Type Prediction of Student's Achievement based on Grey Neural Network Optimized by GA

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Abstract. Students’ learning performance is predicted based on their online learning data, which is of great significance to evaluate the learning effect of school education and the reform and development of online education. In this paper, the characteristics of learning behaviour that constitute the influencing factors of students' achievement are analysed and screened, and then a prediction model based on neural network and intelligent optimization algorithm is proposed. In this paper, the working principle of grey neural network (GNN) is described, the genetic algorithm (GA) is used to optimize the parameters, and the performance of the model is tested by simulation experiment. The experimental results show that, compared with the reference model, the prediction model optimized by GA parameters shows good prediction performance, and the prediction accuracy remains at a high level.

1. Introduction
With the rise of the network teaching platform, all the learning activities of students are completed through such platforms, and the differences in their scores are often closely related to their individual characteristics, learning attitude and learning ability. Using these characteristics produced by students in the learning process, students' learning results can be predicted. Student achievement prediction has also become one of the key research topics in the field of education data mining [1, 2].

GNN can be regarded as a new method of prediction using artificial intelligence, which has strong adaptability and robustness. It can not only ensure the generalization ability, but also meet the needs of system fault tolerance. In this paper, GNN [3] is used to predict students’ achievement. In the training process of GNN, it is necessary to adjust the connection weights of neurons continuously to optimize the grey parameters. In this paper, GA [4,5] algorithm is used to find GNN network parameters, build the student achievement prediction model, and verify the validity of the prediction model by experimental data.

2. Analysis of the indexes affecting students' achievement
Many studies believe that the students’ achievement can be inferred through their online learning behavior, and the achievement prediction model can play a guiding role in students’ learning process. Data analysis and model judgment can be used to predict the learning behavior of some students with poor performance, which can provide basis for the implementation of targeted education, and then provide more effective intervention, and enhance students’ sense of learning. In this paper, the learning behavior of students is summarized as the completion of learning tasks, communication and cooperation, and learning input, including 13 indexes, as shown in Table 1.
Table 1 Observation indexes of students' online learning behavior

| Index name                                               | Description                                                      |
|---------------------------------------------------------|------------------------------------------------------------------|
| Viewing index of video courseware (X1)                  | Number of videos watched by students / total number of videos    |
| Reading index of teaching auxiliary materials (X2)      | Proportion of students' reading materials                        |
| Phased practice completion index (X3)                   | Percentage of students completing staged exercises                |
| Phase test completion index (X4)                        | Percentage of students completing test                           |
| Students submit homework index (X5)                     | Percentage of students submitting assignments                     |
| Participation in course Q & A index (X6)                | Number of students' questions in the process of online teaching  |
| Participation in course teaching index (X7)             | Total online time of students in the process of online teaching  |
| Participation in forum interaction index (X8)           | Sum of the times that students post questions and participate in discussions in the forum |
| Participation in group discussion and work mutual evaluation index (X9) | Sum of the times that students participated in group discussion and homework mutual evaluation |
| Login platform time index (X10)                         | Sum of time for students to log in to the platform               |
| Watch video time index (X11)                            | Sum of time for students to watch teaching video                 |
| Login platform frequency index (X12)                    | Number of times students log in to the platform / week            |
| Watch video frequency index (X13)                       | Number of students watching video / week                          |

When it is used for the prediction of students' achievement, if all the indexes are evaluated and synthesized, the model will be too complex, and there is a certain correlation between the indexes, so the indexes need to be screened before the model is built. In this paper, the variable selection method lasso is used to analyze the factors that affect the final performance [6,7]. The indexes involved in the construction of the prediction model include: x10, x8, x5, x3 and x1.

3. Grey neural network

![Grey neural network diagram](image_url)

Figure 1 Topological structure of grey neural network

Topological structure of grey neural network is shown in Figure 1. It has 4 layers, which are LA, LB, LC and LD, in which, is the serial number of the input parameter, , and mean network prediction value. means network input variables and means network prediction value. means the connection weight from LA to LB, means the connection weights from LB to LC and mean the connection weights from LC to LD. The transfer function of neurons on LB layer is Sigmoid type function: , and that of neurons in other layers is linear function: .
Network initial parameters $w_{11} = a$, $w_{21} = -y_1(0)$, $w_{2j} = 2b_{j-1}/a$ $(i = 1, 2, \cdots, n)$, $w_{3j} = 1 + e^{-at}$ and $(j = 1, 2, \cdots, n)$. The threshold of output contact in LD-layer is:

$$\theta = (1 - e^{-at})(d - y_1(0))$$

(1)

The learning process of grey neural network is as follows:

1) Initialize the network structure according to the characteristics of training data, the initialization parameters are: $a, b$;
2) Calculate $w_{11}, w_{21}, w_{22}, \cdots, w_{3n}, w_{31}, w_{32}, \cdots, w_{3n}$ according to network weights;
3) Input sequence $(t, y(t)), t = 1, 2, 3, \cdots, N$ respectively, and calculate the output of each layer.

LA-layer:

$$l_1 = w_{11}t$$

(2)

LB-layer:

$$l_2 = f(w_{11}t) = \frac{1}{1+e^{-w_{11}t}}$$

(3)

LC-layer:

$$l_{31} = l_2w_{21}, l_{32} = y_2(t)l_2w_{22}, l_{31} = l_2w_{21}, l_{32} = y_2(t)l_2w_{22}, \cdots, l_{3n} = y_n(t)l_2w_{2n}$$

(4)

LD-layer:

$$l_4 = l_{31}w_{31} + l_{32}w_{32} + \cdots + l_{3n}w_{3n} - \theta_y$$

(5)

4) The error between predicted output and expected output is calculated, and the weight and threshold are adjusted according to the error;

Error of LD-layer:

$$\sigma = l_4 - y_1(t)$$

(6)

Error of LC-layer:

$$\sigma_k = \sigma(1 + e^{-w_{11}^k})(k = 1, 2, \cdots, n)$$

(7)

Error of LB-layer:

$$\sigma_{n+1} = \frac{1}{1+e^{-w_{11}^k}}(1 - \frac{1}{1+e^{-w_{11}^k}}) (w_{21}\sigma_1 + w_{22}\sigma_2 + \cdots + w_{2n}\sigma_n)$$

(8)

Weight is adjusted according to predicted error.

Connect weight between LB and LC is adjusted:

$$w_{21} = -y_1(0)$$

(9)

$$w_{22} = w_{22} - \frac{2b_1}{a}\sigma_2l_2, \cdots, w_{2n} = w_{2n} - \frac{2b_{n-1}}{a}\sigma_nl_2$$

(10)

Connect weight between LA and LB is adjusted:

$$w_{11} = w_{11} + at\sigma_{n+1}$$

(11)

Threshold is adjusted:

$$\theta = (1 + e^{-w_{11}^k})(\frac{w_{22}}{2}y_2(t) + \frac{w_{23}}{2}y_3(t) + \cdots + \frac{w_{2n}}{2}y_n(t) - y_1(0))$$

(12)

5) Judge whether the training is over, otherwise, return to step 3).

From the calculation process of grey neural network, it can be seen that its prediction performance is closely related to the selection of $a$, $b_1$, $b_2$, \cdots, $b_{n-1}$ and other parameters. In this paper, if the number of selected indexes is known to be 5, then the related network parameters area, $b_1$, $b_2$, \cdots, $b_5$, and GA algorithm is used for intelligent optimization of the above parameters.

4. Grey neural network model optimized by GA

Genetic algorithm starts from a population which represents the potential solution set of the problem. In this paper, the initialization of the population is realized by real number coding, that is, each individual in the population is composed of neural network parameters $a$, $b_1$, $b_2$, \cdots, $b_5$. After the initial population composition, according to the survival of the fittest and the survival of the fittest principle, individuals are selected according to the size of fitness, and individuals with higher fitness are relatively more likely to be selected to inherit to the next generation. In this paper, the reciprocal of the square sum of prediction error is taken as the fitness function. As shown in formula 13.
\[ f(x) = \frac{1}{\sum_1^n (\hat{y}_i - y_i)^2} \quad (13) \]

In which, \( \hat{y}_i \) is prediction value, \( y_i \) is true value, and \( n \) is the number of samples.

After the fitness of different individuals is determined, an iteration will be completed through genetic operations such as selection, variation and crossover. When the iteration termination conditions are finally met, the output population individual is the optimal solution or near optimal solution of the problem, that is, the network parameter of GNN.

5. Experimental results and analysis

The simulation data used in this paper is obtained from the network learning process data of 1650 students in a network teaching platform, and the learning duration is 16 weeks. The indexes mentioned above are collected separately to form the experimental data set, in which the data of the first 1600 students are used as the training set and the data of the last 50 students are used as the test set. The measurement ranges of each index are quite different, so it is necessary to preprocess the original data, normalize the input indicators, and normalize them to the \([0, 1]\) interval. The transformation formula is shown in formula 14:

\[ \hat{x}_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (14) \]

Root mean square error (RMSE) is selected as the evaluation standard of the prediction effect of the prediction model, as shown in formula 15:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y} - y)^2} \quad (15) \]

In which, \( \hat{y}_i \) is prediction value, \( y_i \) is true value, and \( n \) is the number of samples.

In the GNN structure of the prediction model, 1-1-6-1 is adopted, that is, LA-layer has one node, LB-layer has one node, LC-layer has six nodes and LD-layer has one node. Initial parameters are \( a, b_1, \ldots, b_4 \). The random assignment is set to 0.3 + rand (1) / 4, the learning rate is set to 0.0015, and the number of iterations is set to 1000. GA optimization process is selected according to the proportion, cross operation is based on single point crossing and variation operation is based on basic position variation, the cross probability is 0.4 and variation probability is 0.1, the population size is 30 and the evolution iteration number is 100. In order to verify the validity and accuracy of the prediction model built in this paper, grey neural network and grey neural network model optimized by GA are used to build the prediction model for comparison.

First, GA algorithm is used to get \( a, b_1, \ldots, b_4 \) and other optimal parameters, shown in Table 2.

| Table 2 Parameter value optimized by GA |
|---|---|---|---|---|---|
| a  | b_1 | b_2 | b_3 | b_4 | b_5 |
| 0.5487 | 0.3766 | 0.3238 | 0.3316 | 0.5067 | 0.4235 |

The achievement prediction and errors of GNN and GNN optimized by GA are shown in Figure 1 and 2. It can be seen that the accuracy of prediction model after parameter optimization is significantly higher than that of ordinary GNN. Among them, RMSE of GNN prediction model optimized by GA is 4.89, RMSE of GNN prediction model is 7.61.
6. Conclusion
This paper mainly studies the problem of optimizing grey neural network by genetic algorithm, to realize the prediction of students’ achievement in the network teaching platform. Through the analysis of learning characteristics, this paper selects the input variables of the prediction model. Through experimental verification, the prediction model proposed in this paper can show better prediction performance, the prediction accuracy and RMSE can be kept at 5. This paper only predicts the results of one course, and the horizontal comparison among multiple courses in the network teaching platform is one of the research contents worthy of consideration. In addition, the current network education has gradually tended to the whole process assessment, and a single performance prediction cannot comprehensively assess the cognitive level of students. Therefore, in the future research, the whole process assessment or stage assessment will be used to compare individual students vertically.

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References
[1] PEÑA-AYALA A. Educational data mining: a survey and a data mining - based analysis of recent works [J]. Expert systems with applications, 2014, 41(4): 1432-1462.
[2] ROMERO C, VENTURA S. Educational data mining: a survey from 1995 to 2005 [J]. Expert systems with applications, 2007, 34(1): 135-146
[3] Wu L F, Liu S F, Fang Z G, et al. Properties of the GM(1,1) with Fractional Order Accumulation[J]. Applied Mathematics and Computation, 2015, 252:287-293.

[4] Zhongxing Ye, Improved Genetic Algorithm to Optimal Portfolio with Control[J]. Journal of Shanghai Jiaotong University (Science), 1996, 1(2):9-16.

[5] Xiulan Wen, Aiguo Song, Evolving Neural Networks Using an Improved Genetic Algorithm[J], Journal of Southeast University (English Edition), 2002, 18(4):367-369.

[6] Tibshirani R. Regression Shrinkage and Selection via the Lasso[J]. Journal of the Royal Statistical Society, 1996, 58(1):267-288.

[7] Tibshirani, Robert. Regression shrinkage and selection via the lasso: a retrospective, Journal of the Royal Statistical Society Series B, 2011, 73(3):273-282.