NYC Airbnb Price Analysis

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Introduction

Airbnb, Inc. is an online marketplace for arranging or offering lodging, primarily homestays, or tourism experiences. The company does not own any of the real estate listings, nor does it host events; it acts as a broker, receiving commissions from each booking.

The purpose of this notebook is to perform an exploratory data analysis on the various Airbnb listings data in New York City for the year 2019.

The data, sourced from Kaggle, contains all the Airbnb listings in New York for the year 2019.

Loading the required libraries, frameworks and data:

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.pyplot as plt

import folium
import folium.plugins
from folium.plugins import MarkerCluster
from folium import plugins

import wordcloud
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from wordcloud import WordCloud, ImageColorGenerator

import plotly.express as px
```

In [2]:
```
df = pd.read_csv(r'C:\Users\benny\OneDrive\Desktop\Misc\RandC\Projects\NYC Airbnb Price Analysis\AB_NYC_2019.csv')
df.head()
```

Out[2]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	last_review	reviews_per
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	2018-10-19	
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	2019-05-21	
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	NaN	
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	2019-07-05	
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	2018-11-19	

Data Cleaning

Checking if there are any null values in the data:

In [3]:
```
df.isnull().sum() #finding null values
```

Out[3]:
```
id                                    0
name                                 16
host_id                               0
host_name                            21
neighbourhood_group                   0
neighbourhood                         0
latitude                              0
longitude                             0
room_type                             0
price                                 0
minimum_nights                        0
number_of_reviews                     0
last_review                       10052
reviews_per_month                 10052
calculated_host_listings_count        0
availability_365                      0
dtype: int64
```

We notice that there are quite a few null values in some of the variables. These null values might interefere with our analysis and hence, it is necessary to either remove the null values completely or replace them with a suitable value. Let's replace the null values in the variable 'Reviews per month' with zero and the null values in 'name', 'host name' and 'last review' variables with 'Not Specified'.

```
In [4]: df.fillna({'reviews_per_month':0}, inplace=True) #replace null values in reviews_per_month by zero
        df["name"].fillna("Not Specified", inplace = True)
        df["host_name"].fillna("Not Specified", inplace = True)
        df["last_review"].fillna("Not Specified", inplace = True)
```

```
In [5]: df.isnull().sum()
```

```
Out[5]: id                                0
        name                              0
        host_id                           0
        host_name                         0
        neighbourhood_group               0
        neighbourhood                     0
        latitude                          0
        longitude                         0
        room_type                         0
        price                             0
        minimum_nights                    0
        number_of_reviews                 0
        last_review                       0
        reviews_per_month                 0
        calculated_host_listings_count    0
        availability_365                  0
        dtype: int64
```

Statistical Summary

```
In [6]: df.describe()
```

Out[6]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.090910	7.143982	112.781327
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.597283	32.952519	131.622289
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.000000	1.000000	0.000000
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.040000	1.000000	0.000000
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.370000	1.000000	45.000000
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	1.580000	2.000000	227.000000
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	327.000000	365.000000

Correlation

Let's take a look at how the variables correlate to the price variable.

```
In [7]: CM = df[['price','neighbourhood_group','neighbourhood', 'latitude', 'longitude', 'room_type','minimum_nights','number_of_reviews',
                 'reviews_per_month','calculated_host_listings_count', 'availability_365']]
        cor = CM.corr() #Calculate the correlation of the above variables
        cm=sns.heatmap(cor, cmap = 'Greens', square = True) #Plot the correlation as heat map
        cm.set_xticklabels(cm.get_xticklabels(),
                rotation=45,
            horizontalalignment='right')
        #not very strong correlations except for number of reviews and reviews per month
```

```
Out[7]: [Text(0.5, 0, 'price'),
         Text(1.5, 0, 'latitude'),
         Text(2.5, 0, 'longitude'),
         Text(3.5, 0, 'minimum_nights'),
         Text(4.5, 0, 'number_of_reviews'),
         Text(5.5, 0, 'reviews_per_month'),
         Text(6.5, 0, 'calculated_host_listings_count'),
         Text(7.5, 0, 'availability_365')]
```

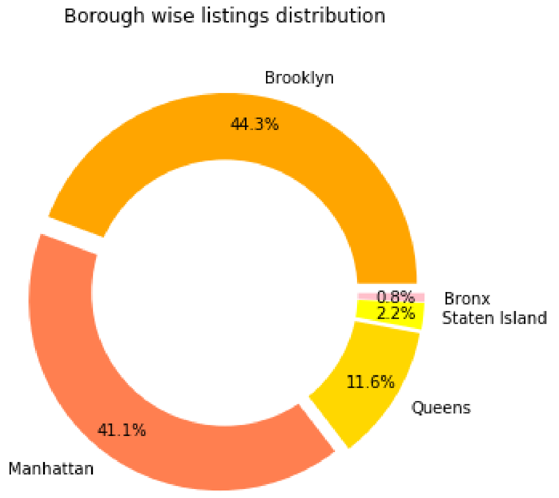
The variables don't seem to correlate very strongly with the price variable apart from the 'number of reviews' and 'reviews per month' variables, depicted using the darker shade of green.

Exploratory Data Analysis

In this section of the notebook, we will explore the data through various visualizations.

By Borough

In [8]:
```
fig1, ax1 = plt.subplots(figsize=(5,5))
# Create a pie chart
ax1.pie(
   df['neighbourhood_group'].value_counts(),
    labels = df.neighbourhood_group.unique(),
    pctdistance=0.85,
    explode = (0.05,0.05,0.05,0.05,0.05),
    colors = ['orange', 'coral', 'gold', 'yellow', 'pink', ],
    # with the percent listed as a fraction
    autopct='%1.1f%%',
    )

#for donut chart
#draw circle
centre_circle = plt.Circle((0,0),0.70,fc='white')
fig2 = plt.gcf()
fig2.gca().add_artist(centre_circle)

ax1.set_title('Airbnb distribution in different Boroughs')

# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')
plt.tight_layout()
plt.title('Borough wise listings distribution')
plt.show()

#manhattan and brooklyn have most airbnbs
```

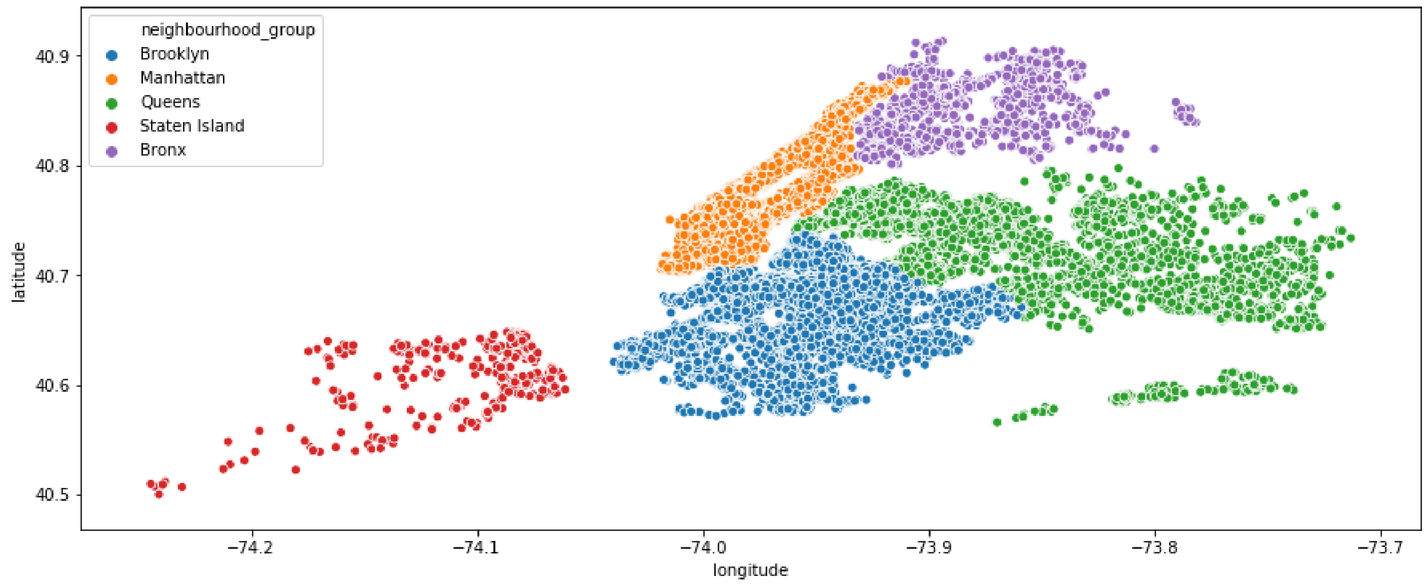


From the donut chart, Brooklyn and Manhattan share the most number of Airbnb listings followed by Queens, with Staten Island and Bronx having the least percentage of Airbnb listings.

Let's visualize the number of listings on the New York City Map.

In [9]:
```
plt.figure(figsize=(15,6))
sns.scatterplot(df.longitude,df.latitude,hue=df.neighbourhood_group)
```

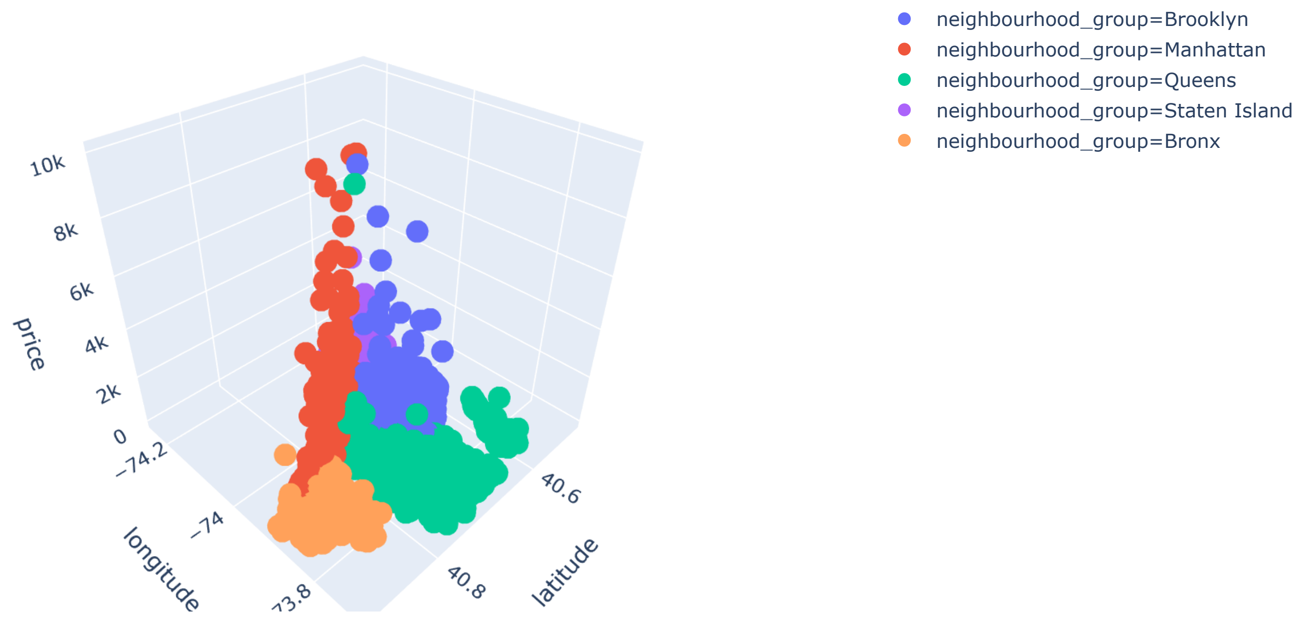
Out[9]: `<matplotlib.axes._subplots.AxesSubplot at 0x182fc2aa9c8>`



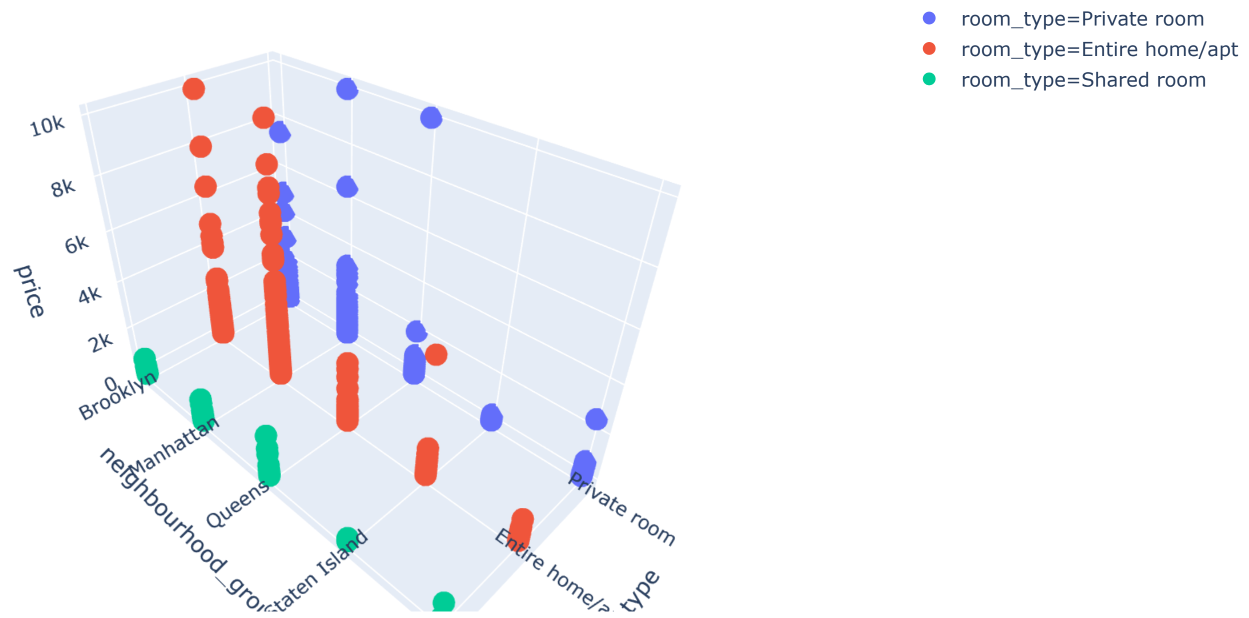
By Price

The 3D visualizations below show the price distribution of the listings by borough and room type. Staten Island seems to contain the least expensive listings as compared to all the other boroughs.

In [10]:
```
fig = px.scatter_3d(df, x='latitude', y='longitude', z='price',
              color='neighbourhood_group')
fig.show()
```

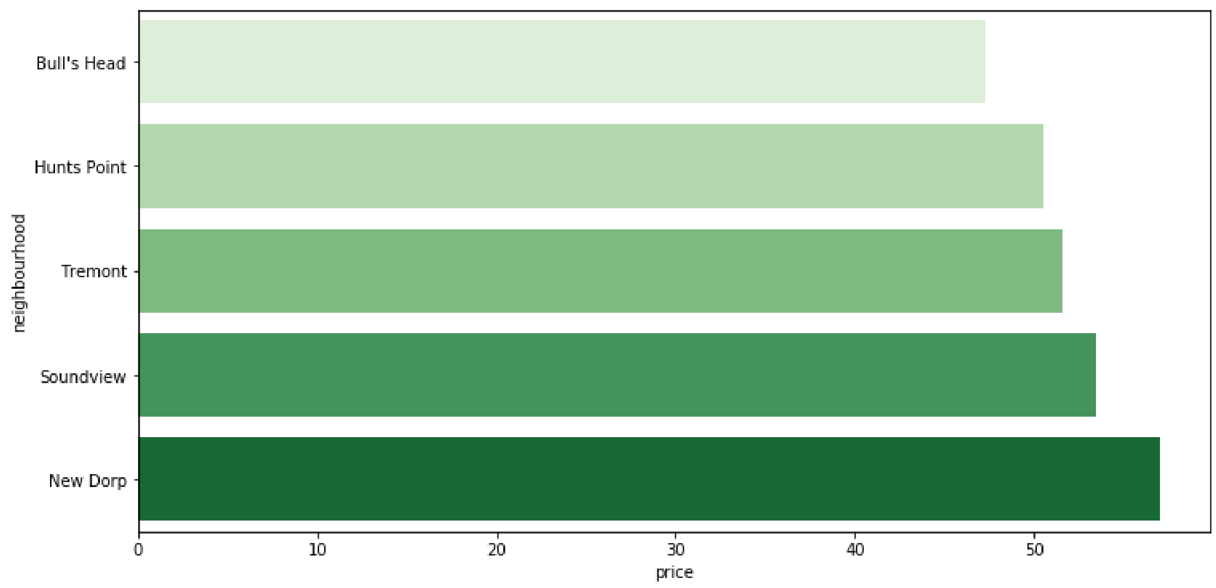


In [11]:
```
fig = px.scatter_3d(df, x='room_type', y='neighbourhood_group', z='price',
              color='room_type')
fig.show()
```



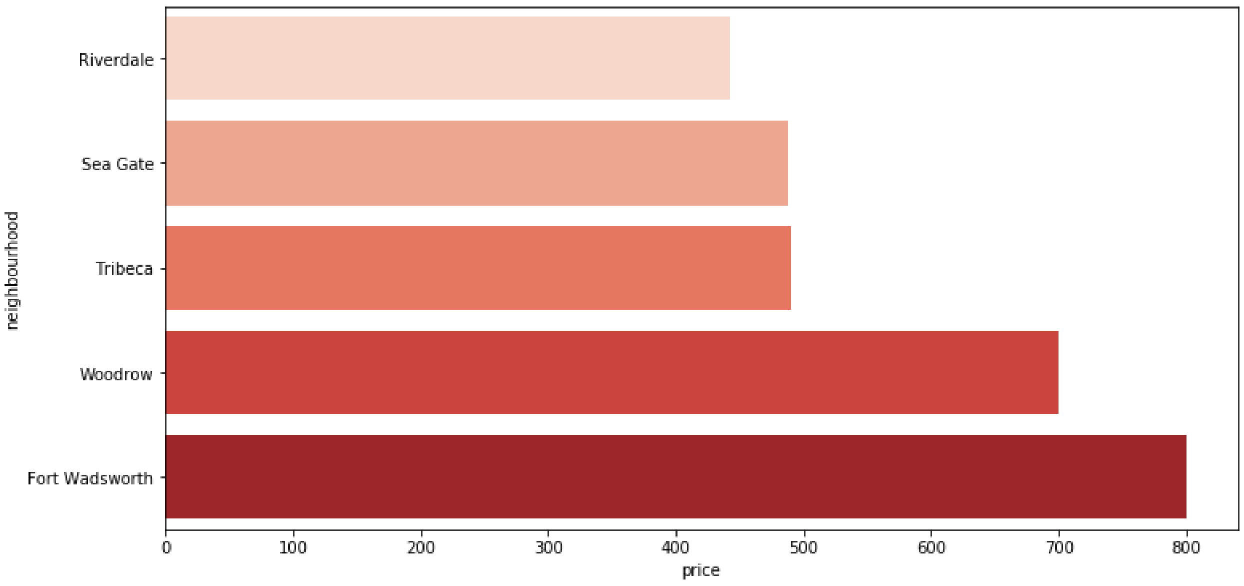
Top 5 neighbourhoods with the least expensive listings:

In [12]:
```
Inexpensive_neighbourhoods = df.groupby('neighbourhood').agg({'price': 'mean'}).sort_values('price').reset_index()
plt.figure(figsize=(12,6))
sns.barplot(y="neighbourhood", x="price", palette = 'Greens', data=Inexpensive_neighbourhoods.head(5))
plt.ioff()
```



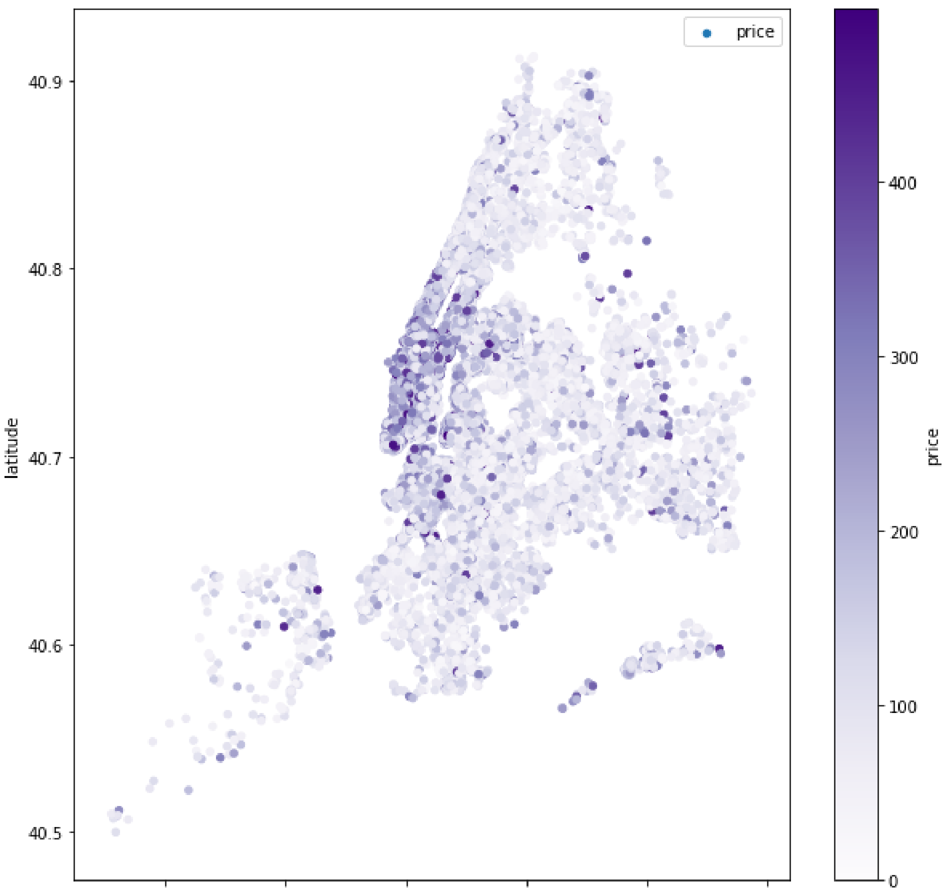
Top 5 neighbourhoods with the most expensive listings:

```
In [13]: plt.figure(figsize=(12,6))
         sns.barplot(y="neighbourhood", x="price", palette = 'Reds', data=Inexpensive_neighbourhoods.tail(5))
         plt.ioff()
```



Plotting all the listings in New York City on a heat map based on their price distribution:

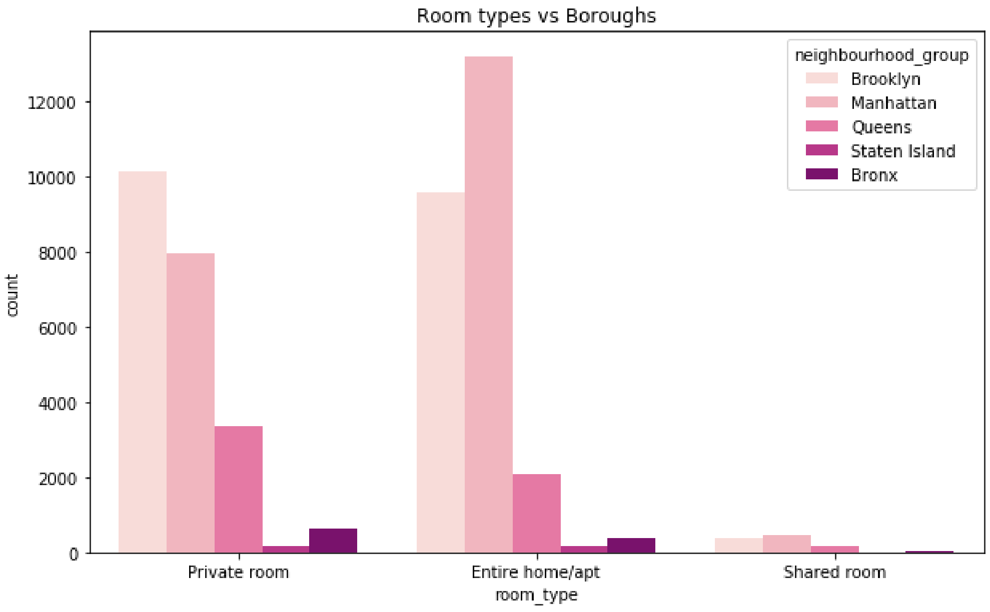
```
In [14]: plt.figure(figsize=(10,6))
         sub=df[df.price<500]
         scat=sub.plot(kind='scatter', x='longitude',y='latitude', label = 'price', cmap = 'Purples', c='price',colorbar=True,figsize=(10,10));
         scat.legend()

Out[14]: <matplotlib.legend.Legend at 0x18280c636c8>

         <Figure size 720x432 with 0 Axes>
```



By Room Type

Brooklyn contains the most number of private room listings. Manhattan tops the list of Entire home/apartment listings. Shared rooms aren't very popular amongst any of the boroughs.

```
In [15]: plt.figure(figsize=(10,6))
         sns.countplot(x = 'room_type',hue = 'neighbourhood_group', palette = 'RdPu', data = df)
         plt.title('Room types vs Boroughs')
         plt.show()
```



By Popularity

Most popular rooms based off the number of reviews:

In [16]:
```python
most_popular=df.sort_values(by=['number_of_reviews'],ascending=False).head(100)
most_popular.head()
```

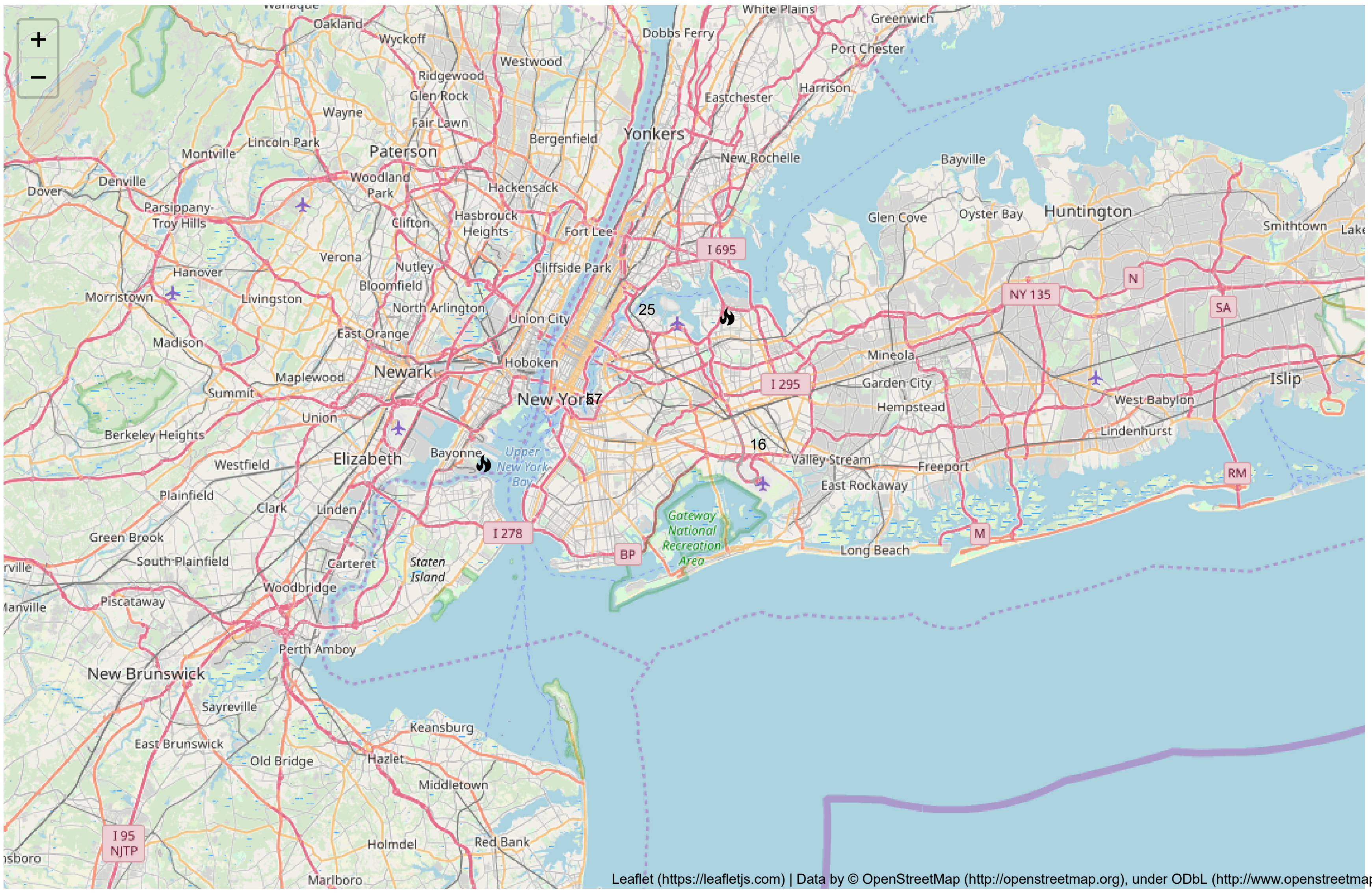
Out[16]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	last_review	reviews_
11759	9145202	Room near JFK Queen Bed	47621202	Dona	Queens	Jamaica	40.66730	-73.76831	Private room	47	1	629	2019-07-05	
2031	903972	Great Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82085	-73.94025	Private room	49	1	607	2019-06-21	
2030	903947	Beautiful Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82124	-73.93838	Private room	49	1	597	2019-06-23	
2015	891117	Private Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82264	-73.94041	Private room	49	1	594	2019-06-15	
13495	10101135	Room Near JFK Twin Beds	47621202	Dona	Queens	Jamaica	40.66939	-73.76975	Private room	47	1	576	2019-06-27	

In [17]:
```python
print('Most Popular Rooms')
map=folium.Map(location = [40.73,-73.93])

map_rooms=plugins.MarkerCluster().add_to(map)

for lat,lon,label in zip(most_popular.latitude,most_popular.longitude,most_popular.name):
    folium.Marker(location=[lat,lon],icon=folium.Icon(icon='fire'),popup=label).add_to(map_rooms)
map.add_child(map_rooms)

map
```

```
Most Popular Rooms
```

Out[17]:



Lastly, let's create a wordcloud to visualize the most commonly used words in listings:

In [18]:
```
#word cloud
text = " ".join(str(each) for each in df.name)
# Create and generate a word cloud image:
wordcloud = WordCloud(max_words=50, background_color="white").generate(text)
plt.figure(figsize=(10,6))
plt.figure(figsize=(15,10))
# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
<Figure size 720x432 with 0 Axes>
```

Conclusion

Through the explorartory data analysis conducted on the Airbnb Listings in New York City for the year 2019, we have successfully extracted a number of insights from the data, and through the different visualizations, identified the many trends and patterns present in the data.