In [ ]:
```
pip install --upgrade xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-pack
ages (2.1.2)
Collecting xgboost
  Downloading xgboost-2.1.3-py3-none-manylinux_2_28_x86_64.whl.metadata (2.1
kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packag
es (from xgboost) (1.26.4)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.10/
dist-packages (from xgboost) (2.23.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packag
es (from xgboost) (1.13.1)
Downloading xgboost-2.1.3-py3-none-manylinux_2_28_x86_64.whl (153.9 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 153.9/153.9 MB 5.5 MB/s eta 0:00:
00
Installing collected packages: xgboost
  Attempting uninstall: xgboost
    Found existing installation: xgboost 2.1.2
    Uninstalling xgboost-2.1.2:
      Successfully uninstalled xgboost-2.1.2
Successfully installed xgboost-2.1.3
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.model_selection import train_test_split, cross_val_score, GridSea
rchCV, KFold, RandomizedSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor, Gradi
entBoostingRegressor
import xgboost as xgb
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from yellowbrick.regressor import PredictionError, ResidualsPlot
import os
import warnings
warnings.filterwarnings("ignore")


pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Read dataset

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')

data = pd.read_csv('/content/drive/My Drive/ML/dataset/AB_NYC_2019.csv')
data.head()
```

```
Mounted at /content/drive
```

Out[ ]:

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

EDA and Data Visualisations

Exploratory Data Analysis was performed on the dataset to have a better understanding of the dataset.

In [ ]:
```
data.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
```

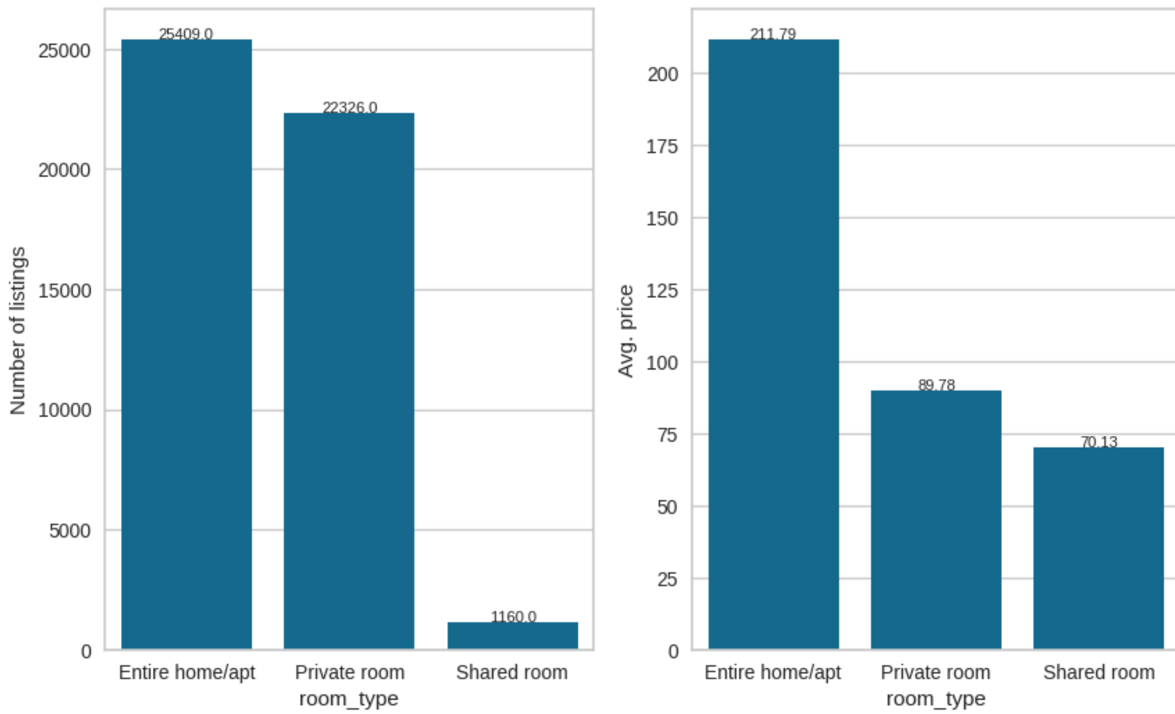
Room type analysis

In [ ]:
```
room_type = data.groupby('room_type').agg(avg_price=('price','mean'),
                                           count=('price','count')).reset_index()

room_type
```

Out[ ]:

	room_type	avg_price	count
0	Entire home/apt	211.794246	25409
1	Private room	89.780973	22326
2	Shared room	70.127586	1160

In [ ]:
```
fig,(chart_1,chart_2) = plt.subplots(1,2,figsize=(10,6))
ax = sns.barplot(x='room_type', y = 'avg_price', data=room_type, ax=chart_2)
for p in chart_2.patches:
    chart_2.annotate("{:.2f}".format(p.get_height()),
                     (p.get_x() + p.get_width()/2., p.get_height()),
                     ha='center',
                     fontsize=8)
chart_2.set_ylabel("Avg. price")

ax = sns.barplot(x='room_type', y = 'count', data=room_type, ax=chart_1)
for p in chart_1.patches:
    chart_1.annotate("{:.1f}".format(p.get_height()),
                     (p.get_x() + p.get_width()/2., p.get_height()),
                     ha='center',
                     fontsize=8)
chart_1.set_ylabel("Number of listings")
plt.show()
```



The dataset has 3 different room types:

- 52% (entire home/apartment)
- 45% (private room)
- 3% (shared room)

Also, Entire home/apt are most expensive.

Neighbourhood_group(large area) analysis

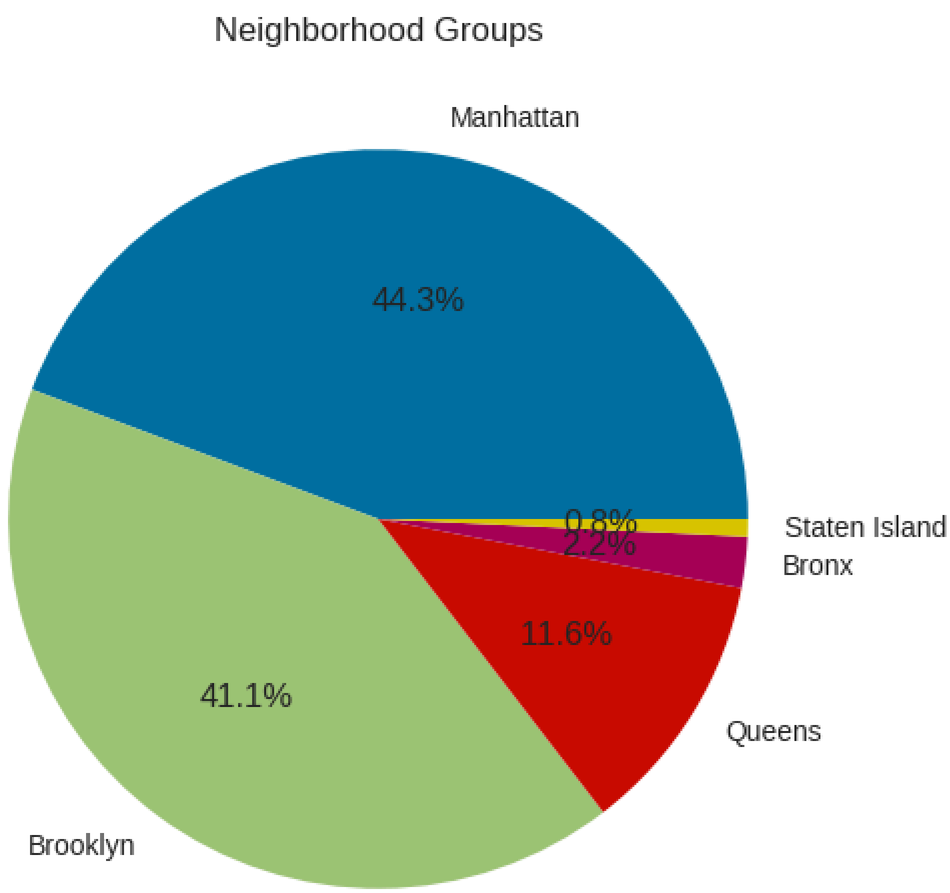
In [ ]:
```
# avg price of neighbourhoods
neighbourhood_group_df = data.groupby('neighbourhood_group').agg(avg_price=('price','mean'),
                       count=('price','count')).reset_index()

neighbourhood_group_df
```

Out[ ]:

	neighbourhood_group	avg_price	count
0	Bronx	87.496792	1091
1	Brooklyn	124.383207	20104
2	Manhattan	196.875814	21661
3	Queens	99.517649	5666
4	Staten Island	114.812332	373

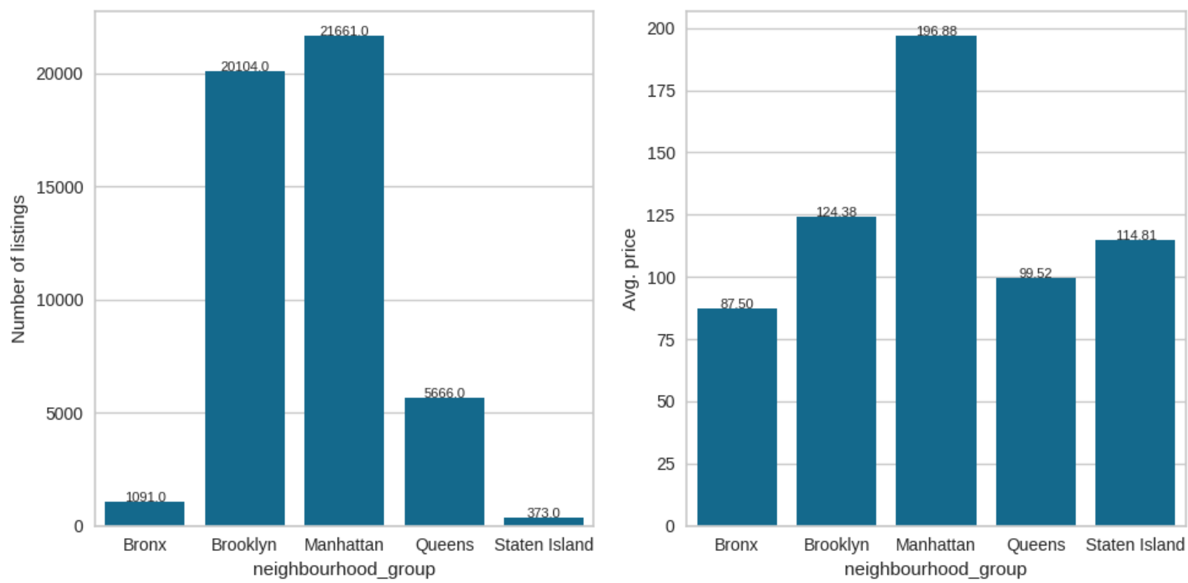
In [ ]:
```
#Pie chart to show listings in each neighbourhood group
ax1 = data.neighbourhood_group.value_counts().plot.pie(title='Neighborhood Gro
ups',
                                              figsize=(6,6),
                                             autopct='%1.1f%%')
ax1.set_ylabel(None)
```

Out[ ]: `Text(0, 0.5, '')`



More than 85% of listings are located in Manhattan and Brooklyn.

In [ ]:
```
fig,(chart_1,chart_2) = plt.subplots(1,2,figsize=(10,5))
ax = sns.barplot(x='neighbourhood_group', y = 'avg_price', data=neighbourhood_
group_df, ax=chart_2)
for p in chart_2.patches:
    chart_2.annotate("{:.2f}".format(p.get_height()),
                     (p.get_x() + p.get_width()/2., p.get_height()),
                     ha='center',
                     fontsize=8)
chart_2.set_ylabel("Avg. price")

ax = sns.barplot(x='neighbourhood_group', y = 'count', data=neighbourhood_grou
p_df, ax=chart_1)
for p in chart_1.patches:
    chart_1.annotate("{:.1f}".format(p.get_height()),
                     (p.get_x() + p.get_width()/2., p.get_height()),
                     ha='center',
                     fontsize=8)
chart_1.set_ylabel("Number of listings")
plt.tight_layout()
plt.show()
```



The pricing for the properties was skewed highly towards Manhattan at $196, while all the other locations fell in the $85-$125 price range.

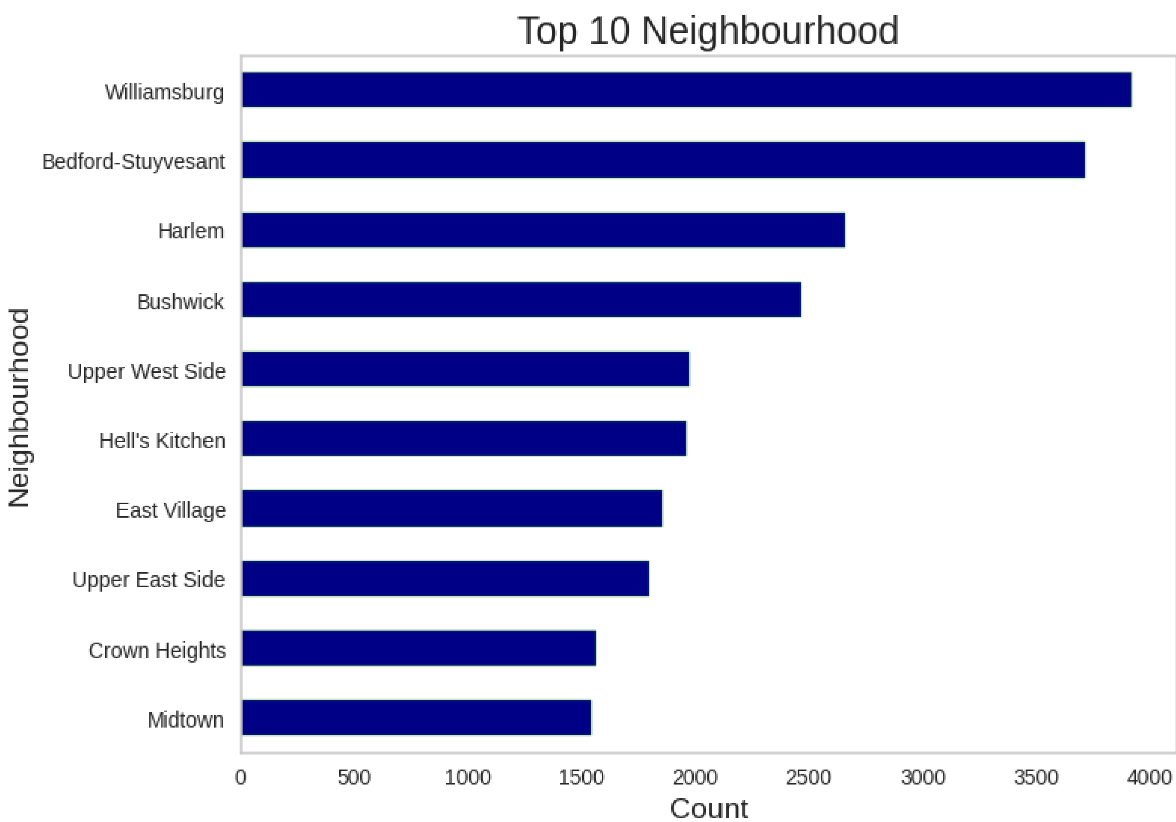
Neighbourhood Analysis

In [ ]:
```
print("There are", data["neighbourhood"].nunique(), "distinct values.")
```

```
There are 221 distinct values.
```

In [ ]:
```
plt.figure(figsize=(8,6))
data["neighbourhood"].value_counts().head(10).sort_values().plot(kind = "bar
h",
                                                               color = "darkbl
ue",
                                                               edgecolor="gree
n",
                                                               grid =False)
ax.bar_label(ax.containers[0], fmt='%.0f', color="black", fontsize=10)
plt.xlabel("Count", size = 14)
plt.ylabel("Neighbourhood", size = 14)
plt.title("Top 10 Neighbourhood", size = 18)
```

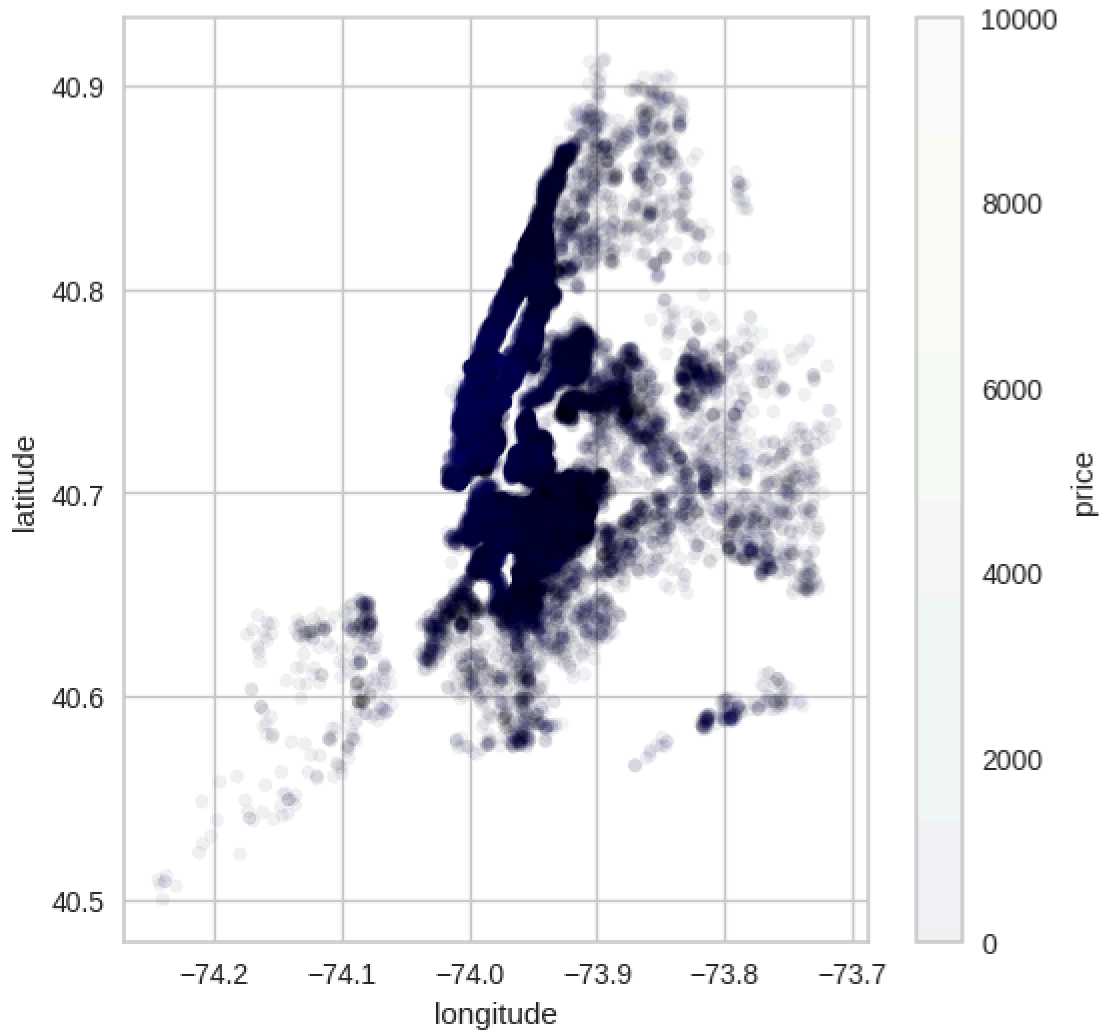
Out[ ]:
```
Text(0.5, 1.0, 'Top 10 Neighbourhood')
```



neighbourhood_group and room type

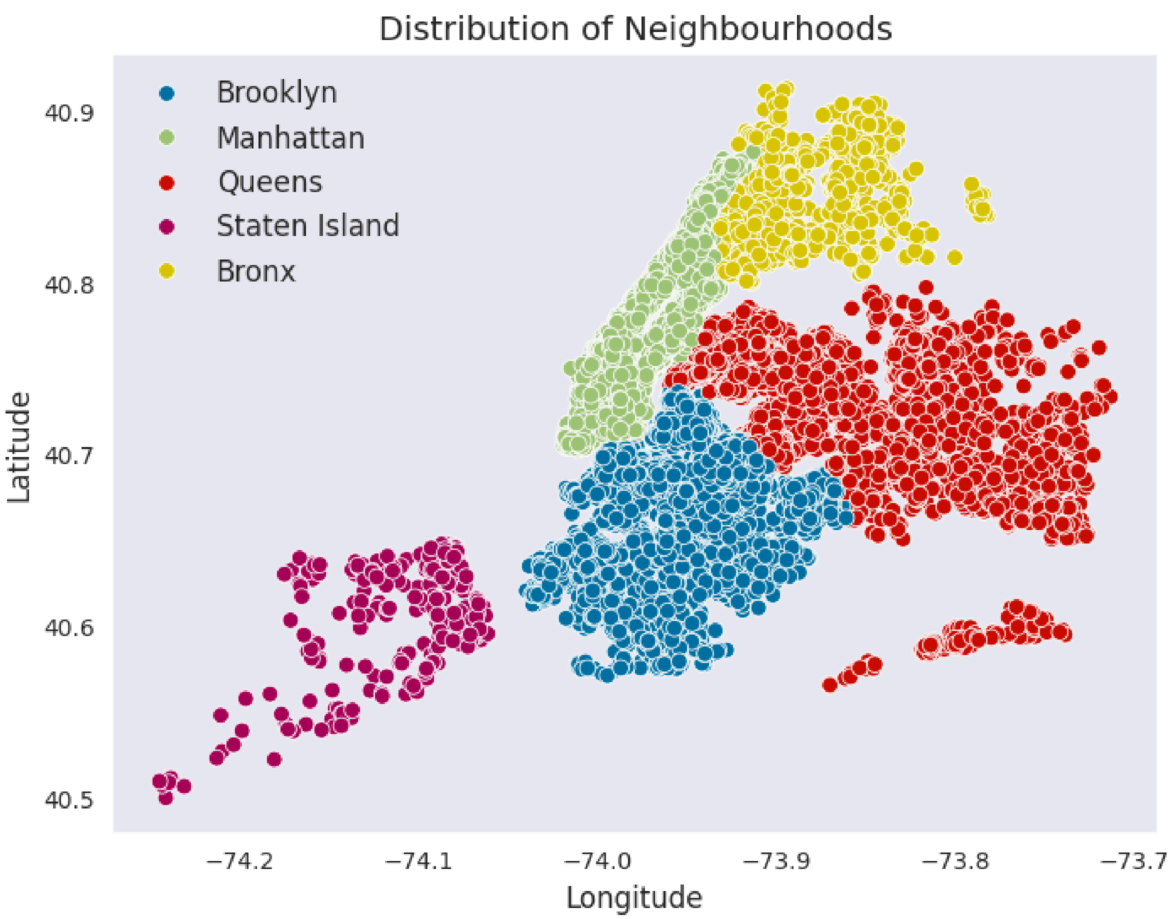
In [ ]:
```
data.plot(kind = "scatter", x = "longitude", y = "latitude", alpha = 0.05,
         figsize = (6,6), c = "price", cmap = plt.get_cmap("gist_earth"),
          colorbar = True
         )
```

Out[ ]: <Axes: xlabel='longitude', ylabel='latitude'>



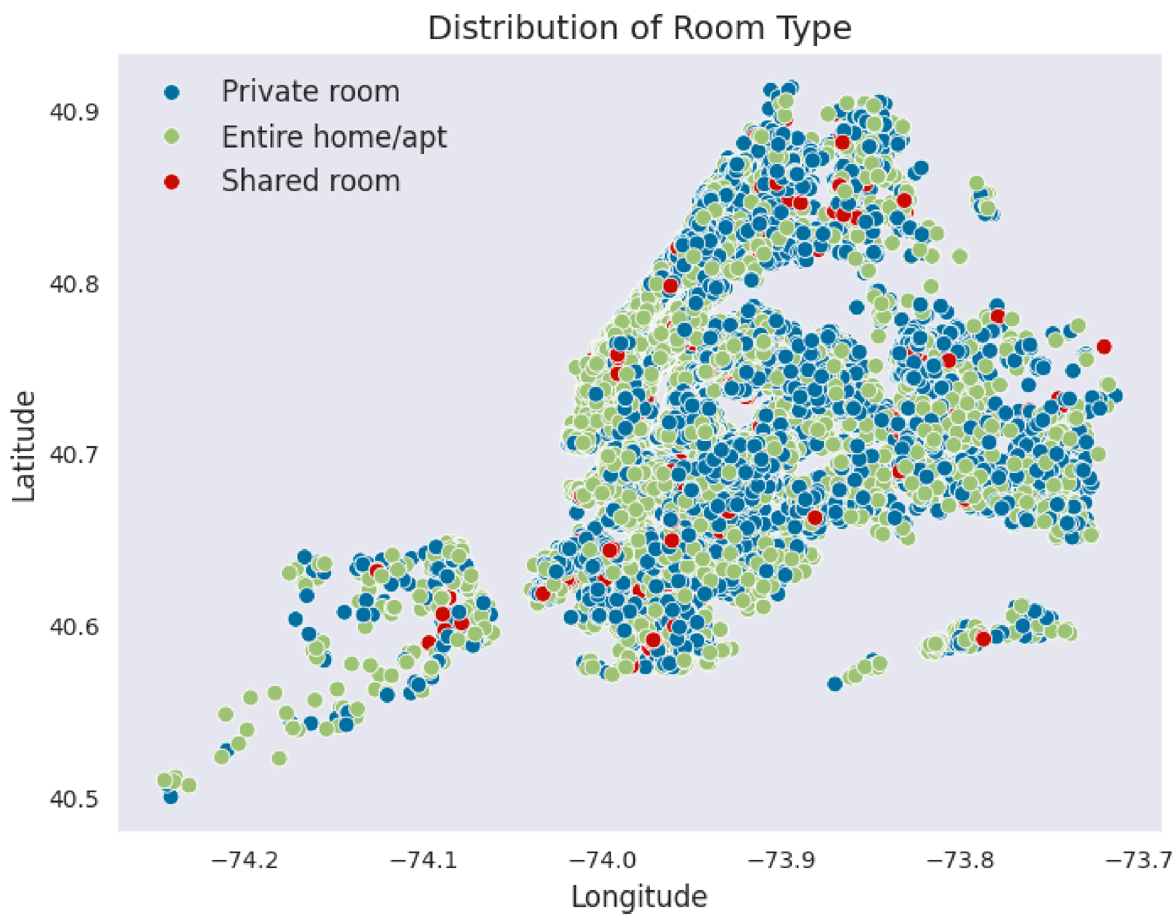
In [ ]:
```
plt.figure(figsize=(8,6))
sns.set_style("dark", {'axes.grid' : False})
sns.scatterplot(data=data, x="longitude", y="latitude", hue="neighbourhood_gro
up")
plt.ylabel("Latitude", fontsize=12)
plt.xlabel("Longitude", fontsize=12)
plt.title("Distribution of Neighbourhoods", fontsize=14)
plt.legend(prop={"size":12})
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x7b97b4f043d0>
```



In [ ]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(data = data, x="longitude", y="latitude", hue="room_type")
plt.ylabel("Latitude", fontsize=12)
plt.xlabel("Longitude", fontsize=12)
plt.title("Distribution of Room Type", fontsize=14)
plt.legend(prop={"size":12})
```

Out[ ]: <matplotlib.legend.Legend at 0x7b97a0b9a0b0>



Price Distribution analysis

In [ ]:
```
#  log transformation
fig, ax = plt.subplots(1,2, figsize = (10,5))
sns.histplot(data=data, x="price", kde=True, ax=ax[0]).set_title("Price Distri
bution Before Log Transformation",
                                                                 size = 12)
sns.histplot(np.log1p(data.price), kde=True, ax=ax[1]).set_title("Price Distri
bution After Log Transformation",
                                                                 size = 12)
```

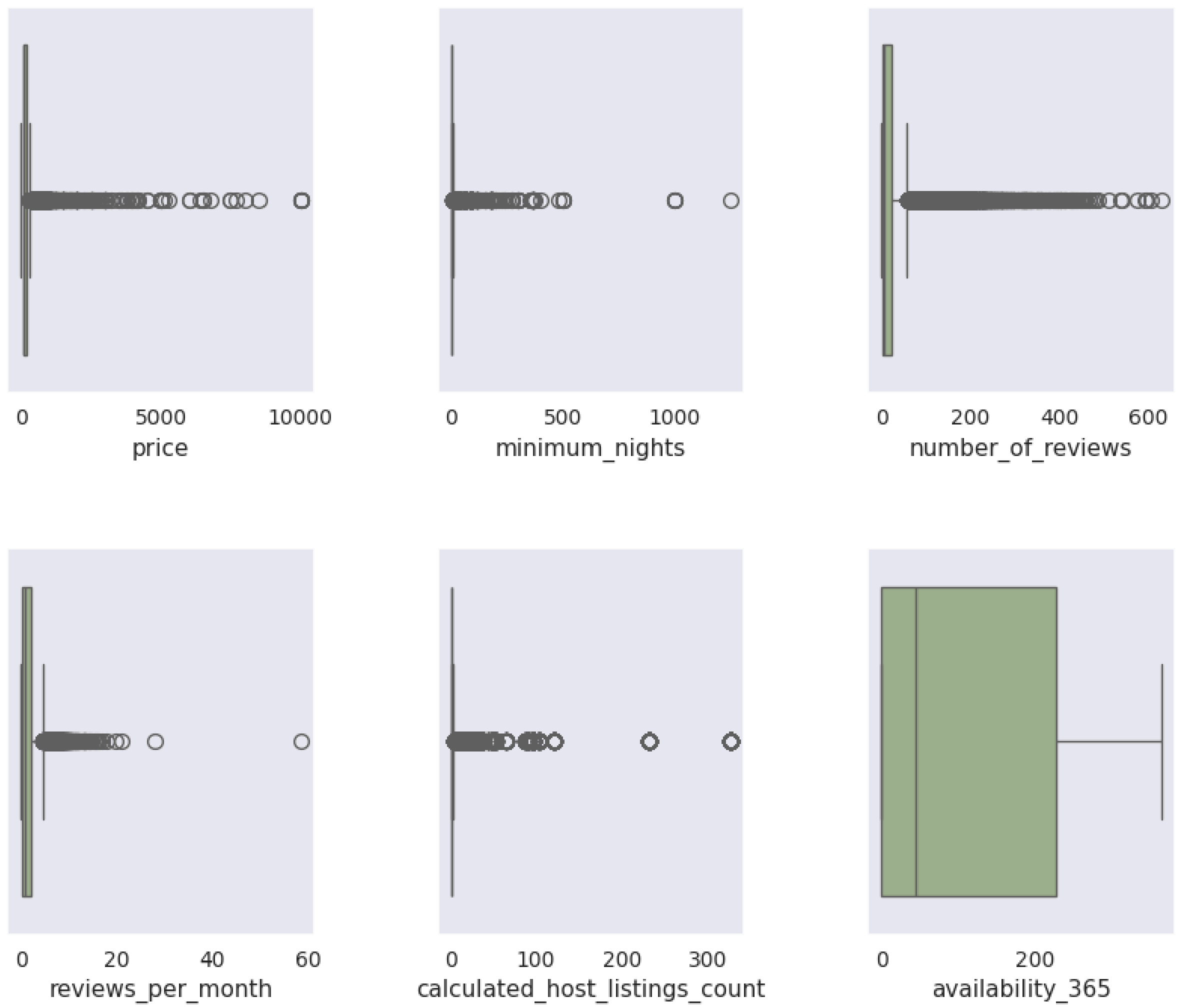
Out[ ]:
```
Text(0.5, 1.0, 'Price Distribution After Log Transformation')
```

The graph on the left shows that there is a right skewed distribution. To make a better statistical analysis and to get better scores, we will be applied log transformation for the price column

Data Cleaning and Preparation

Outlier detection and Removal

In [ ]:
```
columns = ["price", "minimum_nights", "number_of_reviews", "reviews_per_mont
h", "calculated_host_listings_count",
          "availability_365"]
fig = plt.figure(figsize=(10,8))
fig.subplots_adjust(hspace=0.4, wspace=0.4)
for num, column_name in enumerate(columns):
    ax = fig.add_subplot(2, 3, num +1)
    ax = sns.boxplot(x=data[column_name], color='#9db787')
```



In [ ]:
```
q1_price = data["price"].quantile(0.25)
q3_price = data["price"].quantile(0.75)
iqr_price = q3_price - q1_price
lower_limit_price = q1_price - 1.5 * iqr_price
upper_limit_price = q3_price + 1.5 * iqr_price

df_filter_price = data[(data["price"] > lower_limit_price) & (data["price"] <
upper_limit_price)]
```

In [ ]:
```
fig = plt.figure(figsize=(7,4))
fig.subplots_adjust(hspace=0.4, wspace=0.4)

ax = fig.add_subplot(1, 1, 1)
sns.boxplot(x=df_filter_price["price"], color='#9db787')
ax.set_title("Price Distribution")
```

Out[ ]: Text(0.5, 1.0, 'Price Distribution')

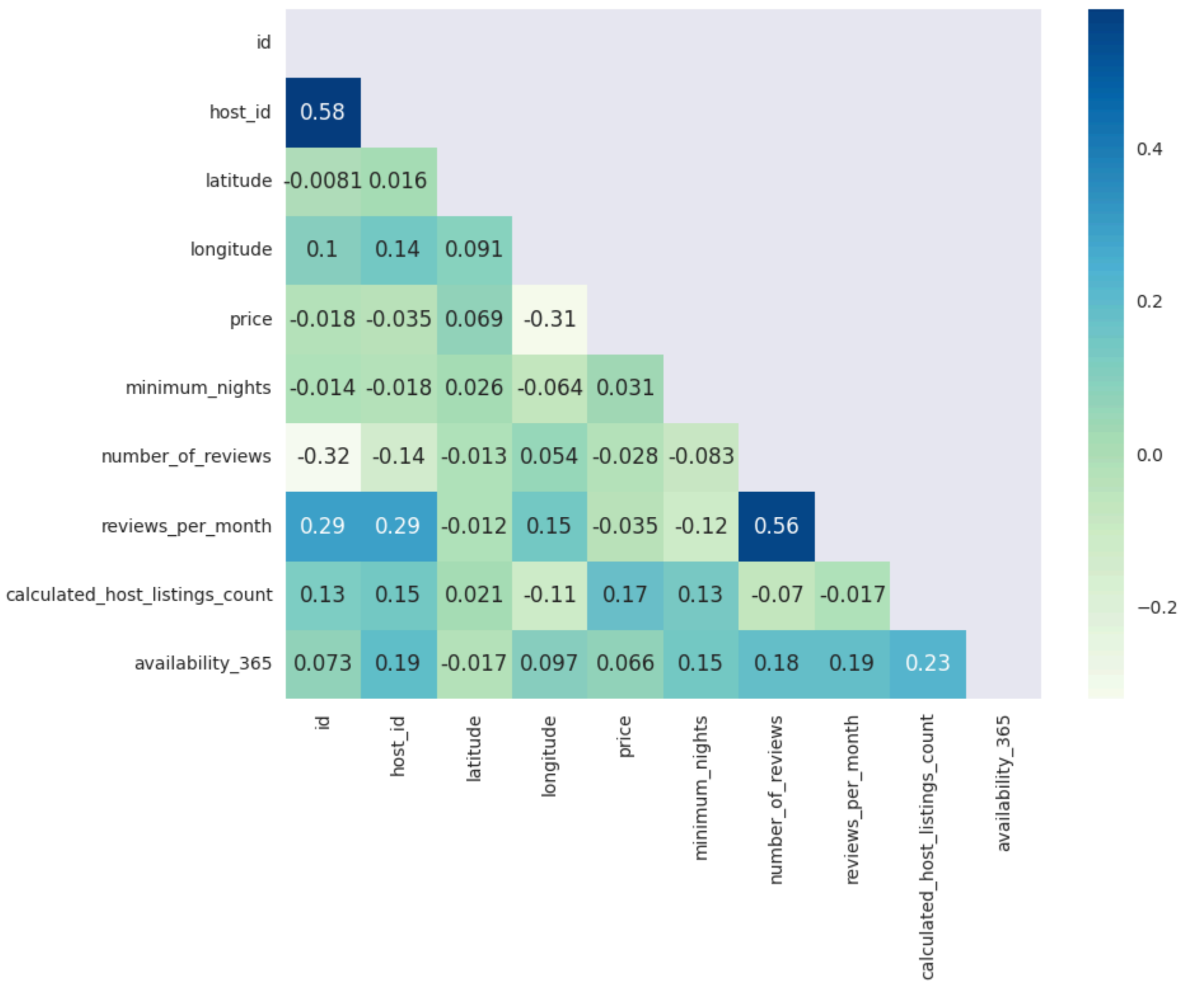
In [ ]:
```
df = df_filter_price
```

Correlation matrix

In [ ]:
```
# Check data types of all columns
print("Numeric columns:", df.select_dtypes(include=[np.number]).columns.tolist
())
print("\nNon-numeric columns:", df.select_dtypes(exclude=[np.number]).columns.
tolist())
```

```
Numeric columns: ['id', 'host_id', 'latitude', 'longitude', 'price', 'minimum
_nights', 'number_of_reviews', 'reviews_per_month', 'calculated_host_listings
_count', 'availability_365']

Non-numeric columns: ['name', 'host_name', 'neighbourhood_group', 'neighbourh
ood', 'room_type', 'last_review']
```

In [ ]:
```
# Get numeric columns only
numeric_df = df.select_dtypes(include=[np.number])

# Create the correlation heatmap
plt.figure(figsize=(10,8))
df_corr = numeric_df.corr()
mask = np.triu(np.ones_like(df_corr, dtype=bool))
sns.heatmap(df_corr, mask=mask, annot=True, cmap="GnBu")
plt.tight_layout()
plt.show()
```



Handling Missing Values

In [ ]:
```
data.isnull().sum()
```

Out[ ]:

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

dtype: int64

In [ ]:
```
data[data['last_review'].isnull()][['number_of_reviews','reviews_per_month']].
head()
```

Out[ ]:

	number_of_reviews	reviews_per_month
2	0	NaN
19	0	NaN
26	0	NaN
36	0	NaN
38	0	NaN

In [ ]:
```
# filling non-values of 'reviews_per_month' with 0
data.fillna({'reviews_per_month':0}, inplace=True)
# Drop 'last_review' feature
data.drop('last_review', inplace=True, axis=1)
data.isnull().sum()
```

Out[ ]:

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

dtype: int64

If a certain listing has a null for its "last_review," that means it has not gotten a review at all(also proved from previous dataframe), so "reviews_per_month" must be 0.

Also, now we can drop the last-review column containing null values from a cleaner dataset.

drop the columns that will not affect the price prediction.

In [ ]:
```
data.drop(["id", "name", "host_id", "host_name"], axis = 1, inplace = True)
```

Applying log transformation for the price column.

In [ ]:
```
data["price"] = np.log1p(data["price"])
X = data.drop("price", axis = 1)
y = data["price"]
```

Splitting data into training and testing sets

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, ran
dom_state = 42)
X_train = X_train.reset_index(drop=True)
X_test = X_test.reset_index(drop=True)
```

Feature Encoding

Encoding is a vital process where categorical variable are transformed into numerical format. One-hot en-coding was adopted on ‘room type’, ‘neighbourhood group’, and ‘neighbourhood’. It was ensured that multi-collinearity was avoided while encoding. It resulted in a total of 235 features.

In [ ]:
```
# Usign One Hot Encoding
ohe = OneHotEncoder(handle_unknown = 'ignore')
columns = ["neighbourhood_group", "neighbourhood", "room_type"]
ohe_df_train = pd.DataFrame(ohe.fit_transform(X_train[columns]).toarray(), col
umns=ohe.get_feature_names_out())
X_train_ohe = X_train.join(ohe_df_train).drop(columns, axis=1)

ohe_df_test = pd.DataFrame(ohe.transform(X_test[columns]).toarray(), columns=o
he.get_feature_names_out())
X_test_ohe = X_test.join(ohe_df_test).drop(columns, axis=1)
```

Feature Scaling

Feature scaling transforms numerical features to have the same range. Here, we utilised the standard scaler from the Scikit-Learn library

In [ ]:
```
# scale the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train_ohe)
X_test = scaler.transform(X_test_ohe)
```

Model Building and Comparison

In [ ]:
```
classic_ml_models = []
ensemble_bagging_methods = []
ensemble_boosting_methods = []
```

Function for prediction and evaluation

In [ ]:
```
def test_models(X_train, X_test, y_train, y_test, model, model_name, models):
    y_pred = model.predict(X_test)

    test_score = r2_score(y_test, y_pred)
    train_score = model.score(X_train, y_train)
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))

    rmse_cv = np.sqrt(-cross_val_score(model, X_train, y_train, scoring='neg_m
ean_squared_error', cv=5).mean())

    row = {"Model": model_name, "Test Sc.": test_score, "Train Sc.": train_sco
re
               ,"MAE": mae, "MSE": mse, "RMSE": rmse, "RMSE CV": rmse_cv}

    display(pd.DataFrame([row]))
    models.append(row)
```

Funtion for visualising the results together for comparison

In [ ]:
```
# Visualization Fuction
sns.set_style("dark", {'axes.grid' : False})
def compare_models(models, rotation):
    display(models.style.highlight_min(subset=["MAE","MSE","RMSE", "RMSE CV"],
color = '#379949', axis = 0)\
                        .highlight_max(subset=["Test Sc."], color = '#379949',
axis = 0)\
                        .highlight_min(subset=["Test Sc.",], color = '#b4241
c', axis = 0)\
                        .highlight_max(subset=["MAE","MSE","RMSE", "RMSE CV"],
color = '#b4241c', axis = 0))
```

Classic ML models

Ridge regression

In [ ]:
```
ridge = Ridge(alpha=1.0)
ridge.fit(X_train, y_train)
test_models(X_train, X_test, y_train, y_test, ridge, "Ridge Regression",classi
c_ml_models )
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Ridge Regression	0.550181	0.537237	0.334657	0.212804	0.461306	0.478069

Lasso Regression

In [ ]:
```
lasso = Lasso(alpha = 0.0001)
lasso.fit(X_train, y_train)
test_models(X_train, X_test, y_train, y_test, lasso, "Lasso Regression", class
ic_ml_models)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Lasso Regression	0.54993	0.537223	0.334679	0.212923	0.461435	0.477871

Decision Tree

In [ ]:
```
# hyperparameter set to intermediate value of 60 to prevent underfitting/ over
fitting
dtr = DecisionTreeRegressor(min_samples_leaf=60)
dtr.fit(X_train, y_train)
test_models(X_train, X_test, y_train, y_test, dtr, "Decision Tree", classic_ml
_models)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Decision Tree	0.571749	0.600147	0.326018	0.2026	0.450111	0.467157

Comparison of classic ML methods

In [ ]:
```
print("Green Highlights the best model, and Red highlights the worst.")
compare_models(pd.DataFrame(classic_ml_models),0)
```

```
Green Highlights the best model, and Red highlights the worst.
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Ridge Regression	0.550181	0.537237	0.334657	0.212804	0.461306	0.478069
1	Lasso Regression	0.549930	0.537223	0.334679	0.212923	0.461435	0.477871
2	Decision Tree	0.571749	0.600147	0.326018	0.202600	0.450111	0.467157

the Decision tree got the highest accuracy and the least errors

Bagging Ensemble Methods

Random Forest

In [ ]:
```
# Baseline random forest regression.
rfr = RandomForestRegressor()
rfr.fit(X_train, y_train)
test_models(X_train, X_test, y_train, y_test, rfr, "Random Forest (Base)", ens
emble_bagging_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Random Forest (Base)	0.61025	0.942988	0.306271	0.184386	0.429402	0.447824

Hyper parameter Tuning

In [ ]:
```
# Parameters currently in use for baseline model.
from pprint import pprint
print('Parameters currently in use: \n')
pprint(rfr.get_params())
```

```
Parameters currently in use:

{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': None,
 'max_features': 1.0,
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'monotonic_cst': None,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

In [ ]:
```
param_grid = {
    'n_estimators': [100, 300, 500],
    'max_depth': [10, 30],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'max_features': ['auto', 'sqrt']
}

rf_random = RandomizedSearchCV(
    estimator=rfr,
    param_distributions=param_grid,
    n_iter=5,
    cv=3,
    verbose=2,
    random_state=42,
    n_jobs=2
)
```

In [ ]:
```
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
```

Out[ ]:
```
▸ RandomizedSearchCV
(https://scikit-learn.org/1.5/modules/generated/sklearn.model_s
▸ best_estimator_: RandomForestRegressor
  ▸ RandomForestRegressor
(https://scikit-learn.org/1.5/modules/generated/sklearn.ensemble.Random
```

In [ ]:
```
rf_random.best_params_
```

Out[ ]:
```
{'n_estimators': 300,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 30}
```

In [ ]:
```
best_rf = rf_random.best_estimator_
test_models(X_train, X_test, y_train, y_test, best_rf, "Random Forest (Tunne
d)", ensemble_bagging_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Random Forest (Tunned)	0.623237	0.819132	0.299825	0.178242	0.422187	0.441452

Boosting Ensemble Methods

Gradient Boosting

In [ ]:
```
gbr = GradientBoostingRegressor()
gbr.fit(X_train,y_train)
test_models(X_train, X_test, y_train, y_test, gbr, "Gradient Boosting", ensemb
le_boosting_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Gradient Boosting	0.592386	0.590188	0.315598	0.192837	0.439132	0.453508

Hyper-parameter Tuning

In [ ]:
```
from pprint import pprint
print('Parameters currently in use: \n')
pprint(gbr.get_params())
```

```
Parameters currently in use:

{'alpha': 0.9,
 'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'init': None,
 'learning_rate': 0.1,
 'loss': 'squared_error',
 'max_depth': 3,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_iter_no_change': None,
 'random_state': None,
 'subsample': 1.0,
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': 0,
 'warm_start': False}
```

In [ ]:
```
param_grid = {
    "learning_rate": [0.01, 0.05, 0.1, 0.2, 0.5],
    "alpha": [0.5, 0.9, 1.2, 1.5],
    "subsample": [0.6, 0.8, 1.0],
    "max_depth": [5, 10, 15, 20, 30],
    "n_estimators": [100, 150, 200, 300],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 5],
    'max_features': ['auto', 'sqrt', 'log2']
}
gbr_random = RandomizedSearchCV(estimator = gbr, param_distributions = param_g
rid,
                               n_iter = 10, cv = 3, verbose=2, random_state=4
2,
                               n_jobs = -1)
```

In [ ]:
```
# Best parameters selected.
gbr_random.fit(X_train, y_train)
gbr_random.best_params_
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

Out[ ]:
```
{'subsample': 1.0,
 'n_estimators': 100,
 'min_samples_split': 10,
 'min_samples_leaf': 5,
 'max_features': 'sqrt',
 'max_depth': 10,
 'learning_rate': 0.2,
 'alpha': 0.5}
```

In [ ]:
```
best_gbr = gbr_random.best_estimator_
test_models(X_train, X_test, y_train, y_test, best_gbr, "Gradient Boosting (Tu
nned)", ensemble_boosting_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Gradient Boosting (Tunned)	0.619605	0.693612	0.304394	0.17996	0.424217	0.445204

XGBoost

In [ ]:
```
xgbr = xgb.XGBRegressor(tree_method='gpu_hist', gpu_id=0)
xgbr.fit(X_train,y_train)
test_models(X_train, X_test, y_train, y_test, xgbr, "XGBoost", ensemble_boosti
ng_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	XGBoost	0.613338	0.692128	0.305603	0.182925	0.427697	0.444667

Hyper-parameter Tuning

In [ ]:
```
from pprint import pprint
print('Parameters currently in use: \n')
pprint(xgbr.get_params())
```

```
Parameters currently in use:

{'base_score': None,
 'booster': None,
 'callbacks': None,
 'colsample_bylevel': None,
 'colsample_bynode': None,
 'colsample_bytree': None,
 'device': None,
 'early_stopping_rounds': None,
 'enable_categorical': False,
 'eval_metric': None,
 'feature_types': None,
 'gamma': None,
 'gpu_id': 0,
 'grow_policy': None,
 'importance_type': None,
 'interaction_constraints': None,
 'learning_rate': None,
 'max_bin': None,
 'max_cat_threshold': None,
 'max_cat_to_onehot': None,
 'max_delta_step': None,
 'max_depth': None,
 'max_leaves': None,
 'min_child_weight': None,
 'missing': nan,
 'monotone_constraints': None,
 'multi_strategy': None,
 'n_estimators': None,
 'n_jobs': None,
 'num_parallel_tree': None,
 'objective': 'reg:squarederror',
 'random_state': None,
 'reg_alpha': None,
 'reg_lambda': None,
 'sampling_method': None,
 'scale_pos_weight': None,
 'subsample': None,
 'tree_method': 'gpu_hist',
 'validate_parameters': None,
 'verbosity': None}
```

In [ ]:
```
param_grid = {
    "learning_rate": [0.01, 0.05, 0.1, 0.2, 0.5],
    "colsample_bytree": [0.6, 0.8, 1.0],
    "subsample": [0.6, 0.8, 1.0],
    "max_depth": [10, 15, 20, 30],
    "n_estimators": [100, 150, 200, 300],
    "reg_lambda": [1, 1.5, 2],
    "gamma": [0, 0.1, 0.3],
    'min_child_weight': [1, 3, 5],
}
xgbr_random = RandomizedSearchCV(estimator = xgbr, param_distributions = param_grid,
                               n_iter = 10, cv = 3, verbose=2, random_state=91,
                               n_jobs = -1)
```

In [ ]:
```
xgbr_random.fit(X_train, y_train)
xgbr_random.best_params_
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

Out[ ]:
```
{'subsample': 0.6,
 'reg_lambda': 1.5,
 'n_estimators': 300,
 'min_child_weight': 5,
 'max_depth': 15,
 'learning_rate': 0.01,
 'gamma': 0,
 'colsample_bytree': 0.6}
```

In [ ]:
```
best_xgb = xgbr_random.best_estimator_
test_models(X_train, X_test, y_train, y_test, best_xgb, "XGBoost (Tunned)", ensemble_boosting_methods)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	XGBoost (Tunned)	0.622568	0.765177	0.301494	0.178558	0.422562	0.440758

Comparison of Boosting Methods

In [ ]:
```
print("Green Highlights the best model, and Red highlights the worst!!!")
compare_models(pd.DataFrame(ensemble_boosting_methods),30)
```

```
Green Highlights the best model, and Red highlights the worst!!!
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Gradient Boosting	0.592386	0.590188	0.315598	0.192837	0.439132	0.453508
1	Gradient Boosting (Tunned)	0.619605	0.693612	0.304394	0.179960	0.424217	0.445204
2	XGBoost	0.613338	0.692128	0.305603	0.182925	0.427697	0.444667
3	XGBoost (Tunned)	0.622568	0.765177	0.301494	0.178558	0.422562	0.440758

Comparison of Ensemble methods

In [ ]:
```
print("Green Highlights the best model, and Red highlights the worst")
compare_models(pd.DataFrame(ensemble_bagging_methods+ensemble_boosting_method
s),45)
```

```
Green Highlights the best model, and Red highlights the worst
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Random Forest (Base)	0.610250	0.942988	0.306271	0.184386	0.429402	0.447824
1	Random Forest (Tunned)	0.623237	0.819132	0.299825	0.178242	0.422187	0.441452
2	Gradient Boosting	0.592386	0.590188	0.315598	0.192837	0.439132	0.453508
3	Gradient Boosting (Tunned)	0.619605	0.693612	0.304394	0.179960	0.424217	0.445204
4	XGBoost	0.613338	0.692128	0.305603	0.182925	0.427697	0.444667
5	XGBoost (Tunned)	0.622568	0.765177	0.301494	0.178558	0.422562	0.440758

Comparing all models together

In [ ]:
```
compare_models(pd.DataFrame(classic_ml_models+ensemble_bagging_methods+ensembl
e_boosting_methods),60)
```

	Model	Test Sc.	Train Sc.	MAE	MSE	RMSE	RMSE CV
0	Ridge Regression	0.550181	0.537237	0.334657	0.212804	0.461306	0.478069
1	Lasso Regression	0.549930	0.537223	0.334679	0.212923	0.461435	0.477871
2	Decision Tree	0.571749	0.600147	0.326018	0.202600	0.450111	0.467157
3	Random Forest (Base)	0.610250	0.942988	0.306271	0.184386	0.429402	0.447824
4	Random Forest (Tunned)	0.623237	0.819132	0.299825	0.178242	0.422187	0.441452
5	Gradient Boosting	0.592386	0.590188	0.315598	0.192837	0.439132	0.453508
6	Gradient Boosting (Tunned)	0.619605	0.693612	0.304394	0.179960	0.424217	0.445204
7	XGBoost	0.613338	0.692128	0.305603	0.182925	0.427697	0.444667
8	XGBoost (Tunned)	0.622568	0.765177	0.301494	0.178558	0.422562	0.440758

Comments

Of all the evaluated models and methods, the hyper-tuned XGBoost model gave the best results and the Lasso regression gave the worst results. The ensemble methods clearly outperform the classical machine learning models for Airbnb price prediction problem because it helps in the reduction in the variance component of prediction errors made by the contributing models. Moreover, the hyper-tuning further improved the results, which can be further enhanced using a grid search instead of a random search.

Neural Networks

In [ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

ann_model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    BatchNormalization(),
    Dropout(0.3),
    Dense(64, activation='relu'),
    BatchNormalization(),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dense(1)
])


early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_w
eights=True)
model_checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss', sav
e_best_only=True)
```

In [ ]:
```
ann_model.compile(optimizer='adam', loss='mean_squared_error', metrics=['ma
e'])
history = ann_model.fit(
    X_train, y_train,
    epochs=100,
    batch_size=32,
    validation_split=0.2,
    callbacks=[early_stopping, model_checkpoint],
    verbose=1
)
```

```
Epoch 1/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - loss: 3.7063 - mae: 1.3502 - val_l
oss: 0.4399 - val_mae: 0.4506
Epoch 2/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 0.5346 - mae: 0.5599 - val_l
oss: 0.3246 - val_mae: 0.3970
Epoch 3/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.4134 - mae: 0.4875 - val_l
oss: 0.3160 - val_mae: 0.3900
Epoch 4/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.3514 - mae: 0.4465 - val_l
oss: 0.2996 - val_mae: 0.3684
Epoch 5/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.3204 - mae: 0.4192 - val_l
oss: 0.2877 - val_mae: 0.3701
Epoch 6/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2830 - mae: 0.3938 - val_l
oss: 0.2690 - val_mae: 0.3554
Epoch 7/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.2747 - mae: 0.3808 - val_l
oss: 0.2536 - val_mae: 0.3527
Epoch 8/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2502 - mae: 0.3650 - val_l
oss: 0.2665 - val_mae: 0.3644
Epoch 9/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2516 - mae: 0.3665 - val_l
oss: 0.2550 - val_mae: 0.3540
Epoch 10/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2356 - mae: 0.3564 - val_l
oss: 0.2465 - val_mae: 0.3489
Epoch 11/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2398 - mae: 0.3545 - val_l
oss: 0.2422 - val_mae: 0.3436
Epoch 12/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2357 - mae: 0.3524 - val_l
oss: 0.2541 - val_mae: 0.3573
Epoch 13/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2370 - mae: 0.3485 - val_l
oss: 0.2675 - val_mae: 0.3474
Epoch 14/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2290 - mae: 0.3456 - val_l
oss: 0.2383 - val_mae: 0.3371
Epoch 15/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2255 - mae: 0.3429 - val_l
oss: 0.2491 - val_mae: 0.3377
Epoch 16/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2289 - mae: 0.3448 - val_l
oss: 0.2502 - val_mae: 0.3510
Epoch 17/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2255 - mae: 0.3398 - val_l
oss: 0.2452 - val_mae: 0.3387
Epoch 18/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2244 - mae: 0.3410 - val_l
oss: 0.2424 - val_mae: 0.3392
Epoch 19/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2321 - mae: 0.3432 - val_l
oss: 0.2409 - val_mae: 0.3397
```

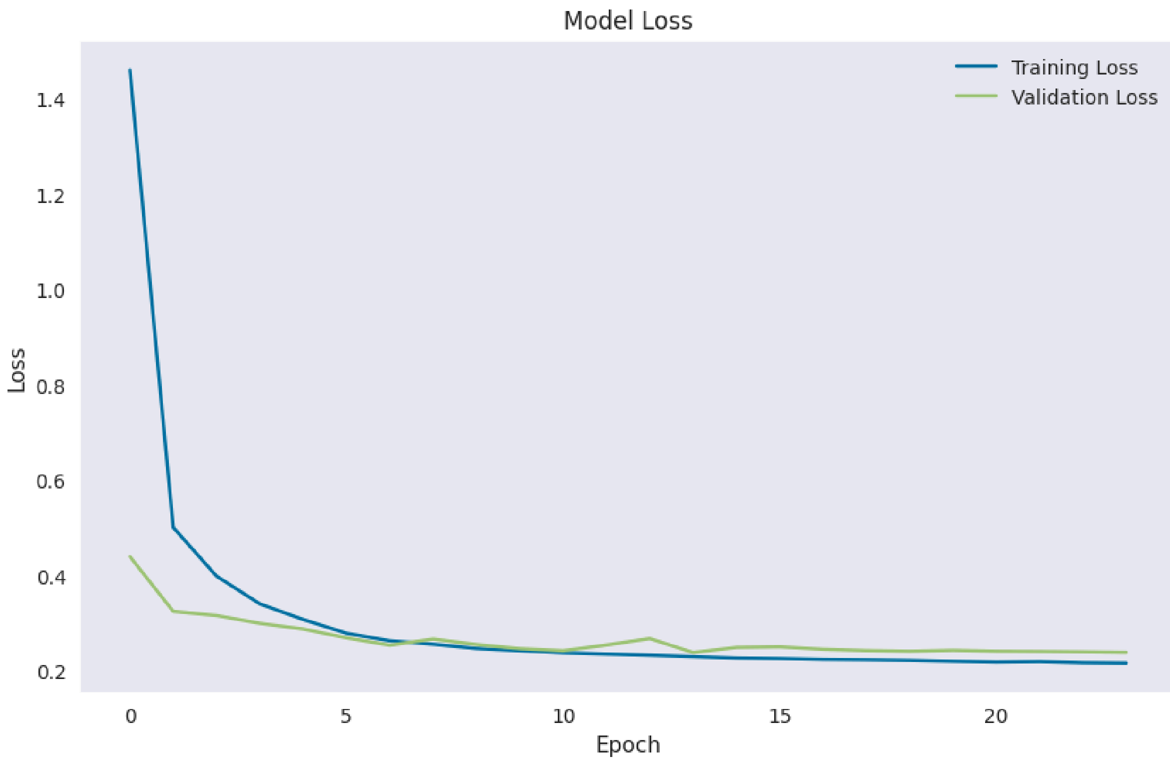
```
Epoch 20/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2172 - mae: 0.3363 - val_l
oss: 0.2430 - val_mae: 0.3365
Epoch 21/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2130 - mae: 0.3345 - val_l
oss: 0.2410 - val_mae: 0.3378
Epoch 22/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 0.2216 - mae: 0.3383 - val_l
oss: 0.2405 - val_mae: 0.3329
Epoch 23/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2206 - mae: 0.3358 - val_l
oss: 0.2397 - val_mae: 0.3361
Epoch 24/100
978/978 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2076 - mae: 0.3290 - val_l
oss: 0.2386 - val_mae: 0.3326
```

In [ ]:

```python
# Evaluate
ann_pred = ann_model.predict(X_test)
print("\nArtificial Neural Network Results:")
print(f"MAE: {mean_absolute_error(y_test, ann_pred):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test, ann_pred)):.4f}")
print(f"R2 Score: {r2_score(y_test, ann_pred):.4f}")
```

```
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step

Artificial Neural Network Results:
MAE: 0.3298
RMSE: 0.4613
R2 Score: 0.5501
```

In [ ]:
```
plt.figure(figsize=(10,6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Hyperparameter Tunning

In [ ]:
```
!pip install scikeras
```

```
Collecting scikeras
  Downloading scikeras-0.13.0-py3-none-any.whl.metadata (3.1 kB)
Requirement already satisfied: keras>=3.2.0 in /usr/local/lib/python3.10/dist
-packages (from scikeras) (3.5.0)
Requirement already satisfied: scikit-learn>=1.4.2 in /usr/local/lib/python3.
10/dist-packages (from scikeras) (1.5.2)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-pack
ages (from keras>=3.2.0->scikeras) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packag
es (from keras>=3.2.0->scikeras) (1.26.4)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-package
s (from keras>=3.2.0->scikeras) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packag
es (from keras>=3.2.0->scikeras) (0.0.8)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-package
s (from keras>=3.2.0->scikeras) (3.12.1)
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packa
ges (from keras>=3.2.0->scikeras) (0.13.1)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-pa
ckages (from keras>=3.2.0->scikeras) (0.4.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-pa
ckages (from keras>=3.2.0->scikeras) (24.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist
-packages (from scikit-learn>=1.4.2->scikeras) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dis
t-packages (from scikit-learn>=1.4.2->scikeras) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python
3.10/dist-packages (from scikit-learn>=1.4.2->scikeras) (3.5.0)
Requirement already satisfied: typing-extensions>=4.5.0 in /usr/local/lib/pyt
hon3.10/dist-packages (from optree->keras>=3.2.0->scikeras) (4.12.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python
3.10/dist-packages (from rich->keras>=3.2.0->scikeras) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/pyth
on3.10/dist-packages (from rich->keras>=3.2.0->scikeras) (2.18.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-p
ackages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->scikeras) (0.1.2)
Downloading scikeras-0.13.0-py3-none-any.whl (26 kB)
Installing collected packages: scikeras
Successfully installed scikeras-0.13.0
```

Hyperparameter Tunning

In [ ]:
```
from scipy.stats import randint, uniform
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import RandomizedSearchCV
from scikeras.wrappers import KerasRegressor

def create_model(neurons1=128, neurons2=64, neurons3=32, dropout1=0.3, dropout
2=0.2, learning_rate=0.001):
    model = Sequential([
        Dense(neurons1, activation='relu', input_shape=(X_train.shape[1],)),
        BatchNormalization(),
        Dropout(dropout1),
        Dense(neurons2, activation='relu'),
        BatchNormalization(),
        Dropout(dropout2),
        Dense(neurons3, activation='relu'),
        Dense(1)
    ])
    model.compile(optimizer=Adam(learning_rate=learning_rate), loss='mean_squa
red_error')
    return model


param_dist = {
    'model__neurons1': randint(64, 256),
    'model__neurons2': randint(32, 128),
    'model__neurons3': randint(16, 64),
    'model__dropout1': uniform(0.1, 0.3),
    'model__dropout2': uniform(0.1, 0.3),
    'model__learning_rate': uniform(0.001, 0.01),
    'batch_size': randint(32, 64),
    'epochs': randint(50, 100)
}


model = KerasRegressor(model=create_model, verbose=0)
random_search = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_dist,
    n_iter=5,
    cv=3,
    verbose=2,
    n_jobs=1
)


random_search.fit(X_train, y_train)


print("Best parameters:", random_search.best_params_)
print("Best score:", random_search.best_score_)

# Use best parameters to create final model
best_model = create_model(**{k.replace('model__', ''): v for k, v in random_se
arch.best_params_.items()
                           if k.startswith('model__')})
```

```python
# Train final model
final_history = best_model.fit(
    X_train, y_train,
    epochs=random_search.best_params_['epochs'],
    batch_size=random_search.best_params_['batch_size'],
    verbose=1
)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
[CV] END batch_size=41, epochs=87, model__dropout1=0.1485219233572097, model_
_dropout2=0.3370253488136214, model__learning_rate=0.0041809010854051715, mod
el__neurons1=109, model__neurons2=70, model__neurons3=32; total time= 2.4min
[CV] END batch_size=41, epochs=87, model__dropout1=0.1485219233572097, model_
_dropout2=0.3370253488136214, model__learning_rate=0.0041809010854051715, mod
el__neurons1=109, model__neurons2=70, model__neurons3=32; total time= 1.9min
[CV] END batch_size=41, epochs=87, model__dropout1=0.1485219233572097, model_
_dropout2=0.3370253488136214, model__learning_rate=0.0041809010854051715, mod
el__neurons1=109, model__neurons2=70, model__neurons3=32; total time= 2.0min
[CV] END batch_size=36, epochs=99, model__dropout1=0.1429466825656761 6, model
__dropout2=0.11323830608935137, model__learning_rate=0.004391039777312497, mo
del__neurons1=237, model__neurons2=113, model__neurons3=17; total time= 2.4mi
n
[CV] END batch_size=36, epochs=99, model__dropout1=0.14294668256567616, model
__dropout2=0.11323830608935137, model__learning_rate=0.004391039777312497, mo
del__neurons1=237, model__neurons2=113, model__neurons3=17; total time= 2.5mi
n
[CV] END batch_size=36, epochs=99, model__dropout1=0.14294668256567616, model
__dropout2=0.11323830608935137, model__learning_rate=0.004391039777312497, mo
del__neurons1=237, model__neurons2=113, model__neurons3=17; total time= 2.5mi
n
[CV] END batch_size=36, epochs=75, model__dropout1=0.3413943528837057, model_
_dropout2=0.1815656253644331, model__learning_rate=0.005807098523600376, mode
l__neurons1=73, model__neurons2=73, model__neurons3=33; total time= 1.9min
[CV] END batch_size=36, epochs=75, model__dropout1=0.3413943528837057, model_
_dropout2=0.1815656253644331, model__learning_rate=0.005807098523600376, mode
l__neurons1=73, model__neurons2=73, model__neurons3=33; total time= 1.9min
[CV] END batch_size=36, epochs=75, model__dropout1=0.3413943528837057, model_
_dropout2=0.1815656253644331, model__learning_rate=0.005807098523600376, mode
l__neurons1=73, model__neurons2=73, model__neurons3=33; total time= 1.8min
[CV] END batch_size=59, epochs=80, model__dropout1=0.2467979824448353, model_
_dropout2=0.33753766195123713, model__learning_rate=0.007263643743275193, mod
el__neurons1=84, model__neurons2=53, model__neurons3=59; total time= 1.5min
[CV] END batch_size=59, epochs=80, model__dropout1=0.2467979824448353, model_
_dropout2=0.33753766195123713, model__learning_rate=0.007263643743275193, mod
el__neurons1=84, model__neurons2=53, model__neurons3=59; total time= 1.4min
[CV] END batch_size=59, epochs=80, model__dropout1=0.2467979824448353, model_
_dropout2=0.33753766195123713, model__learning_rate=0.007263643743275193, mod
el__neurons1=84, model__neurons2=53, model__neurons3=59; total time= 1.4min
[CV] END batch_size=48, epochs=74, model__dropout1=0.26588772235915503, model
__dropout2=0.3011453109290326, model__learning_rate=0.0018375896254714634, mo
del__neurons1=78, model__neurons2=51, model__neurons3=24; total time= 2.0min
[CV] END batch_size=48, epochs=74, model__dropout1=0.26588772235915503, model
__dropout2=0.3011453109290326, model__learning_rate=0.0018375896254714634, mo
del__neurons1=78, model__neurons2=51, model__neurons3=24; total time= 1.6min
[CV] END batch_size=48, epochs=74, model__dropout1=0.26588772235915503, model
__dropout2=0.3011453109290326, model__learning_rate=0.0018375896254714634, mo
del__neurons1=78, model__neurons2=51, model__neurons3=24; total time= 1.7min
Best parameters: {'batch_size': 36, 'epochs': 75, 'model__dropout1': 0.341394
3528837057, 'model__dropout2': 0.1815656253644331, 'model__learning_rate': 0.
005807098523600376, 'model__neurons1': 73, 'model__neurons2': 73, 'model__neu
rons3': 33}
Best score: 0.5546596551886979
Epoch 1/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - loss: 1.5131
Epoch 2/75
```

```
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.3268
Epoch 3/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2704
Epoch 4/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2546
Epoch 5/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2579
Epoch 6/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2544
Epoch 7/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2476
Epoch 8/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2399
Epoch 9/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2459
Epoch 10/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2347
Epoch 11/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2314
Epoch 12/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2352
Epoch 13/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2350
Epoch 14/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2275
Epoch 15/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2249
Epoch 16/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2366
Epoch 17/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2255
Epoch 18/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2255
Epoch 19/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2272
Epoch 20/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2209
Epoch 21/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2222
Epoch 22/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2219
Epoch 23/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2313
Epoch 24/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2240
Epoch 25/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2187
Epoch 26/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2229
Epoch 27/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2219
Epoch 28/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2187
Epoch 29/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2157
Epoch 30/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2207
```

```
Epoch 31/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2252
Epoch 32/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2258
Epoch 33/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2182
Epoch 34/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2164
Epoch 35/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2176
Epoch 36/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 0.2197
Epoch 37/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2194
Epoch 38/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2081
Epoch 39/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2136
Epoch 40/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2175
Epoch 41/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2158
Epoch 42/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2108
Epoch 43/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2157
Epoch 44/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2113
Epoch 45/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2172
Epoch 46/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2156
Epoch 47/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2185
Epoch 48/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2093
Epoch 49/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2142
Epoch 50/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2201
Epoch 51/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2160
Epoch 52/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2205
Epoch 53/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2199
Epoch 54/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2114
Epoch 55/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2114
Epoch 56/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2090
Epoch 57/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2086
Epoch 58/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2147
Epoch 59/75
```

```
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2133
Epoch 60/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2244
Epoch 61/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2143
Epoch 62/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2103
Epoch 63/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2067
Epoch 64/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2178
Epoch 65/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2087
Epoch 66/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2157
Epoch 67/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.2113
Epoch 68/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2145
Epoch 69/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.2123
Epoch 70/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2152
Epoch 71/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2142
Epoch 72/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2125
Epoch 73/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2145
Epoch 74/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2136
Epoch 75/75
1087/1087 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2150
```

In [ ]:

```python
y_pred = best_model.predict(X_test)

print('Hypertuned Model Test Results:')
print(f'MAE: {mean_absolute_error(y_test, y_pred):.4f}')
print(f'RMSE: {np.sqrt(mean_squared_error(y_test, y_pred)):.4f}')
print(f'R2 Score: {r2_score(y_test, y_pred):.4f}')
```

```
306/306 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
Hypertuned Model Test Results:
MAE: 0.3203
RMSE: 0.4480
R2 Score: 0.5757
```

While the prediction enhanced after hyperparametertunning, our artificial neural network is not efficient as the Random Forest model.