

CAR PRICE PREDICTION WITH MACHINE LEARNING

importing libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

pd.options.display.max_rows=500
pd.options.display.max_columns=30
```

In [2]:

```
# reading csv file
df=pd.read_csv("C:\\Users\\ayith\\OneDrive\\Documents\\data sets\\CarPrice_Assignment.cs
```

In [3]:

df.head()

Out[3]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd
3	4	2	audi 100 ls	gas	std	four	sedan	fwd
4	5	2	audi 100ls	gas	std	four	sedan	4wd
4								>

In [4]:

df.shape

Out[4]:

(205, 26)

In [5]:

df.info() # checking file info

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):

#	Column	Non-Null Count	Dtype
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	object
4	aspiration	205 non-null	object
5	doornumber	205 non-null	object
6	carbody	205 non-null	object
7	drivewheel	205 non-null	object
8	enginelocation	205 non-null	object
9	wheelbase	205 non-null	float64
10	carlength	205 non-null	float64
11	carwidth	205 non-null	float64
12	carheight	205 non-null	float64
13	curbweight	205 non-null	int64
14	enginetype	205 non-null	object
15	cylindernumber	205 non-null	object
16	enginesize	205 non-null	int64
17	fuelsystem	205 non-null	object
18	boreratio	205 non-null	float64
19	stroke	205 non-null	float64
20	compressionratio	205 non-null	float64
21	horsepower	205 non-null	int64
22	peakrpm	205 non-null	int64
23	citympg	205 non-null	int64
24	highwaympg	205 non-null	int64
25	price	205 non-null	float64
	(1 (4/0) : 1	(64/0) 1 1/4/	^ \

dtypes: float64(8), int64(8), object(10)

memory usage: 41.8+ KB

In [6]:

```
# checking null values
df.isnull().sum()
```

Out[6]:

car_ID 0 symboling 0 CarName 0 fueltype 0 aspiration 0 doornumber 0 carbody 0 drivewheel 0 enginelocation 0 wheelbase 0 carlength 0 carwidth 0 carheight 0 curbweight 0 enginetype 0 0 cylindernumber enginesize 0 fuelsystem 0 boreratio 0 stroke 0 compressionratio 0 horsepower 0 peakrpm 0 citympg 0 0 highwaympg 0 price dtype: int64

In [7]:

df.columns

Out[7]:

spliting the numerical & categiercal columns

```
In [8]:
```

```
num_col=df.select_dtypes(exclude='object')
```

In [9]:

```
num_col.columns
```

Out[9]:

In [10]:

num_col

Out[10]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	strc
0	1	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.6
1	2	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.6
2	3	1	94.5	171.2	65.5	52.4	2823	152	2.68	3.4
3	4	2	99.8	176.6	66.2	54.3	2337	109	3.19	3.4
4	5	2	99.4	176.6	66.4	54.3	2824	136	3.19	3.4
5	6	2	99.8	177.3	66.3	53.1	2507	136	3.19	3.4
6	7	1	105.8	192.7	71.4	55.7	2844	136	3.19	3.4
7	8	1	105.8	192.7	71.4	55.7	2954	136	3.19	3.4
8	9	1	105.8	192.7	71.4	55.9	3086	131	3.13	3.4
9	10	0	99.5	178.2	67.9	52.0	3053	131	3.13	3.4
4										•

In [11]:

```
# changeing the column name
df.rename(columns={"CarName":"companyname"},inplace=True)
```

In [12]:

```
cat_col=df.select_dtypes(include='object')
```

```
In [13]:
```

```
cat_col.columns
```

Out[13]:

In [14]:

df

Out[14]:

	car_ID	symboling	companyname	fueltype	aspiration	doornumber	carbody	drivewheel	enginelo	
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd		
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd		
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd		
3	4	2	audi 100 ls	gas	std	four	sedan	fwd		
4	5	2	audi 100ls	gas	std	four	sedan	4wd		
5	6	2	audi fox	gas	std	two	sedan	fwd		
6	7	1	audi 100ls	gas	std	four	sedan	fwd		
7	8	1	audi 5000	gas	std	four	wagon	fwd		•
4									•	

In [15]:

```
cat_col.columns
```

Out[15]:

replaceing the company names of cars

In [16]:

```
df.companyname = df.companyname.str.lower()
def replace_name(a,b):
   df.companyname.replace(a,b,inplace=True)
replace_name([ 'nissan rogue',
       'nissan latio', 'nissan titan', 'nissan leaf', 'nissan juke',
'nissan note', 'nissan clipper', 'nissan nv200', 'nissan dayz',
'alfa-romero quadrifoglio'],'alfa-romero')
replace_name(['audi 100 ls', 'audi 100ls', 'audi fox',
       'audi 5000', 'audi 4000', 'audi 5000s (diesel)'],'audi')
replace_name([ 'bmw 320i', 'bmw x1', 'bmw x3', 'bmw z4',
       'bmw x4', 'bmw x5'], 'BMW')
replace_name(['chevrolet impala',
       'chevrolet monte carlo', 'chevrolet vega 2300'],'chevrolet')
replace_name(['honda civic',
       'honda civic cvcc', 'honda accord cvcc', 'honda accord lx',
       'honda civic 1500 gl', 'honda accord', 'honda civic 1300',
       'honda prelude', 'honda civic (auto)'],'Honda')
replace_name(['isuzu mu-x', 'isuzu d-max ', 'isuzu d-max v-cross'],'isuzu')
replace_name(['jaguar xj', 'jaguar xf', 'jaguar xk', 'maxda rx3'],'jaguar')
replace_name(['maxda glc deluxe', 'mazda rx2 coupe',
       'mazda rx-4', 'mazda glc deluxe', 'mazda 626', 'mazda glc',
       'mazda rx-7 gs', 'mazda glc 4', 'mazda glc custom l',
       'mazda glc custom'],'mazda')
replace_name(['buick electra 225 custom',
       'buick century luxus (sw)', 'buick century', 'buick skyhawk', 'buick opel isuzu deluxe', 'buick skylark',
       'buick century special', 'buick regal sport coupe (turbo)'], 'buick')
replace_name(['mitsubishi mirage', 'mitsubishi lancer', 'mitsubishi outlander',
       'mitsubishi g4', 'mitsubishi mirage g4', 'mitsubishi montero',
       'mitsubishi pajero'],'mitsubishi')
replace_name(['plymouth fury iii',
       'plymouth cricket', 'plymouth satellite custom (sw)',
       'plymouth fury gran sedan', 'plymouth valiant', 'plymouth duster'], 'plymouth')
replace_name(['porsche macan',
       'porcshce panamera', 'porsche cayenne', 'porsche boxter'],'porcshce')
replace_name(['renault 12tl', 'renault 5 gtl'],'renault')
replace_name(['saab 99e', 'saab 99le', 'saab 99gle'],'saab')
replace_name(['subaru', 'subaru dl', 'subaru brz',
       'subaru baja', 'subaru r1', 'subaru r2', 'subaru trezia',
       'subaru tribeca'],'subaru')
replace_name(['toyota corona mark ii',
       'toyota corona', 'toyota corolla 1200', 'toyota corona hardtop',
       'toyota corolla 1600 (sw)', 'toyota carina', 'toyota mark ii',
       'toyota corolla', 'toyota corolla liftback',
       'toyota celica gt liftback', 'toyota corolla tercel',
       'toyota corona liftback', 'toyota starlet', 'toyota tercel',
       'toyota cressida', 'toyota celica gt', 'toyouta tercel'],'toyota')
replace_name(['vokswagen rabbit',
       'volkswagen 1131 deluxe sedan', 'volkswagen model 111',
```

finding the unique values of each column

```
In [17]:
df['fueltype'].unique()
Out[17]:
array(['gas', 'diesel'], dtype=object)
In [18]:
df['aspiration'].unique()
Out[18]:
array(['std', 'turbo'], dtype=object)
In [19]:
cat_col.columns
Out[19]:
Index(['companyname', 'fueltype', 'aspiration', 'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'enginetype', 'cylindernumber',
       'fuelsystem'],
      dtype='object')
In [20]:
df['doornumber'].unique()
Out[20]:
array(['two', 'four'], dtype=object)
In [21]:
df2=pd.unique(df[[ 'fueltype', 'aspiration', 'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'enginetype', 'cylindernumber',
       'fuelsystem']].values.ravel('k'))
```

```
In [22]:
```

```
df2
```

Out[22]:

In [23]:

```
num_col.columns
```

Out[23]:

checking the car prices

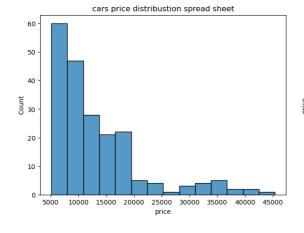
In [24]:

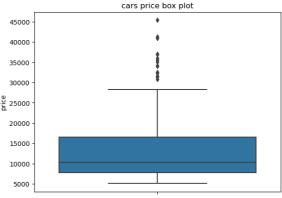
```
plt.figure(figsize=(15,5))

plt.subplot(1,2,1)
plt.title('cars price distribustion spread sheet')
sns.histplot(df.price)

plt.subplot(1,2,2)
plt.title('cars price box plot')
sns.boxplot(y=df.price)

plt.show()
```





In [25]:

```
print(df.price.describe(percentiles=[0.25,0.5,0.85,0.75,0.9,1]))
```

count	205.000000
mean	13276.710571
std	7988.852332
min	5118.000000
25%	7788.000000
50%	10295.000000
75%	16503.000000
85%	18500.000000
90%	22563.000000
100%	45400.000000
max	45400.000000

Name: price, dtype: float64

In [26]:

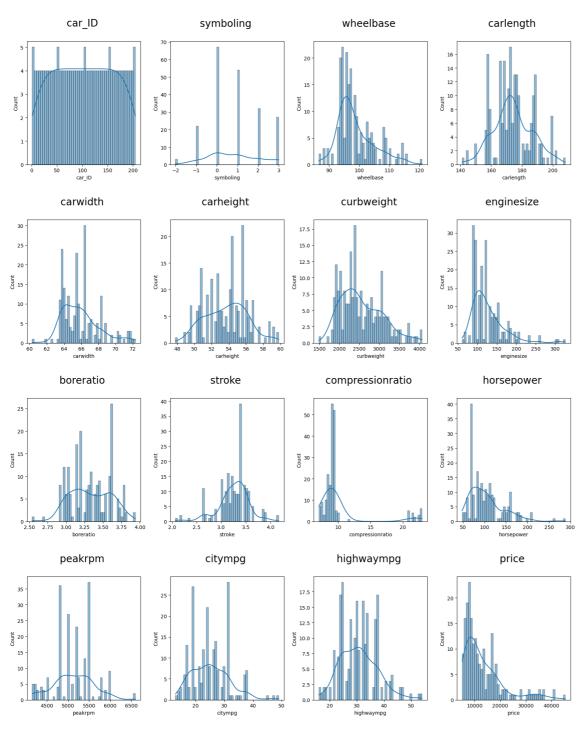
```
cols = num_col.columns

plt.figure(figsize = (16, 20))
plotnumber = 1

for i in range(len(cols)):
    if plotnumber <= 16:
        ax = plt.subplot(4, 4, plotnumber)
        sns.histplot(x = cols[i], data = df, ax = ax, palette='rocket', kde = True, bins plt.title(f"\n{cols[i]} \n", fontsize = 20)

    plotnumber += 1

plt.tight_layout()
plt.show()</pre>
```



checking the outliers of columns

In [27]:

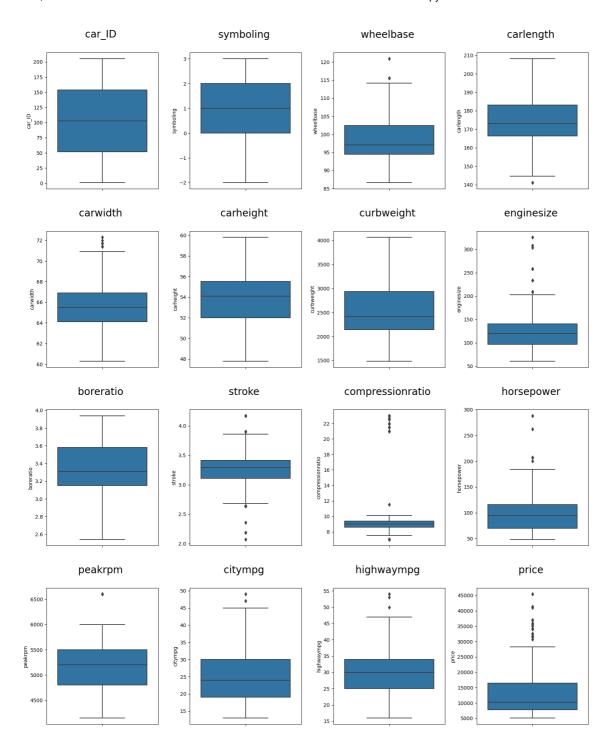
```
cols = num_col.columns

plt.figure(figsize = (16, 20))
plotnumber = 1

for i in range(len(cols)):
    if plotnumber <= 16:
        ax = plt.subplot(4, 4, plotnumber)
        sns.boxplot(y = cols[i], data = df, ax = ax)
        plt.title(f"\n{cols[i]} \n", fontsize = 20)

plotnumber += 1

plt.tight_layout()
plt.show()</pre>
```



In [28]:

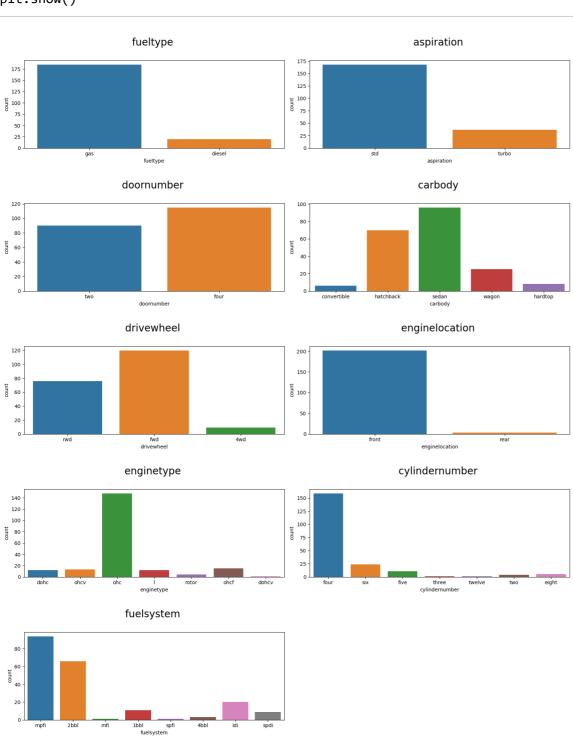
```
cols = cat_col.columns

plt.figure(figsize = (16, 20))
plotnumber = 1

for i in range(1, len(cols)):
    if plotnumber <= 10:
        ax = plt.subplot(5, 2, plotnumber)
        sns.countplot(x = cols[i], data = df, ax = ax)
        plt.title(f"\n{cols[i]} \n", fontsize = 20)

plotnumber += 1

plt.tight_layout()
plt.show()</pre>
```



In [29]:

```
#Bivariate and Multivariate Analysis
cols = num_col.columns

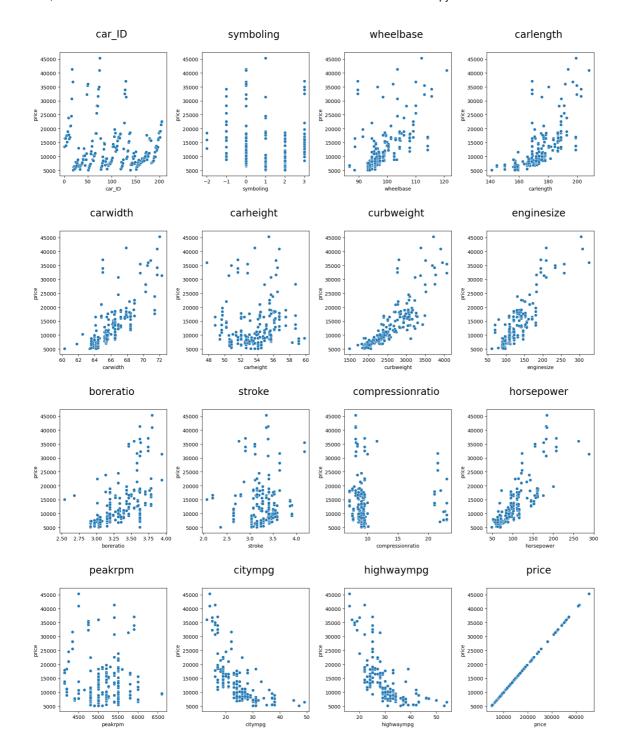
plt.figure(figsize = (16, 20))
plotnumber = 1

# plotting the countplot of each categorical column.

for i in range(len(cols)):
    if plotnumber <= 16:
        ax = plt.subplot(4, 4, plotnumber)
        sns.scatterplot(x = cols[i], y = df['price'], data = df, ax = ax, palette='rocke
        plt.title(f"\n{cols[i]} \n", fontsize = 20)

    plotnumber += 1

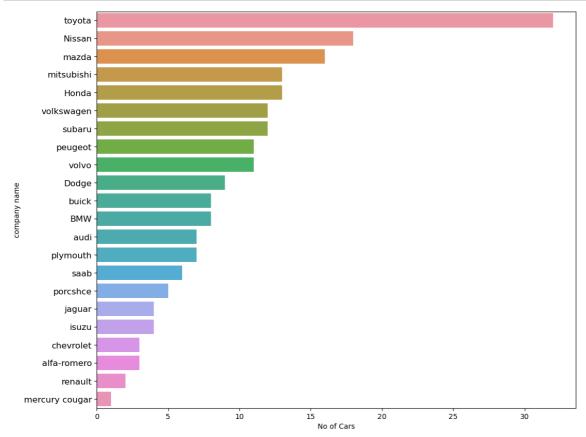
plt.tight_layout()
plt.show()</pre>
```



In [30]:

```
df1 = pd.DataFrame(df['companyname'].value_counts().reset_index())
df1.columns = ['company name', 'No of Cars']

plt.figure(figsize = (12, 10))
sns.barplot(x = 'No of Cars', y = 'company name', data = df1)
plt.yticks(size = 12)
plt.show()
```

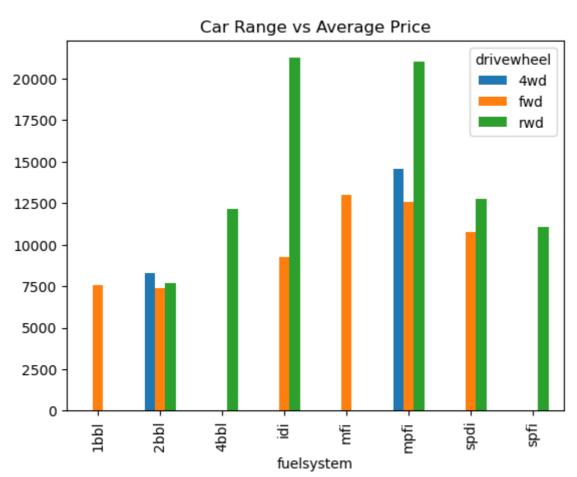


In [31]:

```
plt.figure(figsize=(25, 6))

df1 = pd.DataFrame(df.groupby(['fuelsystem','drivewheel'])['price'].mean().unstack(fill_df1.plot.bar()
plt.title('Car Range vs Average Price')
plt.show()
```

<Figure size 2500x600 with 0 Axes>



In [32]:

```
# Defining the map function
def dummies(x,df):
    temp = pd.get_dummies(df[x], drop_first = True)
    df = pd.concat([df, temp], axis = 1)
    df.drop([x], axis = 1, inplace = True)
    return df
# Applying the function to the cars_lr

cars_lr = dummies('fueltype',df)
cars_lr = dummies('aspiration',df)
cars_lr = dummies('carbody',df)
cars_lr = dummies('drivewheel',df)
cars_lr = dummies('enginetype',df)
cars_lr = dummies('enginetype',df)
```

```
In [33]:
```

```
df['cylindernumber'].value_counts()
```

Out[33]:

four 159 six 24 five 11 eight 5 two 4 three 1 twelve 1

Name: cylindernumber, dtype: int64

In [34]:

```
# creating features and Label variable

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

In [35]:

```
X = pd.get_dummies(X, drop_first = True)
X
```

Out[35]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	strc
0	1	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.6
1	2	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.6
2	3	1	94.5	171.2	65.5	52.4	2823	152	2.68	3.4
3	4	2	99.8	176.6	66.2	54.3	2337	109	3.19	3.4
4	5	2	99.4	176.6	66.4	54.3	2824	136	3.19	3.4
5	6	2	99.8	177.3	66.3	53.1	2507	136	3.19	3.4
6	7	1	105.8	192.7	71.4	55.7	2844	136	3.19	3.4
7	8	1	105.8	192.7	71.4	55.7	2954	136	3.19	3.4
8	9	1	105.8	192.7	71.4	55.9	3086	131	3.13	3.4
9	10	0	99.5	178.2	67.9	52.0	3053	131	3.13	3.4
4										•

In [36]:

```
# checking for multicollinearity using `VIF` and `correlation matrix`
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['VIF'] = [variance_inflation_factor(X, i) for i in range(X.shape[1])]
vif['Features'] = X.columns
vif
```

C:\Users\ayith\anaconda3\lib\site-packages\statsmodels\stats\outliers_infl
uence.py:195: RuntimeWarning: divide by zero encountered in double_scalars
 vif = 1. / (1. - r_squared_i)

Out[36]:

	VIF	Features
0	5.361348e+02	car_ID
1	6.794082e+00	symboling
2	1.906423e+01	wheelbase
3	2.389053e+01	carlength
4	1.621246e+01	carwidth
5	7.377879e+00	carheight
6	4.564945e+01	curbweight
7	6.652621e+01	enginesize
8	1.465711e+01	boreratio
9	6.150801e+00	stroke
10	2.507274e+02	compressionratio
11	5.475149e+01	horsepower
12	6.574496e+00	peakrpm
13	5.440969e+01	citympg
14	4.602128e+01	highwaympg
15	1.114962e+01	companyname_Dodge
16	2.738459e+01	companyname_Honda
17	1.166208e+02	companyname_Nissan
18	5.425691e+00	companyname_alfa-romero
19	1.013191e+01	companyname_audi
20	2.886631e+01	companyname_buick
21	4.488424e+00	companyname_chevrolet
22	9.477336e+00	companyname_isuzu
23	9.461843e+00	companyname_jaguar
24	4.188605e+01	companyname_mazda
25	3.987083e+00	companyname_mercury cougar
26	6.889266e+01	companyname_mitsubishi
27	inf	companyname_peugeot
28	7.834242e+01	companyname_plymouth
29	5.404968e+01	companyname_porcshce
30	2.520523e+01	companyname_renault
31	7.503304e+01	companyname_saab
32	inf	companyname_subaru
33	5.163982e+02	companyname_toyota
34	2.879255e+02	companyname_volkswagen
35	2.654728e+02	companyname_volvo
36	1.461142e+04	fueltype_gas

```
Features
In [37]
 37 6.557001e+00
                             aspiration turbo
from sklearn.model_selection import train_test_split
38 3.871617e+00
                             doornumber two
139 [3638616e+00
                             carbody hardtop
41 2.511357e+01
                              carbody_sedan
142 [ 3231669e+01
                             carbody_wagon
f43m1277756e+01reprocessing drivewheel fwm axScaler
44 1.987256e+01
                              drivewheel rwd
scaler = MinMaxScaler()
nth vars = ['Wheelbase', enginelocation hear, 'enginesize', 'boreratio', 'horsepower', 'carlengt
df[num_vars])
47
              inf
                                enginetype_I
In [40]:
48 1.690185e+01
                             enginetype_ohc
X<sub>4</sub>train.shape,X_test.shape,y_train.shape, y_test.shape
O50t [ 4897694e+00
                             enginetype_ohcv
(5/143, 65), (16/2, 65), (143en)gine(16/2e, 19/4or
52 2.622677e+01
                          cylindernumber_five
In [41]:
53 [43]:
1.328438e+02
                          cylindernumber four
fgam4s44040604-careprocessinginingpontostandardScaler
                         cylindernumber_three
s<sup>55</sup> = Standard<sup>®f</sup>caler()
X56 rai2662856+0fit_transfynrderAuthbeitWelve
X_test = sc.transform(X_test)
                          cylindernumber two
58 [3.236884e+01
                             fuelsystem 2bbl
59 6.265078e+00 fuelsystem 4bbl
from sklearn.preprocessing import StandardScaler
60 1.931060e+03
                               fuelsystem_idi
161 [2:307026e+00
                              fuelsystem mfi
                             fuelsystem mpfi
sc X=StandardScaler()
63 9.476591e+00
                             fuelsystem spdi
I64 [2471209e+00
                              fuelsystem spfi
xtrain = sc X.fit transform(X train)
In [45]:
xtest = sc X.fit transform(X test)
```

In [46]:

```
from sklearn import linear model
from sklearn import svm
classifiers = [
    svm.SVR(),
   linear_model.SGDRegressor(),
   linear_model.BayesianRidge(),
   linear_model.LassoLars(),
   linear_model.ARDRegression(),
   linear_model.PassiveAggressiveRegressor(),
   linear model.TheilSenRegressor(),
   linear_model.LinearRegression()]
for item in classifiers:
   print(item)
   clf = item
   clf.fit(X_train,y_train)
    print(clf.predict(X test),'\n')
SVR()
[10238.12276056 10260.3675765 10257.04914872 10252.80697331
 10247.83027535 10252.30709027 10237.82093074 10243.0421458
 10258.87572884 10240.32069379 10257.81419195 10258.75219862
 10258.6491851 10253.64122035 10249.8864627 10250.9352058
 10249.9143013
                10258.50721112 10242.54048827 10236.34548367
 10248.54212947 10260.89091875 10246.94492443 10251.23455215
 10258.86710926 10243.49461286 10238.29193753 10260.86964611
 10237.79535727 10237.58744636 10246.75804201 10250.25092673
 10256.01630166 10248.40297226 10237.80680512 10263.97459931
 10246.48594743 10257.0731738 10240.2871778 10260.3483104
 10249.80709623 10258.21869406 10263.09304853 10254.77274982
 10250.90913386 10241.34731372 10241.21319864 10252.86536054
 10251.60289828 10247.18733764 10259.57521899 10246.21887302
 10242.03955144 10243.15839881 10258.07314152 10260.04456723
 10249.65723971 10263.28100703 10247.79513392 10240.57649894
 10243.30930862 10256.50528322]
SGDRegressor()
In [47]:
```

```
y_predict=clf.predict(X_test)
```

```
In [48]:
```

```
y_predict
Out[48]:
array([
         6491.33013063,
                                           13871.62658698, -22335.91047974,
                          16517.51546265,
         9077.71912522,
                          11379.62856787,
                                             5731.4533077 ,
                                                              3982.10940929,
                                            20690.87402857,
                                                             37434.70962928,
        16536.45671656,
                           8359.76633075,
                          15853.2478588,
        12553.12739777,
                                             7038.81595548,
                                                             10202.65327457,
        30497.19303664,
                          18312.51556015,
                                             8268.44285146,
                                                              7272.42813068,
         8876.58359759,
                          16347.56964018,
                                                             11709.18691969,
                                           31439.16549892,
        18048.9782788,
                           6930.87381963,
                                             6640.27375018,
                                                             17148.64257305,
                                                             11913.41113717,
         7154.93586799,
                           5025.87584299,
                                             8285.06170759,
        37695.8583478 ,
                           9492.18059157,
                                             6675.38007648,
                                                             30010.03932916,
        14316.34723004,
                          14879.58722212,
                                                             37650.96440879,
                                             4658.13156823,
                          15437.36409643,
                                                             28122.03077554,
         5887.11755297,
                                            33112.28396095,
        11036.38055303,
                           8787.60583286,
                                            7201.73549831,
                                                             13042.90944121,
        10805.01826805,
                          10067.7306153 ,
                                           20606.77026338,
                                                              8077.16199632,
                          10031.69451295,
                                           29743.06854061,
                                                             17956.15323513,
         7588.41881322,
         9505.15189693,
                         18140.31476368,
                                           10017.21479342,
                                                              6561.21526583,
         3925.36278597,
                          14602.13315934])
In [49]:
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train, y_train)
Out[49]:
LinearRegression()
In [50]:
lr.score(X_train, y_train)
Out[50]:
0.9783548097431701
In [59]:
lr.score(X_test, y_predict)
Out[59]:
1.0
In [52]:
from sklearn.linear model import Lasso, LassoCV
```

```
In [53]:
```

```
lassocv = LassoCV(alphas = None, cv = 10, max iter = 10000, normalize = True)
lassocv.fit(X_train, y_train)
C:\Users\ayith\anaconda3\lib\site-packages\sklearn\linear_model\_base.py:1
41: FutureWarning: 'normalize' was deprecated in version 1.0 and will be r
emoved in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a pre
processing stage. To reproduce the previous behavior:
from sklearn.pipeline import make pipeline
model = make_pipeline(StandardScaler(with_mean=False), Lasso())
If you wish to pass a sample_weight parameter, you need to pass it as a fi
t parameter to each step of the pipeline as follows:
kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)
Set parameter alpha to: original_alpha * np.sqrt(n_samples).
 warnings.warn(
Out[53]:
LassoCV(cv=10, max_iter=10000, normalize=True)
In [54]:
lasso = Lasso(alpha = lassocv.alpha_)
lasso.fit(X_train, y_train)
C:\Users\ayith\anaconda3\lib\site-packages\sklearn\linear_model\_coordinat
e_descent.py:647: ConvergenceWarning: Objective did not converge. You migh
t want to increase the number of iterations, check the scale of the featur
es or consider increasing regularisation. Duality gap: 6.261e+07, toleranc
e: 8.925e+05
  model = cd fast.enet coordinate descent(
Out[54]:
Lasso(alpha=0.5743416905388534)
In [55]:
lasso.score(X train, y train)
Out[55]:
0.9774145188740271
In [56]:
lasso.score(X_test, y_test)
Out[56]:
0.7185672985278083
```

In [61]:

```
#y_test=y_test.flatten()
predict = clf.predict(X_test)
compar = pd.DataFrame({'actual':y_test, 'predicted': predict})
compar = compar.reset_index(drop = True)
compar[:10]
```

Out[61]:

	actual	predicted
0	6795.0	6491.330131
1	15750.0	16517.515463
2	15250.0	13871.626587
3	5151.0	-22335.910480
4	9995.0	9077.719125
5	11199.0	11379.628568
6	5389.0	5731.453308
7	7898.0	3982.109409
8	17199.0	16536.456717
9	6529.0	8359.766331

In []:

localhost:8888/notebooks/python pratices/oasis task 3.ipynb