Predicting_Used_Car_Price

February 21, 2022

1 Project: Predicting Used Car Price

In this project we will be performing data analysis on a set of data of used cars and will try to predict a price for a new test data. For this purpose we will use the used car data available from https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data. In total there are 26 columns of which 'Price' will be our target column (label) and other columns will be our features (predictor variables).

[1]:
```
import pandas as pd
import numpy as np
#get the path from the website
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/autos/
↪imports-85.data"

#declare a dataframe by reading a csv file
df = pd.read_csv(url, header =None)

#assigning columns since the csv file did not have any columns
df.columns = ["symboling", "normalized-losses","make","fuel-type",␣
↪"aspiration", "num-of-doors", "body-style","drive-wheels",␣
↪"engine-location", "wheel-base", "length", "width",␣
↪"height","curb-weight","engine-type","num-of-cylinders","engine-size","fuel-system","bore",

#replace all the "?" values with NaN
df = df.replace("?", np.NaN)
df.head()
```

[1]:
```
   symboling normalized-losses         make fuel-type aspiration num-of-doors  \
0          3               NaN  alfa-romero       gas        std          two
1          3               NaN  alfa-romero       gas        std          two
2          1               NaN  alfa-romero       gas        std          two
3          2               164         audi       gas        std         four
4          2               164         audi       gas        std         four

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
0  convertible          rwd           front        88.6  …          130
1  convertible          rwd           front        88.6  …          130
2    hatchback          rwd           front        94.5  …          152
```

```
3        sedan          fwd          front        99.8  …          109
4        sedan          4wd          front        99.4  …          136

  fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0        mpfi  3.47    2.68               9.0        111      5000       21
1        mpfi  3.47    2.68               9.0        111      5000       21
2        mpfi  2.68    3.47               9.0        154      5000       19
3        mpfi  3.19    3.40              10.0        102      5500       24
4        mpfi  3.19    3.40               8.0        115      5500       18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

We can see that values "?" are replaced with NaN which is generalized form for null values. This can also be viewed in form of boolean where True will indicate if value is null and False will indicated a value is not Null. Additionally, total number of missin values for each particular column is also calculated below.

[2]:
```python
missing_data = df.isnull()
missing_data.head()
```

[2]:
```
   symboling  normalized-losses   make  fuel-type  aspiration  num-of-doors  \
0      False               True  False      False       False         False
1      False               True  False      False       False         False
2      False               True  False      False       False         False
3      False              False  False      False       False         False
4      False              False  False      False       False         False

   body-style  drive-wheels  engine-location  wheel-base  …  engine-size  \
0       False         False            False       False  …        False
1       False         False            False       False  …        False
2       False         False            False       False  …        False
3       False         False            False       False  …        False
4       False         False            False       False  …        False

   fuel-system   bore  stroke  compression-ratio  horsepower  peak-rpm  \
0        False  False   False              False       False     False
1        False  False   False              False       False     False
2        False  False   False              False       False     False
3        False  False   False              False       False     False
4        False  False   False              False       False     False
```

```
   city-mpg  highway-mpg  price
0     False        False  False
1     False        False  False
2     False        False  False
3     False        False  False
4     False        False  False

[5 rows x 26 columns]
```

[3]:
```
for column in missing_data.columns.values.tolist():
    if (missing_data[column] == True).any():
        print(column )
        print(missing_data[column].value_counts())
        print("----------------------")
```

```
normalized-losses
False    164
True      41
Name: normalized-losses, dtype: int64
----------------------
num-of-doors
False    203
True       2
Name: num-of-doors, dtype: int64
----------------------
bore
False    201
True       4
Name: bore, dtype: int64
----------------------
stroke
False    201
True       4
Name: stroke, dtype: int64
----------------------
horsepower
False    203
True       2
Name: horsepower, dtype: int64
----------------------
peak-rpm
False    203
True       2
Name: peak-rpm, dtype: int64
----------------------
price
```

```
False    201
True       4
Name: price, dtype: int64
----------------------
```

Specifically looking at data for num-of-doors, four door cars are more than two door cars.

[4]:
```
df['num-of-doors'].value_counts()
```

[4]:
```
four    114
two      89
Name: num-of-doors, dtype: int64
```

1.1 Dealing with Missing Values

There are two ways to apporach solving missing values in our dataset. 1. Drop the missing values: 1. Drop the whole row 2. Drop the whole column

2. Replace the missing value:
    1. Replacing by an average
    2. Replacing by frequency
    3. Replacing by other functions

In this problem, dropping a whole column is not a viable option and neither is dropping a whole row. In this dataset, none of the column is completely empty to be able to dropped. Hence, dropping rows or columns is not a good idea.

However, we can use a mixture of replacing option to achieve a clean dataset. For **normalized-losses, bore, stroke, horsepower, peak-rpm** we will replace missin values with avergae value of that column. For **num-of-doors**, based on the fact that 84 % of sedans are having 4 doors, we replace these values with 4. Finally, **price** row can be dropped since this is our target label and there are only four rows with missing values.

[5]:
```
norm_loss_mean = df['normalized-losses'].astype("float").mean(axis = 0)
print("Average normalized-loss:", norm_loss_mean)
df['normalized-losses'].replace(np.NaN,norm_loss_mean, inplace = True)

bore_mean = df['bore'].astype("float").mean(axis=0)
print("Average bore:", bore_mean)
df['bore'].replace(np.NaN,bore_mean, inplace = True)

stroke_mean = df['stroke'].astype("float").mean(axis = 0)
print("Average stroke:", stroke_mean)
df['stroke'].replace(np.NaN,stroke_mean, inplace = True)

horsepower_mean = df['horsepower'].astype("float").mean(axis = 0)
print("Average horsepower:", horsepower_mean)
df['horsepower'].replace(np.NaN,horsepower_mean, inplace = True)

peak_rpm_mean = df['peak-rpm'].astype("float").mean(axis = 0)
```

```python
print("Average peak-rpm:", peak_rpm_mean)
df['peak-rpm'].replace(np.NaN,peak_rpm_mean, inplace = True)

df['num-of-doors'].replace(np.NaN, 4, inplace = True)

df.dropna(subset = ['price'], axis=0, inplace = True)

df.head()
```

```
Average normalized-loss: 122.0
Average bore: 3.3297512437810957
Average stroke: 3.2554228855721337
Average horsepower: 104.25615763546799
Average peak-rpm: 5125.369458128079
```

[5]:
```
   symboling normalized-losses         make fuel-type aspiration num-of-doors  \
0          3             122.0  alfa-romero       gas        std          two
1          3             122.0  alfa-romero       gas        std          two
2          1             122.0  alfa-romero       gas        std          two
3          2               164         audi       gas        std         four
4          2               164         audi       gas        std         four

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
0  convertible          rwd           front        88.6  …          130
1  convertible          rwd           front        88.6  …          130
2    hatchback          rwd           front        94.5  …          152
3        sedan          fwd           front        99.8  …          109
4        sedan          4wd           front        99.4  …          136

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000       21
1         mpfi  3.47    2.68               9.0        111      5000       21
2         mpfi  2.68    3.47               9.0        154      5000       19
3         mpfi  3.19    3.40              10.0        102      5500       24
4         mpfi  3.19    3.40               8.0        115      5500       18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

One last step here is to check the data types of all columns.

[6]:
```
df.dtypes
```

[6]:
```
symboling              int64
normalized-losses     object
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                  object
stroke                object
compression-ratio    float64
horsepower            object
peak-rpm              object
city-mpg               int64
highway-mpg            int64
price                 object
dtype: object
```

There are few features that seem to have incorrect datatype, like num-of-doors, num-of-cylinders, bore, stroke, horsepower, peak-rpm and price. Let's change these datatypes:

[7]:
```
df[['bore','stroke']] = df[['bore','stroke']].astype("float")
df['horsepower'] = df['horsepower'].astype("int")
df['peak-rpm'] = df['peak-rpm'].astype("int")
df['normalized-losses'] = df['normalized-losses'].astype("float")
df['price'] = df['price'].astype("float")

df.dtypes
```

[7]:
```
symboling              int64
normalized-losses    float64
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
```

```
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                 float64
stroke               float64
compression-ratio    float64
horsepower             int32
peak-rpm               int32
city-mpg               int64
highway-mpg            int64
price                float64
dtype: object
```

Here we have cleaned our data and it is now ready for further pre processing. In this next task, data is standardized for some of the columns. The column of city-mpg and highway-mgp have values in mpg but in order for the data to be more relevant other countries as well, we will add a new column of L/100km.

[8]:
```
df['city-L/100km'] = 235 /df['city-mpg']
df['highwat-L/100km'] = 235 / df['highway-mpg']

df.head()
```

[8]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3              122.0  alfa-romero       gas        std
1          3              122.0  alfa-romero       gas        std
2          1              122.0  alfa-romero       gas        std
3          2              164.0         audi       gas        std
4          2              164.0         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two  convertible          rwd           front        88.6  …
2          two    hatchback          rwd           front        94.5  …
3         four        sedan          fwd           front        99.8  …
4         four        sedan          4wd           front        99.4  …

   bore  stroke  compression-ratio  horsepower peak-rpm city-mpg  highway-mpg  \
```

```
0  3.47    2.68                 9.0         111     5000        21             27
1  3.47    2.68                 9.0         111     5000        21             27
2  2.68    3.47                 9.0         154     5000        19             26
3  3.19    3.40                10.0         102     5500        24             30
4  3.19    3.40                 8.0         115     5500        18             22

     price  city-L/100km  highwat-L/100km
0  13495.0     11.190476         8.703704
1  16500.0     11.190476         8.703704
2  16500.0     12.368421         9.038462
3  13950.0      9.791667         7.833333
4  17450.0     13.055556        10.681818

[5 rows x 28 columns]
```

[9]:
```python
df[['length', 'width', 'height']]
```

[9]:
```
      length  width  height
0      168.8   64.1    48.8
1      168.8   64.1    48.8
2      171.2   65.5    52.4
3      176.6   66.2    54.3
4      176.6   66.4    54.3
..       …      …      …
200    188.8   68.9    55.5
201    188.8   68.8    55.5
202    188.8   68.9    55.5
203    188.8   68.9    55.5
204    188.8   68.9    55.5

[201 rows x 3 columns]
```

1.1.1 Normalization

Feature scaling is a process of transforming values in to a common range. In this case, length, height and width can be normalized since the range of length is quite high than width and height. We will use min-max scaling for that.

[10]:
```python
df['height'] = (df['height'] - df['height'].min()) / (df['height'].max()␣
 ↪-df['height'].min())
df['width'] = (df['width'] - df['width'].min()) / (df['width'].max()␣
 ↪-df['width'].min())
df['length'] = (df['length'] - df['length'].min()) / (df['length'].max()␣
 ↪-df['length'].min())
df[['length', 'width', 'height']].head()
```

[10]:
```
     length     width    height
0  0.413433  0.324786  0.083333
1  0.413433  0.324786  0.083333
2  0.449254  0.444444  0.383333
3  0.529851  0.504274  0.541667
4  0.529851  0.521368  0.541667
```

Lastly, for the columns that will be predictor variable for our training set and having string values must be converted to categorical data. Fuel-type is divided into two values, namely **gas** and **diesel**. Similarly, Aspirations can be also be converted into categorical data.

[11]:
```python
df_fuel = pd.get_dummies(df['fuel-type'])

df_fuel = df_fuel.rename(columns = {'diesel':'fuel-diesel', 'gas':'fuel-gas'})
df = pd.concat([df,df_fuel], axis=1 )
df.drop('fuel-type', axis=1, inplace=True)
```

[12]:
```python
#One-hot encoding Aspiration column

df_asp = pd.get_dummies(df['aspiration'])
df_asp
df_asp = df_asp.rename(columns = {'std':'std_asp', 'turbo':'turbo_asp' })

df = pd.concat([df,df_asp], axis=1)
df.drop('aspiration', axis=1, inplace=True)
df.head()
```

[12]:
```
   symboling  normalized-losses         make num-of-doors   body-style  \
0          3              122.0  alfa-romero          two  convertible
1          3              122.0  alfa-romero          two  convertible
2          1              122.0  alfa-romero          two    hatchback
3          2              164.0         audi         four        sedan
4          2              164.0         audi         four        sedan

  drive-wheels engine-location  wheel-base    length     width  …  peak-rpm  \
0          rwd           front        88.6  0.413433  0.324786  …      5000
1          rwd           front        88.6  0.413433  0.324786  …      5000
2          rwd           front        94.5  0.449254  0.444444  …      5000
3          fwd           front        99.8  0.529851  0.504274  …      5500
4          4wd           front        99.4  0.529851  0.521368  …      5500

   city-mpg highway-mpg    price  city-L/100km highwat-L/100km  fuel-diesel  \
0        21          27  13495.0     11.190476        8.703704            0
1        21          27  16500.0     11.190476        8.703704            0
2        19          26  16500.0     12.368421        9.038462            0
3        24          30  13950.0      9.791667        7.833333            0
4        18          22  17450.0     13.055556       10.681818            0
```

```
   fuel-gas  std_asp  turbo_asp
0         1        1          0
1         1        1          0
2         1        1          0
3         1        1          0
4         1        1          0

[5 rows x 30 columns]
```

Here we have the data that is ready for analysis. We will be performing exploratory data analysis on this to determine which features are effective to determine the outcome of price of a used car.

2 Exploratory Data Analysis

Exploratory data analysis or EDA is a process of determining set of variables or features on which the outcome or predictor variable is dependent. There are handful of tools and methods that are used to carry out this analysis.

1. Grouping
2. Continuous numeric variables
3. Descriptive Statistics
4. Categorical Analysis
5. Co-relation Statistics

2.0.1 Co-relation of Variables

Let's try to comapre and co-relate two variables and plot them to see if they display linear relationship. corr() method is used to display corelation of all the variables as shown below. Value of 1 indicates strongest corelation and this will be accurate as 1 occurs at corelation between two same variables.

[13]:
```
df.corr()
```

[13]:
```
                   symboling  normalized-losses  wheel-base    length  \
symboling           1.000000           0.466264   -0.535987 -0.365404
normalized-losses   0.466264           1.000000   -0.056661  0.019424
wheel-base         -0.535987          -0.056661    1.000000  0.876024
length             -0.365404           0.019424    0.876024  1.000000
width              -0.242423           0.086802    0.814507  0.857170
height             -0.550160          -0.373737    0.590742  0.492063
curb-weight        -0.233118           0.099404    0.782097  0.880665
engine-size        -0.110581           0.112360    0.572027  0.685025
bore               -0.140019          -0.029862    0.493244  0.608971
stroke             -0.008153           0.055045    0.158018  0.123952
compression-ratio  -0.182196          -0.114713    0.250313  0.159733
horsepower          0.075810           0.217300    0.371178  0.579795
peak-rpm            0.279739           0.239544   -0.360301 -0.285973
```

```
city-mpg             -0.035527           -0.225016   -0.470606 -0.665192
highway-mpg           0.036233           -0.181877   -0.543304 -0.698142
price                -0.082391            0.133999    0.584642  0.690628
city-L/100km          0.066171            0.238567    0.476153  0.657373
highwat-L/100km      -0.029807            0.181189    0.577576  0.707108
fuel-diesel          -0.196735           -0.101546    0.307237  0.211187
fuel-gas              0.196735            0.101546   -0.307237 -0.211187
std_asp               0.054615            0.006911   -0.256889 -0.230085
turbo_asp            -0.054615           -0.006911    0.256889  0.230085

                      width    height  curb-weight  engine-size      bore  \
symboling         -0.242423 -0.550160    -0.233118    -0.110581 -0.140019
normalized-losses  0.086802 -0.373737     0.099404     0.112360 -0.029862
wheel-base         0.814507  0.590742     0.782097     0.572027  0.493244
length             0.857170  0.492063     0.880665     0.685025  0.608971
width              1.000000  0.306002     0.866201     0.729436  0.544885
height             0.306002  1.000000     0.307581     0.074694  0.180449
curb-weight        0.866201  0.307581     1.000000     0.849072  0.644060
engine-size        0.729436  0.074694     0.849072     1.000000  0.572609
bore               0.544885  0.180449     0.644060     0.572609  1.000000
stroke             0.188822 -0.060663     0.167438     0.205928 -0.055390
compression-ratio  0.189867  0.259737     0.156433     0.028889  0.001263
horsepower         0.615056 -0.087001     0.757981     0.822668  0.566903
peak-rpm          -0.245803 -0.309971    -0.279360    -0.256734 -0.267395
city-mpg          -0.633531 -0.049800    -0.749543    -0.650546 -0.582027
highway-mpg       -0.680635 -0.104812    -0.794889    -0.679571 -0.591309
price              0.751265  0.135486     0.834415     0.872335  0.543155
city-L/100km       0.673363  0.003811     0.785353     0.745059  0.554610
highwat-L/100km    0.736728  0.084301     0.836921     0.783465  0.559112
fuel-diesel        0.244356  0.281578     0.221046     0.070779  0.054458
fuel-gas          -0.244356 -0.281578    -0.221046    -0.070779 -0.054458
std_asp           -0.305732 -0.090336    -0.321955    -0.110040 -0.227816
turbo_asp          0.305732  0.090336     0.321955     0.110040  0.227816

                     stroke  …  peak-rpm  city-mpg  highway-mpg     price  \
symboling         -0.008153  …  0.279739 -0.035527     0.036233 -0.082391
normalized-losses  0.055045  …  0.239544 -0.225016    -0.181877  0.133999
wheel-base         0.158018  … -0.360301 -0.470606    -0.543304  0.584642
length             0.123952  … -0.285973 -0.665192    -0.698142  0.690628
width              0.188822  … -0.245803 -0.633531    -0.680635  0.751265
height            -0.060663  … -0.309971 -0.049800    -0.104812  0.135486
curb-weight        0.167438  … -0.279360 -0.749543    -0.794889  0.834415
engine-size        0.205928  … -0.256734 -0.650546    -0.679571  0.872335
bore              -0.055390  … -0.267395 -0.582027    -0.591309  0.543155
stroke             1.000000  … -0.063577 -0.033956    -0.034636  0.082269
compression-ratio  0.187871  … -0.435777  0.331425     0.268465  0.071107
horsepower         0.098128  …  0.107884 -0.822192    -0.804579  0.809607
```

```
peak-rpm           -0.063577  …  1.000000 -0.115410    -0.058598 -0.101612
city-mpg           -0.033956  … -0.115410  1.000000     0.972044 -0.686571
highway-mpg        -0.034636  … -0.058598  0.972044     1.000000 -0.704692
price               0.082269  … -0.101612 -0.686571    -0.704692  1.000000
city-L/100km        0.036133  …  0.115829 -0.949713    -0.930028  0.789898
highwat-L/100km     0.047089  …  0.017696 -0.909024    -0.951100  0.801118
fuel-diesel         0.241064  … -0.475809  0.265676     0.198690  0.110326
fuel-gas           -0.241064  …  0.475809 -0.265676    -0.198690 -0.110326
std_asp            -0.218233  …  0.190054  0.189237     0.241851 -0.179578
turbo_asp           0.218233  … -0.190054 -0.189237    -0.241851  0.179578

                   city-L/100km  highwat-L/100km  fuel-diesel  fuel-gas  \
symboling              0.066171        -0.029807    -0.196735  0.196735
normalized-losses      0.238567         0.181189    -0.101546  0.101546
wheel-base             0.476153         0.577576     0.307237 -0.307237
length                 0.657373         0.707108     0.211187 -0.211187
width                  0.673363         0.736728     0.244356 -0.244356
height                 0.003811         0.084301     0.281578 -0.281578
curb-weight            0.785353         0.836921     0.221046 -0.221046
engine-size            0.745059         0.783465     0.070779 -0.070779
bore                   0.554610         0.559112     0.054458 -0.054458
stroke                 0.036133         0.047089     0.241064 -0.241064
compression-ratio     -0.299372        -0.223361     0.985231 -0.985231
horsepower             0.889482         0.840627    -0.169030  0.169030
peak-rpm               0.115829         0.017696    -0.475809  0.475809
city-mpg              -0.949713        -0.909024     0.265676 -0.265676
highway-mpg           -0.930028        -0.951100     0.198690 -0.198690
price                  0.789898         0.801118     0.110326 -0.110326
city-L/100km           1.000000         0.958306    -0.241282  0.241282
highwat-L/100km        0.958306         1.000000    -0.158091  0.158091
fuel-diesel           -0.241282        -0.158091     1.000000 -1.000000
fuel-gas               0.241282         0.158091    -1.000000  1.000000
std_asp               -0.157578        -0.210720    -0.408228  0.408228
turbo_asp              0.157578         0.210720     0.408228 -0.408228

                    std_asp  turbo_asp
symboling          0.054615  -0.054615
normalized-losses  0.006911  -0.006911
wheel-base        -0.256889   0.256889
length            -0.230085   0.230085
width             -0.305732   0.305732
height            -0.090336   0.090336
curb-weight       -0.321955   0.321955
engine-size       -0.110040   0.110040
bore              -0.227816   0.227816
stroke            -0.218233   0.218233
compression-ratio -0.307522   0.307522
```

```
horsepower        -0.251159   0.251159
peak-rpm           0.190054  -0.190054
city-mpg           0.189237  -0.189237
highway-mpg        0.241851  -0.241851
price             -0.179578   0.179578
city-L/100km      -0.157578   0.157578
highwat-L/100km   -0.210720   0.210720
fuel-diesel       -0.408228   0.408228
fuel-gas           0.408228  -0.408228
std_asp            1.000000  -1.000000
turbo_asp         -1.000000   1.000000

[22 rows x 22 columns]
```

Pearson corelation is a metric used to determine the corelation strength and it gives two values. Pearson Coefficient and P value,

if Coefficient = 1 suggest positive linear relationship coefficient = -1 suggest negative linear relationship coefficeint = 0 suggest no linear relationship

whereas p-value provides an indication of how strong the corelation is

for, $p < 0.001$, strong corelation $p < 0.05$, moderate corelation $p < 0.1$, weak corelation $p > 0.1$, no corelation

We can also find corelation between two variables as:

Price - Engine Size

[14]:
```
df[['price','engine-size']].corr()
```

[14]:

	price	engine-size
price	1.000000	0.872335
engine-size	0.872335	1.000000

Determining pearson coefficient and p value, we need to import **stats** function from *scipy* library.

[15]:
```
from scipy import stats

p_coeff, p_value = stats.pearsonr(df['price'], df['engine-size'])

print("Pearson Coefficient for relation between price and engine size is {} and␣
↪p_value is {}.". format(p_coeff,p_value) )
```

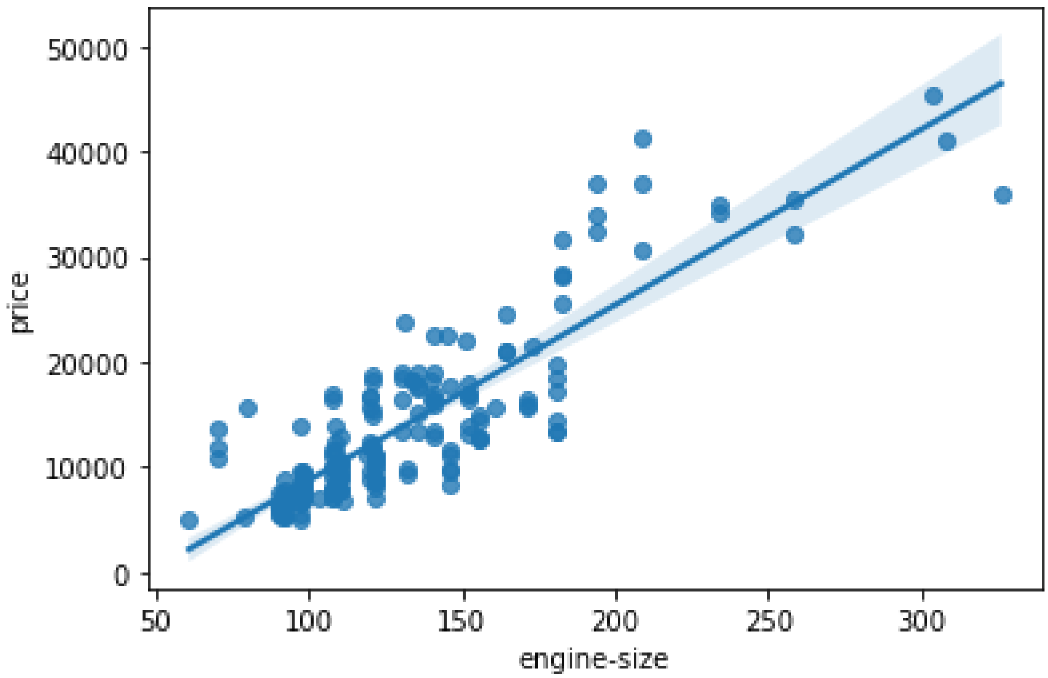
```
Pearson Coefficient for relation between price and engine size is
0.8723351674455186 and p_value is 9.265491622197335e-64.
```

Coefficient value of 0.87 suggests a strong linear relationship and p_value being etremely less than 0.001 suggest a very strong corelation between engine-size and price of the car. Let's visualize this relationship by plotting it using **regplot** fucntion from **seaborn** package which generates a linear line in scatter plot.

[16]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

sns.regplot(x='engine-size', y='price', data = df)
```

[16]: <AxesSubplot:xlabel='engine-size', ylabel='price'>



Similarly, let's try to corelate other numeric variables to find other variables.

Price - Highway MPG

[17]:
```
df[['highway-mpg', 'price']].corr()
```

[17]:

	highway-mpg	price
highway-mpg	1.000000	-0.704692
price	-0.704692	1.000000

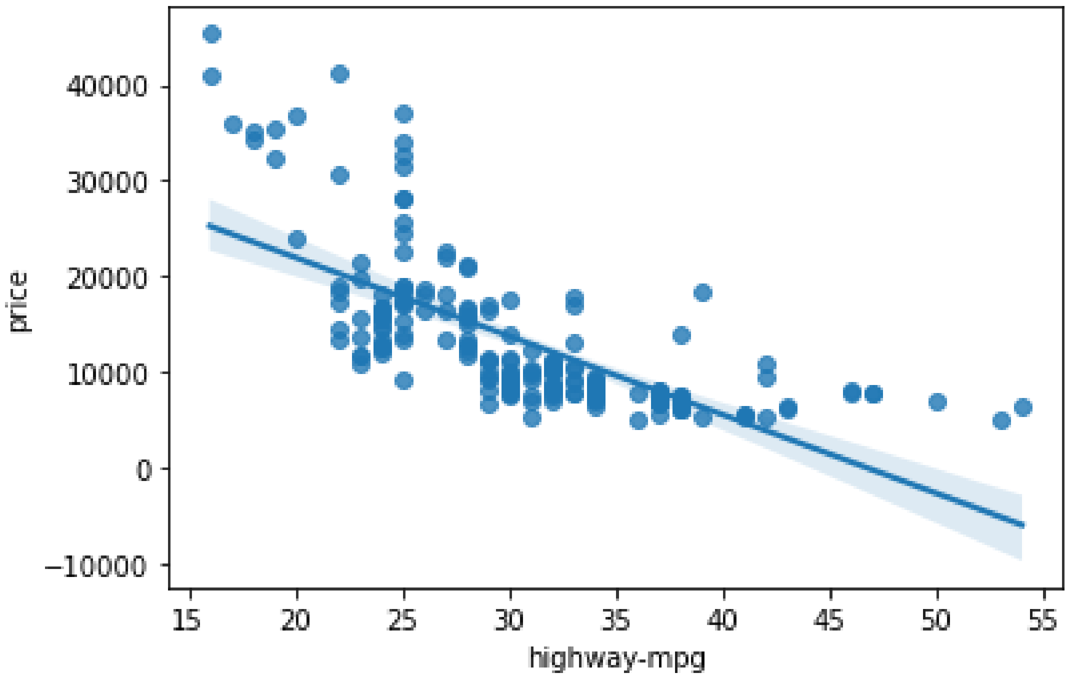
It seems the coefficient value is negative suggesting negative linear relationship.

[18]:
```
p_ceoff_mpg, p_value_mpg = stats.pearsonr(df['highway-mpg'],df['price'])
print("Pearson Coefficient for relation between price and highway-mpg is {} and␣
↪p_value is {}.". format(p_ceoff_mpg,p_value_mpg) )
```

```
Pearson Coefficient for relation between price and highway-mpg is
-0.704692265058953 and p_value is 1.7495471144476358e-31.
```

[19]:
```
sns.regplot(x='highway-mpg', y='price', data =df)
```

[19]: <AxesSubplot:xlabel='highway-mpg', ylabel='price'>



Price - Peak RPM

[20]:
```
df[['peak-rpm', 'price']].corr()
```

[20]:

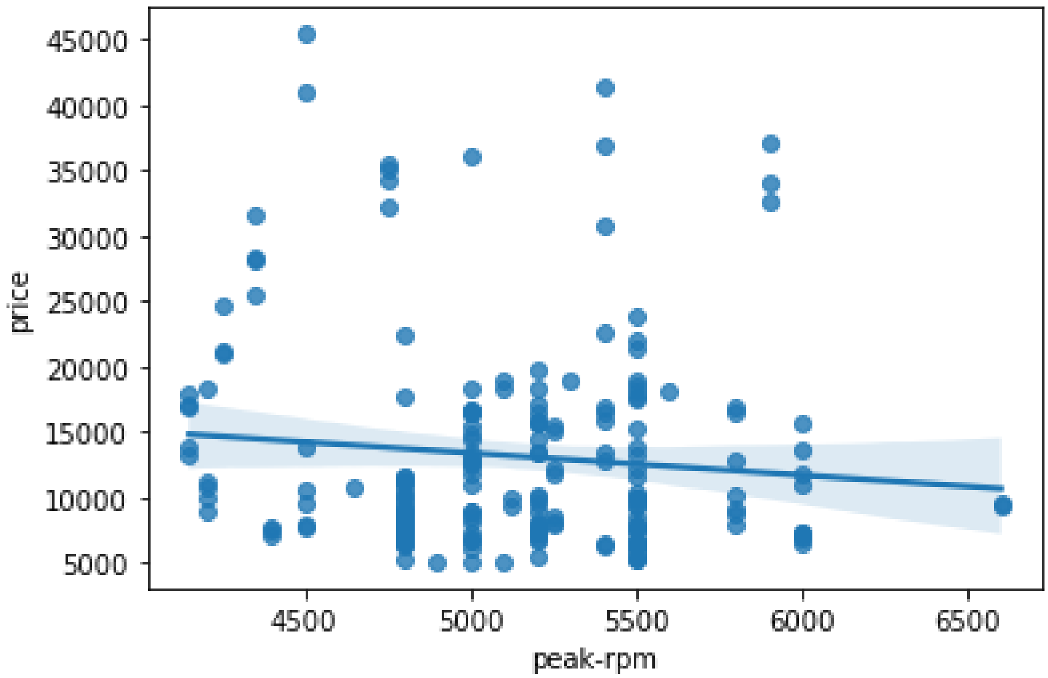
	peak-rpm	price
peak-rpm	1.000000	-0.101612
price	-0.101612	1.000000

[21]:
```
p_ceoff_rpm, p_value_rpm = stats.pearsonr(df['peak-rpm'],df['price'])
print("Pearson Coefficient for relation between price and peak-rpm is {} and␣
↪p_value is {}.". format(p_ceoff_rpm,p_value_rpm) )
```

```
Pearson Coefficient for relation between price and peak-rpm is
-0.10161237413760969 and p_value is 0.1511910706670076.
```

[22]:
```
sns.regplot(x='peak-rpm', y='price', data =df)
```

[22]: <AxesSubplot:xlabel='peak-rpm', ylabel='price'>



Linear relation between price and peak-rpm appears to be very poor and also conclusively from the plot above it is visible that the line is nearly horizontal. Hence, peak-rpm is not a good predictor variable for the prediction of price.

2.1 Categorical Data Analysis

In our dataset there are few variables which are non-numeric and can have impact on the price of the vehicle. To determine this corelation we will use groupby method and plot box bars to visualize its effect on price.

[23]:
```
#grouping by enginer location
df_grouped = df[['engine-location', 'body-style','num-of-doors','price']]
df_grouped_el = df_grouped.groupby(['engine-location'], as_index=False).mean()
df_grouped_el
```

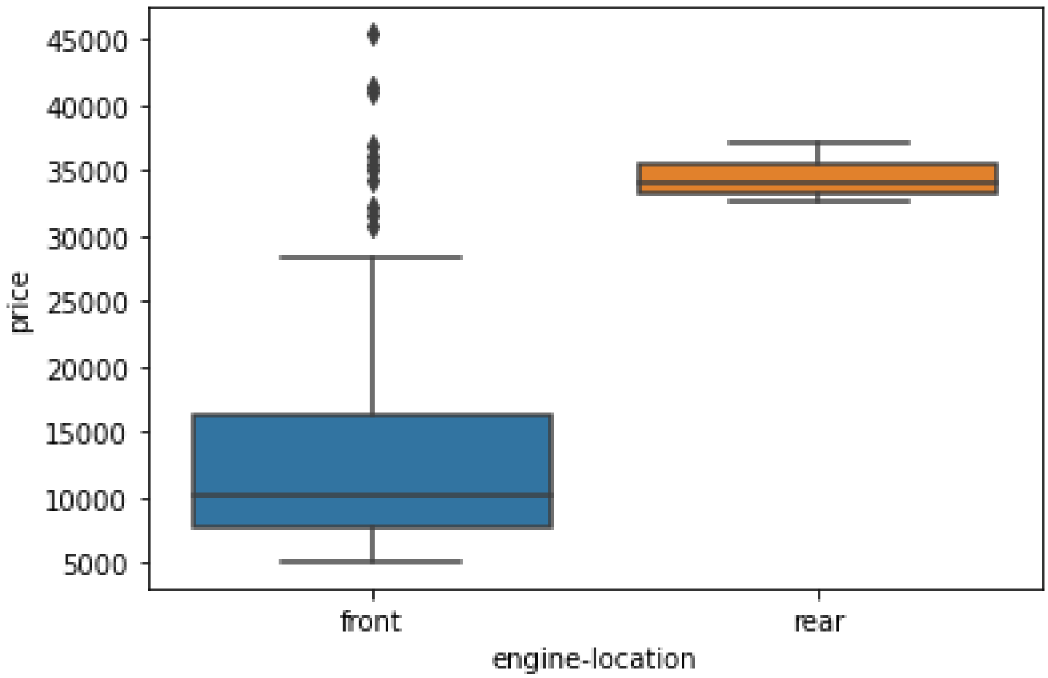
[23]:

	engine-location	price
0	front	12884.085859
1	rear	34528.000000

[24]:
```
#plot a boxplot to visualize the price dependency on egine location

sns.boxplot(x='engine-location', y='price', data=df)
```

[24]: <AxesSubplot:xlabel='engine-location', ylabel='price'>



This high difference in the price range of two engine location makes it a potential feature variable for our analysis. Similarly, let's try to corelate body style and price.

[25]:
```
df_grouped_bs = df_grouped.groupby(['body-style', 'engine-location'],␣
 ↪as_index=False).mean()
df_grouped_bs
```

[25]:

	body-style	engine-location	price
0	convertible	front	18863.000000
1	convertible	rear	37028.000000
2	hardtop	front	18518.666667
3	hardtop	rear	33278.000000
4	hatchback	front	9957.441176
5	sedan	front	14459.755319
6	wagon	front	12371.960000

Above dataframe can be better described in form of a pivot table.

[26]:
```
grouped_pivot = df_grouped_bs.pivot(index='engine-location',␣
 ↪columns='body-style')
grouped_pivot.fillna(0.0)
```

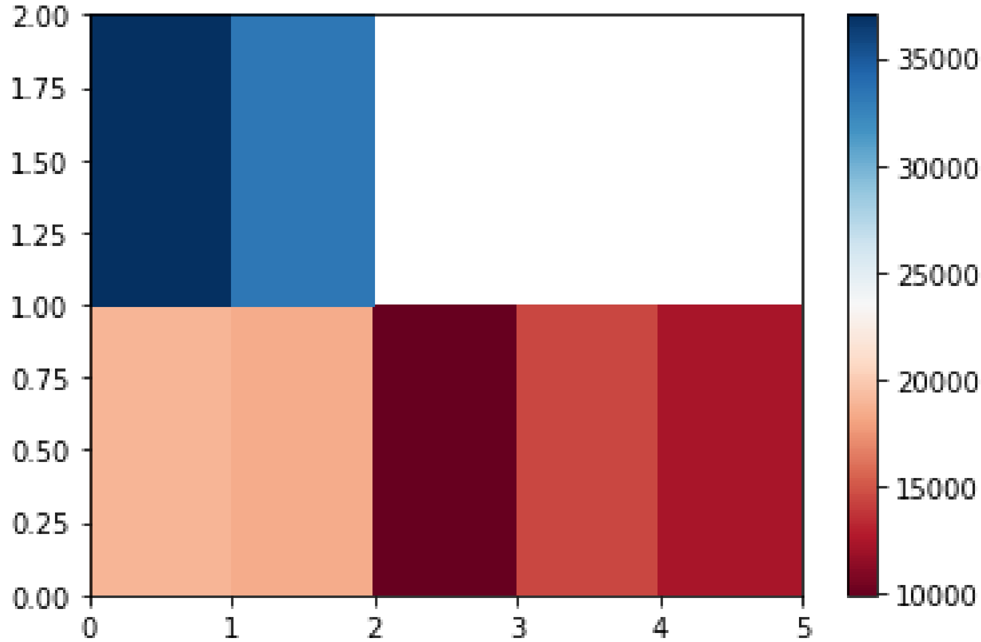
[26]:

```
                      price
body-style      convertible       hardtop     hatchback         sedan      wagon
engine-location
```

```
front                18863.0  18518.666667  9957.441176  14459.755319  12371.96
rear                 37028.0  33278.000000     0.000000      0.000000      0.00
```

[27]:
```
plt.pcolor(grouped_pivot,cmap = 'RdBu')
plt.colorbar()
plt.show()

##plot lavbels and noations will be carried out later
```



From the above plot it is visible that the data is highly skewed for the engine-location relation with price.This can also be determined from the number of values of front and rear engine location numbers.

[28]:
```
df['engine-location'].value_counts().to_frame()
```

[28]:

	engine-location
front	198
rear	3

In conclusion, following features variables are selected: 1. Length 2. Width 3. Curb-weight 4. Engine-size 5. Horsepower 6. City-mpg 7. Highway-mpg 8. Wheel-base 9. Bore 10. Drive-wheels

2.1.1 Linear Regression model

Initially we will use Multivariate Linear Regression model to predict the car prices and evaluate the results.

[29]:
```
#import
from sklearn.linear_model import LinearRegression

#assiging predictor features
X = df[['length','width','curb-weight','engine-size','horsepower',␣
↪'city-mpg','highway-mpg', 'wheel-base','bore']]
y = df[['price']]

#model constructor
model = LinearRegression()
#fitting model
model.fit(X, y)

y_pred = model.predict(X)

#calculating r2 (R squared) score
model.score(X, y)
```

[29]:
```
0.8190670251946173
```

R2 score of training data seems to be 81.90% from above results. However, we should never use testing data for training and hence we will use train_test_split function of sklearn to divide the data into training set and testing set.

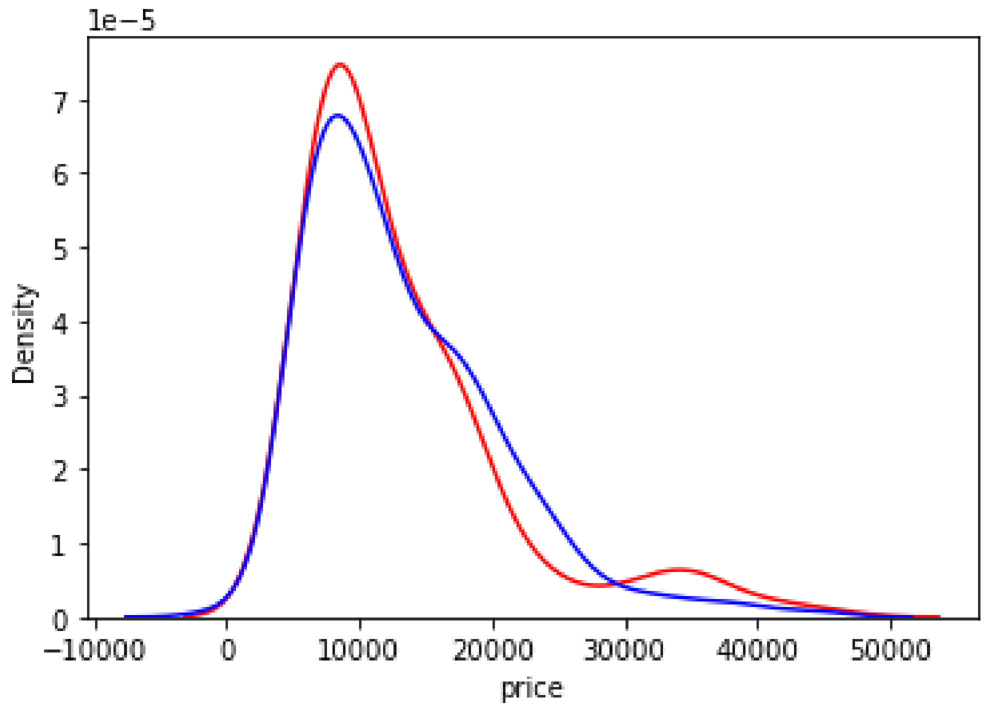
Before that, let's splot a distribution curve to visualize the actual and predicted price from the above linear regression modeling.

[30]:
```
ax = sns.distplot(df['price'], hist=False, color='r')

sns.distplot(y_pred, hist=False,color ='b', ax=ax)
```

```
C:\Users\hardi\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\hardi\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
```

[30]:
```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



The red curve is the actual car price whereas blue curve is predicted car price and from the plot it is quite matching the actual price. Though the predictions are not very accurate for higher prices.

[31]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =0.2,␣
↪random_state=30)
model_1 = LinearRegression()
model_1.fit(X_train, y_train)
y_pred = model_1.predict(X_test)

model_1.score(X_test, y_test)
```

[31]:
```
0.6269668862514672
```

Above model gives a r2 score of 62.69% for the testing data. Let's try to use polynomial features to see if we can further improve the r2 score alond with ridge regression (L2 regularization).

[32]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score

poly_model = PolynomialFeatures(degree=2)
```

```python
#fit and transform the data
X_train_pr = poly_model.fit_transform(X_train)
X_test_pr = poly_model.fit_transform(X_test)

#contruct a ridge model
ridge_model = Ridge(alpha =0.1)

#fit the model
ridge_model.fit(X_train_pr, y_train)

#get the R2 score
ridge_model.score(X_test_pr, y_test)
```

```
C:\Users\hardi\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.py:147:
LinAlgWarning: Ill-conditioned matrix (rcond=5.62041e-17): result may not be
accurate.
  return linalg.solve(A, Xy, sym_pos=True,
```

[32]: 0.7268615629729643

2.2 Conclusion

By using a polynomial features function in a ridge regression model we were able to increase the predictions accuracy of the prices. A higher R2 score suggets a good model with average fit of the data points and hence the predictions are more reliable.

[ ]: