exploratory-data-analysis

October 21, 2019

Exploratory Data Analysis

Welcome!

In this section, we will explore several methods to see if certain characteristics or features can be used to predict car price.

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```

Estimated Time Needed: 30 min

What are the main characteristics which have the most impact on the car price?

1. Import Data from Module 2

Setup

Import libraries

[1]:
```python
import pandas as pd
import numpy as np
```

load data and store in dataframe df:

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

[2]:
```python
path='https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/
↪CognitiveClass/DA0101EN/automobileEDA.csv'
df = pd.read_csv(path)
df.head()
```

[2]:
```
   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]
```

2. Analyzing Individual Feature Patterns using Visualization

To install seaborn we use the pip which is the python package manager.

[3]:
```
%%capture
! pip install seaborn
```

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

[4]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

How to choose the right visualization method?

When visualizing individual variables, it is important to first understand what type of variable you are dealing with. This will help us find the right visualization method for that variable.

[5]:
```
# 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
```

Question #1:

What is the data type of the column "peak-rpm"?

Double-click here for the solution.

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

[7]:
```
df.corr()
```

[7]:
```
                   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.

Question #2:

Find the correlation between the following columns: bore, stroke,compression-ratio , and horsepower.

Hint: if you would like to select those columns use the following syntax: df[['bore','stroke' ,'compression-ratio','horsepower']]

[6]:
```
# Write your code below and press Shift+Enter to execute
df[['bore','stroke' ,'compression-ratio','horsepower']].corr()
```

[6]:

	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

Double-click here for the solution.

Continuous numerical variables:

Continuous numerical variables are variables that may contain any value within some range. Continuous numerical variables can have the type "int64" or "float64". A great way to visualize these variables is by using scatterplots with fitted lines.

In order to start understanding the (linear) relationship between an individual variable and the price. We can do this by using "regplot", which plots the scatterplot plus the fitted regression line for the data.

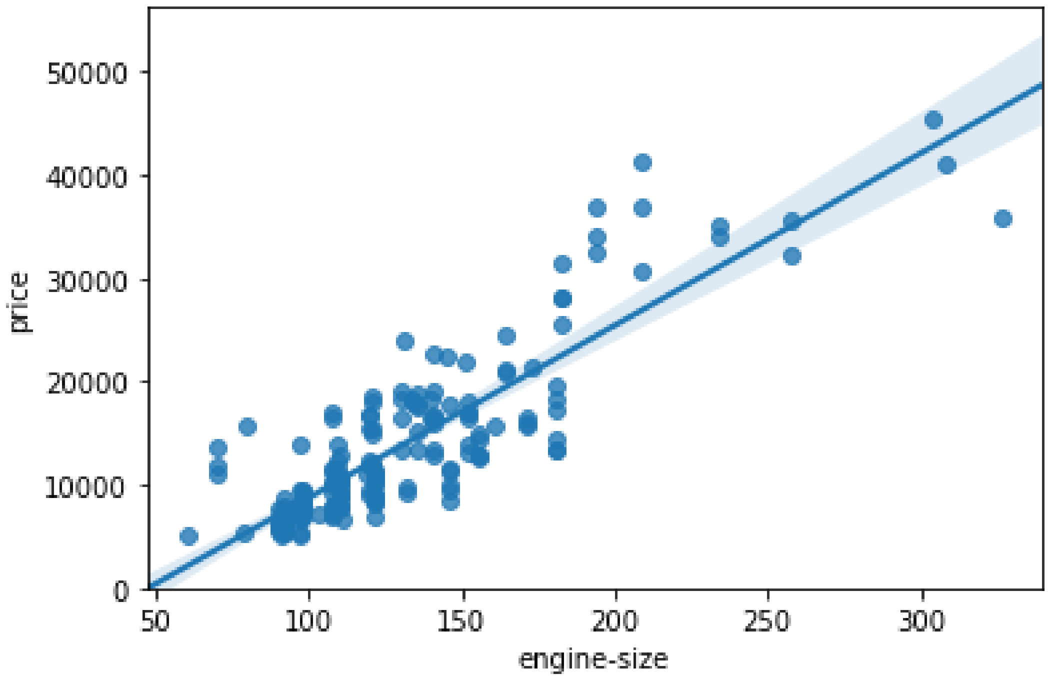
Let's see several examples of different linear relationships:

Positive linear relationship

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

[10]:
```
# Engine size as potential predictor variable of price
sns.regplot(x="engine-size", y="price", data=df)
plt.ylim(0,)
```

[10]: (0, 56197.79968643887)



As the engine-size goes up, the price goes up: this indicates a positive direct correlation between these two variables. Engine size seems like a pretty good predictor of price since the regression line is almost a perfect diagonal line.

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

[11]:
```
df[["engine-size", "price"]].corr()
```

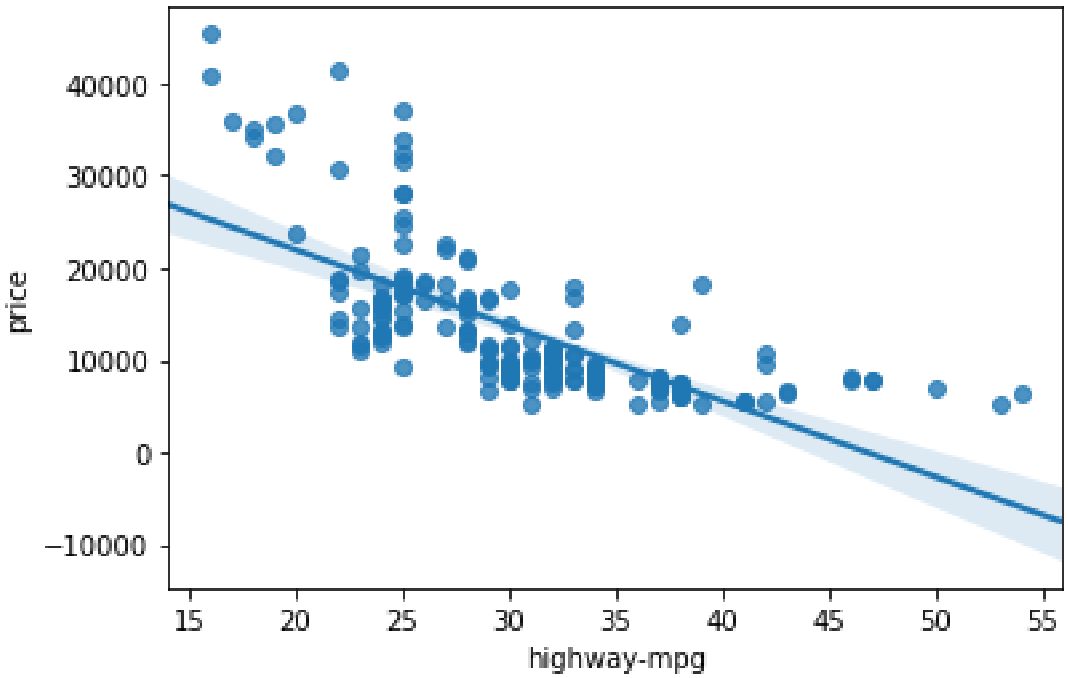
[11]:

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

Highway mpg is a potential predictor variable of price

[12]:
```
sns.regplot(x="highway-mpg", y="price", data=df)
```

[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4844197d68>
```



As the highway-mpg goes up, the price goes down: this indicates an inverse/negative relationship between these two variables. Highway mpg could potentially be a predictor of price.

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

[13]:
```
df[['highway-mpg', 'price']].corr()
```

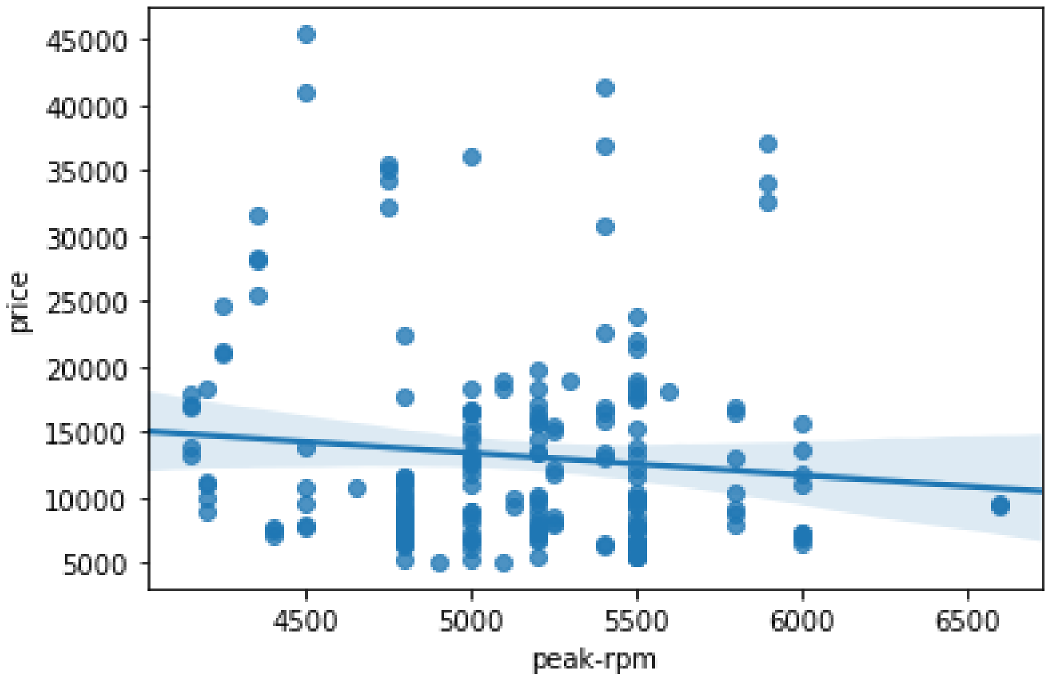
[13]:
```
             highway-mpg     price
highway-mpg     1.000000 -0.704692
price          -0.704692  1.000000
```

Weak Linear Relationship

Let's see if "Peak-rpm" as a predictor variable of "price".

[14]:
```
sns.regplot(x="peak-rpm", y="price", data=df)
```

[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f484410deb8>
```



Peak rpm does not seem like a good predictor of the price at all since the regression line is close to horizontal. Also, the data points are very scattered and far from the fitted line, showing lots of variability. Therefore it's it is not a reliable variable.

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

[15]:
```
df[['peak-rpm','price']].corr()
```

[15]:
```
          peak-rpm     price
peak-rpm  1.000000 -0.101616
price    -0.101616  1.000000
```

Question 3 a):

Find the correlation between x="stroke", y="price".

Hint: if you would like to select those columns use the following syntax: df[["stroke","price"]]

[16]:
```
# Write your code below and press Shift+Enter to execute
df[['stroke','price']].corr()
```

[16]:
```
         stroke    price
stroke  1.00000  0.08231
price   0.08231  1.00000
```

Double-click here for the solution.

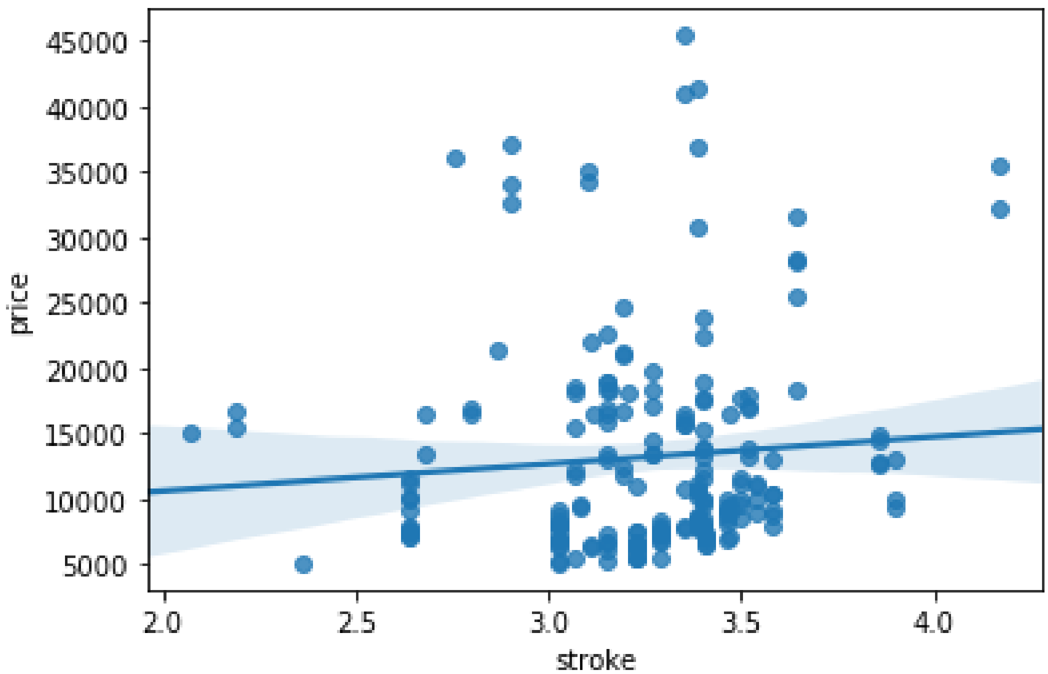
Question 3 b):

Given the correlation results between "price" and "stroke" do you expect a linear relationship?

Verify your results using the function "regplot()".

[21]:
```
# Write your code below and press Shift+Enter to execute
sns.regplot(x='stroke',y='price',data=df)
```

[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48440eb7b8>
```



Double-click here for the solution.

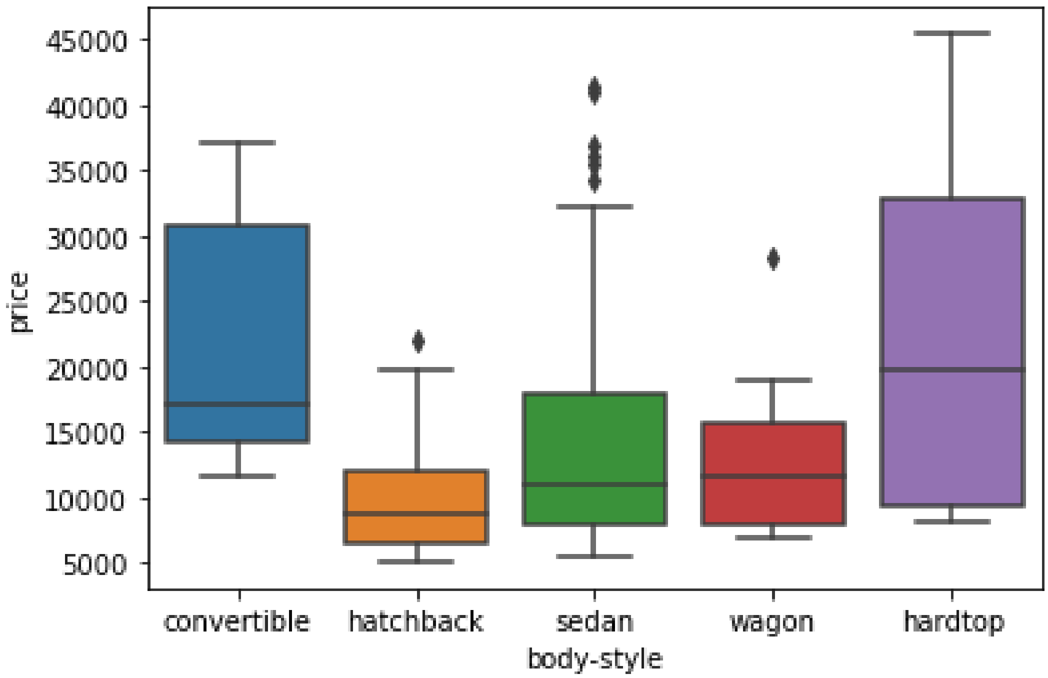
Categorical variables

These are variables that describe a 'characteristic' of a data unit, and are selected from a small group of categories. The categorical variables can have the type "object" or "int64". A good way to visualize categorical variables is by using boxplots.

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

[22]:
```
sns.boxplot(x="body-style", y="price", data=df)
```

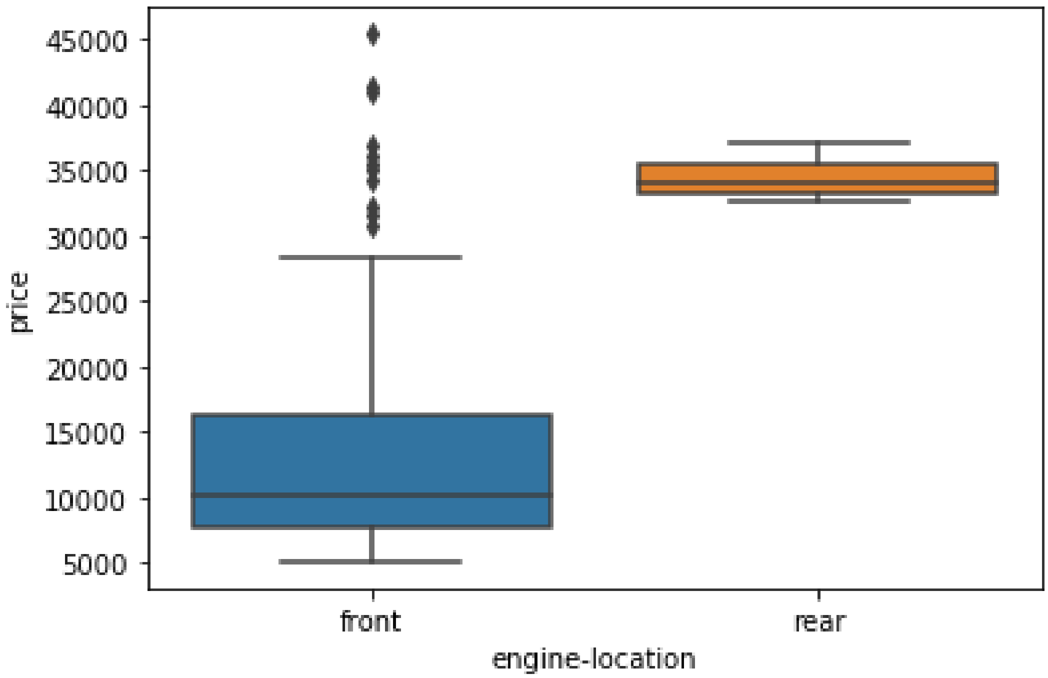
[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f482aab6748>
```



We see that the distributions of price between the different body-style categories have a significant overlap, and so body-style would not be a good predictor of price. Let's examine engine "engine-location" and "price":

[23]:
```
sns.boxplot(x="engine-location", y="price", data=df)
```

[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48472b00b8>

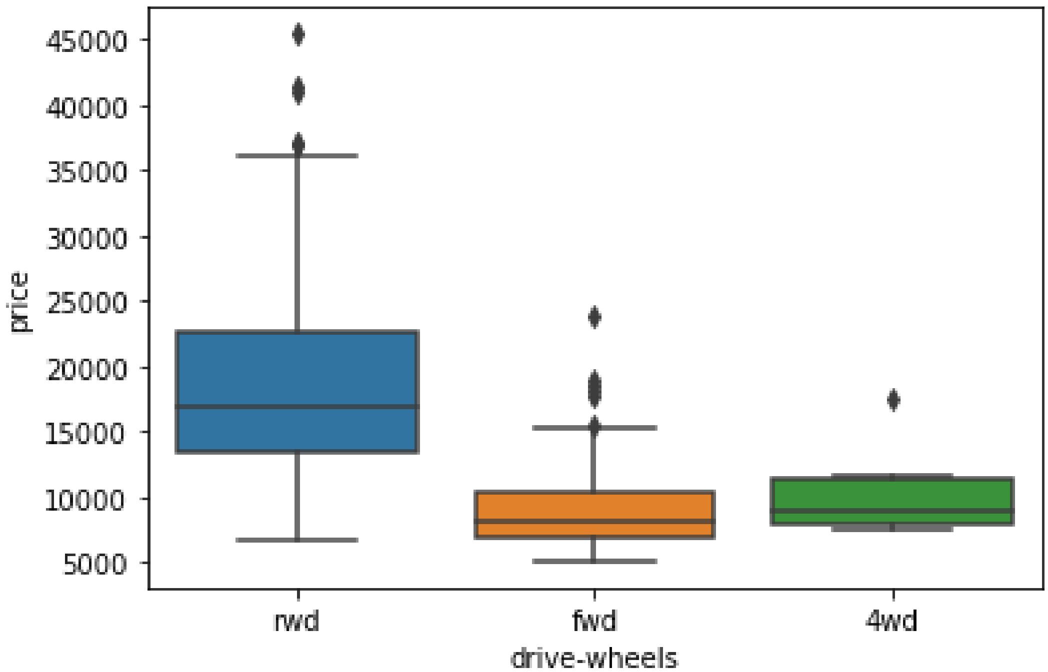


Here we see that the distribution of price between these two engine-location categories, front and rear, are distinct enough to take engine-location as a potential good predictor of price.

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

[24]:
```
# drive-wheels
sns.boxplot(x="drive-wheels", y="price", data=df)
```

[24]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f482aaa6f98>`



Here we see that the distribution of price between the different drive-wheels categories differs; as such drive-wheels could potentially be a predictor of price.

3. Descriptive Statistical Analysis

Let's first take a look at the variables by utilizing a description method.

The describe function automatically computes basic statistics for all continuous variables. Any NaN values are automatically skipped in these statistics.

This will show:

```
<li>the count of that variable</li>
<li>the mean</li>
<li>the standard deviation (std)</li>
<li>the minimum value</li>
<li>the IQR (Interquartile Range: 25%, 50% and 75%)</li>
<li>the maximum value</li>
```

We can apply the method "describe" as follows:

[25]:
```
df.describe()
```

[25]:

	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:

[26]:
```
df.describe(include=['object'])
```

[26]:

	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
```

Value Counts

Value-counts is a good way of understanding how many units of each characteristic/variable we have. We can apply the "value_counts" method on the column 'drive-wheels'. Don't forget the method "value_counts" only works on Pandas series, not Pandas Dataframes. As a result, we only include one bracket "df['drive-wheels']" not two brackets "df[['drive-wheels']]".

[27]:
```
df['drive-wheels'].value_counts()
```

[27]:
```
fwd    118
rwd     75
4wd      8
Name: drive-wheels, dtype: int64
```

We can convert the series to a Dataframe as follows :

[28]:
```
df['drive-wheels'].value_counts().to_frame()
```

[28]:
```
     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'.

[29]:
```
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
drive_wheels_counts.rename(columns={'drive-wheels': 'value_counts'},␣
 ↪inplace=True)
drive_wheels_counts
```

[29]:
```
     value_counts
fwd           118
rwd            75
4wd             8
```

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

[30]:
```python
drive_wheels_counts.index.name = 'drive-wheels'
drive_wheels_counts
```

[30]:
```
              value_counts
drive-wheels
fwd                    118
rwd                     75
4wd                      8
```

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

[31]:
```python
# 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)
```

[31]:
```
                 value_counts
engine-location
front                     198
rear                        3
```

Examining the value counts of the engine location would not be a good predictor variable for the price. This is because we only have three cars with a rear engine and 198 with an engine in the front, this result is skewed. Thus, we are not able to draw any conclusions about the engine location.

4. Basics of Grouping

The "groupby" method groups data by different categories. The data is grouped based on one or several variables and analysis is performed on the individual groups.

For example, let's group by the variable "drive-wheels". We see that there are 3 different categories of drive wheels.

[32]:
```python
df['drive-wheels'].unique()
```

[32]:
```
array(['rwd', 'fwd', '4wd'], dtype=object)
```

If we want to know, on average, which type of drive wheel is most valuable, we can group "drive-wheels" and then average them.

We can select the columns 'drive-wheels', 'body-style' and 'price', then assign it to the variable "df_group_one".

[33]:
```python
df_group_one = df[['drive-wheels','body-style','price']]
```

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

[34]:
```
# grouping results
df_group_one = df_group_one.groupby(['drive-wheels'],as_index=False).mean()
df_group_one
```

[34]:

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

From our data, it seems rear-wheel drive vehicles are, on average, the most expensive, while 4-wheel and front-wheel are approximately the same in price.

You can also group with multiple variables. For example, let's group by both 'drive-wheels' and 'body-style'. This groups the dataframe by the unique combinations 'drive-wheels' and 'body-style'. We can store the results in the variable 'grouped_test1'.

[35]:
```
# 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
```

[35]:

	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

This grouped data is much easier to visualize when it is made into a pivot table. A pivot table is like an Excel spreadsheet, with one variable along the column and another along the row. We can convert the dataframe to a pivot table using the method "pivot " to create a pivot table from the groups.

In this case, we will leave the drive-wheel variable as the rows of the table, and pivot body-style to become the columns of the table:

[53]:
```
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot.columns.levels[1]
```

[53]: Index(['convertible', 'hardtop', 'hatchback', 'sedan', 'wagon'], dtype='object',
name='body-style')

Often, we won't have data for some of the pivot cells. We can fill these missing cells with the value 0, but any other value could potentially be used as well. It should be mentioned that missing data is quite a complex subject and is an entire course on its own.

[37]:
```
grouped_pivot = grouped_pivot.fillna(0) #fill missing values with 0
grouped_pivot
```

[37]:
```
                    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
```

Question 4:

Use the "groupby" function to find the average "price" of each car based on "body-style" ?

[42]:
```
# Write your code below and press Shift+Enter to execute
df_g = df[['body-style','price']]

df_group = df_g.groupby(['body-style'],as_index = False).mean()
df_group
```

[42]:
```
    body-style         price
0  convertible  21890.500000
1      hardtop  22208.500000
2    hatchback   9957.441176
3        sedan  14459.755319
4        wagon  12371.960000
```

Double-click here for the solution.

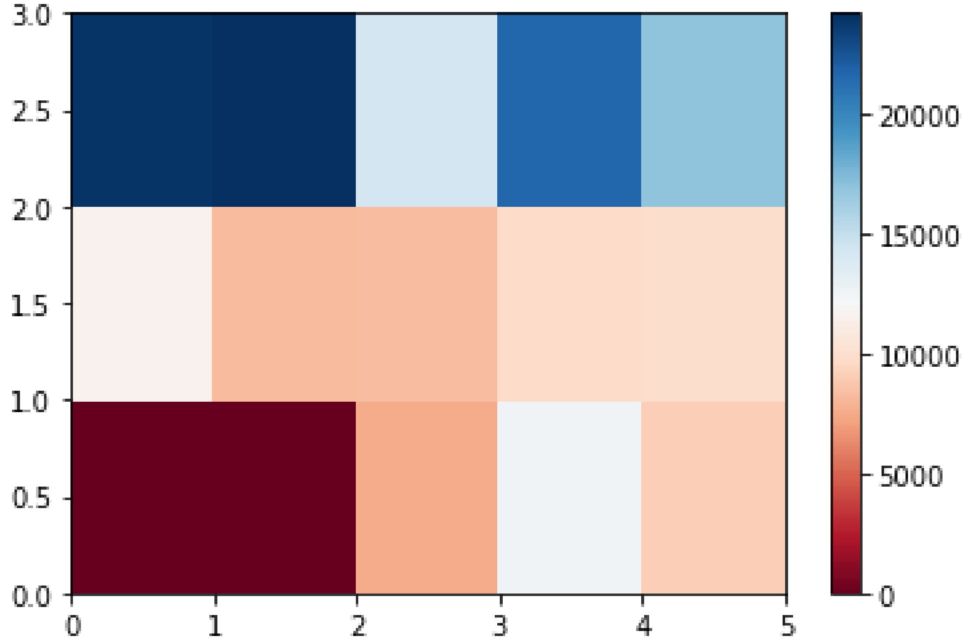
If you did not import "pyplot" let's do it again.

[43]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

Variables: Drive Wheels and Body Style vs Price

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

[44]:
```
#use the grouped results
plt.pcolor(grouped_pivot, cmap='RdBu')
plt.colorbar()
plt.show()
```

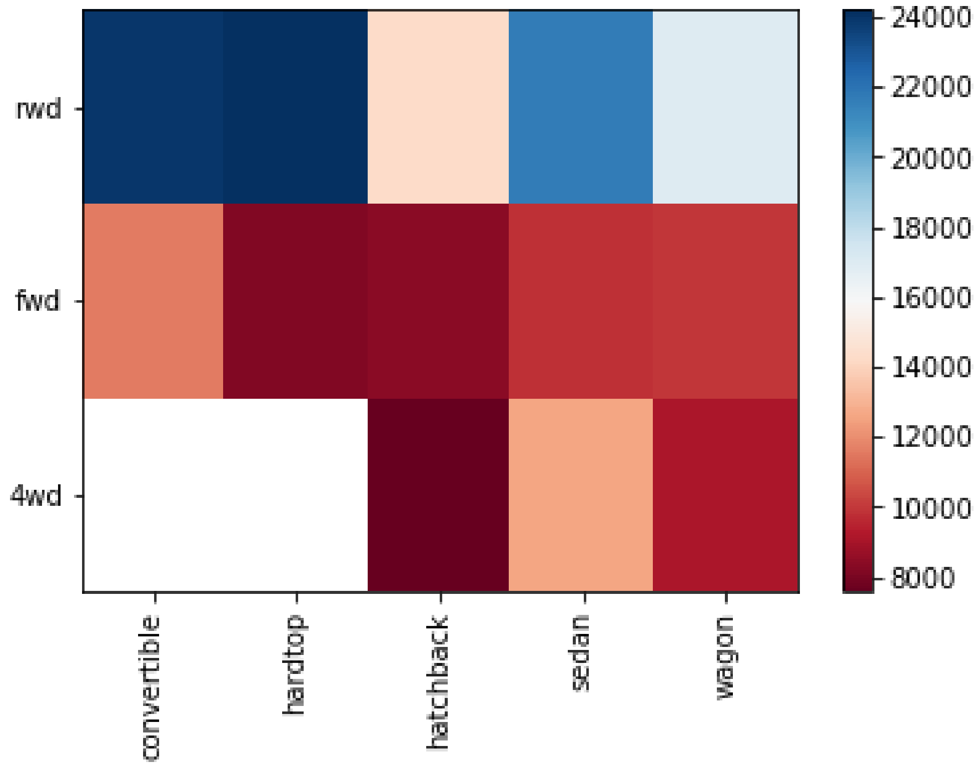


The heatmap plots the target variable (price) proportional to colour with respect to the variables 'drive-wheel' and 'body-style' in the vertical and horizontal axis respectively. This allows us to visualize how the price is related to 'drive-wheel' and 'body-style'.

The default labels convey no useful information to us. Let's change that:

[55]:
```
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()
```



Visualization is very important in data science, and Python visualization packages provide great freedom. We will go more in-depth in a separate Python Visualizations course.

The main question we want to answer in this module, is "What are the main characteristics which have the most impact on the car price?".

To get a better measure of the important characteristics, we look at the correlation of these variables with the car price, in other words: how is the car price dependent on this variable?

5. Correlation and Causation

Correlation: a measure of the extent of interdependence between variables.

Causation: the relationship between cause and effect between two variables.

It is important to know the difference between these two and that correlation does not imply causation. Determining correlation is much simpler the determining causation as causation may require independent experimentation.

Pearson Correlation

The Pearson Correlation measures the linear dependence between two variables X and Y.

The resulting coefficient is a value between -1 and 1 inclusive, where:

1: Total positive linear correlation.
0: No linear correlation, the two variables most likely do not affect each other.</
-1: Total negative linear correlation.

Pearson Correlation is the default method of the function ”corr”. Like before we can calculate the Pearson Correlation of the of the 'int64' or 'float64' variables.

[56]:
```
df.corr()
```

[56]:
```
                   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

```
<li>p-value is $<$ 0.001: we say there is strong evidence that the correlation is significant.<
<li>the p-value is $<$ 0.05: there is moderate evidence that the correlation is significant.</l
<li>the p-value is $<$ 0.1: there is weak evidence that the correlation is significant.</li>
<li>the p-value is $>$ 0.1: there is no evidence that the correlation is significant.</li>
```

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

[57]:
```python
from scipy import stats
```

Wheel-base vs Price

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

[58]:
```python
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 0.5846418222655081  with a P-value of P =
8.076488270732955e-20
```

Conclusion:

Since the p-value is < 0.001, the correlation between wheel-base and price is statistically significant, although the linear relationship isn't extremely strong (~0.585)

Horsepower vs Price

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

[59]:
```
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 =
6.36905742825998e-48
```

Conclusion:

Since the p-value is < 0.001, the correlation between horsepower and price is statistically significant, and the linear relationship is quite strong (~0.809, close to 1)

Length vs Price

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

[63]:
```
pearson, pvalue = stats.pearsonr(df['length'],df['price'])
print("the pearson coeff is :",pearson, "p value is:",pvalue)
#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 coeff is : 0.690628380448364 p value is: 8.016477466159053e-30
```

Conclusion:

Since the p-value is < 0.001, the correlation between length and price is statistically significant, and the linear relationship is moderately strong (~0.691).

Width vs Price

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

[64]:
```
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 0.7512653440522674  with a P-value of P =
9.200335510481426e-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).

0.0.1 Curb-weight vs Price

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

[65]:
```
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 0.8344145257702846  with a P-value of P =
2.1895772388936997e-53
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between curb-weight and price is statistically significant, and the linear relationship is quite strong (~0.834).

Engine-size vs Price

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

[66]:
```
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 0.8723351674455185  with a P-value of P =
9.265491622197996e-64
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between engine-size and price is statistically significant, and the linear relationship is very strong (~0.872).

Bore vs Price

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

[67]:
```
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 0.5431553832626602  with a P-value of P =
8.049189483935364e-17
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between bore and price is statistically significant, but the linear relationship is only moderate (~0.521).

We can relate the process for each 'City-mpg' and 'Highway-mpg':

City-mpg vs Price

[68]:
```
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 -0.6865710067844677  with a P-value of P
=  2.3211320655676368e-29
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between city-mpg and price is statistically significant, and the coefficient of ~ -0.687 shows that the relationship is negative and moderately strong.

Highway-mpg vs Price

[69]:
```
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 -0.7046922650589529  with a P-value of P
=  1.7495471144476807e-31
```

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

6. ANOVA

ANOVA: Analysis of Variance

The Analysis of Variance (ANOVA) is a statistical method used to test whether there are significant differences between the means of two or more groups. ANOVA returns two parameters:

F-test score: ANOVA assumes the means of all groups are the same, calculates how much the actual means deviate from the assumption, and reports it as the F-test score. A larger score means there is a larger difference between the means.

P-value: P-value tells how statistically significant is our calculated score value.

If our price variable is strongly correlated with the variable we are analyzing, expect ANOVA to return a sizeable F-test score and a small p-value.

Drive Wheels

Since ANOVA analyzes the difference between different groups of the same variable, the groupby function will come in handy. Because the ANOVA algorithm averages the data automatically, we do not need to take the average before hand.

Let’s see if different types ’drive-wheels’ impact ’price’, we group the data.

Let’s see if different types ’drive-wheels’ impact ’price’, we group the data.

[97]:
```
grouped_test2=df_gptest[['drive-wheels', 'price']].groupby(['drive-wheels'])
grouped_test2.head()
```

[97]:

	drive-wheels	price
0	rwd	13495.0
1	rwd	16500.0
2	rwd	16500.0

```
3             fwd  13950.0
4             4wd  17450.0
5             fwd  15250.0
6             fwd  17710.0
7             fwd  18920.0
8             fwd  23875.0
9             rwd  16430.0
10            rwd  16925.0
136           4wd   7603.0
140           4wd   9233.0
141           4wd  11259.0
144           4wd   8013.0
```

[98]:
```
df_gptest[['drive-wheels', 'price']]
```

[98]:
```
    drive-wheels    price
0            rwd  13495.0
1            rwd  16500.0
2            rwd  16500.0
3            fwd  13950.0
4            4wd  17450.0
..           …      …
196          rwd  16845.0
197          rwd  19045.0
198          rwd  21485.0
199          rwd  22470.0
200          rwd  22625.0

[201 rows x 2 columns]
```

We can obtain the values of the method group using the method "get_group".

[99]:
```
grouped_test2.get_group('fwd')['price']
```

[99]:
```
3      13950.0
5      15250.0
6      17710.0
7      18920.0
8      23875.0
         …
185    11595.0
186     9980.0
187    13295.0
188    13845.0
189    12290.0
Name: price, Length: 118, dtype: float64
```

we can use the function 'f_oneway' in the module 'stats' to obtain the F-test score and P-value.

[ ]:
```python
# ANOVA
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'], grouped_test2.get_group('rwd')['price'], grouped_test2.get_group('4wd')['price'])

print( "ANOVA results: F=", f_val, ", P =", p_val)
```

This is a great result, with a large F test score showing a strong correlation and a P value of almost 0 implying almost certain statistical significance. But does this mean all three tested groups are all this highly correlated?

Separately: fwd and rwd

[75]:
```python
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'], grouped_test2.get_group('rwd')['price'])

print( "ANOVA results: F=", f_val, ", P =", p_val )
```

```
ANOVA results: F= 130.5533160959111 , P = 2.2355306355677845e-23
```

Let's examine the other groups

4wd and rwd

[76]:
```python
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_test2.get_group('rwd')['price'])

print( "ANOVA results: F=", f_val, ", P =", p_val)
```

```
ANOVA results: F= 8.580681368924756 , P = 0.004411492211225333
```

4wd and fwd

[ ]:
```python
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_test2.get_group('fwd')['price'])

print("ANOVA results: F=", f_val, ", P =", p_val)
```

Conclusion: Important Variables

We now have a better idea of what our data looks like and which variables are important to take into account when predicting the car price. We have narrowed it down to the following variables:

Continuous numerical variables:

```
<li>Length</li>
<li>Width</li>
<li>Curb-weight</li>
<li>Engine-size</li>
<li>Horsepower</li>
<li>City-mpg</li>
<li>Highway-mpg</li>
```

Wheel-base
Bore

Categorical variables:

Drive-wheels

As we now move into building machine learning models to automate our analysis, feeding the model with variables that meaningfully affect our target variable will improve our model's prediction performance.

Thank you for completing this notebook

<p><a href="https://cocl.us/corsera_da0101en_notebook_bottom"><img src="https://s3-api.us-geo.c

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