#Welcome to our Lab practice!

This lab is all about the package, Matplotlib. Are you ready? Let's go!

You will find some small tasks in sections below.

> Try to figure out by yourself, or search for references. Being able to search and find information needed is an important skill that benefits you and your career for a long time.

> Please note this lab is exploratory, and there is no correct solution – Just try your best!

Choose One dataset from the list below, and play with it.

For practice purpose, you can load and play with one or more toy datasets in seaborn package (we are going to learn it in next module). You can get them by:

```
import seaborn as sns
data = sns.load_dataset('NAME')
```

The list of names can be found at Seaborn Datasets:

```
['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes',
 'diamonds', 'dots', 'exercise', 'flights', 'fmri', 'gammas', 'geyser',
'iris', 'mpg', 'penguins', 'planets', 'taxis', 'tips', 'titanic']
```

For example, to play with the dataset *iris*, you can do:

```
import seaborn as sns
data = sns.load_dataset('iris')
```

Set up the environment

Task: import packages and rename them accordingly

```
# your code is here
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Load the dataset

```
# your code is here
data = sns.load_dataset('iris')
```

Play with distribution plots

You can show the data distribution for some attributes interest you.

```
# your code is here
pd.set_option('display.max_rows', None)
data
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
5	5.4	3.9	1.7	0.4	setosa
6	4.6	3.4	1.4	0.3	setosa
7	5.0	3.4	1.5	0.2	setosa
8	4.4	2.9	1.4	0.2	setosa
9	4.9	3.1	1.5	0.1	setosa
10	5.4	3.7	1.5	0.2	setosa
11	4.8	3.4	1.6	0.2	setosa
12	4.8	3.0	1.4	0.1	setosa
13	4.3	3.0	1.1	0.1	setosa
14	5.8	4.0	1.2	0.2	setosa
15	5.7	4.4	1.5	0.4	setosa
16	5.4	3.9	1.3	0.4	setosa
17	5.1	3.5	1.4	0.3	setosa
18	5.7	3.8	1.7	0.3	setosa
19	5.1	3.8	1.5	0.3	setosa
20	5.4	3.4	1.7	0.2	setosa
21	5.1	3.7	1.5	0.4	setosa
22	4.6	3.6	1.0	0.2	setosa
23	5.1	3.3	1.7	0.5	setosa
24	4.8	3.4	1.9	0.2	setosa
25	5.0	3.0	1.6	0.2	setosa
26	5.0	3.4	1.6	0.4	setosa
27	5.2	3.5	1.5	0.2	setosa
28	5.2	3.4	1.4	0.2	setosa
29	4.7	3.2	1.6	0.2	setosa
30	4.8	3.1	1.6	0.2	setosa
31	5.4	3.4	1.5	0.4	setosa
32	5.2	4.1	1.5	0.1	setosa
33	5.5	4.2	1.4	0.2	setosa
34	4.9	3.1	1.5	0.2	setosa
35	5.0	3.2	1.2	0.2	setosa
36	5.5	3.5	1.3	0.2	setosa
37	4.9	3.6	1.4	0.1	setosa
38	4.4	3.0	1.3	0.2	setosa
39	5.1	3.4	1.5	0.2	setosa
40	5.0	3.5	1.3	0.3	setosa
41	4.5	2.3	1.3	0.3	setosa
42	4.4	3.2	1.3	0.2	setosa
43	5.0	3.5	1.6	0.6	setosa

	sepal_length	sepal_width	petal_length	petal_width	species
44	5.1	3.8	1.9	0.4	setosa
45	4.8	3.0	1.4	0.3	setosa
46	5.1	3.8	1.6	0.2	setosa
47	4.6	3.2	1.4	0.2	setosa
48	5.3	3.7	1.5	0.2	setosa
49	5.0	3.3	1.4	0.2	setosa
50	7.0	3.2	4.7	1.4	versicolor
51	6.4	3.2	4.5	1.5	versicolor
52	6.9	3.1	4.9	1.5	versicolor
53	5.5	2.3	4.0	1.3	versicolor
54	6.5	2.8	4.6	1.5	versicolor
55	5.7	2.8	4.5	1.3	versicolor
56	6.3	3.3	4.7	1.6	versicolor
57	4.9	2.4	3.3	1.0	versicolor
58	6.6	2.9	4.6	1.3	versicolor
59	5.2	2.7	3.9	1.4	versicolor
60	5.0	2.0	3.5	1.0	versicolor
61	5.9	3.0	4.2	1.5	versicolor
62	6.0	2.2	4.0	1.0	versicolor
63	6.1	2.9	4.7	1.4	versicolor
64	5.6	2.9	3.6	1.3	versicolor
65	6.7	3.1	4.4	1.4	versicolor
66	5.6	3.0	4.5	1.5	versicolor
67	5.8	2.7	4.1	1.0	versicolor
68	6.2	2.2	4.5	1.5	versicolor
69	5.6	2.5	3.9	1.1	versicolor
70	5.9	3.2	4.8	1.8	versicolor
71	6.1	2.8	4.0	1.3	versicolor
72	6.3	2.5	4.9	1.5	versicolor
73	6.1	2.8	4.7	1.2	versicolor
74	6.4	2.9	4.3	1.3	versicolor
75	6.6	3.0	4.4	1.4	versicolor
76	6.8	2.8	4.8	1.4	versicolor
77	6.7	3.0	5.0	1.7	versicolor
78	6.0	2.9	4.5	1.5	versicolor
79	5.7	2.6	3.5	1.0	versicolor
80	5.5	2.4	3.8	1.1	versicolor
81	5.5	2.4	3.7	1.0	versicolor
82	5.8	2.7	3.9	1.2	versicolor
83	6.0	2.7	5.1	1.6	versicolor
84	5.4	3.0	4.5	1.5	versicolor
85	6.0	3.4	4.5	1.6	versicolor
86	6.7	3.1	4.7	1.5	versicolor
87	6.3	2.3	4.4	1.3	versicolor
88	5.6	3.0	4.1	1.3	versicolor
89	5.5	2.5	4.0	1.3	versicolor
90	5.5	2.6	4.4	1.2	versicolor
91	6.1	3.0	4.6	1.4	versicolor
92	5.8	2.6	4.0	1.2	versicolor
93	5.0	2.3	3.3	1.0	versicolor
94	5.6	2.7	4.2	1.3	versicolor
95	5.7	3.0	4.2	1.2	versicolor

	sepal_length	sepal_width	petal_length	petal_width	species
96	5.7	2.9	4.2	1.3	versicolor
97	6.2	2.9	4.3	1.3	versicolor
98	5.1	2.5	3.0	1.1	versicolor
99	5.7	2.8	4.1	1.3	versicolor
100	6.3	3.3	6.0	2.5	virginica
101	5.8	2.7	5.1	1.9	virginica
102	7.1	3.0	5.9	2.1	virginica
103	6.3	2.9	5.6	1.8	virginica
104	6.5	3.0	5.8	2.2	virginica
105	7.6	3.0	6.6	2.1	virginica
106	4.9	2.5	4.5	1.7	virginica
107	7.3	2.9	6.3	1.8	virginica
108	6.7	2.5	5.8	1.8	virginica
109	7.2	3.6	6.1	2.5	virginica
110	6.5	3.2	5.1	2.0	virginica
111	6.4	2.7	5.3	1.9	virginica
112	6.8	3.0	5.5	2.1	virginica
113	5.7	2.5	5.0	2.0	virginica
114	5.8	2.8	5.1	2.4	virginica
115	6.4	3.2	5.3	2.3	virginica
116	6.5	3.0	5.5	1.8	virginica
117	7.7	3.8	6.7	2.2	virginica
118	7.7	2.6	6.9	2.3	virginica
119	6.0	2.2	5.0	1.5	virginica
120	6.9	3.2	5.7	2.3	virginica
121	5.6	2.8	4.9	2.0	virginica
122	7.7	2.8	6.7	2.0	virginica
123	6.3	2.7	4.9	1.8	virginica
124	6.7	3.3	5.7	2.1	virginica
125	7.2	3.2	6.0	1.8	virginica
126	6.2	2.8	4.8	1.8	virginica
127	6.1	3.0	4.9	1.8	virginica
128	6.4	2.8	5.6	2.1	virginica
129	7.2	3.0	5.8	1.6	virginica
130	7.4	2.8	6.1	1.9	virginica
131	7.9	3.8	6.4	2.0	virginica
132	6.4	2.8	5.6	2.2	virginica
133	6.3	2.8	5.1	1.5	virginica
134	6.1	2.6	5.6	1.4	virginica
135	7.7	3.0	6.1	2.3	virginica
136	6.3	3.4	5.6	2.4	virginica
137	6.4	3.1	5.5	1.8	virginica
138	6.0	3.0	4.8	1.8	virginica
139	6.9	3.1	5.4	2.1	virginica
140	6.7	3.1	5.6	2.4	virginica
141	6.9	3.1	5.1	2.3	virginica
142	5.8	2.7	5.1	1.9	virginica
143	6.8	3.2	5.9	2.3	virginica
144	6.7	3.3	5.7	2.5	virginica
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica

	sepal_length	sepal_width	petal_length	petal_width	species
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

```
plt.scatter(data['sepal_length'], data['petal_length'])
```

```
<matplotlib.collections.PathCollection at 0x1cb616937f0>
```

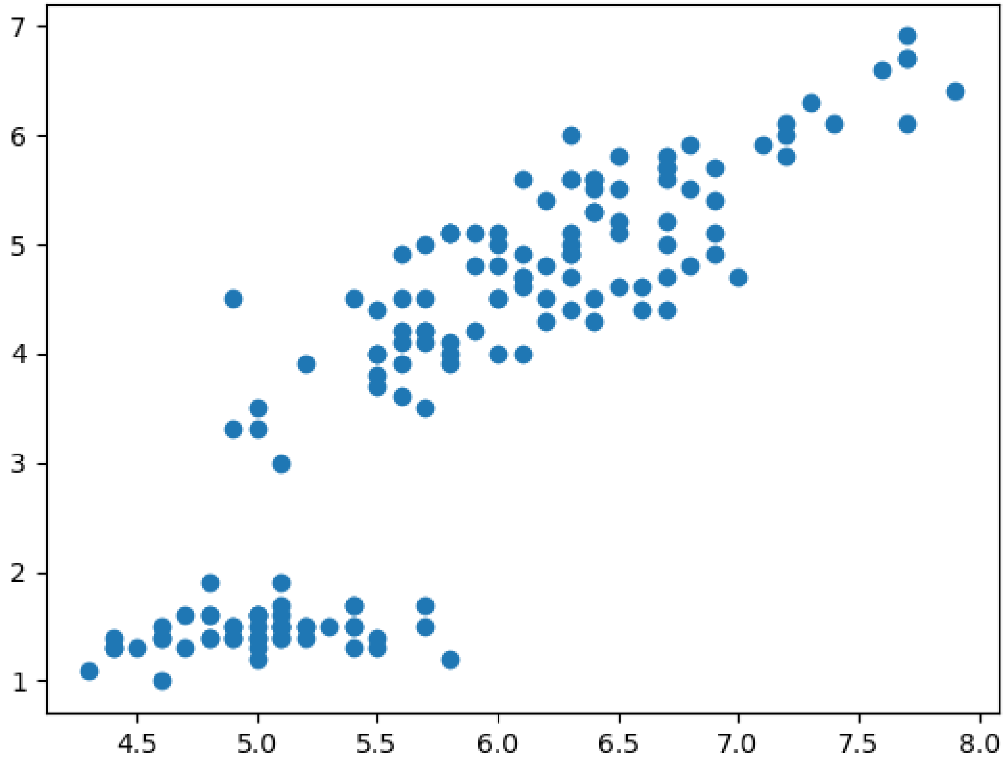


Figure 1: png

```
sns.displot(data=data, kde=True, bins=15,)
```

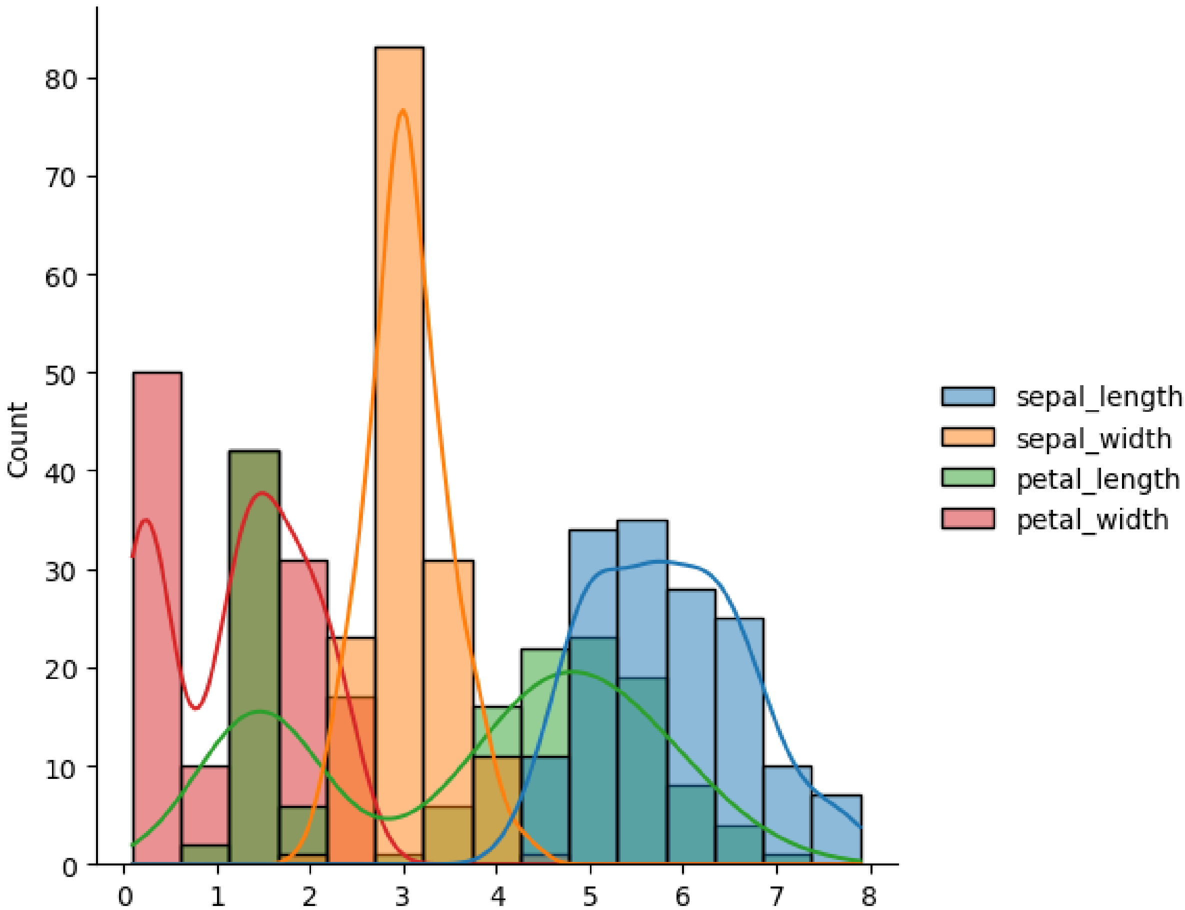
```
<seaborn.axisgrid.FacetGrid at 0x1cb604c4700>
```

Play with relational plots

You can show how two or more attributes are associated.

```
# your code is here
sns.relplot(data['sepal_length'], data['petal_length'], hue= data['species'])
```

```
<seaborn.axisgrid.FacetGrid at 0x1cb5e209af0>
```



Count
80
70
60
50
40
30
20
10
0
0
1
2
3
4
5
6
7
8
sepal_length
sepal_width
petal_length
petal_width

Figure 2: png

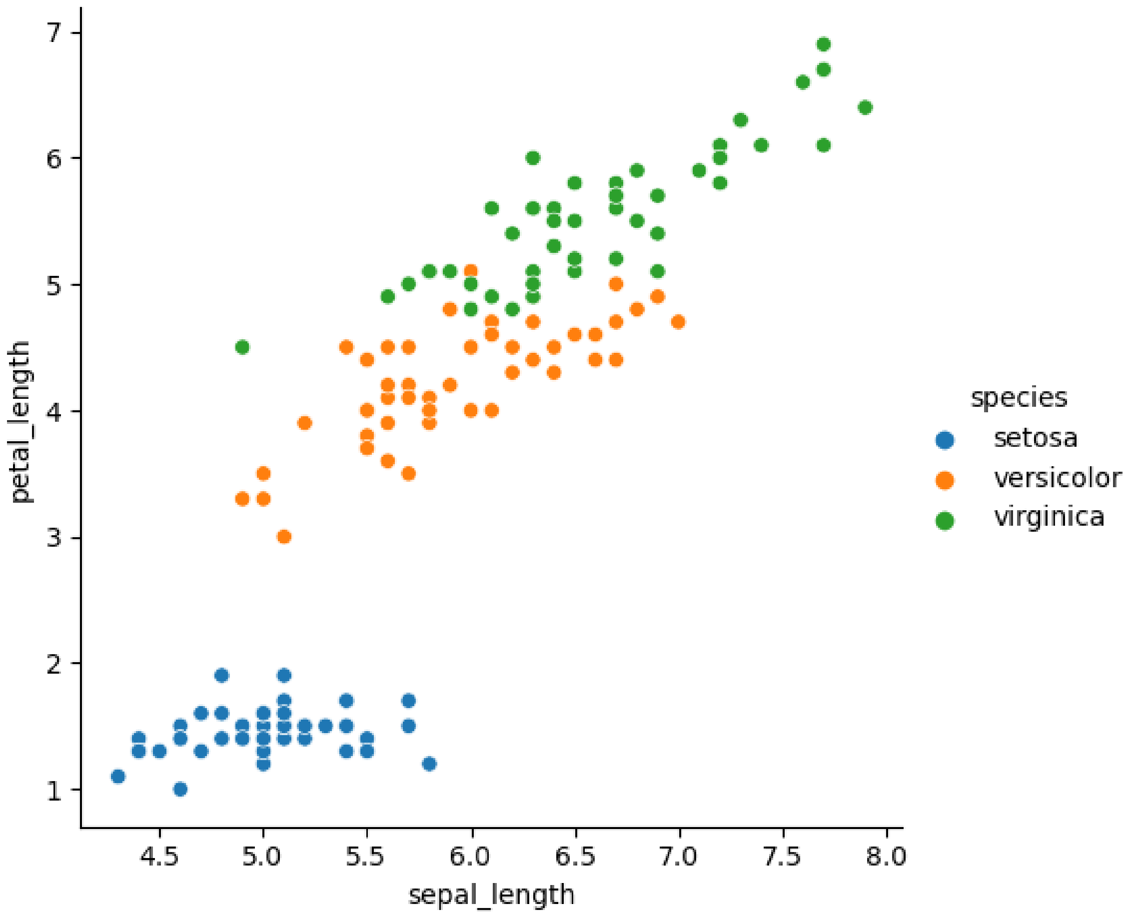

petal_length
sepal_length
1
2
3
4
5
6
7
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
species
setosa
versicolor
virginica

Figure 3: png

Play with other plots

You can play with other plots we learned here. Be as creative as you can and see how the visualization helps you to understand the data better.

```
# your code is here
plt.bar(data.head()['sepal_length'], data.head()['sepal_width'], align = 'edge', edgecolor='black', colo
```

```
<BarContainer object of 5 artists>
```

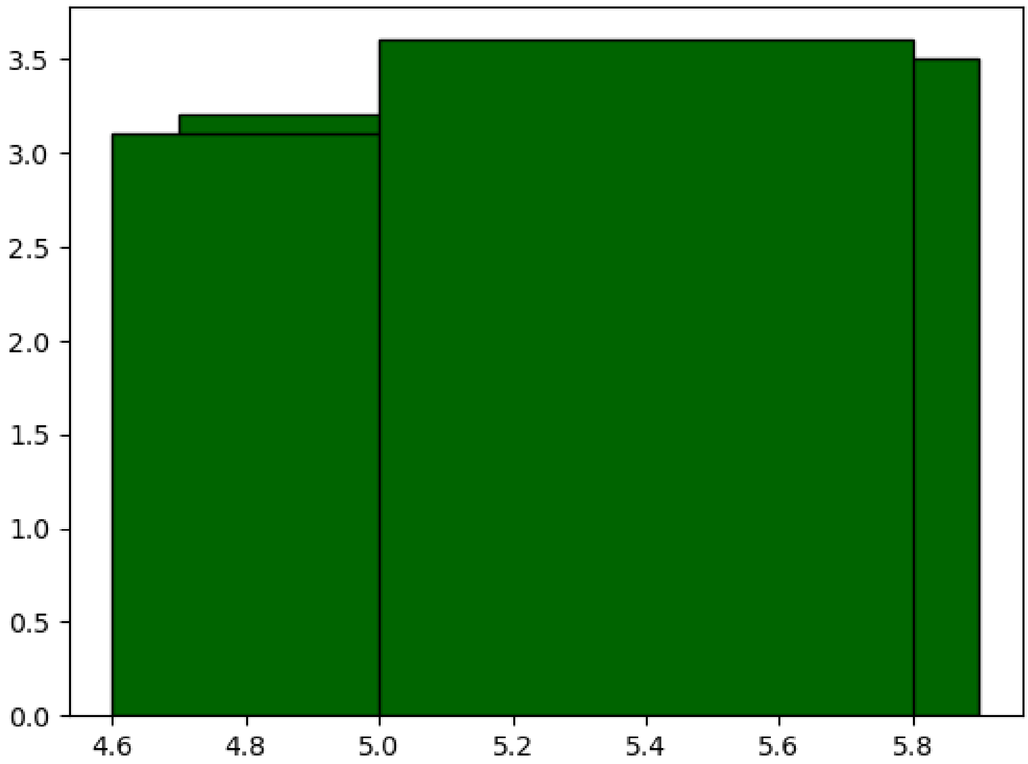


Figure 4: png

Additional Challenge

You may want to create new columns based on existing data using Pandas. You can play with the new columns as well.

```
# your code is here
new_column = data['sepal_length'] / data['petal_length']
data['Test_Column'] = new_column
data.head()
```

	sepal_length	sepal_width	petal_length	petal_width	species	Test_Column
0	5.1	3.5	1.4	0.2	setosa	3.642857
1	4.9	3.0	1.4	0.2	setosa	3.500000
2	4.7	3.2	1.3	0.2	setosa	3.615385
3	4.6	3.1	1.5	0.2	setosa	3.066667
4	5.0	3.6	1.4	0.2	setosa	3.571429

```
data.describe()
```

	sepal_length	sepal_width	petal_length	petal_width	Test_Column
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333	2.018051
std	0.828066	0.435866	1.765298	0.762238	1.061621
min	4.300000	2.000000	1.000000	0.100000	1.050000
25%	5.100000	2.800000	1.600000	0.300000	1.230469
50%	5.800000	3.000000	4.350000	1.300000	1.410603
75%	6.400000	3.300000	5.100000	1.800000	3.176471
max	7.900000	4.400000	6.900000	2.500000	4.833333

Answering the questions

A1: The plots created with seaborn are of a much higher quality and also the best ones to understand the 'iris' data. The relational plot is the best one to point the size differences amongst the species with the virginica being by far greater in length.

A2: The most difficult part is figuring out the parameters for a good representation. Not only it's hard to know which parameters are available, but also the values for those same parameters.

A3: Iris is a poor choice for a table, but once I followed the example, I stuck to it. The only information I can see being provided is that different species have different sizes and the right plot can help us see better these differences in multiple case studies. I learned the relational plot with seaborn was by far the best one for this example.

A4: My learning of visualization has currently changed very little. I wish we had more exercises here with more specifics like we've had so far. I think this was a fall in quality.

A5: I don't know why this question persists.