Understanding Reading Behaviors of Middle School Students

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ABSTRACT
Rich models of students' learning and problem-solving behaviors can support tailored interventions by instructors and scaffolding of complex learning activities. Our goal in this paper is to identify students' reading behaviors as they engage with instructional texts in domain-specific activities. In this work, we apply theory and methodology from the learning sciences to a large-scale middle school dataset within a digital literacy platform, Actively Learn. We compare students' reading behaviors both within and across domains for 12,566 science and 16,240 social studies students. Our findings show that higher-performing students in science engaged in more metacognitively-rich reading activities, such as text annotation; whereas lower-performing students relied more on simple highlighting and took longer to respond to embedded questions. Higher-performing students in social studies, by contrast, engaged more with the vocabulary and took longer to read before attempting question responses. Our finding may be used as recommendations to help both teachers and students engage in and support more effective behaviors.

Author Keywords
Sequence mining; Learner behavior analysis

CCS CONCEPTS
• **Applied computing →Computer-assisted instruction**

INTRODUCTION
Reading to learn is an integral part of learning across domains [6]. Further, mature reading strategies require metacognitive skills, which are a key aspect of self-regulated learning (SRL) [6]. Students in the US, in particular, have lower performance in domain-specific reading comprehension compared to other countries [11].

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The structure of the typical classroom may contribute to this: it is difficult for teachers to monitor and guide students and nearly impossible for teachers to provide one-on-one attention in a class of 25.

Digital reading platforms can provide tools that allow teachers to more closely monitor students' reading progress. By understanding the theory and methodology of reading strategies from learning science and applying it to a large-scale learning environment, we can identify effective and ineffective reading patterns, some of which may be domain-specific. Our objective in this research is to analyze students' reading strategy patterns in two subject domains, and to connect those behaviors with performance.

We answer the following research questions:

RQ1: How can students be grouped according to their assignment performance?

RQ2: How do performance differences connect with reading and SRL behaviors?

We break RQ2 down into two sub-questions:

2a. Do specific reading and SRL behaviors differ between low- and high-performing groups within each subject?

2b. Do observed reading and SRL behaviors differ across domains?

As part of this analysis we clustered students by their performance on embedded questions within a K-12 learning platform, Actively Learn (AL), for middle school physical science and social studies subjects. We then applied differential sequence mining [8] to identify patterns between groups of students within and across two subject domains and to determine if these patterns were different at statistically significant levels.

RELATED WORK
Our review of literature finds an intersection between SRL theory and learner behavior analysis studies. SRL theories and models explain self-regulated learners as active and efficient in maintaining their learning process [13, 15]. We adopted the Winne and Hadwin four-phase model [13] of SRL: task defining, goal setting, enacting tactics and strategies, and metacognitively adapting strategies. We focused specifically on student use of strategies as they engage with text. In the context of reading behaviors, Azevedo examined SRL behaviors, such as taking notes, summarization, and reading notes of the human circulatory system in a hypertext learning environment, Metatutor [3, 4].

Kinnenbrew et al. traced students' SRL patterns in the Betty's Brain platform [8], where students engage in SRL activities, including planning and monitoring to teach Betty. Previous researchers applied sequence mining techniques to identify students' problem-solving patterns in a game-based environment [2], to identify learning patterns for high and low performing students [4], and to generate next step recommendations in the MOOC environment [9].

Our study adapts previously-used data mining methods [4, 8, 12] to examine SRL and reading behaviors across two subjects, science and social studies. We assess AL features related to reading strategies: annotating [3], highlighting [14], and vocabulary lookups, assigning these features to serve as proxies for SRL behaviors.

DATASET

AL reading assignments have text-embedded questions graded on a scale of zero to four. Question formats can be multiple choice (MCQs) and short answer questions (SA) (i.e., fill in the blank and free texts). After cleaning data, we included assignments with class sizes ranging from 10 to 60 for physical science readings and from 10 to 75 for social studies. The final social studies dataset has 16,240 students and 857 assignments. The final science dataset has 12,566 students and 942 assignments.

METHODOLOGY

We began our analysis by using the clustering approach followed by generating sequences, and then applying differential sequence mining.

Clustering Student by Question Performance

We calculated four types of scores for MCQ and SA, resulting in eight performance features. These are: first attempt score, last attempt score, *Norm_Last*, and *Long_Submission*. *Norm_Last* combines a student's attempts and scores on a question. It is the multiplication of the last score by normalized attempts, i.e., the ratio of a student's attempts to all students' attempts on that question in a class. *Long_Submissio*n computes the proportion of attempts a student made after the median time for all students on that question in a class. By introducing this feature, we wanted to get a sense of students' problem-solving attempt behavior relative to other students. A long submit may indicate struggling behavior of a student or a student who is particularly cautious in answer selection. After observing the Silhouette width [7] for resulting clusters K = 2 to 10, we applied K-means clustering with K= 4 on both science and social study data.

Coding Action Sequences

We coded the following question answering and SRL activities: first attempts of MCQ (M) and SA (S), resubmissions of MCQ (m) and SA (s), reading (R), annotating (A), highlighting (H), and vocabulary lookup (V). As the AL system does not record explicit student sessions, we adopted a data-driven approach described by Kovanovic et al. [12] and Adithya et al. [1] to identify sessions. We plotted histograms of time intervals between consecutive actions to identify the last action of any time period. Based upon this analysis we chose a cutoff of 30 minutes as a session duration. We split all student activities within a single assignment by session. We compacted repeated events by + as done by Kinnenbrew et al. [8]. For example, reading (R) followed by two SA attempts (S) and an MCQ attempt (M) was represented by the sequence RSSM and compacted as RS+M.

Differential Sequence Mining

We generated *n*-grams of length n ∈ {2, 3, 4} and included patterns containing at least one letter from the set {R, A, V, H} for each cluster. Differential sequence mining requires two parameters: s-support (frequency of a pattern within a group) and i-support (frequency of a pattern within a one action sequence). We applied s-support = 0.5 to filter patterns exhibited by at least half of students within that group. Next, we applied the non-parametric Kruskal-Wallis test to identify if there was a statistically significant difference in the mean i-support value within the groups (i.e., one group used a pattern more often than the other).

RESULTS

In this section we present results for our two RQs.

Answer to RQ1.

Four resulting science clusters with student counts (n) are: SA_sc (high SA scores in science, n = 4,474), MC_sc (high MCQ scores in science, n = 3114), L_sc (low performers in science, n =2,363), and H_sc (high scores on both MCQ and SA in science, n = 2,636). Similar as in science student clustering, we observed four groups in social studies: H_ss (n = 8,948) , L_ss (n = 2760), MC_ss (n = 2928), and SA_ss (n = 1604).

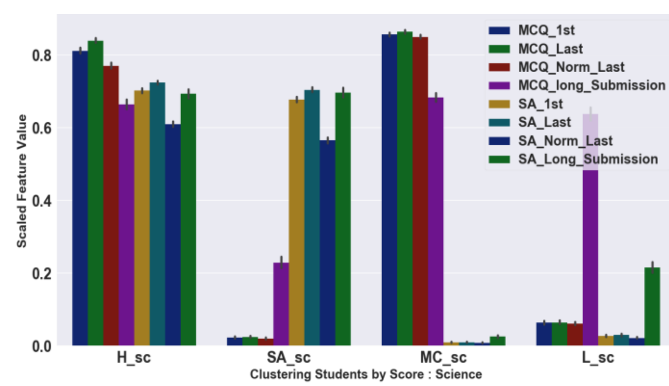

Figure 1. Clustering Students by Score: Science

Answer to RQ2.

We focus primarily on identifying high and low performing student behaviors. Table 1 and 2 present differential patterns for science and social study, respectively. The sequences are sorted in descending order of mean i-support value, as in [4]. A positive I-sup Diff value indicates the pattern was more frequently used by the left side group than the right.

RQ 2a: Differentiable Sequences : Science

Pattern	I-sup-Diff	p	I-sup-Diff	p	I-sup-Diff	p
	H_sc & L_sc		L _sc & Rest		H _sc & Rest	
RS	0.17	***	-0.15	***	0.07	***
RS+	0.08	***	-0.07		0.22	***
SR	0.08	***	-0.06	***	0.04	***
A+	0.03	***	-0.02	***	-	-
V+M	-0.001	**	-	-	-	-
RH+M	-0.002	***	0.001	***	--	--
RM	-0.16	***	0.16	***	--	--

Table 1. Differential patterns: Science. ** = p< 0.05, *** = p < 0.001

Two more frequently used patterns describing SA answering behaviors by H_sc students were RS and RS+. RS and RS+ describe reading prior to attempting one (S) or multiple (S+) SAs. A+ pattern indicates more annotation behavior of H_sc students than L_sc students. Patterns RM, RH+M, and V+M denote a reading (R), reading and highlighting (RH+), and multiple vocabulary lookups (V+) followed by an MCQ submission (M). All three patterns are related with MCQ score behavior of L_sc group students. From Figure 1, we observe L_sc group students have long MCQ submissions and lower last MCQ scores. We conclude L_sc group students struggled in choosing the correct MCQ option.

RQ 2a: Differentiable Sequences : Social Study

Pattern	I-sup-Diff	p	I-sup-Diff	p	I-sup-Diff	p
	H_ss & L_sc		L _ss & Rest		H _ss & Rest	
RS	0.06	***	-0.04	***	0.039	***
RS+	0.04	***	-0.02	***	0.03	***
RS+M	0.02	***	--	--	--	--
SR	0.14	***	--	--	0.009	***
VS	0.013	***	-0.010	***		--
s+R	-0.001	**	0.001	**	--	--
+R	-0.005	**	0.011	***	--	--
S+RS	-0.007	***	--	--	--	--

Table 2. Differential patterns: Social Studies. ** = p< 0.05, *** = p < 0.001

High-performing students in social studies assignments read more frequently before attempting SA (RS and RS+) and MCQ (RS+M). Also, they looked up more vocabulary (VS). Low performing students read after attempting SAs (S+RS). They also had a higher resubmission rate of SA questions followed by the read event (s+R). Our observed patterns explain the way high and low performing students navigated the SAs. We conclude reading and vocabulary lookup to comprehend the concept prior to answering a SA led to score differences for social studies assignments.

RQ 2b: Differentiable Sequences : Cross Domain

Pattern	I-sup-Diff	p	I-sup-Diff	p	I-sup-Diff	p
	H_sc & H_ss		SA_sc & SA_ss		MC _sc & MC_ss	
SR	0.16	***	0.16	***	0.12	***
+R	0.14	***	0.18	***	--	--
S+R	0.12	***	0.14	***	0.11	***
V+	0.05	***	-	-	0.03	***
R+	- 0.175	***	-0.11	***	--	--
R+M	--	--	0.0186	***	0.0192	***
MR+	--	--	0.0192	***	0.0179	***
+R	0.14	***	0.18	***	--	--

Table 3. Differential patterns: Science vs Social Studies. ** = p< 0.05, *** = p < 0.001

Examining descriptive statistics, we noticed the mean SA score was higher in social studies assignments (SA First = 2.56, SA Last = 2.62) compared to science (SA First = 2.46, SA Last = 2.58) ones. Additionally, mean MCQ scores of science were higher (MCQ First = 2.80, MCQ Last = 2.89) than those of social studies (MCQ First = 2.17, MCQ Last = 2.19). Thus, we compared MC_sc vs MC_ss and SA_sc vs SA_ss groups. Additionally, we compared the H_sc and H_ss groups to identify high performing student behavior in these two subjects. Table 3 presents our results.

From the H_sc vs H_ss column, science students exhibited reading behavior *after* submissions, when compared to social studies, as denoted by patterns SR and S+R. SA_sc and SA_ss groups shared similar patterns, except for vocabulary lookups. The relatively lower mean SA score in science can be explained by patterns SR and S+R or relatively harder questions. Interestingly, we observe the difference in frequent patterns while comparing within-domain vs across-domain. RS+ pattern had the highest I-supDiff compared within the domain. This is not the case when comparing science to social studies. Moreover, a negative I-supDiff value of R+ pattern indicates the SA_sc group students exhibited fewer reading activities as compared to SA_ss. Analyzing MC_sc vs MC_ss groups, students with science assignments exhibited more reading behavior before attempting MCQ as described by pattern R+M. Although the two subject domains are different, our analysis shows reading prior to attempting a question was associated with a higher score in both domains.

LIMITATIONS

SRL researchers emphasized considering students' learning contexts [5]. Learning context is nested in nature: geographical, socio-economical, within-school, and within-classroom. We do not have access to students' demographics and teachers' instructions to work on the assignments (in-class or homework). To mitigate this limitation, we considered two features *Norm_Last* and *Long_Submissions* in our clustering. These two features took into account students' performance with respect to each particular *assignment*. Another limitation was that the AL data did not describe defined sessions. We defined sessions by a data-driven approach as done by previous researchers.

IMPLICATIONS AND CONCLUSION

Combining theory from learning science with data-driven analysis, our contributions are: (i) Our findings show that higher-performing students in science engaged in more reading and text annotation, which is in-line with high performing science students' learning pattern in human biology with Metatutor [4]. Low performing students relied more on highlighting and took a longer time to respond to embedded MCQ. Social studies students showed more reading, whereas science students exhibited more vocabulary lookup behaviors. Our findings are in line with findings of Butler and colleagues (see Table 3, [5]). Their classroom study showed that Humanities students reread text more than Information Technology students (58% vs 32%). Researchers of the learning science and educational data mining community can find our results insightful to conduct follow up studies, (ii) Sequence mining results can be used to design recommendation systems aimed at each group of students, as done by Pardos et al. [9], and (iii) Our findings suggest where teachers might focus to make tailored intervention to students. Our patterns are *interpretable* and provide insights of learning behaviors that are *frequent* and *statistically different* within high and low performing students.

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