AirBnb NYC Price Prediction

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1-271c4d46.png

Map Reference

FiveBoroughs-01.jpg

📌 Dataset Overview

📖 Context

Since its inception in 2008, **Airbnb** has transformed the way people travel by offering unique, personalized accommodations beyond traditional hotels. This dataset provides insights into the **Airbnb listings in New York City (NYC) for the year 2019**, capturing key details about hosts, properties, pricing, and availability. By analyzing this dataset, we can explore patterns in **rental prices, geographical distribution, and factors influencing Airbnb listings.**

📂 Dataset Content

The dataset contains essential details required to analyze **host activity, location-based trends, and pricing variations** across different boroughs of NYC. It includes information such as **property characteristics, host details, pricing, room types, review metrics, and availability**. This enables us to build predictive models for Airbnb pricing and extract valuable business insights.

🔍 Key Features

Column	Description
`id`	Unique identifier for each listing
`name`	Name of the listing
`host_id`	Unique identifier for the host
`host_name`	Name of the host
`neighbourhood_group`	Borough or main location of the listing (e.g., Manhattan, Brooklyn)
`neighbourhood`	Specific area within the borough
`latitude`	Geographic latitude coordinate of the listing
`longitude`	Geographic longitude coordinate of the listing
`room_type`	Type of space offered (e.g., Entire home, Private room, Shared room)
`price`	Listing price per night in USD
`minimum_nights`	Minimum required stay duration
`number_of_reviews`	Total number of reviews received
`last_review`	Date of the most recent review
`reviews_per_month`	Average number of reviews per month
`calculated_host_listings_count`	Total number of listings managed by the host
`availability_365`	Number of days the listing is available for booking within a year

🎯 Use Cases

This dataset can be used for various **data analysis and machine learning tasks**, including:
✔ **Price Prediction** – Identifying factors influencing rental prices and building predictive models
✔ **Geospatial Analysis** – Understanding the distribution of listings across NYC
✔ **Host Behavior Insights** – Examining host activity, availability, and review patterns
✔ **Customer Trends** – Analyzing demand patterns based on reviews and availability

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This dataset serves as the foundation for our **Airbnb Price Prediction Model**, where we aim to uncover insights and forecast listing prices based on key attributes. Let's dive into the data! 🚀

Importing Libraries

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

```
from scipy.stats import norm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_absolute_error
from sklearn.model_selection import GridSearchCV
```

Loading the Dataset

```
df = pd.read_csv('./AB_NYC_2019.csv')
```

```
df.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
```

```
df.head(5)
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minim
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	

```
df.shape
```

```
(48895, 16)
```

Checking duplicate and null values

```
df.duplicated().sum()
```

```
0
```

```
df.isna().sum()
```

```
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
```

Data Cleaning

Removing unnecessary columns

To streamline our analysis and focus on meaningful insights, we can remove certain columns that do not significantly contribute to our model.

1. **host_id** – This is a unique identifier for hosts, which does not provide any predictive power. Since it does not impact the price of a listing, it can be safely dropped. To identify the listing, we will retain the **id** column.
2. **host_name** **and** **name** – The listing name and host name are textual data that do not contain numerical or categorical information useful for price prediction. Additionally, these values may introduce unnecessary noise rather than contribute to meaningful analysis.
3. **last_review** – While review counts may be relevant, the exact date of the last review is unlikely to impact pricing patterns significantly.

Thus, we remove these columns to focus on the most relevant factors influencing Airbnb prices.

```
df = df.drop(columns=['host_id', 'name', 'host_name', 'last_review'])

df.columns
```

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

```
df.shape
```

```
(48895, 12)
```

Handling missing values

```
df.isna().sum()
```

```
id                                0
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
reviews_per_month             10052
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

```
df['reviews_per_month'].head(10)
```

```
0    0.21
1    0.38
2     NaN
3    4.64
4    0.10
5    0.59
6    0.40
```

```
7    3.47
8    0.99
9    1.33
Name: reviews_per_month, dtype: float64
```

As we can see, the column `reviews per month` contains `NaN` values. This likely means that the listing has never been reviewed. Hence, I will replace it with 0.

```
# Replacing NaN with 0 for reviews_per_month column
df['reviews_per_month'] = df['reviews_per_month'].fillna(0)

df.isna().sum()
```

```
id                                0
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
reviews_per_month                 0
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

Dropping null values as a safety measure

```
df=df.dropna()

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   neighbourhood_group             48895 non-null  object 
 2   neighbourhood                   48895 non-null  object 
 3   latitude                        48895 non-null  float64
 4   longitude                       48895 non-null  float64
 5   room_type                       48895 non-null  object 
 6   price                           48895 non-null  int64  
 7   minimum_nights                  48895 non-null  int64  
 8   number_of_reviews               48895 non-null  int64  
 9   reviews_per_month               48895 non-null  float64
 10  calculated_host_listings_count  48895 non-null  int64  
 11  availability_365                48895 non-null  int64  
dtypes: float64(3), int64(6), object(3)
memory usage: 4.5+ MB
```

Exploratory Data Analysis

Analyzing numerical data

```
df.describe()
```

	id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calcula
count	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	
mean	1.901714e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.090910	
std	1.098311e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.597283	
min	2.539000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.000000	
25%	9.471945e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.040000	
50%	1.967728e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.370000	
75%	2.915218e+07	40.763115	-73.936275	175.000000	5.000000	24.000000	1.580000	
max	3.648724e+07	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	

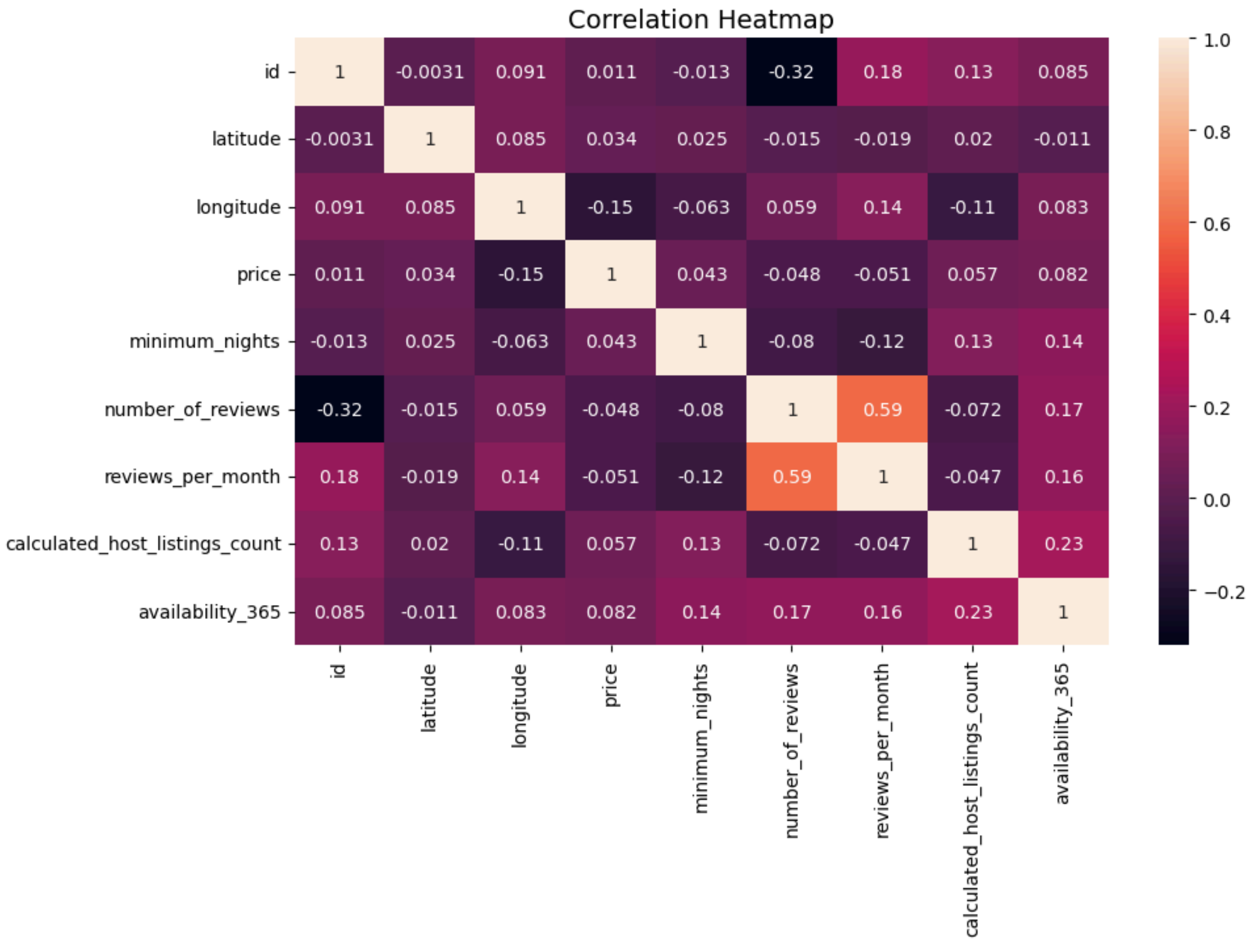
- **Average Price:**
  The average nightly price is **$152.72**, but the **maximum price** reaches an extreme of **$10,000**, suggesting potential **outliers**

- **Minimum Nights:**
  The **median minimum nights** required is **3**, but the **maximum value** of **1,250** indicates some **unusual entries** likely requiring further investigation.
- **Availability:**
  The **average availability** is around **113 days per year**, with some listings available **year-round (365 days)**.

These statistics highlight the **variability** in pricing, availability, and booking policies across listings.

Correlation Analysis

```
# Selecting only numerical columns
numeric_df = df.select_dtypes(include=['int64', 'float64'])

corr_matrix = numeric_df.corr(method='pearson')

plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True)
plt.title("Correlation Heatmap", fontsize=14)

plt.show()
```



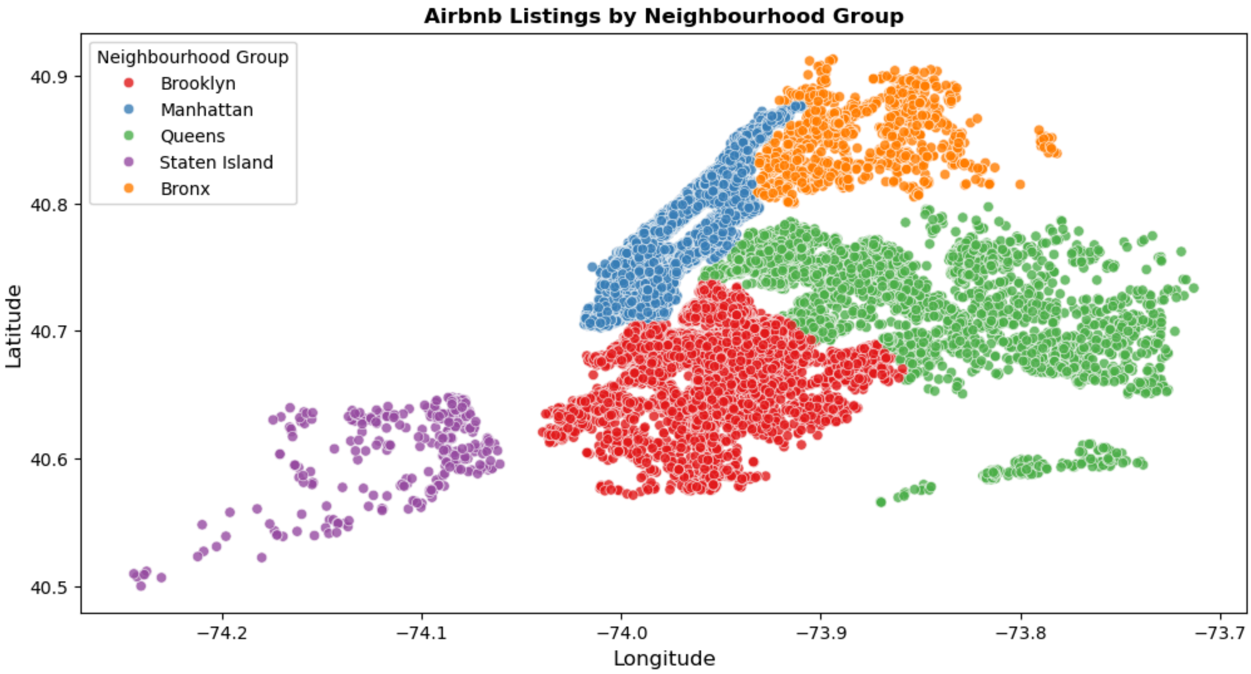
- **Strong Positive Correlation**: `number_of_reviews` and `reviews_per_month` (0.59), indicating that listings with more reviews receive them more frequently. This makes sense.
- **Weak Correlations**: `price` is weakly correlated with all factors. Also, `availability_365` has a slight positive correlation with `calculated_host_listings_count` (0.23).
- **Negative Correlation**: `price` and `longitude` (-0.15) suggests that there is a slight tendency for prices to decrease as longitude increases, which could reflect geographical trends in NYC, such as higher prices in areas closer to Manhattan (lower longitude values).

Overall, most relationships are weak, indicating that key factors such as price and availability are largely independent. This also suggests that no other feature needs to be removed from the dataset.

Georgraphical & Categorical Variable Analysis

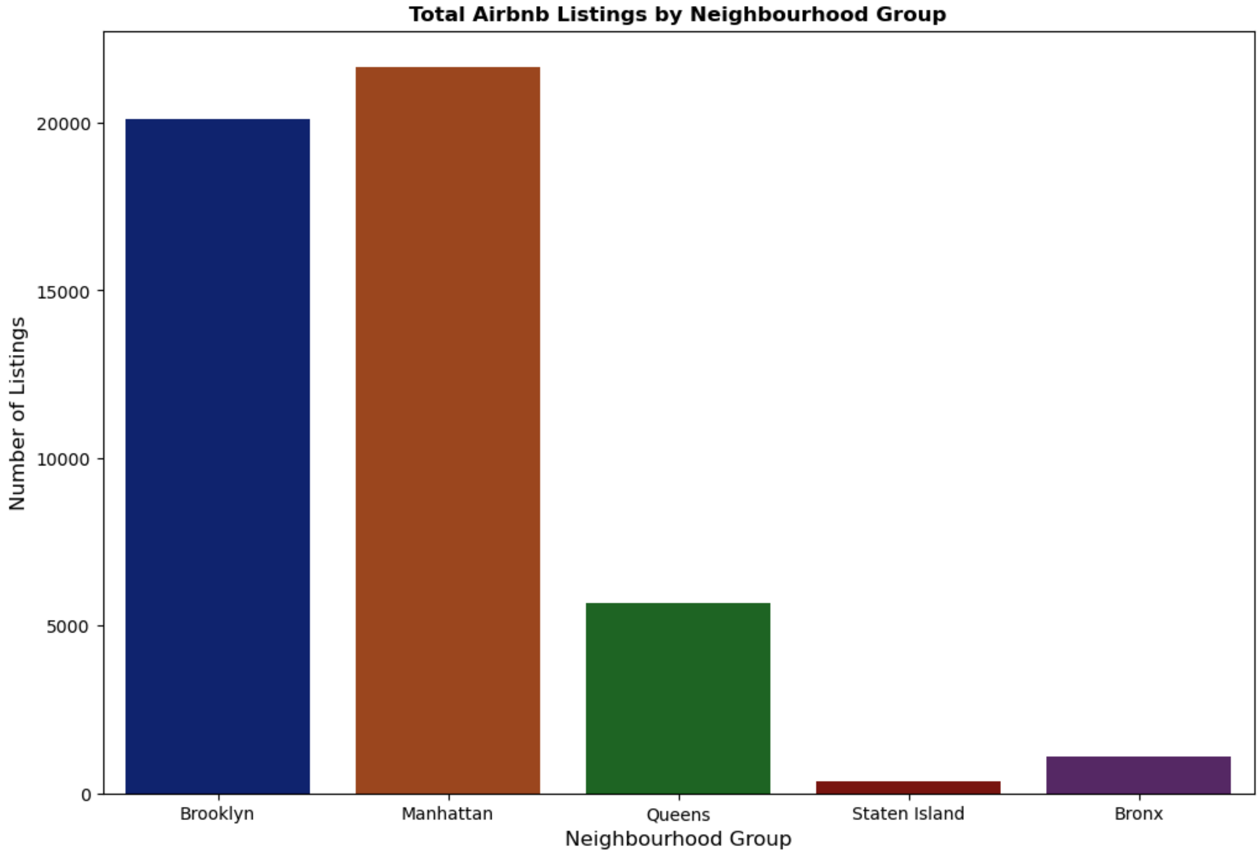
Analyzing Neighbourhood Group

```
plt.style.use("default")
plt.figure(figsize=(12, 6))

sns.scatterplot(
    data=df, x="longitude", y="latitude", hue="neighbourhood_group", palette="Set1", alpha=0.8)

plt.title("Airbnb Listings by Neighbourhood Group", fontsize=12, fontweight="bold")
plt.xlabel("Longitude", fontsize=12)
plt.ylabel("Latitude", fontsize=12)
plt.legend(title="Neighbourhood Group")
plt.show()
```



The scatterplot shows the geographical distribution of Airbnb listings across NYC's neighborhood groups. Manhattan (blue) and Brooklyn (red) have the densest concentration of listings, while Staten Island (purple) has the sparsest. The distribution aligns with NYC's population density and tourism hotspots, with Manhattan being the most central and popular area.

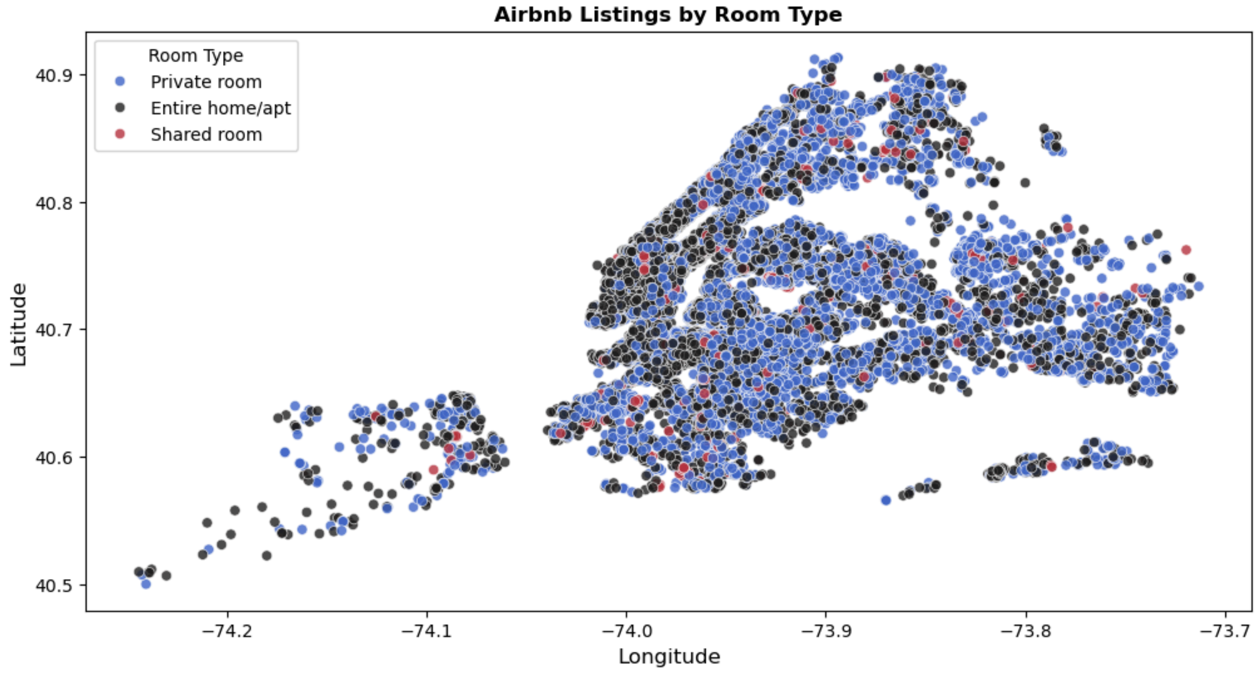
```
plt.figure(figsize=(12, 8))

ax = sns.countplot(data=df, x="neighbourhood_group", palette="dark",hue="neighbourhood_group")

plt.title("Total Airbnb Listings by Neighbourhood Group", fontsize=12, fontweight="bold")
plt.xlabel("Neighbourhood Group", fontsize=12)
plt.ylabel("Number of Listings", fontsize=12)

plt.show()
```



Manhattan and Brooklyn dominate Airbnb listings in NYC, with over 20,000 each, while Staten Island has the fewest at just 373.

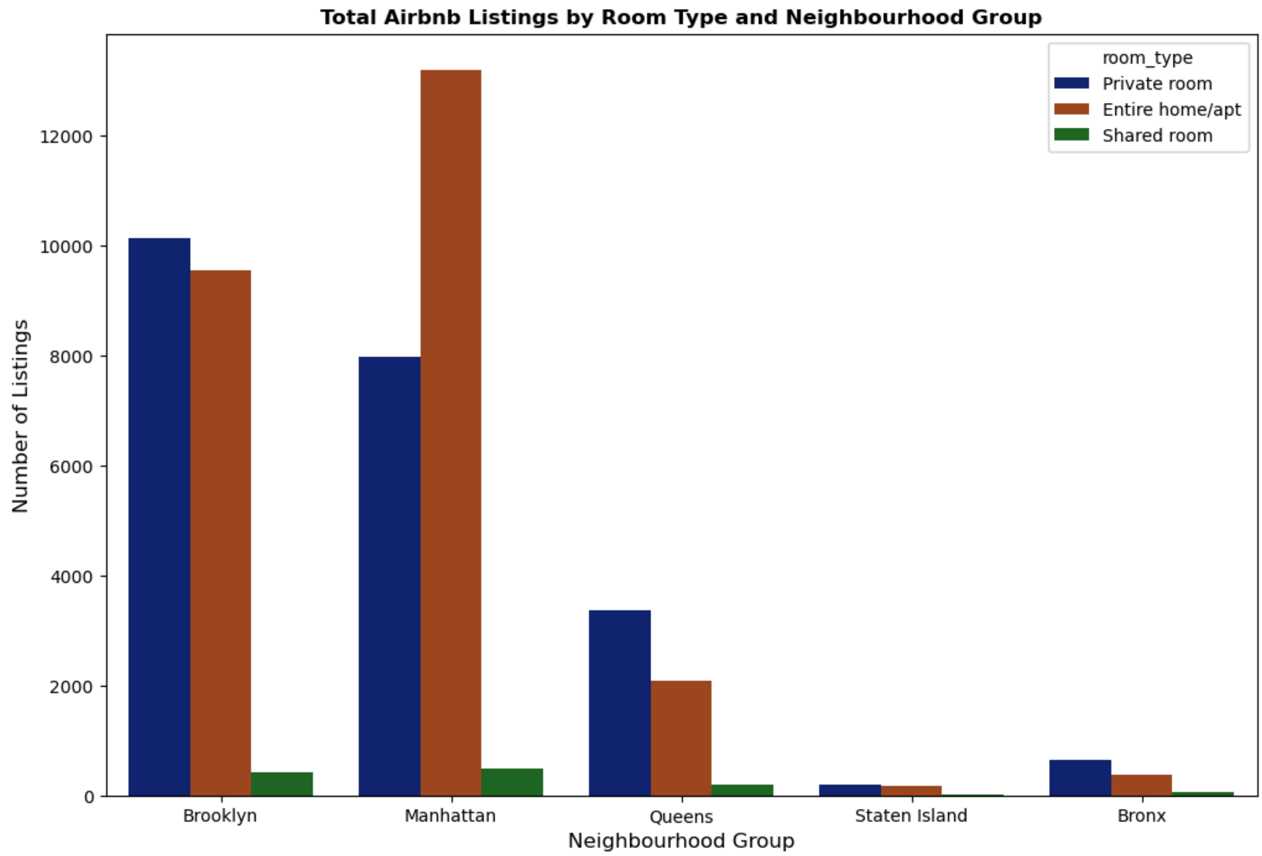
Analyzing Room Type

```
plt.figure(figsize=(12, 6))

sns.scatterplot(
    data=df, x="longitude", y="latitude", hue="room_type", palette="icefire", alpha=0.8)

plt.title("Airbnb Listings by Room Type", fontsize=12, fontweight="bold")
plt.xlabel("Longitude", fontsize=12)
plt.ylabel("Latitude", fontsize=12)
plt.legend(title="Room Type")
plt.show()
```



Entire homes/apartments (black) and private rooms (blue) dominate across all areas, with private rooms being more prevalent. Shared rooms (red) are sparse and scattered, indicating they are less common. The densest clusters of listings are in Manhattan and Brooklyn, reflecting their popularity among hosts and travelers.

```
plt.figure(figsize=(12, 8))

ax = sns.countplot(data=df, x="neighbourhood_group", palette="dark",hue="room_type")

plt.title("Total Airbnb Listings by Room Type and Neighbourhood Group", fontsize=12, fontweight="bold")
plt.xlabel("Neighbourhood Group", fontsize=12)
plt.ylabel("Number of Listings", fontsize=12)

plt.show()
```



The count plot shows that Manhattan and Brooklyn dominate Airbnb listings, with "Entire home/apt" being the most common room type in both boroughs. Private rooms are also significant, especially in Brooklyn, while shared rooms are rare across all neighborhoods. Staten Island and the Bronx have the fewest listings overall in all 3 room types

Numerical Variable Analysis

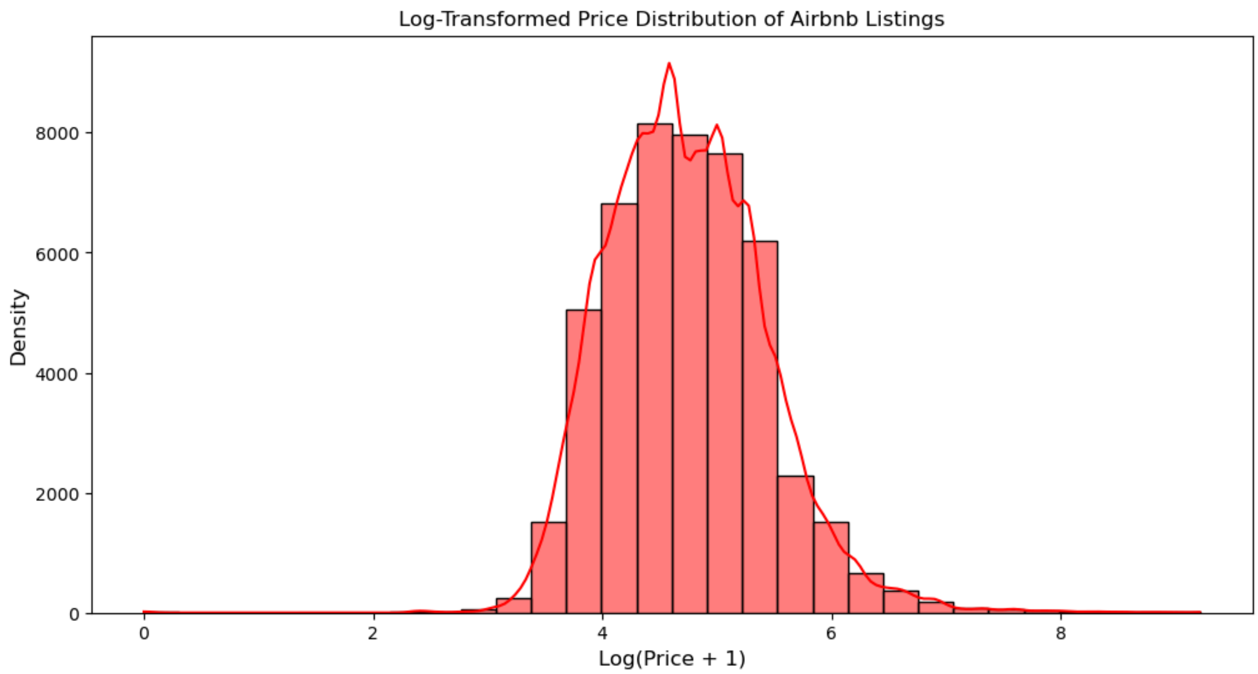
Understanding Price

```
plt.figure(figsize=(12, 6))

sns.histplot(data=df, x='price', bins=30, kde=True, color='red')

plt.title('Price Distribution of Airbnb Listings', fontsize=12)
plt.xlabel('Price ($)', fontsize=12)
plt.ylabel('Density', fontsize=12)

plt.show()
```

The price distribution of Airbnb listings is highly skewed to the right, with most listings concentrated at lower price ranges (under \$500). A few extreme outliers exist, with prices exceeding \$6,000. This suggests that while most listings might be affordable, a small number of luxury or premium properties significantly inflate the price range.

Hence, we can use a logarithmic scale that will help us to visualize the spread of prices effectively.

```
plt.figure(figsize=(12, 6))

sns.histplot(data=df, x=np.log1p(df['price']), bins=30, kde=True, color='red')


plt.title('Log-Transformed Price Distribution of Airbnb Listings', fontsize=12)
plt.xlabel('Log(Price + 1)', fontsize=12)
plt.ylabel('Density', fontsize=12)


plt.show()
```



The log transformation of price reveals a more symmetrical and bell-shaped distribution, making it easier to interpret patterns in the data. Since `log(0)` is undefined, adding 1 ensures that listings with a price of $0 (if any) are handled correctly. The transformed scale allows for better comparisons, as differences between lower prices will be more noticeable.

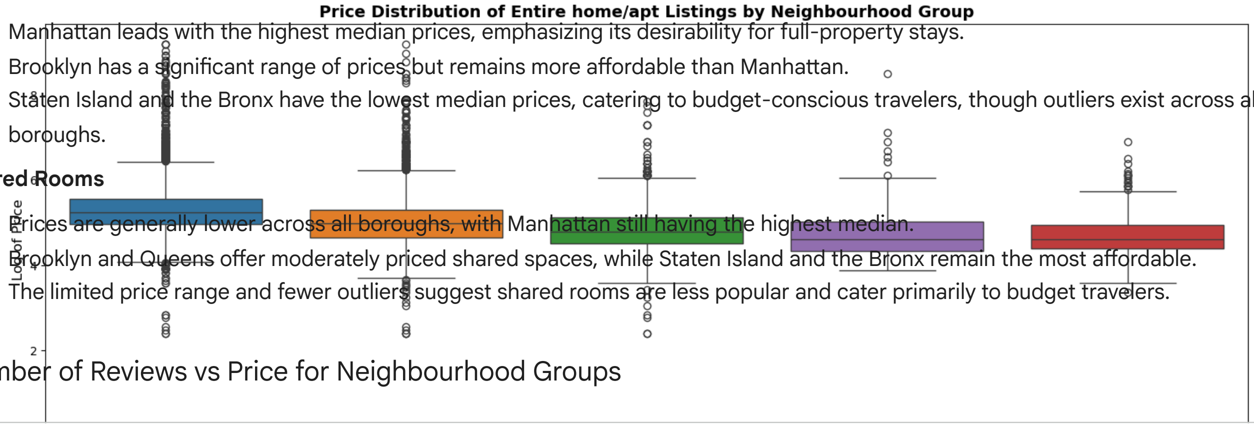
```
df['log_price']=np.log1p(df["price"])
```

Neighbourhood Group vs Log of Price for Room Types

```
plt.figure(figsize=(15, 18))

room_types = df['room_type'].unique()
neighbourhood_order = ['Manhattan', 'Brooklyn', 'Queens', 'Staten Island', 'Bronx']

# Create a violin plot for each room type
for i, room_type in enumerate(room_types):
    plt.subplot(len(room_types), 1, i + 1)  # Create a subplot for each room type
    sns.boxplot(data=df[df['room_type'] == room_type],
                x='neighbourhood_group',
                y='log_price',
                hue='neighbourhood_group', order=neighbourhood_order)

    plt.title(f'Price Distribution of {room_type} Listings by Neighbourhood Group', fontsize=14, fontweight='bold')
    plt.xlabel('Neighbourhood Group', fontsize=12)
    plt.ylabel('Log of Price', fontsize=12)

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

Private Rooms

- Manhattan exhibits the highest median prices, reflecting its premium location and demand.
- Brooklyn follows with slightly lower prices, while Queens, Staten Island, and the Bronx offer more affordable options.
- The presence of outliers in all boroughs indicates some luxury private room listings.



Entire Homes/Apartments

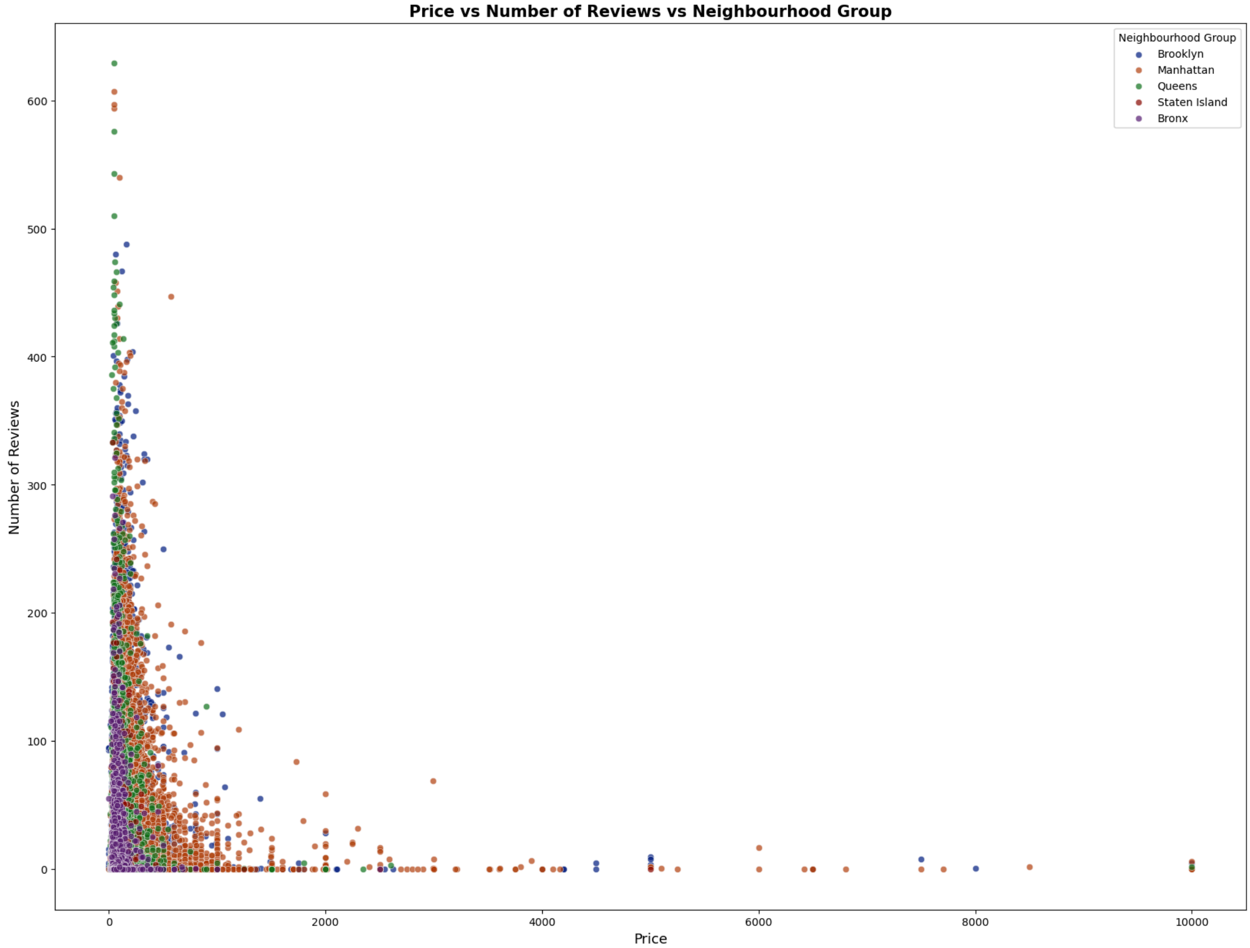
- Manhattan leads with the highest median prices, emphasizing its desirability for full-property stays.
- Brooklyn has a significant range of prices but remains more affordable than Manhattan.
- Staten Island and the Bronx have the lowest median prices, catering to budget-conscious travelers, though outliers exist across all boroughs.

Shared Rooms

- Prices are generally lower across all boroughs, with Manhattan still having the highest median.
- Brooklyn and Queens offer moderately priced shared spaces, while Staten Island and the Bronx remain the most affordable.
- The limited price range and fewer outliers suggest shared rooms are less popular and cater primarily to budget travelers.

Number of Reviews vs Price for Neighbourhood Groups

```
plt.figure(figsize=(20, 15))
sns.set_palette("dark")

for neighborhood in df['neighbourhood_group'].unique():
    sns.scatterplot(x='price', y='number_of_reviews',
                data=df[df['neighbourhood_group'] == neighborhood],
                label=neighborhood, alpha=0.7)

plt.xlabel("Price", size=13)
plt.ylabel("Number of Reviews", size=13)
plt.title("Price vs Number of Reviews vs Neighbourhood Group", size=15, weight='bold')
plt.legend(title='Neighbourhood Group')
plt.show()
```

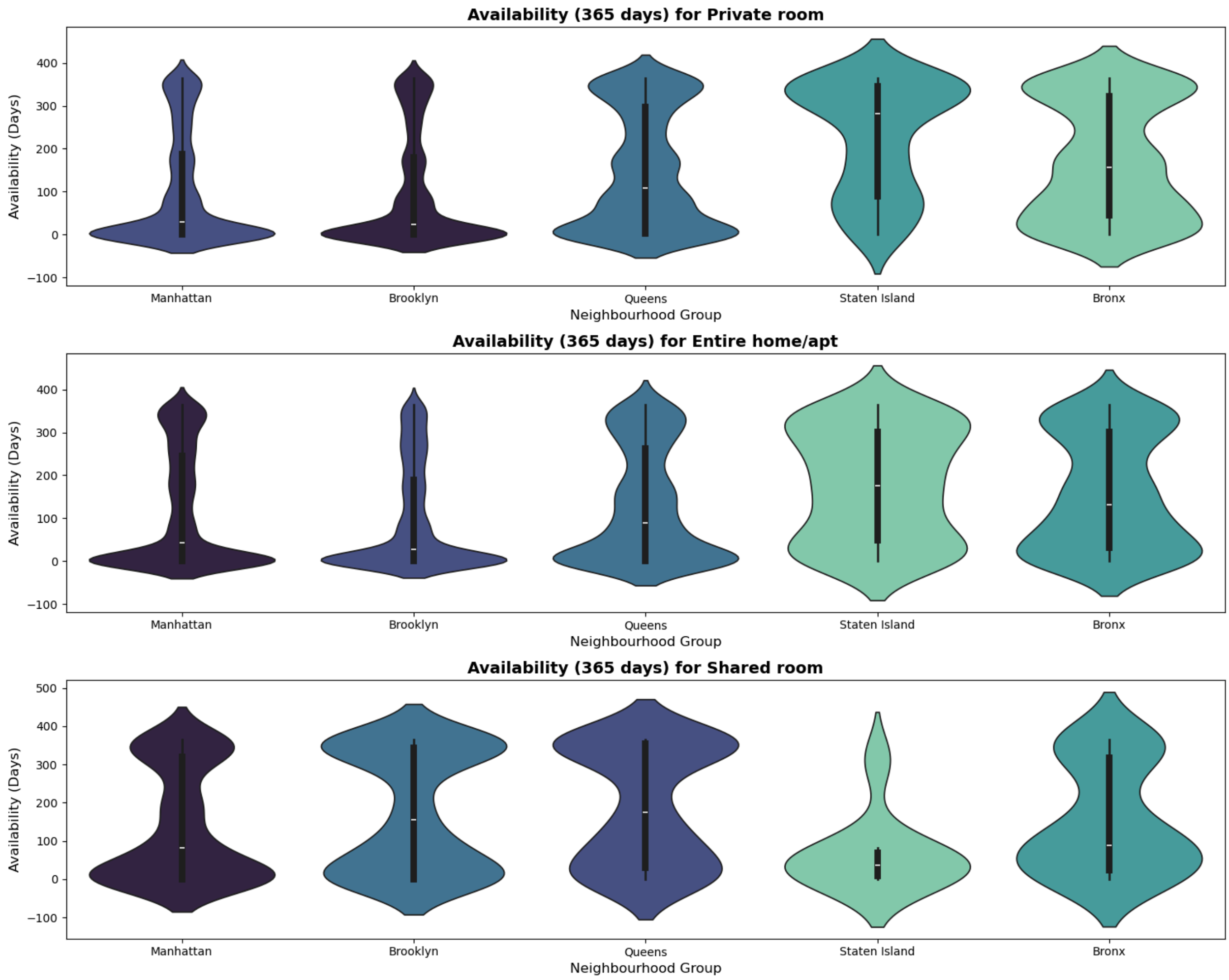


The scatter plot shows that listings with lower prices tend to have a higher number of reviews, indicating an inverse relationship between price and popularity. As price increases, the number of reviews decreases significantly, suggesting that expensive listings cater to a niche audience. The weak negative correlation highlights that affordability is a key factor in driving customer engagement across all neighborhood groups.

Availability vs Neighbourhood Groups for Room Types

```
plt.figure(figsize=(15, 12))

room_types = df['room_type'].unique()
neighbourhood_order = ['Manhattan', 'Brooklyn', 'Queens', 'Staten Island', 'Bronx']
```

```
for i, room in enumerate(room_types):
    plt.subplot(3, 1, i + 1)
    sns.violinplot(x='neighbourhood_group', y='availability_365', data=df[df['room_type'] == room], palette='mako',
                   hue='neighbourhood_group', order=neighbourhood_order)
    plt.title(f'Availability (365 days) for {room}', fontsize=14, weight='bold')
    plt.xlabel('Neighbourhood Group', fontsize=12)
    plt.ylabel('Availability (Days)', fontsize=12)

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



For **private rooms**, the violin plot shows that Manhattan and Brooklyn have a similar distribution, with the median availability around 0-100 days and a high density of listings available for fewer days. Queens, Staten Island, and the Bronx exhibit wider spreads, with Staten Island having a significant proportion of listings available year-round (365 days).

For **entire homes/apartments**, Manhattan and Brooklyn still have a concentration of listings with lower availability (0-100 days), but Staten Island shows higher densities for year-round availability (365 days). This suggests that entire homes are more likely to be consistently available, especially in less central boroughs like Staten Island.

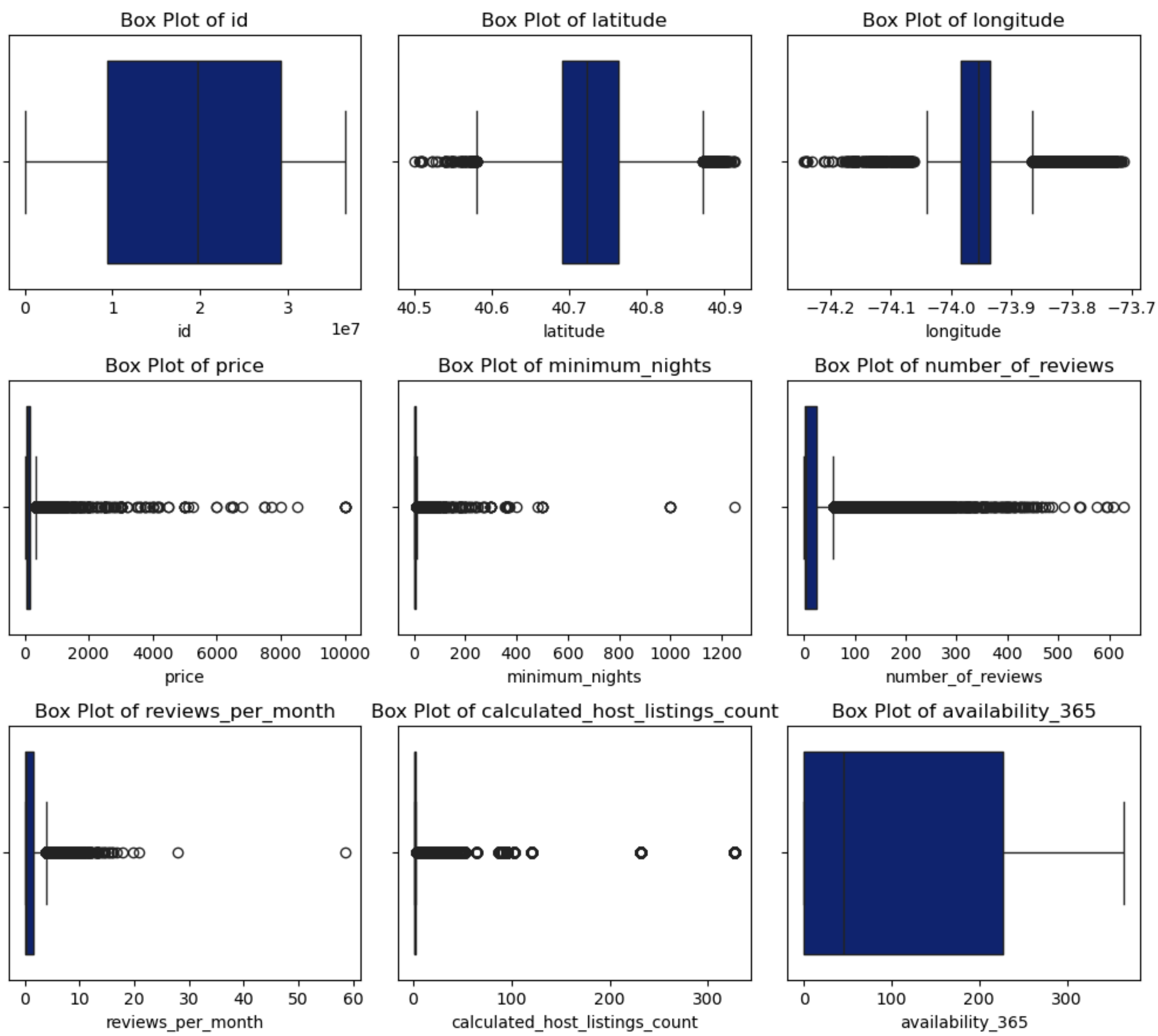
For **shared rooms**, the distribution is narrower overall, with Manhattan showing the highest density around 0-100 days of availability. Brooklyn has a median between 100-200 with almost evenly distributed lower availability listings and higher availability listings. Queens and the Bronx have slightly broader spreads but still show limited year-round availability. Staten Island exhibits an unusual pattern with a small number of listings available for 365 days, reflecting its limited supply of shared rooms compared to other room types.

Data Preprocessing

Outlier Detection

```
df = df.drop(columns=["log_price"])
```

```
num_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()

n_cols = 3
n_rows = np.ceil(len(num_cols) / n_cols)

plt.figure(figsize=(10, 3 * n_rows))
for i, col in enumerate(num_cols):
    plt.subplot(int(n_rows), n_cols, i + 1)
    sns.boxplot(x=df[col])
    plt.title(f'Box Plot of {col}')
plt.tight_layout()
plt.show()
```



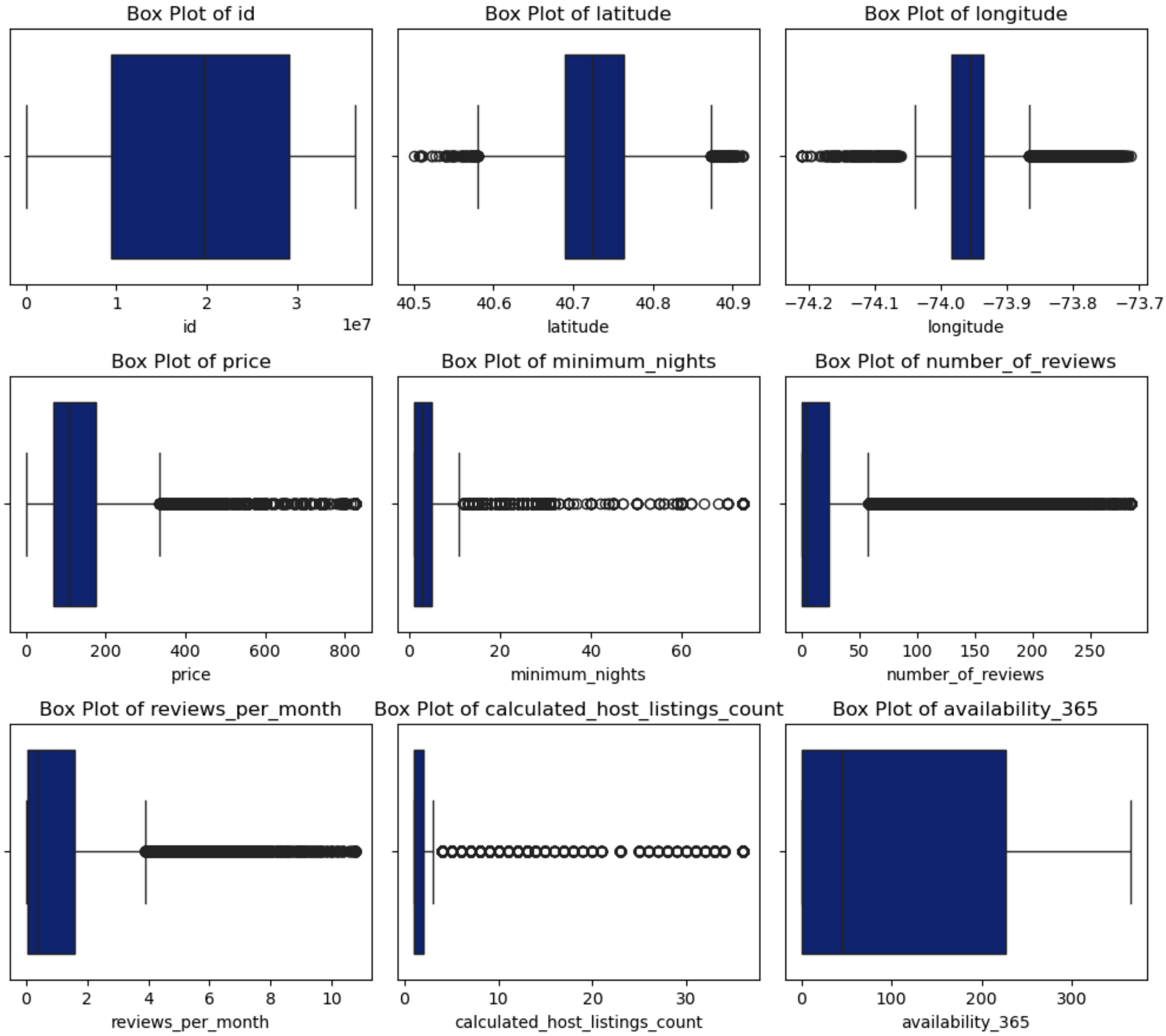
The residual plots reveal several patterns and potential outliers in the data.

- For `price` and `minimum_nights`, there are extreme values far beyond the whiskers, indicating unusually high prices and long minimum stays that may distort analysis.
- Variables like `number_of_reviews` and `reviews_per_month` also show a concentration of data near the lower range, with a few extreme values skewing the distribution.
- Similarly, `calculated_host_listings_count` has many outliers, likely representing hosts with an unusually large number of listings. These outliers highlight the need for preprocessing to ensure meaningful statistical analysis and modeling.

Outlier Removal

```
num_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()

def calculate_outlier_thresholds(dataframe, column_name, lower_quantile=0.05, upper_quantile=0.95):
    q1 = dataframe[column_name].quantile(lower_quantile)
    q3 = dataframe[column_name].quantile(upper_quantile)
    iqr = q3 - q1
    upper_limit = q3 + 1.5 * iqr
    lower_limit = q1 - 1.5 * iqr
    return lower_limit, upper_limit

def has_outliers(dataframe, column_name):
    lower_limit, upper_limit = calculate_outlier_thresholds(dataframe, column_name)
    return (dataframe[column_name] > upper_limit).any() or (dataframe[column_name] < lower_limit).any()

def cap_outliers(dataframe, column_name):
    dataframe[column_name] = dataframe[column_name].astype(float)
    lower_limit, upper_limit = calculate_outlier_thresholds(dataframe, column_name)
    dataframe.loc[dataframe[column_name] < lower_limit, column_name] = lower_limit
    dataframe.loc[dataframe[column_name] > upper_limit, column_name] = upper_limit

for column in num_cols:
    if has_outliers(df, column):
        cap_outliers(df, column)
```

```
num_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()

n_cols = 3
n_rows = np.ceil(len(num_cols) / n_cols)

plt.figure(figsize=(10, 3 * n_rows))
for i, col in enumerate(num_cols):
    plt.subplot(int(n_rows), n_cols, i + 1)
    sns.boxplot(x=df[col])
    plt.title(f'Box Plot of {col}')
plt.tight_layout()
plt.show()
```



The box plots after outlier removal show a much cleaner distribution for most variables, with extreme values significantly reduced.

- For `price`, `minimum_nights`, and `number_of_reviews`, the data is now more concentrated within the whiskers, making it easier to analyze trends without distortion from outliers.
- Similarly, `calculated_host_listings_count` and `reviews_per_month` now have fewer extreme values, improving interpretability.

```
# Checking if any other outliers are to be removed
for col in num_cols:
    print(col, has_outliers(df, col))
```

```
id False
latitude False
longitude False
price False
minimum_nights False
number_of_reviews False
reviews_per_month False
calculated_host_listings_count False
availability_365 False
```

Feature Engineering

```
# Total cost for the minimum nights of stay
df['total_cost'] = df['price'] * df['minimum_nights']

# Estimate of how long the property has been listed in months.
df['listed_months'] = df['number_of_reviews'] / df['reviews_per_month']
df['listed_months'] = df['listed_months'].fillna(0)

# Ratio of how often the property is available in a year.
df['availability_ratio'] = df['availability_365'] / 365
```

```
# Daily average number of reviews received by the host.
df['average_reviews_per_day'] = df['reviews_per_month'] / 30
df['average_reviews_per_day'] = df['average_reviews_per_day'].fillna(0)

# Estimated potential annual income from the property
df['annual_income'] = df['price'] * df['availability_365']

# Occupancy rate, indicating how many days the property is booked in a year.
df['occupancy_rate'] = 365 - df['availability_365']
```

```
df.head()
```

	id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_
0	2539	Brooklyn	Kensington	40.64749	-73.97237	Private room	149.0	1.0	9.0	
1	2595	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225.0	1.0	45.0	
2	3647	Manhattan	Harlem	40.80902	-73.94190	Private room	150.0	3.0	0.0	
3	3831	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89.0	1.0	270.0	
4	5022	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80.0	10.0	9.0	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 18 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   neighbourhood_group             48895 non-null  object
 2   neighbourhood                   48895 non-null  object
 3   latitude                        48895 non-null  float64
 4   longitude                       48895 non-null  float64
 5   room_type                       48895 non-null  object
 6   price                           48895 non-null  float64
 7   minimum_nights                  48895 non-null  float64
 8   number_of_reviews               48895 non-null  float64
 9   reviews_per_month               48895 non-null  float64
 10  calculated_host_listings_count  48895 non-null  float64
 11  availability_365                48895 non-null  int64
 12  total_cost                      48895 non-null  float64
 13  listed_months                   48895 non-null  float64
 14  availability_ratio              48895 non-null  float64
 15  average_reviews_per_day         48895 non-null  float64
 16  annual_income                   48895 non-null  float64
 17  occupancy_rate                  48895 non-null  int64
dtypes: float64(12), int64(3), object(3)
memory usage: 6.7+ MB
```

Encoding

```
def grab_col_names(dataframe, cat_th=10, car_th=20):

  #Returns categorical, numeric, and cardinal variable names#

   cat_cols = [col for col in dataframe.columns if dataframe[col].dtype == "O"]
   num_but_cat = [col for col in dataframe.columns if dataframe[col].nunique() < cat_th and dataframe[col].dtype != "O"]
   cat_but_car = [col for col in dataframe.columns if dataframe[col].nunique() > car_th and dataframe[col].dtype == "O"]

   cat_cols += num_but_cat
   cat_cols = list(set(cat_cols) - set(cat_but_car))  # Exclude cardinal from categorical

   num_cols = [col for col in dataframe.columns if dataframe[col].dtype != "O" and col not in num_but_cat]

   print(f"Observations: {dataframe.shape[0]}")
   print(f"Variables: {dataframe.shape[1]}")
   print(f'cat_cols: {len(cat_cols)}')
   print(f'num_cols: {len(num_cols)}')
   print(f'cat_but_car: {len(cat_but_car)}')
   print(f'num_but_cat: {len(num_but_cat)}')

   return cat_cols, num_cols, cat_but_car, num_but_cat
```

Cardinal variable names refer to categorical variables that have a large number of unique values, often making them unsuitable for standard categorical analysis. These variables can take on a range of values that are distinct but do not have a meaningful ordinal relationship (i.e., they don't represent ordered categories)

```
cat_cols, num_cols, cat_but_car, num_but_cat = grab_col_names(df)

print("\nCategorical Columns:", cat_cols)
print("\nNumeric Columns:", num_cols)
print("\nCategorical but Cardinal Columns:", cat_but_car)
print("\nNumeric but Categorical Columns:", num_but_cat)
```

```
Observations: 48895
Variables: 18
cat_cols: 2
num_cols: 15
cat_but_car: 1
num_but_cat: 0

Categorical Columns: ['neighbourhood_group', 'room_type']

Numeric Columns: ['id', 'latitude', 'longitude', 'price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month', 'calculated_host_listings_c

Categorical but Cardinal Columns: ['neighbourhood']

Numeric but Categorical Columns: []
```

```
df = df.drop(columns=['neighbourhood'])

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 17 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   neighbourhood_group             48895 non-null  object 
 2   latitude                        48895 non-null  float64
 3   longitude                       48895 non-null  float64
 4   room_type                       48895 non-null  object 
 5   price                           48895 non-null  float64
 6   minimum_nights                  48895 non-null  float64
 7   number_of_reviews               48895 non-null  float64
 8   reviews_per_month               48895 non-null  float64
 9   calculated_host_listings_count  48895 non-null  float64
 10  availability_365                48895 non-null  int64  
 11  total_cost                      48895 non-null  float64
 12  listed_months                   48895 non-null  float64
 13  availability_ratio              48895 non-null  float64
 14  average_reviews_per_day         48895 non-null  float64
 15  annual_income                   48895 non-null  float64
 16  occupancy_rate                  48895 non-null  int64  
dtypes: float64(12), int64(3), object(2)
memory usage: 6.3+ MB
```

```
df.shape
```

```
(48895, 17)
```

```
print(df['neighbourhood_group'].unique())
print(df['room_type'].unique())
```

```
['Brooklyn' 'Manhattan' 'Queens' 'Staten Island' 'Bronx']
['Private room' 'Entire home/apt' 'Shared room']
```

```
def one_hot_encoder(dataframe, categorical_cols, drop_first=True):
    df_encoded = pd.get_dummies(dataframe[categorical_cols], drop_first=drop_first)
    df_encoded = df_encoded.astype(int)
    dataframe = pd.concat([dataframe.drop(categorical_cols, axis=1), df_encoded], axis=1)
    return dataframe

df = one_hot_encoder(df, cat_cols)
df.head()
```

	id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availa
0	2539	40.64749	-73.97237	149.0	1.0	9.0	0.21	6.0	
1	2595	40.75362	-73.98377	225.0	1.0	45.0	0.38	2.0	
2	3647	40.80902	-73.94190	150.0	3.0	0.0	0.00	1.0	
3	3831	40.68514	-73.95976	89.0	1.0	270.0	4.64	1.0	
4	5022	40.79851	-73.94399	80.0	10.0	9.0	0.10	1.0	

5 rows × 21 columns

```
# Renaming columns
df.columns = df.columns.str.replace('[^A-Za-z0-9/_]+', '')
df.columns = df.columns.str.replace(' ', '_')
df.columns = df.columns.str.lower()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   latitude                        48895 non-null  float64
 2   longitude                       48895 non-null  float64
 3   price                           48895 non-null  float64
 4   minimum_nights                  48895 non-null  float64
 5   number_of_reviews               48895 non-null  float64
 6   reviews_per_month               48895 non-null  float64
 7   calculated_host_listings_count  48895 non-null  float64
 8   availability_365                48895 non-null  int64
 9   total_cost                      48895 non-null  float64
 10  listed_months                   48895 non-null  float64
 11  availability_ratio              48895 non-null  float64
 12  average_reviews_per_day         48895 non-null  float64
 13  annual_income                   48895 non-null  float64
 14  occupancy_rate                  48895 non-null  int64
 15  neighbourhood_group_brooklyn    48895 non-null  int64
 16  neighbourhood_group_manhattan   48895 non-null  int64
 17  neighbourhood_group_queens      48895 non-null  int64
 18  neighbourhood_group_staten_island  48895 non-null  int64
 19  room_type_private_room          48895 non-null  int64
 20  room_type_shared_room           48895 non-null  int64
dtypes: float64(12), int64(9)
memory usage: 7.8 MB
```

Train-Test Split

```
X = df.drop(["price"], axis=1)
Y = df["price"]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.20, random_state=1)

print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)
```

```
X_train shape: (39116, 20)
X_test shape: (9779, 20)
Y_train shape: (39116,)
Y_test shape: (9779,)
```

Scaling

We should use the RobustScaler here because our dataset likely contains outliers, and this scaler is specifically designed to be robust to them.

```
scaler = RobustScaler()
X_train_s = scaler.fit_transform(X_train)
X_test_s = scaler.transform(X_test)

print("Median of X_train before scaling:\n", X_train.median())
print("\nMedian of X_train after scaling:\n", pd.DataFrame(X_train_s).median())
```

```
Median of X_train before scaling:
 id                                1.973430e+07
latitude                          4.072292e+01
longitude                        -7.395575e+01
minimum_nights                    2.000000e+00
number_of_reviews                 5.000000e+00
reviews_per_month                 3.700000e-01
calculated_host_listings_count    1.000000e+00
availability_365                  4.400000e+01
total_cost                        3.000000e+02
listed_months                     1.463415e+01
availability_ratio                1.205479e-01
average_reviews_per_day           1.233333e-02
annual_income                     4.205000e+03
occupancy_rate                    3.210000e+02
neighbourhood_group_brooklyn      0.000000e+00
neighbourhood_group_manhattan     0.000000e+00
neighbourhood_group_queens        0.000000e+00
neighbourhood_group_staten_island 0.000000e+00
room_type_private_room            0.000000e+00
room_type_shared_room             0.000000e+00
dtype: float64

Median of X_train after scaling:
 0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
5    0.0
6    0.0
7    0.0
8    0.0
9    0.0
10   0.0
11   0.0
12   0.0
13   0.0
14   0.0
15   0.0
16   0.0
17   0.0
18   0.0
19   0.0
dtype: float64
```

Model Building

```
models = {
    "Lasso": Lasso(),
    "XGBoost": XGBRegressor(),
    "Random Forest": RandomForestRegressor(),
    "KNN": KNeighborsRegressor()
}
```

```
results = {}

for name, model in models.items():
    model.fit(X_train_s, Y_train)
    Y_pred = model.predict(X_test_s)
    r2 = r2_score(Y_test, Y_pred)
    mae = mean_absolute_error(Y_test, Y_pred)
    results[name] = {"R2": r2, "MAE": mae}
    print(f"{name} - R²: {r2:.4f}, MAE: {mae:.4f}")

results_df = pd.DataFrame(results).T
```

```
Lasso - R²: 0.6704, MAE: 40.8405
XGBoost - R²: 0.9938, MAE: 3.2324
Random Forest - R²: 0.9965, MAE: 1.0736
KNN - R²: 0.8832, MAE: 23.1961
```

```
plt.figure(figsize=(12, 6))

# R² Score Subplot
plt.subplot(1, 2, 1)
```