responsive Variable: outcome of a study.
explanatory variable: explain or influen changes in a responsive variable.
Display the relation between two quantative variables => Scatterplot
State => Plan => Solve => Conclude.
* put the explanatory variable on x-axis.
Examing: overall pattern/deviations
direction/form/strength
correlation / Pearson correlation coefficient

$$r = \frac{1}{n-1} \sum \left(\frac{x_i - \bar{x}}{s_x}\right)\left(\frac{y_i - \bar{y}}{s_y}\right)$$

r does not change if both x, y are divided.
$r \in (-1, 1)$

Lab 5

September 30, 2021

1 Lab 5

In this lab we discuss scatterplots and how we can measure the linear correlation between two variables.

1.1 Import necessary Python libraries

scipy.stats: https://docs.scipy.org/doc/scipy/reference/stats.html

[1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
```

1.2 Import the data

[2]:
```python
# Read .csv data
auto = pd.read_csv("auto.csv")
# The data is a subset of the Auto dataset available at:
# https://archive.ics.uci.edu/ml/datasets/auto+mpg
# The head() function is used to get the first 5 rows.
auto.head()
```

[2]:

	mpg	horsepower	weight	origin	name
0	18.0	130	3504	American	chevrolet chevelle malibu
1	15.0	165	3693	American	buick skylark 320
2	18.0	150	3436	American	plymouth satellite
3	16.0	150	3433	American	amc rebel sst
4	17.0	140	3449	American	ford torino

Variable description

mpg: miles per gallon horsepower: Engine horsepower weight: Vehicle weight (lbs.) origin: Origin of car (American, European, Japanese) name: Vehicle name

[3]:
```python
# The tail() function is used to get the last 5 rows.
auto.tail()
```

[3]:
```
       mpg  horsepower  weight    origin             name
387   27.0          86    2790  American  ford mustang gl
388   44.0          52    2130  European        vw pickup
389   32.0          84    2295  American    dodge rampage
390   28.0          79    2625  American      ford ranger
391   31.0          82    2720  American       chevy s-10
```

[4]:
```
# Finding the size of the dataset
# Our dataset has 392 rows and 5 columns.
auto.shape
```

[4]:
```
(392, 5)
```

[5]:
```
# Finding the type of each variable
auto.dtypes
```

[5]:
```
mpg           float64
horsepower      int64
weight          int64
origin         object
name           object
dtype: object
```

[6]:
```
# We should convert any obvious categorical variables to categories.
# "name" and "origin" are categorical variables in our dataset.
auto['name'] = auto['name'].astype('category')
auto['origin'] = auto['origin'].astype('category')
auto.dtypes
```

[6]:
```
mpg            float64
horsepower       int64
weight           int64
origin        category
name          category
dtype: object
```

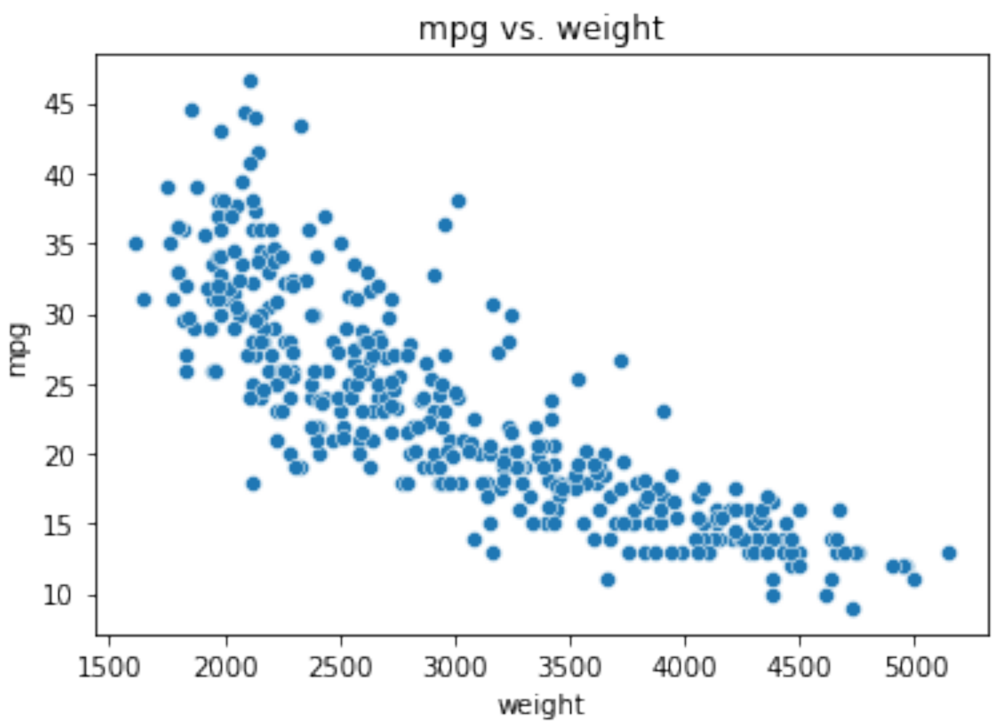
[7]:
```
auto.describe() # calculating summary statistics for the quantitative variables
```

[7]:
```
              mpg  horsepower       weight
count  392.000000  392.000000   392.000000
mean    23.445918  104.469388  2977.584184
std      7.805007   38.491160   849.402560
min      9.000000   46.000000  1613.000000
25%     17.000000   75.000000  2225.250000
50%     22.750000   93.500000  2803.500000
75%     29.000000  126.000000  3614.750000
max     46.600000  230.000000  5140.000000
```

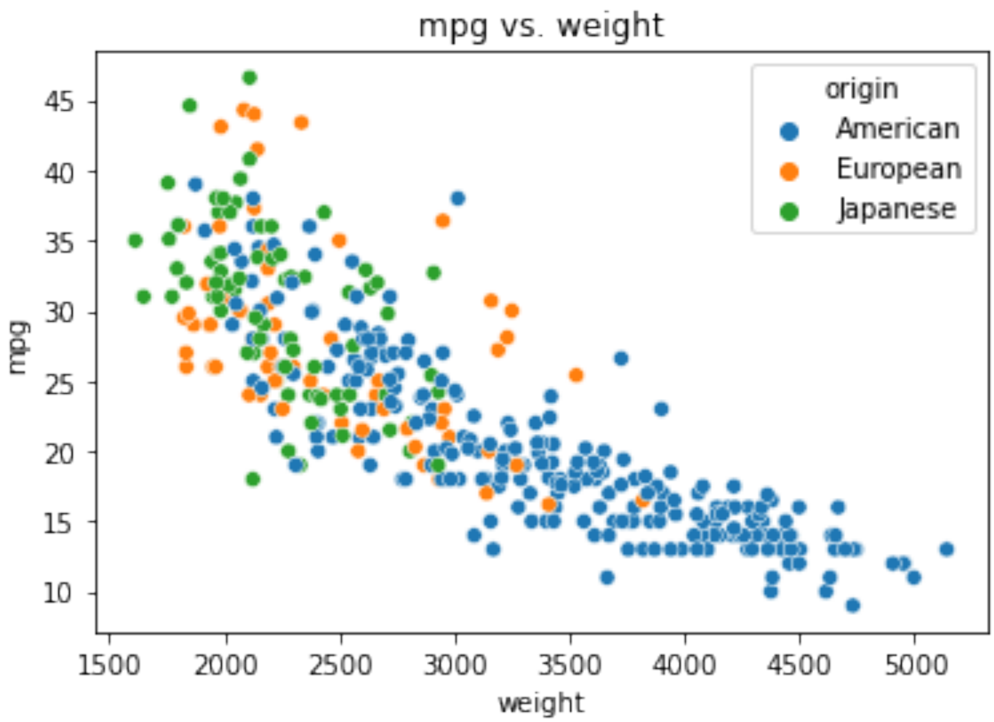
1.3 Scatterplots

sns.scatterplot: https://seaborn.pydata.org/generated/seaborn.scatterplot.html

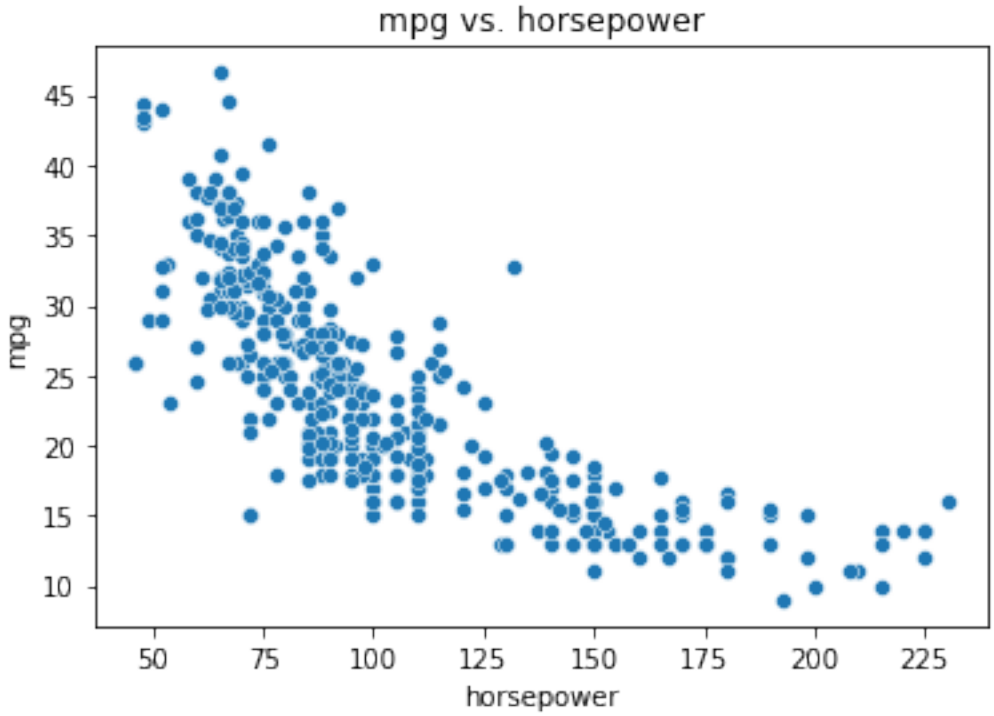
[8]:
```
# Scatter plots are used to observe relationships between variables.
# In the scatterplot the x axis is generally the name of a predictor/
↪independent variable.
# In the scatterplot the y axis is generally the name of a response/dependent␣
↪variable.
# It can be seen that there is a negative relationship between "mpg" (miles per␣
↪gallon) and "weight".
# The heavier the car fewer miles per gallon it will make.
sns.scatterplot(x = "weight", y = "mpg", data = auto)
plt.title("mpg vs. weight")
plt.show()
```



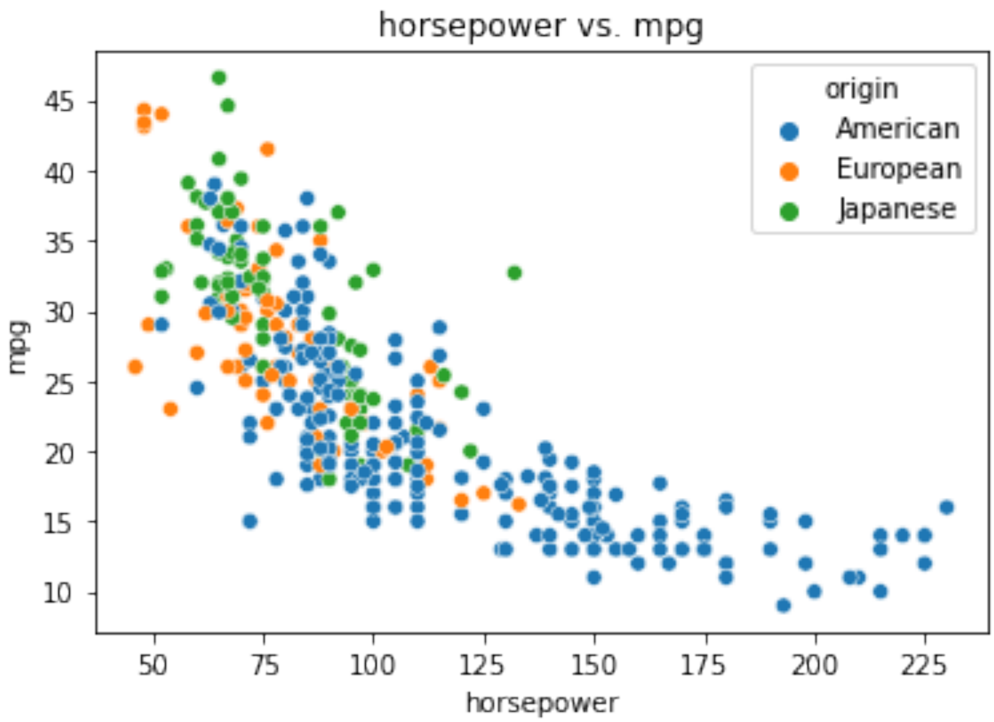
[9]:
```
# coloring the points according to the origin of the car
sns.scatterplot(x = "weight", y = "mpg", hue = 'origin', data = auto)
plt.title("mpg vs. weight")
plt.show()
```



[10]:
```
sns.scatterplot(x = "horsepower", y = "mpg", data = auto)
plt.title("mpg vs. horsepower")
plt.show()
```

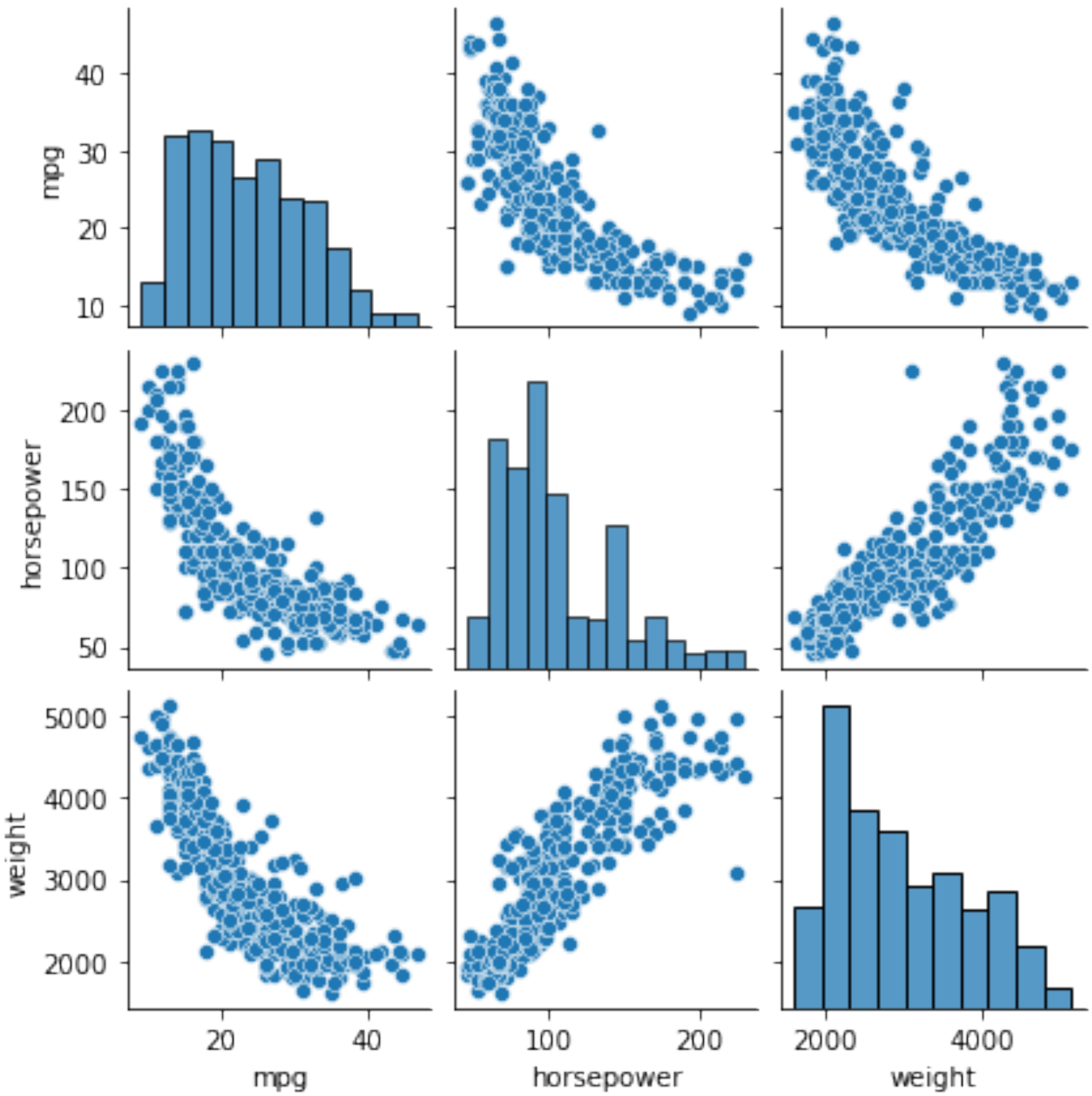


[11]:
```
sns.scatterplot(x = "horsepower", y = "mpg", hue = "origin", data = auto)
plt.title("horsepower vs. mpg")
plt.show()
```



sns.pairplot: https://seaborn.pydata.org/generated/seaborn.pairplot.html

[12]:
```
# The pairplot shows the scatterplots between all pairs of quantitative␣
↪variables in a dataset.
# It also shows the histogram of each individual variable.
sns.pairplot(auto, height = 2, kind = 'scatter')
plt.show()
```



1.4 Correlation coefficient r

stats.pearsonr: https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html

[13]:
```
# The Pearson correlation coefficient is a single number that describes the␣
↪extent
# of the linear relationship between two variables.
# The coefficient varies between -1 and +1 with 0 implying no correlation.
# Correlations of -1 or +1 imply an exact linear relationship.
# Positive correlations imply that as x increases, so does y.
# Negative correlations imply that as x increases, y decreases.
# It seems there is a strong negative correlation between "weight" and "mpg".
r = stats.pearsonr(auto['mpg'], auto['weight'])[0]
```

```
r
```

[13]: -0.8322442148315755

DataFrame.corr: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.corr.html

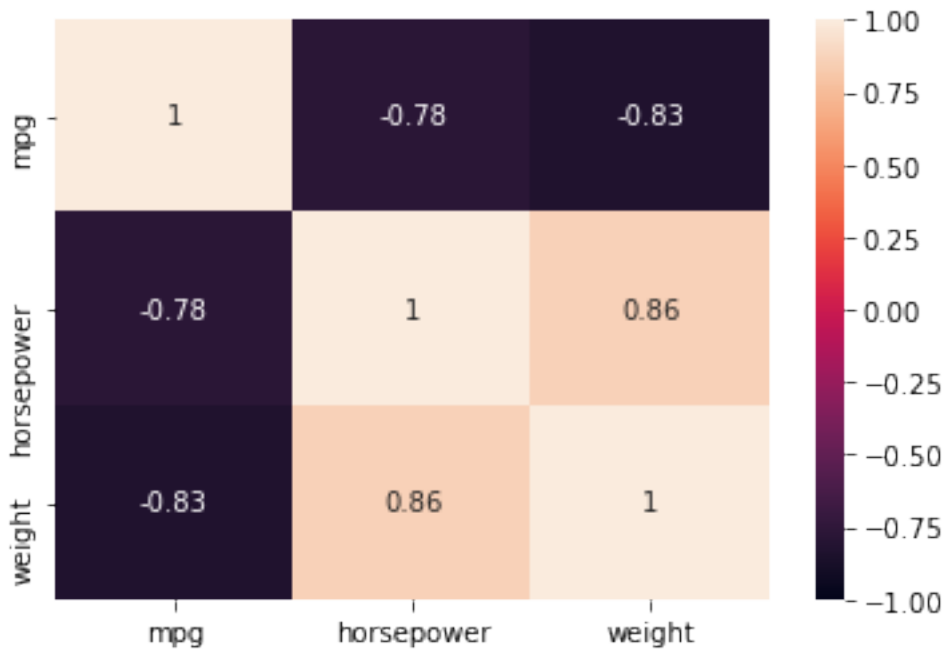
[14]:
```
# A correlation matrix can be used to show the correlation coefficient between
# all pairs of quantitative variables in a dataset.
# Every correlation matrix is symmetrical.
# The correlation between each variable and itself is 1, hence the diagonal.
corr_matrix = auto.corr(method = 'pearson')
round(corr_matrix, 2)
```

[14]:

	mpg	horsepower	weight
mpg	1.00	-0.78	-0.83
horsepower	-0.78	1.00	0.86
weight	-0.83	0.86	1.00

sns.heatmap: https://seaborn.pydata.org/generated/seaborn.heatmap.html

[15]:
```
# Heatmaps replace numbers with colors of varying shades, as indicated by the␣
↪scale on the right.
# This type of visualization can make it easier to spot linear relationships␣
↪between variables than a table of numbers.
sns.heatmap(corr_matrix, vmin = -1, vmax = 1, annot = True)
plt.show()
```



[16]:

```
# heatmap with a different color scheme
sns.heatmap(corr_matrix, vmin = -1, vmax = 1, annot = True,cmap="YlGnBu")
plt.show()
```

[ ]:

```

```