

# ImplementMLProjectPlan

August 11, 2023

## 1 Lab 8: Implement Your Machine Learning Project Plan

In this lab assignment, you will implement the machine learning project plan you created in the written assignment. You will:

1. Load your data set and save it to a Pandas DataFrame.
2. Perform exploratory data analysis on your data to determine which feature engineering and data preparation techniques you will use.
3. Prepare your data for your model and create features and a label.
4. Fit your model to the training data and evaluate your model.
5. Improve your model by performing model selection and/or feature selection techniques to find best model for your problem.

### 1.0.1 Import Packages

Before you get started, import a few packages.

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

Task: In the code cell below, import additional packages that you have used in this course that you will need for this task.

```
[2]: import scipy.stats as stats
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
```

### 1.1 Part 1: Load the Data Set

You have chosen to work with one of four data sets. The data sets are located in a folder named "data." The file names of the three data sets are as follows:

- The "adult" data set that contains Census information from 1994 is located in file `adultData.csv`
- The airbnb NYC "listings" data set is located in file `airbnbListingsData.csv`
- The World Happiness Report (WHR) data set is located in file `WHR2018Chapter20onlineData.csv`
- The book review data set is located in file `bookReviewsData.csv`

Task: In the code cell below, use the same method you have been using to load your data using `pd.read_csv()` and save it to DataFrame `df`.

```
[3]: filename = os.path.join(os.getcwd(), "data", "airbnbListingsData.csv")
df = pd.read_csv(filename, header=0)
df.head()
```

```
[3]:
```

	name \		description \		neighborhood_overview	host_name \		host_location \		host_about	host_response_rate \
0	Skylit Midtown Castle		Beautiful, spacious skylit studio in the heart...		Centrally located in the heart of Manhattan ju...	Jennifer		New York, New York, United States		A New Yorker since 2000! My passion is creatin...	0.80
1	Whole flr w/private bdrm, bath & kitchen(pls r...		Enjoy 500 s.f. top floor in 1899 brownstone, w...		Just the right mix of urban center and local n...	LisaRoxanne		New York, New York, United States		Laid-back Native New Yorker (formerly bi-coast...	0.09
2	Spacious Brooklyn Duplex, Patio + Garden		We welcome you to stay in our lovely 2 br dupl...			NaN		Brooklyn, New York, United States		Rebecca is an artist/designer, and Henoch is i...	1.00
3	Large Furnished Room Near B'way		Please dont expect the luxury here just a bas...		Theater district, many restaurants around here.	Shunichi		New York, New York, United States		I used to work for a financial industry but no...	1.00
4	Cozy Clean Guest Room - Family Apt		Our best guests are seeking a safe, clean, spa...		Our neighborhood is full of restaurants and ca...	MaryEllen		New York, New York, United States		Welcome to family life with my oldest two away...	NaN

	host_acceptance_rate	host_is_superhost	host_listings_count	...	\
0	0.17	True	8.0	...	
1	0.69	True	1.0	...	
2	0.25	True	1.0	...	
3	1.00	True	1.0	...	
4	NaN	True	1.0	...	

	review_scores_communication	review_scores_location	review_scores_value	\
0	4.79	4.86	4.41	
1	4.80	4.71	4.64	
2	5.00	4.50	5.00	
3	4.42	4.87	4.36	
4	4.95	4.94	4.92	

	instant_bookable	calculated_host_listings_count	\
0	False	3	
1	False	1	
2	False	1	
3	False	1	
4	False	1	

	calculated_host_listings_count_entire_homes	\
0	3	
1	1	
2	1	
3	0	
4	0	

	calculated_host_listings_count_private_rooms	\
0	0	
1	0	
2	0	
3	1	
4	1	

	calculated_host_listings_count_shared_rooms	reviews_per_month	\
0	0	0.33	
1	0	4.86	
2	0	0.02	
3	0	3.68	
4	0	0.87	

	n_host_verifications
0	9
1	6
2	3
3	4

```
[5 rows x 50 columns]
```

```
[4]: df.shape
```

```
[4]: (28022, 50)
```

## 1.2 Part 2: Exploratory Data Analysis

The next step is to inspect and analyze your data set with your machine learning problem and project plan in mind.

This step will help you determine data preparation and feature engineering techniques you will need to apply to your data to build a balanced modeling data set for your problem and model. These data preparation techniques may include: \* addressing missingness, such as replacing missing values with means \* renaming features and labels \* finding and replacing outliers \* performing winsorization if needed \* performing one-hot encoding on categorical features \* performing vectorization for an NLP problem \* addressing class imbalance in your data sample to promote fair AI

Think of the different techniques you have used to inspect and analyze your data in this course. These include using Pandas to apply data filters, using the Pandas `describe()` method to get insight into key statistics for each column, using the Pandas `dtypes` property to inspect the data type of each column, and using Matplotlib and Seaborn to detect outliers and visualize relationships between features and labels. If you are working on a classification problem, use techniques you have learned to determine if there is class imbalance.

Task: Use the techniques you have learned in this course to inspect and analyze your data.

Note: You can add code cells if needed by going to the Insert menu and clicking on Insert Cell Below in the drop-down menu.

```
[5]: df.dtypes
```

```
[5]: name                object
      description         object
      neighborhood_overview  object
      host_name           object
      host_location       object
      host_about          object
      host_response_rate   float64
      host_acceptance_rate float64
      host_is_superhost    bool
      host_listings_count  float64
      host_total_listings_count float64
      host_has_profile_pic  bool
      host_identity_verified bool
      neighbourhood_group_cleansed object
      room_type            object
      accommodates         int64
      bathrooms            float64
      bedrooms             float64
```

```

beds float64
amenities object
price float64
minimum_nights int64
maximum_nights int64
minimum_minimum_nights float64
maximum_minimum_nights float64
minimum_maximum_nights float64
maximum_maximum_nights float64
minimum_nights_avg_ntm float64
maximum_nights_avg_ntm float64
has_availability bool
availability_30 int64
availability_60 int64
availability_90 int64
availability_365 int64
number_of_reviews int64
number_of_reviews_ltm int64
number_of_reviews_l30d int64
review_scores_rating float64
review_scores_cleanliness float64
review_scores_checkin float64
review_scores_communication float64
review_scores_location float64
review_scores_value float64
instant_bookable bool
calculated_host_listings_count int64
calculated_host_listings_count_entire_homes int64
calculated_host_listings_count_private_rooms int64
calculated_host_listings_count_shared_rooms int64
reviews_per_month float64
n_host_verifications int64
dtype: object

```

```
[6]: df.describe()
```

```

[6]:      host_response_rate  host_acceptance_rate  host_listings_count  \
count      16179.000000      16909.000000      28022.000000
mean         0.906901         0.791953         14.554778
std         0.227282         0.276732        120.721287
min          0.000000         0.000000         0.000000
25%          0.940000         0.680000         1.000000
50%          1.000000         0.910000         1.000000
75%          1.000000         1.000000         3.000000
max          1.000000         1.000000        3387.000000

      host_total_listings_count  accommodates  bathrooms  bedrooms  \
count      28022.000000      28022.000000      28022.000000      25104.000000

```

mean	14.554778	2.874491	1.142174	1.329708
std	120.721287	1.860251	0.421132	0.700726
min	0.000000	1.000000	0.000000	1.000000
25%	1.000000	2.000000	1.000000	1.000000
50%	1.000000	2.000000	1.000000	1.000000
75%	3.000000	4.000000	1.000000	1.000000
max	3387.000000	16.000000	8.000000	12.000000

	beds	price	minimum_nights	...	review_scores_checkin \
count	26668.000000	28022.000000	28022.000000	...	28022.000000
mean	1.629556	154.228749	18.689387	...	4.814300
std	1.097104	140.816605	25.569151	...	0.438603
min	1.000000	29.000000	1.000000	...	0.000000
25%	1.000000	70.000000	2.000000	...	4.810000
50%	1.000000	115.000000	30.000000	...	4.960000
75%	2.000000	180.000000	30.000000	...	5.000000
max	21.000000	1000.000000	1250.000000	...	5.000000

	review_scores_communication	review_scores_location \
count	28022.000000	28022.000000
mean	4.808041	4.750393
std	0.464585	0.415717
min	0.000000	0.000000
25%	4.810000	4.670000
50%	4.970000	4.880000
75%	5.000000	5.000000
max	5.000000	5.000000

	review_scores_value	calculated_host_listings_count \
count	28022.000000	28022.000000
mean	4.647670	9.581900
std	0.518023	32.227523
min	0.000000	1.000000
25%	4.550000	1.000000
50%	4.780000	1.000000
75%	5.000000	3.000000
max	5.000000	421.000000

	calculated_host_listings_count_entire_homes \
count	28022.000000
mean	5.562986
std	26.121426
min	0.000000
25%	0.000000
50%	1.000000
75%	1.000000
max	308.000000

	calculated_host_listings_count_private_rooms \
count	28022.000000
mean	3.902077
std	17.972386
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	359.000000

	calculated_host_listings_count_shared_rooms	reviews_per_month \
count	28022.000000	28022.000000
mean	0.048283	1.758325
std	0.442459	4.446143
min	0.000000	0.010000
25%	0.000000	0.130000
50%	0.000000	0.510000
75%	0.000000	1.830000
max	8.000000	141.000000

	n_host_verifications
count	28022.000000
mean	5.169510
std	2.028497
min	1.000000
25%	4.000000
50%	5.000000
75%	7.000000
max	13.000000

[8 rows x 36 columns]

[7]: *# Transforming the 'object' categorical features into numerical boolean values*  
*→ using one-hot encoding:*

```
to_encode = list(df.select_dtypes(include=['object']).columns)
df[to_encode].nunique()
```

[7]: name	27386
description	25952
neighborhood_overview	15800
host_name	7566
host_location	1364
host_about	11962
neighbourhood_group_cleansed	5
room_type	4
amenities	25020

dtype: int64

```
[8]: # Taking a look at the unique values, I can see that all columns with the
      ↳ exception of 'host_location', 'neighbourhood_group_cleansed',
      # and 'room_type' are descriptive and therefore require NLP, those columns will
      ↳ be dropped:
```

```
to_drop = ['name', 'description', 'neighborhood_overview', 'host_name',
          ↳ 'host_about', 'amenities']
df.drop(columns = to_drop, inplace = True)
```

```
[9]: # Performing one-hot-encoding on 'host_location':
```

```
top_50_host_location = list(df['host_location'].value_counts().head(50).index)
```

```
[10]: # Using a for loop that loops through every value in top_50_host_location and
      ↳ creates one-hot encoded columns,
      # titled 'host_location + '_' + < host location value > '.
```

```
for value in top_50_host_location:
    df['host_location'+ '_' + value] = np.where(df['host_location']==value,1,0)
```

```
[11]: # Dropping the original, multi-valued host_location column from the DataFrame
      ↳ df.
```

```
# Removing 'host_location' from the to_encode list.
```

```
df.drop(columns = 'host_location', inplace = True)
to_encode.remove('host_location')
```

```
[12]: to_drop = ['name', 'description', 'neighborhood_overview', 'host_name',
          ↳ 'host_about', 'amenities']
```

```
for item in to_drop:
    to_encode.remove(item)
```

```
to_encode
```

```
[12]: ['neighbourhood_group_cleansed', 'room_type']
```

```
[13]: # Performing one-hot-encoding the rest of the columns:
```

```
for value in to_encode:
    temp_df = pd.get_dummies(df[value], prefix = value + '_')
    df = df.join(temp_df)
```

```
[14]: df.drop(columns = to_encode, inplace = True)
df.head()
```

```
[14]:   host_response_rate  host_acceptance_rate  host_is_superhost \
0                0.80                0.17                True
1                0.09                0.69                True
2                1.00                0.25                True
```



3	1.00	1.00	True
4	NaN	NaN	True

	host_listings_count	host_total_listings_count	host_has_profile_pic	\
0	8.0	8.0	True	
1	1.0	1.0	True	
2	1.0	1.0	True	
3	1.0	1.0	True	
4	1.0	1.0	True	

	host_identity_verified	accommodates	bathrooms	bedrooms	...	\
0	True	1	1.0	NaN	...	
1	True	3	1.0	1.0	...	
2	True	4	1.5	2.0	...	
3	True	2	1.0	1.0	...	
4	True	1	1.0	1.0	...	

	host_location_Princeton, New Jersey, United States	\
0	0	
1	0	
2	0	
3	0	
4	0	

	neighbourhood_group_cleansed__Bronx	\
0	0	
1	0	
2	0	
3	0	
4	0	

	neighbourhood_group_cleansed__Brooklyn	\
0	0	
1	1	
2	1	
3	0	
4	0	

	neighbourhood_group_cleansed__Manhattan	\
0	1	
1	0	
2	0	
3	1	
4	1	

	neighbourhood_group_cleansed__Queens	\
0	0	

1	0
2	0
3	0
4	0

	neighbourhood_group_cleansed__Staten Island	room_type__Entire home/apt \
0	0	1
1	0	1
2	0	1
3	0	0
4	0	0

	room_type__Hotel room	room_type__Private room	room_type__Shared room
0	0	0	0
1	0	0	0
2	0	0	0
3	0	1	0
4	0	1	0

[5 rows x 100 columns]

[15]: *# I now need to see if I have any missing data:*

```
df.isnull().values.any()
```

[15]: True

[16]: `df.isnull().head()`

[16]:

	host_response_rate	host_acceptance_rate	host_is_superhost \
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	True	True	False

	host_listings_count	host_total_listings_count	host_has_profile_pic \
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False

	host_identity_verified	accommodates	bathrooms	bedrooms	... \
0	False	False	False	True	...
1	False	False	False	False	...
2	False	False	False	False	...
3	False	False	False	False	...
4	False	False	False	False	...

	host_location_Princeton, New Jersey, United States \		
0		False	
1		False	
2		False	
3		False	
4		False	

	neighbourhood_group_cleansed__Bronx \		
0		False	
1		False	
2		False	
3		False	
4		False	

	neighbourhood_group_cleansed__Brooklyn \		
0		False	
1		False	
2		False	
3		False	
4		False	

	neighbourhood_group_cleansed__Manhattan \		
0		False	
1		False	
2		False	
3		False	
4		False	

	neighbourhood_group_cleansed__Queens \		
0		False	
1		False	
2		False	
3		False	
4		False	

	neighbourhood_group_cleansed__Staten Island	room_type__Entire home/apt \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	room_type__Hotel room	room_type__Private room	room_type__Shared room
0	False	False	False
1	False	False	False
2	False	False	False

3	False	False	False
4	False	False	False

[5 rows x 100 columns]

```
[17]: nan_count = np.sum(df.isnull(), axis = 0)
      nan_count
```

```
[17]: host_response_rate          11843
      host_acceptance_rate       11113
      host_is_superhost           0
      host_listings_count         0
      host_total_listings_count   0
      ...
      neighbourhood_group_cleansed__Staten Island  0
      room_type__Entire home/apt                 0
      room_type__Hotel room                       0
      room_type__Private room                     0
      room_type__Shared room                       0
      Length: 100, dtype: int64
```

```
[18]: # Since not all of the columns have missing data, I will create a condition for
      → them:

      condition = nan_count != 0
      nan_col_names = nan_count[condition].index # to get the column names
      nan_cols = list(nan_col_names) # convert column names to python list
      nan_cols
```

```
[18]: ['host_response_rate', 'host_acceptance_rate', 'bedrooms', 'beds']
```

```
[19]: # I want to fill the columns with a dtype of float64:
```

```
nan_col_types = df[nan_cols].dtypes
nan_col_types
```

```
[19]: host_response_rate    float64
      host_acceptance_rate float64
      bedrooms             float64
      beds                 float64
      dtype: object
```

```
[20]: # Creating dummy variables for missing values:

      df['host_response_rate_na'] = df['host_response_rate'].isnull()
      df['host_acceptance_rate_na'] = df['host_acceptance_rate'].isnull()
      df['bedrooms_na'] = df['bedrooms'].isnull()
      df['beds_na'] = df['beds'].isnull()
```

```
[21]: df.head()
```

```

[21]:  host_response_rate  host_acceptance_rate  host_is_superhost  \
0          0.80          0.17          True
1          0.09          0.69          True
2          1.00          0.25          True
3          1.00          1.00          True
4          NaN          NaN          True

      host_listings_count  host_total_listings_count  host_has_profile_pic  \
0          8.0          8.0          True
1          1.0          1.0          True
2          1.0          1.0          True
3          1.0          1.0          True
4          1.0          1.0          True

      host_identity_verified  accommodates  bathrooms  bedrooms  ...  \
0          True          1          1.0          NaN  ...
1          True          3          1.0          1.0  ...
2          True          4          1.5          2.0  ...
3          True          2          1.0          1.0  ...
4          True          1          1.0          1.0  ...

      neighbourhood_group_cleansed__Queens  \
0          0
1          0
2          0
3          0
4          0

      neighbourhood_group_cleansed__Staten Island  room_type__Entire home/apt  \
0          0          1
1          0          1
2          0          1
3          0          0
4          0          0

      room_type__Hotel room  room_type__Private room  room_type__Shared room  \
0          0          0          0
1          0          0          0
2          0          0          0
3          0          1          0
4          0          1          0

      host_response_rate_na  host_acceptance_rate_na  bedrooms_na  beds_na
0          False          False          True          False
1          False          False          False          False
2          False          False          False          False
3          False          False          False          False

```

4

True

True

False

False

[5 rows x 104 columns]

[22]: *# Filling the values for missing 'host\_response\_rate' column:*

```
mean_host_response_rate = df['host_response_rate'].mean()
df['host_response_rate'].fillna(value=mean_host_response_rate, inplace = True)
```

[23]: *# Filling the values for missing 'host\_acceptance\_rate' column:*

```
mean_host_acceptance_rate = df['host_acceptance_rate'].mean()
df['host_acceptance_rate'].fillna(value=mean_host_acceptance_rate, inplace =   
→ True)
```

[24]: *# Filling the values for missing 'bedrooms' column:*

```
mean_bedrooms = df['bedrooms'].mean()
df['bedrooms'].fillna(value=mean_bedrooms, inplace = True)
```

[25]: *# Filling the values for missing 'beds' column:*

```
mean_beds = df['beds'].mean()
df['beds'].fillna(value=mean_beds, inplace = True)
```

[26]: *# Checking that I successfully replaced all null values*

```
print(np.sum(df['host_response_rate'].isnull(), axis = 0))
print(np.sum(df['host_acceptance_rate'].isnull(), axis = 0))
print(np.sum(df['bedrooms'].isnull(), axis = 0))
print(np.sum(df['beds'].isnull(), axis = 0))
```

0

0

0

0

[27]: *# Making sure I have no missing data:*

```
df.isnull().values.any()
```

[27]: False

### 1.3 Part 3: Implement Your Project Plan

Task: Use the rest of this notebook to carry out your project plan. You will:

1. Prepare your data for your model and create features and a label.
2. Fit your model to the training data and evaluate your model.

3. Improve your model by performing model selection and/or feature selection techniques to find best model for your problem.

Add code cells below and populate the notebook with commentary, code, analyses, results, and figures as you see fit.

```
[28]: # I now want to implement my project plan, and predict the
      ↪ 'review_scores_location' by training various regression
      # models and comparing their performances
```

```
[29]: # to_drop are the columns I am not including in my label and the dummy
      ↪ variables:
```

```
to_drop = ['host_response_rate_na', 'host_acceptance_rate_na',
           ↪ 'bedrooms_na', 'beds_na']
df = df.drop(columns=to_drop)
df.head()
```

```
[29]: host_response_rate  host_acceptance_rate  host_is_superhost  \
0          0.800000          0.170000          True
1          0.090000          0.690000          True
2          1.000000          0.250000          True
3          1.000000          1.000000          True
4          0.906901          0.791953          True

      host_listings_count  host_total_listings_count  host_has_profile_pic  \
0              8.0              8.0              True
1              1.0              1.0              True
2              1.0              1.0              True
3              1.0              1.0              True
4              1.0              1.0              True

      host_identity_verified  accommodates  bathrooms  bedrooms  ...  \
0              True              1              1.0  1.329708  ...
1              True              3              1.0  1.000000  ...
2              True              4              1.5  2.000000  ...
3              True              2              1.0  1.000000  ...
4              True              1              1.0  1.000000  ...

      host_location_Princeton, New Jersey, United States  \
0              0
1              0
2              0
3              0
4              0

      neighbourhood_group_cleansed__Bronx  \
0              0
1              0
```

2	0
3	0
4	0

neighbourhood_group_cleansed__Brooklyn \	
0	0
1	1
2	1
3	0
4	0

neighbourhood_group_cleansed__Manhattan \	
0	1
1	0
2	0
3	1
4	1

neighbourhood_group_cleansed__Queens \	
0	0
1	0
2	0
3	0
4	0

neighbourhood_group_cleansed__Staten Island		room_type__Entire home/apt \
0	0	1
1	0	1
2	0	1
3	0	0
4	0	0

	room_type__Hotel room	room_type__Private room	room_type__Shared room
0	0	0	0
1	0	0	0
2	0	0	0
3	0	1	0
4	0	1	0

[5 rows x 100 columns]

[30]: *# Creating my labeled examples:*

```
y = df['review_scores_location']
X = df.drop(columns = 'review_scores_location', axis = 1)
X
```



```

[30]:      host_response_rate  host_acceptance_rate  host_is_superhost  \
0          0.800000          0.170000          True
1          0.090000          0.690000          True
2          1.000000          0.250000          True
3          1.000000          1.000000          True
4          0.906901          0.791953          True
...          ...          ...          ...
28017        1.000000          1.000000          True
28018        0.910000          0.890000          True
28019        0.990000          0.990000          True
28020        0.900000          1.000000          True
28021        0.906901          0.791953          True

      host_listings_count  host_total_listings_count  host_has_profile_pic  \
0              8.0              8.0          True
1              1.0              1.0          True
2              1.0              1.0          True
3              1.0              1.0          True
4              1.0              1.0          True
...          ...          ...          ...
28017          8.0              8.0          True
28018          0.0              0.0          True
28019          6.0              6.0          True
28020          3.0              3.0          True
28021          0.0              0.0          True

      host_identity_verified  accommodates  bathrooms  bedrooms  ...  \
0              True              1              1.0  1.329708  ...
1              True              3              1.0  1.000000  ...
2              True              4              1.5  2.000000  ...
3              True              2              1.0  1.000000  ...
4              True              1              1.0  1.000000  ...
...          ...          ...          ...  ...
28017          True              2              1.0  1.000000  ...
28018          True              6              1.0  2.000000  ...
28019          True              2              2.0  1.000000  ...
28020          True              3              1.0  1.000000  ...
28021          True              1              1.0  1.000000  ...

      host_location_Princeton, New Jersey, United States  \
0
1
2
3
4
...
28017

```

28018	0
28019	0
28020	0
28021	0

	neighbourhood_group_cleansed__Bronx	\
0	0	
1	0	
2	0	
3	0	
4	0	
...	...	
28017	0	
28018	0	
28019	0	
28020	0	
28021	0	

	neighbourhood_group_cleansed__Brooklyn	\
0	0	
1	1	
2	1	
3	0	
4	0	
...	...	
28017	0	
28018	1	
28019	1	
28020	1	
28021	0	

	neighbourhood_group_cleansed__Manhattan	\
0	1	
1	0	
2	0	
3	1	
4	1	
...	...	
28017	0	
28018	0	
28019	0	
28020	0	
28021	0	

	neighbourhood_group_cleansed__Queens	\
0	0	
1	0	

2	0
3	0
4	0
...	...
28017	1
28018	0
28019	0
28020	0
28021	1

	neighbourhood_group_cleansed__Staten Island \
0	0
1	0
2	0
3	0
4	0
...	...
28017	0
28018	0
28019	0
28020	0
28021	0

	room_type__Entire home/apt	room_type__Hotel room \
0	1	0
1	1	0
2	1	0
3	0	0
4	0	0
...	...	...
28017	0	0
28018	1	0
28019	0	0
28020	1	0
28021	0	0

	room_type__Private room	room_type__Shared room
0	0	0
1	0	0
2	0	0
3	1	0
4	1	0
...	...	...
28017	1	0
28018	0	0
28019	1	0
28020	0	0

```
[28022 rows x 99 columns]
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30,
    ↪random_state = 1234)
X_train.head()
```

20

5214	1
2220	1
16547	0

	neighbourhood_group_cleansed__Manhattan \
16860	0
17993	1
5214	0
2220	0
16547	0

	neighbourhood_group_cleansed__Queens \
16860	0
17993	0
5214	0
2220	0
16547	0

	neighbourhood_group_cleansed__Staten Island \
16860	0
17993	0
5214	0
2220	0
16547	0

	room_type__Entire home/apt	room_type__Hotel room \
16860	0	0
17993	0	0
5214	1	0
2220	1	0
16547	0	0

	room_type__Private room	room_type__Shared room
16860	1	0
17993	1	0
5214	0	0
2220	0	0
16547	1	0

[5 rows x 99 columns]

[32]: *# Creating and fitting the LinearRegression model:*

```
model_LR = LinearRegression()
model_LR.fit(X_train, y_train)
```

[32]: LinearRegression(copy\_X=True, fit\_intercept=True, n\_jobs=None, normalize=False)

```
[33]: # Making predictions on the test data using predict()
y_LR_pred = model_LR.predict(X_test)
```

```
[34]: # Computing the RMSE and R2 values for the LinearRegression model:
```

```
rmse_LR = mean_squared_error(y_test, y_LR_pred, squared=False)
r2_LR = r2_score(y_test, y_LR_pred)

print('[LR] Root Mean Squared Error: {0}'.format(rmse_LR))
print('[LR] R2: {0}'.format(r2_LR))
```

[LR] Root Mean Squared Error: 0.3101082890860899

[LR] R2: 0.44205162858670577

```
[35]: # Creating a dictionary called param_grid that contains possible hyperparameter
      ↪ values for max_depth and
      ↪ min_samples_leaf:
```

```
param_grid = {'max_depth': [4, 8], 'min_samples_leaf': [25, 50]}
```

```
[36]: # Creating a DecisionTreeRegressor model:
```

```
regressor_DT = DecisionTreeRegressor()
```

```
[37]: # Running a Grid Search with 3-fold cross-validation and fitting the grid
      ↪ search:
```

```
grid_DT = GridSearchCV(estimator = regressor_DT, param_grid = param_grid, cv =
      ↪ 3, scoring='neg_root_mean_squared_error')
grid_search_DT = grid_DT.fit(X_train, y_train)
print('Done')
```

Done

```
[38]: # Printing the RMSE score of the best DT model using the best_score_ attribute
      ↪ of the fitted grid:
```

```
rmse_DT = -1 * grid_search_DT.best_score_
print("[DT] RMSE for the best model is : {:.2f}".format(rmse_DT) )
```

[DT] RMSE for the best model is : 0.32

```
[39]: # Printing the best model hyperparameters identified by the grid search:
```

```
best_params_DT = grid_search_DT.best_params_
best_params_DT
```

```
[39]: {'max_depth': 8, 'min_samples_leaf': 50}
```

```
[40]: # Initializing a DecisionTreeRegressor model object, but now I'm supplying the
      ↳ best values of hyperparameters
      # max_depth and min_samples_leaf as arguments:
```

```
model_DT = DecisionTreeRegressor(max_depth=best_params_DT['max_depth'],
      ↳ min_samples_leaf= best_params_DT['min_samples_leaf'])
model_DT.fit(X_train, y_train)
```

```
[40]: DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=8,
      max_features=None, max_leaf_nodes=None,
      min_impurity_decrease=0.0, min_impurity_split=None,
      min_samples_leaf=50, min_samples_split=2,
      min_weight_fraction_leaf=0.0, presort='deprecated',
      random_state=None, splitter='best')
```

```
[41]: # Using the fitted model to make predictions on the test data:
```

```
y_DT_pred = model_DT.predict(X_test)
```

```
[42]: # Computing the RMSE and R2 scores for the DecisionTreeRegressor model:
```

```
rmse_DT = mean_squared_error(y_test, y_DT_pred, squared=False)
r2_DT = r2_score(y_test, y_DT_pred)
```

```
print('[DT] Root Mean Squared Error: {0}'.format(rmse_DT))
print('[DT] R2: {0}'.format(r2_DT))
```

```
[DT] Root Mean Squared Error: 0.31570007897144337
```

```
[DT] R2: 0.4217486631801226
```

```
[43]: # Creating a gradient boosted decision tree model using max_depth = 3 and
      ↳ n_estimators = 300:
```

```
model_GBDT = GradientBoostingRegressor(max_depth=3, n_estimators=300)
model_GBDT.fit(X_train, y_train)
print('Done')
```

Done

```
[44]: # Using the fitted model to make predictions on the test data:
```

```
y_GBDT_pred = model_GBDT.predict(X_test)
```

```
[45]: # Computing the RMSE and R2 scores for the GBDT model:
```

```
rmse_GBDT = mean_squared_error(y_test, y_GBDT_pred, squared=False)
r2_GBDT = r2_score(y_test, y_GBDT_pred)
```

```
print('[GBDT] Root Mean Squared Error: {0}'.format(rmse_DBDT))
print('[GBDT] R2: {0}'.format(r2_GBDT))
```

[GBDT] Root Mean Squared Error: 0.3012938464075124  
[GBDT] R2: 0.47331883448493695

[46]: *# Creating a RandomForestRegressor model using max\_depth = 32 and n\_estimators = 300:*

```
model_RF = RandomForestRegressor(max_depth=32, n_estimators=300)
model_RF.fit(X_train, y_train)
print('Done')
```

Done

[47]: *# Using the fitted model to make predictions on the test data:*

```
y_RF_pred = model_RF.predict(X_test)
```

[48]: *# Computing the RMSE and R2 scores for the RandomForestRegressor model:*

```
rmse_RF = mean_squared_error(y_test, y_RF_pred, squared=False)
r2_RF = r2_score(y_test, y_RF_pred)

print('[RF] Root Mean Squared Error: {0}'.format(rmse_RF))
print('[RF] R2: {0}'.format(r2_RF))
```

[RF] Root Mean Squared Error: 0.304534929154202  
[RF] R2: 0.4619266428758483

[49]: *# Plotting the RMSE and R2 score for each regressor:*

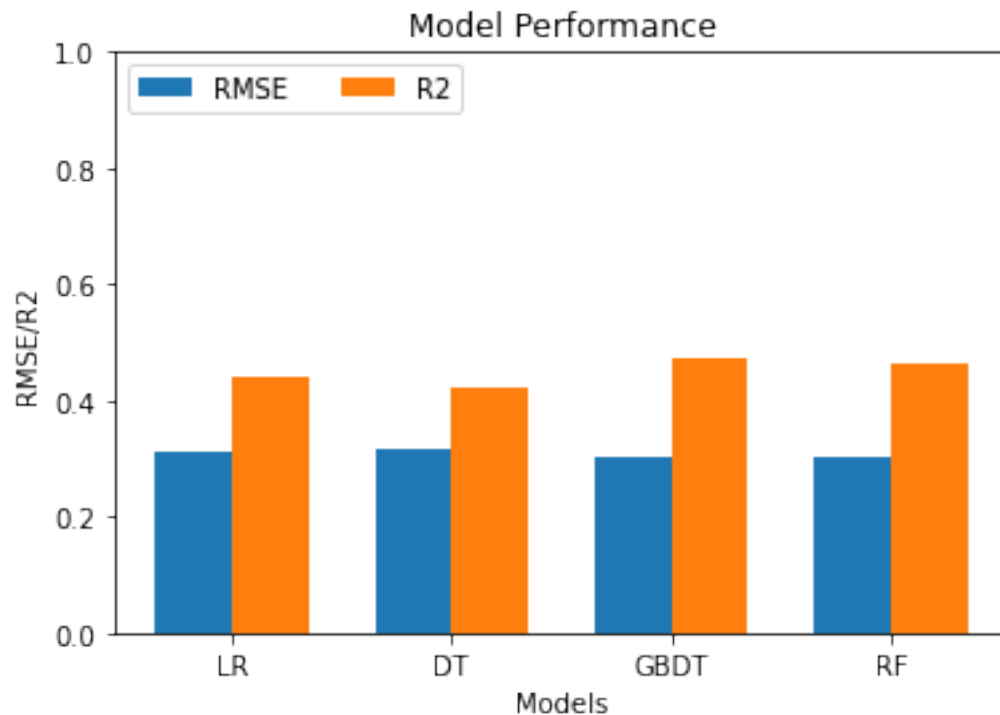
```
RMSE_Results = [rmse_LR, rmse_DT, rmse_DBDT, rmse_RF]
R2_Results = [r2_LR, r2_DT, r2_GBDT, r2_RF]
labels = ['LR', 'DT', 'GBDT', 'RF']

rg= np.arange(4)
width = 0.35
plt.bar(rg, RMSE_Results, width, label="RMSE")
plt.bar(rg+width, R2_Results, width, label='R2')
plt.xticks(rg + width/2, labels)
plt.xlabel("Models")
plt.ylabel("RMSE/R2")
plt.ylim([0,1])

plt.title('Model Performance')
```



```
plt.legend(loc='upper left', ncol=2)
plt.show()
```



Analysis:

From the results above, we can see that the RMSE values of all the regressor models range around the ~0.30-0.31 value, which indicates that my machine learning models generalize well, as its predictions are closer to the actual values in the dataset.

As far as the R2 score goes, the scores acquired are of the range ~0.42-0.47. These results indicate that the model generalizes decently, but does not respond well to the variability in the data set.

Even though all four regressor models behaved similarly, the best performing regressor model for the data set is the GBDT regressor, with the lowest RMSE and highest R2 value.

[ ]: