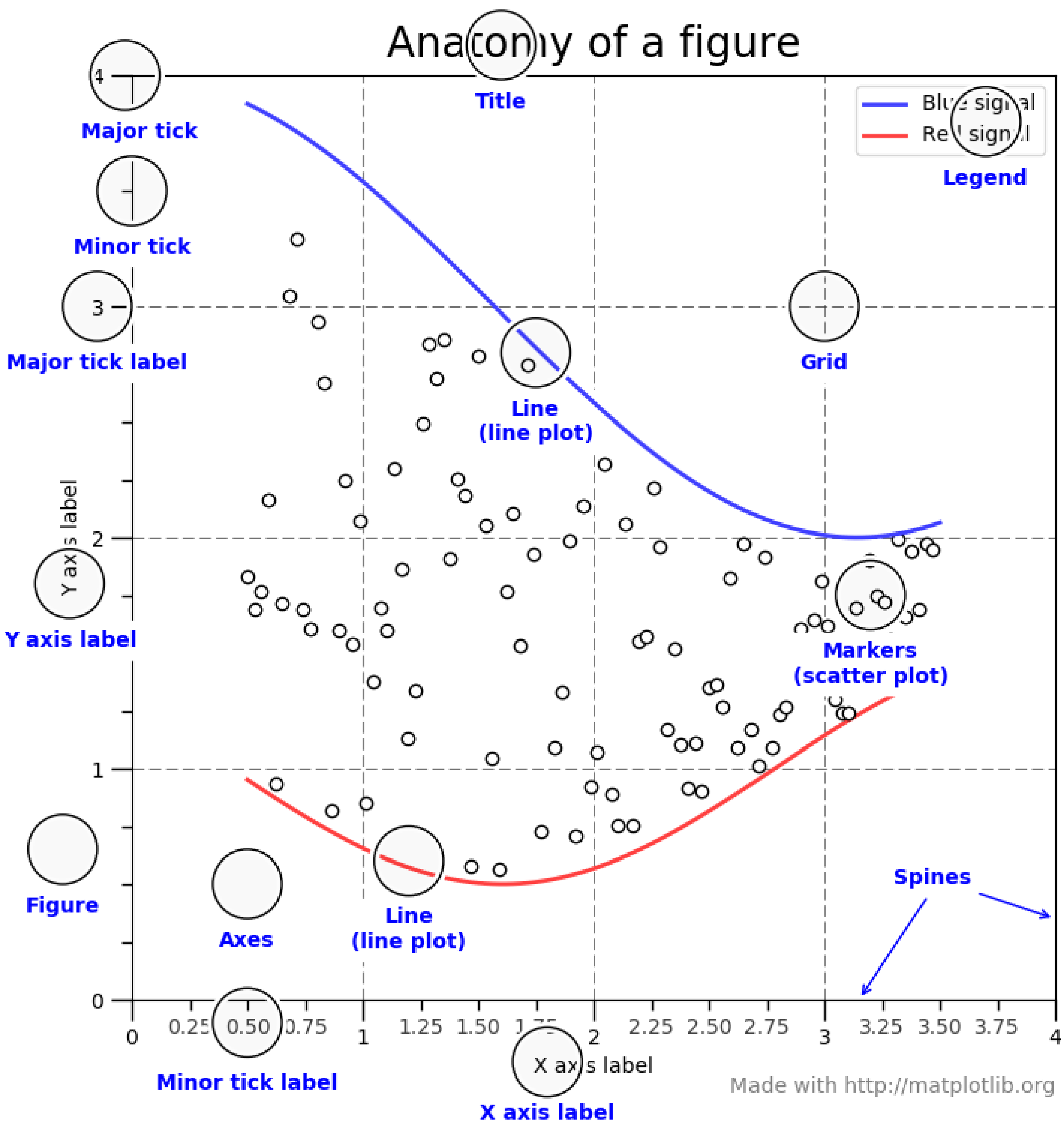
Matplotlib and Seaborn

Matplotlib and Seaborn are Python graphing libraries that are ubiquitious in the machine learning and data science world. Seaborn is an extension to Matplotlib that provides a high level interface to make prettier plots out of the box than Matplotlib.

Matplotlib



Matplotlib graphs data onto `Figure` 's, which can have one or more `Axes` . All markings on the figure like the labels and ticks are called `Artist` 's.
Matplotlib has two ways to access its graphing capabilities: an object oriented api and the PyPlot api. The object oriented api allows the user to explicitly create figures and axes for a plot, whereas the pyplot api automatically creates and manages the figure and axes for a plot.
The object oriented access starts by creating figures and axes manually. To create a figure and axes, one would run

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

To plot data onto these axes, we can use the plot method of the Axes class.

```
ax.plot(x, y, label="myFunc")
```

From there, we can set artists like the title and the labels.

```
ax.set_xlabel('x label')
```

However, for most basic graphs, using pyplot will be most convenient. We don't have to manually create and manage plots using subplots(), instead we can just use the call `plt.plot(x=...,y=...)` where pyplot will manage all of our figures for us. We can still edit our figures by acccessing the methods of the plt variable.

```
plt.ylabel('some numbers')
```

Seaborn

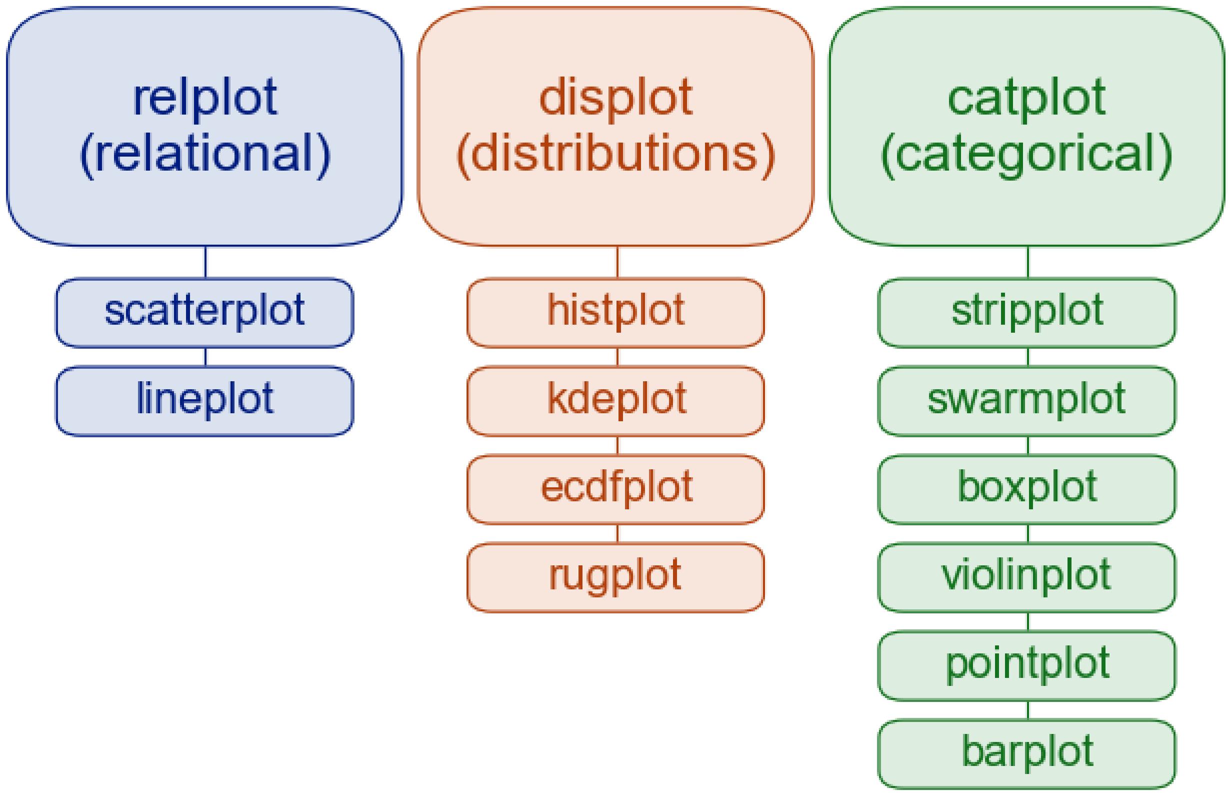
Seaborn is an extension of Matplotlib that allows the user to easily create well styled graphs. It behaves similarly to pyplot, in that you create graphs by calling seaborn functions such as

```
sns.barplot(data=...,x=...,y=...)
```

Using seaborn is very convenient and easy, allowing us to make presentable graphs very fast. There are very few situations that matplotlib alone is preferrable to it.

Figure Level Plots vs Axes Level Plots

Something that might be confusing when jumping into seaborn is understanding **figure level** plots vs **axes level** plots. Axes level functions plot data onto a Seaborn axes object, which is self contained. Figure-level functions offer a unitary interface to its various axes-level functions. For example, when we worked with displot for all the histogram and density curve plots, those were a figure level plot. However, scatterplot was a axes level plot.



relplot, displot, and catplot all create figure level plots, and the rest of the functions underneath them create axis level plots. You can make any axis level plot using the figure level plots by specifying the kind parameter. For instance, instead of using sns.scatterplot, we can use

```
sns.relplot(data=df, x="x_var", y="y_var", kind="scatter")
```

For lineplot, we can use

```
sns.relplot(data=df, x="x_var", y="y_var", kind="line")
```

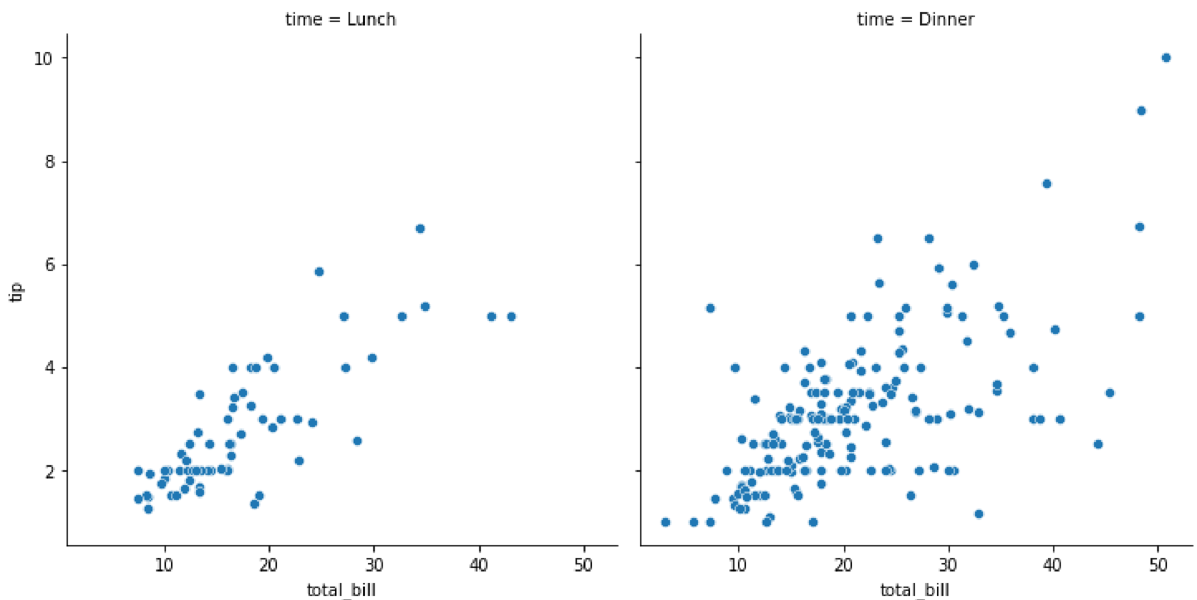
All of the functions like pointplot, barplot, rugplot, etc. create axis level plots, which return a single Axes object that has the data graphed onto it.
Next, we will understand the most common graphing functions in seaborn to give you a handle on how to use them.

Facet Grid

Figure functions return a FacetGrid object, which maps a dataset onto multiple axes arrayed in a grid of rows and columns. The resulting object is like a grid of plots, with row*columns total plots. The FacetGrid class is useful when you want to visualize the distribution of a variable or the relationship between multiple variables separately within subsets of your dataset. Having rows and columns allows us to make multiple plots that change which part of the dataset its looking at. For example, on this toy dataset we can see the grid that setting the `row` and `col` parameters create.

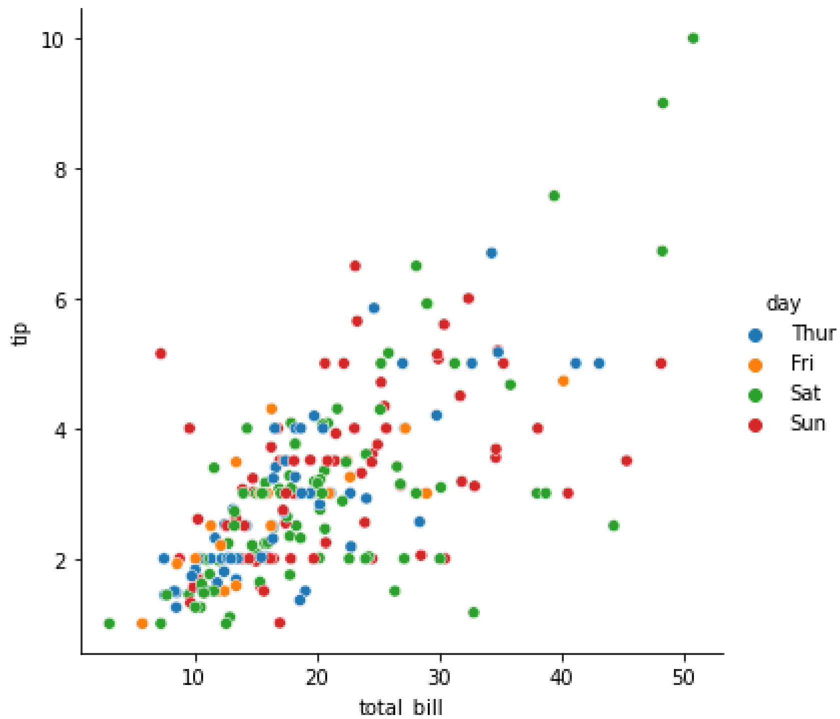
In [ ]:
```
import seaborn as sns
tips = sns.load_dataset("tips")
tips.head()
sns.relplot(data=tips, x="total_bill", y="tip", col="time")
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7ffef6a438>
```



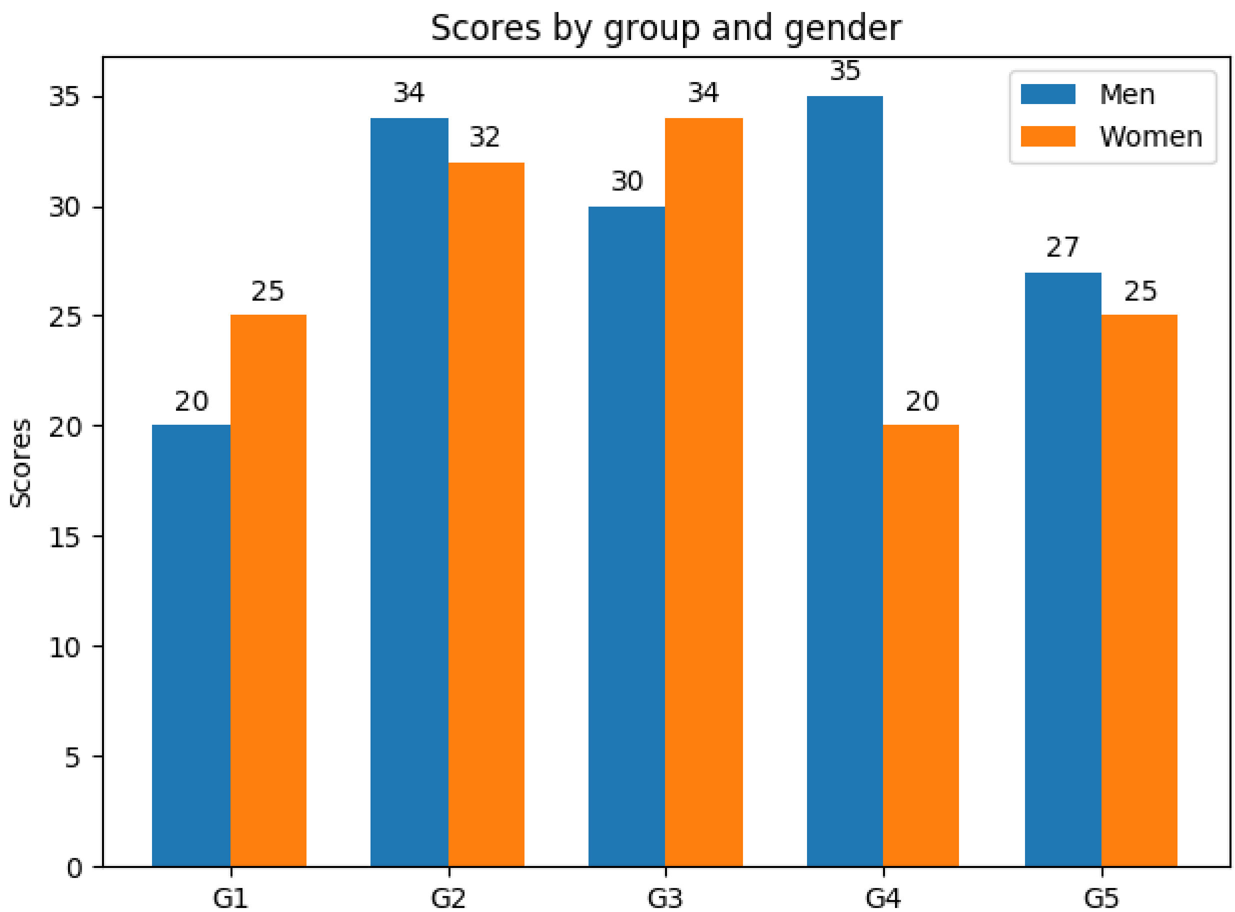
It can also represent levels of a third variable with the hue parameter, which plots different subsets of data in different colors.

```
In [ ]: import matplotlib.pyplot as plt
        sns.relplot(data=tips, x="total_bill", y="tip", hue="day")
```



Setting `row` , `col` , and `hue` allows us to graph many subsets of a dataframe very easily and works for all of the **figure** level functions (catplot, displot, relplot). Only `hue` works on the axis level functions (barplot, histplot etc.)

Bar Plots


Scores by group and gender
Men
Women
Scores
0
5
10
15
20
25
30
35
20
25
34
32
30
34
35
20
27
25
G1
G2
G3
G4
G5

Bar Plots are a visualization technique useful for comparing the values realized by a numerical variable in a data set via the height of each bar. In seaborn, bar plots are specially useful for providing an estimate of a central tendency accross multiple realizations of a numerical variable. By default bar plots in seaborn estimate the mean of the variable of interest for each group defined by the x-axis, but a different estimator can be used. In both plots, the x-axis can be used more flexibly with the option of reflecting a label, useful in categorical data, or a realization of another numerical variable of interest.

When the x-axis forms categorical data which will have few values it may be useful to use matplotlib to stack these values in bars. When lots of data entries are expected in each category, seaborn's estimator representation may be more useful.

Suppose we want to plot a column of groups `x` with a column of realized values `y` in a dataframe `df`. Figure level plot:

```
sns.catplot(data=df, x=x, y=y)
```

Axes level plot:

```
sns.barplot(data=df, x=x, y=y)
```

Using pyplot from matplotlib (as plt):

```
# plt.bar(X, Y, width=0.8, bottom=None, align='center')

plt.bar(range(len(df['col_name'])), df['col_name'])
```

We can also group different plots into one via a third variable. For example, the graph shown above plots the score of each group since this produces two plots for Male and Females we can group them via the Sex variable. To do this in Seaborn we can use the hue parameter:

```
sns.barplot(x="x", y="y", hue="z", data=df)
```

As noted earlier, Seaborn makes it easy to view the bar plots as following a central tendency, i.e typically the mean. However, sometimes its more appropriate to look at other statistically significant variables in each group, such as the median.

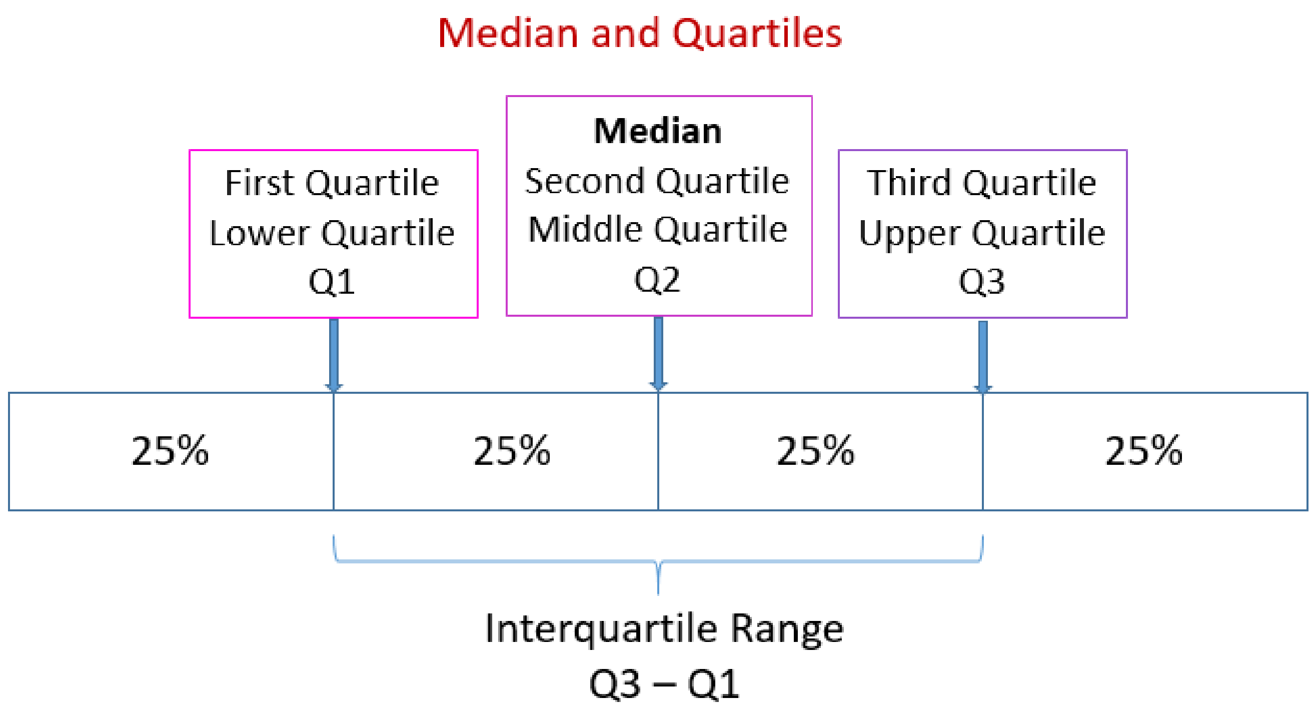
```
from numpy import median
sns.barplot(x="x", y="y", data=df, estimator=median)
```

Error bars in Seaborn bar plots can also reflect preset confidence intervals, we can set the width of the interval in percent via the ci parameter.

```
sns.barplot(x="x", y="y", data=df, ci=68) # or ci='sd' for standard deviatio
n
```

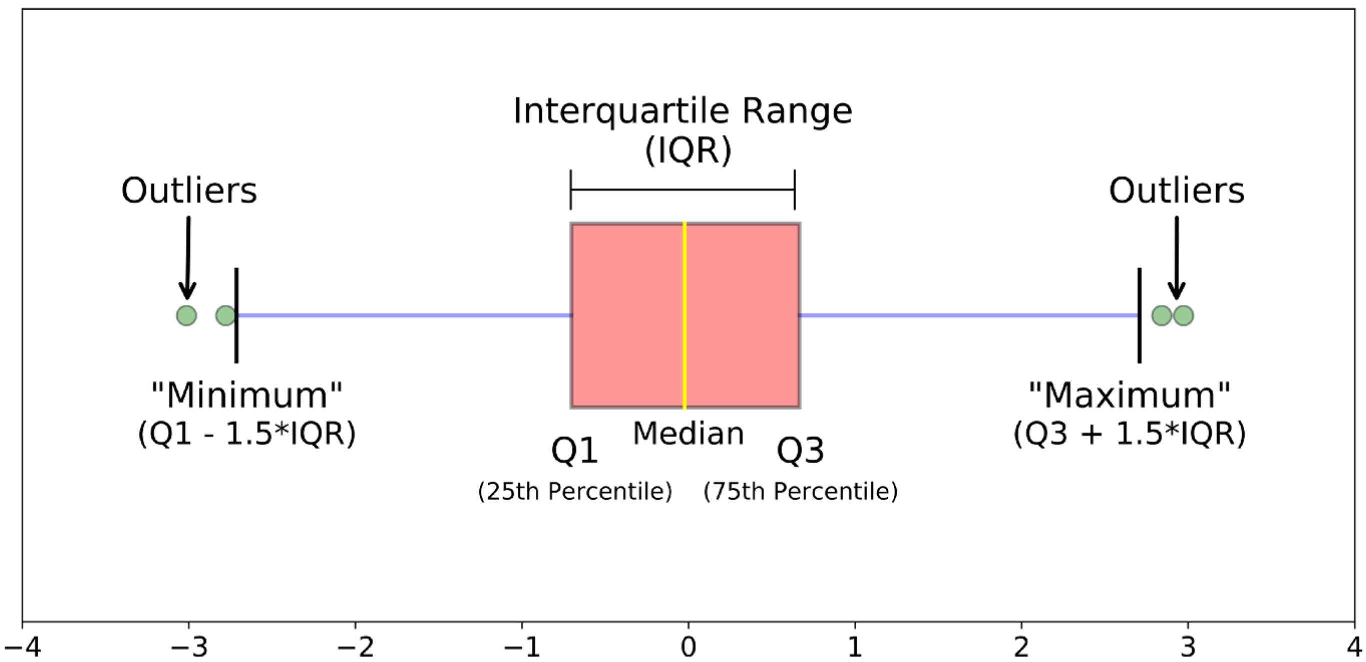
Box Plots

First, it's useful to go over what quartiles are. Quartiles, as the name suggests, split our data up into four equally sized groups (each group contains the same number of datapoints). The first quartile, or lower quartile, acts as the 25th percentile, which means that 25% of our data falls below it. Similarly, the second quartile, which doubles as the median of our data, acts as the 50th percentile while the third quartile, or upper quartile, acts as the 75th percentile.
The Interquartile Range is all the data between the upper and lower quartilea and about 50% of of our data lies in this range.



After viewing the image above, it's useful to think of each quartile as a one of the inner lines splitting a rectangle into fourths.

Box plots are great tools for visualizing the spread of your data. They capture the essence of the data's spread, by transforming it in a "box," where the top line of the box represents the upper quartile, the bottom line of the box represents the lower quartile, and the line between them (which isn't nesscarily in the middle of the box) represents the second quartile, or median. Data points that are more than the interquartile range (IQR) * 1.5 away from the upper or lower quartile are considered outliers.



Boxplots allow us to efficiently identify the median values, variability, potential skewedness, overall shape, and outliers of the dataset at a glance. They are best used for visualiation numerical distrubutions of categorical variables

To create a single box plot using seaborn, run the following command on a dataframe "df" to view the spread of the values within "col_name" Figure level plot:

```
sns.boxplot(x="col_name", data=df)
```

Axes level plot:

```
sns.catplot(x="col_name", data=df, kind="box")
```

Side by side boxplots
Also known as a parallel boxplot or comparative boxplot, a side-by-side boxplot is a visual display comparing the levels (the possible values) of one categorical variable by means of a quantitative variable.

If we wanted to view the distributions of the values in column `y` grouped by the labels in column `x` in the dataframe `df`, we can use the following.
Figure level plots:

```
sns.catplot(x="", y="" data=df, kind="box")
```

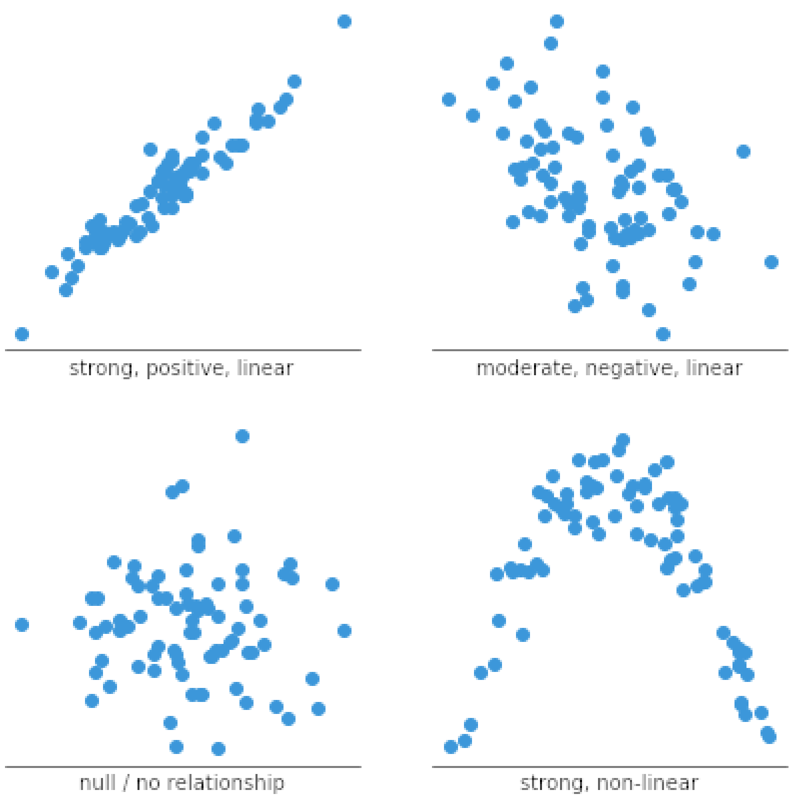
Axes Level Plots

```
sns.boxplot(x="", y="" data=df)
```

Scatterplots

Scatterplots are meant to visualize the relationship between two quantitative varibles, with each varible being represented along one axis. Since we treat one varible like the as the x axis, and another like the y axis, it's almost as though one varible is a function of the other. Because of this relationship, scatterpolts are able to give us useful intutition into the relationships between variables.

Take a look at the image below



Depending on how our data is scattered will determine what type of relationship we have. Strong relationship are characterised by more tightly knit points following a pretty clear curve or line, while weaker relationships are charcterized by seemingly noiser data with little to no underlying structure.

Let's say we had a dataframe df and we wanted to plot the column with name `x` against the column with name `y`.

Figure level plot:

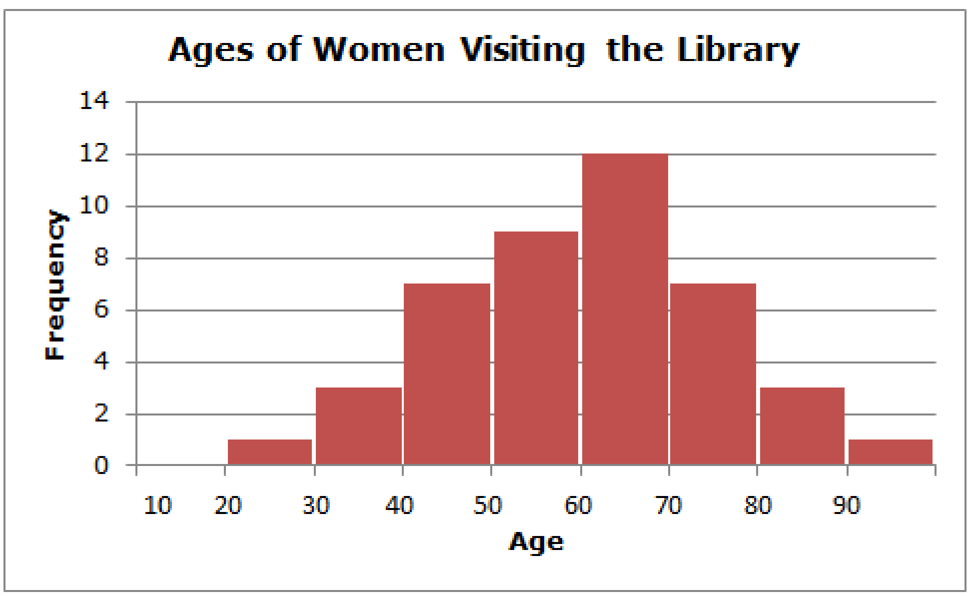
```
sns.displot(data=df, x="x", y="y", kind="scatter")
```

Axes level plot:

```
sns.scatterplot(data=df, x="x",y="y")
```

Histograms

A histogram allows us to visualize the distribution of numerical data. To construct one, we first take the range of values of our data and divide it into discrete "bins" or intervals. Then we count the number of times our data falls into each interval. Our bins should be consecutive and non overlapping, and the same size. *italicized text*



In the above histogram, our bins are age ranges of 10 years. This allows us to visualize the distribution of the ages of women visiting the library. Histograms are useful when we want to visualize the underlying **distribution** of **numerical data**.

Given a pandas dataframe df, and a column name for the column we want to visualize, we can use the following code. num is the number of bins we want in our histogram. Seaborn will automatically bin our data for us, and set our scaling.

Figure level plot:

```
sns.displot(df, x="col_name", bins=num)
```

Axes level plot:

```
sns.histplot(df, x="col_name", bins=num)
```

Density curves

A histogram aims to approximate the underlying probability density function that generated the data by binning and counting observations. Kernel density estimation (KDE) presents a different solution to the same problem. Rather than using discrete bins, a KDE plot smooths the observations with a Gaussian kernel, producing a continuous density estimate. You'll learn how these kernels work in future assignments in this class, so don't worry about it for now.
In seaborn, we can easily add a density curve to our figure level histogram by using the attribute kind="kde", i.e.

```
sns.displot(data=df, x="col_name", kind="kde")
```

For our axes level plot, we can use the `kdeplot` function.

```
sns.kdeplot(data=df, x="x")
```

Joint Plotting

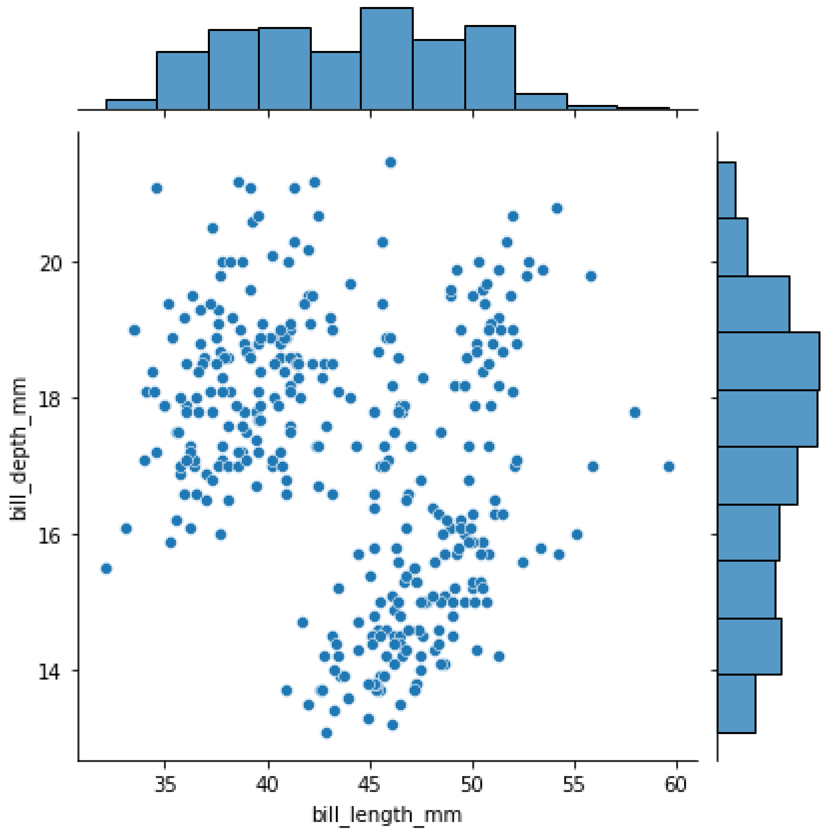
What if we want to visualize both a bivariate and univariate graph at the same time. Seaborn's `jointplot` can be useful for this. If we have a dataframe df, we can visualize it with the following code:

```
sns.jointplot(data=df, x='', y='', kind = '', hue='')
```

The default behavior (i.e. without supplying the kind variable) will return a scatterplot for the relationship and a histogram for the univariate distributions of x and y.

```
In [ ]: penguins = sns.load_dataset("penguins")
        sns.jointplot(data=penguins, x="bill_length_mm", y="bill_depth_mm")
```

```
Out[ ]: <seaborn.axisgrid.JointGrid at 0x7f7ffa055d68>
```



Pair plots

We might want to visualize many variables and their relationships in an effort to get an understanding of many different relationships in our data. The pair plot visualizes all pairwise combination of variables for a dataframe.

```
sns.pairplot(data = df)
```

```
In [ ]: penguins = sns.load_dataset("penguins")
        sns.pairplot(penguins)
```

Text and Annotations

Sometimes we may want to annotate our plots to point out interesting features. Matplotlib provides several text functions that help us do this. When given an Axes `ax` and a Figure `fig`, we can perform the following functions.

`Axes.text`

Adds string `text_to_add` at an arbitrary position (`x` , `y`) on the Axes using the Axes coordinate system.

```
ax.text(x, y, text_to_add)
```

`Axes.annotate`

Draws an arrow from `xytext` to `xy` on an Axes object that has the string `text` drawn at `xytest` .

```
ax.annotate(text=text, xy=(x, y), xytext=(text_x, text_y),
                   arrowprops=dict(arrowstyle="->", connectionstyle="arc3"))
```

`Axes.set_title`

Sets the title as `label` for an Axes object.

```
ax.set_title(label)
```

`Axes.set_ylabel`

Sets the label for the y axis of a given Axes object as ylabel

```
ax.set_ylabel(ylabel)
```

`Axes.set_xlabel`

Sets the label for the x axis of a given Axes object as xlabel

```
ax.set_xlabel(xlabel)
```

`Figure.suptitle`

Sets the title for the entire figure as `fig_title` .

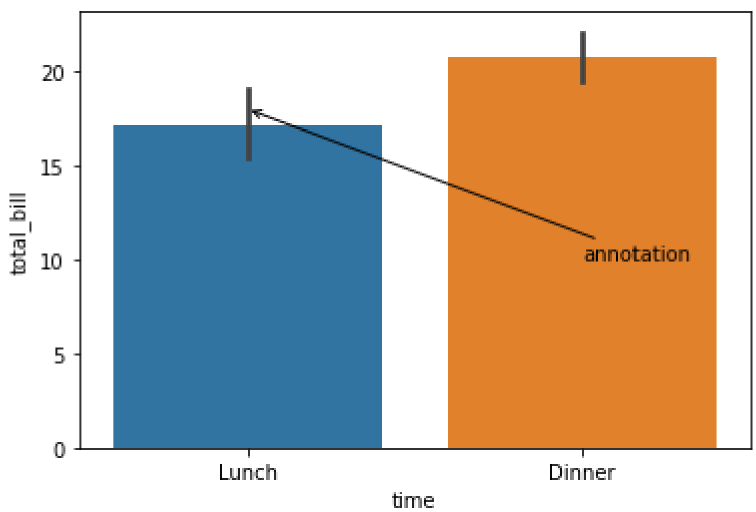
```
fig.suptitle(fig_title)
```

Text and Annotations in Seaborn

In order to use these functions in Seaborn, we must make sure we are working with the Axes and Figure objects. If we just graphed something with one of Seaborn's axes level functions, we can use the methods above directly on them. If we used a figure level plotting function, all of the Axes objects are in FacetGrid's `.axes` attribute, which is a list of all the Axes objects for each plot in the grid. The figure for a FacetGrid is located in the `.fig` attribute.

In [ ]:
```
ax = sns.barplot(data=tips, y="total_bill", x="time")
ax.annotate("annotation",
            xy=(0,18), xycoords='data',
            xytext=(1, 10), textcoords='data',
            arrowprops=dict(arrowstyle="->",
                            connectionstyle="arc3"),
            )
```

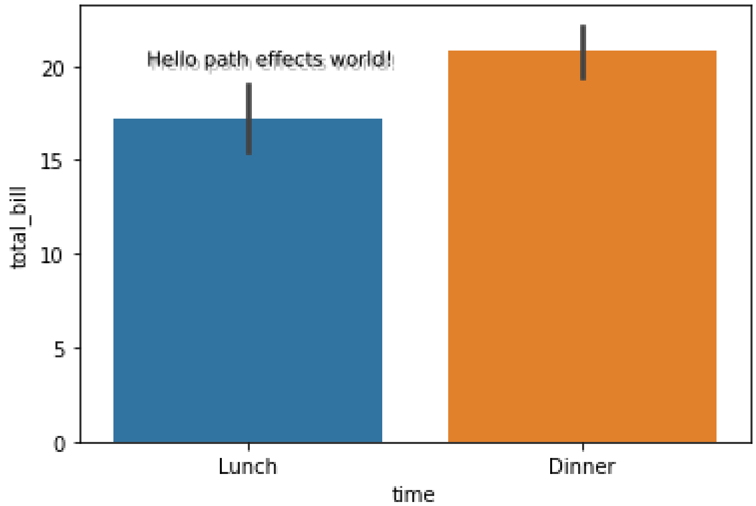
Out[ ]: `Text(1, 10, 'annotation')`



Path effects for artists (annotations, text)

Passing in a `path_effects` paramater allows us to create effects. You can find these effects on the Matplotlib [website (https://matplotlib.org/api/patheffects_api.html#module-matplotlib.patheffects)](https://matplotlib.org/api/patheffects_api.html#module-matplotlib.patheffects).

```
In [ ]: import matplotlib.patheffects as path_effects
        ax = sns.barplot(data=tips, y="total_bill", x="time")
        text = plt.text(-0.3,20, 'Hello path effects world!',
                        path_effects=[path_effects.withSimplePatchShadow()])
```



Sliders in Matplotlib

The matplotlib provides useful widgets one of which is the slider. With sliders we can interactively set a value for a variable. This is specially useful when we seek to plot because it adds interaction to our plot and allows us to see the effects of varying a variable.

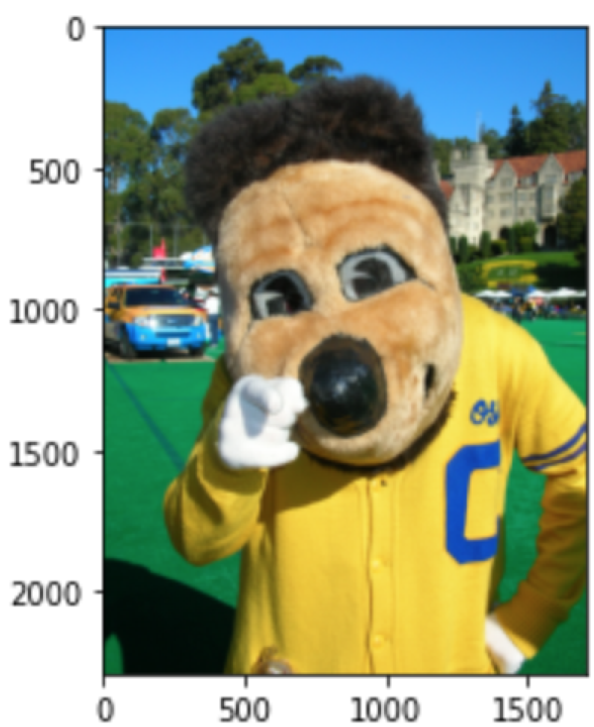
Sliders can be constructed using the following code:

```
# Sliders using matplotlib.widgets
from matplotlib.widgets import Slider, Button, RadioButtons

# First define the range of the parameter:
a_min = 0  # minimum parameter value
a_max = 10 # maximum parameter value
a_init = 1 # default parameter value
slider_axis = plt.axes([0.1, 0.05, 0.8, 0.05])

a_slider = Slider(slider_axis,
                  'a',
                  a_min,
                  a_max,
                  valinit=a_init
                  )

plt.show()
def update(a):
  print(a)
a_slider.on_changed(update)
```

Working with Images

Images are an important tool for visualization, we can bring images (in png format) into our code using the matplotlib image library. This library provides tools for loading, rescaling, and displaying the image within our code environments.

```
 ...
 [0.         0.29803923 0.10980392 1.        ]
 [0.         0.3647059  0.18039216 1.        ]
 [0.         0.34117648 0.16078432 1.        ]]

[[0.         0.40784314 0.1764706  1.        ]
 [0.         0.4        0.17254902 1.        ]
 [0.         0.39607844 0.18039216 1.        ]
 ...
 [0.         0.32941177 0.14117648 1.        ]
 [0.         0.3647059  0.18039216 1.        ]
 [0.         0.3137255  0.12941177 1.        ]]]
<matplotlib.image.AxesImage at 0x7f8e44c3c400>
```



Images can be loaded and stored into Image objects provided by the image library. Using these objects we can view the raw RGB data from our png, or we can print these as image data.

```
import matplotlib.image as mpimg
# Importing a local image
img = mpimg.imread('oski_game.png')

'''
matplot allows us to see the image file in its raw form by printing:
'''
print(img)
'''
matplot also allows us to view the image by calling imshow from pyplot.
'''
plt.imshow(img)
```