*AIR BNB NYC - 2019 Analysis Report *

Problem Overview: To analyze the air bnb data and give recommendations on the basis of data while converting it into meaningful information.

```
### Objectives:
# Which types of hosts should Airbnb prioritize acquiring, and in which locations?
# How can customers be segmented based on their preferences?
# Which neighborhoods should Airbnb target for growth?
# What are the preferred price ranges for customers?
# What types of properties best align with customer preferences?
# What improvements can be made to make properties more appealing to customers?
# Which localities and properties are the most popular?
# How can less popular properties increase their appeal and attract more customers?
```

STEPS OF EXECUTION

1. Import Libraries and load data

```
#Import Libraries and load data
!pip install plotly
!pip install altair vega_datasets
!pip install pyspan
!pip install --upgrade yfinance

# for data cleaning
import pyspan as ps

# data processing
import pandas as pd
```

```
#linear algebra
import numpy as np

#for data visualization
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go

#stock related missing info
import yfinance as yf

# ignoring the warnings
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

%matplotlib inline
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (5.24.1)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly) (9.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from plotly) (24.1)
Requirement already satisfied: altair in /usr/local/lib/python3.10/dist-packages (4.2.2)
Requirement already satisfied: vega_datasets in /usr/local/lib/python3.10/dist-packages (0.9.0)
Requirement already satisfied: entrypoints in /usr/local/lib/python3.10/dist-packages (from altair) (0.4)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from altair) (3.1.4)
Requirement already satisfied: jsonschema>=3.0 in /usr/local/lib/python3.10/dist-packages (from altair) (4.23.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from altair) (1.26.4)
Requirement already satisfied: pandas>=0.18 in /usr/local/lib/python3.10/dist-packages (from altair) (2.2.2)
Requirement already satisfied: toolz in /usr/local/lib/python3.10/dist-packages (from altair) (0.12.1)
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=3.0->altair)
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Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.18->altair) (202
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.18->altair) (2
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->altair) (3.0.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas
Requirement already satisfied: pyspan in /usr/local/lib/python3.10/dist-packages (0.2.7)
```

```
Requirement already satisfied: numpy<2.0.0 in /usr/local/lib/python3.10/dist-packages (from pyspan) (1.26.4)
Requirement already satisfied: pandas<=2.2.2 in /usr/local/lib/python3.10/dist-packages (from pyspan) (2.2.2)
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Requirement already satisfied: yfinance in /usr/local/lib/python3.10/dist-packages (0.2.44)
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Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.10/dist-packages (from yfinance) (1.26.4)
Requirement already satisfied: requests>=2.31 in /usr/local/lib/python3.10/dist-packages (from yfinance) (2.32.3)
Requirement already satisfied: multitasking>=0.0.7 in /usr/local/lib/python3.10/dist-packages (from yfinance) (0.0.11)
Requirement already satisfied: lxml>=4.9.1 in /usr/local/lib/python3.10/dist-packages (from yfinance) (4.9.4)
Requirement already satisfied: platformdirs>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from yfinance) (4.3.6)
Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.10/dist-packages (from yfinance) (2024.2)
Requirement already satisfied: frozendict>=2.3.4 in /usr/local/lib/python3.10/dist-packages (from yfinance) (2.4.6)
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Requirement already satisfied: beautifulsoup4>=4.11.1 in /usr/local/lib/python3.10/dist-packages (from yfinance) (4.12.
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Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.3.0->yfinance)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.31
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfinance)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfin
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfin
```

```
# control warnings
import warnings
warnings.filterwarnings("ignore")
```

2. Load the Airbnb data

```
# Step 2: Load the Airbnb data
file_path = '/content/AB_NYC_2019.csv'
```

```
airbnb = pd.read_csv(file_path)

# Quick check to see the structure of the data
airbnb.head()  # View first few rows
```

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

Next steps: Generate code with airbnb | View recommended plots | New interactive sheet

3. Check the structure of the Dataset

```
# Check the rows and columns of the dataset
airbnb.shape
```

```
(48895, 16)
```

```
#what other columns do we have
len(airbnb.columns)
```

```
16
```

```
#show column names
airbnb.columns
```

```
Index(['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365'],
      dtype='object')
```

Understanding the data structure

```
#Get the summary of the data frame
airbnb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   name                            48879 non-null  object 
 2   host_id                         48895 non-null  int64  
 3   host_name                       48874 non-null  object 
 4   neighbourhood_group             48895 non-null  object 
 5   neighbourhood                   48895 non-null  object 
 6   latitude                        48895 non-null  float64
 7   longitude                       48895 non-null  float64
 8   room_type                       48895 non-null  object 
 9   price                           48895 non-null  int64  
 10  minimum_nights                  48895 non-null  int64  
 11  number_of_reviews               48895 non-null  int64  
```

```
 12  last_review                     38843 non-null  object
 13  reviews_per_month               38843 non-null  float64
 14  calculated_host_listings_count  48895 non-null  int64
 15  availability_365                48895 non-null  int64
dtypes: float64(3), int64(7), object(6)
memory usage: 6.0+ MB
```

```
#Statistics
airbnb.describe()
```

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_p
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	388
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	5

4. Data Cleaning

Handling missing data

```
#handle null values
pd.set_option('display.max_rows', None)
airbnb.isnull().sum()
```

	0
id	0
name	16
host_id	0
host_name	21
neighbourhood_group	0
neighbourhood	0
latitude	0
longitude	0
room_type	0
price	0
minimum_nights	0
number_of_reviews	0
last_review	10052
reviews_per_month	10052
calculated_host_listings_count	0
availability_365	0

dtype: int64

```
#Check duplicates
duplicate_rows = airbnb.duplicated().sum()

print(f"Number of duplicate rows: {duplicate_rows}")
```

```
Number of duplicate rows: 0
```

```
#replace null values "name"

airbnb = ps.handle_nulls(airbnb, columns = 'name', action = 'replace', with_val = "Unknown")

airbnb['name'].value_counts()["Unknown"]
```

16

```
# Remove unncessary columns
airbnb = ps.remove(airbnb, operation='columns', columns=['id','name', 'host_id'], inplace=False)

airbnb.head()
```

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
0	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

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```
# Fill missing values in 'reviews_per_month' and drop unnecessary columns

airbnb.fillna({'reviews_per_month': 0}, inplace=True)

#airbnb.drop(['id', 'name', 'last_review', 'host_id'], axis=1, inplace=True)
```

```
# Check the result
airbnb.head()
```

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
0	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

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```
# recheck null values of reviews_per_month feature
airbnb.reviews_per_month.isnull().sum()
```

```
0
```

```
airbnb.head()
```

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
0	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

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```
# Convert 'last_review' to datetime
airbnb['last_review'] = pd.to_datetime(airbnb['last_review'])


airbnb.head()
```

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
0	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

Next steps: Generate code with airbnb | View recommended plots | New interactive sheet

EXPLORATORY DATA ANALYSIS

5. Remove Outliers

```
# Remove outliers
import pandas as pd


# Show the initial shape of the dataset
print("Initial dataset shape:", airbnb.shape)

# Calculate Q1 (25th percentile) and Q3 (75th percentile) for the 'price' column
Q1 = airbnb['price'].quantile(0.25)
Q3 = airbnb['price'].quantile(0.75)
IQR = Q3 - Q1
```

```
# Determine the outlier boundaries
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter the dataset to remove outliers
data_cleaned = airbnb[(airbnb['price'] >= lower_bound) & (airbnb['price'] <= upper_bound)]

# Show the shape of the cleaned dataset
print("Cleaned dataset shape:", data_cleaned.shape)

# Optionally, display the first few rows of the cleaned dataset
print(data_cleaned.head())
```

```
Initial dataset shape: (48895, 13)
Cleaned dataset shape: (45923, 13)
     host_name neighbourhood_group neighbourhood  latitude  longitude  \
0         John            Brooklyn    Kensington  40.64749  -73.97237
1     Jennifer           Manhattan       Midtown  40.75362  -73.98377
2    Elisabeth           Manhattan        Harlem  40.80902  -73.94190
3  LisaRoxanne            Brooklyn  Clinton Hill  40.68514  -73.95976
4        Laura           Manhattan   East Harlem  40.79851  -73.94399

         room_type  price  minimum_nights  number_of_reviews last_review  \
0     Private room    149               1                  9  2018-10-19
1  Entire home/apt    225               1                 45  2019-05-21
2     Private room    150               3                  0         NaT
3  Entire home/apt     89               1                270  2019-07-05
4  Entire home/apt     80              10                  9  2018-11-19

   reviews_per_month  calculated_host_listings_count  availability_365
0               0.21                               6               365
1               0.38                               2               355
2               0.00                               1               365
3               4.64                               1               194
4               0.10                               1                 0
```

```
# Price Outliers
#Min.night outliers
#number of Reviews
```

```
# Plot price distribution
plt.figure(figsize=(10,5))
plt.hist(airbnb['price'], bins=100)
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Price Distribution')
plt.show()
```


```
airbnb.price.describe()
```

	price
count	48895.000000
mean	152.720687
std	240.154170
min	0.000000
25%	69.000000
50%	106.000000
75%	175.000000
max	10000.000000

dtype: float64

```
# Drop price above 800$
airbnb = airbnb[airbnb.price < 800]
```

```
# Check the percentage of price range above 800$
airbnb[airbnb['price'] > 800].shape[0]/airbnb.shape[0]*100
```

```
0.0
```

```
airbnb.head()
```

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
0	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

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Minimum Night Distribution

```
# minimum Outliers
# Check minimum nights distribution
airbnb.minimum_nights.describe()
```

	minimum_nights
count	48421.000000
mean	6.979596
std	20.291590
min	1.000000
25%	1.000000
50%	3.000000
75%	5.000000
max	1250.000000

dtype: float64

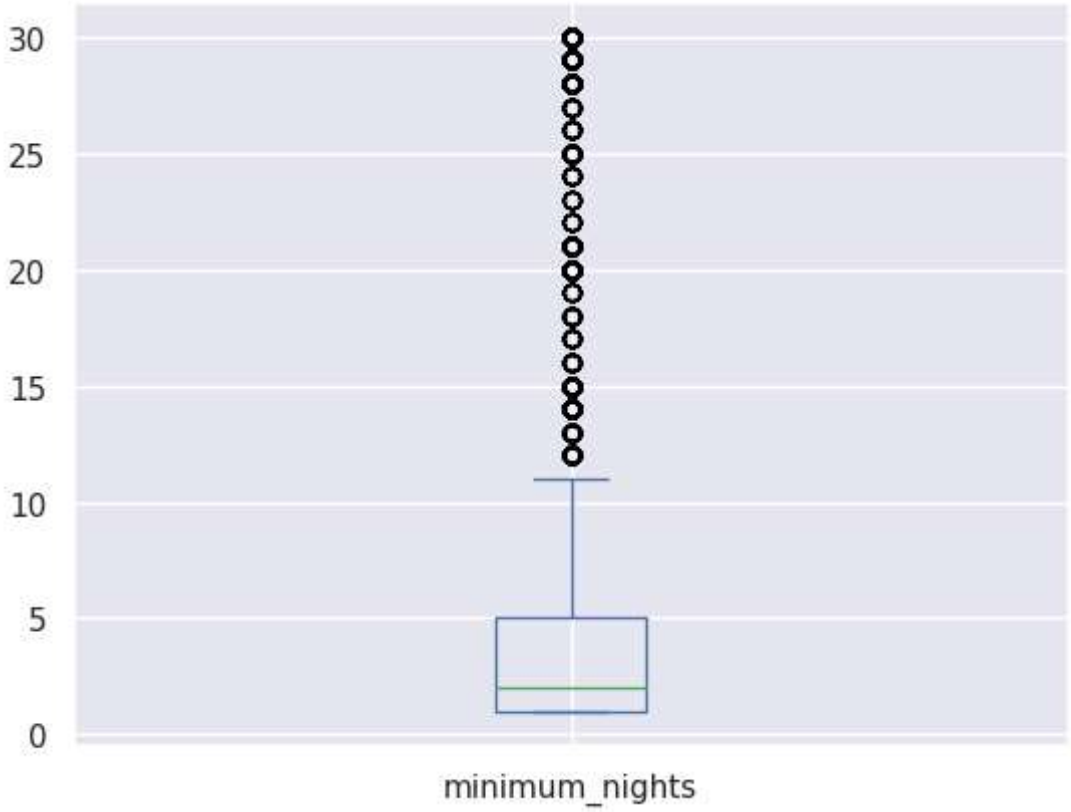
```
# Check the percentage of minimum night above 31 nights$
airbnb[airbnb['minimum_nights'] > 31].shape[0]/airbnb.shape[0]*100
```

```
1.0739142107763162
```

```
# Drop listings with minimum nights > 31
airbnb = airbnb[airbnb.minimum_nights < 31]
```

```
# Recheck the distribution of minimum night
airbnb.minimum_nights.plot.box()
```

```
<Axes: >
```



Number of Reviews

```
airbnb.number_of_reviews.describe()
```

	number_of_reviews
count	47703.000000
mean	23.601241
std	44.860305
min	0.000000
25%	1.000000
50%	5.000000
75%	24.000000
max	629.000000

dtype: float64

```
# Percentage of reviews amount above 100
airbnb[airbnb.number_of_reviews > 300].shape[0]/airbnb.shape[0]*100
```

```
0.27461585225247886
```

```
#Hosts with more than 300 reviews are considered outliers and will be dropped.
# Drop listings with more than 300 reviews
airbnb = airbnb[airbnb.number_of_reviews < 300]
```

```
# Checking the distribution of availibility
airbnb.availability_365.describe()
```

	availability_365
count	47572.00000
mean	110.89086
std	130.86856
min	0.00000
25%	0.00000
50%	42.00000
75%	221.00000
max	365.00000

dtype: float64

```
#check percentage of availability
(airbnb.availability_365.eq(0).sum())/airbnb.shape[0]*100
```

```
36.296561002270245
```

Remove Irrelavant columns

```
# Drop 'availability_365' column
airbnb.drop(columns=['availability_365'], inplace=True)
```

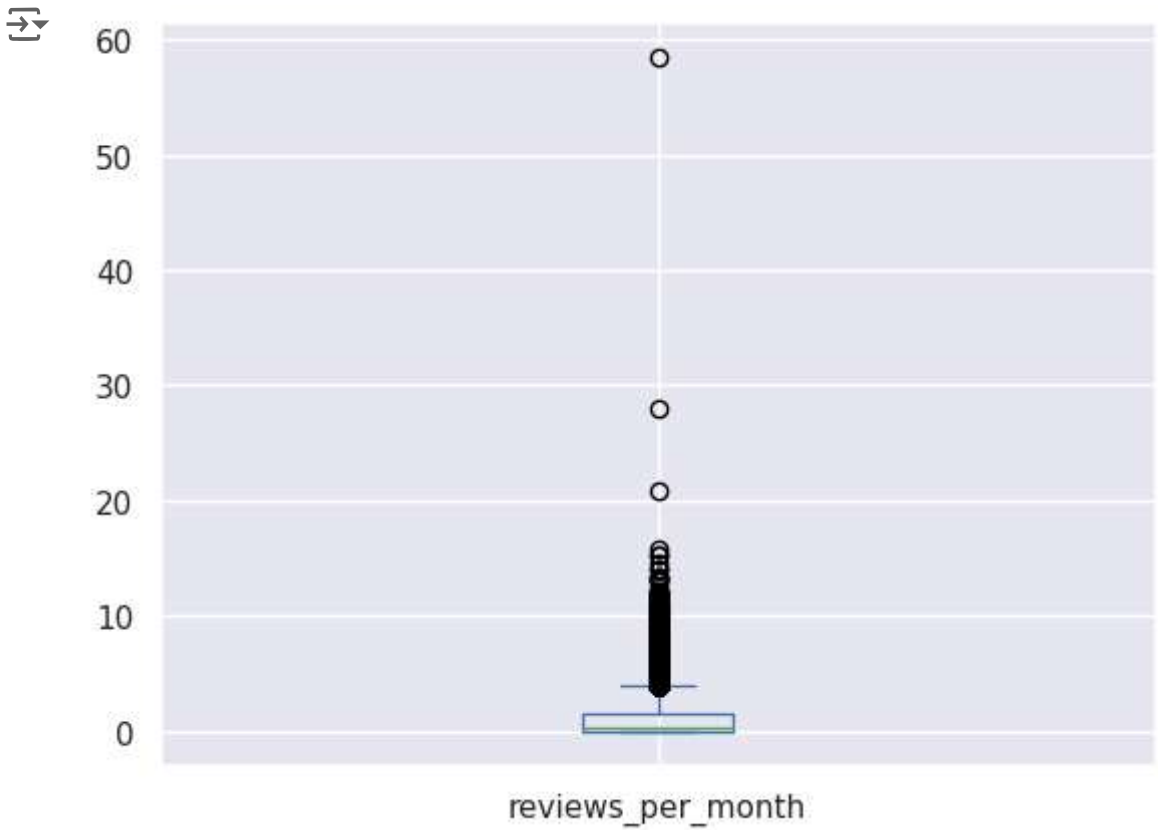
Reviews per month

```
airbnb.reviews_per_month.describe()
```

	reviews_per_month
count	47572.000000
mean	1.092862
std	1.571399
min	0.000000
25%	0.040000
50%	0.380000
75%	1.610000
max	58.500000

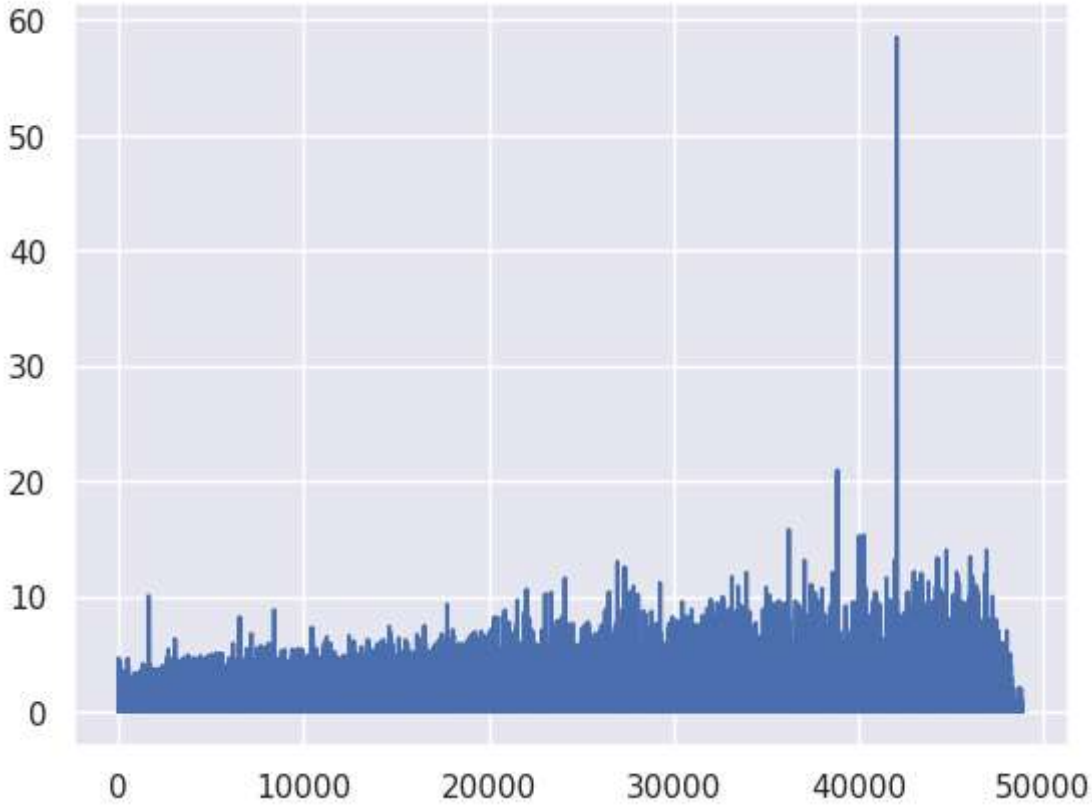
dtype: float64

```
airbnb.reviews_per_month.plot.box()
plt.show()
```




```
# plot graph
plt.plot(airbnb["reviews_per_month"])
```

```
[<matplotlib.lines.Line2D at 0x7c871dbf8c10>]
```



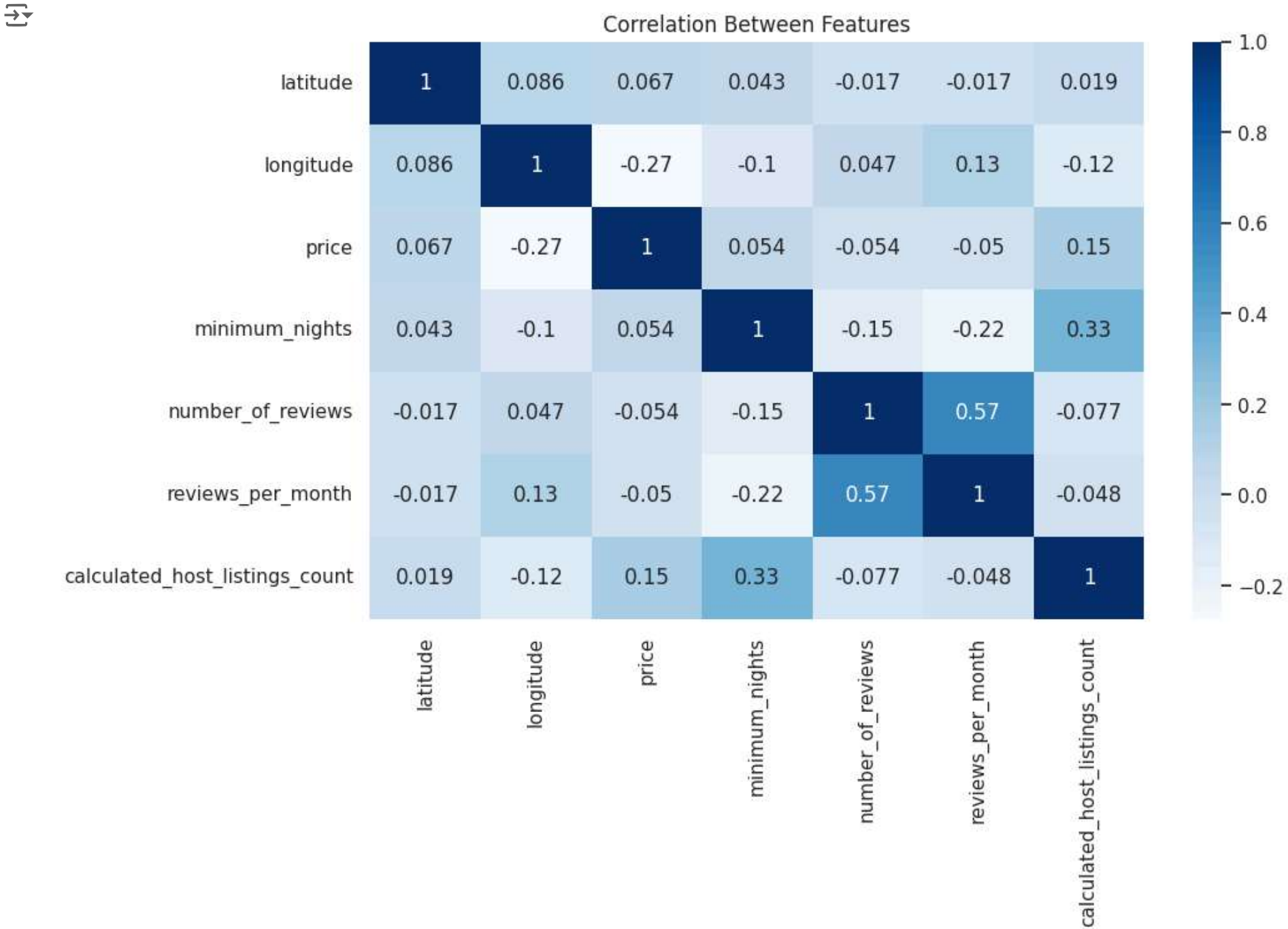
Availability

Around 36% of the hosts have an availability of zero. Therefore, the availability column does not hold statistical significance. Therefore, we will drop this column.

6. Correlation Analysis

```
# Import seaborn and matplotlib in case they were not properly loaded
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Ensure that you're in an interactive environment
%matplotlib inline

# Check if the dataset contains only numeric data for correlation
numeric_data = airbnb.select_dtypes(include=[np.number])

# If the dataset contains numeric values, proceed to correlation
if not numeric_data.empty:
    plt.figure(figsize=(10,6))
    sns.heatmap(numeric_data.corr(), annot=True, cmap='Blues')
    plt.title('Correlation Between Features')
    plt.show()
else:
    print("No numeric data available for correlation.")
```

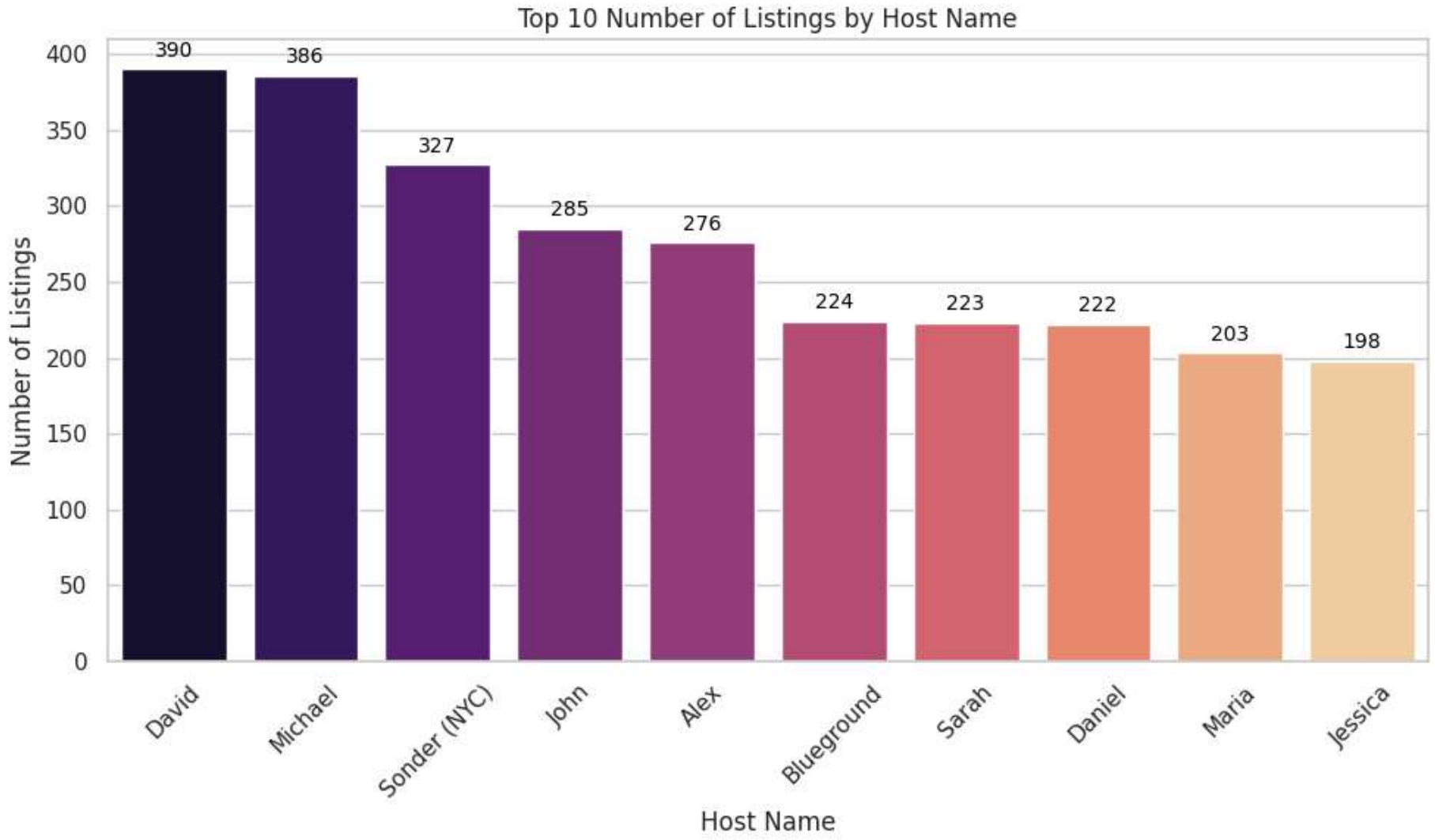

Correlation Between Features
latitude
longitude
price
minimum_nights
number_of_reviews
reviews_per_month
calculated_host_listings_count
1 0.086 0.067 0.043 -0.017 -0.017 0.019
0.086 1 -0.27 -0.1 0.047 0.13 -0.12
0.067 -0.27 1 0.054 -0.054 -0.05 0.15
0.043 -0.1 0.054 1 -0.15 -0.22 0.33
-0.017 0.047 -0.054 -0.15 1 0.57 -0.077
-0.017 0.13 -0.05 -0.22 0.57 1 -0.048
0.019 -0.12 0.15 0.33 -0.077 -0.048 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

Univariate and multivariate analysis

Which types of hosts should Airbnb prioritize acquiring, and in which locations?

Top 10 Hosts by Neighbourhood Group

```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot number of hosts by host name
host_count = airbnb.host_name.value_counts().head(10)
sns.set(style="whitegrid")
plt.figure(figsize=(10,6))

# Use a different palette (coolwarm in this example)
ax = sns.barplot(x=host_count.index, y=host_count.values, palette='magma')

# Add value labels to the bars
for value in ax.containers:
    ax.bar_label(value, fmt='{:,.0f}', label_type='edge', fontsize=10, color='black', padding=4)

# Fix typos in xlabel and ylabel
plt.xticks(rotation=45)
plt.xlabel("Host Name")
plt.ylabel("Number of Listings")
plt.title("Top 10 Number of Listings by Host Name")

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



Insight:

The top 10 hosts mainly provide Entire Home/Apartment and Private Room rentals, with prices ranging from $190 to 400$.

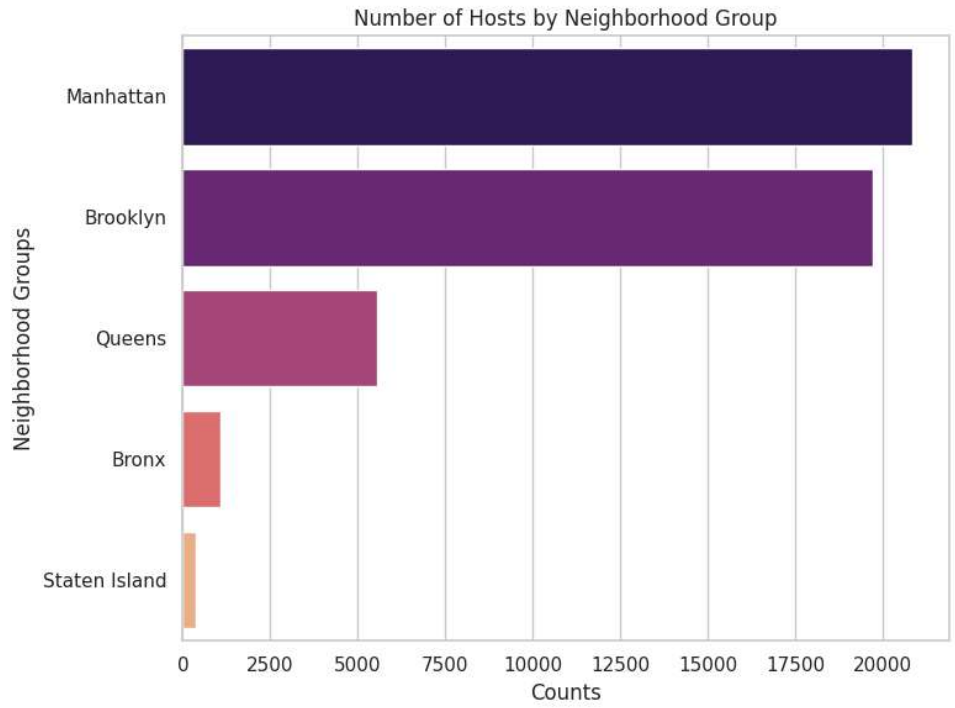
Recommendation:

Airbnb should focus on acquiring hosts that offer Entire Home/Apartment and Private Room rentals within the price range of $190 to$

400, particularly in Manhattan and Brooklyn.

Which neighborhoods should Airbnb target for growth?

```
# Step 1: Group count of hosts and mean price per neighborhood group and room type
group_count = airbnb['neighbourhood_group'].value_counts()
price_mean = airbnb.groupby(['neighbourhood_group', 'room_type'])['price'].mean().reset_index()

# Step 2: Create subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6))

# Plot 1: Number of hosts by neighborhood group
sns.barplot(x=group_count.values, y=group_count.index, palette='magma', ax=axes[0])
axes[0].set_title("Number of Hosts by Neighborhood Group")
axes[0].set_xlabel("Counts")
axes[0].set_ylabel("Neighborhood Groups")

# Plot 2: Average price by neighborhood group and room type
sns.barplot(data=price_mean, x='neighbourhood_group', y='price', hue='room_type', palette='magma', ax=axes[1])
axes[1].set_title("Average Price by Neighborhood Group and Room Type")
axes[1].set_xlabel("Neighborhood Groups")
axes[1].set_ylabel("Average Price")

# Step 3: Adjust layout and show plot
plt.tight_layout()
plt.show()
```



Insight:

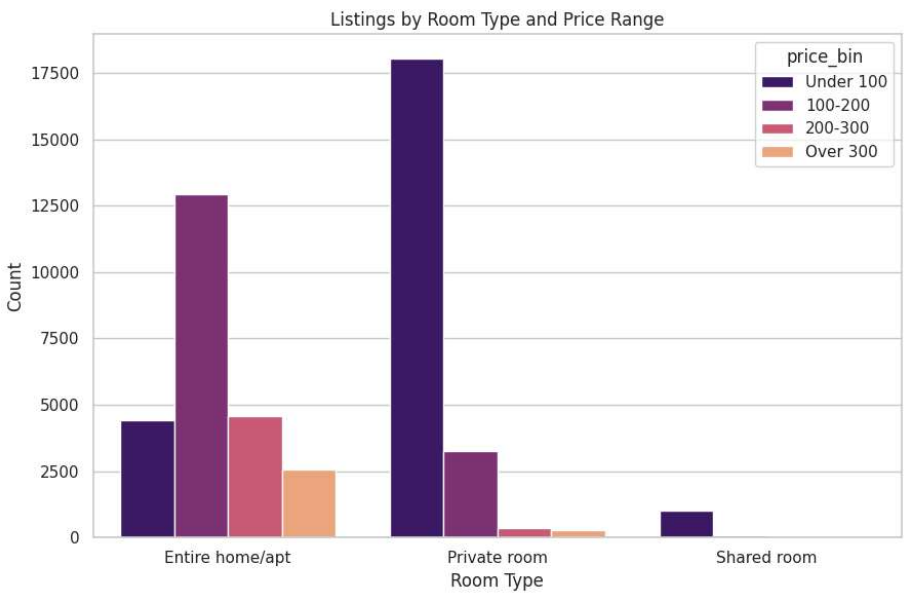
Most listings are concentrated in Manhattan and Brooklyn, with prices in these areas being significantly higher compared to other neighborhoods. Listings priced above $300 make up more than 10% of the total, while the other three neighborhood groups each have fewer than 10% of the listings.

Recommendation:

Given the high demand in Manhattan and Brooklyn, Airbnb should focus more resources and marketing efforts on these areas to attract more guests and boost revenue.

What are the preferred price ranges for customers?

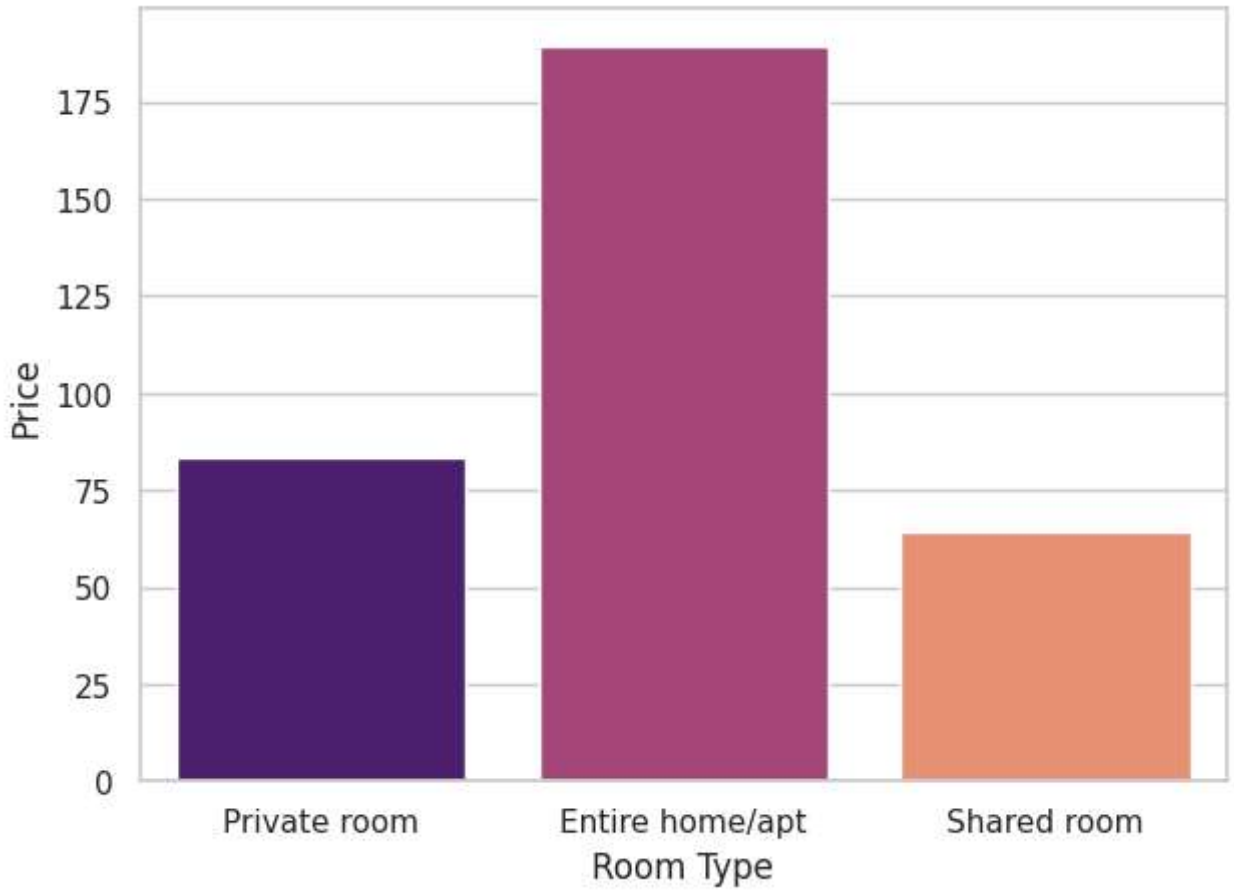
```
# Step 1: Create price bins
price_bins = [0, 100, 200, 300, float('inf')]
price_labels = ['Under 100', '100-200', '200-300', 'Over 300']

airbnb['price_bin'] = pd.cut(airbnb['price'], bins=price_bins, labels=price_labels)

# Step 2: Create subplots
fig, axes = plt.subplots(1, 2, figsize=(18, 6))

# Plot 1: Count of listings by price range
sns.countplot(x='price_bin', data=airbnb, palette='magma', ax=axes[0])
axes[0].set_xlabel("Price Range")
axes[0].set_ylabel("Number of Listings")
axes[0].set_title("Number of Listings by Price Range")

# Plot 2: Count of listings by room type and price range
ax2_data = airbnb.groupby(['room_type', 'price_bin']).size().reset_index(name='count')

sns.barplot(x='room_type', y='count', hue='price_bin', data=ax2_data, palette='magma', ax=axes[1])
axes[1].set_xlabel("Room Type")
axes[1].set_ylabel("Count")
axes[1].set_title("Listings by Room Type and Price Range")

# Step 3: Display the plot
plt.tight_layout()
plt.show()
```



What types of properties best align with customer preferences?

Different types of properties align with customer preferences. Existing properties can be adjusted to better meet these preferences by improving amenities, design, or pricing to enhance guest satisfaction.

```
plt.figure(figsize = (7,5))
ax = sns.barplot(data = airbnb, x = 'room_type', y = 'price', estimator = 'average', ci=None, palette = 'magma')
ax.set_xlabel("Room Type")
ax.set_ylabel("Price")
plt.show()
```



Insight:

Entire Home/Apartment rentals are nearly twice as expensive as other room types.

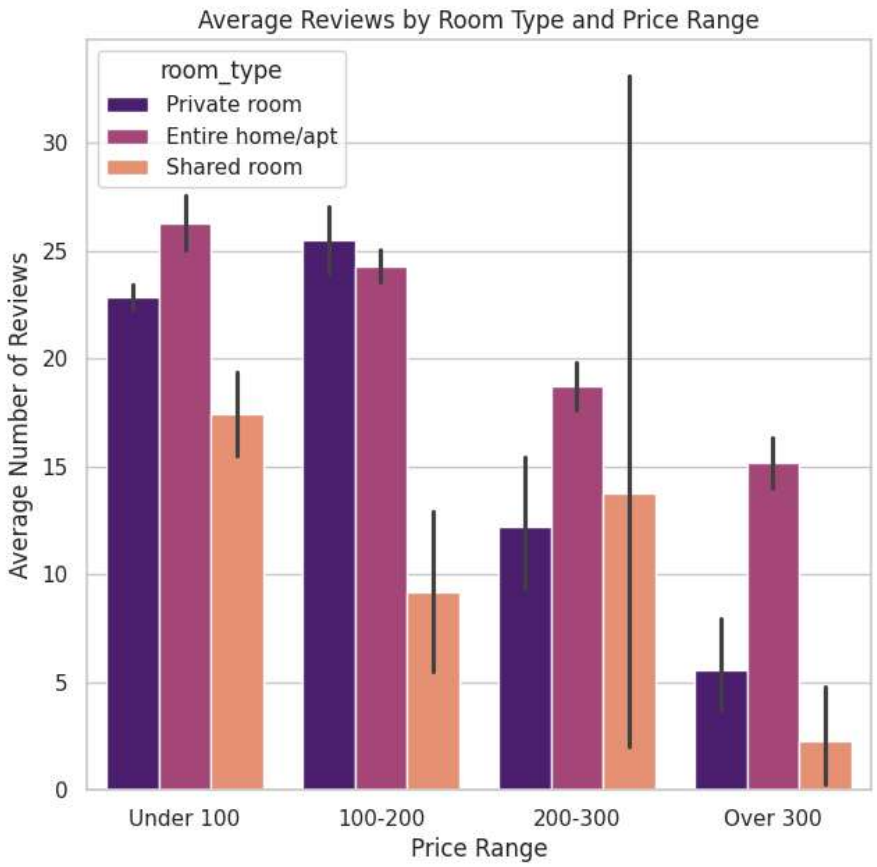
Recommendation:

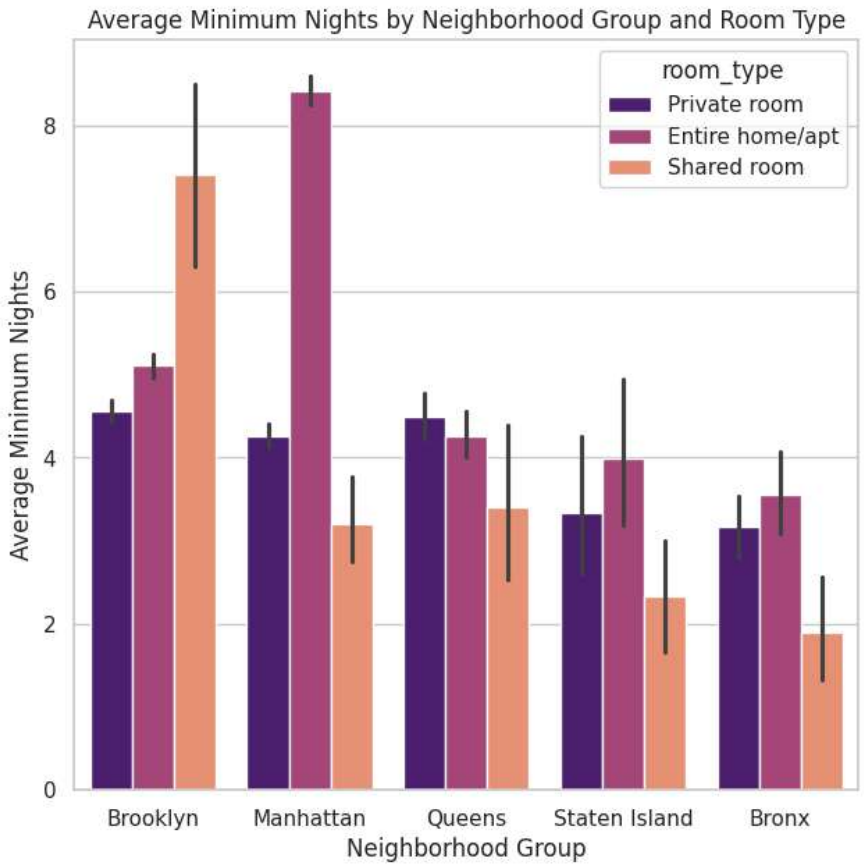
Target customers seeking a premium, exclusive experience to capitalize on the higher prices of Entire Home/Apartment rentals.

What improvements can be made to make properties more appealing to customers?

```
# Customer reviews
# Create subplots
```

```
fig, axes = plt.subplots(1, 2, figsize=(16, 7))

# Plot 1: Average number of reviews by price range and room type
sns.barplot(data=airbnb, x='price_bin', y='number_of_reviews', hue='room_type', estimator='mean', palette='magma', ax=axes[
axes[0].set(xlabel="Price Range", ylabel="Average Number of Reviews", title="Average Reviews by Room Type and Price Range")

# Plot 2: Average minimum nights by neighborhood group and room type
sns.barplot(data=airbnb, x='neighbourhood_group', y='minimum_nights', hue='room_type', estimator='mean', palette='magma', a
axes[1].set(xlabel="Neighborhood Group", ylabel="Average Minimum Nights", title="Average Minimum Nights by Neighborhood Gro

# Show the plots
plt.show()
```

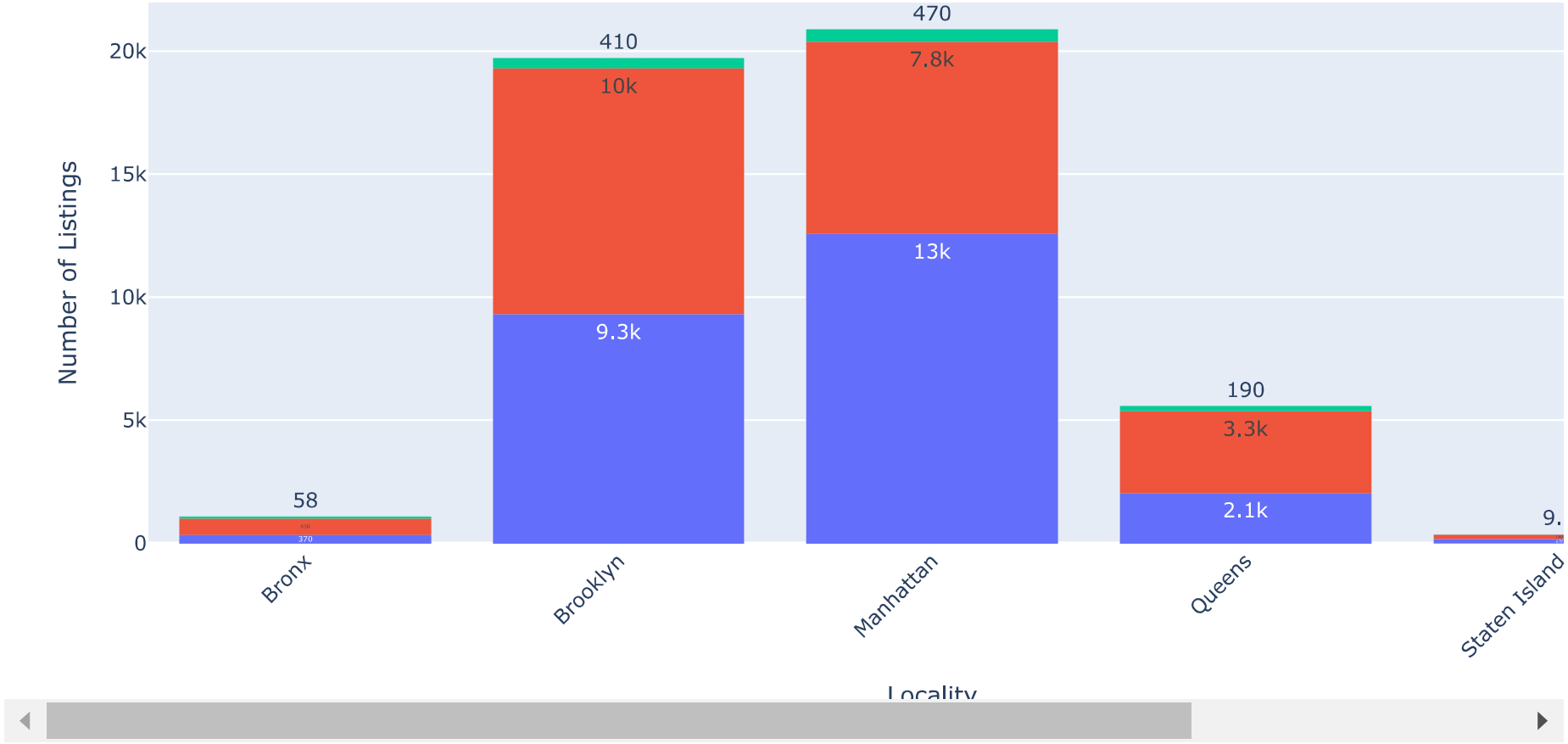




Which localities and properties are the most popular?

```
import pandas as pd
import plotly.express as px

# Step 2: Count the number of listings by locality and room type
```

```
popularity_data = airbnb.groupby(['neighbourhood_group', 'room_type']).size().reset_index(name='count')

# Step 3: Create a dynamic bar chart using Plotly with a different theme
fig = px.bar(
    popularity_data,
    x='neighbourhood_group',
    y='count',
    color='room_type',
    title='Most Popular Localities and Room Types',
    labels={'neighbourhood_group': 'Locality', 'count': 'Number of Listings'},
    text='count',  # Show counts on the bars
    template='plotly'  # Use a different available theme
)

# Step 4: Customize the layout
fig.update_traces(texttemplate='%{text:.2s}', textposition='outside')
fig.update_layout(barmode='stack', xaxis_title='Locality', yaxis_title='Number of Listings', xaxis_tickangle=-45)

# Step 5: Show the plot
fig.show()
```



Insight:

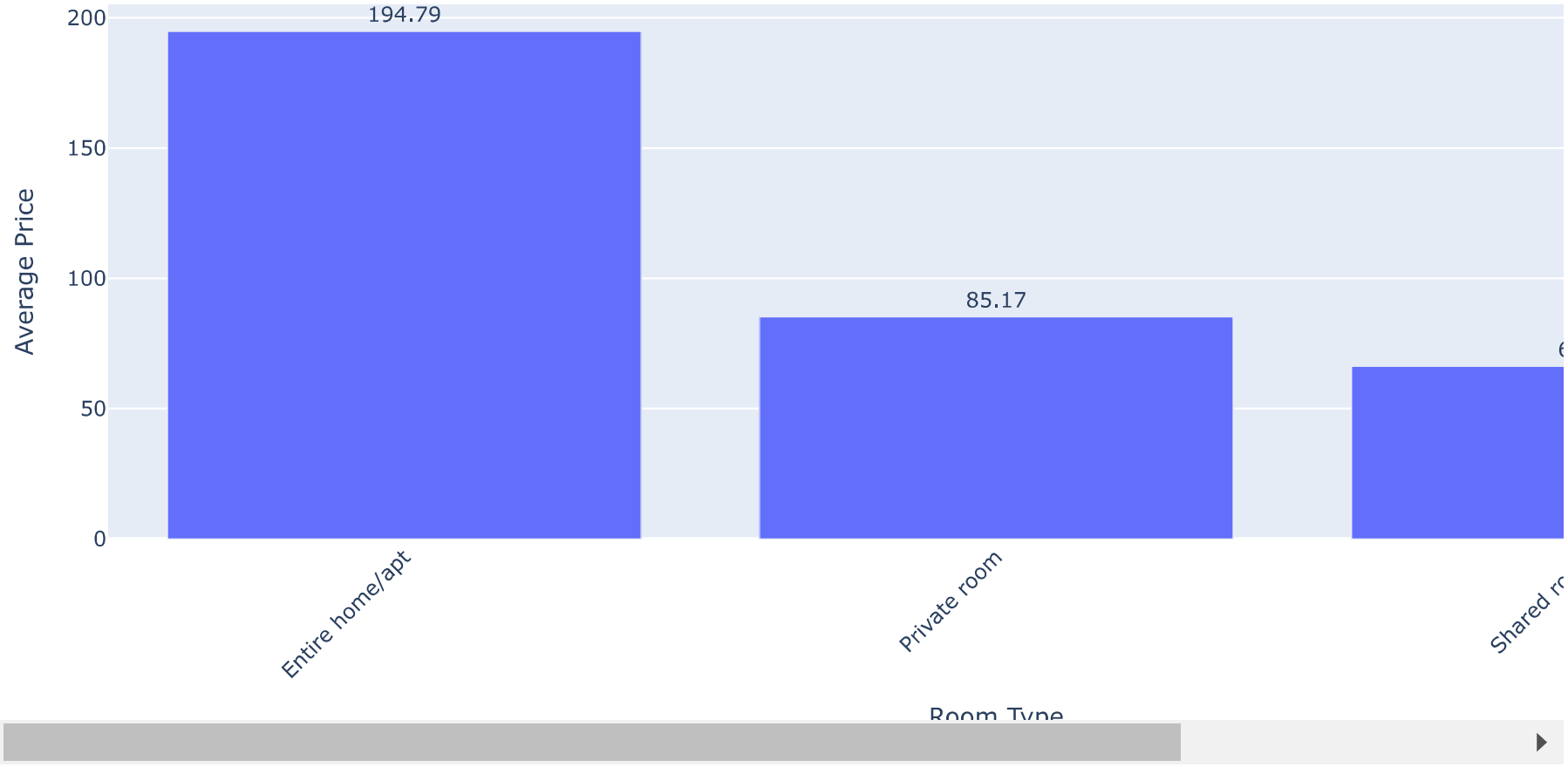
Popular localities, especially Manhattan and Brooklyn, have a higher number of listings across various room types.

Recommendation:

Focus marketing efforts on these key areas to boost bookings and showcase diverse room types to attract more guests.

How can less popular properties increase their appeal and attract more customers?

```
import pandas as pd
import plotly.express as px


# Step 2: Filter for less popular properties (e.g., properties with fewer than a certain number of reviews)
less_popular_threshold = 20  # You can adjust this threshold based on your analysis
less_popular_properties = airbnb[airbnb['number_of_reviews'] < less_popular_threshold]

# Step 3: Calculate average price by room type for less popular properties
avg_price_data = less_popular_properties.groupby('room_type')['price'].mean().reset_index()

# Step 4: Create a bar chart to visualize average prices of less popular properties by room type
fig = px.bar(
    avg_price_data,
    x='room_type',
    y='price',
    title='Average Price of Less Popular Properties by Room Type',
    labels={'room_type': 'Room Type', 'price': 'Average Price'},
    text='price',
    template='plotly'
)

# Step 5: Customize the layout
fig.update_traces(texttemplate='%{text:.2f}', textposition='outside')
fig.update_layout(xaxis_title='Room Type', yaxis_title='Average Price', xaxis_tickangle=-45)

# Step 6: Show the plot
fig.show()
```



Insights:

- Less popular properties often have lower prices but may lack sufficient reviews, indicating limited customer engagement.
- Room types with average prices can vary significantly, suggesting opportunities for strategic pricing adjustments.

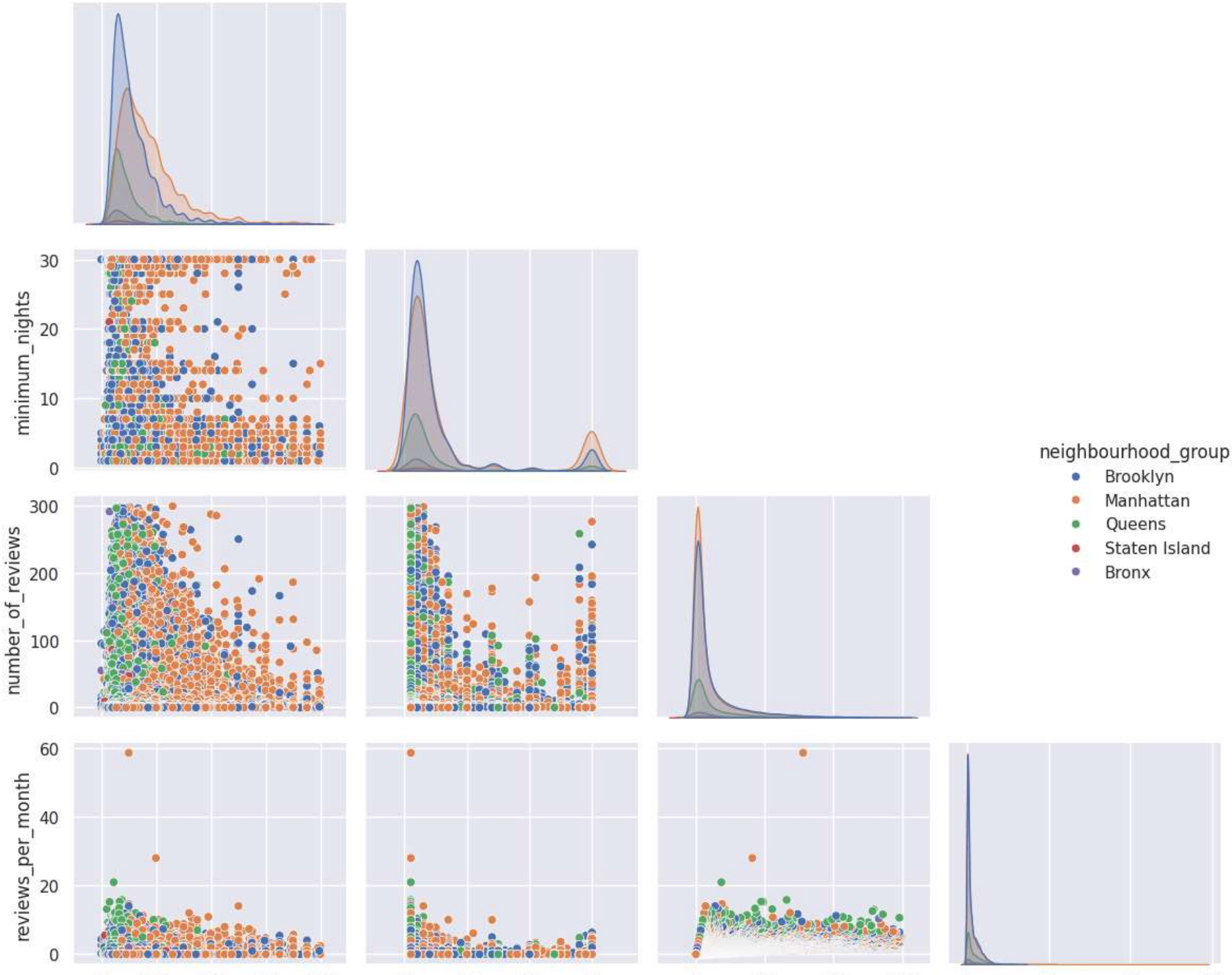
Recommendations:

- **Enhance Visibility**: Improve marketing efforts for properties with fewer reviews.
- **Adjust Pricing**: Consider competitive pricing strategies for less popular room types to attract more customers.
- **Boost Amenities**: Add appealing amenities to increase desirability and encourage positive reviews.

Correlations between Key Metrices

```
#Correlations between Key Metrices
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd


# Selecting relevant columns for pairplot
# Ensure you have appropriate numerical columns in the DataFrame
pairplot_data = airbnb[['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month', 'neighbourhood_group']]

# Create a pairplot
sns.set(style='darkgrid')
plt.figure(figsize=(15, 12))
sns.pairplot(pairplot_data, corner=True, hue='neighbourhood_group')
plt.tight_layout()
plt.show()
```

```
<Figure size 1500x1200 with 0 Axes>
```



Dynamic Bar Chart for Number of Listings by Neighbourhood Group

```
import plotly.express as px
import pandas as pd

# Group data by neighborhood
neighbourhood_group_count = airbnb['neighbourhood_group'].value_counts().reset_index()
neighbourhood_group_count.columns = ['Neighbourhood Group', 'Number of Listings']

# Create dynamic bar chart
fig = px.bar(neighbourhood_group_count, x='Neighbourhood Group', y='Number of Listings',
             color='Neighbourhood Group', title="Number of Airbnb Listings by Neighbourhood Group",
             labels={'Number of Listings': 'Number of Listings'})
fig.show()
```

Number of Airbnb Listings by Neighbourhood Group