

# ImplementMLProjectPlan

August 12, 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.

```
[25]: from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,
↳ StackingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

### 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]: # YOUR CODE HERE
filename = os.path.join(os.getcwd(), 'data', 'airbnbListingsData.csv')
df = pd.read_csv(filename, low_memory=False, header=0)
df.head()
```

```
[3]:
                                name \
0                               Skylit Midtown Castle
1  Whole flr w/private bdrm, bath & kitchen(pls r...
2           Spacious Brooklyn Duplex, Patio + Garden
3           Large Furnished Room Near B'way
4           Cozy Clean Guest Room - Family Apt
```

```
                                description \
0  Beautiful, spacious skylit studio in the heart...
1  Enjoy 500 s.f. top floor in 1899 brownstone, w...
2  We welcome you to stay in our lovely 2 br dupl...
3  Please dont expect the luxury here just a bas...
4  Our best guests are seeking a safe, clean, spa...
```

```
                                neighborhood_overview    host_name \
0  Centrally located in the heart of Manhattan ju...    Jennifer
1  Just the right mix of urban center and local n...  LisaRoxanne
2                                     NaN            Rebecca
3  Theater district, many restaurants around here.    Shunichi
4  Our neighborhood is full of restaurants and ca...  MaryEllen
```

```
                                host_location \
0  New York, New York, United States
1  New York, New York, United States
2  Brooklyn, New York, United States
3  New York, New York, United States
4  New York, New York, United States
```

```
                                host_about    host_response_rate \
0  A New Yorker since 2000! My passion is creatin...    0.80
1  Laid-back Native New Yorker (formerly bi-coast...    0.09
2  Rebecca is an artist/designer, and Henoch is i...    1.00
3  I used to work for a financial industry but no...    1.00
4  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
4	7

[5 rows x 50 columns]

## 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.

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

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

```
[5]: df.columns
```

```
[5]: Index(['name', 'description', 'neighborhood_overview', 'host_name',  
        'host_location', 'host_about', 'host_response_rate',  
        'host_acceptance_rate', 'host_is_superhost', 'host_listings_count',  
        'host_total_listings_count', 'host_has_profile_pic',  
        'host_identity_verified', 'neighbourhood_group_cleansed', 'room_type',  
        'accommodates', 'bathrooms', 'bedrooms', 'beds', 'amenities', 'price',  
        'minimum_nights', 'maximum_nights', 'minimum_minimum_nights',  
        'maximum_minimum_nights', 'minimum_maximum_nights',  
        'maximum_maximum_nights', 'minimum_nights_avg_ntm',  
        'maximum_nights_avg_ntm', 'has_availability', 'availability_30',  
        'availability_60', 'availability_90', 'availability_365',  
        'number_of_reviews', 'number_of_reviews_ltm', 'number_of_reviews_l30d',  
        'review_scores_rating', 'review_scores_cleanliness',  
        'review_scores_checkin', 'review_scores_communication',  
        'review_scores_location', 'review_scores_value', 'instant_bookable',  
        'calculated_host_listings_count',  
        'calculated_host_listings_count_entire_homes',
```

```

        'calculated_host_listings_count_private_rooms',
        'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
        'n_host_verifications'],
        dtype='object')

```

```
[6]: df['review_scores_rating'].head(10)
```

```

[6]: 0    4.70
     1    4.45
     2    5.00
     3    4.21
     4    4.91
     5    4.70
     6    4.56
     7    4.88
     8    4.86
     9    4.87
     Name: review_scores_rating, dtype: float64

```

```
[7]: df.dtypes
```

```

[7]: 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

```

```

[8]: # dropping columns with unstructured text, and feature leakage (review_scores_)
dropped_colnames = list(['description', 'name', 'neighborhood_overview',
    → 'host_about', 'host_name',
    → 'host_location', 'amenities',
    → 'review_scores_cleanliness',
    → 'review_scores_checkin', 'review_scores_communication',
    → 'review_scores_location', 'review_scores_value'])
# , 'review_scores_cleanliness', 'review_scores_checkin',
    → 'review_scores_communication', 'review_scores_location',
    → 'review_scores_value'
dropped_colnames

```

```

[8]: ['description',
      'name',
      'neighborhood_overview',
      'host_about',
      'host_name',
      'host_location',
      'amenities',
      'review_scores_cleanliness',
      'review_scores_checkin',
      'review_scores_communication',
      'review_scores_location',
      'review_scores_value']

```

```
[9]: df = df.drop(dropped_colnames, axis=1)
```

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

```
[10]:
```

	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	neighbourhood_group_cleansed	room_type	\
0	True	Manhattan	Entire home/apt	
1	True	Brooklyn	Entire home/apt	
2	True	Brooklyn	Entire home/apt	
3	True	Manhattan	Private room	
4	True	Manhattan	Private room	

	accommodates	...	number_of_reviews_ltm	number_of_reviews_l30d	\
0	1	...	0	0	
1	3	...	32	0	
2	4	...	1	0	
3	2	...	33	2	
4	1	...	0	0	

	review_scores_rating	instant_bookable	calculated_host_listings_count	\
0	4.70	False	3	
1	4.45	False	1	
2	5.00	False	1	
3	4.21	False	1	
4	4.91	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
4                7

[5 rows x 38 columns]

```

```

[11]: # One-Hot Encoding categorical values
to_encode = list(df.select_dtypes(include=['object']).columns)
df[to_encode].nunique()

```

```

[11]: neighbourhood_group_cleansed    5
room_type                            4
dtype: int64

```

```

[12]: # creating and applying the encoder
encoder = OneHotEncoder(handle_unknown='error', sparse=False)
df_enc = pd.DataFrame(encoder.fit_transform(df[to_encode]))

# reinstating original column names
df_enc.columns = encoder.get_feature_names(to_encode)

df_enc.head()

```

```

[12]: neighbourhood_group_cleansed_Bronx    neighbourhood_group_cleansed_Brooklyn  \
0                0.0                0.0
1                0.0                1.0
2                0.0                1.0
3                0.0                0.0
4                0.0                0.0

    neighbourhood_group_cleansed_Manhattan  \
0                1.0
1                0.0
2                0.0

```



3	1.0
4	1.0

neighbourhood_group_cleansed_Queens \	
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

neighbourhood_group_cleansed_Staten Island		room_type_Entire home/apt \	
0	0.0	1.0	
1	0.0	1.0	
2	0.0	1.0	
3	0.0	0.0	
4	0.0	0.0	

room_type_Hotel room	room_type_Private room	room_type_Shared room
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	1.0
4	0.0	1.0

```
[13]: # dropping original columns we transformed from DataFrame 'df'
df.drop(columns=to_encode, axis=1, inplace=True)
df.head()
```

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	...

	number_of_reviews_ltm	number_of_reviews_l30d	review_scores_rating \
0	0	0	4.70
1	32	0	4.45
2	1	0	5.00
3	33	2	4.21
4	0	0	4.91

	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
4	7

[5 rows x 36 columns]

```
[14]: # joining categorical features in df_enc with df
df = df.join(df_enc)
```

```
df.columns
```

```
[14]: Index(['host_response_rate', 'host_acceptance_rate', 'host_is_superhost',
        'host_listings_count', 'host_total_listings_count',
        'host_has_profile_pic', 'host_identity_verified', 'accommodates',
        'bathrooms', 'bedrooms', 'beds', 'price', 'minimum_nights',
        'maximum_nights', 'minimum_minimum_nights', 'maximum_minimum_nights',
        'minimum_maximum_nights', 'maximum_maximum_nights',
        'minimum_nights_avg_ntm', 'maximum_nights_avg_ntm', 'has_availability',
        'availability_30', 'availability_60', 'availability_90',
        'availability_365', 'number_of_reviews', 'number_of_reviews_ltm',
        'number_of_reviews_l30d', 'review_scores_rating', 'instant_bookable',
        'calculated_host_listings_count',
        'calculated_host_listings_count_entire_homes',
        'calculated_host_listings_count_private_rooms',
        'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
        'n_host_verifications', 'neighbourhood_group_cleansed_Bronx',
        'neighbourhood_group_cleansed_Brooklyn',
        'neighbourhood_group_cleansed_Manhattan',
        'neighbourhood_group_cleansed_Queens',
        'neighbourhood_group_cleansed_Staten Island',
        'room_type_Entire home/apt', 'room_type_Hotel room',
        'room_type_Private room', 'room_type_Shared room'],
        dtype='object')
```

```
[15]: # identifying missingness
nan_count = np.sum(df.isnull(), axis=0)
nan_count
```

```
[15]: host_response_rate      11843
      host_acceptance_rate    11113
      host_is_superhost        0
      host_listings_count      0
      host_total_listings_count 0
      host_has_profile_pic      0
      host_identity_verified    0
      accommodates             0
      bathrooms                0
      bedrooms                 2918
      beds                    1354
      price                    0
      minimum_nights           0
      maximum_nights           0
      minimum_minimum_nights    0
      maximum_minimum_nights    0
      minimum_maximum_nights    0
      maximum_maximum_nights    0
      minimum_nights_avg_ntm    0
```

maximum_nights_avg_ntm	0
has_availability	0
availability_30	0
availability_60	0
availability_90	0
availability_365	0
number_of_reviews	0
number_of_reviews_ltm	0
number_of_reviews_l30d	0
review_scores_rating	0
instant_bookable	0
calculated_host_listings_count	0
calculated_host_listings_count_entire_homes	0
calculated_host_listings_count_private_rooms	0
calculated_host_listings_count_shared_rooms	0
reviews_per_month	0
n_host_verifications	0
neighbourhood_group_cleansed_Bronx	0
neighbourhood_group_cleansed_Brooklyn	0
neighbourhood_group_cleansed_Manhattan	0
neighbourhood_group_cleansed_Queens	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
dtype: int64	

```
[16]: # series of T/F values indicating whether missing values is not 0
nan_detected = nan_count > 0

# series of T/F values indicating whether type of column is int64 or float64
is_int_or_float = df.dtypes != 'object'

# combining binary series values into 'to_impute'
to_impute = nan_detected & is_int_or_float

df.columns[to_impute]
```

```
[16]: Index(['host_response_rate', 'host_acceptance_rate', 'bedrooms', 'beds'],
dtype='object')
```

```
[17]: to_impute_selected = ['host_response_rate', 'host_acceptance_rate', 'bedrooms',
    → 'beds']

# creating dummy variables in new series of T/F values indicating missingness
    → of values
for colname in to_impute_selected:
```

```
df[colname + '_na'] = df[colname].isnull()
```

```
df.head()
```

```
[17]:
```

	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	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	neighbourhood_group_cleansed_Staten Island	room_type_Entire home/apt	\
0	0.0	1.0	
1	0.0	1.0	
2	0.0	1.0	
3	0.0	0.0	
4	0.0	0.0	

	room_type_Hotel room	room_type_Private room	room_type_Shared room	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	1.0	0.0	
4	0.0	1.0	0.0	

	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 49 columns]

```
[18]: # replacing missing values with mean values of columns
for colname in to_impute_selected:
    df[colname].fillna(value=df[colname].mean(), inplace=True)

for colname in to_impute_selected:
    print('{} missing values count: {}'.format(colname, np.sum(df[colname].
    ↳isnull(), axis=0)))
```

```
host_response_rate missing values count: 0
host_acceptance_rate missing values count: 0
bedrooms missing values count: 0
beds missing values count: 0
```

```
[19]: # identifying features with the highest correlation with the label
corrs = df.corr()['review_scores_rating']
corrs
```

```
[19]: host_response_rate      0.092494
      host_acceptance_rate    0.009669
      host_is_superhost      NaN
      host_listings_count     -0.033200
      host_total_listings_count -0.033200
      host_has_profile_pic     NaN
      host_identity_verified   NaN
      accommodates            0.007798
      bathrooms              -0.002080
      bedrooms               0.010882
      beds                   0.000223
      price                   0.045067
      minimum_nights         -0.034514
      maximum_nights         -0.012175
      minimum_minimum_nights -0.042011
      maximum_minimum_nights -0.032373
      minimum_maximum_nights -0.005249
      maximum_maximum_nights -0.015691
      minimum_nights_avg_ntm -0.032653
      maximum_nights_avg_ntm -0.009140
      has_availability        0.030396
      availability_30        -0.130953
      availability_60        -0.108681
```

availability_90	-0.092216
availability_365	-0.080430
number_of_reviews	0.067182
number_of_reviews_ltm	0.045595
number_of_reviews_l30d	0.067435
review_scores_rating	1.000000
instant_bookable	-0.058469
calculated_host_listings_count	-0.066378
calculated_host_listings_count_entire_homes	-0.006858
calculated_host_listings_count_private_rooms	-0.107384
calculated_host_listings_count_shared_rooms	-0.029324
reviews_per_month	0.039317
n_host_verifications	0.050888
neighbourhood_group_cleansed_Bronx	-0.005404
neighbourhood_group_cleansed_Brooklyn	0.051198
neighbourhood_group_cleansed_Manhattan	-0.035686
neighbourhood_group_cleansed_Queens	-0.022995
neighbourhood_group_cleansed_Staten Island	0.014503
room_type_Entire home/apt	0.096000
room_type_Hotel room	-0.025586
room_type_Private room	-0.088418
room_type_Shared room	-0.019015
host_response_rate_na	0.010937
host_acceptance_rate_na	-0.003364
bedrooms_na	-0.019238
beds_na	-0.032018

Name: review\_scores\_rating, dtype: float64

```
[20]: # sorting corrs in descending order
corrs_sorted = corrs.sort_values(axis=0, ascending=False)
corrs_sorted
```

review_scores_rating	1.000000
room_type_Entire home/apt	0.096000
host_response_rate	0.092494
number_of_reviews_l30d	0.067435
number_of_reviews	0.067182
neighbourhood_group_cleansed_Brooklyn	0.051198
n_host_verifications	0.050888
number_of_reviews_ltm	0.045595
price	0.045067
reviews_per_month	0.039317
has_availability	0.030396
neighbourhood_group_cleansed_Staten Island	0.014503
host_response_rate_na	0.010937
bedrooms	0.010882
host_acceptance_rate	0.009669
accommodates	0.007798

beds	0.000223
bathrooms	-0.002080
host_acceptance_rate_na	-0.003364
minimum_maximum_nights	-0.005249
neighbourhood_group_cleansed_Bronx	-0.005404
calculated_host_listings_count_entire_homes	-0.006858
maximum_nights_avg_ntm	-0.009140
maximum_nights	-0.012175
maximum_maximum_nights	-0.015691
room_type_Shared room	-0.019015
bedrooms_na	-0.019238
neighbourhood_group_cleansed_Queens	-0.022995
room_type_Hotel room	-0.025586
calculated_host_listings_count_shared_rooms	-0.029324
beds_na	-0.032018
maximum_minimum_nights	-0.032373
minimum_nights_avg_ntm	-0.032653
host_total_listings_count	-0.033200
host_listings_count	-0.033200
minimum_nights	-0.034514
neighbourhood_group_cleansed_Manhattan	-0.035686
minimum_minimum_nights	-0.042011
instant_bookable	-0.058469
calculated_host_listings_count	-0.066378
availability_365	-0.080430
room_type_Private room	-0.088418
availability_90	-0.092216
calculated_host_listings_count_private_rooms	-0.107384
availability_60	-0.108681
availability_30	-0.130953
host_is_superhost	NaN
host_has_profile_pic	NaN
host_identity_verified	NaN

Name: review\_scores\_rating, dtype: float64

```
[21]: # saving the relevant correlation values to analyze relationships between the
      ↪ features in plots
      corrs_list = list(corrs_sorted.index[1:3])
      corrs_list
```

```
[21]: ['room_type_Entire home/apt', 'host_response_rate']
```

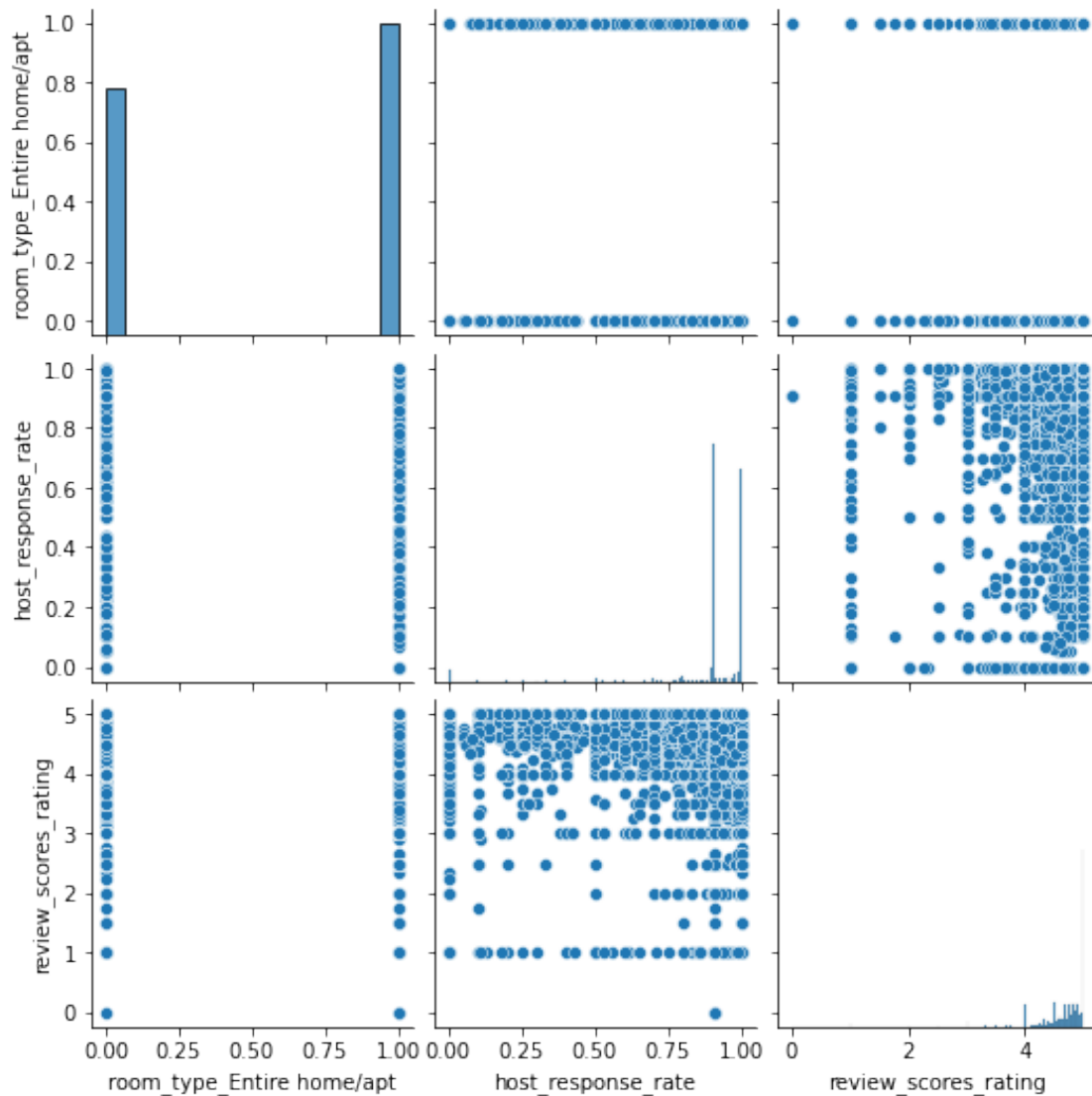
```
[22]: # producing bivariate plots for label and its top correlates
      corrs_list.append('review_scores_rating')

      df_sub = df[corrs_list]

      sns.pairplot(data=df_sub)
```

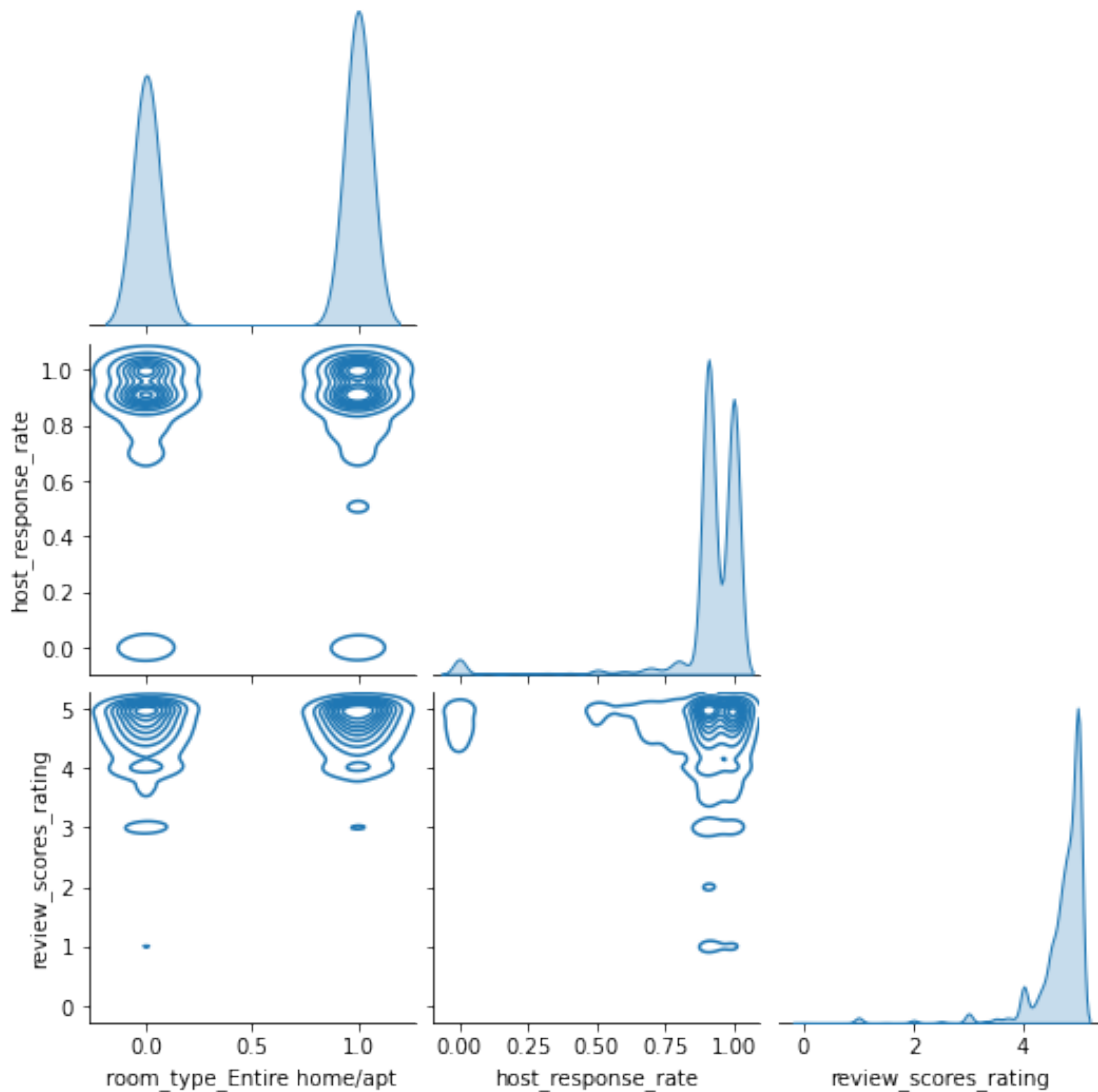


[22]: <seaborn.axisgrid.PairGrid at 0x7f529492f128>



```
[23]: # pairplot specifying kernel density estimator for interpretability of data
sns.pairplot(data=df_sub, kind='kde', corner=True)
```

[23]: <seaborn.axisgrid.PairGrid at 0x7f521261ae80>



### 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.

```
[26]: # creating labeled examples from DataFrame 'df'
      y = df['review_scores_rating']
```

```
X = df.drop(columns='review_scores_rating', axis=1)
```

```
[28]: # splitting labeled examples into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,
    random_state=1234)
```

```
[29]: # specifying four models in a list of tuples

# running a GridSearch cross validation to find the optimal hyperparameters
# is computationally costly, so I specified a normal value for the
    hyperparameters

estimators = [('DT', DecisionTreeRegressor(max_depth=8)),
              ('RF', RandomForestRegressor()),
              ('GBDT', GradientBoostingRegressor(n_estimators=100)),
              ('LR', LinearRegression())
              ]
```

```
[30]: stacking_model = StackingRegressor(estimators=estimators, cv=5,
    passthrough=False)
```

```
[31]: # Obtaining 3-fold cross-validation RMSE scores from cross_val_score()
print('Start')

score = cross_val_score(stacking_model, X_train, y_train,
    scoring='neg_root_mean_squared_error')
rmse_avg = np.mean(-1 * score)

print('End')
print('average score: {}'.format(rmse_avg))
```

Start

End

average score: 0.47517026790431816

```
[33]: # Stacking
# fitting stacking_model to the training data
stacking_model.fit(X_train, y_train)

# using predict() to test use fitted model to make predictions on the test data
stacking_pred = stacking_model.predict(X_test)

# compute the Root Mean Squared Error using mean_squared_error()
rmse = mean_squared_error(y_test, stacking_pred, squared=False)

# compute the R-squared score using r2_score()
r2 = r2_score(y_test, stacking_pred)

print('[Stacking] Root Mean Squared Error: {}'.format(rmse))
```

```
print('[Stacking] R2: {}'.format(r2))
```

[Stacking] Root Mean Squared Error: 0.46313757716339593

[Stacking] R2: 0.1404644625213508

```
[34]: # Linear Regression
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
y_lr_pred = lr_model.predict(X_test)
lr_rmse = mean_squared_error(y_test, y_lr_pred, squared=False)
lr_r2 = r2_score(y_test, y_lr_pred)

print('[LR] Root Mean Squared Error: {}'.format(lr_rmse))
print('[LR] R2: {}'.format(lr_r2))
```

[LR] Root Mean Squared Error: 0.48344439541818285

[LR] R2: 0.06343729826935596

```
[35]: # Decision Tree
dt_model = DecisionTreeRegressor(max_depth=8, min_samples_leaf=50)
dt_model.fit(X_train, y_train)
y_dt_pred = dt_model.predict(X_test)
dt_rmse = mean_squared_error(y_test, y_dt_pred, squared=False)
dt_r2 = r2_score(y_test, y_dt_pred)

print('[DT] Root Mean Squared Error: {}'.format(dt_rmse))
print('[DT] R2: {}'.format(dt_r2))
```

[DT] Root Mean Squared Error: 0.48249391154124927

[DT] R2: 0.06711636734932946

```
[36]: # Gradient Boosted Decision Tree
gbdt_model = GradientBoostingRegressor(max_depth=2, n_estimators=300)
gbdt_model.fit(X_train, y_train)
y_gbdt_pred = gbdt_model.predict(X_test)
gbdt_rmse = mean_squared_error(y_test, y_gbdt_pred, squared=False)
gbdt_r2 = r2_score(y_test, y_gbdt_pred)

print('[GBDT] Root Mean Squared Error: {}'.format(gbdt_rmse))
print('[GBDT] R2: {}'.format(gbdt_r2))
```

[GBDT] Root Mean Squared Error: 0.46721943674764427

[GBDT] R2: 0.12524667571424242

```
[37]: # Random Forest
rf_model = RandomForestRegressor(max_depth=32, n_estimators=300)
rf_model.fit(X_train, y_train)
y_rf_pred = rf_model.predict(X_test)
rf_rmse = mean_squared_error(y_test, y_rf_pred, squared=False)
rf_r2 = r2_score(y_test, y_rf_pred)

print('[RF] Root Mean Squared Error: {0}'.format(rf_rmse))
print('[RF] R2: {0}'.format(rf_r2))
```

```
[RF] Root Mean Squared Error: 0.47331414512804576
[RF] R2: 0.10227614466820589
```

```
[39]: # Plotting the RMSE and R2 score for stacked ensemble model and each regressor
rmse_results = [rmse, lr_rmse, dt_rmse, gbdt_rmse, rf_rmse]
r2_results = [r2, lr_r2, dt_r2, gbdt_r2, rf_r2]
labels = ['SE', 'LR', 'DT', 'GBDT', 'RF']

rg = np.arange(5)
width = 0.35

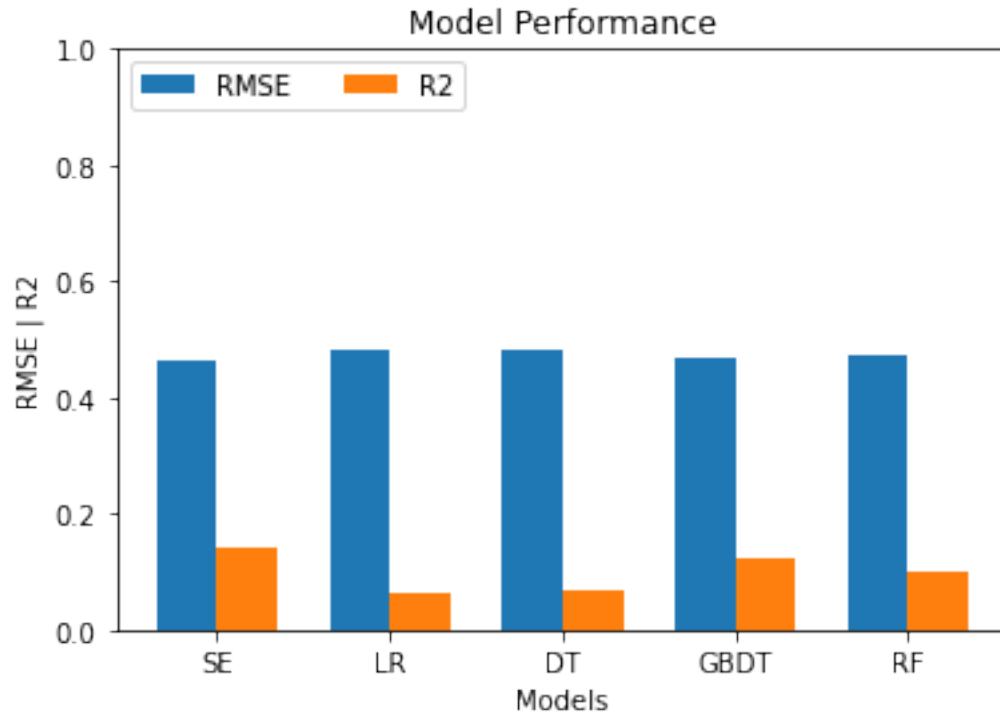
# creating bar plots with RMSE and R2 results
plt.bar(rg, rmse_results, width, label='RMSE')
plt.bar(rg + width, r2_results, width, label='R2')

# calling plt.xticks() to add labels under bars
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
```

```
[39]: <function matplotlib.pyplot.show>
```



Analysis: Analyzing the model performance of our stacking model with the individual models, we can easily see that none of the models performed well. The stacking ensemble seems to perform the best, with the lowest RMSE and highest R2 score. This makes sense because the higher the residual squared score is, the better fit the model is for the data. Overall, I think that model performance could be improved if I did not drop the features with high correlation to 'review\_scores\_rating', such as in the list ['review\_scores\_cleanliness', 'review\_scores\_checkin', 'review\_scores\_communication', 'review\_scores\_location', 'review\_scores\_value']. However, by analyzing the features in my dataset I figured that keeping these features would likely lead to feature leakage, which is not something we want when building and training an optimal model. I think that I could look into predicting other features rather than 'review\_scores\_rating' because there isn't a high correlation with the other features.