Simple Rules For Identifying Students On the Edge

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Abstract—Students seeking enrolment into the bachelor of engineering at Victoria University of Wellington are required to gain a *B* average across their first year engineering papers in order to gain entry into second year. We explore longitudinal historical data in order to predict student progress using their grades from the end of the first trimester. We find that a simple classifier based on the number of *A* grades a student receives in the first trimester can predict which students are likely to gain entry, be near the borderline, or fall short.

I. INTRODUCTION

As part of the engineering program at Victoria University of Wellington (VUW), students must pass a filtering first year. Entry into the first year is open to all students who gain entry into VUW. In order to enter the second year of the programme students must obtain a *B* average across their engineering courses in the first year. Students who fail to meet this criterion have three options: resit papers to try to get a better grade, enrol in the open-entry computer science major, or leave the VUW engineering programme.

The programme contains three specialisations, focusing on software, systems programming, or electronics. The first year for all of these specialisations, while having some common courses, is different for each. This can be further compounded by students who are undecided about their specialisation and take more courses in order to keep their options open. All specialisations take four years to complete, and honours is an integrated part of the course.

In order to help the maximum number of students achieve the required level a wide variety of additional assistance is available to all students. This help comes in a variety of forms, including special tutorials for particular courses, general tutorials to assist first year students, and one-on-one help. While help is available, the student uptake of this help is far from universal among the students who require it.

This paper follows on from previous work performed at VUW to predict student success. Previous work has (with limited success) explored prediction based on high school grades [1], as well as methods to improve retention [2]. In this paper we seek to develop rules to identify which students are on the borderline of the *B* average. These students can then be targeted for special assistance. In particular, pastoral care initiatives can focus on convincing these students to attend the additional help sessions that are already running, and to make use of other support facilities. It is hoped that by finding the students who are close to the borderline, it will be possible to focus the limited resources in play on the part of the student body who will benefit the most from the assistance: those who are close to passing, and can potentially be brought up to the required level, and those who are on the cusp of failing, and can have their previous achievement reinforced.

This paper follows the process of finding a simple rule to identify students of interest. The rule should be intuitive and easy to apply without needing to write a complex program, without complex mathematics, and without requiring instructors to modify courses or collect additional data. The only data we use in the analysis are the student's results from their first-trimester courses. This is both the earliest point at which university-level results are guaranteed to be available for all students, as well as the last data point they are guaranteed before the end of the year.

We document our method, and some pitfalls that needed to be avoided in obtaining a result. We then show that the students of interest are those who achieve exactly one *A* level grade (*A+*, *A*, or *A-*) across their first-trimester papers. More generally, we show that the number of *A* grades achieved in the first trimester is a good indicator of a student's likelihood of gaining entry into the second year.

II. RELATED WORK

VUW has been working on a number of projects to identify struggling students and improve retention. Previous work on using high school grades to predict success in their university courses met with limited success [1]. A pastoral care programme has been instituted which has looked at some social and non-grade-related factors in learning [3]. This work reinforced the idea that the student experience is a very complex and multifaceted problem, and there does not appear to be any single catch-all identifier of problems. All of this research has occurred in the context of a much wider field looking at similar problems; see previous papers in the series for further detail on the particular context of VUW and additional general related work.

Several authors, including de Winter and Dodou [4], Selim and Al-Zarooni [5], and Kelly *et al.* [6] have examined prediction of performance using high-school grades. Such work has shown moderate success, but students often over- or under-performed predictions significantly. Similar results were found in the exact context of VUW in previous work in this series [1]. In all cases, these investigations focus on using specific pieces of high-school data to predict performance so that it can be used as an entrance filter, or to encourage or discourage students from enrolling, but face challenges because of the disunified nature of high-school education. This work instead focuses on measured performance while already at university, where all students are in a much more similar context, and aims in particular to target future pastoral care assistance at vulnerable current students.

Fernando and Mellalieu [7] describe a measurement-based intervention approach they have deployed in introductory engineering courses in New Zealand. Their system measures student behaviour (including attendance, participation, task completion, and assessment results) and correlates measurements with performance. The intention is to discover student behaviour modifications that will increase the probability of success, and to present quantitative data to encourage enacting these modifications. Theirs is the most similar approach to ours, but involves more complex data tracking, and relies on students being motivated by quantitative data presentation (an attractive, but uncertain, idea). The work in this paper potentially has complementary application, as evidence-based self-motivation in this manner and pastoral intervention may be effective on different subpopulations or in different ways: in particular, Fernando and Mellalieu focus on improving overall performance, rather than performance in relation to a fixed benchmark as we do.

Kinnunen *et al.* [8] describe a qualitative, phenomenographic, international study conducted into instructors' own perceptions of factors leading to student success in introductory computer science courses. The authors also discuss a great variety of past work focusing on individual purported axes of variation. The study results report a wide range of different instructor perceptions, including views on path-dependent relationships with learning in earlier courses, and on student attitudes towards the course. While the authors break their results into five categories — qualities of the subject itself, intrinsic traits of the student, past experience of the student, attitude and behaviour of the student, and techniques for developing further student understanding — the overall impression is that both available research and instructor perception show no consensus explanation for differing student performance. In this paper, we seek to sidestep the question of aetiology and focus on finding where measurable outcomes can aid in improving future performance.

Carter *et al.* [9] summarise work on retaining student motivation within courses and programmes. They describe both small- and large-scale approaches to increase student motivation, but do not focus on individual intervention or measuring performance across courses. The described techniques are largely complementary to the work in this paper, and might form part of the individualised intervention or the general structure enabling it.

III. DATA COLLECTION

To carry out our study we collected all of the final grades from the twelve core papers that make up the first year of the engineering degree. Not all students will take all of these papers, but all will take multiple of them depending on their specialisation. The specific courses are:

- COMP 102 (1A): Introduction to programming
- COMP 103 (1B): Introduction to data structures
- ENGR 101: Engineering methodology
- MATH 141: Introductory calculus
- MATH 142: Further calculus
- MATH 151: Linear algebra
- MATH 161: Discrete mathematics and logic
- PHYS 114: Introduction to physics
- PHYS 115: Further physics
- STAT 193: Statistics for natural and social sciences
- SWEN 102: Software modelling

The data we collected ran from 2009–2013. Data from 2014 was not included as this academic year is not yet concluded, and so the data is not available. Data from before 2009 was not included as the engineering program has not been constant since its inception in 2007. By 2009 the courses had stabilised enough to be comparable.

We are interested in students who are trying to pass the first year of the engineering programme. As a result we filter out all course records where a student does not have both a declared engineering major and enrolment in the engineering degree. We also filter out all special grades, such as aegrotat passes and special fails, to make the analysis simpler. This exclusion should not affect the results significantly as special grades are explicitly only used in unusual circumstances, and so do not play a role in the exploration of general trends. We also remove any students from the data set who have not completed any of the recorded courses in Trimester 1.

All of the grades have equivalent numeric values. This is a standard process, and is used to compute student grade averages. The list of grades and their values can be seen in Table I.

A+	A	A-	B+	B	B-	C+	C	D	E
9	8	7	6	5	4	3	2	1	0

TABLE I
GRADES AND THEIR NUMERIC VALUES

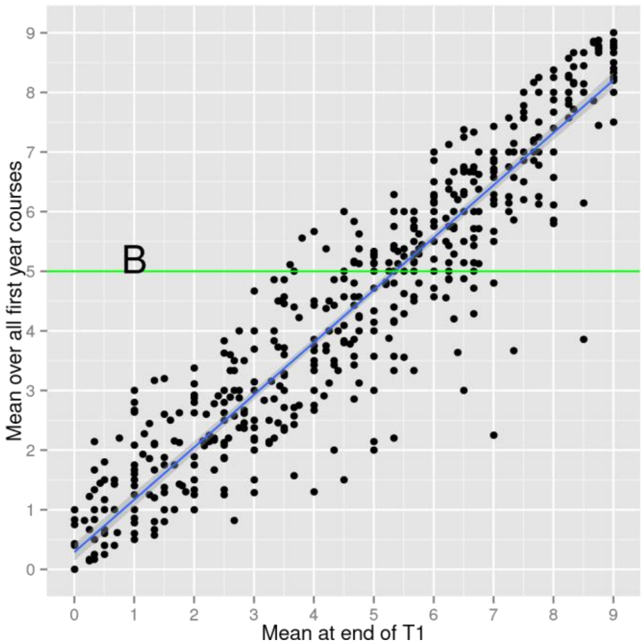
IV. RESULTS

We now look at what relationships we can find in the collected data. All of the data was analysed using R version 3.0.3 (2014-03-06).

A. Trimester One Mean as a Predictor of Year Mean

The obvious approach is to compare the mean of a student's first-trimester courses with their mean for the whole year. Since the first-trimester mean can be calculated before second-trimester courses start, the pastoral care staff can identify vulnerable students before they are too far behind to be helped in the current year.

Fig. 1 shows a student's mean grade at the end of the first trimester (T1) against their full-year mean grade. The horizontal green line represents an overall B grade, and marks the cut off for entry into the second year of the engineering programme. The diagonal blue line is a linear regression.



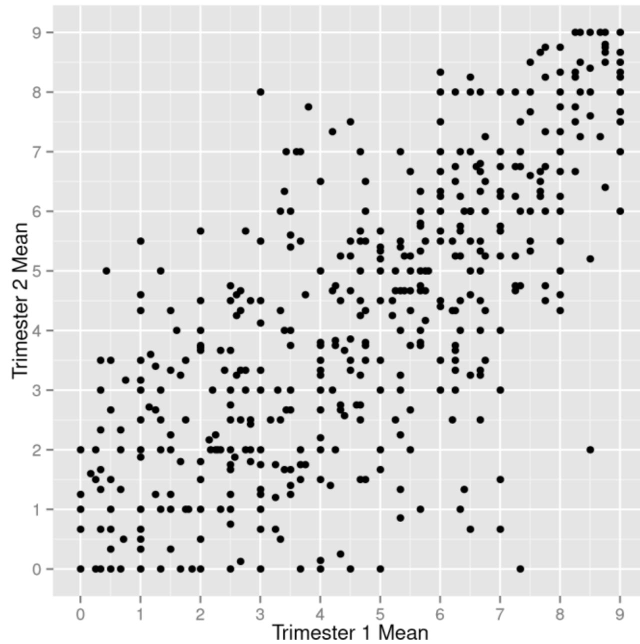


Fig. 1. Student mean mark at the end of first trimester against their full-year mean. The horizontal green line shows the cut off for entry into the engineering program (*B* average). The diagonal blue line shows the result of a linear regression. Note that the data has a strong linear relationship.

Fig. 2. This figure shows the relationship between a student's mean mark in the first trimester and in the second. While there is a relationship, it is not very strong. Many students perform significantly differently between the two trimesters.

Unfortunately, while this is a reasonable first thought of what to look at, it is not actually a valid means of prediction. The problem is that calculating the full-year mean involves all of the data used in the first-trimester mean, and so a strong correlation is to be expected. It is necessary to use two values which are not computed directly from each other.

B. *Predicting Trimester Two Based on Trimester One*

We can instead compare the student's means in the first and second trimesters individually. In this case the courses examined are distinct for each trimester. We hypothesise that students with a high mean in the first trimester will also have a high mean in the second. If this is true, it will suggest that the first-trimester courses are a good indicator of how students will perform in the second trimester.

We show this relationship in Fig. 2. In the ideal case we would see a narrow diagonal line of dots. Instead it shows a very wide diagonal line. The breadth of the spread is an indication of the uncertainty: the wider the line, the more uncertain the relationship. The fact that there does appear to be a line at all (as opposed to dots spread evenly across the graph) suggests that there is some relationship between the two means. We can quantify the strength of the relationship using the Spearman correlation, which gives a value of 0.77. This correlation indicates that a student who does well in the first trimester is likely to do well in the second, but there is significant remaining variation, particularly as there are only ten different grades awarded. Overall, this result suggests that there is not a strong relationship between student performance in the first and second halves of the year, and certainly not enough to predict marks closely.

This approach has a second limitation. We are interested in a student's ability to get a *B* average, which does not require a student to perform well in both trimesters. The better a student performs in the first trimester the more leeway they have in the second to perform poorly. This way of looking at the situation is also limited in the case where second-trimester courses are harder than their first-trimester counterparts. In that case a student will need to do well in the first trimester simply to have a chance of passing in the second. For that reason, as well as there being no strong correlation, it is not entirely clear that we are looking at the right thing regardless.

C. *C. Course-Course Relationships*

Given the lack of success we had looking at the relationships between trimester means, we decided to take a closer look at individual courses. In particular, we have a number of courses that are often believed to be related to each other, either because it is believed that the content from one is related to the content from another, or because they are direct follow-on courses. Therefore, even if we cannot predict the student's mean grade for a trimester, perhaps we can get an indicator of how well they will do in a course they have not yet taken based on courses that they have already completed and we believe are related. The specific course pairs that we look at are:

- COMP 102 (1A) - COMP 103 (1B)
- PHYS 114 (1A) - PHYS 115 (1B)
- MATH 151 (Linear Algebra) - COMP 102 (1A)
- MATH 151 (Linear Algebra) - COMP 103 (1B)
- MATH 161 (Logic) - COMP 103 (1B)
- MATH 151 (Linear Algebra) - MATH 161 (Logic)

COMP 102 and 103 are the introductory programming courses, and one follows from the other directly. PHYS 114 and 115 are the two introductory physics courses and again form a direct sequence. MATH 151 and 161 are the first-year discrete mathematics courses. MATH 151 is in the first trimester and 161 is in the second. While they are largely independent, in the past they were a single larger course and so there may still be a relationship between the grades in both of them. Additionally, both mathematics courses are compared against both programming courses as there is a widespread anecdotal belief that programming and mathematical ability are related.

For each course we present a scatterplot showing the relationship. In order to make the results more readable we add jitter into the x and y positions so that points do not overlap. For students who sat a course multiple times, we report their lowest grade. Students who sat only one of the courses are omitted from the chart.

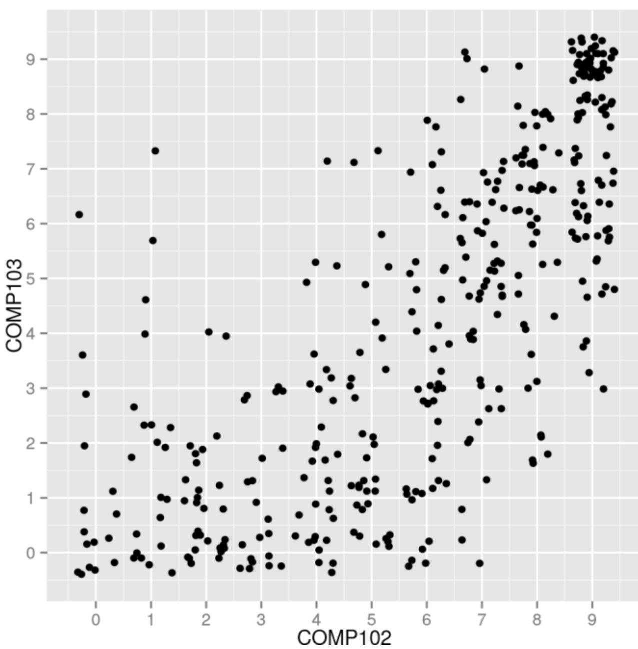


Fig. 3. Fig. 3. This is the relationship between marks in COMP102 and COMP103. There does not seem to be a strong relationship between the two courses, but it does suggest that COMP 103 is harder than 102.

1) COMP 102 - 103: COMP 102 and COMP 103 are directly sequenced courses. It would make sense that students who did poorly in 102 would struggle in 103. This is reflected in the scatter plot, but not quite in the way that we expected. The first thing to notice is that the upper-left triangle of the graph is almost empty. This means that students rarely achieve a better grade in COMP 103 than in COMP 102.

Strictly speaking, this does not represent a substantial problem. However, when we consider students who failed COMP 102 (on the left of the graph), then repeated it and managed to pass, we see that most of these students ultimately failed COMP 103 when they reached it, or achieved a low grade.

Moreover, the bottom right hand triangle is almost full. This means that a student is likely to do worse, and possibly much worse, in COMP 103 than they did in COMP 102. There are many students with a 9 (*A+*) in COMP 102 and then a 5 (*B*) or lower in COMP 103.

In general this suggests that COMP 103 is much harder than COMP 102, and that success in 102 does not provide a strong reason to expect success in 103. There are two simple explanations for this result. The first is that the COMP 102 assessment does not accurately measure the student's understanding or the content or their ability to program at the expected level. The second is that COMP 103 does not in fact build directly on COMP 102, and that therefore understanding COMP 102 is not sufficient to pass COMP 103. Practically, the second option is much more likely, as COMP 102 is an introduction to programming, while COMP 103 is an introduction to data structures, which is more than just slightly more advanced basic programming. Further investigation into the structure of the course would be interesting, and has been left as future work.

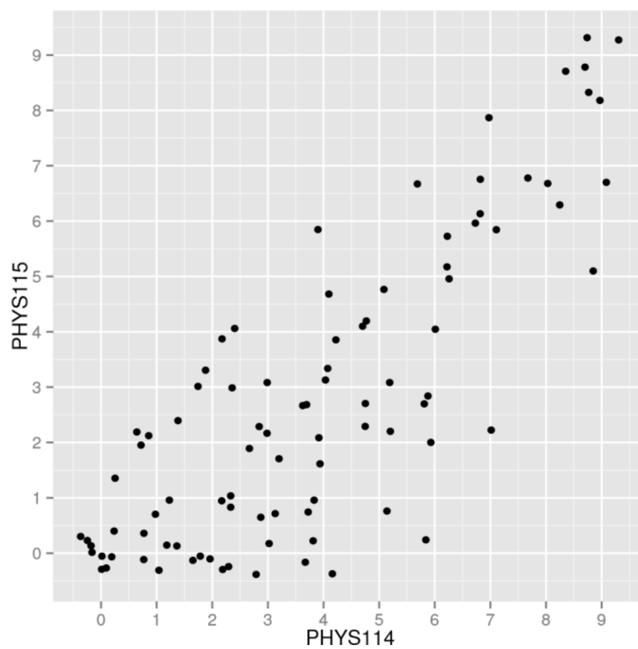


Fig. 4. The relationship between PHYS 114 and PHYS 115. While there does seem be a relationship, there are not many students who take both of these courses.

2) PHYS 114 - 115: The relationship between PHYS 114 and 115 is much less clear. There are not enough students who are taking both of these courses to make a clear pattern. Since our engineering school is largely software based, with a smaller electrical section, this is not too surprising. We can show there is a correlation of 0.78, which is not very strong, and in any case does not have enough students involved to be a useful predictor.

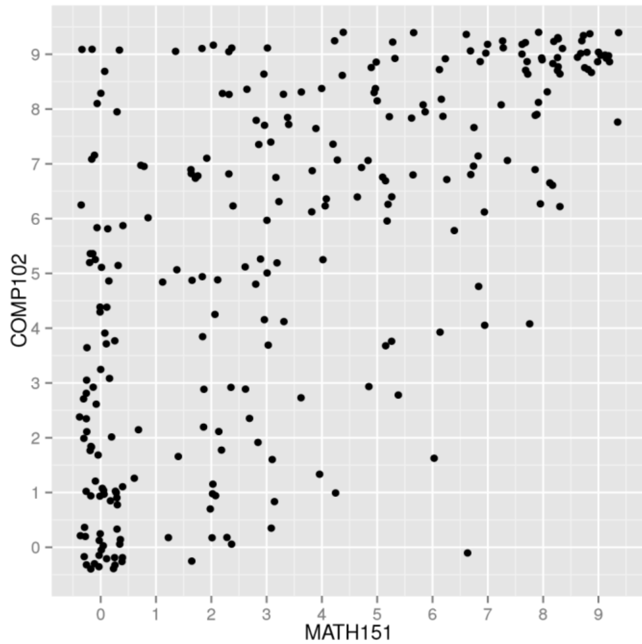


Fig. 5. The relationship between MATH 151 and COMP 102. There does not seem to be any strong relationship, but there is an indication that MATH 151 is the harder of the two courses.

3) MATH 151 - COMP102: This figure has a filled top-left triangle and a nearly-empty bottom right. This suggests that MATH 151 (linear algebra) is harder than COMP 102. Students who did well in COMP 102 received the full range of grades in MATH 151, while students who did well in MATH 151 usually did well in COMP 102 as well. Unfortunately, while this means that MATH 151 could be a filter course for COMP 102, it would be highly unfair as it would exclude many students who would succeed in the course.

4) MATH 151 - COMP 103: We originally hypothesised that COMP 103 and MATH 151 (linear algebra) would have a strong relationship, due to the common argument that mathematical ability and programming ability are related. Moreover, COMP 103 covers data structures and order notation, and so could be considered more mathematical. However, MATH 151 and COMP 103 seem to have no relationship at all, as shown by the roughly even spread of points across the whole chart. This further devalues the suggestion that MATH 151 be used to limit entry into COMP 103. Additionally, linear algebra is not used in the first year computer science courses, so there is little reason to expect it to be strongly correlated.

5) MATH 161 - COMP103: We initially hypothesised that MATH 161 (logic) would be the most relevant to COMP 103 as logic is used frequently in programming. Nonetheless, while there is a relationship between the marks (a pattern that looks like a line), it is very weak and very spread out. It is possible

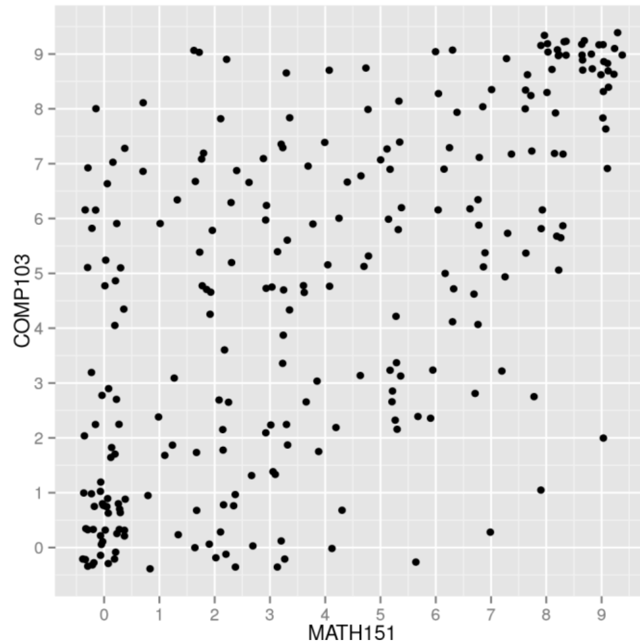


Fig. 6. Relationship between grades in COMP 103 and MATH 151. There does not seem be any clear relationship.

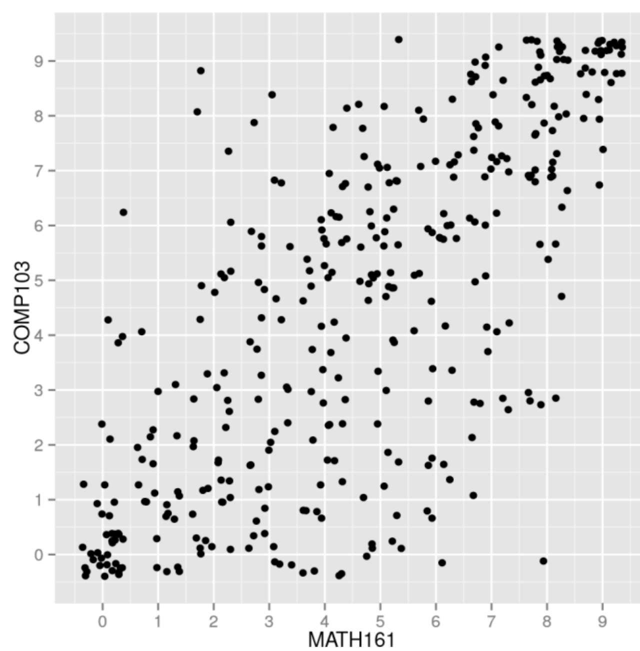


Fig. 7. Relationship between MATH 161 and COMP 103. While there may appear to be some trend in the data, there is too much spread for it to be very useful.

that this is because the way that logic is taught in mathematics is very different from how it is used in computer science. Future work could look at the content of the courses and identify what the actual relationship between course content is. It would be interesting to do a similar comparison in a faculty where logic was taught as a part of computer science / engineering directly.

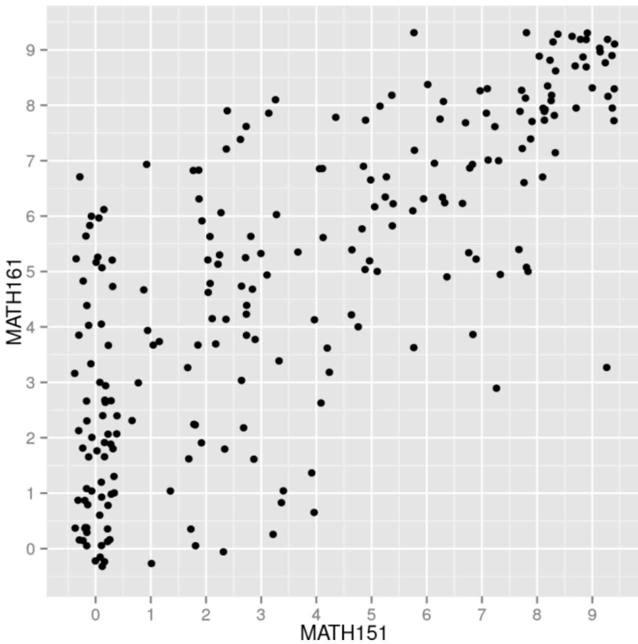


Fig. 8. Relationship between MATH 151 and MATH 161.

6) MATH 151 - MATH161: MATH 151 (Linear Algebra) and 161 (Logic) were in the past a single course, which has now been split into two. We hypothesised that both new courses would have similar outcomes. Moreover, we often hear concepts such as 'mathematical literacy' or 'mathematical maturity' being discussed. These are generally considered to be an indication that a student is able to do well in their computer science / engineering courses. The chart does tell us that MATH 161 is harder than MATH 151: note that the very top left corner is not filled, and there are a few dots still below the diagonal, which is similar to the relationship between COMP 102 and 103. While not having a strong relationship between course grades is reasonable given that the two courses cover unrelated content, it is not a good sign for the general notion of 'mathematical literacy'.

D. *Grade Slack*

We propose a new metric to measure how close a student is to achieving the requisite mean to gain entry into the second year of the engineering programme. We call this metric the *grade slack*.

This metric measures the difference between the student's mean grade for the second trimester and the mean grade they needed to achieve in order to gain the B average required (given their first-trimester grades). Values greater than zero indicate that the student performed well enough to surpass the necessary *B* average. Values below zero indicate that the student did not achieve the *B* average. A value of zero indicates that the student achieved the *B* average exactly. This metric also addresses the issue we faced in comparing trimester means — where performance in the first trimester grants leeway in the second — and accounts for it by only looking at how much better a student did in the second trimester than was required to reach their *B* average.

1) Computing Grade Slack: This metric relies on Table I. Note that the value of a *B* (the required average) is 5. It is also important to note that computing this metric requires knowledge of all of the student's grades. Computing the metric requires the following steps:

Compute the minimum grade sum: This is simply working out how many grade points the student needs to get in total to achieve the *B* average.

$$\text{Min grd sum} = 5 \times < \#\text{ courses taken} >$$

Compute the first-trimester grade sum: The first-trimester grade sum is the sum of all of the student's grades in the first trimester, representing how much of the required grade-point score the student has already obtained.

$$\text{T1 grd sum} = \sum \text{T1 grd}_{class}$$

Compute the second-trimester required sum: Having already obtained some grade points in the first trimester, the student may still require some from their second-trimester courses.

$$\text{T2 req sum} = < \text{Min grd sum} > - < \text{T1 grd sum} >$$

Compute the true trimester two sum: We also need to compute the number of grade points the student scored in the second trimester, which is again simply the sum of grades from all their courses.

$$\text{T2 grd sum} = \sum \text{T2 grd}_{class}$$

Compute the grade slack score: The grade slack score is the difference between the sum of the student's second-trimester points and the number they required in order to obtain a *B* average for the year. This number is then divided by the number of courses that the student is taking in the second trimester, and so represents the amount a student did better in each course than they needed to.

$$\text{Grade Slack} = \frac{< \text{T2 grd sum} > - < \text{T2 req sum} >}{< \#\text{ T2 courses taken} >}$$

2) Using Grade Slack: Although we could not find a relationship between individual courses, we hypothesised that getting *A* grades (*A*+, *A*, or *A*-) is an indicator of a student's likelihood of success. Therefore we explore the idea that the number of *A*s a student achieves in the first trimester is a good indication of the student's likelihood of achieving a *B* average (having a grade slack score of greater than or equal to zero).

Fig. 9 shows the distribution of grade slack by the number of first-trimester *A* grades (*A*+, *A*, or *A*-) that a student received.

Only students enrolled in more than one second-trimester paper were examined. The width of each violin represents the number of students. Notably, we only looked at students from the years 2009 – 2012, leaving us the 2013 data to validate our findings with in the next section.

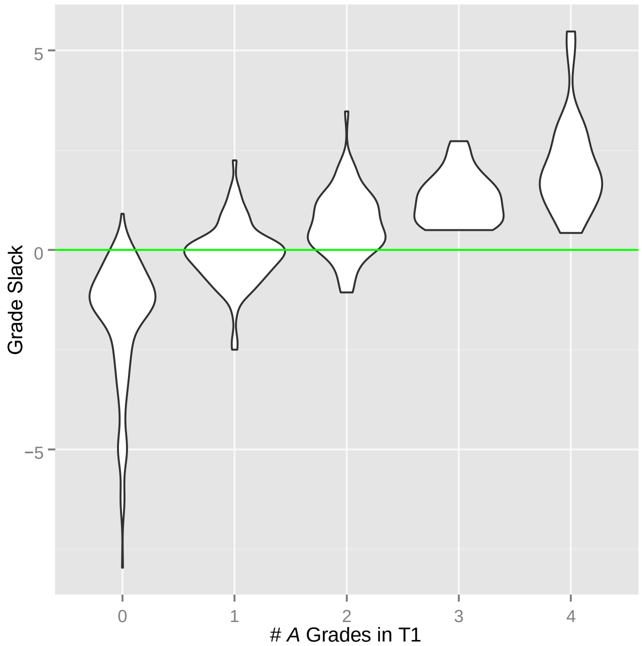


Fig. 9. Plot of the distribution of grade slack by number of *A* grades in T1 for the years 2009 – 2012

It is clear from the figure that the distribution of grade slack scores is very different in each of the five groups. Students who achieved zero *A* grades largely ended up with negative grade slack scores, i.e., most of them did not succeed in achieving a *B* average. In contrast students with 2 – 4 *A* grades largely ended up with positive scores, i.e., achieved the required *B* average. The remaining group, those with exactly one *A* grade had scores close to zero (on either side). These are the students who, whether or not they passed, were close to the borderline: they either passed or failed by a small margin. These are the students who in many ways are interesting. It is possible that with some additional support, or better use of existing support, more of these students could pass. Moreover, these are students who are in some of their courses doing better than the average requires, receiving *A* grades. It is easy to believe that students who are getting *A*s should be considered to be doing well. This analysis suggests, however, that getting a single *A*, despite its being a good grade, does not move you into the probably-safe group, but rather into the borderline group. Meanwhile, students who are only getting *B* grades and below (which is what the *B* average seems to imply is required) are actually overwhelmingly likely not to achieve the required standard. Performing the same analysis where *B+* grades are counted along with *A* grades does not produce as good of a result.

3) Validating Grade Slack: To provide some validation of our result, we repeat the analysis using only the 2013 data. Fig. 10 shows grade slack separated by number of *A* grades for 2013. The data shows the same distribution as in the previous years, suggesting that the trend was not an artefact of the particular years but rather potentially a pattern that holds across years.

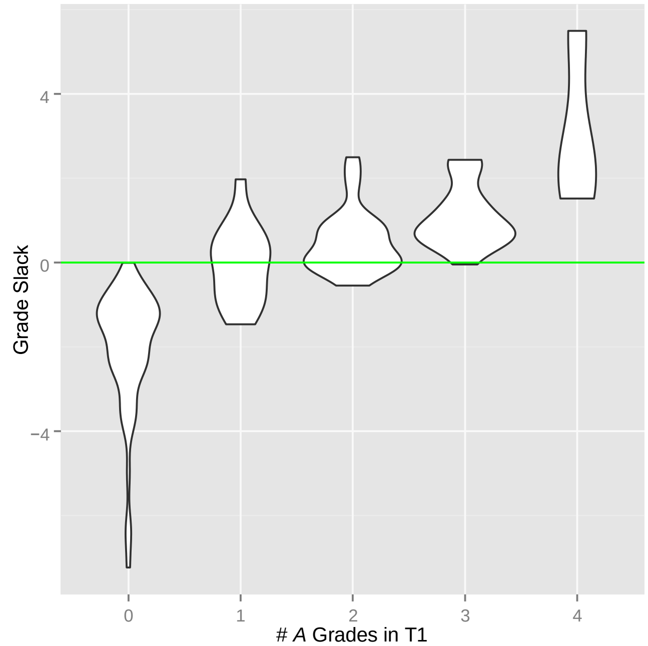


Fig. 10. Plot of the distribution of grade slack by number of *A* grades in T1 for the year 2013. Note that it is the same as for the years 2009 – 2012

Another important property of this validation is to show that *B* grades at or above the required level (*B* or *B*+) are insufficient. Fig. 11 shows the distribution of grade slack in the students who did not get any *A*s. We can see that with no number of *B*s do many students pass, and that having 1, 2, or 3 *B*s makes no real difference: unlike *A* grades, *B* grades are not a predictor. Furthermore, despite what might be expected, simply obtaining many *B*s in the first term does not confer a substantial chance of obtaining a *B* average for the year.

4) Discussion: It is surprising to the authors that it is the number of *A* grades that is important in predicting success, even though this is a significantly higher grade than required for the average. There are a number of possible reasons for this, but we believe that the following two are the most likely:

1) Second-trimester courses are generally harder than first-trimester courses
2) Student grades tend to be highly variable, so high grades are required to balance out low ones.

In order to address the first reason, we can look at the number of *A*s given out in first-trimester courses compared with second-trimester courses.

Table II shows that of the students who get at least one *A* grade, most of them get more *A* grades in the first trimester than the second. In general, this does suggest that the second-trimester courses may be harder than those in the first trimester.

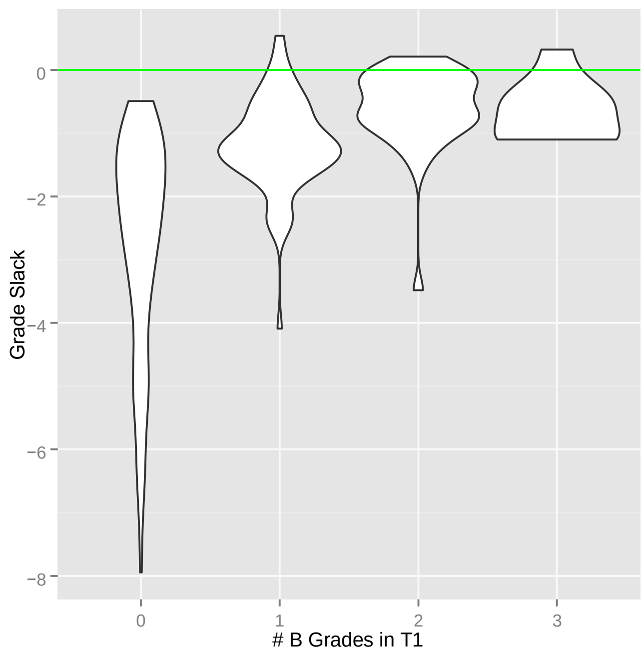


Fig. 11. Grade slack by number of first-trimester B *grades*

	Student achieved more *A*s in the first trimester
FALSE	94
TRUE	231

TABLE II

DID STUDENTS GET MORE *A* GRADES IN THE FIRST TRIMESTER THAN THE SECOND TRIMESTER?

The second reason was that student grades could be highly variable. The findings from the previous sections suggest that in general this is true. If there were low variability in the grades, then grades from one course (or a trimester average) would be able to predict grades in other courses. However, since they were not able to do so, there must be reasonably high variability in the grades.

V. FUTURE WORK

While this paper provides a simple rule for classifying students, there are a number of limitations which would be interesting to explore further.

The most interesting question is whether this pattern is specific to engineering at Victoria University of Wellington, or whether it would apply at other institutions, or in other degree programmes with limited entry, such as Law.

Beyond generalisability, this analysis only uses a very limited data set: we only use the final course grades. Each of the courses is itself made up of a number of assessment items, many of which occur and are marked weeks before the final exam. It is possible that with this additional data it would be possible to identify students with finer granularity. Unfortunately, this data was not available to us at the time of the study; moreover, obtaining this data retrospectively for all the courses is difficult or impossible. In future, we would like to explore how it can be used to extend the analysis.

VI. CONCLUSION

We use a student's first-trimester results to gain an understanding of their chances of obtaining a *B* average on the year, which is required for entry into the Victoria University of Wellington engineering programme. We explore a number of intuitive approaches to the problem and show that:

- student performance in the first trimester is not a strong predictor of their performance in the second trimester; and
- student performance in a single course is a not a good predictor for other, even related, courses.

We go on to define a new metric showing for a student how far in excess of the level they individually required in the second trimester to gain entry into the engineering program they performed. We then use this metric to show that students can be classified by the number of *A* grades (*A+*, *A*, or *A-*) that they achieved in the first trimester. This shows that the students who receive exactly one *A* grade in the first trimester are those on the cusp of gaining entry. A student with no *A* grades at all is overwhelmingly likely not to gain the required *B* average, while having more than one results in a very high likelihood of success.

A. ACKNOWLEDGMENTS

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B. REFERENCES

[1] D. A. Carnegie, C. A. Watterson, P. M. Andreae, and W. N. L. Browne, "Prediction of success in engineering study," in *Proceedings of the IEEE Engineering Education Conference (Educon 2012)*, 2012, pp. 57 – 65.

[2] D. A. Carnegie and C. A. Watterson, "Improving retention rates at first year for modern engineering students," in *Proceedings of the IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE 2013)*. IEEE, 2013, pp. 61 – 66.

[3] C. A. Watterson and D. A. Carnegie, "The development of a pastoral care and student support," in *Proceedings of the 20th Electronics New Zealand Conference*. ENZCon, 2013, pp. 133 – 138.

[4] J. C. F. de Winter and D. Dodou, "Predicting academic performance in engineering using high school exam scores," *International Journal of Engineering Education*, vol. 27, no. 6, 2011.

[5] M. Selim and S. Al-Zarooni, "Do secondary school grades predict the performance of engineering students?" *Australasian Journal of Engineering Education*, vol. 15, no. 3, 2009.

[6] K. Kelly, C. Patroc´ınio, and C. Marshall, "Prediction of student performance in engineering programs: A case study using entrance information," in *Proceedings of the 40th Annual Conference of the European Society for Engineering Education*, 2012.

[7] A. Fernando and P. Mellalieu, "Effectiveness of an evidence-based predictive model for motivating success in freshmen engineering students," in *Proceedings of the 2012 Conference of the Australasian Association for Engineering Education*, 2012.

[8] P. Kinnunen, R. McCartney, L. Murphy, and L. Thomas, "Through the eyes of instructors: A phenomenographic investigation of student success," in *Proceedings of the Third International Workshop on Computing Education Research*, ICER '07. ACM, 2007, pp. 61–72.

[9] J. Carter, D. Bouvier, R. Cardell-Oliver, M. Hamilton, S. Kurkovsky, S. Markham, O. W. McClung, R. McDermott, C. Riedesel, J. Shi, and S. White, "Motivating all our students?" in *Proceedings of the 16th Annual Conference Reports on Innovation and Technology in Computer Science Education - Working Group Reports*. ACM, 2011, pp. 1–18.