Pinpointing Learning Moments; A finer grain P(J) model

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1 Introduction

Educational data mining and knowledge engineering methods have led to increasingly precise models of students' knowledge as they use intelligent tutoring systems. The first stage in this progression was the development of Bayes Nets and Bayesian frameworks that could infer the probability that a student knew a specific skill at a specific time from their pattern of correct responses and non-correct responses (e.g. errors and hint requests) up until that time [cf. 2, 4, 5].

However, while the extensions made in recent years to educational data mining have created the potential for more precise assessment of student knowledge at a specific time, these models do not tell us *when* the knowledge was acquired. Baker, Goldstein, and Heffernan proposed the idea of a model that can infer the probability that a student learned a skill at a specific step during the problem-solving process. This model, **P(J)** for JustLearned, was shown to be a consistent predictor of high eventual $\mathbf{L_n}$ values if a spike in **P(J)** is seen. This ability can potentially allow for engineering intelligent tutoring systems to bias content in a way that can induce these moments of learning. The prior approach achieved a correlation coefficient of 0.446, which leaves considerable room for improving accuracy towards achieving more effective use. Below we will discuss the application of **P(J)** to multiple intelligent tutoring systems as well as our most recent and more accurate attempt at creating a **P(J)** model in the ASSISTment tutoring system.

2 The P(J) Model

The original analysis of **P(J)** used data from 232 students' use of a Cognitive Tutor curriculum for middle school mathematics [3], during the 2002- 2003 school year. These students made 581,785 transactions (either entering an answer or requesting a hint) on 171,987 problem steps covering 253 skills. In [1] it was demonstrated that a model as described above can be created. This model calculates **P(JustLearned)**, **P(J)** for short, which is the probability that a student just learned a skill after a certain problem step. This concept can be expressed in terms of BKT as $\mathbf{P(\sim Ln \wedge T \mid A_{+1+2})}$. For each problem step, [1] used a set of 25 features describing the first action on problem step **N**. These features had in turn been used in prior work to develop automated detectors of off-task behavior [2] and gaming the system. This attempt at a **P(J)** model achieved a correlation coefficient of 0.446 when running Linear Regression, which provides an acceptable level of prediction, but is recognizably limited.

3 Refinements to P(J)

Although the original **P(J)** model was capable of identifying potential moments where learning opportunities happen, the features set constructed for the model did not have an optimally high correlation coefficient. This can perhaps can be attributed to features that were designed to detect guessing and slipping rather than moments of learning, as well as the model only involving the first action of the step whereas learning may occur in subsequent actions.

To improve accuracy, and to demonstrate the ability to create a more accurate model of **P(J)**, we redesigned our feature set and used data from ASSISTments, an intelligent tutoring system led by Professor Neil Heffernan at WPI. This new data set is pulled from 4187 students from New England middle and high schools that were using the system from 2008-2010. This data includes 55 unique skills and 418,513 logged actions. One benefit of using ASSISTments is the fact that it has extensive information about scaffolding problem steps, as well as – importantly – subsequent actions after a student's first attempt at answering. Our new feature set includes 40 features, including information about time spent on scaffolding, number of hints used in scaffolding, and so on. This new model achieves a correlation coefficient of 0.61 when running Linear Regression in Rapid Miner with 6 fold student-level cross validation.

The additional correlation shows our ability to more accurately predict **P(J)**, a construct which has been shown to have potential to recognize moments of student learning.

4 References

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