```python
#Expoloratory Data Analysis

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

import warnings
warnings.filterwarnings('ignore')

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

#Load Data

df = pd.read_csv('Automobile_data.csv')
df.head()
```

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

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

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm
city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000
21
```

```
1         mpfi  3.47    2.68               9.0        111       5000
21
2         mpfi  2.68    3.47               9.0        154       5000
19
3         mpfi  3.19     3.4              10.0        102       5500
24
4         mpfi  3.19     3.4               8.0        115       5500
18

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

[5 rows x 26 columns]

# Data Inspection

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 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   aspiration         205 non-null    object
 5   num-of-doors       205 non-null    object
 6   body-style         205 non-null    object
 7   drive-wheels       205 non-null    object
 8   engine-location    205 non-null    object
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64
 14  engine-type        205 non-null    object
 15  num-of-cylinders   205 non-null    object
 16  engine-size        205 non-null    int64
 17  fuel-system        205 non-null    object
 18  bore               205 non-null    object
 19  stroke             205 non-null    object
 20  compression-ratio  205 non-null    float64
 21  horsepower         205 non-null    object
 22  peak-rpm           205 non-null    object
 23  city-mpg           205 non-null    int64
 24  highway-mpg        205 non-null    int64
 25  price              205 non-null    object
dtypes: float64(5), int64(5), object(16)
memory usage: 41.8+ KB
```

```
df.columns
```

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

```
df.shape
```

```
(205, 26)
```

```
df.describe().round(2)
```

```
       symboling  wheel-base  length   width  height  curb-weight  \
count     205.00      205.00  205.00  205.00  205.00       205.00
mean        0.83       98.76  174.05   65.91   53.72      2555.57
std         1.25        6.02   12.34    2.15    2.44       520.68
min        -2.00       86.60  141.10   60.30   47.80      1488.00
25%         0.00       94.50  166.30   64.10   52.00      2145.00
50%         1.00       97.00  173.20   65.50   54.10      2414.00
75%         2.00      102.40  183.10   66.90   55.50      2935.00
max         3.00      120.90  208.10   72.30   59.80      4066.00

       engine-size  compression-ratio  city-mpg  highway-mpg
count       205.00             205.00    205.00       205.00
mean        126.91              10.14     25.22        30.75
std          41.64               3.97      6.54         6.89
min          61.00               7.00     13.00        16.00
25%          97.00               8.60     19.00        25.00
50%         120.00               9.00     24.00        30.00
75%         141.00               9.40     30.00        34.00
max         326.00              23.00     49.00        54.00
```

```
df = df[~(df["price"] == "?")]
```

```
df["prince"] = df["price"].astype("float64")
```

```
# Exploratory Data Analysis

df.head()

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

    body-style drive-wheels engine-location  wheel-base  ...  fuel-
system  \
0  convertible          rwd           front        88.6  ...
mpfi
1  convertible          rwd           front        88.6  ...
mpfi
2    hatchback          rwd           front        94.5  ...
mpfi
3        sedan          fwd           front        99.8  ...
mpfi
4        sedan          4wd           front        99.4  ...
mpfi

   bore  stroke  compression-ratio horsepower peak-rpm  city-mpg
highway-mpg  \
0  3.47    2.68                9.0        111     5000        21
27
1  3.47    2.68                9.0        111     5000        21
27
2  2.68    3.47                9.0        154     5000        19
26
3  3.19     3.4               10.0        102     5500        24
30
4  3.19     3.4                8.0        115     5500        18
22

   price   prince
0  13495  13495.0
1  16500  16500.0
2  16500  16500.0
3  13950  13950.0
4  17450  17450.0
```

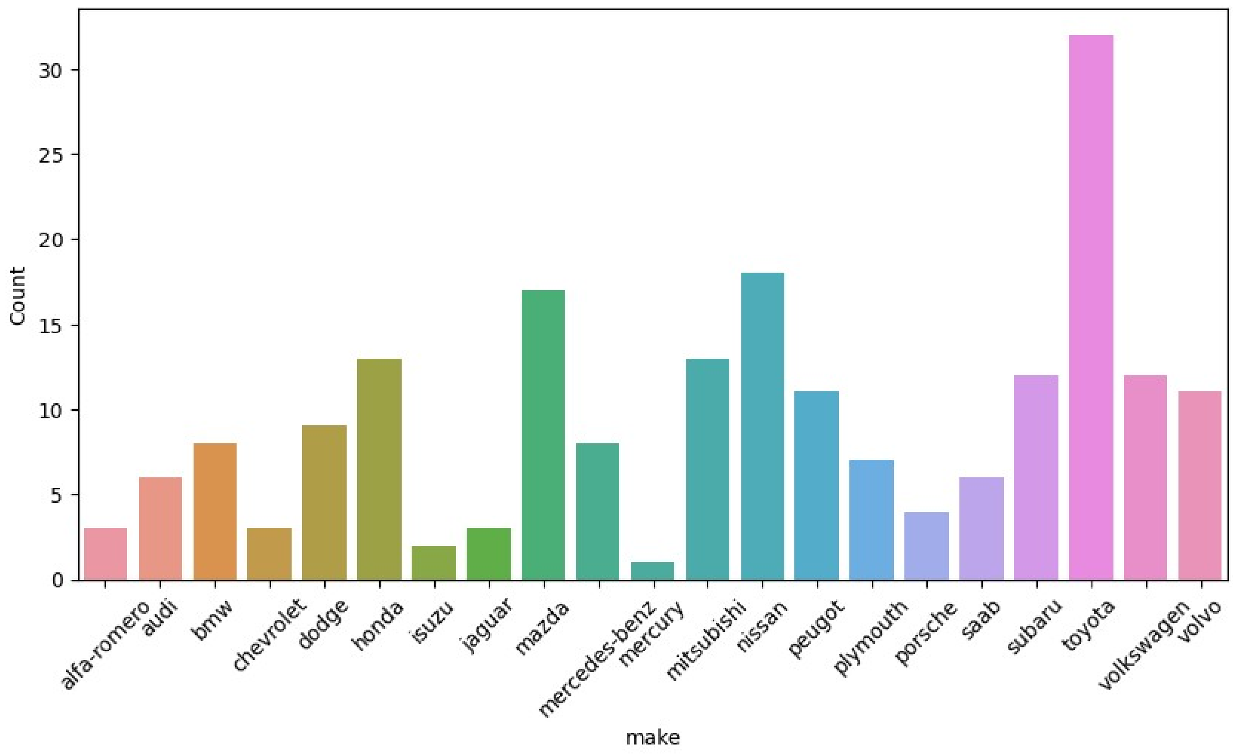
```
[5 rows x 27 columns]

df = df[df["horsepower"] != "?" ]

df["horsepower"] = df["horsepower"].astype("float64")

df.describe().round(2)

       symboling  wheel-base  length   width  height  curb-weight  \
count     199.00      199.00  199.00  199.00  199.00       199.00
mean        0.84       98.82  174.15   65.88   53.78      2556.03
std         1.26        6.09   12.37    2.11    2.45       519.86
min        -2.00       86.60  141.10   60.30   47.80      1488.00
25%         0.00       94.50  166.55   64.10   52.00      2157.00
50%         1.00       97.00  173.20   65.50   54.10      2414.00
75%         2.00      102.40  183.50   66.70   55.55      2930.50
max         3.00      120.90  208.10   72.00   59.80      4066.00

       engine-size  compression-ratio  horsepower  city-mpg  highway-
mpg  \
count       199.00             199.00      199.00    199.00
199.00
mean        126.82              10.18      103.40     25.20
30.68
std          41.75               4.02       37.55      6.45
6.85
min          61.00               7.00       48.00     13.00
16.00
25%          97.50               8.55       70.00     19.00
25.00
50%         119.00               9.00       95.00     24.00
30.00
75%         143.00               9.40      116.00     30.00
34.00
max         326.00              23.00      262.00     49.00
54.00

         prince
count    199.00
mean   13243.43
std     7978.71
min     5118.00
25%     7775.00
50%    10345.00
75%    16501.50
max    45400.00

def count_plot(data, col):
    plt.figure(figsize = (10, 5))
    sns.countplot(data = data, x = col)
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.xticks(rotation = 45);
    plt.show()

def pie_plot(data):
    plt.pie(x = data, autopct = '%1.1f%%', labels = data.index)
    plt.show()

df.columns
```

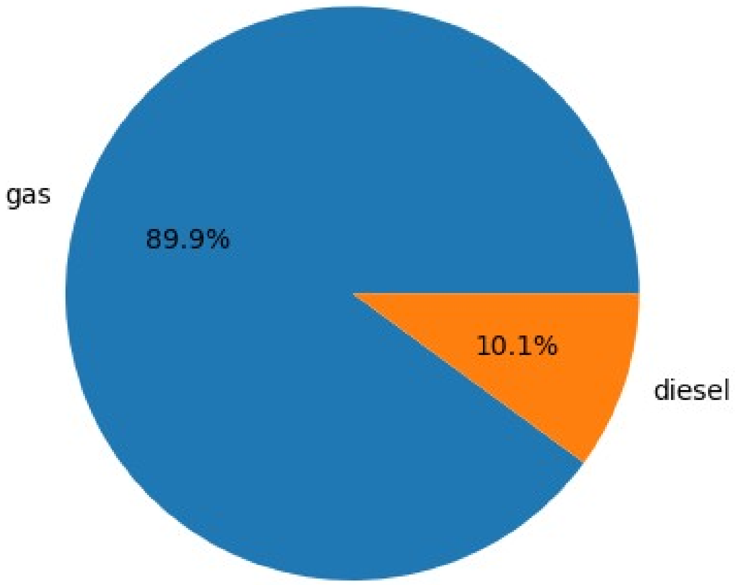
```
Index(['symboling', 'normalized-losses', 'make', 'fuel-type',
'aspiration',
       'num-of-doors', 'body-style', 'drive-wheels', 'engine-
location',
       'wheel-base', 'length', 'width', 'height', 'curb-weight',
'engine-type',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore',
'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price', 'prince'],
      dtype='object')
```

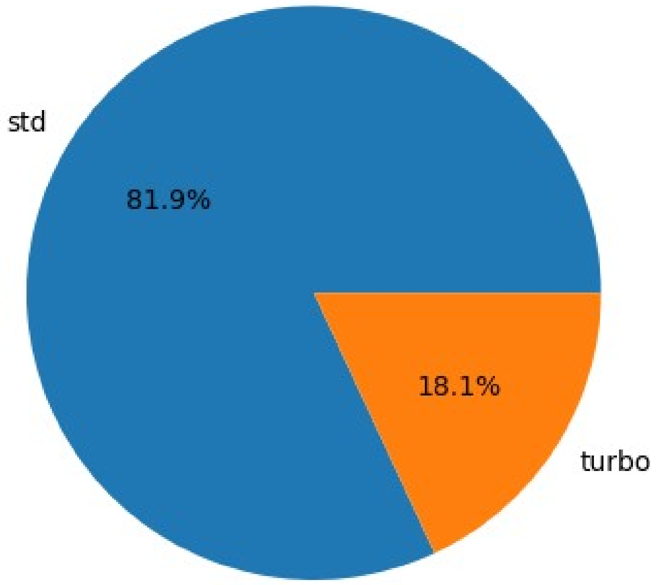
```
col = list(df.columns[2:9]) + list(df.columns[14:18])
col.pop(-2)
col
```

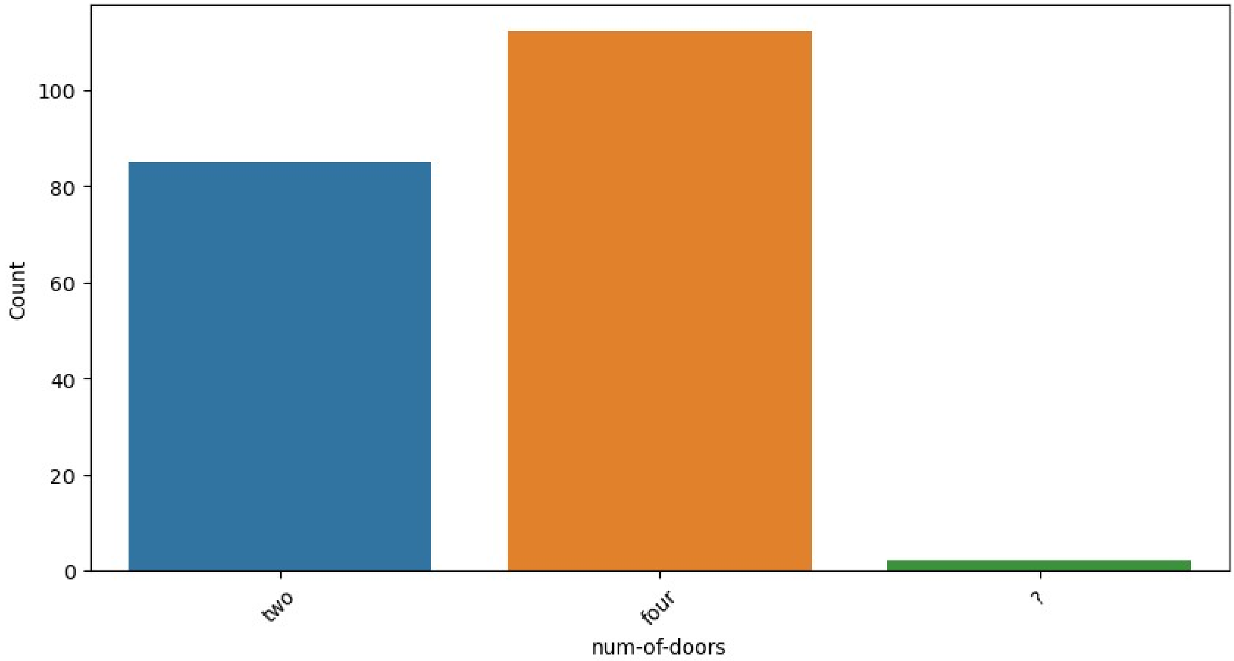
```
['make',
 'fuel-type',
 'aspiration',
 'num-of-doors',
 'body-style',
 'drive-wheels',
 'engine-location',
 'engine-type',
 'num-of-cylinders',
 'fuel-system']
```

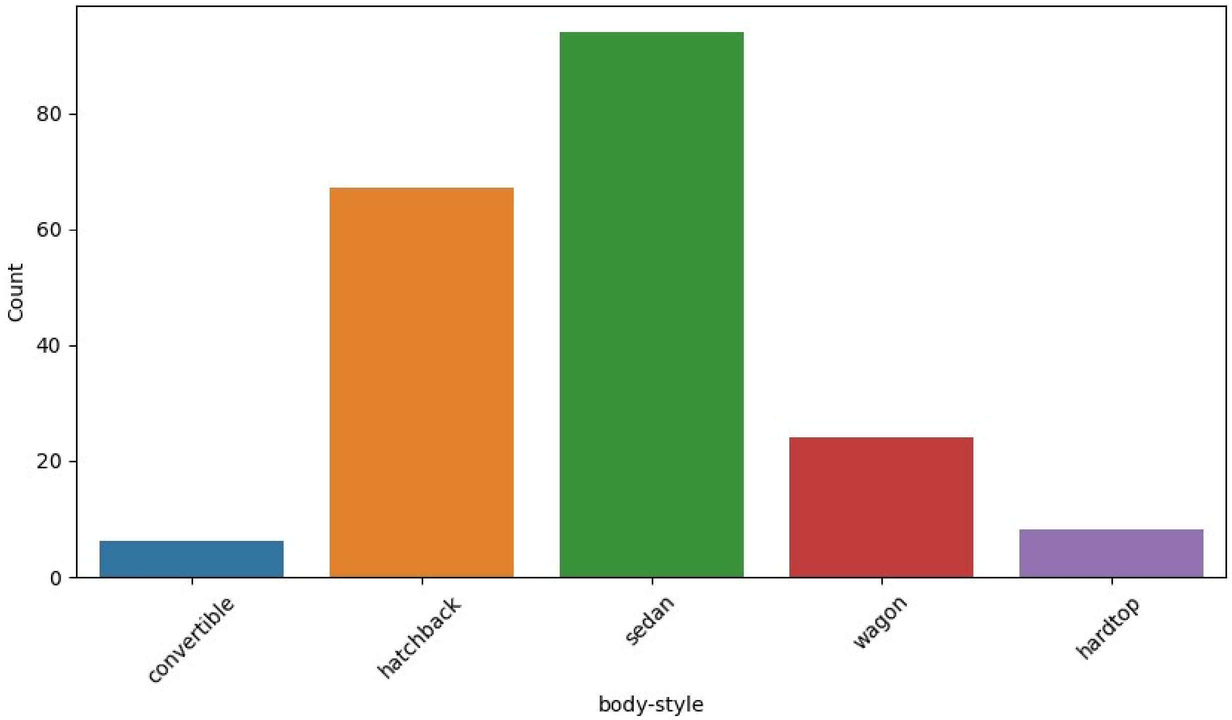
```
for x in col:
    if df[x].value_counts().shape[0] >= 3:
        count_plot(df, x)
    else :
        pie_plot(df[x].value_counts())
```

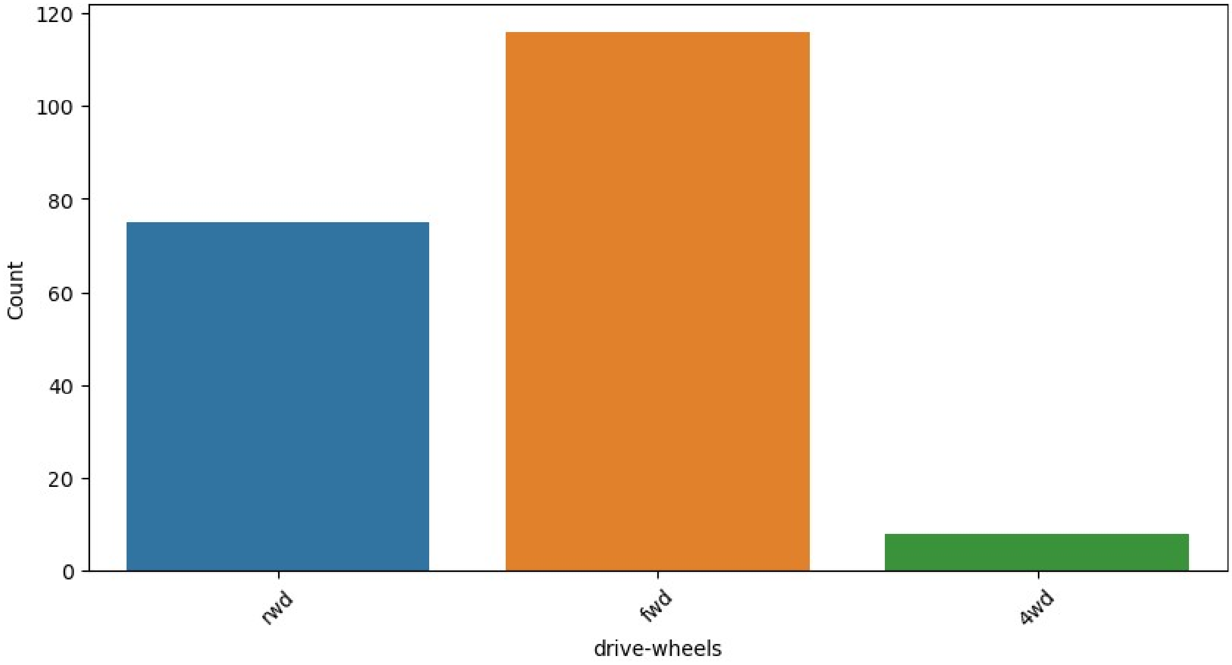

Count
0
5
10
15
20
25
30
make
alfa-romero
audi
bmw
chevrolet
dodge
honda
isuzu
jaguar
mazda
mercedes-benz
mercury
mitsubishi
nissan
peugot
plymouth
porsche
saab
subaru
toyota
volkswagen
volvo

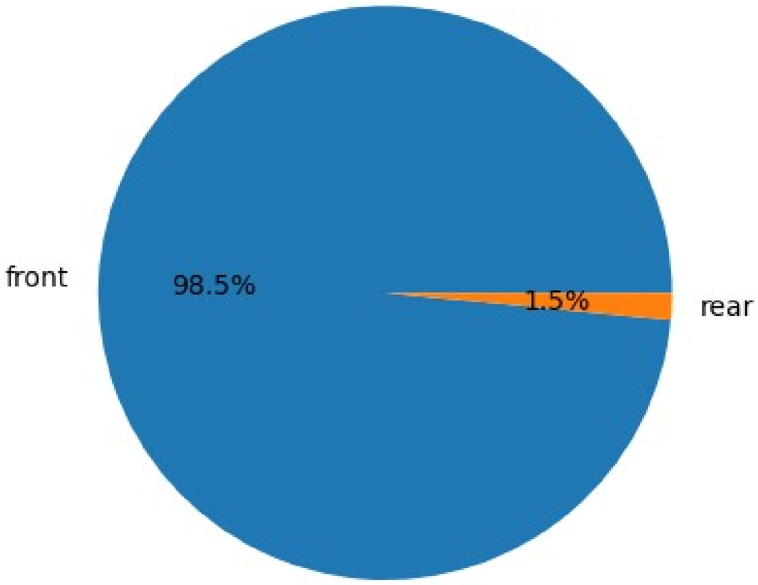

gas
89.9%
10.1%
diesel

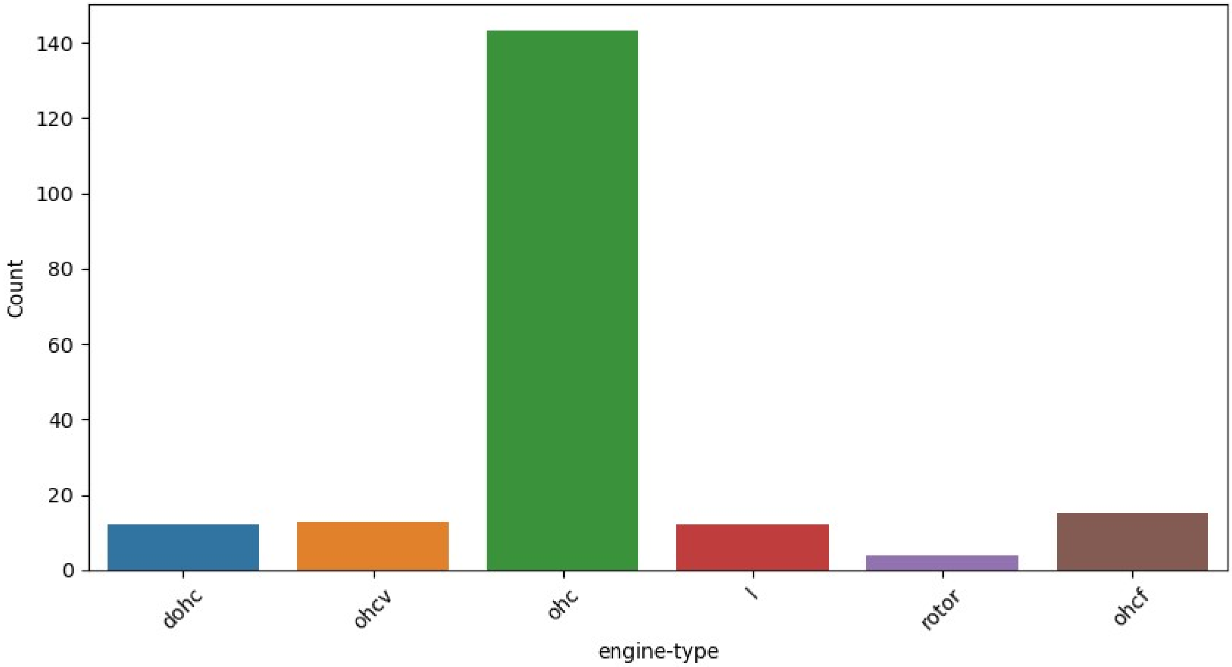

std
81.9%
18.1%
turbo

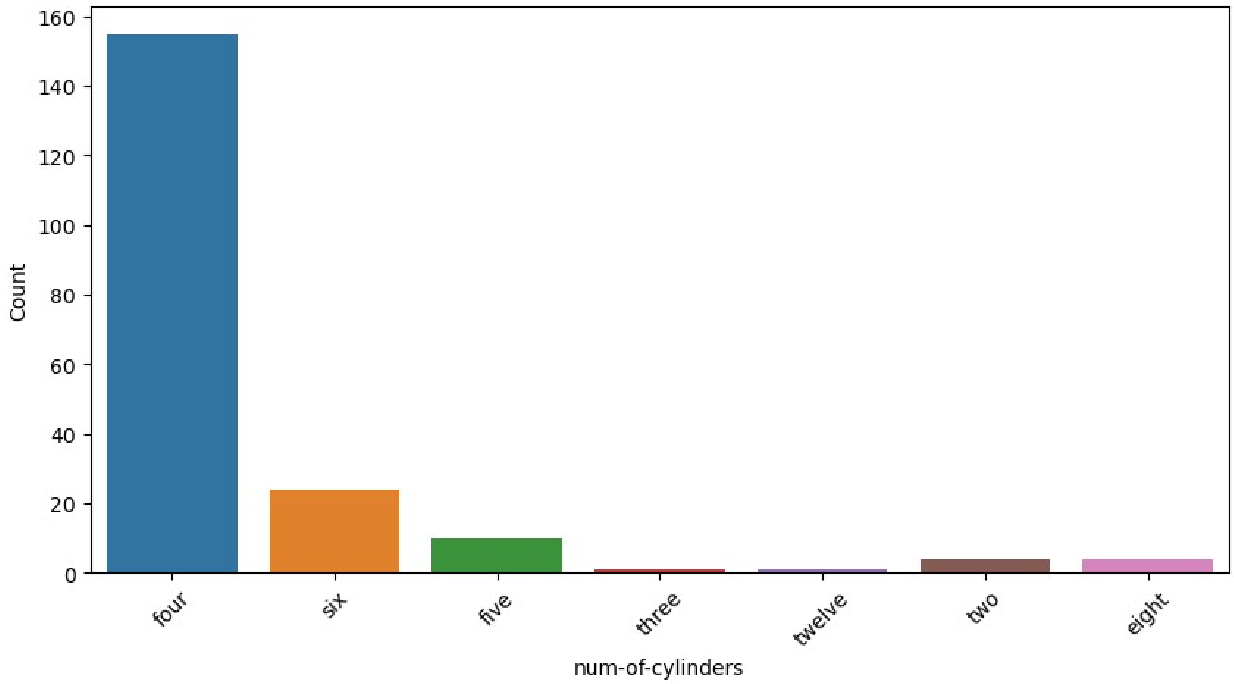

100
80
60
40
20
0
Count
two
four
?
num-of-doors

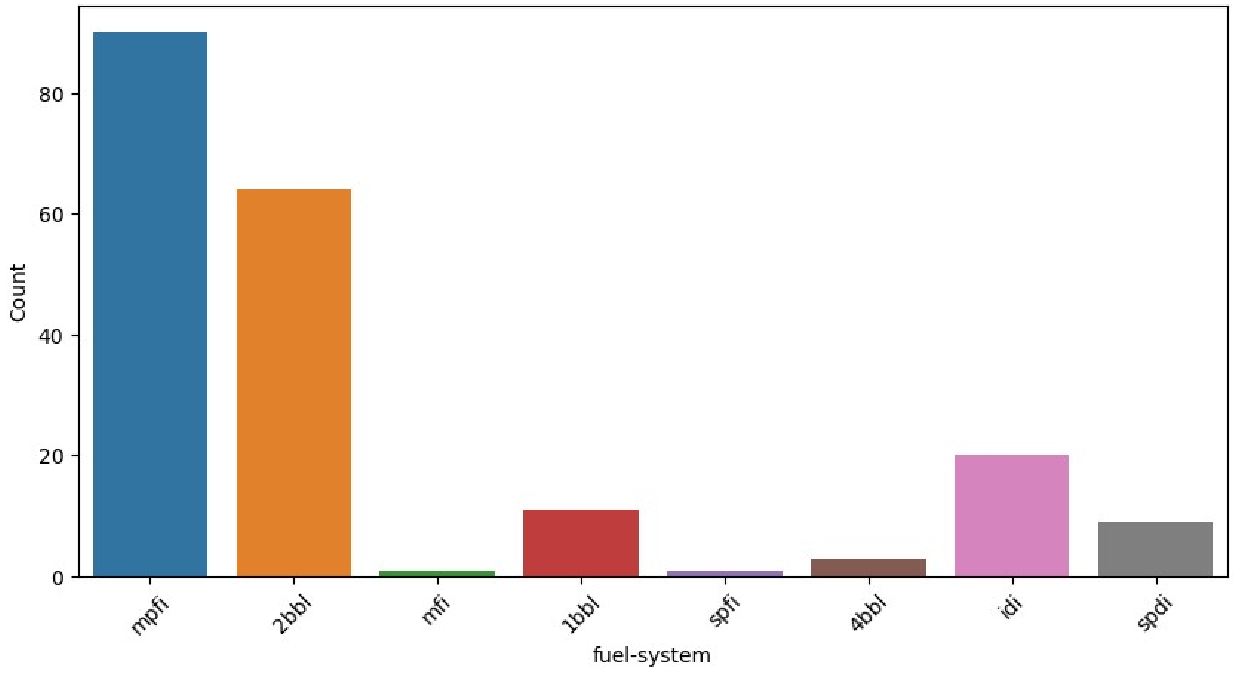

Count
0
20
40
60
80
convertible
hatchback
sedan
wagon
hardtop
body-style


Count
0
20
40
60
80
100
120
rwd
fwd
4wd
drive-wheels


front
98.5%
1.5%
rear


140
120
100
80
60
40
20
0
Count
dohc
ohcv
ohc
l
rotor
ohcf
engine-type





```
def print_count(col_name):
    print(f"\t\t Value Count Of {col_name}")
    print(df[col_name].value_counts())
    print("#" * 50)
    print()
```

```
for i in col:
    print_count(i)
```

```
            Value Count Of make
make
toyota           32
nissan           18
mazda            17
honda            13
mitsubishi       13
volkswagen       12
subaru           12
volvo            11
peugot           11
dodge             9
bmw               8
mercedes-benz     8
plymouth          7
saab              6
audi              6
porsche           4
alfa-romero       3
jaguar            3
chevrolet         3
isuzu             2
mercury           1
Name: count, dtype: int64
##################################################

            Value Count Of fuel-type
fuel-type
gas       179
diesel     20
Name: count, dtype: int64
##################################################

            Value Count Of aspiration
aspiration
std      163
turbo     36
Name: count, dtype: int64
##################################################

            Value Count Of num-of-doors
num-of-doors
four    112
two      85
?         2
Name: count, dtype: int64
##################################################
```

```
            Value Count Of body-style
body-style
sedan          94
hatchback      67
wagon          24
hardtop         8
convertible     6
Name: count, dtype: int64
##################################################

            Value Count Of drive-wheels
drive-wheels
fwd    116
rwd     75
4wd      8
Name: count, dtype: int64
##################################################

            Value Count Of engine-location
engine-location
front    196
rear       3
Name: count, dtype: int64
##################################################

            Value Count Of engine-type
engine-type
ohc      143
ohcf      15
ohcv      13
dohc      12
l         12
rotor      4
Name: count, dtype: int64
##################################################

            Value Count Of num-of-cylinders
num-of-cylinders
four      155
six        24
five       10
two         4
eight       4
three       1
twelve      1
Name: count, dtype: int64
##################################################

            Value Count Of fuel-system
```

```
fuel-system
mpfi    90
2bbl    64
idi     20
1bbl    11
spdi     9
4bbl     3
mfi      1
spfi     1
Name: count, dtype: int64
##################################################
```

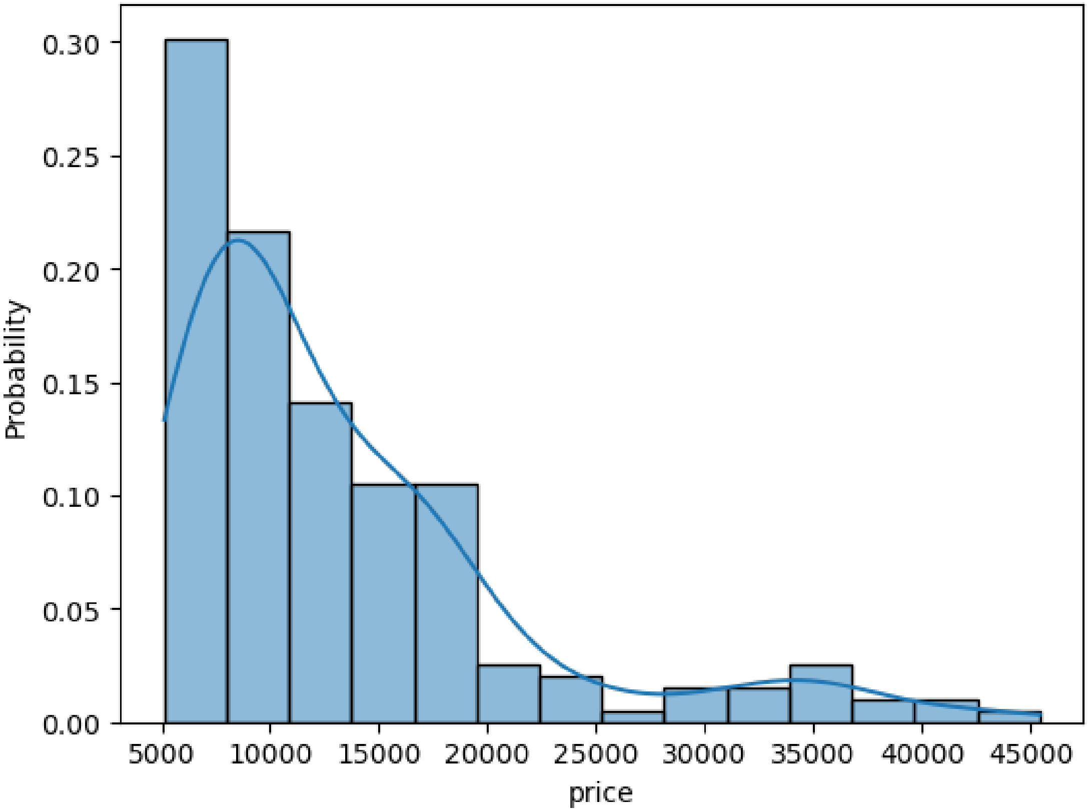
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 199 entries, 0 to 204
Data columns (total 27 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          199 non-null    int64  
 1   normalized-losses  199 non-null    object 
 2   make               199 non-null    object 
 3   fuel-type          199 non-null    object 
 4   aspiration         199 non-null    object 
 5   num-of-doors       199 non-null    object 
 6   body-style         199 non-null    object 
 7   drive-wheels       199 non-null    object 
 8   engine-location    199 non-null    object 
 9   wheel-base         199 non-null    float64
 10  length             199 non-null    float64
 11  width              199 non-null    float64
 12  height             199 non-null    float64
 13  curb-weight        199 non-null    int64  
 14  engine-type        199 non-null    object 
 15  num-of-cylinders   199 non-null    object 
 16  engine-size        199 non-null    int64  
 17  fuel-system        199 non-null    object 
 18  bore               199 non-null    object 
 19  stroke             199 non-null    object 
 20  compression-ratio  199 non-null    float64
 21  horsepower         199 non-null    float64
 22  peak-rpm           199 non-null    object 
 23  city-mpg           199 non-null    int64  
 24  highway-mpg        199 non-null    int64  
 25  price              199 non-null    object 
 26  prince             199 non-null    float64
dtypes: float64(7), int64(5), object(15)
memory usage: 43.5+ KB
```

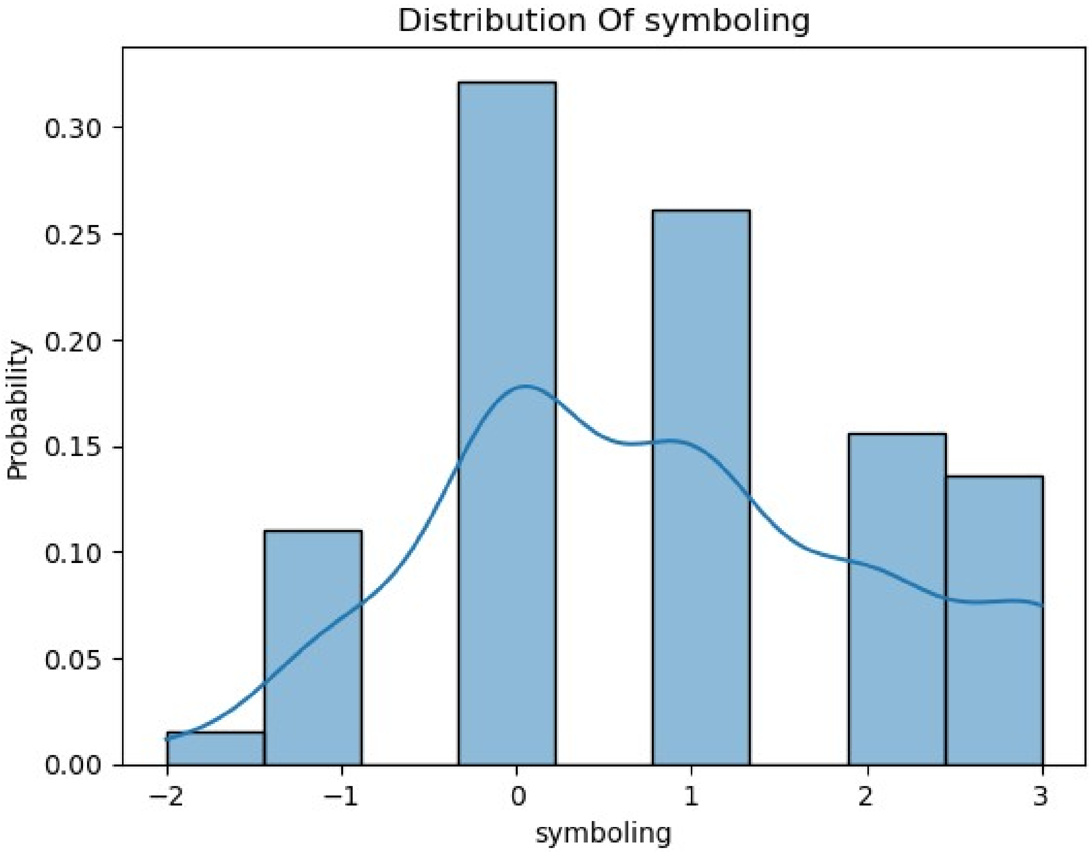
```
df.describe().round(2)
```

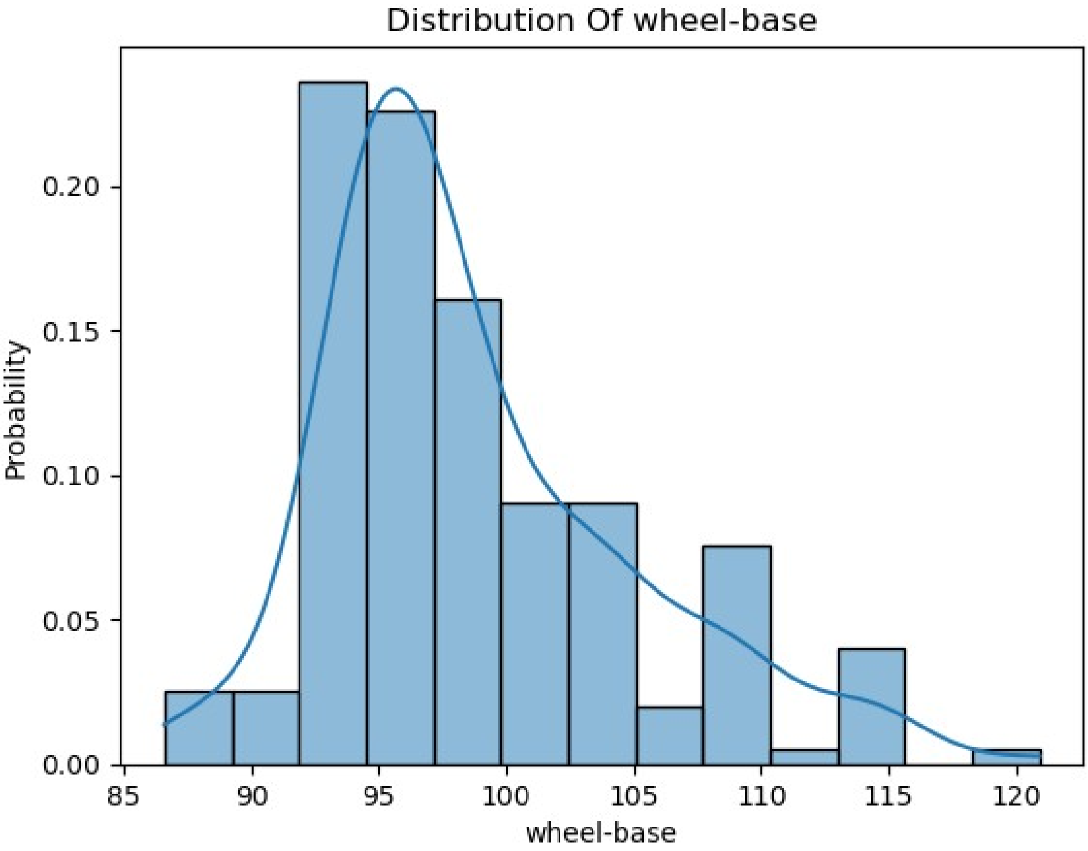
```
       symboling  wheel-base  length   width  height  curb-weight  \
count     199.00      199.00  199.00  199.00  199.00       199.00
mean        0.84       98.82  174.15   65.88   53.78      2556.03
std         1.26        6.09   12.37    2.11    2.45       519.86
min        -2.00       86.60  141.10   60.30   47.80      1488.00
25%         0.00       94.50  166.55   64.10   52.00      2157.00
50%         1.00       97.00  173.20   65.50   54.10      2414.00
75%         2.00      102.40  183.50   66.70   55.55      2930.50
max         3.00      120.90  208.10   72.00   59.80      4066.00

       engine-size  compression-ratio  horsepower  city-mpg  highway-
mpg  \
count       199.00             199.00      199.00    199.00
199.00
mean        126.82              10.18      103.40     25.20
30.68
std          41.75               4.02       37.55      6.45
6.85
min          61.00               7.00       48.00     13.00
16.00
25%          97.50               8.55       70.00     19.00
25.00
50%         119.00               9.00       95.00     24.00
30.00
75%         143.00               9.40      116.00     30.00
34.00
max         326.00              23.00      262.00     49.00
54.00

         prince
count    199.00
mean   13243.43
std     7978.71
min     5118.00
25%     7775.00
50%    10345.00
75%    16501.50
max    45400.00
```

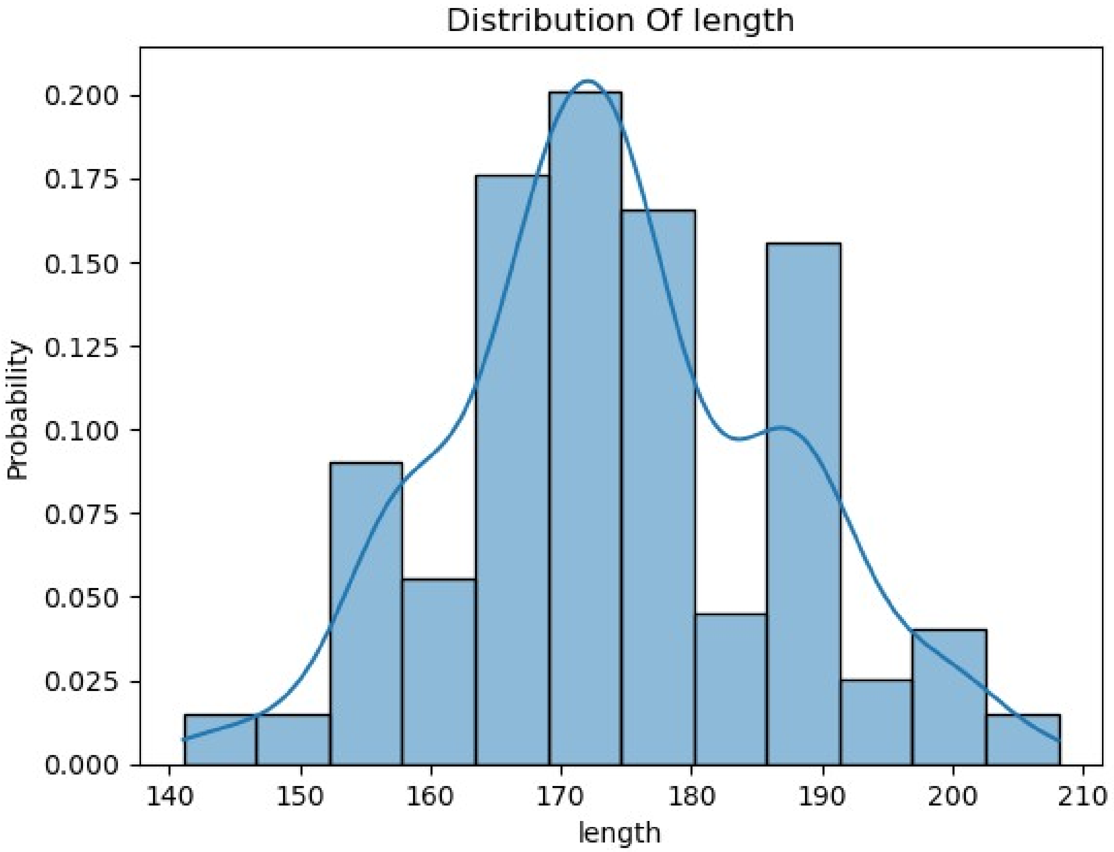
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df['price'] = pd.to_numeric(df['price'], errors='coerce')

df = df.dropna(subset=['price'])

sns.histplot(data=df, x='price', kde=True, stat='probability')
plt.show()
```

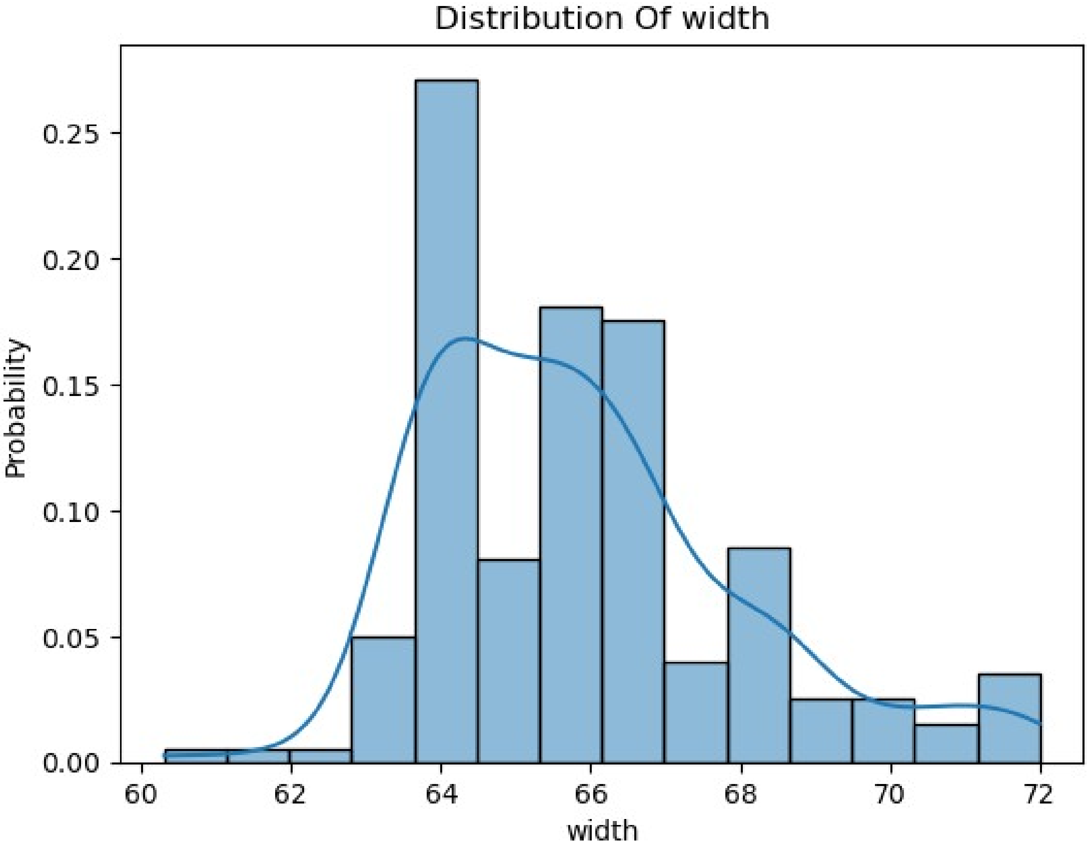


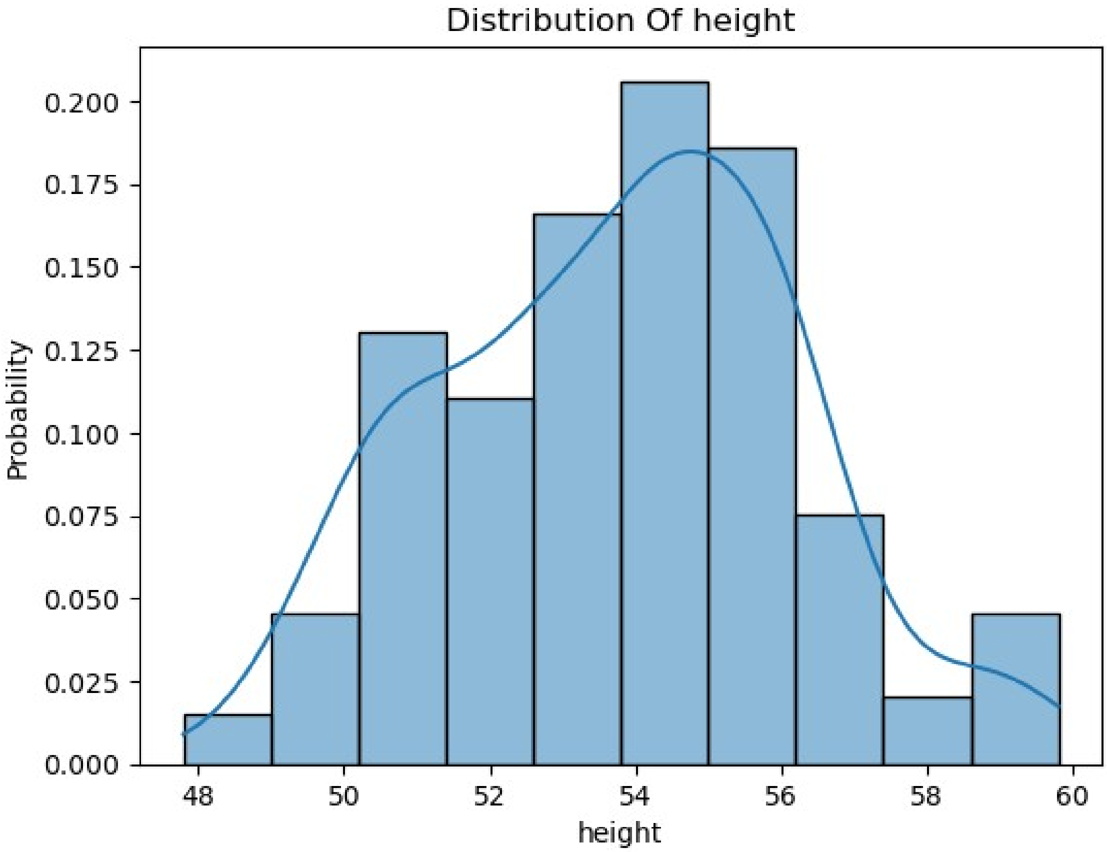
```python
col_num = ['symboling', 'wheel-base', 'length', 'width', 'height',
'curb-weight', 'engine-size', 'compression-ratio', 'city-mpg',
'highway-mpg', 'price', 'horsepower']

def plot_dist(col):
    plt.title(f"Distribution Of {col}")
    sns.histplot(data = df, x = col, stat = 'probability', kde = True)
    plt.show()

for i in col_num:
    plot_dist(i)
```

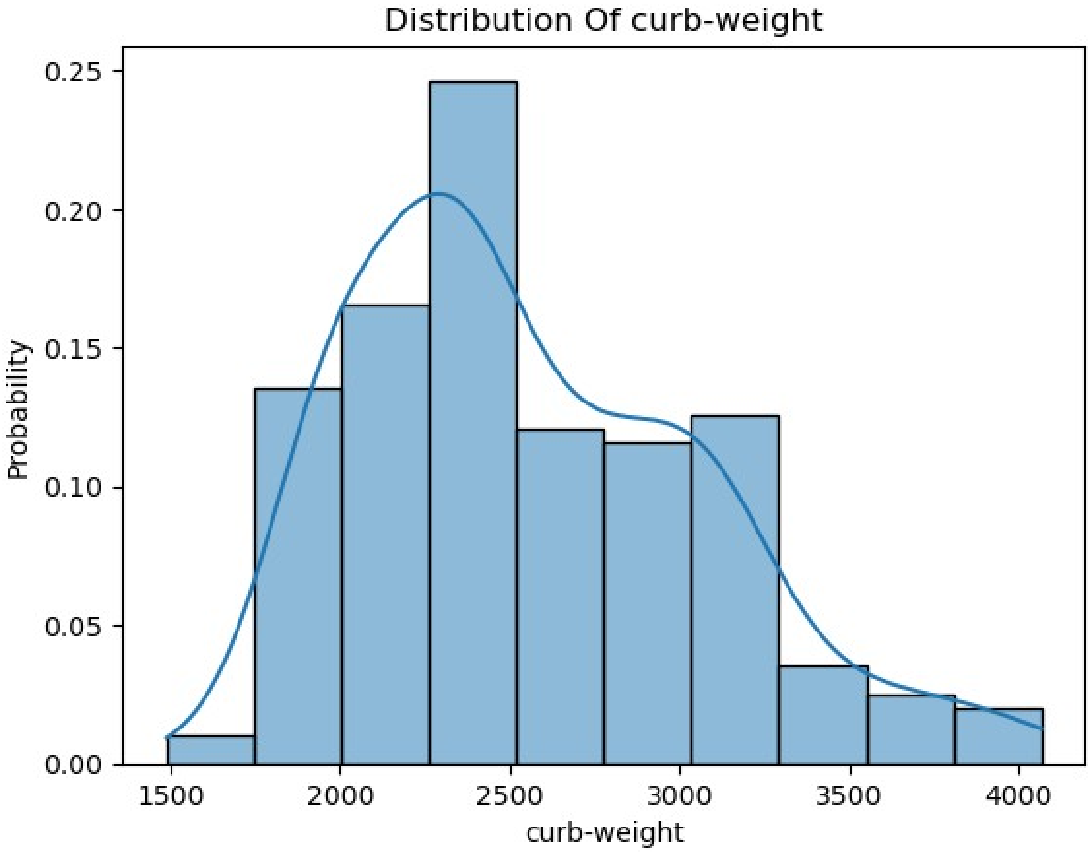

Distribution Of symboling
Probability
0.00
0.05
0.10
0.15
0.20
0.25
0.30
−2
−1
0
1
2
3
symboling

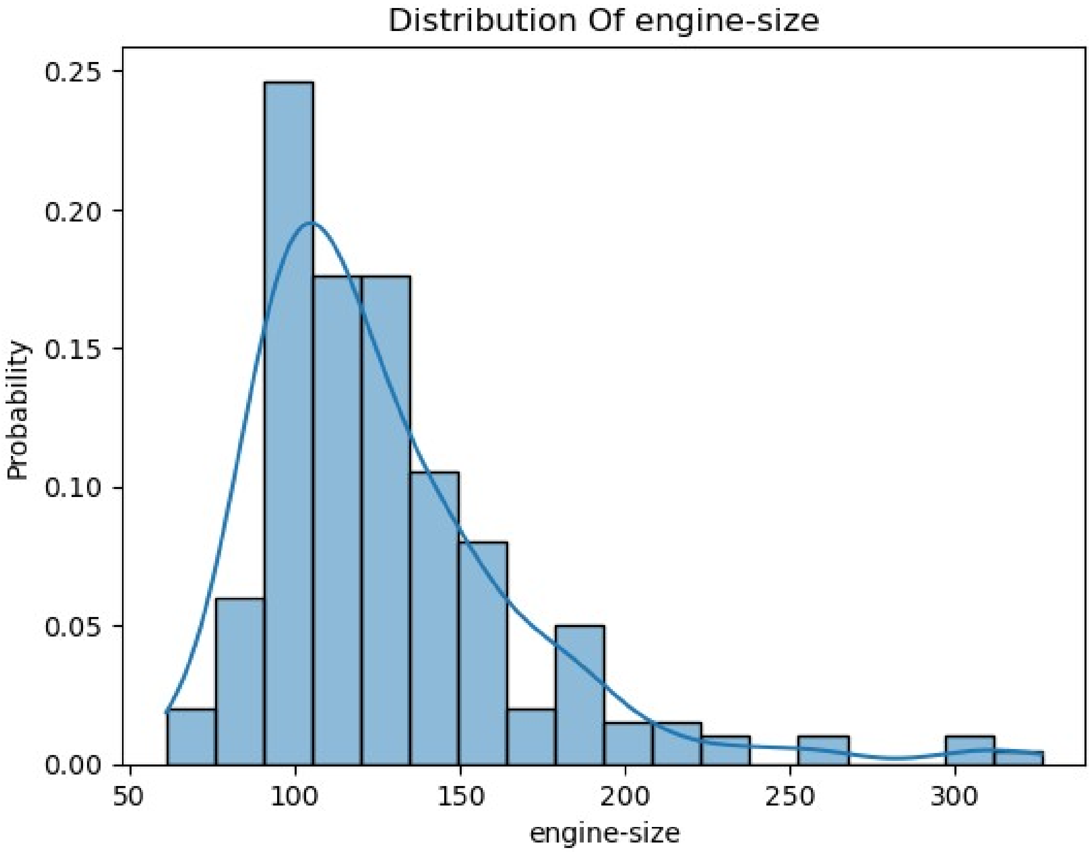

Distribution Of wheel-base
Probability
0.00
0.05
0.10
0.15
0.20
85
90
95
100
105
110
115
120
wheel-base

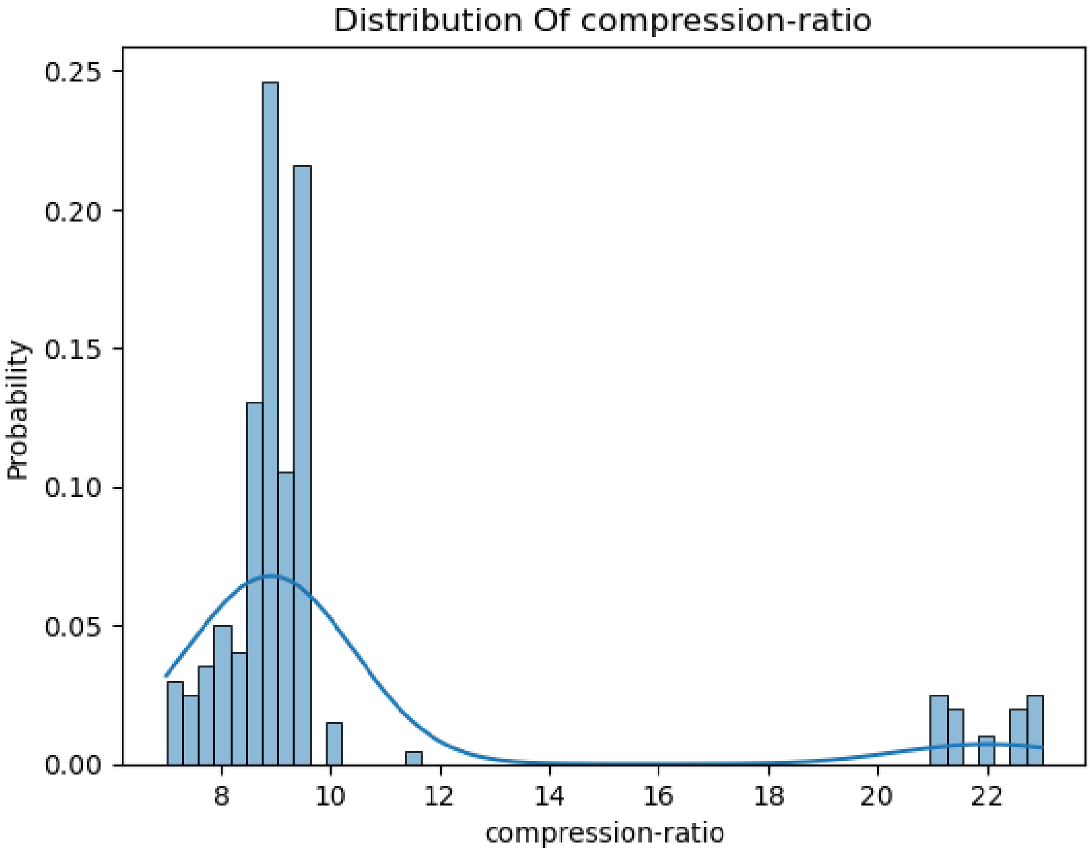

Distribution Of length
Probability
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
140
150
160
170
180
190
200
210
length

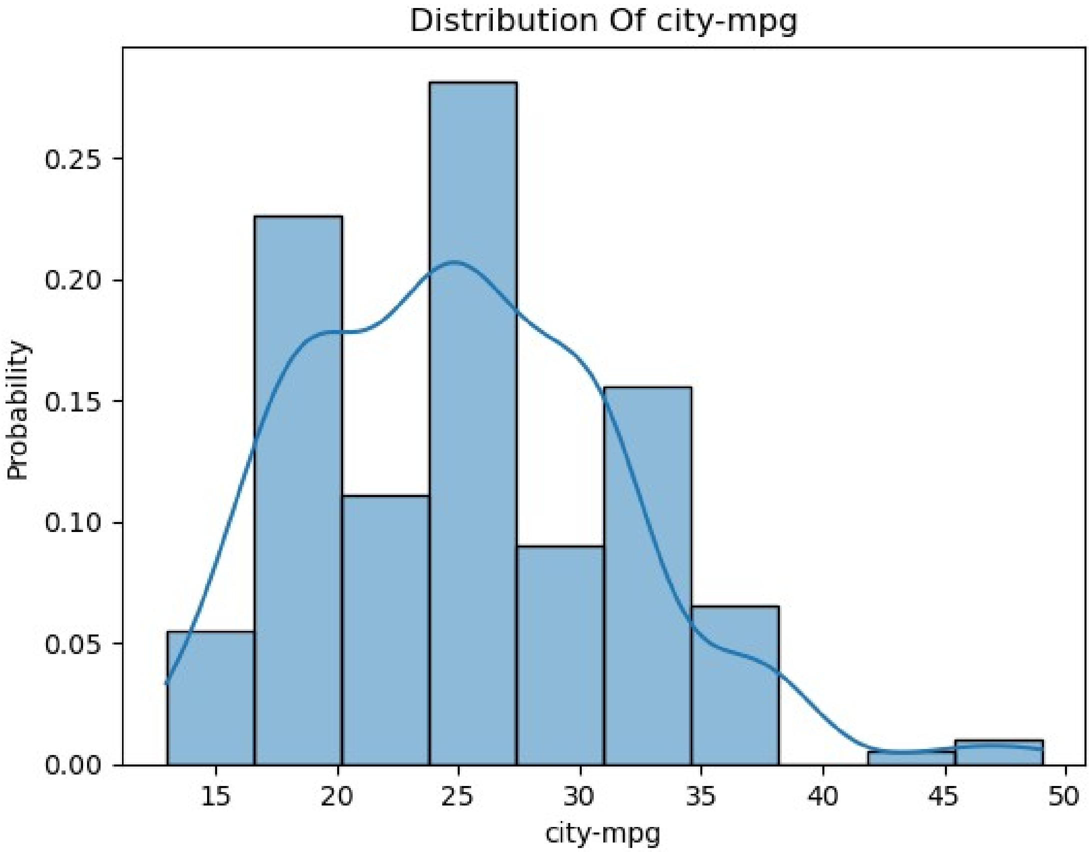

Distribution Of width
Probability
0.00
0.05
0.10
0.15
0.20
0.25
60
62
64
66
68
70
72
width

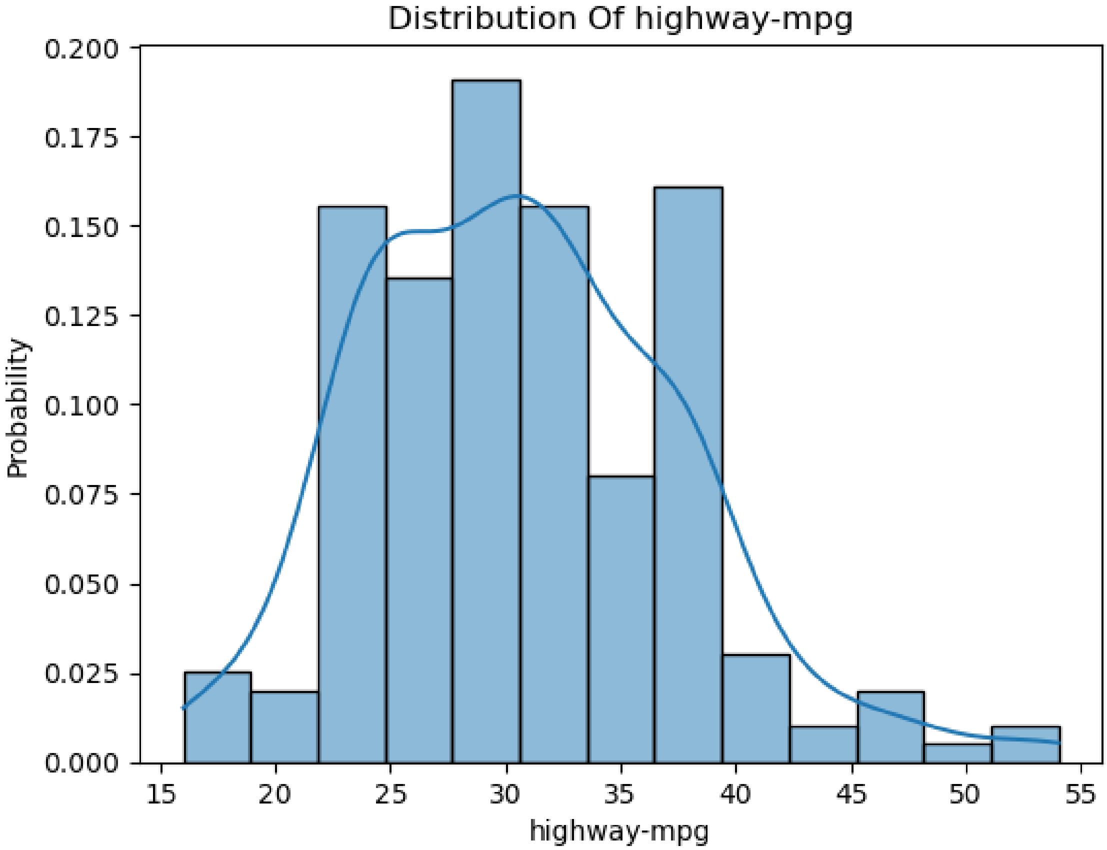

Distribution Of height
Probability
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
48
50
52
54
56
58
60
height

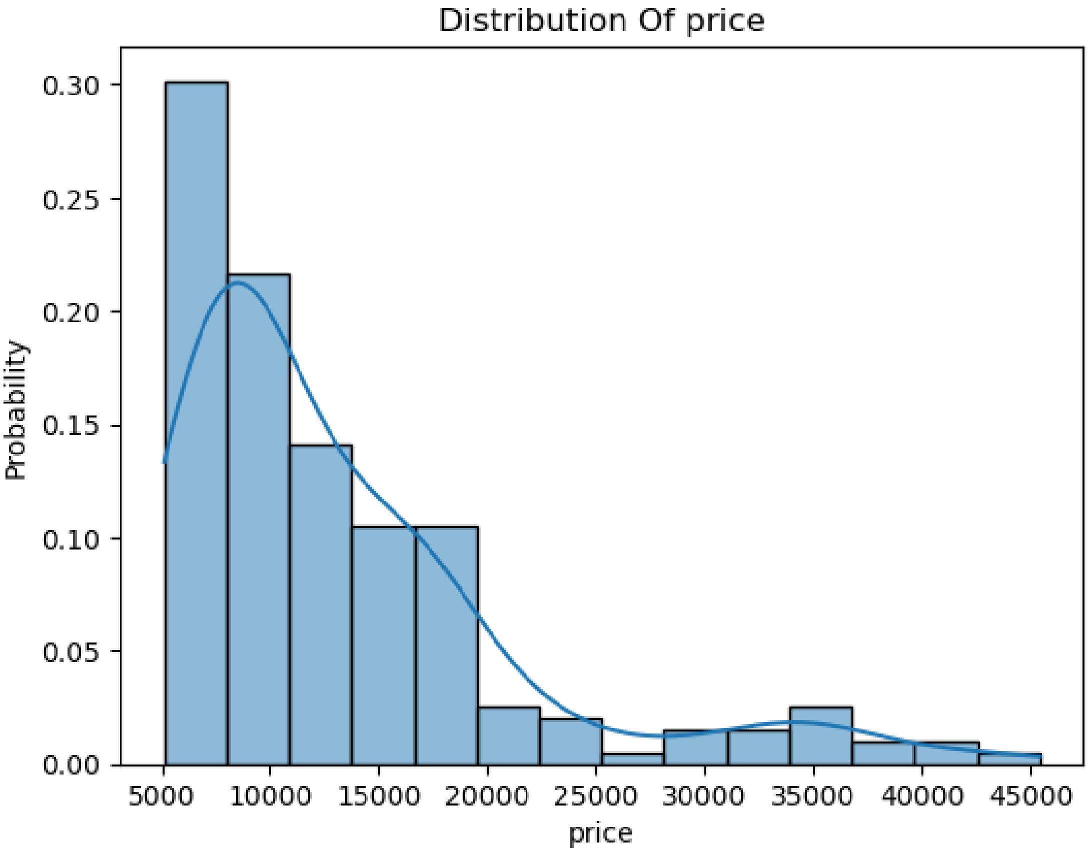

Distribution Of curb-weight
Probability
0.25
0.20
0.15
0.10
0.05
0.00
1500
2000
2500
3000
3500
4000
curb-weight

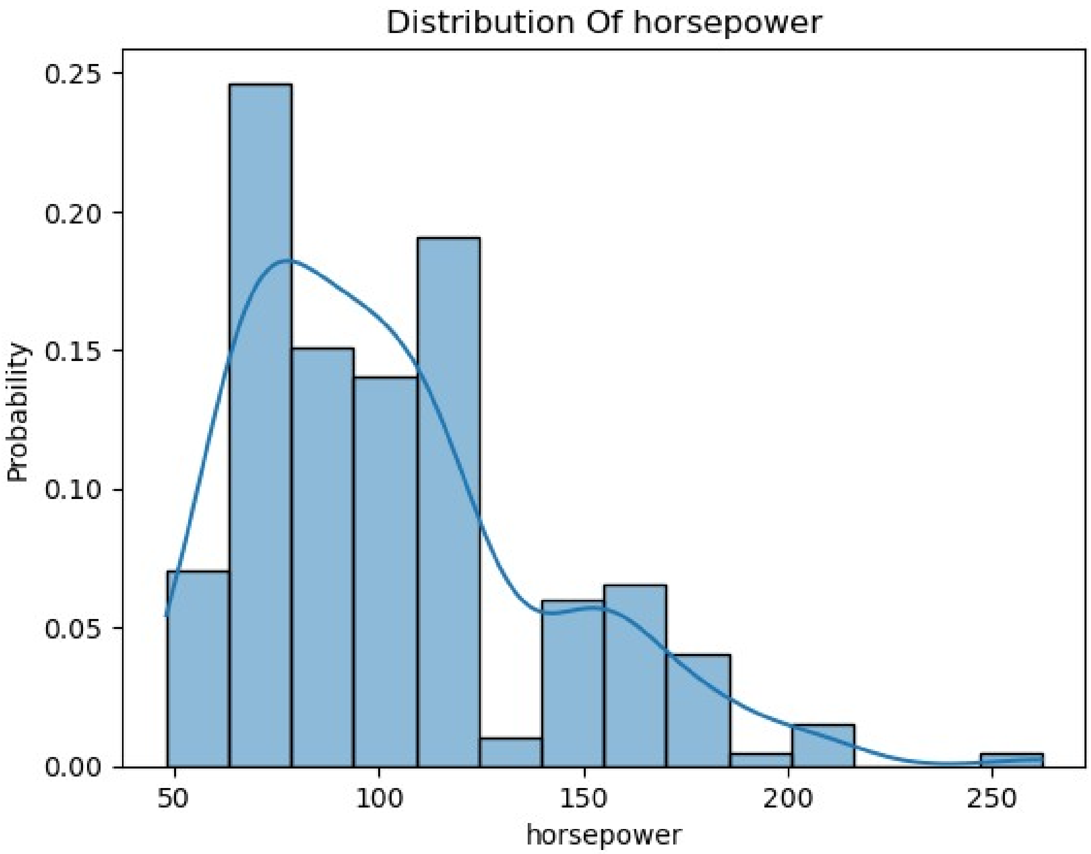

Distribution Of engine-size
Probability
0.25
0.20
0.15
0.10
0.05
0.00
50
100
150
200
250
300
engine-size


Distribution Of compression-ratio
Probability
0.25
0.20
0.15
0.10
0.05
0.00
8
10
12
14
16
18
20
22
compression-ratio


Distribution Of city-mpg
Probability
0.00
0.05
0.10
0.15
0.20
0.25
15
20
25
30
35
40
45
50
city-mpg


Distribution Of highway-mpg
Probability
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
15
20
25
30
35
40
45
50
55
highway-mpg


Distribution Of price
Probability
0.30
0.25
0.20
0.15
0.10
0.05
0.00
5000
10000
15000
20000
25000
30000
35000
40000
45000
price

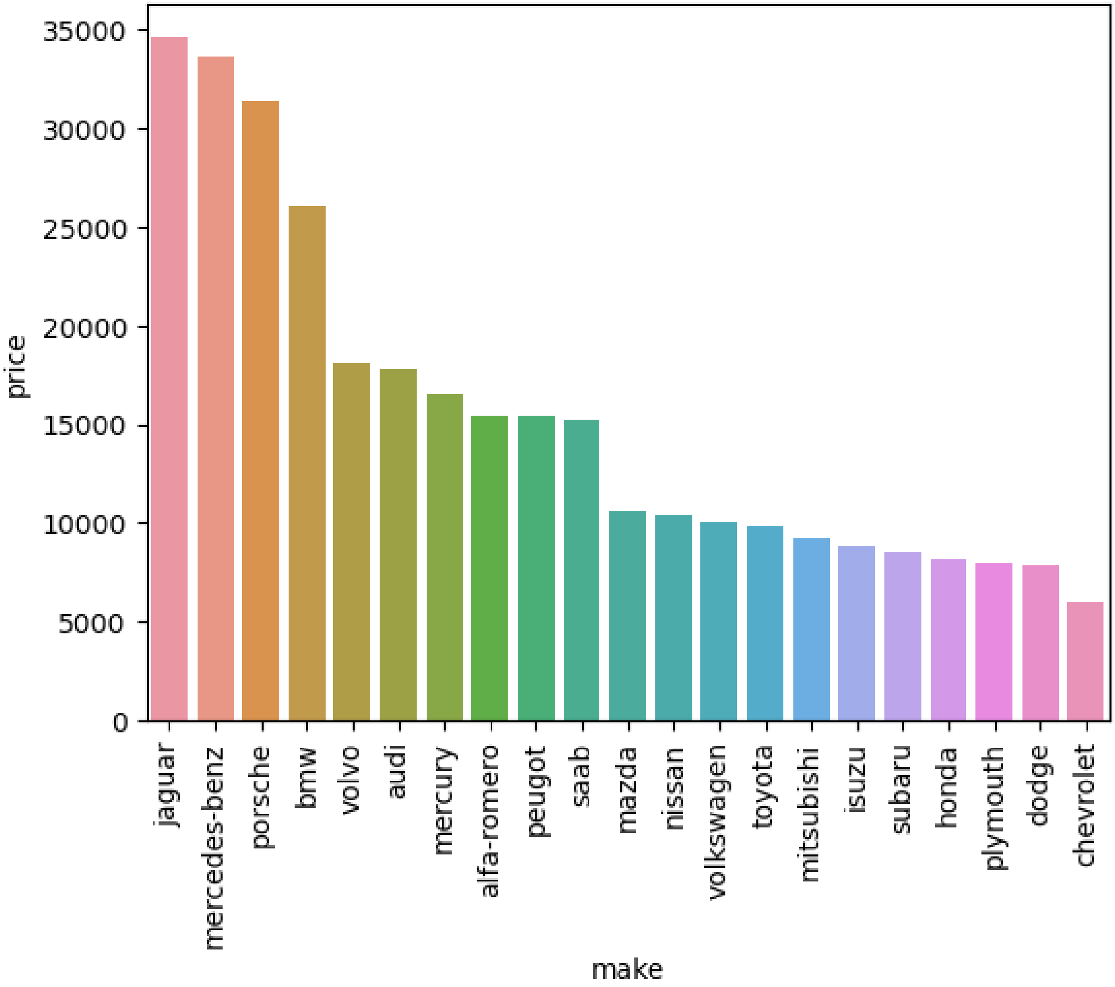


```
avg_make = df.groupby('make')
['price'].mean().round(2).sort_values(ascending =
False).to_frame().reset_index()
avg_make
```

```
             make     price
0          jaguar  34600.00
1   mercedes-benz  33647.00
2         porsche  31400.50
3             bmw  26118.75
4           volvo  18063.18
5            audi  17859.17
6         mercury  16503.00
7     alfa-romero  15498.33
8          peugot  15489.09
9            saab  15223.33
10          mazda  10652.88
11         nissan  10415.67
12     volkswagen  10077.50
13         toyota   9885.81
14     mitsubishi   9239.77
15          isuzu   8916.50
16         subaru   8541.25
```

```
17          honda   8184.69
18       plymouth   7963.43
19          dodge   7875.44
20      chevrolet   6007.00
```

```
sns.barplot(x=avg_make['make'], y = avg_make['price'])
plt.xticks(rotation = 90);
```



```
df[df['price'] == df['price'].max()]
```

```
    symboling normalized-losses           make fuel-type aspiration  \
74          1                 ?  mercedes-benz       gas        std

   num-of-doors body-style drive-wheels engine-location  wheel-
base  ...  \
74          two    hardtop          rwd           front
112.0  ...

    fuel-system  bore  stroke  compression-ratio horsepower peak-
```

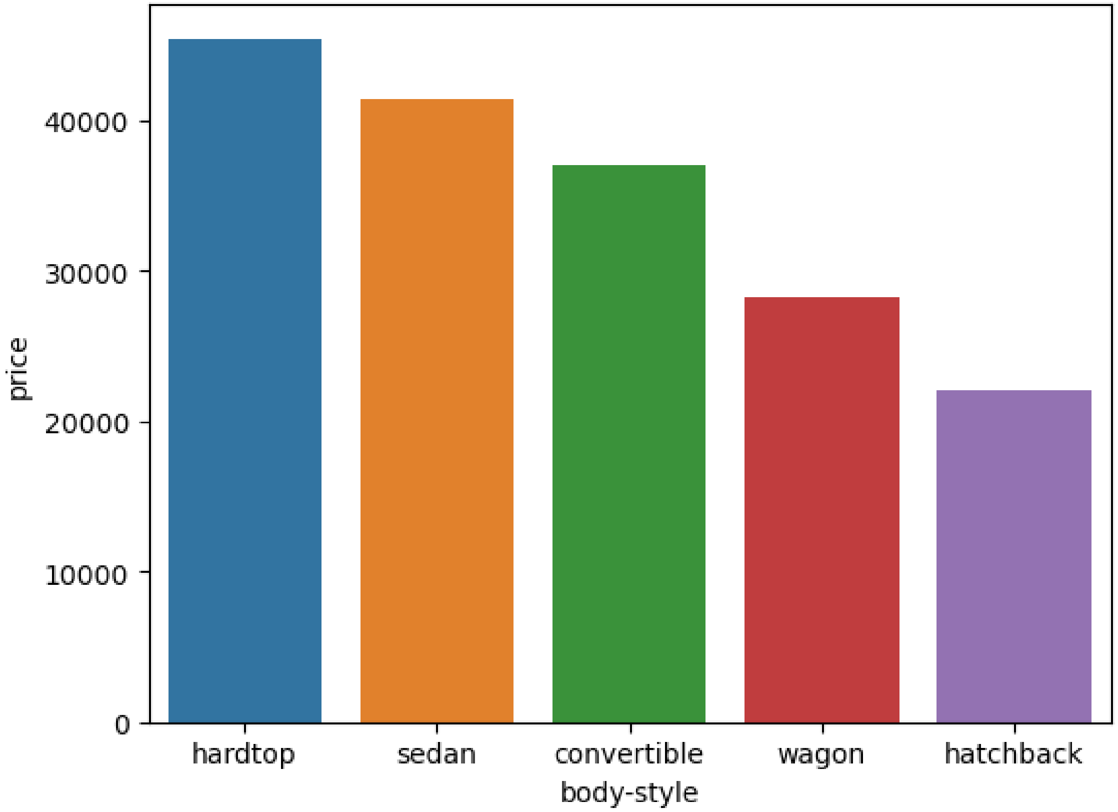
```
rpm  \
74          mpfi   3.8    3.35                     8.0       184.0     4500


    city-mpg highway-mpg  price   prince
74        14          16  45400  45400.0

[1 rows x 27 columns]
```

```
x = df.groupby('body-style')
['price'].max().to_frame().reset_index().sort_values(by='price',
ascending = False)
x
```

```
    body-style  price
1      hardtop  45400
3        sedan  41315
0  convertible  37028
4        wagon  28248
2    hatchback  22018
```

```
sns.barplot(x = x['body-style'], y = x['price'])
```

```
<Axes: xlabel='body-style', ylabel='price'>
```

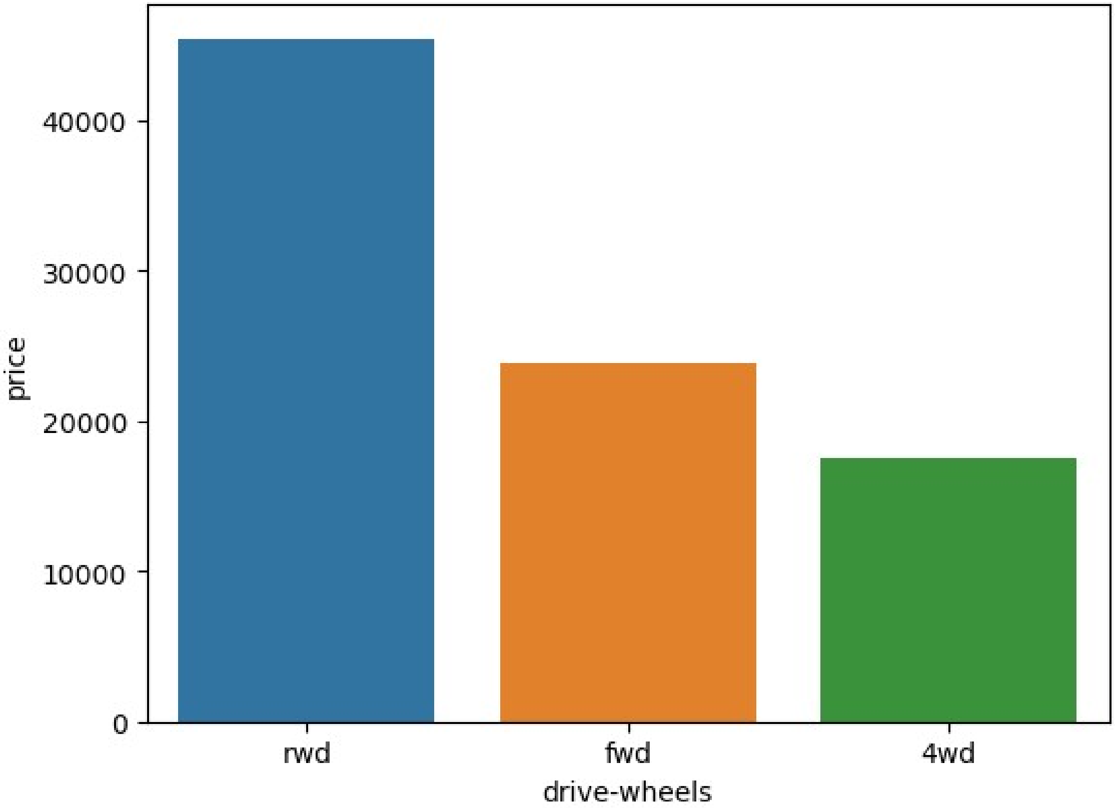


```
x = df.groupby('drive-wheels')
['price'].max().to_frame().sort_values(by='price', ascending =
False).reset_index()
x
```

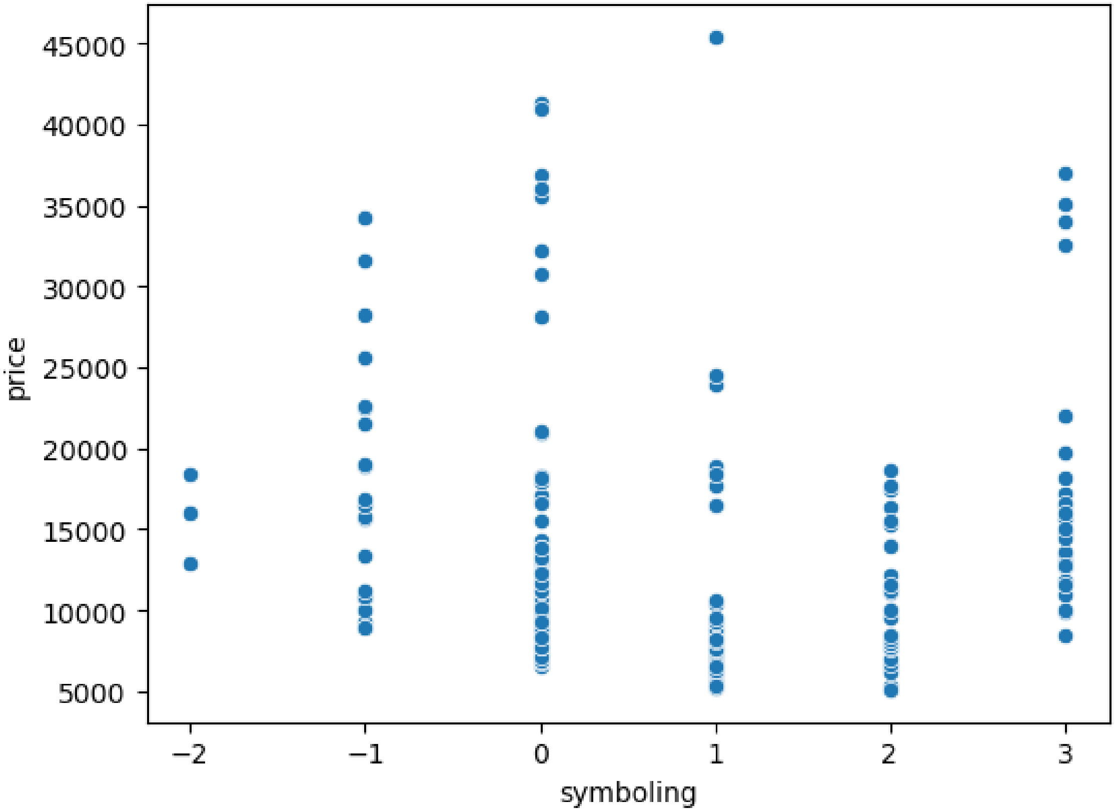
```
  drive-wheels  price
0          rwd  45400
1          fwd  23875
2          4wd  17450
```

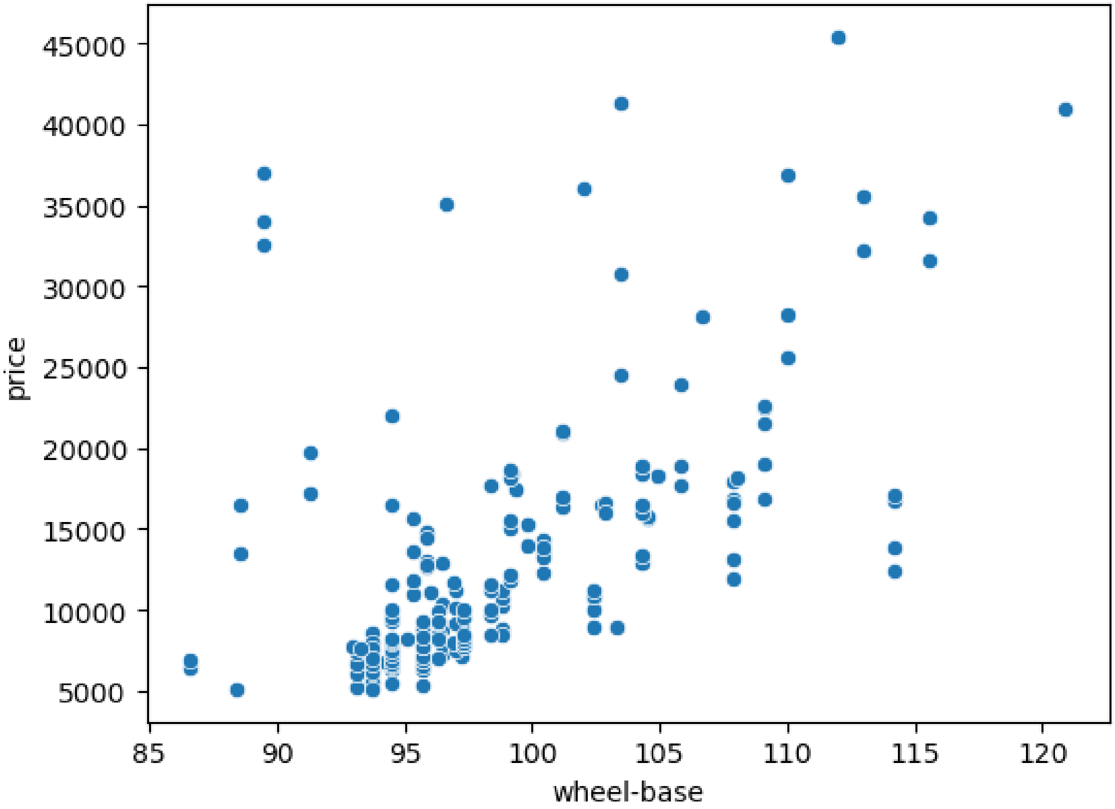
```
sns.barplot(data = x, x = 'drive-wheels', y = 'price')
```

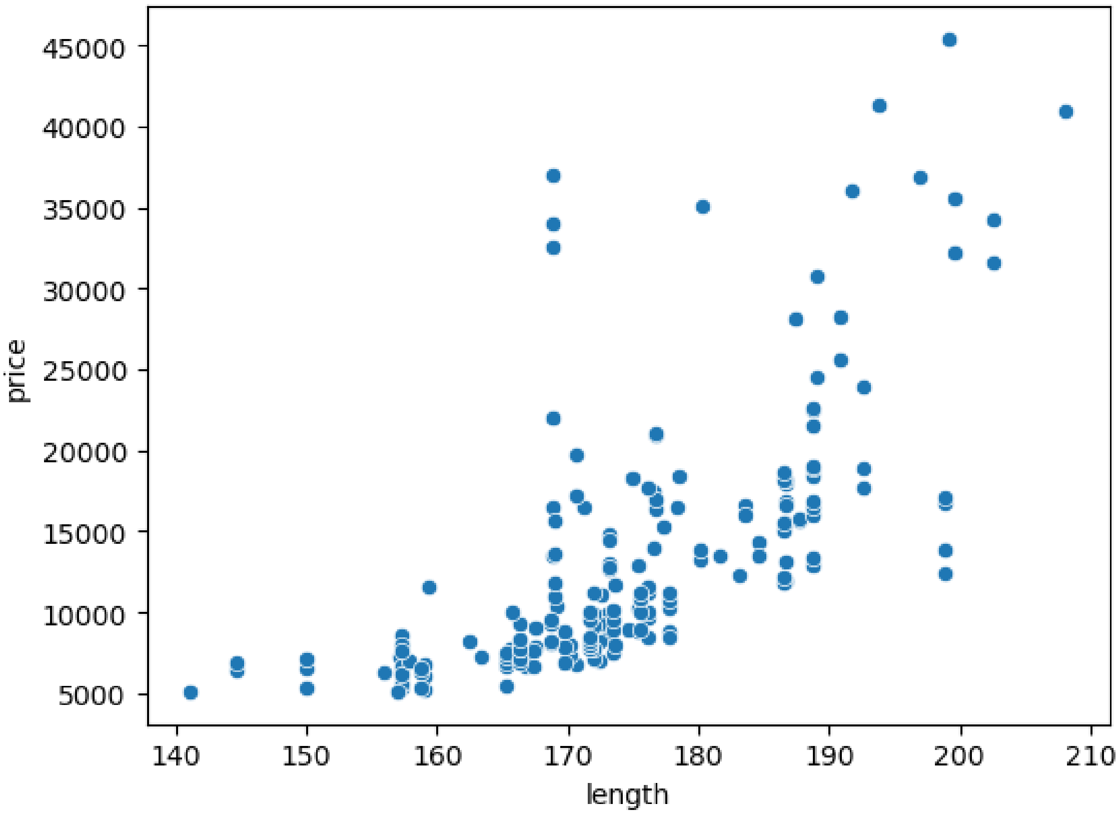
```
<Axes: xlabel='drive-wheels', ylabel='price'>
```

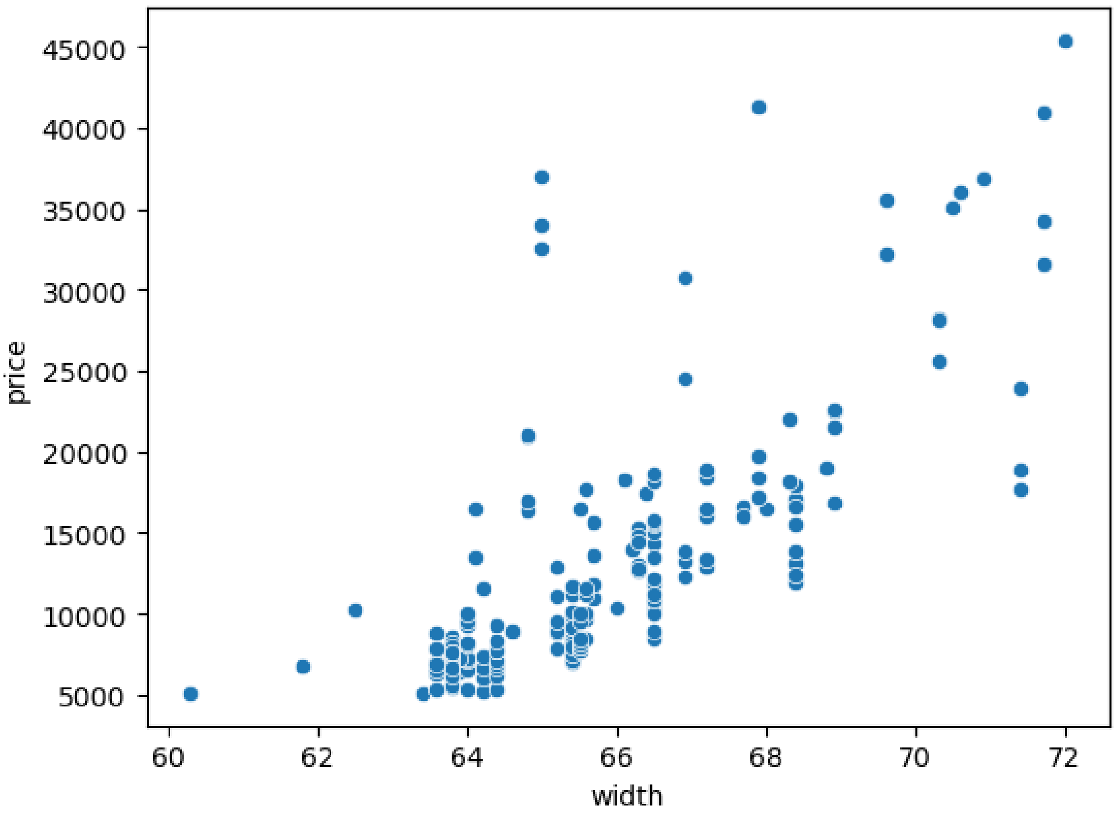


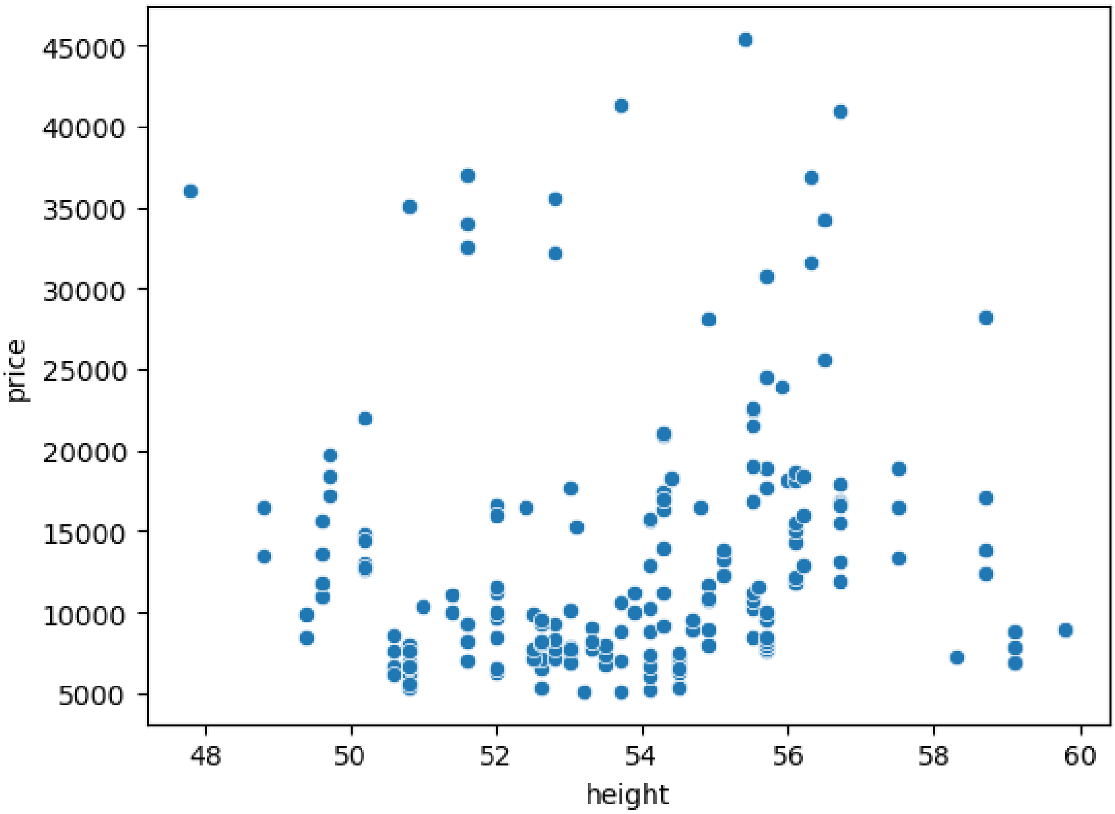
```
for i in col_num:
    sns.scatterplot(data = df, x = i, y = 'price')
    plt.show()
```

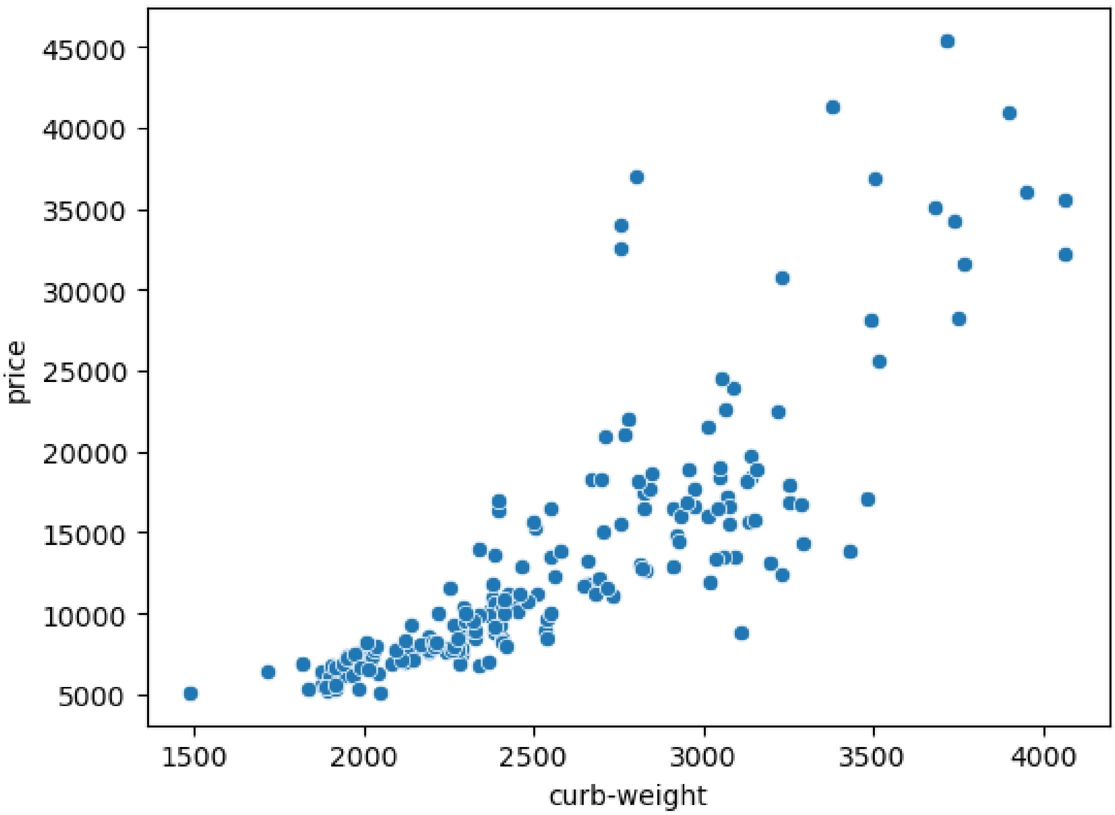

45000
40000
35000
30000
25000
20000
15000
10000
5000
price
−2
−1
0
1
2
3
symboling

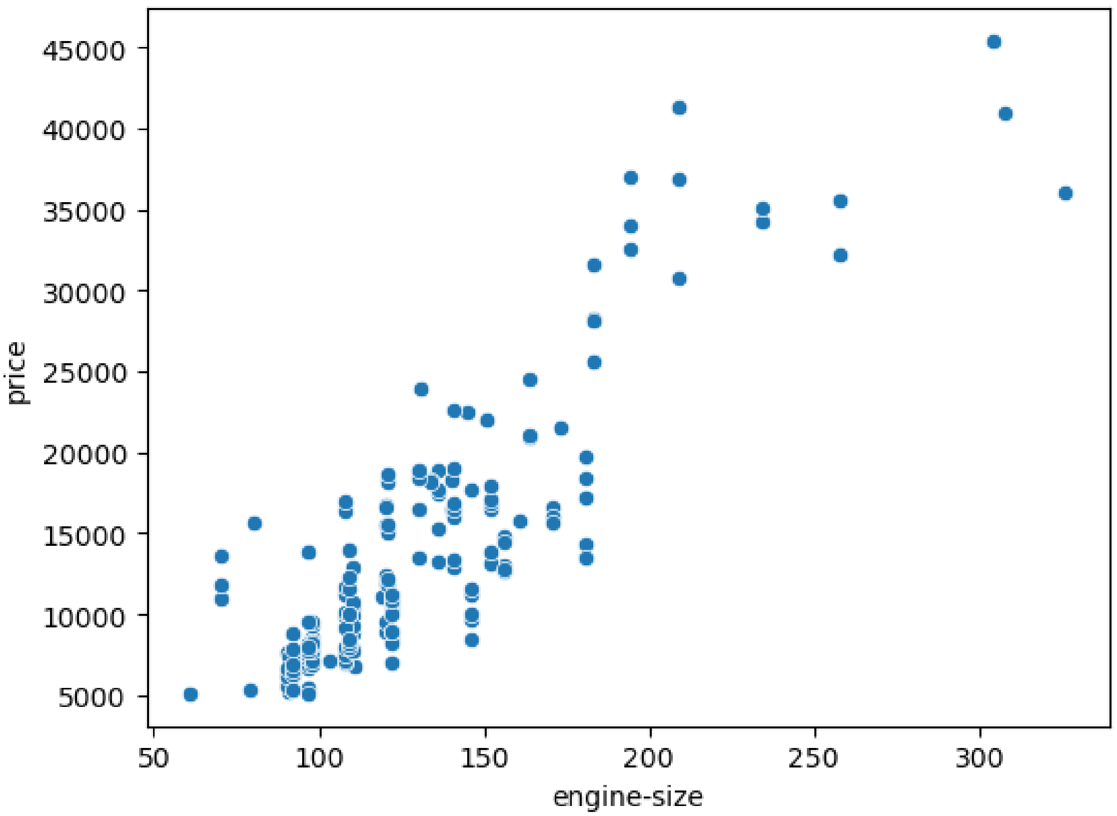

45000
40000
35000
30000
25000
20000
15000
10000
5000
price
85
90
95
100
105
110
115
120
wheel-base

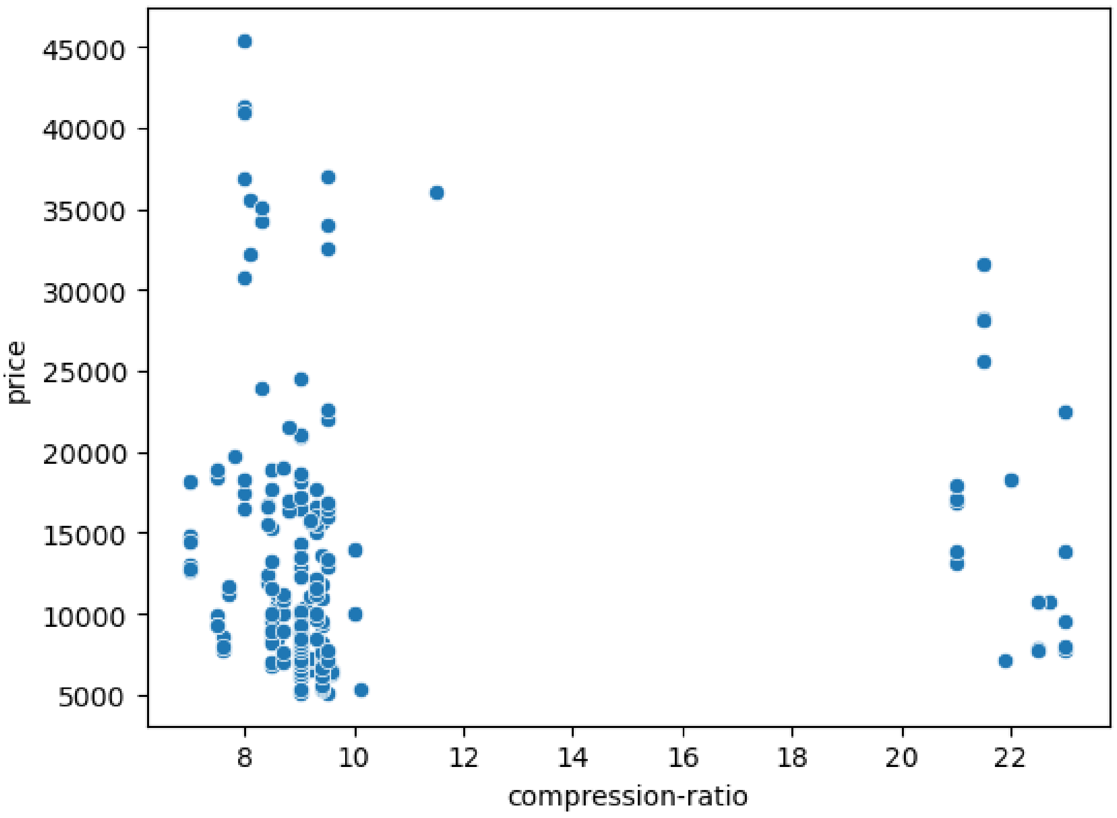

45000
40000
35000
30000
25000
20000
15000
10000
5000
price
140
150
160
170
180
190
200
210
length

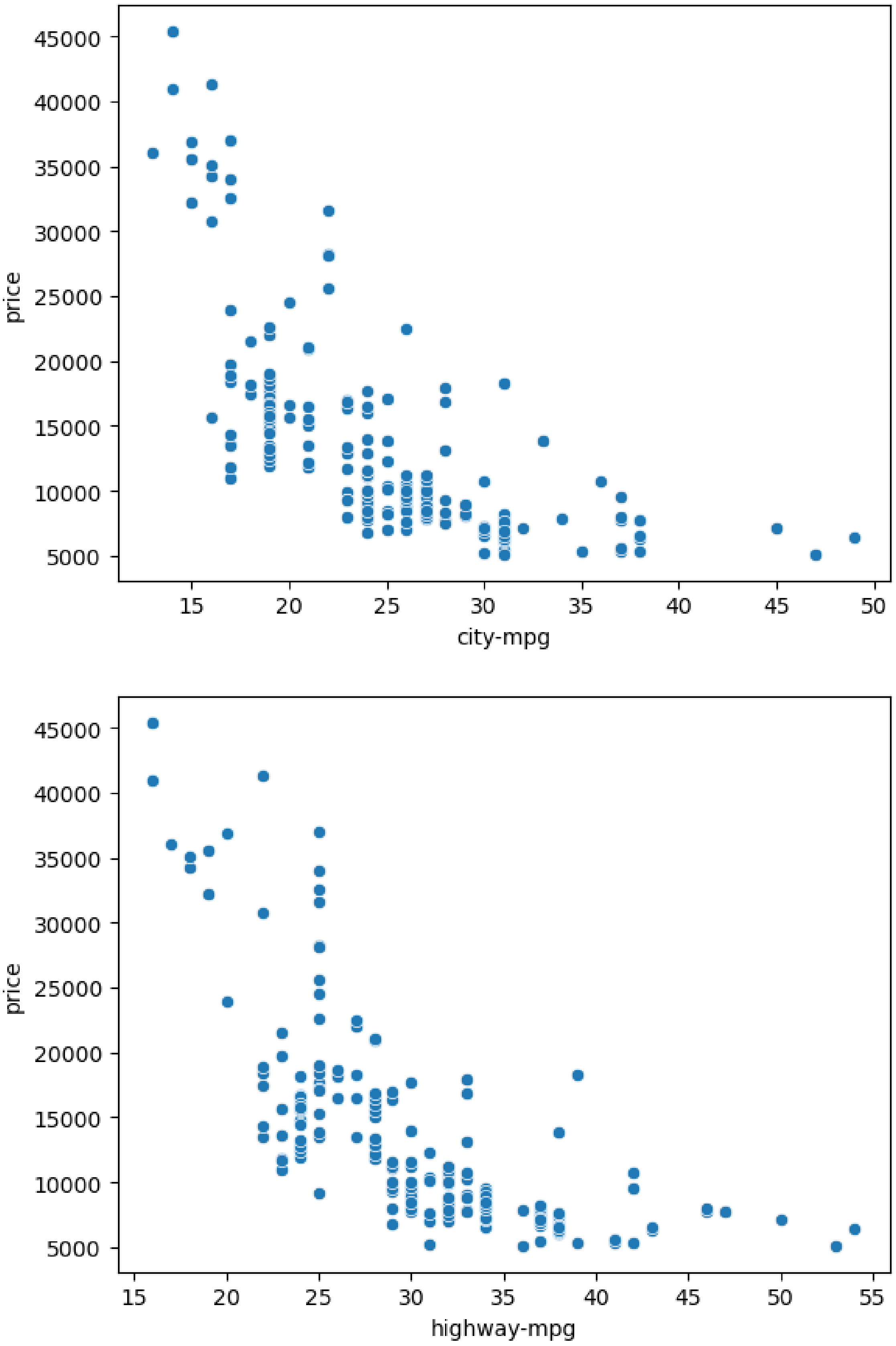

45000
40000
35000
30000
25000
20000
15000
10000
5000
price
60
62
64
66
68
70
72
width

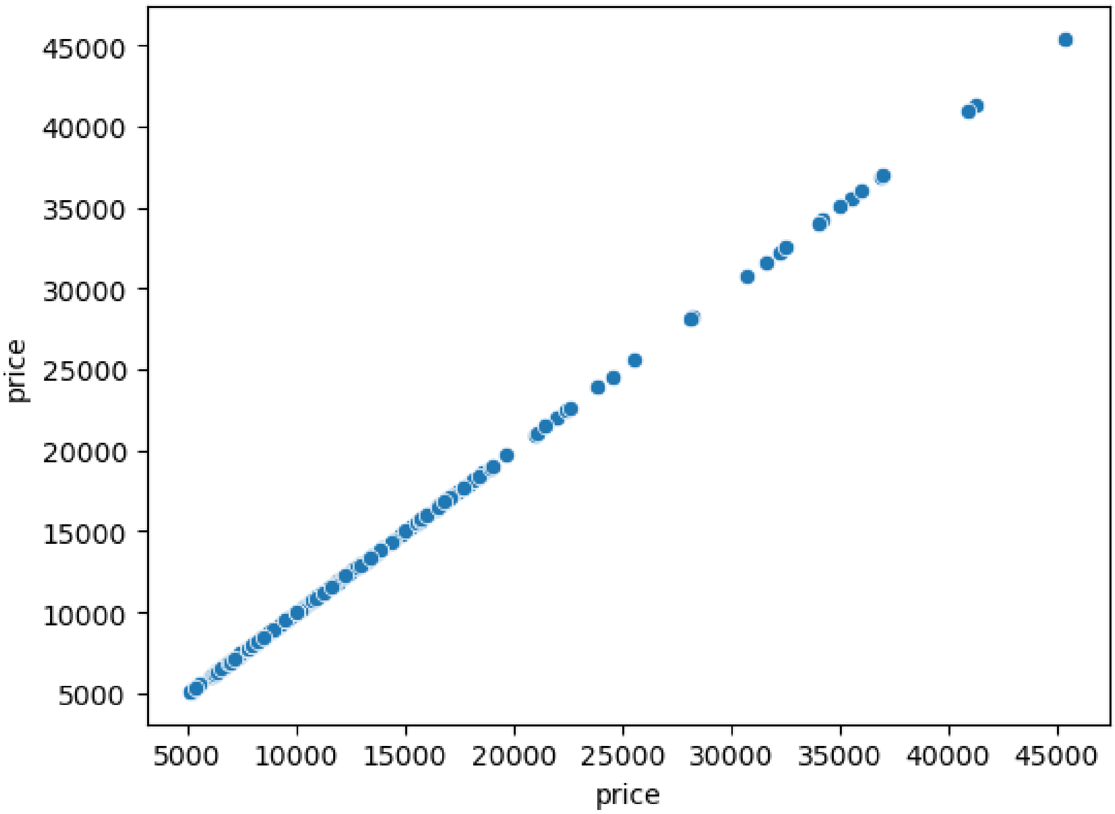

price
45000
40000
35000
30000
25000
20000
15000
10000
5000
48
50
52
54
56
58
60
height

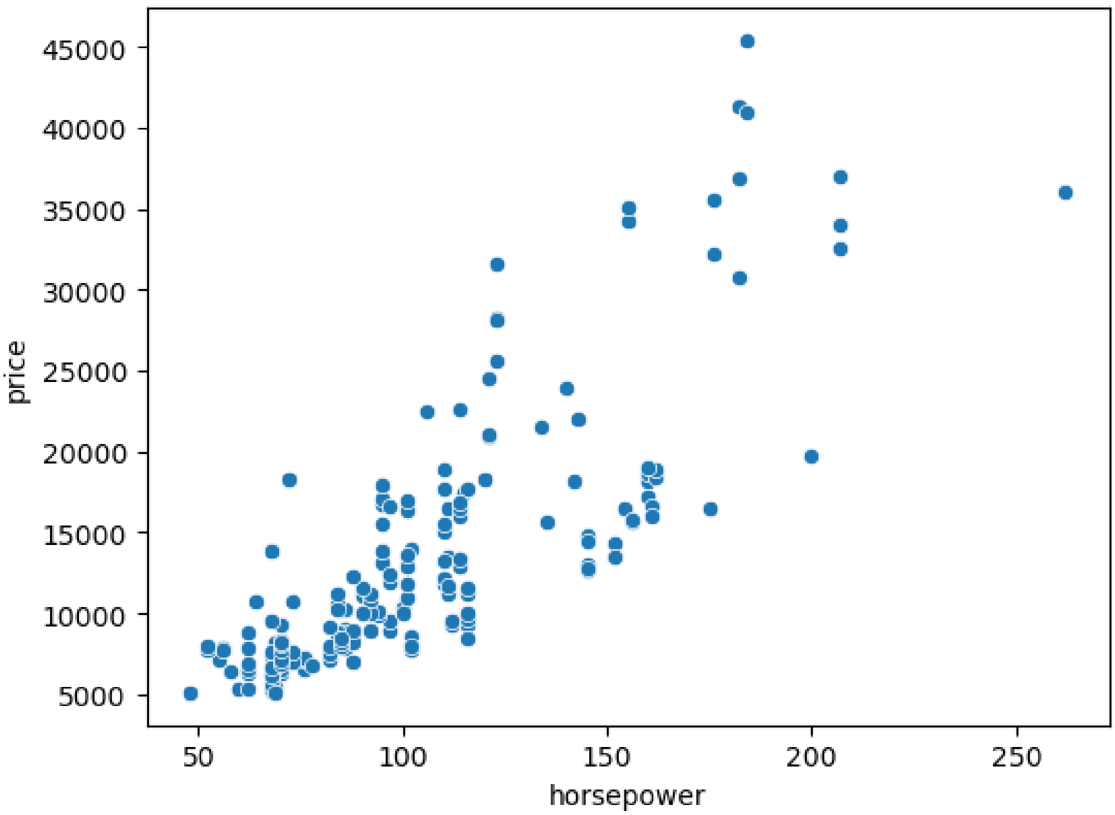

price
45000
40000
35000
30000
25000
20000
15000
10000
5000
1500
2000
2500
3000
3500
4000
curb-weight


price
45000
40000
35000
30000
25000
20000
15000
10000
5000
50
100
150
200
250
300
engine-size


price
45000
40000
35000
30000
25000
20000
15000
10000
5000
8
10
12
14
16
18
20
22
compression-ratio


45000
40000
35000
30000
25000
20000
15000
10000
5000
price
15
20
25
30
35
40
45
50
city-mpg
45000
40000
35000
30000
25000
20000
15000
10000
5000
price
15
20
25
30
35
40
45
50
55
highway-mpg


45000
40000
35000
30000
25000
20000
15000
10000
5000
price
5000
10000
15000
20000
25000
30000
35000
40000
45000
price


45000
40000
35000
30000
25000
20000
15000
10000
5000
price
50
100
150
200
250
horsepower

```
df[col_num].corr()
```

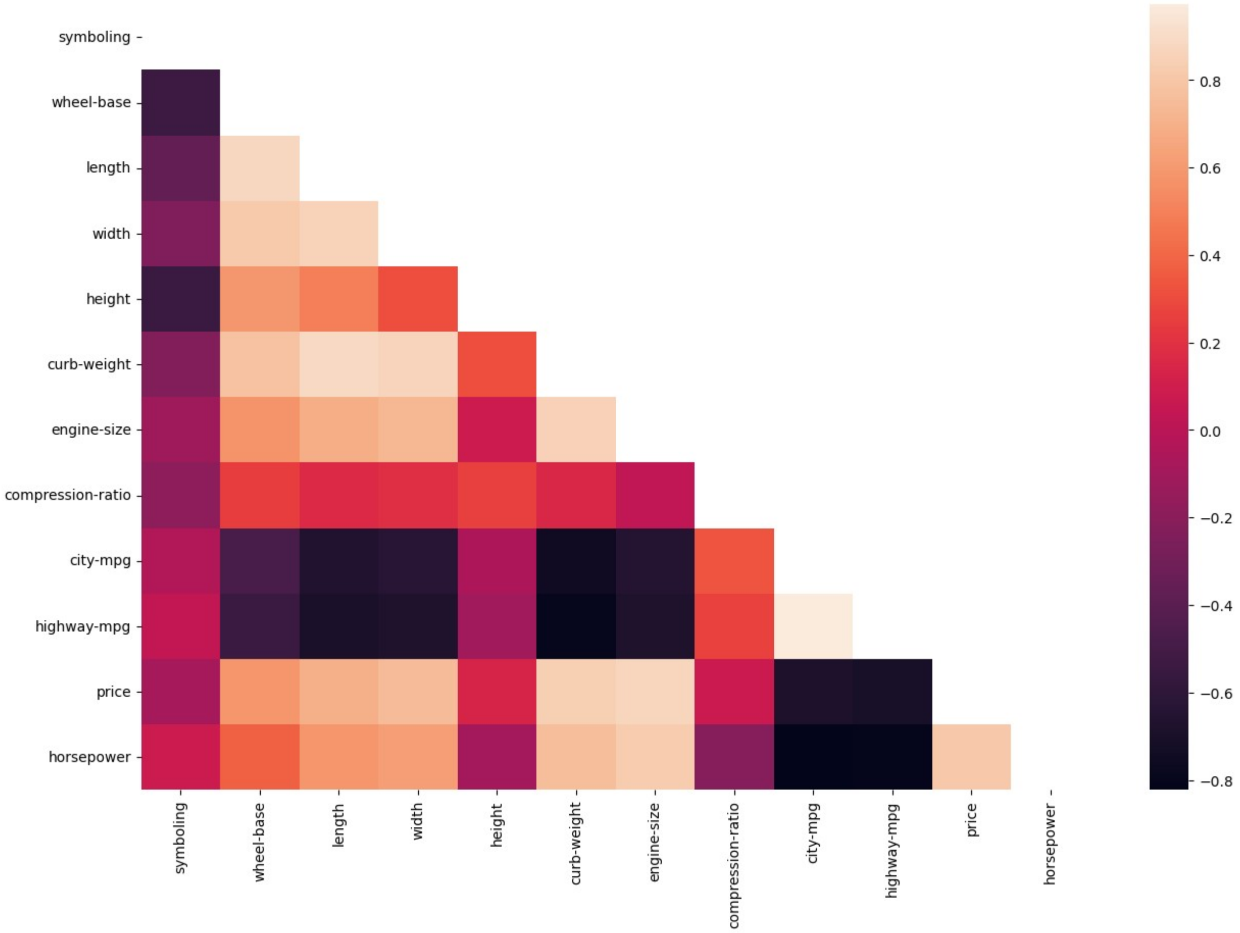
```
                   symboling  wheel-base    length     width    height
\
symboling           1.000000   -0.537706 -0.365957 -0.243933 -0.546717

wheel-base         -0.537706    1.000000  0.879582  0.817145  0.592809

length             -0.365957    0.879582  1.000000  0.857225  0.494880

width              -0.243933    0.817145  0.857225  1.000000  0.309223

height             -0.546717    0.592809  0.494880  0.309223  1.000000

curb-weight        -0.232893    0.782636  0.881688  0.866965  0.307881

engine-size        -0.111110    0.573197  0.685260  0.729466  0.075569

compression-ratio  -0.182446    0.249088  0.161486  0.191254  0.259914

city-mpg           -0.035228   -0.472877 -0.664865 -0.633139 -0.051387

highway-mpg         0.036293   -0.543647 -0.699033 -0.681131 -0.105200

price              -0.082465    0.583797  0.693965  0.753871  0.134990

horsepower          0.076038    0.371621  0.580309  0.615315 -0.087407


                   curb-weight  engine-size  compression-ratio  city-
mpg  \
symboling            -0.232893    -0.111110          -0.182446 -
0.035228
wheel-base            0.782636     0.573197           0.249088 -
0.472877
length                0.881688     0.685260           0.161486 -
0.664865
width                 0.866965     0.729466           0.191254 -
0.633139
height                0.307881     0.075569           0.259914 -
0.051387
curb-weight           1.000000     0.849301           0.156294 -
0.750287
engine-size           0.849301     1.000000           0.029366 -
0.650552
compression-ratio     0.156294     0.029366           1.000000
0.330587
city-mpg             -0.750287    -0.650552           0.330587
1.000000
highway-mpg          -0.794937    -0.679688           0.268819
0.972777
```

```
price                      0.835090     0.873887           0.069549 -
0.689253
horsepower                 0.758063     0.822713          -0.214576 -
0.822617
```

```
                   highway-mpg     price  horsepower
symboling             0.036293 -0.082465    0.076038
wheel-base           -0.543647  0.583797    0.371621
length               -0.699033  0.693965    0.580309
width                -0.681131  0.753871    0.615315
height               -0.105200  0.134990   -0.087407
curb-weight          -0.794937  0.835090    0.758063
engine-size          -0.679688  0.873887    0.822713
compression-ratio     0.268819  0.069549   -0.214576
city-mpg              0.972777 -0.689253   -0.822617
highway-mpg           1.000000 -0.705230   -0.804596
price                -0.705230  1.000000    0.810533
horsepower           -0.804596  0.810533    1.000000
```

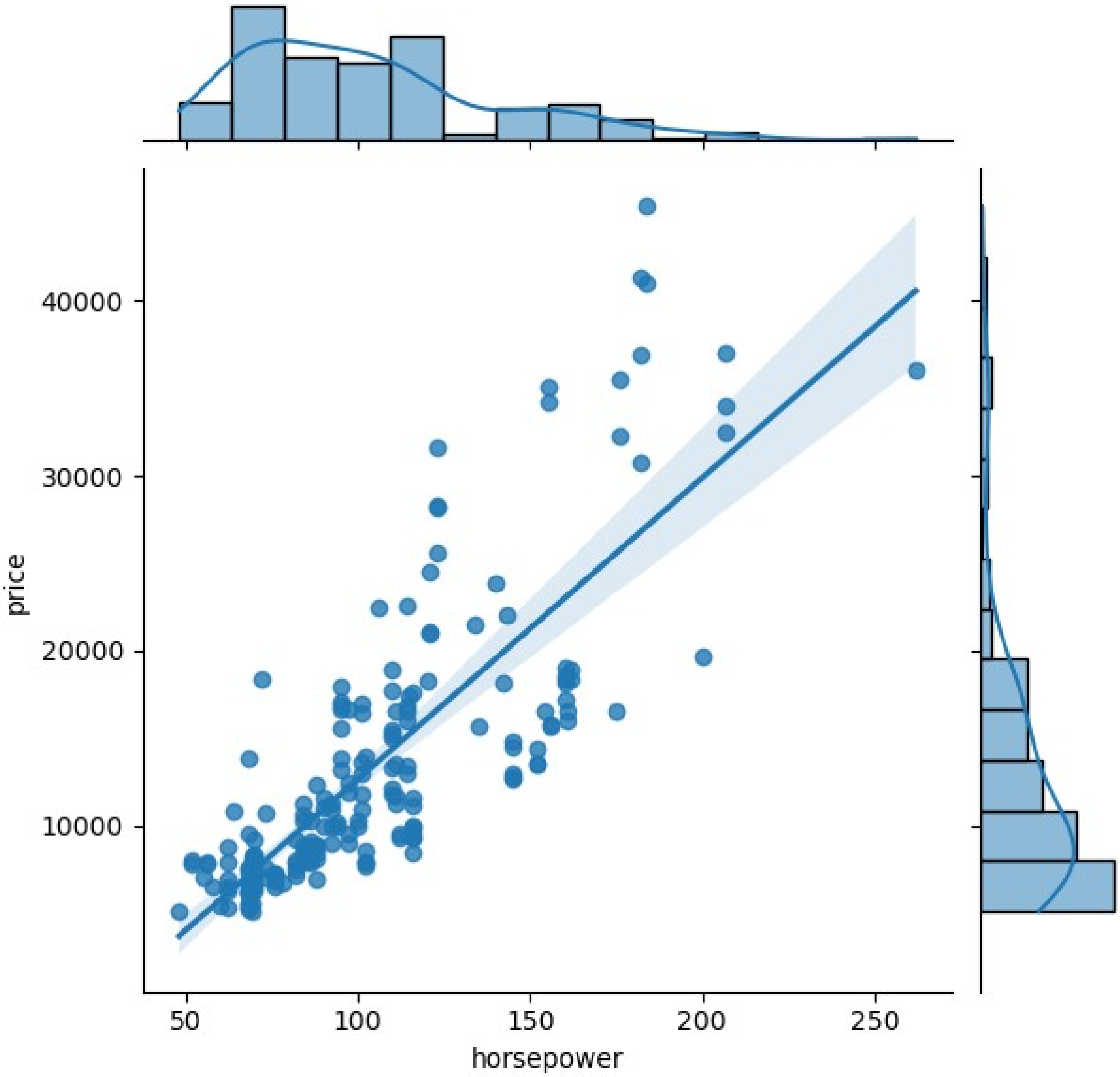
```
plt.figure(figsize = (15, 10))
mask = np.triu(np.ones_like(df[col_num].corr(), dtype=bool))
sns.heatmap(df[col_num].corr(), annot = True, mask = mask)
```

```
<Axes: >
```



```
sns.jointplot(data=df, x = 'horsepower', y = 'price', kind = 'reg')
```

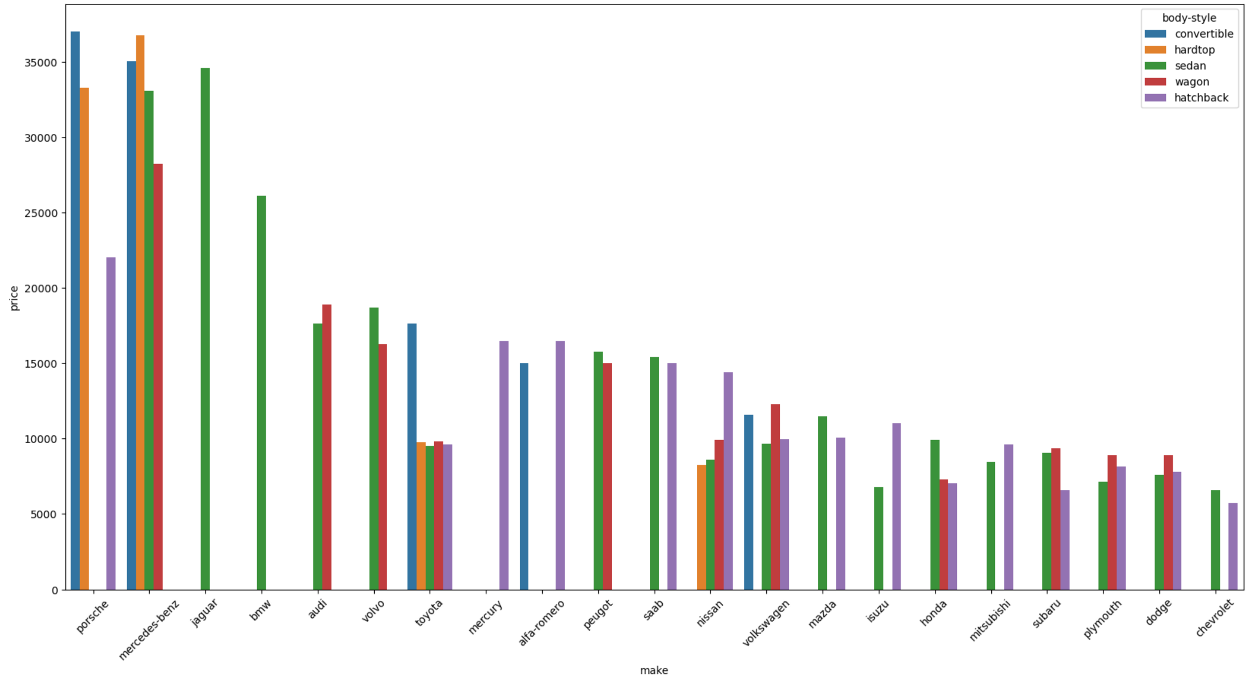
```
<seaborn.axisgrid.JointGrid at 0x22626a9d410>
```



```
x = pd.pivot_table(data = df, index = ['make', 'body-style'], values =
['price'], aggfunc = 'mean').sort_values(by='price', ascending =
False)
x

                                    price
make           body-style
porsche        convertible  37028.000000
mercedes-benz  hardtop      36788.000000
               convertible  35056.000000
jaguar         sedan        34600.000000
porsche        hardtop      33278.000000
mercedes-benz  sedan        33074.000000
               wagon        28248.000000
bmw            sedan        26118.750000
```

```
porsche        hatchback    22018.000000
audi           wagon        18920.000000
volvo          sedan        18726.875000
toyota         convertible  17669.000000
audi           sedan        17647.000000
mercury        hatchback    16503.000000
alfa-romero    hatchback    16500.000000
volvo          wagon        16293.333333
peugot         sedan        15758.571429
saab           sedan        15433.333333
peugot         wagon        15017.500000
saab           hatchback    15013.333333
alfa-romero    convertible  14997.500000
nissan         hatchback    14409.000000
volkswagen     wagon        12290.000000
               convertible  11595.000000
mazda          sedan        11464.142857
isuzu          hatchback    11048.000000
mazda          hatchback    10085.000000
volkswagen     hatchback     9980.000000
honda          sedan         9945.000000
nissan         wagon         9915.666667
toyota         wagon         9836.000000
               hardtop       9762.333333
volkswagen     sedan         9673.888889
toyota         hatchback     9616.000000
mitsubishi     hatchback     9597.888889
toyota         sedan         9542.200000
subaru         wagon         9342.000000
               sedan         9070.600000
plymouth       wagon         8921.000000
dodge          wagon         8921.000000
nissan         sedan         8604.555556
mitsubishi     sedan         8434.000000
nissan         hardtop       8249.000000
plymouth       hatchback     8130.500000
dodge          hatchback     7819.800000
               sedan         7619.666667
honda          wagon         7295.000000
plymouth       sedan         7150.500000
honda          hatchback     7054.428571
isuzu          sedan         6785.000000
subaru         hatchback     6591.333333
chevrolet      sedan         6575.000000
               hatchback     5723.000000
```

```
y = x.reset_index()
plt.figure(figsize = (20, 10))
sns.barplot(data= y, x = 'make', y = 'price', hue = 'body-style')
plt.xticks(rotation = 45);
```


body-style
convertible
hardtop
sedan
wagon
hatchback
price
0
5000
10000
15000
20000
25000
30000
35000
porsche
mercedes-benz
jaguar
bmw
audi
volvo
toyota
mercury
alfa-romero
peugot
saab
nissan
volkswagen
mazda
isuzu
honda
mitsubishi
subaru
plymouth
dodge
chevrolet
make