Cognitive Diagnosis Models

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In the field of education, cognitive diagnosis is crucial for achieving personalized learning. The widely adopted DINA (Deterministic Inputs, Noisy And gate) model uncovers students' mastery of essential skills necessary to answer questions correctly. However, existing DINA-based approaches overlook the dependency between knowledge points, and their model training process is computationally inefficient for large datasets.

Keywords: cognitive diagnosis ; DINA model ; bayesian networks

1. Introduction

The emergence of the online education industry has revolutionized traditional educational approaches. Leveraging information technology, online education offers students convenient access to a vast array of courses and learning materials, thus promoting resource sharing and ensuring educational equity. However, with the exponential growth of available learning resources, accurately assessing a student's mastery level of specific skills and knowledge has become a pressing challenge. Cognitive diagnosis models (CDMs), initially introduced by [1], have been developed to quantify the latent abilities that significantly impact students' performance. CDMs [2][3] have gained widespread recognition and interest from both academic and industry domains by providing insights into the cognitive skills underlying students' overall scores [4].

The DINA (Deterministic Inputs, Noisy And gate) model [5] is recognized as a prominent cognitive diagnosis approach, which effectively integrates the Q-matrix and students' response patterns to assess their mastery level and identify potential error patterns within each knowledge point. By employing statistical techniques such as maximum likelihood estimation [6], the DINA model equips educators with a comprehensive cognitive diagnostic tool, enabling the formulation of personalized teaching strategies that cater to individuals' performance across diverse knowledge points.

2. Different Models of Cognitive Diagnosis

Cognitive diagnosis, initially proposed by educational psychologists for psychological measurement, has its roots in the 1990s. Frederiksen et al. [7] were credited with formally introducing the theories and concepts related to cognitive diagnosis in 1993, while Nichols et al. [8] further provided a comprehensive summary and categorization of these theories and concepts in 1995. Leighton et al. [9] considered CDM as a promising evaluation model that can delve into the underlying structure of a field and identify problems and areas that need improvement in 2007. Lee et al. [10] proposed that tests informed by the Cognitive Diagnosis Algorithm (CDA) can specify the underlying knowledge structure behind the overall test score, and this specification can serve as feedback to meet individual and group needs through remedial instruction and improve instruction to enhance learning and competency in 2009. As a diagnostic approach to assessment, CDA needs statistical and mathematical models to operationalize the assumptions. CDMs are psychometric models that make use of an item response pattern in order to determine test-takers' cognitive abilities [11]. In all CDA studies, the selection of statistical models is a critical step and requires close attention and consideration of model selection criteria. However, in most CDA studies, tests applying a predetermined CDM are chosen based on the characteristics of the model and the practicality issue. So Li et al. [12] carefully studied the considerations required for CDM selection for reading comprehension tests and found that when the relationship between cognitive skills is not completely clear, it is safe to use a saturated (more complex) CDM, which can flexibly adapt to different types of relationships between skills in 2016. Currently, cognitive diagnosis can be defined in both broad and narrow terms. Broadly speaking, cognitive diagnosis leverages modern technologies such as computer-based testing and statistical methods to assess users' cognitive abilities and structures [13][14]. On the other hand, in a narrower sense, cognitive diagnosis classifies users based on their mastery level of specific knowledge points, with the classification results used for personalized educational interventions.

The application of cognitive diagnosis in the education industry has led to a shift towards personalized education in traditional online classrooms [15][16]. Cognitive diagnosis models can be differentiated from two perspectives. Firstly, they can be classified as continuous diagnosis models or discrete diagnosis models, depending on their ability to diagnose continuous scores. Secondly, cognitive diagnosis models can be classified based on their approach to handling dimensions of students' cognitive abilities. This categorization results in one-dimensional skill diagnosis models and multidimensional skill diagnosis models. Currently, there are more than 60 cognitive diagnosis models available. These models include the rule-based model, attribute hierarchy model, Deterministic Inputs, Noisy And gate (DINA) model, as well as various variations [17][18] such as the Fuzzy CDF model [19]. Improved versions of the DINA model, such as the HO-DINA [20], P-DINA [21], G-DINA [22], and Incremental DINA (I-DINA) model [23], are also among the existing models used in cognitive diagnosis research.

The history of Bayesian networks dates back to the early 1980s. In 1988, Pearl et al. [24] first introduced the fundamental concepts and inference methods of Bayesian networks in their seminal paper. Notably, Pearl's work also introduced the concept of the "causal graph", which expanded probabilistic graph models to incorporate causal relationships, thereby establishing the groundwork for further development. In the 1990s, research in the field expanded from representation issues to encompass inference and learning [25], making Bayesian networks more practical in various applications. With the advancement of computational power and the exponential growth of data in the 21st century, Bayesian networks have found widespread application in diverse domains such as medicine [26], finance [27], and natural language processing [28]. Research in the field has also made significant progress in reasoning, learning, and the application of Bayesian networks [29].

In recent research, the integration of Bayesian networks and the DINA model has gained attention, with notable applications in student modeling, knowledge tracing, and skill topology. For instance, Conati et al. [30] applied Bayesian networks to the Andes project [31], an intelligent educational system focused on Newtonian physics, to model uncertainty within students' reasoning and learning processes. In the domain of knowledge tracing [32], Pelánek [33] introduced Bayesian Knowledge Tracing (BKT), which employed Bayesian networks to infer latent student variables within knowledge-tracing models. Furthermore, Käser et al. [32] utilized dynamic Bayesian networks (DBN) to model skill topology in knowledge tracking. While these works have made significant contributions to the application of Bayesian networks, their main focus lies in student modeling, knowledge tracing, and skill topology. In parallel, recent breakthroughs in asynchronous federated meta-learning, exemplified by AFMeta, have effectively addressed issues such as straggler and over-fitting, resulting in a substantial improvement in model performance and a notable reduction in learning time [34]. In the field of education-based information analysis, the examination of student learning assessment methods based on text data has emerged as a crucial research area. Liu et al. [35] introduced an innovative learning evaluation method based on real-time text data attributes, overcoming the limitations of traditional evaluation methods. The outcomes highlight the superior effectiveness of utilizing real-time attribute text data in measuring students' learning outcomes.

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