CSE 351 HW1

March 12, 2023

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

[2]:
```python
df = pd.read_csv("drive/MyDrive/AB_NYC_2019.csv")
df.head()
```

[2]:
```
     id                                              name  host_id  \
0  2539                Clean & quiet apt home by the park     2787
1  2595                             Skylit Midtown Castle     2845
2  3647               THE VILLAGE OF HARLEM…NEW YORK !     4632
3  3831                   Cozy Entire Floor of Brownstone     4869
4  5022  Entire Apt: Spacious Studio/Loft by central park     7192

     host_name neighbourhood_group neighbourhood  latitude  longitude  \
0         John            Brooklyn    Kensington  40.64749  -73.97237
1     Jennifer           Manhattan       Midtown  40.75362  -73.98377
2    Elisabeth           Manhattan        Harlem  40.80902  -73.94190
3  LisaRoxanne            Brooklyn  Clinton Hill  40.68514  -73.95976
4        Laura           Manhattan   East Harlem  40.79851  -73.94399

         room_type  price  minimum_nights  number_of_reviews last_review  \
0     Private room    149               1                  9  2018-10-19
1  Entire home/apt    225               1                 45  2019-05-21
2     Private room    150               3                  0         NaN
3  Entire home/apt     89               1                270  2019-07-05
4  Entire home/apt     80              10                  9  2018-11-19

   reviews_per_month  calculated_host_listings_count  availability_365
0               0.21                               6               365
1               0.38                               2               355
2                NaN                               1               365
3               4.64                               1               194
4               0.10                               1                 0
```

[3]:
```
df.describe()
```

[3]:
```
                 id       host_id      latitude     longitude         price  \
count  4.889500e+04  4.889500e+04  48895.000000  48895.000000  48895.000000
mean   1.901714e+07  6.762001e+07     40.728949    -73.952170    152.720687
std    1.098311e+07  7.861097e+07      0.054530      0.046157    240.154170
min    2.539000e+03  2.438000e+03     40.499790    -74.244420      0.000000
25%    9.471945e+06  7.822033e+06     40.690100    -73.983070     69.000000
50%    1.967728e+07  3.079382e+07     40.723070    -73.955680    106.000000
75%    2.915218e+07  1.074344e+08     40.763115    -73.936275    175.000000
max    3.648724e+07  2.743213e+08     40.913060    -73.712990  10000.000000

       minimum_nights  number_of_reviews  reviews_per_month  \
count    48895.000000       48895.000000       38843.000000
mean         7.029962          23.274466           1.373221
std         20.510550          44.550582           1.680442
min          1.000000           0.000000           0.010000
25%          1.000000           1.000000           0.190000
50%          3.000000           5.000000           0.720000
75%          5.000000          24.000000           2.020000
max       1250.000000         629.000000          58.500000

       calculated_host_listings_count  availability_365
count                    48895.000000      48895.000000
mean                         7.143982        112.781327
std                         32.952519        131.622289
min                          1.000000          0.000000
25%                          1.000000          0.000000
50%                          1.000000         45.000000
75%                          2.000000        227.000000
max                        327.000000        365.000000
```

[4]:
```
len(df)
```

[4]: 48895

##Task 1 ###Use the built-in function dropna() in pandas to drop rows which contain invalid data (row that contains at least one null value) ###In addition, we consider rows to be invalid if the price or availability equal to 0.

[5]:
```
df = df.dropna()
df = df[df["price"] > 0]
df = df[df["availability_365"] > 0]
```

##Task 2

###part a ####Find Top 5 and Bottom 5 neighborhood based on the price of the Airbnb in that neighborhood

[6]:
```
# select only neighborhoods with more than 5 listings
neighbourhood_count = df["neighbourhood"].value_counts()
target_neighbourhood = neighbourhood_count[neighbourhood_count > 5]
target_df = df[df["neighbourhood"].isin(target_neighbourhood.index)]
```

[7]:
```
# prices_by_neighbourhood contains the mean prices of each neighborhood in␣
↪descending order.
prices_by_neighbourhood = target_df.groupby("neighbourhood").mean()["price"].
↪sort_values(ascending = False)
print(prices_by_neighbourhood)
```

```
neighbourhood
Tribeca              535.868421
Flatiron District    342.000000
NoHo                 339.909091
SoHo                 312.821782
Midtown              296.498567
                        …
Parkchester           55.625000
Tremont               55.571429
Soundview             53.818182
Bronxdale             51.166667
Hunts Point           45.266667
Name: price, Length: 170, dtype: float64
```

[8]:
```
top_5_neighbourhood = prices_by_neighbourhood[:5] # top 5 neighborhoods with␣
↪the highest mean prices.
bottom_5_neighbourhood = prices_by_neighbourhood[len(prices_by_neighbourhood)-5:
↪] # bottom 5 neighborhoods with the lowest mean prices.
```

top 5 neighborhood based on price

[9]:
```
print(top_5_neighbourhood)
```

```
neighbourhood
Tribeca              535.868421
Flatiron District    342.000000
NoHo                 339.909091
SoHo                 312.821782
Midtown              296.498567
Name: price, dtype: float64
```

bottom 5 neighborhood based on price

[10]:
```
print(bottom_5_neighbourhood)
```

```
neighbourhood
Parkchester     55.625000
```

```
Tremont          55.571429
Soundview        53.818182
Bronxdale        51.166667
Hunts Point      45.266667
Name: price, dtype: float64
```

###part b ####According to the graph, there is a significant difference in price variation among various neighborhoods.

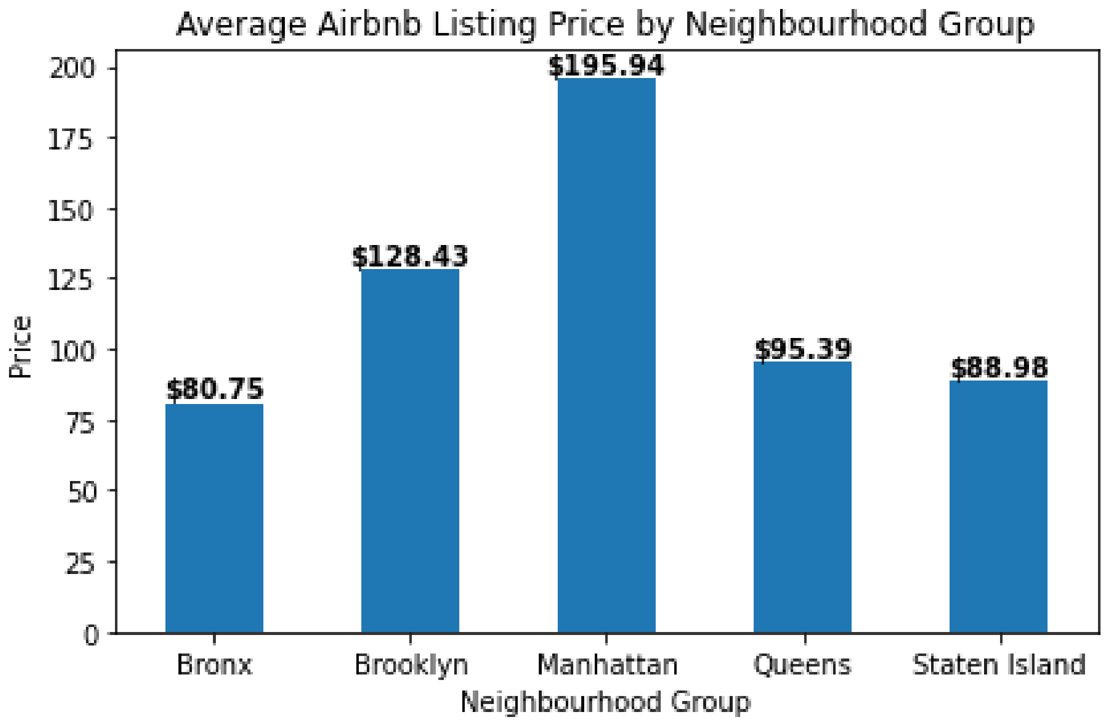
####- Manhattan has the highest average price at $195.94, which is significantly higher than the other boroughs.

####- The Bronx has the lowest average price at $80.75

[11]:
```python
df.groupby("neighbourhood_group").mean()[["price"]]
```

[11]:
```
                          price
neighbourhood_group
Bronx                 80.745358
Brooklyn             128.430020
Manhattan            195.935245
Queens                95.387452
Staten Island         88.975610
```

[12]:
```python
ax = df.groupby("neighbourhood_group").mean()["price"].plot(kind="bar")
plt.xticks(rotation=0)
plt.ylabel("Price")
plt.xlabel("Neighbourhood Group")
# plt.gcf().set_dpi(150)
plt.title("Average Airbnb Listing Price by Neighbourhood Group")

for i, v in enumerate(df.groupby("neighbourhood_group").mean()["price"]):
    ax.text(i, v, "${:.2f}".format(v), ha='center', va='bottom',␣
 ↪fontweight='bold')


overall_avg_price = df['price'].mean()

plt.tight_layout()


plt.show()
```



0.1 Task 3

####The most positive correlation is calculated_host_listings_count and availability_365. The most negative correlation is minimum_nights and number_of_reviews.

[13]:
```
corr = df[["minimum_nights", "number_of_reviews",␣
↪"calculated_host_listings_count", "availability_365", "price"]].
↪corr(method="pearson")
corr
```

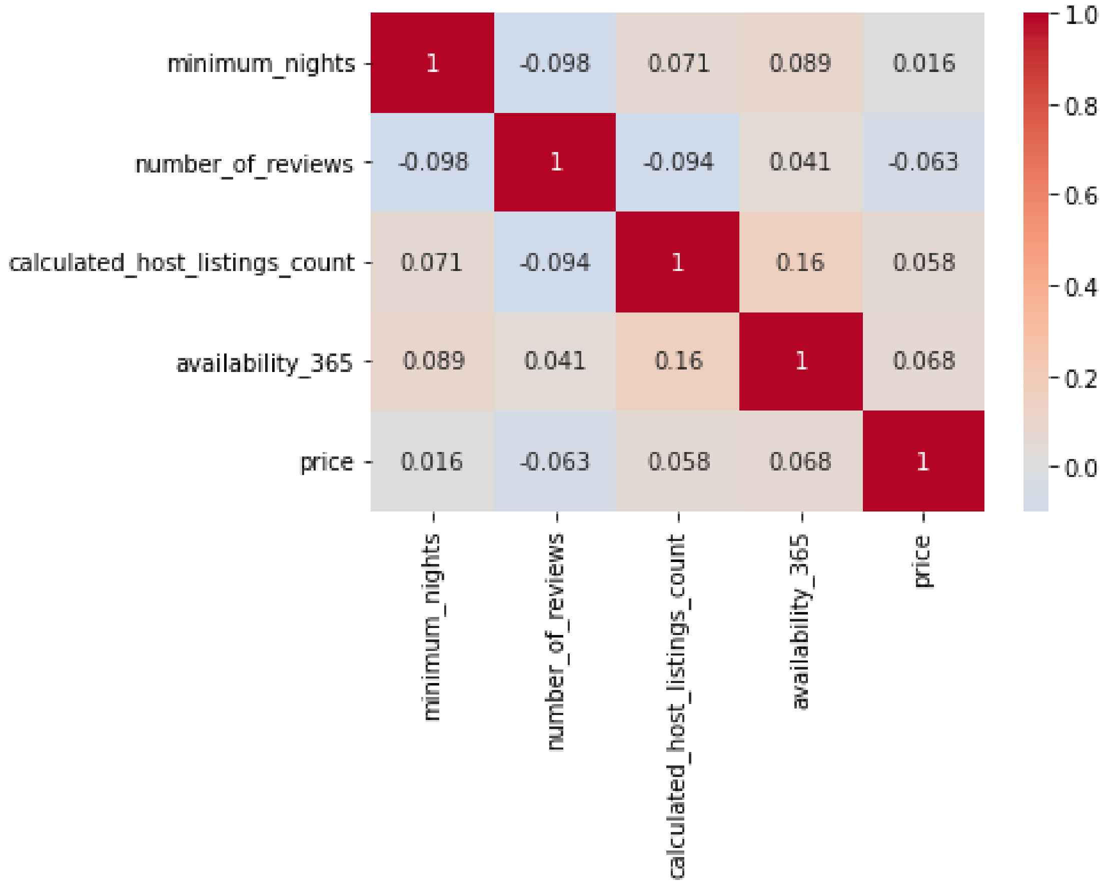
[13]:

	minimum_nights	number_of_reviews
minimum_nights	1.000000	-0.097877
number_of_reviews	-0.097877	1.000000
calculated_host_listings_count	0.071037	-0.094344
availability_365	0.089409	0.040741
price	0.015594	-0.063265

	calculated_host_listings_count
minimum_nights	0.071037
number_of_reviews	-0.094344
calculated_host_listings_count	1.000000
availability_365	0.155553
price	0.057901

```
                                availability_365     price
minimum_nights                          0.089409  0.015594
number_of_reviews                       0.040741 -0.063265
calculated_host_listings_count          0.155553  0.057901
availability_365                        1.000000  0.067848
price                                   0.067848  1.000000
```

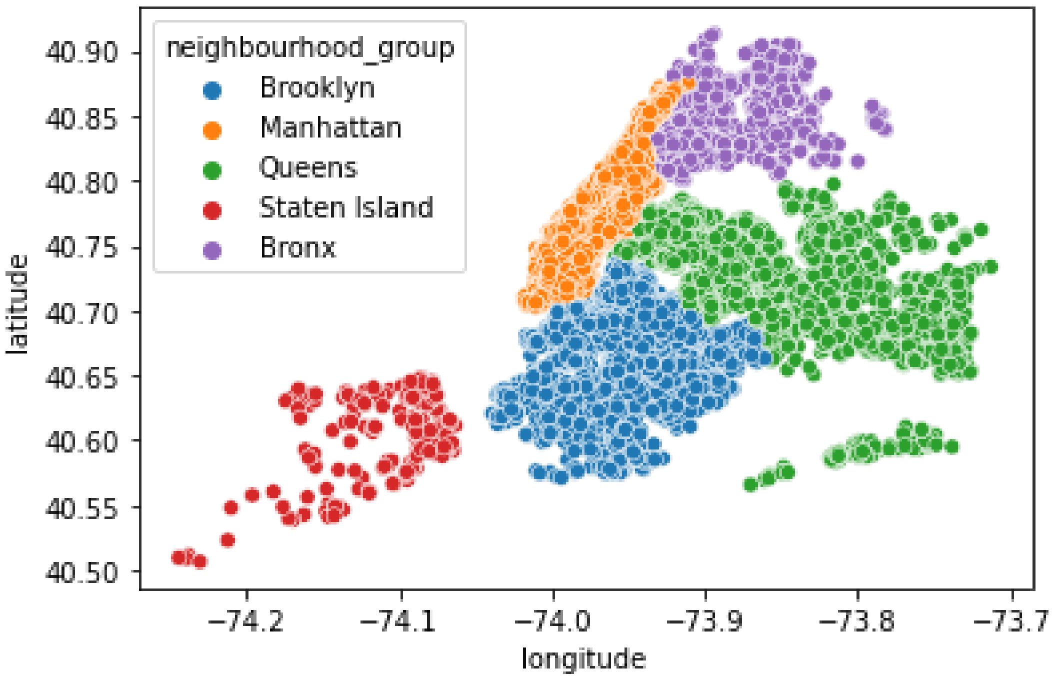
[14]:
```python
sns.heatmap(corr, cmap='coolwarm', annot=True, center=0)
plt.show()
```



##Task 4

0.1.1 part a

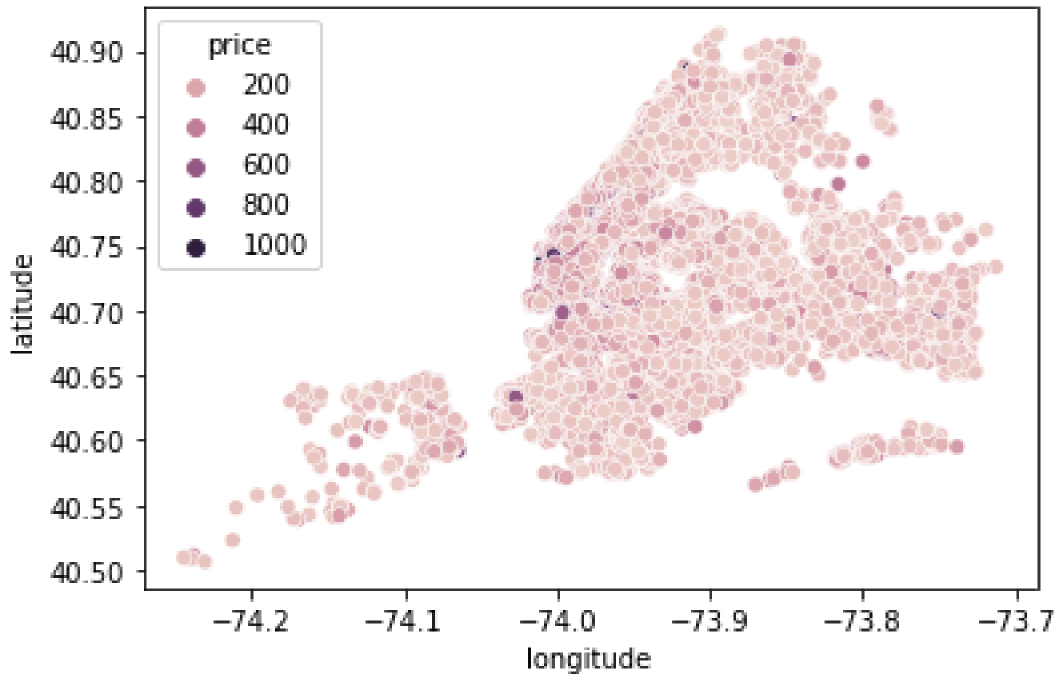
[15]:
```python
sns.scatterplot(data=df, x=df["longitude"], y=df["latitude"],␣
 ↪hue=df["neighbourhood_group"])

plt.show()
```



0.1.2 part b

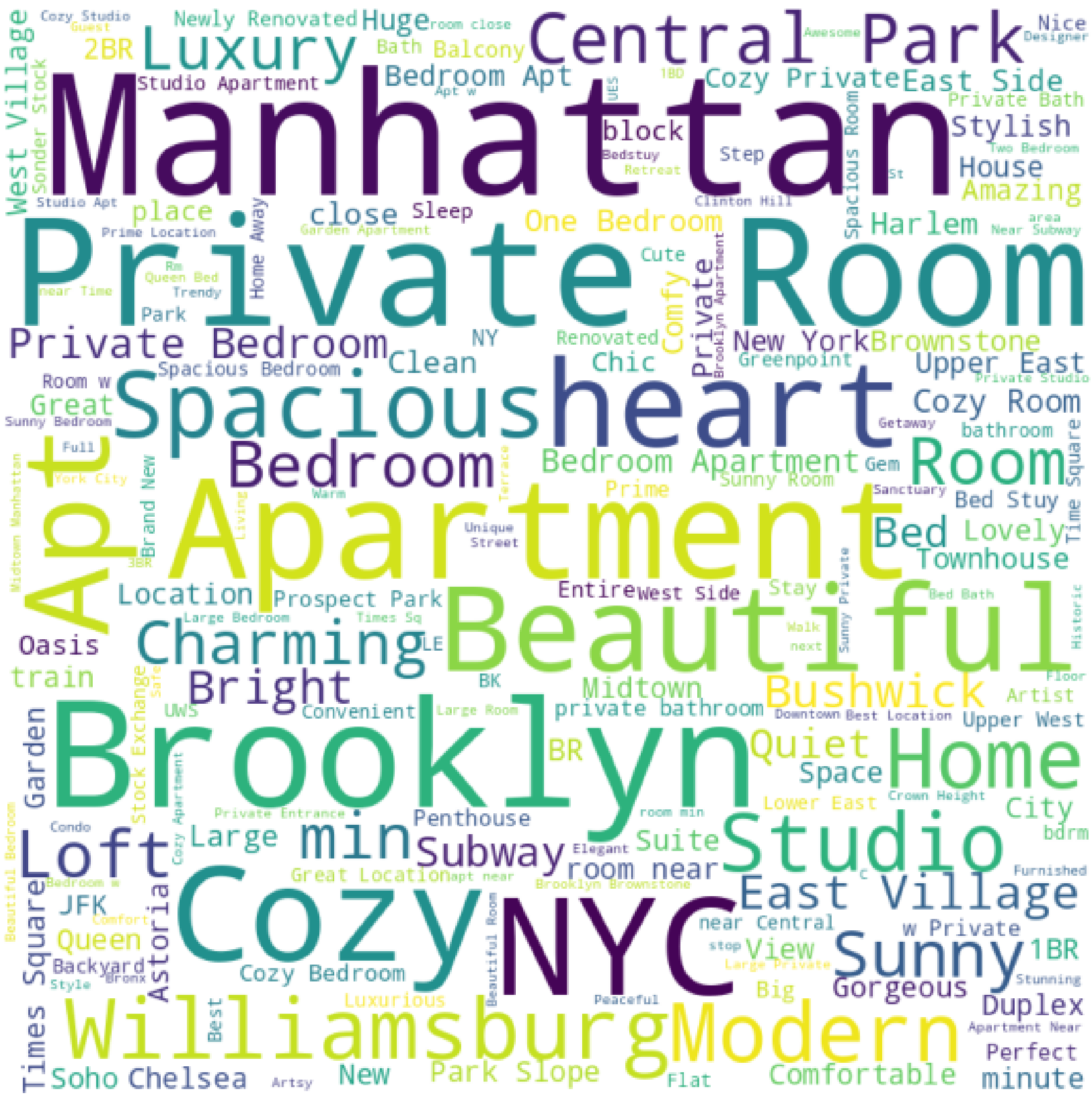
####According to the plot, Manhattan neighborhood group is most expensive

[16]:
```
df_less_than_1000 = df[df["price"] <= 1000]

sns.scatterplot(data=df_less_than_1000, x=df_less_than_1000["longitude"],␣
↪y=df_less_than_1000["latitude"], hue=df_less_than_1000["price"])

plt.show()
```



0.2 Task 5

[17]:
```
text = ' '.join([str(n) for n in df["name"]])

wordcloud = WordCloud(width=800, height=800, background_color='white',␣
↪min_font_size=10).generate(text)

plt.figure(figsize=(8,8))
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad=0)

plt.show()
```



0.3 Task 6

####Eastchester has the busiest host

[18]:
```python
unique_hosts_df = df.drop_duplicates(subset=["host_id"])

host_listing_by_neighbourhood = unique_hosts_df.groupby("neighbourhood").mean().pivot_table(index='neighbourhood')["calculated_host_listings_count"].sort_values(ascending=False)
host_listing_by_neighbourhood
```

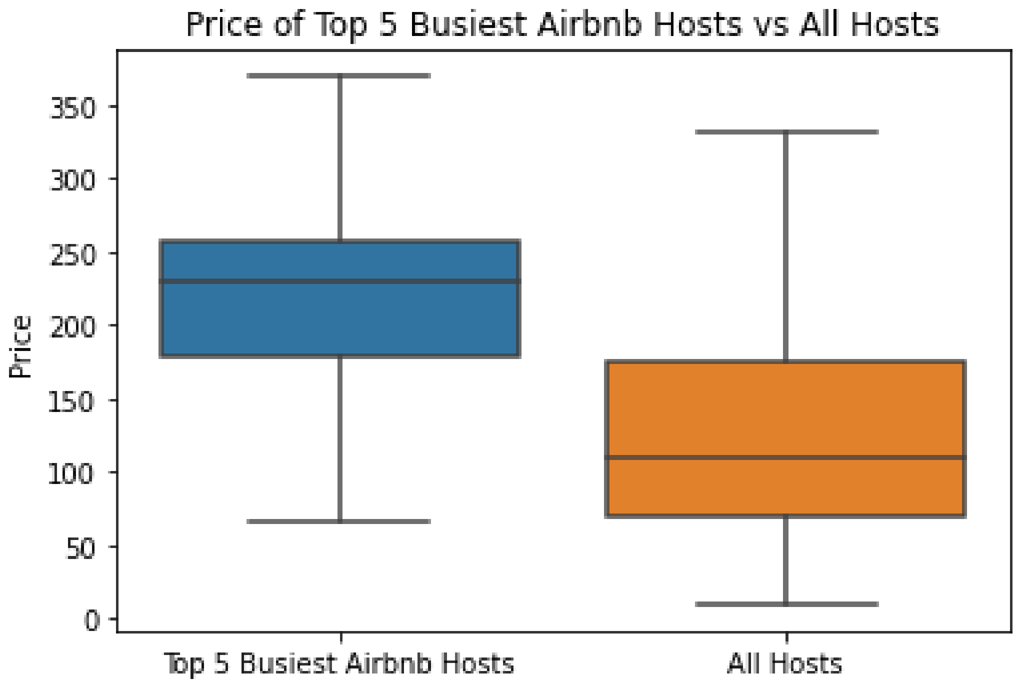
[18]:
```
neighbourhood
Eastchester            13.000000
```

```
Financial District     6.220859
Far Rockaway           4.833333
Concord                3.400000
Little Neck            3.000000
                         …
Stuyvesant Town        1.000000
Richmondtown           1.000000
Todt Hill              1.000000
Mill Basin             1.000000
Mount Eden             1.000000
Name: calculated_host_listings_count, Length: 216, dtype: float64
```

[19]:
```
df_top_5_listings = unique_hosts_df.
 ↪sort_values("calculated_host_listings_count", ascending=False).head(5)
df_busiest_5_hosts = df[df["host_id"].isin(df_top_5_listings["host_id"])]
```

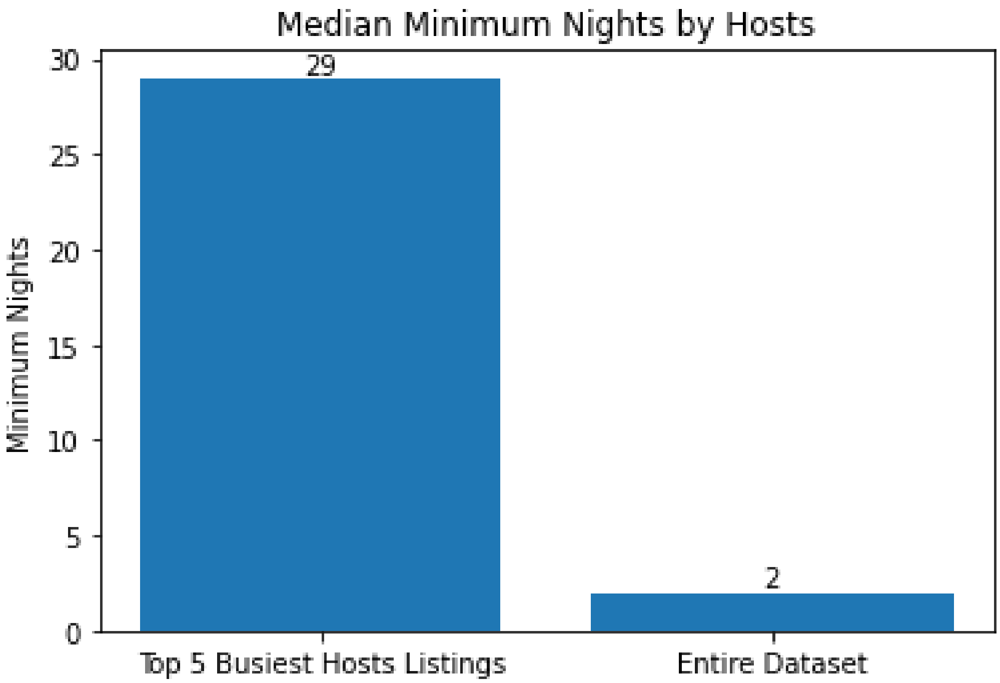
####Price - The top 5 busiest hosts charge a higher price compared to the average host, which could potentially make their properties less appealing to prospective renters and result in a longer duration on the market.

[20]:
```
ax = sns.boxplot(data = [list(df_busiest_5_hosts["price"]), list(df["price"])],␣
 ↪showfliers=False)
ax.set_ylabel("Price")
ax.set_title("Price of Top 5 Busiest Airbnb Hosts vs All Hosts")

ax.set_xticklabels(["Top 5 Busiest Airbnb Hosts", "All Hosts"])

plt.show()
```



####minimum_nights - The top 5 busiest hosts have a much higher minimum-night requirement compared to the average host, which may make their properties less desirable to potential renters who are not interested in renting for a long period of time. As a result, their listings may stay on the market for a longer duration.

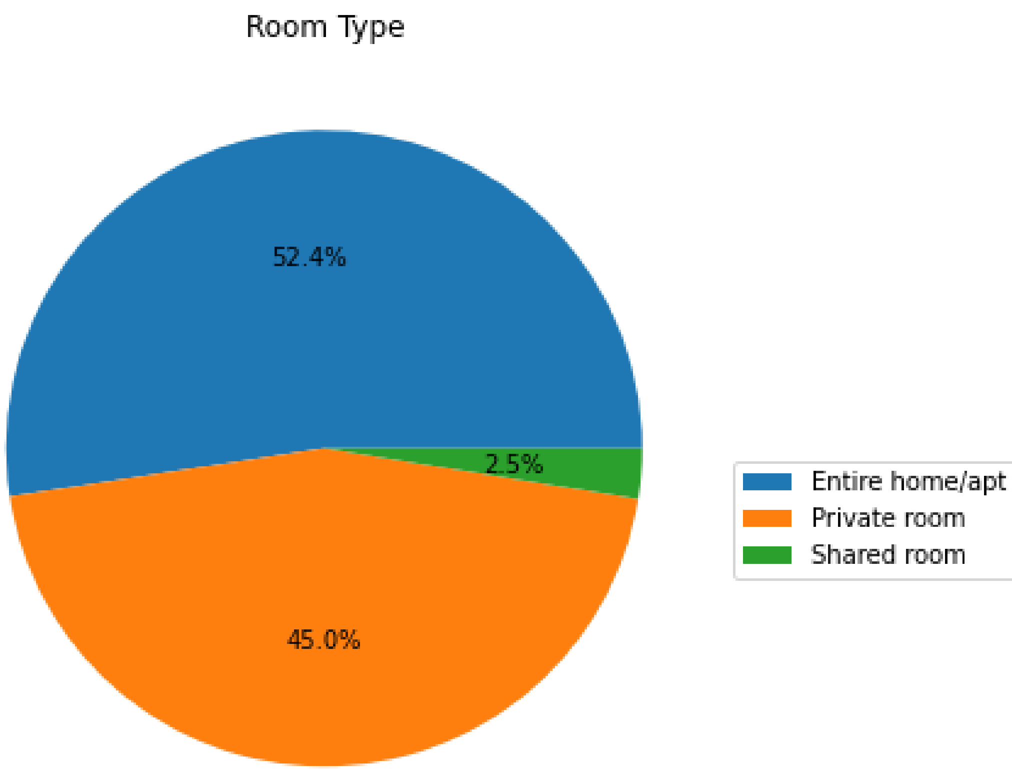
[21]:
```
median_top_5_hosts = df_busiest_5_hosts["minimum_nights"].median()
median_entire_dataset = df["minimum_nights"].median()

fig, ax = plt.subplots()
bars = ax.bar(['Top 5 Busiest Hosts Listings', 'Entire Dataset'],␣
↪[median_top_5_hosts, median_entire_dataset])

ax.set_ylabel('Minimum Nights')

ax.set_title('Median Minimum Nights by Hosts')

for i, bar in enumerate(bars):
    ax.text(bar.get_x() + bar.get_width() / 2, bar.get_height(), f"{int(bar.
↪get_height())}",
            ha='center', va='bottom', fontsize=10)

plt.show()
```



0.4 Task 7

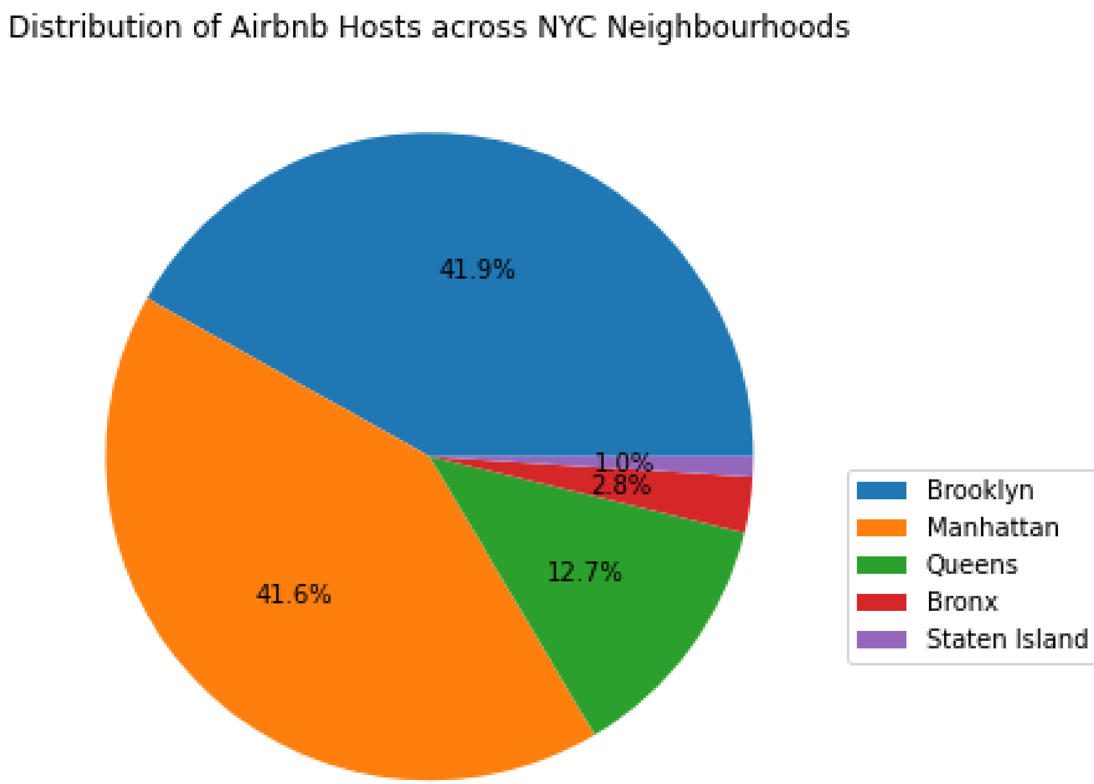
The pie chart depicts that the market is dominated by entire home/apartment listings, whereas shared rooms have the smallest market share. Therefore, if someone plans to become an Airbnb host in the future, it would be advisable for them to avoid listing a shared room.

[22]:
```
roomtype_series = df["room_type"].value_counts()
fig, ax = plt.subplots(figsize=(8, 6))
ax = roomtype_series.plot(kind="pie",labels=None, autopct='%1.1f%%')
ax.set_title('Room Type', horizontalalignment='center')
ax.set_ylabel("")
ax.legend(labels=roomtype_series.index, bbox_to_anchor=(1, 0.5))
plt.show()
```



The pie chart provides a clear illustration of how Airbnb hosts are distributed across the various neighborhoods in New York City. The largest proportion of hosts is from Manhattan, accounting for 41.9% of the total, while Brooklyn comes in second with 41.6%.

[23]:
```
neighbourhood_group_series = unique_hosts_df["neighbourhood_group"].
  ↪value_counts()
fig, ax = plt.subplots(figsize=(8, 6))
ax = neighbourhood_group_series.plot(kind="pie",labels=None, autopct='%1.1f%%')
ax.set_title('Distribution of Airbnb Hosts across NYC Neighbourhoods',␣
  ↪horizontalalignment='center')
ax.set_ylabel("")
ax.legend(labels=neighbourhood_group_series.index, bbox_to_anchor=(1, 0.5))
plt.show()
```


Distribution of Airbnb Hosts across NYC Neighbourhoods
41.9%
41.6%
12.7%
2.8%
1.0%
Brooklyn
Manhattan
Queens
Bronx
Staten Island