Exploratory Data Analysis

Estimated time needed: **30** minutes

Objectives

After completing this lab you will be able to:

- Explore features or characteristics to predict price of car
- Analyze patterns and run descriptive statistical analysis
- Group data based on identified parameters and create pivot tables
- Identify the effect of independent attributes on price of cars

Import Data from Module 2

Import libraries:

```
#install specific version of libraries used in lab
#! mamba install pandas==1.3.3
#! mamba install numpy=1.21.2
#! mamba install scipy=1.7.1-y
#!  mamba install seaborn=0.9.0-y

import pandas as pd
import numpy as np
import piplite
await piplite.install('seaborn')
```

Download the updated dataset by running the cell below.

The functions below will download the dataset into your browser and store it in dataframe `df`:

This dataset was hosted on IBM Cloud object. Click HERE for free storage.

```
from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())


file_path= "https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-
SkillsNetwork/labs/Data%20files/automobileEDA.csv"
```

```
await download(file_path, "usedcars.csv")
file_name="usedcars.csv"

df = pd.read_csv(file_name, header=0)
```

Note: This version of the lab is working on JupyterLite, which requires the dataset to be downloaded to the interface.While working on the downloaded version of this notebook on their local machines(Jupyter Anaconda), the learners can simply **skip the steps above,** and simply use the URL directly in the `pandas.read_csv()` function. You can uncomment and run the statements in the cell below.

```
#filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/automobileEDA.csv'
#df = pd.read_csv(filepath, header=None)
```

View the first 5 values of the updated dataframe using `dataframe.head()`

```
df.head()
```

```
   symboling  normalized-losses         make aspiration num-of-doors  \
0          3                122  alfa-romero        std          two

1          3                122  alfa-romero        std          two

2          1                122  alfa-romero        std          two

3          2                164         audi        std         four

4          2                164         audi        std         four


    body-style drive-wheels engine-location  wheel-base    length  ...  \
0  convertible          rwd           front        88.6  0.811148  ...

1  convertible          rwd           front        88.6  0.811148  ...

2    hatchback          rwd           front        94.5  0.822681  ...

3        sedan          fwd           front        99.8  0.848630  ...

4        sedan          4wd           front        99.4  0.848630  ...


   compression-ratio  horsepower  peak-rpm city-mpg highway-mpg  price  \
0                9.0       111.0    5000.0       21          27  13495.0
```

```
1                 9.0       111.0    5000.0        21          27
16500.0
2                 9.0       154.0    5000.0        19          26
16500.0
3                10.0       102.0    5500.0        24          30
13950.0
4                 8.0       115.0    5500.0        18          22
17450.0

  city-L/100km  horsepower-binned  diesel  gas
0    11.190476             Medium       0    1
1    11.190476             Medium       0    1
2    12.368421             Medium       0    1
3     9.791667             Medium       0    1
4    13.055556             Medium       0    1

[5 rows x 29 columns]
```

Analyzing Individual Feature Patterns Using Visualization

To install Seaborn we use pip, the Python package manager.

Import visualization packages "Matplotlib" and "Seaborn". Don't forget about "%matplotlib inline" to plot in a Jupyter notebook.

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# list the data types for each column
print(df.dtypes)
```

```
symboling               int64
normalized-losses       int64
make                   object
aspiration             object
num-of-doors           object
body-style             object
drive-wheels           object
engine-location        object
wheel-base            float64
length                float64
width                 float64
height                float64
curb-weight             int64
engine-type            object
num-of-cylinders       object
engine-size             int64
fuel-system            object
```

```
bore                    float64
stroke                  float64
compression-ratio       float64
horsepower              float64
peak-rpm                float64
city-mpg                  int64
highway-mpg               int64
price                   float64
city-L/100km            float64
horsepower-binned        object
diesel                    int64
gas                       int64
dtype: object
```

```python
# Write your code below and press Shift+Enter to execute
df['peak-rpm'].dtypes
```

```
dtype('float64')
```

For example, we can calculate the correlation between variables of type "int64" or "float64" using the method "corr":

```python
df.corr()
```

```
<ipython-input-12-2f6f6606aa2c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  df.corr()
```

```
                   symboling  normalized-losses  wheel-base    length  \
symboling           1.000000           0.466264   -0.535987 -0.365404

normalized-losses   0.466264           1.000000   -0.056661  0.019424

wheel-base         -0.535987          -0.056661    1.000000  0.876024

length             -0.365404           0.019424    0.876024  1.000000

width              -0.242423           0.086802    0.814507  0.857170

height             -0.550160          -0.373737    0.590742  0.492063

curb-weight        -0.233118           0.099404    0.782097  0.880665

engine-size        -0.110581           0.112360    0.572027  0.685025

bore               -0.140019          -0.029862    0.493244  0.608971

stroke             -0.008245           0.055563    0.158502  0.124139
```

```
compression-ratio  -0.182196           -0.114713    0.250313  0.159733
horsepower          0.075819            0.217299    0.371147  0.579821
peak-rpm            0.279740            0.239543   -0.360305 -0.285970
city-mpg           -0.035527           -0.225016   -0.470606 -0.665192
highway-mpg         0.036233           -0.181877   -0.543304 -0.698142
price              -0.082391            0.133999    0.584642  0.690628
city-L/100km        0.066171            0.238567    0.476153  0.657373
diesel             -0.196735           -0.101546    0.307237  0.211187
gas                 0.196735            0.101546   -0.307237 -0.211187

                      width    height  curb-weight  engine-size
bore  \
symboling         -0.242423 -0.550160    -0.233118    -0.110581 -
0.140019
normalized-losses  0.086802 -0.373737     0.099404     0.112360 -
0.029862
wheel-base         0.814507  0.590742     0.782097     0.572027
0.493244
length             0.857170  0.492063     0.880665     0.685025
0.608971
width              1.000000  0.306002     0.866201     0.729436
0.544885
height             0.306002  1.000000     0.307581     0.074694
0.180449
curb-weight        0.866201  0.307581     1.000000     0.849072
0.644060
engine-size        0.729436  0.074694     0.849072     1.000000
0.572609
bore               0.544885  0.180449     0.644060     0.572609
1.000000
stroke             0.188829 -0.062704     0.167562     0.209523 -
0.055390
compression-ratio  0.189867  0.259737     0.156433     0.028889
0.001263
horsepower         0.615077 -0.087027     0.757976     0.822676
0.566936
peak-rpm          -0.245800 -0.309974    -0.279361    -0.256733 -
0.267392
city-mpg          -0.633531 -0.049800    -0.749543    -0.650546 -
0.582027
```

```
highway-mpg        -0.680635 -0.104812    -0.794889    -0.679571 -
0.591309
price               0.751265  0.135486     0.834415     0.872335
0.543155
city-L/100km        0.673363  0.003811     0.785353     0.745059
0.554610
diesel              0.244356  0.281578     0.221046     0.070779
0.054458
gas                -0.244356 -0.281578    -0.221046    -0.070779 -
0.054458

                      stroke  compression-ratio  horsepower  peak-
rpm  \
symboling          -0.008245          -0.182196    0.075819  0.279740

normalized-losses  0.055563          -0.114713    0.217299  0.239543

wheel-base          0.158502           0.250313    0.371147 -0.360305

length              0.124139           0.159733    0.579821 -0.285970

width               0.188829           0.189867    0.615077 -0.245800

height             -0.062704           0.259737   -0.087027 -0.309974

curb-weight         0.167562           0.156433    0.757976 -0.279361

engine-size         0.209523           0.028889    0.822676 -0.256733

bore               -0.055390           0.001263    0.566936 -0.267392

stroke              1.000000           0.187923    0.098462 -0.065713

compression-ratio  0.187923           1.000000   -0.214514 -0.435780

horsepower          0.098462          -0.214514    1.000000  0.107885

peak-rpm           -0.065713          -0.435780    0.107885  1.000000

city-mpg           -0.034696           0.331425   -0.822214 -0.115413

highway-mpg        -0.035201           0.268465   -0.804575 -0.058598

price               0.082310           0.071107    0.809575 -0.101616

city-L/100km        0.037300          -0.299372    0.889488  0.115830

diesel              0.241303           0.985231   -0.169053 -0.475812

gas                -0.241303          -0.985231    0.169053  0.475812
```

```
                   city-mpg  highway-mpg     price  city-L/100km
diesel  \
symboling         -0.035527     0.036233 -0.082391      0.066171 -
0.196735
normalized-losses -0.225016    -0.181877  0.133999      0.238567 -
0.101546
wheel-base        -0.470606    -0.543304  0.584642      0.476153
0.307237
length            -0.665192    -0.698142  0.690628      0.657373
0.211187
width             -0.633531    -0.680635  0.751265      0.673363
0.244356
height            -0.049800    -0.104812  0.135486      0.003811
0.281578
curb-weight       -0.749543    -0.794889  0.834415      0.785353
0.221046
engine-size       -0.650546    -0.679571  0.872335      0.745059
0.070779
bore              -0.582027    -0.591309  0.543155      0.554610
0.054458
stroke            -0.034696    -0.035201  0.082310      0.037300
0.241303
compression-ratio  0.331425     0.268465  0.071107     -0.299372
0.985231
horsepower        -0.822214    -0.804575  0.809575      0.889488 -
0.169053
peak-rpm          -0.115413    -0.058598 -0.101616      0.115830 -
0.475812
city-mpg           1.000000     0.972044 -0.686571     -0.949713
0.265676
highway-mpg        0.972044     1.000000 -0.704692     -0.930028
0.198690
price             -0.686571    -0.704692  1.000000      0.789898
0.110326
city-L/100km      -0.949713    -0.930028  0.789898      1.000000 -
0.241282
diesel             0.265676     0.198690  0.110326     -0.241282
1.000000
gas               -0.265676    -0.198690 -0.110326      0.241282 -
1.000000

                        gas
symboling          0.196735
normalized-losses  0.101546
wheel-base        -0.307237
length            -0.211187
width             -0.244356
height            -0.281578
```

```
curb-weight         -0.221046
engine-size         -0.070779
bore                -0.054458
stroke              -0.241303
compression-ratio   -0.985231
horsepower           0.169053
peak-rpm             0.475812
city-mpg            -0.265676
highway-mpg         -0.198690
price               -0.110326
city-L/100km         0.241282
diesel              -1.000000
gas                  1.000000
```

The diagonal elements are always one; we will study correlation more precisely Pearson correlation in-depth at the end of the notebook.

```
# Write your code below and press Shift+Enter to execute
df[['bore','stroke','compression-ratio','horsepower']].corr()
```

	bore	stroke	compression-ratio	horsepower
bore	1.000000	-0.055390	0.001263	0.566936
stroke	-0.055390	1.000000	0.187923	0.098462
compression-ratio	0.001263	0.187923	1.000000	-0.214514
horsepower	0.566936	0.098462	-0.214514	1.000000

Let's see several examples of different linear relationships:

Positive Linear Relationship

Let's find the scatterplot of "engine-size" and "price".

```
# Engine size as potential predictor variable of price
3
```

```
3
```

We can examine the correlation between 'engine-size' and 'price' and see that it's approximately 0.87.

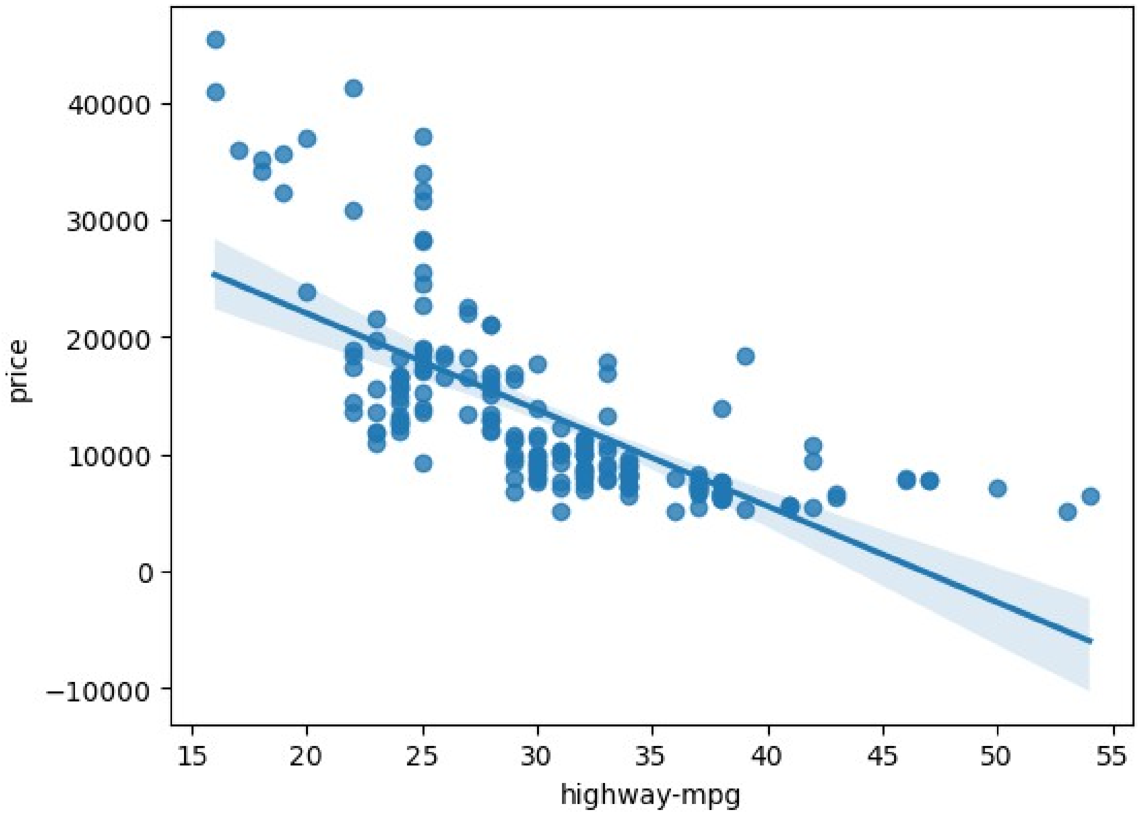
```
df[["engine-size", "price"]].corr()
```

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

Highway mpg is a potential predictor variable of price. Let's find the scatterplot of "highway-mpg" and "price".

```
sns.regplot(x="highway-mpg", y="price", data=df)
```

```
<AxesSubplot:xlabel='highway-mpg', ylabel='price'>
```



We can examine the correlation between 'highway-mpg' and 'price' and see it's approximately -0.704.

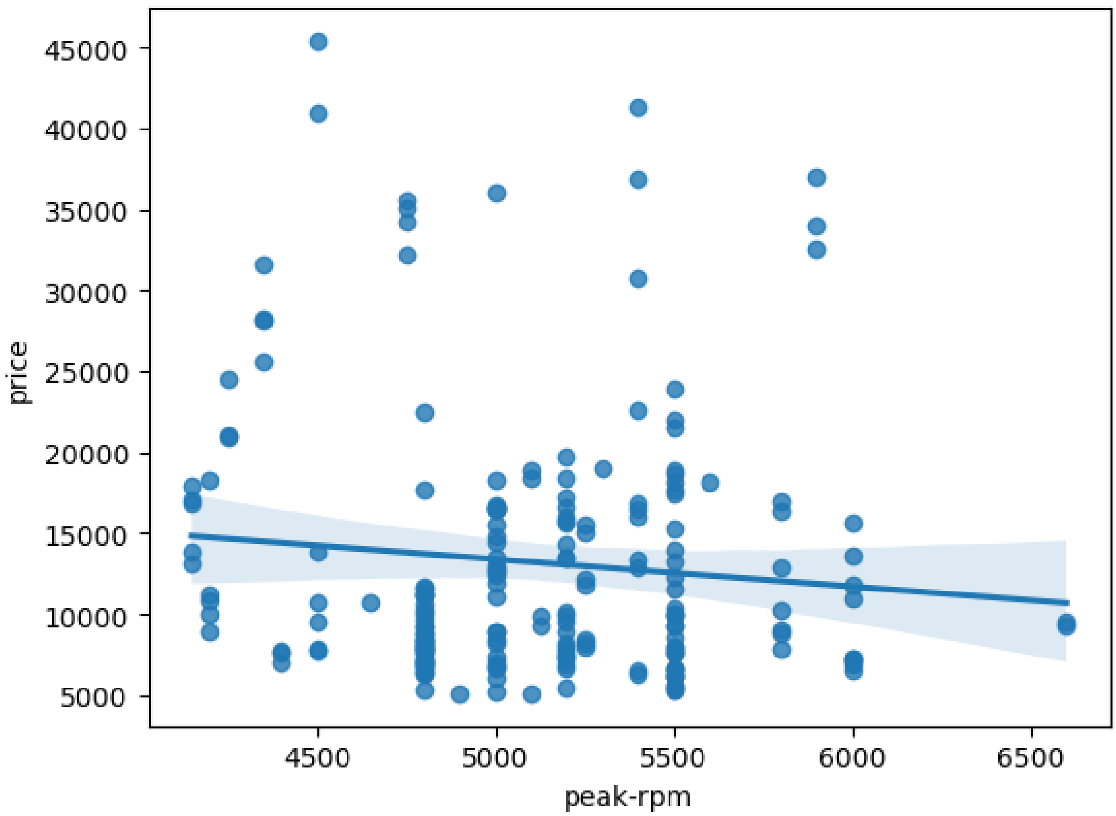
```
df[['highway-mpg', 'price']].corr()
```

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

Let's see if "peak-rpm" is a predictor variable of "price".

```
sns.regplot(x="peak-rpm", y="price", data=df)
```

```
<AxesSubplot:xlabel='peak-rpm', ylabel='price'>
```



We can examine the correlation between 'peak-rpm' and 'price' and see it's approximately -0.101616.

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

```
          peak-rpm     price
peak-rpm  1.000000 -0.101616
price    -0.101616  1.000000
```

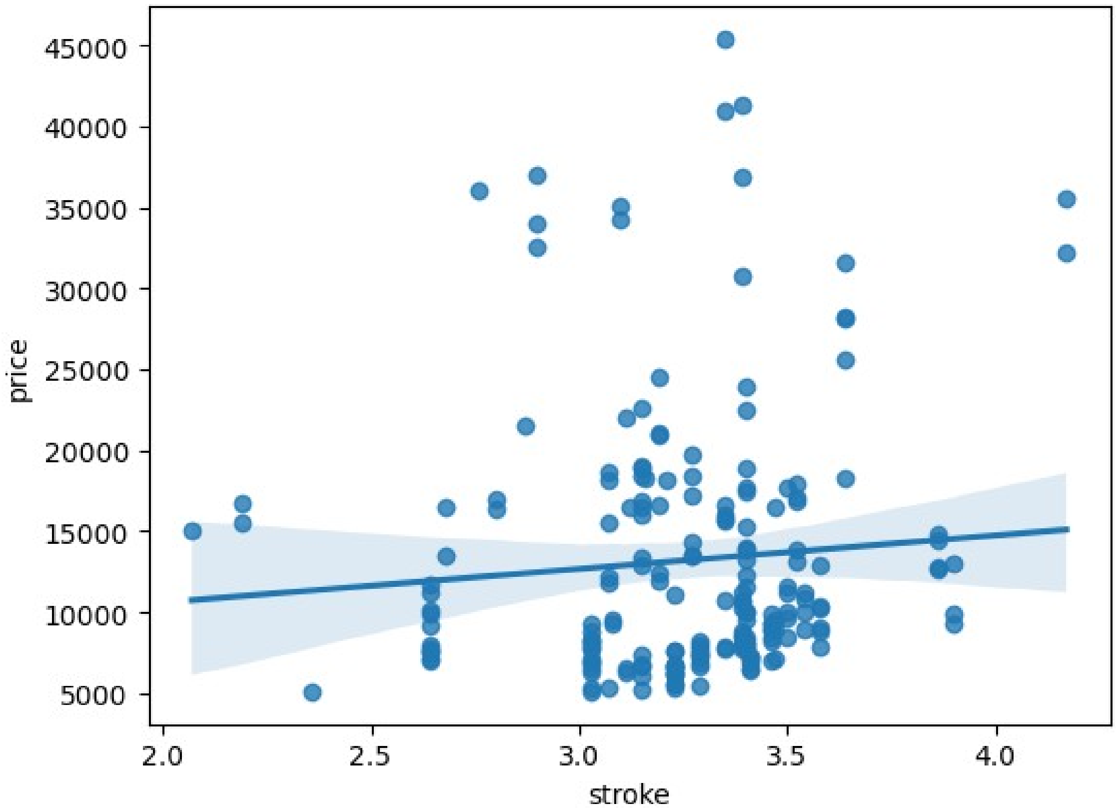
Question 3 a):

```
# Write your code below and press Shift+Enter to execute
df[["stroke","price"]].corr()
```

```
         stroke    price
stroke  1.00000  0.08231
price   0.08231  1.00000
```

```
# Write your code below and press Shift+Enter to execute
sns.regplot(x="stroke", y="price", data=df)
```

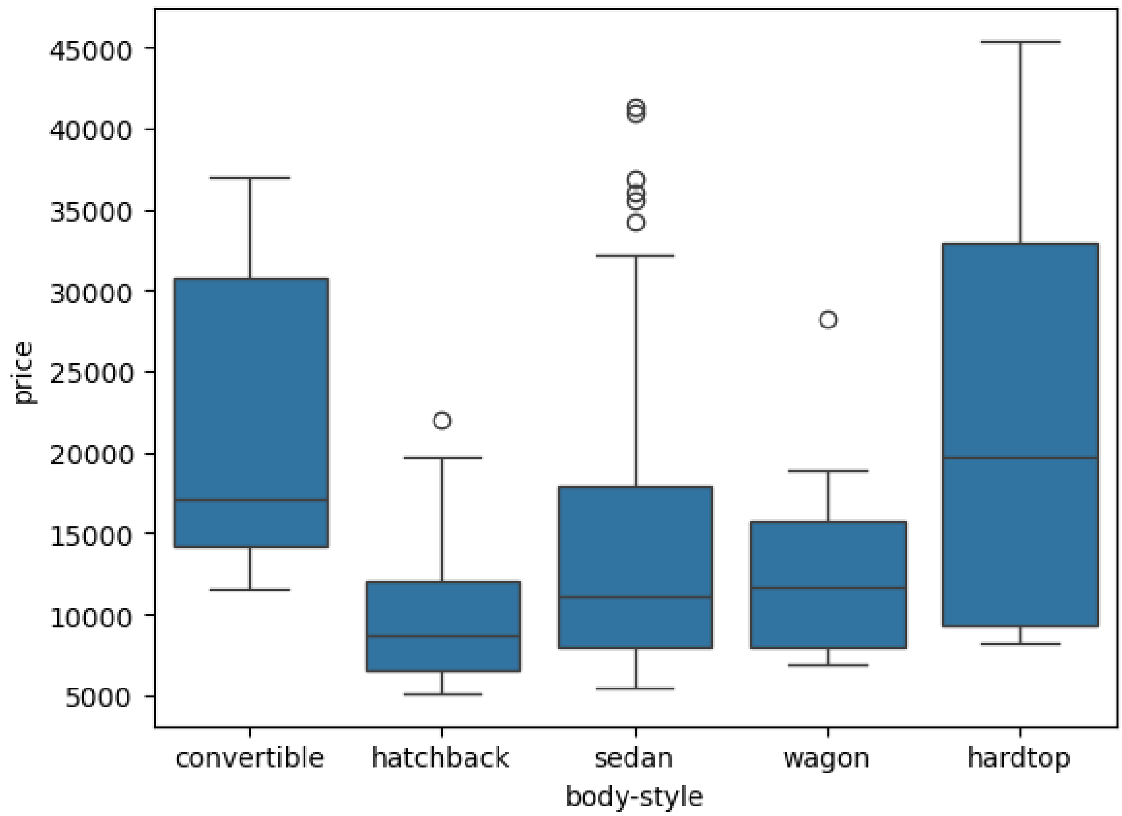
```
<AxesSubplot:xlabel='stroke', ylabel='price'>
```



Let's look at the relationship between "body-style" and "price".

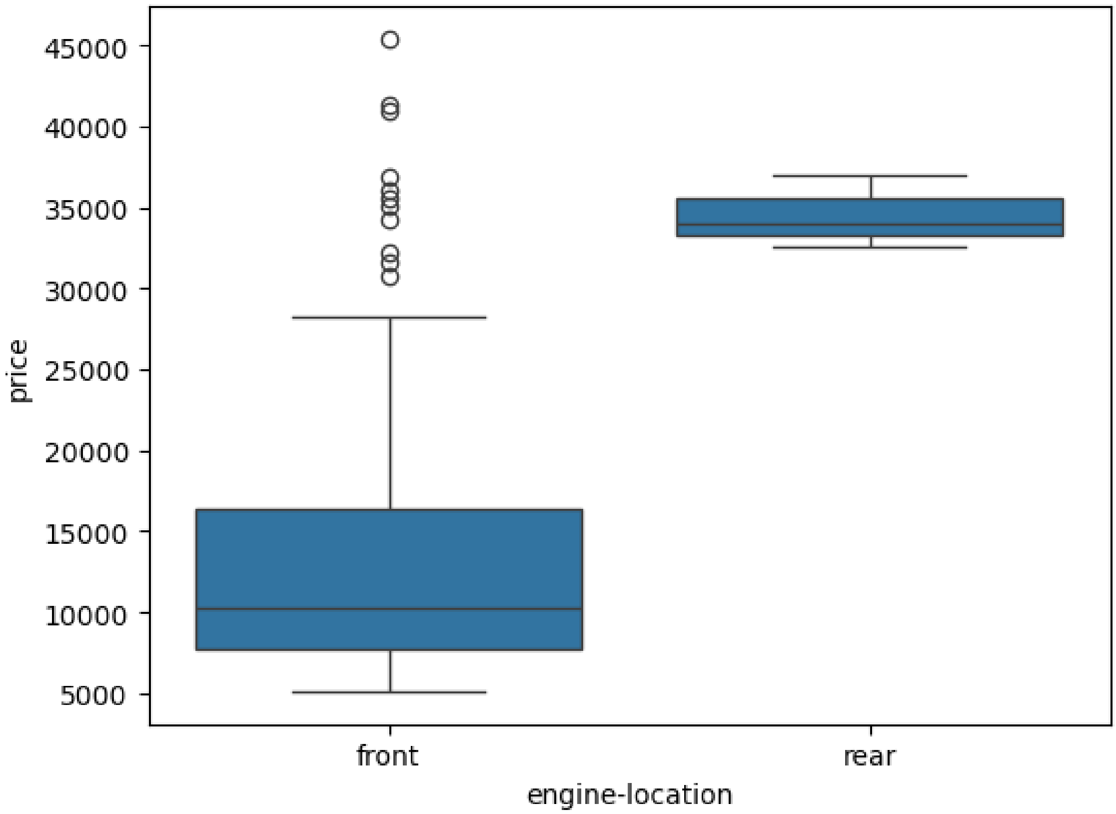
```
sns.boxplot(x="body-style", y="price", data=df)
```

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




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

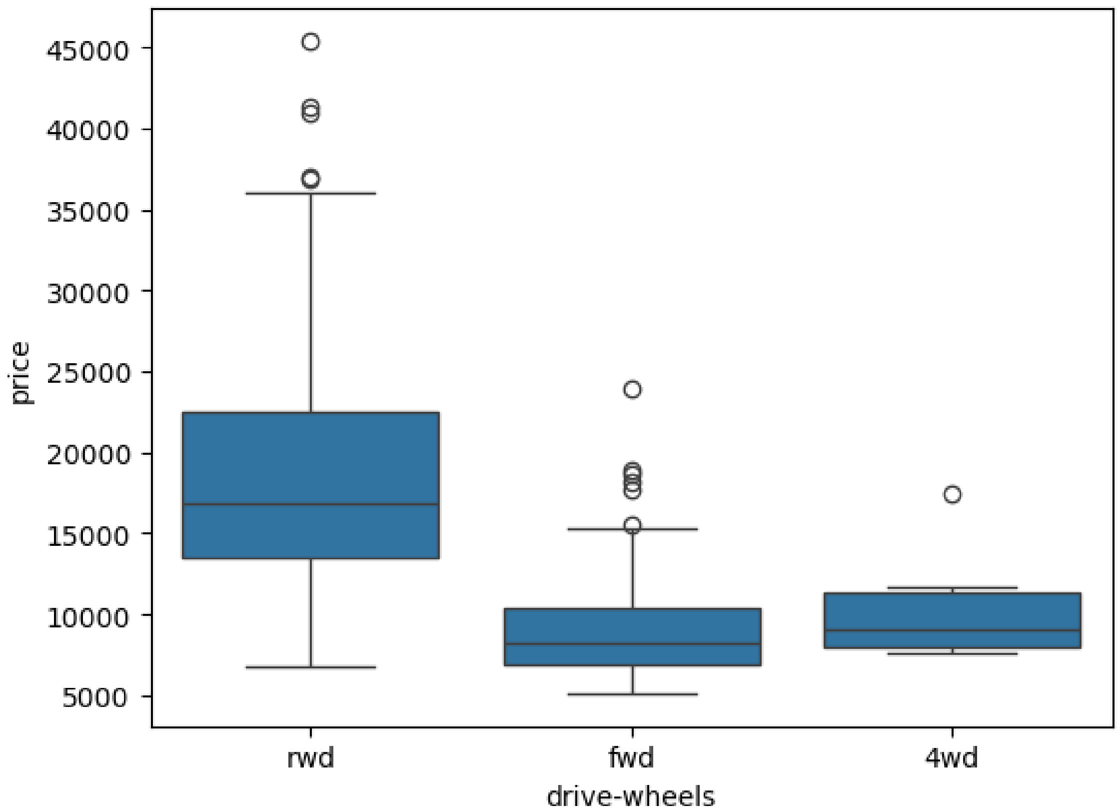
```
<AxesSubplot:xlabel='engine-location', ylabel='price'>
```



Let's examine "drive-wheels" and "price".

```
# drive-wheels
sns.boxplot(x="drive-wheels", y="price", data=df)
```

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



Descriptive Statistical Analysis

This will show: the count of that variable the mean the standard deviation (std) the minimum value the IQR (Interquartile Range: 25%, 50% and 75%) the maximum value

We can apply the method "describe" as follows:

```
df.describe()
```

```
        symboling  normalized-losses  wheel-base      length
width  \
count  201.000000          201.00000  201.000000  201.000000
201.000000
mean     0.840796          122.00000   98.797015    0.837102
0.915126
std      1.254802           31.99625    6.066366    0.059213
0.029187
min     -2.000000           65.00000   86.600000    0.678039
0.837500
25%      0.000000          101.00000   94.500000    0.801538
0.890278
50%      1.000000          122.00000   97.000000    0.832292
0.909722
75%      2.000000          137.00000  102.400000    0.881788
```

```
0.925000
max      3.000000          256.00000  120.900000    1.000000
1.000000

           height  curb-weight  engine-size        bore      stroke  \
count  201.000000   201.000000   201.000000  201.000000  197.000000
mean    53.766667  2555.666667   126.875622    3.330692    3.256904
std      2.447822   517.296727    41.546834    0.268072    0.319256
min     47.800000  1488.000000    61.000000    2.540000    2.070000
25%     52.000000  2169.000000    98.000000    3.150000    3.110000
50%     54.100000  2414.000000   120.000000    3.310000    3.290000
75%     55.500000  2926.000000   141.000000    3.580000    3.410000
max     59.800000  4066.000000   326.000000    3.940000    4.170000

       compression-ratio  horsepower     peak-rpm    city-mpg
highway-mpg  \
count         201.000000  201.000000   201.000000  201.000000
201.000000
mean           10.164279  103.405534  5117.665368   25.179104
30.686567
std             4.004965   37.365700   478.113805    6.423220
6.815150
min             7.000000   48.000000  4150.000000   13.000000
16.000000
25%             8.600000   70.000000  4800.000000   19.000000
25.000000
50%             9.000000   95.000000  5125.369458   24.000000
30.000000
75%             9.400000  116.000000  5500.000000   30.000000
34.000000
max            23.000000  262.000000  6600.000000   49.000000
54.000000

              price  city-L/100km      diesel         gas
count    201.000000    201.000000  201.000000  201.000000
mean   13207.129353      9.944145    0.099502    0.900498
std     7947.066342      2.534599    0.300083    0.300083
min     5118.000000      4.795918    0.000000    0.000000
25%     7775.000000      7.833333    0.000000    1.000000
50%    10295.000000      9.791667    0.000000    1.000000
75%    16500.000000     12.368421    0.000000    1.000000
max    45400.000000     18.076923    1.000000    1.000000
```

The default setting of "describe" skips variables of type object. We can apply the method "describe" on the variables of type 'object' as follows:

```
df.describe(include=['object'])
```

```
          make aspiration num-of-doors body-style drive-wheels  \
count      201        201          201        201          201
unique      22          2            2          5            3
top     toyota        std         four      sedan          fwd
freq        32        165          115         94          118

       engine-location engine-type num-of-cylinders fuel-system  \
count              201         201              201         201
unique               2           6                7           8
top              front         ohc             four        mpfi
freq               198         145              157          92

       horsepower-binned
count                200
unique                 3
top                  Low
freq                 115
```

```
df['drive-wheels'].value_counts()
```

```
fwd    118
rwd     75
4wd      8
Name: drive-wheels, dtype: int64
```

We can convert the series to a dataframe as follows:

```
df['drive-wheels'].value_counts().to_frame()
```

```
     drive-wheels
fwd           118
rwd            75
4wd             8
```

Let's repeat the above steps but save the results to the dataframe "drive_wheels_counts" and rename the column 'drive-wheels' to 'value_counts'.

```
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
drive_wheels_counts.rename(columns={'drive-wheels': 'value_counts'},
inplace=True)
drive_wheels_counts
```

```
     value_counts
fwd           118
rwd            75
4wd             8
```

Now let's rename the index to 'drive-wheels':

```
drive_wheels_counts.index.name = 'drive-wheels'
drive_wheels_counts
```

```
              value_counts
drive-wheels
fwd                    118
rwd                     75
4wd                      8
```

We can repeat the above process for the variable 'engine-location'.

```
# engine-location as variable
engine_loc_counts = df['engine-location'].value_counts().to_frame()
engine_loc_counts.rename(columns={'engine-location': 'value_counts'},
inplace=True)
engine_loc_counts.index.name = 'engine-location'
engine_loc_counts.head(10)
```

```
                 value_counts
engine-location
front                     198
rear                        3
```

Basics of Grouping

```
df['drive-wheels'].unique()
```

```
array(['rwd', 'fwd', '4wd'], dtype=object)
```

```
df_group_one = df[['drive-wheels','body-style','price']]
```

We can then calculate the average price for each of the different categories of data.

```
# grouping results
df_group_one = df_group_one.groupby(['drive-
wheels'],as_index=False).mean()
df_group_one
```

```
<ipython-input-34-10e240e527d5>:2: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.mean is deprecated. In a future
version, numeric_only will default to False. Either specify
numeric_only or select only columns which should be valid for the
function.
  df_group_one = df_group_one.groupby(['drive-
wheels'],as_index=False).mean()
```

```
  drive-wheels         price
0          4wd  10241.000000
1          fwd   9244.779661
2          rwd  19757.613333
```

```
# grouping results
df_gptest = df[['drive-wheels','body-style','price']]
grouped_test1 = df_gptest.groupby(['drive-wheels','body-
style'],as_index=False).mean()
grouped_test1
```

```
   drive-wheels   body-style         price
0           4wd    hatchback   7603.000000
1           4wd        sedan  12647.333333
2           4wd        wagon   9095.750000
3           fwd  convertible  11595.000000
4           fwd      hardtop   8249.000000
5           fwd    hatchback   8396.387755
6           fwd        sedan   9811.800000
7           fwd        wagon   9997.333333
8           rwd  convertible  23949.600000
9           rwd      hardtop  24202.714286
10          rwd    hatchback  14337.777778
11          rwd        sedan  21711.833333
12          rwd        wagon  16994.222222
```

```
grouped_pivot = grouped_test1.pivot(index='drive-
wheels',columns='body-style')
grouped_pivot
```

```
                   price                                            \
body-style   convertible       hardtop     hatchback         sedan
drive-wheels
4wd                  NaN           NaN   7603.000000  12647.333333
fwd              11595.0   8249.000000   8396.387755   9811.800000
rwd              23949.6  24202.714286  14337.777778  21711.833333


body-style           wagon
drive-wheels
4wd            9095.750000
fwd            9997.333333
rwd           16994.222222
```

```
grouped_pivot = grouped_pivot.fillna(0) #fill missing values with 0
grouped_pivot
```

```
                   price                                            \
body-style   convertible       hardtop     hatchback         sedan
drive-wheels
4wd                  0.0      0.000000   7603.000000  12647.333333
fwd              11595.0   8249.000000   8396.387755   9811.800000
rwd              23949.6  24202.714286  14337.777778  21711.833333


body-style           wagon
```

```
drive-wheels
4wd             9095.750000
fwd             9997.333333
rwd            16994.222222
```

```
# Write your code below and press Shift+Enter to execute
df_gptest2 = df[['body-style','price']]
grouped_test_bodystyle = df_gptest2.groupby(['body-style'],as_index=
False).mean()
grouped_test_bodystyle
```

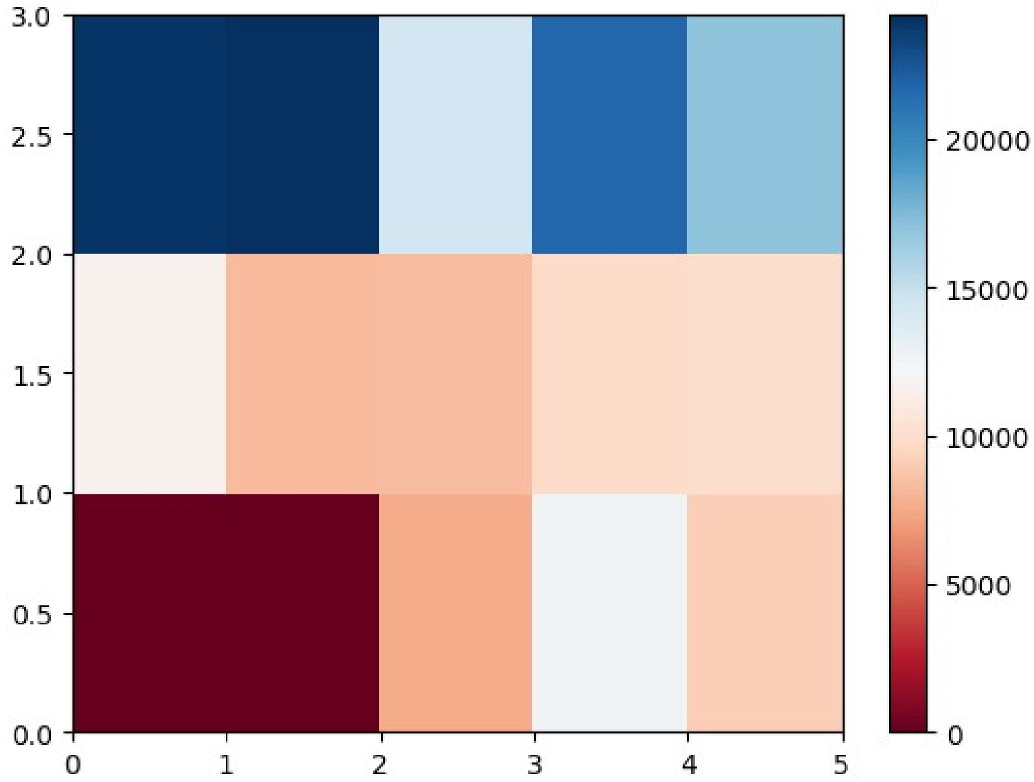
	body-style	price
0	convertible	21890.500000
1	hardtop	22208.500000
2	hatchback	9957.441176
3	sedan	14459.755319
4	wagon	12371.960000

If you did not import "pyplot", let's do it again.

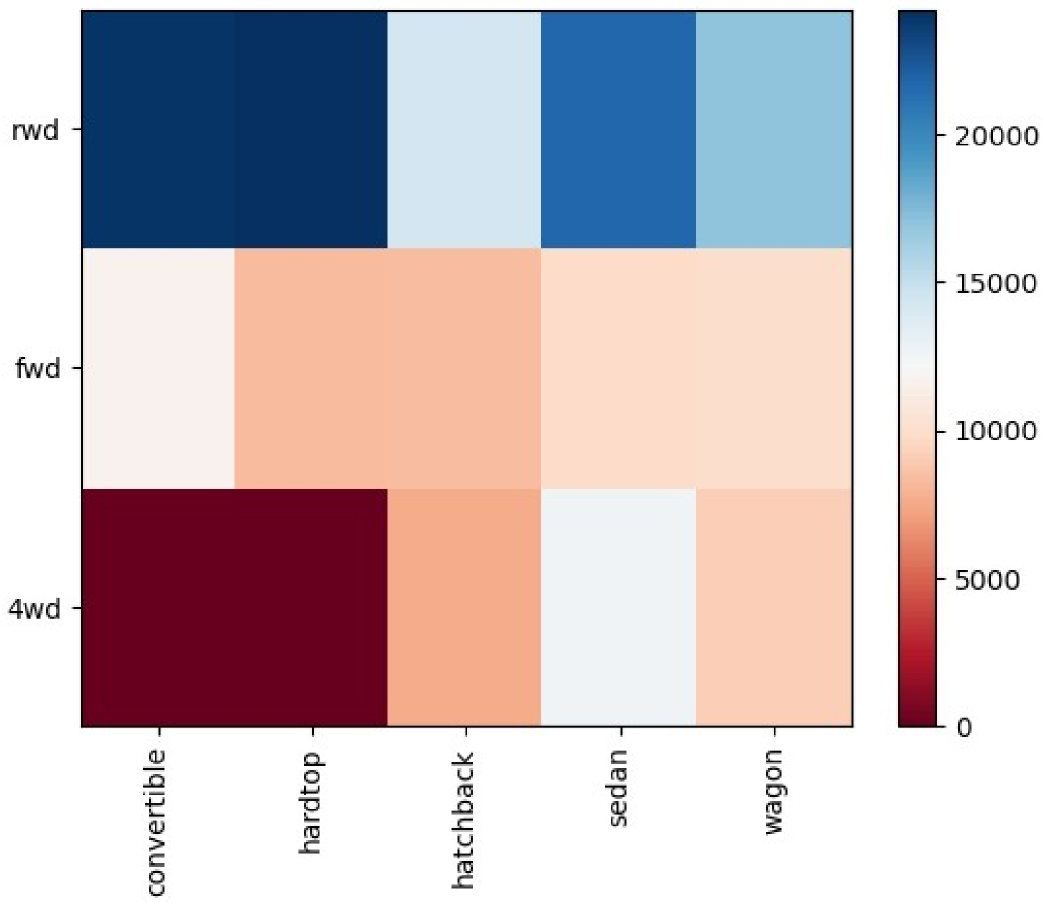
```
import matplotlib.pyplot as plt
%matplotlib inline
```

Let's use a heat map to visualize the relationship between Body Style vs Price.

```
#use the grouped results
plt.pcolor(grouped_pivot, cmap='RdBu')
plt.colorbar()
plt.show()
```




```
fig, ax = plt.subplots()
im = ax.pcolor(grouped_pivot, cmap='RdBu')

#label names
row_labels = grouped_pivot.columns.levels[1]
col_labels = grouped_pivot.index

#move ticks and labels to the center
ax.set_xticks(np.arange(grouped_pivot.shape[1]) + 0.5, minor=False)
ax.set_yticks(np.arange(grouped_pivot.shape[0]) + 0.5, minor=False)

#insert labels
ax.set_xticklabels(row_labels, minor=False)
ax.set_yticklabels(col_labels, minor=False)

#rotate label if too long
plt.xticks(rotation=90)

fig.colorbar(im)
plt.show()
```



Correlation and Causation

```
df.corr()

<ipython-input-42-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  df.corr()

                   symboling  normalized-losses  wheel-base    length
\
symboling           1.000000           0.466264   -0.535987 -0.365404

normalized-losses   0.466264           1.000000   -0.056661  0.019424

wheel-base         -0.535987          -0.056661    1.000000  0.876024

length             -0.365404           0.019424    0.876024  1.000000

width              -0.242423           0.086802    0.814507  0.857170

height             -0.550160          -0.373737    0.590742  0.492063
```

```
curb-weight        -0.233118          0.099404   0.782097  0.880665
engine-size        -0.110581          0.112360   0.572027  0.685025
bore               -0.140019         -0.029862   0.493244  0.608971
stroke             -0.008245          0.055563   0.158502  0.124139
compression-ratio  -0.182196         -0.114713   0.250313  0.159733
horsepower          0.075819          0.217299   0.371147  0.579821
peak-rpm            0.279740          0.239543  -0.360305 -0.285970
city-mpg           -0.035527         -0.225016  -0.470606 -0.665192
highway-mpg         0.036233         -0.181877  -0.543304 -0.698142
price              -0.082391          0.133999   0.584642  0.690628
city-L/100km        0.066171          0.238567   0.476153  0.657373
diesel             -0.196735         -0.101546   0.307237  0.211187
gas                 0.196735          0.101546  -0.307237 -0.211187

                      width    height  curb-weight  engine-size
bore  \
symboling         -0.242423 -0.550160    -0.233118    -0.110581 -
0.140019
normalized-losses  0.086802 -0.373737     0.099404     0.112360 -
0.029862
wheel-base         0.814507  0.590742     0.782097     0.572027
0.493244
length             0.857170  0.492063     0.880665     0.685025
0.608971
width              1.000000  0.306002     0.866201     0.729436
0.544885
height             0.306002  1.000000     0.307581     0.074694
0.180449
curb-weight        0.866201  0.307581     1.000000     0.849072
0.644060
engine-size        0.729436  0.074694     0.849072     1.000000
0.572609
bore               0.544885  0.180449     0.644060     0.572609
1.000000
stroke             0.188829 -0.062704     0.167562     0.209523 -
0.055390
compression-ratio  0.189867  0.259737     0.156433     0.028889
```

```
0.001263
horsepower          0.615077 -0.087027     0.757976     0.822676  
0.566936
peak-rpm           -0.245800 -0.309974    -0.279361    -0.256733 -
0.267392
city-mpg           -0.633531 -0.049800    -0.749543    -0.650546 -
0.582027
highway-mpg        -0.680635 -0.104812    -0.794889    -0.679571 -
0.591309
price               0.751265  0.135486     0.834415     0.872335  
0.543155
city-L/100km        0.673363  0.003811     0.785353     0.745059  
0.554610
diesel              0.244356  0.281578     0.221046     0.070779  
0.054458
gas                -0.244356 -0.281578    -0.221046    -0.070779 -
0.054458

                     stroke  compression-ratio  horsepower  peak-
rpm  \
symboling         -0.008245          -0.182196    0.075819  0.279740

normalized-losses  0.055563          -0.114713    0.217299  0.239543

wheel-base         0.158502           0.250313    0.371147 -0.360305

length             0.124139           0.159733    0.579821 -0.285970

width              0.188829           0.189867    0.615077 -0.245800

height            -0.062704           0.259737   -0.087027 -0.309974

curb-weight        0.167562           0.156433    0.757976 -0.279361

engine-size        0.209523           0.028889    0.822676 -0.256733

bore              -0.055390           0.001263    0.566936 -0.267392

stroke             1.000000           0.187923    0.098462 -0.065713

compression-ratio  0.187923           1.000000   -0.214514 -0.435780

horsepower         0.098462          -0.214514    1.000000  0.107885

peak-rpm          -0.065713          -0.435780    0.107885  1.000000

city-mpg          -0.034696           0.331425   -0.822214 -0.115413

highway-mpg       -0.035201           0.268465   -0.804575 -0.058598

price              0.082310           0.071107    0.809575 -0.101616
```

```
city-L/100km       0.037300          -0.299372    0.889488  0.115830

diesel             0.241303           0.985231   -0.169053 -0.475812

gas               -0.241303          -0.985231    0.169053  0.475812


                   city-mpg  highway-mpg     price  city-L/100km
diesel  \
symboling         -0.035527     0.036233 -0.082391      0.066171 -
0.196735
normalized-losses -0.225016    -0.181877  0.133999      0.238567 -
0.101546
wheel-base        -0.470606    -0.543304  0.584642      0.476153
0.307237
length            -0.665192    -0.698142  0.690628      0.657373
0.211187
width             -0.633531    -0.680635  0.751265      0.673363
0.244356
height            -0.049800    -0.104812  0.135486      0.003811
0.281578
curb-weight       -0.749543    -0.794889  0.834415      0.785353
0.221046
engine-size       -0.650546    -0.679571  0.872335      0.745059
0.070779
bore              -0.582027    -0.591309  0.543155      0.554610
0.054458
stroke            -0.034696    -0.035201  0.082310      0.037300
0.241303
compression-ratio  0.331425     0.268465  0.071107     -0.299372
0.985231
horsepower        -0.822214    -0.804575  0.809575      0.889488 -
0.169053
peak-rpm          -0.115413    -0.058598 -0.101616      0.115830 -
0.475812
city-mpg           1.000000     0.972044 -0.686571     -0.949713
0.265676
highway-mpg        0.972044     1.000000 -0.704692     -0.930028
0.198690
price             -0.686571    -0.704692  1.000000      0.789898
0.110326
city-L/100km      -0.949713    -0.930028  0.789898      1.000000 -
0.241282
diesel             0.265676     0.198690  0.110326     -0.241282
1.000000
gas               -0.265676    -0.198690 -0.110326      0.241282 -
1.000000

                        gas
```

```
symboling            0.196735
normalized-losses  0.101546
wheel-base          -0.307237
length              -0.211187
width               -0.244356
height              -0.281578
curb-weight         -0.221046
engine-size         -0.070779
bore                -0.054458
stroke              -0.241303
compression-ratio  -0.985231
horsepower           0.169053
peak-rpm             0.475812
city-mpg            -0.265676
highway-mpg         -0.198690
price               -0.110326
city-L/100km         0.241282
diesel              -1.000000
gas                  1.000000
```

Sometimes we would like to know the significant of the correlation estimate.

P-value What is this P-value? The P-value is the probability value that the correlation between these two variables is statistically significant. Normally, we choose a significance level of 0.05, which means that we are 95% confident that the correlation between the variables is significant.

By convention, when the p-value is ¿ 0.001: we say there is strong evidence that the correlation is significant. the p-value is ¿ 0.05: there is moderate evidence that the correlation is significant. the p-value is ¿ 0.1: there is weak evidence that the correlation is significant. the p-value is ¿ 0.1: there is no evidence that the correlation is significant.

We can obtain this information using "stats" module in the "scipy" library.

```
from scipy import stats
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'wheel-base' and 'price'.

```
pearson_coef, p_value = stats.pearsonr(df['wheel-base'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is 0.5846418222655085  with a P-value of P = 8.076488270732338e-20
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'horsepower' and 'price'.

```
pearson_coef, p_value = stats.pearsonr(df['horsepower'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.8095745670036559  with a P-value of P =  6.36905742825956e-48
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'length' and 'price'.

```
pearson_coef, p_value = stats.pearsonr(df['length'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.6906283804483643  with a P-value of P =  8.016477466158871e-30
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'width' and 'price':

```
pearson_coef, p_value = stats.pearsonr(df['width'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =", p_value )
```

```
The Pearson Correlation Coefficient is 0.7512653440522663  with a P-value of P = 9.200335510485071e-38
```

Conclusion:

Since the p-value is < 0.001, the correlation between width and price is statistically significant, and the linear relationship is quite strong (~0.751).

Curb-Weight vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'curb-weight' and 'price':

```
pearson_coef, p_value = stats.pearsonr(df['curb-weight'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.8344145257702845  with a P-value of P =  2.1895772388939654e-53
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'engine-size' and 'price':

```
pearson_coef, p_value = stats.pearsonr(df['engine-size'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is 0.8723351674455188  with a P-value of P = 9.26549162219582e-64
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'bore' and 'price':

```
pearson_coef, p_value = stats.pearsonr(df['bore'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a 
P-value of P =  ", p_value )

The Pearson Correlation Coefficient is 0.5431553832626601  with a P-
value of P =   8.049189483935384e-17
```

We can relate the process for each 'city-mpg' and 'highway-mpg':

```
pearson_coef, p_value = stats.pearsonr(df['city-mpg'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a 
P-value of P = ", p_value)

The Pearson Correlation Coefficient is -0.6865710067844684  with a P-
value of P =  2.3211320655672357e-29

pearson_coef, p_value = stats.pearsonr(df['highway-mpg'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with 
a P-value of P = ", p_value)

The Pearson Correlation Coefficient is -0.7046922650589532  with a P-
value of P =  1.7495471144475574e-31
```

Conclusion:

Since the p-value is < 0.001, the correlation between highway-mpg and price is statistically significant, and the coefficient of about -0.705 shows that the relationship is negative and moderately strong.

Continuous numerical variables: Length Width Curb-weight Engine-size Horsepower City-mpg Highway-mpg Wheel-base Bore

Categorical variables: Drive-wheels

Thank you for completing this lab!

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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2023-09-28	2.2	Abhishek Gagneja	Updated instructions
2020-10-30	2.1	Lakshmi	changed URL of csv
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab