Predict NYC Airbnb rental price

As of August 2019, this data set contains almost 50 thousand airbnb listings in NYC. The purpose of this task is to predict the price of NYC Airbnb rentals based on the data provided and any external dataset(s) with relevant information.

Columns -

id - listing ID

Name- name of the listing

host_id - host ID

Host_name - name of the host

Neighbourhood group - location

Neighbourhood - area

Latitude - latitude coordinates

Longitude - longitude coordinates

room_typelisting space type

Price - price in dollars

Minimum_nights - amount of nights minimum

Number_of_reviews - number of reviews

Last_review - latest review

Reviews_per_month - number of reviews per month

Calculated_host_listings_count - amount of listing per host

Availability_365 - number of days when listing is available for booking

In [206…

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

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor, GradientBoosting
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor

import tensorflow as tf

from scipy.stats import skew

import warnings
warnings.filterwarnings('ignore')
```

In [207…

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

Out[207…

```
(48895, 16)
```

In [208…

```
df.head()
```

Out[208…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longituc
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.972:
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.9837
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.941(
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.9597
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.943(

In [209…

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

Out[209…

```
id                                    0
name                                 16
host_id                               0
host_name                            21
neighbourhood_group                   0
neighbourhood                         0
latitude                              0
longitude                             0
room_type                             0
price                                 0
minimum_nights                        0
number_of_reviews                     0
last_review                       10052
reviews_per_month                 10052
calculated_host_listings_count        0
availability_365                      0
dtype: int64
```

In [210…

```
(df.isnull().sum()*100)/len(df)
```

Out[210…

```
id                                 0.000000
name                               0.032723
host_id                            0.000000
host_name                          0.042949
neighbourhood_group                0.000000
neighbourhood                      0.000000
latitude                           0.000000
longitude                          0.000000
room_type                          0.000000
```

```
price                              0.000000
minimum_nights                     0.000000
number_of_reviews                  0.000000
last_review                       20.558339
reviews_per_month                 20.558339
calculated_host_listings_count     0.000000
availability_365                   0.000000
dtype: float64
```

In [211…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   name                            48879 non-null  object 
 2   host_id                         48895 non-null  int64  
 3   host_name                       48874 non-null  object 
 4   neighbourhood_group             48895 non-null  object 
 5   neighbourhood                   48895 non-null  object 
 6   latitude                        48895 non-null  float64
 7   longitude                       48895 non-null  float64
 8   room_type                       48895 non-null  object 
 9   price                           48895 non-null  int64  
 10  minimum_nights                  48895 non-null  int64  
 11  number_of_reviews               48895 non-null  int64  
 12  last_review                     38843 non-null  object 
 13  reviews_per_month               38843 non-null  float64
 14  calculated_host_listings_count  48895 non-null  int64  
 15  availability_365                48895 non-null  int64  
dtypes: float64(3), int64(7), object(6)
memory usage: 6.0+ MB
```

In [212…

```
df.nunique()
```

Out[212…

```
id                                48895
name                              47905
host_id                           37457
host_name                         11452
neighbourhood_group                   5
neighbourhood                       221
latitude                          19048
longitude                         14718
room_type                             3
price                               674
minimum_nights                      109
number_of_reviews                   394
last_review                        1764
reviews_per_month                   937
calculated_host_listings_count       47
availability_365                    366
dtype: int64
```

In [213…

```
(df.nunique()*100)/len(df)
```

Out[213…

```
id                                100.000000
name                               97.975253
host_id                            76.607015
host_name                          23.421618
```

```
neighbourhood_group                0.010226
neighbourhood                      0.451989
latitude                          38.956949
longitude                         30.101237
room_type                          0.006136
price                              1.378464
minimum_nights                     0.222927
number_of_reviews                  0.805808
last_review                        3.607731
reviews_per_month                  1.916351
calculated_host_listings_count     0.096124
availability_365                   0.748543
dtype: float64
```

In [214…

```
df[df['reviews_per_month'].isnull()]['number_of_reviews'].unique()
```

Out[214…

```
array([0], dtype=int64)
```

In [215…

```
df[df['reviews_per_month'].isnull()]['number_of_reviews'].unique()
```

Out[215…

```
array([0], dtype=int64)
```

Findings and Assumptions

First, we will attempt to clean the data. The below steps will be done. Additional steps might be done as we progress

- The columns - 'id', 'name', 'host_id' - have a lot of unqiue values. We can proceed with dropping these columns.
- 'host_name' can also be dropped.
- Wherever there is a NaN value in 'reviews_per_month', the value is '0' for 'number_of_reviews'. We can change all these NaN values to '0'.
- Some hosts seem to have multiple listings. We will check for duplicate data.
- For the catgorical columns, we will perform encoding before building the models.
- For a NN architecture, we would need to standardize on the data.

In [216…

```
# Replacing NaN values under 'reviews_per_month' with 0.

df['reviews_per_month'].fillna(0, inplace=True)
```

In [217…

```
dup_host_id = df[df.duplicated('host_id')]
dup_host_id.sort_values('host_id')
```

Out[217…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude
13583	10160215	Torre del Lago Room.	2787	John	Brooklyn	Gravesend	40.60755

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude
13688	10267242	Cinque Terre Room. Clean and Quiet Queen Bedroom	2787	John	Brooklyn	Gravesend	40.60810
10372	7937553	Riomaggiore Room. Queen Bedroom in Bklyn Townh...	2787	John	Brooklyn	Bensonhurst	40.60951
21556	17263207	Brooklyn home. Comfort and clean. Liguria room.	2787	John	Brooklyn	Bensonhurst	40.60877
13963	10593675	La Spezia room. Clean, quiet and comfortable bed	2787	John	Brooklyn	Bensonhurst	40.60951
...	...	...	...	...	...	...	...
48633	36351030	Brand New Privated Room for NYC Traveler	273354185	Lee & Luffy	Bronx	Castle Hill	40.81709
48631	36350749	NYC Traveler Get Away Private ROOM #3	273354185	Lee & Luffy	Bronx	Castle Hill	40.81572
48687	36384346	✨Superior King Room , Manhattan View✨	273392981	Giorgio Residence	Queens	Long Island City	40.75615
48696	36388492	✨Premier King Room , City View✨	273392981	Giorgio Residence	Queens	Long Island City	40.75559
48863	36469741	Comfortable & Big room with 2 beds!	274012871	Stefan	Queens	Long Island City	40.76726

11438 rows × 16 columns

It would seem that some hosts own more than one apartment. We will not drop any row.

In [218…

```
df.head()
```

Out[218…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longituc
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.972
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.9837
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.941
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.9597
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.943

In [219…

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

Out[219…

```
array([  6,   2,   1,   4,   3,   5,   7,  13,  28,  11,   8,   9,  52,
        18,  15,  19,  10,  39,  26,  29,  12,  21,  96,  14,  34,  43,
       121,  37,  49,  31,  91,  16,  87,  33,  23,  50,  20,  25, 232,
        17,  47, 103,  65,  30,  27, 327,  32], dtype=int64)
```

In [220…

```
len(df['calculated_host_listings_count'].unique())
```

Out[220…

47

In [221…

```
df[df['calculated_host_listings_count']==327]
```

Out[221…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	lc
38293	30181691	Sonder | 180 Water | Incredible 2BR + Rooftop	219517861	Sonder (NYC)	Manhattan	Financial District	40.70637	-
38294	30181945	Sonder | 180 Water | Premier 1BR + Rooftop	219517861	Sonder (NYC)	Manhattan	Financial District	40.70771	-

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	lo
38588	30347708	Sonder | 180 Water | Charming 1BR + Rooftop	219517861	Sonder (NYC)	Manhattan	Financial District	40.70743	-
39769	30937590	Sonder | The Nash | Artsy 1BR + Rooftop	219517861	Sonder (NYC)	Manhattan	Murray Hill	40.74792	-
39770	30937591	Sonder | The Nash | Lovely Studio + Rooftop	219517861	Sonder (NYC)	Manhattan	Murray Hill	40.74771	-
...	...	...	...	...	...	...	...	
47691	35871510	Sonder | 116 John | Vibrant Studio + Fitness Room	219517861	Sonder (NYC)	Manhattan	Financial District	40.70818	-
47692	35871511	Sonder | 116 John | Vibrant 1BR + Fitness Room	219517861	Sonder (NYC)	Manhattan	Financial District	40.70691	-
47693	35871515	Sonder | 116 John | Stunning 1BR + Rooftop	219517861	Sonder (NYC)	Manhattan	Financial District	40.70772	-
47814	35936418	Sonder | 116 John | Polished Studio + Gym	219517861	Sonder (NYC)	Manhattan	Financial District	40.70840	-
47821	35937891	Sonder | 116 John | Simple Studio + Gym	219517861	Sonder (NYC)	Manhattan	Financial District	40.70707	-

327 rows × 16 columns

In [222…

```
df[df['calculated_host_listings_count']==32].head(8)
```

Out[222…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	lo
40966	31874576	Chic Private Bedroom in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79884	-7
40967	31875616	Cozy Private Bedroom in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79966	-7
40969	31875827	Artsy Private Bedroom in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.80014	-7
40970	31876014	Modern Bedroom in the Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79880	-7
40971	31876398	Airy Private Bedroom in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79821	-7
40973	31876645	Artistic Private BR in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79971	-7
40975	31876724	Vibrant Bedroom in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79887	-7
40976	31877020	Calming Private BR in Upper West Side 107	238321374	Eyal	Manhattan	Upper West Side	40.79959	-7

WOW! Some users do seem to be loaded and own a lot of property.

Owning a lot of property would not mean that the value could increase/decrease. Ideally, the location would dictate pricing. We can proceeding with dropping this column too.

In [223…

```
# Dropping columns not required

df.drop(['id', 'name', 'host_id', 'host_name', 'last_review', 'calculated_host_listings_
```

In [224…

```
df.head(7)
```

Out[224…

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
0	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	
5	Manhattan	Murray Hill	40.74767	-73.97500	Entire home/apt	200	3	
6	Brooklyn	Bedford-Stuyvesant	40.68688	-73.95596	Private room	60	45	

We will now work with the above Data.

Before proceeding with creating a model, let us perform some analysis to understand the data.

In [225…

```
# Function to clean the data

def cleaning_data():
    df = pd.read_csv('AB_NYC_2019.csv')
    df['reviews_per_month'].fillna(0, inplace=True)
    df.drop(['id', 'name', 'host_id', 'host_name', 'last_review', 'calculated_host_list
    return df
```

Creating some Visuals for Data Analysis

In [226…

```
df["neighbourhood_group"].value_counts()
```

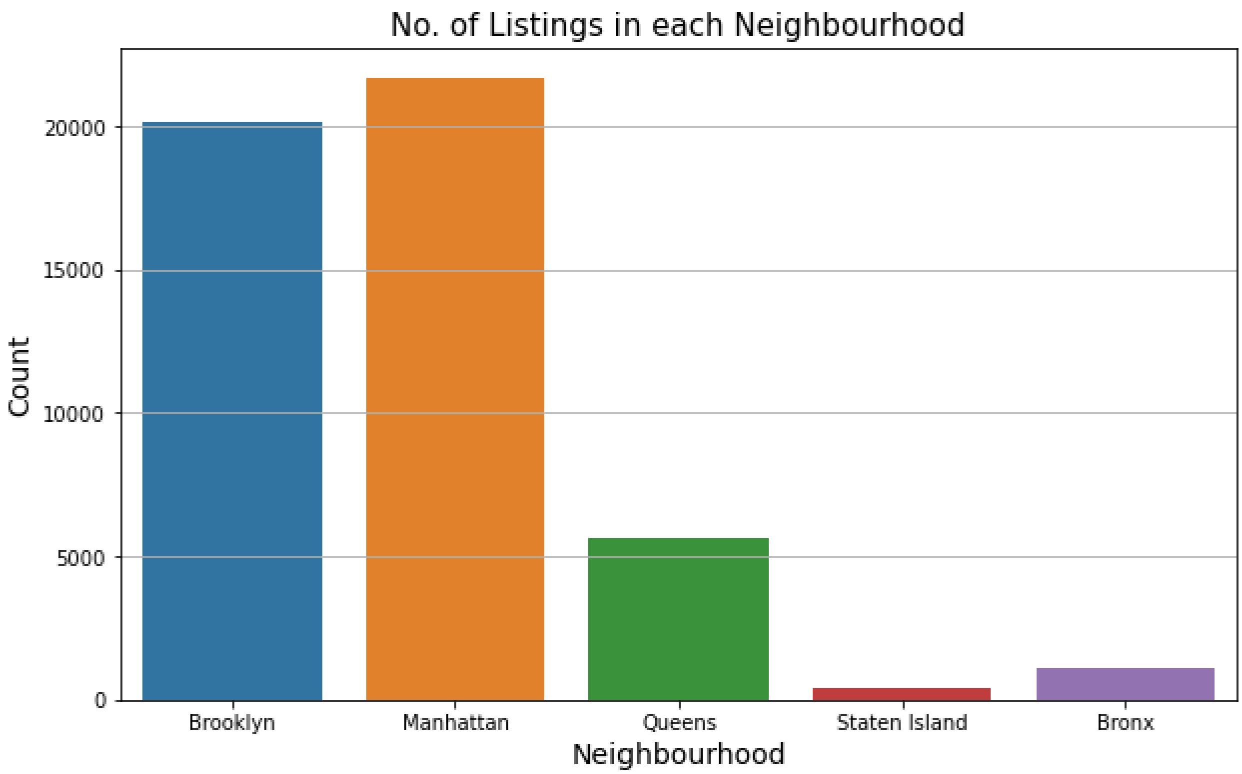
Out[226…

```
Manhattan        21661
Brooklyn         20104
Queens            5666
```

```
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

In [227…

```python
plt.figure(figsize=(10,6))
sns.countplot(data=df, x="neighbourhood_group")
plt.grid(axis='y')
plt.title('No. of Listings in each Neighbourhood', fontsize=15)
plt.xlabel('Neighbourhood', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.show()
```



Most of the listings in the dataset are for Brooklyn and Manhattan.

In [228…

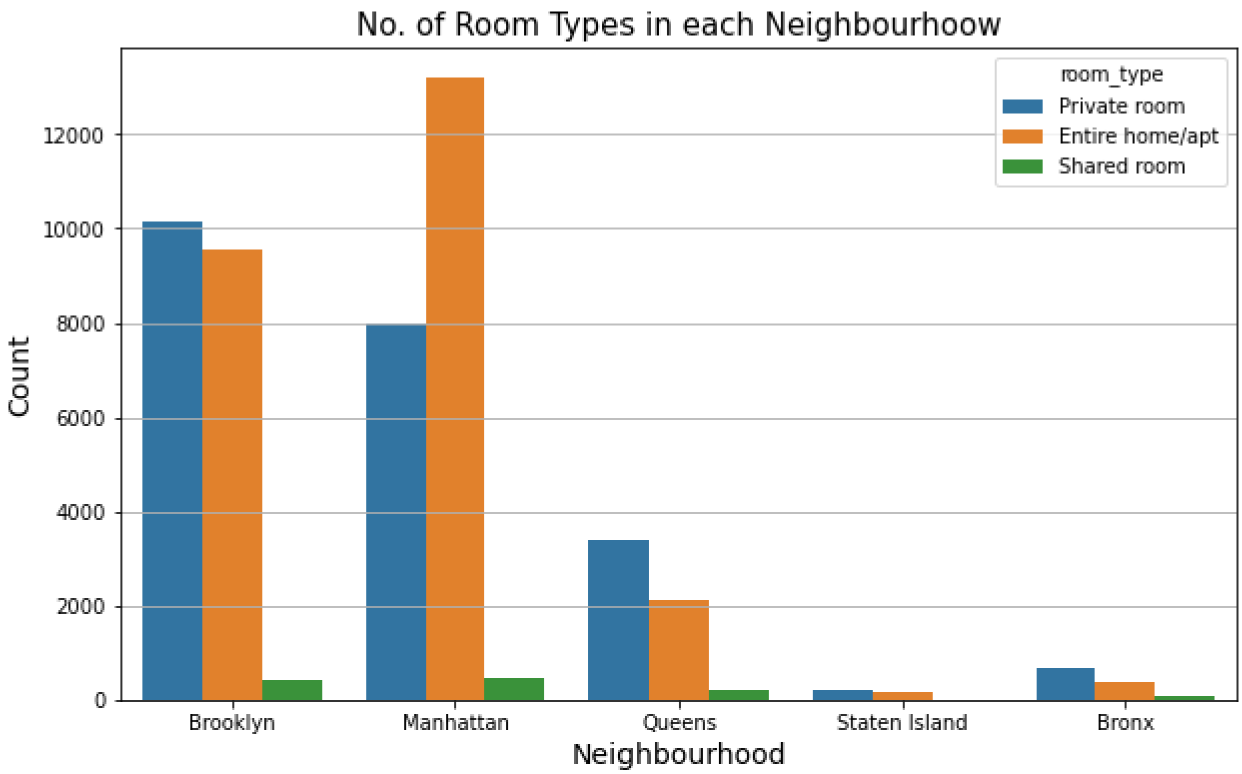
```python
df.groupby(["neighbourhood_group"])["room_type"].value_counts()
```

Out[228…

```
neighbourhood_group  room_type      
Bronx                Private room         652
                     Entire home/apt      379
                     Shared room           60
Brooklyn             Private room       10132
                     Entire home/apt     9559
                     Shared room          413
Manhattan            Entire home/apt    13199
                     Private room        7982
                     Shared room          480
Queens               Private room        3372
                     Entire home/apt     2096
                     Shared room          198
Staten Island        Private room         188
                     Entire home/apt      176
                     Shared room            9
Name: room_type, dtype: int64
```

In [229…

```
plt.figure(figsize=(10,6))
sns.countplot(data=df, x="neighbourhood_group", hue="room_type")
plt.grid(axis='y')
plt.title('No. of Room Types in each Neighbourhoow', fontsize=15)
plt.xlabel('Neighbourhood', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.show()
```



Most of the rooms are available in Brooklyn and Manhattan. And they are mainly 'Private Rooms' and 'Entire home/apt'. Not many for rent are shared, and very few are available in 'Staten Island' and the 'Bronx'.

In [230…

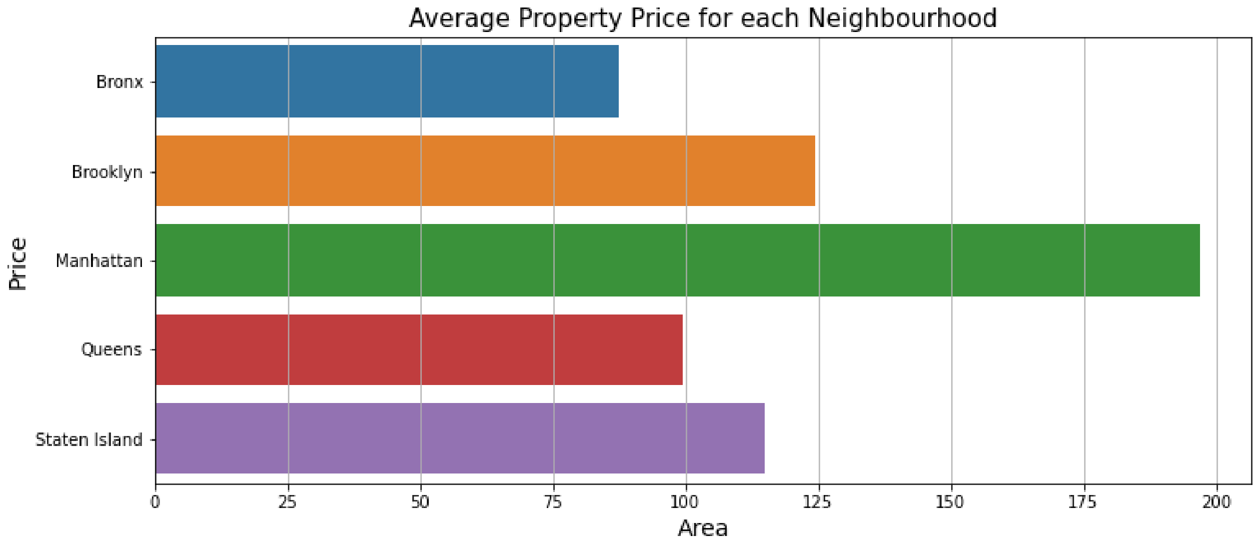
```
df.groupby(["neighbourhood_group"])["price"].mean()
```

Out[230…

```
neighbourhood_group
Bronx             87.496792
Brooklyn         124.383207
Manhattan        196.875814
Queens            99.517649
Staten Island    114.812332
Name: price, dtype: float64
```

In [231…

```
plt.figure(figsize=(12,5))
sns.barplot(y=df.groupby(["neighbourhood_group"])["price"].mean().index, x=df.groupby([
plt.grid(axis='x')
plt.title('Average Property Price for each Neighbourhood', fontsize=15)
plt.xlabel('Area', fontsize=14)
plt.ylabel('Price', fontsize=14)
plt.show()
```



Manhattan is the most expensive area to rent as compared to the other 4 areas.

In [232…

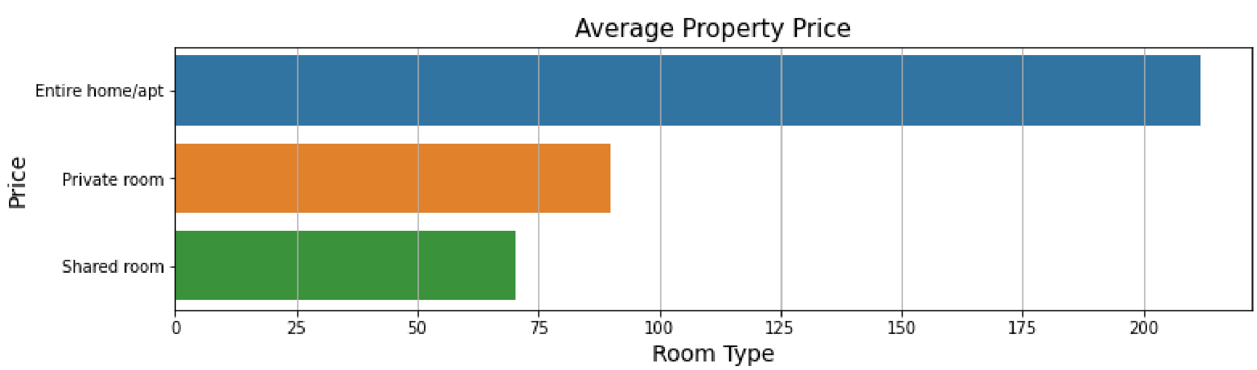
```
df.groupby("room_type")["price"].mean()
```

Out[232…

```
room_type
Entire home/apt    211.794246
Private room        89.780973
Shared room         70.127586
Name: price, dtype: float64
```

In [233…

```
plt.figure(figsize=(12,3))
sns.barplot(y=df.groupby(["room_type"])["price"].mean().index, x=df.groupby(["room_type
plt.grid(axis='x')
plt.title('Average Property Price', fontsize=15)
plt.xlabel("Room Type", fontsize=14)
plt.ylabel('Price', fontsize=14)
plt.show()
```

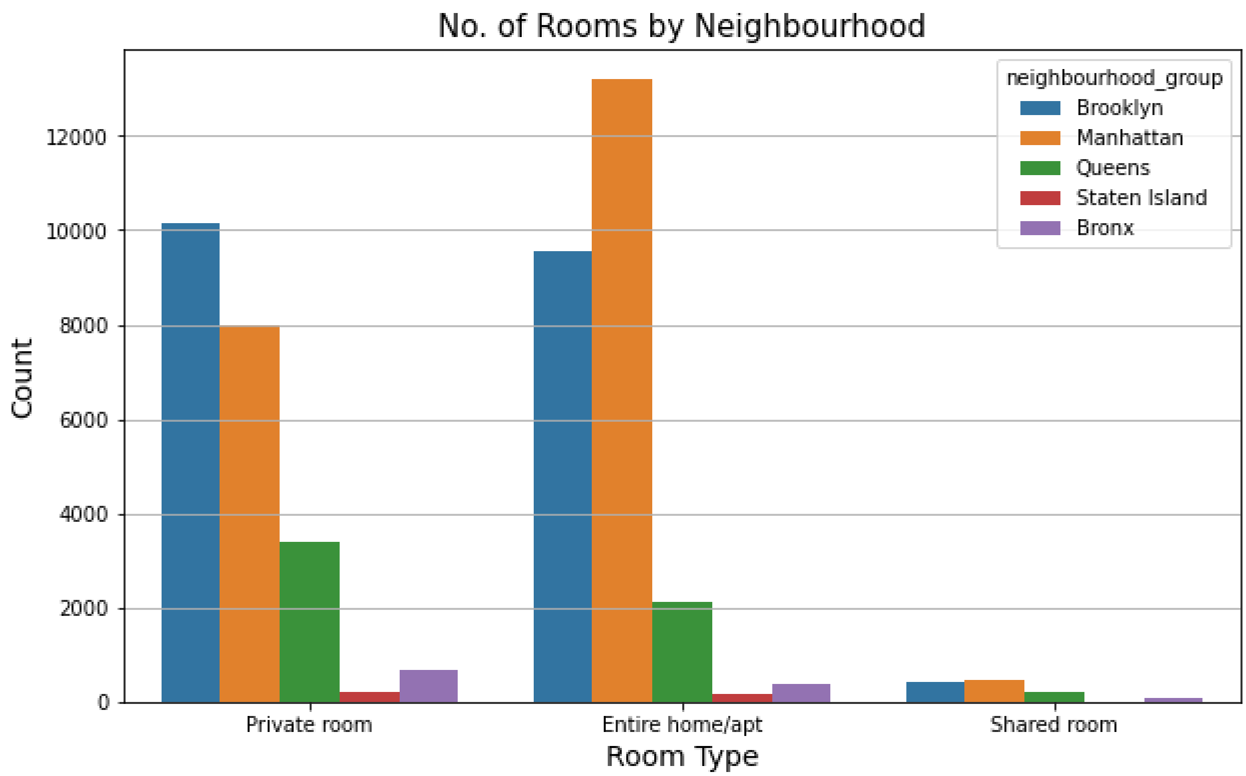


Taking the average room price, renting an Entire Home/Apt would be most expensive.

In [234…

```
plt.figure(figsize=(10,6))
sns.countplot(data=df, x="room_type", hue="neighbourhood_group")
plt.grid(axis='y')
```

```
plt.title('No. of Rooms by Neighbourhood', fontsize=15)
plt.xlabel("Room Type", fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.show()
```



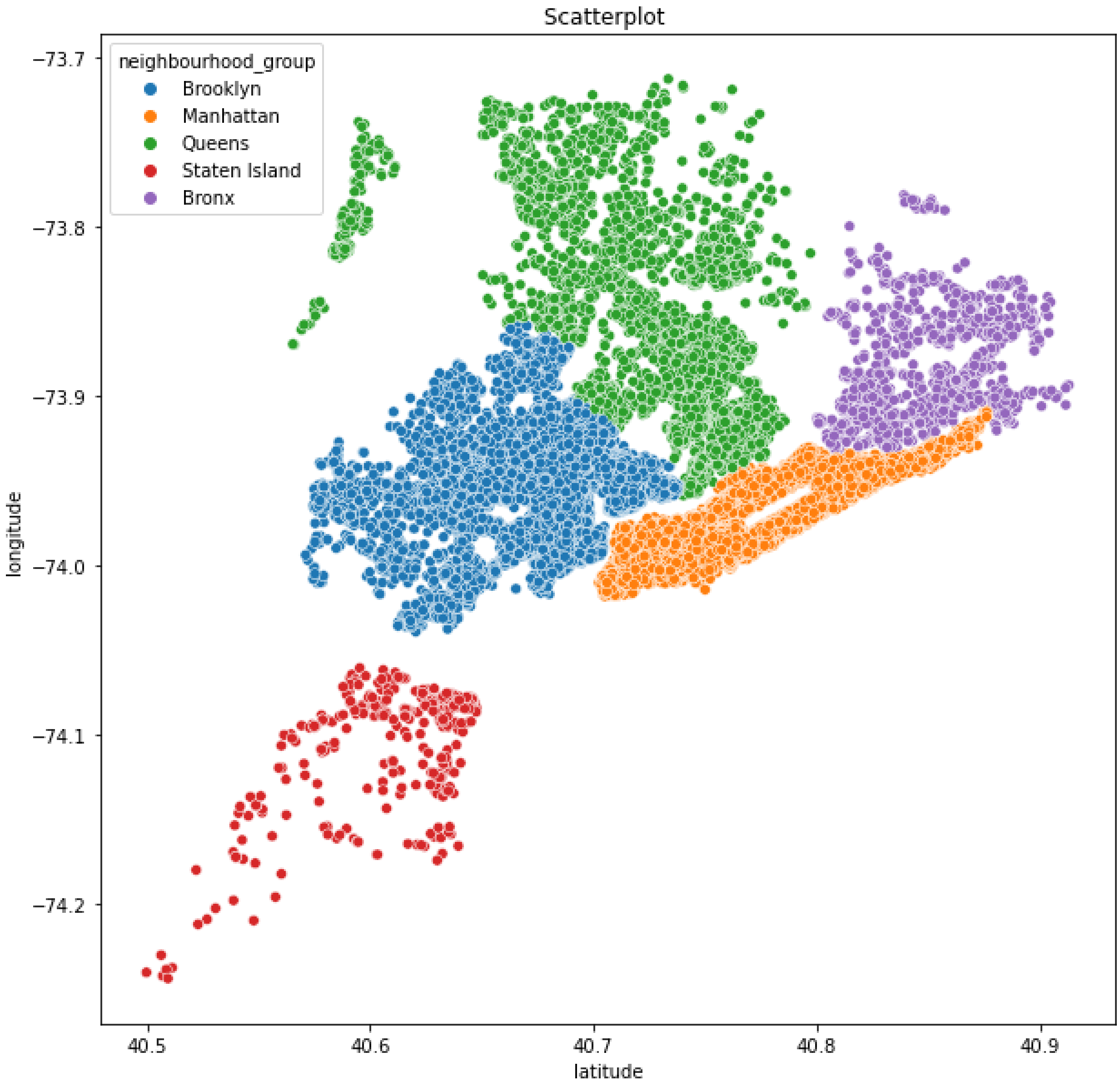
Not many hosts offer the option to share an apartment. Most of the available property on rent are either 'Private Rooms' or an 'Entire Home/Apt'

---

df.groupby(["neighbourhood_group","room_type"])["price"].mean()plt.figure(figsize=(10,6)) sns.barplot(data=df, x="neighbourhood_group", y="price", hue="room_type") plt.grid(axis='y') plt.title('No. of Rooms by Neighbourhood', fontsize=15) plt.xlabel("Area") plt.ylabel("Price") plt.show()

In [235…

```
plt.figure(figsize=(10,10))
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df['neighbourhood_group'])
plt.title('Scatterplot ')
plt.show()
```

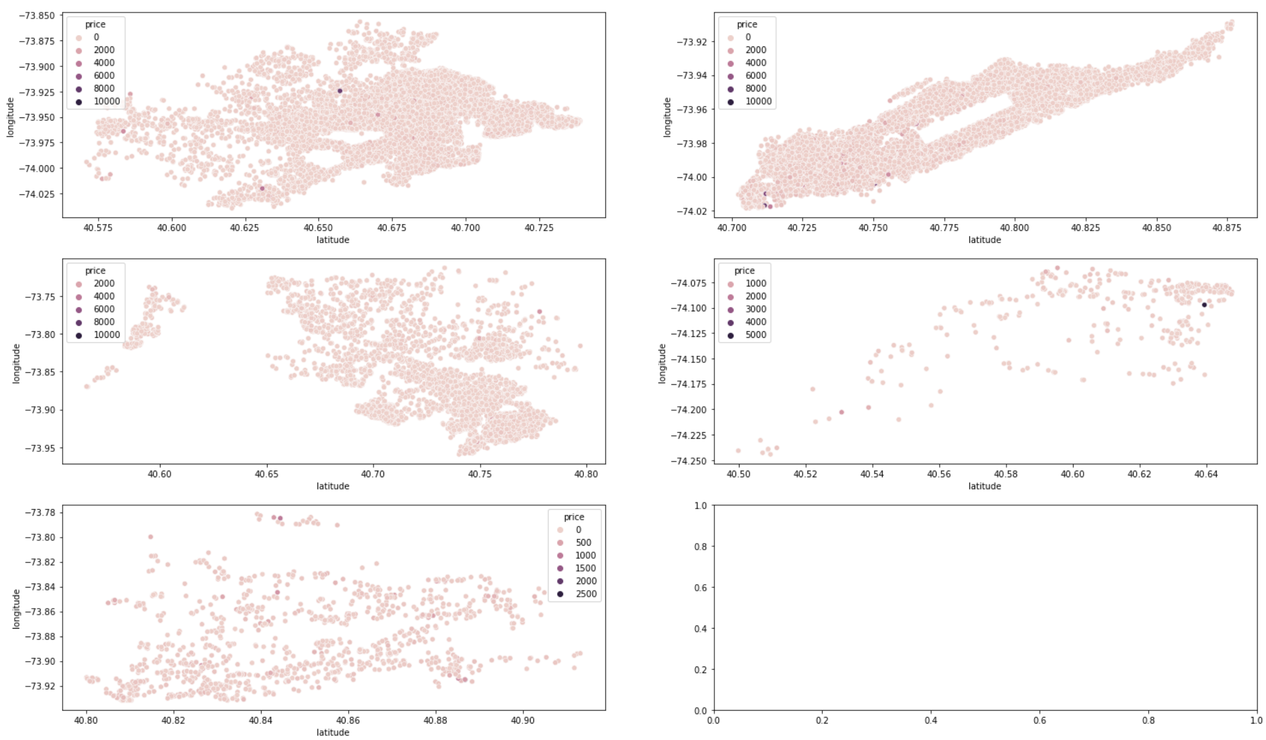


In [236…

```
fig, axes = plt.subplots(3, 2, figsize=(25,15))

fig.suptitle("Scatterplot of Price for each Neighbourhood (Longitutde on y-axis / Latit
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df[df['neighbourhood_group'] =
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df[df['neighbourhood_group'] =
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df[df['neighbourhood_group'] =
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df[df['neighbourhood_group'] =
sns.scatterplot(x=df['latitude'], y=df['longitude'], hue=df[df['neighbourhood_group'] =
plt.show()
```

Scatterplot of Price for each Neighbourhood (Longitutde on y-axis / Latitude on x-axis)



In [237…

```
df_cat = df[['neighbourhood_group', 'neighbourhood', 'room_type']]
df_cat.head()
```

Out[237…

	neighbourhood_group	neighbourhood	room_type
0	Brooklyn	Kensington	Private room
1	Manhattan	Midtown	Entire home/apt
2	Manhattan	Harlem	Private room
3	Brooklyn	Clinton Hill	Entire home/apt
4	Manhattan	East Harlem	Entire home/apt

In [238…

```
df_num = df.drop(df_cat.columns.tolist() + ['price'], axis=1)
df_num.head()
```

Out[238…

	latitude	longitude	minimum_nights	number_of_reviews	reviews_per_month	availability_365
0	40.64749	-73.97237	1	9	0.21	365
1	40.75362	-73.98377	1	45	0.38	355
2	40.80902	-73.94190	3	0	0.00	365
3	40.68514	-73.95976	1	270	4.64	194
4	40.79851	-73.94399	10	9	0.10	0

In [239…

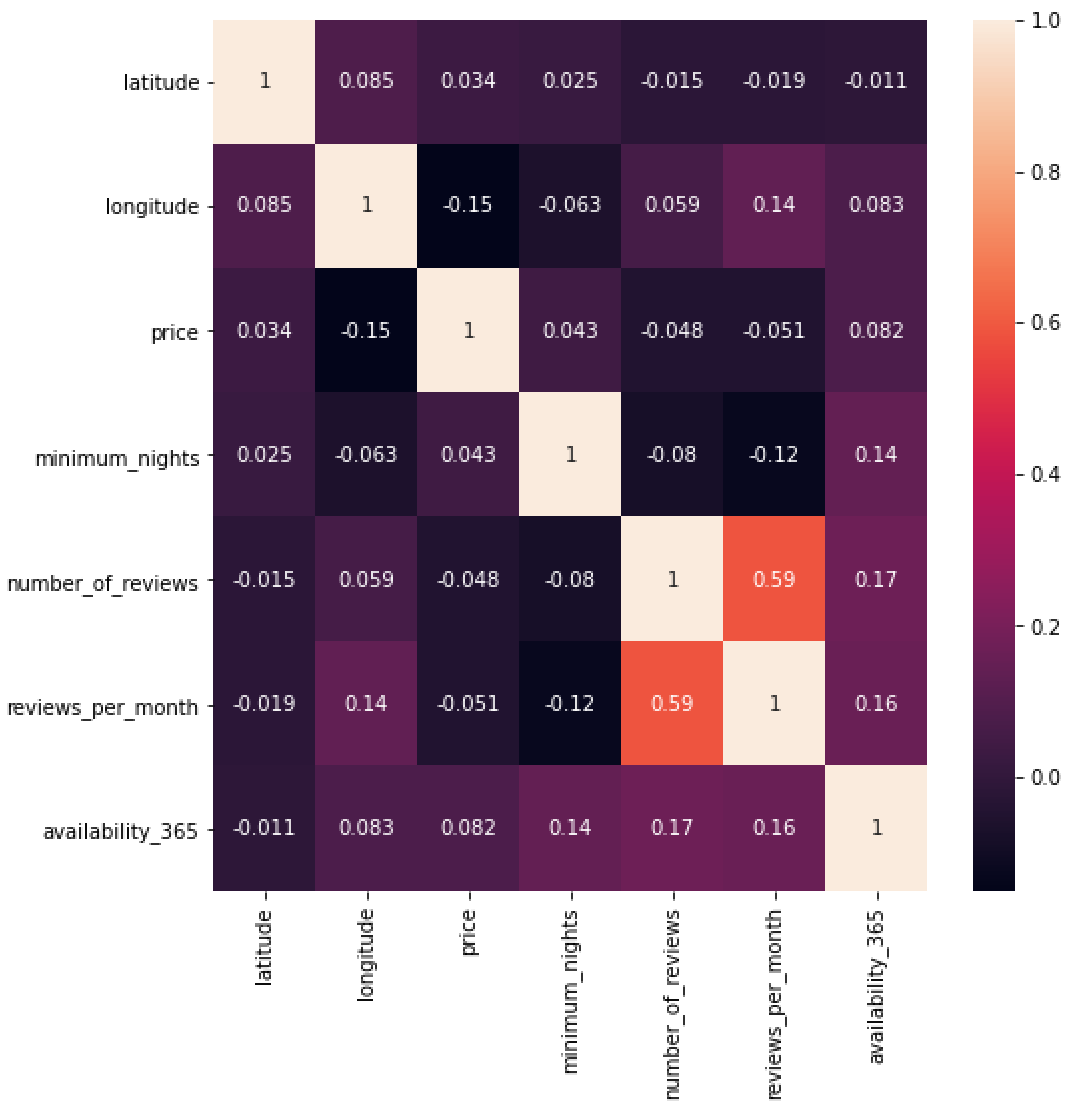
```
df.corr()
```

Out[239…

	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_m
latitude	1.000000	0.084788	0.033939	0.024869	-0.015389	-0.01
longitude	0.084788	1.000000	-0.150019	-0.062747	0.059094	0.13
price	0.033939	-0.150019	1.000000	0.042799	-0.047954	-0.05
minimum_nights	0.024869	-0.062747	0.042799	1.000000	-0.080116	-0.12
number_of_reviews	-0.015389	0.059094	-0.047954	-0.080116	1.000000	0.58
reviews_per_month	-0.018758	0.138516	-0.050564	-0.124905	0.589407	1.00
availability_365	-0.010983	0.082731	0.081829	0.144303	0.172028	0.16

In [240…

```
plt.figure(figsize=(8,8))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Creating Models

All the models will be based on Regression Algorithms as price is Continuous.

First Models

In [241…

```
for cols in df_cat:
    le = LabelEncoder()
    df[cols] = le.fit_transform(df[cols])
```

In [242…

```
df.head()
```

Out[242…

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
0	1	108	40.64749	-73.97237	1	149	1	
1	2	127	40.75362	-73.98377	0	225	1	
2	2	94	40.80902	-73.94190	1	150	3	
3	1	41	40.68514	-73.95976	0	89	1	
4	2	61	40.79851	-73.94399	0	80	10	

In [243…

```
x = df.drop('price', axis=1)
y = df["price"]
```

In [244…

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1
```

In [245…

```
def ml_model(model):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print("MSE :", mean_squared_error(y_test, y_pred))
    print("RMSE :", np.sqrt(mean_squared_error(y_test, y_pred)))
    print("R2 Score ;", r2_score(y_test, y_pred))
```

In [246…

```
ml_model(RandomForestRegressor())
```

```
MSE : 59121.28162384134
RMSE : 243.14868213469992
R2 Score ; 0.07830128357551436
```

In [247…

```
ml_model(LinearRegression())
```

```
MSE : 59373.83791464113
RMSE : 243.66747405971347
R2 Score ; 0.07436393981940026
```

In [248…

```
ml_model(AdaBoostRegressor())
```

```
MSE : 273130.9148316313
RMSE : 522.6192828739017
R2 Score ; -3.2581014264521837
```

In [249…

```
ml_model(GradientBoostingRegressor())
```

```
MSE : 56111.66594842787
RMSE : 236.87901120282453
R2 Score ; 0.12522108688101263
```

In [250…

```
ml_model(DecisionTreeRegressor())
```

```
MSE : 124694.14643624093
RMSE : 353.12058342192535
R2 Score ; -0.943977389515573
```

In [251…

```
ml_model(XGBRegressor())
```

```
MSE : 57479.32319499006
RMSE : 239.748458170204
R2 Score ; 0.10389935815589191
```

In [252…

```
ss = StandardScaler()

X_train_ss = ss.fit_transform(X_train)
X_test_ss = ss.transform(X_test)
```

In [253…

```
nn_model = tf.keras.Sequential([
    tf.keras.layers.Dense(3, activation='relu', input_shape=(X_train_ss.shape[1],)),
    tf.keras.layers.Dense(4, activation='relu'),
    tf.keras.layers.Dense(5, activation='relu'),
    tf.keras.layers.Dense(3, activation='relu'),
    tf.keras.layers.Dense(1)
])
```

In [254…

```
nn_model.compile(optimizer='adam', loss='mse')
```

In [255…

```
nn_model.fit(X_train_ss, y_train, epochs=50, batch_size=10)
```

```
Epoch 1/50
3912/3912 [==============================] - 5s 1ms/step - loss: 78900.9297
Epoch 2/50
3912/3912 [==============================] - 4s 1ms/step - loss: 77854.3984
Epoch 3/50
3912/3912 [==============================] - 4s 1ms/step - loss: 76843.1328
Epoch 4/50
3912/3912 [==============================] - 4s 1ms/step - loss: 75864.7891
Epoch 5/50
3912/3912 [==============================] - 5s 1ms/step - loss: 74916.3516
Epoch 6/50
3912/3912 [==============================] - 5s 1ms/step - loss: 73988.7812
Epoch 7/50
3912/3912 [==============================] - 4s 1ms/step - loss: 73101.4297
Epoch 8/50
3912/3912 [==============================] - 4s 979us/step - loss: 72224.4531
Epoch 9/50
```

```
3912/3912 [==============================] - 4s 1ms/step - loss: 71395.1172
Epoch 10/50
3912/3912 [==============================] - 4s 1ms/step - loss: 70572.7109
Epoch 11/50
3912/3912 [==============================] - 4s 949us/step - loss: 69786.3594
Epoch 12/50
3912/3912 [==============================] - 4s 965us/step - loss: 69032.6875
Epoch 13/50
3912/3912 [==============================] - 5s 1ms/step - loss: 68303.4922
Epoch 14/50
3912/3912 [==============================] - 4s 999us/step - loss: 67610.2734
Epoch 15/50
3912/3912 [==============================] - 4s 1ms/step - loss: 66937.7812
Epoch 16/50
3912/3912 [==============================] - 4s 1ms/step - loss: 66286.0859
Epoch 17/50
3912/3912 [==============================] - 4s 909us/step - loss: 65656.5938
Epoch 18/50
3912/3912 [==============================] - 3s 883us/step - loss: 65068.9570
Epoch 19/50
3912/3912 [==============================] - 4s 1ms/step - loss: 64492.3672
Epoch 20/50
3912/3912 [==============================] - 4s 944us/step - loss: 63958.3555
Epoch 21/50
3912/3912 [==============================] - 4s 953us/step - loss: 63441.6250
Epoch 22/50
3912/3912 [==============================] - 4s 966us/step - loss: 62942.2500
Epoch 23/50
3912/3912 [==============================] - 6s 2ms/step - loss: 62475.1523
Epoch 24/50
3912/3912 [==============================] - 4s 994us/step - loss: 62033.2188
Epoch 25/50
3912/3912 [==============================] - 4s 1ms/step - loss: 61609.2773
Epoch 26/50
3912/3912 [==============================] - 4s 1ms/step - loss: 61210.6953
Epoch 27/50
3912/3912 [==============================] - 4s 1ms/step - loss: 60826.0078
Epoch 28/50
3912/3912 [==============================] - 4s 992us/step - loss: 60467.2852
Epoch 29/50
3912/3912 [==============================] - 4s 954us/step - loss: 60134.7891
Epoch 30/50
3912/3912 [==============================] - 4s 942us/step - loss: 59822.4883
Epoch 31/50
3912/3912 [==============================] - 4s 926us/step - loss: 59535.0195
Epoch 32/50
3912/3912 [==============================] - 4s 920us/step - loss: 59261.8086
Epoch 33/50
3912/3912 [==============================] - 4s 934us/step - loss: 58998.3203
Epoch 34/50
3912/3912 [==============================] - 4s 946us/step - loss: 58760.4219
Epoch 35/50
3912/3912 [==============================] - 4s 946us/step - loss: 58540.2500
Epoch 36/50
3912/3912 [==============================] - 4s 925us/step - loss: 58334.5781
Epoch 37/50
3912/3912 [==============================] - 4s 1ms/step - loss: 58139.5352
Epoch 38/50
3912/3912 [==============================] - 4s 1ms/step - loss: 57960.7422
Epoch 39/50
3912/3912 [==============================] - 5s 1ms/step - loss: 57794.9375
Epoch 40/50
3912/3912 [==============================] - 5s 1ms/step - loss: 57636.9961
Epoch 41/50
3912/3912 [==============================] - 5s 1ms/step - loss: 57496.2539A: 0s -
```

```
Epoch 42/50
3912/3912 [==============================] - 5s 1ms/step - loss: 57368.2812
Epoch 43/50
3912/3912 [==============================] - 6s 2ms/step - loss: 57254.3711
Epoch 44/50
3912/3912 [==============================] - 6s 2ms/step - loss: 57144.5508
Epoch 45/50
3912/3912 [==============================] - 5s 1ms/step - loss: 57047.7305
Epoch 46/50
3912/3912 [==============================] - 5s 1ms/step - loss: 56956.6836
Epoch 47/50
3912/3912 [==============================] - 5s 1ms/step - loss: 56872.3164
Epoch 48/50
3912/3912 [==============================] - 5s 1ms/step - loss: 56798.8125
Epoch 49/50
3912/3912 [==============================] - 5s 1ms/step - loss: 56728.4453
Epoch 50/50
3912/3912 [==============================] - 5s 1ms/step - loss: 56666.1797
```

Out[255…

```
<tensorflow.python.keras.callbacks.History at 0x25693f44c40>
```

In [256…

```
y_pred = nn_model.predict(X_test_ss)
mean_squared_error(y_test, y_pred)
```

Out[256…

```
64681.986188186325
```

In [257…

```
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[257…

```
254.32653457354056
```

In [258…

```
r2_score(y_test, y_pred)
```

Out[258…

```
-0.008389906442695771
```

Scores are very high. Let us perform One-Hot-Encoding on the data.

Second Models

In [259…

```
df = cleaning_data()
```

In [260…

```
df.head()
```

Out[260…

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
0	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
3	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

In [261...

```
neighbourhood_group = pd.get_dummies(df['neighbourhood_group'])
room_type = pd.get_dummies(df['room_type'])
```

In [262...

```
neighbourhood_group.head()
```

Out[262...

	Bronx	Brooklyn	Manhattan	Queens	Staten Island
0	0	1	0	0	0
1	0	0	1	0	0
2	0	0	1	0	0
3	0	1	0	0	0
4	0	0	1	0	0

In [263...

```
room_type.head()
```

Out[263...

	Entire home/apt	Private room	Shared room
0	0	1	0
1	1	0	0
2	0	1	0
3	1	0	0
4	1	0	0

In [264...

```
df = pd.concat([df, neighbourhood_group, room_type], axis=1)
df.head()
```

Out[264...

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
0	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	nun
3	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	

In [265…

```
df_cat.head()
```

Out[265…

	neighbourhood_group	neighbourhood	room_type
0	Brooklyn	Kensington	Private room
1	Manhattan	Midtown	Entire home/apt
2	Manhattan	Harlem	Private room
3	Brooklyn	Clinton Hill	Entire home/apt
4	Manhattan	East Harlem	Entire home/apt

In [266…

```
for cols in df_cat:
    le = LabelEncoder()
    df[cols] = le.fit_transform(df[cols])
```

In [267…

```
df.drop(['neighbourhood_group', 'room_type'], axis=1, inplace=True)
```

In [268…

```
x = df.drop('price', axis=1)
y = df["price"]
```

In [269…

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1
```

In [270…

```
ml_model(RandomForestRegressor(n_estimators=200))
```

```
MSE : 57757.89047693442
RMSE : 240.3287133842613
R2 Score ; 0.09955650395595117
```

In [271…

```
ml_model(LinearRegression())
```

```
MSE : 58850.47607474975
RMSE : 242.5911706446666
R2 Score ; 0.08252313263126443
```

In [272…

```
ml_model(AdaBoostRegressor())
```

```
MSE : 104219.00016951977
RMSE : 322.82967671749105
R2 Score ; -0.6247705740626726
```

In [273…
```
ml_model(GradientBoostingRegressor())
```

```
MSE : 56268.06976480065
RMSE : 237.20891586279097
R2 Score ; 0.12278275684426065
```

In [274…
```
ml_model(DecisionTreeRegressor())
```

```
MSE : 123745.18969219757
RMSE : 351.7743448465189
R2 Score ; -0.9291831870067018
```

In [275…
```
ml_model(XGBRegressor())
```

```
MSE : 57485.17655094336
RMSE : 239.76066514535566
R2 Score ; 0.10380810454093703
```

In [276…
```
ss = StandardScaler()

X_train_ss = ss.fit_transform(X_train)
X_test_ss = ss.transform(X_test)
```

In [277…
```
nn_model = tf.keras.Sequential([
    tf.keras.layers.Dense(3, activation='relu', input_shape=(X_train_ss.shape[1],)),
    tf.keras.layers.Dense(4, activation='relu'),
    tf.keras.layers.Dense(5, activation='relu'),
    tf.keras.layers.Dense(3, activation='relu'),
    tf.keras.layers.Dense(1)
])
```

In [278…
```
nn_model.compile(optimizer='adam', loss='mse')
```

In [279…
```
nn_model.fit(X_train_ss, y_train, epochs=50, batch_size=10)
```

```
Epoch 1/50
3912/3912 [==============================] - 4s 999us/step - loss: 54816.9453
Epoch 2/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49970.9023
Epoch 3/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49785.3125
Epoch 4/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49708.4805
Epoch 5/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49646.0508
Epoch 6/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49603.8281
Epoch 7/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49566.5156
Epoch 8/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49547.4766
Epoch 9/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49505.4688
Epoch 10/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49488.5781
```

```
Epoch 11/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49463.7031
Epoch 12/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49433.2266
Epoch 13/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49418.4727
Epoch 14/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49405.9922
Epoch 15/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49372.7422
Epoch 16/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49351.8516
Epoch 17/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49347.6016
Epoch 18/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49312.0586
Epoch 19/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49283.0781
Epoch 20/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49265.9961
Epoch 21/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49241.1562
Epoch 22/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49211.7383
Epoch 23/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49231.0117
Epoch 24/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49204.8398
Epoch 25/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49182.2344
Epoch 26/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49176.9492
Epoch 27/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49152.0312
Epoch 28/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49158.3750
Epoch 29/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49144.4883
Epoch 30/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49133.5117
Epoch 31/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49128.5898
Epoch 32/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49121.4023
Epoch 33/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49070.1602
Epoch 34/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49098.2930
Epoch 35/50
3912/3912 [==============================] - 4s 975us/step - loss: 49094.4414
Epoch 36/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49077.9492
Epoch 37/50
3912/3912 [==============================] - 4s 961us/step - loss: 49028.1016
Epoch 38/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49047.0859
Epoch 39/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49052.0195
Epoch 40/50
3912/3912 [==============================] - 4s 1ms/step - loss: 49032.7227
Epoch 41/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49033.4609
Epoch 42/50
3912/3912 [==============================] - 5s 1ms/step - loss: 49014.0898
Epoch 43/50
```

```
3912/3912 [==============================] - 4s 1ms/step - loss: 49008.2812
Epoch 44/50
3912/3912 [==============================] - 5s 1ms/step - loss: 48979.3242
Epoch 45/50
3912/3912 [==============================] - 6s 1ms/step - loss: 48991.7930
Epoch 46/50
3912/3912 [==============================] - 4s 1ms/step - loss: 48983.7969
Epoch 47/50
3912/3912 [==============================] - 4s 1ms/step - loss: 48980.1055
Epoch 48/50
3912/3912 [==============================] - 4s 1ms/step - loss: 48972.9141
Epoch 49/50
3912/3912 [==============================] - 4s 1ms/step - loss: 48966.6328
Epoch 50/50
3912/3912 [==============================] - 4s 1ms/step - loss: 48966.8672
```

Out[279… <tensorflow.python.keras.callbacks.History at 0x2569558daf0>

In [280…

```
y_pred = nn_model.predict(X_test_ss)
mean_squared_error(y_test, y_pred)
```

Out[280… 57552.796025528

In [281…

```
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[281… 239.90163823018798

In [282…

```
r2_score(y_test, y_pred)
```

Out[282… 0.10275391929294975

Even with one-hot enoding, our scores are not good. Let us look at the data once more.

Third Models

In [283…

```
df = cleaning_data()
df.head()
```

Out[283…

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

In [284…

```
df_num
```

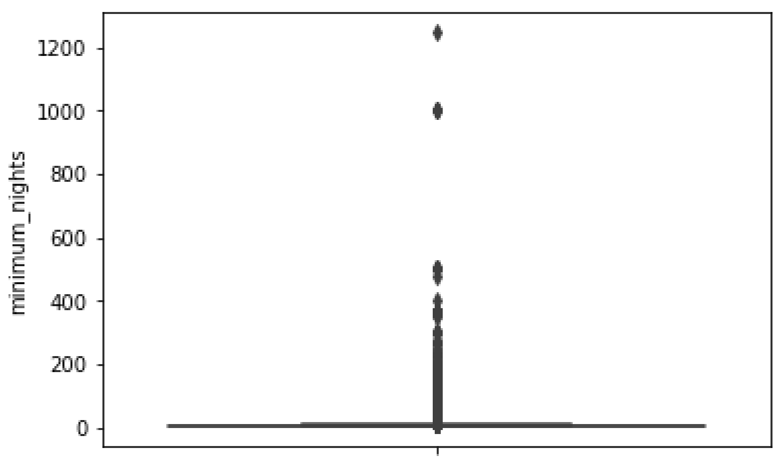
Out[284…

	latitude	longitude	minimum_nights	number_of_reviews	reviews_per_month	availability_365
0	40.64749	-73.97237	1	9	0.21	365
1	40.75362	-73.98377	1	45	0.38	355
2	40.80902	-73.94190	3	0	0.00	365
3	40.68514	-73.95976	1	270	4.64	194
4	40.79851	-73.94399	10	9	0.10	0
...	...	...	...	...	...	...
48890	40.67853	-73.94995	2	0	0.00	9
48891	40.70184	-73.93317	4	0	0.00	36
48892	40.81475	-73.94867	10	0	0.00	27
48893	40.75751	-73.99112	1	0	0.00	2
48894	40.76404	-73.98933	7	0	0.00	23

48895 rows × 6 columns

In [285…

```
plt.figure()
sns.boxplot(y=df['minimum_nights'])
plt.show()
```



In [286…

```
min(df['minimum_nights'])
```

Out[286… 1

In [287…

```
max(df['minimum_nights'])
```

Out[287… 1250

The below link is to an article stating short-term AirBnb stays in New York

https://sharedeconomycpa.com/blog/nyc-airbnb-law/#:~:text=Airbnb%20NYC%20Law%3A%20How%20It%20Works&text=Rentals%20can%20exceed%2(

The article states that -

- You can’t rent out an entire apartment for fewer than 30 days, even if you own or live in the building.
- If you are renting out a portion of your home for less than 30 days, you must be present during your guests’ stay.

Let us take a look at 'minimum_nights' for rows with values greater than 30 and less than 31.

In [288…
```
len(df[df['minimum_nights']>30][df['room_type'] == 'Private room'])
```
Out[288… 226

In [289…
```
len(df[df['minimum_nights']>30][df['room_type'] == 'Shared room'])
```
Out[289… 17

In [290…
```
len(df[df['minimum_nights']>30][df['room_type'] == 'Entire home/apt'])
```
Out[290… 504

In [291…
```
len(df[df['minimum_nights']<31][df['room_type'] == 'Private room'])
```
Out[291… 22100

In [292…
```
len(df[df['minimum_nights']<31][df['room_type'] == 'Shared room'])
```
Out[292… 1143

In [293…
```
len(df[df['minimum_nights']<31][df['room_type'] == 'Entire home/apt'])
```
Out[293… 24905

- From the above, we can see that most of the property given on rent have a minimum stay of 30 days or less. We can assume that the owner would be present when leasing out property for less than 30 days.

- Earlier, we saw that some owners had more than one listing. We can assume that they might only rent out one at a time, or that the property might actually be under a company. If under a company, the rules might be different. Meaning that the home owner would not need to be present when leasing out the property.

For the above two reasons, we will exclude all rows where the minimum stay is more than 30.

In [294…

```
to_remove = df[df['minimum_nights']>30].index.tolist()
len(to_remove)
```

Out[294… 747

In [295…

```
df.drop(to_remove, inplace=True)
```

In [296…

```
for cols in df_cat:
    le = LabelEncoder()
    df[cols] = le.fit_transform(df[cols])
```

In [297…

```
df.head()
```

Out[297…

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	num
0	1	108	40.64749	-73.97237	1	149	1	
1	2	127	40.75362	-73.98377	0	225	1	
2	2	94	40.80902	-73.94190	1	150	3	
3	1	41	40.68514	-73.95976	0	89	1	
4	2	61	40.79851	-73.94399	0	80	10	

In [298…

```
x = df.drop('price', axis=1)
y = df["price"]
```

In [299…

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1
```

In [300…

```
def ml_model(model):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print("MSE :", mean_squared_error(y_test, y_pred))
    print("RMSE :", np.sqrt(mean_squared_error(y_test, y_pred)))
    print("R2 Score ;", r2_score(y_test, y_pred))
```

In [301…

```
ml_model(RandomForestRegressor())
```

```
MSE : 46404.175541754936
RMSE : 215.41628430031685
R2 Score ; 0.011742957106600449
```

In [302…

```
ml_model(LinearRegression())
```

```
MSE : 41660.21414696948
```

```
RMSE : 204.10833923916357
R2 Score ; 0.1127738062678485
```

In [303…

```
ml_model(AdaBoostRegressor())
```

```
MSE : 89738.13011626135
RMSE : 299.56323225032367
R2 Score ; -0.9111284290285584
```

In [304…

```
ml_model(GradientBoostingRegressor())
```

```
MSE : 39686.78794883877
RMSE : 199.2154310008107
R2 Score ; 0.15480132461429919
```

In [305…

```
ml_model(DecisionTreeRegressor())
```

```
MSE : 116629.13842159917
RMSE : 341.51008538782446
R2 Score ; -1.483818882807709
```

In [306…

```
ml_model(XGBRegressor())
```

```
MSE : 44983.0180243639
RMSE : 212.09200367850715
R2 Score ; 0.04200896031053292
```

In [307…

```
ss = StandardScaler()

X_train_ss = ss.fit_transform(X_train)
X_test_ss = ss.transform(X_test)
```

In [308…

```
nn_model = tf.keras.Sequential([
    tf.keras.layers.Dense(3, activation='relu', input_shape=(X_train_ss.shape[1],)),
    tf.keras.layers.Dense(4, activation='relu'),
    tf.keras.layers.Dense(5, activation='relu'),
    tf.keras.layers.Dense(3, activation='relu'),
    tf.keras.layers.Dense(1)
])
```

In [309…

```
nn_model.compile(optimizer='adam', loss='mse')
```

In [310…

```
nn_model.fit(X_train_ss, y_train, epochs=50, batch_size=10)
```

```
Epoch 1/50
3852/3852 [==============================] - 3s 834us/step - loss: 52175.8828
Epoch 2/50
3852/3852 [==============================] - 3s 872us/step - loss: 46477.7891
Epoch 3/50
3852/3852 [==============================] - 3s 904us/step - loss: 46299.1719
Epoch 4/50
3852/3852 [==============================] - 4s 934us/step - loss: 46195.6875
Epoch 5/50
3852/3852 [==============================] - 4s 918us/step - loss: 46112.7734
Epoch 6/50
```

```
3852/3852 [==============================] - 4s 922us/step - loss: 46092.8555
Epoch 7/50
3852/3852 [==============================] - 4s 910us/step - loss: 46065.1406
Epoch 8/50
3852/3852 [==============================] - 3s 908us/step - loss: 46008.9648
Epoch 9/50
3852/3852 [==============================] - 3s 899us/step - loss: 45974.2500
Epoch 10/50
3852/3852 [==============================] - 4s 914us/step - loss: 45962.7656
Epoch 11/50
3852/3852 [==============================] - 3s 904us/step - loss: 45903.1484
Epoch 12/50
3852/3852 [==============================] - 4s 923us/step - loss: 45857.6602
Epoch 13/50
3852/3852 [==============================] - 3s 897us/step - loss: 45770.8164
Epoch 14/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45742.8125
Epoch 15/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45652.7305
Epoch 16/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45596.4531
Epoch 17/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45533.7969
Epoch 18/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45481.5156
Epoch 19/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45451.8477
Epoch 20/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45419.1445
Epoch 21/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45385.7383
Epoch 22/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45384.5312
Epoch 23/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45383.4219
Epoch 24/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45363.6289
Epoch 25/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45277.2227
Epoch 26/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45327.6602
Epoch 27/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45311.5195
Epoch 28/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45310.3203
Epoch 29/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45283.8672
Epoch 30/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45267.7617
Epoch 31/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45268.5508
Epoch 32/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45241.8164
Epoch 33/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45254.3281
Epoch 34/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45264.2070
Epoch 35/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45233.6992
Epoch 36/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45256.5547
Epoch 37/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45228.1914
Epoch 38/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45240.3281
```

```
Epoch 39/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45228.3164
Epoch 40/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45224.7109
Epoch 41/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45211.9180
Epoch 42/50
3852/3852 [==============================] - 6s 1ms/step - loss: 45234.6094
Epoch 43/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45186.5547
Epoch 44/50
3852/3852 [==============================] - 5s 1ms/step - loss: 45221.6758
Epoch 45/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45232.1836
Epoch 46/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45211.5117
Epoch 47/50
3852/3852 [==============================] - 4s 990us/step - loss: 45219.3633
Epoch 48/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45192.4141
Epoch 49/50
3852/3852 [==============================] - 4s 1ms/step - loss: 45182.6055
Epoch 50/50
3852/3852 [==============================] - 4s 952us/step - loss: 45210.7695
```

Out[310…

```
<tensorflow.python.keras.callbacks.History at 0x256938cb4c0>
```

In [311…

```
y_pred = nn_model.predict(X_test_ss)
mean_squared_error(y_test, y_pred)
```

Out[311…

```
39913.05137583964
```

In [312…

```
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[312…

```
199.78251018505009
```

In [313…

```
r2_score(y_test, y_pred)
```

Out[313…

```
0.14998265425387858
```

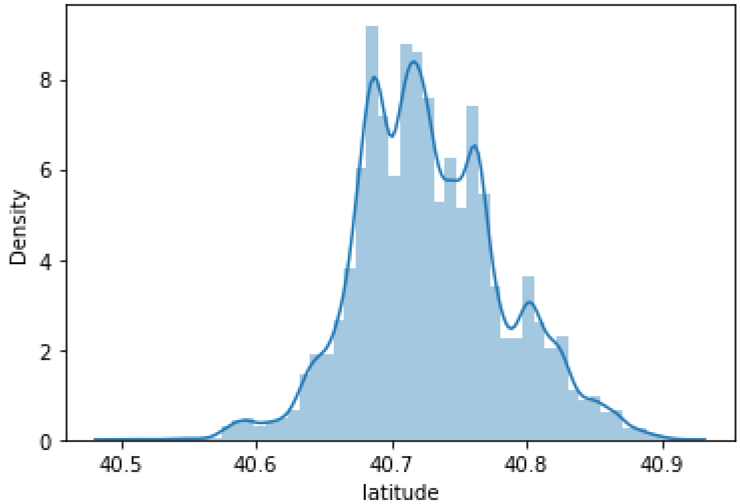
There does seem to be a slight improvement with the scores. We will try to improve them further.

Forth Models

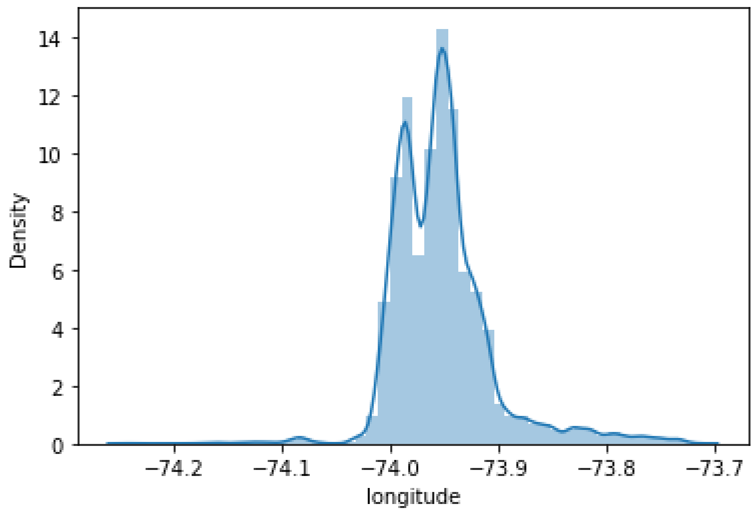
In [314…

```
for cols in df_num:
    plt.figure()
    print(cols, "-", skew(df[cols]))
    sns.distplot(df[cols])
    plt.show()
    print()
```

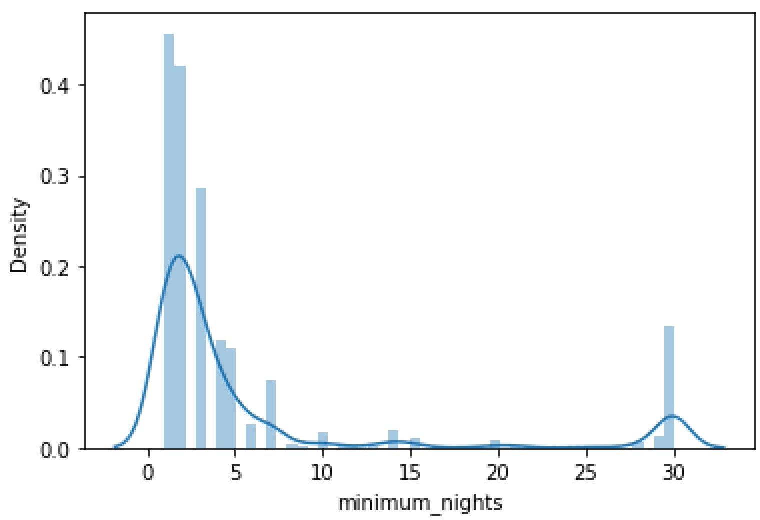
```
latitude - 0.23885551401666058
```



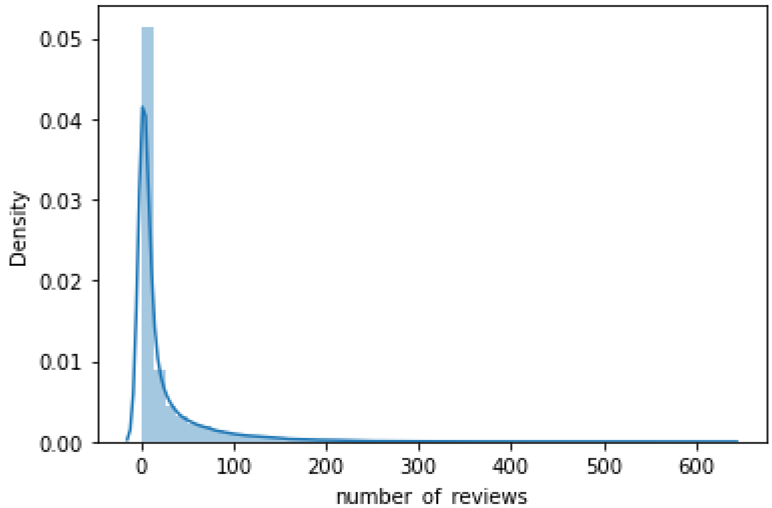
longitude - 1.2821791065131867



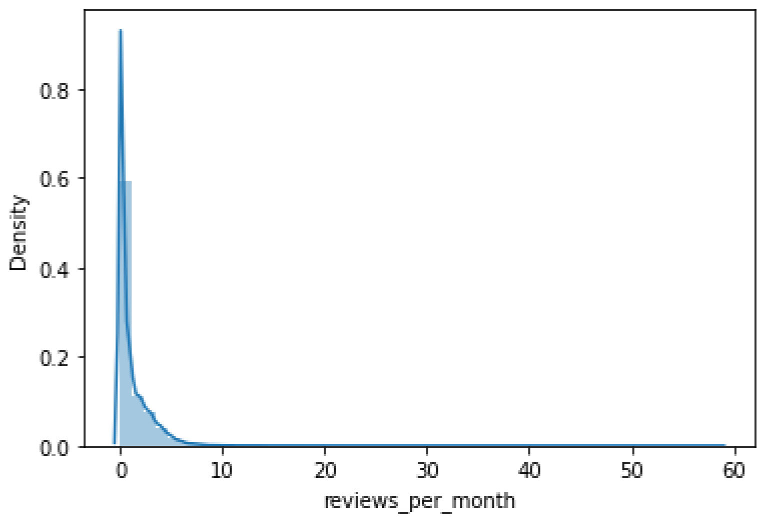
minimum_nights - 2.3519440868448553



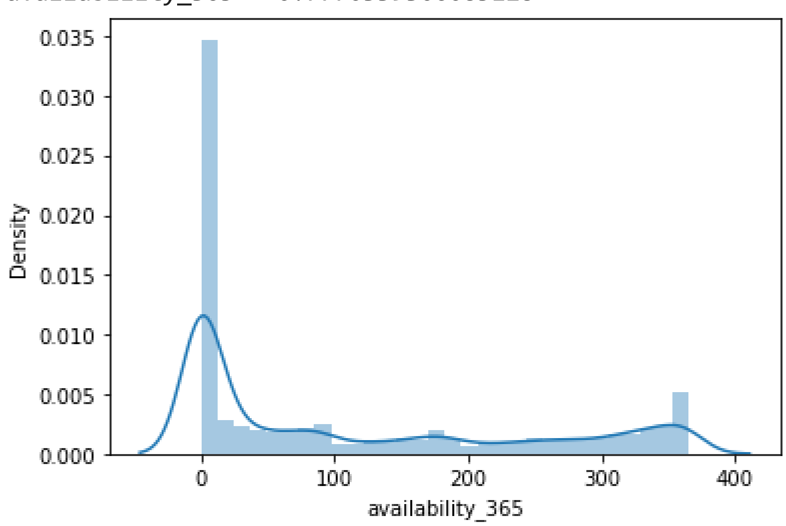
number_of_reviews - 3.674934014833137



reviews_per_month - 3.2850380814956788



availability_365 - 0.7770339306085128



df['minimum_nights'] = np.log(df['minimum_nights']) df['number_of_reviews'] = np.log(df['number_of_reviews']) df['reviews_per_month'] = np.log(df['reviews_per_month'])

The above block of code change some of the values to '-inf'. This is because the log of 0 is -infinity.

Adding a small value, 0.1, would give us a negative value. Our data cannot have any negative value.

For this, we will add 1 to each value, so that the log of 1 will give us a 0 value.

In [315…

```
df['minimum_nights'] = np.log(df['minimum_nights']+1)
df['number_of_reviews'] = np.log(df['number_of_reviews']+1)
df['reviews_per_month'] = np.log(df['reviews_per_month']+1)
```

In [316…

```
x = df.drop('price', axis=1)
y = df["price"]
```

In [317…

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1
```

In [318…

```
def ml_model(model):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print("MSE :", mean_squared_error(y_test, y_pred))
    print("RMSE :", np.sqrt(mean_squared_error(y_test, y_pred)))
    print("R2 Score ;", r2_score(y_test, y_pred))
```

In [319…

```
ml_model(RandomForestRegressor())
```

```
MSE : 48792.606826054005
RMSE : 220.8904860469414
R2 Score ; -0.03912281112694105
```

In [320…

```
ml_model(LinearRegression())
```

```
MSE : 41336.30850373095
RMSE : 203.31332593740862
R2 Score ; 0.11967193621900707
```

In [321…

```
ml_model(AdaBoostRegressor())
```

```
MSE : 398520.98232558486
RMSE : 631.285183039793
R2 Score ; -7.487192433139407
```

In [322…

```
ml_model(GradientBoostingRegressor())
```

```
MSE : 39759.297445517026
RMSE : 199.3973356028536
R2 Score ; 0.15325710968250994
```

In [323…

```
ml_model(DecisionTreeRegressor())
```

```
MSE : 113476.27840083074
RMSE : 336.86240277126615
R2 Score ; -1.4166732847143266
```

In [324…

```
ml_model(XGBRegressor())
```

```
MSE : 44982.96553520027
RMSE : 212.09187993697512
```

```
R2 Score ; 0.04201007815790381
```

In [325…

```python
ss = StandardScaler()

X_train_ss = ss.fit_transform(X_train)
X_test_ss = ss.transform(X_test)
```

In [332…

```python
nn_model = tf.keras.Sequential([
    tf.keras.layers.Dense(3, activation='relu', input_shape=(X_train_ss.shape[1],)),
    tf.keras.layers.Dense(4, activation='relu'),
    tf.keras.layers.Dense(5, activation='relu'),
    tf.keras.layers.Dense(3, activation='relu'),
    tf.keras.layers.Dense(1)
])
```

In [333…

```python
nn_model.compile(optimizer='adam', loss='mse')
```

In [338…

```python
nn_model.fit(X_train_ss, y_train, epochs=50, batch_size=10)
```

```
Epoch 1/50
3852/3852 [==============================] - 4s 1ms/step - loss: 69242.5469
Epoch 2/50
3852/3852 [==============================] - 4s 1ms/step - loss: 68368.1484
Epoch 3/50
3852/3852 [==============================] - 4s 1ms/step - loss: 67537.6406
Epoch 4/50
3852/3852 [==============================] - 5s 1ms/step - loss: 66741.6641
Epoch 5/50
3852/3852 [==============================] - 5s 1ms/step - loss: 65955.0625
Epoch 6/50
3852/3852 [==============================] - 4s 992us/step - loss: 65200.1797
Epoch 7/50
3852/3852 [==============================] - 4s 946us/step - loss: 64474.9688
Epoch 8/50
3852/3852 [==============================] - 4s 923us/step - loss: 63776.6406
Epoch 9/50
3852/3852 [==============================] - 4s 926us/step - loss: 63104.3398
Epoch 10/50
3852/3852 [==============================] - 4s 921us/step - loss: 62454.9961
Epoch 11/50
3852/3852 [==============================] - 4s 929us/step - loss: 61838.5234
Epoch 12/50
3852/3852 [==============================] - 4s 921us/step - loss: 61243.6367
Epoch 13/50
3852/3852 [==============================] - 4s 1ms/step - loss: 60675.9727
Epoch 14/50
3852/3852 [==============================] - 4s 1ms/step - loss: 60133.5664
Epoch 15/50
3852/3852 [==============================] - 6s 1ms/step - loss: 59619.0273
Epoch 16/50
3852/3852 [==============================] - 6s 2ms/step - loss: 59129.0156
Epoch 17/50
3852/3852 [==============================] - 8s 2ms/step - loss: 58651.2227
Epoch 18/50
3852/3852 [==============================] - 7s 2ms/step - loss: 58204.8398
Epoch 19/50
3852/3852 [==============================] - 4s 1ms/step - loss: 57782.4258
Epoch 20/50
3852/3852 [==============================] - 4s 1ms/step - loss: 57374.0430
```

```
Epoch 21/50
3852/3852 [==============================] - 5s 1ms/step - loss: 57001.4062
Epoch 22/50
3852/3852 [==============================] - 5s 1ms/step - loss: 56640.1562
Epoch 23/50
3852/3852 [==============================] - 4s 1ms/step - loss: 56305.6172
Epoch 24/50
3852/3852 [==============================] - 5s 1ms/step - loss: 55987.9531
Epoch 25/50
3852/3852 [==============================] - 4s 1ms/step - loss: 55691.4102
Epoch 26/50
3852/3852 [==============================] - 4s 1ms/step - loss: 55412.2109
Epoch 27/50
3852/3852 [==============================] - 5s 1ms/step - loss: 55153.0781
Epoch 28/50
3852/3852 [==============================] - 4s 1ms/step - loss: 54913.4141
Epoch 29/50
3852/3852 [==============================] - 4s 1ms/step - loss: 54687.1602
Epoch 30/50
3852/3852 [==============================] - 5s 1ms/step - loss: 54476.8398
Epoch 31/50
3852/3852 [==============================] - 6s 1ms/step - loss: 54282.5898
Epoch 32/50
3852/3852 [==============================] - 6s 2ms/step - loss: 54103.0703
Epoch 33/50
3852/3852 [==============================] - 7s 2ms/step - loss: 53929.7617
Epoch 34/50
3852/3852 [==============================] - 6s 2ms/step - loss: 53773.6250
Epoch 35/50
3852/3852 [==============================] - 6s 2ms/step - loss: 53636.1953
Epoch 36/50
3852/3852 [==============================] - 5s 1ms/step - loss: 53506.0039
Epoch 37/50
3852/3852 [==============================] - 5s 1ms/step - loss: 53385.8516
Epoch 38/50
3852/3852 [==============================] - 5s 1ms/step - loss: 53275.1680
Epoch 39/50
3852/3852 [==============================] - 9s 2ms/step - loss: 53177.1133
Epoch 40/50
3852/3852 [==============================] - 7s 2ms/step - loss: 53085.7969
Epoch 41/50
3852/3852 [==============================] - 5s 1ms/step - loss: 53002.5273
Epoch 42/50
3852/3852 [==============================] - 6s 2ms/step - loss: 52926.7578
Epoch 43/50
3852/3852 [==============================] - 5s 1ms/step - loss: 52857.9805
Epoch 44/50
3852/3852 [==============================] - 4s 1ms/step - loss: 52797.0273
Epoch 45/50
3852/3852 [==============================] - 4s 979us/step - loss: 52736.7031
Epoch 46/50
3852/3852 [==============================] - 4s 1ms/step - loss: 52685.8828
Epoch 47/50
3852/3852 [==============================] - 4s 1ms/step - loss: 52637.6797
Epoch 48/50
3852/3852 [==============================] - 4s 1ms/step - loss: 52595.6914
Epoch 49/50
3852/3852 [==============================] - 4s 954us/step - loss: 52555.5234
Epoch 50/50
3852/3852 [==============================] - 4s 990us/step - loss: 52519.3438
```

Out[338…

```
<tensorflow.python.keras.callbacks.History at 0x256a160a310>
```

In [339…

```
y_pred = nn_model.predict(X_test_ss)
```

```
mean_squared_error(y_test, y_pred)
```

Out[339… 47288.25422180912

In [340…

```
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[340… 217.45862645986045

In [341…

```
r2_score(y_test, y_pred)
```

Out[341… -0.007085024897934611

Conclusion

The models that produced the best scores were GradientBoosting and NeuralNetwork from the 3rd model set.