Using predictive analytics to support students: Case study 2

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Abstract:

This paper showcases how predictive learning analytics (PLA) can support teaching practice and enhance student retention and performance. It presents the evaluation of an institutional PLA intervention, OU Analyse (OUA), which uses machine learning methods to improve student retention. OUA is informed by a predictive model drawing on two data sets to identify 'at risk' students: demographic data and usage data from the virtual learning environment. It provides weekly early warning indicators of students who may be at risk of not submitting their next assignment, which can be used by teaching staff to quickly identify students who may be in need of additional support. It has been piloted with more than 20 online courses with positive findings in terms of effectiveness. Interviews with teaching staff revealed the usefulness of the tool for complementing their teaching practice and being 'on top' of what students are doing in distance learning settings. This paper is the second of two linked papers that draw on evidence from the Open University's Early Alert Indicators Project[1].

Keywords:

predictive analytics; retention; distance learning

Messages:

- Predictive learning analytics are particularly useful in supporting teaching practice in online only settings.
- Predictive learning analytics use by teachers can improve student retention and performance.
- Identifying and intervening with students predicted as 'at risk' of not submitting their next assignment can support student experience.

Introduction:

The education sector, in recent years, has witnessed a proliferation of powerful analytics engines (Joksimović, Gašević, Loughin, Kovanović, & Hatala, 2015; Macfadyen & Dawson, 2010; Romero, López, Luna, & Ventura, 2013), twinned with skilfully designed visualisations (Ali, Hatala, Gašević, & Jovanović, 2012; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; González-Torres, García-Peñalvo, & Therón, 2013), all powered by the increased availability of large datasets. As such, institutions and teachers have an opportunity to leverage these advances in technology and use the experience of the past to create supportive, insightful models of primary (and perhaps real-time) learning processes (Ferguson & Buckingham Shum, 2012; Mor, Ferguson, & Wasson, 2015; Papamitsiou & Economides, 2014).

In recent years several institutions have started to adopt Predictive Learning Analytics (PLA) using a range of advanced computational techniques (e.g., Bayesian modelling, cluster analysis, predictive modelling) to identify which students are going to pass a course, and which of them are at-risk (Calvert, 2014; Gasevic, Dawson, Rogers, & Gasevic, 2016; Joksimović et al., 2015; Tempelaar, Rienties, & Giesbers, 2015). PLA data may provide useful, complementary information to teachers to help them identify students at-risk while also allowing them to support other groups of students and maximise their potential.

[1] [Using predictive analytics to support students: Case study 1]

A wide body of literature has identified that predictive learning analytics (PLA) can potentially help teachers and institutions to identify which groups of learners and individual students might need extra support to reach desired learning outcomes (Conijn, R., Snijders, C., Kleingeld, A. and Matzat, U. 2017; Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M. and Naydenova, G. 2017; Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R.S. and Hatala, M. 2015; Scheffel, M., Drachsler, H., de Kraker, J., Kreijns, K., Slootmaker, A. and Specht, M. 2017; Tempelaar, D.T., Rienties, B., Mittelmeier, J. and Nguyen, Q. 2017.) For example, Scheffel et al. found that visualising relative performance to 172 students using PLA supported learning processes over time. In a cross-module study amongst 17 blended online courses followed by 5K students, Conijn et al. found that PLA results varied substantially. However, in line with Tempelaar et al., Conijn et al. concluded that VLE engagement and click data are of limited value for effective prediction and possible interventions. While an emerging body of learning analytics literature has highlighted mixed results about the effectiveness of PLA for actionable interventions, the jury is still out as to whether PLA can effectively support teachers to intervene on time, on a large scale basis, and across a range of disciplinary contexts.

As recognised by recent learning analytics research (Dyckhoff et al., 2012; van Leeuwen, Janssen, Erkens, & Brekelmans, 2014; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013) and wider literature on the role of teachers in blended learning settings (Mazzolini & Maddison, 2003; Norton, Richardson, Hartley, Newstead, & Mayes, 2005), teachers have an essential role to play in transforming insights gathered from 3 PLA into actionable support and interventions that help students. For example, van Leeuwen et al. (2014, p. 28) indicated that:

> *"… because the amount of data can be quite large, it may be impossible for the teacher to read or interpret all available information […] So called teacher supporting tools are specifically added to a digital learning environment to present summaries, visualisations, and analyses of student data to the teacher".*

For many teachers, it is a challenge to be able to filter relevant information from the Virtual Learning Environment (VLE) in PLA tools, and access predictive data about each of their students. While we recognise that VLE and PLA tools provide rich and detailed information about student progression, they may also lead to information overload which may restrict teachers' abilities to provide effective support to learners (van Leeuwen et al., 2014). Also, PLA data can negatively impact learning if their applications are not well-routed into existing educational theory (Gašević, Dawson, Siemens, 2015).

A well-known application of PLA in education, Course Signals (Tanes, Arnold, King, Remnet, 2011), identified students at risk and provided warning signals to teachers and students. The authors analysed the content of feedback messages sent to students as a response to the signals received by the system. The type of feedback most often given to students was summative whereas instructive or process feedback on how to overcome difficulties was almost absent. Aligning with existing research, summative feedback had no effect on students' learning. Although PLA might provide teachers with some powerful tools, several researchers (Gasevic et al., 2016; Greller & Drachsler, 2012; Tempelaar et al., 2015) indicate that most institutions and teachers in particular may not be ready for PLA results. Indeed, recently several researchers reported mixed effects about providing PLA data and visualisations to teachers (van Leeuwen et al., 2014; van Leeuwen, Janssen, Erkens, & Brekelmans, 4 2015). While these studies provide important insights about how teachers in relatively smallscale settings used simple learning analytics visualisations to identify groups of learners that were less active, to the best of our knowledge, no study has yet unpacked how teachers are using actual PLA data across large distance learning courses. This paper showcases how predictive analytics can support the teaching practice by predicting students at risk of not submitting their next assignment.

The OU Analyse Tool:

OU Analyse (OUA) is a predictive system that is designed to enable teachers identify learners who may be struggling with their studies. On a weekly basis, OUA predicts whether or not a given student is likely to submit their next assignment. It uses a traffic light system to highlight:

- in red those students who are at risk of not submitting the next assignment,
- in amber those with a moderate risk of not submitting the next assignment (including those who are likely to submit and fail) and
- in green those who are unlikely to fail.

The validity, accuracy and recall of OUA has been widely tested amongst 45K students and across 40+ modules (Hlosta, M., Zdrahal, Z. and Zendulka, J. 2017; Huptych, M., Bohuslavek, M., Hlosta, M. and Zdrahal, Z. 2017. Measures for recommendations based on past students' activity; Wolff, A., Zdrahal, Z., Nikolov, A. and Pantucek, M. 2013.) and has been relatively widely cited in the Learning Analytics & Knowledge community.

OUA uses Machine Learning Algorithms, which take into account students' demographic data and course activity in the Virtual Learning Environment (VLE), based on which predictions are calculated. The system employs machine learning methods to develop four predictive models:

1. Bayesian classifier,
2. Classification and regression tree,
3. k-Nearest Neighbours (k-NN) with demographic data, and
4. k-NN with VLE data.

These four models consider different properties of student data and complement each other. Each model classifies each student into classes: (a) will/will-not submit next assessment and (b) will fail/pass the course. The final verdict of the prediction is done by combining the outcomes and using voting techniques from all four models The OUA dashboard visualises predictive information about who is at risk, engagement with VLE and assignment submission rates at the course level, and probabilities to submit the next assignment for individual students.

Figure 1: OU Analyse (OUA) dashboard showing predictions for individual students

Methodology:

59 distance learning courses (N=59) were included in this mixed-methods study. Data was collected from the cohort of students registered on these course in 2015–2016. Participating courses were self-selected. An invitation to participate in the research was sent to course chairs across the university. Courses expressing interest in participating were included in this study. Some courses have optional face-to-face elements, such as meetings between students and teachers to discuss course-related issues. Each course involves a range of activities which include assimilative activities, finding and handling information, communication, productive, experiential, interactive activities, and assessment. Each course emphasises some or most of these activities as dictated by the learning design of the module. Assessment criteria varies between courses and includes examinations and assignments.

Each course has a number of teachers – Associate Lecturers (ALs) – who support students at a distance. Each AL is responsible for a group of 15–20 students and their role is to provide support and guidance to students in their group when needed. Associate Lecturers, for the most part, are well versed in the use of information communication technology (ICT) for teaching and supporting students, accessing information in relation to students, facilitating contact with academic units, and dealing with administrative responsibilities.

Course/Year	Teachers	Students
Arts - 2015	3	55
Social Science - 2015	3	69
Education - 2015	11	262
Health care - 2015	2	24
Maths - 2015	8	186
Engineering - 2015	6	152
Technology - 2015	11	239
Technology - 2016	6	92
Law - 2015	9	246
Total	59	1325

Table 1: Number of courses, teachers, and students participating in the study

ALs who participated in the study did so voluntarily. Being self-selecting, the ALs (see Table 1) were subject to the obvious (self-selecting) biases (Torgerson & Torgerson, 2008). No financial incentives were offered to participating teachers. In addition to being given access to the OUA dashboard, ALs also had access to training and support. Data related to the ALs' access to the OUA dashboard was collected. This data enabled us to generate insights about teachers' usage patterns and their relation (if any) to student performance.

Results:

The following tables (Tables 2 & 3) present descriptive statistics about the continuous and categorical variables entered in the model, including the two dependent variables (pass and completion). Two binary logistic regression analyses were performed with dependent variables completion and pass indicators.

Variable	Description	Min	Max	M	SD	N
Teacher Variables						
OUA Weekly usage	Usage of OUA relative to the length of each course (%)	0.00	0.91	0.22	0.21	1,325

Course Presentations per teacher	Number of course presentations an AL has completed	1	119	26	21	1,325
Students per course presentation	Number of students assigned to a teacher	10	32	21	4	1,325
Student Variables						
Age	Age of the student	13	79	33	11	1,325
Sum of previous credits	Sum of the credits previously achieved and linked to the current qualification	0	340	32	66	1,249
Best overall previous score	Best overall course score from previous study	0	98	51	34	*642*

Table 2: Continuous variables entered into the regression model

Pass rates		
Passed	802	60.5%
Failed	523	39.5%
Total	1,325	100%
Completion rates		
Completion		63.8%
Non-completion		28.9%
Total	1,228	100%
Gender		
Male		53.7%
Female		46.3%
Total	1,325	100%
Disability		
Yes		17.5%
No		82.5 %
Total	1,325	100%
Ethnicity		
Asian		4.5%
Black		3.9%
Mixed		2.2%
White		86.9%
Total	1,325	100%
Qualifications		
A Level or Equivalent to two A levels.		45.1%
HE qualification.		13%
Lower than A Level.		36.5%
No formal qualification.		2.9%
Postgraduate qualification.		2.3%
Missing		0.2%
Total	1,325	100%

IMD band		
0-25%		22%
25-50%		26.3%
50-75%		24.5%
75-100%		23.2%
Total	1,274	100%
New/Continuous		
New		54.8%
Continuous		45.2%
Total	1,325	100%
Courses		
Arts		4.2%
Social science		5.2%
Education		19.8%
Health care		1.8%
Maths		14%
Engineering		11.5%
Technology (2015)		18%
Technology (2016)		7%
Law		18.6%
Total	1,325	100%

Table 3: Categorical data entered into the regression model

In terms of completion, a test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between students who complete and students who do not complete a course ($X2(24) = 80.84$, $p < .001$). Nagelkerke's $R2$ of .181 indicated a moderately 19 weak relationship between prediction and grouping (18% of variance explained by the proposed model in completion rates). Prediction success overall was 72.9% (25.4 % for not completing a course and 92.4% for completing a course). The Wald criterion demonstrated that only OUA weekly usage (*p*=.003) and students' best previous course score (*p*=.003) made a significant contribution to prediction. All other predictors were not significant. In terms of effect size, the odds ratio was examined. Exp (B) value indicates that when OUA usage is raised by one unit (increase in weekly usage by one unit) the odds ratio is 7 times as large and therefore students are 7 times more likely to complete the course (see Table 4). These findings indicate that increasing engagement with OUA predictions and greater best overall previous score are associated with an increase in the likelihood of completing a course. However, it is noted that a low percentage of prediction suggests that additional variables are likely to explain variability in the outcome variable. One such variable may be the AL's general engagement with students (i.e., interactions to provide support, resolve questions). For example, a proactive AL who does not make use of OUA may have students with better performance outcomes compared to teachers that are less supportive and systematically engaged with students.

Variable	*B*	*SE*	*Wald*	*p value*	*Exp(B)*
OUA weekly usage	1.998	.667	8.987	.003*	7.377
Couse presentations per teacher	.003	.006	.315	.575	1.003
Students per course presentation	-.016	.027	.349	.554	.984
Age	.010	.010	.916	.339	1.010
Disability	.000	.000	2.389	.122	1.000
Sum of previous credits	.004	.002	2.456	.117	1.004
Best overall previous score	.012	.004	8.808	.003*	1.012
New/Continuous	-.545	.374	2.130	.144	.580
Gender	-.098	.233	.178	.673	.906
Arts	-.749	1.199	.391	.532	.473
Social science	-.547	1.240	.195	.659	.579
Maths	-.213	1.153	.034	.854	.808
Engineering	-.953	1.179	.653	.419	.386
Technology (x presentations)	-.973	1.170	.692	.406	.378
Law	.071	1.154	.004	.951	1.074
Education course	.117	1.159	.010	.920	1.124
Ethnicity Asian	1.026	.938	1.199	.274	2.791
Ethnicity Black	-.667	.741	.810	.368	.513
Ethnicity White	-.356	.618	.331	.565	.701
IMD band	.063	.092	.463	.496	1.065
A Level or Equiv.	1.161	.684	2.883	.090	3.193
No formal qualification	-.162	.842	.037	.847	.850
HE qualification	1.049	.706	2.208	.137	2.856
Lower than A Level	.671	.678	.978	.323	1.956
(constant)	-.112	1.618	.005	.945	.894

Model χ^2=80.84, *df*=24, *p*<.001

Table 4: Logistic Regression Model estimating effects of independent variables on completion (N=1325)

In terms of passing the course, a similar picture was revealed (*X2* (24) =84.83, *p*< .001). Nagelkerke's *R2* of .177 indicated a moderately weak relationship between prediction and grouping. The model explains 18% of the variance in passing rates and correctly classified over 69% of the cases. In particular, prediction success overall was 69.5% (35.5 % for not passing a course and 87.6% for passing a course). The Wald criterion demonstrated that only OUA weekly usage (*p*=.001) and students' best previous course score (*p*=.001) made a significant contribution to prediction. Exp (B) value indicated that when OUA usage is raised by one unit 20 (increase in weekly usage by one unit) the odds ratio is 7 times as large and therefore students are 7 times more likely to pass the module. Also, Exp (B) value indicates that when the best overall previous module score of a student is raised by one unit, the odds ratio is raised by one time and therefore students are one time more likely to pass the module (see Table 5). In line with existing studies suggesting that the instructor's role (e.g., Ma, et al., 2015; Arbaugh, 2014) and students' success in previous courses (e.g., Hachey et al., 2014) are predicting performance, these findings indicate that the increasing engagement of teacher with OUA predictions along with the students' greater best overall previous score are associated with an increase in the likelihood of passing a course.

Variable	*B*	*S.E.*	*Wald*	*p value*	*Exp(B)*
OUA weekly usage	2.010	.617	10.595	.001	7.461
Couse presentations per teacher	.002	.005	.111	.739	1.002
Students per course presentation	.002	.026	.008	.928	1.002
Age	.009	.009	.932	.334	1.009
Disability	.000	.000	3.067	.080	1.000
Sum of previous credits	.002	.002	.865	.352	1.002
Best overall previous score	.012	.004	10.084	.001	1.012
New/Continuous	-.740	.369	4.029	.045	.477
Gender	-.191	.220	.750	.386	.826
Arts	-1.110	1.180	.884	.347	.330
Social science	-.300	1.212	.061	.805	.741
Maths	-.272	1.144	.057	.812	.762
Engineering	-1.007	1.170	.741	.389	.365
Technology (x presentations)	-1.720	1.158	2.207	.137	.179
Law	-.113	1.144	.010	.921	.893
Education course	-.292	1.145	.065	.799	.747
Ethnicity Asian	.912	.842	1.174	.278	2.490
Ethnicity Black	-.317	.699	.206	.650	.728
Ethnicity White	-.287	.569	.255	.614	.750
IMD band	.024	.086	.076	.783	1.024
A Levels or Equiv.	1.158	.617	3.518	.061	3.183
No formal qualification	.249	.796	.098	.754	1.283
HE qualification	1.132	.637	3.160	.075	3.102
Lower than A Level	.745	.614	1.474	.225	2.107
(constant)	-.205	1.553	.017	.895	.814

Model χ^2=84.83, df=24, p<.001

Table 5: Logistic Regression Model estimating effects of independent variables on completion (N=1325)

Conclusions and recommendations for the future:

This study about the use of predictive learning analytics data by 59 teachers and 1,325 students at a distance learning higher education institution illustrates Associate Lecturers' actual uses and practices in relation to the data. The study indicates a variation in ALs' degree and quality of engagement with learning analytics. Despite the relative lack of engagement, greater PLA usage was found to predict better completion and pass rates, suggesting that systematic engagement with PLA should become a significant aspect of the teaching practice as it can improve student performance and attainment.

The data analyses shows that the best predictors of students' success performance were the instructors' role and students' success in previous courses. However, the ALs' limited engagement with OUA highlights that, at this early stage of PLA development and diffusion in the teaching and learning practice, access to PLA did not result in PLA application to the teaching practice; insights from this study reveal that teachers did not make systematic use of PLA.

Further piloting of PLA needs to be undertaken to understand how PLA can be used to support students including understanding what intervention strategies work best as well as applying PLA insights to ‘live’ or retrospective changes to the learning design of a course. The Early Alert Indicators project has been set up to examine the impact of specific intervention strategies on students' retention with Associate Lecturers across disciplines and faculties. The two-year project is expected to gather more evidence on the usefulness and effectiveness of using predictive data to support students.

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