A Comprehensive Survey on Deep Learning Techniques in Educational Data Mining

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Abstract-Educational Data Mining (EDM) has emerged as a vital field of research, which harnesses the power of computational techniques to analyze educational data. With the increasing complexity and diversity of educational data, Deep Learning techniques have shown significant advantages in addressing the challenges associated with analyzing and modeling this data. This survey aims to systematically review the state-of-the-art in EDM with Deep Learning. We begin by providing a brief introduction to EDM and Deep Learning, highlighting their relevance in the context of modern education. Next, we present a detailed review of Deep Learning techniques applied in four typical educational scenarios, including knowledge tracing, undesirable student detecting, performance prediction, and personalized recommendation. Furthermore, a comprehensive overview of public datasets and processing tools for EDM is provided. Finally, we point out emerging trends and future directions in this research area.

Index Terms—Educational data mining, Deep learning, Reinforcement learning, Educational datasets

I. INTRODUCTION

ments in recent years, revolutionizing diverse domains, including education. Deep learning, a form of machine learning, relies on artificial neural networks to facilitate the discovery of hierarchical features, which enhances the ability to recognize patterns [1]. In contrast to conventional machine learning approaches that require manual feature engineering, deep learning allows a machine to automatically discover intricate structures in large data by using multiple layers of abstraction. This layered feature learning process enables deep learning models to learn complicated patterns in data and achieve state-of-the-art performance across domains such as speech recognition, image classification, and natural language processing [1]. In general, three primary

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categories of algorithms exist in the domain of Deep Learning: supervised learning, unsupervised learning, and reinforcement learning [2]. Applying Deep Learning algorithms suitable for different application scenarios can greatly increase their performance. With increasing computing power, Deep Learning has achieved major breakthroughs and outstanding results in many fields.

Education fields have been revolutionized by traditional machine learning and Deep Learning algorithms, and exploring previous research is key to understanding its applications. There are two main terms which are currently used in education, Educational Data Mining (EDM) and Learning Analytics (LA) [3]. These two fields are typically interdisciplinary, including but not limited to information retrieval, data analysis, psycho-pedagogy, cognitive psychology, etc. EDM encompasses computerized techniques and tools that facilitate the automated identification and extraction of meaningful patterns and valuable information from extensive datasets obtained within educational settings [4, 5]. On the other hand, LA involves the systematic gathering, examination, and presentation of data pertaining to learners and their learning environments [6].

Integrating Deep Learning into educational scenarios is driven by the aspiration to harness the potential of Artificial Intelligence and machine learning, thereby enriching the teaching and learning experience [1, 7]. Deep Learning models possess remarkable capabilities, enabling them to effectively process and analyze vast amounts of educational data. By uncovering meaningful patterns and making accurate predictions, these models provide valuable insights that can inform and enhance educational practices [8, 9, 10]. Educators and researchers can leverage these insights to adapt teaching strategies, personalize instruction, and optimize learning outcomes. By harnessing the power of Deep Learning, the educational community can unlock new opportunities for improved efficiency, effectiveness, and adaptability in education through intelligent data processing and adaptive methodologies [11]. In addition, Deep Learning has also made significant achievements in completing specific scenario tasks in EDM. Currently, EDM scenarios are often divided into: knowledge tracing, undesirable student detection, performance prediction, and personalized recommendation. Each subfield has distinct specific data input patterns and task requirements. Deep Learning based knowledge tracing algorithms were classified into Deep Knowledge Tracking (DKT) and its variants, e.g., DKT based on Memory networks, Attention mechanisms and Graph structures [8]. Complex neural network models can be applied to Student Dropout Prediction (SDP), which is a task of undesirable student detection [12]. Similarly, neural networks can also provide quite reliable accuracy in the EDM scenario of performance prediction [13]. In the field of personalized recommendation, hybrid techniques based recommendation algorithms may be gradually taking the dominant position, but the emerging privacy issues also need close attention [14].

In fact, researchers have also been utilizing diverse traditional machine learning algorithms for educational data mining across varied educational contexts [15]. For instance, the TLBO-ML model [16] constructed by Artificial Neural Network (ANN) and Support Vector Machine (SVM) can be used to predict grades of students in final exam. However, the traditional machine learning algorithms come with certain limitations. These conventional models often rely on manual feature engineering, necessitating expert knowledge in the field to design effective features. This process can be laborious and time-consuming. Besides, handling complex and high-dimensional data, such as natural language text and multimedia content, which are prevalent in educational settings, can pose challenges for traditional machine learning methods.

Deep Learning techniques offer numerous advantages over traditional machine learning methods when applied in educational scenarios. One notable advantage is the automatic learning of hierarchical representations from raw data, eliminating the need for manual feature engineering. This characteristic makes Deep Learning models highly suitable for analyzing various types of educational data, including student performance data, educational videos, and text-based learning materials. The capability of Deep Learning models to detecting complex connections and intricate patterns within the data leads to more accurate predictions and personalized recommendations. A telling difference is shown by a research [7] that approximate 67% of papers report Deep Learning demonstrated superior performance compared to the "traditional" machine learning baselines in all conducted experiments.

Data Collection Methodology Followings are rules we applied to include or exclude papers:

- Search terms: Deep Learning and Educational Data Mining are the two keywords mainly involved in our survey. In order to access more related publications, we also used specific educational scenarios as our search terms (*e.g.*, knowledge tracing, performance prediction etc.).
- Search Sources: We searched for articles containing the above keywords through Google Scholar and downloaded the articles that matched the requirements from the corresponding major databases.
- The articles we have studied include only high-level publications from international conferences and top journals based on the application of Deep Learning to educational scenarios.

We plotted the collected papers according to their publication years and corresponding application scenarios as shown in Fig. 1, and to ensure the frontiers of research, it can be seen that EDM based on Deep Learning has emerged since 2018.

Related Work. Chen et al. [17] present a comprehensive analysis of the application of Deep Learning in the field of educational big data mining. It provides detailed descriptions of Deep Learning algorithms and explores their advancements

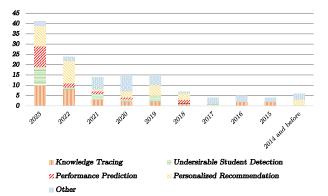


Fig. 1: Distribution of year-wise publications (until 2023) according to different educational scenarios.

in educational big data. They also list the development of teaching aids and examination tools based on Deep Learning. Additionally, the article showcases a list of institutions that have already implemented Deep Learning in their educational practices. Meanwhile, Zhang et al. [18] provide a comprehensive overview of the educational data field, covering a range of classic Deep Learning models such as Stacked Auto-Encoder (SAE), Deep Belief Network (DBN), and various Deep Neural Networks (DNN). It further investigates distinct Deep Learning techniques tailored for different types of educational data, including large-scale, heterogeneous, real-time, and low-quality data. By examining these topics, the article offers valuable insights into the application of Deep Learning in educational data analysis, contributing to the advancement of data-driven educational research and practice.

Our Contribution. Building upon the previous works, we have made improvements and advancements in our research. This survey encompasses a diverse collection of state-of-theart studies that categorize Deep Learning algorithms based on their application in educational settings. The articles are classified into three classification: supervised learning, unsupervised learning, and reinforcement learning. Furthermore, the articles are further categorized based on the specific educational scenarios where Deep Learning techniques are employed. These scenarios encompass knowledge tracing, undesirable student detecting, performance prediction, and personalized recommendation. By adopting this systematic approach, we provides a structured and in-depth analysis of the wide range of research conducted on the intersection of Deep Learning and education.

This survey not only summarizes the latest Deep Learning algorithms, but also includes a discussion of relevant datasets and data tools. By including a comprehensive analysis of datasets and data tools, the main objective of this survey is to offer the reader a thorough understanding of the considerations and challenges when implementing Deep Learning solutions in EDM. Furthermore, We put forward some promising areas for further research in Deep Learning-based EDM. The potential directions contain learning analysis and intervention, social network analysis and collaboration, explainable AI in EDM, Large Language Models for education, multimodal learning

analytics, benchmark datasets and evaluation metrics, fairness and privacy.

In summary, the application of Deep Learning to education has the potential to revolutionize the way traditional teaching and learning is done. By leveraging the benefits of Deep Learning, educators can gain valuable insights, make data-based decisions, and create personalized learning experiences. This survey aims to provide a integrate overview of Deep Learning applications in education, covering various algorithms and educational scenarios while considering the available datasets and data tools.

II. METHODOLOGY

In recent years, Deep Learning has emerged as a state-of-the-art technology that can be applied to various fields. The ability of neural networks to extract higher-level abstract features by learning the features of data has made Deep Learning a highly successful method.

Deep Learning is a technology derived from machine learning. It mimics the structure and working mode of human brain neural network. Realizing the recognition and classification task through model training. Compared to conventional machine learning algorithms, Deep Learning is able to handle more complicated tasks and datasets which will bring a higher presentation and generalization abilities. The development of Deep Learning has gone through many stages, from the initial DBN [19] to the subsequent emerging Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), etc, which have led to the Deep Learning that we care about and use today. With the progress of Deep Learning algorithms and computing power, Deep Learning has been widely applied to areas such as image recognition, speech recognition and so on. In this survey, we will mainly focus on the Deep Learning algorithms which are contributed to educational scenarios like course recommendation, student behavior detection and knowledge tracing.

We divide those models in three parts which are supervised learning, unsupervised learning and reinforcement learning, listed in the Table I.

A. Supervised Learning

The requirement of large amounts of labeled historical data makes supervised learning suitable for knowledge tracing and performance prediction. These data can be used to train supervised learning models to establish mappings between inputs and outputs and predict students' knowledge mastery and future performance.

CNN stands as a representative example of Deep Learning models which be widely used in computer vision and image process field. The theory of CNN is to extract and feature and reduce the dimension of image through convolution and pooling operations. Finally, the high-dimensional image is converted into one-dimensional vector data which can be used to the classification and regression tasks.

It is worth mentioning that the activation function ReLU of CNN is a non-linear function, which is helpful to improve

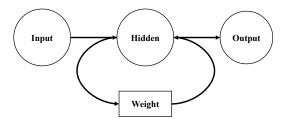


Fig. 2: The process of Recurrent Neural Network [22]

the nonlinear ability of the model and help the network learn features better.

$$ReLU: f(x) = max(0, x), \tag{1}$$

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where x refers to the input data. To some certain extent, CNN can be used for knowledge tracing. A Deep Knowledge Tracing based on Spatial and Temporal Deep Representation Learning for Learning Performance Prediction (DKT-STDRL) proposed by Lyu et al. [20]. In this model, CNN plays the role of extracting the spatial features information from students' exercise sequences.

RNN is primarily employed for handling sequential data, such as text and speech, in various applications. The neural nodes of RNN are able to receive the former status information to realize the memorability. The special property allows RNN to be applied to knowledge tracing, student behaviors detection and similar educational scenarios. The following is a basic RNN equation for it to be able to implement cycling:

$$h_t = \sigma(W_{ih}x_t + W_{hh}h_{t-1} + b_h), \tag{2}$$

where x_t refers to input vector, The h_t is the hidden state vector, W_{ih} and W_{hh} are the weight matrices connecting the input to the hidden state and the hidden state to the hidden state, b_h is the bias vector, and σ is a nonlinear activation function.

Fig. 2 simply shows the work process of RNN. Also because of the special nature of RNN, it is difficult to obtain early information when hidden data is accumulated continuously. Based on that, a Deep Knowledge Tracing model (DKT) implemented with RNN was proposed by Piech et al. [21] This DKT model employs a significant number of artificial neuron vectors to represent potential knowledge states and temporal dynamics, ultimately demonstrating a 25% improvement in accuracy compared to the previous optimal result in the knowledge tracking benchmark.

Long Short-Term Memory (LSTM) is a special RNN which contains three gate units and a memory cell. The memory and processing of sequential data are realized through the control of information flow by gated unit. The forgetting gate is a key component in LSTM to control whether the previous moment's memory cell state is forgotten, shown in Eq. 3 [23].

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \tag{3}$$

where f_t denotes the state of the forgotten gate, W_f is the weight matrix, $[h_{t-1}, x_t]$ denotes the connection between the output from the previous moment and the input from the current moment, b_f is the bias vector, and σ is the sigmoid function.

Algorithm Classification Method Advantage Disadvantage Application Scenario CNN Knowledge tracing Features can be extracted Large computation automatically Good ability Poor interpretation Student behaviors detection to avoid overfitting RNN Good at processing se-Prone to gradient vanishing Knowledge tracing quence data or gradient explosion Student behaviors detection Recursive NN Able to handle NLP Difficult to capture the hi-Knowledge tracing erarchy in the data. Student behaviors detection Personalized recommendation Supervised Learning LSTM Effectively process data Massive computation Knowledge tracing with long-term dependen-Student behaviors detection **GNN** Student behaviors detection Able to process graph Noise sensitivity structure data Strong ex-Large computation Personalized recommendation pansibility Poor interpretation Parallelizable Knowledge tracing Attention Large computation Poor interpretation Student behaviors detection Personalized recommendation GAN Data without labels can be Difficult to evaluate Personalized recommendation used DBN Able to handle complex High computational cost Knowledge tracing high dimensional data High data quality Require-Student behavior detection Unsupervised Learning Personalized recommendation ment VAE Excellent data process per-Large data requirements Student classification Complex training process Student behavior detection formance Personalized learning Resources generation Value Function Approach Personalized orientation Hard to capture all the de-Personalized learning path Self-adaptive adjustment tails and factors Intelligent tutoring and feedback

multiple

Suitable

action space

tasks

educational scenarios and

Able to handle continuous

Personalized orientation

Real-time feedback

Large computation

Poor interpretability

Large sample demand

Difficult to train

auirement

High hyperparameters re-

TABLE I: Deep Learning Algorithms in Educational Scenarios

Graph Neural Network (GNN) is a Deep Learning model used to process image data. GNN is often applied to detect student behaviors and recommend courses because it uses the information of nodes and edges in graph structure to calculate, finally learns and deduces the features of nodes and edges. Take Recurrent GNN as an example, the recurrently update formula of a node's hidden state can be defined by [24]

Policy Search Method

Actor-Critic Algorithm

Reinforcement Learning

$$\mathbf{h}_v^{(t)} = \sum_{u \in N(v)} f(\mathbf{X}_v, \mathbf{X}_{(v,u)}^{\mathbf{e}}, \mathbf{X}_u, \mathbf{h}_u^{(t-1)}), \tag{4}$$

where f represents the parametric function and $\mathbf{h}_u^{(t-1)}$ is initialized randomly. \mathbf{X}_v refers to feature vector of node v, $\mathbf{X}_{(v,u)}^{\mathbf{e}}$ denotes edge vector of node (v,u).

Because of its excellent graph processing capability, a Knowledge Augmented User Representation (KAUR) [25] model has applied GNN to obtain the initial representation of a specific node within the Collaborative Knowledge Graph (CKG), for the message aggregation and propagation.

Recursive Neural Network (Recursive NN) is a type of neural network that is capable of modeling natural language. It uses a bottom-up approach to represent input sentences

as vectors, which can be utilized for various tasks such as sentiment analysis and language translation. The core principle of Recursive NN is the recursive computation based on a tree structure. This structure allows for the representation of learning components as trees, with nodes containing multiple concepts or knowledge points. Through iterative computation of these nodes, the network is able to update its knowledge status in a continuous manner.

Personalized recommendation

Learning environment design

Personalized recommendation

Intelligent tutoring system

Attention is mainly used to enhance the model's focus and understanding of key information. The core idea is to assign weights to different parts of the input according to task requirements, allowing the model to selectively focus on specific information. The typical Self-Attention mechanism can be expressed by the following formula:

$$Attention(Q, K, V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V,$$
 (5)

Where Q means a matrix packaged from queries, K refers to the key, V means value and d_k is the key dimension. By calculating the similarity between the query and the key and normalizing it, the Attention weight distribution is calculated

and ultimately used to weight the sum values to obtain the final representation. Attention-based networks [26], dispensing with recurrence and convolutions operation. It can been train in parallel and achieve better performance.

B. Unsupervised Learning

Unsupervised learning is a good approach to solving undesirable student detection, since this task relies more on discovering latent patterns and clustering structures in student behavior data without the need for explicit labeling. Unsupervised learning can identify differences between student groups and detect students who behave abnormally by clustering, dimensionality reduction, and other techniques.

Generative Adversarial Network (GAN) is a combination of generator neural network and discrimination neural network. The target of GAN is to learn and generate samples that resemble real data, and with a high degree of diversity. The loss function of discriminator is listed as follows:

$$L_D = -[\log(D(x)) + \log(1 - D(G(z)))]$$

$$L_G = -\log(D(G(z))),$$
(6)

where x denotes real samples, D(x) is the output of discriminator towards real sample, G(z) is the sample generated by generator and 1-D(G(z)) is the output of discriminator towards generator samples. Similarly, the lost function of generator is as following, z is a random sample get from noise distribution, G(z) is the sample generated by generator and D(x) is the output of discriminator towards sample x.

The most common use of GAN in education scenarios is personalized recommendation because of its ability to generate samples. For instance, a Recurrent Generative Adversarial Network (RecGAN) that leverages tailored GRU to obtain latent features of users and items from short/long-term temporal profiles was introduced by Bharadhwaj et al. [27]. By evaluating, this method has improved the relevance of recommended items.

DBN is a DNN made of multiple Restricted Boltzmann Machines (RBM). Variational Autoencoder (VAE) is also an unsupervised learning model. It is a generative model based on autoencoder. They can both be applied to realize knowledge tracing, student behaviors detection, personalized recommendation etc. The Boltzmann distribution formula [28] is the core formula used in DBN to compute conditional probability distributions that describe the joint distribution relationship between the hidden and visible layers:

$$p(v,h) = \frac{1}{Z}e^{-E(v,h)},$$
 (7)

where v denotes the state of the visible layer, h denotes the state of the hidden layer, E(v,h) denotes the energy function, and Z is the normalization constant.

In VAE, the marginal likelihood lower bound estimator [29] based on mini-batches, can be expressed as:

$$\mathcal{L}(\theta, \phi; \mathbf{X}) \simeq \widetilde{\mathcal{L}}^M(\theta, \phi; \mathbf{X}^M) = \frac{N}{M} \sum_{i=1}^M \widetilde{\mathcal{L}}(\theta, \phi; \mathbf{x}^i),$$
 (8)

where θ and ϕ are two sets of parameters in the VAE model that control the structure and parameters of the encoder and

decoder, respectively. \mathbf{X} is the training dataset, where each sample \mathbf{x}^i is a D-dimensional vector, i is the index of the sample, and N is the total number of samples in the dataset. M is the mini-batch size used in VAE, *i.e.*, the number of samples randomly selected from the dataset at a time.

Besides, DBN is more suitable for classification tasks while VAE is more appropriate for generative tasks. For example, a Deep Belief Network for Large-Scale Online Education (DBNLS) model is proposed by Zhang et al. [30] to be used in identifying and classifying the various types of learning styles among students. The model incorporates DBN to detect and learn individual students' learning style, and fine-tunes it with the aid of Backpropagation Neural Network (BPNN).

C. Reinforcement Learning

In contrast to supervised and unsupervised learning, the training data used in reinforcement learning is traditionally generated through the interaction of an intelligent body with its environment. Therefore, reinforcement learning is suitable for personalized recommendation which is an intelligent tutoring task, it allows the model to interact dynamically and continuously adjust recommendation strategies to maximize long-term rewards. It can optimize recommendation effectiveness based on real-time user feedback.

In reinforcement learning [31], an intelligent body takes a specific action by observing the state of the environment and evaluates its behavior based on the reward or punishment given by the environment. The goal of the intelligent body is to optimize the cumulative reward.

1) Value Function Approach

Value Function Approaches refers to the algorithm's ability to achieve the global optimal payoff by obtaining the best action. That is, the optimal gain is produced through the optimal action a^* under the optimal strategy π^* . This strategy can be represented by the Bellman optimality equation:

$$v_{\pi}^{*}(s) = \max_{a} \mathbb{E}[R_{t+1} + \gamma v_{\pi}^{*}(S_{t} + 1) | S_{t} = s, A_{t} = a]$$

$$= \max_{a} \sum_{s', r} p(s', r | s, a) [r + \gamma v_{\pi}^{*}(s')], \tag{9}$$

where $\mathbb{E}[\cdot]$ denotes the expectation of the reward R_{t+1} and value function $\gamma v_{\pi}^*(S_t+1)$ for the next state in the case of the current state s and taking action a.

The ability of the value function to take into account long-term benefits allows the model to make more informed decisions, not just localized immediate rewards. However, the solution of certain value function methods may take a longer time to reach convergence. Especially in complex environments or large-scale problems, more iterations and samples may be required to obtain accurate value function estimates and optimal strategies.

2) Policy Search Method

The Policy Search method maximizes the expected return in a direct optimization of strategies that are influenced by a set of policy parameters θ_t . As an example, the gradient-based policy search method uses the Gradient Ascent method, which maximizes the strategy performance J with respect to

the parameter θ by iteratively updating the strategy parameters, and the equation can be simply expressed as:

$$\theta_{t+1} = \theta_t + \alpha \nabla J(\theta), \tag{10}$$

where θ_{t+1} refers to the parameter of policy at time t+1, $\nabla J(\theta)$ is the gradient of θ_t -based policy's performance. α is a learning rate which controls the step size of each parameter update.

In addition to gradient-based policy search algorithms, there is a Monte Carlo policy gradient-based method called RE-INFORCE for optimizing policies in reinforcement learning. It estimates the policy gradient by Monte Carlo sampling and uses the gradient ascent method to update the policy parameters. Specifically, the REINFORCE algorithm can be implemented by the following equation:

$$\nabla J(\theta) \propto \sum_{s} \mu(s) \sum_{a} \nabla_{\theta} \pi(a|s,\theta) q_{\pi}(s,a)$$

$$\doteq \mathbb{E}_{\pi} \left[\sum_{a} \nabla_{\theta} \pi(a|S_{t},\theta) q_{\pi}(S_{t},a) \right], \tag{11}$$

where \propto denotes "be proportional to", $\mu(s)$ is called "on-policy" under the policy π . $q_{\pi}(s,a)$ refers to the value function of policy π choosing action a in state s.

3) Actor-Critic Algorithm

The Actor-Critic algorithm is a reinforcement learning algorithm for solving the problem of learning optimal policies in unknown environments. The core idea of the Actor-Critic algorithm is to guide Actor's policy improvement through the estimation of value functions provided by Critic, which in turn estimates the value of a state or state action pair based on the current policy and environment interaction data Critic then evaluates the merit of a policy based on the current policy and environment interaction data.

Take one-step Actor-Critic algorithm as an example, the equation of θ update can be expressed as:

$$\theta_{t+1} \doteq \theta_t + \alpha (R_{t+1} + \gamma \hat{v}(S_{t+1}, w) - \hat{v}(S_t, w)) \frac{\nabla_{\theta} \pi(A_t | S_t, \theta_t)}{\pi(A_t | S_t, \theta_t)}, \quad (12)$$

where R_{t+1} denotes the reward at time t+1. γ is the discount factor that controls the importance of future rewards. $\hat{v}(S_t, w)$ refers to the state value function learned by Critic and will be used as baseline.

III. EDUCATIONAL SCENARIOS AND CORRESPONDING ALGORITHMS

To provide a comprehensive overview of the literature on DL for different application scenarios, we have included information on the algorithms and models used in each paper for four educational scenarios in Table II. This table also lists the evaluation metrics and datasets employed in each study.

A. Knowledge Tracing

Knowledge tracing is an educational assessment technology that tracks students' learning process and predicts their mastery of knowledge points. In a knowledge tracing scenario, students' learning process is usually recorded, including learning time, answer status, homework completion, etc.

According to previous studies proposed by Song et al. [8], the problem of knowledge tracing in intelligent education systems involves three main elements: the student S, the exercise E, and the corresponding knowledge concept C. The interactions X among these elements are the main activities in such systems. Specifically, given a student's historical exercise interactions $s \in S$, where each interaction $X_t \in X$ corresponds to an exercise $e \in E$ and denotes the correctness $a_t \in \{0,1\}$ of the result obtained at step t, the knowledge tracing task aims to predict the next interaction X_{t+1} for a specific concept $c \in C$ [8].

A simple schema of knowledge tracing is shown as Fig. 3. The correct rate of a student in a certain exercise on a specific knowledge point can affect the model's judgment of the proficiency level of students on this knowledge point. For example, in Fig. 3, the student's correct rate on the derivative knowledge point is 100%, so his/her mastery level on that knowledge point is much higher than other knowledge points.

1) Supervised Learning

The application of supervised learning in the field of knowledge tracing is mainly focused on various kinds of neural networks, *e.g.*, LSTM, CNN, GNN and RNN.

Among them, LSTM mainly through managing the forgetting and learning behaviors of student to update knowledge state, so as to realize knowledge tracing. A GFLDKT model based on LSTM was presented by Zhao et al. [32], in which a Gating-controlled Forgetting and Learning mechanism was employed to effectively update the knowledge state and facilitate accurate prediction of subsequent student responses.

In addition, Nagatani et al. [34] proposed a DFKT model considering forgetting processes of student. Specifically, DFKT applies LSTM and Neural Factorization Machine (NFM), the former is used to represent knowledge state of student as low dimensional dense vectors, the later combines student knowledge states and other related information include relevant forgetting data, to predict student performance.

CNN also plays an essential role in knowledge tracing by being able to process the spatial sequence data. Lyu et al. [20] introduced a DKT-STDRL model which employs CNN to extract spatial features from students' learning sequences and LSTM to process temporal features.

Knowledge Graph (KG) is a crucial component of knowledge tracing, as it accounts for the interplay between a student's learning history and specific areas of expertise. By leveraging the power of the KG, models can more accurately capture learning trajectories and interactions between different points of knowledge. Yang et al. [39] put forth a Graph-based Interaction model for Knowledge Tracing (GIKT) constructed using Graph Convolutional Network (GCN). The proposed model addresses data sparsity and multi-skills challenges by harnessing high-order question-skill correlations, thus improves model performance.

Moreover, a heterogeneous graph based algorithm called HHKST proposed by Ni et al. [38], which utilizes a GNN-based base feature extractor (BFE) to extract interaction and knowledge structure features from the heterogeneous graph.

As a neural network architecture designed for handling sequential data, RNN also holds a significant position in the

TABLE II: Overview of DL Algorithms for Different Educational Scenarios.

Scenario	Model	Algorithm Classification	Method	Evaluation Strategy	Dataset	Year
	GFLDKT [32] LFBKT [33] DFKT [34] MRTKT [35] PGN [36]		LSTM LSTM LSTM NN NN	AUC/ACC AUC/ACC AUC/ACC/MAP AUC/ACC AUC/ACC/RMSE	ASSISTments15/17/JunyiAcademy ASSISTment12 ASSISTment12 ASSISTment09/10/12/13 ASSISTment15/17/Statics2011	2023 2022 2019 2023 2023
Knowledge Tracing	XGBoost [37] DKT-STDRL [20] DKT [21] HHSKT [38] GIKT [39] KTMFF [40] AKT [41] SAKT [42]	Supervised Learning	DT CNN RNN GNN GCN DKVMN Attention Self-Attention	AUC/ACC AUC/ACC/RMSE/r ² AUC	ASSISTment09/Algebra08 ASSISTment09/15/Statics2011 ASSISTment09/10 ASSISTment09/11/Junyi15 ASSISTment09/12/EdNet ASSISTment09/15/Statics2011 ASSISTment09/10/12/13/KDD Cup2012 ASSISTment09/10/5/Statics2011	2023 2022 2015 2023 2021 2023 2020 2019
	AdaptKT [43]	Unsupervised Learning	Autoencoder	AUC	zx.math/ax.physics	2022
	CL4KT [44]	Self-supervised	CL	AUC/RMSE	ASSISTment09/Algebra05/06	2022
	KTM [45] RL-KTNet [46] IEKT [47] KADT [48]	Reinforcement Learning	AC AC Policy Gradient DPG	AUC AUC/r ² AUC/ACC AUC	ASSISTment09/10 ASSISTment09/10/KKD2010 ASSISTment09/12/EdNet/Junyi ASSITment09/IMDB/MovieLens/CIFAR-100	2019 2020 2021 2023
Undesirable Student Detecting	VB-DTW [49] DCNN [50] ATGCN [51] Faster R-CNN [52] CFIN [53] Tree-Based Model [54] LR-KNN-RF [55] EVA-MLP [56] DPBN [57] XGBoost [58]	Supervised Learning	CNN CNN CNN CNN CNN DT KNN MLP BN DT	ACC/VSE Recall/Precision/F1 ACC ACC/Precision/DR/FDR AUC/F1 ACC/Recall/Precision/F1 AUC/ACC/Recall/Precision/F1 Recall/Precision/F1 AUC/ACC/F1 ACC/Recall/Precision/F1 ACC/Recall/Precision/F1/NPV	SCB-13 FER2013 N/A TCE Classroom KDD Cup2015/XuetangX N/A Kaggle Student Journals OULAD BPS12-14	2023 2023 2023 2023 2019 2023 2023 2023 2023 2023
	FTGAN [59]	Unsupervised Learning	GAN	AUC/ACC/Recall/Precision/F1	N/A	2021
Performance Prediction	DTRM [60] ProbSAP [61] DL-MLP [62] CRN [63] SDPNN [64] MLP-12Ns [65] TLBO-ML [16] SAPP [66]	Supervised Learning	DT DT MLP CNN DNN MLP ANN LSTM	ACC/Recall/Precision/F-measure RMSE/MAE/MAPE/C/r ² ACC FDR/Sens/FPR/MCC/F1/NPV/FNR ACC RMSE ACC/Recall/Precision/FM/F1/MCC ACC/Recall/Precision/F-measure	SAD Dean Office SQL Pennsylvania School Performance Profile Kaggle N/A Kaggle OULAD OULAD	2023 2023 2023 2023 2023 2023 2023 2023
	SAPPANN [67]	Semisupervised	ANN	ACC	OULAD	2023
	CGAN [68]	Unsupervised Learning	GAN	AUC	Self-collected	2022
	ADSLS [69] NCAT [70]	Reinforcement Learning	Q-Learning Q-Learning	N/A AUC/ACC	N/A ASSISTment09/12/15/KDD Cup2010	2013 2022
Peronalized Recommendation	BERT [71] MCR-C-FGM [72] SODNN [10] LSTM-CNN [73] CSEM-BCR [74] ARGE [75] KNN-NCF [76] KALUR [25] TCRKDS [77] FRS [78] MRCRec [79] KG-based [80]	Supervised Learning	DNN DNN CNN CNN KNN KNN GNN LSTM LSTM MR KG	Recall/Precision/F1 Precision Precision Recall/Precision/F1 Recall/Precision/MAP/AP AUC MAE/HR/ARHR Recall/NDCG ACC/Recall/Precision/F-measure/FDR AUC/Precision/RSME HR/HR/NDCG/MRR UE/ER/IL	MOOCCube edX Learning Data UBOB Kaggle CourseTalk LastFM/Moviclens-100K/Yelp Kaggle MovicLens-100K/Amazon-book/LFM-1B Kaggle ASSISTment MOOCCube/XuetangX N/A	2023 2022 2023 2023 2022 2023 2022 2023 2023 2018 2023 2023
	RecGAN [27] DBNLS [30]	Unsupervised Learning	GAN DBN	NDCG/MRR/MAP Act/Ref/Sen/Int	MPF StarC	2018 2020
	RLALS [81] CSEAL [82] MEUR [83] QLeamRec [84] RILS [85] DARL [86] HELAR [87] HRRL [88] HRI-NAIS [89] KERL [90]	Reinforcement Learning	AC AC AC Q-Learning Q-Learning REINFORCE REINFORCE REINFORCE MONTH OF THE MO	N/A AUC/Recall/F1/MAP IR/HR/NDCG/MRR N/A N/A HR/NDCG HR/NDCG HR/NDCG HR/NDCG HR/NDCG HR/NDCG HR/NDCG HR/NDCG	N/A Junyi MOOCCube Self-Collected Self-Collected MOOCCourse/XuetangX MOOCCourse/XuetangX MOOCCourse/XuetangX XuetangX Amazon/LastFM	2018 2019 2023 2019 2014 2021 2022 2022 2019 2020

field of knowledge tracing. DKT [21] utilized considerable amounts of artificial neurons from RNN to construct knowledge tracing model. The principle contribution of this article is the introduction of a novel method that encoding student interactions into RNN inputs and improved the AUC to a certain level compared to previous.

In knowledge tracing, the application of Attention mechanisms has been explored. Ghosh et al. [41] introduced a method called Context-Aware Attentive Knowledge Tracing (AKT), which combines a flexible DNN with heuristic cognitive and psychometric models. The proposed Attention mechanism is used to dynamically adjust predictions based on contextual information about learners. This integration of

Attention allows the model to adapt its predictions according to the specific context of each learner.

Additionally, Pandey and Karypis [42] proposed the Self-Attentive Knowledge Tracing model (SAKT), which leverages a self-attentive mechanism to identify and predict the mastery level of students for specific knowledge points. The experimental results demonstrate that SAKT outperforms traditional methods and RNN-based models, achieving significantly faster performance by an order of magnitude.

2) Unsupervised Learning

In fact, unsupervised learning has been used relatively little in this field. This is because unsupervised learning requires dealing with a large amount of unlabeled data, while in

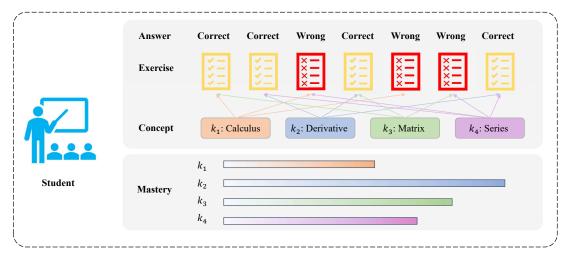


Fig. 3: A simple knowledge tracing schema. Different exercises contains multiple types of concepts with different colors. Whether the exercises are correct or not will affect knowledge tracing's judgment of the student's mastery of a certain knowledge point or exercise [91].

knowledge tracing there is usually only a limited amount of labeled data, making it difficult to train accurate models using unsupervised learning methods. However, in recent years, with the rapid development of Deep Learning, some researchers have started to explore the use of unsupervised learning in knowledge tracing.

For instance, Cheng et al. [43] proposed a Autoencoder based DKT which combines knowledge tracing and transfer learning. The Autoencoder here is used to convert question text to high-level semantic embedding. In addition, the model also applies Bi-LSTM and Attention mechanism to capture knowledge state of student and predicts next answer of learner by Softmax.

3) Reinforcement Learning

Reinforcement learning is able to learn the knowledge status and level of students by rewarding or punishing through decisions and actions they make without the pre-labeled data. The learning process in knowledge tracing can be considered as a sequential decision problem, students need to make different decisions according to different knowledge points, which might affect the future learning process.

Ding et al. [46] consider that some supervised learning such as LSTM or GRU, are heavily influence by NLP and is not specially designed for knowledge tracing. Therefore, the authors design a RL-KTNet algorithm which adopt reinforcement learning to automatically generate recurrent neural network cells used in knowledge tracing. It outperforms models employing LSTM cells in terms of performance.

In addition, Long et al. [47] proposed a model called Individual Estimation Knowledge Tracing (IEKT) which incorporates reinforcement learning for auxiliary model training. Specifically, Long et al. employed Policy Gradient and ϵ -greedy to update the model parameters. Additionally, reinforcement learning is utilized to estimate student knowledge states and sensitivity towards knowledge acquisition.

B. Undesirable Student Detecting

In the current era, both traditional and online educational systems have been generating massive amounts of data. The extraction of useful knowledge and underlying patterns from this voluminous data can enable decision-makers to enhance teaching and learning by identifying unfavorable student behaviors [12] and predicting student performance. This educational data can be considered as an invaluable source of information that can facilitate data-driven educational research and innovation.

The objective is to identify undesirable students' behaviors like low motivation, low engagement, cheating, dropout and procrastination [92]. There is a simple process of undesirable student detection shown is Fig. 4.

1) Supervised Learning

The applications of supervised learning in this field are relatively diverse, and in addition to neural networks such as CNN, Decision Tree, K-Nearest Neighbor (KNN) and Bayesian Network are also applied.

Benefits from the superior image processing capabilities of CNN, Qiu et al. [51] proposed a ATGCN model based on CNN to detect students' undesirable behaviors in the classroom such as napping etc.

In addition, Song et al. [54] introduced a Tree-Based model applies if-then-else rule to detect the probability of student dropout. Three types of classifier model employed in that paper, which is Decision Tree, Logistic Regression and SVM.

In terms of classification models. Chi et al. [55] present a LR-KNN-RF model which contains Logistic Regression, KNN and Random Forest. Analyzing the dropout rate of MOOC from learners own characteristics and learning behaviors. The experiment result is Random Forest performs best among three classification algorithms.

Furthermore, a model called DPBN based on Bayesian Network (BN) is proposed by Shi et al. [57]. The model is constructed by mutal information and pruning, also generate parameters by Maximum Likelihood Estimation (MLE). The

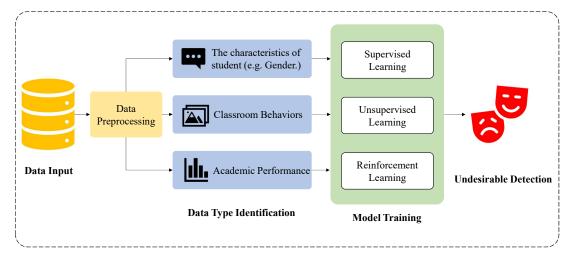


Fig. 4: A simple undesirable student detecting schema. Different types of data require different models for detection (*i.e.*, CNN is suitable for processing image and video data).

model is relatively explainable because it can demonstrate the effect of individual features on dropout rates.

Feng et al. [53] proposed a Context-aware Feature Interaction Network (CFIN) model for predicting user dropout behaviors in MOOCs. The CFIN model incorporates a context smoothing technique to enhance the feature values across different contexts and employs an Attention mechanism to integrate user and course information within the modeling framework. Subsequently, the authors demonstrate the exceptional performance of this model.

2) Unsupervised Learning

In addition to the K-means algorithm, which is similar to the classification model described above and detects student misbehavior by clustering behaviors, there is an unsupervised learning that can be applied to this field.

Stenton et al. [59] introduced a FTGAN which means Fine-Tuning GAN to predict the attrition rate of student. The authors demonstrate that the more epochs the GAN classifier model is trained, the more its accuracy shows a certain level of increase.

3) Reinforcement Learning

There are two reasons why reinforcement learning may not be the most appropriate method for predicting student dropout rates or detecting undesirable behavior:

- Students' behavior is often influenced by many factors, such as social and cultural background, family environment, and personal circumstances, which are difficult to describe in terms of simple states and actions.
- It is difficult to define the rewards and punishments for student behaviors that lead to dropout outcomes. For example, poor student behavior may be subject to some reward in the short term but lead to dropout in the long term, which makes reinforcement learning difficult to handle effectively.

Therefore, this paper did not collect literature on the detection of student undesirable behaviors by reinforcement learning.

C. Performance Prediction

Performance prediction [13] refers to the use of various data and analytic techniques to predict student performance in certain tasks or areas, such as test scores, academic performance, course completion rates, etc. The difference between it and the knowledge tracking task is that performance prediction focuses on predicting students' overall future task or test performance based on historical learning data, while knowledge tracing focuses on students' understanding and mastery of specific knowledge concepts during the learning process.

By predicting student performance, teachers and educational institutions can better understand students' learning and needs in order to provide more effective support and guidance. Predictions can also help students understand their performance and potential difficulties and take steps to improve learning outcomes.

Furthermore, cognitive diagnosis [93] is a related concept wherein the aim is to identify students' level of mastery in specific knowledge domains by analyzing their performance on exercise records. This analysis facilitates providing tailored guidance for their subsequent studies [94, 95]. In contrast, performance prediction focuses more on predicting students' overall scores on tests. The former analyzes knowledge dimensions, while the latter emphasizes general ability. Cognitive diagnosis outputs concept proficiency levels, whereas performance prediction directly predicts total scores.

1) Supervised Learning

Supervised learning algorithms can provide teachers and students with useful information to help them better understand student performance and needs. In addition to classic algorithms like SVM, Deep Learning models such as MLP, CNN, Recurrent NN, LSTM, and DNN have been applied to predict student performance in various educational contexts.

Nayani et al. [63] introduced a hybrid model called CRN which is a combination of CNN and Recurrent NN to predict the students' grade, and improves the performance by tuning hyper parameters through Galactic Rider Swarm Optimization (GRSO) algorithms.

The robustness of Decision Tree as a predictive model is attributed to its decision mechanism, whereby the output predictions are deemed erroneous only if more than half of the decision trees (DT) yield incorrect judgments. Chen and Ding [60] have conducted a comparative analysis of the predictive performance of seven distinct models, which has led them to conclude that Decision Tree exhibits a commendable level of generalizability across all the evaluated datasets.

In addition, Neha et al. [64] presented a SDPNN model applied a linear classifier based DNN to prediction student academic performance. There are two hidden layers with 300 neurons be defined. Activation function is ReLU and Softmax.

softmax
$$(z_i) = \frac{e^{z_i}}{\sum_{i=1}^{K} e^{z_j}}, \quad i = 1, 2, ..., K,$$
 (13)

where z_i represents the i_{th} element of the input vector and K is the number of categories.

Kukkar et al. [66] proposed a SAPP system which utilize four layers stacked LSTM, Random Forest and Gradient Boosting. LSTM here is used to extract features while Random Forest and Gradient Boosting are applied to predict. The proposed system has an accuracy rate of 96% and performs well to some extent.

2) Unsupervised Learning

Although grade prediction usually relies on labeled datasets for supervised learning, some unsupervised learning algorithms, such as GAN, can also be used for grade prediction tasks. GAN can perform grade prediction by taking a student's historical grades as input and using generators and discriminators to generate predicted values for future grades. The generator can use the student's prior grades and other relevant factors to generate predictions of future grades, and the discriminator is used to determine whether the generated predictions are similar to the true grades.

Sarwat et al. [68] proposed a model combined with Conditional GAN (CGAN) and Deep-Layer-Based SVM to predict students' grade according to school or home tutoring. CGAN was used to generate performance score data to address the issue of small dataset size, and the model using a combination of CGAN and SVM was experimentally shown to have a positive effect on the prediction results.

3) Reinforcement Learning

Generally speaking, reinforcement learning is not suitable for student performance prediction. However, reinforcement learning can set reward strategies based on student behavior to optimize the student's learning path. In this case, reinforcement learning also needs to assess the current performance of students and predict the optimized performance for the purpose.

Dorça et al. [69] proposed a ADSLS model to automatically detect and precisely adjust students' learning styles. An important part of this is that the model predicts and assesses student performance on a point and rewards performance while updating learning strategies. The proposed method's efficacy and efficiency have been demonstrated by the results.

Zhuang et al. [70] introduced an NCAT model that utilizes reinforcement learning to enhance the effectiveness of etesting systems. The NCAT model employs deep reinforcement learning to dynamically optimize test terms based on given conditions. With the proposed algorithms, the e-testing system can provide more comprehensive and accurate performance predictions.

D. Personalized Recommendation

In the current era of explosive growth in online information, recommendation systems [14] undoubtedly offer an effective means of addressing this issue and providing necessary assistance to individual users. Even outside the educational context, recommendation systems remain one of the most widely studied technological approaches. Zhang et al. [96] gives a detailed definition of a recommendation system that is: Assuming the presence of M users and N items, we denote the interaction matrix and predicted interaction matrix as R and \hat{R} , respectively. The user preference for item i is represented as r_{ui} , while the predicted score is denoted by \hat{r}_{ui} . There will also be two partially observed vector, one represents a specific user u, i.e., $r^{(u)} = \{r^{u1}, ..., r^{uN}\}$. Another one represents a specific item i, i.e., $r^{(i)} = \{r^{1i}, ..., r^{Mi}\}$.

In the education scenarios, item is replaced with educational resources such as courses. The primary objective of a course recommendation system is to suggest the most suitable course to a user at time t+1, taking into account their past learning activities and learner profiles prior to time t. The primary challenge faced by such recommendation systems is to provide personalized recommendations by precisely depicting and conceptualizing user inclinations through analysis of user data [97]. Fig. 5 demonstrate a simple schema of personalized recommendation.

1) Supervised Learning

The application of supervised learning in course recommendation [72] focuses on a wide variety of neural network models, due to the greater flexibility and expressiveness of neural networks, which can better handle user behavior sequences and nonlinear features. At the same time, neural networks can automatically extract features from the data to more accurately predict users' interests in the recommendation process.

Some optimized neural network models play a role in the field of personalized recommendation. SODNN, a novel model consist of synchronous sequences, heterogeneous features and DNN has been introduced by Safarov et al. [10]. At the same time, in order to solve cold-start problem, *i.e.*, Large errors caused by missing user data during the initialization of the recommendation system, the author try to concatenate additional features to overcome it.

Furthermore, classical neural networks can also be employed in Recommendation Systems. In contrast to the conventional positive sequence modeling approach, Gao et al. [74] proposed a novel CSEM-BCR model that adopts negative sequence modeling. Specifically, this model constructs the course-learning sequence as a negative sequence pattern, wherein the negative term refers to the principle that students should not select or operate courses inappropriately. The negative sequence pattern is then processed using CNN for feature learning, which generates a list of recommended courses for each user. The suggested approach presents a

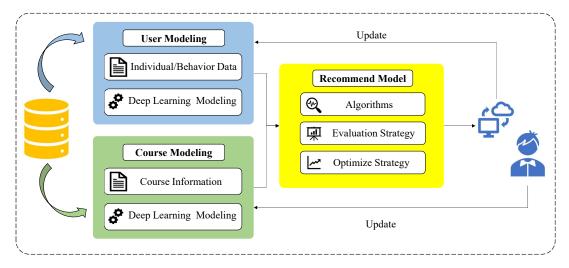


Fig. 5: A general process framework for personalized recommendation in EDM. The recommendation system uses user data and course data for modeling. After recommending to users, the associated data between users and courses will be updated to improve accuracy.

fresh perspective on personalized recommendation and offers a potential solution to the issue of recommending courses to learners with different needs and preferences.

KG is an important part of personalized recommendation. It can effectively address the sparsity issue in recommender systems. A ARGE model based on multiple paths RNN encoder is proposed by Zhao et al. [75]. The model solves the problem that traditional RNN do not consider the association between paths for encoding, and the AUC and Precision in the experimental outcomes demonstrate the model's capacity to effectively address the issue of sparse interaction between users and items.

GNN, as a neural network model specifically for processing graph structures, has also been applied by many scholars to deal with recommender systems. Ma et al. [25] presented a KAUR model which applies GNN to learn node representations for each node in the collaborative KG. The model treats the node information and its neighboring node information that has been propagated as positive contrastive pairs, and then leverages contrastive learning to improve the quality of the node representations.

Zhou et al. [78] proposed Full-path Recommendation System (FRS) based on LSTM and a clustering algorithm. The clustering algorithm is utilized to categorize learners based on their similar learning features, which in turn helps classify the learning paths according to the previous results. Consequently, this approach effectively addresses the cold start problem. LSTM is employed for predicting learning performance, and if the result is unsatisfactory, the system will select the most relevant learning path for users based on their individual learning features.

In addition to different kinds of neural networks, other supervised algorithms can also be used for personalized recommendations, for instance, Jena et al. [76] introduced a KNN-NCF model based on KNN. KNN is used here to cluster courses that have different comments for the purpose of optimizing the output.

2) Unsupervised Learning

In recommender systems, user preferences and behaviors are often incomplete and inaccurate, and tagging data is very difficult and expensive to collect. On this basis, unsupervised learning is a great means to achieve personalized recommendation. Unsupervised learning can extract potential interests and preferences from users' historical behaviors and infer the similarity and interest relevance of users through clustering, and feature learning to achieve personalized recommendations.

Bharadhwaj et al. [27] introduced a hybrid RecGAN model based on GAN and Recurrent NN. The generator and discriminator are both constructed with GRU-Based Recurrent NN. The generator is then allowed to play a Mini-Max game with the discriminator, i.e., there exists a true distribution $D_{real|t}$ in time index t, and a probability distribution generated by the generator $D_{gen|t}$. The goal of this minimal-maximization game is to minimize the generation error of the generator, while maximizing the discriminator's ability to distinguish false ratings from true ratings.

Unsupervised learning can also be applied to classify different types of learning style in order to recommend the most suitable education resources to distinct groups. A DBN-based DBNLS model proposed by Zhang et al. [30] is used to detect and classify learning styles. The core component of DBNLS is multilayer RBM and Back Propagation network layer, where Back Propagation is used to fit the DBNLS model and to finetune and train the DBN.

3) Reinforcement Learning

The application of reinforcement learning in personalized recommendation has high research value and development prospects. Reinforcement learning algorithms can learn the optimal recommendation strategy based on students' feedback to improve the recommendation effect, and can be optimized based on different evaluation metrics, such as recommendation accuracy, recall, coverage, etc.

A cognitive structure enhanced framework for adaptive learning named CSEAL was proposed by Liu et al. [82],

to achieve personalized learning path recommendation. This framework views learning path as a Markov Decision Process (MDP) and applies actor-critic to identify appropriate learning projects for individual learners. CSEAL comprehensively considers the learner's knowledge level and the knowledge structure of the learning project. Experimental results demonstrate that CSEAL can enhance learners' efficiency compared with current adaptive learning methods.

Liang et al. [83] presented a MEUR model based on Graph Convolution Network and reinforcement learning. The author considered the learning process as a MDP. Applying a user-centric reasoning method and maximize cumulative reward G by actor-critic algorithm, G is defined as bellow:

$$G(\theta) = \frac{1}{m} \sum_{u=1}^{m} \sum_{a,t=0} \pi(a|s_t, A(s_t)) \gamma^t R(s_{t+1}), \tag{14}$$

where θ is the parameter of the Actor network, m is the number of samples, u is the sample index, a and t are the time step and action indexes, $\pi(a|s_t, A(s_t))$ is the probability of selecting action a in state s_t , $R(s_{t+1})$ is the immediate reward obtained in state s_{t+1} , and γ is the tuning parameter.

It is worth mentioning that the user's learning process is dynamic, which also assumes that this user's interest in the course may change as the cognitive level increases. Based on this, Lin et al. [86] proposes a DARL which is able to automatically capture user preferences in interactions and update the Attention weights of the corresponding courses. Specifically, a dynamic Attention mechanism is added to the model, and experimental results showcase the effectiveness, adaptiveness, and time cost advantages of the method.

The Attention mechanism also serves other purposes. For instance, when a user has enrolled in multiple courses, it becomes challenging to identify the most pertinent historical courses that can aid in predicting the courses that the user is genuinely interested in. In order to tackle this concern, Lin et al. [88] introduced a HRRL algorithm which applies Attention-based recommend system and Recurrent Reinforcement Learning (RRL). By sharing the embeddings of user profiles during training, the model is able to reconstruct user profiles that enhance the accuracy of the recommendation system.

However, Attention mechanisms also have drawbacks, such as a decrease in the accuracy of the recommendation model when a user is interested in multiple courses simultaneously. Therefore, Zhang et al. [89] proposed a HRL-NAIS algorithm for modifying user profiles. Specifically, the model analyzes and identifies historical courses, and removes noisy historical courses to modify the user profile. Afterwards, the agent obtains delayed rewards from the environment and modifies the policy accordingly to achieve more accurate recommendations.

In addition, KG can also assist reinforcement learning in course recommendation. a KG-enhanced reinforcement learning course recommendation algorithm KERL was presented by Wang et al. [90], which formalizes the sequential recommendation task as MDP and provides a composite reward function. The model has been proven to be effective on four real-world datasets

$$R(s_t, a_t) = R_{seq}(i_{t:t+k}, \hat{i}_{t:t+k}) + R_{kg}(i_{t:t+k}, \hat{i}_{t:t+k}), \quad (15)$$

where functions $R_{seq}(\cdot, \cdot)$ and $R_{kg}(\cdot, \cdot)$ are used to calculate rewards at the sequence-level and knowledge-level, respectively. These functions take as input both the ground-truth subsequence $i_{t:t+k}$ and the recommended subsequence $\hat{i}_{t:t+k}$, and approximate the overall performance over a k-step period.

IV. DATASETS AND PROCESSING TOOLS

A. Datasets

To provide a more comprehensive overview of commonly used public datasets in educational settings, we have curated a selection of datasets, as presented in Table III. The table is adapted from Romero et al.'s paper [114] and Mihaescu et al.'s paper [116]. These datasets have been widely employed in various educational research studies and have contributed significantly to the advancement of the field. Table III offers essential information about each dataset, including its name, URL, description, application scenarios, and literature applied.

We classify the collected datasets by source into three categories: Datasets Used for Competitions, Datasets from Online Education Platforms, and Open Data Repository.

1) Datasets Used for Competitions

a) ASSISTments

The ASSISTments dataset has many versions, such as Assistment 2009, 2012 and 2017, which have been used in several educational data mining competitions to promote research and development on educational technology and learning analytics. One of the most well-known competitions is ASSISTments Data Mining Competition.

b) KDD Cup 2010

This dataset is used in the KDD Cup 2010 Educational Data Mining Challenge, which requires participants to use the student interaction logs contained in the provided dataset to train a new learning model and ultimately judge the results based on how accurately their model predicts student responses to new questions. This dataset is therefore also widely used for problems such as Knowledge Tracking.

2) Datasets from Online Education Platforms

a) Junyi Academy Online Learning Activity Dataset

The dataset was sourced from the Junyi Academy online learning platform, which provides personalized learning resources and support for students. The dataset consists of over 72,000 students' records of more than 16 million practice attempts on the platform within one year, from August 2018 to July 2019.

b) Canvas Network Dataset

The Canvas Network dataset is derived from the Canvas Network platform, which provides educational institutions and educators with the tools and resources to create and deliver online courses. The dataset contains a lot of course information as well as user interaction logs, etc.

c) Learn Moodle

Learn Moodle is derived from the Moodle Learning Management System, a widely used open source online learning platform that supports educational institutions and teachers in creating, managing and delivering online courses.

TABLE III: Dataset Information

Dataset Name	URL	Description	Application Scenario	Literature Applied
ASSITments	Click here	A knowledge tracing dataset based on knowledge decomposition theory in education, including problem-solving records. Aimed for developing and evaluating intelligent education systems.	Used for researching and evaluating intelligent education systems based on knowledge decomposition theory, such as adaptive learning and personalized education systems, using machine learning and Deep Learning techniques.	[21] [32] [38] [98] [36] [37] [99] [33] [40] [20] [35] [70] [39] [93] [47] [41] [42] [100]
Junyi Academy Online Learning Activity Dataset	Click here	Junyi dataset is an educational dataset that contains a large amount of online learning behavior data of primary and secondary school students, including learning and answering records, learning behavior features, and other information.	The dataset is designed to support data mining and ML research in education, as well as building more personalized and intelligent educational applications.	[32] [38] [98] [36] [82] [78] [47]
KDD Cup 2010	Click here	This dataset contains logs of student interactions with computer-aided-tutoring systems, including problem-solving transactions. Key terms include problem, step and knowledge component.	It can be applied to the development and evaluation of intelligent educational systems, personalized learning systems, and other machine learning and Deep Learning-based educational technologies.	[99] [101] [102] [103] [104]
MOOCCube	Click here	MOOCCube is an open data warehouse for NLP, KG, and data mining researchers in large-scale online education. It includes 706 real online courses, 38,181 instructional videos, 114,563 concepts, 199,199 MOOC users' hundreds of thousands of course selection and video watching records.	The data set can be used to study learner behavior pattern, recommendation system, data mining and other fields.	[105] [79] [106] [83]
xAPI- Educational Mining Dataset	Click here	This dataset contains 480 student records and 16 features, including demographic attributes (gender, nationality), academic background information (educational stage, grade level, section), and behavioral indicators (raising hand in class, accessing resources, parental survey responses, school satisfaction).	xAPI-educational mining dataset can be used to develop and evaluate learning analytics models and personalized learning systems in the education domain.	[27] [107] [108]
Open University Learning Analytics Dataset	Click here	The Open University Learning Analytics Dataset is a comprehensive educational dataset that includes over 300,000 students' demographic information, course information, interaction data, and achievement data from seven courses, and has been used in various educational research studies.	Predicting student success and dropout rates in higher education, as well as understanding learning behavior patterns in online courses.	[67] [57] [66] [77]
Canvas Network Dataset	Click here	Online courses data collected from Canvas Network platform, including course metadata, enrollment, and interaction logs.	Predicting and understanding student performance and behavior in online courses, and designing personalized interventions to improve learning outcomes.	[109] [110] [111] [112] [113]
Learn Moodle	Click here	The Learn Moodle dataset is a collection of student activity logs, discussions, quizzes, and more from various Moodle courses. It is used for researching student behavior patterns, learning outcomes, course design, and Moodle platform functionality in online education.	This dataset is mainly used to study student behavior patterns, learning outcomes, course design, and Moodle platform functionalities in online education, aiming to improve teaching quality and efficiency in online education.	[114]
XuetangX	Click here	XuetangX is a Chinese dataset, which covers courses and learning behavior data of Chinese users on the online platform of XuetangX. This includes student registration information, course access records, video viewing behavior, homework submission, discussion participation etc.	The data set can be used in the research and application of learner behavior analysis, just tracking, recommendation system and online learning research.	[89] [79] [83] [86] [87] [88] [115] [53]
EdNet	Click here	EdNet is a large-scale educational dataset collected from Santa, an AI tutoring service with over 780K users. It contains multivariate data on student interactions across platforms, including materials consumed, responses given, and time spent on learning activities. The key properties are its large scale, detailed student behavior data, and collection from a deployed system with numerous real users.	EdNet enables personalized learning, knowledge diagnosis, cognitive modeling, and educational optimization through its large-scale, detailed data on student behaviors and interactions.	[35] [39] [47]

TABLE IV: Dataset Processing Tools Information

Tool Name	URL	Description
GISMO	<u>Click here</u>	Graphical Interactive Student Monitoring Tool for Moodle (GISMO) provides an intuitive graphical interface to visually display information about student learning activities, engagement, grades, and progress.
Meerkat-ED	Click here	Meerkat-ED is an educational data analysis tool designed to help educators and researchers conduct in-depth analysis of student learning data. It generates comprehensive summaries of participants' engagement in discussion forums, illustrating their interactions, identifying discussion leaders and peripheral students, and providing various additional insights
Datashop	Click here	DataShop is a collection of datasets and tools for educational mining. It not only collects and provides a large amount of educational data, including students' interaction data, response records, learning trajectories, assessment results, etc. in online learning environments, but also provides a series of tools and APIs for processing and analyzing these data, facilitating researchers to perform data mining, model building and evaluation.
SNAPP	Click here	Social Networks Adapting Pedagogical Practice (SNAPP) is a software tool that allows users to visualize the network of interactions generated by posts and responses in discussion forums. And the network visualization of forum interactions will provide teachers with the opportunity to quickly identify patterns of user behavior.
LOCO-Analyst	Click here	LOCO-Analyst is an advanced educational tool designed to support teachers in evaluating and improving web-based learning environments. It provides valuable insights and feedback covering all aspects of the learning process, helping educators to enhance the content and structure of their online courses and providing targeted feedback and recommendations so they can optimize course design and pedagogy.
StREAM	Click here	Stream is a Student Engagement Analytics Platform which is also a predictive algorithm developed by Solutionpath that provides educators with visualization of student engagement levels and identification of students who need help with certain tasks. For students, it provides information about the progress and status of their learning, enabling students and educators to adjust their learning or teaching strategies in a timely manner to improve teaching effectiveness.

d) XuetangX

The XuetangX dataset is derived from the online education platform XuetangX. It is a well-known online education platform in China, established in 2013, which provides MOOCs and other online learning resources, video viewing behavior, assignment submission and discussion participation, etc.

e) EdNet

EdNet is an extensive educational dataset amassed by Santa, an AI-based online teaching platform with a user base of 780,000 in South Korea. It encompasses two years' worth of student learning behavior data and offers a plethora of information on student-system interaction, including knowledge tracking, cognitive processes, learning analysis data, and comprehensive records of students' online learning activities.

3) Open Data Repository

a) MOOCCube

MOOCCube is an open data repository for researchers in natural language processing, KG, and data mining related to large-scale online education, containing 706 real online courses, 38,181 instructional videos, 114,563 concepts, hundreds of thousands of course selections from 199,199 MOOC users, video viewing records, and a supplemental repository containing hundreds of thousands of academic paper resources related to in-class concepts. The concept description data is from Baidu and Wikipedia, and the course data and student behavior data is from XuetangX. Academic paper data is obtained from Aminer, a large-scale academic search engine.

b) xAPI-Educational Mining Dataset

xAPI-Educational Mining Dataset refers to a dataset based on the Experience API (xAPI) standard. xAPI is an open learning technology specification for recording learner behavior and interaction data in a variety of learning environments. The links in the table point to a publicly available xAPI-compliant

database, Students' Academic Performance Dataset, stored on Kaggle, which contains 480 samples with sixteen features.

B. Processing Tools

There are many commonly used tools for processing and analyzing educational data in educational scenarios to provide powerful support and insight for educational researchers and teachers. This section will focus on several representative tools, including LOCO-Analyst, Datashop, SNAPP, GISMO, and Meerkat-ED etc. These tools have unique functions and features in educational data processing that can help education practitioners better understand the learning process and optimize instructional design and practice. By using a combination of these tools, educational researchers and teachers can deeply analyze data on student learning behaviors, engagement, and learning outcomes, and gain valuable insights from them. The names, links, and detailed descriptions of these tools are provided in Table IV. The table is adapted from Romero et al.'s paper "Educational data mining and learning analytics: an updated survey" [114] and Romero et al.'s paper "Data mining in education" [117].

V. FUTURE DIRECTIONS

Deep Learning has shown great promise in EDM. Successful techniques in EDM based on Deep Learning can provide valuable insights to improve teaching, learning, and assessment. Here are several potential insights into successful techniques for EDM using Deep Learning:

A. Learning Analysis and Intervention

Existing EDM methods often involve offline analysis. Future work could investigate the use of real-time learning algorithms, *e.g.*, deep reinforcement learning [118] or real-time recurrent learning algorithms [119], to offer timely insights and

interventions for a more responsive educational environment. In addition, we can combine Multi-Task Learning [120] with Attention mechanisms to analyze student interaction data from learning management systems or other educational platforms, providing knowledge tracing and option tracing [121] into engagement and learning patterns. Multi-Task Learning can also be used to identify learners at risk of struggling academically and dropping out, thus allowing for early interventions and support.

B. Social Network Analysis and Collaboration

By learning directly from the graph structure and node features, GCNs can capture complex patterns in social networks, helping to analyze social networks within educational settings, revealing patterns of collaboration and communication among students. These insights can help educators design group activities and assignments more effectively or identify students who may benefit from additional support or social engagement opportunities. Besides, future work should encourage collaborations between computer scientists, educators, and psychologists. Although this direction does not focus on a specific algorithm, it emphasizes the importance of interdisciplinary knowledge in refining existing algorithms or developing new ones for EDM. For example, to make cross-domain recommendations for users in the educational environment, we can use the preference-aware Graph Attention Network [122], which leverages collaborative KG to capture user preferences within-domain and across-domain.

C. Explainable AI in EDM

Given the 'black box' problem associated with Deep Learning models, efforts should be made to create more transparent and interpretable models. Especially in EDM, making these models explainable and transparent becomes increasingly important, since education usually places great emphasis on the scientific nature and causal relationships of things. Future research could aim to develop or improve methods for generating understandable explanations of model predictions, e.g., Deep Learning Important FeaTures DeepLIFT) [123] for the interpretable models used in student performance prediction, and Local Interpretable Model-Agnostic Explanations (LIME) [124] or KGs for explainable recommendation systems. Moreover, for applications that involve sequential data, such as studying student interaction with a learning management system over time, models like LSTM or GRU could be enhanced with explainability features. To this end, sequence interpretation methods, e.g., Layer-wise Relevance Propagation (LRP) [125], can be used to explain sequential learning patterns.

D. Large Language Models for Education

Large Language Models (LLMs) [126] are transforming many fields, including EDM. Their capacity to understand, generate, and complete texts makes them a valuable tool in education. For instance, LLMs could be used to generate personalized educational content tailored to each learner's

needs, interests, and proficiency level. To this end, we could focus on fine-tuning LLMs, such as GPT-4, on specific educational datasets to achieve better performance in such tasks. Besides, LLMs could help create advanced Intelligent Tutoring Systems (ITSs) [127] that can understand and respond to student queries in a contextually appropriate manner. Future work should integrate LLMs into existing ITSs and examining their impact on student learning outcomes.

It would be interesting that GPT-based architectures [128, 129] are employed to automatically score student essays or assess written responses, which can reduce the workload for educators and provide consistent evaluation. Such architectures are also competent to analyze and understand student language use, enabling educators to identify areas where students even teachers struggle with understanding or communication.

E. Multimodal Learning Analytics

Many current EDM methods primarily rely on structured data. However, educational experiences produce a wealth of unstructured and semi-structured data (e.g., image, audio, video, and even biometric data), which provide a more comprehensive understanding of student learning experiences. Deep Multimodal Learning algorithms [130], which combine CNNs for image/video data, RNNs or LSTMs for temporal data, and Transformers for textual data, could be used to leverage this wealth of information. These insights can inform the design of multimodal learning environments and interventions, accommodating diverse learning styles and preferences.

Based on the above representation of multimodal learning, multimodal affective computing and emotion recognition may be a promising line in EDM. To this end, we need well-designed models to analyze student facial expressions, speech, or physiological signals to infer emotional states and engagement during learning activities. In this way, they help educators adapt their teaching strategies to better meet students' emotional needs and improve overall learning experiences. For instance, hybrid contrastive learning [131] can be employed for multimodal sentiment analysis, in which semi-contrastive learning and intra-/inter-modal contrastive learning learn multiple relationships from cross-modal interactions.

F. Benchmark Datasets and Evaluation Metrics

Currently, there's a lack of universally accepted benchmark datasets in EDM. Future work should focus on creating large, diverse, and representative datasets that cover various aspects of the educational process. This task might involve techniques from data collection and preprocessing, data anonymization (for privacy concerns), and even synthetic data generation methods. Generative models (e.g., GANs) could be useful for creating synthetic educational data that maintain the statistical properties of real-world data while ensuring student privacy. Additionally, different studies in EDM often employ different metrics for evaluation, making it difficult to compare results across studies. Future work should aim to define and standardize evaluation metrics that effectively reflect the performance of deep learning models in EDM. For example, deep metalearning [132] could be employed to assess and compare the

performance of different algorithms on EDM tasks. AutoML frameworks [133], which automatically search for the best machine learning pipelines for a given task, could also be utilized to identify the most suitable algorithms for specific datasets or tasks in EDM.

G. Fairness and Privacy

Dealing with student data brings ethical considerations and privacy concerns to the forefront. Firstly, ensuring that EDM models do not perpetuate or amplify biases is a significant challenge. Future work could focus on developing and implementing fairness algorithms, such as equality of opportunity in supervised learning [134], which can help to identify and rectify biases in predictive models. Additionally, research could aim to improve techniques for bias detection in training data and outcomes. Secondly, to protect students' privacy, the development and application of privacy-preserving data mining techniques should be a key focus. Differential privacy [135], a framework that adds noise to the data or query results to ensure that individual records cannot be reidentified, offers a promising approach. For example, we can adopt Differential Privacy Stochastic Gradient Descent (DP-SGD) [136] or Private Aggregation of Teacher Ensembles (PATE) [137] to train models without directly accessing sensitive data. Lastly, future work could explore the implementation and optimization of federated learning algorithm [138] in EDM. It enables model training on local data without having to share it with a central server, thereby protecting student information.

In summary, while Deep Learning has already demonstrated its potential in EDM, there are quantities of exciting opportunities for further exploration and innovation. By focusing on the future directions highlighted above, we hope to promote significant progress in the field, contributing to the transformation of educational practices and the improvement of educational experiences.

VI. CONCLUSION

Deep Learning algorithms have been widely applied in various fields. They have shown great potential in EDM to assist in improving the quality of modern education. In this survey, we first offer an extensive outline of the current stateof-the-art in Deep Learning-based EDM, highlighting three categories of Deep Learning (i.e., unsupervised learning, supervised learning, and reinforcement learning) applied to four main educational scenarios. Additionally, we draw designs for knowledge tracing schema, undesirable student detecting schema, and personalized recommendation framework, to demonstrate their principles intuitively. Secondly, a thorough overview of public datasets and processing tools for EDM is elaborated. Lastly, to provide new opportunities for innovation and improvement in this area, we put forward some promising future directions. This survey aims to inspire further research, collaboration, and progress toward broadening the application scope of EDM with Deep Learning.

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