Modeling step duration to enhance the Additive Factors Analysis Model

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ABSTRACT: In this paper, we explore how we can use step duration as a feature for predicting student performance. In particular, we aim to implement an enhanced version of a standard cognitive student model, the Additive Factors Analysis Model (AFM) using step duration as a quadratic predictive feature. Our work builds on related research that suggests that response time can provide information with respect to correctness and that the relationship between response time and student performance is non-linear. The model we implement here will support extensive testing of the approach using various datasets and it will contribute to gaining insight with respect to the relationship between response time and student.

Keywords: student modeling, step duration, intelligent tutoring systems

1 INTRODUCTION

In this paper, we propose the implementation of an Additive Factors Analysis Model (AFM) (Cen, Koedinger, & Junker, 2006, 2008) enhanced with a quadratic, step duration parameter. The motivation is to use the aspect of time in order to improve the performance of student models. Related research has explored the use of response or reaction time to model students' activity in learning tasks (I.-A. Chounta & Avouris, 2015). Even though research studies have shown that response time can potentially be a good predictor of post-test scores, it does not always predict performance in individual learning steps (Lin, Shen, & Chi, 2016). At the same time, prior studies suggest that the relationship between response time and student performance is non-linear (Carvalho, Gao, Motz, & Koedinger, 2018; Daniel & Broida, 2004). On the one hand, a student needs a minimum amount of time in order to process the problem, retrieve appropriate information, and to construct a correct response. If the student attempts to respond too fast, this can mean that either they did not really process the task as required or that the student attempts to game the system. On the other hand, if the student takes too long to respond, this may indicate lack of background knowledge, failure to retrieve critical information, and inability to address the step (I. A. Chounta & Carvalho, 2018).

In this paper, we propose a new modeling approach for predicting student performance using the student's response time. In particular, we build on the hypothesis that there is no linear relationship between student response time and correctness: a student who takes either too little time or too long to respond to a step (where a step can be either a tutor's question or task), will most likely be unsuccessful for this particular step. Therefore, we argue that modeling a student's response time as a quadratic factor - rather that a linear one – will result in more accurate and better performing student models (I.-A. Chounta & Carvalho, 2019). This rationale is depicted in **Figure 1**.

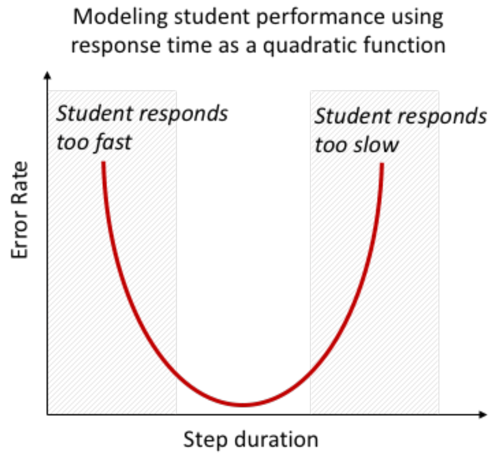

Figure 1. The research hypothesis of this work is that a student who takes either too little time (left grey area) or too long (right grey area) to respond to a step, will most likely be unsuccessful for this particular step resulting to a high error rate in student's performance. Here we explore whether modeling a student's response time as a quadratic factor will result in more accurate student models.

The significance of this work is two-fold: first, being able to use response time consistently as a predictive feature will contribute towards improving the performance of student models; second, it will offer insight with respect to the relationship between response time and student performance.

2 WORKFLOW METHOD

2.1 Data Inputs

As data input, our workflow uses standard PSLC DataShop transaction-level datasets (Koedinger et al., 2010). In particular, we use the following fields: *Anon Student Id, Duration (sec), Tutor Response Type, Attempt At Step, Outcome* and *KC (Single-KC, Unique-step, Default)*. Moreover, there is the need for an additional field that will contain information about practice opportunities on the KC-level. That is, how many times a student practiced a specific KC until this given moment.

After importing the data, minor data processing is required in order to discard outliers or to treat specific conditions (like for example, hints). Additionally, the student-step roll up datasets can be used. In this case, we use the following fields: *Anon Student Id, First Attempt, Step Duration(sec), KC (Single-KC, Unique-step, Default)* and *Opportunity (Single-KC, Unique-step, Default)*. Like before, minor data cleaning and preprocessing is necessary.

2.2 Workflow Model

Our model builds on the AFM and enhances it by adding response time (or else, step duration) as a quadrative feature. For the implementation of the AFM model, we followed Datashop's proposed approach[1] shown in the regression formula (1):

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[1] https://pslcdatashop.web.cmu.edu/help?page=rSoftware

(1) AFM = Outcome ~ Student + KC + KC:Opportunity

where:

- *Outcome* is the result per step – correct or incorrect;
- *Student* stands for the student id of the student who carries out this step;
- *KC* is the skill involved in this step;
- *KC:Opportunity* stands for the number of previous attempts a student had on this particular skill.

In order to take into account students' response time when predicting performance, we enhance the standard AFM by adding step duration as a quadratic component to the original AFM model. This is depicted in the regression formula (2).

(2) AFM-QT = Outcome ~ Student + KC + KC:Opportunity + step_duration + (step_duration)^2

where:

- *Outcome* is the result per step – correct or incorrect;
- *Student* stands for the student id of the student who carries out this step;
- *KC* is the skill involved in this step;
- *KC:Opportunity* is the number of previous attempts a student had on this particular skill.
- *step_duration* is the time the student took to carry out this step (in seconds).

The AFM-QT model has been implemented and tested in R[2]. We are currently working on the Tigris implementation. Our goal is to have the model ready before the workshop so that we can test it extensively and together with other participants.

2.3 Workflow Outputs

Our objective is to compare the predictive performance of the AFM-QT model with respect to different data inputs – that is, the transaction-level and the student-step roll up – and with respect to other modeling implementations – that's is, the AFM and potentially the Performance Factors Analysis Model (PFM) (Pavlik Jr, Cen, & Koedinger, 2009) and the Instructional Factors Analysis Model (IFM) (Chi, Koedinger, Gordon, Jordon, & VanLahn, 2011). Thus, we expect – as outcomes – measures of the models' quality and performance that can be used to assess the predictive fit of the model to data. In particular, we would aim for the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Cross-Validation estimate of Accuracy (CV.ACC) and the Root Mean Square Error (RMSE). These metrics have been used in related work for choosing between parametric models with different numbers of parameters (Cen et al., 2006; Pavlik Jr et al., 2009)

[2] https://cran.r-project.org/

Additionally, we aim to retrieve predictions of student performance from the AFM-QT model on the transaction and step levels as well as to use learning curves for data visualization.

3 DISCUSSION

Our overarching goal is to identify an appropriate way to model response time as a predictor of student performance. Taking into account that the relationship between response time and performance in terms of correctness is not linear, we propose to model step duration as a quadratic parameter. To do that, we build on a standard cognitive model (AFM) and we enhance it by adding a quadratic, step duration parameter (AFM-QT).

To further study the effect and potential benefits of this approach, we aim to test and compare the AFM and the AFM-QT over a wide range of datasets. This is a time-consuming process that requires processing and manipulation of extremely big datasets as well as computationally demanding procedures for comparing the performance of different student models.

With this work, we aim:

- to communicate this research line to users of Datashop and LearnSphere and to provide them with tools that will allow them to apply our approach on their data;

- to encourage other researchers to reproduce our study and to pursue further collaboration;

- to support our work by developing a tool that will help us test our research hypothesis on multiple datasets in a cost-efficient and automated way.

For future work, we plan to extend this approach in combination with the Performance Factors Analysis Model (PFM). We envision this is an important step because PFM differentiates between correct and incorrect steps and thus, it allows modeling step duration separately for correct and incorrect outcomes.

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