

## Enhancing Student Modeling for Collaborative Intelligent Tutoring Systems

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**Abstract.** This paper presents an extension of the Additive Factors Model to predict learning for students by accounting for aspects of collaboration. The results indicate that student performance is predicted more accurately when the model includes parameters that capture influences of working collaboratively.

**Keywords:** additive factors model, collaborative learning, intelligent tutoring

A strength of intelligent tutoring systems (ITSs) is that they can be modified through offline student modeling to provide better instruction for students. Although ITSs have been shown to support students working in groups [2], the statistical models that are used to refine and support ITSs often do not take into account features of collaboration (e.g., partner knowledge). Student modeling might be improved and learning might be supported even better, if we took into account collaborative features. Thus, we extended the Additive Factors Model (AFM), which is a logistic regression model frequently used in offline analyses of ITSs [1]. The standard AFM [1] calculates the log-odds that a given student correctly solves a given step in a problem as a function of three estimated parameters that capture the student's initial proficiency, the ease of the skills involved in the step, and the learning rates for those skills. We modified the standard AFM so that the model has separate learning rates depending on if a skill is being learned in an individual or collaborative environment (AFM+C) since the learning processes may differ. Further, to better understand how a student's partner's knowledge may impact the prediction of a student's learning, we analyzed four different variations to take into account partner knowledge: partner pretest score classified as low/average/high (AFM+PPS), absolute difference between student's and partner's pretest scores classified as homogeneous or heterogeneous (AFM+AD), and two directional differences between student's and partner's pretest scores including lower/similar/higher (AFM+DD) and lowest/lower/similar/higher/highest (AFM+LD).

We hypothesized that the models with collaborative/individual learning rates and the models with partner knowledge would be a better fit than the standard AFM. We used two datasets consisting of log data from conceptually or procedurally-oriented ITSs. In each data set, students were working individually or collaboratively. We measured the accuracy with which the models predicted student performance for both

datasets using log likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC). The log likelihood does not take into account the complexity of the model while the AIC and BIC do account for the complexity of the model.

**Table 1.** Prediction accuracy for all models. The asterisks mark the best performing model while a plus sign indicates that the model performed worse than the baseline for that measure.

Model Name	Log Likelihood	AIC	BIC	Comparison to Standard AFM
Conceptually-oriented ITS				
Standard AFM	-8769.7	17549.3	17589.1	
AFM+C	-8731.2*	17478.3*	17542.0*	$\chi^2(3)=77.0, p<0.001$
AFM+PPS	-8759.3	17534.6	17598.2+	$\chi^2(3)=20.8, p<0.001$
AFM+AD	-8768.6	17553.3+	17616.9+	$\chi^2(3)=2.1, p=0.56$
AFM+DD	-8761.2	17538.4	17602.1+	$\chi^2(3)=16.9, p<0.001$
AFM+LD	-8760.5	17536.9	17600.6+	$\chi^2(3)=18.4, p<0.001$
Procedurally-oriented ITS				
Standard AFM	-7991.3	15992.6	16032.0	
AFM+C	-7942.8*	15901.5*	15964.5*	$\chi^2(3)=97.1, p<0.001$
AFM+PPS	-7989.0	15994.0+	16057.1+	$\chi^2(3)=4.6, p=0.20$
AFM+AD	-7989.2	15994.4+	16057.4+	$\chi^2(3)=4.2, p=0.24$
AFM+DD	-7988.7	15993.5+	16056.5+	$\chi^2(3)=5.2, p=0.16$
AFM+LD	-7987.9	15991.9	16054.9+	$\chi^2(3)=6.8, p=0.08$

The models with collaborative/individual learning rates were a better fit than the standard AFMs as shown in the AFM+C rows of Table 1. The models with variations of the partner's pretest were a better fit only for the conceptually-oriented data as shown in the comparison column in Table 1. This may be caused by different types of talk occurring around conceptual and procedural knowledge with a partner, which may have an influence on learning. Overall, our results show that by including collaborative features within a model, we can improve the learning prediction. With a more accurate learning prediction for an ITS, in future work, we may be able to better refine the instructional support used in individual and collaborative ITSs.

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