OPEN-ENDED KNOWLEDGE TRACING

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ABSTRACT

Knowledge tracing refers to the problem of estimating each student’s knowledge component/skill mastery level from their past responses to questions in educational applications. One direct benefit knowledge tracing methods provide is the ability to predict each student’s performance on the future questions. However, one key limitation of most existing knowledge tracing methods is that they treat student responses to questions as binary-valued, i.e., whether the responses are correct or incorrect. Response correctness analysis/prediction is easy to navigate but loses important information, especially for open-ended questions: the exact student responses can potentially provide much more information about their knowledge states than only response correctness. In this paper, we present our first exploration into open-ended knowledge tracing, i.e., the analysis and prediction of students’ open-ended responses to questions in the knowledge tracing setup. We first lay out a generic framework for open-ended knowledge tracing before detailing its application to the domain of computer science education with programming questions. We define a series of evaluation metrics in this domain and conduct a series of quantitative and qualitative experiments to test the boundaries of open-ended knowledge tracing methods on a real-world student code dataset.

Keywords Knowledge tracing · Code generation

1 Introduction

Knowledge tracing (KT) [11] refers to the problem of estimating student mastery of concepts/skills/knowledge components from their responses to questions/items and using these estimates to predict their future performance. KT methods have been foundational in today’s large-scale educational scenarios in which students far outnumber expert instructors. In these scenarios, KT methods are utilized to automatically estimate the mastery levels for millions of students to provide each of them personalized feedback and recommendations, which ultimately leads to improved learning outcomes [13, 27, 40]. KT methods mainly consist of two essential components: a knowledge update component that updates student knowledge estimates given their most recent observed response, and a response prediction component to predict their response to a future question. Typical methods for KT treat student knowledge as a latent variable. For example, classic Bayesian knowledge tracing (BKT) methods [21, 35, 49] treat student knowledge as a binary-valued variable. The knowledge update and response prediction components are noisy binary channels, resulting in excellent interpretability of the model parameters. Factor analysis-based methods such as learning factor analysis [6], performance factor analysis [56], and the item difficulty, student ability, skill, and student skill practice history (DAS3H) method [8] use features and latent ability parameters to model student knowledge. The response prediction component in these methods relies on item response theory (IRT) models [43]. More recently, deep learning-based KT methods [16, 33, 34, 37, 48, 50] treat student knowledge as hidden states in neural networks. The knowledge update component often relies on recurrent neural networks [19], resulting in models that excel at accurately predicting future performance but often suffer from limited interpretability.

One common property for almost all existing KT methods is that they only analyze and predict binary-valued student responses to questions, i.e., the correctness of the response; the response prediction component is often a simple binary classifier. As a result, one can broadly apply KT methods to any common types of questions: multiple-choice, short-answer, and even open-ended ones, as long as student responses are graded. There exist few KT methods for predicting

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non-binary-valued responses such as option tracing [17], which predicts the exact option students select on each
multiple-choice question. In general, one can use polytomous IRT models [32] as the response prediction component in
KT methods to predict categorical-valued (such as options in multiple-choice questions) and ordinal-valued (such as
partial credit) responses [46, 23].

Unfortunately, analyzing and predicting binary-valued graded student response has a significant limitation: it does
not make use of the exact question and student response, especially for open-ended questions. Students’ open-ended
responses to such questions contain rich, meaningful information on their knowledge states, e.g., having a “buggy
rule” [4], exhibiting a certain misconception [14, 15, 42], or a general lack of mastery of certain skills [2], which is not
captured by response correctness. This limitation may prevent KT methods from extracting knowledge estimates that
reflect specific errors and making personalized recommendations that help students correct these errors.

Recent advances in neural language models, especially generative ones, are capable of problem solving in certain
domains [12, 5]. In these domains, it is possible to use these models to predict students’ full open-ended responses
via generation. For example, for programming, text-to-code capabilities offered by models such as CodeX [7] can
generate short chunks of codes from natural language instructions. For grade-school level math problems, language
models fine-tuned on mathematical content can generate short solutions consisting of a mixture of text and mathematical
expressions [9, 18]. On the contrary, existing works only use these models to encode questions or student responses
as input to KT methods rather than predict open-ended responses as output. For example, [28, 47] use pre-trained
word embeddings such as word2vec [31] to encode questions and obtain better question representations in the response
prediction component. For programming, [30, 52] use code representation techniques such as ASTNN [51] and
code2vec [1] to convert student code into vectors and use them as input to the knowledge update component.

1.1 Contributions

In this paper, we present the first attempt at extending KT methods to both analyze and predict open-ended student
responses to questions. Our goal is to explore how to fully leverage students’ open-ended responses to estimate their
knowledge states and test the limit of predicting open-ended responses in certain subject domains. Our contributions
can be summarized as follows:

• First, we define the open-ended knowledge tracing (OKT) framework, a novel, generic framework that analyzes
and predicts open-ended student responses. One can view existing KT methods for binary-valued responses
as a special case of OKT. We hope that OKT will open up a new direction in KT research that leverages
generative content models.

• Second, we focus on the subject domain of computer science education and apply OKT to open-ended
programming questions where we both analyze and predict student code submissions. We address the key
technical challenge of fusing the knowledge update component in KT methods with code generation models,
treating student code prediction as a controlled generation problem. We also show that OKT is compatible
with several popular KT methods that were originally developed for binary-valued student responses.

• Third, we apply our OKT method for programming questions to a real-world student code dataset used in the
second CSEDM challenge [4] and conduct extensive quantitative and qualitative evaluation. We show that OKT
is capable of capturing variations and specific errors in student code in their knowledge states and making
reasonably accurate predictions of actual student-submitted code.

2 The Open-Ended Knowledge Tracing Problem

In this section, we introduce our novel open-ended knowledge tracing framework, henceforth referred to as OKT. We
present various components in OKT, compare its problem setup with existing KT methods, and highlight the differences.
The OKT framework consists of three main components:

a) Knowledge representation, which converts full question prompts/statements and open-ended student responses to
continuous representations that are used as input to the knowledge update component. This component is different
from most existing KT methods that only leverage question ID/response correctness-based representations except a
few recent works: [47, 28] use word embeddings to represent question text while [30, 52] use programming code
embedding techniques to represent student code.

b) Knowledge update, which updates the student’s knowledge state after observing their response to a question. This
component is the same as that for existing KT methods.

[https://sites.google.com/ncsu.edu/csedm-dc-2021/]
Response generation, which predicts the exact open-ended response of the student to an open-ended question using a domain-specific generative content model. The generation of (possibly long) open-ended response predictions makes OKT significantly different from existing KT methods whose response prediction components are simple binary classifiers. This component takes as input both the full question prompt and student knowledge states produced by the knowledge update component.

Figure 1 shows an illustration of the OKT framework. Given a set of $N$ students, we denote each student’s question-response record as $s_i = \{(p_{i1}, x_{i1}, y_{i1}), \ldots, (p_{iT_i}, x_{iT_i}, y_{iT_i})\}$, where the triple $(p_{it}, x_{it}, y_{it})$ is student $i$’s response to a question at time step $t$ (a total of $T_i$ time steps). $p_{it}$ denotes the question prompt (often in the form of text but possibly contains other modalities such as mathematical/scientific symbols or code), $x_{it}$ is the student’s open-ended response, and $y_{it}$ is its correctness (which we include for completeness of our problem formulation). In what follows, for simplicity and clarity, we restrict our discussions to a single student and omit the student index $i$ unless necessary. Given a sequence of questions and responses from time step 1 to time step $t-1$, $\{(p_1, x_1), \ldots, (p_{t-1}, x_{t-1})\}$, OKT aims to generate and predict open-ended student responses to future questions, starting with $x_t$ (rather than binary-valued response correctness $y_t$) at time step $t$.

Formally, the OKT framework can be characterized as follows:

$$q_t = E_1(p_1, \ldots, p_t)$$

$$c_t = E_2(x_1, \ldots, x_t)$$

$$h_t = KT((q_1, c_1, h_1), \ldots, (q_{t-1}, c_{t-1}, h_{t-1}), q_t)$$

$$\hat{x}_t = G(q_t, h_t).$$

In Eq. (1) $q$ and $c$ denote the question and response representations, respectively, while $E_1$ and $E_2$ are their corresponding encoders in the knowledge representation component. In Eq. (2) $KT$ is the knowledge update component and $h_t$ represents the student’s knowledge state at time step $t$, which is updated from previous questions, responses, and knowledge states using the current question representation. This formulation encompasses most existing KT methods: for latent variable-based BKT [11] and recurrent neural network-based DKT [37], $q_t = E_1(p_t)$, $c_t = E_2(x_t)$, $h_t = KT(q_{t-1}, c_{t-1}, h_{t-1})$. For attention-based KT methods such as AKT [16], the question/response representations are fully contextualized and the knowledge state is retrieved from these representations at all prior time steps. In Eq. (3) the response generation component $G$ uses the student’s current knowledge state $h_t$ and question $q_t$ to generate and predict the open-ended response $\hat{x}_t$.

Most existing KT methods are optimized using the binary cross entropy loss due to the binary-valued prediction target ($y_t$). In contrast, in OKT, the components $E_1$, $E_2$, $KT$, and $G$ are jointly optimized through minimizing the OKT loss function

$$Loss = \sum_i \sum_t \ell(x_t, \hat{x}_t)$$

where $\ell$ is a domain-specific loss function comparing the predicted and actual student responses.
Open-Ended Knowledge Tracing

Figure 2: An illustration of applying OKT to students’ code submissions for programming questions in computer science education scenarios. We update the current knowledge state $h_t$ using past question $p_t$ and actual student code $x_t$ and combine it with the next problem statement $p_{t+1}$ to generate our prediction of the actual student code $\hat{x}_{t+1}$.

We emphasize that OKT is a general model that extends many existing KT methods to enable tracing and predictions of students’ open-ended solutions. The choices of the three OKT components are highly flexible, enabling OKT to be applied to a wide range of real-world KT scenarios where open-ended solutions abound. In the remainder of this paper, we focus on a particular domain to demonstrate the utility of OKT but we emphasize that OKT applies broadly to many other domains.

3 Application of OKT to Computer Science Education

In this section, we apply the OKT framework to a specific domain: computer science (CS) education, where we focus on analyzing students’ code submissions to programming questions. Figure 2 illustrates the three OKT components designed for the CS education domain, visualized for a single student code submission. Our key technical challenges are (i) how to represent and combine the programming questions and students’ code submissions (knowledge representation, Section 3.1) and use them to update the students’ knowledge states (knowledge update, Section 3.2); (ii) how to combine the knowledge state with the question prompt to generate student code (response generation, Section 3.3); and (iii) how to efficiently perform optimization to train the OKT components (Section 3.4). Next, we address the above challenges and describe our design choices for each OKT component for CS education.
3.1 Knowledge Representation

**Question Representation:** Question prompts in programming assignments are usually in natural language. We thus use a pre-trained neural language model to convert them into embedding vectors. We adopt the popular GPT-2 [38] for prompt representation: Given a prompt \( p \), GPT-2 tokenizes it into a sequence of \( M \) word tokens, where each token has an embedding \( \bar{p}_i \in \mathbb{R}^K \). For GPT-2, the dimension of these embeddings is \( K = 768 \). This procedure produces a sequence of token embeddings \( \{\bar{p}_1, \bar{p}_2, \ldots, \bar{p}_M\} \). We then average the embeddings of each prompt token to get our prompt embedding \( \bar{p} = \frac{1}{M} \sum_{i=1}^{M} \bar{p}_i \) where the average is computed element-wise on vectors.

**Code Representation:** In order to preserve both semantic and syntactic properties of programming code in the embeddings, we utilize ASTNN [51], a popular tool for code representation. We first parse a student-submitted response code into an abstract syntax tree (AST). We then split each full AST into a sequence of non-overlapping statement trees (ST-trees) through preorder traversal. Each ST-tree contains a statement node as the root and its corresponding AST nodes as children. We then pass the ST-trees through a recurrent statement encoder to obtain embedding vectors and use a bidirectional gated recurrent unit network [3] to capture the naturalness of the statements and further enhance the capability of the recurrent layer. Eventually, we apply a max-pooling layer to capture the most important semantics for each dimension of the embedding. We denote this process as

\[ c = \text{ASTNN}(x), \]

where \( x \) is the student-submitted code and \( c \) is its code embedding vector, which we use as input to the knowledge update component. We refer readers to [51] for more details on ASTNN.

3.2 Knowledge Update

We use a long short-term memory (LSTM) model [19] to update a student’s knowledge state given their previous response at the last time step. Instead of one-hot embeddings for questions and responses or more sophisticated, graph-based embeddings that rely on question/concept IDs [37], we use the combination of the question prompt and code embeddings detailed above as the input to our knowledge update component. Our knowledge update component can be summarized as

\[ h_t = \text{LSTM}(h_{t-1}, \bar{q}_t, \bar{c}_t), \]

where \( h_t \) is the student’s knowledge state at time step \( t \). We will use \( h_t \) as input to the response generation component to predict actual student code submissions.

In principle, we can leverage any existing KT method as the knowledge update component. We validate in our experiments (Section 4) that OKT is compatible with two other representative KT methods, DKVMN [50] and AKT [16].

3.3 Response Generation

We now turn our attention to the response generation component, the most important component of OKT. We use GPT-2 as our base generative model to fine-tune a text-to-code model \( P_b \) with parameter \( \Theta \) on our dataset (we detail the reason for this choice in Section 3.3). We choose language models over other code generation approaches since their text-to-code generation pipeline suits OKT well.

Our key technical challenge is how to use knowledge states as control in the code generation model to make personalized code predictions for each student. At time step \( t \), GPT-2 tokenizes the question prompt \( p_t \) into a sequence of \( M \) tokens as input to the model, with original token embeddings \( \{\bar{p}^{(1)}_t, \bar{p}^{(2)}_t, \ldots, \bar{p}^{(M)}_t\} \), where \( \bar{p}^{(m)}_t \in \mathbb{R}^K \). Our approach for injecting student knowledge states into the code generation model is to replace these token embeddings with knowledge-adjusted embeddings using a function, i.e., \( \bar{p}^{(i)}_t = f(\bar{p}^{(i)}_t, h_t) \) for \( i = 1, \ldots, M \). Then we obtain our final input embeddings to GPT-2 as

\[ \{\bar{p}^{(1)}_t, \ldots, \bar{p}^{(M)}_t\} = \{f(\bar{p}^{(1)}_t, h_t), \ldots, f(\bar{p}^{(M)}_t, h_t)\}. \]

Intuitively, this (possibly learnable) alignment function aligns the space of knowledge states with the space of question prompt text. Thus, knowledge states are responsible for predicting different code submitted to the same programming question by different students.

In this paper, we explore four different alignment functions to combine knowledge states with question prompt token embeddings:

\[ \text{One can freely choose any language model; we choose GPT-2 since our response generation component for student code is also built on GPT-2} \]
Open-Ended Knowledge Tracing

- Addition, i.e., $p_t = p_t + h_t$.
- Averaging, i.e., $p_t = \frac{p_t + h_t}{2}$.
- Weighted addition, i.e., introducing a learnable weight on the knowledge state, $p_t = p_t + \alpha \cdot h_t$.
- Linear combination, i.e., introducing a learnable affine transformation to the knowledge states before adding it to token embeddings as $p_t = p_t + A h_t + b$.

The latter two functions are learnable with parameters $\alpha \in \mathbb{R}$, $A \in \mathbb{R}^{B \times K}$, and $b \in \mathbb{R}^K$. Given the student-submitted code tokens $x = \{x^{(1)}, x^{(2)}, \ldots, x^{(N)}\}$ (we remove the time step index $t$ for now for clarity and $N$ denotes the number of code tokens) and the input question prompt token embeddings $\{p^{(1)}, \ldots, p^{(M)}\}$, the generative model for the student’s submitted code is

$$x \sim P_{\Theta}(x|\{p^{(1)}, \ldots, p^{(M)}\}),$$

(5)

where $\Theta$ denotes the set of parameters in the response prediction component, including both the text-to-code generation language model parameters and (when applicable) learnable parameters in the alignment function $f(\cdot)$. Since GPT-2 is an autoregressive language model, we can further decompose Eq. (5) into

$$x \sim \prod_{j=1}^{N} P_{\Theta}(x^{(j)}|\{p^{(1)}, \ldots, p^{(M)}\}, \{x^{(j')}\}_{j'=1}^{j-1}),$$

(6)

where $x^{(j)}$ denotes the $j$th code token.

3.4 Optimization

During the training process, we jointly optimize the parameters of the knowledge update model and the response generation model; we keep the knowledge representation encoders $E_1$ and $E_2$ fixed. The objective for one student is simply the negative log-likelihood/cross entropy loss for all code tokens, i.e.,

$$Loss = \sum_{j=1}^{N} - \log P_{\Theta}(x^{(j)}|\{p^{(1)}, \ldots, p^{(M)}\}, \{x^{(j')}\}_{j'=1}^{j-1}),$$

(7)

while the total training objective sums this loss over all students.

We also design an efficient training setup for OKT. For existing neural network-based KT methods, at each training step, we use a batch of student (question, response) sequences to compute the correctness prediction loss across all time steps and all students in the batch. We cannot use this training method since OKT’s loss for one student is the sum of code prediction losses over all time steps, whereas the loss at each time step is itself the sum of a sequence of cross entropy losses for code token predictions. As a result, if we use the training setup for existing KT methods, at each training step, we need to call the response generator for a total of $T \times B$ times where $T$ is the number of time steps and $B$ is the batch size, which will significantly slow down training. Instead of batching over students, we use a batch of (student, time step) pairs. Then, at each training step, we first apply the knowledge update component in OKT to compute the knowledge states for students in the batch, extract the knowledge states corresponding to the sampled time steps in the batch, and then feed them into the response generator. This setup enables efficient training for OKT.

3.5 Pre-training Models

Before training OKT, we pre-train its knowledge update component using the binary-valued correctness prediction loss with question and code embeddings as input, following [30, 52]. We also pre-train the response generation component to adapt GPT-2 to the text-to-code task with actual code. Since we cannot directly use CodeX [7] due to our need to adjust the input embeddings with student knowledge states, we use a similar pre-training strategy to fine-tune a standard GPT-2 model on the Funcom dataset [24], which contains 2.1 million Java code snippets together with textual descriptions in natural language.

4 Experiments

We now present a series of quantitative and qualitative experiments to explore the capabilities of our proposed OKT approach for programming questions on a real-world dataset with student coding exercises. We first introduce the dataset and various quantitative metrics on which we will evaluate our method. Since OKT is a new task without benchmark baselines to compare with, we define several variants of our proposed OKT method to demonstrate its applicability and compatibility with several representative knowledge tracing methods and code generation models. Finally, we present qualitative evaluation results to illustrate that our OKT method (i) learns meaningful structures of
the students’ knowledge and (ii) generates coding solutions that, although not always exactly matching the students’ solutions, capture students’ coding patterns and types of mistakes they make.

**Dataset.** We use the dataset from the CSED Data Challenge, henceforth referred to as the CSED dataset. To our knowledge, this is the only college-level, publicly-available dataset with students’ actual code submissions. The dataset contains 246 college students’ full submissions on each of the 50 programming assignments over the course of an entire semester. Instead of predicting the correctness of the last 20 problems given the previous answers for a student, which is the goal of the CSED Data Challenge, we repurpose this dataset for our task of open-ended knowledge tracing. Here, for each student, we would like to predict the student’s next full code solution, instead of its correctness, given the student’s history of solving the programming assignments. The dataset contains rich textual information on the problem prompt and the students’ code answers as well as other relevant metadata such as each problem’s knowledge components and the error messages returned by the compiler, if the students’ solution resulted in an error. The detailed data statistics and preprocessing steps are available in Section A1 in the Appendix.

**Evaluation Metrics.** Evaluating generative models is generally a challenging problem. In the context of predicting students’ code submissions, we need a variety of different metrics to fully understand the effectiveness of OKT. We thus use two types of evaluation metrics. First, we need metrics that can measure OKT’s ability to predict student code on the test set after training. For this purpose, we use two metrics, including the average test loss computed using OKT methods with the best validation loss during training. The other metric is CodeBLEU [39], a variant of the classic BLEU metric adapted to code, which measures the similarity between predicted code and actual student code. Second, we need metrics that can measure the diversity of the generated code since we do not want the OKT methods to memorize typical student codes in the training data. For this purpose, we use the dist- metric [25] that computes the ratio of unique N-grams in the generations over all N-grams. We choose N = 1 in this work.

**Methods for Comparison.** Because OKT is a novel task, there are no existing baselines to which we can compare. We thus compare among a few variants of our default OKT method to demonstrate that the OKT framework is highly flexible and extensible. These features enable one to plug-and-play with a variety of existing methods for the different components in the OKT framework. In this work, we primarily investigate variations of the knowledge updating component in OKT which lies at the core of the OKT framework and connects to the knowledge representation and response generation modules. For this comparison, as detailed above, we compare three representative KT methods, DKT, DKVMN, and AKT; we emphasize that any existing KT method can be applied and it is up to the user to select the appropriate method given the application context. We report the results on KT model variations in Section 4.1. Additionally, we compare among several different approaches for our key technical challenge: using knowledge states as the control for the code generation model in a variety of ways. We also compare several training settings including 1) whether we pre-train KT model and the answer prediction model and 2) whether we train with the language modeling loss only (single-task) or together with the binary answer correctness prediction loss (multi-task). We report the results of the above design choices as an ablation study in Section 4.2.

**Experimental Setup** We consider two experimental settings in our experiments that are similar but arguably capture different aspects of OKT. First, we analyze all code submissions from each student, including multiple consecutive attempts at the same question. This setting is used by most existing KT methods and traces students’ knowledge evolution while they gradually build up their code. Therefore, in this setting, knowledge states capture not only a student’s mastery of different coding concepts but also their ability to correct errors through debugging. Second, we also analyze only their first attempt at each question, ignoring later attempts. This setting is also used in the literature to predict correctness on first attempt [22] where consecutive time steps correspond to different questions. Therefore, in this setting, knowledge states mostly capture a student’s mastery of coding concepts. We choose not to use the final attempt since most students were able to write correct code in their final attempt at questions in the CSED dataset.

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Table 1 shows the quantitative results evaluating OKT on the CSED dataset comparing DKT, AKT, and DKVMN as the knowledge update component. We see that these KT methods perform similarly with each other, with AKT slightly outperforming the other two methods on most metrics in both experimental settings. DKT’s performance is consistent across both settings, whereas DKVMN performs better when predicting students’ first code submissions to each question than when predicting all code submissions. These results suggest that DKT and AKT are effective models for the knowledge update component of OKT since DKT is simple and efficient while AKT achieves the overall best performance at the expense of a more complicated model architecture requiring more computational resources.

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3The dataset is referred to as “CodeWorkout data Spring 2019” accessed via DataShop (pslcdatashop.web.cmu.edu).
Open-Ended Knowledge Tracing

| setting        | KT model | CodeBLEU ↑ | Dist-1 ↑ | Test Loss ↓ |
|----------------|----------|------------|----------|-------------|
| first submission | DKT      | 0.563      | 0.388    | 0.215       |
|                | AKT      | 0.576      | 0.395    | 0.200       |
|                | DKVMN    | 0.577      | 0.395    | 0.202       |
| all submissions | DKT      | 0.545      | 0.388    | 0.137       |
|                | AKT      | 0.565      | 0.396    | 0.133       |
|                | DKVMN    | 0.519      | 0.388    | 0.145       |

Table 1: Student code prediction performance for OKT on the CSEDM dataset. Using DKT, AKT, and DKVMN as the knowledge update component result in similar performance, with AKT slightly outperforming the other two.

| Combine Method | CodeBLEU ↑ | Dist-1 ↑ | Test Loss ↓ |
|----------------|------------|----------|-------------|
| add            | 0.550      | 0.390    | 0.217       |
| average        | 0.541      | 0.390    | 0.218       |
| weight         | 0.549      | 0.389    | 0.217       |
| linear         | 0.563      | 0.388    | 0.215       |

| Pre-train LSTM | CodeBLEU ↑ | Dist-1 ↑ | Test Loss ↓ |
|----------------|------------|----------|-------------|
| yes            | 0.549      | 0.387    | 0.217       |
| no             | 0.495      | 0.409    | 0.326       |

| Pre-train GPT  | CodeBLEU ↑ | Dist-1 ↑ | Test Loss ↓ |
|----------------|------------|----------|-------------|
| yes            | 0.549      | 0.387    | 0.217       |
| no             | 0.176      | 0.480    | 0.967       |

| Multi-task     | CodeBLEU ↑ | Dist-1 ↑ | Test Loss ↓ |
|----------------|------------|----------|-------------|
| yes            | 0.593      | 0.406    | 0.399       |
| no             | 0.563      | 0.388    | 0.215       |

Table 2: Ablation studies comparing various OKT setups. In general, linearly combining knowledge states and the prompt token embeddings, pre-training both knowledge update and response generation components, and using a multi-task loss improve OKT performance.

Across the two experimental settings, analyzing students’ first submissions leads to much higher test loss than analyzing all submissions while performance on the other two metrics does not vary much. These results can be explained by our observation that students rarely make substantial changes to their code across different submissions, often making minor tweaks; therefore, predicting a later code submission given previous submissions becomes an easier task than predicting the first submission to a new question. Since these metrics are computed over all questions, we perform a more detailed evaluation of OKT’s code prediction performance across questions and report our findings in Section A3 of the Appendix.

Overall, we observe that OKT is able to predict actual student code reasonably well; in terms of CodeBLEU, OKT with AKT as its KT model outperforms the simple baseline of majority student code by about 0.08; as a reference, the CodeBLEU value for the third example in Table 3 is 0.65, which is 0.08 higher than for the average performance of OKT. This observation suggests that despite OKT being able to capture major variations in student code, there is plenty of room for improvement on student code prediction.

We also conduct a preliminary experiment to examine OKT’s performance on the standard KT prediction task, i.e., predicting the binary-valued correctness of the next response. We observe that OKT, with its additional code prediction loss in the objective, achieves a correctness prediction AUC (area under the ROC curve) value of 0.825; without this loss, the AUC value drops to 0.821, although there is no statistically significant difference. This comparison suggests that OKT has the potential to benefit the standard KT task of response correctness prediction. We leave the detailed investigation of how to use OKT to improve response correctness prediction performance as future work.

4.2 OKT Framework Design Choices

We conduct an ablation study to understand how each design choice in OKT impacts its performance on predicting student code submissions. For this experiment, we analyze only the first code submission for each question made by every student. We compare four different model design aspects: First, we compare different alignment functions between knowledge states and prompt token embeddings in the response generation component that we detailed above in
Open-Ended Knowledge Tracing

Section 3.3 Second and third, we test whether knowledge update component pre-training and response generation component pre-training are effective. Fourth, we compare whether using a multi-task training objective where we add the typical correctness prediction loss to the code prediction loss in Eq. 7 during OKT training leads to improved code prediction accuracy.

Table 2 shows the results of the ablation studies. First, we see that aligning the knowledge state space with the prompt token embedding space with a learnable linear function appears to be the most effective, although other alignment functions are only slightly worse. Therefore, there is a need to explore other, more flexible alignment functions across these two spaces. Second, we see that pre-training the knowledge update and response generation components result in significant improvements in OKT’s code prediction performance. This result suggests that existing KT methods for response correctness prediction are useful in warm-starting OKT training, while fine-tuning pre-trained LMs on actual student code helps code prediction significantly.

The unusually high diversity scores when the knowledge update and response generation components are not pre-trained is due to their inability to generate coherent code, as reflected in their low CodeBLEU scores. Finally, we observe that a multi-task OKT training objective improves code prediction performance. This result suggests that like other tasks in natural language processing and computer vision, multi-task learning with multiple objectives helps us learn better representations of data, i.e., the knowledge state representations in OKT.

4.3 Case Study: Interpreting the Learnt Knowledge State Space

We now use a case study to demonstrate the interpretability of the knowledge state space learned by OKT. We show that the knowledge states learned by OKT capture the variation in the content and structure of student code submissions and effectively trace students’ multiple attempts when responding to each question. Figure 3 visualizes the learned knowledge states (projected to a 2-dimensional space via t-SNE) for the following question:

Write a function in Java that implements the following logic: Your cell phone rings. Return true if you should answer it. Normally you answer, except in the morning you only answer if it is your mom calling. In all cases, if you are asleep, you do not answer.

The middle part of Figure 3 shows the knowledge states of all students when they respond to this question, where each dot represents the submission at a time step (a student may have multiple submissions at multiple time steps) and each color represents a student. We see that there are distinct clusters in these knowledge states that correspond to different student code. To further demonstrate this observation, we zoom in into two areas in the knowledge state space, shown in the two small plots on the left side of Figure 3 together with the corresponding actual student code submissions. We clearly see that the codes within each cluster share similar structural and syntactic properties and that codes from different clusters differ significantly. This result suggests that the OKT-learnt knowledge state space aligns with actual student code submissions; existing KT methods cannot do that. In Figure 4, we compare the learned knowledge state space for OKT against that for existing KT methods. We see that DKT learns knowledge states that belong to a few highly overlapping groups with little difference within each group, which is not surprising since it analyzes only binary-valued response correctness. The KT method [30] learns a slightly more disentangled knowledge state space using actual student code only as input. On the contrary, OKT’s knowledge states are highly structured with obvious clustering patterns that correspond to actual student code.

We also show how the learnt knowledge state space can be useful for tracing and understanding students’ consecutive submissions to the same question. On the right-hand side of Figure 3 we show the knowledge state trajectories of two students responding to this question. The colors in these two figures represent knowledge states that correspond to wrong, partially correct and fully correct codes at different time steps. We see that both students start with a wrong solution. However, one student gradually proceeded to the correct solution after a few edits, whereas the other student got stuck after a few unsuccessful edits and eventually gave up on solving this prompt. The steady progress versus getting stuck is clearly visualized in these figures, where for the former student, the knowledge states gradually moves from the upper right corner in the knowledge state space to the lower left, whereas for the latter student, the knowledge states circle around and bounce back and forth in the space. We also show four selected submissions by each student during their response process, further illustrating how the first student made steady progress, i.e., adding the return statement (first two code submissions) and correcting logic (last two code submissions), and how the second student got stuck, i.e., making reasonable changes initially but then some repetitive edits.

Overall, these qualitative results demonstrate that the knowledge states learned by OKT capture important aspects of programming knowledge for each student. Therefore, OKT has potential for downstream analytic and intervention tasks such as hint generation and predicting when a student gets stuck and needs help.
4.4 Case Study: Knowledge-aware Predictions of Students’ Code Submissions

We now use a case study to demonstrate OKT’s ability to predict student-submitted code. Similar to most existing text-to-code models [20, 29], exact prediction of the actual student code is very difficult. However, OKT can still be effective in capturing student’s coding styles and even predicting some error types with the help of the learned knowledge states. The top two rows in Table 3 shows the predicted code versus the actual student code for two students on the same question. We see that even though the two selected students write code in very different ways, our predicted codes are able to follow their structure, capturing their habits to use while and for loops. The middle example shows that even though calling the concat function is not commonly found in students’ responses to this question (only 1% of the submissions do so), OKT is still able to predict it for the student. This example suggests that OKT can capture both code structures and possible gaps in knowledge on programming concepts for individual students, while existing KT methods that only analyze response correctness cannot. The bottom part shows an example from a different question. While the code prediction is less accurate than the other two examples, OKT can still capture the main logic and most important parts of the student’s actual code. From this example, it is clear how the student makes a mistake in this question and OKT is able to successfully predict that. These results show that OKT can potentially be used to provide automated feedback to both students and instructors.
Open-Ended Knowledge Tracing

Figure 4: Comparison of the knowledge state spaces learned by DKT (left), DKT with code embeddings as input [30] (middle), and OKT (right). OKT learns a structured knowledge space with distinct clusters that capture variations in actual student code while existing KT methods cannot.

Table 3: OKT generated code vs. actual student code for two questions. The differences are highlighted in red boxes.

| predicted code                                                                 | actual student code                                                                 |
|-------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| `public String sigep(String str)`                                              | `public String sigep(String str)`                                                 |
| `{                                                                       | `{                                                                       |
|   for (int i = 0; i < str.length() - 2; i++)                                |   for (int i = 0; i < str.length() - 2; i++)                                       |
|     if (str.charAt(i) == ' ' && str.charAt(i + 2) == '_')                    |     if (str.charAt(i) == ' ' && str.charAt(i + 2) == '_')                           |
|       str.replace("", str.substring(i + 1));                                |       str.replace("", str.substring(i + 1));                                      |
|   }                                                                       |   }                                                                                 |
| return str;                                                                  | return str;                                                                          |
| `public String sigep(String str)`                                              | `public String sigep(String str)`                                                 |
| `{                                                                       | `{                                                                       |
|   String newstr = "";                                                       |   String newstr = "";                                                               |
|   int i = 0;                                                                 |   int i = 0;                                                                       |
|   while (i < str.length()) {                                                  |   while (i < str.length()) {                                                       |
|     String strk = Character.toString(str.charAt(i));                        |     String strk = Character.toString(str.charAt(i));                              |
|     if (Character.isWhitespace(str.charAt(i))) &&                          |     if (Character.isWhitespace(str.charAt(i))) &&                                 |
|       (Character.isWhitespace(str.charAt(i + 2)))                           |       (Character.isWhitespace(str.charAt(i + 2)))                                |
|       newstr = newstr.concat("sp");                                        |       newstr = newstr.concat("sp");                                              |
|       i = i + 2;                                                             |       i = i + 2;                                                                   |
|   } else                                                                   |   } else                                                                             |
|     newstr = newstr.concat(strk);                                            |     newstr = newstr.concat(strk);                                                  |
|     i++;                                                                    |     i++;                                                                            |
| }                                                                           | }                                                                                   |
| return newstr;                                                               | return newstr;                                                                      |
| `public boolean evenlySpaced(int a, int b, int c)`                           | `public boolean evenlySpaced(int a, int b, int c)`                                  |
| `{                                                                       | `{                                                                       |
|   int diffone = b - a;                                                      |   int diffone = b - a;                                                             |
|   int difftwo = c - b;                                                      |   int difftwo = c - b;                                                            |
|   if (diffone == difftwo) {                                                 |   if (diffone == difftwo) {                                                      |
|     return true;                                                            |     question = true;                                                               |
|   } else                                                                    |     return question;                                                              |
|     return false;                                                           | }                                                                                   |

5 Conclusions

In this paper, we have proposed a framework for open-ended knowledge tracing, i.e., tracking student knowledge acquisition while predicting their full responses to open-ended questions. We demonstrated how our framework can be applied to the computer science education domain where we analyze students’ code submissions to programming questions. We addressed the key technical challenge of integrating student knowledge representations into code generation methods, e.g., text-to-code models based on fine-tuned GPT-2. Since exactly predicting open-ended responses, especially longer ones, can be difficult, we also defined a series of metrics to evaluate the performance of
open-ended knowledge tracing methods. Through extensive experiments on a real-world dataset, we discussed the effectiveness and limitations of our framework, both quantitatively and qualitatively.

There are many avenues for future work. First, we need to dig deeper and find the best ways to inject knowledge states into generative models of student code, such as using prefixes [26]. Second, we need to explore standardization techniques for code to further pre-process student code using semantic equivalence. Third, we can explore the applicability of our framework to other domains such as mathematics, where many pre-trained models for mathematical problem solving have been developed [10] [18] [41] and explore whether students consistently exhibit certain errors [45].

Finally, we can develop knowledge tracing models that capture more specific aspects of knowledge, i.e., debugging skills, which is reflected in the change in student code across submissions to the same question after receiving automated feedback generated by the compiler or test cases. Last and most importantly, we need to explore ways to use OKT to provide meaningful feedback to students and instructors. Therefore, we may use the generated responses to predict the types of error a student might make, capturing more fine-grained skills than commonly identified programming skills. We may also expand the list of code predictions made by OKT’s response generation component from the most likely prediction to a list of top predictions to reflect more aspects of student knowledge.

References

[1] U. Alon, M. Zilberstein, O. Levy, and E. Yahav. code2vec: Learning distributed representations of code. *Proceedings of the ACM on Programming Languages*, 3(POPL):1–29, 2019.
[2] J. R. Anderson and R. Jeffries. Novice lisp errors: Undetected losses of information from working memory. *Human–Computer Interaction*, 1(2):107–131, 1985.
[3] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.
[4] J. S. Brown and R. R. Burton. Diagnostic models for procedural bugs in basic mathematical skills. *Cognitive science*, 2(2):155–192, 1978.
[5] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, et al. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*, 2020.
[6] H. Cen, K. Koedinger, and B. Junker. Learning factors analysis–A general method for cognitive model evaluation and improvement. In *Proc. Int. Conf. on Intelligent Tutoring Systems*, pages 164–175, 2006.
[7] M. Chen, J. Tworek, H. Jun, Q. Yuan, H. P. d. O. Pinto, J. Kaplan, H. Edwards, Y. Burda, N. Joseph, G. Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.
[8] B. Choffin, F. Popineau, Y. Bourda, and J.-J. Vie. DAS3H: Modeling student learning and forgetting for optimally scheduling distributed practice of skills. In *Proc. Int. Conf. on Educational Data Mining*, pages 29–38, 2019.
[9] K. Cobbe, V. Kosaraju, M. Bavarian, J. Hilton, R. Nakano, C. Hesse, and J. Schulman. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.
[10] K. Cobbe, V. Kosaraju, M. Bavarian, J. Hilton, R. Nakano, C. Hesse, and J. Schulman. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.
[11] A. Corbett and J. Anderson. Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-adapted Interaction*, 4(4):253–278, Dec. 1994.
[12] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
[13] S. Doroudi, V. Aleven, and E. Brunskill. Where’s the reward? *International Journal of Artificial Intelligence in Education*, 29(4):568–620, 2019.
[14] M. Q. Feldman, J. Y. Cho, M. Ong, S. Gulwani, Z. Popović, and E. Andersen. Automatic diagnosis of students’ misconceptions in K-8 mathematics. In *Proc. CHI Conference on Human Factors in Computing Systems*, pages 1–12, 2018.
[15] J. Feng, B. Zhang, Y. Li, and Q. Xu. Bayesian diagnosis tracing: Application of procedural misconceptions in knowledge tracing. In *Proc. Int. Conf. on Artificial Intelligence in Education*, pages 84–88, Springer, 2019.
[16] A. Ghosh, N. Heffernan, and A. S. Lan. Context-aware attentive knowledge tracing. In *Proc. ACM SIGKDD Int. Conf. on Knowledge Discovery & Data Mining*, pages 2330–2339, 2020.
[17] A. Ghosh, J. Raspat, and A. Lan. Option tracing: Beyond correctness analysis in knowledge tracing. In *Int. Conf. on Artificial Intelligence in Education*, pages 137–149. Springer, 2021.
Open-Ended Knowledge Tracing

[18] D. Hendrycks, C. Burns, S. Kadavath, A. Arora, S. Basart, E. Tang, D. Song, and J. Steinhardt. Measuring mathematical problem solving with the math dataset. In Proc. Conference on Advances in Neural Information Processing, 2021.

[19] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural Computation, 9(8):1735–1780, Nov. 1997.

[20] S. Iyer, I. Konstas, A. Cheung, and L. Zettlemoyer. Mapping language to code in programmatic context. arXiv preprint arXiv:1808.09588, 2018.

[21] M. Khajah, Y. Huang, J. González-Brenes, M. Mozer, and P. Brusilovsky. Integrating knowledge tracing and item response theory: A tale of two frameworks. In Proc. International Workshop on Personalization Approaches in Learning Environments, volume 1181, pages 7–15, 2014.

[22] A. S. Lan, C. G. Brinton, T. Yang, and M. Chiang. Behavior-based latent variable model for learner engagement. In Proc. Intl. Conf. Educ. Data Min., pages 64–71, June 2017.

[23] A. S. Lan, C. Studer, A. E. Waters, and R. G. Baraniuk. Tag-aware ordinal sparse factor analysis for learning and content analytics. In Proc. 6th Intl. Conf. Educ. Data Min., pages 90–97, July 2013.

[24] A. LeClair and C. McMillan. Recommendations for datasets for source code summarization. arXiv preprint arXiv:1904.02660, 2019.

[25] J. Li, M. Galley, C. Brockett, J. Gao, and B. Dolan. A diversity-promoting objective function for neural conversation models. In Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol., pages 110–119, June 2016.

[26] X. L. Li and P. Liang. Prefix-tuning: Optimizing continuous prompts for generation. arXiv preprint arXiv:2101.00190, 2021.

[27] R. Lindsey, J. Shroyer, H. Pashler, and M. Mozer. Improving students’ long-term knowledge retention through personalized review. Psychological Science, 25(3):639–647, Jan. 2014.

[28] Q. Liu, Z. Huang, Y. Yin, E. Chen, H. Xiong, Y. Su, and G. Hu. Ekt: Exercise-aware knowledge tracing for student performance prediction. IEEE Transactions on Knowledge and Data Engineering, 33(1):100–115, 2019.

[29] S. Lu, D. Guo, S. Ren, J. Huang, A. Svyatkovskiy, A. Blanco, C. Clement, D. Drain, D. Jiang, D. Tang, et al. Codexglue: A machine learning benchmark dataset for code understanding and generation. arXiv preprint arXiv:2102.04664, 2021.

[30] Y. Mao, Y. Shi, S. Marwan, T. W. Price, T. Barnes, and M. Chi. Knowing" when" and" where": Temporal-astnn for student learning progression in novice programming tasks. International Educational Data Mining Society, 2021.

[31] T. Mikolov, I. Sutskever, K. Chen, G. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In Proc. NeurIPS, pages 3111–3119, 2013.

[32] R. Ostini and M. L. Nering. Polytomous item response theory models. Sage, 2006.

[33] S. Pandey and G. Karypis. A self attentive model for knowledge tracing. In Proc. Int. Conf. on Educational Data Mining, pages 384–389, July 2019.

[34] S. Pandey and J. Srivastava. Rkt: Relation-aware self-attention for knowledge tracing. arXiv preprint arXiv:2008.12736, 2020.

[35] Z. A. Pardos and N. T. Heffernan. Modeling individualization in a Bayesian networks implementation of knowledge tracing. In Proc. Int. Conf. on User Modeling, Adaptation, and Personalization, pages 255–266, 2010.

[36] P. Pavlik Jr, H. Cen, and K. Koedinger. Performance factors analysis—A new alternative to knowledge tracing. In Proc. Int. Conf. on Artificial Intelligence in Education, 2009.

[37] C. Piech, J. Bassen, J. Huang, S. Ganguli, M. Sahami, L. J. Guibas, and J. Sohl-Dickstein. Deep knowledge tracing. In Proc. Conference on Advances in Neural Information Processing Systems, pages 505–513, 2015.

[38] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, et al. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.

[39] S. Ren, D. Guo, S. Lu, L. Zhou, S. Liu, D. Tang, N. Sundaresan, M. Zhou, A. Blanco, and S. Ma. CodeBLEU: a Method for Automatic Evaluation of Code Synthesis. arXiv e-prints, page arXiv:2009.10297, Sept. 2020.

[40] S. Ritter, J. R. Anderson, K. R. Koedinger, and A. Corbett. Cognitive tutor: Applied research in mathematics education. Psychological Bulletin & Review, 14(2):249–255, 2007.

[41] D. Saxton, E. Grefenstette, F. Hill, and P. Kohli. Analysing mathematical reasoning abilities of neural models, 2019.
Appendix

A1 Dataset Statistics and Preprocessing Steps

Since we choose to use the AST representation for code, we perform a preprocessing step to remove student solutions that cannot be converted to AST format. Overall, about 85% of all student solutions are AST-convertible, which means that this preprocessing step does not result in significant data loss. Table A1 describes the summary statistics of the original dataset and the resulting preprocessed dataset that we use for all our experiments. For KT, we follow standard procedure in the literature \cite{49, 37, 16, 50} by setting the maximum solution sequence for any student to 200. For students with more than 200 solutions, we split their solutions into separate sequences of length 200.

| Statistic                   | Raw     | Processed |
|-----------------------------|---------|-----------|
| #codes                      | 46825   | 39796     |
| #avg. lines of code per submission | 17.52   | 17.64     |
| #avg. submissions per student | 190.34  | 161.77    |
| #avg. submissions per problem | 936.5   | 795.9     |

Table A1: Dataset statistics comparing the raw and our processed dataset, the latter of which is used throughout our experiments.

A2 Experiment Setup Details

In both settings, we split all students in the dataset into disjoint (train, validation, test) sets with a 80% − 10% − 10% ratio and report all metrics on the test set. In the default setting, we add knowledge states into token embeddings for the question prompt as input to the response generation component using a linear projection layer as detailed above. We
pre-train both the knowledge update and response generation components of OKT on the training data with a correctness prediction objective (i.e., pre-train an existing KT method) and a prompt-to-code supervised generation objective, respectively. For the knowledge update component, we follow the original DKT, DKVMN, and AKT methods with 768 hidden units in their models. When combining DKVMN or AKT with the answer generator, we use the context reader output from DKVMN and the hidden state from AKT, respectively, as input to the answer generator at each time step. We refer readers to [50][16] for more details. For the response generation component, we use a small GPT-2 with 12 transformer decoder layers [38]. We use the RMSProp optimizer for the knowledge update component and the Adam optimizer for the response generation component, both with a default learning rate of 0.00001. Also, we freeze the parameters of the question and code representation models and only train the KT model and the answer prediction model, Although the former two components can also be optimized.

We run all experiments using a single NVIDIA Quadro RTX 8000 GPU. The KT model pre-training usually takes less than 5 minutes per epoch of wall clock time. The OKT training with DKT as the KT model takes about 10 minutes and 30 minutes per epoch of wall clock time for the the two scenarios, namely, using only students’ first submitted code and all submitted code that can be converted to AST format, respectively. OKT training with AKT as the KT model takes about the same time as DKT as the KT model while with DKVMN, training is about 1.5 times slower due to the more expensive memory computation [50].

### A3 Additional Results

![Figure A1](image)

**Figure A1:** Visualization of CodeBLEU metric versus number of student responses (left), rate of correct submissions (middle) and Dist-1 metric (right) in each question. Each point represents one question.

**Visualizing the quantitative results.** Following the results in Section 4.1 and Table 1, we additionally examine the model performance across questions and measure the correlation between its CodeBLEU score and some features (i.e. difficulty level, response diversity). Figure A1 shows that model performance has a positive correlation with the rate of correctness, while a negative correlation with the number of student responses. That is to say, an easy question with fewer submissions is more likely to achieve better prediction results. However, CodeBLEU is not closely correlated to the diversity in student responses. Also, the range of CodeBLEU performance across questions is relatively big, with the highest of 0.82 and lowest of 0.30.