Validating the Effectiveness of the Moodle Engagement Analytics Plugin to Predict Student Academic Performance

Completed Research Paper

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Abstract

Given the focus on boosting retention rates and the potential benefits of pro-active and early identification of students who may require support, higher education institutions are looking at the data already captured in university systems to determine if they can be used to identify such students. This paper uses historical student data to validate an existing learning analytics tool, the Moodle Engagement Analytics Plugin (MEAP). We present data on the utility of the MEAP to identify students 'at risk' based on proxy measurements of online activity for three courses/units in three different disciplines. Our results suggest that there are real differences in the predictive power of the MEAP between different courses due to differences in the extent and structure of the learning activities captured in the learning management system.

Keywords

Learning Analytics, Moodle Engagement Analytics Plugin, Academic Performance, Data Mining.

Introduction

According to the National Center for Education Statistics (NCES 2015) the graduation rates for students obtaining a bachelor's degree in the US in 2012 was 59%. Estimates of university degree completion in Australia vary between 72 and 85% (ACER 2011). It is challenging to obtain accurate figures as students often change degrees, institutions, their enrolment mode (from full-time to part-time and vice versa), or suspend their enrolment to resume study at a later stage, or withdraw altogether. According to Gilling (2010), in some universities only half of all first year students end up graduating. This has an emotional cost for those leaving their studies, but also comes with a financial cost for individuals, educational institutions, and governments (Lobo and Matas 2011). In our Australian context, improving student retention and success has become a priority for Australian universities as the Commonwealth Government has included retention (along with progression rates and student experience data) on its list of indicators for funding of higher education (DEEWR 2009).

The earlier a student is identified as possibly being in need of support, the better the opportunity they have to improve their academic performance (Jayaprakash et al. 2014). Identification and intervention within the first four to eight weeks of semester are instrumental in enhancing students' success and increasing retention (Fusch 2011). Effective early warning or student tracking systems are pro-active rather than reactive; institutions which initiate active individual contact with students (rather than provide services which require students to self-refer) retain more students than institutions that do not (Simpson 2005).

Given the focus on boosting retention rates and the potential benefits of pro-active and early identification of students who may require support, higher education institutions are looking at the data already captured in university systems to determine if they can be used to identify such students. The increasing availability of these large datasets offers great potential for data interrogation with the goal of informing and enhancing learning and teaching practices and environments (Pardo 2014). In many universities, the most common e-learning technologies in use are Learning Management Systems (LMSs), such as Moodle or Blackboard Learn. Such LMSs automatically capture records of users' activities, recording who accessed what and when. These rich datasets can be used at the unit of study level to target and support learners (van Barneveld et al. 2012), by identifying variables such as mid-semester grades, class attendance, and LMS interactions which can act as flags or triggers for poor performance. Prompt feedback to students and to those who can assist students are an essential element in the effectiveness of these systems (Tinto 1993).

This paper introduces a project that seeks in its first phase to use historical data to validate an existing learning analytics tool, the Moodle Engagement Analytics Plugin (MEAP) (Dawson and Apperley 2012). We present data on the utility of the MEAP to identify students 'at risk' based on proxy measurements of online activity. Learning analytics practitioners and researchers apply the term 'at risk' to a number of scenarios (Campbell and Oblinger 2007), including early attrition (Agnihotri and Ott 2014), retention but failure (Brown and Evagelistis 2011), or retention but unsatisfactory performance (Jayaprakash et al. 2014). In this paper, we define students who are academically 'at risk' as those who fail a discrete unit of study (final grade less than 50%), because at our institution this has actual financial and progression repercussions. If the MEAP is found to be useful in identifying students at risk, in subsequent phases the project plans to extend the MEAP to facilitate sending alerts to students. The next section introduces the MEAP and related analytics tools, followed by the method used to initially validate the MEAP, our results, conclusions, and next steps.

The Moodle Engagement Analytics Plugin

Moodle is used internationally in 225 countries, with the United States (US) and Australia among the top 10 user countries (https://moodle.net/stats/). The MEAP is a tool that monitors students' engagement behaviours in the LMS, including assessment submissions, forum activity, and logins. Within a program of study, such as a degree or major, students tend to enrol in one or more courses/units/subjects/topics/papers within each study session. A number of staff (e.g. administrators, faculty, academics, tutors, supervisors, adjuncts, sessional staff) will be involved with the unit in a range of administrative and teaching roles. In the context of our institution, the person responsible for managing and monitoring the academic activities and performance of the enrolled students for a specific unit is known as the unit convener. The MEAP provides unit conveners with a configurable set of risk indicators that can be used to assess student engagement in a unit.

The MEAP includes a block that provides a 'traffic light' snapshot of the students in a particular unit based on configurable risk calculations. It also provides a report on all students in the unit, as well as an explanation of how risk is calculated for each student. The built-in indicators of engagement/risk in the MEAP are:

- Assessment activity: are students submitting their assessed work, and are they submitting on time?
- Forum activity: are students reading, posting, and replying?
- Login activity: how often, how recently, and how long are students logging in?

Early warning or early alert systems typically monitor student engagement as proxies for predicted academic performance. These systems often, but not always, include direct outreach to students in academic or other difficulties which may interfere with academic success. In the Australian Higher Education context, several examples of such tools are reported in the literature, such as Edith Cowan University's Connect for Success, University of New England's Automated Wellness Engine, Open University Australia's Personalized Adaptive Study Success, the University of New South Wales' Student at Academic Risk Report, and Queensland University of Technology's organizational analytics project (Atif et al., 2013, Siemens et al., 2013). These systems tend to be proprietary (i.e. not available to other institutions) and/or are developed using commercial software that presents a black box to the institution.

We wanted a solution that we could tailor to our institution and potentially to the various needs of the different faculties, schools, and departments, as well as be able to understand how the tool was working. Therefore, we chose to extend the MEAP, which has been released as open source (Dawson and Apperley 2012). Thus, the enhancements we make also have the possibility to benefit other institutions using Moodle as the basis of their LMS.

However, before Moodle users, including our institution, can decide to adopt such technology or invest effort to extend the technology, there must be confidence that the tool has the potential to deliver accurate outputs. That is the aim of the project reported here. The research question we seek to answer is: *Does the Moodle Engagement Analytics Plugin predict the academic performance of students in a given unit?*

Methods

The MEAP typically calculates and reports a 'live' risk rating based on all available and relevant data in the Moodle database. To analyze subsets of historical data, a customized version of the MEAP was installed in Moodle v2.7 (build 20150115). This customized version (open source code available from https://github.com/atomsheep) allowed us to analyze the historical data on assessment, forum, and login activity by specifying the date and time limits on database queries. Because the MEAP would typically be used by unit conveners at intervals of every 2-3 weeks, we selected six periods over the 13-week semester to request reports from the MEAP. This was performed by setting the date and time limits to query data from Monday of week 1 to Friday of week 2, then Monday of week 1 to Friday of week 4, then weeks 6, 8, 10, and 12. The default parameters provided by the MEAP (weighting of assessment (34%), forum (33%), and login (33%) indicators, and threshold values of 0.5 new forum posts per week, 1 read post per week, 1 forum reply per week, 1 total post per week, 2 expected logins per week and in the past week, 10 minutes expected average session length, and 7 days expected between logins) were used in order to determine if a drop-in (i.e. non-customized) installation of the MEAP would be useful and informative.

We analyzed the historical data from three introductory (first-year) undergraduate units (Table 1); all three units were delivered in blended mode, with a Moodle unit site supporting on-campus classes. These units did not undertake any MEAP-related interventions, since our research question was purely to assess the ability of the MEAP outputs (risk ratings) to predict academic performance. We used a number of criteria to select the units for this analysis. These criteria were to ensure that we obtained units that would most effectively reveal whether the MEAP was a useful tool. The first criterion was that the unit needed to have a relatively high failure rate (>10%). The second was that the unit required students to engage in online activities that the MEAP could track and provide a risk rating for. The unit must require the student to complete various activities such as forums and spend time online, for example by completing quizzes. The last criterion was that the unit, to provide sufficient numbers of students from which to extrapolate statistical relationships, must be relatively large (>60 students).

The failure rates for the units selected were high (>14%), making them important candidates for evaluating a tool that may be able to identify at-risk students. In addition, the unit sites contained a mixture of assessment and forum activities, and a substantial amount of unit content was available online (Table 1). The online materials of the Computing unit included weekly quizzes (<15% of final grade), three online assignments for submission every four weeks (<30% of final grade), and resources for weekly lectures and tutorials. The online materials of the Archaeology unit included weekly quizzes (30% of final grade), two extended written submissions at the middle and end of semester (60% of final grade), and resources for weekly lectures and tutorials, for which participation was assessed. The structure of the Sociology unit was similar to that of the Archaeology unit. Finally, the number of enrolments for the units were relatively high (>60).

One of the key reporting outputs from the MEAP is a list of student names accompanied by a traffic light - a green light is used where the total risk rating is less than 60%, yellow light between 60 and 80%, and red light above 80%. The total risk rating (calculated and weighted according to user-configurable parameters) is used to derive the traffic light representation, and may be more informative in identifying students at risk. We wanted to determine if these outputs (total risk rating and traffic light) were associated with student performance, whether the traffic light representation was sufficient to inform instructors of student risk, and how early in the semester could the MEAP accurately predict student risk. To do this, we analyzed the MEAP outputs at weeks 2, 4, 6, 8, 10, and 12 for each unit independently. Each time a MEAP report was requested, the risk ratings for assessment, forum, and login activity were calculated, along with a total risk rating which is a combination of these three indicators. The risk ratings were reported as percentages, with a higher rating suggesting higher risk. We analyzed the total risk rating for each student against their final mark. Data were collated, analyzed, and graphed using Excel (Microsoft), and statistical calculations were performed using SPSS version 22 (IBM).

Unit	Number of students	Online assessments	Online forums	Other online content
Computing	64	Weekly quizzes or tutorial submissions	1 general discussion forum, 1 assignment forum	Lecture notes and recordings, tutorial notes, assignment information
Archaeology	151	Weekly quizzes, online assignments	1 general discussion, 1 assignment forum, 1 forum for external students, 2 forums on unit topics	Lecture slides and recordings, readings, maps, assessments
Sociology	309	Weekly quizzes, online assignments	1 general discussion forum, 12 forums on unit topics	Lecture slides and recordings, readings, assessments

Table 1 - Characteristics of the units analyzed.

Results

Using just the traffic light representations and the default MEAP parameters, no students were classified with red lights in any of the units examined, at any stage in the semester (Figure 1). In the Archaeology and Sociology unit, the yellow light classification included some at-risk students (those with a final grade of less than 50%, a passing grade at our institution). However, the majority of these at-risk students in the units analyzed were classified in the green light category at all six reporting periods over the semester (Figure 1). This suggested that the traffic light representation did not accurately reflect student performance at any point in the semester for the units analyzed.

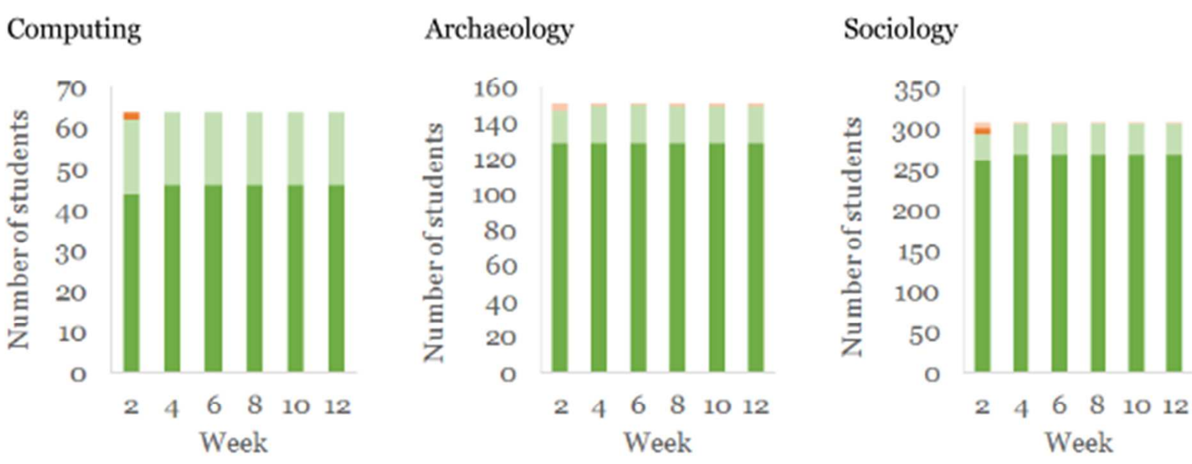

Figure 1 - Association between MEAP traffic light colors and students' pass/fail final grade. Lighter shades of green and amber represent students who failed but were classified as green or yellow lights, respectively. Darker shades of green and amber represent students who passed and were classified as green and yellow lights, respectively. No students in any of these units were classified as red lights.

Using the total risk rating in the three units analyzed, the final grade of each student was significantly correlated to their total risk rating at each of the six reporting periods, except for week 2 in the Computing unit (Table 2). For all three units, the strength of the relationship between total risk rating and final grade tended to increase over each of the successive reporting periods, with the trend most evident in the Archaeology unit (Figure 2).

Unit	Week 2	Week 4	Week 6	Week 8	Week 10	Week 12
Computing	-0.159	-0.575*	-0.568*	-0.572*	-0.628*	-0.617*
Archaeology	-0.578*	-0.515*	-0.624*	-0.702*	-0.724*	-0.803*
Sociology	-0.397*	-0.396*	-0.521*	-0.576*	-0.532*	-0.614*

Table 2 - Correlation between final grade in each of three undergraduate units and bi-weekly MEAP risk ratings. Pearson correlation coefficients reported; * indicates 2-tailed significance at < 0.01 level.

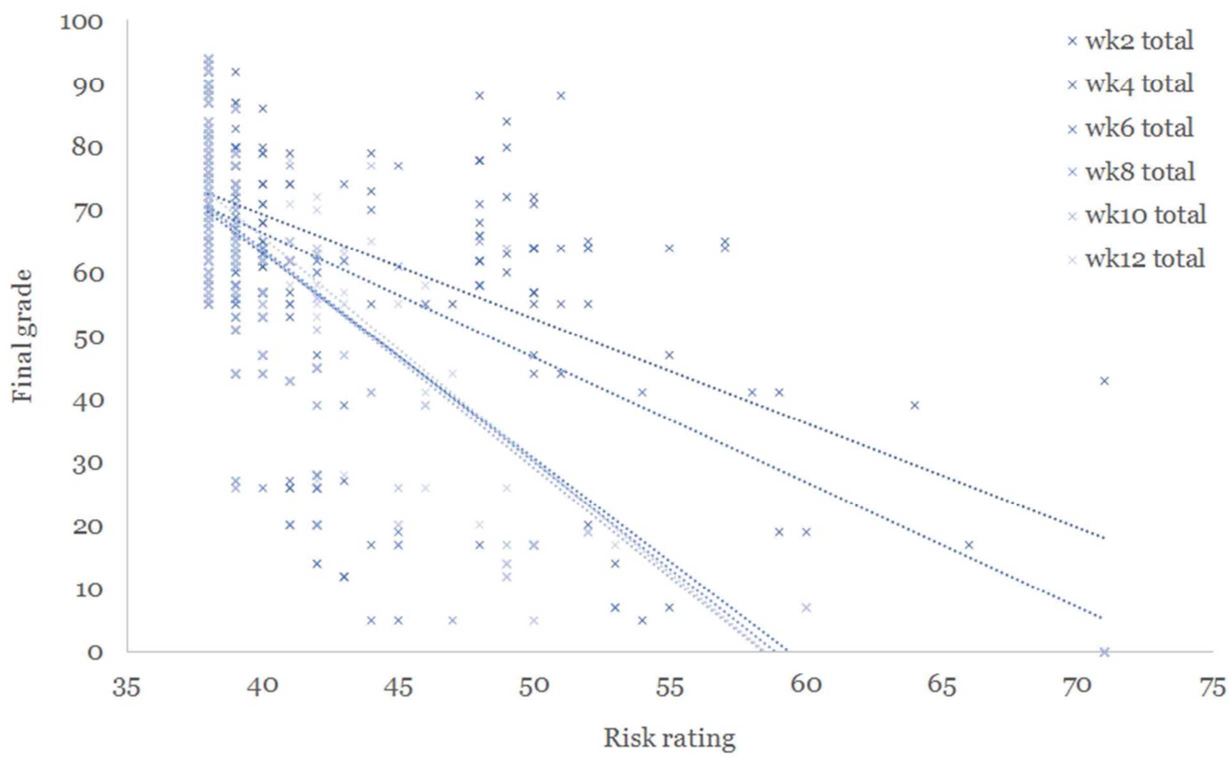

Figure 2 - Correlation between final grade and the total risk rating for each student in the Archaeology unit over the six reporting periods. Dashed line represents the trendline for each reporting period.

Although the correlation between final grade and total risk rating tended to improve over the semester, early intervention necessarily involves identifying and assisting potentially at-risk students as early as possible. Because this correlation is weaker earlier in the semester, there is a higher probability that students may be incorrectly identified as at-risk (false positives), or incorrectly identified as not at-risk (false negatives). The number of false positive and false negative identifications will also depend on the threshold risk rating used to select students. For example, if a risk rating of 42 and above in the Archaeology unit (Figure 3) was used in week 2 to identify at-risk students, there would be 2 false negatives and 31 false positives. In week 4, there would be 6 false negatives and 18 false positives. In the

Computing unit (Figure 4), there would be 4 false negatives and 24 false positives in week 2, and 4 false negatives and 21 false positives in week 4. These measurements can be represented by the metrics recall (true positives / (true positives + true negatives)), false positive (FP) rate (1 - true negatives/(true negatives + false positives)), accuracy ((true positives + true negatives)/total), and precision (true positives/(true positives + false positives)), with a high recall and low false positive rate indicating a better performing indicator (Jayaprakash et al. 2014).

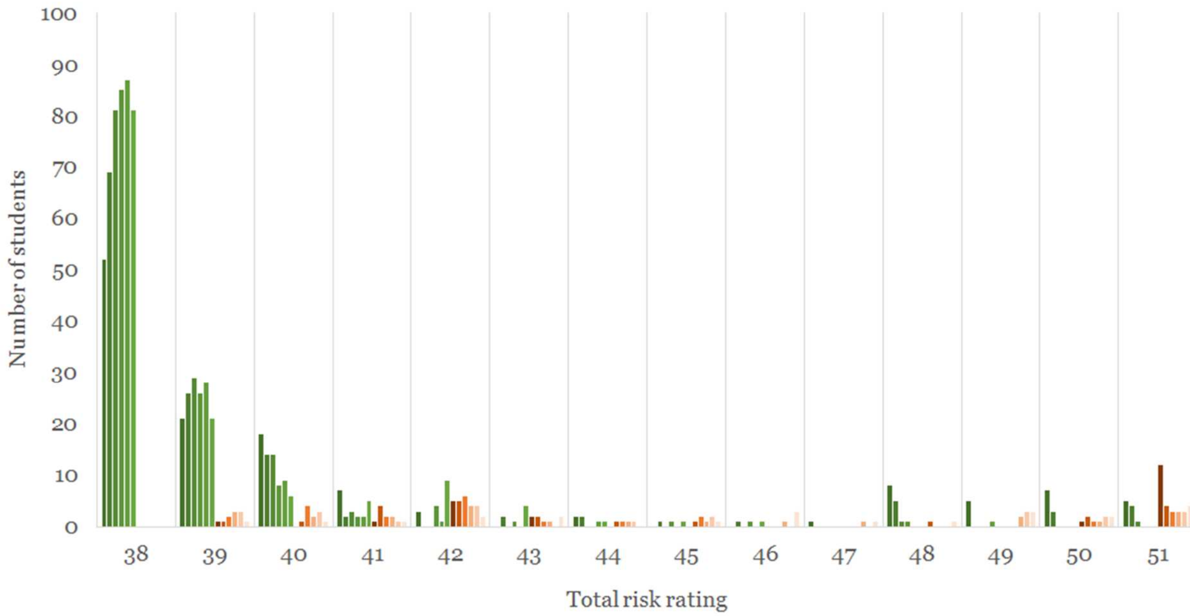

Figure 3 - Number of students in the Archaeology unit with each risk rating over the six reporting periods. Green and orange represent the students with a passing (>= 50) or failing (<50) final grade, respectively. Dark to light shading represents the six reporting periods as the semester progressed. No students had a risk rating lower than 38.

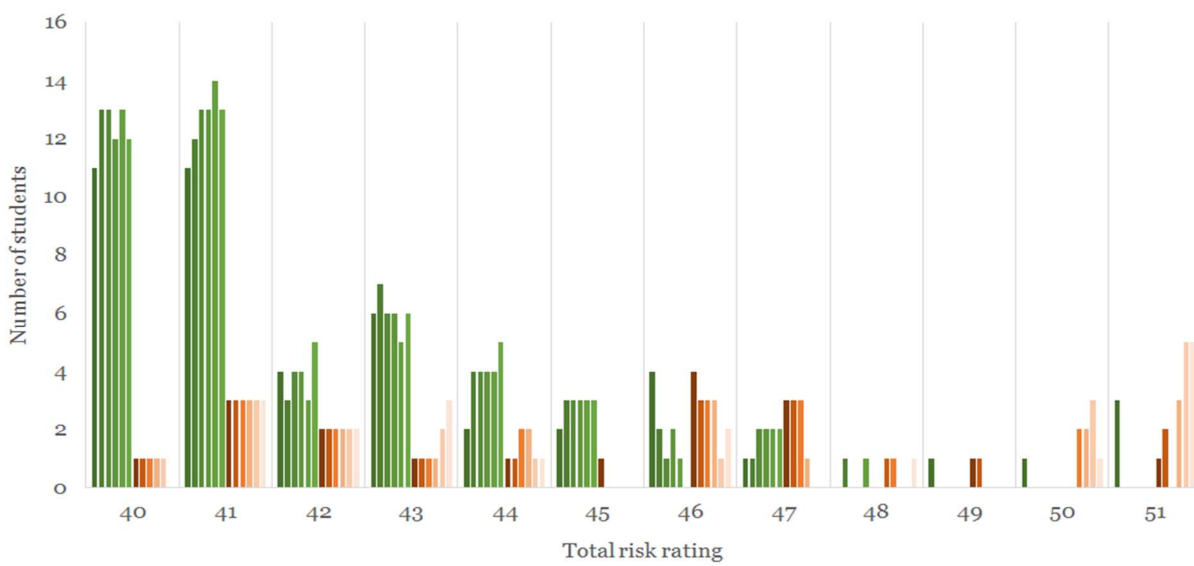

Figure 4 - Number of students in the Computing unit with each risk rating over the six reporting periods. Green and orange represent students with a passing (>= 50) or failing (<50) final grade, respectively. Dark to light shading represents the six reporting periods as the semester progressed. No students had a risk rating lower than 40.

Based on these metrics, one may select a risk rating of 41 and above in the Archaeology unit, 42 and above in the Computing unit, and 38 or above in the Sociology unit, to identify at-risk students while reducing the number of false alarms (Figure 5), although these selections can be somewhat subjective. The point in semester at which the MEAP is applied may, for some units, also affect its predictive performance (Figure 6). Only a subset of results have been presented graphically. A full set of results is available on request.

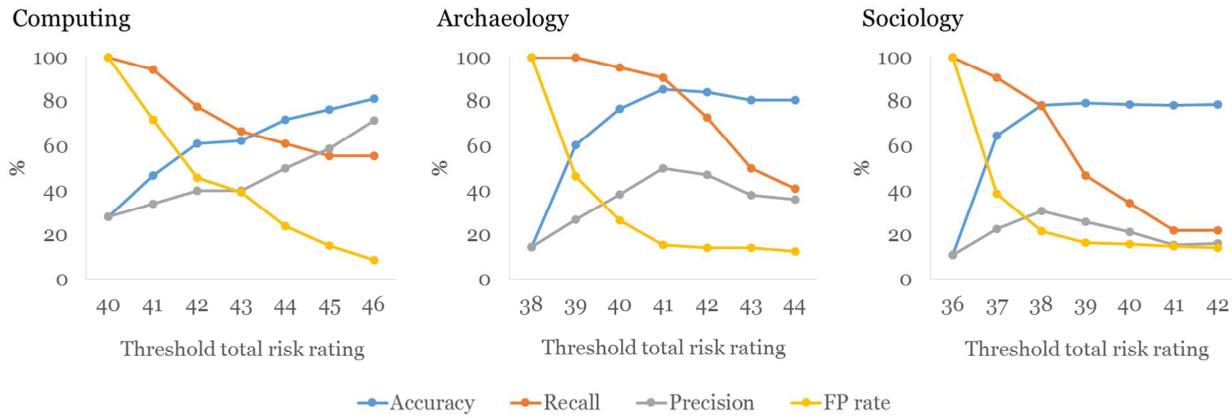

Figure 5 - Predictive metrics of a range of threshold total risk ratings in two units at the week 4 reporting period. Week 4 is an optimal reporting period, balancing the availability of data and being sufficiently early in the semester for useful intervention.

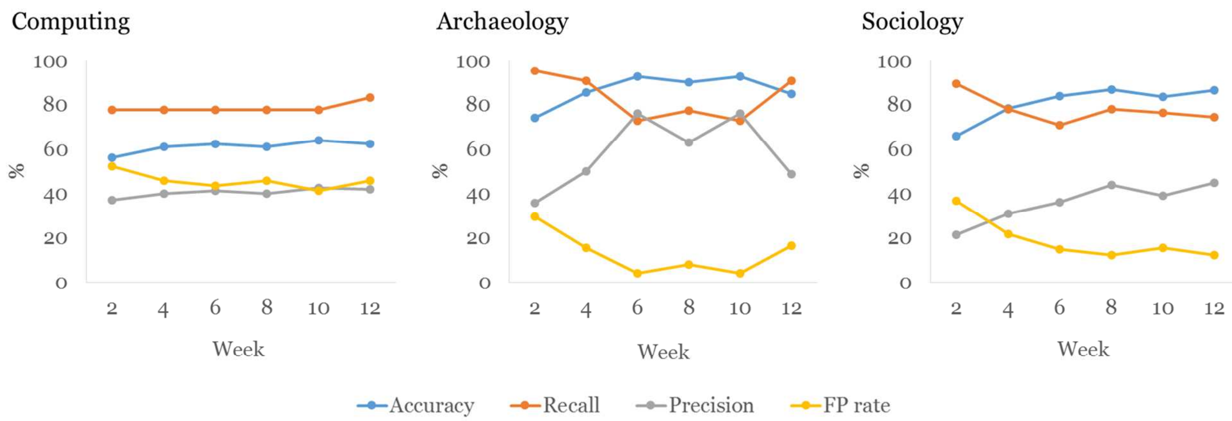

Figure 6 - Predictive metrics over the range of reporting periods in two units, with threshold total risk rating of 42, 41, and 38 for Computing, Archaeology, and Sociology, respectively.

Discussion

The MEAP reports to instructors a total risk rating which is calculated based on pre-determined parameters and data on student behaviours, namely assessment, forum, and login activities in Moodle. In this paper, we have applied the MEAP independently to historical data from three undergraduate units of study to evaluate the predictive performance of this tool, using student final grade as a proxy for student performance (Romero and Ventura 2013). To our knowledge, this is the first publication to attempt to evaluate the MEAP in this way.

Similar to the Purdue Course Signals learning analytics tool (Arnold and Pistilli 2012), the MEAP represents student at-risk status using a series of traffic light icons. Our results suggested that this representation of student at-risk status in the MEAP was not necessarily reliable, as there were high proportions of students classified as green lights with a final grade below 50. In part, this may be due to the insensitivity of the binning used by MEAP to classify students' total risk ratings into traffic light colors. The utility of such representations is not lost, however, as there is some evidence to suggest that students classified at high (red light) or moderate (yellow light) risk by the Purdue Course Signals tool were able to move into a lower risk category after intervention (Arnold and Pistilli 2012). This is an area of further investigation in the next phase of our project, where the MEAP predictions will be used by unit conveners to action student interventions. It will be interesting to compare such results with Course Signals, since the MEAP only displays the traffic light information to instructors and not students, so students cannot self-regulate based on the MEAP output. We also plan to compare such results with student outcomes in the same courses prior to MEAP-related interventions.

A more informative representation of student at-risk status in the MEAP was found to be the total risk rating. This was correlated with student final grade, and as such provided a more meaningful predictor of student performance. However, since the total risk rating is not a direct prediction of the final grade, selecting the threshold at which to classify students as at-risk is more subjective than if the prediction was a final grade. In the units analyzed here, it was possible to determine a threshold risk rating which maximized recall and reduced false positive rate, early on in the semester; however, this was with the power of hindsight. It is not inconceivable that a poorly selected threshold would result in substantial type I and type II errors, although increasing type I errors may be an acceptable risk so as not to miss the students who need assistance (Macfadyen and Dawson 2010). We are currently investigating using analyses from previous offerings of units to inform selection of optimal threshold risk ratings for future offerings.

Fundamentally, the MEAP total risk rating is an algorithmic representation of student online behaviours, namely assessment submission, forum interaction, and login activity. Assessment completion, discussion forum interaction, and login activity have been positively correlated with student performance (Romero et al. 2008; Dawson et al. 2008; Macfadyen and Dawson 2010; Macfadyen and Dawson 2012; Jayaprakash et al. 2014), and our results suggest that the MEAP representations of these activities also correlate with student performance. However, if available, there are substantially more powerful predictors such as early formative assessment results (Tempelaar et al. 2014), data which the MEAP is currently unable to consume. Despite the somewhat stochastic nature of student online behaviours detected by the MEAP, our results suggest that the total risk rating calculated by the MEAP can inform interventions by the fourth week of semester, which is important as early intervention provides students with the opportunity to correct ineffective learning strategies (Jayaprakash et al. 2014). Regardless of the predictors or predictions of learning analytics tools, the impact on students will ultimately arise only from thoughtful interpretation of indicators and sensible interventions based on an understanding of the human context of learning (Richards 2011).

During the analysis of the data we also observed that the learning design together with the assessment structure of a unit may influence the predictions of the MEAP. Where a unit had a learning design that required students to engage in activities online that either directly or indirectly contributed to their final grade, there was a stronger correlation between the total risk rating and the final grade. For example, in the Archaeology unit the assessments included 30% for completing the weekly quizzes in the LMS. Students also needed to complete an essay and paper worth 60% of the assessment. Forums were used by the students to ask questions and provide answers to some of the key issues in the assessment tasks. In addition, the learning design included an activity where students would meet each other online through an 'ice breaker' activity, which introduced students to the use of forums. Therefore, there was a strong incentive for students to spend time online and participate in forums since these activities contributed either directly or indirectly to their final grades. This was in contrast to another unit which we examined (not reported in this paper) where the learning and assessment designs did not relate to the online activities; that is, whilst the students did complete activities online, these were not related to their assessments. As a consequence, we found that there was only a weak correlation between the total risk rating reported by the MEAP and students' final grades in that unit. These observations are consistent with assessment being a powerful extrinsic motivator, and resonate with the interrelationship between learning analytics and learning design (Lockyer et al. 2013). We are seeking to investigate the utility of the MEAP in a wider range of disciplines with differing unit structures to evaluate this phenomenon. These observations suggest that when deciding to use a tool like the MEAP, it is important that practitioners and researchers examine the learning and assessment designs to ensure that the activities that students complete are aligned with assessment, and that these activities are measurable by the tool. Moreover, it is striking to note the effect that particular learning designs have on the utility of learning analytics tools.

Conclusions and future directions

This paper reported the results of the first phase of a larger project at our institution to evaluate how learning analytics tools such as the MEAP could be used across a range of disciplines to detect students at risk. Our results suggest that there are real differences in the predictive power of the MEAP between different units. Since students are taught and assessed at the unit level, it is sensible to evaluate such learning analytics tools unit by unit. Other authors have also found that predictive models were more informative when applied in this way (Wolff et al. 2013). However, since the structure of each unit is different, the default MEAP parameters may need to be tailored for each unit. Our data suggest that a drop-in implementation of the MEAP may not adequately differentiate students' total risk ratings, leading to low utility of the traffic light representations, although there were significant correlations between the unbinned total risk ratings and student performance. We are currently investigating the predictive power of the MEAP by comparing default parameters with those determined through the use of machine learning methods and those selected by unit conveners. We will be interested to find out if unit conveners are aware of what parameters might be predictive, as well as determining the conditions under which the MEAP may be useful.

In the next phase of our project, we intend to use the MEAP with other blended and fully online units to trial its usefulness in informing unit conveners, and possibly student support staff, of students at risk. Additionally, student and teacher needs, attitudes, and preferences concerning the use of early alerts will be gathered and compared with student performance. This will further clarify the potential value of the MEAP, and involve extending the MEAP to consume additional data from Moodle and facilitate the sending of student alerts.

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