Data Visualization Basics in Python

Disclaimer: These notes and examples are an adaptation from the references listed at the end. They are compiled to fit the scope of this specific course.

Introduction

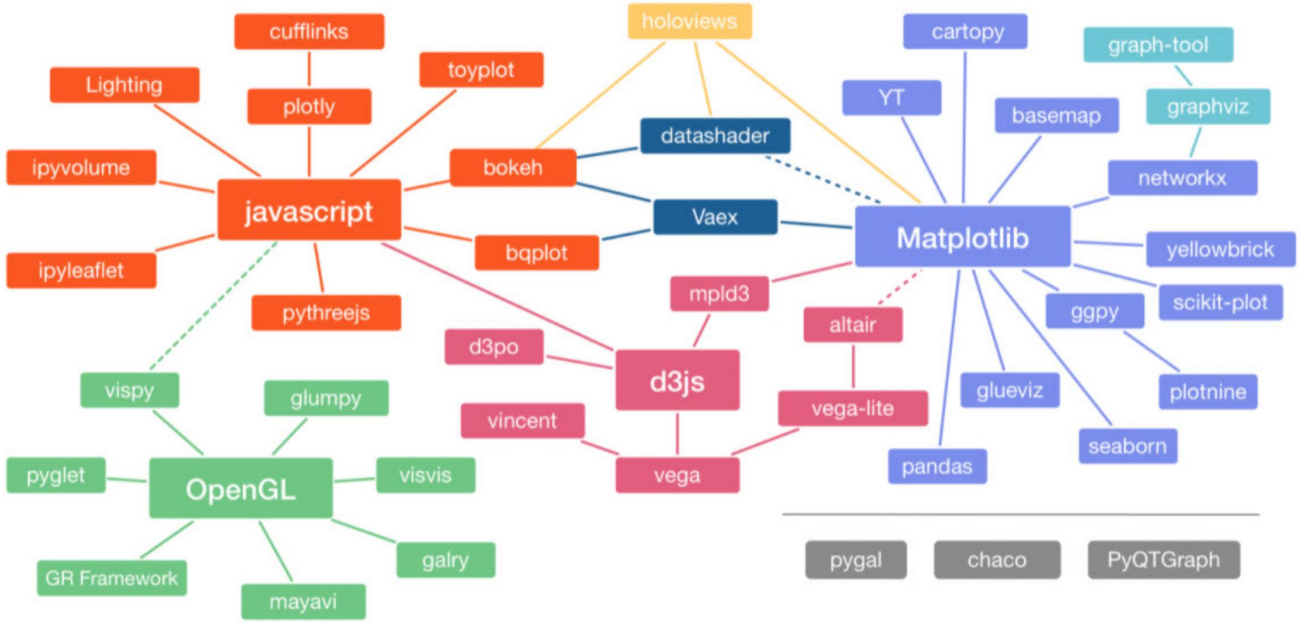
Python offers variety of tools and packages for visualization. The following is a list of popular packages available in python for visualization

- `matplotlib`
- `seaborn`
- `pandas`
- `altair`
- `bokeh`
- `plotly`

Trying to understand which package to use, how to use it, and what graph to use for visualizing your data can be a challenging task. In this introductory handout, we will learn about `matplotlib` , `seaborn` and `pandas` three of the most commonly used visualization packages in python.

Python visualization landscape

The https://pyviz.org/index.html website provides an accurate image of python's most visualization tools. This platform helps users decide on the best python data visualization tools, their purposes, with links, overviews, comparisons, and examples. The following graphics is taken from https://pyviz.org/overviews/index.html. The most important part of this landscape is noticing the libraries inner-dependencies.



As you can see a lot of python visualization libraries heavily depend on `matplotlib`.

`matplotlib`

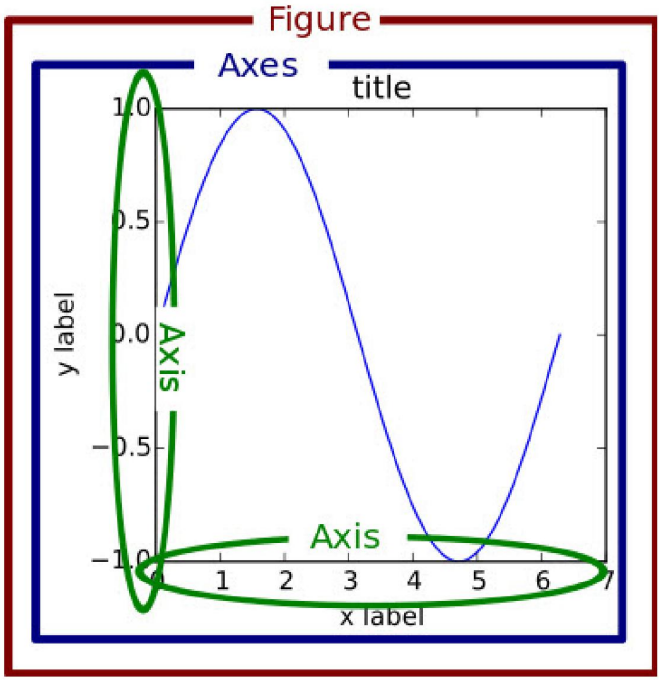
`matplotlib` is the grandfather of python visualization tools! As it is clear from the above landscape, a lot of python's visualization tools -- most notably `seaborn` -- are just a user friendly skin (wrapper) over `matplotlib`. `matplotlib` is very powerful and complicated. Even though you can accomplish most of your visualization tasks with `matplotlib`, a lot of users try to avoid using `matplotlib` due to its complexity. However, due to different package's dependency on `matplotlib`, we will learn basics before switching to `seaborn` and visualization using `pandas`.

plotting with `matplotlib`

`matplotlib` (https://matplotlib.org/) is the most-widely used visualization library in python. The **Example** section of this library available at https://matplotlib.org/stable/gallery/index.htmlIts shows variety of graphs you can plot using `matplotlib`. Jupyter notebook and python source code for each of these examples are available for download in each example web-page.

For `anaconda` users, `matplotlib` is already available to you. However, if you need to install it, try `pip install matplotlib`. Let's understand the anatomy of a plot. Key components of a plot are `Figure` and `Axes`.

- **`Figure`:** A `Figure` is the top-level container for everything that will be plotted. You can consider `Figure` to be a piece of paper or a canvas you can draw and write on.
- **`Axes`:** Contained within a `Figure` is one or more `Axes`. An `Axes` is a plotting surface. An `Axes` is the area on which we plot our data, add all the associated labels/ticks. Each `Axes` has one `X-Axis` and one `Y-Axis` (and possibly one `Z-Axis`). The following shows anatomy of a plot.



Note 1: `Axes` is NOT a plural of `Axis`; they are completely separate concepts. An `Axes` is the plotting surface and may contain `X-Axis`, `Y-Axis`, or `Z-Axis`.

Note 2: Please do not confuse concept of `axis` in `numpy`, `pandas`, and `Axes` in `matplotlib` as they are very different concepts. In `numpy` and `pandas` the setting of `axis = 0` or `axis = 1` is used to dictate calculations for columns or rows; whereas, in `matplotlib` `Axes` is a plotting area and `Axis` is for X, Y, or Z axis.

Plotting in `matplot` is done using its `pyplot` module. `matplotlib` suggests importing `pyplot` using

```
import matplotlib.pyplot as plt
```

- Older versions of `Jupyter notebook` users: you need to include the line `%matplotlib inline` in your notebook. This will direct `matplotlib` to display plots in the notebook.
- If you are using other IDEs such as `pycharm` or `spyder` you need to add `plt.show()` instead.

There are two approaches for creating plots in `matplotlib` as

- **functional approach**
- **Object oriented approach**

Rule of thumb: Almost all `matplotlib` plot types (linear, bar, histogram, etc) accept arrays (`python` arrays, `numpy` arrays, `pandas` `Series` , or `pandas` `DataFrame`) for values of `x` and `y` .

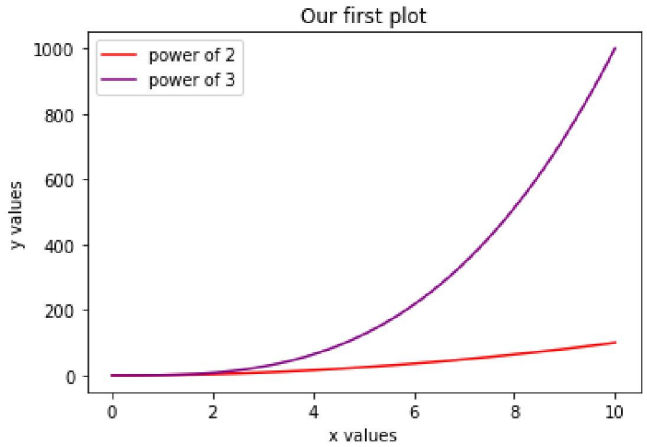
Use `matplotlib` functional approach for plotting

Here is an example:

Example

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

arr_x = np.linspace(0, 10)
arr_y_1 = arr_x ** 2
arr_y_2 = arr_x ** 3

plt_1 = plt.plot(arr_x, arr_y_1, "red", label="power of 2")
plt_2 = plt.plot(arr_x, arr_y_2, "purple", label="power of 3")

# optional but highly recommended features
plt.title("Our first plot")
plt.xlabel("x values")
plt.ylabel("y values")

# default labels
plt.legend()
```

yields a plot with two lines plotted. Legend will also be shown, default of plot legend is the provided plot labels.



`matplotlib` default is plotting just one plot on the canvas. We can create multi-plots on the same figure (canvas) using `.subplot` method. This method has three arguments:

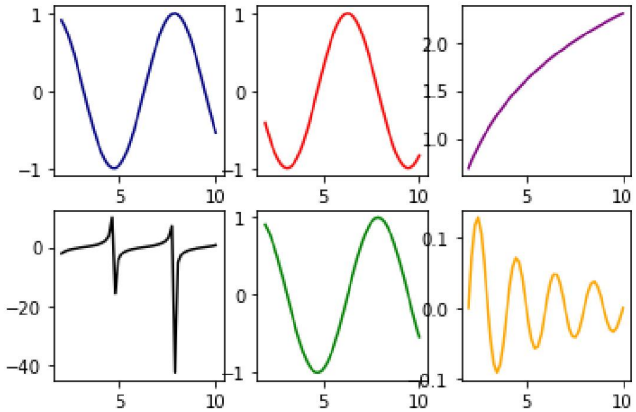
- `nrows` : number of rows in the `Figure`
- `ncols` : number of columns in the `Figure`
- `plot_number` : refers to a specific plot in the `Figure`

The following snippet will create 6 subplots, plot different functions in each subplot

> **Example**
>
> ```
> import numpy as np
> import matplotlib.pyplot as plt
>
> arr_x = np.linspace(2, 10)
> arr_y_1_1 = np.sin(arr_x)
> arr_y_1_2 = np.cos(arr_x)
> arr_y_1_3 = np.log(arr_x)
> arr_y_2_1 = np.tan(arr_x)
> arr_y_2_2 = np.sin(arr_x)
> arr_y_2_3 = np.sinc(arr_x)
>
> plt.subplot(2, 3, 1)
> plt.plot(arr_x, arr_y_1_1, "navy")
>
> plt.subplot(2, 3, 2)
> ```

```
plt.plot(arr_x, arr_y_1_2, "red")

plt.subplot(2, 3, 3)
plt.plot(arr_x, arr_y_1_3, "purple")

plt.subplot(2, 3, 4)
plt.plot(arr_x, arr_y_2_1, "black")

plt.subplot(2, 3, 5)
plt.plot(arr_x, arr_y_2_2, "green")

plt.subplot(2, 3, 6)
plt.plot(arr_x, arr_y_2_3, "orange")
```

yields six plots in one `Figure`



Use `matplotlib` object oriented approach for plotting

This is the most common way of creating plots. The main idea is to create a `Figure` object; then create one or more `Axes` in that `Figure` object; call the necessary methods off the `Figure` and `Axes` to customize contents of a plot.

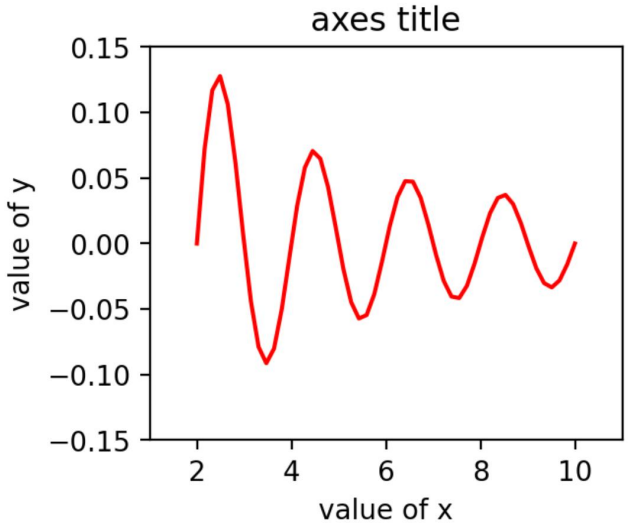
Use `plt.figure()`

Here is an example

Example

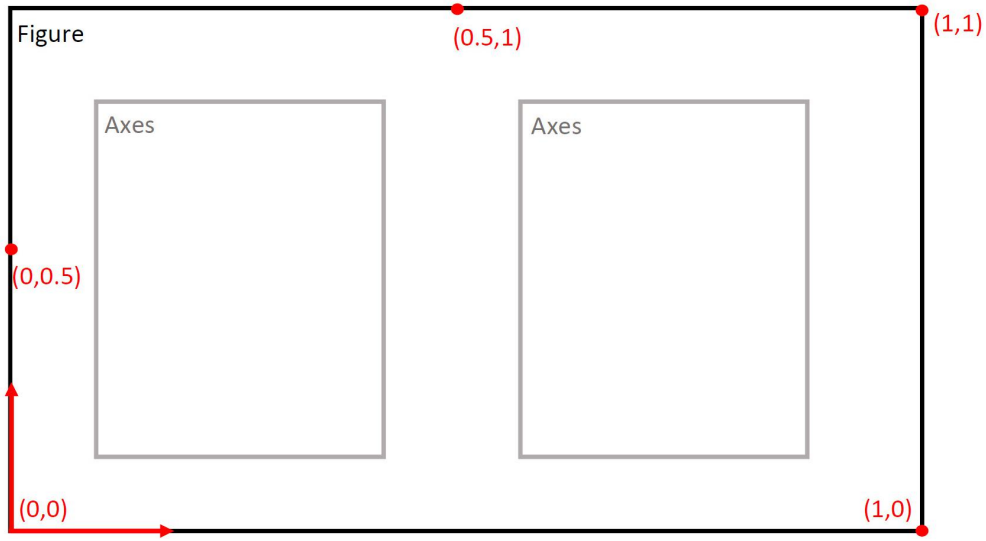
```python
import numpy as np
import matplotlib.pyplot as plt

# create data
arr_x = np.linspace(2, 10)
arr_y_1 = np.sinc(arr_x)

#create a figure. This is similar to a canvas surface
fig_1 = plt.figure()

# create an empty plot. We call it axes
axes_1 = fig_1.add_axes([0.1, 0.2, 0.4, 0.5])

# plot in axes_1
axes_1.plot(arr_x, arr_y_1, "red")

# set axes_1 settings
axes_1.set(
    xlim=(1, 11),
    ylim=(-0.15, 0.15),
    xlabel="value of x",
    ylabel="value of y",
    title="axes title",
)
```

creates a `figure` called `fig_1`; adds an `Axes` called `axes_1` at `x_0 = 0.1`, `y_0 = 0.2`, `width = 0.4`, and `height = 0.5`; plots a red curve, and sets specific settings for the plot



Explanation:

- `fig_1 = plt.figure()` creates a `Figure` object and calls it `fig_1`. `Figure` coordinates go `0` to `1`, where `(0,0)` is the lower left corner and `(1,1)` is the upper right corner. A coordinate of y=1.05 is hence slightly outside the figure.



- `axes_1 = fig_1.add_axes([0.1, 0.2, 0.4, 0.5])` creates an `Axes` object. The syntax of `add_axes([x_0, y_0, w, h])` creates an `Axes`; `(x_0, y_0)` is the lower left point of the new axes in figure coordinates, `w` is its width and `h` is its height. So the axes is positioned in absolute coordinates on the canvas.
- `axes_1.plot(arr_x, arr_y_1, "red")` plots a red curve based on the given data points.
- `axes_1.set()` method is used to set `axes_1` settings.

Adding one more Axes: In the next snippet, we will add one more `Axes` to the same canvas (`Figure` object) and plot two different functions. This time we will add more settings for the `Figure` and finally we will save it.

> **Example**
>
> ```
> import numpy as np
> import matplotlib.pyplot as plt
>
> # create data
> arr_x = np.linspace(2, 10)
> arr_y_1 = np.sinc(arr_x)
> arr_y_2 = np.log(arr_x)
>
> # create a figure. This is similar to a canvas surface
> fig_1 = plt.figure()
>
> # create empty plots
> ```

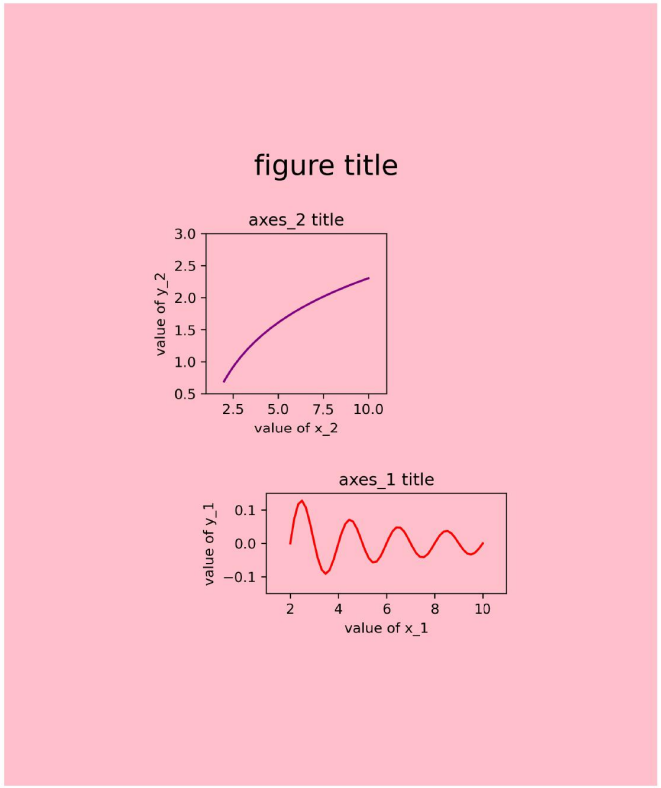
```
axes_1 = fig_1.add_axes([0.1, 0.0, 0.4, 0.25])
axes_2 = fig_1.add_axes([0.0, 0.5, 0.3, 0.4])

# plot in axes_1
axes_1.plot(arr_x, arr_y_1, "red")

# plot in axes_2
axes_2.plot(arr_x, arr_y_2, "purple")

# set axes_1 settings
axes_1.set(
   xlim=(1, 11),
   ylim=(-0.15, 0.15),
   xlabel="value of x_1",
   ylabel="value of y_1",
   title="axes_1 title",
)

# set axes_2 settings
axes_2.set(
   xlim=(1, 11),
   ylim=(0.5, 3),
   xlabel="value of x_2",
   ylabel="value of y_2",
   title="axes_2 title",
)

# figure settings
fig_1.suptitle("figure title", size=20, x=0.2, y=1.1)
```

in this snippet we will added two `Axes` to the `Figure` object; customized their settings; and finally, added a figure title with font size of 20 at coordinates of (0.2, 1.1) relative to lower left corner of the canvas

Default size of a canvas (`Figure`) in `matplotlib` is `(6, 4)` inches (6 inches in width and 4 inches in height) which is not the actual size of it on the screen, but would be the exact size if you saved the `Figure` to a file (with a dpi of 100 pixels per inch); we can confirm that by calling `fig_1.get_size_inches()` . We can further customize that by calling `fig_1.set_size_inches(12,5)` . Additionally, you can save an image using `savefig()` method; as in

```
# save the file
fig_1.savefig(
    "save_1.png",             # file name
    bbox_inches="tight",      # saves the file in a tight fit
```

```
    pad_inches=1.5,           # space around the figure
    transparent=True,         # transparency of axes
    facecolor="pink",         # face color is pink
    orientation="landscape",  # image orientation
    dpi = 300                 # dot per inch
)
```



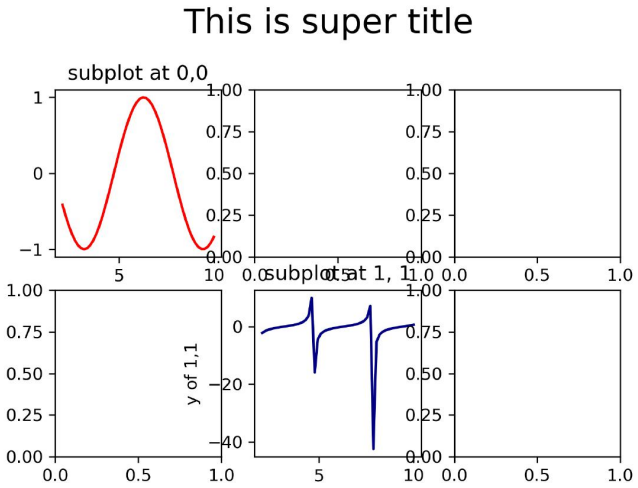
- `dpi` stands for *dot per inch*. This value dictates the figure resolution in dots per inch; higher number means higher resolution (and bigger image file size). For most applications `dpi` in the range of 200 to 400 suffices.

Use `plt.subplots(nrows, ncols)`

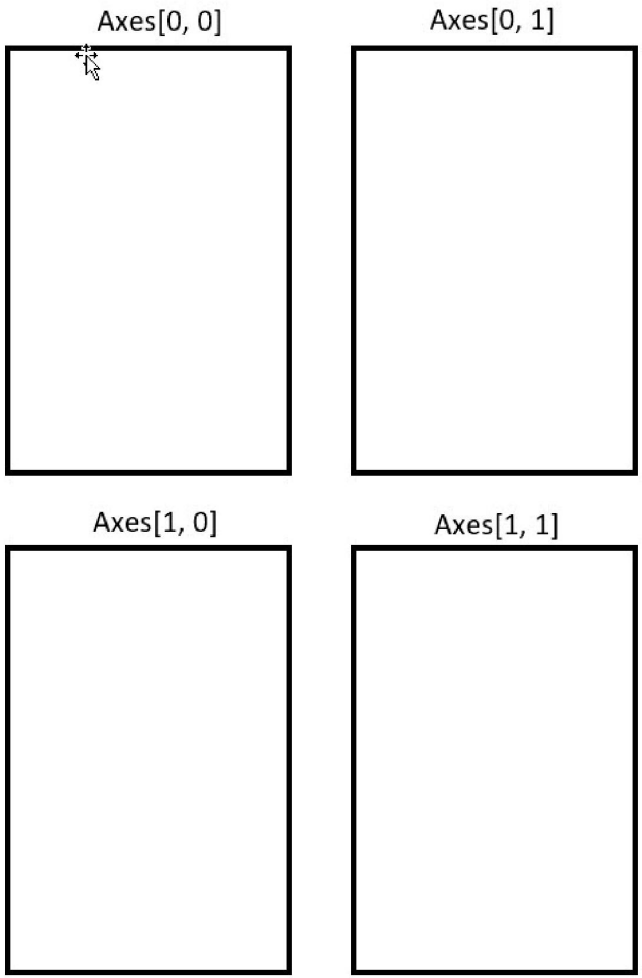
We can create multiple plots in the object-oriented approach using `.subplots()` method, and NOT `.subplot()` . `.subplots()` method takes two arguments `nrows` , for number of rows in the `Figure` and `ncols` for the number of columns in the `Figure` .

Example

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

# generate data
arr_x = np.linspace(2, 10)
arr_y_1 = np.cos(arr_x)
arr_y_2 = np.tan(arr_x)

fig, axes = plt.subplots(nrows=2, ncols=3)

axes[0, 0].plot(arr_x, arr_y_1, "red")
axes[1, 1].plot(arr_x, arr_y_2, "navy")

axes[0, 0].set(xlabel="x of 0,0", title="subplot at 0,0")
axes[1, 1].set(ylabel="y of 1,1", title="subplot at 1, 1")

fig.suptitle("This is super title", size=20, x=0.5, y=1.05)
```



Explanation: The `.subplots(nrows, ncols)` function returns a two-item tuple object containing a `Figure` and one or more `Axes` objects (here 6 `Axes`). The second item in the tuple of `.subplots(nrows, ncols)` is a `numpy` array containing all the `Axes`. You can check that by calling `axes`. We can use 0-based indexing to access each `Axes` and customize the plot and its features. The following shows the location of each `Axes` when using `.subplots()` method:

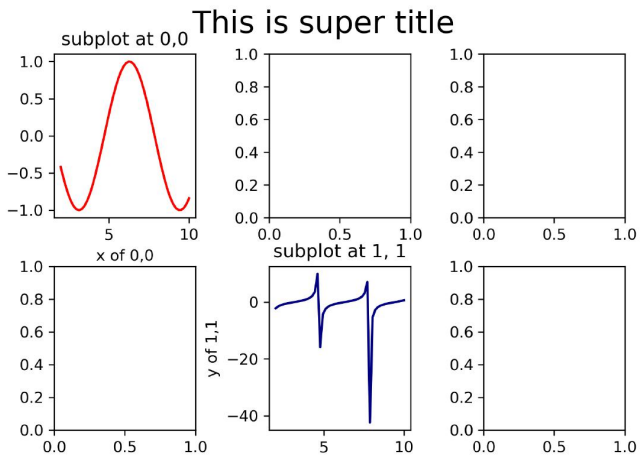


Setting up the spacing between subplots

Subplots in `Matplotlib` are multiple plots within the same `figure`. As you can see there is an issue of overlapping in the subplots we have created. The spacing attribute determines how far apart the subplots are in the figure. We can handle that issue by utilizing `.tight_layout()` method. By adding `plt.tight_layout()`, subplots will be spaced out further away from each other. The following snippet will generate same `figure` and `subplots`; this time with better spacing between `subplots`.

> **Example**

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

arr_x = np.linspace(2, 10)
arr_y_1 = np.cos(arr_x)
arr_y_2 = np.tan(arr_x)

fig, axes = plt.subplots(nrows=2, ncols=3)

axes[0, 0].plot(arr_x, arr_y_1, "red")
axes[1, 1].plot(arr_x, arr_y_2, "navy")

plt.tight_layout()            # control spacing

axes[0, 0].set(xlabel="x of 0,0", title="subplot at 0,0")
axes[1, 1].set(ylabel="y of 1,1", title="subplot at 1, 1")

fig.suptitle("This is super title", size=20, x=0.5, y=1.05)
```

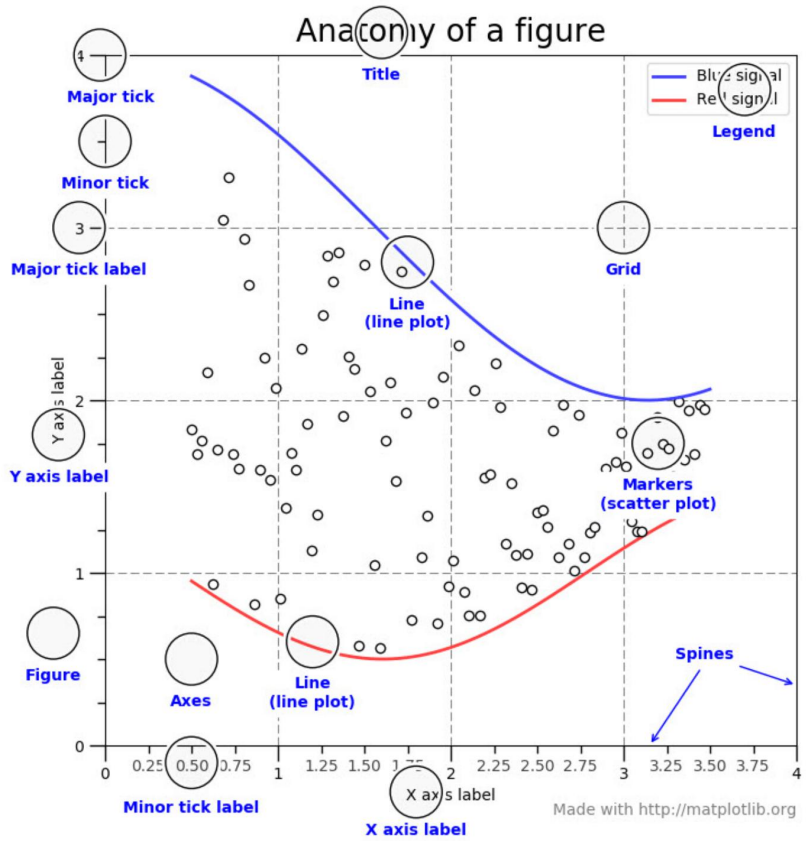


Note: `plt.tight_layout()` has an optional argument of `pad` with default value of `1.08`. By increasing that number, the spacing between subplots will increase.

Side note: `plt.tight_layout()` has optional arguments of `h_pad` and `w_pad` as well. I will leave exploring these options to you!

Fine-tuning `matplotlib` `figure`

One of the best features of `matplotlib` is its capability to customize every possible component of a plot. The following image is taken from `matplotlib` website and shows a deeper look at the components of a `matplotlib` `figure`.

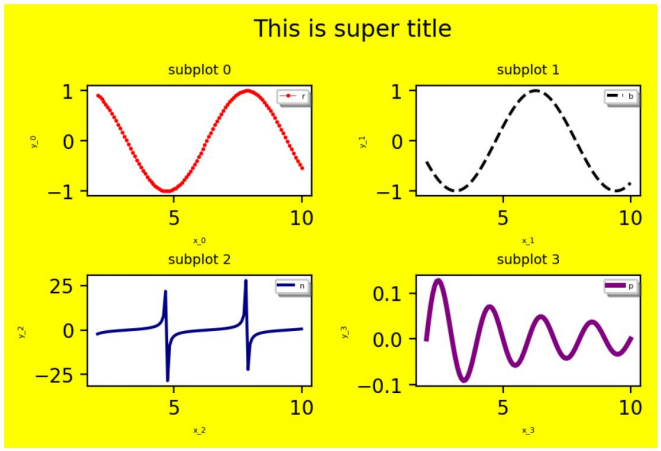


While this is an attractive feature, with this level of flexibility comes complexity, lots of frustration, and confusion. In this section, we will learn about most important customization we might need for a `figure`. For further `figure` customization, please consult with `matplotlib` 3489-page-long documentation at https://matplotlib.org/stable/Matplotlib.pdf.

Let's look at one self-explanatory example:

> **Example**
>
> ```
> import numpy as np
> import matplotlib.pyplot as plt
> ```

```
arr_x = np.linspace(2, 10, 100)

# set figure settings at initiation
fig, axes = plt.subplots(nrows=2, ncols=2, figsize = (5, 3), dpi = 200)
plt.tight_layout(pad = 2)

#plotting
axes[0, 0].plot(arr_x, np.sin(arr_x), "red", linewidth = 0.3, marker = 'o', markersize = 1,
label = 'r')

axes[0, 1].plot(arr_x, np.cos(arr_x), "black", label = 'b', linestyle = '--')

axes[1, 0].plot(arr_x, np.tan(arr_x), "navy", label = 'n')

axes[1, 1].plot(arr_x, np.sinc(arr_x), "purple", linewidth = 2.5, label = 'p')

# common notation for changing settings of all subplots all at once
for i, sub_p in enumerate(fig.axes):
   sub_p.set_xlabel("x_" + str(i), fontsize = 4)
   sub_p.set_ylabel("y_" + str(i), fontsize = 4)
   sub_p.set_title('subplot '+ str(i), fontsize = 7)
   sub_p.legend(loc='upper right', shadow = True, fontsize = 4)

fig.suptitle("This is super title", size=12, x=0.5, y=1.05)

fig.savefig("save_me.png", bbox_inches="tight", facecolor = 'yellow')
```



Note 1: `linestyle` and `marker` arguments are used to control plot appearance. A whole list of what is possible can be found at https://matplotlib.org/stable/api/markers_api.html and https://matplotlib.org/2.0.1/api/lines_api.html.

Note 2: You can generate high quality images from `matplotlib` `figure`. You can use `.savefig()` method to save a `figure` in a variety of formats such as `jpg`, `jpeg`, `png`, `svg`, `pdf`, etc.

Optional: One can confirm existence of the above generated image file by running the following snippet

> **Optional**
>
> ```
> import matplotlib.image as mpimg
> plt.imshow(mpimg.imread('save_me.png'))
> ```
>
> this will read the image file `save_me.png` and will display it.

Commonly used plots in `matplotlib`

A quick look at `matplotlib` gallery available at https://matplotlib.org/stable/gallery/index.html# reveals vast variety of plots that can be generated using `matplotlib`. However, a small set of relatively limited number of plot types is used in most practical situations. The rest of this handout will provide quick examples of each of these plot types

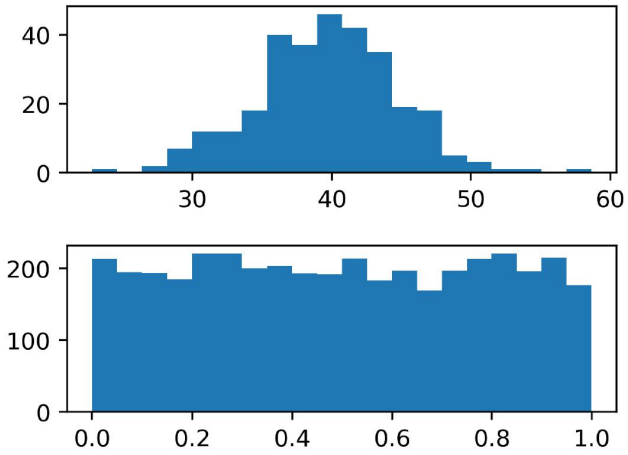
Histogram

- **Application:** Displays `shape` of the data. A histogram is the standard way to show a (statistical) distribution of a numerical value.
- **Common syntax:** Use `.hist()` method with most common syntax of `ax.hist(x, bins = , range = , cumulative = )`

Parameter	Optional?	Description
x	No	array or sequence of arrays
bins	Yes	Most common format: integer number. It defines the number of equal-width bins in the range
range	Yes	A tuple. The lower and upper range of the bins. Lower and upper outliers are ignored. If not provided, range is (x.min(), x.max())
cumulative	Yes	Default: False If set True, it returns cumulative histogram of the data

> **Histogram Example**

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

# Generate data
data_1 = np.random.normal(40, 5, size = 300)
data_2 = np.random.random(size = 4000)

fig, axs = plt.subplots(nrows = 2, ncols = 1, figsize = (4, 3), dpi = 150)
plt.tight_layout()

axs[0].hist(data_1, bins=20)
axs[1].hist(data_2, bins=20)
```



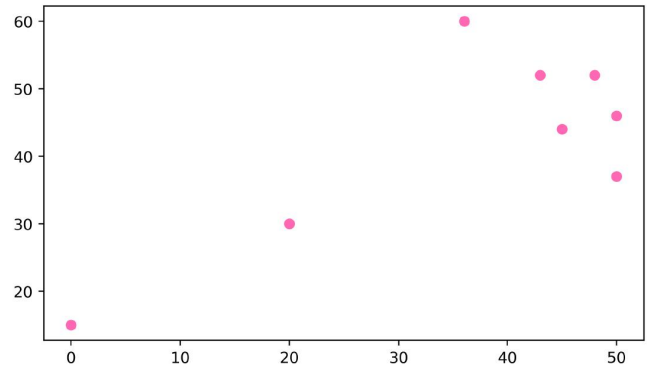
Scatter plots

- **Application:** Visualizes how two numerical values are related or affected by each other; this plot helps us understand the relationships between variables.
- **Common syntax:** Use `.scatter()` method with most commonly used syntax of `ax.scatter(x, y, color = )`.

Parameter	Optional?	Description
x	No	sequence of scalars. The data x coordinates
y	No	sequence of scalars. The data y coordinates
color	Yes	Optional array or list of colors or color

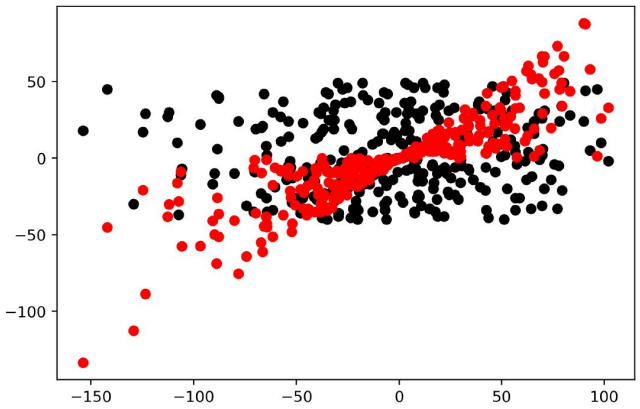
Scatter plot Example 1

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

midterm_grades = [43, 20, 50, 45, 36, 0, 50, 48]
final_grades = [52, 30, 37, 44, 60, 15, 46, 52]

fig, ax = plt.subplots(figsize=(7, 4), dpi=100)
ax.scatter(midterm_grades, final_grades, color="hotpink")
```



Scatter plot Example 2

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

# Generate data
data_1 = np.random.normal(1, 50, size = 300)
temp_1 = np.random.random(size = 300)
temp_2 = np.random.randint(-40,50, size = 300)
data_2 = data_1 * temp_1

fig, ax = plt.subplots()
plt.tight_layout()

ax.scatter(data_1, temp_2, color = 'black')
ax.scatter(data_1, data_2, color = 'red')
```



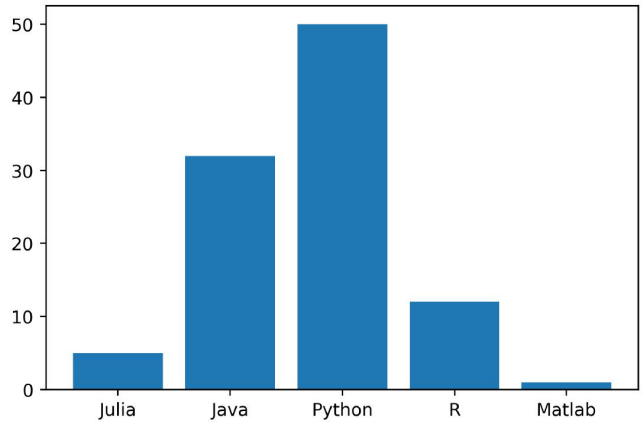
Bar chart

- **Application:** Presents categorical data with vertical or horizontal bars with heights or lengths proportional to the values that they represent.
- **Common syntax:** Use `.bar()` method with most common syntax of `ax.bar(x, height)`

Parameter	Optional?	Description
x	No	sequence of scalars representing the x coordinates of the bars.
bins	No	scalar or sequence of scalars representing the height(s) of the bars.
width	Yes	The width of the bars. Default = 0.8 scalar or array-like, optional.
bottom	Yes	The y coordinate(s) of the bars bases. default is 0 Used mostly for building stacked bar chart

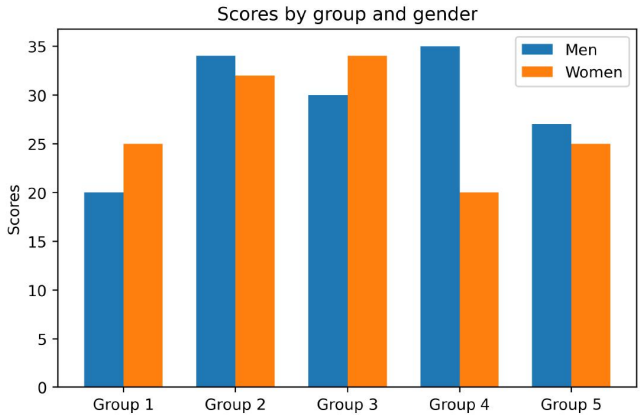
Bar chart Example 1

```
import matplotlib.pyplot as plt

fig, ax = plt.subplots()

enrollment = [5,32,50,12,1]

languages = ['Julia', 'Java', 'Python', 'R', 'Matlab']
ax.bar(languages,enrollment)
```



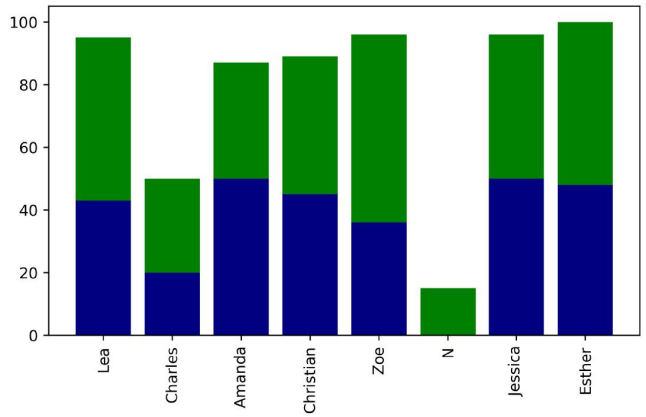
Bar chart Example 2 (taken from `matplotlib` website)

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

labels = ['Group 1', 'Group 2', 'Group 3', 'Group 4', 'Group 5']
men_scores = [20, 34, 30, 35, 27]
women_scores = [25, 32, 34, 20, 25]

x = np.arange(len(labels))  # the label locations
width = 0.35                # the width of the bars

fig, ax = plt.subplots()

# avoiding overlaps by deducting and adding width/2
bar_1 = ax.bar(x - width/2, men_scores, width, label='Men')
bar_2 = ax.bar(x + width/2, women_scores, width, label='Women')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Scores')
ax.set_title('Scores by group and gender')
ax.set_xticks(x)
ax.set_xticklabels(labels)
ax.legend()


fig.tight_layout()
```



Bar chart Example 3 (stacked bar chart)

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

students = ["Lea", "Charles", "Amanda", "Christian", "Zoe", "N", "Jessica", "Esther"]
midterm_grades = [43, 20, 50, 45, 36, 0, 50, 48]
final_grades = [52, 30, 37, 44, 60, 15, 46, 52]

fig, ax = plt.subplots(figsize=(7, 4), dpi=100)
ax.bar(
   students,
   midterm_grades,
   color="navy",
)

ax.bar(
   students,
   final_grades,
   bottom=midterm_grades,
   color="green",
)

ax.set_xticklabels(students, rotation=90)
```



Note: Use `.barh()` for horizontal bar chart.

seaborn

`Matplotlib` is python's most important visualization library because many other visualization libraries in python depend on `matplotlib`. Though `matplotlib` offers high customization, it involves a lot of coding and hence working with `matplotlib` could be very time-consuming. `seaborn` library offers simple, quick (low code), and attractive visualizations especially for data analysis. One of the most important aspects of `seaborn` is that it focuses just on the key elements of the charts. `seaborn` integrates well with `pandas` as well.

`seaborn` is built over `matplotlib` and simplifies many of its operations. We will use aspects of `matplotlib` in visualizing with `seaborn` because some of the `seaborn` operations return `matplotlib` objects.

`seaborn` documentation suggests importing it as `sns`

```
import seaborn as sns
```

because of inner dependency of `seaborn` to `matplotlib.pyplot`; it is highly recommended that whenever you use `seaborn`, you should have

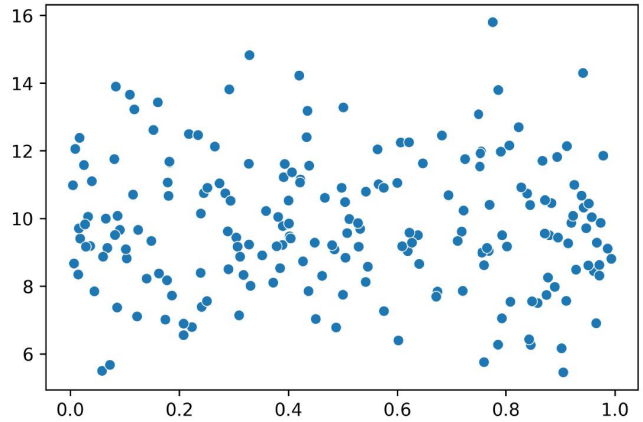
```
import matplotlib.pyplot as plt
```

as well.

Let's start with a simple scatter plot.

> **Example**

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

arr_1 = np.random.random(size=200)
arr_2 = np.random.normal(loc=10, scale=2, size=200)

axes = sns.scatterplot(x = arr_1, y = arr_2)
```



Note about passing data to `seaborn`: One of the many differences between `seaborn` and `matplotlib` is that in using `seaborn` it is highly recommended to determine values of `x` and `y` explicitly.

Passing `pandas` objects to `seaborn`: Often times we pass columns of a `pandas` `DataFrame` as values of `x` and `y`. This could be done in at least two different ways:

- `(x = df["col_1"], y = df["col_2"])` where `col_1` and `col_2` are valid columns in `DataFrame` df.
- The syntax of `(data = df, x = 'col_1', y = 'col_2')` can work equivalently well.

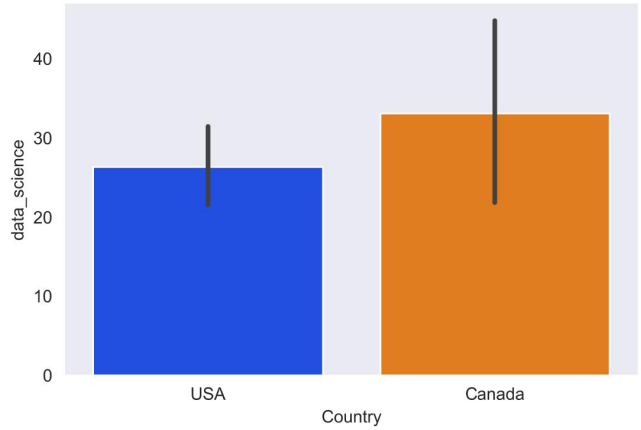
In the remaining of this handout, we will use `clean_search_history.csv` data-set.

`sns.barplot`

Bar plot is used for visualizing categorical columns vs numerical columns. Lets create a barplot of `data_science` popularity for each category value (here `0` and `1`) of `categorical` column.

Example

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("clean_search_history.csv")

sns.set_style("dark")

axes = sns.barplot(data=df, x="categorical", y="data_science", palette="bright")

axes.set(xlabel="Country", xticklabels=["USA", "Canada"])
```



This will set height of every bar equal to the average values in `data_science` column for each value of the `caetgorical` variable (0 and 1 here). `barplot` has an optional argument `estimator` that can controls height of each bar. Try `estimator = sum`, `estimator = len`, or `estimator = median`.

`sns.boxplot`

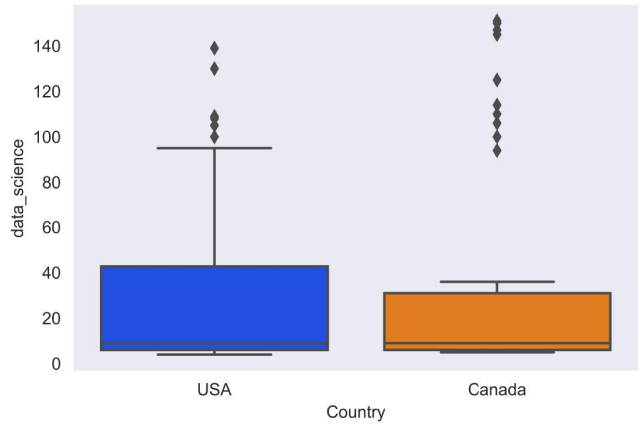
A `boxplot` shows distributions with respect to categories. A `boxplot` is a visual representation of five point summary statistics of a given data set. A five point summary includes `minimum`, `first quartile (25th percentile)`, `median (second quartile or 50th percentile)`, `third quartile (75th percentile)`, and `maximum`. According to `seaborn` documentation:

> A box plot (or box-and-whisker plot) shows the distribution of quantitative data in a way that facilitates comparisons between variables or across levels of a categorical variable. The box shows the quartiles of the dataset while the whiskers extend to show the rest of the distribution, except for points that are determined to be "outliers" using a method that is a function of the inter-quartile (IQ) range.

Technical note: Inter-quartile (`IQ`) of a dataset is defined as `IQ = Q3-Q1` where `Q3` is the 3rd quartile and `Q1` is the 1st quartile. According to Inter-Quartile method, any observation outside `[Q1-3*IQ, Q3+3*IQ]` is considered an `outlier`.

Here is an example:

> **Example**
>
> ```
> import numpy as np
> import pandas as pd
> import matplotlib.pyplot as plt
> import seaborn as sns
>
> df = pd.read_csv("clean_search_history.csv")
>
> sns.set_style("dark")
>
> axes = sns.boxplot(data=df, x="categorical", y="data_science", palette="bright")
>
> axes.set(xlabel="Country", xticklabels=["USA", "Canada"])
> ```



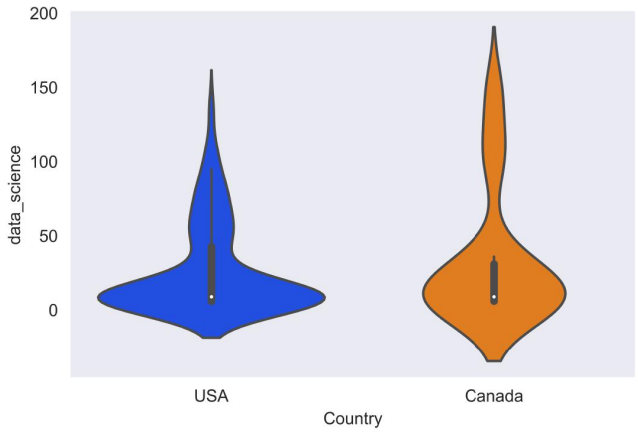
- `boxplot` has an optional argument of `orient`. Try `orient = 'h'`

sns.violinplot

A `violinplot` is a combination of a `boxplot` and a `distplot`. A `boxplot` or a `violinplot` are created for `categorical-continuous` variables (which means that if the `x-axis` is `categorical` and `y-axis` is `continuous`). Here is an example

Example

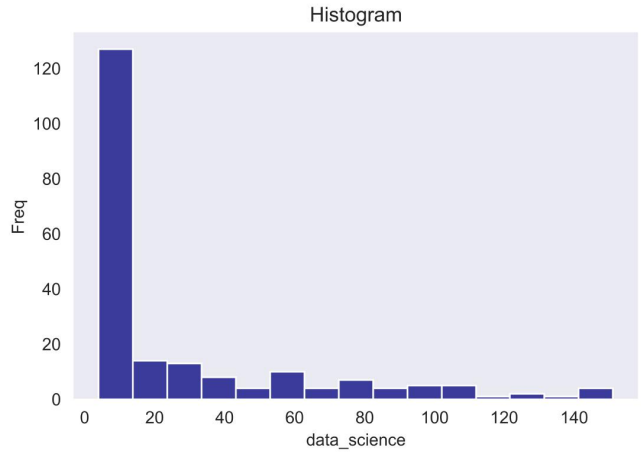
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("clean_search_history.csv")

sns.set_style("dark")

axes = sns.violinplot(
   data=df,
   x="categorical",
   y="data_science",
   palette="bright",
)

axes.set(xlabel="Country", xticklabels=["USA", "Canada"])
```



sns.histplot

Use `sns.histplot` to visualize the distribution of one or more variables. Here are a few example

> **Example**
>
> ```
> import numpy as np
> import pandas as pd
> import matplotlib.pyplot as plt
> import seaborn as sns
>
> df = pd.read_csv("clean_search_history.csv")
>
> sns.set_style("dark")
>
> axes = sns.histplot(data=df, x="data_science", color="navy", bins=15, palette="bright")
> axes.set(ylabel="Freq", title="Histogram")
> ```



- One acceptable rule of thumb for number of bins is $\sqrt{\text{number of rows}}$
- Instead of `bins`, one can pass `binwidth` value.
- A histogram with horizontal bars can be achieved simply by determining value of `y` instead of `x`.
- a kernel density estimate can be added by passing `kde = True` to the `sns.histplot()` method. This provides (smoothed) information about the shape of the distribution. More about kernal density estimate at https://en.wikipedia.org/wiki/Kernel_density_estimation
- `hue` parameter can be used for mapping values a categorical variable. Try `hue = 'categorical`

- If stacked histogram is desired, use `multiple = 'stack'`
- If neither `x` nor `y` is assigned, a histogram is drawn for each numeric column in `data`.
- When both `x` and `y` are assigned, a bi-variate histogram is computed and shown as a `heatmap`

sns.distplot

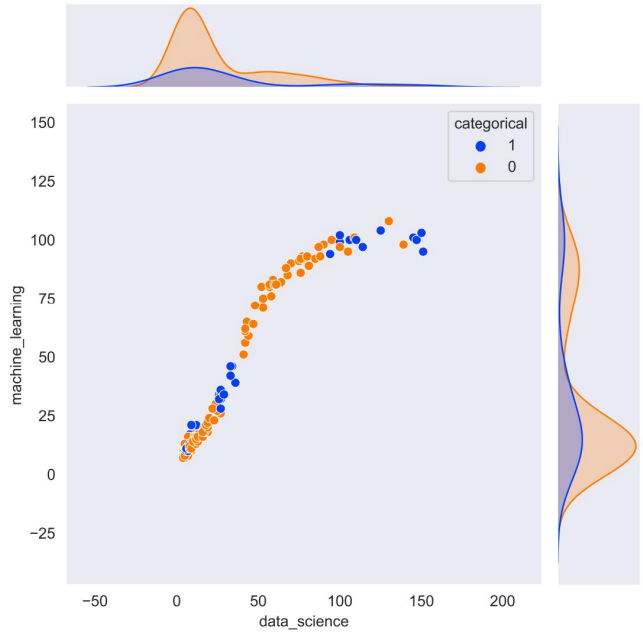
A closely related plot is `sns.distplot` to visualize the distribution of one or more variables.

sns.jointplot

This method draw a plot of two variables with bi-variate (scatter plot) and uni-variate (histogram) graphs. A Joint-Plot takes two variables and creates Histogram and Scatter plot together.

Scatter plot is used for visual inspection of correlation and histogram is used for inspecting approximate shape of data distribution.

> **Example**
>
> ```
> import numpy as np
> import pandas as pd
> import matplotlib.pyplot as plt
> import seaborn as sns
>
> df = pd.read_csv("clean_search_history.csv")
>
> sns.set_style("dark")
>
> axes = sns.jointplot(
>    data=df,
>    x="data_science",
>    y="machine_learning",
>    hue="categorical",    # categorical variable for mapping color of plot elements
>    hue_order=[1, 0],     # order of plotting for categorical levels of the hue
>    color="navy",
>    palette="bright",
> )
> ```

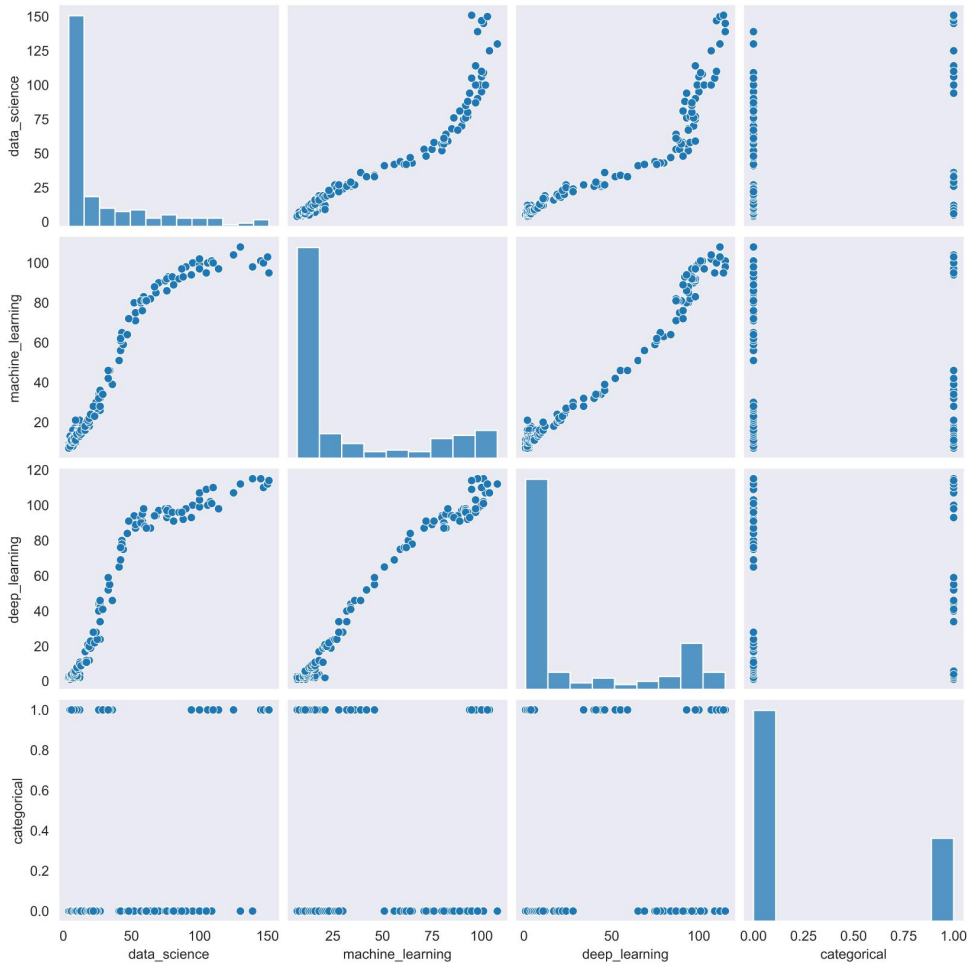


Note: `jointplot()` has an optional argument of `kind` with default value of `scatter`. Try: `kind = reg`, `kind = resid`, `kind = kde` and `kind = hist`. How do you think you can use `kind=resid`?

sns.pairplot

A `pairplot` visualizes a pairwise relationships among numerical values in a data-set.

> **Example**
>
> ```
> import numpy as np
> import pandas as pd
> import matplotlib.pyplot as plt
> import seaborn as sns
>
> df = pd.read_csv("clean_search_history.csv")
>
> sns.set_style("dark")
>
> axes = sns.pairplot(data = df)
> ```



- The diagonal part shows the `distplot` or `histogram` with kernel density estimation. The upper and lower part of the `Pairplot` shows the `scatterplot`.
- The `hue` parameter can be used to color the plot using categorical columns.
- The `kind` parameter is similar to `jointplot`.

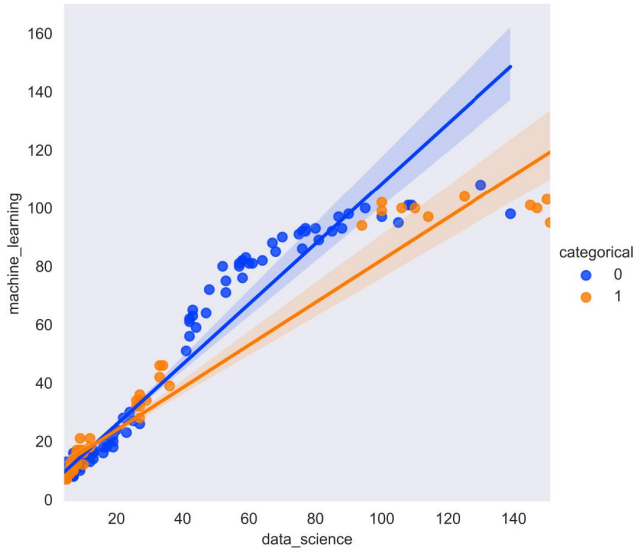
Try `axes = sns.pairplot(data=df, kind="reg", hue="categorical")`

sns.lmplot

You are familiar with `lmplot` from linear regression part of the course. `lmplot` is a plot that fits the ordinary least square regression line to the data-set showing as `scatterplot` (s).

> **Example**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("clean_search_history.csv")

sns.set_style("dark")

axes = sns.lmplot(data = df, x = 'data_science', y = 'machine_learning', hue = 'categorical',
palette = 'bright')
```

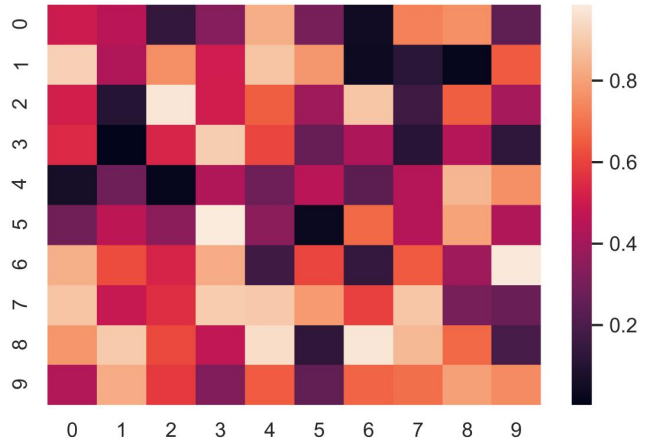


sns.heatmap

`heatmap` One of the most popular plots provided by `seaborn`. Let's look at several cool `heatmaps` taken from `seaborn` website.

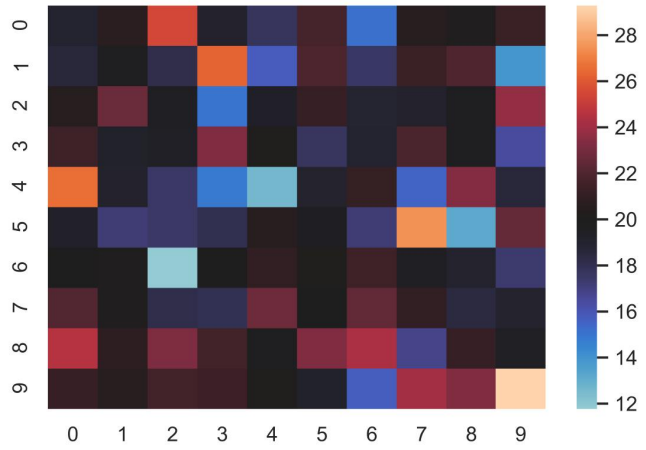
> **Uniform `heatmap` example**

```
import numpy as np
import seaborn as sns
sns.set_theme()
uniform_data = np.random.random(size = (10, 10))
ax = sns.heatmap(uniform_data)
```



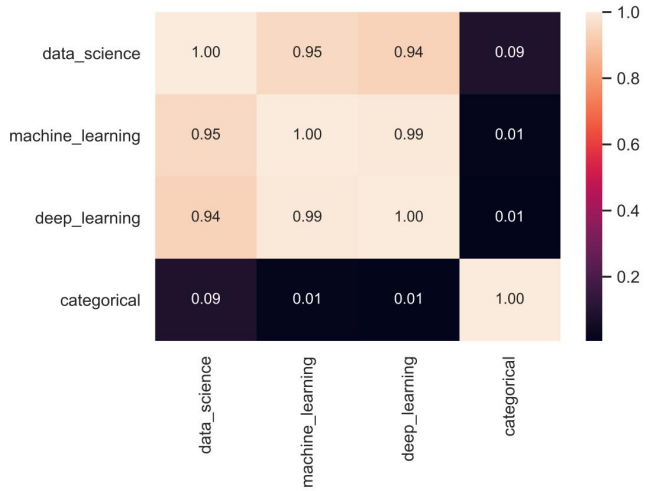
> **Normal `heatmap` example**

```
import numpy as np
import seaborn as sns

sns.set_theme()
normal_data = np.random.normal(loc=20, scale=3, size=(10, 10))
ax = sns.heatmap(normal_data, center=20)
```



Besides making cool-looking plots(!), in data analytics it is very common to use `heatmap` to show all the correlations between variables in a dataset. Here is an example

> **`heatmap` for visualizing correlation example**
>
> ```
> import numpy as np
> import pandas as pd
> import matplotlib.pyplot as plt
> import seaborn as sns
>
> df = pd.read_csv("clean_search_history.csv")
>
> sns.set_style("dark")
>
> axes = sns.heatmap(df.corr(), annot=True, fmt=".2f")
> ```



saving a `sns` plot

Similar to `matplotlib`, `savefig()` method could be used to save a `seaborn` plot. Here is the most common syntax used for `savefig`:

```
plt.savefig("file_name.extension", dpi = , facecolor = , edgecolor = , bbox_inches='tight', pad_inches = 0.5)
```

References

This document is an adaption from the following references:

1- *Python online documentation*; available at https://docs.python.org/3/

2- *Exploratory Data Analysis with Python*; Suresh Kumar Mukhiya and Usman Ahmed, Packt publications, 2020

3- *Introduction to programming in Python*; available at https://introcs.cs.princeton.edu/Python/home

4- *Introduction to Computation and Programming Using Python: With Application to Understanding Data*, John Guttag, The MIT Press, 2nd edition, 2016

5- *Introduction to Python for Computer Science and Data Science*, Paul J. Deitel, Harvey Deitel, Pearson, 1st edition, 2019

6- *Data Mining for Business Analytics*, Galit Shmueli, Peter C. Bruce, Peter Gedeck, Nitin R. Patel, Wiley, 2020

7- *Interactive Data Visualization with Python*; Abha Belorkar, Sharath Chandra Guntuka, Shubhangi Hora, and Anshu Kumar. Packt publications, 2020

8- *Simulation Modeling with Python*; Giuseppe Ciaburro, Packt publication, 2020

9- https://betterprogramming.pub/

10- https://www.learnpython.org/

11- https://seaborn.pydata.org/

12- https://pyviz.org/index.html

13- https://numpy.org/

14- https://pandas.pydata.org/

15- *Pandas Cookbook*, Matt Harrison and Theodore Petrou, Packt publications, 2020