A Study of Personalized Learning Behavior Evaluation Method Based on Deep Neural Network

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Abstract: The development of computer technology has greatly changed and influenced human production and life style. With the development of computer technology, the intelligent algorithm of neural network has also been developing rapidly. Deep learning is a method that can learn the intrinsic characteristics of data, which interprets data by simulating human brain to construct multi-layer neural network. In this paper, the deep neural network algorithm was optimized, analyzed and applied to the research of personalized learning behavior evaluation method, and then the most specific application effect was analyzed and evaluated. The comparative analysis shows that this method is superior to other traditional algorithm methods, it has better applicability and learning effect and has certain promotion value and significance.

1. Introduction

With the development and application of modern computer technology, computer technology has been applied in various industries, and achieved very good results. More and more neural network structures have been applied to various machine learning tasks. Deep learning algorithm is devoted to mining the unknown structure of the input data to find a good data representation. Many researchers have found that the representation of data has a significant impact on the performance of the learning algorithm [1]. Everyone has their own different ways of thinking, habits, hobbies and so on. If every student can be taught in accordance with their aptitude, then better learning results can be achieved. Modern learning emphasizes more on individualized learning to achieve the desired learning objectives [2]. By introducing modern intelligent algorithms into the evaluation of personalized learning behavior, it is possible to construct a model by collecting more learning behavior, conduct specific behavior analysis, identification and evaluation, and then analyze and evaluate the results, or put forward suggestions and measures. This provides a certain reference for the summary and application of modern learning methods, and it has a certain practical value and significance for the promotion and implementation of personalized learning methods.

2. Deep Neural Network

2.1. Commonly used activation functions

Neural network refers to two kinds: one is biological neural network and the other is artificial neural network. Biological neural network generally refers to the biological brain neurons, cells, contacts and other components of the network, which is used to generate biological awareness and help organisms to think and act [3]. Artificial Neural Networks (ANNs), also called Neural Networks (NNs) or Connection Model, is an algorithmic mathematical model that imitates the behavioral characteristics of animal neural networks and performs distributed parallel information processing [4]. Depending on the complexity of the system, this network can process information by adjusting the interconnection between a large number of internal nodes. The research contents of neural network are quite extensive, which reflects the characteristics of multi-disciplinary cross-cutting technology. On the basis of theoretical model research, a concrete neural network model is constructed to realize computer simulation or prepare hardware, including the study of network learning algorithm. This work is also called technical model research [5].

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The basic structure of deep neural networks is neurons, as shown in figure 1. In the figure, x_1, x_2 and x_3 are the inputs of the neuron; w_1, w_2 and w_3 are the weights of the corresponding inputs; x_0 is fixed to 1; $w_0 = b$ is the bias of the neuron.

Therefore, the input of the neuron is:

$$a = w_1 x_1 + w_2 x_2 + w_3 x_3 + b \tag{1}$$

The output is:

$$y = f(a) \tag{2}$$

The function $f(a)$ is the activation function. Next, several commonly used activation functions will be introduced. Activation function usually has the following properties:

The first is nonlinearity. Only when the activation function is non-linear can a two-layer neural network approach all functions. But the identical activation function is an exception [6]. When the identical activation function is used in the multi-layer neural network, the network is equivalent to a single-layer network. The second is that it is continuously differentiable. This condition is the premise of using gradient-based optimization method. The third is that the range of output is limited. When the output range of the activation function is limited, the gradient-based training method will be more stable [7]. The last one is monotonicity. When the activation function is a monotone function, the loss function of the single-layer network model is determined to be a convex function.

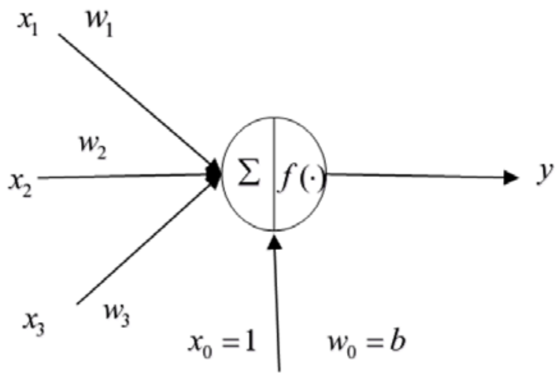

Fig.1. Basic neuronal structure

It approximates the identity function near the origin. When the activation function approaches the identical function near the origin, the learning efficiency of the neural network will be faster if the smaller values of the weights are randomly initialized. If the activation function is not close to the identity function near the origin, then special techniques are needed to initialize the weight.

2.2. Deep network structure

Current research has found that many deep neural networks that have been trained on data sets have a common phenomenon: in the first layer of the network, the features they learn are generally some directed edges and color blocks [8]. This phenomenon not only exists in a specific image data set, but also widely exists in a variety of data sets for image classification tasks. In this kind of network, the data characteristics will eventually change from general to special before the last layer, which provides the possibility of using deep neural network for migration learning. In addition, training a new neural network from scratch may consume a lot of manpower and material resources. On the one hand, it may need to collect data and label it manually. On the other hand, for large-scale deep neural networks with complex structures, retraining means longer time and cost. From another point of view, discarding a large number of training data also means wasteful.

Therefore, exploring how to combine the deep learning technology with the neural network technology can improve the accuracy of the model, and make the training faster and the cost lower. Compared with the traditional non-in-depth learning evaluation methods, the in-depth learning evaluation method directly improves the learning effect of the model on different tasks [9]. Moreover, in-depth learning directly learns from the original data, so it has two advantages over traditional non-in-depth learning methods: the process of feature extraction is not artificial, and the network automatically extracts features through training, which is more expressive.

The convolution layer consists of some learnable filters. Spatially, each filter is not large along the width and height of the input, but the depth of the input is the same. That is to say, the depth of the filter is the same as that of the convolution layer. For example, the size of the first convolution layer of a convolution neural network with three-channel images as input may be 4*4*3 (width and height are 4, and depth is the same as the number of channels of the image, as 3). In the feed forward process, each filter slides along the width or height of the input (generally from left to right, and from top to bottom) gradually (the sliding step is the width or height of the filter), and calculates the weight of the corresponding position filter and the dot product of the input. With the gradual sliding of the filter, each filter will eventually form a two-dimensional feature mapping. Each location of the mapping gives the response of the filter at the corresponding location. Intuitively, the filters learned by convolutional neural networks are activated (greater than zero) when they "see" certain kinds of features. For example, the filter in the first layer is usually activated when it encounters some directed edges, and some high-level filters may be activated when it encounters honeycomb-like features. Ultimately, multiple two-dimensional features from multiple filters are stacked together as input to the next layer. When dealing with high-dimensional inputs such as images, it is unrealistic to establish connections between each neuron. On the contrary, each neuron in the posterior layer has only connections with neurons in some area of the anterior layer [10]. The size of the junction region is a hyperparameter, which becomes the receptive field of the neuron. For example, assuming that the size of the input image is 28*28*3 and the size of the receptive field (filter) is 5*5, then each neuron in the convolution layer will be connected to a 5*5*3 input region, and there will be a total of 5*5*3=75 weight parameters (plus a bias parameter).

3. Comparative Study of Results

3.1 Applicability evaluation

In order to verify the applicability of the deep neural network algorithm proposed in this paper, the data set of Office-31 is selected for experiment, and the accuracy of several traditional algorithms is compared. Among them, the PCAD method based on MMD regularization is A; the widely used method based on traditional transfer learning is B, which connects source domain and target domain by constructing multiple sub-spaces; and the research method proposed in this paper is C. Established data sets are input for accuracy verification. According to the standard rules of unsupervised domain adaptation, all source domain data have labels, and all target domain data have no labels. For each task, the accuracy and average error rates of the proposed method are compared with those of the previous methods. The experimental results are shown in table 1.

Table 1 Experimental results of deep neural network and other algorithms

Method	Accuracy rate
A	28.9%
B	63.%
C	78.4%

From table 1, it can be seen that the proposed algorithm is obviously better than the other two methods, and it achieved higher accuracy and better applicability.

3.2 Evaluation of learning effectiveness

Deep network neural algorithm is further used to analyze the learning effect of personalized recommendation learning. Through the comparative experiment, the effect of this method is compared with that of the traditional learning evaluation method. Forty students are selected for the control experiment. Forty students come from the same major and class in a university, and their learning abilities and foundations are comparable. By randomized grouping, 20 people in each group are divided into control group B and experimental group A. The experimental group used the personalized recommendation learning evaluation method based on the deep network neural algorithm, while the control group used the traditional learning evaluation method. A kind of learning course in universities is selected as the course content for learning, and online learning method is adopted. According to the different effects and behaviors of online learning, learning schemes are recommended to achieve different learning processes for different students. After completing the study, the course assessment is carried out. The assessment responds to the performance indicators and divides the corresponding intervals, so as to compare the different learning effects of the two methods.

After two months' study, the learning effect of the control group and the experimental group is shown in figure 2.

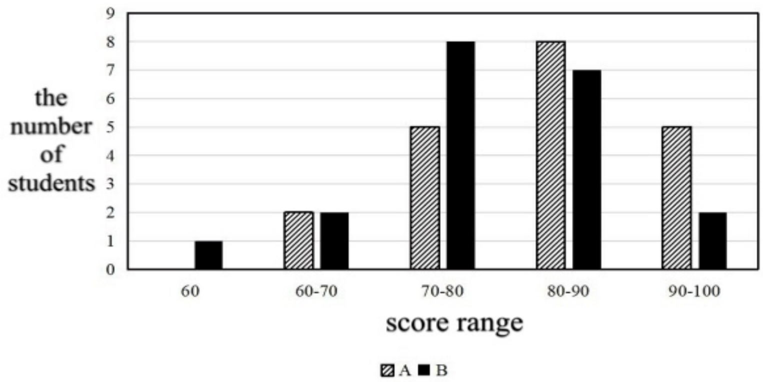

Fig.2. Contrastive study of learning effectiveness

As can be seen from figure 2, in the scorer range of 60 points and below, the number of students in group A and group B is 0 and 1 respectively; in the score range of 60-70 points, the number of students in group A and group B is 2 and 2 respectively; in the score range of 70-80 points, the number of students in group A and group B is 5 and 8 respectively; in the score range of 80-90 points, the number of students in group A and group B is 8 and 7 respectively; in the score range of more than 90 points, the number of students in group A and group B is 5 and 2 respectively. From the distribution, the score of students in group A is mainly over 80 points, with a total of 13 people, accounting for 65%; the core of students in group B is mainly over 80 points, with a total of 9 people, accounting for 45%. In the scorer range that under 60 points, there are no students in group A and 1 in group B. Group B students are mainly distributed in 70-90 points. Comprehensive analysis shows that the learning effect of group A is significantly better than that of group B, which verifies the beneficial effect of deep neural network learning method on learning effect.

4. Conclusion

Compared with other traditional algorithms, the method proposed in this paper has better applicability. After introducing the data set for experiment, the accuracy rate reaches 78.4%. Further comparative analysis of the learning effect of this method shows that compared with the traditional learning method, this method can achieve better learning effect. Thus, the proposed algorithm and method can be applied to personalized learning evaluation, so as to replace the traditional method according to actual needs.

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