Cross-Course Learner Modeling Based on Deep Cognitive Diagnosis

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Abstract. With the rapid development of online education and the advent of the big data era, how to accurately recommend learning resources and effectively diagnose learners' cognitive states has become an urgent issue to be addressed in the field of education. Cognitive diagnosis and cross-domain recommendation are both very important applications in education, they can help teachers better understand students' learning states and capabilities, and also assist students in finding learning resources and methods that are more suitable for them. This paper aims to research cross-course learner modeling based on deep cognitive diagnosis to enhance learners' cognitive levels and knowledge transfer abilities. By combining deep learning models with cognitive diagnostic techniques, it is possible to accurately assess and predict learners' capabilities, and through cross-domain recommendation technology, achieve personalized cross-course knowledge transfer to evaluate learners' cognitive states and learning outcomes in new courses. This study has designed a series of experiments to verify the effectiveness of this method and to analyze and discuss the results. The experimental outcomes indicate that cross-course learner modeling based on deep cognitive diagnosis can significantly improve learners' cognitive levels and knowledge transfer abilities, providing beneficial insights for personalized learning and intelligent education in the educational field.

Keywords:deep learning, cognitive diagnosis, cross-domain recommendation, cross-course learner modeling

1 Introduction

Deep cognitive diagnosis is a method that uses deep neural networks to assess learners' cognitive states. By collecting learners' behavioral and physiological data and combining them with deep learning models for analysis, it can accurately assess learners' cognitive levels and learning outcomes. However, relying solely on deep cognitive diagnosis may not meet learners' knowledge transfer needs. Cross-course learner transfer technology is a method that transfers knowledge and skills from one domain to another, thereby accelerating the learning process. Therefore, this study

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introduces cross-course learner transfer technology into deep cognitive diagnosis to achieve knowledge transfer across domains. Cross-course learner transfer technology enables learners to gain a broader range of knowledge and skills through learning in different courses or tasks and to apply these knowledge and skills to new courses or tasks. Based on this, the paper proposes a cross-course learner transfer technology based on deep cognitive diagnosis to enhance learners' cognitive levels and knowledge transfer capabilities. We will design experiments to verify the effectiveness of this method and analyze and discuss the results. Ultimately, we hope that this research can provide beneficial insights for research and practice in the fields of education and cognitive science, promoting learners' cognitive development and enhancement of knowledge transfer capabilities.

2 Related Research

2.1 Cognitive Diagnosis

Cognitive diagnosis is based on the following basic assumptions: (1) the reactions of learners in learning activities (such as the correctness of answers) depend on their latent knowledge states (such as the mastery of various knowledge points), and (2) each learner's knowledge state is relatively stable over a short period of time. In intelligent education systems, cognitive diagnosis collects learners' problem-solving records to assess and analyze their individual micro knowledge states, determining the learners' mastery of different knowledge points. For example, by analyzing learners' answer records, one can judge the degree of mastery of a certain knowledge point by the learners, thus providing a reference for subsequent teaching. As shown in Fig. 1, two learners, u1 and u2, have just taken the same exam with five tasks/exercises, each requiring different skills. Although these two users have the same total score (i.e., 60 points), cognitive diagnosis can reveal significant differences in their proficiency in specific skills from the radar chart[1].

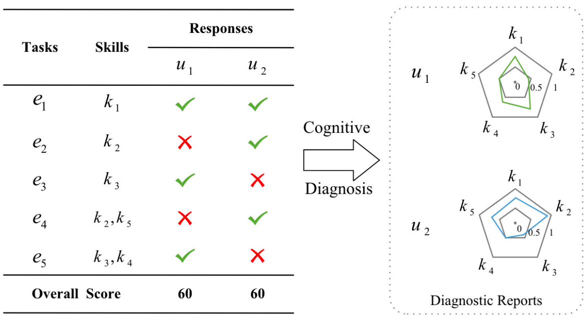

Fig. 1. Examples of cognitive diagnostic processes.

Traditional psychometric-based methods include Item Response Theory (IRT)[2], Multidimensional Item Response Theory (MIRT) [3], and the Deterministic Input, Noisy And Gate, DINA model[4]. These methods take into account the learner's ability to discern items, the difficulty of the items, and the Q-matrix that represents the relationship between exercises and knowledge (The Q-matrix, also known as the item-knowledge matrix, defines the range of knowledge points covered by each exercise, represented by a set of manifest knowledge/skills, typically annotated by educational experts such as teachers). However, traditional cognitive diagnosis models rely on artificially defined linear interaction functions to combine learners with the characteristics of exercises, which may not be sufficient to capture more complex relationships between the two. To address these issues, machine learning-based cognitive diagnosis models have emerged. The Neural Cognitive Diagnostics (NeuralCD) model[5] uses neural networks to model complex nonlinear interactions, eliminating the need for artificially defined functions. Specifically, to ensure the interpretability of the model, NeuralCD introduces the monotonicity assumption of knowledge state changes during the learning process. The relation graph-driven cognitive diagnosis model [6][7] is based on a learner-exercise-knowledge point relation graph, integrating the modeling of knowledge structure and learning activities, and designs an extensible diagnostic function to predict learners' answer patterns. Additionally, the ECD model [8] introduces learning context features [Learning context features mainly include characteristics related to the learner's family, school, and personal information, such as the education level of the learner's parents, the teaching attitude of the learner's teachers, etc.] to model the impact of the educational environment and improve the quality of diagnosis.

2.2 Cross-Domain Recommendation

Cross-domain recommendation algorithms (Cross-domain Recommendation, CDR) aim to use the richer user interaction records in the source domain and model the correlations between different domains to improve the recommendation accuracy in the sparse target domain, providing a promising solution to alleviate the cold start problem (referring to providing recommendations for new users or new items in recommendation systems). The core task of CDR is to connect users' preferences in the source domain and the target domain, also known as preference transfer[9]. Mainstream cross-domain recommendation algorithms can be divided into two categories based on different migration information sources[10]: (1) content-based migration methods and (2) embedding-based migration methods. Content-based migration methods aim to solve cross-domain recommendation problems with content relevance, establishing connections between different domains through the correlation of content information contained in different domains (such as social tags[11] and user-submitted comments[12]). Embedding-based migration methods are mainly applied to cross-domain recommendation scenarios with user relevance and item relevance. These methods first use collaborative filtering models to obtain the embedding representations of users (or items) in different domains, and then learn the migration function based on the embedding representations of common users (or items) between different domains. Compared with content-based migration methods, embedding-based migration methods rely more on machine learning technologies, such as transfer learning[13] and neural networks[14]. To achieve personalized cross-domain mapping for each user's preferences, PTUPCDR[14] proposes a meta-learning network using user embedding representations to generate personalized cross-domain mapping functions. However, cross-domain modeling methods are currently mainly used in the field of recommendation systems, and how to effectively use multi-course information transfer to solve the cold start problem in the modeling process of new courses in the education field still faces many challenges.

An algorithm that combines cognitive diagnosis and cross-domain recommendation can fully leverage the advantages of both. Firstly, by using cognitive diagnosis algorithms to deeply analyze learners' answer behaviors, it is possible to accurately understand learners' cognitive states and knowledge levels. Then, based on these analysis results and factors such as learners' interests and hobbies, cross-domain recommendation algorithms can be used to recommend suitable learning resources to learners. At the same time, by feeding the recommendation results back to the cognitive diagnosis algorithm, the accuracy and specificity of the diagnosis can be further optimized. Based on this, the paper will combine deep cognitive diagnosis models and cross-domain recommendation algorithms to address the issue of data sparsity in the modeling tasks of target courses (new courses), improving the accuracy of knowledge state assessment for beginners in the courses.

3 Model Construction

Cross-course learner modeling based on deep cognitive diagnosis (CCLM_DCD) can be divided into three tasks：

3.1 Learner Auxiliary Course Knowledge State Modeling

The study of auxiliary courses has a certain supplementary effect on the learning of target courses. To better understand the learners' knowledge background and improve the efficiency and accuracy of multi-course knowledge transfer, it is first necessary to model the knowledge state of learners in auxiliary courses. Here we use the deep cognitive diagnostic model DCD to build the model. We uniformly represent the learner's knowledge state as

$$U_{\mathrm{i}}^{s} = DCD(S_i; W_L) \tag{1}$$

Where S_i represents the learner's index and W_L represents the parameters of DCD. The generated U_{i}^{s} represents the knowledge state information of learners in the auxiliary course and can be used in the personalized mapping stage of multi-course learners' knowledge state.

3.2 Personalized Mapping of Multi-Course Learner Knowledge States

To effectively use the learning record data of learners in auxiliary courses, it is necessary to study how to map the knowledge states of learners between different courses. In addition, considering the differences in learners' knowledge background and abilities, it is necessary to customize personalized mapping schemes for them. Here we use the meta-learning network to design a personalized mapping function for each learner. Specifically, the meta-learning network is formulated as:

$$W_{\mathrm{u}_i} = G(U_i^s; W_g) \tag{2}$$

where W_{g} is the parameter and W_{u_i} is the parameter of the knowledge mapping function.

Based on the knowledge mapping function generated by the meta-learning network, we use the personalized mapping functionto generate leaner representations in the target curriculum:

$$U_{\mathrm{i}}^t = F_{u_i}(U_i^s; W_{u_i}) \tag{3}$$

When use the following loss function for training:

$$L = \mathrm{loss}_{DCD}(U_{\mathrm{i}}^t, other\_inputs) \tag{4}$$

where loss_{DCD} indicates the loss function of the selected learner model, and $other\_inputs$ indicates other auxiliary parameters in the selected learner model.

3.3 Inference of Learner Target Course Knowledge States

To obtain the knowledge state of learners in target courses, it is necessary to study how to efficiently infer the knowledge state in target courses using the mapping relationship of knowledge states between different courses. Given any learner sj who is new to the target course, its personalized knowledge mapping function $F_{U_{\mathrm{j}}}(U_{\mathrm{j}}^s; W_{U_j})$ can be used to efficiently infer the state of the learner's knowledge in the target course $U_j^t = F_{U_j}(U_j^s; W_{U_j})$.

4 Experiment and Result Analysis

4.1 DataSet

The dataset PTADisc[15] is derived from PTA, an online learning platform developed by Hangzhou PAT Education Technology Co., LTD. PTA is an automatic program evaluation and open teaching aid platform for universities and society. Given the close cooperation between parent-teacher associations and universities, it is common for students to take a series of courses at the same time that are aligned with their training programs. As of July 2023, PTA has attracted more than 1,000 organizations, 9,000 teachers, and 3.9 million users, and provides a problem library of more than 290,000 questions referenced by the curriculum problem set and exam. The point of the PTA is that it covers a large number of students enrolled in multiple courses. This feature perfectly meets the need to conduct cross-curriculum research and explore student characteristics between courses.

We selected one of the sub-datasets containing 29,454 students taking 5 courses simultaneously for cross-course learner modeling, which contains Q matrix and student response logs. The Q matrix stores the relationships between problems and concepts. Students have a high degree of relevance in Python programming (Python) and Java programming (Java). This high degree of correlation makes these two courses well suited to solving cold start problems. We choose Python programming as source course. To simulate the cold start scenario, 7% of student log data from Java programming was selected as the target course. Each student's response log was divided into training, validation, and test datasets at a ratio of 70%/10%/20%, respectively. We compare the traditional algorithm MIRT with our algorithm CCLM_DCD in this paper. The evaluation indexes of the experiment include area under ROC curve (AUC), prediction accuracy (ACC) and root mean square error (RMSE), and the results are shown in Table 1. The results show that the cross-curriculum learner modeling based on deep cognitive diagnosis has improved the accuracy compared with the traditional algorithm.Table 1 shows the result of cross-course learner modeling based on deep cognitive diagnosis.

Table 1. Experiment result

	CCLM_DCD	MIRT
AUC	**0.7208**	0.7156
ACC	**0.7886**	0.7812
RMSE	**0.4013**	0.3904

5 Conclusions

This paper has successfully integrated the principles and methods of cognitive diagnosis and cross-domain recommendation algorithms through in-depth research and applied them to the field of education. The experimental results fully prove the effectiveness and attractiveness of this combined algorithm. It not only improves the efficiency of educational resource utilization and learning outcomes but also solves the limitations in cognitive diagnosis and cross-domain recommendation algorithms, improving recommendation accuracy and user satisfaction. In the future, we will continue to explore the application of this combined algorithm in other fields, contributing to the deep integration of artificial intelligence and education.

With the continuous development of artificial intelligence technology and continuous innovation in the field of education, we believe that intelligent educational assistants that integrate cognitive diagnosis and cross-domain recommendation will have a broader application prospect. First, by introducing more psychological theories and advanced data analysis techniques, we can further optimize cognitive diagnostic algorithms and improve their accuracy and reliability. Secondly, the cross-domain recommendation algorithm will also benefit from more user behavior data and more complex recommendation algorithm design, so as to provide users with more personalized and accurate learning resource recommendation. In addition, combined with other fields of technology and methods, such as natural language processing and machine vision, we can further enrich the functions of intelligent educational assistants, such as automatic generation of learning reports, intelligent question answering, etc.

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