

# Programming for psychologists

**Lecture 4: Data visualization**

Matthias Nau

# Data viz in Python



# Why do good data viz skills matter?



## The obvious

- Summarizing complex information to make inferences.
- Finding patterns in data that may otherwise be missed (incl. outliers and anomalies).
- Communicating results to (non-expert) readers.
- Enhancing credibility of your research while reducing risk of misinterpretation.

## The less obvious (maybe)

- Plotting makes coding more fun: you see what your code is doing.
- Plotting data after each processing step is central for debugging.
- Good figures get people's attention, bad figures can make them turn away.  
You will feel the difference when attending a conference.

# Key libraries for data viz in Python



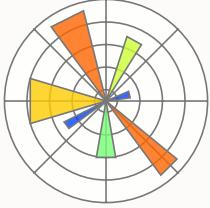
There are **many libraries in Python** with data visualization functionality

**Most relevant to research psychologists are the following:**

- **Matplotlib**: Foundational library for creating static and animated plots.
- **Seaborn**: High-level interface for beautiful graphics, built on top of Matplotlib
- **Pandas**: Built-in visualization functions for dataframes, built on top of Matplotlib
- **Plotly & Bokeh**: Interactive plots, including web-based applications  
(simple example: <https://demo.bokeh.org/sliders>)

# Matplotlib





# Matplotlib

The **most popular** Python library for creating **almost any type of figure.**

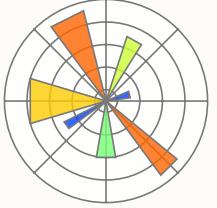
Comes with a large range of **customization options** (line color, width, etc).

Heavily inspired by plotting functionality of **MatLab**.

Check out their **Gallery**:

<https://matplotlib.org/2.0.2/gallery.html>





# Matplotlib – The basics

The **most basic way** of using Matplotlib is calling the **plot function**.

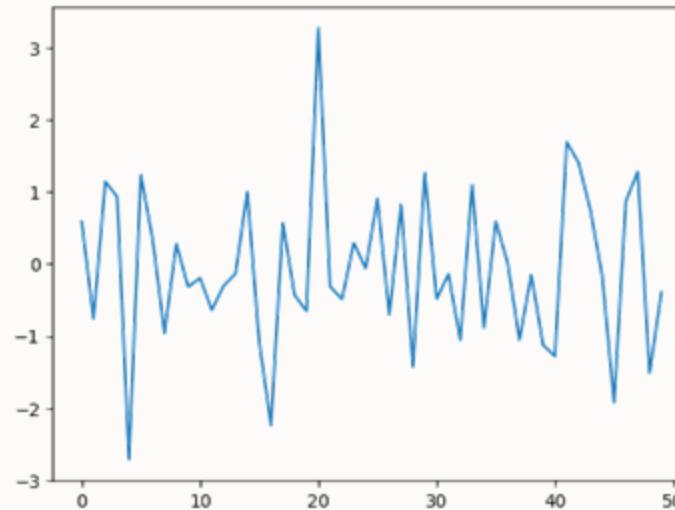
**Do this...**

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

# plot
plt.plot(np.random.randn(50))
```

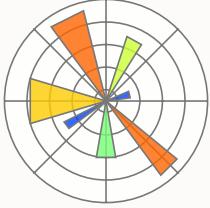
*Note: Community convention is to  
import matplotlib.pyplot as plt*

**...to get that**



*Note: Plotting a few random numbers  
here generated with NumPy*

This works in notebooks. If you are using scripts, add the **plt.show()** command underneath.



# Matplotlib – The basics

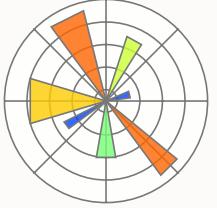
The **plot function** is great for quick visualization, but its customization options are limited. In most cases, what we actually want is a **Figure object**.

A figure object is essentially a **blank canvas** that waits for things to be plotted.

We create a figure (called fig1) with size 3x3 using the following command: **fig1 = plt.figure(figsize=(3,3))**

Now, we could plot into fig1 using the plot function, but really **figures** begin to shine after adding **Axes!**

Nothing to  
see here yet



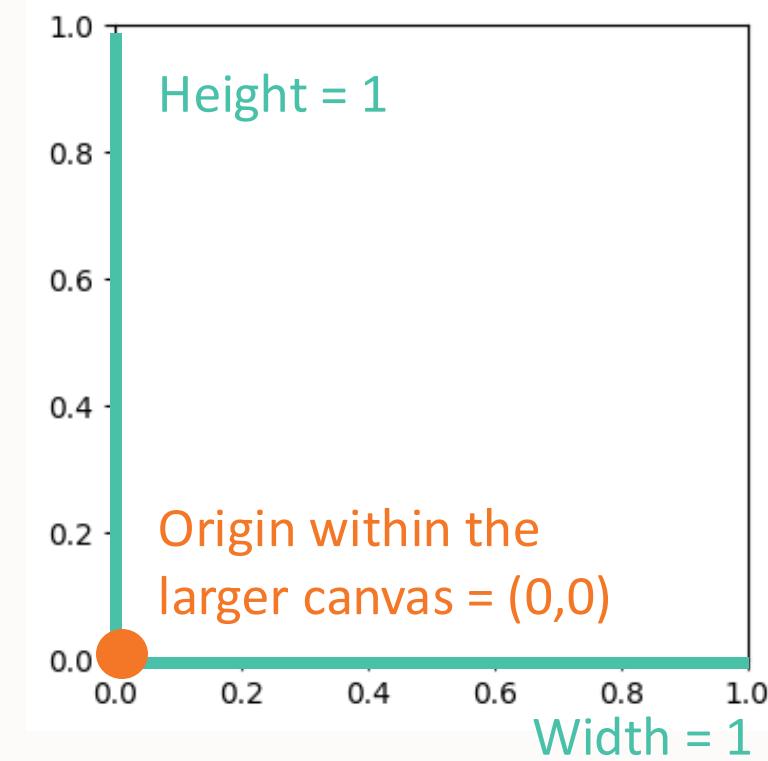
# Matplotlib – The basics

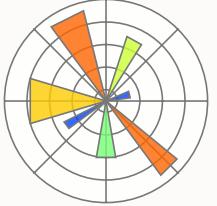
Axes allow **controlling the size and position of the final plot** within the larger canvas

```
# create figure
fig1 = plt.figure(figsize=(3,3))

# add axes
ax1 = fig1.add_axes([0, 0, 1, 1])
# [left, bottom, width, height]
plt.show()
```

There can be **multiple axes** within the same canvas (i.e. multiple plots)!





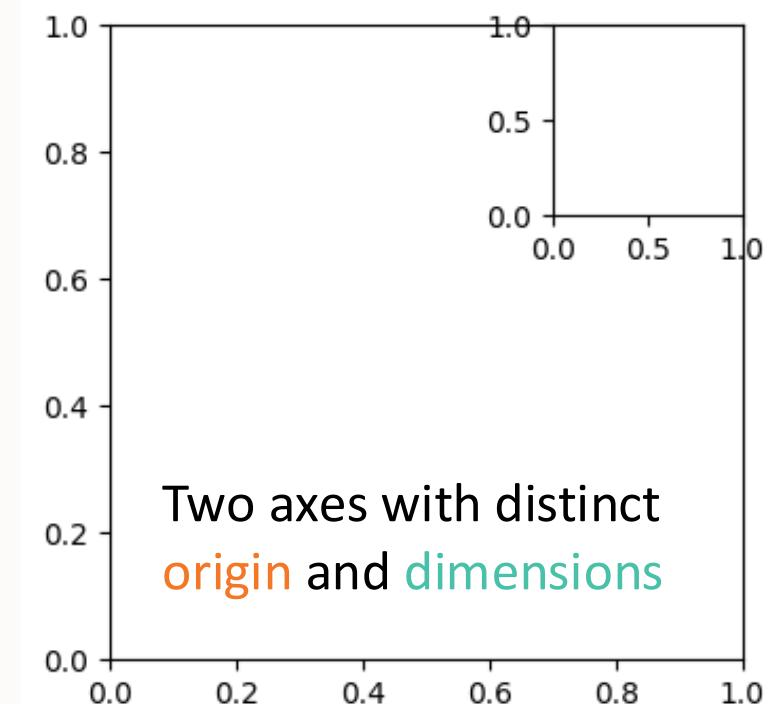
# Matplotlib – The basics

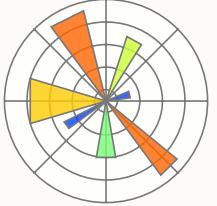
Axes allow **controlling the size and position of the final plot** within the larger canvas

```
# create figure
fig1 = plt.figure(figsize=(3,3))

# add axes
ax1 = fig1.add_axes([0, 0, 1, 1])
ax2 = fig1.add_axes([0.7, 0.7, 0.3, 0.3])
plt.show()
```

There can be **multiple axes** within the same canvas (i.e. multiple plots)!





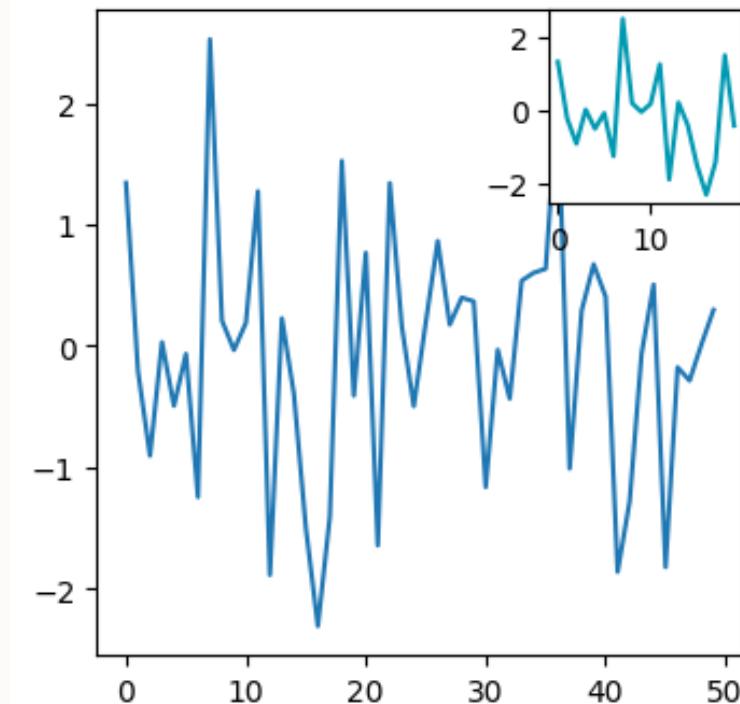
# Matplotlib – The basics

Axes allow **controlling the size and position of the final plot** within the larger canvas

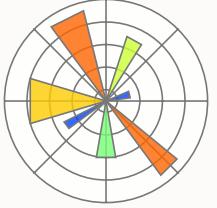
```
# create figure
fig1 = plt.figure(figsize=(3,3))

# add axes
ax1 = fig1.add_axes([0, 0, 1, 1])
ax2 = fig1.add_axes([0.7, 0.7, 0.3, 0.3])

# plot some random data
x = np.random.randn(50)
ax1.plot(x)
ax2.plot(x[0:20], color=[0,0.6,0.7])
plt.show()
```



**Multiple plots within the same figure (e.g., great for inserts)**



# Matplotlib – The basics

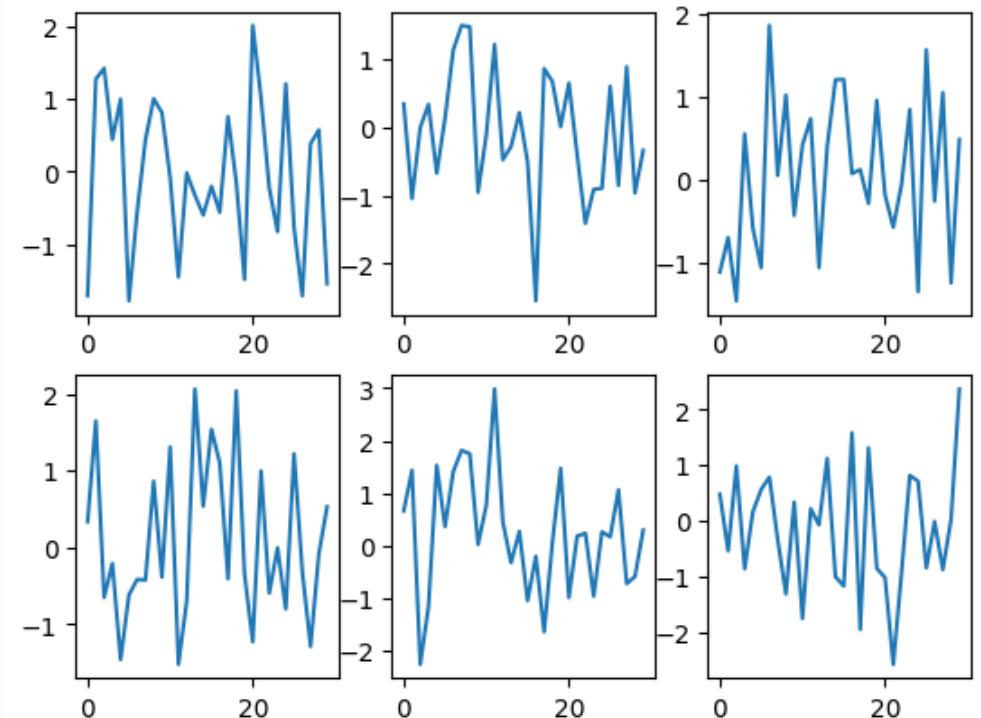
As the number of **subplots** increases, defining all origins and dimensions becomes infeasible.

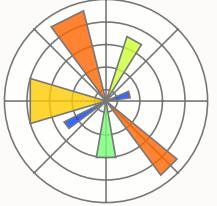
Luckily, there is pre-written function called **plt.subplots()** that does this for us automatically.

It outputs the **figure object** and the **axes**.

```
# create figure with subplots
fig, axes = plt.subplots(nrows=2, ncols=3)

# plot random numbers into each
for ax in axes.reshape(-1):
    ax.plot(np.random.randn(30))
```





# Matplotlib – Styling & plot types

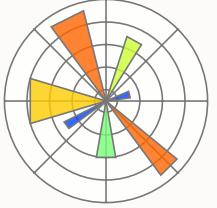
Matplotlib comes with a wide range of customization options (e.g., to change colors).

```
# fake data
np.random.seed(42)
data      = [np.random.randn(100).cumsum() for ii in range(6)]

# settings
colors    = plt.cm.viridis([0.1, 0.25, 0.4, 0.55, 0.7, 0.85])
conditions = ['Condition A', 'Condition B', 'Condition C', 'Condition D', 'Condition E', 'Condition F']
markers   = ['o', 'x', 'v', 'p', 'D', '*']

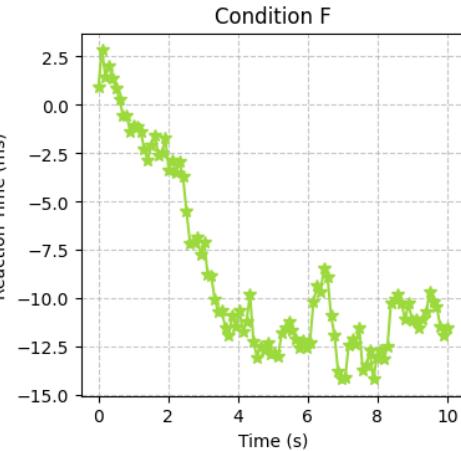
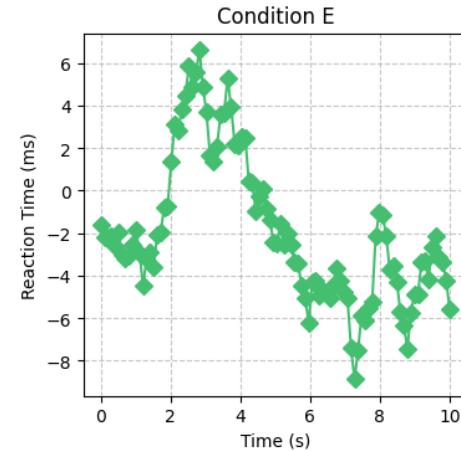
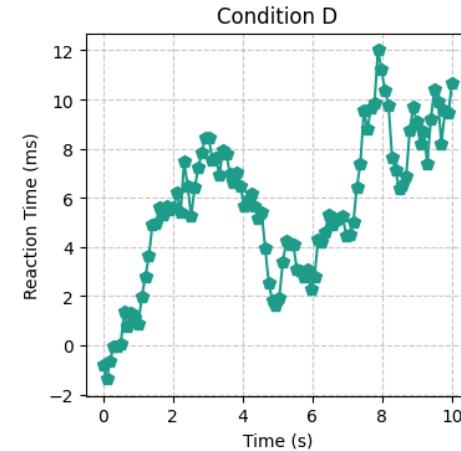
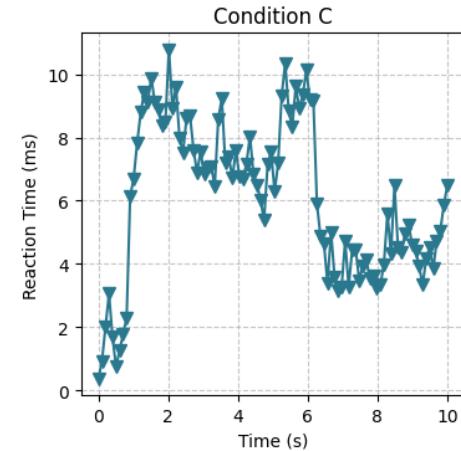
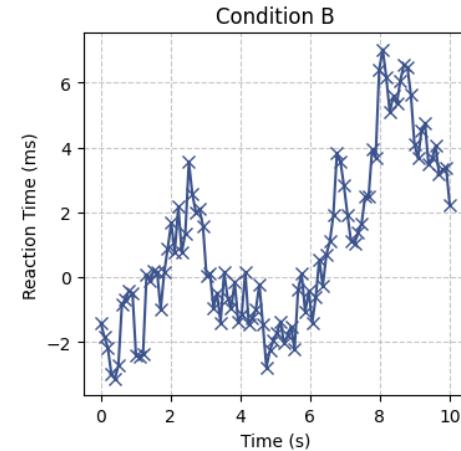
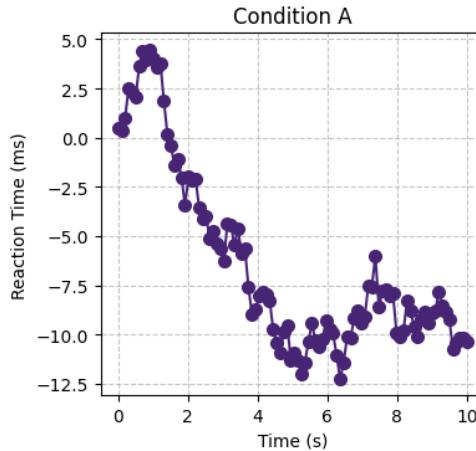
# Create 2x3 subplots, plot, and customize
fig, axs = plt.subplots(2, 3, figsize=(12, 8))
for i, ax in enumerate(axs.flat):
    ax.plot(np.linspace(0, 10, 100), data[i],
            color=colors[i], label=conditions[i], linestyle='-', marker=markers[i], markersize=7)
    ax.set_title(f'{conditions[i]}', fontsize=12)
    ax.set_xlabel('Time (s)', fontsize=10)
    ax.set_ylabel('Reaction Time (ms)', fontsize=10)
    ax.grid(True, linestyle='--', alpha=0.7)

# Adjust layout to prevent overlap
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).

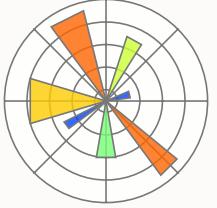


Line plots

Various marker types

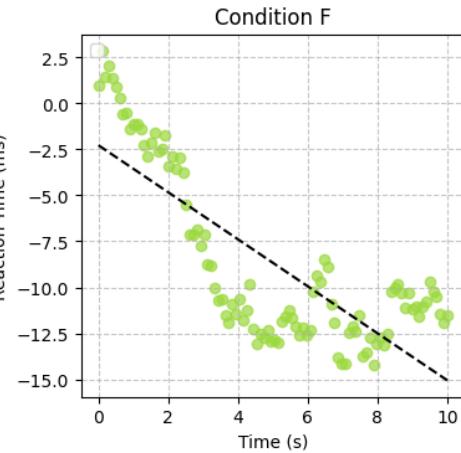
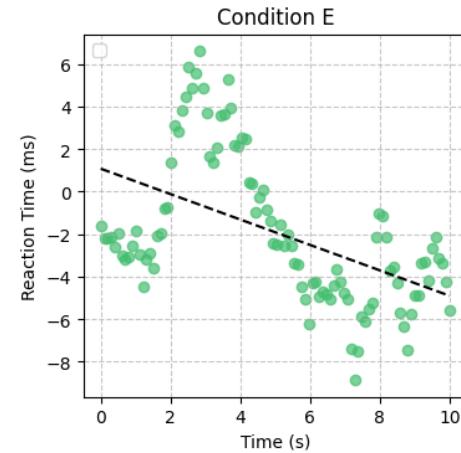
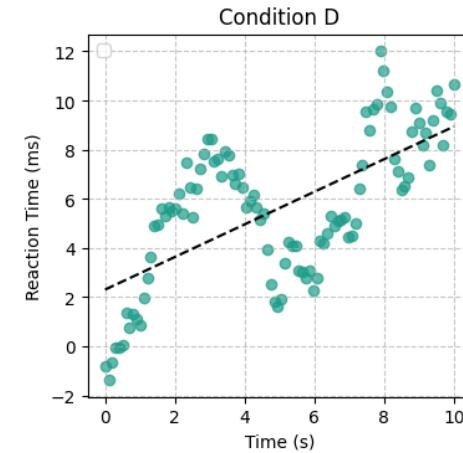
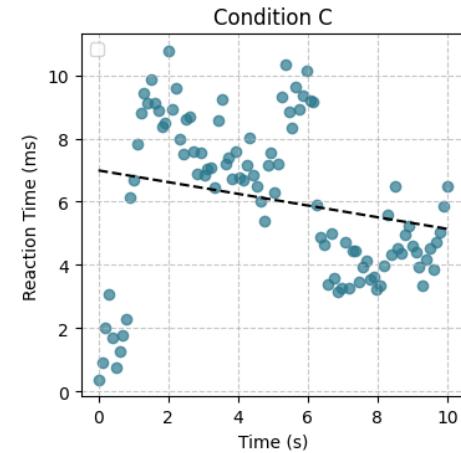
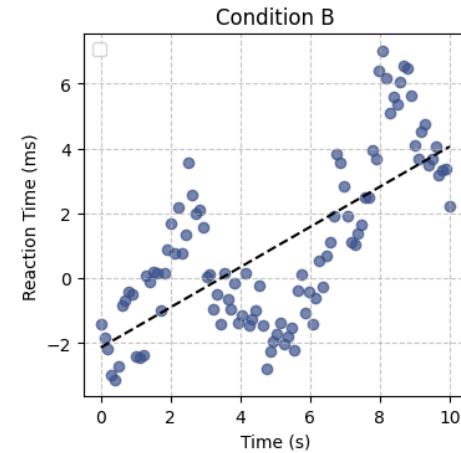
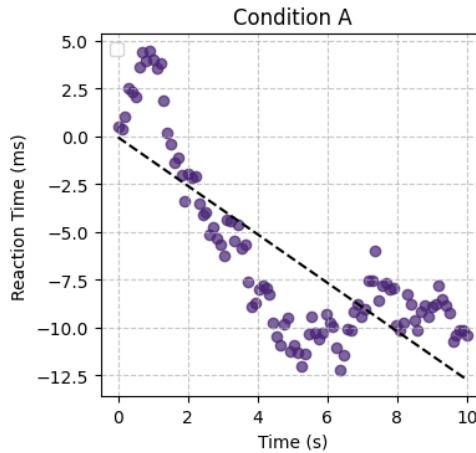
Various colors

Various labels and titles



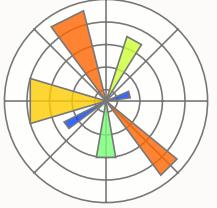
# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).



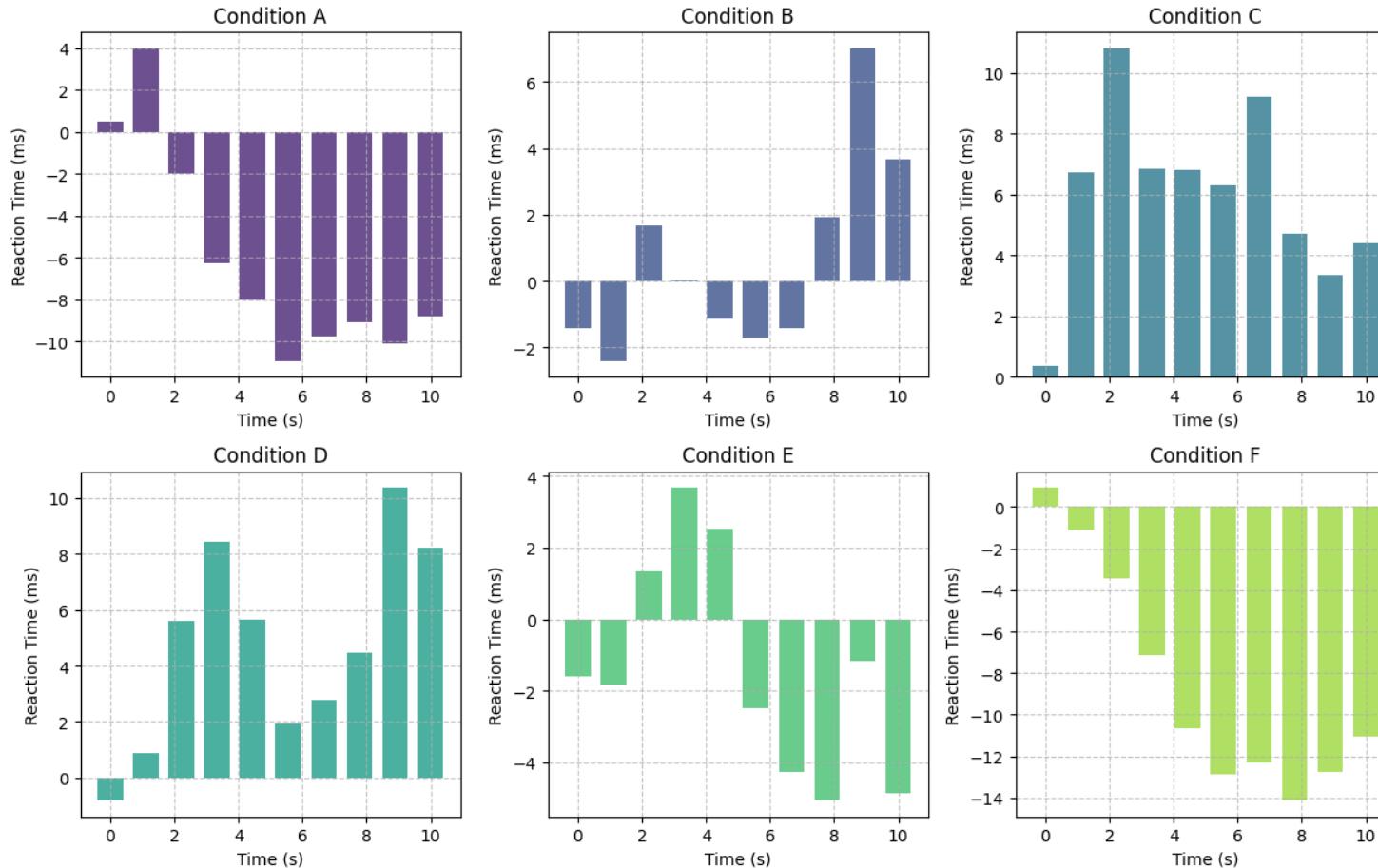
Scatter plots

Dashed trend line

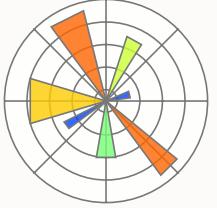


# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).

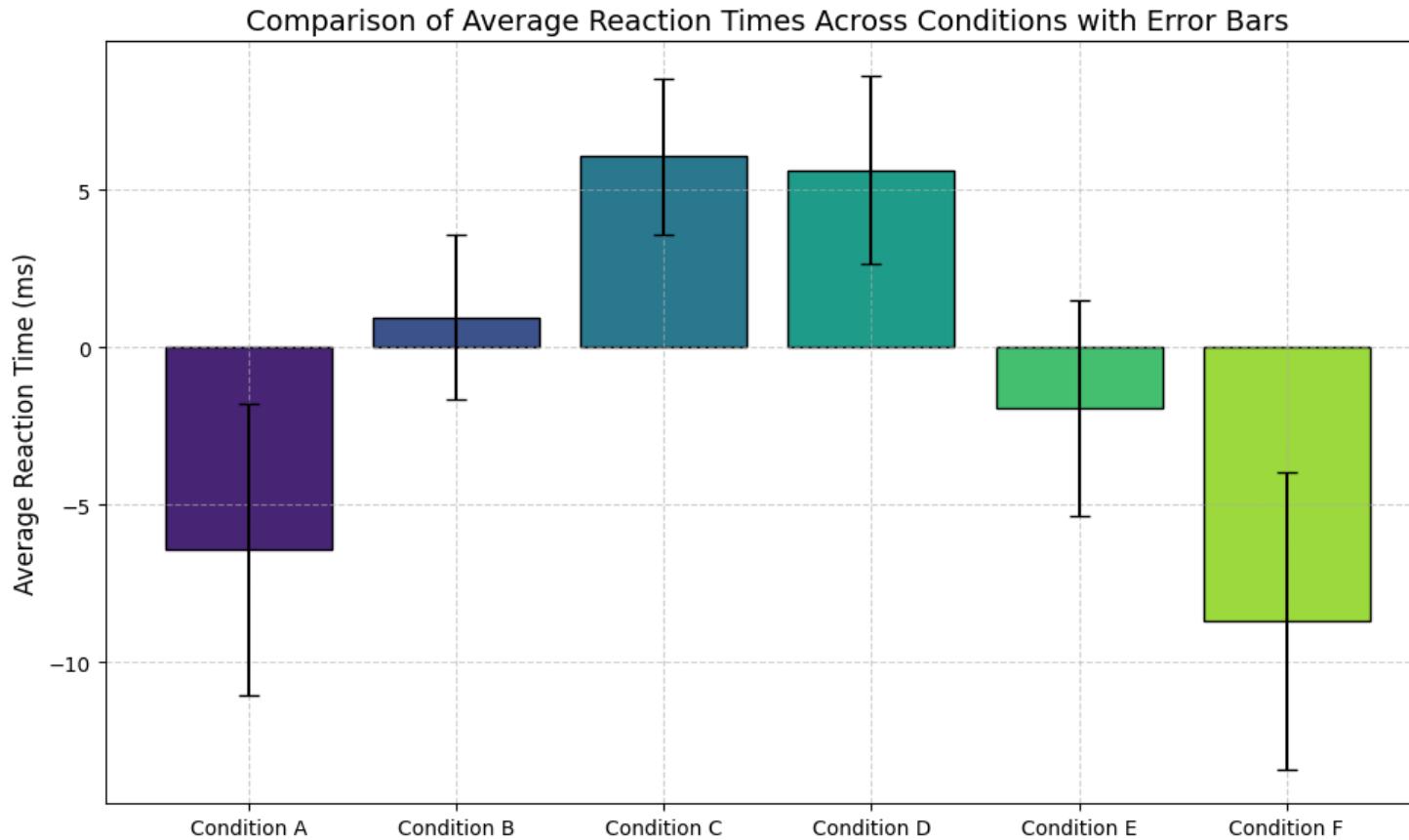


Bar plots



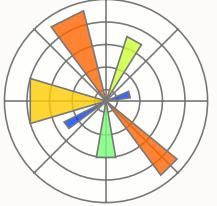
# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).



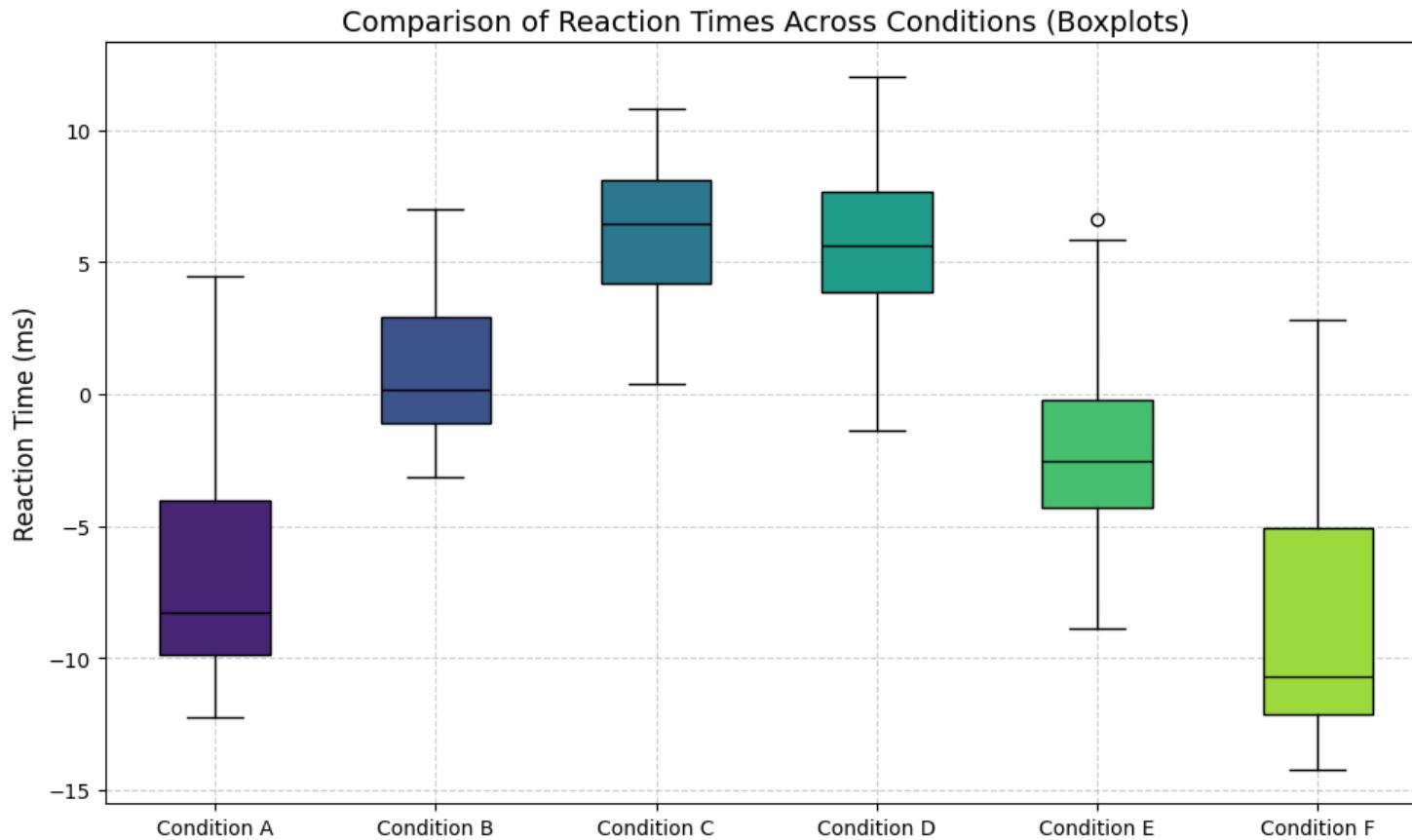
## Bar plots

- Box: data mean
- Error bars: standard deviation



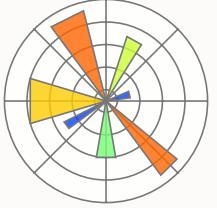
# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).



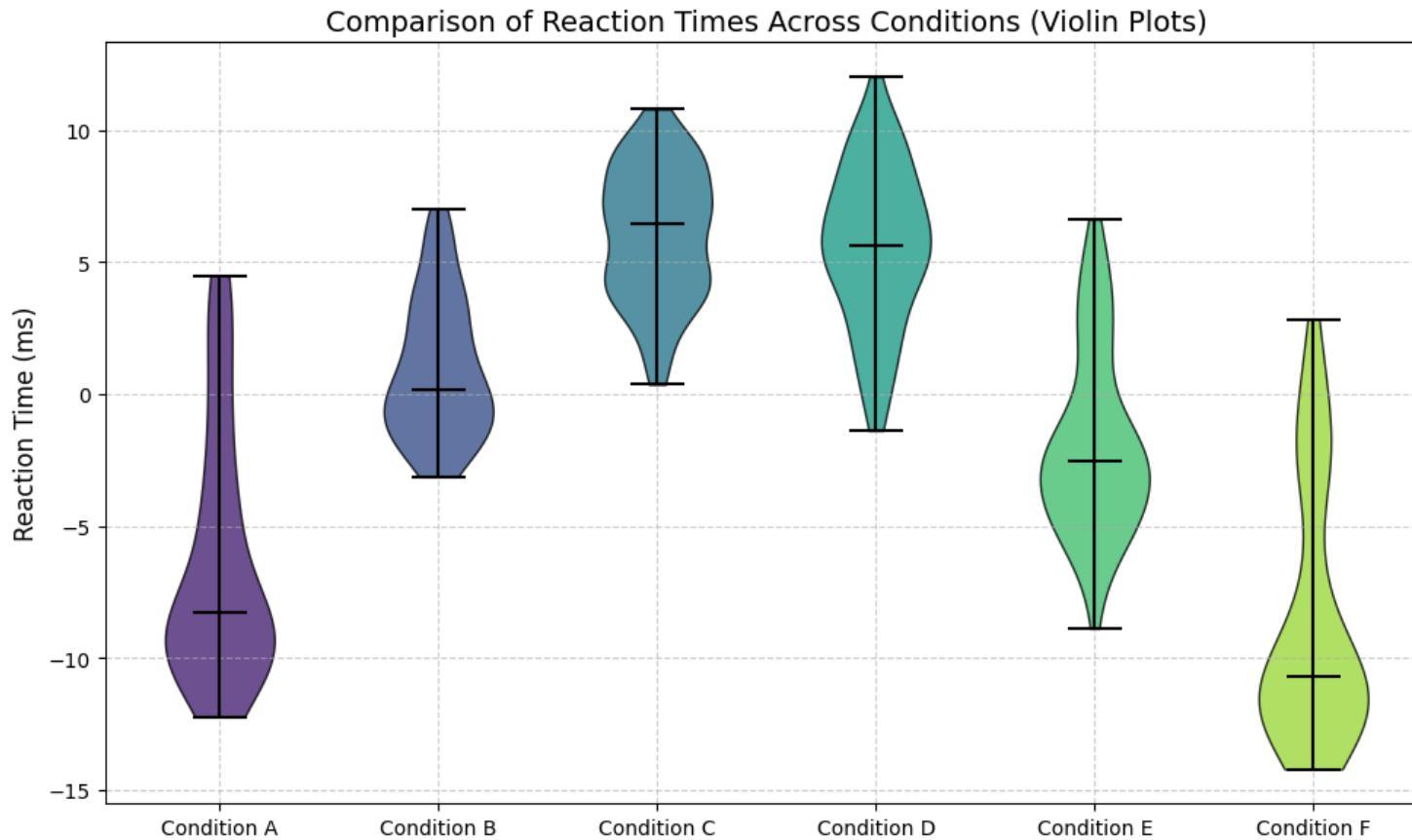
## Box plots

- Black line: median
- Box: 50% of data
- Whiskers:  $1.5 \times$  interquartile range
- Dots: outliers



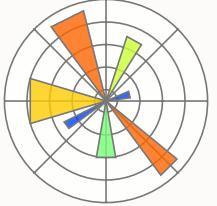
# Matplotlib – Styling & plot types

Matplotlib comes with a wide range of customization options (e.g., to change colors).



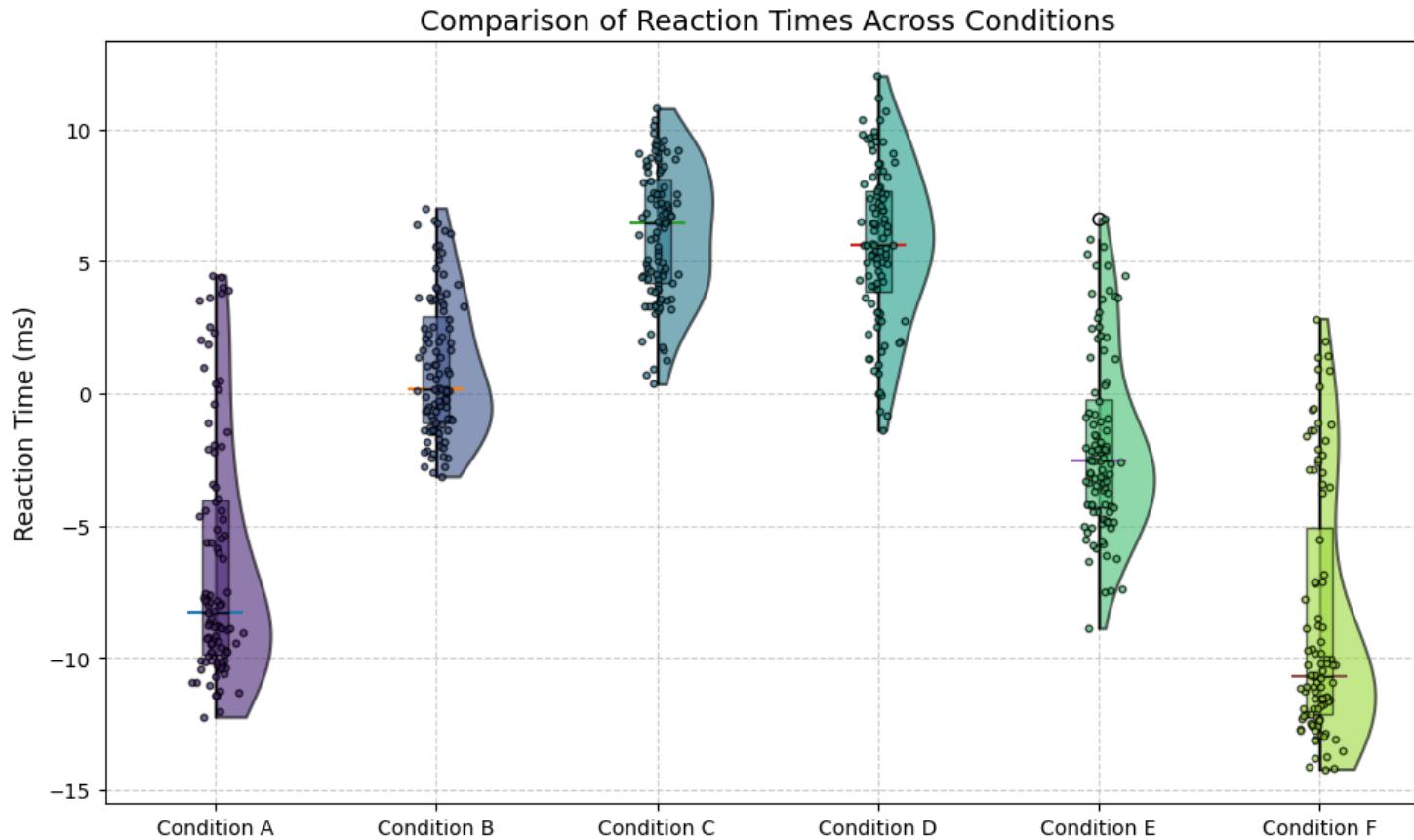
## Violin plots

- Black line: median
- Smoother data distribution



# Matplotlib – Styling & plot types

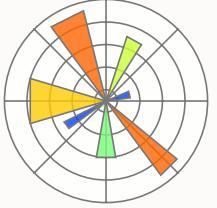
Matplotlib comes with a wide range of customization options (e.g., to change colors).



Rain cloud plots

- Raw data, boxplots, and violin plots all together

Many more options, check out [matplotlib gallery!](https://matplotlib.org)  
<https://matplotlib.org>

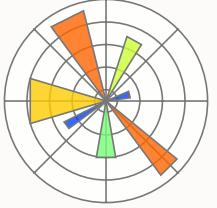


# Matplotlib – Color palettes

When picking a color palette, make sure they are appropriate for **color blindness**, which concerns ~5% of the population.



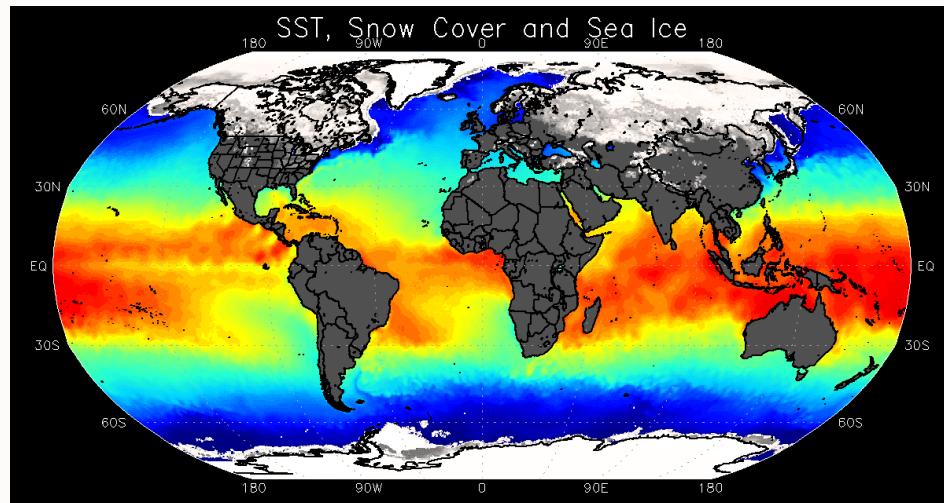
Matplotlib's default colormap is **Viridis**, which is perceptually uniform and suited color blindness



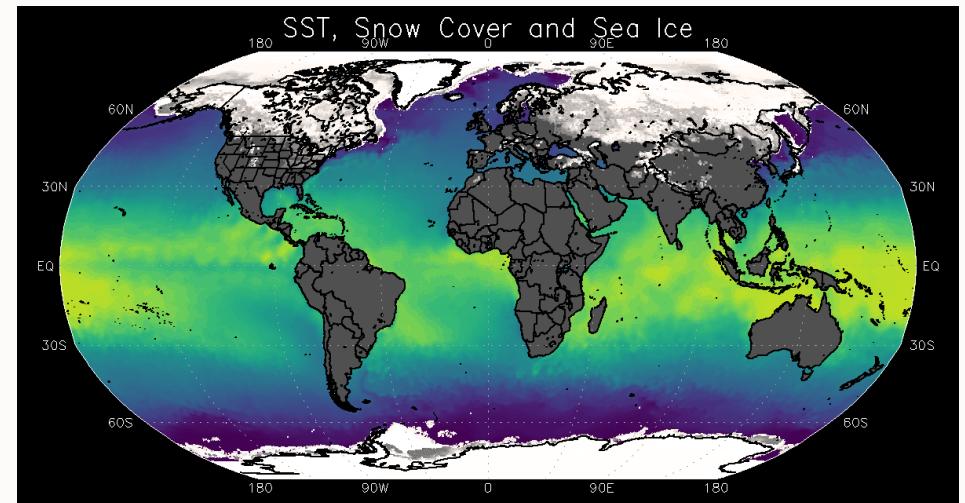
# Matplotlib – Color palettes

When picking a color palette, make sure it is **perceptually uniform**, meaning that a change in color values corresponds to an equal change in perceived color.

Jet (non-uniform)



Viridis (uniform)



These maps of water temperature show the same data, but temperature gradients look more extreme in the one on the left – falsely so!

# Seaborn



# Seaborn - Examples



**Matplotlib** is great for controlling the appearance of your plots, especially highly customized visualizations. A downside is that it requires **many lines of code**.

**Seaborn** is an alternative that creates attractive, informative statistical plots quickly, with minimal effort and **fewer lines of code** than Matplotlib.

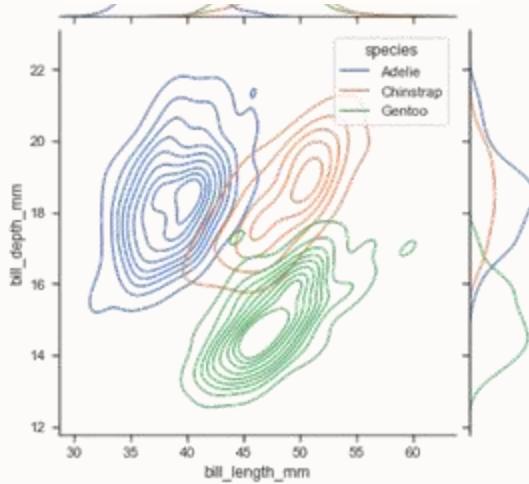
Built on-top of Matplotlib, Seaborn was designed to work with **Pandas DataFrames**, a super useful DataType that you will want to read up on in the future!

**Check out the Seaborn introduction and tutorial online**  
<https://seaborn.pydata.org/tutorial/introduction.html>

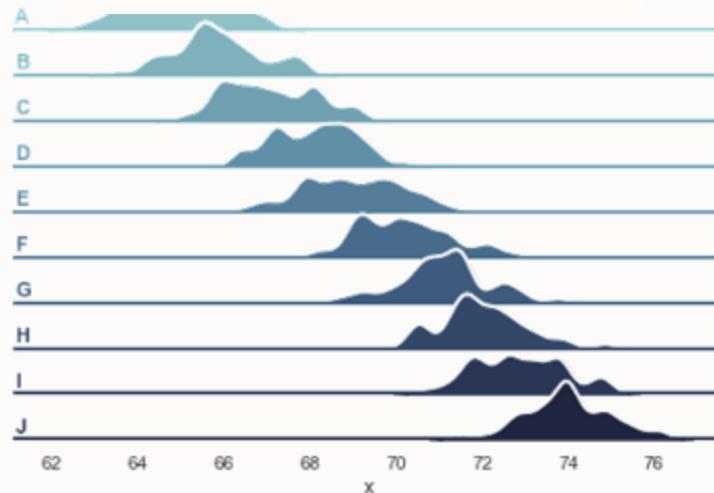
# Seaborn - Examples



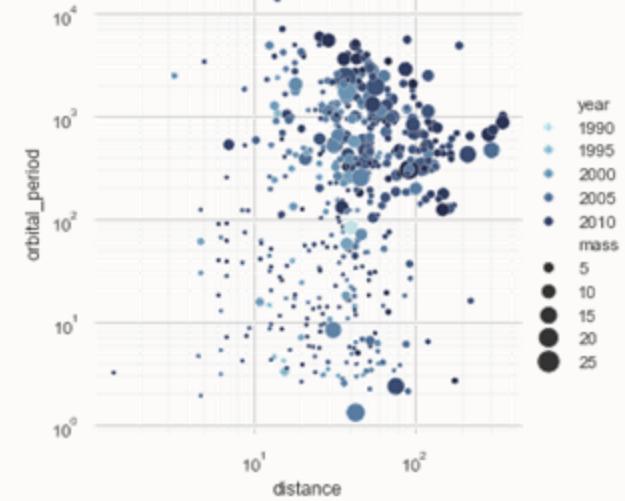
## Joint plots



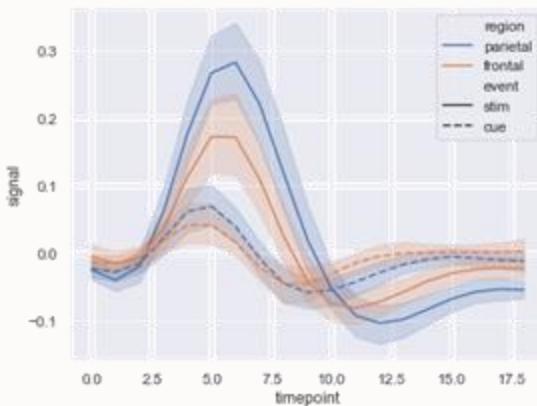
## “Joy Division” plots



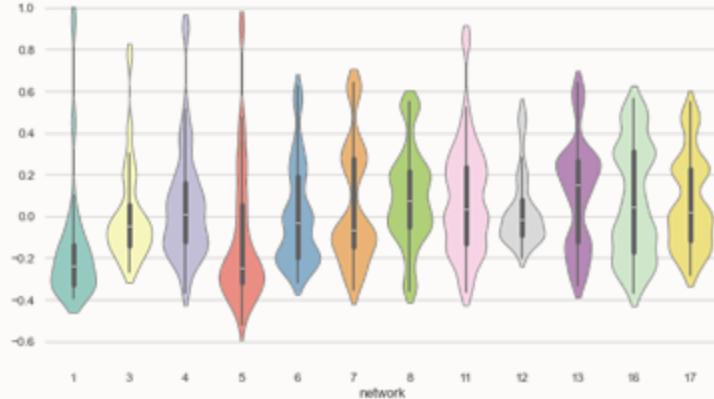
## Great scatter plots



## Shaded error bars



## Simple violinplots



## Annotated heatmaps



Many more!

# Seaborn - Examples



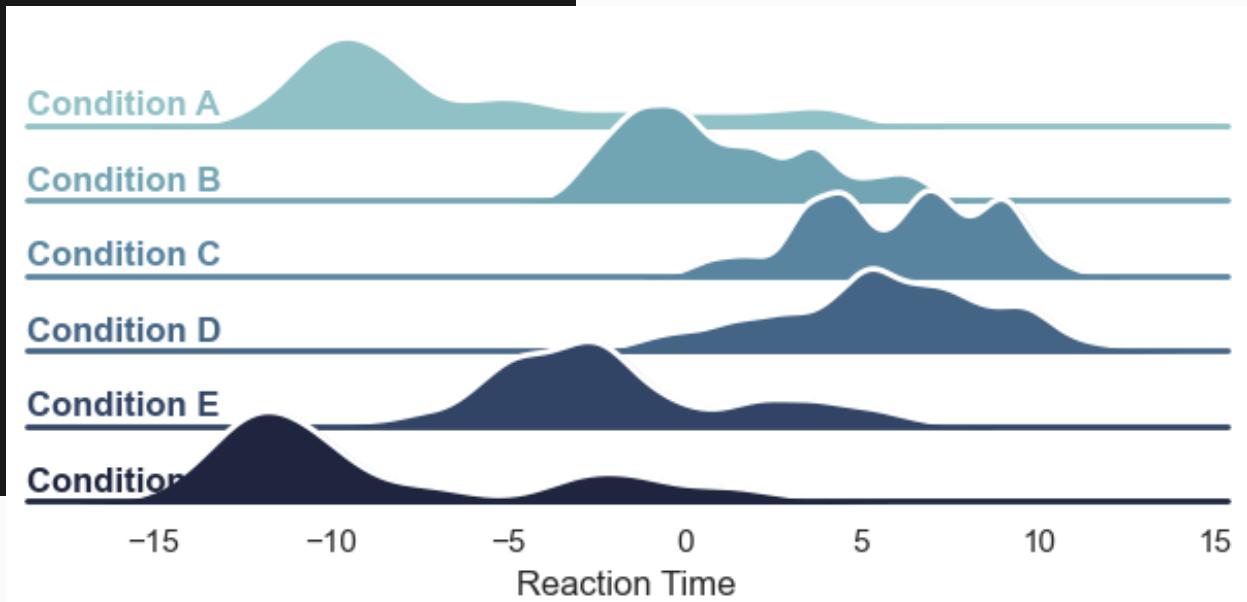
```
# Create DataFrame
df = pd.DataFrame({'Reaction Time': np.concatenate(data), 'Condition': np.repeat(conditions, 100)})

# Initialize FacetGrid object
sns.set_theme(style="white", rc={"axes.facecolor": (0, 0, 0, 0)})
pal = sns.cubehelix_palette(6, rot=-.25, light=.7) # Use a color palette
g = sns.FacetGrid(df, row="Condition", hue="Condition", aspect=15, height=.5, palette=pal)

# Draw densities
g.map(sns.kdeplot, "Reaction Time", bw_adjust=.5, clip_on=False, fill=True, alpha=1, linewidth=1.5)
g.map(sns.kdeplot, "Reaction Time", clip_on=False, color="w", lw=2, bw_adjust=.5)
g.refline(y=0, linewidth=2, linestyle="-", color=None, clip_on=False)

# label axes coordinates
def label(x, color, label):
    ax = plt.gca()
    ax.text(0, .2, label, fontweight="bold", color=color,
            ha="left", va="center", transform=ax.transAxes)
g.map(label, "Reaction Time")

# adjust figure overlap
g.figure.subplots_adjust(hspace=-.25)
g.set_titles("")
g.set(yticks=[], ylabel="")
g.despine(bottom=True, left=True)
plt.show()
```



The code looks wild,  
but trust me, creating  
this figure in Matplotlib  
would be even wilder!

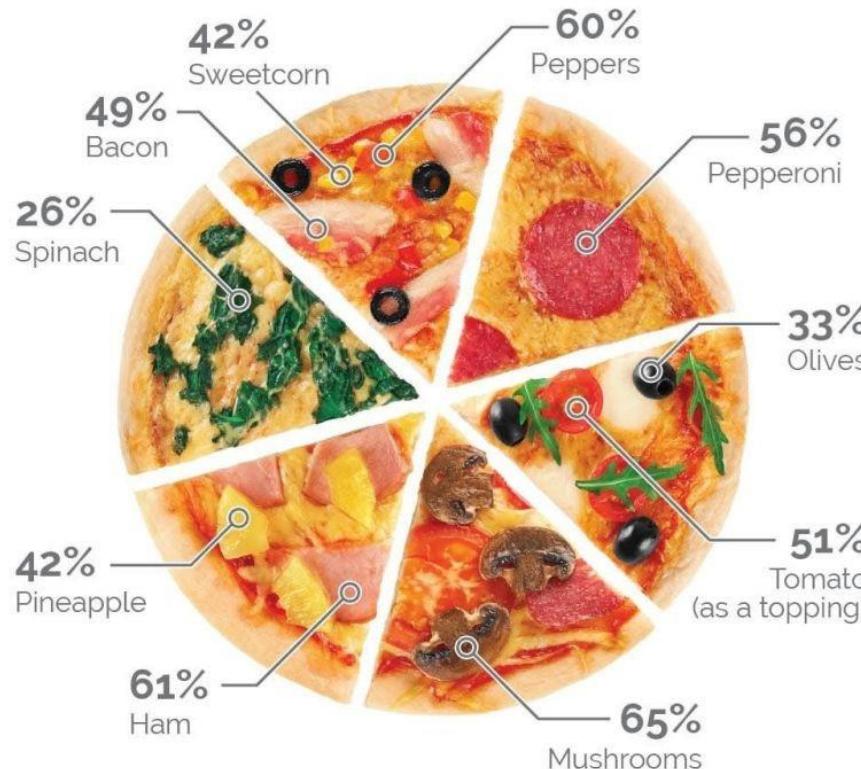
# Data viz fails



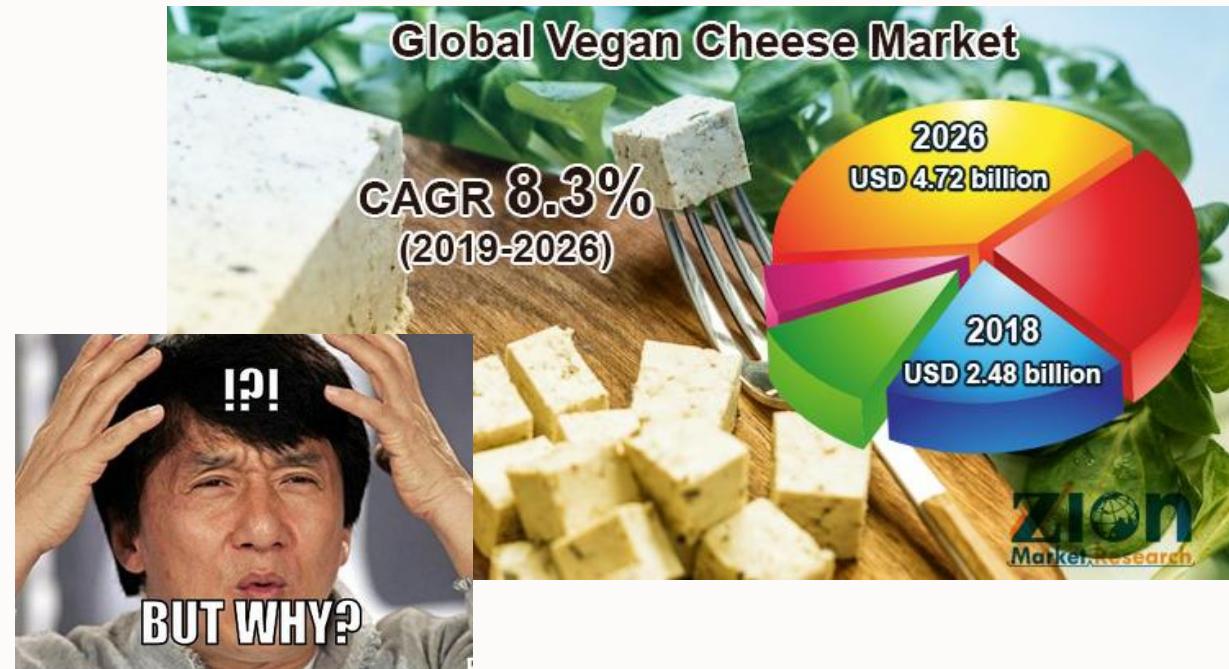
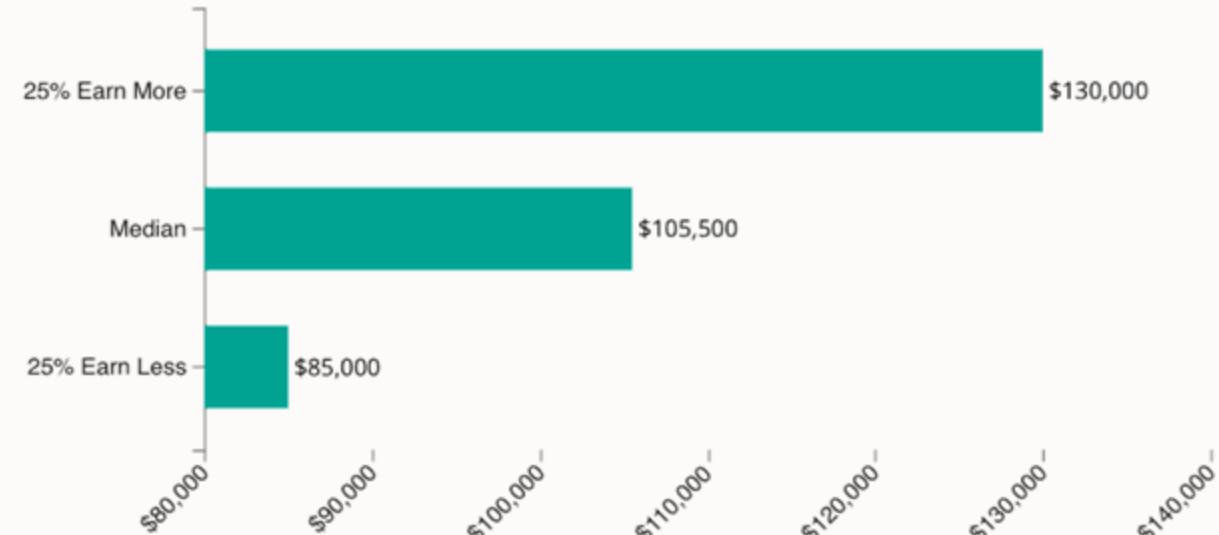
# Data viz fails

## Mushroom is the UK's most liked pizza topping

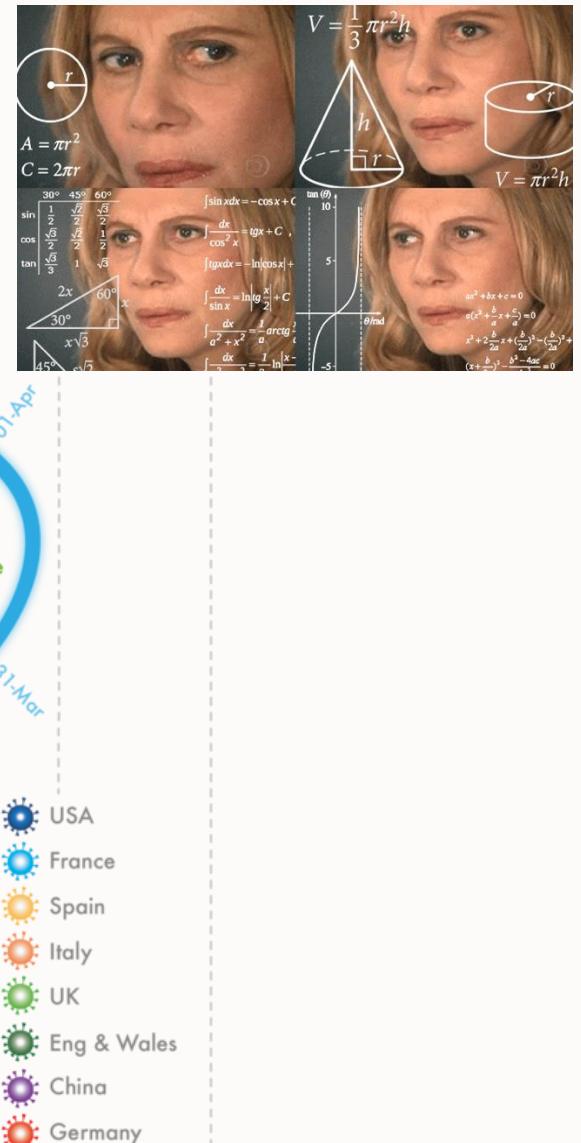
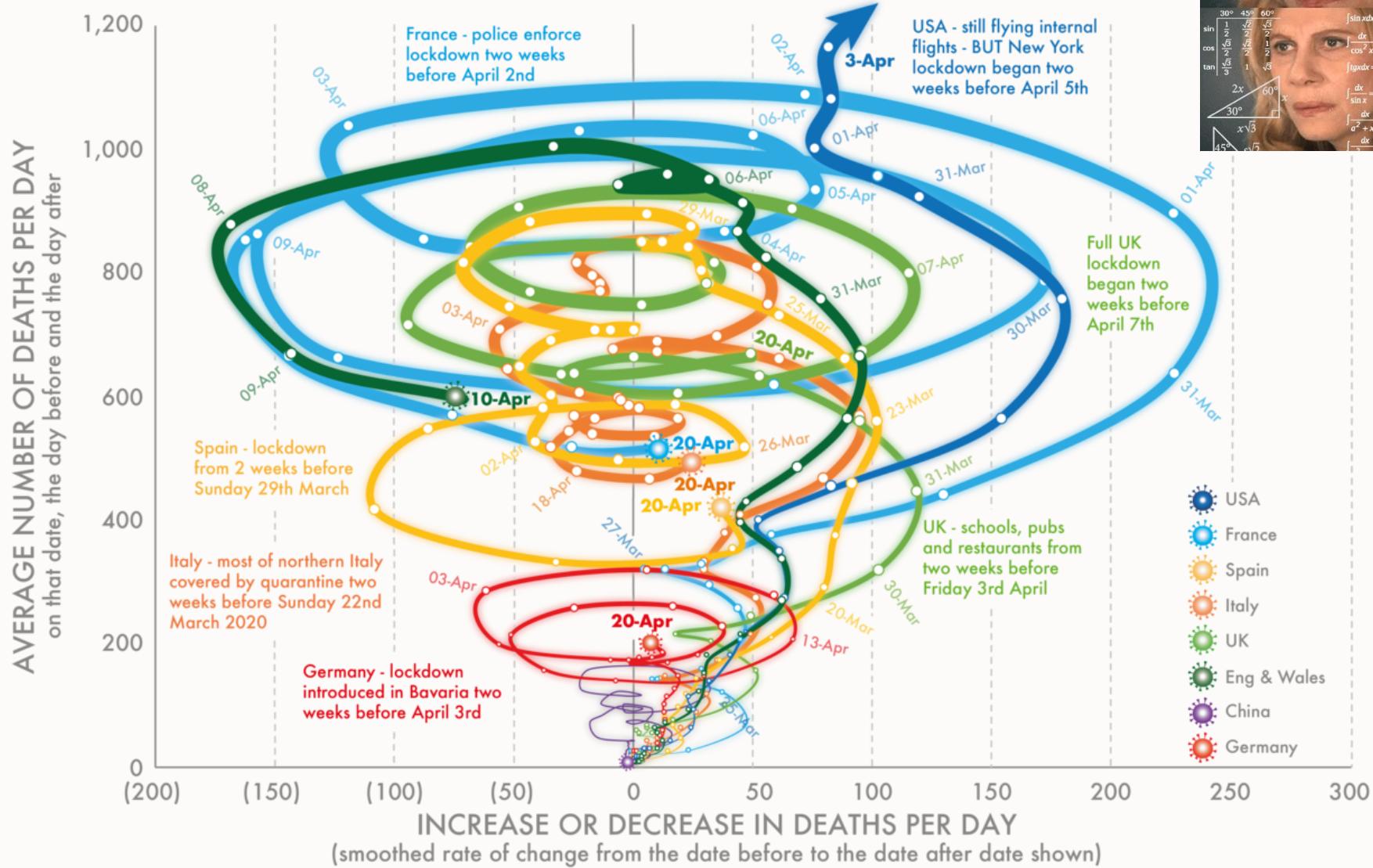
Generally speaking, which of the following toppings do you like on a pizza? Select as many as you like



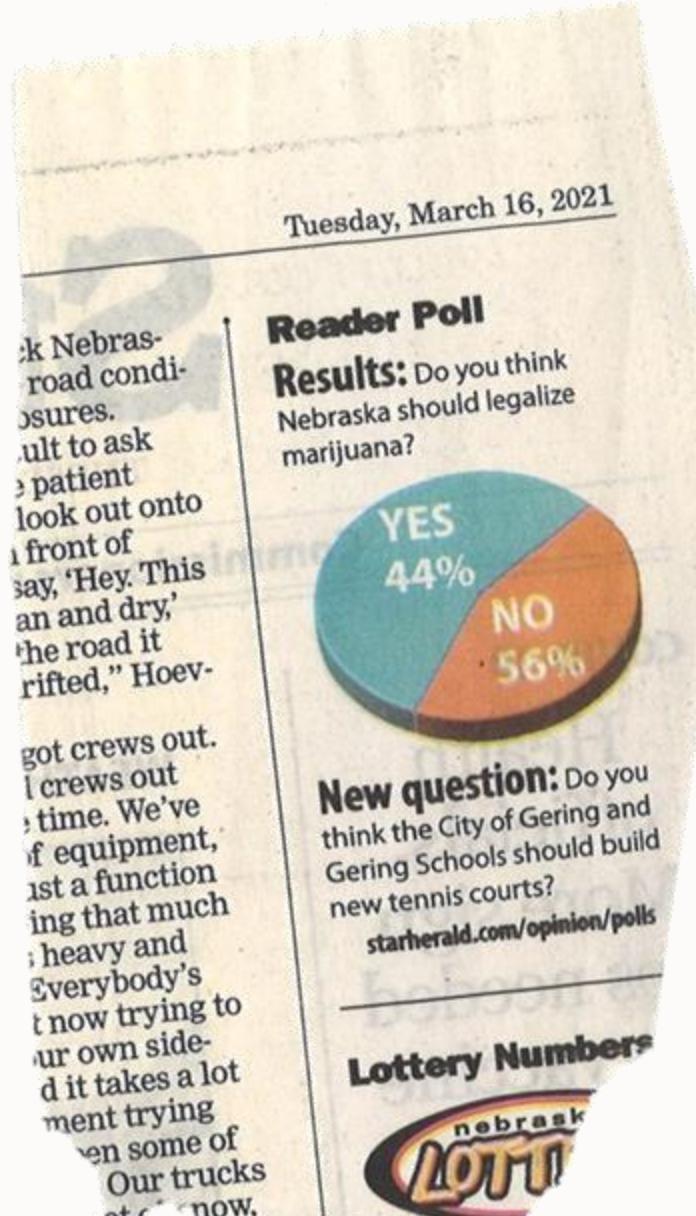
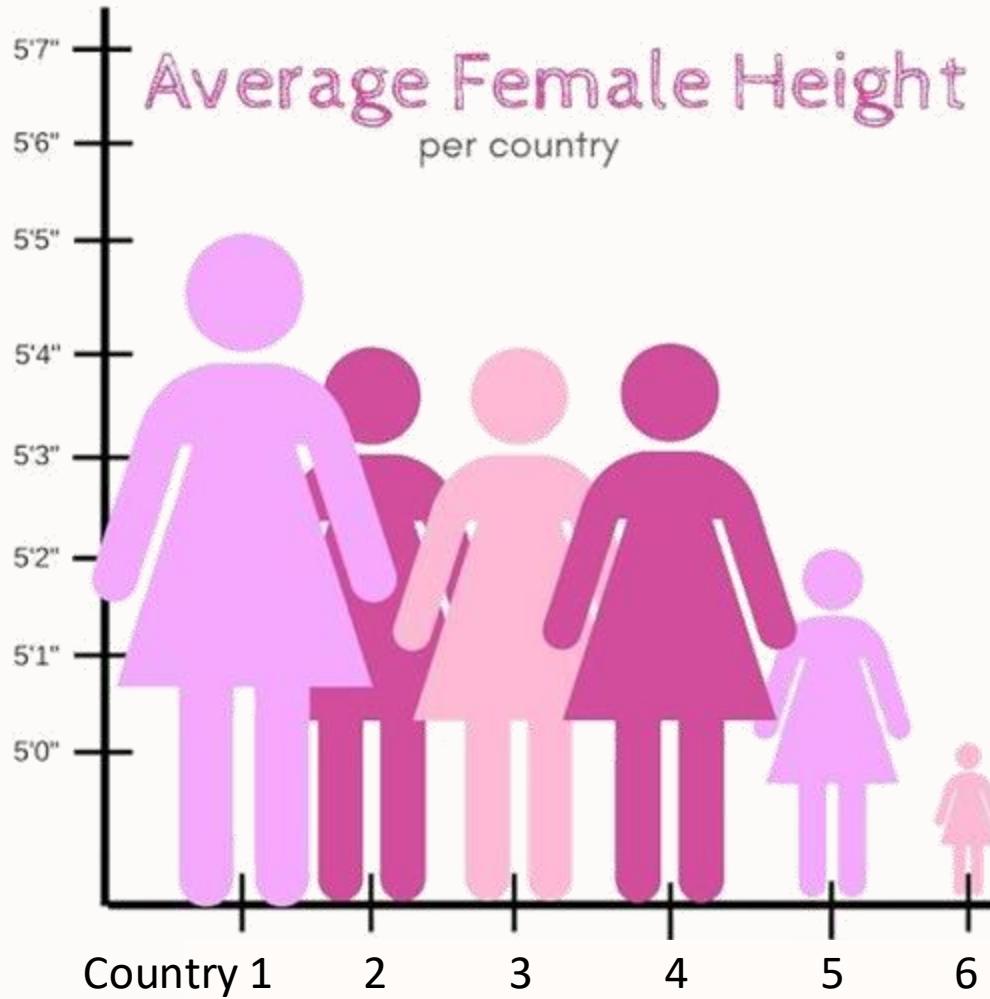
Other items not depicted include: onions (62%), chicken (56%), beef (36%), chillies (31%), jalapeños (30%), pork (25%), tuna (22%), anchovies (18%). 2% of people say they only like Margherita pizzas



# Data viz fails



# Data viz fails



(I checked. It's still illegal!)

## **Complete the data survey**

- 1) Go to Canvas, Module 4
- 2) Click on “Data\_survey”
- 3) Answer the questions
- 4) Have fun!

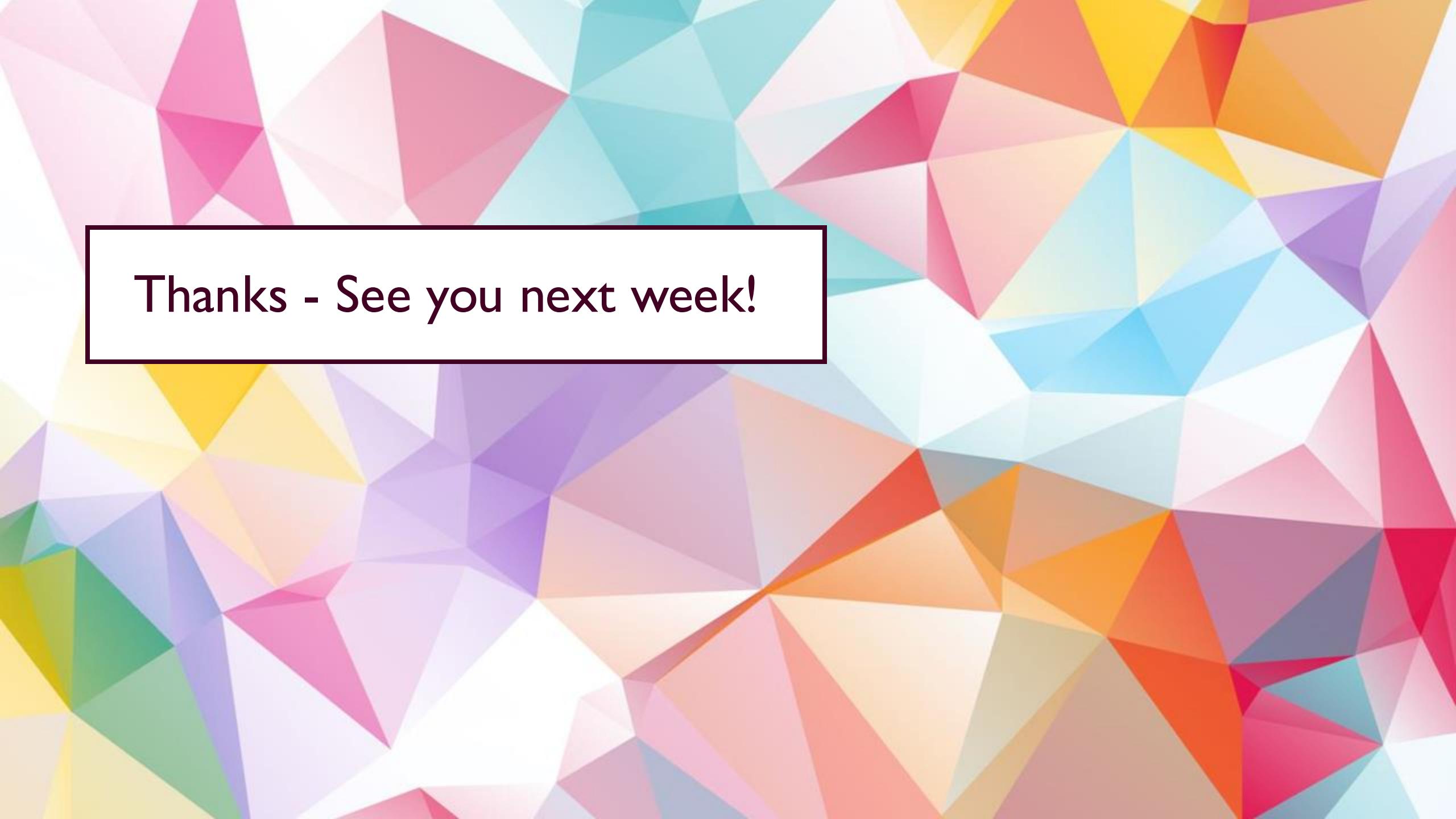


# Before the next practical, go through these slides again!

**Do you know what the following terms mean?**

- Matplotlib
- Seaborn
- Plotting
- Figure
- Axes
- Subplots
- Figure styling
- Line plots
- Scatter plots
- Bar plots
- Boxplots
- Violin plots
- Rain cloud plots
- Heatmaps
- Color palette
- Perceptual uniformity





Thanks - See you next week!