Investigating effects of considering mobile and desktop learning data on predictive power of learning management system (LMS) features on student success

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ABSTRACT

The research area of analyzing log file trace data to build academic performance prediction models has tremendous potential for pedagogical support. Currently, these learner models are developed from logs that are composed of one intermixed stream of data, treated in the same manner regardless of which platform (mobile, desktops) the data came from. In this paper, we designed a correlational study using log data from two offerings of a blended course to investigate the effects of the variables, derived from the use of varying platforms, on the prediction of students' academic success. Given that learners use a combination of devices when engaging in learning activities, it is apparent that weighing the logs based on the platform they originate from might generate different (possibly better) models, with varying priority assigned to different model features. For instance, our results show that the overall frequency of course material access is a less powerful indicator of academic performance compared to the frequency of course material access 'from mobile devices', probably due to the benefits associated with ubiquitous any-time access available to mobile learners. Thus, the primary goal of this study is to bring to light the potential for improvement of prediction power of models after considering the learner's platform of access, within the learning analytics community and the fields of user modeling and recommender systems, in general.

Keywords

Learner Models, Learning Success, Learning Analytics, Mobile Learning

1. INTRODUCTION

The performance prediction models use students' logs from various learning activities that are available for measurement such as logging in, reading files, viewing posts, posting discussions and accessing feedback. However, research has provided evidence suggesting not all activities (features) are equally effective as predictors of outcomes [3]. Moreover, research has also suggested that not all the learning activities are performed using a single technological modality [4, 6] but are often interleaved between devices such as mobile and desktop. In other words, depending on the utility and preference for a modality, the predictive power of learning indices (variables describing the frequency and/or quality of interaction with the LMS tool) in a regression model could be positively or negatively impacted. Building upon these inferences, we further posit that acknowledging the differences in the source of the log trace data used for modeling and predicting academic success, would promote increased accuracy of prediction models and explain anomalies. This hypothesis is supported by the results from a recent study [5] where the authors found a significant impact of the students' adopted platforms (and patterns of usage) for various learning activities on the final course grade.

The review of the literature reveals that the performance prediction models draw benefits from the students' 'event-driven logs' [1] from various learning activities that are available for measurement in a web-based learning management systems (LMSs) such as logging in, reading files, viewing posts, posting discussions and accessing feedback; all of which provide early indicators of student academic performance [8, 9, 2]. These logs, however, are composed of one intermixed stream of data, treated in the same manner regardless of which modality (mobile, desktops) the data came from. As a rule of thumb, the data concerning each predictor action, such as posting discussions and viewing course videos – actions that more often than not, emanate from different modalities and last for different durations – is generally pooled across all modalities. For instance, the frequency of access to course material from desktops, mobiles and tablets is typically used in the predictive model as one cumulative count measure i.e. *course_material_access*, counting all occurrences of course material access in the log file. This is done mainly due to the lack of awareness regarding the utility of technological context or merely to facilitate ease of data processing. Either way, the omission of technological modality variables in a model has potential to, at minimum, discard some useful information and as a result lower the prediction accuracy of the model, or more critically, cause serious threat to its interpretation. Thus, the primary aim of this paper is to create awareness of the role of modalities in predictive analyses of academic performance.

The exploration of the impact of modalities on predictive analytics is justified and highly recommended since: (a) learning activities are often completed by students using multiple modalities, used either sequentially or simultaneously [4, 7], and (b) identification of modalities that are ill-aligned to a task is important as they could undermine knowledge construction and may lead to unintended consequences in academic outcomes [5]. This paper thus investigates the usefulness of a modality-inclusive learner model, over and above a generalized model, for predicting learner success (operationalized by academic performance).

2. METHODOLOGY

2.1 Study Design

The study follows a correlational design as it investigates the effects of the variables derived from the trace data from different modalities, on the prediction of student's academic success, operationalized via percent mark - a continuous variable ranging from 0% to 100%. The data was collected over two semesters (Fall 2017 and Fall 2018) from two subsequent offerings of the same course. The course lasted 13 weeks and had a combined enrolment of 165 students (83+82). The course used blended delivery, utilizing the university's learning management system (LMS) to support learning activities and students' overall schoolwork. In addition to the web-browser versions of the LMS (desktop/ laptop/ mobile), students had access to the mobile app version provided by the LMS vendor. Upon comparison of the features and functionalities offered by the two versions, no apparent differences were revealed. In the next section, we describe the various kinds of variables that were derived from log files.

2.2 Feature Engineering from LMS trace data

To investigate the effect of modality on different types of commonly included learning-related activities and their traces in the online courses, we selected 10 features (5 counts + 5 time spents for each activity) for inclusion in our analyses as predictors of academic success. Variables derived from the LMS trace data include information about the usage of the following tools/features: syllabus, course material (lecture + tutorial slides and instructor provided supplementary material), assignments, feedback on the assignments and calendar. Table 1 contains the types and total counts of learning actions, categorized into activities, captured by the LMS.

Table 1: Breakdown of activities and access (in terms of the number of actions) from different modalities.

Activity	Desktop	Mobile	Tablet
Assignments	15,929	2,474	23
Calendar	1,734	4,687	43
Course Material	24,850	1,279	147
Submission Feedback	1,954	2,968	6
Syllabus	1,952	155	8

Next, for each student we extracted the number of times and the time spent on using a particular feature by aggregating individual operations such as adding student's assignment views across all four assignment tasks to compute *count_assignment*. We call these variables *LMS features*. Each of these variables was split up further to account for the platform used to access that particular feature. For instance, in addition to having total number of assignment views for a student, we compute three more variables - mobile views, desktop views and tablet views- which indicate the respective number of course logins from each of the three main modalities. We call such variables *Modality features*.

The trace data for both LMS and modality features were initially collected as continuous variables. However, tablets were not used by many students, and therefore variables accessed from tablets were dichotomized into the *Accessed* and *Did not access* categories. Additionally, highly skewed variables were transformed using Box-cox transformations to correct their skewness. If the skewness still persisted, they were transformed into categorical variables and the cut-offs were decided arbitrarily to best represent the data.

2.3 Statistical Analyses

For each of the ten learning features introduced in Section 2.2, two regression models (Figure 1) were built using (a) LMS action variable, i.e. LMS feature (Model 1: simple linear regression), and (b) LMS action variable with information on modality source, i.e. Modality features (Model 2: multiple linear regression), to assess the importance of the platform source of the log data for predicting student percent marks. For each of the ten features, a change in R^2 from Model 1 to Model 2 is calculated to present the percentage of variability in student percent mark explained by Modality features over and above the LMS features. To ascertain whether the change was statistically significant, an ANOVA analysis using F-test of the statistical significance of the increase in R^2 was conducted.

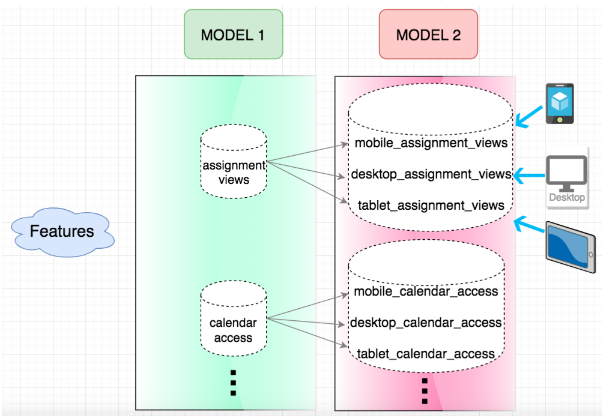

Figure 1: Feature selection for the two models.

3. RESULTS AND DISCUSSION

The results of the regression models featuring the associations between students' use of features from logged data – calculated cumulatively vs. partitioned based on the modality – and student course grades are presented in Table 2, along with the subsequent model comparisons using ANOVA analyses (columns 5-6 in Table 2).

Table 2: The association between the variables of students' use of the LMS and Modality features and ln (log natural) student course grades: results of multiple linear regression models.

Activity (a)	Measure (m)	Model 1 $R^2 \times 100$ (p value)	Model 2 $R^2 \times 100$ (p value)	F-value	p-value	Modality features	β Coefficients
Syllabus	count	1.4% (p = 0.12)	3.9% (p = 0.03)	3.16	**0.041**	Desktop_Accessed 6-15 times vs. up to 5 times	12.36
						Desktop_Accessed more than 15 times vs. up to 5 times	**31.86**
						Mobile_Accessed 1-2 times vs. Did not Access	**-23.11**
						Mobile_Accessed more than 2 times vs. Did not Access	-8.35
	time spent	0% (p = 0.56)	1.4% (p = 0.18)	2.59	0.078	**Desktop_Accessed (20, 40] hours vs. up to 20 hours**	**38.90**
						Desktop_Accessed more than 40 hours vs. up to 20 hours	4.90
						Mobile_Accessed (0, 2] hours vs. Did not Access	**-12.89**
						Mobile_Accessed more than 2 hours vs. Did not Access	-16.08
Assignment	count	7.3% (p <0.001)	11.5% (p <0.001)	2.92	**0.023**	**Desktop_Accessed 51-80 times vs. up to 50 times**	**40.43**
						Desktop_Accessed 81-100 times vs. up to 50 times	**66.56**
						Desktop_Accessed more than 100 times vs. up to 50 times	**73.53**
						Mobile_Accessed 1-10 times vs. Did not Access	-10.91
						Mobile_Accessed 11-20 times vs. Did not Access	6.54
						Mobile_Accessed more than 20 times vs. Did not Access	7.24
	time spent	9.5% (p <0.001)	13.4% (p <0.001)	8.20	**0.004**	**ln assignment_time_Desktop**	**0.71**
						Mobile_Accessed up to 1 hour vs. Did not Access	17.39
						Mobile_Accessed (1, 2] hour vs. Did not Access	**60.31**
						Mobile_Accessed more than 2 hours vs. Did not Access	5.13
Submission Feedback	count	2.9% (p = 0.03)	8.8% (p <0.001)	6.18	**0.002**	**Desktop_Accessed 11-20 times vs. up to 10 times**	**26.55**
						Desktop_Accessed more than 20 times vs. up to 10 times	**55.08**
						Mobile_Accessed 1-10 times vs. Did not Access	3.28
						Mobile_Accessed more than 10 times vs. Did not Access	0.66
	time spent	3.2% (p = 0.01)	5.1% (p = 0.005)	4.21	**0.041**	**ln submissionfdbk_time_Desktop**	**4.68**
						ln submissionfdbk_time_Mobile	0.98
Calendar	count	1.4% (p = 0.50)	1.9% (p = 0.92)	0.16	0.976	Desktop_Accessed 1-10 times vs. Did not Access	-8.11
						Desktop_Accessed more than 10 times vs. Did not Access	1.63
						Mobile_Accessed 1-10 times vs. Did not Access	-0.06
						Mobile_Accessed more than 10 times vs. Did not Access	1.48
	time spent	0.5% (p = 0.80)	2.1% (p = 0.74)	0.85	0.468	Desktop_Accessed (0, 30] hours vs. Did not Access	-8.35
						Desktop_Accessed (30, 60] hours vs. Did not Access	-7.79
						Desktop_Accessed more than 60 hours vs. Did not Access	-4.39
						Mobile_Accessed (0, 30] hours vs. Did not Access	12.17
						Mobile_Accessed (30, 60] hours vs. Did not Access	-13.44
						Mobile_Accessed more than 60 hours vs. Did not Access	9.91
Course Material	count	0.3% (p = 0.20)	1.6% (p = 0.18)	1.52	0.198	**Desktop_Accessed 51-100 times vs. up to 50 times**	**46.43**
						Desktop_Accessed more than 100 times vs. up to 50 times	**41.59**
						Mobile_Accessed 1-5 times vs. Did not Access	-10.24
						Mobile_Accessed more than 5 times vs. Did not Access	0.85
	time spent	1.9% (p = 0.04)	0.7% (p = 0.24)	0.01	0.989	ln material_time_Desktop	11.50
						Mobile_Accessed (0, 10] hours vs. Did not Access	0.29
						Mobile_Accessed more than 10 hours vs. Did not Access	5.74

Based on our results of the multiple regression models, we can confirm that the choice of modality for a particular activity in a learning environment plays an important role in the overall model fit and subsequent model interpretation. The significant ANOVA results imply that an increased proportion of variability in student course grades can be explained if the activity measures are calculated across modalities (Model 2) instead of using the cumulative measure (Model 1).

Interestingly, there was a notable difference in the impact (positive or negative) on the students' course grades explained by the type of modality – desktop vs. mobile – used to perform the activity. For example, the results of the multiple linear regression analyses performed on the time spent on syllabus access indicated that the mobile access was a significant predictor of student learning outcome whereby course grades of students who used mobile phones for substantive duration (1-2 hours) to access the syllabus were about 13% *lower* than those of their counterparts who did not spend any time accessing the syllabus from the mobile phone modality ($\beta = -12.9$, p = 0.04). On the contrary, looking at the time spent on viewing the course assignments, the mobile phone modality reflected a positive association with course grades and explained a greater amount of variance, such that the course grades of students who used mobile phones to view the assignments for 1-2 hours were about 60% *higher* than those of their counterparts who did not use the mobile phone modality at all ($\beta = 60.3$, p = 0.01).

More importantly, the impact of these modalities in explaining the overall fit was not consistent across activities in the learning environment, both in their presence and magnitude. That is to say, *some modalities may or may not play a role in determining student's course grade depending upon the activity performed using the modality.* For instance, the duration of time spent on a desktop for viewing the assignments was a significant predictor of student course grades whereby a 10% increase in time spent resulted in around 7% increase in student course grades. On the contrary, the same modality was not significant at all when the activity involved engaging with the course material. However, the desktop modality was again found significant for the submission feedback activity where this effect was seven times larger compared to assignment viewing i.e. a 10% increase in time spent on engaging with the feedbacks on assignment submissions resulted in around 47% increase in student course grades.

4. LIMITATIONS FUTURE WORK

Since the feature space in our study is high-dimensional and could easily include interactions and non-linear effects, our immediate next steps involve comparison of machine learning classification methods to test the same hypotheses thoroughly. To further broaden the discussion, there are in fact many features that can be computed from trace data and that are used in the prediction models. As we saw improvements in the 'crude' features that we investigated, it is conceivable that we can see improvement in other derived features and therefore improve fidelity of the models.

Furthermore, it would also be interesting to devise, using a bigger participant pool and diverse activity pool, the most optimal learner model comprising a combination of highly explanatory LMS and Modality features from various learning activities as predictors. This, in turn, would require knowledge of several activities in a learning environment for which, modality features can explain more variance in learning outcomes compared to standard cumulative LMS features.

Our methodology involved tracking user interaction with the LMS and this may raise a concern about the extent to which our results were dependent upon the activities targeted in the LMS and the design of the LMS (both browser and app) itself. The types of activities included in our study are quite common in instructional design and usually captured in the same way, thereby rendering good generic results. However, there might be variances in how learning activities are structured and presented in LMS and some LMS can offer even more fine grained tracking to see the influence of modality features from various other activities on the learning outcomes.

5. CONCLUSIONS

Taking up the research on use of mobile and desktop devices in learning environments and its ramifications on learning outcomes one step further, in this paper we looked at how modalities used by students for carrying out learning-related activities in the LMS, could act as powerful indicators of academic success. We designed separate prediction models using measures (e.g., counts and time spent) of activities in the learning environment aggregated across (a) all log data and (b) each individual modality in the log data. We observed that acknowledging a learner's modality context – i.e. a dynamic entity constructed by the learner through interaction with the learning management system from desktop and mobile devices – led to improvements in the accuracy of models.

To further illustrate the significance of these improvements in predictive power, statistical analyses confirmed the improvements to be significant for most of the predictor measures assessed in this study. While the magnitude of improvements may not be of particular interest, the major take away from the study is that interpretations and subsequent interventions based off of generalized learner models may be improved by utilizing modality-inclusive models, since modalities contribute differently to the learning process depending on the activity they are used for. Further, the significance of this research lies in the simplicity of the method by which the modality of access for a learning action/activity can be readily available through capturing the 'user-agent' from the students' log data and the potential high impact it has on the prediction process.

The major highlights from the paper include:

1. Tracing the modality source of log data improves accuracy of learner models
2. Some modalities are better predictors of learning outcomes than others
3. Magnitude of outcome variance explained by modality differs based on the activity
4. Direction of outcome variance explained by modality differs based on the activity

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