New York City Airbnb Exploratory Data Analysis

A) Background

Context

Since 2008, guests and hosts have used Airbnb to expand on traveling possibilities and present more unique, personalized way of experiencing the world. This dataset describes the listing activity and metrics in NYC, NY for 2019.

Content

This data file includes all needed information to find out more about hosts, geographical availability, necessary metrics to make predictions and draw conclusions.

Acknowledgements

This public dataset is part of Airbnb, I pulled this data from Kaggle *https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data*

Some Questions to answer :

1) What can we learn about different hosts and areas?

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

3) Which hosts are the busiest and why?

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

B) Import the Libraries :

```
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
from matplotlib import rcParams

import warnings
warnings.filterwarnings('ignore')
```

C) Get the Data (Read the .csv file) :

```
data = pd.read_csv('/content/AB_NYC_2019.csv')
```

D) Let's explore the data :

```
  i.   Data Overview
  ii.  No. of Records & Features
  iii. Summary & info
  iv. Conclusion
```

i. Data Overview :

```
# Top 5 records :

data.head(5)

     id  ... availability_365
0  2539  ...              365
1  2595  ...              355
2  3647  ...              365
3  3831  ...              194
4  5022  ...                0

[5 rows x 16 columns]
```

ii. No. of Records & Features :

```
# Let's know our features:

print('SHAPE OF OUR DATASET :',data.shape)

print('\n WHAT ARE OUR FEATURES ? : \n',data.columns)
```

```
SHAPE OF OUR DATASET : (48895, 16)

 WHAT ARE OUR FEATURES ? :
 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')
```

OBSERVATION :

1) There are around 48895 records in our dataset.

2) We have 16 features :

```
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
```

iii. Descriptive Summary

```
data.describe()
```

```
                 id  ...  availability_365
count  4.889500e+04  ...      48895.000000
mean   1.901714e+07  ...        112.781327
std    1.098311e+07  ...        131.622289
min    2.539000e+03  ...          0.000000
25%    9.471945e+06  ...          0.000000
50%    1.967728e+07  ...         45.000000
75%    2.915218e+07  ...        227.000000
max    3.648724e+07  ...        365.000000

[8 rows x 10 columns]
```

```
# INFO

data.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
```

iv. Conclusion :

- We have total 16 features, out of which "*last_review*", "*name*","*host_name*" are least important in my opinion. (So we'll ignore it)
- Factors/Metrics to look into

  ```
    a) price   b) number_of_reviews   c) reviews_per_month  d) availability_365  e) calculated_host_listings_count
  ```

- We can group the data based on

  ```
    a) host_id, host_name   b) neighbourhood_group   c) neighbourhood   d) room_type
  ```

- We can utilise Longitude & Latitude values for geospatial visualization
- We have some features with *null* values.

E) Data Wrangling :

```
i. Duplicate Values
ii. Missing Values
```

i. Duplicate Values :

```
# For [id] :

print("Total no. of id values :", data['id'].count())
print("No. of unique id values :",len(data['id'].unique()))

# For [name] :

print("\nTotal no. of name values : ",data['name'].count())
print("No. of unique name values : ",len(data['name'].unique()))
```

```
# For [host_id] :

print("\nTotal no. of host_id values :", data['host_id'].count())
print("No. of unique host_id values :",len(data['host_id'].unique()))

# For [host_name] :

print("\nTotal no. of host_name values : ",data['host_name'].count())
print("No. of unique host_name values :
",len(data['host_name'].unique()))
```

```
Total no. of id values : 48895
No. of unique id values : 48895

Total no. of name values :  48879
No. of unique name values :  47906

Total no. of host_id values : 48895
No. of unique host_id values : 37457

Total no. of host_name values :  48874
No. of unique host_name values :  11453
```

Observation :

- As we can see, we have some duplicate records when it comes to '*name*' & '*host_name*'
- We don't need these 3 features:

  `a) name    b) host_name   c) last_review`

  `So, we'll drop these features.`
- Also, we even have null values in this features & they don't seem really helpful. So, let's drop them.

 # Drop these 3 features in our DataFrame

```
# Drop the features from the dataframe

cleaned_data = data.drop(['name','host_name','last_review'], axis=1)

cleaned_data
```

```
             id   host_id  ... calculated_host_listings_count
availability_365
0          2539      2787  ...                              6
365
```

```
1          2595      2845  ...                             2
355
2          3647      4632  ...                             1
365
3          3831      4869  ...                             1
194
4          5022      7192  ...                             1
0
...         ...       ...  ...                           ...
...
48890  36484665   8232441  ...                             2
9
48891  36485057   6570630  ...                             2
36
48892  36485431  23492952  ...                             1
27
48893  36485609  30985759  ...                             6
2
48894  36487245  68119814  ...                             1
23

[48895 rows x 13 columns]
```

ii. Missing Values :

```
# Find the missing / NaN values :

print(cleaned_data.isnull().sum())

id                                    0
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                 10052
calculated_host_listings_count        0
availability_365                      0
dtype: int64
```

Observation :

- There's just 1 feature with huge no. of missing values i.e. *reviews_per_month*
- Let's replace this missing values with '0'

```
# Fill the missing values :

cleaned_data.fillna(value = 0,inplace = True)
```

```
# New Cleaned Data

cleaned_data
```

```
             id   host_id  ... calculated_host_listings_count
availability_365
0          2539      2787  ...                              6
365
1          2595      2845  ...                              2
355
2          3647      4632  ...                              1
365
3          3831      4869  ...                              1
194
4          5022      7192  ...                              1
0
...         ...       ...  ...                            ...
...
48890  36484665   8232441  ...                              2
9
48891  36485057   6570630  ...                              2
36
48892  36485431  23492952  ...                              1
27
48893  36485609  30985759  ...                              6
2
48894  36487245  68119814  ...                              1
23

[48895 rows x 13 columns]
```

F) Exploratory Data Analysis :

```
i.     Host
ii.    price
iii.   room_type
iv.    Area (neighborhood, neighborhood_group)
v.     availability_365
```

i. Host

- Who are the busiest hosts?
- Which areas do these hosts cater to ?

```
cleaned_data['host_id'].value_counts()
```

```
219517861    327
107434423    232
30283594     121
137358866    103
12243051      96
            ...
1641589        1
4070519        1
208106618      1
235939247      1
1288080        1
Name: host_id, Length: 37457, dtype: int64
```

Q1 . Who is the most busiest host in New York City?

```
cleaned_data['host_id'].mode()
```

```
0    219517861
dtype: int64
```

Observation :

- *'219517861'* is the most busiest host
- *'107434423'*, *'30283594'*, *'137358866'*, *'12243051'* are the other top hosts

```
top_hosts = [219517861,107434423,30283594,137358866,12243051]

top_hosts
```

```
[219517861, 107434423, 30283594, 137358866, 12243051]
```

```
print('Top Hosts Name : \n')

for i in top_hosts:
    print(data[data['host_id'] == i].host_name.unique())
```

```
Top Hosts Name :

['Sonder (NYC)']
['Blueground']
['Kara']
['Kazuya']
['Sonder']
```

Q2. What are the areas these busiest hosts belong to ?

```
features = ['host_id','neighbourhood_group']

busiest_hosts = cleaned_data[cleaned_data['host_id'].isin(top_hosts)]

busiest_hosts_areas = busiest_hosts.loc[:,
```

```
['host_id','neighbourhood_group']]
busiest_hosts_areas.drop_duplicates(inplace = True)

busiest_hosts_areas
```

```
         host_id neighbourhood_group
9740    30283594           Manhattan
26137  107434423           Manhattan
30637   12243051           Manhattan
32718  137358866           Manhattan
33268  137358866              Queens
36698  137358866            Brooklyn
38293  219517861           Manhattan
39275  107434423            Brooklyn
```

Observation :

- *'Sonder (NYC) ',' Blueground ',' Kara ',' Kazuya ',' Sonder '* are the busiest hosts.
- These busiest hosts mostly belong to *Manhattan, Brooklyn & Queens*.

ii. Price

- Price distribution
- Median Price in $
- Price Statistic
- At what price do the busiest/top hosts offer their services?
- Prices across different regions

```
prices_df = cleaned_data.loc[:,
['id','host_id','neighbourhood_group','price']]

prices_df
```

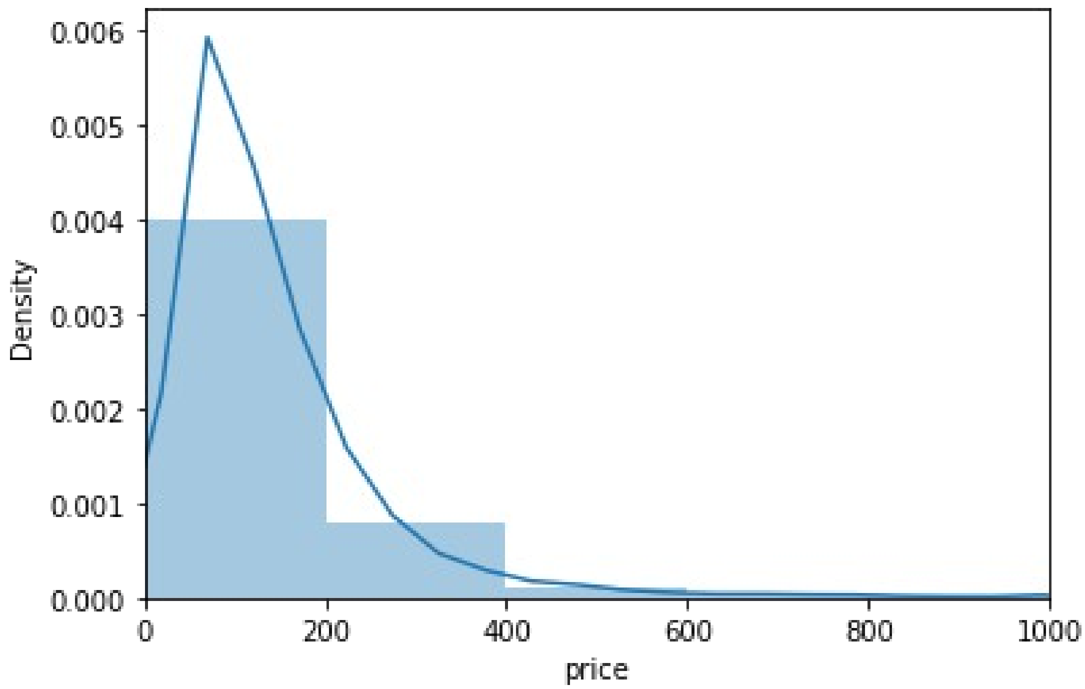
```
             id   host_id neighbourhood_group  price
0          2539      2787            Brooklyn    149
1          2595      2845           Manhattan    225
2          3647      4632           Manhattan    150
3          3831      4869            Brooklyn     89
4          5022      7192           Manhattan     80
...         ...       ...                 ...    ...
48890  36484665   8232441            Brooklyn     70
48891  36485057   6570630            Brooklyn     40
48892  36485431  23492952           Manhattan    115
48893  36485609  30985759           Manhattan     55
48894  36487245  68119814           Manhattan     90

[48895 rows x 4 columns]
```

Price Distribution :

```
sns.distplot(prices_df['price'])
```

```
plt.xlim(0, 1000)
```

```
(0.0, 1000.0)
```



\# **Median Price in $:**

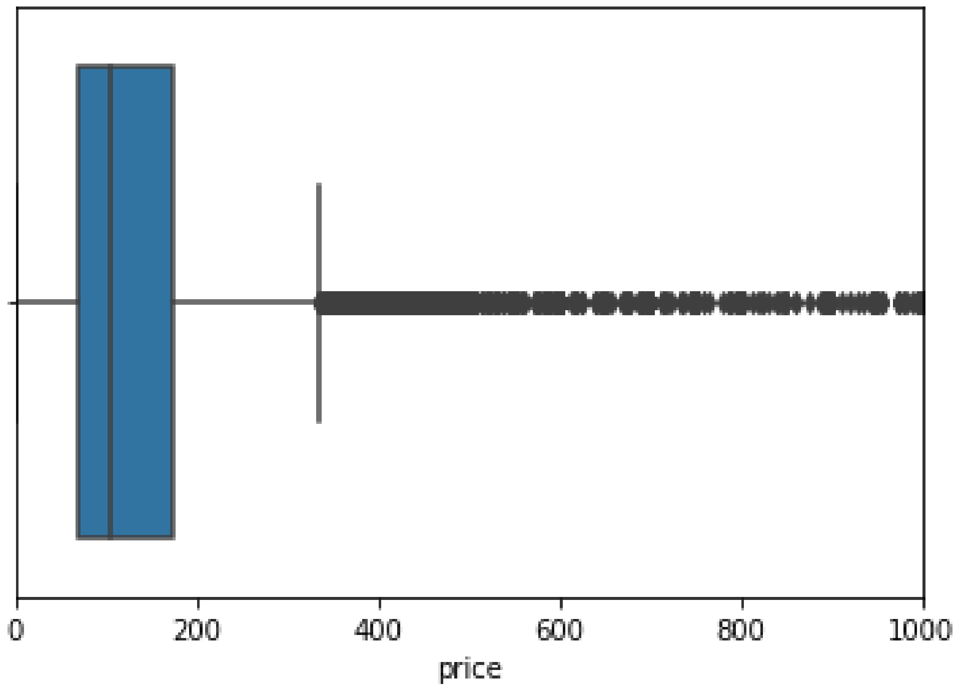
```
print('Median Price ',prices_df['price'].median())
```

```
Median Price  106.0
```

\# **Price Statistic :**

```
sns.boxplot(x = prices_df['price'])
plt.xlim(0,1000)
```

```
(0.0, 1000.0)
```




```
# Percentile values :

print('\n25th percentile :',prices_df['price'].quantile(q=0.25))
print('\n50th percentile :',prices_df['price'].quantile(q=0.5))
print('\n75th percentile :',prices_df['price'].quantile(q=0.75))
print('\n99th percentile :',prices_df['price'].quantile(q=0.99))
```

```
25th percentile : 69.0

50th percentile : 106.0

75th percentile : 175.0

99th percentile : 799.0
```

Observation :

- Mostly the prices lies between $ 69 & $ 175
- Median price across all of New York City is $ 106
- Also, our price data contains huge amount of outliers (which is why we used Median in place of Averages/Mean value)

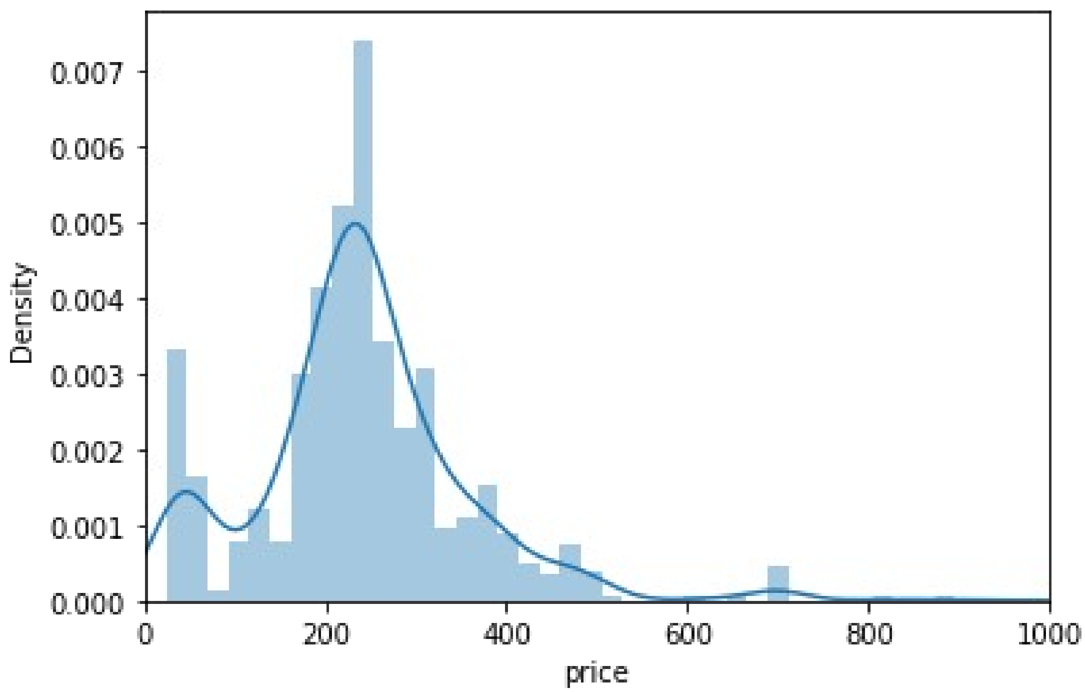
At what price do the busiest/top hosts offer their services?

```
busiest_hosts_prices = busiest_hosts.loc[:,['host_id','price']]

busiest_hosts_prices
```

```
         host_id  price
9740    30283594    169
10075   30283594    135
10335   30283594    369
10398   30283594    335
10490   30283594    129
...          ...    ...
48723  107434423    316
48724  107434423    385
48725  107434423    267
48726  107434423    278
48727  107434423    365

[879 rows x 2 columns]
```

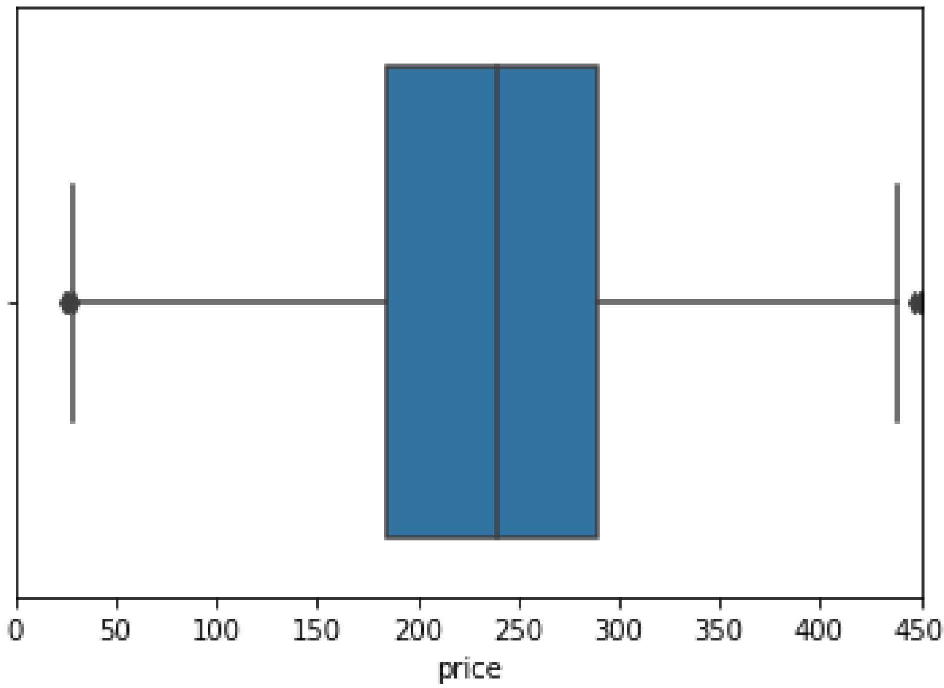
```
sns.distplot(busiest_hosts_prices['price'])

plt.xlim(0, 1000)
```

```
(0.0, 1000.0)
```




```
sns.boxplot(x = busiest_hosts_prices['price'])
plt.xlim(0,450)
```

```
(0.0, 450.0)
```




```
# Percentile values :

print('\n25th
percentile :',busiest_hosts_prices['price'].quantile(q=0.25))
print('\n50th
percentile :',busiest_hosts_prices['price'].quantile(q=0.5))
print('\n75th
percentile :',busiest_hosts_prices['price'].quantile(q=0.75))
print('\n99th
percentile :',busiest_hosts_prices['price'].quantile(q=0.99))
```

```
25th percentile : 185.0

50th percentile : 239.0

75th percentile : 289.0

99th percentile : 699.0
```

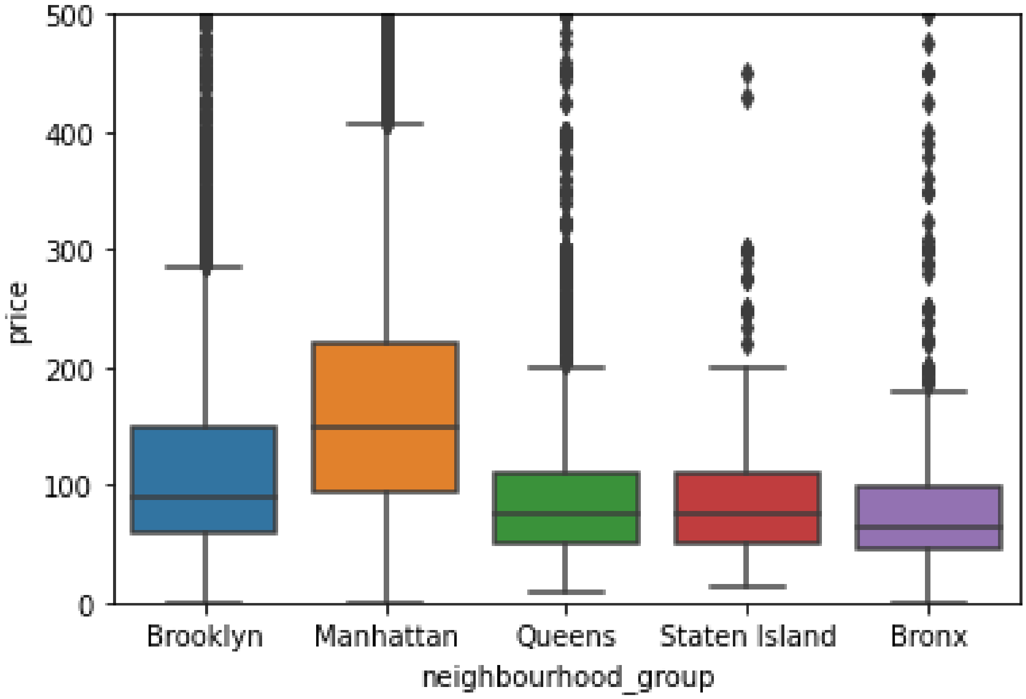
Observation :

- Turns out that the Busiest host's in New York City cost a little more expensive than others. i.e. between $ *185 & $ 289*

Prices across different regions :

```
sns.boxplot(x="neighbourhood_group", y="price", data = prices_df)
plt.ylim(0,500)
```

```
(0.0, 500.0)
```



Observation :

- Manhattan is the most expensive area. (highest price)
- Manhattan & Brooklyn turns out to be the most expensive areas.
- Rest, { Queens, Staten Island, Bronx } have similar prices and are cheaper than Manhattan & Brooklyn.

iii. Room Type :

- Which room types are more popular?
- Which room types are more cheaper than others?

```
roomtype_df = cleaned_data.loc[:,['id','room_type','price']]

roomtype_df
```

	id	room_type	price
0	2539	Private room	149
1	2595	Entire home/apt	225
2	3647	Private room	150
3	3831	Entire home/apt	89
4	5022	Entire home/apt	80
...	...	...	...
48890	36484665	Private room	70
48891	36485057	Private room	40
48892	36485431	Entire home/apt	115
48893	36485609	Shared room	55

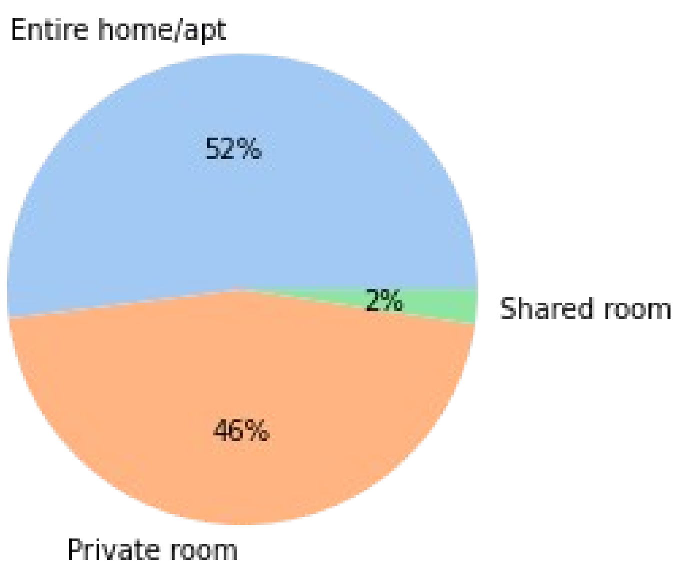
```
48894  36487245     Private room     90

[48895 rows x 3 columns]
```

Popularity of different room_types :

```
print('Distribution of Room Types : \n\
n',roomtype_df['room_type'].value_counts())
```

```
Distribution of Room Types :

 Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

```
# Visualize the above result in form of pie-chart :

count = [25409,22326,1160]
labels = ['Entire home/apt','Private room','Shared room']
colors = sns.color_palette('pastel')
plt.pie(count, labels=labels,colors = colors, autopct = '%0.0f%%')
plt.show()
```



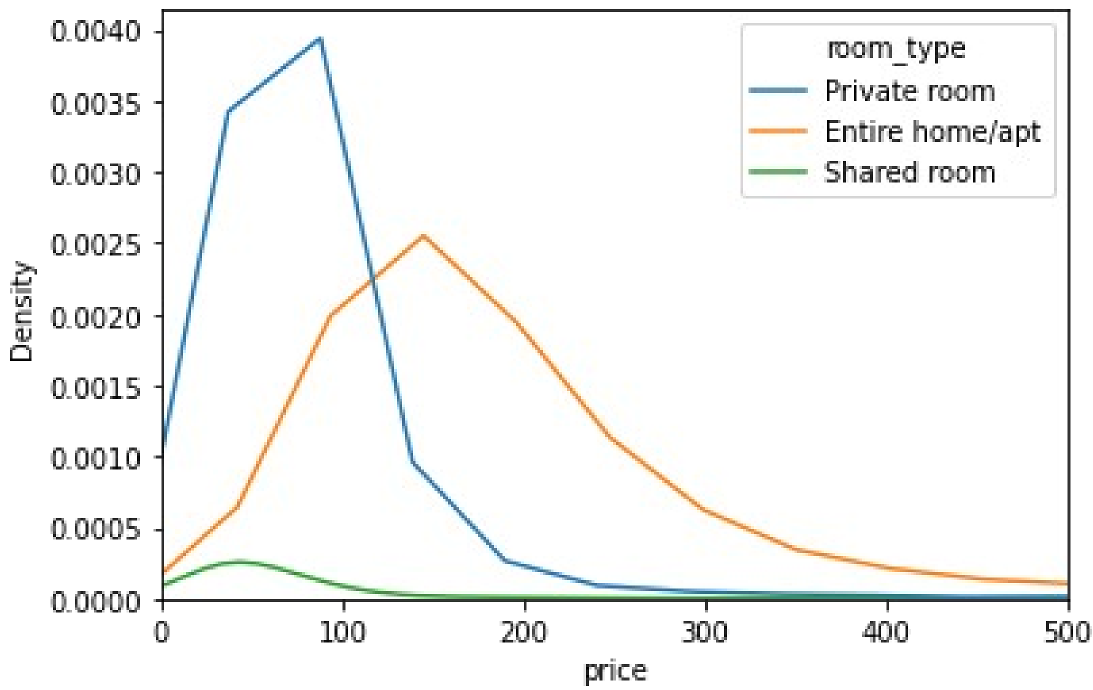
Observation :

- As we can clearly see, '*Entire home/apt*' and '*Private room*' are the more popular room types.
- Shared room is the least preffered room type contributing to just 2 % of all bookings.

Price of different room_types

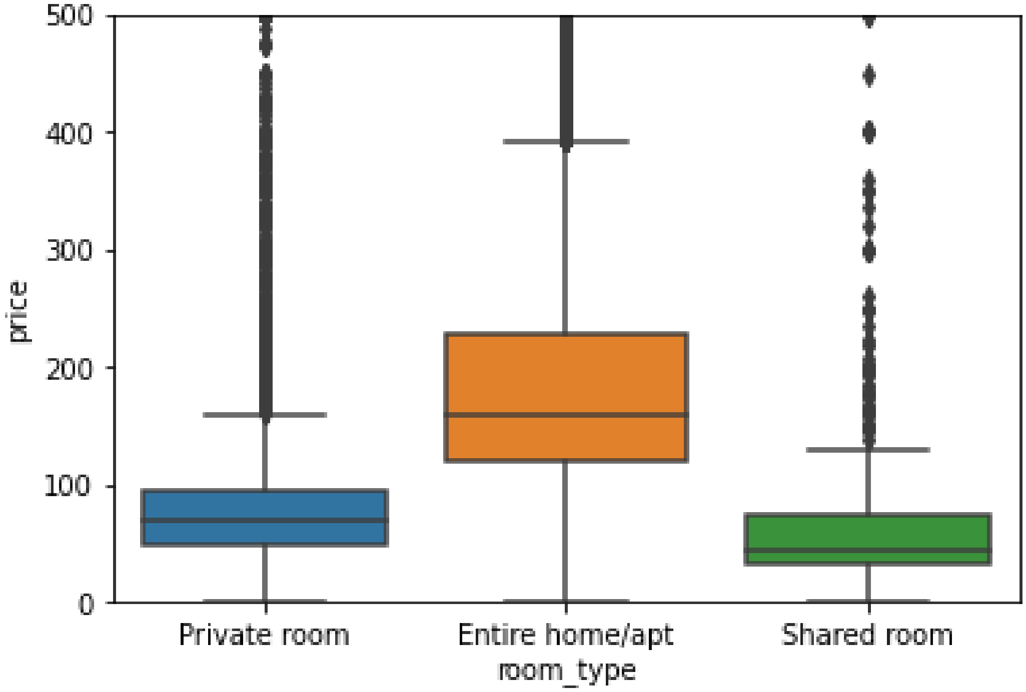
```
sns.kdeplot(data = roomtype_df, x="price", hue="room_type")
plt.xlim(0,500)
```

```
(0.0, 500.0)
```




```
sns.boxplot(x="room_type", y="price", data = roomtype_df)
plt.ylim(0,500)
```

```
(0.0, 500.0)
```



Observation :

- "Entire Home/Apt" is the most expensive room type.
- "Private Room" & "Shared Room" are almost comparable in terms of Price.
- "Shared Room" is the cheapest room type.

iv. Area (neighbourhood_group, neighbourhood):

- Which are the most busiest/popular areas in New York City?

```
neighbour_group = cleaned_data.groupby(by='neighbourhood_group')

neighbour_group
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at
0x7fcfce117f50>
```

```
neighbour_group.describe()
```

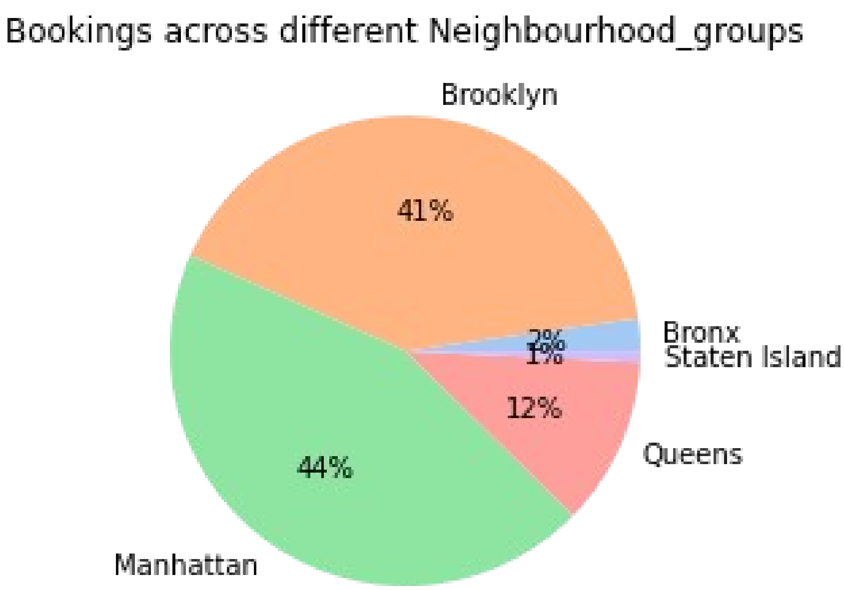
```
                            id                                   ...
availability_365
                         count          mean          std  ...
50%    75%    max
neighbourhood_group                                        ...

Bronx                   1091.0  2.273492e+07  1.023402e+07  ...
148.0  313.5  365.0
Brooklyn               20104.0  1.825685e+07  1.083320e+07  ...
28.0  188.0  365.0
Manhattan              21661.0  1.877494e+07  1.116793e+07  ...
```

```
36.0  230.0  365.0
Queens                5666.0  2.175500e+07  1.037687e+07  ...
98.0  286.0  365.0
Staten Island          373.0  2.159747e+07  1.039310e+07  ...
219.0  333.0  365.0

[5 rows x 80 columns]
```

```
neighbour_group['id'].count()
```

```
neighbourhood_group
Bronx             1091
Brooklyn         20104
Manhattan        21661
Queens            5666
Staten Island      373
Name: id, dtype: int64
```

```
g = dict(neighbour_group['id'].count())

keys = list(g.keys())
values = list(g.values())

plt.title('Bookings across different Neighbourhood_groups')
colors = sns.color_palette('pastel')
plt.pie(values, labels=keys, colors = colors, autopct = '%0.0f%%')
plt.show()
```



Observation :

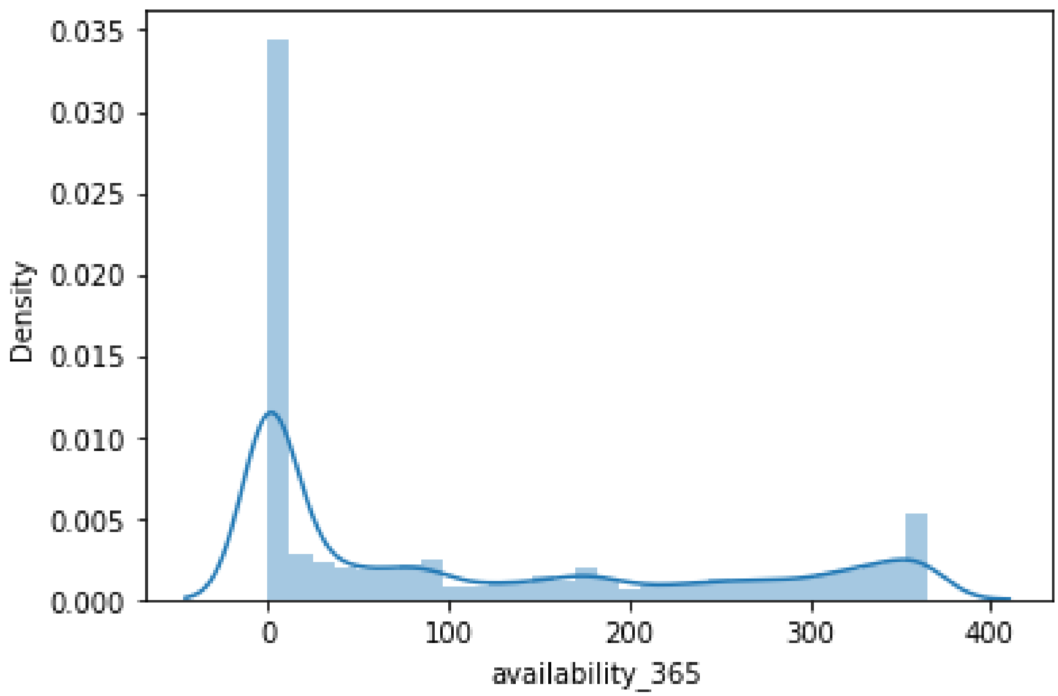
- Manhattan & Brooklyn are the busiest areas (neighbourhood_group). These two contributes to around 85 % of the total traffic

vi. Availability_365 :

Availability across all hosts :

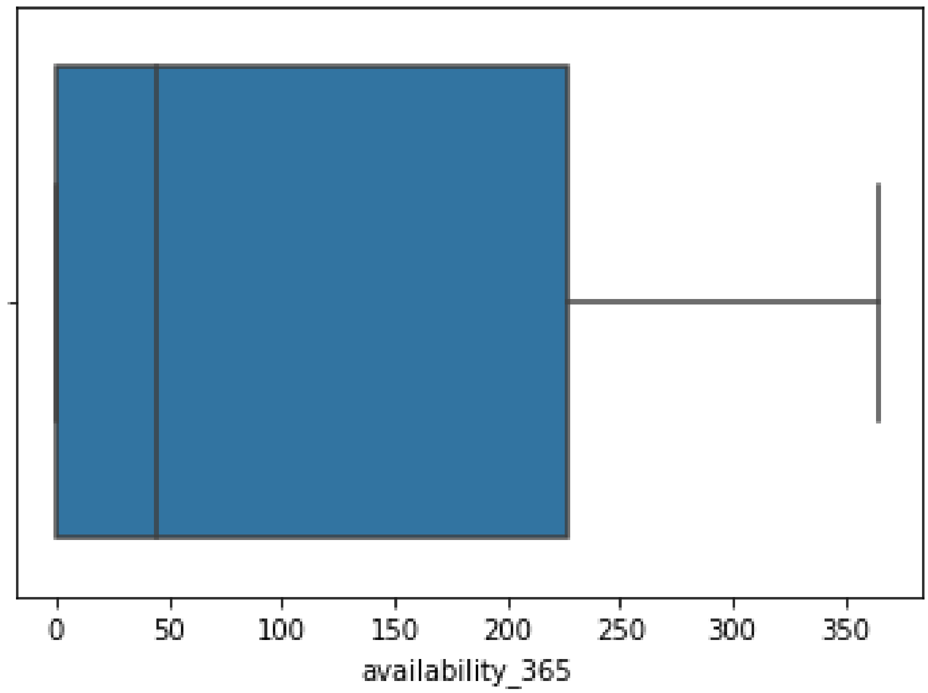
```
sns.distplot(cleaned_data['availability_365'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfca71ded0>
```




```
sns.boxplot(x=cleaned_data['availability_365'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfcd275690>
```




```
# Percentile values :

print('\n25th
percentile :',cleaned_data['availability_365'].quantile(q=0.25))
print('\n50th
percentile :',cleaned_data['availability_365'].quantile(q=0.5))
print('\n75th
percentile :',cleaned_data['availability_365'].quantile(q=0.75))
print('\n99th
percentile :',cleaned_data['availability_365'].quantile(q=0.99))
```

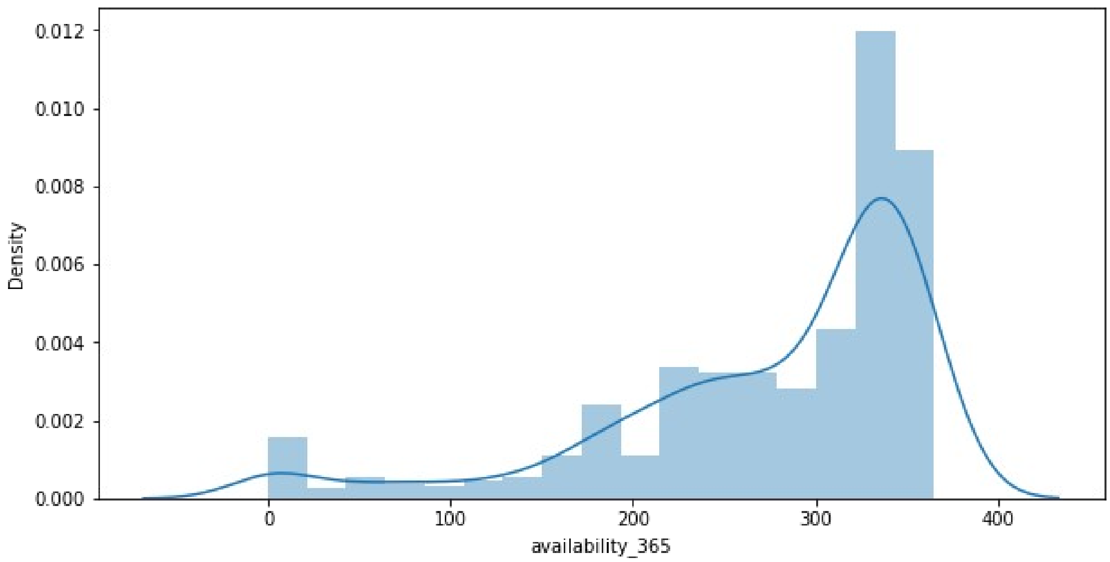
```
25th percentile : 0.0

50th percentile : 45.0

75th percentile : 227.0

99th percentile : 365.0
```

Observation :

- Most of the Airbnb host's offer their services for over 0 to 227 days in a year.

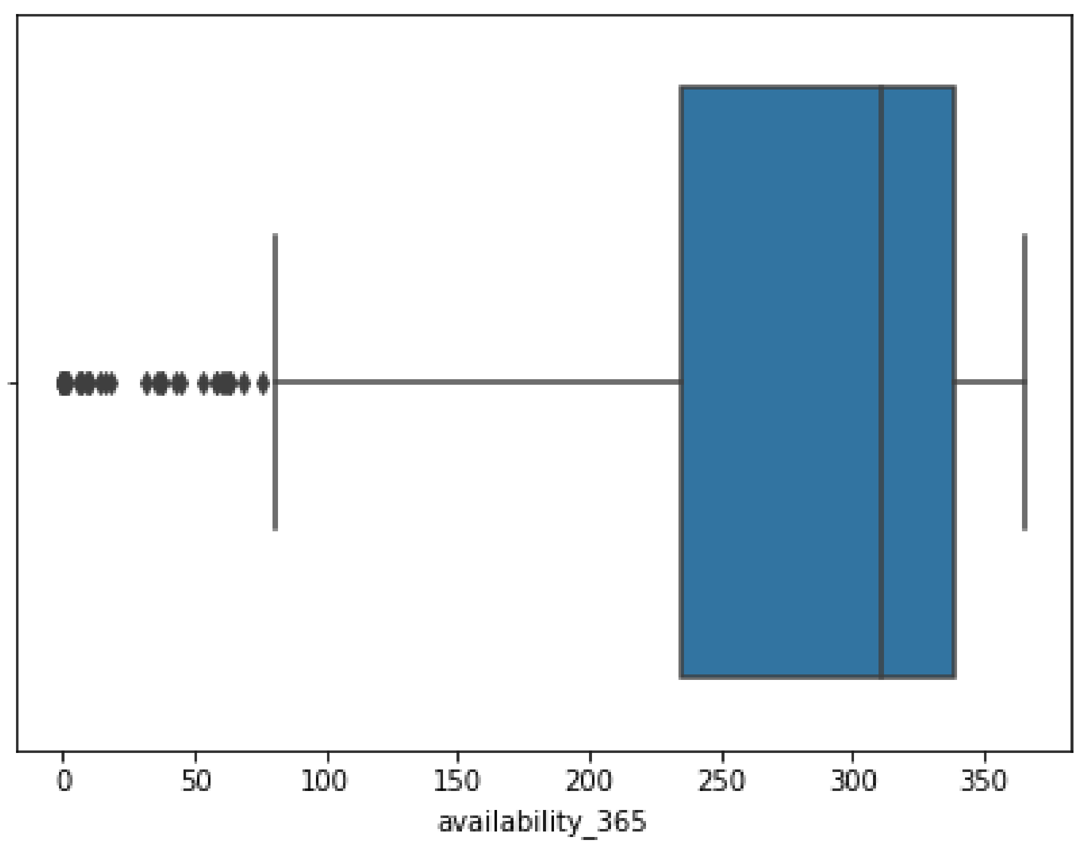
Availability across the busiest hosts :

```
sns.distplot(busiest_hosts['availability_365'])
rcParams['figure.figsize'] = 7,5
```




```
sns.boxplot(x=busiest_hosts['availability_365'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfcb003d10>
```




```
# Percentile values :

print('\n25th
```

```
percentile :',busiest_hosts['availability_365'].quantile(q=0.25))
print('\n50th
percentile :',busiest_hosts['availability_365'].quantile(q=0.5))
print('\n75th
percentile :',busiest_hosts['availability_365'].quantile(q=0.75))
print('\n99th
percentile :',busiest_hosts['availability_365'].quantile(q=0.99))
```

```
25th percentile : 235.0

50th percentile : 311.0

75th percentile : 339.0

99th percentile : 365.0
```

Observation :

- The busiest Airbnb host's offer their services for over 235 to 339 days in a year.

G) Correlation between Features :

```
new_df = cleaned_data.drop(['longitude','latitude'], axis=1)

corr_df = new_df.corr()

sns.heatmap(corr_df, cmap="YlGnBu", annot=True)
rcParams['figure.figsize'] = 18,8
plt.show()
```

H) Conclusion :

- Our Dataset contained 48,895 Airbnb booking records around New York City for the year of 2019.
- We were provided with 16 features, out of which we used some of the features for the purpose of analysis.
- *'Sonder (NYC) ',' Blueground ',' Kara ',' Kazuya ',' Sonder '* are the busiest hosts. These hosts cater around *Manhattan & Brooklyn* areas.
- Manhattan & Brooklyn are the most popular areas in New York City with the busiest traffic. These areas are also the most expensive ones. (contributing to 85% of the total traffic)
- Manhattan is the most expensive area.
- 'Entire home/Apt' and 'Private room' are the most preffered room categories.
- 'Entire home/Apt' is the most expensive room category.
- 'Shared rooms' are hardly booked(only 2% out of total bookings), even though it is the cheapest room category.
- While most of the Airbnb host's offer their services for over 0 to 227 days in a year. The busiest Airbnb hosts offer their services from 235 to 339 days in a year. (which is so much more than other hosts)

I) Recommendation :

- Customers surely seems to value '**quality experience**' over '**money**'. So, Airbnb should advise their hosts to prioitize on providing a high quality experience & then later align their prices.
- **Manhattan**, **Brooklyn** and **Queens** receives the best traffic among all the neighbourhood areas. So, Airbnb should find more hosts catering to these areas.
- **'Shared Rooms'** don't get much customer traffic. So it would be a wise idea to remove this room category from the Airbnb services.