Exploring Learning Management System Interaction Data: Combining Data-driven and Theory-driven Approaches

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ABSTRACT
This research connects several data-driven educational data mining approaches to a framework for interaction developed in educational research. In particular, 10 million usage data points collected by a Learning Management System used by students and teachers in 450 online undergraduate courses were analyzed with this framework. A range of educational data mining techniques were employed, including K-means clustering, multiple regression, and classification, to both explore and predict student final grades and course completion rates. Findings show that support for the overall model varied with the way data were mapped to the framework (e.g., static vs. temporal features) and the analysis technique used (with clustering and classification providing more useful insights).

Keywords
Learning Management System, Interactions in Online Learning, Clustering, Prediction

1. INTRODUCTION
Educational data mining (EDM) studies have typically relied upon data-driven techniques in order to extract useful patterns and information from large-scale educational datasets [11]. While these data-driven approaches have provided important contributions, some have argued that their inherent a-theoretic nature may fall short in terms of providing insight into the development of educational theory and practice [6]. As such, more studies are needed that better connect EDM findings to educational theory, research, and practice.

To address this need, this paper integrates a theory-driven approach with a data-driven approach to explore student learning outcomes, activities, and patterns as they interact with course content using a popular Learning Management System (LMS), called Canvas. Specifically, for the theory-driven approach, we apply an interaction framework [2] to explore how patterns in the LMS data are related to student final grades and course completion rates at a course level – a macro-perspective. Here, we use K-means clustering and multiple regression analysis. For the data-driven approach, we build classifiers based on machine learning algorithms to predict a student's final grade and whether a student will complete a course or not, providing a micro-perspective.

In particular, we conducted three tasks by addressing following research questions: 1) How many clusters of courses are found based on users' interaction patterns? Are there relationships between individual interaction clusters and course features (size, content, level)? 2) Do the interaction patterns significantly predict student final grades and course completion rates? 3) Can we build effective classifiers to predict an individual student's final grade and whether each student will complete a course? Are the pre-built classifiers still robust and effective for the next semester's data? How many weeks in a semester are needed to discover low performing students or non-course completers (i.e., who may drop out a course)?

2. BACKGROUND
2.1 Interaction in Online Learning
Interaction has long been a significant research topic in the field of educational technology. Nonetheless, it remains a hard concept to define, as it is multifaceted and complex [1, 7]. Some researchers have taken a more restrictive view by excluding non-human factors, and focusing only on human interactions [5]. However, others argued that both human and non-human interactions are integral aspects of the educational experience [1, 2, 4]. Further, supporting various combinations of interaction among teacher, student and the content can help foster a community of inquiry in online learning [4].

In particular, Moore [7] categorized interaction into three types: (i) learner-content interaction, (ii) learner-instructor interaction and (iii) learner-learner interaction. Anderson and Garrison [2] expanded Moore's categorization by differentiating between teacher-content and student-content interaction. In their final model, teacher-content (TC) interaction refers to teachers creating content and learning activities. Student-content (SC) interaction refers to students' interactions with various forms of educational content including reading texts, completing assignments, and working on projects. Student-teacher (ST) interaction includes both asynchronous and synchronous communication between students and teachers. Finally, student-student (SS) interaction

Table 1: Characteristics of 450 courses.

Course characteristics		|Courses|	Percent
STEM Non-STEM	STEM	116	25.8%
	Non-STEM	334	74.2%
Course size	Small (<21)	107	23.8%
	Med (<51)	210	46.7%
	Large (51+)	133	29.5%
Course level	1000 level	156	34.7%
	2000 level	79	17.5%
	3000 level	157	34.9%
	4000 level	58	12.9%

refers to interaction between individual students.

There have been several empirical studies investigating the relationships between different types of interaction and student learning. For example, Bernard et al. [3] conducted a meta-analysis on the effects of the three types of interactions (i.e., SC, ST and SS) on student performance in online learning. They found that the effects of SS interaction and SC interaction were significantly larger than the effect of ST interaction in terms of student performance.

In this paper, we use this interaction framework to explore how interaction is related to student performance and course completion rates in online courses by analyzing and exploring LMS interaction data.

2.2 Educational Data Mining in Learning Management Systems

A LMS provides a wide range of features to support interactions between students, teachers, and content [9]. Moreover, the LMS typically captures interactions with these features in various formats and at diverse granularity levels. The most widely used methods in EDM studies using LMS data are prediction, clustering, and distillation for human judgment (visualization) [10]. Prior studies have found that usage variables related to SS interaction (i.e., the number of discussion messages posted) and SC interaction (i.e., the number of completed assignments) were significant predictors of student performance [6, 12].

However, prior studies using LMS data analyzed student-level data, rather than looking at the various levels and kinds of interactions between teachers, students, and contents. In this paper, we used course level data as well as individual student level data to provide both macro- and micro-perspectives on interactions between students, teacher, and contents in online learning. In this way, our research complements the existing research base.

3. DATASET AND METHODS

3.1 Dataset

For the present study, data were extracted from the Canvas LMS deployed at a mid-sized public university located in the western U.S. The LMS automatically captures all teacher and student online interactions. Note that an academic support unit at the university extracted and anonymized these data, and Institutional Review Board (IRB) approved using the data for research purposes.

We conducted data preprocessing by transforming raw data into an appropriate shape for analysis. First, we performed data cleaning in the following three steps: 1) selected courses offered between Fall 2014 and Spring 2015; 2) selected only online undergraduate courses; and 3) excluded low enrollment courses (i.e., the number of enrolled students is less than 5). After conducting the data cleaning process, our dataset consisted of 450 courses including 10,576,718 interactions, and anonymized 21,171 student profiles (8,844 distinct student profiles) and 450 teacher profiles (228 distinct teacher profiles).

Table 1 shows the number of courses in our dataset, categorized by STEM vs. non-STEM, size, and course level. 25.8% courses are Science, Technology, Engineering, and Mathematic (STEM) courses. A full range of course sizes is represented and is centered around medium-sized enrollments (i.e., 21-50 students). The largest number of courses is 1000 level (34.7%) and 3000 level (34.9%) courses.

3.2 Data Mining Methods and Features

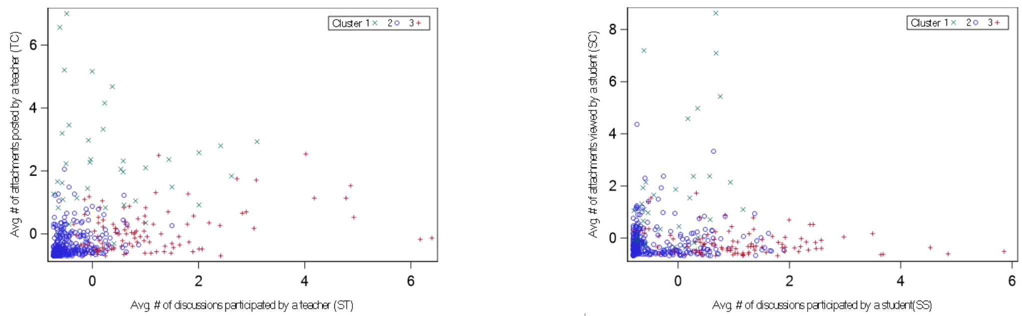
In this study, we used three data mining methods for three tasks – one method for each task: (i) K-means clustering to find groups of courses each of which has similar interaction patterns at a course level; (ii) multiple regression to measure the relationship between each interaction feature/variable and average student final grade and course completion rates at a course level; and (iii) classification algorithms to predict each student's final grade and whether the student will complete a course or not. The first two methods provided a macro perspective focusing on courses, while the last method provided a micro perspective focusing on individual students.

Task 1. We used K-means clustering to identify how online courses were clustered based on interaction patterns. We used the PROC FASTCLUS method in SAS, as missing values were replaced with an adjusted distance using the non-missing values [8]. We used Euclidean distance to measure distance between each node (i.e., a course) and a centroid. To find the optimal K, we examined the agglomeration schedule to determine the optimal number of clusters.

Task 2. We conducted multiple regressions using SAS to test whether each interaction type significantly predicted outcome variables – average final grades and course completion rates.

For Tasks 1 and 2, we grouped Canvas features (variables) into four categories (TC, SC, SS, ST) based on Anderson and Garrison's interaction framework [2]. Table 2 presents four categories associated with the Canvas features, and each feature's mean, standard deviation (SD) and minimum and maximum values obtained from the 450 courses.

Task 3. We applied classification algorithms (i.e., SVM, Random Forest, J48 and AdaBoost) to predict each student's final grade and whether the student will complete a course or not. Effectiveness of classifiers depends on quality of features. For this task, we used 129 features consisting of 52 static features and 77 temporal features as shown in Table 3. These features consisted of not only the main interaction features that we used in the first and second tasks (while they were average values in the first and second tasks, individual student feature values were used in the third task),



(a) ST interaction vs. TC interaction (z-transformed data).

(b) SS interaction vs. SC interaction (z-transformed data).

Figure 1: Scatter plots showing how courses in clusters are distributed differently.

Table 2: Descriptive statistics of 450 courses analyzed by 12 interaction features associated with four categories.

Category	Features	Mean	SD	Min-Max
Teacher-Content	Avg. # of attachments posted by a teacher (tc_atta)	15.97	22.86	0-176
	Avg. # of discussion topics posted by a teacher (tc_disc)	18.55	15.54	0-107
	Avg. # of wiki topics posted by a teacher (tc_wiki)	13.58	13.96	0-74
	Avg. # of quizzes posted by a teacher (tc_quiz)	9.72	9.48	0-56
	Avg. # of assignments posted by a teacher (tc_assi)	15.30	12.97	0-75
Student-Content	Avg. # of attachments viewed by a student (sc_atta)	118.19	174.57	0-1,625
	Avg. # of discussions viewed by a student (sc_disc)	48.05	44.88	0-296
	Avg. # of wiki viewed by a student (sc_wiki)	54.42	51.92	0-387
	Avg. ratio of completed quiz by a student (sc_quiz)	0.88	0.12	0.10-1
	Avg. ratio of completed assignments by a student (sc_assi)	0.78	0.16	0.10-1
Student-Student	Avg. # of discussions participated by a student (ss_disc)	12.21	15.13	0-101
Student-Teacher	Avg. # of discussions participated by a teacher (st_disc)	50.15	68.63	0-489

but also additional features (e.g., the number of views of the grade and announcement pages, course information and temporal features). In particular, temporal features were extracted from a series of daily snapshots of each student's interaction record. Given a course and interaction information of a student who took the course, we represented the student by using the 129 features.

4. EXPERIMENTAL RESULTS

In the previous section, we described our dataset and three data mining methods for conducting three tasks. In this section, we present results of these experiments using each of the methods for each task.

Table 3: 129 Features extracted from each student and each corresponding course.

Static Features	
Features	|Features|
Course level and Department offering the course	2
Total # of views and total # of participation by a student	2
# of views and participation in each of the 24 items by a student	48

Temporal Features	
Features	|Features|
Total # of participated weeks (i.e., we add +1 if a student did participation at least once in a week)	1
Mean and standard deviation of weekly view count and weekly participation count	4
Each week's view count and participation count	36
Accumulated weekly view count and accumulated weekly participation count	36

4.1 Task 1: Clustering Courses and Analyzing Characteristics of Clusters

In Task 1, our research goal was to cluster courses based on interaction patterns and analyze characteristics of the clusters. First, we standardized the interaction features/variables (raw scores) by following the recommendation in the literature [8]. The raw scores were z-transformed to a mean of 0 and standard deviation of 1 for either the course or semester level data.

K-means clustering requires an input K. To make sure we chose an optimal K, we examined the agglomeration schedule. The demarcation point indicated that $K = 3$ would produce the optimal result. Clusters 1, 2 and 3 contained 41, 300 and 109 courses, respectively. The root mean squared standard deviations (RMSSTD) for each cluster were 1.32, 0.71, 0.98 respectively, indicating that the courses in cluster 1 are more widely dispersed than the others.

We further drew two scatter plots to help understand characteristics of the three clusters as shown in Figure 1. Figure 1(a) represents a scatter plot of ST interaction (*st_disc*) vs. TC (*tc_atta*) interaction. Courses in cluster 1 had higher TC interaction than those in the other clusters, whereas courses in cluster 3 had higher ST interaction than the other two clusters. Figure 1(b) shows a scatter plot of SS interaction (*ss_disc*) vs. SC interaction (*sc_atta*). Courses in cluster 1 showed higher student-content interaction than the other two clusters. On the contrary, courses in cluster 3 showed higher SS interaction than the other two clusters.

Table 4: Means and standard deviations of clusters. $*$ indicates the highest value among the three clusters.

Feature	Cluster 1 (n=41) Content-interaction		Cluster 2 (n=300) Low-interaction		Cluster 3 (n=109) Inter-person interaction	
	M	SD	M	SD	M	SD
tc_atta	2.12	1.78	-0.32	0.44	0.09	0.67
tc_disc	0.26	0.96	-0.44	0.59	1.1	1.04
tc_wiki	1.53	1.31	-0.37	0.64	0.43	0.98
tc_quiz	0.68	1.32	-0.05	0.99	-0.12	0.76
tc_assi	0.38	1.23	-0.28	0.77	0.62	1.14
(T-C) mean	0.99*	0.66	-0.29	0.43	0.42	0.55
sc_atta	1.47	2.27	-0.14	0.62	-0.18	0.47
sc_disc	-0.04	0.52	-0.46	0.55	1.22	1.02
sc_wiki	1.8	1.62	-0.23	0.68	-0.07	0.7
sc_quiz	-0.18	1.04	0.02	0.92	0.02	1.19
sc_assi	-0.18	1.15	0.03	1.04	-0.01	0.84
(S-C) mean	0.57*	0.85	-0.16	0.46	0.2	0.42
(S-S)	-0.2	0.59	-0.38	0.58	1.05*	1.22
(S-T)	0.29	1.02	-0.43	0.33	1.07*	1.33
final grades	**2.77**	**0.59**	**3.01**	**0.57**	**3.05***	**0.38**
complet. rates	**84.04**	**12.95**	**86.84**	**12.75**	**88.09***	**9.18**

Next, we examined descriptive statistics for the predictors and outcome variables (final grades and completion rates) for each cluster as shown in Table 4[1]. The results showed that cluster 1, dubbed *"Content-Interaction courses"*, had the highest means for both TC interaction ($M = 0.99, SD = 0.66$) and SC interaction ($M = 0.57, SD = 0.85$). Cluster 2, dubbed *"Low-Interaction courses"*, had the lowest means for all interaction variables. Lastly, cluster 3, dubbed *"Inter-person Interaction"*, had higher means for SS interaction ($M = 1.05, SD = 1.22$) and ST interaction ($M = 1.07, SD = 1.33$). The analysis revealed that courses in each cluster had different course emphases: content interaction in cluster 1, non-interaction in cluster 2, and person interaction in cluster 3.

Then, we compared the three clusters in terms of average student final grades and course completion rates. As shown in Table 4, the cluster 3 had the highest mean in student final grades ($M = 3.05, SD = 0.38$) and course completion rates ($M = 88.09, SD = 9.18$) among the three clusters. The cluster 1 had the lowest mean in student final grades ($M = 2.77, SD = 0.59$) and course completion rates ($M = 84.04, SD = 12.95$). This finding reveals that the positive impact of courses focusing on interactions between participants.

Next, we conducted chi-squared tests to compare STEM and Non-STEM courses in the three clusters. As shown in Table 5, the distribution of the STEM and Non-STEM courses was significantly different across the three clusters, $\chi^2(6, N = 450) = 7.80$, $p < .05$. STEM courses were infrequent overall, but even more scarce in the cluster 3.

Then, we analyzed how many courses in the three clusters had small, medium and large enrollments. Table 6 shows the analytical results. The result of a chi-squared test showed significant differences among the three clusters, $\chi^2(4, N = 450) = 15.31$, $p < .05$. The cluster 1 had the largest proportion of large courses, whereas the cluster 3 had the smallest proportion of large courses. The findings suggest that promoting interaction among participants is rarer in large courses.

[1]The meaning of each feature's acronym is described in Table 2.

Table 5: The number of STEM and Non-STEM courses in three clusters.

Cluster	Non-STEM	STEM	Total
C1	29 (70.7%)	12 (29.3%)	41
C2	21 (71.0%)	87 (29.0%)	300
C3	92 (84.4%)	17 (15.6%)	109
Total	334	116	450

Table 6: The number of small, medium, large courses in three clusters.

Cluster	Small	Medium	Large	Total
C1	13(31.7%)	13(31.7%)	15(36.6%)	41
C2	78(26.0%)	130(43.3%)	92(30.7%)	300
C3	16(14.6%)	67(61.4%)	26(24.0%)	109
Total	107	210	133	450

Lastly, we examined how many courses in the three clusters were at the 1000, 2000, 3000 and 4000 levels. A chi-squared test found no significant differences in the distribution of the course levels among the clusters, $\chi^2(6, N = 450) = 8.79$, $p > .05$.

4.2 Task 2: Prediction Using Multiple Regression Analysis

In task 2, first we conducted a multiple regression analysis to examine the influence of interaction features or feature category listed in Table 2 in predicting average student final grades in each course. Table 7 shows regression results of significant variables. The results indicated that the explanatory variables accounted for a modest 15.8% of the variance ($R^2 = 0.16$, $F(12, 411) = 6.41$, $p < .05$). Several significant and negative predictors were found in teacher-content interaction. In particular, as *tc_disc*, *tc_wiki*, and *tc_assi* increased, final grades tended to decrease. Findings in the student-content interaction category were the opposite. Final grades tended to increase when *sc_quiz* and *sc_assi* increased and the same is true in the student-teacher interaction category.

A second multiple regression analysis was conducted to test the influence of each interaction feature or each feature category on course completion rates. The explained variance was a modest at 15.7%($R^2 = 0.16$, $F(12, 411) = 6.64$). Only a single teacher-content variable *tc_wiki* was negatively significant. Student-content interaction features *sc_quiz* and *sc_assi* were significant and positive again in relation to course completion rates. Taken together, these findings suggest that certain teacher activities related to content were less productive, whereas student activities related to content were more positively productive in both final grades and course completion rates.

Table 7: **Multiple regression results (* indicates the feature is significant at the 0.05 level, and the table includes only significant features).**

Category	Feature	final grades B	SE(B)	β	t	p	completion rates B	SE(B)	β	t	p
Intercept		0.000	0.089	0.000	29.600	0.001	0.000	0.089	0.000	29.600	<.0001
Teacher-Content Interaction	tc_disc	-0.006	0.003	-0.177*	-2.240	0.026	-0.078	0.060	-0.059	-0.990	0.324
	tc_wiki	-0.011	0.002	-0.295*	-4.540	0.001	-0.241	0.054	-0.202*	-3.710	0.000
	tc_assi	0.004	0.002	0.106*	1.970	0.050	0.037	0.048	0.033	0.690	0.490
Student-Content Interaction	sc_wiki	0.001	0.001	0.141*	2.140	0.033	0.125	0.015	0.029	1.900	0.058
	sc_quiz	0.003	0.001	0.164*	3.250	0.001	0.284	0.019	0.107*	5.650	<.0001
	sc_assi	0.003	0.001	0.177*	3.530	0.001	0.115	0.019	0.044*	2.290	0.023
Student-Teacher Interaction	st_disc	0.001	0.001	0.160*	2.340	0.020	0.130	0.011	0.022	1.910	0.057

Table 8: Feature Sets

Feature Set	Features (# of features)
A	Course level and department offering the course, total # of views and total # of participation (4)
B	feature set *A* + # of views and participation in each of the 24 items by a student (52)
C	feature set *B* + total # of participated weeks (53)
D	feature set *C* + mean and standard deviation of weekly view count and weekly participation count (57)
E	feature set *D* + each week's view count and participation count, and accumulated weekly view count and participation count (129)

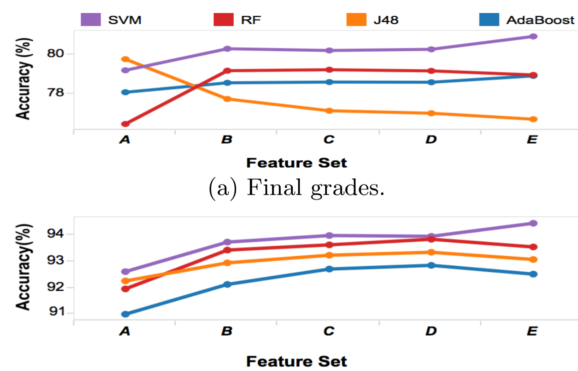
4.3 Task 3: Predicting Individual Student's Final Grade and Course Completion

So far, experiments in Tasks 1 and 2 were conducted at the course levels, providing a macro perspective. Now we turn to building classifiers to predict individual student's final grade and course completion (i.e., whether the student will complete the course or not) by using a data-driven approach, providing a micro perspective, and then evaluating effectiveness of the classifiers. In task 3, predicting a student's final grade means predicting whether the student will belong to a high performance group (i.e., obtaining one of A, A-, B+, B and B-) or a low performance group (i.e., obtaining one of C+, C, C-, D+, D, F and W).

4.3.1 Prediction in 2014 Fall Semester Dataset

In this experiment, we used the 2014 Fall semester dataset consisting of 229 courses with 4,314,425 interactions and anonymized 10,003 student profiles. To build highly accurate classifiers, proposing and using features which have significant distinguishing power is important. To test this, the 129 features listed in Table 3 were sampled to make five feature sets entitled feature sets *A*, *B*, *C*, *D* and *E* as shown in Table 8. As we chose from feature set *A* to *E*, the number of features increased by including the previous features but also additional features. Feature sets *A* and *B* consisted of only static features, while feature sets *C*, *D* and *E* consisted of static features and temporal features.

Since we didn't know apriori which classification algorithm would perform the best, we chose 4 popular classification algorithms – SVM, Random Forest, J48 and AdaBoost. Given the 2014 Fall semester dataset, we did 10-fold cross-validation by dividing the dataset to 10 sub-samples. Each sub-sample



(a) Final grades.

(b) Course completion.

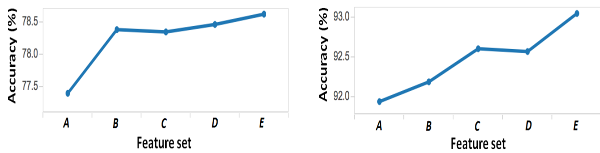
Figure 2: Prediction results of SVM, Random Forest, J48 and AdaBoost based classifiers with five feature sets.

became a test set, the other 9 sub-samples became a training set. We conducted a classification experiment for each of the 10 pairs of training and test sets. Then, we averaged the 10 classification results. We repeated this process for each classification algorithm.

Figure 2 shows prediction results for final grades/performance groups and course completions. SVM based classifier outperformed Random Forest, J48 and AdaBoost based classifiers, achieving 80.95% accuracy, 0.79 F-measure and 0.72 AUC in final grade prediction and 94.41% accuracy, 0.94 F-measure and 0.85 AUC in course completion prediction. As we added more features (changing from feature set ***A*** to ***E***), SVM classifier's accuracy has increased in both predictions. Compared with the *baseline*, which was measured by a percent of the majority class instances and achieved 68% accuracy in final grade prediction and 84% in course completion prediction, our SVM based classifier improved 19% ($= \frac{80.95}{68} - 1$) accuracy in final grades prediction, and 12.4% ($= \frac{94.41}{84} - 1$) accuracy in course completion prediction.

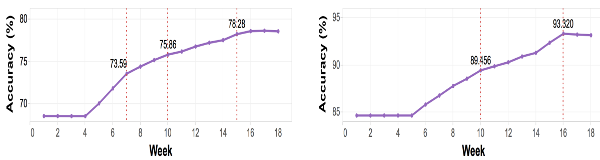
4.3.2 Robustness of Our Prediction Model

In Section 4.3.1, we evaluated effectiveness of our classification approach for both final grades prediction and course completion prediction. Now we are interested in how much the pre-built model is robust when we apply it to data generated in the future (i.e., future semesters). To simulate this scenario, we used the 2014 Fall semester dataset as a



(a) Final grades. (b) Course completion.

Figure 3: Prediction results obtained by applying SVM-based classifiers trained by 2014 Fall dataset to 2015 Spring dataset.



(a) Final grades. (b) Course completion.

Figure 4: Prediction results over time.

training set and the 2015 Spring semester dataset as a test set (consisting of 221 courses with 6,262,293 interactions and anonymized 11,168 student profiles). We built a SVM-based classifier and predicted each student's final grade and course completion in the test set.

Figure 3 shows prediction results as we used feature set A to E. Again, using all the features (feature set E) produced the best results, achieving 78.64% accuracy and 0.682 AUC in final grades prediction and 93.06% accuracy and 0.817 AUC in course completion prediction. Compared with the previous experimental results in Section 4.3.1, there were only small reductions – 2.31% (final grades) and 1.35% (course completion). The experimental results confirmed that our proposed approach is robust and can be applied to future semesters.

4.3.3 Early Prediction

The previous experimental results showed that our approach was effective in predicting final grades and course completion. In practice, it is better to produce prediction earlier so that a tool/system can automatically identify and alert which students are at risk of receiving a low grade or dropping out a course thereby requiring intervention by a teacher. To address this need, we used daily snapshot of data including student profiles, course information and interaction logs, and then simulated the scenario by building a SVM-based classifier in each week. In other words, we built a classifier and evaluated its performance in each week. By doing this, we examined how the classifier's performance changed over time, and when we could achieve a reasonable accuracy.

Figure 4 shows prediction results in the 2014 Fall dataset. In final grades prediction, when we built classifiers in the 7th week, 10th week and 15th week, we achieved 73.59%, 75.86% and 78.28% accuracy, respectively. Similarly, in course completion prediction, we achieved 89.4% and 93.3% accuracy in 10th week and 16th week, respectively. Overall, adding more data improved performance of our classifiers. This study reveals that it is possible to detect students early who have a higher chance of receiving low grades or dropping out a course.

5. CONCLUSIONS

The purpose of this study was to explore relationships between theoretically defined constructs extracted from a Learning Management System and student learning outcomes. Three different tasks employing three different methods were used to explore these relationships. The first two tasks were conducted at the macro-level and thus aligned with a theory-driven approach, whereas the last task at the micro level aligned with a data-driven approach.

Results from the cluster analysis revealed that courses with high inter-person (SS, ST) interaction had higher final grades and completion rates than courses in the other clusters (low-interaction and content-interaction), aligning with results from previous studies [6, 12]. Results also suggested that STEM and large courses tended to exhibit fewer of these productive interactions. The micro-level, data-driven machine learning analysis using prediction with SVM enabled the discovery of at-risk students with high accuracy. It achieved the best performance when all temporal features (complete feature set) were taken into consideration and was robust when predicting future data.

In sum, for this dataset comprised of LMS interactions drawn from online undergraduate courses, the interaction framework was useful for interpreting at both macro and micro levels.

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