FAST: Feature-Aware Student Knowledge Tracing

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Various kinds of e-learning systems, such as Massively Open Online Courses and intelligent tutoring systems, are now producing large amounts of feature-rich data from students solving items at different levels of proficiency over time. To analyze such data, researchers often use Knowledge Tracing [4], a 20-year old method that has become the de-facto standard for inferring student knowledge from performance data. Knowledge Tracing uses Hidden Markov Models (HMM) to estimate the latent cognitive state (student knowledge) from the students' performance answering items. Since the original Knowledge Tracing formulation does not allow to model general features, a considerable amount of research has focused on ad-hoc modifications to the Knowledge Tracing algorithm to enable modeling a specific feature of interest. This has led to a plethora of different Knowledge Tracing reformulations for very specific purposes. For example, Pardos et al. [5] proposed a new model to measure the effect of students' individual characteristics, Beck et al. [2] modified Knowledge Tracing to assess the effect of help in a tutor system, and Xu and Mostow [7] proposed a new model that allows measuring the effect of subskills. These ad hoc models are successful for their own specific purpose, but they do not generalize to arbitrary features. Other student modeling methods which allow more flexible features have been proposed. For example, Performance Factor Analysis [6] uses logistic regression to model arbitrary features, but unfortunately it does not make inferences of whether the student has learned a skill.

We present FAST (Feature-Aware Student knowledge Tracing), a novel method that allows general features into Knowledge Tracing. FAST combines Performance Factor Analysis (logistic regression) with Knowledge Tracing, by leveraging previous work on unsupervised learning with features [3]. Therefore, FAST is able to infer student knowledge while also allowing for arbitrary features, combining the strengths of Knowledge Tracing and Performance Factor Analysis. FAST allows general features into Knowledge Tracing by replacing the generative emission probabilities (often called guess and slip probabilities) with logistic regression [3], so that these probabilities can change with time to infer students knowledge. FAST allows arbitrary features to train the logistic regression model and the HMM jointly. Training the parameters simultaneously enables FAST to learn from the features. This differs from using regression to analyze the slip and guess probabilities [1].

To validate our approach, we use data collected from real students interacting with a tutor. We present experimental results comparing FAST with Knowledge Tracing and Performance Factor Analysis. We investigate the effect of using features in Knowledge Tracing, such as item difficulty, and prior successes and failures of a student for the skill (or multiple skills) associated with the item.

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