Development of Airbnb Price Prediction Models for NYC and Investigation of the Impact of NYC's Local Law 18 on Airbnb Prices

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The goal of this research project is to perform regression analysis to develop accurate price prediction models for New York City Airbnb listings while identifying the most relevant features that influence the prices of Airbnb listings.

The measurable progress indicator for this project is the development of accurate regression models with high predictive performance for NYC Airbnb listing prices. Key metrics such as mean squared error, root mean square error, and R-squared will quantify the models' performance and effectiveness.

Inside Airbnb provides data on Airbnb listings in New York City on a 12-month rolling period, currently containing data on Airbnb listings from February 2023 to April 2024.

The datasets include various features of host information, property details/amenities, borough and neighborhood location, longitude and latitude coordinates, customer reviews, and prices for each listing. Incorporating these features will uncover patterns and trends in Airbnb listings, particularly in with pricing dynamics.

This research project will also include a case study to investigate the causal effects of Local Law 18 using a Difference-in-Differences (Diff-in-Diff) model.

Data Sources:

- Airbnb Listings Data: http://insideairbnb.com/get-the-data/
- Transit Data: http://web.mta.info/developers/developer-data-terms.html#data
- Data Dictionary: https://docs.google.com/spreadsheets/d/1iWCNJcSutYqpULSQHlNyGInUvHg2BoUGoNRIGa6Szc4/edit?usp=sharing

Loading & Formatting Data and Dropping Duplicates

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import re
from sklearn.metrics.pairwise import haversine_distances
from math import radians, sqrt
import warnings
#!pip install geopandas
```

```python
import geopandas as gpd
from geopandas.datasets import get_path
import geopandas.tools as gpd_tools
from shapely.geometry import Point
from sklearn.preprocessing import LabelEncoder, OneHotEncoder,
StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import Pipeline
from sklearn.svm import SVR
from sklearn.exceptions import ConvergenceWarning
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_squared_error as mse
import statsmodels.api as sm
from datetime import datetime

warnings.filterwarnings('ignore', category=FutureWarning)
warnings.filterwarnings('ignore', category=ConvergenceWarning)

df_02_23 = pd.read_csv('airbnb_data_02_23.csv', dtype={'license':
'object'})
df_03_23 = pd.read_csv('airbnb_data_03_23.csv', dtype={'license':
'object'})
df_04_23 = pd.read_csv('airbnb_data_04_23.csv', dtype={'license':
'object'})
df_05_23 = pd.read_csv('airbnb_data_05_23.csv', dtype={'license':
'object'})
df_06_23 = pd.read_csv('airbnb_data_06_23.csv')
df_07_23 = pd.read_csv('airbnb_data_07_23.csv')
df_08_23 = pd.read_csv('airbnb_data_08_23.csv')
df_09_23 = pd.read_csv('airbnb_data_09_23.csv')
df_10_23 = pd.read_csv('airbnb_data_10_23.csv')
df_11_23 = pd.read_csv('airbnb_data_11_23.csv')
df_12_23 = pd.read_csv('airbnb_data_12_23.csv')
df_01_24 = pd.read_csv('airbnb_data_01_24.csv')
df_02_24 = pd.read_csv('airbnb_data_02_24.csv')
df_03_24 = pd.read_csv('airbnb_data_03_24.csv')
df_04_24 = pd.read_csv('airbnb_data_04_24.csv')


frames = [df_02_23, df_03_23, df_04_23, df_05_23,
          df_06_23, df_07_23, df_08_23, df_09_23,
          df_10_23, df_11_23, df_12_23, df_01_24,
          df_02_24, df_03_24, df_04_24]

df_original = pd.concat(frames)
```

```
df_original.shape
```

```
(616740, 75)
```

The dataset has 616740 observations and 75 features.

```
df_original.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 616740 entries, 0 to 38376
Data columns (total 75 columns):
 #   Column                                          Non-Null Count  
Dtype
---  ------                                          --------------  
-----
 0   id                                              616740 non-null 
int64
 1   listing_url                                     616740 non-null 
object
 2   scrape_id                                       616740 non-null 
int64
 3   last_scraped                                    616740 non-null 
object
 4   source                                          616740 non-null 
object
 5   name                                            616691 non-null 
object
 6   description                                     527453 non-null 
object
 7   neighborhood_overview                           356376 non-null 
object
 8   picture_url                                     616740 non-null 
object
 9   host_id                                         616740 non-null 
int64
 10  host_url                                        616740 non-null 
object
 11  host_name                                       616654 non-null 
object
 12  host_since                                      616654 non-null 
object
 13  host_location                                   484219 non-null 
object
 14  host_about                                      341629 non-null 
object
 15  host_response_time                              390557 non-null 
object
 16  host_response_rate                              390557 non-null 
object
```

```
 17  host_acceptance_rate                                      428876 non-null
object
 18  host_is_superhost                                         573379 non-null
object
 19  host_thumbnail_url                                        616654 non-null
object
 20  host_picture_url                                          616654 non-null
object
 21  host_neighbourhood                                        493296 non-null
object
 22  host_listings_count                                       616654 non-null
float64
 23  host_total_listings_count                                 616654 non-null
float64
 24  host_verifications                                        616740 non-null
object
 25  host_has_profile_pic                                      616654 non-null
object
 26  host_identity_verified                                    616654 non-null
object
 27  neighbourhood                                             356391 non-null
object
 28  neighbourhood_cleansed                                    616740 non-null
object
 29  neighbourhood_group_cleansed                              616740 non-null
object
 30  latitude                                                  616740 non-null
float64
 31  longitude                                                 616740 non-null
float64
 32  property_type                                             616740 non-null
object
 33  room_type                                                 616740 non-null
object
 34  accommodates                                              616740 non-null
int64
 35  bathrooms                                                 72377 non-null
float64
 36  bathrooms_text                                            615976 non-null
object
 37  bedrooms                                                  382935 non-null
float64
 38  beds                                                      562521 non-null
float64
 39  amenities                                                 616740 non-null
object
 40  price                                                     561519 non-null
object
 41  minimum_nights                                            616740 non-null
```

```
int64
 42  maximum_nights                                              616740 non-null
int64
 43  minimum_minimum_nights                                      616680 non-null
float64
 44  maximum_minimum_nights                                      616680 non-null
float64
 45  minimum_maximum_nights                                      616680 non-null
float64
 46  maximum_maximum_nights                                      616680 non-null
float64
 47  minimum_nights_avg_ntm                                      616680 non-null
float64
 48  maximum_nights_avg_ntm                                      616680 non-null
float64
 49  calendar_updated                                            0 non-null
float64
 50  has_availability                                            582731 non-null
object
 51  availability_30                                             616740 non-null
int64
 52  availability_60                                             616740 non-null
int64
 53  availability_90                                             616740 non-null
int64
 54  availability_365                                            616740 non-null
int64
 55  calendar_last_scraped                                       616740 non-null
object
 56  number_of_reviews                                           616740 non-null
int64
 57  number_of_reviews_ltm                                       616740 non-null
int64
 58  number_of_reviews_l30d                                      616740 non-null
int64
 59  first_review                                                454214 non-null
object
 60  last_review                                                 454214 non-null
object
 61  review_scores_rating                                        454264 non-null
float64
 62  review_scores_accuracy                                      450329 non-null
float64
 63  review_scores_cleanliness                                   450477 non-null
float64
 64  review_scores_checkin                                       450266 non-null
float64
 65  review_scores_communication                                 450399 non-null
float64
```

```
 66  review_scores_location                        450224 non-null
float64
 67  review_scores_value                           450231 non-null
float64
 68  license                                       30848 non-null
object
 69  instant_bookable                              616740 non-null
object
 70  calculated_host_listings_count                616740 non-null
int64
 71  calculated_host_listings_count_entire_homes   616740 non-null
int64
 72  calculated_host_listings_count_private_rooms  616740 non-null
int64
 73  calculated_host_listings_count_shared_rooms   616740 non-null
int64
 74  reviews_per_month                             454214 non-null
float64
dtypes: float64(22), int64(17), object(36)
memory usage: 357.6+ MB
```

```
df_original['last_scraped'] =
pd.to_datetime(df_original['last_scraped'])

df_original['date'] = df_original['last_scraped'].dt.strftime('%Y-%m')

df_original['price'] = df_original['price'].replace('[\$,]', '',
regex=True).astype(float)

df_original.columns
```

```
Index(['id', 'listing_url', 'scrape_id', 'last_scraped', 'source',
'name',
       'description', 'neighborhood_overview', 'picture_url',
'host_id',
       'host_url', 'host_name', 'host_since', 'host_location',
'host_about',
       'host_response_time', 'host_response_rate',
'host_acceptance_rate',
       'host_is_superhost', 'host_thumbnail_url', 'host_picture_url',
       'host_neighbourhood', 'host_listings_count',
       'host_total_listings_count', 'host_verifications',
       'host_has_profile_pic', 'host_identity_verified',
'neighbourhood',
       'neighbourhood_cleansed', 'neighbourhood_group_cleansed',
'latitude',
       'longitude', 'property_type', 'room_type', 'accommodates',
'bathrooms',
       'bathrooms_text', 'bedrooms', 'beds', 'amenities', 'price',
       'minimum_nights', 'maximum_nights', 'minimum_minimum_nights',
```

```
       'maximum_minimum_nights', 'minimum_maximum_nights',
       'maximum_maximum_nights', 'minimum_nights_avg_ntm',
       'maximum_nights_avg_ntm', 'calendar_updated',
'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'calendar_last_scraped',
'number_of_reviews',
       'number_of_reviews_ltm', 'number_of_reviews_l30d',
'first_review',
       'last_review', 'review_scores_rating',
'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'license', 'instant_bookable',
       'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms',
'reviews_per_month',
       'date'],
      dtype='object')
```

```
df_original['id'].nunique()
```

```
62872
```

There are 62872 unique Airbnb listings in New York City

```
df_original.duplicated(subset=['id', 'host_name', 'latitude',
'longitude', 'price']).sum()
```

```
365995
```

```
df = df_original.drop_duplicates(subset=['id', 'host_name',
'latitude', 'longitude', 'price'])
```

Based on the subset of assuming that previous listings appear in later scrapes, 365995 duplicates were found. These observations will be dropped from the DataFrame.

```
df.shape
```

```
(250745, 76)
```

After dropping the duplicates, there are 250745 observations remaining.

```
# List of features to be dropped
drop_col = ['id', 'listing_url', 'scrape_id', 'source', 'name',
'description', 'neighborhood_overview',
            'picture_url', 'host_id', 'host_url', 'host_name',
```

```
'host_since', 'host_location', 'host_about',
            'host_response_time', 'host_response_rate',
'host_thumbnail_url', 'host_picture_url',
            'host_total_listings_count', 'host_verifications',
'host_has_profile_pic', 'host_neighbourhood',
            'neighbourhood', 'property_type', 'bathrooms',
'minimum_minimum_nights', 'maximum_minimum_nights',
            'minimum_maximum_nights', 'maximum_maximum_nights',
'minimum_nights_avg_ntm', 'maximum_nights_avg_ntm',
            'calendar_updated', 'has_availability', 'availability_30',
'availability_60', 'availability_90',
            'availability_365', 'calendar_last_scraped',
'number_of_reviews', 'number_of_reviews_ltm',
            'number_of_reviews_l30d', 'first_review', 'last_review',
'review_scores_accuracy',
            'review_scores_cleanliness', 'review_scores_checkin',
'review_scores_communication',
            'review_scores_location', 'review_scores_value',
'license', 'calculated_host_listings_count',
            'calculated_host_listings_count_entire_homes',
'calculated_host_listings_count_private_rooms',
            'calculated_host_listings_count_shared_rooms',
'reviews_per_month', 'last_scraped']

df = df.drop(drop_col, axis=1)
df.shape
```

```
(250745, 20)
```

```
df.columns
```

```
Index(['host_acceptance_rate', 'host_is_superhost',
'host_listings_count',
       'host_identity_verified', 'neighbourhood_cleansed',
       'neighbourhood_group_cleansed', 'latitude', 'longitude',
'room_type',
       'accommodates', 'bathrooms_text', 'bedrooms', 'beds',
'amenities',
       'price', 'minimum_nights', 'maximum_nights',
'review_scores_rating',
       'instant_bookable', 'date'],
      dtype='object')
```

The features stored in `drop_col` are either represented more thoroughly in another feature (repetitive) or are redundant and don't provide insight in the price prediction models. After dropping those columns, there are 20 features remaining

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

```
651
```

```
df = df.drop_duplicates()

df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 250094 entries, 0 to 38376
Data columns (total 20 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   host_acceptance_rate          219125 non-null  object
 1   host_is_superhost             235480 non-null  object
 2   host_listings_count           250073 non-null  float64
 3   host_identity_verified        250073 non-null  object
 4   neighbourhood_cleansed        250094 non-null  object
 5   neighbourhood_group_cleansed  250094 non-null  object
 6   latitude                      250094 non-null  float64
 7   longitude                     250094 non-null  float64
 8   room_type                     250094 non-null  object
 9   accommodates                  250094 non-null  int64
 10  bathrooms_text                249822 non-null  object
 11  bedrooms                      167286 non-null  float64
 12  beds                          239422 non-null  float64
 13  amenities                     250094 non-null  object
 14  price                         232310 non-null  float64
 15  minimum_nights                250094 non-null  int64
 16  maximum_nights                250094 non-null  int64
 17  review_scores_rating          181057 non-null  float64
 18  instant_bookable              250094 non-null  object
 19  date                          250094 non-null  object
dtypes: float64(7), int64(3), object(10)
memory usage: 40.1+ MB

df = df.rename(columns={'neighbourhood_cleansed':'neighborhood',
'neighbourhood_group_cleansed':'borough'})
df['date'] = df['date'].astype('datetime64[ns]')

df.columns

Index(['host_acceptance_rate', 'host_is_superhost',
'host_listings_count',
       'host_identity_verified', 'neighborhood', 'borough',
'latitude',
       'longitude', 'room_type', 'accommodates', 'bathrooms_text',
'bedrooms',
       'beds', 'amenities', 'price', 'minimum_nights',
'maximum_nights',
       'review_scores_rating', 'instant_bookable', 'date'],
      dtype='object')

df['price'] = df['price'].replace('[\$,]', '',
regex=True).astype(float)
```

```
df['host_acceptance_rate'] = df['host_acceptance_rate'].replace('%',
'', regex=True).astype(float)
```

In the first of the previous two cells, I rename columns to make it more interperatable and change the `date` type to datatime64. In the previous cell, I format the `price` and `host_acceptance_rate` features to make the floats by removing special characters $,%

```
df.loc[:,['date', 'host_acceptance_rate', 'host_is_superhost',
          'host_listings_count', 'host_identity_verified', 'borough',
'latitude',
          'longitude', 'room_type', 'accommodates']].head()
```

```
        date  host_acceptance_rate host_is_superhost
host_listings_count  \
0 2023-02-01                  21.0                 f
7.0
1 2023-02-01                  82.0                 t
2.0
2 2023-02-01                  50.0                 f
1.0
3 2023-02-01                  82.0                 f
1.0
4 2023-02-01                   NaN                 f
1.0

  host_identity_verified    borough  latitude  longitude
room_type  \
0                      t  Manhattan  40.75356  -73.98559  Entire
home/apt
1                      t   Brooklyn  40.68535  -73.95512     Private
room
2                      t   Brooklyn  40.66265  -73.99454  Entire
home/apt
3                      f  Manhattan  40.76076  -73.96156  Entire
home/apt
4                      t  Manhattan  40.80380  -73.96751     Private
room

   accommodates
0             1
1             2
2             4
3             3
4             1
```

```
df.loc[:,['bathrooms_text', 'bedrooms', 'beds', 'amenities', 'price',
          'minimum_nights', 'maximum_nights', 'review_scores_rating',
          'instant_bookable']].head()
```

```
  bathrooms_text  bedrooms  beds  \
0         1 bath       NaN   1.0
1            NaN       1.0   1.0
2      1.5 baths       2.0   2.0
3         1 bath       1.0   1.0
4  1 shared bath       1.0   1.0

                                           amenities  price
minimum_nights  \
0  ["Keypad", "Extra pillows and blankets", "TV",...  150.0
30
1  ["Kitchen", "Wifi", "Long term stays allowed",...   60.0
30
2  ["Carbon monoxide alarm", "HDTV with Disney+, ...  275.0
21
3  ["Hot water", "Essentials", "Carbon monoxide a...  295.0
4
4  ["Hot water", "Breakfast", "Essentials", "Wifi...   75.0
2

   maximum_nights  review_scores_rating instant_bookable
0            1125                  4.68                f
1             730                  4.52                f
2            1125                  5.00                f
3            1125                  4.90                f
4              14                  4.91                f
```

In the previous two cells, I take a quick look at what type of values each feature takes.

Handling Missing Values

```
df.isnull().sum()
```

```
host_acceptance_rate      30969
host_is_superhost         14614
host_listings_count          21
host_identity_verified       21
neighborhood                  0
borough                       0
latitude                      0
longitude                     0
room_type                     0
accommodates                  0
bathrooms_text              272
bedrooms                  82808
beds                      10672
amenities                     0
price                     17784
minimum_nights                0
maximum_nights                0
```

```
review_scores_rating      69037
instant_bookable              0
date                          0
dtype: int64
```

```
df = df.dropna(subset=['price'])
df = df[df['price'] != 0]
```

Prices that contained NaN or 0's are dropped to avoid manipulating the target feature.

```
df.isnull().sum()
```

```
host_acceptance_rate      19835
host_is_superhost         14537
host_listings_count          16
host_identity_verified       16
neighborhood                  0
borough                       0
latitude                      0
longitude                     0
room_type                     0
accommodates                  0
bathrooms_text              211
bedrooms                  69722
beds                       3412
amenities                     0
price                         0
minimum_nights                0
maximum_nights                0
review_scores_rating      63116
instant_bookable              0
date                          0
dtype: int64
```

```
missing_numeric_cols = ['host_acceptance_rate', 'host_listings_count', 
'bedrooms', 'beds',
                        'review_scores_rating']

for col in missing_numeric_cols:
    df.loc[:, col] = df[col].fillna(df[col].median())

missing_categorical_cols = ['host_is_superhost', 
'host_identity_verified', 'bathrooms_text']

for col in missing_categorical_cols:
    df[col] = df[col].fillna(df[col].mode()[0])
```

All other features containing NaN are replaced with the median value of each respective feature. This is to help retain as much data as possible.

```
df.isnull().sum()
```

```
host_acceptance_rate      0
host_is_superhost         0
host_listings_count       0
host_identity_verified    0
neighborhood              0
borough                   0
latitude                  0
longitude                 0
room_type                 0
accommodates              0
bathrooms_text            0
bedrooms                  0
beds                      0
amenities                 0
price                     0
minimum_nights            0
maximum_nights            0
review_scores_rating      0
instant_bookable          0
date                      0
dtype: int64
```

Handling Outliers

A function `detect_outliers` uses the interquartile range method to detect observations that are out of the range +/- 1.5 * Q1 and Q3. The outliers are visualized to see which the degree of skewed data for each feature.

The bar charts after the `detect_outliers` function visualize the number of outliers of the features that were detected to contain outliers.

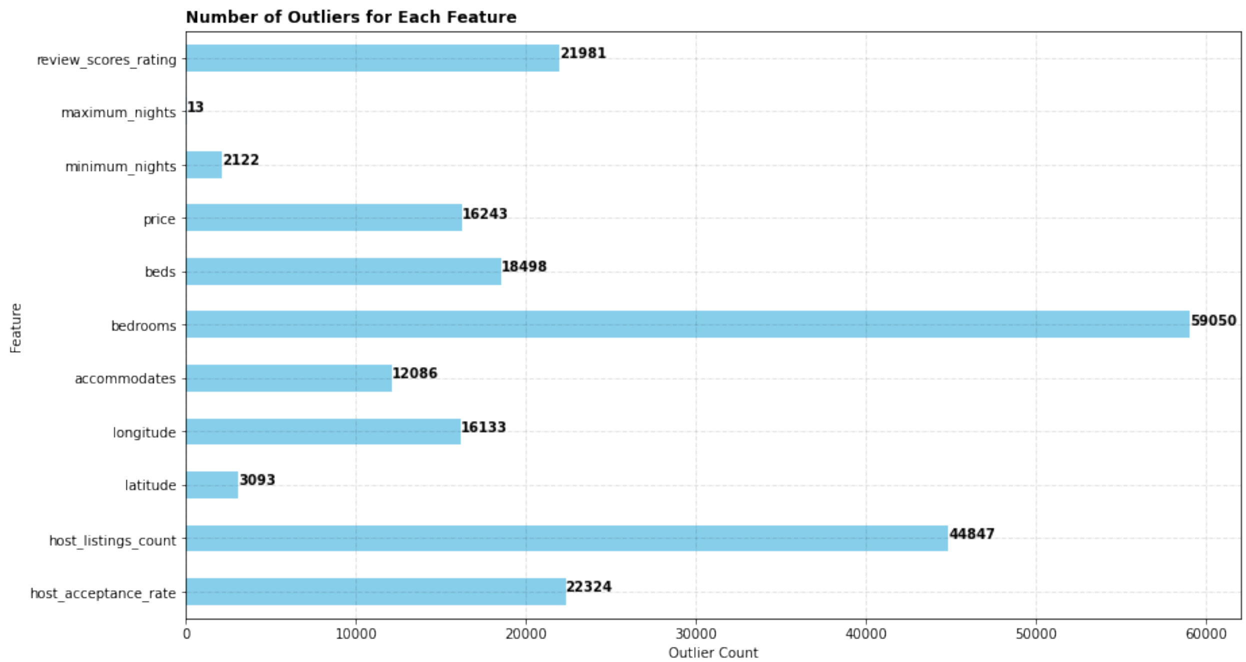
The outliers for the `price` feature are removed to avoid manipulating the target feature, and the remaining features are replaced with the median from their respective column. The `latitude` and `longitude` features are left unchanged.

```
def detect_outliers(df, cols):
    # Create a new DataFrame to store total outlier counts
    df_outliers_count = pd.DataFrame(index=['total_outliers'])

    for col in df.columns:
        if df[col].dtype=='float64' or df[col].dtype=='int64':
            # Calculate quartiles and IQR for the column
            q1 = df[col].quantile(0.25)
            q3 = df[col].quantile(0.75)
            iqr = q3 - q1

            # Identify outliers using the IQR method
```

```
            lower = q1 - 1.5 * iqr
            upper = q3 + 1.5 * iqr
            outliers = ((df[col] < lower) | (df[col] > upper))

            # Count the total number of outliers for each column
            total_outliers = outliers.sum()

            # Store total outlier counts in the new DataFrame
            df_outliers_count[col] = total_outliers

    return df_outliers_count

outlier_detected_cols = ['host_acceptance_rate',
'host_listings_count', 'accommodates',
                         'bedrooms', 'beds', 'price',
'minimum_nights', 'review_scores_rating']
outliers_df = detect_outliers(df, df.columns)

outliers_df
```

```
                host_acceptance_rate  host_listings_count  latitude  \
total_outliers                 22324                44847      3093

                longitude  accommodates  bedrooms   beds  price  \
total_outliers      16133         12086     59050  18498  16243

                minimum_nights  maximum_nights  review_scores_rating
total_outliers            2122              13                 21981
```

```
outliers_count = outliers_df.iloc[0]

fig, ax = plt.subplots(figsize=(14, 8))

# Plot outliers
outliers_count.plot(kind='barh', color='skyblue')

# Add gridlines
ax.grid(color='black', linestyle='-.', linewidth=0.5, alpha=0.2)

# Add annotation to bars
for i, v in enumerate(outliers_count):
    plt.text(v + 0.2, i, str(round(v, 2)), fontdict={'fontsize':10,
'fontweight':'bold'})

ax.set_title('Number of Outliers for Each Feature', loc='left',
fontweight='bold')

plt.xlabel('Outlier Count')
plt.ylabel('Feature')
plt.show()
```




```
def remove_outliers(df, cols):

    # Create a copy of the DataFrame to avoid modifying the original
    df_outliers = df.copy()

    # Iterate for each column
    for col in cols:
        # Save the original dtype
        original_dtype = df_outliers[col].dtype

        # Calculate the upper and lower limits using IQR
        Q1 = df_outliers[col].quantile(0.25)
        Q3 = df_outliers[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_limit = Q1 - 1.5 * IQR
        upper_limit = Q3 + 1.5 * IQR

        # Identify and remove outliers
        outliers = (df_outliers[col] < lower_limit) |
(df_outliers[col] > upper_limit)
        df_outliers = df_outliers.loc[~outliers]

        # Assign original dtype back to each column
        df_outliers[col] = df_outliers[col].astype(original_dtype)

    return df_outliers

def replace_outliers(df, columns):

    # Create a copy of the DataFrame to avoid modifying the original
```

```
    df_outliers = df.copy()

    # Iterate for each column
    for col in columns:
        # Save the original dtype
        original_dtype = df_outliers[col].dtype

        # Calculate the upper and lower limits using IQR
        Q1 = df_outliers[col].quantile(0.25)
        Q3 = df_outliers[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_limit = Q1 - 1.5 * IQR
        upper_limit = Q3 + 1.5 * IQR

        # Identify and replace outliers with median
        outliers = (df_outliers[col] < lower_limit) |
(df_outliers[col] > upper_limit)
        median_value = df[col].median()
        df_outliers.loc[outliers, col] = median_value

        # Assign original dtype back to each column
        df_outliers[col] = df_outliers[col].astype(original_dtype)

    return df_outliers

outlier_price = ['price']
df_outliers = remove_outliers(df, outlier_price)

outlier_replace = ['host_acceptance_rate', 'host_listings_count',
'accommodates',
                   'bedrooms', 'beds', 'minimum_nights',
'maximum_nights']

df = replace_outliers(df_outliers, outlier_replace)

df.columns
```

```
Index(['host_acceptance_rate', 'host_is_superhost',
'host_listings_count',
       'host_identity_verified', 'neighborhood', 'borough',
'latitude',
       'longitude', 'room_type', 'accommodates', 'bathrooms_text',
'bedrooms',
       'beds', 'amenities', 'price', 'minimum_nights',
'maximum_nights',
       'review_scores_rating', 'instant_bookable', 'date'],
      dtype='object')
```

Feature Extraction

In this section, features extraction is performed for `bathrooms_text` and `amenities`. Plots are also created for bathroom features and amenity features.

Bathroom Features:

- `shared_bathroom`
- `bathrooms`

```
df['bathrooms_text'].unique()

array(['1 bath', '1.5 baths', '1 shared bath', '1 private bath',
       '2 baths', '1.5 shared baths', '2.5 baths', '2 shared baths',
       '3 baths', '0 baths', '0 shared baths', 'Private half-bath',
       'Shared half-bath', '4.5 baths', '2.5 shared baths', '3.5
baths',
       'Half-bath', '4 baths', '3 shared baths', '3.5 shared baths',
       '4 shared baths', '6 baths', '4.5 shared baths', '6 shared
baths',
       '5.5 baths', '5 baths', '5.5 shared baths', '7.5 baths',
       '11.5 shared baths', '7 baths', '16 baths'], dtype=object)

df['shared_bathroom'] = df['bathrooms_text'].apply(lambda x: 1 if
(isinstance(x, str) and re.search(r'\bShared\b', x, re.IGNORECASE))
else 0)
```

The `bathroom_text` feature contains floats and the string 'shared bathroom(s)'.

To derive meaning from the string, I create a separate column `shared_bathroom`. Inserting a 1 for each observation implies the listing has a shared bathroom and a 0 implies the listing has a private bathroom.

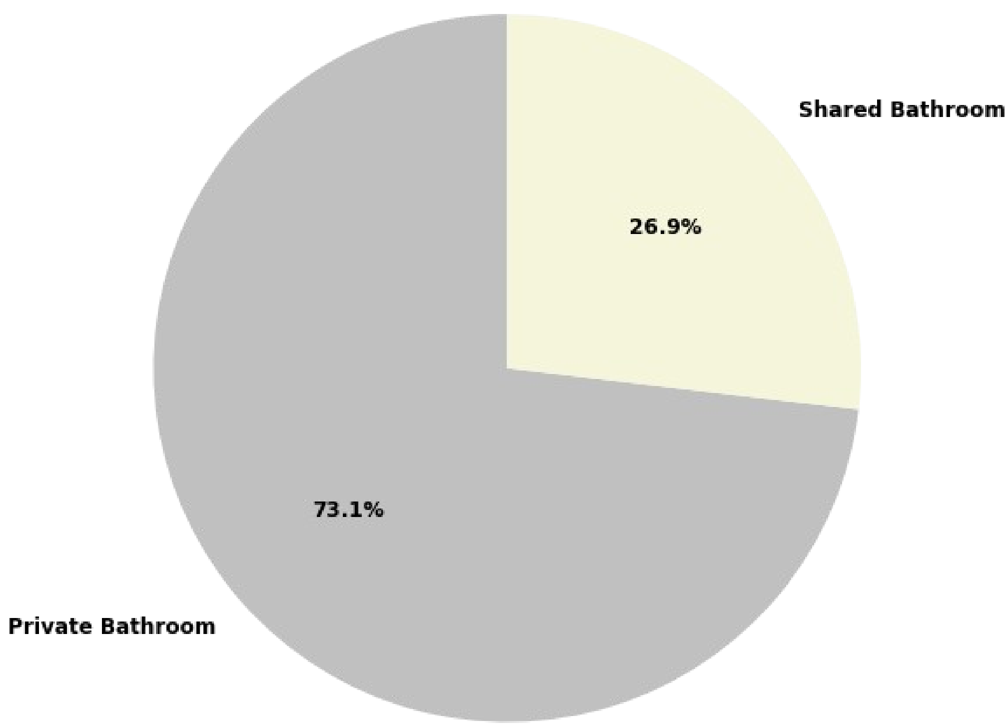
```
def extract_number(text):
    if isinstance(text, str):
        # Use regular expression to find numeric values
        matches = re.findall(r'\d+\.?\d*', text)
        # Convert the first match to float if it exists, else return
NaN
        return float(matches[0]) if matches else np.nan
    else:
        return np.nan

df['bathrooms'] = df['bathrooms_text'].apply(extract_number)
df['bathrooms'].unique()

array([ 1. ,  1.5,  2. ,  2.5,  3. ,  0. ,  nan,  4.5,  3.5,  4. ,  6.
,
        5.5,  5. ,  7.5, 11.5,  7. , 16. ])
```

The function `extract_number` returns a new column for the floats from the `bathroom_text` feature to represent the new column for number of bathrooms.

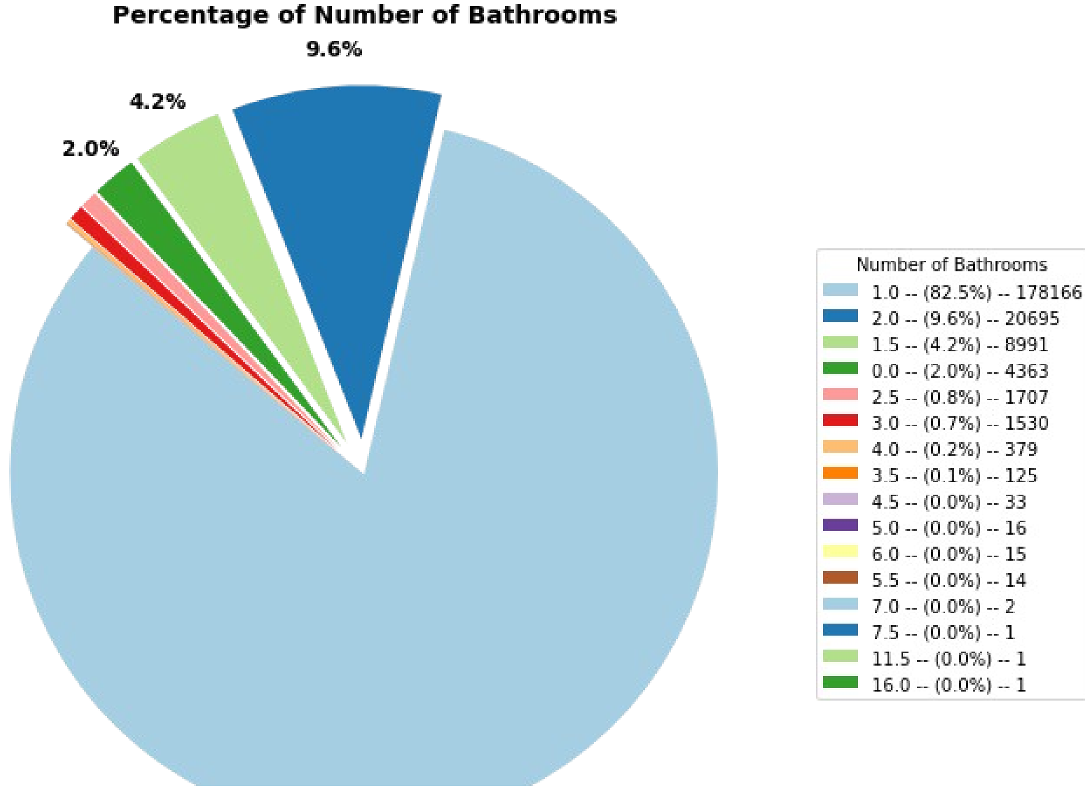
```
df = df.drop('bathrooms_text', axis=1)

df.isnull().sum()

host_acceptance_rate          0
host_is_superhost             0
host_listings_count           0
host_identity_verified        0
neighborhood                  0
borough                       0
latitude                      0
longitude                     0
room_type                     0
accommodates                  0
bedrooms                      0
beds                          0
amenities                     0
price                         0
minimum_nights                0
maximum_nights                0
review_scores_rating          0
instant_bookable              0
date                          0
shared_bathroom               0
bathrooms                   265
dtype: int64

df['bathrooms'] = df['bathrooms'].fillna(df['bathrooms'].median())

fig, axes = plt.subplots(2, 1, figsize=(15, 15))

# Create a pie chart for Shared Bathrooms

shared_bathrooms_count = df['shared_bathroom'].value_counts()

axes[0].pie(shared_bathrooms_count, labels=['Private Bathroom',
'Shared Bathroom'],
            colors=['silver', 'beige'], autopct='%1.1f%%',
startangle=90,
            textprops={'fontweight': 'bold', 'fontsize': 12})
axes[0].set_title('Percentage of Shared Bathrooms',
                  fontdict={'fontsize': 14, 'fontweight': 'bold'})


# Create a pie chart for Number of Bathrooms

bathrooms_count = df['bathrooms'].value_counts()
```

```python
# Filter slices with percentages less than 10%
small_slices = bathrooms_count[bathrooms_count / bathrooms_count.sum()
< 0.1]

# Explode slices with percentages less than 10%
explode = [0.1 if index in small_slices.index else 0 for index in
bathrooms_count.index]
wedges, texts, autotexts = axes[1].pie(bathrooms_count, labels=None,
autopct=lambda p: f'{p:.1f}%' if p > 1 else '', pctdistance=1.105,
                                  explode=explode, startangle=140,
colors=plt.cm.Paired.colors, textprops={'fontsize': 12, 'fontweight':
'bold'})

# Add legend with corresponding percentages and counts
legend_labels = [f'{label} -- ({bathrooms_count[label] /
bathrooms_count.sum():.1%}) -- {bathrooms_count[label]}' for label in
bathrooms_count.index]
axes[1].legend(wedges, legend_labels, title='Number of Bathrooms',
loc='center left', bbox_to_anchor=(1, 0, 0.5, 1))

axes[1].set_title('Percentage of Number of Bathrooms',
fontdict={'fontsize': 14, 'fontweight': 'bold'})

# Adjust layout to prevent overlap
plt.tight_layout()

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

Percentage of Shared Bathrooms



Percentage of Number of Bathrooms



```
df['bathrooms'] = np.where(df['bathrooms'] > 3, 2, df['bathrooms'])
```

Observations containing more than 3 bathrooms are replaced with 2.

Amenities Features:

- `has_ac`
- `has_heating`
- `has_wifi`
- `has_essentials`
- `has_kitchen`
- `has_tv`
- `has_washer`
- `has_safety`
- `has_workspace`
- `children_pet_friendly`
- `has_gym`
- `has_pool`
- `has_fireplace`
- `has_views`
- `has_parking`

```
df['amenities'].unique()
```

```
array(['["Keypad", "Extra pillows and blankets", "TV", "Refrigerator",
"Long term stays allowed", "Baking sheet", "Coffee maker", "Carbon
monoxide alarm", "Oven", "Paid parking off premises", "Cleaning
available during stay", "Ethernet connection", "Stove", "Wifi", "Free
street parking", "Dishes and silverware", "Heating", "Dedicated
workspace", "Luggage dropoff allowed", "Smoke alarm", "Hot water",
"Bed linens", "Hangers", "Cooking basics", "Fire extinguisher",
"Essentials", "Bathtub", "Kitchen", "Self check-in", "Iron", "Hair
dryer", "Air conditioning"]',
       '["Kitchen", "Wifi", "Long term stays allowed", "Heating", "Air
conditioning"]',
       '["Carbon monoxide alarm", "HDTV with Disney+, HBO Max,
standard cable, Roku, Netflix", "Kitchen", "Wifi", "Outdoor
furniture", "Long term stays allowed", "Heating", "Refrigerator",
"Outdoor dining area", "Dryer", "Washer", "Smoke alarm", "Private
patio or balcony", "Private backyard \\u2013 Fully fenced", "BBQ
grill", "Hair dryer", "Air conditioning", "Children\\u2019s books and
toys"]',
       ...,
       '["Toaster", "Extra pillows and blankets", "Safe",
"Conditioner", "Dedicated workspace", "Building staff", "Hot water",
"Paid parking garage off premises", "Shampoo", "Hair dryer",
"Elevator", "Microwave", "Long term stays allowed", "Fire
extinguisher", "Luggage dropoff allowed", "Essentials", "Shower gel",
```

```
"Babysitter recommendations", "Smoke alarm", "Heating", "Pets
allowed", "Coffee maker", "Bathtub", "Hangers", "Kitchenette", "Body
soap", "Shared gym in building", "Wifi", "Iron", "Room-darkening
shades", "Self check-in", "Air conditioning", "Cleaning available
during stay", "Carbon monoxide alarm", "TV with standard cable", "Mini
fridge", "Bed linens", "Hot water kettle", "Pack \\u2019n play/Travel
crib", "Dishes and silverware"]',
       '["Toaster", "Sound system", "TV", "First aid kit", "Dedicated
workspace", "Hand and shoulder  shampoo", "Hot water", "Microwave",
"Coffee maker: drip coffee maker, espresso machine", "Lock on bedroom
door", "Essentials", "Blender", "Dishes and silverware", "Smoke
alarm", "Central heating", "Wine glasses", "Window AC unit", "Ethernet
connection", "Hangers", "Dishwasher", "Gas stove", "Portable heater",
"Wifi", "Refrigerator", "Cooking basics", "Freezer", "Carbon monoxide
alarm", "Movie theater", "Kitchen"]',
       '["Keypad", "TV", "Dedicated workspace", "Shampoo", "Hair
dryer", "Elevator", "Essentials", "Fire pit", "Outdoor furniture",
"Dishes and silverware", "Smoke alarm", "Heating", "Free parking on
premises", "Pets allowed", "Free washer \\u2013 In unit", "Exercise
equipment", "Coffee maker", "Hangers", "Dishwasher", "Outdoor
kitchen", "Shared gym in building", "Wifi", "BBQ grill",
"Refrigerator", "Cooking basics", "Iron", "Self check-in", "Carbon
monoxide alarm", "City skyline view", "Free dryer \\u2013 In unit",
"Central air conditioning", "Outdoor dining area", "Kitchen"]'],
      dtype=object)

ac_keywords = ['AC', 'air conditioning']
df['has_ac'] = df['amenities'].apply(lambda x: 1 if any(re.search(r'\
b{}\b'.format(keyword), x, re.IGNORECASE) for keyword in ac_keywords)
else 0)

df['has_heating'] = df['amenities'].apply(lambda x: 1 if re.search(r'\
bHeating\b', x, re.IGNORECASE) else 0)

wifi_keywords = ['wifi', 'ethernet']
df['has_wifi'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in wifi_keywords) else 0)

essentials_keywords = ['essentials', 'toilet paper', 'hand soap',
'body soap', 'towel', 'pillow', 'per guest', 'linens']
df['has_essentials'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in essentials_keywords) else 0)

df['has_kitchen'] = df['amenities'].apply(lambda x: 1 if re.search(r'\
bkitchen\b', x, re.IGNORECASE) else 0)

tv_keywords = ['TV', 'cable']
df['has_tv'] = df['amenities'].apply(lambda x: 1 if any(re.search(r'\
```

```
b{}\b'.format(keyword), x, re.IGNORECASE) for keyword in tv_keywords)
else 0)

df['has_washer'] = df['amenities'].apply(lambda x: 1 if re.search(r'\
bWasher\b', x, re.IGNORECASE) else 0)

safety_keywords = ['security alarm', 'smoke alarm', 'carbon monoxide
alarm', 'fire extinguisher', 'first-aid kit']
df['has_safety'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in safety_keywords) else 0)

workspace_keywords = ['office', 'workspace', 'work', 'remote']
df['has_workspace'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in workspace_keywords) else 0)

children_pets_keywords = ['high chair', 'crib', 'baby safety gates',
'furniture covers', 'bowls for pet food and water', 'pet', 'pets',
'dog', 'cat']
df['children_pet_friendly'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in children_pets_keywords) else 0)

gym_keywords = ['gym', 'fitness equipment', 'exercise', 'weight',
'training']
df['has_gym'] = df['amenities'].apply(lambda x: 1 if any(re.search(r'\
b{}\b'.format(keyword), x, re.IGNORECASE) for keyword in gym_keywords)
else 0)

df['has_pool'] = df['amenities'].apply(lambda x: 1 if re.search(r'\
bpool\b', x, re.IGNORECASE) else 0)

fireplace_keywords = ['fireplace', 'pit']
df['has_fireplace'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in fireplace_keywords) else 0)

views_keywords = ['city views', 'city skyline view', 'skyline',
'views', 'cityscape']
df['has_views'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in views_keywords) else 0)

parking_keywords = ['parking', 'garage', 'car']
df['has_parking'] = df['amenities'].apply(lambda x: 1 if
any(re.search(r'\b{}\b'.format(keyword), x, re.IGNORECASE) for keyword
in parking_keywords) else 0)
```

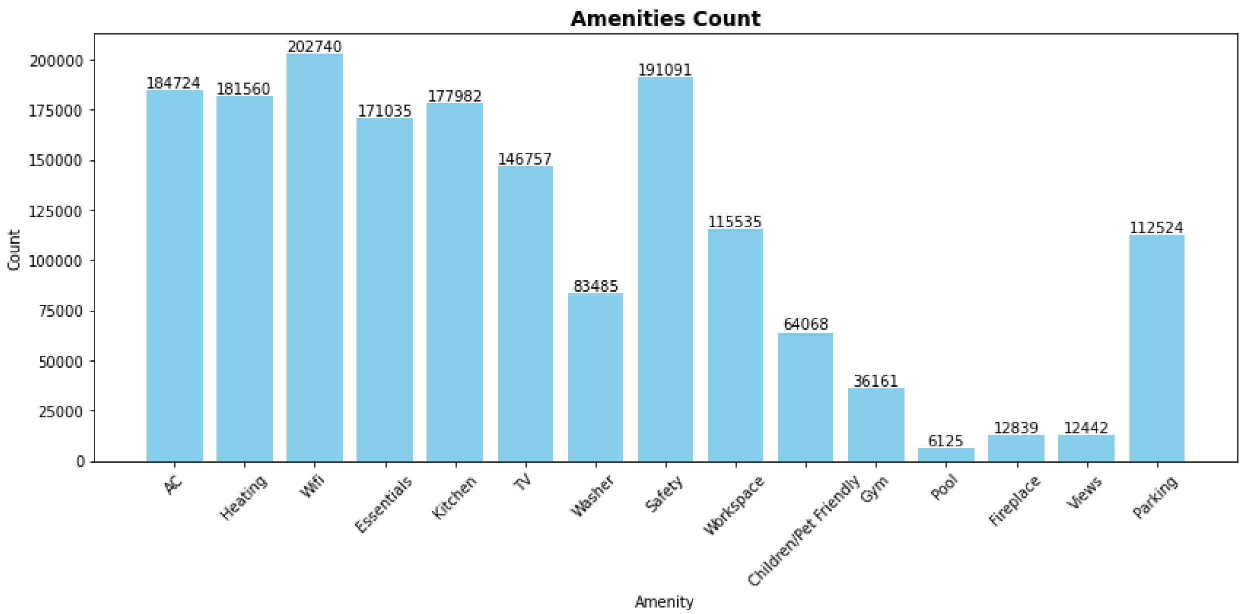
The `amenities` feature contains a list of multiple amenities, which makes it difficult to derive insight. Regular expression operators are used to extract key words of popular amenities. If the key word(s) are in the list of amenities, a new column is created with the value 1 to indicate its presence and 0 otherwise.

```
amenities_cols = ['has_ac', 'has_heating', 'has_wifi',
'has_essentials', 'has_kitchen', 'has_tv',
                  'has_washer', 'has_safety', 'has_workspace',
'children_pet_friendly', 'has_gym',
                  'has_pool', 'has_fireplace', 'has_views',
'has_parking']

for col in amenities_cols:
    print(f"'{col}':{(df[col] == 1).sum()},")
```

```
'has_ac':184724,
'has_heating':181560,
'has_wifi':202740,
'has_essentials':171035,
'has_kitchen':177982,
'has_tv':146757,
'has_washer':83485,
'has_safety':191091,
'has_workspace':115535,
'children_pet_friendly':64068,
'has_gym':36161,
'has_pool':6125,
'has_fireplace':12839,
'has_views':12442,
'has_parking':112524,
```

```
amenities_dict = {'AC':184724,
                  'Heating':181560,
                  'Wifi':202740,
                  'Essentials':171035,
                  'Kitchen':177982,
                  'TV':146757,
                  'Washer':83485,
                  'Safety':191091,
                  'Workspace':115535,
                  'Children/Pet Friendly':64068,
                  'Gym':36161,
                  'Pool':6125,
                  'Fireplace':12839,
                  'Views':12442,
                  'Parking':112524}

# Bar chart for Amenities
amenities = list(amenities_dict.keys())
values = list(amenities_dict.values())
```

```
fig = plt.figure(figsize=(12,6))
bars = plt.bar(amenities, values, color='skyblue')
plt.title('Amenities Count', fontdict={'fontsize':14,
'fontweight':'bold'})
plt.xticks(rotation=45)
plt.xlabel('Amenity')
plt.ylabel('Count')

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval + 0.05,
round(yval, 2), ha='center', va='bottom', fontsize=10)

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




```
df = df.drop(['amenities'], axis = 1)
```

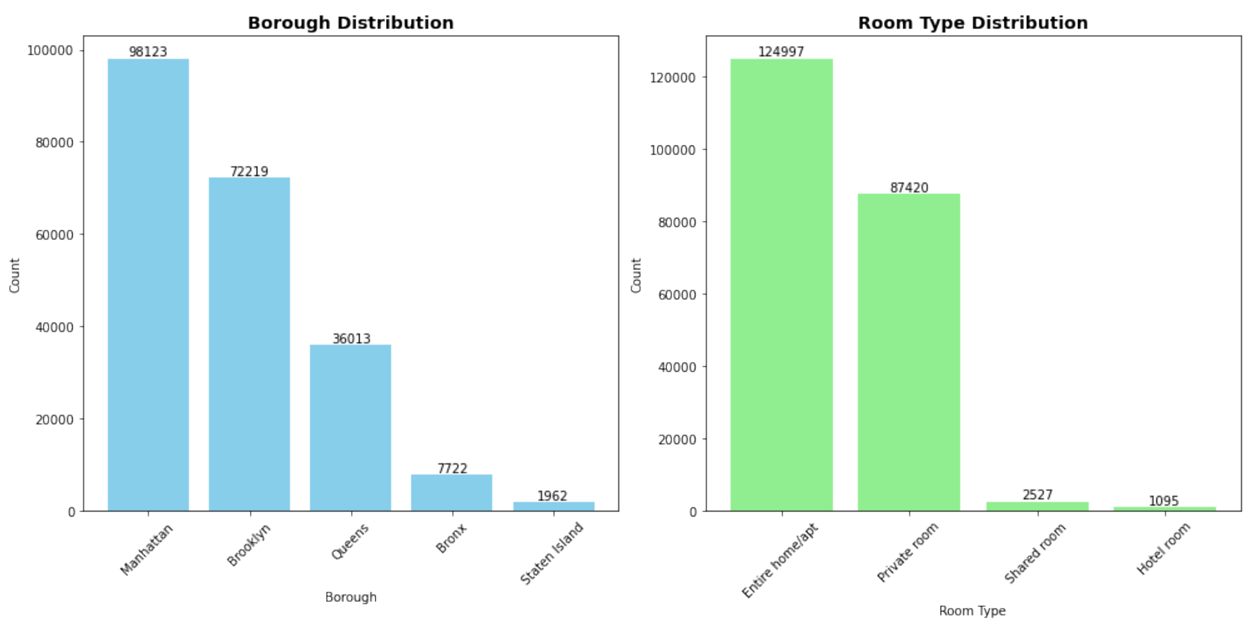
The original `amenities` column is dropped.

Geospatial Analysis

This section provides insight to the location of each Airbnb listing. The Airbnb dataset provides latitude and longitude coordiates that are utilized to create maps with highlighted features. In addition, a feature is extracted `nearest_transit_mi` using additional datasets from the MTA.

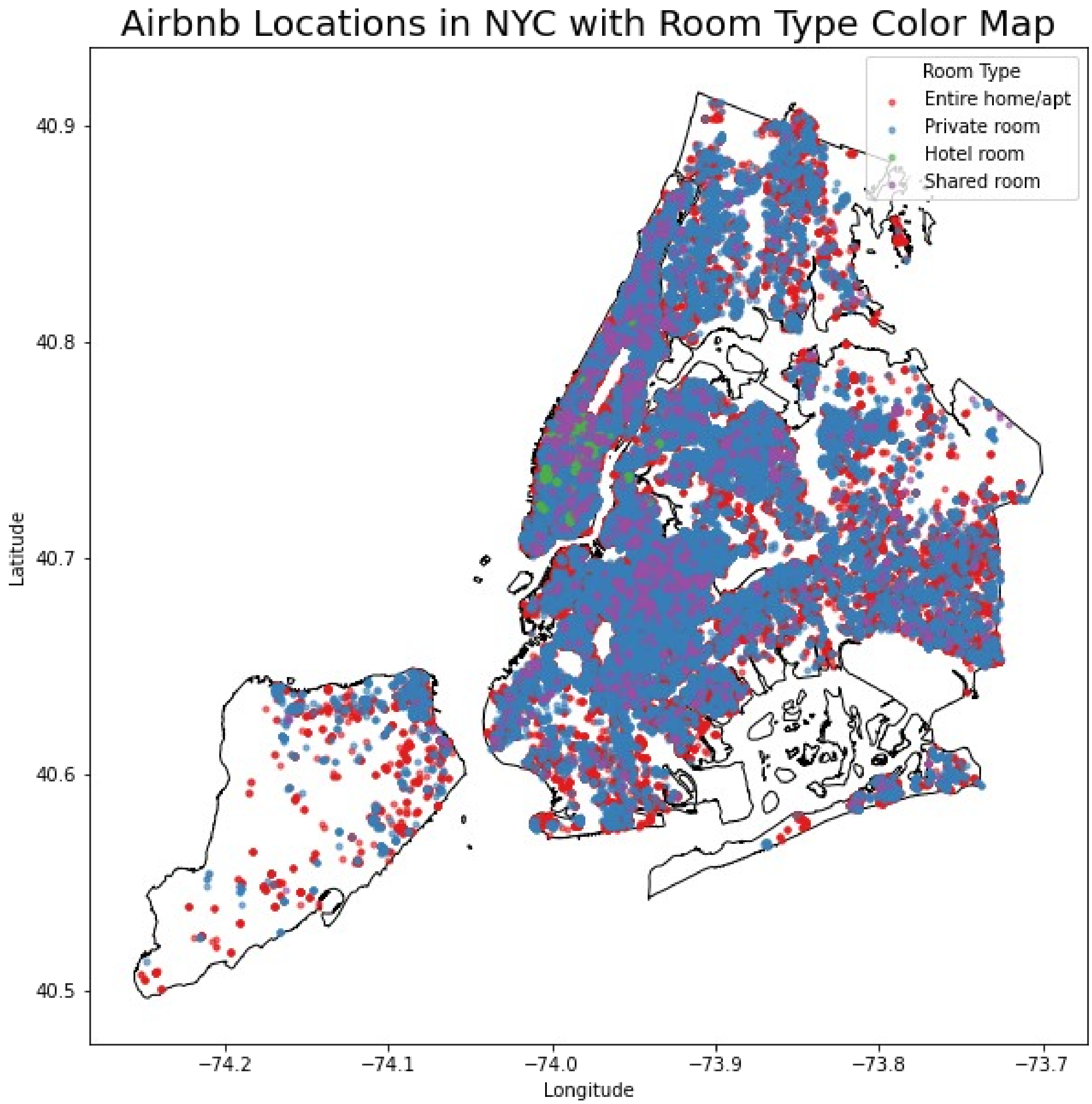
```
borough_counts = df['borough'].value_counts()
room_type_counts = df['room_type'].value_counts()

fig, axes = plt.subplots(1, 2, figsize=(14, 7))
```

```python
# Bar chart for Boroughs
axes[0].bar(borough_counts.index, borough_counts, color='skyblue')
axes[0].set_title('Borough Distribution', fontdict={'fontsize':14,
'fontweight':'bold'})
axes[0].set_xlabel('Borough')
axes[0].set_ylabel('Count')
axes[0].tick_params(axis='x', rotation=45)

for i, v in enumerate(borough_counts):
    axes[0].text(i, v + 0.2, str(v), ha='center', va='bottom')

# Bar chart for Property Types
axes[1].bar(room_type_counts.index, room_type_counts,
color='lightgreen')
axes[1].set_title('Room Type Distribution', fontdict={'fontsize':14,
'fontweight':'bold'})
axes[1].set_xlabel('Room Type')
axes[1].set_ylabel('Count')
axes[1].tick_params(axis='x', rotation=45)

for i, v in enumerate(room_type_counts):
    axes[1].text(i, v + 0.2, str(v), ha='center', va='bottom')

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



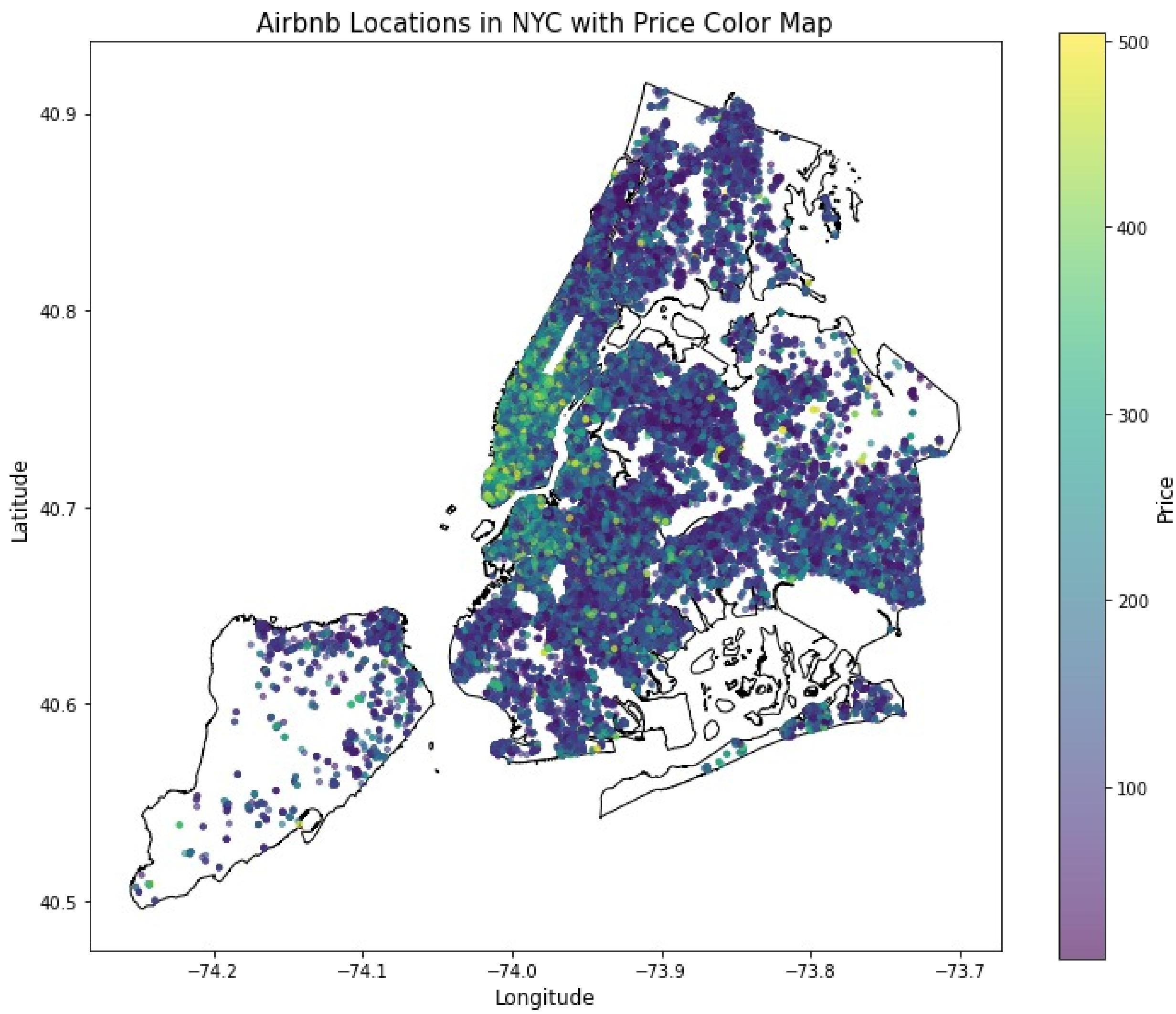

```python
geometry = [Point(xy) for xy in zip(df['longitude'], df['latitude'])]
gdf_airbnb = gpd.GeoDataFrame(df, geometry=geometry, crs="EPSG:4326")
```

```python
# Load NYC boroughs shapefile from geodatasets
nybb = get_path('nybb')
boroughs = gpd.read_file(nybb)

# Plot boroughs
fig, ax = plt.subplots(figsize=(12, 10))
boroughs.to_crs("EPSG:4326").plot(ax=ax, color="white",
edgecolor="black")

# Create Seaborn color palette for room types
room_type_palette = sns.color_palette("Set1",
n_colors=len(gdf_airbnb['room_type'].unique()))

# Create scatter plot with different colors for each room type
for room_type, color in zip(gdf_airbnb['room_type'].unique(),
room_type_palette):
    subset = gdf_airbnb[gdf_airbnb['room_type'] == room_type]
    subset.plot(ax=ax, markersize=10, color=color, alpha=0.6,
label=room_type)

# Add legend
ax.legend(title='Room Type')

# Set plot title and labels
plt.title('Airbnb Locations in NYC with Room Type Color Map',
fontsize=20)
plt.xlabel('Longitude')
plt.ylabel('Latitude')

plt.show()
```




```
geometry = [Point(xy) for xy in zip(df['longitude'], df['latitude'])]
gdf_airbnb = gpd.GeoDataFrame(df, geometry=geometry, crs="EPSG:4326")

# Load NYC boroughs shapefile from geodatasets
nybb = gpd.datasets.get_path('nybb')
boroughs = gpd.read_file(nybb)

# Plot boroughs
fig, ax = plt.subplots(figsize=(12, 10))
boroughs.to_crs("EPSG:4326").plot(ax=ax, color="white",
edgecolor="black")
```

```python
# Create Seaborn color palette for price
price_palette = sns.color_palette('viridis', as_cmap=True)

# Create scatter plot with different colors for each room type
scatter = ax.scatter(
    x=gdf_airbnb['longitude'],
    y=gdf_airbnb['latitude'],
    c=gdf_airbnb['price'],  # Color based on price
    cmap=price_palette,  # Use viridis color map
    s=10,
    alpha=0.6,
    label=gdf_airbnb['room_type']
)

# Add color bar
cbar = plt.colorbar(scatter, label='Price')
cbar.set_label('Price', fontsize=12)

# Set plot title and labels
plt.title('Airbnb Locations in NYC with Price Color Map', fontsize=15)
plt.xlabel('Longitude', fontsize=12)
plt.ylabel('Latitude', fontsize=12)

plt.show()
```



Feature Extraction of Location

In this section, I attempt to create a new variable for distance to `nearest_transit_mi`.

I load data from MTA's Data Feed that includes coordinates of buses and subways across all 5 boroughs. I use the `haversine_distances` function from `sklearn.metrics.pairwise` to create a distance matrix of all Airbnb listings and all transit stops. The minimum distance is extracted for each listing and placed in a new column `nearest_transit_mi`.

Unfortunately in the later section, it is shown that this feature is not well correlated to the price feature. Therefore it will not be used in the machine learning model predictions.

```
airbnb_df = df[['latitude', 'longitude']].copy()
airbnb_df = airbnb_df.drop_duplicates(subset=['latitude',
'longitude'])
airbnb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60134 entries, 0 to 38328
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   latitude   60134 non-null  float64
 1   longitude  60134 non-null  float64
dtypes: float64(2)
memory usage: 1.4 MB
```

```
# Load csv file of metro and bus station coordinates of NYC
transit_df = pd.read_csv('bus_metro.csv')

# Convert latitude and longitude to radians
airbnb_df['lat_rad'] = airbnb_df['latitude'].apply(radians)
airbnb_df['lon_rad'] = airbnb_df['longitude'].apply(radians)
transit_df['lat_rad'] = transit_df['stop_lat'].apply(radians)
transit_df['lon_rad'] = transit_df['stop_lon'].apply(radians)

earth_radius_mi = 3963.1906

# Calculate haversine distances
distances = haversine_distances(transit_df[['lat_rad',
'lon_rad']].values,
                                airbnb_df[['lat_rad',
'lon_rad']].values) * earth_radius_mi

# Extract minimum distance, Store it as a DataFrame, and add to
airbnb_df
nearest_transit = distances.min(axis=0)
nearest_transit_df = pd.DataFrame(nearest_transit,
columns=['nearest_transit'])
airbnb_df['nearest_transit_mi'] =
nearest_transit_df['nearest_transit']
airbnb_df.columns
```

```
Index(['latitude', 'longitude', 'lat_rad', 'lon_rad',
'nearest_transit_mi'], dtype='object')
```

```
# Merge airbnb_df with the df using the common columns 'latitude' and
'longitude'
airbnb_df = airbnb_df.drop(columns=['lat_rad', 'lon_rad'])
airbnb_df.info()
df = pd.merge(df, airbnb_df, how='left', on=['latitude', 'longitude'])
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60134 entries, 0 to 38328
Data columns (total 3 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   latitude            60134 non-null  float64
```

```
 1   longitude           60134 non-null  float64
 2   nearest_transit_mi  60134 non-null  float64
dtypes: float64(3)
memory usage: 1.8 MB
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 216039 entries, 0 to 216038
Data columns (total 36 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   host_acceptance_rate    216039 non-null  float64
 1   host_is_superhost       216039 non-null  object
 2   host_listings_count     216039 non-null  float64
 3   host_identity_verified  216039 non-null  object
 4   neighborhood            216039 non-null  object
 5   borough                 216039 non-null  object
 6   latitude                216039 non-null  float64
 7   longitude               216039 non-null  float64
 8   room_type               216039 non-null  object
 9   accommodates            216039 non-null  int64
 10  bedrooms                216039 non-null  float64
 11  beds                    216039 non-null  float64
 12  price                   216039 non-null  float64
 13  minimum_nights          216039 non-null  int64
 14  maximum_nights          216039 non-null  int64
 15  review_scores_rating    216039 non-null  float64
 16  instant_bookable        216039 non-null  object
 17  date                    216039 non-null  datetime64[ns]
 18  shared_bathroom         216039 non-null  int64
 19  bathrooms               216039 non-null  float64
 20  has_ac                  216039 non-null  int64
 21  has_heating             216039 non-null  int64
 22  has_wifi                216039 non-null  int64
 23  has_essentials          216039 non-null  int64
 24  has_kitchen             216039 non-null  int64
 25  has_tv                  216039 non-null  int64
 26  has_washer              216039 non-null  int64
 27  has_safety              216039 non-null  int64
 28  has_workspace           216039 non-null  int64
 29  children_pet_friendly   216039 non-null  int64
 30  has_gym                 216039 non-null  int64
 31  has_pool                216039 non-null  int64
 32  has_fireplace           216039 non-null  int64
 33  has_views               216039 non-null  int64
 34  has_parking             216039 non-null  int64
 35  nearest_transit_mi      216039 non-null  float64
dtypes: datetime64[ns](1), float64(10), int64(19), object(6)
memory usage: 61.0+ MB
```

```
df.to_csv('airbnb.csv', index=False)
```

Feature Importance & Feature Selection

In this section, I first **label encode** and **one hot encode** categorical features.

I then create a **Correlation Heatmap** of all the features to visually compare which features are more correlated with the `price` feature. I select features that have a correlation coefficient with the `price` feature of |±0.10|. I run a **second Correlation Heatmap** to have a bigger picture of which features were selected. Afterwards, I conduct a **p-value analysis** at the α = 0.05 level to confirm that the features selected show feature importance.

Lastly, I create **two OLS Regressions** with the selected features but with different outcome features: **`price`** and **`log_price`**. The purpose is to compare the R2 values of each regression to see **whether there is a benefit of applying the natural logarithmic function to the `price` feature.**

```
df.columns

Index(['host_acceptance_rate', 'host_is_superhost',
'host_listings_count',
       'host_identity_verified', 'neighborhood', 'borough',
'latitude',
       'longitude', 'room_type', 'accommodates', 'bedrooms', 'beds',
'price',
       'minimum_nights', 'maximum_nights', 'review_scores_rating',
       'instant_bookable', 'date', 'shared_bathroom', 'bathrooms',
'has_ac',
       'has_heating', 'has_wifi', 'has_essentials', 'has_kitchen',
'has_tv',
       'has_washer', 'has_safety', 'has_workspace',
'children_pet_friendly',
       'has_gym', 'has_pool', 'has_fireplace', 'has_views',
'has_parking',
       'nearest_transit_mi'],
      dtype='object')
```

Label Encoding

As shown four cells below, all of the label encoded features and one-hot encoded features were transformed properly.

```
le = LabelEncoder()

object_cols = ['host_is_superhost', 'host_identity_verified',
'instant_bookable']

print('Label Encoder Transformation')
for col in object_cols :
```

```
    df[col] = le.fit_transform(df[col])

print(col,':',df[col].unique(),'=',le.inverse_transform(df[col].unique
()))
```

```
Label Encoder Transformation
host_is_superhost : [0 1] = ['f' 't']
host_identity_verified : [1 0] = ['t' 'f']
instant_bookable : [0 1] = ['f' 't']
```

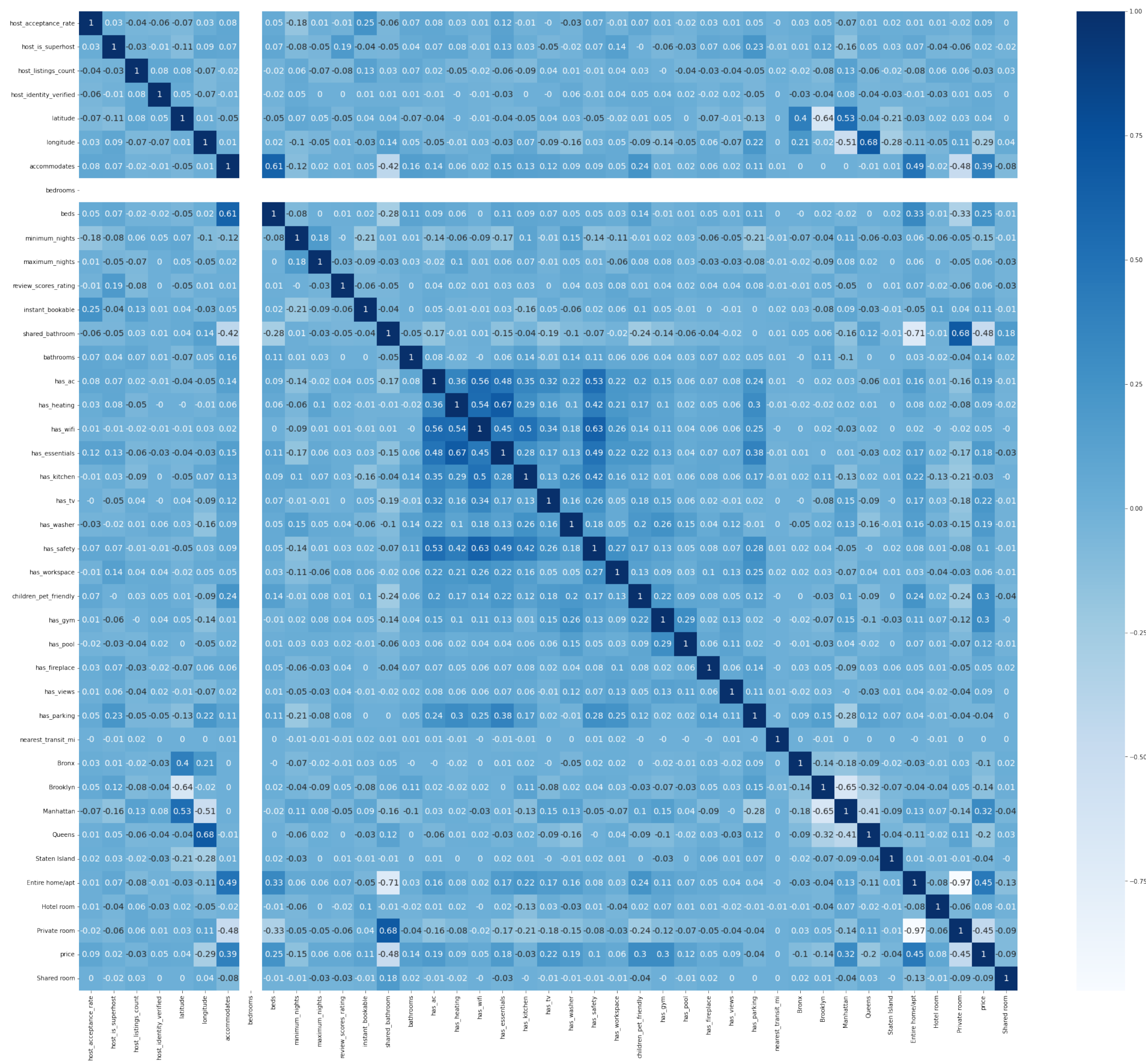
```
df_boroughs = pd.get_dummies(df['borough'], prefix='', prefix_sep='')
df_room_type = pd.get_dummies(df['room_type'], prefix='',
prefix_sep='')
df = pd.concat([df, df_boroughs, df_room_type], axis=1, join='inner')

df = df.drop(columns=['neighborhood', 'borough', 'room_type'])

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 216039 entries, 0 to 216038
Data columns (total 42 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   host_acceptance_rate    216039 non-null  float64
 1   host_is_superhost       216039 non-null  int64
 2   host_listings_count     216039 non-null  float64
 3   host_identity_verified  216039 non-null  int64
 4   latitude                216039 non-null  float64
 5   longitude               216039 non-null  float64
 6   accommodates            216039 non-null  int64
 7   bedrooms                216039 non-null  float64
 8   beds                    216039 non-null  float64
 9   price                   216039 non-null  float64
 10  minimum_nights          216039 non-null  int64
 11  maximum_nights          216039 non-null  int64
 12  review_scores_rating    216039 non-null  float64
 13  instant_bookable        216039 non-null  int64
 14  date                    216039 non-null  datetime64[ns]
 15  shared_bathroom         216039 non-null  int64
 16  bathrooms               216039 non-null  float64
 17  has_ac                  216039 non-null  int64
 18  has_heating             216039 non-null  int64
 19  has_wifi                216039 non-null  int64
 20  has_essentials          216039 non-null  int64
 21  has_kitchen             216039 non-null  int64
 22  has_tv                  216039 non-null  int64
 23  has_washer              216039 non-null  int64
 24  has_safety              216039 non-null  int64
 25  has_workspace           216039 non-null  int64
```

```
 26  children_pet_friendly   216039 non-null  int64
 27  has_gym                 216039 non-null  int64
 28  has_pool                216039 non-null  int64
 29  has_fireplace           216039 non-null  int64
 30  has_views               216039 non-null  int64
 31  has_parking             216039 non-null  int64
 32  nearest_transit_mi      216039 non-null  float64
 33  Bronx                   216039 non-null  uint8
 34  Brooklyn                216039 non-null  uint8
 35  Manhattan               216039 non-null  uint8
 36  Queens                  216039 non-null  uint8
 37  Staten Island           216039 non-null  uint8
 38  Entire home/apt         216039 non-null  uint8
 39  Hotel room              216039 non-null  uint8
 40  Private room            216039 non-null  uint8
 41  Shared room             216039 non-null  uint8
dtypes: datetime64[ns](1), float64(10), int64(22), uint8(9)
memory usage: 57.9 MB
```

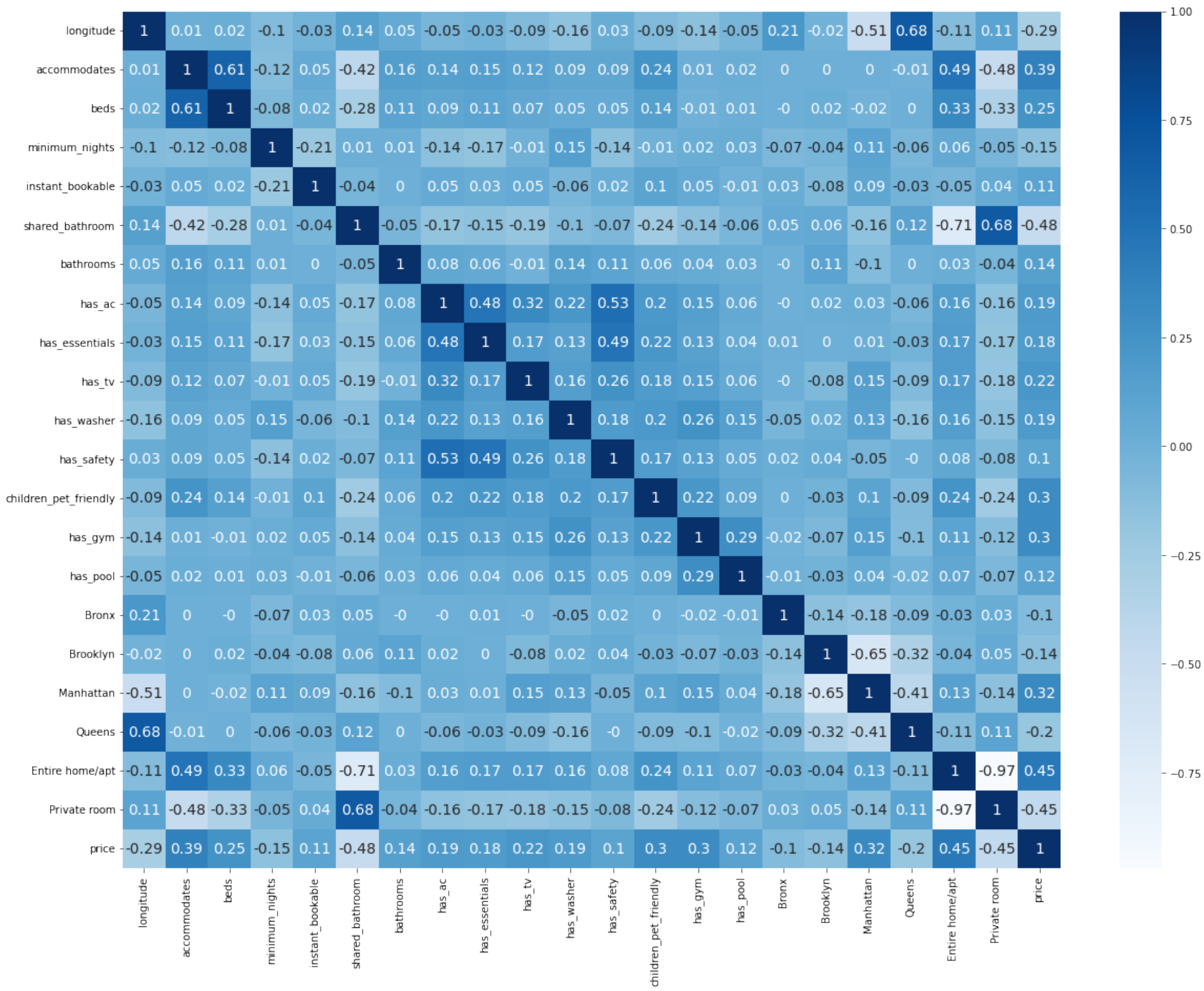
Correlation Heatmaps

```
# Shift 'price' feature to the end of the DataFrame for correlation
analysis
col = df.pop('price')
df.insert(40, col.name, col)

correlation_matrix = df.corr().round(2)
plt.figure(figsize=(35, 30))
sns.heatmap(correlation_matrix, cmap='Blues', annot=True,
annot_kws={'fontsize': 14})
plt.show()
```



```
correlated_features=[]
for col in correlation_matrix.columns:
    correlation = correlation_matrix.loc[col, 'price']
    if abs(correlation) >= 0.1:
        correlated_features.append(col)

correlated_features

['longitude',
 'accommodates',
 'beds',
 'minimum_nights',
 'instant_bookable',
 'shared_bathroom',
 'bathrooms',
```

```
 'has_ac',
 'has_essentials',
 'has_tv',
 'has_washer',
 'has_safety',
 'children_pet_friendly',
 'has_gym',
 'has_pool',
 'Bronx',
 'Brooklyn',
 'Manhattan',
 'Queens',
 'Entire home/apt',
 'Private room',
 'price']

correlation_matrix = df[correlated_features].corr().round(2)
plt.figure(figsize=(20, 15))
sns.heatmap(correlation_matrix, cmap='Blues', annot=True,
annot_kws={'fontsize': 14})
plt.show()
```



P-value Analysis & Natural Logarithmic Transformation

The code in cell [72] contains the OLS Regression Results of the selected features and the `price` feature.

The code in cell [74] contains the OLS Regression Results of the selected features and the `log_price` feature.

```
X = df[['longitude', 'accommodates', 'beds', 'minimum_nights', 
'instant_bookable', 'shared_bathroom',
        'bathrooms','has_ac', 'has_essentials', 'has_tv', 
'has_washer', 'has_safety', 'children_pet_friendly',
        'has_gym', 'has_pool', 'Bronx', 'Brooklyn', 'Manhattan', 
'Queens', 'Entire home/apt', 'Private room']]

y = df['price']

# Add a constant term to the features matrix
X = sm.add_constant(X)
```

```
# Fit the multivariate linear regression model
price_model = sm.OLS(y, X).fit()

df['log_price'] = np.log(df['price'])

X = df[['longitude', 'accommodates', 'beds', 'minimum_nights',
'instant_bookable', 'shared_bathroom',
        'bathrooms', 'has_ac', 'has_essentials', 'has_tv',
'has_washer', 'has_safety', 'children_pet_friendly',
        'has_gym', 'has_pool', 'Bronx', 'Brooklyn', 'Manhattan',
'Queens', 'Entire home/apt', 'Private room']]

y = df['log_price']

# Add a constant term to the features matrix
X = sm.add_constant(X)

# Fit the multivariate linear regression model
log_price_model = sm.OLS(y, X).fit()
print(log_price_model.summary())

                            OLS Regression Results

======================================================================
========
Dep. Variable:              log_price   R-squared:
0.587
Model:                            OLS   Adj. R-squared:
0.587
Method:                 Least Squares   F-statistic:
1.460e+04
Date:                Thu, 05 Sep 2024   Prob (F-statistic):
0.00
Time:                        17:49:45   Log-Likelihood:            -
1.2482e+05
No. Observations:              216039   AIC:
2.497e+05
Df Residuals:                  216017   BIC:
2.499e+05
Df Model:                          21

Covariance Type:            nonrobust

======================================================================
===================
                            coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------------
const                  -175.3801      2.052    -85.480      0.000    -
```

```
179.401    -171.359
longitude                     -2.4236      0.028    -87.557      0.000
-2.478      -2.369
accommodates                   0.0701      0.001     75.131      0.000
0.068       0.072
beds                           0.0257      0.002     14.435      0.000
0.022       0.029
minimum_nights                -0.0101   7.14e-05   -140.851      0.000
-0.010      -0.010
instant_bookable               0.0314      0.002     14.094      0.000
0.027       0.036
shared_bathroom               -0.3604      0.003   -117.582      0.000
-0.366      -0.354
bathrooms                      0.0851      0.002     35.290      0.000
0.080       0.090
has_ac                         0.0797      0.003     23.528      0.000
0.073       0.086
has_essentials                 0.0686      0.003     24.543      0.000
0.063       0.074
has_tv                         0.0611      0.002     27.990      0.000
0.057       0.065
has_washer                     0.0496      0.002     23.431      0.000
0.045       0.054
has_safety                    -0.1102      0.004    -30.007      0.000
-0.117      -0.103
children_pet_friendly          0.1107      0.002     49.613      0.000
0.106       0.115
has_gym                        0.2220      0.003     80.098      0.000
0.217       0.227
has_pool                       0.0774      0.006     13.177      0.000
0.066       0.089
Bronx                          0.5276      0.013     41.869      0.000
0.503       0.552
Brooklyn                       0.6041      0.011     55.478      0.000
0.583       0.625
Manhattan                      0.8154      0.011     77.173      0.000
0.795       0.836
Queens                         0.6906      0.012     56.542      0.000
0.667       0.715
Entire home/apt                0.2889      0.008     37.329      0.000
0.274       0.304
Private room                  -0.0246      0.007     -3.337      0.001
-0.039      -0.010
==============================================================================
========
Omnibus:                     2285.906   Durbin-Watson:
1.703
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
3132.972
```

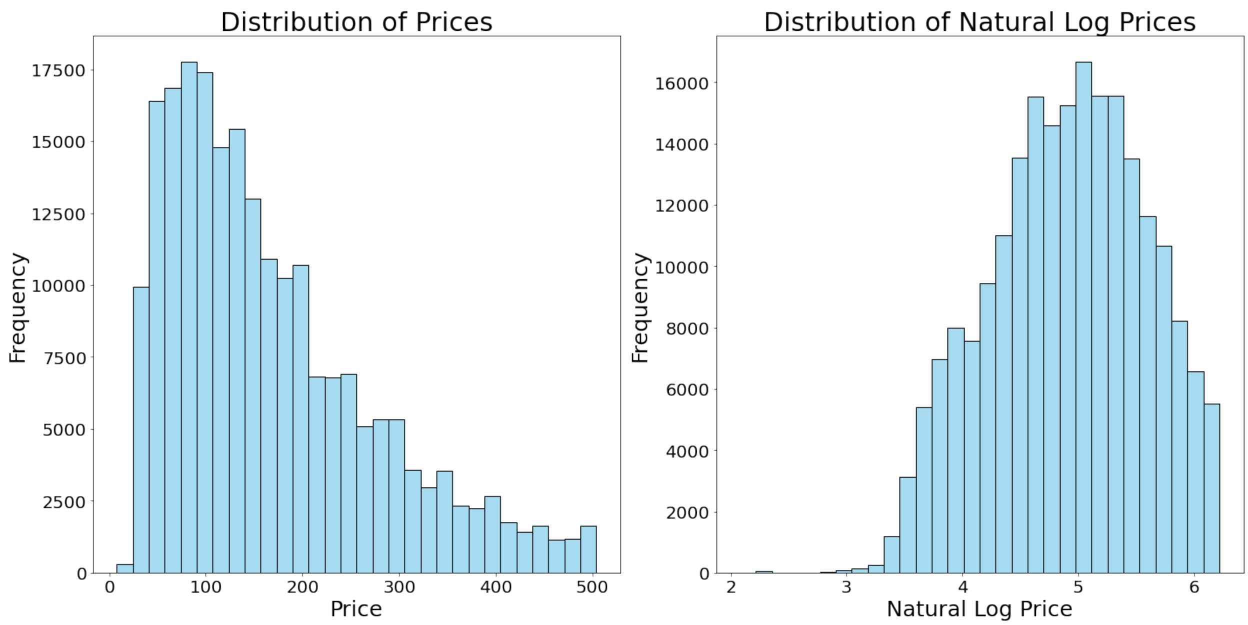
```
Skew:                              0.147   Prob(JB):
0.00
Kurtosis:                          3.512   Cond. No.
1.68e+05
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.68e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

```
print('R2 of Price OLS Model:', price_model.rsquared.round(4),
      '\nR2 of Log Price OLS Model:',
log_price_model.rsquared.round(4))
```

```
R2 of Price OLS Model: 0.4747
R2 of Log Price OLS Model: 0.5867
```

The `log_price` OLS Regression Model performed 23.59% better than the `price` OLS Regression Model. This confirms that applying the natural logarithmic transformation to the `price` feature improves the performance of price prediction models.

```
# Set up the matplotlib figure
fig, axes = plt.subplots(1, 2, figsize=(20, 10))

# Distribution of Prices
sns.histplot(df['price'], ax=axes[0], color='skyblue', bins=30)
axes[0].set_title('Distribution of Prices', fontsize=30)
axes[0].set_xlabel('Price', fontsize=25)
axes[0].set_ylabel('Frequency', fontsize=25)
axes[0].tick_params(axis='both', which='major', labelsize=20)

# Distribution of Natural Log Prices
sns.histplot(df['log_price'], ax=axes[1], color='skyblue', bins=30)
axes[1].set_title('Distribution of Natural Log Prices', fontsize=30)
axes[1].set_xlabel('Natural Log Price', fontsize=25)
axes[1].set_ylabel('Frequency', fontsize=25)
axes[1].tick_params(axis='both', which='major', labelsize=20)


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



The graphs above show that the distribution of `price` is skewed to the right while the distribution of `log_price` is normal. This also confirms that applying the natural logarithmic transformation to the `price` feature reduces the variance and improves the R2 value.

Model Implementation

The machine learning models implemented are as follows: Linear Regression, Support Vector Regressor, Decision Tree Regressor, Random Forest Regressor, and XGBoost Regressor.

Train and test evaluation metrics of all models are calculated for the basic models. The code for the Support Vector Regressor was commented out in the final Run because it is computationally expensive (3 hours to run), but the metrics are provided in the proceeding cell. For each model, the metrics are printed for each regressor.

Later on, hyperparameter tuning will be performed on the Decision Tree Regressor, Random Forest Regressor, and XGBoost Regressor. The best parameters of the Decision Tree Regressor were implemented in the Random Forest Regressor.

```
df.columns
```

```
Index(['host_acceptance_rate', 'host_is_superhost',
'host_listings_count',
       'host_identity_verified', 'latitude', 'longitude',
'accommodates',
       'bedrooms', 'beds', 'minimum_nights', 'maximum_nights',
       'review_scores_rating', 'instant_bookable', 'date',
'shared_bathroom',
       'bathrooms', 'has_ac', 'has_heating', 'has_wifi',
'has_essentials',
       'has_kitchen', 'has_tv', 'has_washer', 'has_safety',
'has_workspace',
```

```
       'children_pet_friendly', 'has_gym', 'has_pool',
'has_fireplace',
       'has_views', 'has_parking', 'nearest_transit_mi', 'Bronx',
'Brooklyn',
       'Manhattan', 'Queens', 'Staten Island', 'Entire home/apt',
'Hotel room',
       'Private room', 'price', 'Shared room', 'log_price'],
      dtype='object')
```

```
features = ['longitude', 'accommodates', 'beds', 'minimum_nights',
'instant_bookable', 'shared_bathroom',
            'bathrooms', 'has_ac', 'has_essentials', 'has_tv',
'has_washer', 'has_safety',
            'children_pet_friendly', 'has_gym', 'has_pool', 'Bronx',
'Brooklyn', 'Manhattan', 'Queens',
            'Staten Island', 'Entire home/apt', 'Private room', 'Hotel
room']

X = df[features]
y = df.log_price

X.describe()
```

```
           longitude   accommodates           beds  minimum_nights  \
count  216039.000000  216039.000000  216039.000000   216039.000000
mean      -73.944152       2.690852       1.407079       17.149223
std         0.056846       1.412000       0.661654       14.099404
min       -74.251907       1.000000       0.000000        1.000000
25%       -73.983640       2.000000       1.000000        2.000000
50%       -73.953500       2.000000       1.000000       30.000000
75%       -73.923250       4.000000       2.000000       30.000000
max       -73.710870       7.000000       3.000000       70.000000

       instant_bookable  shared_bathroom      bathrooms         has_ac
\
count     216039.000000    216039.000000  216039.000000  216039.000000

mean           0.254542         0.268632       1.125139       0.855049

std            0.435604         0.443249       0.399446       0.352052

min            0.000000         0.000000       0.000000       0.000000

25%            0.000000         0.000000       1.000000       1.000000

50%            0.000000         0.000000       1.000000       1.000000

75%            1.000000         1.000000       1.000000       1.000000

max            1.000000         1.000000       3.000000       1.000000
```

```
       has_essentials         has_tv  ...        has_gym
has_pool  \
count   216039.000000  216039.000000  ...  216039.000000
216039.000000
mean         0.791686       0.679308  ...       0.167382
0.028351
std          0.406104       0.466744  ...       0.373317
0.165975
min          0.000000       0.000000  ...       0.000000
0.000000
25%          1.000000       0.000000  ...       0.000000
0.000000
50%          1.000000       1.000000  ...       0.000000
0.000000
75%          1.000000       1.000000  ...       0.000000
0.000000
max          1.000000       1.000000  ...       1.000000
1.000000

               Bronx       Brooklyn      Manhattan         Queens  \
count  216039.000000  216039.000000  216039.000000  216039.000000
mean        0.035744       0.334287       0.454191       0.166697
std         0.185650       0.471742       0.497898       0.372706
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       1.000000       1.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

       Staten Island  Entire home/apt   Private room     Hotel room
count  216039.000000    216039.000000  216039.000000  216039.000000
mean        0.009082         0.578585       0.404649       0.005069
std         0.094864         0.493787       0.490825       0.071013
min         0.000000         0.000000       0.000000       0.000000
25%         0.000000         0.000000       0.000000       0.000000
50%         0.000000         1.000000       0.000000       0.000000
75%         0.000000         1.000000       1.000000       0.000000
max         1.000000         1.000000       1.000000       1.000000

[8 rows x 23 columns]
```

```
X.shape
```

```
(216039, 23)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Instantiate the Linear Regression model
reg_model = LinearRegression()
```

```
# Fit the model
reg_model.fit(X_train, y_train)

# Predict the model
y_pred_train_reg = reg_model.predict(X_train)
y_pred_test_reg = reg_model.predict(X_test)

# Evaluation Metrics for Linear Regression
r2_train_reg = r2_score(y_train, y_pred_train_reg).round(4)
mse_train_reg = mse(y_train, y_pred_train_reg).round(4)
rmse_train_reg = (mse_train_reg**0.5).round(4)

r2_test_reg = r2_score(y_test, y_pred_test_reg).round(4)
mse_test_reg = mse(y_test, y_pred_test_reg).round(4)
rmse_test_reg = (mse_test_reg**0.5).round(4)

reg_metrics = {'R2':[r2_train_reg, r2_test_reg],
               'MSE':[mse_train_reg, rmse_test_reg],
               'RMSE':[rmse_train_reg, rmse_test_reg]}

reg_metrics_df = pd.DataFrame(reg_metrics)
reg_metrics_df = reg_metrics_df.rename(index={0:'Linear Regression
Train Metrics',
                                              1:'Linear Regression
Test Metrics'})

print('Linear Regression Metrics:\n')
print(reg_metrics_df)
```

```
Linear Regression Metrics:

                                     R2     MSE    RMSE
Linear Regression Train Metrics  0.5886  0.1853  0.4305
Linear Regression Test Metrics   0.5939  0.4265  0.4265
```

```
# # Instantiate the Support Vector Regressor model
# svr_model = Pipeline([
#     ('scaler', StandardScaler()),
#     ('svr', SVR(kernel='rbf', max_iter=200000))])

# # Fit the model with train data
# svr_model.fit(X_train, y_train)

# # Predict the model with train and test data
# y_pred_train_svr = svr_model.predict(X_train)
# y_pred_test_svr = svr_model.predict(X_test)

# # Evaluation Metrics for Support Vector Regressor
# r2_train_svr = r2_score(y_train, X_train).round(4)
# mse_train_svr = mse(y_train, X_train).round(4)
```

```
# rmse_train_svr = (mse_train_svr**0.5).round(4)

# r2_test_svr = r2_score(y_test, X_test).round(4)
# mse_test_svr = mse(y_test, X_test).round(4)
# rmse_test_svr = (mse_test_svr**0.5).round(4)

r2_train_svr = 0.7115
mse_train_svr = 0.1300
rmse_train_svr = 0.3606

r2_test_svr = 0.7027
mse_test_svr = 0.1332
rmse_test_svr = 0.3650

svr_metrics = {'R2':[r2_train_svr, r2_test_svr],
               'MSE':[mse_train_svr, mse_test_svr],
               'RMSE':[rmse_train_svr, rmse_test_svr]}

svr_metrics_df = pd.DataFrame(svr_metrics)
svr_metrics_df = svr_metrics_df.rename(index={0:'Support Vector Train
Metrics',
                                              1:'Support Vector Test
Metrics'})

print('Support Vector Regressor Metrics:\n')
print(svr_metrics_df)
```

```
Support Vector Regressor Metrics:

                                  R2     MSE    RMSE
Support Vector Train Metrics  0.7115  0.1300  0.3606
Support Vector Test Metrics   0.7027  0.1332  0.3650
```

```
# Instantiate the Decision Tree Regressor model
decision_tree = DecisionTreeRegressor()

# Fit the model with train data
decision_tree.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_og_dt = decision_tree.predict(X_train)
y_pred_test_og_dt = decision_tree.predict(X_test)

# Evaluation Metrics for Decision Tree Regressor model
r2_train_og_dt = r2_score(y_train, y_pred_train_og_dt).round(4)
mse_train_og_dt = mse(y_train, y_pred_train_og_dt).round(4)
rmse_train_og_dt = (mse_train_og_dt**0.5).round(4)

r2_test_og_dt = r2_score(y_test, y_pred_test_og_dt).round(4)
mse_test_og_dt = mse(y_test, y_pred_test_og_dt).round(4)
rmse_test_og_dt = (mse_test_og_dt**0.5).round(4)
```

```
og_dt_metrics = {'R2':[r2_train_og_dt, r2_test_og_dt],
                 'MSE':[mse_train_og_dt, mse_test_og_dt],
                 'RMSE':[rmse_train_og_dt, rmse_test_og_dt]}

og_dt_metrics_df = pd.DataFrame(og_dt_metrics)
og_dt_metrics_df = og_dt_metrics_df.rename(index={0:'Decision Tree
Train Metrics',
                                                  1:'Decision Tree
Test Metrics'})

print('Decision Tree Regressor Metrics:\n')
print(og_dt_metrics_df)
```

```
Decision Tree Regressor Metrics:

                                 R2     MSE    RMSE
Decision Tree Train Metrics  0.9514  0.0219  0.1480
Decision Tree Test Metrics   0.7340  0.1192  0.3453
```

```
# Instantiate the Random Forest Regressor model
random_forest = RandomForestRegressor()

# Fit the model with train data
random_forest.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_og_rf = random_forest.predict(X_train)
y_pred_test_og_rf = random_forest.predict(X_test)

# Evaluation Metrics for Random Forest Regressor model
r2_train_og_rf = r2_score(y_train, y_pred_train_og_rf).round(4)
mse_train_og_rf = mse(y_train, y_pred_train_og_rf).round(4)
rmse_train_og_rf = (mse_train_og_rf**0.5).round(4)

r2_test_og_rf = r2_score(y_test, y_pred_test_og_rf).round(4)
mse_test_og_rf = mse(y_test, y_pred_test_og_rf).round(4)
rmse_test_og_rf = (mse_test_og_rf**0.5).round(4)

og_rf_metrics = {'R2':[r2_train_og_rf, r2_test_og_rf],
                 'MSE':[mse_train_og_rf, mse_test_og_rf],
                 'RMSE':[rmse_train_og_rf, rmse_test_og_rf]}

og_rf_metrics_df = pd.DataFrame(og_rf_metrics)
og_rf_metrics_df = og_rf_metrics_df.rename(index={0:'Random Forest
Train Metrics',
                                                  1:'Random Forest
Test Metrics'})

print('Random Forest Regressor Metrics:\n')
print(og_rf_metrics_df)
```

```
Random Forest Regressor Metrics:

                                R2     MSE    RMSE
Random Forest Train Metrics  0.9351  0.0292  0.1709
Random Forest Test Metrics   0.8048  0.0874  0.2956
```

```
# Instantiate the XGBoost Regressor model
xgboost = XGBRegressor()

# Fit the model with train data
xgboost.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_og_xgb = xgboost.predict(X_train)
y_pred_test_og_xgb = xgboost.predict(X_test)

# Evaluation Metrics for XGBoost Regressor model
r2_train_og_xgb = r2_score(y_train, y_pred_train_og_xgb).round(4)
mse_train_og_xgb = mse(y_train, y_pred_train_og_xgb).round(4)
rmse_train_og_xgb = (mse_train_og_xgb**0.5).round(4)

r2_test_og_xgb = r2_score(y_test, y_pred_test_og_xgb).round(4)
mse_test_og_xgb = mse(y_test, y_pred_test_og_xgb).round(4)
rmse_test_og_xgb = (mse_test_og_xgb**0.5).round(4)

og_xgb_metrics = {'R2':[r2_train_og_xgb, r2_test_og_xgb],
                  'MSE':[mse_train_og_xgb, mse_test_og_xgb],
                  'RMSE':[rmse_train_og_xgb, rmse_test_og_xgb]}

og_xgb_metrics_df = pd.DataFrame(og_xgb_metrics)
og_xgb_metrics_df = og_xgb_metrics_df.rename(index={0:'XGBoost Train
Metrics',
                                                    1:'XGBoost Test
Metrics'})

print('XGBoost Regressor Metrics:\n')
print(og_xgb_metrics_df)
```

```
XGBoost Regressor Metrics:

                          R2     MSE    RMSE
XGBoost Train Metrics  0.7382  0.1179  0.3434
XGBoost Test Metrics   0.7243  0.1235  0.3514
```

Hyperparameter Tuning

Hyperparameter tuning will be applied on the Decision Tree Regressor, Random Forest Regressor, and XGBoost Regressor.

A GridSearch was performed on the Decision Tree Regressor with parameters 'max_depth', 'max_leaf_nodes', and 'min_samples_leaf'. The best parameters of the Decision Tree Regressor were implemented in the Decision Tree Regressor and Random Forest Regressor.

A GridSearch was performed and applied on the XGBoost Regressor with parameters 'eta', 'subsample', and 'colsample_bytree'.

```
# Define the hyperparameter grid for Decision Tree Regressor
decision_tree_param_grid = {'max_depth': [20, 25, 30],
                            'max_leaf_nodes': [2500, 3750, 5000],
                            'min_samples_leaf': [2, 5, 7]}

# Instantiate GridSearchCV for Decision Tree Regressor
decision_tree_grid_search = GridSearchCV(decision_tree,
decision_tree_param_grid)

# Fit GridSearchCV to the data
decision_tree_grid_search.fit(X_train, y_train)

print("Best hyperparameters for Decision Tree Regressor: ",
decision_tree_grid_search.best_params_)
```

```
Best hyperparameters for Decision Tree Regressor:  {'max_depth': 30,
'max_leaf_nodes': 5000, 'min_samples_leaf': 5}
```

```
# Instantiate Tuned Decision Tree Regressor
decision_tree_model = DecisionTreeRegressor(max_depth=30,
max_leaf_nodes=5000, min_samples_leaf=5)

# Fit the model with train data
decision_tree_model.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_dt = decision_tree_model.predict(X_train)
y_pred_test_dt = decision_tree_model.predict(X_test)

# Evaluation Metrics for Tuned Decision Tree Regressor model
r2_train_dt = r2_score(y_train, y_pred_train_dt).round(4)
mse_train_dt = mse(y_train, y_pred_train_dt).round(4)
rmse_train_dt = (mse_train_dt**0.5).round(4)

r2_test_dt = r2_score(y_test, y_pred_test_dt).round(4)
mse_test_dt = mse(y_test, y_pred_test_dt).round(4)
rmse_test_dt = (mse_test_dt**0.5).round(4)

dt_metrics = {'R2':[r2_train_dt, r2_test_dt],
              'MSE':[mse_train_dt, mse_test_dt],
              'RMSE':[rmse_train_dt, rmse_test_dt]}

dt_metrics_df = pd.DataFrame(dt_metrics)
dt_metrics_df = dt_metrics_df.rename(index={0:'Decision Tree (Tuned)
```

```
Train Metrics',
                                                            1:'Decision Tree (Tuned)
Test Metrics'})

print('Tuned Decision Tree Regressor Metrics:\n')
print(dt_metrics_df)
```

```
Tuned Decision Tree Regressor Metrics:

                                         R2     MSE    RMSE
Decision Tree (Tuned) Train Metrics  0.7951  0.0923  0.3038
Decision Tree (Tuned) Test Metrics   0.7375  0.1176  0.3429
```

```
# Instantiate the Tuned Random Forest Regressor model
random_forest_model = RandomForestRegressor(n_estimators=100,
max_depth=30, max_leaf_nodes=5000,
                                            min_samples_leaf=5,
random_state=42)

# Fit the model with train data
random_forest_model.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_rf = random_forest_model.predict(X_train)
y_pred_test_rf = random_forest_model.predict(X_test)

# Evaluation Metrics for Tuned Random Forest Regressor model
r2_train_rf = r2_score(y_train, y_pred_train_rf).round(4)
mse_train_rf = mse(y_train, y_pred_train_rf).round(4)
rmse_train_rf = (mse_train_rf**0.5).round(4)

r2_test_rf = r2_score(y_test, y_pred_test_rf).round(4)
mse_test_rf = mse(y_test, y_pred_test_rf).round(4)
rmse_test_rf = (mse_test_rf**0.5).round(4)

rf_metrics = {'R2':[r2_train_rf, r2_test_rf],
              'MSE':[mse_train_rf, mse_test_rf],
              'RMSE':[rmse_train_rf, rmse_test_rf]}

rf_metrics_df = pd.DataFrame(rf_metrics)
rf_metrics_df = rf_metrics_df.rename(index={0:'Random Forest (Tuned)
Train Metrics',
                                            1:'Random Forest (Tuned)
Test Metrics'})

print('Tuned Random Forest Regressor Metrics:\n')
print(rf_metrics_df)
```

```
Tuned Random Forest Regressor Metrics:

                                         R2     MSE    RMSE
```

```
Random Forest (Tuned) Train Metrics  0.8216  0.0803  0.2834
Random Forest (Tuned) Test Metrics   0.7736  0.1014  0.3184
```

```
# Define the hyperparameter grid for XGBoost Regressor
xgboost_param_grid = {'eta': [0.05, 0.075, 0.1],
                      'subsample': [0.625, 0.75, 0.875],
                      'colsample_bytree': [0.625, 0.75, 0.875]}

# Instantiate GridSearchCV for XGBoost Regressor
xgboost_grid_search = GridSearchCV(xgboost, xgboost_param_grid)

# Fit GridSearchCV to the data
xgboost_grid_search.fit(X_train, y_train)

print("Best hyperparameters for XGBoost Regressor: ",
xgboost_grid_search.best_params_)
```

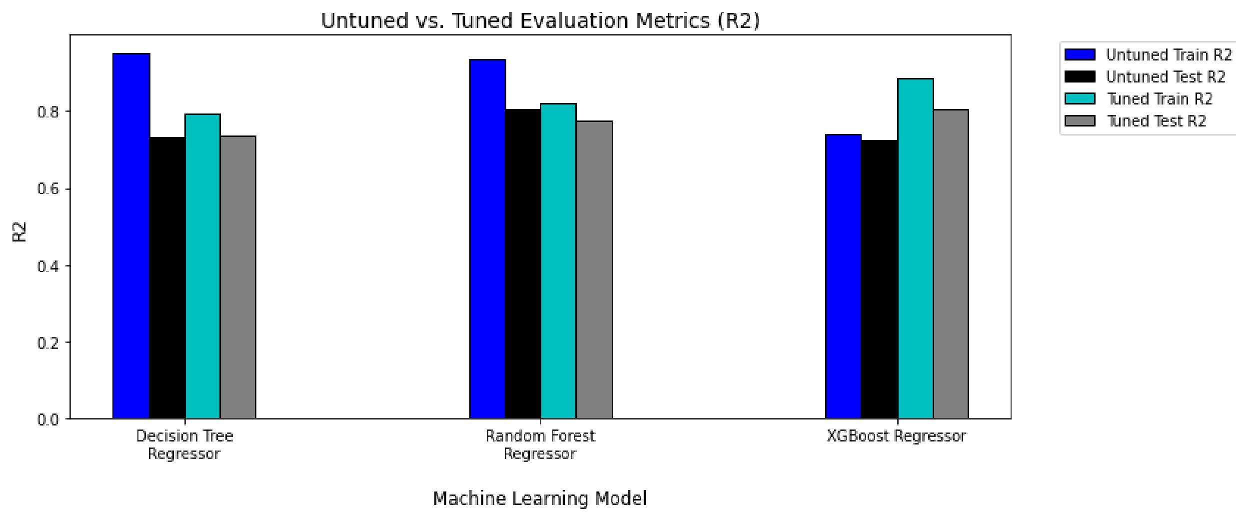
```
Best hyperparameters for XGBoost Regressor:  {'colsample_bytree':
0.875, 'eta': 0.05, 'subsample': 0.875}
```

```
# Instantiate the XGBoost Regressor model
xgboost_model = XGBRegressor(n_estimators=100, max_depth=20, eta=0.05,
subsample=0.875, colsample_bytree=0.875)

# Fit the model with train data
xgboost_model.fit(X_train, y_train)

# Predict the model with train and test data
y_pred_train_xgb = xgboost_model.predict(X_train)
y_pred_test_xgb = xgboost_model.predict(X_test)

# Evaluation Metrics for XGBoost Regressor model
r2_train_xgb = r2_score(y_train, y_pred_train_xgb).round(4)
mse_train_xgb = mse(y_train, y_pred_train_xgb).round(4)
rmse_train_xgb = (mse_train_xgb**0.5).round(4)

r2_test_xgb = r2_score(y_test, y_pred_test_xgb).round(4)
mse_test_xgb = mse(y_test, y_pred_test_xgb).round(4)
rmse_test_xgb = (mse_test_xgb**0.5).round(4)

xgb_metrics = {'R2':[r2_train_xgb, r2_test_xgb],
               'MSE':[mse_train_xgb, mse_test_xgb],
               'RMSE':[rmse_train_xgb, rmse_test_xgb]}

xgb_metrics_df = pd.DataFrame(xgb_metrics)
xgb_metrics_df = xgb_metrics_df.rename(index={0:'XGBoost (Tuned) Train
Metrics',
                                              1:'XGBoost (Tuned) Test
Metrics'})
```

```python
print('Tuned XGBoost Regressor Metrics:\n')
print(xgb_metrics_df)
```

```
Tuned XGBoost Regressor Metrics:

                                   R2     MSE    RMSE
XGBoost (Tuned) Train Metrics  0.8875  0.0507  0.2252
XGBoost (Tuned) Test Metrics   0.8036  0.0880  0.2966
```

```python
untuned_train_metrics = [r2_train_og_dt, r2_train_og_rf,
r2_train_og_xgb]
untuned_test_metrics = [r2_test_og_dt, r2_test_og_rf, r2_test_og_xgb]
tuned_train_metrics = [r2_train_dt, r2_train_rf, r2_train_xgb]
tuned_test_metrics = [r2_test_dt, r2_test_rf, r2_test_xgb]

# Calculate the positions for each group of bars
x = np.arange(len(untuned_train_metrics))

# Create the bar chart
fig, ax = plt.subplots(figsize=(12, 5))

ax.bar(x - 0.15, untuned_train_metrics, width=0.1, color='b',
edgecolor='black', label='Untuned Train R2')
ax.bar(x - 0.05, untuned_test_metrics, width=0.1, color='k',
edgecolor='black', label='Untuned Test R2')
ax.bar(x + 0.05, tuned_train_metrics, width=0.1, color='c',
edgecolor='black', label='Tuned Train R2')
ax.bar(x + 0.15, tuned_test_metrics, width=0.1, color='grey',
edgecolor='black', label='Tuned Test R2')

# Set title, labels, and ticks
plt.title('Untuned vs. Tuned Evaluation Metrics (R2)', fontsize=14)
plt.xlabel('\nMachine Learning Model', fontsize=12)
plt.ylabel('R2', fontsize=12)
ax.set_xticks(x)
ax.set_xticklabels(['Decision Tree\nRegressor', 'Random Forest\
nRegressor', 'XGBoost Regressor'])
ax.legend(loc='best', bbox_to_anchor=(0.75, 0.5, 0.5, 0.5))

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




```
tuned_dt_metrics_df = pd.concat([og_dt_metrics_df, dt_metrics_df])
tuned_rf_metrics_df = pd.concat([og_rf_metrics_df, rf_metrics_df])
tuned_xgb_metrics_df = pd.concat([og_xgb_metrics_df, xgb_metrics_df])
print(tuned_dt_metrics_df)
print(tuned_rf_metrics_df)
print(tuned_xgb_metrics_df)
```

```
                                        R2     MSE    RMSE
Decision Tree Train Metrics         0.9514  0.0219  0.1480
Decision Tree Test Metrics          0.7340  0.1192  0.3453
Decision Tree (Tuned) Train Metrics 0.7951  0.0923  0.3038
Decision Tree (Tuned) Test Metrics  0.7375  0.1176  0.3429
                                        R2     MSE    RMSE
Random Forest Train Metrics         0.9351  0.0292  0.1709
Random Forest Test Metrics          0.8048  0.0874  0.2956
Random Forest (Tuned) Train Metrics 0.8216  0.0803  0.2834
Random Forest (Tuned) Test Metrics  0.7736  0.1014  0.3184
                                  R2     MSE    RMSE
XGBoost Train Metrics         0.7382  0.1179  0.3434
XGBoost Test Metrics          0.7243  0.1235  0.3514
XGBoost (Tuned) Train Metrics 0.8875  0.0507  0.2252
XGBoost (Tuned) Test Metrics  0.8036  0.0880  0.2966
```

Hyperparameter tuning worked provided benefits across all three Regressors.

For the Decision Regressor, the tuned test R2 only increased 0.28% compared to the untuned test R2. However, the tuned train R2 decreased 15.63%. This shows that applying hyperparameter tuning worked well on providing a more robust model by being able to generalize better on unseen data.

For the Random Forest Regressor, the tuned test R2 decreased 3.12% compared to the untuned test R2, but the tuned train R2 decreased 11.35%. Although the test R2 decreased, the trade-off is that the model generalizes better with the hyperparameters. In addition, this model still performs better than the Decision Tree Regressor.

For the XGBoost Regressor, the tuned train and test R2 increased by 14.93% and 7.93% respectively compared to the untuned train and test R2. Although the test R2 increased significantly after tuning, the train R2 increased almost 2x as much as the test R2. This shows that hyperparameter tuning for the XGBoost Regressor exhibits some degree of overfitting, so it doesn't generalize unseen data as well as the Random Forest Regressor. However, the tuned test R2 of 0.8036 makes the tuned XGBoost Regressor the most accurate predictor.

```
fig = plt.subplots(figsize =(10, 5))

# Define the variables to store the data
train_metrics = [r2_train_reg, r2_train_svr, r2_train_dt, r2_train_rf,
r2_train_xgb]
test_metrics = [r2_test_reg, r2_test_svr, r2_test_dt, r2_test_rf,
r2_test_xgb]

# Set position of each bar
train_bar = np.arange(len(train_metrics))
test_bar = [x + 0.2 for x in train_bar]


# Create Bar Chart with labels
plt.bar(train_bar, train_metrics, color ='c', width = 0.2, edgecolor
='black', label ='Train R2')
plt.bar(test_bar, test_metrics, color ='grey', width = 0.2, edgecolor
='black', label ='Test R2')
plt.title('Train vs. Test Evaluation Metrics (R2)', fontsize=14)
plt.xlabel('\nMachine Learning Model')
plt.ylabel('R2')
plt.xticks([r + 0.1 for r in range(len(train_metrics))],
           ['Linear Regression', 'Support Vector\nRegressor',
'Decision Tree\nRegressor (Tuned)',
            'Random Forest\nRegressor (Tuned)', 'XGBoost\nRegressor
(Tuned)'])

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


```
metrics_train = {'R2':[r2_train_reg, r2_train_svr, r2_train_dt,
r2_train_rf, r2_train_xgb],
                 'MSE':[mse_train_reg, mse_train_svr, mse_train_dt,
mse_train_rf, mse_train_xgb],
                 'RMSE':[rmse_train_reg, rmse_train_svr,
rmse_train_dt, rmse_train_rf, rmse_train_xgb]}

metrics_test = {'R2':[r2_test_reg, r2_test_svr, r2_test_dt,
r2_test_rf, r2_test_xgb],
                'MSE':[mse_test_reg, mse_test_svr, mse_test_dt,
mse_test_rf, mse_test_xgb],
                'RMSE':[rmse_test_reg, rmse_test_svr, rmse_test_dt,
rmse_test_rf, rmse_test_xgb]}

metrics_train_df = pd.DataFrame(metrics_train)
metrics_train_df.rename(index={0:'Linear Regression', 1:'Support
Vector Regressor',
                               2:'Decision Tree Regressor (Tuned)',
3:'Random Forest Regressor (Tuned)',
                               4:'XGBoost Regressor (Tuned)'},
inplace=True)

metrics_test_df = pd.DataFrame(metrics_test)
metrics_test_df.rename(index={0:'Linear Regression', 1:'Support Vector
Regressor',
                              2:'Decision Tree Regressor (Tuned)',
3:'Random Forest Regressor (Tuned)',
                              4:'XGBoost Regressor (Tuned)'},
inplace=True)
```

```
print('Train Metrics\n',  metrics_train_df, '\n')
print('Test Metrics\n', metrics_test_df)
```

```
Train Metrics
                                   R2     MSE    RMSE
Linear Regression              0.5886  0.1853  0.4305
Support Vector Regressor       0.7115  0.1300  0.3606
Decision Tree Regressor (Tuned) 0.7951  0.0923  0.3038
Random Forest Regressor (Tuned) 0.8216  0.0803  0.2834
XGBoost Regressor (Tuned)      0.8875  0.0507  0.2252

Test Metrics
                                   R2     MSE    RMSE
Linear Regression              0.5939  0.1819  0.4265
Support Vector Regressor       0.7027  0.1332  0.3650
Decision Tree Regressor (Tuned) 0.7375  0.1176  0.3429
Random Forest Regressor (Tuned) 0.7736  0.1014  0.3184
XGBoost Regressor (Tuned)      0.8036  0.0880  0.2966
```

Overall, I would select the Random Forest Regressor as the most superior price prediction model since it has the second highest test R2, it generalizes well with unseen data, and its computational resources are reasonable (unlike the Support Vector Regressor).

Price Comparison

To show the predicted prices, I added the predictions of the Linear Regression, Decision Tree Regressor, Random Forest Regressor, and XGBoost Regressor to the X_test DataFrame and sliced the last 5 columns. Since the Support Vector Regressor was not part of the final Run, it its predictions are excluded in the comparison.

Although these price predictions are not perfect, it hopefully provides insight on how each listing is priced based on each machine learning model. Large errors may reveal that the listing is either under-priced or over-priced depending on the sign of the difference in errors.

```
X_test['Price'] = np.exp(y_test)

X_test['Linear Regression Price'] = np.exp(y_pred_test_reg).round(2)
X_test['Decision Tree Price'] = np.exp(y_pred_test_dt).round(2)
X_test['Random Forest Price'] = np.exp(y_pred_test_rf).round(2)
X_test['XGBoost Price'] = 
np.exp(y_pred_test_xgb.astype(np.float64)).round(2)

price_comparison = X_test.iloc[:,-5:]

price_comparison
```

```
        Price  Linear Regression Price  Decision Tree Price  \
4868     69.0                    88.05                72.41
128972  300.0                   179.05               209.43
80268   178.0                   167.04               160.98
```

```
187153  118.0                        96.99                    99.09
106947   84.0                        73.25                    62.14
...       ...                          ...                      ...
178342  150.0                       140.83                   208.42
3947    149.0                       184.55                   193.65
191902   84.0                       262.83                   133.75
94570   491.0                       162.68                   271.63
197090  500.0                       211.19                   213.02

        Random Forest Price  XGBoost Price
4868                  84.76          79.94
128972               232.66         225.54
80268                157.40         171.30
187153               100.06         102.46
106947                71.17          64.34
...                     ...            ...
178342               150.76         156.83
3947                 187.98         177.03
191902               154.20         160.80
94570                268.16         261.89
197090               196.81         205.44

[43208 rows x 5 columns]
```

Difference-in-Differences Analysis

In September 2023, New York City enacted Local Law 18, which introduced stringent guidelines for short-term rentals. It mandates hosts to register their properties with the Mayor's Office of Special Enforcement (OSE). The law's objectives are to address concerns related to illegal short-term rentals, ensure traveler safety, and alleviate pressure on the city's housing market.

Enforcement of this law requires the vast majority of Airbnb listings to have a minimum stay of at least 30 nights, unless exempted by the OSE. The aim of the Difference-in-Differences (DiD) analysis in this study is to provide reliable estimates of the causal effects of this enforcement with statistical significance and to identify any shifts in pricing of NYC Airbnb listings following the implementation of Local Law 18.

The findings suggest that average prices of short-term Airbnb listings are $90.97 higher than long-term Airbnb listings before the enforcement of Local Law 18.

```
df_original = df_original.fillna(df_original['price'].mean())

df_original['date'] = df_original['date'].astype('datetime64[ns]')
df_original['price'] = df_original['price'].replace('[\$,]', '',
regex=True).astype(float)

df_original = df_original[(df_original['date'] >= '03-2023') &
(df_original['date'] < '03-2024')]
```

```python
month_count_df = df_original.groupby('id')
['date'].nunique().reset_index()

month_count_df.rename(columns={'date': 'month_count'}, inplace=True)

df_original = pd.merge(df_original, month_count_df, on='id',
how='outer')

df_12_months = df_original[df_original['month_count']==12]

df_diff = df_12_months[['price', 'minimum_nights', 'date']].copy()
```

The dates of this study is between February 2023 to March 2024 (6 months prior and following the Local Law 18 implementation. I am only selecting Airbnb listings that were present throughout all 12 months by ensuring that the `month_count` for the Airbnb id is equal to 12

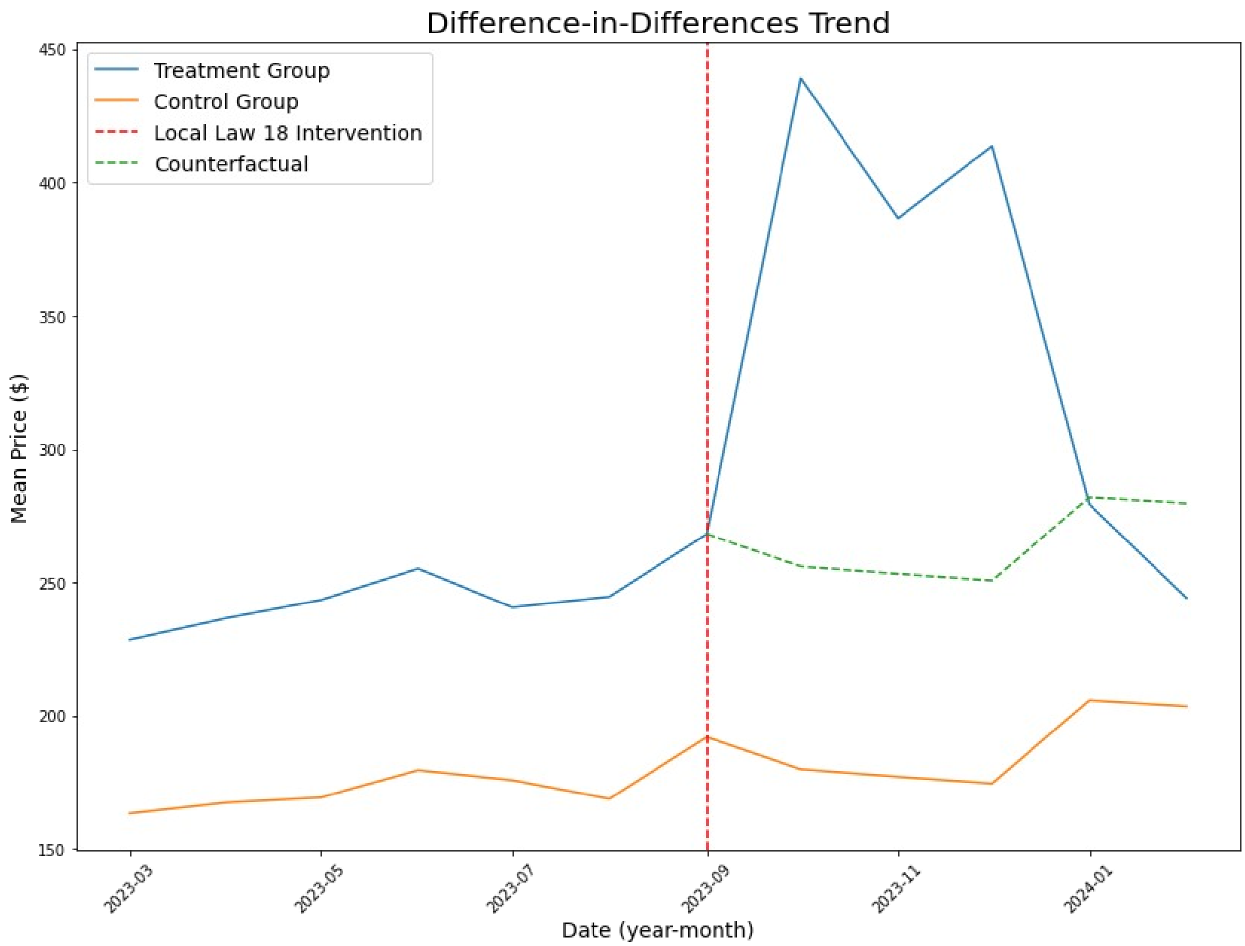
Although panel data is typically used for DiD Analysis, the data provided for this study represents repeated cross-sectional data that works to emulate panel data. This approach I am creating can simulate panel data by tracking changes in averages or distributions within the treatment and control groups over time.

The DataFrame used for this study is `df_diff`, which contains Airbnb listings that show trends throughout all 12 months with columns ['price', 'minimum_nights', 'date'].

```python
df_diff.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 319968 entries, 0 to 418527
Data columns (total 3 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   price           319968 non-null  float64
 1   minimum_nights  319968 non-null  int64
 2   date            319968 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(1), int64(1)
memory usage: 9.8 MB

df_diff[df_diff['minimum_nights']>=30].count()

price             244574
minimum_nights    244574
date              244574
dtype: int64

df_diff[df_diff['minimum_nights']<30].count()

price             75394
minimum_nights    75394
date              75394
dtype: int64
```

```python
# Construct DiD variables
df_diff['treatment'] = (df_diff['minimum_nights'] < 30).astype(int)
df_diff['post'] = (df_diff['date'] > '2023-09').astype(int)
df_diff['treatment_post'] = df_diff['treatment'] * df_diff['post']

# Find the mean price of the Treatment Group for each month
treatment_group = df_diff[df_diff['treatment'] == 1]
treatment_mean = treatment_group.groupby('date')['price'].mean()

# Find the mean price of the Control Group for each month
control_group = df_diff[df_diff['treatment'] == 0]
control_mean = control_group.groupby('date')['price'].mean()

# Indicate the treatment date and ensure it is in datetime format
treatment_start = pd.to_datetime('2023-09')

# Find the Counterfactual to plot after the treatment_start
counterfactual = df_diff[(df_diff['treatment'] == 0) &
(df_diff['date'] >= '2023-09')]
counterfactual_mean = counterfactual.groupby('date')['price'].mean()

# Filter the DataFrame for the control and treatment group and the
date '2023-09'
treatment_group_september = df_diff[(df_diff['treatment'] == 1) &
(df_diff['date'] == '2023-09')]
mean_price_september_treatment =
treatment_group_september['price'].mean()

control_group_september = df_diff[(df_diff['treatment'] == 0) &
(df_diff['date'] == '2023-09')]
mean_price_september_control = control_group_september['price'].mean()

# Calculate the difference of the mean price to plot the
Counterfactual of the treatment group
difference = mean_price_september_treatment -
mean_price_september_control

# Plot the trend for the treatment group, control group, and
counterfactual control group
plt.figure(figsize=(14, 10))
sns.lineplot(x=treatment_mean.index, y=treatment_mean.values,
label='Treatment Group')
sns.lineplot(x=control_mean.index, y=control_mean.values,
label='Control Group')
plt.axvline(x=treatment_start, color='red', linestyle='--',
label='Local Law 18 Intervention')
sns.lineplot(x=counterfactual_mean.index, y=difference +
counterfactual_mean,
             label='Counterfactual', linestyle='--')
plt.title('Difference-in-Differences Trend', fontsize=20)
```

```
plt.xlabel('Date (year-month)', fontsize=14)
plt.ylabel('Mean Price ($)', fontsize=14)
plt.legend(fontsize=14, loc=2)
plt.xticks(rotation=45)
plt.tick_params(axis='both', which='major', labelsize=10)
plt.show()
```



The graph above provides a visual representation to assess the effectiveness of the intervention and the validity of the DiD approach. Prior to the intervention period, both the treatment and control groups are expected to follow a parallel trend, indicating that the Mean Price for both groups changes at a similar rate over time. Any noticeable discrepancies in the trends indicate issues with the parallel trends assumption for a DiD Analysis.

Upon observation, small discrepencies before intervention are shown above. This may be caused by:

- **the imbalance of the distribution of the treatment group and control group.**
- **the data being used. DiD Analysis is performed with panel data (longitudinal), but the data in this study is repeated cross-sectional data.**

- **missing prices being replaced with the mean price. This data manipulation may have affected the parallel trend assumption.**

The Mean Price of the control group is lower than those of the treatment group. A potential reason for this difference is that hosts offer a better unit rate per night for the longer minimum stay. Comparing the treatment and control groups post-intervention reveals the treatment effect, usually measured as the difference in the changes observed in the treatment group compared to the counterfactual.

```
# Estimate the DiD model
X = df_diff[['treatment', 'post', 'treatment_post']]
X = sm.add_constant(X)
y = df_diff['price']
model = sm.OLS(y, X).fit()

print(model.summary(title='Difference-in-Differences (DiD) Regression
Results'))
```

```
              Difference-in-Differences (DiD) Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.004
Model:                            OLS   Adj. R-squared:
0.004
Method:                 Least Squares   F-statistic:
408.6
Date:                Thu, 05 Sep 2024   Prob (F-statistic):
6.36e-265
Time:                        18:24:21   Log-Likelihood:             -
2.4920e+06
No. Observations:              319968   AIC:
4.984e+06
Df Residuals:                  319964   BIC:
4.984e+06
Df Model:                           3

Covariance Type:            nonrobust

======================================================================
============
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
------------
const           174.8839      1.680    104.101      0.000     171.591
178.177
treatment        67.8111      2.826     23.993      0.000      62.272
73.351
```

```
post                 13.1949      2.361      5.590      0.000      8.568
17.822
treatment_post    90.9741      6.840     13.301      0.000     77.569
104.379
======================================================================
========
Omnibus:                     1239493.840   Durbin-Watson:
0.767
Prob(Omnibus):                     0.000   Jarque-Bera (JB):
2557329020814.567
Skew:                             92.390   Prob(JB):
0.00
Kurtosis:                      13851.636   Cond. No.
7.67
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

The treatment coefficient (67.8111) suggests that, on average, short-term Airbnb listings are $67.81 higher than long-term Airbnb listings, holding the other variables constant.

The post coefficient (13.1949) suggests that prices of Airbnb listings increased on average an additional $13.19 on average after September 2023, holding the other variables constant.

The treatment_post coefficient (90.97) suggests that short-term Airbnb listings on average are higher in price by $47.75 on average after the implementation of Local Law 18 in September 2023 compared to long-term Airbnb listings before September 2023, holding the other variables constant.

All of the coefficients are statistically significant. The statistical significance of the `treatment_post` coefficient highlight the significance of factoring time variables and policy interventions when analyzing the effect of pricing within the Airbnb market concerning the enforcement of Local Law 18.