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

In [2]:
```
df = pd.read_csv("cars.csv")
df.head()
```

Out[2]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	eng
0	3	?	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc	
1	3	?	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc	
2	1	?	alfa-romero	gas	hatchback	rwd	front	65.5	52.4	ohcv	
3	2	164	audi	gas	sedan	fwd	front	66.2	54.3	ohc	
4	2	164	audi	gas	sedan	4wd	front	66.4	54.3	ohc	

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          205 non-null    int64  
 1   normalized-losses  205 non-null    object 
 2   make               205 non-null    object 
 3   fuel-type          205 non-null    object 
 4   body-style         205 non-null    object 
 5   drive-wheels       205 non-null    object 
 6   engine-location    205 non-null    object 
 7   width              205 non-null    float64
 8   height             205 non-null    float64
 9   engine-type        205 non-null    object 
 10  engine-size        205 non-null    int64  
 11  horsepower         205 non-null    object 
 12  city-mpg           205 non-null    int64  
 13  highway-mpg        205 non-null    int64  
 14  price              205 non-null    int64  
dtypes: float64(2), int64(5), object(8)
memory usage: 24.1+ KB
```

In [4]:
```
df.isna().sum()
```

Out[4]:
```
symboling           0
normalized-losses   0
make                0
fuel-type           0
body-style          0
drive-wheels        0
engine-location     0
width               0
height              0
engine-type         0
engine-size         0
horsepower          0
city-mpg            0
highway-mpg         0
price               0
dtype: int64
```

In [5]:
```
df["normalized-losses"].value_counts()
```

Out[5]:
```
?      41
161    11
91      8
150     7
128     6
104     6
134     6
65      5
103     5
94      5
74      5
168     5
102     5
95      5
85      5
118     4
122     4
93      4
106     4
148     4
125     3
154     3
83      3
101     3
137     3
115     3
164     2
153     2
129     2
81      2
145     2
194     2
192     2
188     2
89      2
108     2
87      2
197     2
110     2
158     2
113     2
119     2
256     1
77      1
231     1
107     1
121     1
90      1
98      1
78      1
142     1
186     1
Name: normalized-losses, dtype: int64
```

In [6]:
```
df["horsepower"].value_counts()
```

Out[6]:

68	19
70	11
69	10
116	9
110	8
95	7
101	6
62	6
114	6
88	6
160	6
102	5
97	5
145	5
82	5
84	5
76	5
111	4
123	4
92	4
86	4
121	3
90	3
182	3
85	3
152	3
207	3
73	3
155	2
161	2
162	2
176	2
56	2
?	2
94	2
156	2
112	2
52	2
100	2
184	2
60	1
262	1
106	1
143	1
120	1
134	1
72	1
55	1
48	1
58	1
115	1
78	1
154	1
64	1

```
135     1
140     1
142     1
175     1
288     1
200     1
Name: horsepower, dtype: int64
```

In [7]:
```
#replacing the missing values with (np.nan)
df["normalized-losses"].replace("?", np.nan, inplace=True)
df["horsepower"].replace("?", np.nan, inplace=True)

#changing the datatype
df["normalized-losses"] = df["normalized-losses"].astype("float")
df["horsepower"] = df["horsepower"].astype("float")

#get Mean
nlmean = df["normalized-losses"].mean()
hpmean = df["horsepower"].mean()

#using Fillna
df["normalized-losses"].fillna(nlmean, inplace=True)
df["horsepower"].fillna(hpmean, inplace=True)
```

In [8]:
```
df["normalized-losses"].value_counts
```

Out[8]:
```
<bound method IndexOpsMixin.value_counts of 0      122.0
1      122.0
2      122.0
3      164.0
4      164.0
       ...
200     95.0
201     95.0
202     95.0
203     95.0
204     95.0
Name: normalized-losses, Length: 205, dtype: float64>
```

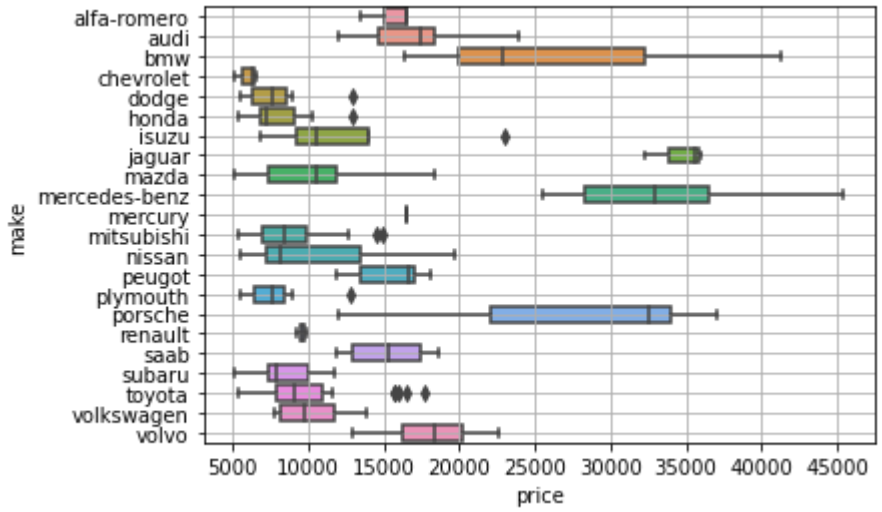
In [9]:
```
df["horsepower"].value_counts
```

Out[9]:
```
<bound method IndexOpsMixin.value_counts of 0      111.0
1      111.0
2      154.0
3      102.0
4      115.0
       ...
200    114.0
201    160.0
202    134.0
203    106.0
204    114.0
Name: horsepower, Length: 205, dtype: float64>
```

Clearing all the OutLiers

In [10]:
```
#searching for all the outliers that are present in the dataset
```

In [11]:
```
sns.boxplot(data=df, x="price", y="make")
plt.grid(True)
```



In [12]:
```
#selecting the particular data which has outliers present in them
```

In [13]:
```
df[(df["make"]=="dodge") & (df["price"]>11000)]
```

Out[13]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	engi s
29	3	145.0	dodge	gas	hatchback	fwd	front	66.3	50.2	ohc	

In [14]:
```
#dropping the outliers using drop function
```

In [15]:
```
df.drop(29, inplace=True)
```

In [16]:
```
df[(df["make"]=="honda") & (df["price"]>11000)]
```

Out[16]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	engine-size
41	0	85.0	honda	gas	sedan	fwd	front	65.2	54.1	ohc	110

In [17]:
```
df.drop(41, inplace=True)
```

In [18]:
```
df[(df["make"]=="isuzu") & (df["price"]>20000)]
```

Out[18]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	engine-size
45	0	122.0	isuzu	gas	sedan	fwd	front	63.6	52.0	ohc	90

In [19]:
```
df.drop(45, inplace=True)
```

In [20]:
```
df[(df["make"]=="mitsubishi") & (df["price"]>13000)]
```

Out[20]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	e
83	3	122.0	mitsubishi	gas	hatchback	fwd	front	66.3	50.2	ohc	
84	3	122.0	mitsubishi	gas	hatchback	fwd	front	66.3	50.2	ohc	

In [21]:
```
df.drop([83,84], inplace=True)
```

In [22]:
```
df[(df["make"]=="plymouth") & (df["price"]>10000)]
```

Out[22]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	e
124	3	122.0	plymouth	gas	hatchback	rwd	front	66.3	50.2	ohc	

In [23]:
```
df.drop(124, inplace=True)
```

In [24]:
```
df[(df["make"]=="toyota") & (df["price"]>12000)]
```

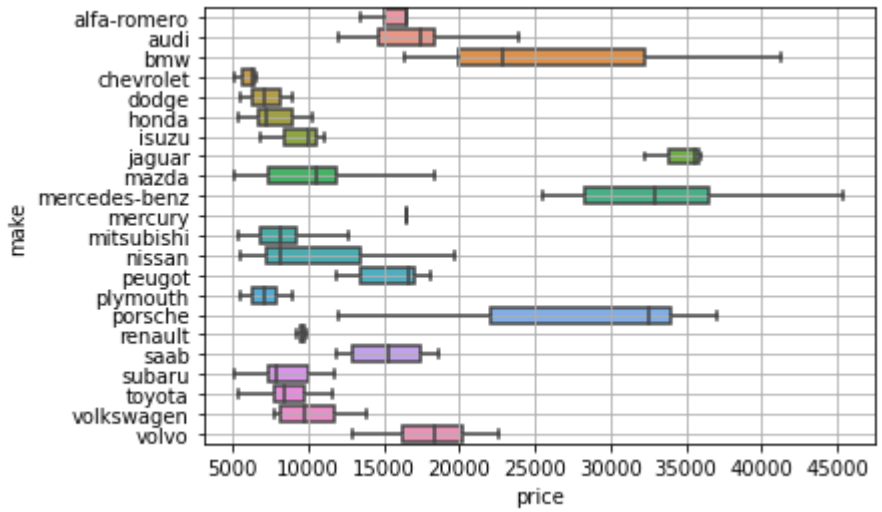
Out[24]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	en
172	2	134.0	toyota	gas	convertible	rwd	front	65.6	53.0	ohc	
178	3	197.0	toyota	gas	hatchback	rwd	front	67.7	52.0	dohc	
179	3	197.0	toyota	gas	hatchback	rwd	front	67.7	52.0	dohc	
180	-1	90.0	toyota	gas	sedan	rwd	front	66.5	54.1	dohc	
181	-1	122.0	toyota	gas	wagon	rwd	front	66.5	54.1	dohc	

In [25]:
```
df.drop([172,178,179,180,181], inplace=True)
```

In [26]:
```
#by this process of cleaning the outliers we get a clear dataset shown below
```

In [27]:
```
sns.boxplot(data=df, x="price", y="make")
plt.grid(True)
```



Label Encoding

In [28]:
```
df.head()
```

Out[28]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	eng
0	3	122.0	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc	
1	3	122.0	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc	
2	1	122.0	alfa-romero	gas	hatchback	rwd	front	65.5	52.4	ohcv	
3	2	164.0	audi	gas	sedan	fwd	front	66.2	54.3	ohc	
4	2	164.0	audi	gas	sedan	4wd	front	66.4	54.3	ohc	

In [29]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 194 entries, 0 to 204
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          194 non-null    int64  
 1   normalized-losses  194 non-null    float64
 2   make               194 non-null    object 
 3   fuel-type          194 non-null    object 
 4   body-style         194 non-null    object 
 5   drive-wheels       194 non-null    object 
 6   engine-location    194 non-null    object 
 7   width              194 non-null    float64
 8   height             194 non-null    float64
 9   engine-type        194 non-null    object 
 10  engine-size        194 non-null    int64  
 11  horsepower         194 non-null    float64
 12  city-mpg           194 non-null    int64  
 13  highway-mpg        194 non-null    int64  
 14  price              194 non-null    int64  
dtypes: float64(4), int64(5), object(6)
memory usage: 28.3+ KB
```

In [30]:
```
#dividing the dataset into two parts i.e, df_cat(catagorical), df_num(numerical)
```

In [31]:
```
df_cat = df.select_dtypes(object)
df_num = df.select_dtypes(["float64", "int64"])
```

In [32]:
```
df_cat
```

Out[32]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type
0	alfa-romero	gas	convertible	rwd	front	dohc
1	alfa-romero	gas	convertible	rwd	front	dohc
2	alfa-romero	gas	hatchback	rwd	front	ohcv
3	audi	gas	sedan	fwd	front	ohc
4	audi	gas	sedan	4wd	front	ohc
...	...	...	...	...	...	...
200	volvo	gas	sedan	rwd	front	ohc
201	volvo	gas	sedan	rwd	front	ohc
202	volvo	gas	sedan	rwd	front	ohcv
203	volvo	diesel	sedan	rwd	front	ohc
204	volvo	gas	sedan	rwd	front	ohc

194 rows × 6 columns

In [33]:
```
df_num
```

Out[33]:

	symboling	normalized-losses	width	height	engine-size	horsepower	city-mpg	highway-mpg	price
0	3	122.0	64.1	48.8	130	111.0	21	27	13495
1	3	122.0	64.1	48.8	130	111.0	21	27	16500
2	1	122.0	65.5	52.4	152	154.0	19	26	16500
3	2	164.0	66.2	54.3	109	102.0	24	30	13950
4	2	164.0	66.4	54.3	136	115.0	18	22	17450
...	...	...	...	...	...	...	...	...	...
200	-1	95.0	68.9	55.5	141	114.0	23	28	16845
201	-1	95.0	68.8	55.5	141	160.0	19	25	19045
202	-1	95.0	68.9	55.5	173	134.0	18	23	21485
203	-1	95.0	68.9	55.5	145	106.0	26	27	22470
204	-1	95.0	68.9	55.5	141	114.0	19	25	22625

194 rows × 9 columns

In [34]:
```
df_cat["fuel-type"].value_counts()
```

Out[34]:
```
gas       174
diesel     20
Name: fuel-type, dtype: int64
```

In [35]:
```
df_cat["fuel-type"].value_counts
```

Out[35]:
```
<bound method IndexOpsMixin.value_counts of 0         gas
1         gas
2         gas
3         gas
4         gas
        ...
200       gas
201       gas
202       gas
203    diesel
204       gas
Name: fuel-type, Length: 194, dtype: object>
```

In [36]:
```
pd.get_dummies(df_cat["fuel-type"])
```

Out[36]:

	diesel	gas
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
...	...	...
200	0	1
201	0	1
202	0	1
203	1	0
204	0	1

194 rows × 2 columns

In [37]:
```
df["make"].nunique()
```

Out[37]: 22

Type *Markdown* and LaTeX: α^2

In [ ]:
```

```

In [38]:
```
#now by using LabelEncoder we change the df_cat dataset from catagricat to numeri
```

In [39]:
```
from sklearn.preprocessing import LabelEncoder
```

In [40]:
```
#first we chage the (fuel-type) data into numerical form
```

In [41]:
```
le = LabelEncoder()
le.fit_transform(df_cat["fuel-type"])
```

Out[41]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1])
```

In [42]:
```
#by using for loop now we change the whole dataset into numerical form
```

In [43]:
```
for col in df_cat:
    le = LabelEncoder()
    df_cat[col] = le.fit_transform(df_cat[col])
```

In [44]:
```
df_cat
```

Out[44]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type
0	0	1	0	2	0	0
1	0	1	0	2	0	0
2	0	1	2	2	0	5
3	1	1	3	1	0	3
4	1	1	3	0	0	3
...	...	...	...	...	...	...
200	21	1	3	2	0	3
201	21	1	3	2	0	3
202	21	1	3	2	0	5
203	21	0	3	2	0	3
204	21	1	3	2	0	3

194 rows × 6 columns

In [45]:
```
df = pd.concat([df_cat, df_num],axis=1)
```

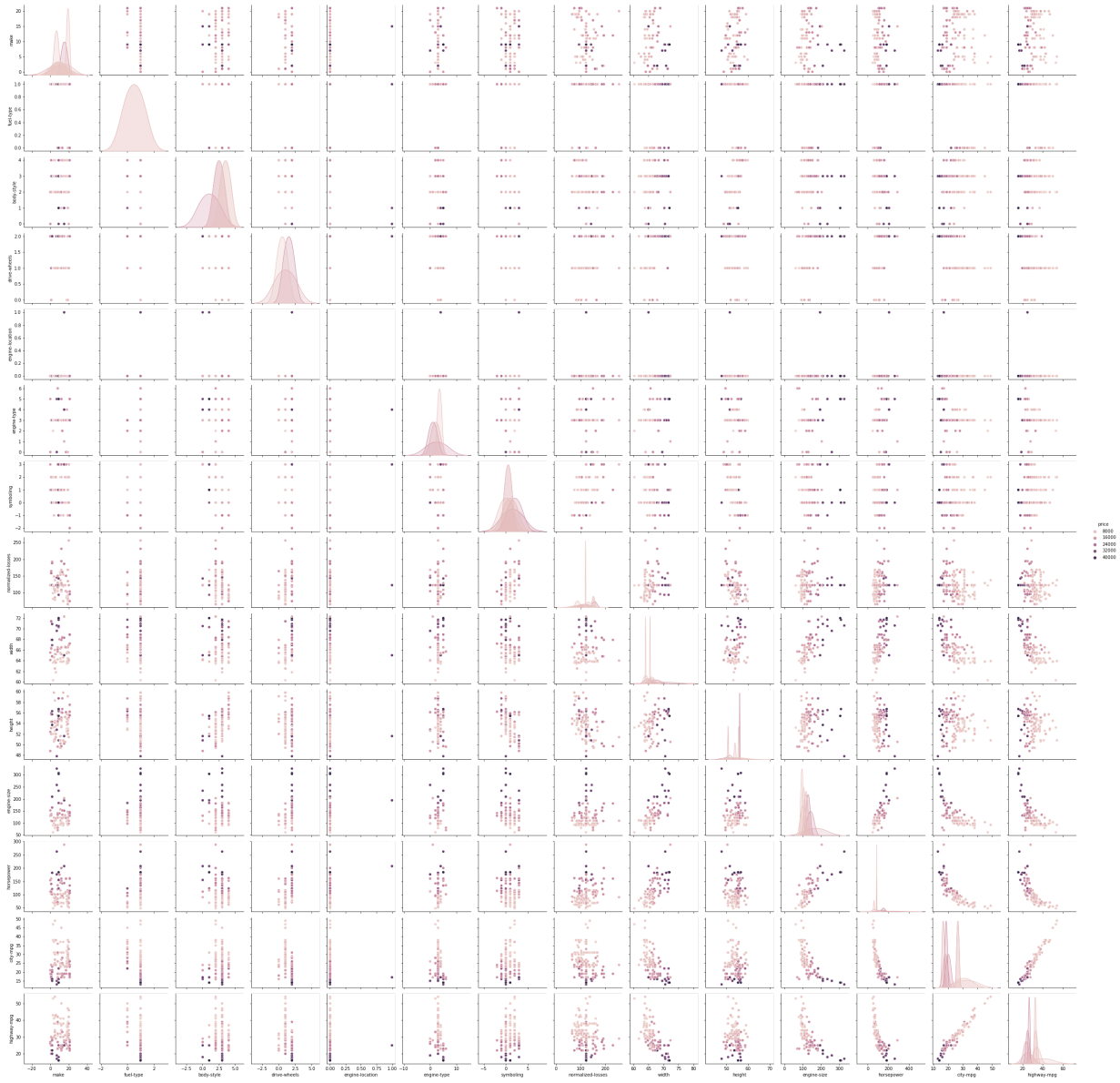
In [46]:
```
df.head()
```

Out[46]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type	symboling	normalized-losses	width	height	engine-size
0	0	1	0	2	0	0	3	122.0	64.1	48.8	130
1	0	1	0	2	0	0	3	122.0	64.1	48.8	130
2	0	1	2	2	0	5	1	122.0	65.5	52.4	152
3	1	1	3	1	0	3	2	164.0	66.2	54.3	109
4	1	1	3	0	0	3	2	164.0	66.4	54.3	136

In [47]:
```
sns.pairplot(data=df, hue="price")
```

Out[47]:
```
<seaborn.axisgrid.PairGrid at 0x8f5aabd6a0>
```



Creating the model

In [48]:
```
x = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [49]:
```
x
```

Out[49]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type	symboling	normalized-losses	width	height	engine-size
0	0	1	0	2	0	0	3	122.0	64.1	48.8	130
1	0	1	0	2	0	0	3	122.0	64.1	48.8	130
2	0	1	2	2	0	5	1	122.0	65.5	52.4	152
3	1	1	3	1	0	3	2	164.0	66.2	54.3	109
4	1	1	3	0	0	3	2	164.0	66.4	54.3	136
...	...	...	...	...	...	...	...	...	...	...	...
200	21	1	3	2	0	3	-1	95.0	68.9	55.5	141
201	21	1	3	2	0	3	-1	95.0	68.8	55.5	141
202	21	1	3	2	0	5	-1	95.0	68.9	55.5	173
203	21	0	3	2	0	3	-1	95.0	68.9	55.5	145
204	21	1	3	2	0	3	-1	95.0	68.9	55.5	141

194 rows × 14 columns

In [50]:
```
y
```

Out[50]:
```
0      13495
1      16500
2      16500
3      13950
4      17450
       ...
200    16845
201    19045
202    21485
203    22470
204    22625
Name: price, Length: 194, dtype: int64
```

In [51]:
```
from scipy.stats import skew
```

In [52]:
```
df_num
```

Out[52]:

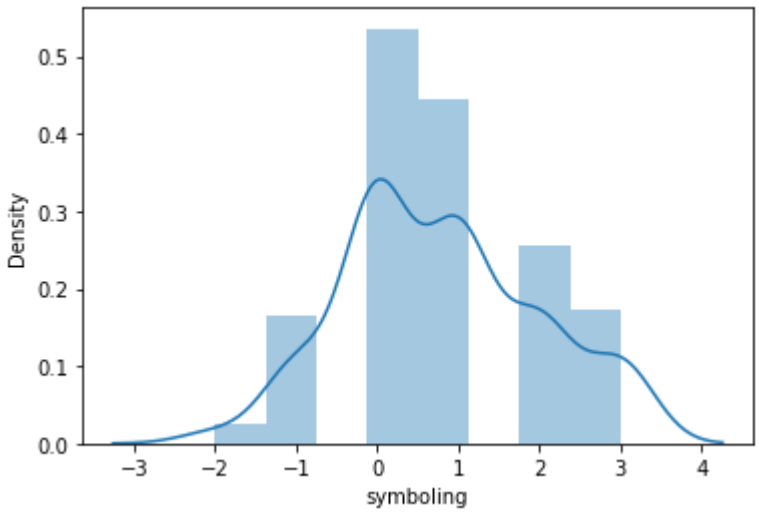
	symboling	normalized-losses	width	height	engine-size	horsepower	city-mpg	highway-mpg	price
0	3	122.0	64.1	48.8	130	111.0	21	27	13495
1	3	122.0	64.1	48.8	130	111.0	21	27	16500
2	1	122.0	65.5	52.4	152	154.0	19	26	16500
3	2	164.0	66.2	54.3	109	102.0	24	30	13950
4	2	164.0	66.4	54.3	136	115.0	18	22	17450
...	...	...	...	...	...	...	...	...	...
200	-1	95.0	68.9	55.5	141	114.0	23	28	16845
201	-1	95.0	68.8	55.5	141	160.0	19	25	19045
202	-1	95.0	68.9	55.5	173	134.0	18	23	21485
203	-1	95.0	68.9	55.5	145	106.0	26	27	22470
204	-1	95.0	68.9	55.5	141	114.0	19	25	22625

194 rows × 9 columns

In [53]:
```
for col in df_num:
    print(col)
    print(skew( df_num[col] ))

    plt.figure()
    sns.distplot(df_num[col])
    plt.show()
```

```
symboling
0.21386866184357742
```



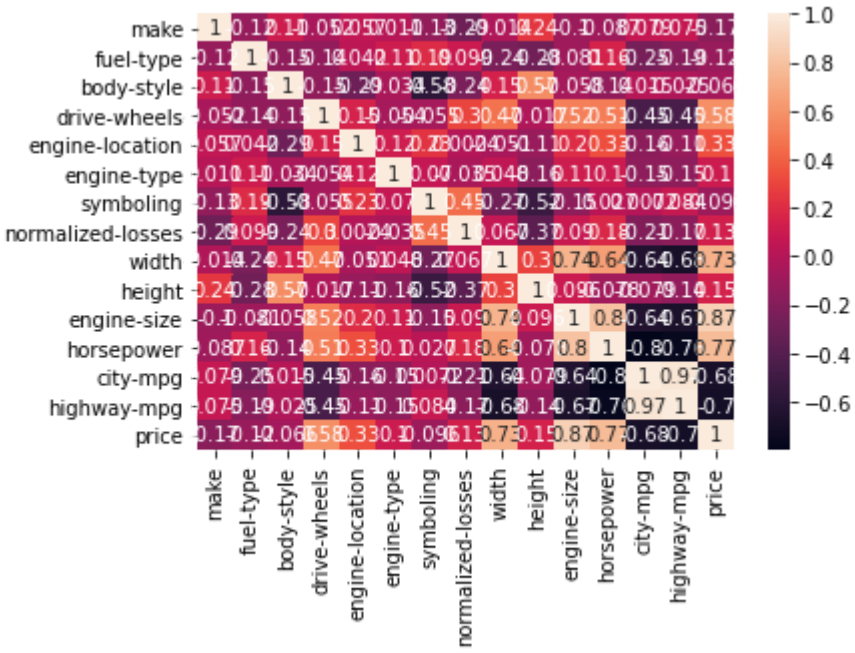
In [54]:
```
df.corr()
```

Out[54]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type	symboling	normalize losse
make	1.000000	-0.119746	0.109203	-0.052044	0.057249	0.010788	-0.133413	-0.29237
fuel-type	-0.119746	1.000000	-0.146577	-0.143825	0.042490	0.112181	0.194923	0.09905
body-style	0.109203	-0.146577	1.000000	-0.149962	-0.291270	-0.033920	-0.584658	-0.23841
drive-wheels	-0.052044	-0.143825	-0.149962	1.000000	0.154729	-0.053643	-0.055088	0.30358
engine-location	0.057249	0.042490	-0.291270	0.154729	1.000000	0.116897	0.231375	0.00239
engine-type	0.010788	0.112181	-0.033920	-0.053643	0.116897	1.000000	0.070345	-0.03510
symboling	-0.133413	0.194923	-0.584658	-0.055088	0.231375	0.070345	1.000000	0.44792
normalized-losses	-0.292370	0.099052	-0.238410	0.303588	0.002392	-0.035104	0.447922	1.00000
width	-0.013582	-0.238744	0.145147	0.470463	-0.051210	0.048240	-0.272388	0.06662
height	0.243751	-0.279480	0.574268	-0.016925	-0.114057	-0.162899	-0.521495	-0.36854
engine-size	-0.100960	-0.081435	-0.057853	0.518208	0.204366	0.109809	-0.153671	0.09025
horsepower	-0.087388	0.155486	-0.143735	0.511362	0.334271	0.101747	0.027074	0.18338
city-mpg	0.079432	-0.253782	0.015181	-0.448046	-0.161467	-0.152574	0.007189	-0.21227
highway-mpg	0.075333	-0.185979	-0.024926	-0.450402	-0.109265	-0.152407	0.084238	-0.16890
price	-0.173792	-0.115791	-0.065831	0.584485	0.333620	0.102758	-0.095905	0.12997

In [55]:
```
sns.heatmap(df.corr(), annot=True)
```

Out[55]: <AxesSubplot:>



In [56]:
```
np.log(-3)
```

Out[56]: nan

In [57]:
```
np.sqrt(-3)
```

Out[57]: nan

In [58]:
```
df_num["normalized-losses"] =np.sqrt(df_num["normalized-losses"])
```

In [59]:
```
skew(df_num["normalized-losses"])
```

Out[59]: 0.4136415061835428

In [60]:
```
from sklearn.model_selection import train_test_split, cross_val_score
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size = 0.3, random_stat
```

In [61]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
```

In [97]:
```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

In [98]:
```
def mymodel(model):
    model.fit(xtrain, ytrain)
    ypred = model.predict(xtest)
    ac = (r2_score(ytest, ypred))
    mse = mean_squared_error(ytest, ypred)
    mae = mean_absolute_error(ytest, ypred)
    rmse = np.sqrt(mse)
    print(f"Accuracy :- {ac}/n/nMSE :- {mse}/n/nRMSE :- {rmse}/n/nMAE :- {mae}")
```

In [99]:
```
models = []

models.append(("Linreg        -: ", LinearRegression()))
models.append(("KNN           -: ", KNeighborsRegressor()))
models.append(("SVM-l         -: ", SVR(kernel="linear")))
models.append(("SVM-r         -: ", SVR(kernel="rbf")))


for name, model in models:
    print(name)
    mymodel(model)
    print("\n\n")
```

```
Linreg        -:
Accuracy :- 0.7872533647503879/n/nMSE :- 14568791.32741768/n/nRMSE :- 3816.9086
087326846/n/nMAE :- 2568.578977315566



KNN           -:
Accuracy :- 0.7266971249115963/n/nMSE :- 18715654.664406776/n/nRMSE :- 4326.159
343390715/n/nMAE :- 2604.9016949152538



SVM-l         -:
Accuracy :- 0.7187520141543107/n/nMSE :- 19259732.179711815/n/nRMSE :- 4388.591
138362267/n/nMAE :- 2587.2902509163678



SVM-r         -:
Accuracy :- -0.17748516694338834/n/nMSE :- 80633640.42491509/n/nRMSE :- 8979.62
3623789312/n/nMAE :- 5394.447269864856
```

In [100]:
```
linreg = LinearRegression()
linreg.fit(xtrain, ytrain)
ypred = linreg.predict(xtest)
```

In [101]:
```
train = linreg.score(xtrain, ytrain)
test =  r2_score(ytest, ypred)

print(f"Training Result -: {train}")
print(f"Test Result     -: {test}")
```

```
Training Result -: 0.8746947367858329
Test Result     -: 0.7872533647503879
```

In [102]:
```
linreg.coef_
```

Out[102]:
```
array([-1.88388809e+02, -1.35614579e+03,  9.60396622e+01,  2.31554489e+03,
        1.07132919e+04,  8.96539296e+01,  2.81435900e+02, -1.51192911e+01,
        8.88448341e+02,  2.20890197e+02,  7.49622351e+01,  4.11780705e+01,
       -4.89978638e+00, -3.18332548e+01])
```

In [103]:
```
from sklearn.linear_model import Ridge, Lasso
```

In [104]:
```
#Ridge
```

In [105]:
```
l2 = Ridge(alpha=10)
```

In [106]:
```
l2.fit(xtrain, ytrain)
ypred = l2.predict(xtest)
```

In [107]:
```
print(r2_score(ytest, ypred))
```

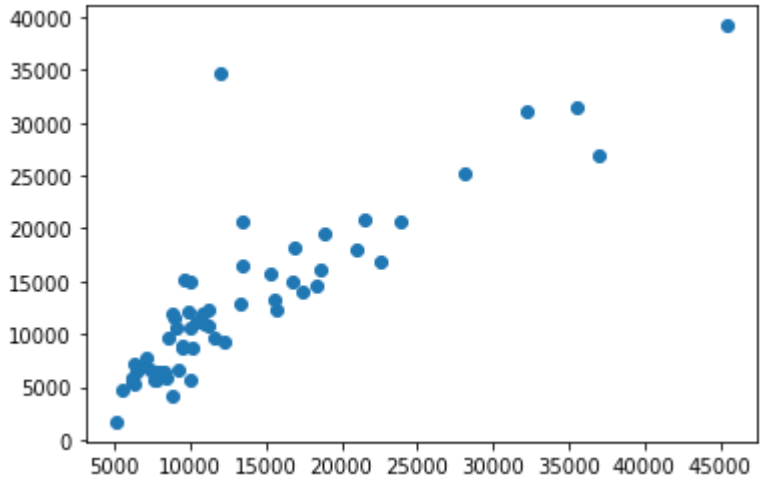
```
0.7446755037448582
```

In [108]:
```
l2.coef_
```

Out[108]:
```
array([-162.36497185, -996.82774462, -220.92859501, 1845.47528303,
       1300.29035686,  112.887593  ,  356.37816602,  -13.80861823,
        680.56398422,  347.44073799,   79.53038111,   63.28044251,
          2.62673725,    4.73681121])
```

In [109]:
```
plt.scatter(ytest, ypred)
```

Out[109]:
```
<matplotlib.collections.PathCollection at 0x8f53ce8b80>
```



In [110]:
```
#Lasso
```

In [111]:
```
l1 = Lasso(alpha=10)
```

In [112]:
```
l1.fit(xtrain, ytrain)
ypred = l1.predict(xtest)
```

In [113]:
```
print(r2_score(ytest, ypred))
```

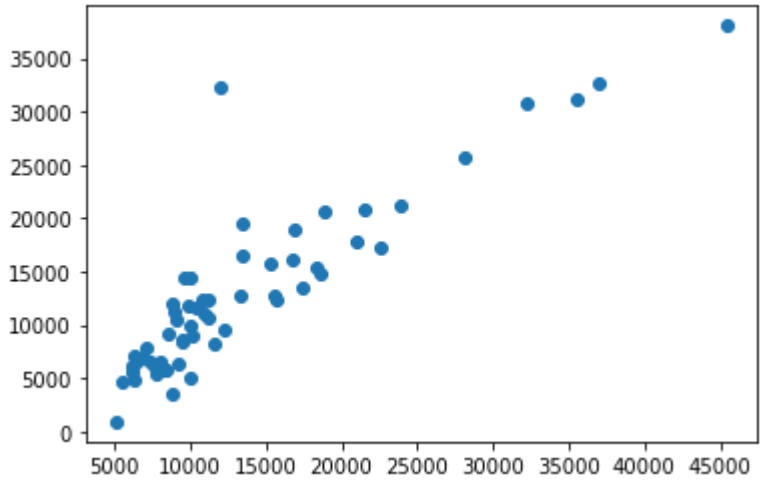
```
0.7845447689773163
```

In [114]:
```
l1.coef_
```

Out[114]:
```
array([-1.84907763e+02, -1.28035315e+03,  2.37417559e+01,  2.27849945e+03,
        9.72464957e+03,  8.61808657e+01,  2.68105178e+02, -1.47775973e+01,
        8.65335349e+02,  2.36756798e+02,  7.54992815e+01,  4.34037541e+01,
       -2.99077374e+00, -2.81059070e+01])
```

In [115]:
```
plt.scatter(ytest, ypred)
```

Out[115]:
```
<matplotlib.collections.PathCollection at 0x8f64f3e250>
```



In [116]:
```
for i in range(100):
    l2 = Ridge(alpha=i)
    l2.fit(xtrain, ytrain)
    print(f"{i} -: {l2.score(xtest, ytest)}")
```

```
0 -: 0.7872533647503897
1 -: 0.767302806500241
2 -: 0.7582177046817948
3 -: 0.7533125714156794
4 -: 0.7503556031941556
5 -: 0.7484405699868022
6 -: 0.7471368782034529
7 -: 0.7462162055202609
8 -: 0.7455474945883274
9 -: 0.7450509055949546
10 -: 0.7446755037448582
11 -: 0.7443875782337195
12 -: 0.7441641395087408
13 -: 0.7439891142571227
14 -: 0.7438510254378199
15 -: 0.7437415281634403
16 -: 0.7436544582832081
17 -: 0.743585198420644
18 -: 0.7435302462564803
19 -: 0.7434869148951573
20 -: 0.7434531213913576
21 -: 0.7434272352621618
22 -: 0.7434079685186195
23 -: 0.7433942948783849
24 -: 0.7433853897719231
25 -: 0.743380585351132
26 -: 0.7433793364450809
27 -: 0.7433811945865134
28 -: 0.7433857880449168
29 -: 0.7433928063688346
30 -: 0.743401988340527
31 -: 0.7434131125320974
32 -: 0.7434259898585334
33 -: 0.7434404576734668
34 -: 0.7434563750638734
35 -: 0.743473619081783
36 -: 0.743492081712139
37 -: 0.7435116674218893
38 -: 0.7435322911701185
39 -: 0.7435538767855336
40 -: 0.7435763556378825
41 -: 0.7435996655454999
42 -: 0.7436237498732815
43 -: 0.7436485567848099
44 -: 0.7436740386196952
45 -: 0.743700151372995
46 -: 0.7437268542581246
47 -: 0.7437541093382882
48 -: 0.7437818812143111
49 -: 0.7438101367590783
50 -: 0.7438388448905591
51 -: 0.7438679763769426
```

```
52 -: 0.7438975036685125
53 -: 0.7439274007519229
54 -: 0.7439576430232493
55 -: 0.7439882071768664
56 -: 0.7440190711076899
57 -: 0.7440502138247547
58 -: 0.7440816153744236
59 -: 0.744113256771842
60 -: 0.7441451199394373
61 -: 0.7441771876514977
62 -: 0.744209443483989
63 -: 0.7442418717689181
64 -: 0.7442744575526635
65 -: 0.7443071865577545
66 -: 0.7443400451477066
67 -: 0.7443730202945285
68 -: 0.7444060995486053
69 -: 0.7444392710107006
70 -: 0.7444725233058402
71 -: 0.7445058455588931
72 -: 0.744539227371684
73 -: 0.7445726588014745
74 -: 0.7446061303407194
75 -: 0.7446396328979472
76 -: 0.7446731577797072
77 -: 0.7447066966734659
78 -: 0.7447402416314038
79 -: 0.7447737850550248
80 -: 0.7448073196805303
81 -: 0.7448408385649135
82 -: 0.7448743350726974
83 -: 0.7449078028633038
84 -: 0.7449412358790084
85 -: 0.7449746283334276
86 -: 0.7450079747005297
87 -: 0.7450412697041273
88 -: 0.745074508307829
89 -: 0.7451076857054193
90 -: 0.7451407973116617
91 -: 0.7451738387534725
92 -: 0.7452068058614869
93 -: 0.7452396946619533
94 -: 0.7452725013689848
95 -: 0.7453052223771136
96 -: 0.7453378542541569
97 -: 0.7453703937343716
98 -: 0.7454028377118849
99 -: 0.7454351832343926
```

In [117]:
```
l2 = Ridge(alpha=0)
l2.fit(xtrain, ytrain)
ypred = l2.predict(xtest)

print(r2_score(ytest, ypred))
```

```
0.787253364750389 7
```

In [118]:
```
for i in range(0,1000,50):
    l1 = Lasso(alpha=i)
    l1.fit(xtrain, ytrain)
    print(f"{i} -: {l1.score(xtest, ytest)}")
```

```
0 -: 0.78725336475039
50 -: 0.7659283362102931
100 -: 0.7397789106535343
150 -: 0.7312865128312395
200 -: 0.7333720072320571
250 -: 0.7330361793350894
300 -: 0.7321466777653632
350 -: 0.731729076002716
400 -: 0.731674552125494
450 -: 0.7324943095892767
500 -: 0.7322486638458842
550 -: 0.7325708026281421
600 -: 0.73353993479164
650 -: 0.7344494557905592
700 -: 0.735304724500026
750 -: 0.7361072960479971
800 -: 0.7368479400706667
850 -: 0.7375354588157039
900 -: 0.738165257991201
950 -: 0.7387387724658839
```

In [119]:
```
l1 = Lasso(alpha=0)
l1.fit(xtrain, ytrain)
ypred = l1.predict(xtest)
print(r2_score(ytest, ypred))
```

```
0.78725336475039
```

Cross Validation

In [123]:
```
cvs = cross_val_score(l1, x,y, cv=4)
```

In [124]:
```
cvs
```

Out[124]:
```
array([0.75135279, 0.8578691 , 0.37303229, 0.38158495])
```

In [125]:
```
cvs.mean()
```

Out[125]:
```
0.5909597821083946
```

In [ ]: