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Attention-Based Knowledge Tracing with Heterogeneous Information Network Embedding

Abstract

Knowledge tracing is a key area of research contributing to personalized education. In recent times, deep knowledge tracing has achieved great success. However, the sparsity of students' practice data still limits the performance and application of knowledge tracing. An additional complication is that the contribution of the answer record to the current knowledge state is different at each time step. To solve these problems, we propose Attention-based Knowledge Tracing with Heterogeneous Information Network Embedding (AKTHE). First, we describe questions and their attributes with a heterogeneous information network and generate meaningful node embeddings. Second, we capture the relevance of historical data to the current state by using attention mechanism. Experimental results on four benchmark datasets verify the superiority of our method for knowledge tracing.

Keywords

information, heterogeneous, network, tracing, embedding, knowledge, attention-based

Disciplines

Engineering | Science and Technology Studies

Publication Details

Zhang, N., Du, Y., Deng, K., Li, L., Shen, J. & Sun, G. (2020). Attention-Based Knowledge Tracing with Heterogeneous Information Network Embedding. *Lecture Notes in Computer Science*, 12274 95-103.

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Attention-based Knowledge Tracing with Heterogeneous Information Network Embedding

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Abstract. Knowledge tracing is a key area of research contributing to personalized education. In recent times, deep knowledge tracing has achieved great success. However, the sparsity of students' practice data still limits the performance and application of knowledge tracing. An additional complication is that the contribution of the answer record to the current knowledge state is different at each time step. To solve these problems, we propose Attention-based Knowledge Tracing with Heterogeneous Information Network Embedding (AKTHE). First, we describe questions and their attributes with a heterogeneous information network and generate meaningful node embeddings. Second, we capture the relevance of historical data to the current state by using attention mechanism. Experimental results on four benchmark datasets verify the superiority of our method for knowledge tracing.

Keywords: Knowledge Tracing · Network Embedding · Attention Mechanism · Student Assessment.

1 Introduction

Knowledge tracing (KT) is a modeling based on student behavior sequence. With the presence of KT, we can exactly grasp the students' mastery and the understanding of knowledge concepts. Accurate knowledge tracing enables us to grasp the current needs of students and to recommend questions accurately. This task means that students can be provided with resources according to their personal needs [1]. Knowledge tracing is the core and key to build an adaptive education system.

There exist two types of knowledge tracing models now: traditional knowledge tracing models and deep knowledge tracing models. Bayesian Knowledge Tracing (BKT) [2] is a very famous model among traditional knowledge tracing models. It is a Markov model with hidden variables. Recently, Deep Knowledge Tracing (DKT) [3] based on students' recent learning performance has shown high performance. It can model the relationship between complex knowledge concepts.

Although knowledge tracing based on deep learning has made great progress, there are still some open issues. For example, the sparsity of students' behavior. Specifically, students usually use fragmented time to study, which only spend little time on the platform [4]. As a result, each student may only practice a small part of the test questions in system so that the mastery of a large part of knowledge is still unknown, which affects the knowledge tracing and limits the further application.

Our view of solving sparse problem depends on attribute information of questions. Specifically, the correct rate of the same student answering questions with similar difficulty or discrimination at the same knowledge concept is similar. Some existing work that study attributes of questions is primarily about mining them [5]. Other work try to use attributes of questions in knowledge tracing [6], but they do not specifically apply question attributes to deep knowledge tracing. By analyzing the various types of nodes and the various link relationships in the network, heterogeneous information network (HIN) [7] can accurately distinguish the different meanings in the network and mine more meaningful knowledge. Questions and their attributes can be expressed as a heterogeneous information network. Features of each question are thus captured by network embedding, which can guide us to better understand knowledge states.

In the sequence of student history questions, the contribution of each question to whether the next question can be answered correctly is different. For example, the next question mainly examines the mastery of integer multiplication, then the questions related to this concept in the past have a greater impact on the current state. Inspired by the attention mechanism used in machine translation where the mechanism can be used to capture the words corresponding to the original sentence and make the translation more accurate [8], we apply the attention mechanism to knowledge tracing problem to achieve better results.

In this paper, we focus on modeling the attribute information of questions with heterogeneous information network and generate meaningful question embeddings to model and predict students' knowledge states from a large number of learning logs. Our contributions are as follows:

- We use a heterogeneous information network to model questions and their attributes to learn the effective representations of questions.
- We propose *Attention-based Knowledge Tracing with Heterogeneous Information Network Embedding* to model students' current knowledge states.
- We evaluate our model and results show that our AKTHE model has better performance in knowledge tracing.

The rest of this paper is organized as follows. Section 2 gives a clear description on the problem definition. Section 3 is the detailed descriptions of proposed model. Experimental results on four datasets are shown in Section 4. Finally, we conclude the paper in Section 5.

2 Problem Definition

Definition 1 (Question Difficulty.) Given a question, difficulty refers to the proportion or percentage of correct answers given by students in history, which is also known as the *ease of question*. The difficulty is defined as:

$$D_i = k_i / N_i, \quad (1)$$

where k_i is the number of students who answered question i correctly, and N_i is the total number of students who answered question i .

The value of question difficulty is between 0 and 1. Instead of using difficulty value directly, we categorize every question into one of 10 difficulty levels:

$$Category(i) = \begin{cases} \lfloor D_i \cdot c \rfloor, & \text{if } |N_i| \geq 4; \\ 5, & \text{else,} \end{cases} \quad (2)$$

where $c = 10$, the number of levels.

Definition 2 (Question Discrimination.) The discrimination refers to the ability of questions to distinguish academic performance between students. For simplicity, the following definition is used:

$$D'_i = D_i^1 - D_i^2, \quad (3)$$

where D'_i is the discrimination of question i . We rank the total score of all students from high to low, the top 30% students is the high-level group and the last 30% students is the low-level group. D_i^1 and D_i^2 are the difficulty of question i for high-level group and low-level group respectively using (1). Table 1 is a criterion for evaluating the discrimination of question.

Table 1: The division of question discrimination

Discrimination	Bad	General	Good	Nice
Range	$(-1, 0.19)$	$(0.2, 0.29)$	$(0.3, 0.39)$	$(0.4, 1)$

Definition 3 (Heterogeneous Information Network (HIN) [7].) HIN is a directed graph $G = (V, E)$. Meanwhile, each node v and each link e has a type. Let A and R represent the sets of node type and link type respectively where $|A| + |R| > 2$. For each node v , we have $\phi(v) : V \rightarrow A$; for each link e , we have $\psi(e) : E \rightarrow R$.

Definition 4 (Meta-Path [9].) A meta-path is defined as a path. The specific form is $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \dots A_{l-1} \xrightarrow{R_{l-1}} A_l$. It represents a compound relationship between node types A_1 and A_l .

We express questions and their attributes using a HIN in Fig.1(a) where the node types are *question*, *difficulty* and *discrimination*. There exist two types of links between nodes: (i) the *question-difficulty* link, and (ii) the *question-discrimination* link. Nodes in the network can be connected into different kinds of

meta-paths, e.g., “question-difficulty-question” (QDQ) and “question-discrimination-question” (QDQ).

3 Methodology

We present *Attention-based Knowledge Tracing with Heterogeneous Information Network Embedding*, called *AKTHE*. Fig.1 represents the overall schematic illustration of AKTHE.

Fig. 1: The architecture of AKTHE.

3.1 Heterogeneous Information Network Embedding

Heterogeneous information network embedding (HINE) aims to generate meaningful node sequence. To this end, both DeepWalk [10] and node2vec [11] can be applied where a random walker traverses the heterogeneous information network from node to node along the edge between them.

Meta-Path Based Random Walk In the literature of HIN, meta-path [9] can depict the semantic concept accurately. Inspired by this, we use meta-path based random walk method. At step t , the walker moves from node v_t to v_{t+1} , one of its neighbors, at the normalized probability $P(v_{t+1}|v_t)$. Note v_t and v_{t+1} can be of any type. Similarly, Given a HIN $G = (V, E)$ and a meta-path $\rho : A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \dots A_t \xrightarrow{R_t} A_{t+1} \dots \xrightarrow{R_{l-1}} A_l$, the probability that the walker will take one step specified in the path is:

$$P(v_{t+1}|v_t, \rho) = \begin{cases} \frac{1}{|N_{t+1}(v_t)|}, & (v_t, v_{t+1}) \in E, \phi(v_{t+1}) = A_{t+1}; \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where v_t is the t th node in random walk, as well as $N_{t+1}(v_t)$ is set of first-order neighbor nodes of v_t .

Heterogeneous Skip-Gram For a given meta-path, we use a fixed-length window to obtain the neighborhood $N(v)$ for node v . Following node2vec [11], we use heterogeneous skip-gram to learn node embeddings for a HIN $G = (V, E)$ by maximizing

$$\max_g \sum_{v \in V} \log P(N(v)|g(v)), \quad (5)$$

where g is a function to get node embedding.

Embedding Fusion For a node v , different embeddings on O meta-paths can be represented as a set $\{e_q^{(l)}\}_{l=1}^{|O|}$, where $e_q^{(l)}$ is the embedding of question q about the l th meta-path. In our model, we only focus on the embeddings of questions, so we only select nodes with the type *question*.

For different representations of a question, we assume that the contribution of each meta-path to this question is equal. Then we use linear function as our fusion function:

$$e_q = \frac{1}{|O|} \sum_{l=1}^{|O|} (\mathbf{M}^{(l)} e_q^{(l)} + \mathbf{b}^{(l)}), \quad (6)$$

where e_q is the final representation of question q .

3.2 Attention-based Knowledge Tracing with HINE

We use DKT model as the basic model because it is superior compared to BKT. In addition, we also added the attention mechanism to our model to learn better distribution of each question which may lead to more accurate prediction.

Input Formally, an interaction $\{q_t, a_t\}$ can be transformed into a vector x_t . We use $\delta(q_t)$ to represent question q_t , which is a one-hot encoding. x_t is a Cartesian product of q_t and a_t . Before passing into LSTM, the embedding vector x_t and e_t in (6) are integrated by concatenation:

$$\mathbf{v}_t = x_t \oplus e_t. \quad (7)$$

Attention Mechanism We employ the attention mechanism that concatenate the hidden layer and the historical questions $\{q_1, q_2, \dots, q_t\}$, which scores the importance of each question in the history for new question q_{t+1} :

$$u_t^i = \mathbf{v}^T \tanh(\mathbf{W}_1 h_t + \mathbf{W}_2 \delta(q_i)), \quad (8)$$

where $\delta(q_i)$ is the one-hot encoding of question q_i in historical questions and h_t is hidden state.

Then attention state can be represented as the weighted sum of all questions in this step by using attention scores as weights. That is,

$$s_t = \sum_{i=1}^t a_t^i u_t^i, \quad a_t^i = \frac{\exp(\mathbf{W}_a u_t^i)}{\sum_{j=1}^t \exp(\mathbf{W}_a u_t^j)}. \quad (9)$$

Output Finally, based on the updated hidden state h_t and attention state s_t , we can get the probability of answering each question correctly:

$$\mathbf{y}_t = \sigma(\mathbf{W}(s_t \oplus h_t) + \mathbf{b}). \quad (10)$$

Optimization The purpose of AKTHK is to predict next interaction performance. In this paper, we use the cross-entropy loss function to learn the parameters:

$$\mathcal{L} = - \sum_t (a_{t+1} \log(\mathbf{y}_t^T \boldsymbol{\delta}(q_{t+1})) + (1 - a_{t+1}) \log(1 - \mathbf{y}_t^T \boldsymbol{\delta}(q_{t+1}))), \quad (11)$$

where $\boldsymbol{\delta}(q_{t+1})$ and a_{t+1} are the one-hot encoding and the true label of next question q_{t+1} .

4 Experiments

In this section, we demonstrate the effectiveness of our proposed AKTHE model by comparing it with baselines on four datasets.

4.1 Experimental Setup

Datasets For our experiments, we test on four public datasets: ASSISTments2009, ASSISTments2015, Statics2011 and Synthetic-5. The statistical information of datasets is reported in Table 2.

Table 2: Dataset statistics.

Datasets	Students	Exercises	Records
ASSISTments2009	4,151	110	325,637
ASSISTments2015	19,840	100	683,801
Synthetic-5	4,000	50	200,000
Statics2011	333	1,223	189,297

Baselines To demonstrate performance of our AKTHE model, we compare with multiple baselines in each dataset:

Bayesian Knowledge Tracing (BKT) : In BKT [2] model, a hidden variable about knowledge states of students is proposed. BKT is to track changes in state of students’ knowledge.

Deep Knowledge Tracing (DKT): DKT [3] is the most widely used knowledge tracing model. Its performance on a variety of open datasets is basically better than traditional models.

Dynamic Key-Value Memory Networks (DKVMN): DKVMN [12] is a state-of-the-art KT model. This model uses a static matrix key to store all knowledge concepts and a dynamic matrix value to store and update learners’ mastery of concepts.

4.2 Performance Analysis

The performance of knowledge tracing is customarily evaluated by area under the curve (AUC). The higher the AUC, the better the model performance. The AUC Results of models on all datasets are shown in Table 3.

Table 3: The AUC results on all datasets.

Model	ASSISTments2009	ASSISTments2015	Synthetic-5	Statics2011
BKT	0.623	0.631	0.650	0.730
DKT	0.805	0.725	0.803	0.802
DKVMN	0.816	0.727	0.827	0.828
DKT+Attention	0.827	0.739	0.835	0.834
DKT+HINE	0.818	0.735	0.829	0.832
AKTHE	0.831	0.741	0.837	0.838

From Table 3, we can get two points of view. Firstly, compared with the benchmark models, our model has higher AUC, which means a better prediction performance. Concretely speaking, the average AUC obtained by AKTHE on two ASSISTments datasets is 1.8% higher than the most advanced model DKVMN. Compared with DKVMN, the average improvement rates are 1.1% in synthetic-5 and statics2011 datasets. Secondly, models based on neural network perform better than traditional model on four datasets, which means that the neural network can capture more useful information.

The results of ablation experiments show that the combination of HINE or attention with DKT can all improve the prediction effect. Adding attention to DKT contributes to the better results, which means that the attention mechanism provides more useful information.

5 Conclusion

In this paper, we mainly focus on exploring the attribute information of questions in knowledge tracing. We describe questions and their attributes with a heterogeneous information network, which is desirable for this application. With the help of heterogeneous network embedding, the learned node embeddings can be integrated into deep knowledge tracing model. We also add the attention mechanism to deep knowledge tracing model. On four datasets for knowledge tracing, our model has better performance than BKT, DKT and DKVMN.

In the future, we intend to introduce the relationship between concepts contained in the questions by using the method of graph embedding.

Acknowledgements

This research was supported by NSFC (Grants No. 61877051), and Natural Science Foundation Project of CQ, China (Grants No. cstc2018jscx-msyb1042, and cstc2018jscx-msybX0273). Li Li is the corresponding author for the paper.

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