Hindawi
Scientific Programming
Volume 2022, Article ID 9993271, 8 pages
https://doi.org/10.1155/2022/9993271

Research Article

Personalized Learning Behavior Evaluation Method Based on Deep Neural Network

Hengyao Tang, Guosong Jiang, and Qingdong Wang

Computer School of Huanggang Normal University, Huanggang, Hubei 43800, China

Correspondence should be addressed to Qingdong Wang; wangqingdong@hgnu.edu.cn

Received 11 February 2022; Revised 4 March 2022; Accepted 10 March 2022; Published 22 April 2022

Academic Editor: Baiyuan Ding

In recent years, the research on personalized learning under the background of "Internet +" mainly focuses on the theory, design, and application and there is less research on learning evaluation. As an important means to measure the learning process and results, learning assessment plays an important role in supporting the effectiveness of personalized learning. From the perspective of educational services, how to realize learning evaluation that meets the needs of personalized learning is an important issue to be studied in the field of personalized learning. In this paper, the big data generated by learners on the online learning platform are used as the research target, and according to the level of learners' learning ability, a deep neural network is established to cluster and group them according to the cognitive thinking method. In order to reduce data redundancy and improve processing efficiency, a deep neural network with five hidden layers is used to extract typical features, so as to obtain more accurate evaluation results. Finally, the neural network model is used to obtain the clustering results of different groups of learning behaviors and the evaluation curves of the five-course knowledge points of learners at different levels. From the experimental results, the proposed personalized evaluation method can effectively analyze the learning differences between learners with different ability levels, and it is basically consistent with the evaluation standards of artificial experts.

1. Introduction

Personalized learning in the context of Internet+ aims at the development of students' individuality, respects individual differences of students, and emphasizes the individual support of information technology. This way of learning can promote students' individual potential to be maximized, which is very in line with the current needs of talent training in colleges and universities [1–3]. The development of information technology, especially the application of the Internet in education, enables learners to obtain abundant resources according to their own interests and learning needs, receive personalized services and guidance, and control the learning process autonomously, making learning more personalized change [4].

The current society is entering the information age and the "Internet +" age from the industrial age. With the improvement of social and economic level and living standards, people's educational needs are developing from standardized teaching to personalized learning and life-long learning, and the supply of educational services will also change from "standardized supply" to "personalized service." Relevant statistics show that in recent years, the research on personalized learning under the background of "Internet +" mainly focuses on the theory, design, and application, and there is less research on learning evaluation [5–7]. As an important means to measure the learning process and results, learning assessment plays an important role in supporting the effectiveness of personalized learning. Although personalized learning can simplify the cost and operation mode of learners, there is currently a lack of suitable means for evaluating the teaching effect of personalized learning; especially, some unique characteristics displayed by personalized learning, such as learners before starting to learn. The cognition of the knowledge structure and scope that one has, the knowledge blind spots that should be made up after a period of study, the improvement of learning ability and preferences after the study is over. If the characteristics of this personalized learning are not accurately grasped, it will be difficult to achieve the true sense of teaching students in accordance with their aptitude. In addition, if the traditional artificial force is used to analyze the activities of each learner, it is impossible to face the vast ocean of data generated every moment on the learning platform. Using information technology, the machine analyzes the big data generated by the user's learning behavior, retains key and effective features, and generates a complete and accurate personalized evaluation. From the perspective of educational services, how to realize learning evaluation that meets the needs of personalized learning is an important issue to be studied in the field of personalized learning [8–12].

In response to this core issue, many researchers have conducted in-depth research from various aspects. For example, for the massive big data generated on the learning platform, Hadoop technology is used to aggregate, store, and obtain massive learning data; the literature forms a multidimensional three-dimensional household data model by recording learners' online learning behaviors, records, habits and preferences, and other activities to quantify the behavior patterns of learners in the process of personalized learning, so as to provide targeted personalized services, use the gradient descent method to synthesize the data, obtain relevant data models for learning evaluation, and put forward an intelligent learning guidance environment [13, 14, 15]. No matter which method is used, the core of the evaluation is how to effectively classify the data generated by the learner in the learning process and to effectively reduce the dimension of the multidimensional data features that describe the learner's behavior in an appropriate way, which can ensure the uniqueness of the data features [16–19]. It is representative and can ensure that the system platform can realize the calculation with the minimum calculation cost. And how to improve the accuracy of the classification and effectively use the classification results to provide help for subsequent processing, the performance of the deep neural network in this aspect is very significant. At present, neural networks have good performance in almost all problem areas related to classification [20].

In view of the advantages of deep neural network in feature training, a method based on deep neural network learning is proposed in this paper. First, the feature vectors of the original learning data generated by the learners are automatically clustered, and then, the multidimensional data vector features are dimensionally reduced and cleaned by using the deep learning network DNN to ensure the real validity and real-time performance of the evaluation data. Finally, through the relevant experimental data, the validity of this personalized evaluation behavior is verified [21–24].

2. Analysis of the Existing Problems in Personalized Learning Evaluation

In the "Internet +" environment, more and more students' personalized learning evaluations use process evaluation methods. Process evaluation is an evaluation activity aimed at optimizing the learning process, improving the learning effect, and promoting the development of individual life. Process-oriented learning evaluation can be used as an effective means to focus, record, guide, motivate, and promote learners' learning experience and growth and is a key link in the quality assurance of online education. Through literature analysis and teaching practice, the author found that there are some problems in the process of implementing personalized learning evaluation.

2.1. Analysis of Evaluation Subjects. The subject of evaluation refers to the implementer of evaluation activities, that is, the evaluator. The evaluation concept of the evaluator should be considered from two aspects, one is the current knowledge level of the evaluator, and the other is its possible development potential. The main problems of evaluation subjects are as follows. (1) There is over-emphasis on the diversification of evaluation subjects, such as students' self-evaluation and mutual evaluation, intragroup and intergroup evaluation, teachers' evaluation, and even the evaluation of students' parents, but such a multievaluation method is not suitable to evaluate personalized learning, because personalized learning focuses on changes in the learning process, not just learning results, and self-evaluation and mutual evaluation lack the necessary process data support. (2) There is lack of personalized evaluation standards, even if the same students in a teaching class vary in their knowledge level, learning ability, personal goals, academic mood, etc. It is difficult to use unified evaluation standards to provide students with personalized and accurate evaluations, and it is difficult to help students achieve their own learning goals. (3) The evaluation is based on a single source of data, and the learning effect evaluation of learners is often only measured by academic performance, lacking data support for learning behaviors, such as independent study, participation in problem discussions, completion of homework, display and sharing of works, etc.

2.2. Evaluation Object Analysis. The object of evaluation refers to the recipient of the evaluation activity, that is, the person being evaluated. Contemporary college students have flexible thinking, strong ability to accept new things, high enthusiasm for professional learning and ability improvement, and advocating competition and have a positive and enterprising spirit. However, it is undeniable that with the continuous changes in the international and domestic situation, under the combined effect of ambivalence such as enjoying life and employment pressure, some students are anxious and confused in their hearts. Some problems include not knowing oneself correctly, failing to find a suitable learning method for oneself, and lack of self-confidence to become an excellent student.

2.3. Analysis of the Evaluation Process. Process evaluation should be able to effectively guide students' learning process, adjust learning behavior, and timely feedback of learning results, which has a positive impact on improving students' learning motivation and guiding students' future development direction. At present, the traditional procedural evaluation process has the following problems: (1) lack of individualized assessment of learners; (2) lack of data tracking of learning behavior in the learning process; (3) lack of timely feedback of learning results.

3. Construction of the Personalized Learning Evaluation Model from the Perspective of Education Service

In the "Internet +" environment, the process evaluation of personalized learning requires appropriate service processes to solve the actual problems and solve the problems that lack the evaluation of learners' personalized characteristics, the lack of data tracking of learning behavior in the learning process, and the lack of learning results timely feedback and other issues. This research builds a personalized learning evaluation model from the perspective of educational services, which mainly provides services such as learner personalized feature testing, personalized learning evaluation plan matching, personalized learning process data tracking, and timely feedback of learning results. The specific evaluation service process is described as follows.

3.1. Personalized Trait Testing for Learners. The evaluation service first evaluates the evaluation object, that is, the knowledge level of the learner, and then accurately selects a personalized evaluation plan according to the learning goal selected by the learner: (1) to test the knowledge level, it is necessary to understand the learner before the learning evaluation service. Match the appropriate individualized assessment plan through the knowledge level; (2) after the learners complete the knowledge level test, the selected learning objectives are divided into mastery and understanding; (3) test the academic mood; Academic Mood Self-assessment is a subjective test for learners. The purpose of testing learners' academic emotions is to study the impact of personalized learning evaluation services on students' personalized learning.

3.2. Automatic Evaluation Scheme Matching for Learners. The results of the learner's knowledge level test and the choice of learning objectives determine the type of learning. According to the learning type, the learning evaluation plan is automatically matched from the preset personalized evaluation plan library. In different evaluation schemes, for learners with high knowledge levels and learning goals, the evaluation standard will be higher; for learners with low knowledge levels and low learning goals, the evaluation standard will be appropriately lowered, requiring them to complete basic learning. The content can be improved on an original basis.

3.3. Personalized Learning Process Tracking for Learners. The purpose of tracking the learning process of individualized learning is to grasp the first-hand information of the learner's learning status. Based on the concept of big data, the learner's learning activities and learning results are recorded in detail. Through data analysis, problems are identified, and timely reminders and help are given. Intervention and adjustment of learners' learning behaviors are carried out through learning process tracking and data analysis methods.

3.4. Giving Learners Feedback on the Results of Learning Activities. The learning activities and learning results of the personalized learning process must have accurate and timely feedback. Quantitative feedback should be given to the learning activities that learners participate in, such as the degree of interaction, participation in discussions, resource utilization, etc., and the learning points will be recorded according to the set rules; in the correction of homework, the objective questions will be feedback immediately, and the subjective questions will be given within a limited time limit. Feedback is given inside; the test results of each stage are displayed in visual graphics so that learners can keep abreast of the trend of their academic performance; excellent practical works are displayed and exchanged, and their advantages and disadvantages are pointed out. This service link not only allows learners to understand their own test scores in time but also understands the results of their own learning behavior investment, so as to clarify the next step forward.

4. Deep Neural Network Evaluation Model

4.1. Deep Neural Network. DNN is developed based on artificial neural network, and the main difference between the two is that a deep neural network contains multiple hidden layers and the number of network nodes. DNN hidden layers discover the inherent properties of the data, thereby improving the modeling ability of neural networks to learn multiple layers of abstract data. Multiple neurons in DNN can obtain common core features of the dataset from a small amount of training data and have powerful modeling capabilities for complex problems. The specific process of DNN is as follows.

After the data is preprocessed, the initialization data are passed from the input layer to the first hidden layer. The input-output relationship of the first hidden layer is

$$r_1 = f\left(w_1 \cdot x + b_1\right). \quad (1)$$

Suppose all output values in r_1 are the original column vector x transformed by the activation function f:

$$r_{1,m} = f\left\{\sum_{i=1}^{n} w_{1,m,i}\cdot x_i + b_{1,m}\right\}. \tag{2}$$

According to the principle of DNN, the output r_p of the Pth hidden layer in the DNN model can be obtained.

$$r_p = f\left(w_p\cdot r_{p-1} + b_p\right). \tag{3}$$

The value of all elements in the output r_p of the hidden layer of $r_{p,m}$ layer P is

$$r_{p,m} = f\left\{\sum_{i=1}^{q} w_{p,m,i}\cdot r_{p-1,i} + b_{p,m}\right\}. \tag{4}$$

After the input vector X is processed by the input layer and all hidden layers, it will be transmitted to the output layer. The result is as follows:

$$y = g\left(w_{n+1}\cdot r_n\right) + b_{n+1}. \tag{5}$$

For a training set $\{(x_1,y_1),\ldots,(x_m,y_m)\}$ containing m labeled samples, during the neural network training process, the cost function of each sample (x, y) is

$$G(W,b) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left\|h_{W,b}\left(x^i\right) - y^i\right\|^2. \tag{6}$$

Using the gradient descent method can obtain a good convergence effect and reach the local optimal value, so the parameters W and b are set, and the update formula is as follows:

$$\begin{aligned} W_{ij}^{l} &= W_{ij}^{l} - \alpha\frac{\partial}{\partial W_{ij}^{l}}G(W,b),\\ b_i^l &= b_i^l - \alpha\frac{\partial}{\partial b_i^l}G(W,b). \end{aligned} \tag{7}$$

4.2. An Efficient Clustering Method Based on Multidimensional Data Vectors. According to Bloom's theory, human cognitive thinking is divided into six levels: memory, understanding, application, analysis, evaluation, and creation. Therefore, two levels are adopted for the abstraction of online learning behavior data features. The first level is low-level features, which mainly includes login time, learning time, number of learning times, selected knowledge points, number of discussion, number of questions asked, number of questions answered, number of questions solved, time to complete the test, success rate of completing the test, homework score, etc. $U_{\text{low}} = \{x_1, x_2, \ldots, x_n\}$. The second layer is the high-level feature, which mainly includes the degree of homework completion, the accuracy rate of homework completion, the quality of learning questions, the quality of answering questions, the quality of problem-solving solutions, etc. $U_{high} = \{y_1, y_2, \ldots, y_n\}$. Each sample can be further divided into multidimensional features, such as $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ and $y_i = (y_{i1}, y_{i2}, \ldots, y_{in})$, where each component represents a characteristic of learning activities, such as logging in times and study time. After obtaining multidimensional data, a clustering algorithm can be used to divide the required data features.

4.3. Feature Extraction Methods for Clustered Data. The feature extraction of clustered data adopts the hidden Markov model based on DNN, which is a forward neural network with multiple hidden layers. The input layer represents the underlying features of the clustered data, and the output layer represents the typical features after dimensionality reduction. The nonlinear activation function of each node in the hidden layer adopts SIGMOD, and the nonlinear output value of each node is

$$\begin{aligned} y_j^h &= \mathrm{Sig}\left(x_j\right) = \frac{1}{1+e^{-x_j}},\\ x_j &= b_j + \sum_i y_j^{h-1} w_{ij}. \end{aligned} \tag{8}$$

Among them, y_j^h is the nonlinear output value of the jth node in the hth layer; x_j is the node input value; b_j is the bias; w_{ij} is the connection weight between node j and i. The DNN training parameters are obtained by iterative training of the BP network propagation algorithm.

$$J = \left(w_1, b_1, w_2, b_2\right) = \frac{1}{N}\sum_{i=1}^{N}\left(x_i' - x_i\right)^2. \tag{9}$$

The initial network parameters are initialized by the RBM restricted Boltzmann machine.

$$\begin{cases} \dfrac{\partial \log\, p(v|\theta)}{\partial w_{i,j}} \approx \dfrac{1}{N}\displaystyle\sum_{n=1}^{N}\left[v_i^n h_j^{(n)} - v_i^n h_j^{(n)}\right],\\[2ex] \dfrac{\partial \log\, p(v|\theta)}{\partial b_i} \approx \dfrac{1}{N}\displaystyle\sum_{n=1}^{N}\left[v_i^n - v_i^n\right],\\[2ex] \dfrac{\partial \log\, p(v|\theta)}{\partial b_j} \approx \dfrac{1}{N}\displaystyle\sum_{N=1}^{N}\left[h_j^{(n)} - h_j^{(n)}\right]. \end{cases} \tag{10}$$

In this paper, the deep neural network modeling unit is used as the basic unit. As shown in Figure 1, each multidimensional feature is divided into three HMM states, and all multidimensional feature HMM states correspond one-to-one with each node of the DNN output layer. In the experiment, 8-dimensional features are used as input, and 5 hidden layers are used, and each hidden layer has 1024 nodes.

As shown in Figure 1, the input of the deep neural network is the learning activity data, and the output corresponds to the key typical features after dimensionality reduction and cleaning. After the layered processing of the neural network, the distinguishing degree of the features is enhanced. Some distinguishing degrees are relatively poor and are not used. The feature quantities that highlight the characteristics of the learner are processed by the hidden layer, which can ensure that the final extracted features can

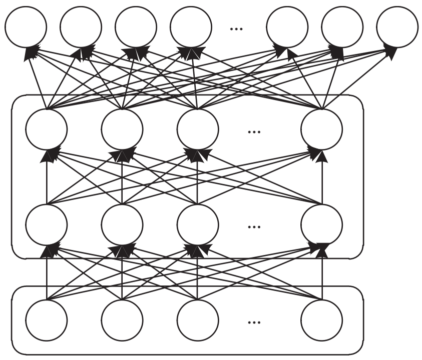

Figure 1: Deep neural network structure.

greatly reduce the dimension while maintaining the maximum degree of discrimination. The activation of each hidden layer node of the deep neural network is mainly determined by the output value of the node. In order to make the feature distribution more similar to the Gaussian distribution, the output value of the hidden layer is averaged to make the feature output close to the Gaussian distribution.

The obtained clustering feature is denoted as $\cup\sigma_i$, where σ_i corresponds to the i-th learning feature, and the mean value of this feature in the hidden layer is obtained through the neural network.

$$H_{i,t} = \frac{1}{L}\left(h_{i,1} + h_{i,2} + \cdots + h_{i,L}\right). \tag{11}$$

Among them, $h_{i,L}$ is the nonlinear output vector of the i-th feature on the L-th layer, and the average value of each hidden layer feature is taken as the network feature of the feature.

$$F = \frac{1}{T}\sum_{i=1}^{N}\sum_{i=1}^{N} H_{i,t}. \tag{12}$$

In order to obtain the effective feature components in the mean feature of the hidden layer, the effective feature after the final dimension reduction is obtained by using

$$E = H_{i,t} - F. \tag{13}$$

5. Analysis of Results

In the experiment, a well-known video teaching website in China was used as the test platform, and the records of 900 students' learning activities on the platform were compared and analyzed. First, the experimental samples are divided into three groups: elementary, intermediate, and advanced according to the level of learning ability, and each group includes 300 students' records of learning activities of a certain knowledge point in 5 online courses within one month.

The knowledge points of different courses basically show a normal distribution pattern for learners at different levels. Regardless of the level of the learner's ability, the mastery of the knowledge points of the course basically conforms to the same principle. Since the difficulty coefficient of each course is different, different courses also show different degrees of distinction. For example, it can be found that the distribution state and style of the intermediate group and the advanced group are basically the same, while the distribution of the elementary group is different from the other two. There are clear differences between groups. This shows that for the five courses currently tested, the level of entry level still has a certain influence on the establishment of learners' later learning behavior.

Figure 2 shows the performance curves of learning each course in different groups, mainly showing the clustering results of learning knowledge points of different courses. As can be seen from Figure 2(a), since the "Web Technology Fundamentals" course does not require very high prerequisite knowledge for learners and the knowledge points are simple, the primary group surpasses the intermediate and advanced groups, which may be related to the learners' learning experience mentality related. Figures 2(b) and 2(c) two courses have higher requirements for preknowledge and need to have a certain computer and mathematics foundation, so it can be found that the students in the advanced group have a better grasp of knowledge points than the other two groups. As Figures 2(d) and 2(e) are both programming courses, the knowledge points to be learned are similar and the difficulty is equal, so the performance curves are basically similar, but it is obvious that the primary group's mastery of knowledge points is similar to other. There is still a small difference between the two groups. It can be seen that the learning ability and behavior of the advanced group samples are significantly higher than those of the intermediate group and the primary group, which are related to the learners' previous learning experience, knowledge accumulation, learning habits, and understanding ability, which also shows that the learning ability high and low is a step-by-step cultivation process.

In order to further measure the accuracy of the evaluation method in this experiment, the method of manual expert review was introduced to compare with the method of machine learning evaluation. Experienced teachers are selected in this major to evaluate the knowledge points of each course according to different levels of groups. The main basis of manual evaluation methods still uses traditional methods, such as class attendance rate, homework completion rate, completion quality, test scores, project capability, and other easily quantifiable indicators, and in order to ensure statistical fairness, all human experts are set to have the same weight. The results of the statistical analysis are shown in Figure 3. It can be seen from the figure that due to the advantages of learning background and ability, the curve of the advanced group is slightly different from that of the other level groups and the manual group, while the curve obtained by the primary group and the intermediate group is highly consistent with the curve obtained by the manual review, indicating that the machine learning evaluation is not effective. The method can truly reflect the human evaluation criteria for the learning effect.

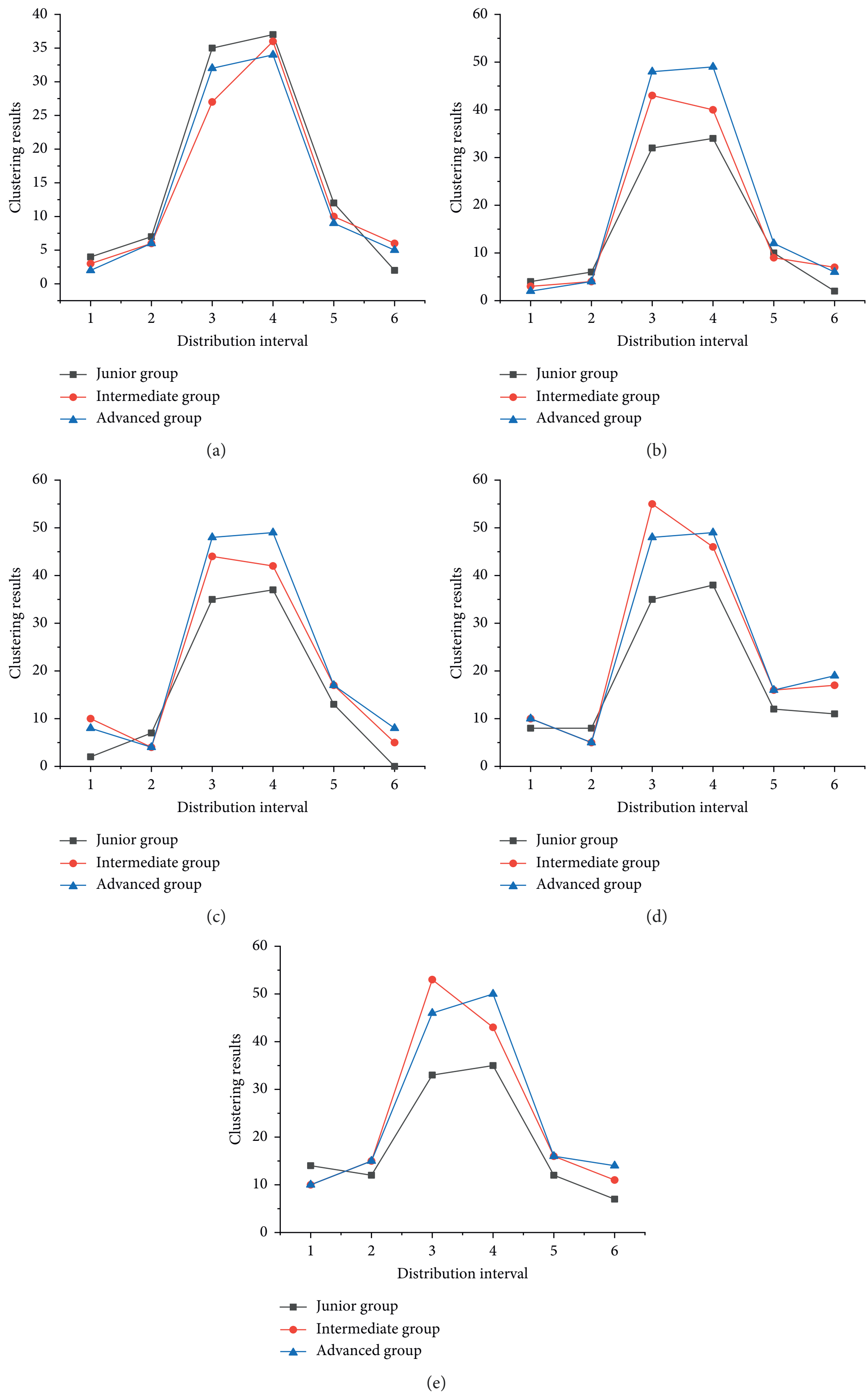

Figure 2: Evaluation curves of different courses for learners at different levels. (a) Assessment of knowledge points in the basic course of web technology. (b) Assessment of knowledge points in artificial intelligence courses. (c) Evaluation of knowledge points in the data structure course. (d) Evaluation of knowledge points in the python degree design courses. (e) Evaluation of knowledge points in a java programming course.

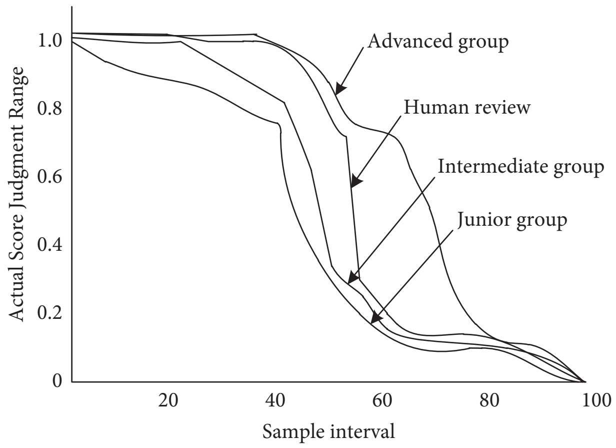

Figure 3: Comparison of results between human expert evaluation and machine statistical evaluation.

6. Conclusion

The development of information technology will inevitably bring about fundamental changes in traditional learning methods. How generate personalized and accurate learning behavior evaluation for learning users, so that learners can better understand their learning situation. The state and behavior state truly realize the "targeted" and "individualized teaching" of the learning method. This paper uses machine learning to classify the user data generated by the network platform and then uses the deep neural network to reduce the dimension of the feature data to extract typical features, which can not only reduce the computational cost of training but also ensure that the training features are the best. It can reflect the characteristics of learners' individual learning. Judging from the experimental results, the evaluation results obtained by machine learning are basically consistent with the evaluation results obtained by manual expert review, which shows that under the premise of ensuring the amount of data, machine evaluation can replace manual evaluation, and machine evaluation is more objective and comparative. However, according to the latest research results, the gradient of the deep neural network will be unstable during training, and the existence of this phenomenon will affect the performance of the neural network. The next research can consider introducing different learning methods to analyze the learning data, in order to obtain a more general personalized learning evaluation method.

Data Availability

The dataset can be accessed upon request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. Shin and O. Bulut, "Building an intelligent recommendation system for personalized test scheduling in computerized assessments: a reinforcement learning approach," *Behavior Research Methods*, vol. 54, no. 2, 2021.

[2] X. Tang, Y. Chen, X. Li, J. Liu, and Z. Ying, "A reinforcement learning approach to personalized learning recommendation systems," *The British journal of Mathematical and Statistical Psychology*, vol. 72, no. 1, 2018.

[3] F. Zhang and S.-X. Feng, "The process of personalized learning based on flipped classroom," *Sino-US English Teaching*, vol. 14, no. 4, 2017.

[4] D. H. C. Nguyen, N. Arch-Int, and S. Arch-Int, "FUSE: a fuzzy-semantic framework for personalizing learning recommendations," *International Journal of Information Technology and Decision Making*, vol. 17, no. 4, 2018.

[5] Y. Chen, "Research on resource personalization recommendation algorithm and model based on computer deep learning," *Journal of Physics: Conference Series*, vol. 1915, no. 2, 2021.

[6] A. Shemshack, Kinshuk, and J. M. Spector, "A comprehensive analysis of personalized learning components," *Journal of Computers in Education*, vol. 8, no. 4, 2021.

[7] H. Almed, "Determinant factors and adaptation features of mobile personalized learning system," *Journal of Physics: Conference Series*, vol. 1858, no. 1, 2021.

[8] S. Chaichumpa, S. Wicha, and P. Temdee, "Personalized learning in a virtual learning environment using modification of objective distance," *Wireless Personal Communications*, vol. 118, pp. 2055–2072, 2021.

[9] L. Fulton, D. L. Hoffman, and S. Paek, "Language learning in an era of datafication and personalized learning," *Educational Technology Research and Development*, vol. 69, no. 5, 2020.

[10] D. Zou and H. Xie, "Personalized word-learning based on technique feature analysis and learning analytics," *Journal of Educational Technology & Society*, vol. 21, no. 2, 2018.

[11] L. Zhang, J. D. Basham, and S. Yang, "Understanding the implementation of personalized learning: a research synthesis," *Educational Research Review*, vol. 31, 2020.

[12] W. Intayoad, T. Becker, and P. Temdee, "Social context-aware recommendation for personalized online learning," *Wireless Personal Communications*, vol. 97, no. 1, 2017.

[13] C. Troussas, K. Chrysafiadi, and M. Virvou, "An intelligent adaptive fuzzy-based inference system for computer-assisted language learning," *Expert Systems with Applications*, vol. 127, 2019.

[14] A. T. Tadesse and P. . I. Davidsen, "Framework to support personalized learning in complex systems," *Journal of Applied Research in Higher Education*, vol. 12, no. 1, 2020.

[15] X. Su, "Personalized learning resource recommendation methods from the perspective of deep learning," *Organic Chemistry: An Indian Journal*, vol. 14, no. 3, 2017.

[16] H. Wang and W. Fu, "Personalized learning resource recommendation method based on dynamic collaborative filtering," *Mobile Networks and Applications*, vol. 26, pp. 473–487, 2020.

[17] "Personalized learning environment in higher education through big data and blended learning analytics," *International Journal of Recent Technology and Engineering*, vol. 8, no. 3, 2019.

[18] M. Alberto, "Optimizing student-driven learning (SdL) through a framework designed for tailoring personal student paths," *Education Sciences*, vol. 10, no. 9, 2020.
[19] H. Xie, Di Zou, R. Zhang, M. Wang, and R. Kwan, "Personalized word learning for university students: a profile-based method for e-learning systems," *Journal of Computing in Higher Education*, vol. 31, no. 2, 2019.
[20] H. A. Alamri, S. Watson, and W. Watson, "Learning technology models that support personalization within blended learning environments in higher education," *TechTrends*, vol. 65, no. 3, 2020.
[21] M. Somasundaram, K. A. Mohamed Junaid, and M. Srinivasan, "Artificial intelligence (AI) enabled intelligent quality management system (IQMS) for personalized learning path," *Procedia Computer Science*, vol. 172, no. C, 2020.
[22] F. M. Andi Besse, Y. Norazah, and B. Ahmad Hoirul, "Personalized learning model based on deep learning algorithm for student behaviour analytic," *Procedia Computer Science*, vol. 163, no. C, 2019.
[23] X. Duan, "Automatic generation and evolution of personalized curriculum based on genetic algorithm," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 14, no. 12, 2019.
[24] M. Zhang, J. Zhu, Z. Wang, and Y. Chen, "Providing personalized learning guidance in MOOCs by multi-source data analysis," *World Wide Web*, vol. 22, no. 3, 2019.