Classroom size, activity and attendance: scaling up drivers of learning space occupation

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ABSTRACT

Teaching face-to-face is still a major education mode in many universities, yet institutions are increasingly tasked with improving efficient use of teaching spaces. This need to understand space use can be coupled with learning and teaching data to better inform student attendance and subsequently participation. Here, we analyse thermal sensor data used to monitor traffic into classrooms; these data are associated with the timetable to provide knowledge of the course and the teaching mode (such as lecture, tutorial or workshop). Further, we integrate these traffic data with student feedback data to investigate the drivers of student attendance patterns, and aim to also include online activity and behaviour to develop broad models of both room occupancy and student attendance. Combining space utilisation data with information on teaching modality and in-class and out-of-class participation can inform on how to both improve learning and design effective and efficient teaching spaces.

CCS CONCEPTS

• **Applied computing** → **Education**; • **Hardware** → **Sensor applications and deployments**; • **General and reference** → *Surveys and overviews*;

KEYWORDS

Class attendance

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1 INTRODUCTION

The learning analytics field is growing quickly as new data sources, particularly those *not* directly related to student online activity, are integrated with existing models of student behaviour [11, 14, 24]. The role of technology in higher education is expanding beyond online learning management systems to include more general 'smart' hardware, such as sensors of various types (motion, thermal, radio-frequency identification (RFID), etc) [6].

Data collected by such sensors feeds into two related broader contexts. The first is the issue of how best to utilise and manage the physical space of higher education campuses: the 'power of built pedagogy' [17]. This utilisation question has been a field of interest for many years [9, 13, 16, 17, 22], however as Temple and Barnett point out, rigorous evaluations of the impact on learning of newly-designed spaces are often lacking [23].

The second context that can be enhanced by the exploitation of sensor data is in measuring the effect of different teaching pedagogies; by providing another view of student behaviour beyond their outcomes or online engagement, these can provide additional feedback to instructors. A pertinent example is the hypothesis that physical class attendance drives academic performance, for which the data can now be populated by technology rather than manually-recorded attendance or self-reported student behaviour. Considerable research on this driver of performance can be found in the literature, with some work finding significant correlation between increased attendance and improved academic outcomes (e.g. [1, 2, 12]), and others finding that the relationship is only significant for some groups [3] or that it is not significant at all [4, 19]. Much of the data-collection for this research is carried out through the use of student-level attendance tracking, by requiring students to sign in (whether with wireless proximity cards or with swipe access cards). However several institutes have found this process to be time-consuming, or have expressed concerns surrounding student privacy [10, 21].

Thermal sensors, which record movement of people in and out of a room, offer an alternative way to track occupancy of Learning and Teaching spaces. Such sensors are used widely in industries around the world such as retail, transport, security and leisure to measure footfall traffic. They have more recently been employed in higher education campuses to study learning space utilisation and occupancy, and to improve efficiency of both space and energy use. When connected to a timetabling system, they can provide attendance data at a class level, enabling study of student attendance patterns and behaviour, from which considerable insight can still be obtained without requiring individual-level data.

However, linking this new data source to other established datasets, such as student feedback from course surveys and online activity, is where the potential for insights becomes most apparent. This work describes insights garnered from room occupancy data collected by thermal sensors at RMIT University; ongoing work seeks to further

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develop an understanding of how it relates to student experience and online behaviour contexts. Using an automated attendance-recording method allows us to understand student traffic along a temporal axis, and provides us a scaleable tool to understand broader university patterns associated with class schedule and delivery.

2 THERMAL SENSOR INSTALLATION

Thermal sensors were installed in early 2017 in 223 rooms around RMIT University, at campuses in Australia (n=213) and Vietnam (n=10). Previous physical space audits providing annual occupancy snapshots had identified rooms with historically low utilisation, and these rooms were selected by Property Services for sensor deployment. The sensors are designed to sit above all entrances to a room, and use a thermal lens to detect the body heat of anyone passing underneath. As a result, they are strictly anonymous and do not record any attendance at an individual level. The sensors are able to count bi-directional movement, and provide an estimate of the room occupancy every 30 minutes by averaging the occupancy of shorter 'resolution' time periods. The sensors also include a video lens, used for auditing during the calibration process, and following this process are expected to have an accuracy greater than 95%.

Occupancy data for semester 1 of 2017 were integrated with data from the University timetabling system, and so a database was constructed containing scheduled class, type of class, room capacity, and 30-minute timestamped occupancy. Since most classes have a duration greater than 30 minutes, the maximum reported measure during the booking duration was taken as the room occupancy for that entire booking.[1] During this process, many 'no-show' classes were identified, and certain extreme examples were immediately apparent, such as a practical class for 77 students where only twelve were expected to show up.

Due to the nature of the timetabling system, most classes were assigned a room for the entirety of semester, meaning occupancy data was recorded for most classes every week, and attendance patterns over time could therefore be examined. To ensure the integrity of such cumulative measures as mean and median, distinct classes were required to have at least four weeks' worth of recorded occupancy data within the same teaching space.

3 OBSERVING ATTENDANCE PATTERNS

Underutilisation of rooms. In theory, efficient room use and rooms at capacity would result in a 1:1 relationship between room occupancy and room capacity. However, most classes deviated from this expectation (fig. 1); the vast majority of classes were clearly under-filled, and it is this under-utilisation of space that this work in part seeks to address.

Comparison of two classes. We illustrate room occupancy patterns with two tutorial-type classes, to establish hypotheses for later testing. These two tutorials, A and B, were held in the same room over the twelve weeks of the semester[2] where the room capacity

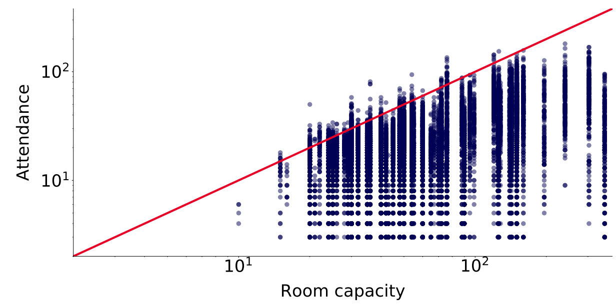

Figure 1: The room capacity and maximum recorded attendance for every class-booking in every room with a thermal sensor in semester 1, 2017. The red line denotes a 1:1 relationship.

was 30 people (fig. 2). Class A showed consistently high attendance throughout the semester, except for week twelve when the instructor was on sick leave. In week three, the room was slightly over-full, as this was when overseas students began attending class. The attendance pattern of class B, on the other hand, shows a decline over the first three weeks and consistently low attendance throughout the remainder of the semester. (No data was collected for this class in week eight.) Questions around the attendance drivers in these two classes immediately arise from observing the longer-term attendance patterns, while the importance of seeking context from the instructors to understand short-term changes is clear.

Examining attendance and size of space. The thermal sensors were placed in rooms with capacities ranging from ten to 350, so we may ask the question: are student attendance patterns dependent on the size of the space? Figure 3 depicts summary plots of occupancy for all bookings, grouped into three-week blocks, for small (capacity < 50) and large (capacity ≥ 150) teaching spaces. Both room sizes display a significant decrease in occupancy over time: the median occupancy of small rooms decreased by a third from the first quarter to the last quarter of the semester, while the largest rooms saw almost 40% decrease in median occupancy over the same time period. In both cases, the statistical difference between the first and last quarters was highly significant.

Examining attendance and type of class. These differences dependent on the room size may also indicate a dependance on activity type: larger rooms are more likely to contain lecture-type classes, in which students have less direct engagement, and often are able to access relevant material online in the form of lecture notes and recordings, whereas smaller rooms are more likely to host tutorial- or practical-style classes, where students are directly engaged in work and where material and/or personal assistance may not be accessible online. Alternatively, poor teaching in tutorials may be a more effective driver of physical attendance, particularly if students are able to attend alternative streams.

We therefore classify attendance according to activity type, to assess the dependance level of physical attendance upon activity. Fig. 4 summarises the attendance of all bookings according to class type, where the maximum recorded occupancy of the semester is used as a proxy for class enrolments, and is incorporated as an

[1] It would be possible and interesting to examine the occupancy fluctuations within single classes from this data, however such an investigation is outside the scope of this work.

[2] No data were recorded for week one as tutorials do not generally commence until week two.

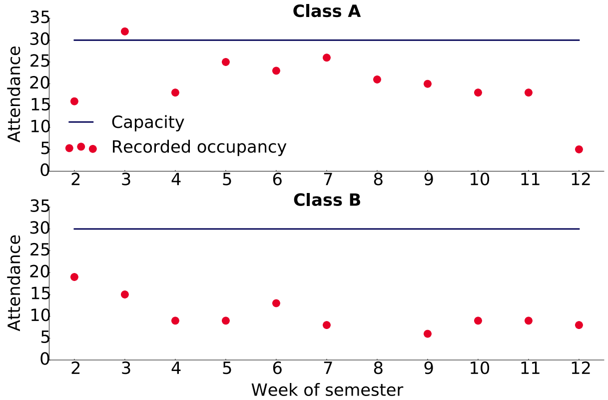

Figure 2: Attendance over the semester of two similar classes for different courses. Both inhabit the same teaching space, which has a capacity of 30 people, represented by the solid line.

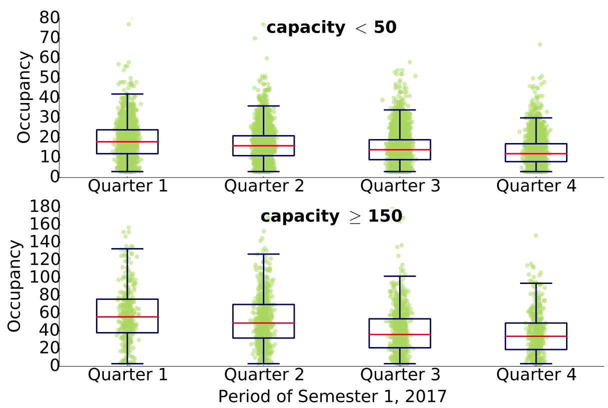

Figure 3: The decrease in occupancy over the semester, for small rooms (top) and very large rooms (bottom). The underlying data is shown in green.

inverse scale factor. High-school classes[3] and short-term intensive classes have generally higher attendance, while lectures and lectorials demonstrate the lowest average scaled occupancy.

Further work here will attempt to formalise the dependence on room size and class type, grouping these effects into a single model.

4 INVESTIGATING THE DRIVERS OF CLASS ATTENDANCE

In addition to recording student attendance patterns, important questions about the drivers of such attendance behaviours must be addressed, as these feed into Learning and Teaching (L&T) pedagogy. Much work has already been done in this area (e.g. [8, 15, 18, 20]). Both Billings-Gagliardi and Mazor [5] and Clay and Breslow [7] found that student decisions about whether to attend class were

[3]RMIT also offers Victorian Certificate of Education courses.

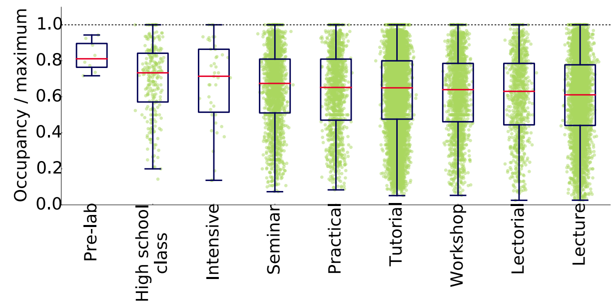

Figure 4: The scaled occupancy measures of every booking, classified by activity type. Almost all activity types demonstrate very low occupancy rates, but with large positive tails. The underlying data is shown in green.

driven by their expectations of the class quality and the effectiveness of the instructor in presenting the material. We would expect these two variables to be reflected in student feedback for a class, particularly when attendance is not compulsory; linking feedback and sensor data is therefore a valuable step in further understanding the significant factors in student attendance behaviours.

Two additional datasets were constructed from RMIT's Course Experience Survey (CES), available to all students toward the end of each semester to provide their feedback separately for every course they undertake, and linked to the class attendance data described above. The first dataset measured the student satisfaction with a given course; based on their responses to a question regarding their degree of satisfaction with the course, students were classified as 'satisfied' or 'not satisfied', and the percentage of 'satisfied' students was calculated. As with all survey data used in this work, survey data for a course was only included if the number of responses was considered to be acceptable relative to the size of the total population, and a reliable result could be obtained.

The second dataset was slightly more specific: the percentage of students satisfied with the teaching quality, provided at an instructor level, calculated from a combination of six questions within the CES related to teacher performance. Since the timetabling data used in this work does not provide a method of identifying which particular course instructor was in the room installed with a thermal sensor, we restrict this teaching-score dataset to courses with only a single instructor. Both the course satisfaction and instructor satisfaction scores have been developed over several years at the University, and are used as Key Performance Indicators for internal processes; they are not expected to be independent.

The percentages of students satisfied with the class and with the instructor were then linked by course to the average class attendance scaled by the maximum class attendance of the semester. Since lectures are a very common class type for which attendance is often not compulsory or recorded, and for which attendance is hypothesised to be driven in part by teaching performance, we look for a relationship between these attendance and class satisfaction data for lecture-type classes only (fig. 5).

There was a small but significant positive correlation between the percentage of overall satisfied students and the average scaled attendance (r = 0.1, p = 0.03, n = 527; data were transformed to meet parametric assumptions). However, no correlation was observed between the percentage of students satisfied with the instructor and the average scaled attendance (r = 0.2, p = 0.12, n = 73). Of note, there are very few courses with low satisfaction and very high average attendance (fig. 5).

Ongoing work on this project seeks to marry additional datasets to those of the thermal sensors and student feedback surveys. One such dataset is that produced by student online activity: if students don't attend class physically, are they attending virtually by, say, accessing the material online or watching recorded lectures? This question may depend on the availability of such material, ease of access and organisation, so online course infrastructure, as well as online instructor engagement, are also active avenues of investigation.

4.1 Lifting student attendance

The work described here is not only advantageous for analysing student attendance patterns, but can be useful for developing strategies for lifting the room occupancy and therefore improving both student outcomes and efficiency of L&T space usage. Table 1 defines categories based on physical attendance and survey feedback, and describes some general methods for addressing low attendance in each case. This also describes further analytic approaches for ongoing work. As further data sources are integrated, such as online student activity, further categorisation and methods will become possible.

5 CONCLUSION

As long as face-to-face teaching remains a major education mode in many universities, developing an understanding of student attendance behaviours is critical to maximising the effectiveness and efficiency of physical teaching spaces. This work describes part of an ongoing initiative to study student attendance in class through the use of anonymous thermal sensors which record room occupancy, and to link this to potential drivers of student behaviour. Distinct attendance patterns are observable over time, and may be useful for instructors to assess their own class attendance at a glance, or as a starting point for course coordinators to compare classes within their course. Such class-level investigation is expected to help identify instructors who may need further assistance to improve their teaching practices, aimed at increasing student in-person participation and ultimately improving student outcomes. Course coordinators may also use this type of data when considering their room requirements for timetabling, potentially leading to additional improvements in space use efficiency. Further, for Property Services and Space Management departments the data collected will support better planning and strategic decisions, and provide a more detailed understanding of the population profile identifying the University's future vertical transport, security and facility management requirements.

As any instructor might expect, attendance patterns are also observed on a larger scale to depend on variables such as room capacity and class type. The median occupancy in small and large teaching spaces decreased significantly over the semester. Almost all class types were often less than 50% attended throughout semester, however all demonstrated many instances of overfull classes, including tutorials with twice as many people in the room as it could hold. Such wide ranges of scaled occupancy indicate the difficulty of selecting a teaching space appropriate for a semester's worth of classes, as well as the need for a deeper understanding and modelling of student attendance behaviours. Ongoing work will attempt to formalise these relationships within an attendance model.

New data sources are most interesting, however, when linked to existing data, and a more comprehensive and complex model can undergo development. Student feedback data from the Course Experience Survey has been linked to the attendance data, and a small correlation between overall student satisfaction and average attendance was observed, as well as almost no instances of low satisfaction and very high attendance. Next we seek to marry thermal sensor data to student online behaviour, such as material downloads and lecture recording views; this forms the main ongoing line of inquiry. Further integration with additional data sources, along with ongoing investigation into the student feedback, will lead to new insights both within the broader contexts of learning and teaching pedagogy and improving efficiency of room utilisation. Additionally, these insights can inform on how to design new teaching spaces, thus feeding into the strategic and planning decisions of the institution.

More generally, this work describes an approach within the learning analytics field to effectively exploit any new data source that becomes available: following analysis and visualisation of the data independently, it may then be integrated with existing data sources, to provide an orthogonal approach from which valuable new insights may be garnered. However, as with all data analysis within learning analytics, input from instructors is essential to maximising our comprehension of the drivers behind student learning patterns and behaviour. This approach is summarised as

(1) Visualise new dataset
(2) Join with datasets from known sources
(3) Analyse patterns
(4) Engage with instructors
(5) Integrate analysis with experience to prescribe solutions

New methods for measuring general class performance provide us with additional handles for understanding student behaviour, and therefore handles to improve outcomes for both students and institutions.

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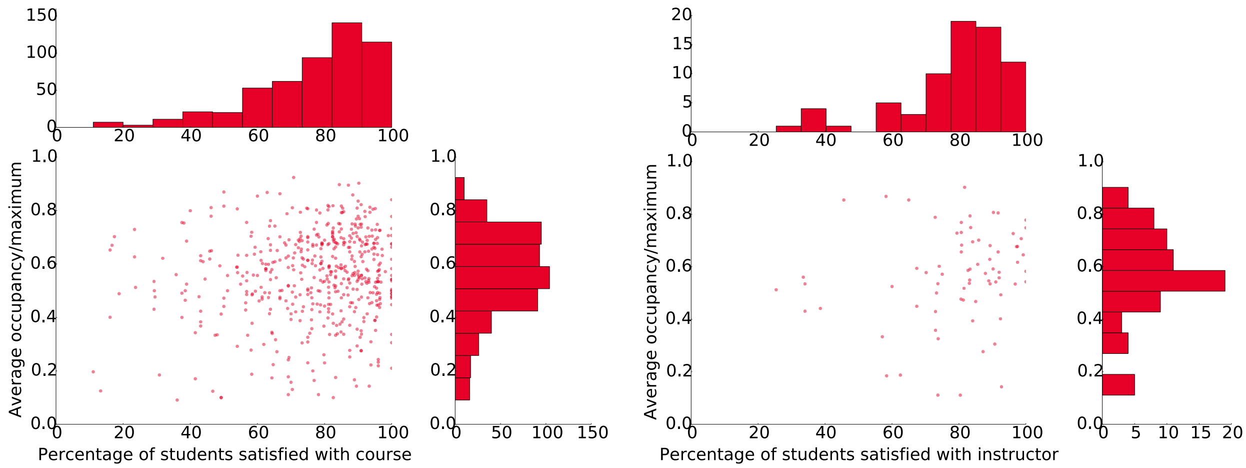

Figure 5: The relationship between average scaled attendance and percentage of students satisfied with the course (left) or with the instructor (right), for all lecture-type classes. Note that the latter dataset was restricted to courses with a single instructor only.

Table 1: Categories and corresponding strategies for addressing teaching space inefficiencies.

Physical attendance	Student feedback	Strategy
High	Positive	Request insight from instructor regarding their approach to incentivising physical attendance in class
High	Negative	Request insight from course coordinator regarding method for predicting attendance and room-booking
Low	-	Assess methods for room-booking: check for unrealistic attendance expectations, and for mismatches between requested and available L&T spaces
Low	Positive	Share insights from instructors of high-attendance classes; examine survey results (including free text responses) further to determine reasons for positive student feedback
Low	Negative	Examine survey results further to determine reasons for poor student feedback

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