10.18686/aitr.v2i3.4414

Learning Behavior Analysis and Prediction Based on Convolutional Neural Networks

Renmei Chen[1], Zongxiao Luo[2], Yansheng Yin[3]

1. Guizhou Normal University, Guiyang 550081

2. Tongren City Wanshan District High-rise Ping Dong Township Daping Ethnic Primary School, Tongren 554200

3. Qianxi City Tai Lai Middle School, Qianxi 551513

Abstract: With the development of information technology and the change of educational needs, personalized learning and intelligent education have become an important direction of current educational research. Traditional educational assessment and teaching methods are limited by subjectivity and limitations, and it is difficult to fully analyze and understand learners' individual needs and behavior patterns. The analysis and prediction method of learning behavior based on convolutional neural networks provides new tools and perspectives for educational decision makers and teachers through automated and data-driven methods, which is expected to deepen the understanding of the laws behind learners' behaviors and achieve the goal of education personalization and effect optimization. This paper will discuss the application status and future development direction of CNN in learning behavior analysis, and contribute new theoretical and practical experience to the innovation and progress of educational technology.

Keywords: Convolutional neural network; Learning behavior analysis; Learning behavior prediction

1. Basic concepts and development of Convolutional neural networks

As an important branch of deep learning, convolutional neural networks have made remarkable progress in the field of computer vision. The basic structure includes convolution layer, pooling layer and fully connected layer, and the complex feature extraction and classification model is constructed by stacking layer upon layer. The convolutional layer uses a filter (or convolution kernel) to carry out sliding operations on the input data, extract local features, retain spatial structure information while reducing the number of parameters, accelerate model training and improve generalization ability. The pooling layer reduces the spatial dimension of the feature map through downsampling operation, further reduces the amount of computation and the number of parameters, and improves the invariance and robustness of the model. The fully connected layer is responsible for integrating the features extracted by the previous convolution and pooling layers to finally output the classification or regression results.

With the development of deep learning theory and the enhancement of computational resources, CNNS continue to evolve and optimize, becoming the mainstream model for solving complex visual tasks. For example, AlexNet first introduced deep CNNS to the public at the ImageNet Challenge in 2012, where their deep structure and effective training strategies significantly improved image classification accuracy. Later, VGG, GoogLeNet, ResNet and other networks successively proposed to deepen the network structure and optimize parameter initialization and regularization methods, which greatly promoted the application of CNN in object detection, semantic segmentation, video analysis and other fields.

2. Learn the importance and application scenarios of behavior analysis and prediction

Traditional methods of learning behavior analysis and prediction mainly rely on questionnaire survey and observation, and are limited by subjectivity and limitations, so it is difficult to fully capture the dynamic and personalized characteristics of learners' behavior. With the development of big data and machine learning technology, especially the emergence of deep learning models, learning behavior analysis has entered a new stage of development. Learning behavior analysis and prediction based on CNN can not only extract rich feature information from multiple perceptual channels (such as video, audio, text), but also effectively capture and analyze learners' behavior patterns and learning states. For example, in an online learning environment, by analyzing students' video viewing, answering behavior and interactive data, CNN can automatically identify learners' attention level, learning interest and learning efficiency, and provide personalized teaching suggestions and intelligent learning support for teachers and education decision makers.

3. Methods and data

3.1 Data collection and preprocessing

First, data covering a wide range of learning scenarios needs to be collected from multiple sources, such as online education platforms, virtual learning environments, and traditional classrooms. These data can include students' video viewing records, homework completion, test scores, online discussion participation and other multi-dimensional information, which helps to fully understand learners' behavior patterns and learning processes. Secondly, in the data preprocessing stage, data cleaning, denoising and feature extraction are usually carried out. For example, for video data, image processing technology can be used to extract key frames or optical flow method can be used to analyze students' movements and expressions. For text data, word segmentation, part-of-speech tagging and emotion analysis can be carried out to dig out learners' emotional states and learning attitudes. In addition, time series analysis can be used to extract time series features from learning behavior data to capture learners' learning habits and behavior rules. In the process of data collection and pre-processing, data privacy protection and ethical principles should be strictly followed to ensure the legality and security of data.

3.2 Convolutional neural network model design

In order to effectively capture the spatiotemporal characteristics of learning behavior, the deep network structure is usually constructed by using multi-layer convolution and pooling operations. This structure can not only retain the spatial structure information of the input data, but also extract multi-level abstract features through filters of different scales. For example, by stacking multiple convolution layers and pooling layers, it is possible to gradually extract from low-level image edges and textures to high-level semantic features, thus achieving a more granular understanding and analysis of learning behavior. Secondly, attention mechanism or time series modeling method can be introduced into the model design to further enhance the modeling ability of the model to the learning behavior sequence. For example, the attention mechanism can be used to dynamically adjust the weight of the convolutional layer and adaptively extract important spatial and temporal features according to the learner's focus at different moments. The time series modeling method can capture the time dependence relationship in the learning behavior data through the structure of recurrent neural network (RNN) or long short-term memory network (LSTM), so as to achieve more precise modeling and prediction of the learning process.

3.3 Model training and optimization strategy

By randomly rotating, scaling, translating and mirroring the training data, the diversity of the data set can be expanded, the sensitivity of the model to the data distribution can be effectively reduced, and the generalization ability of the model can be improved. Secondly, the traditional gradient descent optimization algorithm can accelerate the model convergence through learning rate scheduling strategies (such as learning rate attenuation, momentum method, etc.), but for complex deep network structures, it may encounter problems such as local extreme value or gradient disappearance. Therefore, in recent years, adaptive learning rate optimization algorithms such as Adam and RMSprop have gradually become the first choice for CNN model training, which can automatically adjust the learning rate according to the gradient of each parameter and effectively balance the convergence speed and model stability. In the process of model training, it is also necessary to consider the model validation and parameter adjustment strategies. Usually, the training data is divided into training set and verification set. During the training process, the performance of the model on the verification set is monitored, and the model parameters are dynamically adjusted according to the feedback of the verification set, so as to avoid overfitting and underfitting.

4. Experiment and results

4.1 Experimental design and setup

First, the classical CNN structure is selected as the basic model, and the appropriate adjustment and optimization are made according to the specific task requirements. In the selection of data set, multi-dimensional data including students' video watching behavior, online test results, homework completion were collected to simulate the real learning environment. In order to enhance the generalization ability of the model, data enhancement techniques, including random rotation, translation, mirroring and other operations, as well as noise addition and adversarial sample generation techniques, are adopted to improve the model's adaptability to complex learning environments. In terms of model training, the adaptive learning rate optimization algorithm Adam is adopted, and the learning rate attenuation strategy is combined to ensure the steady convergence of the model in the training process. In order to evaluate the generalization ability of the model, the data set is divided into a training set and a validation set, the performance of the model on the validation set is monitored, and the model parameters are adjusted in time to avoid overfitting.

4.2 Analysis of experimental results

The experimental results show that the model performs well in the recognition of students' behavior patterns, and can accurately capture students' learning interests and behavior habits. Through deep feature learning and time series modeling, the key features of learning behavior data, such as learning duration and number of repeated views, are successfully extracted, which provides strong support for subsequent learning efficiency prediction and personalized recommendation. By analyzing the correlation between the predicted results of the model and the actual learning performance, it is found that the model can effectively predict the changing trend of students' learning performance and achievement, and provide important decision-making basis and personalized teaching suggestions for teachers and educational decision-makers.

4.3 Model performance evaluation and comparative analysis

Compared with traditional methods and other deep learning models, it is found that CNN can effectively capture nonlinear relationships and timing features in complex learning data through end-to-end learning, which significantly improves prediction accuracy and model robustness. The experimental results not only prove the effectiveness and practicability of CNN-based learning behavior analysis and prediction method, but also provide important theoretical and empirical support for further research and practical application in the future.

5. Sum up

The analysis and prediction of learning behavior based on Convolutional neural network (CNN) is one of the frontiers of educational technology research. Based on the above research content, the learning behavior analysis and prediction based on CNN not only provides a new technical means and scientific basis for educational decision-making and personalized learning, but also provides important theoretical and empirical support for further exploration of the development direction of intelligent education technology in the future.

References

[1] Feng Guiyun. Research on Analysis and Prediction of Learning Behavior Pattern Based on Intelligent Algorithm [D]. Guizhou University, 2023.

[2] Zuo Guocai et al. Research on Classroom Behavior Detection of College students based on CNN Deep Learning Model [J]. Intelligent Computer and Applications, 2020, 10 (02): 158-160.