Project Name -

Project Type - Airbnb Booking Analysis EDA

Contribution - Individual

Project Summary -

Since 2008, guests and hosts have used Airbnb to expand on traveling possibilities and present a more unique, personalized way of experiencing the world. Today, Airbnb became one of a kind service that is used and recognized by the whole world. Data analysis on millions of listings provided through Airbnb is a crucial factor for the company. These millions of listings generate a lot of data - data that can be analyzed and used for security, business decisions, understanding of customers' and providers' (hosts) behavior and performance on the platform, guiding marketing initiatives, implementation of innovative additional services and much more.

This dataset has around 49,000 observations in it with 16 columns and it is a mix between categorical and numeric values. Explore and analyze the data to discover key understandings (not limited to these) such as :

What can we learn about different hosts and areas?

What can we learn from predictions? (ex: locations, prices, reviews, etc)

Which hosts are the busiest and why?

Is there any noticeable difference of traffic among different areas and what could be the reason for it?

GitHub Link -

https://github.com/arun-saraswat/Data_Analysis

Let's Begin !

1. Know Your Data

Import Libraries

```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Dataset Loading

```
# Load Dataset
from google.colab import drive
drive.mount('/content/drive')
#using pandas library and 'read_csv' to read Airbnb csv file
airbnb=pd.read_csv("/content/drive/MyDrive/Colab Notebooks/Airbnb NYC 2019.csv")
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Dataset First View

```
# Dataset First Look
airbnb.head()
```

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

Dataset Rows & Columns count

```
# Dataset Rows & Columns count
airbnb.shape
```

```
(48895, 16)
```

Dataset Information

```
# Dataset Info
airbnb.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
```

Duplicate Values

```
# Dataset Duplicate Value Count
airbnb.duplicated().sum()
```

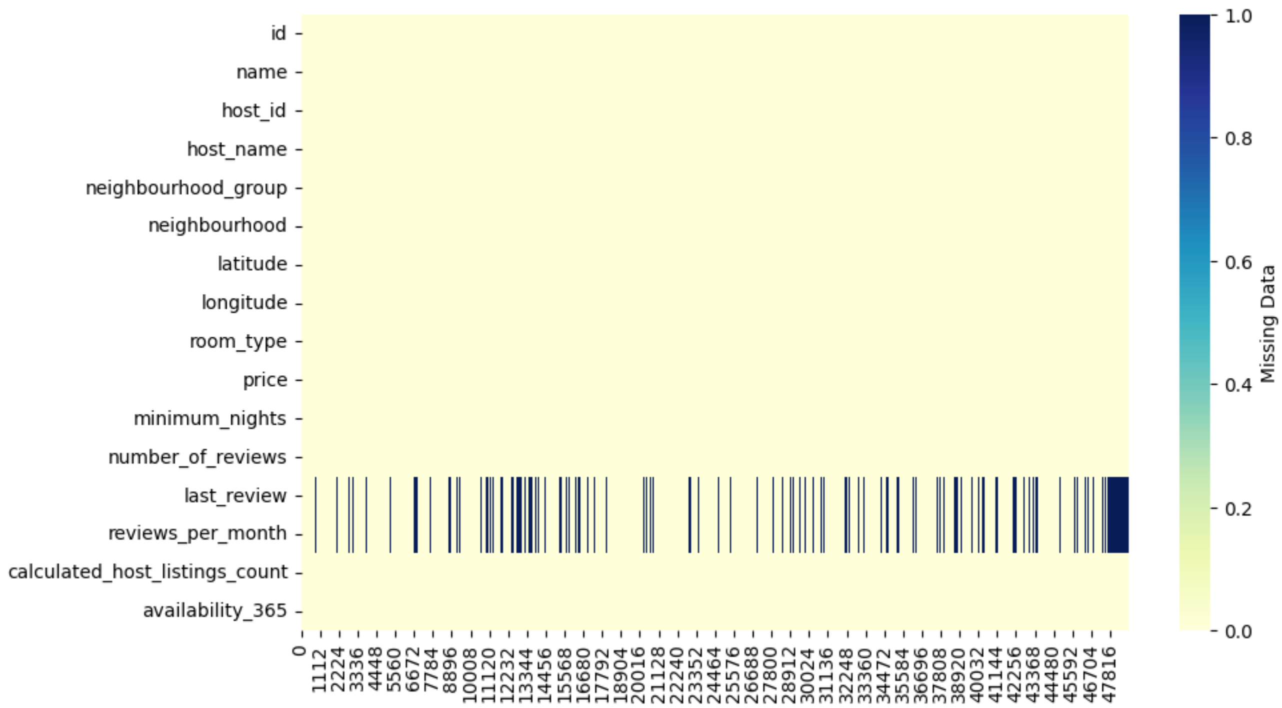
```
0
```

Missing Values/Null Values

```
# Missing Values/Null Values Count
airbnb.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
```

```
# Visualizing the missing values
# visualising using seaborn heatmap
plt.figure(figsize=(10,6))
sns.heatmap(airbnb.isnull().transpose(),
            cmap="YlGnBu",
            cbar_kws={'label': 'Missing Data'})
plt.show()
```



What did you know about your dataset?

This dataset has around 49,000 observations in it with 16 columns and it is a mix between categorical and numeric values.

2. Understanding Your Variables

```
# Dataset Columns
airbnb.columns
```

```
Index(['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
```

```
          'availability_365'],
         dtype='object')
```

```
# Dataset Describe
airbnb[['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365']].describe()
```

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

Check Unique Values for each variable.

```
# Check Unique Values for each variable.
unique_airbnb = pd.unique(airbnb[['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365']].values.ravel())
unique_airbnb
```

```
array([2539, 'Clean & quiet apt home by the park', 2787, ..., 36487245,
       "Trendy duplex in the very heart of Hell's Kitchen", 68119814],
      dtype=object)
```

3. ***Data Wrangling***

Data Wrangling Code

```
# Write your code to make your dataset analysis ready.

#replace the null values in reviews per month and last_review with zero
airbnb.reviews_per_month.fillna(0, inplace=True)
airbnb.last_review.fillna(0, inplace=True)

#after cleaning
airbnb.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                        0
reviews_per_month                  0
```

```
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

```
#last five rows
airbnb.tail()
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_n:
48890	36484665	Charming one bedroom - newly renovated rowhouse	8232441	Sabrina	Brooklyn	Bedford-Stuyvesant	40.67853	-73.94995	Private room	70	
48891	36485057	Affordable room in Bushwick/East Williamsburg	6570630	Marisol	Brooklyn	Bushwick	40.70184	-73.93317	Private room	40	
48892	36485431	Sunny Studio at Historical Neighborhood	23492952	Ilgar & Aysel	Manhattan	Harlem	40.81475	-73.94867	Entire home/apt	115	
48893	36485609	43rd St. Time Square-cozy single bed	30985759	Taz	Manhattan	Hell's Kitchen	40.75751	-73.99112	Shared room	55	
48894	36487245	Trendy duplex in the very heart of Hell's Kitchen	68119814	Christophe	Manhattan	Hell's Kitchen	40.76404	-73.98933	Private room	90	

```
#type of rooms in this data
number_of_room_type = airbnb['room_type'].unique()
number_of_room_type
```

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

```
#number of locations
number_of_place=airbnb["neighbourhood_group"].unique()
number_of_place
```

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

```
#total rooms by locations
total_room_by_location= airbnb.groupby(['neighbourhood_group', 'room_type']).size().reset_index(name="total_room")
print (total_room_by_location)
```

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

```
#location vise total availability
average_availability= airbnb.groupby(['neighbourhood_group'])['availability_365'].sum().reset_index()
average_availability
```

	neighbourhood_group	availability_365
0	Bronx	180843
1	Brooklyn	2015070
2	Manhattan	2425586

```
#locations with total reviews
location_reviews =airbnb.groupby(['neighbourhood_group'])['number_of_reviews'].sum().reset_index()
location_reviews
```

	neighbourhood_group	number_of_reviews
0	Bronx	28371
1	Brooklyn	486574
2	Manhattan	454569
3	Queens	156950
4	Staten Island	11541

```
#price preditions with the help of reviews
price_area = airbnb.groupby(['price'])['number_of_reviews'].max().reset_index()
price_reviews=price_area.head(5)
price_reviews
```

	price	number_of_reviews
0	0	95
1	10	93
2	11	113
3	12	8
4	13	9

```
#top five busiest hosts
busiest_hosts = airbnb.groupby(['host_name','host_id','room_type'])['number_of_reviews'].max().reset_index()
busiest_hosts = busiest_hosts.sort_values(by='number_of_reviews', ascending=False).head()
busiest_hosts
```

	host_name	host_id	room_type	number_of_reviews
10279	Dona	47621202	Private room	629
17708	Jj	4734398	Private room	607
25566	Maya	37312959	Private room	543
6235	Carol	2369681	Private room	540
8947	Danielle	26432133	Private room	510

```
#maximum bookings in hotelst type with locations
traffic_areas = airbnb.groupby(['neighbourhood_group','room_type'])['minimum_nights'].count().reset_index()
traffic_areas = traffic_areas.sort_values(by='minimum_nights', ascending=False)
traffic_areas
```

	neighbourhood_group	room_type	minimum_nights
6	Manhattan	Entire home/apt	13199
4	Brooklyn	Private room	10132
3	Brooklyn	Entire home/apt	9559
7	Manhattan	Private room	7982
10	Queens	Private room	3372
9	Queens	Entire home/apt	2096
0	Bronx	Entire home/apt	379
14	Staten Island	Shared room	9

What all manipulations have you done and insights you found?

Answer Here.

4. Data Vizualization, Storytelling & Experimenting with charts : Understand the relationships between variables

Chart - 1

```
# Chart - 1 visualization code
#total hotels chart
plt.figure(figsize=(10,6))
plt.title("total hotels on location",fontsize = 16)
sns.countplot(data=airbnb,x='neighbourhood_group')
plt.xlabel("neighbourhood_group",fontsize = 16)
plt.ylabel("count",fontsize = 16)
plt.show()
```

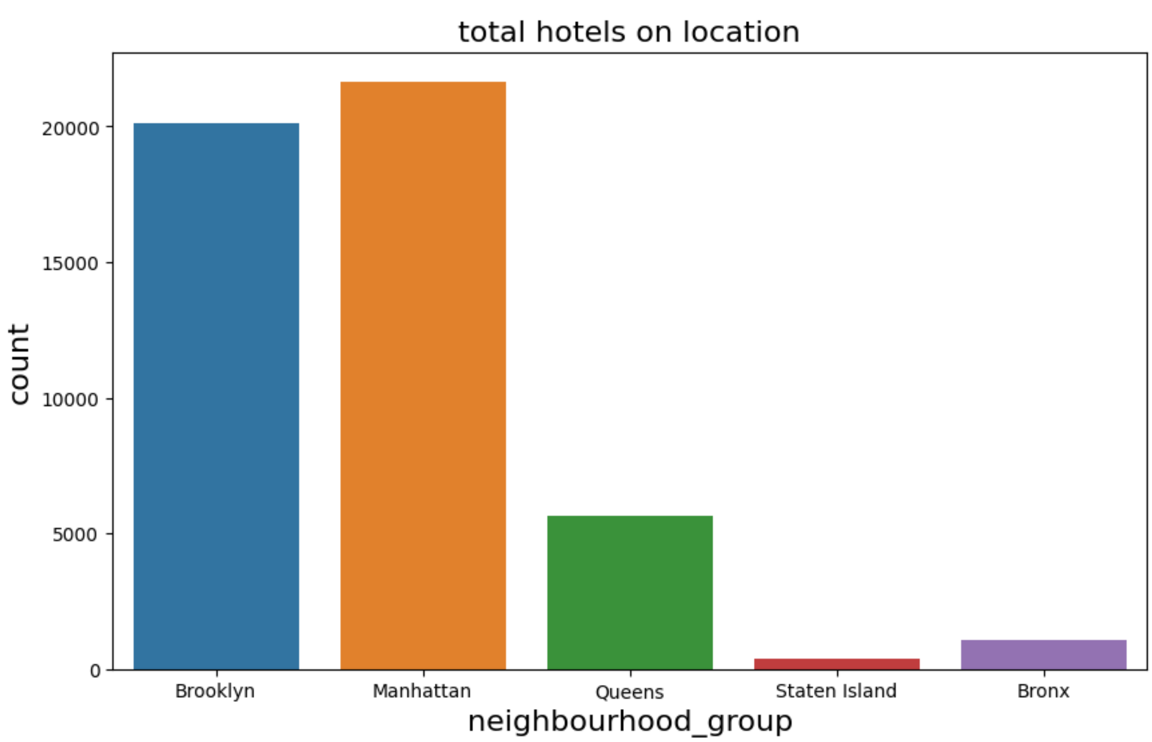
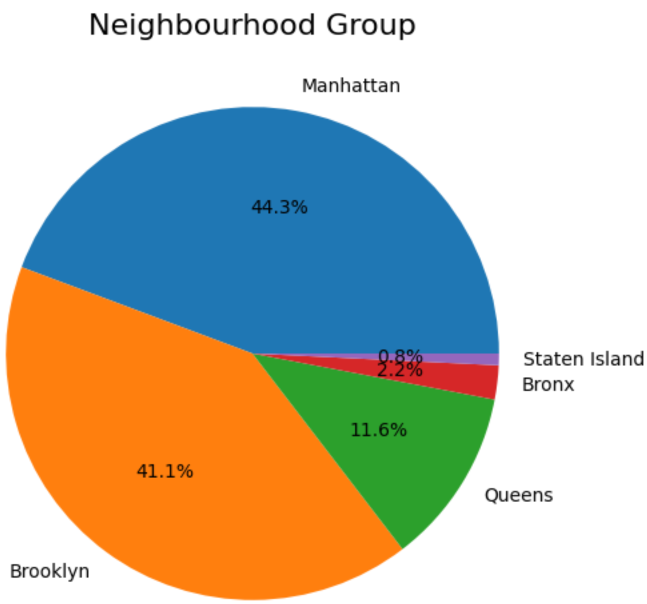


Chart - 2

```
# Chart - 2 visualization code
#hotel share per location
plt.figure(figsize=(10,6))
```

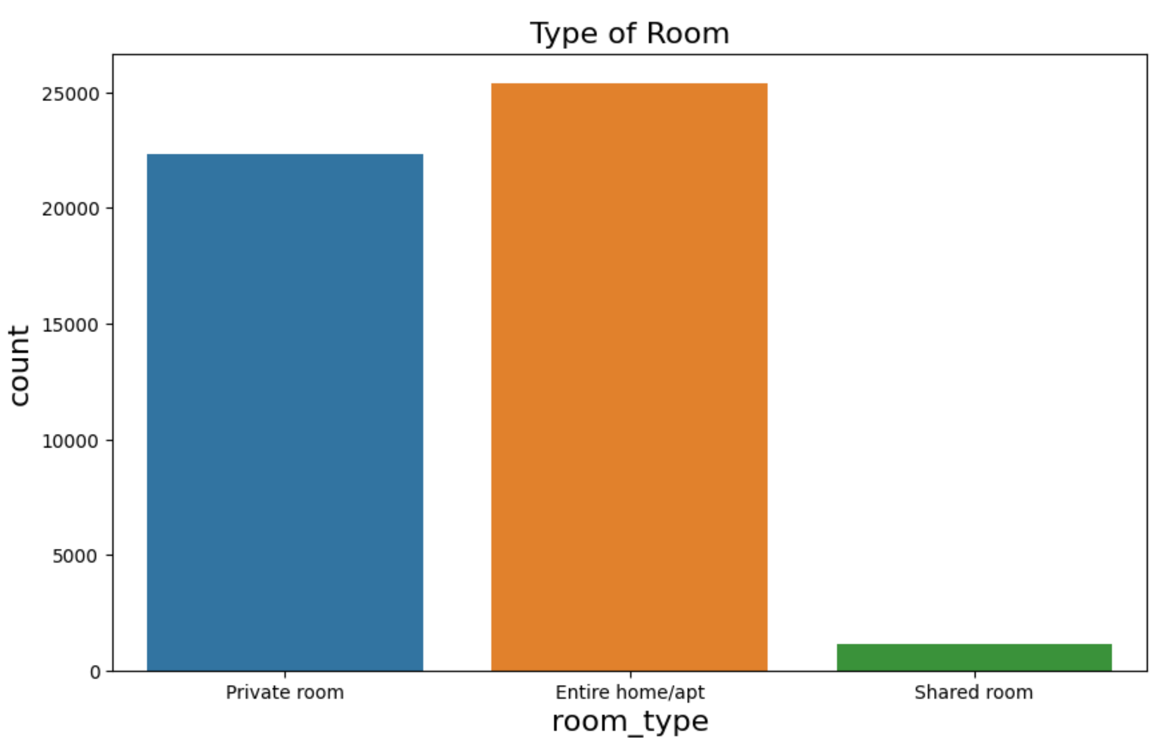
```
plt.title("Neighbourhood Group",fontsize = 16)
plt.pie(airbnb.neighbourhood_group.value_counts(), labels=airbnb.neighbourhood_group.value_counts().index,autopct='%1.1f%%')
plt.show()
```



The pie and bar chart above shows that Airbnb Listings in Manhattan, and Brooklyn has the highest share of hotels.

Chart - 3

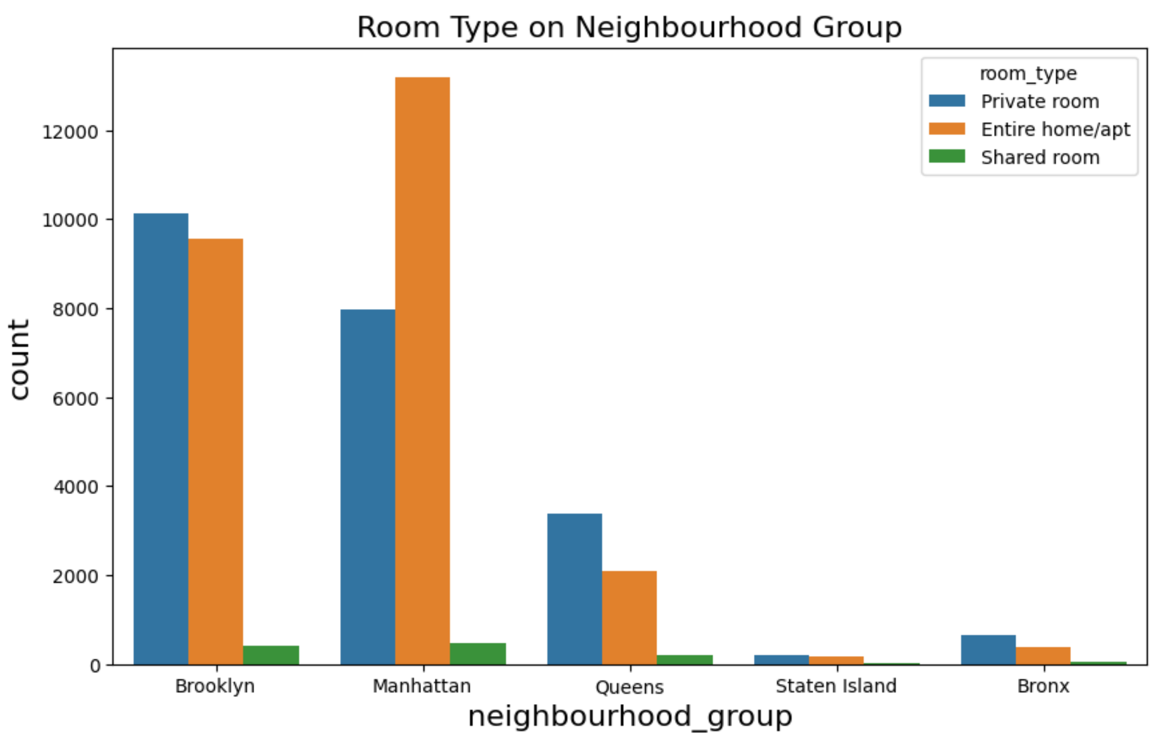
```
# Chart - 3 visualization code
#types of room
plt.figure(figsize=(10,6))
plt.title("Type of Room",fontsize = 16)
sns.countplot(data=airbnb,x='room_type')
plt.xlabel("room_type",fontsize=16)
plt.ylabel("count",fontsize=16)
plt.show()
```



We can see that the Entire Home/Apartment has the highest share, followed by the Private Room, and the least preferred is Shared Room.

Chart - 4

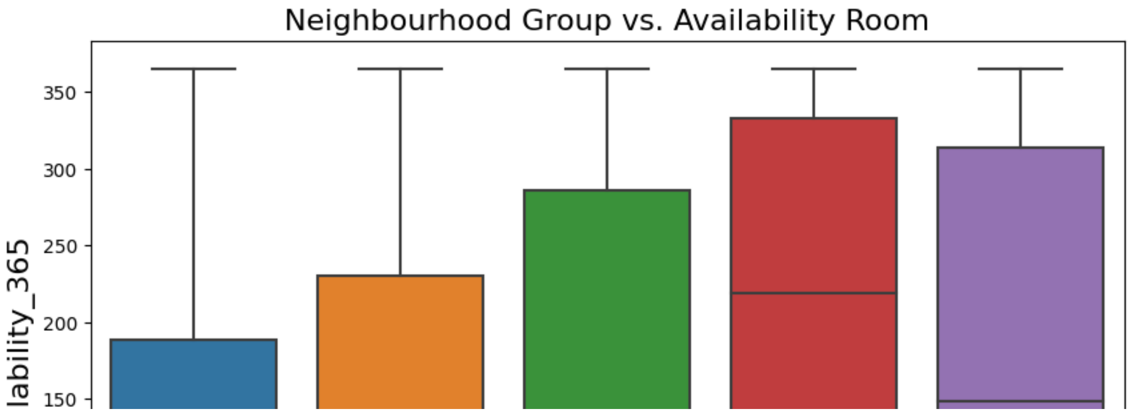
```
# Chart - 4 visualization code
#rooms type per location
plt.figure(figsize=(10,6))
plt.title("Room Type on Neighbourhood Group",fontsize=16)
sns.countplot(data=airbnb,x='neighbourhood_group',hue=airbnb.room_type)
plt.xlabel("neighbourhood_group",fontsize=16)
plt.ylabel("count",fontsize=16)
plt.show()
```



The graph shows that the Entire Home/Apartment is listed most near Manhattan, while Private Rooms and Apartments Near Brooklyn are Nearly equal.

Chart - 5

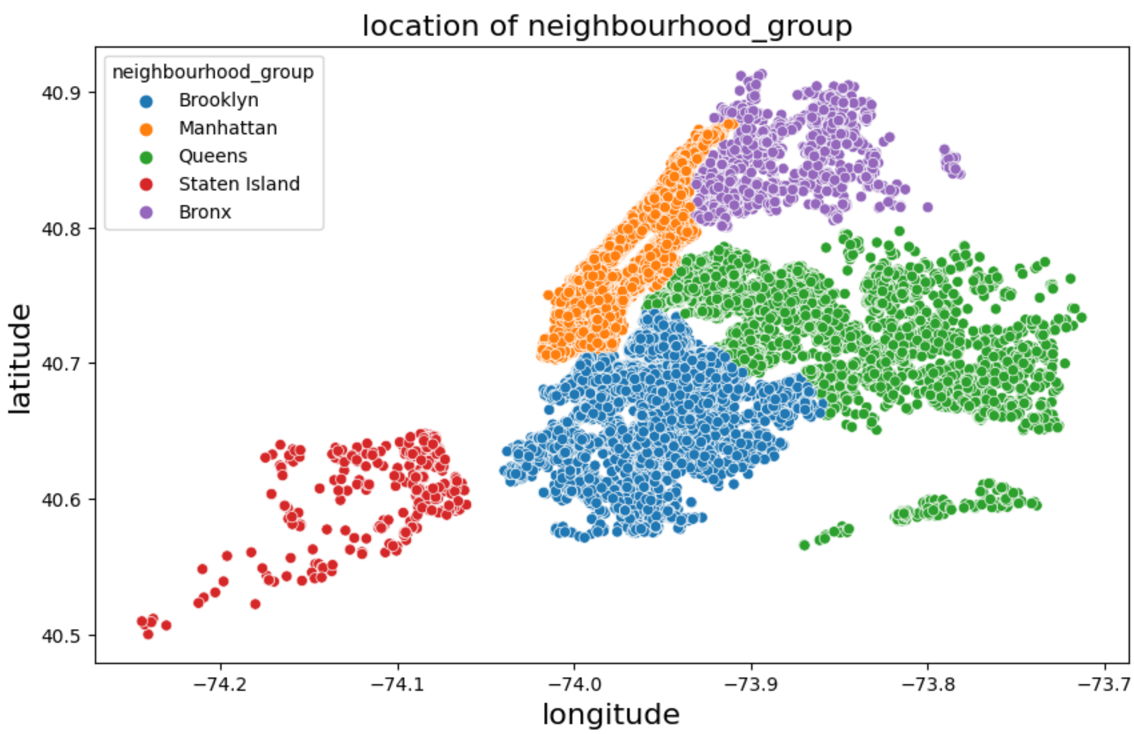
```
# Chart - 5 visualization code
#availability per year
plt.figure(figsize=(10,6))
plt.title("Neighbourhood Group vs. Availability Room",fontsize=16)
sns.boxplot(data=airbnb, x='neighbourhood_group',y='availability_365')
plt.xlabel('neighbourhood_group',fontsize=16)
plt.ylabel("availability_365",fontsize=16)
plt.show()
```



The above box plot shows the relationship between the availability room and neighborhood group.

Chart - 6

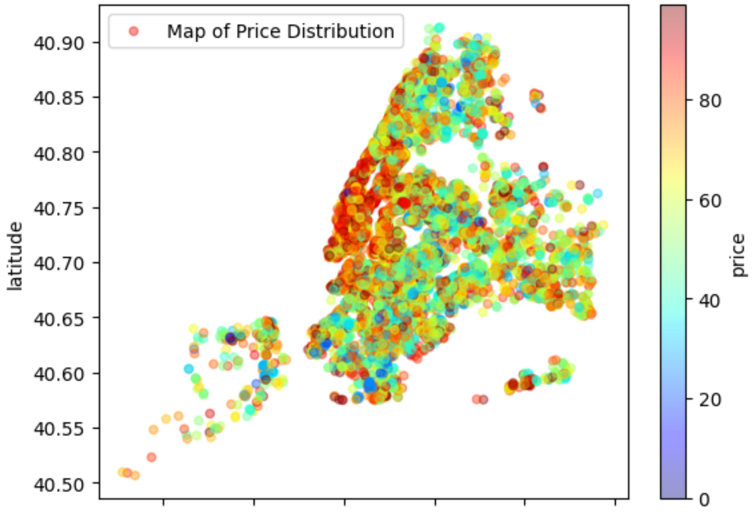
```
# Chart - 6 visualization code
#locations
plt.figure(figsize=(10,6))
sns.scatterplot(x=airbnb.longitude,y=airbnb.latitude,hue=airbnb.neighbourhood_group)
plt.xlabel("longitude",fontsize=16)
plt.ylabel("latitude",fontsize=16)
plt.title("location of neighbourhood_group ",fontsize=16)
plt.show()
```



above scatterplot shows that the hotels listed by location

Chart - 7

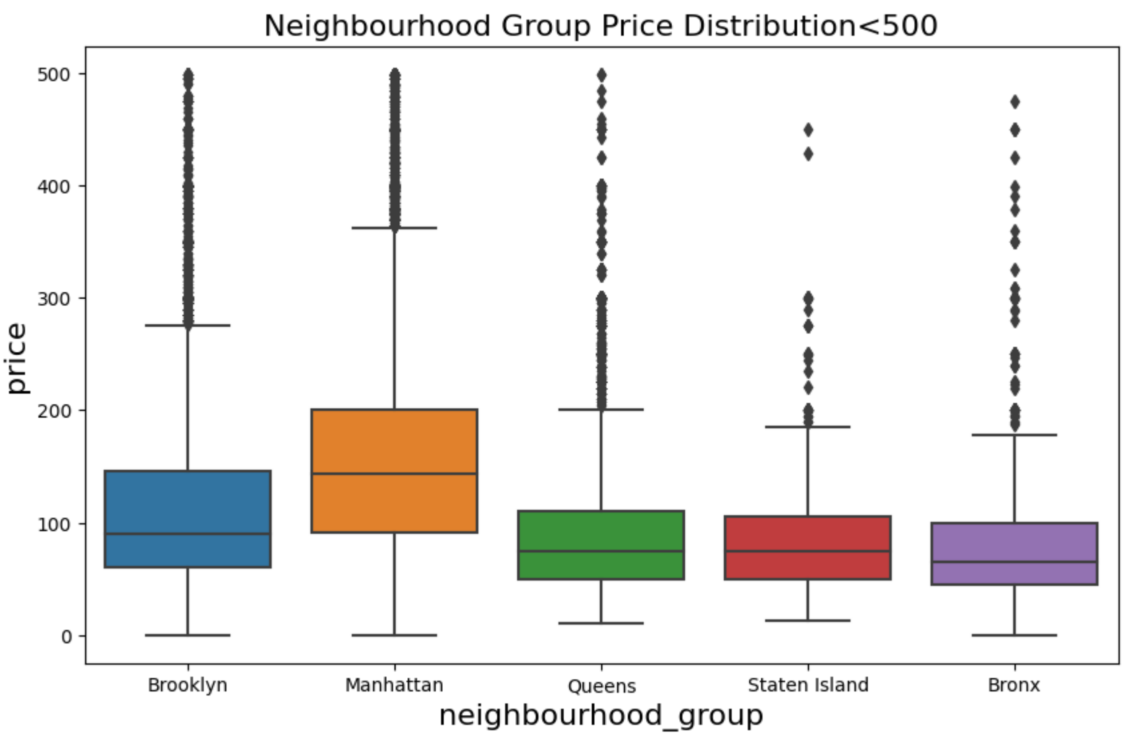
```
# Chart - 7 visualization code
#price hike
airbnb[airbnb.price<100].plot(kind='scatter', x='longitude',y='latitude',label='Map of Price Distribution',c='price',cmap=plt.get_cmap('jet')
plt.show()
```



The information we got from the graph above is red color dots are the rooms with a higher price. Also, we can see that the Manhattan region has a more expensive room price.

Chart - 8

```
# Chart - 8 visualization code
#prices per location
plt.figure(figsize=(10,6))
plt.title("Neighbourhood Group Price Distribution<500",fontsize=16)
sns.boxplot(y="price",x ='neighbourhood_group',data = airbnb[airbnb.price<500])
plt.xlabel("neighbourhood_group",fontsize=16)
plt.ylabel("price",fontsize=16)
plt.show()
```



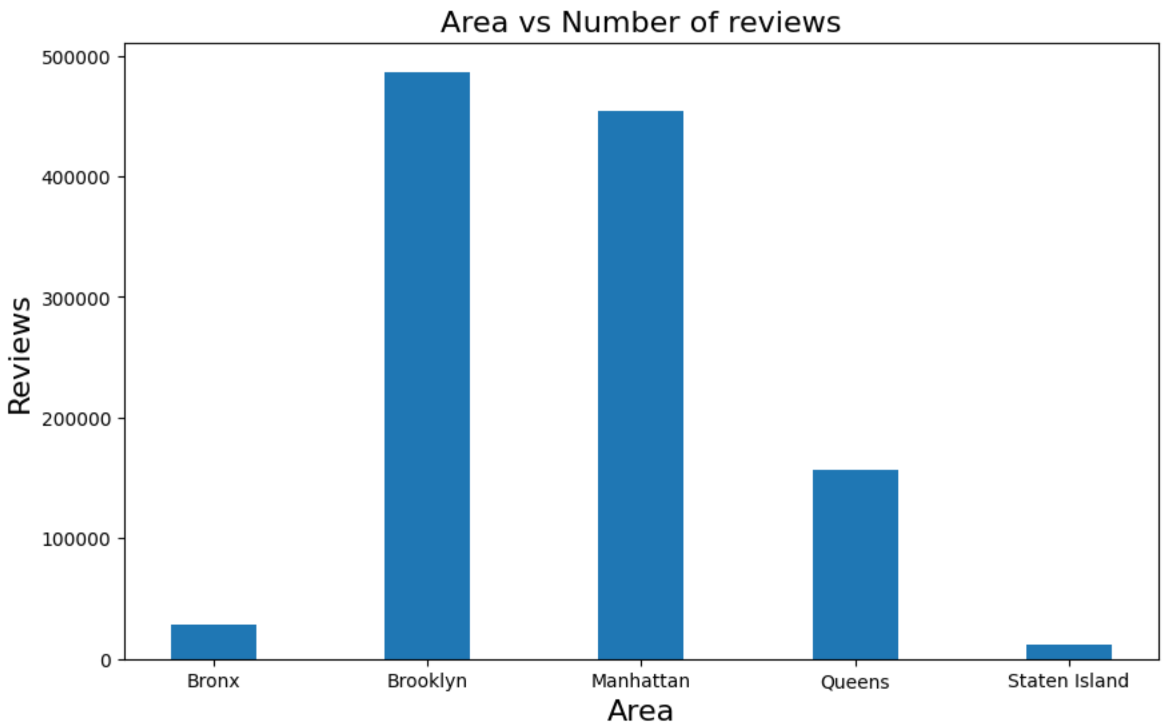
*1-We can say that the Manhattan has the highest price range for the listings,*followed by Brooklyn

2-Queens and Staten Island seem to have a very similar distribution,

3-*The Bronx is the cheapest*.

Chart - 9

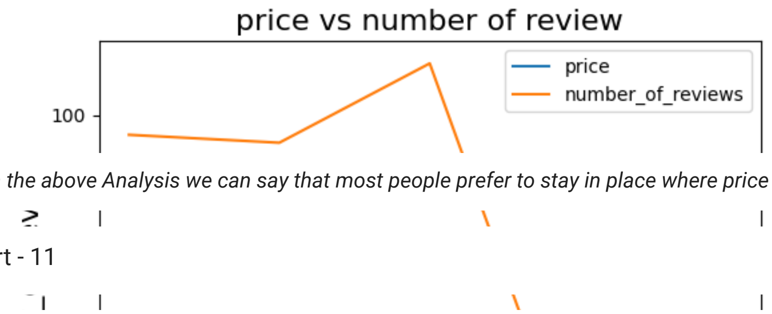
```
# Chart - 9 visualization code
#number of reviews per area
area = location_reviews['neighbourhood_group']
review = location_reviews['number_of_reviews']

fig = plt.figure(figsize = (10, 6))
plt.bar(area,review, width = 0.4)
plt.title("Area vs Number of reviews",fontsize=16)
plt.xlabel("Area",fontsize=16)
plt.ylabel("Reviews",fontsize=16)
plt.show()
```



above bar plot shows that the brooklyn has a most number of reviews followed by manhattan , least reviews on staten island

Chart - 10

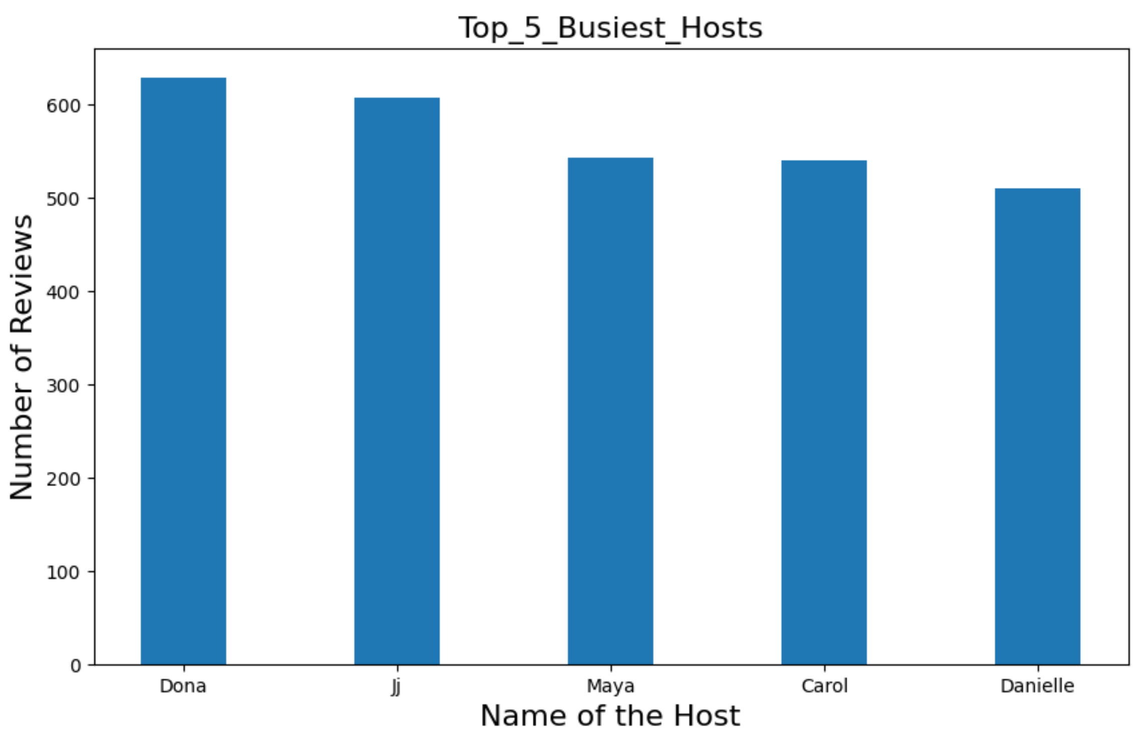
```
# Chart - 10 visualization code
#prices and review relation
price_reviews.plot()
plt.title('price vs number of review',fontsize = 16)
plt.xlabel("Price",fontsize = 16)
plt.ylabel("Number_of_review",fontsize = 16)
plt.show()
```



From the above Analysis we can say that most people prefer to stay in place where price is less.

Chart - 11

```
# Chart - 11 visualization code
#top most hosts were maximum booking
name = busiest_hosts['host_name']
reviews = busiest_hosts['number_of_reviews']

fig = plt.figure(figsize = (10,6))
plt.bar(name, reviews ,width = 0.4)
plt.xlabel("Name of the Host",fontsize = 16)
plt.ylabel("Number of Reviews",fontsize = 16)
plt.title("Top_5_Busiest_Hosts",fontsize = 16)
plt.show()
```



from the above bar chart we have a top five busiest hosts..

1-*Dona*

2-*Jj*

3-*Maya*

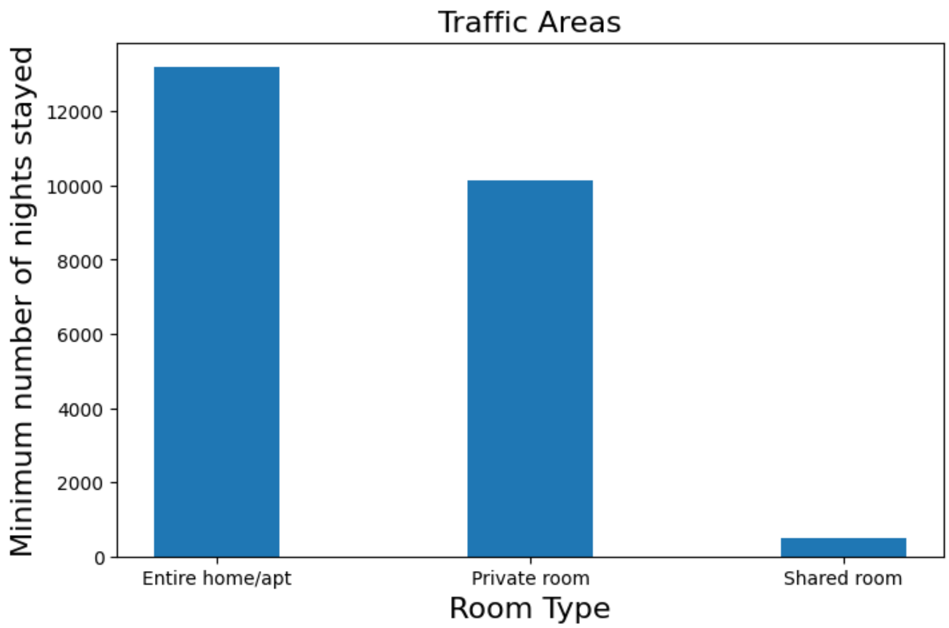
4-*Carol*

5-*Danielle*

Chart - 12

```
# Chart - 12 visualization code
#traffic areas in hotel type
room_type = traffic_areas['room_type']
stayed = traffic_areas['minimum_nights']

fig = plt.figure(figsize = (8,5))
```

```
plt.bar(room_type, stayed,width = 0.4)
plt.xlabel("Room Type",fontsize = 16)
plt.ylabel("Minimum number of nights stayed",fontsize = 16)
plt.title("Traffic Areas",fontsize = 16)
plt.show()
```



From the Above Analysis We can Say that People are preferring Entire home/apt or Private room which are present in Manhattan, Brooklyn, Queens and people are preferring listings which are less in price.

Conclusion

1- The people who prefer to stay in an Entire home or Apartment are going to stay a bit longer in that particular Neighborhood only.

2- The people who prefer to stay in a Private room won't stay longer as compared to a Home or Apartment.

3- Most people prefer to pay less price.

4- If there are more number of reviews for a particular neighborhood group that means that a place is a tourist place.

5- If people are not staying more than one night means they are travelers.

6- For the given data set I found that there are a total of 221 different areas out of which “Williamsburg” has a maximum number of listings.

7- There are a total of 37457 hosts and the host with host id- 219517861 “Sonder” is the top host with 327 listings.

8- No strong correlation was observed between price, reviews, and location.

9- Out of 5 different locations in the dataset, Manhattan is the most crowded location with 44.3% of listings.*

10- Top five busiest host are Dona,Jj,Maya,Carol,Danielle.

Hurrah! You have successfully completed your EDA Capstone Project !!!

0s completed at 1:00 PM