In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import os
%matplotlib inline
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("Downloads/CarPrice_Assignment.csv")
```

In [3]:
```
df
```

Out[3]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	en
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	
...	...	...	...	...	...	...	...	...	
200	201	-1	volvo 145e (sw)	gas	std	four	sedan	rwd	
201	202	-1	volvo 144ea	gas	turbo	four	sedan	rwd	
202	203	-1	volvo 244dl	gas	std	four	sedan	rwd	
203	204	-1	volvo 246	diesel	turbo	four	sedan	rwd	
204	205	-1	volvo 264gl	gas	turbo	four	sedan	rwd	

205 rows × 26 columns

In [4]:
```
#Make a Copy of the Original dataset Which can help me in future
df1 = df.copy(deep=True)
df2 = df.copy(deep=True)
```

Data Preprocessing

In [5]:
```
df.describe()
```

Out[5]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enç
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326

In [6]:
```
df.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
```

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
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
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'price'],
      dtype='object')
```

EXPLORATORY DATA ANALYSIS

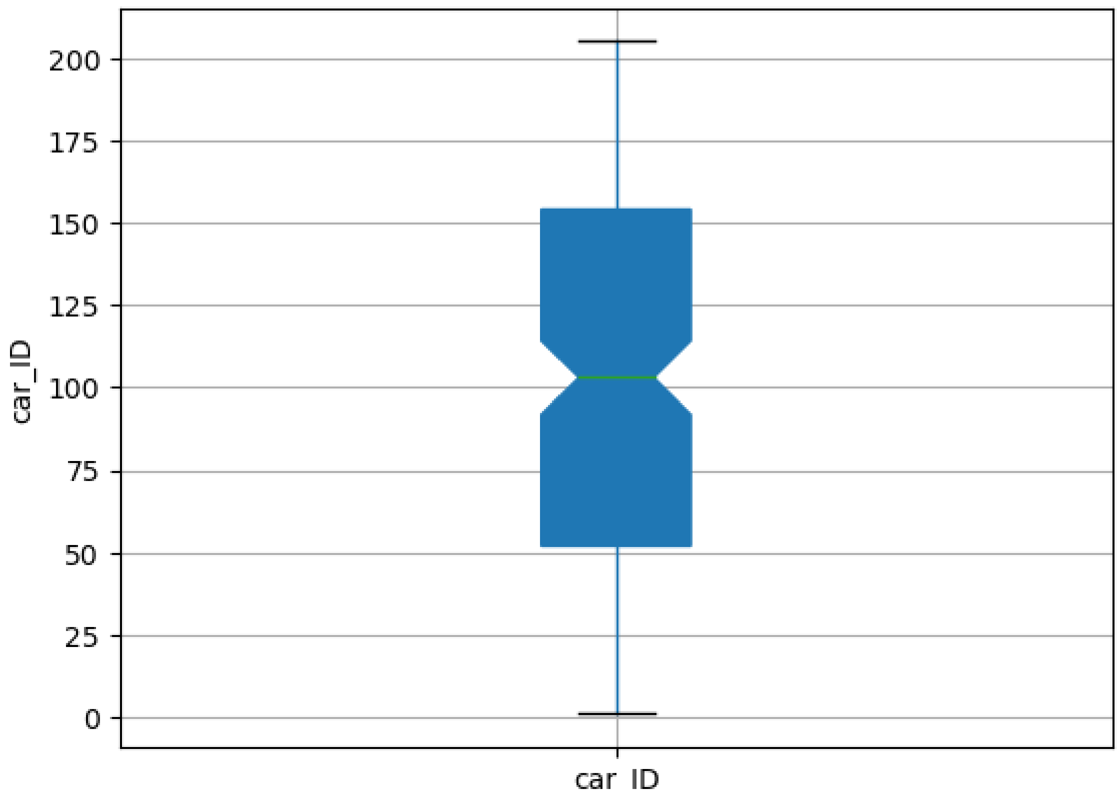
In [9]:
```
#First Of all we seperate categorical and numerical data
cat = df.select_dtypes(include="object")
num = df.select_dtypes(include="number")
```

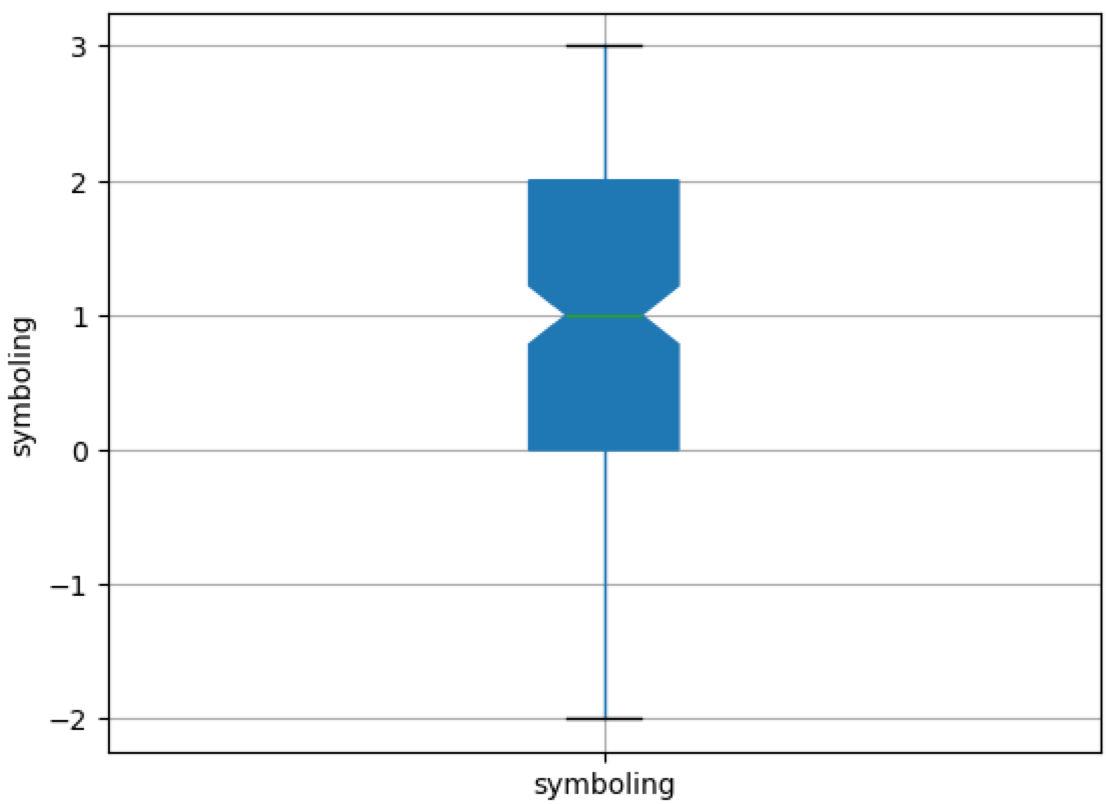
In [10]:
```
cat.head()
```

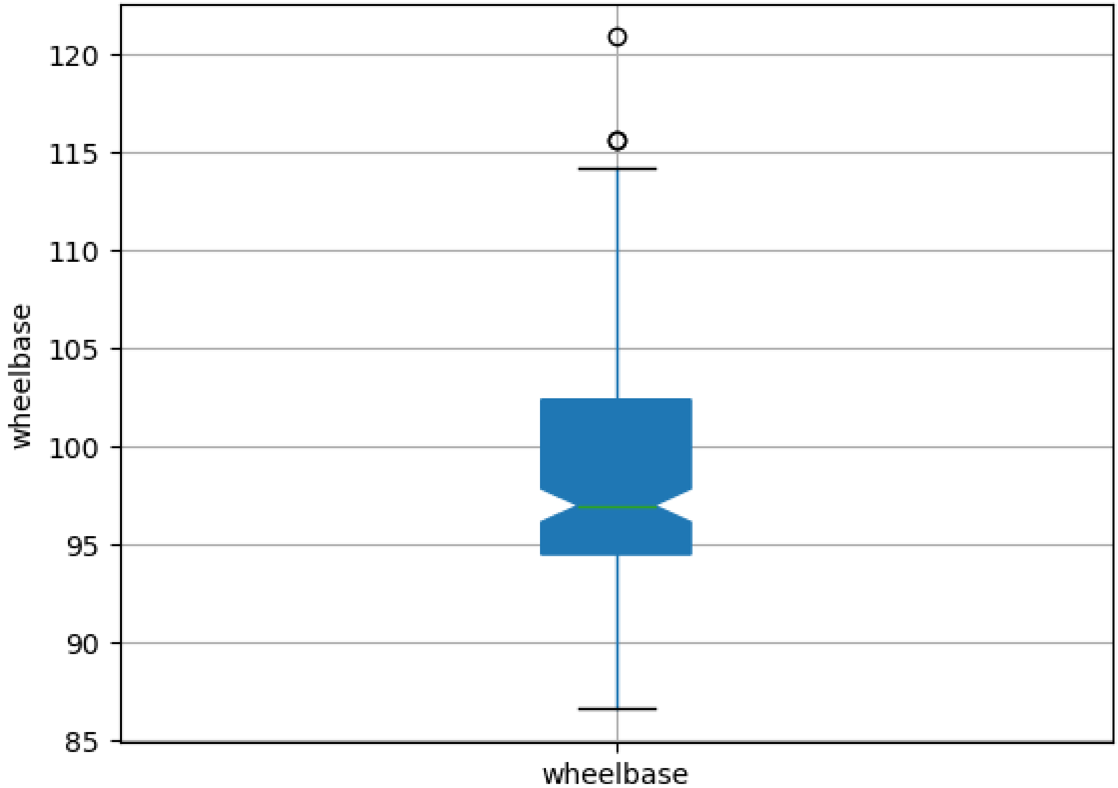
Out[10]:

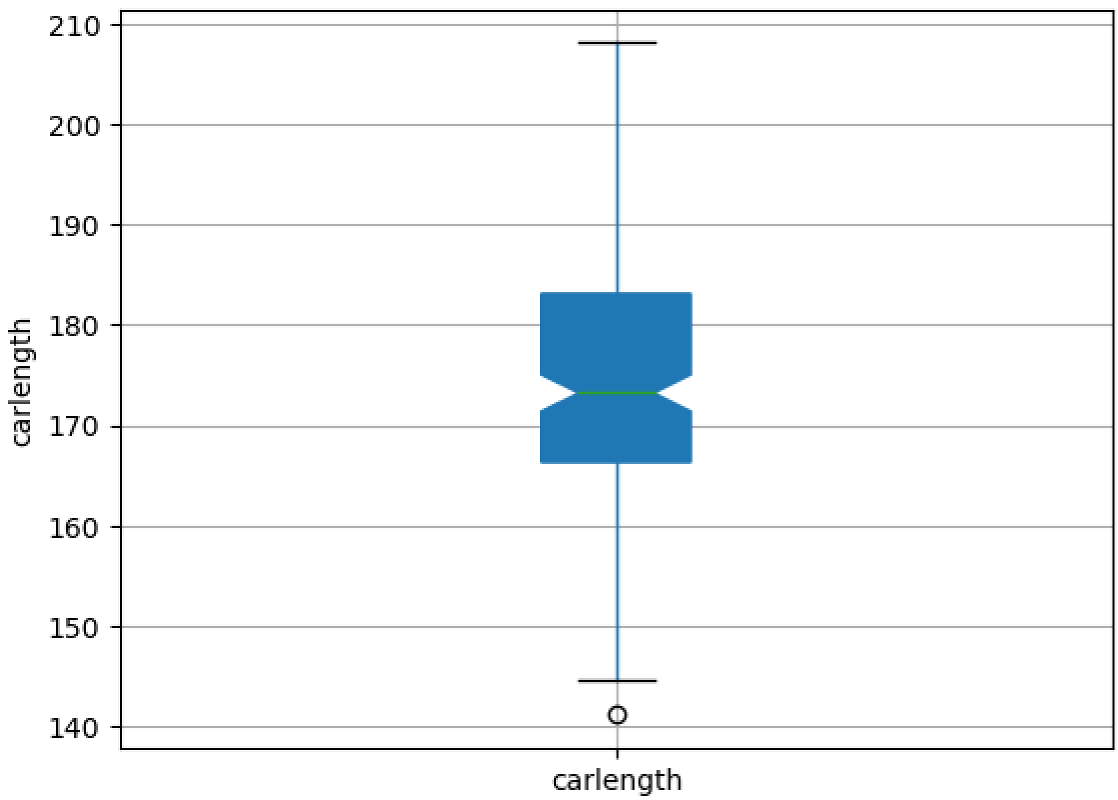
	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	enginetyp
0	alfa-romero giulia	gas	std	two	convertible	rwd	front	dol
1	alfa-romero stelvio	gas	std	two	convertible	rwd	front	dol
2	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	oh
3	audi 100 ls	gas	std	four	sedan	fwd	front	ol
4	audi 100ls	gas	std	four	sedan	4wd	front	ol

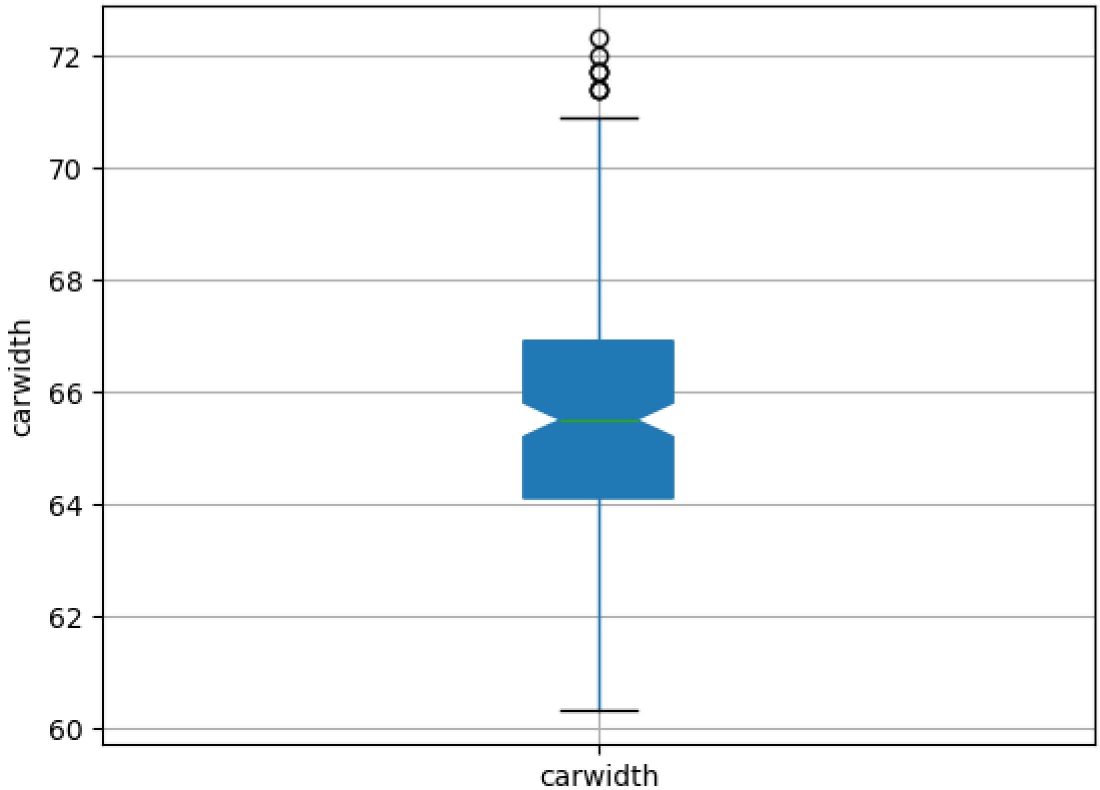
In [11]:
```
#for numerical distrubition
for i in num:
    num.boxplot(column=i,patch_artist = True, notch ='True')
    plt.ylabel(i)
    plt.show()
```

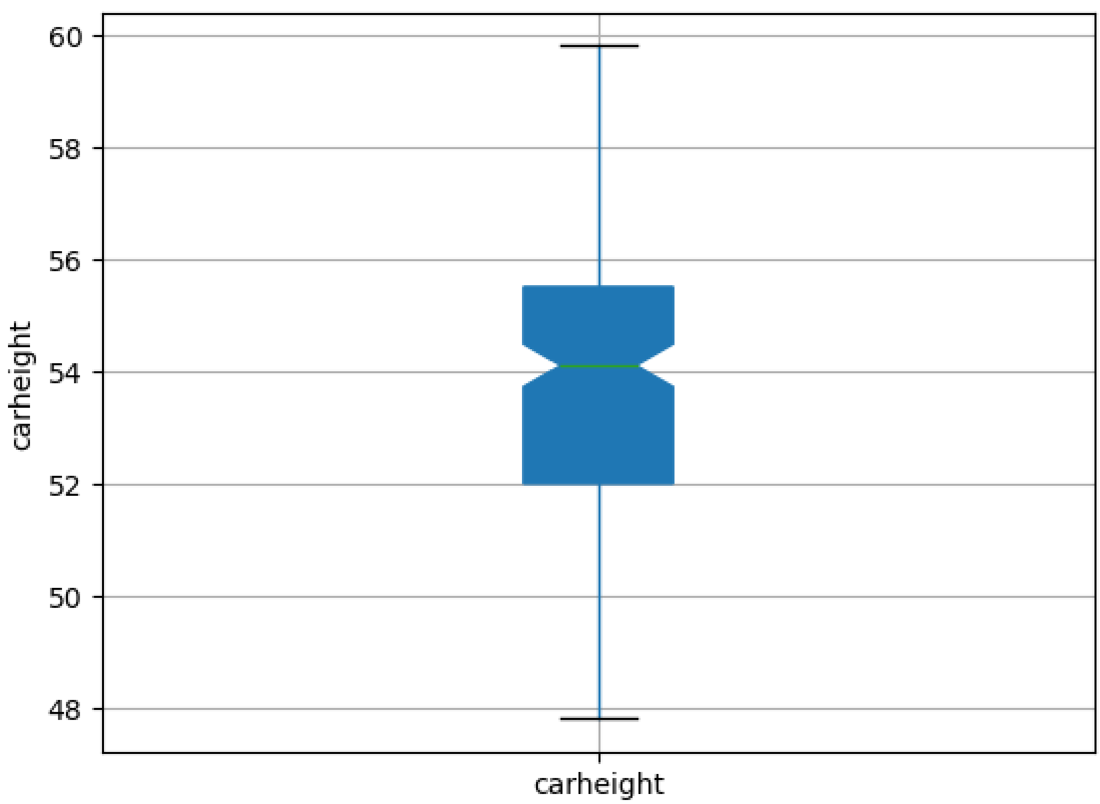

200
175
150
125
100
75
50
25
0
car_ID
car_ID

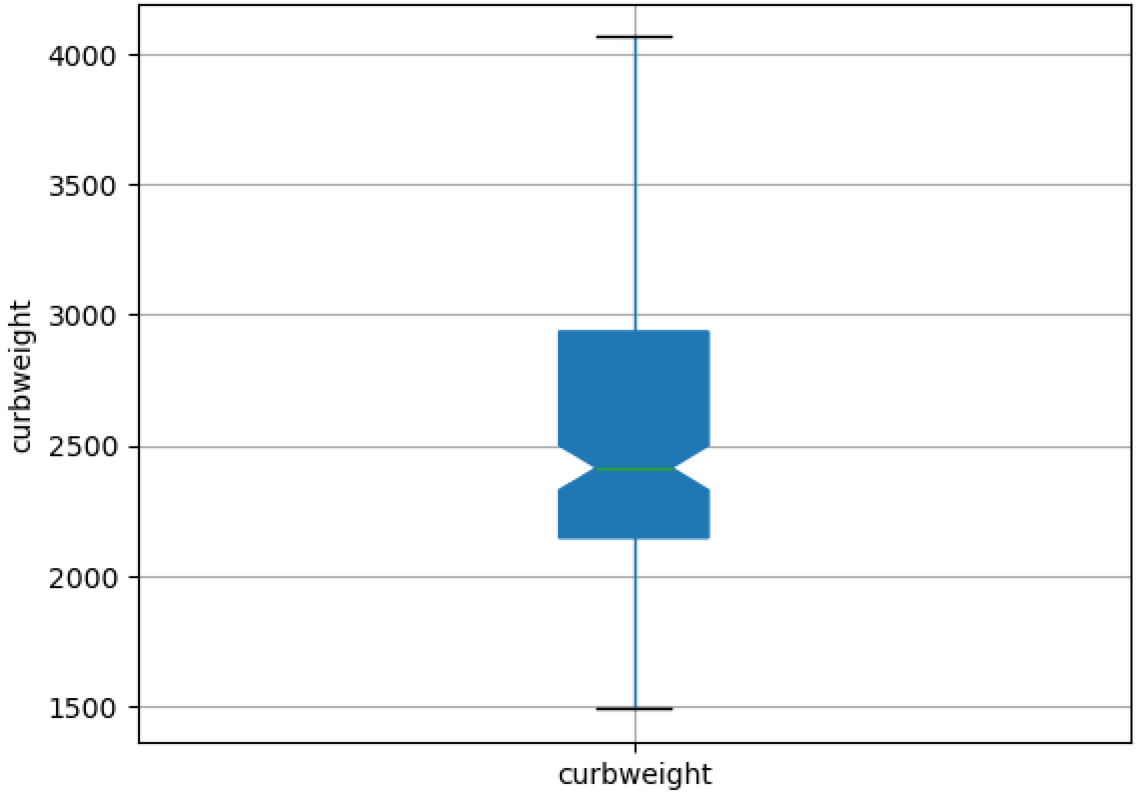

3
2
1
0
−1
−2
symboling
symboling

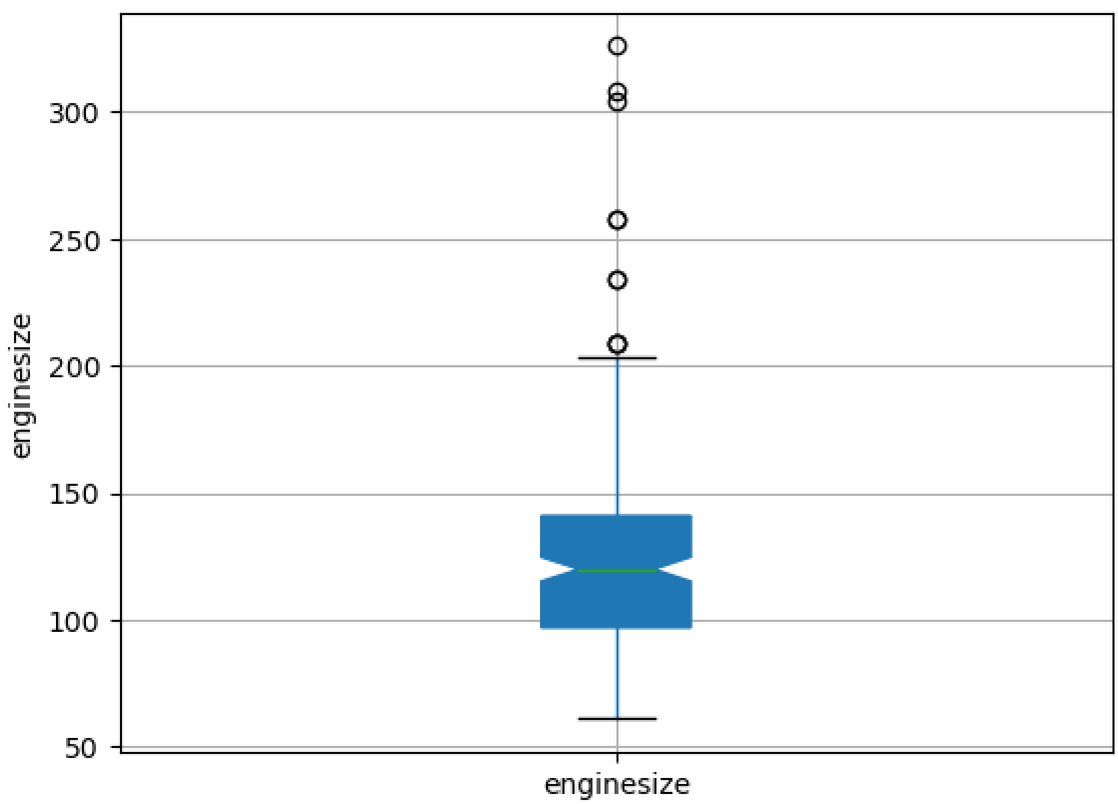

120
115
110
105
100
95
90
85
wheelbase
wheelbase

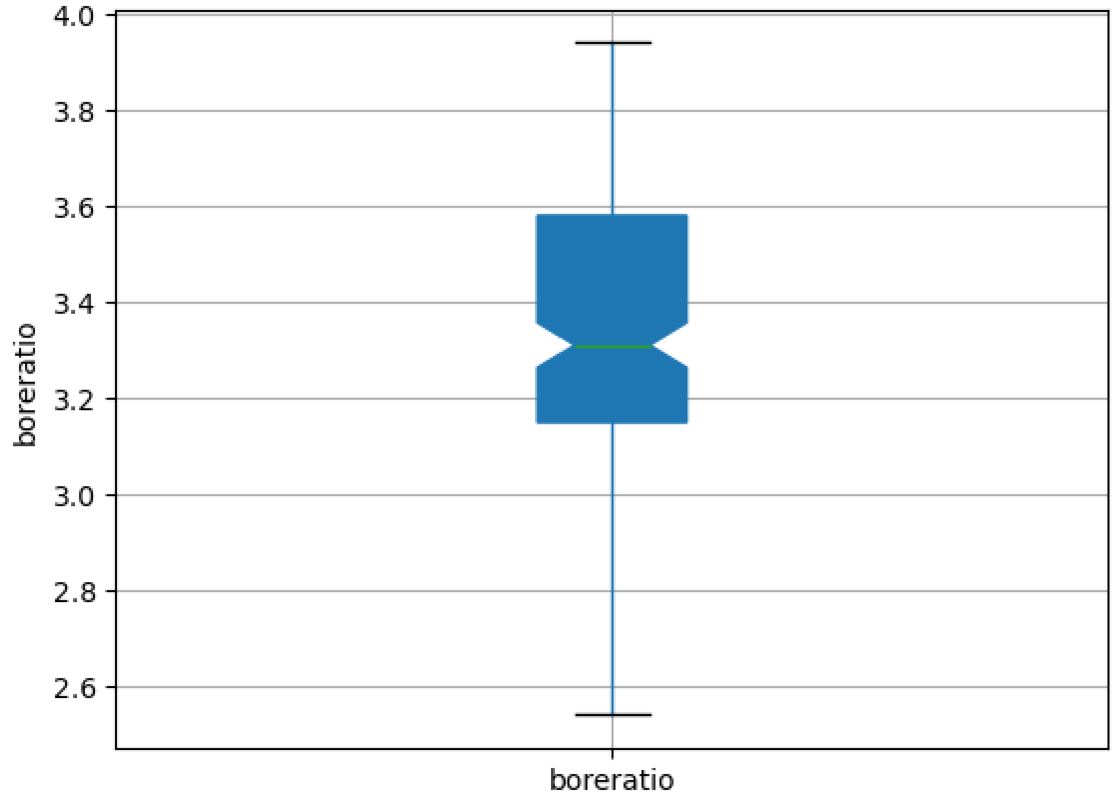

210
200
190
180
170
160
150
140
carlength
carlength

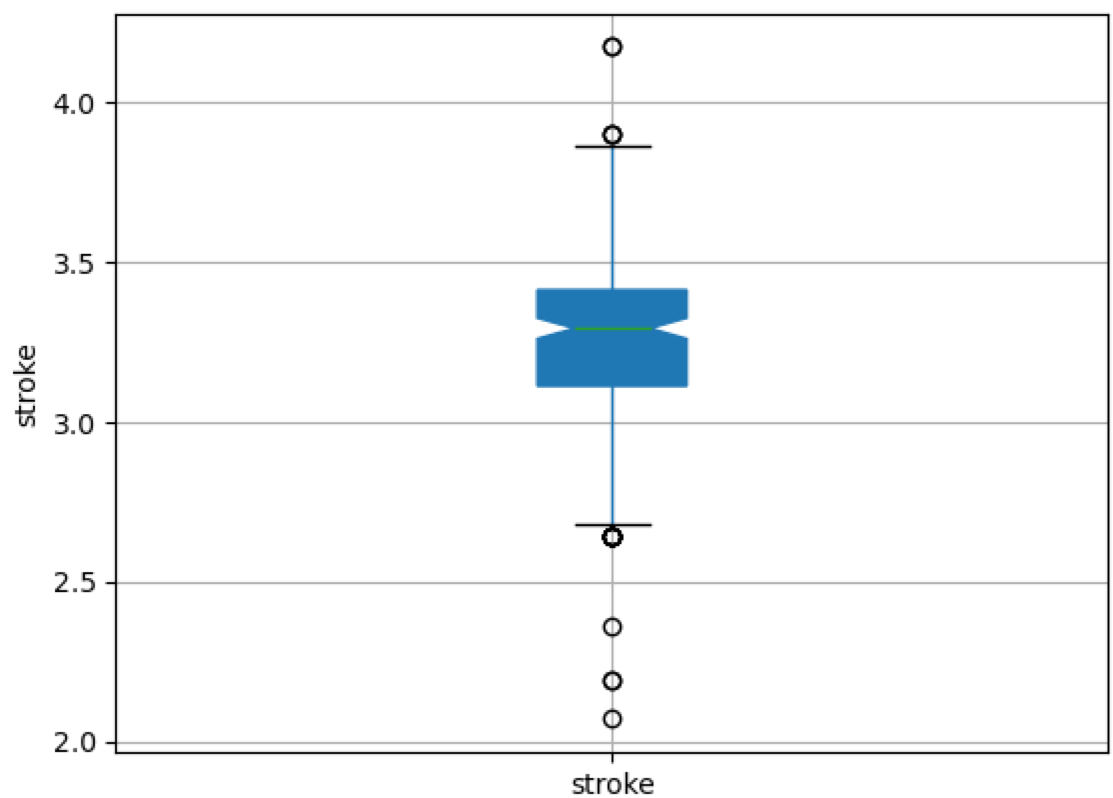

72
70
68
66
64
62
60
carwidth
carwidth

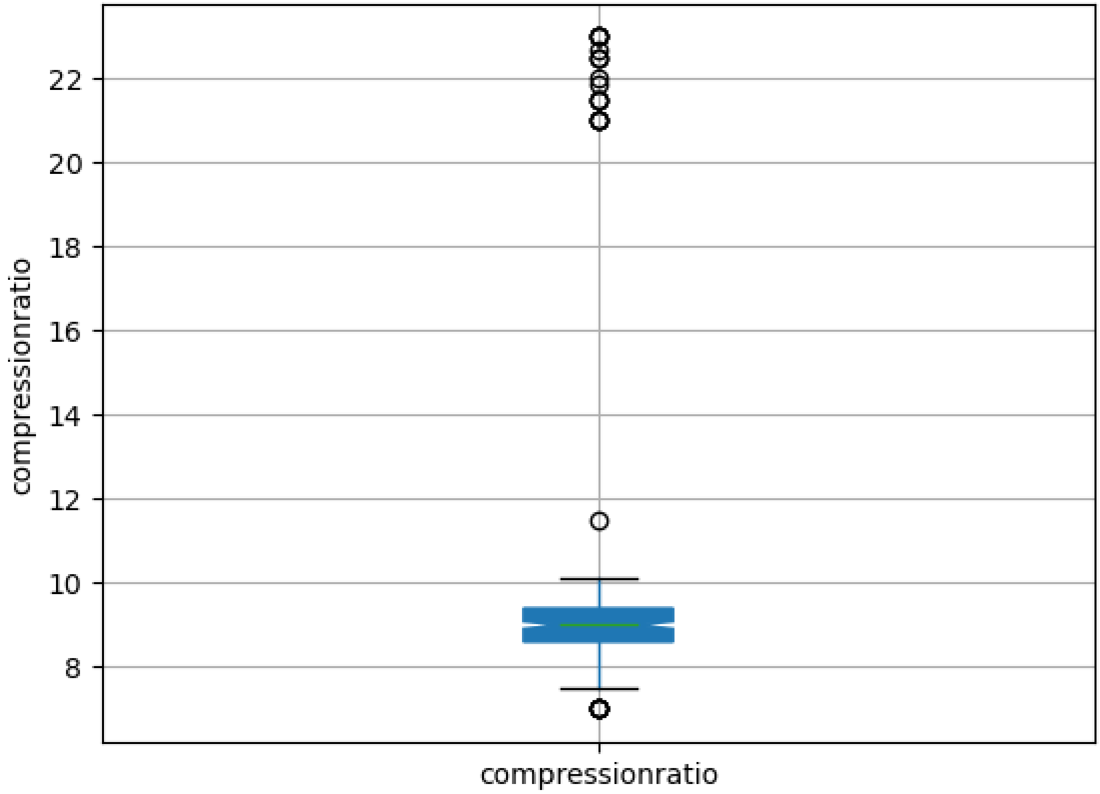

60
58
56
54
52
50
48
carheight
carheight


4000
3500
3000
2500
2000
1500
curbweight
curbweight

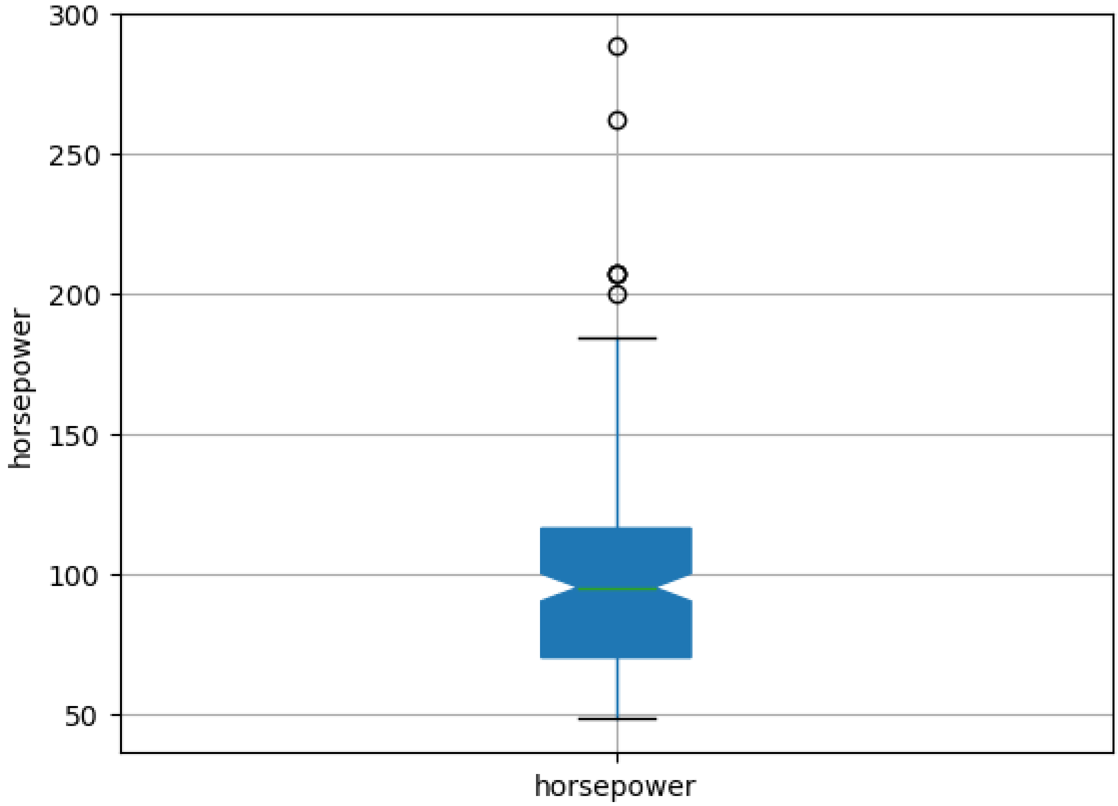

300
250
200
150
100
50
enginesize
enginesize


4.0
3.8
3.6
3.4
3.2
3.0
2.8
2.6
boreratio
boreratio

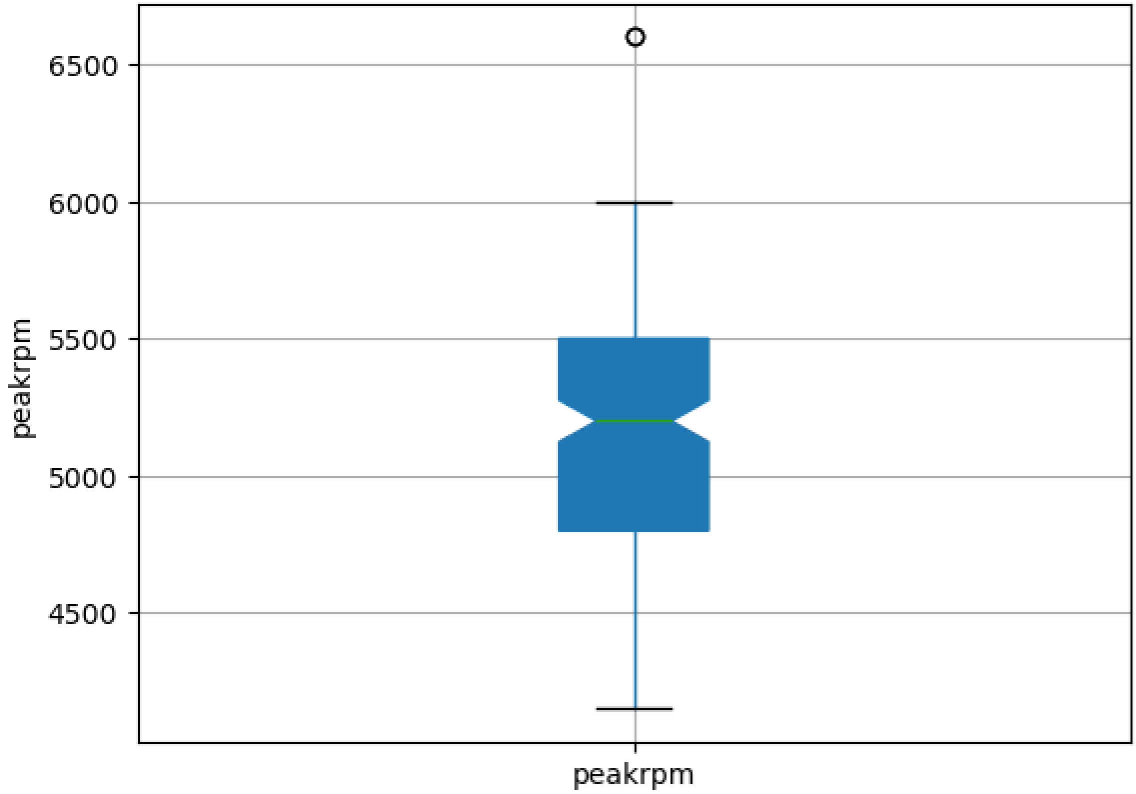

4.0
3.5
3.0
2.5
2.0
stroke
stroke

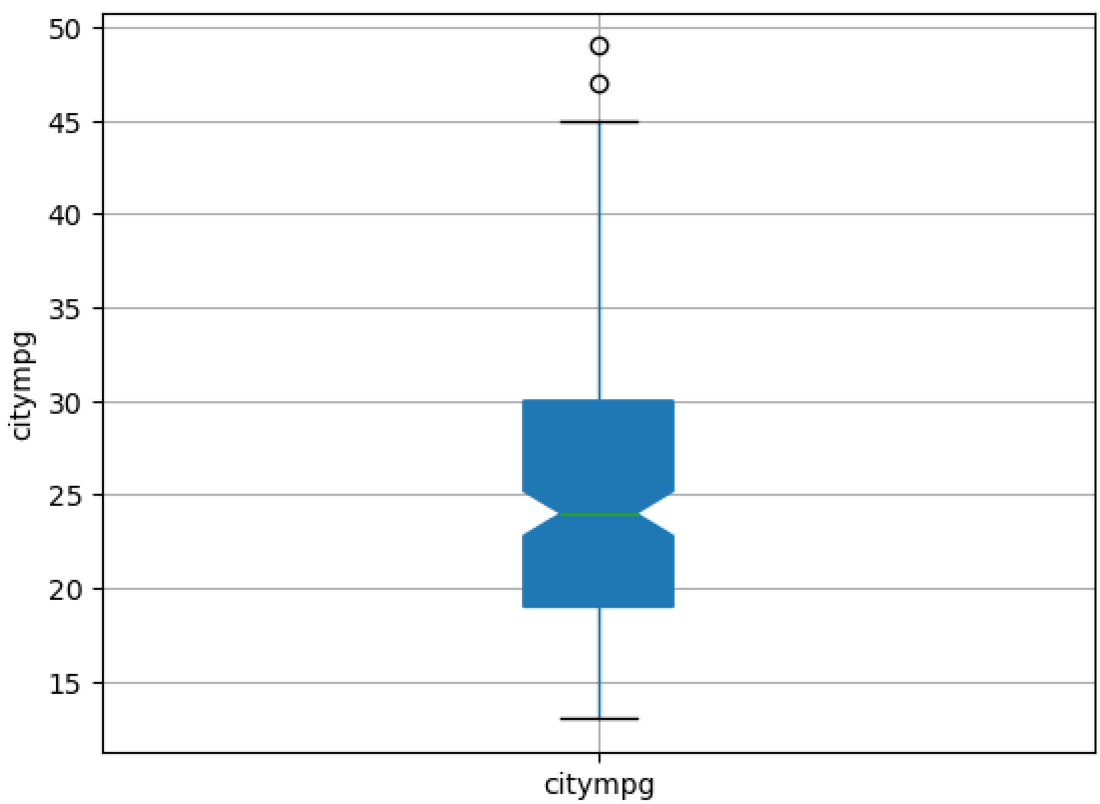


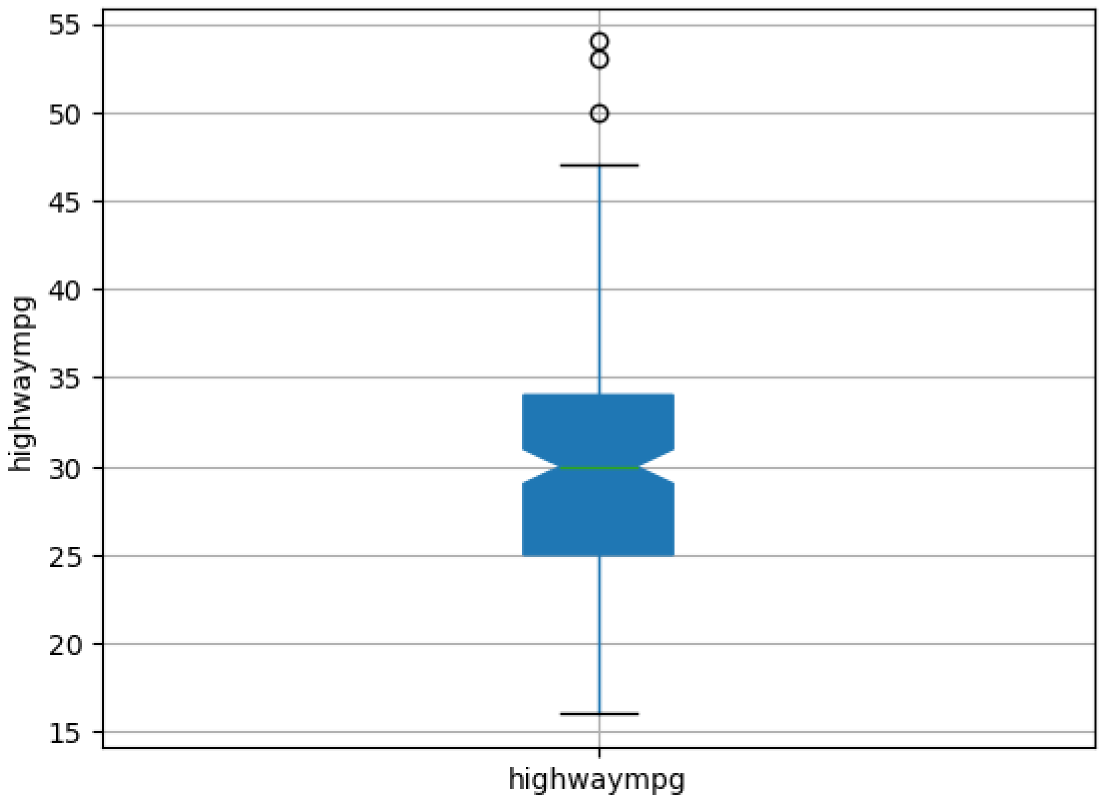
22
20
18
16
14
12
10
8
compressionratio
compressionratio

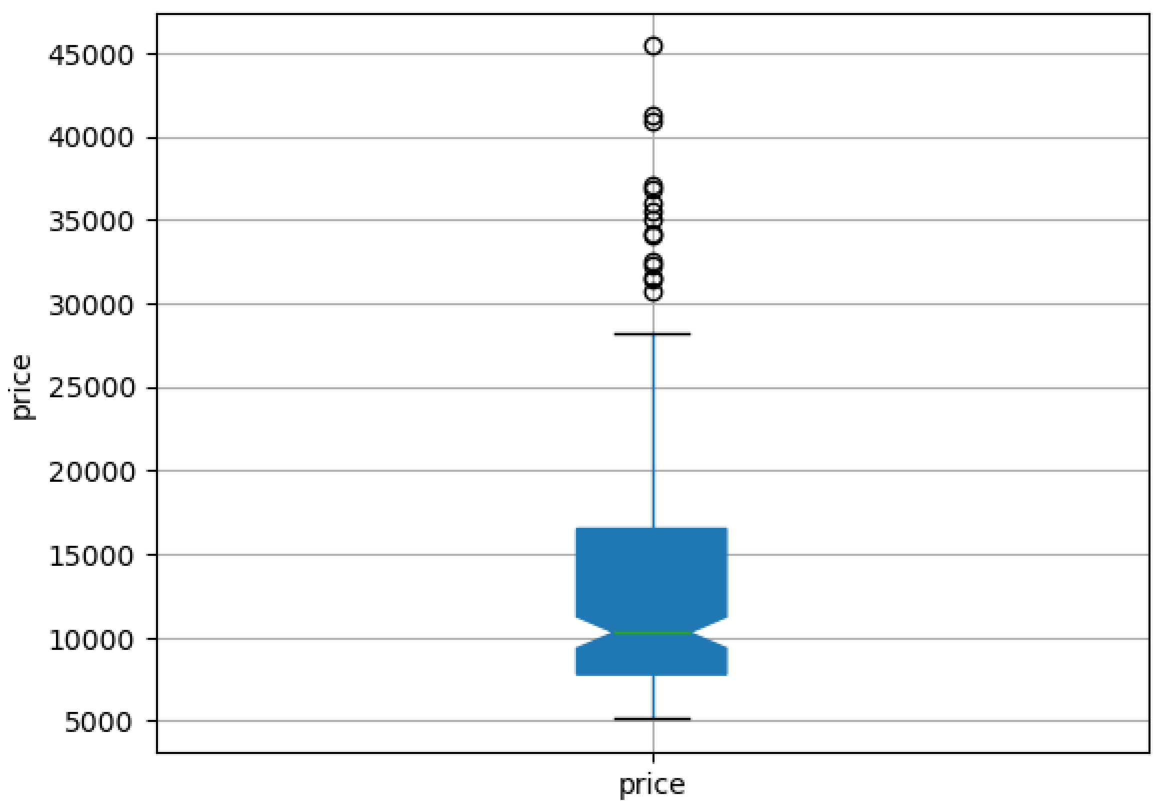


300
250
200
150
100
50
horsepower
horsepower


6500
6000
5500
5000
4500
peakrpm
peakrpm

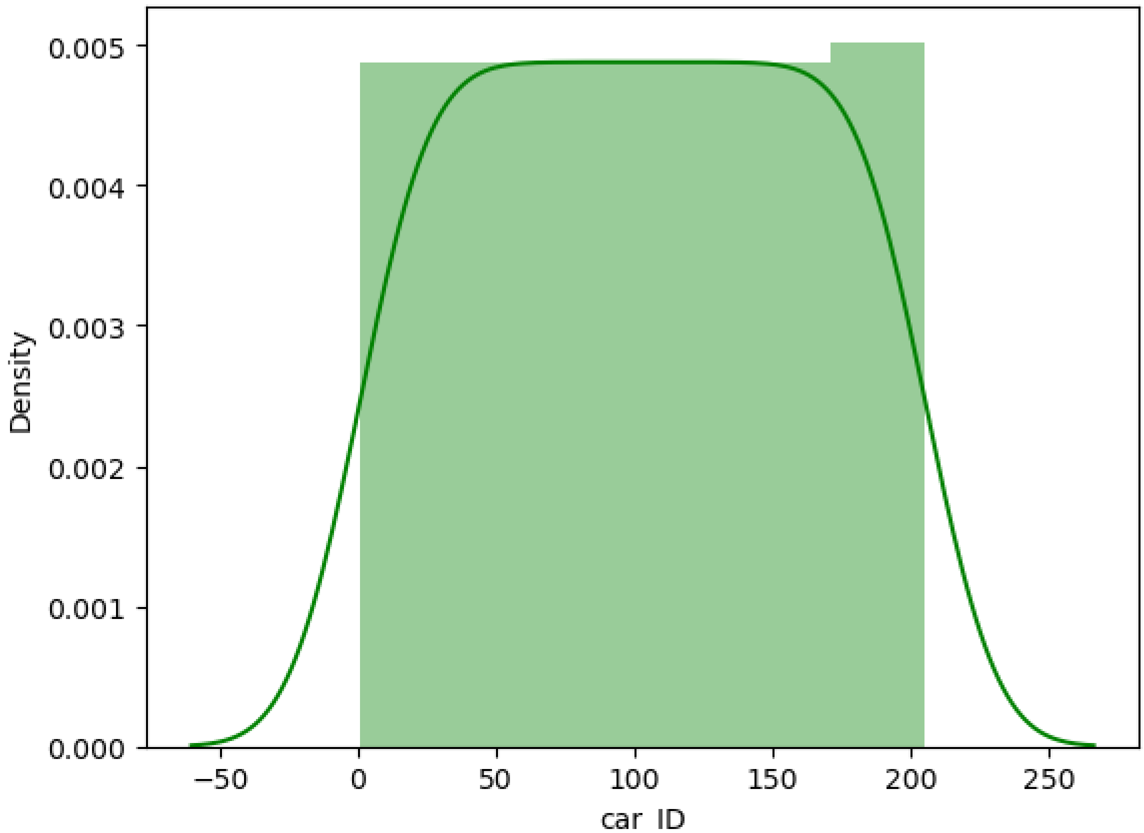

50
45
40
35
30
25
20
15
citympg
citympg

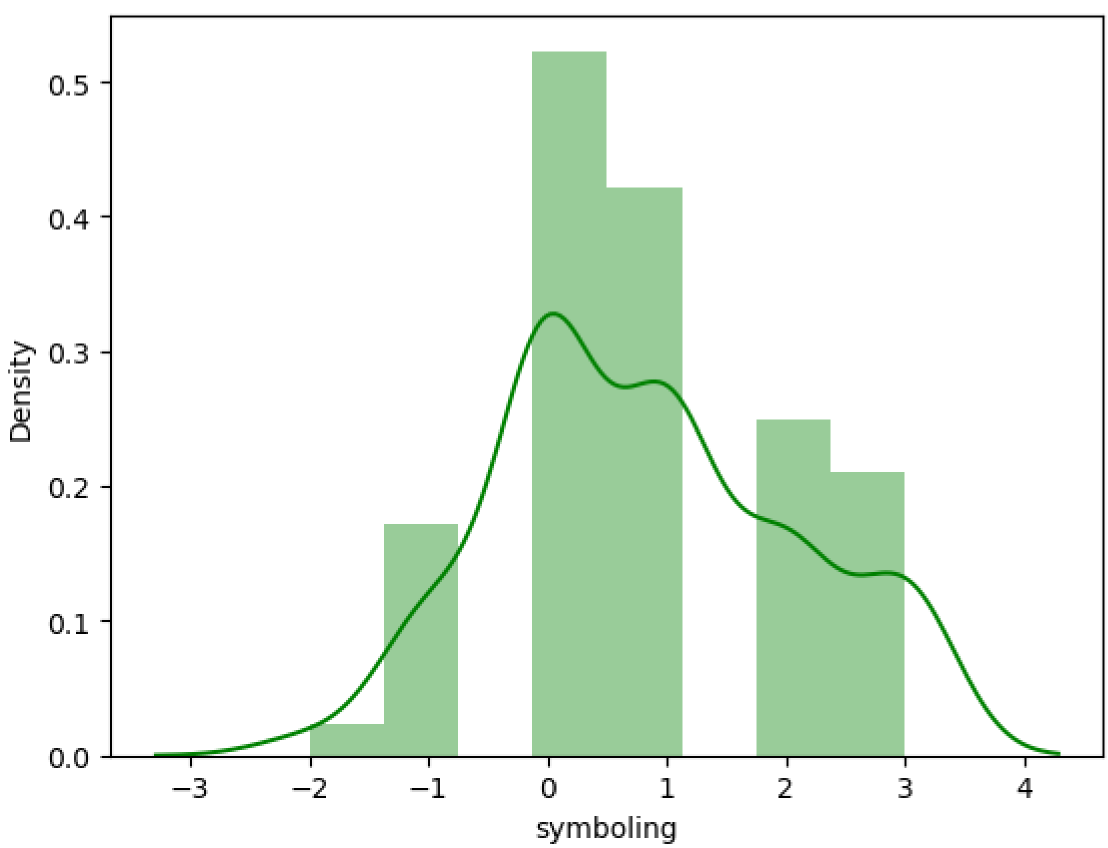


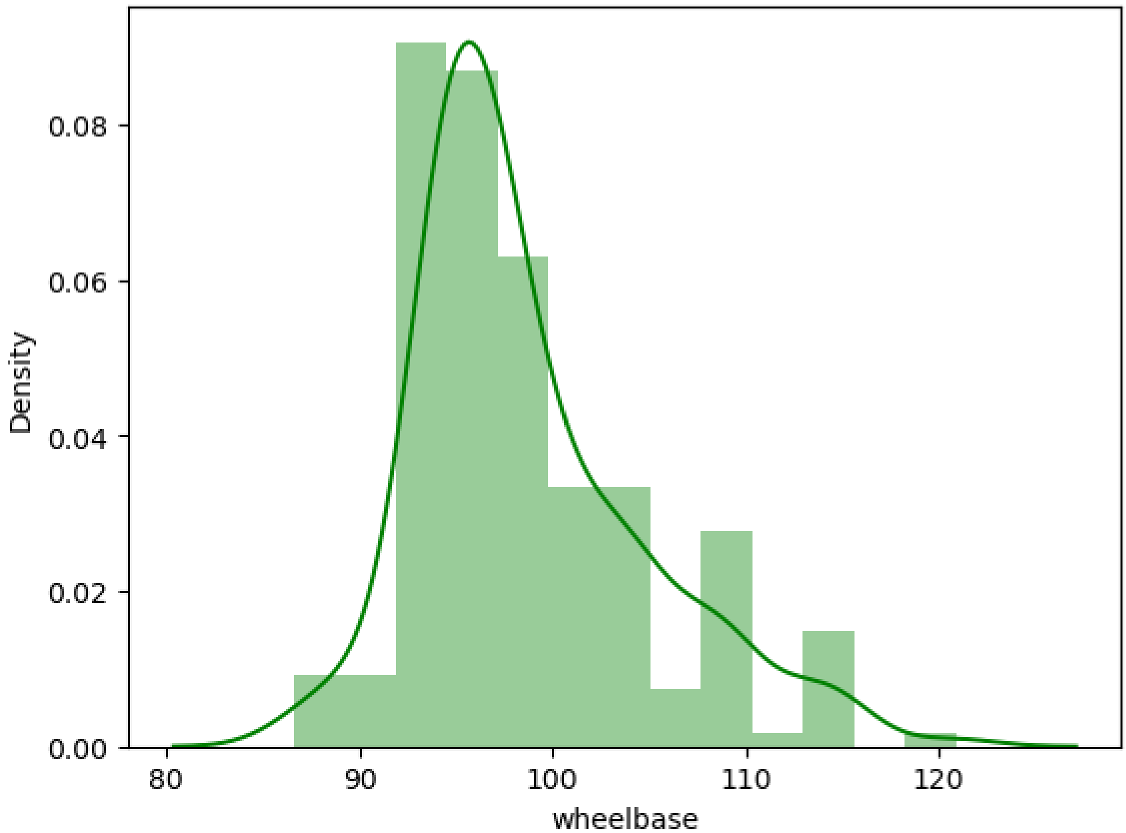


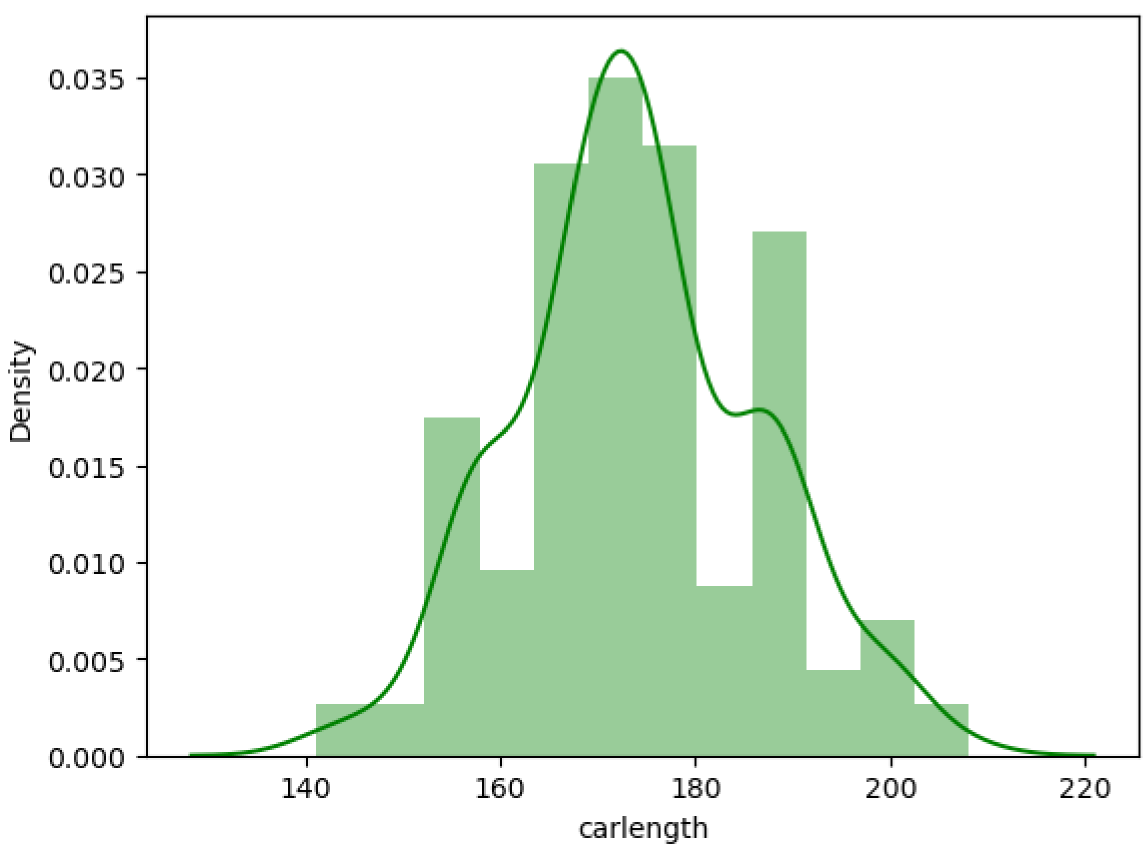
In [12]:
```
#we check distrubition of the numerical data
```

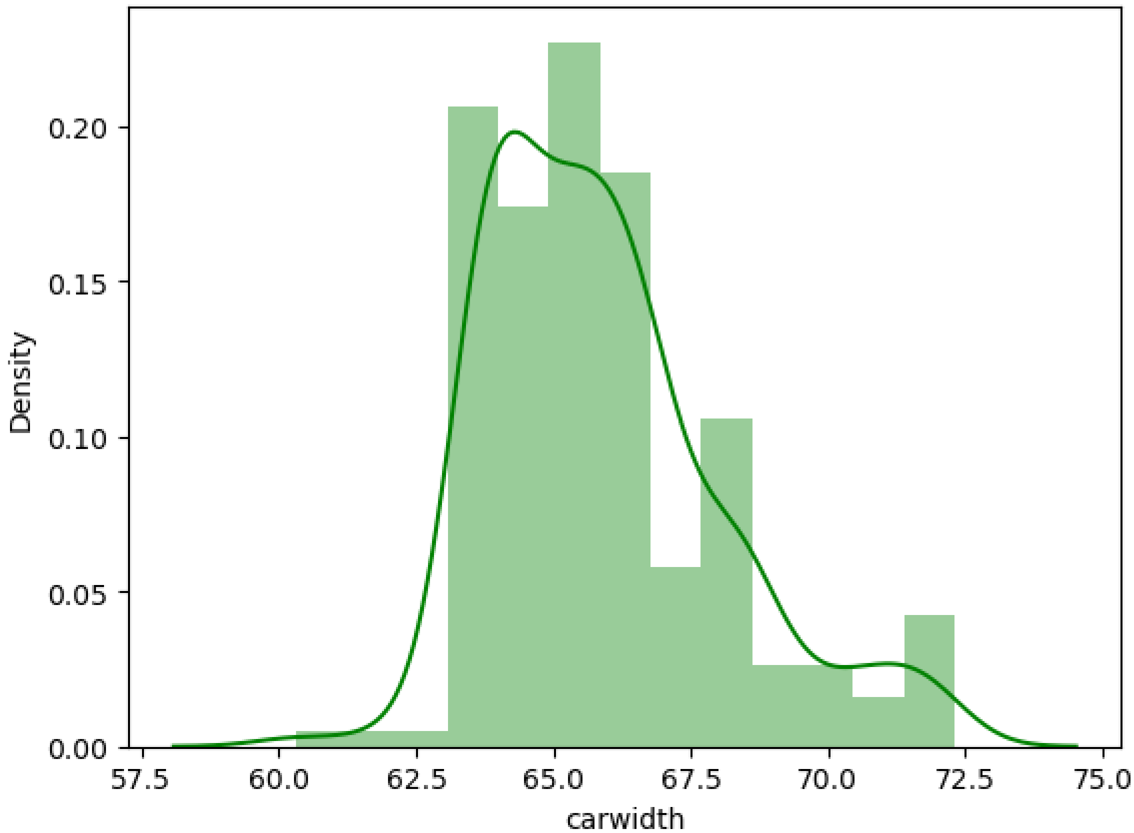
In [13]:
```
for i in num:
    sns.distplot(df[i], kde = True, color = 'green')
    plt.show()
```

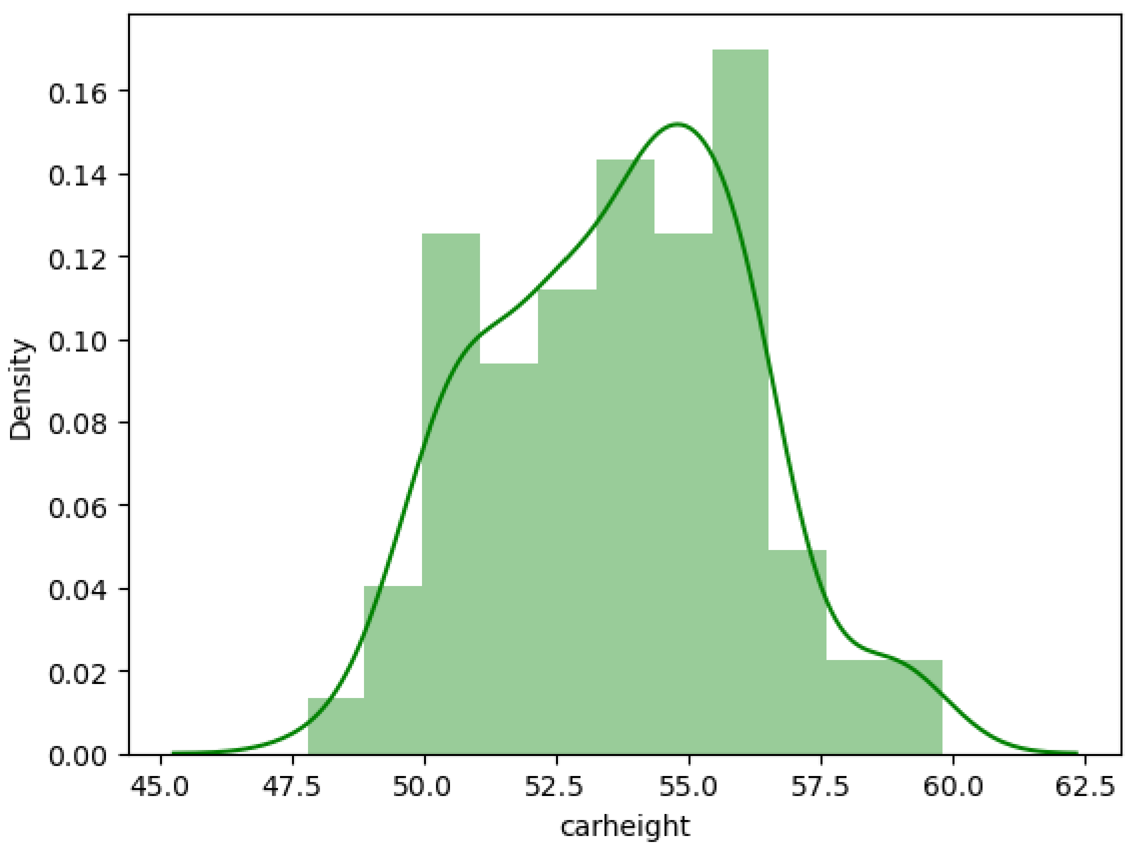

0.005
0.004
0.003
0.002
0.001
0.000
Density
−50
0
50
100
150
200
250
car_ID

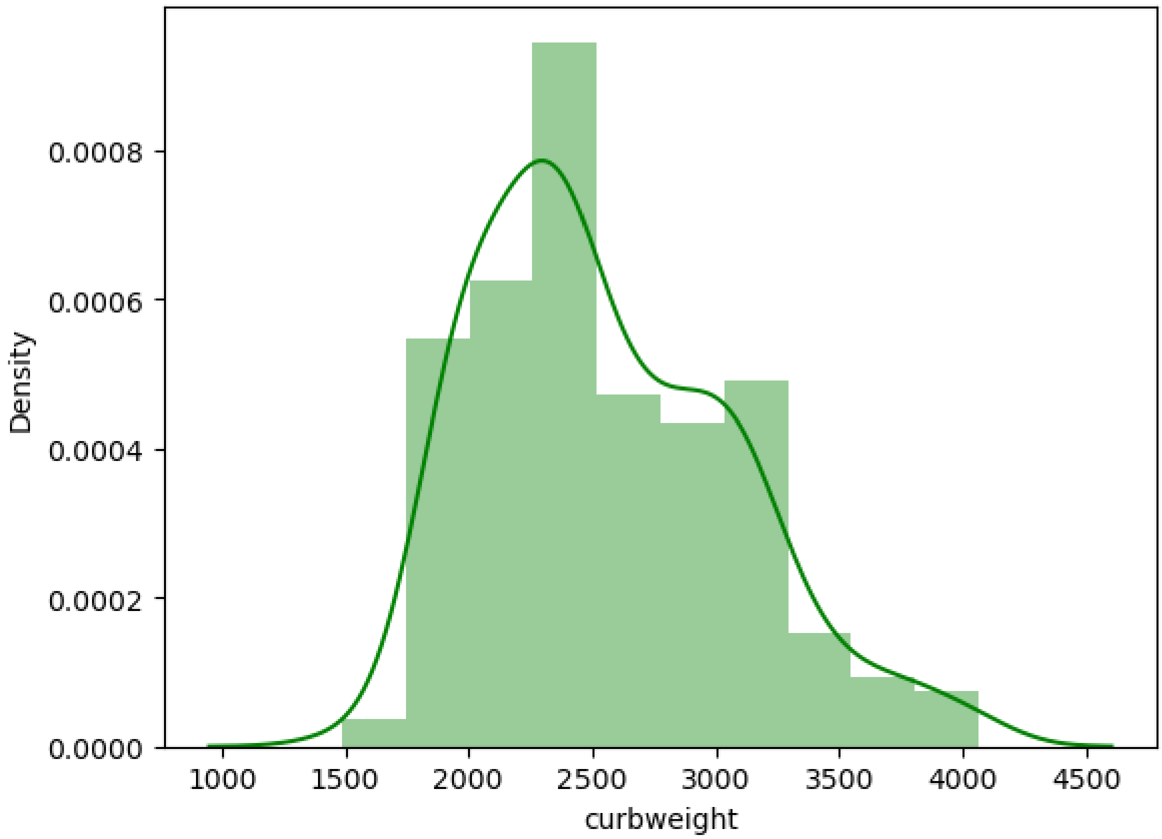

0.5
0.4
0.3
0.2
0.1
0.0
Density
−3
−2
−1
0
1
2
3
4
symboling

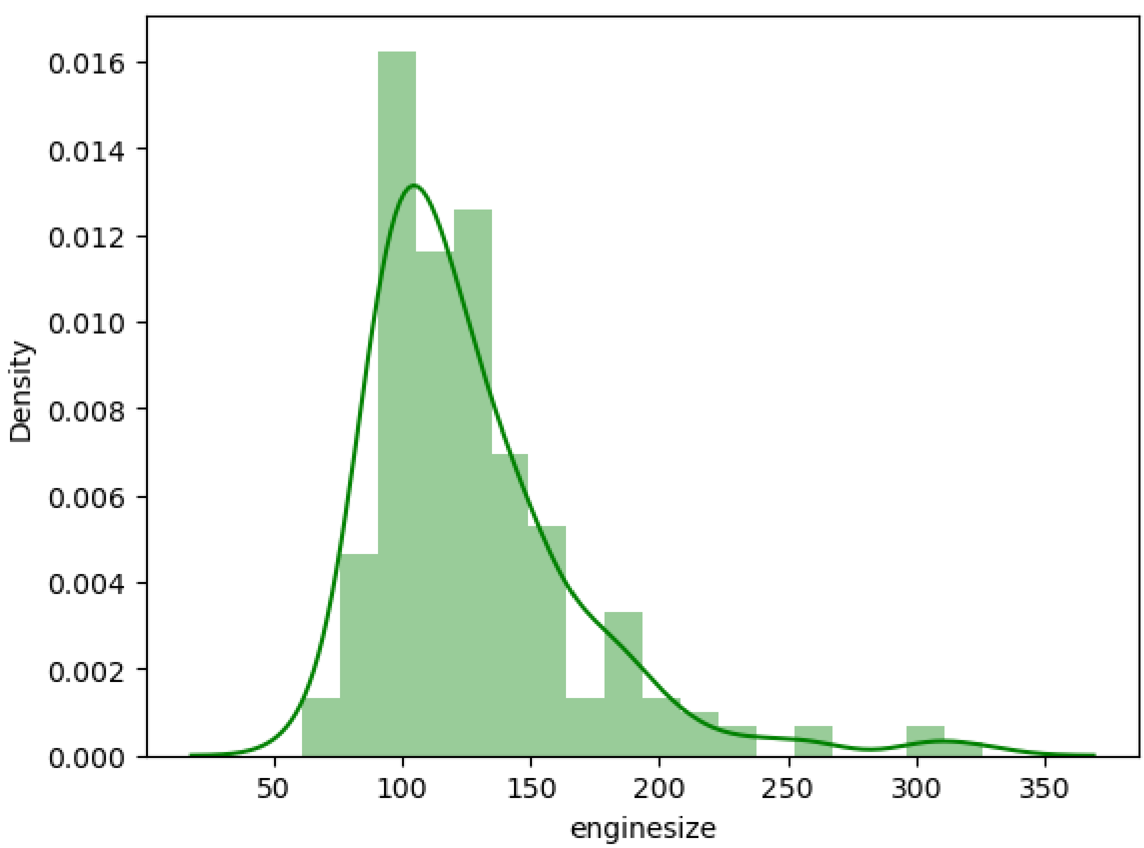

0.08
0.06
0.04
0.02
0.00
Density
80
90
100
110
120
wheelbase

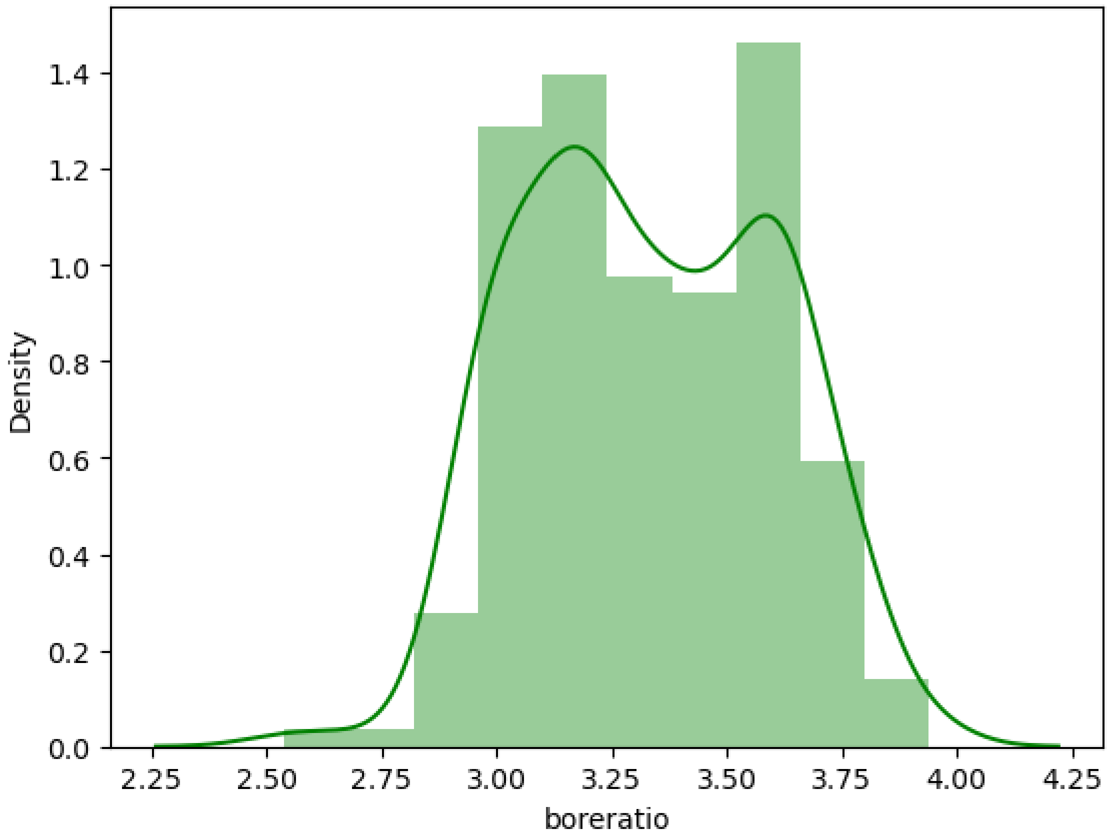

0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
140
160
180
200
220
carlength

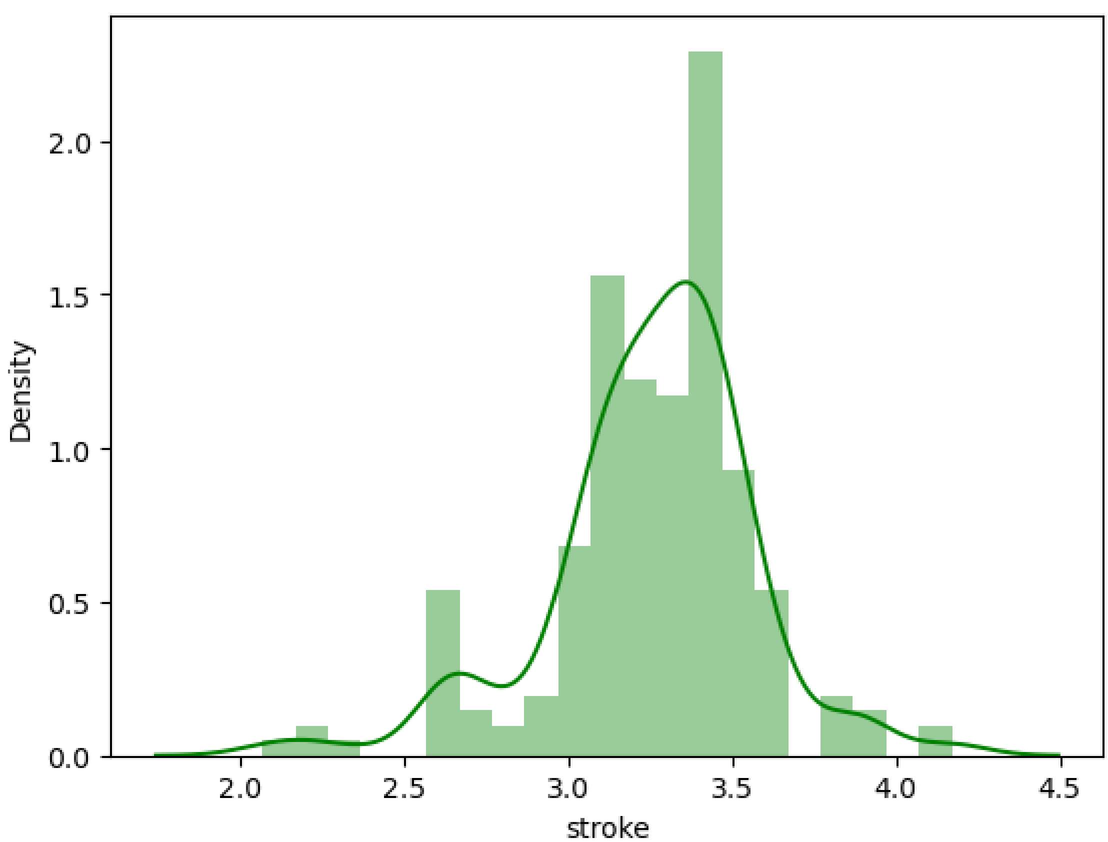

0.20
0.15
0.10
0.05
0.00
Density
57.5
60.0
62.5
65.0
67.5
70.0
72.5
75.0
carwidth

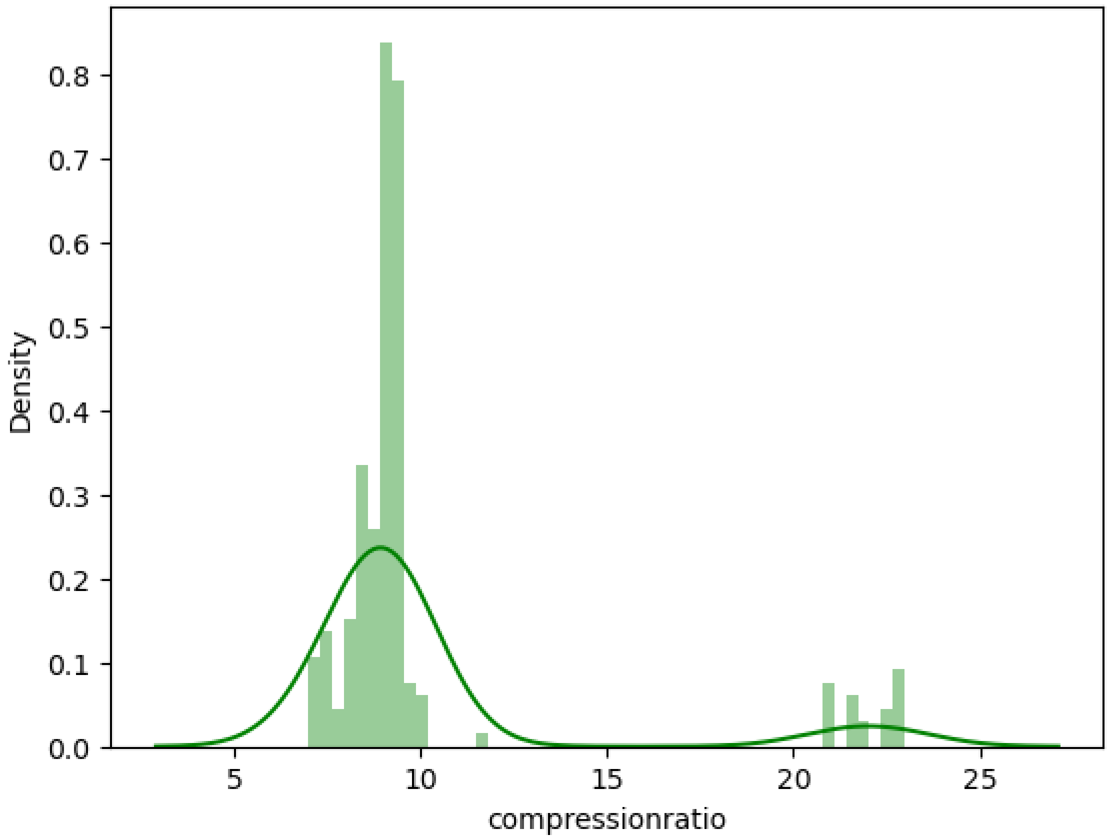

0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Density
45.0
47.5
50.0
52.5
55.0
57.5
60.0
62.5
carheight


0.0008
0.0006
0.0004
0.0002
0.0000
Density
1000
1500
2000
2500
3000
3500
4000
4500
curbweight

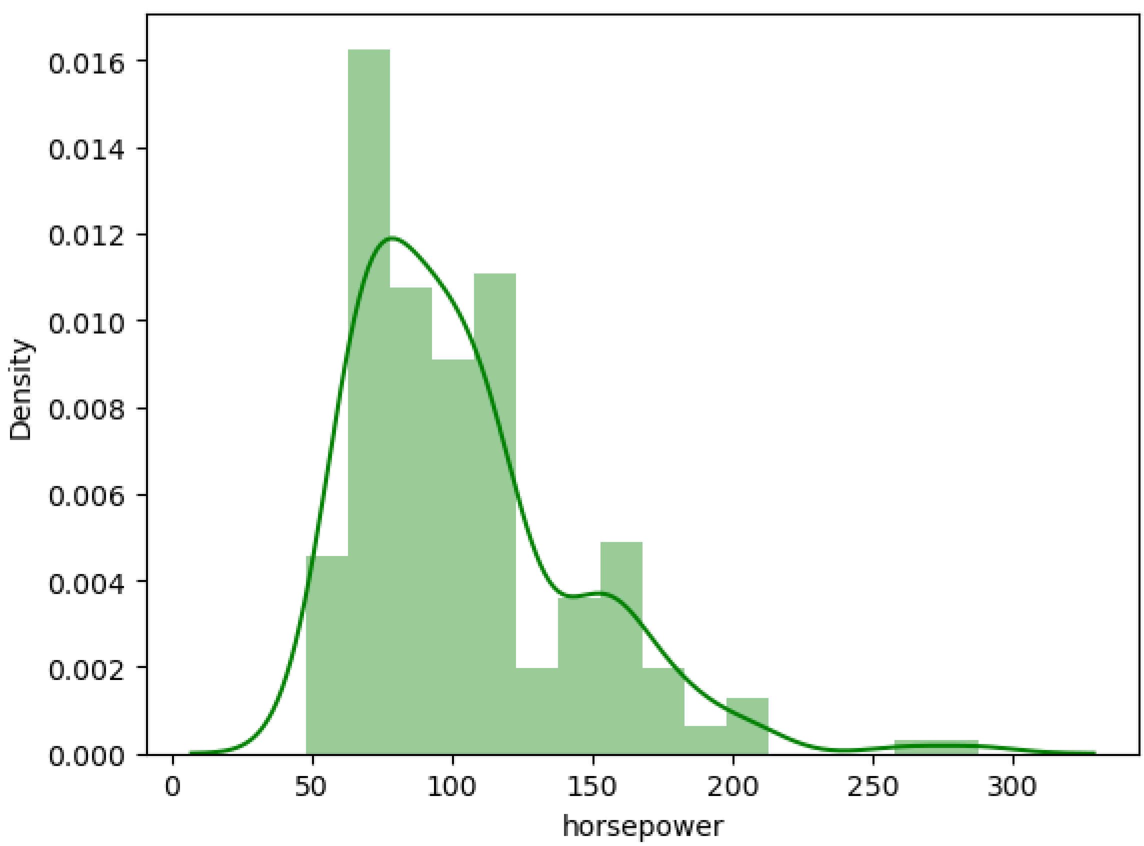

0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
50
100
150
200
250
300
350
enginesize


Density
boreratio
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25

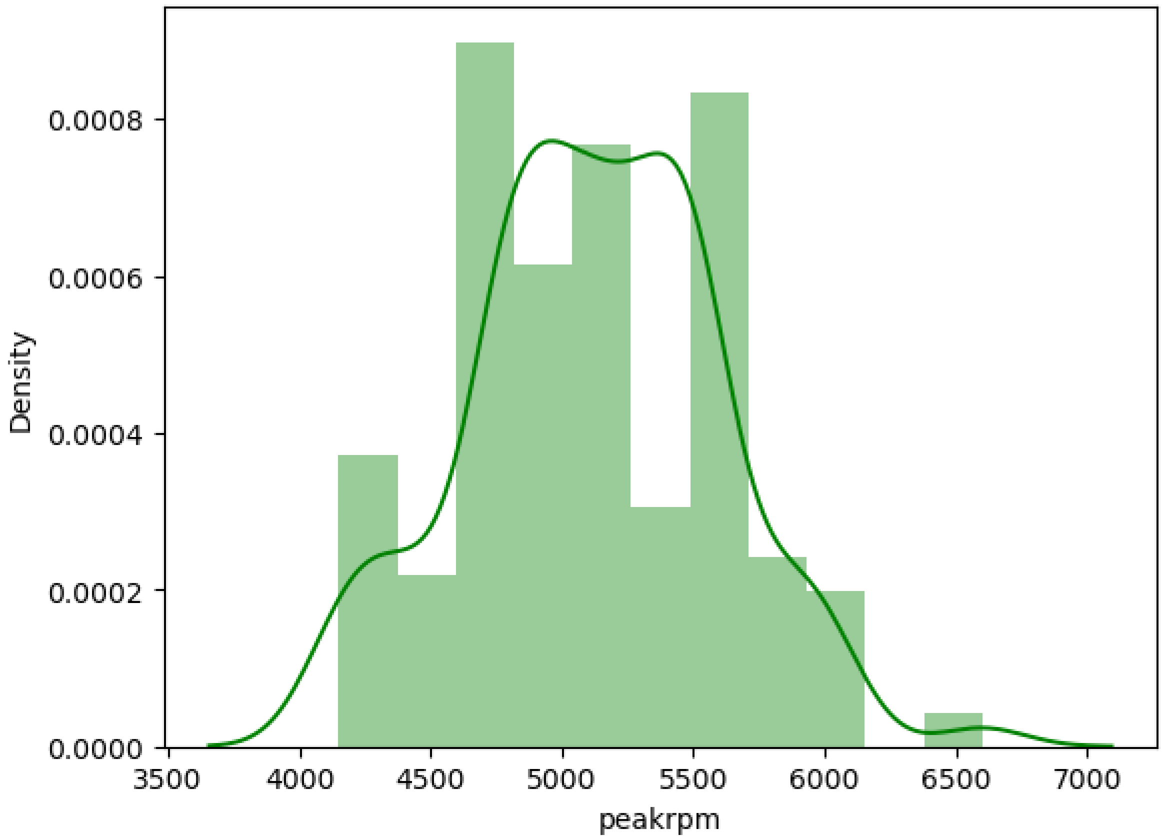

Density
stroke
0.0
0.5
1.0
1.5
2.0
2.0
2.5
3.0
3.5
4.0
4.5

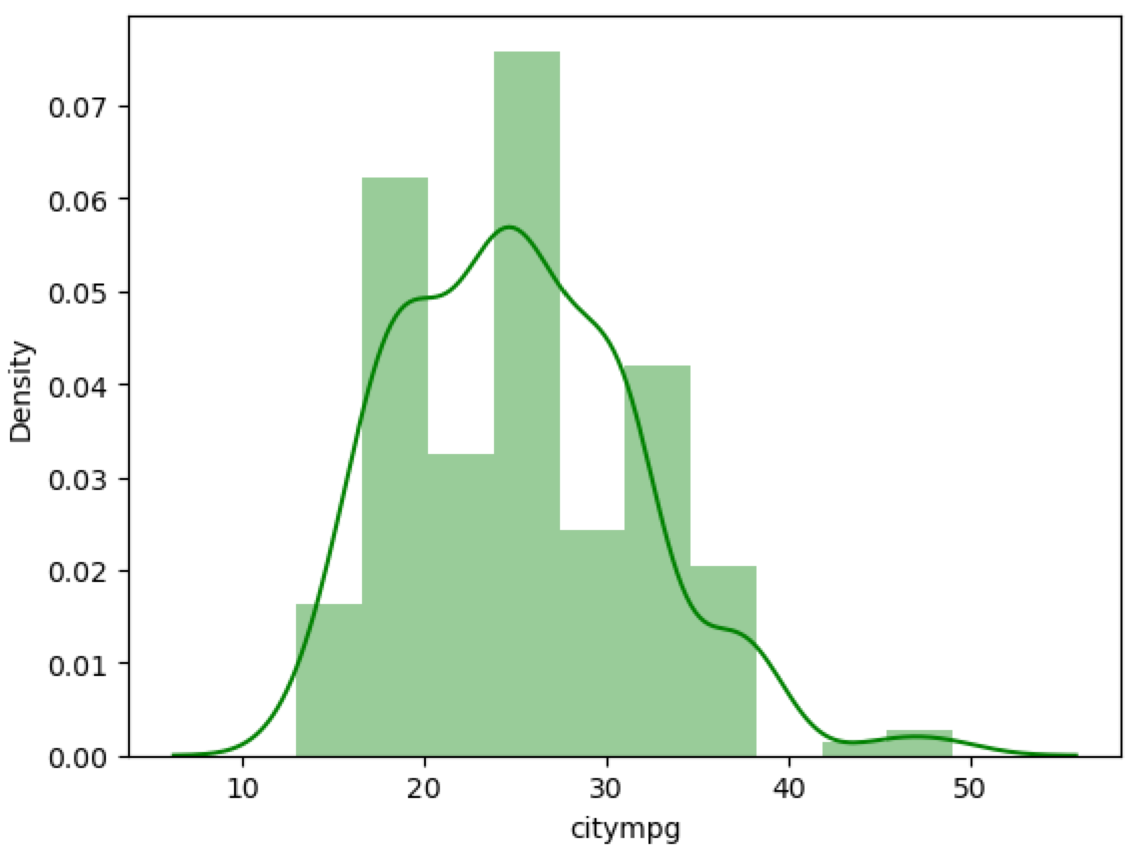


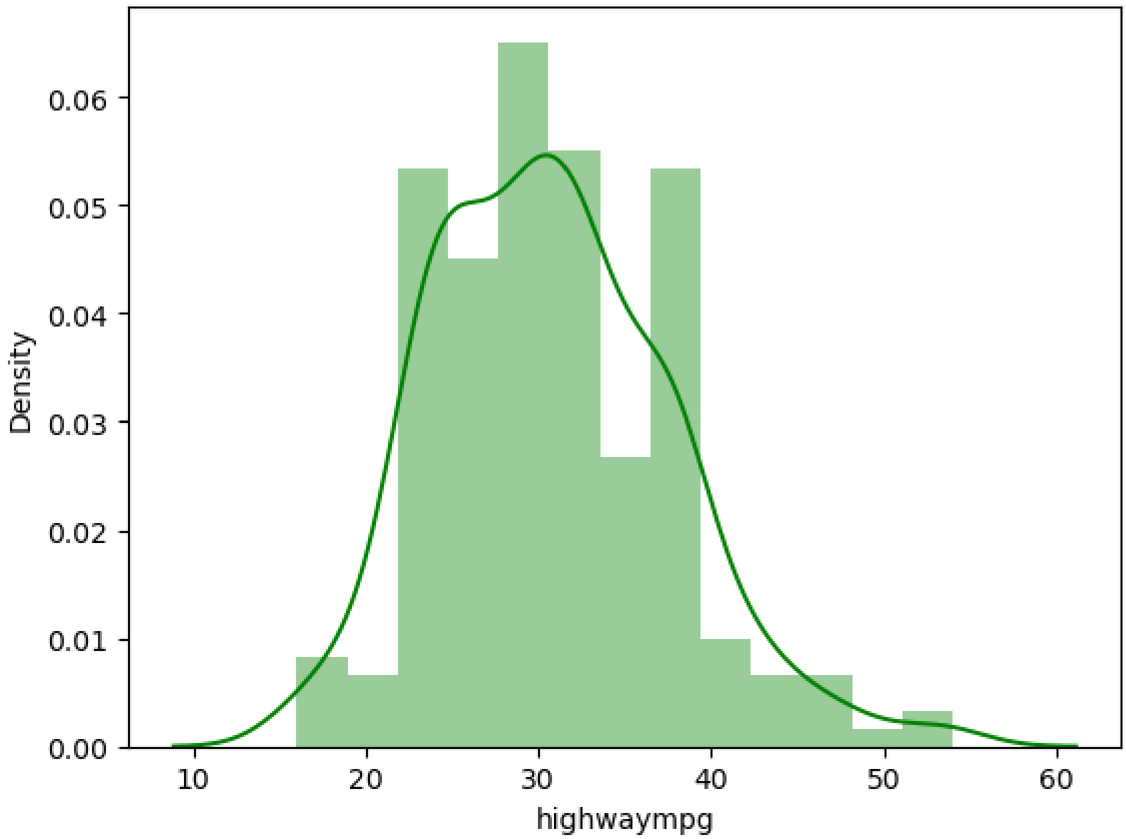
Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
5
10
15
20
25
compressionratio

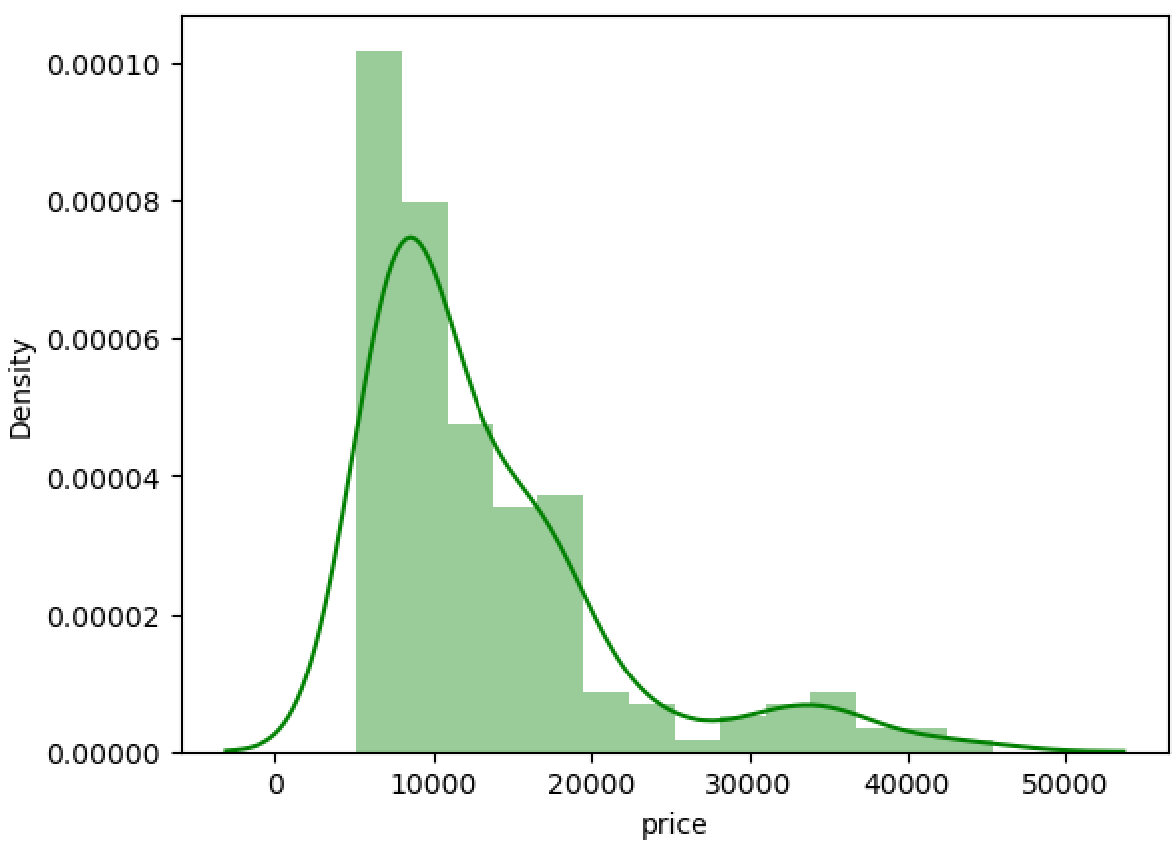


Density
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016
0
50
100
150
200
250
300
horsepower

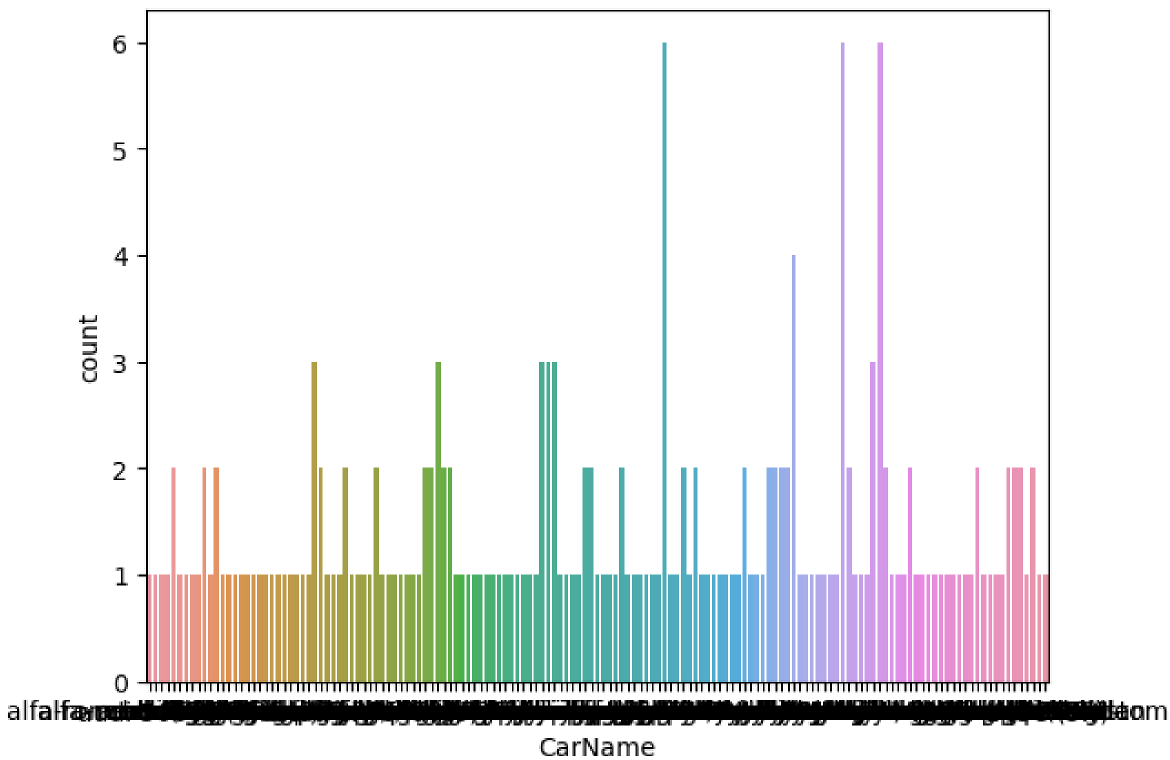

0.0008
0.0006
0.0004
0.0002
0.0000
Density
3500
4000
4500
5000
5500
6000
6500
7000
peakrpm

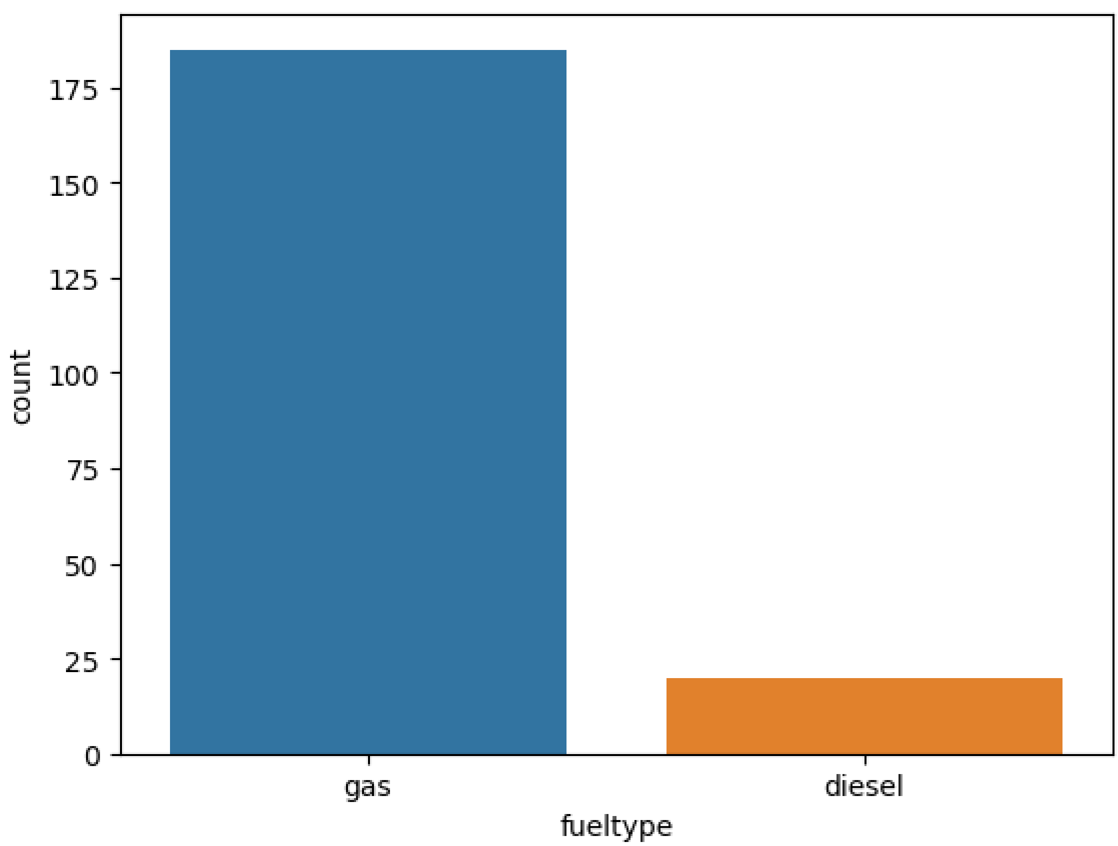

0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Density
10
20
30
40
50
citympg

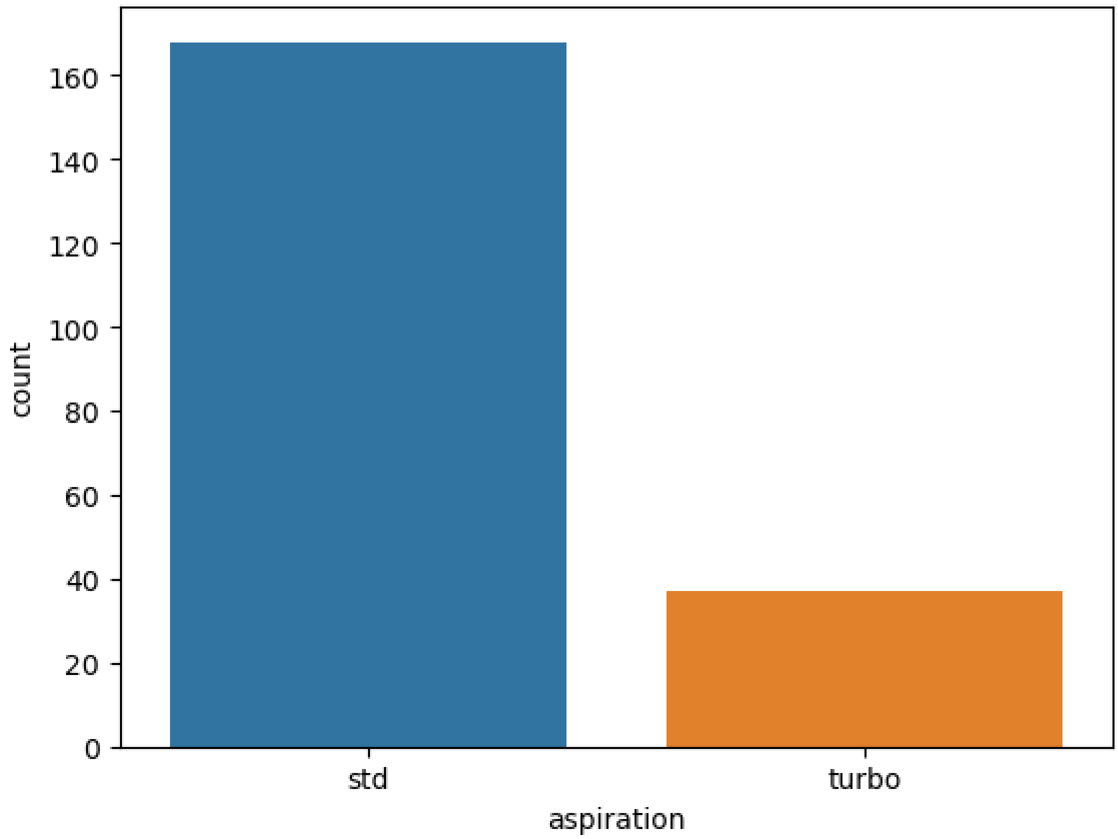

0.06
0.05
0.04
0.03
0.02
0.01
0.00
Density
10
20
30
40
50
60
highwaympg


0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Density
0
10000
20000
30000
40000
50000
price

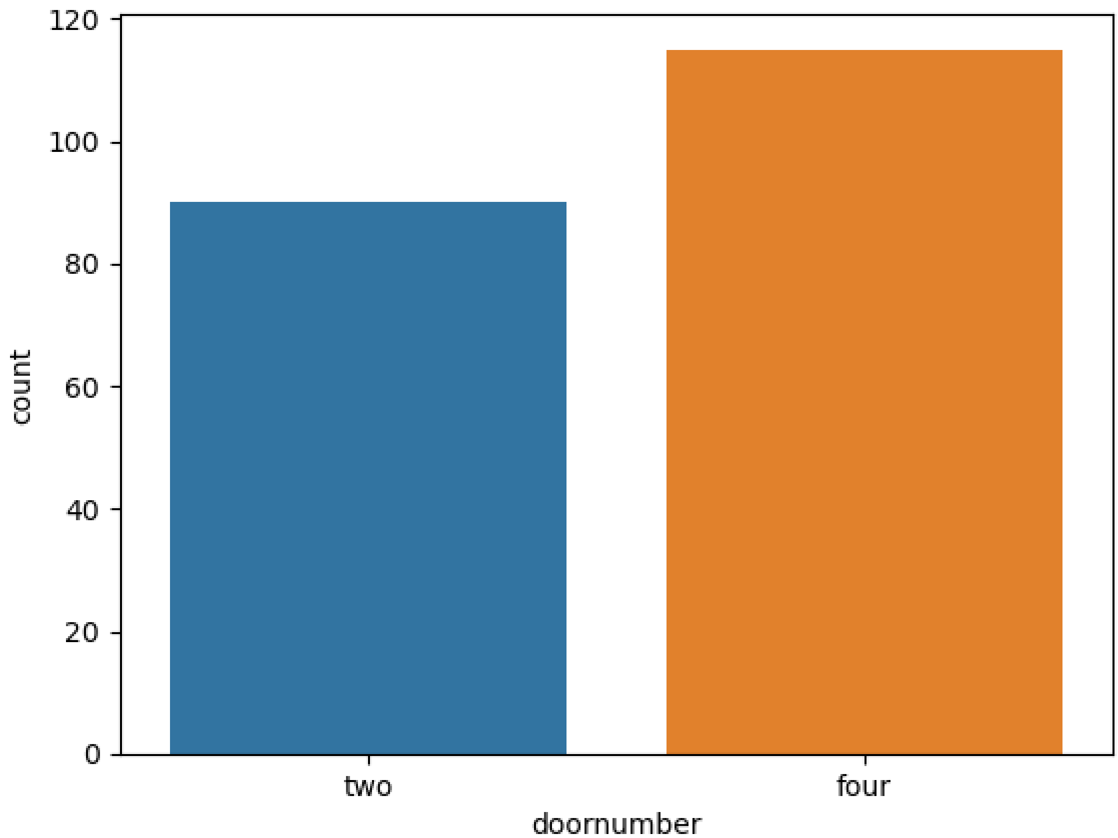
In [14]:
```
#Now, we can check the categorical features count
for i in cat:
    sns.countplot(x=cat[i])
    plt.show()
```


count
CarName

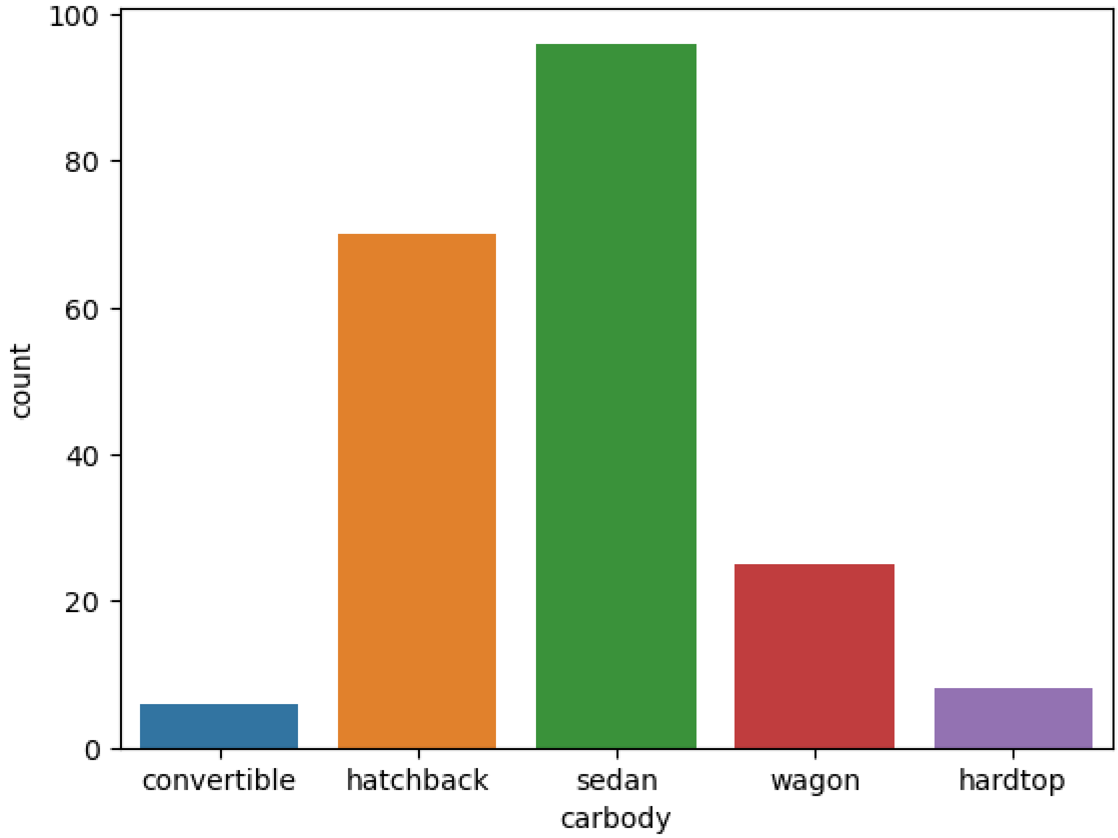

0
25
50
75
100
125
150
175
count
gas
diesel
fueltype

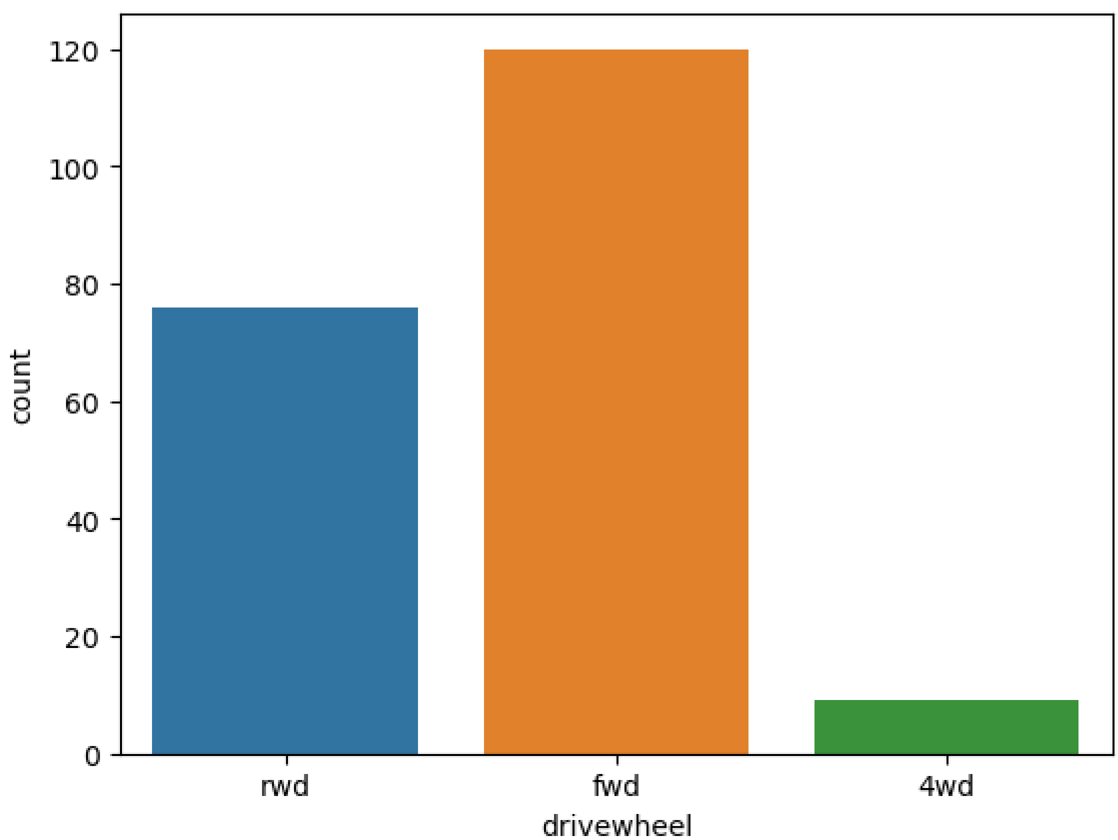


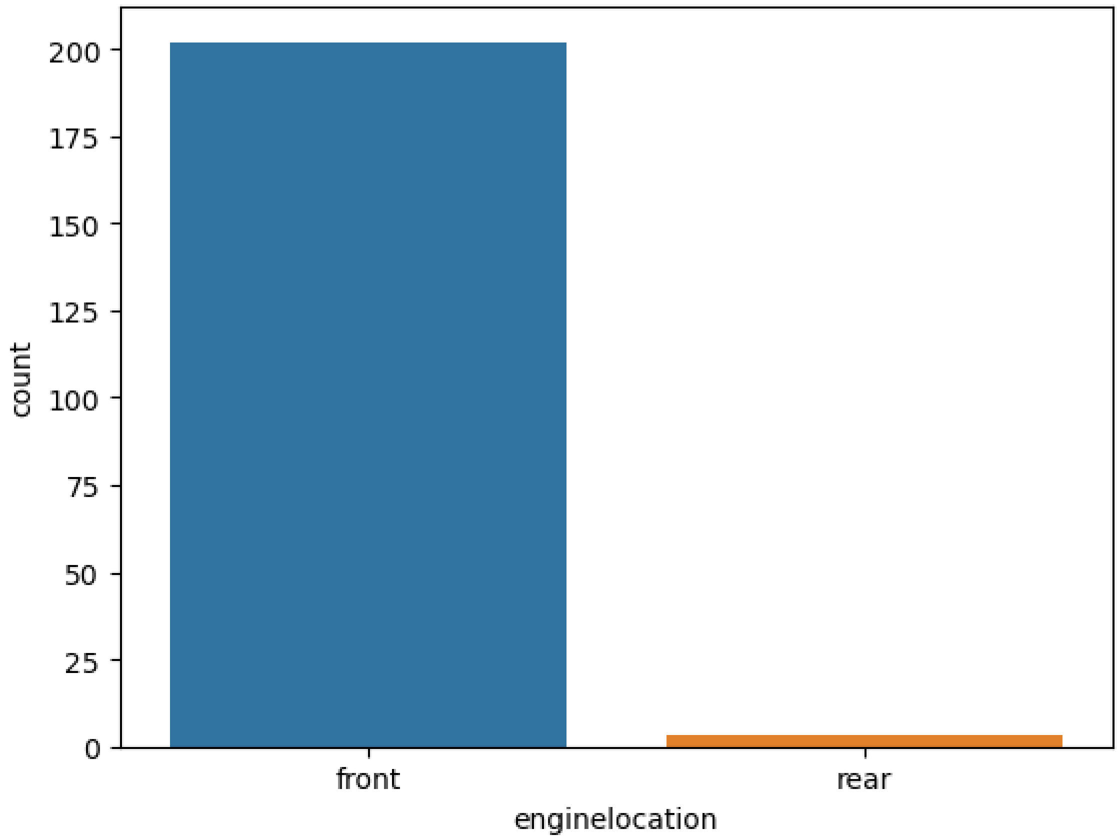
count
160
140
120
100
80
60
40
20
0
std
turbo
aspiration

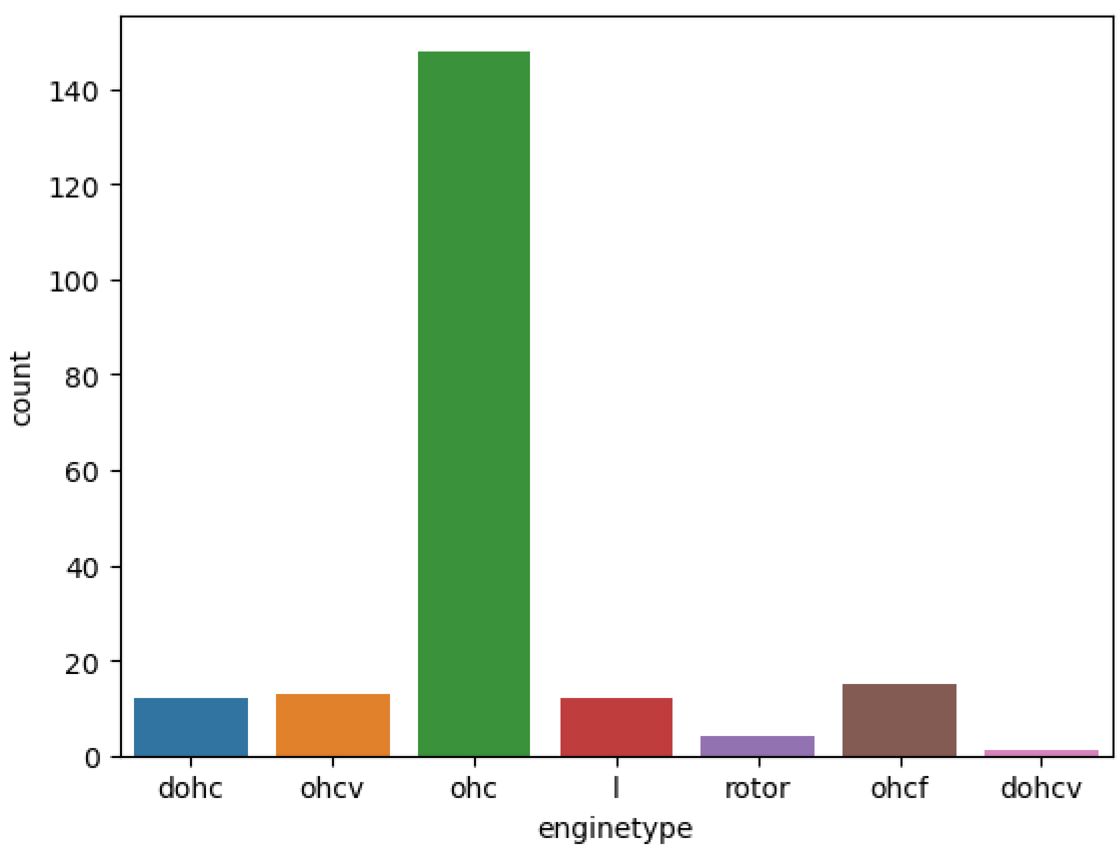


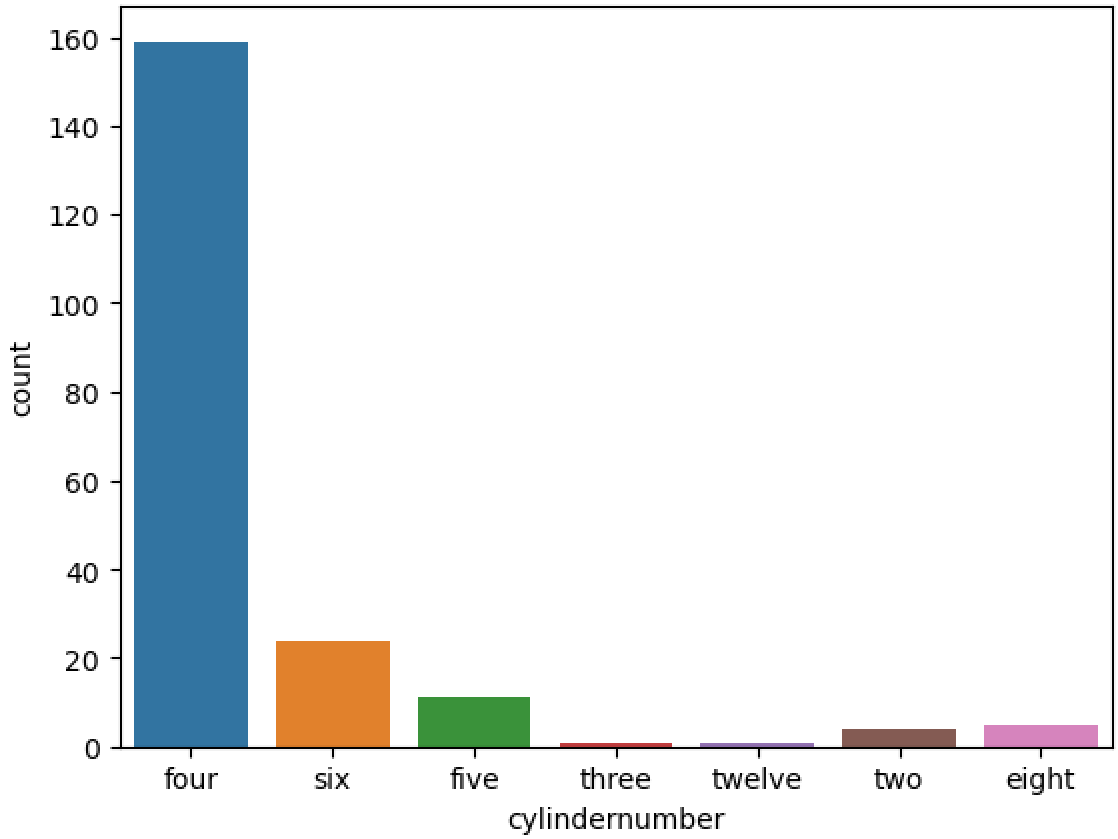
count
120
100
80
60
40
20
0
two
four
doornumber


count
100
80
60
40
20
0
convertible
hatchback
sedan
wagon
hardtop
carbody

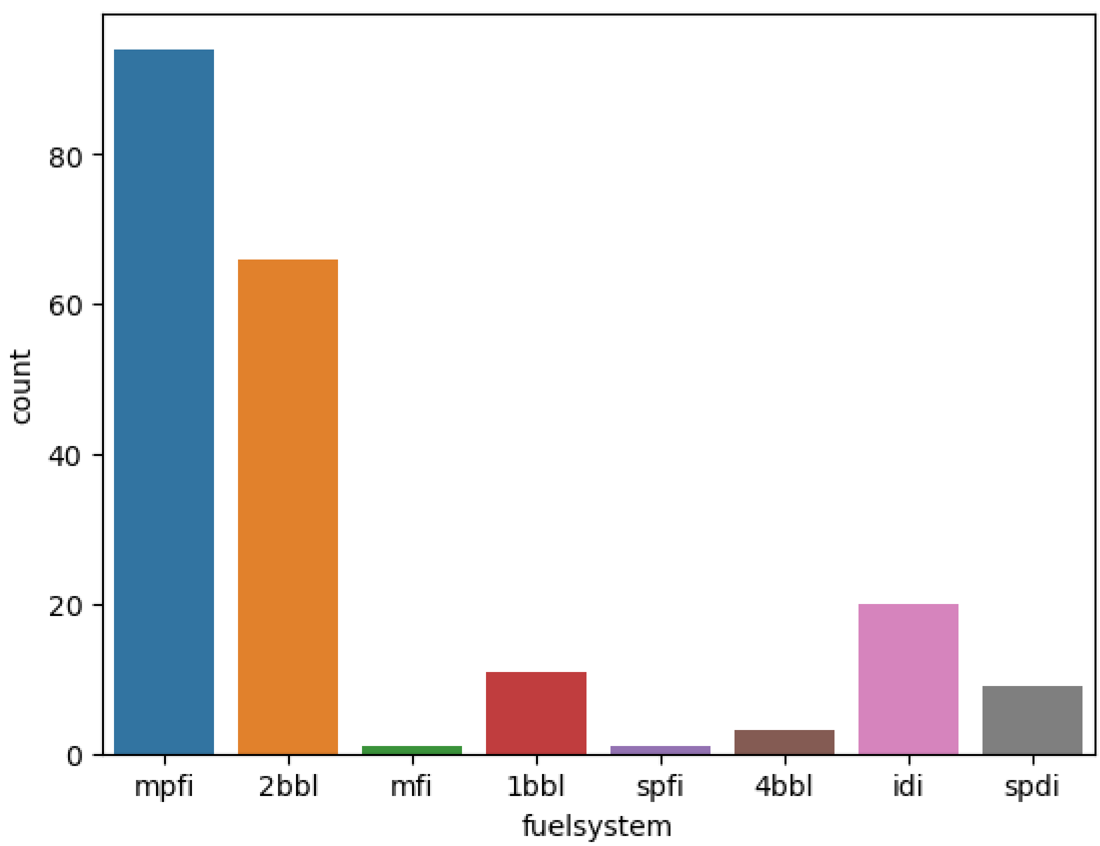

count
120
100
80
60
40
20
0
rwd
fwd
4wd
drivewheel


200
175
150
125
100
75
50
25
0
count
front
rear
enginelocation


140
120
100
80
60
40
20
0
count
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
enginetype

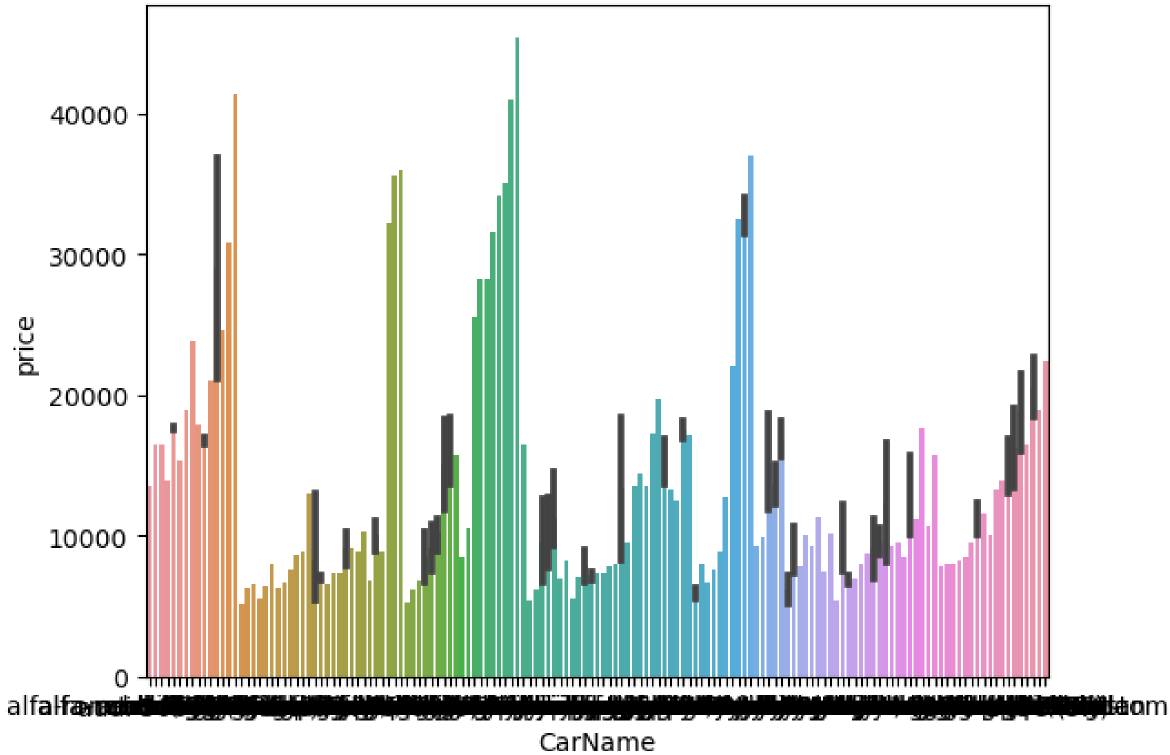


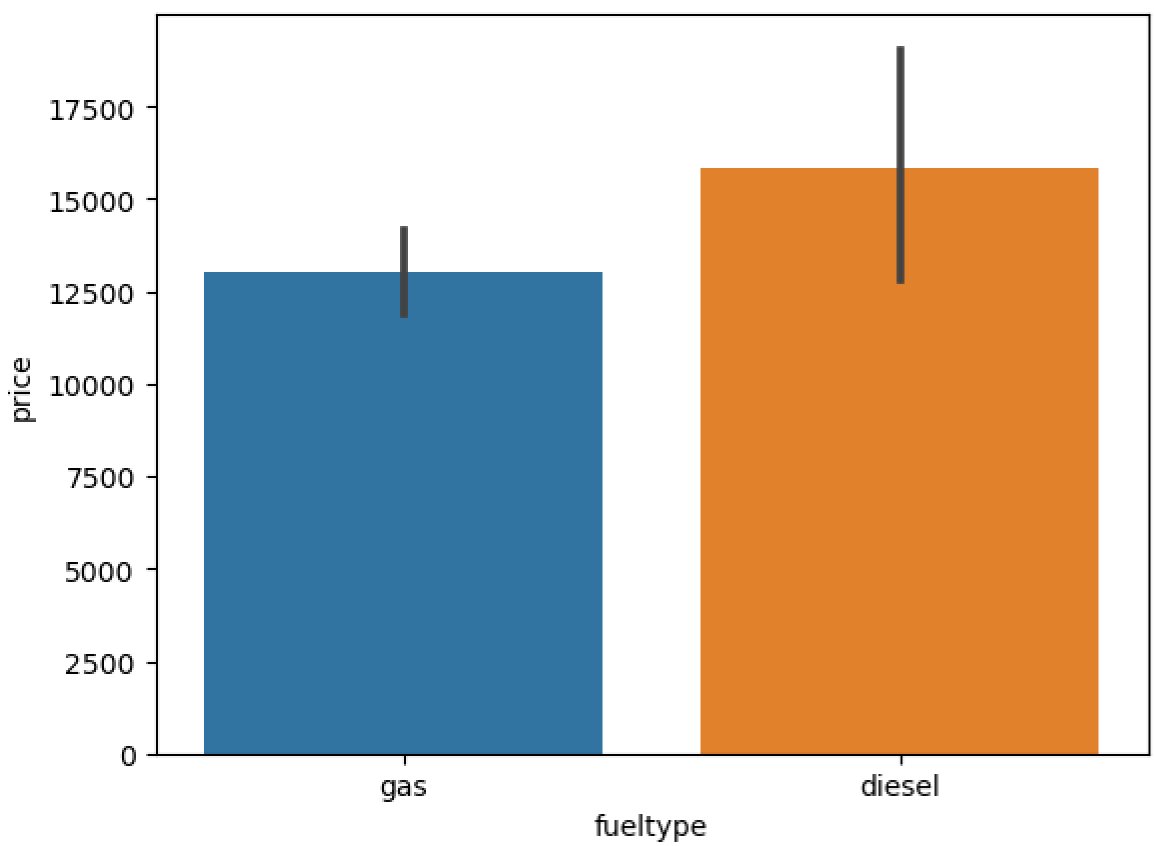
count
160
140
120
100
80
60
40
20
0
four
six
five
three
twelve
two
eight
cylindernumber

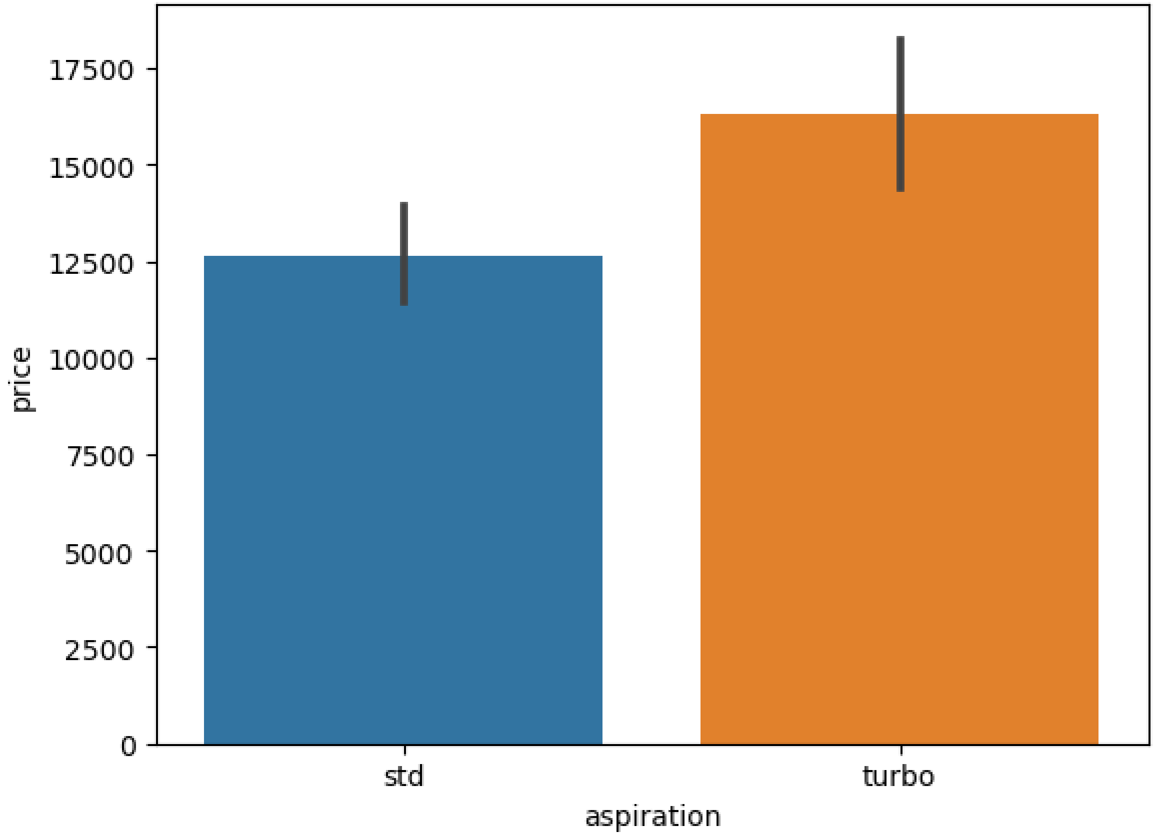


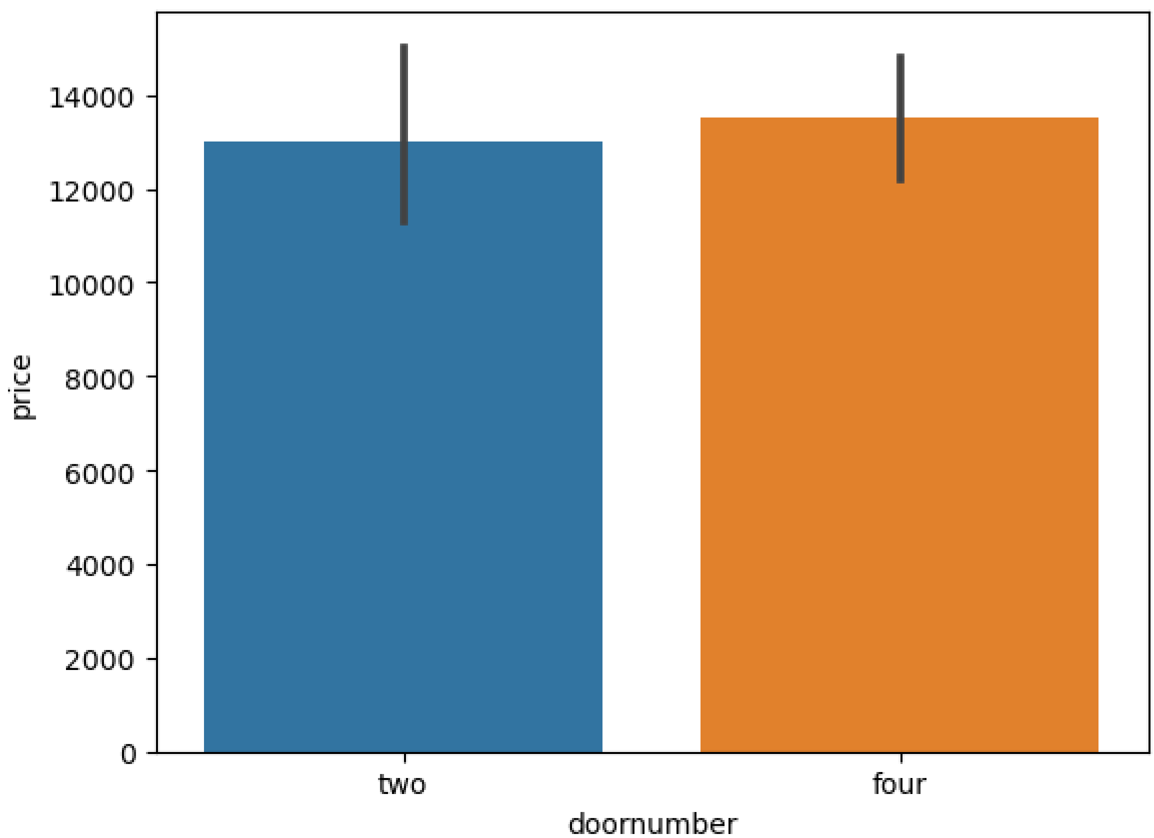
count
80
60
40
20
0
mpfi
2bbl
mfi
1bbl
spfi
4bbl
idi
spdi
fuelsystem

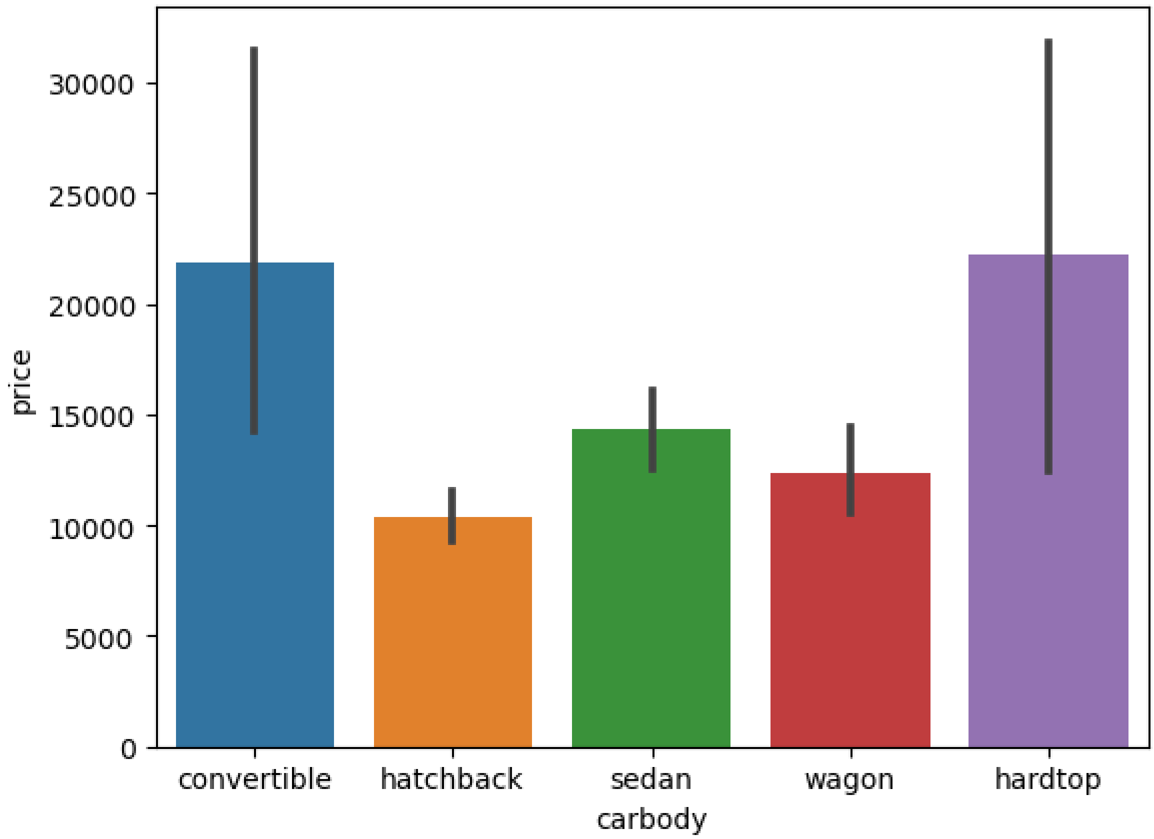
In [15]:
```
for i in cat:
    sns.barplot(df, x=df[i], y=df["price"])
    plt.show()
```

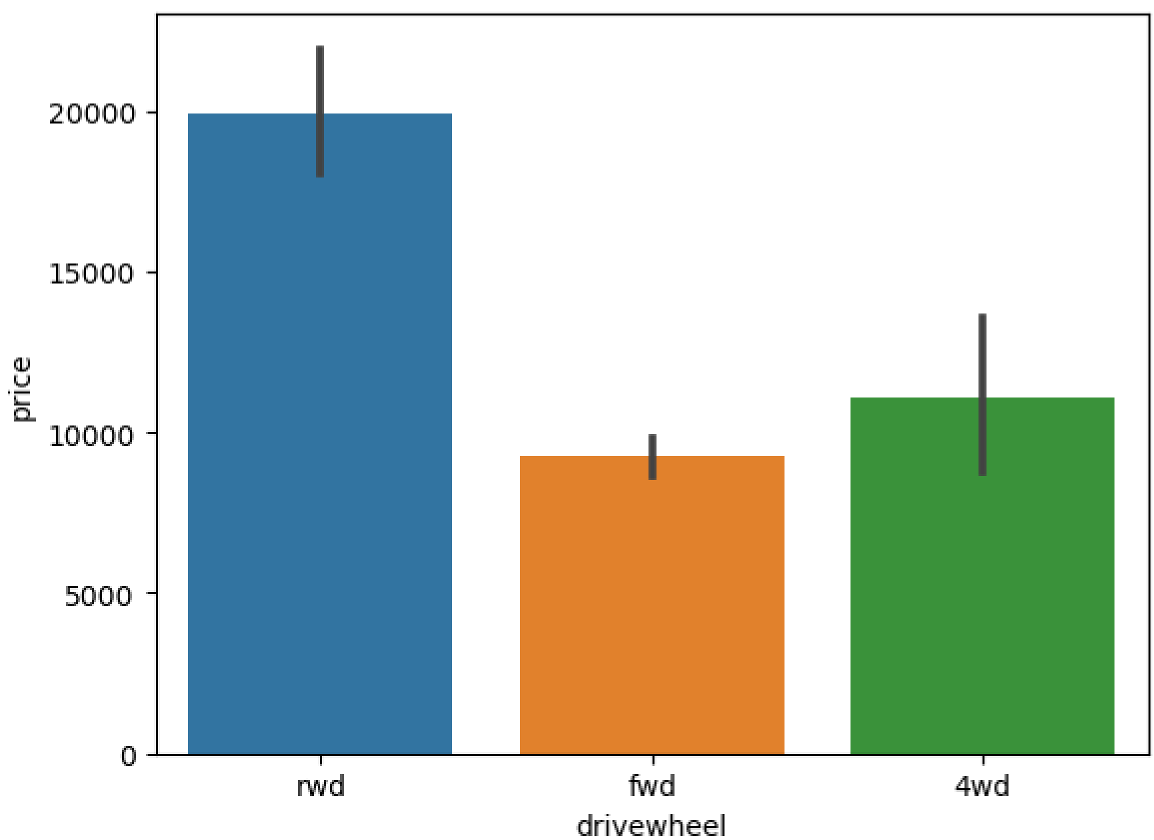

price
CarName
0
10000
20000
30000
40000

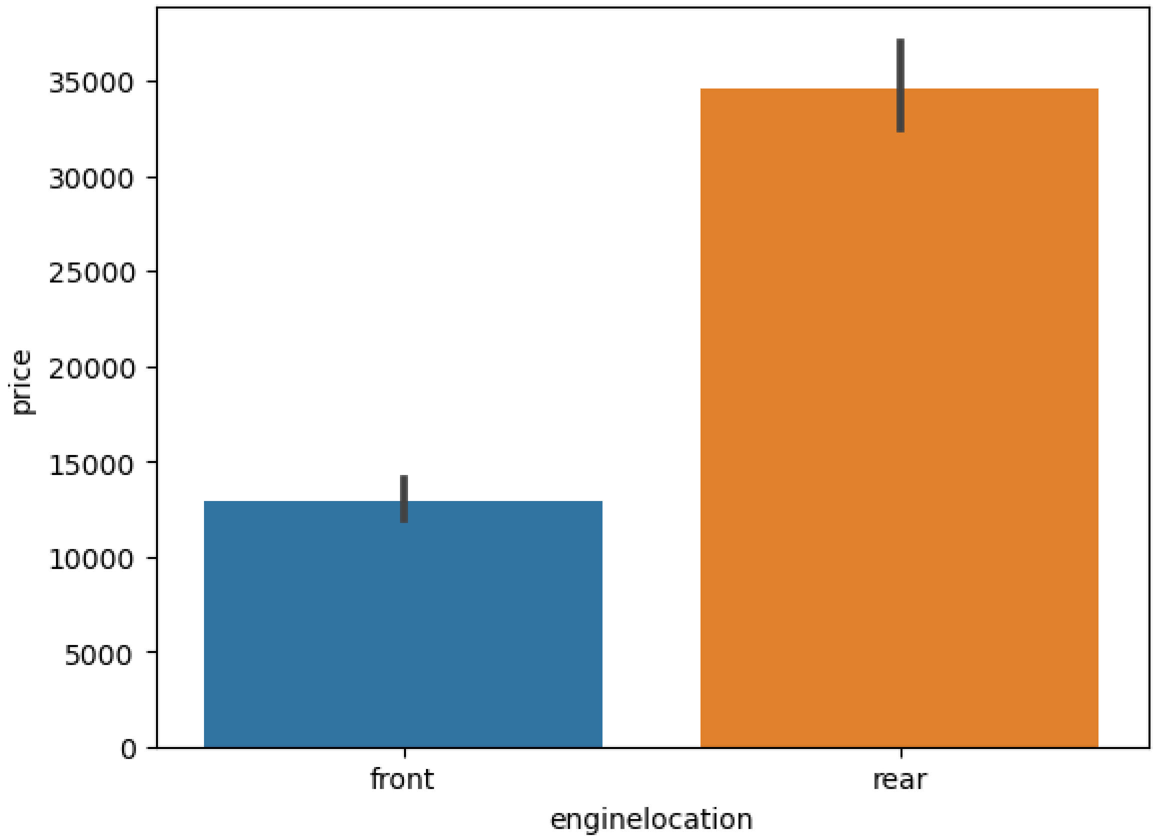

price
fueltype
gas
diesel
0
2500
5000
7500
10000
12500
15000
17500


17500
15000
12500
10000
7500
5000
2500
0
price
std
turbo
aspiration

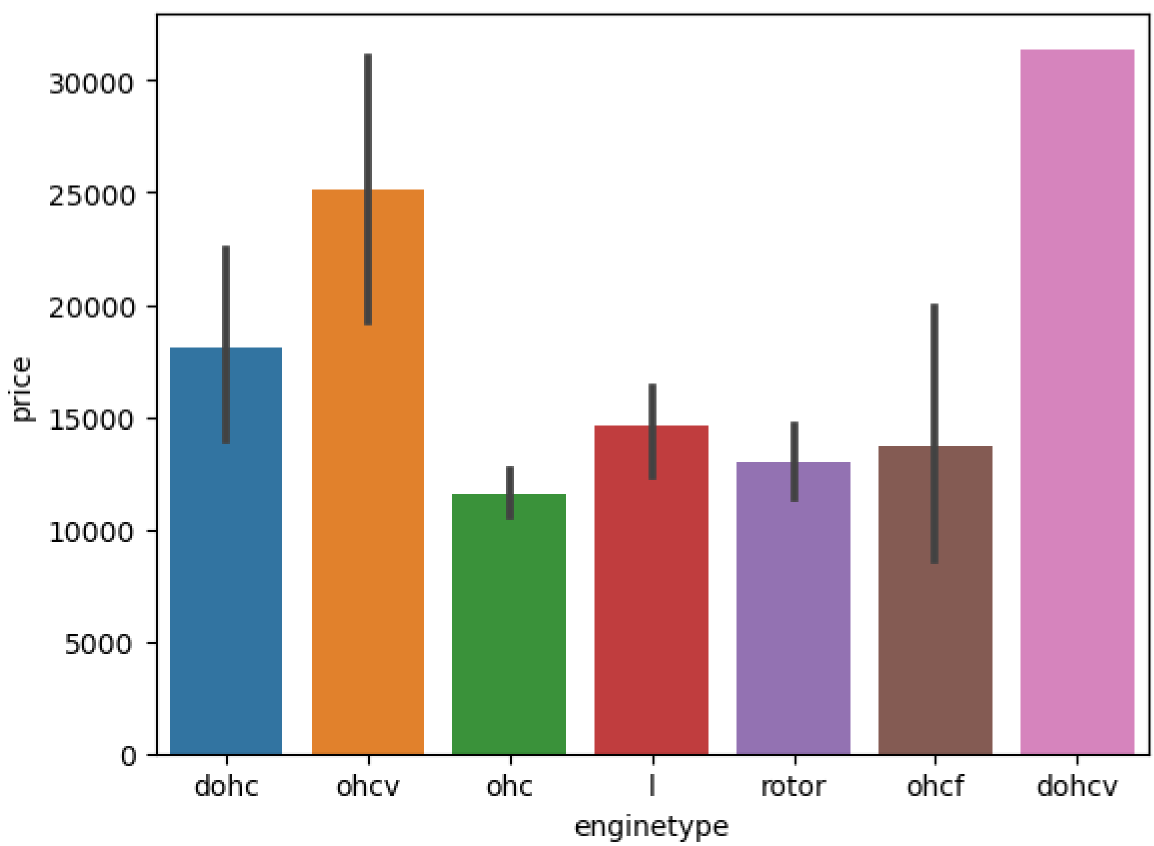

14000
12000
10000
8000
6000
4000
2000
0
price
two
four
doornumber


30000
25000
20000
15000
10000
5000
0
price
convertible
hatchback
sedan
wagon
hardtop
carbody

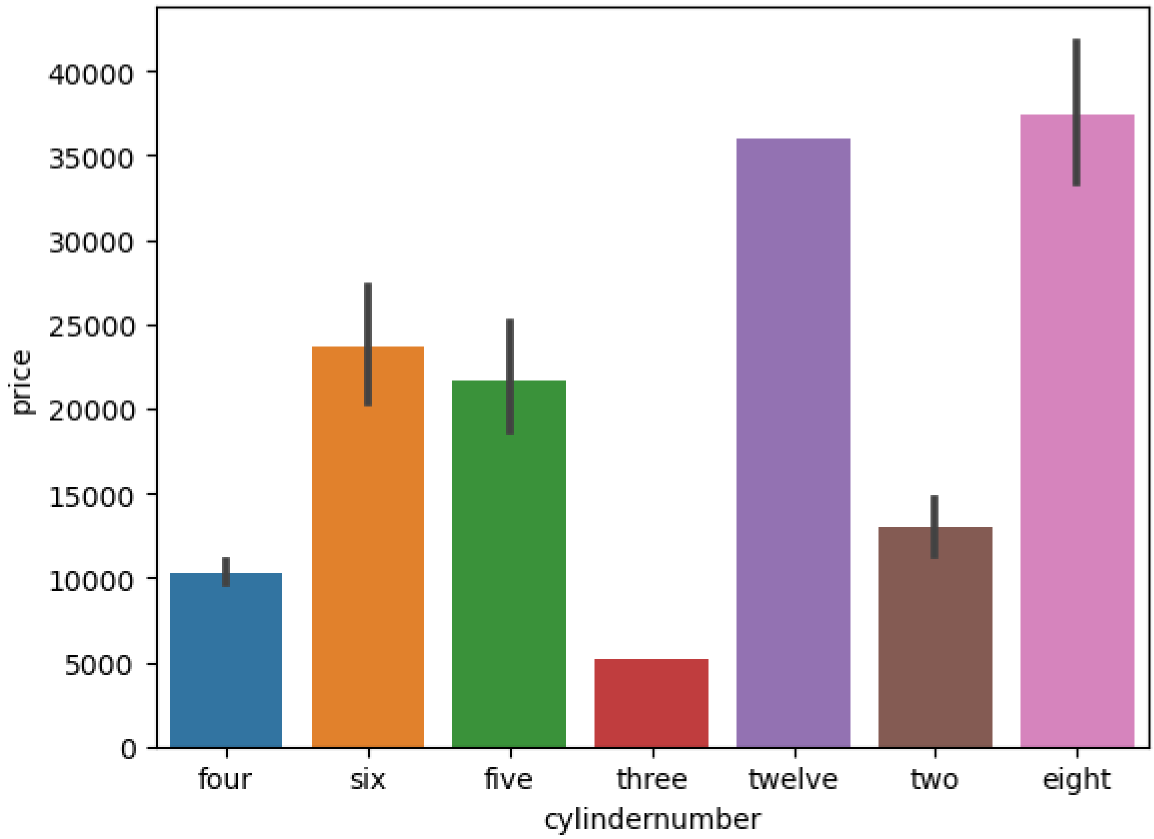

20000
15000
10000
5000
0
price
rwd
fwd
4wd
drivewheel

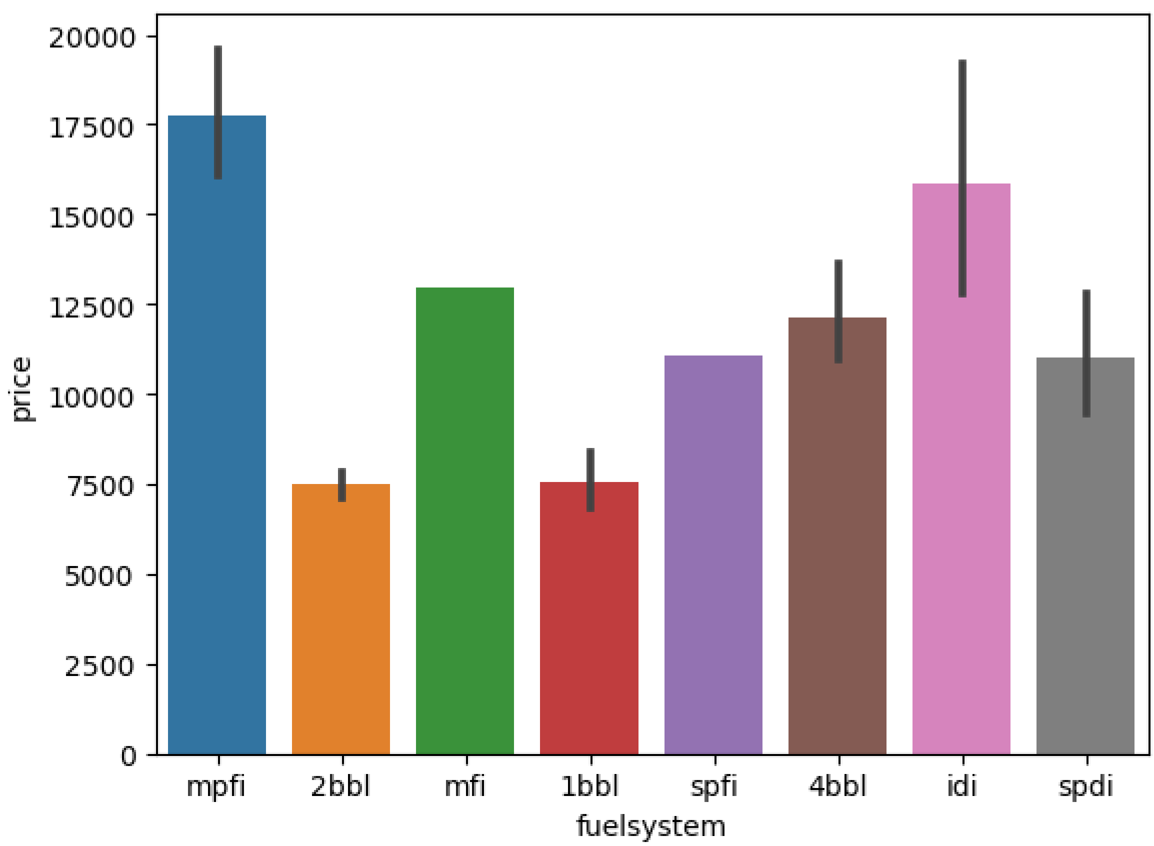


price
0
5000
10000
15000
20000
25000
30000
35000
front
rear
enginelocation



price
0
5000
10000
15000
20000
25000
30000
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
enginetype


price
40000
35000
30000
25000
20000
15000
10000
5000
0
four
six
five
three
twelve
two
eight
cylindernumber


price
20000
17500
15000
12500
10000
7500
5000
2500
0
mpfi
2bbl
mfi
1bbl
spfi
4bbl
idi
spdi
fuelsystem

Seperate data in X and Y as well as Split data into train and Test

In [16]:
```
df.columns
```

Out[16]:
```
Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'price'],
      dtype='object')
```

In [17]:
```
# I am using a df1 data which was copy of the original data set.
x = df1.drop(["car_ID", "price"], axis=1)
y = df1["price"]
```

In [18]:
```
#for train test split import neccasary library
from sklearn.model_selection import train_test_split
train_x, test_x, train_y, test_y = train_test_split(x, y, random_state=50, tes
t_size=0.2)
```

In [19]:
```
train_x
```

Out[19]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocatio
180	-1	toyota starlet	gas	std	four	sedan	rwd	fror
38	0	honda civic 1300	gas	std	two	hatchback	fwd	fror
156	0	toyota mark ii	gas	std	four	sedan	fwd	fror
40	0	honda accord	gas	std	four	sedan	fwd	fror
195	-1	volvo 144ea	gas	std	four	wagon	rwd	fror
...	...	...	...	...	...	...	...	.
132	3	saab 99e	gas	std	two	hatchback	fwd	fror
33	1	honda accord cvcc	gas	std	two	hatchback	fwd	fror
109	0	peugeot 504 (sw)	gas	std	four	wagon	rwd	fror
139	2	subaru dl	gas	std	two	hatchback	fwd	fror
176	-1	toyota corolla	gas	std	four	sedan	fwd	fror

164 rows × 24 columns

In [20]:
```
#we can reset index
train_x.reset_index(inplace=True, drop=True)
test_x.reset_index(inplace=True, drop=True)

train_y.reset_index(inplace=True, drop=True)
test_y.reset_index(inplace=True, drop=True)
```

Encoding using Catboost Encoder

In [21]:
```
#for create encoding for input variables we can seperate dataof numerical and categorical
train_cat = train_x.select_dtypes(include="object")
train_num = train_x.select_dtypes(include="number")

test_cat = test_x.select_dtypes(include="object")
test_num = test_x.select_dtypes(include="number")
```

In [22]:
```
train_cat
```

Out[22]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	enginetyp
0	toyota starlet	gas	std	four	sedan	rwd	front	doh
1	honda civic 1300	gas	std	two	hatchback	fwd	front	oh
2	toyota mark ii	gas	std	four	sedan	fwd	front	oh
3	honda accord	gas	std	four	sedan	fwd	front	oh
4	volvo 144ea	gas	std	four	wagon	rwd	front	oh
...	...	...	...	...	...	...	...	
159	saab 99e	gas	std	two	hatchback	fwd	front	oh
160	honda accord cvcc	gas	std	two	hatchback	fwd	front	oh
161	peugeot 504 (sw)	gas	std	four	wagon	rwd	front	
162	subaru dl	gas	std	two	hatchback	fwd	front	oh
163	toyota corolla	gas	std	four	sedan	fwd	front	oh

164 rows × 10 columns

In [23]:
```
import category_encoders as ce
encoder = ce.CatBoostEncoder()
encoder.fit(train_cat, train_y)
```

Out[23]:

```
CatBoostEncoder

CatBoostEncoder(cols=['CarName', 'fueltype', 'aspiration', 'doornumber',
                      'carbody', 'drivewheel', 'enginelocation', 'enginetyp
e',
                      'cylindernumber', 'fuelsystem'])
```

In [24]:
```
train_cat = encoder.transform(train_cat)
test_cat = encoder.transform(test_cat)
```

In [25]:
```
train_cat
```

Out[25]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	engin
0	13121.513551	13434.368051	13069.674208	13789.064262	14623.968470	20484.766260	1329
1	13685.540652	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	1329
2	10282.385163	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	1329
3	10625.180217	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	1329
4	15381.846884	13434.368051	13069.674208	13789.064262	12587.501767	20484.766260	1329
...	...	...	...	...	...	...	
159	14718.513551	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	1329
160	13685.540652	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	1329
161	13685.540652	13434.368051	13069.674208	13789.064262	12587.501767	20484.766260	1329
162	9609.708130	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	1329
163	11270.135163	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	1329

164 rows × 10 columns

In [26]:
```
# Now, we concat the both categorical and numerical data
train_x1 = pd.concat([train_num, train_cat], axis=1)
test_x1 = pd.concat([test_num, test_cat], axis=1)
```

In [27]:
```
train_x1.head()
```

Out[27]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	strok
0	-1	104.5	187.8	66.5	54.1	3131	171	3.27	3.3
1	0	96.5	167.5	65.2	53.3	2289	110	3.15	3.5
2	0	95.7	166.3	64.4	53.0	2081	98	3.19	3.0
3	0	96.5	175.4	62.5	54.1	2372	110	3.15	3.5
4	-1	104.3	188.8	67.2	57.5	3034	141	3.78	3.1

5 rows × 24 columns

Scaling Using MinmaxScaler

In [28]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
scaler = MinMaxScaler()
scaler.fit(train_x1)
```

Out[28]:
```
▾ MinMaxScaler
MinMaxScaler()
```

In [29]:
```
train_x1 = pd.DataFrame(scaler.transform(train_x1), columns=train_x1.columns)
test_x1 = pd.DataFrame(scaler.transform(test_x1), columns=test_x1.columns)
```

In [30]:
```
train_x1.head()
```

Out[30]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	str
0	0.2	0.617241	0.759350	0.516667	0.525000	0.637316	0.415094	0.521429	0.60٤
1	0.4	0.341379	0.429268	0.408333	0.458333	0.310706	0.184906	0.435714	0.71٤
2	0.4	0.313793	0.409756	0.341667	0.433333	0.230023	0.139623	0.464286	0.457
3	0.4	0.341379	0.557724	0.183333	0.525000	0.342901	0.184906	0.435714	0.71٤
4	0.2	0.610345	0.775610	0.575000	0.808333	0.599690	0.301887	0.885714	0.514

5 rows × 24 columns

Model Building And Evaluation

In [31]:
```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.svm import SVR
import xgboost as Xgb
import catboost as cb
```

In [32]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [33]:
```
#LinerRegression
log_model = LinearRegression()
log_model.fit(train_x1, train_y)
pred_log = log_model.predict(test_x1)
mea_log = mean_absolute_error(test_y, pred_log)
mea_log
```

Out[33]: 1862.0754026991408

In [34]:
```
log_model.score(train_x1, train_y)
```

Out[34]: 0.9145827618690593

In [35]:
```
log_model.score(test_x1, test_y)
```
Out[35]: 0.8439860393076992

In [36]:
```
#KNEARASTNEIGHBORS REGRESSOR
knn_model = KNeighborsRegressor(n_neighbors=10)
knn_model.fit(train_x1, train_y)
pred_knn = knn_model.predict(test_x1)
mea_knn = mean_absolute_error(test_y, pred_knn)
mea_knn
```
Out[36]: 2346.491056097561

In [37]:
```
knn_model.score(train_x1, train_y)
```
Out[37]: 0.7583043733079329

In [38]:
```
knn_model.score(test_x1, test_y)
```
Out[38]: 0.7295957720460675

In [39]:
```
# SUPPORT VECTOR REGRESSOR
svm_model = SVR(kernel="rbf")
svm_model.fit(train_x1, train_y)
pred_svm = svm_model.predict(test_x1)
mea_svm = mean_absolute_error(test_y, pred_svm)
mea_svm
```
Out[39]: 4405.829720847327

In [40]:
```
#DECISION TREE REGRESSOR
dt_model = DecisionTreeRegressor(random_state=50)
dt_model.fit(train_x1, train_y)
pred_dt = dt_model.predict(test_x1)
mea_dt = mean_absolute_error(test_y, pred_dt)
mea_dt
```
Out[40]: 1873.0365853658536

In [41]:
```
dt_model.score(train_x1, train_y)
```
Out[41]: 0.9990939296264457

In [42]:
```
dt_model.score(test_x1, test_y)
```
Out[42]: 0.835366233138423

In [43]:
```
#XGBOOST REGRESSOR
xgb_model = Xgb.XGBRegressor(n_estimators=100)
xgb_model.fit(train_x1, train_y)
pred_xgb = xgb_model.predict(test_x1)
mea_xgb = mean_absolute_error(test_y, pred_xgb)
mea_xgb
```

Out[43]: 1492.0071217606708

In [44]:
```
xgb_model.score(train_x1, train_y)
```

Out[44]: 0.9990933614444724

In [45]:
```
xgb_model.score(test_x1, test_y)
```

Out[45]: 0.904477001109033

In [46]:
```
#RANDOM FOREST REGRESSOR
rfc_model = RandomForestRegressor(random_state=50)
rfc_model.fit(train_x1, train_y)
pred_rfc = rfc_model.predict(test_x1)
mea_rfc = mean_absolute_error(test_y, pred_rfc)
mea_rfc
```

Out[46]: 1312.5139427642275

In [47]:
```
rfc_model.score(train_x1, train_y)
```

Out[47]: 0.9891398153002534

In [48]:
```
rfc_model.score(test_x1, test_y)
```

Out[48]: 0.9235170839824554

In [49]:
```
#ADABOOST REGRESSOR
from sklearn.ensemble import AdaBoostRegressor
adb_model = AdaBoostRegressor(random_state=50)
adb_model.fit(train_x1, train_y)
pred_adb = adb_model.predict(test_x1)
mea_adb = mean_absolute_error(test_y, pred_adb)
mea_adb
```

Out[49]: 1722.7102183490472

In [50]:
```
adb_model.score(train_x1, train_y)
```

Out[50]: 0.960733954988325

In [51]:
```
adb_model.score(test_x1, test_y)
```

Out[51]: 0.8941449598689841

HYPERPARAMTER TUNING

In [52]:
```
from sklearn.model_selection import GridSearchCV
```

In [53]:
```
#HYPERPERAMETER TUING OF KNN
knn =KNeighborsRegressor()
params_knn= {'algorithm' :['auto', 'ball_tree', 'kd_tree', 'brute'], 'weight
s': ['uniform', 'distance'],
         "n_neighbors" : [1,25,14,13,26,85,45]}
clf2 = GridSearchCV(knn, params_knn, cv=5, scoring="neg_mean_absolute_error")
clf2.fit(train_x1, train_y)
print(clf2.best_params_)
print(-(clf2.best_score_))
```

```
{'algorithm': 'auto', 'n_neighbors': 14, 'weights': 'distance'}
2494.429238083901
```

In [54]:
```
#HYPERPERAMETER TUNING OF SUPPORT VECTOR
svm = SVR()
params_svm = {"gamma" :["scale", "auto"]}
clf4 = GridSearchCV(svm, params_svm, cv=5, scoring="neg_mean_absolute_error")
clf4.fit(train_x1, train_y)
print(clf4.best_params_)
print(-(clf4.best_score_))
```

```
{'gamma': 'scale'}
5857.0948700388735
```

In [55]:
```
#HYPERPERAMETER TUNING OF DECISION TREE
dt = DecisionTreeRegressor()
params_dt = { 'max_depth' :[1,25,14,13,45,75,26],'splitter':['best', 'rando
m']}
clf5 = GridSearchCV(dt, params_dt, cv=5, scoring="neg_mean_absolute_error")
clf5.fit(train_x1, train_y)
print(clf5.best_params_)
print(-(clf5.best_score_))
```

```
{'max_depth': 26, 'splitter': 'best'}
2079.834215151515
```

In [56]:
```
#HYPERPERAMETER TUNING OF RANDOMFOREST
rfc = RandomForestRegressor()
params_rfc = {"n_estimators" : [10,15,125,10,8,85],"max_depth" : [10,25,48,85,
42,3]}
clf6 = GridSearchCV(rfc, params_rfc, cv=5, scoring="neg_mean_absolute_error")
clf6.fit(train_x1, train_y)
print(clf6.best_params_)
print(-(clf6.best_score_))
```

```
{'max_depth': 10, 'n_estimators': 10}
1608.045970352032
```

In [57]:
```
#HYPERPERAMETER TUNING OF XGBOOST
xgb = Xgb.XGBRegressor()
params_xgb = {'eta': [0.1, 0.2, 0.3,0.4,0.5], 'n_estimators' : [10, 50, 100,12,15], 'max_depth': [3, 6, 9,14]}
clf7 = GridSearchCV(xgb, params_xgb, cv=5, scoring="neg_mean_absolute_error")
clf7.fit(train_x1, train_y)
print(clf7.best_params_)
print(-(clf7.best_score_))
```

```
{'eta': 0.3, 'max_depth': 3, 'n_estimators': 12}
1654.4771265676786
```

In [58]:
```
#HYPERPERAMETER TUNING OF ADABOOST
adb = AdaBoostRegressor()
params_adb = {'n_estimators' : [10, 50, 100,12,15]}
clf8 = GridSearchCV(adb, params_adb, cv=5, scoring="neg_mean_absolute_error")
clf8.fit(train_x1, train_y)
print(clf8.best_params_)
print(-(clf8.best_score_))
```

```
{'n_estimators': 12}
1942.4232639553607
```

In [59]:
```
#best perameter for model
print("KNeighborsRegressor score is :", clf2.best_params_)
print("Support vector machine score is :", clf4.best_params_)
print("DecisionTreeRegressor score is :", clf5.best_params_)
print("RandomForestRegressor score is :", clf6.best_params_)
print("XGBOOST score is :", clf7.best_params_)
print("AdaBoostRegressor score is :", clf8.best_params_)
```

```
KNeighborsRegressor score is : {'algorithm': 'auto', 'n_neighbors': 14, 'weights': 'distance'}
Support vector machine score is : {'gamma': 'scale'}
DecisionTreeRegressor score is : {'max_depth': 26, 'splitter': 'best'}
RandomForestRegressor score is : {'max_depth': 10, 'n_estimators': 10}
XGBOOST score is : {'eta': 0.3, 'max_depth': 3, 'n_estimators': 12}
AdaBoostRegressor score is : {'n_estimators': 12}
```

In [60]:
```
#Score for all model
print("KNeighborsRegressor score is :", -clf2.best_score_)
print("Support vector machine score is :", -clf4.best_score_)
print("DecisionTreeRegressor score is :", -clf5.best_score_)
print("RandomForestRegressor score is :", -clf6.best_score_)
print("XGBOOST score is :", -clf7.best_score_)
print("AdaBoostRegressor score is :", -clf8.best_score_)
```

```
KNeighborsRegressor score is : 2494.429238083901
Support vector machine score is : 5857.0948700388735
DecisionTreeRegressor score is : 2079.834215151515
RandomForestRegressor score is : 1608.045970352032
XGBOOST score is : 1654.4771265676786
AdaBoostRegressor score is : 1942.4232639553607
```

Feature Selection

In [61]:
```
corr = train_x1.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[61]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize
symboling	1.000000	-0.578304	-0.390113	-0.248365	-0.526122	-0.250262	-0.134253
wheelbase	-0.578304	1.000000	0.867582	0.771214	0.591112	0.759793	0.529871
carlength	-0.390113	0.867582	1.000000	0.827044	0.470846	0.876853	0.674825
carwidth	-0.248365	0.771214	0.827044	1.000000	0.237273	0.867648	0.735210
carheight	-0.526122	0.591112	0.470846	0.237273	1.000000	0.242780	0.031296
curbweight	-0.250262	0.759793	0.876853	0.867648	0.242780	1.000000	0.863212
enginesize	-0.134253	0.529871	0.674825	0.735210	0.031296	0.863212	1.000000
boreratio	-0.162739	0.472559	0.602451	0.558945	0.153063	0.651217	0.567905
stroke	-0.094843	0.233869	0.159160	0.187711	0.021950	0.177018	0.175712
compressionratio	-0.138442	0.276306	0.162644	0.175197	0.256479	0.156818	0.030569
horsepower	0.041720	0.320702	0.542183	0.639089	-0.132944	0.760007	0.812254
peakrpm	0.298979	-0.359770	-0.263725	-0.199603	-0.323789	-0.230956	-0.208542
citympg	-0.010920	-0.444372	-0.667301	-0.639629	-0.015309	-0.757775	-0.650781
highwaympg	0.071724	-0.524224	-0.706315	-0.670228	-0.079328	-0.800212	-0.673568
CarName	-0.010792	0.258350	0.307601	0.369344	0.068102	0.382338	0.339512
fueltype	-0.168656	0.340227	0.218323	0.224837	0.294276	0.218850	0.064077
aspiration	-0.139669	0.309735	0.256531	0.291672	0.155802	0.329624	0.094739
doornumber	-0.660961	0.485944	0.419589	0.202060	0.555275	0.210491	0.039682
carbody	0.059908	0.079006	0.211546	0.132693	0.032433	0.237191	0.382170
drivewheel	-0.080845	0.470344	0.533570	0.515855	-0.001609	0.691589	0.563847
enginelocation	0.237181	-0.212719	-0.059901	-0.061146	-0.124708	0.052068	0.213736
enginetype	0.067769	0.154616	0.304882	0.349761	-0.136303	0.502473	0.585707
cylindernumber	-0.007060	0.314598	0.428817	0.571120	-0.051041	0.634563	0.745415
fuelsystem	0.015097	0.472859	0.633303	0.602246	0.135930	0.674265	0.544771

In [62]:
```
def correlation(dataset, threshold):
    col_corr = set()
    corr_matrix = dataset.corr()
    for i in range (len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i,j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [63]:
```
corr_features = correlation(train_x1, 0.7)
len(set(corr_features))
```

Out[63]: 9

In [64]:
```
corr_features
```

Out[64]:
```
{'carlength',
 'carwidth',
 'citympg',
 'curbweight',
 'cylindernumber',
 'enginesize',
 'fueltype',
 'highwaympg',
 'horsepower'}
```

In [65]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_selection import SelectKBest, chi2
label_encoder = LabelEncoder()
categorical_labels = label_encoder.fit_transform(train_y)

selector = SelectKBest(score_func=chi2, k=9)
selector.fit(train_x1, categorical_labels)
```

Out[65]:
```
SelectKBest
SelectKBest(k=9, score_func=<function chi2 at 0x0000026D07CE2320>)
```

In [66]:
```
train_x1.columns[selector.get_support()]
```

Out[66]:
```
Index(['compressionratio', 'fueltype', 'aspiration', 'doornumber',
       'drivewheel', 'enginelocation', 'enginetype', 'cylindernumber',
       'fuelsystem'],
      dtype='object')
```

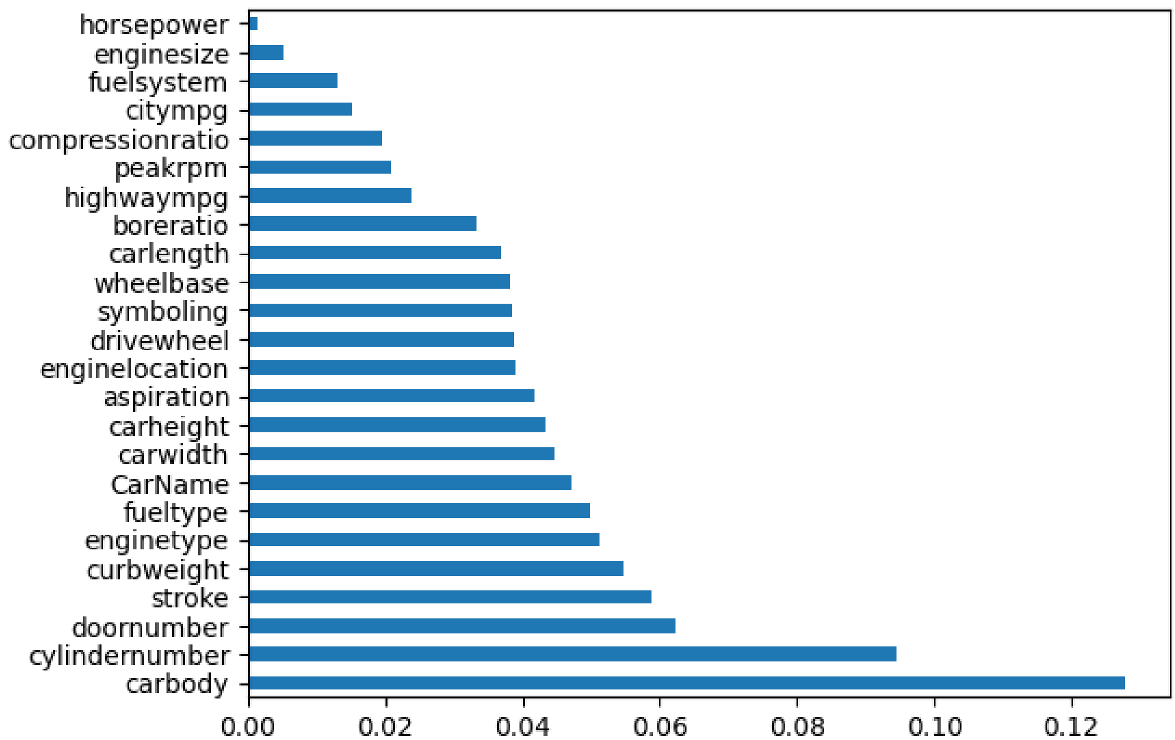
In [67]:
```
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
model.fit(train_x1, categorical_labels)
```

Out[67]:
```
ExtraTreesClassifier
ExtraTreesClassifier()
```

In [68]:
```
print(model.feature_importances_)
```

```
[0.03838191 0.0470145  0.04979188 0.04186319 0.06225254 0.12788082
 0.03876581 0.03906442 0.03808178 0.03694287 0.04472997 0.04336357
 0.05476364 0.05119548 0.09452813 0.00513165 0.01301257 0.03345145
 0.05890118 0.01966169 0.00134083 0.02081258 0.01515469 0.02391286]
```

In [69]:
```
feat_importance = pd.Series(model.feature_importances_, index=x.columns)
feat_importance.nlargest(26).plot(kind="barh")
plt.show()
```



In [70]:
```
#Apply SelectKbest class to extract top Features
from sklearn.feature_selection import SelectKBest, chi2
bestfeatures = SelectKBest(score_func=chi2, k=7)
fit = bestfeatures.fit(train_x1,categorical_labels)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(x.columns)
features = pd.concat([dfcolumns, dfscores], axis=1)
features.columns = ["specs", "score"]
features
```

Out[70]:

	specs	score
0	symboling	18.022609
1	CarName	16.372104
2	fueltype	12.133704
3	aspiration	10.996294
4	doornumber	13.152871
5	carbody	16.141302
6	drivewheel	16.246778
7	enginelocation	10.689274
8	wheelbase	5.988593
9	carlength	46.766794
10	carwidth	19.838707
11	carheight	15.116577
12	curbweight	16.580375
13	enginetype	14.208251
14	cylindernumber	14.744994
15	enginesize	143.533333
16	fuelsystem	137.000000
17	boreratio	69.236559
18	stroke	32.983696
19	compressionratio	95.168704
20	horsepower	161.000000
21	peakrpm	90.965309
22	citympg	80.619337
23	highwaympg	57.424042

In [71]:
```
from sklearn.ensemble import RandomForestClassifier
fe_model = RandomForestClassifier(random_state=50)

fe_model.fit(train_x1, categorical_labels)
```

Out[71]:
```
RandomForestClassifier
RandomForestClassifier(random_state=50)
```

In [72]:
```
feature_scores = pd.Series(fe_model.feature_importances_, index=train_x.column
s).sort_values(ascending=False)
feature_scores
```

Out[72]:
```
carbody             0.110586
cylindernumber      0.080961
doornumber          0.072819
carwidth            0.056263
curbweight          0.054876
fueltype            0.054374
aspiration          0.052511
enginetype          0.050929
carlength           0.049689
drivewheel          0.048289
CarName             0.045783
stroke              0.045180
enginelocation      0.044269
carheight           0.043742
wheelbase           0.043452
symboling           0.039086
boreratio           0.028178
peakrpm             0.019195
highwaympg          0.017722
compressionratio    0.013915
citympg             0.011500
fuelsystem          0.010661
enginesize          0.003963
horsepower          0.002058
dtype: float64
```

After Feature Selection drop the features of noies and regenerate the model

In [73]:
```
df2.columns
```

Out[73]:
```
Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'price'],
      dtype='object')
```

In [74]:
```
X = df2.drop(["car_ID", "enginesize", "horsepower", "price", "enginelocation",
'carlength', 'carwidth', 'carheight', 'curbweight', 'fuelsystem', 'citympg'],
axis=1)
Y = df2["price"]
```

In [75]:
```
X
```

Out[75]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	wheelbase
0	3	alfa-romero giulia	gas	std	two	convertible	rwd	88.6
1	3	alfa-romero stelvio	gas	std	two	convertible	rwd	88.6
2	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	94.5
3	2	audi 100 ls	gas	std	four	sedan	fwd	99.8
4	2	audi 100ls	gas	std	four	sedan	4wd	99.4
...	...	...	...	...	...	...	...	...
200	-1	volvo 145e (sw)	gas	std	four	sedan	rwd	109.1
201	-1	volvo 144ea	gas	turbo	four	sedan	rwd	109.1
202	-1	volvo 244dl	gas	std	four	sedan	rwd	109.1
203	-1	volvo 246	diesel	turbo	four	sedan	rwd	109.1
204	-1	volvo 264gl	gas	turbo	four	sedan	rwd	109.1

205 rows × 15 columns

In [76]:
```
train_X, test_X, train_Y, test_Y = train_test_split(X,Y, random_state=50, test
_size=0.2)
```

In [77]:
```
train_X.head()
```

Out[77]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	wheelbase	e
180	-1	toyota starlet	gas	std	four	sedan	rwd	104.5	
38	0	honda civic 1300	gas	std	two	hatchback	fwd	96.5	
156	0	toyota mark ii	gas	std	four	sedan	fwd	95.7	
40	0	honda accord	gas	std	four	sedan	fwd	96.5	
195	-1	volvo 144ea	gas	std	four	wagon	rwd	104.3	

In [78]:
```
#we can reset index
train_X.reset_index(inplace=True, drop=True)
test_X.reset_index(inplace=True, drop=True)

train_Y.reset_index(inplace=True, drop=True)
test_Y.reset_index(inplace=True, drop=True)
```

In [79]:
```
train_cat1 = train_X.select_dtypes(include="object")
train_num1 = train_X.select_dtypes(include="number")

test_cat1 = test_X.select_dtypes(include="object")
test_num1 = test_X.select_dtypes(include="number")
```

In [80]:
```
train_cat1
```

Out[80]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginetype	cylindernumb
0	toyota starlet	gas	std	four	sedan	rwd	dohc	
1	honda civic 1300	gas	std	two	hatchback	fwd	ohc	fc
2	toyota mark ii	gas	std	four	sedan	fwd	ohc	fc
3	honda accord	gas	std	four	sedan	fwd	ohc	fc
4	volvo 144ea	gas	std	four	wagon	rwd	ohc	fc
...	...	...	...	...	...	...	...	
159	saab 99e	gas	std	two	hatchback	fwd	ohc	fc
160	honda accord cvcc	gas	std	two	hatchback	fwd	ohc	fc
161	peugeot 504 (sw)	gas	std	four	wagon	rwd	l	fc
162	subaru dl	gas	std	two	hatchback	fwd	ohcf	fc
163	toyota corolla	gas	std	four	sedan	fwd	ohc	fc

164 rows × 8 columns

In [81]:
```
encoder.fit(train_cat1, train_Y)
train_cat1 = encoder.transform(train_cat1)
test_cat1 = encoder.transform(test_cat1)
```

In [82]:
```
train_cat1
```

Out[82]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	eng
0	13121.513551	13434.368051	13069.674208	13789.064262	14623.968470	20484.766260	18707
1	13685.540652	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	11808
2	10282.385163	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	11808
3	10625.180217	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	11808
4	15381.846884	13434.368051	13069.674208	13789.064262	12587.501767	20484.766260	11808
...	...	...	...	...	...	...	
159	14718.513551	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	11808
160	13685.540652	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	11808
161	13685.540652	13434.368051	13069.674208	13789.064262	12587.501767	20484.766260	14742
162	9609.708130	13434.368051	13069.674208	13550.384829	10777.771565	9273.942533	15047
163	11270.135163	13434.368051	13069.674208	13789.064262	14623.968470	9273.942533	11808

164 rows × 8 columns

In [83]:
```
train_X = pd.concat([train_num1, train_cat1], axis=1)
test_X = pd.concat([test_num1, test_cat1], axis=1)
```

In [84]:
```
train_X
```

Out[84]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarN
0	-1	104.5	3.27	3.35	9.20	5200	24	13121.51
1	0	96.5	3.15	3.58	9.00	5800	33	13685.54
2	0	95.7	3.19	3.03	9.00	4800	37	10282.38
3	0	96.5	3.15	3.58	9.00	5800	33	10625.18
4	-1	104.3	3.78	3.15	9.50	5400	28	15381.84
...	...	...	...	...	...	...	...	
159	3	99.1	3.54	3.07	9.31	5250	28	14718.51
160	1	93.7	2.91	3.41	9.20	6000	34	13685.54
161	0	114.2	3.46	3.19	8.40	5000	24	13685.54
162	2	93.7	3.62	2.64	8.70	4400	31	9609.70
163	-1	102.4	3.31	3.54	8.70	4200	32	11270.13

164 rows × 15 columns

In [85]:
```
scaler.fit(train_X)
train_X = pd.DataFrame(scaler.transform(train_X), columns=train_X.columns)
test_X = pd.DataFrame(scaler.transform(test_X), columns=test_X.columns)
```

In [86]:
```
test_X.head()
```

Out[86]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarNam
0	0.4	0.951724	0.657143	0.057143	0.08750	0.346939	0.210526	0.37206
1	0.8	0.406897	0.771429	0.680952	0.14375	0.265306	0.368421	0.26448
2	0.4	0.503448	0.550000	0.533333	0.12500	0.040816	0.315789	0.26448
3	0.4	1.182759	0.900000	0.609524	0.06250	0.142857	0.000000	0.26448
4	0.4	0.358621	0.771429	0.271429	0.04375	0.265306	0.342105	0.26448

In [87]:
```
#KNeighborsRegressor
knn1 = KNeighborsRegressor(algorithm="auto", n_neighbors=14, weights="distanc
e")
knn1.fit(train_X, train_Y)
pred1 = knn1.predict(test_X)
mea_knn1 = mean_absolute_error(test_Y,pred1)
mea_knn1
```

Out[87]: 2336.4669472990554

In [88]:
```
knn1.score(test_X, test_Y)
```

Out[88]: 0.667114714416121

In [89]:
```
#SVR
svm1 = SVR(gamma="scale")
svm1.fit(train_X, train_Y)
pred2 = svm1.predict(test_X)
mea_svm = mean_absolute_error(test_Y, pred2)
mea_svm
```

Out[89]: 4411.585208835385

In [90]:
```
#DecisionTreeRegressor
dt1 = DecisionTreeRegressor( max_depth=45, splitter="best")
dt1.fit(train_X, train_Y)
pred3 = dt1.predict(test_X)
mea_dt = mean_absolute_error(test_Y, pred3)
mea_dt
```

Out[90]: 1500.621951219512

In [91]:
```
dt1.score(test_X, test_Y)
```

Out[91]: 0.8344006282029793

In [92]:
```
#RandomForestRegressor
rfc1 = RandomForestRegressor(max_depth=25 ,n_estimators= 15)
rfc1.fit(train_X, train_Y)
pred4 = rfc1.predict(test_X)
mea_rfc = mean_absolute_error(test_Y, pred4)
mea_rfc
```
Out[92]: 1178.684498102981

In [93]:
```
rfc1.score(test_X, test_Y)
```
Out[93]: 0.942488779940313

In [94]:
```
rfc1.score(train_X, train_Y)
```
Out[94]: 0.9789761134166135

In [95]:
```
#XGBRegressor
xgb = Xgb.XGBRegressor(eta=0.3 ,max_depth=3 ,n_estimators= 12)
xgb.fit(train_X, train_Y)
pred5 = xgb.predict(test_X)
mea_xgb = mean_absolute_error(test_Y, pred5)
mea_xgb
```
Out[95]: 1363.2071265243903

In [96]:
```
xgb.score(train_X, train_Y)
```
Out[96]: 0.9569576336137279

In [97]:
```
xgb.score(test_X, test_Y)
```
Out[97]: 0.9326547476323311

In [98]:
```
#AdaBoostRegressor
adb = AdaBoostRegressor(n_estimators= 15)
adb.fit(train_X, train_Y)
pred6 = adb.predict(test_X)
mea_adb1 = mean_absolute_error(test_Y, pred6)
mea_adb1
```
Out[98]: 1418.285329668117

In [99]:
```
adb.score(test_X, test_Y)
```
Out[99]: 0.9243458301093536

In [100]:
```
print('KNeighborsRegressor MAE is: ', mea_knn1)
print('KNeighborsRegressor training score is: ', knn1.score(train_X, train_Y))
print('KNeighborsRegressor test score is : ', knn1.score(test_X, test_Y))
print()
print('DecisionTreeRegressor MAE is :', mea_dt)
print('DecisionTreeRegressor training score is: ', dt1.score(train_X, train_
Y))
print('DecisionTreeRegressor test score is : ', dt1.score(test_X, test_Y))
print()
print('RandomForestRegressor MAE is :', mea_rfc)
print('RandomForestRegressor training score is: ', rfc1.score(train_X, train_
Y))
print('RandomForestRegressor test score is : ', rfc1.score(test_X, test_Y))
print()
print('xgboostregression MAE is :', mea_xgb)
print('xgboostregression training score is: ', xgb.score(train_X, train_Y))
print('xgboostregression test score is : ', xgb.score(test_X, test_Y))
print()
print('AdaBoostRegressor MAE is :', mea_adb1)
print('AdaBoostRegressor training score is: ', adb.score(train_X, train_Y))
print('AdaBoostRegressor test score is : ', adb.score(test_X, test_Y))
print()
```

```
KNeighborsRegressor MAE is:  2336.4669472990554
KNeighborsRegressor training score is:  0.9989318339613448
KNeighborsRegressor test score is :  0.667114714416121

DecisionTreeRegressor MAE is : 1500.621951219512
DecisionTreeRegressor training score is:  0.9989318339613448
DecisionTreeRegressor test score is :  0.8344006282029793

RandomForestRegressor MAE is : 1178.684498102981
RandomForestRegressor training score is:  0.9789761134166135
RandomForestRegressor test score is :  0.942488779940313

xgboostregression MAE is : 1363.2071265243903
xgboostregression training score is:  0.9569576336137279
xgboostregression test score is :  0.9326547476323311

AdaBoostRegressor MAE is : 1418.285329668117
AdaBoostRegressor training score is:  0.9440312926868266
AdaBoostRegressor test score is :  0.9243458301093536
```

Testing the Model

In [101]:
```
X.head(1)
```

Out[101]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	wheelbase	en
0	3	alfa-romero giulia	gas	std	two	convertible	rwd	88.6	

In [102]:
```
new_df = {'symboling': 0, 'CarName':"bmw X2", 'fueltype' : 'gas', 'aspiration':"turbo" ,
          "doornumber":"four", "carbody":"convertible", 'drivewheel': "rwd", 'wheelbase':98.0,
          'enginetype':'ohcf',  'cylindernumber':'four', 'boreratio': 4.51, 'stroke':3.68,
          'compressionratio':9.0,  'peakrpm': 5500, 'highwaympg': 22}
index = [0]
```

In [103]:
```
new_df = pd.DataFrame(new_df, index=index)
```

In [104]:
```
new_df
```

Out[104]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	wheelbase	en
0	0	bmw X2	gas	turbo	four	convertible	rwd	98.0	

In [105]:
```
new_cat = new_df.select_dtypes(include="object")
new_num = new_df.select_dtypes(include="number")
```

In [106]:
```
new_cat = encoder.transform(new_cat)
```

In [107]:
```
new_cat
```

Out[107]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginety
0	13685.540652	13434.368051	16720.882416	13789.064262	20718.36295	20484.76626	15047.1185

In [108]:
```
new_df = pd.concat([new_num, new_cat], axis=1)
```

In [109]:
```
new_df
```

Out[109]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarNar
0	0	98.0	4.51	3.68	9.0	5500	22	13685.5406

In [110]:
```
new_df =pd.DataFrame(scaler.transform(new_df), columns=new_df.columns)
new_df
```

Out[110]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarName
0	0.4	0.393103	1.407143	0.766667	0.125	0.55102	0.157895	0.26448

In [111]:
```
Pred_new = rfc1.predict(new_df)
```

In [112]:
```
Pred_new
```

Out[112]:
```
array([15973.51111111])
```

In [113]:
```
X["enginetype"].unique()
```

Out[113]:
```
array(['dohc', 'ohcv', 'ohc', 'l', 'rotor', 'ohcf', 'dohcv'], dtype=object)
```

In [114]:
```
new_df1 = {'symboling': 3, 'CarName':"wagon R", 'fueltype' : 'gas', 'aspiratio
n':"std" ,
          "doornumber":"four", "carbody":"wagon", 'drivewheel': "rwd", 'wheelb
ase':98.0,
          'enginetype':'dohc',  'cylindernumber':'three', 'boreratio': 4.51,
'stroke':4,
          'compressionratio':8.0,  'peakrpm': 5000, 'highwaympg': 29}
index = [0]
```

In [115]:
```
new_df1 = pd.DataFrame(new_df1, index=index)
```

In [116]:
```
new_df1
```

Out[116]:

	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	wheelbase	engi
0	3	wagon R	gas	std	four	wagon	rwd	98.0	

In [117]:
```
new_cat = new_df1.select_dtypes(include="object")
new_num = new_df1.select_dtypes(include="number")
```

In [118]:
```
new_cat = encoder.transform(new_cat)
```

In [119]:
```
new_cat
```

Out[119]:

	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginet
0	13685.540652	13434.368051	13069.674208	13789.064262	12587.501767	20484.76626	18707.867

In [120]:
```
new_df1 = pd.concat([new_num, new_cat], axis=1)
new_df1
```

Out[120]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarNar
0	3	98.0	4.51	4	8.0	5000	29	13685.5406

In [121]:
```
new_df1 =pd.DataFrame(scaler.transform(new_df1), columns=new_df1.columns)
new_df1
```

Out[121]:

	symboling	wheelbase	boreratio	stroke	compressionratio	peakrpm	highwaympg	CarName
0	1.0	0.393103	1.407143	0.919048	0.0625	0.346939	0.342105	0.26448

In [122]:
```
pred_new = rfc1.predict(new_df1)
pred_new
```

Out[122]:
```
array([19505.56666667])
```

Conclusion

In conclusion, our car price prediction journey involved a comprehensive and systematic process that encompassed various essential steps. We began with Exploratory Data Analysis (EDA), gaining valuable insights into the dataset's characteristics and distributions. This allowed us to better understand the relationships between different features and the target variable, setting the stage for effective modeling.

Following EDA, we carefully partitioned our dataset into training and test sets, ensuring an unbiased evaluation of model performance. Encoding categorical variables and applying feature scaling were crucial steps that facilitated optimal model training by transforming and normalizing the data appropriately.

Hyperparameter tuning played a pivotal role in fine-tuning the models' configurations. This process allowed us to identify the best set of hyperparameters that maximized predictive accuracy and generalization. We meticulously searched through various parameter combinations to strike the right balance between bias and variance.

Feature selection, a key aspect of model refinement, involved choosing the most relevant and informative features to enhance model efficiency and interpretability. By excluding noise and redundant information, we aimed to improve the model's ability to generalize to new, unseen data.

Throughout this journey, the RandomForestRegressor emerged as the most promising model for car price prediction. Its robust performance was a result of its adaptability to complex relationships, demonstrated by its low Mean Absolute Error (MAE), which is a 1178.684498102981, high training score is (97%) 0.9789761134166135, and impressive test score is (94%) 0.942488779940313. This model's ability to capture intricate patterns and its consistent performance across various evaluation metrics make it a strong contender for accurate car price predictions.