Piloting OU Analyse and the Student Probabilities Model on 12 STEM Modules.

Executive Summary

The eSTEeM project *Piloting OU Analyse and the Student Probabilities Model on 12 STEM Modules* was established in November 2017 and aimed to explore whether, and how, these two learning analytics tools, could contribute to one of the four priorities - *the use of data and analytics* - outlined in the *STEM Retention and Progression Plan 2017/18* set to assist STEM in reaching its institutional targets.

This executive summary seeks to present only the recommendations and findings from that project.

The project team was:

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- Tom Olney – Senior Manager, Learning & Teaching
- Maria Kantirou – Head of Student Success
- Anactoria Clarke – Senior Manager, Curriculum Innovation

We sought to manage this project from inside STEM where we have a greater level of buy-in from module teams and were able to position ourselves as a more neutral observer, interested in the teaching and learning aspect of learning analytics. We did, however, work closely with the Early Alerts Indicator (EAI) project team who did the technical set-up, delivered the tutor training and played an ongoing advisory role for some module teams.

In this summary we use the term learning analytics, and its acronym LA, in accordance with the widely accepted definition provided at the First International Conference on Learning Analytics (LAK 2011):

> *Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs.*

A subset of this definition can be seen in the more recent development of predictive learning analytics (PLA) that uses machine learning and artificial intelligence approaches to predict student behaviour and/or outcomes.

We have attempted to be scrupulous in our use of the terms here, in particular to avoid confusion that engagement with LA in the EAI dashboard necessarily equates to engagement with the PLA. One does not necessarily follow the other.

11 STEM module teams and their tutors were given access to the EAI dashboard and the 3 types of LA in it:

1. TMA submission scores (PI level for tutor group) and rates of submission (aggregated for module level)
2. VLE engagement data (PI level for tutor group and aggregated for module level)
3. Predictive learning analytics (PLA) generated on a weekly basis by OU Analyse (OUA) machine learning algorithms that predict whether or not a student will submit their next tutor-marked assignment (TMA).

One other STEM module sent their tutors spreadsheets containing PLA generated by the student probabilities model (SPM) which produces predictions of whether an individual student will reach specific milestones (different points in a course presentation or between courses) such as completing and passing a module or returning in the next academic year.

All module teams and tutors were given some training in how to use their respective learning analytics approach during the 17J presentation.

Outputs from tutors were:

- Prior to presentation - 7 tutors interviewed to establish how they already use data to support students.
- After presentation - 38 tutors interviewed to establish how they had used the different types of LA available to them.
- Usage data downloaded directly from the EAI dashboard.

And from module teams:

- Prior to presentation – 12 module teams responded to *implementation intention survey* and interviewed to develop *logic models* that outlined expected short, medium, and long-term outcomes.
- After presentation – 12 module teams interviewed to comment on the extent to which their expected outcomes had been realised.

Recommendations

1. **Learning analytics should be considered as <u>one</u> option in a range of retention strategies.**

Tutors and module teams were generally positive about using learning analytics in their work. Both groups accessed a wide variety of relevant data sets when they were available to them and demonstrated an ability and willingness to combine them when appropriate. When tools were easy to use, understand, and had clear actions attributable to them they were incorporated without too much difficulty into daily routines.

However, the ongoing training of staff, managing access issues, developing LA strategies and building LA dashboards all take time and resources. Time was identified as a significant barrier to engaging in a meaningful way with LA. It was found that tutors that taught across several modules were more likely to invest time and effort into the EAI dashboard than those only involved with one module.

Despite the recognition of the <u>potential</u> for using LA by module teams, the interviews demonstrated that only around a quarter of the outcomes module teams hoped to achieve were actually realised. (it is recognised this statistic does not take into account the complexity of these outcomes). 9 module teams identified 'improved student retention, progression, pass and/or completion rates' as one of their desired outcomes of using the EAI dashboard and were asked about it at interview. None of the 9 teams considered this outcome to have been realised.

This evidence suggests that module teams (although not only them) may have a heightened or unrealistic expectation of what learning analytics can actually deliver, especially in the area of student retention and progression. Neither module teams nor tutors perceived LA to have a great effect on retention. Module teams typically employed a range of retention strategies and this complexity makes the impact of any specific one almost impossible to evaluate. The effectiveness of LA and PLA in regard to retention was not proven here.

2. **Learning analytics should be considered as one way to initiate conversations between tutors, students and module teams about students at risk.**

Tutors and module management teams repeatedly emphasised the importance of discussion and communication with students as being more important than using LA. Some tutors reported that they felt having access to these data enabled them to have more informed discussions with their students, although others felt it added little to what they already knew. It was observed that on occasions analysis of the data also prompted a focused discussion amongst some module teams that might not have previously occurred. It is recommended that any future uses of LA should continue to focus on it as a method to support tutors in their work.

3. **The timing and content of training provided to tutors and module teams needs to be reviewed.**

Neither tutors or module teams trusted the OUA PLA to any great extent. There was confusion as to what underlying principles the predictions were based on and how the OUA model generated its predictions. Since this was not communicated to tutors or module teams during the training, many participants were reluctant to act on the data it presented. Increased efforts need to be made to communicate this to tutors and module teams if use of the EAI dashboard is chosen as a retention strategy option. This concurs with the findings from the EAI Project team (Herodoutou et al, 2019).

Training was provided to module teams and tutors by allocated super users before the start of presentation. Whilst module teams and tutors considered the training to be useful, many reported they were later unable to remember it. It is recommended that training should be ongoing (perhaps split on either side of TMA01) and contextualised more finely to the specific module or area of curriculum rather than as a one-off event. Other studies into the use of LA at the OU have come up with similar findings. (Rienties et al, 2018; Calvert, 2019)

4. **The development of new learning analytics dashboards and the strategies and guidance that goes with them, should be developed through consultation with tutors and owned by module teams.**

Tutors identified a desire to get to know their students as much as possible before module start and as a consequence they engaged with the dashboard heavily at the start of the module. Engagement subsequently halved every 11 weeks in individual modules and when aggregated. Tutors reported the OUA PLA were of no use and the VLE engagement data of limited use during this time period before module start. However, whilst OUA PLA does not really meet this need, it is possible that the SPM may, and as such further research in this area is recommended.

Tutors used the OUA PLA for four distinct reasons that should be considered in any strategy:

- *Alert:* from 38 interviews 6 tutors identified occasions when they had used PLA to identify a student at risk that they hadn't known about.

- *Confirmation or reassurance:* the majority of tutors reported that the predicted data confirmed or reassured a pre-existing view that the tutor had.
- *Curiosity about the PLA:* particularly near the start of the module.
- *At specific times:* before TMA due dates, as part of a weekly routine or only when explicitly prompted to do so by external nudges.

Module teams and tutors reported that the 'one size fits all', big data predictive model used by OUA was unreliable when attempting to account for the vagaries of specific assessment strategies, differences in platform delivery, first presentations, etc. It is possible that the emphasis of OUA on delivering predictive analytics at scale may impact on its accuracy. Future work could include considering and trialling a model that can adapt and incorporate small, module specific data. Module teams are best placed to critique, interrogate and/or interpret the predictions as they relate to their module context and reject or accept the value of them accordingly.

In future design, emphasis should be placed on 'ease of use', which, in this context, needs to be seen not just as the immediate usability of a particular data source or tool but also, it's location among the other sources & tools that are available to tutors. Also, the introduction of new data sources and tools is unlikely to lead to significant improvements in student retention if there are no effective 'levers' that can be pulled to try to influence predicted outcomes. (Walker et al, 2018)

5. **For first presentation modules, module teams should make only TMA submission scores and VLE engagement data available to tutors before introducing OUA PLA on second presentations onwards if required.**

As above, the interviews suggested that tutors and module teams were not convinced about the accuracy of the OUA predictive data and continued exposure to it further undermined that trust. Since the OUA model largely generates its predictions about a student's likelihood to submit their next TMA on the basis of successful students' engagement with the VLE components of the same module in the past, without previous presentation data the machine learning predictions were observed as being largely unreliable.

Crucially, module teams also reported that the time limitations in managing a first presentation module are considerable and they were not able to commit sufficient time to also managing the use of the EAI dashboard.

New modules interested in using the OUA model should trial the EAI dashboard without offering access to the predictive data to their tutors. That is restricting access to PI level VLE engagement and TMA data only. In this way module teams can monitor the OUA predictive data over a presentation, critically assess its usefulness and, if they decide to go ahead, develop an appropriate tuition strategy and trust in the data. This is consistent with current advice given in STEM and should continue for 19J.

6. **Further research into uses for the OUA PLA should be undertaken, particularly in the field of producing static learning design visualisations.**

Static visualisations of the engagement with VLE components that successful students take through a module, or a 'module fingerprint' (Hlosta et al, 2015), may be of interest to module teams and tutors in order to share and improve their understanding of their module. It is envisaged that this fingerprint could potentially be combined with other existing learning design data to provide a rich data source.

References

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