An Empirical Comparison of Deep Learning Models for Knowledge Tracing on Large-Scale Dataset

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Abstract

Knowledge tracing (KT) is the problem of modeling each student’s mastery of knowledge concepts (KCs) as (s)he engages with a sequence of learning activities. It is an active research area to help provide learners with personalized feedback and materials. Various deep learning techniques have been proposed for solving KT. Recent release of large-scale student performance dataset [Choi et al. 2019] motivates the analysis of performance of deep learning approaches that have been proposed to solve KT. Our analysis can help understand which method to adopt when large dataset related to student performance is available. We also show that incorporating contextual information such as relation between exercises and student forget behavior further improves the performance of deep learning models.

Introduction

The availability of large-scale student performance dataset has attracted researchers to develop models for predicting students’ knowledge state aimed at providing proper feedback [Self 1990]. For developing such models, knowledge tracing (KT) is considered to be an important problem and is defined as tracing a student’s knowledge state, which represents her mastery level of KCs, based on her past learning activities. KT can be formalized as a supervised sequence learning task - given student’s past exercise interactions \( X = (x_1, x_2, \ldots, x_t) \), predict some aspect of her next interaction \( x_{t+1} \). On the question-answering platform, the interactions are represented as \( x_t = (e_t, r_t) \), where \( e_t \) is the exercise that the student attempts at timestamp \( t \) and \( r_t \) is the correctness of the student’s answer. KT aims to predict whether the student will be able to answer the next exercise correctly, i.e., predict \( p(r_{t+1} = 1|e_{t+1}, X) \).

Among various deep learning models, Deep Knowledge Tracing (DKT) [Piech et al. 2015] and its variant [Yeung and Yeung 2018] use Recurrent Neural Network (RNN) to model a student’s knowledge state in one summarized hidden vector. Dynamic Key-value memory network (DKVMN) [Zhang et al. 2017] exploits Memory Augmented Neural Network [Santoro et al. 2016] for KT. It maps the exercises to the underlying KCs and then utilizes the student mastery at those KCs to predict whether the student will

To summarize, figure 1 represents the difference between the four models we have analyzed in this work. First DKT uses a summarized hidden vector to model the knowledge state. Second, DKVMN maintains the concept state for each concept simultaneously and all concept states constitute the knowledge state of a student. Third, SAKT assigns weights to the past interaction using self-attention mechanism to identify the relevant ones. It then uses the weighted combination of these past interactions to estimate student knowledge on the involved KCs and predict her performance. Finally, RKT improves over SAKT by introducing a relation coefficient added to the attention weights learned from SAKT. The relation coefficient are learned from the contextual information explicitly modelling the relation between exercises involved in the past interactions and student forget behavior of students.

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Methods

KT predicts whether a student will be able to answer the next exercise $e_t$ based on his/her previous interaction sequence $X = x_1, x_2, \ldots, x_{t-1}$. The deep learning methods transform the problem of KT into a sequential modeling problem. It is convenient to consider the model with inputs $x_1, x_2, \ldots, x_{t-1}$ and the exercise sequence with one position ahead, $e_2, e_3, \ldots, e_t$ and the output being the correctness of the response to exercises $r_2, r_3, \ldots, r_t$. The interaction tuple $x_t = (e_t, r_t)$ is presented to the model as a number $y_t = e_t + r_t \times E$, where $E$ is the total number of exercises. Thus, the total values that an element in the interaction sequence can take is $2E$, while elements in the exercise sequence can take $E$ possible values.

Deep Knowledge Tracing

Deep Knowledge Tracing (DKT) [Piech et al. 2015] employs a Recurrent Neural Network (RNN) as its backbone model. As each interaction can be identified by a unique ID, it can be represented using the encoding vector $x_t$. After the transformation, DKT passes the $x_t$ to the hidden layer and computes the hidden state $h_t$ using the vanilla RNN or LSTM-RNN. As the hidden state summarizes the information from the past, the hidden state in the DKT can be treated as the latent knowledge state of student resulting from past learning trajectory. This latent knowledge state is then fed to the output layer to compute the output vector $y_t$, which represents the probabilities of answering each question correctly. The objective of the DKT is to predict the next interaction performance, so the target prediction is extracted by performing a dot product of the output vector $y_t$ and the one-hot encoded vector of the next question $e_t$. Based on the predicted output $p_t$ and the target output $r_t$, the loss function $\mathcal{L}$ can be expressed as follows:

$$\mathcal{L} = -\sum_t r_t \log(p_t) + (1 - r_t) \log(1 - p_t)$$  \hspace{1cm} (1)

Dynamic Key-Value Memory Network

Dynamic Key-Value Memory Network (DKVMN) [Zhang et al. 2017] exploits the relationship between concepts and the ability to trace each concept state. DKVMN model maps each exercise with the underlying concepts and maintains a concept state for each concept. At each timestamp, the knowledge of the related concept states of the attempted exercise gets updated. DKVMN consists of two matrices, a static matrix called key, which stores the concept representations and the other dynamic matrix called value, which stores and updates the student’s understanding (concept state) of each concept. The memory, denoted as $M^k$, is an $N \times d$ matrix, where $N$ is the number of memory locations, and $d$ is the embedding size. At each timestamp $t$, the input is $x_t$. The embedding vector $x_t$ is used to compute the read weight $w_t^r$ and the write weight $w_t^w$. The intuition of the model is that when a student answers the exercise that has been stored in the memory with the same response, $x_t$ will be written to the previously used memory locations and when a new exercise arrives or the student gets a different response, $x_t$ will be written to the least recently used memory locations.

In DKVMN, when a student attempts an exercise, the student mastery over associated concepts is retrieved as weighted sum of all memory slots in the value matrix, where the weight is computed by taking the softmax activation of the inner product between $x_t$ and each key slot $M^k(i)$:

$$r_t = \sum_{i=1}^{N} w_t(i) M_t^k(i),$$

$$w_t(i) = \text{Softmax}(x_t^T M^k(i)).$$  \hspace{1cm} (2)

The calculated read content $r_t$ is treated as a summary of the student’s mastery level of this exercise. Finally to predict the performance of the student:

$$f_t = \text{Tanh}(W_1^T [r_t, x_t] + b_1), p_t = \text{Sigmoid}(W_2^T f_t + b_2)$$  \hspace{1cm} (3)

$p_t$ is a scalar that represents the probability of answering $e_t$ correctly.

After the student answers the exercise $e_t$, the model updates the value matrix according to the correctness of the student’s answer. For this, it computes an erase vector $e_t$ and an add vector $a_t$ as:

$$e_t = \text{Sigmoid}(E^T v_t + b_e), a_t = \text{Tanh}(D^T v_t + b_a)$$  \hspace{1cm} (4)

where the transformation matrices $E, D \in \mathbb{R}^{d_e \times d_v}$.

The memory vectors of value component $M_t^v(i)$ from the previous timestamp are modified as follows:

$$M_t^v(i) = \tilde{M}_{t-1}^v(i) + w_t(i) a_t,$$  \hspace{1cm} (5)

$$\tilde{M}_{t}^v(i) = M_{t-1}^v(i) [1 - w_t(i) e_t].$$  \hspace{1cm} (6)

![Figure 1: Model differences among DKT, DKVMN, SAKT and RKT.](image-url)
Self-Attention for Knowledge Tracing

Self-Attention Model for Knowledge Tracing (SAKT) (Pandey and Karypis 2019) is a purely transformer based model for KT. The idea behind SAKT is that in the KT task, the skills that a student builds while going through the sequence of learning activities, are related to each other and the performance on a particular exercise is dependent on his performance on the past exercises related to that exercise. SAKT first identifies relevant KCs from the past interactions and then predicts student’s performance based on his/her performance on those KCs. To identify the relevant interaction, it employs a self-attention mechanism which computes the dot-product between the past interaction representation and the next exercise representation. Essentially, the student ability to answer next question is encoded in the vector \( y_t \) and is computed as:

\[
y_t = \sum_{j=1}^{t-1} \alpha_j x_j W^V, \quad \alpha_j = \frac{\exp(e_j)}{\sum_{k=1}^{t-1} \exp(e_k)},
\]

(7)

\[
e_j = e_j W^Q(x_j W^K)^T, \quad d = \text{const}
\]

(8)

where \( d \) is the embedding size, \( W^Q, W^K \in \mathbb{R}^{d \times d} \), \( W^V \in \mathbb{R}^{d \times d} \) and \( W^K \in \mathbb{R}^{d \times d} \) are projection matrices for query and key, respectively.

Point-Wise Feed-Forward Layer: In addition, a PointWise Feed-Forward Layer (FFN) is applied to the output of SAKT. The FFN helps incorporate non-linearity in the model and considers the interactions between different latent dimensions. It consists of two linear transformations with a ReLU nonlinear activation function between the linear transformations. The final output of FFN is \( F = \text{ReLU}(y_t W^{(1)} + b^{(1)})W^{(2)} + b^{(2)} \), where \( W^{(1)} \in \mathbb{R}^{d \times d}, W^{(2)} \in \mathbb{R}^{d \times d} \) are weight matrices and \( b^{(1)} \in \mathbb{R}^{d} \) and \( b^{(2)} \in \mathbb{R}^{d \times d} \) are the bias vectors.

Besides of the above modeling structure, we added residual connections (He et al. 2016) after both self-attention layer and Feed forward layer to train a deeper network structure. We also applied the layer normalization (Ba, Kiros, and Hinton 2016) and the dropout (Srivastava et al. 2014) to the output of each layer, following (Vaswani et al. 2017).

Relation-aware Self-attention for Knowledge Tracing

Similar to SAKT, Relation-aware Self-attention for Knowledge Tracing (RKT) (Pandey and Srivastava 2020) also identifies the past interaction relevant for solving the next exercise. Furthermore, it improves over SAKT by incorporating contextual information. This contextual information integrates both the exercise relation information through their similarity as well as student performance data and the forget behavior information through modeling an exponentially decaying kernel function. Essentially, RKT exploits the fact that students acquire their skills while solving exercises and each such interaction has a distinct impact on student ability to solve a future exercise. This impact is characterized by 1) the relation between exercises involved in the interactions and 2) student forget behavior.

| Exercise | Incorrect | Correct | Total |
|----------|-----------|---------|-------|
| Exercise | \( n_{00} \) | \( n_{01} \) | \( n_{0n} \) |
| Exercise | \( n_{10} \) | \( n_{11} \) | \( n_{1n} \) |
| Total    | \( n_{0} \) | \( n_{1} \) | \( n \) |

RKT explicitly models the relation between exercises. To incorporate that it utilizes textual content of the exercises. In the absence of information about the textual content of exercises, we leverage the skill tags associated with each exercise. Exercises \( i, j \) with the same skill tag are given similarity value, \( \text{sim}_{i,j} = 1 \), otherwise \( \text{sim}_{i,j} = 0 \). The correlation between exercises can also be determined from the learner’s performance data. Essentially, RKT determines relevance of the knowledge gained from exercise \( j \) to solve exercise \( i \) by building a contingency table as shown in Table 1 considering only the pairs of \( i \) and \( j \), where \( j \) occurs before \( i \) in the learning sequence. Then it computes Phi coefficient that describes the relation from \( j \) to \( i \), as:

\[
\phi_{i,j} = \frac{n_{11}n_{00} - n_{01}n_{10}}{\sqrt{n_{1a}n_{0a}n_{11}n_{00}}}.
\]

(9)

Finally, the relation of exercise \( j \) with exercise \( i \) is calculated as:

\[
A_{i,j} = \begin{cases} 
\phi_{i,j} + \text{sim}_{i,j} & \text{if } \text{sim}_{i,j} + \phi_{i,j} > \theta \\
0 & \text{otherwise},
\end{cases}
\]

(10)

where \( \theta \) is a threshold that controls sparsity of relation matrix.

RKT also models student forget behavior by employing a kernel function with exponentially decaying curve with time to reduce the importance of interaction as time interval increases following the idea from forgetting curve theory. Specifically, given the time sequence of interaction of a student \( t = (t_1, t_2, \ldots, t_{n-1}) \) and the time at which the student attempts next exercise \( t_n \), we compute the relative time interval between the next interaction and the \( t \)th interaction as \( \Delta_j = t_n - t_t \). Thus, we compute forget behavior based relation coefficients, \( R^p = (\text{exp}(-\Delta_1/S_u), \text{exp}(-\Delta_2/S_u), \ldots, \text{exp}(-\Delta_{n-1}/S_u)) \), where \( S_u \) refers to relative strength of memory of student \( u \) and is a trainable parameter in our model. The resultant relation coefficients

\[
R = \text{softmax}(R^E + R^p),
\]

(11)

RKT also adopts the self-attention architecture (Vaswani et al. 2017) similar to SAKT. To incorporate the relation coefficients into the learned attention weights, it adds the two weights:

\[
\beta_j = \lambda \alpha_j + (1 - \lambda) R_j,
\]

(12)

where \( \lambda \) is computed using Eq. 3, \( R \), is the \( j \)th element of the relation coefficient \( R \), \( \lambda \) is a tunable parameter. The representation of output at the \( i \)th interaction, \( o \in \mathbb{R}^d \), is ob-
tained by the weighted sum of linearly transformed interaction embedding and position embedding:
\[ y_t = \sum_{j=1}^{n-1} \beta_j x_j W^V, \] (13)

where \( W^V \in \mathbb{R}^{d \times d} \) is the projection matrix for value space. The further architecture remains same as the SAKT described above.

**Data**

To compare the deep-learning methods for KT, we use large-scale student interaction dataset, EdNet released in (Choi et al. 2019). EdNet consists of all student-system interactions collected over a period spanning two years by Santa, a multi-platform AI tutoring service with approximately 780,000 students. It has collected a total of 131,441,538 student interactions with each student generating on average of 441.20 interactions. The dataset consists a total 13,169 problems and 1,021 lectures tagged with 293 types of skills, and each of them has been consumed 95,294,926 times and 601,805 times, respectively.

**Evaluation Setting**

The prediction of student performance is considered in a binary classification setting i.e., answering an exercise correctly or not. Hence, we compare the performance using the Area Under Curve (AUC) and Accuracy (ACC) metric. Similar to evaluation procedure employed in (Piech et al. 2015), we train the model with the interactions in the training phase and during the testing phase, we update the model after each exercise response is received. The updated model is then used to perform the prediction on the next exercise. Generally, the value 0.5 of AUC or ACC represents the performance prediction result by randomly guessing, and the larger, the better.

To ensure fair comparison, all models are trained with embeddings of size 200. The maximum allowed sequence length for self-attention is set as 50. The model is trained with mini-batch size of 128. We use Adam optimizer with a learning rate of 0.001. The dropout rate is set to 0.1 to reduce overfitting. The L2 weight decay is set to 0.00001.

**Results and Discussions**

**Quantitative Results**

Figure 2 shows the performance comparison of deep-learning models for KT on Ednet dataset. Different kinds of baselines demonstrate noticeable performance gaps. SAKT model shows improvement over DKT and DKVMN model which can be traced to the fact that SAKT identifies the relevance between past interactions and next exercise. RKT performs consistently better than all the baselines. Compared with other baselines, RKT is able to explicitly captures the relations between exercises based on student performance data and text content. Additionally, it models learner forget behavior using a kernel function which is more interpretable and proven way to model human memory (Ebbinghaus 2013). The results reveal that provided enough data, attention-based models surpass the other sequence encoder techniques such as RNN, LSTM and Memory Augmented Networks. Furthermore, incorporating contextual data such as relation between exercises and domain knowledge such as student forget behavior attribute to performance gain even after availability of the massive dataset. This motivates us to further explore Knowledge Guided Machine Learning in the KT task.

**Qualitative Analysis**

Benefiting from a purely attention mechanism, RKT and SAKT models are highly interpretable for explaining the prediction result. Such interpretability can help understand which past interactions played an important role in predicting student performance on the next exercise. To this end, we compared the attention weights obtained from both RKT and SAKT. We selected one student from the dataset and obtain the attention weights corresponding to the past interactions for predicting her performance at an exercise. Figure 3 shows the heatmap of attention weight matrix where \((i, j)\)th element represents the attention weight on \(j\)th element when predicting performance on \(i\)th interaction. We compare the generated heatmap for both SAKT and RKT. This comparison shows the effect of relation information for revising the attention weights. Without relation information the attention weights are more distributed over previous interaction, while the relation information concentrates the attention weights to specific relevant interactions.

Finally we also performed experiment to visualize the attention weights averaged over multiple sequences by RKT and SAKT. Recall that at time step \(t_s\), the relation-aware self-attention layer in our model revises the attention weights on the previous interactions depending on the time elapsed since the interaction, and the relations between the exercises involved. To this end, we examine all sequences and seek to reveal meaningful patterns by showing the average attention weights on the previous interactions. Note that when we calculate the average weight, the denominator is the number of valid weights, so as to avoid the influence of padding for short sequences. Figure 4 compares average attention weights assigned by SAKT and RKT. This comparison shows the effect of relation information for revising the attention weights. Without relation information the attention weights are more distributed over previous interaction, while the relation information concentrates the attention weights closer to diagonal. Thus, it is beneficial to consider relations between exercises for KT.

**Conclusion**

In this work, we analyzed the performance of various deep learning models for Knowledge Tracing. Analysis of these models on large dataset with approximately 780,000 students revealed that self-attention based models such as SAKT and RKT outperform RNN-based models such as DKT. In addition, RKT which leverages additional information such as relation between exercises and student forget behavior and explicitly models these components gains further improvement.
Figure 2: Performance Comparison. RKT performs best among the models.

Figure 3: Visualization of attention weights of an example student from EdNet by SAKT and RKT. Each subfloat depicts the attention weights assigned by the models for that student.

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