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Experiences with IoT and AI in a Smart Campus for Optimizing Classroom Usage

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ABSTRACT : Increasing demand for university education is putting pressure on campuses to make better use of their real estate resources. Evidence indicates that enrollments are rising, yet attendance is falling due to diverse demands on student time and easy access to online content. This paper outlines our efforts to address classroom under-utilization in a real University campus arising from the gap between enrollment and attendance. We do so by instrument classrooms with IoT sensors to measure real-time usage, using AI to predict attendance, and performing optimal allocation of rooms to courses so as to minimize space wastage. Our first contribution undertakes an evaluation of several IoT sensing approaches for measuring class occupancy, and comparing them in terms of cost, accuracy, privacy, and ease of deployment/operation. Our second contribution instruments 9 lecture halls of varying capacity across campus, collects and cleans live occupancy data spanning about 250 courses over two sessions, and draws insights into attendance patterns, including identification of canceled lectures and class tests, while also releasing our data openly to the public. Our third contribution is to use AI techniques for predicting classroom attendance, applying them to real data, and accurately predicting future attendance with an RMSE error as low as 0.16. Our final contribution is to develop an optimal allocation of classes to rooms based on predicting attendance rather than enrollment, resulting in over 10% savings in room costs with very low risk of room overflows.

KEYWORDS : IoT, smart campus, classroom occupancy, AI, prediction.

I. INTRODUCTION

Higher education institutes continue to experience steady growth in enrollment demand . A major factor limiting universities in fulfilling this demand is real-estate, since enrollment in a course 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. This presents an opportunity for education institutes to better optimize the usage of classroom space based on attendance rather than enrollments. Since class attendance can vary significantly between courses and across weeks of semester, visibility into actual class attendance and ability to predict future attendance based on historical data are needed to dynamically re-allocate courses to rooms while minimizing risk of overcrowded lecture rooms where class attendance exceeds room capacity.

C.Nagarajan et al [17,18] proposed several methods are available to count the number of people in an indoor space, such as WiFi-based approach, camera image processing, thermal imaging, ultrasound imaging, and beam counters affixed to entryways. Each method has its own pros and cons across various dimensions such as cost, power, communications, ease of deployment and operations, privacy, and accuracy. For example, using WiFi data and cameras endanger privacy, thermal and ultrasound imaging have low accuracy, and camera-based image processing is computationally expensive. Furthermore, a method that works well in a small room may not be as effective in a larger lecture theater, and cost/accuracy may also be impacted by the layout of the room, the number/width of doorways, and

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the availability of power and wired/wireless network connections. Hence understanding both benefits and challenges of various approaches in order to adopt the most suitable methods for the nature of the room is important for the real deployment of classroom occupancy monitoring system.

This paper describes our experiences in adopting IoT to measure and AI to predict the attendance of lectures in courses at our University campus, and to use these to optimize the usage of lecture rooms. Our specific contributions are fourfold:

1). We begin by testing several sensing methods in a lab environment and characterizing their trade-offs in aspects such as cost, ease of installation, method of data extraction, privacy, and accuracy.

2). We then make appropriate sensor selections, build a full system, and deploy it across 9 lecture theaters of varying size across the university campus. We collect and clean the data to obtain visibility of occupancy across these rooms in real-time over a period of 18 weeks (i.e., a full semester in 2019 and half a semester in 2020), integrate it with University timetabling data to infer attendance patterns of over 250 courses, and highlight interesting findings such as attendance trends, canceled lectures, and class tests. We also make our occupancy data openly available to the research community.

3) We develop machine-learning models to predict classroom attendance using three algorithms namely multiple regression, random forest, and support vector regression (SVR). We employ regression technique, allowing asymmetric penalties for under-prediction and over prediction of attendance. Our models are able to predict attendance in advance with a root-mean-square error (RMSE) of less than 0.16. We also make our attendance dataset openly available to the research community.

4) Finally, we develop an optimization algorithm for allocating classes to rooms based on predicted attendance rather than static enrollments, and show potential saving of over 10% in room costs.

II.SENSING CLASSROOM OCCUPANCY

In this section, we describe various sensing methods for counting people, outline their relative trade-offs with a view towards making appropriate selections suitable for a larger scale deployment across the campus, and briefly explain our system architecture for collecting, cleansing, and visualizing sensing data.

A. People Counting Methods:

Sensors: We investigated several commercial sensors and straight-away eliminated those that send data to the vendor's cloud servers, since we wanted to: (a) keep the data entirely on-premises and not risk it leaving our campus infrastructure; and (b) not be beholden to a vendor to access our own data, hence freeing us from ongoing service costs. In other words, we wanted a "sale" model of the device so we could have unfettered access to our data without any ongoing "service" fees. We were quite happy to buy spares of the units to cover for device failures; further, this model allows us to integrate data into a centralized repository to facilitate better analytics across the many data feeds we have on campus. We narrowed our lab trials to four Types of commercial sensors: Evolve Plus Wireless Beam Counter, Evolve Plus Overhead Camera , HPD Camera (pre-market release), and Presence Detector. In addition, the University IT department provided us with time stamped connections logs from two WiFi access points (one inside our lab and one just outside), so we could compare our approaches to those obtained from WiFi logs. We note that the WiFi logs gave us personal user information such as their device MAC address, user-ID, and connection durations; we therefore obtained ethics clearance (UNSW Human Research Ethics Advisory Panel approval number HC17140) for this experiment.

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. It communicates the counts (for "in" and "out" directions) to a gateway every 30 seconds using a 0propriety wireless protocol, and the gateway then posts these readings via Ethernet to an SQL database (DB) server hosted on a VM in our on premises cloud infrastructure. The Overhead Camera is a thermal sensor mounted on the ceiling close to the entrance facing downwards, and counts the number of people passing below it. It also communicates the counts in each direction to the same gateway as the beam counter, which then forwards it on to the SQL DB. We wrote a script that pulls data from the SQL DB, stamps the data with the time

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and the unique UUID of the gateway, and posts as a JSON string to our master database (which holds data from many sources) via a REST API. The HPD Camera (pre-market release) is a people counting sensor mounted in a corner with full view of the room. It uses built-in image processing to compute the number of people present within a configurable zone of interest. It is powered over Ethernet, and comes pre-configured with a server that be queried via a REST API. We wrote a "broker" script that polls the camera every 30 seconds to get the people count, and posts the time-stamped and sensor UUID-stamped data in JSON format to our master database. The Presence Detector is a passive infrared (PIR) sensor mounted on the ceiling in the middle of the room, and detects motion. Though it does not count the number of people in a room, it gives a binary indication on whether the room is occupied or not – this sensor can be used as a way to calibrate the other counting sensors which may accumulate errors with time. The PIR sensor sends its binary occupancy state every 60 seconds to its corresponding gateway via a propriety wireless interface, which then posts it to a broker script that again time- and sensor-UUID-stamps the data and posts to our master database. Lastly, we receive a CSV file of daily WiFi connection logs for the two access points from our IT department every morning at 7am – real-time feed of data was not possible due to technical limitations of the AP vendor. We wrote a script to parse the log file and compute the number of unique users connected to each AP every 30 seconds – this was also posted to our master database. With possibility of sourcing data from various sensing devices, one may want to perform sensor fusion for an accurate occupancy measurement. At a very minimum, a combination of PIR sensor and passing people counters (i.e., beam counter and overhead camera) seems reasonable. PIR sensors are fairly accurate in detecting whether a room is empty which can be useful for resetting the errors accumulated over time via the people counting sensors. It is important to note that detecting presence is not a trivial task for a large lecture theater due to limited coverage of PIR sensors, and thus configuring non overlapping zones for multiple units of PIR sensors can be quite challenging. For a second step of fusion, adding WiFi data or HPD camera would help infer an accurate occupancy since these methods measure occupants count instantaneously without keeping states (i.e., not cumulative). But, as explained next, these sensors come with their own short comings. We note that deploying a collection of sensors at the scale of a university campus can significantly increase the cost. Therefore, our primary focus in this paper is to select and deploy one sensor type for each classroom, and demonstrate its value in optimal allocation of rooms to courses.

B. Sensor Evaluation and Selection:

Our lab trial helped us compare the various counting methods in terms of their ease of installation, calibration, power and communications requirements, accuracy, cost, and privacy, as summarized in Table I. Our comparison across these measures is qualitative rather than quantitative. Even aspects such as accuracy, that can be quantified, depend on factors like room size and layout, mounting position, number of doors, and width of doorways, which can vary widely across deployment environments. We therefore resort to qualitative measures (low, medium, and high) in this table, derived from our experience across the rooms we instrumented, and we back these up with several data points presented later in the paper.

Installation: The thermal camera, HPD camera, and PIR sensor needed professional installation by certified tradesmen, since each needed special mounting brackets and extra wiring for mounting on (or near) the ceiling. We could install the beam counter sensor easily by ourselves using two-sided adhesive strips on the door frame at around waist-height.

Positioning: Sensor positioning is another key factor in our comparison. The thermal camera needs to be positioned at a certain height range (i.e. 2.2m - 4.4m) recommended by the manufacturer and close to the entrance allowing the best coverage to count everyone that passes underneath. This requirement makes it hard or impossible to use the thermal camera in very large lecture halls with high ceilings. Beam counters require to be mounted at around waist height (too low causes each leg to get counted separately, and too high causes the swinging arms to get counted!). Once an appropriate height is chosen for the beam counters, doors of all classrooms need to be outfitted in the same way. The HPD camera needs prior configuration for zone of interest that can vary across rooms depending on the room size and the place at which the camera is mounted. The PIR sensor is positioned at the center of the room (on the ceiling) to have a symmetrical coverage over an area that can also vary across rooms depending on their seating arrangement.

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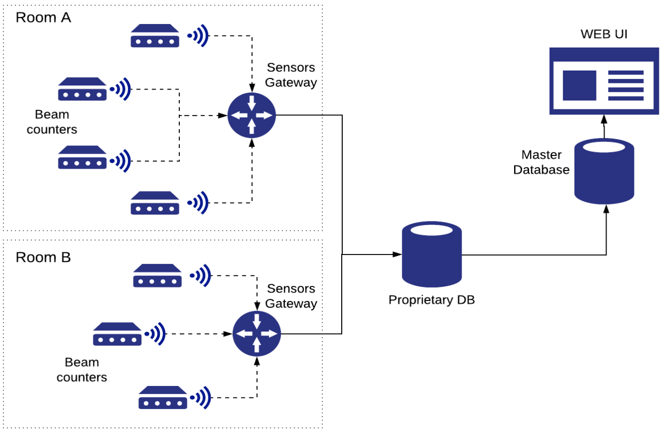
Power and Communications: Provisioning power was challenging for the thermal camera and PIR sensor, since the campus has pre-built and fixed wiring only in certain locations in each classroom. Therefore our Facilities Management was required to supply new exterior wiring for these three sensors. The beam counters are battery powered (with stated battery life in excess of a year), and the HPD camera required a special POE switch that provides Ethernet for both power and communications. The corresponding gateways for the beam counter, thermal camera, and PIR sensor were hidden inside a closet with available power and Ethernet. Accuracy: We performed several spot measurements in our lab to extract ground truth on occupancy. We found that the beam counter is the most accurate among the four techniques. We note that the beam counter has very good accuracy when the door is narrow, like in our lab. However, for a wider doorway its accuracy is worse, since it does not always capture individuals walking in/out side-by-side (this became more evident in our field-trial, described in the next section). We found the accuracy of the thermal camera to be very sensitive to mounting position and distance from the entrance. Moreover, since the door of our lab opens inwards, it was not very conducive for the overhead thermal camera (mounting it on the outside of the room was not an option as it was a busy corridor). The HPD camera tended to have a non-zero absolute count error, which made its relative error high when the number of people in a room is small (e.g. less than 10) and low when the number of people is high (e.g. more than. We could not test its accuracy scaling to larger counts as our lab can only accommodate around 40 people. Lastly, the people count derived from the WiFi access points was wildly inaccurate, because our lab is adjacent to a busy corridor and study space that is busy with students during regular hours, and we could not distinguish who was inside versus outside the room.



III. DATA PROCESSING AND VISUALIZATION

A. Occupancy and Attendance Calculation:

We compare two methods of data processing to deduce the occupancy from the number of entries and exits at each door:

Method 1: Room-based: Our first (naive) method for deriving occupancy is to set it to the cumulative number of entries minus the cumulative number of exits across all doorways of a classroom. However, errors arise when students walk in/out in groups; though we reset counts to zero at midnight each day, errors accumulating during the day can become significant.

Method 2: Course-based: To reduce the errors accumulating during the day, we enhance our method by computing course attendance independent of each other by linking our sensor data with course timetable databases obtained from our University. We assume that students may enter the room up to 10 minutes prior to start of the scheduled lecture time, and may leave up to 10 minutes after the scheduled lecture time. Attributing each entry and exit to a specific lecture therefore allows us to compute attendance per-course, and errors are not carried over from one lecture to the next even if they are adjacent in time to each other.

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B. Data Visualization:

Tool: To provide an intuitive user interface (UI) for real time occupancy monitoring, we developed a web application using R Shiny . The tool allows the user to view the attendance pattern of a course for different timeslots.

Insights: Our UI provides some interesting insights into attendance patterns. Our visualization tool also provides visibility into attendance pattern of all courses scheduled in the classrooms where sensors were installed. The interface allows campus managers to track classroom utilization, with a view towards more optimal allocation.

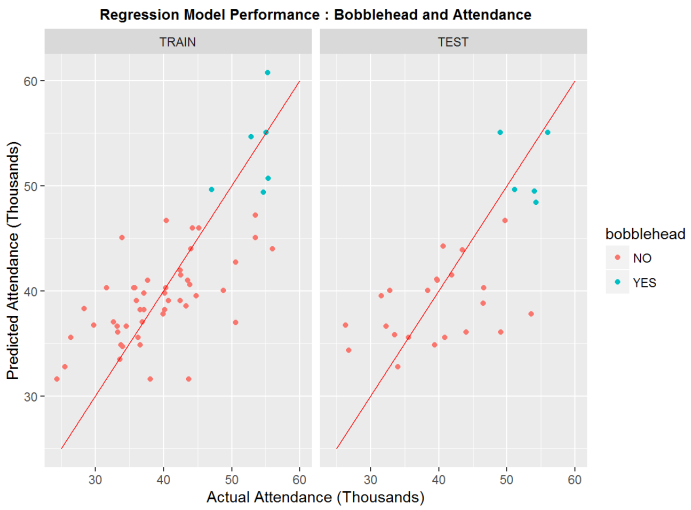
Prediction Of Classroom Attendance:

Prediction Modeling:

Multiple Regression: Multiple linear regression (MLR) is one of the simplest prediction algorithms. It is the most common form of linear regression where the value of a variable is predicted based on the value of two or more attributes. The algorithm finds the best fit for the training data by minimizing the sum of the squares of residues to obtain the resulting model.

Random Forest: Random forests (RF) is an ensemble learning method that can be used for both classification and regression problems. During training, multiple decisions trees are created from the training set, where a random selection of features is used to split each node of a tree.The final prediction result is obtained from majority voting, where mean is used for regression trees.

Support Vector Regression: Support vector regression (SVR) applies the same principles as support vector machine (SVM) to the data but for a regression problem. The algorithm involves transforming the training data into a higher dimensional feature space, where linear regression is performed with a tolerance margin provided by the boundary lines. In our model, radial basis kernel is used to map data to higher dimensions.



Attendance Prediction within Semester: We first apply our prediction models to a testing set containing attendance data of classes from the same sem / year. For this, we use DS1 to train the model and DS2 for testing.SVR algorithms achieve the best predictive performance in both cross-validation and testing, with values within a range of 0:120 and 0:135. Linear models on the other hand, yield the highest errors of over 0:16 RMSE on the validation set. This suggests that attendance and course attributes are not linearly correlated and such non-linear relationship is better modeled by RF and SVR. By imposing higher cost to under-prediction, we can see that quantile regression methods give better performance in terms of WMAE when compared to their default regression.

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Attendance Prediction for Future Semester:

We now predict the attendance for semester 2, 2020.(i.e., DS3) while the model was trained by the data from the same semester but in 2019 (i.e., DS1). Results of all the models. In terms of RMSE, it is seenthat RF achieves the best performance with a value of 0:157– slightly higher than the result from testing DS2. Looking at WMAE, quantile RF give the most accurate result with the error of 0:047. From the predictions vs. actual attendance. we observe wider dispersions from the fitted line compared to the scatter plots in for the within-semester attendance prediction. RF and quantile RF (blue dots) show the lowest deviation from the fitted lines compared to predictions from linear regression models (red dots) and SVR models.

IV. OPTIMIZATION RESULTS AND ANALYSIS

We run our optimization algorithm and obtain the cost of allocation for each day. We then compute the weekly cost of allocation by adding daily costs across the week. We plot the weekly total cost in Fig. 10 – total costs are normalized with respect to the enrollment-based scenario as a baseline (solid red line). Unsurprisingly, the enrollment-based approach results a constant cost (i.e., upper bound) as it tries to meet the fixed constraints every week. On the other hand, total cost obtained from various scenarios of attendance-based allocation (dashed lines) falls gradually due to falling pattern of attendance for majority of the courses. We note that even though allocation based on actual attendance yields the best result with lowest cost, it is not feasible in practice. It is seen that the prediction-based allocation yields a cost slightly higher than when actual attendance is considered, but still it is beneficial to the campus by saving on average of 12% per week of operation (as shown by dotted green lines with no margin). Obviously, adding margin to the predicted attendance count would reduce the cost saving, for example 20% margin gives a saving of about 5% per week. In addition, we capture the number of overflow classes (i.e., the room capacity is lower than the actual attendance of the class) as a proxy for the students experience (or discomfort) from dynamic allocation of classrooms. As we expect, allocations based on enrollment and actual attendance count yield no overflow since rooms capacities are well provisioned.

V.CONCLUSIONS

In this paper we have outlined our efforts to address classroom under-utilization in a real University campus arising from the gap between enrollment and attendance. We instrumented classrooms with IoT sensors to measure real-time usage, used AI to predict attendance, and performed optimal allocation of rooms to courses minimizing space wastage. We undertook a lab evaluation of various commercial IoT sensors and compared them in terms of cost, ease of operation, and accuracy. We then deployed our sensors in 9 real classrooms of varying sizes across campus and collected data over two semesters covering 250+ courses, which we release to the public. Our data and visualization reveal interesting insights into course attendance patterns and class utilization measures. Based on this real data, we developed AI based methods to predict classroom attendance which fed into our optimization algorithm for dynamic allocation of classes to classrooms based on predicted attendance rather than enrollments, and showed gains of 10% in room costs with a very low risk of room overflows.

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