Airbnb business analysis

Introduction

Airbnb is the number one platform for accommodation rentals in the United States (Similarweb, 2023), with more than 8.4 billion US dollars in worldwide revenue in 2022 (Airbnb, 2023). This report will assess growth opportunities in New York with a 2019 public dataset. Through exploratory data analysis, machine learning, and visualisations along with analysis of relationships between location and price, the report proposes to answer the question:

“Can we identify distinct areas for increased revenue potential?"

Pre-processing

The dataset consisted of 16 fields and 48,895 observations. After the removal of listings with zero price or zero availability this reduced to 31,354. Missing values were replaced and there were no duplicates present.

Exploratory Data Analysis (EDA)

The dataset was explored through visualisations such as bar charts, box plots, distribution plots, correlation plots (heatmaps and pair plots), and data distributions overlaid on a map of New York. For our business question, the variables `price` and `neighbourhood`_group were of particular importance. Essential categorical variables were label encoded to prepare for clustering methods, numerical variables were standardised for an equal interpretation of features with different magnitudes and distributions. The skewness and spread of the variables were investigated, and variables were log-transformed were necessary.

Price alone was found to not be a good indicator for revenue because of the large variation in room availability. Therefore, a new variable `revenue_opportunity` was created to show the maximum commission that Airbnb could make on each room assuming it was booked every day it is available at 17% commission (Airbnb, 2020). Manhattan has the highest revenue opportunity by some margin, followed by Brooklyn, then Queens. This variable was log-transformed to normalise the distribution. `revenue_opportunity` by `neighbourhood_group` and the log distribution are shown in figure 1.

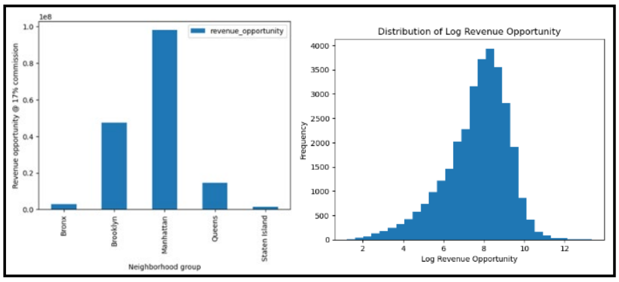


Figure 1. Revenue opportunity

Using the number of people living in each neighbourhood group (United States Census Bureau, 2023), the number of listings per resident was calculated (figure 2). This shows that Manhattan has the highest proportion of listings per resident.

Neighbourhood Group	Listings	Population	Listings per Resident
Manhattan	13,559	1,629,000	0.00832
Brooklyn	12,253	2,577,000	0.00475
Queens	4,298	2,271,000	0.00189
Bronx	913	1,476,000	0.00062
Staten Island	331	476,000	0.0007

Figure 2. Proportion of listings per resident

Using the mean `revenue_opportunity` for each `neighbourhood_group`, the potential additional revenue for each group was calculated **assuming they could all be raised to the same level as Manhattan**; 0.00832 listings per resident. If all groups could be increased to the same level as Manhattan, Queens has the highest additional revenue opportunity (figure 3).

Neighbourhood Group	Listings * 0.00832	Mean Revenue	Current Revenue Opportunity	Potential Revenue * 0.00832	Potential Revenue Increase
Manhattan	13,553	$ 7,227	$ 98.0M	$ 98.0M	$ 0.0M
Brooklyn	21,441	$ 3,882	$ 47.6M	$ 83.2M	$ 35.7M
Queens	18,895	$ 3,421	$ 14.7M	$ 64.6M	$ 49.9M
Bronx	12,280	$ 3,146	$ 2.9M	$ 38.6M	$ 35.8M
Staten Island	3,960	$ 4,657	$ 1.5M	$ 18.4M	$ 16.9M

Figure 3. Potential revenue increase if all groups have the same ratio as Manhattan

Various clustering models were built using k-prototype because it performs well with numerical and categorical values, k-means when using only numerical variables, and DBSCAN because it performs well with outliers. A DBSCAN model using `log_revenue_opportunity`, `room_type`, and `neighbourhood_group` provided some useful results (figure 4). It only achieved a silhouette score of 0.144, which is relatively low. However, the clusters can be seen to be meaningful with each containing a single `neighbourhood_group` and `room_type` - except cluster -1 with 43 outliers from across all categories which were effectively dropped.

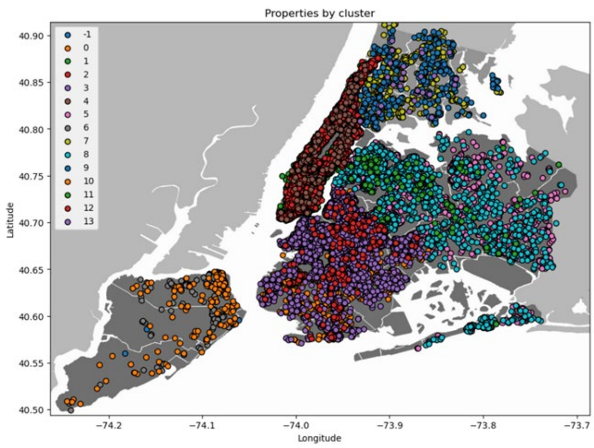


Figure 4. DBSCAN Clustering

`price`, `revenue_opportuniy` (figure 5), and `availability_365` were compared between the clusters. Focusing on Queens, as the highest additional revenue opportunity, shows that 'Private room' (cluster 5) has good availability but low price and low revenue opportunity. 'Entire home/apt' (cluster 8) has good availability, high price, and high revenue opportunity. 'Shared room' (cluster 11) has very low price, high availability but low revenue opportunity. Comparing `neighbourhood_group` clusters, 'Entire home/appt' listings in Queens have a lower price than Manhattan and Brooklyn, but availability is similar to Manhattan and higher than Brooklyn, making the revenue opportunity for these types of listings comparable to Brooklyn, although still lower than Manhattan. So based upon all those factors, a focus for Airbnb could be increasing the number of 'Entire home/appt' listings in Queens.

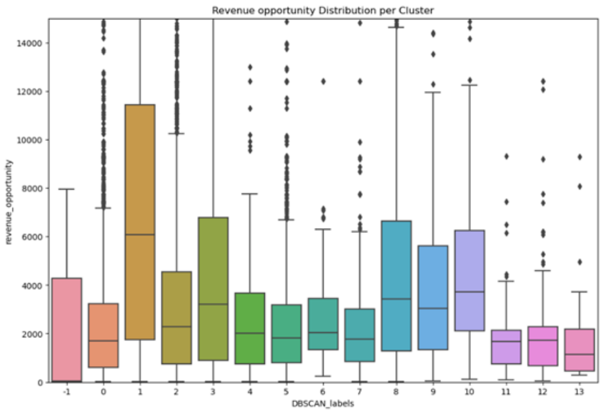


Figure 5. Revenue opportunity distribution per cluster

Linear regression was used to try to predict the revenue opportunity in Queens based on location, using the three Queens clusters previously generated (figure 6).

Neither longitude nor latitude gave a reliable prediction for revenue. There was, however, a weak correlation between both longitude and latitude with `revenue_opportunity`, trending slightly higher with a higher longitude and with a lower latitude. This suggests `revenue_opportunity` is slightly higher further West and South in Queens. As already stated, the correlation was weak and could not be used to predict revenues so the prediction results are not included here.

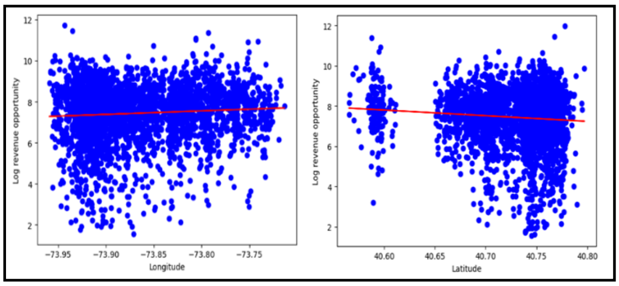


Figure 6. Linear Regression

A k-means model was built on `revenue_opportunity` using the Queens `neighbourhood_group`; clusters 5, 8, and 11 from the DBSCAN, with four clusters as a compromise between the silhouette and elbow methods (figure 7). The silhouette score was 0.525 which is considered a good level of cohesion. Looking at the mean values of `revenue_opportunity`, `latitude`, and `longitude` for each cluster (figure 8) shows mean `revenue_opportunity` increasing with lower latitude and higher longitude, which supports the weak findings from the linear regression that `revenue_opportunity` increases further South and West in Queens.

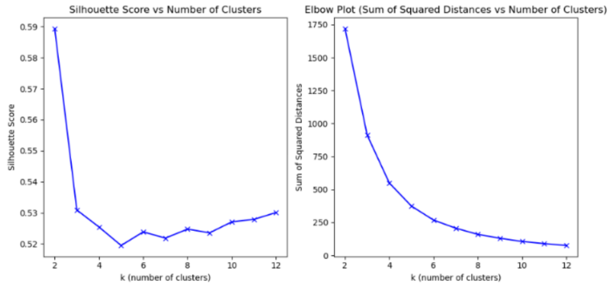


Figure 7. K-means silhouette and elbow

cluster	Mean Log Rev Opp	Mean Latitude	Mean Longitude
2	-2.629761	40.739832	-73.886560
3	-0.843104	40.731542	-73.867199
0	0.171818	40.726851	-73.862784
1	1.033938	40.725164	-73.863788

Figure 8. Mean latitude and longitude per cluster

Limitations

The analysis and report are limited to the provided data with the addition of population data. A more comprehensive and detailed analysis could have been performed with the inclusion of additional fields in the listings such as detailed room information (number of bedrooms, bathrooms), detailed host information (enrolment in the database, response time), short-term and long-term availability (from 30 days to 90 days), host acceptance rates, review accuracy, cleanliness, and square metres. Also, the provision of additional datasets such as detailed calendar data (information for specific date ranges, including availability, price, and minimum overall stay allowed) would allow a time series analysis and detailed review of data, including exploring the frequency of commonly used words for sentiment analysis. Such information is publicly available (insideairbnb, 2023).

Conclusion and Recommendations

This report has identified a distinct area of potential increased revenue for Airbnb in New York, namely Queens. This was managed through data analysis and applying machine learning techniques such as clustering.

The recommendations are therefore that Airbnb invests its resources there with a particular focus on 'Entire home/apt' listings due to the promising returns these types of listings can offer, leading to a considerable increase in revenue.

Finally, to gain a deeper understanding of the differences between these neighbourhoods, Airbnb can pay attention to answering the following question: *Why is Queens currently relatively underpopulated in terms of Airbnb?*

Word count: 1,061

References:

Airbnb (2020) How much does Airbnb charge Hosts? Available from: https://www.airbnb.co.uk/resources/hosting-homes/a/how-much-does-airbnb-charge-hosts-288 [Accessed 08 June 2023].

Airbnb (2023) Airbnb Q4 2022 and full-year financial results. Available from: https://news.airbnb.com/airbnb-q4-2022-and-full-year-financial-results/ [Accessed 7 June 2023]

Inside Airbnb (2023) Get the data. Available from: http://insideairbnb.com/get-the-data/ [Accessed 07 June 2023]

Similarweb (2023) aibnb.com. Available from: https://www.similarweb.com/website/airbnb.com/#overview [Accessed 07 June 2023]

United States Census Bureau (2023) 2020 Census Results, Available from: https://www.census.gov/programs-surveys/decennial-census/decade/2020/2020-census-results.html [Accessed 08 June 2023].

Appendix: Exploratory Data Analysis on AB_NYC_2019 dataset

PLEASE NOTE:

This notebook contains only the code that is required for the charts, tables, and visualisations presented in the Airbnb business analysis report. The complete EDA and thought process can be found in the full notebook.

Import Libraries

In [65]:

```
%pip install kmodes
```

In [66]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
import scipy.stats as st
from sklearn import linear_model
from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.metrics import r2_score
from sklearn.metrics import silhouette_score
from kmodes.kprototypes import KPrototypes
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import LabelEncoder, StandardScaler
import warnings
# ignore future deprecation
warnings.filterwarnings('ignore')
```

Read the AB_NYC_2019.csv file

In [67]:

```
airbnb = pd.read_csv("AB_NYC_2019.csv")
```

There are a lot of missing variables, especially last_review and reviews_per_month.

Replace null values with appropriate values:

- name is categorical so will simply be replaced with "Replaced name"
- host_name is categorical so will simply be replaced with "Replaced host name"
- last_review is date so will be replaced with 0 (0 is not ideal for dates but we won't be using this variable, null value is replaced to avoid any errors)
- review_per_month is a continuous variable so will be replaced with 0

In [68]:

```
airbnb['name'].fillna('Replaced name', inplace=True)
airbnb['host_name'].fillna('Replaced host name', inplace=True)
airbnb['last_review'].fillna(0, inplace=True)
airbnb['reviews_per_month'].fillna(0, inplace=True)
```

In [69]:

```
airbnb.drop(airbnb[airbnb.price == 0].index, inplace=True)
airbnb.drop(airbnb[airbnb.availability_365 == 0].index, inplace=True)
```

Log transform price to normalise the distribution

In [70]:

```
airbnb['log_price'] = np.log(airbnb['price'])
```

Price is the charge per night which isn't a particularly helpful figure for Airbnb on its own.

We will therefore calculate the total revenue opportuity to Airbnb for each room if it were to be booked for every day that it is available. This is of course unlikely, but it is a useful comparrison as to the potential maximum revenue of each room. The commission for each room is 17% of the price charged, made-up of 3% host fee and 14% guest fee: https://www.airbnb.co.uk/resources/hosting-homes/a/how-much-does-airbnb-charge-hosts-288

Revenue_opportunity = price *availability_365* 0.17

In [71]:

```
airbnb['revenue_opportunity'] = airbnb['price'] * airbnb['availability_365'] *
0.17
```

Also log transform revenue_opportunity

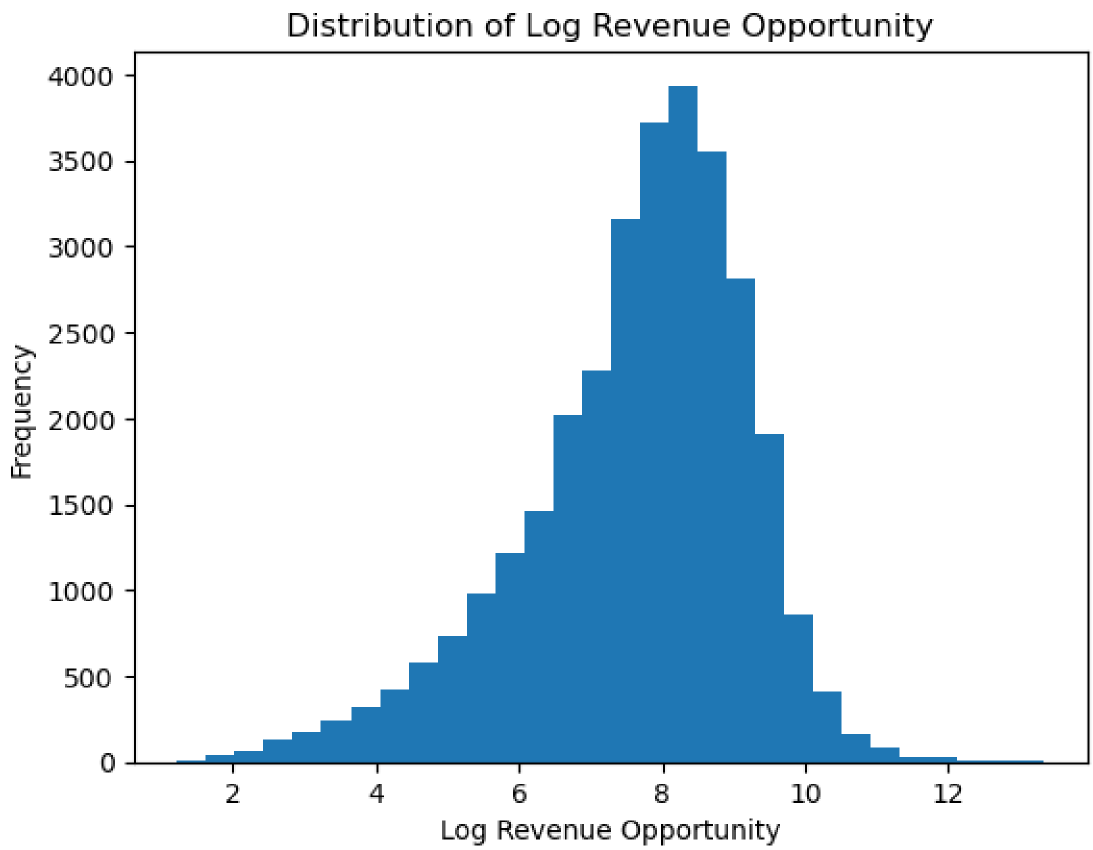
In [72]:

```
airbnb['log_revenue_opportunity'] = np.log(airbnb['revenue_opportunity'])
```

Figure 1. Revenue opportunity

In [73]:

```
plt.hist(airbnb['log_revenue_opportunity'], bins=30)
plt.xlabel('Log Revenue Opportunity')
plt.ylabel('Frequency')
plt.title('Distribution of Log Revenue Opportunity')
plt.show()
```



In [74]:

```
neighbourhood_group = airbnb.pivot_table(index ='neighbourhood_group',values =
'revenue_opportunity', aggfunc = np.sum)
```

```
neighbourhood_group.plot(kind = 'bar')
plt.xlabel('Neighbourhood group')
plt.ylabel('Revenue opportunity @ 17% commission')
```

Out[74]:

```
Text(0, 0.5, 'Revenue opportunity @ 17% commission')
```

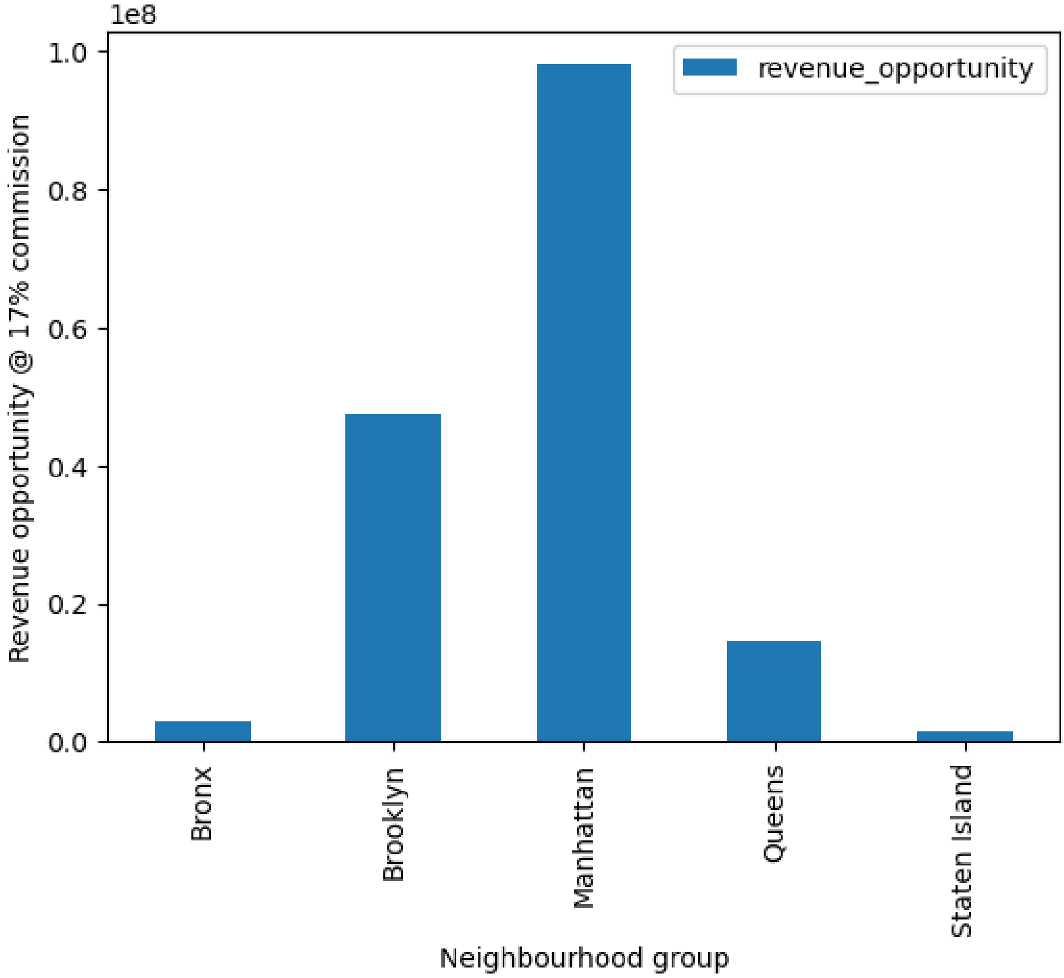


Figure 2. Proportion of listings per resident

In [75]:

```
# Create new dataframe, .reset_index() to convert series into dataframe
counts_df = airbnb.neighbourhood_group.value_counts().reset_index()
counts_df.columns = ['Neighbourhood Group', 'Listings']

# Create population dict from cencus data
population_dict = {
    'Manhattan': 1.629e6,
    'Brooklyn': 2.577e6,
    'Queens': 2.271e6,
    'Bronx': 1.476e6,
    'Staten Island': 476e3
}

# Add population column to df
counts_df['Population'] = counts_df['Neighbourhood
Group'].map(population_dict).apply(lambda x: int(x))

# Add listings per resident to df
counts_df['Listings per Resident'] = (counts_df['Listings'] /
counts_df['Population']).round(5)
```

```
counts_df
```

Out[75]:

	Neighbourhood Group	Listings	Population	Listings per Resident
0	Manhattan	13559	1629000	0.00832
1	Brooklyn	12253	2577000	0.00475
2	Queens	4298	2271000	0.00189
3	Bronx	913	1476000	0.00062
4	Staten Island	331	476000	0.00070

In [76]:

```
styled_df = counts_df.style.background_gradient(
    cmap='Blues'
).hide_index().format(
    {
        "Listings": "{:,.0f}",
        "Population": "{:,.0f}",
        "Listings per Resident": "{:.5g}"
    }
).set_table_styles(
    [
        {
            'selector': 'th',
            'props': [
                ('padding', '1px'),
                ('text-align', 'left')
            ]
        },
        {
            'selector': 'td',
            'props': [
                ('padding', '1px'),
                ('text-align', 'center')
            ]
        }
    ]
).set_properties(**{'width': '70px'})

styled_df
```

Out[76]:

Neighbourhood Group	Listings	Population	Listings per Resident
Manhattan	13,559	1,629,000	0.00832
Brooklyn	12,253	2,577,000	0.00475
Queens	4,298	2,271,000	0.00189
Bronx	913	1,476,000	0.00062
Staten Island	331	476,000	0.0007

Figure 3. Potential revenue increase if all groups have the same ratio as Manhattan

In [77]:

```
mean_revenue_dict =
airbnb.groupby('neighbourhood_group')['revenue_opportunity'].mean().to_dict()
mean_revenue_dict

revenue_opportunity_dict = airbnb.pivot_table(index='neighbourhood_group',
values='revenue_opportunity', aggfunc=np.sum).to_dict()['revenue_opportunity']
revenue_opportunity_dict
```

Out[77]:

```
{'Bronx': 2872252.1700000004,
 'Brooklyn': 47567733.830000006,
 'Manhattan': 97984186.9,
 'Queens': 14702861.91,
 'Staten Island': 1541384.73}
```

In [78]:

```
table_2 = pd.DataFrame()

# Build columns
table_2['Neighbourhood Group'] = counts_df['Neighbourhood Group']
table_2['Listings * 0.00832'] = counts_df['Population'] * 0.00832
table_2['Mean Revenue'] = table_2['Neighbourhood Group'].map(mean_revenue_dict)
table_2['Current Revenue Opportunity'] = table_2['Neighbourhood
Group'].map(revenue_opportunity_dict)
table_2['Potential Revenue * 0.00832'] = table_2['Mean Revenue'] *
table_2['Listings * 0.00832']

# Hardcode Manhattan back since that is the baseline and rounding changes the
value
table_2.loc[table_2['Neighbourhood Group'] == 'Manhattan', 'Potential Revenue *
0.00832'] = 97984186.9

table_2['Potential Revenue Increase'] = table_2['Potential Revenue * 0.00832'] -
table_2['Current Revenue Opportunity']

table_2
```

Out[78]:

	Neighbourhood Group	Listings * 0.00832	Mean Revenue	Current Revenue Opportunity	Potential Revenue * 0.00832	Potential Revenue Increase
0	Manhattan	13553.28	7226.505413	97984186.90	9.798419e+07	0.000000e+00
1	Brooklyn	21440.64	3882.129587	47567733.83	8.323534e+07	3.566761e+07
2	Queens	18894.72	3420.861310	14702861.91	6.463622e+07	4.993335e+07
3	Bronx	12280.32	3145.949803	2872252.17	3.863327e+07	3.576102e+07
4	Staten Island	3960.32	4656.751450	1541384.73	1.844223e+07	1.690084e+07

In [79]:

```
# Currency format func
def format_currency_in_millions(value):
    return "$ {:.1f}M".format(value / 1_000_000)

# format
styled_table_2 = table_2.style.format({
    'Listings * 0.00832': "{:,.0f}",
```

```
    'Mean Revenue': "$ {:,.0f}",
    'Current Revenue Opportunity': format_currency_in_millions,
    'Potential Revenue * 0.00832': format_currency_in_millions,
    'Potential Revenue Increase': format_currency_in_millions
}).background_gradient(cmap='Blues', subset=['Listings * 0.00832', 'Mean Revenue',
'Current Revenue Opportunity', 'Potential Revenue * 0.00832', 'Potential Revenue
Increase']).hide_index().set_table_styles([
    {
        'selector': 'th',
        'props': [
            ('padding', '1px'),
            ('text-align', 'left')
        ]
    },
    {
        'selector': 'td',
        'props': [('padding', '1px'),
          ('text-align', 'center')]
    },
]).set_properties(**{'width': '60px'})

styled_table_2
```

Out[79]:

Neighbourhood Group	Listings * 0.00832	Mean Revenue	Current Revenue Opportunity	Potential Revenue * 0.00832	Potential Revenue Increase
Manhattan	13,553	$ 7,227	$ 98.0M	$ 98.0M	$ 0.0M
Brooklyn	21,441	$ 3,882	$ 47.6M	$ 83.2M	$ 35.7M
Queens	18,895	$ 3,421	$ 14.7M	$ 64.6M	$ 49.9M
Bronx	12,280	$ 3,146	$ 2.9M	$ 38.6M	$ 35.8M
Staten Island	3,960	$ 4,657	$ 1.5M	$ 18.4M	$ 16.9M

Figure 4. DBSCAN Clustering

In [80]:

```
# keeping less than we're dropping so just picking those features
cluster_data = airbnb[['price', 'log_price', 'neighbourhood_group', 'latitude',
'longitude', 'room_type', 'revenue_opportunity', 'log_revenue_opportunity',
'availability_365']]
cluster_data

# Create a copy of the data
cluster_data_prepared = cluster_data.copy()

# Encode categorical variables
le = LabelEncoder()
cluster_data_prepared['room_type_xform'] =
le.fit_transform(cluster_data['room_type'])
cluster_data_prepared['neighbourhood_group_xform'] =
le.fit_transform(cluster_data['neighbourhood_group'])
```

In [81]:

```
dbscan=DBSCAN(eps=0.9,min_samples=9)
dbscan.fit(cluster_data_prepared[['log_revenue_opportunity','room_type_xform','nei
ghbourhood_group_xform']])
```

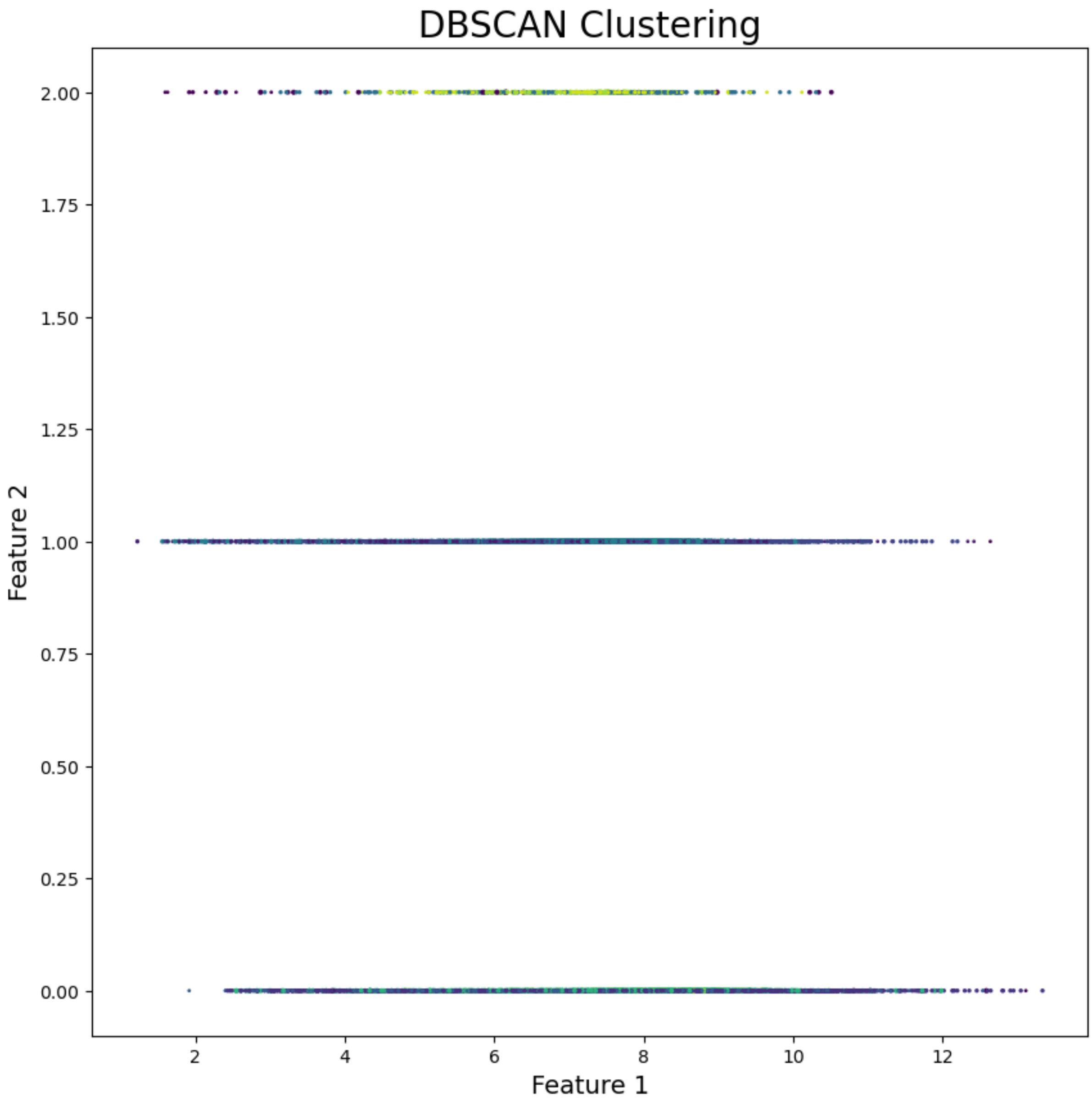
Out[81]:

DBSCAN

DBSCAN(eps=0.9, min_samples=9)

In [82]:

```
cluster_data_prepared['DBSCAN_labels']=dbscan.labels_
plt.figure(figsize=(10,10))
plt.scatter(cluster_data_prepared['log_revenue_opportunity'],cluster_data_prepared
['room_type_xform'],cluster_data_prepared['neighbourhood_group_xform'],c=cluster_d
ata_prepared['DBSCAN_labels'])
plt.title('DBSCAN Clustering',fontsize=20)
plt.xlabel('Feature 1',fontsize=14)
plt.ylabel('Feature 2',fontsize=14)
plt.show()
```



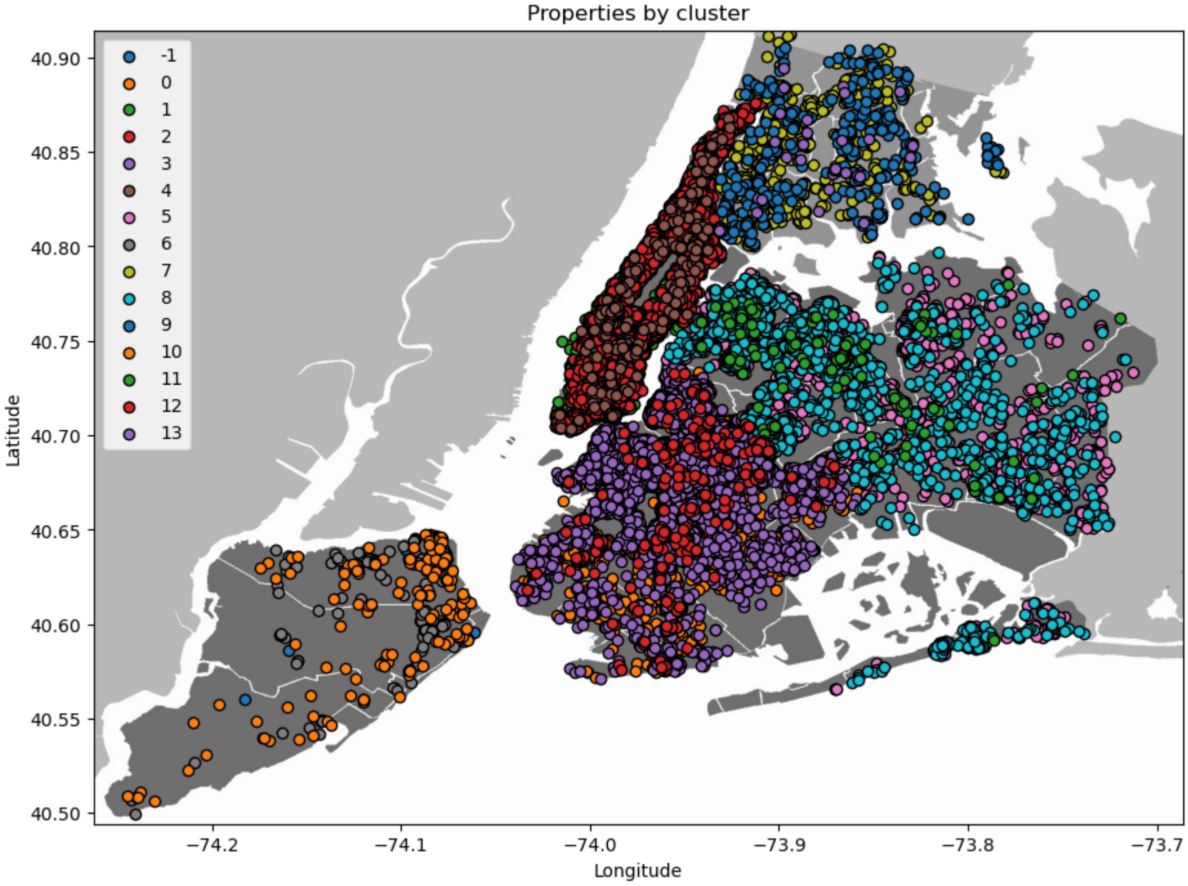
In [83]:

```
plt.figure(figsize=(12,8))
plt.style.use('fast')
# Set the boundary of the map using longitude and latitude obtained from Google
Maps
coordinates = (-74.2623, -73.6862, 40.4943, 40.9144)
map = mpimg.imread("New_York_City.jpg")
plt.imshow(map,extent=coordinates)
groups = cluster_data_prepared.groupby('DBSCAN_labels')
for name,group in groups :
```

```
    plt.scatter(group['longitude'],group['latitude'], label=name, edgecolors='black')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Properties by cluster')
plt.legend()
```

Out[83]:

```
<matplotlib.legend.Legend at 0x1437fbbb0>
```



plot queens here since this is used for the LR in figure 6

In [84]:

```
plt.figure(figsize=(12,8))
plt.style.use('fast')
# Set the boundary of the map using longitude and latitude obtained from Google Maps
coordinates = (-74.2623, -73.6862, 40.4943, 40.9144)
map = mpimg.imread("New_York_City.jpg")
plt.imshow(map,extent=coordinates)
Queens = cluster_data_prepared[(cluster_data_prepared['DBSCAN_labels'] == 5) |
(cluster_data_prepared['DBSCAN_labels'] == 8) |
(cluster_data_prepared['DBSCAN_labels'] == 11)]
groups = Queens.groupby('DBSCAN_labels')
for name,group in groups :
    plt.scatter(group['longitude'],group['latitude'], label=name, edgecolors='black')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Properties by cluster')
plt.legend()
```

Out[84]:

```
<matplotlib.legend.Legend at 0x143594910>
```

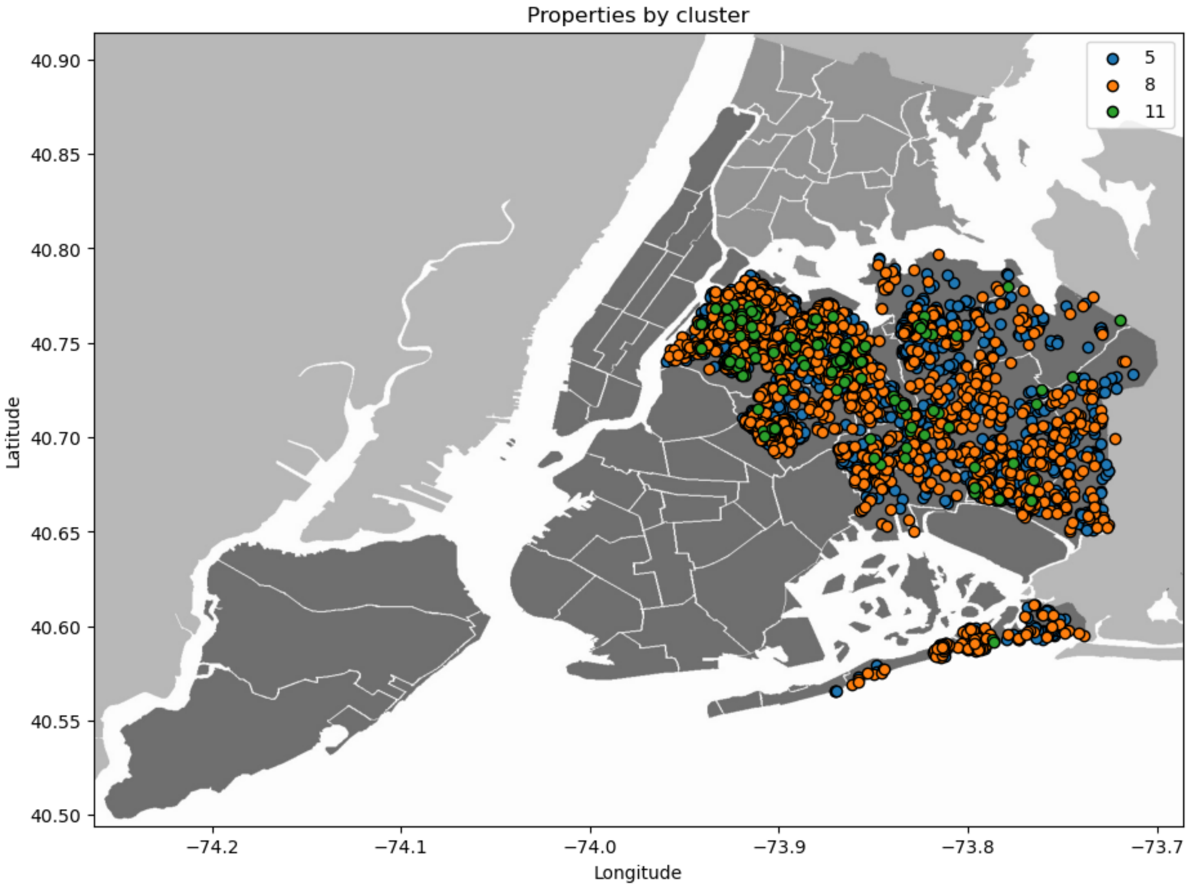


Figure 5. Revenue opportunity distribution per cluster

In [85]:

```
plt.figure(figsize=(12, 8))
sns.boxplot(x='DBSCAN_labels', y='revenue_opportunity',
data=cluster_data_prepared)
plt.title('Revenue opportunity Distribution per Cluster')
plt.axis(ymin=0, ymax=15000)
plt.show()
```

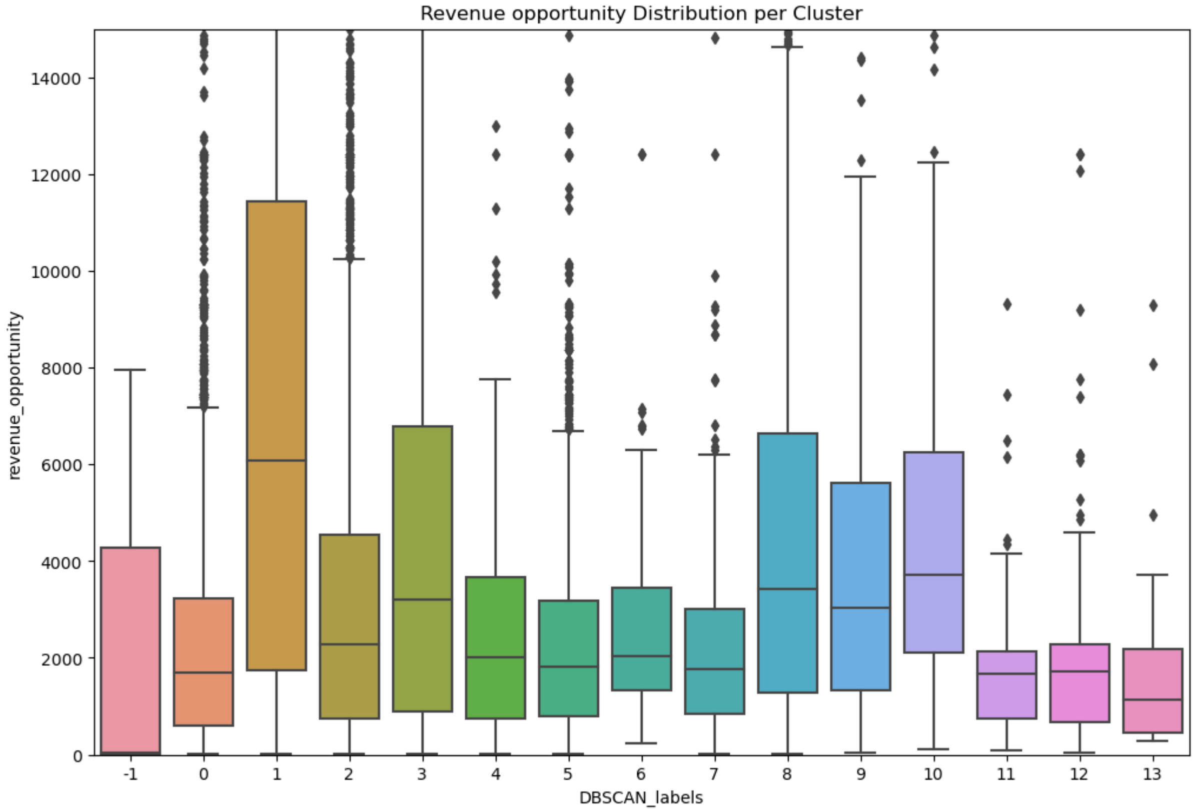


Figure 6. Linear Regression

In [86]:

```
msk=np.random.rand(len(Queens))<0.8
train=Queens[msk]
test=Queens[~msk]
```

Using sklearn package for data modelling

longitude

In [87]:

```
regr=linear_model.LinearRegression()
train_x=np.asanyarray(train[['longitude']])
train_y=np.asanyarray(train[['log_revenue_opportunity']])

regr.fit(train_x, train_y)
# The coefficients
print('Coefficients:', regr.coef_)
print('Intercept:', regr.intercept_)
```

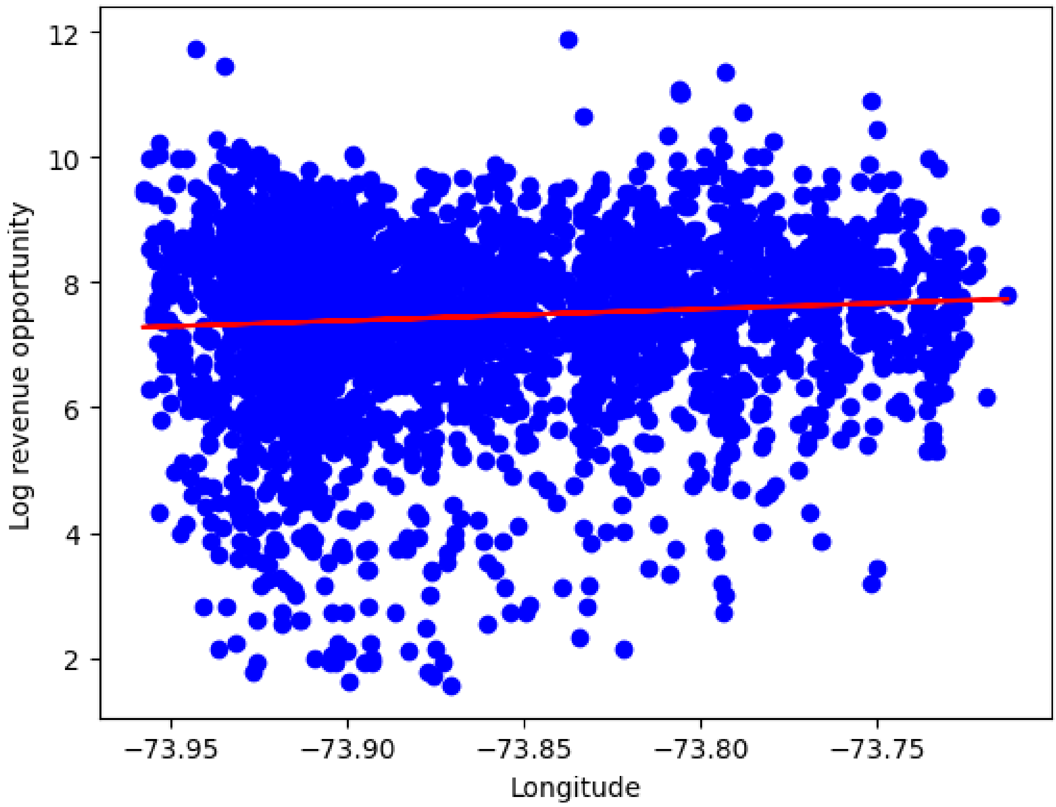
```
Coefficients: [[1.84684823]]
Intercept: [143.86871794]
```

In [88]:

```
# Plot outputs
plt.scatter(train.longitude,train.log_revenue_opportunity,color='blue')
plt.plot(train_x,regr.coef_[0][0]*train_x + regr.intercept_[0],'-r')
plt.xlabel("Longitude")
plt.ylabel("Log revenue opportunity")
```

Out[88]:

```
Text(0, 0.5, 'Log revenue opportunity')
```



latitude

In [89]:

```
regr=linear_model.LinearRegression()
train_x=np.asanyarray(train[['latitude']])
train_y=np.asanyarray(train[['log_revenue_opportunity']])

regr.fit(train_x, train_y)
# The coefficients
print('Coefficients:', regr.coef_)
print('Intercept:', regr.intercept_)
```

```
Coefficients: [[-3.08822326]]
Intercept: [133.22685362]
```

In [90]:

```
# Plot outputs
plt.scatter(train.latitude,train.log_revenue_opportunity,color='blue')
plt.plot(train_x,regr.coef_[0][0]*train_x + regr.intercept_[0],'-r')
plt.xlabel("Latitude")
plt.ylabel("Log revenue opportunity")
```

Out[90]:

```
Text(0, 0.5, 'Log revenue opportunity')
```

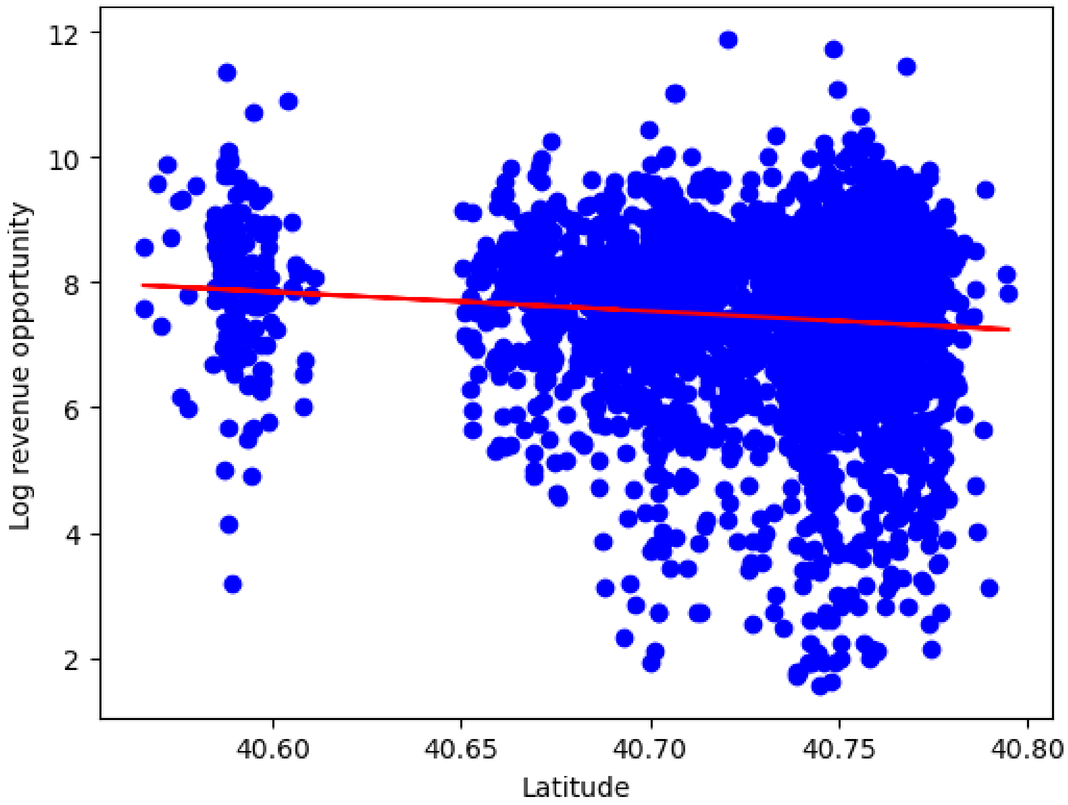


Figure 7. K-means silhouette and elbow

In [91]:

```
# create reduced dataframe
kmeans_run = Queens[['log_revenue_opportunity']]
kmeans_run
```

Out[91]:

	log_revenue_opportunity
46	8.466216
77	8.257282
143	3.169686
161	7.433773
181	9.985874
...	...
48858	8.339195
48863	5.399700
48866	7.357390
48878	7.182200
48889	7.496181

4288 rows × 1 columns

Standardise (not really required with one variable, but still normalising for consistency)

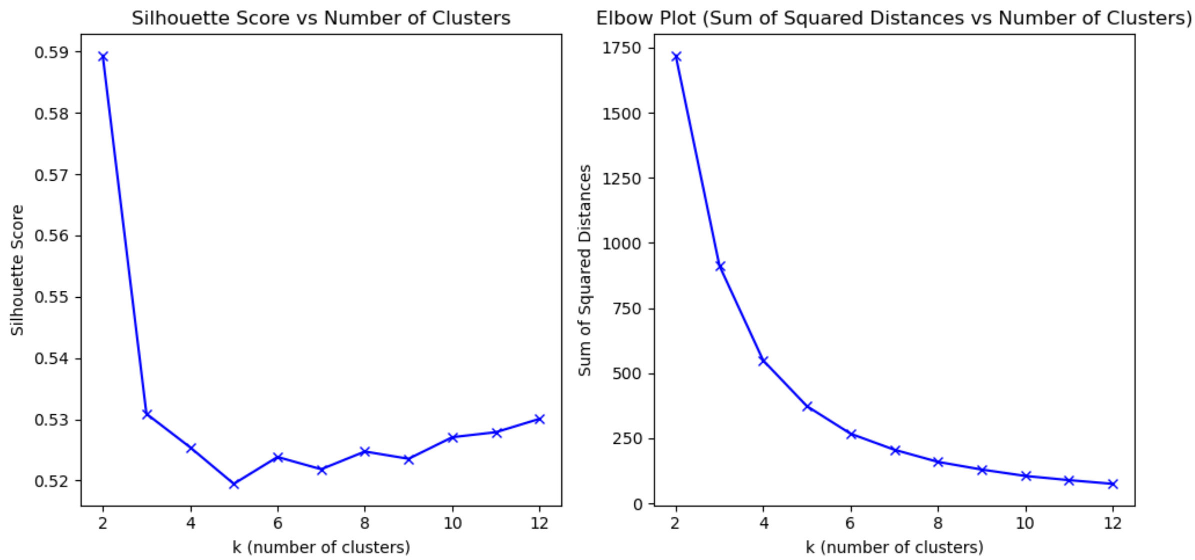
In [92]:

```
# standardise numeric variables
scaler = StandardScaler()
kmeans_run[['log_revenue_opportunity']] =
scaler.fit_transform(kmeans_run[['log_revenue_opportunity']])
```

In [93]:

```
k_values = []
sil_scores = []
sq_distances = []

for i in range(2,13):
    # Initialize KMeans algorithm
    # 12 times per run to find the optimal centroids
    # random_state to ensure the same clusters every time we run this
    kmeans = KMeans(n_clusters=i, init='k-means++', n_init=12, random_state=0)

    # Fit and predict clusters
    clusters = kmeans.fit_predict(kmeans_run)

    # Compute silhouette score
    SScore = silhouette_score(kmeans_run, clusters, metric='euclidean')

    # Append to the lists
    k_values.append(i)
    sil_scores.append(SScore)
    sq_distances.append(kmeans.inertia_)  # Sum of squared distances to closest
centroid

    print("Silhouette score for k (clusters) = " + str(i) + " is " + str(SScore))

# Plot silhouette scores
plt.figure(figsize=(10,5))
plt.subplot(1, 2, 1)
plt.plot(k_values, sil_scores, 'bx-')
plt.xlabel('k (number of clusters)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score vs Number of Clusters')

# Plot sum of squared distances (for the elbow plot)
plt.subplot(1, 2, 2)
plt.plot(k_values, sq_distances, 'bx-')
plt.xlabel('k (number of clusters)')
plt.ylabel('Sum of Squared Distances')
plt.title('Elbow Plot (Sum of Squared Distances vs Number of Clusters)')

plt.tight_layout()
plt.show()
```

```
Silhouette score for k (clusters) = 2 is 0.5893624681654775
Silhouette score for k (clusters) = 3 is 0.530886924845948
Silhouette score for k (clusters) = 4 is 0.5254176792839207
Silhouette score for k (clusters) = 5 is 0.5194508357370409
Silhouette score for k (clusters) = 6 is 0.523834365832839
Silhouette score for k (clusters) = 7 is 0.5218336849536875
Silhouette score for k (clusters) = 8 is 0.5247260216642161
Silhouette score for k (clusters) = 9 is 0.5235383488660361
Silhouette score for k (clusters) = 10 is 0.5270604910271481
Silhouette score for k (clusters) = 11 is 0.5278831498609623
Silhouette score for k (clusters) = 12 is 0.5300666182194343
```



In [94]:

```
# Initialize KMeans algorithm
# 12 times per run to find the optimal centroids
# random_state to ensure the same clusters every time we run this
kmeans_optimal = KMeans(n_clusters=4, init='k-means++', n_init=12, random_state=0)

# Fit and predict clusters
clusters_optimal = kmeans_optimal.fit_predict(kmeans_run)
```

In [95]:

```
kmeans_run['cluster'] = clusters_optimal
kmeans_run
```

Out[95]:

	log_revenue_opportunity	cluster
46	0.753796	3
77	0.600156	0
143	-3.141014	2
161	-0.005412	0
181	1.871278	3
...	...	...
48858	0.660391	3
48863	-1.501170	1
48866	-0.061580	0
48878	-0.190406	0
48889	0.040480	0

4288 rows × 2 columns

Place original lat & long back so the results can be plotted on the map

In [96]:

```
kmeans_run['latitude'] = Queens[['latitude']]
kmeans_run['longitude'] = Queens[['longitude']]
```

In [97]:

```
plt.figure(figsize=(12,8))
plt.style.use('fast')

# Set the boundary of the map using longitude and latitude obtained from Google
Maps
coordinates = (-74.2623, -73.6862, 40.4943, 40.9144)

map = mpimg.imread("New_York_City.jpg")
plt.imshow(map,extent=coordinates)

# Group by cluster labels instead of neighbourhood group
clusters = kmeans_run.groupby('cluster')

# Loop through each cluster and plot the listings in it
for name, group in clusters:
    plt.scatter(group['longitude'], group['latitude'], label=name,
edgecolors='black')

plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Properties by Cluster')
plt.legend()
```

Out[97]:

```
<matplotlib.legend.Legend at 0x286dc6b30>
```

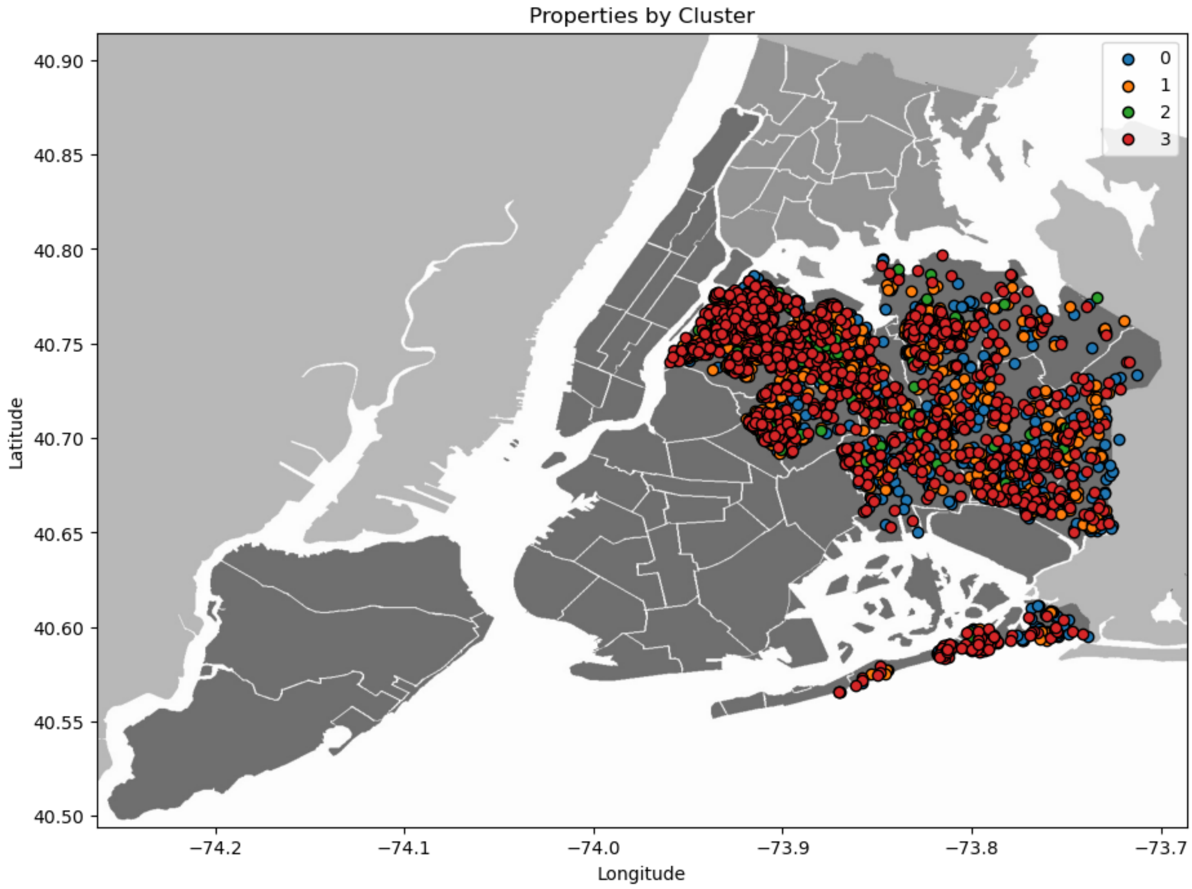


Figure 8. Mean latitude and longitude per cluster

In [98]:

```
latitude_mean = kmeans_run.groupby('cluster')['latitude'].mean()
print(latitude_mean)

longitude_mean = kmeans_run.groupby('cluster')['longitude'].mean()
```

```
print(longitude_mean)

log_rev_opp__mean =
kmeans_run.groupby('cluster')['log_revenue_opportunity'].mean()
print(log_rev_opp__mean)
```

```
cluster
0    40.726851
1    40.731542
2    40.739832
3    40.725164
Name: latitude, dtype: float64
cluster
0   -73.862784
1   -73.867199
2   -73.886560
3   -73.863788
Name: longitude, dtype: float64
cluster
0    0.171818
1   -0.843104
2   -2.629761
3    1.033938
Name: log_revenue_opportunity, dtype: float64
```

In [99]:

```
# Convert series to df
kmeans_queens = log_rev_opp__mean.reset_index()

# Merge the mean latitude and longitude with the original DataFrame
kmeans_queens = kmeans_queens.merge(latitude_mean, on='cluster', how='left')
kmeans_queens = kmeans_queens.merge(longitude_mean, on='cluster', how='left')

# Rename columns
kmeans_queens.columns = ['cluster', 'Mean Log Rev Opp', 'Mean Latitude', 'Mean
Longitude']
kmeans_queens = kmeans_queens.sort_values(by=['Mean Log Rev Opp'])

kmeans_queens
```

Out[99]:

	cluster	Mean Log Rev Opp	Mean Latitude	Mean Longitude
2	2	-2.629761	40.739832	-73.886560
1	1	-0.843104	40.731542	-73.867199
0	0	0.171818	40.726851	-73.862784
3	3	1.033938	40.725164	-73.863788

In [100]:

```
styled_df = kmeans_queens.style.background_gradient(
    cmap='Blues', subset=['Mean Log Rev Opp', 'Mean Latitude', 'Mean Longitude']
).hide_index().set_table_styles(
    [
        {
            'selector': 'th',
            'props': [
                ('padding', '1px'),
                ('text-align', 'left')
            ]
        },
```

```
        {
            'selector': 'td',
            'props': [
                ('padding', '1px'),
                ('text-align', 'center')
            ]
        }
    ]
).set_properties(**{'width': '70px'})

styled_df
```

Out[100]:

cluster	Mean Log Rev Opp	Mean Latitude	Mean Longitude
2	-2.629761	40.739832	-73.886560
1	-0.843104	40.731542	-73.867199
0	0.171818	40.726851	-73.862784
3	1.033938	40.725164	-73.863788