PredictEd: Using VLE Data to Provide Weekly Automated Feedback on Student Engagement

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Class Size
1100 students in year one 1370 for the second iteration

Discipline/Subject Area
Multi-Disciplinary

Feedback Approaches
Feed forward, learning analytics based automated feedback

Technologies
Institution VLE (Moodle), Institution Student Record System (ITS), student email, Course management system (Guru)

Challenge & Aim

The challenge that we had is that many first-year students have never used a VLE before entering the university. Therefore, we wanted to provide regular timely feedback to large numbers of first year students on their engagement with the course material on the VLE. The aims of this case study are threefold: 1) Provide regular timely feedback to first year students with respect to their engagement with the VLE 2) To improve first year students' engagement with course materials and therefore by association hopefully improve overall progression rates through improved grades 3) Demonstrate how the VLE can be harnessed to advance course design.

We used Support Vector Machines (SVMs) to mine data and to build classifiers. Students were then separated into two alternate groups based on the modules they were enrolled in.

Category 1 students were sent weekly emails, based on our prediction of whether they would pass or fail. Students in this category group were divided again resulting in four groups "bad" and "poor" for those predicted to fail, "good", and "great" for those predicted to pass. Each group was sent a customised email giving them feedback. The mail was personalized and the content of the message was dependent on which category group they were in. For example,

students in the "bad" sub category for instance receiving an email saying how students need to work harder, while those in the "great" group were told they are progressing well. The feedback was further personalized by recommending resources on the VLE course page that the student had not yet accessed – essentially "feed-forward" as opposed to just providing feedback. (Y1Feedback, 2016) Finally, each mail also included contact details for the lecturer and for student support services.

Category 2 students in the remaining modules were broken into 10 equally sized groups based on their overall prediction ranking. Their feedback was a little more detailed. Emails were sent to each student detailing what percentile group they fall into, giving them an awareness of how their progression compares to their peers. A more encouraging email was sent to the bottom 50% of the class. This may encourage healthy competition among students, motivating them to work harder as they see their progress in the feedback loop. This process was repeated on a week-by-week basis, with the most recent log data downloaded from the Moodle log files. Predictions were generated for each module as previously outlined. Every week each student who opted in to PredictEd received a new email.

We also provided feedback to lecturers and course coordinators through a dashboard, illustrating the relative activity of each of the students on a weekly basis. This information then helped the staff identify students at risk very early within the semester as opposed to at the end of the semester when exam results are processed.

Evidence from the Literature

There are existing examples of utilising students' online behaviour to either monitor their performance or predict their exam results. In order to identify "at-risk" students and improve retention The Open University used predictive modelling with inputs being engagement with VLE resources, assessment performance, previous exam performance and demographics of the students (Wolff et al., 2013). Here the researchers demonstrated demographics play a less pivotal role than VLE engagement, and the preferred approach in analysing data is in a module-by-module fashion. While their prediction target resembled ours as module failures were predicted at regular intervals during semester, specifically, every time there was an exam, some salient differences exist between our approach and theirs. The Open University student sample is more diverse with many working part/full-time while doing modules and they had a larger sample (n= 7,000). Furthermore, Wolff and colleagues predicted the set of students most in need of help, and left it up to the module organiser to intervene.

Inspired by the four-step framework for analysing VLE data: collect data, process data, perform data mining/machine learning steps and deploy results (Romero, Ventura & Garcia, 2008), the Purdue Signals project harnesses a variety of factors such as time spent on a particular task and past performance in other exams to predict a student's exam score (Arnold & Pistilli, 2012). Here a different mechanism is used to deliver predictions to students; they discover how well they are doing via a web application showing if they are classified as "green", "orange" or "red" for a given module.

Evidence from the Literature

Aiming to find students in need of learning reinforcement, Calvo-Flores and colleagues (2006) predicted user exam scores based on VLE log data. Tested on 240 students enrolled in one module, this work demonstrated that features derived from the access logs (i.e., total resource views) had a prediction accuracy of above 80 % for student success. While our approach is similar, we retrain model for each week, allowing us to recalculate predictions on a weekly basis, which make our insights more actionable.

While the use of learning analytics connected to the VLE is widespread in the literature there are very few examples of where the data processed is use to provide students feedback in this manner

Feedback Approach

We used activity data from previous students' online behaviour on the institution VLE, plus their exam outcomes, to predict outcomes for current students. Target students were first semester, first year undergraduates. Moodle (our institution VLE) activity logs, including times accessed and content viewed were used to predict likely semester-end marks on a weekly basis using module outcomes from previous years to train machine learning predictors. Our research builds on existing research from the Open University and other key players but differs in that we return student data directly to the students as feedback. First year students across ten diverse modules were given the opportunity to participate in the study. They were sent weekly emails incorporating a prediction of whether they would pass or fail/what percentile group they fall into relative to their classmates. Students who chose not to opt in to the Predicted process were used as the control group.

This project was conducted over two years with two separate cohorts. Significant improvements in the type of feedback provided, informed by the literature, were made between iterations. The first major improvement was the level of communication that we provided to students. We provided more detailed information to the students in advance of providing the feedback which included what to expect and how to take action following receipt of feedback. The second improvement was that we provided the students with personal recommendations of resources/activities that they should look at on their course pages – material that they had not looked at but their classmates had.

Outcomes

Benefits

Those who opted-in for PredictEd saw an average increase of +2.67 % in their final exam scores, all other things being equal. When considered on a module-by-module basis, there was a significantly higher performance for PredictEd students in three modules. Furthermore there was an improved performance in five other modules.

By sharing the results with the staff involved in the study, they became more aware of what content on the course pages that students engaged with.

Drawbacks

As Educational Data Analytics is a new area of research, there is a paucity of previous relevant studies identifying potential ethical issues. Therefore the wide scale implementation of this approach requires extensive ethical consideration.

Some students were resistant to the process as they were wary of being observed. Although positive results were obtained, it is difficult to negate the presence of the Hawthorne effect (i.e., the alteration of behaviour by the subjects of a study due to their awareness of being observed). Overtime this effect may dissipate, however its presence at this crucial stage in first year may be sufficient to change students' mind frames in the long term and allow them to progress through to second year.

A summary of results was presented at various internal meetings throughout the university using this case study as an example of the benefits for student learning when the VLE is used to its potential. Therefore there was an overall increase in awareness amongst staff of the benefits of the VLE which in itself is a significant benefit from undertaking this project..

Student Response

The student's response to this initiative was very positive from the very beginning. Firstly, we asked the students to opt-in to this study rather than opt out and over 70% of the students asked, opted in. At the end of the project we completed a survey and a series of focus groups to specifically gauge students' opinion. A third of students changed how they used the VLE (local name "Loop"), indicating they studied more:

"Read some other articles online",

"I tried harder to engage with my modules on Loop".

This increased use of Loop also extended into other "non-PredictEd" related modules:

"Felt more motivated to increase my Loop usage in general for all subjects".

When questioned over why they got involved, students indicated that they took part as they wanted to learn and monitor their performance. Other reasons were that they were curious, had an interest in the research component, whilst the remaining students participated as they were following advice or were indifferent. Students' survey responses on a Likert scale (1= not at all easy, 5= extremely easy) also indicated it was easy to understand the content of the emails 3.97 (SD= 1.07).

Recommendations

- The first tip that I would give is to ensure that you communicate thoroughly with the students and staff involved in this project. Tell students in advance what to expect, how they will receive feedback and how they should interpret and use the feedback provided. We conducted this project over two years with two separate cohorts and we noticed a significant difference between cohorts when we improved our initial communication with students.

- The second tip is that if you decide to use VLE data please ensure that you get appropriate ethical clearance first

Useful Links/Further Information

https://predictedanalytics.wordpress.com/

References

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Cite as;

Corrigan, O., Glynn, M., Smeaton, A. & Smith, S. 2017. PredictEd: using VLE data to Provide Weekly automated Feedback on Student Engagement. IN: Technology-Enabled Feedback Approaches for First-Year: Y1 Feedback Case Studies in Practice: Y1Feedback. Available from: https://www.y1feedback.ie