Pattern Recognition Method of Training Japanese Talents in Online Education

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Abstract. Aiming at the problem of poor recognition accuracy and poor recognition sensitivity caused by the poor feature extraction effect of the traditional talent training pattern recognition model. This paper proposes a method to identify the training pattern of Japanese talents in colleges and universities in online education. The principle of separability is used in the process of extracting the target feature quantity. Based on the extracted feature wavelet neural network architecture is constructed. The parameters of the neural network are trained to obtain the optimal parameters. Construct a talent training pattern recognition model through optimal parameters to realize the recognition of talent training patterns. The experimental results show that the accuracy of the recognition method is 92.93% on average, and it can obtain better talent training effect in application.

Keywords: Online education · College education · Talent training mode · Pattern recognition

1 Introduction

College education is a professional education based on ability, and talent training should highlight the ability requirements. With the rapid development of modern society, the practical application ability of students is highly required [1]. The training mode of professional talents in Colleges and universities affects the employment choice and employment prospect of students to a certain extent [2]. Japanese is a basic course in language learning, which is second only to English. The traditional teaching mode has been unable to meet the teaching needs of the Internet era [3]. Under the background of the rapid development of online education, how to make full use of existing teaching resources and improve classroom efficiency is of great significance to the reform and development of College Japanese teaching. Traditional education takes the form of classroom teaching, so it is difficult for teachers to teach students in accordance with their aptitude according to the characteristics of each student [4]. In the classroom, teachers teach mainly, so students' subjective initiative can not be fully mobilized. In addition, the traditional education uses paper teaching materials as the main classroom materials, which has great limitations and is not rich enough. Compared with the traditional education, online education is more convenient and abundant, and it is promoted and developed in Colleges and universities.

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Online education means "large scale open network course", which is the latest form of network teaching. Under the background of the rapid development and popularization of Internet technology, online education, which spans time and space, uses Internet technology and applied information technology for content dissemination and learning, so that excellent educational resources can be shared, which attracts worldwide attention. It has the functions of recording, discussing, teaching and so on. These functions make online teaching content and form more colorful. As the consolidation and supplement of the new teaching content, as well as stimulating the desire of students' autonomous learning, it plays an irreplaceable role. Professional network teaching platform and public teaching resource platform are also very convenient, not only convenient for students to learn, test and so on [5, 6]. In view of the different ways and methods of online education, the online Japanese talent training mode in Colleges and universities is also different. In order to achieve the optimal effect of talent training, it is necessary to identify the talent training mode. Traditional talent training pattern recognition methods use shallow information for recognition. Because of the problems of inaccurate pattern feature extraction and low classification recognition rate of classifiers, the accuracy and sensitivity of recognition methods are poor. Based on the above analysis, in order to improve the training effect of online Japanese education, this paper will study the pattern recognition method of College Japanese talent training in online education. First, the hierarchical relationship between attributes is used to determine the attributes of the Japanese talent training model. Based on the known attributes of the Japanese talent training model, the characteristics of the talent training model are extracted. An adaptive algorithm is used to adjust the learning rate of the neural network. In this way, the recognition of talent training mode can be realized.

2 Pattern Recognition Method of Japanese Talents Training in Colleges and Universities in Online Education

2.1 Determine the Attribute of Japanese Talent Training Mode

In this paper, rule space model is used to distinguish the attributes of Japanese talent training mode. The rule space model does not have a unified definition of attributes. It is generally believed that attributes are the cognitive processing, skills or knowledge that the subjects need to complete a certain work successfully, and are the procedural and specific knowledge required for a specific field of work [7]. Attributes can be independent of each other without association, or they can have a certain hierarchical relationship, that is to say, there is a certain logical or psychological order among the attributes is needed in a test item. If attribute $A2$ is mastered, first master the attribute $A1$. To master the attribute $A1$ is a prerequisite for mastering attribute AZ, otherwise, $A2$ cannot be mastered. This hierarchical relationship between attributes is obtained through qualitative logical analysis.

The rule space model assumes that the performance of subjects on test items depends on a set of specific skills or abilities called attributes. Only when the subjects master these attributes can they correctly answer these items. The first step of the rule space model is to determine the attributes needed to answer the test items and the position of the attributes in the hierarchical relationship. There are many ways to determine the attributes of a test. This paper chooses to make clear what specific cognitive skills the attributes and the relationship between attributes are needed to solve a series of problems in the field of Japanese talent training before compiling the test If test items are compiled before the hierarchical relationship between attributes is determined, these items may not reflect the hierarchical relationship between attributes to be tested by the diagnostic test. The measurement validity of a test also depends on the ability of curriculum experts and test makers to correctly determine the attributes needed to solve specific content domain problems, clarify the relationship between attributes, and develop test items to measure these attributes purposefully and systematically.

The relationship between attributes in the regular space model is characterized by the binary connection matrix A of $K \times K$ (K refers to the number of attributes). The connection matrix only reflects the direct logical relationship between attributes. It indicates that one attribute has or has no direct logical relationship with another. There are only two values of 0 and 1 in the matrix. 0 indicates that there is no direct logical relationship between the two attributes, and 1 indicates that there is a direct one-way logical relationship between the two attributes. As shown in Fig. 1, there are direct unidirectional logical relationships between attributes $A1$ and AZ, Al and $A4$, AZ and $A3$ respectively [8].

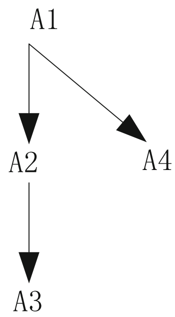

Fig. 1. Hierarchical relationship between attributes

In connection matrix A (see Table 1), it can be seen that the one-way logical relations between $A1$ and $A2$, $A4$, $A2$ and $A3$ are represented by 1, and the rest are represented by 0.

The connection matrix only reflects the direct relationship between attributes, but not the indirect relationship between attributes. Tatsuoka uses reachability matrix R of $K \times K$ to describe the direct and indirect relationships between attributes (K is the number of attributes, 1 indicates that there is a relationship between attributes, and 0 indicates that there is no relationship between attributes). The reachability matrix R of Fig. 1 is shown in Table 2 [9].

Table 1. Connection matrix A

Attribute	Attribute			
	A1	A2	A3	A4
A1	0	1	0	1
A2	0	0	1	0
A3	0	0	0	0
A4	0	0	0	0

Table 2. Attainable matrix R

Attribute	Attribute			
	A1	A2	A3	A4
A1	1	1	1	1
A2	0	1	1	0
A3	0	0	1	0
A4	0	0	0	0

From the first row of Table 2, it can be seen that attribute A1 is related to all attributes, and in the second row, $A2$ is related to $A3$, but not to $A4$. The reachable matrix R is obtained by Boolean addition and multiplication of the connection matrix according to the following formula.

$$R = (A + I)^n \tag{1}$$

In the above formula, I is the identity matrix; $n = 1$. When N changes and R no longer changes, the attainable matrix R is obtained. R the diagonal elements of a matrix are all I, indicating the fact that an attribute is related to itself. After determining the attributes of Japanese talent training mode, the characteristics of Japanese talent training mode are extracted.

2.2 Feature Extraction of Online Japanese Talent Training Mode

In general, the number of original features obtained by analyzing the actual online education data is relatively large. Assuming that all the features are used as classification features, this will not only make the structure of the recognizer more complex and the amount of calculation increase, but also will not make the classification effect better. Generally, there are m methods to reduce the n number of features: $m < n$, feature extraction and feature selection. The extraction of feature quantity can follow the separability criterion of category. It is assumed that the feature selection is to select the two most effective n values from one feature, while for feature selection, C_n^m of the m features are selected, with a total of 6 combinations. However, it is impossible to determine which is the best classification effect, so a standard is set m. Similarly, for feature extraction, it is difficult to know which transformation is the most effective for classification, so a metric is needed. Generally, the error probability of the classifier is used as the criterion, that is, the group with the least error probability is the most effective feature vector. The greater the distance between the samples, the greater the separability of classes:

$$P_{ij} = \frac{1}{2}\sum_{i=1}^{c} P_i \sum_{j=1}^{c} P_j \frac{1}{N_i N_j} \sum_{x^{ij} \in \omega_i} \sum_{x^j \in \omega_j} D\left(x^i, x^j\right) \tag{2}$$

In the above formula, c is the number of categories; N_i is the number of samples in ω_i categories; N_j is the number of samples in ω_j categories; P_i and P_j are the corresponding categories and prior probability [10, 11]; $D\left(x^i, x^j\right)$ is the distance between samples.

European distance [12, 13] is adopted, namely:

$$D\left(x^i, x^j\right) = \left(x^i - x^j\right)^T \left(x^i - x^j\right) \tag{3}$$

The m_i mean vector representing the sample set of the i kind is used

$$m_i = \frac{1}{N_i} \sum_{x^j \in \omega_j} x^i \tag{4}$$

m is the total average vector of various samples, and the calculation formula is as follows:

$$m = \sum_{i=1}^{c} P_i m_i \tag{5}$$

In the process of talent training pattern recognition, firstly, the separability criterion P is selected, and the criterion value of each feature is calculated, and the feature with the highest criterion value is selected, and the hypothesis is x_1. All the two-dimensional vectors including x_1 are selected and the criterion value of each two-dimensional vector is calculated, and then the two-dimensional vector with the highest criterion value is selected. And so on until the required combination of feature vector dimensions is selected. According to the characteristics of talent training mode extracted above, neural network is used to identify.

2.3 Adjustment of Neural Network Learning Rate

In the process of network initialization, the learning rate will directly affect the convergence speed of the network. Usually, the adaptive method can be used to select the learning rate to improve the convergence speed of the network. The general method is: first a random learning rate is set. After one iteration, the error function $\Delta E > 0$ is multiplied by the learning rate η by a number less than n. If $\Delta E < 0$, multiply learning rate η by a number greater than 1. Multiply and continue to iterate. Although this can adjust the learning rate, there are too many temporary data to save when writing code, which makes the whole process very troublesome. In this paper, specific steps for learning rate selection: if $\Delta E > 0$ is iterated for η times, the constant α less than 1 is multiplied by learning rate η; if $\Delta E < 0$ is iterated for n times, the constant β greater than 1 is multiplied by learning rate η. In general, when the error function value increases, the new learning rate does not need to be recalculated along the original direction. Because the direction of the parameter adjustment vector $\Delta\vec{r} = -\eta\Delta E$, that is, $\Delta\vec{r}$, of the error function is the same as that of the negative gradient of the error function, even if the error function increases after iteration, the learning rate decreases, and there is no need to recalculate along the original direction. The direction of the corresponding learning vector is consistent with the direction of the negative gradient, and the error function can ensure that the direction of the negative gradient continues to decrease. The selection of the parameters α and β of the neural network can directly affect the convergence speed of the network. Generally speaking, α is slightly less than 1 and β is slightly greater than 1. Using the training sample set to train the parameters of neural network, so as to realize the recognition of talent training mode.

2.4 Realize Talent Training Pattern Recognition

In this paper, wavelet neural network is used to identify the talent training mode. The number of neurons in the input layer is 9, the number of neurons in the output layer is 5, and the number of neurons in the hidden layer is 15. $x_1, x_2, \ldots, x_9$ represents the input parameters, $y_1, y_2, \ldots, y_5$ represents the output parameters, and ω represents the network weight. In the wavelet neural network [14, 15] with multiple input variables and multiple output variables, the relationship between input and output is as follows:

$$y_j^P(x) = f\left[\sum_{h=1}^{15} \omega_{jh}\psi\left(\frac{\left(\sum_{i=1}^{9} \omega_{hi}x_i^p + b1_h\right) - b_h}{a_h}\right)\right] + b2_j \tag{6}$$

Where, x_i^p is the input component of the i input neuron of the p sample in the input layer; y_j^P is the actual output value of the j output neuron in the output layer under the p mode sample; $b1_h$ is the threshold of the h hidden layer neuron; $b2_j$ is the threshold of the j output neuron; a_h is the output value of the fifth output neuron in the output layer Is the stretching coefficient of the h hidden layer neuron; b_h is the translation coefficient of the h hidden layer neuron; ω_{hi} is the weight connecting the hidden layer neuron and the input neuron; ω_{jh} is the weight connecting the hidden layer neuron and the output neuron. After the network is initialized, the network is trained by the training sample set, and the network parameters are adjusted by correcting the output error. The network with definite parameters is used for pattern recognition. Through the above contents, this paper has completed the research on the pattern recognition method of College Japanese talents training in online education, and the feasibility of this method will be verified below.

3 Experimental Verification and Analysis

Online education is a new attempt for talent training. This section will verify the feasibility and effectiveness of the identification method proposed above through experiments.

3.1 Experimental Content

In order to ensure the validity of the experimental results, this experiment adopts the form of comparative experiment. This paper studies the online education in College Japanese talent training pattern recognition method as the verification group, the traditional talent training pattern feature extraction pattern recognition method as the control group. The performance of the two recognition methods is evaluated by comparing the recognition accuracy, recognition efficiency and the number of iterations in the feature extraction process.

3.2 Experimental Preparation and Process

Experiment 1: in the simulation experiment, the training sample set is used to test the recognition accuracy, recognition sensitivity and iteration times of the two groups of pattern recognition methods. The experimental data set is input into two computer simulation platforms with identical configuration, and the experimental images are extracted and recognized by verification group and control group method. Record the experimental data corresponding to each contrast item, and use the data processing software configured in the simulation platform to process the recorded experimental data. The final conclusion of this experiment is obtained by analyzing the experimental data, and the experimental verification is completed.

Experiment 2: 300 Japanese major students in a university were selected as the object of case verification, and the students were divided into two groups. One group of students used the training mode identified by the method in this paper for teaching and training, and the group was marked as the experimental group; the other group of students adopted the talent training mode identified by traditional methods,

The group was labeled as control group. The indicators of all the validation objects before validation were in line with the standard, with statistical significance. In the process of validation, all validation objects were the same except for the different cultivation mode. After the training process is completed according to the training mode of the experimental group and the control group, the experts in the major of the training object are invited to score the application-oriented ability of the verification object, and the ability of all the verification objects is scored. The formula for calculating the ability score s of a single student is as follows.

$$S = \frac{\sum_{j=1}^{n} g_j}{j} \tag{7}$$

In formula (7), j is the number of items of a certain ability score, and g_j is the score of each item of the ability of the student. Mathematical processing software is used to process the scores of all case objects, and according to the data processing results, the application-oriented ability histogram of two groups of case verification objects is drawn. Analysis of the experimental results, draw a conclusion of example verification.

3.3 Experimental Data and Analysis

Two methods are used to extract the characteristics of talent training mode. The comparison results are shown in Fig. 2. The relationship between the curves in the diagram is analyzed.

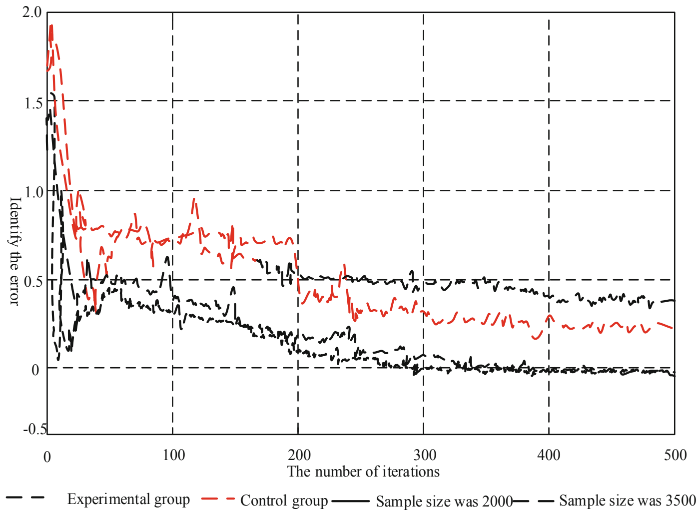

Fig. 2. Comparison of pattern recognition iterations

Analysis of the above figure shows that when the number of experimental samples is 2000, the control group method needs more iterations to achieve the minimum recognition error, and the iteration curve fluctuation of the control group method is more severe than that of the verification group. When the number of samples is 3500, the iterative curve of the two methods is similar to that of 2000. With the increase of the number of experimental samples, the verification group method still needs less iterations to achieve smaller recognition error. The above results show that the verification group method has less iterations and better feature extraction effect.

According to the extracted characteristics of talent training mode, the verification group and the control group are applied to recognize the talent training pattern. The recognition accuracy and efficiency of the two methods are shown in Table 3.

The results show that the recognition rate of the whole group is less than that of the control group, and the time required to verify the method is much shorter than that of the control group. The minimum time difference between the validation group method and the control group method was 26.7 Ms. The average recognition accuracy of the verification group method was 92.93%, and that of the control group was 78.70%, which

Table 3. Comparison of accuracy and recognition efficiency of talent training pattern recognition methods

Serial number	Validation group			Control group		
	Accuracy/%	Sensitivity/%	Recognition tim /MS	Accuracy/%	Sensitivity/%	Recognition time/MS
1	92.7	93.2	18.8	77.4	73.6	49.9
2	94.2	89.4	20.9	79.6	69.5	58.7
3	95.3	93.6	18.2	78.9	72.3	61.4
4	94.7	93.5	18.2	77.2	71.7	55.3
5	93.1	88.9	18.2	80.1	69.8	47.9
6	92.5	91.6	21.0	76.2	73.4	55.5
7	91.6	90.8	20.8	80.4	71.8	59.6
8	92.4	91.5	19.6	75.5	72.6	53.4
9	94.3	91.1	19.7	78.9	70.2	52.7
10	91.8	93.0	21.1	77.7	72.1	60.8
11	95.2	89.7	20.1	80.8	71.7	61.2
12	91.0	89.5	21.2	78.6	73.4	58.6
13	91.5	91.0	21.5	77.6	71.5	58.6
14	92.2	91.5	20.9	78.3	71.4	59.8
15	93.5	90.9	21.0	78.5	71.3	59.7
16	94.4	92.3	20.7	79.1	71.5	58.5
17	92.3	91.1	19.3	80.2	72.8	60.2
18	91.2	90.8	19.4	79.6	70.4	60.1
19	91.0	89.7	19.5	80.1	73.6	59.3
20	93.8	92.5	19.6	79.4	72.1	60.0

was about 1/6 higher than that of the control group. The higher the sensitivity of the identification method, the better the stability of the identification method. According to the analysis of Fig. 2, the verification group method can obtain the minimum recognition error with the minimum number of iterations. That is to say, the pattern recognition method of College Japanese talent training in this paper has the advantages of high recognition accuracy and short time-consuming, and its performance is superior to the traditional recognition method.

The result of example verification is shown in Fig. 3, and the conclusion is drawn by analyzing the figure below.

Analysis of Fig. 3 shows that the ability scores of the control group are lower than those of the experimental group. In terms of international vision and knowledge and skills, the score of the control group was much lower than that of the experimental group. In terms of academic knowledge, there was no significant difference between the two

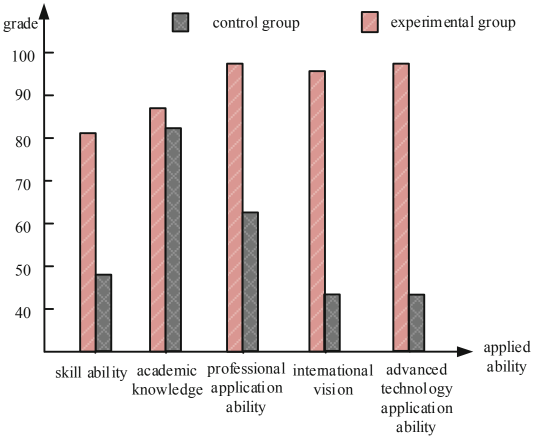

Fig. 3. Example verification results

groups, but the score of the experimental group was slightly higher than that of the control group. According to the scores of all applied abilities, the scores of the experimental group are more balanced than those of the control group, which indicates that the talents trained by the talent training mode identified by this method have more application-oriented abilities. To sum up, the talent training mode identified by the Japanese talent training pattern recognition method in online education studied in this paper can cultivate more balanced talents with application-oriented ability, and has more advantages.

4 Conclusion

In the era of online education, the traditional college Japanese teaching has been unable to meet the actual needs, the traditional teaching methods are mainly through teaching materials, offline classroom and recitation based exam oriented education. However, online education provides students with rich resources and broad space, so that students have the opportunity to choose their own course content or even choose their own teachers. By accepting Japanese knowledge from different channels, the independence and autonomy of Japanese learning will be greatly improved. In order to improve the training effect of Japanese talents in online education, this paper studies the pattern recognition method of Japanese talents training in online education. The effectiveness of the research method is proved by the combination of simulation and example verification.

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