BU Sustainability: Water Bottle Stations

Team E

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Introduction

As BU Sustainability supports the transformation of BU's planning, operations, and culture toward a sustainable and equitable future, it encourages everyone to utilize refillable water bottles instead of single-use plastic water bottles as part of BU's commitment to zero waste. Installing water bottle stations will benefit the university, the environment, and the users in the long run. The university can lower waste management costs associated with disposing of plastic waste and individuals will be less inclined to purchase bottled water and save money. Additionally, the reduction of plastic waste will promote resource conservation.

This project aims to help the BU Sustainability team determine additional locations to install new water bottle filling stations within the Charles Campus based on multiple factors: foot traffic, maintenance, mechanical ventilation, and distance. Our team was recommended to provide a priority list of the buildings to install new stations from the clients and the number of potential users for each location. After analyzing the provided datasets and applying the extension question, we came up with 16 buildings that require water bottle filling stations in the order of significance.

Base Analysis

Key Question 1

The BU Sustainability team required the number of students and employees impacted by each water filling station in the current inventory as one of the key questions. We used the Wifi dataset for foot traffic to answer this query. Even though not all people in the building use the refilling station, we assumed that they were all potential users of the stations, allowing us to determine the number of people based on their connection with the BU Wifi at every building from 7 AM to 2 AM.

The Bottles Inventory List dataset recorded all buildings with water bottle filling stations. We filtered these locations in the Wifi dataset that saved the number of people connected to the Wifi per building and took the mean of the sum to determine the daily usage of each station. Specifically, we calculated the number of potential users on an average day by using the groupby function in pandas by building_desc and hour column of the Wifi Data and took the sum of the mean of capacity based on the hour. In other words, we computed the mean of the people from a specific building at every hour and added all of them to calculate the capacity of the building for an average day.

Below is the list of buildings with water bottle filling stations and the number of potential users per station. The code for this key question is in the EarlyInsightReportNotebook.ipynb file in the deliverables/early_insight_report directory of GitHub under branch “team-e”.

1. On an average day, 1305 people benefitted from the existing water bottle station at 1019 COMMONWEALTH AVENUE
2. On an average day, 1237 people benefitted from the existing water bottle station at 111 CUMMINGTON MALL
3. On an average day, 1357 people benefitted from the existing water bottle station at 110-112 CUMMINGTON MALL

4. On an average day, 136 people benefitted from the existing water bottle station at 154 BAY STATE ROAD
5. On an average day, 126 people benefitted from the existing water bottle station at 156 BAY STATE ROAD
6. On an average day, 171 people benefitted from the existing water bottle station at 196 BAY STATE ROAD
7. On an average day, 1246 people benefitted from the existing water bottle station at 2 CUMMINGTON MALL
8. On an average day, 4347 people benefitted from the existing water bottle station at 25 BUICK STREET
9. On an average day, 1339 people benefitted from the existing water bottle station at 270 BAY STATE ROAD
10. On an average day, 4930 people benefitted from the existing water bottle station at 300 BABCOCK STREET
11. On an average day, 1524 people benefitted from the existing water bottle station at 33 HARRY AGGANIS WAY
12. On an average day, 1295 people benefitted from the existing water bottle station at 36 CUMMINGTON MALL
13. On an average day, 771 people benefitted from the existing water bottle station at 48 CUMMINGTON MALL
14. On an average day, 2956 people benefitted from the existing water bottle station at 5 CUMMINGTON MALL
15. On an average day, 1140 people benefitted from the existing water bottle station at 96 CUMMINGTON MALL

16. On an average day, 2317 people benefitted from the existing water bottle station at 64 CUMMINGTON MALL
17. On an average day, 2375 people benefitted from the existing water bottle station at 565 COMMONWEALTH AVENUE
18. On an average day, 1968 people benefitted from the existing water bottle station at 881 COMMONWEALTH AVENUE
19. On an average day, 366 people benefitted from the existing water bottle station at 517 BEACON STREET
20. On an average day, 1118 people benefitted from the existing water bottle station at 712 BEACON STREET
21. On an average day, 1121 people benefitted from the existing water bottle station at 233 BAY STATE ROAD (Admissions)
22. On an average day, 1967 people benefitted from the existing water bottle station at 820 COMMONWEALTH AVENUE (Booth)
23. On an average day, 3915 people benefitted from the existing water bottle station at 1 UNIVERSITY ROAD (BUA)
24. On an average day, 0.0 people benefitted from the existing water bottle station at 675 - 725 COMMONWEALTH AVENUE (CAS)
25. On an average day, 9534 people benefitted from the existing water bottle station at 285 BABCOCK STREET (Case Center)
26. On an average day, 4352 people benefitted from the existing water bottle station at 890 COMMONWEALTH AVENUE (CELOP)

27. On an average day, 3735 people benefitted from the existing water bottle station at 855 COMMONWEALTH AVENUE (CFA)
28. On an average day, 3381 people benefitted from the existing water bottle station at 871 COMMONWEALTH AVENUE
29. On an average day, 1151 people benefitted from the existing water bottle station at 273 BABCOCK STREET (Claflin)
30. On an average day, 3113 people benefitted from the existing water bottle station at 640 COMMONWEALTH AVENUE (COM)
31. On an average day, 692 people benefitted from the existing water bottle station at 512 BEACON STREET (Danielson)
32. On an average day, 2642 people benefitted from the existing water bottle station at 730 COMMONWEALTH AVENUE (EMA)
33. On an average day, 1403 people benefitted from the existing water bottle station at 44 CUMMINGTON MALL (ENG)
34. On an average day, 32744 people benefitted from the existing water bottle station at 915 COMMONWEALTH AVENUE (Fitrec)
35. On an average day, 4916 people benefitted from the existing water bottle station at 808 COMMONWEALTH AVENUE (Fuller Building)
36. On an average day, 613 people benefitted from the existing water bottle station at 704 COMMONWEALTH AVENUE (GRS)
37. On an average day, 5634 people benefitted from the existing water bottle station at 775 COMMONWEALTH AVENUE (GSU)

38. On an average day, 1476 people benefitted from the existing water bottle station at 575 COMMONWEALTH AVENUE (HOJO)
39. On an average day, 2149 people benefitted from the existing water bottle station at 91 BAY STATE ROAD (Kilachand)
40. On an average day, 4379 people benefitted from the existing water bottle station at 765 COMMONWEALTH AVENUE (LAW)
41. On an average day, 575 people benefitted from the existing water bottle station at 621 COMMONWEALTH AVENUE (Linguistics)
42. On an average day, 2567 people benefitted from the existing water bottle station at 985 COMMONWEALTH AVENUE (Marcom)
43. On an average day, 415 people benefitted from the existing water bottle station at 735 COMMONWEALTH AVENUE (Marsh)
44. On an average day, 6227 people benefitted from the existing water bottle station at 590 COMMONWEALTH AVENUE (Metcalf)
45. On an average day, 1311 people benefitted from the existing water bottle station at 771 COMMONWEALTH AVENUE (Mugar)
46. On an average day, 2115 people benefitted from the existing water bottle station at 610 BEACON STREET (Myles Standish)
47. On an average day, 3498 people benefitted from the existing water bottle station at 8 ST. MARY'S STREET (Photonics)
48. On an average day, 5501 people benefitted from the existing water bottle station at 595 COMMONWEALTH AVENUE (Questrom)

49. On an average day, 1238 people benefitted from the existing water bottle station at 277 BABCOCK STREET (Rich)
50. On an average day, 1847 people benefitted from the existing water bottle station at 635 COMMONWEALTH AVENUE (Sargent)
51. On an average day, 1867 people benefitted from the existing water bottle station at 928 COMMONWEALTH AVENUE (SHA)
52. On an average day, 2059 people benefitted from the existing water bottle station at 275 BABCOCK STREET (Sleeper)
53. On an average day, 1972 people benefitted from the existing water bottle station at 745 COMMONWEALTH AVENUE (STH)
54. On an average day, 1089 people benefitted from the existing water bottle station at 140 BAY STATE ROAD (TOWERS)
55. On an average day, 11043 people benefitted from the existing water bottle station at 100 ASHFORD STREET (TTC)
56. On an average day, 3158 people benefitted from the existing water bottle station at 700 COMMONWEALTH AVENUE (WARREN)
57. On an average day, 1778 people benefitted from the existing water bottle station at 2 SILBER WAY (WHEELOCK)
58. On an average day, 2390 people benefitted from the existing water bottle station at 100 BAY STATE ROAD (YAWKEY)
59. On an average day, 475 people benefitted from the existing water bottle station at 255 BAY STATE ROAD (The CASTLE)

60. On an average day, 5016 people benefitted from the existing water bottle station at 120 ASHFORD STREET
61. On an average day, 324 people benefitted from the existing water bottle station at 226 BAY STATE ROAD
62. On an average day, 3023 people benefitted from the existing water bottle station at 610 COMMONWEALTH AVENUE
63. On an average day, 2131 people benefitted from the existing water bottle station at 750 COMMONWEALTH AVENUE
64. On an average day, 44 people benefitted from the existing water bottle station at 925 COMMONWEALTH AVENUE
65. On an average day, 2289 people benefitted from the existing water bottle station at 24 CUMMINGTON MALL

During this process, we noticed that three buildings known to have an inventory of stations were not listed in the Wifi data. They are Myles Annex (632 Beacon Street), SSW (264 Bay State Road), and 68 Cummington Mall. Furthermore, the information for 675 - 725 Commonwealth Avenue (#24 on the list above) seemed inaccurate, as the Wifi data reported that 0 people were connected to the wifi on an average day. Therefore, we decided to disregard these four locations.

Key Question 2

The BU Sustainability team also requested the full list of factors and criteria for the installation of new filling stations. Based on the data provided by the clients, we established five significant factors to determine the locations of additional filling stations.

1. Kitchen Availability

    a. The clients recommended users refill their water bottles from the kitchen.
    b. Therefore, buildings with kitchens do not require the installation of water bottle stations.

2. Mechanical Ventilation
    a. Buildings without air ventilation are prioritized for new stations since the heat waves can cause people to become more thirsty
3. Maintenance
    a. Water filling stations require regular maintenance on the filters to protect the cleanliness of the water. Therefore, locations without maintenance are not good candidates for water refilling stations.
4. Density & Foot Traffic
    a. Installing water filling stations in locations where more people have access is a crucial component for the efficiency of these stations.
    b. Therefore, locations where more people gather are highly prioritized
5. Cost
    a. According to the clients, water bottle stations near plumbing locations are recommended due to the cost of transporting water.

Even though we established the five major factors above, kitchen availability (#1) and cost (#5) were removed from consideration.

Recognizing that all buildings in the Wifi dataset have a kitchen according to the dataset, applying the kitchen availability factor became meaningless. Our team communicated this issue with the clients and asked whether information regarding the accessibility of the kitchens was available (if the buildings have kitchens but are accessible to specific types of people, it would imply that some people cannot refill their bottles). However, they did not provide any additional specifications, allowing us to disregard the kitchen availability factor.

During the client meeting, the clients mentioned not to worry about the cost factor. Additionally, the dataset lacked information regarding the availability of plumbing for each building.

Key Questions 3 & 4

The clients requested a priority list of new water filling stations and the number of potential users per station along with the geospatial map of them. These two questions are answered below and continued in the extension analysis, along with an explanation of the steps we took.

As mentioned above in key question 2, we established six factors to consider for this project. Among the criteria, we believed that the most significant feature was the foot traffic data since the intention of water bottle filling stations is to benefit as many people as possible by allowing them to refill their bottles and reduce waste, aligning with the goal of the BU Sustainability team.

Using the number of potential users per existing station acquired from key question 1, we came up with two threshold values to filter the buildings without refilling stations: the mean and the median. During the process, we realized that some locations have more than one station. Hence, we divided the number of potential users by the total number of water stations because we assumed that every water bottle station within one building is used equally among the users (no information was given on the usage per station). For example, 226 Bay State Road has 2 stations that potentially benefit 273 people, indicating that each station within 226 Bay State Road has 273 / 2 = 136.5 → 136 people.

Below are the visualizations of two threshold values we evaluated and the buildings that marked a higher number of potential users than the values.

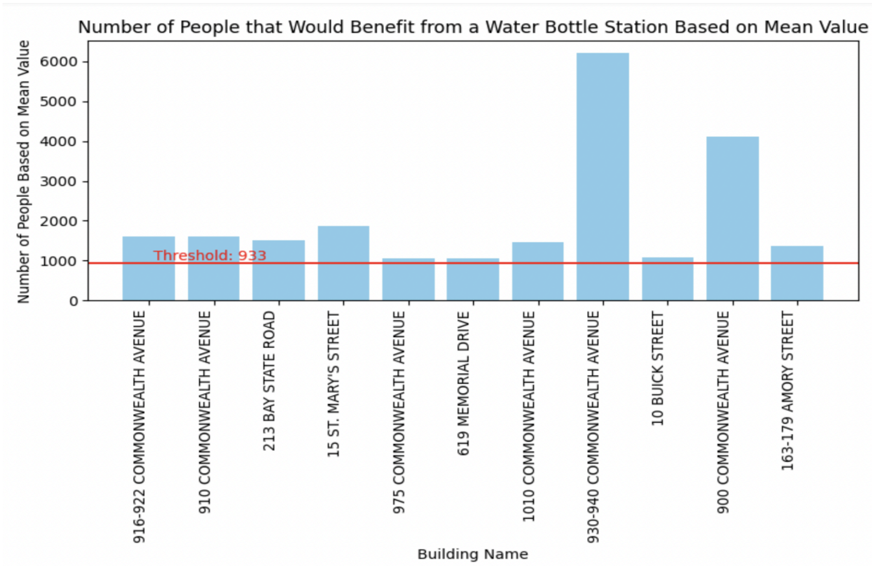

Figure 1: This visualization shows the number of people who would potentially benefit from a water bottle station based on the mean threshold value of 933. The y-axis represents the number of people and the x-axis represents each unique building.

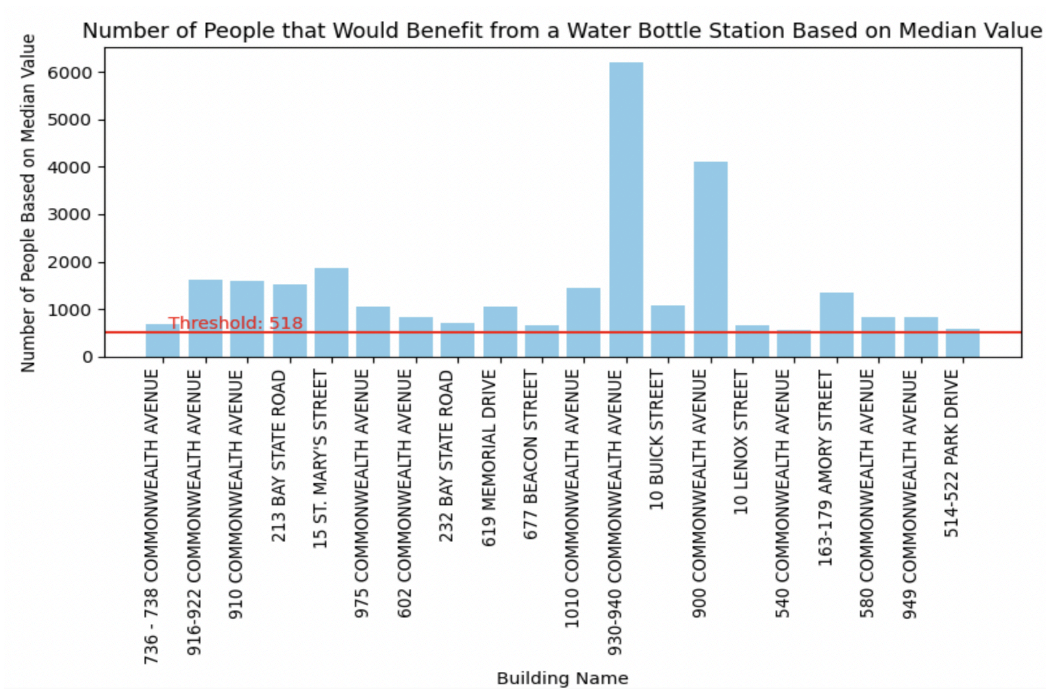

Figure 2: This visualization shows the number of people who would potentially benefit from a water bottle station based on the median threshold value of 518. Similar to Figure 1, the y-axis represents the number of people and the x-axis represents each unique building.

Notice that 11 and 20 buildings had higher potential users than the mean and median threshold values, respectively. Since our goal was to determine a priority list of buildings in order instead of a fixed number of them, we believed that providing a longer list was crucial to the clients. Therefore, we used the 20 buildings acquired from the median threshold value and applied other factors to finalize the recommendations.

Applying maintenance to the 20 buildings was the next step we took since it could eliminate some of the locations and shorten the priority list. Even if the building does not have mechanical ventilation, the lack of regular maintenance would struggle to provide clean water to the users. According to the Inventory of Campus Buildings and Rooms with Kitchen dataset, four (916 - 922 Commonwealth Avenue, 1010 Commonwealth Avenue, 930-940 Commonwealth Avenue, and 900 Commonwealth Avenue) of the 20 buildings were deleted from consideration due to the absence of maintenance.

Finally, the mechanical ventilation factor was utilized to determine which of the 16 remaining buildings necessarily demanded new stations. The Inventory of Campus Buildings and Rooms with Kitchen dataset recorded that three buildings (736-738 Commonwealth Avenue, 232 Bay State Road, 514-522 Park Drive) did not have mechanical ventilation.

Deeper/Extension Analysis

Since the clients did not provide a specific number of new water refilling stations but insisted on coming up with all of the buildings in the order of significance, our extension analysis regarded ranking the three buildings without mechanical ventilation and the remaining 13 buildings.

Installing new stations in locations where a water bottle refilling station already exists at a nearby distance is inefficient. Therefore, we prioritized building new stations that are further away from the existing stations since users will have to walk less distance to refill their reusable bottles. In other words, the extension analysis regarded the distance between stations as an additional criterion.

Instead of simply comparing the distance between the 16 locations and the closest water refilling stations seemed ineffective as our goal was to maximize efficiency. Consider a scenario where six buildings close to each other are on one side of the campus and two buildings are on the opposite side. The most efficient way to benefit the majority would be installing new stations on both sides of the campus even if one side of the campus has more potential users. In other words, we also considered the effect of installing new stations in other buildings to rank them in order of importance.

Therefore, we developed an algorithm, shown below, that efficiently applies the distance factor.

1. Assume we build a water bottle station in one of the buildings from above.
2. Find the closest distance from the remaining buildings to buildings that already have water bottle filling stations (including the station we assumed to build from the previous step).
3. Assume we build a water bottle station at the building where the value calculated from the previous step is the largest. This is because the value indicates that the total distance people traveled is the highest at that building and installing a station at that specific location is the most efficient.
4. Repeat steps 2 - 3 until all buildings have a water bottle filling station.
5. Repeat steps 1 - 4 for all the buildings.
6. Rank the buildings in order of importance by assigning scores.

When calculating the distance between buildings in step two of the algorithm, we manually searched the longitude and latitude pairs of the addresses of the buildings using the website https://www.gps-coordinates.net/ and applied Manhattan distance between the two longitude and latitude pairs instead of Euclidean distance. This is because people typically do not ignore traffic and walk across the road diagonally to reach their destination but walk on the sideway. In addition, we ignored the amount of time people wait for the traffic lights to cross the street.

Step six of the algorithm requires ranking the buildings in order of importance by providing scores for each building. We assigned the scores based on the location of their appearance on the list. Once step four of the algorithm is complete, a list of the buildings will appear in the order of significance. The first building on the list indicates that it is furthest apart from the existing water bottle filling stations and will be provided with a maximum score, which is the length of the list. Following the first building, the score will decrease by 1 as it goes down the list.

For clarity, below is an example.

[A, B, C, D, E]

Here, five buildings A, B, C, D, and E are listed in order of significance once building F is assigned as the starting point to install a new station. Building A will be assigned a score of 5 (the length of the list), Building B a score of 4, Building C a score of 3, Building D a score of 2, and Building E a score of 1.

Once step five of the algorithm is completed, numerous lists for each building as a starting point will be provided and the scores per building will be added. The higher the score of a building, the greater the demand for a refilling station in the building. If two buildings have the same score, the building with more potential users will rank upper on the priority list.

In the last section of the base analysis, we concluded that three of the 16 buildings were more prioritized locations than the rest of the 13 buildings due to the lack of mechanical ventilation. Hence, we ran the algorithm above twice, using two different sets of buildings.

Since the three locations that do not have mechanical ventilation were more demanding places, we initially ran the algorithm on them, providing the three lists below.

1. ['514-522 Park Drive, '232 Bay State Road']
2. ['736 - 738 Commonwealth Avenue', '514-522 Park Drive']
3. ['736 - 738 Commonwealth Avenue', '232 Bay State Road']

By applying the scores explained above, we get

['736 - 738 Commonwealth Avenue', 6]

['514-522 Park Drive', 5]

['232 Bay State Road', 4]

Similarly, we ran the algorithm for the remaining 13 buildings with mechanical ventilation. Since the installation of these 13 buildings only come after the installation of the three prioritized buildings locations above, we assumed that those three buildings have a water bottle filling station installed when running the remaining 13 buildings.

1. ['10 Lenox Street, '949 Commonwealth Avenue, '213 Bay State Road', '580 Commonwealth Avenue, '619 Memorial Drive, '540 Commonwealth Avenue', '10 Buick Street, "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
2. ['10 Lenox Street', '940 Commonwealth Avenue', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
3. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']

4. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
5. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '163-179 Amory Street']
6. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
7. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '602 Commonwealth Avenue', '163-179 Amory Street']
8. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
9. ['949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']

10. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
11. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary’s Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue']
12. ['10 Lenox Street', '949 Commonwealth Avenue', '213 Bay State Road', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']
13. ['10 Lenox Street', '213 Bay State Road', '580 Commonwealth Avenue', '619 Memorial Drive', '910 Commonwealth Avenue', '540 Commonwealth Avenue', '10 Buick Street', "15 St. Mary's Street", '975 Commonwealth Avenue', '677 Beacon Street', '602 Commonwealth Avenue', '163-179 Amory Street']

By applying the scores explained above, we get

['10 Lenox Street', 144]

['949 Commonwealth Avenue', 133]

['213 Bay State Road', 122]

['580 Commonwealth Avenue', 111]

['619 Memorial Drive', 100]

['910 Commonwealth Avenue', 89]

['540 Commonwealth Avenue', 78]

['10 Buick Street', 67]

["15 St. Mary’s Street", 56]

['975 Commonwealth Avenue', 45]

['677 Beacon Street', 34]

['602 Commonwealth Avenue', 23]

['163-179 Amory Street', 12]

The code for the algorithm and the results are within the distance.ipynb file in the deliverables/final_report directory in GitHub.

After running the algorithm above for the two sets of building data, the final priority list of buildings to install water bottle stations is listed below in the order of significance, along with the number of potential users.

1. 736 - 738 Commonwealth Avenue (benefits 692 people)
2. 514-522 Park Drive (benefits 598 people)
3. 232 Bay State Road (benefits 720 people)
4. 10 Lenox Street (benefits 659 people)
5. 949 Commonwealth Avenue (benefits 830 people)
6. 213 Bay State Road (benefits 1511 people)
7. 580 Commonwealth Avenue (benefits 845 people)
8. 619 Memorial Drive (benefits 1067 people)
9. 910 Commonwealth Avenue (benefits 1607 people)
10. 540 Commonwealth Avenue (benefits 563 people)
11. 10 Buick Street (benefits 1081 people)
12. 15 St. Mary’s Street (benefits 1868 people)
13. 975 Commonwealth Avenue (benefits 1054 people)

14. 677 Beacon Street (benefits 667 people)

15. 602 Commonwealth Avenue (benefits 829 people)

16. 163-179 Amory Street (benefits 1359 people)

However, it is important to note that some of the locations listed above may already have a water bottle refilling station installed. The clients reported that some existing water bottle filling stations were not listed in the dataset, indicating that the dataset was incomplete (only 80% of the stations exist in the dataset).

We also created a visualization of the BU Charles Campus map that plots the buildings based on their longitude and latitude coordinates.

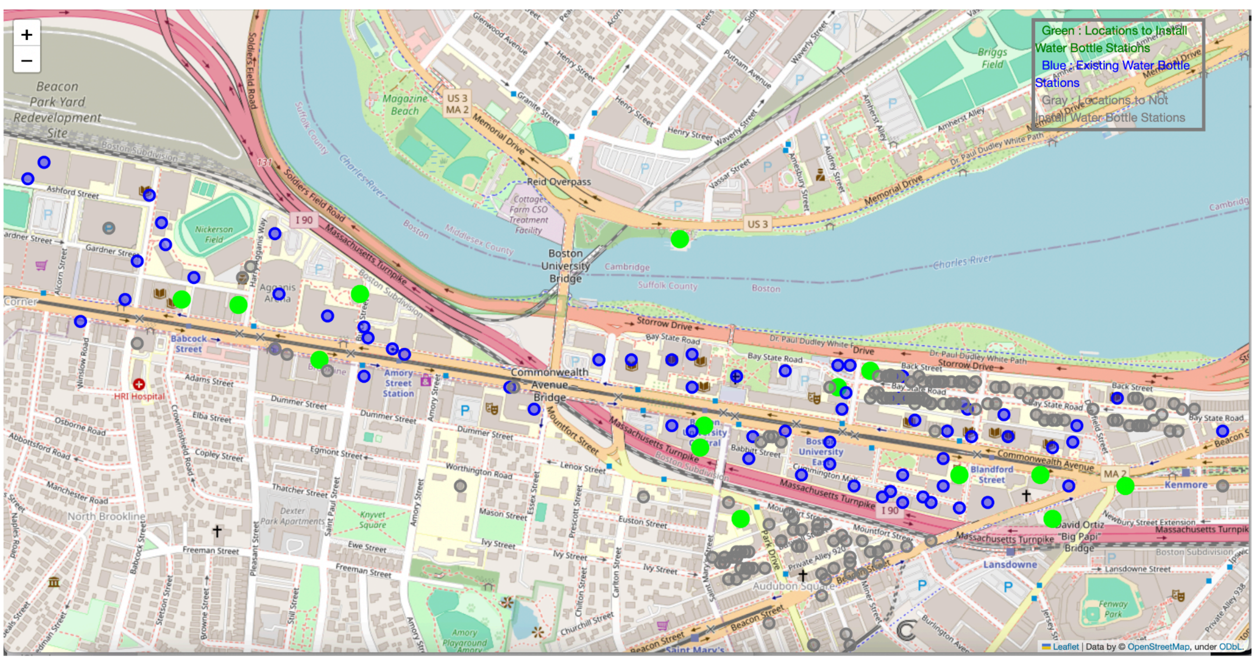

Figure 3: This visualization is the map of the BU that displays all the buildings provided in the dataset. The colors indicate different categories of buildings, with the labels on the upper right corner displaying what each color represents. The x-axis represents the latitude and the y-axis represents the longitude

The light green coordinates represent the buildings recommended for building a new station, the blue coordinates represent the buildings that already have water bottle filling stations, and the gray coordinates represent the buildings not recommended for building a new station. Users can click the coordinates to discover the complete address of the location.

The HTML file for the map is located in the final_report folder in the deliverables/final_report directory and can be reproducible by running the map.ipynb file in the same directory.

Future Scope

The project can be extended by collecting additional features and updating the dataset to have a complete list of existing water bottle refilling stations. As mentioned above, the clients reported that the dataset recorded only 80% of the current stations. Furthermore, the kitchen and density data were insignificant because every building contained a kitchen, and the density data only provided four locations. Therefore, we were unable to apply the kitchen availability feature to the project. Rerunning our codes and algorithms with an updated dataset can derive different results and suggest new locations. Furthermore, the BU Sustainability team can collect more features that would impact the decision, such as the total amount of water refilled using the stations per station, feedback from the students/faculty through a survey, and the number of plastic waste bottles saved through the water bottle stations. Such additional criteria can allow people to apply machine learning and classifying algorithms to determine locations to install new stations.

The clients can also extend this project by applying the code to all campuses at Boston University instead of restricting the locations to the Charles River campus (the Medical Campus, for example). Moreover, the BU Sustainability team can encourage students and faculties to use the refillable stations by developing a mobile application that displays the inventory of the current stations, similar to the application that reports the current status of BU buses.

Team Contribution

Through weekly meetings with full attendance of the team members, we set up weekly schedules and divided the tasks equally so that all members contributed to the project.

1. Data Cleaning and Analysis

Each team member was assigned different datasets to clean and analyze. Once each member extracted significant features within their dataset, we discussed the importance of those features and provided feedback as a team. Below is the list of the datasets organized per member.

   a. Junho – Inventory of Known/Existing Filling Stations & BU Floor Descriptions
   b. Ryan – BU Map of Water Filling Stations
   c. Jeong Yong – BU Wifi Data for Foot Traffic, Inventory of Campus Buildings and Rooms with Kitchen
   d. Woohyeon – BU High Volume Event Spaces

In addition, we equally divided the WiFi data to discover the number of potential users for every unique building.

2. Presentations to the Clients

Woohyeon was chosen as the team representative to attend weekly PM meetings and update our progress to clients through presentations. Ryan, Jeong Yong, and Junho collaborated to create the presentations before the client meetings while Woohyeon prepared his script.

3. Base Question & Deeper/Extension Analysis

Jeong Yong narrowed down the number of buildings to consider by applying the threshold value based on the median and mean potential users from existing water bottle filling stations. Following his completion, Ryan, Woohyeon, and Junho each applied the kitchen availability, mechanical ventilation, and maintenance factors, respectively. Jeong Yong and Junho worked on the distance.ipynb file while Ryan and Woohyeon created the map visualization of BU on the map.ipynb file.

4. Report

The whole team collaborated in writing the early insight and final report.