ep7absbyi

January 19, 2023

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

from sklearn.metrics import r2_score, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from xgboost import XGBRegressor
from sklearn.ensemble import AdaBoostRegressor, RandomForestRegressor

import warnings
warnings.filterwarnings("ignore")
```

4. Build a predictive model to predict the MPG based on other data. What is your optimal error metric on the test set?

[2]:
```
# Reading the data
cars = pd.read_csv('cars.csv', sep=';')
```

[3]:
```
print("Sample of the data")
print(cars.head())
```

```
Sample of the data
                         Car     MPG Cylinders Displacement Horsepower  \
0                     STRING  DOUBLE       INT       DOUBLE     DOUBLE
1  Chevrolet Chevelle Malibu    18.0         8        307.0      130.0
2          Buick Skylark 320    15.0         8        350.0      165.0
3         Plymouth Satellite    18.0         8        318.0      150.0
4              AMC Rebel SST    16.0         8        304.0      150.0

   Weight Acceleration Model Origin
0  DOUBLE       DOUBLE   INT    CAT
1   3504.         12.0    70     US
2   3693.         11.5    70     US
3   3436.         11.0    70     US
4   3433.         12.0    70     US
```

[4]:

```python
# Dropping the first row with data_type information
print(f"First row with data_type {cars.iloc[0]}")
cars.drop(0, axis = 0, inplace = True)
```

```
First row with data_type Car             STRING
MPG             DOUBLE
Cylinders          INT
Displacement    DOUBLE
Horsepower      DOUBLE
Weight          DOUBLE
Acceleration    DOUBLE
Model              INT
Origin             CAT
Name: 0, dtype: object
```

[5]:

```python
# Converting the data columns to their actual data_type
cars['Car'] = cars['Car'].astype(str)
cars['MPG'] = cars['MPG'].astype(float)
cars['Cylinders'] = cars['Cylinders'].astype(int)
cars['Displacement'] = cars['Displacement'].astype(float)
cars['Horsepower'] = cars['Horsepower'].astype(float)
cars['Weight'] = cars['Weight'].astype(float)
cars['Acceleration'] = cars['Acceleration'].astype(float)
cars['Model'] = cars['Model'].astype(int)
cars['Origin'] = cars['Origin'].astype("category")
```

[6]:

```python
# Removing the rows where the data is incomplete
cars.drop(cars[cars.MPG == 0.0].index, axis=0, inplace=True)
cars.drop(cars[cars.Horsepower == 0.0].index, axis=0, inplace=True)
print(cars.describe())
```

```
              MPG   Cylinders  Displacement  Horsepower       Weight  \
count  392.000000  392.000000    392.000000  392.000000   392.000000
mean    23.445918    5.471939    194.411990  104.469388  2977.584184
std      7.805007    1.705783    104.644004   38.491160   849.402560
min      9.000000    3.000000     68.000000   46.000000  1613.000000
25%     17.000000    4.000000    105.000000   75.000000  2225.250000
50%     22.750000    4.000000    151.000000   93.500000  2803.500000
75%     29.000000    8.000000    275.750000  126.000000  3614.750000
max     46.600000    8.000000    455.000000  230.000000  5140.000000

       Acceleration       Model
count    392.000000  392.000000
mean      15.541327   75.979592
std        2.758864    3.683737
min        8.000000   70.000000
25%       13.775000   73.000000
50%       15.500000   76.000000
```

```
75%       17.025000   79.000000
max       24.800000   82.000000
```

0.1 1. Find the car with the highest MPG

[7]:
```
print(f"Car with highest MPG: {cars[cars.MPG == cars.MPG.max()]}")
```

```
Car with highest MPG:             Car   MPG  Cylinders  Displacement  Horsepower
Weight  \
330  Mazda GLC  46.6          4          86.0        65.0  2110.0

     Acceleration  Model Origin
330          17.9     80  Japan
```

0.2 2. Find the average MPG per Cylinder count

[8]:
```
print(f"Average MPG per Cylinder count: {cars.groupby('Cylinders').MPG.mean()}")
```

```
Average MPG per Cylinder count: Cylinders
3    20.550000
4    29.283920
5    27.366667
6    19.973494
8    14.963107
Name: MPG, dtype: float64
```

0.2.1 3. Find each make's average MPG (Cherry, Ford, etc)

[9]:
```
# Extracting Make of the Car from the Car name
cars['Make'] = cars.Car.str.split(' ').str[0]
```

[10]:
```
# Replacing misspelled Make
misspelled = {'Chevrolete': 'Chevrolet',
              'Hi': 'Harvester',
              'Mercedes-Benz': 'Mercedes',
              }
cars['Make'] = cars['Make'].replace(misspelled)
```

[11]:
```
print(f"Average MPG by Make: {cars.groupby('Make').MPG.mean()}")
```

```
Average MPG by Make: Make
AMC            18.070370
Audi           26.714286
BMW            23.750000
Buick          19.182353
Cadillac       19.750000
Capri          25.000000
Chevrolet      20.206667
```

```
Chevy          20.500000
Chrysler       17.266667
Datsun         31.113043
Dodge          22.060714
Fiat           28.912500
Ford           19.475000
Harvester       9.000000
Honda          33.761538
Mazda          30.058333
Mercedes       23.966667
Mercury        19.118182
Nissan         36.000000
Oldsmobile     21.100000
Opel           25.750000
Peugeot        23.687500
Plymouth       21.703226
Pontiac        20.012500
Renault        29.666667
Saab           23.900000
Subaru         30.525000
Toyota         28.165385
Triumph        35.000000
Volkswagen     31.840909
Volvo          21.116667
Name: MPG, dtype: float64
```

0.2.2 4. Build a predictive model to predict the MPG based on other data. What is your optimal error metric on the test set?

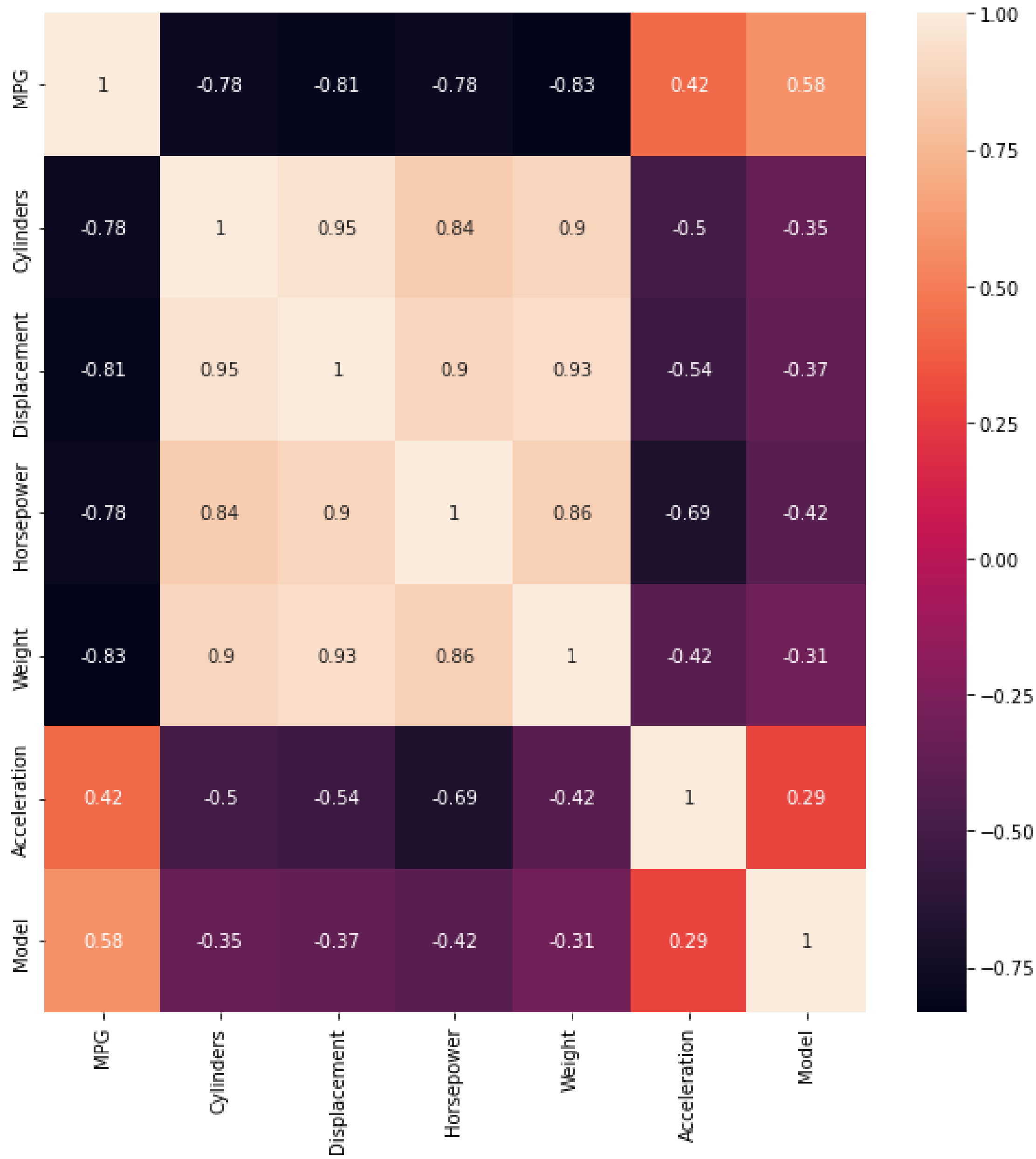
[12]:
```
cars.head()
```

[12]:
```
                         Car   MPG  Cylinders  Displacement  Horsepower  \
1  Chevrolet Chevelle Malibu  18.0          8         307.0       130.0
2          Buick Skylark 320  15.0          8         350.0       165.0
3         Plymouth Satellite  18.0          8         318.0       150.0
4              AMC Rebel SST  16.0          8         304.0       150.0
5                Ford Torino  17.0          8         302.0       140.0

   Weight  Acceleration  Model Origin       Make
1  3504.0          12.0     70     US  Chevrolet
2  3693.0          11.5     70     US      Buick
3  3436.0          11.0     70     US   Plymouth
4  3433.0          12.0     70     US        AMC
5  3449.0          10.5     70     US       Ford
```

[13]:
```
plt.figure(figsize=(10,10))
sns.heatmap(cars.corr(), annot=True)
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa07e95afd0>



[14]:
```
cars.head()
```

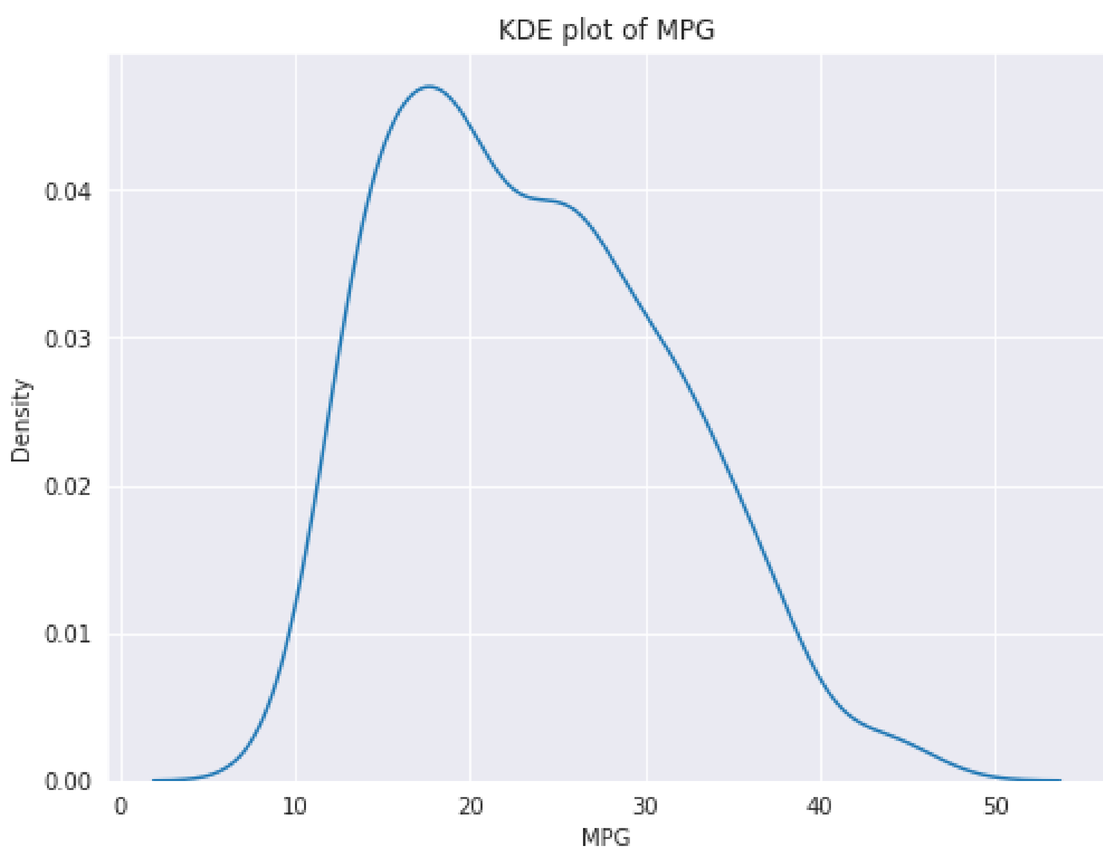
[14]:
```
                         Car   MPG  Cylinders  Displacement  Horsepower  \
1  Chevrolet Chevelle Malibu  18.0          8         307.0       130.0
2          Buick Skylark 320  15.0          8         350.0       165.0
3         Plymouth Satellite  18.0          8         318.0       150.0
4              AMC Rebel SST  16.0          8         304.0       150.0
```

```
5                 Ford Torino  17.0          8          302.0        140.0

   Weight  Acceleration  Model Origin        Make
1  3504.0          12.0     70     US   Chevrolet
2  3693.0          11.5     70     US       Buick
3  3436.0          11.0     70     US    Plymouth
4  3433.0          12.0     70     US         AMC
5  3449.0          10.5     70     US        Ford
```

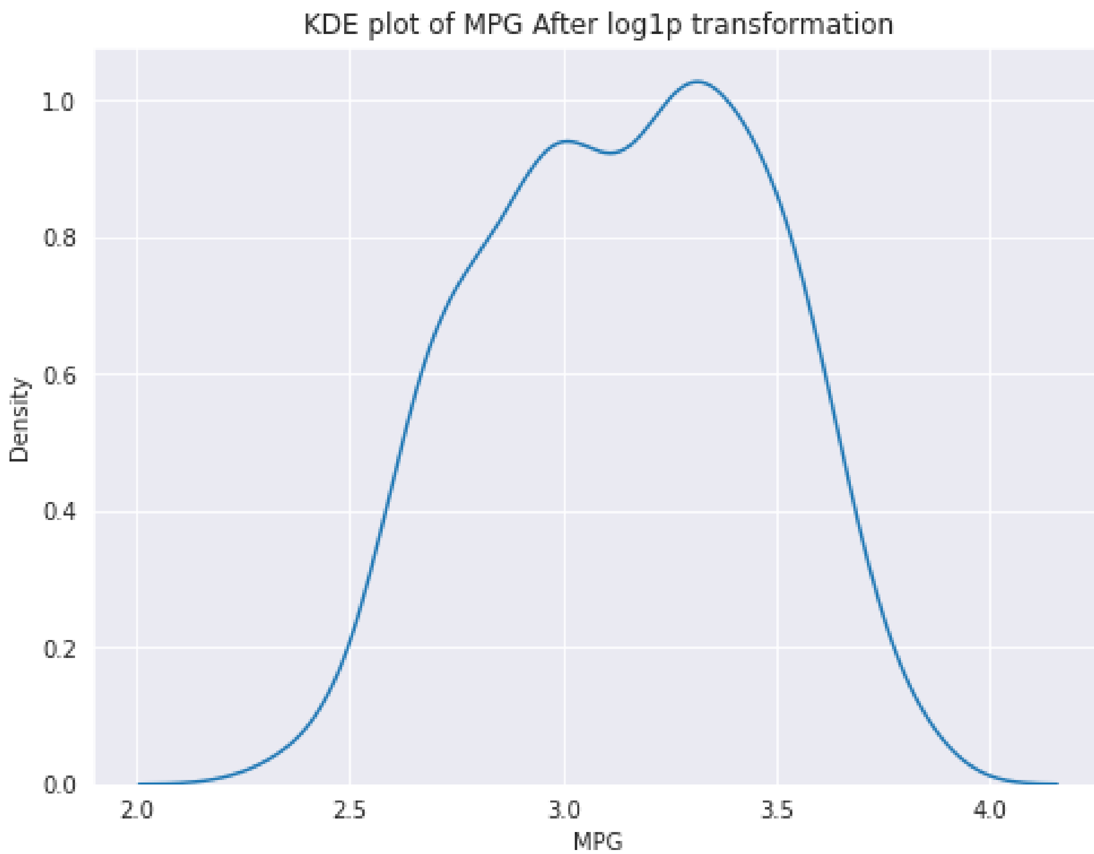
Target (MPG)

[15]:
```
sns.set_style('darkgrid')
plt.figure(figsize = (8, 6))
sns.kdeplot(cars.MPG)
plt.title("KDE plot of MPG")
plt.show()
```



[16]:
```
cars['MPG'] = np.log1p(cars.MPG)
```

[17]:
```
sns.set_style('darkgrid')
plt.figure(figsize = (8, 6))
sns.kdeplot(cars.MPG)
plt.title("KDE plot of MPG After log1p transformation")
plt.show()
```



0.2.3 One Hot Encoding the feature columns

[18]:
```
cars = pd.get_dummies(cars, columns=['Cylinders','Origin','Make'],␣
 ↪drop_first=True)
```

Train test split

[19]:
```
X = cars.drop(['MPG', 'Car'], axis = 1)
y = cars['MPG']
X_train, X_test, y_train, y_test = train_test_split(X , y,test_size  = 0.2,␣
 ↪random_state = 116)

print(f'X_train Shape: {X_train.shape}\nX_test Shape: {X_test.shape}')
print(f'y_train Shape: {y_train.shape}\ny_test Shape: {y_test.shape}')
```

```
X_train Shape: (313, 41)
X_test Shape: (79, 41)
y_train Shape: (313,)
y_test Shape: (79,)
```

[20]:
```
ss_train = StandardScaler()
ss_test = StandardScaler()
```

[21]:
```
X_train = ss_train.fit_transform(X_train)
X_test = ss_test.fit_transform(X_test)
```

0.2.4 Predictive Models

XGBRegressor

[22]:
```
# Using grid search to find the optimal hyper parameters
param_dict = {'n_estimators':[100,300,500,800], 'max_depth':[2,4,6,8]}
gs = GridSearchCV(XGBRegressor(), param_grid=param_dict,␣
 ↪scoring='neg_mean_squared_error', cv=5, n_jobs=-1, verbose=6, refit=True)
gs.fit(X_train, y_train)
xgb = gs.best_estimator_
print(f"Best parameters are {gs.best_params_}")
print(f"Best score is {gs.best_score_}")
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
[03:21:52] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Best parameters are {'max_depth': 4, 'n_estimators': 100}
Best score is -0.011596114380163728
```

[23]:
```
xgb_predict_train = xgb.predict(X_train)
xgb_predict_test = xgb.predict(X_test)
print(f"RMSE for train is {np.sqrt(mean_squared_error(y_train,␣
 ↪xgb_predict_train))}")
print(f"RMSE for test is {np.sqrt(mean_squared_error(y_test,␣
 ↪xgb_predict_test))}")
print(f"R2 score for train is {r2_score(y_train, xgb_predict_train)}")
print(f"R2 score for test is {r2_score(y_test, xgb_predict_test)}")
```

```
RMSE for train is 0.047263764672025727
RMSE for test is 0.10003268892242662
R2 score for train is 0.9790792342822849
R2 score for test is 0.8971481122614369
```

AdaBoostRegressor

[24]:
```
# Using grid search to find the optimal hyper parameters
param_dict = {'n_estimators':[100,300,500,800], 'learning_rate':[1, 10, 100]}
```

```
gs = GridSearchCV(AdaBoostRegressor(), param_grid=param_dict,␣
 ↪scoring='neg_mean_squared_error', cv=5, n_jobs=-1, verbose=6, refit=True)
gs.fit(X_train, y_train)
adb = gs.best_estimator_
print(f"Best parameters are {gs.best_params_}")
print(f"Best score is {gs.best_score_}")
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Best parameters are {'learning_rate': 1, 'n_estimators': 300}
Best score is -0.012704844987428038
```

[25]:

```
adb_predict_train = adb.predict(X_train)
adb_predict_test = adb.predict(X_test)
print(f"RMSE for train is {np.sqrt(mean_squared_error(y_train,␣
 ↪adb_predict_train))}")
print(f"RMSE for test is {np.sqrt(mean_squared_error(y_test,␣
 ↪adb_predict_test))}")
print(f"R2 score for train is {r2_score(y_train, adb_predict_train)}")
print(f"R2 score for test is {r2_score(y_test, adb_predict_test)}")
```

```
RMSE for train is 0.09215409571460667
RMSE for test is 0.12674693451504776
R2 score for train is 0.9204664739044881
R2 score for test is 0.8348786199013394
```

RandomForestRegressor

[26]:

```
# Using grid search to find the optimal hyper parameters
param_dict = {'n_estimators':[100,300,500,800], 'max_depth':[2,4,6,8]}
gs = GridSearchCV(RandomForestRegressor(), param_grid=param_dict,␣
 ↪scoring='neg_mean_squared_error', cv=5, n_jobs=-1, verbose=6, refit=True)
gs.fit(X_train, y_train)
rf = gs.best_estimator_
print(f"Best parameters are {gs.best_params_}")
print(f"Best score is {gs.best_score_}")
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
Best parameters are {'max_depth': 8, 'n_estimators': 500}
Best score is -0.011909681134343712
```

[27]:

```
rf_predict_train = rf.predict(X_train)
rf_predict_test = rf.predict(X_test)
print(f"RMSE for train is {np.sqrt(mean_squared_error(y_train,␣
 ↪rf_predict_train))}")
print(f"RMSE for test is {np.sqrt(mean_squared_error(y_test,␣
 ↪rf_predict_test))}")
print(f"R2 score for train is {r2_score(y_train, rf_predict_train)}")
print(f"R2 score for test is {r2_score(y_test, rf_predict_test)}")
```

```
RMSE for train is 0.046098621415487095
RMSE for test is 0.1056302082728609
R2 score for train is 0.9800979950734561
R2 score for test is 0.885315519052923
```

[28]:
```
print(
"""
XGBRegressor model has the best performance on the test set.

Root Mean Square Error for test set: 0.10003268892242662 (lower is better)

R2 score for the test set: 0.8971481122614369 (higher is better)
"""
)
```

```
XGBRegressor model has the best performance on the test set.

Root Mean Square Error for test set: 0.10003268892242662 (lower is better)

R2 score for the test set: 0.8971481122614369 (higher is better)
```

XGBRegressor model has the best performance on the test set.

Root Mean Square Error for test set: 0.10003268892242662 (lower is better)

R2 score for the test set: 0.8971481122614369 (higher is better)