How do students handle atypical subject choices?

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Introduction

With an increasing breadth of subjects and educational topics provided by tertiary educational institutions (Noorden, 2015), it is reasonable to question how student enrolment in diverse coursework will affect their performance. Research into indicators of university students' performance has a long history (Berdie & Sutter, 1950). More recently, educational researchers have started to analyze whether the diversity of topics covered by students predicts their performance (Lowe, Wilkinson, Machet, & Johnston, 2019; Shulruf, Li, McKimm, & Smith, 2012). These studies used a diversity metric based on categorical separation of coursework depending on the subject material taught. A student portfolio of subjects was considered to be diverse if they were enrolled in subjects covering a wide range of predetermined categories.

Such deductive categorization requires knowledge of the subject matter taught in each class and is prone to potentially changeable interpretations. This caveat is particularly pronounced in contemporary more flexible university degrees where boundaries between disciplinary categories are becoming increasingly fluid.

This paper proposes and illustrates the use of an alternative inductive data-driven metric of students' subject choice diversity, based on their enrollments relative to other students in their cohort. The score on this atypicality metric is higher for students who choose unusual combinations of classes compared to their peers and low for students who follow the typical choices of their peers, past and present, regardless of whether these mainstream choices cross pre-defined disciplinary categories. This measure is entirely data-driven and reflects changing student populations and offered coursework. We demonstrate how this measure of atypicality to students' performance trend overtime to answer the question, how students handle atypical subject choices?

Methods

Data

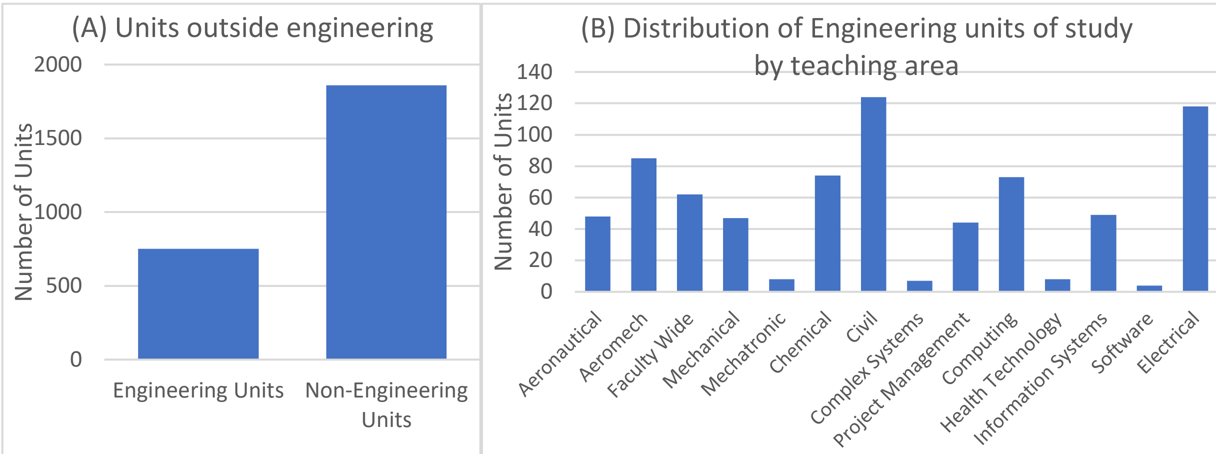

Figure 1 (a) Number of classes present in the dataset under School of Engineering and IT compared to those outside Engineering and (b)distribution of Engineering classes according to teaching area

We use anonymous data of 21,727 engineering students enrolled at a major Australian University. Excluding the 224 postgraduate research students, the data contains 7,644 undergraduate and 13,839 postgraduate coursework students enrolled in civil (≈19%), aeronautical (≈2%), mechanical (≈10%), chemical (≈6%), electrical (≈8%), project management (≈13%) and other fields. Of these there were 5,730 students in a combined degree pursuing more than one degree on the same enrollment (most commonly engineering combined with science, commerce, architecture, or law). In this data, 11,232 students completed their requirements for their degrees, 3,983 students are currently enrolled either as part-time or full-time students and the remaining students changed courses or withdrew their enrolment.

In aggregate, the Faculty of Engineering students have completed 2610 unique units of study in our dataset. It is important to note that these units are offered by different departments across the university, including non-engineering departments (see Figure 1 (a) and (b) for the distribution). For example, engineering students took 1810 units of study outside the faculty. Sometimes this maybe as a compulsory unit (e.g. all undergraduates take math, and all students combined with commerce take core business units), but most are as free electives. Approximately 1300 units outside of engineering were taken by 10 engineering students or less during the 10-year time frame of this study (usually as a single engineering student in a much larger class of humanities or science students). Enrolments involving classes with agreed grades without a specified mark range were excluded (for example project classes, industry internships, etc.).

Analysis

A bipartite network M is defined where $M_{ij} = 1$ if student i has completed their enrolment in unit j and otherwise is 0. From this a subnetwork of units is extracted, where two units are connected if some students enrolled in both of them anytime during the course of their entire studies. This projection gives a weighted network N in which weight of edge N_{ij} is the number of users enrolled in both units i and j.

Unit of study enrollments are highly skewed (Figure 2) and even a small proportion of the total students enrolled in large units, could skew the overall similarity scores. For example, a large number of mutual students between two large compulsory units does not indicate similarity in interests of the students enrolled in these two units.

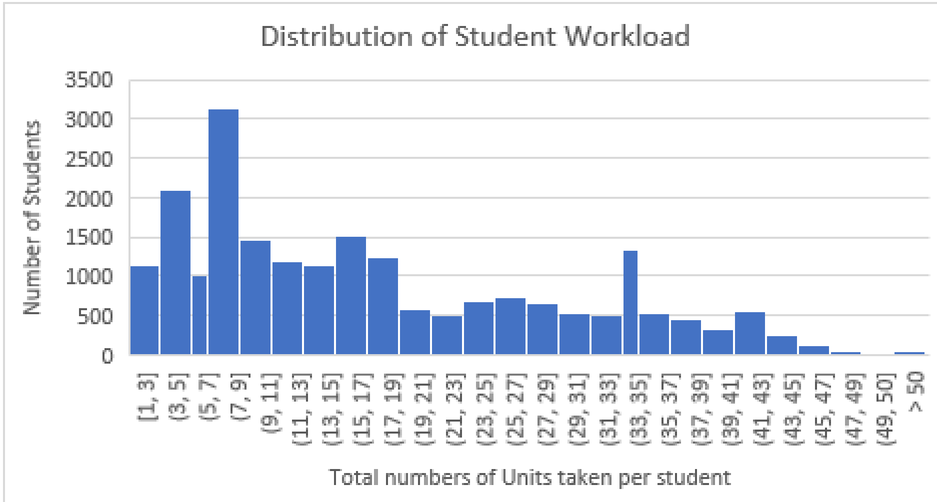

Figure 2 Distribution of number of classes registered per student

To account for this phenomenon, the edges of the weighted network were processed using a modified backbone extraction algorithm (Serrano, Boguñá, & Vespignani, 2009), which has shown to be highly effective in reducing and filtering unipartite projections of bipartite networks (Ahn, Ahnert, Bagrow, & Barabási, 2011; Olson & Neal, 2015). This algorithm replaces each symmetric undirected edge N_{ij} with asymmetric bidirectional edges with weights X_{ij} and X_{ji} where $X_{ij} = N_{ij} / i_n$ with i_n being the total number of students enrolled in unit *i* and where $X_{ji} = N_{ij} / j_n$ with j_n being the total number of students enrolled in unit *j*. All directed edges with weights below a threshold *α* set between 0 to 1 are removed. In other words, a directed edge from *unit i* to unit *j* is preserved only if the number of mutual students between two units is higher than a certain proportion of all students enrolled in unit *i*. To recombine these directed edges between two nodes, the two directed edges are replaced with a single undirected edge whose weight is the average of the two directed edges.

The results reported in this article are based on $\alpha = 0.05$. Robustness tests that we do not report here because of space limitations showed that variations in the threshold do not qualitatively impact the results. We have tested that the enrolment association network is robust to addition of new data in the form of new nodes and edges and maintains connectedness when irrelevant edges have been filtered out.

We reverse the weights of the edges (by subtracting 1.01), so that now units with high student overlap have low values and vice-versa. We calculate the distance between any pair of classed by summing the reversed edge weights on the shortest pathway between the two units in the developed network. Any list of two or more classes can be assigned an "atypicality score", thus the atypicality of a student's enrolment is basically the atypicality score calculated for all the classes in which the student enrolled. When evaluating the atypicality for a list of classes, the number of unique pairs possible between classes follows the formula $\big(n(n-1)\big)/2$, where *n* is the number of classes being evaluated. The final atypicality measure for this specific list is the average atypicality of all possible pairs of classes in the list.

The weights were inverted for the distance algorithm, but it still provides a direct interpretation of student atypicality. A student with an atypicality score of 0.3 has on average 70% *(1 - 0.3)* of the same student population between any two of his classes.

The network was constructed and analyzed using MATLAB toolboxes Curve Fitting Toolbox (MathWorks, 2019) and Graph Package (Tun, 2009) and visualized in Gephi (Bastian, Heymann, & Jacomy, 2009).

Results

Figure 3 shows the student enrolment network (for $\alpha = 0.05$). This network is visualized using a force directed algorithm, so spatial proximity is an indicator of a general similarity of classes in terms of their student enrollments. The colors indicate schools of the Faculty of Engineering or complimentary departments that provide the unit (Math, Civil, Aeronautics, Physics, etc.); units provided by other faculties are grey. Units with high cross-over in student enrolments are close together in the diagram.

The distribution of the atypicality scores are shown in Figure 4. Most students enroll in common class combinations and therefore the atypicality score is skewed toward the lower side of the scale. A large portion of students have an atypicality score of around 0.25, meaning on average, any two of their classes has 75% *(1 - 0.25)* of the same students.

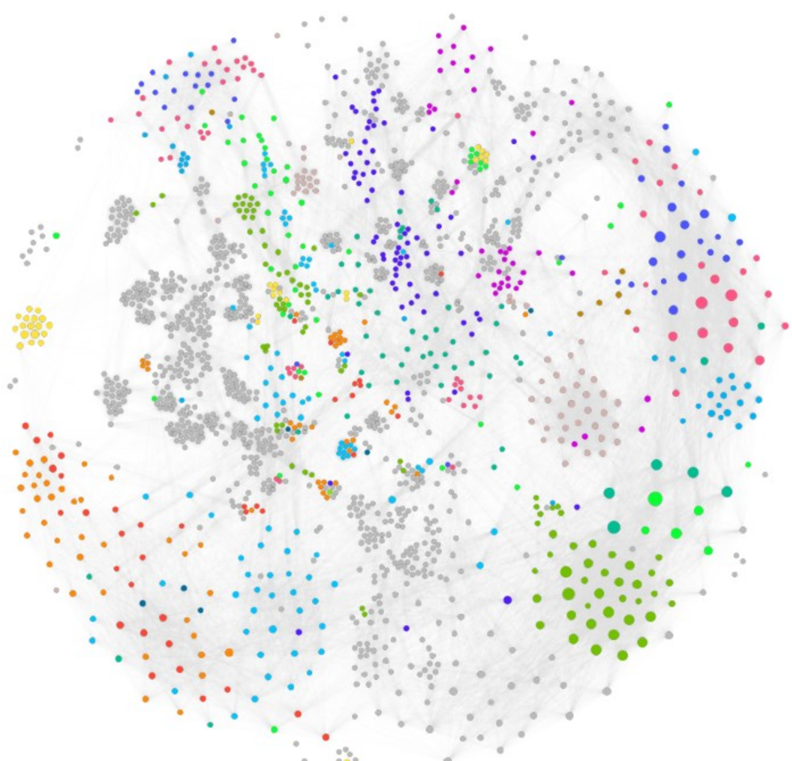

Figure 3 Enrolment map showing the relation of classes (nodes) with each other based on student enrolment. Positions are determined by force directed visualization algorithm. Node size corresponds to number of students registered. Engineering and associated specializations (Physics, Chemistry, Math, and Statistics) are colored.

It has been shown that the breadth of students' subject choices, as defined by their classification in pre-defined disciplinary categories, is weakly associated (r=0.102, p-value not reported) with students' academic performance measured by Weighted Average Marks (WAM) (Lowe, Wilkinson, Machet, & Johnston, 2019). Unit marks can range from 0 to 100, with marks below 50 indicating fail.

The correlation between students' atypicality and WAM appears somewhat stronger (r=0.023, p-value<0.001) and opens an intriguing opportunity for future research on the relationship between students' atypicality of subject choices and their performance. The relationship is not linear. Our preliminary exploration suggests that on average, the students who choose a more atypical pathway in their curriculum tend to perform worse than those who do not step out of their standard pathway (Figure 5).

Furthermore, longitudinal analysis reveals that also in the long term, students with overall lower grades who enroll in an atypical combination of subjects from diverse fields worsen their performance over time (Figure 6a). Specifically, those with overall WAM below the median of 69, saw a drop in their performance if they chose atypical subjects (slope = -24; r-square = 0.023; p-value < 0.0001). However, this is not the case for generally higherperforming students (Figure 6b). There is no significant change for students with WAM over 69.

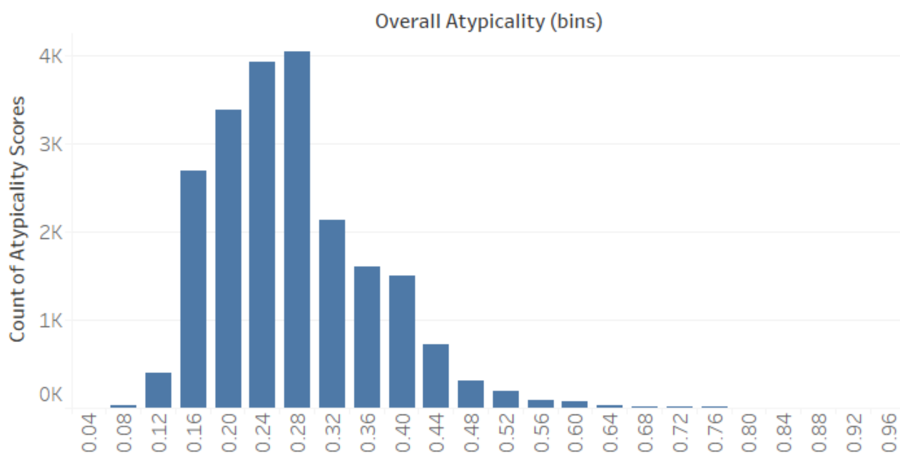

Figure 4 Distribution of atypicality scores for all students in the dataset

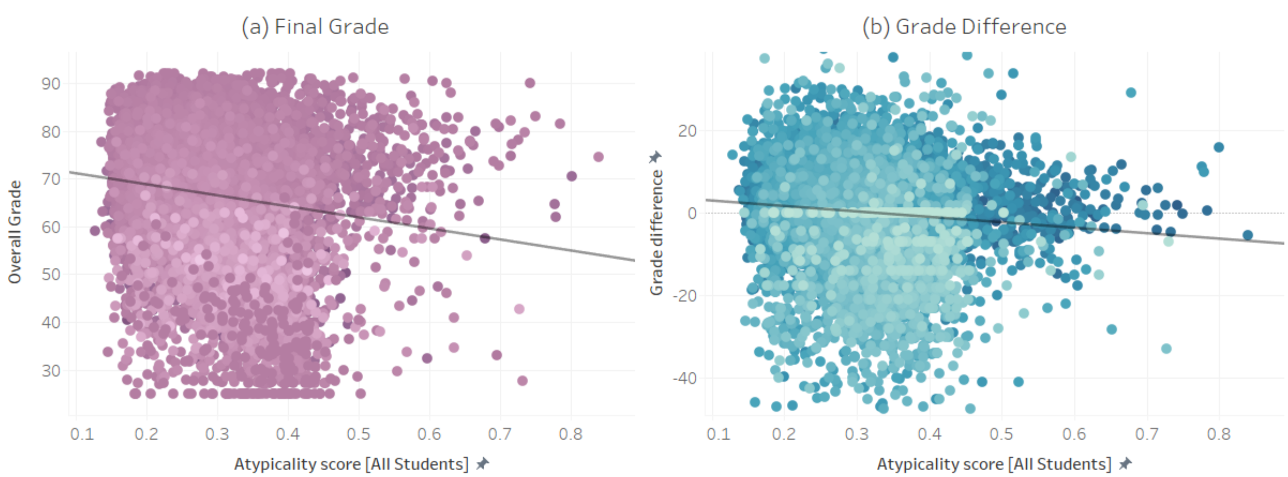

Figure 5 Atypicality scores for all students when compared to (a) Overall Grade of the student [Slope = -23, p-value < 0.001]; and (b) Difference in grade between late and early enrolments of the student [Slope = -13, p-value < 0.001]

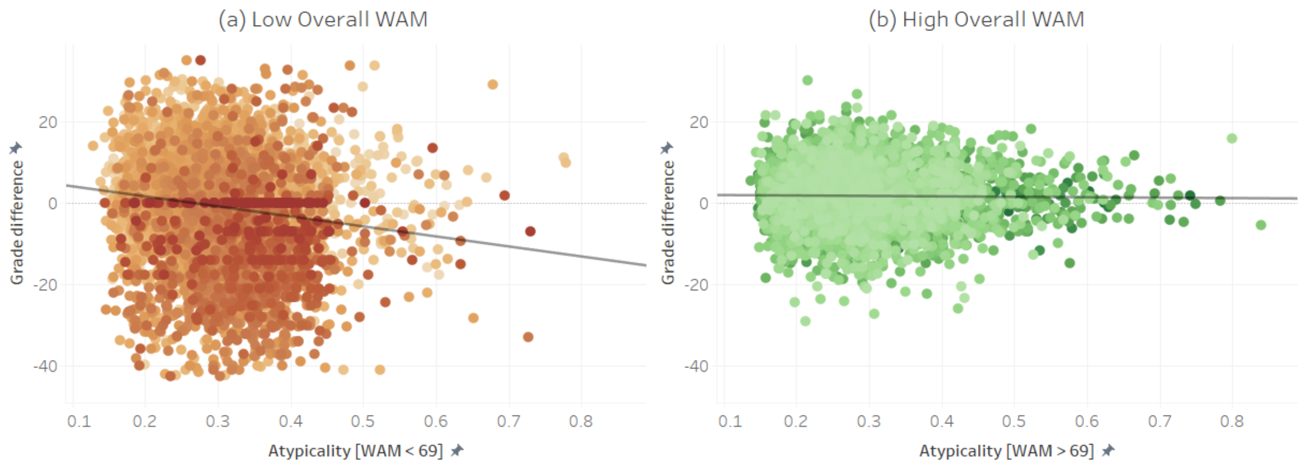

Figure 6 Comparing change in average grades (WAM) between the first half and second half of student's coursework to overall atypicality of the student for (a) Students with overall WAM below 69 [slope = -24, p-value < 0.001]; and (b) students with overall WAM above 69 [slope = 1.05, p-value = 0.23]. (Median WAM is 69.)

Discussion

In this article, we have illustrated how to visually map similarity of university courses based on students' enrollment choices. These maps can show how students move from subject to subject as they are working towards the completion of their degree. These maps can be easily recreated to provide a dynamic view of student enrolment pattern changes without being fixed to any predetermined disciplinary categories or interpretation of the course content.

An atypicality metric derived from the course association network is robust to changes in the course structure and student population and would be a useful measure in models of variety of student outcomes. A very preliminary analysis presented in this paper suggests that students with unique atypical subject choices as compared to the peers in their cohort perform worse. This trend is more noticeable among students with lower grades who enroll in an atypical combination of subjects from diverse fields. This detriment is non-negligible. This model predicts that, on average a student graduating with a WAM of 60 who selected the most atypical classes suffered a performance drop of about 20 WAM points more than a peer who graduated with the same WAM but focused on the most common subjects.

Although our results parallel previous findings with different methods (Lowe, Wilkinson, Machet, & Johnston, 2019), the present analysis is too preliminary to be used as an argument for discouraging students with lower grades from enrolling in multidisciplinary offerings. It appears that lower performing students might have additional difficulties coping with atypical multidisciplinary combinations of subjects that their peers do not take but, at this stage, we do not attempt to propose causal mechanism for these longitudinal trends. One of the limitations is that for privacy and ethical reasons, we have worked only with completely anonymized data, preventing us to explore potentially important personal factors related to students' choices and performance.

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