MAST90107

Detailed Analysis Report

Optimisation of university space based on a supply and demand analysis

A case study on staff meeting rooms and student toilet facilities on campus

THE UNIVERSITY OF MELBOURNE

Group 3

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Abstract

Optimally utilizing the space for meeting rooms and toilet facilities is extremely important for effective campus planning and proper space allocation. In this project, we were tasked with the objective of suggesting reasonable recommendations of space optimization opportunities by performing analysis of the provided data using data science tools and techniques. In order to provide these recommendations and give a deeper analysis of the data, we transformed these general objectives into a prediction problem that lies in the domain of Informative Path Planning (IPP).

In this report, we perform the proper transformation of the objectives and represent the problem formally. We are going to transform the provided campus space into several specialized graphs with respect to different buildings and floors. We will propose a novel non-randomized anytime orienteering algorithm for finding k-optimal goals that maximize reward on a specialized graph with budget constraints. We will also explain the cost and reward function modeling with their corresponding hyperparameters tuning process. Using this algorithm, we will present the results of several buildings with a supply-demand problem. This report also provides an analysis of our proposed algorithm. Our experimental results suggest reasonable space optimization opportunities across different campuses of the University of Melbourne.

Signed Declaration

I certify that this report does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university and that to the best of my knowledge and belief it does not contain any material previously published or written by another person where due reference is not made in the text. The report is 9960 words in length (excluding text in images, tables, bibliographies, and appendices).

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In addition, we would like to thank the University of Melbourne's Spatial Analytics and Space Management department for giving us this opportunity to work on their supply-demand problem. Finally, we would like to thank Michael Kirley and Marika Benetti-Hille for organizing and managing a highly productive and experience providing Data Science project.

Contents

1 Introduction

The university has spent its second-largest expense on space allocation and the arrangement of meeting rooms and toilets has long been recognized as a major concern in campus planning. It is important to ensure optimal space utilization as under-utilization of these facilities entails extra cost penalties for maintenance. In this project, the space arrangement of staff meeting rooms and student toilets will be optimized by proposing solutions that can efficiently use the current supply of resources. Generally, the number of existing meeting rooms and toilets is considered as “supply” while the number of staff and enrolled students are considered as “demand”. By analyzing space, employee, and timetabling data, we will first explore if the supply meets current demand, then propose different predictive models that will help our client to suggest the usage of current resources more efficiently.

Our client for this project is the Spatial Analytics and Space Management department of the University of Melbourne. This department works in future space design, better space allocation, and optimizing usage of resources for the university. As stated by our client, the expected outcome of this project can be summarized as:

- We need to suggest how the **space arrangement** of meeting rooms and toilets can be optimized, and advise how the overall space on campus can be better planned.
- We are expected to deliver a **detailed analysis report**. The analysis is expected to be conducted by campus, by building, and by different meeting rooms and toilet types, etc. The report should include interactive maps, charts with the interpretation of findings.
- We need to use different **analytical methods** such as spatial analysis, correlation analysis, etc.
- We need to provide **reasonable recommendations** of space optimization opportunities based on the analysis.

From the data science perspective, this project involves extensive exploratory data analysis of supply and demand, complicated data mutations, joins, and preprocessing. We also need to perform a correlation analysis among different factors and spatial analysis using QGIS. To suggest the current usage of resources more effectively, we need to construct predictive statistical models using well-defined constraints. The models pose an integration challenge of python models with QGIS spatial layers. Also, models are supposed to be extremely generic so that they can provide support for analyzing any building on any campus. Moreover, identifying appropriate factors for correlation analysis from the provided data is a difficult and daunting task that we’ll be exploring in this project.

This report is organized as follows: Section 2 describes problem objective and formulation. We present our results for exploratory data analysis and factor analysis in section 3. Section 4 discusses proposed methodologies and section 5 shows findings for spatial and floor algorithms. Finally, an analysis of the algorithm is presented in section 6 and we conclude our work in section 7.

2 Related Work

In this section, we will be reviewing literature and research articles that follow closely to our provided problem and proposed solution. In 1987, Golden, Bruce, and others introduced the term `The Orienteering Problem` which is analogous to an outdoor sport played in heavily forested areas. According to them, forests are having "control points" associated with a score and the task is to visit each control point (node n) from a starting point with the objective of maximizing the cumulative collected score[1]. They proposed the complexity of solving this problem to be NP-hard and provided a gravity heuristic for relaxing and solving this problem[1]. In 2014, Yu, Jingjin, and others proposed a novel non-linear extension to the orienteering problem (OP) which they termed as `Correlated Orienteering Problem (COP)`[2]. They assumed spatial correlations among the reward providing nodes and proposed quadratic extension for the OP to incorporate such correlations in the informative path planning phase[2].

Due to the NP-hard nature of this problem, S. Arora and others proposed a randomized algorithm for informative path planning with budget constraints in 2017[3]. Their research inspired the problem formulation and proposed algorithm introduced in this report. They transformed the OP domain into a constraint satisfaction problem and proposed several versions of the randomized anytime algorithm to provide the most rewarding path respecting the budget constraint[3]. In addition to this, Wei, Yongyong, and others introduced a Reinforcement Learning based approach for solving an informative path planning problem in 2020[4]. Their work inspired the cost-reward representation idea that we have implemented for formulating our problem. Finally, we explored the mathematical understanding of Min-Max Heaps and Generalized Priority Queues as introduced by Atkinson and others[5]. This helped us to grasp the space and time complexity domain that motivated the design of our proposed algorithm.

3 Problem Description

In this section, we will give informal intuition of our problem and then formally define it as a constraint satisfaction problem which is analogous to an orienteering problem.

3.1 Problem Objective

Our objective is to propose an optimization of university space based on a supply and demand analysis specific to staff meeting rooms and student toilet facilities. We are required to analyze the spatial data, employee data, timetabling data, and meetings held data to advise if the supply of meeting rooms and toilets on campus meets the current demand, and how the arrangement and maintenance services can be optimized accordingly.

Using the provided data, we performed the initial data analysis to get the basic idea of the supply-demand problem across campuses, buildings, and corresponding floors. To propose an optimization of current university space for using supply-demand effectively, we aimed at devising solutions that can efficiently use the current supply of the resources. Using this intuition, we transformed this general objective into a prediction problem that aims at predicting the best entity that can give the best supply of the resources based on demand and other preferences or factors. These prediction objectives enabled us to get a deeper insight into the data and can be informally stated as follows:

- **Finding the k-best nearest buildings**: In this objective, we are aiming to find the k-best nearest buildings from a particular building that is having a good supply of meeting room or student toilet facilities based on factors like easy availability, excellent conditions, COVID-19 lockdown, etc.
- **Finding the k-best nearest floors**: In this objective, we are aiming to find the k-best nearest floors in a particular building based on supply and demand of meeting rooms and student toilet facilities. We also enabled the filtering of results based on factors like easy availability, excellent conditions, COVID-19 lockdown, etc.

These prediction-based objectives helped us to represent a general space optimization problem into more concrete strategy-based objectives. The above prediction objectives aim is to provide a critical understanding of the supply-demand that can help us to create strategies that will lead to the usage of the current supply of the resources more effectively. We will now formally represent these objectives in the below section.

3.2 Problem Formulation

In this section, we will represent previously stated prediction objectives into a formal constraint satisfaction mathematical problem which can then be solved using our proposed non-randomized orienteering algorithm. Both of our objectives of finding the k-best nearest buildings and floors based on supply, demand, and factors can be formally described using the same problem as shown below.

The idea of our problem is to find the k-best optimal building or floor within a provided radius or provided number of floors which maximizes the reward of booking a meeting room or using a toilet facility based on different factors. We can define this idea by considering a traveling budget B, provided objective O, and a set of factors F. Here, $O \in \{$*book meeting room*, *use toilet facility*$\}$, $F \in \{$*easy availability, room conditions, COVID-19 lockdown, ...* $\}$ and $B \in \mathbb{R}_0^+ \cup \{\infty\}$. We will now formulate our domain-related optimal building finding problem into a generic orienteering problem (OP) for a specialized graph. We can represent our situation of finding k-the best optimal building or floor from a particular building or floor using a specialized graph as described below.

Let us assume a weighted directed specialized graph $G_s = (V, E)$ for n number of nodes where $v_s \in V$ is the pre-defined start node such that,

$$V = \{v_1, v_2, v_3, ..., v_n\} \tag{1}$$

$$E = \{(v_s, v_i) \setminus (v_s, v_s) \mid \forall\, i \in [1, n]\,\} \tag{2}$$

Here, v_s is having n out-degree with 0 in-degree (i.e. v_s is connected to every other node in V) and $v_i\, \forall\, i \in [1, n] \setminus v_s$ is connected to only v_s with 1 in-degree and 0 out-degree.

Let v_g be the set of k-optimal goal nodes s.t. $v_g \in V$ and $k \leq n$. These goals are attained in the decreasing order of their gained rewards after respecting budget constraints (i.e. $v_{g1} > v_{g2} > ... > v_{gk}$).

Let r be the set of nodes which we can visit such that $r \subseteq V \setminus v_s$.

For each r, let $R(r, o, f)$ be the reward function where $R : (r, o, f) \to \mathbb{R}_0^+ \cup \{\infty\}$ calculates the reward based on the provided set of factors $f \subseteq F$ and objective $o \in O$.

Let $I(r) = R(r, o, f)$ be the reward gained by visiting each node in r.

Let the cost of traversal be given by $C(r) = C(v_s, v_i^r)$, where v_i is the i^{th} element in r, $\forall i \in [1, |r|]$.

Let $L \in \mathbb{R}_0^+ \cup \{\infty\}$ be the constraint limit.

Using the above notations, the hard-constraint problem can then be defined by the equation 3.

$$\arg\max_{r \subseteq V} I(r)\ \textit{subject to}\ C(r) \leq B \leq L \tag{3}$$

We can relax the above hard-constraint by introducing a hyper-parameter δ to formulate a soft-constraint problem as shown in the equation 4.

$$\arg\max_{r \subseteq V} I(r)\ \textit{subject to}\ C(r) \leq B + \delta \leq L \tag{4}$$

where $\delta \in \mathbb{R}_0^+ \cup \{\infty\}$.

Informally, the solution to our stated problem is a set of ordered k-optimal goal nodes, such that the reward obtained by visiting the node is maximized while the path cost stays within a specified traveling budget B.

3.2.1 Example: Applying formulation for finding 3-best nearest buildings

In this section, we will use the above formulation to implement an example problem of finding the 3-best nearest building for booking a meeting room from building 220 (780 Elizabeth St) in the Parkville campus. We will first generate a specialized graph of all the buildings, as described in the above formulation, from building 220 where a snapshot of the example graph is shown below.

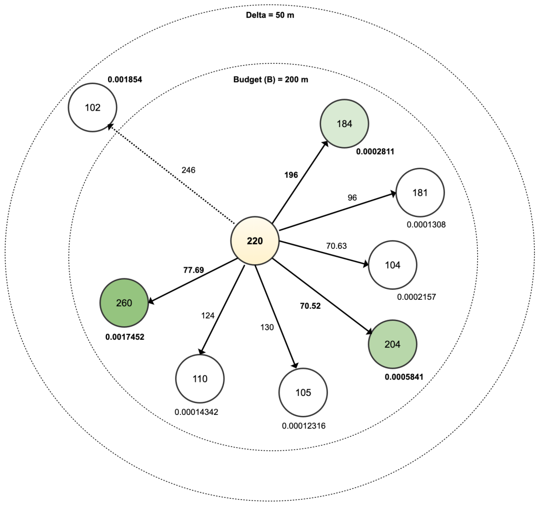


Figure 1: Specialized graph from Building 220 to all nearby buildings with their corresponding rewards

Now, as per our above graph, we have Budget $B = 200$ metres, $o = \{book\ meeting\ room\} \in O$, and $F \in \{easy\ availability,\ COVID\ lockdown,\ ....\ \}$. Let $V_c = \{220, 184, 181, 104, 204, 105, 110, 260, 102\}$ be the set of 10 buildings in a campus $c = PARKVILLE$. Let $v_s = 220$ be the starting building such that $v_s \in V_c$. Let $r = \{184, 181, 104, 204, 105, 110, 260, 102\}$ be the set of buildings a person can visit s.t. $r \subseteq V_c \setminus v_s$. For each r, the reward gained $I(r) = R(r, o, f)$ by visiting each building in r, for provided objective $o \in O$ and factors $f \in F$ can be stated as shown using below table with respective cost $C(r)$.

$r \subseteq V_c \setminus v_s$	$o \in O$	$f \in F$	$I(r) = R(r, o, f)$	$C(r) = C(220, v_i^r)$
184	*book meeting room*	$\emptyset$	0.0002811	196
181	*book meeting room*	$\emptyset$	0.0001308	96
104	*book meeting room*	$\emptyset$	0.0002157	70.63
204	*book meeting room*	$\emptyset$	0.0005841	70.52
105	*book meeting room*	$\emptyset$	0.00012316	130
110	*book meeting room*	$\emptyset$	0.00014342	124
260	*book meeting room*	$\emptyset$	0.0017452	77.69
102	*book meeting room*	$\emptyset$	0.001854	246

Table 1: Example problem cost-reward table for finding 3-best nearest buildings

Now, we need to find the set of goal building v_g s.t. $v_g \in V_c$ and satisfies below hard constraint.

$$\arg\max_{r \subseteq V_c} I(r)\ subject\ to\ C(r) \leq B = 200 \tag{5}$$

Similarly, we can also find the set of goal building v_g* s.t. $v_g* \in V_c$ and satisfies below soft constraint.

$$\arg\max_{r \subseteq V_c} I(r)\ subject\ to\ C(r) \leq B + \delta = 200 + 50 = 250 \tag{6}$$

where $\delta = 50 \in \mathbb{R}_0^+ \cup \{\infty\}$.

We will solve these equations using our proposed non-randomized orienteering algorithm as discussed in the section 5.

4 Data Analysis

In this section, we will give brief overview of the provided data for solving our university space optimization problem. We have been provided with the following datasets:

#	Dataset Name	Dataset Description
1	`uom-space`	Space metadata of all rooms across campuses and buildings
2	`rm-category-type`	Definition of all UoM standard room categories and types
3	`fl-name`	Dataset to provide more information about building floors
4	`av-equipment`	Audio Visual equipment data including its location information
5	`em-location`	De-identified employee/staff location data
6	`2020-timetable-v2`	Latest class scheduling data including a class's time and its location
7	`meeting-room-usage`	Collected data of meeting room usage

Table 2: Provided datasets

4.1 Exploratory Data Analysis

In this section, we have explored all the provided datasets to understand their properties, size, and scale. We have also performed an analysis of how these datasets correlate with the provided problem.

4.1.1 What are the different properties, size, and scale of data?

After importing all the provided datasets using `pandas` python package, we deduced the following summary of the data as shown in the below tables.

#	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 equipment, 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 3: 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 4: Important numerical variables data summary

4.1.2 How is the data distributed across problem statement?

In our analysis, we explored different categorical and numerical features of the datasets to get more depth about the data. Initially, we saw that most of the data is provided for the `Parkville` campus as shown in Figure 2. Due to this huge skewness, we have performed most of our data and correlation analysis on the Parkville campus, which can be easily extended to other campuses.

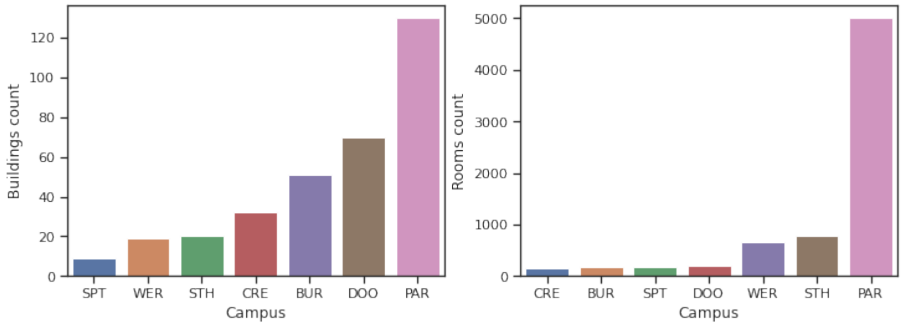


Figure 2: Distribution of buildings and rooms across campuses

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 3. 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.

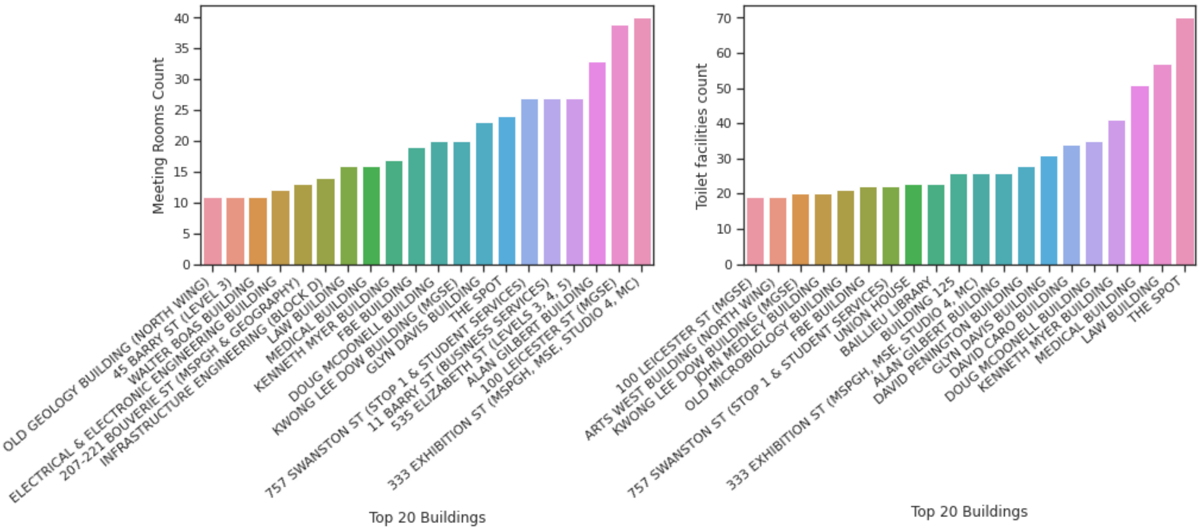


Figure 3: Distribution of meeting rooms and toilet facilities across buildings in Parkville Campus

4.1.3 Supply-demand Analysis

After exploring different properties and aspects of the data, we tried to see and understand how data can be used to get the basic intuition of the problem by performing supply-demand analysis across buildings on different campuses.

4.1.3.1 Parkville Campus

We created several supply-demand plots across various covariates which helped to see the need for space optimization in the Parkville Campus. 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 4. As per the plot, we can see space optimization problems in terms of supply and demand proportion especially in the `Law Building`, `Doug Mcdonell building`, and `Kenneth Myer building`.

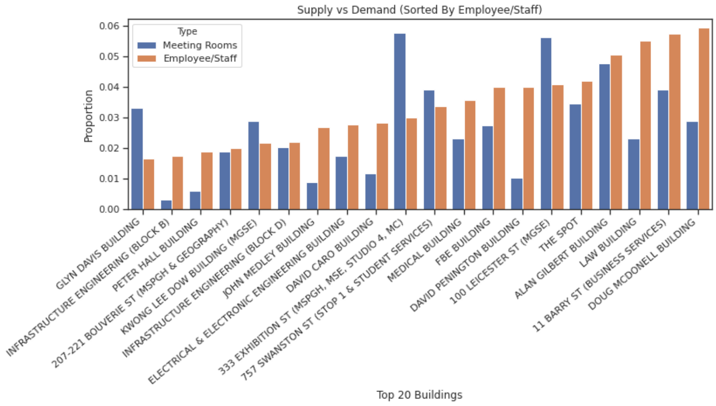


Figure 4: Supply vs Demand of meeting rooms across buildings in Parkville Campus

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 5. Again, we can see that the space optimization problem in terms of supply and demand proportion, especially for `Redmond barry building`.

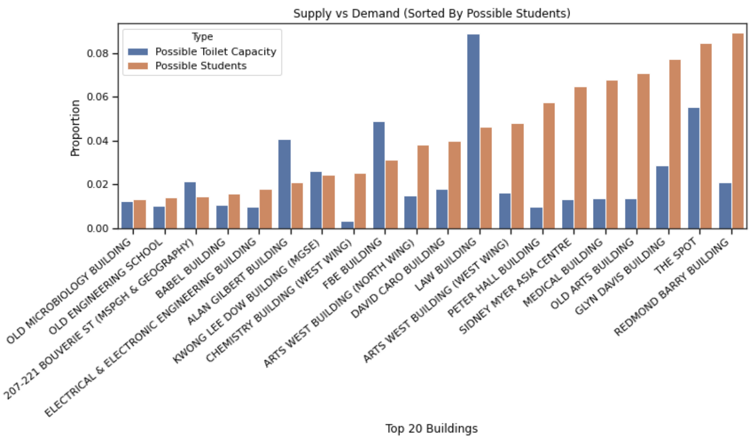


Figure 5: Supply vs Demand of toilet facilities across buildings in Parkville Campus

We have explored several other covariates or factors concerning supply-demand in Section 4.2 which will eventually help us to perform space optimization on the underlying problem.

4.1.3.2 Other Campuses

We extended our analysis of supply-demand to campuses other than Parkville in order to get more ideas about the space optimization problem. We used the absolute supply-demand proportion for the meeting room's capacity with respect to the demand and created plot for different campuses as shown in the Figure 6. The results can be summarized as follows.

- **Southbank Campus:** As per the Southbank plot, we can clearly highlight the supply-demand problem with respect to the meeting rooms, especially for the `Elisabeth Murdoch Building`. This campus seems to have a high number of supply-demand imbalance as mostly all of the buildings for which data was provided seems to have space optimization issue as seen from the Figure 6.

- **Werribee Campus:** As per the Werribee plot, we can clearly identify a major space optimization problem in terms of supply-demand of meeting rooms in `Werribee Pathology Building` as per the provided data. We can also see that the other buildings seem to have an adequate proportion of supply to balance the demand.

- **Creswick Campus:** We were able to find 3 buildings which provided both supply-demand data for meeting rooms analysis. As per the plot, we can see that the demand in `Creswick Research Laboratories` is high as compared to the supply of the meeting rooms where other buildings seem to have an adequate supply.

- **Shepparton Campus:** We couldn't find much supply-demand data in terms of meeting rooms for this campus. As per the Shepparton plot, we could only find 1 building for which we have adequate supply-demand data and the `49 Graham St, Shepparton` building seems to have a supply-demand problem as the proportion for the demand of meeting rooms is higher than the supply.

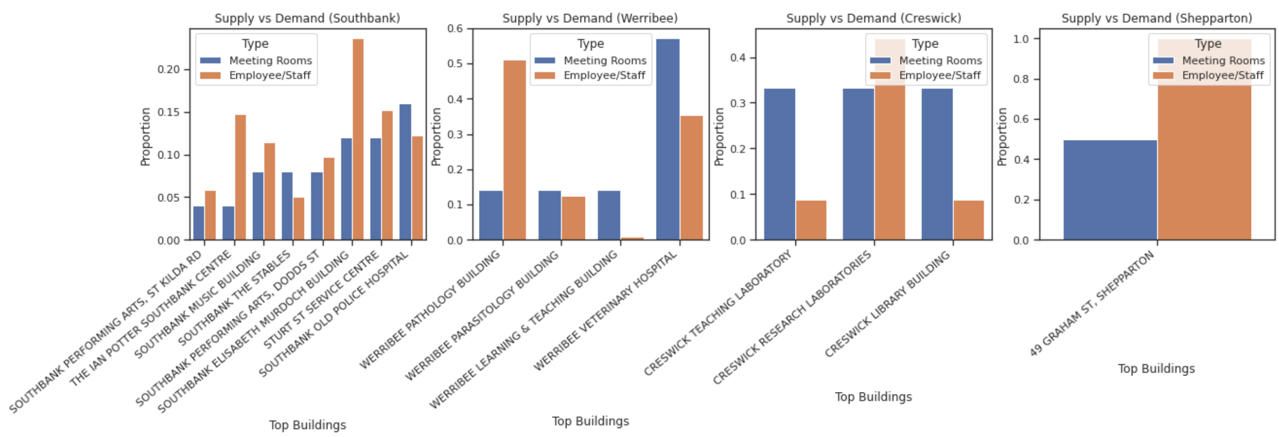


Figure 6: Supply vs Demand of meeting rooms across buildings in different campuses

Similarly, we used the absolute supply-demand proportion for the toilet facilities capacity with respect to the demand and created a plot for different campuses as shown in the Figure 7. The results can be summarized as follows.

- **Southbank Campus:** As per the Southbank plot, we can clearly highlight the supply-demand problem with respect to the toilet facilities, especially for the `Ian Potter Southbank Centre`. This is followed by `Southbank Music Building` and `Southbank Art Studios 1`. Other buildings inside the campus seem to have a good supply-demand balance in terms of students attending classes and provided toilet facilities.

- **Werribee Campus:** As per the Werribee plot, we can clearly identify a major space optimization problem in terms of supply-demand of toilet facilities in `Werribee Learning & Teaching Building` as per the provided data. We couldn't find supply-demand data for more buildings on this campus in terms of toilet facilities and student classes.

- **Creswick Campus:** We were able to find only 1 building which provided both supply-demand data for toilet facilities analysis. As per the plot, we can clearly see that the demand in the `Creswick Seminar Centre` is high as compared to the supply of the toilet facilities. We couldn't find supply-demand data for more buildings on this campus in terms of toilet facilities and student classes.

- **Shepparton Campus:** We couldn't find much supply-demand data in terms of toilet facilities for this campus. As per the Shepparton plot, `Dookie-Swinburne Hall` building seems to have a supply-demand problem as the proportion for the demand for toilet facilities is higher than the supply.

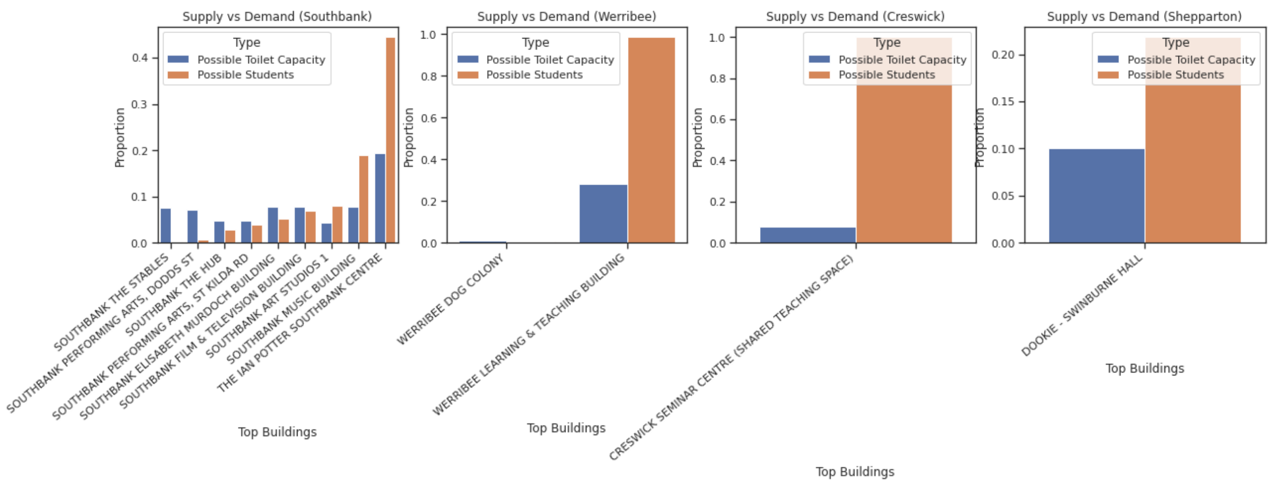


Figure 7: Supply vs Demand of toilet facilities across buildings in different campuses

4.2 Factors Analysis

In this section, we will explore different preferences or factors that concern the effect of booking a meeting room or using a toilet facility. These factors directly impact the expected reward from a building or floor, thereby used extensively in solving the same problem from different situations.

4.2.1 Factors for booking a meeting room

In this section, we will look at different factors that can impact the probability of booking a meeting room.

1. **Same Building**: Using this factor, the employee wants to book a meeting room in the same building. This is a default factor that is considered automatically while solving our optimization problem of finding the nearest building from a particular building.

2. **Same Floor**: Using this factor, the employee wants to book a meeting room on the same floor in a particular building. Again, this is a default factor that is considered automatically while solving our optimization problem of finding the nearest floor from a particular floor.

3. **COVID-19 Lockdown Situation**: Using this factor, an employee can express the COVID-19 lockdown scenario which can directly impact the expected rewards gained from the targeted buildings or floors. This factor can be used to represent `Strict Lockdown` condition which means there is no demand at all, `Medium Lockdown` condition which means there is 25% demand, and `Low Lockdown` condition which means there is 50% demand.

4. **High Capacity:** Using this factor, an employee can target the situation of booking a meeting room with high capacity. This can be inferred using the average room size provided by the data for each meeting room.

5. **Required Capacity(C):** Using this factor, an employee can target the situation of booking a meeting room with a very specific capacity requirement C. This can be inferred using the supply of room capacity provided by the data for each meeting room.

6. **With Equipment:** Using this factor, an employee can express the requirement of booking a meeting room with useful equipment. This can be inferred using the `av-equipment` dataset that helps us to understand the equipment capacity distribution across different buildings and floors.

7. **Room Conditions:** Using this factor, employee can express the requirement of booking a meeting room with `Excellent`, `Very Good` or `Good` condition. This can be inferred using the room condition property provided in the space dataset.

8. **Easy Availability**: Using this factor, an employee wants to book a meeting room that is easily available which can be inferred using meeting room usage data. **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 8.

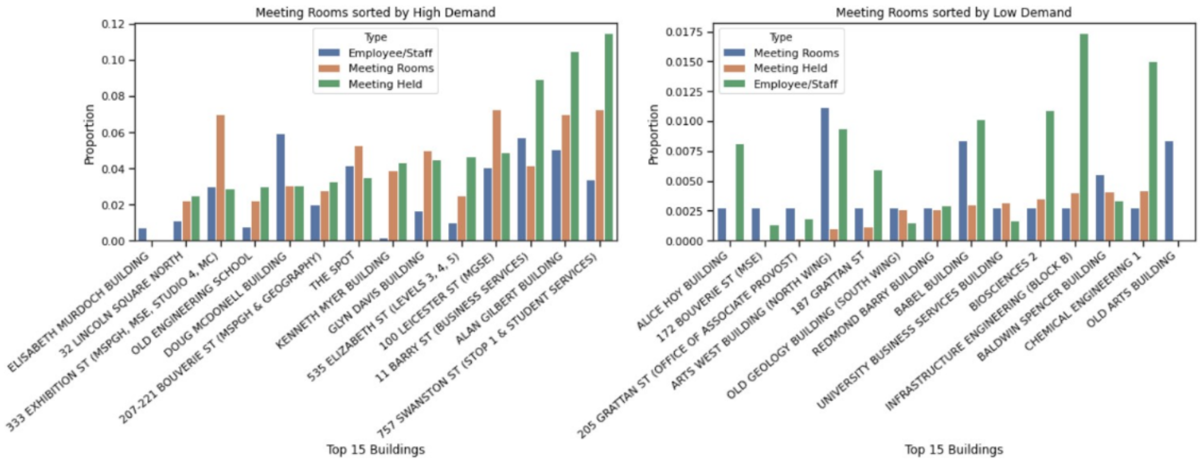


Figure 8: Supply vs demand analysis for easy availability factor

4.2.2 Factors for using a toilet facility

In this section, we will look at different factors that can impact the probability of using a toilet facility.

1. **Same Building**: Using this factor, a student wants to use a toilet facility in the same building. This is a default factor that is considered automatically while solving our optimization problem of finding the nearest building from a particular building.

2. **Same Floor**: Using this factor, a student wants to use a toilet facility on the same floor in a particular building. Again, this is a default factor that is considered automatically while solving our optimization problem of finding the nearest floor from a particular floor.

3. **COVID-19 Lockdown Situation**: Using this factor, a student can express the COVID-19 lockdown scenario which can directly impact the expected rewards gained from the targeted buildings or floors. This factor can be used to represent `Strict Lockdown` condition which means there is no demand at all, `Medium Lockdown` condition which means there is 25% demand, and `Low Lockdown` condition which means there is 50% demand.

4. **High Capacity:** Using this factor, the situation can be targeted using a toilet facility with high capacity. This can be inferred using the average room size provided by the data for each toilet room.

5. **Required Capacity(C):** Using this factor, the situation can be targeted at using a toilet facility with a very specific capacity requirement C. This can be inferred using the supply of

room capacity provided by the data for each toilet room.

6. **Easy Availability**: Using this factor, a student wants to use a toilet facility which is easily available that can be inferred using the average duration of classes in a building or a particular floor. If classes have a longer duration in a building or floor, then that building should have facilities with better capacity as availability will be less. As per our analysis, it can be seen that the Old Physics building has a very long duration of lectures but it has 1% of the total capacity of toilets.

7. **Room Conditions**: Using this factor, student can express the requirement of using a toilet facility with `Excellent`, `Very Good` or `Good` condition. This can be inferred using the room condition property provided in the space dataset. 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 supply-demand as shown in Figure 9.

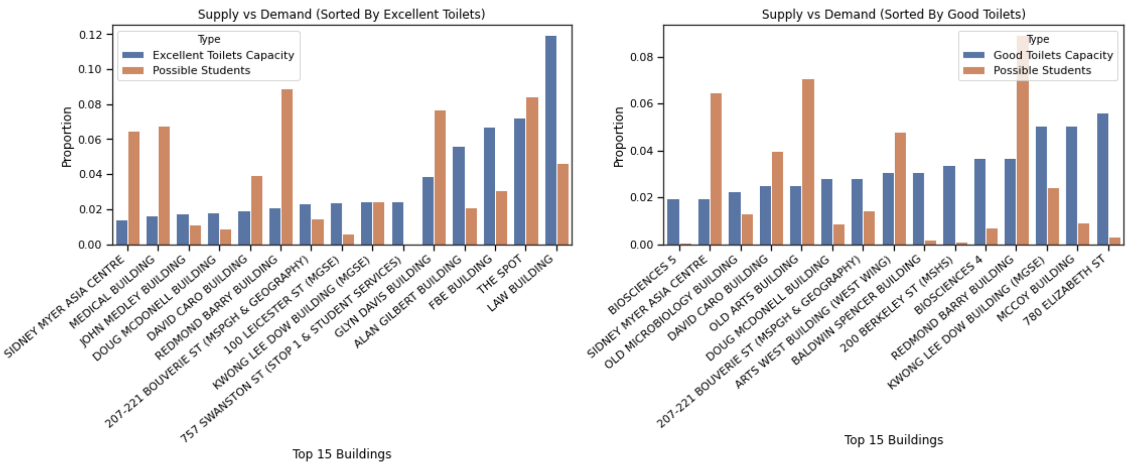


Figure 9: Supply vs demand analysis with toilet room conditions factor

5 Proposed Methodologies

In this section, we will describe our proposed methodology for solving the problem shown in equation 3 and 4. In addition to this, we will also show how we can optimize hyper-parameters B and δ of our problem using clustering and grid-searching techniques.

5.1 Non-randomized Anytime Orienteering Algorithm

In this section, we will propose a novel non-randomized anytime orienteering algorithm for finding k-optimal goals that maximize reward on a specialized graph with budget constraints. This specialized graph represents a real-world scenario that is analogous to an orienteering problem of finding k-most optimal goal states.

5.1.1 Algorithm Description

We propose a novel way of solving the problem formulation shown in equation 3 and 4 which is inspired by the general randomized algorithm for IPP problems [3].

The algorithm starts with a priority queue and creates r subset s.t. $r \subseteq V \setminus v_s$. Then, for each node in r, path cost $C(r)$ and node reward $I(r)$ is calculated. It is then ensured that the budget constraint is satisfied and the selected node is pushed into the priority queue with a negative reward as the priority. We can pop the queue item with minimum priority k-times to find the k-most optimal goal nodes. This process is described in Algorithm 1.

Algorithm 1 Non-Randomized Anytime Orienteering to find k-optimal goals for a specialized graph

Inputs: $G_s = (V, E), v_s, B, L, k, \delta,\ o \in O,\ f \subseteq F$
Output: $v_g = \{v_{g1}, .., v_{gk}\}$ s.t. $v_{g1} > ... > v_{gk}$
queue := new priority queue
$v_g = \emptyset$
$r := r \subseteq V \setminus v_s$
for v_i *in* r **do**
  $I(r) = R(v_i, o, f)$ `//node reward`
  $C(r) = C(v_s, v_i)$ `//path cost`
  if $C(r) \leq B + \delta \leq L$ **then**
    $priority = -1 * I(r)$
    queue.insert($v_i, priority$)
  end
end
while *not queue.empty()* **do**
  $\rho :=$ queue.pop-min() `//best node`
  if $len(v_g) < k$ **then**
    $v_g := v_g \cup \rho$
  end
end

5.1.2 Cost Function

The cost function $C(v_s, v_i)$ plays an important role in our algorithm as it is used to decide whether the budget is achieved or not. Using this function, we calculate the cost of moving from node v_s to the node v_i. The idea of this cost function is to be domain-specific, i.e. domain-related situation and the problem can be mapped accordingly with this cost function depending upon the significance of the budget constraint.

In order to simulate the scenario of finding k-most optimal nearest building with the provided budget B and δ, we define our cost function as follows.

$$C(v_s, v_i) = \texttt{The distance to travel from building } v_s \texttt{ to building } v_i \texttt{ (in metres)} \quad (7)$$

Here, the cost function is unconstrained as the distance could be very large.

Similarly, we can easily change our cost function to adapt the scenario of finding k-most optimal nearest floors in the building with the provided budget B and δ as follows.

$$C(v_s, v_i) = \texttt{The number of floors to take from level } v_s \texttt{ to level } v_i \tag{8}$$

Here, the cost function is constrained as the number of floors cannot be large than the provided floors in the building. So, in this scenario, $C(v_s, v_i) \leq Floors(building)$.

5.1.3 Reward Function

The Reward function $R(v_i, o, f)$ is the next important component in our algorithm as it is used to decide the reward given by a building or floor v_i based on the provided factors $f \subseteq F$ and objective $o \in O$. Using this function, we can easily simulate different factors on which the reward provided can be controlled based on different objectives. In our case, we implemented this reward function for our problem objectives as described below.

5.1.3.1 Reward Function Equations for Meeting Rooms Objective

In this section, we will describe our reward function for the problem objective of booking a meeting room as per the different factors described in section 4.2. The resulting equations implemented in the reward function can be described as follows.

- $f = \phi$: If there are no factors provided for booking a meeting room, then the reward calculated for node v_i can be stated as:

$$R(v_i, o, f) = \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \tag{9}$$

- $f =$ **{Book a meeting room with required capacity C}**: Using the provided capacity C, the reward calculated for node v_i can be stated as:

$$R(v_i, o, f) = \begin{cases} \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} & \text{s.t. } supply >= C \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

- $f =$**{Book a meeting room in COVID-19 lockdown situation}**: We can also map COVID-19 lockdown scenario using the flexible factors set space by which rewards can be manipulated. Depending upon the different situations of the lockdown, we can calculate reward for node v_i as follows:

$$R(v_i, o, f) = \begin{cases} \texttt{supply of meeting rooms at } v_i & f = \texttt{\{Strict\}} \\ \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i \times 0.25} & f = \texttt{\{Medium\}} \\ \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i \times 0.50} & f = \texttt{\{Low\}} \end{cases} \tag{11}$$

- $f =$ **{Book a meeting room with high capacity}**: We deduced the factor of high capacity by considering the proportion of average room size with respect to the provided supply and demand of meeting rooms. This can be used to calculate a reward for node v_i as follows:

$$R(v_i, o, f) = \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \frac{\texttt{average room size at } v_i}{\texttt{total average room size}} \tag{12}$$

- $f =$ **{Book a meeting room with easy availability}**: In order to deduce easy availability of the meeting rooms, we used the provided meeting rooms usage data by which we were able to get the proportion of meeting rooms being held at a particular node of the graph. This can be used to calculate the reward for the node v_i as follows:

$$R(v_i, o, f) = \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \left(1 - \frac{\texttt{total meetings held at } v_i}{\texttt{overall meetings}}\right) \tag{13}$$

- $f =$ **{Book a meeting room with equipment}**: In order to deduce the meeting rooms with equipment, we used the provided `av-equipment` data that helped us to figure out the distribution of equipment across the graph. This data can be used to calculate the reward for the node v_i as follows:

$$R(v_i, o, f) = \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \frac{\texttt{equipment count at } v_i}{\texttt{total equipment count}} \tag{14}$$

- $f =$ **{Book a meeting room with different room conditions}**: We were provided with the room conditions in the space data, which can be used to deduce the preference of booking a meeting room with different room conditions. This can be used to calculate the reward for the provided node v_i as follows:

$$R(v_i, o, f) = \begin{cases} \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \frac{\texttt{excellent rooms at } v_i}{\texttt{overall excellent rooms}} & f = \{\texttt{Excellent}\} \\ \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \frac{\texttt{very good rooms at } v_i}{\texttt{overall very good rooms}} & f = \{\texttt{Very Good}\} \\ \frac{\texttt{supply of meeting rooms at } v_i}{\texttt{demand of meeting rooms at } v_i} \times \frac{\texttt{good rooms at } v_i}{\texttt{overall good rooms}} & f = \{\texttt{Good}\} \end{cases} \tag{15}$$

5.1.3.2 Reward Function Equations for Toilet Facilities Objective

In this section, we will describe our reward function for the problem objective of using a toilet facility in order to get a deeper understanding of the supply and demand situation as per the different factors described in the section 4.2. The resulting equations implemented in the reward function for the toilet objective can be described as follows.

- $f = \phi$: If there are no factors provided for using a toilet facility, then the reward calculated for node v_i can be stated as:

$$R(v_i, o, f) = \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \tag{16}$$

- $f =$ **{Search a toilet facility with required capacity C}**: Using the provided capacity C, the reward calculated for node v_i can be stated as:

$$R(v_i, o, f) = \begin{cases} \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} & \text{s.t. } \textit{supply} >= C \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

- f =**{Search a toilet facility in COVID-19 lockdown situation}**: We can also map COVID-19 lockdown scenario using the flexible factors set space by which rewards can be manipulated. Depending upon the different situations of the lockdown, we can calculate reward for node v_i as follows:

$$R(v_i, o, f) = \begin{cases} \texttt{supply of toilet facilities at } v_i & f = \texttt{\{Strict\}} \\ \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i \times 0.25} & f = \texttt{\{Medium\}} \\ \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i \times 0.50} & f = \texttt{\{Low\}} \end{cases} \tag{18}$$

- f = **{Search a toilet facility with high capacity}**: We deduced the factor of high capacity by considering the proportion of average room size with respect to the provided supply and demand of toilet facilities. This can be used to calculate a reward for node v_i as follows:

$$R(v_i, o, f) = \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \times \frac{\texttt{average room size at } v_i}{\texttt{total average room size}} \tag{19}$$

- f = **{Search a toilet facility with easy availability}**: In order to deduce easy availability of the toilet facility, we used the provided timetable data to figure out the corresponding class duration at the target nodes. If the average class duration is high, then it can be considered a low availability situation. This can be used to calculate the reward for the node v_i as follows:

$$R(v_i, o, f) = \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \times \left(1 - \frac{\texttt{average class duration at } v_i}{\texttt{overall class duration}}\right) \tag{20}$$

- f = **{Search a toilet facility with different room conditions}**: We were provided with the room conditions in the space data, which can be used to deduce the preference of using a toilet facility with different room conditions. This can be used to calculate the reward for the provided node v_i as follows:

$$R(v_i, o, f) = \begin{cases} \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \times \frac{\texttt{excellent rooms at } v_i}{\texttt{overall excellent rooms}} & f = \{\texttt{Excellent}\} \\ \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \times \frac{\texttt{very good rooms at } v_i}{\texttt{overall very good rooms}} & f = \{\texttt{Very Good}\} \\ \frac{\texttt{supply of toilet facilities at } v_i}{\texttt{demand of toilet facilities at } v_i} \times \frac{\texttt{good rooms at } v_i}{\texttt{overall good rooms}} & f = \{\texttt{Good}\} \end{cases} \tag{21}$$

5.1.4 Time Complexity

If we assume a standard binary heap implementation of the priority queue, then the insertion and deletion time complexity is $O(log n)$, where n is the size of the input [5]. This can be further optimized by several customizations [6]. Hence, the time complexity of our proposed algorithm for the best and the worst case can be stated as

$$O(n - 1 \, * \, log\, n) + O(k \, * \, log\, n) \leq O(n \, log\, n) \tag{22}$$

5.1.5 Space Complexity

If we again assume a heap data structure implementation of the priority queue, then the space complexity of storing n elements in the priority queue is $O(n)$[5]. Hence, the best and worst-case space complexity of our proposed algorithm is $O(n)$.

5.2 Hyper-parameters Tuning and Clustering Algorithms

In this section, few clustering algorithms are discussed and how the hyper-parameters for calculating the optimum budget and delta constraints are tuned/calculated.

5.2.1 Clustering Algorithms

1. **Agglomerative Hierarchical Clustering** - In this algorithm, the data points are clustered according to the similarity using an underlying hierarchical algorithm. This clustering technique works in a `bottom-up` approach, where each cluster begins as a single independent cluster. It can be implemented using three linkage strategies viz, `single linkage strategy, complete linkage strategy, average linkage strategy`. [7] Mathematically it is given as,

   A `d`-dimensional circle of radius `r` and center `y`,

   $$B_r^d(y) := \{x \mid ||x - y|| \leq r\}$$

   and the distance is calculated using Euclidean distance. Here, $C_k = \{C_1, C_2.., C_k\}$ is the collection of k clusters, diameters be $C \subset \mathbb{R}^d$ and the collection C contains at most one cluster $1 \leq k \leq |X|$.

2. **BIRCH (balanced iterative reducing and clustering using hierarchies)** - This algorithm performs hierarchical clustering, and it is very fast as compared to other algorithms and also can be parallelized. In this method, it uses closeness of the data points to assign it to the clusters locally rather than scanning either a single cluster or all clusters for the data points globally. It treats dense clusters as a single entity, and sparse clusters are treated as outliers and removed optionally. Given as `N` dimensional data in $\overrightarrow{X_i}$ where `i = 1,..,N`, $\overrightarrow{X_0}$ as the centroid, `R` as radius and `D` as diameter[8].

   $$\overrightarrow{X_0} = \sum_{i=1}^{N} \overrightarrow{X_i}/N$$

   $$R = (\sum_{i=1}^{N} (\overrightarrow{X_i} - \overrightarrow{X_0})^2/N)^{1/2}$$

   $$D = (\sum_{i=1}^{N} \sum_{j=1}^{N} (\overrightarrow{X_i} - \overrightarrow{X_j})^2/N(N-1))^{1/2}$$

3. **Mini Batch K-Means** - This algorithm is an extension to `K-Means`. This algorithm divides

the data into small random batches. The following samples are then randomly selected, clusters are then updated until they converge. While computing the clusters it minimizes the objective function. The mathematics behind the algorithm is very similar to K-Means except it subjects the data into random batches and is computationally faster.[9]

$$SSE = \sum_{i=1}^{K} \sum_{j \in C_m} dis(c_i, j)^2$$

Here, `k` represents cluster centers, c_i represents `i` centers, `j` represents sample points and `dis` is the Euclidean distance.

4. **K-Means** - This is one most popular algorithms used in unsupervised learning. This algorithm tries to satisfy a criterion by optimizing the division of data into `K` clusters. The initial step includes choosing the data to plot the focal points, then remaining data points are used to get the initial classification based on the criterion of minimizing the sum of squared distance between the points and the centroids i.e minimizing the Euclidean distance. Since it depends on choosing the initial points and sample data to form clusters it always changes with respect to the mentioned factor. It tries to find the local minima [10] [11]. Given as

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x}\text{-}\boldsymbol{\mu}_i\|^2$$

where `x` is the set of observations, μ_i is the mean of the cluster S_i.

5. **GMM(Gaussian Mixture Models)** - This approach is also similar to `K-Means` and in fact, this algorithm is used when K-Means fails to identify the data points in the overlapping clusters. Clusters are defined using mean, weight, and co-variance. Its parameters are trained using `Expectation - Maximization`. Instead of assigning the nearest cluster to the data points, Gaussian parameters for each cluster are calculated, and then based on these probabilities data points are assigned to the clusters [12]. Mathematically it is given as,

$$p(X) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k)$$

Here, $\mathcal{N}(x|\mu_k, \Sigma_k)$ represents cluster with mean μ_k, co-variance Σ_k and weights as π_k.

5.2.2 Tuning budget constraint(B)

In this section, steps to tune budget constraint is discussed.

1. Extract `Reward` and `Cost` from the function mentioned in Algorithm 1.

2. Identify number of clusters using `Silhouette` process.

3. Fit the data into the clustering algorithm.

4. Calculate the average of each cluster.

5. Identify and return the cluster having the highest reward and the lower bound of its corresponding range is the Budget constraint.

5.2.3 Tuning delta constraint(δ)

1. Using the cluster from the above section, iterate over all the points to calculate the highest rewarding building in the cluster.

2. Subtract the corresponding cost of the identified data point from the lower bound of the cluster, it is called δ constraint.

6 Results

6.1 Spatial Algorithm Findings

6.1.1 Meeting Rooms Objective

In this section, we will explain our findings of different buildings from the perspective of supply and demand analysis. We have used our previously described algorithm with the objective of finding $k-$best nearest buildings for booking a meeting room for different factors. We have completed the analysis for the following buildings where there is a high supply-demand problem:

- Doug McDonell Building, Parkville (168) - Appendix Table 7
- 11 Barry St, Parkville (266) - Appendix Table 8
- Law Building, Parkville (106) - Appendix Table 9
- David Penington Building, Parkville (102) - Appendix Table 10
- FBE Building, Parkville (105) - Appendix Table 11
- Medical Building, Parkville (181) - Appendix Table 12
- Elisabeth Murdoch Building, Southbank (860) - Appendix Table 13
- Werribee Pathology Building, Werribee (416) - Appendix Table 14

We will be summarising results for `Doug McDonell Building`, `David Penington Building` and `Elisabeth Murdoch Building` as discussed in the below section.

6.1.1.1 Doug McDonell Building (Parkville Campus)

As per our previous shown data analysis, this building is having the highest supply-demand problem as shown in the Figure 10.

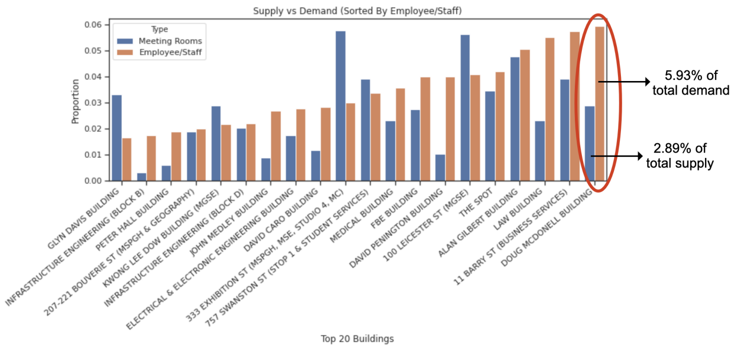


Figure 10: Supply vs Demand Problem in Doug McDonell Building

As per the above plot, we can expect that there is a high chance that staff members are not able to find adequate meeting rooms in this building. Hence, we used our algorithm to find other best nearest buildings from Doug McDonell Building based on the different factors as interpreted below.

- **Best nearby buildings with no preference:** As shown in the Appendix Table 7, a staff member needs to walk at least `302 metres` (Budget) from Doug McDonell Building to get rewarding buildings with an adequate supply of meeting rooms. We also suggest a relaxing budget (δ) of `96 metres` so that employee doesn't miss out a high supply providing building. Using these constraints, we suggest `University Health Services Building (385)` as the most rewarding building with the cost of `432 metres` as shown in the Figure 11.

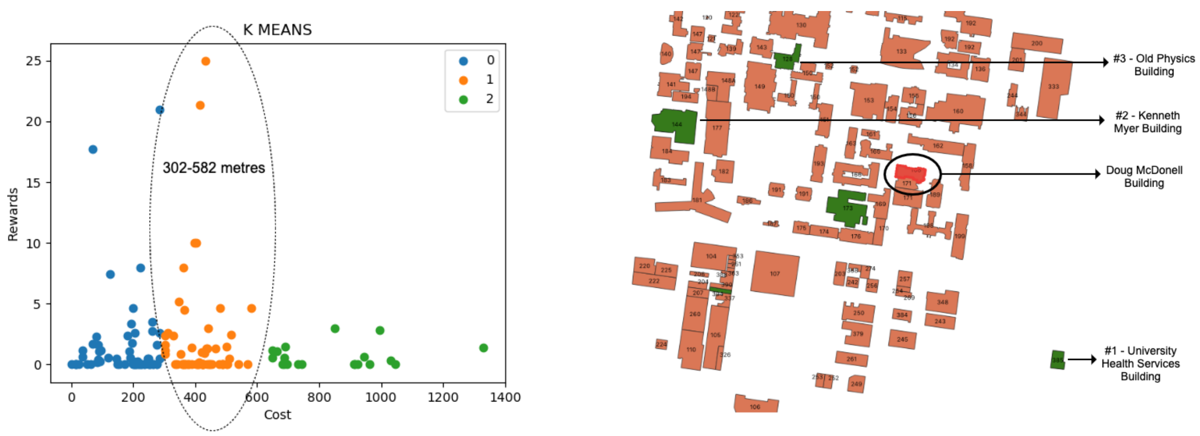


Figure 11: Best rewarding cluster (left) and 3 most optimal buildings from Doug McDonell (right)

- **Best nearby buildings under COVID-19 Strict Lockdown:** As shown in the Appendix Table 7 with COVID-19 strict factor, a staff member should be willing to walk at least `648 metres` (Budget) from Doug McDonell Building to get very high rewarding buildings under COVID-19 lockdown with the relaxing budget(δ) of at least `16 metres`. Using these constraints, we suggest `The Spot building (110)` as the most rewarding building with the cost of `501 metres` followed by `Alan Gilbert building (104)` with `353 metres`.

- **Best nearby buildings with other factors:** In the appendix Table 7, we have also shown other factors such as finding meeting rooms with equipment, excellent conditions and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `Kenneth Myer Building (173) - 414 metres` is the most rewarding building for meeting rooms with equipment and finding meeting rooms in excellent condition. `University Health Services Building (385) - 432 metres` is the most rewarding building for finding easily available meeting rooms.

  The results of some of the above-discussed factors are summarized below using clustering diagrams.

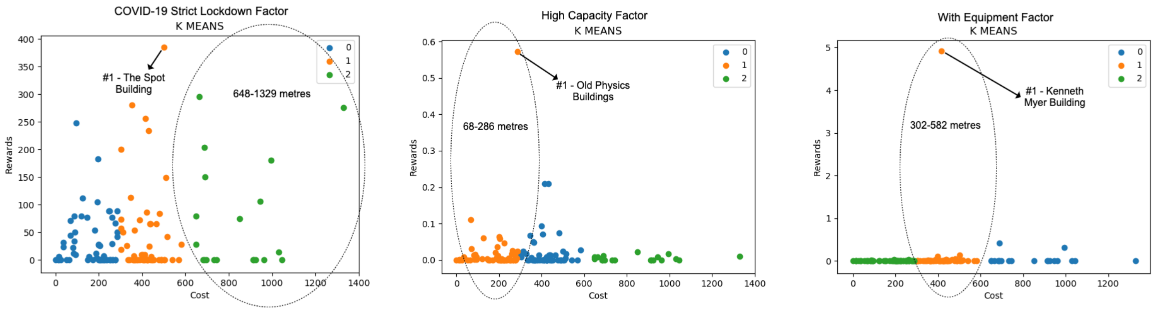


Figure 12: Best rewarding clusters of nearby buildings from Doug McDonell based on different factors

6.1.1.2 David Penington Building (Parkville Campus)

As per our previous shown data analysis, this building is having a supply-demand problem as shown in the Figure 13.

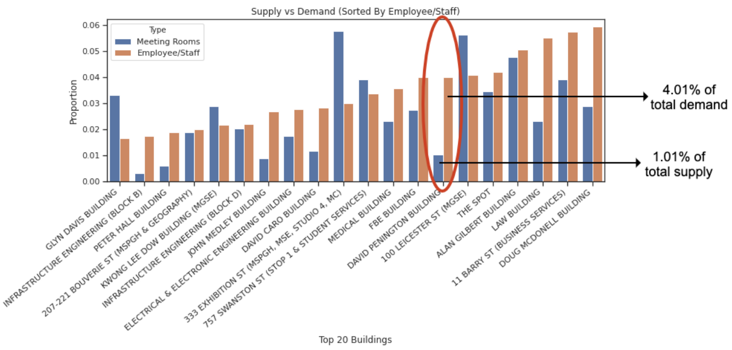


Figure 13: Supply vs Demand Problem in David Penington Building

- **Best nearby buildings with no preference:**

  As shown in the Appendix Table 10, a staff member needs to walk at least `439 metres` (Budget) from David Penington Building to get rewarding buildings with an adequate supply of meeting rooms. We also suggest a relaxing budget (δ) of `100 metres` so that employee doesn't miss out a high supply providing building. Using these constraints, we suggest `Kenneth Myer Building (144)` as the most rewarding building with the cost of `439 metres` as shown in the Figure 14.

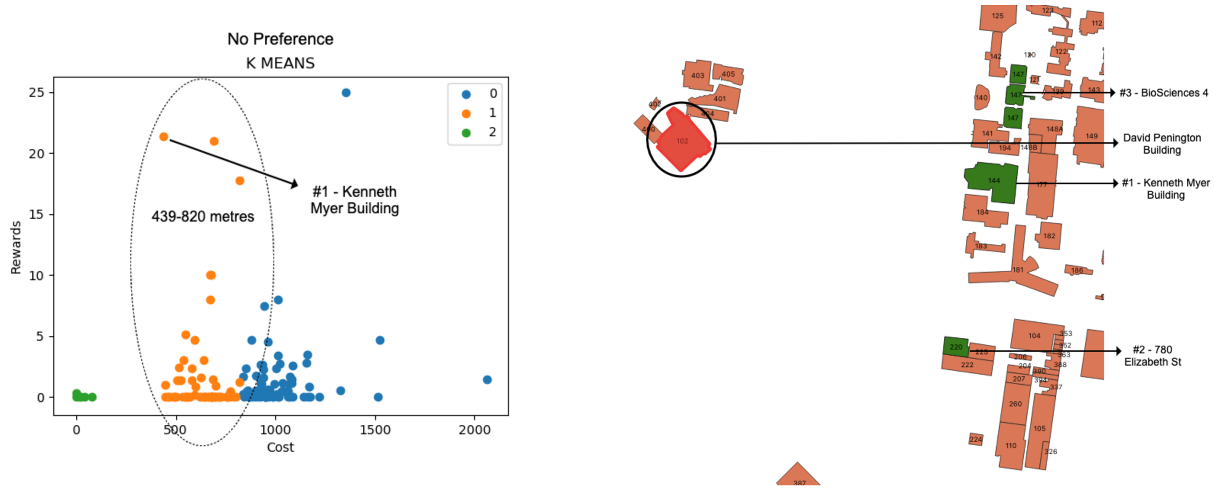


Figure 14: Best rewarding cluster (left) and 3 most optimal buildings from David Penington Building (right)

- **Best nearby buildings with high capacity:** As shown in the Appendix Table 10 with high capacity factor, a staff member can easily find a high supply of meeting rooms providing buildings from David Penington building within the budget of `690 metres`. Using these constraints, we suggest `Old Physics Buildings (128)` as the most rewarding building with the cost of `689 metres` followed by `Kenneth Myer Building (144)` with `439 metres` and `141 Barry St (390)` with `670 metres`.

- **Best nearby buildings with other factors:** In the appendix Table 7, we have also shown other factors such as COVID-19 lockdown, finding meeting rooms with equipment, excellent conditions and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `Kenneth Myer Building (173) - 439 metres` is the most rewarding building for meeting rooms with equipment and finding easily available rooms. `The Spot Building (385) - 685 metres` is the most rewarding building in the COVID-19 strict lockdown situation.

The results of some of the above-discussed factors are summarized below using clustering diagrams.

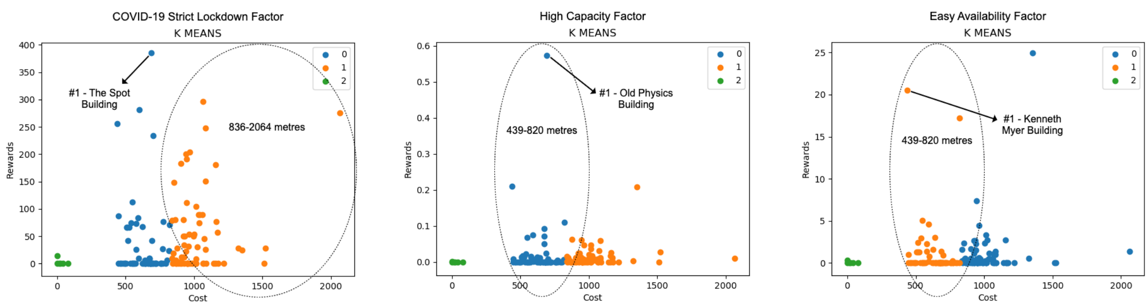


Figure 15: Best rewarding clusters of nearby buildings from David Penington Building based on different factors

6.1.1.3 Southbank Elisabeth Murdoch Building (Southbank Campus)

As per our previous shown data analysis, this is another building which is having supply-demand problem as shown in the Figure 16.

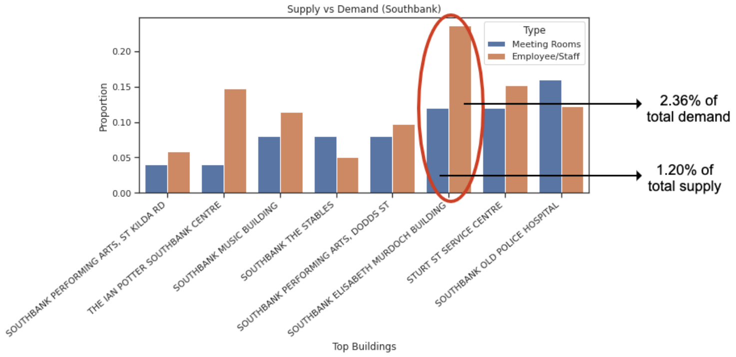


Figure 16: Supply vs Demand Problem in Southbank Elisabeth Murdoch Building

- **Best nearby buildings with no preference:** As shown in the Appendix Table 13, a staff member needs to walk at least `130 metres` (Budget) from Elisabeth Murdoch Building to get rewarding buildings with an adequate supply of meeting rooms. Using these constraints, we suggest `Southbank old police hospital (865)` as the most rewarding building with the cost of `109 metres` as shown in the Figure 17.

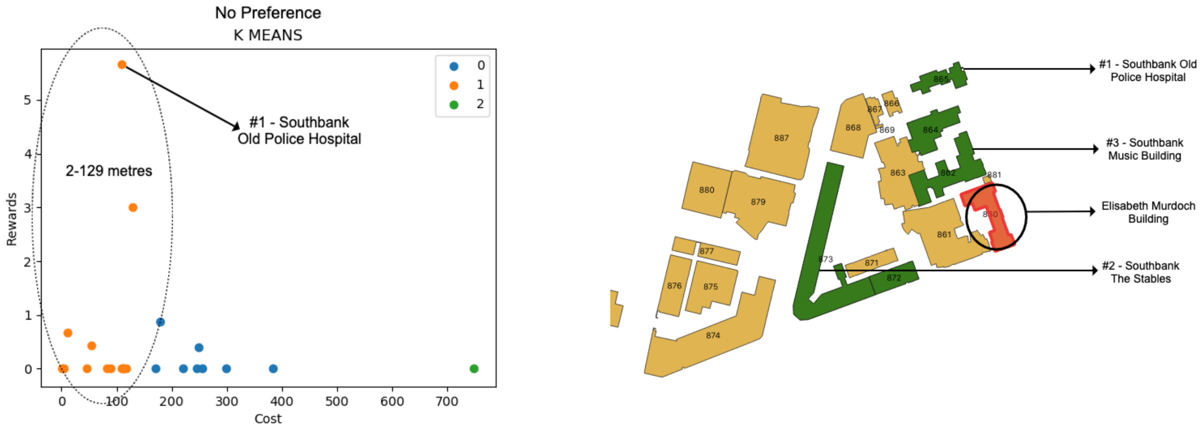


Figure 17: Best rewarding cluster (left) and 3 most optimal buildings from Elisabeth Murdoch Building (right)

- **Best nearby buildings under COVID-19 Strict Lockdown:** As shown in the Appendix Table 13 with COVID-19 strict factor, a staff member should be willing to walk at least `130 metres` (Budget) from Elisabeth Murdoch Building to get very high rewarding buildings under COVID-19 lockdown. Using these constraints, we again suggest `Southbank old police hospital (865)` as the most rewarding building with the cost of `109 metres` followed by `Southbank music building (862)` with `10 metres` cost.

- **Best nearby buildings with other factors:** In the appendix Table 13, we have also shown other factors such as finding meeting rooms with equipment, excellent conditions and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `Ian potter Southbank centre (880) - 248 metres` is the most rewarding building for meeting rooms with equipment. `Southbank old police hospital (865)` remains as the most rewarding building for finding easy available, excellent condition and high capacity meeting rooms.

6.1.2 Toilet Facilities Objective

In this section, we will explain our findings of different buildings from the perspective of supply and demand analysis. We have completed the analysis for the following buildings where there is a high supply-demand problem:

- Redmond Building, Parkville (115) - Appendix Table 16
- The Spot Building, Parkville (110) - Appendix Table 17
- Glyn Davis Building, Parkville (133) - Appendix Table 18
- Old Arts Building, Parkville (149) - Appendix Table 19
- Medical Building, Parkville (181) - Appendix Table 20
- The Ian Potter South Bank Centre Building, Southbank (880) - Appendix Table 21
- Werribee Pathology Building, Werribee (416) - Appendix Table 22

We will be summarising results for `Redmond Barry Building`, `The Spot Building`, `Ian Potter Centre Building` and `Werribee Pathology Building`as discussed in the below section.

6.1.2.1 Redmond Barry Building (Parkville Campus)

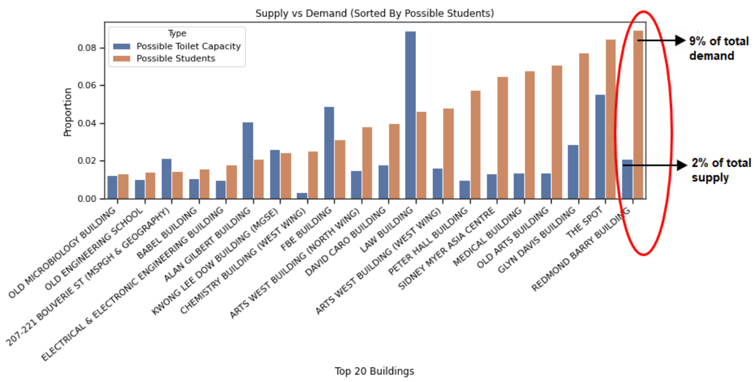


Figure 18: Supply vs Demand Problem in Redmond Barry Building

From the above plot, it can be seen that there is a high chance the students might not be able to find toilet facilities in the mentioned building. Hence, by using the proposed algorithm, we find the nearest building from Redmond Barry building based on the different factors as explained below.

- **Best nearby buildings with no preference:** As given in the appendix Table 16, a student needs to walk at least `422` meters from Redmond Barry Building to use the toilet facilities with an adequate supply of the mentioned facilities. The results also suggest a relaxing parameter (δ) of `186.24` meters so that the students can do not miss out on a highly rewarding building. Using these constraints, it suggests that `OLD PHYSICS BUILDING (128)` the most rewarding building with the cost of `189.14` meters as shown in Figure 19.

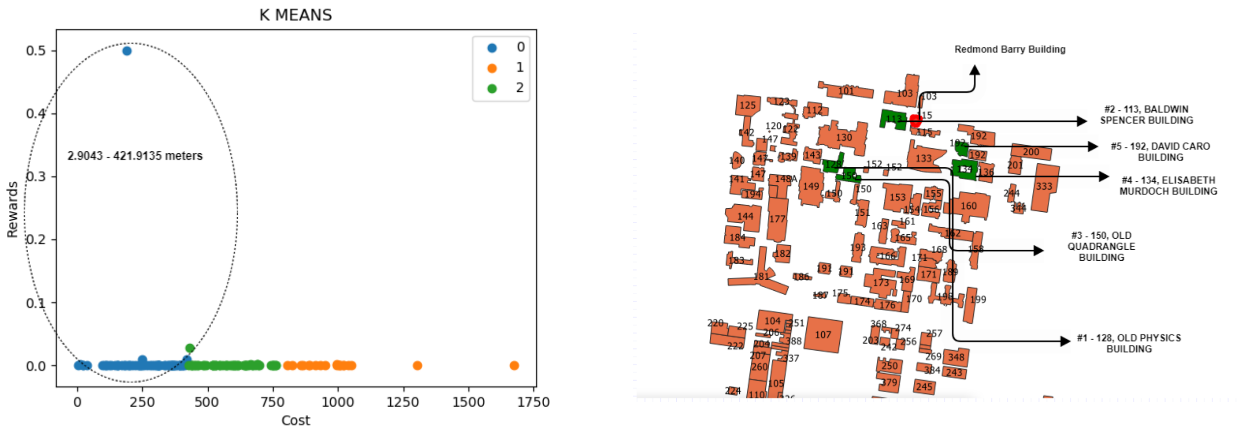


Figure 19: Best rewarding cluster (left) and 3 most optimal buildings from Redmond Barry Building (right)

- **Best nearby buildings with Good Toilet Room Conditions:** In the appendix Table 16, we have room condition as one of the factors with its budget and relaxing budgets. Using this data, we suggest that a student should walk at least `2.9043` meters to get to the rewarding building and the relaxing parameter would get a student to an even more rewarding building if a student decides to walk `186.24` meters from the current building. The most rewarding building is `Old Physics Building (128)` and followed by `Baldwin Spencer (113), David Caro (192) buildings` in order with costs `11.78,103.28,96.91,144.02` meters.

- **Best nearby buildings with other factors:** In the appendix Table 16, we have also shown other factors such as finding toilet rooms with high capacity, strict covid-19 lockdown, and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `Old Physics Building (128) - 189.14 meters` is the most rewarding building for toilets with high capacity and for finding toilets which are easily available and using the results mentioned in the table, it is seen that `The Law Building(106)` has the highest reward with `822.75` meters as the cost.

  The results of some of the above-discussed factors are summarized below using clustering diagrams.

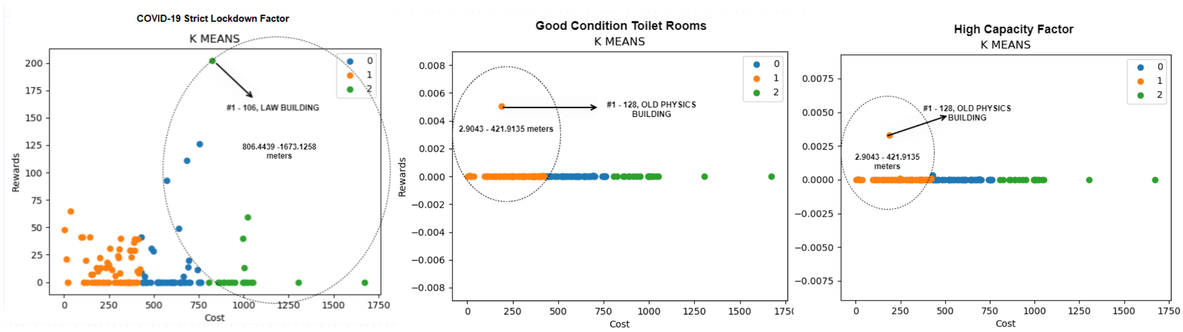


Figure 20: Best rewarding clusters of nearby buildings from Redmond Barry Building based on different factors

6.1.2.2 The Spot Building (Parkville Campus)

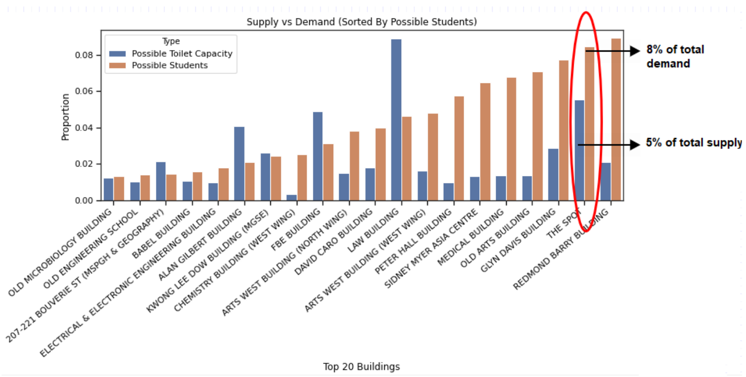


Figure 21: Supply vs Demand Problem in The Spot Building

- **Best nearby buildings with no preference:** As given in the appendix Table 17, a student needs to walk just `356.38` meters from The Spot Building to use the toilet facilities with an adequate supply of the mentioned facilities. The results also suggest a relaxing parameter (δ) of `199.29` meters so that the students can do not miss out on a high rewarding building. Using these constraints, it suggests that `OLD PHYSICS BUILDING (128)` is the most rewarding building with the cost of `555.68` meters, as shown in Figure 22.

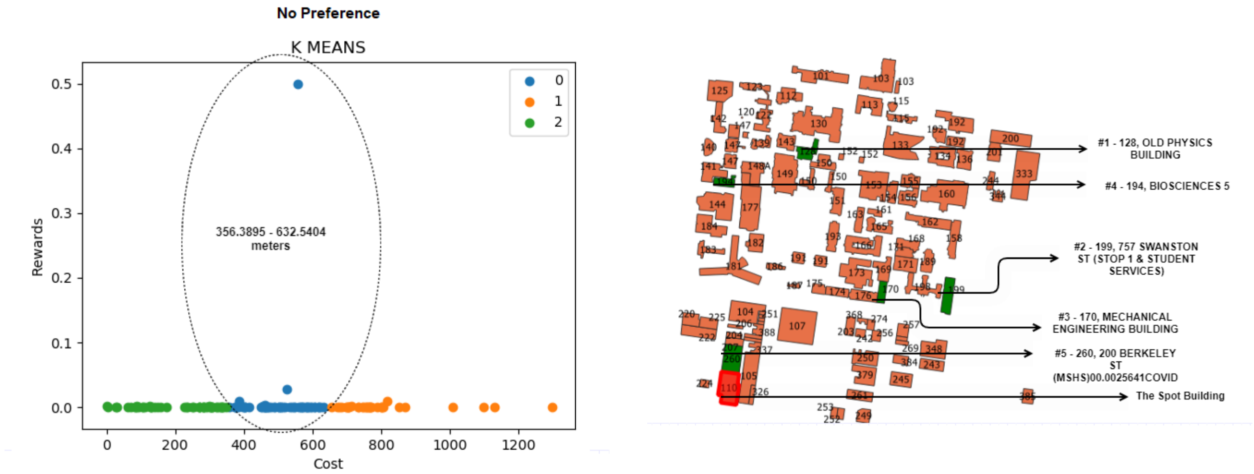


Figure 22: Best rewarding cluster (left) and 3 most optimal buildings from The Spot Building (right)

- **Best nearby buildings under COVID-19 Strict Lockdown:** As given in the appendix Table 17 with COVID-19 strict factor, a student should be willing to walk at least `348` meters from the mentioned building to be able to get to the buildings having an adequate supply of toilet facilities. Using the above budget, `The Law Building` is the most rewarding building with the cost of 86.79 metres.

- **Best nearby buildings with other factors:** In the appendix Table 20, we have also shown other factors such as finding toilet rooms with high capacity with their budgets and relaxing budgets. Using those constraints, we suggest that `Old Physics Building (128) - 555.68 meters` is the most rewarding building for toilets with high capacity. The `Law Building (106)` has the highest reward with `86.79` meters as the cost for excellent toilet room condition and `The Spot building` within the budget of `357` metres.

  The results of some of the above-discussed factors are summarized below using clustering diagrams.

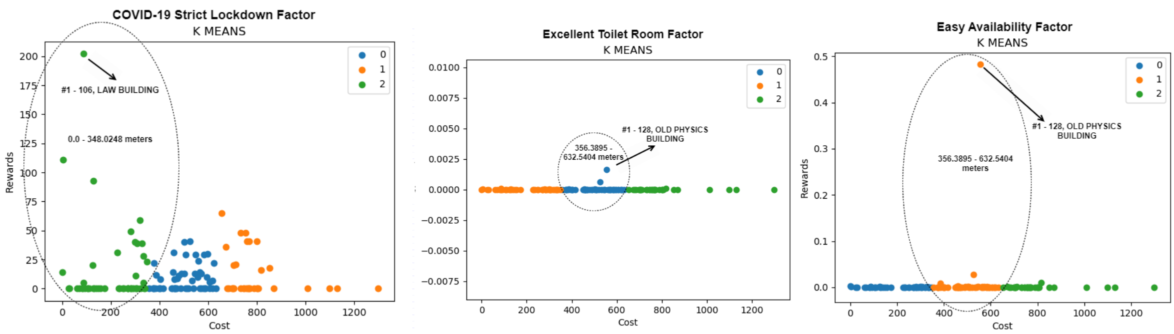


Figure 23: Best rewarding clusters of nearby buildings from The Spot Building based on different factors

6.1.2.3 Ian Potter Southbank Centre Building (Southbank Campus)

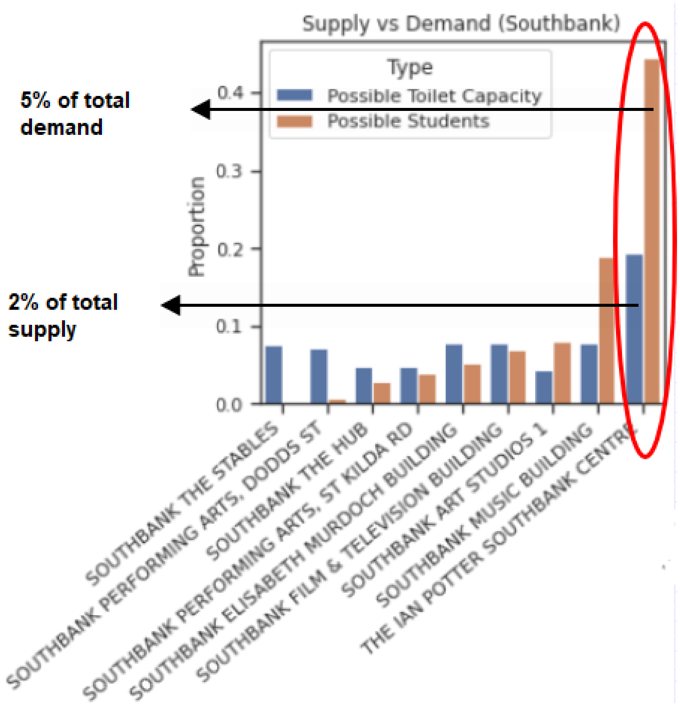


Figure 24: Supply vs Demand Problem in The Ian Potter Southbank Centre Building

- **Best nearby buildings with no preference:** As given in the appendix Table 21, a student needs to walk just at least `114` meters from Ian Potter Southbank Centre Building to use the toilet facilities with adequate supply of the mentioned facilities. Using the above budget, it suggests that `The Stables (873)` is the most rewarding building with the cost of `97.82` meters, as shown in Figure 25

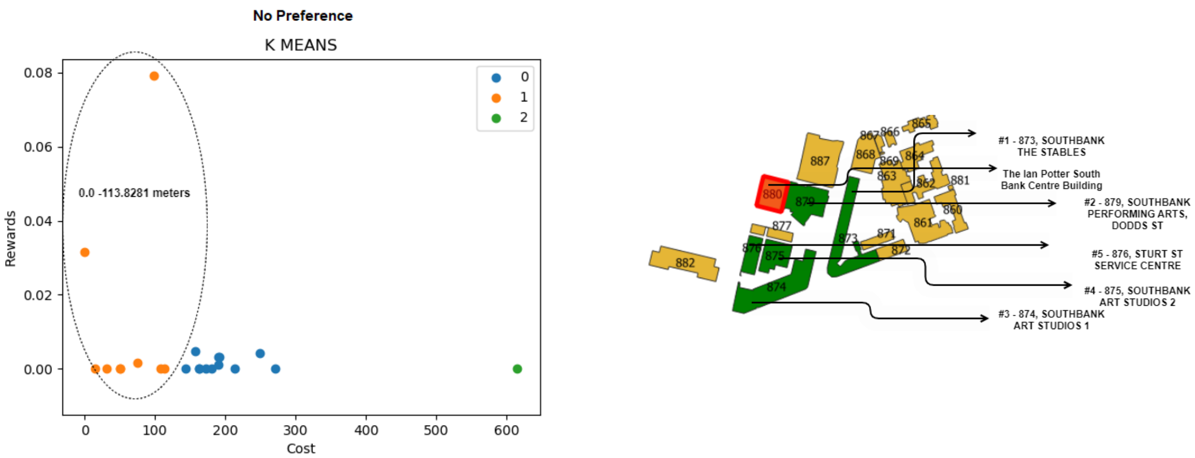


Figure 25: Best rewarding cluster (left) and 3 most optimal buildings from The Ian Potter Southbank Centre Building (right)

- **Best nearby buildings under COVID-19 Strict Lockdown:** As given in the appendix Table 21 with COVID-19 strict factor, a student should be willing to walk `143.56` meters from the mentioned building to be able to get to the buildings having an adequate supply of toilet facilities. A relaxation parameter (δ) of `46.1` meters could help a student to find a high rewarding building. Using the results mentioned in the table, it is seen that the `Music Building (862)` has the highest reward with `189.67` meters as the cost.

- **Best nearby buildings with other factors:** In the appendix Table 21, we have also shown other factors such as finding toilet rooms with high capacity, good toilet condition, with their budgets and relaxing budgets. Using those constraints, we suggest that `The Stables Buildings (873) - 97.82 meters` is the most rewarding building for toilets with high capacity, easy availability, and good conditions.

  The results of some of the above-discussed factors are summarized below using clustering diagrams.

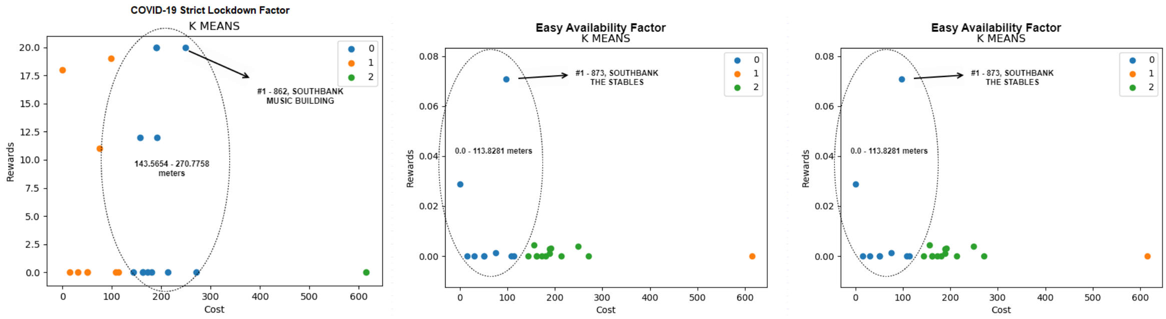


Figure 26: Best rewarding clusters of nearby buildings from The Ian Potter Southbank Centre Building based on different factors

6.2 Floor Algorithm Findings

6.2.1 Meeting Rooms Objective

In this section, we will explain our findings for buildings across different campuses. As per our previous shown data analysis, buildings with the supply-demand problems as shown in the below figure are analyzed. Those buildings are also chosen because of their higher floor levels. Hence, we have a better prediction when different factors are incorporated. We have completed the analysis for the following buildings:

- Doug McDonell Building, Parkville (168) - Appendix Table 24
- Alan Gilbert Building, Parkville (104) - Appendix Table 25
- Law Building, Parkville (106) - Appendix Table 26
- Stop 1 Building, Parkville (199) - Appendix Table 27
- 100 Leicester St, Parkville (278) - Appendix Table 28
- Glyn Davis Building, Parkville (133) - Appendix Table 29

- Elisabeth Murdoch Building, Southbank (860) - Appendix Table 30
- Werribee Veterinary Hospital, Werribee (411) - Appendix Table 31

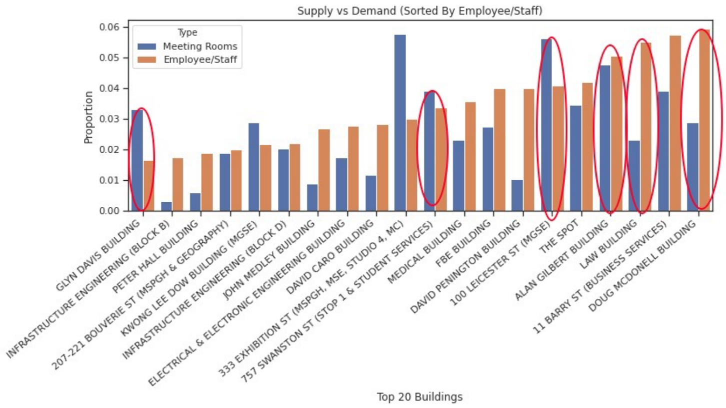


Figure 27: Supply vs Demand Problem in Parkville Campus

6.2.1.1 Alan Gilbert Building (Parkville Campus)

In this section, we will explain our findings of Alan Gilbert Building from the perspective of supply and demand analysis.

- **Best nearby floors with no preference:** As shown in the Appendix Table 25, a staff member needs to walk at least `1 level` (Budget) in Alan Gilbert Building to get rewarding floors with an adequate supply of meeting rooms. We also suggest a relaxing budget (δ) of `3 levels` so that employee doesn't miss out on a high supply providing floors. Using these constraints, we suggest `level 5` as the most rewarding floor with the cost of `4 floors` followed by `level 4` with `3 floors` and `level 2` with `1 floor` as shown in the Figure 28.

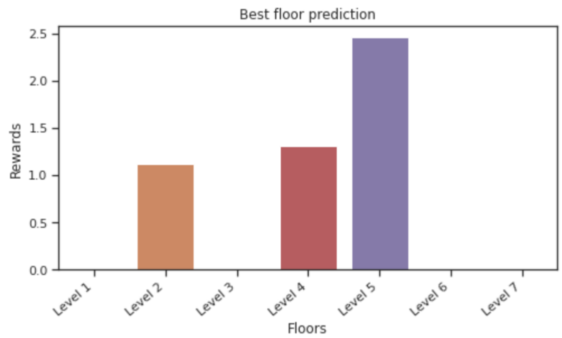


Figure 28: Best rewarding floors from Alan Gilbert

- **Best nearby floors under COVID-19 Strict Lockdown:** As shown in the Appendix Table 25 with COVID-19 high factor, a staff member needs to walk at least `1 level` (Budget) in Alan Gilbert Building to get rewarding floors under COVID-19 lockdown with the relaxing budget (δ) of `3 levels` so that employee doesn't miss out a high supply providing floors. Using these constraints, we suggest `level 5` as the most rewarding floor with the cost of `4 floors` followed by `level 4` with `3 floors` and `level 2` with `1 floor` as shown in the Figure 29.

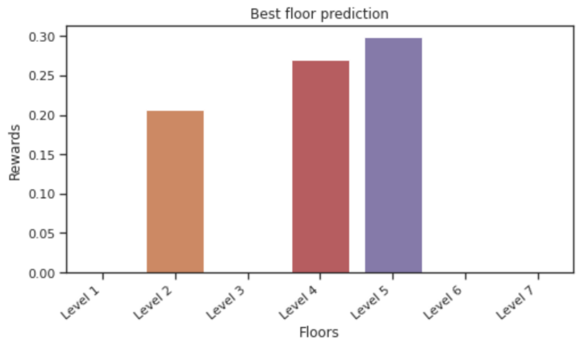


Figure 29: Best rewarding floors from Alan Gilbert with COVID lockdown

- **Best nearby floors with other factors:** In the appendix Table 25, we have also shown other factors such as finding meeting rooms with high capacity, equipment, and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `level 5` is the most rewarding floor for all those factors.

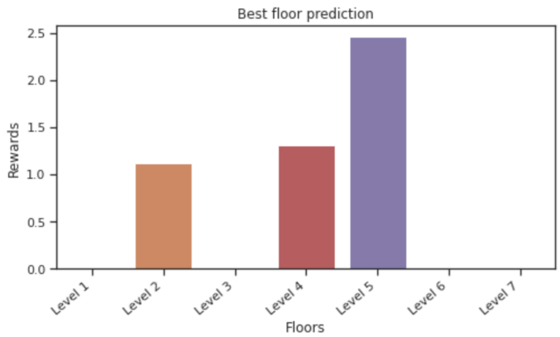


Figure 30: Best rewarding floors from Alan Gilbert with other factors

6.2.1.2 Law Building (Parkville Campus)

In this section, we will explain our findings of Law Building from the perspective of supply and demand analysis.

- **Best nearby floors with no preference:** As shown in the Appendix Table 26, a staff member needs to walk at least `1 level` (Budget) in Law Building to get rewarding floors with an adequate supply of meeting rooms. We also suggest a relaxing budget (δ) of `4 levels` so that employee doesn't miss out on a high supply providing floors. Using these constraints, we suggest `level 2` as the most rewarding floor with the cost of `1 floor` followed by `level 3` with `2 floors` and `level 6` with `5 floors` as shown in the Figure 31.

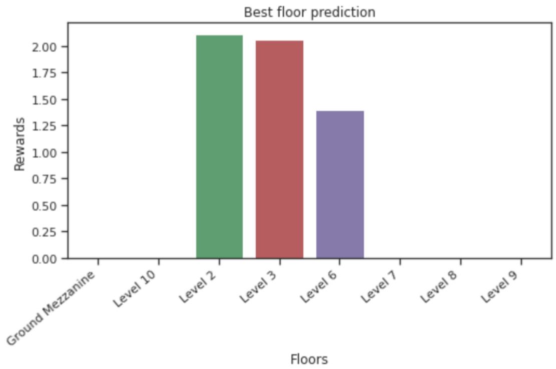


Figure 31: Best rewarding floors from Law Building

- **Best nearby floors with equipment:** As shown in the Appendix Table 26 with equipment factor, a staff member needs to walk at least `1 level` (Budget) in Law Building to get rewarding floors to have an excellent meeting room with a relaxing budget (δ) of `4 levels` so that employee doesn't miss out a high supply providing floors. Using these constraints, we suggest `level 6` as the most rewarding floor with the cost of `5 floors` followed by `level 2` with `1 floor` and `level 3` with `2 floors` as shown in the Figure 32.

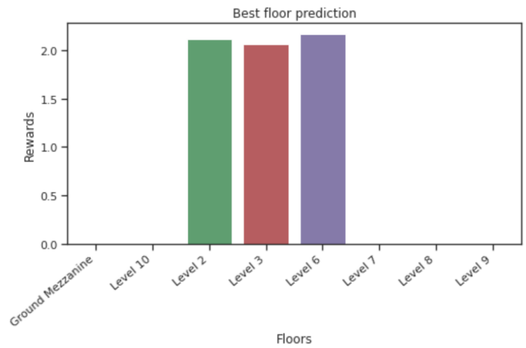


Figure 32: Best rewarding floors from Law with equipment

- **Best nearby floors with other factors:** In the appendix Table 26, we have also shown other factors such as finding meeting rooms with high capacity, excellent room condition, and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `level 2` is the most rewarding floor for all those factors.

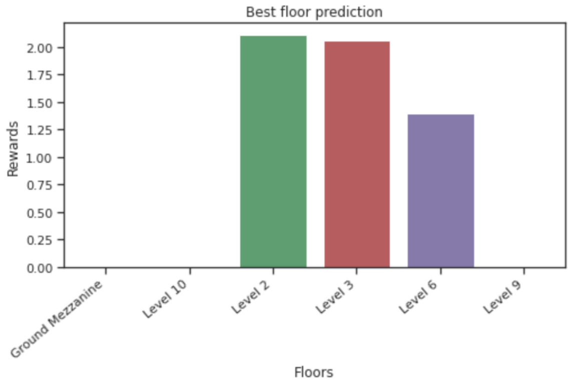


Figure 33: Best rewarding floors from Law with other factors

6.2.1.3 Elisabeth Murdoch Building (Southbank Campus)

In this section, we will explain our findings of Elisabeth Murdoch Building from the perspective of supply and demand analysis.

- **Best nearby floors with no preference:** As shown in the Appendix Table 30, a staff member needs to walk at least `1 level` (Budget) in Elisabeth Murdoch Building to get rewarding floors with an adequate supply of meeting rooms. We also suggest a relaxing budget (δ) of `1 level` so that employee doesn't miss out a high supply providing floors. Using these constraints, we suggest `level 3` as the most rewarding floor with the cost of `2 floors` followed by `level 2` with `1 floor` as shown in the Figure 34.

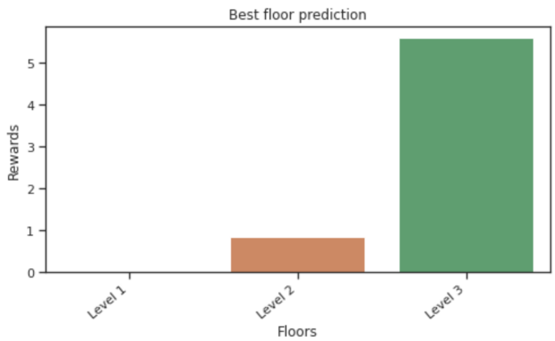


Figure 34: Best rewarding floors from Elisabeth Murdoch Building

- **Best nearby floors with equipment:** As shown in the Appendix Table 30 with equipment factor, a staff member needs to walk at least `1 level` (Budget) in Elisabeth Murdoch Building to get rewarding floors to have an excellent meeting room with the relaxing budget (δ) of `1 level` so that employee doesn't miss out a high supply providing floors. Using these constraints, we suggest `level 2` as the most rewarding floor with the cost of `1 floor` followed by `level 3` with `2 floors` as shown in the Figure 35.

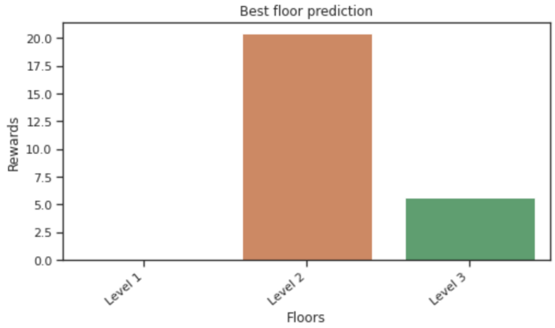


Figure 35: Best rewarding floors from Elisabeth Murdoch Building with equipment

- **Best nearby floors with other factors:** In the appendix Table 30, we have also shown other factors such as finding meeting rooms with high capacity, excellent room condition, and easy availability with their budgets and relaxing budgets. Using those constraints, we suggest that `level 3` is the most rewarding floor for all factors.

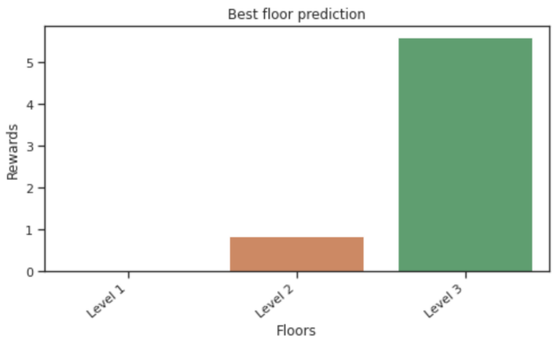


Figure 36: Best rewarding floors from Elisabeth Murdoch Building with other factors

6.2.2 Toilet Facilities Objective

In this section, we will explain our findings for buildings across different campuses. As per our previous shown data analysis, buildings with a supply-demand problem as shown in the Figure 37 will be explored. We have completed the analysis for the following buildings where there is a supply-demand problem:

- Redmond Barry Building, Parkville (115) - Appendix Table 32
- The Spot, Parkville (110) - Appendix Table 33
- Glyn Davis Building, Parkville (133) - Appendix Table 34
- Medical Building, Parkville (181) - Appendix Table 35
- David Caro Building, Parkville (192) - Appendix Table 36
- Old Microbiology, Parkville (184) - Appendix Table 37
- Ian Potter Southbank Centre Building, Southbank (880) - Appendix Table 38

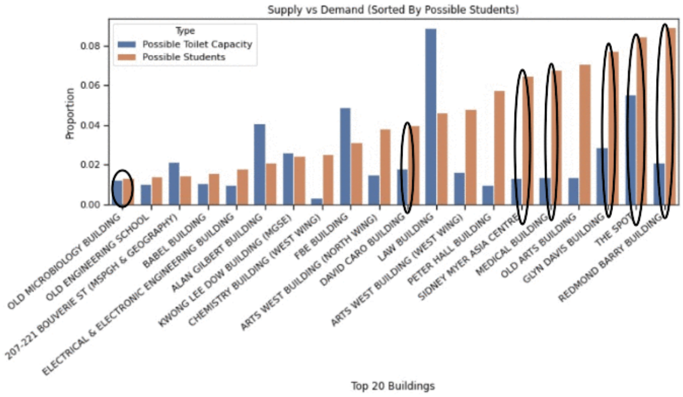


Figure 37: Supply vs Demand Problem in Parkville Campus

6.2.2.1 Medical Building (Parkville Campus)

This section discusses the findings with respect to Medical Building for supply and demand analysis, and the current location is set as `Level 5`.

- **Best nearby floors with no preference:** The Appendix Table 35 shows that a student needs to walk at least `1 level` in the building to get rewarding floors. It is also suggested that a relaxing parameter (δ) of `3` can help students find highly rewarding floors. The most rewarding floor is `Level 7` and followed by `Level 9, Level 2` in order with costs `2, 4, 3 floors`.

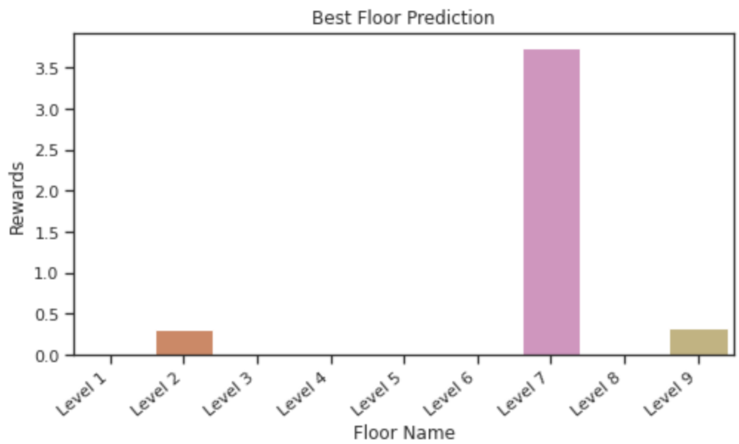


Figure 38: Best rewarding floors of Medical Building with no preference

- **Best nearby floors with high capacity:** From the Appendix Table 35, we find out that a student needs to walk at least `1 level` in the building to get rewarding floors with high capacity. It is also suggested that a relaxing parameter (δ) of `3` can help students find better rewarding floors. The result indicates that `Level 1` as the most rewarding floor with the cost of `4 floors` followed by `Level 7` with `2 floors` and `Level 9` with `4 floors` as shown in the Figure 39.

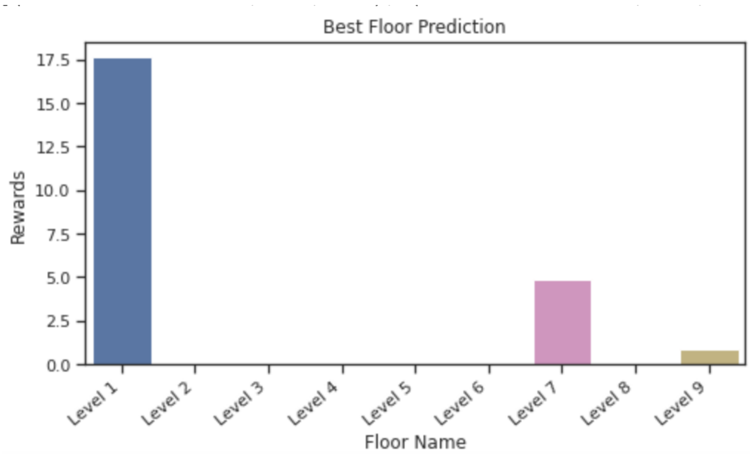


Figure 39: Best rewarding floors of Medical Building with high capacity

- **Best nearby floors with other factors:**

  Other factors are also evaluated in the Appendix Table 35, such as finding toilets with easy availability and under COVID-19 Strict Lockdown. Using those constraints, we suggest that `Level 7` is the most rewarding floor with finding toilets with easy availability, or under COVID-19 Strict Lockdown. These are summarized in the below figures.

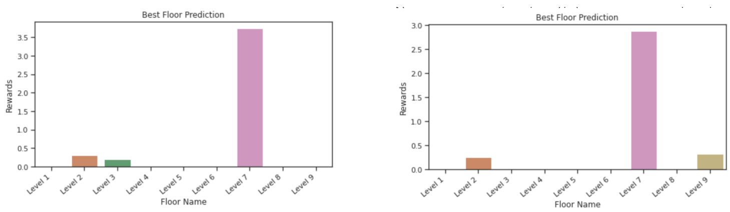


Figure 40: Best rewarding floors of nearby floors of Medical Building under COVID-19 Medium Lockdown (left) and easy availability (right)

6.2.2.2 David Caro Building (Parkville Campus)

This section discusses the findings of the David Caro Building for supply and demand analysis, and the current location is set as `Level 4`.

- **Best nearby floors with no preference:** The Appendix Table 36 shows that a student needs to walk at least `1 level` in the building to get rewarding floors. It is also suggested that a relaxing parameter (δ) of `1` can help students find highly rewarding floors. The most rewarding floor is `Level 1` and followed by `Level 3, Level 2` in order with costs `3, 1, 2 floors`.

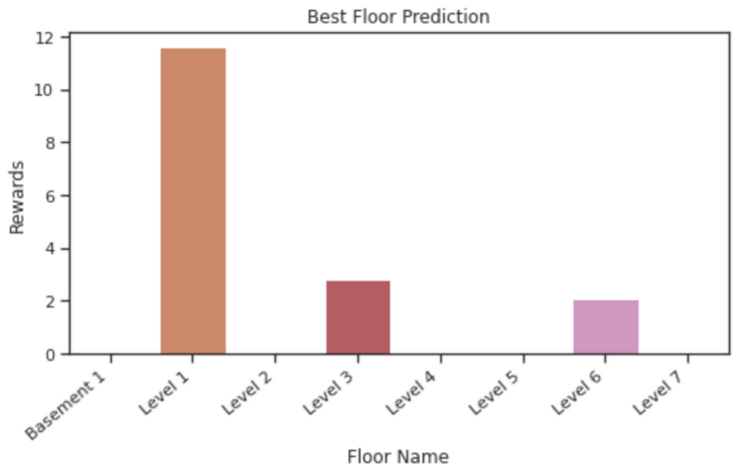


Figure 41: Best rewarding floors of David Caro Building with no preference

- **Best nearby floors under COVID-19 Strict Lockdown:** Under COVID-19 Strict Lockdown, we find out that a student needs to walk at least `1 level` in the building to get rewarding floors with a sufficient supply of toilets based on the Appendix Table 36. It is suggested that a relaxing parameter (δ) of `2` can help students find highly rewarding floors. The result indicates that `Level 2` as the most rewarding floor with the cost of `3 floors` followed by `Level 3` with `1 floor` and `Level 1` with `2 floors` as shown in the Figure 42.

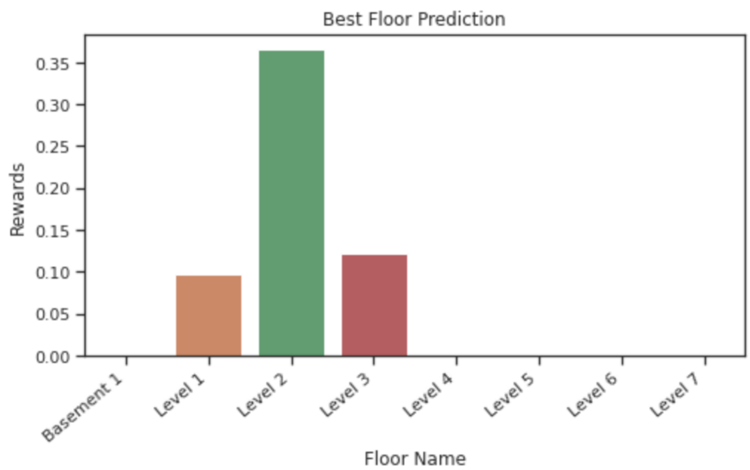


Figure 42: Best rewarding floors of David Caro Building under COVID-19 Strict Lockdown

- **Best nearby floors with other factors:** Other factors are also explored, such as finding toilets with easy availability, good condition, and high capacity. Using those constraints, we suggest that `Level 1` is the most rewarding floor with finding toilets with easy availability, or good condition. These are summarized in the below figures.

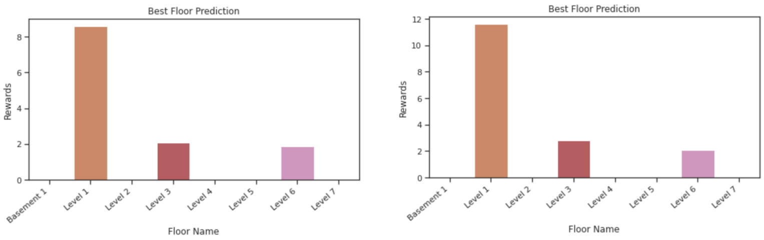


Figure 43: Best rewarding floors of nearby floors of David Caro Building with easy availability (left) and good condition (right)

6.2.2.3 Ian Potter Southbank Centre Building (Southbank Campus)

This section discusses the findings in terms of Ian Potter Southbank Centre Building for supply and demand analysis, and the current location is set as `Level 7`.

- **Best nearby floors with no preference:** The Appendix Table 38 shows that a student needs to walk at least `1 level` in the building to get rewarding floors. It is also suggested that a relaxing parameter (δ) of `2` can help students find highly rewarding floors. The most rewarding floor is `Level 5` and followed by `Level 4, Level 8` in order with costs `2, 3, 1 floors`.

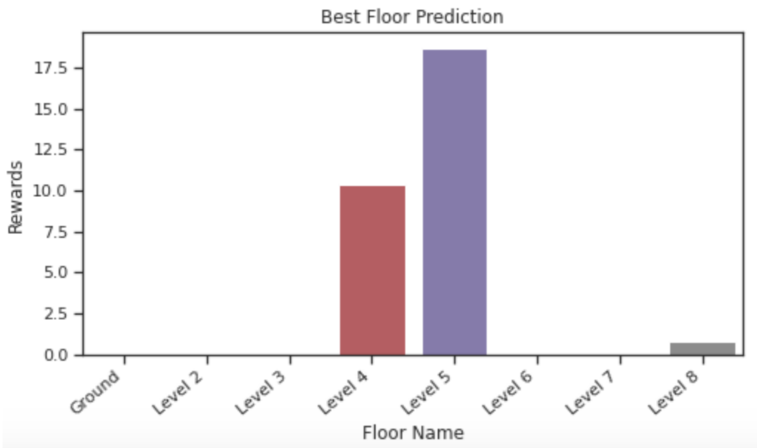


Figure 44: Best rewarding floors of Ian Potter SouthBank Centre Building with no preference

- **Best nearby floors with high capacity:** From the Appendix Table 38, we find out that a student needs to walk at least `1 level` in the building to get rewarding floors with high capacity. It is also revealed that a relaxing parameter (δ) of `2` can help students find highly rewarding floors. The result indicates that `Level 5` as the most rewarding floor with the cost of `2 floors` followed by `Level 4` with `3 floors` and `Level 3` with `4 floors` as shown in the Figure 45.

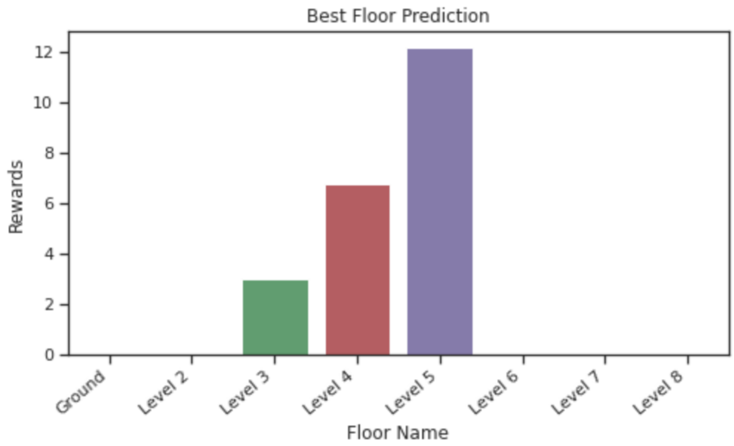


Figure 45: Best rewarding floors of Ian Potter SouthBank Centre Building with high capacity

- **Best nearby floors with other factors:** We have also shown other factors such as finding toilets under COVID-19 Medium Lockdown or with easy availability in the Appendix Table 38. Using those constraints, we suggest that `Level 5` is the most rewarding floor with finding toilets with high capacity, or excellent condition. These are summarized in the below figures.

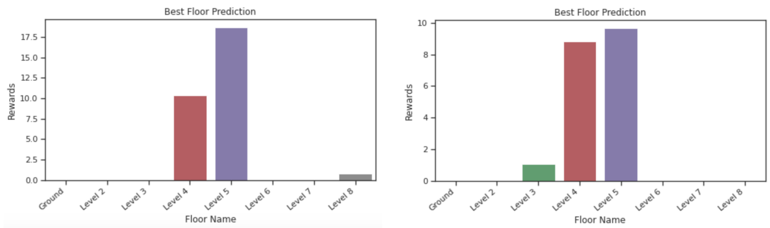


Figure 46: Best rewarding floors of nearby floors of Old Microbiology under COVID-19 Medium Lockdown (left) and easy availability (right)

6.3 Comparison of clustering algorithms

In this section, we will be comparing different clustering algorithms as discussed in the section 5.2.1. Although only a few results are shown here, they are enough to understand the motive behind choosing the algorithm that performs consistently. The buildings discussed are `Doug McDonell Building` and `Redmond Barry Building` for Meeting Room and Toilet Facilities respectively.

6.3.1 Doug McDonell Building (Parkville Campus) - Meeting Rooms

As shown in the Appendix Table 15, it can be seen that although the budget constraint is the same for KMEANS and MINI KMEANS, the rewards for both the algorithms are different. While the KMEANS result is consistent, whereas the results for MINI KMEANS vary because of the randomness it introduces while selecting the data. Hence the average reward for KMEANS is `2.07` in both the iterations but it changes from `1.91` to `2.07` for MINI KMEANS. Figure 47 and 48 shows the clustering output by various algorithms across 2 iterations.

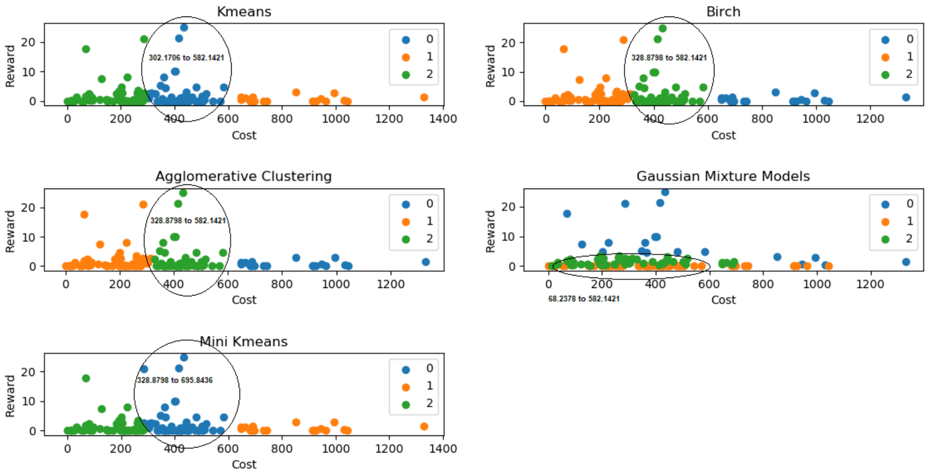


Figure 47: Comparison of clustering algorithms: Iteration 1

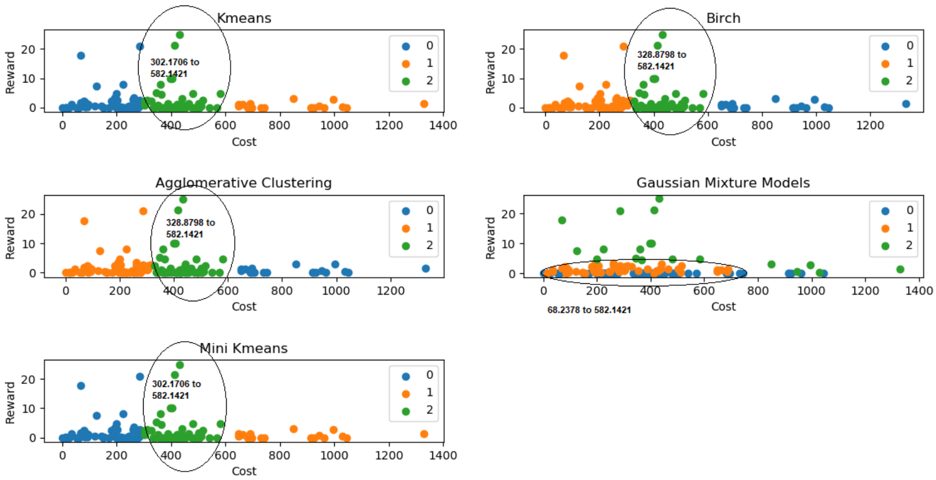


Figure 48: Comparison of clustering algorithms: Iteration 2

6.3.2 Redmond Barry Building (Parkville Campus) - Toilet Facility

As shown in the Appendix Table 23, it can be seen that KMEANS and MINI KMEANS have similar rewards but the budget constraint changes for KMEANS are `3-422 meters` in both the iteration while for MINI KMEANS it changes from `3-431` meters to `3-443` meters. Figure 49 and 50 shows the clustering output by various algorithms across 2 iterations.

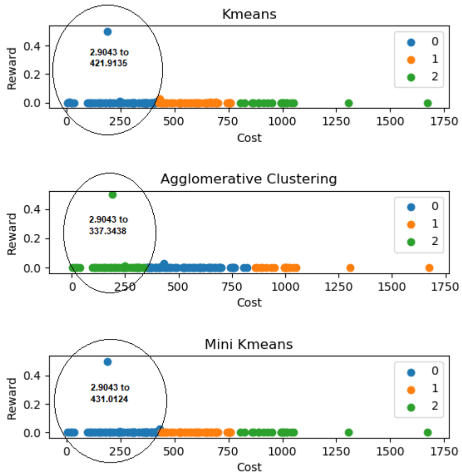


Figure 49: Comparison of clustering algorithms: Iteration 1

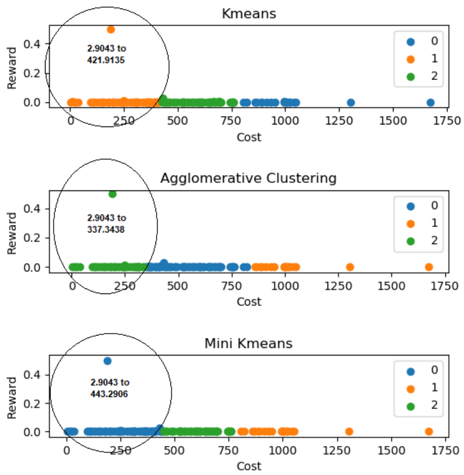


Figure 50: Comparison of clustering algorithms: Iteration 2

7 Algorithm Analysis

In this section, we will perform an analysis of certain important aspects and properties of our proposed algorithm with applications and limitations.

7.1 Algorithm Applications

Our proposed non-randomized algorithm can be extended beyond the field of solving this current problem. Some of the potential applications of our algorithm are:

- **Recommendation Systems:** The algorithm has the ability to recommend different entities based on cost and reward modelling. Using this modelling property, this algorithm can be used for recommending different types of information after proper data representation.

- **Efficient Resource Allocation:** This algorithm can be used to perform a deeper analysis of space with supply-demand knowledge which can enhance the resource allocation process. Utilising cost constraint, rewards can be distributed efficiently resulting in a more effective resource allocation.

- **Ability to map any domain-related orienteering problem:** Our reward function can be enhanced to include any domain-related factors. This gives our algorithm the ability to work in any domain as the working only needs proper modelling of cost and reward functions. After proper modelling, our algorithm is mature enough to predict the required results with a great execution speed.

7.2 Algorithm Data Requirements

Our proposed algorithm is highly dependent on the provided quality of the data for getting unbiased and appropriate predicted results. As shown in the Figure 51, if provided data is imbalanced or missing, then the algorithm will most likely take the building as the most rewarding for which data is properly provided leading to biased results. Due to this, `Knowg Lee Dow Building` is usually picked as the answer for meeting rooms with equipment since the data is not properly provided for the other buildings. In contrast, if data is properly provided, then results are unbiased as other buildings are having the chance to compete in the rewards-based selection process.

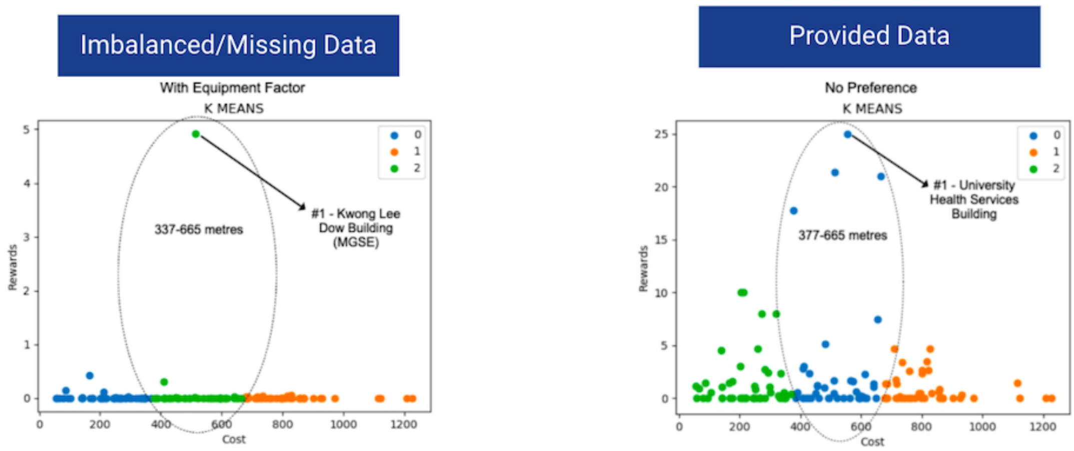


Figure 51: Algorithm data requirements

7.3 Limitations of the Algorithm

Our algorithm relies on the assumption that the graph is a specialized weighted directed graph with one central node (0 in-degree and n out-degree) and n isolated nodes connected with only one central node. Due to this assumption, the algorithm is efficient and applicable only for such versions of the specialized graph and cannot be extended implicitly to any general weighted directed graph.

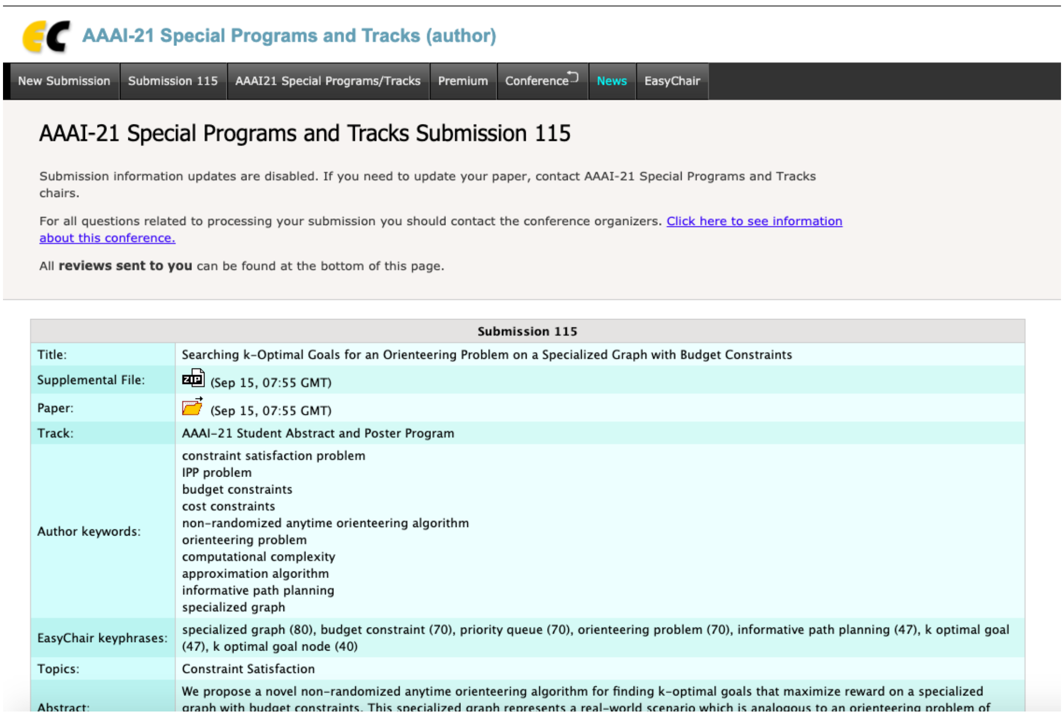
8 Conclusion & Achievements

In this report, we have analyzed the supply and demand of meeting rooms and toilet facilities for different campuses across the University of Melbourne based on our Non-randomized Anytime Orienteering Algorithm. To meet different requirements and situations when either a meeting room or a toilet facility is needed, we introduced different factors in our algorithm. Therefore, it will find the best results depending on the specific needs.

We have done researches on the most demanding buildings and have obtained desirable results. When different factors such as COVID-19 lockdown, easy availability, and high capacity are incorporated, we can get different advice from our algorithm to guide us to find the best buildings and floors. `Doug McDonell Building` is a good example here. With no preference provided, `University Health Services Building`, `Kenneth Myer Building`, and `Old Physics Building` are the most rewarding buildings to book a meeting room.

Hence, when different requirements were passed to our algorithm, we can find the most suitable buildings for university staff who wants to book a meeting room or a student who wants to use toilet facility in the nearby buildings or even within the building that can meet those requirements. `University Spatial Analytics and Space Management` department can use this information to plan and allocate meeting room and toilet resources efficiently to better utilize them without occurring extra expenses.

As an achievement, we submitted our novel algorithm as a research paper[9.4] in AAAI 21 student abstract program's constraint satisfaction problem track as shown below.


AAAI-21 Special Programs and Tracks (author)

New Submission | Submission 115 | AAAI21 Special Programs/Tracks | Premium | Conference | News | EasyChair

AAAI-21 Special Programs and Tracks Submission 115

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All **reviews sent to you** can be found at the bottom of this page.

Submission 115	
Title:	Searching k-Optimal Goals for an Orienteering Problem on a Specialized Graph with Budget Constraints
Supplemental File:	(Sep 15, 07:55 GMT)
Paper:	(Sep 15, 07:55 GMT)
Track:	AAAI-21 Student Abstract and Poster Program
Author keywords:	constraint satisfaction problem IPP problem budget constraints cost constraints non-randomized anytime orienteering algorithm orienteering problem computational complexity approximation algorithm informative path planning specialized graph
EasyChair keyphrases:	specialized graph (80), budget constraint (70), priority queue (70), orienteering problem (70), informative path planning (47), k optimal goal (47), k optimal goal node (40)
Topics:	Constraint Satisfaction
Abstract:	We propose a novel non-randomized anytime orienteering algorithm for finding k-optimal goals that maximize reward on a specialized

Figure 52: AAAI 21 Student Abstract Program Submission

Unfortunately, our submission was not selected but we received valuable feedback that can be used for continuing research on this problem. In the end, we successfully published our research in the Cornell arXiv as shown with the link below.

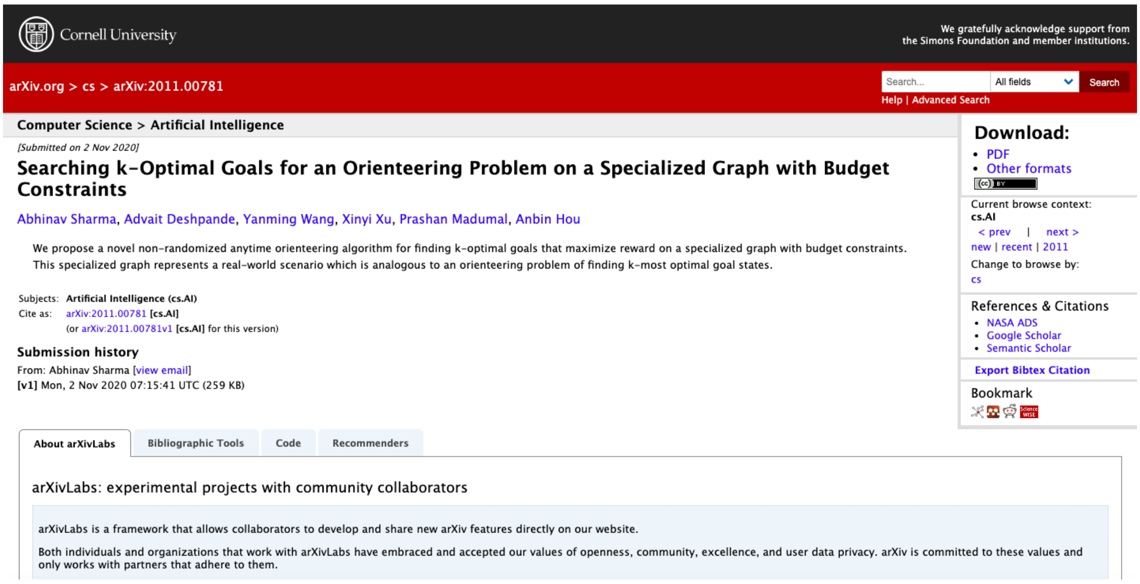

Figure 53: Research published in arXiv: `https://arxiv.org/abs/2011.00781`

In conclusion, our non-randomized anytime orienteering algorithm is not limited to solve the spatial optimization problem only as it is a generalized algorithm that can be expanded to other areas as well. This will require further studies.

9 Appendix

9.1 Project Management

In this section, we will be explaining how we have maintained part-1 and part-2 of the project using GitHub. We have used the concept of branches, issues, pull requests, and Kanban board using GitHub projects to track and maintain progress throughout the project.

9.1.1 GitHub Project Repository

We have maintained our entire project using the following GitHub repository:

`https://github.com/abhinavcreed13/project-space-optimisation-group-3`

This repository was kept private and the access was shared with our supervisor Prashant Madumal (@prashanm) and our client Anbin Hou (@anbinhou). With the approval of our client, we have deleted the sensitive data and repository is made public for evaluation purposes.

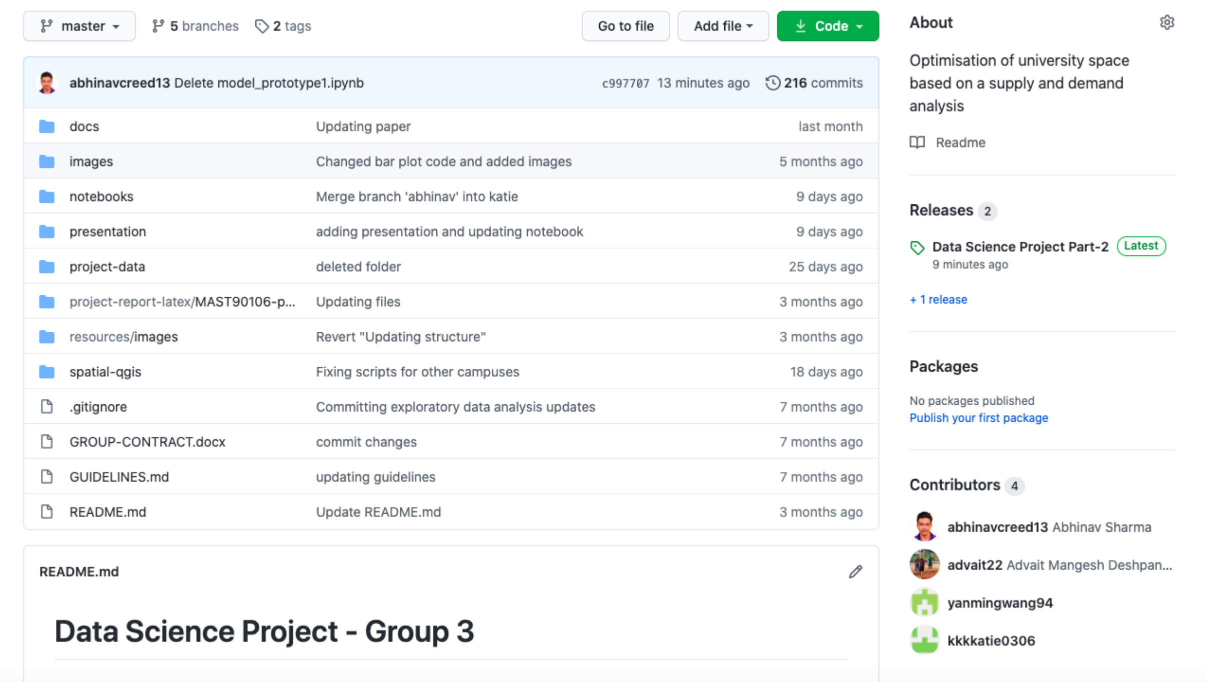

Figure 54: Project's GitHub Repository with tagged releases

The code and contributions in this repository are maintained using the concept of branching which is heavily used in this project as shown in the figure below.

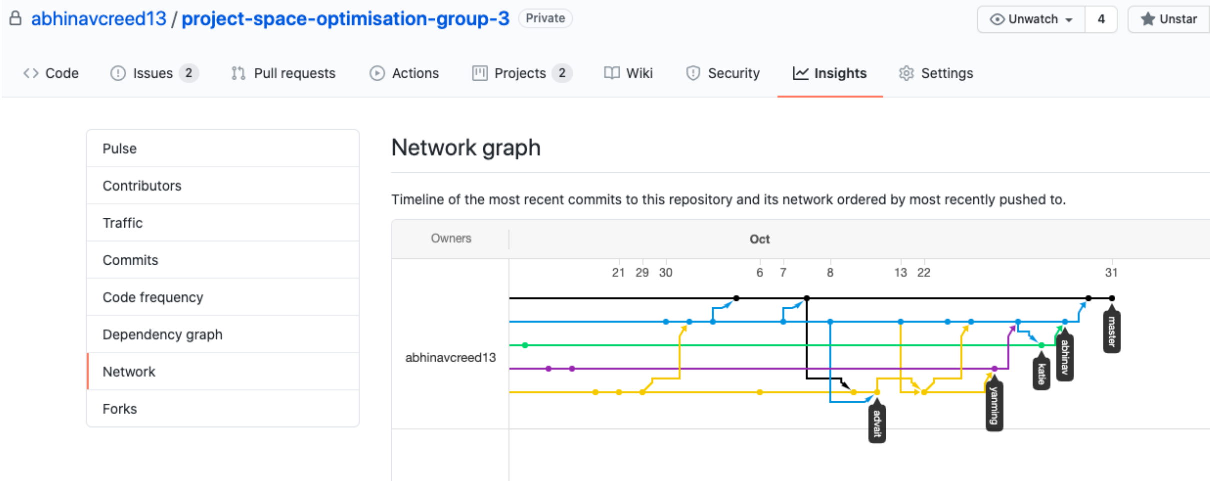

Figure 55: GitHub branching concept for effective work distribution and contribution

These individual person's branches are effectively merged across each other throughout the project to keep progress in sync using the pull requests feature of GitHub as shown in the figure below.

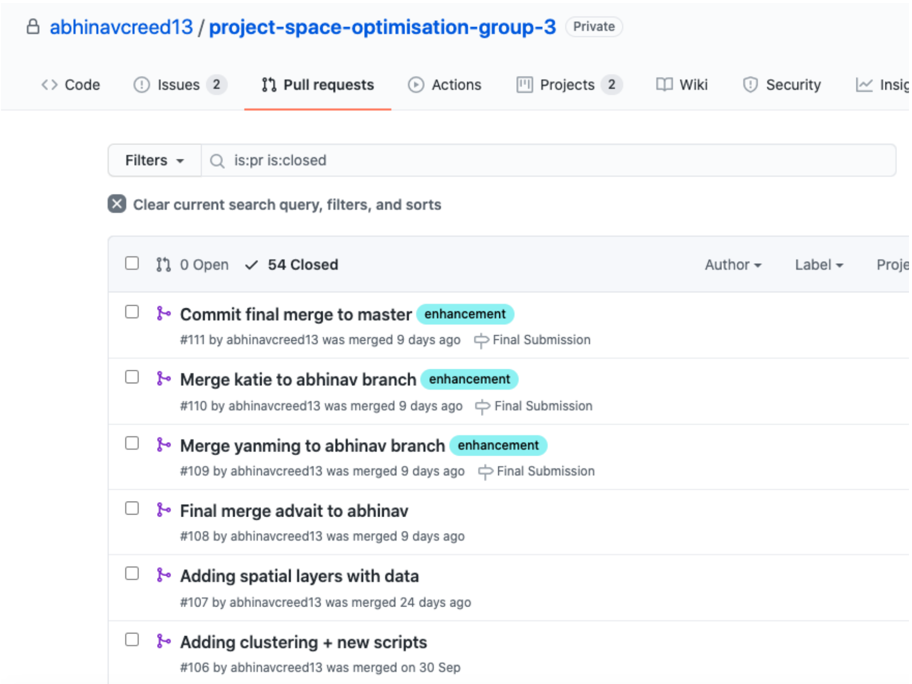

Figure 56: GitHub pull requests used for syncing branches

9.1.2 GitHub Project Tracking

In order to track the progress of our team in the project, we used several inbuilt features of the GitHub. First, we created several milestones throughout the part-1 and part-2 of the project and assigned issues to the corresponding milestones for effective tracking of the progress. A snapshot of the recent milestones is shown in the figure below.

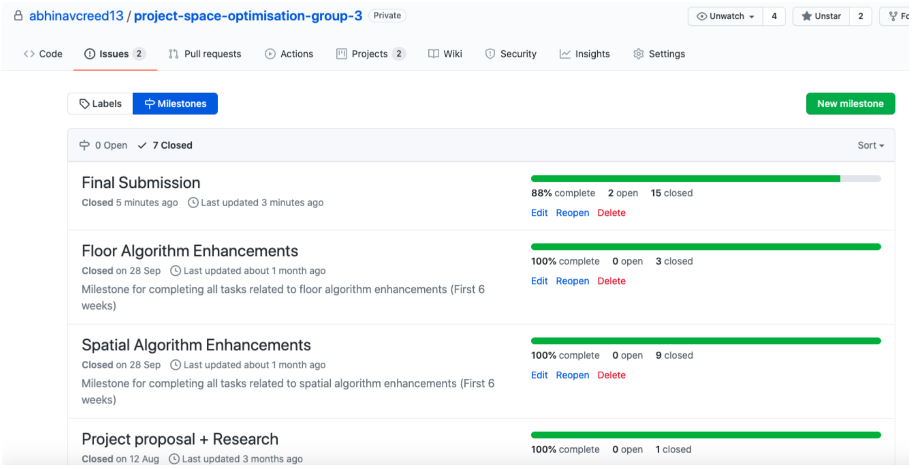

Figure 57: GitHub milestones for tracking progress

These milestones are connected with their corresponding issues that are assigned to the team members so that their contribution and progress can be tracked. A snapshot of the closed issues is shown in the figure below.

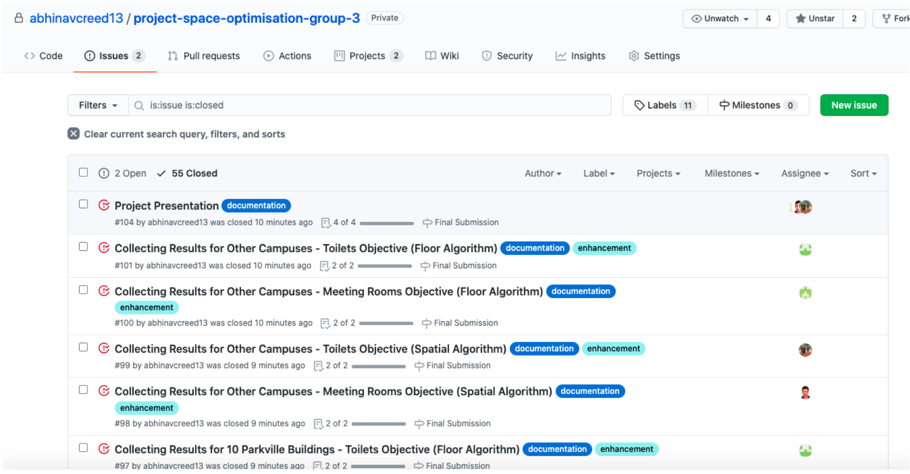

Figure 58: GitHub issues feature for assigning tasks to the team-mates

In order to effectively manage these issues and their corresponding status, we have also used the GitHub projects feature where we can track all the issues and pull requests collectively as shown in the figure below.

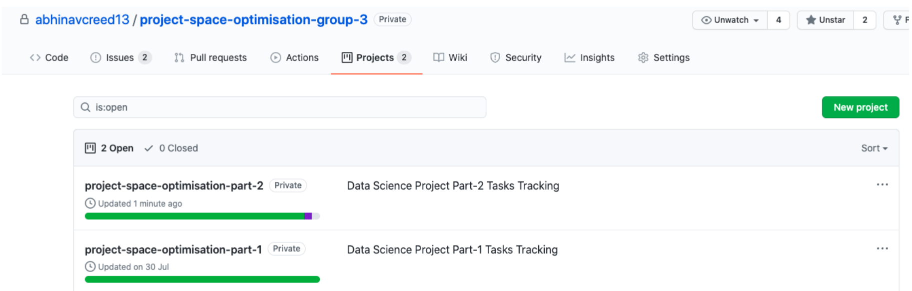

Figure 59: GitHub projects for part-1 and part-2

Finally, these projects are effectively used with the kanban board to view the tasks that are required to be picked by the teammate, tasks that are in progress, and tasks that are already completed. These board-based tracking helped us a lot in effectively viewing the progress of the project and showing this progress to our supervisor and the client. A snapshot of our project's part-2 kanban board is shown in the figure below.

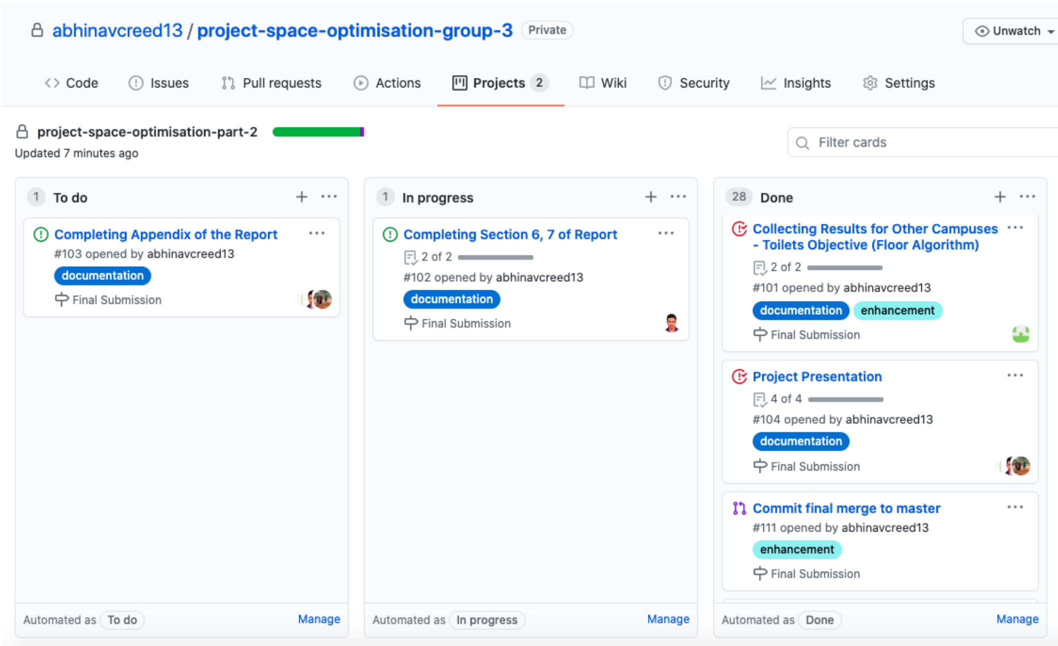

Figure 60: GitHub project part-2 kanban board

9.1.3 Client & Supervisor Meeting Logs

In this section, we will be showing complete meeting logs with our client and supervisor for both part-1 and part-2 of the project. We will also show the meeting timings with their corresponding agenda.

9.1.3.1 Data Science Project Part-1 Logs

Meeting Week	Meeting Date & Time	Meeting Hosts	Meeting Agenda
Week 4	3/27/2020, 3:00 - 4:00 PM	Jade Germantis (Client) Anbin Hou (Client) Prashan Madumal (Super)	- First meeting with the client - Project introduction
Week 5	4/4/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- First meeting with the supervisor - Project plan discussion
Week 6	4/21/2020 , 12:00 - 1:00 PM	Anbin Hou (Client) Prashan Madumal (Super)	- Project data-based questions with client - Supply Demand Correlations Analysis presentation
Week 6	4/24/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Report discussion - Data Analysis progress presentation
Week 7	5/1/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- EDA progress - Correlation analysis progress
Week 8	5/8/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Spatial data analysis progress - Data preprocessing discussion
Week 9	5/15/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Client meeting presentation discussion
Week 9	5/15/2020, 3:15 - 4:15 PM	Anbin Hou (Client) Prashan Madumal (Super)	- Spatial data analysis QGIS 3 showcase - Floor prediction model showcase
Week 10	5/22/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Model prototype discussion - Finalising powerpoint presentation structure
Week 11	5/29/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Models + Methods discussion - Finalising report structure
Week 12	6/5/2020, 10:00 - 11:00 AM	Prashan Madumal (Super)	- Final project proposal report discussion - Clarifying report content + changes
Week 12+	7/9/2020, 10 AM	Anbin Hou (Client)	- Sent report + presentation feedback to the client
Week 12+	7/14/2020, 11:30 - 12:00 AM	Anbin Hou (Client)	- Presentation showcase - Project proposal showcase
Week 12+	7/22/2020, 9:00 - 10:00 AM	Jade Germantis (Client) Anbin Hou (Client)	- Data science project part-1 presentation - Presenting key findings of the project

Table 5: Data Science Project Part-1 Meeting Logs

9.1.3.2 Data Science Project Part-2 Logs

Meeting Week	Meeting Date & Time	Meeting Hosts	Meeting Agenda
Week 1	08/06/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Next Steps Discussion - Potential project part-2 plan
Week 2	08/13/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- QGIS 3 Python Algorithm Implementation - Initial Results Discussion
Week 3	08/17/2020, 10:00 - 11:00 AM	Anbin Hou (Client) Prashan Madumal (Super)	- QGIS 3 Spatial Algorithm Form Showcase - QGIS 3 Spatial Algorithm Results Showcase
Week 4	08/27/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- QGIS 3 correlations implementation - Floor Algorithm basic results showcase
Week 5	09/03/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Problem mathematical formulation - Problem formulation examples
Week 6	09/10/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- AAAI 21 research paper rough draft - Algorithm research paper discussion
Week 7	09/16/2020, 8 AM	Anbin Hou (Client)	- AAAI 21 research paper submitted - Submitted paper sent to the client
Week 7	09/17/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Results collection discussion with algo - Initial report structure discussion
Week 8	09/21/2020, 10:00 - 11:00 AM	Anbin Hou (Client) Prashan Madumal (Super)	- Research paper showcase - Initial analysis report structure showcase
Week 9	10/01/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Spatial algorithm results presentation - Floor algorithm results presentation
Week 10	10/15/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Powerpoint presentation structure discussion - Finalising report structure
Week 11	10/22/2020, 2:00 - 3:00 PM	Anbin Hou (Client) Prashan Madumal (Super)	- Presenting complete project to the client - Presenting submitted ds project presentation - Final report discussion + feedback
Week 12	10/29/2020, 2:00 - 3:00 PM	Prashan Madumal (Super)	- Final report structure finalised - Feedback discussed

Table 6: Data Science Project Part-2 Meeting Logs

9.2 QGIS 3 Processing Framework Scripts Guide

9.2.1 Overview

QGIS is a user friendly Open Source Geographic Information System (GIS) licensed under the GNU General Public License[13]. This platform is widely used to perform spatial data analysis. We have implemented our proposed algorithm as described in the paper using the QGIS processing framework[14]. This framework provides a geoprocessing environment that can be used to call native and third-party algorithms from QGIS, making your spatial analysis tasks more productive and easy to accomplish.

QGIS processing framework provides the ability to create custom processing logic using python scripts[15]. Using this framework, we were able to design the UI interface for our prediction algorithm implicitly without creating any UI controls and functionalities. The complete QGIS interface with our prediction algorithm processing script is shown in the Figure 61.

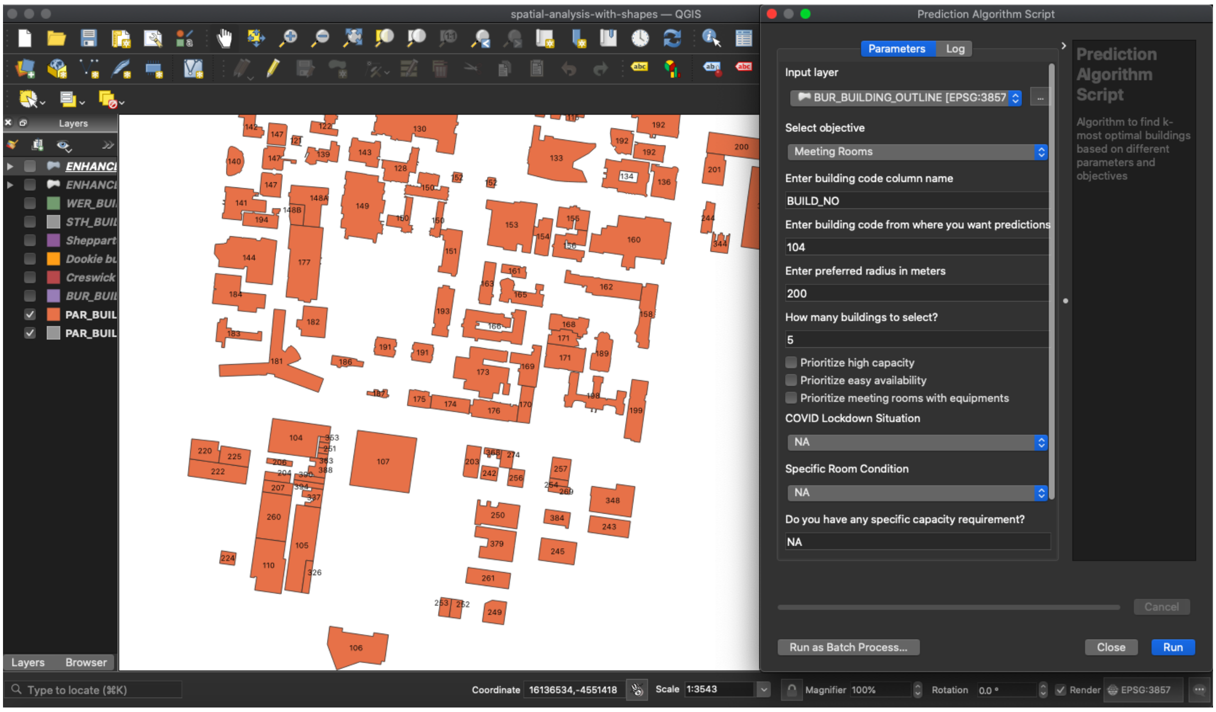

Figure 61: QGIS interface with map outline and prediction algorithm processing script

9.2.2 Prerequisites

In order to load and execute QGIS 3 python processing scripts, we need the following software installed in the machine:

- **QGIS 3.14+**: We have tested our scripts on the QGIS 3.14 version so it is expected to run correctly on this version and above. This can be downloaded using URL: `https://qgis.org/en/site/forusers/download.html`.

- **Python 3+**: The scripts are implemented on python 3.6 version and it is expected to run correctly on the version above 3.6. This can be download using URL: `https://www.python.org/downloads/`.

9.2.3 Installing required python packages & configuring QGIS 3

QGIS 3 installation comes with pyQGIS 3 which is already installed with the required libraries needed for executing our custom created processing scripts. Hence, other processing scripts can run without any installation, except `finding optimal radius script`. In order to execute our `finding optimal radius script` which is internally using the `sklearn k-means` algorithm, the package should be installed and connected with the QGIS space. This can be achieved using the following steps:

- Step-1: First, we are required to install 'sklearn' package in the python space. This can be achieved using the following command in the windows cmd or Linux/macOS terminal: `pip install -U scikit-learn` as shown below.

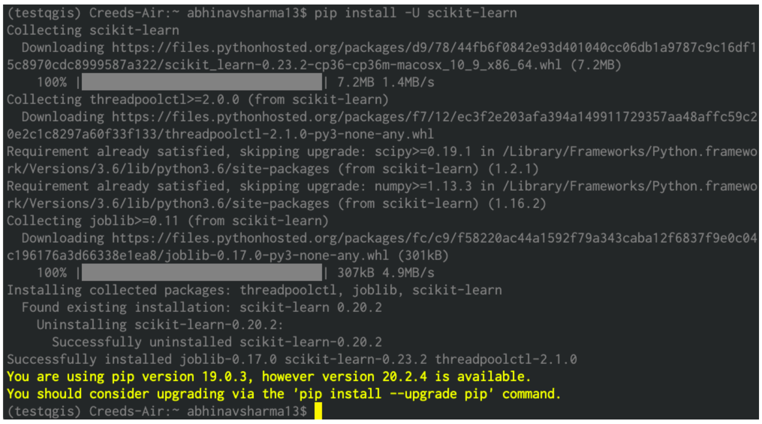

Figure 62: Step-1: Installing sklearn package

- Step-2: After installation of the above package, we need to grab the site-packages path of the python. This can be achieved using the following command in windows cmd or Linux/macOS terminal: `python3 -m site` as shown below.

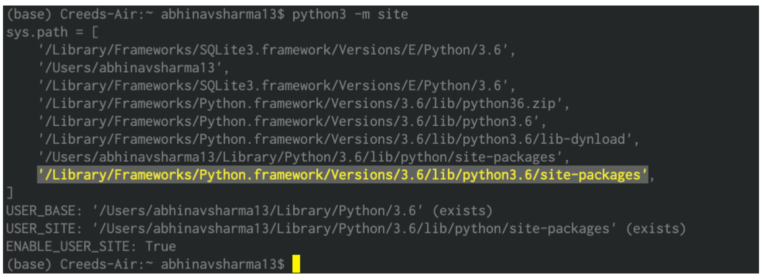

Figure 63: Step-2: Get python3 site-packages path

- Step-3: After the site-packages location is found, we can open the QGIS 3 and go to preferences/settings to reach the environment section as shown below.

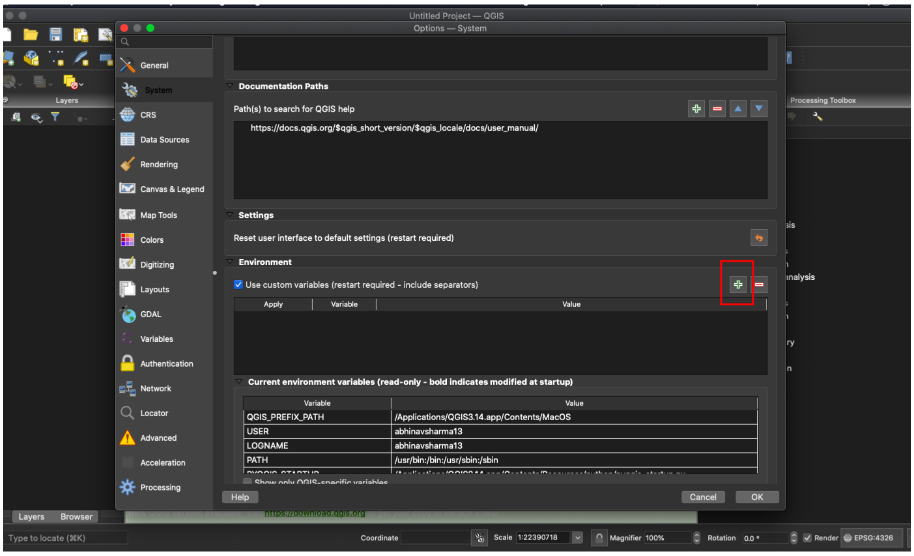

Figure 64: Step-3: Add custom environment

- Step-4: Finally, we will add the copied site package path as the custom environment in the QGIS space using `append` option on the `PYTHONPATH` variable as shown below.

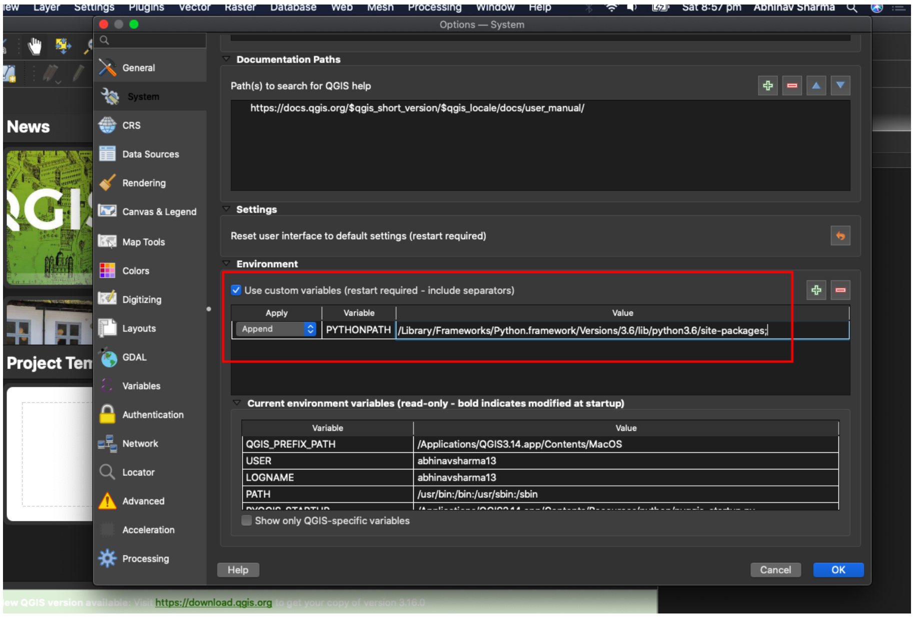

Figure 65: Step-4: Appending python site package path in the PYTHONPATH of QGIS 3

These steps will effectively configure the QGIS 3 space to run all our custom python processing scripts without any errors or exceptions.

9.2.4 Executing QGIS data loader script

QGIS process scripts can be accessed and loaded by following the below steps.

- Step-1: Open the project and then click on the highlighted icon to open the processing script toolbox.

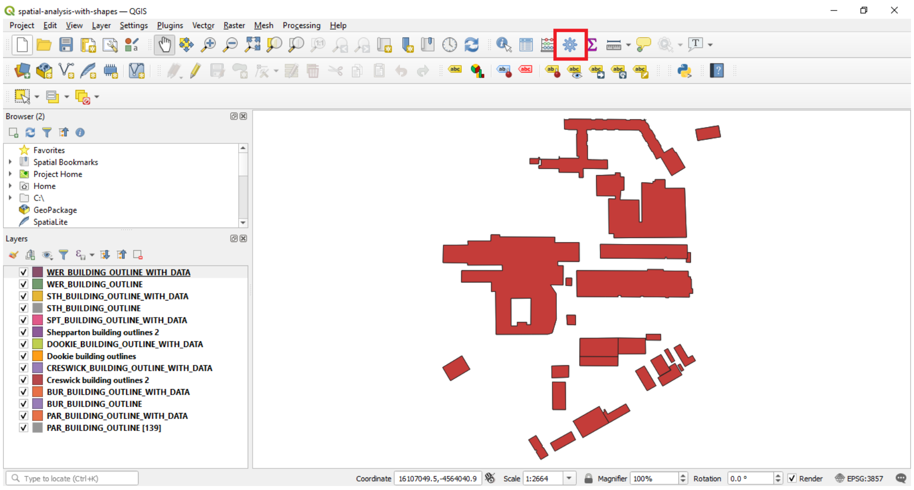

Figure 66: Step-1: Accessing Python Process Toolbox of QGIS 3

- Step-2: Click on the highlighted icon and then click on `Add Script to toolbox`. To add the script to the processing toolbox.

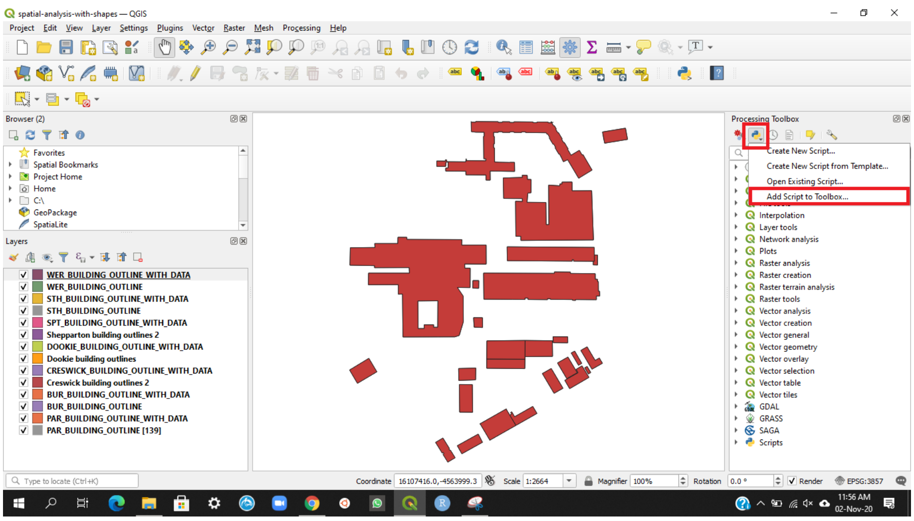

Figure 67: Step-2: Adding Scripts to Process Toolbox of QGIS 3

- Step-3: After clicking on the above option. Select a script file that you need to import, in this case, it would be `FINAL_qgis_data_loader_script`.

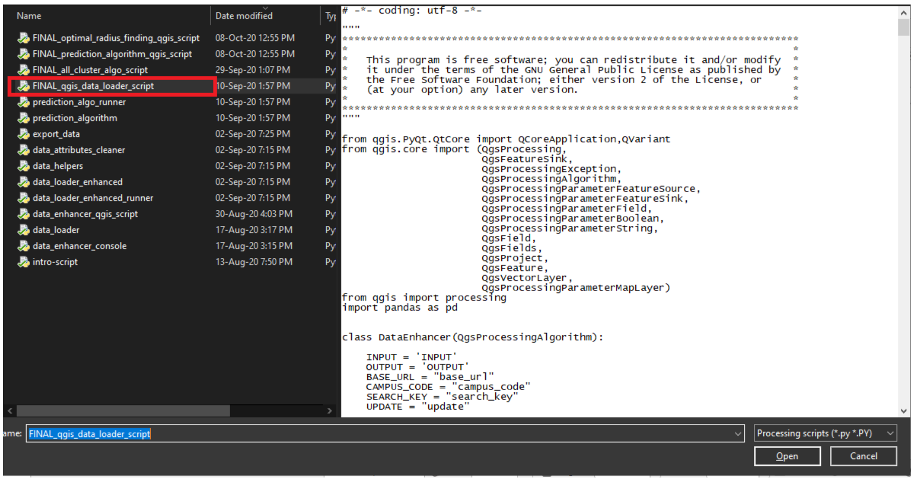

Figure 68: Step-3: Select Scripts to add to the Process Toolbox of QGIS 3

- Step-4: Script will be added to the following directory in the processing toolbox.

Figure 69: Step-4: View Scripts added to the Process Toolbox of QGIS 3

- Step-5: Right-click on the `Data Loader Script` and it will open a dialog box. Fill the information into the required fields. There is an option to update the base layer and not create the new layer, which can be selected as per the convenience and click on execute.

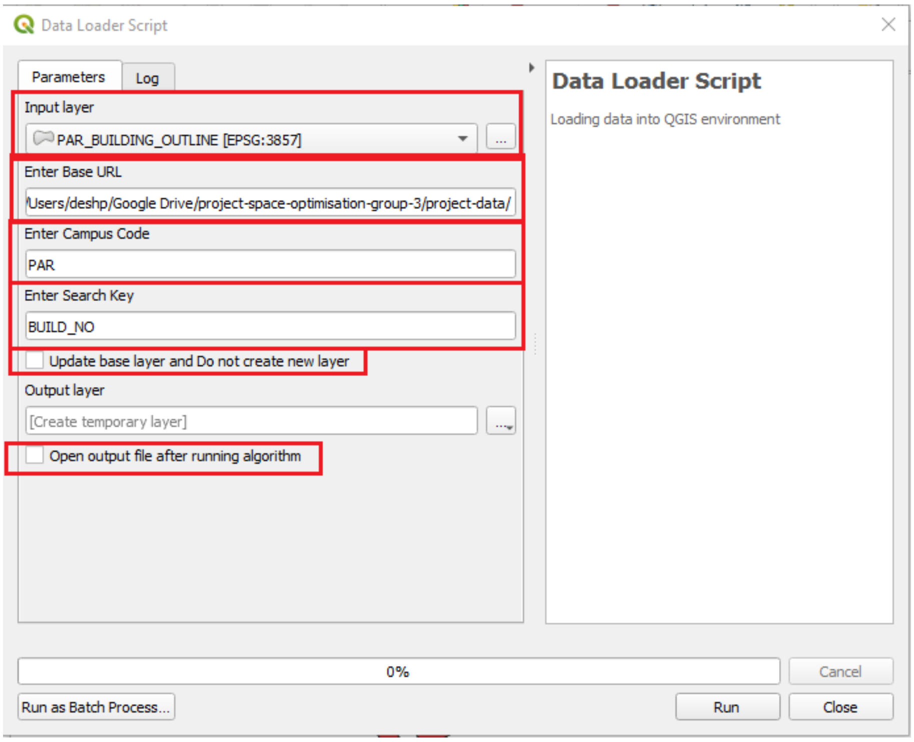

Figure 70: Step-5: Execute Data Loader script in QGIS 3

- Step-6: After clicking on `Run`, without selecting the `Update base layer and do not create new layer option`, the script will execute with the following logs.

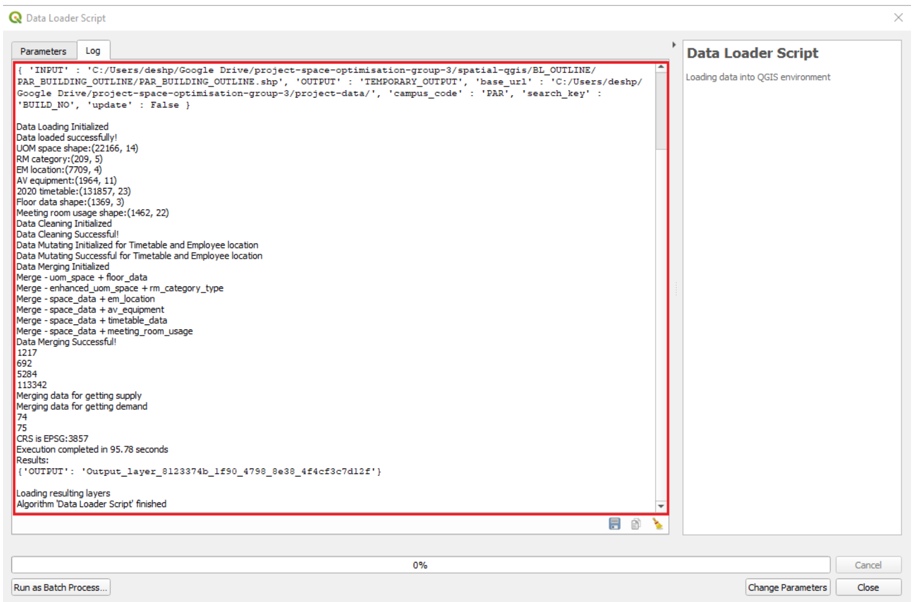

Figure 71: Step-6: Logs after executing Data Loader script in QGIS 3

- Step-7: If the option `Update base layer and do not create new layer option` was selected, the script will stop with an error but the layer would be updated. An error was introduced to stop the script execution. The following figure shows the error message and execution of the script.

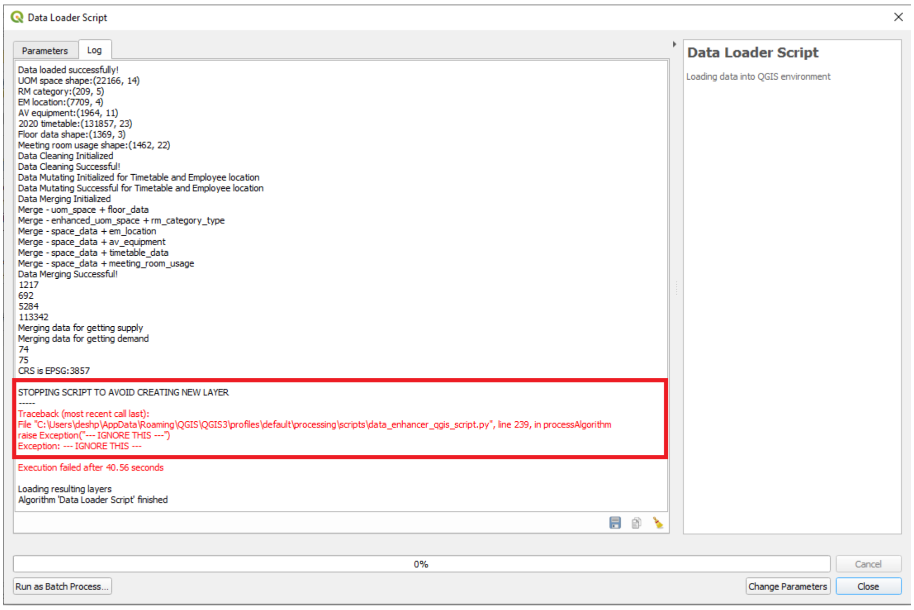

Figure 72: Step-7: Logs after executing Data Loader script with Base layer update in QGIS 3

9.2.5 Executing QGIS finding optimal radius script

After loading the data into the QGIS environment, we need to use to calculate the optimal hyper-parameters (B and δ). Following steps from step-2 to step-4 from the above process, you need to add `FINAL_optimal_radius_finding_qgis_script`.

- Step-1: After adding `FINAL_optimal_radius_finding_qgis_script` to the toolbox. Right click on the highlighted script and click on execute.

Figure 73: Step-1: Adding Optimal radius finding script in QGIS 3

- Step-2: A form will open, fill out all the details into the form, select the input layer with all the enriched data from Data Loader, Select objective, Building Code Column Name, Building Code, Path to store plots, etc.

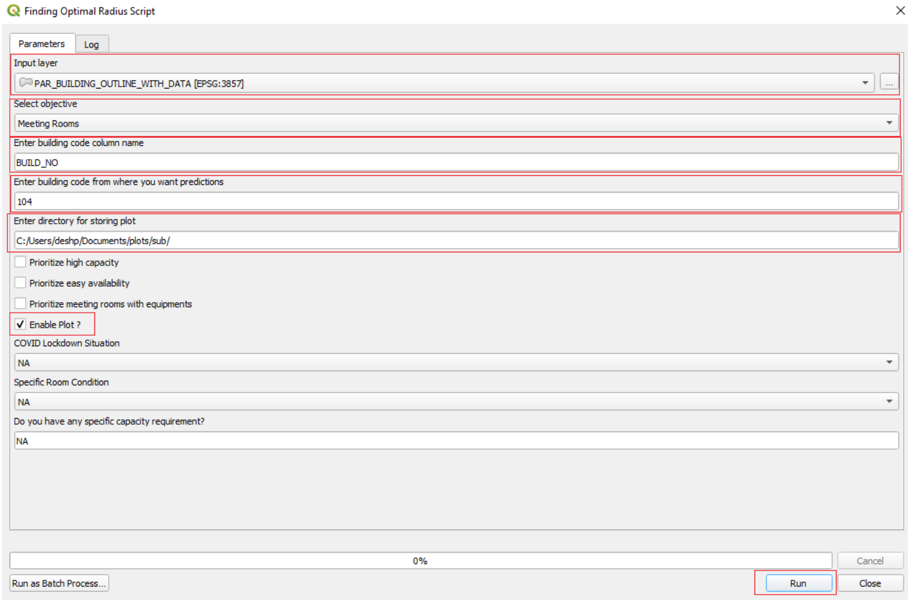

Figure 74: Step-2: Executing Optimal radius finding script in QGIS 3

- Step-3: After running the script, the following message appears in the logs. Giving the optimal radius and delta parameter.

Figure 75: Step-3:Logs after executing Optimal radius finding script in QGIS 3

9.2.6 Executing QGIS prediction algorithm script

After getting the values for both the constraints from the previous algorithm to find the rewarding buildings. Following steps from step-2 to step-4 from Data Loader steps, you need to add `FINAL_prediction_algorithm_qgis_script`.

- Step-1: After adding `FINAL_prediction_algorithm_qgis_script` to the toolbox. Right click on the highlighted script and click on execute.

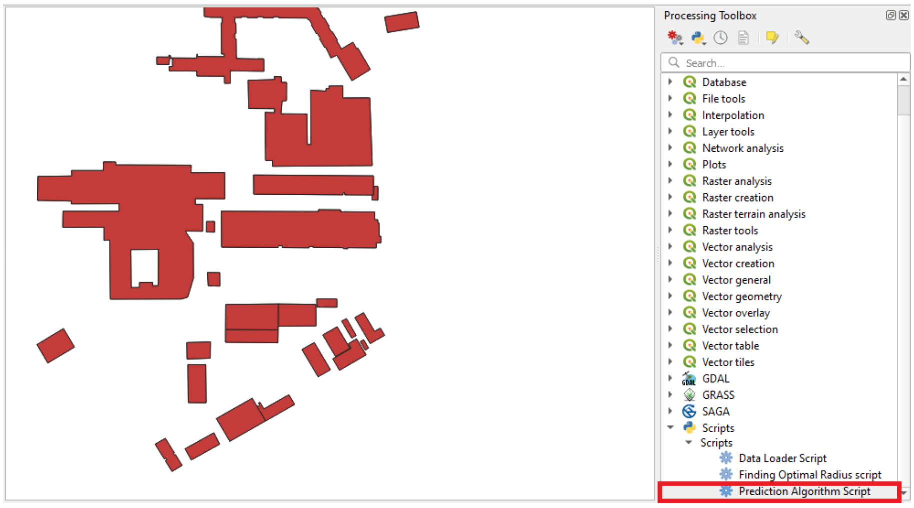

Figure 76: Step-1: Adding Prediction Algorithm script in QGIS 3

- Step-2: A form will open, fill out all the details into the form, select the input layer with all the enriched data from Data Loader, Select objective, Building Code Column Name, Building Code, Path to store plots, etc. and use the values of `radius`, `delta` from the previous algorithm. Choose the same factors that were chosen to get the constraint values.

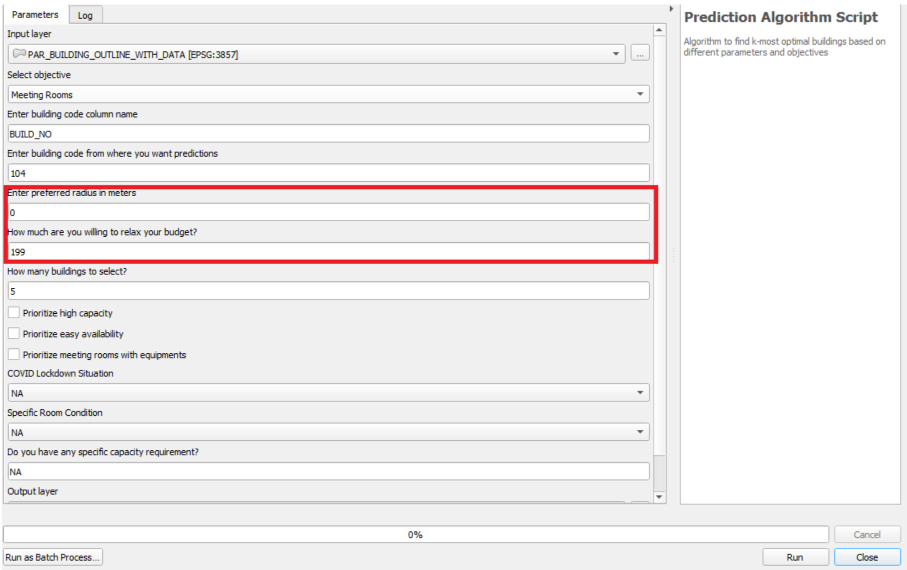

Figure 77: Step-2: Executing Prediction Algorithm script in QGIS 3

- Step-3: After running the script, the following message appears in the logs. The results of the top `k` buildings are displayed in the logs. Do not worry about the error message it is just to stop the execution of the script.

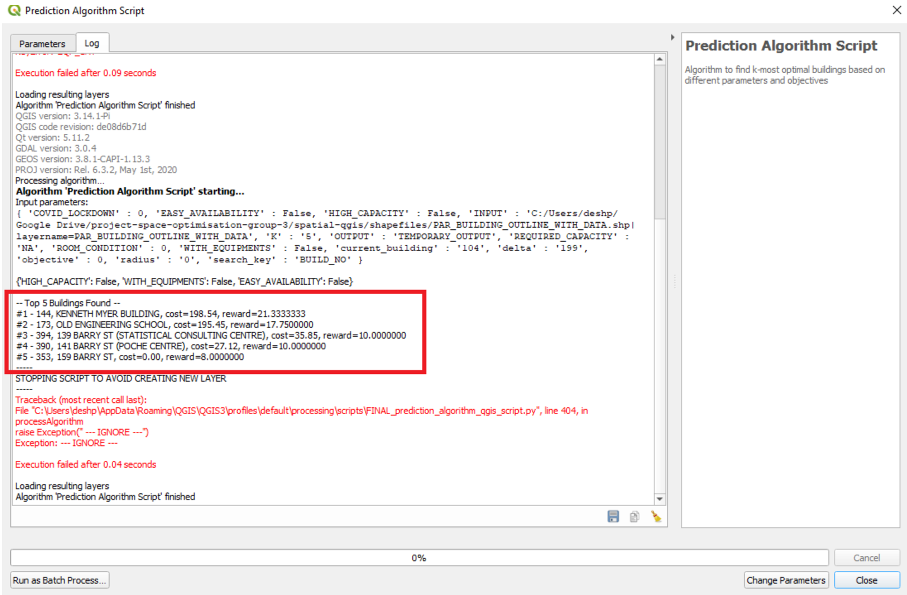

Figure 78: Step-3: Logs after executing Prediction Algorithm script in QGIS 3

9.3 Collected Results

9.3.1 Spatial Algorithm Results

9.3.1.1 Meeting Rooms Objective

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	302.1706	130.63	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	432.80	25.000000	302.1706 to 582.1421
			#2 - 144, KENNETH MYER BUILDING	414.39	21.333333	
			#3 - 128, OLD PHYSICS BUILDING	286.48	21.000000	
			#4 - 173, OLD ENGINEERING SCHOOL	68.24	17.750000	
			#5 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	404.29	10.000000	
COVID-19-Strict-Lockdown	648.5517	15.69	#1 - 110, THE SPOT	501.23	385.000000	648.5517 to 1329.8051
			#2 - 104, ALAN GILBERT BUILDING	353.24	281.000000	
			#3 - 144, KENNETH MYER BUILDING	414.39	256.000000	
			#4 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	94.79	248.000000	
			#5 - 105, FBE BUILDING	429.19	234.000000	
High Capacity	0.0000	286.48	#1 - 128, OLD PHYSICS BUILDING	286.48	0.573286	0.0 to 286.4775
			#2 - 173, OLD ENGINEERING SCHOOL	68.24	0.110552	
			#3 - 177, BAILLIEU LIBRARY	346.02	0.067436	
			#4 - 203, SECURITY OFFICE	200.65	0.062996	
			#5 - 155, OLD GEOLOGY BUILDING (NORTH WING)	125.92	0.061053	
With equipment	302.1706	112.22	#1 - 144, KENNETH MYER BUILDING	414.39	4.923077	302.1706 to 582.1421
			#2 - 390, 141 BARRY ST (POCHE CENTRE)	398.41	0.109890	
			#3 - 201, THOMAS CHERRY BUILDING	262.55	0.038462	
			#4 - 134, ELISABETH MURDOCH BUILDING	192.59	0.037221	
			#5 - 139, BABEL BUILDING	387.59	0.030272	
Excellent Meeting Rooms	302.1706	112.22	#1 - 144, KENNETH MYER BUILDING	414.39	1.014552	
			#2 - 173, OLD ENGINEERING SCHOOL	68.24	0.234117	302.1706 to 582.1421
			#3 - 155, OLD GEOLOGY BUILDING (NORTH WING)	125.92	0.138708	
			#4 - 177, BAILLIEU LIBRARY	346.02	0.107823	
			#5 - 133, GLYN DAVIS BUILDING	196.38	0.055243	
Easy availability	302.1706	130.63	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	432.80	24.981827	302.1706 to 582.1421
			#2 - 144, KENNETH MYER BUILDING	414.39	20.498123	
			#3 - 173, OLD ENGINEERING SCHOOL	68.24	17.220697	
			#4 - 155, OLD GEOLOGY BUILDING (NORTH WING)	125.92	7.383591	
			#5 - 177, BAILLIEU LIBRARY	346.02	5.033909	

Table 7: Results collected for Doug McDonell Building, Parkville (168)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	543.3778 ∼543 metres	125.17 ∼126 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	668.55	25	543.3778 to 831.8305
			#2 - 173, OLD ENGINEERING SCHOOL	551.58	17.75	
			#3 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	372.05	10	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	380.02	10	
			#5 - 353, 159 BARRY ST	440.22	8	
COVID-19-Strict	520.9727 ∼521 metres	0 ∼No Relaxation	#1 - 110, THE SPOT	231.15	385	0.0 to 520.9727
			#2 - 278, 100 LEICESTER ST (MGSE)	66.47	296	
			#3 - 104, ALAN GILBERT BUILDING	419.4	281	
			#4 - 105, FBE BUILDING	224.16	234	
			#5 - 379, 207-221 BOUVERIE ST (MSPGH & GEOGRAPHY)	344.4	200	
High Capacity	543.3778 ∼543 metres	138.68 ∼139 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	668.55	0.2087699	543.3778 to 831.8305
			#2 - 173, OLD ENGINEERING SCHOOL	551.58	0.1105521	
			#3 - 390, 141 BARRY ST (POCHE CENTRE)	380.02	0.0925584	
			#4 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	372.05	0.0706981	
			#5 - 177, BAILLIEU LIBRARY	650.04	0.0674358	543.3778 to 831.8305
With equipment	543.3778 ∼543 metres	138.68 ∼139 metres	#1 - 263, KWONG LEE DOW BUILDING (MGSE)	48.06	0.4266876	
			#2 - 232, 535 ELIZABETH ST (LEVELS 3, 4, 5)	219.96	0.310783	
			#3 - 110, THE SPOT	231.15	0.1436865	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	380.02	0.1098901	
			#5 - 220, 780 ELIZABETH ST	445.56	0.0271493	
Excellent Meeting Rooms	543.3778 ∼543 metres	138.68 ∼139 metres	#1 - 173, OLD ENGINEERING SCHOOL	551.58	0.2341167	543.3778 to 831.8305
			#2 - 177, BAILLIEU LIBRARY	650.04	0.1078226	
			#3 - 110, THE SPOT	231.15	0.1022892	
			#4 - 278, 100 LEICESTER ST (MGSE)	66.47	0.0581004	
			#5 - 379, 207-221 BOUVERIE ST (MSPGH & GEOGRAPHY)	344.4	0.0545515	
Easy availability	543.3778 ∼543 metres	125.17 ∼126 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	668.55	24.9818271	543.3778 to 831.8305
			#2 - 173, OLD ENGINEERING SCHOOL	551.58	17.2206968	
			#3 - 177, BAILLIEU LIBRARY	650.04	5.0339094	
			#4 - 261, 203 BOUVERIE ST (BIOMEDICAL ENGINEERING)	302.78	4.4731963	
			#5 - 207, 202-206 BERKELEY ST (MDHS)	368.03	2.9955246	

Table 8: Results collected for 11 Barry St, Parkville (266)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	377.5145 ∼378 metres	178.22 ∼179 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	555.73	25	377.5145 to 665.4125
			#2 - 144, KENNETH MYER BUILDING	514.18	21.3333333	
			#3 - 173, OLD ENGINEERING SCHOOL	377.51	17.75	
			#4 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	203.31	10	
			#5 - 390, 141 BARRY ST (POCHE CENTRE)	211.28	10	
COVID-19-Strict	368.9632 ∼368 metres	0 ∼No relaxation	#1 - 110, THE SPOT	86.79	385	54.4592 to 368.9632
			#2 - 278, 100 LEICESTER ST (MGSE)	141.31	296	
			#3 - 104, ALAN GILBERT BUILDING	250.72	281	
			#4 - 105, FBE BUILDING	65.03	234	
			#5 - 266, 11 BARRY ST (BUSINESS SERVICES)	103.75	204	
High Capacity	408.5138 ∼409 metres	256.9 ∼257 metres	#1 - 128, OLD PHYSICS BUILDING	665.41	0.5732861	408.5138 to 685.951
			#2 - 144, KENNETH MYER BUILDING	514.18	0.2098769	
			#3 - 385, UNIVERSITY HEALTH SERVICES BUILDING	555.73	0.2087699	
			#4 - 173, OLD ENGINEERING SCHOOL	377.51	0.1105521	
			#5 - 390, 141 BARRY ST (POCHE CENTRE)	211.28	0.0925584	
With equipment	377.5145 ∼377 metres	136.67 ∼137 metres	#1 - 263, KWONG LEE DOW BUILDING (MGSE)	165.15	0.4266876	377.5145 to 665.4125
			#2 - 232, 535 ELIZABETH ST (LEVELS 3, 4, 5)	409	0.310783	
			#3 - 110, THE SPOT	86.79	0.1436865	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	211.28	0.1098901	
			#5 - 220, 780 ELIZABETH ST	293.13	0.0271493	
Excellent Meeting Rooms	408.5138 ∼409 metres	105.67 ∼106 metres	#1 - 144, KENNETH MYER BUILDING	514.18	1.014552	408.5138 to 685.951
			#2 - 173, OLD ENGINEERING SCHOOL	377.51	0.2341167	
			#3 - 177, BAILLIEU LIBRARY	481.3	0.1078226	
			#4 - 110, THE SPOT	86.79	0.1022892	
			#5 - 278, 100 LEICESTER ST (MGSE)	141.31	0.0581004	
Easy availability	408.5138 ∼409 metres	147.22 ∼148 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	555.73	24.9818271	408.5138 to 685.951
			#2 - 144, KENNETH MYER BUILDING	514.18	20.498123	
			#3 - 173, OLD ENGINEERING SCHOOL	377.51	17.2206968	
			#4 - 177, BAILLIEU LIBRARY	481.3	5.0339094	
			#5 - 261, 203 BOUVERIE ST (BIOMEDICAL ENGINEERING)	138.03	4.4731963	

Table 9: Results collected for Law Building, Parkville (106)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	439.3898 ∼439 metres	100 metres	#1 - 144, KENNETH MYER BUILDING	439.39	21.3333333	439.3898 to 820.6447
			#2 - 220, 780 ELIZABETH ST	516.62	2.4705882	
			#3 - 147, BIOSCIENCES 4	527.15	1.3469388	
			#4 - 147, BIOSCIENCES 4	513.82	1.3469388	
			#5 - 147, BIOSCIENCES 4	505.89	1.3469388	
COVID-19-Strict	836.9822 ∼837 metres	230.1 ∼230 metres	#1 - 110, THE SPOT	685.08	385	836.9822 to 2064.3964
			#2 - 104, ALAN GILBERT BUILDING	599.74	281	
			#3 - 144, KENNETH MYER BUILDING	439.39	256	
			#4 - 105, FBE BUILDING	699.19	234	
			#5 - 266, 11 BARRY ST (BUSINESS SERVICES)	970.44	204	
High Capacity	439.3898 ∼439 metres	250.38 ∼251 metres	#1 - 128, OLD PHYSICS BUILDING	689.77	0.5732861	439.3898 to 820.6447
			#2 - 144, KENNETH MYER BUILDING	439.39	0.2098769	
			#3 - 390, 141 BARRY ST (POCHE CENTRE)	670.98	0.0925584	
			#4 - 123, BIOSCIENCES 1	592.04	0.0746485	
			#5 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	674.78	0.0706981	
With equipment	439.3898 ∼439 metres	100 metres	#1 - 144, KENNETH MYER BUILDING	439.39	4.9230769	439.3898 to 820.6447
			#2 - 147, BIOSCIENCES 4	527.15	0.0296031	
			#3 - 147, BIOSCIENCES 4	513.82	0.0296031	
			#4 - 147, BIOSCIENCES 4	505.89	0.0296031	
			#5 - 220, 780 ELIZABETH ST	516.62	0.0271493	
Excellent Meeting Rooms	439.3898 ∼439 metres	100 metres	#1 - 144, KENNETH MYER BUILDING	439.39	1.014552	439.3898 to 820.6447
			#2 - 147, BIOSCIENCES 4	527.15	0.0165146	
			#3 - 147, BIOSCIENCES 4	513.82	0.0165146	
			#4 - 147, BIOSCIENCES 4	505.89	0.0165146	
			#5 - 184, OLD MICROBIOLOGY BUILDING	445.32	0.0159783	
Easy availability	439.3898 ∼439 metres	100 metres	#1 - 144, KENNETH MYER BUILDING	439.39	20.498123	439.3898 to 820.6447
			#2 - 220, 780 ELIZABETH ST	516.62	2.4589684	
			#3 - 147, BIOSCIENCES 4	527.15	1.3373011	
			#4 - 147, BIOSCIENCES 4	513.82	1.3373011	
			#5 - 147, BIOSCIENCES 4	505.89	1.3373011	

Table 10: Results collected for David Penington Building, Parkville (102)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	622.551 ∼623 metres	40.03 ∼41 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	662.58	25	622.551 to 1274.8715
			#2 - 144, KENNETH MYER BUILDING	328.33	21.3333333	
			#3 - 128, OLD PHYSICS BUILDING	494.39	21	
			#4 - 173, OLD ENGINEERING SCHOOL	275.64	17.75	
			#5 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	17.75	10	
COVID-19-Strict	305.1517 ∼306 metres	0 ∼No relaxation	#1 - 110, THE SPOT	4.41	385	0.0 to 305.1517
			#2 - 278, 100 LEICESTER ST (MGSE)	284.4	296	
			#3 - 104, ALAN GILBERT BUILDING	72.17	281	
			#4 - 266, 11 BARRY ST (BUSINESS SERVICES)	224.16	204	
			#5 - 379, 207-221 BOUVERIE ST (MSPGH & GEOGRAPHY)	232.07	200	
High Capacity	300.4323 ∼301 metres	193.95 ∼194 metres	#1 - 128, OLD PHYSICS BUILDING	494.39	0.5732861	300.4323 to 583.1081
			#2 - 144, KENNETH MYER BUILDING	328.33	0.2098769	
			#3 - 173, OLD ENGINEERING SCHOOL	275.64	0.1105521	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	35.64	0.0925584	
			#5 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	27.54	0.0706981	
With equipment	300.4323 ∼301 metres	27.9 ∼28 metres	#1 - 144, KENNETH MYER BUILDING	328.33	4.9230769	300.4323 to 583.1081
			#2 - 263, KWONG LEE DOW BUILDING (MGSE)	304.4	0.4266876	
			#3 - 110, THE SPOT	4.41	0.1436865	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	35.64	0.1098901	
			#5 - 220, 780 ELIZABETH ST	130.83	0.0271493	
Excellent Meeting Rooms	300.4323 ∼301 metres	27.9 ∼28 metres	#1 - 144, KENNETH MYER BUILDING	328.33	1.014552	300.4323 to 583.1081
			#2 - 173, OLD ENGINEERING SCHOOL	275.64	0.2341167	
			#3 - 177, BAILLIEU LIBRARY	300.43	0.1078226	
			#4 - 110, THE SPOT	4.41	0.1022892	
			#5 - 278, 100 LEICESTER ST (MGSE)	284.4	0.0581004	
Easy availability	622.551 ∼623 metres	40.03 ∼41 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	662.58	24.9818271	622.551 to 1274.8715
			#2 - 144, KENNETH MYER BUILDING	328.33	20.498123	
			#3 - 173, OLD ENGINEERING SCHOOL	275.64	17.2206968	
			#4 - 155, OLD GEOLOGY BUILDING (NORTH WING)	544.43	7.3835912	
			#5 - 177, BAILLIEU LIBRARY	300.43	5.0339094	

Table 11: Results collected for FBE Building, Parkville (105)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	259.7771 ∼260 metres	0 ∼No Relaxation	#1 - 144, KENNETH MYER BUILDING	36.31	21.3333333	14.1813 to 259.7771
			#2 - 128, OLD PHYSICS BUILDING	241.58	21	
			#3 - 173, OLD ENGINEERING SCHOOL	192.36	17.75	
			#4 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	133.47	10	
			#5 - 390, 141 BARRY ST (POCHE CENTRE)	124.73	10	
COVID-19-Strict	555.8317 ∼556 metres	0 ∼No Relaxation	#1 - 110, THE SPOT	227.19	385	555.8317 to 1470.1156
			#2 - 278, 100 LEICESTER ST (MGSE)	555.83	296	
			#3 - 104, ALAN GILBERT BUILDING	47.7	281	
			#4 - 144, KENNETH MYER BUILDING	36.31	256	
			#5 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	453.79	248	
High Capacity	259.7771 ∼260 metres	0 ∼No Relaxation	#1 - 128, OLD PHYSICS BUILDING	241.58	0.5732861	14.1813 to 259.7771
			#2 - 144, KENNETH MYER BUILDING	36.31	0.2098769	
			#3 - 173, OLD ENGINEERING SCHOOL	192.36	0.1105521	
			#4 - 390, 141 BARRY ST (POCHE CENTRE)	124.73	0.0925584	
			#5 - 394, 139 BARRY ST (STATISTICAL CONSULTING CENTRE)	133.47	0.0706981	
With equipment	266.8577 ∼267 metres	22.13 ∼23 metres	#1 - 144, KENNETH MYER BUILDING	36.31	4.9230769	14.1813 to 266.8577
			#2 - 110, THE SPOT	227.19	0.1436865	
			#3 - 390, 141 BARRY ST (POCHE CENTRE)	124.73	0.1098901	
			#4 - 139, BABEL BUILDING	219.43	0.0302716	
			#5 - 147, BIOSCIENCES 4	243.13	0.0296031	
Excellent Meeting Rooms	259.7771 ∼260 metres	0 ∼No Relaxation	#1 - 144, KENNETH MYER BUILDING	36.31	1.014552	14.1813 to 259.7771
			#2 - 173, OLD ENGINEERING SCHOOL	192.36	0.2341167	
			#3 - 177, BAILLIEU LIBRARY	19.55	0.1078226	
			#4 - 110, THE SPOT	227.19	0.1022892	
			#5 - 105, FBE BUILDING	169.49	0.0384874	
Easy availability	555.8317 ∼556 metres	153.1 ∼154 metres	#1 - 385, UNIVERSITY HEALTH SERVICES BUILDING	708.93	24.9818271	555.8317 to 1470.1156
			#2 - 144, KENNETH MYER BUILDING	36.31	20.498123	
			#3 - 173, OLD ENGINEERING SCHOOL	192.36	17.2206968	
			#4 - 155, OLD GEOLOGY BUILDING (NORTH WING)	412.56	7.3835912	
			#5 - 177, BAILLIEU LIBRARY	19.55	5.0339094	

Table 12: Results collected for Medical Building, Parkville (181)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	129.109 ∼130 metres	0 ∼No relaxation	#1 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	5.6666667	1.5788 to 129.109
			#2 - 873, SOUTHBANK THE STABLES	129.11	3	
			#3 - 862, SOUTHBANK MUSIC BUILDING	10.64	0.6666667	
			#4 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	0.4285714	
			#5 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
COVID-19-Strict	129.109 ∼130 metres	0 ∼No relaxation	#1 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	34	1.5788 to 129.109
			#2 - 862, SOUTHBANK MUSIC BUILDING	10.64	18	
			#3 - 873, SOUTHBANK THE STABLES	129.11	12	
			#4 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	6	
			#5 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
High Capacity	129.109 ∼130 metres	0 ∼No relaxation	#1 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	0.4697745	1.5788 to 129.109
			#2 - 873, SOUTHBANK THE STABLES	129.11	0.2949083	
			#3 - 862, SOUTHBANK MUSIC BUILDING	10.64	0.0555505	
			#4 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	0.0386107	
			#5 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
With equipment	169.8122 ∼170 metres	78.69 ∼79 metres	#1 - 880, THE IAN POTTER SOUTHBANK CENTRE	248.51	0.1647059	169.8122 to 384.2936
			#2 - 862, SOUTHBANK MUSIC BUILDING	10.64	0	
			#3 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	0	
			#4 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	0	
			#5 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
Excellent Meeting Rooms	129.109 ∼130 metres	0 ∼No relaxation	#1 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	2.1407407	1.5788 to 129.109
			#2 - 862, SOUTHBANK MUSIC BUILDING	10.64	0.0740741	
			#3 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	0.0285714	
			#4 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
			#5 - 861, SOUTHBANK FILM & TELEVISION BUILDING	3.47	0	
Easy availability	129.109 ∼130 metres	0 ∼No relaxation	#1 - 865, SOUTHBANK OLD POLICE HOSPITAL	109.21	2.9426311	1.5788 to 129.109
			#2 - 862, SOUTHBANK MUSIC BUILDING	10.64	0.6646884	
			#3 - 864, SOUTHBANK PERFORMING ARTS, ST KILDA RD	54.59	0.4281475	
			#4 - 872, SOUTHBANK GRANT STREET THEATRE & LIONEL'S CAFE	82.07	0	
			#5 - 861, SOUTHBANK FILM & TELEVISION BUILDING	3.47	0	

Table 13: Results collected for Southbank Elisabeth Murdoch Building, Southbank (860)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No Factors	43.464 ∼44 metres	0 ∼No relaxation	#1 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	10	5.1228 to 43.464
			#2 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	4.3333333	
			#3 - 417, WERRIBEE PARASITOLOGY BUILDING	11.6	0.5454545	
			#4 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#5 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
COVID-19-Strict	43.464 ∼44 metres	0 ∼No relaxation	#1 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	26	5.1228 to 43.464
			#2 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	10	
			#3 - 417, WERRIBEE PARASITOLOGY BUILDING	11.6	6	
			#4 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#5 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
High Capacity	43.464 ∼44 metres	0 ∼No relaxation	#1 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	4.6511892	5.1228 to 43.464
			#2 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	1.022411	
			#3 - 417, WERRIBEE PARASITOLOGY BUILDING	11.6	0.1068248	
			#4 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#5 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
With equipment	43.464 ∼44 metres	0 ∼No relaxation	#1 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	10	5.1228 to 43.464
			#2 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#3 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
			#4 - 414, WERRIBEE RURAL CREDIT ANIMAL HOUSE	43.46	0	
			#5 - 415, WERRIBEE BIOHAZARD DEPOT	19.7	0	
Excellent Meeting Rooms	43.464 ∼44 metres	0 ∼No relaxation	#1 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	2.9885057	5.1228 to 43.464
			#2 - 417, WERRIBEE PARASITOLOGY BUILDING	11.6	0.1128527	
			#3 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#4 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
			#5 - 414, WERRIBEE RURAL CREDIT ANIMAL HOUSE	43.46	0	
Easy availability	43.464 ∼44 metres	0 ∼No relaxation	#1 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	7.3778308	5.1228 to 43.464
			#2 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	4.3230036	
			#3 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#4 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
			#5 - 414, WERRIBEE RURAL CREDIT ANIMAL HOUSE	43.46	0	

Table 14: Results collected for Werribee Pathology Building, Werribee (416)

Algorithm	**Radius Range(meters)**	**Delta(meters)**	**Average Reward**
KMEANS	302.1706 to 582.1421 meters	96.24 meters	2.07
Agglomerative Clustering	328.8798 to 582.1421 meters	85.513 meters	2.1
BIRCH	328.8798 to 582.1421 meters	85.513 meters	2.1
Mini KMEANS	286.0693 to 582.1421 meters	0.40 meters	2.4
GMM	68.2378 to 582.1421 meters	-1.981 meters	9.4
Iteration 2			
KMEANS	302.1706 to 582.1421 meters	96.24 meters	2.07
Agglomerative Clustering	328.8798 to 582.1421 meters	85.513 meters	2.1
BIRCH	328.8798 to 582.1421 meters	85.513 meters	2.1
Mini KMEANS	302.1706 to 582.1421 meters	96.24 meters	2.07
GMM	68.2378 to 582.1421 meters	-1.981 meters	9.4

Table 15: Results collected for Doug McDonell Building, Parkville (168)

9.3.1.2 Toilet Facilities Objective

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	2.9043 ~3 meters	186.24 ~187 meters	#1 - 128, OLD PHYSICS BUILDING	189.1	0.5	2.9043 to 421.9135
			#2 - 113, BALDWIN SPENCER BUILDING	11.78	0.0018898	
			#3 - 150, OLD QUADRANGLE BUILDING	182.7	0.0005868	
			#4 - 134, ELISABETH MURDOCH BUILDING	122.7	0.000318	
			#5 - 192, DAVID CARO BUILDING	103.3	0.0001793	
COVID-19-Strict	806.4439~807 meters	16.31~17 meters	#1 - 106, LAW BUILDING	822.8	202	806.4439 to 1673.1258
			#2 - 110, THE SPOT	753.7	126	
			#3 - 105, FBE BUILDING	684.5	111	
			#4 - 104, ALAN GILBERT BUILDING	572.5	93	
			#5 - 133, GLYN DAVIS BUILDING	36.44	65	
High Capacity	2.9043~3 meters	186.24~187 meters	#1 - 128, OLD PHYSICS BUILDING	189.1	0.0032877	2.9043 to 421.9135
			#2 - 113, BALDWIN SPENCER BUILDING	11.78	0.0000184	
			#3 - 150, OLD QUADRANGLE BUILDING	182.7	0.0000047	
			#4 - 134, ELISABETH MURDOCH BUILDING	122.7	0.0000036	
			#5 - 192, DAVID CARO BUILDING	103.3	0.0000015	
Good Toilets Rooms	2.9043~3 meters	186.24~187 meters	#1 - 128, OLD PHYSICS BUILDING	189.1	0.0050251	2.9043 to 421.9135
			#2 - 113, BALDWIN SPENCER BUILDING	11.78	0.0000522	
			#3 - 192, DAVID CARO BUILDING	103.3	0.0000041	
			#4 - 192, DAVID CARO BUILDING	96.91	0.0000041	
			#5 - 192, DAVID CARO BUILDING	144	0.0000041	
Easy Availability	2.9043~3 meters	186.24~187 meters	#1 - 128, OLD PHYSICS BUILDING	189.1	0.4835717	2.9043 to 421.9135
			#2 - 113, BALDWIN SPENCER BUILDING	11.78	0.0018546	
			#3 - 150, OLD QUADRANGLE BUILDING	182.7	0.0005763	
			#4 - 134, ELISABETH MURDOCH BUILDING	122.7	0.0003127	
			#5 - 192, DAVID CARO BUILDING	103.3	0.0001769	

Table 16: Results collected for Redmond Barry Building, Parkville (115)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	356.3895 ~357 meters	199.29~200 meters	#1 - 128, OLD PHYSICS BUILDING	555.68	0.5	356.3895 to 632.5404
			#2 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	525.28	0.0280822	
			#3 - 170, MECHANICAL ENGINEERING BUILDING	386.32	0.0092521	
			#4 - 194, BIOSCIENCES 5	460.05	0.0025641	
			#5 - 260, 200 BERKELEY ST (MSHS)	0	0.0020361	
COVID-19-Strict	0~0 meters	86.79~87 meters	#1 - 106, LAW BUILDING	86.79	202	0.0 to 348.0248
			#2 - 105, FBE BUILDING	4.41	111	
			#3 - 260, 200 BERKELEY ST (MSHS)	0	14	
			#4 - 204, 208-210 BERKELEY ST (MCM PRACTICE ROOMS)	86.81	5	
			#5 - 326, 95-109 BARRY ST (FBE)	30.01	0	
High Capacity	356.3895 ~357 meters	199.29~200 meters	#1 - 128, OLD PHYSICS BUILDING	555.68	0.0032877	356.3895 to 632.5404
			#2 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	525.28	0.0003413	
			#3 - 170, MECHANICAL ENGINEERING BUILDING	386.32	0.0000912	
			#4 - 260, 200 BERKELEY ST (MSHS)	0	0.000022	
			#5 - 163, WALTER BOAS BUILDING	455.78	0.0000201	
Excellent Toilets Rooms	356.3895 ~357 meters	199.29~200 meters	#1 - 128, OLD PHYSICS BUILDING	555.68	0.0016295	356.3895 to 632.5404
			#2 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	525.28	0.0006254	
			#3 - 106, LAW BUILDING	86.79	0.0000811	
			#4 - 170, MECHANICAL ENGINEERING BUILDING	386.32	0.0000603	
			#5 - 104, ALAN GILBERT BUILDING	128.96	0.000039	
Easy Availability	356.3895 ~357 meters	199.29~200 meters	#1 - 128, OLD PHYSICS BUILDING	555.68	0.4835717	356.3895 to 632.5404
			#2 - 199, 757 SWANSTON ST (STOP 1 & STUDENT SERVICES)	525.28	0.0276167	
			#3 - 170, MECHANICAL ENGINEERING BUILDING	386.32	0.0090858	
			#4 - 194, BIOSCIENCES 5	460.05	0.0024977	
			#5 - 260, 200 BERKELEY ST (MSHS)	0	0.0019925	

Table 17: Results collected for The Spot Building, Parkville (110)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	13.2271 ∼14 meters	147.1 ∼148 meters	#1 - 128, OLD PHYSICS BUILDING	160.33	0.5	13.2271 to 313.8194
			#2 - 163, WALTER BOAS BUILDING	140.22	0.001992	
			#3 - 113, BALDWIN SPENCER BUILDING	27.19	0.0018898	
			#4 - 162, ALICE HOY BUILDING	131.2	0.0008643	
			#5 - 150, OLD QUADRANGLE BUILDING	118.59	0.0005868	
COVID-19-Strict	709.6478 ∼710 meters	4.96 ∼5 meters	#1 - 106, LAW BUILDING	714.61	202	709.6478 to 1540.0525
			#2 - 110, THE SPOT	653.57	126	
			#3 - 105, FBE BUILDING	583.11	111	
			#4 - 104, ALAN GILBERT BUILDING	475.22	93	
			#5 - 379, 207-221 BOUVERIE ST (MSPGH & GEOGRAPHY)	524.4	49	
High Capacity	13.2271 ∼14 meters	147.1 ∼148 meters	#1 - 128, OLD PHYSICS BUILDING	160.33	0.0032877	13.2271 to 313.8194
			#2 - 163, WALTER BOAS BUILDING	140.22	0.0000201	
			#3 - 113, BALDWIN SPENCER BUILDING	27.19	0.0000201	
			#4 - 162, ALICE HOY BUILDING	131.2	0.0000058	
			#5 - 150, OLD QUADRANGLE BUILDING	118.59	0.0000047	
Good Toilets Rooms	13.2271 ∼14 meters	147.1 ∼148 meters	#1 - 128, OLD PHYSICS BUILDING	189.14	0.0050251	13.2271 to 313.8194
			#2 - 113, BALDWIN SPENCER BUILDING	27.19	0.0000522	
			#3 - 192, DAVID CARO BUILDING	22.08	0.0000041	
			#4 - 192, DAVID CARO BUILDING	57.2	0.0000041	
			#5 - 192, DAVID CARO BUILDING	56.65	0.0000041	
Easy Availability	13.2271 ∼14 meters	147.1 ∼148 meters	#1 - 128, OLD PHYSICS BUILDING	160.33	0.4835717	13.2271 to 313.8194
			#2 - 163, WALTER BOAS BUILDING	140.22	0.0019656	
			#3 - 113, BALDWIN SPENCER BUILDING	27.19	0.0018546	
			#4 - 162, ALICE HOY BUILDING	131.2	0.0008434	
			#5 - 150, OLD QUADRANGLE BUILDING	118.59	0.0005763	

Table 18: Results collected for Glyn Davis Building, Parkville (133)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	2.5913 ∼3 meters	0 ∼0 meters	#1 - 128, OLD PHYSICS BUILDING	2.59	0.5	2.5913 to 278.9747
			#2 - 194, BIOSCIENCES 5	90.05	0.0025641	
			#3 - 163, WALTER BOAS BUILDING	157.46	0.001992	
			#4 - 113, BALDWIN SPENCER BUILDING	184.12	0.0018898	
			#5 - 162, ALICE HOY BUILDING	278.11	0.0008643	
COVID-19-Strict	2.5913 ∼3 meters	276.32 ∼277 meters	#1 - 104, ALAN GILBERT BUILDING	278.91	93	2.5913 to 278.9747
			#2 - 133, GLYN DAVIS BUILDING	211.92	65	
			#3 - 115, REDMOND BARRY BUILDING	257.12	48	
			#4 - 115, REDMOND BARRY BUILDING	243.51	48	
			#5 - 168, DOUG MCDONELL BUILDING	275.39	40	
High Capacity	2.5913 ∼3 meters	0 ∼0 meters	#1 - 128, OLD PHYSICS BUILDING	2.59	0.0032877	2.5913 to 278.9747
			#2 - 163, WALTER BOAS BUILDING	157.46	0.0000201	
			#3 - 194, BIOSCIENCES 5	90.05	0.0000201	
			#4 - 113, BALDWIN SPENCER BUILDING	184.12	0.0000058	
			#5 - 104, ALAN GILBERT BUILDING	278.91	0.0000047	
Good Toilets Rooms	2.5913 ∼3 meters	0 ∼0 meters	#1 - 128, OLD PHYSICS BUILDING	2.59	0.0050251	2.5913 to 278.9747
			#2 - 113, BALDWIN SPENCER BUILDING	184.12	0.0000522	
			#3 - 194, BIOSCIENCES 5	90.05	0.0000451	
			#4 - 147, BIOSCIENCES 4	97.66	0.0000226	
			#5 - 147, BIOSCIENCES 4	75.17	0.0000226	
Easy Availability	2.5913 ∼3 meters	0 ∼0 meters	#1 - 128, OLD PHYSICS BUILDING	2.59	0.4835717	2.5913 to 278.9747
			#2 - 194, BIOSCIENCES 5	90.05	0.0024977	
			#3 - 163, WALTER BOAS BUILDING	157.46	0.0019656	
			#4 - 113, BALDWIN SPENCER BUILDING	184.12	0.0018546	
			#5 - 162, ALICE HOY BUILDING	278.11	0.0008434	

Table 19: Results collected for Old Arts Building, Parkville (149)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	14.1813∼15 meters	227.4 ∼228 meters	#1 - 128, OLD PHYSICS BUILDING	241.58	0.5	14.1813 to 266.8577
			#2 - 194, BIOSCIENCES 5	119.38	0.0025641	
			#3 - 260, 200 BERKELEY ST (MSHS)	158.54	0.0020361	
			#4 - 204, 208-210 BERKELEY ST (MCM PRACTICE ROOMS)	129.08	0.0014603	
			#5 - 220, 780 ELIZABETH ST	96.54	0.0010485	
COVID-19-Strict	14.1813∼15 meters	213.01 ∼214 meters	#1 - 110, THE SPOT	227.19	126	14.1813 to 259.7771
			#2 - 105, FBE BUILDING	169.49	111	
			#3 - 104, ALAN GILBERT BUILDING	47.7	93	
			#4 - 191, JOHN MEDLEY BUILDING	83.6	39	
			#5 - 191, JOHN MEDLEY BUILDING	133.54	39	
High Capacity	14.1813∼15 meters	227.4 ∼228 meters	#1 - 128, OLD PHYSICS BUILDING	241.58	0.0032877	14.1813 to 266.8577
			#2 - 260, 200 BERKELEY ST (MSHS)	158.54	0.000022	
			#3 - 194, BIOSCIENCES 5	119.38	0.0000197	
			#4 - 204, 208-210 BERKELEY ST (MCM PRACTICE ROOMS)	129.08	0.000013	
			#5 - 104, ALAN GILBERT BUILDING	47.7	0.0000108	
Excellent Toilets Rooms	14.1813∼15 meters	227.4 ∼228 meters	#1 - 128, OLD PHYSICS BUILDING	241.58	0.0016295	14.1813 to 266.8577
			#2 - 104, ALAN GILBERT BUILDING	47.7	0.000039	
			#3 - 105, FBE BUILDING	169.49	0.0000375	
			#4 - 110, THE SPOT	227.19	0.0000168	
			#5 - 191, JOHN MEDLEY BUILDING	83.6	0.0000093	
Easy Availability	14.1813∼15 meters	227.4 ∼228 meters	#1 - 128, OLD PHYSICS BUILDING	241.58	0.4835717	14.1813 to 266.8577
			#2 - 194, BIOSCIENCES 5	119.38	0.0024977	
			#3 - 260, 200 BERKELEY ST (MSHS)	158.54	0.0019925	
			#4 - 204, 208-210 BERKELEY ST (MCM PRACTICE ROOMS)	129.08	0.0014401	
			#5 - 220, 780 ELIZABETH ST	96.54	0.0010324	

Table 20: Results collected for Medical Building, Parkville (181)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	0∼0 meters	97.82 ∼98 meters	#1 - 873, SOUTHBANK THE STABLES	97.82	0.0791667	0.0 to 113.8281
			#2 - 879, SOUTHBANK PERFORMING ARTS, DODDS ST	0	0.0315789	
			#3 - 874, SOUTHBANK ART STUDIOS 1	75.3	0.0014938	
			#4 - 875, SOUTHBANK ART STUDIOS 2	50.77	0	
			#5 - 876, STURT ST SERVICE CENTRE	51.03	0	
COVID-19-Strict	143.5654 ∼144 meters	46.1∼47 meters	#1 - 862, SOUTHBANK MUSIC BUILDING	189.67	20	143.5654 to 270.7758
			#2 - 861, SOUTHBANK FILM & TELEVISION BUILDING	189.55	20	
			#3 - 873, SOUTHBANK THE STABLES	97.82	19	
			#4 - 879, SOUTHBANK PERFORMING ARTS, DODDS ST	0	18	
			#5 - 863, SOUTHBANK THE HUB	156.89	12	
High Capacity	0∼0 meters	97.82 ∼98 meters	#1 - 873, SOUTHBANK THE STABLES	97.82	0.0063322	0.0 to 113.8281
			#2 - 879, SOUTHBANK PERFORMING ARTS, DODDS ST	0	0.0024123	
			#3 - 874, SOUTHBANK ART STUDIOS 1	75.3	0.0024123	
			#4 - 875, SOUTHBANK ART STUDIOS 2	50.77	0	
			#5 - 876, STURT ST SERVICE CENTRE	51.03	0	
Good Toilets Rooms	0∼0 meters	0∼0 meters	#1 - 879, SOUTHBANK PERFORMING ARTS, DODDS ST	0	0.0026316	0.0 to 113.8281
			#2 - 874, SOUTHBANK ART STUDIOS 1	75.3	0.0002282	
			#3 - 875, SOUTHBANK ART STUDIOS 2	50.77	0	
			#4 - 876, STURT ST SERVICE CENTRE	51.03	0	
			#5 - 877, SOUTHBANK END-OF-TRIP FACILITIES	30.62	0	
Easy Availability	0∼0 meters	97.82 ∼98 meters	#1 - 873, SOUTHBANK THE STABLES	97.82	0.0709154	0.0 to 113.8281
			#2 - 879, SOUTHBANK PERFORMING ARTS, DODDS ST	0	0.0289459	
			#3 - 874, SOUTHBANK ART STUDIOS 1	75.3	0.001347	
			#4 - 875, SOUTHBANK ART STUDIOS 2	50.77	0	
			#5 - 876, STURT ST SERVICE CENTRE	51.03	0	

Table 21: Results collected for The Ian Potter South Bank Centre Building, SouthBank (880)

Factors	Budget (metres)	Relaxing Budget	Best Nearby Buildings	Cost	Reward	Rewarding Radius
No factors	113.3536∼114 meters	40.15 ∼41 meters	#1 - 420, WERRIBEE DOG COLONY	153.5	0.0069444	113.3536 to 153.5042
			#2 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	0.0069444	
			#3 - 434, WERRIBEE RESEARCH LABORATORY	63.38	0	
			#4 - 442, WERRIBEE CATTLE TRAINING FACILITY	136.9	0	
			#5 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
COVID-19-Strict	5.1228 ∼6 meters	28.56∼29 meters	#1 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	25	5.1228 to 43.464
			#2 - 415, WERRIBEE BIOHAZARD DEPOT	19.7	0	
			#3 - 411, WERRIBEE VETERINARY HOSPITAL	9.55	0	
			#4 - 417, WERRIBEE PARASITOLOGY BUILDING	11.6	0	
			#5 - 439, WERRIBEE DEMOUNTABLE LAUNDRY	5.1	0	
High Capacity	113.3536∼114 meters	40.15 ∼41 meters	#1 - 420, WERRIBEE DOG COLONY	153.5	0.0006142	113.3536 to 153.5042
			#2 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	0.0006142	
			#3 - 434, WERRIBEE RESEARCH LABORATORY	63.38	0	
			#4 - 442, WERRIBEE CATTLE TRAINING FACILITY	136.9	0	
			#5 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
Excellent Toilets Rooms	113.3536∼114 meters	23.55 ∼24 meters	#1 - 434, WERRIBEE RESEARCH LABORATORY	63.38	0	113.3536 to 153.5042
			#2 - 442, WERRIBEE CATTLE TRAINING FACILITY	136.9	0	
			#3 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	
			#4 - 425, WERRIBEE CHICKEN HOUSE	73.13	0	
			#5 - 421, WERRIBEE CAMPUS SERVICES WORKSHOP/STORE	39.14	0	
Easy Availability	113.3536∼114 meters	40.15 ∼41 meters	#1 - 420, WERRIBEE DOG COLONY	153.5	0.0050232	113.3536 to 153.5042
			#2 - 418, WERRIBEE LEARNING & TEACHING BUILDING	33.68	0.0006371	
			#3 - 434, WERRIBEE RESEARCH LABORATORY	63.38	0	
			#4 - 442, WERRIBEE CATTLE TRAINING FACILITY	136.9	0	
			#5 - 423, WERRIBEE AVIAN ISOLATION UNIT	43.46	0	

Table 22: Results collected for Werribee Pathology Building, (416)

Algorithm	Radius Range(meters)	Delta(meters)	Average Reward
KMEANS	2.9043 to 421.9135 meters	8.87 meters	0.01
Agglomerative Clustering	2.9043 to 337.3438 meters	8.87 meters	0.01
BIRCH	2.9043 to 337.3438 meters	8.87 meters	0.01
Mini KMEANS	2.9043 to 431.0124 meters	8.87 meters	0.01
GMM	189.1402 to 431.0124 meters	-4.99 meters	0.14
Iteration 2			
KMEANS	2.9043 to 421.9135 meters	8.87 meters	0.01
Agglomerative Clustering	2.9043 to 337.3438 meters	8.87 meters	0.01
BIRCH	2.9043 to 337.3438 meters	8.87 meters	0.01
Mini KMEANS	2.9043 to 443.2906 meters	8.87 meters	0.01
GMM	189.1402 to 431.0124 meters	-4.99 meters	0.14

Table 23: Results collected for Redmond Barry Building, Parkville (115)

9.3.2 Floor Algorithm Results

9.3.2.1 Meeting Rooms Objective

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	3	4	Level 8	7	2.957477
			Level 4	3	0.808377
			Level 7	6	0.772713
COVID-lockdown high	5	2	Level 8	7	0.314136
			Level 7	6	0.136126
			Level 6	5	0.109948
High Capacity	3	4	Level 8	7	2.957477
			Level 4	3	0.808377
			Level 7	6	0.772713
With-equipment	2	8	Level 8	7	2.957477
			Level 4	3	1.313613
			Level 9	8	1.111518
Excellent Meeting room	2	8	Level 8	7	3.265191
			Level 9	8	1.227168
			Level 4	3	0.892486
Easy Availability	3	2	Level 4	3	0.808377
			Level 6	5	0.719318
			Level 3	2	0.544100

Table 24: Floor results for Doug McDonell Building, Parkville (168)

Factors	**Budget(floors)**	**Relaxing Budget(floors)**	**Best floors**	**Cost**	**Reward**
No factor	1	3	Level 5	4	2.458719
			Level 4	3	1.308562
			Level 2	1	1.113237
COVID-lockdown high	1	3	Level 5	4	0.298932
			Level 4	3	0.270463
			Level 2	1	0.206406
High Capacity	1	3	Level 5	4	2.458719
			Level 4	3	1.308562
			Level 2	1	1.113237
With-equipment	1	3	Level 5	4	2.458719
			Level 4	3	1.480741
			Level 2	1	1.113237
Excellent Meeting room	3	3	Level 5	4	3.183871
			Level 4	3	1.694497
			Level 7	6	1.111828
Easy Availability	1	3	Level 5	4	2.458719
			Level 4	3	1.308562
			Level 2	1	1.113237

Table 25: Floor results for Alan Gilbert Building, Parkville (104)

Factors	**Budget(floors)**	**Relaxing Budget(floors)**	**Best floors**	**Cost**	**Reward**
No factor	1	4	Level 2	1	2.114362
			Level 3	2	2.059444
			Level 6	5	1.395107
COVID-lockdown high	1	2	Ground Mezzanine	0.5	0.154362
			Level 2	1	0.147651
			Level 3	2	0.120805
High Capacity	1	4	Level 2	1	2.114362
			Level 3	2	2.059444
			Level 6	5	1.395107
With-equipment	1	4	Level 6	5	2.170167
			Level 2	1	2.114362
			Level 3	2	2.059444
Excellent Meeting room	1	4	Level 2	1	2.114362
			Level 3	2	2.059444
			Level 6	5	1.395107
Easy Availability	1	4	Level 2	1	2.114362
			Level 3	2	2.059444
			Level 6	5	1.395107

Table 26: Floor results for Law Building, Parkville (106)

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	1	4	Level 6	5	3.406106
			Level 5	4	1.041563
			Level 2	1	0.999257
COVID-lockdown high	1	3	Level 4	3	0.322581
			Level 5	4	0.185484
			Level 2	1	0.173387
High Capacity	1	4	Level 6	5	3.406106
			Level 5	4	1.041563
			Level 2	1	0.999257
With-equipment	3	2	Level 6	5	4.667627
			Level 4	3	1.103831
			Level 5	4	1.041563
Excellent Meeting room	1	4	Level 6	5	3.406106
			Level 5	4	1.041563
			Level 2	1	0.999257
Easy Availability	1	4	Level 6	5	3.406106
			Level 5	4	1.041563
			Level 2	1	0.999257

Table 27: Floor results for Stop 1 Building, Parkville (199)

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	1	5	Level 6	5	1.000596
			Level 2	1	0.800029
			Level 7	6	0.753912
COVID-lockdown high	1	5	Level 2	1	0.141892
			Level 6	5	0.128378
			Level 7	6	0.108108
High Capacity	1	7	Level 9	8	2.656931
			Level 6	5	1.000596
			Level 2	1	0.800029
With-equipment	1	5	Level 6	5	1.263911
			Level 4	3	0.801031
			Level 2	1	0.800029
Excellent Meeting room	1	4	Level 6	5	1.057773
			Level 2	1	0.845745
			Level 5	4	0.728022
Easy Availability	1	5	Level 6	5	1.000596
			Level 2	1	0.800029
			Level 7	6	0.753912

Table 28: Floor results for 100 Leicester St, Parkville (278)

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	1	2	Level 4	3	1.429662
			Level 3	2	0.607294
			Level 2	1	0.316568
COVID-lockdown high	1	2	Level 4	3	0.414201
			Level 3	2	0.278107
			Basement 1	0.9	0.106509
High Capacity	1	2	Level 4	3	1.429662
			Level 3	2	0.607294
			Basement 1	0.9	0.106509
With-equipment	1	2	Level 4	3	1.633900
			Level 3	2	0.607294
			Level 2	1	0.316568
Excellent Meeting room	1	2	Level 4	3	1.429662
			Level 3	2	0.607294
			Level 2	1	0.316568
Easy Availability	1	2	Level 4	3	1.429662
			Level 3	2	0.607294
			Level 2	1	0.316568

Table 29: Floor results for Glyn Davis Building, Parkville (133)

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	1	1	Level 3	2	5.60
			Level 2	1	0.84
			Level 1	0	0
COVID-lockdown high	1	1	Level 3	2	0.5
			Level 2	1	0.3
			Level 1	0	0
High Capacity	1	1	Level 3	2	5.60
			Level 2	1	0.84
			Level 1	0	0
With-equipment	1	1	Level 2	1	20.44
			Level 3	2	5.6
			Level 1	0	0
Excellent Meeting room	1	1	Level 3	2	5.60
			Level 2	1	0.84
			Level 1	0	0
Easy Availability	1	1	Level 3	2	5.60
			Level 2	1	0.84
			Level 1	0	0

Table 30: Floor results for Elisabeth Murdoch Building, Southbank (860)

Factors	Budget(floors)	Relaxing Budget(floors)	Best floors	Cost	Reward
No factor	1	0	Gournd	1	1
COVID-lockdown high	1	0	Gournd	1	1
High Capacity	1	0	Gournd	1	1
With-equipment	1	0	Gournd	1	1
Excellent Meeting room	1	0	Gournd	1	1
Easy Availability	1	0	Gournd	1	1

Table 31: Floor results for Werribee Veterinary Hospital, Werribee (411)

9.3.2.2 Toilet Facilities Objective

Factors	**Budget**	**Relaxing Budget**	**Floor**	**Cost**	**Reward**
No factors	2	1	#1 - Level 4	2	4.61119
			#2 - Level 6	4	2.18184
			#3 - Level 5	3	1.93258
COVID-19-Strict	1	2	#1 - Basement 2	3	0.14583
			#2 - Level 5	3	0.10417
			#3 - Level 3	1	0.08333
High Capacity	1	3	#1 - Level 4	2	2.30559
			#2 - Level 6	3	1.09092
			#3 - Level 3	4	0.80407
Excellent Toilet Rooms	1	1	#1 - Level 4	2	4.61119
			#2 - Level 5	3	1.93258
			#3 - Level 3	1	1.20610
Easy Availability	1	2	#1 - Level 4	2	4.12661
			#2 - Level 5	3	1.77079
			#3 - Level 3	1	1.08550

Table 32: Results collected for Redmond Barry Building, Parkville (115)

Factors	**Budget (floors)**	**Relaxing Budget (floors)**	**Floors**	**Cost**	**Reward**
No factors	1	2	#1 - Level 1	2	2.91181
			#2 - Level 6	3	2.09270
			#3 - Level 4	1	0.71838
COVID-19-Low	2	3	#1 - Level 1	2	5.82362
			#2 - Level 6	3	4.18540
			#3 - Level 4	1	1.43676
High Capacity	1	3	#1 - Level 1	2	1.66389
			#2 - Level 4	1	0.41050
			#3 - Level 2	1	0.25215
Excellent Toilet Rooms	1	2	#1 - Level 1	2	3.05740
			#2 - Level 4	1	0.75430
			#3 - Level 2	1	0.46333
Easy Availability	1	1	#1 - Level 1	2	2.58385
			#2 - Level 6	3	1.82262
			#3 - Level 4	1	0.62864

Table 33: Results collected for The Spot, Parkville (110)

Factors	Budget (floors)	Relaxing Budget (floors)	Floors	Cost	Reward
No factors	1	2	#1 - Level 3	3	20.94346
			#2 - Level 2	2	1.56023
			#3 - Level 1	1	1.22564
COVID-19-Strict	1	1	#1 - Basement 1	1	0.20000
			#2 - Level 2	2	0.18462
			#3 - Level 1	1	0.15385
High Capacity	2	3	#1 - Level 3	3	30.93189
			#2 - Level 4	4	13.55349
			#3 - Level 2	2	2.30434
Excellent Toilet Rooms	2	2	#1 - Level 3	3	20.94346
			#2 - Level 4	4	9.17684
			#3 - Level 2	2	1.56023
Easy Availability	2	2	#1 - Level 3	3	20.94346
			#2 - Level 4	4	9.17684
			#3 - Level 2	2	1.56023

Table 34: Results collected for Glyn Davis Building, Parkville (133)

Factors	Budget (floors)	Relaxing Budget (floors)	Floors	Cost	Reward
No factors	1	3	#1 - Level 7	2	3.74057
			#2 - Level 9	4	0.32258
			#3 - Level 2	3	0.31240
COVID-19-Medium	1	1	#1 - Level 7	2	3.74057
			#2 - Level 2	3	0.31240
			#3 - Level 3	2	0.19848
High Capacity	1	3	#1 - Level 1	4	17.63888
			#2 - Level 7	2	4.82654
			#3 - Level 9	4	0.83247
Excellent Toilet Rooms	2	2	#1 - Level 1	4	6.83507
			#2 - Level 7	2	3.74057
			#3 - Level 9	4	0.32258
Easy Availability	1	1	#1 - Level 7	2	2.87967
			#2 - Level 2	3	0.25119
			#3 - Level 3	2	0.17409

Table 35: Results collected for Medical Building, Parkville (181)

Factors	Budget (floors)	Relaxing Budget (floors)	Floors	Cost	Reward
No factors	1	1	#1 - Level 1	3	11.61926
			#2 - Level 3	1	2.79309
			#3 - Level 2	2	2.05046
COVID-19-Strict	1	2	#1 - Level 2	2	0.36585
			#2 - Level 3	1	0.12195
			#3 - Level 1	3	0.09756
High Capacity	1	3	#1 - Level 3	1	2.72497
			#2 - Level 6	2	2.05046
			#3 - Level 2	2	0.40737
Good Toilet Rooms	1	1	#1 - Level 1	3	11.61926
			#2 - Level 3	1	2.79309
			#3 - Level 6	2	2.05046
Easy Availability	1	1	#1 - Level 1	3	8.58798
			#2 - Level 3	1	2.09244
			#3 - Level 6	2	1.84471

Table 36: Results collected for David Caro Building, Parkville (192)

Factors	Budget (floors)	Relaxing Budget (floors)	Floors	Cost	Reward
No factors	1	2	#1 - Level 2	1	4.94015
			#2 - Ground	1	0.25000
			#3 - Level 3	2	0.07143
COVID-19-Strict	1	3	#1 - Ground	1	0.25000
			#2 - Level 2	1	0.21429
			#3 - Level 3	2	0.07143
High Capacity	1	3	#1 - Level 2	1	8.46882
			#2 - Ground	1	0.50000
			#3 - Level 5	4	0.09184
Good Toilet Rooms	1	2	#1 - Level 2	1	4.94015
			#2 - Ground	1	0.25000
			#3 - Level 3	2	0.07143
Easy Availability	1	1	#1 - Level 2	1	1.65662
			#2 - Ground	1	0.25000
			#3 - Level 5	4	0.10714

Table 37: Results collected for Old Microbiology Building (184)

Factors	Budget	Relaxing Budget	Floor	Cost	Reward
No factors	1	2	#1 - Level 5	2	18.72971
			#2 - Level 4	3	10.40539
			#3 - Level 8	1	0.74637
COVID-19-Medium	1	3	#1 - Level 5	2	18.72971
			#2 - Level 4	3	10.40539
			#3 - Level 8	1	0.74637
High Capacity	1	2	#1 - Level 5	2	12.23164
			#2 - Level 4	3	6.79536
			#3 - Level 3	4	2.98030
Easy Availability	1	3	#1 - Level 5	2	9.69092
			#2 - Level 4	3	8.83616
			#3 - Level 3	4	1.04258

Table 38: Results collected for Ian Potter South Bank Centre Building, SouthBank (880)

9.4 Research Paper

9.4.1 Searching k-Optimal Goals for an Orienteering Problem on a Specialized Graph with Budget Constraints

Searching k-Optimal Goals for an Orienteering Problem on a Specialized Graph with Budget Constraints

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Abstract

We propose a novel non-randomized anytime orienteering algorithm for finding k-optimal goals that maximize reward on a specialized graph with budget constraints. This specialized graph represents a real-world scenario which is analogous to an orienteering problem of finding k-most optimal goal states.

Introduction

Orienteering Problem (OP) is a special case of the Informative Path Planning (IPP) problem where rewards at different nodes are calculated independently of each other. However, the OP is considered to be NP-hard and mostly solved with heuristic-based search strategies and customized algorithms (Wei and Zheng 2020). We aim to solve a domain-related orienteering problem which can be formalized for a specialized directed weighted graph. First, we initialize a specialized graph for mapping the Parkville campus of the University of Melbourne. We then use this graph to formalize our problem of finding the most optimal nearest building from a starting building such that the reward can be maximized within the provided travelling budget constraint. The proposed non-randomized algorithm is applied to find k-most optimal nearest buildings inside the campus from a given starting building, discussed in the results section. We also show how COVID-19 lock-down restrictions can be incorporated into our algorithm to solve our defined orienteering problem.

Problem Formulation

We formulate our domain-related optimal building finding problem into a generic orienteering problem (OP) for a specialized graph below.

Let us assume a weighted directed specialized graph $G_s = (V, E)$ for n number of nodes where $v_s \in V$ is the pre-defined start node such that $V = \{v_1, v_2, v_3, ..., v_n\}$ and $E = \{(v_s, v_i) \setminus (v_s, v_s) \mid \forall\, i \in [1, n]\,\}$. Here, v_s is having n out-degree with 0 in-degree (i.e. v_s is connected to every other node in V) and $v_i \,\forall\, i \in [1, n] \setminus v_s$ is connected to only v_s with 1 in-degree and 0 out-degree.

Let v_g be the set of k-optimal goal nodes s.t. $v_g \in V$ and $k \leq n$. These goals are attained in the decreasing order of their gained rewards after respecting budget constraints (i.e. $v_{g1} > v_{g2} > ... > v_{gk}$). Let r be the set of nodes which we can visit such that $r \subseteq V \setminus v_s$. Let B be the travelling budget which will enable the budget constraints. Let O be the generic objectives and F be the generic factors which can be used to tweak the reward function of the problem.

For each r, let $R(r, o, f)$ be the reward function where $R : (r, o, f) \rightarrow \mathbb{R}_0^+ \cup \{\infty\}$ calculates the reward based on the provided set of factors $f \subseteq F$ and objective $o \in O$. Let $I(r) = R(r, o, f)$ be the reward gained by visiting each node in r. Let the cost of traversal be given by $C(r) = C(v_s, v_i^r)$, where v_i is the i^{th} element in r, $\forall i \in [1, |r|]$. Let $L \in \mathbb{R}_0^+ \cup \{\infty\}$ be the constraint limit. Using above notations, the hard-constraint problem can then be defined by equation 1.

$$\arg\max_{r \subseteq V} I(r) \textit{ subject to } C(r) \leq B \leq L \tag{1}$$

We can relax the above hard-constraint by introducing a hyper-parameter δ to formulate a soft-constraint problem as shown in equation 2.

$$\arg\max_{r \subseteq V} I(r) \textit{ subject to } C(r) \leq B + \delta \leq L \tag{2}$$

where $\delta \in \mathbb{R}_0^+ \cup \{\infty\}$.

Informally, the solution to our stated problem is a set of ordered k-optimal goal nodes, such that the reward obtained by visiting the node is maximized while the path cost stays within a specified travelling budget B.

Non-randomized Anytime Orienteering

In this section, we propose a novel way of solving the problem formulation shown in equation 2 which is inspired by the general randomized algorithm for IPP problems (Arora and Scherer 2017).

The algorithm starts with a priority queue and creates r subset s.t. $r \subseteq V \setminus v_s$. Then, for each node in r, path cost $C(r)$ and node reward $I(r)$ is calculated. It is then ensured that the budget constraint is satisfied and the selected node is pushed into the priority queue with negative reward as the priority. We can pop the queue item with minimum priority k-times to find the k-most optimal goal nodes. This process is described in Algorithm 1.

Algorithm 1: Non-Randomized Anytime Orienteering to find k-optimal goals for a specialized graph

Inputs: $G_s = (V, E), v_s, B, L, k, \delta, o \in O, f \subseteq F$
Output: $v_g = \{v_{g1}, .., v_{gk}\}$ s.t. $v_{g1} > ... > v_{gk}$
queue := new priority queue
$v_g = \emptyset$
$r := r \subseteq V \setminus v_s$
for $v_i \ in \ r$ **do**
  $I(r) = R(v_i, o, f)$ `//node reward`
  $C(r) = C(v_s, v_i)$ `//path cost`
  if $C(r) \leq B + \delta \leq L$ **then**
    $priority = -1 * I(r)$
    queue.insert($v_i, priority$)
  end
end
while *not queue.empty()* **do**
  ρ := queue.pop-min() `//best node`
  if $len(v_g) < k$ **then**
    $v_g := v_g \cup \rho$
  end
end

Time Complexity. If we assume a standard binary heap implementation of the priority queue, then the insertion and deletion time complexity is $O(log\ n)$, where n is the size of the input (Atkinson et al. 1986). This can be further optimized by several customizations (Edelkamp, Elmasry, and Katajainen 2017). Hence, the time complexity of our proposed algorithm for the best and the worst case can be stated as $O(n - 1 * log\, n) + O(k * log\, n) \leq O(n\, log\, n)$.

Space Complexity. If we again assume a heap data structure implementation of the priority queue, then the space complexity of storing n elements in the priority queue is $O(n)$ (Atkinson et al. 1986). Hence, the best and worst case space complexity of our proposed algorithm is $O(n)$.

Limitations. Our algorithm relies on the assumption that the graph is a specialized weighted directed graph with one central node (0 in-degree and n out-degree) and n isolated nodes connected with only one central node. Due to this assumption, the algorithm is efficient and applicable only for such versions of the specialized graph and cannot be extended implicitly to any general weighted directed graph.

Experimental Results

In this section, we show experimental results for a domain-specific orienteering problem solved using our proposed algorithm. Here, our goal is to find the k-most optimal nearest building inside the Parkville campus of the University of Melbourne. These buildings should be within a specific radius (B) that maximises the chances (reward) of either booking a meeting room or using a toilet facility based on supply, demand and other preferences or factors. A specific scenario is shown in Figure 1 where $R(.)$ are the rewards given by the buildings with no factors and $R(COVID)$ are the rewards based on COVID-19 lock-down restrictions.

Table 1 shows the results for the stated scenario for 3-optimal nearest buildings using our proposed algorithm. In addition, we were also able to simulate a COVID-19 restriction scenario by enhancing the reward function $R(r, o, f)$, obtaining results as shown in the Table 2.

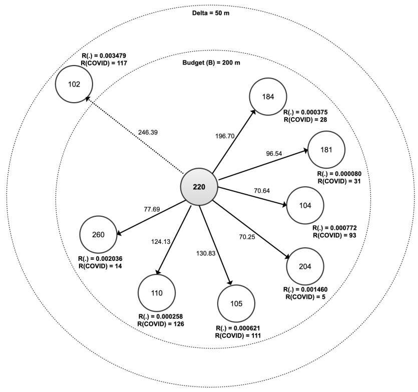

Figure 1: Finding $k = 3$ most optimal nearest building from $v_s = 220$ that maximises the chances (reward) of booking a meeting room within $B = 200$ meters and $\delta = 50$ meters

Goals	Cost	$R(.)$
$v_{g1} = 260$	77.69	0.0020
$v_{g2} = 204$	70.25	0.0014
$v_{g3} = 104$	70.64	0.0007

Goals	Cost	$R(.)$
$v_{g1} = 102$	246.39	0.0034
$v_{g2} = 260$	77.69	0.0020
$v_{g3} = 204$	70.25	0.0014

Table 1: $k = 3$ most optimal nearest buildings without any factors with $B = 200\ m$ hard-constraint (left) and $B + \delta = 250\ m$ soft-constraint (right)

Goals	Cost	$R(COVID)$
$v_{g1} = 110$	124.13	126
$v_{g2} = 105$	130.83	111
$v_{g3} = 104$	70.64	93

Goals	Cost	$R(COVID)$
$v_{g1} = 110$	124.13	126
$v_{g2} = 102$	246.39	117
$v_{g3} = 105$	130.83	111

Table 2: $k = 3$ most optimal nearest buildings in COVID lockdown situation with $B = 200\ m$ hard-constraint (left) and $B + \delta = 250\ m$ soft-constraint (right)

References

Arora, S.; and Scherer, S. 2017. Randomized algorithm for informative path planning with budget constraints. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 4997–5004.

Atkinson, M. D.; Sack, J.-R.; Santoro, N.; and Strothotte, T. 1986. Min-Max Heaps and Generalized Priority Queues. *Commun. ACM* 29(10): 996–1000. ISSN 0001-0782. doi:10.1145/6617.6621. URL https://doi.org/10.1145/6617.6621.

Edelkamp, S.; Elmasry, A.; and Katajainen, J. 2017. Optimizing Binary Heaps. *Theory of Computing Systems* 61. doi:10.1007/s00224-017-9760-2.

Wei, Y.; and Zheng, R. 2020. Informative Path Planning for Mobile Sensing with Reinforcement Learning. doi:10.1109/INFOCOM41043.2020.9155528.

References

[1] Bruce Golden, L. Levy, and Rakesh Vohra. "The orienteering problem". In: *Nav Res Logist* 34 (June 1987), pp. 307–318. DOI: 10.1002/1520-6750(198706)34:3<307::AID-NAV3220340302>3.0.CO;2-D.

[2] Jingjin Yu, Mac Schwager, and Daniela Rus. "Correlated Orienteering Problem and its Application to Informative Path Planning for Persistent Monitoring Tasks". In: *IEEE International Conference on Intelligent Robots and Systems* (Feb. 2014). DOI: 10.1109/IROS.2014.6942582.

[3] S. Arora and S. Scherer. "Randomized algorithm for informative path planning with budget constraints". In: *2017 IEEE International Conference on Robotics and Automation (ICRA)*. 2017, pp. 4997–5004.

[4] Yongyong Wei and Rong Zheng. "Informative Path Planning for Mobile Sensing with Reinforcement Learning". In: Apr. 2020. DOI: 10.1109/INFOCOM41043.2020.9155528.

[5] M. D. Atkinson et al. "Min-Max Heaps and Generalized Priority Queues". In: *Commun. ACM* 29.10 (Oct. 1986), pp. 996–1000. ISSN: 0001-0782. DOI: 10.1145/6617.6621. URL: https://doi.org/10.1145/6617.6621.

[6] Stefan Edelkamp, Amr Elmasry, and Jyrki Katajainen. "Optimizing Binary Heaps". In: *Theory of Computing Systems* 61 (Apr. 2017). DOI: 10.1007/s00224-017-9760-2.

[7] Marcel R. Ackermann et al. "Analysis of Agglomerative Clustering". In: *28th International Symposium on Theoretical Aspects of Computer Science, STACS 2011*. 2011, pp. 308–319.

[8] Tian Zhang, Raghu Ramakrishnan, and Miron Livny. "BIRCH: An Efficient Data Clustering Method for Very Large Databases". In: *Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data*. SIGMOD '96. Montreal, Quebec, Canada: Association for Computing Machinery, 1996, pp. 103–114. ISBN: 0897917944. DOI: 10.1145/233269.233324. URL: https://doi.org/10.1145/233269.233324.

[9] B. Xiao et al. "SMK-means: An improved mini batch k-means algorithm based on mapreduce with big data". In: *Computers, Materials and Continua* 56 (Jan. 2018), pp. 365–379. DOI: 10.3970/cmc.2018.01830.

[10] S. Na, L. Xumin, and G. Yong. "Research on k-means Clustering Algorithm: An Improved k-means Clustering Algorithm". In: *2010 Third International Symposium on Intelligent Information Technology and Security Informatics*. 2010, pp. 63–67.

[11] Youguo Li and Haiyan Wu. "A Clustering Method Based on K-Means Algorithm". In: *Physics Procedia* 25 (Dec. 2012), pp. 1104–1109. DOI: 10.1016/j.phpro.2012.03.206.

[12] R. Sridharan. "Gaussian mixture models and the EM algorithm". In: 2014.

[13] QGIS Project. https://www.qgis.org/en/site/.

[14] QGIS Processing Framework. https://docs.qgis.org/3.10/en/docs/user_manual/processing/intro.html.

[15] Writing new Processing algorithms as Python scripts. https://docs.qgis.org/3.10/en/docs/user_manual/processing/scripts.html.