1 Case Study

[231]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

mean_data= pd.read_csv("airbnb_listings.csv",encoding="latin1")
mean_data.head()
```

[231]:
```
    host_id host_name      city state     zipcode        country   latitude  \
0   5867023   Michael  New York    NY  10022-4175  United States  40.756852
1   2631556    Denise  New York    NY         NaN  United States  40.830599
2   4601412      Miao  Brooklyn    NY       11221  United States  40.692189
3    198425      Sara  New York    NY       10011  United States  40.734751
4  22590025   Charles  New York    NY       10011  United States  40.745282

   longitude property_type        room_type  …  beds bed_type square_feet  \
0 -73.964754     Apartment  Entire home/apt  …   1.0  Real Bed         NaN
1 -73.941014     Apartment  Entire home/apt  …   3.0  Real Bed         NaN
2 -73.924120     Apartment     Private room  …   2.0  Real Bed         NaN
3 -74.002592     Apartment  Entire home/apt  …   1.0  Real Bed         NaN
4 -73.997836     Apartment  Entire home/apt  …   2.0  Real Bed         NaN

      price availability_365  number_of_reviews review_scores_rating  \
0  $160.00               322                 62                 86.0
1  $105.00               348                 22                 85.0
2   $58.00               227                 35                 98.0
3  $185.00               274                 26                 96.0
4  $195.00               365                  1                100.0

   review_scores_cleanliness  review_scores_location  review_scores_value
0                        7.0                    10.0                  9.0
1                        8.0                     7.0                  8.0
2                       10.0                     9.0                 10.0
3                        9.0                    10.0                  9.0
4                       10.0                    10.0                 10.0
```

```
[5 rows x 23 columns]
```

[232]:
```python
#convert data type of price column to float and remove $ and , from the price␣
 ↪column
mean_data['price'] = mean_data['price'].replace({'\$': '', ',': ''},␣
 ↪regex=True).astype(float)
mean_data['price']
```

[232]:
```
0        160.0
1        105.0
2         58.0
3        185.0
4        195.0
         …
27387    130.0
27388    139.0
27389     99.0
27390     55.0
27391    110.0
Name: price, Length: 27392, dtype: float64
```

2 1. Define problem statement and perform Exploratory Data Analysis

2.0.1 a. Observations on shape of data and data types of all attributes

[233]:
```python
#checl shape of the data
print(mean_data.shape)
mean_data.info()
```

```
(27392, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27392 entries, 0 to 27391
Data columns (total 23 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   host_id                      27392 non-null  int64
 1   host_name                    27392 non-null  object
 2   city                         27392 non-null  object
 3   state                        27390 non-null  object
 4   zipcode                      27230 non-null  object
 5   country                      27391 non-null  object
 6   latitude                     27392 non-null  float64
 7   longitude                    27392 non-null  float64
 8   property_type                27386 non-null  object
```

```
 9   room_type                    27392 non-null  object 
 10  accommodates                 27392 non-null  int64  
 11  bathrooms                    26929 non-null  float64
 12  bedrooms                     27252 non-null  float64
 13  beds                         27294 non-null  float64
 14  bed_type                     27392 non-null  object 
 15  square_feet                  1006 non-null   float64
 16  price                        27392 non-null  float64
 17  availability_365             27392 non-null  int64  
 18  number_of_reviews            27392 non-null  int64  
 19  review_scores_rating         18735 non-null  float64
 20  review_scores_cleanliness    18661 non-null  float64
 21  review_scores_location       18660 non-null  float64
 22  review_scores_value          18658 non-null  float64
dtypes: float64(11), int64(4), object(8)
memory usage: 4.8+ MB
```

2.0.2 b. Check for missing value (if any)

[234]:
```python
# check for missing values
mean_data.isnull().sum()
```

[234]:
```
host_id                          0
host_name                        0
city                             0
state                            2
zipcode                        162
country                          1
latitude                         0
longitude                        0
property_type                    6
room_type                        0
accommodates                     0
bathrooms                      463
bedrooms                       140
beds                            98
bed_type                         0
square_feet                  26386
price                            0
availability_365                 0
number_of_reviews                0
review_scores_rating          8657
review_scores_cleanliness     8731
review_scores_location        8732
review_scores_value           8734
dtype: int64
```

2.0.3 c. Display the statistical summary

[235]:
```
mean_data.describe()
```

[235]:

	host_id	latitude	longitude	accommodates	bathrooms
count	2.739200e+04	27392.000000	27392.000000	27392.000000	26929.000000
mean	8.518927e+06	40.733070	-73.964276	2.892779	1.116287
std	7.510027e+06	0.048968	0.035162	1.755137	0.369832
min	2.830000e+02	40.509611	-74.239539	1.000000	0.000000
25%	2.104498e+06	40.699655	-73.988449	2.000000	1.000000
50%	6.119374e+06	40.728024	-73.966075	2.000000	1.000000
75%	1.392422e+07	40.764030	-73.947260	4.000000	1.000000
max	2.546867e+07	40.907704	-73.726710	16.000000	8.000000

	bedrooms	beds	square_feet	price
count	27252.000000	27294.000000	1006.000000	27392.000000
mean	1.135660	1.531289	720.210736	171.256900
std	0.667599	1.098971	652.795558	224.690732
min	0.000000	1.000000	0.000000	10.000000
25%	1.000000	1.000000	371.250000	85.000000
50%	1.000000	1.000000	650.000000	130.000000
75%	1.000000	2.000000	913.250000	199.000000
max	10.000000	16.000000	12000.000000	8000.000000

	availability_365	number_of_reviews	review_scores_rating
count	27392.000000	27392.000000	18735.000000
mean	262.919210	10.130221	92.218895
std	125.668249	18.665400	8.336264
min	0.000000	0.000000	20.000000
25%	177.000000	0.000000	89.000000
50%	333.000000	3.000000	94.000000
75%	363.000000	11.000000	99.000000
max	365.000000	221.000000	100.000000

	review_scores_cleanliness	review_scores_location	review_scores_value
count	18661.000000	18660.000000	18658.000000
mean	9.011093	9.248660	9.125737
std	1.163870	0.973474	0.906612
min	2.000000	2.000000	2.000000
25%	8.000000	9.000000	9.000000
50%	9.000000	10.000000	9.000000
75%	10.000000	10.000000	10.000000
max	10.000000	10.000000	10.000000

2.0.4 d. Univariate Analysis and Bivariate Analysis of all the attributes

Univeriate

[236]:
```python
# select price column as target variable
target_variable=mean_data['price']
```

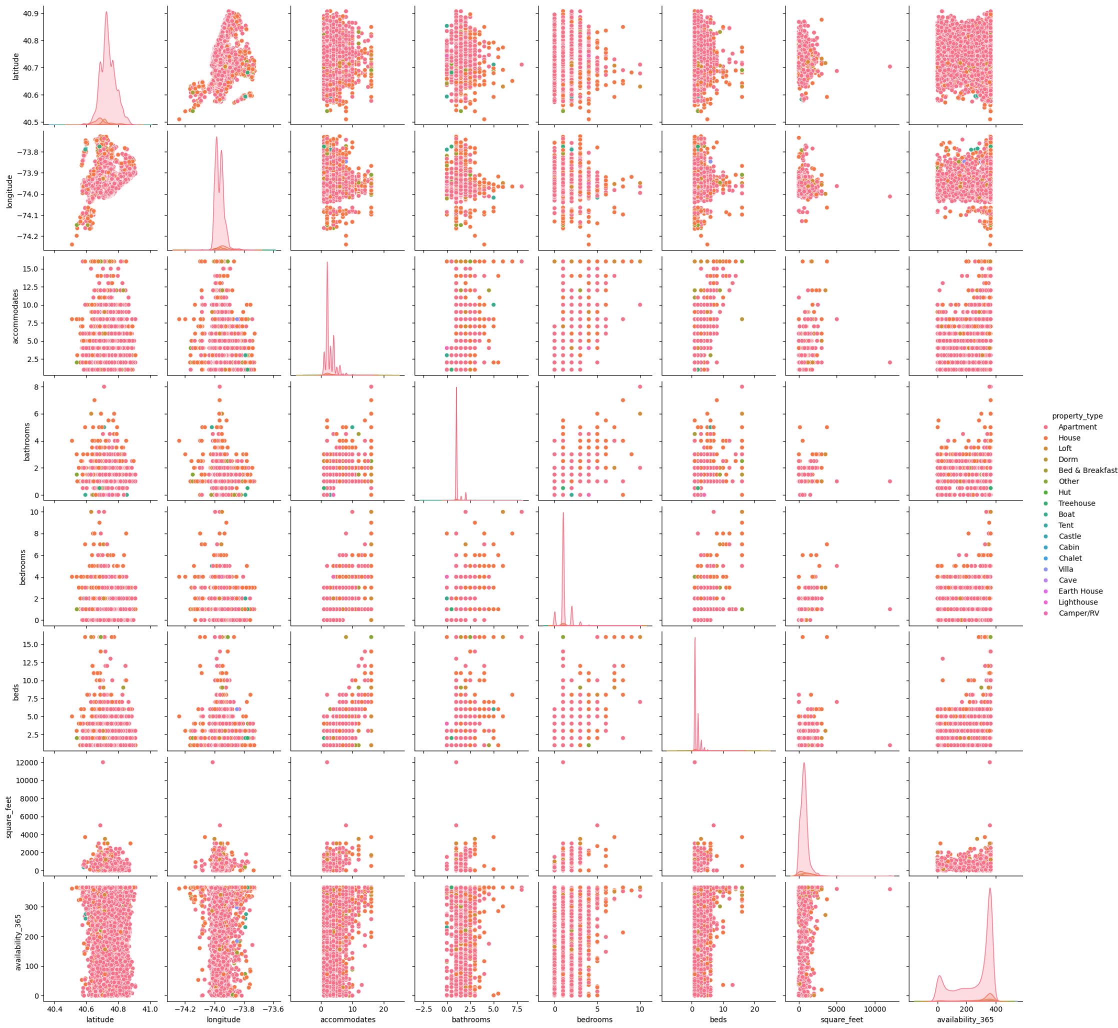
[237]:
```python
# create a list of numerical and categorical columns
numerical_data= mean_data.select_dtypes(include=["int","float"]).columns
categorical_data= mean_data.select_dtypes(include=['object']).columns
mean_data[numerical_data]
```

[237]:
```
        host_id   latitude  longitude  accommodates  bathrooms  bedrooms  \
0       5867023  40.756852 -73.964754             2        1.0       1.0
1       2631556  40.830599 -73.941014            10        1.0       3.0
2       4601412  40.692189 -73.924120             2        1.0       1.0
3        198425  40.734751 -74.002592             2        1.0       1.0
4      22590025  40.745282 -73.997836             2        1.0       1.0
…           …         …          …             …          …        …
27387   1485898  40.742363 -73.981968             2        NaN       1.0
27388   5944682  40.759642 -73.985343             2        1.0       1.0
27389   2675644  40.645741 -74.080955             6        1.0       2.0
27390    322716  40.669931 -73.946820             3        1.0       1.0
27391   2695451  40.753941 -73.993232             1        1.0       1.0

       beds  square_feet  price  availability_365  number_of_reviews  \
0       1.0          NaN  160.0               322                 62
1       3.0          NaN  105.0               348                 22
2       2.0          NaN   58.0               227                 35
3       1.0          NaN  185.0               274                 26
4       2.0          NaN  195.0               365                  1
…      …            …     …                 …                  …
27387   1.0          NaN  130.0               365                  3
27388   1.0          NaN  139.0               332                 47
27389   3.0          NaN   99.0               357                  2
27390   1.0        350.0   55.0                93                  3
27391   1.0          NaN  110.0               362                  4

       review_scores_rating  review_scores_cleanliness  \
0                      86.0                        7.0
1                      85.0                        8.0
2                      98.0                       10.0
3                      96.0                        9.0
4                     100.0                       10.0
…                     …                        …
27387                  98.0                        9.0
27388                  95.0                        9.0
27389                  90.0                        9.0
27390                 100.0                       10.0
27391                  90.0                        9.0
```

```
       review_scores_location  review_scores_value
0                        10.0                  9.0
1                         7.0                  8.0
2                         9.0                 10.0
3                        10.0                  9.0
4                        10.0                 10.0
…                           …                    …
27387                    10.0                  9.0
27388                    10.0                  9.0
27389                     9.0                  8.0
27390                     9.0                 10.0
27391                    10.0                 10.0

[27392 rows x 15 columns]
```

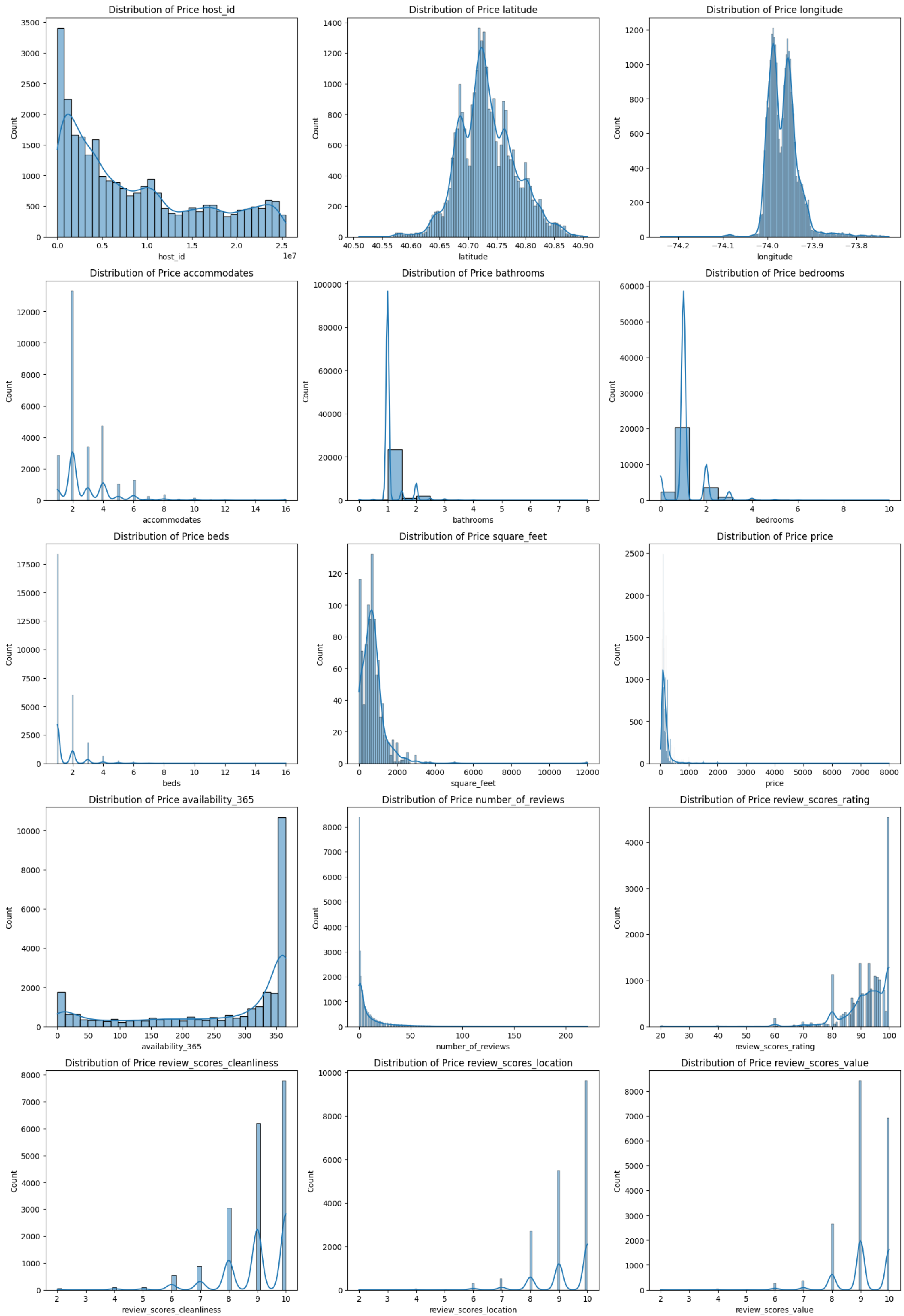
[238]:
```python
# check for correlation between numerical columns
sns.pairplot(mean_data, vars=['latitude', 'longitude', 'accommodates',␣
 ↪'bathrooms', 'bedrooms', 'beds','square_feet','availability_365'],␣
 ↪hue="property_type")
```

[238]:
```
<seaborn.axisgrid.PairGrid at 0x2a1bf2ae390>
```

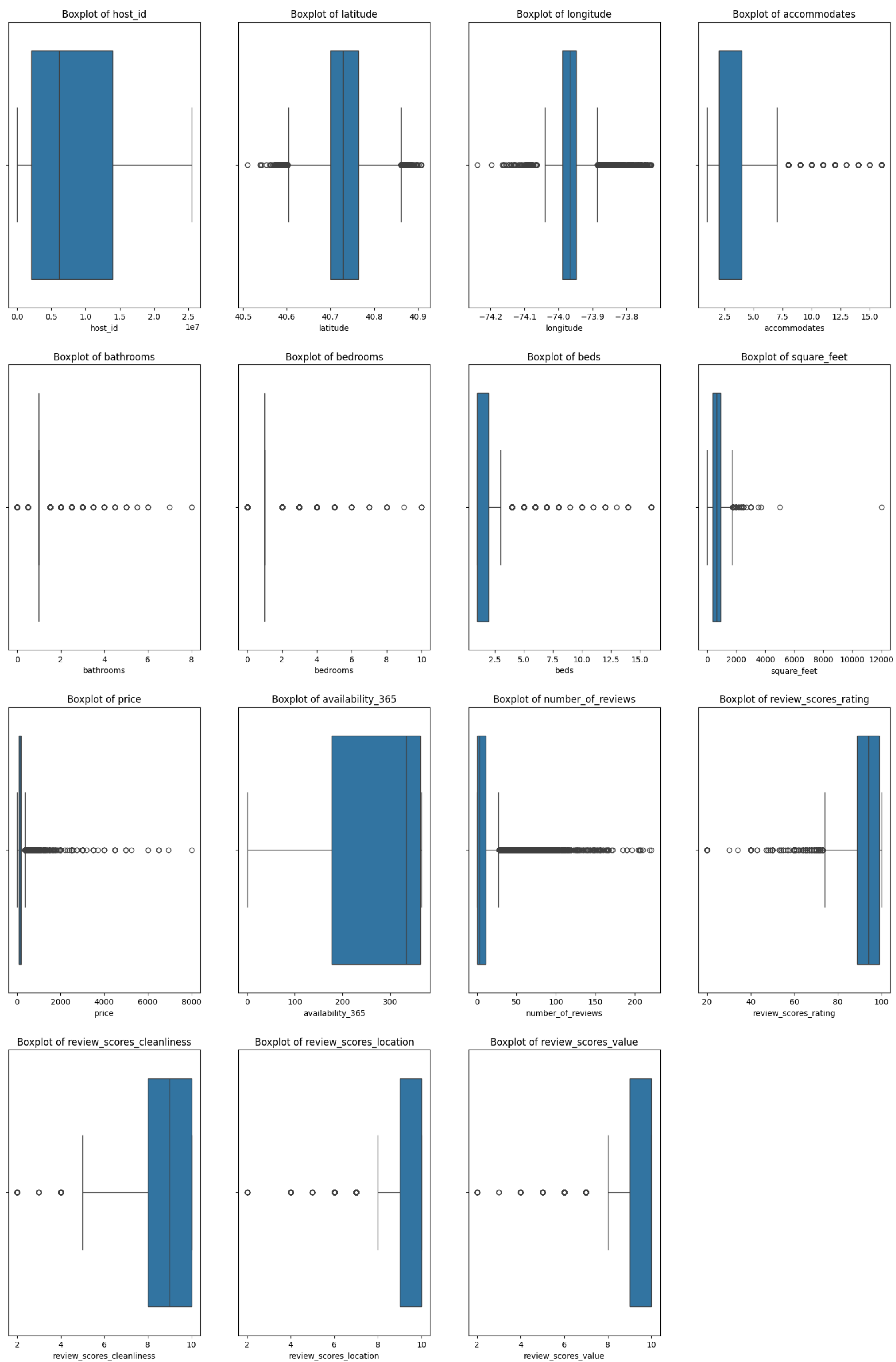


[239]:
```
# create a histplot for numerical columns
i = 1
plt.figure(figsize=(20,30))
for col in numerical_data:
    plt.subplot(5,3,i)
    sns.histplot(mean_data[col], kde=True)
    plt.title(f"Distribution of Price {col}")
    i+=1

plt.show
```

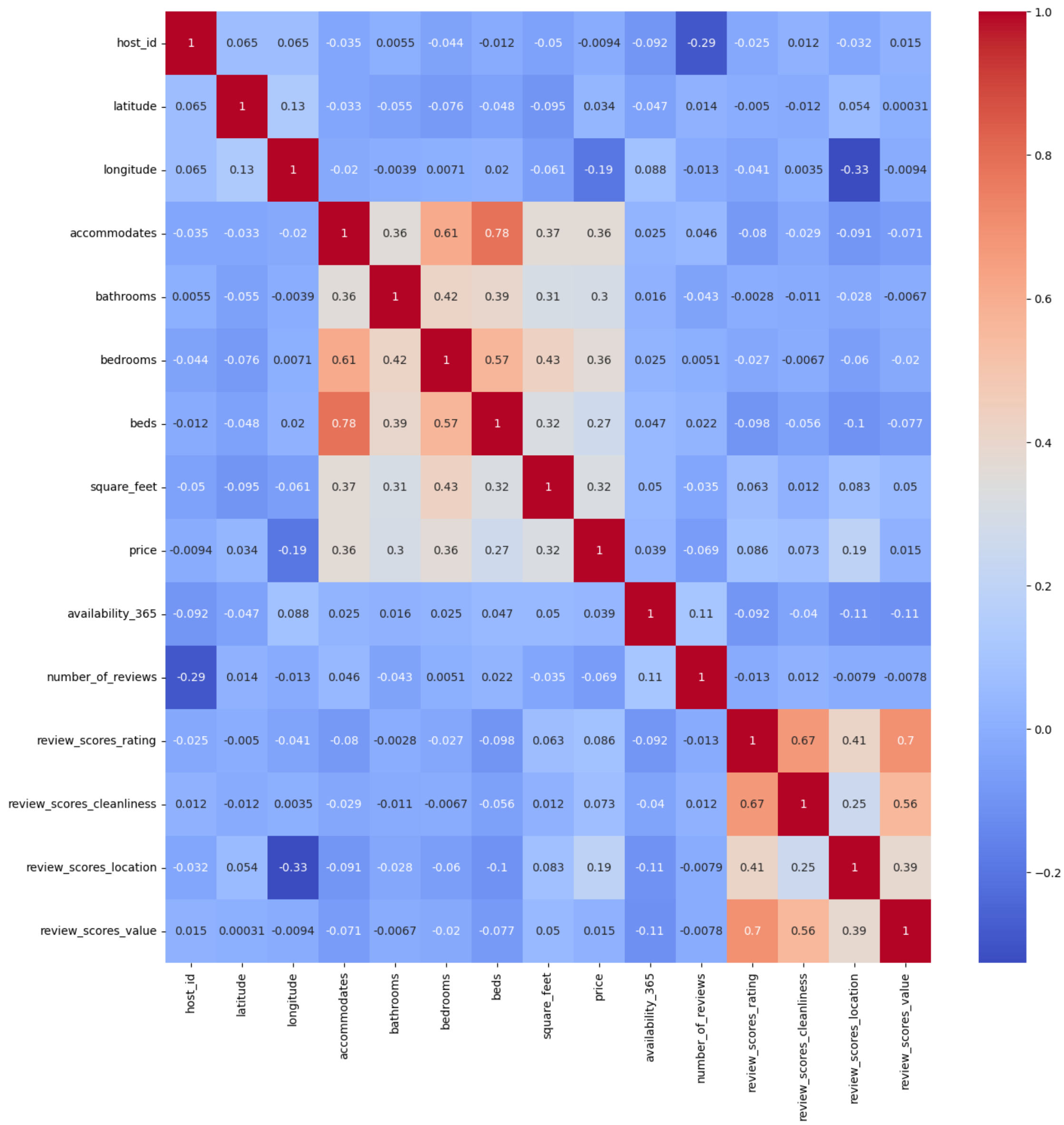
[239]: <function matplotlib.pyplot.show(close=None, block=None)>


Distribution of Price host_id
host_id
1e7
Count
Distribution of Price latitude
latitude
Distribution of Price longitude
longitude
Distribution of Price accommodates
accommodates
Distribution of Price bathrooms
bathrooms
Distribution of Price bedrooms
bedrooms
Distribution of Price beds
beds
Distribution of Price square_feet
square_feet
Distribution of Price price
price
Distribution of Price availability_365
availability_365
Distribution of Price number_of_reviews
number_of_reviews
Distribution of Price review_scores_rating
review_scores_rating
Distribution of Price review_scores_cleanliness
review_scores_cleanliness
Distribution of Price review_scores_location
review_scores_location
Distribution of Price review_scores_value
review_scores_value

[240]:
```
# create a boxplot for numerical columns
i = 1
plt.figure(figsize=(20,30))
for col in numerical_data:
    plt.subplot(4,4,i)
    sns.boxplot(x=mean_data[col])
    plt.title(f"Boxplot of {col}")
    i+=1
plt.show()
```


Boxplot of host_id
0.0 0.5 1.0 1.5 2.0 2.5
1e7
host_id
Boxplot of latitude
40.5 40.6 40.7 40.8 40.9
latitude
Boxplot of longitude
−74.2 −74.1 −74.0 −73.9 −73.8
longitude
Boxplot of accommodates
2.5 5.0 7.5 10.0 12.5 15.0
accommodates
Boxplot of bathrooms
0 2 4 6 8
bathrooms
Boxplot of bedrooms
0 2 4 6 8 10
bedrooms
Boxplot of beds
2.5 5.0 7.5 10.0 12.5 15.0
beds
Boxplot of square_feet
0 2000 4000 6000 8000 10000 12000
square_feet
Boxplot of price
0 2000 4000 6000 8000
price
Boxplot of availability_365
0 100 200 300
availability_365
Boxplot of number_of_reviews
0 50 100 150 200
number_of_reviews
Boxplot of review_scores_rating
20 40 60 80 100
review_scores_rating
Boxplot of review_scores_cleanliness
2 4 6 8 10
review_scores_cleanliness
Boxplot of review_scores_location
2 4 6 8 10
review_scores_location
Boxplot of review_scores_value
2 4 6 8 10
review_scores_value

[241]:
```python
# create a heatmap for numerical columns
plt.figure(figsize=(15,15))
sns.heatmap(data=mean_data[numerical_data].corr(), annot=True, cmap='coolwarm')
plt.show()
```

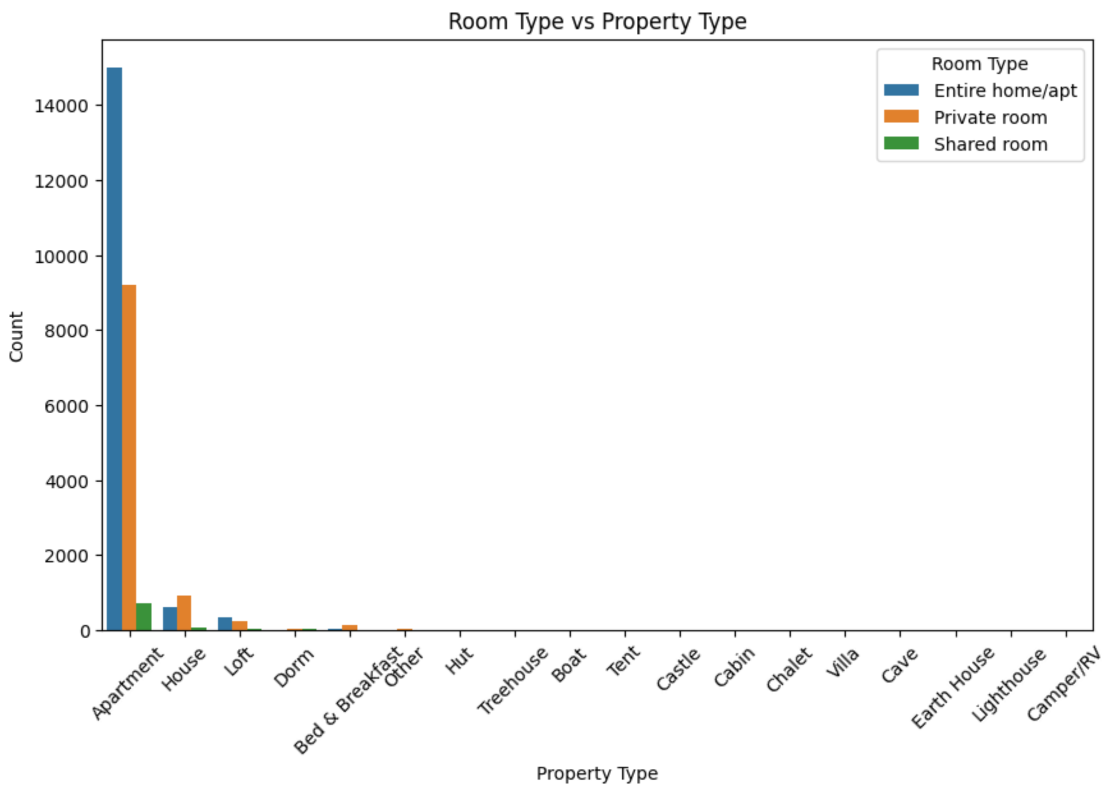


Bivariate

[242]:
```python
mean_data[categorical_data].head()
```

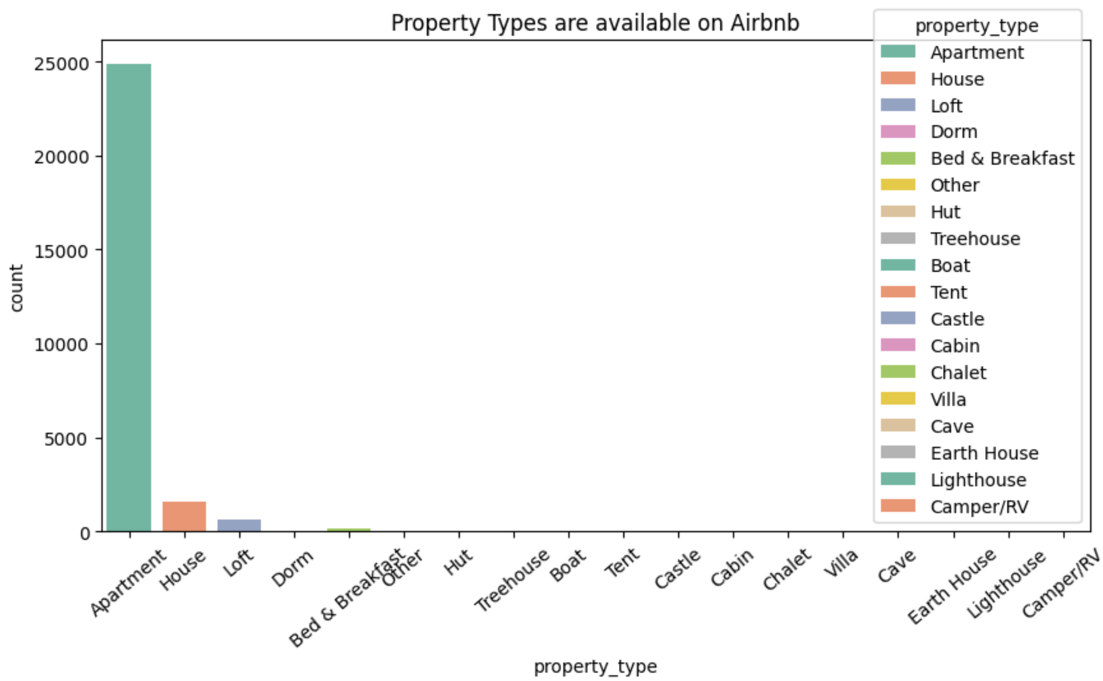
[242]:
```
  host_name      city state     zipcode        country property_type  \
0   Michael  New York    NY  10022-4175  United States     Apartment
1    Denise  New York    NY         NaN  United States     Apartment
2      Miao  Brooklyn    NY       11221  United States     Apartment
3      Sara  New York    NY       10011  United States     Apartment
4   Charles  New York    NY       10011  United States     Apartment

         room_type  bed_type
0  Entire home/apt  Real Bed
1  Entire home/apt  Real Bed
2     Private room  Real Bed
3  Entire home/apt  Real Bed
4  Entire home/apt  Real Bed
```

[243]:
```python
# Room Type vs Property Type
plt.figure(figsize=(10, 6))
sns.countplot(data=mean_data, x='property_type', hue='room_type')
plt.title('Room Type vs Property Type')
plt.xlabel('Property Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Room Type')
plt.show()
```



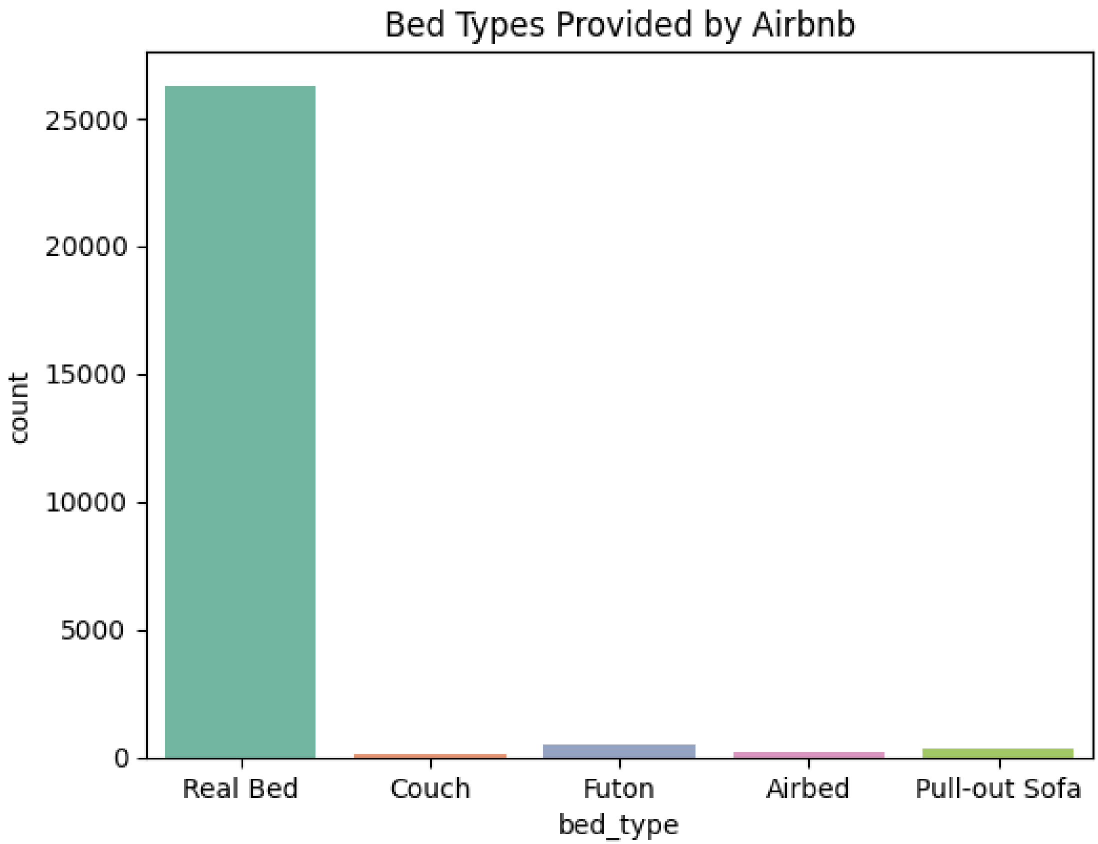
[244]:

```
#Property Types are available on Airbnb
plt.figure(figsize=(10,5))
plt.title("Property Types are available on Airbnb")
sns.
 ↪countplot(x="property_type",data=mean_data,palette="Set2",hue="property_type")
plt.xticks(rotation=40)
plt.show()
```

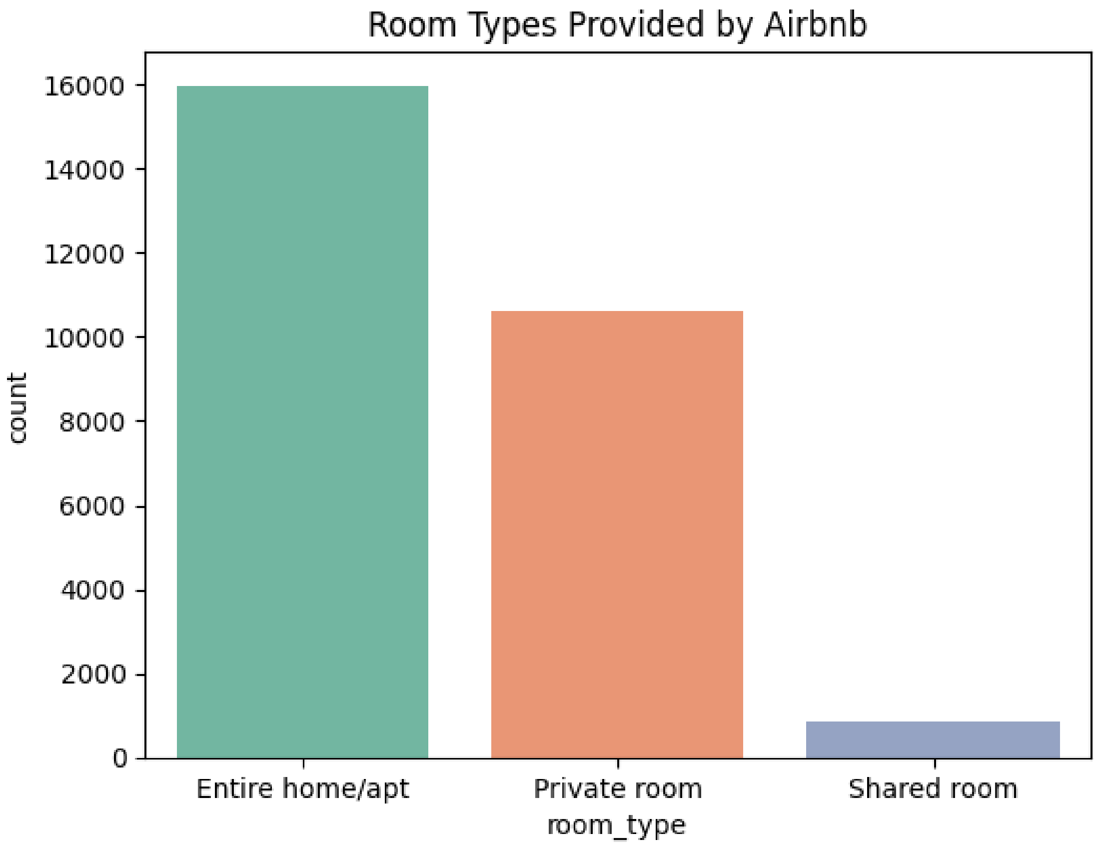


[245]:

```
# Bed Types Provided by Airbnb
sns.countplot(x="bed_type",data=mean_data,palette="Set2",hue="bed_type")
plt.title("Bed Types Provided by Airbnb")
plt.show()
```

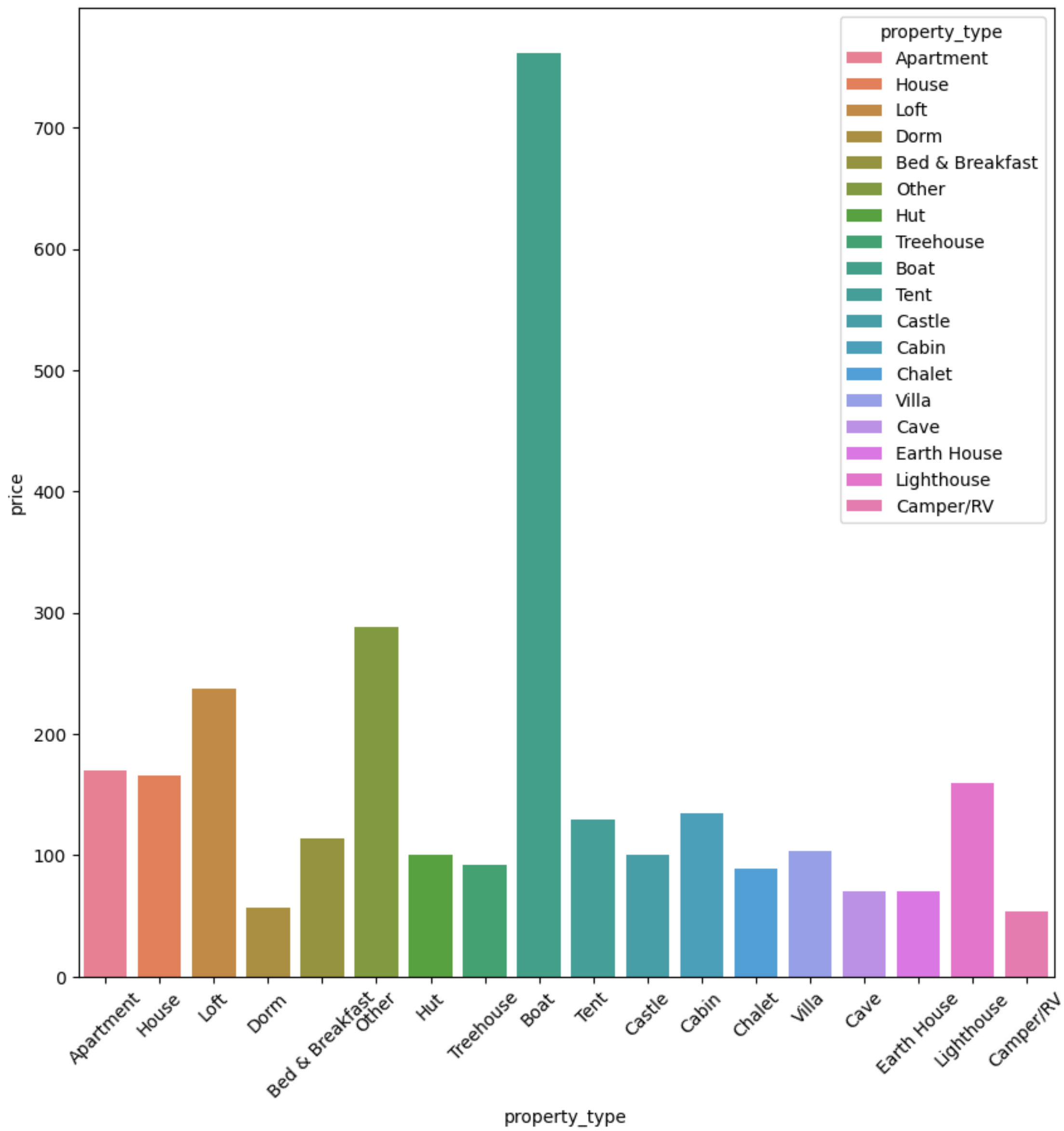


[246]:
```
#Room Types Provided by Airbnb
sns.countplot(x="room_type",data=mean_data,palette="Set2",hue="room_type")
plt.title("Room Types Provided by Airbnb")
plt.show()
```



[247]:
```
plt.figure(figsize=(10,10))
sns.
 ↪barplot(data=mean_data,x="property_type",y="price",hue="property_type",errorbar=None)
plt.xticks(rotation=45)
plt.show
```

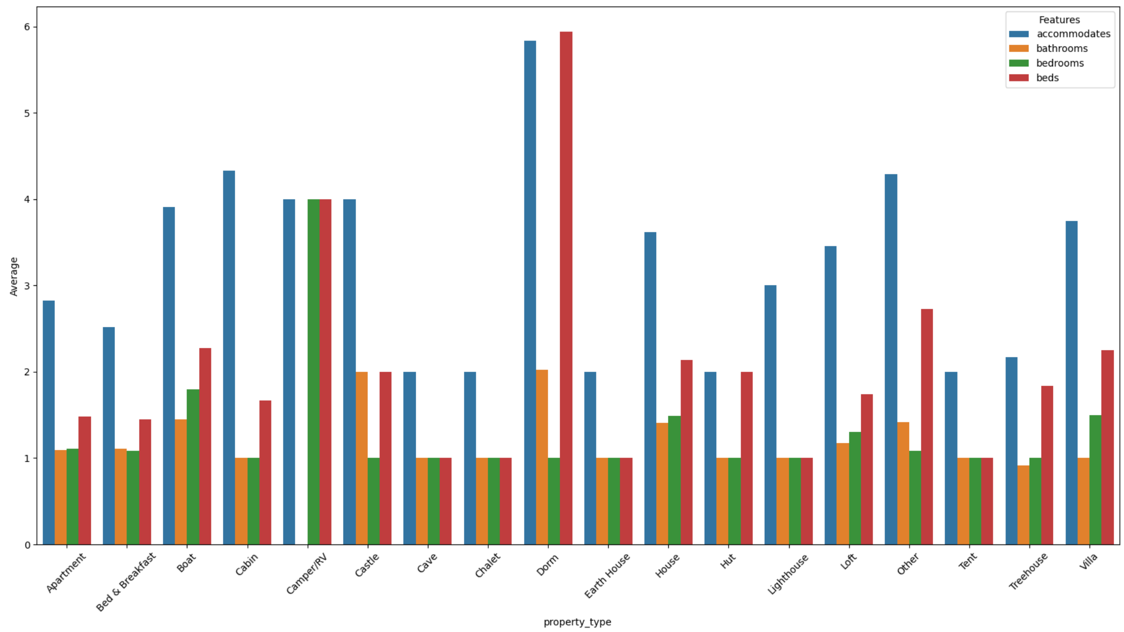
[247]: <function matplotlib.pyplot.show(close=None, block=None)>



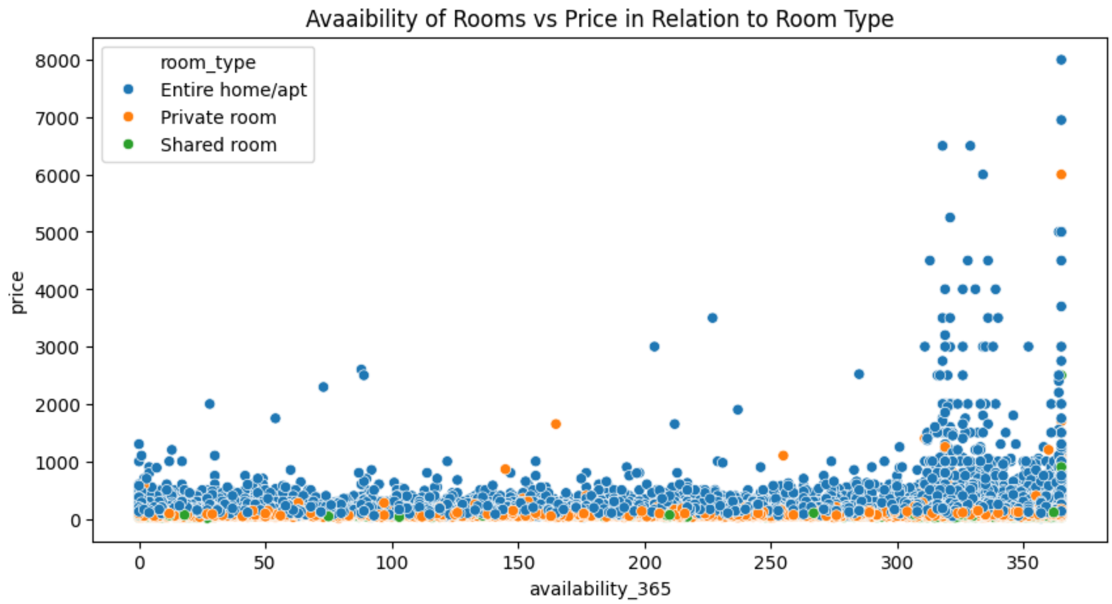
[248]:
```
grouped_data=(mean_data.groupby(['property_type']).agg({"accommodates":"mean",
                                                        "bathrooms":"mean",
                                                        "bedrooms":"mean",
                                                        "beds":"mean",}).
 ↪reset_index())

melt_data=grouped_data.
 ↪melt(id_vars="property_type",var_name="Features",value_name="Average",value_vars=["accommod

plt.figure(figsize=(20,10))
```

```
sns.
 ↪barplot(data=melt_data,x="property_type",y="Average",hue="Features",errorbar=None)
plt.xticks(rotation=45)
plt.show
```

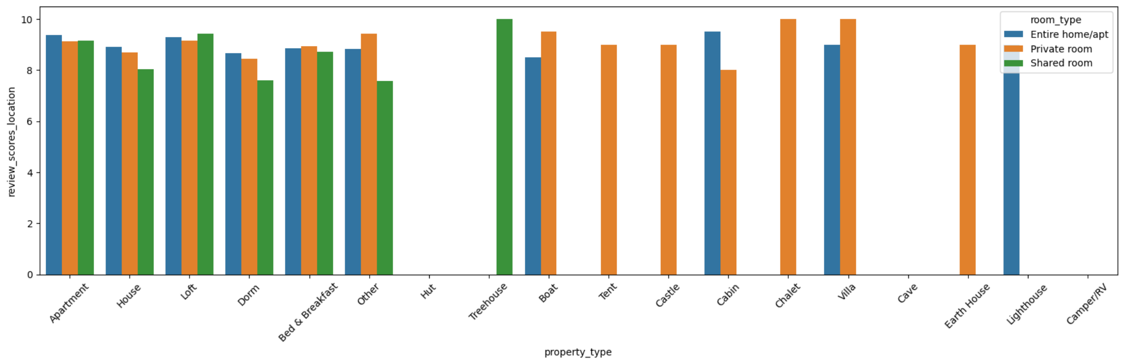
[248]: <function matplotlib.pyplot.show(close=None, block=None)>



[249]:
```
plt.figure(figsize=(10,5))
sns.scatterplot(data=mean_data,x="availability_365",y="price",hue="room_type")
plt.title("Avaaibility of Rooms vs Price in Relation to Room Type")
plt.show()
```

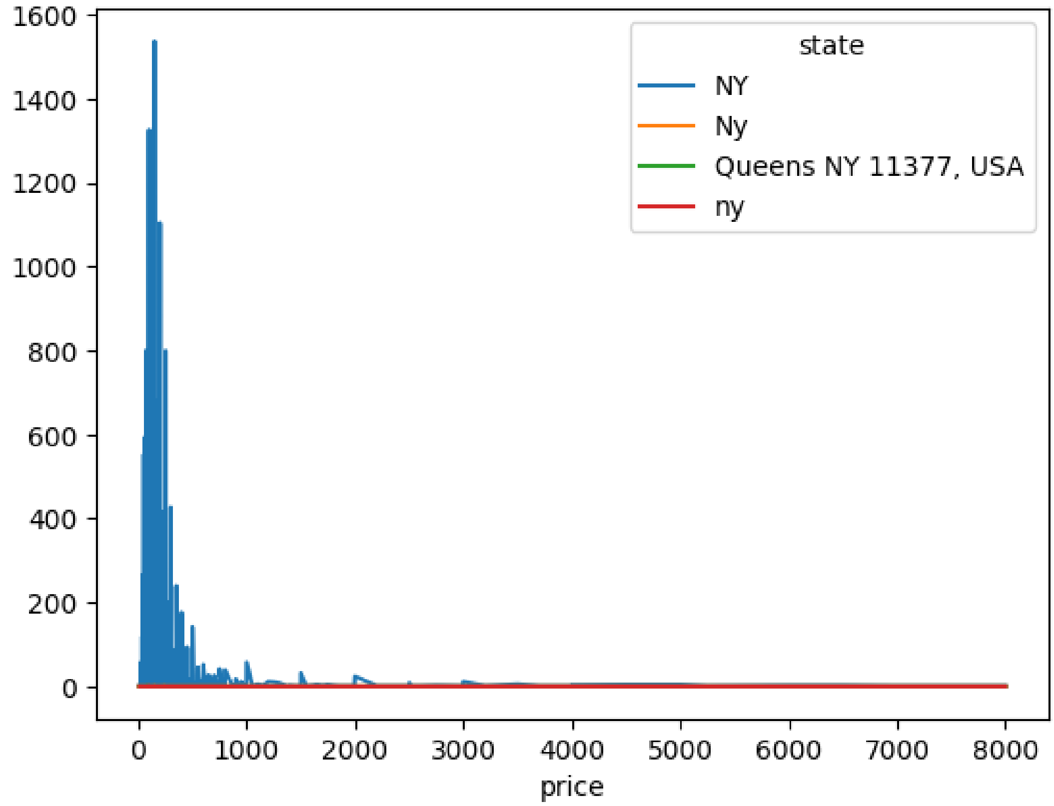


[250]:
```
plt.figure(figsize=(20,5))

sns.
 ↪barplot(data=mean_data,x="property_type",y="review_scores_location",hue="room_type",errorba
plt.xticks(rotation=45)
plt.show()
```

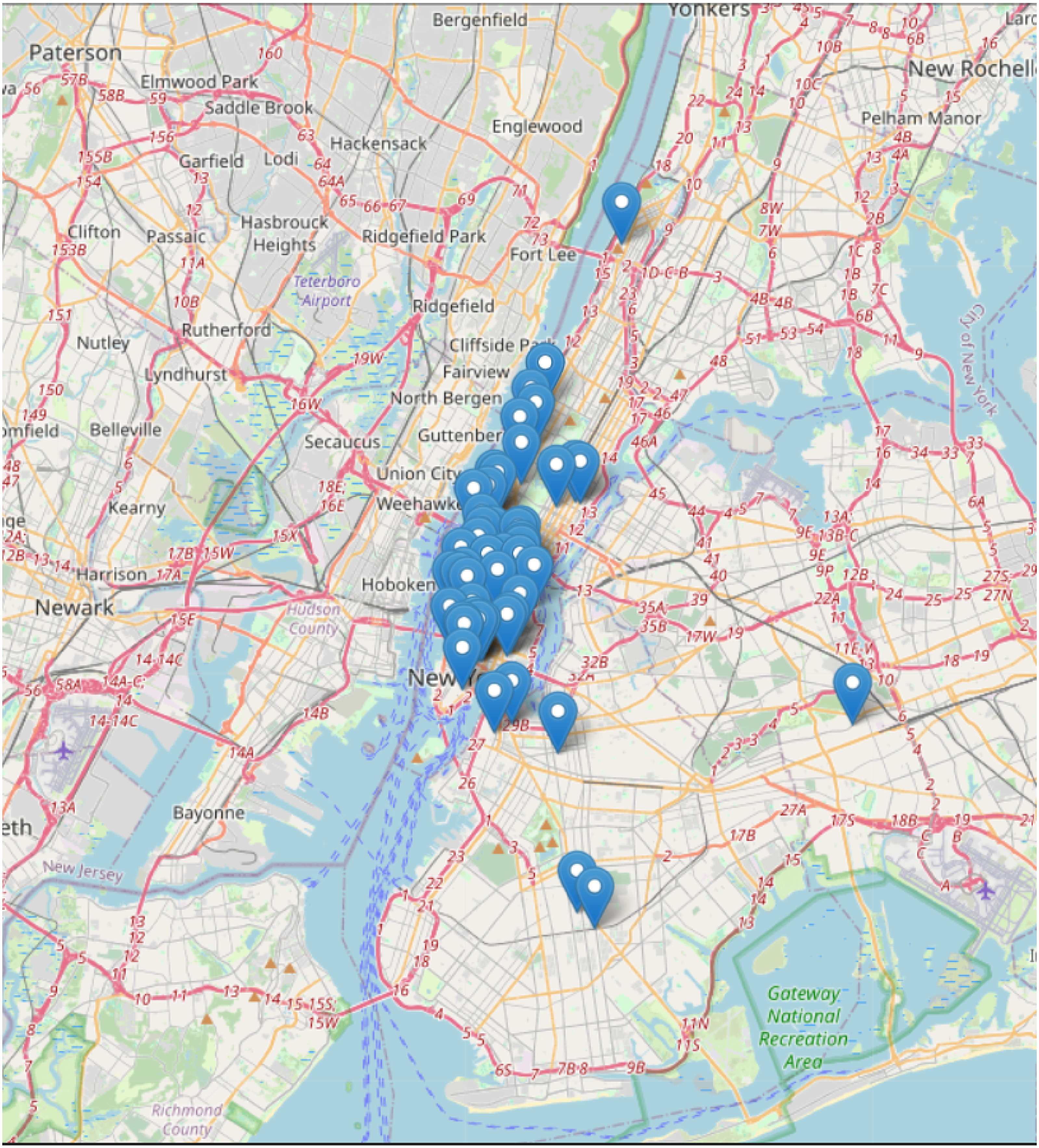


[251]:
```
crosstab = pd.crosstab(target_variable, mean_data['state'])
plt.figure(figsize=(10, 20))
crosstab.plot()
plt.show()
```

```
<Figure size 1000x2000 with 0 Axes>
```



[252]:
```
import folium as fl

# Define data_most_expensive as the subset of mean_data with the highest prices
data_map = mean_data.nlargest(100, 'price')

# Sample 50 rows from the most expensive region data
data_sample = data_map.sample(50, random_state=1)

# Calculate the average location for centering the map
average_location = [data_sample['latitude'].mean(), data_sample['longitude'].
 ↪mean()]

# Create the map object
map_sample = fl.Map(location=average_location, zoom_start=14,␣
 ↪control_scale=True)

# Add markers to the map
for _, location_info in data_sample.iterrows():
    marker_location = [location_info['latitude'], location_info['longitude']]
    marker_popup = location_info['property_type']
    fl.Marker(location=marker_location, popup=marker_popup).add_to(map_sample)
```


Yonkers
Bergenfield
Paterson
Elmwood Park
Saddle Brook
New Rochelle
Pelham Manor
Englewood
Hackensack
Garfield
Lodi
Clifton
Passaic
Hasbrouck Heights
Ridgefield Park
Fort Lee
Teterboro Airport
Ridgefield
Nutley
Rutherford
Cliffside Park
Fairview
Lyndhurst
North Bergen
Belleville
Secaucus
Guttenberg
Union City
Kearny
Weehawken
Harrison
Hoboken
Newark
Hudson County
New York
Bayonne
New Jersey
City of New York
Gateway National Recreation Area
Richmond County

```
map_sample
```

[252]: <folium.folium.Map at 0x2a1b239c9d0>

3 2. Data Preprocessing

A. check duplicate values

[253]:
```
duplicate=mean_data.duplicated()
duplicate.sum()
duplicate.shape
mean_data.nunique()
```

[253]:
```
host_id                        22342
host_name                       7381
city                             185
state                              4
zipcode                          185
country                            1
latitude                       27373
longitude                      27357
property_type                     18
room_type                          3
accommodates                      16
bathrooms                         15
bedrooms                          11
beds                              15
bed_type                           5
square_feet                      182
price                            452
availability_365                 366
number_of_reviews                171
review_scores_rating              56
review_scores_cleanliness          9
review_scores_location             8
review_scores_value                9
dtype: int64
```

b. Feature Engineering

[254]:
```
mean_data['location_group'] = pd.cut(mean_data['latitude'], bins=5,␣
 ↪labels=False).astype(str) + "_" + \
                           pd.cut(mean_data['longitude'], bins=5, labels=False).
 ↪astype(str)
```

[255]:
```
mean_data['price_per_accommodation'] = mean_data.apply(
```

```
        lambda row: row['price'] / row['accommodates'] if row['accommodates'] >␣
↪0 else None, axis=1)
```

[256]:
```
new_data = mean_data.drop(['square_feet','state','host_id',␣
↪'host_name','country','review_scores_rating','number_of_reviews','number_of_reviews','revie
↪axis=1)
new_data.head()
```

[256]:
```
        city     zipcode   latitude  longitude property_type        room_type  \
0  New York  10022-4175  40.756852 -73.964754     Apartment  Entire home/apt
1  New York         NaN  40.830599 -73.941014     Apartment  Entire home/apt
2  Brooklyn       11221  40.692189 -73.924120     Apartment     Private room
3  New York       10011  40.734751 -74.002592     Apartment  Entire home/apt
4  New York       10011  40.745282 -73.997836     Apartment  Entire home/apt

   accommodates  bathrooms  bedrooms  beds  bed_type  price  availability_365  \
0             2        1.0       1.0   1.0  Real Bed  160.0               322
1            10        1.0       3.0   3.0  Real Bed  105.0               348
2             2        1.0       1.0   2.0  Real Bed   58.0               227
3             2        1.0       1.0   1.0  Real Bed  185.0               274
4             2        1.0       1.0   2.0  Real Bed  195.0               365

  location_group  price_per_accommodation
0            3_2                     80.0
1            4_2                     10.5
2            2_3                     29.0
3            2_2                     92.5
4            2_2                     97.5
```

c. Missing value treatment

[257]:
```
# Identify Missing Values
missing_values_data = new_data.isnull().sum()
print( missing_values_data[missing_values_data > 0])
```

```
zipcode          162
property_type      6
bathrooms        463
bedrooms         140
beds              98
dtype: int64
```

[258]:
```
#the percentage of missing values
missing_percentage = round((missing_values_data / len(new_data)) * 100,2)
missing_data_summary = pd.DataFrame({
 'Missing Values': missing_values_data[missing_values_data > 0],
 'Percentage (%)': missing_percentage[missing_values_data > 0]
```

```
}).sort_values(by='Percentage (%)', ascending=False)
missing_data_summary
```

[258]:

	Missing Values	Percentage (%)
bathrooms	463	1.69
zipcode	162	0.59
bedrooms	140	0.51
beds	98	0.36
property_type	6	0.02

[259]:

```
from sklearn.impute import SimpleImputer
numerical_cols = new_data.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = new_data.select_dtypes(include=['object']).columns.tolist()


# Impute numerical columns
num_imputer = SimpleImputer(strategy='mean')
new_data[numerical_cols] = pd.DataFrame(
    num_imputer.fit_transform(new_data[numerical_cols]),
    columns=numerical_cols,
    index=new_data.index
)

# Impute categorical columns
cat_imputer = SimpleImputer(strategy='most_frequent')
new_data[categorical_cols] = pd.DataFrame(
    cat_imputer.fit_transform(new_data[categorical_cols]),
    columns=categorical_cols,
    index=new_data.index
)

# Verify missing values
print("Missing values after treatment:")
print(new_data.isnull().sum())
```

```
Missing values after treatment:
city                      0
zipcode                   0
latitude                  0
longitude                 0
property_type             0
room_type                 0
accommodates              0
bathrooms                 0
bedrooms                  0
beds                      0
bed_type                  0
```

```
price                      0
availability_365           0
location_group             0
price_per_accommodation    0
dtype: int64
```

[260]:
```
new_data.head()
```

[260]:
```
       city     zipcode   latitude  longitude property_type        room_type  \
0  New York  10022-4175  40.756852 -73.964754     Apartment  Entire home/apt
1  New York       11211  40.830599 -73.941014     Apartment  Entire home/apt
2  Brooklyn       11221  40.692189 -73.924120     Apartment     Private room
3  New York       10011  40.734751 -74.002592     Apartment  Entire home/apt
4  New York       10011  40.745282 -73.997836     Apartment  Entire home/apt

   accommodates  bathrooms  bedrooms  beds  bed_type  price  availability_365  \
0           2.0        1.0       1.0   1.0  Real Bed  160.0             322.0
1          10.0        1.0       3.0   3.0  Real Bed  105.0             348.0
2           2.0        1.0       1.0   2.0  Real Bed   58.0             227.0
3           2.0        1.0       1.0   1.0  Real Bed  185.0             274.0
4           2.0        1.0       1.0   2.0  Real Bed  195.0             365.0

  location_group  price_per_accommodation
0            3_2                     80.0
1            4_2                     10.5
2            2_3                     29.0
3            2_2                     92.5
4            2_2                     97.5
```

d. Outlier Treatment

[261]:
```
from scipy.stats import zscore
def remove_outliers(df, col):
    z_scores = zscore(df[col])
    abs_z_scores = np.abs(z_scores)
    return df[abs_z_scores < 3]

# Apply outlier treatment to numerical columns (excluding target)
for col in numerical_cols:
    if col != 'price':  # Keep 'price' outliers for pricing analysis
        original_count = new_data.shape[0]
        data = remove_outliers(new_data, col)
        new_count = data.shape[0]
        print(f"{col}: Removed {original_count - new_count} outliers.")
```

```
latitude: Removed 139 outliers.
longitude: Removed 582 outliers.
accommodates: Removed 340 outliers.
```

```
bathrooms: Removed 483 outliers.
bedrooms: Removed 256 outliers.
beds: Removed 515 outliers.
availability_365: Removed 0 outliers.
price_per_accommodation: Removed 204 outliers.
```

e. Encoding categorical columns

[262]:
```python
cat_new_data= new_data.select_dtypes(include=["object"]).columns
from sklearn.preprocessing import LabelEncoder

label_encoded_data = new_data[cat_new_data].copy()
label_encoders = {}
for column in label_encoded_data.columns:
    le = LabelEncoder()
    label_encoded_data[column] = le.fit_transform(label_encoded_data[column].
 ↪astype(str)) + 1
    label_encoders[column] = le

label_encoded_data.head()
```

[262]:

	city	zipcode	property_type	room_type	bed_type	location_group
0	105	23	1	1	5	14
1	105	108	1	1	5	17
2	33	118	1	2	5	12
3	105	13	1	1	5	11
4	105	13	1	1	5	11

[263]:
```python
num_new_data= new_data.select_dtypes(include=["int","float"]).columns
balanced_data = pd.concat([label_encoded_data,new_data[num_new_data]],axis=1)

balanced_data.to_csv('balanced.csv',index=False)
balanced_data.head()
```

[263]:

	city	zipcode	property_type	room_type	bed_type	location_group	\
0	105	23	1	1	5	14	
1	105	108	1	1	5	17	
2	33	118	1	2	5	12	
3	105	13	1	1	5	11	
4	105	13	1	1	5	11	

	latitude	longitude	accommodates	bathrooms	bedrooms	beds	price	\
0	40.756852	-73.964754	2.0	1.0	1.0	1.0	160.0	
1	40.830599	-73.941014	10.0	1.0	3.0	3.0	105.0	
2	40.692189	-73.924120	2.0	1.0	1.0	2.0	58.0	
3	40.734751	-74.002592	2.0	1.0	1.0	1.0	185.0	
4	40.745282	-73.997836	2.0	1.0	1.0	2.0	195.0	

```
   availability_365  price_per_accommodation
0             322.0                     80.0
1             348.0                     10.5
2             227.0                     29.0
3             274.0                     92.5
4             365.0                     97.5
```

f. Scaling

[264]:
```python
from sklearn.preprocessing import StandardScaler
dt=pd.read_csv('balanced.csv')
dt.head()
```

[264]:
```
   city  zipcode  property_type  room_type  bed_type  location_group  \
0   105       23              1          1         5              14
1   105      108              1          1         5              17
2    33      118              1          2         5              12
3   105       13              1          1         5              11
4   105       13              1          1         5              11

    latitude  longitude  accommodates  bathrooms  bedrooms  beds  price  \
0  40.756852 -73.964754           2.0        1.0       1.0   1.0  160.0
1  40.830599 -73.941014          10.0        1.0       3.0   3.0  105.0
2  40.692189 -73.924120           2.0        1.0       1.0   2.0   58.0
3  40.734751 -74.002592           2.0        1.0       1.0   1.0  185.0
4  40.745282 -73.997836           2.0        1.0       1.0   2.0  195.0

   availability_365  price_per_accommodation
0             322.0                     80.0
1             348.0                     10.5
2             227.0                     29.0
3             274.0                     92.5
4             365.0                     97.5
```

[265]:
```python
scaler_std=StandardScaler()
scaled_data=dt.drop('price',axis=1)
scaled_data[scaled_data.columns]=scaler_std.fit_transform(scaled_data)
scaled_data['price']=dt['price']
scaled_data
```

[265]:
```
           city   zipcode  property_type  room_type  bed_type  location_group  \
0      0.703824 -0.784637      -0.301575  -0.805791   0.18498        0.957679
1      0.703824  0.923042      -0.301575  -0.805791   0.18498        2.411473
2     -1.290235  1.123946      -0.301575   0.996907   0.18498       -0.011517
3      0.703824 -0.985540      -0.301575  -0.805791   0.18498       -0.496115
4      0.703824 -0.985540      -0.301575  -0.805791   0.18498       -0.496115
…           …         …            …          …        …             …
```

```
27387  0.703824 -0.905179      -0.301575  -0.805791   0.18498         -0.496115
27388  0.703824 -0.844908      -0.301575   0.996907   0.18498          0.957679
27389  1.673158 -0.161836       2.990737  -0.805791   0.18498         -2.434507
27390 -1.290235  0.963223      -0.301575  -0.805791   0.18498         -0.496115
27391  0.703824 -0.864998      -0.301575   2.799605   0.18498          0.957679

       latitude  longitude  accommodates  bathrooms  bedrooms      beds  \
0      0.485675  -0.013597     -0.508676   -0.31713 -0.203730 -0.484318
1      1.991744   0.661566      4.049458   -0.31713  2.799819  1.338864
2     -0.834870   1.142040     -0.508676   -0.31713 -0.203730  0.427273
3      0.034330  -1.089716     -0.508676   -0.31713 -0.203730 -0.484318
4      0.249385  -0.954450     -0.508676   -0.31713 -0.203730  0.427273
…           …          …            …       …        …       …
27387  0.189784  -0.503145     -0.508676    0.00000 -0.203730 -0.484318
27388  0.542663  -0.599135     -0.508676   -0.31713 -0.203730 -0.484318
27389 -1.783446  -3.318345      1.770391   -0.31713  1.298044  1.338864
27390 -1.289425   0.496461      0.061091   -0.31713 -0.203730 -0.484318
27391  0.426233  -0.823502     -1.078442   -0.31713 -0.203730 -0.484318

       availability_365  price_per_accommodation  price
0              0.470142                 0.239937  160.0
1              0.677039                -0.800377  105.0
2             -0.285831                -0.523459   58.0
3              0.088177                 0.427044  185.0
4              0.812319                 0.501887  195.0
…                   …                        …     …
27387          0.812319                 0.015409  130.0
27388          0.549718                 0.082767  139.0
27389          0.748658                -0.710565   99.0
27390         -1.352150                -0.683123   55.0
27391          0.788446                 0.688993  110.0

[27392 rows x 15 columns]
```

4 3. Model building with hyperparameter tuning

a. Linear Regression using Regularization

Linear Regression

[266]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score

y=scaled_data['price']
X=scaled_data.drop('price',axis=1)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

[267]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)
train_pred_lr = lr.predict(X_train)
test_pred_lr = lr.predict(X_test)

lr_train_mse = mean_squared_error(y_train, train_pred_lr)
lr_train_r2 = r2_score(y_train, train_pred_lr)

lr_test_mse = mean_squared_error(y_test, test_pred_lr)
lr_test_r2 = r2_score(y_test, test_pred_lr)

print("LinerRegression Training MSE:", lr_train_mse)
print("LinerRegression Test MSE:", lr_test_mse)
print("\nLinerRegression Training R²:", round((lr_train_r2)*100,2))
print("LinerRegression Test R²:",round((lr_test_r2)*100,2))
```

```
LinerRegression Training MSE: 17499.083986446334
LinerRegression Test MSE: 11551.184053107245

LinerRegression Training R²: 66.47
LinerRegression Test R²: 73.52
```

Ridge Regression

[268]:
```
ridge = Ridge()
ridge.fit(X_train, y_train)
y_train_pred_ridge = ridge.predict(X_train)
y_test_pred_ridge = ridge.predict(X_test)

# Training metrics
train_mse_ridge = mean_squared_error(y_train, y_train_pred_ridge)
train_r2_ridge = r2_score(y_train, y_train_pred_ridge)

# Test metrics
test_mse_ridge = mean_squared_error(y_test, y_test_pred_ridge)
test_r2_ridge = r2_score(y_test, y_test_pred_ridge)

print("Ridge Regression Training MSE:", train_mse_ridge)
print("Ridge Regression Test MSE:", test_mse_ridge)
print("\nRidge Regression Training R²:", round((train_r2_ridge)*100,2))
print("Ridge Regression Test R²:",round((test_r2_ridge)*100,2))
```

```
Ridge Regression Training MSE: 17499.084150225695
Ridge Regression Test MSE: 11551.362638584276
```

```
Ridge Regression Training R²: 66.47
Ridge Regression Test R²: 73.52
```

Lasso Regression

[269]:
```python
lasso = Lasso()
lasso.fit(X_train, y_train)

train_pred_lasso = lasso.predict(X_train)
test_lasso_preds = lasso.predict(X_test)

# Training metrics
train_mse_lasso = mean_squared_error(y_train, train_pred_lasso)
train_r2_lasso = r2_score(y_train, train_pred_lasso)

# Test metrics
test_mse_lasso = mean_squared_error(y_test, test_lasso_preds)
test_r2_lasso = r2_score(y_test, test_lasso_preds)

print("Ridge Regression Training MSE:", train_mse_lasso)
print("Ridge Regression Test MSE:", test_mse_lasso)
print("\nRidge Regression Training R²:", round((train_r2_lasso)*100,2))
print("Ridge Regression Test R²:",round((test_r2_lasso)*100,2))
```

```
Ridge Regression Training MSE: 17515.758300116646
Ridge Regression Test MSE: 11503.002362579202

Ridge Regression Training R²: 66.44
Ridge Regression Test R²: 73.63
```

b. RandomForest

[270]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

[271]:
```python
# Random Forest Regressor
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)
rf_regressor.fit(X_train, y_train)

# Predictions
train_pred_rf = rf_regressor.predict(X_train)
y_pred = rf_regressor.predict(X_test)

rf_train_mse = mean_squared_error(y_train, train_pred_rf)
rf_test_mse = mean_squared_error(y_test, y_pred)
```

```
rf_test_r2=r2_score(y_test,y_pred)
rf_train_r2 = r2_score(y_train, train_pred_rf)

print("RandomForestRegressor Training MSE:", rf_train_mse)
print("RandomForestRegressor Test MSE:", rf_test_mse)
print("\nRandomForestRegressor Training R²:", round((rf_train_r2)*100,2))
print("RandomForestRegressor Test R²:",round((rf_test_r2)*100,2))
```

```
RandomForestRegressor Training MSE: 454.4614311687127
RandomForestRegressor Test MSE: 1353.3323437853624

RandomForestRegressor Training R²: 99.13
RandomForestRegressor Test R²: 96.9
```

c. XGBoost

[272]:
```
from sklearn.model_selection import GridSearchCV
from xgboost import XGBRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, r2_score
```

[273]:
```
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('model', XGBRegressor(objective='reg:squarederror', random_state=1))
])

param_grid = {
    'model__n_estimators': [100, 200, 300],
    'model__max_depth': [3, 5, 7],
    'model__learning_rate': [0.01, 0.1, 0.2],
    'model__subsample': [0.8, 1.0],
    'model__colsample_bytree': [0.8, 1.0]
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='r2', n_jobs=-1)

grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Predictions
y_train_pred = grid_search.best_estimator_.predict(X_train)
y_test_pred = grid_search.best_estimator_.predict(X_test)

# Calculate R2 scores
```

```
r2_train_score = r2_score(y_train, y_train_pred)
r2_test_score = r2_score(y_test, y_test_pred)

# Calculate MSE
mse_train = mean_squared_error(y_train, y_train_pred)
mse_test = mean_squared_error(y_test, y_test_pred)

print(f'Best Parameters: {best_params}')
print(f'Best Cross-Validation R2 Score: {best_score}')
print(f'/nTrain R2 Score: {round(r2_train_score * 100, 2)}')
print(f'Test R2 Score: {round(r2_test_score * 100, 2)}')
print(f'/nTrain MSE: {mse_train}')
print(f'Test MSE: {mse_test}')
```

```
Best Parameters: {'model__colsample_bytree': 1.0, 'model__learning_rate': 0.1,
'model__max_depth': 3, 'model__n_estimators': 100, 'model__subsample': 1.0}
Best Cross-Validation R2 Score: 0.9127564055025706
/nTrain R2 Score: 95.8
Test R2 Score: 90.2
/nTrain MSE: 2192.7498810631755
Test MSE: 4277.011548598878
```

5 4. Evaluation

5.0.1 a. Comparison on the performance of each model using training, validation and test data

Result Table

[274]:
```
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3,␣
↪random_state=0)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5,␣
↪random_state=0)

#linear regression validation MSE and R2
val_pred_lr = lr.predict(X_val)
lr_val_mse = mean_squared_error(y_val, val_pred_lr)
lr_val_r2 = r2_score(y_val, val_pred_lr)


# ridge validation  MSE and R2
val_pred_ridge = ridge.predict(X_val)
ridge_val_mse = mean_squared_error(y_val, val_pred_ridge)
ridge_val_r2 = r2_score(y_val, val_pred_ridge)


#lasso validation MSE and R2
val_pred_lasso = lasso.predict(X_val)
```

```
lasso_val_mse = mean_squared_error(y_val, val_pred_lasso)
lasso_val_r2 = r2_score(y_val, val_pred_lasso)


#redom forest validation MSE and R2
val_pred_rf = rf_regressor.predict(X_val)
rf_val_mse = mean_squared_error(y_val, val_pred_rf)
rf_val_r2 = r2_score(y_val, val_pred_rf)


#xgboost validation MSE and R2
val_pred_xgb = xgb_regressor.predict(X_val)
xgb_val_mse = mean_squared_error(y_val,val_pred_xgb)
xgb_val_r2 = r2_score(y_val, val_pred_xgb)
```

[275]:
```
# Tabulate the results

meanse = pd.DataFrame({
    'Model': ['Linear Regression', 'Ridge Regression', 'Lasso Regression',␣
 ↪'Random Forest', 'XGBoost'],
    '|': ['|', '|', '|', '|', '|'],
    'Training MSE': [lr_train_mse, train_mse_ridge, train_mse_lasso,␣
 ↪rf_train_mse, mse_train],
    'Validation MSE': [lr_val_mse, ridge_val_mse, lasso_val_mse, rf_val_mse,␣
 ↪xgb_val_mse],
    'Test MSE': [lr_test_mse, test_mse_ridge, test_mse_lasso, rf_test_mse,␣
 ↪mse_test],
    '||': ['||', '||', '||', '||', '||'],
    'Training R2': [round((lr_train_r2)*100, 2), round((train_r2_ridge)*100,␣
 ↪2), round((train_r2_lasso)*100, 2), round((rf_train_r2)*100, 2),␣
 ↪round((r2_train_score)*100, 2)],
    'Validation R2': [round((lr_val_r2)*100, 2), round((ridge_val_r2)*100, 2),␣
 ↪round((lasso_val_r2)*100, 2), round((rf_val_r2)*100, 2),␣
 ↪round((xgb_val_r2)*100, 2)],
    'Test R2': [round((lr_test_r2)*100, 2), round((test_r2_ridge)*100, 2),␣
 ↪round((test_r2_lasso)*100, 2), round((rf_test_r2)*100, 2),␣
 ↪round((r2_test_score)*100, 2)]
})
meanse.index = meanse.index + 1
meanse
```

[275]:
```
               Model  |  Training MSE  Validation MSE      Test MSE  ||  \
1  Linear Regression  |  17499.083986    14908.295121  11551.184053  ||
2   Ridge Regression  |  17499.084150    14908.181243  11551.362639  ||
3   Lasso Regression  |  17515.758300    14843.104098  11503.002363  ||
4      Random Forest  |    454.461431     1328.336719   1353.332344  ||
```

```
5            XGBoost  |   2192.749881     3791.121280   4277.011549  ||

   Training R2  Validation R2  Test R2
1        66.47          67.90    73.52
2        66.47          67.90    73.52
3        66.44          68.04    73.63
4        99.13          97.14    96.90
5        95.80          91.84    90.20
```

b. COMMENTS ON INSIGHTS AND RECOMMENDATION-

insights

1. Regularizastion methods (Ridge, Lasso) reduce overfitting but don't improve performance much compared to Linear Regression.
2. Random Forest and XGBoost perform significantly better because they capture non-linear patterns in the data
3. XGBoost performs the best on the test set, showing it is highly effective for this dataset.

Recommendations

1. Best Modek Use XGBoost for the best predictions. Fine-tune it for even better results.
2. Simple Model: lf you need an easy-to-interpret model go with Ridge Regression
3. Improve Data: Work on handling outiers and improving feature encoding for better results.
4. Business Tip: High-priced Fsting s Iike vilas, need special attention to madmize revenue