Deliverable 2 Report

Task Division

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Problem Statement:

The Massachusetts Bay Transportation Authority (MBTA) is not just a transit system, but a crucial lifeline for over a million daily commuters in the Boston area, significantly contributing to the region's economy with an estimated annual value of $11.5 billion. Yet, the quality of bus service and its performance varies across different neighborhoods, raising concerns about equitable access to transportation. This disparity has implications for economic opportunities, environmental sustainability, and social equity. To address this, there is a need for a comprehensive, data-driven analysis of MBTA's bus service performance trends, with a focus on geographic and demographic disparities. This project, in collaboration with BU Spark!, aims to uncover these trends, highlight potential inequities, and inform decision-making to enhance transit accessibility for all Boston residents.

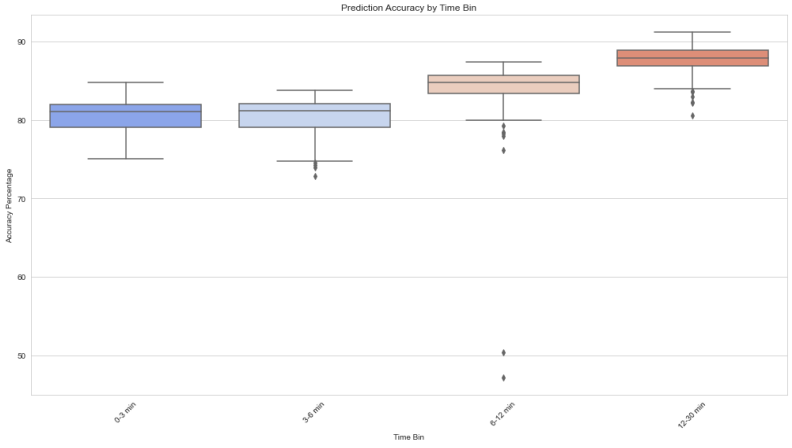
Data Collection and Preprocessing

In order to address questions including:

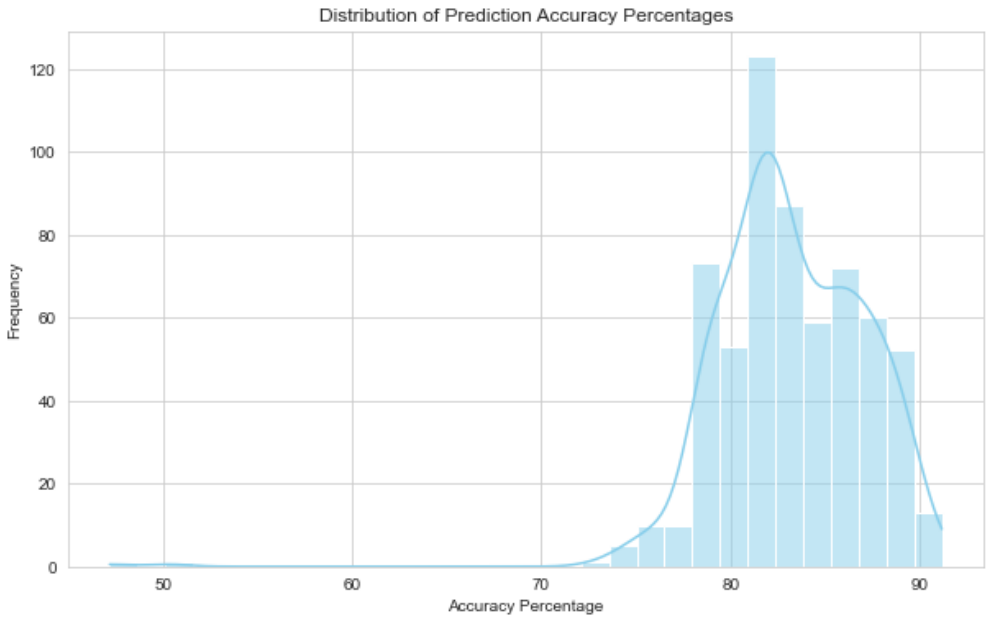
1. What are the end-to-end travel times for different bus routes
2. Are there disparities in the service levels of different routes? (which lines are late more often than others)
3. What are the population sizes and characteristics of the communities serviced by different bus routes (e.g. race, ethnicity, age, people with disabilities/ vulnerabilities)?
4. If there are service level disparities, are there differences in the characteristics of the people most impacted?
5. This can include questions about traffic information, which neighborhoods are served better/worse by the MTBA bus system, which routes are better/worse, differences in quality of service by class/race, contributing variables, ect.

We mainly collected data from MBTA Open Data Portal and Analyze Boston website. The datasets that we processed are Boston Neighborhoods Boundaries data from 2020, Bus Network Redesign Draft Bus Routes, Rapid Transit and Bus Prediction Accuracy, Commuter Rail Reliability, MBTA Bus Arrival Departure time, and Bus Ridership. For certain question, we analyzed certain dataset solely. And for certain questions such as the third one, we used combinations of several datasets in order to present a specific result.

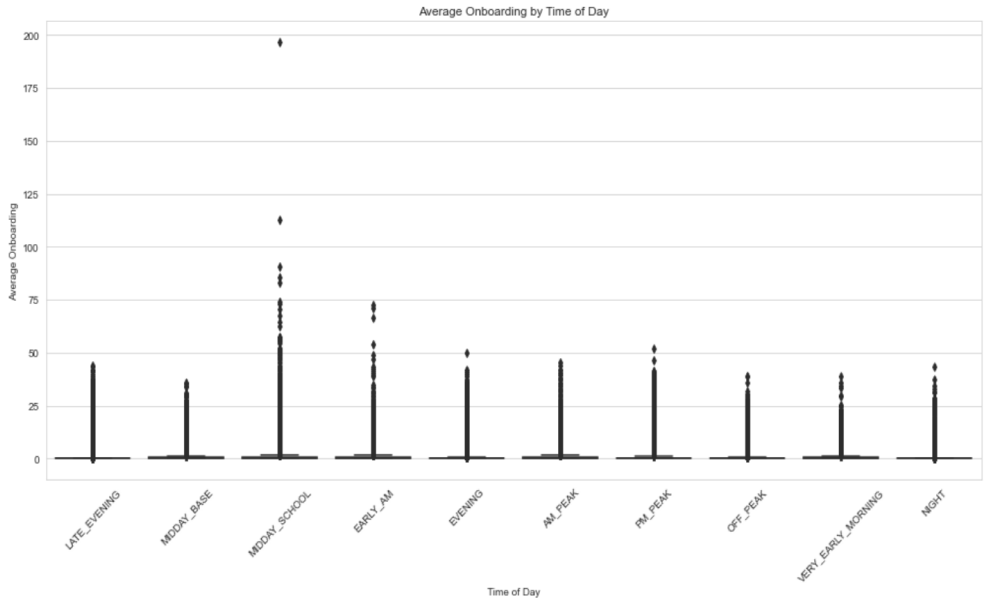
Through **EDA**, we got:



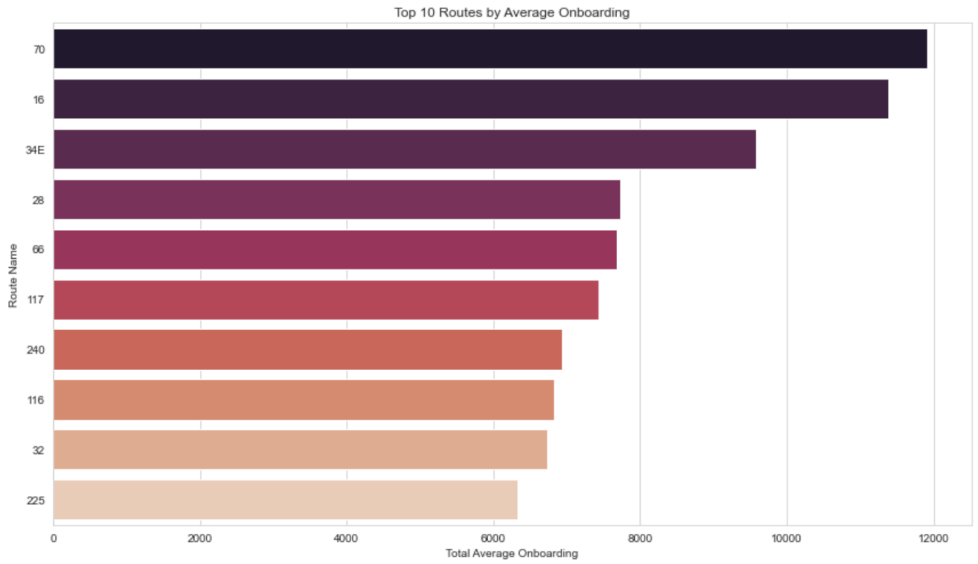
The median accuracy is consistently high across all time bins, hovering around the 80-90% range. The shorter duration predictions (e.g., "0-3 min" and "3-6 min") have slightly tighter interquartile ranges, indicating more consistent prediction accuracies. Longer duration predictions (e.g., "12-30 min") have wider interquartile ranges, suggesting more variability in their accuracies.



Also, most of the predictions seem to be clustered around 75% to 90% accuracy, indicating that a significant portion of the bus predictions are fairly accurate.



The "AM_PEAK" time period shows the highest median onboarding, indicating that morning commutes have a high influx of passengers. The "MIDDAY_BASE" time period also has a relatively high median onboarding, suggesting steady ridership during midday hours. Time periods like "EARLY_AM" and "LATE_EVENING" have lower medians and narrower interquartile ranges, implying lesser and more consistent ridership during these hours.



And here lists the top 10 routes grouped by average onboarding.

Analyze Data

To address base question 1:

We process the data to filter out the transit type which are not bus.

```
# Filtering the data to consider only bus routes
df_bus_reliability = df_reliability[df_reliability['mode_type'] == 'Bus']
```

We processed the data of bus arrival and departure time to calculate the end-to-end travel time.
In order to get the end-to-end travel times for different bus routes represent the average duration it takes for a bus to travel from the starting point to the endpoint of a specific route.
Follow the following procedure:
Filtering the data to consider only bus routes
Extracting the earliest and latest time points for each route and direction
Merging the two dataframes to get both min and max times in one dataframe
Calculating the end-to-end travel time for each route and direction
Displaying the end-to-end travel times for different bus routes
We got:

		route_id	direction_id	travel_time_seconds	average_travel_time
1					
2	0	01	Inbound	2186.178082191781	0 days 00:36:26.178082192
3	1	01	Outbound	2036.2826523777628	0 days 00:33:56.282652378
4	2	04	Inbound	1362.3664122137404	0 days 00:22:42.366412214
5	3	04	Outbound	1295.1330798479087	0 days 00:21:35.133079848
6	4	07	Inbound	983.1116687578419	0 days 00:16:23.111668758
7	5	07	Outbound	876.9397590361446	0 days 00:14:36.939759036
8	6	08	Inbound	2973.036211699164	0 days 00:49:33.036211699
9	7	08	Outbound	3279.767441860465	0 days 00:54:39.767441860

To address base question 2:

	weekly	mode	route_id	bin	arrival_departure	num_predictions	num_accurate_predictions	ObjectId	accuracy_percentage
2	2021-01-22 05:00:00+00:00	bus	Unknown	12-30 min	departure	1530075	1394979	400	91.17062889074064
3	2021-03-05 05:00:00+00:00	bus	Unknown	12-30 min	departure	1612256	1463544	224	90.7761546553401
4	2020-10-30 04:00:00+00:00	bus	Unknown	12-30 min	departure	1652403	1499831	352	90.76665922296195
5	2021-01-29 05:00:00+00:00	bus	Unknown	12-30 min	departure	1619321	1469203	204	90.72957122151816
6	2020-12-11 05:00:00+00:00	bus	Unknown	12-30 min	departure	1528106	1382793	376	90.49064659127049
7	2022-01-28 05:00:00+00:00	bus	Unknown	12-30 min	departure	1566549	1410309	296	90.02648496791355

	gtfs_route_id	reliability_score
2	9703	32.00941915227626
3	449	40.25524468576182
4	448	40.630198757585696
5	459	42.997043635764754
6	747	45.480942004577706
7	195	49.19917090635013
8	19	49.205904165525475
9	41	49.24615399524695
10	70A	49.418184535977765
11	wad	51.08695652173913
12	14	51.162260512605286
13	8	51.44105297509801
14	701	51.50904158891645

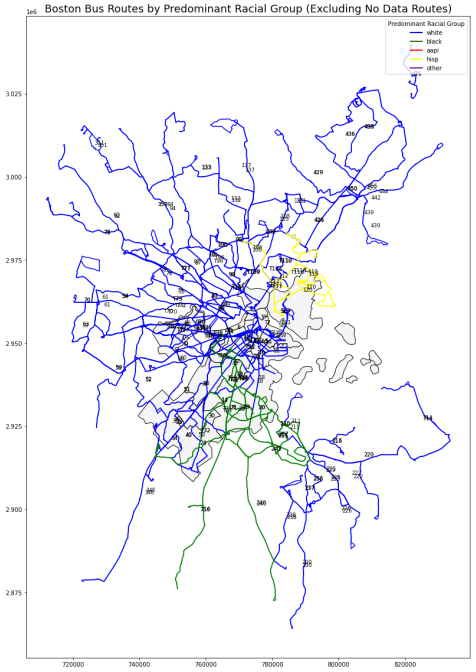
Then we calculated the accuracy percentage using the Rapid Transit and Bus Prediction Accuracy dataset. We also used another dataset of Commuter Rail Reliability to calculate the reliability score for specific bus routes.

To address base question 3:

It's about the different characteristics for different bus routes,
we combined the usage of 4 different data files.

```
# Load datasets
neighborhoods_path = "/Users/lijunyi/Downloads/Census2020_BG_Neighborhoods/Census2020_BG_Neighborhoods.shp"
bus_routes_path = "/Users/lijunyi/Downloads/cs506/Bus_Network_Redesign_Draft_Bus_Routes/Bus_Network_Redesign_Draf
neighborhood_data_path = "/Users/lijunyi/Downloads/Boston_Neighborhood_Boundaries_approximated_by_2020_Census_Blo
coordinates_map = pd.read_csv('/Users/lijunyi/Downloads/coordinates_map.txt', sep="\t", header=None, names=["Long
```

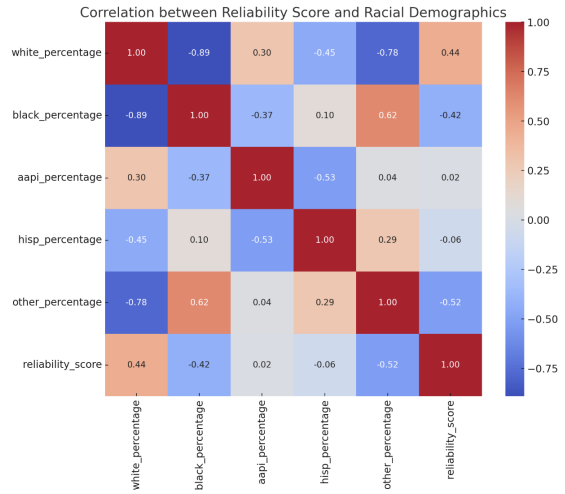
Then follow the procedure:
Convert the CRS of bus_routes to match that of neighborhoods; Determine intersecting neighborhoods; Extract relevant columns from neighborhood_data for merging and merge; Determine the predominant racial group for each bus route; Merge color data back to bus_routes; Plot each racial group
Eventually got a plot:



This visualize the predominant racial groups with respect to specific bus routes. For example, for bus routes that are map to green, the predominant races within the area is Black. Hence, we can easily capture the relationship between racial group and bus routes through the graph.

To address base question 4:

To address the question about service level disparities and the characteristics of the most impacted people, we need to merge these datasets based on the bus route IDs and then analyze the relationship between the reliability scores and the demographic data. And then generate this heatmap based on the merged dataset:

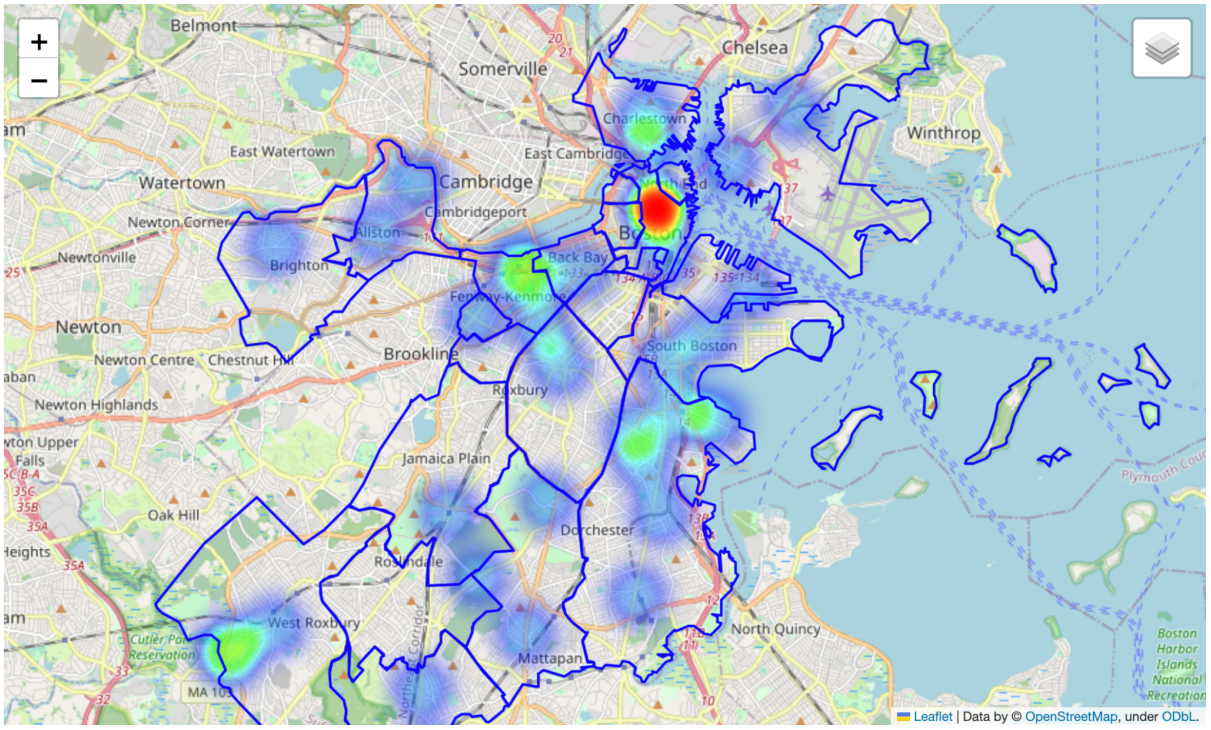


A value close to 1 indicates a strong positive correlation. A value close to -1 indicates a strong negative correlation. A value around 0 suggests little to no correlation.

To address base question 5:

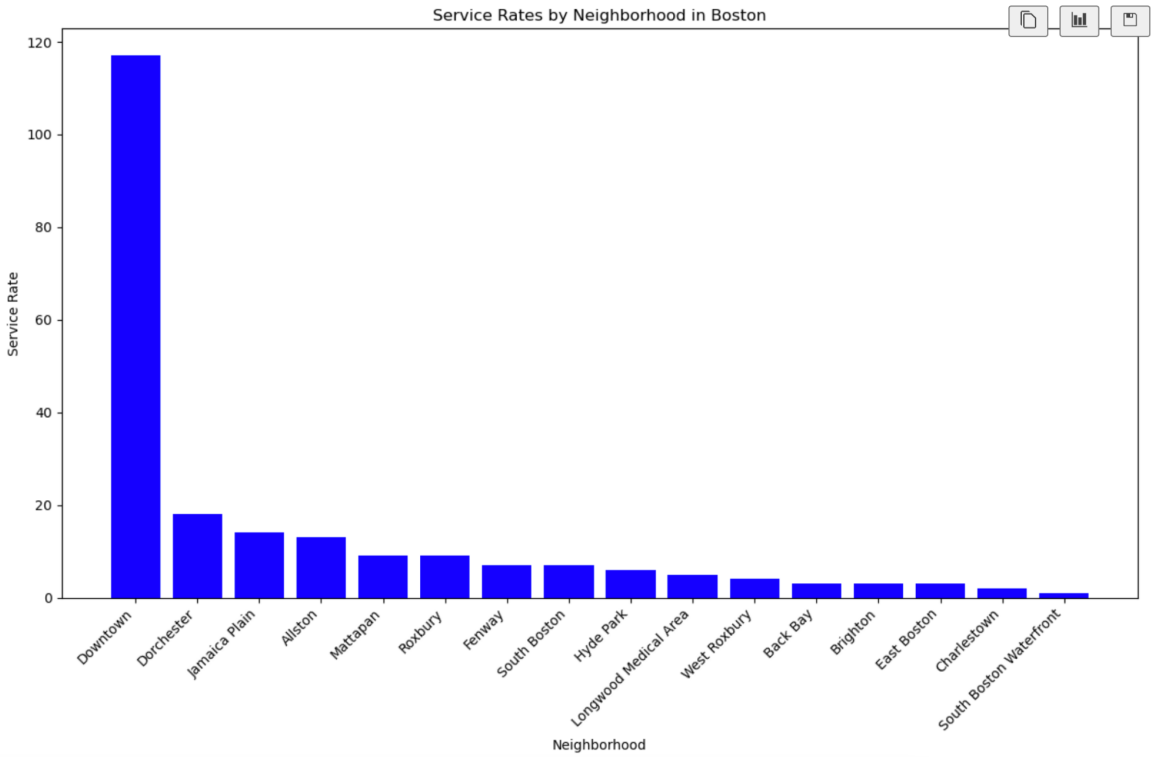
For this question, we used *Boston_Neighborhood_Boundaries_Approximated_by_2020_Census_Tracts*, which contains the Boston neighborhood boundaries, estimated by the 2020 census data, in GeoJson format. We also dived into *MBTA Bus, Commuter Rail, & Rapid Transit Reliability* dataset provided by MBTA. This dataset provides the historical reliability data under different metrics for the bus lines from 2015 to 2023. We only extracted the reliability data in 2023 for better reference of the current service quality of MBTA bus. For further study, we plan to compare the service between seasons and across the years.

Figure: Heatmap for Boston neighborhood according to service density

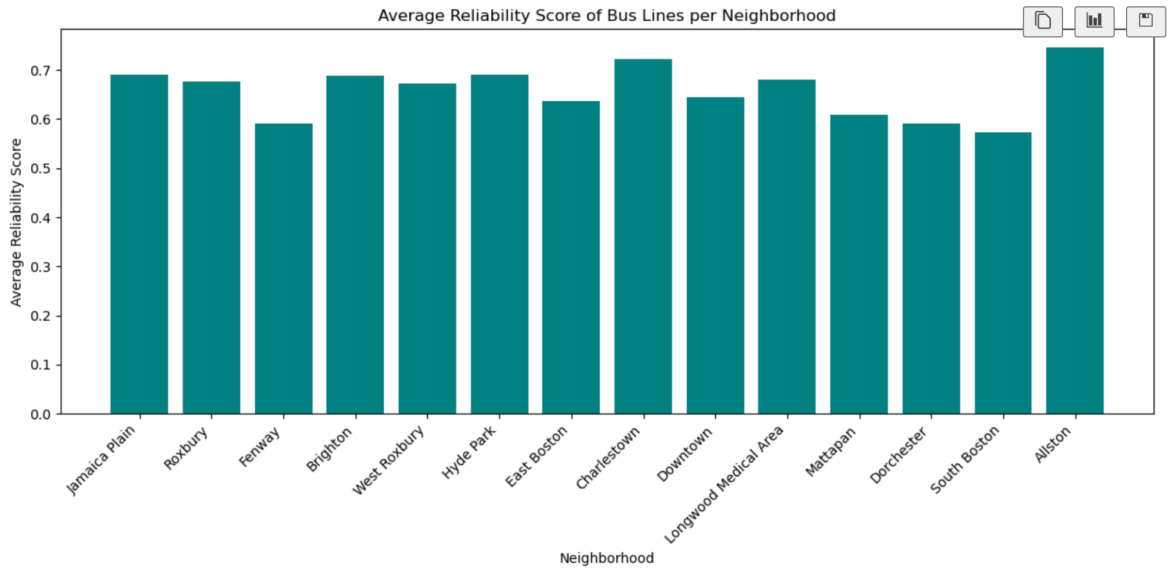


This map visualizes the service level of each neighborhood in the greater Boston area. The blue lines indicate the boundaries of different Boston neighborhoods. To better visualize the service level across the neighborhoods, we used a heat map by the number of bus lines serving a specific area instead of marking the bus terminals on the map (what we did for deliverable 1). As we can see from the first sight, Downtown area has the most dense service level, followed by Allston, Jamaica Plain, Mattapan, and Dorchester.

Figure: Bar plot for service rates across neighborhoods



This figure shows the level of service (number of bus lines) serving different Boston neighborhoods. Downtown, Dorchester, Jamaica Plain, Allston, and Mattapan are the top 5 neighborhood with the highest service level.



This figure shows the average reliability scores of bus lines for each neighborhood. The metric type of the reliability score is “Headway/Schedule Adherence”, which is the on-time rate across the origin station, midway checkpoint station, and end station. According to MBTA, if the bus arrives within 3 min of the scheduled departure time, the bus is considered on time. We processed the *MBTA Bus, Commuter Rail, & Rapid Transit Reliability* dataset and grouped each bus line’s reliability score with the same metric type. The image shown below is the aggregated data.

Figure: Service reliability for individual bus route

	gtfs_route_id_modified	metric_type	aggregated_otp_numerator	aggregated_otp_denominator	final_result
0	10	Headway / Schedule Adherence	79832.0	144490.0	0.552509
1	100	Headway / Schedule Adherence	76673.0	94523.0	0.811157
2	105	Headway / Schedule Adherence	23640.0	34222.0	0.690784
3	106	Headway / Schedule Adherence	74699.0	102093.0	0.731676
4	108	Headway / Schedule Adherence	64667.0	93414.0	0.692262

The bar plot gives us insight into the service reliability of different neighborhoods. Allston has the best reliability score of over 0.7, with a top 5 service rate. For other well-serviced areas like Dorchester and Mattapan, their reliability is significantly lower than other areas. Therefore, we can conclude that there are service disparities between different neighborhoods with different service levels.

Answer to Base Questions:

- For question 1:

The average_trip_durations.csv file in our repo provides specific end-to-end average travel times for bus routes in seconds and a more readable duration format. For instance, route 1 inbound has an average travel time of 36 minutes and 26 seconds, while route 1 outbound averages at 33 minutes and 56 seconds. Similarly, route 4 inbound averages at 22 minutes and 42 seconds, and outbound at 21 minutes and 35 seconds. Most of them have end-to-end travel time within 40 min.

- For question 2:

The conclusion is that there exist great disparities in the service levels between different bus routes
The disparity in service levels between routes is pronounced when comparing the extremes:

- Route 9703 has the lowest reliability score at 32.01, which is significantly lower than the highest reliability score of 92.59 for route CR-Shuttle003.
- Route 449 with a score of 40.26 and route 448 with 40.63 are far below route CR-Shuttle002 and CR-Shuttle001, both of which have a score of 85.82.
- Even between the fifth lowest and fifth highest, route 747 scores 45.48 in contrast to route 73, which scores 81.98.

There are more details in the csv file in our repo.

- For question 3:

The bus_routes_race_data.csv file contains demographic data related to bus routes, including total population and the number of people from different racial and ethnic groups, along with their respective percentages of the total population for each bus route.
For example, the bus route labeled as "10" services a community with a total population of 539,832 people. Among them, 210,242 identify as White (38.95%), 145,108 as Black (26.88%), 66,182 as Asian American and Pacific Islander (AAPI) (12.26%), 107,284 as Hispanic (19.87%), and 11,016 as Other (2.04%).
Some routes, like route "100", have zero population recorded for all racial groups, which may indicate missing data or an error in the dataset.

This data can be used to characterize the populations serviced by different bus routes, highlighting the diversity and potential vulnerabilities within communities. It is essential to analyze this data further to understand the impact of bus service levels on these diverse groups.

- For question 4:
Here is the conclusion for differences in the characteristics of the people most impacted

-White Percentage: There is a positive correlation (0.44) between the percentage of white individuals in an area and the reliability score. This suggests that areas with a higher percentage of white individuals may experience better bus service reliability.

-Black Percentage: There is a negative correlation (-0.42) between the percentage of Black individuals in an area and the reliability score. This indicates that areas with a higher percentage of Black individuals may be more likely to experience less reliable bus service.

-AAPI Percentage: The correlation here is negligible (0.02), implying that the percentage of AAPI individuals in an area does not significantly correlate with bus service reliability.

-Hispanic Percentage: The correlation is slightly negative (-0.06), but close to zero, suggesting that the percentage of Hispanic individuals in an area does not have a strong correlation with the reliability of bus services.

-Other Percentage: There is a negative correlation (-0.52) between the percentage of individuals of other races in an area and the reliability score. This may suggest that areas with a higher percentage of individuals from other races might experience lower reliability in bus services.

- For question 5:
Our conclusion Boston's Downtown, Allston, Dorchester, Jamaica Plain, Mattapan, and Roxbury are the neighborhoods served best by the MBTA bus. However, service level disparities exist within these five areas. Allston has the best reliability score, whereas Dorchester and Mattapan experience the most delay compared to others. Now we cannot conclude which racial group is most impacted by these desparities. General census data could be inaccurate while depicting the demographic group experiencing the service level disparities since the generalized population data is different from the actual ridership data (many of the neighborhoods are dominated by whites, but it doesn't mean that white people ride the buses more). We plan to put the analysis of racial data in the extension project by adding layers such as the average income of these areas and demographic data of frequent riders.

Challenges & Limitations:

1. **Neighborhood boundaries are only limited to the Boston Area**. We are not able to include neighborhoods like Cambridge, Brookline, and Quincy.
2. **Lack of detailed census data for now**. The census data divides each neighborhood into grids and aggregates the data in each grid as the total data for the neighborhood. Currently, we're unable to identify the exact geographical location of these small grids.
3. **Matching data from different datasets**; e.g some bus id of a certain dataset is missing but it contains other useful information.
4. **Lack of exact locations for smaller bus stops (non-terminal)**. For now, we're only able to use the data fetched from Google Maps API, which, for some of the bus terminals, is not accurate.

Assumptions:

Given the outlined challenges and limitations, we must assume that our analysis is constrained by the geographic scope of the Boston Area and may not account for nuanced socio-demographic dynamics outside this region. The lack of detailed census data necessitates a cautious interpretation of demographic impacts, acknowledging the potential for missing or underrepresented variables that could influence service level disparities. The difficulty in matching data from different datasets is likely to introduce gaps in our understanding of service reliability across all bus routes; thus, we proceed with the available data while recognizing the incomplete picture it may present. The absence of exact locations for smaller bus stops suggests that our analysis may better reflect service reliability at larger terminals rather than along entire routes.

Next Steps:

The next steps would include seeking more comprehensive datasets, enhancing the precision of stop locations, and potentially using advanced data-matching techniques to bridge the information gaps between different sources. We will search for more accurate and broader neighborhood boundaries and bus stop location data to refine our model. Modify the Data Preprocessing Section to better handle missing data, to match the pattern across different datasets, and eliminate the shortcoming of missing bus id.

Project Completion Plan:

To address the challenges and limitations identified in the preliminary stages of our analysis, our project completion plan involves several strategic steps. We will intensify efforts to acquire more comprehensive datasets, including detailed census data and more accurate neighborhood boundary delineations. We recognize the need to refine the precision of bus stop locations and will look to utilize alternative sources beyond the Google Maps API to rectify inaccuracies. Find detailed census data within each neighborhood and ridership data. Pair it with the bus stop coverage/reliability data to see which demographic group is more impacted. Add alternative mobility data around the bus stops/lines with the least reliability score. Additionally, we plan to develop advanced data-matching techniques to reconcile discrepancies between different datasets, especially where bus IDs are missing or inconsistent. This will improve the robustness of our data and the validity of our findings. Our data preprocessing protocols will be adjusted to mitigate the issues stemming from the lack of granular data at smaller bus stop levels, aiming to create a more representative and accurate depiction of service reliability across the Boston Area.

We are trying to complete all the steps mentioned above in 1-2 weeks.

Extension Proposal:
Extension Pitch
In the proposed extension, we aim to dive deeper into the relationship between public transit reliability and socioeconomic factors within the Boston Area. By integrating additional data sets, such as income levels and employment statistics alongside our current demographic and service reliability figures, we can uncover more nuanced insights into how and why certain communities are underserved by public transit.
We also propose to study the intersection of public transit data, specifically focusing on BlueBikes and bus data in Boston. The goal is to uncover insights into how different modes of transit interplay and affect urban mobility. This project is rooted in the hypothesis that there is a significant correlation between the accessibility of Blue Bike stations and bus stops and the overall effectiveness of the city's public transit system.Also, we are focusing on how service changes and accessibility influence public transit usage and urban mobility.

Rationale: Understanding the dynamics between different transit systems is crucial for improving urban mobility. This extension is vital as it will reveal patterns and potential gaps in the transit network, especially in relation to bike-sharing systems and bus routes. It is of particular interest to our team to explore how these modes of transit complement each other and what improvements can be made for better service integration.Combining our existing geospatial data with information on service disruptions and accessibility will allow us to understand the resilience of the transit network. It will also highlight areas where improved accessibility could enhance the overall efficiency and inclusivity of the system.

Questions for Analysis

- What area does bus stops and blue bike stations covered, and how could that make blue bike a possible alternate for bus?
- Are there underserved areas in Boston that could benefit from better integration of these transit systems?
- What are the peak usage times for both Blue Bikes and buses, and how do they correlate?
- What is the distribution of income situation within each neighborhood the bus routes cover?
- What are the accessibility gaps in the current transit network, and how might they affect riders with disabilities?

Data Sets & Sources

We will use the following datasets:

- Blue Bike data: Details of bike usage, station locations, and trip information.
- Bus data: Bus routes, stop locations, and ridership statistics.
- Boston income data: To analyze the socio-economic factors affecting transit use.
- Updated GeoJSON files combining bus stops and Blue Bike stations.

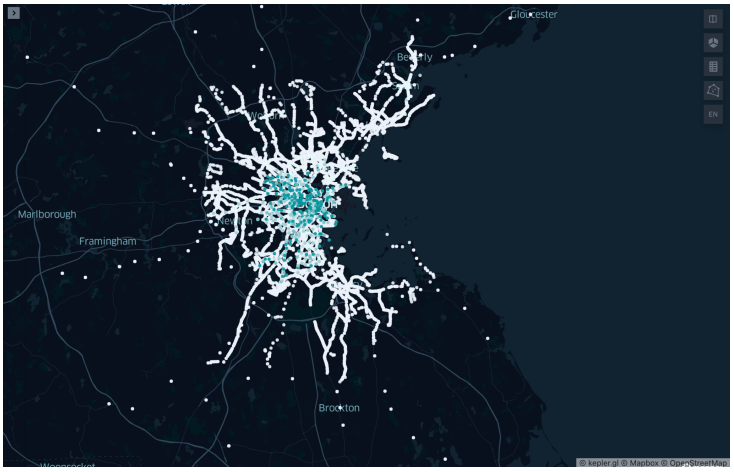
Data Visualizations

- Heatmaps showing the density of Blue Bike stations and bus stops.
- Correlation plots between bike and bus usage.
- Socio-economic overlays on transit maps to identify service gaps.
- Charts correlating service disruptions with changes in Blue Bike usage.
- Accessibility heatmaps indicating potential areas for infrastructure improvement.
- GeoJSON map with combination of bus and blue bike stops

Additional Information

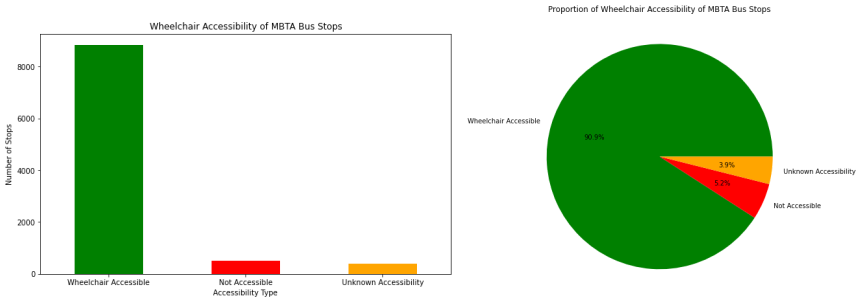
Our preliminary analysis has shown interesting trends in transit usage across different Boston neighborhoods. This extended analysis will provide a more comprehensive view, potentially guiding city planners and policymakers in enhancing urban transit systems.

Early EDA and Insights of Extension:



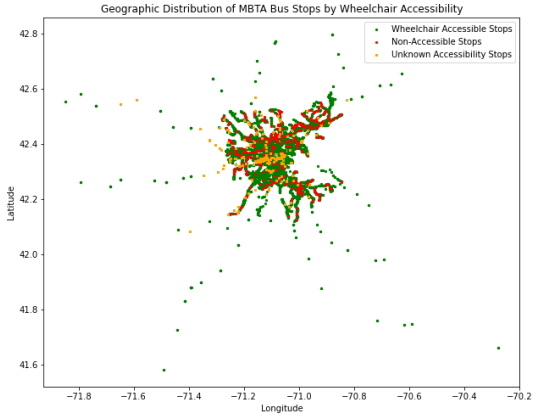
The map visualizing bus stops and Blue Bike stations in Boston was produced by first examining and parsing the geospatial data of bus stops from a CSV file into GeoJSON format. This data was then merged with an existing GeoJSON file containing the locations of Blue Bike stations. The combined dataset was saved as an updated GeoJSON file, which was likely visualized using a mapping platform such as Kepler.gl, as seen in the watermark of the provided map.

It displays a dense network of bus stops, and Blue Bike stations concentrated in the central city areas, signifying robust multimodal transit options likely catering to higher population densities and commercial activities. As one moves towards the outskirts, a notable thinning of this network indicates potential transit service gaps. The close proximity of bike stations to bus stops in the center suggests good integration for efficient transfers, but this integration appears to diminish outwardly. This spatial data could inform transit authorities about potential areas for infrastructure expansion, aid in urban planning for better service coverage, and support environmental goals by encouraging reduced car usage through accessible public transit options.

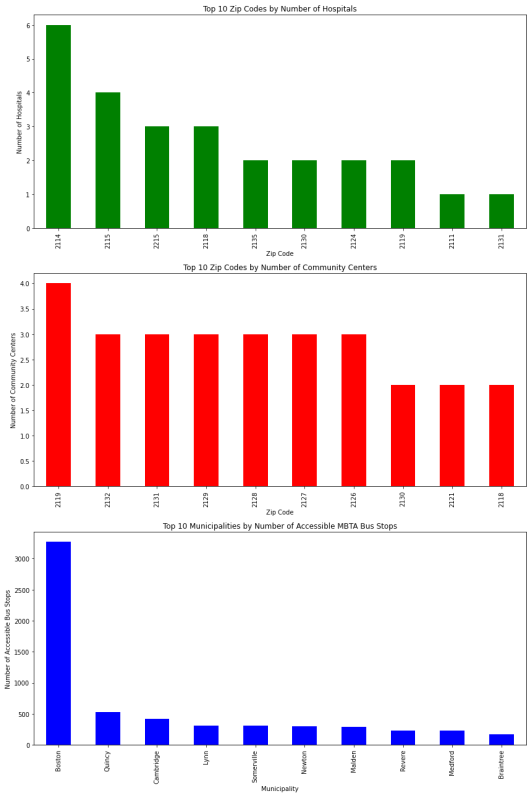


A significant majority of stops are wheelchair accessible, as indicated by the green segments in both charts.

A small fraction of stops are not accessible (red), and a relatively minor portion has an unknown status (orange).



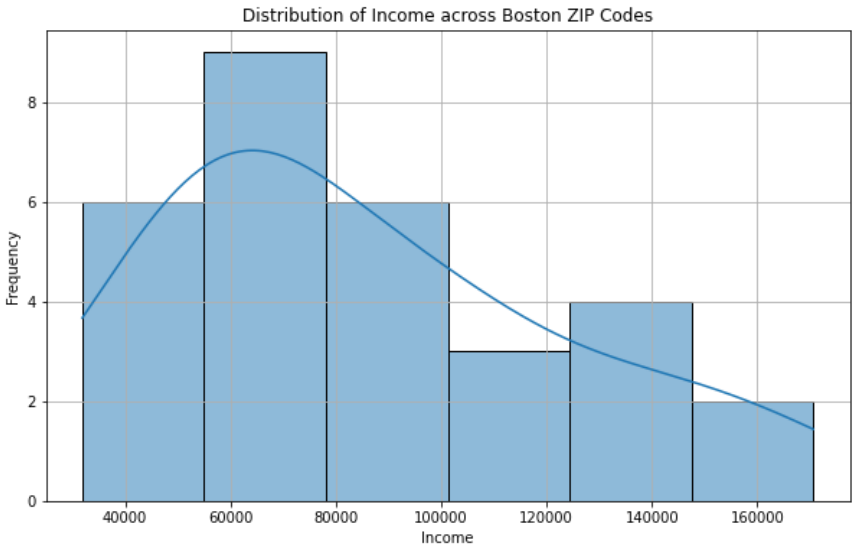
This visualization provides a clear geographic perspective on the accessibility of the MBTA bus network, emphasizing the focus on making the majority of stops wheelchair accessible.

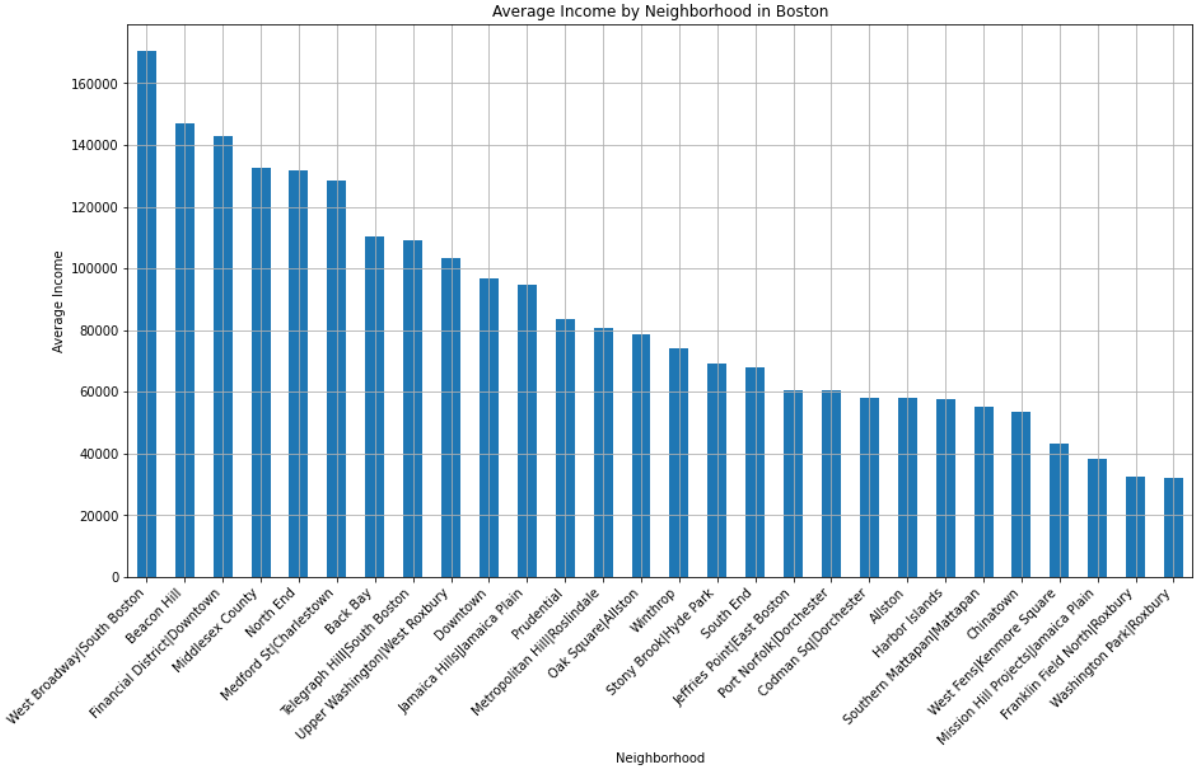


Concentration of Hospitals: Certain zip codes have a notably higher concentration of hospitals, indicating areas that are major healthcare hubs. This information is crucial for understanding which areas might offer better healthcare accessibility, especially for individuals reliant on public transportation.

Availability of Community Centers: The distribution of community centers varies significantly by zip code, with some areas having a dense presence. These centers are essential for local community activities and services, and their accessibility via public transportation is vital for inclusive community engagement.

Accessible Public Transportation: The chart showing the number of accessible bus stops in different municipalities highlights the areas with enhanced public transport accessibility. This is particularly important for individuals with disabilities, as it impacts their ability to access essential services like healthcare and community activities.





The histograms and summary statistics depict a right-skewed income distribution across Boston neighborhoods, with an average income of approximately $85,316 and a wide range from $31,900 to $170,588. This suggests significant economic diversity, with a concentration of wealth in neighborhoods like West Broadway/South Boston and Beacon Hill, contrasted by lower-income areas such as Chinatown and Washington Park/Roxbury. The observed income disparity highlights the varying economic challenges and affluence across the city, which could inform policy decisions related to urban development, social services, and resource allocation to address the needs of different communities.

Personal Contribution:

Junyi Li:
Focus on solving base questions 1,2,3. Forming extension proposal and doing EDA for questions related to income indicators, blue bike as an alternate, and disabling access

Qinfeng Li:
Data collection for ridership data and alternative transportation data.

Jialu Li:
Answered base question 4,5. Geographical data visualization/representation and service quality analysis with historical data. Processed demographic and ridership data to provide detailed insights into the impact on different racial groups.

Yifei Zhou:
Data collection on Boston neighborhood geographic data.

Laksanawisit Mutiraj: summarize challenges and limitations and help formulate future plan