

Demo Abstract: A Tool to Access and Visualize Classroom Attendance Data from a Smart Campus

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ABSTRACT

This demo presents our web-tool to access and visualize student attendance data obtained from instrumenting a pilot set of classrooms with people counting sensors in a large university campus in Sydney, Australia. We showcase two aspects: (1) how to access and process our open data-set containing time-stamped occupancy counts for 9 lecture rooms of varying size in which over 250 courses are conducted over a 12-week semester; and (2) visualizing occupancy at multiple spatial (per-room and per-course) and temporal (over a day, week, or semester) granularities, enabling new insights into student attendance and room usage patterns.

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1 INTRODUCTION

Higher education institutes continue to experience steady growth in enrollment demand [1]. A major factor limiting Universities in fulfilling this demand is real-estate, since course enrollment is capped by the capacity of the classroom to which the course is allocated. However, with recent trends towards student lifestyles that mix study with work and other commitments, as well as greater access to online content, there is ample anecdotal evidence that classroom attendance is often well below the enrollment number.

Several methods are available to count the number of people in an indoor space, ranging from WiFi-based locationing to thermal/ultrasound imaging to beam counting. Each method has its own pros and cons in various aspects such as cost, power, communications, ease of deployment and operations, privacy, and accuracy. Understanding both the benefits and the challenges in measuring

classroom attendance in a large campus of varying lecture-rooms requires experimental field-work in deploying, integrating, operating and evaluating the various systems aspects in a real campus. We [4] instrumented a pilot set of classrooms in our University campus with sensors to measure classroom attendance, in a cost-effective and scalable manner without endangering student privacy.

This demonstration complements our efforts outlined in [4]. Our specific contributions are as follows: (1) we show how to access our dataset containing real attendance counts across 9 lecture halls of varying size covering 250 courses over a 12-week semester; and (2) we demonstrate our tool to visualize attendance at multiple spatial (per-room and per-course) and temporal (over a day, week, or semester) scales, providing new insights into attendance patterns.

2 CLASSROOM ATTENDANCE DATA

Our university main campus is located on a 38 hectare site in Sydney with 50,000-plus students. The university centrally supports and maintains over 200 classrooms on campus. These spaces facilitate a wide variety of learning and teaching styles, from traditional lectures to active, blended and small-group learning. For our pilot, we worked with Learning Environments team to choose a small set of classrooms of varying size: BUS105 and BUS115 (1 door each, capacity 35 and 53); MathewsThC and MathewsThD (2 doors each, capacity 110 each); MathewsThB and CLB8 (3 doors each, capacity 246 and 231); CLB7 (4 doors, capacity 497); MathewsThA (6 doors, capacity 472); and PhysicsTh (4 doors, capacity 369)

Prior to our pilot study, we tried various sensing technologies in our lab, evaluated their individual trade-offs [4], and selected the beam counter sensor based on its relatively lower cost, easy deployment, high accuracy, and good protection of privacy. The Beam Counter comprises a pair of infrared (IR) break-beam sensors mounted on the door frame, and counts the number of people passing through in each direction. We outfitted all doors of each classroom with beam sensors and collected the real-time data over a period of 12 weeks. The raw data of counts (for “in” and “out” directions) were collected every 10 seconds. We then applied our method [4] to the raw data for deducing the cumulative occupancy count based on the number of entries and exits at each door. Note that sensors of a given room are not synced, thus we have more than 6 records of occupancy counts per minute.

Our weekly classroom occupancy data-set is openly available for download [2]. Each record of the data represents the real-time

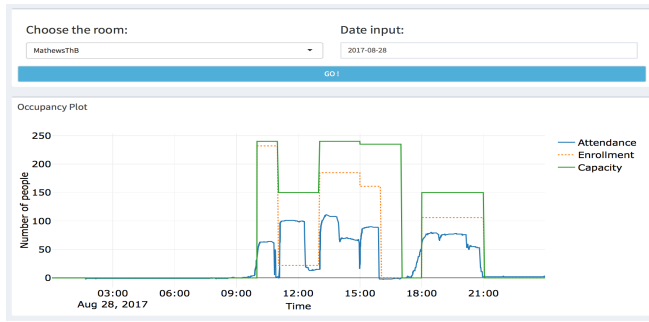
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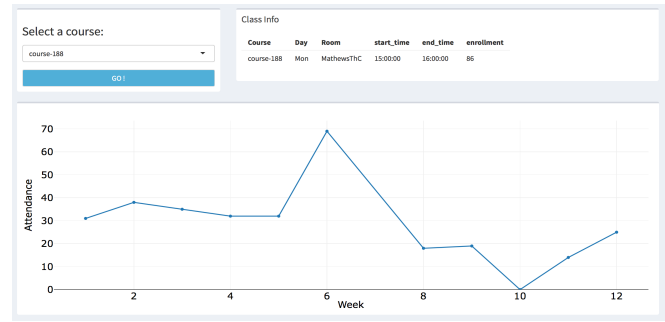
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(a) Classroom attendance of room MathewsThB on 2017-08-23.



(b) Attendance of course-188 over a session.

Figure 1: (a) Course attendance, and (b) Course attendance.

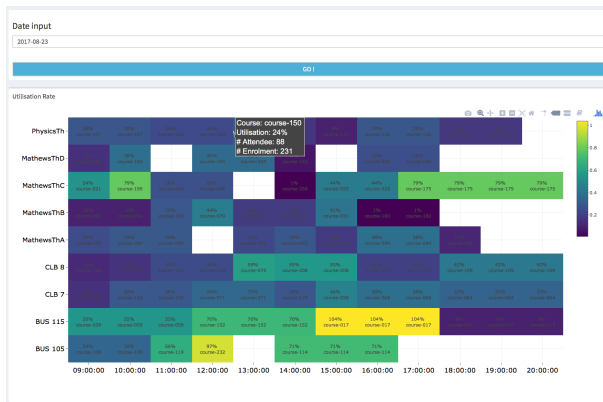


Figure 2: Heatmap of campus on day 2017-08-23

measurement from beam sensors comprising *time-stamp*; *week of semester*; room information including *room name*, *number of doorways*, and *number of seats*; course information including *course-id* (we have intentionally obfuscated actual course names), *course start-time*, and *end-time*; sensor measurements including *count-in*, *count-out*; and *computed occupancy*. We encourage other researchers to use and analyze our open dataset drawing interesting insights into attendance patterns or finding special events such as canceled lectures or class tests.

3 VISUALIZING CLASSROOM ATTENDANCE

We developed a tool to provide an intuitive user-interface for real-time occupancy monitoring, using Shiny, an R web framework. Our web-tool is publicly available at [3]. The user can input date and classroom to view real-time occupancy level along with the course capacity and enrollments number, as shown in Fig. 1(a) for a chosen room (MathewsThB) on 23-Aug-2017. It shows the number of attendees (solid green lines), enrollments (dotted orange lines), and the capacity (dashed blue lines) for six lectures scheduled between 9am to 6pm. In general, attendance varies widely across courses, and can be in a range of 25-50% of enrollments. We can also see that the lecture scheduled for 4-6pm has an enrollment of 103, but close to zero attendance; this indicates that the lecture was probably canceled, leading to a waste of allocated classroom space on that day. This shows the benefit of our tool in quantifying space utilization that is otherwise largely unknown to estate managers. Similarly, we can see the attendance pattern of a course (course

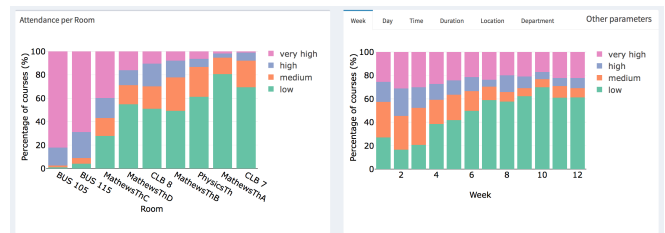


Figure 3: Spatial and temporal profile of attendance.

dashboard tab) over a session. Fig. 1(b) shows a sudden rise in attendance of course-188 in week 6 (indicative of a class-test), and it also depicts a canceled lecture in week-10 with zero attendance.

The tool also allows the user to view the utilization rate (ratio of attendance to classroom capacity) in a form of “heatmap” on a chosen day. The heat map interface in Fig. 2 allows campus managers to track overview classrooms utilization – bright (yellow) cells depict a utilization approaching 1, while dark (blue) cells represent poor utilization closer to 0. Lastly, Fig. 3 shows that our tool can visualize the attendance profile at various spatial and temporal scales. The left stacked bar chart depicts the distribution of number of courses in each room by four bins of attendance (very-high: 80-100%, high: 60-80%, medium: 40-60%, low: 0-40%) – we can see that smaller rooms (e.g. BUS105) are well attended while larger rooms (e.g. CLB7) suffer from low attendance. The right stacked bar chart (aggregated over all classrooms and all courses) shows that the fraction of low attendance increases over semester.

4 CONCLUSION

In this demonstration, we have showcased our open dataset containing the occupancy counts of 9 classrooms of varying size collected over a 12-week semester. We have also demonstrated our web-tool for visualizing the classroom attendance revealing interesting insights into course attendance patterns and class utilization measures.

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