Don't Disturb The Student
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02. Aug. 2019
Introductions

- Cameron Gray, FHEA

- Teaching Assistant and Ph.D. Candidate in Computer Science at Bangor, studying Learning Analytics.

- Part of the Learning Analytics Initiative at Bangor, in partnership with our Centre for Excellence in Learning and Teaching (CELT)

- Contactable at c.gray@bangor.ac.uk.
How This All Started…

- Doctoral work surrounds using Data Science methods to add an ‘Early Warning System’ to our Learning Analytics platform.

- To assist with the earliest possible identification of students in potential difficulty, we discounted data sets that could not be provided from day one.

- The prime data set we identified is student attendance at scheduled events, such as lectures, tutor meetings, employability sessions, etc.
Anecdotally, teachers and lecturers have correlated attending with academic achievement for years. Usually in the form ‘show up and do the work, you pass’.

Multiple studies have shown this correlation to be correct [1-3] and visible across institutions and cohorts.

Institutions start to collect this data from the very first activity/session.

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We explored various options to summarise all of the attendance information into a single metric.

- Ratio of Sessions Attended.
- Raw Counts.
- Derivatives
- Etc.

With help from CELT, we defined a summary metric.

**Making Sense of the Data**

- +1 Point for attending a session.
- -1 Point for missing a session.

**Definition The Bangor Engagement Metric**
We conducted a series of Machine Learning experiments to determine the best settings to maximise identification of poor outcomes, at the earliest possible juncture.

The results prove in both seen and unseen data, that we can predict the outcome of students from the first 3 weeks’ attendance values of the BEM.

- 84.79% Identical Match Accuracy
- 97.33% ‘On-Mission’ Accuracy.
Our guiding principle is a reworking of Blackstone’s Formulation (applying to Criminal Justice).

“It is better to intervene with 10 students that would pass unaided, than to miss one student that would fail.”

The model is designed to minimise the number of would-be failing students that get missed.
‘Real World’ Model Testing

- We conducted a ‘Field Trial’ during semester 1 A/Y 2017/18.

- The predictions from our model were compared against the previous ‘Low Engagement Report’ used at Bangor.

- The report showed an additional 63 students (within the School of Computer Science) with low rankings, that were not identified as ‘at-risk’ by Week 3.
How’d That Happen..? 

Downturn begins..

Teaching Week 1  
Teaching Week 5
Wha..? ... Oh wait...
When are Reading Weeks in other schools?
At this point we knew that Reading Weeks occur, but as a School that doesn’t use them we had no idea when they fall in the calendar.

We set about using the data set we already had to try to find this event prior to obtaining the actual dates.

As a side benefit, this work provided an answer to ‘can we spot disturbances that may impact student achievement?’
Methodology for Detecting Disturbances

- We examined all students as a whole population and school by school.

- First, we calculated the number of students above and below the average BEM measure for each population (at that week).

- Next, we calculated the variance of those counts between adjacent weeks.

- We then included a 3-value rolling average, to deal with any extreme outliers.
Variance Analysis of Student Numbers (Across All Schools)

- Students Above Average
- 3-week Above Average Mean
- Students Below Average
- 3-week Below Average Mean

Week Number

Variance (Squared Deviation from Mean) in Count

n=15392
Detecting Disturbances Results (2)

Variance Analysis of Student Numbers (No Reading Week)

Variance Analysis of Student Numbers (With Reading Week)

Students Above Average
3-week Above Average Mean
Students Below Average
3-week Below Average Mean
LS Above Average
LS Below Average

n=4330

n=11062
Observations

Overall Observations

- Attendance patterns stabilise at teaching week 3 and 4.

- Once that pattern is interrupted, the same level of variance never returns, implying that the interruption has introduced change.

Split RW/NRW Observations

- In schools without a reading week, there is natural tendency toward non-attendance by the end of a semester.

- The cross over point between the two trends for NRW schools is week 4. This week seems to be significant in student attendance patterns.
Analysing the Trend

By adding a Least Squares Trend Line over both populations, we arrive at these trends.

This graph reveals:

Students that are below average attendance do not seem affected (roughly the same gradient).

Above Average gradients diverge significantly.
What the Trend Tells Us

<table>
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<tr>
<th>Student Type</th>
<th>Effect</th>
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<tr>
<td>High Flyers</td>
<td>Always attend irrespective of outside influences.</td>
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<tr>
<td>Volatile</td>
<td>Highly susceptible to outside influences, only requires a nudge to fall either way.</td>
</tr>
<tr>
<td>Average</td>
<td>Generally keeps up, may benefit from occasional interventions.</td>
</tr>
<tr>
<td>Below Average</td>
<td>Likely immune to interventions unless very specific.</td>
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The difference in gradients allow us to infer structure in student achievement groups.

The lower end appears to be largely immune to retention efforts, but cannot be ignored.

The higher end are also likely to perform no matter what efforts or disturbances occur.

The important group is the one just above average, but below the high flyers. These students are the ones most affected by changes.
Nudge Theory [1] holds that reinforcement and indirect suggestion can vastly alter the decision making processes of groups or individuals.

Students without reading weeks are affected disproportionately than students that do. We hypothesise that this is a nudge effect of students not keeping to their pattern.

The observation that following a reading week student attendance doesn’t immediately return to pre-break levels, would also imply there is a nudge effect present.

Escaping Negative Nudges

- We observed that there are three Schools at Bangor that have been affected far less significantly.

- Those schools either have a very structured set of reading week activities (just not normal lectures), or a very insular community.

- Negative nudges, such as peer pressure, changing patterns of classes, etc. need to be considered when designing any ‘non-standard’ or pattern-breaking element of a course.
Decisions, decisions...

- In order to confirm our observations, a longitudinal study is required.

- In the mean time, our data provides a wealth of insight in order to make better decisions; Data Driven Decisions (D3) [1].

- We’re not proposing scrapping reading weeks, but we as educators need to determine if the break in routine serves our students best.

- Potentially, different forms of activity could enhance the experience without the negative nudging effect.

If you would like to know more...
Contact Us

Learning Analytics Initiative,
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