# Project Name -

AirBnb Bookings Analysis

**Project Type** - EDA

**Name** Amit Singh

# Project Summary -

**Introduction** Airbnb has transformed the travel industry ,offering of millions of listings worldwide.The project analyse the dataset of 49000 listings to extract a key insighs,focusing on user behaviour,pricing and host performance.

**Objective** The goal is to identify trends and patterns in Airbnb listings to inform business strategies,enhance user experience,and optimise pricing.

**Data oberview** The dataset includes both categorical(property type,neighbourhood) and numeric variables(price,reviews), offering a snapshot of airbnbs global presence.

**Analysis Approach**

1.**Data Cleaning:** Handle missing values,outliers,and standardize formats.

2.**Exploratory Data Analysis(EDA):** Examine statistics,distributions,and categorical frequencies.

3.**Trends and Patterns:** Analyse pricing ,host performance,and customer preferences.

# GitHub Link -

https://github.com/amit-singh-tech

# Problem Statement

The goal is to analyse Airbnb dataset to uncover thr key patterns that inform strategic decisions. The focus areas are:

1.**Key Pricing Factors**: Idenbtify how property types , location, and amenities effect prices and optimise revenue.

2.**Host Perfomance**: Evaluates hostv ratings,response times, and listing to support or improve performance.

3.**Customer Preferences**: Analyse booking patterns and understand user satisfaction and property popularity.

The analysis will offer actionable recommentations to improve service,host performance and pricing strategies.

**Define Your Business Objective**

The project aims tob use AirBnb listing data to enhance decision making and operational efficiency by:

<1> **Optimise Pricing**: recommended data_driven pricing strategies based on property type,location, and amenities to maximise host revenue.

<2> **Improve Host Perfomance**: Provide insights to enhance host ratings , response times,and service quality.

<3> **Understanding Customer Preferences**: Analyse booking patterns to tailor offerings and marketing strategies.

<4> **Forcastinf Trends**: Build models to predict pricing and demands for strategic planning.

The goal is to boost AirBnb competitiveness ,revenue,user satisfaction and market growth.

# ***Let's Begin !***

## ***1. Know Your Data***

# Import Libraries

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

# Dataset Loading

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mour
```

```
# Load Dataset
data=pd.read_csv("/Airbnb NYC 2019 (6).csv")
data
```

| | id | name | host_id | host_name | neighbourhood_group | neighbourho |
|---|---|---|---|---|---|---|
| **0** | 2539 | Clean & quiet apt home by the park | 2787 | John | Brooklyn | Kensingt |
| **1** | 2595 | Skylit Midtown Castle | 2845 | Jennifer | Manhattan | Midto |
| **2** | 3647 | THE VILLAGE OF HARLEM....NEW YORK ! | 4632 | Elisabeth | Manhattan | Harle |
| **3** | 3831 | Cozy Entire Floor of Brownstone | 4869 | LisaRoxanne | Brooklyn | Clinton H |
| **4** | 5022 | Entire Apt: Spacious Studio/Loft by central park | 7192 | Laura | Manhattan | East Harle |
| **...** | ... | ... | ... | ... | ... | |
| **48890** | 36484665 | Charming one bedroom - newly renovated rowhouse | 8232441 | Sabrina | Brooklyn | Bedfo Stuyvesa |
| **48891** | 36485057 | Affordable room in Bushwick/East Williamsburg | 6570630 | Marisol | Brooklyn | Bushw |
| **48892** | 36485431 | Sunny Studio at Historical Neighborhood | 23492952 | Ilgar & Aysel | Manhattan | Harle |
| **48893** | 36485609 | 43rd St. Time Square-cozy single bed | 30985759 | Taz | Manhattan | Hell's Kitch |
| **48894** | 36487245 | Trendy duplex in the very heart of Hell's Kitchen | 68119814 | Christophe | Manhattan | Hell's Kitch |

48895 rows × 16 columns

Next steps: View recommended plots New interactive sheet

## Dataset First View

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

| | id | belongs_to_collection | budget | genres | homepage | imdb_id |
|---|---|---|---|---|---|---|
| **0** | 1 | [{'id': 313576, 'name': 'Hot Tub Time Machine ... | 14000000 | [{'id': 35, 'name': 'Comedy'}] | NaN | tt2637294 |
| **1** | 2 | [{'id': 107674, 'name': 'The Princess Diaries ... | 40000000 | [{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam... | NaN | tt0368933 |
| **2** | 3 | NaN | 3300000 | [{'id': 18, 'name': 'Drama'}] | http://sonyclassics.com/whiplash/ | tt2582802 |
| **3** | 4 | NaN | 1200000 | [{'id': 53, 'name': 'Thriller'}, {'id': 18, 'n... | http://kahaanithefilm.com/ | tt1821480 |
| **4** | 5 | NaN | 0 | [{'id': 28, 'name': 'Action'}, {'id': 53, 'nam... | NaN | tt1380152 |

5 rows × 23 columns

## Dataset Rows & Columns count

```
# Dataset Rows & Columns count
print('number of rows in the dataset are',data.shape[0])
print('number of columns in the dataset are',data.shape[1])
```

```
number of rows in the dataset are 29203
number of columns in the dataset are 16
```

## Dataset Information

```
# Dataset Info
print('dataset completer information',data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29203 entries, 0 to 29202
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              29203 non-null  int64
 1   name                            29187 non-null  object
 2   host_id                         29202 non-null  float64
 3   host_name                       29184 non-null  object
 4   neighbourhood_group             29202 non-null  object
 5   neighbourhood                   29202 non-null  object
 6   latitude                        29202 non-null  float64
 7   longitude                       29202 non-null  float64
 8   room_type                       29202 non-null  object
 9   price                           29202 non-null  float64
 10  minimum_nights                  29202 non-null  float64
 11  number_of_reviews               29202 non-null  float64
 12  last_review                     24373 non-null  object
 13  reviews_per_month               24373 non-null  float64
 14  calculated_host_listings_count  29202 non-null  float64
 15  availability_365                29202 non-null  float64
dtypes: float64(9), int64(1), object(6)
memory usage: 3.6+ MB
dataset completer information None
```

## Duplicate Values

```
# Dataset Duplicate Value Count
print('no. of duplicates are',data.duplicated().sum())
```

```
no. of duplicates are 0
```

## Missing Values/Null Values

```
# Missing Values/Null Values Count
print(data.isnull().sum().sum())
```

```
20141
```

```
# Visualizing the missing values
print('percentage wise missing value',round(data.isnull().sum()/len(data)*100))
```

```
percentage wise missing value id                                0.0
name                            0.0
host_id                         0.0
host_name                       0.0
neighbourhood_group             0.0
neighbourhood                   0.0
```

```
latitude                          0.0
longitude                         0.0
room_type                         0.0
price                             0.0
minimum_nights                    0.0
number_of_reviews                 0.0
last_review                      17.0
reviews_per_month                17.0
calculated_host_listings_count    0.0
availability_365                  0.0
dtype: float64
```

## 2. Understanding Your Variables

```
# Dataset Columns
data.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
data.describe()
```

| | id | host_id | latitude | longitude | price | minimum_night |
|---|---|---|---|---|---|---|
| **count** | 2.920300e+04 | 2.920200e+04 | 29202.000000 | 29202.000000 | 29202.000000 | 29202.0000( |
| **mean** | 1.141531e+07 | 3.418226e+07 | 40.729139 | -73.954652 | 148.219095 | 7.06146 |
| **std** | 6.882951e+06 | 4.006633e+07 | 0.053707 | 0.041836 | 226.261213 | 22.48812 |
| **min** | 2.539000e+03 | 2.571000e+03 | 40.499790 | -74.242850 | 0.000000 | 1.0000( |
| **25%** | 5.371022e+06 | 4.843862e+06 | 40.689350 | -73.982610 | 70.000000 | 2.0000( |
| **50%** | 1.152941e+07 | 1.812999e+07 | 40.722750 | -73.956745 | 109.000000 | 3.0000( |
| **75%** | 1.760850e+07 | 4.805519e+07 | 40.763847 | -73.939863 | 174.000000 | 5.0000( |
| **max** | 2.240994e+07 | 1.640484e+08 | 40.911690 | -73.712990 | 10000.000000 | 1250.0000( |

Double-click (or enter) to edit

## Check Unique Values for each variable.

```
# Check Unique Values for each variable.
#unique value for variable "name"
data['name'].unique()
```

```
array(['Clean & quiet apt home by the park', 'Skylit Midtown Castle',
       'THE VILLAGE OF HARLEM....NEW YORK !', ...,
       'Sunny Studio at Historical Neighborhood',
       '43rd St. Time Square-cozy single bed',
       "Trendy duplex in the very heart of Hell's Kitchen"], dtype=object)
```

```
data['host_id'].unique()
```

```
array([     2787,      2845,      4632, ..., 274321313,  23492952,
        68119814])
```

```
data['host_name'].unique()
```

```
array(['John', 'Jennifer', 'Elisabeth', ..., 'Mohamad', 'Zeleke',
       'Jarryd'], dtype=object)
```

# 3. ***Data Wrangling***

## Data Wrangling Code

```
#we will  neglect the data where price=0
data=data[data['price']>0]
```

Therefore 11 data has been removed from dataset where price=0

```
# in order to fill missing values firstly we need to check
# weather the data followed a normal distribution or it is skewed
#select the column with missing values
missing_values= data[['last_review','reviews_per_month','name','host_name']]

for i in missing_values:
  if data[i].dtype != 'object':
      skewness = data[i].skew()
      print(f'skewness of {i} is :{skewness:.2f}')
  else:
      print(f'skewness of {i} is not applicable (non-numeric column)')
```

```
#imputing the numerical column  with skewed data-------------->median
#imputing the non numerical column --------->mode
from sklearn.impute import SimpleImputer
impute_median = SimpleImputer(strategy='median')
impute_mode= SimpleImputer(strategy='most_frequent')

data[['reviews_per_month']] = impute_median.fit_transform(data[['reviews_per_month']])
data[['last_review','name','host_name']]=impute_mode.fit_transform(data[['last_review','name','host_name']])
```

```
# changing last_review data type from object to date
data['last_review']=pd.to_datetime(data['last_review'])
```

## What all manipulations have you done and insights you found?

**Filtering out 0 in price column**

<> Upon discovering the **price** column had a minimum value of **0**, which is not plausible for rental price.I applied a filter to remove these entries.The filter **df[df['price']>0]** was used to exclude records where the price was **0**, ensuring the dataset reflects the only valid active listings .

**Imputation of Missing Values**

For numerical column with skeqed distributions, such as <> For numerical column with skewed distributions, such as **reviews_per_month**, missing values are limputed using the median . The approach helps address skewness and provide a central measure of the data.

<> For categorical columns **(last_review,name,host_name)**, missing values were imputed using the mode.This strategy replaces the missing values with the most frequently occuring values in each column, ensuring a common value is used to fill gap.

**Datatype conversion**:

<> The **last_review** column , initially of type object , was converted to datetime . This conversion allows for more accurate data-based operations and analysis, such as time series analysis or date comparisons.

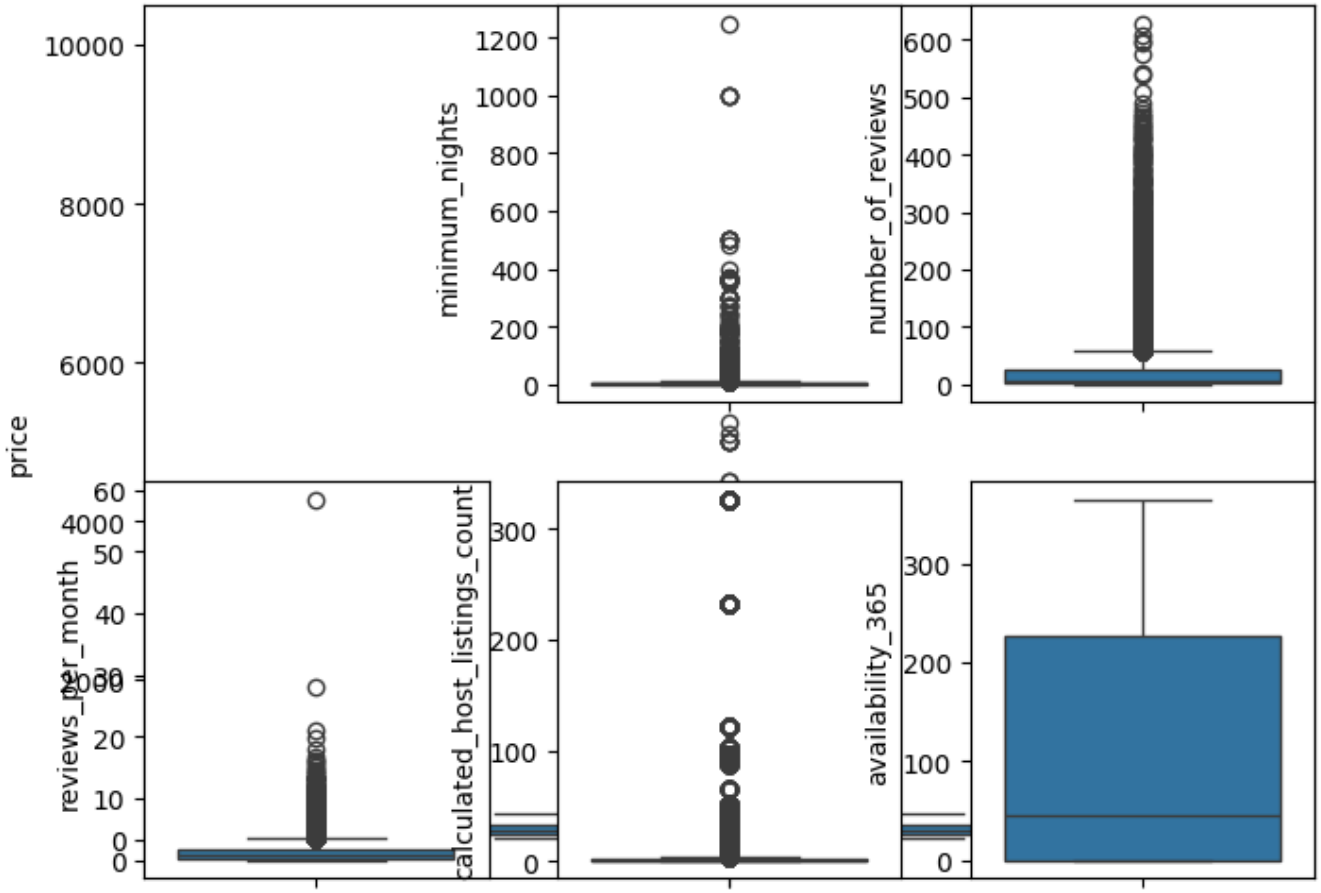
# *4. Data Vizualization, Storytelling & Experimenting with charts : Understand the relationships between variables*

## Chart - 1

```
# Chart - 1 visualization code
f, ax =plt.subplots(figsize=(8,6))
sns.boxplot(data['price'])

plt.subplot(2,3,2)
sns.boxplot(data['minimum_nights'])

plt.subplot(2,3,3)
sns.boxplot(data['number_of_reviews'])

plt.subplot(2,3,4)
```

```
sns.boxplot(data['reviews_per_month'])

plt.subplot(2,3,5)
sns.boxplot(data['calculated_host_listings_count'])

plt.subplot(2,3,6)
sns.boxplot(data['availability_365'])
```

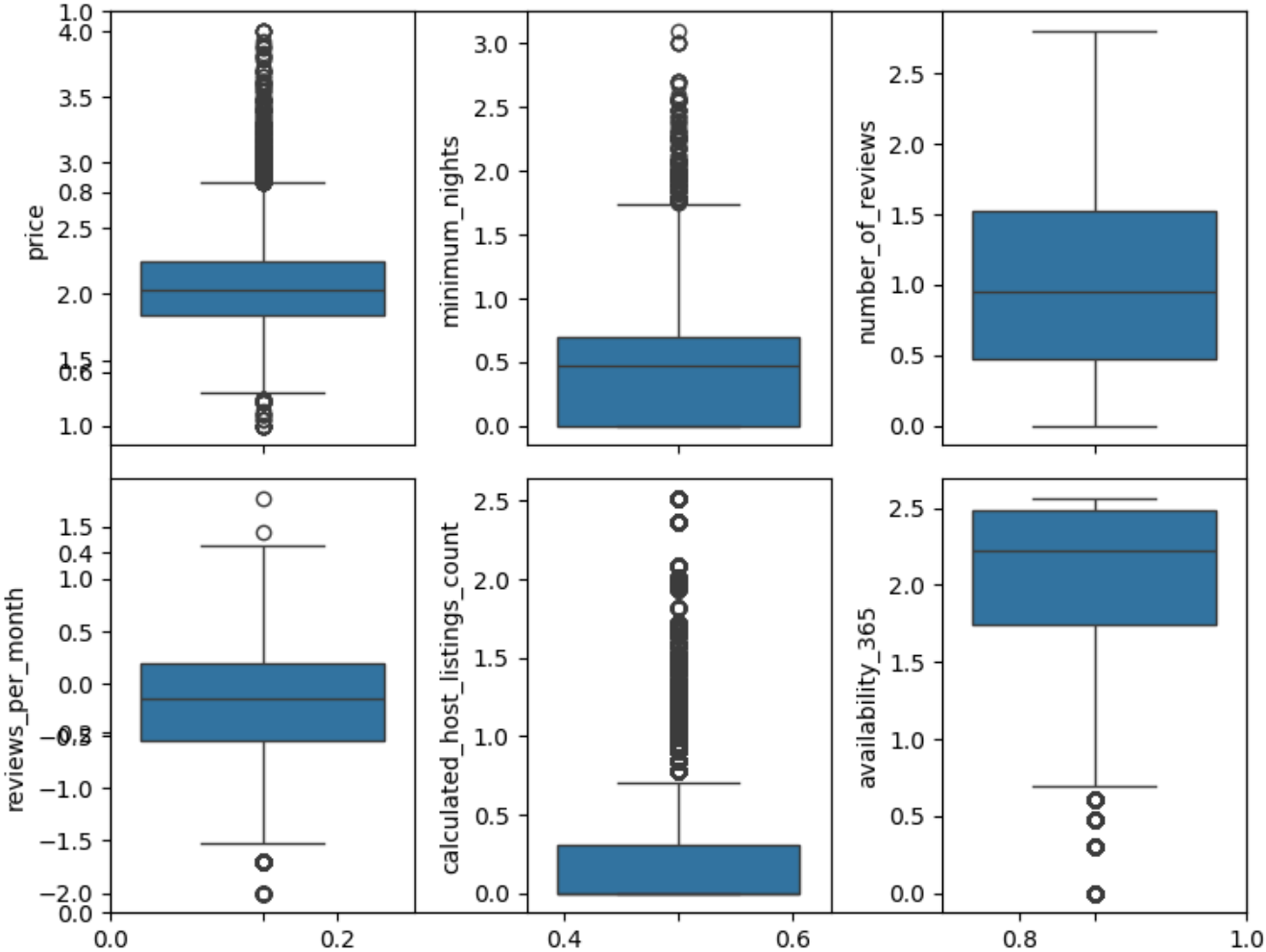
```
<Axes: ylabel='availability_365'>
```




```
# log transformations of variables
# chart 1.1 visualisation code
f , ax = plt.subplots(figsize =(8,6))

plt.subplot(2,3,1)
sns.boxplot(np.log10(data['price']))

plt.subplot(2,3,2)
sns.boxplot(np.log10(data['minimum_nights']))

plt.subplot(2,3,3)
sns.boxplot(np.log10(data['number_of_reviews']))

plt.subplot(2,3,4)
sns.boxplot(np.log10(data['reviews_per_month']))

plt.subplot(2,3,5)
sns.boxplot(np.log10(data['calculated_host_listings_count']))

plt.subplot(2,3,6)
sns.boxplot(np.log10(data['availability_365']))
```

```
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py:399: RuntimeWarning: di
  result = getattr(ufunc, method)(*inputs, **kwargs)
/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py:399: RuntimeWarning: di
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




## 1. Why did you pick the specific chart?

The initial box plot was created to visualize the distribution of the selected numeric variables (price,minimum_nights,number_of_reviews,reviews_per_month).Boxplot are ideal for identifying outliers and understanding the spread and central tendency of the data.

.

## 2. What is/are the insight(s) found from the chart?

<1>. **Low reviews per month : *** The reviews per month for each host are generally very low, including either a low engagement from guests or a potentially small number of bookings.

<2>. **Median Availabolity :** The median value of availability_365 , is around 50, suggesting that many properties are only available for 50 days a year. this could imply that a significant portion of host are not truly time renters.

<3>. **Price Outliers :** The price column contain many outliers , which could indicate a wide range of pricing strategies among hosts or thee presence of extremely high price listings that may distortthe overall data listings.

4.

```
# This is formatted as code
```

## 3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

<1> **Low reviews per month: opportunity** : Encourage guest reviews through follow ups or incentives to boost engagement. **impact** : More reviews enhance creadibility , driving bookings and revenue growth.

<2> **Median Availibility**(50 Days) : **Opportunity** : Encourage hosts to increase availibility with targeted campaigns. **Impact** : More availibility leads to increased bookings and revenue.

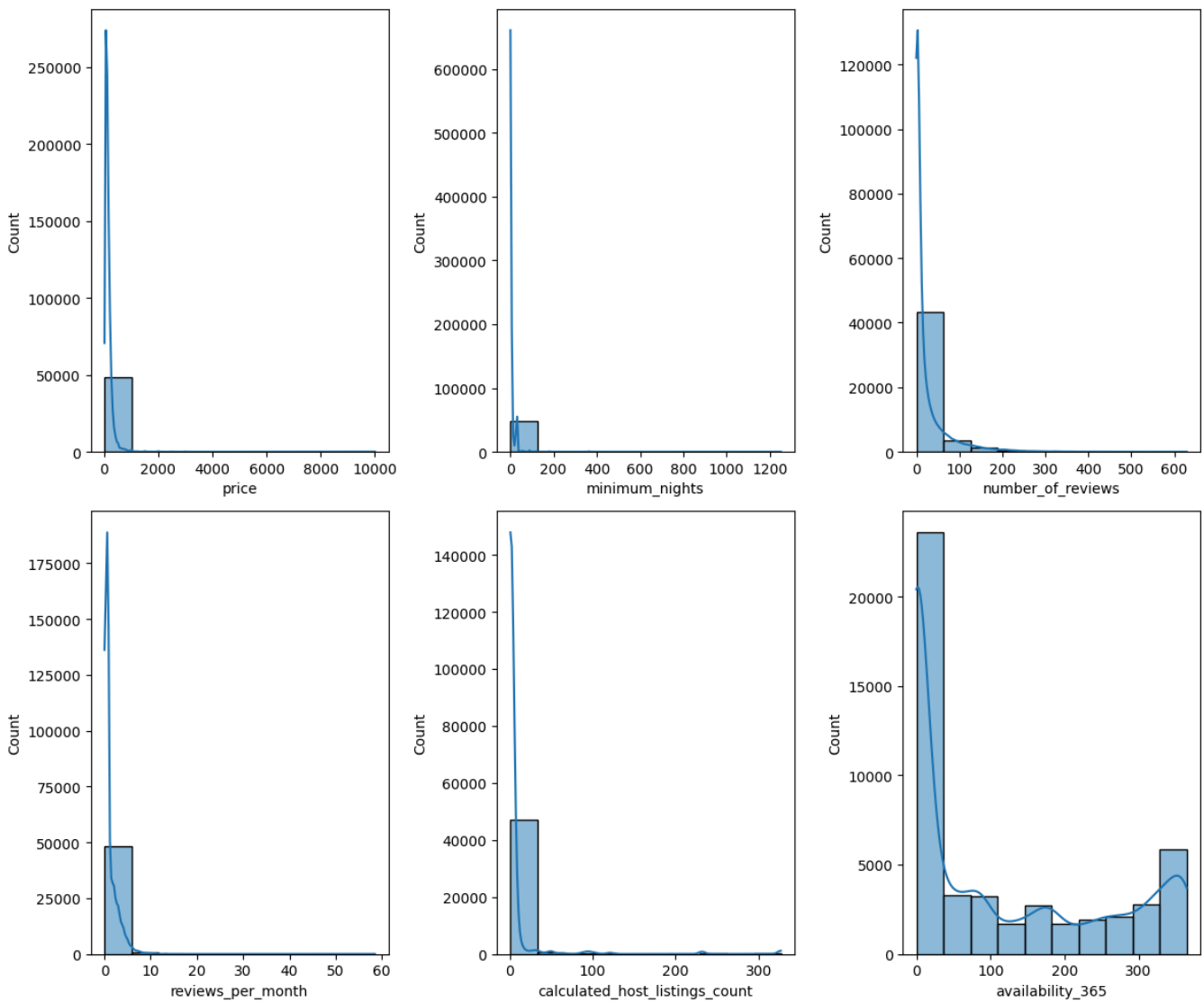
<3> **Price Outliers** : **Opportunity** : Offer pricing tools to help hosts set competitive rates. **Impact** : Optimized pricing boosts occupancy and revenue for the hosts and airbnb.

Double-click (or enter) to edit

## Chart - 2

```
# Chart - 2 visualization code
f, ax = plt.subplots(figsize =(12,10), nrows=2, ncols=3)

plt.subplot(2,3,1)
sns.histplot(data['price'], kde = True, bins = 10, ax=ax[0,0])

plt.subplot(2,3,2)
sns.histplot(data['minimum_nights'], kde = True, bins = 10, ax=ax[0,1])

plt.subplot(2,3,3)
sns.histplot(data['number_of_reviews'], kde = True, bins = 10, ax=ax[0,2])

plt.subplot(2,3,4)
```

```
sns.histplot(data['reviews_per_month'], kde =True, bins = 10 , ax=ax[1,0])

plt.subplot(2,3,5)
sns.histplot(data['calculated_host_listings_count'],kde=True,bins=10,ax=ax[1,1])

plt.subplot(2,3,6)
sns.histplot(data['availability_365'],kde=True,bins=10,ax=ax[1,2])

plt.tight_layout()
plt.show()
```




## 1. Why did you pick the specific chart?

A histogram is used to visualize the distribution of a single numeric variable by showing the frequency of data points with specified bins.It is particularly useful for understanding the distribution of the data, including the shape (e.g normal distribution ), central tendency and spread. In this case , the histogram helps in assessing how frequently different values occur or weather the

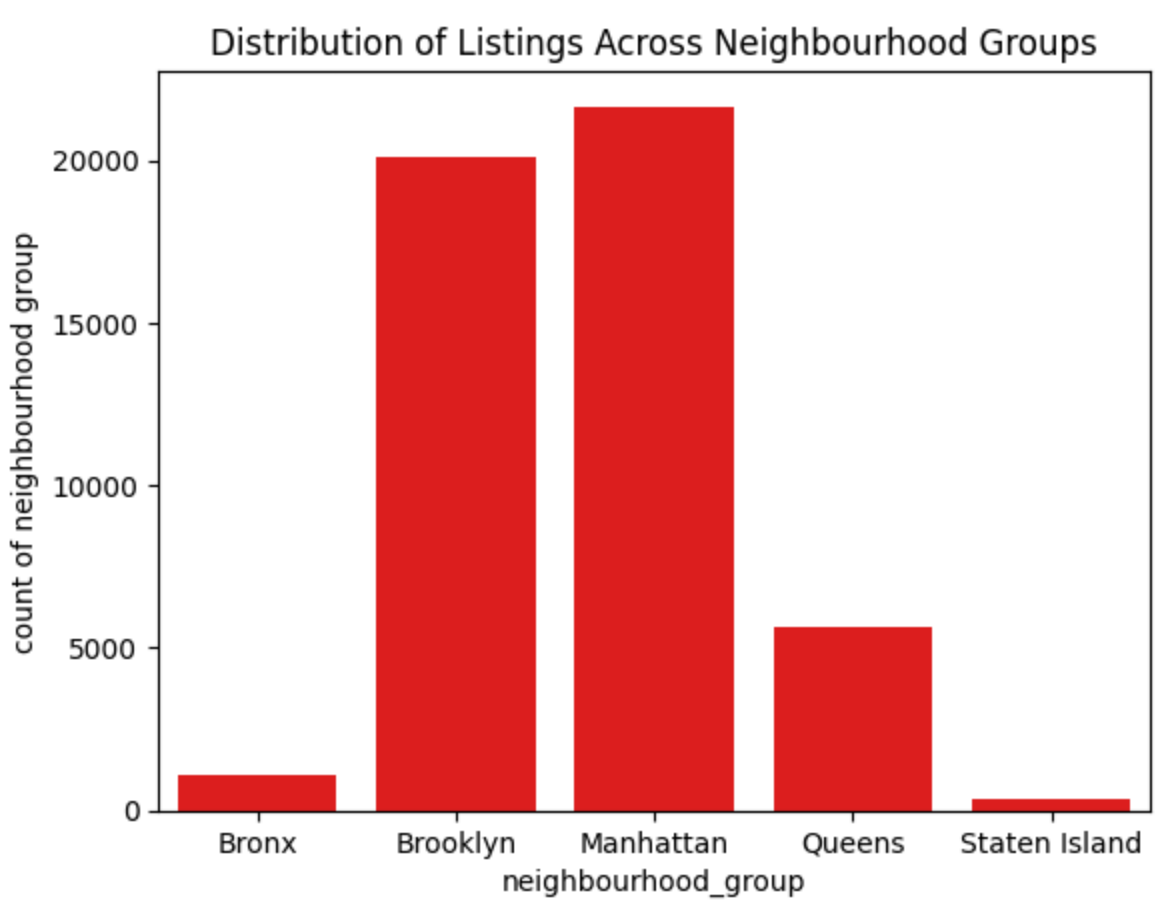
data follow a normal distribution or exhibits skewness. The insights is valueable for making decisions about data transformation and understanding the underlying patterns in your dataset.

Answer Here.

## Chart - 3

```
a = data.groupby('neighbourhood_group').count().reset_index()
```

```
# Chart - 3 visualization code
sns.barplot(x = a['neighbourhood_group'], y=a['id'], color ='red')
plt.xlabel('neighbourhood_group')
plt.ylabel('count of neighbourhood group')
plt.title('Distribution of Listings Across Neighbourhood Groups')
plt.show()
```




1. Why did you pick the specific chart?

The bar plot was specifically choosen to highlight the distribution of AirBnb listings across different neighbouring groups . By visualizing the number of listing in each group, we can quickly identify which neighbourhoods have a high concentration of listings and which one have fewer.This helps

in understranding the popularity of saturation of listings in various areas , providing insights that are crucial for market analysis and decision making

### 2. What is/are the insight(s) found from the chart?

The barplot reveals the Manhattan and brooklyn dominate the airbnb market with over 20000 listings each, making them most popular neighbourhood for hosts. In contrast queens has a moderate number of listings, with around 5500, while the Bronx and Staten island are the least popular, with approximately 1000 and 300 listings , respectively. These insight suggests that hosts and traveller alike favor certain neighbourhoods , with Manhatten and Brooklyn being the clear leaders in term of Airbnb presence.

Double-click (or enter) to edit

### 3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

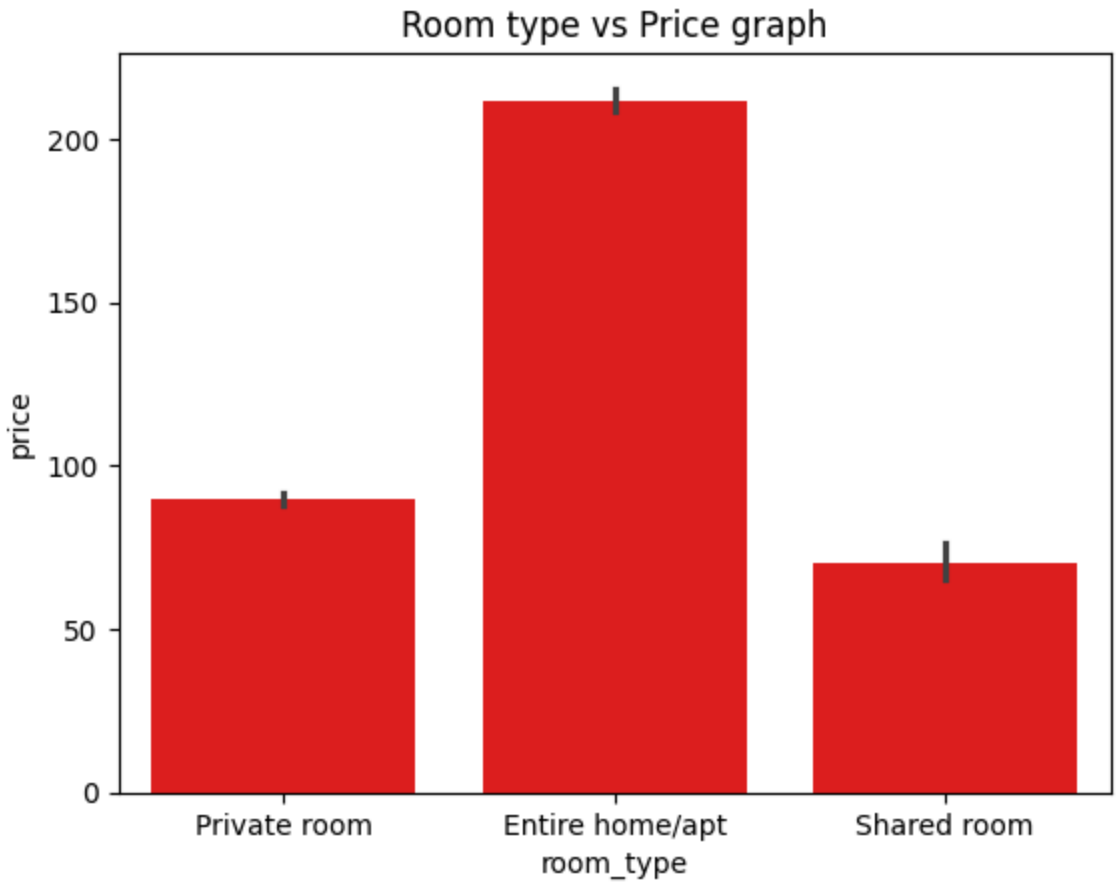
**Positive business impact** The gain insights can indeed contribute to a positive business impact . Understanding the Manhatten and Brooklyn have the higher number of airbnb listings can help property owners,hosts,and business maked informed decisions about where to invest and expand their operation . By focussing in these high demand areas business can target a large market and potentially increase their revenue.Additionally making strategies can be tailored to attract more guesits to these popular neighbourhood, further boosting business opportunities.

**Potential insights leading to negetive growth** The insights also indicate that the Bronx and Staten island have significantly fewer listings compared to other neighbourhoods, with only about 1000 and 300 listings respectively. This could signal a lack of demand in these areas , potentially leading to a negetive growth if resources are invested here without propoer market analysis.The lower number of listings might due to factor such as lower tourist interest , less desirable locations or inadequate infrastructure . Investing in these areas without addressing these underlying issues could result in poor returns and business stagnation.

↳ 1 cell hidden

## Chart - 4

```
# Chart - 4 visualization code
sns.barplot(x=data['room_type'], y = data['price'], color = 'red')
plt.title('Room type vs Price graph')
plt.show()
```




1. Why did you pick the specific chart?

I choose the barplot between room type and price to effectively showcase the price ranges of different room types avai;lable on airbnb. This visualization allows for a clear comparison of how prices varies across various room categories, such as entire homes, private rooms and shared spaces .By using this chart, we can easily identify which room types command higher price and which ones are more budget friendly, providing valueable insights into pricing trends across different accomodations options.

2. What is/are the insight(s) found from the chart?

The bar plot reveals that average pricing of private rooms and shared rooms hovers around Dollar 100, making them more budget friendly options for travellers .In contrast, the average price for an entire home or apartment, is significantly higher , at around dollar 200. This indicates that entire homes and apartment are priced at a premium compared to other room types, likely due to the added privacy and space they offer.

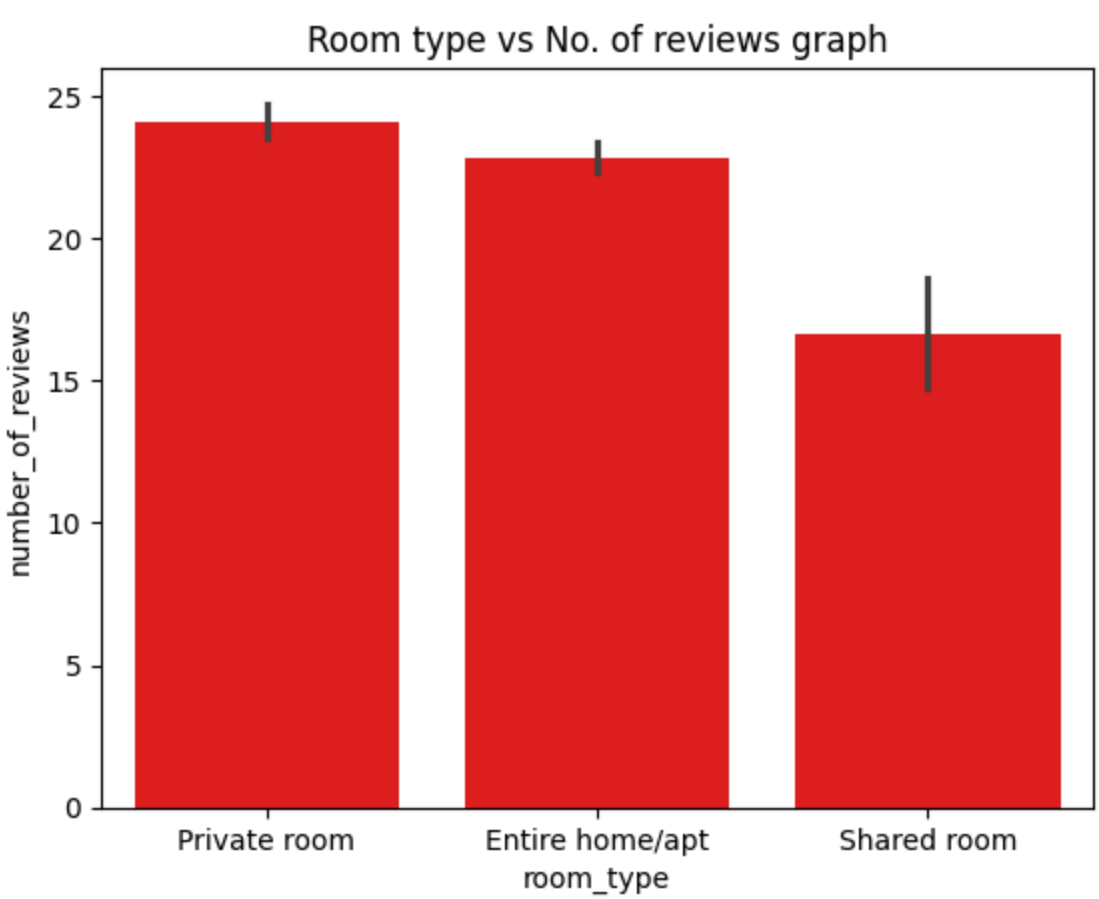
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason. The insights gained from the chart can lead to a positive business impact by informing pricing strategies and market positioning . Lnowing that private rooms and shared rooms are generally priced around dollar 100, business can target budget conciopus travellers by offering competitive rates or value added services within this price range. On mthe other hand recognizing,that entire homes or apartments are priced higher around dollar 200, allows hosts and property managers to caters to travellers seeking more privacy and space. By adjusting more pricing and marketing strategies accordingly,business can bettter needs of different customer segments , thereby increasing occupancy rates and profitability.

The insights gain from the chart can lead to a positive business impact by informing pricing strategies and markrt positioning. Knowing that private rooms and shared rooms are generally priced around dollar 100, business can target budget concious travelers by offering competitive rates and value added services within thios price range. On the other hand, recogniged that entire homes and apartment are priced higher around dollar 200, allows host and party managers to cater to traveller seeking more privacy and space. By adjusting pricing and marketing strategies accordingly, business can better meet the needs of different customers segments , thereby increasing the occupancy rate and profitability.

## Chart - 5

```
# Chart - 5 visualization code
sns.barplot(y =data['number_of_reviews'], x = data['room_type'], color = 'red')
plt.title('Room type vs No. of reviews graph')
plt.show()
```




1. Why did you pick the specific chart?
   A bar plot was choosen to compare the number of reviews across different room types . The type of chart is effective for visualizing categorical data,as it allows for straight forward comparison between distinct categories- in thus case the different room types. By displaying the number of reviews for each room types as bars, the chart clearly illustrates how review counts vary among the various types of accomodations . This comparison helps ius to understanding whicgh room types are more frequently reviewed, potentially reflecting their popularity or the level of guest engagement.

2. What is/are the insight(s) found from the chat? The bar plots indicate that : <> Private rooms : These have the highest number of reviews compared to the other room types .This suggest that the private room are the most popular of frequently looked type of accomodations, possibly due to their balance of cost and privacy.

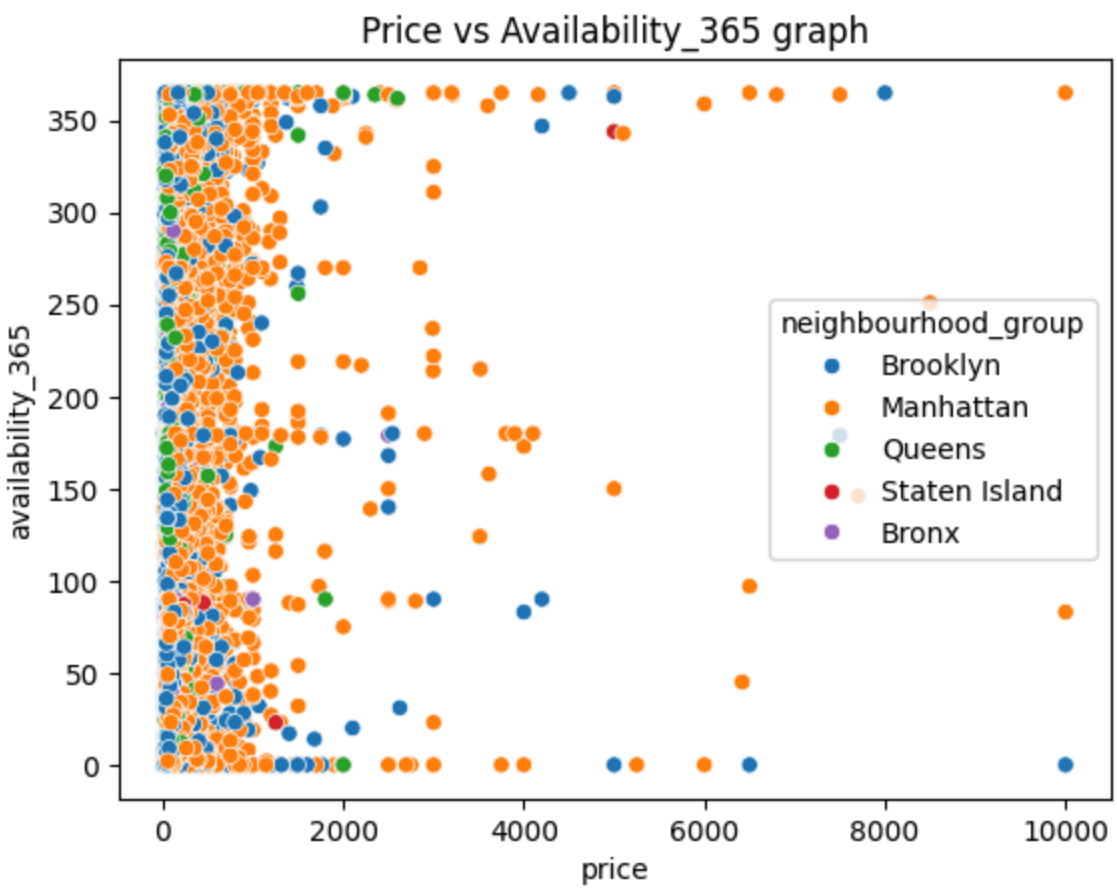
<> Entire room/apartment : This room type follows with a specific number of reviews . The highest review counts for entire homes/apartments indicate that they are also popular, likely among guests seekinng more space and privacy for longer stays.

<>Shared rooms : This have the fewest reviuew among the three categories . The lower number of reviews could reflect the less popularity or a differentmarket segments, such as budget travellers

who preferred shared accomodations.

## Chart - 6

```
# Chart - 6 visualization code
sns.scatterplot(x = data['price'], y = data['availability_365'], hue = data['neighbourhood_group'])
plt.title('Price vs Availability_365 graph')
plt.show()
```




## 1. Why did you pick the specific chart?

Ascatteer plot is choosen to analyse the relation between price and availability_365 for listings .Scatter plot are particularly effective for identifying potential correlations between two numerical variables.

2. What is/are the insight(s) found from the chart?

No significant corelations exists between botyh variables. Aditionally the scatter plot reveals that Manhatten has the highest number of available days.

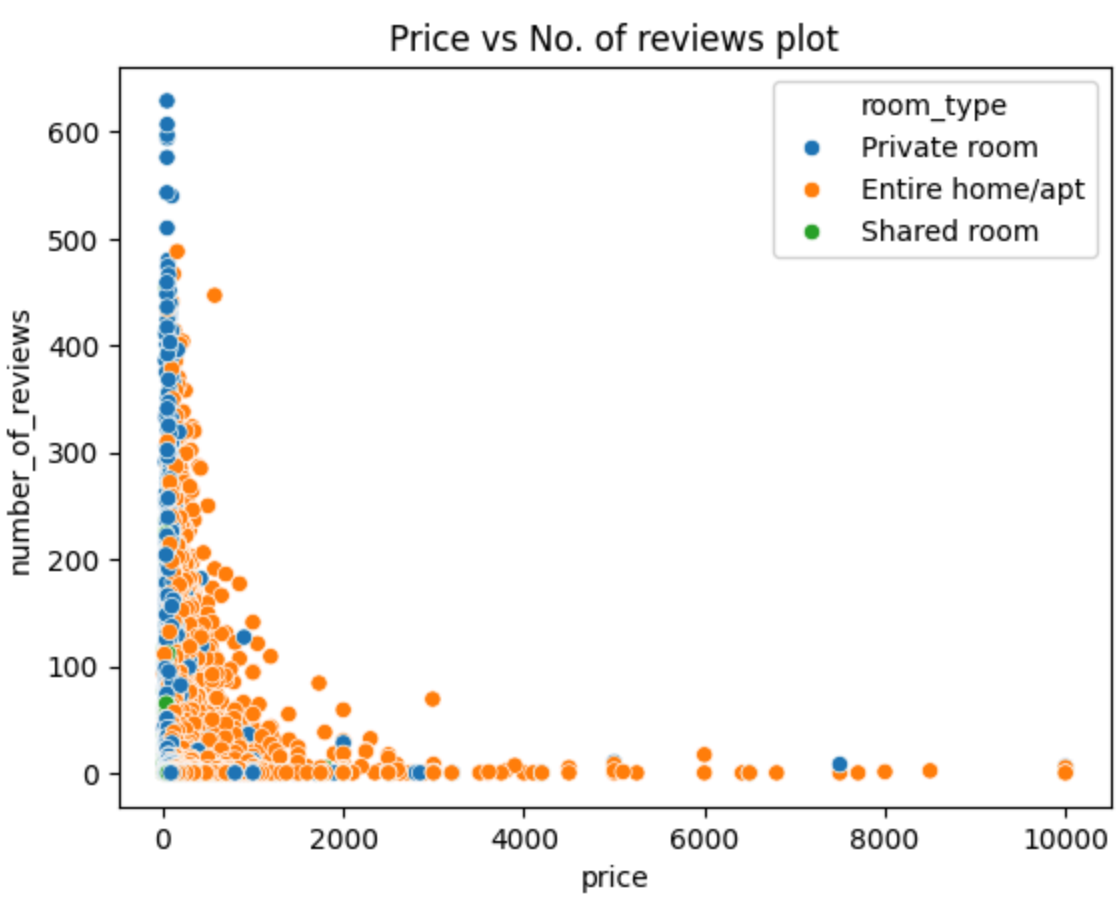
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

With manhatten having the highest number of available days, business should condider focussing marketing eddorts or adjusting strategies for this area.

## Chart - 7

```
# Chart - 7 visualization code
sns.scatterplot(x = data['price'], y = data['number_of_reviews'], hue = data['room_type'])
plt.title('Price vs No. of reviews plot')
plt.show()
```




1. Why did you pick the specific chart?

A scatter plot was choosen to analyse the relationship between price and number_of_reviews.This chart is ideal for examining how changes in price might correlate with the number of reviews a listings receives.

2. What is/are the insight(s) found from the chart?

The scatter plot shows no clear correlations between the price of listings and the number_of_reviews it receives.Entire home apartment apper to receive the largest number of reviews. This indicate that the guests are more inclined to book and review entire homes or apartments.

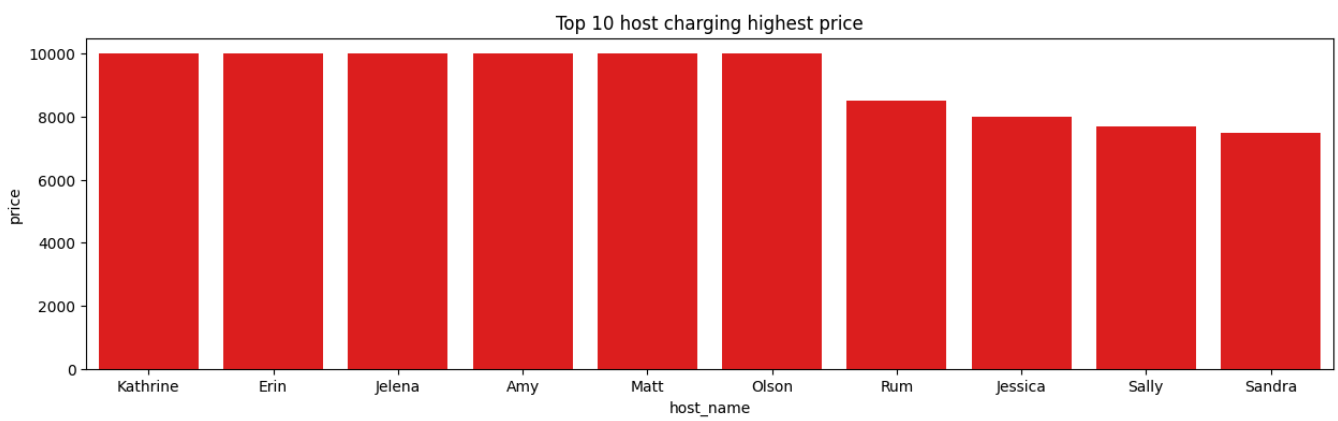
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

The insight that entire home and apartments recieves the largest number of review suggests a strong preference among guests for this type of accomodations. This can inform the business strategies to increase the availability or improve the quality of nentire ,house/apartments listings. By catering this demand business can enhance guests satisfactions and potentially increase bookings.

## Chart - 8

```
# Chart - 8 visualization code
b= data.sort_values('price', ascending = False)[['host_name','price']].reset_index().head(10)
plt.figure(figsize=(15,4))
sns.barplot(x = b['host_name'], y = b['price'], color = 'red')
plt.title('Top 10 host charging highest price')
plt.show()
```




## 1. Why did you pick the specific chart?

A bar plot was choosen to visualize the top 10 Data charging the highest price.Parplot are particularly effective for comparing the prices charged by different hosts because they provide a clear and straightforward way to rank and display the relative values across categories.

2. What is/are the insight(s) found from the chart?

Top high priced hosts : The chart reveals the host such as Jelena,Erin,Kathrine,Amy and Matt Olson charge in the highest price range, approximately around $10000.This indicates that these host are positioned at the premium end of the market potentially offering high end of luxury accomodations .

Secondary high priced group : Hosts like Rum,Jessica,Sally and Jack charges in the $8000 range . While slightly lower than the top group, these hosts are command high prices,suggesting that they are positioned at high value options within the market.

Price range segmentation : The distinct price ranges help categorize the hosts based on their pricing strategies . The clear sepration between the top group(10000 range) and the secondary group ($8000 range) suggests different tier of high end offerings.

Answer Here

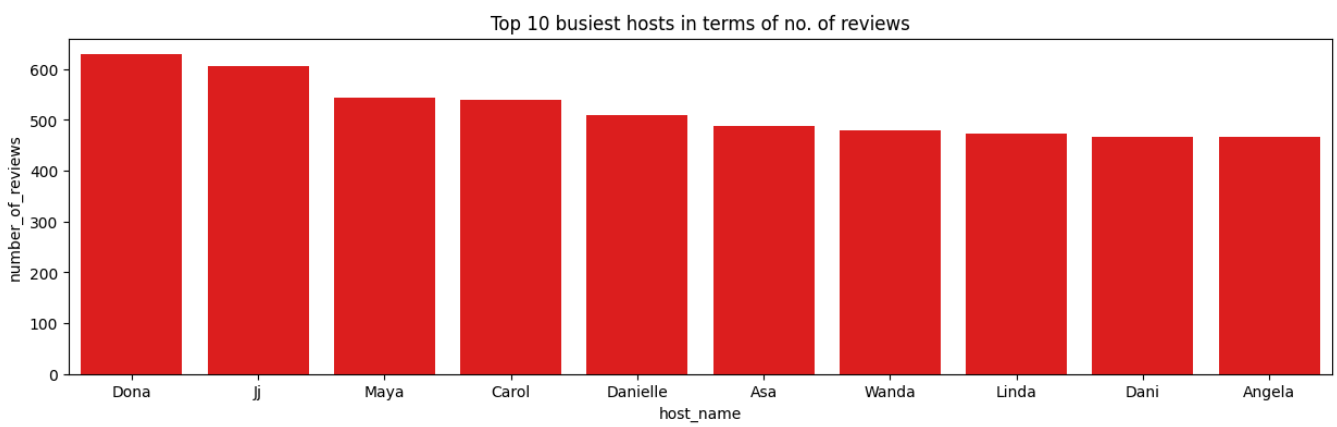
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

The insight reveal that the hosts are positioned at the top end of the price range. This can help the other business and hosts to understanmd the marketfor high end accomodations and potentially develop strategies to compete or differentiate themselves in the premium segments.

## Chart - 9

```
# Chart - 9 visualization code
c = data.groupby(['host_id','host_name'])['number_of_reviews'].max().reset_index()
c = c.sort_values('number_of_reviews',ascending = False).head(10)
plt.figure(figsize=(15,4))
sns.barplot(x = c['host_name'], y = c['number_of_reviews'], color = 'red')
plt.title('Top 10 busiest hosts in terms of no. of reviews')
plt.show()
```



1. Why did you pick the specific chart?

A bar plot was choosen to visualize the top 10 busiests hosts in terms of number of reviews .Bar plot are particularly effective for ranking and comparing categories , making them ideal for highlighting the hosts who have received the most guest reviews.

2. What is/are the insight(s) found from the chart?

The barplot reveals that the Dona is the busiest host, with the highest number of reviews.This suggest donas listings are very popular among guests, possible due to factors like exceptional service ,desirable locations, or competitive pricings .Angela completes the list of the top 10 busiest hosts. While still within the top ranks.

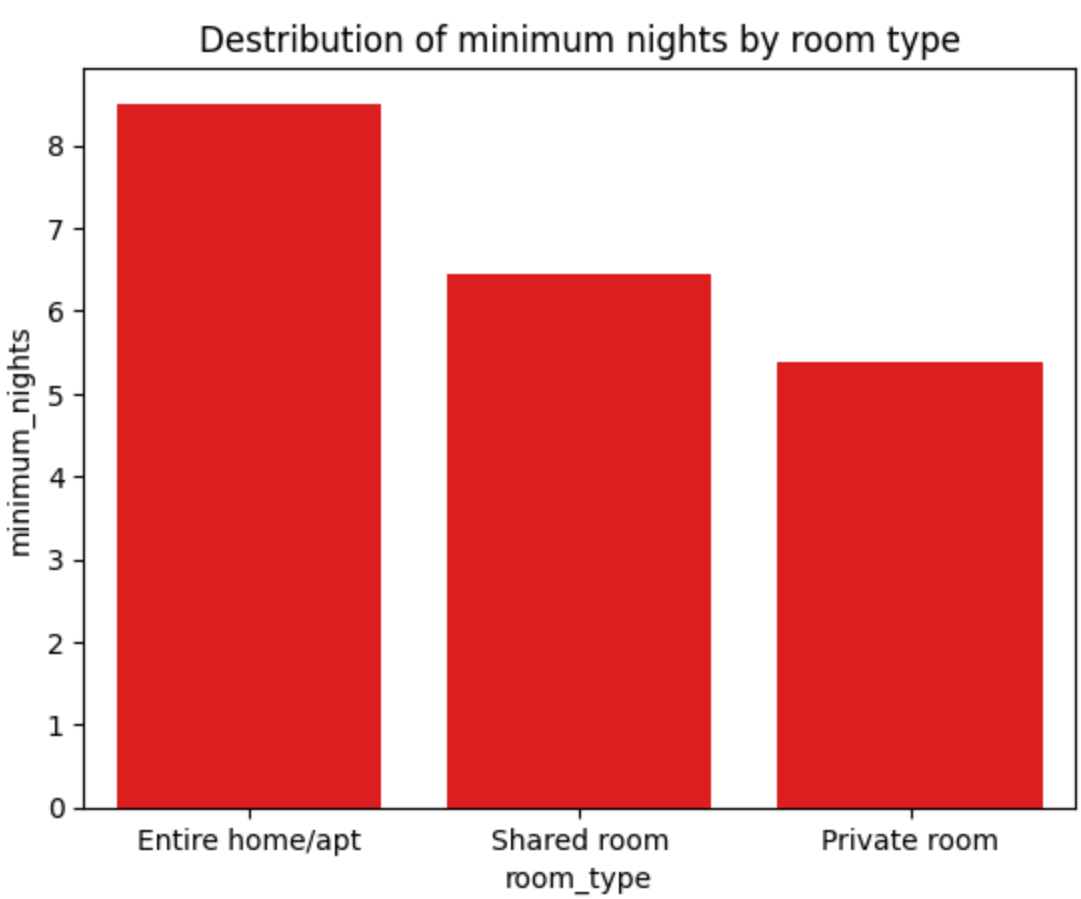
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

The insights from the bar plot identifying the top 10 busiest hosts can help business initiate targeted loyalty programs. By encouraging repeat bookings with these high reviewed hosts,business can strengthen customers relationships, increase guests satisfactions, and boosts overall bookings rates. For instance,offering discounts or special perks for returning guests could drive more bookings for these popular hosts , enhancing their revenue and guests engagement.

## Chart - 10

```
# Chart - 10 visualization code
d = data.groupby('room_type')['minimum_nights'].mean().reset_index()
d = d.sort_values('minimum_nights', ascending= False)
sns.barplot(x=d['room_type'], y =d['minimum_nights'], color = 'red')
plt.title('Destribution of minimum nights by room type')
plt.show()
```




1. Why did you pick the specific chart?

A bar plot is choosen to to compare the minimum nights across the different room type categories.Bar plots are effective for displaying and comparing categorical data, making them ideal for visualizing how the required minimum stay varies between different types of accomodations.

2. What is/are the insight(s) found from the chart?

<> The entire home/apartment : Bar plots shows that listing are categorized as "Entire Home/Apartment" have the highest average number of minimum nights , with more than 8 minimum.This suggest that this room type are often associated with longer minimum stays requirement, makint it a prefered choice for guests .

<> Shared rooms : Shared rooms comes in the second place with minimum nights as 6 which reveals suitability for the budget friendly travellers.

<> Private Rooms: private rooms comes to the last position with aberage 5.

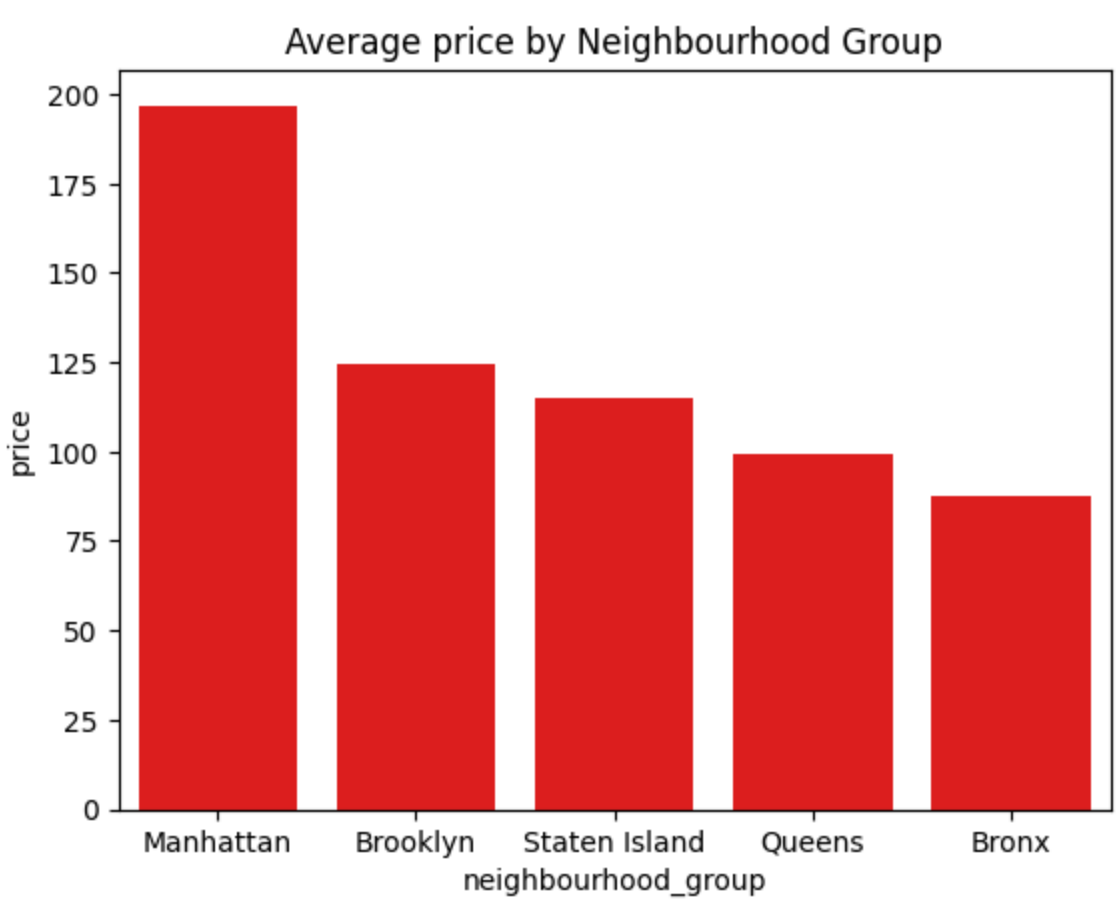
3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

Understanding that entire home/apartments listings tend to have higher minimum nights requirements can help business target marketing efforts towards travellers looking for longer stays,such as families or business travellers.Offering discounts or special deals for extended stays could attract more bookings in this category , leading to increased occupancy and revenue.

## Chart - 11

```
# Chart - 11 visualization code
e = data.groupby('neighbourhood_group')['price'].mean().reset_index()
e = e.sort_values('price', ascending = False)
sns.barplot(x =e['neighbourhood_group'], y = e['price'], color = 'red')
plt.title('Average price by Neighbourhood Group')
plt.show()
```




```
# This is formatted as code
```

## 1. Why did you pick the specific chart?

A bar plot was choosen to compare the average price of listings across different neighbourhood_group categories . Bar plots are particularly effective for illustriating the differences in categorical data, makingb them ideal for viusualizing how average price varies across different neighbourhood.

### 2. What is/are the insight(s) found from the chart?

<> The barplpot reveals that Manhatten has the highest average price, around $200.This indicates that the listings in manhatten are generally more expensive compared to other neighbourhood, which can be attributed to the area in high demand,prime locations, and premium amenities.

<> The average price in Brooklyn,Staten island,Queensand the Bronx are relatively similar and fall within the lower price range compared to Manhatten. This suggests that these neighbourhood are more affordable for guests,which might be due to lower demand, different property type and varing local market conditions.

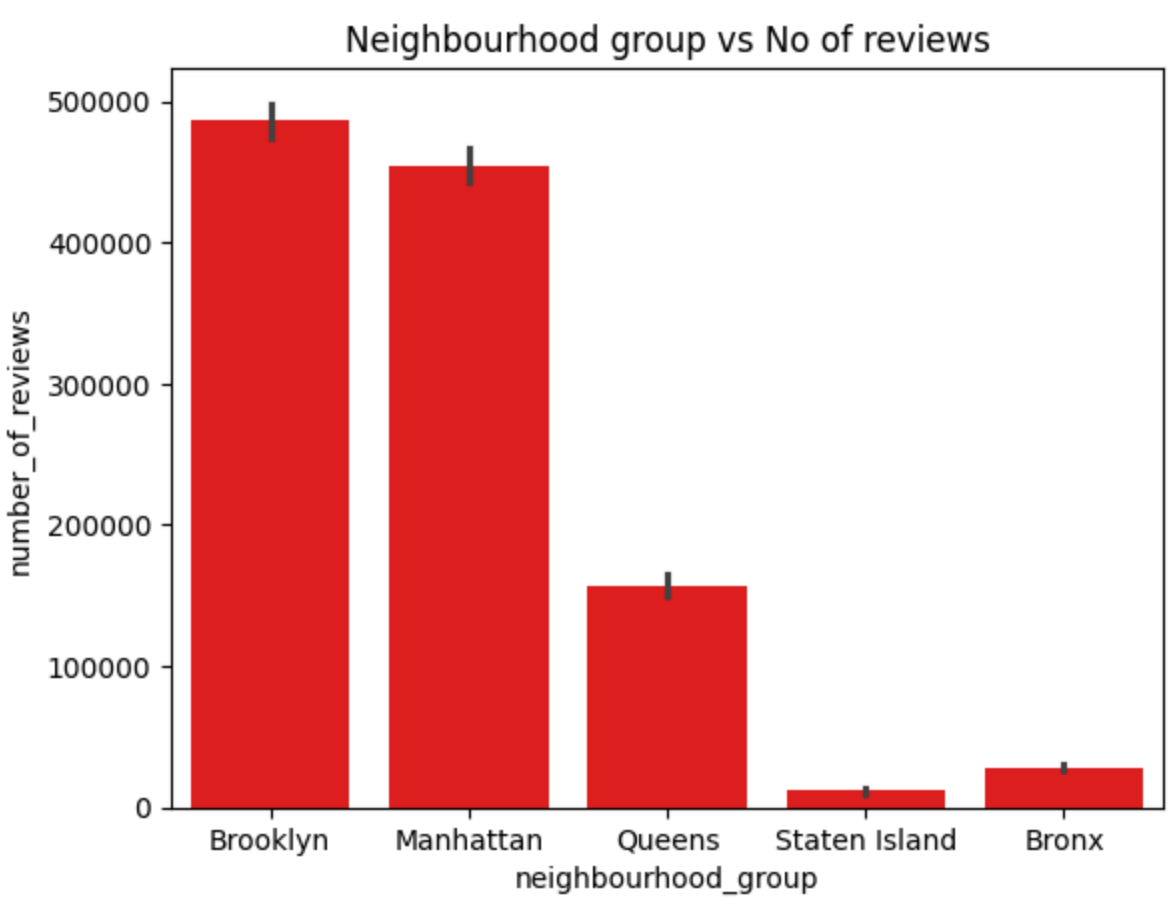
### 3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

Understanding that Manhatten has the highest average price can help the business tailor their pricing strategies to maximize the revenue.For listings in manhatten,business might consider premium pricing for upscale offerings to allign with the high demand and willingne3ss of the guest to pay more in this area. Cpmversaly, for listings in more affordable neighbourhoods like brooklyn and queens,business can attract pricing to attract price sensitive travellers , potentially increasing occupancy rates.

## Chart - 12

```
# Chart - 12 visualization code
sns.barplot(y = data['number_of_reviews'], x = data['neighbourhood_group'], estimator = sum, color ='red')
plt.title('Neighbourhood group vs No of reviews')
plt.show()
```




1. Why did you pick the specific chart?

Bar plot is choosen to realise the number of reviews across different neighbourhood_group categories.Bar plot are effective for comparing quantities among discrete categories.

2. What is/are the insight(s) found from the chart?

<> Brooklyn Leads in Reviews : The bar plot shows that the brooklyn have the highest number of reviews,approximately 500000 .This suggests that Brooklyn is the most popular neighbourhood group among guests,potentially due to the diverse attraction,accomodations options, tob overall appeal.

<> Manhatten Close Behind : Manhatten is mjust below brooklyn in terms in the number of revies.With the significant numbe of reviews,manhatten also attract ahigh volume of guests,which align with its ststus as a major travel destination.

<> Queens and Moderate reviews :Queens has around 150000 reviews,indicate a moderate level of guests activity compared to Brooklyn and Manhatten. It is less popular than top of two neighbourhoods but still attracts a noteable amount of visitors.

<> Bronx and Staten island Lowest : The Bronx and Staten island have the lowest number of reviews,with very few reviews as compared to the other neighbourhood .This suggests that these areas may be less frequented by guests,potentially due to fewer attractions,less assessibility,or other factors influencing their popularity.

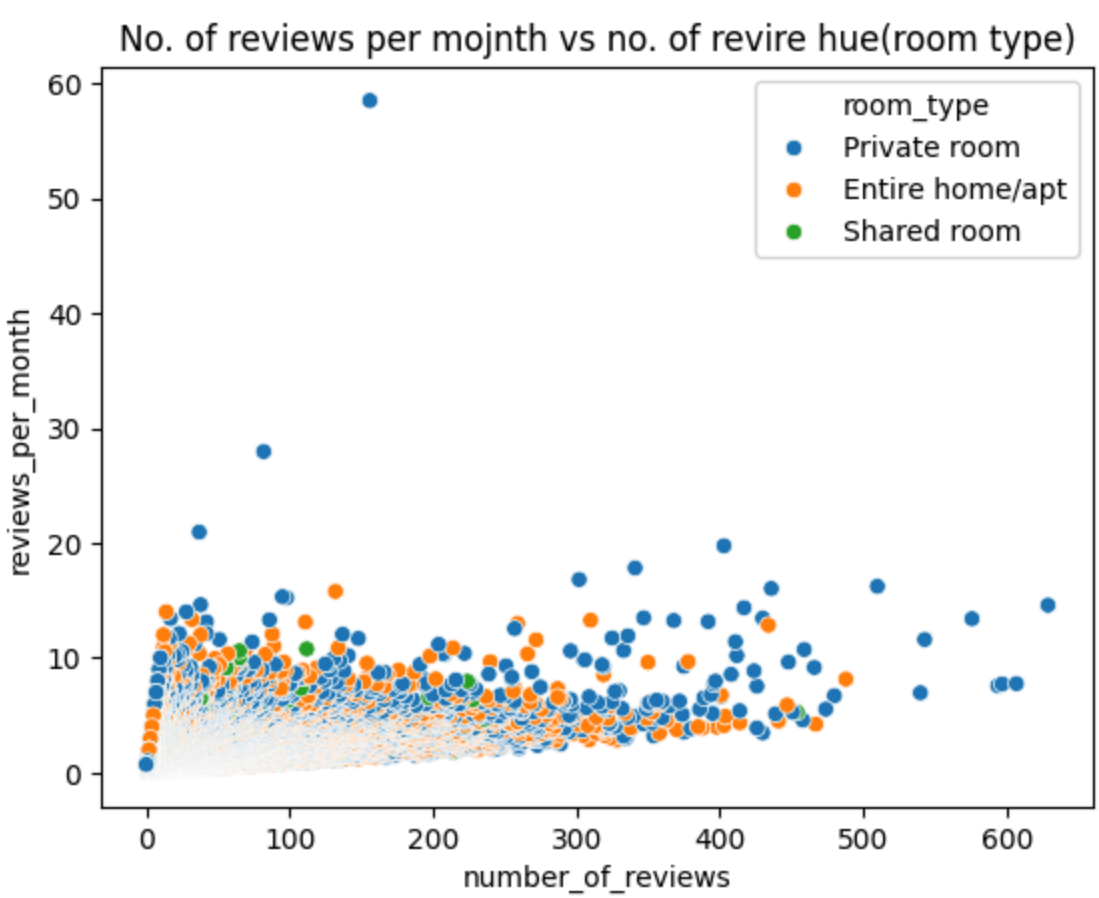
## 3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

The insights that Brooklyn and Manhatten have the highest number of reviews can guide targeted marketing efforts .Business can focus their potential activities on these high traffic areas to attract more guests.For example special deals and exclusive offer in brooklyn could capiutalize on its popularity and further boosts booking.

## Chart - 13

```
# Chart - 13 visualization code
sns.scatterplot(x= data['number_of_reviews'], y = data['reviews_per_month'],hue = data['room_type'])
plt.title('No. of reviews per mojnth vs no. of revire hue(room type)')
plt.show()
```



### 1. Why did you pick the specific chart?

A scatter plot with number_of_reviews_per_month vs number_of_reviews and hue representing room_type was selected to examine the relationship between the frequency of reviews and the total number of reviews,while differentiating the data by room type.

### 2. What is/are the insight(s) found from the chart?

The scatter plot shows a positive relationship between number_of_reiews_per_month and number_of_reviews .This suggests listings with a higher frequency or reviews per month tend to accomodate more total reviews over time.In other words properties that recieve frequent reviews are likely to have a higher overall review count.

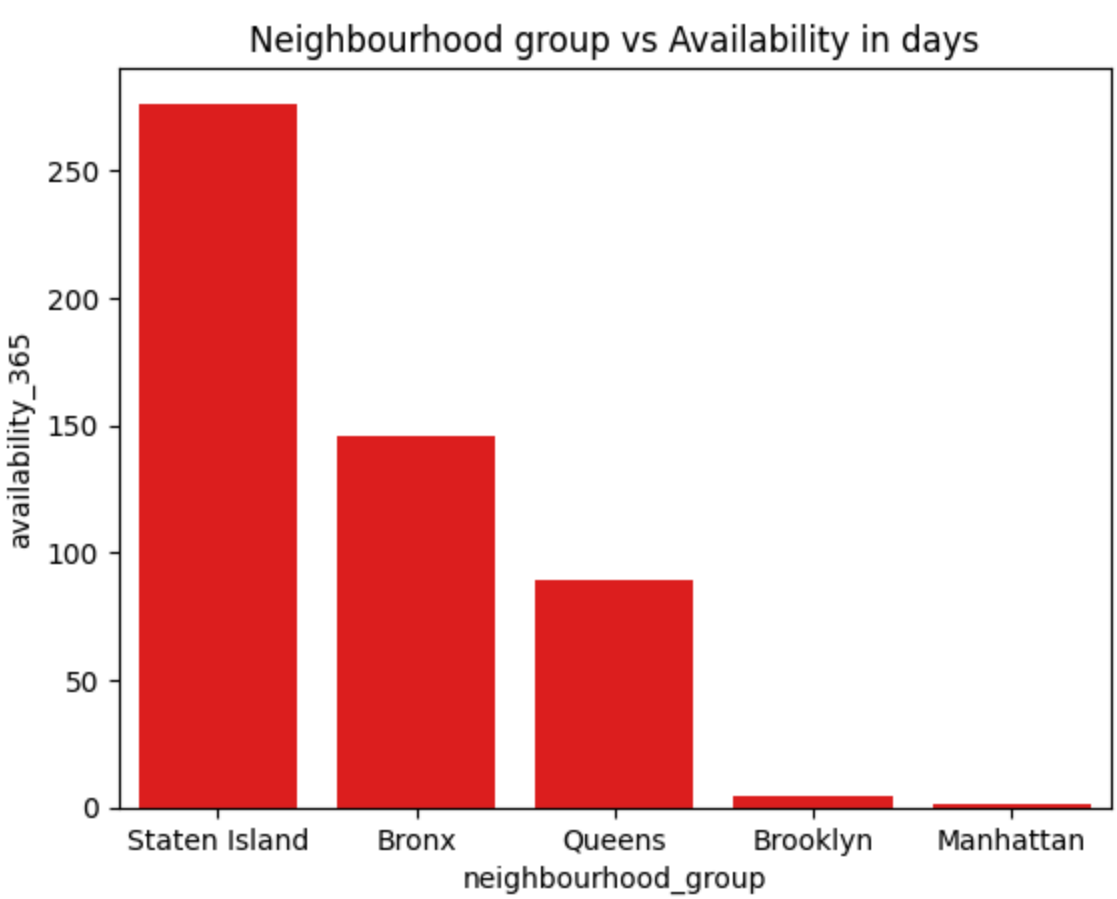
### 3. Will the gained insights help creating a positive business impact?

Are there any insights that lead to negative growth? Justify with specific reason.

If popular room types(homes/apartments) show lower number _of_reviews_per_month compared to other room types , this might suggest that these properties are not receiving as many reviews on a monthly basis despite being popular.

## Chart - 14

```
f= data.groupby('neighbourhood_group')['availability_365'].median().reset_index()
f= f.sort_values('availability_365', ascending = False)
sns.barplot(x= f['neighbourhood_group'], y = f['availability_365'], color = 'red')
plt.title('Neighbourhood group vs Availability in days')
plt.show()
```




1. Why did you pick the specific chart?

Barploits are ideal for comparing a categorical variable(neighbourhood_group) against a summary of numerical variable (available_365).It visually conveys how availability varies across different neighbourhoods.

2. What is/are the insight(s) found from the chart?

Staten island stand with out with over 200 days of availability, indicating that properties in this neighbourhood are generally available for booking much longer than in other areas.This could suggests lower demand for short term rentals, or perhaps hosts keep their property open for more extended periods

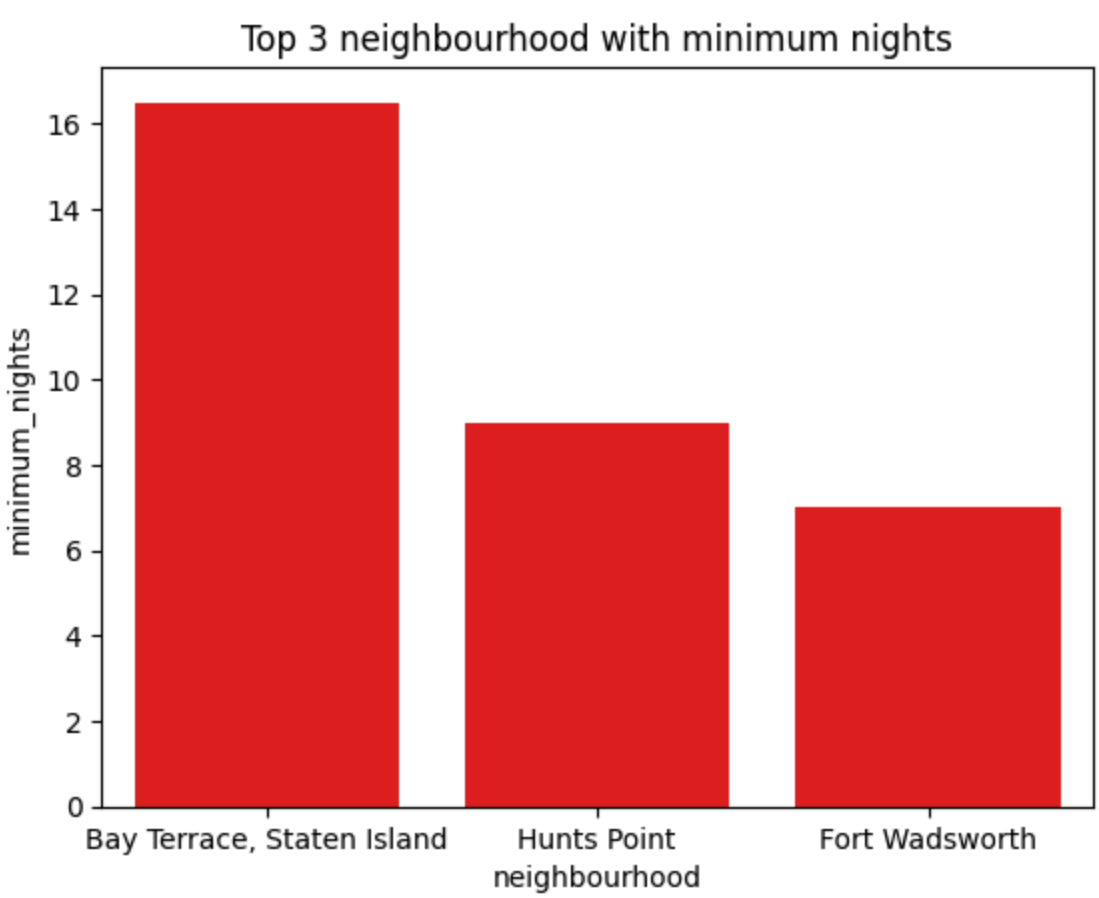
Bronx and queens shows around 150 days and 100 days of availability,respectively indicating moderate availability.These neighbourhood may have moderate demand for rentals,with some properties being booked while other remain available for longer periods.

Manhatten and Brooklyn both have less than 50 days of availability,which could indicate for a high demand for short term rentals.Properties in this area are likely booked frequently,leading to fewer

daus of availability throughout the year.

# CHART - 16

```
data.columns
y = data.groupby('neighbourhood')['minimum_nights'].median().reset_index()
y = y.sort_values('minimum_nights',ascending = False).head(3)
sns.barplot(x = y['neighbourhood'], y = y['minimum_nights'], color = 'red')
plt.title('Top 3 neighbourhood with minimum nights')
plt.show()
```

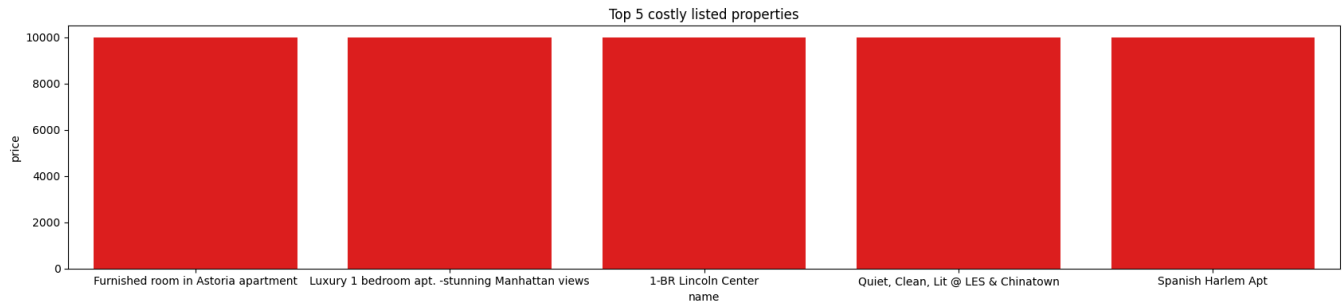



## What are the insights found from the data ?

Bay Terrace,State island has the highest median minimum nights of 16 nights, suggestingb that the property in the neighbourhood typically require guests to book longer stays .This could indicate either lower demand for a sort stays or a strategy by hosts to focus on longer term renters.

# CHART - 17

```
data.columns
z = data.groupby('name')['price'].max().reset_index()
plt.figure(figsize = (17,4))
z = z.sort_values('price',ascending = False).head(5)
plt.title("Top 5 costly listed properties")
sns.barplot(x = z['name'],y = z['price'], color = 'red')
plt.tight_layout()
plt.show()
```

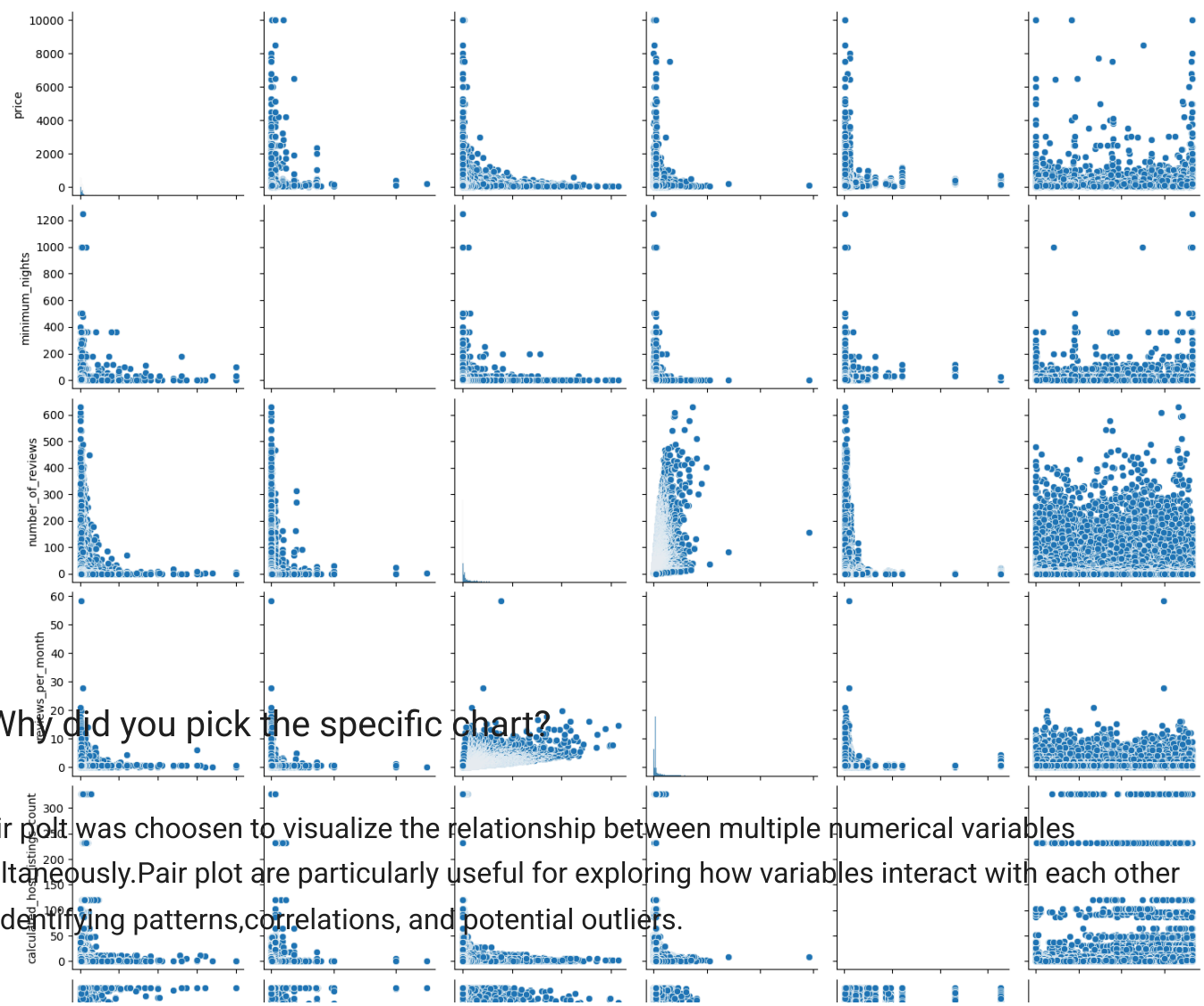



## What are the insights found from the data ?

The Bar plot graph reveals that these 5 properties are 5 top costly and high demand. They are costly maybe they are in high posh area or business area

# CHART - 18 - PAIR PLOT

```
data.columns
num = data[['price','minimum_nights','number_of_reviews','last_review','reviews_per_month','calculated_host_listings_count','availability_365']
sns.pairplot(num)
plt.show()
```




## Why did you pick the specific chart?

A pair polt was choosen to visualize the relationship between multiple numerical variables simultaneously.Pair plot are particularly useful for exploring how variables interact with each other and identifying patterns,correlations, and potential outliers.