaluate students' progress mainly by their subject performance (PAs). However, student learning is a complicated process. Student performance can also be affected by NPAs, e.g. an active learner tends to have better communication skill than a passive learner. And each student would be affect by the same attribute in different degree. For example, an active learner would be affected by communication skill, while a passive learner would not be affected by communication skill that much as an active learner. In addition, both PAs and NPAs may affect among each other. To model such complicated relationships and infer changes among the attributes, we can also apply BP-NN to predict the causal relationship among PAs and NPAs, i.e. to predict the impact factors of one attribute on the others, which is formulated by Eq. 15, to analyze changes of SAMs and infer the causal relationship among the attributes in a SAM.

$$\nabla SAM_j = SAM_i - SAM_j \tag{15}$$

First, we get the difference matrix ∇SAM_j of SAM. In Eq. 15, SAM_i is student performance of SAM at test *i*, and SAM_j is the student performance of SAM at test *j*, and ∇SAM_j is the difference of SAM between the two tests.

Second, we unified ∇SAM_j by setting the changes of an attribute that affect the others to be 1, then the changes of the other attributes would be considered as impact degrees of the attribute on the others.

Third, we apply BP-NN to find the impact degree of an attribute on the others, i.e. if an attribute has been improved, how much the other attributes make progress. To predict a student attribute casual relationship, the training data is still selected from the group that the student belongs to, which will make the predication more accurate. The prior data is the difference of the student's SAM between two tests. The verification of the prediction method is given in section IV.B.

3.4 Student Progress Indicators

We classified students into different types of groups to analyze student progress and their development, which are *learning attribute groups (LAGs)* and *student groups (SGs)*. LAGs are generated to support local measurement. They divide students into groups to maintain subsets of learning attributes. These groups are:

- **Subject Group:** to assess subject (or LA) specific knowledge or skills. In our experiments, we possess groups for Arts, Science and all subjects.
- **Learning Stage Group:** to assess students at appropriate cognitive levels during different stages. Learning stages contain three stages to represent students' early, interim, and mature stages respectively. The early stage evaluates students' basic knowledge in cognitive levels. The interim stage evaluates students' progress potential in non-performance related attributes to observe if they have balanced development, in the meantime, evaluates attributes in **Affective and Psychomotor domains** to observe their generic outcomes. And the mature stage evaluates students' advanced knowledge in cognitive levels.

SGs are generated to support a more general analysis. They can be constructed manually or automatically, which include:

- **Study Group:** study group divides students based on subject of study, e.g. Arts and Sciences. For example, student S60 has better performance on Art subjects than that on Science subjects, so student S60 belongs to Art group. Besides, we also consider individual or all students as general groups. All these groups' types could be manually pre-defined.
- **Performance Group:** performance group divides students based on their performance associated to skills, i.e. best, good, satisfactory, below average, and disqualified students, which forms *performance metrics* describing teacher expectations on students with different performance. Such metrics may also be automatically generated by applying performance information from the performance of previous students. Because we also define students' attribute values in a fuzzy meaning which indicates the degree of requirements for each aspect, so we can apply these fuzzy values to measure the degrees of belonging to groups. And in Fuzzy C-mean clustering method, each student has a degree of belonging to groups, rather than completely belonging to just one group. Students on the edge of a group may have a less degree than students in the center of group. When analyze students' real performance, we apply Fuzzy C-mean clustering method [30] to divide students into groups based on their SAMs, where student *performance metrics* defined by teachers forms the representatives of groups. For example, in terms of attribute values of SAM, student S60's performance is below teacher's expectation, so S60 belongs to "Disqualified" group.

We can use the data of grouped students to analyze student characteristic and estimate student performance to make the analysis results and estimation results more accurate.

4. Experiments Results and Discussions

In order to analyze student learning progress with our BP-NN based student progress indicator by finding out attribute causal relationship, to predict student potential with improved Progress potential function, and to test the student performance estimator based on BP-NN model, we have collected academic data over 6 subjects of 60 high school students from No.83 Xi'an Middle School, China. These data contains their test results in both year 1 and year 2. And also, we ask 6 teachers who taught the 6 subjects to set their learning outcomes by the PAs and NPAs.

Results are collected from 4 assessments completed by the students over two years. All students studied the same 6 subjects, including Math, English, Physics, Chemistry, Political economy, and History. Math, Physics, and Chemistry belong to Science subjects, while the others belong to Arts subjects. Requirements of PAs and NPAs of each subject are set by *corresponding* subject teachers.

4.1 Experiment on Progress Potential Prediction

We have applied the method proposed in section III. 2) to calculate students' potential to make progress, and unified the value of potential to [0,1] by Eq. (16).

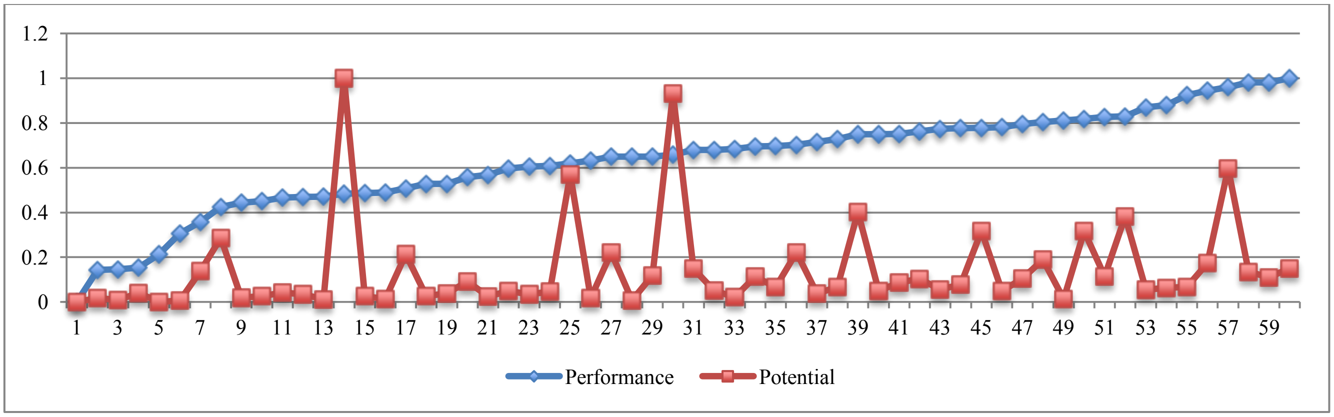

Fig. 1. Comparison on student progress potential and their performance.

$$P = \frac{P_i - P_{min}}{P_{max} - P_{min}} \tag{16}$$

where P is student's potential, P_i is student i's potential, P_{min} is the minimum value of student potential, and P_{max} is the maximum value of student potential. In Fig. 1, we have sorted data of student performance from low to high, shown as the blue line, and the red line shows corresponding progress potential of each student. We can see that low performance student may have high potential to make progress, while high performance student may not have enough potential to make progress. For those students who have high performance but low potential, their abilities may not be evenly developed, if they cannot master different skills, they cannot make further improvement and reach better performance. For those students who have low performance but high potential, they can more evenly develop their learning skills by taking current courses, so they can quickly learn knowledge by taking different types of learning activities, and make further improvement efficiently. For those students who have high performance and high progress potential, their abilities have been evenly developed, they do not only have solid foundation of different types of knowledge, and they also can quickly make further improvement. For those students who have low performance and low progress potential, they may be need more effort to get more abilities and learning skills, otherwise, it is hard for them to get improved. Overall, only 20% students' potential is larger than 0.2, which means that most students' performance has been greatly limited due to that their abilities have not been evenly developed. Students cannot only be good at one or two things, because what they are bad at would greatly limit their overall performance.

4.2 Student Performance Estimation

1) Student attributes estimation

In this experiment, we use the data of the first 59 students to estimate the attribute values of the 60th student (S60) in SAM matrix. Assuming we have no idea about the 6 attribute values of the last student's cognitive domain, we consider the data of 59 students as training data, and consider attributes of affective (5 values), psychomotor (7 values) as well as the attributes regarding learning styles (10 values) and learning modes (2 values) of student S60 as priority data. This experiment applies Levenburg-Marquardt method [31] as the training method, and chooses the number of hidden layer as 14 according to experience equation $L = \sqrt{i+o} + a$, where a is a constant between 0 and 10. The following figure shows that the input layer has 24 nodes, the hidden layer has 14 nodes, and the output layer has one node. We can use BP-NN to estimate the 6 attribute values at one time.

Shown as Fig. 2, after 153 times iteration, the MSE has reached lower than 10^{-7} (Fig. 3), and the results show that BP-NN model estimates the 6 attribute values of cognitive domain to be the "Estimation results" row in table 3, while the actual values of the 6 attribute values of cognitive domain are the "Actual values" row in table 3. In order to verify if the two groups of data have significant difference, we have applied one-way ANOVA [32] and F-test to test them. Both of the two methods can be used to compare the similarity of multi-groups of data. Table 4 shows the result given by one-way ANOVA, and Table 5 gives the results provided by F-test.

Table 3
Student attributes estimation results.

Attributes	1	2	3	4	5	6
Estimation results	101.196	65.254	72.671	124.707	192.477	137.204
Actual values	81.876	63.347	63.748	131.9	184.85	133.4

Table 4
Analysis Of Variance (One-Way)

Summary						
Groups	**Sample size**	**Sum**	**Mean**	**Variance**		
A	6	659.121	109.8535	2,347.25460		
B	6	693.50925	115.58488	2,208.96666		
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**p-level**	**F crit**
Between Groups	98.54598	1	98.54598	0.04326	0.83942	4.96460
Within Groups	22,781.10633	10	2,278.11063			
Total	22,879.65231	11				

Table 5
F-Test Two-Sample For Variances

Descriptive Statistics			
VAR	B	A	
Sample size	6	6	
Mean	115.58488	109.8535	
Variance	2,208.96666	2,347.25460	
Standard Deviation	46.99965	48.44847	
Mean Standard Error	19.18752	19.77901	
Summary			
F	1.06260	**F Critical value (5%)**	5.05033
p-level 1-tailed	0.47425	**p-level 2-tailed**	0.94850
H0 (5%)?	Accepted		

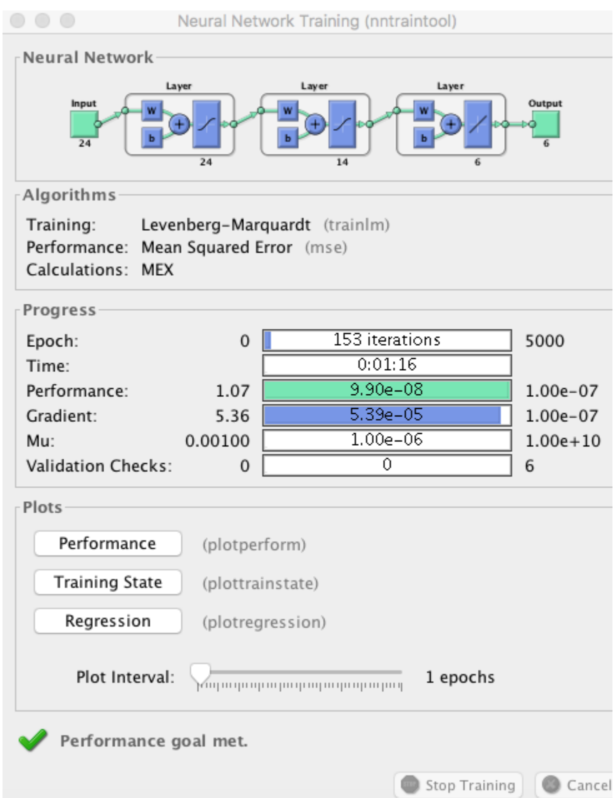

Fig. 2. 3-layer BP-NN model.

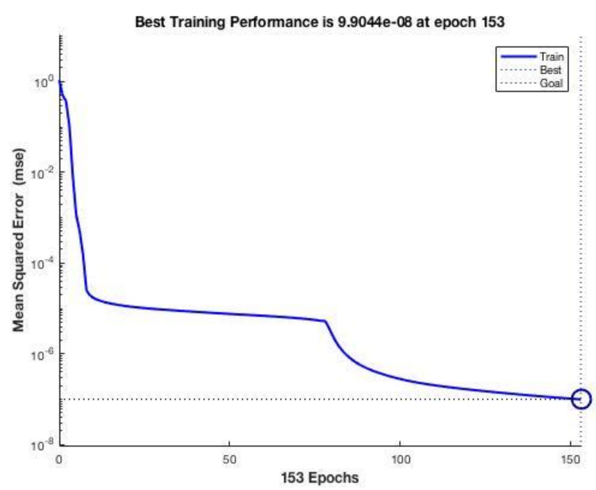

Fig. 3. Performance-MSE.

Table 4 shows that $F < F_{crit}$, while significant level $\alpha = 0.05$, which means the possibility that two groups are similar is 95%. Table 5 also shows that $F < F_{crit}$, while significant level $\alpha = 0.05$, which means the possibility that two groups are similar is 95%. Both evaluation methods prove that the two groups of data do not have significant difference, which means the estimate values are enough close to actual values. So we can estimate student attribute values in a convincible way.

2) Performance estimation by grouping

In this experiment, we estimate a student's performance on a certain subject by different groups of data. Assuming that we estimate the math score of the 60th student, according to the grouping method given in section 3.2, we can make sure that the student belong to Art group by subject grouping, and also belongs to Disqualified group by performance grouping. The full math score is 150 during the math test. Then we estimate his math score by the data of science group, the data of "disqualified" group, and the data of all students, respectively, to see which results is closest to the real value.

For all students, we consider the data of 59 students as training data, and consider the scores of other 5 subjects of the 60th student as priority data. We also apply Levenburg-Marquardt method as the training method, and choose the number of hidden layer as 5 according to experience equation $L = \sqrt{i+o} + a$. The following figure shows that the input layer has 6 nodes, the hidden layer has 5 nodes, and the output layer has one node.

After 5000 times iteration and 28 seconds, the MSE has reached to 0.0438, and the results show that BP-NN model estimates the math score of the 60th student to be [117.58], shown as table 6, while the actual values is [46].

Table 7
Student Attribute Estimation Results

	Sample number	Estimated value	Real value	Difference Error
All students	60	[101.196 65.254 72.671 124.707 192.477 137.204]		4.0170
Art group	29	[85.63121 64.00934 62.74586 140.93 188.2896 135.5102]	[81.876 63.347 63.748 131.9 184.85 133.4]	1.7746
Disqualified group	5	[84.34357 61.71654 60.1995 137.8089 177.3762 132.2118]		1.7758

Table 6
Performance Estimation Results

	Sample number	Estimated value	Real value	Difference Error
All students	60	117.58		71.58
Art group	29	48.23	46	2.23
Disqualified group	5	49.72		3.72

Similarly, given the data of science group, where the "Art" group includes 29 students, who are S1, S4, S5, S7, S9, S15, S16, S21, S24, S26, S27, S29, S30, S32, S35, S37, S39, S42, S45, S46, S47, S49, S50, S51, S52, S53, S56, S59, S60, and S61, and the estimated value is [48.23], and the iteration times is 2250, which costs 12 seconds.

Given the data of "disqualified" group, where the "disqualified" group includes only 5 students, who are S45, S51, S53, S59, and S60, and the estimated value is [49.72], and the iteration times is only 3, which costs nearly 0 second.

From table 6, we found that both data given by Art group and disqualified group can provide close results to the real value, while data from all students cannot. Even though the number of sample in "All student" is the largest, its result is still not satisfied, and it requires more iteration and takes more time. On the contrary, the other two groups of data take less time and less iteration, which has smaller number of data, but provide much more accurate results. Especially, the "Disqualified group" only has 5 sample number, but still can generate satisfied result, and almost does not take time.

We applied the same approach to estimate the values of student attributes, according to the data of different groups. The difference error is given by Eq. 17.

$$\text{error} = \sqrt{\frac{\sum_{n=1}^{N}(Ev-Rv)^2}{N}} \quad (17)$$

where Ev is the estimated vector, Rv is the real vector, N is the number of estimated data. From table 7, we found that even BP-NN method can provide correct results by the data from all students, which has been approved in section C.1, the results given by grouping data are more accurate, and the computation is faster.

Besides, the above experiments also approve that large number of samples cannot generate good results, but effective grouping data can. The results also approve that the student classification results are correct and meaningful, so that the group of data can work more effective.

4.3 Experiment on Attribute Casual Relationship Prediction

This experiment predicts attribute causal relationship according to the differences of SAM. As we collected 4 groups of tests, and each group of test including test results on the 6 subjects, so we can get 4 different SAMs. Assuming we would like to predict the casual relationship between the first attribute and the rest attributes, i.e. if a student has made improvement on the first attribute, how the other attributes changes, or if we know the changes of the other attributes, how the changes would affect the changes of the first attributes. Given two SAMs from the first test SAM_1 and the second test SAM_2, we can get the difference of the two SAMs by (SAM_1-SAM_2). Now, students have their 4th test. And we can use the difference of the 4th SAM and 2nd SAM on the other attributes to predict the changes on the first attributes.

In this experiment, we want to predict how the other attributes' changes would affect the change of student S60's first attribute. As student S60 belongs to group of "bad performance students", so we use SAM data of "bad performance students". The difference of the 1st SAM and the 2nd experiment is considered as training data, and the difference of 2nd SAM and 4th SAM on the other attributes is considered as priori data, both training data and priori data are selected to predict the difference of 2nd SAM and 4th SAM on the first attribute. In fact, the difference of 2nd SAM and 4th SAM of student S60 is as follows,

[4.82599999999999	6.00999999999999	5.57700000000000	4.91700000000000	7.41800000000000	7.25200000000000	0
6.33300000000001	7.12600000000001	7.66200000000001	7.81100000000000	7.06700000000001	0	0
5.39400000000000	4.07800000000000	5.45400000000000	4.82400000000000	5.75500000000000	5.44900000000000	5.04600000000000
15.9000000000000	20.1000000000000	0	0	0	0	0
17	19	0	0	0	0	0
14.8000000000000	21.2000000000000	0	0	0	0	0
15.9000000000000	20.1000000000000	0	0	0	0	0
23.1500000000000	12.8500000000000	0	0	0	0	0
21.1000000000000	14.9000000000000	0	0	0	0	0]

We can see that the change of the first attribute is actually 4.83. By using BP-NN, the predicted value of the change of the first attribute is 5.02. The predicted value is very close to the actual value. So we can use BP-NN to predict the attribute causal relationship.

5. Conclusion

We proposed student attribute descriptors (student attribute matrix and progress potential descriptor), student performance estimator, attribute causal relationship predicator, and student progress indicators. While student attribute matrix mathematically models both students' PAs and NPAs, and progress potential descriptor can identify if a student has developed his abilities evenly, and indicate if the student can make further improvement. Student performance estimator can estimate students' attribute values, such as a student's scores on subjects, or his scores of learning abilities, etc. Attribute causal relationship predicator reflects how attributes affect a student performance, or how attributes affect a student learning abilities, so that students can get known which factors limited their performance or their abilities. Student progress indicators provide different grouping ways of students, which can be used to analyze student progress and their development, and make the analysis results and estimation results more accurate.

We have carried out experiments with 60 students, and the experiment results show that the predicted progress potential can intuitively express students' potential to make progress in terms of their abilities and performance. The experiment results also show that estimated student attributes, estimated student performance, and the predicated attribute causal relationship are accurate. Especially, the estimated performance based on grouping generated more accurate results and took less time using fewer number of training data, which also approved that student classification results are correct and meaningful.

Provided with the proposed student performance estimation, student progress analysis, and student potential prediction tools, we can get to know an individual student's learning, including his learning performance, learning abilities, learning progress, and potentials, etc. And also, we can identify the key factors that limit his abilities or performance, so that we can help him to get improved on purpose. Also, we can help a group of students, or all students using the proposed tools as well.

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Highlights

1. Formulated student model by Student Attribute Matrix is the foundation of student progress analysis.
2. Proposed student performance estimation tool which uses BP Neural Network based on classification, is fast and accurate.
3. Proposed student progress indicators and attribute causal relationship predicator finds factors affecting student.
4. Proposed an improved student potential function better evaluates student achievement and development of such attributes.