EDA

January 12, 2024

1 Exploratory Data Analysis

Lab component by Dhesika

Estimated time needed: **30** minutes

1.1 Objectives

- 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

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

1.2 Import Data from Module 2

Setup

Import libraries:

[1]:
```
#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
```

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
```

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.

[3]:
```
'''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())'''
```

[3]:
```
'from pyodide.http import pyfetch\n\nasync def download(url, filename):\n
response = await pyfetch(url)\n    if response.status == 200:\n        with
open(filename, "wb") as f:\n            f.write(await response.bytes())'
```

[4]:
```
#file_path= "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪automobileEDA.csv"
```

[5]:
```
file_name="usedcars.csv"
```

[6]:
```
df = pd.read_csv(file_name)
```

[7]:
```
#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()`

[8]:
```
df.head()
```

[8]:
```
   Unnamed: 0  symboling  normalized-losses         make num-of-doors  \
0           0          3                122  alfa-romero          two
1           1          3                122  alfa-romero          two
2           2          1                122  alfa-romero          two
3           3          2                164         audi         four
4           4          2                164         audi         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  …

   peak-rpm  city-mpg  highway-mpg    price city-L/100km  horsepower-binned  \
```

```
0    5000.0        21     8.703704  13495.0    11.190476                Low
1    5000.0        21     8.703704  16500.0    11.190476                Low
2    5000.0        19     9.038462  16500.0    12.368421             Medium
3    5500.0        24     7.833333  13950.0     9.791667                Low
4    5500.0        18    10.681818  17450.0    13.055556                Low

  fuel-type-diesel  fuel-type-gas  aspiration-std  aspiration-turbo
0            False           True            True             False
1            False           True            True             False
2            False           True            True             False
3            False           True            True             False
4            False           True            True             False

[5 rows x 31 columns]
```

1.3 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.

[9]:
```
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.

[10]:
```
# list the data types for each column
print(df.dtypes)
```

```
Unnamed: 0             int64
symboling              int64
normalized-losses      int64
make                  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             int64
peak-rpm             float64
city-mpg               int64
highway-mpg          float64
price                float64
city-L/100km         float64
horsepower-binned     object
fuel-type-diesel        bool
fuel-type-gas           bool
aspiration-std          bool
aspiration-turbo        bool
dtype: object
```

[11]:
```
df['peak-rpm'].dtypes
```

[11]:
```
dtype('float64')
```

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

[12]:
```
numeric_df = df.select_dtypes(include=['float64', 'int64'])
numeric_df.corr()
```

[12]:
```
                   Unnamed: 0  symboling  normalized-losses  wheel-base  \
Unnamed: 0           1.000000  -0.162764          -0.241092    0.125517
symboling           -0.162764   1.000000           0.466264   -0.535987
normalized-losses   -0.241092   0.466264           1.000000   -0.056661
wheel-base           0.125517  -0.535987          -0.056661    1.000000
length               0.161848  -0.365404           0.019424    0.876024
width                0.043976  -0.242423           0.086802    0.814507
height               0.252015  -0.550160          -0.373737    0.590742
curb-weight          0.064820  -0.233118           0.099404    0.782097
engine-size         -0.047764  -0.110581           0.112360    0.572027
bore                 0.244734  -0.140019          -0.029862    0.493244
stroke              -0.162490  -0.008153           0.055045    0.158018
compression-ratio    0.144301  -0.182196          -0.114713    0.250313
horsepower          -0.022505   0.075810           0.217300    0.371178
peak-rpm            -0.195662   0.279740           0.239543   -0.360305
city-mpg             0.027956  -0.035527          -0.225016   -0.470606
highway-mpg         -0.078346  -0.029807           0.181189    0.577576
price               -0.118214  -0.082391           0.133999    0.584642
city-L/100km        -0.099157   0.066171           0.238567    0.476153

                     length     width    height  curb-weight  engine-size  \
```

Unnamed: 0	0.161848	0.043976	0.252015	0.064820	-0.047764
symboling	-0.365404	-0.242423	-0.550160	-0.233118	-0.110581
normalized-losses	0.019424	0.086802	-0.373737	0.099404	0.112360
wheel-base	0.876024	0.814507	0.590742	0.782097	0.572027
length	1.000000	0.857170	0.492063	0.880665	0.685025
width	0.857170	1.000000	0.306002	0.866201	0.729436
height	0.492063	0.306002	1.000000	0.307581	0.074694
curb-weight	0.880665	0.866201	0.307581	1.000000	0.849072
engine-size	0.685025	0.729436	0.074694	0.849072	1.000000
bore	0.608971	0.544885	0.180449	0.644060	0.572609
stroke	0.123952	0.188822	-0.060663	0.167438	0.205928
compression-ratio	0.159733	0.189867	0.259737	0.156433	0.028889
horsepower	0.579795	0.615056	-0.087001	0.757981	0.822668
peak-rpm	-0.285970	-0.245800	-0.309974	-0.279361	-0.256733
city-mpg	-0.665192	-0.633531	-0.049800	-0.749543	-0.650546
highway-mpg	0.707108	0.736728	0.084301	0.836921	0.783465
price	0.690628	0.751265	0.135486	0.834415	0.872335
city-L/100km	0.657373	0.673363	0.003811	0.785353	0.745059

	bore	stroke	compression-ratio	horsepower \
Unnamed: 0	0.244734	-0.162490	0.144301	-0.022505
symboling	-0.140019	-0.008153	-0.182196	0.075810
normalized-losses	-0.029862	0.055045	-0.114713	0.217300
wheel-base	0.493244	0.158018	0.250313	0.371178
length	0.608971	0.123952	0.159733	0.579795
width	0.544885	0.188822	0.189867	0.615056
height	0.180449	-0.060663	0.259737	-0.087001
curb-weight	0.644060	0.167438	0.156433	0.757981
engine-size	0.572609	0.205928	0.028889	0.822668
bore	1.000000	-0.055390	0.001263	0.566903
stroke	-0.055390	1.000000	0.187871	0.098128
compression-ratio	0.001263	0.187871	1.000000	-0.214489
horsepower	0.566903	0.098128	-0.214489	1.000000
peak-rpm	-0.267392	-0.063561	-0.435780	0.107884
city-mpg	-0.582027	-0.033956	0.331425	-0.822192
highway-mpg	0.559112	0.047089	-0.223361	0.840627
price	0.543155	0.082269	0.071107	0.809607
city-L/100km	0.554610	0.036133	-0.299372	0.889482

	peak-rpm	city-mpg	highway-mpg	price	city-L/100km
Unnamed: 0	-0.195662	0.027956	-0.078346	-0.118214	-0.099157
symboling	0.279740	-0.035527	-0.029807	-0.082391	0.066171
normalized-losses	0.239543	-0.225016	0.181189	0.133999	0.238567
wheel-base	-0.360305	-0.470606	0.577576	0.584642	0.476153
length	-0.285970	-0.665192	0.707108	0.690628	0.657373
width	-0.245800	-0.633531	0.736728	0.751265	0.673363
height	-0.309974	-0.049800	0.084301	0.135486	0.003811

curb-weight	-0.279361	-0.749543	0.836921	0.834415	0.785353
engine-size	-0.256733	-0.650546	0.783465	0.872335	0.745059
bore	-0.267392	-0.582027	0.559112	0.543155	0.554610
stroke	-0.063561	-0.033956	0.047089	0.082269	0.036133
compression-ratio	-0.435780	0.331425	-0.223361	0.071107	-0.299372
horsepower	0.107884	-0.822192	0.840627	0.809607	0.889482
peak-rpm	1.000000	-0.115413	0.017694	-0.101616	0.115830
city-mpg	-0.115413	1.000000	-0.909024	-0.686571	-0.949713
highway-mpg	0.017694	-0.909024	1.000000	0.801118	0.958306
price	-0.101616	-0.686571	0.801118	1.000000	0.789898
city-L/100km	0.115830	-0.949713	0.958306	0.789898	1.000000

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

[13]:
```
# Write your code below and press Shift+Enter to execute
df[['bore', 'stroke', 'compression-ratio', 'horsepower']].corr()
```

[13]:

	bore	stroke	compression-ratio	horsepower
bore	1.000000	-0.055390	0.001263	0.566903
stroke	-0.055390	1.000000	0.187871	0.098128
compression-ratio	0.001263	0.187871	1.000000	-0.214489
horsepower	0.566903	0.098128	-0.214489	1.000000

Continuous Numerical Variables:

Continuous numerical variables are variables that may contain any value within some range. They can be of 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 use "regplot" which plots the scatterplot plus the fitted regression line for the data. This will be useful later on for visualizing the fit of the simple linear regression model as well.

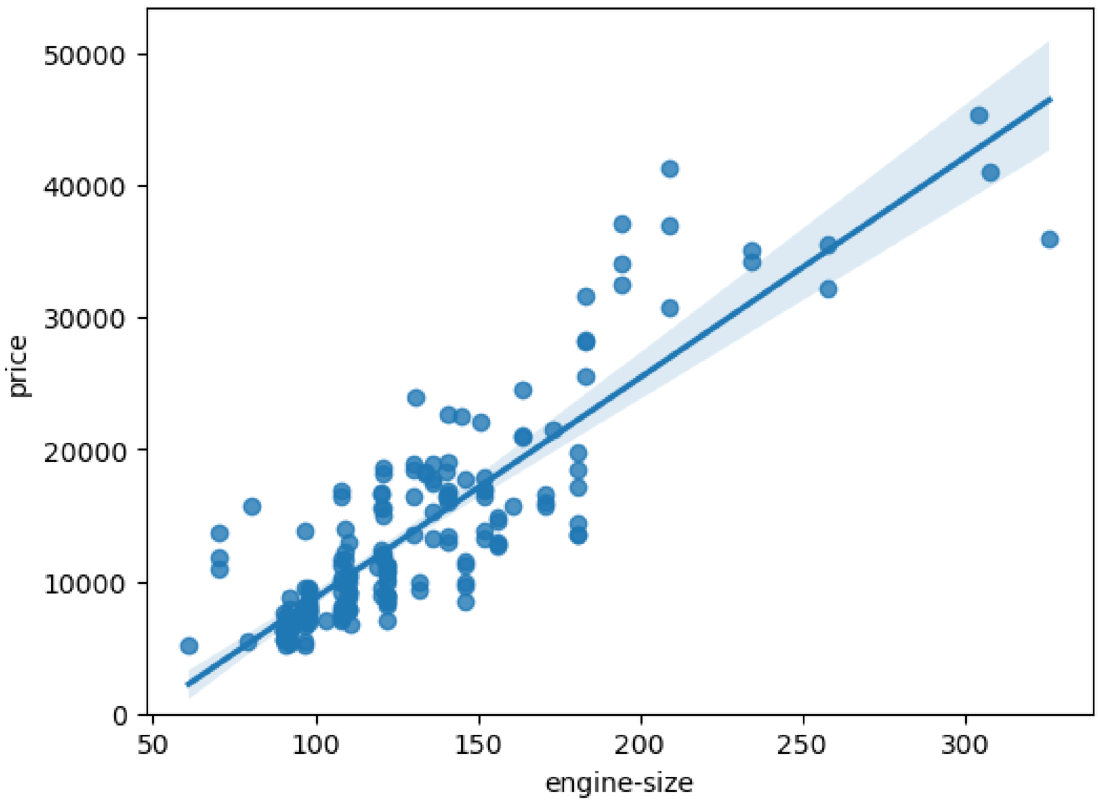
Let's see several examples of different linear relationships:

Positive Linear Relationship

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

[14]:
```
# Engine size as potential predictor variable of price
sns.regplot(x="engine-size", y="price", data=df)
plt.ylim(0,)
```

[14]: (0.0, 53407.189223961206)



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 that it's approximately 0.87.

[15]:
```
df[["engine-size", "price"]].corr()
```

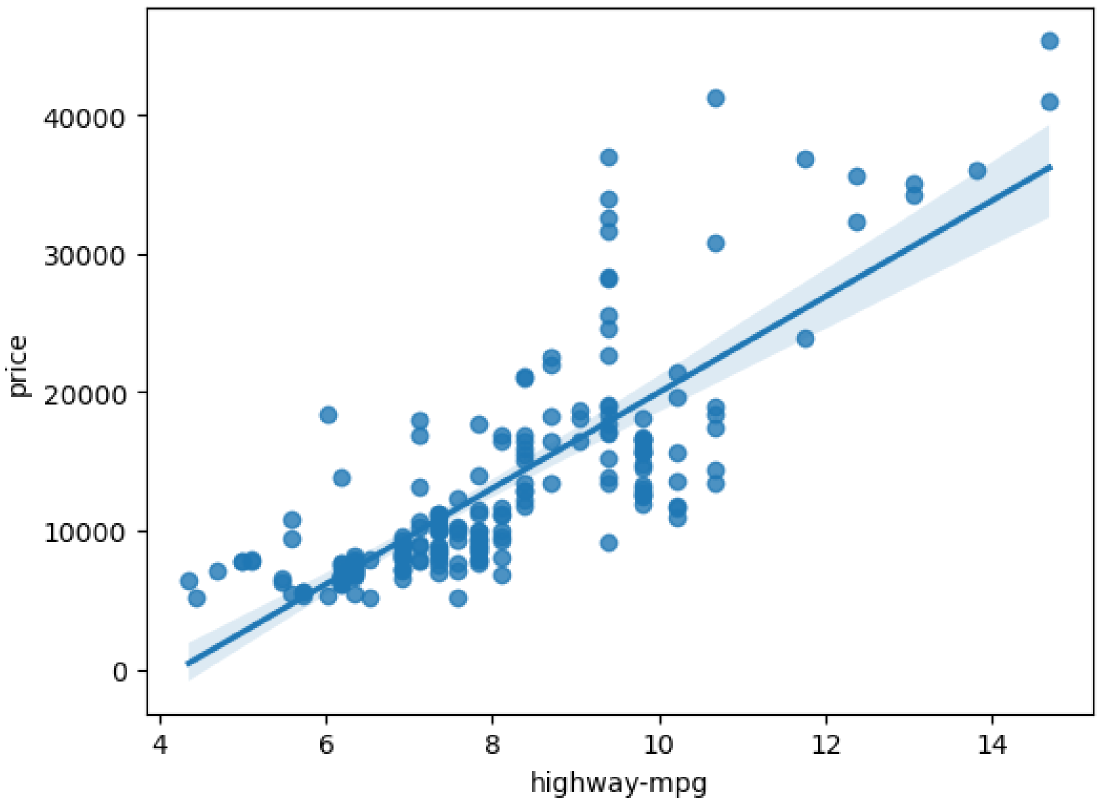
[15]:

	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".

[16]:
```
sns.regplot(x="highway-mpg", y="price", data=df)
```

[16]: <Axes: xlabel='highway-mpg', ylabel='price'>



As 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.

[17]:
```
df[['highway-mpg', 'price']].corr()
```

[17]:

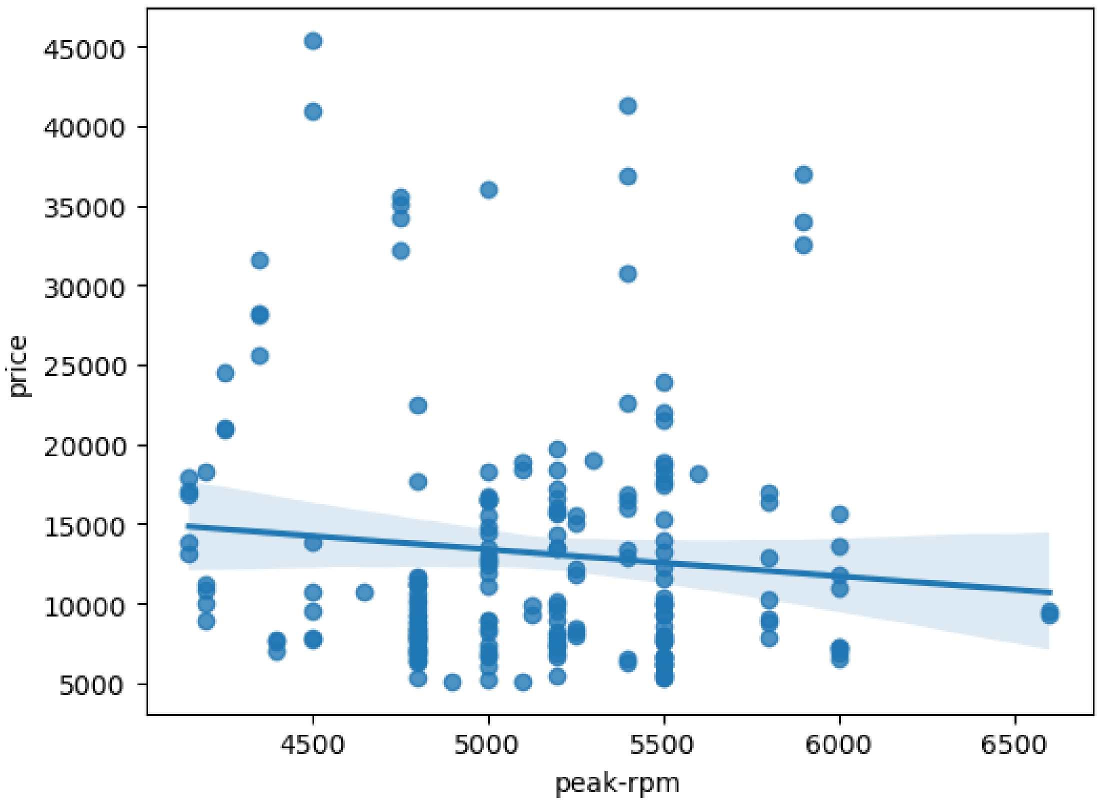
	highway-mpg	price
highway-mpg	1.000000	0.801118
price	0.801118	1.000000

Weak Linear Relationship

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

[18]:
```
sns.regplot(x="peak-rpm", y="price", data=df)
```

[18]: <Axes: 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 not a reliable variable.

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

[19]:
```
df[['peak-rpm','price']].corr()
```

[19]:

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

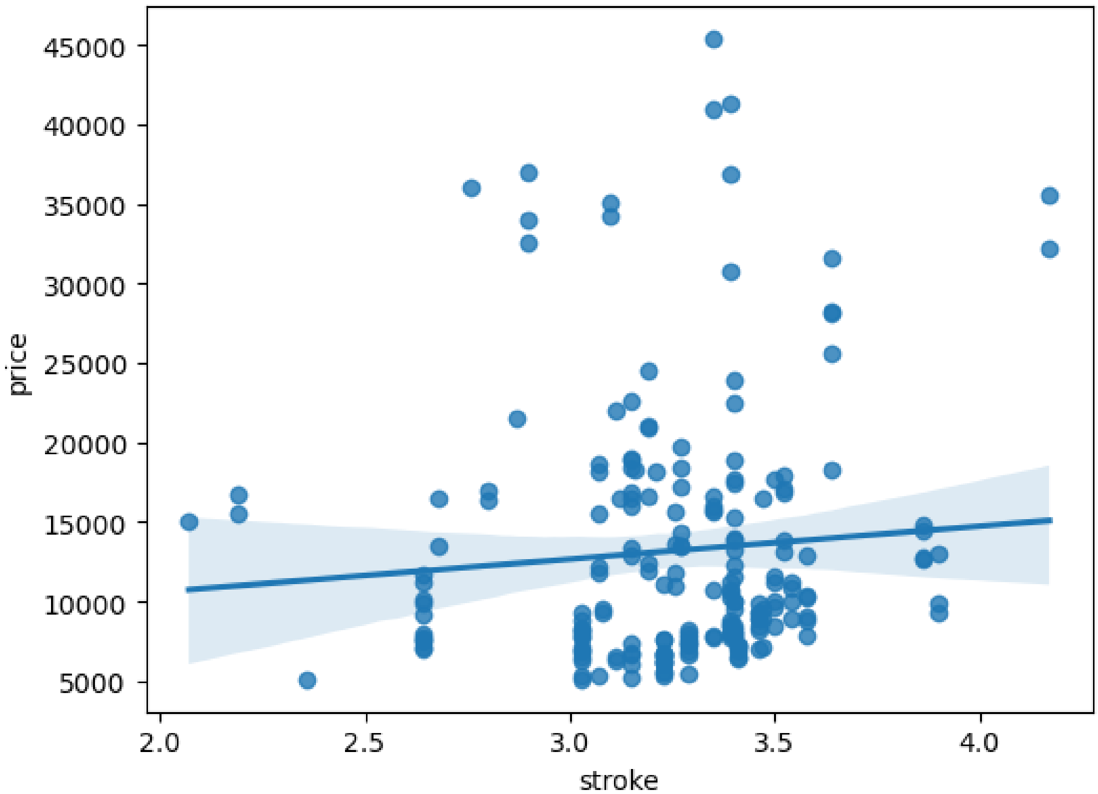
[20]:
```
# Write your code below and press Shift+Enter to execute
df[["stroke","price"]].corr()
```

[20]:

	stroke	price
stroke	1.000000	0.082269
price	0.082269	1.000000

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

[21]: <Axes: xlabel='stroke', ylabel='price'>



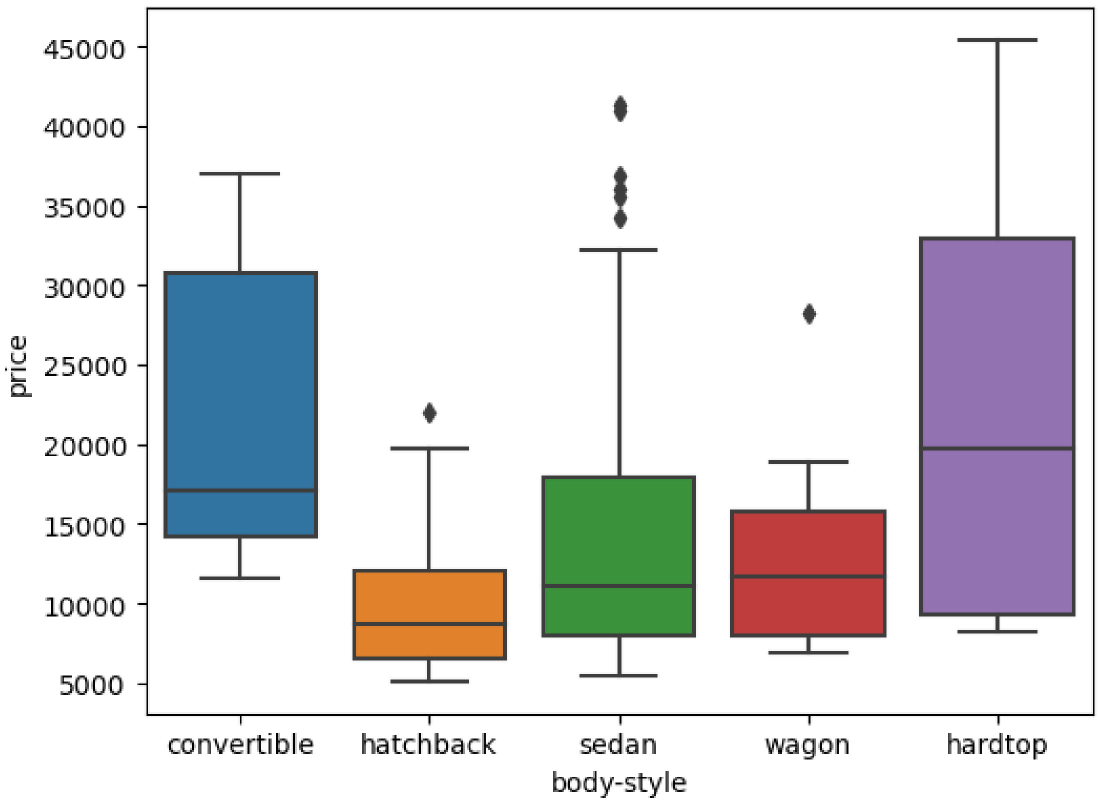
Categorical Variables

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)
```

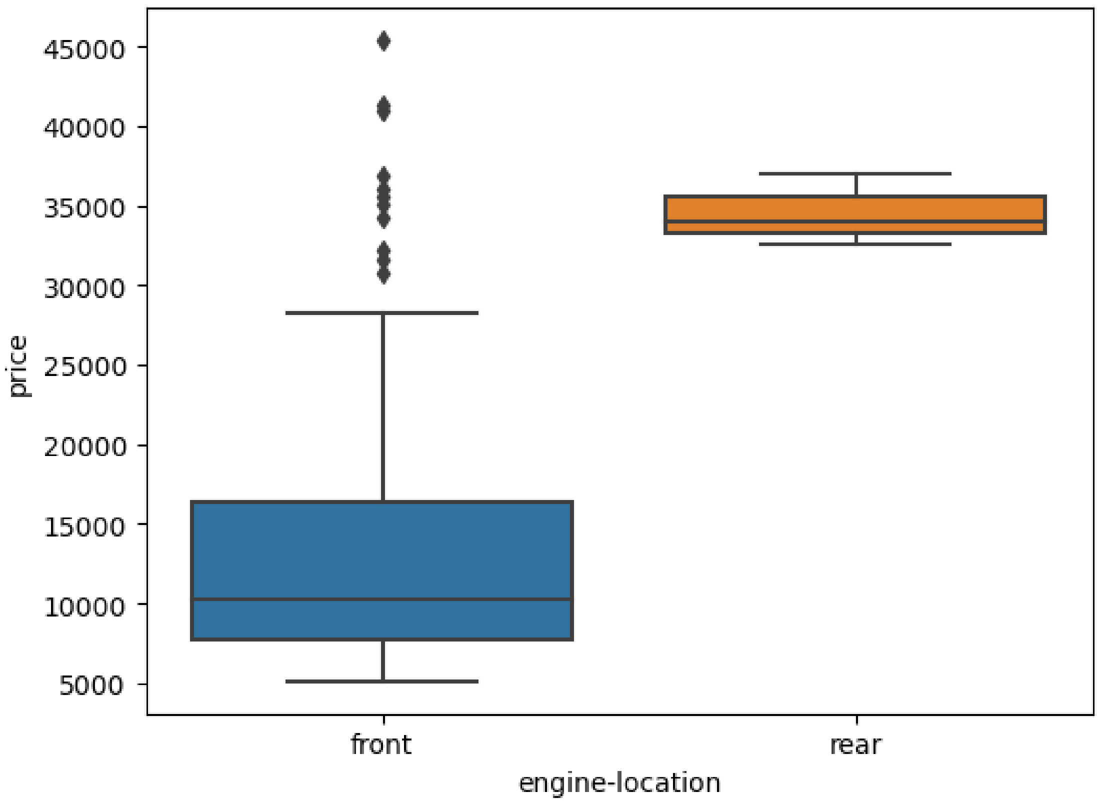
[22]: <Axes: xlabel='body-style', ylabel='price'>



We see that the distributions of price between the different body-style categories have a significant overlap, 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]: `<Axes: xlabel='engine-location', ylabel='price'>`

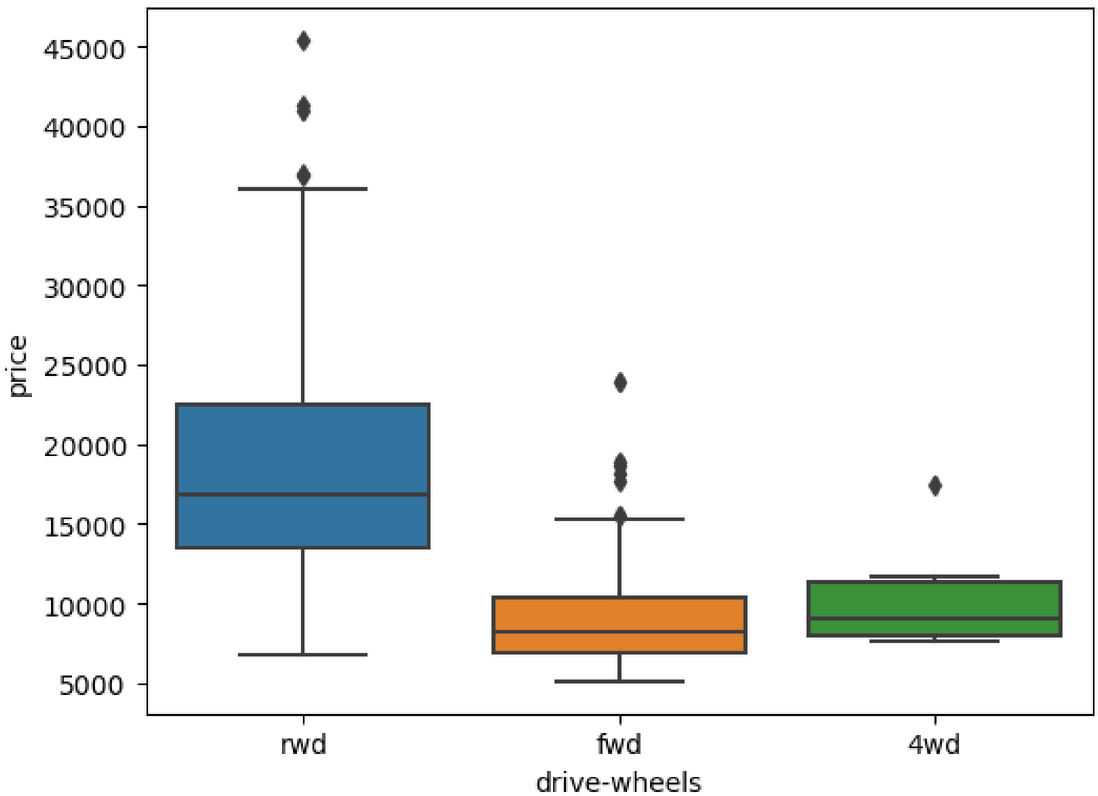


Here we see that the distribution of price between these two engine-location categories, front and rear, are distinct enough to take engine-location as a potential good predictor of price.

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

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

[24]:
```
<Axes: xlabel='drive-wheels', ylabel='price'>
```



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.

1.4 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:

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

[25]:
```
       Unnamed: 0   symboling  normalized-losses  wheel-base      length  \
count  201.000000  201.000000          201.00000  201.000000  201.000000
mean   100.000000    0.840796          122.00000   98.797015    0.837102
std     58.167861    1.254802           31.99625    6.066366    0.059213
min      0.000000   -2.000000           65.00000   86.600000    0.678039
25%     50.000000    0.000000          101.00000   94.500000    0.801538
50%    100.000000    1.000000          122.00000   97.000000    0.832292
75%    150.000000    2.000000          137.00000  102.400000    0.881788
max    200.000000    3.000000          256.00000  120.900000    1.000000

            width      height  curb-weight  engine-size        bore  \
count  201.000000  201.000000   201.000000   201.000000  201.000000
mean     0.915126    0.899108  2555.666667   126.875622    3.330692
std      0.029187    0.040933   517.296727    41.546834    0.268072
min      0.837500    0.799331  1488.000000    61.000000    2.540000
25%      0.890278    0.869565  2169.000000    98.000000    3.150000
50%      0.909722    0.904682  2414.000000   120.000000    3.310000
75%      0.925000    0.928094  2926.000000   141.000000    3.580000
max      1.000000    1.000000  4066.000000   326.000000    3.940000

           stroke  compression-ratio  horsepower     peak-rpm    city-mpg  \
count  201.000000         201.000000  201.000000   201.000000  201.000000
mean     3.256874          10.164279  103.402985  5117.665368   25.179104
std      0.316048           4.004965   37.365650   478.113805    6.423220
min      2.070000           7.000000   48.000000  4150.000000   13.000000
25%      3.110000           8.600000   70.000000  4800.000000   19.000000
50%      3.290000           9.000000   95.000000  5125.369458   24.000000
75%      3.410000           9.400000  116.000000  5500.000000   30.000000
max      4.170000          23.000000  262.000000  6600.000000   49.000000

       highway-mpg         price  city-L/100km
count   201.000000    201.000000    201.000000
mean      8.044957  13207.129353      9.944145
std       1.840739   7947.066342      2.534599
min       4.351852   5118.000000      4.795918
25%       6.911765   7775.000000      7.833333
50%       7.833333  10295.000000      9.791667
75%       9.400000  16500.000000     12.368421
max      14.687500  45400.000000     18.076923
```

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 num-of-doors body-style drive-wheels engine-location  \
count      201          201        201          201             201
unique      22            2          5            3               2
top     toyota         four      sedan          fwd           front
freq        32          115         94          118             198

       engine-type num-of-cylinders fuel-system horsepower-binned
count          201              201         201               201
unique           6                7           8                 3
top            ohc             four        mpfi               Low
freq           145              157          92               153
```

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

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

We can convert the series to a dataframe as follows:

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

[28]:
```
              count
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]:
```python
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]:
```
              count
drive-wheels
fwd             118
rwd              75
```

```
4wd                8
```

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

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

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

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

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

After examining the value counts of the engine location, we see that 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, so this result is skewed. Thus, we are not able to draw any conclusions about the engine location.

1.5 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]:
```
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]:
```
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]:
```python
# Assuming you want to analyze 'price' column based on 'drive-wheels'
df_group_one = df.groupby(['drive-wheels'], as_index=False)['price'].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 by multiple variables. For example, let's group by both 'drive-wheels' and 'body-style'. This groups the dataframe by the unique combination of 'drive-wheels' and 'body-style'. We can store the results in the variable 'grouped_test1'.

[35]:
```python
# 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-wheels variable as the rows of the table, and pivot body-style to become the columns of the table:

[36]:
```python
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot
```

[36]:
```
                      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
```

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]:
```python
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
```

[38]:
```python
df_gptest2 = df[['body-style','price']]
grouped_test_bodystyle = df_gptest2.groupby(['body-style'],as_index= False).
 ↪mean()
grouped_test_bodystyle
```

[38]:
```
    body-style         price
0  convertible  21890.500000
1      hardtop  22208.500000
2    hatchback   9957.441176
3        sedan  14459.755319
4        wagon  12371.960000
```

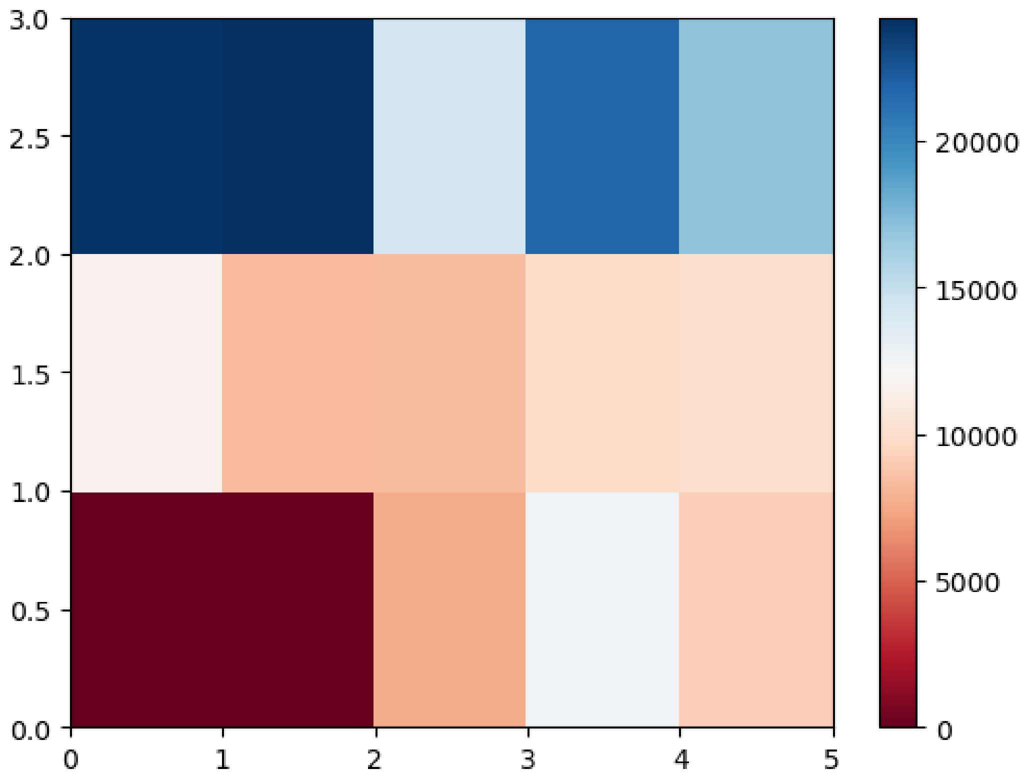
If you did not import "pyplot", let's do it again.

[39]:
```
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.

[40]:
```
#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' on 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:

[41]:
```
fig, ax = plt.subplots()
im = ax.pcolor(grouped_pivot, cmap='RdBu')

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

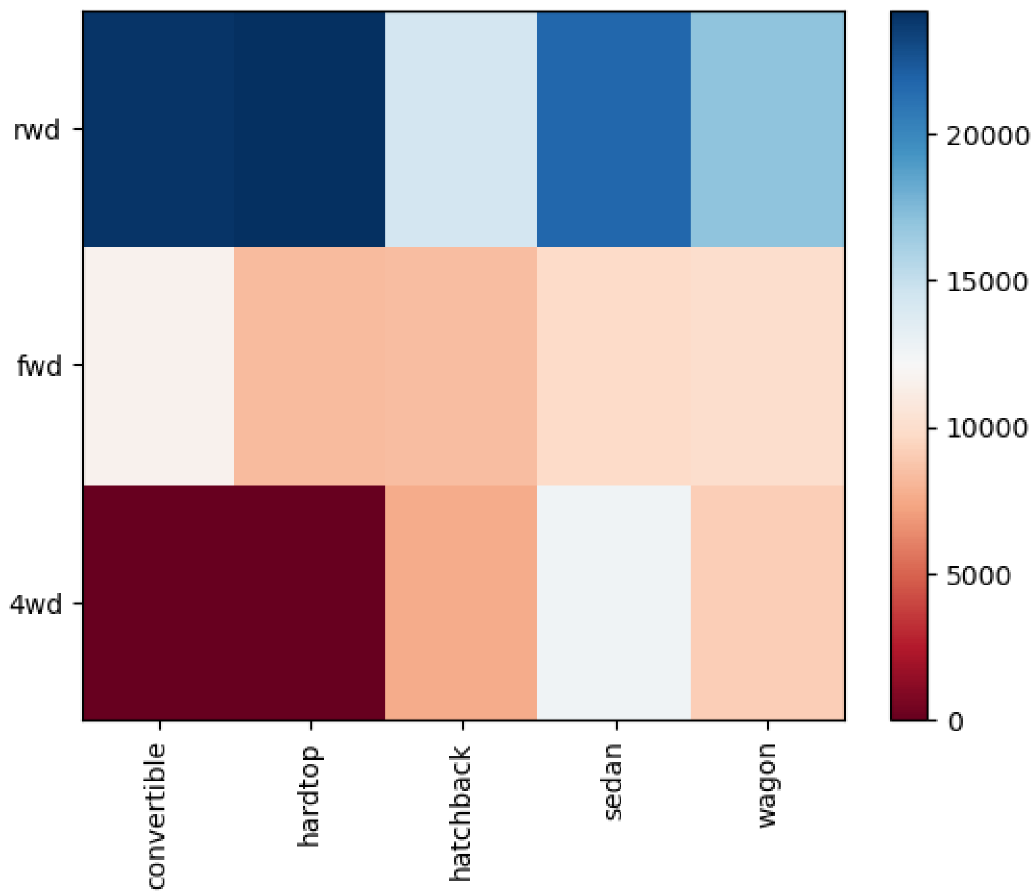
```
col_labels = grouped_pivot.index

#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?

1.6 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. 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: Perfect positive linear correlation.

0: No linear correlation, the two variables most likely do not affect each other.

-1: Perfect 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.

[42]:
```
numeric_df = df.select_dtypes(include=['float64', 'int64'])
numeric_df.corr()
```

[42]:

	Unnamed: 0	symboling	normalized-losses	wheel-base	\
Unnamed: 0	1.000000	-0.162764	-0.241092	0.125517	
symboling	-0.162764	1.000000	0.466264	-0.535987	
normalized-losses	-0.241092	0.466264	1.000000	-0.056661	
wheel-base	0.125517	-0.535987	-0.056661	1.000000	
length	0.161848	-0.365404	0.019424	0.876024	
width	0.043976	-0.242423	0.086802	0.814507	
height	0.252015	-0.550160	-0.373737	0.590742	
curb-weight	0.064820	-0.233118	0.099404	0.782097	
engine-size	-0.047764	-0.110581	0.112360	0.572027	
bore	0.244734	-0.140019	-0.029862	0.493244	
stroke	-0.162490	-0.008153	0.055045	0.158018	
compression-ratio	0.144301	-0.182196	-0.114713	0.250313	
horsepower	-0.022505	0.075810	0.217300	0.371178	
peak-rpm	-0.195662	0.279740	0.239543	-0.360305	
city-mpg	0.027956	-0.035527	-0.225016	-0.470606	
highway-mpg	-0.078346	-0.029807	0.181189	0.577576	
price	-0.118214	-0.082391	0.133999	0.584642	
city-L/100km	-0.099157	0.066171	0.238567	0.476153	

	length	width	height	curb-weight	engine-size	\
Unnamed: 0	0.161848	0.043976	0.252015	0.064820	-0.047764	
symboling	-0.365404	-0.242423	-0.550160	-0.233118	-0.110581	
normalized-losses	0.019424	0.086802	-0.373737	0.099404	0.112360	
wheel-base	0.876024	0.814507	0.590742	0.782097	0.572027	
length	1.000000	0.857170	0.492063	0.880665	0.685025	
width	0.857170	1.000000	0.306002	0.866201	0.729436	
height	0.492063	0.306002	1.000000	0.307581	0.074694	
curb-weight	0.880665	0.866201	0.307581	1.000000	0.849072	
engine-size	0.685025	0.729436	0.074694	0.849072	1.000000	
bore	0.608971	0.544885	0.180449	0.644060	0.572609	
stroke	0.123952	0.188822	-0.060663	0.167438	0.205928	
compression-ratio	0.159733	0.189867	0.259737	0.156433	0.028889	
horsepower	0.579795	0.615056	-0.087001	0.757981	0.822668	
peak-rpm	-0.285970	-0.245800	-0.309974	-0.279361	-0.256733	
city-mpg	-0.665192	-0.633531	-0.049800	-0.749543	-0.650546	
highway-mpg	0.707108	0.736728	0.084301	0.836921	0.783465	
price	0.690628	0.751265	0.135486	0.834415	0.872335	
city-L/100km	0.657373	0.673363	0.003811	0.785353	0.745059	

	bore	stroke	compression-ratio	horsepower	\
Unnamed: 0	0.244734	-0.162490	0.144301	-0.022505	
symboling	-0.140019	-0.008153	-0.182196	0.075810	
normalized-losses	-0.029862	0.055045	-0.114713	0.217300	
wheel-base	0.493244	0.158018	0.250313	0.371178	
length	0.608971	0.123952	0.159733	0.579795	
width	0.544885	0.188822	0.189867	0.615056	
height	0.180449	-0.060663	0.259737	-0.087001	
curb-weight	0.644060	0.167438	0.156433	0.757981	
engine-size	0.572609	0.205928	0.028889	0.822668	
bore	1.000000	-0.055390	0.001263	0.566903	
stroke	-0.055390	1.000000	0.187871	0.098128	
compression-ratio	0.001263	0.187871	1.000000	-0.214489	
horsepower	0.566903	0.098128	-0.214489	1.000000	
peak-rpm	-0.267392	-0.063561	-0.435780	0.107884	
city-mpg	-0.582027	-0.033956	0.331425	-0.822192	
highway-mpg	0.559112	0.047089	-0.223361	0.840627	
price	0.543155	0.082269	0.071107	0.809607	
city-L/100km	0.554610	0.036133	-0.299372	0.889482	

	peak-rpm	city-mpg	highway-mpg	price	city-L/100km
Unnamed: 0	-0.195662	0.027956	-0.078346	-0.118214	-0.099157
symboling	0.279740	-0.035527	-0.029807	-0.082391	0.066171
normalized-losses	0.239543	-0.225016	0.181189	0.133999	0.238567
wheel-base	-0.360305	-0.470606	0.577576	0.584642	0.476153
length	-0.285970	-0.665192	0.707108	0.690628	0.657373

```
width              -0.245800 -0.633531     0.736728  0.751265       0.673363
height             -0.309974 -0.049800     0.084301  0.135486       0.003811
curb-weight        -0.279361 -0.749543     0.836921  0.834415       0.785353
engine-size        -0.256733 -0.650546     0.783465  0.872335       0.745059
bore               -0.267392 -0.582027     0.559112  0.543155       0.554610
stroke             -0.063561 -0.033956     0.047089  0.082269       0.036133
compression-ratio -0.435780  0.331425    -0.223361  0.071107      -0.299372
horsepower          0.107884 -0.822192     0.840627  0.809607       0.889482
peak-rpm            1.000000 -0.115413     0.017694 -0.101616       0.115830
city-mpg           -0.115413  1.000000    -0.909024 -0.686571      -0.949713
highway-mpg         0.017694 -0.909024     1.000000  0.801118       0.958306
price              -0.101616 -0.686571     0.801118  1.000000       0.789898
city-L/100km        0.115830 -0.949713     0.958306  0.789898       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.

[43]:
```
from scipy import stats
```

Wheel-Base vs. Price

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

[44]:
```
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 0.5846418222655083  with a P-value of P =
8.076488270732552e-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'.

[45]:
```
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 0.8096068016571052  with a P-value of P =
6.273536270651023e-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'.

[46]:
```
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 0.6906283804483644  with a P-value of P =
8.016477466158383e-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':

[47]:
```
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 0.7512653440522665  with a P-value of P =
9.200335510484122e-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).

1.6.1 Curb-Weight vs. Price

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

[48]:
```
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 0.8344145257702849  with a P-value of P =
2.189577238893391e-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':

[49]:
```
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 =
9.265491622198793e-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':

[50]:
```
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 0.5431553832626606  with a P-value of P =
8.049189483935034e-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

[51]:
```
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 -0.6865710067844681  with a P-value of P
=  2.3211320655673725e-29
```

Conclusion:

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

Highway-mpg vs. Price

[52]:

```python
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 0.8011176263981971  with a P-value of P =
3.046784581041982e-46
```

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.

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.

[ ]:

```python

```