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1 EDA(as per the Instructions) Using SQL Script

1.0.1 Import necessary libraries

In [14]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from termcolor import colored
%matplotlib inline
from termcolor import cprint
import warnings
warnings.filterwarnings('ignore')
```

In [15]:
```
!pip install pymysql
```

```
Requirement already satisfied: pymysql in c:\users\user\anaconda3\lib\site-p
ackages (1.1.0)
```


1.0.2 Setup SQL and Python Intergation

In [2]:
```
import pymysql
```

In [3]:
```
conn=pymysql.connect(host='localhost', user='root', password='1307')
```

In [4]:
```
cursor=conn.cursor()
```

In [5]:
```
conn=pymysql.connect(host='localhost', user='root', password='1307', database=
```

In [6]:
```
q1='use PRT_db'
cursor.execute(q1)
```

Out[6]: 0

In [7]:
```
q2='show tables'
cursor.execute(q2)
```

Out[7]: 1

1.0.3 Importing script with python to perform EDA using SQL Script

1.0.3 Importing script with python to perform EDA using SQL Script

In [9]:
```
query = "SELECT * FROM sql_prt"
df = pd.read_sql(query, conn)
```

In [19]:
```
cprint('Head of the Dataset:', 'white', 'on_grey', attrs=['bold'])

df.head().style.set_properties(**{'background-color':'#F4DA59','color':'black'
```

Head of the Dataset:

Out[19]:

	id	name	host_id	host_name	neighbourhood_group	neighbou
0	2539.000000	Clean & quiet apt home by the park	2787.000000	John	Brooklyn	Ke
1	2595.000000	Skylit Midtown Castle	2845.000000	Jennifer	Manhattan	
2	3647.000000	THE VILLAGE OF HARLEM....NEW YORK !	4632.000000	Elisabeth	Manhattan	
3	3831.000000	Cozy Entire Floor of Brownstone	4869.000000	LisaRoxanne	Brooklyn	Cl
4	5022.000000	Entire Apt: Spacious Studio/Loft by central park	7192.000000	Laura	Manhattan	Eas

In [20]:
```
cprint('Tail of the Dataset:', 'white', 'on_grey', attrs=['bold'])

df.tail().style.set_properties(**{'background-color':'#CDC0B0','color':'black'
```

In [20]:
```
cprint('Tail of the Dataset:', 'white', 'on_grey', attrs=['bold'])

df.tail().style.set_properties(**{'background-color':'#CDC0B0','color':'black'
```

```
Tail of the Dataset:
```

Out[20]:

	id	name	host_id	host_name	neighbourhood_group	neighb
6598	174527.000000	Cozy private family home in Bushwick	833926.000000	Kris	Brooklyn	
6599	174966.000000	Luxury 2Bed/2.5Bath Central Park View	836168.000000	Henry	Manhattan	Uppe
6600	176135.000000	Cosy Sunny 1brm in Prospect Heights	842125.000000	Jennifer	Brooklyn	Cr
6601	176653.000000	East Village bedroom w rooftop	844862.000000	Cj	Manhattan	
6602	nan	None	nan	None	None	

2 Exploratory Data Analysis

In [130]:
```
cprint('Shape of the Dataset:','red','on_yellow', attrs=['bold'])

print('The Shape of the dataset is : ',df.shape)
```

```
Shape of the Dataset:
The Shape of the dataset is :  (6603, 16)
```

In [131]:
```
cprint('Dimention of the Dataset:','red','on_yellow', attrs=['bold'])
df.ndim
```

```
Dimention of the Dataset:
```

Out[131]: 2

In [25]:
```
cprint('Features of the Dataset:','red','on_yellow', attrs=['bold'])

for i in df.columns:
    print(i)
```

In [25]:
```
cprint('Features of the Dataset:','red','on_yellow', attrs=['bold'])

for i in df.columns:
    print(i)
```

```
Features of the Dataset:
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
```

In [26]:
```
cprint('Basic Summary of the Dataset:','red','on_yellow', attrs=['bold'])

df.info()
```

```
Basic Summary of the Dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6603 entries, 0 to 6602
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              1497 non-null   float64
 1   name                            1497 non-null   object
 2   host_id                         1497 non-null   float64
 3   host_name                       1494 non-null   object
 4   neighbourhood_group             1497 non-null   object
 5   neighbourhood                   1497 non-null   object
 6   latitude                        1497 non-null   float64
 7   longitude                       1497 non-null   float64
 8   room_type                       1497 non-null   object
 9   price                           1497 non-null   float64
 10  minimum_nights                  1497 non-null   float64
 11  number_of_reviews               1497 non-null   float64
 12  last_review                     1443 non-null   datetime64[ns]
 13  reviews_per_month               1443 non-null   float64
 14  calculated_host_listings_count  1497 non-null   float64
 15  availability_365                1497 non-null   float64
dtypes: datetime64[ns](1), float64(10), object(5)
memory usage: 825.5+ KB
```

In [132]:
```
cprint('Count of Null Values in the Dataset:','red','on_yellow', attrs=['bold'
df.isnull().sum()
```

In [132]:
```
cprint('Count of Null Values in the Dataset:','red','on_yellow', attrs=['bold'
df.isnull().sum()
```

Count of Null Values in the Dataset:

Out[132]:
```
id                                5106
name                              5106
host_id                           5106
host_name                         5109
neighbourhood_group               5106
neighbourhood                     5106
latitude                          5106
longitude                         5106
room_type                         5106
price                             5106
minimum_nights                    5106
number_of_reviews                 5106
last_review                       5160
reviews_per_month                 5160
calculated_host_listings_count    5106
availability_365                  5106
dtype: int64
```

2.0.1 As we can see there are large count of null values so if we will them using feature negineering orr using mean, mode, median , It will make a drastic impact on our dataset. so we will remove these NULL VALUES

In [133]:
```
cprint('Dropping Null Values:','red','on_yellow', attrs=['bold'])

df_1=df.dropna()
```

Dropping Null Values:

In [134]:
```
cprint('Successfuly removed the null values from the dataset:','red','on_yello

df_1.isnull().sum()
```

Successfuly removed the null values from the dataset:

Out[134]:
```
id                                0
name                              0
host_id                           0
host_name                         0
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
last_review                       0
reviews_per_month                 0
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

In [135]:
```
cprint('Shape of our dataset after removing Null Values:','red','on_yellow', a

df_1.shape
```

In [135]:
```
cprint('Shape of our dataset after removing Null Values:','red','on_yellow', a
df_1.shape
```

Shape of our dataset after removing Null Values:

Out[135]: (1440, 16)

In [136]:
```
cprint('Statisticall Summary of the Dataset:','red','on_yellow', attrs=['bold'
df.describe()
```

Statisticall Summary of the Dataset:

Out[136]:

	id	host_id	latitude	longitude	price	minimum_nights	n
count	1497.000000	1.497000e+03	1497.000000	1497.000000	1497.000000	1497.000000	
mean	72188.370741	3.215084e+05	40.729359	-73.963020	152.246493	8.006012	
std	50802.734234	3.977468e+05	0.051561	0.032062	127.003505	16.395328	
min	2539.000000	2.787000e+03	40.586150	-74.085460	33.000000	1.000000	
25%	28321.000000	7.485700e+04	40.686560	-73.984190	85.000000	2.000000	
50%	62452.000000	2.561610e+05	40.721850	-73.962180	125.000000	3.000000	
75%	112100.000000	4.535190e+05	40.759610	-73.947940	189.000000	5.000000	
max	176653.000000	6.197784e+06	40.897470	-73.761330	2000.000000	200.000000	

In [137]:
```
cprint('Statistical Summary of the important features of the Dataset:','red','
df_1[['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month',
    'calculated_host_listings_count', 'availability_365']].describe()
```

Statistical Summary of the important features of the Dataset:

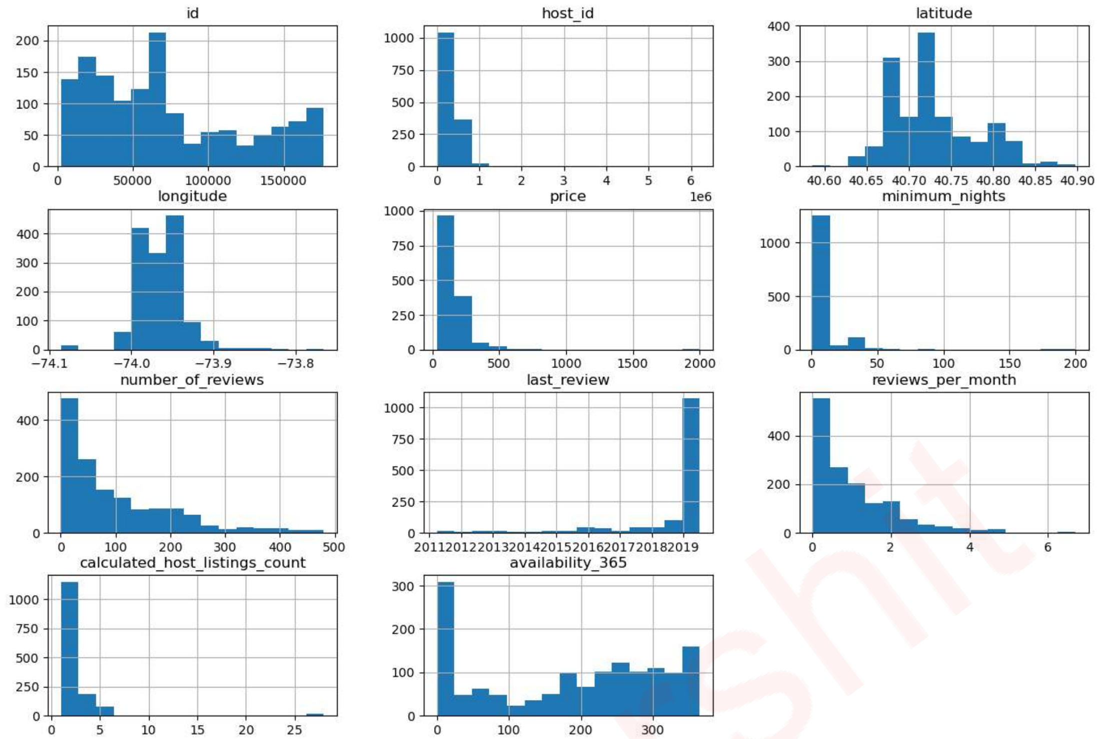
Out[137]:

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_h
count	1440.000000	1440.000000	1440.000000	1440.000000	
mean	152.120833	7.804167	98.354167	1.042271	
std	126.867780	16.061314	99.180987	1.028708	
min	33.000000	1.000000	1.000000	0.010000	
25%	85.000000	2.000000	22.750000	0.270000	
50%	125.000000	3.000000	61.000000	0.680000	
75%	185.000000	5.000000	150.000000	1.577500	
max	2000.000000	200.000000	480.000000	6.700000	

In [138]:
```
cprint('Visualization of the features of the Dataset:','red','on_yellow', attr
df_1.hist(bins=15, figsize=(15,10));
```

In [138]:
```
cprint('Visualization of the features of the Dataset:','red','on_yellow', attr

df_1.hist(bins=15, figsize=(15,10));
```

Visualization of the features of the Dataset:



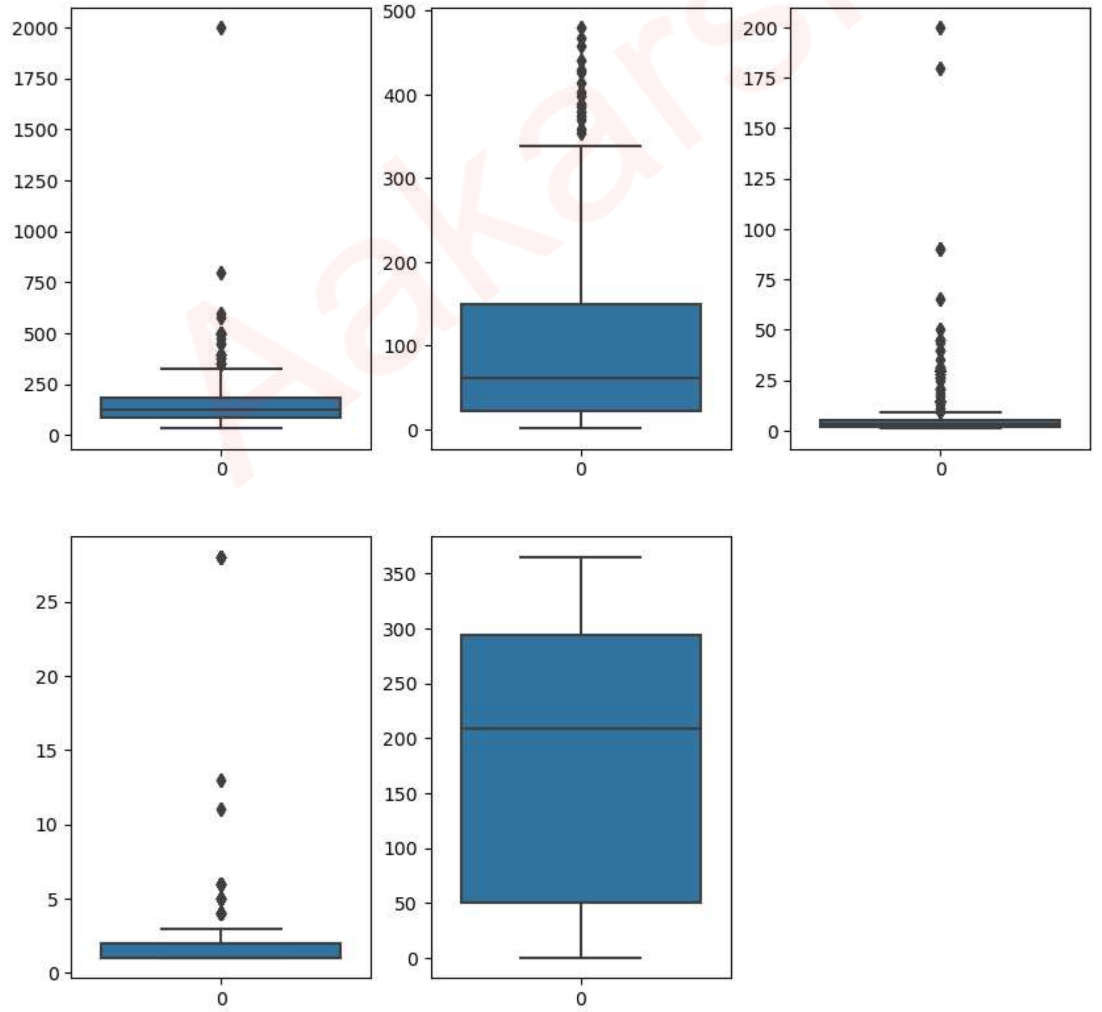
In [139]:
```
cprint('Checking for the outliers:','red','on_yellow', attrs=['bold'])

plt.figure(figsize=(10,20))
plt.subplot(4,3,1)
```

In [139]:

```
cprint('Checking for the outliers:','red','on_yellow', attrs=['bold'])

plt.figure(figsize=(10,20))
plt.subplot(4,3,1)
sns.boxplot(df_1['price'])

plt.subplot(4,3,2)
sns.boxplot(df_1['number_of_reviews'])

plt.subplot(4,3,3)
sns.boxplot(df_1['minimum_nights'])

plt.subplot(4,3,4)
sns.boxplot(df_1['calculated_host_listings_count'])

plt.subplot(4,3,5)
sns.boxplot(df_1['availability_365'])
```

Checking for the outliers:

Out[139]: <Axes: >



2.0.2 this data is a hotel data so removing outliers cannot be a good solution because the prices of rooms are based on the peak dayss, festivals, holidays

2.0.3 Insead of removing the outliers we can analyse data with

festivals, holidays
2.0.2 this data is a hotel data so removing outliers cannot be a good solution because the prices of rooms are based on the peak dayss,
2.0.3 Insead of removing the outliers we can analyse data with

In [140]:
```
cprint('Count of Type of Room Based on Neightbourhood:','red','on_yellow', att

df_1.groupby(['room_type'])['neighbourhood'].count()
```

Count of Tyoe of Room Based on Neightbourhood:

Out[140]:
```
room_type
Entire home/apt    846
Private room       582
Shared room         12
Name: neighbourhood, dtype: int64
```

2.0.4 we can clearly see that the homes and appartment are frequently booked they have the highest number of booking while shared rooms are booked very less

2.0.5 so we have to keep in ming that the managiing cost of above two categories will be high and the demand of above two categories is also very high.

In [141]:
```
cprint('Count of Tyoe of Room Based on Neightbourhood_group:','red','on_yellow

df_1.groupby(['room_type'])['neighbourhood_group'].count()
```

Count of Tyoe of Room Based on Neightbourhood_group:

Out[141]:
```
room_type
Entire home/apt    846
Private room       582
Shared room         12
Name: neighbourhood_group, dtype: int64
```

In [142]:
```
cprint('Count of Type of Room Based on Price:','red','on_yellow', attrs=['bold

df_1.groupby(['room_type'])['price'].sum()
```

Count of Tyoe of Room Based on Price:

Out[142]:
```
room_type
Entire home/apt    162852.0
Private room        55425.0
Shared room           777.0
Name: price, dtype: float64
```

In [200]:
```
cprint('Count of Type of Room Based on MInimum NIghts:','red','on_yellow', att

m_night = df.groupby(['minimum_nights'])['room_type'].count().reset_index()
m_night = m_night.sort_values(by='minimum_nights', ascending=False)
```

In [200]:
```
cprint('Count of Type of Room Based on MInimum NIghts:','red','on_yellow', att

m_night = df.groupby(['minimum_nights'])['room_type'].count().reset_index()
m_night = m_night.sort_values(by='minimum_nights', ascending=False)
print('Top 5',m_night.head(5))
print('Bottom 5', m_night.tail(5))
```

```
Count of Type of Room Based on MInimum NIghts:
Top 5      minimum_nights  room_type
34           200.0          3
33           180.0          3
32            90.0          9
31            65.0          3
30            60.0          3
Bottom 5     minimum_nights  room_type
4             5.0        102
3             4.0        132
2             3.0        330
1             2.0        399
0             1.0        162
```

In [144]:
```
cprint('Count of Neightbourhood:','red','on_yellow', attrs=['bold'])

df_1.groupby(['neighbourhood_group'])['neighbourhood_group'].count()
```

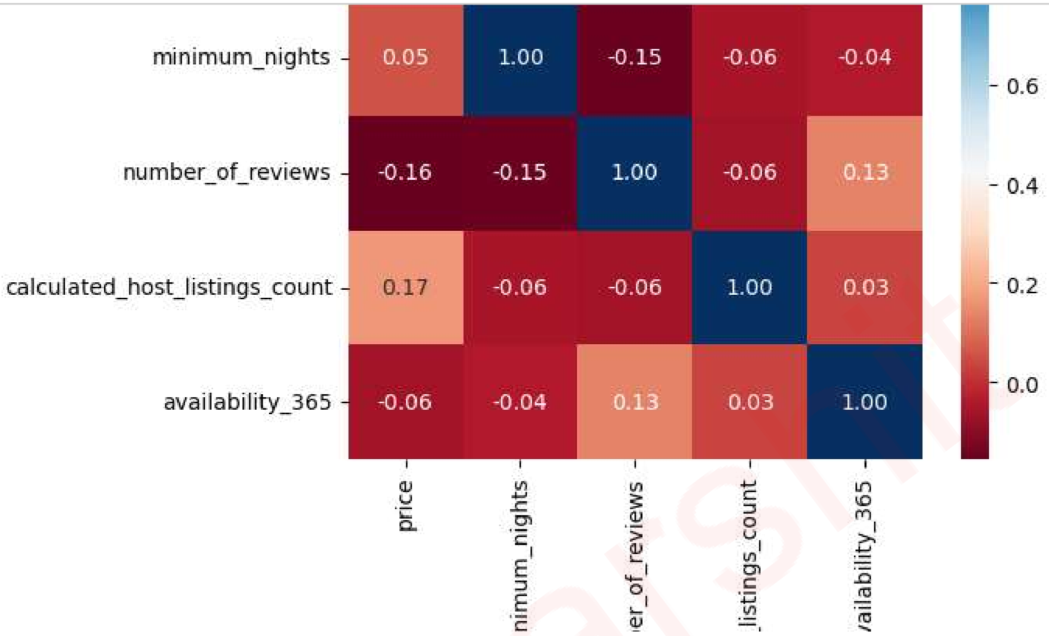
```
Count of Neightbourhood:
```

Out[144]:
```
neighbourhood_group
Bronx              18
Brooklyn          687
Manhattan         657
Queens             63
Staten Island      15
Name: neighbourhood_group, dtype: int64
```


2.0.6 group 'Brooklyn','Manhattan' have the maximum count of group as compare to the other groups

2.0.6 group 'Brooklyn','Manhattan' have the maximum count of group as compare to the other groups

In [145]:
```
cprint('Correlation Bbetween different features:','red','on_yellow', attrs=['b
corr = df_1[['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_
sns.heatmap(corr, cmap='RdBu', fmt='.2f', square=True, linecolor='white', annc
```

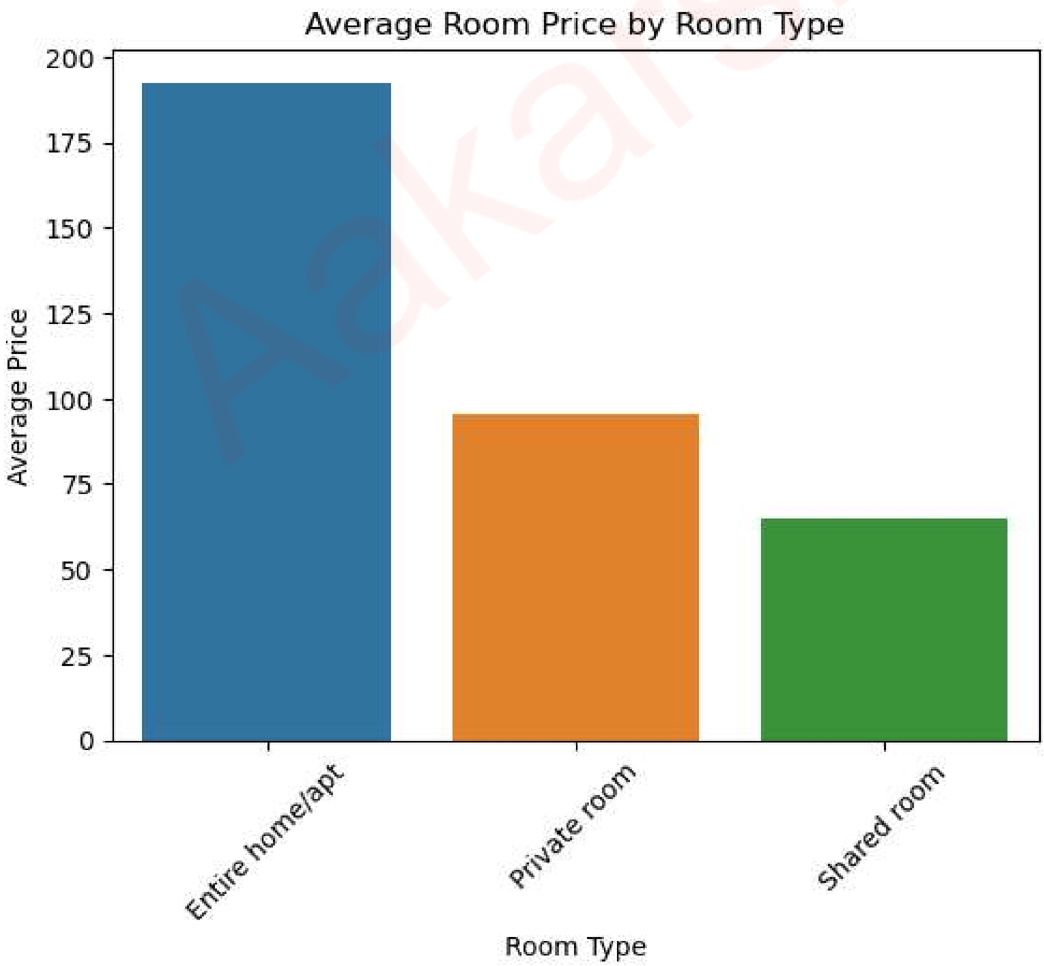


2.0.7 As we can see with the above heat map not even a single feature has a high correlation with other. so based on this analysis we can see our model will may show less accuracy

2.0.7 As we can see with the above heat map not even a single feature has a high correlation with other. so based on this analysis we can see our model will may show less accuracy

In [146]:
```
cprint('Average Room Price:','red','on_yellow', attrs=['bold'])

#average price per room type
avg_room_price = round(df_1.groupby('room_type').price.mean(), 2).sort_values(
print(avg_room_price)
avg_room_price=pd.DataFrame(avg_room_price).reset_index()
avg_room_price
sns.barplot(x='room_type', y='price', data=avg_room_price)
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.xlabel('Room Type')
plt.ylabel('Average Price')
plt.title('Average Room Price by Room Type')
plt.show()
```

```
Average Room Price:
room_type
Entire home/apt    192.50
Private room        95.23
Shared room         64.75
Name: price, dtype: float64
```

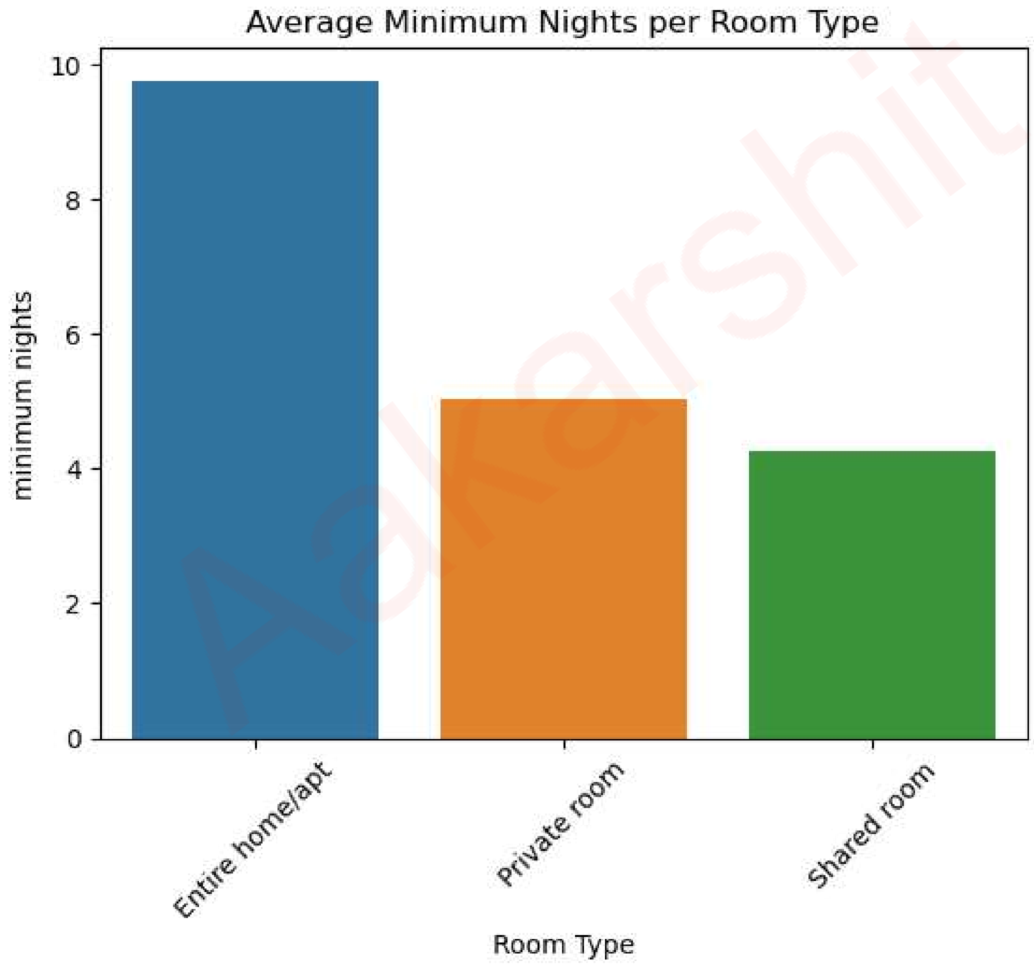


In [148]:
```
cprint('Average minimum nights based on room type:','red','on_yellow', attrs=[

avg_room_type_nights = round(df_1.groupby('room_type').minimum_nights.mean(),
# print(avg_room_type_nights)
```

In [148]:
```
cprint('Average minimum nights based on room type:','red','on_yellow', attrs=[

avg_room_type_nights = round(df_1.groupby('room_type').minimum_nights.mean(),
# print(avg_room_type_nights)
avg_room_type_nights=pd.DataFrame(avg_room_type_nights).reset_index()
print(avg_room_type_nights)
sns.barplot(x='room_type', y='minimum_nights', data=avg_room_type_nights)
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.xlabel('Room Type')
plt.ylabel('minimum nights')
plt.title('Average Minimum Nights per Room Type')
plt.show()
```

Average minimum nights based on room type:

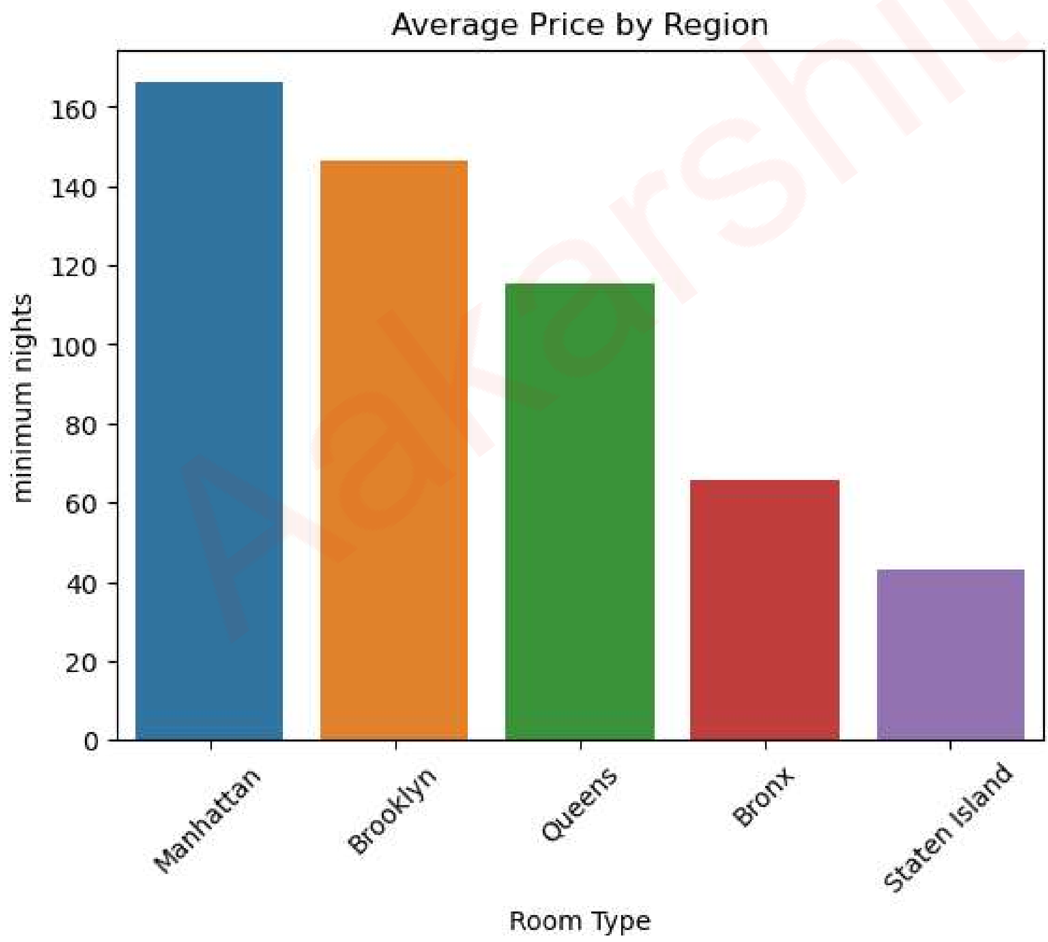
```
        room_type  minimum_nights
0  Entire home/apt            9.76
1     Private room            5.04
2      Shared room            4.25
```



In [201]:
```
cprint('Avrage price based on Neighbourhood_group:','red','on_yellow', attrs=[

avg_price_region = round(df_1.groupby('neighbourhood_group').price.mean().sort
avg_price_region=pd.DataFrame(avg_price_region).reset_index()
```

In [201]:
```
cprint('Avrage price based on Neighbourhood_group:','red','on_yellow', attrs=[

avg_price_region = round(df_1.groupby('neighbourhood_group').price.mean().sort
avg_price_region=pd.DataFrame(avg_price_region).reset_index()
print(avg_price_region)
sns.barplot(x='neighbourhood_group', y='price', data=avg_price_region)
plt.xticks(rotation=45)
plt.xlabel('Room Type')
plt.ylabel('minimum nights')
plt.title('Average Price by Region')
plt.show()
```

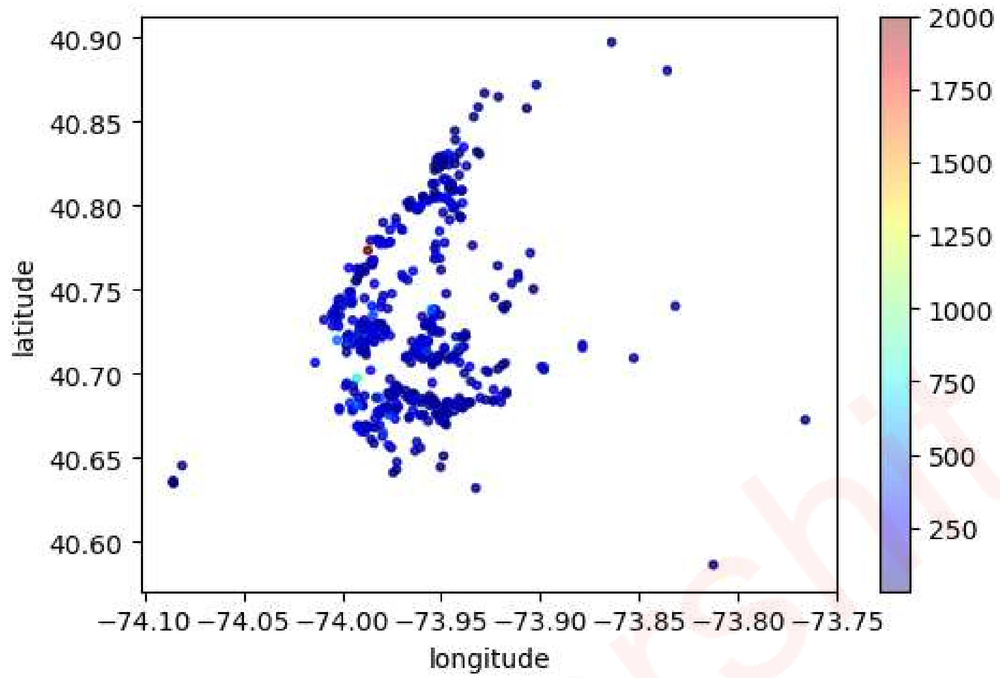
```
Avrage price based on Neighbourhood_group:
  neighbourhood_group   price
0           Manhattan  166.18
1            Brooklyn  146.68
2              Queens  115.43
3               Bronx   65.67
4       Staten Island   43.20
```



In [188]:
```
cprint('Price of the hotel rooms based on location:','red','on_yellow', attrs=

df_1.plot(kind='scatter', x='longitude', y='latitude', alpha=0.4, c=df_1['pric
```

In [188]:
```
cprint('Price of the hotel rooms based on location:','red','on_yellow', attrs=
df_1.plot(kind='scatter', x='longitude', y='latitude', alpha=0.4, c=df_1['pric
```

Price of the hotel rooms based on location:



3 Machine Learning Model

3.1 Price Prediction Based on Features

In [155]:
```
from sklearn.preprocessing import OrdinalEncoder
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

In [152]:
```
oe=OrdinalEncoder()
```

In [163]:
```
df_1['neighborhood_group_new']=oe.fit_transform(df_1[['neighbourhood_group']])
df_1['neighbourhood_new']=oe.fit_transform(df_1[['neighbourhood']])
df_1['room_type_new']=oe.fit_transform(df_1[['room_type']])
```

In [169]:
```
x=df_1[[ 'minimum_nights', 'number_of_reviews', 'reviews_per_month','neighborh
        'neighbourhood_new','room_type','room_type_new']]
y=df_1['price']
```

In [174]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, rando
```

In [170]:
```
lr = LinearRegression()
```

In [170]:
```
lr = LinearRegression()
```

In [175]:
```
lr.fit(x_train,y_train)
```

Out[175]:
```
▾ LinearRegression
LinearRegression()
```

In [176]:
```
y_pred=lr.predict(x_test)
```

In [177]:
```
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

In [189]:
```
print('Mean Square Error',mse)
print('Mean Aboslute Error',mae)
print('R2 score',r2)
```

```
Mean Square Error 19370.861368870956
Mean Aboslute Error 65.68597703266502
R2 score 0.12359856465823793
```

4 Random Forest Model

In [180]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [183]:
```
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.2, rando
```

In [184]:
```
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model
```

Out[184]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [185]:
```
rf_model.fit(X_train, Y_train)
```

Out[185]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [186]:
```
y_pred = rf_model.predict(X_test)
```

In [190]:
```
mse_1 = mean_squared_error(y_test, y_pred)
mae_1 = mean_absolute_error(y_test, y_pred)
r2_1= r2_score(y_test, y_pred)
```

In [190]:
```
mse_1 = mean_squared_error(y_test, y_pred)
mae_1 = mean_absolute_error(y_test, y_pred)
r2_1= r2_score(y_test, y_pred)

print('Mean Square Error',mse_1)
print('Mean Aboslute Error',mae_1)
print('R2 score',r2_1)
```

```
Mean Square Error 821.4243256944444
Mean Aboslute Error 14.698333333333336
R2 score 0.9628360636961593
```

4.0.1 As we can see Linear model is far better than Random Forest Model

4.0.2 The Result of Linear Regression model is 65% which is not that much good but there can be a lot's of reaons like:

4.0.3 1. Our dataset is highly imbalance

4.0.4 2. It has lots of missing values (around 5k)

4.0.5 3. we can improve our model by adding dummie data to increase the model accuracy

4.0.6 4. we can use different models and there Hyper Parameters to increase the accuracy of the model

In [ ]:

In [ ]: