DM_Assignment_2

August 16, 2021

0.1 5. Choose an appropriate application, find a solution using linear regression and express its performance measures.

Car Price Prediction

[ ]:
```
# importing necessary packages

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


%matplotlib inline
```

[ ]:
```
cars_info = pd.read_csv("/content/drive/MyDrive/AI-ML/DM/CarPrice_Assignment.
 ↪csv")
cars_info.head()
```

[ ]:
```
   car_ID  symboling                   CarName  … citympg highwaympg    price
0       1          3        alfa-romero giulia  …      21         27  13495.0
1       2          3       alfa-romero stelvio  …      21         27  16500.0
2       3          1  alfa-romero Quadrifoglio  …      19         26  16500.0
3       4          2               audi 100 ls  …      24         30  13950.0
4       5          2                audi 100ls  …      18         22  17450.0

[5 rows x 26 columns]
```

[ ]:
```
# basic infos

cars_info.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
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

[ ]:
```
cars_info.describe()
```

[ ]:
```
           car_ID   symboling   wheelbase  …     citympg  highwaympg
price
count  205.000000  205.000000  205.000000  …  205.000000  205.000000
205.000000
mean   103.000000    0.834146   98.756585  …   25.219512   30.751220
13276.710571
std     59.322565    1.245307    6.021776  …    6.542142    6.886443
7988.852332
min      1.000000   -2.000000   86.600000  …   13.000000   16.000000
5118.000000
25%     52.000000    0.000000   94.500000  …   19.000000   25.000000
7788.000000
50%    103.000000    1.000000   97.000000  …   24.000000   30.000000
10295.000000
75%    154.000000    2.000000  102.400000  …   30.000000   34.000000
16503.000000
max    205.000000    3.000000  120.900000  …   49.000000   54.000000
45400.000000
```

```
[8 rows x 16 columns]
```

[ ]:
```
# checking for null values

cars_info.isnull().sum()
```

[ ]:
```
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
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

[ ]:
```
#Check the correlation between each of the columns
cars_info.corr()

# There is good correlation between
# 1. engine size and horse power
# 2. curb weight and car length
# 3. car width and car length
# 4. Engine size and price
# 5. curbweight and price
```

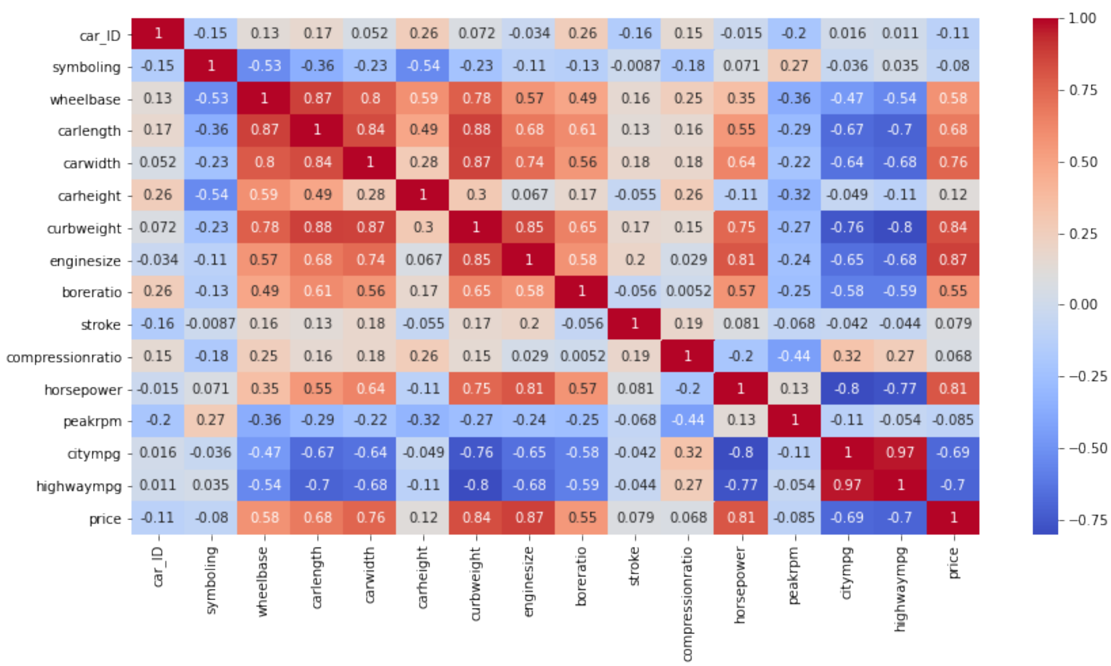
[ ]:
```
                    car_ID  symboling  …  highwaympg     price
car_ID            1.000000  -0.151621  …    0.011255 -0.109093
```

```
symboling        -0.151621   1.000000  …   0.034606 -0.079978
wheelbase         0.129729  -0.531954  …  -0.544082  0.577816
carlength         0.170636  -0.357612  …  -0.704662  0.682920
carwidth          0.052387  -0.232919  …  -0.677218  0.759325
carheight         0.255960  -0.541038  …  -0.107358  0.119336
curbweight        0.071962  -0.227691  …  -0.797465  0.835305
enginesize       -0.033930  -0.105790  …  -0.677470  0.874145
boreratio         0.260064  -0.130051  …  -0.587012  0.553173
stroke           -0.160824  -0.008735  …  -0.043931  0.079443
compressionratio  0.150276  -0.178515  …   0.265201  0.067984
horsepower       -0.015006   0.070873  …  -0.770544  0.808139
peakrpm          -0.203789   0.273606  …  -0.054275 -0.085267
citympg           0.015940  -0.035823  …   0.971337 -0.685751
highwaympg        0.011255   0.034606  …   1.000000 -0.697599
price            -0.109093  -0.079978  …  -0.697599  1.000000

[16 rows x 16 columns]
```

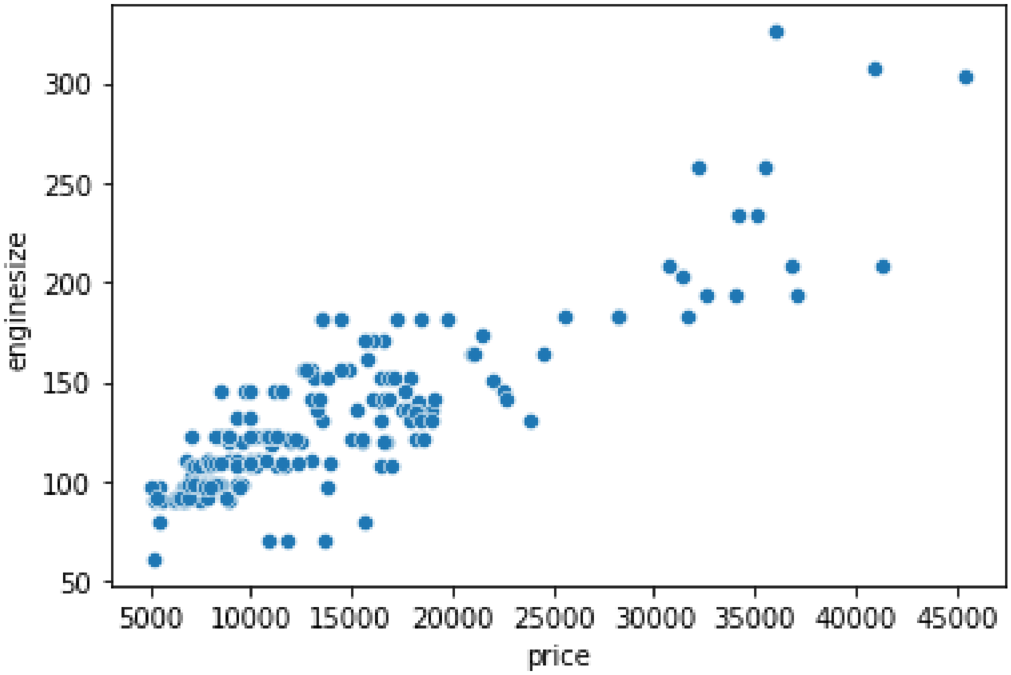
[ ]:

```python
# visulaizing correlation using heat map

plt.figure(figsize=(14,7))
sns.heatmap(cars_info.corr(),annot=True,cmap='coolwarm')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f90eacbd350>



[ ]:
```
# highest correlation is engine size vs price

# scatter plot

sns.scatterplot(x='price',y='enginesize',data=cars_info)
plt.show()
```



[ ]:
```
# dropping these columns

cars_info.
 ↪drop(['car_ID','CarName','fuelsystem','enginetype'],axis=1,inplace=True)
```

[ ]:
```
cars_info.head()
```

[ ]:
```
   symboling fueltype aspiration  … citympg highwaympg    price
0          3      gas        std  …      21         27  13495.0
1          3      gas        std  …      21         27  16500.0
2          1      gas        std  …      19         26  16500.0
3          2      gas        std  …      24         30  13950.0
4          2      gas        std  …      18         22  17450.0

[5 rows x 22 columns]
```

[ ]:
```
# encoding strings to number to use it in the model

# mapping

cars_info['fueltype'] = cars_info['fueltype'].map({'gas':'0','diesel':'1'})
cars_info['aspiration'] = cars_info['aspiration'].map({'std':'0','turbo':'1'})
cars_info['doornumber'] = cars_info['doornumber'].map({'two':'2','four':'4'})
cars_info['carbody'] = cars_info['carbody'].map({'convertible':'0','hatchback':
↪'1','sedan':'2','wagon':'3','hardtop':'4'})
cars_info['drivewheel'] = cars_info['drivewheel'].map({'rwd':'0','fwd':
↪'1','4wd':'2'})
cars_info['enginelocation'] = cars_info['enginelocation'].map({'front':
↪'0','rear':'1'})
cars_info['cylindernumber'] = cars_info['cylindernumber'].map({'four':'4','six':
↪'6','five':'5','three':'3','twelve':'12','two':'2','eight':'8'})
# checking
cars_info.head()
```

[ ]:
```
   symboling fueltype aspiration  … citympg highwaympg    price
0          3        0          0  …      21         27  13495.0
1          3        0          0  …      21         27  16500.0
2          1        0          0  …      19         26  16500.0
3          2        0          0  …      24         30  13950.0
4          2        0          0  …      18         22  17450.0

[5 rows x 22 columns]
```

Model building part

[ ]:
```
# taking price as the label or target


from sklearn.model_selection import train_test_split

X = cars_info.drop('price',axis=1)
y= cars_info['price']

X_train,X_test,y_train,y_test= train_test_split(X,y,test_size=0.
↪3,random_state=55)
```

[ ]:
```
# training or fitting the curve

from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train,y_train, )
```

[ ]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[ ]:
```
# prediction part

prediction = lr.predict(X_test)
```

0.1.1 Perfomance measures

[ ]:
```
# r2 score

from sklearn.metrics import r2_score
print(r2_score(y_test,prediction))

# got 78% accuracy
```

```
0.7784967344806435
```

[ ]:
```
# The explained_variance_score computes the explained variance regression score.

from sklearn.metrics import explained_variance_score

explained_variance_score(y_test, prediction, multioutput='raw_values')
```

[ ]:
```
array([0.77858187])
```

[ ]:
```
# The max_error function computes the maximum residual error ,
# a metric that captures the worst case error between the predicted
# value and the true value.

from sklearn.metrics import max_error
max_error(y_test, prediction)
```

[ ]:
```
16867.0309776942
```

[ ]:
```
# Mean Abosulute Error

from sklearn.metrics import mean_absolute_error

mean_absolute_error(y_test, prediction, multioutput='raw_values')
```

[ ]:
```
array([2343.26176044])
```

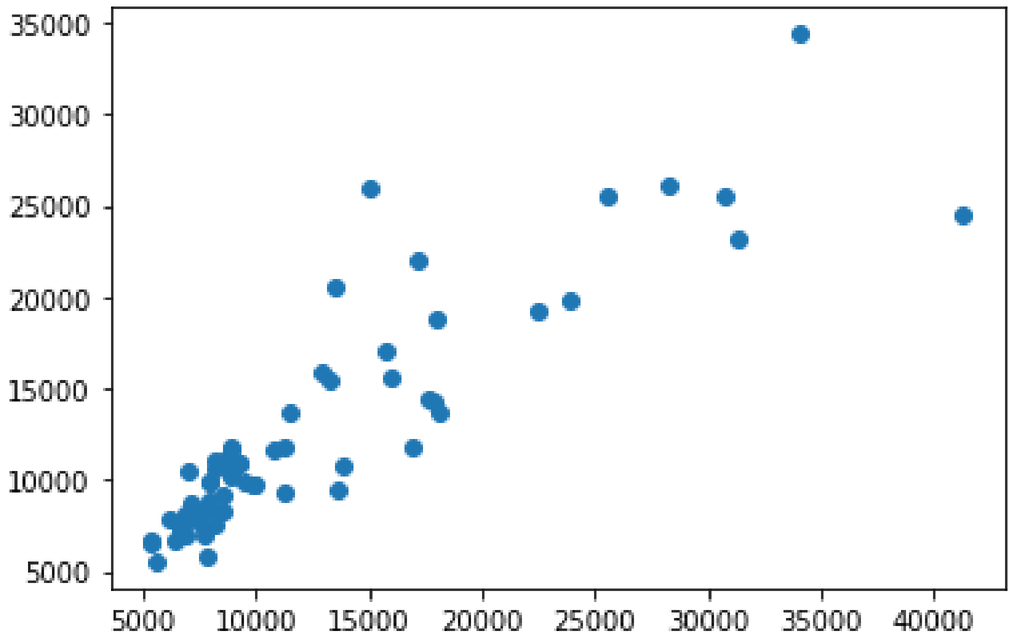
[ ]:
```
# Mean squared error

from sklearn.metrics import mean_squared_error

mean_squared_error(y_test, prediction)
```

[ ]:
```
13119405.902743611
```

[ ]:

```
# test data vs prediction

plt.scatter(y_test, prediction)
```

[ ]: <matplotlib.collections.PathCollection at 0x7f90e734e610>



[ ]: