Modifying Deep Knowledge Tracing for Multi-step Problems

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Introduction

- Previous studies suggest that Deep Knowledge Tracing (DKT) has fundamental limitations that prevent it from supporting mastery learning on multi-step problems.
- We believe DKT's loss function does not evaluate predictions for skills and steps that do not have an observed ground truth value.
- We revised the loss function and evaluated the revised DKT model on human students' data.
- Our analysis shows that the modified loss function produced improvements in the consistency of DKT model's predictions.

Challenges with DKT

- Even though DKT has many advantages over other knowledge tracing models like Bayesian Knowledge Tracing (BKT), Streak Model and Performance Factor Analysis (PFA), the model still has several limitations.
- DKT models are difficult to interpret.
- DKT makes inconsistent predictions.
- DKT only consider the correctness of skills that are observed on each time step.

Correctness		✗	✗	✗	✓	✓	✓	✗	✓
DKT Mastery	36%	0%	0%	100%	0%	0%	0%	2%	0%

Figure 1: An example showing DKT model predictions on a single knowledge component given one student correctness sequence.

Methodology

- We revised the loss function of DKT by using $\hat{a}$ to represent the updated ground truth values that populate missing cells using the value from the next observation of each skill.
- In Figure 2, the colored cells denote observed student performance (0/red equals incorrect and 1/green equals correct). Cells with white backgrounds are extrapolated from the next observation of each skill.

Skill 1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Skill 2	0	0	0	1	1	1	1	1	1	1	1	1			
Skill 3	0	0	0	0	1	1	1								

Figure 2: Graphical depiction of $\hat{a}$.

- The original DKT loss function and the revised loss function are presented below.

$$L_{Original} = \frac{1}{\sum_{i=1}^{n}(T_i - 1)} \sum_{i=1}^{n} \sum_{t=1}^{T_i - 1} l\left(y_t \cdot \delta\left(q_{t+1}^i\right), a_{t+1}^i\right)$$

Function 1 : The original DKT loss function.

$$L_{Next} = \frac{1}{\sum_{i=1}^{n}\sum_{k=1}^{K}(T_{i,k} - 1)} \sum_{i=1}^{n} \sum_{k=1}^{K} \sum_{t=1}^{T_{i,k} - 1} l\left(y_{t,k}, \hat{a}_{t+1,k}^i\right)$$

Function 2 : The revised DKT loss function.

Model Evaluation

- We downloaded data from DataShop, took a complete student sequence and generated correctness predictions for each skill using the DKT model.
- In the top heatmap in Figure 3, the DKT predictions fluctuate over time. There is also a pattern of inconsistent predictions on several knowledge components.
- In the bottom heatmap, the problem of wavy DKT predictions (alternating correct and incorrect predictions for different skills) is largely addressed.

Conclusion

- We revised DKT's loss function to improve prediction consistency across all KCs over time.
- We proposed a novel way of modifying the DKT loss function.
- The DKT model trained with the revised loss function showed much smoother, more consistent predictions that started lower and improved steadily over the course of training.

Future Works

- Make another revision of the DKT loss function by weighting each evaluation with a decay factor γ.
- Move online and evaluate how well the revised DKT model operates in an online mastery learning context.

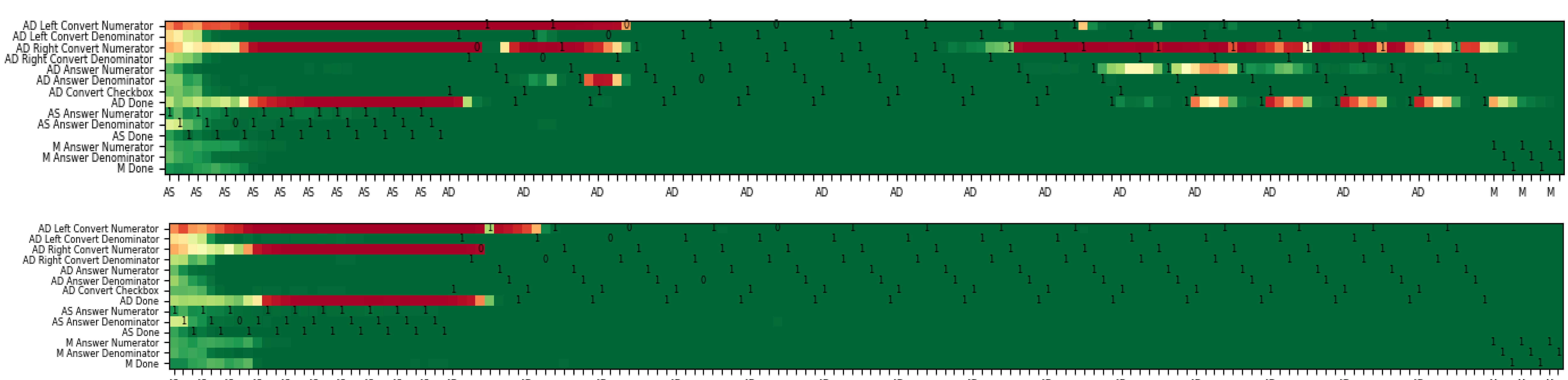

Figure 3: Model performance comparison between DKT models trained with the original and revised loss functions.

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