INCORPORATING DATA MINING INTO COURSE EVALUATION: A CASE STUDY OF K-12 VIRTUAL SCHOOL

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ABSTRACT

This study aimed to propose a new approach of course evaluation through analyses of student learning logs and demographic data in order to support reflections on teaching and learning at the K-12 level. A case study was conducted with a total of 7,539 students (23,854,527 learning logs in 883 courses). Clustering analysis was applied to construct student profiles. Findings include (a) female students performed better than male students in most subject areas. (b) Students younger than 16.6-year-old performed better older students. (c) Student geographic location is not an important factor for academic success.

Keywords: Educational Data Mining; Course Evaluation; K-12 Virtual School

INTRODUCTION

The flexibility, convenience, just-in-time availability and personalized learning opportunities available in online courses have fueled exponential growth in US K-12 online programs and schools. Although exact numbers are difficult to obtain, a survey of school district administrators found that more than a million US K–12 students took online courses in the 2007-08 school year [1]. Other reports predict 1.4 million children will be taking online courses in cyber-charter schools by 2014 [2]. However, a 2010 report from the International Association for Online Learning (iNACOL) indicates that this number has already been surpassed with an estimated 1.5 million US K-12 students enrolled in online programs [3]. We also know state-led virtual schools and online learning initiatives account for almost half a million enrollments in 39 states—a near 40% increase over the previous year. Full time virtual schools continue growing in number: currently 27 states with an estimated 200,000 students. Although difficult to track, an estimated 50% of US K-12 school districts across the country have online or blended program in place [4]. [5], in their book "Disrupting Class," estimate that by the year 2019, 50% of all US high school courses will be online.

Traditionally, instructors and institutional administrators rely on course evaluation surveys to evaluate course effectiveness and generate information for decision making. Lacking direct observation opportunities, and aiming to provide more customized learning experiences, online instructors need effective tools, other than course evaluations, to track students' online learning activities and to improve student outcomes through personalizing instruction, identifying struggling students, adjusting teaching strategies, and improving course design. Institutional administrators need to track students' online learning activities in order to effectively oversee courses, depict students' general learning characteristics, study trends across courses or years, and implement institutional strategies for improved student outcomes. Each of these needs can be addressed by incorporating data mining into student evaluation.

PURPOSE OF THIS STUDY

The purpose of this study aimed to propose a new approach of course evaluation through analyses of student learning logs and demographic data in order to support reflections on teaching and learning at the K-12 level. The new approach

RELATED WORK

Educational data mining

Data mining (DM) is a series of data analysis techniques applied to extract hidden knowledge from server log data [6] by performing two major tasks: pattern discovery and predictive modeling [7].

Related techniques have been widely used in business fields, especially in e-commerce, for providing personalized business services [8], identifying potential customers [9], adjusting marketing strategies [10, pp. 1189-1220], improving website design [11], and more. Modern online education relies heavily on learning management systems (LMS) or course management systems (CMS). These LMS/CMS automatically record navigational behavior of individual users as server logs. Therefore, data mining techniques can also be applied to solve issues of online teaching and learning.

However, Educational Data Mining (EDM) is faced with special challenges due to the dynamic characteristics of e-learning in five aspects:

1. Behaviors: Learning behaviors are complex, including different types of interactions (student-content, student-student, student-instructor, etc.) and varied sequences of learning interactions [12][13][14, pp. 41-56].

2. Target variables: The most common target variable in e-commerce studies is buying or not buying. In e-learning studies, however, a common target variable is learning outcomes or performance [15], which requires a rather wide range of varying assessments and indicators.
3. Goals: The major goal of data mining in e-commerce is to increase profit, which is tangible and can be measured quantitatively. On the other hand, the major goal of data mining in e-learning is to improve online teaching and learning, which might be difficult to measure or quantify [16].
4. Techniques: With different behaviors, target variables, and goals, only specific data mining techniques are suitable for analyzing educational questions [16]. In addition, data for educational data mining need different modifications from e-commerce studies.
5. Data collection: Only interactions which occurred in LMS/CMS can be tracked. However, a great deal of learning might occur outside the LMS.

Although EDM, in comparison with commercial data mining applications, has the above constraints, external variables such as demographic information and survey investigation are more easily collected at educational institutions than from commercial websites. Those possibilities provide great potential in EDM, especially for result interpretation and evaluation.

METHOD

Data source

Data were collected from a statewide K-12 supplemental online institution that serves over 16,000 students virtually in a northwestern state of the US including three types of data: 1) LMS activity logs and 2) student demographic data. The online K-12 institution serves an important need in a state that is primarily rural, providing course offerings to students in resource-poor school districts who would otherwise not have access. It also serves the state by providing online professional development training to teachers. Their courses, delivered using the Blackboard LMS, provide a rich source of data from a diverse student and teacher population across a broad region.

LMS activity logs

The sources for data mining were the LMS (Blackboard) activity logs for the duration of Fall 2009 to Spring 2010. A total of 23,854,527 activity logs were collected from 7,539 students in 883 courses.

Demographic data

The following demographic data were collected for data analysis: age, gender, graduation year, city, school district, number of online course taken, number of online course passed, number of online course failed, and final grade average.

Analytic tools

SAS (Institute Inc., Cary, NC, USA) Enterprise Miner 6.1 was employed to perform the following data mining tasks in this study: 1) Learner profiling: describe shared characteristics of students who passed or failed the course. 2) Perception and performance predictions: identify key predictors to predict course satisfaction, instruction satisfaction, and final grade.

RESULTS

Table 1 lists variables collected from Blackboard and student management database. Some variables were transformed by calculation in order to generate more meaningful variables for analysis. For example, student's birth year was transformed to age. The summary of all learning activities was aggregated to a new variable called "frequency of clicks." It represents each student's total frequency of clicks on the Blackboard Learning Management System. If students took more than one course during the analysis period, variables of learning activities (e.g. frequency of total clicks and frequency of course access) and performance (e.g. final grade) were averaged.

TABLE 1 Variables for data mining

Variables	Descriptions
stuID	Student's ID
Age	Student's age
City	Student's residential city
District	Student's school district
Grade_Avg	Average course grade
Click_Avg	Average frequency of click/course
Content_Access_Avg	Average frequency of course content accessed/course
Course_Access_Avg	Average frequency of course accessed/course
Page_Access_Avg	Average frequency of page accessed/course
DB_Entry_Avg	Average number of discussion board entries/course
Tab_Access_Avg	Average frequency of tab accessed/course
Login_Avg	Average frequency of logins/course
Module_Avg	Average frequency of module accessed/course

Gender	Gender
HSGradYear	High school graduation year
School	Student's school
No_Course	Number of course taken
No_Fail	Number of course failed
No_Pass	Number of course passed
Pass rate	Course pass rate (>= 0 and <=1)

Online learning interactions

Engagement is thought to be a key variable for enabling and encouraging learners to interact with the material, with the instructor, and with one another, as well as for learning generally [17]. In this study, engagement level was measured by frequency of various learning interactions happened in the Learning Management System.

Clustering analysis

Clustering analysis was applied to group students based on their shared characteristics. A pass rate equals to 1 means a student passed all courses during the period of analysis. Pass rate equals to zero means a student failed all courses during the period of analysis. Pass rate between 0 and 1 means a student passed partial courses during the period of analysis. In this study, pass rate was set up as the standard for classification and 6 clusters were generated after clustering analysis.

Table 2 shows results of clustering analysis in academic year 2009/10. Below are shared characteristics of each cluster.

Cluster 1 (316 students, pass rate 55.07%, all males): Cluster 1 consists of students who are older than clusters 3-6. They were lower-engaged students than Clusters 5 and 6 but higher than Clusters 3 and 4. On average, each student took 2.76 courses and failed around half of them.

Cluster 2 (320 students, pass rate 56.11%, all females): Similar to Cluster 1, Cluster 2 consists of students who are older than clusters 3-6. They are lower-engaged than clusters 5 and 6 but higher than Clusters 3 and 4. On average, each student took 3.03 courses and failed around half of the courses.

Cluster 3 (594 students, pass rate 0%, all males): Clusters 3 and 4 include lowest-engaged students. Cluster 3 students are all male. On average, each student took 1.43 courses and failed all of them.

Cluster 4 (601 students, pass rate 0%, all females): Cluster 4 includes lowest-engaged female students. On average, each student took 1.39 courses and failed all of them.

Cluster 5 (2,311 students, pass rate = 100%, all males): Clusters 5 and 6 represent highest-engaged students. Cluster 5 students are all male. On average, each student took 1.59 courses and passed all of them.

Cluster 6 (3,397 students, pass rate = 100%, all females): Cluster 6 represents highest-engaged female students who passed all their courses. On average, each student took 1.64 courses.

TABLE 2 Clustering analyses in the academic year 2009/10

Clusters	CL1	CL2	CL3	CL4	CL5	CL6
Number of Students	316	320	594	601	2311	3397
Pass rate =0	0	0	594	601	0	0
Pass rate (<0 and >1)	316	320	0	0	0	0
Pass rate =1	0	0	0	0	2311	3397
GenderF	0	320	0	601	0	3397
GenderM	316	0	594	0	2311	0
Age	16.9	17.1	16.7	16.8	16.6	16.59
Grade_Avg	50.1	52.8	22.4	20.9	81.75	85.4
Click_Avg	583	549	440	416	892.5	881.7
Content_Access_Avg	113	112	93.8	89.4	180.3	178
Course_Access_Avg	170	172	134	142	281.5	284.2
DB_Entry_Avg	4.08	5.28	2.78	4.22	8.28	9.57
Login_Avg	29.4	24.4	23.6	19.2	47.92	46.42
Module_Access_Avg	156	145	113	102	249.2	240.8
Page_Access_Avg	99.6	89.4	72	62.5	145.4	142.4
Tab_Access_Avg	41.9	37.8	30	26	62.04	60.72
No_Fail	1.23	1.33	1.43	1.39	0	0
No_Pass	1.52	1.7	0	0	1.59	1.64
No_course	2.76	3.03	1.43	1.39	1.59	1.64

Geographical distributions

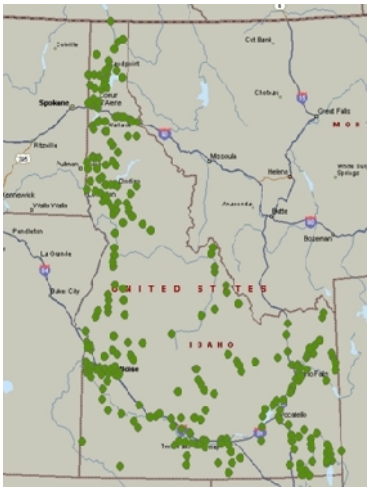
The clusters generated from cluster analysis were associated with one geographical variable (school) to reveal geographic distribution of each cluster. Figure 1 shows clustering distributions by city for the whole academic year of 2009/10.

Figure 1 reveals that clusters 1 to 4 consist of similar geographical distributions. The results indicate student failure in online courses was not limited to specific areas or cities. However, many successful male students are from one larger city at Northwestern. On the other hand, many successful female students are from the other two larger cities.

FIGURE 1 Cluster Geographical Distributions of the whole 2009 Academic Year

Cluster 1 (316 students, pass rate 55.07%, all males)

Cluster 2 (320 students, pass rate 56.11%, all females)

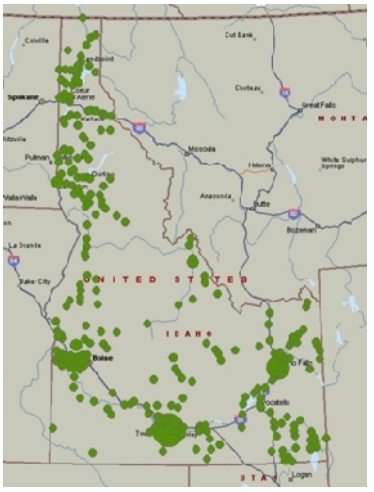


Cluster 3 (594 students, pass rate 0%, all males)

Cluster 4 (601 students, pass rate 0%, all females)

Cluster 5 (2,311 students, pass rate = 100%, all males)

Cluster 6 (3,397 students, pass rate = 100%, all females)



Subject areas

Table 4 shows students' average frequencies of total clicks and performances per course in different subject areas. Total clicks are equal to the summarized frequency of overall learning activities. Table 4 shows that Math and Science have the highest number of total clicks per course and of total clicks per student per course. However, the average of students' final grades (56.70 and 64.41 accordingly) are lower than overall average (71.11). The results indicate students participated actively in courses of these two subject areas; however, they failed to achieve expected outcomes. Therefore, it is necessary to examine course designs and teaching strategies in these two subject areas.

On the other hand, teachers in English courses need to motivate students' participations because the low final grade might result from low engagement level. Students in Foreign Language and Health not only participated in learning activities actively but also obtained highest grades in each of these two subject areas.

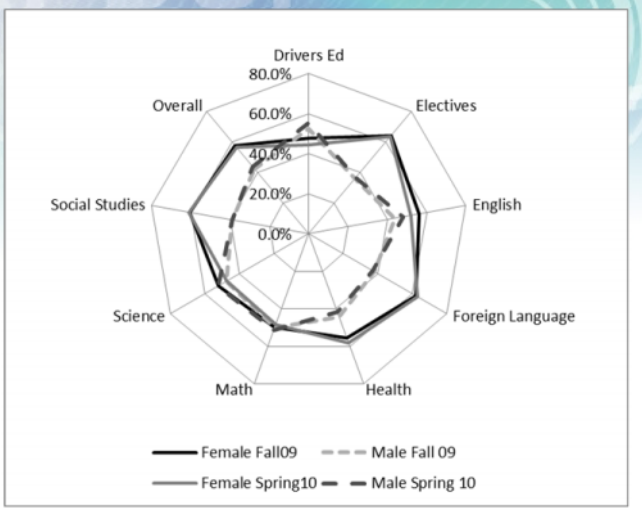
TABLE 4 Average engagement levels and performances in different subject areas

Subject Areas	Total Clicks	Total Clicks/student	No of Students	Final Grade
Drivers Ed	4808	227.97	21.09	78.4
Electives	5353.63	247.69	21.61	76.59
English	4807.79	239.98	20.03	62.09
Foreign Language	7824.63	439.4	17.81	76.54
Health	6641.8	269.99	24.6	83.58
Math	7898.35	444.05	17.79	56.7
Science	9015.16	603.53	14.94	64.41
Social Studies	4740.92	235.97	20.09	70.58
Average	6386.29	323.43	19.75	71.11

Subject preferences

Figure 2 shows percentages of female and male students in different subject areas. Subject preferences of male and female students are revealed by comparing gender percentages of each subject with the overall percentages. The results indicate female students prefer to take Electives, Foreign Language, and Social Science. Male students prefer to take Drivers Education, Math and Science.

FIGURE 2 Gender distribution in different subject areas



Pass rate in different subject areas

Table 5 consists of two parts. The first part examines whether pass rates of female and male students in different subjects have significant differences. Table 5 lists subject pass rates of female and male students. "F vs M" compares gender pass rate difference using t-tests. The second part examines pass rate difference between Fall 2009 and Spring 2010 within the same gender. For example, "F vs F" compares pass rate difference between Fall 2009 and Spring 2010 female students in difference subjects by using t-tests. Numbers marked with asterisks represent differences have statistical significance.

TABLE 5 Pass rate differences of female and male students in different subject areas

Terms	Fall 2009			Spring 2010			Fall 2009 vs. Spring 2010	
Gender	F	M	F vs M	F	M	F vs M	F vs F	M vs M
Drivers Ed	0.91	0.89	0.623	0.96	0.86	0.044*	0.156	0.779
Electives	0.85	0.79	0.000*	0.91	0.87	0.000*	0.025*	0.019*
English	0.69	0.57	0.000*	0.83	0.72	0.000*	0.000*	0.000*
Foreign Language	0.83	0.8	0.088	0.91	0.89	0.121	0.006*	0.036*
Health	0.92	0.9	0.023*	0.97	0.97	0.058	0.067	0.084
Math	0.55	0.54	0.769	0.72	0.7	0.761	0.000*	0.000*
Science	0.71	0.67	0.223	0.85	0.81	0.418	0.000*	0.000*
Social Studies	0.79	0.74	0.000*	0.89	0.84	0.000*	0.000*	0.002*
Overall	0.24	0.31	0.000*	0.13	0.2	0.000*	0.000*	0.000*

Based on the results of Table 5, female significant performed better than male students, especially in the following subject areas: Electives, English, and Social Science.

In addition, Spring 2010 pass rate is significant higher than Fall 2009, especially in those subjects with lower pass rate such as English, Math, Science, and Social Science.

Summary of findings

Findings below were summarized by combining results from the academic year of 2009/10 and from Spring 2010 only.

1. Students with higher engagement level usually have higher performance. In addition, these students usually have twice as many of all learning activities as low-engaged students.

2. Optimal course number is 1 to 2 per semester.

3. Low-engaged students (who failed in all courses) were about 15.9% on average per course. High-engaged students (who passed in all courses) were about 75.7% students on average. Mid-engaged students (who passed partial courses) were about 8.4 on average per course.

4. Students who were younger than 16.6-year-old had higher pass rate than students who were older than 16.6-year-old. In addition, older students tended to take more than two courses with around 54.09-56.11% pass rates. Therefore, further facilitations should be in place for students who are older than 16.6 and take more than one course.

5. Female students had higher pass rates and final grades than male students, especially in the following subject areas: Electives, English, and Social Science. In addition, Female students were more active than male students in online discussion (with higher DB_Entry avg frequency).

6. In this study, graphical location is not an important factor for academic success because failure in online courses was not limited to specific areas or cities. However, gender plays an interesting role in successful students because many successful male students are from one larger city and many successful female students are from the other two larger cities.

7. Female students preferred to take Electives, Foreign Language, and Social Science and male students preferred to take Drivers Education, Math and Science. Students in Math and Science had the lowest pass rates in all subject areas with the highest average engagement levels. The results indicated the course design in these two subject areas should be re-examined. On the other hand, students in in English courses need to be motivated in order to increase their engagement level for cultivating successful students.

8. Overall, students in Spring 2010 semester performed significantly better than those in Fall 2009 because interventions implemented in Spring 2010.

CONCLUSION

This study has made the following contributions: 1) It explored potential applications at the K-12 level for educational data mining that has already been broadly adopted in higher education institutions. 2) It proposed a new course evaluation approach by combining student learning logs with demographic data to generate in-depth knowledge for decision making. 3) The case study identified profiles of potential at-risk students. The finding can be adopted by the K-12 online institutions to create an intervention system (or early alarm system) to help these students being successful.

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