Supply and Demand Analysis: A case study on staff meeting rooms and student toilet facilities on campus

Key Findings

July 23, 2020

Abstract

The university has spent its second-largest expense to space allocation and the arrangement of meeting rooms and toilets has long been recognised as a major concern in campus planning. It is important to ensure optimal space utilisation as under-utilisation of these facilities entails extra cost penalties for maintenance. In this project, the space arrangement of staff meeting rooms and student toilets will be optimised by proposing solutions that can be efficiently use the current supply of resources.

1 Key findings

1.1

#	Dataset Name	Dataset Description
1	`uom-space`	7 campuses, 331 buildings, 28 floor codes, 5703 rooms, 185 room types
2	`rm-category-type`	209 different room types
3	`fl-name`	floor information of all possible floor codes
4	`av-equipment`	1964 equipments, 32 manufacturers in 11 campuses across 142 buildings
5	`em-location`	7709 employees across 130 buildings and 1565 room codes
6	`2020-timetable-v2`	52 departments, 1577 modules across 248 activity dates
7	`meeting-room-usage`	890 meeting rooms across 8 campuses, 125 buildings

Table 1: Important categorical variables data summary

#	Dataset Name	Dataset Description
1	`uom-space`	Room Capacity: 0-599 with an μ of 4.0627 and σ of 17.2592
2	`uom-space`	Room Area m^2: 0.22-5696.90 with an μ of 30.70 and σ of 118.3070
3	`2020-timetable-v2`	Planned Size: 0-684 with average of 50 students
4	`2020-timetable-v2`	Class Duration(min): 30-675 with an average of 94.336
5	`meeting-room-usage`	Meetings: 0-1000 with an average of 241 meetings

Table 2: Important numerical variables data summary

1.2

Using room category data and merging it with space metadata, we were able to figure out the distribution of meeting rooms and toilet facilities across buildings in the Parkville campus as shown in Figure 1. We saw that `333 Exhibition st` buildings have the highest number of meeting rooms and `The spot` building has the highest number of toilet facilities.

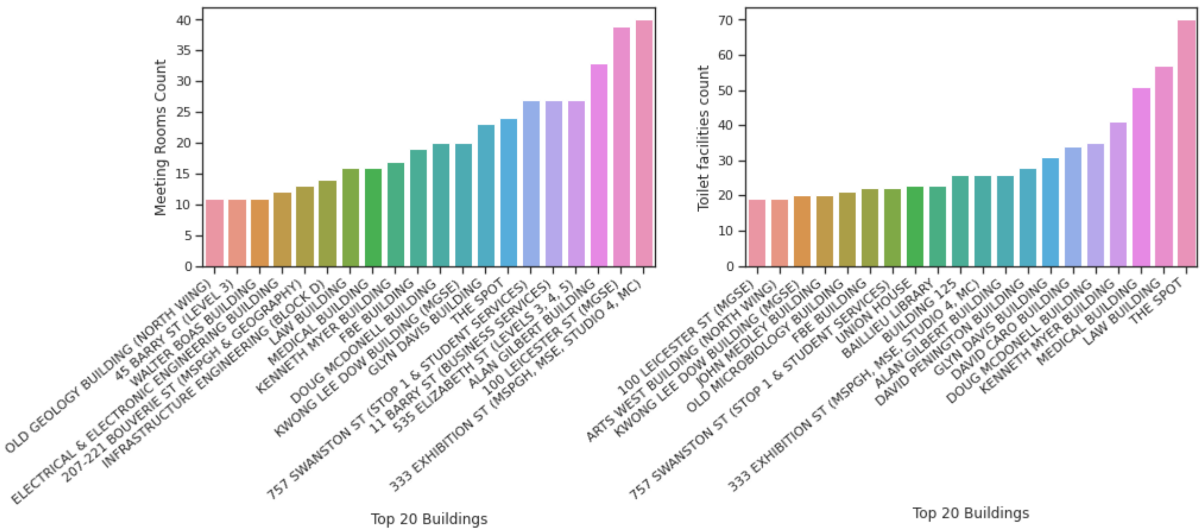

Figure 1: Distribution of meeting rooms and toilet facilities across buildings

1.3

Initially, we created supply-demand plots based on the very trivial preference of staff members trying to book a meeting room in the same building where they are located. This plot is shown in Figure 2. As per the plot, we can see space optimization problem in terms of supply and demand proportion especially in the `Law Building`, `Doug Mcdonell building` and `Kenneth Myer building`.

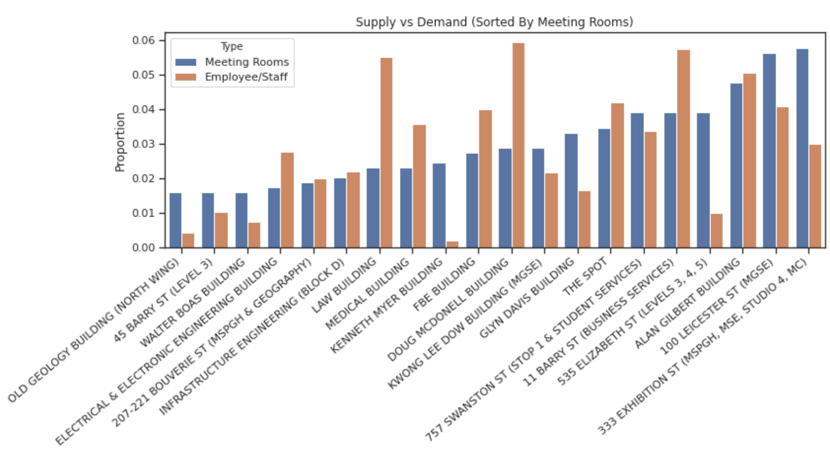

Figure 2: Supply vs Demand of meeting rooms across buildings

Similarly, we created a supply-demand plot on the same trivial preference of students trying to access a toilet facility in the same building which is shown in Figure 3. Again, we can see that the space optimization problem in terms of supply and demand proportion, especially for `Redmond barry building`.

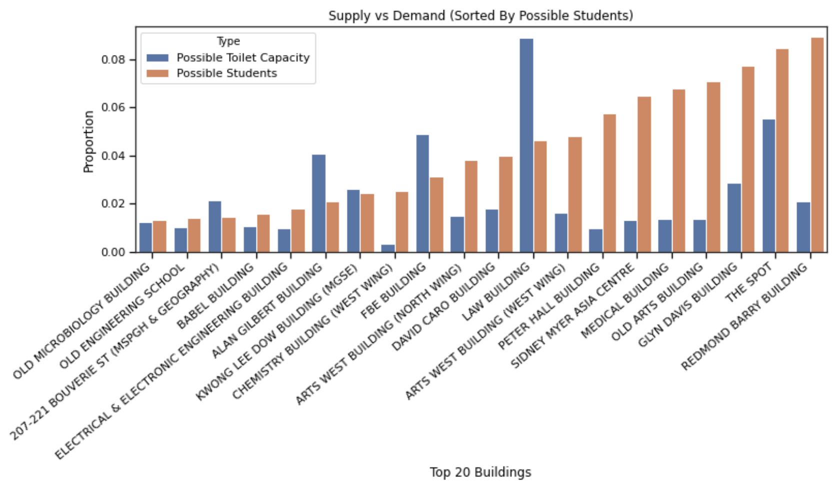

Figure 3: Supply vs Demand of toilet facilities across buildings

1.4

Meeting room usage and booking can be related to the usage of the meeting room and if they are located at a longer distance from the employee location. Stop 1 has the most number of excellent rooms based on the usage data and out of all the meeting rooms, only 3% can be booked. Buildings with low demand have low usage of the meeting rooms as shown in Figure 4.

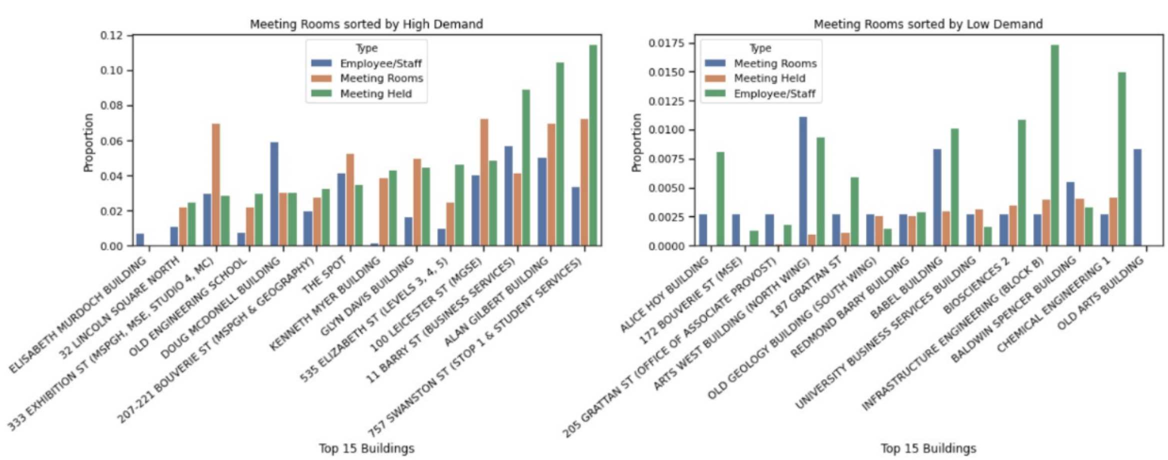

Figure 4: Supply vs demand analysis with meeting room usage correlation

1.5

Students usually prefer accessing the toilet facilities which are in good condition and in the same building where their respective classes are conducted. We can observe this correlation with respect to supply demand as shown in Figure 5. It can be seen that **Redmond Barry** has the most number of classes with 8% of total student and it has mere 2% of the total excellent toilet capacity to hold possible students. In contrast, **Law building** has approximately 12% of the total toilet capacity and around 3% of total students are attending classes in that building.

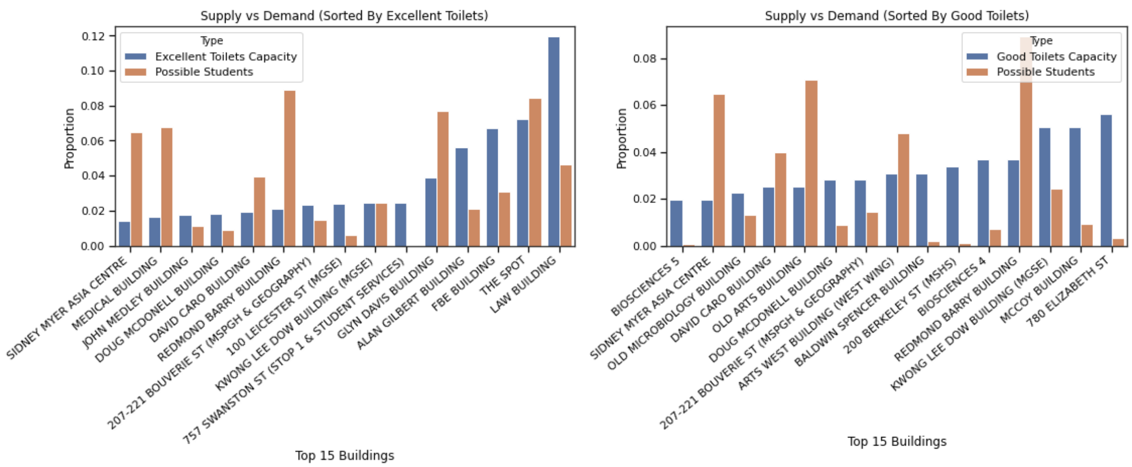

Figure 5: Supply vs demand analysis with toilet conditions correlation

1.6

QGIS provides visualisation of the "heat-map" of the average meeting room capacity per staff, which is calculated using the total capacity of meeting rooms divided by the amount of staff as shown in Figure 10. The dark (blue) cell represents high availability and the green colour indicates that either the meeting room or staff number is zero. Using this analysis, we can deduce following results:

- `Doug McDonell building(168)`, `11 Barry Street(266)` and `Law building(106)` have a significant number of staffs and therefore stronger demand for meeting rooms. The following analysis assumes that 3-minute walk is the distance people are willing to walk. And based on the average walking speed of an adult, a three-minute walk is about 240 meters.
- For staffs in `Doug McDonell(168)`, `Old Engineering School(173)`and `Walter Boas(163)` are merely 150 meters away and both buildings have a comparatively small number of staffs and high meeting room capacities.
- `11 Barry Street(266)` is near `Law building(106)`, and other surrounding buildings such as `Kwong Lee Dow building(263)`, `The Spot(110)` and `FBE building(105)` also have lots of staffs.
- Also, all of these buildings have low ratios, indicating that those staffs may need to use meeting rooms in other buildings as well. Choices are including `MDHS(207)`, `Statistical Consulting`

`Center(394)` and `University Business Service building(384)`, however, their meeting rooms capacity is around 20, and it might be difficult for them to support those high-demand buildings nearby.

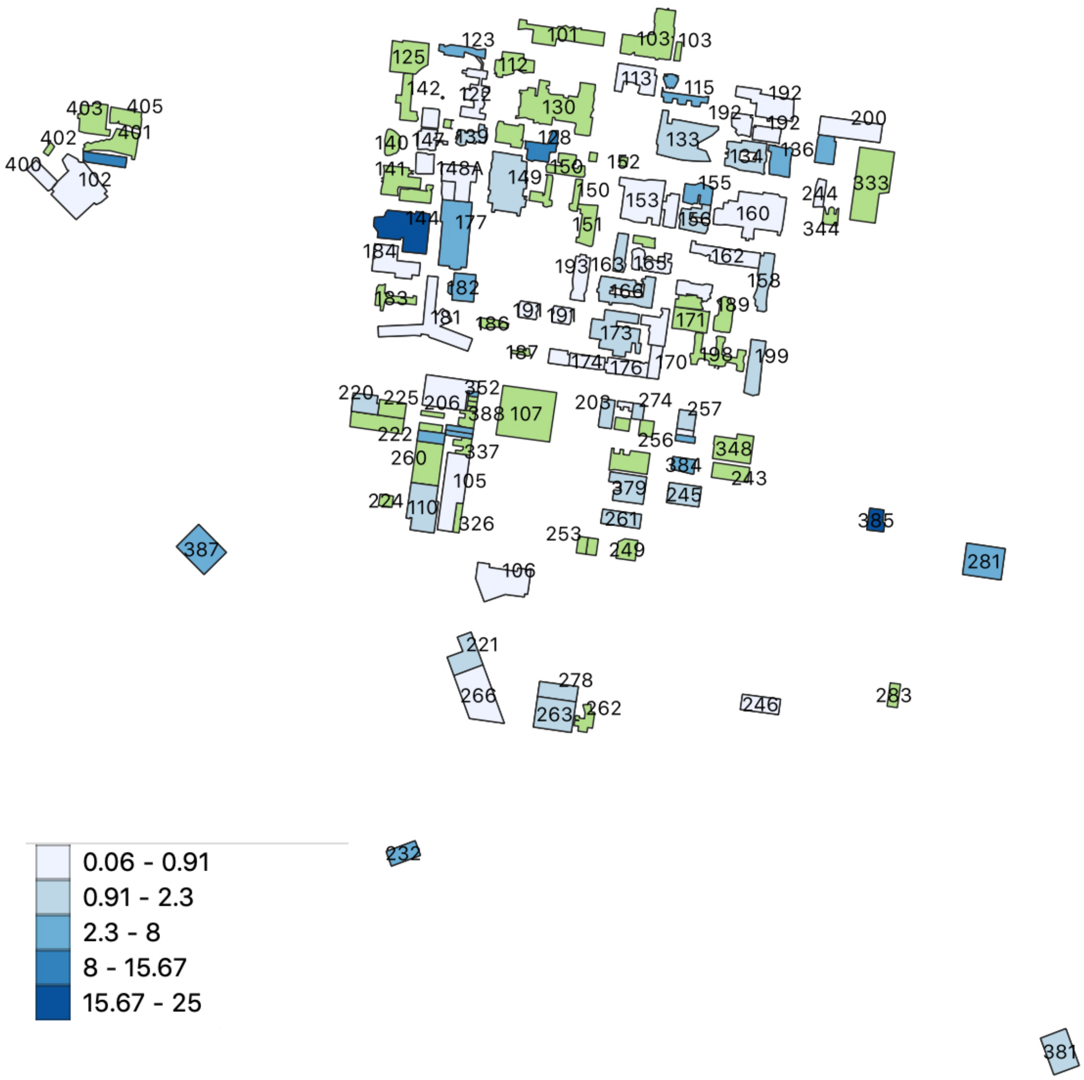

Figure 6: Spatial Analysis: Capacity of meeting rooms with respect to Staff

1.7

The initial results of spatial algorithm on Current Building **B** as Alan gilbert building (Building No: 104), Radius **R** as 400m and 600m, and Objective **O** as meeting rooms are shown below.

Algorithm 1 Find the most optimal nearest building

Inputs: Current Building **B**, Radius **R**, Objective **O**, Penalty **P**

1: Find all the nearest buildings within the radius R
2: Calculate the *weights* of these buildings: $weights = \frac{\text{Supply of the objective}}{\text{Demand of the objective}}$
3: Update *weights* by including correlations of the objective.
4: Calculate $probabilities = softmax(weights)$
5: Penalize *probabilities* to get *scores* as per their physical distance from **B** and using penalty **P**.
6: Optimal nearest building: $argmax(scores)$

Figure 7: Preliminary results for Building 104 with 400m and 600m radius

The initial results as shown in Figure 7 suggests that there is a high chance that user is not able to book a meeting room in building 104 as the weight is quite less (shown with little shade of red colour). ***Currently, these weights and probabilities are not getting updated as per step 3 and 5 of the algorithm.*** So, based entirely on the supply-demand weighting scheme, algorithm running with 400m radius will suggest `building 207 (MDHS)` and 600m radius will suggest `building 144 (Kenneth Myer)` as the most optimal nearest buildings.

1.8

The model predictions using floor algorithm for Current Building **B** as Kwong lee dow building (Building 263), Current Floor **F** where the user is located as Level 3, Objective **O** as meeting rooms and Penalty **P** as 0.005 is shown below.

Algorithm 2 Find the most optimal nearest floor

Inputs: Current Building **B**, Current Floor **F**, Objective **O**, Penalty **P**

1: Get all the floors in the provided current building

2: Calculate *props* for supply on each floor: $props = \frac{\text{Supply of the objective at each level}}{\text{Total Supply of the objective in building}}$

3: Calculate *props* for demand on each floor: $props = \frac{\text{Demand of the objective at each level}}{\text{Total Demand of the objective in building}}$

4: Calculate *weights* for each floor: $weights = \frac{\text{Supply of the objective} \times props \text{ for supply}}{\text{Demand of the objective} \times props \text{ for demand}}$

5: Update *weights* by including correlations of the objective.

6: Calculate $probabilities = softmax(weights)$

7: Penalize *probabilities* to get *scores* as per their physical distance from **F** and using penalty **P**.

8: Optimal nearest floor: $argmax(scores)$

	Floor Code	Floor Name	Room Code	weights	probs	penalize	scores
0	0	Ground	50	0.228571	0.046933	-0.015	0.031933
1	1	Level 1	27	0.500000	0.061569	-0.010	0.051569
2	2	Level 2	38	2.400000	0.411641	-0.005	0.406641
3	3	Level 3	83	0.602540	0.068217	0.000	0.068217
5	5	Level 5	31	2.400000	0.411641	-0.010	0.401641

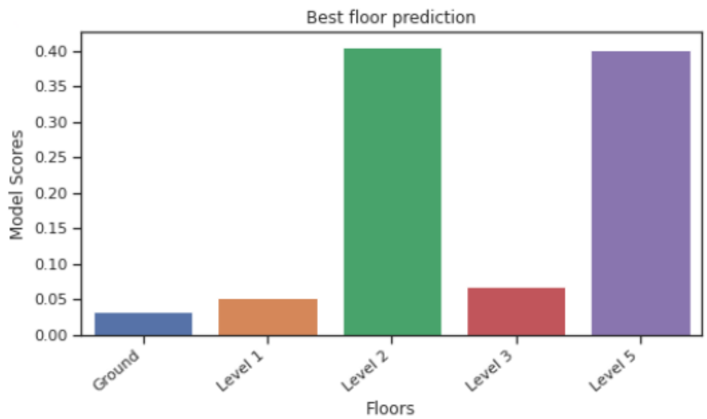

Figure 8: Model scores prediction for Building 263

Using the above predictions, we can say that `Level 2` will be the most optimal nearest floor for booking a meeting room after considering supply-demand weighting scheme. These results are still not considering **Step 5** of the algorithm which will further enhance the accuracy of the scores.

Similarly, we can do model predictions for Current Building **B** as Redmond barry building (Building 115), Current Floor **F** where user is located as Level 1, Objective **O** as toilet facilities and Penalty **P** as 0.005. The results are shown below.

	Floor Code	Floor Name	weights	probs	penalize	scores
1	0.2	Basement 2	0.823529	0.157057	-0.015	0.142057
7	2.0	Level 2	0.000006	0.068930	-0.075	-0.006070
8	3.0	Level 3	0.000096	0.068936	-0.090	-0.021064
9	4.0	Level 4	0.001872	0.069058	-0.105	-0.035942
10	5.0	Level 5	0.000395	0.068956	-0.120	-0.051044
11	6.0	Level 6	0.000419	0.068958	-0.135	-0.066042
12	7.0	Level 7	0.000611	0.068971	-0.150	-0.081029
13	8.0	Level 8	0.000970	0.068996	-0.165	-0.096004
14	9.0	Level 9	0.588235	0.124128	-0.180	-0.055872
3	10.0	Level 10	0.000273	0.068948	-0.015	0.053948
4	11.0	Level 11	0.000416	0.068958	-0.030	0.038958
5	12.0	Level 12	0.352941	0.098103	-0.045	0.053103

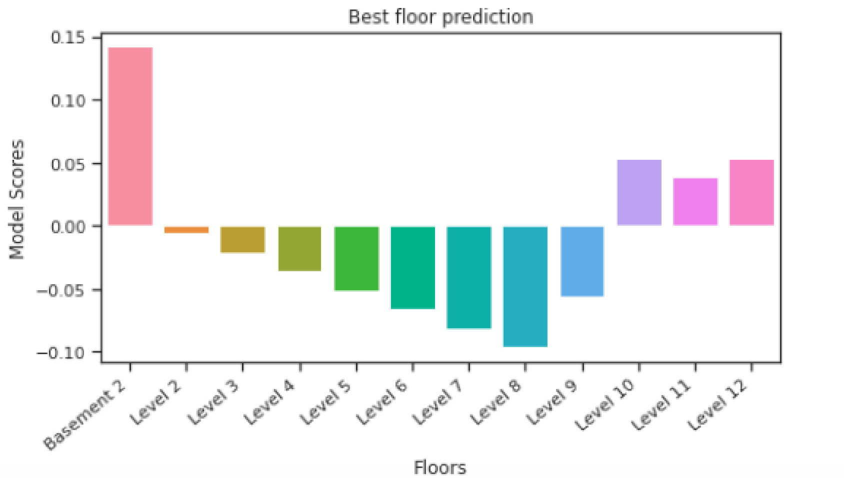

Figure 9: Model scores prediction for Building 115

Using the above predictions, we can say that `Basement 2` will be the most optimal nearest floor for using a toilet facility, considering all the supply-demand constraints. Again, these results are still not considering **Step 5** of the algorithm which will be implemented in the next phase of the project.