Deep Learning vs. Bayesian Knowledge Tracing: Student Models for Interventions

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Bayesian Knowledge Tracing (BKT) is a commonly used approach for student modeling, and Long Short Term Memory (LSTM) is a versatile model that can be applied to a wide range of tasks, such as language translation. In this work, we directly compared three models: BKT, its variant Intervention-BKT (IBKT), and LSTM, on two types of student modeling tasks: post-test scores prediction and learning gains prediction. Additionally, while previous work on student learning has often used skill/knowledge components identified by domain experts, we incorporated an automatic skill discovery method (SK), which includes a nonparametric prior over the exercise-skill assignments, to all three models. Thus, we explored a total of six models: BKT, BKT+SK, IBKT, IBKT+SK, LSTM, and LSTM+SK. Two training datasets were employed, one was collected from a natural language physics intelligent tutoring system named Cordillera, and the other was from a standard probability intelligent tutoring system named Pyrenees. Overall, our results showed that BKT and BKT+SK outperformed the others on predicting post-test scores, whereas LSTM and LSTM+SK achieved the highest accuracy, F1-measure, and area under the ROC curve (AUC) on predicting learning gains. Furthermore, we demonstrated that by combining SK with the BKT model, BKT+SK could reliably predict post-test scores using only the earliest 50% of the entire training sequences. For learning gain early prediction, using the earliest 70% of the entire sequences, LSTM can deliver a comparable prediction as using the entire training sequences. The findings yield a learning environment that can foretell students' performance and learning gains early, and can render adaptive pedagogical strategy accordingly.

Keywords: student modeling, learning gain, interventions, LSTM, BKT

1. Introduction

The impetus for the development of many intelligent tutoring systems (ITSs) was the desire to capture the practical learning experience provided by human one-on-one instruction (Merrill et al., 1992). ITSs have shown a positive impact on learning, but vary depending on an individual's motivation, aptitude, attitude, engagement and incoming competence, etc, in what is generally known as an aptitude treatment interaction (Cronbach and Snow, 1981).

The primary objective of this work is to build an analytic model that can both actively track whether a student has embarked upon an unprofitable learning experience and accurately identify those who may fail the corresponding test as early as possible so that adaptive recommendation can be offered. Many existing ITSs are *elicit-centric*, meaning the system-student interactions can be viewed as a temporal sequence of steps (VanLehn, 2006) in which each step the tutor *elicits* the subsequent step from the student. This can be done with prompting, but often done without it (e.g., in a free form equation entry window where each equation is a step). When a student enters an attempt on a step, the ITS records whether it is a success or failure and may give feedback and/or hints based on that entry. Students' first attempts recorded on each step are then extracted for student modeling.

Bayesian Knowledge Tracing (BKT; Corbett and Anderson 1994) is one of the most popular student modeling approaches that keeps track of students' knowledge over time. Conventional BKT infers students' hidden knowledge states mainly from their performance (i.e., *correct*, *incorrect*) on each step. Nevertheless, student performance can be noisy because many ITSs allow students to refer to external resources for information. The ability to solicit help from external resources obscures the fact of whether a student has truly learned or not. On the other hand, ever since the mid-1950s, response time has been used as a preferred dependent variable in cognitive psychology (Thomas et al., 1986). Student response time has been mainly used to assess student learning because it can indicate how active and accessible student knowledge is. For example, it has been shown that response time reveals student proficiency (Schnipke and Scrams, 2002) and there is a significant negative correlation between student average response time and student final exam score taken at the end of the semester (González-Espada and Bullock, 2007). Also, response time has been suggested as an indicator of student engagement in answering questions (Beck, 2005) as well as an important factor for predicting motivation in e-learning environments (Cocea and Weibelzahl, 2006). Previously, we explored three types of observations: the conventional *performance*, the proposed *student response time*, and the *combined* observations; our results showed using the *combined* observation is more effective than using either of them alone (Lin and Chi, 2017). Therefore, in this work, we used both performance and student response time to infer student hidden knowledge level.

Furthermore, much of the prior research on student modeling has been conducted on datasets collected from *elicit-centric* ITSs. In *elicit-centric* ITSs (Aleven and Koedinger, 2002; Graesser et al., 2004, for eg. Cognitive Tutor, AutoTutor), the activities are mainly guided by tutors who *elicit* the next step from students. However, some ITS are not *elicit-centric*. For example, the two datasets used in this work were collected from Cordillera and Pyrenees where the tutors are able to choose to *elicit* the next step information from students, or to *tell* them the next step directly (see Figure 1). Figure 1 compares a pair of dialogues extracted from logs in this study. Both dialogues begin and end with the same tutor turn (lines 1 and 6 in (a) and 1 and 4 in (b)). In dialogue (a) the tutor chooses to elicit twice (lines 2-3 and 4-5 respectively). Dialogue (b), by contrast, covers the same domain content with two tell actions (lines 2 and 3). As a consequence, tutorial dialogue (a) is more interactive than (b). In this example, both elicits and tells are *instructional interventions*. At each step, the system needs to initiate one of the interventions to carry out the next step. Both *elicit* and *tell* provide students with learning opportunities. On the other hand, unlike *elicit*, *tell* does not generate direct observations about the student's performance (i.e., *correct*, *incorrect*). Therefore, we proposed Intervention-BKT (IBKT), an extension of BKT, which incorporates the effect of multiple types of instructional interventions on student modeling (Lin and Chi, 2016). In this work, we investigated the effectiveness of BKT

(a) Elicit Version	(b) Tell Version
1. **T:** So let's start with determining the value of v1. 2. **T:** Which principle will help you calculate the rock's instantaneous magnitude of velocity at T1? {**ELICIT**} 3. **S:** definition of kinetic energy 4. **T:** Please write the equation for how the definition of kinetic energy applies to this problem at T1 {**ELICIT**} 5. **S:** ke1 =0.5*m*v1^2 6. **T:** From KE1 = 0.5*m*v1^2, ···	1. **T:** So let's start with determining the value of v1. 2. **T:** To calculate the rock's instantaneous magnitude of velocity at T1, we will apply the definition of kinetic energy again. {**TELL**} 3. **T:** Let me just write the equation for you: KE1 = 0.5*m*v1^2. {**TELL**} 4. **T:** From KE1 = 0.5*m*v1^2, ···

Figure 1: Elicit vs. Tell

and IBKT. Furthermore, both models were compared against a deep learning based model.

Long Short Term Memory (LSTM; Hochreiter and Schmidhuber 1997) is a special type of deep learning model. LSTM is a variant of the Recurrent Neural Network (RNN) that was proposed to solve vanishing and exploding gradient problems (Hochreiter and Schmidhuber, 1997). Therefore, LSTM is effective in capturing underlying temporal structures in time series data, and it captures long-term dependencies more effectively than conventional RNN (LeCun et al., 2015). More specifically, instead of arbitrarily squashing the previous state every step with a sigmoid, LSTM builds up memory by feeding the previous hidden state as an additional input into the subsequent step. This makes the model particularly suitable for modeling dynamic information in student modeling, where there are strong statistical dependencies between student learning events over long-time intervals. In recent years, LSTM has been shown to be able to discover intricate structures in large datasets, achieving state-of-the-art results in a wide range of domains (Graves et al., 2013; Luong and Manning, 2015; Ng et al., 2015; Xingjian et al., 2015). In this work, we implement two Bayesian models, BKT and IBKT, and one deep learning model, LSTM, to model student learning with instructional interventions.

Often times in ITSs, the completion of a single step requires students to apply either a single Knowledge Components (KC) or multiple KCs. A *Knowledge Component* is "a generalization of everyday terms like concept, principle, fact, or skill, and cognitive science terms like schema, production rule, misconception, or facet" (VanLehn et al., 2007). They are the atomic units of knowledge. Generally speaking, student modeling is more challenging for steps involving multiple KCs than steps requiring only a single KC. While many previous studies on student modeling have relied on domain experts and/or educators to identify which KCs are associated with each step, a method, known as skill discovery has been proposed to discover KCs automatically (Lindsey et al., 2014, SK) . In the present study, we explore the impact of using automatically discovered KCs on the effectiveness of the three models. Combining SK with the three models (i.e., BKT, IBKT and LSTM) results in three new variations (i.e., BKT+SK, IBKT+SK, and LSTM+SK). These six models are applied to two important student modeling tasks: 1) predicting students' post-test scores, and 2) predicting their learning gains.

Post-test scores obtained at the end of training process were used represent students' *learning outcomes*: the higher the post-test score, the more likely the student has mastered the knowledge. Learning gain, on the other hand, measures how much a student has learned: the higher a student's learning gain, the more the student benefits from the tutor. Both post-test scores and learning gains are important outcomes for student learning. Note that students with a higher post-test score may not have a higher learning gain and vice versa. Therefore, our goal is to explore which of the six models is more effective at a particular task. Last but not least, we also want to develop a predictive tool that will identify students at high risk of failing the post-test; and those that will fail to benefit from a tutoring system as early as possible. Motivated by this, we investigate two important research questions regarding post-test prediction and learning gain prediction respectively: 1) for the task of post-test score prediction, which of the six models is best: BKT, BKT+SK, IBKT, IBKT+SK, LSTM or LSTM+SK? 2) for the task of learning gain prediction, which of the six models is best? This research sheds some lights on predicting post-test and learning gains and the resulting best models to employ for carrying out adaptive pedagogical strategies, and further advanced personalized learning.

2. Related Work

2.1. Modeling Student Learning

Modeling student cognitive processes is highly complex since it is influenced by many factors such as motivation, aptitude and learning habit. The high volume of features and tools provided by computer-based learning environments confound the task of tracking student knowledge even further. An accurate student model is a building block for any computer-based educational software that provides adaptivity and personalization. Student modeling has been widely and extensively explored in previous research. For example, prior research has proposed a series of approaches based on logistic regression including Item Response Theory (Tatsuoka, 1983), Learning Factor Analysis (Cen et al., 2006), Learning Decomposition (Beck and Mostow, 2008), Instructional Factors Analysis (Chi et al., 2011), Performance Factors Analysis (Pavlik et al., 2009), and Recent-Performance Factors Analysis (Galyardt and Goldin, 2014). These models were implemented with different parameters to better understand and model student learning and were shown to be very successful. In this work, however, we mainly focus on BKT, IBKT and LSTM.

BKT (Corbett and Anderson, 1994) is one of the most widely investigated student modeling approaches. It models a student's performance in solving problems related to a given concept using a binary variable (i.e., correct, incorrect) and continually updates its estimation on his/her learning state of that concept. Many extensions of BKT have been proposed to capture the complex and diverse aspects of student learning. Pardos and Heffernan (2010) explored individualized prior knowledge parameters based on students' overall competence. Their results showed that the proposed model outperformed conventional BKT in predicting students' responses to the last question at the end of the entire training. Additionally, Yudelson et al.

(2013) parameterized student learning rates in BKT models and the results showed that the new model outperformed conventional BKT in predicting whether the students' next responses were going to be correct/incorrect. Baker et al. (2008) investigated contextualized guess and slip rates to deal with the issues of identifiability and model degeneracy commonly observed in conventional BKT. Their results suggested that the proposed models achieved better performance in predicting students' next-step response than BKT. Pardos and Heffernan (2011) introduced problem difficulty to BKT and found substantial performance improvement in predicting student step-by-step responses over BKT. In short, BKT and BKT-based models have been shown to be effective in many student modeling tasks. While previous studies mainly applied BKT to *elicit-centric* ITSs, our studies applied BKT based models to ITSs involving multiple instructional interventions. Additionally, previous studies used students' performance (i.e., correct, incorrect) as observations, whereas we used both *performance* and *student response time* as observations for training the BKT based models.

In our prior work, Lin and Chi (2016) proposed Intervention-BKT (IBKT) that incorporates tutor's intervention (e.g., elicit and tell). Our proposed model outperformed conventional BKT in post-test score prediction, and demonstrated great potential in providing personalized intervention. Lin et al. (2016) further incorporated the effect of student response time to IBKT. The proposed IBKT model was applied to predict students' next-step responses and post-test scores and demonstrated great improvement over conventional BKT.

The Bayesian family models are straightforward and robust. Nonetheless, it's inherently difficult to fully capture the complexity and diversity of data due to its restricted functional form as a graphical model. On the other hand, deep neural network based approach such as recurrent neural network (RNN) exhibits greater flexibility compared to BKT-based models. First, they do not require explicitly encoded domain concepts. Second, they allow multivariate inputs as long as each variate can be vectorized. Finally, they are capable of learning long-term dependencies modeling complicated rules without many assumptions or prior knowledge from human experts. LSTM is a variation of RNN that addresses the exploding and vanishing gradient problems commonly observed in RNN. These deep recurrent models have shown great success in many domains such as speech recognition (Graves et al., 2013), language translation (Luong and Manning, 2015), video classification (Ng et al., 2015), and rainfall intensity prediction (Xingjian et al., 2015), etc. Their success in all these domains has opened up a new line of research in educational data mining (Piech et al., 2015; Tang et al., 2016; Khajah et al., 2016; Wilson et al., 2016; Xiong et al., 2016; Lin and Chi, 2017). For example, Lin and Chi (2017) compared both RNN and LSTM against conventional BKT to predict student learning gains and found deep learning-based models have superior performance. For the task of predicting students' responses to exercises, LSTM was shown to outperform conventional BKT (Piech et al., 2015) and Performance Factors Analysis (Pavlik et al., 2009). However, RNN and LSTM did not always have better performance when the simple, conventional models incorporated other parameters (Khajah et al., 2016; Wilson et al., 2016).

While most of the previous studies on student modeling focus on predicting students' success and failure in the next-step attempt, Feng et al. (2008) and Ritter et al. (2013) used student-tutor interaction data to predict student post-test scores. In this work, we explore the prediction of both post-test scores and student learning gains; more importantly, we investigated the early prediction of both tasks. As far as we know, none of the previous studies have explored both tasks for tutoring systems with multiple instructional interventions.

2.2. Knowledge Component Discover or Skill Discovery (SK)

In the intelligent tutoring literature, it is commonly considered that relevant knowledge in domains such as math and science is structured as a set of independent but co-occurring Knowledge Components (KCs). It is assumed that the student's knowledge state at one KC has no impact on the student's understanding of any other KCs. This is an idealization, but it has served ITS developers well for many decades and is a fundamental assumption made by many student models (Corbett and Anderson, 1994). Therefore, determining the set of skills or knowledge components required to solve a step, a problem, or an exercise is of great importance regardless of what models are used.

Cen et al. (2006) proposed Learning Factors Analysis (LFA) to improve the cognitive model by splitting or merging the KCs based on expert-identified difficulty factors. Although this method achieved better statistical scores and is highly interpretable, it heavily relies on domain expertise. González-Brenes and Mostow (2012) proposed a fully automatic method – Dynamic Cognitive Tracing, which achieved a comparable estimate on true cognitive model from which the synthetic data was created; however, it does not scale well due to the fact that both the memory and run-time grow exponentially with the number of items and skills, respectively. Barnes (2005) applied Q-matrix method to explore the question-concept relationships based on student responses; however, one assumption of the Q-matrix is that student knowledge states are static. This assumption does not often hold as students can learn from question to question when training on ITSs.

Furthermore, Thai-Nghe et al. (2012) proposed Matrix Factorization which decomposed large matrices into the product of two smaller matrices and took student dynamic knowledge states into account. Their results showed that the proposed method outperformed the original Matrix Factorization method without temporal effects (Thai-Nghe et al., 2010) in predicting whether students' next step performance is correct or wrong. Later, some studies have been conducted to apply factorization methods to derive Q-matrices that maps exercises to skills. For example, Desmarais and Naceur (2013) proposed Alternate Least-square Factorization to refine the expert-designed Q-matrices from data, and their results showed the refined Q-matrices generated better prediction results than the original expert-defined Q-matrix. Lan et al. (2014) proposed Sparse Factor Analysis to uncover skills for exercises using student performance data and they further extended the model to incorporate expert-provided skills, which outperformed existing state-of-the-art collaborative filtering techniques in terms of predicting missing student responses. Additionally, Gonzalez-Brenes and Mostow (2013) applied a Topical Hidden Markov Model for automatic skill discovery: their data-driven cognitive diagnostic model showed marginal improvement over the expert-labeled model. In this work, we applied the Skill Discovery (SK) method proposed by Lindsey et al. (2014), which can both leverage expert-provided skills and also discover new skills from student performance data automatically. More specifically, it employs a nonparametric prior to the exercise-skill assignments based on expert-designed skills and a weighted Chinese restaurant process (WCRP; Ishwaran and James 2003). By incorporating the expert-provided skills, we hypothesize that the SK approach can balance expert predefined skills and machine automatically discovered skills.

3. Method

3.1. BKT

BKT is a student modeling method extensively used in ITS. Figure 2 shows a graphical representation of the model and a possible sequence of student observations. The shaded nodes S represent hidden knowledge states. The unshaded nodes O represent observation of students' behaviors. The edges between the nodes represent their conditional dependence.

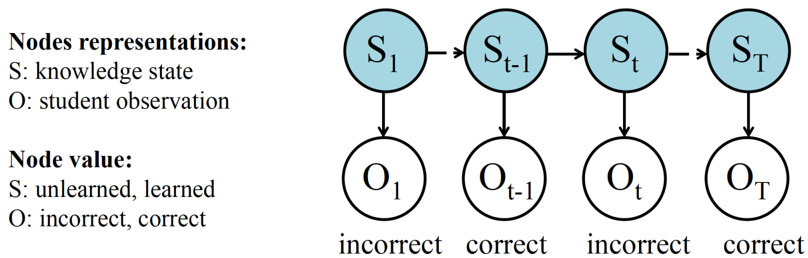


Figure 2: The Bayesian network topology of the standard Knowledge Tracing model

Fundamentally, the BKT model is a two-state Hidden Markov Model (HMM; Eddy 1996) characterized by five basic elements: 1) **N**, the number of different types of hidden state; 2) **M**, the number of different types of observation; 3) **Π**, the initial state distribution $P(S_0)$; 4) **T**, the state transition probability $P(S_{t+1}|S_t)$ and 5) **E**, the emission probability $P(O_t|S_t)$. Note that both **N** and **M** are predefined before training occurs, while **Π**, **T** and **E** are learned from the students' observation sequence.

Conventional BKT assumes there are two types of hidden knowledge state (**N**=2) corresponding to student knowledge states of *unlearned* and *learned*. It also assumes there are two types of student observation (**M**=2) correspondint to student performance of *incorrect* and *correct*. BKT makes two assumptions about its conditional dependence as reflected in the edges in Figure 2. The first assumption BKT makes is a student's knowledge state at a time t is only contingent on her knowledge state at time $t-1$. The second assumption is a student's performance at time t is only dependent on her current knowledge state. These two assumptions are captured by the state transition probability **T** and the emission probability **E**. To fit in the context of student learning, BKT further defines five parameters:

Prior Knowledge = P(S_0=learned)
Learning Rate = P(learned|unlearned)
Forget = P(unlearned | learned)
Guess = P(correct | unlearned)
Slip = P(incorrect | learned)

Baum-Welch algorithm (or EM method) is used to iteratively update the model's parameters until a maximized probability of observing the training sequence is achieved.

3.2. Intervention-BKT

Intervention-BKT is build by incorporating different types of instructional interventions into BKT. Its Bayesian network topology is displayed in Figure 3. Compared with BKT, Intervention-BKT adds a sequence of unshaded input nodes I. The arrows between input nodes I and student observation nodes O represent how instructional interventions affect a student's performance. The arrows between input nodes I and knowledge state nodes S represent how instructional interventions affect a student's hidden knowledge state.

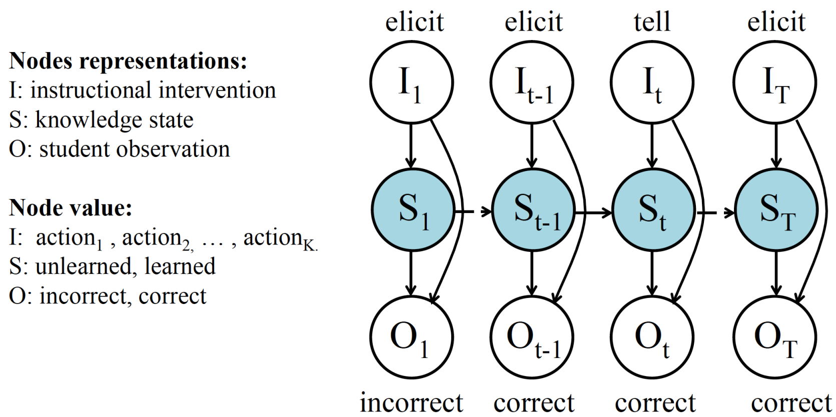


Figure 3: The Bayesian network topology of the Intervention-BKT model

Intervention-BKT is a special case of Input Output Hidden Markov Model (Marcel et al., 2000), which is extended from HMM. This model is characterized by six basic elements: 1) **K**, the number of different types of input; 2) **N**, the number of different types of hidden state; 3) **M**, the number of different types of observation; 4) **Π**, the initial state distribution $P(S_0)$; 5) **T**, the state transition probability $P(S_t|I_t, S_{t-1})$, and 6) **E**, the emission probability $P(O_t|I_t, S_t)$

Intervention-BKT makes two distinctions compared to BKT. First, it employs a parameter K representing the number of input types, that is, the instructional intervention types. Second, Intervention-BKT makes two different assumptions about its conditional dependence as represented by the edges in Figure 3: 1) a student's knowledge state at a time t is contingent on her previous state at time $t-1$ **as well as the current intervention** $\mathbf{I_t}$, and 2) a student's performance at time t is dependent on her current knowledge state S_t **as well as the current intervention** $\mathbf{I_t}$. Similarly, Our Intervention-BKT employs $1+4\times K$ parameters (compared with 5 parameters of BKT) to describe its conditional probability. The **Prior Knowledge** share the same definition as conventional BKT: **Prior Knowledge**= P(S_0=learned). For each of the K types of interventions $A_j, j \in [1, K]$, Intervention-BKT defines four parameters:

$$\textbf{Learning Rate}_{\mathbf{A_j}} = \text{P(learned}|\text{unlearned, } \mathbf{I_t} = \mathbf{A_j}\text{)}$$
$$\textbf{Forget}_{\mathbf{A_j}} = \text{P(unlearned}|\text{learned, } \mathbf{I_t} = \mathbf{A_j}\text{)}$$
$$\textbf{Guess}_{\mathbf{A_j}} = \text{P(correct}|\text{unlearned, } \mathbf{I_t} = \mathbf{A_j}\text{)}$$
$$\textbf{Slip}_{\mathbf{A_j}} = \text{P(incorrect}|\text{learned, } \mathbf{I_t} = \mathbf{A_j}\text{)}$$

In this work, we mainly focus on modeling two types of instructional intervention *elicit* and *tell*. A possible sequence of instructional interventions is suggested above input node in Figure 3. Note that the conventional BKT model is trained from a sequence of output representing student performance, whereas the Intervention-BKT model is trained from a sequence of instructional interventions and the corresponding sequence of student performance.

3.3. LSTM

LSTM (Hochreiter and Schmidhuber, 1997) is a special type of RNN which is explicitly designed to avoid the long-term dependency problem, and was refined and popularized by many people in recent works (Gers et al., 1999; Gers and Schmidhuber, 2000; Gers and Schmidhuber, 2000; Kalchbrenner et al., 2015; Xu et al., 2015). LSTM can avoid the vanishing (and exploding) gradient problem and work tremendously well on a large variety of problems.

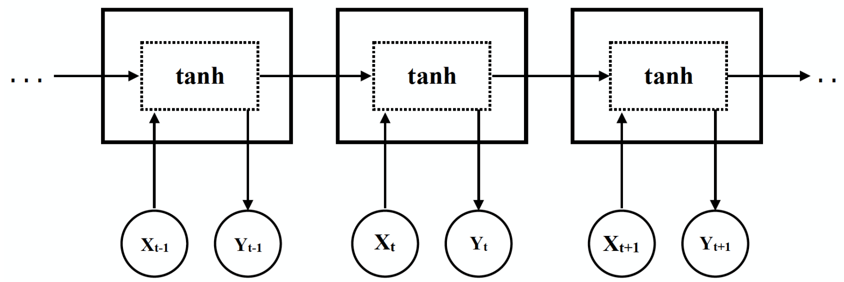


Figure 4: The network structure of an RNN (X_t represents input; Y_t represents output)

All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer, as shown in Figure 4. LSTMs also take the form of a chain like structure, but the repeating module has a different structure. The internal structure of each LSTM module is shown in Figure 5. Instead of having a single neural network layer, there are three major components including Forget, Input, and Output, thus resulting in a more complex structure than RNN. These components interact with each other to control how information flows.

In the first step, a function of the previous hidden state and the new input passes through the forget gate, indicating what is probably irrelevant and can be taken out of the cell state. The forget component will calculate a weight f_t between 0 to 1 for each element in hidden state vector C_{t-1}. An element with a weight of 0 should be completely forgotten whereas an element with a weight of 1 needs to be entirely remembered. The formula to calculate f_t is shown below where W_f and b_f are the weights and intercept, respectively for the forget component.

$$f_t = sigmoid(W_f \cdot [Y_{t-1}, X_t] + b_f) \tag{1}$$

There are two steps involved in Input component's calculation. In the first step, a tanh layer calculates a candidate vector C_t^* that could be added to the current hidden state. In the second step, the input components calculate a weight vector i_t (ranging from 0 to 1) to determine to what extend C_t^* should update the current memory state.

$$C_t^* = \tanh(W_C \cdot [h_{t-1}, x_t] + b_c) \tag{2}$$

$$i_t = sigmoid(W_i \cdot [Y_{t-1}, X_t] + b_i) \tag{3}$$

With the Forget and Input Components, the module is able to throw away the expired information in the previous cell state by calculating $C_{t-1} \cdot f_t$ and process new information by

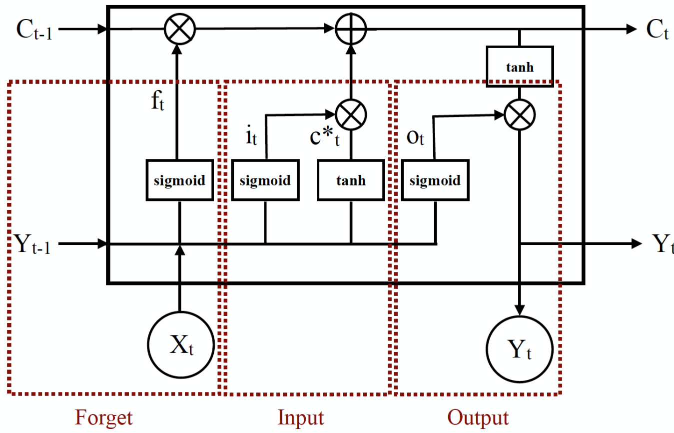


Figure 5: The network architecture within a LSTM module

computing $C_t^* \cdot i_t$. Consequently, the formula to update the current memory cell is shown below. Note that the current memory cell state C_t is then passed to the next LSTM module.

$$C_t = C_{t-1} \cdot f_t + C_t^* \cdot i_t \tag{4}$$

Finally, the output component is simply an activation function that filters elements in C_t. The C_t can be converted to a value between -1 to 1 by the $\tanh$ function. The output component calculates a weight vector

$$O_t = sigmoid(W_a \cdot [H_{t-1}, X_t] + b_o) \tag{5}$$

that determines how much information is allowed to be revealed.

$$Y_t = O_t * tanh(C_t) \tag{6}$$

To apply LSTM to our task, each student's trajectory can be seen as $\{< X_1, ...X_i, ..., X_T >, Y\}$ where T is the total number of steps, X_i is the input for a given student at timestamp i, and Y is the output: the student's post-test score or learning gain. More specifically, X_i contains the following features: 1) the skills (either designed by the expert or discovered by the SK) involved in the step i, 2) the corresponding instructional intervention determined by the tutor (e.g., *elicit* or *tell*), 3) the student's performance on the step (e.g., *correct* or *incorrect*), and 4) the student's response speed (e.g., *fast* or *slow*).

3.4. Automatic Skill Discovery

The automatic Skill Discovery (SK) method is a generative probabilistic model for student problem-solving. Following the terms used in the original paper (Lindsey et al., 2014), we will use *exercise* to refer to *steps* or *items* in our training data, and use the term *skill* to refer to KC. The SK consists of two steps: (1) apply weighted Chinese restaurant process (WCRP) to assign a prior probability of skills to each exercise (Ishwaran and James, 2003) and (2) apply BKT to calculate the likelihood of a sequence of responses produced by a student on exercises requiring a common skill.

WCRP is an extension of Chinese restaurant process (CRP; Aldous 1985), which describes a scenario in which each entering customer needs to choose a table, and each customer has a fixed affiliation and prefers to sit at tables with customers having similar affiliations. In the mapping of the WCRP to our domain, customers correspond to exercises, tables to distinct skills, and affiliations to expert labels. Thus, in our prediction tasks, we need to assign a skill to each exercise, which carries its affiliation towards the expert-identified skills. X_i denotes the expert label associated with exercise i, and Y_i represents the skill assigned to exercise i. The probability an occupied skill $y \in \{1, ..., N_{skill}\}$ is chosen when a new exercise is observed is specified via:

$$P(Y_i = y | X_i, \mathbf{X}^{(y)}) \propto n_y \frac{1 + \beta(\kappa_y^{x_i} - 1)}{1 + \beta({N_{skill}}^{-1} - 1)} \tag{7}$$

where $\mathbf{X}^{(y)}$ is the set of affiliations of exercises assigned to skill y and n_y is the number of exercises assigned to skill y. β is the previously mentioned bias, an exercise is equally likely to have any affiliation when $\beta = 0$ and all exercises of a skill will take the skill's affiliation if $\beta = 1$. κ_y^{α} is a softmax function that tends toward 1 if α is the most common affiliation among exercises of skill y, and tends toward 0 otherwise. In the WCRP, a new skill $N_{skill} + 1$ is selected with probability:

$$P(Y_i = N_{skill} + 1) \propto \alpha \tag{8}$$

Here α is defined as $\alpha = \alpha'(1 - \beta)$ and thus α' is free to modulate the expected number of the occupied skills while the term $1 - \beta$ is constricted to assign new skill when the bias is high.

The conditional probability for Y_i given the other variables is proportional to the product of the WCRP prior term and the joint likelihood of each students response sequence, where Equations 7 and 8 provide the former. For an existing table, the likelihood is given by the BKT HMM emission sequence probability. For a new table, an extra step is required to calculate the emission sequence probability because the BKT parameters do not have conjugate priors. The formula 8 from (Neal, 2000) is adopted here, and it efficiently produces a Monte Carlo approximation of the intractable data likelihood, linking BKT parameters for the new table.

Formally, the method assigns each exercise label to a latent skill such that a students expected accuracy on a sequence of same-skill exercises improves monotonically with practice (Lindsey et al., 2014). In place of discarding the expert-provided skills, the method incorporates a nonparametric prior to the exercise-skill assignments that are based on the expert-provided skills and WCRP.

4. Experiments

4.1. Training Datasets

Two training datasets were used: one was collected from a natural language tutoring system named Cordillera that teaches physics, and the other was from a standard Intelligent Tutoring System named Pyrenees that teaches probability. Both Cordillera and Pyrenees provide two types of instructional interventions: *elicit* and *tell*. When training on both tutoring systems, students went through a standard "pretest-training-posttest" procedure. It is important to note that while our definition of learning gain is based on student pre-test and post-test scores, we only used **the student-ITS interaction trajectories** to predict student post-test scores and learning gains.

4.1.1. Cordillera

Cordillera (Figure 6) is a natural language ITS for college-level introductory physics. Five domain experts identified 7 primary KCs, and they labeled each step with corresponding KCs, kappa > 0.8. All participants in our training corpus went through the following procedures: 1) completed a survey, 2) read a textbook, 3) took a pretest, 4) solved seven training problems, and 5) took a post-test at the end.

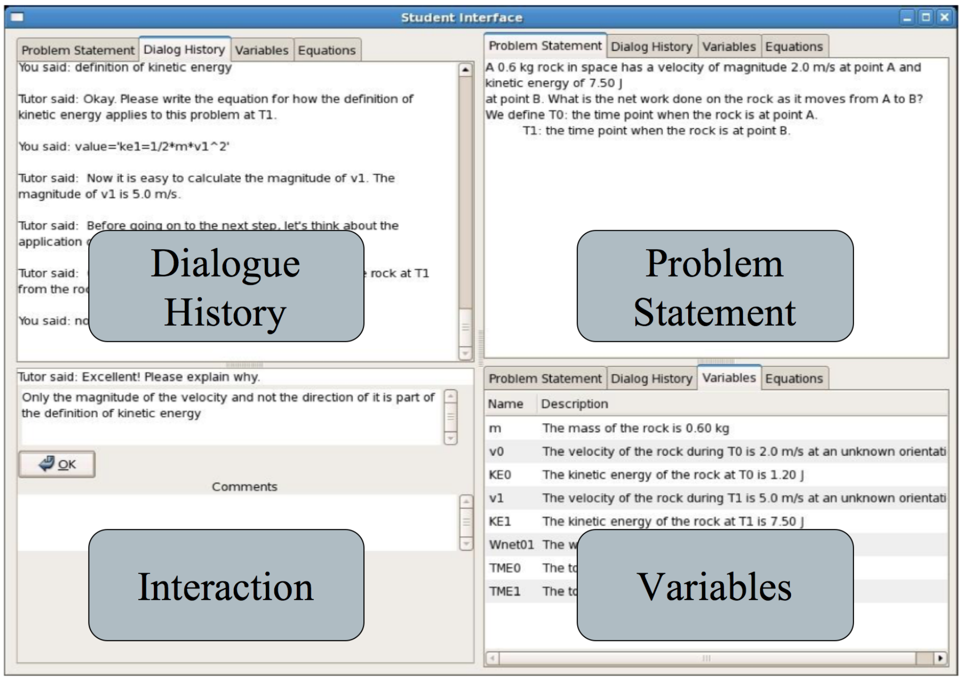


Figure 6: The Cordillera Interface

In total, there are 44,323 data points from 169 students. Each student completed around 300 training problem steps. A data point in our training dataset is either the first student attempt in response to a tutor *elicit*, or a tutor *tell* indicating the next step. The pretest and post-test have the same 33 test items. All of the tests were graded in a double-blind manner by a single domain expert (not the authors). Each test question was assigned two types of grades: an overall grade and a KC-based grade. The overall grade was a score in the range [0, 1] describing the correctness of an answer as a whole, while the KC-based grade was a score in the same range describing the correctness regarding a particular KC.

4.1.2. Pyrenees

Overall, Pyrenees' dataset is comprised of 68,740 data points from 475 students. Pyrenees is a web-based ITS teaching probability, which covers 10 major KCs, such as the Addition Theorem, the Complement Theorem, and Bayes Rule, etc. Domain experts both identified the 10 KCs and labeled each step/exercise with the corresponding KCs, kappa > 0.9. Figure 7 shows the interface of Pyrenees which consists of a problem statement window, a variable and equation window, and a tutor-student dialogue window. Through the dialogue window, Pyrenees provides messages to the students. It can explain a worked example or prompt the student to complete the next step. Students can enter their inputs in the text area. Any variable or equation that is defined through this process is displayed on left side of the screen for reference. In Pyrenees, whenever an answer is submitted, the tutor provides immediate feedback. In addition to this, Pyrenees can also provide on-demand hints. The bottom-out hint tells the student exactly how to solve a problem.

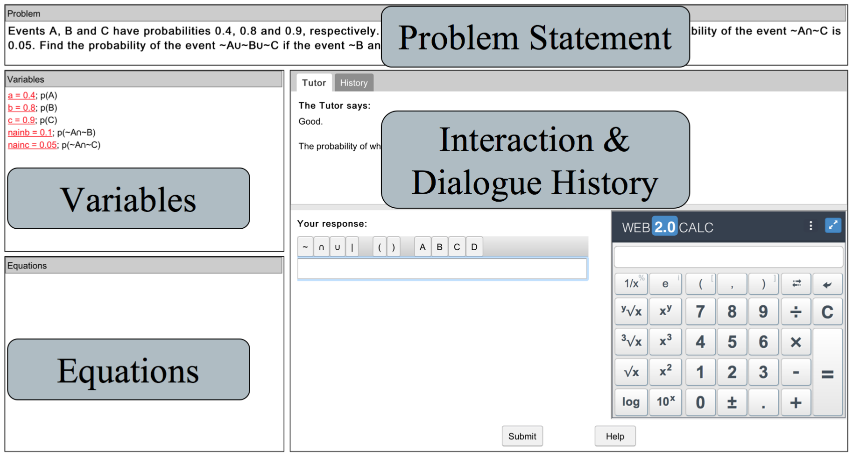


Figure 7: The Pyrenees Interface

When training on Pyrenees, students were required to complete 4 phases: 1) pre-training, 2) pretest, 3) training, and 4) post-test. During the pre-training phase, all students studied the domain principles from a probability textbook. The students then took a pretest which contained 10 problems. The textbook was not available. They were not given feedback on their answers, nor were they allowed to go back to earlier questions. During the training phase, students received the same 12 training problems in the same order on Pyrenees. Each domain concept was applied at least twice. The minimum number of steps needed to solve each training problem ranged from 10 to 50. The number of domain principles required to solve each problem ranged from 3 to 11. Finally, all of the students took a post-test with 16 problems. As with Cordillera, both pretests and post-tests were graded in a double-blind manner by a single experienced grader. The scores were normalized using a range of [0,1].

4.2. Quantized Learning Gain

In our study, the models were not only applied for post-test scores prediction, but also learning gains prediction. We argue the latter is much more challenging because students who perform well in the pretest or during the training often perform well in the post-test, but may or may not benefit from the tutor. For example, on both datasets used here, we found a significant strong positive correlation between students' pre- and post-test scores: $r = 0.76$ and $p = 4.60 \times 10^{-33}$ for Cordillera, and $r = 0.673$ and $p = 6.04 \times 10^{-46}$ for Pyrenees respectively; however, no strong correlation was found between students' pretest and Normalized Learning Gain: $r = -0.04$ and $p = 0.607$ for Cordillera, and $r = -0.02$ and $p = 0.683$ for Pyrenees.

The concept of *learning gain* is formally defined as the difference between the skills, competencies, content knowledge and personal development demonstrated by students at two points in time (McGrath et al., 2015). Many studies used *Learning Gain* (LG), calculated as $LG = post - pre$, where pre and $post$ refer to a student's pre-test and post-test scores (Luckin et al.,

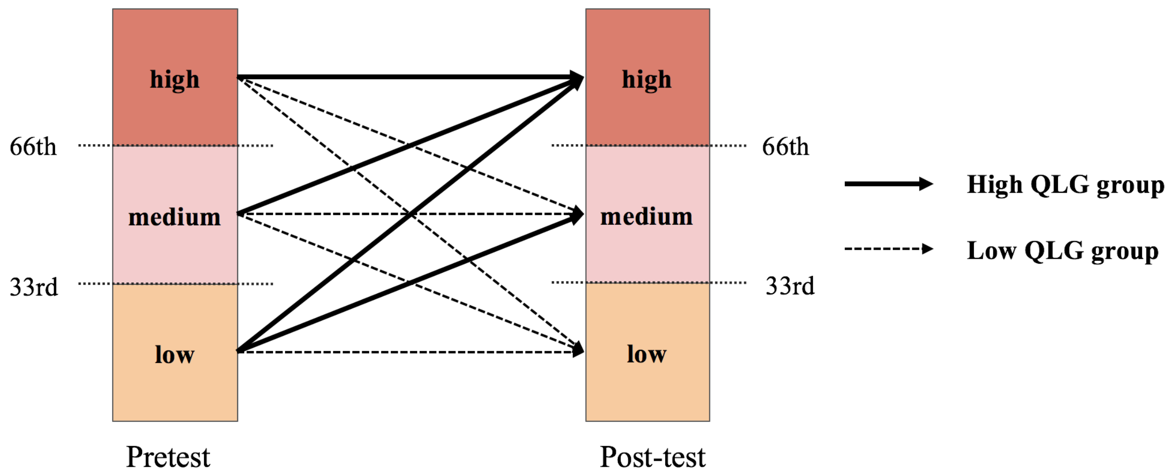


Figure 8: Quantized Learning Gain

2007). A widely used adjusted measurement, *Normalized Learning Gain* (NLG) was proposed to ensure a consistent analysis over a population with different levels of proficiency: NLG = $\frac{post-pre}{1-pre}$ (Hake, 2002) where 1 is the maximum score for pre- and post-tests. Fundamentally, the NLG can be seen as how much a student improves from pretest to post-test ($post - pre$) divided by how much he/she can improve ($1 - pre$). The values of NLG range from (-∞, 1]. A negative NLG occurs when a student gets higher pretest score than post-test score. Thus, NLG can be problematic for students with high pretest scores in that even a modest decline in post-test score from the pre-test can result in large negative NLG. For example, a student who scored 0.99 in the pretest and 0.95 in the post-test would have an NLG of -4 while if he/she scored 0.95 in the pretest and 0.99 in the post-test would have an NLG of 0.8. Such asymmetry is one of the main criticisms of using NLG. Therefore, we used a qualitative measurement called *Quantized Learning Gain* (QLG; Lin and Chi 2017) to determine whether a student has benefited from a learning environment.

Our QLG is a *binary* qualitative measurement on students' learning gains from pretest to the posttest: High vs. Low. To infer QLGs, students were split into low, medium, and high based on whether they scored below the 33rd percentile, between the 33rd and 66th percentile, or higher than the 66th percentile in pre-test and post-test respectively. Once a student's pre- and post-test performance groups are decided, the student is a "High" QLG if he/she moved from a lower performance group to a higher performance group from pre-test to post-test or remained in "high" performance groups; whereas a "Low" QLG is assigned to the student if he/she either moved from a higher performance group to a lower performance group from pre-test to post-test, or stayed at a "low" or "medium"groups (as shown in Figure 8). In Figure 8, solid lines represented the formation of the *High* QLG groups and dashed lines represents the formation of the *Low* QLG groups, and they will be coded with "1" and "0" respectively for QLG prediction.

4.3. Models Configuration

In our work, six models (BKT, IBKT, LSTM, BKT+SK, IBKT+SK, LSTM+SK) were evaluated across two datasets (*Cordillera*, *Pyrenees*), where SK indicates the incorporation of the automatically discovered KCs. For the implementation of the SK method, parameter settings from original study (Lindsey et al., 2014) were adopted and fed to the two datasets used. We focused on two prediction tasks. The first task was to predict their post-test scores, referred to as "post-test scores predictions". The second task was to predict their Quantized Learning Gain (QLG), referred to as "learning gain predictions".

Unlike the conventional BKT family models, which only use students' performance (e.g., *correct* and *incorrect*), we also included their speed of response. It is denoted by one of two symbols: *quick* and *slow*. The symbols were assigned by comparing the student's response time on that step with the median response time of all students on the same step. If the time is greater than the median, we classify it as *slow*, otherwise, *quick*. Thus, we combined students' performance and speed, resulting in four different values: *correct-quick*, *correct-slow*, *incorrect-quick*, and *incorrect-slow*. Following the classic BKT assumption that students never forget the knowledge once they have learned it, we also set $P(unlearned|learned) = 0$ for all the BKT based models in this study.

To train BKT based models, two steps were involved. In the first step, the probability of a student being in the *learned* state on each KC at the last attempt was learned from the BKT/IBKT models. In the second step, the output of the first step was computed as features for our prediction tasks. That is, the number of features involved here equals to the total number of KCs involved. Linear regression and logistic regression were applied to predict post-test scores and QLG respectively. Here linear regression and logistic regression are selected as our prediction models because they are the activation functions used by LSTM models to predict the post-test scores and QLG respectively (described in next paragraph). Additionally, we also compared linear regression and logistic regression against other popular models such as Support Vector Machine, and the former two had better performance, therefore, they are used for comparing BKT based models with LSTM based ones.

To train LSTM, sequences of tuples representing student-system interactions were extracted. The tuples consist of four elements: 1) the assignment of KCs, 2) the instructional interventions, 3) the student response time, and 4) performance. Instead of directly applying an existing LSTM module, we explored the effectiveness of two-layer LSTM with an output layer to make a final prediction. The same as the BKT based models, linear was selected for post-test prediction and sigmoid was used for QLG prediction. Different numbers of units ranging from 5 to 200 were tested and the best model was chosen based on the 5-fold cross-validation results. We also applied early stopping callbacks to avoid the potential overfitting problem.

5. Results

5.1. Automatic Skill Discovery Results

The overall results from automatic skill discovery are presented in Table 1. The column *Dataset* indicates the two training datasets, and the *Students* column gives us the total number of students in each training dataset. The column *Items* shows the number of unique exercises, steps, or items in each dataset, and we note that each item only involves one KC based on expert labels. And the rightmost two columns display the number of expert-designed KCs and the total number of KCs discovered by SK. The SK method tends to find more skills than those identified by the experts: 24 vs. 7 on Cordillera, and 15 vs. 10 on Pyreness. The discrepancy in the skills identified accross the two datasets might be explained by the fact that physics taught in Cordillera may involve more KCs than probability taught in Pyrenees.

Table 1: Results of the SK Discovery Method

Dataset	Students	Items	Expert Skills	Discovered Skills
Cordillera	169	1187	7	24
Pyrenees	475	176	10	15

Furthermore, some preliminary explorations on the skills discovered by the SK method showed that they are indeed different from the expert labels. For example, in Pyrenees, the expert originally labeled both $P(D|B)$ and $P(D|A \cap B \cap C)$ with the same KC, "the Bayes rule". However, two different KCs were assigned to them by SK, more specifically, "the Bayes rule to an atomic event" is assigned to $P(D|B)$ while "the Bayes rule to a combination of events" is assigned to $P(D|A \cap B \cap C)$.

5.2. Post-test Prediction

5-fold cross-validation Root Mean Square Error (RMSE) was used to evaluate the models (Table 2). RMSE measures the difference between the predicted post-test scores and the actual post-test scores: the lower the value, the higher the predictive accuracy.

5.2.1. Comparison between Models

Table 2: RMSE in Post-test Score Prediction

Model		Data	
		Cordillera	Pyrenees
Non-SK models			
1	BKT	**0.147***	0.162
2	IBKT	0.177	0.168
3	LSTM	0.183	0.179
SK models			
4	BKT+SK	0.149	**0.159***
5	IBKT+SK	0.179	0.160
6	LSTM+SK	0.175	0.180
Note: best model in **bold** and *			

Table 2 shows the performance of the six models on the post-test score prediction using the entire student training trajectories on the corresponding ITS. The best model is labeled in *bold* and *. Among the three basic models (row 1, 2, 3), conventional BKT outperformed both IBKT and LSTM across two datasets. The same pattern was found when incorporating automatic skill discovery into the three models (row 4, 5, 6): BKT+SK generated lower RMSE than IBKT+SK and LSTM+SK. BKT and BKT+SK are the two best models for both datasets in the task of predicting students post-test scores.

On the other hand, it was not very clear how much SK helps for each model when using the entire sequences to predict students' post-test scores. Overall, the improvement of using SK over using the expert-designed KCs can be negligible. For the three basic models, sometimes SK can help: LSTM+SK outperformed LSTM for Cordillera, BKT+SK and IBKT+SK outperformed BKT and IBKT respectively for Pyrenees. But sometimes SK can even reduce the performance: BKT+SK is worse than BKT, IBKT+SK is worse than IBKT for Cordillera and LSTM+SK is worse than LSTM for Pyrenees.

5.2.2. Early Prediction on Post-test Scores

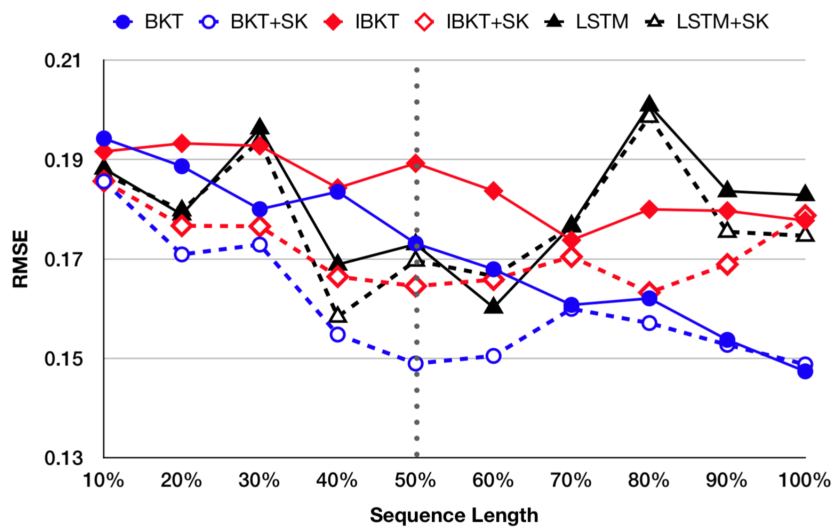


Figure 9: RMSE for Post-test Early Prediction On Cordillera

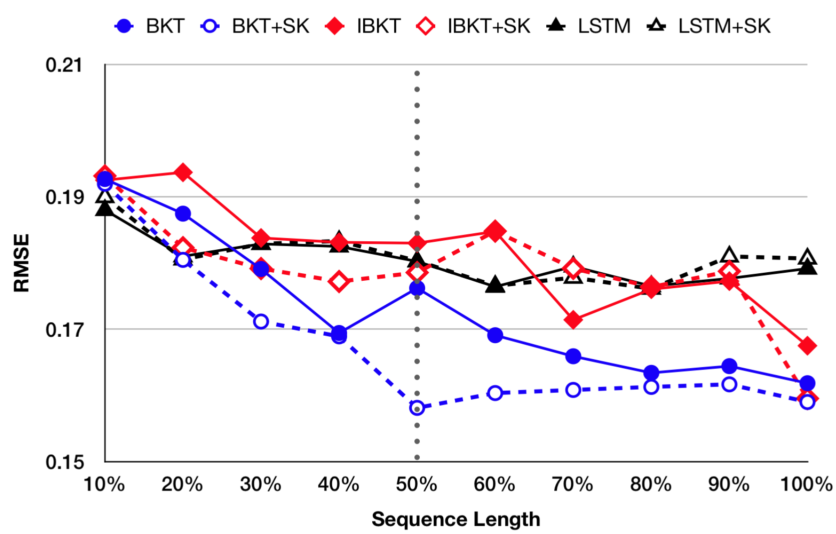


Figure 10: RMSE for Post-test Early Prediction On Pyrenees

Next, we investigated all the models' power on post-test score early prediction. Figure 9 and Figure 10 show the 5-fold cross-validation RMSE for Cordillera and Pyrenees respectively.

BKT models are in blue with circular symbols, IBKT models are in red with square symbols, and LSTM models are in black with triangular symbols. Solid lines with solid symbols represent basic models (BKT, IBKT, and LSTM), and dashed lines with blank symbols represent models with SK (BKT+SK, IBKT+SK and LSTM+SK). The y-axis is the RMSE and the x-axis is the sequence length used for early prediction.

While BKT and BKT+SK perform similarly when using the entire sequences, Figure 9 and Figure 10 show that BKT+SK is the best model. Indeed, it outperforms the other models substantially which is evident by the fact that BKT+SK outperformed all the other models starting from 20% all the way to 100%. The results are consistent with both tutoring systems.

More importantly, for both tutoring systems, BKT+SK can predict post-test scores using only 50% of the sequences as effectively as using the entire sequences. Take Cordillera as an example (Figure 9), the RMSE is improved from 10% to 40% (0.186 to 0.155); from 40% to 50%, the improvement becomes moderate (0.155 to 0.149); from 50% to the remaining of the sequences, there is no improvement (0.149 to 0.149). A similar pattern is observed for Pyrenees (Figure 10). From 10% to 50%, the RMSE decreases gradually as more observations become available (from 0.192 to 0.158); however, from 50% to 100%, the RMSE is seemingly stabilized (from 0.158 to 0.159). For BKT, on the other hand, it does not predict post-test scores as reliably as using the entire sequences when using the Cordillera dataset. The same is true when 80% of the entire sequences are used for Pyrenees.

In short, our early prediction results clearly show the benefits of using SK. Most notably, BKT+SK achieves the best results: it reliably predicts post-test scores using only 50% of the training sequences for both systems.

5.3. QLG Prediction

For QLG prediction, we are primarily interested in identifying students with *low* learning gain. This is because we believe it is more important to recognize those who do not benefit from the tutor preferably as soon as possible since these students may have benefited from the system if other interventions were available.

5-fold cross-validation accuracy, recall, F1-measure, and AUC are reported in Table 3 for QLG prediction. Accuracy measures the fraction of correctly classified students; recall measures the fraction of low learning gain students that are correctly retrieved by the models; F1-measure is the weighted average of recall and precision (measuring the percentage of the predicted low learning gain students whose learning gain is indeed low) and thus F1-measure tells us how robust the model is; and AUC measures the ability of models to discriminate low learning gain students from the high group. For all measurements, the closer to 1, the better.

5.3.1. Comparison between Models

Table 3 shows the performance of the six models using the entire training sequences to predict students' QLG on Cordillera (Table 3(a)) and Pyrenees (Table 3(b)). The first rows in both tables are the baseline models using majority vote. Note that we ignore the Recall and F1-measure of the simple Majority baseline. Table 3(a) shows that two LSTM-based models (row 4, 7) outperformed all other models on every measure except Recall. IBKT achieves the highest recall (0.761), and LSTM achieves the second-best recall (0.739). Table 3(b) shows that two LSTM-based models (row 4, 7) outperformed all other models on every measure on

Table 3: QLG Prediction Results on Cordillera and Pyrenees for All Seven Models

	Model	Accuracy	Recall	F1-measure	AUC
1	Majority	0.544	-	-	0.5
		Non-SK models			
2	BKT	0.663	0.641	0.674	0.665
3	IBKT	0.615	**0.761***	0.683	0.601
4	LSTM	**0.740***	0.739	**0.756** *	0.740
		SK models			
5	BKT+SK	0.674	0.739	0.712	0.668
6	IBKT+SK	0.633	0.685	0.670	0.628
7	LSTM+SK	**0.740***	0.696	0.744	**0.744***
Note: best model in **bold** and *					

(a) Cordillera dataset

	Model	Accuracy	Recall	F1-measure	AUC
1	Majority	0.562	-	-	0.5
		Non-SK models			
2	BKT	0.665	0.685	0.697	0.662
3	IBKT	0.659	0.749	0.712	0.646
4	LSTM	0.724	**0.790***	0.763	0.715
		SK models			
5	BKT+SK	0.682	0.674	0.705	0.683
6	IBKT+SK	0.665	0.783	0.724	0.649
7	LSTM+SK	**0.733***	0.772	**0.765***	**0.727***
Note: best model in **bold** and *					

(b) Pyrenees dataset

Pyrenees. Therefore, among the three basic models BKT, IBKT, and LSTM, LSTM has the best performance for both tutoring systems.

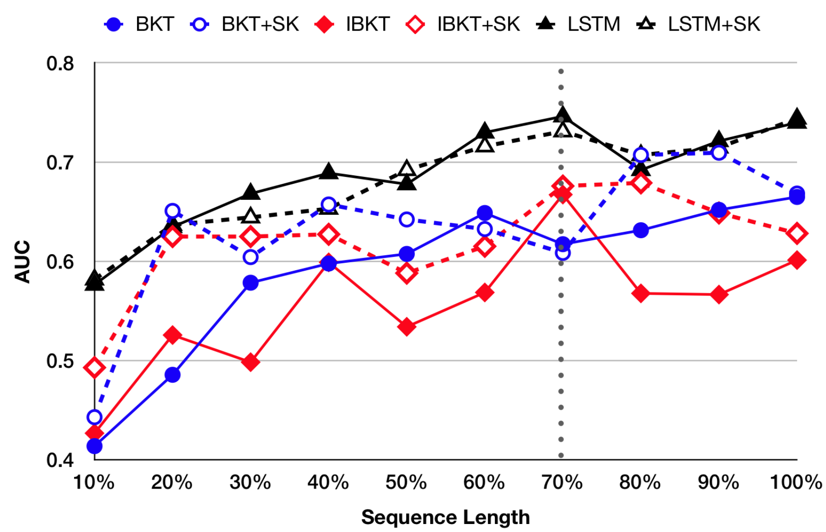
Comparing models using SK, again, LSTM+SK generally has the best performance for both tutoring systems. When comparing LSTM and LSTM+SK, it seems that SK improves accuracy and AUC, but not on recall. On both datasets, LSTM+SK performs worse than LSTM on recall, which may also explain the decline of the F1-measure in Cordillera.

5.3.2. Early Prediction of QLG

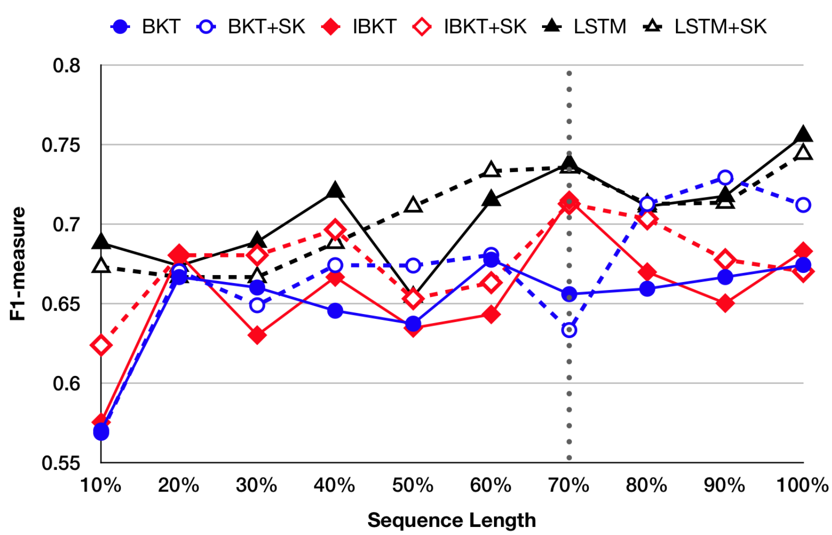
Since AUC calculates the tradeoff between recall and specificity, and F1 is the harmonic mean of Precision and Recall that sets their trade-off, in the following, we will mainly use F1 and AUC to compare different models on early prediction of QLG. For both measures, the higher, the better.

Figure 11 shows the six model's performances on the early prediction of QLG for Cordillera.

Figure 11 shows that two LSTM models in black (LSTM, LSTM+SK) outperform the other four Bayesian models at most points across the x-axis on Cordillera. Between the two LSTM models, LSTM (solid black) seems to be more powerful than LSTM+SK (dashed black) especially between 20% to 40%, while LSTM+SK has better F1-measure between 50% to 70%. For the LSTM model, both AUC and F1-measure increase from 10% to 40%: from 0.576 to 0.689 for AUC and from 0.688 to 0.720 for F1-measure; the increase becomes moderate (from 0.688 to 0.746 for AUC; from 0.720 to 0.738 for F1-measure) from 40% to 70%, and finally there is only a slight increase on F1-measure (from 0.738 to 0.756), and a slight decrease on AUC (from

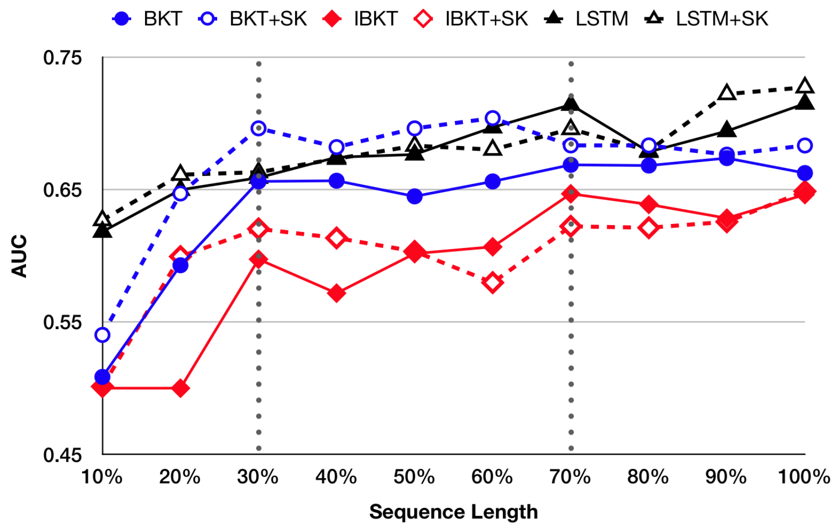


(a) AUC

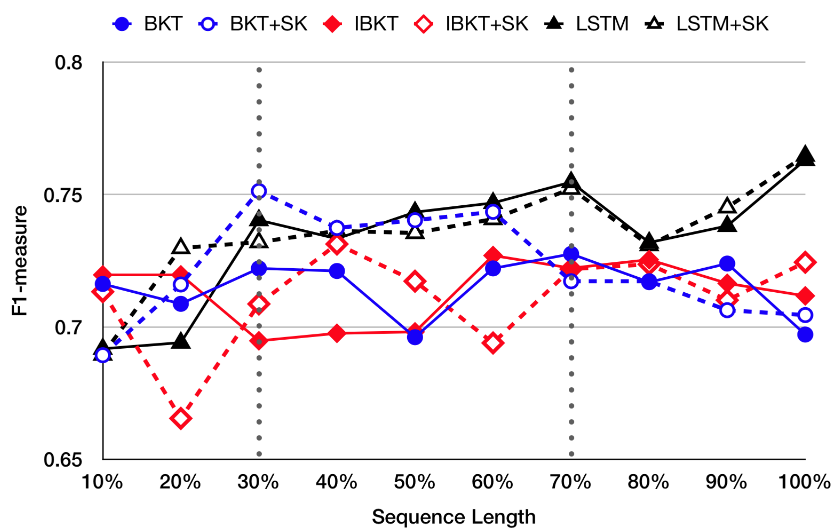


(b) F1-measure

Figure 11: AUC and F1-measure for Low QLG Detection On Cordillera



(a) AUC



(b) F1-measure

Figure 12: AUC and F1-measure for Low QLG Detection On Pyrenees

0.746 to 0.740) between 70% to 100%. The results suggest that a *reasonable* prediction of QLG can be accomplished by using the first 40% of the entire sequences, and that using the earliest 70% of the sequences is as good as using the entire sequences.

Figure 12 shows the six model's performances on QLG early prediction on Pyrenees. When the entire sequences (100%) are used, the two LSTM models in black obtain the highest scores on both AUC and F1-measure. However, for early prediction, BKT+SK achieves a better or a comparable performance compared to the two LSTM models when using 20% to 60% of training sequences. Indeed, BKT+SK (blue dashed line with circle points) exhibits an excellent prediction on QLG with only the first 30% of the entire sequences, 0.696 on AUC and 0.751 on F1-measure. Both measures are close to the best model LSTM using the entire training sequences. By contrast, LSTM only achieves 0.659 on AUC and 0.740 on F1-measure with

30% of the sequence. Note that this results only hold for Pyrenees dataset.

Additionally, from 70% to 100%, the two LSTM models outperform other models, and when using 70% of the entire sequences, the LSTM reach a similar result (0.714 on AUC and 0.755 on F1-measure) compared to the results of using the entire sequences.

6. Discussions, Limitations, and Future Work

In this work, we investigated three basic student models: BKT, IBKT, and LSTM, as well as their SK variants: BKT+SK, IBKT+SK, and LSTM+SK. Among the six models, four of them belong to the Bayesian family (BKT, BKT+SK, IBKT, and IBKT+SK), and the other two fall in the deep learning group (LSTM, LSTM+SK). The effectiveness of these models was tested using two training datasets involving instructional interventions. The models were applied to two different student modeling tasks: post-test scores and learning gains.

For the task of post-test score prediction, while BKT and BKT+SK are the best models when using the entire training sequence, BKT+SK is shown to be the best model for post-test early prediction. BKT+SK can reliably predict post-test scores when the earliest 50% of its training sequence is used and the result is comparable to using the entire sequence for both training datasets. One potential explanation is that the SK method tends to enrich the skill set and generate more skills than expert KC models which may also be a better model for the domain. Since the performance of BKT models generally heavily depends on the effectiveness of KC models, it can explain why BKT+SK outperformed BKT models on the early prediction of post-test scores.

For the task of the QLG prediction, LSTM and LSTM+SK are the best two models when the entire sequence is used and LSTM is the best model for QLG early prediction as it can reliably predict QLG. Using the earliest 70% of the training sequences, LSTM achieves similar performance as when the entire sequence is used. Back to the internal structure of these models, LSTM is much more complicated than BKT and IBKT, which enables it to capture the changes of *students'* learning state better. And we believe that LSTM is able to discover the hidden information that BKT-based models missed and also it explains why the SK method did not help much here.

Overall, we make the following contributions: 1) our work compared the effectiveness of Bayesian based models and deep neural network-based models on two important student modeling tasks: post-test scores and learning gains prediction, 2) we explored the robustness and the effectiveness of the proposed models on *early prediction* tasks for both post-test scores and learning gains on two training datasets involving different instructional interventions, and 3) for both Bayesian based models and deep neural network based models, we explored the impact of using automatically discovered KCs.

Despite our best efforts, our work has the following limitations. First of all, the observations on *tell* interventions are noisy because it is impossible to know the exact duration that a student spent on a *tell* step and thus we used "fast and no performance observed" for all tells regardless. While our systems logged the time when the action *tell* is carried out, students often do not read the text until a related question is asked and thus it is not clear how long students actually read the text presented on the screen. We believe that this is probably the reason why the IBKT and LSTM models did not outperform the BKT models on post-test scores prediction. In order to accurately model the impact of *tell*, we should consider using eye tracking techniques for the future.

Additionally, here we explored two important student modeling tasks: post-test scores and QLG predictions, but these two scores are not always available for many public educational datasets. So, a general method is needed for handling datasets without these scores. Moreover, both of the two datasets in this work involve two instructional interventions: *elicit* and *tell*. It is not clear whether the same conclusions still hold for datasets involving either only one of the interventions (e.g., elicit only) or other types of interventions, such as *skip* (*elicit* a question without asking students for responses) and *justify* (ask students to explain after they provide an answer).

Moreover, we can further improve our models by defining better observation symbols. In our work, we split students' response time into two levels: *fast* and *slow* and a more reasonable approach may be splitting it into three levels: *fast*, *normal*, and *slow*. Also, we applied QLG to instantiate students' learning gains, which also has some limitations. For example, the current QLG definition would label a student who scored 1% and 32% in the pre- and post-test as Low QLG, the same category as another student who scored 32% and 30% in the pre-test and post-test respectively even though the performance of the former student improved while the performance for the latter student decreased. In future work, we can come up with a composite score including QLG and other metrics, e.g., NLG, to measure students' learning gain with greater accuracy.

Finally, we will continue to investigate the automatic skills discovered in this work and to improve our SK method. The current SK method heavily relied on the labels from domain experts, so it is not clear whether it can fully recover or even outperform the expert labels if starting from scratch. On the other hand, the interpretability of the latent discovered skills has not been fully explored and further work is needed. Finally, compared with the high interpretability of BKT based models, it is more challenging to interpret the learned LSTM models and what factors are indeed impact student learning gains. Moreover, in this work, the hyperparameters such as the number of neurons in each layer was manually tuned. For future work, we will not only explore how to tune hyperparameters through a more systematic approach, but also investigate the following questions: 1) how to determine what patterns are predictable for students' learning gain through the trained parameters; 2) how to predict students' learning gain at a very early stage when few observations are available and suggest effective intervention accordingly.

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8. EDITORIAL STATEMENT

Min Chi had no involvement with the journal's handling of this article in order to avoid a conflict with her Special Track Editor role. The entire review process was managed by Special Track Editor Irena Koprinska with oversight from JEDM Editor Andrew Olney.

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