Berliner Hochschule für Technik

VISUALIZE NEWYORK CITY AIRBNB DATA

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1. Introduction

Data visualization is a graphical representation of data that expresses its significance. It reveals insights and patterns that are not immediately visible in the raw data. It is an art through which information, numbers, and measurements can be made more understandable. In our project, we visualize the Airbnb data for New York City. We try to make some graphical representations of the features and also demonstrate the relationship between features.

Airbnb stands for "Air Bed and Breakfast," a name that reflects the company's early origins—its co-founders invited paying guests to sleep on an air mattress in their living room to help cover the rent. Airbnb is an American company that operates an online marketplace and hospitality service for people to lease or rent short-term lodging including holiday cottages, apartments, homestays, hostel beds, or hotel rooms, to participate in or facilitate experiences related to tourism such as walking tours, and to make reservations at restaurants. The company does not own any real estate or conduct tours; it is a broker which receives percentage service fees in conjunction with every booking. Like all hospitality services, Airbnb is an example of collaborative consumption and sharing. The company has over 4 million lodging listings in 65,000 cities and 191 countries and has facilitated over 260 million check-ins.

2. The data set

The data set is collected from kaggle.com. Since 2008, guests and hosts have used Airbnb to expand on traveling possibilities and present a more unique, personalized way of experiencing the world. This dataset describes the listing activity and metrics in NYC, NY for 2019. This data file includes all needed information to find out more about hosts, geographical availability, and necessary metrics to make predictions and draw conclusions.

Features of the Dataset:

1. **id:** The id assigned to each airbnb to identify them uniquely.
2. **name:** The name assigned to each airbnb.
3. **host_id:** The id assigned to each host to identify them uniquely.
4. **host_name:** The name assigned to each host.
5. **neighbourhood_group:** The 5 boroughs that New York City is divided into: Manhattan, Queens, Brooklyn, Staten Island and Bronx.
6. **neighbourhood:** The neighborhood where the airbnb is located within the boroughs.
7. **latitude:** The latitude of the location where the airbnb is situated.
8. **longitude:** The longitude of the location where the airbnb is situated.
9. **room_type:** The type of airbnb which is divided into two: Entire home/Apartment, Private room and Shared Room.
10. **price:** The rent of the airbnb per night.
11. **minimum_nights:** The minimum number of nights the airbnb can be rented for.
12. **number_of_reviews:** Total number of reviews posted by customers.
13. **last_review:** Date of the last review posted by a customer.
14. **reviews_per_month:** Monthly total of reviews posted by customers.
15. **calculated_host_listings_count:** Number of total listings by a host.
16. **availability_365:** Yearly number of days the airbnb is available for rent.

3. Visualizing the data of Airbnb data sets

3.1 Basic statistics of the dataset: In this portion we load the data set and see some basic statistics of different features.

3.1.1 Data load in Pandas: At first we load the data from csv file to pandas data-frame.

```
# load dataset
df = pd.read_csv('../data/AB_NYC_2019.csv')
```

Figure 01- data loading

3.1.2 Observe the data type: In this section we analyze the data type of different features.

```
# see the data types of each columns
print(df.dtypes)
```

```
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
```

Figure 02- get the data type for each columns

3.1.3 Statistical Analysis of Numerical Data: Here, we have analyzed the statistical properties (count, mean, standard deviation, min, max, and percentile) of the numeric data.

```
print(df.describe())
```

```
                 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
```

Figure 03- Analysis Numeric features

3.1.4 Categorical Feature Analysis: After observing the numeric data, in this portion, we analyzed the categorical features. We have total 3 categorical features in our data set. These are neighbourhood_group, neighborhood, and room_type.

3.1.4.1 Neighbourhood_group: Here, we have found a total of five unique neighborhood groups. These are 'Brooklyn', 'Manhattan', 'Queens', 'Staten Island', and 'Bronx'.

```
ngh_group = list(df['neighbourhood_group'].unique())
print(f'Total unique neighbourhood group: {len(ngh_group)}')
print(f'Neighbourhoods group are: {ngh_group}')
```

```
Total unique neighbourhood group: 5
Neighbourhoods group are: ['Brooklyn', 'Manhattan', 'Queens', 'Staten Island', 'Bronx']
```

Figure 04- Analysis Categorical features (neighbourhood_group)

3.1.4.2 Neighbourhood: There are total 221 neighborhood are listing in this datasets. We get top 10 neighborhood based on the counts of arbnb.

```
neighbourhood = list(df['neighbourhood'].unique())
print(f'Total unique neighbourhood: {len(neighbourhood)}')

mpn_list = list((df.neighbourhood.value_counts().head(10)).index)

print(mpn_list)
```

```
Total unique neighbourhood: 221
['Williamsburg', 'Bedford-Stuyvesant', 'Harlem', 'Bushwick', 'Upper West Side', "Hell's Kitchen", 'East Village', 'Upper East S
ide', 'Crown Heights', 'Midtown']
```

Figure 05- Analysis Categorical features (neighborhood)

3.1.4.3 room_type: Based on the data set, we counted three types of arbnb in NYC. These are 'Private room', 'Entire home / apt' and 'Shared room'.

```
room_type = list(df['room_type'].unique())
print(f'Total unique room type: {len(room_type)}')
print(f'Room types are: {room_type}')
```

```
Total unique room type: 3
Room types are: ['Private room', 'Entire home/apt', 'Shared room']
```

Figure 06- Analysis Categorical features (room type)

3.1.5 Null Value Analysis: At this stage, we have counted exactly how many null values are in each column. At the end of the count, we see that the highest number of null values are in the review-related features. There are ten thousand and fifty-two (10052) null values in each of this feature. These features have the highest number of null values as customers do not give reviews.

```
# null value count
print(df.isnull().sum())
```

```
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
```

Figure 07- Null value analysis

3.2 Univariate analysis: In this portion analyze the univariate features. For these type of analysis, at first we get the numbers and plot them in different figures.

3.2.1 Count neighborhood group: We calculated the number of arbnb in each group. After getting the count we plot the data into a bar-plot.

```
nh_group = df.groupby(['neighbourhood_group'])['neighbourhood_group'].count().reset_index(name='counts')

groups = list(nh_group.neighbourhood_group)
counts = list(nh_group.counts)

nh_group
```

	neighbourhood_group	counts
0	Bronx	1091
1	Brooklyn	20104
2	Manhattan	21661
3	Queens	5666
4	Staten Island	373

```
def addlabels(x, y, z):
    for i in range(len(x)):
        plt.text(i, y[i], z[i], ha = 'center')

ax = nh_group.plot.bar(x='neighbourhood_group', y='counts', rot=0, \
                       title='Counts of Airbnb in different neighbourhood group')

cnt_percentage = [f'{str(round(d*100/sum(counts),1))}%' for d in counts]
addlabels(groups, counts, cnt_percentage)

plt.savefig('../report/fig/plot_1.png',  bbox_inches='tight')
plt.show()
```

Figure 08- Code and output of neighborhood group data

Analysis: In the bar chart, we can clearly see that Manhattan has the highest number of Airbnb with the percentage of 44.3%. Staten Island has the lowest number of Airbnb, and the count is only 373 (0.6%). The Bronx has about 2.2% of Airbnb which is 2nd lowest in NYC. And lastly, 41.1% and 11.6% of Airbnb are situated Brooklyn and Queens respectively.

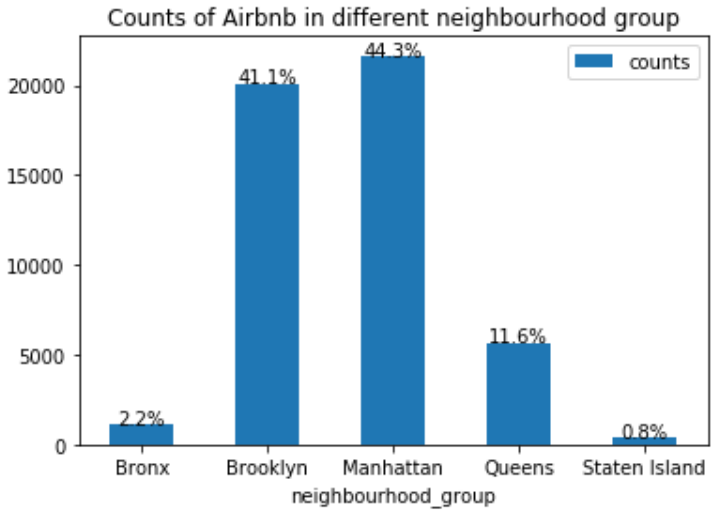


Figure 09- Analysis of the number of Airbnb within different neighborhood group

3.2.2 Count Airbnb in for neighborhood: Here, we get the number of Airbnb in each group and try to visualize the data on a bar-plot. As there are more than 200 neighborhood present in the data set, we picked top 10 of them.

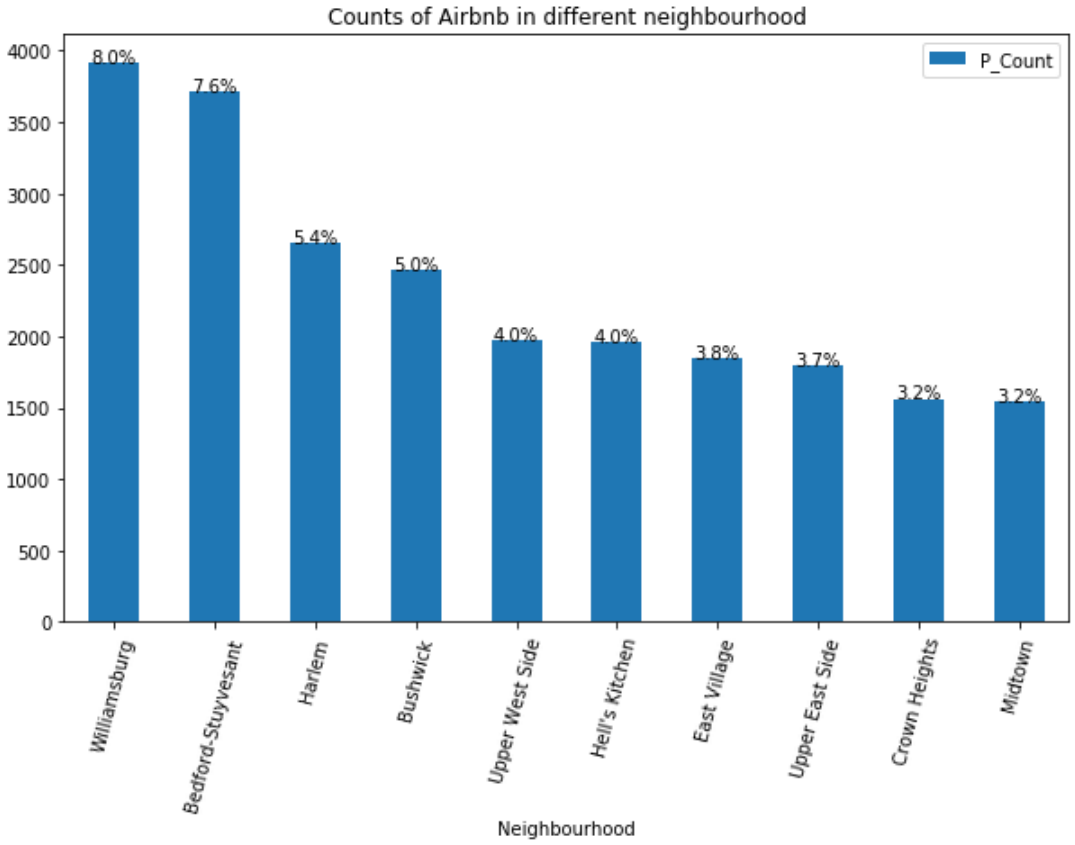
```
mpn_df = pd.DataFrame(df.neighbourhood.value_counts())
mpn_df.reset_index(inplace=True)

mpn_df.rename(columns={'index':'Neighbourhood', 'neighbourhood':'P_Count'}, inplace=True)
mpn_df.head(10)
```

	Neighbourhood	P_Count
0	Williamsburg	3920
1	Bedford-Stuyvesant	3714
2	Harlem	2658
3	Bushwick	2465
4	Upper West Side	1971
5	Hell's Kitchen	1958
6	East Village	1853
7	Upper East Side	1798
8	Crown Heights	1564
9	Midtown	1545

```
def addlabels(x, y, z):
    for i in range(len(x)):
        plt.text(i, y[i], z[i], ha = 'center')


groups = list(mpn_df.head(10).Neighbourhood)
counts = list(mpn_df.head(10).P_Count)
print(f'Total number of percentage for top 10 neighborhood is: \
     {round((sum(counts) * 100 / sum(list(mpn_df.P_Count))),2)}')

ax = mpn_df.head(10).plot.bar(x='Neighbourhood', y='P_Count', rot=75, \
                title='Counts of Airbnb in different neighbourhood', figsize=(10,6))

ax.set_xticklabels(groups, fontsize = 10)

cnt_percentage = [f'{str(round(d*100/sum(list(mpn_df.P_Count)),1))}%' for d in counts]
addlabels(groups, counts, cnt_percentage)

plt.savefig('../report/fig/plot_2.png',  bbox_inches='tight')
plt.show()
```

```
Total number of percentage for top 10 neighborhood is:      47.95
```

Figure 10- Code and output of neighborhood data with the count



Analysis: In this figure we have top 10 (based on apartment count) neighborhood in NYC. From the figure it is clear that, Williamsburg, and Bedford-Stuyvesant has the maximum number of arbnb which is 8.0% and 7.6% respectively. Rest of the neighborhood have around 5% or less apartments. And more interestingly almost half (47.95%) of the arbnb are situated on these 10 neighborhood.

Figure 11- Plot and interpreted information based on neighborhood

3.2.3 Count of Apartment type: As there are only three types of arbnb is the dataset. So we fetched the count of each group and plot them in a pie-chart.

```
arbnb_type = df.groupby(['room_type'])['room_type'].count().reset_index(name='counts')
types = list(arbnb_type.room_type)
counts = list(arbnb_type.counts)

arbnb_type
```

	room_type	counts
0	Entire home/apt	25409
1	Private room	22326
2	Shared room	1160

```
explode = (0.05, 0.05, 0.1)

fig1, ax1 = plt.subplots()
ax1.pie(counts, explode=explode, labels=types, autopct='%1.1f%%', shadow=True, \
        colors=['#FEAE65', '#7CDDDD', '#AADEA7'])
ax1.axis('equal')

plt.title('Percentage of Different \ntypes of Airbnb\n')
plt.savefig('../report/fig/plot_3.png',  bbox_inches='tight')

plt.show()
```

Figure 12- Implementation of Airbnb type with counts

Analysis: The pie chart shows that the number of "entire homes/apartments" is higher than the other two types, and the percentage is about 52.0%. The number of "shared room" has minimum counts with 2.4% of apartments. The "private room" type airbnb has 45.7% of the apartments.

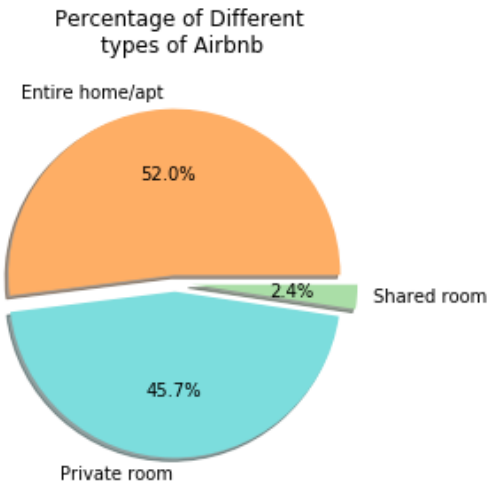


Figure 13- Pie-chart of apartment type

3.2.4 Counts of minimum night stay feature: To analyze this figure we used a box-plot. And implementation, graph, and interpretations are given bellow:

```
mn_df = df.minimum_nights.fillna(0)

print(f'Minimum: {mn_df.min()} and Maximum: {mn_df.max()}')

plt.boxplot(mn_df, vert=False)
plt.title('Minimum night stay in Airbnb dataset')
plt.savefig('../report/fig/plot_4.png',  bbox_inches='tight')
plt.show()
```

```
Minimum: 1 and Maximum: 1250
```

Analysis: The minimum and maximum night's stay in the dataset are 1 and 1250 respectively. The numbers between 1-100 are more densely populated in the graph, which means a huge percentage of the apartment has a minimum night stay value in this range. There also have some values from 100-300 (approximately). The rest of the numbers are some sort of outliers.

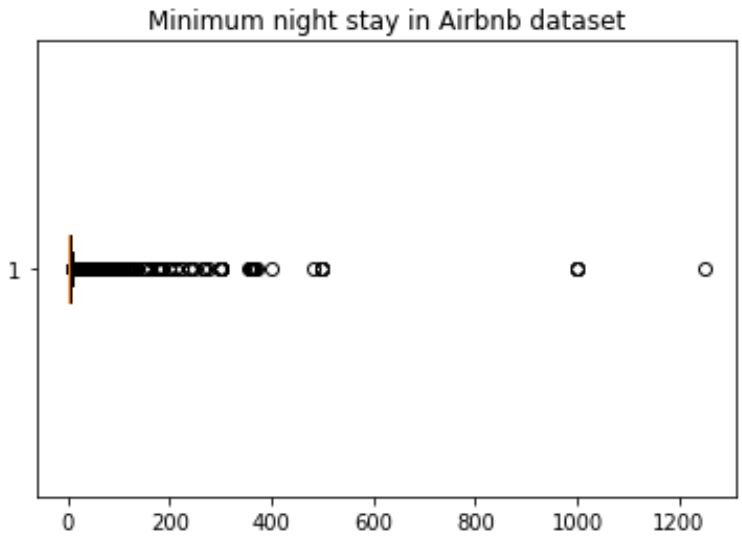


Figure 14- Analysis of minimum night stay feature

3.2.5 Analyze the calculated host listing feature: This feature represents the number of apartments listed by a host. We fetched the data and created a box plot of this feature.

```
chl_df = df.calculated_host_listings_count.fillna(0)
plt.boxplot(chl_df, vert=False)
plt.title('Host listing count of Airbnb data')

print(f'Minimum: {chl_df.min()} and Maximum: {chl_df.max()}')

plt.savefig('../report/fig/plot_5.png',  bbox_inches='tight')
plt.show()
```

```
Minimum: 1 and Maximum: 327
```

Analysis: According to the figure, we can see that a single host listed 327 apartments, which is pretty high compared with other hosts. Most of the hosts listed 1-50 apartments as the graph has much dense population is this section.

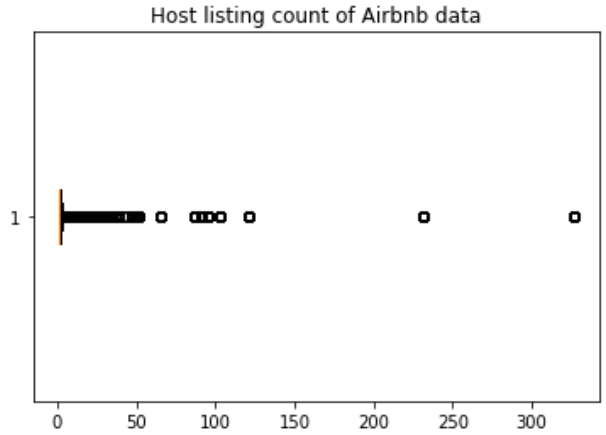


Figure 15- Analysis of host listing in the data set

3.2.6 Get top most listed host: In this part, we have calculated which hosts have been listed with the most apartments. And we've listed the top ten hosts (host IDs) that have been rented more frequently.

```
# get top-most host
top_host = df.host_id.value_counts().head(10)

top_host_df = pd.DataFrame(top_host)
top_host_df.reset_index(inplace=True)
top_host_df.rename(columns={'index':'Host_ID', 'host_id':'P_Count'}, inplace=True)
top_host_df
```

	Host_ID	P_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

```
top_host_plot=sns.barplot(x="Host_ID", y="P_Count", data=top_host_df, palette='Blues_d')
top_host_plot.set_title('Hosts with the most listings Airbnb in NYC')
top_host_plot.set_ylabel('Count of listings')
top_host_plot.set_xlabel('Host IDs')
top_host_plot.set_xticklabels(top_host_plot.get_xticklabels(), rotation=45)

plt.savefig('../report/fig/plot_6.png',  bbox_inches='tight')
plt.show()
```

Figure 16- Code implementation of most top host

Analysis: Looking at the drawn bar chart, it can be seen that this host id 219517861 has been used the most, that is, more than 300 times. Host 7503643 has been used a little more than about fifty times, and this host has been used the least number of times in the top 10 hosts.

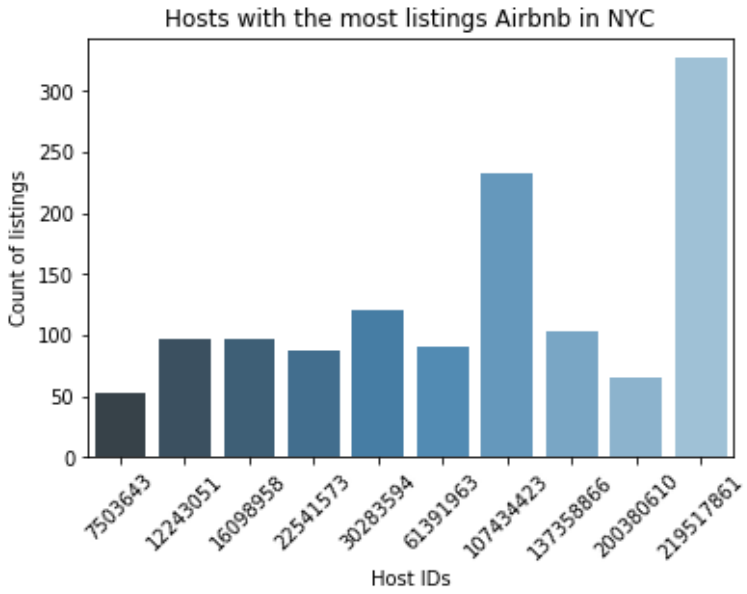


Figure 17- Bar chat and insight of host id feature

3.2.7 Analysis of the 'number of reviews' feature: To analyze this column, we fill all the empty cells with zero. Then we plot all the data into a box plot.

```
review_df = df.number_of_reviews.fillna(0)
plt.boxplot(review_df, vert=False)
plt.title('Number of review in the Airbnb dataset')

print(f'Minimum: {review_df.min()} and Maximum: {review_df.max()}')

plt.savefig('../report/fig/plot_7.png',  bbox_inches='tight')
plt.show()
```

```
Minimum: 0 and Maximum: 629
```

Analysis: It is clear from the figure that the most number of reviews of the dataset is distributed into 100-400. Also, some apartments have more than 400 reviews.

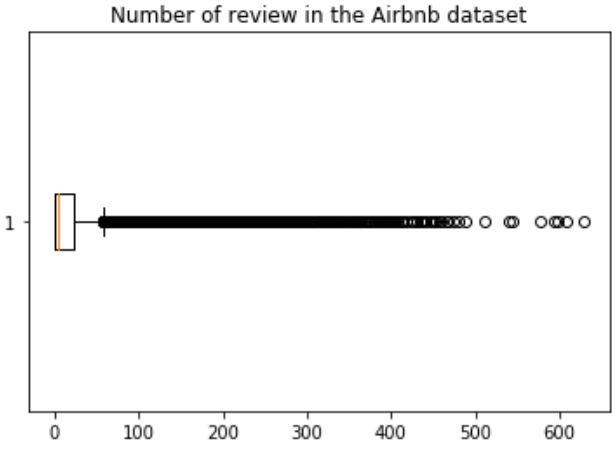


Figure 18- Implementation and box-plot of 'number of reviews'

3.2.8 **Analysis the price of Airbnb:** To analyze the price, we draw two different type plot i.e. the box-plot and scatter plot.

```
df.price.plot(kind='box', vert=False, figsize=(8,5))

plt.title('Boxplot of the price of Airbnb')
plt.xticks(list(range(0, int(max(df.price)*1.1), 1000)))

plt.savefig('../report/fig/plot_8.png',  bbox_inches='tight')
plt.show()
```

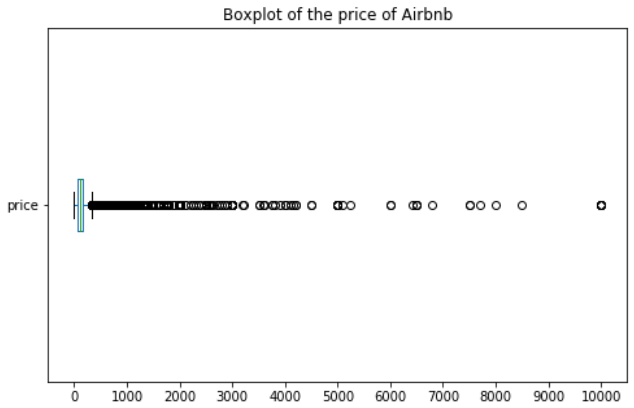


Fig:- Box-plot

```
plt.scatter(df.price.index, df.price)
plt.title('Scatter plot of the price of Airbnb')
plt.xlabel('index of Airbnb')
plt.ylabel('price')
plt.yticks(list(range(0, int(max(df.price)*1.1), 1000)))

plt.savefig('../report/fig/plot_9.png',  bbox_inches='tight')
plt.show()
```

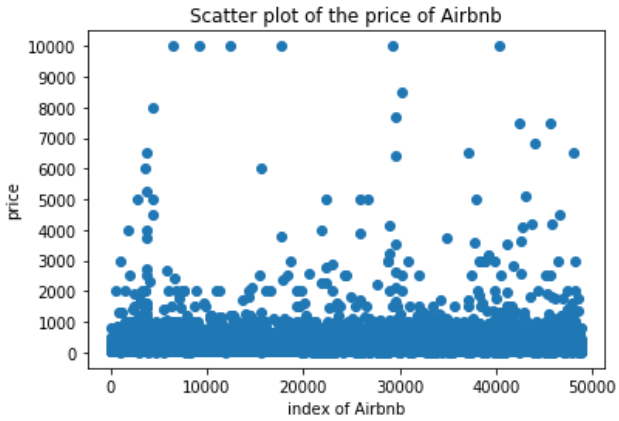


Fig:- Scatter plot

Analysis: To analyze the box-plot and scatter-plot we can decide that, most of rent of the apartment are in between 100-1000. Also there are some costly apartment are visible in the graph.

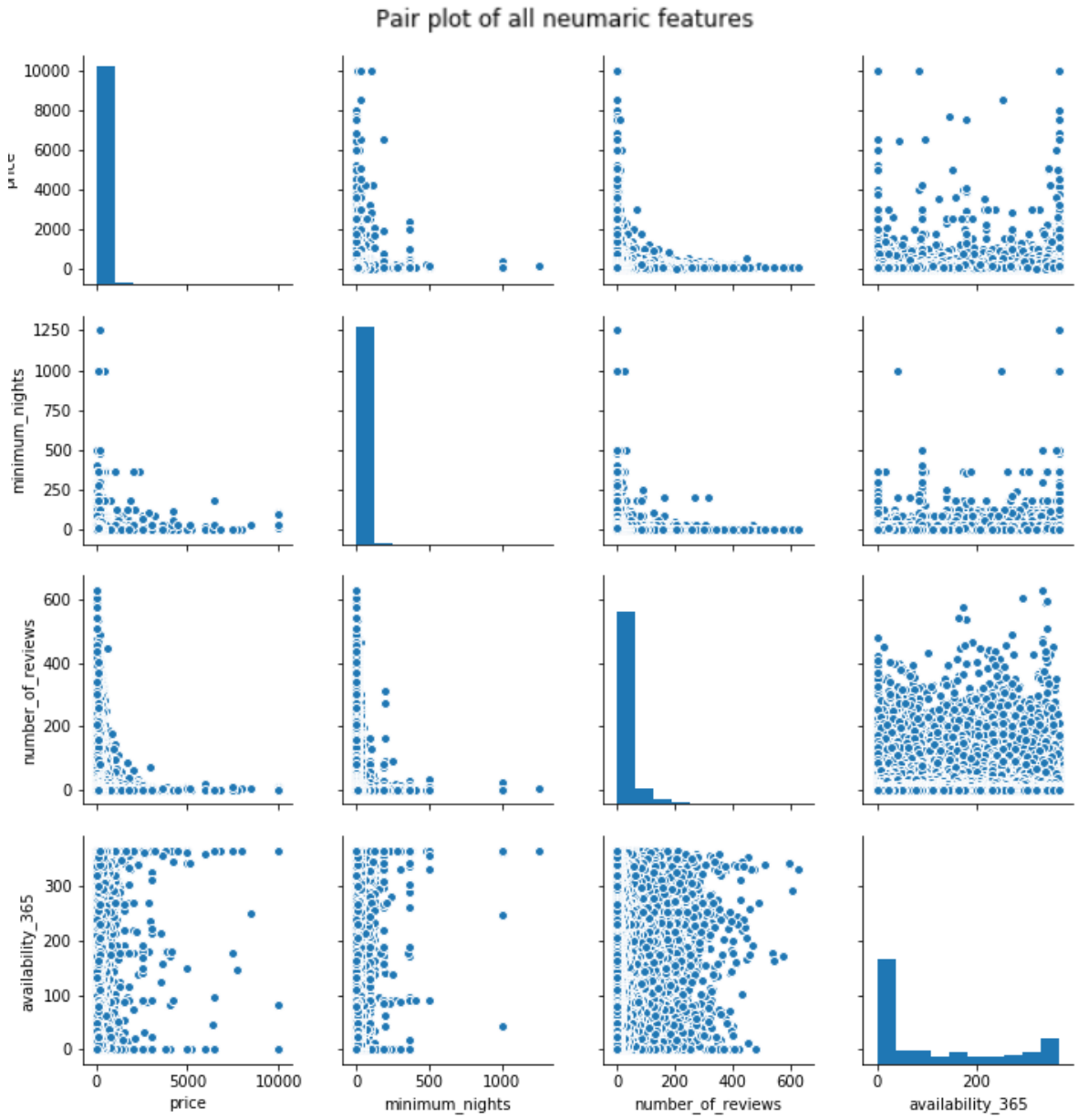
Figure 19- Analysis price data from arbnb dataset

3.3 Bibariate analysis: In this portion we do bivariate features analysis.

3.3.1 **Drawing Pair plot:** To analyze the numeric features we make a new dataframe. Then we plot the data into a pair plot.

```
p_plot = sns.pairplot(cor_df, kind='scatter', )
p_plot.fig.suptitle('Pair plot of all neumaric features', y=1.05)
plt.savefig('../report/fig/plot_10.png')
plt.show()
```

Figure 20- Implementation of pair plot



Analysis: From the above graph, we can see a correlation plot of the numerical variables of our data set. A Correlation Plot represents the strength of linear relation among the numerical variables. We assumed at least some linear relation between the numerical variables initially (At least the price and the popularity of the housing). Here, the number_of_reviews variable is our way to understand the popularity of an arbnb. However, we don't see any significant relationship. So, we can say that the price of the housings is not linearly dependent on any other variable of our dataset and there is no significant linear relationship among the numerical features of our data set.

Figure 21- Pair plot and its interpretations

3.3.2 **Correlation matrix of the numeric data:** In these section we calculate the correlation matrix and also draw them in a heat-map.

```
corr_matrix = cor_df.corr()
corr_matrix
```

	price	minimum_nights	number_of_reviews	availability_365
price	1.000000	0.042799	-0.047954	0.081829
minimum_nights	0.042799	1.000000	-0.080116	0.144303
number_of_reviews	-0.047954	-0.080116	1.000000	0.172028
availability_365	0.081829	0.144303	0.172028	1.000000

```
corr_hm = sns.heatmap(corr_matrix, annot = True)

corr_hm.set(xlabel = 'Airbnb NYC features', ylabel = 'Airbnb NYC features', \
            title = "Correlation matrix of Airbnb dataset\n")

corr_hm.set_xticklabels(corr_matrix.index, rotation=45)
plt.savefig('../report/fig/plot_11.png',  bbox_inches='tight')
plt.show()
```

Figure 22- Implementation of correlation matrix

Analysis: As per the value from the matrix and figure we clearly see the correlation between each figure is very small. The highest positive correlation is 0.17 which is between number of reviews and availability_365. And the maximum negative correlation between two features is -0.08 (minimum night and number of reviews).

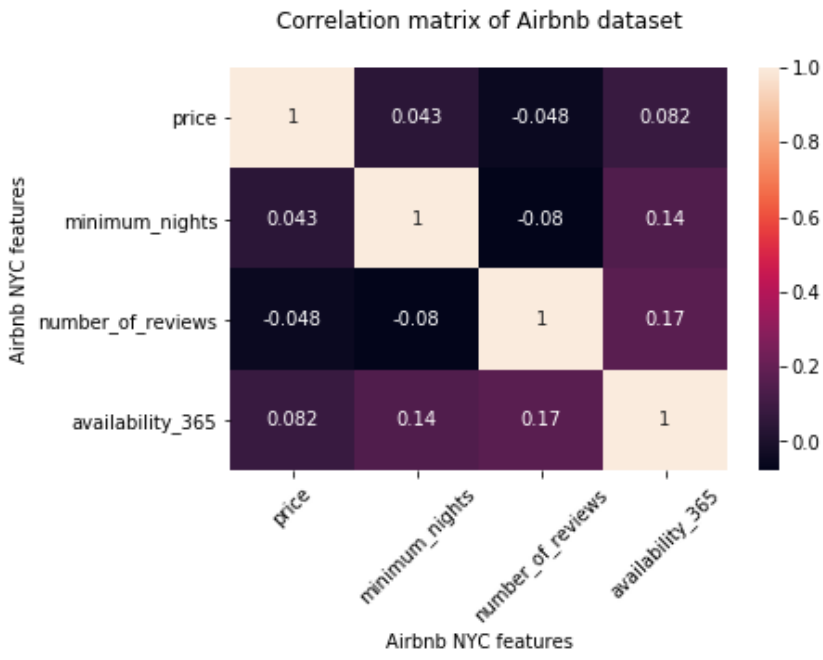


Figure 23- Heat map of correlation matrix

3.3.3 Price VS Neighborhood group: In this portion, we have calculated the mean and median prices for each neighborhood group in NYC. We converted this stat into a bar chart.

```
nhg_df = df[['neighbourhood_group', 'price']]
nhg_mean = nhg_df.groupby('neighbourhood_group').mean()
nhg_median = nhg_df.groupby('neighbourhood_group').median()

nhg_mean.rename(columns={'price':'Mean Price'}, inplace=True)
nhg_median.rename(columns={'price':'Median Price'}, inplace=True)

nhg_mean_meadian = nhg_mean.join(nhg_median)
nhg_mean_meadian.insert(loc=0, column='Neighbour Group', value=list(nhg_mean_meadian.index))
nhg_mean_meadian.reset_index(inplace=True, drop='index')
```

```
labels = list(nhg_mean_meadian['Neighbour Group'])

_means = list(nhg_mean_meadian['Mean Price'])
_medians = list(nhg_mean_meadian['Median Price'])

width = 0.35

fig, ax = plt.subplots(figsize=(10,6))

x = np.arange(len(nhg_mean_meadian))

ax.set_ylabel('Airbnb price (per night)',  fontsize = 12)
ax.set_title('Airbnb price with Neighbor group', fontsize = 16)
ax.set_xlabel('Neighbor group', fontsize = 12)

ax.set_xticks(np.arange(len(labels)))
ax.set_xticklabels(labels, rotation = 0, fontsize = 11)

rects1 = ax.bar(x - width/2, _means, width, label='Mean')
rects2 = ax.bar(x + width/2, _medians, width, label='Median')

ax.legend(bbox_to_anchor=(1, 1),fancybox=True, shadow=True, ncol=1)

def addlabels(x, m, w):
    for i in range(len(x)):
        plt.text(i, m[i], f'{str(round(m[i], 1))}', ha = 'right', fontsize = 10)
        plt.text(i, w[i], f'{str(round(w[i], 1))}', ha = 'left', fontsize = 10)

addlabels(labels, _means, _medians)

plt.show()
```

Figure 24- Implementation of the relationship between price and neighborhood group

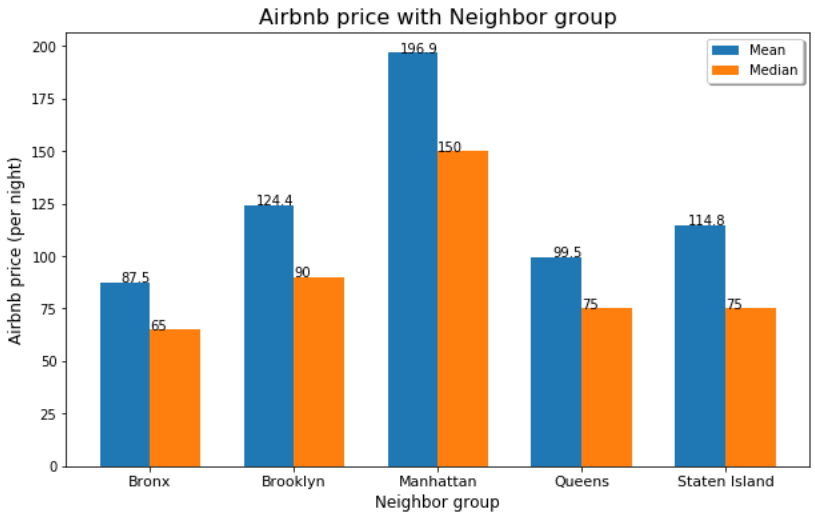


Figure 25- Bar plot of the relationship between price and neighborhood group

Analysis: The bar chart shows that both the mean and median prices of the Manhattan group's Airbnb are higher than the other groups. The mean price of this group is around 200, and the median price is approximately 150. The lowest cost Airbnb is available in the Bronx. The other three groups that have Airbnbs have an almost similar price.

3.3.4 Price VS Neighborhood: At this stage, out of 221 neighborhoods, we have listed the top ten neighborhoods in terms of mean and median prices. This means we have listed the first ten neighborhoods for the mean price and the first ten neighborhoods for the median price.

```
# most costly neighbourhood

nh_df = df[['neighbourhood', 'price']]
nh_mean = nh_df.groupby('neighbourhood').mean()
nh_median = nh_df.groupby('neighbourhood').median()

nh_mean.rename(columns={'price':'Mean Price'}, inplace=True)
nh_median.rename(columns={'price':'Median Price'}, inplace=True)

nh_mean_meadian = nh_mean.join(nh_median)
nh_mean_meadian.insert(loc=0, column='Neighbour', value=list(nh_mean_meadian.index))
nh_mean_meadian.reset_index(inplace=True, drop='index')

mcn_df1 = nh_mean_meadian[['Neighbour', 'Mean Price']].nlargest(10, 'Mean Price')
mcn_df2 = nh_mean_meadian[['Neighbour', 'Median Price']].nlargest(10, 'Median Price')

nh_mean_meadian.head()
```

	Neighbour	Mean Price	Median Price
0	Allerton	87.595238	66.5
1	Arden Heights	67.250000	72.5
2	Arrochar	115.000000	65.0
3	Arverne	171.779221	125.0
4	Astoria	117.187778	85.0

```
def addlabels(x, y):
    for i in range(len(x)):
        plt.text(i, y[i], f'{str(round(y[i],1))}', ha = 'center', fontsize=10)

ax = mcn_df1.plot.bar(x='Neighbour', y='Mean Price', rot=90, title='Neighbourhood mean price in NYC')

ax.set_xlabel('Neighbour', fontsize=12)
ax.set_ylabel('Mean price')

addlabels(list(mcn_df1['Neighbour']), list(mcn_df1['Mean Price']))

plt.show()
```

```
def addlabels(x, y):
    for i in range(len(x)):
        plt.text(i, y[i], f'{str(round(y[i],1))}', ha = 'center', fontsize=10)

ax = mcn_df2.plot.bar(x='Neighbour', y='Median Price', rot=90, title='Neighbourhood median price in NYC')

ax.set_xlabel('Neighbour', fontsize=12)
ax.set_ylabel('Median price')

addlabels(list(mcn_df2['Neighbour']), list(mcn_df2['Median Price']))

plt.show()
```

Figure 26- Implementing the relationship between price and neighborhood

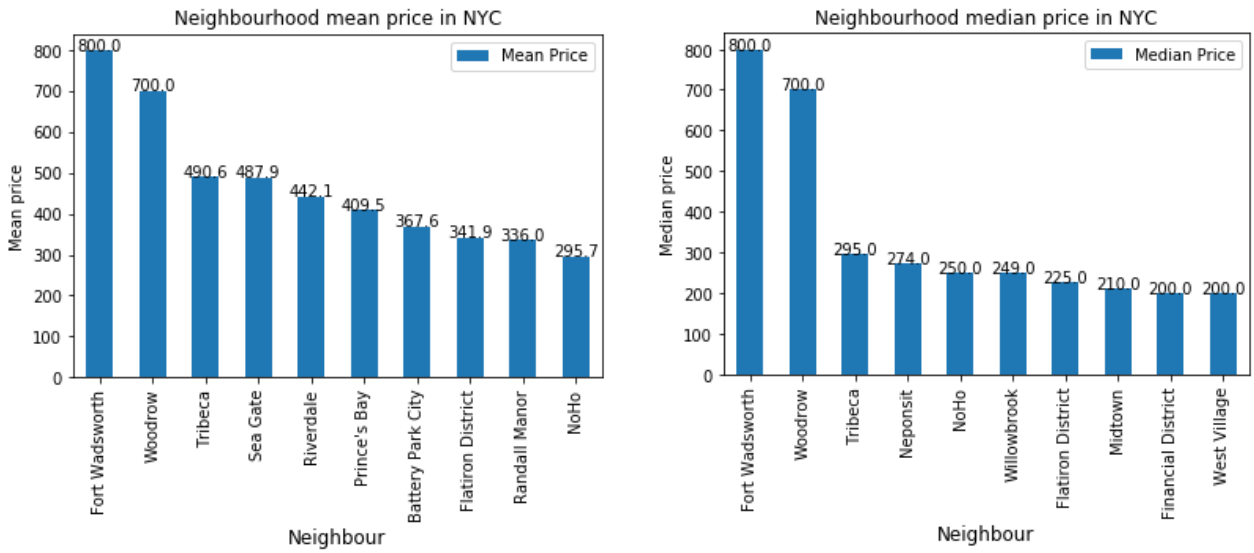


Figure 27- Plotting the relationship between price and neighborhood

Analysis: For this figure, it is clear that if we consider mean and median price as our price estimator, we can get different set of neighborhoods. But both of the case most expensive neighborhood remain Fort Wadsworth.

3.3.5 Price VS Airbnb type: In this section, we have calculated the mean and median prices for all three types of Airbnb. Then, we plotted the stat using a bar chart.

```
apt_df = df[['room_type', 'price']]
apt_mean = apt_df.groupby('room_type').mean()
apt_median = apt_df.groupby('room_type').median()

apt_mean.rename(columns={'price':'Mean Price'}, inplace=True)
apt_median.rename(columns={'price':'Median Price'}, inplace=True)

apt_mean_meadian = apt_mean.join(apt_median)
apt_mean_meadian.insert(loc=0, column='Room Type', value=list(apt_mean_meadian.index))
apt_mean_meadian.reset_index(inplace=True, drop='index')

apt_mean_meadian
```

	Room Type	Mean Price	Median Price
0	Entire home/apt	211.794246	160
1	Private room	89.780973	70
2	Shared room	70.127586	45

```
labels = list(apt_mean_meadian['Room Type'])

_means = list(apt_mean_meadian['Mean Price'])
_medians = list(apt_mean_meadian['Median Price'])

width = 0.35

fig, ax = plt.subplots(figsize=(10,6))

x = np.arange(len(apt_mean_meadian))

ax.set_ylabel('Airbnb price (per night)')
ax.set_title('Airbnb price with apartment type')

ax.set_xlabel('apartment type')

ax.set_xticks(np.arange(len(labels)))
ax.set_xticklabels(labels, rotation = 0)

rects1 = ax.bar(x - width/2, _means, width, label='Mean')
rects2 = ax.bar(x + width/2, _medians, width, label='Median', color='#f0bc85')

ax.legend(bbox_to_anchor=(1, 1),fancybox=True, shadow=True, ncol=1)

def addlabels(x, m, w):
    for i in range(len(x)):
        plt.text(i, m[i], f'{str(round(m[i], 1))}', ha = 'right', fontsize = 10)
        plt.text(i, w[i], f'{str(round(w[i], 1))}', ha = 'left', fontsize = 10)

addlabels(labels, _means, _medians)

plt.show()
```

Figure 28- Implementation of the relationship between price and Airbnb type

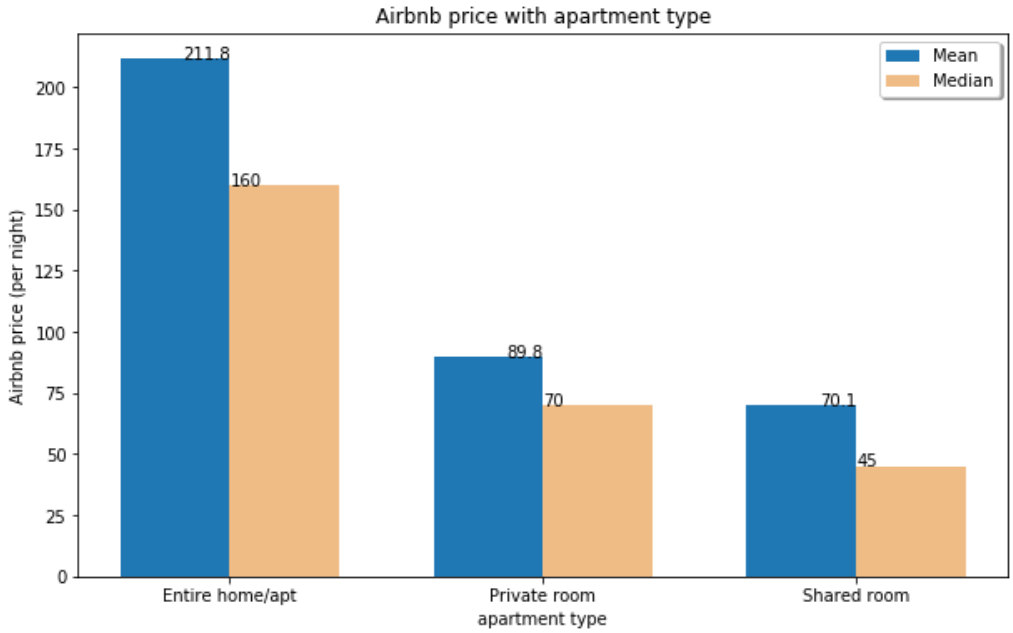


Figure 29- Plot of the relationship between price and Airbnb type

Analysis: The bar chart shows that both prices (mean and median) for the entire home/apartment type are the highest. The lowest price is the shared room. Though both types of parameters private-room are in the middle position, the values are much lower than the entire home/apartment.

3.3.6 Room type VS Neighborhood group: At this stage, we have counted how many Airbnb there are in each neighborhood group. Then, we plotted the data from the list in the form of graphs.

```
# neighbourhood_group vs apt.type

apt_nhg_df = df[['id', 'room_type', 'neighbourhood_group']]
apt_nhg_df = apt_nhg_df.groupby(['room_type','neighbourhood_group'], as_index=False)['id'].count()

apt_nhg_df.rename(columns={'id':'ID_Counts','neighbourhood_group': 'Neighbourhood_Group', \
                           'room_type': 'Room_Type' }, inplace=True)
apt_nhg_df
```

	Room_Type	Neighbourhood_Group	ID_Counts
0	Entire home/apt	Bronx	379
1	Entire home/apt	Brooklyn	9559
2	Entire home/apt	Manhattan	13199
3	Entire home/apt	Queens	2096
4	Entire home/apt	Staten Island	176
5	Private room	Bronx	652
6	Private room	Brooklyn	10132
7	Private room	Manhattan	7982
8	Private room	Queens	3372
9	Private room	Staten Island	188
10	Shared room	Bronx	60
11	Shared room	Brooklyn	413
12	Shared room	Manhattan	480
13	Shared room	Queens	198
14	Shared room	Staten Island	9

```
labels = list(apt_nhg_df['Neighbourhood_Group'].unique())

entire_home = list(apt_nhg_df['ID_Counts'][apt_nhg_df['Room_Type'] == 'Entire home/apt'])
private_apt = list(apt_nhg_df['ID_Counts'][apt_nhg_df['Room_Type'] == 'Private room'])
shared_apt = list(apt_nhg_df['ID_Counts'][apt_nhg_df['Room_Type'] == 'Shared room'])

width = 0.25

fig, ax = plt.subplots(figsize=(12,6))

ax.set_title('Neighborhood group wise counts of different types of Airnbs')

x = np.arange(len(labels))

ax.set_xticks(np.arange(len(labels)))
ax.set_xticklabels(labels, rotation = 0)

rects1 = ax.bar(x-width, entire_home, width, label='Entire Apt', color='#003f5c')
rects2 = ax.bar(x, private_apt, width, label='Private Apt', color='#f0bc85')
rects3 = ax.bar(x + width, shared_apt, width, label='Shared Apt', color='#75a67c')

ax.legend(bbox_to_anchor=(1, 1),fancybox=True, shadow=True, ncol=1)

def addlabels(x, e, p, s):
    for i in range(len(x)):
        plt.text(i+.25, s[i], f'{str(round(s[i], 1))}', ha = 'center', fontsize = 11)
        plt.text(i, p[i], f'{str(round(p[i], 1))}', ha = 'center', fontsize = 11)
        plt.text(i-.25, e[i], f'{str(round(e[i], 1))}', ha = 'center', fontsize = 11)


addlabels(labels, entire_home, private_apt, shared_apt)

plt.savefig('../report/fig/plot_15.png',  bbox_inches='tight')
plt.show()
```

Figure 30- Implementation of the relationship between neighborhood group and Airbnb type

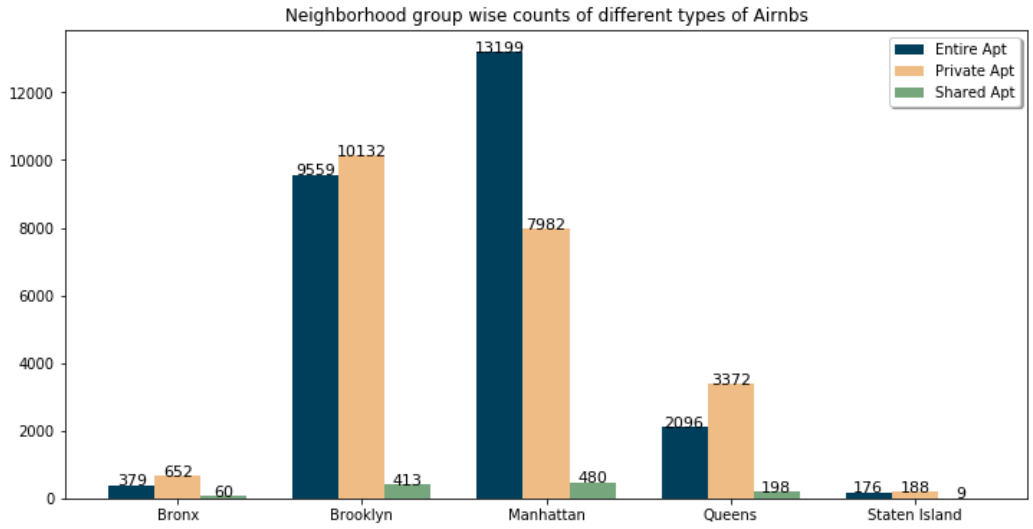


Figure 31- Bar plot of the relationship between neighborhood group and Airbnb type

Analysis: From the graph, we can get some assumption. Firstly, largest number of entire home/apt, and shared apartment are situated in Manhattan. Secondly, Brooklyn has maximum number of private apartment. Lastly, Staten Island has less Airbnb in all three types.

3.3.7 Get top reviewed host: In this portion, we find out the top 10 host with number of given review. At first we fetched top most host ids and then plot the data into a bar plot.

```
# get top-reviewd host
top_review_df = df[['host_id', 'number_of_reviews']].nlargest(10, 'number_of_reviews')

unique_host = set(list(top_review_df['host_id']))

top_review_df.reset_index(inplace=True, drop='index')
top_review_df.rename(columns={'host_id':'Host_ID', 'number_of_reviews':'R_Count'}, inplace=True)

top_review_df
```

	Host_ID	R_Count
0	47621202	629
1	4734398	607
2	4734398	597
3	4734398	594
4	47621202	576
5	37312959	543
6	2369681	540
7	26432133	510
8	12949460	488
9	792159	480

```
top_reviewed_host_plot = sns.barplot(x = top_review_df.index, y = "R_Count", \
                                     data = top_review_df, palette='Blues_d')

top_reviewed_host_plot.set_title('Hosts with the most reviewed Airbnb in NYC')
top_reviewed_host_plot.set_ylabel('Review of listings')
top_reviewed_host_plot.set_xlabel('Host IDs')
top_reviewed_host_plot.set_xticklabels(top_review_df.Host_ID, rotation=45)

plt.savefig('../report/fig/plot_16.png',  bbox_inches='tight')
plt.show()
```

Figure 32- Implementation of the relationship between host_id and review

Analysis: In this plot, it is clearly seen that the most popular host id is 47621202 with more than 600 reviews. First 8 of them has more than 500 reviews.

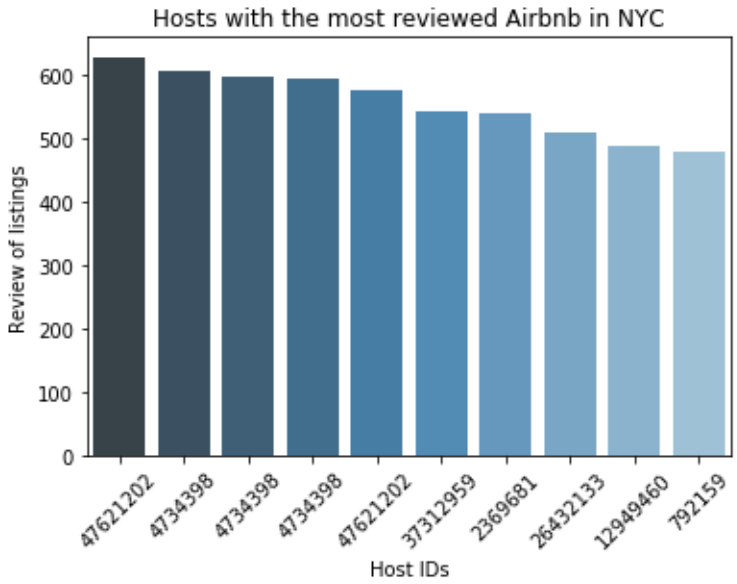


Figure 33- Plot of the relationship between host_id and review

4. Final Discussion

In this section we will summarize our finding according to the dataset and our analysis.

1. Almost all the data set is null free except two review related columns.
2. In NYC the Airbnb are situated on all 5 neighborhood group and 221 neighbor.
3. There is not linear relationship among the numeric feature of the dataset.
4. Renting entire apt/home is most popular type as more than 50% of the data situated on this category also it is most expensive one.
5. Least costly Airbnb type is shared room also it is least popular.
6. Most Expensive Airbnb(s) are situated in Manhattan and also become most popular among other group.

5. References

1. https://blog.datawrapper.de/beautifulcolors/
2. https://www.schemecolor.com/flat-orange-blue-green-pie-chart.php
3. https://writing.wisc.edu/handbook/assignments/planresearchpaper/
4. https://www.kaggle.com/datasets/dgomonov/new-york-city-airbnb-open-data