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]:
```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import StackingRegressor
```

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 `WHR2018Chapter2OnlineData.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`.

[63]:
```
# Load the Airbnb data set
filename = os.path.join(os.getcwd(), "data", "airbnbListingsData.csv")
df = pd.read_csv(filename)
```

[64]:
```
df.head()
```

[64]:
```
                                                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-drown menu.

1.2.1 a. Reduce size of dataframe

[5]:
```python
# Identify columns with highest correlation
corrs_sorted = df.corr()['review_scores_rating'].sort_values(ascending=False)#␣
 ↪YOUR CODE HERE
corrs_sorted
```

[5]:
```
review_scores_rating                                1.000000
review_scores_value                                 0.820631
review_scores_cleanliness                           0.758213
review_scores_communication                         0.727749
review_scores_checkin                               0.688152
review_scores_location                              0.574464
host_response_rate                                  0.121477
number_of_reviews_l30d                              0.067435
number_of_reviews                                   0.067182
n_host_verifications                                0.050888
number_of_reviews_ltm                               0.045595
price                                               0.045067
reviews_per_month                                   0.039317
```

```
has_availability                                0.030396
host_acceptance_rate                            0.012542
bedrooms                                        0.011528
accommodates                                    0.007798
beds                                            0.000233
bathrooms                                      -0.002080
minimum_maximum_nights                         -0.005249
calculated_host_listings_count_entire_homes    -0.006858
maximum_nights_avg_ntm                         -0.009140
maximum_nights                                 -0.012175
maximum_maximum_nights                         -0.015691
calculated_host_listings_count_shared_rooms    -0.029324
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
minimum_minimum_nights                         -0.042011
instant_bookable                               -0.058469
calculated_host_listings_count                 -0.066378
availability_365                               -0.080430
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
```

[6]:
```python
# Reduce size of dataframe by only keeping relevant features
columns_to_keep = ['review_scores_rating',
 ↪'host_response_rate','n_host_verifications', 'price', 'room_type',
 ↪'host_acceptance_rate', 'bedrooms', 'accommodates', 'beds', 'bathrooms']
df = df[columns_to_keep]
df.head()
```

[6]:
```
   review_scores_rating  host_response_rate  n_host_verifications  price  \
0                  4.70                0.80                     9  150.0
1                  4.45                0.09                     6   75.0
2                  5.00                1.00                     3  275.0
3                  4.21                1.00                     4   68.0
4                  4.91                 NaN                     7   75.0

         room_type  host_acceptance_rate  bedrooms  accommodates  beds  \
0  Entire home/apt                  0.17       NaN             1   1.0
1  Entire home/apt                  0.69       1.0             3   3.0
2  Entire home/apt                  0.25       2.0             4   2.0
```

```
3     Private room                    1.00       1.0               2   1.0
4     Private room                     NaN       1.0               1   1.0

   bathrooms
0        1.0
1        1.0
2        1.5
3        1.0
4        1.0
```

1.2.2 b. Address missing values

[7]:
```python
# Check number of missing values
nan_count = np.sum(df.isnull(), axis=0) # sum all null vals by col
nan_count
```

[7]:
```
review_scores_rating        0
host_response_rate      11843
n_host_verifications        0
price                       0
room_type                   0
host_acceptance_rate    11113
bedrooms                 2918
accommodates                0
beds                     1354
bathrooms                   0
dtype: int64
```

[8]:
```python
# Find mean values for columns with missing values
mean_host_response_rate, mean_host_acceptance_rate = df['host_response_rate'].
 ↪mean(), df['host_acceptance_rate'].mean()
mean_bedrooms, mean_beds = df['bedrooms'].mean(), df['beds'].mean()

# Fill missing values with mean values
df['host_response_rate'].fillna(value=mean_host_response_rate, inplace=True)
df['host_acceptance_rate'].fillna(value=mean_host_acceptance_rate, inplace=True)
df['bedrooms'].fillna(value=mean_bedrooms, inplace=True)
df['beds'].fillna(value=mean_beds, inplace=True)
```

[9]:
```python
df.head()
```

[9]:
```
   review_scores_rating  host_response_rate  n_host_verifications  price  \
0                  4.70            0.800000                     9  150.0
1                  4.45            0.090000                     6   75.0
2                  5.00            1.000000                     3  275.0
3                  4.21            1.000000                     4   68.0
4                  4.91            0.906901                     7   75.0
```

```
        room_type  host_acceptance_rate  bedrooms  accommodates  beds  \
0  Entire home/apt              0.170000  1.329708             1   1.0
1  Entire home/apt              0.690000  1.000000             3   3.0
2  Entire home/apt              0.250000  2.000000             4   2.0
3     Private room              1.000000  1.000000             2   1.0
4     Private room              0.791953  1.000000             1   1.0

   bathrooms
0        1.0
1        1.0
2        1.5
3        1.0
4        1.0
```

1.2.3 c. One-hot encode categorical values

[10]:
```python
# Find columns with object data type
to_encode = list(df.select_dtypes(include=['object'])) # only 'room_type' is an␣
 ↪object

# Get a list of all room types
room_types = list(df['room_type'].value_counts().index)

# Create one-hot encode columns for each room type
for value in room_types:
    df['room_type_'+ value.lower().replace(' ', '_')] = np.
 ↪where(df['room_type']==value,1,0)

df.drop(columns = 'room_type', inplace=True)

df.head()
```

[10]:
```
   review_scores_rating  host_response_rate  n_host_verifications  price  \
0                  4.70            0.800000                     9  150.0
1                  4.45            0.090000                     6   75.0
2                  5.00            1.000000                     3  275.0
3                  4.21            1.000000                     4   68.0
4                  4.91            0.906901                     7   75.0

   host_acceptance_rate  bedrooms  accommodates  beds  bathrooms  \
0              0.170000  1.329708             1   1.0        1.0
1              0.690000  1.000000             3   3.0        1.0
2              0.250000  2.000000             4   2.0        1.5
3              1.000000  1.000000             2   1.0        1.0
4              0.791953  1.000000             1   1.0        1.0

   room_type_entire_home/apt  room_type_private_room  room_type_shared_room  \
```

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

   room_type_hotel_room
0                     0
1                     0
2                     0
3                     0
4                     0
```

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.

1.3.1 a. Create training and testing data sets

[11]:
```
# Create Labeled Examples
X = df.drop(columns='review_scores_rating', axis=0)
y = df['review_scores_rating']
```

[12]:
```
# Split labeled examples into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
↪random_state=42)
```

1.3.2 b. Linear regression model

Analysis: The linear regression model has a reasonable level of prediction accuracy, but the extremely R^2 indicates that this model is not best suited for capturing the complex relationships in the data

[28]:
```
# Create linear regression model and fit to training data
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)


# Make predictions on the test data and compute RMSE/R^2
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 RMSE and R^2
print('[LR] RMSE: {:.4f}'.format(lr_rmse))
print('[LR]  R^2: {:.4f}'.format(lr_r2))
```

```
[LR] RMSE: 0.4970
[LR]  R^2: 0.0244
```

1.3.3 c. Create Decision Tree Regression Model

Analysis: The decision tree regression model has a reasonable level of prediction accuracy, but the extremely low R^2 indicates that this model is not best suited for capturing the complex relationships in the data. Although the RMSE is lower than the linear regression model, it has a better R^2.

[34]:
```
# Parameters for Grid Search
param_grid = {
    'max_depth': [2**i for i in list(range(10))],
    'min_samples_leaf': [2**i for i in list(range(10))]
}

# Create a DecisionTreeRegressor model and run a Grid Search with 3-fold␣
↪cross-validation
dt_regressor = DecisionTreeRegressor()
dt_grid = GridSearchCV(dt_regressor, param_grid, cv = 3,␣
↪scoring='neg_root_mean_squared_error')# YOUR CODE HERE
dt_grid_search = dt_grid.fit(X_train, y_train)

# Save best parameters to dt_best_params
dt_best_params = dt_grid_search.best_params_
```

[36]:
```
# Create final DecisionTreeRegressor regression model and fit to training data
dt_model = DecisionTreeRegressor(max_depth=dt_best_params['max_depth'],␣
↪min_samples_leaf=dt_best_params['min_samples_leaf'])
dt_model.fit(X_train, y_train)

# Make predictions on the test data and compute RMSE/R^2
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 RMSE and R^2
print('[DT] RMSE: {:.4f}'.format(dt_rmse))
print('[DT]  R^2: {:.4f}'.format(dt_r2))
```

```
[DT] RMSE: 0.4934
[DT]  R^2: 0.0384
```

1.3.4 d. Create Gradient Boosting Regression Model

[49]:
```
# Parameters for Grid Search
param_grid = {
    'n_estimators': [100, 300, 700],
    'max_depth': [2, 4, 8, 16, 32]
}

# Create a GradientBoostingRegressor model and run a Grid Search with 3-fold␣
↪cross-validation
gbdt_regressor = GradientBoostingRegressor()
gbdt_grid = GridSearchCV(gbdt_regressor, param_grid, cv=3,␣
↪scoring='neg_root_mean_squared_error')
gbdt_grid_search = gbdt_grid.fit(X_train, y_train)

# Save best parameters to gbdt_best_params
gbdt_best_params = gbdt_grid_search.best_params_
```

[50]:
```
# Create final GradientBoostingRegressor model with best parameters and fit to␣
↪training data
gbdt_model = GradientBoostingRegressor(
    n_estimators=gbdt_best_params['n_estimators'],
    max_depth=gbdt_best_params['max_depth']
)
gbdt_model.fit(X_train, y_train)

# Make predictions on the test data and compute RMSE/R^2
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 RMSE and R^2
print('[GBDT] RMSE: {:.4f}'.format(gbdt_rmse))
print('[GBDT] R^2: {:.4f}'.format(gbdt_r2))
```

```
[GBDT] RMSE: 0.4920
[GBDT] R^2: 0.0441
```

1.3.5 e. Create Random Forest Regression Model

[51]:
```
# Parameters for Grid Search
param_grid = {
    'n_estimators': [100, 300, 700],
    'max_depth': [2, 4, 8, 16, 32]
}

# Create a GradientBoostingRegressor model and run a Grid Search with 3-fold␣
↪cross-validation
```

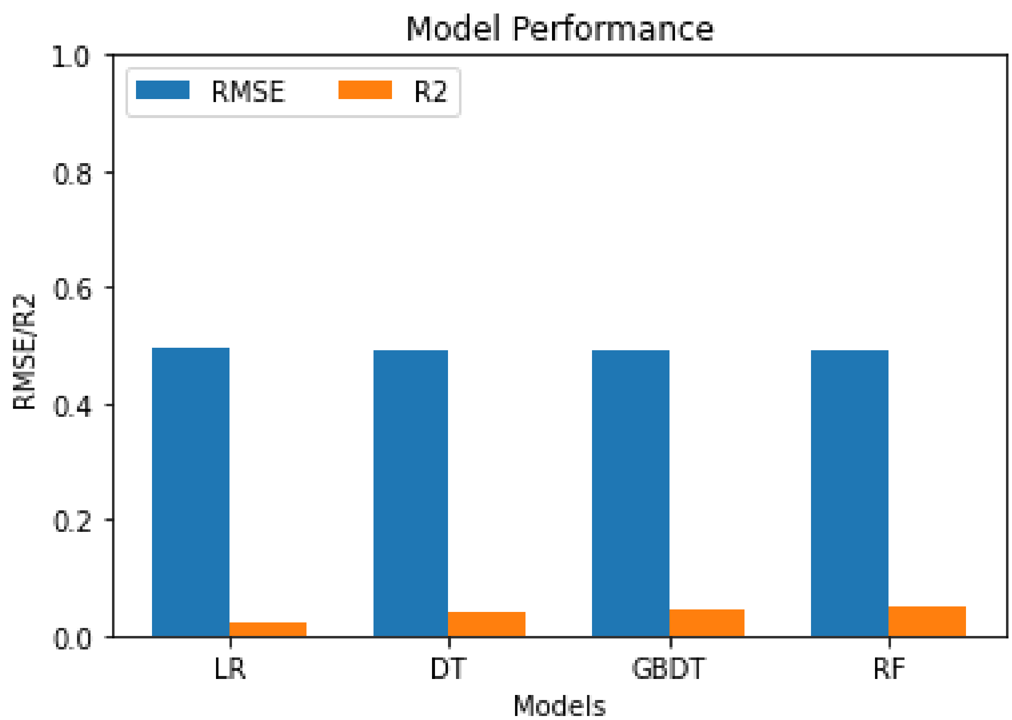
```
rf_regressor = RandomForestRegressor()
rf_grid = GridSearchCV(rf_regressor, param_grid, cv=3,␣
↪scoring='neg_root_mean_squared_error')
rf_grid_search = rf_grid.fit(X_train, y_train)

# Save best parameters to gbdt_best_params
rf_best_params = rf_grid_search.best_params_
```

[52]:
```
# Create final RandomForest model with best parameters and fit to training data
rf_model = RandomForestRegressor(
    n_estimators=rf_best_params['n_estimators'],
    max_depth=rf_best_params['max_depth']
)
rf_model.fit(X_train, y_train)

# Make predictions on the test data and compute RMSE/R^2
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 RMSE and R^2
print('[RF] RMSE: {:.4f}'.format(rf_rmse))
print('[RF] R^2: {:.4f}'.format(rf_r2))
```

```
[RF] RMSE: 0.4910
[RF] R^2: 0.0479
```

1.3.6 f. Visualize results

[53]:
```
RMSE_Results = [lr_rmse, dt_rmse, gbdt_rmse, rf_rmse]
R2_Results = [lr_r2, dt_r2, gbdt_r2, rf_r2]
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()
```



1.3.7 g. Create stacking regressor model using previous models

[54]:
```
estimators_best = [("DT", dt_model),
                   ("RF", rf_model),
                   ("GBDT", gbdt_model),
                   ("LR", lr_model)
                  ]
```

[58]:
```
s_model = StackingRegressor(estimators = estimators_best, cv = 3,␣
 ↪passthrough=False)
s_model.fit(X_train, y_train)
```

[58]:
```
StackingRegressor(cv=3,
                  estimators=[('DT',
                               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=128,
                                                     min_samples_split=2,
min_weight_fraction_leaf=0.0,
```

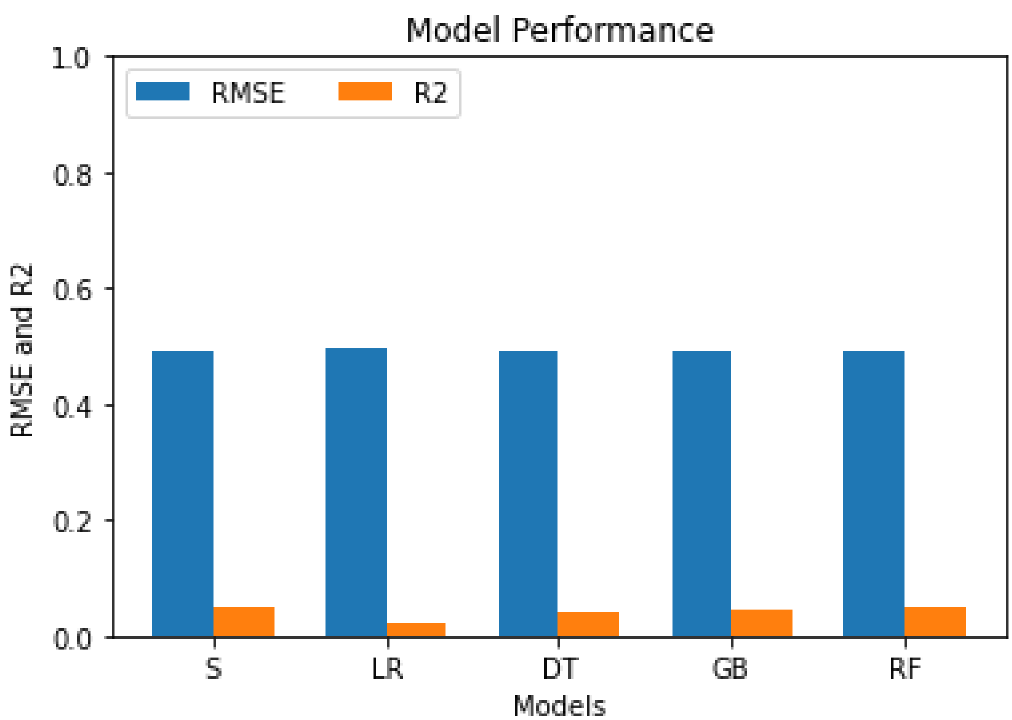
```
                                                       presort='deprecated',
                                                       random_state=None,
                                                       splitter='best')),
                                 ('RF',
                                  RandomForestRegressor(bo...
                                                           min_samples_split=2,
min_weight_fraction_leaf=0.0,

                                                           n_estimators=300,
                                                           n_iter_no_change=None,
                                                           presort='deprecated',
                                                           random_state=None,
                                                           subsample=1.0,
                                                           tol=0.0001,
validation_fraction=0.1,

                                                           verbose=0,
                                                           warm_start=False)),
                                 ('LR',
                                  LinearRegression(copy_X=True, fit_intercept=True,
                                                   n_jobs=None,
                                                   normalize=False))],
                  final_estimator=None, n_jobs=None, passthrough=False,
                  verbose=0)
```

[59]:
```
s_y_pred = s_model.predict(X_test)
s_rmse = mean_squared_error(y_test, s_y_pred, squared=False)
s_r2 = r2_score(y_test, s_y_pred)

print('[GBDT] RMSE: {:.4f}'.format(s_rmse))
print('[GBDT] R^2: {:.4f}'.format(s_r2))
```

```
[GBDT] RMSE: 0.4899
[GBDT] R^2: 0.0519
```

[62]:
```
RMSE_Results = [s_rmse, lr_rmse, dt_rmse, gbdt_rmse, rf_rmse]
R2_Results = [s_r2, lr_r2, dt_r2, gbdt_r2, rf_r2]

rg= np.arange(5)
width = 0.35

# 1. Create bar plot with RMSE results
# YOUR CODE HERE
plt.bar(rg, RMSE_Results, width, label='RMSE')

# 2. Create bar plot with R2 results
# YOUR CODE HERE
plt.bar(rg + width, R2_Results, width, label='R2')
```

```
# 3. Call plt.xticks() to add labels under the bars indicating which model the␣
 ↪pair of RMSE
# and R2 bars correspond to
# YOUR CODE HERE
plt.xticks(rg + width / 2, ['S', 'LR', 'DT', 'GB', 'RF'])

# 4. Label the x and y axis of the plot: the x axis should be labeled "Models"␣
 ↪and the y axis
# should be labeled "RMSE and R2"
# YOUR CODE HERE
plt.xlabel('Models')
plt.ylabel('RMSE and R2')

plt.ylim([0,1])
plt.title('Model Performance')
plt.legend(loc='upper left', ncol=2)
plt.show()
```



1.4 Summarizing Findings

The stacking model performed the best out of the 5 models. However, the models do not have a high R^2 value. That means that the models are not good at dealing with variation in the data. There could be more features that impact Airbnb ratings like location, and additional information not included in the dataset (amenities, decor, cleanliness rating not by the customers, etc.). In addition, the average rating of the Airbnbs in the dataset is 4.6, which is high and count explain why the model cannot effectively reason variation in the data.