Report for the Airbnb NYC data analysis

Farzaneh Ahmadi (400422012)

April 7, 2022

We first import the required packages for our analysis.

[3]:
```
#Importing necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

As the first step, the goal is to have an overview of the data features, the number of columns/rows, etc.

0.1 Preview data

[5]:
```
ab_ny.head()
```

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

[6]:
```
ab_ny.shape
```

[6]: (48895, 16)

[7]:
```
# An overview of numerical data
ab_ny.describe()
```

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	38843.000000	48895.
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.373221	7.
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.680442	32.
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.010000	1.
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.190000	1.
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.720000	1.
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	2.020000	2.
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	327.

[8]:
```
ab_ny.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   name                            48879 non-null  object
 2   host_id                         48895 non-null  int64
 3   host_name                       48874 non-null  object
 4   neighbourhood_group             48895 non-null  object
 5   neighbourhood                   48895 non-null  object
 6   latitude                        48895 non-null  float64
 7   longitude                       48895 non-null  float64
 8   room_type                       48895 non-null  object
 9   price                           48895 non-null  int64
 10  minimum_nights                  48895 non-null  int64
 11  number_of_reviews               48895 non-null  int64
 12  last_review                     38843 non-null  object
 13  reviews_per_month               38843 non-null  float64
 14  calculated_host_listings_count  48895 non-null  int64
 15  availability_365                48895 non-null  int64
dtypes: float64(3), int64(7), object(6)
memory usage: 6.0+ MB
```

[9]:
```
ab_ny.dtypes
```

[9]:
```
id                                 int64
name                              object
host_id                            int64
host_name                         object
neighbourhood_group               object
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
price                              int64
```

```
minimum_nights                     int64
number_of_reviews                  int64
last_review                       object
reviews_per_month                float64
calculated_host_listings_count     int64
availability_365                   int64
dtype: object
```

0.2 Data cleaning (Task 1)

In this part, the goal is to deal with missing values, outliers, unnecessary columns and duplication.

[10]:
```
#Checking for missing values
ab_ny.isna().sum()
```

[10]:
```
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
```

name, host_name, last_review, review_per_month are the columns with missing values.

[11]:
```
#Dropping unnecessary columns
ab_ny.drop(['id','name','host_name','last_review'],axis=1, inplace= True)
```

[12]:
```
#Replacing NaN values in 'reviews per month' with the mean
ab_ny.fillna({'reviews_per_month':ab_ny['reviews_per_month'].mean()}, inplace=␣
 ↪True)
#Checking for changes
ab_ny.isna().sum()
```

[12]:
```
host_id                           0
neighbourhood_group               0
neighbourhood                     0
```

```
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
reviews_per_month                 0
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

[13]:
```python
#Delete columms with inappropriate values (proeprties with zero price).
ab_ny[ab_ny['price'] == 0.0].shape[0]
```

[13]:
```
11
```

[14]:
```python
ab_ny = ab_ny.drop(ab_ny[ab_ny['price']== 0.0].index)
ab_ny.shape
```

[14]:
```
(48884, 12)
```

Checking for duplication

[15]:
```python
ab_ny.duplicated().sum()
```

[15]:
```
0
```

Outlier treatment

In this method, the mean and standard deviation of the residuals are calculated and compared. If a value is a 3 of standard deviations away from the mean, that data point is identified as an outlier.

[16]:
```python
from re import I
for cols in ab_ny.columns:
    if ab_ny[cols].dtype == 'int64' or ab_ny[cols].dtype == 'float64':
        upper_range = ab_ny[cols].mean() + 3 * ab_ny[cols].std()
        lower_range = ab_ny[cols].mean() - 3 * ab_ny[cols].std()

        indexs = ab_ny[(ab_ny[cols] > upper_range) | (ab_ny[cols] <␣
 ↪lower_range)].index
        immo = ab_ny.drop(indexs)
```

[17]:
```python
ab_ny.shape
```

[17]:
```
(48884, 12)
```

Let us check the cleaned data

[18]:
```python
ab_ny.sample(10)
```

	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month
19496	100202479	Brooklyn	Bedford-Stuyvesant	40.68642	-73.92864	Entire home/apt	100	3	86	3.02
17807	29224381	Bronx	Norwood	40.86853	-73.88301	Entire home/apt	120	10	7	0.20
20262	17167740	Brooklyn	South Slope	40.66593	-73.98790	Private room	93	2	34	1.11
40012	163603458	Queens	Queens Village	40.72218	-73.73396	Entire home/apt	79	1	59	9.03
34439	205777414	Manhattan	West Village	40.73858	-74.00619	Entire home/apt	199	4	1	0.10
35949	92523072	Queens	Rockaway Beach	40.58862	-73.81276	Entire home/apt	150	2	14	7.24
24736	61689461	Manhattan	Financial District	40.70498	-74.01063	Private room	55	3	2	0.08
10345	41747327	Manhattan	Lower East Side	40.71909	-73.99028	Entire home/apt	95	1	98	2.13
23318	131530792	Brooklyn	Sheepshead Bay	40.59019	-73.96123	Entire home/apt	105	2	22	0.87
36956	213781715	Manhattan	NoHo	40.72872	-73.99199	Entire home/apt	179	1	1	0.68

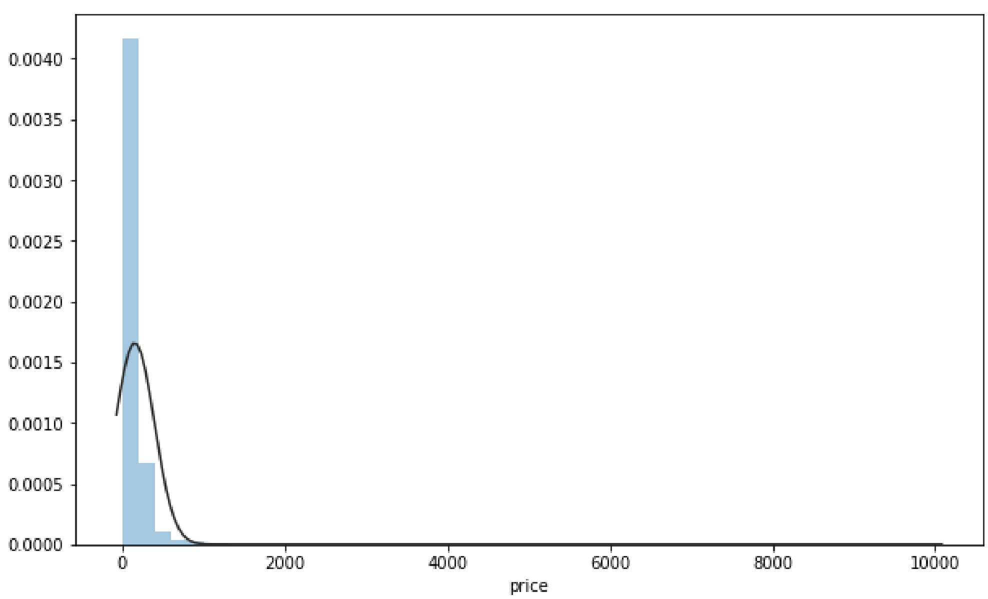
0.3 Data visualization (Task 2)

In this part the goal is to visualize data features and extract some useful information from the plots.

1. Price distribution

Here I use seaborn.distplot to show the price distribution plot and check its skewed.

[19]:
```python
#Price range distribution plot
from scipy.stats import norm
fig,ax = plt.subplots(figsize=(10,6))
sns.distplot(a=ab_ny.price,kde= False, fit=norm)
#ax.set_xlim(0, 500)
```



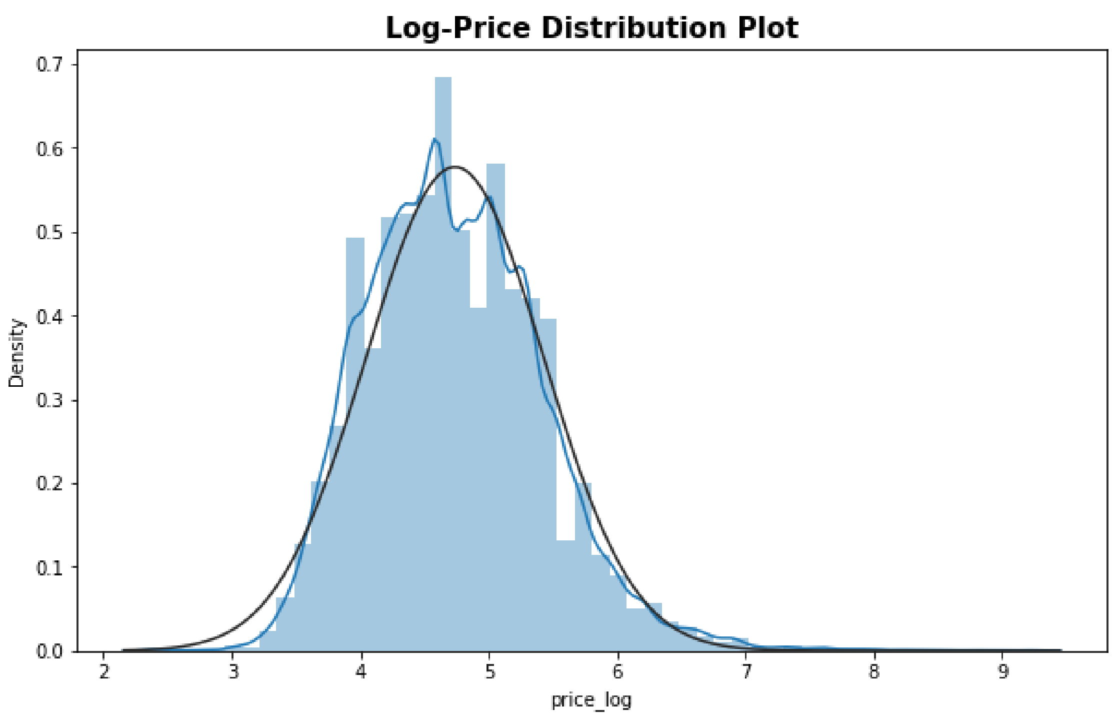
The plot shows that: There is a right-skewed distribution on price and price factor has an unstable distribution

To transform this highly skewed plot into a more normalized distribution, I use np.log method.

[20]:
```
#Log transformation
ab_ny['price_log'] = np.log(ab_ny.price+1)
```

[21]:
```
plt.figure(figsize=(10,6))
sns.distplot(ab_ny['price_log'], fit=norm)
plt.title("Log-Price Distribution Plot",size=15, weight='bold')
```

[21]: Text(0.5, 1.0, 'Log-Price Distribution Plot')



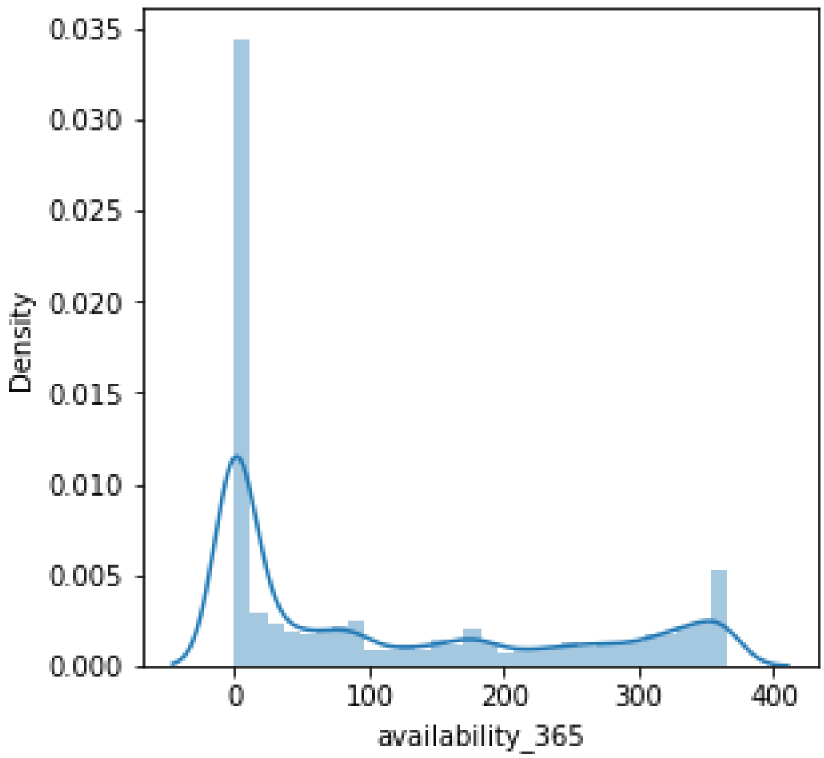
With log transformation, price feature has normal distribution.

---

2. Distribution of availability_365

[22]:
```
#Availability_365 distribution plot
plt.subplot(224)
sns.distplot(ab_ny['availability_365'])
fig = plt.gcf()
```

```
fig.set_size_inches(10,10)
```



The plot shows that Availability_365 has right skewed distribution

---

3. Number of AirBnb in different neighbourhood groups

[23]:
```
# How many neighbourhood groups are there?
ab_ny.neighbourhood_group.unique()
```

[23]:
```
array(['Brooklyn', 'Manhattan', 'Queens', 'Staten Island', 'Bronx'],
      dtype=object)
```

[24]:
```
# How many properties are there in each neighbourhood?
neighbourhood_group_count = pd.DataFrame({'count' : ab_ny.
 ↪groupby(['neighbourhood_group']).size()}).reset_index()
neighbourhood_group_count
```

[24]:

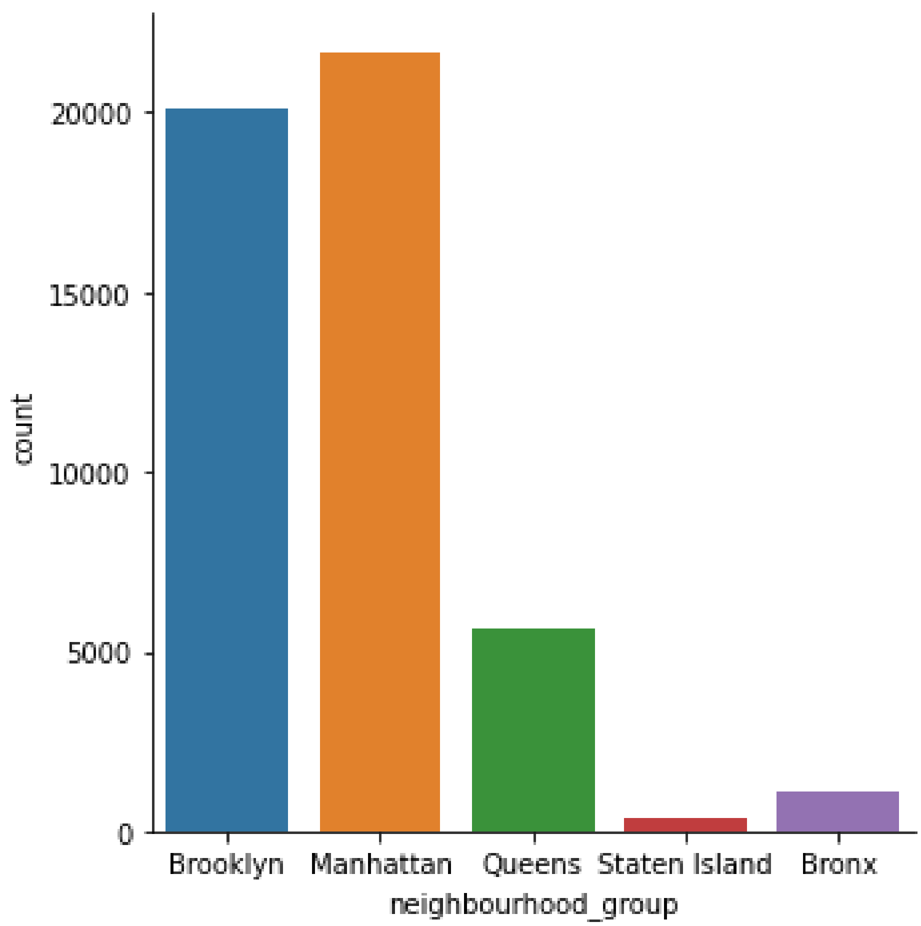
	neighbourhood_group	count
0	Bronx	1090
1	Brooklyn	20095
2	Manhattan	21660

```
3              Queens   5666
4       Staten Island    373
```

[25]:
```
plt.figure(figsize=(12, 6))
sns.catplot(x="neighbourhood_group", kind="count", data=ab_ny)
```

[25]:
```
<seaborn.axisgrid.FacetGrid at 0x7f9148adda50>
```

```
<Figure size 864x432 with 0 Axes>
```



Histogram shows the number of Airbnbs in different neighborhood groups.

- Manhattan has the most number of Airbnbs.

---

4. Distribution of price across location

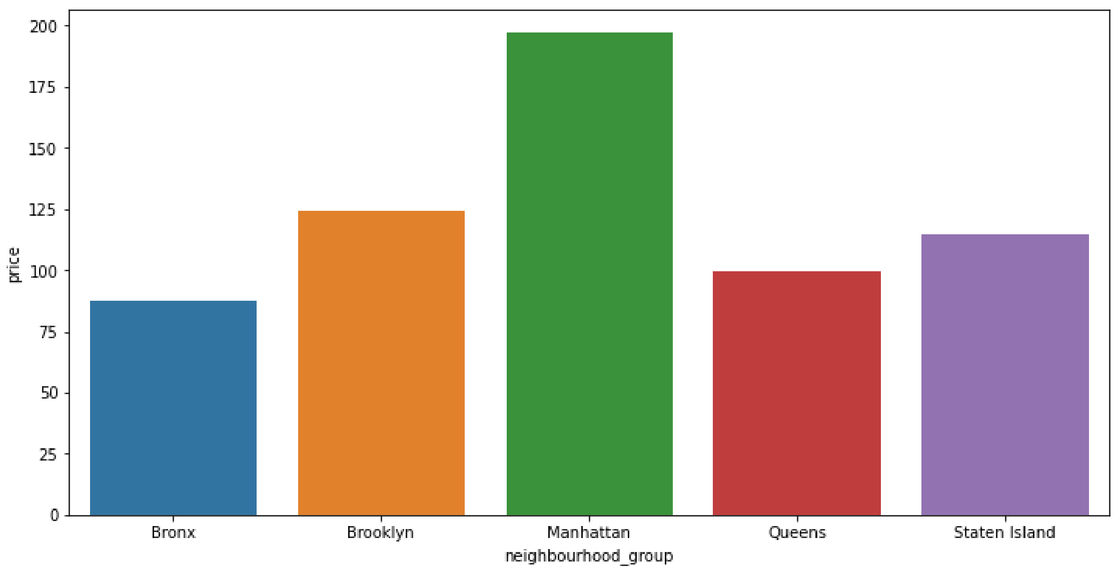
[26]:
```
neighbourhood_group_price = ab_ny[['neighbourhood_group', 'price']]
neighbourhood_group_price = ab_ny.groupby(['neighbourhood_group'],␣
 ↪as_index=False)[['price']].mean()
neighbourhood_group_price
```

[26]:

	neighbourhood_group	price
0	Bronx	87.577064
1	Brooklyn	124.438915
2	Manhattan	196.884903
3	Queens	99.517649
4	Staten Island	114.812332

[27]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x="neighbourhood_group",y="price", data=neighbourhood_group_price)
```

[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9148b4f4d0>



The plot shows that Manhattan is the most expensive neighborhood with an average price of 196.88 and Bronx is the cheapest one, with an average price of 87.57

Does the number of listing in each borough affect the price?

Concatenating the two DataFrames, namely neighbourhood_group_count and neighbourhood_group_price will have a better vision about the relation between the price and the number of properties in each neighbourhood group.

[28]:
```
borough_price_count =pd.concat([neighbourhood_group_count,␣
 ↪neighbourhood_group_price.reindex(neighbourhood_group_count.index)], axis=1)
borough_price_count = borough_price_count.T.drop_duplicates().T
```

```
borough_price_count
```

[28]:

```
  neighbourhood_group  count       price
0               Bronx   1090   87.577064
1            Brooklyn  20095  124.438915
2           Manhattan  21660  196.884903
3              Queens   5666   99.517649
4       Staten Island    373  114.812332
```

Correlation between the price and the number of properties in each neighbourhood group.

[29]:

```
neighbourhood_group_count['count'].corr(neighbourhood_group_price['price'])
```

[29]:

```
0.775843902058638
```

Conclusion : price and the number of properties in each naighbourhood are almost correlated (0.77), which means boroughs with more number of listing in Airbnb, are more expensive.

---

5. Preferred room type

[30]:

```
# How many room types are there?
ab_ny['room_type'].unique()
```

[30]:

```
array(['Private room', 'Entire home/apt', 'Shared room'], dtype=object)
```

[31]:

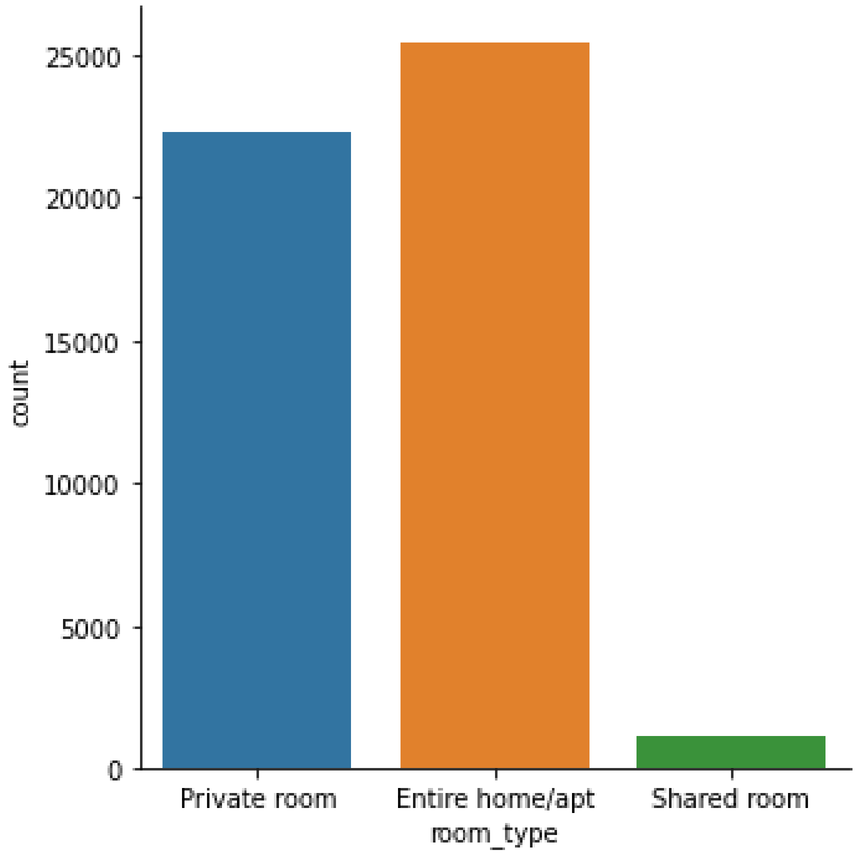
```
# wHich room type is the most preferred?
room_type_count= ab_ny.groupby('room_type').size()
room_type_count
```

[31]:

```
room_type
Entire home/apt    25407
Private room       22319
Shared room         1158
dtype: int64
```

[32]:

```
#Histogram
sns.catplot(x="room_type", kind="count", data=ab_ny);
```



- "Entire home" and "apartment" are the most preferred room types. Shared room is the least one.

---

6. Price distribution across room types

[33]:
```
newdf2= ab_ny[['neighbourhood_group','room_type', 'price']]
newdf2 = newdf2.groupby(['neighbourhood_group','room_type'],␣
 ↪as_index=False)[['price']].mean()
newdf2
```

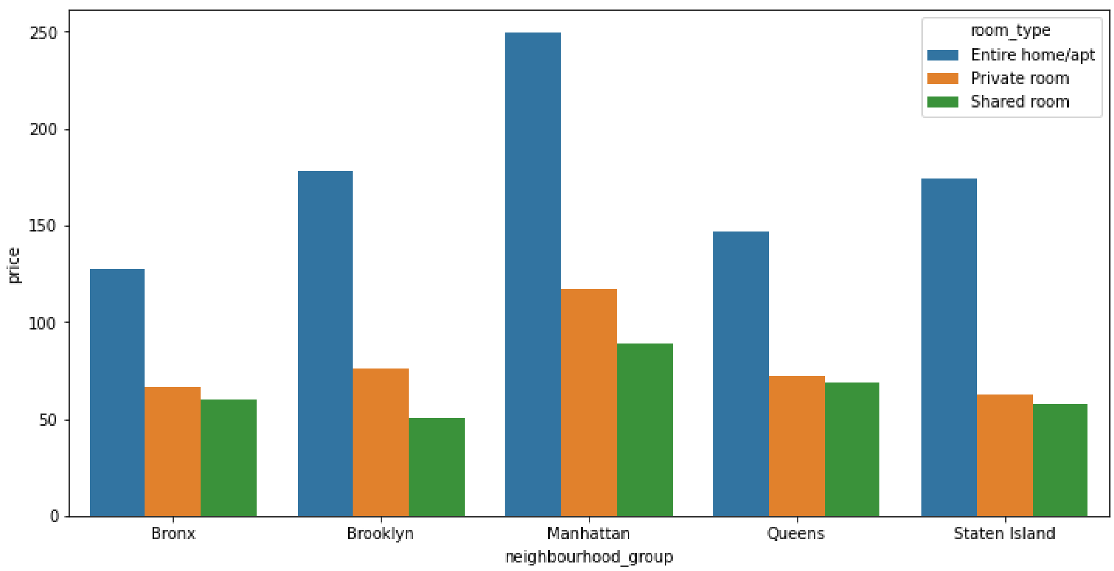
[33]:

	neighbourhood_group	room_type	price
0	Bronx	Entire home/apt	127.506596
1	Bronx	Private room	66.890937
2	Bronx	Shared room	59.800000
3	Brooklyn	Entire home/apt	178.346202
4	Brooklyn	Private room	76.545428
5	Brooklyn	Shared room	50.773723
6	Manhattan	Entire home/apt	249.257994
7	Manhattan	Private room	116.776622

```
8          Manhattan     Shared room   88.977083
9             Queens  Entire home/apt  147.050573
10            Queens     Private room   71.762456
11            Queens      Shared room   69.020202
12     Staten Island  Entire home/apt  173.846591
13     Staten Island     Private room   62.292553
14     Staten Island      Shared room   57.444444
```

[34]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='neighbourhood_group',y='price', hue='room_type', data=newdf2)
```

[34]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9148a0ff10>
```



- The plot shows that price is not affected by the boroughs, but is affected by the room type. "Entire home" is the most expensive room type (regardless of neighbourhood).

0.4 Hosts analyse (Task 3 and 4)

- Finding hosts with the most listings in NYC.

[35]:
```
#Top 10 hosts having the most listing in NYC
top_host=ab_ny.host_id.value_counts().head(10)
top_host
```

[35]:
```
219517861    327
107434423    232
30283594     121
137358866    103
```

```
12243051      96
16098958      96
61391963      91
22541573      87
200380610     65
7503643       52
Name: host_id, dtype: int64
```

[36]:
```
# Checking the correctness of top_host by using an already existing column␣
↪called 'calculated_host_listings_count'
ab_ny.calculated_host_listings_count.max()
```

[36]: 327

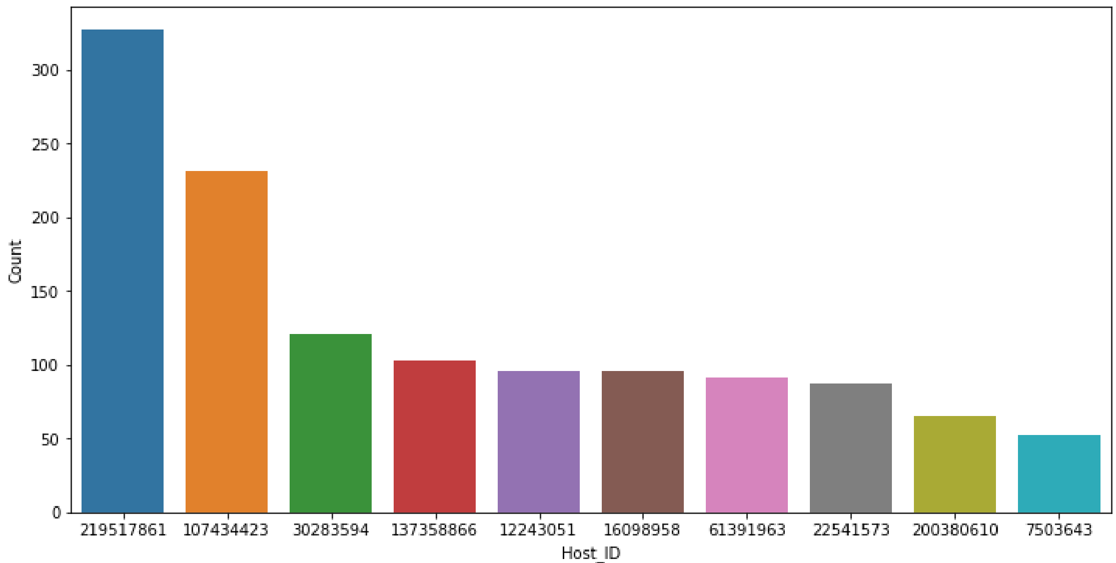
[37]:
```
# Convert list to data frame
top_host_df=pd.DataFrame(top_host)
top_host_df.reset_index(inplace=True)
top_host_df.rename(columns={'index':'Host_ID', 'host_id':'Count'}, inplace=True)
top_host_df
```

[37]:

	Host_ID	Count
0	219517861	327
1	107434423	232
2	30283594	121
3	137358866	103
4	12243051	96
5	16098958	96
6	61391963	91
7	22541573	87
8	200380610	65
9	7503643	52

[38]:
```
#Histogram
plt.figure(figsize=(12, 6))
sns.barplot(x='Host_ID',y='Count', data=top_host_df , order=top_host_df.
↪sort_values('Count',ascending = False).Host_ID)
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9148938550>



The host with maximum number of listings in NewYork has 372 listings.

- Finding hosts with the most reviews.

[39]:
```
# Top 10 hosts having the most reviews
top_host_review= ab_ny[['host_id', 'number_of_reviews']]
top_host_review = ab_ny.groupby(['host_id'])[['number_of_reviews']].sum()
top_host_review.number_of_reviews.sort_values(ascending=False).head(10)
```

[39]:
```
host_id
37312959     2273
344035       2205
26432133     2017
35524316     1971
40176101     1818
4734398      1798
16677326     1355
6885157      1346
219517861    1281
23591164     1269
Name: number_of_reviews, dtype: int64
```

[40]:
```
#Converting list to data frame
top_host_review_df=pd.DataFrame(top_host_review.number_of_reviews.
 ↪sort_values(ascending=False).head(10))
top_host_review_df.reset_index(inplace=True)
top_host_review_df.rename(columns={'index':'Host_ID'}, inplace=True)
top_host_review_df
```

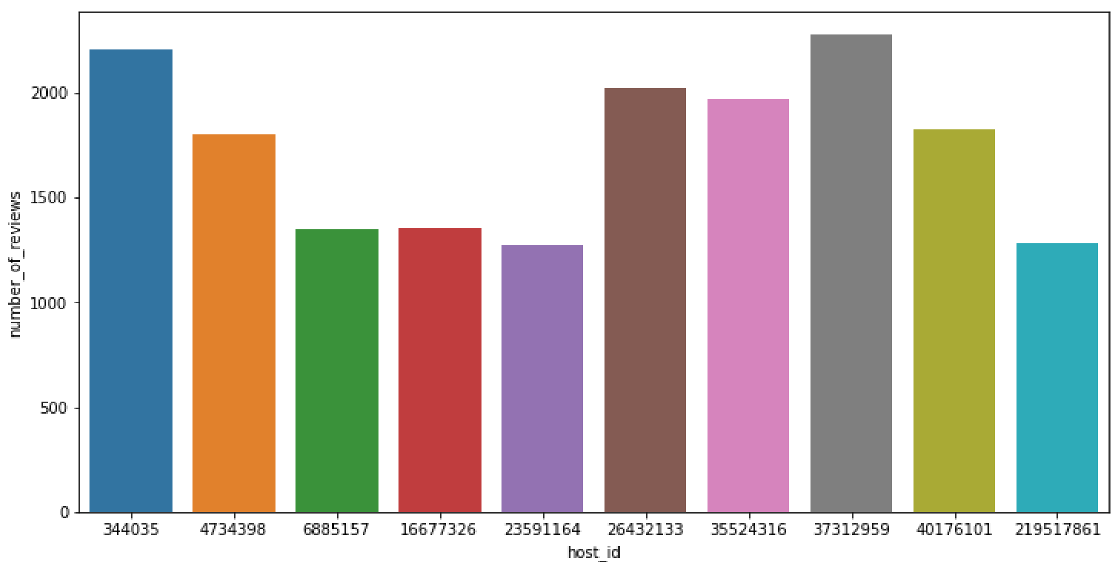
[40]:

	host_id	number_of_reviews
0	37312959	2273
1	344035	2205
2	26432133	2017
3	35524316	1971
4	40176101	1818
5	4734398	1798
6	16677326	1355
7	6885157	1346
8	219517861	1281
9	23591164	1269

[41]:

```
# Histogram
plt.figure(figsize=(12, 6))
sns.barplot(x='host_id',y='number_of_reviews', data=top_host_review_df)
```

[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9148952e10>



The plot shows top 10 hosts having the most customers (reviews).

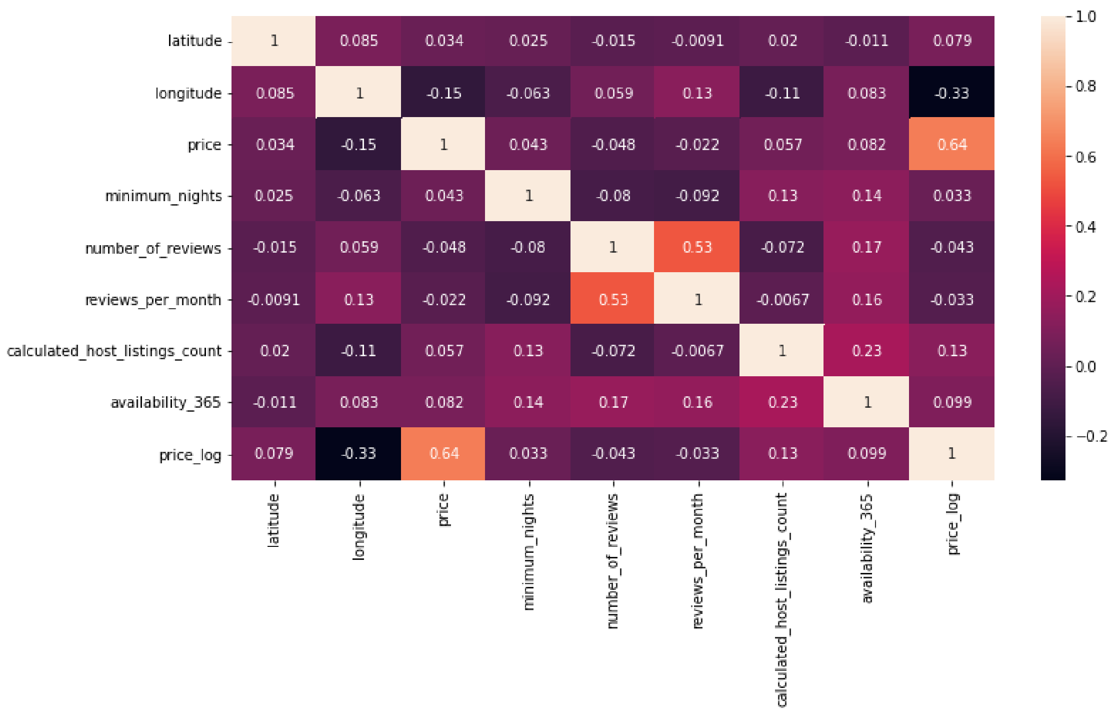
- Which featurs affect the number of reviews?

[42]:

```
#Correlation
newairb= ab_ny.drop(['host_id'],axis=1)
```

[43]:

```
plt.figure(figsize=(12, 6))
corrMatrix = newairb.corr()
sns.heatmap(corrMatrix, annot=True)
plt.show()
```



The correlation table shows that our features are not coorelated and there is no strong relationship between the number of reviews and other features.

- Which borough has the most reviews? (Does borough affect the number of reviews?)

[44]:
```
top_borough_review= ab_ny[['neighbourhood_group','number_of_reviews']]
top_borough_review = ab_ny.
 ↪groupby(['neighbourhood_group'])[['number_of_reviews']].sum()
top_borough_review.number_of_reviews.sort_values(ascending=False).head()
```

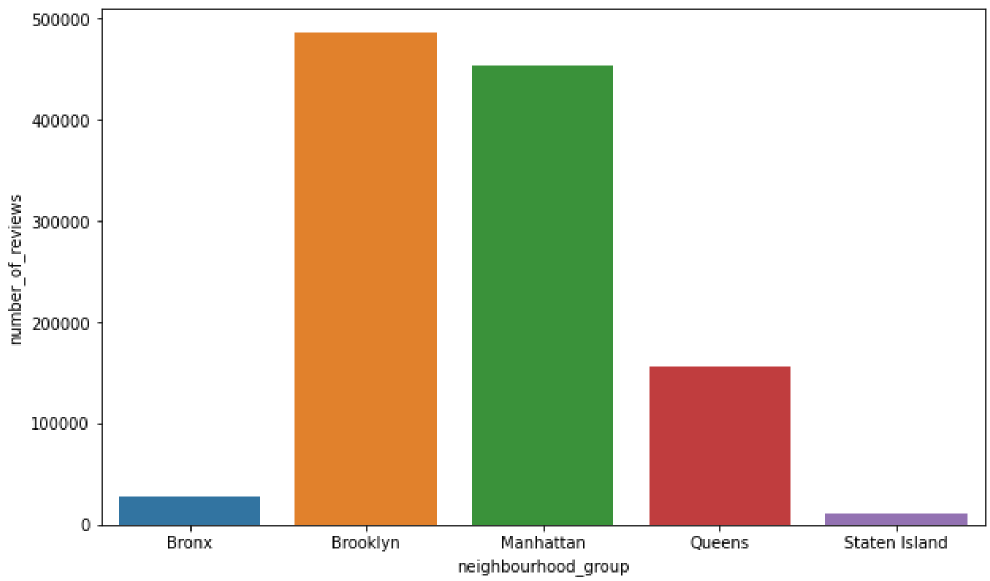
[44]:
```
neighbourhood_group
Brooklyn         486252
Manhattan        454569
Queens           156950
Bronx             28316
Staten Island     11541
Name: number_of_reviews, dtype: int64
```

[45]:
```
# Converting list to data frame
top_borough_review_df = pd.DataFrame(top_borough_review)
top_borough_review_df.reset_index(inplace=True)
top_borough_review_df.rename(columns={'index':'borough', 'host_id':
 ↪'number_of_review'}, inplace=True)
top_borough_review_df
```

[45]:
	neighbourhood_group	number_of_reviews
0	Bronx	28316
1	Brooklyn	486252
2	Manhattan	454569
3	Queens	156950
4	Staten Island	11541

[46]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='neighbourhood_group',y='number_of_reviews',␣
↪data=top_borough_review_df)
```

[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9148acc6d0>



The plot shows that Brooklyn and Manhattan have the most number of reviews.

Thus, borough **affects** the number of reviews.

0.5 Hypothesis test (Task 5)

Shapiro Test :

Test 1

- H0 (null Hypothesis): Price distribution is not normal
- H1 (Alternate Hypothesis): Price distribution is not normal

[47]:
```
import scipy.stats as st
st.shapiro(ab_ny.price)
```

[47]: (0.30034202337265015, 0.0)

The p value is 0.0 and thus less than alpha (5%). This implies that the null hypothesis should be rejected and the distribution is not normal.

Conclusion: Price distribution is not normal. (Price distribution plot has been shown in "Data visualization")

Levene Test:

Test 2

H0 (null hypothesis): variance(private_room) = variance(shared_room) = variance(entire_home)

H1 (alternate hypothesis): variance(private_room) != variance(shared_room) != variance(entire_home)

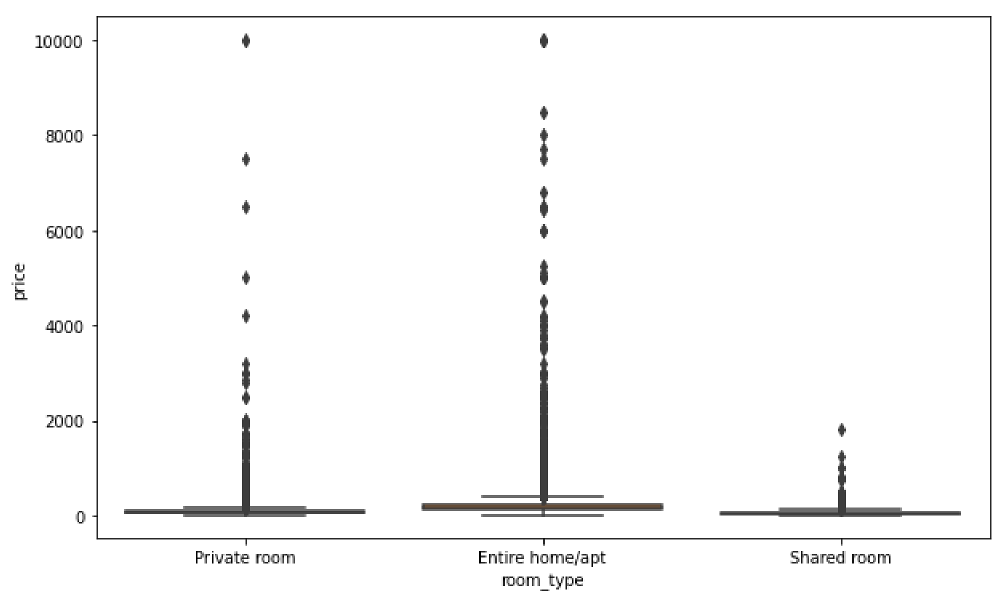
[48]:
```
pv = ab_ny[ab_ny['room_type'] == 'Private room']
share = ab_ny[ab_ny['room_type'] == 'Shared room']
apt = ab_ny[ab_ny['room_type'] == 'Entire home/apt']
st.levene(pv.price, share.price, apt.price)
```

[48]: LeveneResult(statistic=404.81916838266966, pvalue=4.2599555983973533e-175)

Conclusion: The p value is approximatly 0.0 and thus less than alpha (5%). This implies that the null hypothesis should be rejected.

[49]:
```
plt.figure(figsize=(10,6))
sns.boxplot(y='price',x='room_type',data=ab_ny)
```

[49]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9148a97150>



Test 3

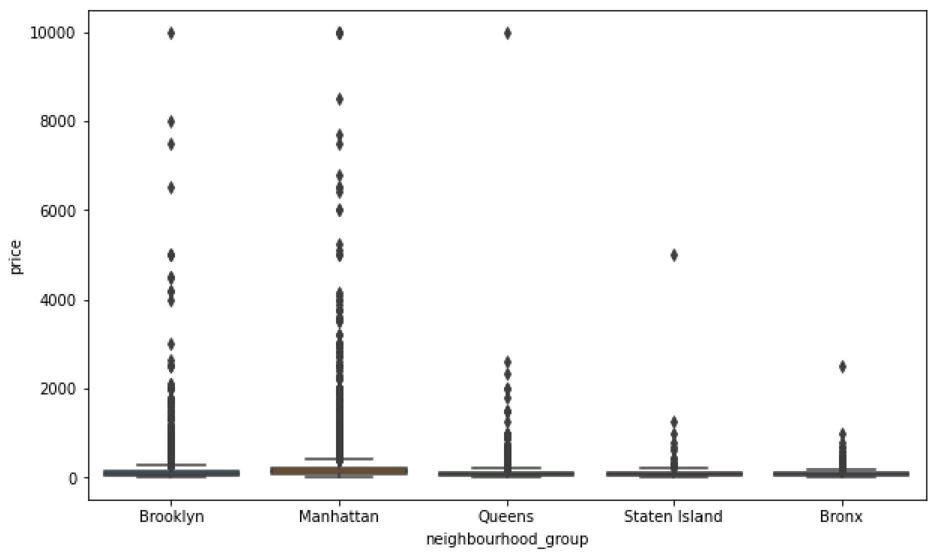
- H0 (null hypothesis): variance(Brooklyn) = variance(Manhattan) = ….. = variance(Bronx)
- H1 (alternate hypothesis): variance(Brooklyn) != variance(Manhattan) != ….. != variance(Bronx)

[50]:
```
borough1 = ab_ny[ab_ny['neighbourhood_group'] == 'Brooklyn']['price']
borough2 = ab_ny[ab_ny['neighbourhood_group'] == 'Manhattan']['price']
borough3 = ab_ny[ab_ny['neighbourhood_group'] == 'Queens']['price']
borough4 = ab_ny[ab_ny['neighbourhood_group'] == 'Staten Island']['price']
borough5 = ab_ny[ab_ny['neighbourhood_group'] == 'Bronx']['price']
st.levene(borough1,borough2,borough3,borough4,borough5)
```

[50]:
```
LeveneResult(statistic=120.45120282270643, pvalue=1.858173022081869e-102)
```

[51]:
```
plt.figure(figsize=(10,6))
sns.boxplot(y='price',x='neighbourhood_group',data=ab_ny)
ax.set_title(label = 'Distribution of prices acros location', fontsize = 30)
```

[51]:
```
Text(0.5, 1.0, 'Distribution of prices acros location')
```



Conclusion: The p value is approximately 0.0 and thus less than alpha (5%). This implies that the null hypothesis should be rejected.

Kruskal Wallis Test:

Test 4

- H0 (null hypothesis): mean_price(private_room) = mean_price(shared_room) = mean_price(entire_home/apt)
- H1 (alternate hypothesis): mean_price(private_room) != mean_price(shared_room) != mean_price(entire_home/apt)

[52]:
```
st.kruskal(pv.price,share.price,apt.price)
```

[52]:
```
KruskalResult(statistic=22414.838451732678, pvalue=0.0)
```

Conclusion: The p value is approximatly 0.0 and thus less than alpha (5%). This implies that the null hypothesis should be rejected.

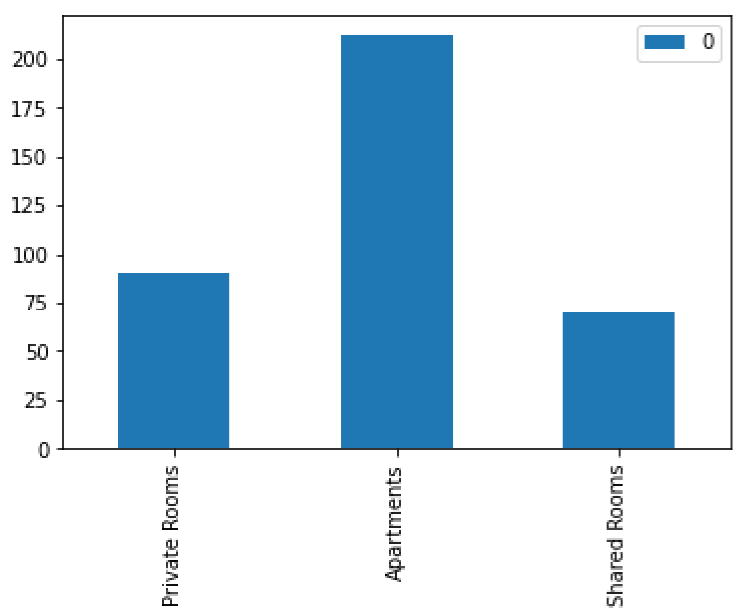
[53]:
```
ind = ['Private Rooms','Apartments','Shared Rooms']
x = pd.DataFrame([pv.price.mean(),apt.price.mean(),share.price.mean()],
 ↪index=ind)
x
```

[53]:

	0
Private Rooms	89.809131
Apartments	211.810918
Shared Rooms	70.248705

[54]:
```
plt.figure(figsize=(10,6))
x.plot.bar()
plt.show()
```

<Figure size 720x432 with 0 Axes>



The plot shows that the average price in private rooms, apartments and shared room is not the same and apartments are more expensive with an average price of 211.81.

Kruskal Wallis Test: **Test 5**

- H0 (null hypothesis): mean_price(Brooklyn) = mean_price(Manhattan) = ….. = mean_price(Bronx)
- H1 (null hypothesis): mean_price(Brooklyn) != mean_price(Manhattan) != ….. != mean_price(Bronx)

[55]:
```
borough1 = ab_ny[ab_ny['neighbourhood_group'] == 'Brooklyn']['price']
borough2 = ab_ny[ab_ny['neighbourhood_group'] == 'Manhattan']['price']
borough3 = ab_ny[ab_ny['neighbourhood_group'] == 'Queens']['price']
borough4 = ab_ny[ab_ny['neighbourhood_group'] == 'Staten Island']['price']
borough5 = ab_ny[ab_ny['neighbourhood_group'] == 'Bronx']['price']
st.kruskal(borough1,borough2,borough3,borough4,borough5)
```

[55]:
```
KruskalResult(statistic=7023.124698515672, pvalue=0.0)
```

Conclusion: The p value is 0.0 and thus less than alpha (5%). This implies that the null hypothesis should be rejected and the average price in different neighborhood is not the same.

Chi Squared Test:

Test 6

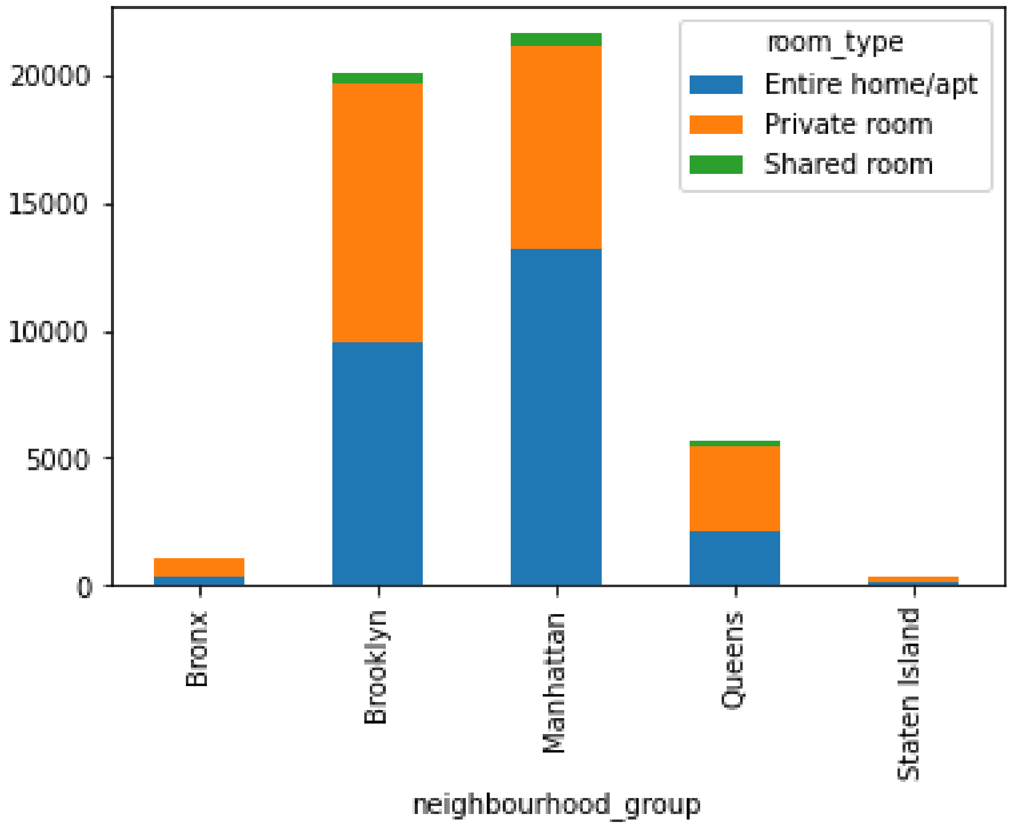
- H0 (null hypothesis): There is no association between Room Type and Neighbourhood Group.
  H1 (alternate hypothesis): There is an association between Room Type and Neighbourhood Group.

[56]:
```
tab = pd.crosstab(ab_ny['room_type'],ab_ny['neighbourhood_group'])
```

[57]:
```
st.chi2_contingency(tab)
```

[57]:
```
(1558.4325467152619,
 0.0,
 8,
 array([[5.66517265e+02, 1.04441876e+04, 1.12575816e+04, 2.94485030e+03,
         1.93863248e+02],
        [4.97662016e+02, 9.17478735e+03, 9.88932043e+03, 2.58692934e+03,
         1.70300855e+02],
        [2.58207184e+01, 4.76025080e+02, 5.13097946e+02, 1.34220358e+02,
         8.83589723e+00]]))
```

[58]:
```
y = pd.crosstab(ab_ny['neighbourhood_group'],ab_ny['room_type'])
y.plot.bar(stacked=True)
plt.show()
```



The p value is 0.0 and less than alpha (0.05) and This implies that the null hypothesis should be rejected and there is an association between Room types and neighbourhood groups.

0.6 Model building

[59]:
```
# Import usefull libraries
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
```

[60]:
```
# Dropping some variables that do not help
dfModel = ab_ny.drop(["latitude","longitude", "host_id", "neighbourhood"],axis=1)
dfModel.head()
```

	neighbourhood_group	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365	price_log
0	Brooklyn	Private room	149	1	9	0.210000	6	365	5.010635
1	Manhattan	Entire home/apt	225	1	45	0.380000	2	355	5.420535
2	Manhattan	Private room	150	3	0	1.373221	1	365	5.017280
3	Brooklyn	Entire home/apt	89	1	270	4.640000	1	194	4.499810
4	Manhattan	Entire home/apt	80	10	9	0.100000	1	0	4.394449

[61]:

```
# Convert categorical data to dummies variables
dfmodel_new = pd.get_dummies(dfModel,␣
↪columns=['neighbourhood_group',"room_type"])
dfmodel_new.head()
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365	price_log	neighbourhood_group_Bronx	neigh
0	149	1	9	0.210000	6	365	5.010635	0	
1	225	1	45	0.380000	2	355	5.420535	0	
2	150	3	0	1.373221	1	365	5.017280	0	
3	89	1	270	4.640000	1	194	4.499810	0	
4	80	10	9	0.100000	1	0	4.394449	0	

[62]:

```
# Split dataset into test and training data
y = dfmodel_new['price']
x = dfmodel_new.drop(columns = ['price'])
print(x.shape)
print(y.shape)
```

```
(48884, 14)
(48884,)
```

[63]:

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20,␣
↪random_state=0)
```

Feature scaling

[64]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

Linear Regression Model Here I use a linear approach for modeling the relationship between price and other features and calculate the error to estimate the accuracy of model with error visualization.

[65]:
```
# Fitting Linear regression
reg = LinearRegression().fit(x_train, y_train)
```

[66]:
```
# R2 value
print("R2 score: ",reg.score(x_train, y_train))
```

```
R2 score:  0.4526356329681537
```

[72]:
```
# Predicting
y_pred = reg.predict(x_test)
print("y_pred: ", reg.predict(x_test))
```

```
y_pred:  [ 94.08078281  82.28842103 124.02908637 ...  84.98392587  93.27602322
   7.25452825]
```

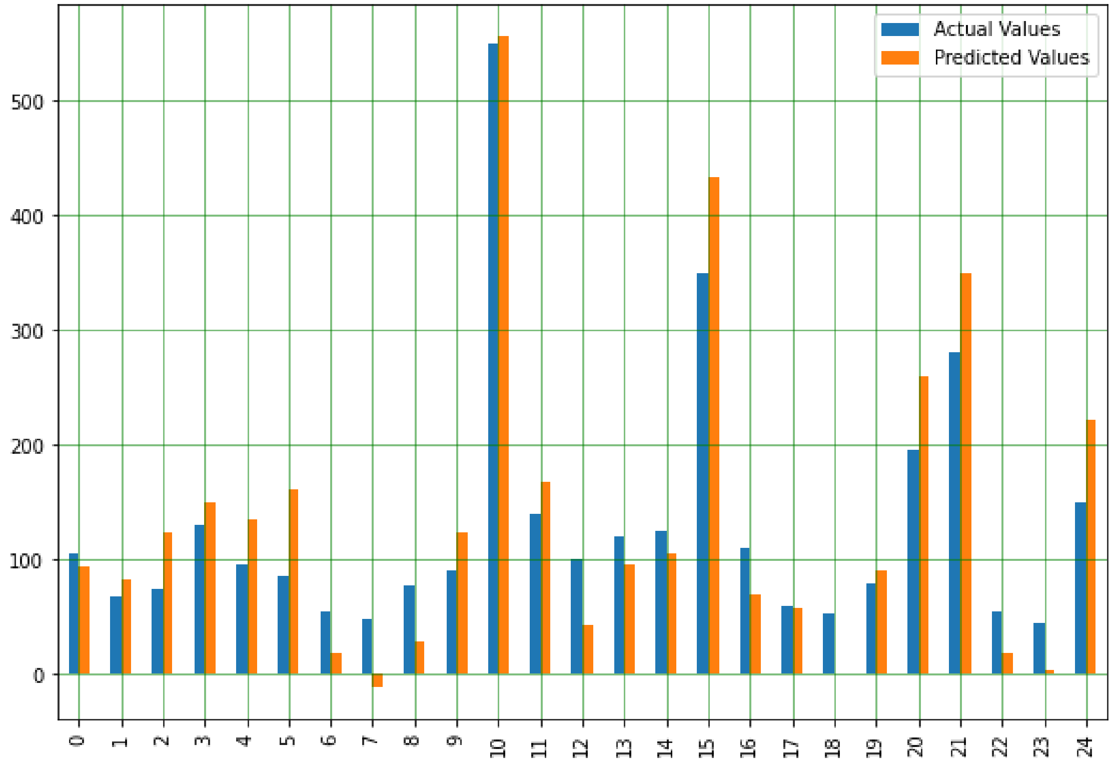
[73]:
```
# Calculating RMSE
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ",rmse)
```

```
RMSE:  182.75319767029436
```

[74]:
```
#Error
errordf = pd.DataFrame({'Actual Values': np.array(y_test).flatten(), 'Predicted␣
↪Values': y_pred.flatten()})
print(errordf.head(5))
```

```
   Actual Values  Predicted Values
0            105         94.080783
1             68         82.288421
2             75        124.029086
3            130        149.291654
4             95        134.349660
```

[75]:
```
# Error visualization
df1 = errordf.head(25)
df1.plot(kind='bar',figsize=(10,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



The plot shows the relationship between Actual Values and Predicted Values.In this model R squared equals to 0.45 which shows accuracy of this model is not quite good.

Tree Regression

[76]:
```
#Preparing a Decision Tree Regression
from sklearn.tree import DecisionTreeRegressor
DTree=DecisionTreeRegressor(min_samples_leaf=.0001)
DTree.fit(x_train,y_train)
y_pred=DTree.predict(x_test)
```

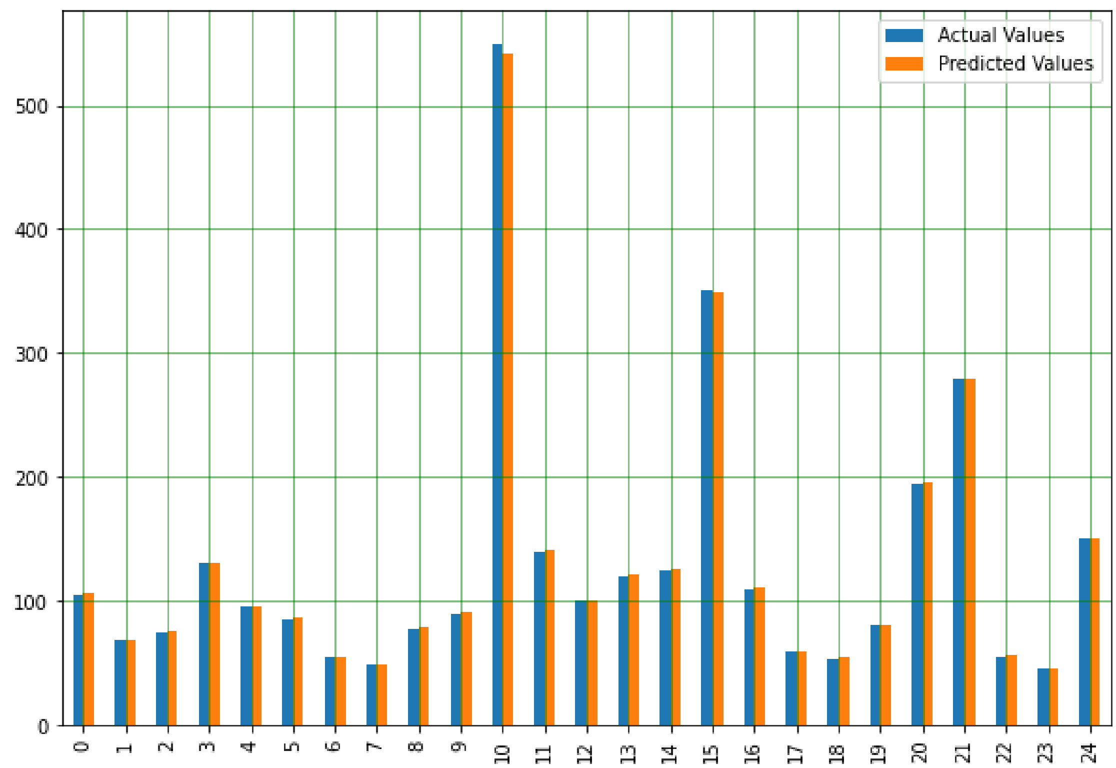
[77]:
```
from sklearn.metrics import r2_score
print("R2 score: ",r2_score(y_test,y_pred)*100)
print("RMSE: ",np.sqrt(mean_squared_error(y_test,y_pred)))
```

```
R2 score:  99.86906540185383
RMSE:  8.910702258318334
```

[78]:
```
#Error
errordf2 = pd.DataFrame({'Actual Values': np.array(y_test).flatten(), 'Predicted␣
↪Values': y_pred.flatten()})
print(errordf2.head(5))
```

```
   Actual Values  Predicted Values
0            105             106.0
1             68              69.0
2             75              76.0
3            130             131.0
4             95              96.0
```

[79]:
```
#Error visualization
df2 = errordf2.head(25)
df2.plot(kind='bar',figsize=(10,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



The plot shows the relationship between Actual Values and Predicted Values in tree regression model.In this model R squared equals to 0.99 which shows accuracy is quite good.

Lasso Regression

[80]:
```
regL1 = Lasso(alpha=0.01)
regL1.fit(x_train, y_train)

y_pred=regL1.predict(x_test)
```

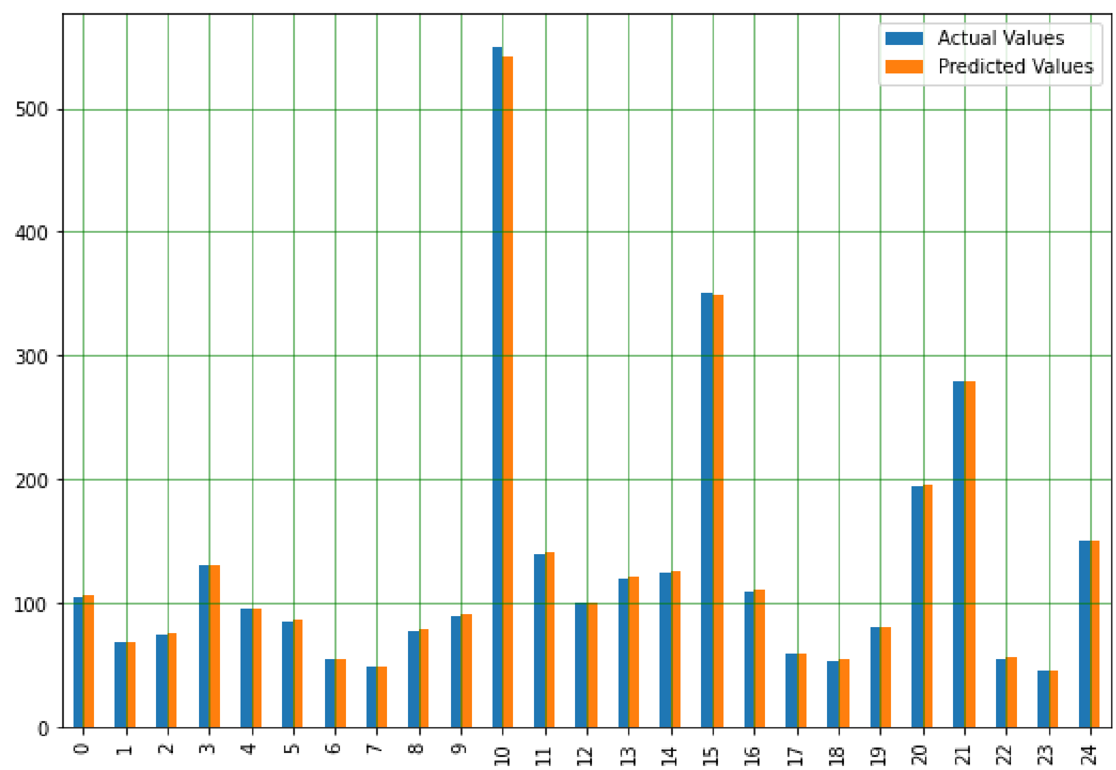
[81]:
```
from sklearn.metrics import r2_score
print("R2 score: ",r2_score(y_test,y_pred)*100)
print("RMSE: ",np.sqrt(mean_squared_error(y_test,y_pred)))
```

```
R2 score:  44.92807149831059
RMSE:  182.74683536709176
```

[82]:
```
#Error
errordf3 = pd.DataFrame({'Actual Values': np.array(y_test).flatten(), 'Predicted␣
↪Values': y_pred.flatten()})
print(errordf3.head(5))
```

```
   Actual Values  Predicted Values
0            105         94.179935
1             68         82.413071
2             75        124.079193
3            130        149.377894
4             95        134.383399
```

[83]:
```
#Error visualization
df2 = errordf2.head(25)
df2.plot(kind='bar',figsize=(10,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



The plot shows the relationship between Actual Values and Predicted Values in Lasso regression model. In this model R squared equals to 0.44 which shows accuracy is not quite good.

Conclusion: Tree regression is the best prediction model among other models, as its R2 is 0.99

0.7 Bonus Task

Does the number of museums in each borough affect the price?

The data I've been using is from Wikipedia "List of museums in New York City" that has been converted to a csv file.

[84]:
```
! ls '/gdrive/MyDrive/Data-Mining/nyc_museums'
```

```
table-1.csv
```

[85]:
```
#Uploading data...
root = '/gdrive/MyDrive/Data-Mining/nyc_museums/'
mus= pd.read_csv(root + "table-1.csv")
```

[86]:
```
#Overview
mus.head()
```

	Name	Neighborhood	Borough	Type	Focus	Summary
0	9/11 Tribute Museum	Lower Manhattan	Manhattan	History	American and NY history	History of the September 11 attacks and tours ...
1	African Burial Ground National Monument	Lower Manhattan	Manhattan	History	African and African-American	Visitor center and memorial to an 18th-century...
2	AIGA National Design Center	Lower Manhattan	Manhattan	Art	Design, decorative arts, architecture	website, public gallery of the AIGA dedicated ...
3	A.I.R. Gallery	Dumbo	Brooklyn	Art	Contemporary art	Contemporary art by female artists
4	Alice Austen House	Rosebank	Staten Island	Historic house	Photography, film, new media	Home of photographer Alice Austen, also featur...

[87]:
```
mus.groupby(['Borough']).size()
```

[87]:
```
Borough
Bronx             17
Brooklyn          29
Manhattan        133
Queens            24
Staten Island     14
dtype: int64
```

[88]:
```
#Converting to DataFrame
mus_borough_count = pd.DataFrame({'NumberOfMuseums' : mus.groupby(['Borough']).
 ↪size()}).reset_index()
mus_borough_count
```

[88]:

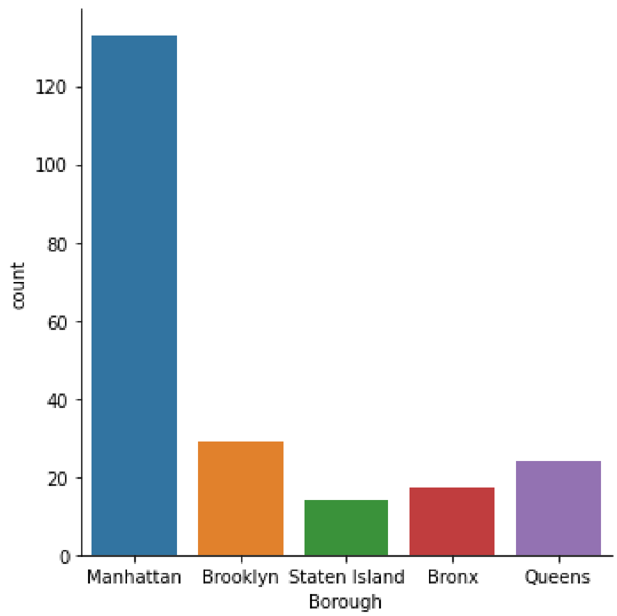
	Borough	NumberOfMuseums
0	Bronx	17
1	Brooklyn	29
2	Manhattan	133
3	Queens	24
4	Staten Island	14

The list above shows the number of museums in each borough.

Boroughs with the most number of musuems in descending order are Manhathan, Brooklyn, Queens, Bronx, and Staten Island.

[89]:
```
sns.catplot(x="Borough", kind="count", data=mus)
```

[89]: <seaborn.axisgrid.FacetGrid at 0x7f9145c1b790>



Here I use the data frame that we already have (in the data visualization section), called "neighborhood_group_price". This data frame shows the price distribution across the neighbourhoods. Merging these two data frames will help us to find the correlation between the number of museums and the price in each neighbourhood.

[90]:
```
neighbourhood_group_price
```

[90]:

	neighbourhood_group	price
0	Bronx	87.577064
1	Brooklyn	124.438915
2	Manhattan	196.884903
3	Queens	99.517649
4	Staten Island	114.812332

```
[91]: mus_price = pd.concat([neighbourhood_group_price, mus_borough_count.
       ↪reindex(neighbourhood_group_price.index)], axis=1)
      mus_price = mus_price.drop(['Borough'], axis=1)
      mus_price
```

[91]:

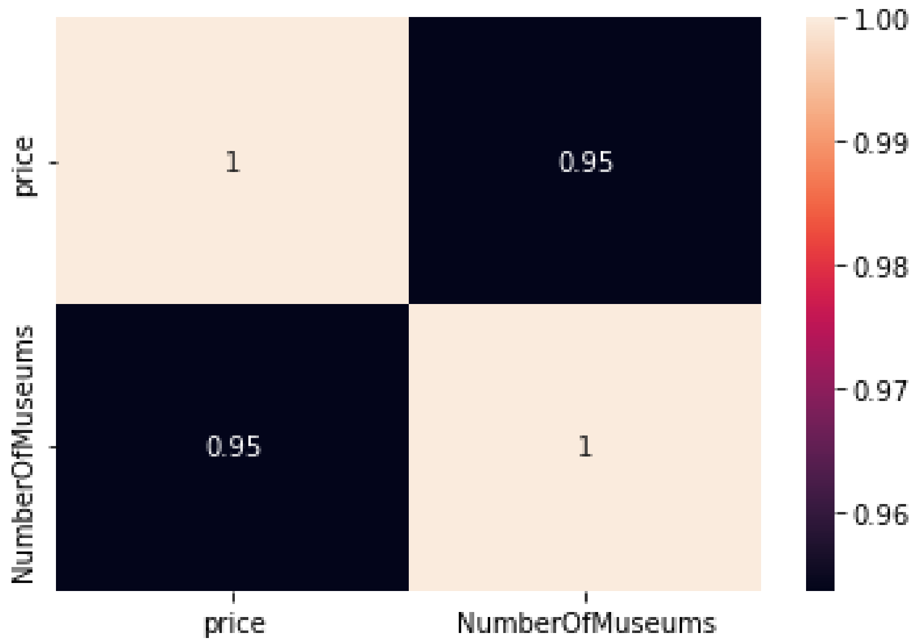
	neighbourhood_group	price	NumberOfMuseums
0	Bronx	87.577064	17
1	Brooklyn	124.438915	29
2	Manhattan	196.884903	133
3	Queens	99.517649	24
4	Staten Island	114.812332	14

```
[92]: mus_price.corr()
```

[92]:

	price	NumberOfMuseums
price	1.000000	0.953753
NumberOfMuseums	0.953753	1.000000

```
[93]: #plt.figure(figsize=(12, 6))
      sns.heatmap(mus_price.corr(), annot=True)
      plt.show()
```



The plot shows that the correlation between the two features (price and number of museums) is high. Thus these features are related and the number of museums in each neighbourhood, affect the price of properties.