# Capstone Project

# The Battle of the Neighborhoods

# (Leveraging location data for problem solving)

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## 1. Introduction

### 1.1. Background

Relocating for work can be intimidating – even more so when you have to relocate to another country which you have never been to before and now you have to take your partner or family into account as well. It's an overwhelming life event that makes you start thinking - what should I do, where do I begin and how do I approach this? The idea for this Capstone Project is to show how leveraging location data from FourSquare and other data sources can assist you with making decisions based on your individual needs when having to relocate. The approach will be to follow and apply the systematic data science methodology to our scenario where I will:

1. Understand the problem and identify our approach
2. Identify the required data
3. Collect and understand the data
4. Prepare the data
5. Analyze the data
6. Model the data
7. Evaluate the model

### 1.2. Problem

In this scenario the individual needs to relocate to Boston, United States where he will be working. He needs to take his partner (who is a chef) into consideration as she will be relocating with him and will also have to look for a new job. He also needs to take his child into consideration for a school.

He starts off by listing his and his family's basic wants and needs to identify how to approach the problem and to identify what data is required.

| | |
|---|---|
| **Security** | **To live in a safe environment** |
| **Close to working locations** | Must have loads of restaurants in the area, Close to Museum |
| **Public Elementary school** | Neighborhood close to school |

# 2. Data

## 2.1. Data acquisition

From the basic wants and needs list in the scenario description the following data is required

1. Crime data
2. School data
3. FourSquare data on restaurants and work location

Open source data from Analyze Boston is obtained which is the City of Boston's open data hub. From here the crime data is obtained as well as school data. This will assist in identifying safe neighborhoods to live in as well as where the options are for Elementary schools.

The FourSquare API to query is used for geographical data on restaurants. It will be ideal to stay in the neighborhood or close to the neighborhood where there are many restaurants as a potential work option for the wife. FourSquare is also used to identify the location of the museum so that it can be taken into consideration when identifying possible neighborhoods to minimize extensive travel where possible. For each dataset used in this study a similar approach is followed to first explain where the data comes from, what is contained in the data and how the data is prepared in order to start working with a clean dataset.

## 2.2. Data Cleaning and Feature Selection

### 2.2.1. Boston Crime Data

The Boston Crime dataset can be downloaded from Github. This is a dataset containing records for crime incident reports as provided by the Chicago Police Department and includes types of incidents as well as when and where it occurred. This data will allow to identify lower crime neighborhoods and to consider these as possible options for neighborhood selections. The libraries required to extract the data is installed and the data is read into a pandas dataframe. From the dataframe there is information such as incident number, type of offense, district, date and location. Not all of these attributes is the dataset are required. Thus the following data was imported to create a new dataframe as we only need to know the type of offense and where and when it occurred. This data will allow to monitor the trend with regards to the crime in the neighborhoods.

- Primary type
- Year
- Date
- Location description
- Lat
- Long

| | OFFENSE_CODE_GROUP | OFFENSE_DESCRIPTION | YEAR | MONTH | STREET | OCCURRED_ON_DATE | Lat | Long | Location |
|---|---|---|---|---|---|---|---|---|---|
| 0 | NaN | ASSAULT - AGGRAVATED | 2019 | 10 | RIVERVIEW DR | 2019-10-16 00:00:00 | NaN | NaN | (0.00000000, 0.00000000) |
| 1 | NaN | VERBAL DISPUTE | 2019 | 12 | DAY ST | 2019-12-20 03:08:00 | 42.325122 | -71.107779 | (42.32512200, -71.10777900) |
| 2 | NaN | INVESTIGATE PERSON | 2019 | 10 | GIBSON ST | 2019-10-23 00:00:00 | 42.297555 | -71.059709 | (42.29755500, -71.05970900) |
| 3 | NaN | WARRANT ARREST - OUTSIDE OF BOSTON WARRANT | 2019 | 11 | BROOKS ST | 2019-11-22 07:50:00 | 42.355120 | -71.162678 | (42.35512000, -71.16267800) |
| 4 | NaN | SICK ASSIST | 2019 | 11 | WASHINGTON ST | 2019-11-05 18:00:00 | 42.309718 | -71.104294 | (42.30971800, -71.10429400) |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 463072 | NaN | INVESTIGATE PERSON | 2020 | 1 | HARRISON AVE | 2020-01-05 00:00:00 | 42.339541 | -71.069408 | (42.33954100, -71.06940800) |
| 463073 | NaN | DISTURBING THE PEACE/ DISORDERLY CONDUCT/ GATH... | 2020 | 1 | HANOVER ST | 2020-01-01 01:02:00 | 42.364167 | -71.054070 | (42.36416700, -71.05407000) |
| 463074 | NaN | WARRANT ARREST - OUTSIDE OF BOSTON WARRANT | 2019 | 11 | NaN | 2019-11-30 21:00:00 | 42.360866 | -71.061316 | (42.36086600, -71.06131600) |
| 463075 | NaN | INVESTIGATE PERSON | 2019 | 11 | HYDE PARK AVE | 2019-11-25 16:30:00 | 42.256215 | -71.124019 | (42.25621500, -71.12401900) |
| 463076 | NaN | THREATS TO DO BODILY HARM | 2019 | 11 | MORA ST | 2019-11-12 12:00:00 | 42.282081 | -71.073648 | (42.28208100, -71.07364800) |

463077 rows × 9 columns

An example of the Crime Dataframe with only the required data can be seen after the unused columns have been removed.

### 2.2.2. Boston School Data

The Boston School dataset can be downloaded from the Analyze Boston data portal. This dataset gives general information about each school building, the type of schools as well as location data. This dataset contains information more pertaining to school building investments, but contains much more information than the standard public school dataset which might be required and thus is the dataset of choice. Knowing the type of school as well as the location will assist in deciding the neighborhood to live in. The data is first extracted and read into a pandas dataframe. From the dataset, the information seems quite cryptic, but there are additional documents on the website that describes the data keys. This is used to assist in extracting the required data and renaming the columns to a better description. From the information extracted there are 141 data entries and 251 columns. The following describes the data keys and associated information required:

- BPS_School_Name: School Name
- BPS_Address: School Address
- SMMA_latitude: Latitude
- SMMA_longitude: Longitude
- SMMA_Typology: Type of School
- Phone number

```
The new dataframe size is: (48, 6)
```

| | School_Name | Address | Neighborhood | Latitude | Longitude | Type |
|---|---|---|---|---|---|---|
| 0 | Adams, Samuel Elementary | 165 Webster St East Boston, MA 02128 | East Boston | 42.365553 | -71.034917 | Elementary School |
| 1 | Alighieri, Dante Montessori School | 37 Gove Street East Boston, MA 02128 | East Boston | 42.371565 | -71.037608 | Elementary School |
| 4 | Bates, Phineas Elementary | 426 Beech St Roslindale, MA 02131 | Roslindale | 42.277663 | -71.135353 | Elementary School |
| 5 | Beethoven, Ludwig Van Elementary | 5125 Washington St West Roxbury, MA 02132 | West Roxbury | 42.263520 | -71.155824 | Elementary School |
| 6 | Blackstone, William Elementary | 380 Shawmut Ave Boston, MA 02118 | South End | 42.341012 | -71.072056 | Elementary School |

### 2.2.3. FourSquare

Data Now location data on work location and restaurants can be scraped from FourSquare which is an independent location data and technology platform. The FourSquare website is queried to also obtain additional data about the restaurants. The idea behind acquiring this data is to assist in identifying location and density of restaurants in each neighborhood and to consider the distance between working and school locations when mapped out. Both the Museum location data and various restaurants' location data that's in the vicinity is required, as it would be ideal to have both partners' work location close to one another or close to the chosen neighborhood. The Museum's location data (i.e. coordinates) is obtained based on the known address. Chicago's size is approximately 232 km2 , so to attempt to capture all possible restaurant options, a query is defined to search for restaurants within a 100km radius from the museum and to transform the data into a pandas dataframe. We will initially keep the range quite wide as not to limit options when only cleaning the data. The dataframe is then cleaned to only include sensible information pertaining to restaurants and location. The category range remains quite wide initially, as not too limit potential options for places for a chef too work at. Any city information not pertaining to Boston was also removed.

| | name | categories | address | lat | lng | labeledLatLngs | distance | postalCode | cc | city | state | country | formattedAddress | neighborhood | id |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Q Restaurant | Hotpot Restaurant | 660 Washington St | 42.351707 | -71.062715 | [{'label': 'display', 'lat': 42.35170662953259... | 1723 | 02111 | US | Boston | MA | United States | [660 Washington St (at Beach St.), Boston, MA ... | NaN | 4c91546ab641236ab6a68079 |
| 3 | Billy Tse's Restaurant | Sushi Restaurant | 240 Commercial St | 42.363832 | -71.051115 | [{'label': 'display', 'lat': 42.36383163608474... | 1405 | 02109 | US | Boston | MA | United States | [240 Commercial St, Boston, MA 02109, United S... | NaN | 4b1afebdf964a5200cf623e3 |
| 4 | Great Taste Bakery & Restaurant | Bakery | 31 Beach St | 42.351291 | -71.060165 | [{'label': 'display', 'lat': 42.35129067813932... | 1828 | 02111 | US | Boston | MA | United States | [31 Beach St, Boston, MA 02111, United States] | NaN | 4ae310cef964a520399021e3 |
| 6 | Montien Boston - Thai Restaurant | Thai Restaurant | 63 Stuart St | 42.351094 | -71.064498 | [{'label': 'display', 'lat': 42.35109416020406... | 1761 | 02116 | US | Boston | MA | United States | [63 Stuart St (Tremont St), Boston, MA 02116, ... | NaN | 4a04e5aff964a5203e721fe3 |
| 7 | Primo's Restaurant | Pizza Place | 28 Myrtle St | 42.359324 | -71.065583 | [{'label': 'display', 'lat': 42.35932373996034... | 843 | 02114 | US | Boston | MA | United States | [28 Myrtle St, Boston, MA 02114, United States] | NaN | 4aa91a1af964a520fe5120e3 |
| 8 | Thornton's Restaurant & Cafe | Diner | 150 Huntington Ave | 42.345288 | -71.082010 | [{'label': 'display', 'lat': 42.34528762816119... | 2660 | 02115 | US | Boston | MA | United States | [150 Huntington Ave (at W Newton St), Boston, ... | NaN | 4aec58d2f964a52035c621e3 |
| 9 | Pulcinella Mozzarella Bar and Restaurant | Italian Restaurant | 78 Salem St | 42.363693 | -71.055872 | [{'label': 'display', 'lat': 42.36369287757674... | 1033 | 02113 | US | Boston | MA | United States | [78 Salem St, Boston, MA 02113, United States] | NaN | 502bd747e4b082dc2d00820d |
| 10 | Last Corner Restaurant | Diner | 49 High Street | 42.376570 | -71.063172 | [{'label': 'display', 'lat': 42.37657, 'lng': ... | 1157 | 01867 | US | Boston | MA | United States | [49 High Street (Chute St), Boston, MA 01867, ... | NaN | 4b57b367f964a520af3c28e3 |
| 11 | New Jumbo Seafood Restaurant | Chinese Restaurant | 5 Hudson St | 42.350902 | -71.059895 | [{'label': 'display', 'lat': 42.35090215936083... | 1876 | 02111 | US | Boston | MA | United States | [5 Hudson St, Boston, MA 02111, United States] | NaN | 4b08321cf964a520ff0523e3 |
| 12 | The Causeway Restaurant and Pub | BBQ Joint | 65 Causeway St | 42.364659 | -71.062912 | [{'label': 'display', 'lat': 42.3646590394464,... | 459 | 02114 | US | Boston | MA | United States | [65 Causeway St (Lancaster), Boston, MA 02114,... | NaN | 534f07e9498e5cc70137182b |
| 15 | Moon Villa Restaurant | Chinese Restaurant | 19 Edinboro St | 42.351884 | -71.059554 | [{'label': 'display', 'lat': 42.35188354712937... | 1784 | 02111 | US | Boston | MA | United States | [19 Edinboro St (Near Beach St.), Boston, MA 0... | NaN | 4bb21286f964a52094b63ce3 |
| 19 | Toro Restaurant | Tapas Restaurant | 1704 Washington Street | 42.336988 | -71.075924 | [{'label': 'display', 'lat': 42.33698768, 'lng... | 3378 | 02118 | US | Boston | MA | United States | [1704 Washington Street (at Massachusetts Ave),... | NaN | 43e9e7eff964a520202f1fe3 |
| 21 | International Restaurant & Pub | Restaurant | 184 High St | 42.357344 | -71.052514 | NaN | 1631 | 02110 | US | Boston | MA | United States | [184 High St, Boston, MA 02110, United States] | NaN | 40b28c80f964a520bff71ee3 |
| 22 | Carrie Nation Restaurant & Cocktail Club | American Restaurant | 11 Beacon St | 42.358316 | -71.061458 | [{'label': 'display', 'lat': 42.35831564666699... | 1070 | 02108 | US | Boston | MA | United States | [11 Beacon St (at Somerset St), Boston, MA 021... | NaN | 518564e8498e25e8f94c2679 |
| 23 | Saus Restaurant | Belgian Restaurant | 33 Union St | 42.361076 | -71.057054 | [{'label': 'display', 'lat': 42.36107632380333... | 1081 | 02108 | US | Boston | MA | United States | [33 Union St (Marsh Lane), Boston, MA 02108, U... | NaN | 4bf18c843506ef3bea63bd22 |
| 24 | Amrheins Restaurant | Bar | 80 W Broadway | 42.341816 | -71.055311 | [{'label': 'display', 'lat': 42.34181624208448... | 2956 | 02127 | US | Boston | MA | United States | [80 W Broadway, South Boston, MA 02127, United... | NaN | 4a7783edf964a520b7e41fe3 |
| 28 | Pearl Villa Restaurant | Chinese Restaurant | 25 Tyler St | 42.350690 | -71.061010 | [{'label': 'display', 'lat': 42.35069, 'lng': ... | 1869 | 02111 | US | Boston | MA | United States | [25 Tyler St (at Kneeland St), Boston, MA 0211... | NaN | 4af4e050f964a5202af721e3 |
| 29 | No Name Restaurant | Seafood Restaurant | 15 Fish Pier St W | 42.350384 | -71.038321 | [{'label': 'display', 'lat': 42.35038402915641... | 3028 | 02210 | US | Boston | MA | United States | [15 Fish Pier St W, Boston, MA 02210, United S... | NaN | 4b9011b7f964a520a87333e3 |
| 31 | Toscano Restaurant | Italian Restaurant | 47 Charles St | 42.357360 | -71.070026 | [{'label': 'display', 'lat': 42.35736019165299... | 1060 | 02114 | US | Boston | MA | United States | [47 Charles St, Boston, MA 02114, United States] | NaN | 3fd66200f964a5204dec1ee3 |

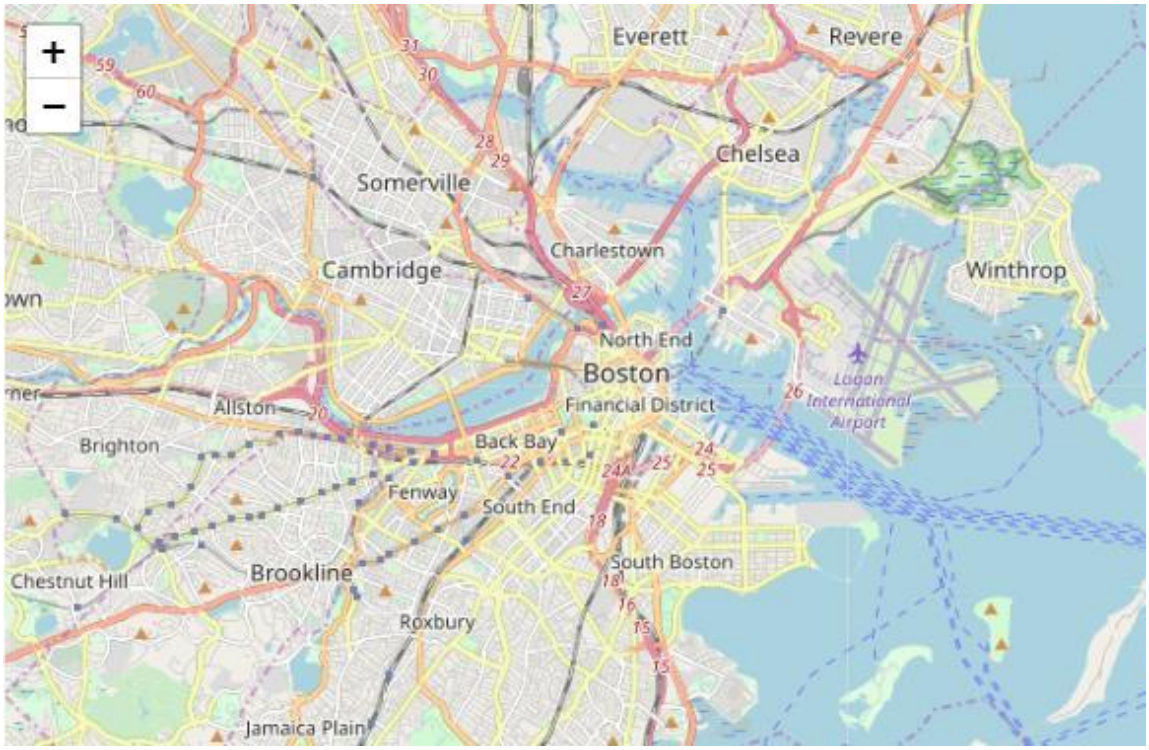
An example of the cleaned and ready to be analyzed Restaurant dataset.

# 3. Methodology

## 3.1. Exploratory

Data Analysis Now that the data is cleaned up it's ready to be explored and analyzed in order to obtain insights. The data will be analyzed in the following order:

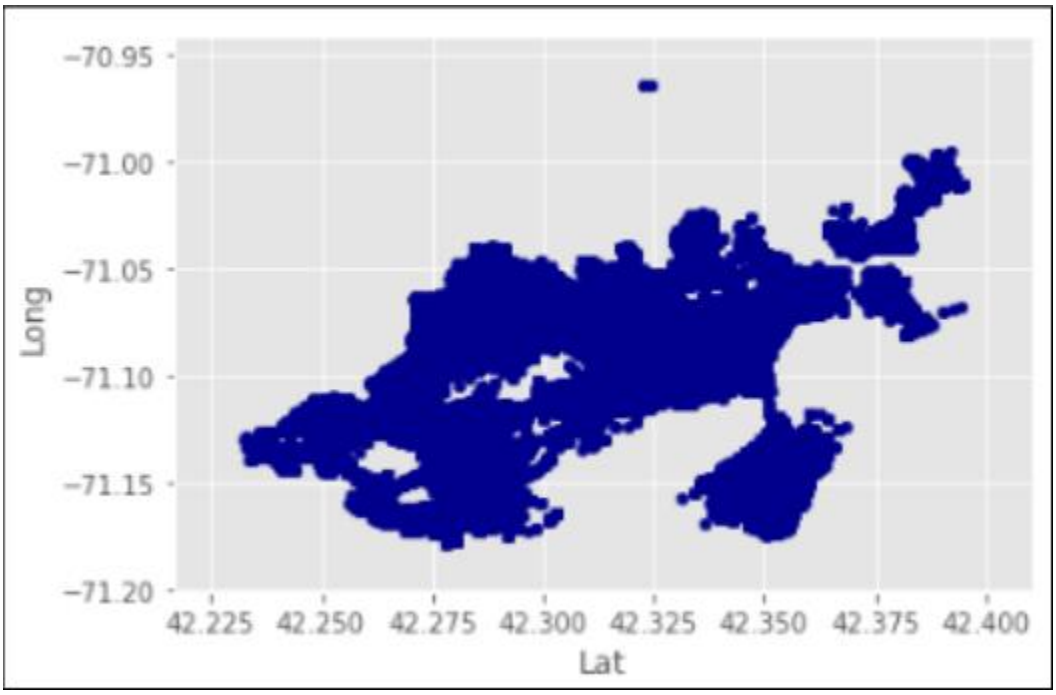
1. Crime data
2. School data
3. FourSquare data




map for Boston IL USA

And this is a

As there are so many entries of crime data, the entries were plotted on a scatter plot of latitude vs. longitude to see if there are any further outliers after cleaning the dataset.



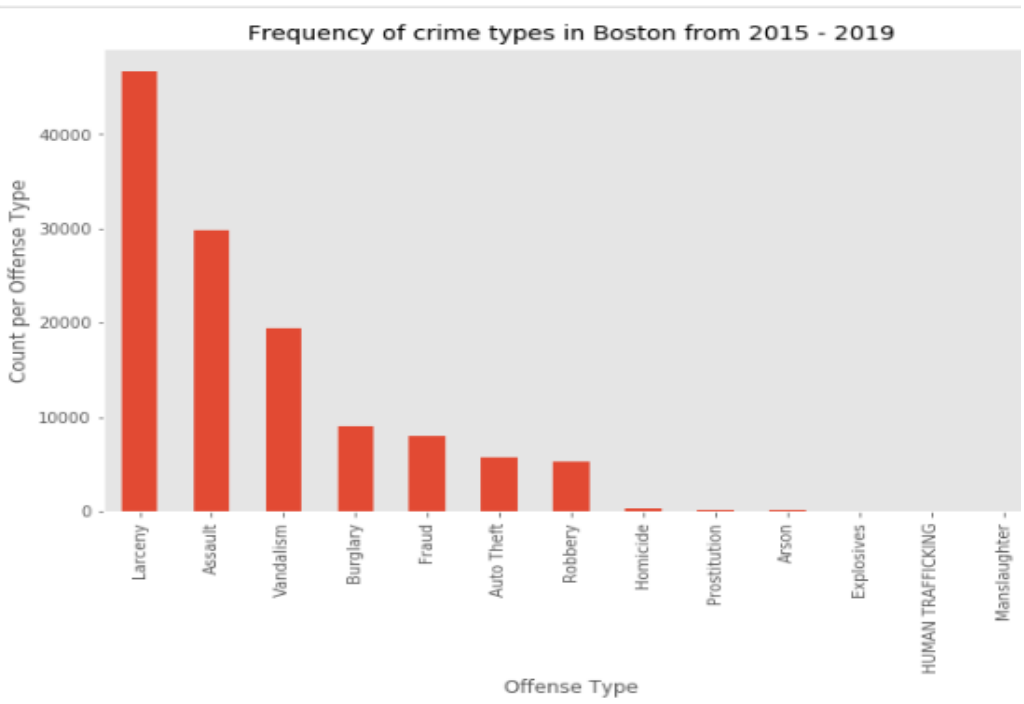

The outlying coordinates (~42.3”N,70.96”W) we’re identified to still be around the Boston area (more around the nearby islands) and thus remained in the dataset. The rest of the data look well grouped to the Boston location. Crime trends over the supplied time period, from 2015 to 2019, was not provided and had to be calculated. The top crime streets were identified to be Washington Street followed by Boylston Street.

| STREET | GroupByStreet |
|---|---|
| WASHINGTON ST | 6182 |
| BOYLSTON ST | 4341 |
| BLUE HILL AVE | 2699 |
| TREMONT ST | 2238 |
| DORCHESTER AVE | 2170 |
| MASSACHUSETTS AVE | 1957 |
| HARRISON AVE | 1861 |
| HUNTINGTON AVE | 1808 |
| COMMONWEALTH AVE | 1780 |
| NEWBURY ST | 1653 |
| CENTRE ST | 1507 |
| RIVER ST | 1181 |
| COLUMBIA RD | 1173 |
| HYDE PARK AVE | 955 |
| COLUMBUS AVE | 943 |
| WARREN ST | 899 |
| DUDLEY ST | 890 |
| BEACON ST | 815 |
| SUMMER ST | 760 |
| BOWDOIN ST | 716 |

The data was then grouped by type of crime from where it became apparent that the top crime type in Boston is larceny, followed by assault and then vandalism.

GroupByType

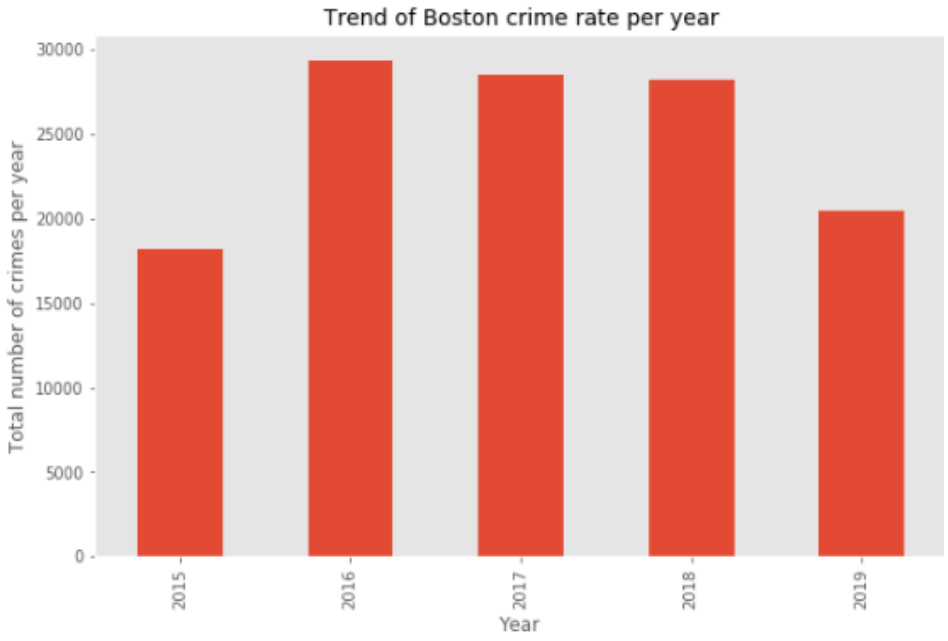
| OFFENSE_CODE_GROUP | |
|---|---|
| Larceny | 46743 |
| Assault | 29876 |
| Vandalism | 19376 |
| Burglary | 9093 |
| Fraud | 8070 |
| Auto Theft | 5766 |
| Robbery | 5264 |
| Homicide | 257 |
| Prostitution | 252 |
| Arson | 105 |
| Explosives | 30 |
| HUMAN TRAFFICKING | 11 |
| Manslaughter | 8 |



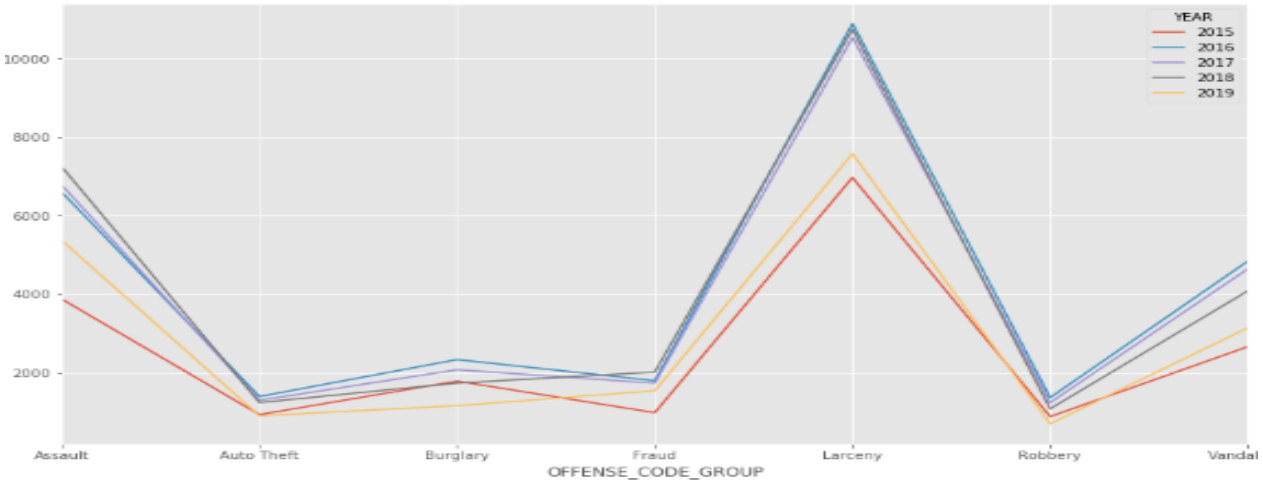

The number of crimes for each year was plotted to determine the crime trend.

GroupByYear

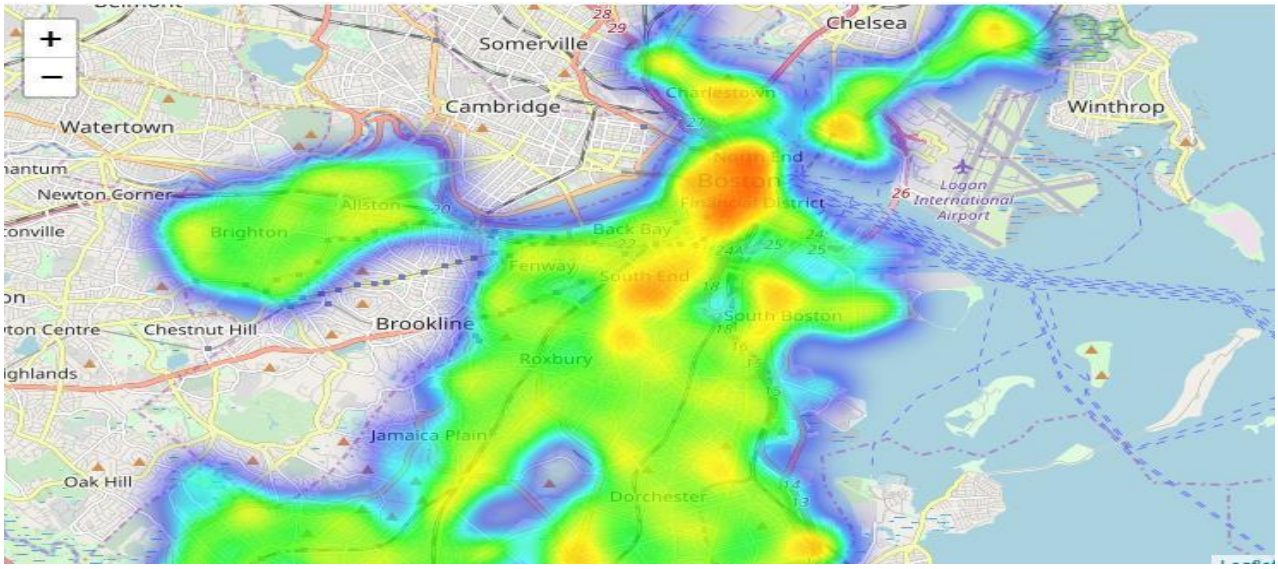
| YEAR | |
|---|---|
| 2015 | 18193 |
| 2016 | 29391 |
| 2017 | 28506 |
| 2018 | 28271 |
| 2019 | 20490 |



the Boston crime trend, it can be seen that although there has been a significant increase in crime from 2015 to 2016, the crime rate has almost reverted back in 2019 to the rate seen in 2015 and the trend currently indicates a decrease in crime. The top 7 crimes were then evaluated, and it was identified, as seen in Figure 9, that the top 3 contributing crimes (assault, larceny and vandalism) has been the main cause for the increase in crime rate for the period 2016-2018, but decreased in 2019. Comparing the lower crime rate years, 2015 and 2019, it is apparent that only burglary and robbery rates are lower in 2019 whereas all the other crime type rates have either remained the same or increased.

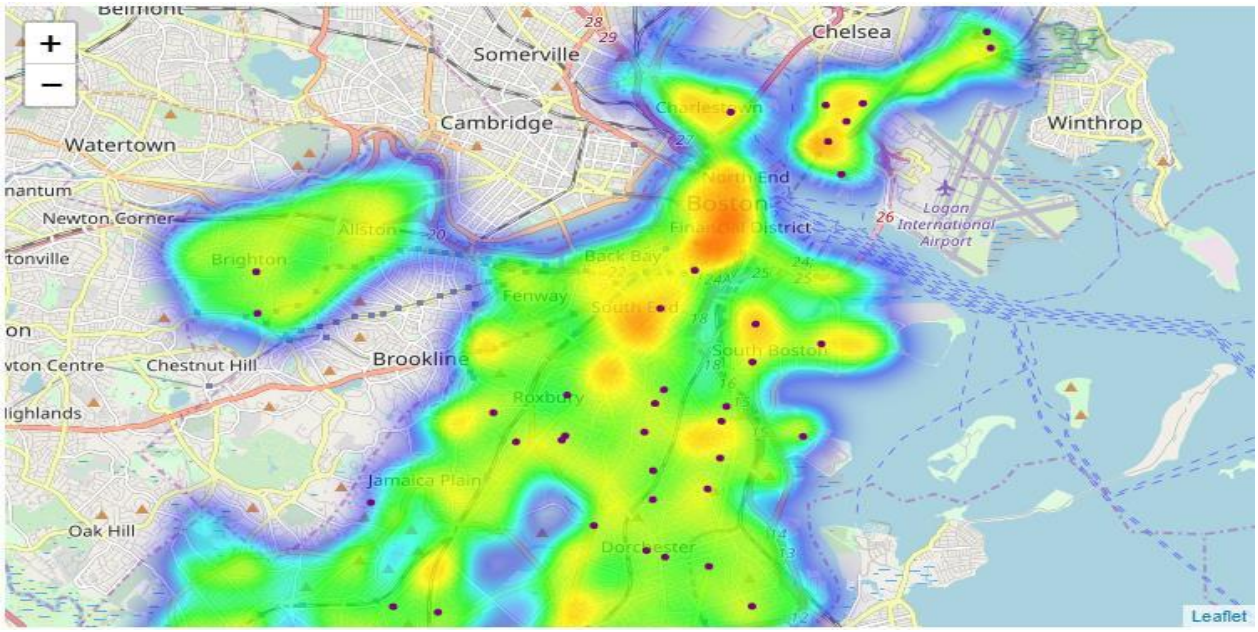



The data was then further reduced indicate current or latest trends and only included data for the year 2019, this reduced the dataset to 20 490 entries. The data was then grouped per coordinates to indicate based on the most recent data the high crime streets in Boston. This data was then superimposed on the base Boston map to visually identify high crime areas.



### 3.1.2. School Data

For the school data it was ideal to highlight which neighborhood contains more than one elementary school. The schools were thus grouped by neighborhood and to display the density of schools per location visually, the data was overlaid as purple markers on the Boston base map which now included the crime data as well.



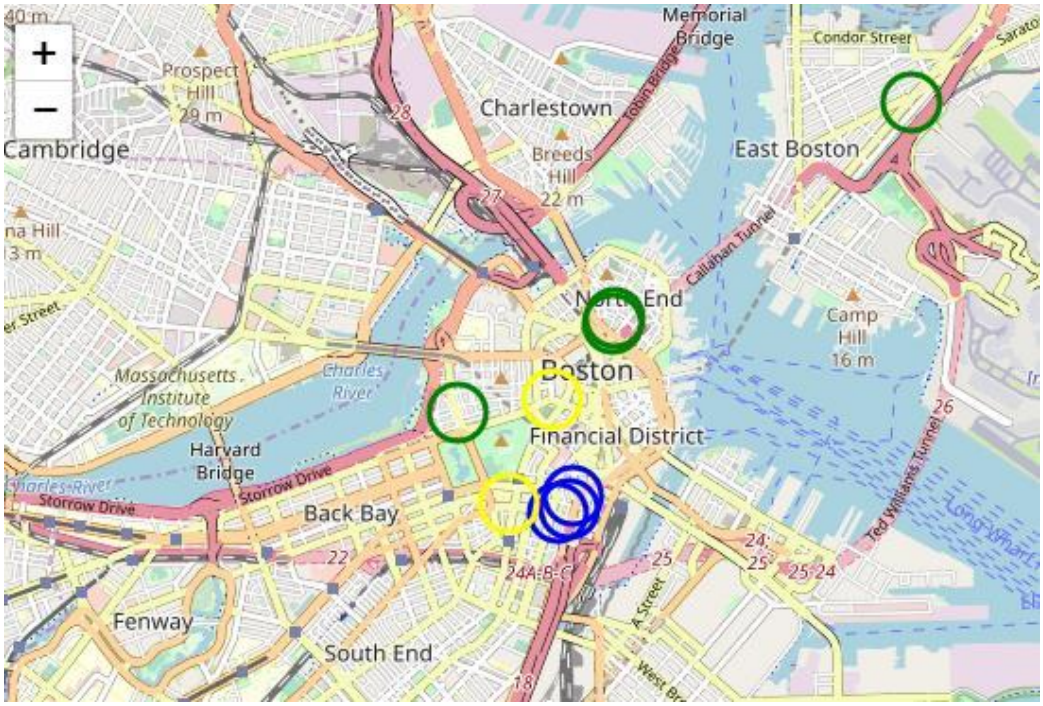

### 3.1.3. FourSquare Data

The Museum's location was then marked on the Boston base map as this will identify the center location to take into consideration when choosing a neighborhood to live in.

The data of the restaurants are then described below. It can be seen that there are 27 entries with the mean location at coordinates latitude = 42.356070, longitude = -71.058684 and that the general distance of the restaurants from the museum is approximately 1km. The furthest restaurant data entry is about 4.3km from the museum location.

| | lat | lng | distance |
|---|---|---|---|
| **count** | 27.000000 | 27.000000 | 27.000000 |
| **mean** | 42.356070 | -71.058684 | 1915.740741 |
| **std** | 0.011424 | 0.013074 | 1000.221191 |
| **min** | 42.331051 | -71.084968 | 459.000000 |
| **25%** | 42.350796 | -71.063835 | 1082.500000 |
| **50%** | 42.357344 | -71.060165 | 1726.000000 |
| **75%** | 42.362485 | -71.055591 | 2654.000000 |
| **max** | 42.379929 | -71.027055 | 4342.000000 |

The various types of restaurants in the data are then identified. It is ideal to see the top three restaurant type spread across Boston, as this will allow a chef to see the location's desired cuisine allowing for an additional variable to take into consideration when choosing a neighborhood.

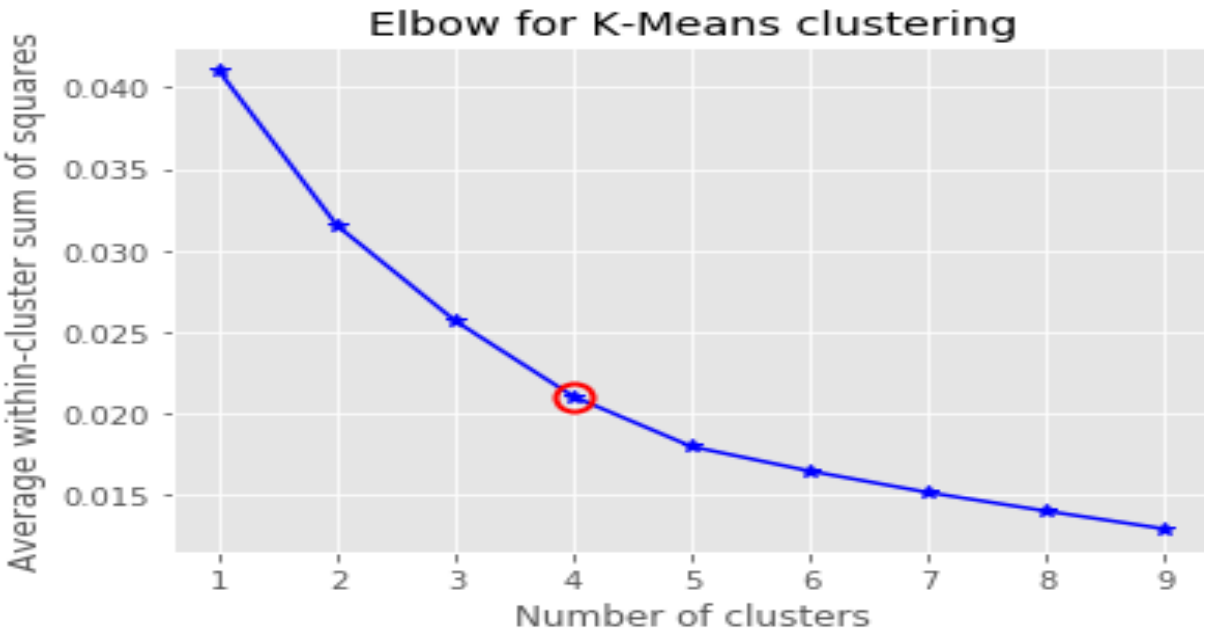



| categories | name |
|---|---|
| Italian Restaurant | 4 |
| Chinese Restaurant | 3 |
| American Restaurant | 2 |
| Bar | 2 |
| Pizza Place | 2 |

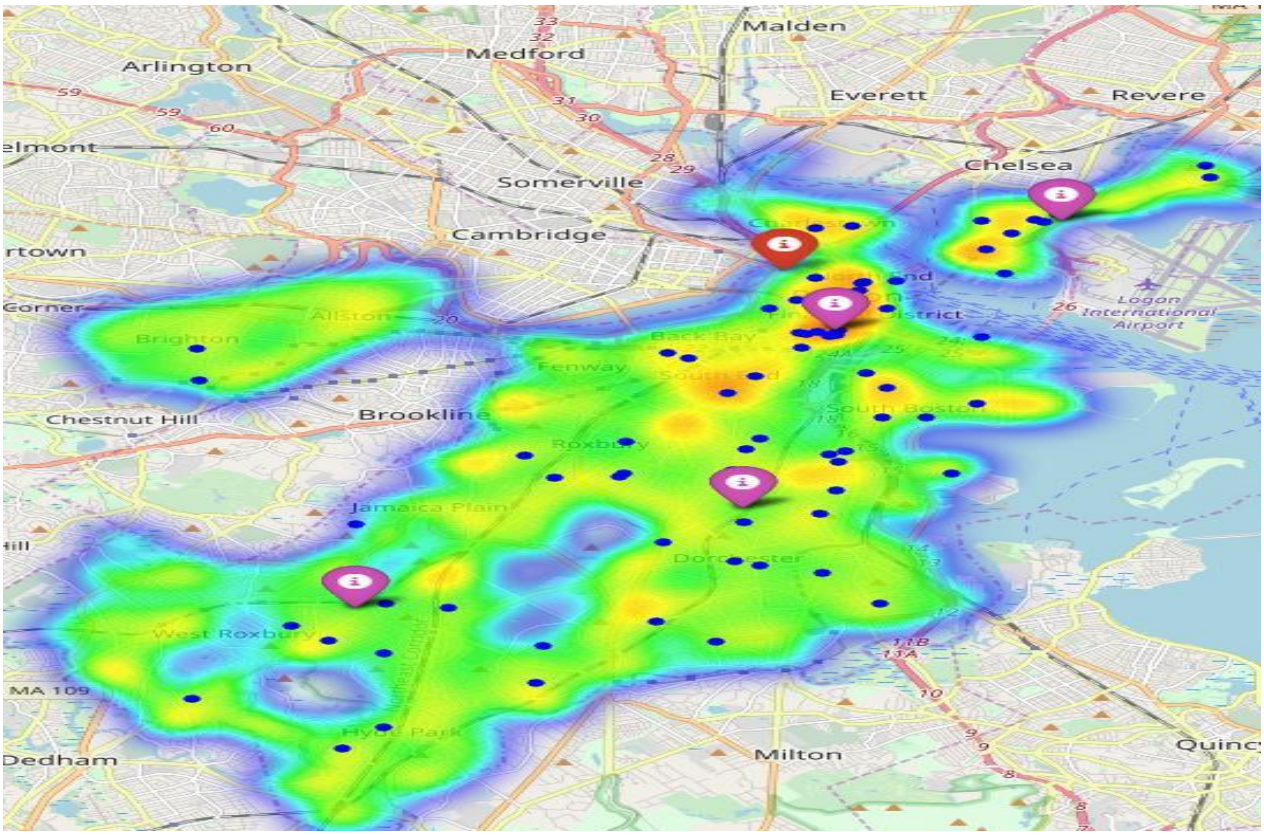
it is visible that it's not that easy to identify an ideal neighborhood based on mapping all the preferences on a single map. Therefore, predictive modeling is required to assist in identifying an ideal neighborhood.

## 3.2. Predictive Modeling

The type of model that will assist in solving the problem needs to be identified. As the intent is to identify an area or neighborhood that features most of the location preferences, clustering is recognized as the ideal exploratory data analysis technique. Clustering is the grouping of data based on shared characteristics. One type of partitioned based clustering algorithm is K-means Clustering. K-means is an iterative algorithm that uses distance-based measurements to determine similarity between data points. It's one of the simplest and most popular unsupervised machine learning algorithms. The data to use for the model needs to be prepared to only include numerical data. K-means clustering will be used to identify ideal neighborhoods, so that indicates focusing on positive traits and thus only restaurant and school data will be used and the crime data will be excluded. The restaurant and school data is combined into a new dataframe and the dataframe is cleaned up to only include numerical data. First the cluster centroids need to be determined. The Euclidean distance for each point is calculated from the centroid and an elbow curve is developed to visually show the ideal number of clusters to continue with based on the data. It can be seen from figure 19 that a good K to use in the model will be 4.



The K-means model is then developed, and the data fitted to the model. 4 Clusters are then obtained and visually marked on the Boston map with a crime heat map, the museum data and the school data in the background as seen in the down pic.




## 4. Results

From the results the highest crime area is located around the Financial District (downtown Boston) close by Chinatown. This would not be an ideally suited neighborhood to select. Directing attention to the school data, it is beneficial if a neighborhood is chosen that provides multiple options, but it's important to take note that where there are more options the neighborhood might also be considerably bigger than other neighborhoods. From the school results no conclusion can be made as yet on a preferred neighborhood as there are no immediate visible clusters. From the restaurant data, apart from the Chinese cuisine type clustered in Chinatown, there seems to be quite a variety of restaurants with various cuisine types all over Boston allowing for a variety of restaurants for a chef to work at. This data on its own does not provide a concrete solution for a neighborhood. From the clustering results of desirable traits (schools and restaurants) in a location, 4 neighborhoods were marked on a heat map of crime locations. These locations can then be further evaluated based on closer inspection or a zoomed in view of the map. As a final result, the four ideal neighborhoods to live in was marked with the following coordinates and upon further investigation the neighborhoods were determined:

- [ 42.30965123, -71.07414251] – Roxbury,
- [ 42.28570345, -71.13181767] – Roslindale,
- [ 42.35243914, -71.06025271] – Chinatown,
- [ 42.37861659, -71.0266932] – East Boston.

These markers only considered the positive attributes of neighborhoods, so when looking at figure 20 and including the crime heat map, it can be seen that Chinatown is located in a high crime location and is thus eliminated as a possible option for a neighborhood to consider. Final desirable neighborhoods to live in based on the induvial needs and location from the museum ideal neighborhoods to consider are then East Boston, Roxbury and Roslindale in no specific order.

## 5. Discussion

The recommended neighborhoods should be considered as a starting point for further, more detailed analysis where other preferences such as housing or traffic data can then be taken into consideration. Prioritization of needs can also be applied to assist in decision making. Even though the crime rate has decreased, crime remains everywhere and thus when finally deciding on a neighborhood, it is important to look out for high-crime locations or streets in the chosen neighborhood and to also consider the type of crime in that area. It would also be desirable to have more data pertaining to schools (where possible) as well as restaurants. The analysis indicates that deciding on a neighborhood to fully adhere to the parameters of the individuals needs can be tricky but doable, especially when a machine learning algorithm is implemented to point out possible neighborhoods more clearly by means of clustering. There is definitely room for improvement on this project and with more work this can be developed into a fully pledged application to assist individuals when relocating. Additional data can be included such as traffic or property trends and school costs etc. and a wider area can also be considered. More detail can also be supplied with regards to the final results.

## 6. Conclusion

The purpose of this project was met to leverage location data to assist an individual in his/her decision of which neighborhood to live in when relocating to an unfamiliar location The model developed assists in narrowing down ideal neighborhoods to select from based on stakeholder needs or preferences. Through clustering preferences, the cluster locations created is an ideal starting point for final exploration by the stakeholders. Final decision on the chosen neighborhood will be made by each stakeholder taking in their own needs and priorities into consideration.