s-on-activity-3-1-data-analysis-1

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0.0.1 Correlation Analysis in Python

Objectives: Part 1: The Dataset Part 2: Scatterplot Graphs and Correlatable Variables Part 3: Calculating Correlation with Python Part 4: Visualizing

##Scenario/Background Correlation is an important statistical relationship that can indicate whether the variable values are linearly related. In this lab, you will learn how to use Python to calculate correlation. In Part

1, you will setup the dataset. In Part 2, you will learn how to identify if the variables in a given dataset are correlatable. Finally, in Part 3, you will use Python to calculate the correlation between two sets of variable.

Required Resources 1 PC with Internet access Raspberry Pi version 2 or higher Python libraries: pandas, numpy, matplotlib, seaborn Datafiles: brainsize.txt

0.1 Part 1: The Dataset

You will use a dataset that contains a sample of 40 right-handed Anglo Introductory Psychology students at a large Southwestern university. Subjects took four subtests (Vocabulary, Similarities, Block Design, and Picture Completion) of the Wechsler (1981) Adult Intelligence Scale-Revised. The researchers used Magnetic Resonance Imaging (MRI) to determine the brain size of the subjects. Information about gender and body size (height and weight) are also included. The researchers withheld the weights of two subjects and the height of one subject for reasons of confidentiality. Two simple modifications were applied to the dataset:

1. Replace the quesion marks used to represent the withheld data points described above by the 'NaN' string. The substitution was done because Pandas does not handle the question marks correctly.
2. Replace all tab characters with commas, converting the dataset into a CSV dataset. The prepared dataset is saved as brainsize.txt. Step 1: Loading the Dataset From a File. Before the dataset can be used, it must be loaded onto memory.

In the code below,

The first line imports the pandas modules and defines pd as a descriptor that refers to the module.

The second line loads the dataset CSV file into a variable called brainFile.

The third line uses read_csv(), a pandas method, to convert the CSV dataset stored in brainFile into a dataframe. The dataframe is then stored in the brainFrame variable.

Run the cell below to execute the described functions.

[7]:
```
# Import the pandas library
import pandas as pd

# Define the file path
brainFile = '/content/brainsize.txt'

# Read the CSV file into a DataFrame using variable-length whitespace as the␣
↪column delimiter
brainFrame = pd.read_csv(brainFile,delim_whitespace=True)
```

Step 2: Verifying the dataframe. To make sure the dataframe has been correctly loaded and created, use the head() method. Another Pandas method, head() displays the first five entries of a dataframe.

[8]:
```
# code that display first five entries of a dataframe

brainFrame.head()
```

[8]:

	Gender	FSIQ	VIQ	PIQ	Weight	Height	MRI_Count
0	Female	133	132	124	118.0	64.5	816932
1	Male	140	150	124	NaN	72.5	1001121
2	Male	139	123	150	143.0	73.3	1038437
3	Male	133	129	128	172.0	68.8	965353
4	Female	137	132	134	147.0	65.0	951545

0.2 Part 2: Scatterplot Graphs and Correlatable Variables

Step 1: The pandas describe() method.

The pandas module includes the describe() method which performs same common calculations against a given dataset. In addition to provide common results including count, mean, standard deviation, minimum, and maximum, describe() is also a great way to quickly test the validity of the values in the dataframe.

Run the cell below to output the results computed by describe() against the brainFrame dataframe.

[9]:
```
# code that performs same common calculations against a given dataset

brainFrame.describe()
```

[9]:

	FSIQ	VIQ	PIQ	Weight	Height	MRI_Count
count	40.000000	40.000000	40.00000	38.000000	39.000000	4.000000e+01
mean	113.450000	112.350000	111.02500	151.052632	68.525641	9.087550e+05
std	24.082071	23.616107	22.47105	23.478509	3.994649	7.228205e+04
min	77.000000	71.000000	72.00000	106.000000	62.000000	7.906190e+05

```
25%     89.750000   90.000000   88.25000  135.250000  66.000000  8.559185e+05
50%    116.500000  113.000000  115.00000  146.500000  68.000000  9.053990e+05
75%    135.500000  129.750000  128.00000  172.000000  70.500000  9.500780e+05
max    144.000000  150.000000  150.00000  192.000000  77.000000  1.079549e+06
```

Step 2: Scatterplot graphs

Scatterplot graphs are important when working with correlations as they allow for a quick visual verification of the nature of the relationship between the variables. This lab uses the Pearson correlation coefficient, which is sensitive only to a linear relationship between two variables. Other more robust correlation methods exist but are out of the scope of this lab.

a. Load the required modules.

Before graphs can be plotted, it is necessary to import a few modules, namely numpy and matplotlib. Run the cell below to load these modules.

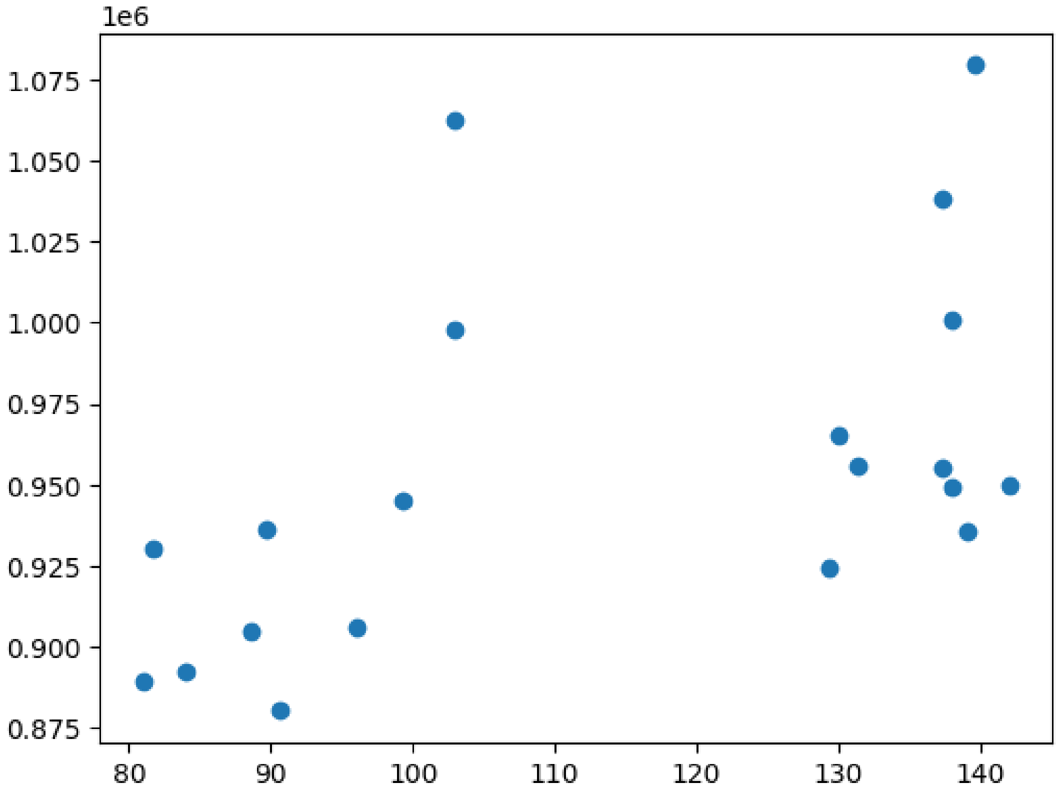
[10]:
```
# Code to import numpy and matplotlib library

import numpy as np
import matplotlib.pyplot as plt
```

b. Separate the data. To ensure the results do not get skewed because of the differences in male and female bodies, the dateframe is split into two dataframes: one containing all male entries and another with only female instances. Running the cell below creates the two new dataframes, menDf and womenDf, each one containing the respective entries.

[11]:
```
# Code that separate the two dataframes men and women

menDf = brainFrame[(brainFrame.Gender == 'Male')]
womenDf = brainFrame[(brainFrame.Gender == 'Female')]
```

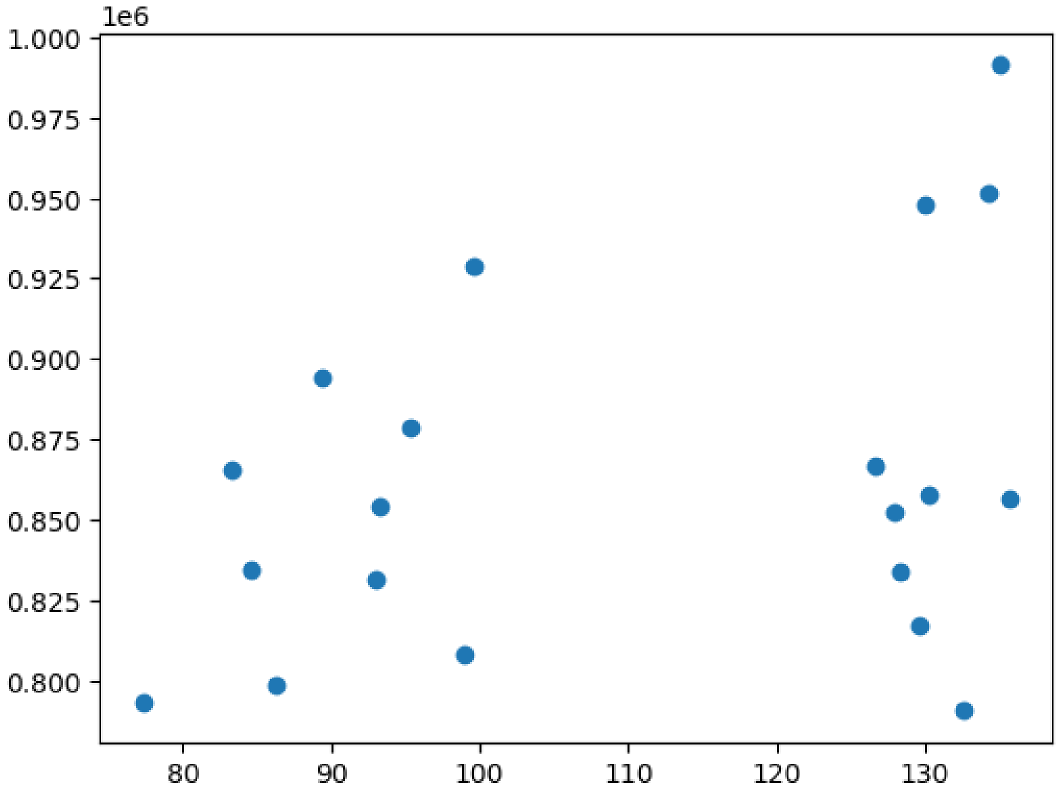
c. Plot the graphs. Because the dataset includes three different measures of intelligence (PIQ, FSIQ, and VIQ), the first line below uses Pandas mean() method to calculate the mean value between the three and store the result in the menMeanSmarts variable. Notice that the first line also refers to the menDf, the filtered dataframe containing only male entries. The second line uses the matplotlib method scatter() to create a scatterplot graph between the menMeanSmarts variable and the MRI_Countattribute. The MRI_Count in this dataset can be thought as of a measure of the physical size of the subjects' brains. The third line simply displays the graph. The fourth line is used to ensure the graph will be displayed in this notebook.

[12]:
```
# code that display the graph between the menMeanSmarts variable and the␣
↪MRI_Countattribute

menMeanSmarts = menDf[["PIQ", "FSIQ", "VIQ"]].mean(axis=1)
plt.scatter(menMeanSmarts, menDf["MRI_Count"])
plt.show()
%matplotlib inline
```



Similarly, the code below creates a scatterplot graph for the women-only filtered dataframe.

[14]:
```
# code that display the graph between the womenMeanSmarts variable and the␣
↪MRI_Countattribute

womenMeanSmarts = womenDf[["PIQ", "FSIQ", "VIQ"]].mean(axis=1)
plt.scatter(womenMeanSmarts, womenDf["MRI_Count"])
plt.show()
%matplotlib inline
```



0.2.1 Part 3: Calculating Correlation with Python

Step 1: Calculate correlation against brainFrame. The pandas corr() method provides an easy way to calculate correlation against a dataframe. By simply calling the method against a dataframe, one can get the correlation between all variables at the same time.

[17]:
```python
# Code that display the correlation between all variables at the same time

brainFrame.corr(method='pearson')
```

```
<ipython-input-17-cab48f3abe05>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  brainFrame.corr(method='pearson')
```

[17]:

	FSIQ	VIQ	PIQ	Weight	Height	MRI_Count
FSIQ	1.000000	0.946639	0.934125	-0.051483	-0.086002	0.357641
VIQ	0.946639	1.000000	0.778135	-0.076088	-0.071068	0.337478
PIQ	0.934125	0.778135	1.000000	0.002512	-0.076723	0.386817
Weight	-0.051483	-0.076088	0.002512	1.000000	0.699614	0.513378
Height	-0.086002	-0.071068	-0.076723	0.699614	1.000000	0.601712

```
 MRI_Count  0.357641  0.337478  0.386817  0.513378  0.601712   1.000000
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4ac5a80>
```

```
from matplotlib import pyplot as plt
_df_1['FSIQ'].plot(kind='hist', bins=20, title='FSIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_2['VIQ'].plot(kind='hist', bins=20, title='VIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_3['PIQ'].plot(kind='hist', bins=20, title='PIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_4['Weight'].plot(kind='hist', bins=20, title='Weight')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4adeaa0>
```

```
from matplotlib import pyplot as plt
import seaborn as sns
_df_5.groupby('index').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4c6eb60>
```

```
from matplotlib import pyplot as plt
_df_6.plot(kind='scatter', x='FSIQ', y='VIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_7.plot(kind='scatter', x='VIQ', y='PIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_8.plot(kind='scatter', x='PIQ', y='Weight', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_9.plot(kind='scatter', x='Weight', y='Height', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4b54850>
```

```
from matplotlib import pyplot as plt
_df_10['FSIQ'].plot(kind='line', figsize=(8, 4), title='FSIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_11['VIQ'].plot(kind='line', figsize=(8, 4), title='VIQ')
```

```
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_12['PIQ'].plot(kind='line', figsize=(8, 4), title='PIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_13['Weight'].plot(kind='line', figsize=(8, 4), title='Weight')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4b54e80>
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_14['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_14, x='FSIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_15['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_15, x='VIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_16['index'].unique()))
plt.figure(figsize=figsize)
```

```
sns.violinplot(_df_16, x='PIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_17['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_17, x='Weight', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

Notice at the left-to-right diagonal in the correlation table generated above. Why is the diagonal filled with 1s? Is that a coincidence? Explain.

They are not coincidence because it is always presented as 1 since it's one property of correlational matrices, where if you correlating a variable to itself the result is the same since you are just comparing it to itself that result to value of 1

Still looking at the correlation table above, notice that the values are mirrored; values below the 1 diagonal have a mirrored counterpart above the 1 diagonal. Is that a coincidence? Explain.

It is not coicindence because that value shown below and above the diagonal is a consequence of the symmetric nature of correlation coefficients used in presenting correlational matrices.

Using the same corr() method, it is easy to calculate the correlation of the variables contained in the female-only dataframe:

[18]:
```
# code that display the female dataframe that used corr() method in calcuting
↪the correlation of variables

womenDf.corr(method='pearson')
```

```
<ipython-input-18-a6271751808a>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  womenDf.corr(method='pearson')
```

[18]:

	FSIQ	VIQ	PIQ	Weight	Height	MRI_Count
FSIQ	1.000000	0.955717	0.939382	0.038192	-0.059011	0.325697
VIQ	0.955717	1.000000	0.802652	-0.021889	-0.146453	0.254933
PIQ	0.939382	0.802652	1.000000	0.113901	-0.001242	0.396157
Weight	0.038192	-0.021889	0.113901	1.000000	0.552357	0.446271
Height	-0.059011	-0.146453	-0.001242	0.552357	1.000000	0.174541

```
 MRI_Count  0.325697  0.254933  0.396157  0.446271  0.174541   1.000000
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3ee05e0>
```

```
from matplotlib import pyplot as plt
_df_35['FSIQ'].plot(kind='hist', bins=20, title='FSIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_36['VIQ'].plot(kind='hist', bins=20, title='VIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_37['PIQ'].plot(kind='hist', bins=20, title='PIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_38['Weight'].plot(kind='hist', bins=20, title='Weight')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3ee0e80>
```

```
from matplotlib import pyplot as plt
import seaborn as sns
_df_39.groupby('index').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c407f310>
```

```
from matplotlib import pyplot as plt
_df_40.plot(kind='scatter', x='FSIQ', y='VIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_41.plot(kind='scatter', x='VIQ', y='PIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_42.plot(kind='scatter', x='PIQ', y='Weight', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_43.plot(kind='scatter', x='Weight', y='Height', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3ee1810>
```

```
from matplotlib import pyplot as plt
_df_44['FSIQ'].plot(kind='line', figsize=(8, 4), title='FSIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_45['VIQ'].plot(kind='line', figsize=(8, 4), title='VIQ')
```

```
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_46['PIQ'].plot(kind='line', figsize=(8, 4), title='PIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_47['Weight'].plot(kind='line', figsize=(8, 4), title='Weight')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3ee1db0>
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_48['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_48, x='FSIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_49['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_49, x='VIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_50['index'].unique()))
plt.figure(figsize=figsize)
```

```
sns.violinplot(_df_50, x='PIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_51['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_51, x='Weight', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

And the same can be done for the male-only dataframe:

[19]:
```
# code that display the Male dataframe that used corr() method in calcuting the
↪correlation of variables
# Use corr() for the male-only dataframe with the pearson method

menDf.corr(method='pearson')
```

```
<ipython-input-19-5da904ba66b9>:4: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  menDf.corr(method='pearson')
```

[19]:

	FSIQ	VIQ	PIQ	Weight	Height	MRI_Count
FSIQ	1.000000	0.944400	0.930694	-0.278140	-0.356110	0.498369
VIQ	0.944400	1.000000	0.766021	-0.350453	-0.355588	0.413105
PIQ	0.930694	0.766021	1.000000	-0.156863	-0.287676	0.568237
Weight	-0.278140	-0.350453	-0.156863	1.000000	0.406542	-0.076875
Height	-0.356110	-0.355588	-0.287676	0.406542	1.000000	0.301543
MRI_Count	0.498369	0.413105	0.568237	-0.076875	0.301543	1.000000

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4ac57b0>
```

```
from matplotlib import pyplot as plt
_df_18['FSIQ'].plot(kind='hist', bins=20, title='FSIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_19['VIQ'].plot(kind='hist', bins=20, title='VIQ')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_20['PIQ'].plot(kind='hist', bins=20, title='PIQ')
```

```
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_21['Weight'].plot(kind='hist', bins=20, title='Weight')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c466a920>
```

```
from matplotlib import pyplot as plt
import seaborn as sns
_df_22.groupby('index').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c4b54850>
```

```
from matplotlib import pyplot as plt
_df_23.plot(kind='scatter', x='FSIQ', y='VIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_24.plot(kind='scatter', x='VIQ', y='PIQ', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_25.plot(kind='scatter', x='PIQ', y='Weight', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_26.plot(kind='scatter', x='Weight', y='Height', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c44ed840>
```

```
from matplotlib import pyplot as plt
_df_27['FSIQ'].plot(kind='line', figsize=(8, 4), title='FSIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_28['VIQ'].plot(kind='line', figsize=(8, 4), title='VIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_29['PIQ'].plot(kind='line', figsize=(8, 4), title='PIQ')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_30['Weight'].plot(kind='line', figsize=(8, 4), title='Weight')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c44eded0>
```

```
<string>:5: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in
```

```
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_31['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_31, x='FSIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_32['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_32, x='VIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_33['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_33, x='PIQ', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_34['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_34, x='Weight', y='index', inner='stick', palette='Dark2')
```

```
sns.despine(top=True, right=True, bottom=True, left=True)
```

0.2.2 Part 4: Visualizing

Step 1: Install Seaborn. To make it easier to visualize the data correlations, heatmap graphs can be used. Based on coloredsquares, heatmap graphs can help identify correlations in a glance.

The Python module named seaborn makes it very easy to plot heatmap graphs. First, run the cell below to download and install the seaborn module.

[20]:
```
# Code cell 11

!pip install seaborn
```

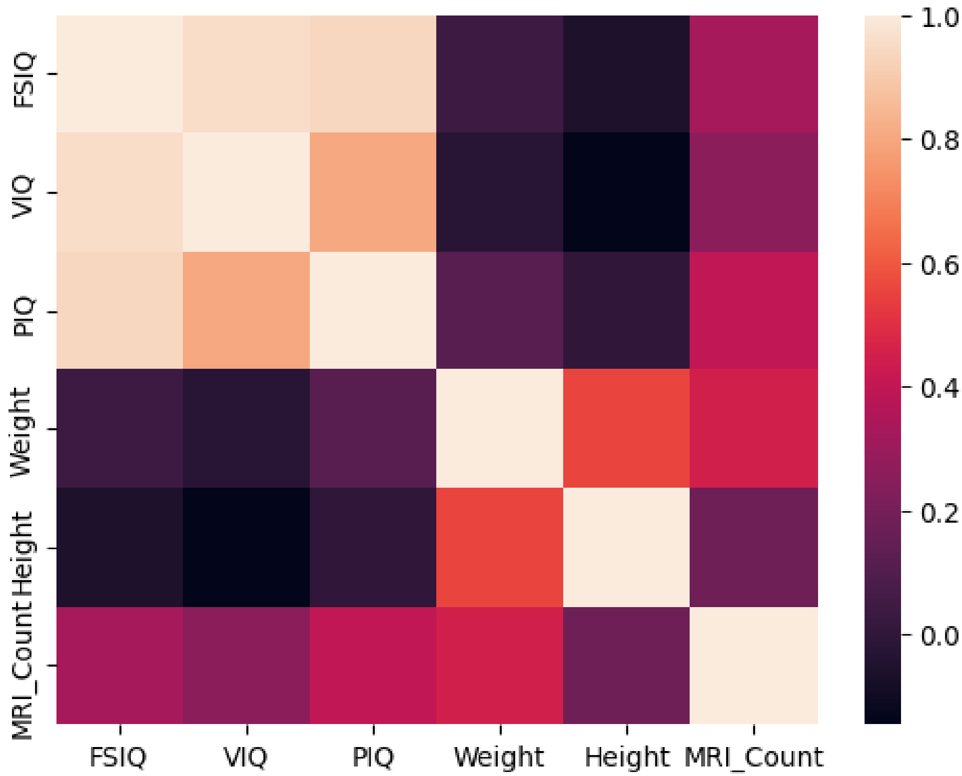
```
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-
packages (0.13.1)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (1.23.5)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-
packages (from seaborn) (1.5.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.2->seaborn) (2023.4)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
```

Step 2: Plot the correlation heatmap. Now that the dataframes are ready, the heatmaps can be plotted. Below is a breakdown of the code in the cell below: Line 1: Generates a correlation table based on the womenNoGenderDf dataframe and stores it on wcorr. Line 2: Uses the seaborn heatmap() method to generate and plot the heatmap. Notice that heatmap() takes wcorr as a parameter. Line 3: Use to export and save the generated heatmap as a PNG image. While the line 3 is not active (it has the comment # character preceding it, forcing the interpreter to ignore it), it was kept for informational purposes.

[22]:
```python
# Code cell 12

import seaborn as sns
wcorr = womenDf.corr()
sns.heatmap(wcorr)
#plt.savefig('attribute_correlations.png', tight_layout=True)
```

```
<ipython-input-22-3e1a5c274a49>:4: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  wcorr = womenDf.corr()
```

[22]: <Axes: >

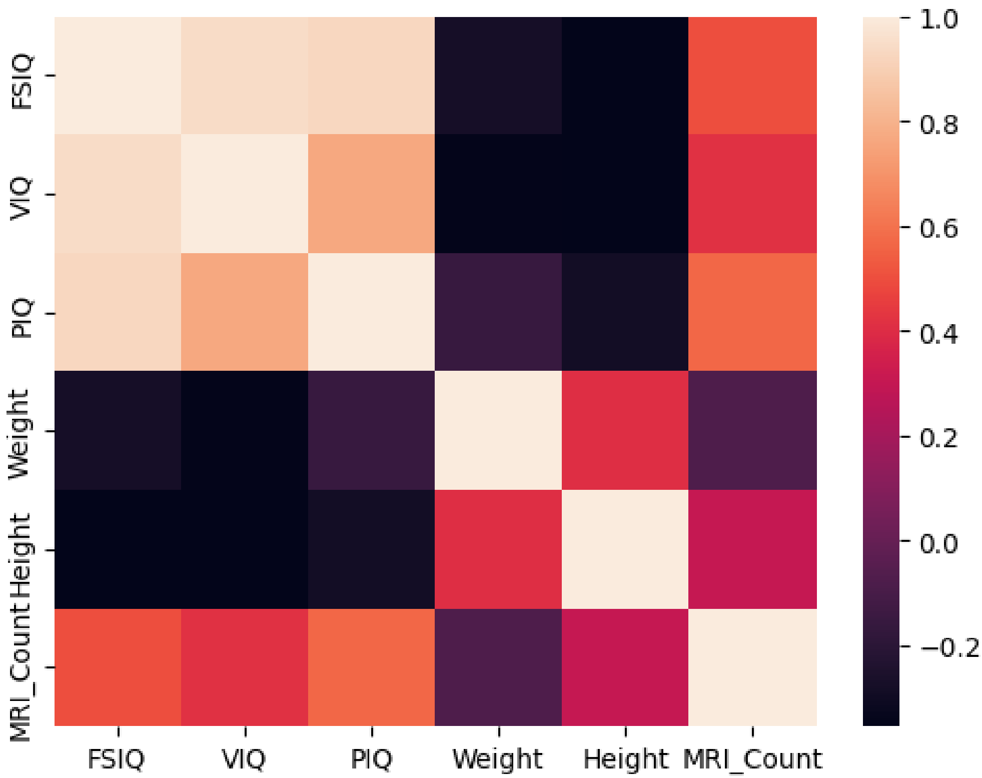


Similarly, the code below creates and plots a heatmap for the male-only dataframe.

[23]:
```
# Code cell 14

mcorr = menDf.corr()
sns.heatmap(mcorr)
#plt.savefig('attribute_correlations.png', tight_layout=True)
```

```
<ipython-input-23-bbd46dc5ccce>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  mcorr = menDf.corr()
```

[23]: <Axes: >



Many variable pairs present correlation close to zero. What does that mean?

It means that the values being compared has a weak relationship or no linear relationship between the variables

---

Why separate the genders?

As discussed earlier it may differ to the data type needed of the 2 genders

---

What variables have stronger correlation with brain size (MRI_Count)? Is that expected? Explain.

It is not expected because having a greate brain size can be link to a higher intellectual intellegence. It can be correlate to education and bioethics that suggest there knowledge on cognitive development

---

###SUPPLEMENTARY ACTIVITY

[25]:
```
# Import the pandas library
import pandas as pd

# Define the file path
laptopFile = '/content/laptop.csv'

# Read the CSV file into a DataFrame using variable-length whitespace as the␣
↪column delimiter
laptopFrame = pd.read_csv(laptopFile)
```

[27]:
```
# code that display first five entries of a dataframe

laptopFrame.head()
```

[27]:
```
   Unnamed: 0 Company   TypeName  Inches                    ScreenResolution  \
0           0   Apple  Ultrabook    13.3  IPS Panel Retina Display 2560x1600
1           1   Apple  Ultrabook    13.3                            1440x900
2           2      HP   Notebook    15.6                   Full HD 1920x1080
3           3   Apple  Ultrabook    15.4  IPS Panel Retina Display 2880x1800
4           4   Apple  Ultrabook    13.3  IPS Panel Retina Display 2560x1600

                          Cpu   Ram               Memory  \
0        Intel Core i5 2.3GHz   8GB            128GB SSD
1        Intel Core i5 1.8GHz   8GB  128GB Flash Storage
2  Intel Core i5 7200U 2.5GHz   8GB            256GB SSD
3        Intel Core i7 2.7GHz  16GB            512GB SSD
4        Intel Core i5 3.1GHz   8GB            256GB SSD

                           Gpu  OpSys  Weight        Price
0  Intel Iris Plus Graphics 640  macOS  1.37kg   71378.6832
1        Intel HD Graphics 6000  macOS  1.34kg   47895.5232
2         Intel HD Graphics 620  No OS  1.86kg   30636.0000
3            AMD Radeon Pro 455  macOS  1.83kg  135195.3360
4  Intel Iris Plus Graphics 650  macOS  1.37kg   96095.8080
```

[28]:
```
# code that performs same common calculations against a given dataset

laptopFrame.describe()
```

[28]:

	Unnamed: 0	Inches	Price
count	51.000000	51.000000	51.000000
mean	25.000000	14.905882	49531.877365
std	14.866069	1.552857	33806.159923
min	0.000000	10.100000	10224.432000
25%	12.500000	13.300000	22847.529600
50%	25.000000	15.600000	42624.000000
75%	37.500000	15.600000	68209.056000
max	50.000000	17.300000	152274.240000

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3f3b280>
```

```
from matplotlib import pyplot as plt
_df_52['Unnamed: 0'].plot(kind='hist', bins=20, title='Unnamed: 0')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_53['Inches'].plot(kind='hist', bins=20, title='Inches')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_54['Price'].plot(kind='hist', bins=20, title='Price')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3f3b1c0>
```

```
from matplotlib import pyplot as plt
import seaborn as sns
_df_55.groupby('index').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3f39de0>
```

```
from matplotlib import pyplot as plt
_df_56.plot(kind='scatter', x='Unnamed: 0', y='Inches', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_57.plot(kind='scatter', x='Inches', y='Price', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3f3aec0>
```

```
from matplotlib import pyplot as plt
_df_58['Unnamed: 0'].plot(kind='line', figsize=(8, 4), title='Unnamed: 0')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_59['Inches'].plot(kind='line', figsize=(8, 4), title='Inches')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
from matplotlib import pyplot as plt
_df_60['Price'].plot(kind='line', figsize=(8, 4), title='Price')
plt.gca().spines[['top', 'right']].set_visible(False)
```

```
<google.colab._quickchart_helpers.SectionTitle at 0x7ad1c3f3b970>
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_61['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_61, x='Unnamed: 0', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_62['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_62, x='Inches', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(_df_63['index'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(_df_63, x='Price', y='index', inner='stick', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

[29]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[33]:
```
inchesDf = laptopFrame[(laptopFrame.Company == 'Inches')]
weightDf = laptopFrame[(laptopFrame.Company == 'Weight')]
```

[ ]:
```

```

Conclusion

While doing the activity I realized that I am not good enough to read or to visualize the datas. I upon trying to do the procedure I got a hard time to understand how the correlation word that is why I got pressured by the time and did not finish the activity.