DefineAndSolveMLProblem

August 1, 2025

1 Lab 8: Define and Solve an ML Problem of Your Choosing

[20]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
```

In this lab assignment, you will follow the machine learning life cycle and implement a model to solve a machine learning problem of your choosing. You will select a data set and choose a predictive problem that the data set supports. You will then inspect the data with your problem in mind and begin to formulate a project plan. You will then implement the machine learning project plan.

You will complete the following tasks:

1. Build Your DataFrame
2. Define Your ML Problem
3. Perform exploratory data analysis to understand your data.
4. Define Your Project Plan
5. Implement Your Project Plan:
    - Prepare your data for your model.
    - Fit your model to the training data and evaluate your model.
    - Improve your model's performance.

1.1 Part 1: Build Your DataFrame

You will have the option to choose one of four data sets that you have worked with in this program:

- The "census" data set that contains Census information from 1994: `censusData.csv`
- Airbnb NYC "listings" data set: `airbnbListingsData.csv`
- World Happiness Report (WHR) data set: `WHR2018Chapter2OnlineData.csv`
- Book Review data set: `bookReviewsData.csv`

Note that these are variations of the data sets that you have worked with in this program. For example, some do not include some of the preprocessing necessary for specific models.

Load a Data Set and Save it as a Pandas DataFrame The code cell below contains filenames (path + filename) for each of the four data sets available to you.

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

You can load each file as a new DataFrame to inspect the data before choosing your data set.

[21]:
```
# File names of the four data sets
adultDataSet_filename = os.path.join(os.getcwd(), "data", "censusData.csv")
airbnbDataSet_filename = os.path.join(os.getcwd(), "data", "airbnbListingsData.
 ↪csv")
WHRDataSet_filename = os.path.join(os.getcwd(), "data",␣
 ↪"WHR2018Chapter2OnlineData.csv")
bookReviewDataSet_filename = os.path.join(os.getcwd(), "data", "bookReviewsData.
 ↪csv")


df = pd.read_csv(airbnbDataSet_filename)

df.head()
```

[21]:
```
                                                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 don't 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: Define Your ML Problem

Next you will formulate your ML Problem. In the markdown cell below, answer the following questions:

1. List the data set you have chosen.
2. What will you be predicting? What is the label?
3. Is this a supervised or unsupervised learning problem? Is this a clustering, classification or regression problem? Is it a binary classificaiton or multi-class classifiction problem?
4. What are your features? (note: this list may change after your explore your data)
5. Explain why this is an important problem. In other words, how would a company create value with a model that predicts this label?

1. the data set I will chose is the airbnbDataSet
2. I will be predicting the rating of the airbnb from the guests based on the other features listed.
3. This is a supervised learning problem because we have known features and a known label. This is a regression problem since the rating is on a 0-100 scale. This can turn into a binary classification problem as we can seperate the ratings between 0-60, and 60-100, to classify if it is a high rating or not a high rating.
4. My features will be Host information: host_location, host_identity, host_neighbourhood, host_acceptance_rate, host_response_rate, Airbnb details:Bathrooms, beds, amenities, price.
5. This is an important problem because it shows the predicted rating, which is important for the company so they can know what needs to improve to make their rating higher, and so more people can come to their company.

1.3 Part 3: Understand Your Data

The next step is to perform exploratory data analysis. Inspect and analyze your data set with your machine learning problem in mind. Consider the following as you inspect your data:

1. What data preparation techniques would you like to use? These data preparation techniques may include:
    - addressing missingness, such as replacing missing values with means
    - finding and replacing outliers

- renaming features and labels
- finding and replacing outliers
- performing feature engineering techniques such as one-hot encoding on categorical features
- selecting appropriate features and removing irrelevant features
- performing specific data cleaning and preprocessing techniques for an NLP problem
- addressing class imbalance in your data sample to promote fair AI

2. What machine learning model (or models) you would like to use that is suitable for your predictive problem and data?

    - Are there other data preparation techniques that you will need to apply to build a balanced modeling data set for your problem and model? For example, will you need to scale your data?

3. How will you evaluate and improve the model's performance?

    - Are there specific evaluation metrics and methods that are appropriate for your model?

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. You can import additional packages that you have used in this course that you will need to perform this task.

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.

[22]:
```
print(df.describe())
print(df.dtypes)
```

```
       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]
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
```

1.4 Part 4: Define Your Project Plan

Now that you understand your data, in the markdown cell below, define your plan to implement the remaining phases of the machine learning life cycle (data preparation, modeling, evaluation) to solve your ML problem. Answer the following questions:

- Do you have a new feature list? If so, what are the features that you chose to keep and remove after inspecting the data?
- Explain different data preparation techniques that you will use to prepare your data for modeling.
- What is your model (or models)?
- Describe your plan to train your model, analyze its performance and then improve the model. That is, describe your model building, validation and selection plan to produce a model that generalizes well to new data.

1. Yes I have a new feature list, I decided not to keep the names of the hosts, or id, or the

name of the room, or the hosts about as they are not important. The features that I have chosen to keep are accommodates, bedrooms, bathrooms, price, number_of_reviews, reviews_per_month, room_type, neighbourhood_group.
2. Different data preperation techniques that I will use is getting rid of null and missing value. I can also drop columns that I know is irrelevant to the model. I will one hot encode different features such as room_type and neighborhood_group.
3. My models that I am going to use is LogisticRegression and RandomForests
4. I will first split the cleaned data, then create a LinearRegression model. From there, I will train the model and capture its RSME and R^2 scores. Then, I will implement a Random Forest model and also capture its RMSE and R^2 scores. After that, I plan to tune the hyperparameters of Random Forest and use Grid Search to improve the accuracy of the model overfitting. Finally, I will compare the models based on the RSME and R2 scores, and select the best-performing model

1.5 Part 5: Implement Your Project Plan

Task: In the code cell below, import additional packages that you have used in this course that you will need to implement your project plan.

[23]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
```

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

You will:

1. Prepare your data for your model.
2. Fit your model to the training data and evaluate your model.
3. Improve your model's performance 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.

[24]:
```
print(df.columns.tolist())
df.drop(columns=['name', 'description', 'neighborhood_overview', 'host_name',␣
↪'host_about', 'host_location'], inplace=True)


df.dropna(inplace=True)


df['host_is_superhost'] = df['host_is_superhost'].astype(int)
```

```
## one hot encoding
categorical_cols = ['room_type', 'neighbourhood_group_cleansed']

df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

df_encoded = df.select_dtypes(include=['int64', 'float64'])
```

```
['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']
```

[25]:
```
# okay so train train train

y = df_encoded['review_scores_rating']
X = df_encoded.drop(columns = 'review_scores_rating')
```

[26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30,␣
↪random_state = 1234)
```

[27]:
```
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: {0}'.format(lr_rmse))
print('[LR] R2: {0}'.format(lr_r2))
```

```
[LR] Root Mean Squared Error: 0.20212997126420046
[LR] R2: 0.8447732968760235
```

[28]:
```
#random forests
print('Begin RF Implementation...')

rf_model = RandomForestRegressor(max_depth = 32, n_estimators = 300)
rf_model.fit(X_train, y_train)
print('End')

y_rf_pred = rf_model.predict(X_test)


#Compute the RMSE
rf_rmse = mean_squared_error(y_test, y_rf_pred, squared = False)

# 3. Compute the R2 score
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))
```

```
Begin RF Implementation…
End
[RF] Root Mean Squared Error: 0.21154310295031606
[RF] R2: 0.829978929697045
```

[50]:
```
# grid search to improve
param_grid = {
    'n_estimators': [200],
    'max_depth': [ 20, 30],
    'min_samples_split': [10,20],
    'min_samples_leaf': [5],
}


print("starting grid search")

rf_regressor = RandomForestRegressor(random_state = 1234)



rf_grid = GridSearchCV(rf_regressor, param_grid, cv = 3, scoring =␣
↪'neg_root_mean_squared_error',  n_jobs=-1)



rf_grid_search = rf_grid.fit(X_train, y_train)

print('Done')
```

```
starting grid search
Done
```

[51]:
```
rmse_rf = -1 * rf_grid_search.best_score_
print("[DT] RMSE for the best model is : {:.2f}".format(rmse_rf) )
```

```
[DT] RMSE for the best model is : 0.21
```

[55]:
```
rf_best_params = rf_grid_search.best_params_

rf_best_params
```

[55]:
```
{'max_depth': 20,
 'min_samples_leaf': 5,
 'min_samples_split': 20,
 'n_estimators': 200}
```

[57]:
```
rf_model = RandomForestRegressor(max_depth = 20, min_samples_leaf =␣
↪5,min_samples_split = 20, n_estimators = 200 )
rf_model.fit(X_train, y_train)
```

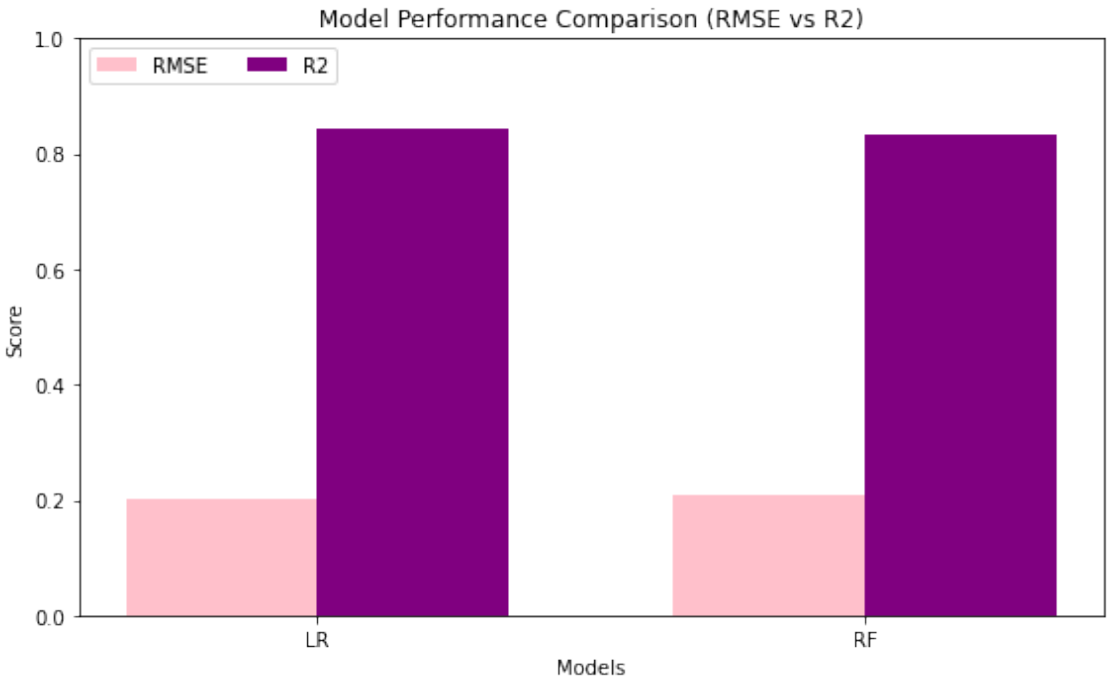
[57]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=20, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=5,
                      min_samples_split=20, min_weight_fraction_leaf=0.0,
                      n_estimators=200, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[58]:
```
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('[DT] Root Mean Squared Error: {0}'.format(rf_rmse))
print('[DT] R2: {0}'.format(rf_r2))
```

```
[DT] Root Mean Squared Error: 0.20940694760206727
[DT] R2: 0.8333953272638573
```

[59]:
```
import numpy as np
import matplotlib.pyplot as plt
```

```
RMSE_Results = [lr_rmse, rf_rmse]
R2_Results = [lr_r2, rf_r2]

rg = np.arange(2)
width = 0.35


plt.figure(figsize=(8, 5))


plt.bar(rg, RMSE_Results, width=width, label='RMSE', color='pink')


plt.bar(rg + width, R2_Results, width=width, label='R2', color='purple')

#
labels = ['LR', 'RF']
plt.xticks(rg + width / 2, labels)
plt.xlabel("Models")
plt.ylabel("Score")
plt.ylim([0, 1])
plt.title('Model Performance Comparison (RMSE vs R2)')
plt.legend(loc='upper left', ncol=2)

plt.tight_layout()
plt.show()
```



[60]:
```
# overfiting check for randomforests
y_train_pred = rf_model.predict(X_train)


train_rmse = mean_squared_error(y_train, y_train_pred, squared=False)
train_r2 = r2_score(y_train, y_train_pred)

# Predict on test set
y_test_pred = rf_model.predict(X_test)


test_rmse = mean_squared_error(y_test, y_test_pred, squared=False)
test_r2 = r2_score(y_test, y_test_pred)

print(f"Train RMSE: {train_rmse:.3f}, Train R2: {train_r2:.3f}")
print(f"Test RMSE: {test_rmse:.3f}, Test R2: {test_r2:.3f}")
```

```
Train RMSE: 0.157, Train R2: 0.893
Test RMSE: 0.209, Test R2: 0.833
```

[49]:
```
# overfiting/underfitting check for linear regression

y_train_pred = lr_model.predict(X_train)


train_rmse = mean_squared_error(y_train, y_train_pred, squared=False)
train_r2 = r2_score(y_train, y_train_pred)

# Predict on test set
y_test_pred = lr_model.predict(X_test)


test_rmse = mean_squared_error(y_test, y_test_pred, squared=False)
test_r2 = r2_score(y_test, y_test_pred)

print(f"Train RMSE: {train_rmse:.3f}, Train R2: {train_r2:.3f}")
print(f"Test RMSE: {test_rmse:.3f}, Test R2: {test_r2:.3f}")
```

```
Train RMSE: 0.198, Train R2: 0.831
Test RMSE: 0.202, Test R2: 0.845
```

[ ]:
```

```