Methodology Document

Case Study Purpose: **Methodological Document For Data Analysis on Airbnb, NYC**

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Methodology Approach in Detail:

Tools Used: Python, Tableau, Excel

1. Problem Background:

For the past few months, Airbnb has noticed a major decline in revenue due to the lockdown imposed during the pandemic.

Currently that the limitations have started lifting and people have started to travel more. Hence, Airbnb wants to make sure that it is fully prepared for this change.

2. Business Understanding:

Airbnb is an American company based in San Francisco, California. It operates an online marketplace for lodging, primarily homestays for vacation rentals, and tourism activities. The platform is accessible via a website and mobile app.

Thereafter, being an online marketplace for hosting personal homestays and private apartments in the majority, the company had two types of customers. One hosts their place and the other books the place for a particular time that is the end consumer utilizing the hosted place. Airbnb earns commission from both ends and hence has to make sure both of its customers can generate value from their business. They also have to make the hosted place offered on their platform provide the best services at reasonable prices and look out for the best technology to ease out the booking process for the end consumer without hassle.

3. Type of Data required to Analyse:

Fall in the revenue could be for two major causes, either the sites hosted on the platform are not able to deliver a better user experience or there could be a competitor in the market catching the market share. Keeping the above in mind, we first try to work on the first reason as that is something internal to the company and can have the data in hand to identify the reasons behind the plummeting revenue. Hence, we use the information of the hosted places on the platform to see where and what can be done to improve the end consumer experience. The data would majorly include the location and region of the hosted places, in our case we are targeting Borough (New York City) — the Bronx, Brooklyn, Manhattan, Queens and Staten Island, followed by their host's details, prices of the hosted sites and reviews received by the end consumer

4. How was the Data was obtained?

The provided data is captured from the CRM tool used by Airbnb to manage their customers that are hosting sites on their platform.

The reviews provided in the data frame are assumed to be positive as it is not mentioned whether they are negative or positive reviews.

5. Whom are we presenting?

Data Analysis Managers: These people manage the data analysts directly for processes and their technical expertise is basic.

Lead Data Analyst: The lead data analyst looks after the entire team of data and business analysts and is technically sound.

Head of Acquisitions and Operations, NYC: This head looks after all the property and hosts acquisitions and operations. Acquisition of the best properties, price negotiation, and negotiating the services the properties offer falls under the purview of this role.

Head of User Experience, NYC: The head of a user experience looks after the customer preferences and also handles the properties listed on the website and the Airbnb app. The head of a user experience tries to optimize the order of property listing in certain neighborhoods and cities to get every property the optimal amount of traction.

6. Recommendations:

One-to-one interaction with some property owners in Staten Island, Queens and Bronx to identify their challenges for being fully functional for the maximum number of days in a year and allow a booking of more than 10 days of minimum night stay.

Create some sort of interaction between the Top 5 hosts to share their experience with the rest of the community for better improvement and value-generating ideas.

Provide discounted commission rates to property owners on keeping the minimum night stay booking window for more than 10 days and property functional for the maximum number of days in a year.

Method Analysis Code with Python:

1. Data Understanding and Preparation:

Before we start the basic understanding of the data in hand, we imported relevant libraries available in Python. Below are the libraries that we imported,

```
import pandas as pd, numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

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

We started with Understanding the Data in hand provided by running basic functions to load and interpret the variables, data types of the variables, dimensions and size of the dataframe. Below is the code used for the same

```
# LOADING THE DATA SET

ab_nyc = pd.read_csv('AB_NYC_2019.csv')

ab_nyc.head()
```

```
# DIMENSION

ab_nyc.shape
```

2. Columns With DATA-TYPES :

```
# LOOKING DATA TYPES

ab_nyc.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
```

Column Description:

Column	Description
id	listing ID
name	name of the listing
host_id	host ID
host_name	name of the host
neighbourhood_group	location
neighbourhood	area
latitude	latitude coordinates
longitude	longitude coordinates
room_type	listing space type
price	
minimum_nights	amount of nights minimum
number_of_reviews	number of reviews
last_review	latest review
reviews_per_month	number of reviews per month
calculated_host_listings_count	amount of listing per host
availability_365	number of days when listing is available for booking

The above understandings lead us to perform basic Numeric and Categorical analysis in depth by using the following function:

Numerical Columns Data

```
ab_nyc[['price', 'minimum_nights', 'number_of_reviews',
        'reviews_per_month', 'calculated_host_listings_count',
        'availability_365']].describe()
```

```
# Analyzing categorical values

airbnb.select_dtypes(include=['object']).describe()
```

3. Handling Missing Values and Outliers:

Using Isolation forest:

Using Isolation Forest, we can not only detect anomalies faster but we also require less memory compared to other algorithms. Isolation Forest isolates anomalies in the data points instead of profiling normal data points.

```
# Importing Isolation Forest library
from sklearn.ensemble import IsolationForest
```

```
# Setting the Model with Data set
model = IsolationForest(n_estimators=100, max_samples=50000, contamination=0.02)
model.fit(ab_nyc[['price']])
```

Handling outliers on Price

```
# predicting outliers, +1: not outlier; -1: outlier
ab_nyc['price_anomaly'] = model.predict(ab_nyc[['price']])

# anamoly scores
ab_nyc['price_scores'] = model.decision_function(ab_nyc[['price']])
```

```
# price outliers percentage

anomaly_p = len(ab_nyc.loc[ab_nyc['price_anomaly'] == -1])
print('anomaly detection of price values: ', round((anomaly_p/len(ab_nyc))*100,4), '%')
```

```
anomaly detection of price values:  1.9374 %
```

```
# Cleaning Price Outliers
nyc_clean = ab_nyc.loc[ab_nyc['price_anomaly'] == 1]

nyc_clean.drop(['price_scores','price_anomaly'], axis=1, inplace=True)
nyc_clean.info()
```

Handling outliers on Minimum Night

```
# amount of Minimum night outliers

anomalies = len(nyc_clean.loc[(nyc_clean['minimum_nights'] > 60)])
print('anomaly detection of minimum nights values: ', round((anomalies/len(nyc_clean))*100,4), '%')
```

```
anomaly detection of minimum nights values:  0.6467 %
```

```
nyc_clean = nyc_clean.loc[nyc_clean['minimum_nights'] <= 60]
nyc_clean.info()
```

Handling outliers on availability_365

```
anomaly = len(nyc_clean.loc[(ab_nyc['availability_365'] == 0)])
print(anomaly)
print('anomaly detection of minimum nights values: ', round((anomaly/len(nyc_clean))*100,4), '%')
```

```
17277
anomaly detection of minimum nights values:  36.2795 %
```

Why so many data with 0 days available?
hypothesis: Those places were already rented on the date the dataset was generated?
Users have suspended the ad on the platform?
Reason :
Because the amount of data is representative in this case, and may not represent an outlier, we will not remove them

```
# null values in last_review are filled with 'Not recieved'

ab_nyc.last_review.fillna('Not Recieved', inplace= True)
```

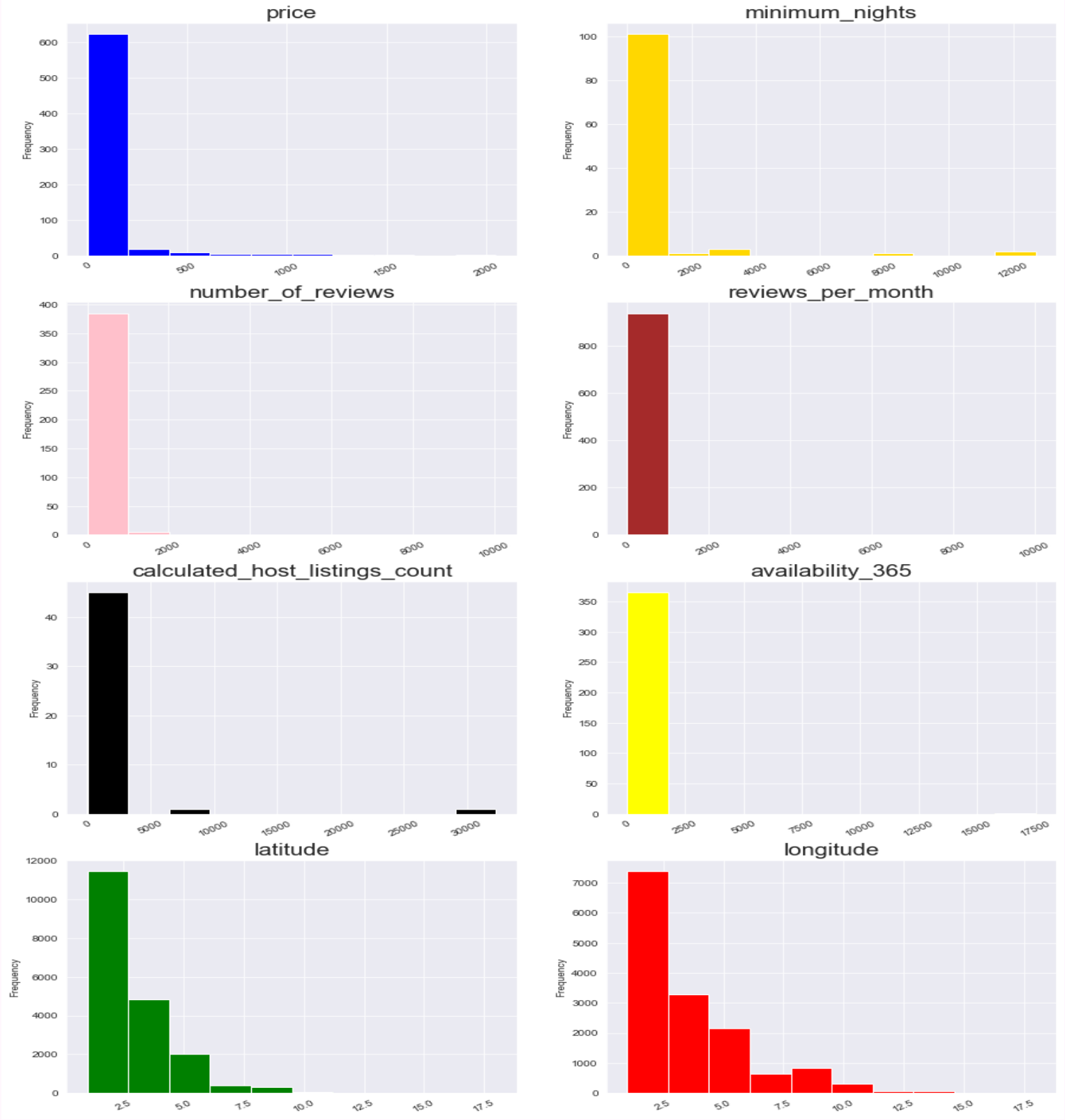
```
# null values in host_name is filled with others

ab_nyc.host_name.fillna('others', inplace= True)
```

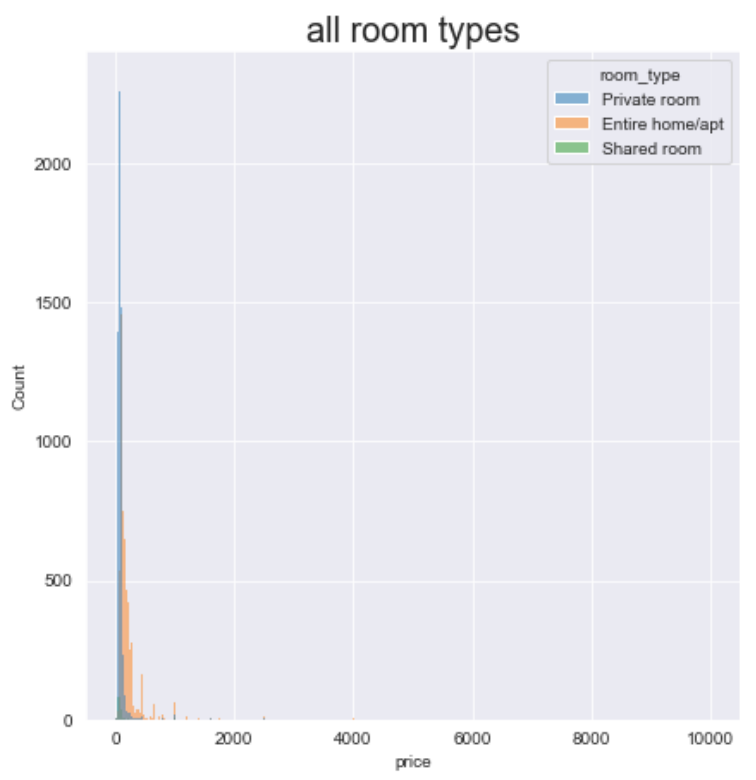
```
# And Remainig null Values are Droped
ab_nyc.dropna(inplace = True)
```

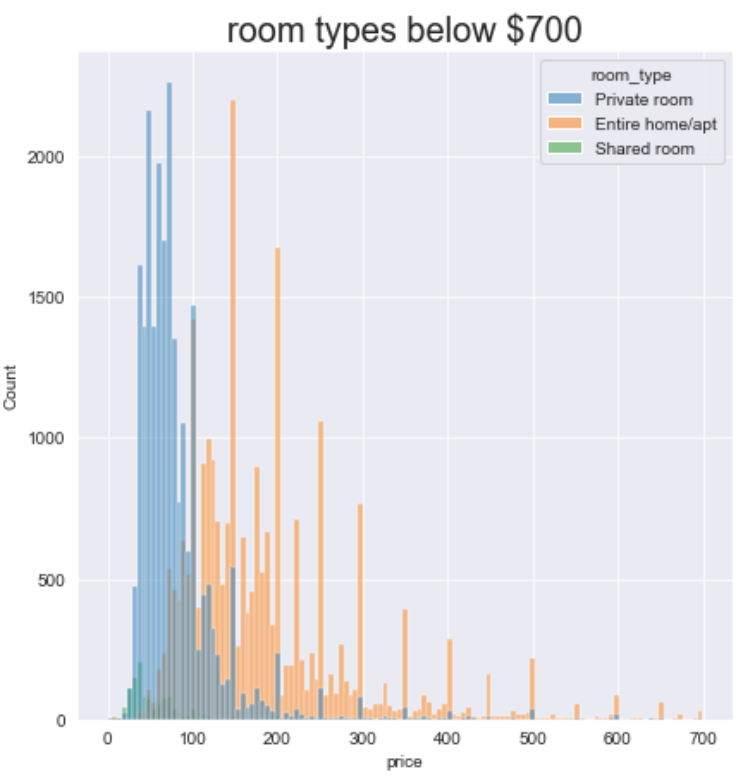
4. Analyzing Methods and Data Distribution :

a. Univariate Analysis:

General Univariate Analysis on Numeri columns. For numeric columns used count histplots

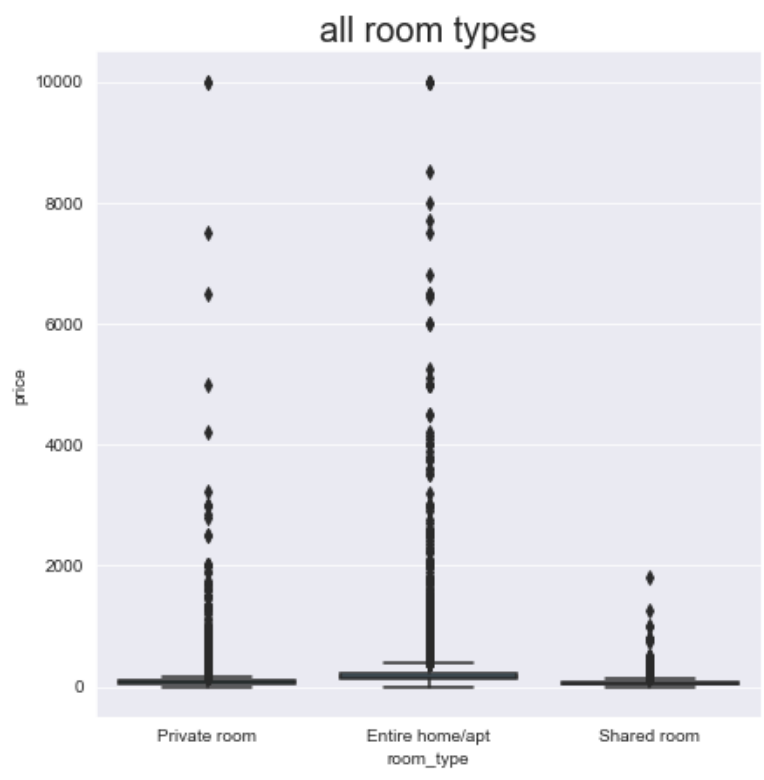


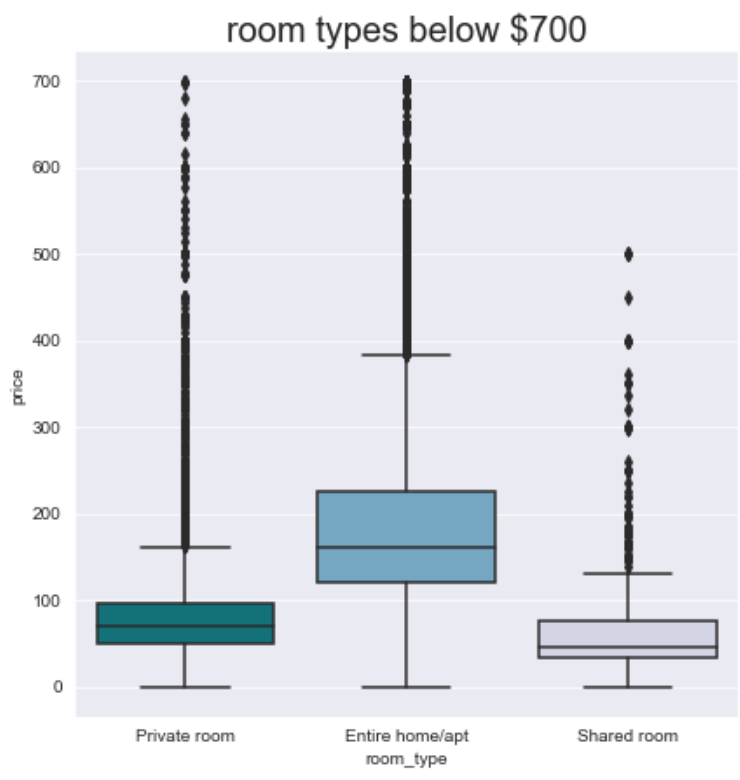


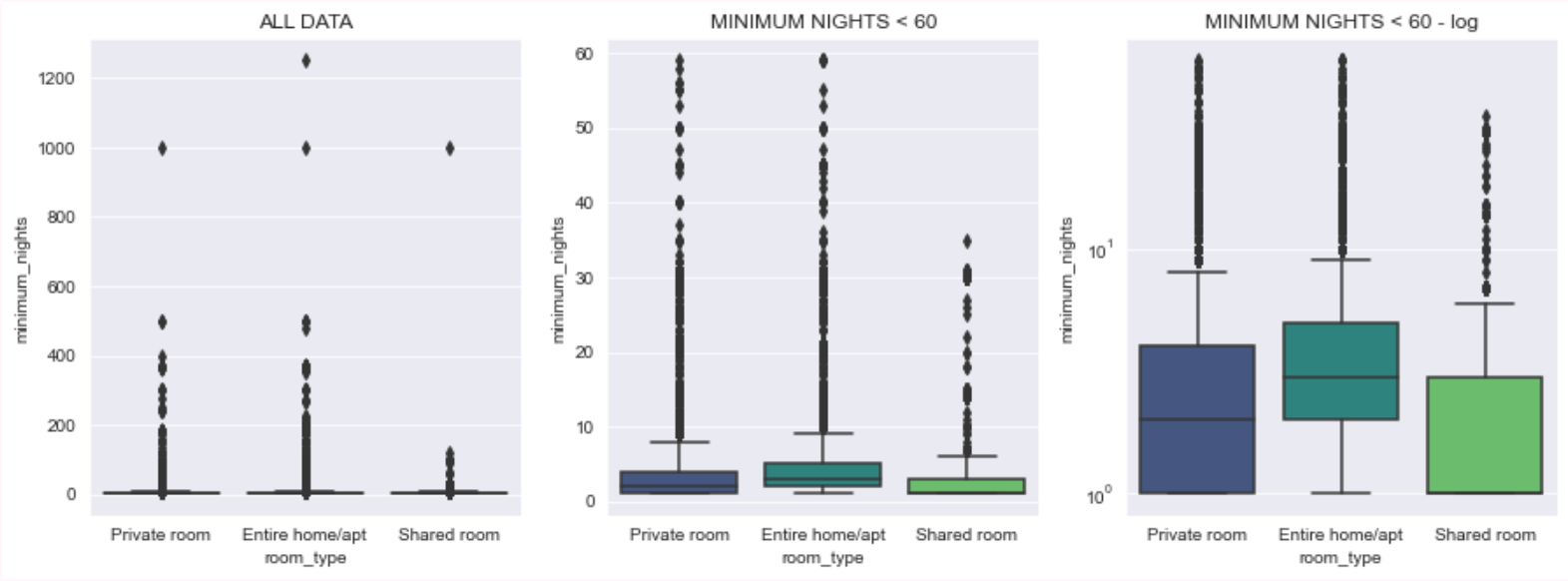


b. **Bi-Multivariate Analysis**:

Here we first plotted a pairplot of all the numeric columns using seaborn library in Python itself. Below is the code for the same.







5. Matrix used for Analysis:

In order to measure our analysis we created a categorical and Numerical Matrix to provide us a direction while creating graphs using different Dimensions and Measures. This matrix involved the values needed to create the graphs. which helps in identifying which all dimensions and measures have been consolidated to get the insights from the data. Below is the Matrix

1. Categorical & Numerical
2. Categorical & Categorical
3. Numerical & Numerical
4. Numerical & Categorical

6. Evaluation of Methods:

conducted an empirical evaluation of whether doing good or doing in the right way to check at every step by creating relevant questions to see what we are trying to extract from the raw data. its significantly, to extract the relevant information that we want to recommend to our target audience. Above matrix taken as a resource for creating graphs and charts taking insights from them to Answer the following questions.

1. Which locations are getting more traction?
2. Which locations are price and review sensitive?
3. Which properties are available for more days in a year and in which location?
4. In what time period the properties have received more or less number or reviews?
5. What are the pricing ranges preferred by end customers?
6. What type of properties are preferred by the customers?
7. What are the most popular localities and properties in New York currently?
8. Which properties and room types have more or less minimum night stay?
9. Which are the locations that are not performing well based on reviews and other parameters?
10. Which are the room types that are not performing well?
11. How many sites are hosted by a single host and what are its success metrics?
12. Which hosts have received better reviews?
13. Is there any correlation between the prices and reviews or other parameters?
14. Which location has properties functioning for more than 300 days in a year or less than 50 days?
15. Which parameter makes the customer prefer the property and provide a review?

Findings & Insights:

7. Basic Data Interpretation:

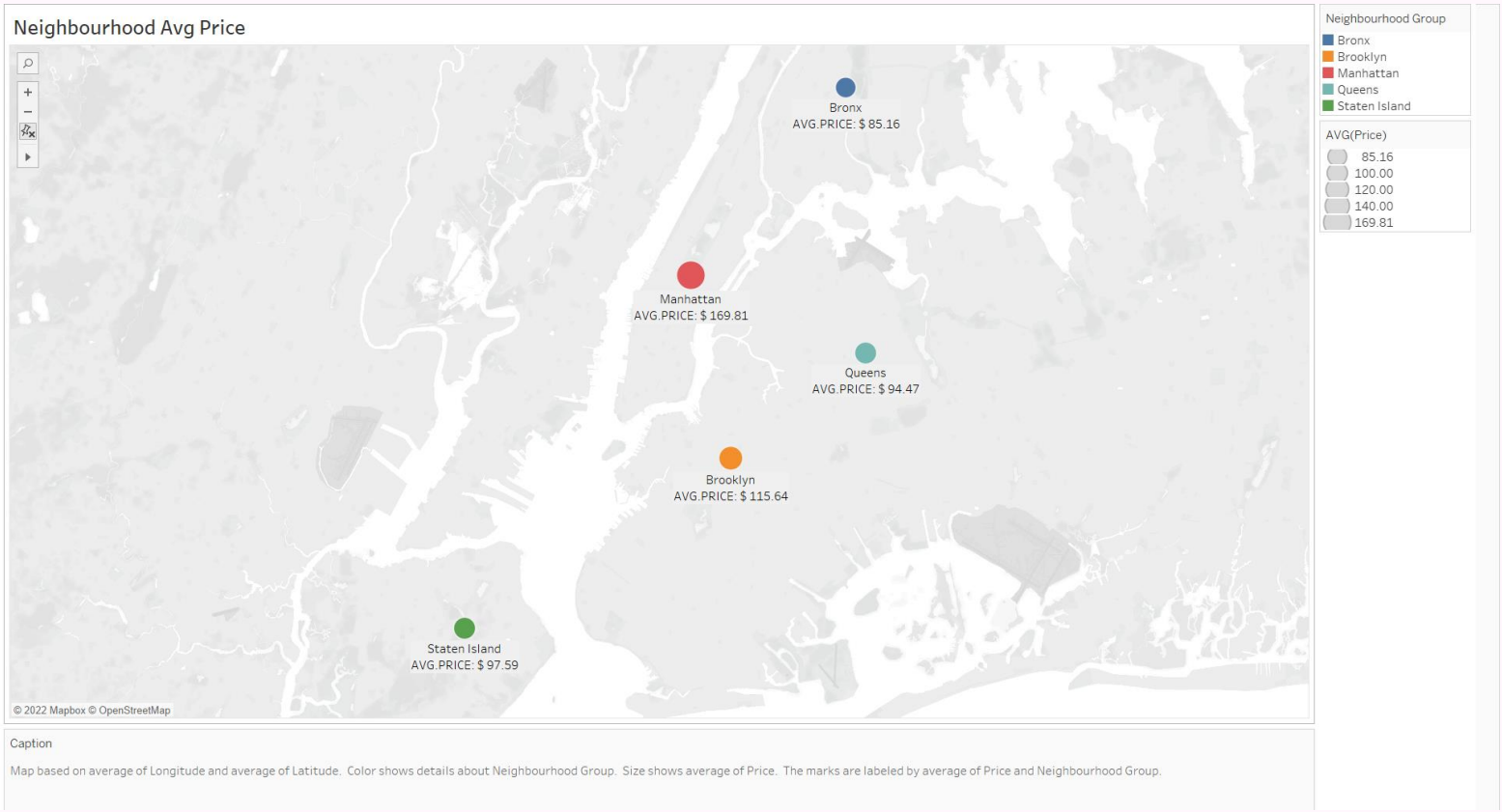
There are 16 columns and 48895 rows in the dataframe.

There are 3 floats, 7 integers and 6 objects data type values in the data frame.

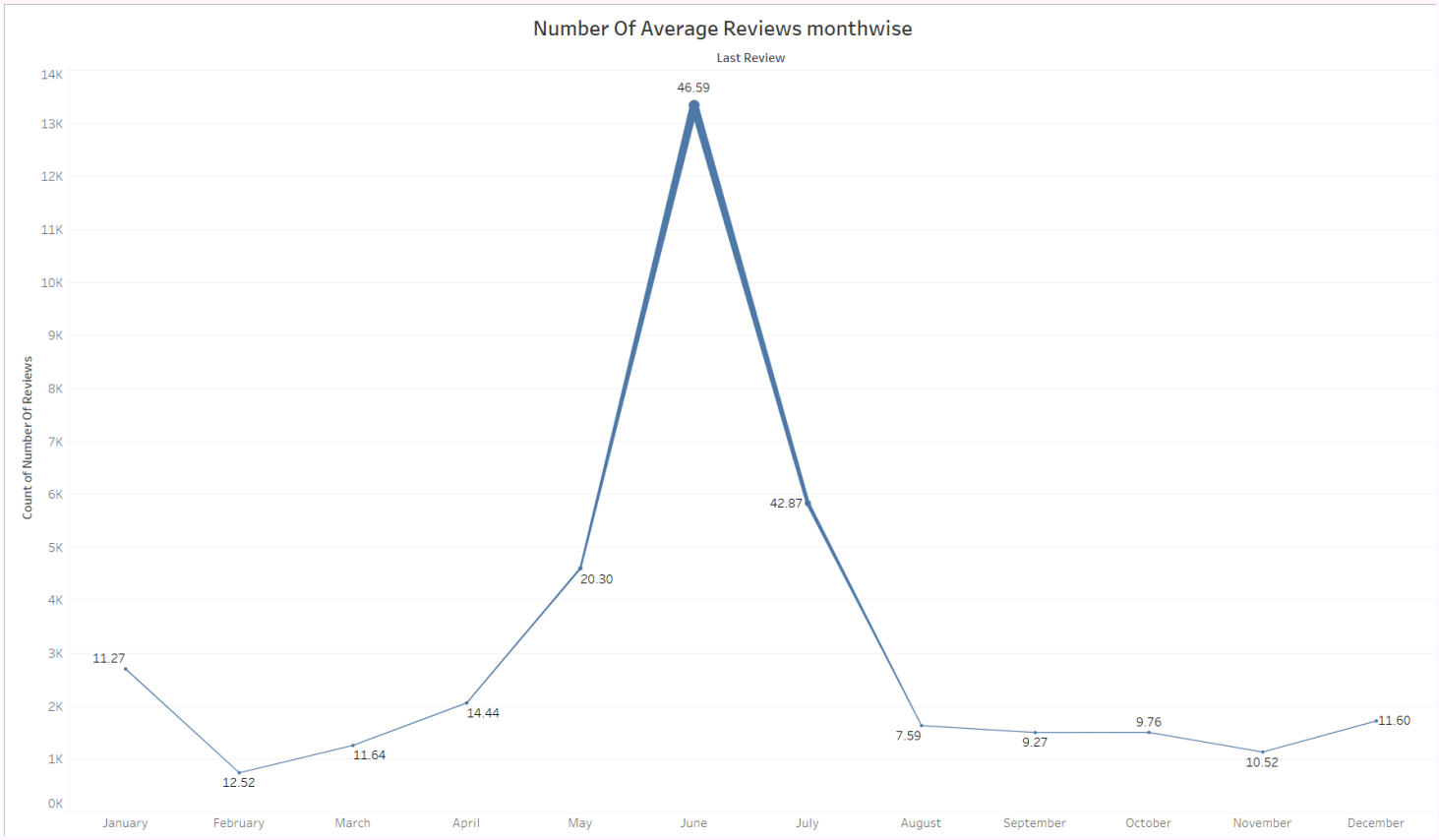
There seems to be many columns with missing values.

8. Visualisation Analysis:

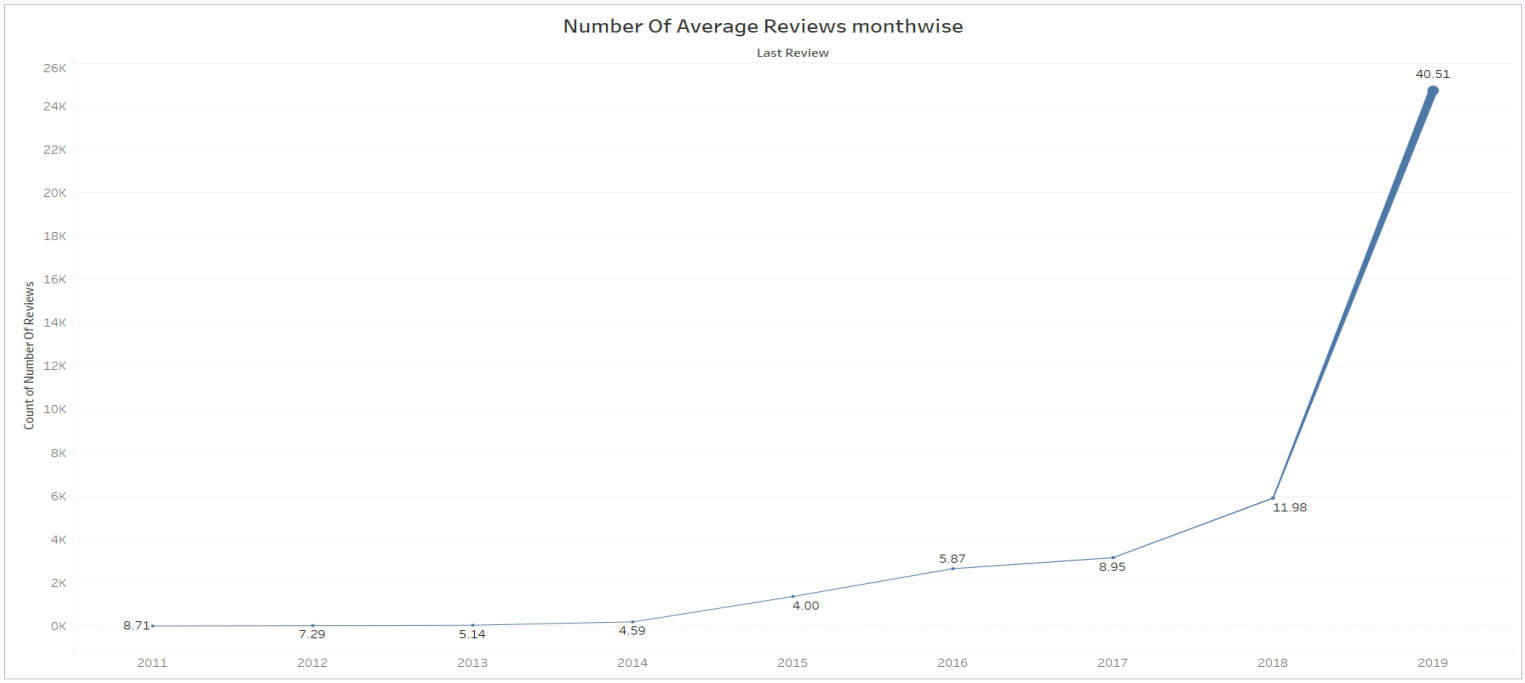
1. Overview of the Major Boroughs (New York City) based on Average Price Range



2. The trend of count of Number Of Reviews for Last Review Month



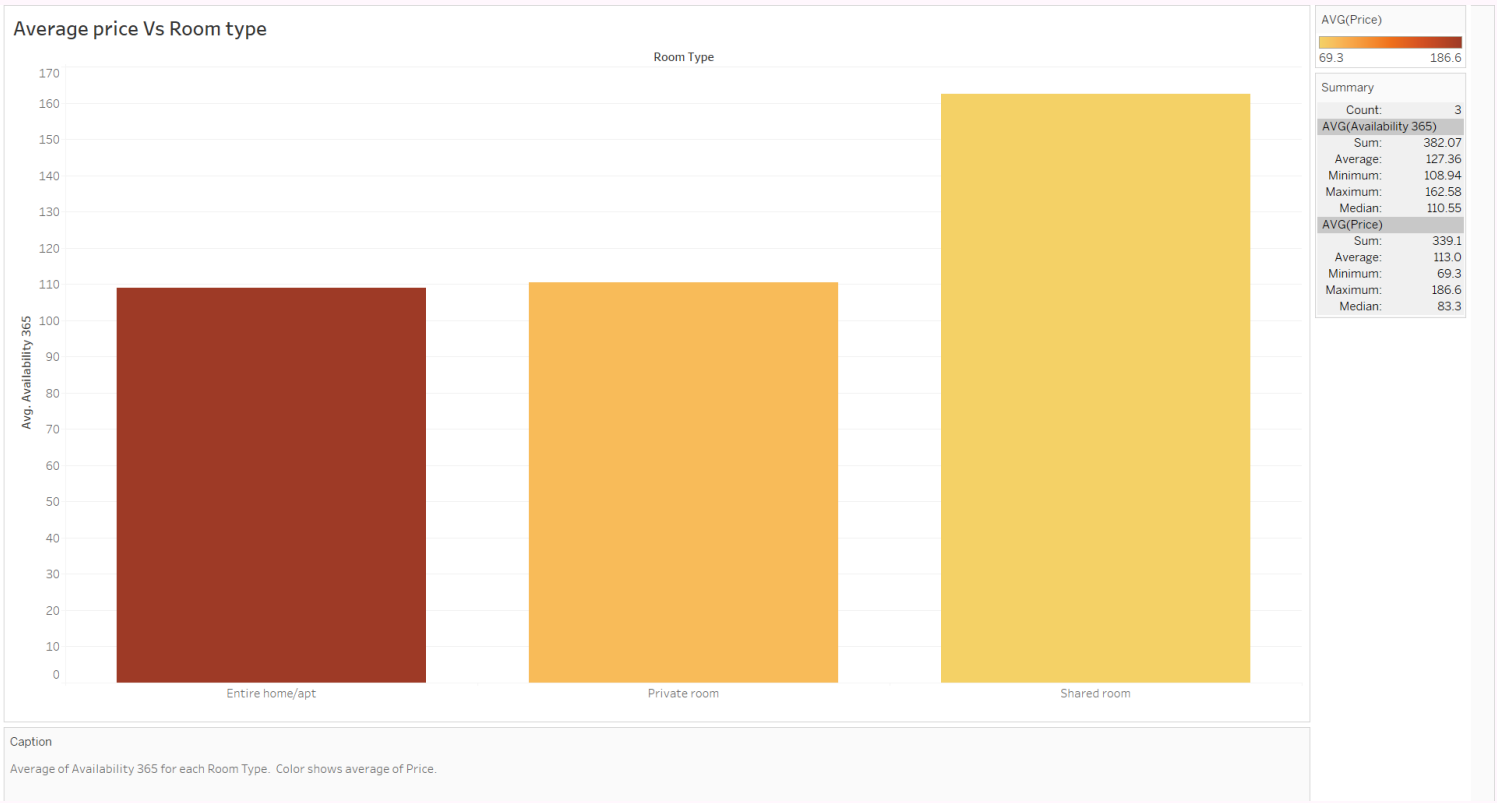
3. The trend of count of Number Of Reviews for Last Review year



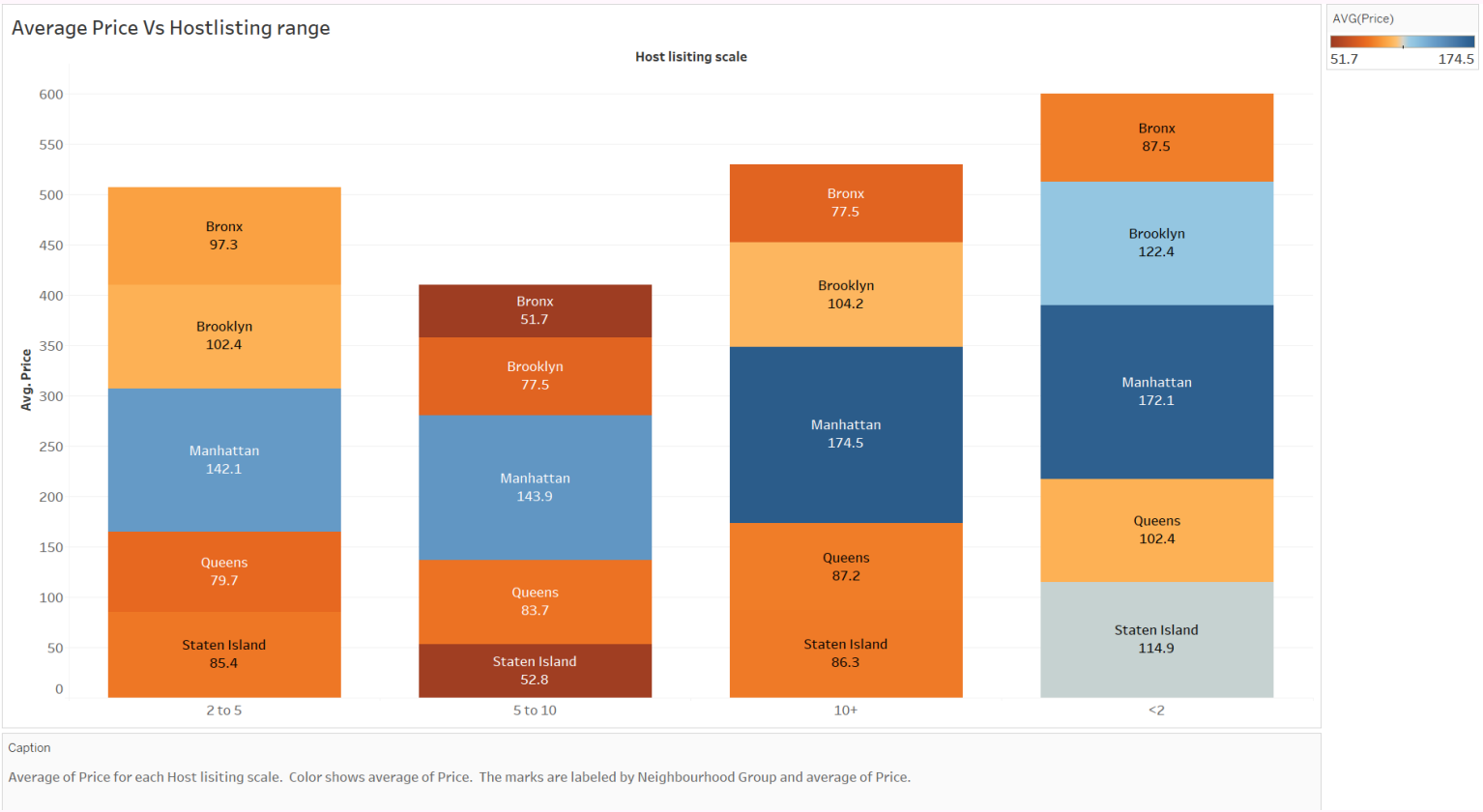
Caption

The trend of count of Number Of Reviews for Last Review Year. Size shows sum of Number Of Reviews. The marks are labeled by average of Number Of Reviews. The data is filtered on Last Review Month, which excludes Null.

4. Overview on Room Availability on with Room types, colour code shows insights for Average Price Range



5. Overview on Hosts vs average Price, colour code shows insights for Average Price Range on different Neighbourhood groups



Caption

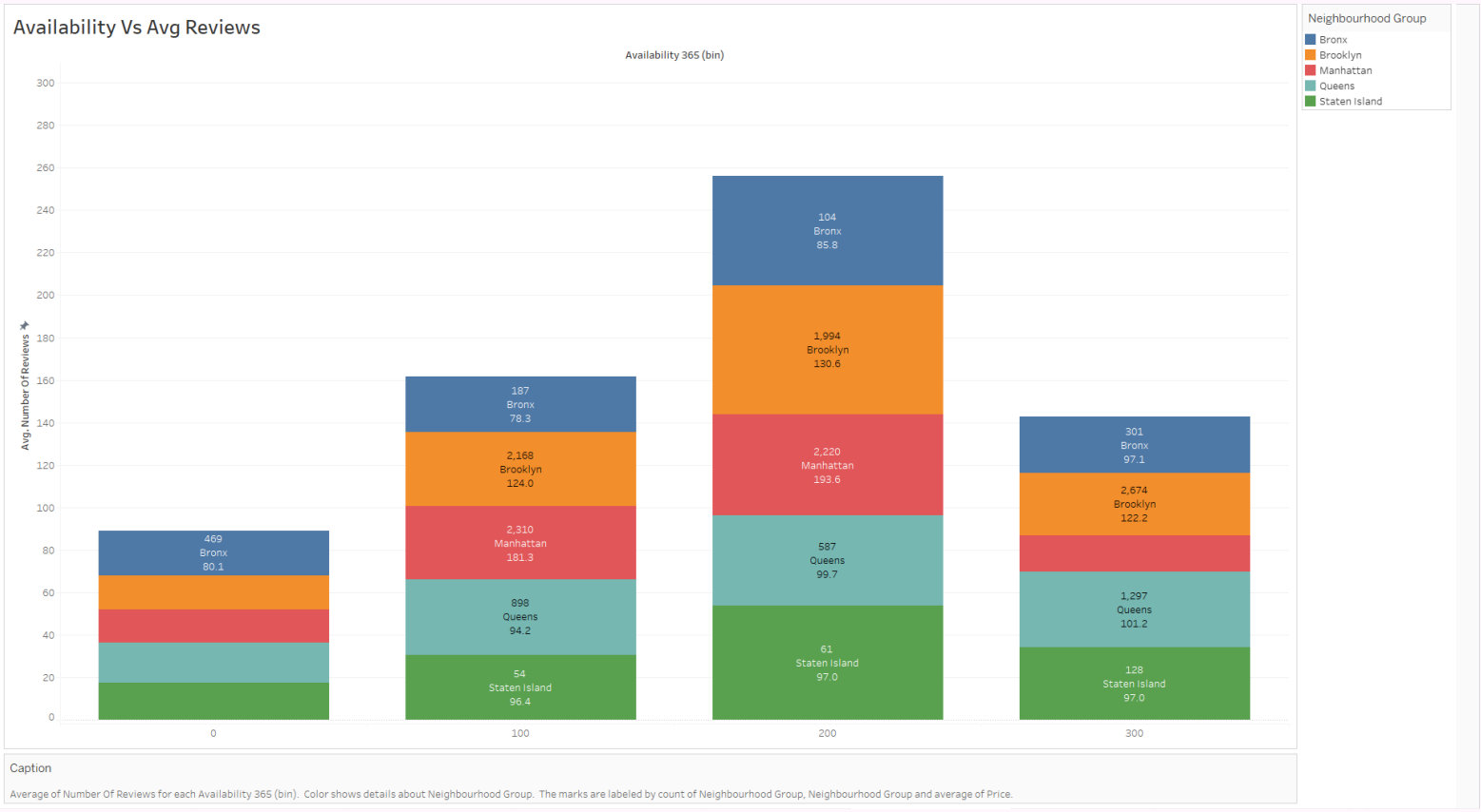
Average of Price for each Host lisiting scale. Color shows average of Price. The marks are labeled by Neighbourhood Group and average of Price.

6. Overview on Availability vs average Price, colour code shows insights for Average Price Range on different Neighbourhood groups

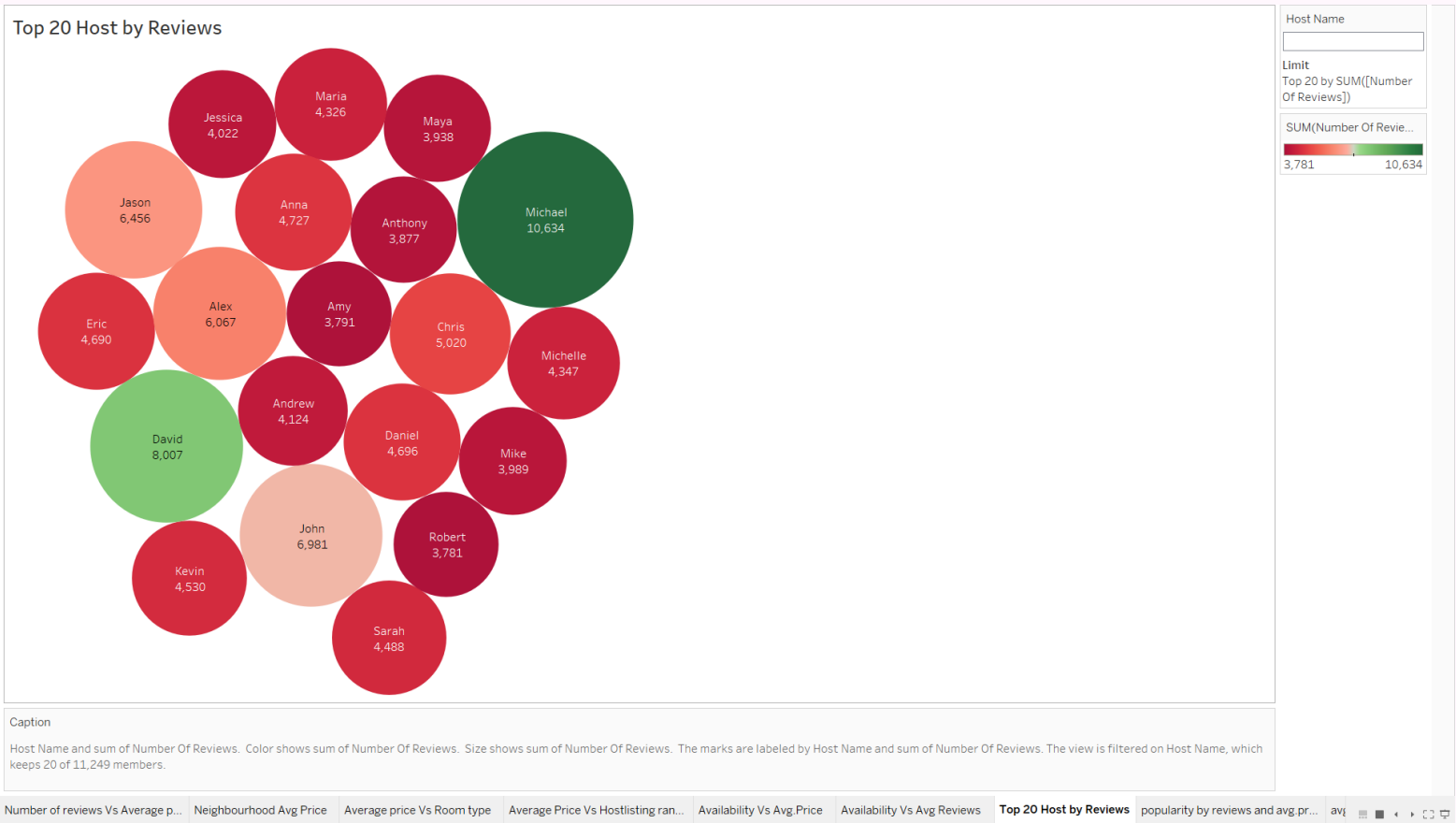
Caption

Average of Price for each Availability 365 (bin). Color shows details about Neighbourhood Group. The marks are labeled by Neighbourhood Group and average of Price. The view is filtered on Availability 365 (bin), which keeps 0, 100, 200 and 300.

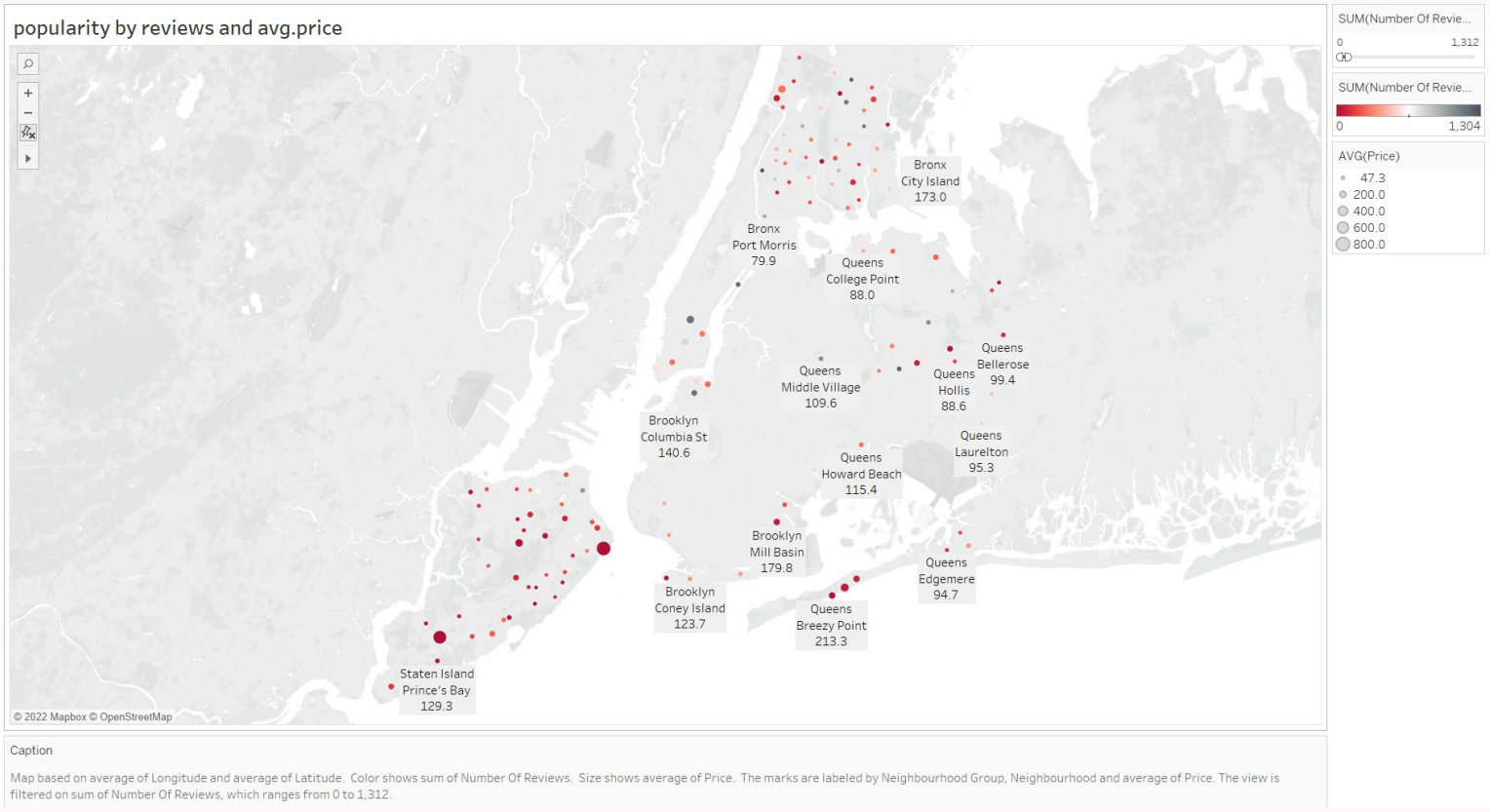
7. Overview on Number of Reviews vs Availability, colour code shows insights for count of different Neighbourhood groups with average price



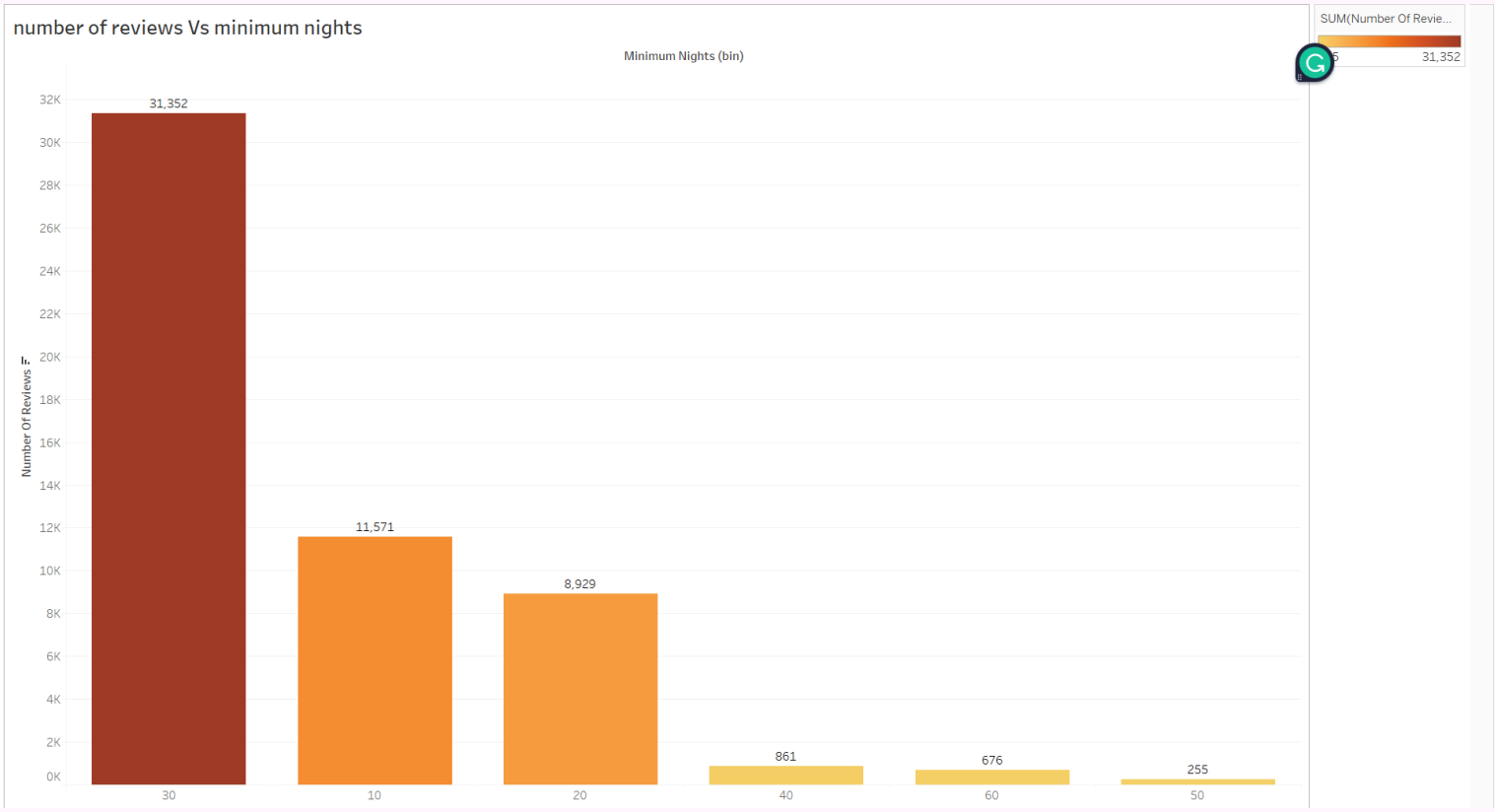
8. Overview on Top 20 Hosts by Reviews, colour code shows insights for sum of reviews



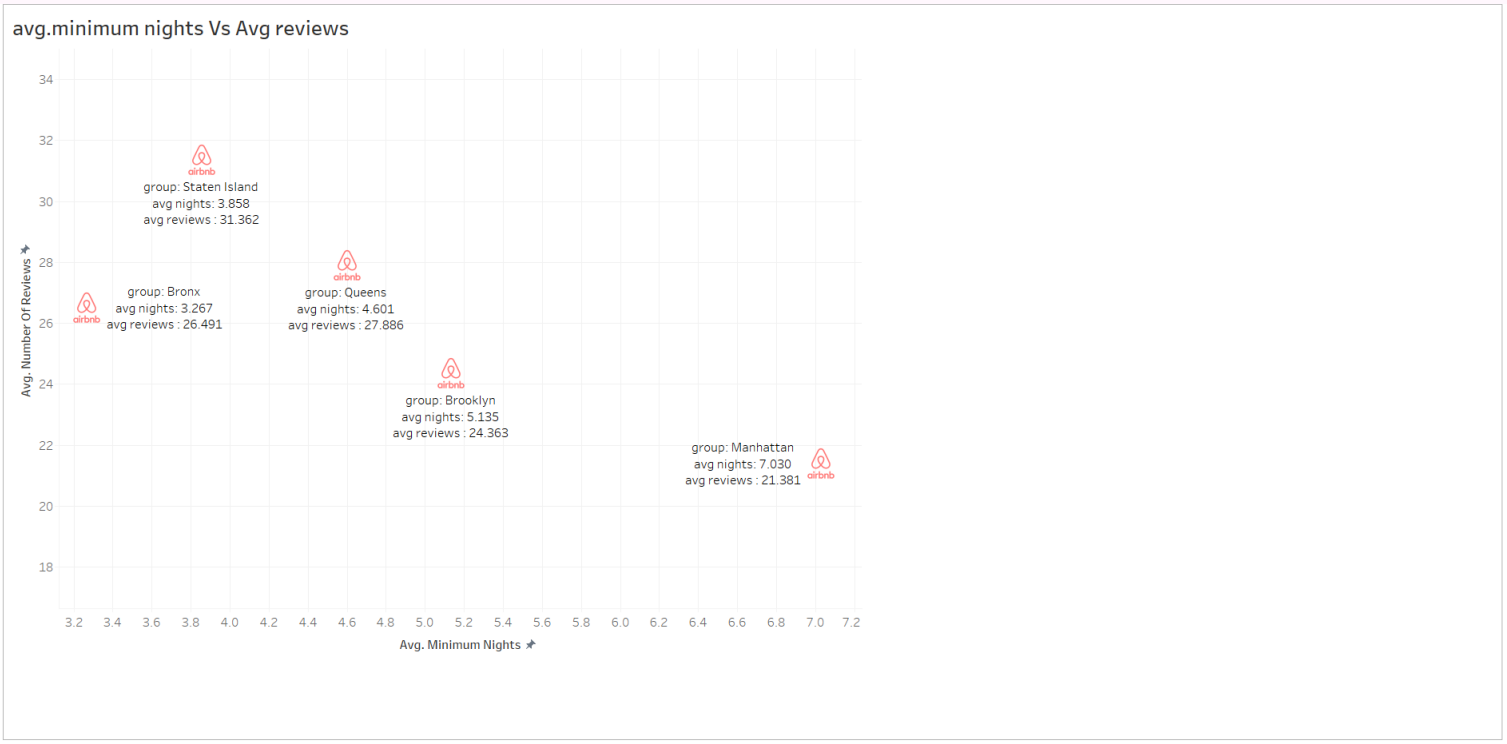
9. Map Showing the Location most reviewed neighbourhood groups and size showing the estimation of average price range



10. Number of Reviews Vs Minimum Nights Graph Showing the Number Review taken with minimum night stay



11. Number Reviews taken by the Neighbourhood with average minimum Stay and average Reviews



Caption

Average of Minimum Nights vs. average of Number Of Reviews. The marks are labeled by Neighbourhood Group, average of Number Of Reviews and average of Minimum Nights.

12. Average Price charges by the Neighbourhood with minimum nights

Caption

Average of Minimum Nights vs. average of Price. The marks are labeled by average of Minimum Nights, average of Price and Neighbourhood Group. Details are shown for Neighbourhood Group.

9. Key Findings from the Above Graphs:

- The marks are labelled by average of Price and Neighbourhood Group, Manhattan is having a highest Average Price of $169.81 , followed by the Broklyn and Manhattan are dominating when it comes to listed hostings followed by Queens.
- Most of the Reviews are received In the month of June with average 46.69, from the month May to July most of the Reviews are received.
- Initial years which were 2011 till 2014, last reviews were negligible. After that it is slowly going up and most of the last reviews are received in the recent years of the data that is 2019 and 2018.
- Most of the sites hosted have less than 100 days availability in comparison to all 365 days. Also, majority of them have provided 0 days availability which has to be cross-checked by the Hosting Acquisition and Operations teams to know the reason.
- Majority of the hosts have less than 2 sites hosted by them on the platform.
- Most of the sites have received less than 2 reviews per month which indicates bad customer experience offered by majority sites.
- Also, Majority of the sites have received less than 50 reviews till date which is kind of less as per social norms.
- Majority of the sites provide less than 10 nights stay at a time.
- Majority of the sites hosted are either Private rooms or Entire apartments but very less Shared rooms.

Conclusion:

Important Insights from the Data:

1) There appears to be no positive or any type of correlation between the numerical variables.
2) Highest Price range Manhattan is the only Neighbourhood in the Borough that lies in offering the Highest Price range of properties on the platform followed by others with a Medium Price range on average. Prices offered above 120$ on average are considered to be a High Price, between 80$ and 120$, Medium Price range and less than 80$ to be considered Low Price range properties.

3) Having a high price range, Entire home/apt types rooms are available for less than 100 days on average followed by Private rooms on an average of 105 days and Shared rooms around 155 days on average being the lowest in price.
4) Manhattan has the highest number of places listed around more than 10 by a single host with an average price of 230$ followed by Brooklyn with an average price of 108$. On the other hand, all the hosts have less than 2 properties listed in either of the Borough on an average price range between 80$ and 170 $.
5) Brooklyn has received the highest number of reviews based on the availability to stay open for more than 200 days in a year. This is followed by Staten Island and then the Bronx. On the other hand, there are some sites in Staten Island which are not open for a single day at all and hence could be the reason they have received very low reviews from the end consumer. We need to check which are these places and what issues are they facing.
6) Majority of the customers prefer a price range of 120$ to 130$ on average for a stay. As most of them have provided a good number of reviews within this price range.
7) Michael, David, Alex, John and Daniel are the Top 5 hosts that seem to have received the highest number of reviews for their listed sites and have also sites listed with a High price range.
8) Staten Island - Silver Lake, Staten Island - Richmondtown, Staten Island - Eltingville, Staten Island - Huguenot and Brooklyn - Manhattan Beach are the Top 5 locations with Low Price ranges that have received the highest number of reviews on average being the lowest in the Price range. On the contrary, Queens - Neposit, Manhattan - NoHo, Manhattan - Tribeca, Staten Island - Willowbrook and Manhattan - Flatiron District is the highest in the Price range and have received a low number of reviews.
9) “WELCOME TO BROOKLYN" PARKSIDE VIEW STUDIO APT", “Oasis on the Park”, “HELLO BROOKLYN" PARKSIDE VIEW NEWLY RENO APT”, “Comfy Home Away From Home/Multiple rooms”, “LOVE BROOKLYN" Newly Renovated Studio APT” and “Cozy Retreat" in North Crown Heights” are the Top 6 listed places that have received the highest number of reviews.
10) On average Entire home/apt types are preferred more by the customers followed by Private rooms and then Shared Rooms. Mostly because they are also available for a higher number of minimum nights stay window booking as compared to Private and Shared rooms.
11) “Modern Duplex - Central Chelsea!!!” in Manhattan-Chelsea, “Spacious & Bright 3BRs Near Subways, Parks, Shops” in Brooklyn-Cobble Hill, “NYC LUXURY3 BEDROOMS IN MIDTOWN EAST & GYM& BALCONY” in Manhattan-Murray Hill, “An Artist's Inspiration: Sun-Soaked Chelsea Loft” in Manhattan-Chelsea and “Upper West Side elegance. Riverside” in Manhattan-Upper West Side are the Top 5 hosted places with highest price offerings.

12) “Brooklyn-Williamsburg”, “Brooklyn-Bedford-Stuyvesant”, “Manhattan-Harlem”, “Brooklyn-Bushwick” and “Manhattan-Upper West Side” are some places providing the highest number of minimum nights window to bookmaking Manhattan and Brooklyn the top neighbourhoods in offering maximum minimum nights stay.
13) The average number of reviews started increasing exponentially after 2015-2016. And the majority of the customers provide a higher number of reviews either between the months of May till July or at the starting of the year which shows a higher booking window in a year.
14) 5766 properties are open for more than 300 days a year. Around 2286 of them are from Brooklyn followed by Manhattan around 1947 properties. And on the other hand, the properties that stay open for less than 50 days a year belong to Queens or Staten Island. 15. We can confirm that the greatest parameter for any customer to prefer a property and provide a review is having a maximum or minimum night stay window booking and their probability of being open for more days in a year to some extent.

Thank you

project Done By Paramesh E