Data Analysis with Python

Estimated time needed: **30** minutes

Objectives

After completing this lab you will be able to:

- Explore features or charecteristics to predict price of car

Table of content

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

1. Import Data from Module 2

Setup

Import libraries

In [2]:
```
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 (https://cocl.us/DA101EN_object_storage) for free storage

In [3]:
```
path='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNet
df = pd.read_csv(path)
df.head()
```

Out[3]:

	symboling	normalized-losses	make	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	compressi ra
0	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	
1	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	
2	1	122	alfa-romero	std	two	hatchback	rwd	front	94.5	0.822681	...	
3	2	164	audi	std	four	sedan	fwd	front	99.8	0.848630	...	1
4	2	164	audi	std	four	sedan	4wd	front	99.4	0.848630	...	

5 rows × 29 columns

2. Analyzing Individual Feature Patterns using Visualization

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

In [4]:
```
%%capture
! pip install seaborn
```

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

In [5]:
```
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.

In [6]:
```python
# 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"?

In [6]:
```python
# Write your code below and press Shift+Enter to execute
df["peak-rpm"].dtypes
```

Out[6]:
```
dtype('float64')
```

Click here for the solution

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

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

Out[7]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	
symboling	1.000000	0.466264	-0.535987	-0.365404	-0.242423	-0.550160	-0.233118	-0.110581	-0.140019	-
normalized-losses	0.466264	1.000000	-0.056661	0.019424	0.086802	-0.373737	0.099404	0.112360	-0.029862	
wheel-base	-0.535987	-0.056661	1.000000	0.876024	0.814507	0.590742	0.782097	0.572027	0.493244	
length	-0.365404	0.019424	0.876024	1.000000	0.857170	0.492063	0.880665	0.685025	0.608971	
width	-0.242423	0.086802	0.814507	0.857170	1.000000	0.306002	0.866201	0.729436	0.544885	
height	-0.550160	-0.373737	0.590742	0.492063	0.306002	1.000000	0.307581	0.074694	0.180449	-
curb-weight	-0.233118	0.099404	0.782097	0.880665	0.866201	0.307581	1.000000	0.849072	0.644060	
engine-size	-0.110581	0.112360	0.572027	0.685025	0.729436	0.074694	0.849072	1.000000	0.572609	
bore	-0.140019	-0.029862	0.493244	0.608971	0.544885	0.180449	0.644060	0.572609	1.000000	-
stroke	-0.008245	0.055563	0.158502	0.124139	0.188829	-0.062704	0.167562	0.209523	-0.055390	
compression-ratio	-0.182196	-0.114713	0.250313	0.159733	0.189867	0.259737	0.156433	0.028889	0.001263	
horsepower	0.075819	0.217299	0.371147	0.579821	0.615077	-0.087027	0.757976	0.822676	0.566936	
peak-rpm	0.279740	0.239543	-0.360305	-0.285970	-0.245800	-0.309974	-0.279361	-0.256733	-0.267392	-
city-mpg	-0.035527	-0.225016	-0.470606	-0.665192	-0.633531	-0.049800	-0.749543	-0.650546	-0.582027	-
highway-mpg	0.036233	-0.181877	-0.543304	-0.698142	-0.680635	-0.104812	-0.794889	-0.679571	-0.591309	-
price	-0.082391	0.133999	0.584642	0.690628	0.751265	0.135486	0.834415	0.872335	0.543155	
city-L/100km	0.066171	0.238567	0.476153	0.657373	0.673363	0.003811	0.785353	0.745059	0.554610	
diesel	-0.196735	-0.101546	0.307237	0.211187	0.244356	0.281578	0.221046	0.070779	0.054458	
gas	0.196735	0.101546	-0.307237	-0.211187	-0.244356	-0.281578	-0.221046	-0.070779	-0.054458	-

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']]

In [9]:
```
# Write your code below and press Shift+Enter to execute
df[['bore','stroke' ,'compression-ratio','horsepower']].corr()
```

Out[9]:

	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

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.

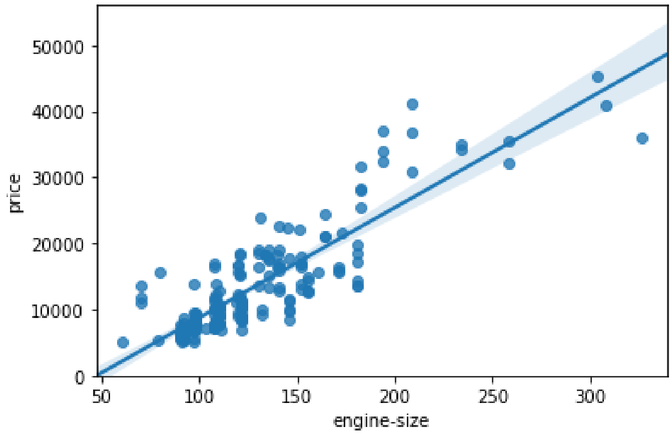
Let's see several examples of different linear relationships:

Positive linear relationship

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

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

Out[10]:
```
(0.0, 56060.53671614262)
```



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

In [29]:
```
df[["engine-size", "price"]].corr()
```

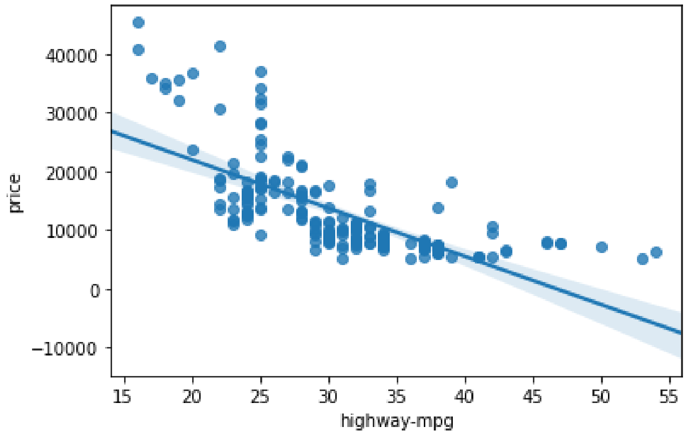
Out[29]:

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

Highway mpg is a potential predictor variable of price

In [30]:
```python
sns.regplot(x="highway-mpg", y="price", data=df)
```

Out[30]: <AxesSubplot:xlabel='highway-mpg', ylabel='price'>



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

In [31]:
```python
df[['highway-mpg', 'price']].corr()
```

Out[31]:

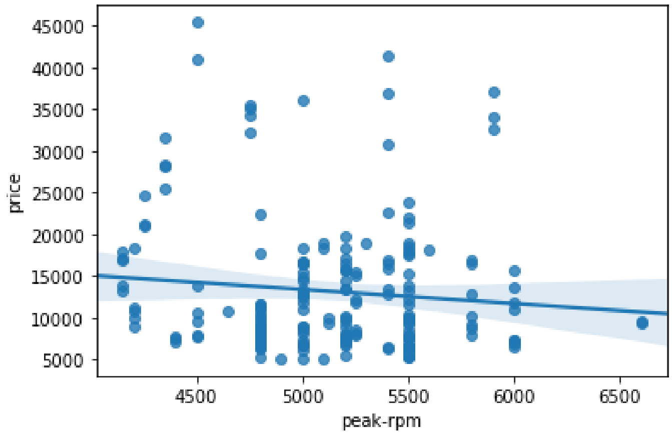
	highway-mpg	price
highway-mpg	1.000000	-0.704692
price	-0.704692	1.000000

Weak Linear Relationship

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

In [27]:
```
sns.regplot(x="peak-rpm", y="price", data=df)
```

Out[27]: <AxesSubplot:xlabel='peak-rpm', ylabel='price'>



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

In [28]:
```
df[['peak-rpm','price']].corr()
```

Out[28]:

	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"]]

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

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()".

In [ ]:
```
# Write your code below and press Shift+Enter to execute
#There is a weak correlation between the variable 'stroke' and 'price.' as such regression wil
# We can see this using "regplot" to demonstrate this.
sns.regplot(x="stroke", y="price", data=df)
```

Click here for the solution

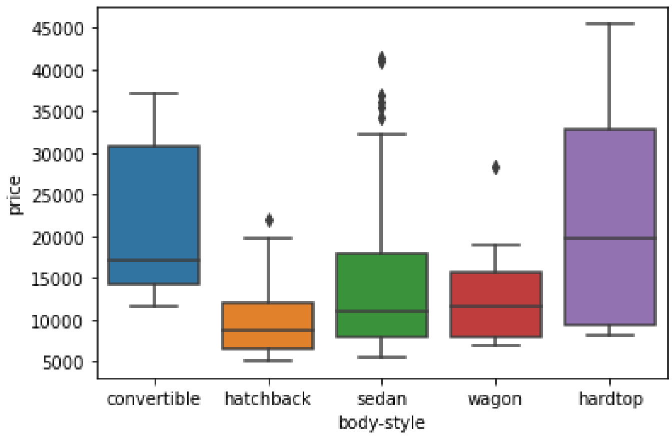
Categorical variables

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".

In [26]:
```
sns.boxplot(x="body-style", y="price", data=df)
```

Out[26]:
```
<AxesSubplot:xlabel='body-style', ylabel='price'>
```



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":

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

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".

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

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:

- 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:

In [11]:
```
df.describe()
```

Out[11]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bo
count	201.000000	201.00000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.00000
mean	0.840796	122.00000	98.797015	0.837102	0.915126	53.766667	2555.666667	126.875622	3.33069
std	1.254802	31.99625	6.066366	0.059213	0.029187	2.447822	517.296727	41.546834	0.26807
min	-2.000000	65.00000	86.600000	0.678039	0.837500	47.800000	1488.000000	61.000000	2.54000
25%	0.000000	101.00000	94.500000	0.801538	0.890278	52.000000	2169.000000	98.000000	3.15000
50%	1.000000	122.00000	97.000000	0.832292	0.909722	54.100000	2414.000000	120.000000	3.31000
75%	2.000000	137.00000	102.400000	0.881788	0.925000	55.500000	2926.000000	141.000000	3.58000
max	3.000000	256.00000	120.900000	1.000000	1.000000	59.800000	4066.000000	326.000000	3.94000

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

In [12]:
```
df.describe(include=['object'])
```

Out[12]:

	make	aspiration	num-of-doors	body-style	drive-wheels	engine-location	engine-type	num-of-cylinders	fuel-system	horsepower-binned
count	201	201	201	201	201	201	201	201	201	200
unique	22	2	2	5	3	2	6	7	8	3
top	toyota	std	four	sedan	fwd	front	ohc	four	mpfi	Low
freq	32	165	115	94	118	198	145	157	92	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']]".

In [13]:
```
df['drive-wheels'].value_counts()
```

Out[13]:
```
fwd     118
rwd      75
4wd       8
Name: drive-wheels, dtype: int64
```

We can convert the series to a Dataframe as follows :

In [14]:
```
df['drive-wheels'].value_counts().to_frame()
```

Out[14]:

	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'.

In [15]:
```
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
drive_wheels_counts.rename(columns={'drive-wheels': 'value_counts'}, inplace=True)
drive_wheels_counts
```

Out[15]:

	value_counts
fwd	118
rwd	75
4wd	8

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

In [16]:
```
drive_wheels_counts.index.name = 'drive-wheels'
drive_wheels_counts
```

Out[16]:

	value_counts
drive-wheels	
fwd	118
rwd	75
4wd	8

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

In [17]:
```
# 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)
```

Out[17]:

	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.

In [18]:
```
df['drive-wheels'].unique()
```

Out[18]:
```
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".

In [19]:
```
df_group_one = df[['drive-wheels','body-style','price']]
```

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

In [20]:
```
# grouping results
df_group_one = df_group_one.groupby(['drive-wheels'],as_index=False).mean()
df_group_one
```

Out[20]:

	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'.

In [21]:
```
# 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
```

Out[21]:

	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:

In [22]:
```
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot
```

Out[22]:

	price				
body-style	convertible	hardtop	hatchback	sedan	wagon
drive-wheels					
4wd	NaN	NaN	7603.000000	12647.333333	9095.750000
fwd	11595.0	8249.000000	8396.387755	9811.800000	9997.333333
rwd	23949.6	24202.714286	14337.777778	21711.833333	16994.222222

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.

In [23]:
```
grouped_pivot = grouped_pivot.fillna(0) #fill missing values with 0
grouped_pivot
```

Out[23]:

	price				
body-style	convertible	hardtop	hatchback	sedan	wagon
drive-wheels					
4wd	0.0	0.000000	7603.000000	12647.333333	9095.750000
fwd	11595.0	8249.000000	8396.387755	9811.800000	9997.333333
rwd	23949.6	24202.714286	14337.777778	21711.833333	16994.222222

Question 4:

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

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

Click here for the solution

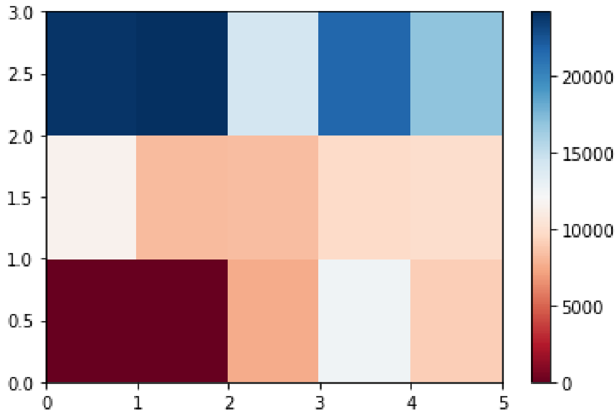
If you did not import "pyplot" let's do it again.

In [ ]:
```
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.

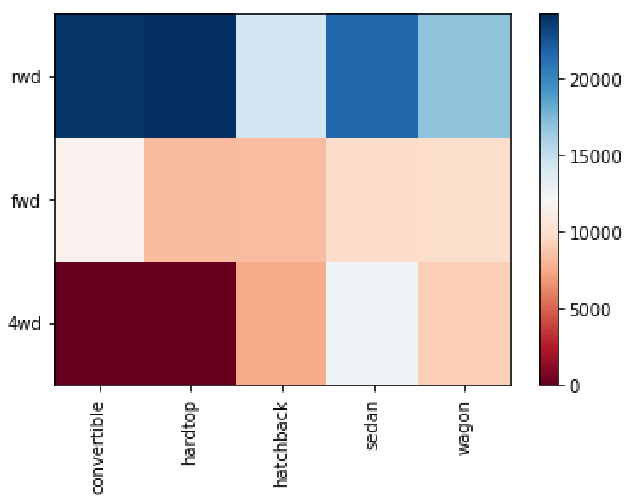
In [24]:
```
#use the grouped results
plt.pcolor(grouped_pivot, cmap='RdBu')
plt.colorbar()
plt.show()
```



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:

In [25]:
```
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.

In [7]:

```
df.corr()
```

Out[7]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	
symboling	1.000000	0.466264	-0.535987	-0.365404	-0.242423	-0.550160	-0.233118	-0.110581	-0.140019	-
normalized-losses	0.466264	1.000000	-0.056661	0.019424	0.086802	-0.373737	0.099404	0.112360	-0.029862	
wheel-base	-0.535987	-0.056661	1.000000	0.876024	0.814507	0.590742	0.782097	0.572027	0.493244	
length	-0.365404	0.019424	0.876024	1.000000	0.857170	0.492063	0.880665	0.685025	0.608971	
width	-0.242423	0.086802	0.814507	0.857170	1.000000	0.306002	0.866201	0.729436	0.544885	
height	-0.550160	-0.373737	0.590742	0.492063	0.306002	1.000000	0.307581	0.074694	0.180449	-
curb-weight	-0.233118	0.099404	0.782097	0.880665	0.866201	0.307581	1.000000	0.849072	0.644060	
engine-size	-0.110581	0.112360	0.572027	0.685025	0.729436	0.074694	0.849072	1.000000	0.572609	
bore	-0.140019	-0.029862	0.493244	0.608971	0.544885	0.180449	0.644060	0.572609	1.000000	-
stroke	-0.008245	0.055563	0.158502	0.124139	0.188829	-0.062704	0.167562	0.209523	-0.055390	
compression-ratio	-0.182196	-0.114713	0.250313	0.159733	0.189867	0.259737	0.156433	0.028889	0.001263	
horsepower	0.075819	0.217299	0.371147	0.579821	0.615077	-0.087027	0.757976	0.822676	0.566936	
peak-rpm	0.279740	0.239543	-0.360305	-0.285970	-0.245800	-0.309974	-0.279361	-0.256733	-0.267392	-
city-mpg	-0.035527	-0.225016	-0.470606	-0.665192	-0.633531	-0.049800	-0.749543	-0.650546	-0.582027	-
highway-mpg	0.036233	-0.181877	-0.543304	-0.698142	-0.680635	-0.104812	-0.794889	-0.679571	-0.591309	-
price	-0.082391	0.133999	0.584642	0.690628	0.751265	0.135486	0.834415	0.872335	0.543155	
city-L/100km	0.066171	0.238567	0.476153	0.657373	0.673363	0.003811	0.785353	0.745059	0.554610	
diesel	-0.196735	-0.101546	0.307237	0.211187	0.244356	0.281578	0.221046	0.070779	0.054458	
gas	0.196735	0.101546	-0.307237	-0.211187	-0.244356	-0.281578	-0.221046	-0.070779	-0.054458	-

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.

In [8]:

```
from scipy import stats
```

Wheel-base vs Price

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

In [9]:
```
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_valu
```

```
The Pearson Correlation Coefficient is 0.584641822265508  with a P-value of P = 8.07648827073
3218e-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'.

In [ ]:
```
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_val
```

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'.

In [ ]:
```
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_val
```

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':

In [ ]:
```
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_valu
```

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':

In [ ]:
```
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_va
```

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':

In [ ]:
```
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_valu
```

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':

In [ ]:
```
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_va
```

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

In [ ]:
```
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_val
```

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

In [ ]:
```
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_va
```

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.

In [ ]:
```
grouped_test2=df_gptest[['drive-wheels', 'price']].groupby(['drive-wheels'])
grouped_test2.head(2)
```

In [ ]:
```
df_gptest
```

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

In [ ]:
```
grouped_test2.get_group('4wd')['price']
```

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

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

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

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

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

Let's examine the other groups

4wd and rwd

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

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

4wd and fwd

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

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:

- Length
- Width
- Curb-weight
- Engine-size
- Horsepower
- City-mpg
- Highway-mpg
- 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.