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Research on Neurocognitive Diagnosis and Online Learning Recommendation System Based on Computer Intelligence

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Abstract: In the context of Education Informatization 3.0, this article proposes an online learning optimization method that integrates neurocognitive diagnosis and time aware recommendation to address the issues of insufficient accuracy in traditional cognitive diagnostic models and lack of personalization in recommendation systems. The study constructed an empirical Q-matrix neurocognitive diagnostic model NCD-EQ, which fitted the student exercise interaction relationship through deep neural networks and optimized the Q-matrix definition through exploratory factor analysis, significantly improving the relevance of knowledge points and diagnostic interpretability. Further design the BiasTSVD collaborative filtering recommendation algorithm, introducing time preference weight factors to dynamically adjust user preferences, effectively alleviating data sparsity and enhancing recommendation timeliness. The experiment on the ASSIST dataset shows that the BiasTSVD algorithm reduces RMSE and MAE to their minimum values at K=80, reducing errors by 4.51% compared to traditional algorithms, improving accuracy by 11.68%, and increasing recall stability by 18.69%. The study verified the advantages of the NCD-EQ model in knowledge diagnosis accuracy and the comprehensive performance improvement of the BiasTSVD algorithm in personalized recommendation. In the future, knowledge path map construction and natural language processing technology can be explored to deepen the accuracy of cognitive diagnosis and expand recommendation scenarios.

1 Introduction

With the continuous innovation of artificial intelligence, cloud computing, data mining and mobile Internet technology, education informatization has become the core driving force of global education reform. The implementation of the Education Informatization 2.0 Action Plan marks that the education field is accelerating the integration of information technology and intelligent technology, aiming to comprehensively improve the informatization literacy of teachers and students and promote the fundamental reform of teaching mode by building the "education+Internet" platform system. Currently, the concept of Education Informatization 3.0 has attracted much attention, characterized by the deep empowerment of intelligent technology in the entire teaching process. For example, the smart classroom created by Squirrel AI intelligent learning machine in cooperation with Alibaba Cloud and Lenovo, as well as the intelligent teaching system constructed by Headmaster Education, all reflect the transformation from a "teacher centered" to a "student-centered" learning mode, significantly enhancing learners' subjective initiative. However, despite breaking the limitations of time and space, reconstructing the educational resource system, and promoting educational equity, online learning platforms still face many challenges. Traditional cognitive diagnostic models are difficult to accurately assess students' knowledge levels and cannot fully explore the complex relationship between students and test questions; At the same time, existing recommendation systems lack in-depth analysis of student behavior, making it difficult to achieve truly personalized recommendations. To address these issues, this article proposes an online learning method based on cognitive diagnosis. This method is based on students' answer data and combines neural networks and data mining techniques to construct an empirical Q-matrix neurocognitive diagnostic model to achieve accurate diagnosis of students' knowledge attribute mastery level. Furthermore, this article proposes a BiasTSVD collaborative filtering recommendation algorithm based on online learning, which combines the diagnostic results of NCD-EQ with student behavior analysis, and introduces time preference weight factors to optimize recommendation performance. The main contribution of this article lies in: firstly, by introducing empirical Q-matrix, it enhances the connection between knowledge points and improves the accuracy and interpretability of cognitive diagnostic models; The second is to improve the recommendation algorithm to better meet the personalized needs of students, thereby enhancing the efficiency and quality of online learning. In terms of paper structure, this article first elaborates on the research background and significance, then provides a detailed introduction to the proposed model and algorithm, and finally verifies the effectiveness of the method through experiments, and looks forward to future research directions.

2 Correlation theory

The field of online learning is undergoing a paradigm shift driven by technology, with artificial intelligence and big data technology becoming the core engines. Under the framework of Education Informatization 3.0, online education supported by intelligent terminals breaks through the limitations of time and space, and achieves fair allocation of resources through the accumulation of educational big data. However, there are shortcomings such as feedback delay and lack of cognitive status monitoring. The existing research presents three major technological branches: in the field of cognitive diagnosis, a dual path of static diagnosis and dynamic tracking is formed. Static models **错误!未找到引用源。**, such as DINA, use Q-matrix theory **错误!未找到引用源。** to achieve binary judgment of knowledge point mastery. Fuzzy cognitive diagnosis framework introduces fuzzy set theory to improve diagnostic granularity. The neural cognitive diagnosis framework uses deep learning to capture student exercise interaction features, and its vector representation method demonstrates advantages in interpretability and model generality; In terms of dynamic tracking, the EERNN framework 错误!未找到引用源。integrates bidirectional LSTM to achieve semantic mining of exercise texts, and the EKT model further constructs a knowledge state matrix to enhance tracking accuracy, but faces the challenge of modeling multi concept knowledge states. Personalized recommendation systems are showing a mixed trend, with collaborative filtering algorithms based on cognitive diagnosis integrating group behavior and individual cognitive features. Improved algorithms improve recommendation accuracy by introducing knowledge attribute constraints of the test questions to be recommended, but there are limitations such as cold start and data sparsity. Knowledge reasoning technology relies on knowledge graphs to achieve semantic association mining. Convolutional neural networks and reinforcement learning models perform outstandingly in knowledge completion and path reasoning tasks, but the causal reasoning ability in educational scenarios still needs to be strengthened. Current research has made breakthroughs in diagnostic accuracy, recommendation timeliness, and interpretability of reasoning, but cross modal data fusion, long-term learning behavior modeling, and ethical constraint mechanisms remain unresolved challenges.

3 Research method

3.1 Integrated Multidimensional Evaluation & Deep Learning for Educational Measurement

Cognitive diagnostic theory 错误!未找到引用源。 and item response theory 错误!未找到引用源。, as the core theoretical frameworks in the field of educational measurement, have respectively deepened the scientificity of learner assessment from the perspectives of cognitive structure analysis and potential ability quantification. CDA has constructed a refined diagnostic system based on knowledge attribute mastery using tools such as the DINA model and Q-matrix theory. The DINA model quantifies the correlation between students' answer performance and knowledge point mastery using the "all or nothing" hypothesis, and characterizes cognitive errors through error parameters and guess parameters; The Q-matrix theory maps the relationship between test questions and potential knowledge attributes using a 0-1 matrix, providing a structured framework for cognitive structure diagnosis. At the same time, IRT establishes a functional relationship between student ability θ and test answer probability P (θ) through a three parameter logistic model 错误!未找到引用源。, characterizing test characteristics with difficulty, discrimination, and guessing parameters, breaking through the limitations of classical testing theory, and supporting cross group ability equivalent comparison and adaptive assessment system construction. The multidimensional item response theory further extends the IRT framework by introducing multidimensional latent feature and discriminative, constructing a nonlinear evaluation model to capture multidimensional performance in complex cognitive tasks. Deep neural networks rely on multi-layer nonlinear mapping capabilities, receiving raw learning behavior data through the input layer, extracting high-order abstract features through the hidden layer, and generating diagnostic results through the output layer. They break through the traditional model's dependence on the preset Q matrix in a data-driven manner, and enhance nonlinear expression ability through the combination of Sigmoid activation function in their forward propagation process. Although MIRT and DNN have methodological differences - the former builds explicit parameter models based on probability measurement theory, while the latter captures hidden patterns in data through black box mechanisms - they complement each other in the field of cognitive diagnosis: MIRT provides an interpretable theoretical framework, DNN achieves deep analysis of complex cognitive interactions, and the combination of the two can synchronously achieve precise quantification of the diagnostic process and dynamic mining of higher-order cognitive features, providing methodological support for the intelligent transformation of educational evaluation.

3.2 Application of Collaborative Filtering Recommendation Technology

The collaborative filtering recommendation algorithm 错误!未找到引用源。, as the core technology of personalized recommendation systems, achieves accurate recommendations by analyzing user behavior patterns. Its core lies in using the similarity of users or items for prediction. This algorithm system includes three mainstream methods: neighbor based collaborative filtering generates recommendations by directly calculating user or item similarity, among which user based collaborative filtering algorithm constructs a user rating matrix, integrates explicit feedback 错误!未找到引用源。 and implicit feedback data, quantifies user correlation using cosine similarity, Pearson correlation coefficient or Jaccard coefficient, and predicts target user preferences based on Top-N neighbor set 错误!未找到引用源。 while item based collaborative filtering achieves recommendations by calculating item similarity as shown in Figure 1

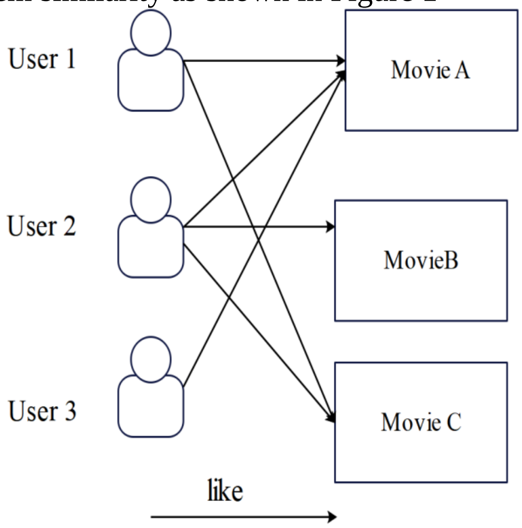

Figure 1 Example of project-based collaborative filtering recommendation

Model based collaborative filtering further introduces matrix decomposition techniques, such as FunkSVD decomposing high-dimensional rating matrices into low dimensional user feature matrices P and item feature matrices Q, and optimizing predicted ratings through gradient descent; BiasSVD introduces a bias term based on this, combined with the global average value μ, user bias, and item bias, to improve recommendation accuracy. Although collaborative filtering algorithms have advantages such as mining user interests, filtering redundant information, and scene universality, they still face challenges such as similarity calculation bias caused by data sparsity, cold start problems (lack of historical behavior data for new users/items), and high scalability requirements (exponential increase in computational complexity caused by the growth of user/item volume). Therefore, it is necessary to alleviate these challenges by optimizing algorithm efficiency and integrating multi-source information

3.3 Feature-driven Personalized Recommendation

Content based recommendation algorithms construct accurate personalized recommendation models by deeply analyzing item attribute features and user historical behavior data. The algorithm first collects multi-source data, covering the content features of items and user behavior trajectories. Then, it uses natural language processing, computer vision, or neural network technology to extract high-order features, convert item attributes into structured vectors, and generate feature matrices. Based on user historical preferences, the algorithm learns the complex mapping relationship between user and item features through methods such as matrix factorization, deep learning, or graph neural networks, and then calculates the similarity between items to generate a recommendation list. Taking movie recommendation as an example, the system will include items that highly match the user's interests in the recommendation sequence due to their preference for a specific type. The core advantage of this algorithm lies in: firstly, the recommendation logic is independent of user interaction data, which can effectively cover obscure or newly launched items, significantly improving the diversity of recommendation results; Secondly, by accurately capturing users' personalized preferences, the accuracy of recommendations and user satisfaction can be improved, thereby enhancing platform user stickiness. However, algorithms still face technical challenges in processing multimedia content feature extraction and cross domain recommendation.y.

4 Results and discussion

4.1 A neurocognitive diagnostic model based on empirical Q-matrix

The empirical Q-matrix neurocognitive diagnostic model integrates data-driven empirical Q-matrix and neurocognitive diagnostic framework, breaking through the subjective limitations of traditional expert defined Q-matrix and achieving accurate evaluation of students' knowledge mastery. As shown in Figure 2,

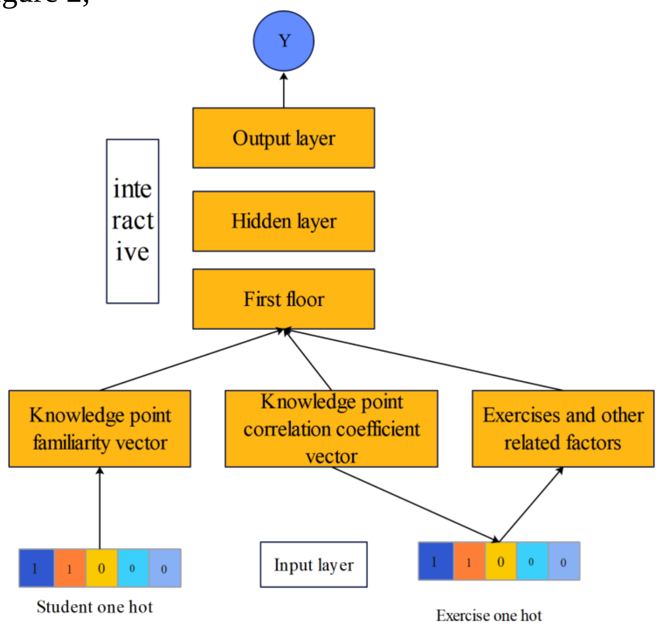

Figure 2 Structure diagram of neurocognitive diagnosis

The model is centered around a multi-layer neural network, which takes in one hot vectors of students and exercises. Through training, it generates parameters such as proficiency vectors of knowledge points, knowledge correlation coefficient vectors, and exercise discrimination, quantifying the interaction between students and exercises and predicting answer performance. The student factor is obtained by multiplying the one hot vector with the trainable matrix A to obtain the knowledge point proficiency vector K, which reflects the student's mastery of each knowledge point; The exercise factors are decomposed into knowledge relevance K (obtained by multiplying the empirical Q matrix with the exercise one hot vector) and knowledge difficulty and exercise discrimination (generated through the sigmoid function and trainable matrices B and D). The interaction function uses deep neural networks to fit complex relationships. The first layer constructs a universal interaction function based on the MIRT model. The subsequent three fully connected layers output predicted answer probabilities through nonlinear activation functions and optimize model parameters by minimizing the cross entropy loss function. To construct an empirical Q matrix, this paper uses exploratory factor analysis 错误!未找到引用源。to perform variance maximization rotation on the expert Q matrix, extract the factor loading matrix, and set a threshold to generate a binary empirical Q matrix keep the original calibration rules. Furthermore, the model proposes the NCD-EQ framework, which integrates the empirical Q matrix into the neurocognitive diagnostic process: the one hot vectors of students and exercises generate proficiency, correlation coefficients, difficulty, and discrimination through matrices A, B, D and the empirical Q matrix. The interaction information is captured through three fully connected layers, and the performance of unanswered questions is finally predicted. This model effectively alleviates the subjective limitations of traditional Q-matrices, strengthens the correlation of knowledge attributes, and significantly improves the accuracy and interpretability of cognitive diagnosis

4.2 BiasTSVD recommendation algorithm based on cognitive diagnosis and time perception

This paper proposes a BiasTSVD recommendation algorithm based on cognitive diagnosis and time perception to address the issues of data sparsity, cold start, and dynamic changes in student preferences in online learning platforms. The algorithm framework consists of four core modules: firstly, the NCD-EQ model proposed in Chapter 3 is used to model students' cognitive abilities, and one hot encoding is used to represent students and test characteristics. Combined with empirical Q matrix, knowledge proficiency is quantified and answer performance is predicted; Secondly, the time preference weight factor is introduced, and a dynamic weight function is designed based on the Ebbinghaus forgetting curve. The student's answer time and score are integrated into a two-dimensional coordinate system, and the preference weight is adjusted by the distance from the reference time, accurately capturing the temporal characteristics of learning behavior; Subsequently, singular value decomposition was used to reduce the dimensionality and complete the student answer matrix, alleviating the impact of data sparsity on recommendation quality; Finally, based on the BiasSVD algorithm, time weight factors were integrated to construct an improved BiasTSVD prediction model 错误!未找到引用源。. By integrating user bias, item bias, global mean, and time dynamic weights, personalized and timely recommendation results were generated. Experiments have shown that this algorithm effectively improves recommendation accuracy, especially suitable for online education scenarios where knowledge points are highly correlated and learning behavior evolves over time.

4.3Comparative analysis of evaluation effects

This article validates the effectiveness of the BiasTSVD algorithm on the ASSIST dataset, which includes student answer records and knowledge point association information. The experiment uses root mean square error, mean absolute error, accuracy, and recall as evaluation indicators. By comparing the UserCF, ItemCF, and BiasSVD algorithms, the impact of different K values on recommendation performance is analyzed. The experimental environment is configured with Windows 10 system, Python language and Pytorch framework, and the hardware is a Lenovo laptop with 16GB of memory. The results show that BiasTSVD is significantly better than other algorithms in terms of RMSE and MAE metrics, especially with the smallest error at K=80 and a 4.51% reduction in MAE compared to traditional algorithms; In terms of accuracy, BiasTSVD steadily increases to 0.271 with the increase of K value, which is 11.68% higher than BiasSVD; The recall rate tends to stabilize after K=40, and the overall performance is better than the comparison model. Experimental results have shown that BiasTSVD effectively alleviates data sparsity and user preference solidification problems by integrating time preference weight factors with the knowledge diagnosis results of the NCD-EQ model, significantly improving recommendation accuracy and stability.

5 Conclusion

With the deepening development and widespread application of educational information technology, online learning platforms have accumulated massive amounts of educational behavior data, providing a solid foundation for comprehensive analysis and evaluation of students' learning situations. However, traditional cognitive diagnostic models have shortcomings in accurately assessing students' knowledge levels and exploring complex relationships between students and test questions. At the same time, traditional exercise recommendation methods also lack in-depth analysis of student behavior, making it difficult to achieve personalized recommendations. To address these issues, this article constructs an empirical Q-matrix neurocognitive diagnostic model NCD-EQ based on student test records from online education platforms, integrating neural networks, neurocognitive diagnostic frameworks, and personalized recommendation theory. It also proposes a BiasTSVD collaborative filtering recommendation algorithm based on online learning. The NCD-EQ model improves the fitting degree between students and knowledge attributes through DNN neural network, enhances the connection between knowledge points through empirical Q matrix, and achieves accurate diagnosis of students' proficiency in knowledge points. The experimental results show that the model outperforms traditional models in terms of diagnostic performance and interpretability. Furthermore, the BiasTSVD algorithm combines the diagnostic results of NCD-EQ with student behavior analysis, and introduces a time preference weight factor to optimize the recommendation performance, significantly improving the overall performance of the recommendation algorithm. Future research can explore the introduction of knowledge attribute cohesion coefficient to construct a knowledge point learning path map, as well as the use of natural language processing technology to extract knowledge attributes from textual test questions, thereby further optimizing the accuracy of cognitive diagnosis. At the same time, personalized recommendation systems can provide customized educational resources based on knowledge structure and learning styles, and develop towards intelligent learning management, fully supporting students' learning path planning and process management.

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