```
# import libraries

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
import warnings
warnings.filterwarnings("ignore")

dataset = pd.read_csv("CarPrice_Assignment.csv")
dataset.head()
```

```
   car_ID  symboling                   CarName fueltype aspiration
doornumber  \
0       1          3        alfa-romero giulia      gas        std
two
1       2          3       alfa-romero stelvio      gas        std
two
2       3          1  alfa-romero Quadrifoglio      gas        std
two
3       4          2               audi 100 ls      gas        std
four
4       5          2                audi 100ls      gas        std
four

       carbody drivewheel enginelocation  wheelbase  ...
enginesize  \
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


   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm
citympg  \
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

   highwaympg    price
0          27  13495.0
1          27  16500.0
2          26  16500.0
3          30  13950.0
4          22  17450.0

[5 rows x 26 columns]
```

```
dataset.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
```

```
dataset.duplicated().sum()
```

```
0
```

```python
dataset = dataset.drop(['CarName'], axis=1)
```

```python
dataset.describe()
```

```
           car_ID   symboling   wheelbase   carlength    carwidth  
carheight  \
count  205.000000  205.000000  205.000000  205.000000  205.000000  
205.000000   
mean   103.000000    0.834146   98.756585  174.049268   65.907805   
53.724878   
std     59.322565    1.245307    6.021776   12.337289    2.145204   
2.443522   
min      1.000000   -2.000000   86.600000  141.100000   60.300000   
47.800000   
25%     52.000000    0.000000   94.500000  166.300000   64.100000   
52.000000   
50%    103.000000    1.000000   97.000000  173.200000   65.500000   
54.100000   
75%    154.000000    2.000000  102.400000  183.100000   66.900000   
55.500000   
max    205.000000    3.000000  120.900000  208.100000   72.300000   
59.800000   

        curbweight  enginesize   boreratio      stroke  
compressionratio  \
count   205.000000  205.000000  205.000000  205.000000  
205.000000   
mean   2555.565854  126.907317    3.329756    3.255415  
10.142537   
std     520.680204   41.642693    0.270844    0.313597  
3.972040   
min    1488.000000   61.000000    2.540000    2.070000  
7.000000   
25%    2145.000000   97.000000    3.150000    3.110000  
8.600000   
50%    2414.000000  120.000000    3.310000    3.290000  
9.000000   
75%    2935.000000  141.000000    3.580000    3.410000  
9.400000   
max    4066.000000  326.000000    3.940000    4.170000  
23.000000   

       horsepower      peakrpm     citympg  highwaympg         price  
count  205.000000   205.000000  205.000000  205.000000    205.000000  
mean   104.117073  5125.121951   25.219512   30.751220  13276.710571  
std     39.544167   476.985643    6.542142    6.886443   7988.852332  
min     48.000000  4150.000000   13.000000   16.000000   5118.000000  
25%     70.000000  4800.000000   19.000000   25.000000   7788.000000  
```

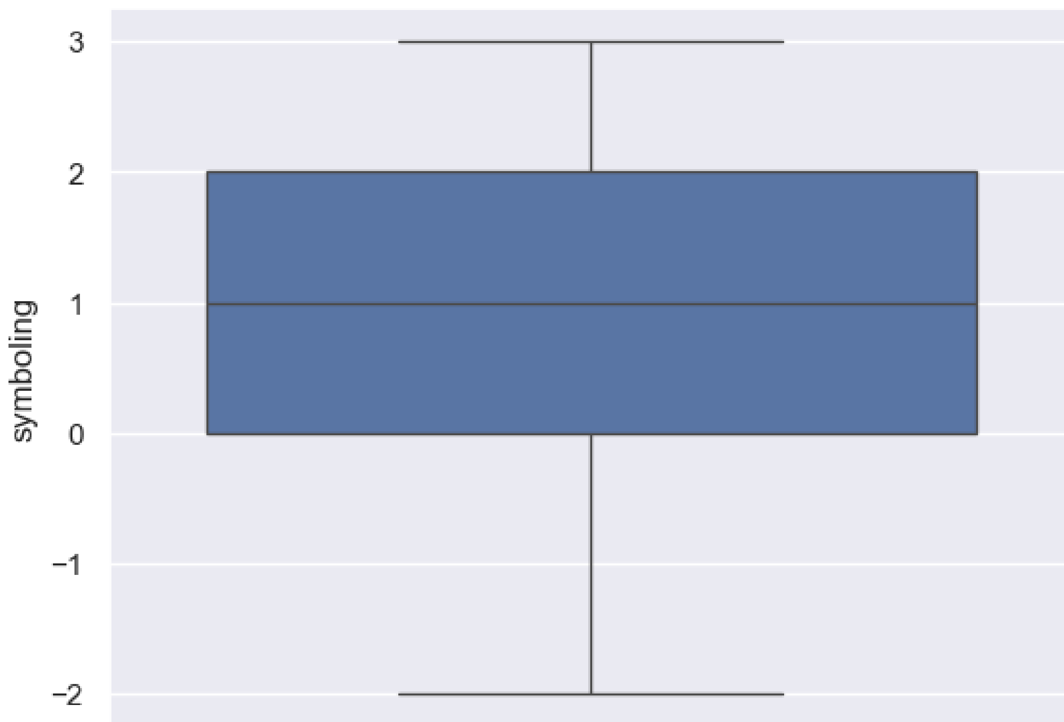
```
50%     95.000000  5200.000000   24.000000   30.000000  10295.000000
75%    116.000000  5500.000000   30.000000   34.000000  16503.000000
max    288.000000  6600.000000   49.000000   54.000000  45400.000000
```

```
# Checking missing values

dataset.isnull().sum()
```

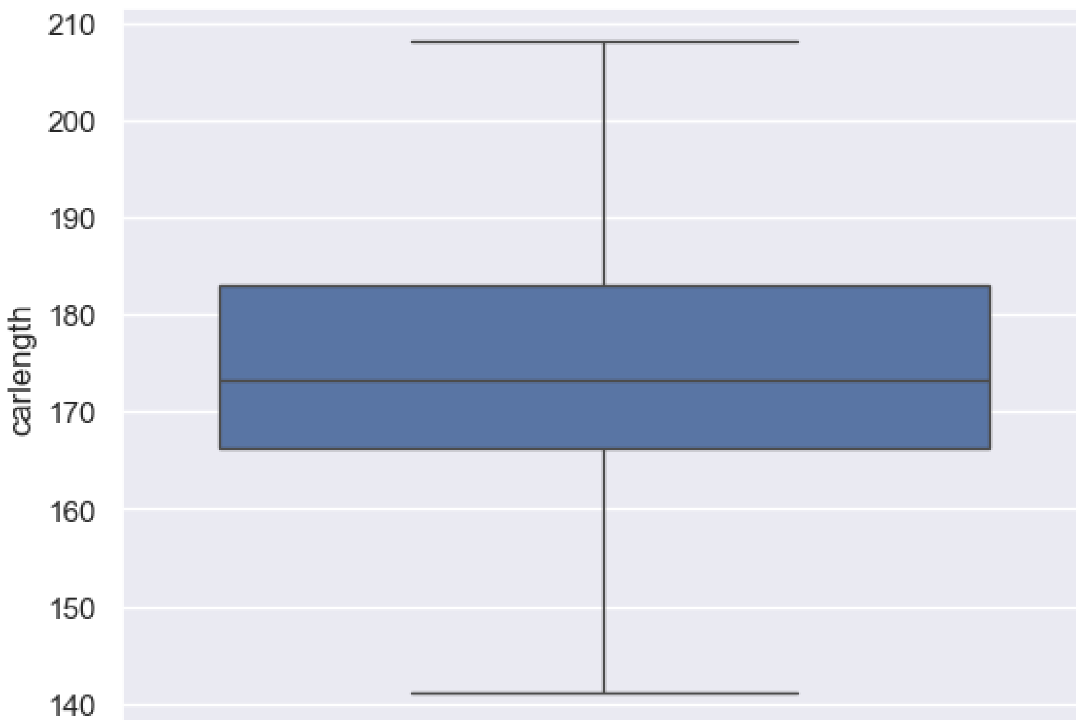
```
car_ID              0
symboling           0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          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
```

```
# we have to handle outlier for the listed variables
# wheelbase, carlength, carwidth, enginesize, stroke,
compressionratio, horsepower, peakrpm, citympg, highwaympg

columns_to_check = ['wheelbase', 'carlength', 'carwidth',
'enginesize', 'stroke',
                    'compressionratio', 'horsepower', 'peakrpm',
'citympg', 'highwaympg']

# Function to detect and treat outliers
def treat_outliers(dataset, columns):
    for col in columns:
        # Calculate Q1, Q3, and IQR
        Q1 = dataset[col].quantile(0.25)
        Q3 = dataset[col].quantile(0.75)
```

```
        IQR = Q3 - Q1

        # Define lower and upper bounds
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Cap the outliers
        dataset[col] = dataset[col].apply(lambda x: upper_bound if x >
upper_bound else (lower_bound if x < lower_bound else x))

    return dataset

# Apply the function
dataset = treat_outliers(dataset, columns_to_check)

def boxplots(col):
    sns.boxplot(dataset[col])
    plt.show()

for i in list(dataset.select_dtypes(exclude=['object']).columns)[0:]:
    boxplots(i)
```


3
2
1
0
−1
−2
symboling


115
110
105
100
95
90
wheelbase



210
200
190
180
170
160
150
140
carlength

70
68
66
64
62
60
carwidth

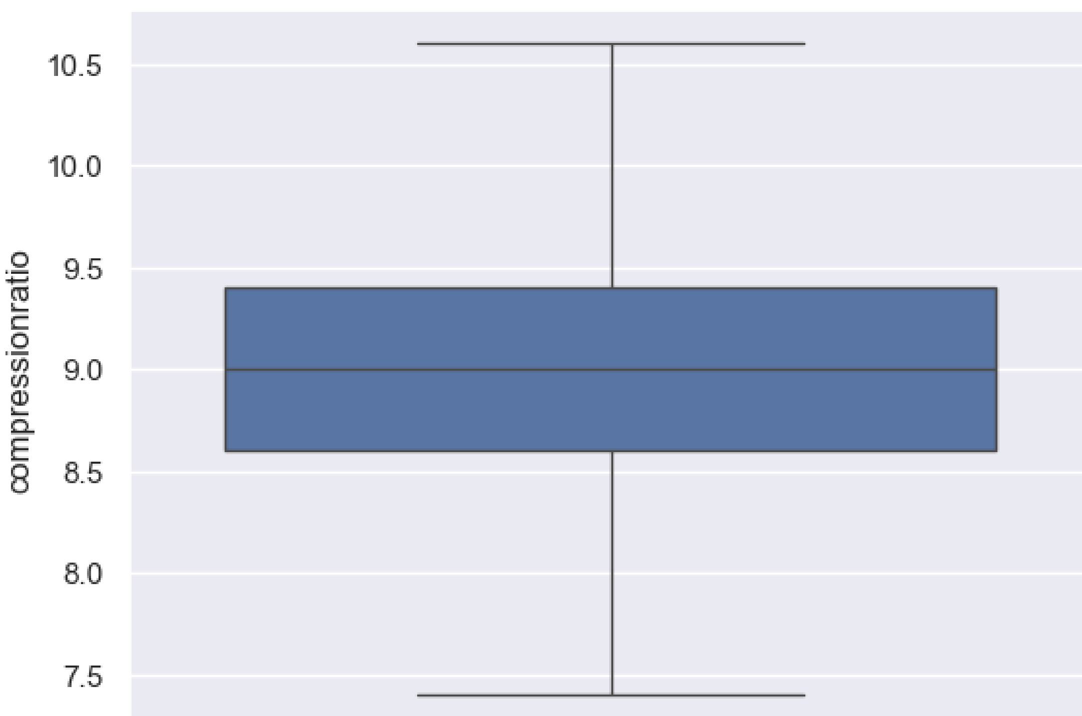

60
58
56
54
52
50
48
carheight


4000
3500
3000
2500
2000
1500
curbweight

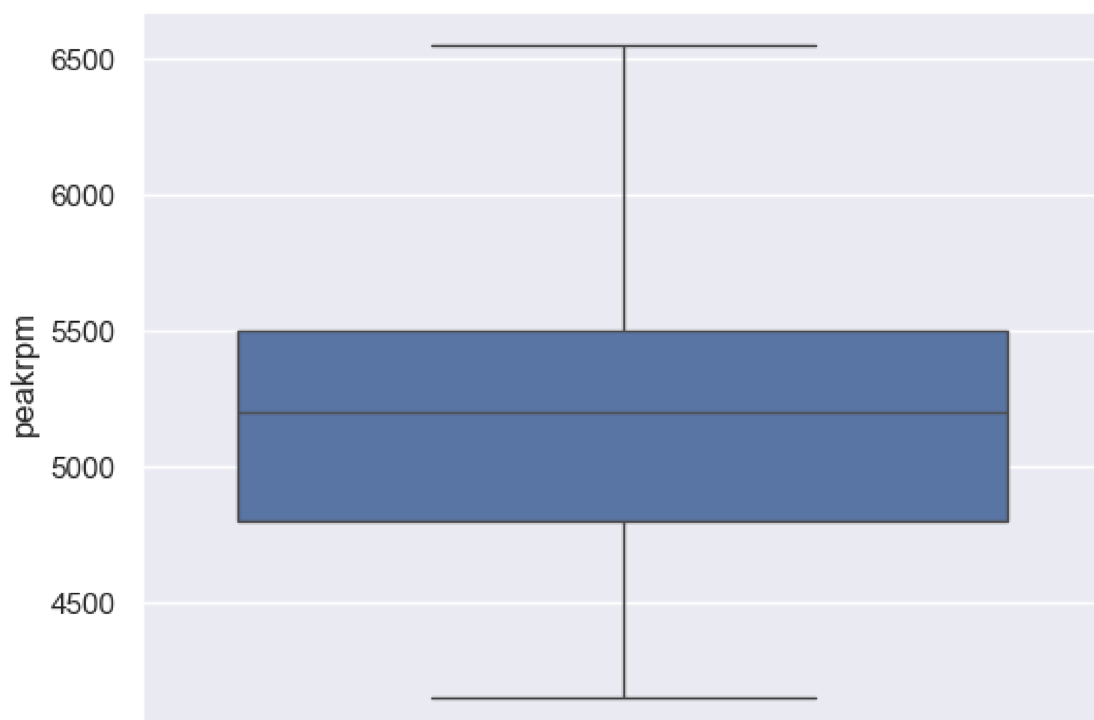

200
180
160
140
120
100
80
60
enginesize

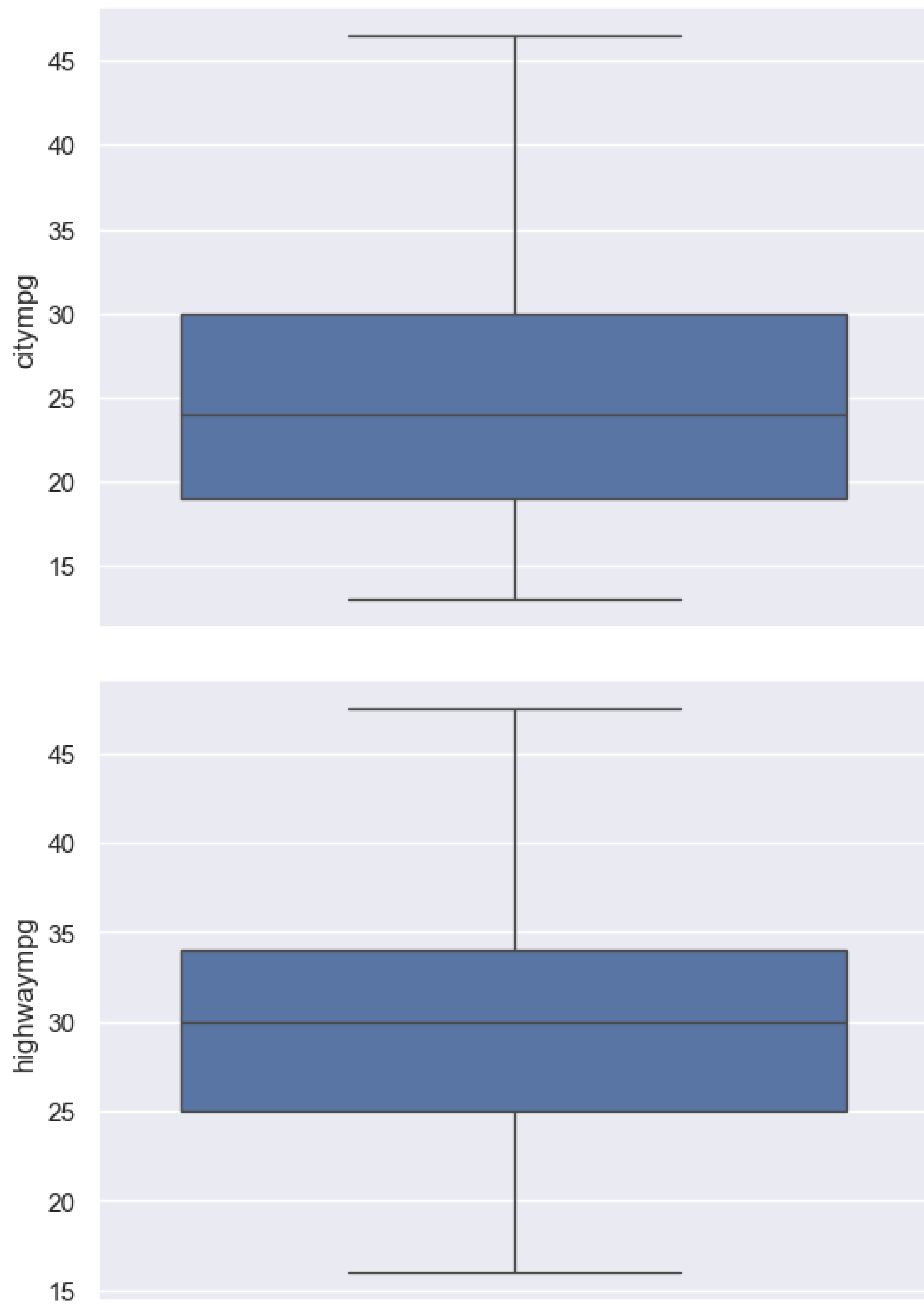

4.0
3.8
3.6
3.4
3.2
3.0
2.8
2.6
boreratio

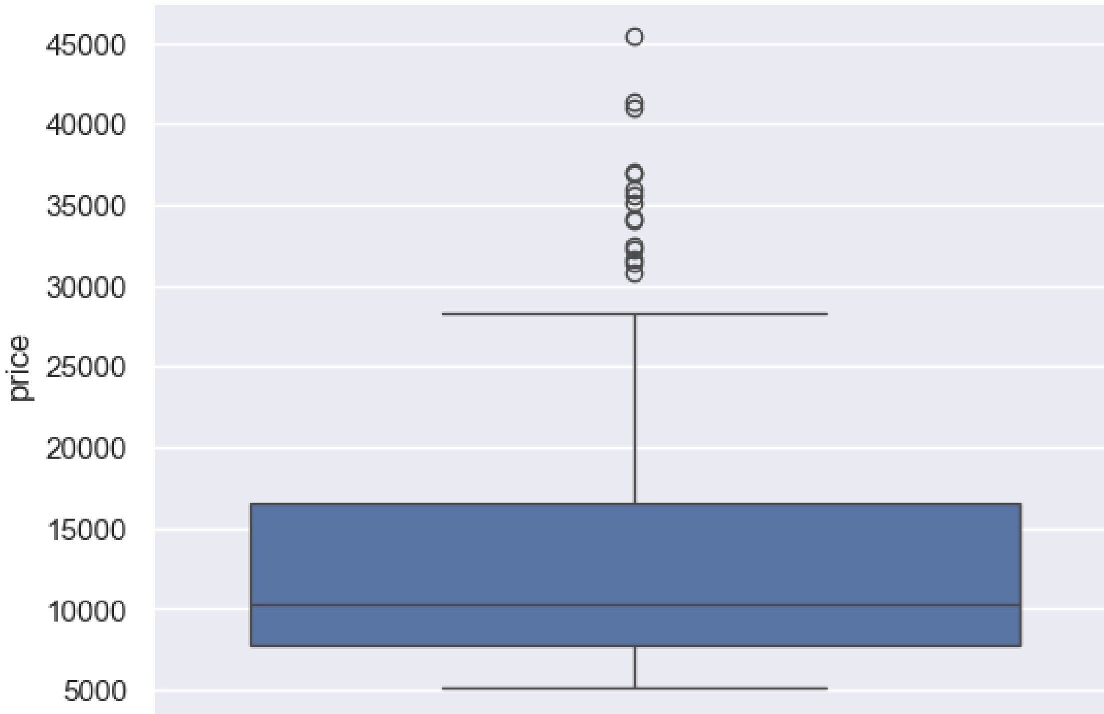

3.8
3.6
3.4
3.2
3.0
2.8
2.6
stroke


10.5
10.0
9.5
9.0
8.5
8.0
7.5
compressionratio


180
160
140
120
100
80
60
horsepower


6500
6000
5500
5000
4500
peakrpm


45
40
35
30
25
20
15
citympg
45
40
35
30
25
20
15
highwaympg




```
#Convert categorical features (fueltype, aspiration, doornumber, carbody, drivewheel, enginelocation,
#enginetype, cylindernumber, fuelsystem)
#into numerical using Label Encoding.

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
dataset['fueltype']= le.fit_transform(dataset['fueltype'])
dataset['aspiration']= le.fit_transform(dataset['aspiration'])
dataset['doornumber']= le.fit_transform(dataset['doornumber'])
dataset['carbody']= le.fit_transform(dataset['carbody'])
dataset['drivewheel']= le.fit_transform(dataset['drivewheel'])
dataset['enginelocation']= le.fit_transform(dataset['enginelocation'])
dataset['enginetype']= le.fit_transform(dataset['enginetype'])
dataset['cylindernumber']= le.fit_transform(dataset['cylindernumber'])
dataset['fuelsystem']= le.fit_transform(dataset['fuelsystem'])

dataset.head()

   car_ID  symboling  fueltype  aspiration  doornumber  carbody
drivewheel  \
0       1          3         1           0           1        0
2
1       2          3         1           0           1        0
2
2       3          1         1           0           1        2
2
```

```
3       4          2          1            0            0         3
1
4       5          2          1            0            0         3
0

   enginelocation  wheelbase  carlength  ...  enginesize
fuelsystem  \
0               0       88.6      168.8  ...       130.0           5

1               0       88.6      168.8  ...       130.0           5

2               0       94.5      171.2  ...       152.0           5

3               0       99.8      176.6  ...       109.0           5

4               0       99.4      176.6  ...       136.0           5


   boreratio  stroke  compressionratio  horsepower  peakrpm
citympg  \
0       3.47    2.68               9.0       111.0   5000.0     21.0

1       3.47    2.68               9.0       111.0   5000.0     21.0

2       2.68    3.47               9.0       154.0   5000.0     19.0

3       3.19    3.40              10.0       102.0   5500.0     24.0

4       3.19    3.40               8.0       115.0   5500.0     18.0


   highwaympg    price
0        27.0  13495.0
1        27.0  16500.0
2        26.0  16500.0
3        30.0  13950.0
4        22.0  17450.0

[5 rows x 25 columns]

x = dataset.iloc[:,0:-1] # Independent variable
y = dataset.iloc[:,-1] # Dependent variable (Price)

x.head()

   car_ID  symboling  fueltype  aspiration  doornumber  carbody
drivewheel  \
0       1          3         1           0           1        0
2
1       2          3         1           0           1        0
2
```

```
2       3          1         1           0           1        2
2
3       4          2         1           0           0        3
1
4       5          2         1           0           0        3
0

   enginelocation  wheelbase  carlength  ...  cylindernumber
enginesize  \
0               0       88.6      168.8  ...               2
130.0
1               0       88.6      168.8  ...               2
130.0
2               0       94.5      171.2  ...               3
152.0
3               0       99.8      176.6  ...               2
109.0
4               0       99.4      176.6  ...               1
136.0

   fuelsystem  boreratio  stroke  compressionratio  horsepower
peakrpm  \
0           5       3.47    2.68               9.0       111.0
5000.0
1           5       3.47    2.68               9.0       111.0
5000.0
2           5       2.68    3.47               9.0       154.0
5000.0
3           5       3.19    3.40              10.0       102.0
5500.0
4           5       3.19    3.40               8.0       115.0
5500.0

   citympg  highwaympg
0     21.0        27.0
1     21.0        27.0
2     19.0        26.0
3     24.0        30.0
4     18.0        22.0

[5 rows x 24 columns]
```

```
y.head()
```

```
0    13495.0
1    16500.0
2    16500.0
3    13950.0
4    17450.0
Name: price, dtype: float64
```

```python
# Feature Scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
sc_x = scaler.fit_transform(x)
pd.DataFrame(sc_x)
```

```
            0         1         2         3         4         5
6   \
0   -1.723622  1.743470  0.328798 -0.469295  1.130388 -3.050975
1.213330
1   -1.706724  1.743470  0.328798 -0.469295  1.130388 -3.050975
1.213330
2   -1.689826  0.133509  0.328798 -0.469295  1.130388 -0.717207
1.213330
3   -1.672928  0.938490  0.328798 -0.469295 -0.884652  0.449677 -
0.589081
4   -1.656029  0.938490  0.328798 -0.469295 -0.884652  0.449677 -
2.391492
..        ...       ...       ...       ...       ...       ...
...
200  1.656029 -1.476452  0.328798 -0.469295 -0.884652  0.449677
1.213330
201  1.672928 -1.476452  0.328798  2.130854 -0.884652  0.449677
1.213330
202  1.689826 -1.476452  0.328798 -0.469295 -0.884652  0.449677
1.213330
203  1.706724 -1.476452 -3.041381  2.130854 -0.884652  0.449677
1.213330
204  1.723622 -1.476452  0.328798  2.130854 -0.884652  0.449677
1.213330

            7         8         9  ...        14        15
16  \
0   -0.121867 -1.723005 -0.426521  ... -0.147475  0.160196  0.869568

1   -0.121867 -1.723005 -0.426521  ... -0.147475  0.160196  0.869568

2   -0.121867 -0.717590 -0.231513  ...  1.112210  0.809329  0.869568

3   -0.121867  0.185580  0.207256  ... -0.147475 -0.459430  0.869568

4   -0.121867  0.117416  0.207256  ... -1.407161  0.337232  0.869568

..        ...       ...       ...  ...       ...       ...       ...

200 -0.121867  1.770387  1.198549  ... -0.147475  0.484762  0.869568

201 -0.121867  1.770387  1.198549  ... -0.147475  0.484762  0.869568

202 -0.121867  1.770387  1.198549  ...  1.112210  1.428955  0.869568
```

```
203 -0.121867  1.770387  1.198549  ...  1.112210  0.602787 -0.126306

204 -0.121867  1.770387  1.198549  ... -0.147475  0.484762  0.869568


           17        18        19        20        21        22
23
0    0.519071 -2.106623 -0.049433  0.229801 -0.262757 -0.649321 -
0.552143
1    0.519071 -2.106623 -0.049433  0.229801 -0.262757 -0.649321 -
0.552143
2   -2.404880  0.753841 -0.049433  1.441341 -0.262757 -0.958163 -
0.702161
3   -0.517266  0.500383  1.214121 -0.023777  0.791357 -0.186058 -
0.102086
4   -0.517266  0.500383 -1.312986  0.342502  0.791357 -1.112584 -
1.302237
..        ...       ...       ...       ...       ...       ...
...
200  1.666445 -0.404828  0.582344  0.314327  0.580534 -0.340479 -
0.402124
201  1.666445 -0.404828 -0.428499  1.610393  0.369711 -0.958163 -
0.852180
202  0.926204 -1.418663 -0.302143  0.877834  0.791357 -1.112584 -
1.152218
203 -1.183483  0.500383  1.972253  0.088924 -0.684403  0.122783 -
0.552143
204  1.666445 -0.404828  0.582344  0.314327  0.580534 -0.958163 -
0.852180

[205 rows x 24 columns]
```

```
pd.DataFrame(sc_x).describe()
```

```
                  0             1             2             3
4  \
count  2.050000e+02  2.050000e+02  2.050000e+02  2.050000e+02
2.050000e+02
mean  -6.932124e-17  4.332578e-17 -7.798640e-17  6.282238e-17
1.039819e-16
std    1.002448e+00  1.002448e+00  1.002448e+00  1.002448e+00
1.002448e+00
min   -1.723622e+00 -2.281433e+00 -3.041381e+00 -4.692953e-01 -
8.846517e-01
25%   -8.618111e-01 -6.714717e-01  3.287980e-01 -4.692953e-01 -
8.846517e-01
50%    0.000000e+00  1.335090e-01  3.287980e-01 -4.692953e-01 -
8.846517e-01
75%    8.618111e-01  9.384897e-01  3.287980e-01 -4.692953e-01
```

```
1.130388e+00
max    1.723622e+00  1.743470e+00  3.287980e-01  2.130854e+00
1.130388e+00

                  5             6             7             8
9  \
count  2.050000e+02  2.050000e+02  2.050000e+02  2.050000e+02
2.050000e+02
mean  -1.646380e-16 -1.126470e-16 -8.665155e-18 -1.065814e-15
3.691356e-15
std    1.002448e+00  1.002448e+00  1.002448e+00  1.002448e+00
1.002448e+00
min   -3.050975e+00 -2.391492e+00 -1.218667e-01 -2.063824e+00 -
2.677244e+00
25%   -7.172069e-01 -5.890807e-01 -1.218667e-01 -7.175899e-01 -
6.296552e-01
50%    4.496773e-01 -5.890807e-01 -1.218667e-01 -2.915663e-01 -
6.900603e-02
75%    4.496773e-01  1.213330e+00 -1.218667e-01  6.286445e-01
7.354037e-01
max    1.616562e+00  1.213330e+00  8.205689e+00  2.647996e+00
2.766741e+00

       ...            14            15            16            17  \
count  ...  2.050000e+02  2.050000e+02  2.050000e+02  2.050000e+02
mean   ... -1.386425e-16 -1.992986e-16  1.039819e-16  2.252940e-15
std    ...  1.002448e+00  1.002448e+00  1.002448e+00  1.002448e+00
min    ... -2.666846e+00 -1.875720e+00 -1.620116e+00 -2.923049e+00
25%    ... -1.474754e-01 -8.135028e-01 -1.122179e+00 -6.653141e-01
50%    ... -1.474754e-01 -1.348641e-01  8.695675e-01 -7.312136e-02
75%    ... -1.474754e-01  4.847625e-01  8.695675e-01  9.262039e-01
max    ...  4.891266e+00  2.432160e+00  1.865441e+00  2.258638e+00

                 18            19            20            21
22  \
count  2.050000e+02  2.050000e+02  2.050000e+02  2.050000e+02
2.050000e+02
mean   2.980813e-15  6.845473e-16 -2.057974e-17 -6.932124e-16
2.469569e-16
std    1.002448e+00  1.002448e+00  1.002448e+00  1.002448e+00
1.002448e+00
min   -2.179040e+00 -2.071118e+00 -1.545246e+00 -2.054752e+00 -
1.884688e+00
25%   -5.496614e-01 -5.548541e-01 -9.253886e-01 -6.844030e-01 -
9.581629e-01
50%    1.020901e-01 -4.943268e-02 -2.210047e-01  1.588884e-01 -
1.860584e-01
75%    5.365910e-01  4.559888e-01  3.706777e-01  7.913570e-01
7.404671e-01
max    2.165970e+00  1.972253e+00  2.314777e+00  3.004997e+00
```

```
3.288412e+00

                  23
count  2.050000e+02
mean   9.856614e-17
std    1.002448e+00
min   -2.202350e+00
25%   -8.521802e-01
50%   -1.020860e-01
75%    4.979894e-01
max    2.523244e+00

[8 rows x 24 columns]
```

```
# It's multiple linear regression, hence we have to check "Multicollinearity"
variable = sc_x
variable.shape
```

```
(205, 24)
```

To check Multicollinearity - VIF (Variance Inflation Factor)

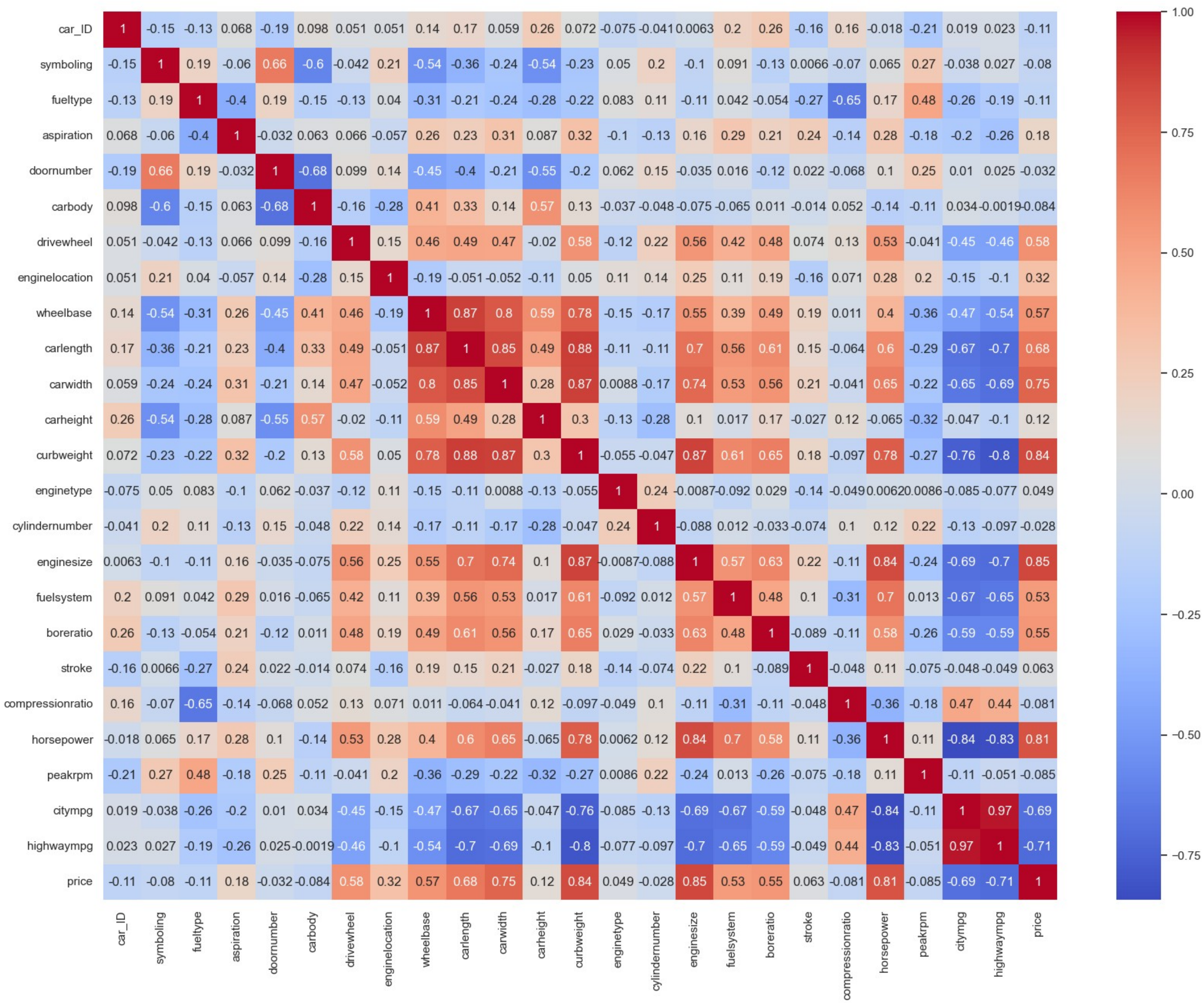
```
# VIF value is more than 5 means there is a multicollinearity there in the features
from statsmodels.stats.outliers_influence import variance_inflation_factor
variable = sc_x
vif = pd.DataFrame()
vif['variance_inflation_factor'] = [variance_inflation_factor(variable, i) for i in range(variable.shape[1])]

vif['Features'] = x.columns

vif
```

	variance_inflation_factor	Features
0	1.479131	car_ID
1	2.828315	symboling
2	5.584468	fueltype
3	3.122923	aspiration
4	2.780304	doornumber
5	2.813480	carbody
6	2.626872	drivewheel
7	1.805014	enginelocation
8	10.551627	wheelbase
9	11.537443	carlength
10	8.040508	carwidth
11	2.929516	carheight

12	18.449284	curbweight
13	1.442345	enginetype
14	2.204296	cylindernumber
15	16.377475	enginesize
16	2.757890	fuelsystem
17	2.491841	boreratio
18	1.697226	stroke
19	4.315996	compressionratio
20	17.445684	horsepower
21	2.970193	peakrpm
22	23.176338	citympg
23	22.110875	highwaympg

Finding correlation

```
plt.figure(figsize=(20,15))
#corr = Housing.corr()
sns.heatmap(dataset.corr(), annot=True, cmap='coolwarm')
plt.show()
```



We have multicorrelated variables hence we need to apply PCA for dimensionality reduction

```
# Apply PCA
from sklearn.decomposition import PCA

pca = PCA(n_components=0.95)  # Retain 95% of the variance
X_pca = pca.fit_transform(sc_x)

# Let's check the explained variance ratio to understand how much
information each principal component retains

explained_variance = pca.explained_variance_ratio_
explained_variance
```

```
array([0.32886298, 0.16703802, 0.08388498, 0.06767003, 0.05224637,
       0.04496342, 0.04141339, 0.03759184, 0.02859023, 0.02565239,
       0.02152603, 0.01876589, 0.01566118, 0.01416775, 0.01235966])
```

```
# Split the Data into Train and Test Sets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_pca, y,
test_size=0.2, random_state=42)
```

Linear Regression

```
# Apply Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

# Initialize the Linear Regression model
lr_model = LinearRegression()

# Train the model
lr_model.fit(X_train, y_train)

# Make predictions
y_pred_lr = lr_model.predict(X_test)
y_pred_lr
```

```
array([24495.64959172, 21391.61915098,  9280.41659459, 14280.61097737,
       26711.1821066 ,  6593.44981859,  7609.43157162,  6705.47725175,
       10787.37603735,  6103.55009794, 15386.77862939,  7481.39209327,
       15623.12078086, 11115.45256861, 33341.20982346,  4873.97687978,
       -4220.80495503, 14118.81572874,  9798.09584758, 11299.01521206,
       11299.17916788, 21308.15377546,  6883.26415079,  1776.51983521,
        6805.8324699 , 25958.839732  , 13889.49843904, 15831.3596836 ,
        4929.01094257, 17103.50952177, 27360.17456389,  6120.31202415,
        4707.26111497, 22375.70714452,  7819.91713441, 28456.93563104,
       10164.205043  , 10447.43562098,  5516.22217562, 14293.09217264,
        9136.07052383])
```

```
# Evaluate the Linear Regression model
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)

print("Linear Regression Evaluation:")
print(f"MAE: {mae_lr}")
print(f"MSE: {mse_lr}")
print(f"R-squared: {r2_lr}")
```

```
Linear Regression Evaluation:
MAE: 2664.127335130712
MSE: 15831151.943431232
R-squared: 0.7994635721992898
```

Random Forest Regression

```
# Apply Random Forest Regression
from sklearn.ensemble import RandomForestRegressor

# Initialize the Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_model.predict(X_test)
y_pred_rf
```

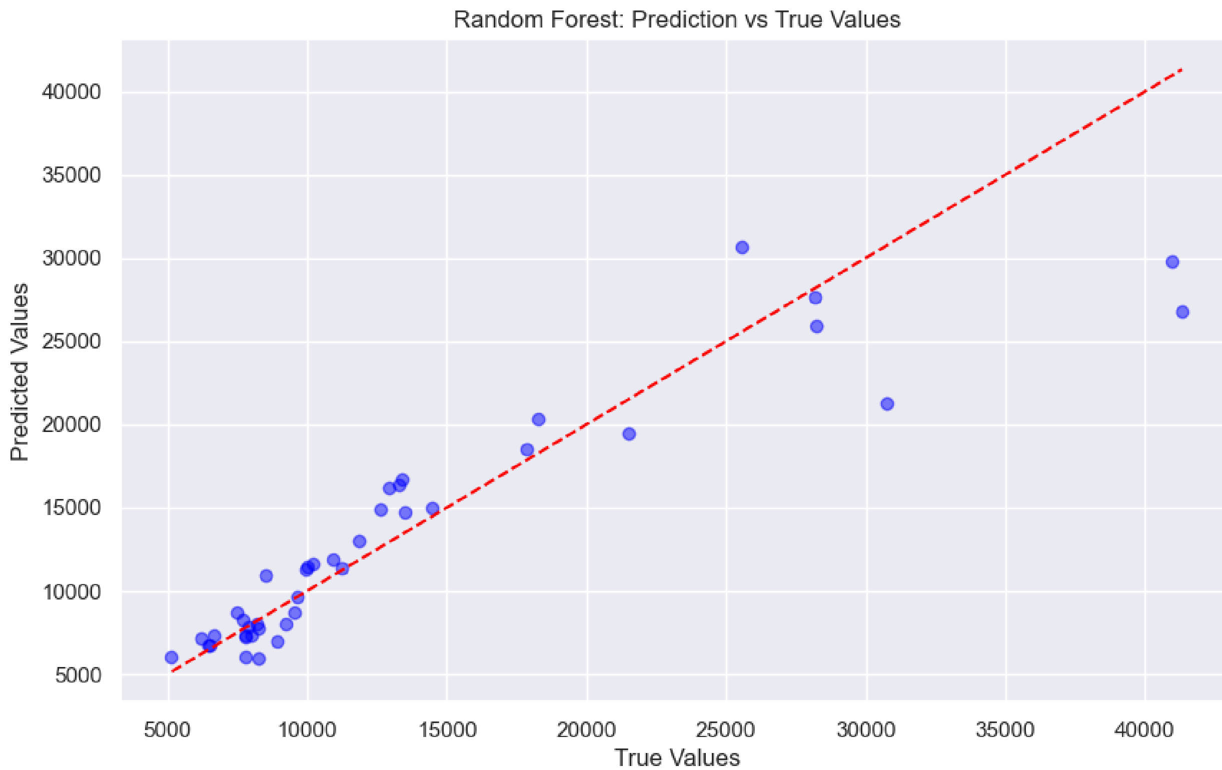
```
array([21234.63 , 18537.87 ,  8714.31 , 13026.23 , 25965.325,
6058.375,
        7265.   ,  7981.51 , 11639.49 ,  7341.47 , 16354.65 ,  7795.71
,
       20358.115, 11458.66 , 29814.24 ,  6725.2  ,  6060.105, 14912.97
,
        8046.03 , 11253.13 , 10940.97 , 14698.61 ,  5919.275,  6733.36
,
        7302.65 , 26782.405,  9648.25 , 16688.52 ,  7312.43 , 16223.62
,
       30686.165,  7150.98 ,  7857.12 , 19450.63 ,  8308.2  ,
27680.455,
       11402.46 , 11931.18 ,  6975.285, 15020.66 ,  8733.14 ])
```

```
# Evaluate the Random Forest model
mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print("\nRandom Forest Regression Evaluation:")
print(f"MAE: {mae_rf}")
print(f"MSE: {mse_rf}")
print(f"R-squared: {r2_rf}")
```

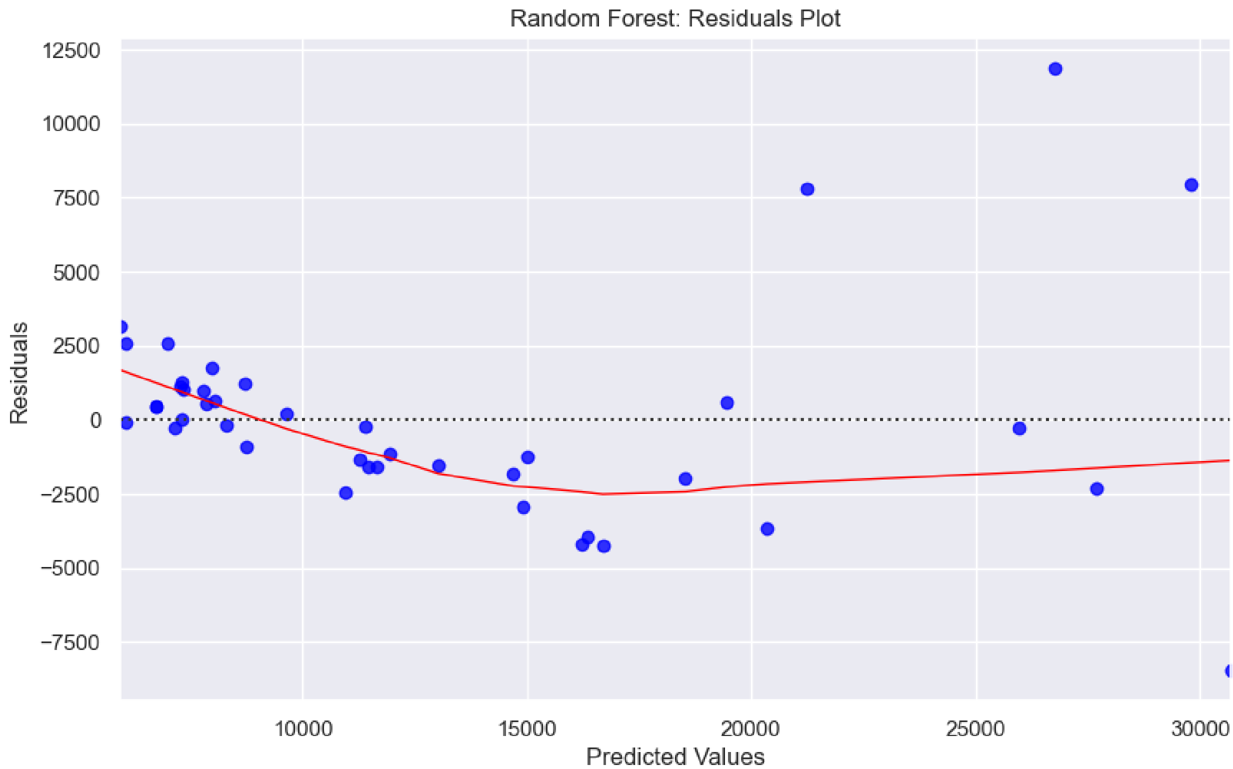
```
Random Forest Regression Evaluation:
MAE: 2090.739463414634
MSE: 13142203.156256925
R-squared: 0.8335250344507925
```

```
# Prediction vs True Values Plot (for Random Forest)
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_rf, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
color='red', linestyle='--')
plt.title('Random Forest: Prediction vs True Values')
```

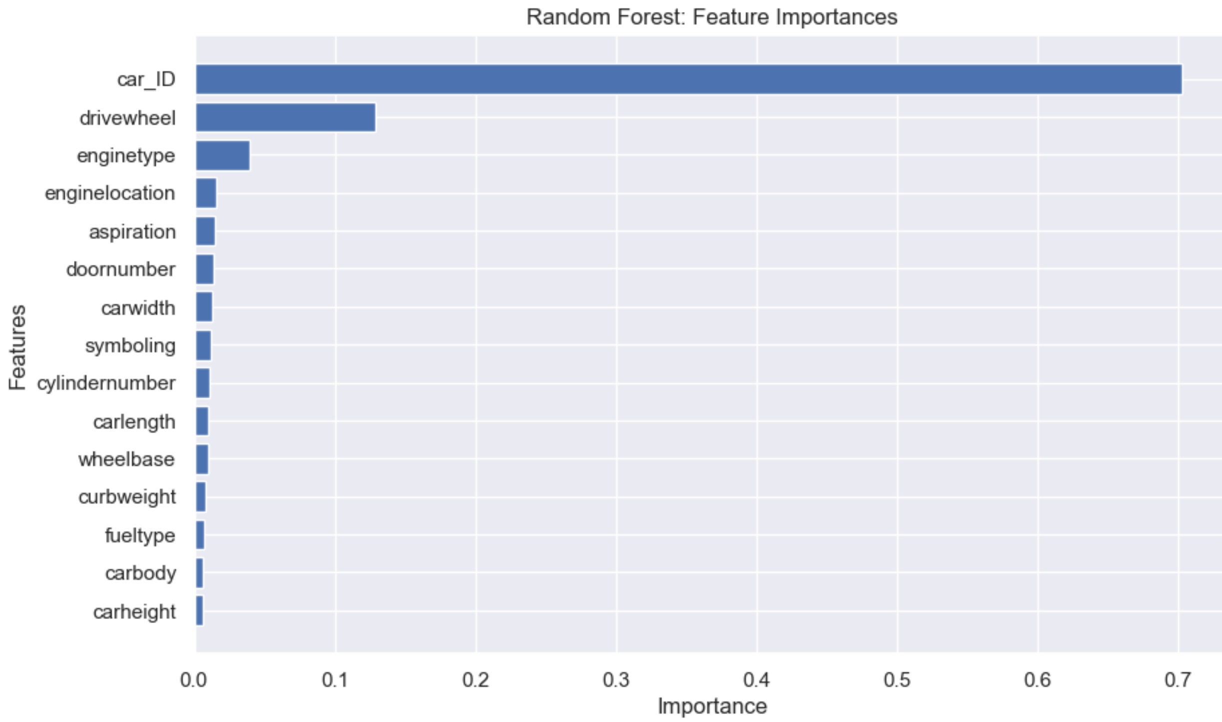
```
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.show()
```




```
# Residuals Plot (Random Forest)
residuals_rf = y_test - y_pred_rf
plt.figure(figsize=(10, 6))
sns.residplot(x=y_pred_rf, y=residuals_rf, lowess=True, color='blue',
line_kws={'color': 'red', 'lw': 1})
plt.title('Random Forest: Residuals Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```




```python
# Feature Importance (Random Forest)
importances = rf_model.feature_importances_
features = x.columns

# Sort feature importances in descending order
indices = importances.argsort()

plt.figure(figsize=(10, 6))
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.title('Random Forest: Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.show()
```



Ridge Regression

```python
from sklearn.linear_model import Ridge, Lasso

# Ridge Regression
ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_train, y_train)

# Make predictions and evaluate Ridge
y_pred_ridge = ridge_model.predict(X_test)
print("Ridge Regression Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred_ridge)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_ridge)}")
print(f"R-squared: {r2_score(y_test, y_pred_ridge)}")
```

```
Ridge Regression Performance:
MAE: 2660.1791265483457
MSE: 15824634.958824884
R-squared: 0.7995461241713546
```

Lasso Regression

```python
# Lasso Regression
lasso_model = Lasso(alpha=0.1)
lasso_model.fit(X_train, y_train)

# Make predictions and evaluate Lasso
y_pred_lasso = lasso_model.predict(X_test)
```

```
print("\nLasso Regression Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred_lasso)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_lasso)}")
print(f"R-squared: {r2_score(y_test, y_pred_lasso)}")
```

```
Lasso Regression Performance:
MAE: 2664.0331372881587
MSE: 15830174.791726185
R-squared: 0.7994759499790653
```

Gradient Boosting Regressor

```
from sklearn.ensemble import GradientBoostingRegressor

# Apply Gradient Boosting Regressor
gb_model = GradientBoostingRegressor(n_estimators=100,
learning_rate=0.1, max_depth=3, random_state=42)
gb_model.fit(X_train, y_train)

# Make predictions and evaluate GB
y_pred_gb = gb_model.predict(X_test)
print("\nGradient Boosting Regression Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred_gb)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_gb)}")
print(f"R-squared: {r2_score(y_test, y_pred_gb)}")
```

```
Gradient Boosting Regression Performance:
MAE: 2151.261016339273
MSE: 13214894.044313649
R-squared: 0.8326042441585482
```

XGBoost Regressor

```
import xgboost as xgb

# Apply XGBoost Regressor
xgb_model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1,
max_depth=3, random_state=42)
xgb_model.fit(X_train, y_train)

# Make predictions and evaluate XGBoost
y_pred_xgb = xgb_model.predict(X_test)
print("\nXGBoost Regression Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred_xgb)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_xgb)}")
print(f"R-squared: {r2_score(y_test, y_pred_xgb)}")
```

```
XGBoost Regression Performance:
```

```
MAE: 1991.606135480183
MSE: 11071641.628366638
R-squared: 0.8597532592716014
```