How Deep is Knowledge Tracing?

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ABSTRACT

In theoretical cognitive science, there is a tension between highly structured models whose parameters have a direct psychological interpretation and highly complex, general-purpose models whose parameters and representations are difficult to interpret. The former typically provide more insight into cognition but the latter often perform better. This tension has recently surfaced in the realm of educational data mining, where a deep learning approach to predicting students' performance as they work through a series of exercises—termed *deep knowledge tracing* or *DKT*—has demonstrated a stunning performance advantage over the mainstay of the field, *Bayesian knowledge tracing* or *BKT*. In this article, we attempt to understand the basis for DKT's advantage by considering the sources of statistical regularity in the data that DKT can leverage but which BKT cannot. We hypothesize four forms of regularity that BKT fails to exploit: recency effects, the contextualized trial sequence, inter-skill similarity, and individual variation in ability. We demonstrate that when BKT is extended to allow it more flexibility in modeling statistical regularities—using extensions previously proposed in the literature—BKT achieves a level of performance indistinguishable from that of DKT. We argue that while DKT is a powerful, useful, general-purpose framework for modeling student learning, its gains do not come from the discovery of novel representations—the fundamental advantage of deep learning. To answer the question posed in our title, knowledge tracing may be a domain that does *not* require 'depth'; shallow models like BKT can perform just as well and offer us greater interpretability and explanatory power.

1. INTRODUCTION

In the past forty years, machine learning and cognitive science have undergone many paradigm shifts, but few have been as dramatic as the recent surge of interest in *deep learning* [16]. Although deep learning is little more than a re-branding of neural network techniques popular around 1990, deep learning has achieved some remarkable results thanks to much faster computing resources and much larger data sets than were available in 1990. Deep learning underlies state-of-the-art systems in speech recognition, language processing, and image classification [16, 26]. Deep learning also is responsible for systems that can produce captions for images [29], create synthetic images [9], play video games [19] and even Go [27].

The 'deep' in deep learning refers to multiple levels of representation transformation that lie between model inputs and outputs. For example, an image-classification model may take pixel values as input and produce a labeling of the objects in the image as output. Between the input and output is a series of representation transformations that construct successively higher-order features—features that are less sensitive to lighting conditions and the position of objects in the image, and more sensitive to the identities of the objects and their qualitative relationships. The features discovered by deep learning exhibit a complexity and subtlety that make them difficult to analyze and understand (e.g., [31]). Furthermore, no human engineer could wire up a solution as thorough and accurate as solutions discovered by deep learning. Deep learning models are fundamentally *non-parametric*, in the sense that interpreting individual weights and individual unit activations in a network is pretty much impossible. This opacity is in stark contrast to parametric models, e.g., linear regression, where each of the coefficients has a clear interpretation in terms of the problem at hand and the input features.

In one domain after the next, deep learning has achieved gains over traditional approaches. Deep learning discards hand-crafted features in favor of representation learning, and deep learning often ignores domain knowledge and structure in favor of massive data sets and general architectural constraints on models (e.g., models with spatial locality to process images, and models with local temporal constraints to process time series).

It was inevitable that deep learning would be applied to student-learning data [22]. This domain has traditionally been the purview of the educational data mining community, where *Bayesian knowledge tracing*, or *BKT*, is the dominant computational approach [3]. The deep learning approach to modeling student data, termed *deep knowledge tracing* or *DKT*, created a buzz when it appeared at the Neural Information Processing Systems Conference in December 2015, including press inquiries (N. Heffernan, personal communication) and descriptions of the work in the blogosphere (e.g., [7]). Piech et al. [22] reported substantial improvements in prediction performance with DKT over BKT on two real-world data sets (Assistments, Khan Academy) and one synthetic data set which was generated under assumptions that are not tailored to either DKT or BKT. DKT achieves a reported 25% gain in AUC (a measure of prediction quality) over the best previous result on the Assistments benchmark.

In this article, we explore the success of DKT. One approach to this exploration might be to experiment with DKT, removing components of the model or modifying the input data to determine which model components and data characteristics are essential to DKT's performance. We pursue an alternative approach in which we first formulate hypotheses concerning the signals in the data that DKT is able to exploit but that BKT is not. Given these hypotheses, we propose extensions to BKT which provide it with additional flexibility, and we evaluate whether the enhanced BKT can achieve results comparable to DKT. This procedure leads not only to a better understanding of how BKT and DKT differ, but also helps us to understand the structure and statistical regularities in the data source.

1.1 Modeling Student Learning

The domain we're concerned with is electronic tutoring systems which employ cognitive models to track and assess student knowledge. Beliefs about what a student knows and doesn't know allow a tutoring system to dynamically adapt its feedback and instruction to optimize the depth and efficiency of learning.

Ultimately, the measure of learning is how well students are able to apply skills that they have been taught. Consequently, student modeling is often formulated as time series prediction: given the series of exercises a student has attempted previously and the student's success or failure on each exercise, predict how the student will fare on a new exercise. Formally, the data consist of a set of binary random variables indicating whether student s produces a correct response on trial t, $\{X_{st}\}$. The data also include the exercise labels, $\{Y_{st}\}$, which characterize the exercise. Secondary data has also been incorporated in models, including the student's utilization of hints, response time, and characteristics of the specific exercise and the student's particular history with related exercises [2, 30]. Although such data improve predictions, the bulk of research in this area has focused on the primary measure—whether a response is correct or incorrect—and a sensible research strategy is to determine the best model based on the primary data, and then to determine how to incorporate secondary data.

The exercise label, Y_{st}, might index the specific exercise, e.g., $3+4$ versus $2+6$, or it might provide a more general characterization of the exercise, e.g., *single digit addition*. In the latter case, exercise are grouped by the *skill* that must be applied to obtain a solution. Although we will use the term skill in this article, others refer to the skill as a *knowledge component*, and the authors of DKT also use the term *concept*. Regardless, the important distinction for the purpose of our work is between a label that indicates the particular exercise and a label that indicates the general skill required to perform the exercise. We refer to these two types of labels as *exercise indexed* and *skill indexed*, respectively.

1.2 Knowledge Tracing

BKT models skill-specific performance, i.e., performance on a series of exercises that all tap the same skill. A separate instantiation of BKT is made for each skill, and a student's raw trial sequence is parsed into skill-specific subsequences that preserve the relative ordering of exercises within a skill but discard the ordering relationship of exercises across skills. For a given skill σ, BKT is trained using the data from each student s, $\{X_{st}|Y_{st}=\sigma\}$, where the relative trial order is preserved. Because it will become important for us to distinguish between absolute trial index and the relative trial index within a skill, we use t to denote the former and use i to denote the latter.

BKT is based on a theory of all-or-none human learning [1] which postulates that the knowledge state of student s following the i'th exercise requiring a certain skill, K_{si}, is binary: 1 if the skill has been mastered, 0 otherwise. BKT, formalized as a hidden Markov model, infers K_{si} from the sequence of observed responses on trials $1 \ldots i$, $\{X_{s1}, X_{s2}, \ldots, X_{si}\}$. BKT is typically specified by four parameters: $P(K_{s0}=1)$, the probability that the student has mastered the skill prior to solving the first exercise; $P(K_{s,i+1}=1 \mid K_{si}=0)$, the transition probability from the not-mastered to mastered state; $P(X_{si}=1 \mid K_{si}=0)$, the probability of correctly *guessing* the answer prior to skill mastery; and $P(X_{si}=0 \mid K_{si}=1)$, the probability of answering incorrectly due to a *slip* following skill mastery. Because BKT is typically used in modeling practice over brief intervals, the model assumes no forgetting, i.e., K cannot transition from 1 to 0.

BKT is a highly constrained, structured model. It assumes that the student's knowledge state is binary, that predicting performance on an exercise requiring a given skill depends only on the student's binary knowledge state, and that the skill associated with each exercise is known in advance. If correct, these assumptions allow the model to make strong inferences. If incorrect, they limit the model's performance. The only way to determine if model assumptions are correct is to construct an alternative model that makes different assumptions and to determine whether the alternative outperforms BKT. DKT is exactly this alternative model, and its strong performance directs us to examine BKT's limitations. First, however, we briefly describe DKT.

Rather than constructing a separate model for each skill, DKT models all skills jointly. The input to the model is the complete sequence of exercise-performance pairs, $\{(X_{s1}, Y_{s1}) \ldots (X_{st}, Y_{st}) \ldots (X_{sT}, Y_{sT})\}$, presented one trial at a time. As depicted in Figure 1, DKT is a recurrent neural net which takes (X_{st}, Y_{st}) as input and predicts $X_{s,t+1}$ for each possible exercise label. The model is trained and evaluated based on the match between the actual and predicted $X_{s,t+1}$ for the tested exercise ($Y_{s,t+1}$). In addition to the input and output layers representing the current trial and the next trial, respectively, the network has a hidden layer with fully recurrent connections (i.e., each hidden unit connects back to all other hidden units). The hidden layer thus serves to retain relevant aspects of the input history as they are use-

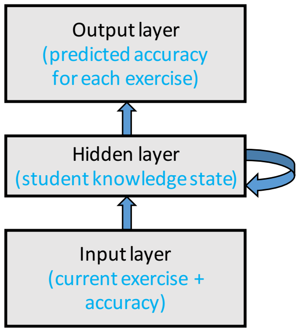

Figure 1: Deep knowledge tracing (DKT) architecture. Each rectangle depicts a set of processing units; each arrow depicts complete connectivity between each unit in the source layer and each unit in the destination layer.

ful for predicting future performance. The hidden state of the network can be conceived of as embodying the student's knowledge state. Piech et al. [22] used a particular type of hidden unit, called an LSTM (long short-term memory) [10], which is interesting because these hidden units behave very much like the BKT latent knowledge state, K_{si}. To briefly explain LSTM, each hidden unit acts like a memory element that can hold a bit of information. The unit is triggered to turn on or off by events in the input or the state of other hidden units, but when there is no specific trigger, the unit preserves its state, very similar to the way that the latent state in BKT is sticky—once a skill is learned it stays learned. With 200 LSTM hidden units—the number used in simulations reported in [22]—and 50 skills, DKT has roughly 250,000 free parameters (connection strengths). Contrast this number with the 200 free parameters required for embodying 50 different skills in BKT.

With its thousand-fold increase in flexibility, DKT is a very general architecture. One can implement BKT-like dynamics in DKT with a particular, restricted set of connection strengths. However, DKT clearly has the capacity to encode learning dynamics that are outside the scope of BKT. This capacity is what allows DKT to discover structure in the data that BKT misses.

1.3 Where Does BKT Fall Short?

In this section, we describe four regularities that we conjecture to be present in the student-performance data. DKT is flexible enough that it has the potential to discover these regularities, but the more constrained BKT model is simply not crafted to exploit the regularities. In following sections, we suggest means of extending BKT to exploit such regularities, and conduct simulation studies to determine whether the enhanced BKT achieves performance comparable to that of DKT.

1.3.1 Recency Effects

Human behavior is strongly recency driven. For example, when individuals perform a choice task repeatedly, response latency can be predicted by an exponentially decaying average of recent stimuli [12]. Intuitively, one might expect to observe recency effects in student performance. Consider, for example, a student's time varying engagement. If the level of engagement varies slowly relative to the rate at which exercises are being solved, a correlation would be induced in performance across local spans of time. A student who performed poorly on the last trial because they were distracted is likely to perform poorly on the current trial. We conducted a simple assessment of recency using the ASSISTMENTS data set (the details of this data set will be described shortly). Similarly to [5], we built an autoregressive model that predicts performance on the current trial as an exponentially weighted average of performance on past trials, with a decay half life of about 5 steps. We found that this single parameter model fit the ASSISTMENTS data reliably better than classic BKT. (We are not presenting details of this simulation because we will evaluate a more rigorous variant of the idea in a following section. Our goal here is to convince the reader that there is likely some value to the notion of recency-weighted prediction.)

Recurrent neural networks tend to be more strongly influenced by recent events in a sequence than more distal events [20]. Consequently, DKT is well suited to exploiting recent performance in making predictions. In contrast, the generative model underlying BKT supposes that once a skill is learned, performance will remain strong, and that a slip at time t is independent of a slip at $t + 1$.

1.3.2 Contextualized Trial Sequence

The psychological literature on practice of multiple skills indicates that the sequence in which an exercise is embedded influences learning and retention (e.g., [24, 25]). For example, given three exercises each of skills A and B, presenting the exercises in the *interleaved* order A_1–B_1–A_2–B_2–A_3–B_3 yields superior performance relative to presenting the exercises in the *blocked* order A_1–A_2–A_3–B_1–B_2–B_3. (Performance in this situation can be based on an immediate or delayed test.)

Because DKT is fed the entire sequence of exercises a student receives in the order the student receives them, it can potentially infer the effect of exercise order on learning. In contrast, because classic BKT separates exercises by skill, preserving only the relative order of exercises within a skill, the training sequence for BKT is the same regardless of whether the trial order is blocked or interleaved.

1.3.3 Inter-Skill Similarity

Each exercise presented to a student has an associated label. In typical applications of BKT—as well as two of the three simulations reported in Piech et al. [22]—the label indicates the skill required to solve the problem. Any two such skills, S_1 and S_2, may vary in their degree of relatedness. The stronger the relatedness, the more highly correlated one would expect performance to be on exercises tapping the two skills, and the more likely that the two skills will be learned simultaneously.

DKT has the capacity to encode inter-skill similarity. If each hidden unit represents student knowledge state for a particular skill, then the hidden-to-hidden connections encode the degree of overlap. In an extreme case, if two skills are highly similar, they can be modeled by a single hidden knowledge state. In contrast, classic BKT treats each skill as an independent modeling problem and thus can not discover or leverage inter-skill similarity.

DKT has the additional strength, as demonstrated by Piech et al., that it can accommodate the absence of skill labels. If each label simply indexes a specific exercise, DKT can discover interdependence between exercises in exactly the same manner as it discovers interdependence between skills. In contrast, BKT requires exercise labels to be skill indexed.

1.3.4 Individual Variation in Ability

Students vary in ability, as reflected in individual differences in mean accuracy across trials and skills. Individual variation might potentially be used in a predictive manner: a student's accuracy on early trials in a sequence might predict accuracy on later trials, regardless of the skills required to solve exercises. We performed a simple verification of this hypothesis using the ASSISTMENTS data set. In this data set, students study one skill at a time and then move on to the next skill. We computed correlation between mean accuracy of all trials on the first n skills and the mean accuracy of all trials on skill $n+1$, for all students and for $n \in \{1, ..., N-1\}$ where N is the number of skills a student studied. We obtained a correlation coefficient of 0.39: students who tend to do well on the early skills learned tend to do well on later skills, regardless of the skills involved.

DKT is presented with a student's complete trial sequence. It can use a student's average accuracy up to trial t to predict trial $t + 1$. Because BKT models each skill separately from the others, it does not have the contextual information needed to estimate a student's average accuracy or overall ability.

2. EXTENDING BKT

In the previous section, we described four regularities that appear to be present in the data and which we conjecture that DKT exploits but which the classic BKT model cannot. In this section, we describe three extensions to BKT that would bring BKT on par with DKT with regard to these regularities.

2.1 Forgetting

To better capture recency effects, BKT can be augmented to allow for forgetting of skills. Forgetting corresponds to fitting a BKT parameter $F \equiv P(K_{s,i+1} = 0 \mid K_{si} = 1)$, the probability of transitioning from a state of knowing to not knowing a skill. In standard BKT, $F = 0$.

Without forgetting, once BKT infers that the student has learned, even a long run of poorly performing trials cannot alter the inferred knowledge state. However, with forgetting, the knowledge state can transition in either direction, which allows the model to be more sensitive to the recent trials: A run of unsuccessful trials is indicative of not knowing the skill, regardless of what preceded the run. Forgetting is not a new idea to BKT, and in fact was included in the original psychological theory that underlies the notion of binary knowledge state [1]. However, it has not typically been incorporated into BKT. When it has been included in BKT [23], the motivation was to model forgetting from one day to the next, not forgetting that can occur on a much shorter time scale.

Incorporating forgetting can not only sensitize BKT to recent events but can also contextualize trial sequences. To explain, consider an exercise sequence such as A_1–A_2–B_1–A_3–B_2–B_3–A_4, where the labels are instances of skills A and B. Ordinary BKT discards the absolute number of trials between two exercises of a given skill, but with forgetting, we can count the number of intervening trials and treat each as an independent opportunity for forgetting to occur. Consequently, the probability of forgetting between A_1 and A_2 is F, but the probability of forgetting between A_2 and A_3 is $1 - (1 - F)^2$ and between A_3 and A_4 is $1 - (1 - F)^3$. Using forgetting, BKT can readily incorporate some information about the absolute trial sequence, and therefore has more potential than classic BKT to be sensitive to interspersed trials in the exercise sequence.

2.2 Skill Discovery

To model interactions among skills, one might suppose that each skill has some degree of influence on the learning of other skills, not unlike the connection among hidden units in DKT. For BKT to allow for such interactions among skills, the independent BKT models would need to be interconnected, using an architecture such as a factorial hidden Markov model [6]. As an alternative to this somewhat complex approach, we explored a simpler scheme in which different exercise labels could be collapsed together to form a single skill. For example, consider an exercise sequence such as A_1–B_1–A_2–C_1–B_2–C_2–C_3. If skills A and B are highly similar or overlapping, such that learning one predicts learning the other, it would be more sensible to treat this sequence in a manner that groups A and B into a single skill, and to train a single BKT instantiation on both A and B trials. This approach can be used whether the exercise labels are skill indices or exercise indices. (One of the data sets used by Piech et al. [22] to motivate DKT has exercise-indexed labels).

We recently proposed an inference procedure that automatically discovers the cognitive skills needed to accurately model a given data set [18]. (A related procedure was independently proposed in [8].) The approach couples BKT with a technique that searches over partitions of the exercise labels to simultaneously (1) determine which skill is required to correctly answer each exercise, and (2) model a student's dynamical knowledge state for each skill. Formally, the technique assigns each exercise label to a latent skill such that a student's expected accuracy on a sequence of same-skill exercises improves monotonically with practice according to BKT. Rather than discarding the skills identified by experts, our technique incorporates a nonparametric prior over the exercise-skill assignments that is based on the expert-provided skills and a weighted Chinese restaurant process [11].

In the above illustration, our technique would group A and B into one skill and C into another. This procedure collapses like skills (or like exercises), yielding better fits to the data by BKT. Thus, the procedure performs a sort of *skill discovery*.

2.3 Incorporating Latent Student-Abilities

To account for individual variation in student ability, we have extended BKT [14, 13] such that slip and guess probabilities are modulated by a latent *ability* parameter that is inferred from the data, much in the spirit of item-response theory [4]. As we did in [14], we assume that students with stronger abilities have lower slip and higher guess probabilities. When the model is presented with new students, the posterior predictive distribution on abilities is used initially, but as responses from the new student are observed, uncertainty in the student's ability diminishes, yielding better predictions for the student.

3. SIMULATIONS

3.1 Data Sets

Piech et al. [22] studied three data sets. One of the data sets, from Khan Academy, is not publicly available. Despite our requests and a plea from one of the co-authors of the DKT paper, we were unable to obtain permission from the data science team at Khan Academy to use the data set. We did investigate the other two data sets in Piech et al., which are as follows.

ASSISTMENTS is an electronic tutor that teaches and evaluates students in grade-school math. The 2009-2010 "skill builder" data set is a large, standard benchmark, available by searching the web for *assistment-2009-2010-data*. We used the train/test split provided by Piech et al., and following Piech et al., we discarded all students who had only a single trial of data.

SYNTHETIC is a synthetic data set created by Piech et al. to model virtual students learning virtual skills. The training and test sets each consist of 2000 virtual students performing the same sequence of 50 exercises drawn from 5 skills. The exercise on trial t is assumed to have a difficulty characterized by δ_t and require a skill specified by σ_t. The exercises are labeled by the *identity of the exercise*, not by the underlying skill, σ_t. The ability of a student, denoted, α_t varies over time according to a drift-diffusion process, generally increasing with practice. The response correctness on trial t is a Bernoulli draw with probability specified by guessing-corrected item-response theory with difficulty and ability parameters δ_t and α_t. This data set is challenging for BKT because the skill assignments, σ_t, are not provided and must be inferred from the data. Without the skill assignments, BKT must be used either with all exercises associated with a single skill or each exercise associated with its own skill. Either of these assumptions will miss important structure in the data. SYNTHETIC is an interesting data set in that the underlying generative model is neither a perfect match to DKT or BKT (even with the enhancements we have described). The generative model seems realistic in its assumption that knowledge state varies continuously.

We included two additional data sets in our simulations. SPANISH is a data set of 182 middle-school students practicing 409 Spanish exercises (translations and application of simple skills such as verb conjugation) over the course of a 15-week semester, with a total of 578,726 trials [17]. STATICS is from a college-level engineering statics course with 189,297 trials and 333 students and 1,223 exercises [28], available from the PSLC DataShop web site [15].

3.2 Methods

We evaluated five variants of BKT[1], each of which incorporates a different subset of the extensions described in the previous section: a base version that corresponds to the classic model and the model against which DKT was evaluated in [22], which we'll refer to simply as *BKT*; a version that incorporates forgetting (*BKT+F*), a version that incorporates skill discovery (*BKT+S*), a version that incorporates latent abilities (*BKT+A*), and a version that incorporates all three of the extensions (*BKT+FSA*). We also built our own implementation of DKT with LSTM recurrent units[2]. (Piech et al. described the LSTM version as better performing, but posted only the code for the standard recurrent neural net version.) We verified that our implementation produced results comparable to those reported in [22] on ASSISTMENTS and SYNTHETIC. We then also ran the model on SPANISH and STATICS.

For ASSISTMENTS, SPANISH, and STATICS, we used a single train/test split. The ASSISTMENTS train/test split was identical to that used by Piech et al. For SYNTHETIC, we used the 20 simulation sets provided by Piech et al. and averaged results across the 20 simulations.

Each model was evaluated on each domain's test data set, and the performance of the model was quantified with a discriminability score, the *area under the ROC curve* or *AUC*. AUC is a measure ranging from .5, reflecting no ability to discriminate correct from incorrect responses, to 1.0, reflecting perfect discrimination. AUC is computed by obtaining a prediction on the test set for each trial, across all skills, and then using the complete set of predictions to form the ROC curve. Although Piech et al. [22] do not describe the procedure they use to compute AUC for DKT, code they have made available implements the procedure we describe, and not the obvious alternative procedure in which ROC curves are computed on a per-skill basis and then averaged to obtain an overall AUC.

3.3 Results

Figure 2 presents the results of our comparison of five variants of BKT on the four data sets. We walk through the data sets from left to right.

On ASSISTMENTS, classic BKT obtains an AUC of 0.73, better than the 0.67 reported for BKT by Piech et al. We are not sure why the scores do not match, although 0.67 is close to the AUC score we obtain if we treat all exercises as associated with a single skill or if we compute AUC on a per-skill basis and then average.[3] BKT+F obtains an AUC of 0.83,

[1] https://github.com/robert-lindsey/WCRP/tree/forgetting
[2] https://github.com/mmkhajah/dkt
[3] Piech et al. cite Pardos and Heffernan [21] as obtaining BKT's best reported performance on ASSISTMENTS—an AUC of 0.69. In [21], the overall AUC is computed by averaging the per-skill AUCs. This method yields a lower score than the method used by Piech et al., for two reasons. First, the Piech procedure weighs all *trials* equally, whereas the Pardos and Heffernan procedure weighs all *skills* equally. With the latter procedure, the overall AUC will be dinged if the model does poorly on a skill with just a few trials, as we have observed to be the case with ASSISTMENTS. The latter procedure also produces a lower overall AUC because it suppresses any lift due to being able to predict the relative accuracy of different skills. In summary, it appears that

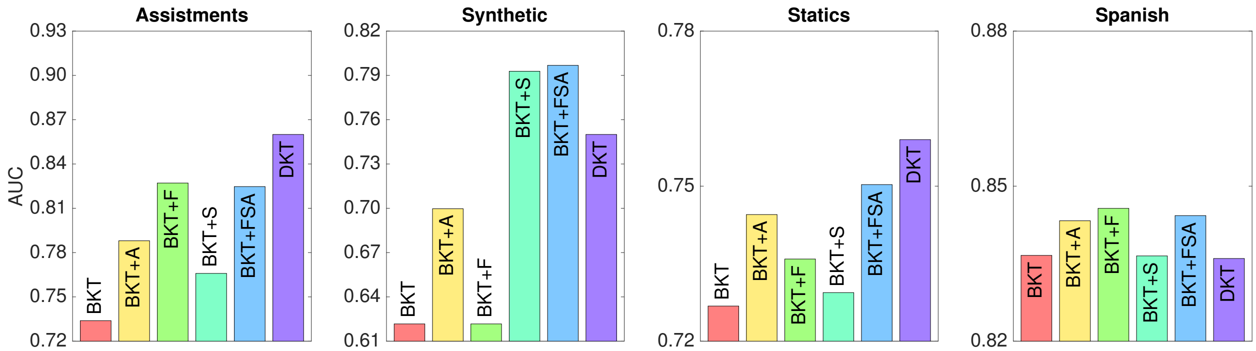

Figure 2: A comparison of six models on four data sets. Model performance on the test set is quantified by AUC, a measure of how well the model discriminates (predicts) correct and incorrect student responses. The models are trained on one set of students and tested on another set. Note that the AUC scale is different for each graph, but tic marks are always spaced by .03 units in AUC. On Assistments **and** Synthetic**, DKT results are from Piech et al. [22]; on** Statics **and** Spanish **DKT results are from our own implementation. BKT= classic Bayesian knowledge tracing; BKT+A= BKT with inference of latent student abilities; BKT+F= BKT with forgetting; BKT+S= BKT with skill discovery; BKT+FSA= BKT with all three extensions; DKT= deep knowledge tracing**

not quite as good as the 0.86 value reported for DKT by Piech et al. Examining the various enhancements to BKT, AUC is boosted both by incorporating forgetting and by incorporating latent student abilities. We find it somewhat puzzling that the combination of the two enhancements, embodied in BKT+FSA, does no better than BKT+F or BKT+A, considering that the two enhancements tap different properties of the data: the student abilities help predict transfer from one skill to the next, whereas forgetting facilitates prediction within a skill.

To summarize the comparison of BKT and DKT, 31.6% of difference in performance reported in [22] appears to be due to the use of a biased procedure for computing the AUC for BTK. Another 50.6% of the difference in performance reported vanishes if BKT is augmented to allow for forgetting. We can further improve BKT if we allow the skill discovery algorithm to operate with exercise labels that index individual exercises, as opposed to labels that index the skill associated with each exercise. With exercise-indexed labels, BKT+S and BKT+FSA both obtain an AUC of 0.90, beating DKT. However, given DKT's ability to perform skill discovery, we would not be surprised if it also achieved a similar level of performance when allowed to exploit exercise-indexed labels.

Turning to Synthetic, classic BKT obtains an AUC of 0.62, again significantly better than the 0.54 reported by Piech et al. In our simulation, we treat each exercise as having a distinct skill label, and thus BKT learns nothing more than the mean performance level for a specific exercise. (Because the exercises are presented in a fixed order, the exercise identity and the trial number are confounded. Because performance tends to improve as trials advance in the synthetic data, BKT is able to learn this relationship.) It is possible here that Piech et al. treated all exercises as associated with a single skill or that they used the biased procedure for computing AUC; either of these explanations is consistent with their reported AUC of 0.54.

Regarding the enhancements to BKT, adding student abilities (BKT+A) improves prediction of Synthetic which is understandable given that the generative process simulates students with abilities that vary slowly over time. Adding forgetting (BKT+F) does not help, consistent with the generative process which assumes that knowledge level is on average increasing with practice; there is no systematic forgetting in the student simulation. Critical to this simulation is skill induction: BKT+S and BKT+FSA achieve an AUC of 0.80, better than the reported 0.75 for DKT in [22].

On Statics, each BKT extension obtains an improvement over classic BKT, although the magnitude of the improvements are small. The full model, BKT+FSA, obtains an AUC of 0.75 and our implementation of DKT obtains a nearly identical AUC of 0.76. On Spanish, the BKT extensions obtain very little benefit. The full model, BKT+FSA, obtains an AUC of 0.846 and again, DKT obtains a nearly identical AUC of 0.836. These two sets of results indicate that for at least some data sets, classic BKT has no glaring deficiencies. However, we note that BKT model accuracy can be improved if algorithms are considered that use exercise labels which are indexed by exercise and not by skill. For example, with Statics, performing skill discovery using exercise-indexed labels, [17] obtain an AUC of 0.81, much better than the score of 0.73 we report here for BKT+S based on skill-indexed labels.

In summary, enhanced BKT appears to perform as well on average as DKT across the four data sets. Enhanced BKT outperforms DKT by 20.0% (.05 AUC units) on Synthetic and by 3.0% (.01 AUC unit) on Spanish. Enhanced BKT underperforms DKT by 8.3% (.03 AUC units) on Assistments and by 3.5% (.01 AUC unit) on Statics. These percentages are based on the difference of AUCs scaled by by $\mathrm{AUC}_{\mathrm{DKT}} - 0.5$, which takes into account the fact that an AUC of 0.5 indicates no discriminability.

inconsistent procedures may have been used to compute performance of BKT versus DKT in [22], and the procedure for BKT is biased to yield a lower score.

4. DISCUSSION

Our goal in this article was to investigate the basis for the impressive predictive advantage of deep knowledge tracing over Bayesian knowledge tracing. We found some evidence that different procedures may have been used to evaluate DKT and BKT in [22], leading to a bias against BKT. When we replicated simulations of BKT reported in [22], we obtained significantly better performance: an AUC of 0.73 versus 0.67 on ASSISTMENTS, and an AUC of 0.62 versus 0.54 on SYNTHETIC.

However, even when the bias is eliminated, DKT obtains real performance gains over BKT. To understand the basis for these gains, we hypothesized various forms of regularity in the data which BKT is not able to exploit. We proposed enhancements to BKT to allow it to exploit these regularities, and we found that the enhanced BKT achieved a level of performance on average indistinguishable from that of DKT over the four data sets tested. The enhancements we explored are not novel; they have previously been proposed and evaluated in the literature. They include forgetting [23], latent student abilities [14, 13, 21], and skill induction [17, 8].

We observe that different enhancements to BKT matter for different data sets. For ASSISTMENTS, incorporating forgetting is key; forgetting allows BKT to capture recency effects. For SYNTHETIC, incorporating skill discovery yielded huge gains, as one would expect when the exercise-skill mapping is not known. And for STATICS, incorporating latent student abilities was relatively most beneficial; these abilities enable the model to tease apart the capability of a student and the intrinsic difficulty of an exercise or skill. Of the three enhancements, forgetting and student abilities are computationally inexpensive to implement, whereas skill discovery adds an extra layer of computational complexity to inference.

The elegance of DKT is apparent when one considers the effort we have invested to bring BKT to par with DKT. DKT did not require its creators to analyze the domain and determine sources of structure in the data. In contrast, our approach to augmenting BKT required some domain expertise, a thoughtful analysis of BKT's limitations, and distinct solutions to each limitation. DKT is a generic recurrent neural network model [10], and it has no constructs that are specialized to modeling learning and forgetting, discovering skills, or inferring student abilities. This flexibility makes DKT robust on a variety of datasets with little prior analysis of the domains. Although training recurrent networks is computationally intensive, tools exist to exploit the parallel processing power in graphics processing units (GPUs), which means that DKT can scale to large datasets. Classic BKT is inexpensive to fit, although the variants we evaluated—particularly the model that incorporates skill discovery—require computation-intensive MCMC methods that have a distinct set of issues when it comes to parallelization.

DKT's advantages come at a price: interpretability. DKT is massive neural network model with tens of thousands of parameters which are near-impossible to interpret. Although the creators of DKT did not have to invest much up-front time analyzing their domain, they did have to invest substantive effort to understand what the model had actually learned. Our proposed BKT extensions achieve predictive performance similar to DKT whilst remaining interpretable: the model parameters (forgetting rate, student ability, etc.) are psychologically meaningful. When skill discovery is incorporated into BKT, the result is clear: a partition of exercises into skills. Reading out such a partitioning from DKT is challenging and only an approximate representation of the knowledge in DKT.

Finally, we return to the question posed in the paper's title: How deep is knowledge tracing? Deep learning refers to the discovery of representations. Our results suggest that representation discovery is not at the core of DKT's success. We base this argument on the fact that our enhancements to BKT bring it to the performance level of DKT *without* requiring any sort of subsymbolic representation discovery.[4] Representation discovery is clearly critical in perceptual domains such as image or speech classification. But the domain of education and student learning is high level and abstract. The input and output elements of models are psychologically meaningful. The relevant internal states of the learner have some psychological basis. The characterization of exercises and skills can—to at least a partial extent—be expressed symbolically.

Instead of attributing DKT's success to representation discovery, we attribute DKT's success to its flexibility and generality in capturing statistical regularities directly present in the inputs and outputs. As long as there are sufficient data to constrain the model, DKT is more powerful than classic BKT. BKT arose in a simpler era, an era in which data and computation resources were precious. DKT reveals the value of relaxing these constraints in the big data era. But despite the wild popularity of deep learning, there are many ways to relax the constraints and build more powerful models other than creating a black box predictive device with a vast interconnected tangle of connections and parameters that are nearly impossible to interpret.

5. ACKNOWLEDGMENTS

This research was supported by NSF grants SES-1461535, SBE-0542013, and SMA-1041755.

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