Identifying relevant user behavior, predicting learning, and persistence in an ITS-based afterschool program

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ABSTRACT
ALEKS (Assessment and Learning in Knowledge Spaces) has recently shown promise for effectively training mathematics at equivalent levels to human teachers. However, not much is known about how the system accomplished this. In this paper, we describe the use of three data mining techniques used to analyze student data from an afterschool program with ALEKS. Our first analysis used DMM modeling and k-clustering to identify important groups of behaviors within ALEKS users and to show the importance of context for elements. Our second analysis focused on identifying learner behaviors that predict student learning during the program. The final analysis presents a method for determine learner persistence within the afterschool program.

Keywords
ALEKS, Afterschool programs, learning strategies, help seeking, persistence

1. INTRODUCTION
ALEKS is a web-based learning system with artificial intelligence components that are based in Knowledge Space Theory [1]. Instead of giving scores to measure a student's overall mastery of the subject, the theory allows for a precise assessment of what the student knows, does not know, and is ready to learn next. The probability of mastery for a knowledge state increases as students correctly answer questions containing that problem type.

ALEKS is a highly effective educational technology program shown to perform at the same level as other major ITS systems in mathematics [2]. In a four year evaluation of ALEKS in an afterschool setting, the students tutored by ALEKS or taught by expert teachers in one after-school program showed the same level of performance in a mathematics state test [3,4], and outperformed controls not participating in the program[5].

1.1 Current investigation
1.1.1 ALEKS afterschool program
The afterschool program was implemented for 25-week after school. It was held twice a week for 2 hours each day. Students received three 20-minute learning segments with a 20-minute break between each. Student logs were recorded by ALEKS. The students were from five middle schools in west Tennessee. The schools were located in a mid-sized city and the surrounding rural area, having a largely economically disadvantaged population (68.2%) and large minority student enrollment (56.3% African American, 39.3% White, and 4.4% others). None of the five schools reach an average SES level of Tennessee (i.e., 54.4% of the students eligible for free or reduced-price lunch).

1.1.2 Research question
While the afterschool program demonstrated that students using ALEKS could perform at the same levels as student in teacher-led classrooms [3.5], the student's learning process that led to this result is still unclear. Summaries of three methods are presented to show how popular data mining techniques can be applied to ALEKS log files to better understand student's behavior in the ALEKS afterschool program.

2. Learning strategies with DMM
There are distinct advantages for analyzing sequences over raw frequencies. The frequency counts could indicate that the two students used the same strategy. However in context, the two students act differently because the patters have different sequences. Modeling learning sequences is not as direct as frequency counting. One way to measure sequence is to calculate similarities in sequences, and then cluster the sequences using the similarities. A method, modeling learning sequences with Discrete Markov Models (DMM) and clustering with a k-means algorithm, has successfully discovered help-seeking strategies in ITS [6].

The analysis used 55,281 learning sequences of 372 students on ALEKS system. Typical activities students made include: correct, wrong, explain, mastery (added to pie), failed, and left the attempt. We recoded the same actions in a row as action - action2 - action3 – action3 for easy interpretation.

With DMM modeling and k-means clustering for all transitions, ten learning strategies emerged. These strategies were Cluster 1 – three correct practices in a row and reach mastery (9%), Cluster 2 – Quick mastery (11%), Cluster 3 – keep practice after mastery (6%), Cluster 4 – Frequently request worked examples and only try when confident (7%), Cluster 5 – Request worked examples after wrong and get correct and mastery finally (12%), Cluster 6 – Request worked examples then quit without practice (13%), Cluster 7 – Request worked examples after wrong but still get wrong then quit (17%), Cluster 8 – Correct at 1st practice but wrong at 2nd & 3rd, then request worked examples but only get half practices correct then. (6%), Cluster 9 – All practice are wrong, request worked example after 2 wrongs, still get wrong, quit or reach failure. (9%), and Cluster 10 – All practice are wrong, reach failure and then 2nd failure (9%).

3. Learning behaviors and learning outcome
A sample from 204 students was used to predict students learning using behaviors within ALEKS. The learning behaviors recorded in ALEKS log files were categorized into help-seeking and practice. We utilized logistic mixed effects models to investigate the relationship of help-seeking and practice with learning outcome. Topics and students were random variables. The model also included student's pretest which was measured by 5^{th} grade TCAP score. The learning outcome was topic mastery (1 or 0).

3.1 Help-seeking and learning outcome

The results of logistic mixed effects model indicated four significant help-seeking behaviors were predictive of learning (R^2 = .81, For full results See Table 1). We used 10-fold cross validation to validate the mixed effects model of help-seeking.

Table 1.
Student help-seeking behaviors that predict learning outcomes

Learning behaviors	Coefficient	Std. Err	z	p
Pretest	.35	.08	4.32	.000
Reading Explain first	.42	.14	3.12	.00
Proportion explain	-46.86	1.51	-31.13	.000
Explain after mistake	-.36	.35	-1.05	.29
Explain request latency	-.01	1.29	27.79	.000
Explain avoid mistake	35.99	.01	-2.40	.02

3.2 Practice and learning outcome

The results of logistic mixed effect model indicated five significant patters of making mistakes were related to learning (R^2 = .75, See Table 2 for results). A 10-fold cross validation was adopted to validate the mixed effects model of practice.

Table 2
Student practice behaviors that predict learning outcomes

Learning behaviors	Coefficient	Std. Err	z	p
Pretest	.17	.10	1.64	.10
Initial Mistake	.64	.09	7.23	.000
Mistake (%)	-5.35	.32	-16.85	.000
Success (%)	12.65	.49	26.04	.000
Self-correction	-1.3	.24	-5.52	.000
Self-correction time	.01	.003	2.23	.03

4. Prior knowledge, difficulty on persistence

A sample from 114 student log files utilizing 92,235 lines of log files data from years two and three of the program that included date, time, topics attempted and the result of each trial were used to predict student's persistence using prior knowledge topic difficulty and time period. The number of trials (T) was chosen as the measure of persistence. Then, three levels of persistence were defined: high persistence ($T>15$), medium persistence ($10<=T<15$), and non-persistence ($T<5$ and not reach mastery).

4.1 Results

Logistic regressions were performed to explore the effects of prior knowledge, topic difficulty and time period the learning took place on the likelihood of participant's persistence related behavior. For high persistence, the model was significant, $\chi2(3)$ = 124.14, p < .001, explaining 2.8% (Nagelkerke R^2) of the variance of highly persistence students and correctly classified 96.2% of cases. For medium persistence, the model was significant, $\chi2(3)$ = 118.68, p < .001, explaining 1.8% (Nagelkerke R^2) of the variance in medium persistence and correctly classified 93.3% of cases. Increasing topic difficulty was associated with increased persistence, but increasing prior knowledge and days learning in the system was associated with a reduction in persistence. For non-persistence, the model was statistically significant, $\chi^2(3)$ = 864.88, *p* < .001, explaining 6.8% (Nagelkerke R^2) of the variance in non-persistence and correctly classified 62.5% of cases. Increasing topic difficulty was associated with an increased non-persistence. Increasing prior knowledge was associated with a reduction in non-persistence.

5. Discussion/conclusion

The current paper present three methods to analyze learner performance which identify important clusters of learner strategies during learning with ALEKS, help seeking behaviors that predict learning, and persistence. The first analysis clustered learner strategies and demonstrated that context is important when looking at clusters. Thus identical elements or techniques can serve different functions when the sequence occurs at a different point in the learning process. The second two analyses use features from the ALEKS data logs to predict learning and persistence. The second analysis found that latency to seek help was negatively related to mastering a topic. This is a validation that ALEKS is working in that increase practice with the system was predictive of mastery of topics. For student persistence, while predicted variability was small, the models were very reliable and able to classify a large proportion of the data. The pattern of data for non-persistent behavior was interesting finding that lower prior knowledge students work on problems projected to be of greater individual difficulty which is predictive of lower persistence. Taken together these techniques indicate patterns that are easily detected and corrected within systems like ALEKS.

6. ACKNOWLEDGMENTS

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7. REFERENCES

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