CENTER FOR SCALABLE DATA ANALYTICS
AND ARTIFICIAL INTELLIGENCE

Data Visualization

Robert Haase

Reusing Materials from Jan Ewald and Mara Lampert (ScaDS.AI, Uni Leipzig) and Marcelo Leomil Zoccoler (TU Dresen)

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für Forschung, Technologie
und Raumfahrt

SACHSEN

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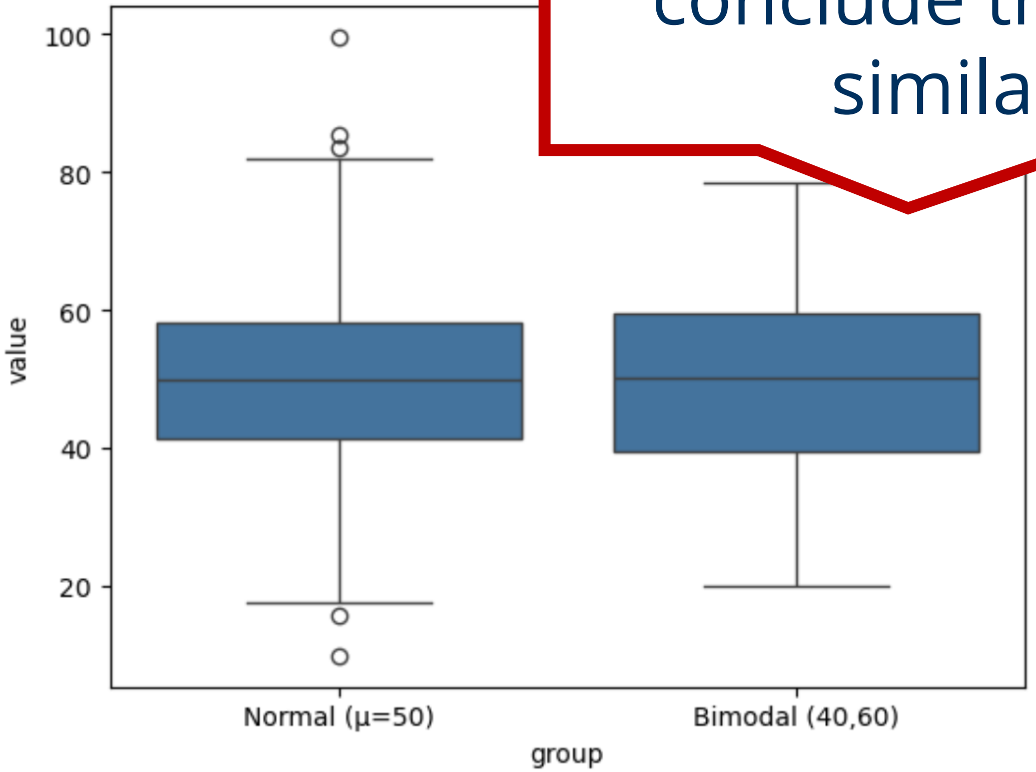
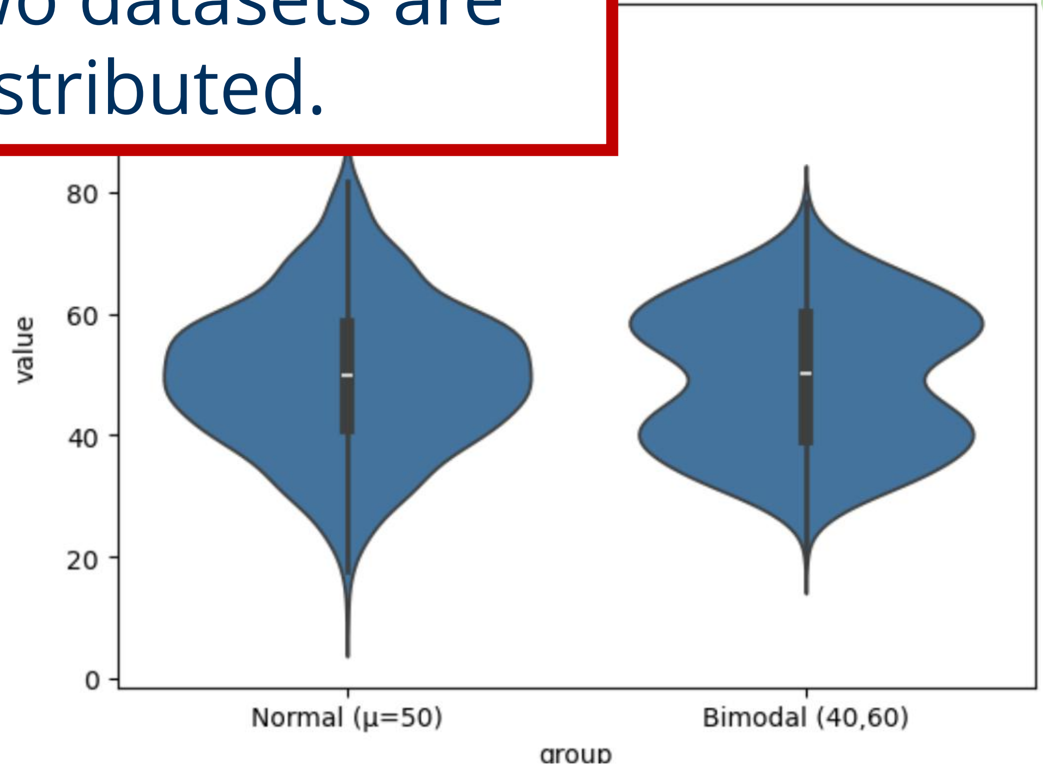
Take home message: choose plots wisely

From such a visualization you may conclude that two datasets are similarly distributed.




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




```
sns.violinplot(data=df, x="group", y="value")
```

First things first.

What would you like to show?

- **Comparison**
- **Relationship**
- **Composition**
- **Distribution**

How many variables?

Time axis?

Cyclic axis?

Categorical data?

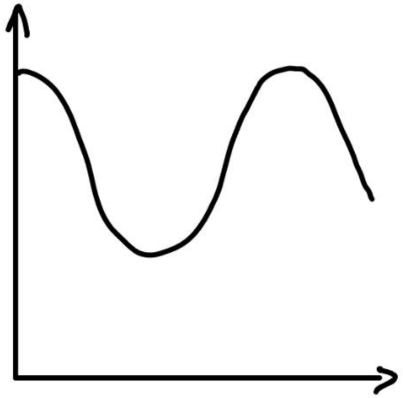
...

Distribution of data

Distribution

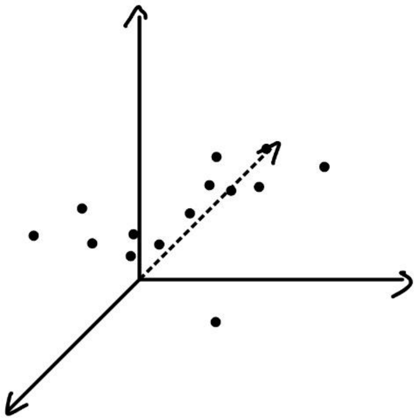
- **Single Variable**
  - *Few Data Points*
  - *Many Data Points*
- **Two Variables**
- **Three Variables**

Histogram



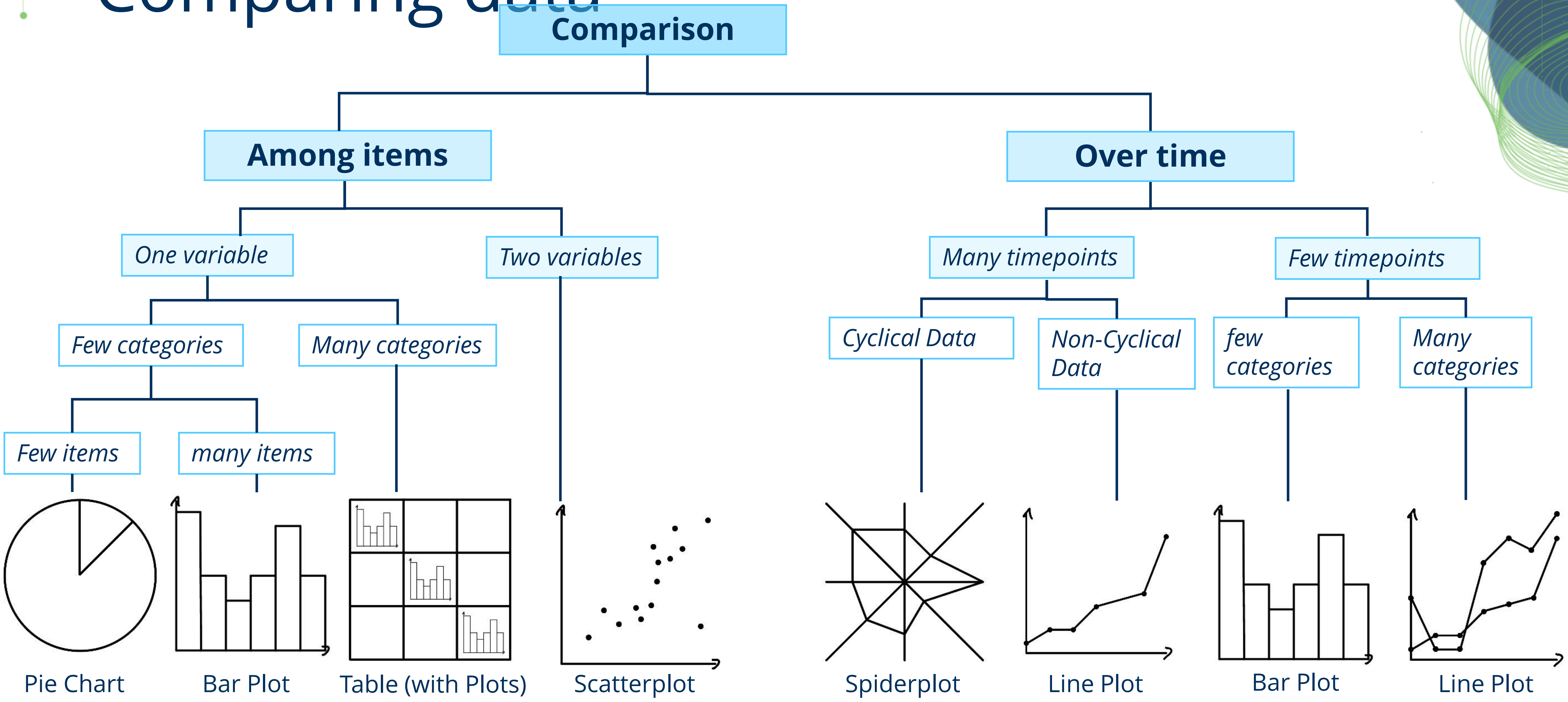
Line Plot

Scatterplot

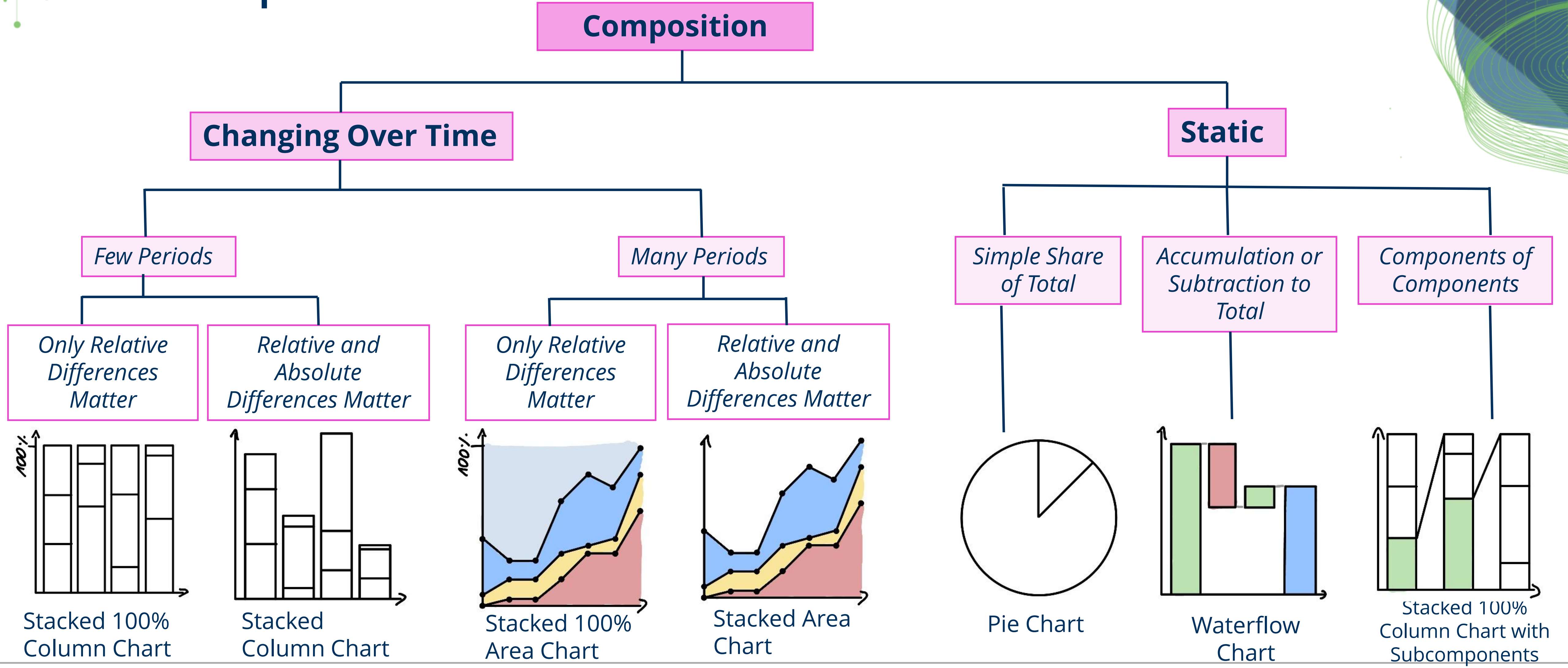


3D Plot (e.g. 3D Scatterplot)

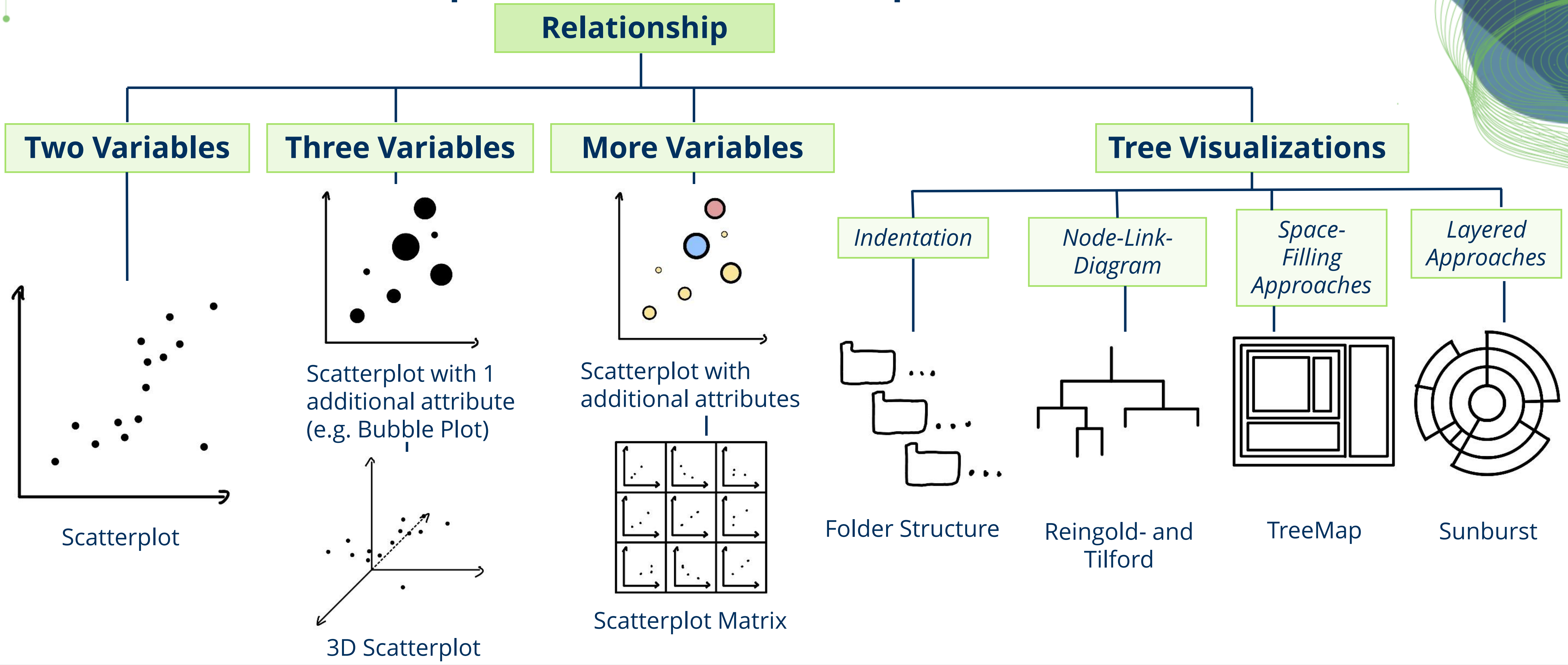
Comparing data



Composition of data



Relationships between aspects of data



AI School
Leibniz IOM
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October 2025

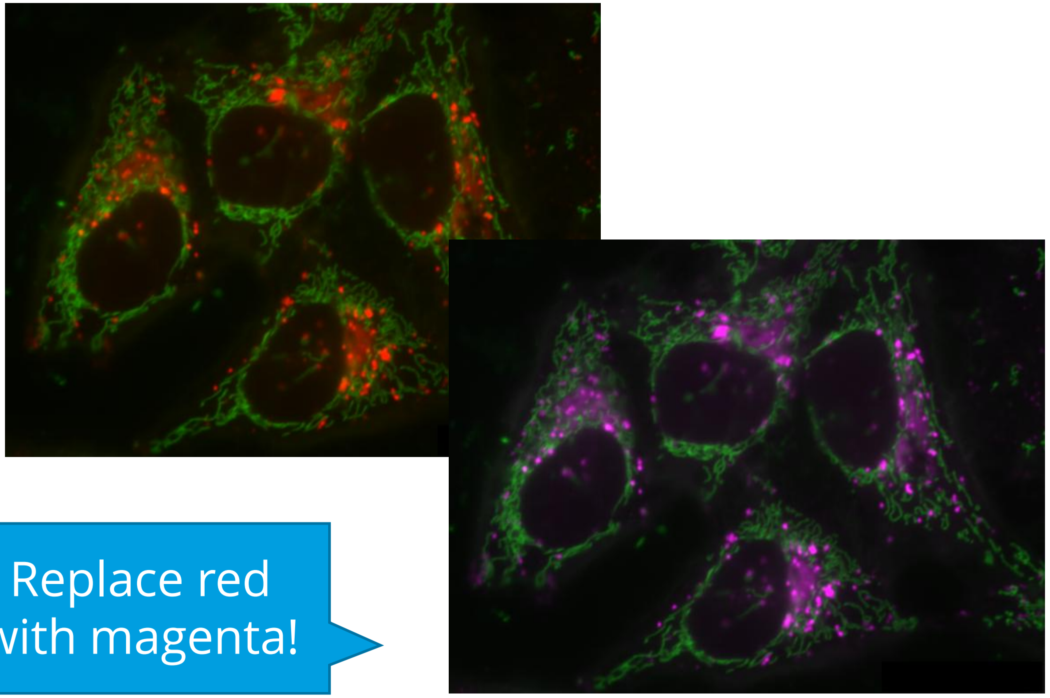
Inspired by [A. Abela 2009]

Color maps / lookup tables

Choose visualization of your color tables wisely!

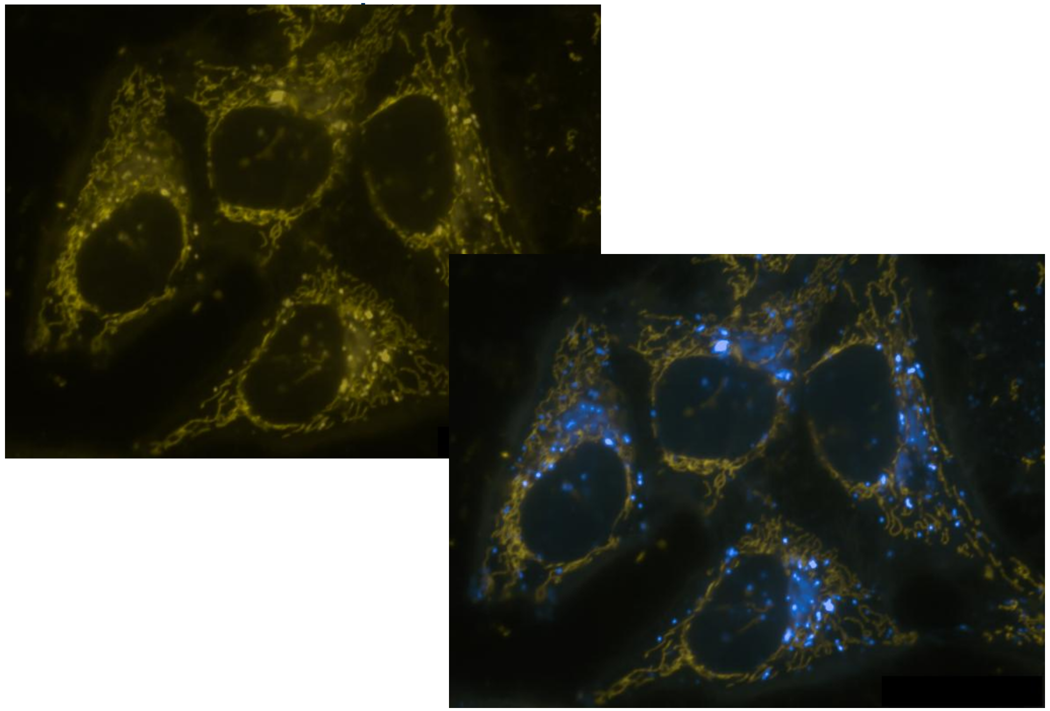
Think of people with red/green blindness!

Default view



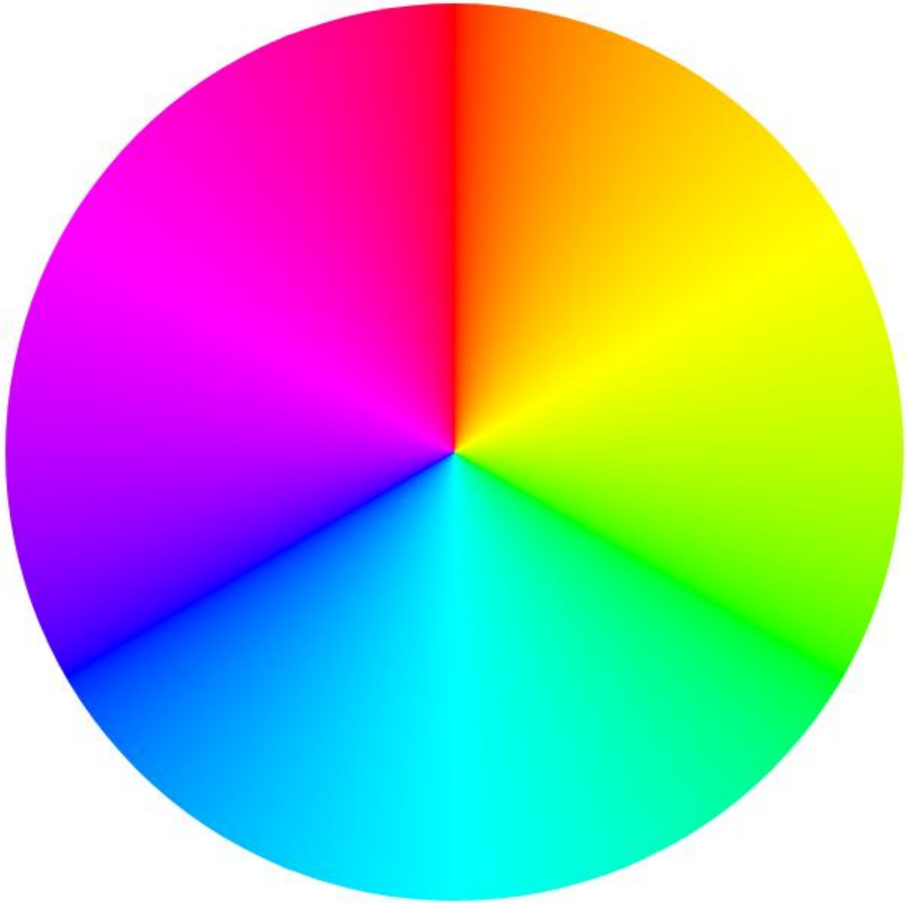
Replace red with magenta!

Red/green blind people see it like



Colour theory

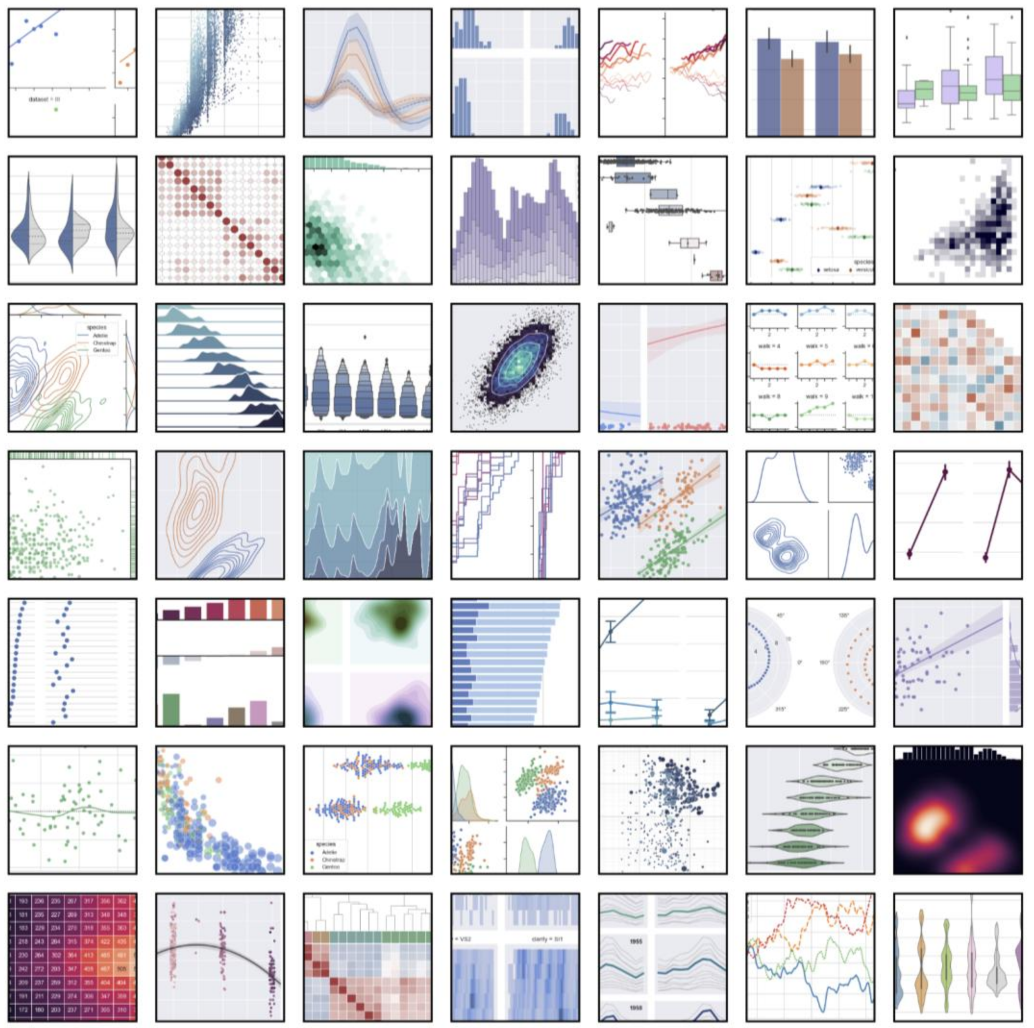
- Humans may not see the difference between adjacent colors properly
- Use opposite colours instead.



Data visualization using seaborn

Seaborn is a community standard library for advanced data visualization, based on matplotlib.

We strongly discourage data scientists from using plain matplotlib.



https://seaborn.pydata.org/tutorial/introduction.html

https://seaborn.pydata.org/examples/index.html

API comparison & philosophies

matplotlib

seaborn

seaborn.objects

intuitive

good/nice plots

↔

flexibility

…

fast implementation

code readibility

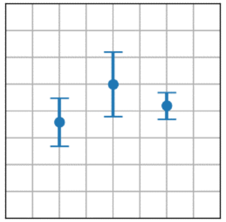
Plot type driven ↔ **Data and geometry driven**

API comparison & philosophies

Data:

	a	b

Plot:



matplotlib

```
x=data[‘a’]
y=data[‘b’]
yerr = sd(y)

errorbar(x,y, yerr)
```

1) Choose plot type
2) Extract or calculate variables
3) Stuff into plot API

seaborn

```
pointplot(
        data,
        x=‘a’, y=‘b’,
        errorbar=‘sd’
        )
```

1) Choose basic type
2) Define data and variables

seaborn.objects

```
so.Plot(data,x=‘a’, y=‘b’)
 .add(   so.Dot(),
         so.Agg())
 .add(   so.Range(),
         so.Est(errorbar=‘sd’))
```

1) Define data and variables
2) Choose plot geometries
3) Define statistics

Plot type driven ⟷ **Data and geometry driven**

Concepts behind seaborn

Figure-level

Axes-level

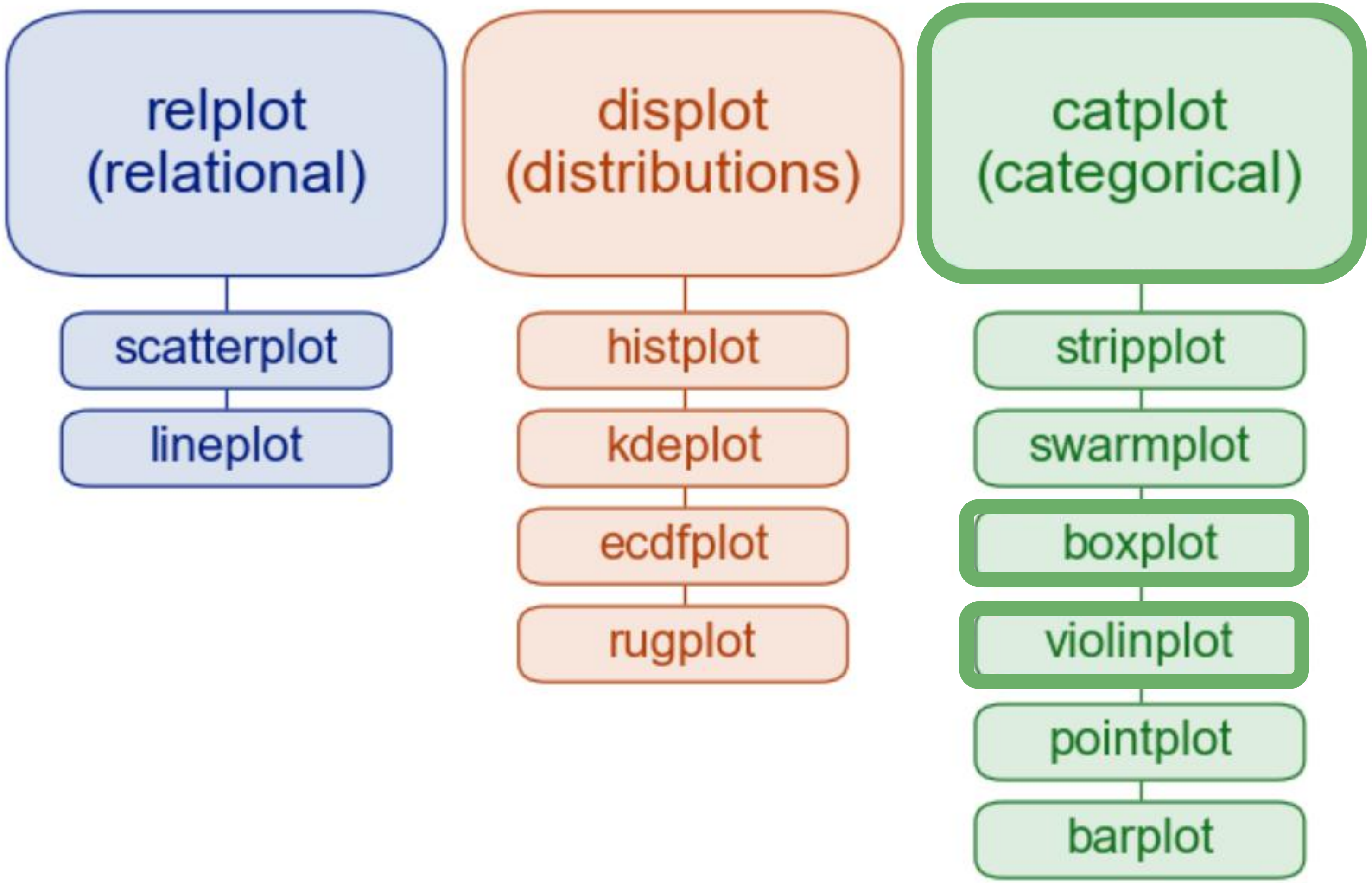
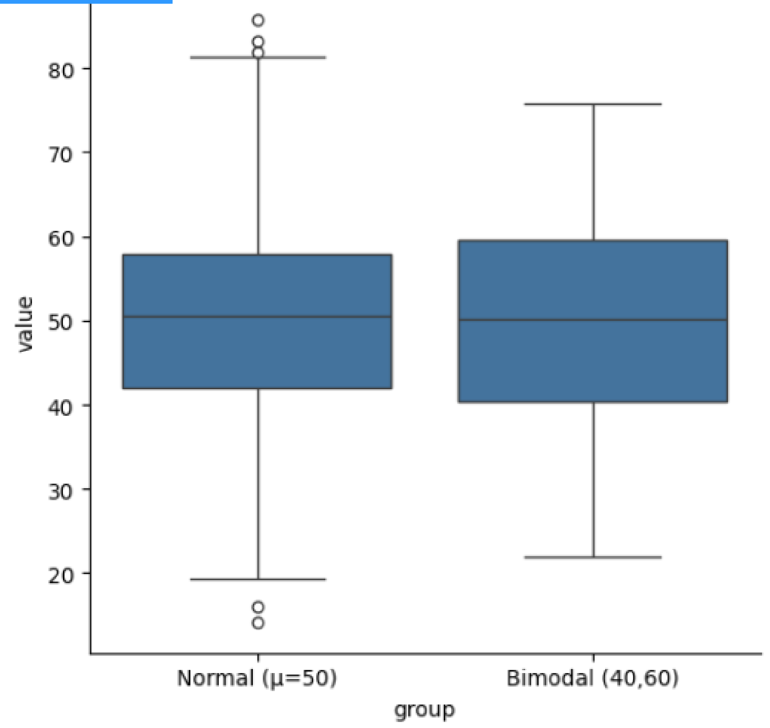


Figure level versus axes level

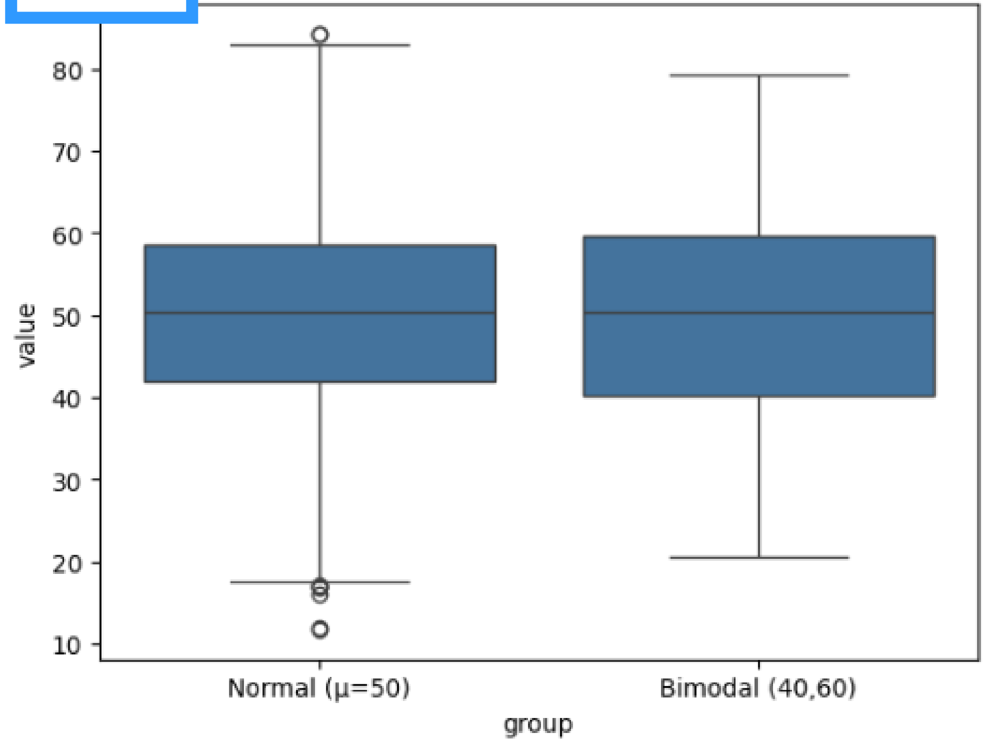
Figure level

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



Axes level

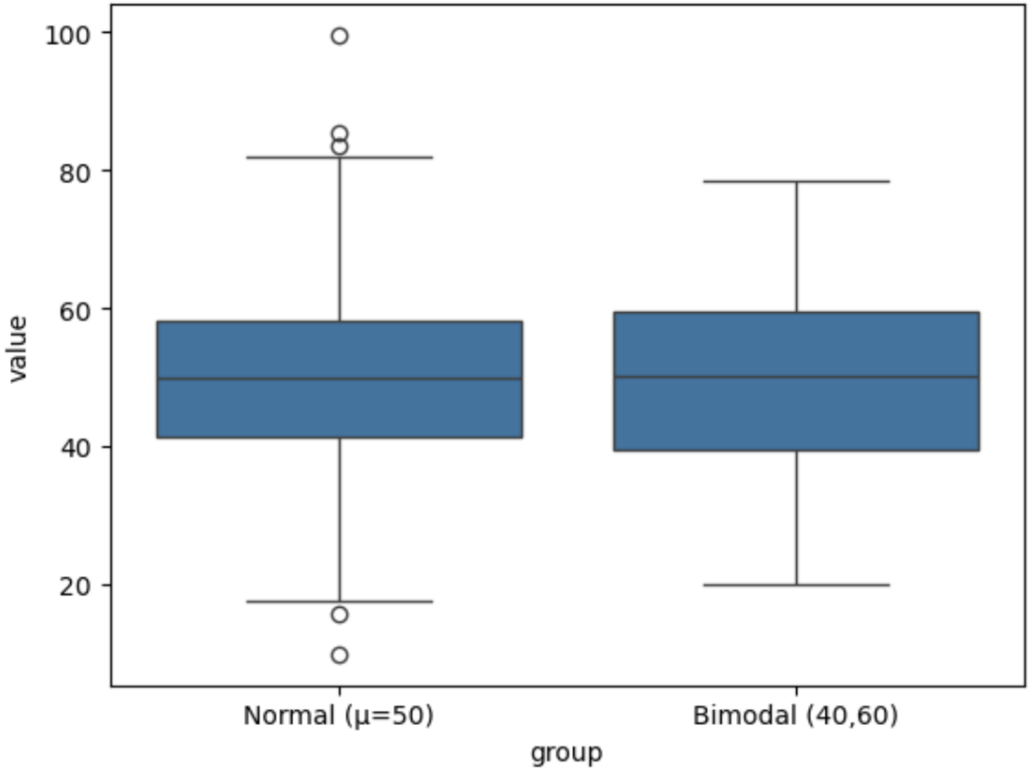
```
sns.boxplot(data=df,
            x="group",
            y="value");
```



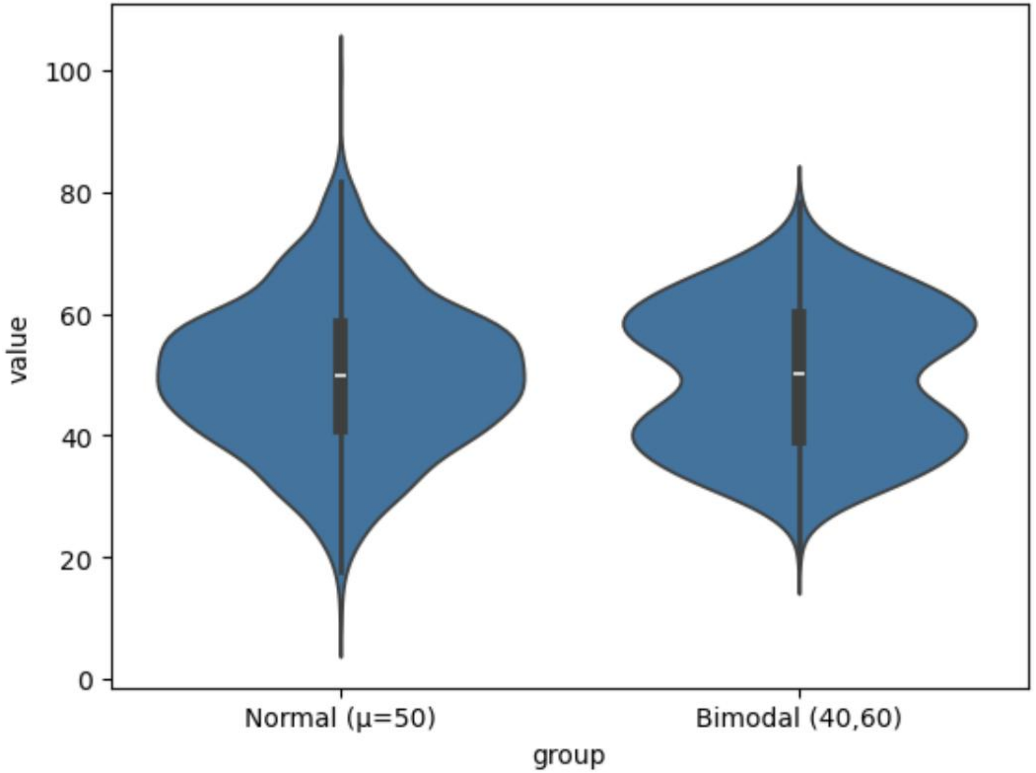
Comparison based on categories

Easy to switch plot type

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



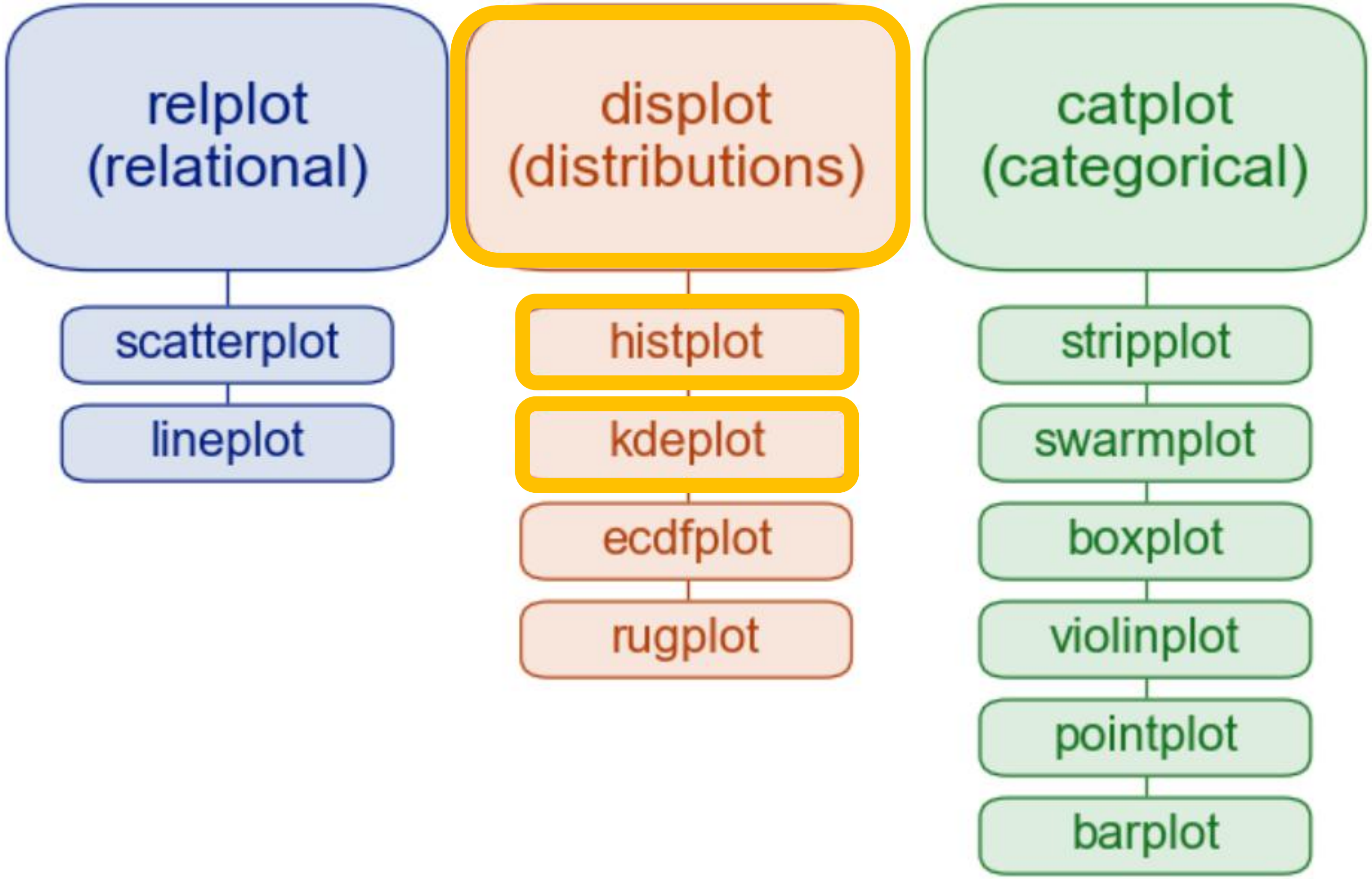

```
sns.violinplot(data=df, x="group", y="value")
```



Concepts behind seaborn

Figure-level

Axes-level



Distributions

Figure level

```
sns.histplot(data=data, x='value', hue='series')
```

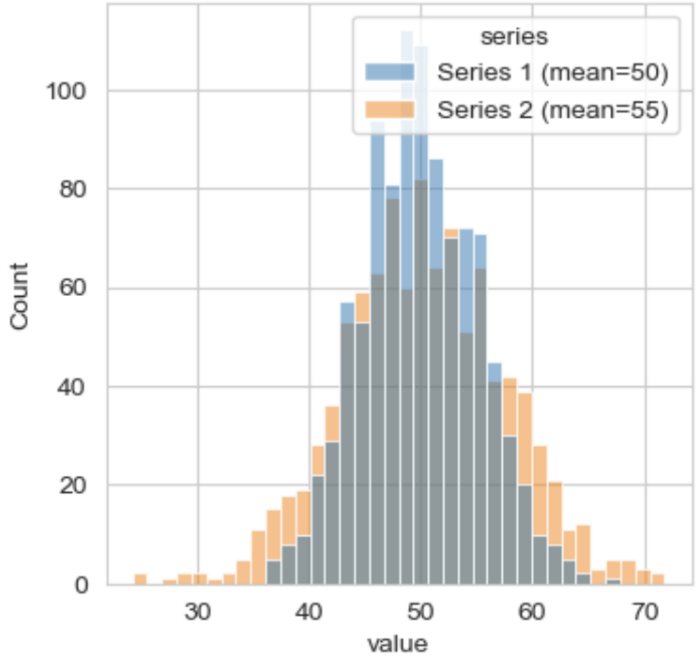
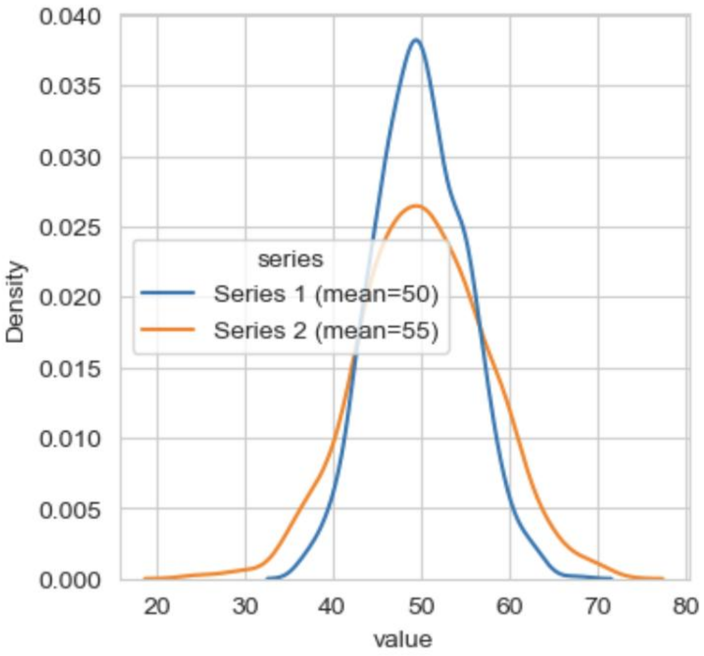


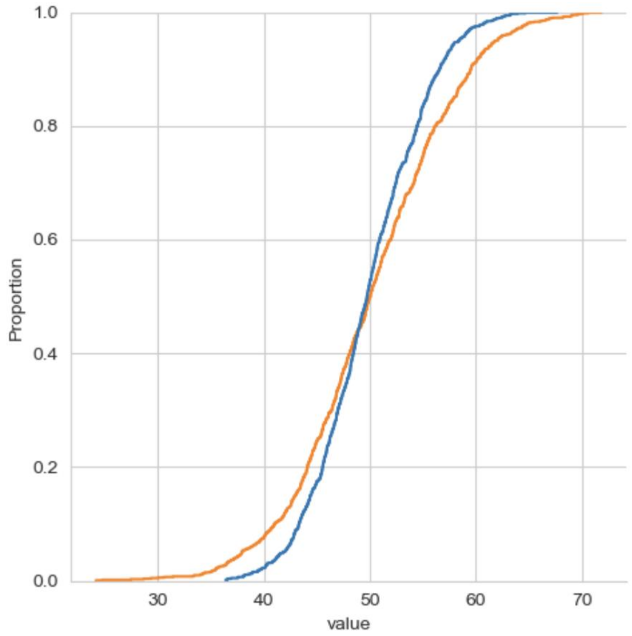
Figure level

```
sns.kdeplot(data=data, x='value', hue='series')
```

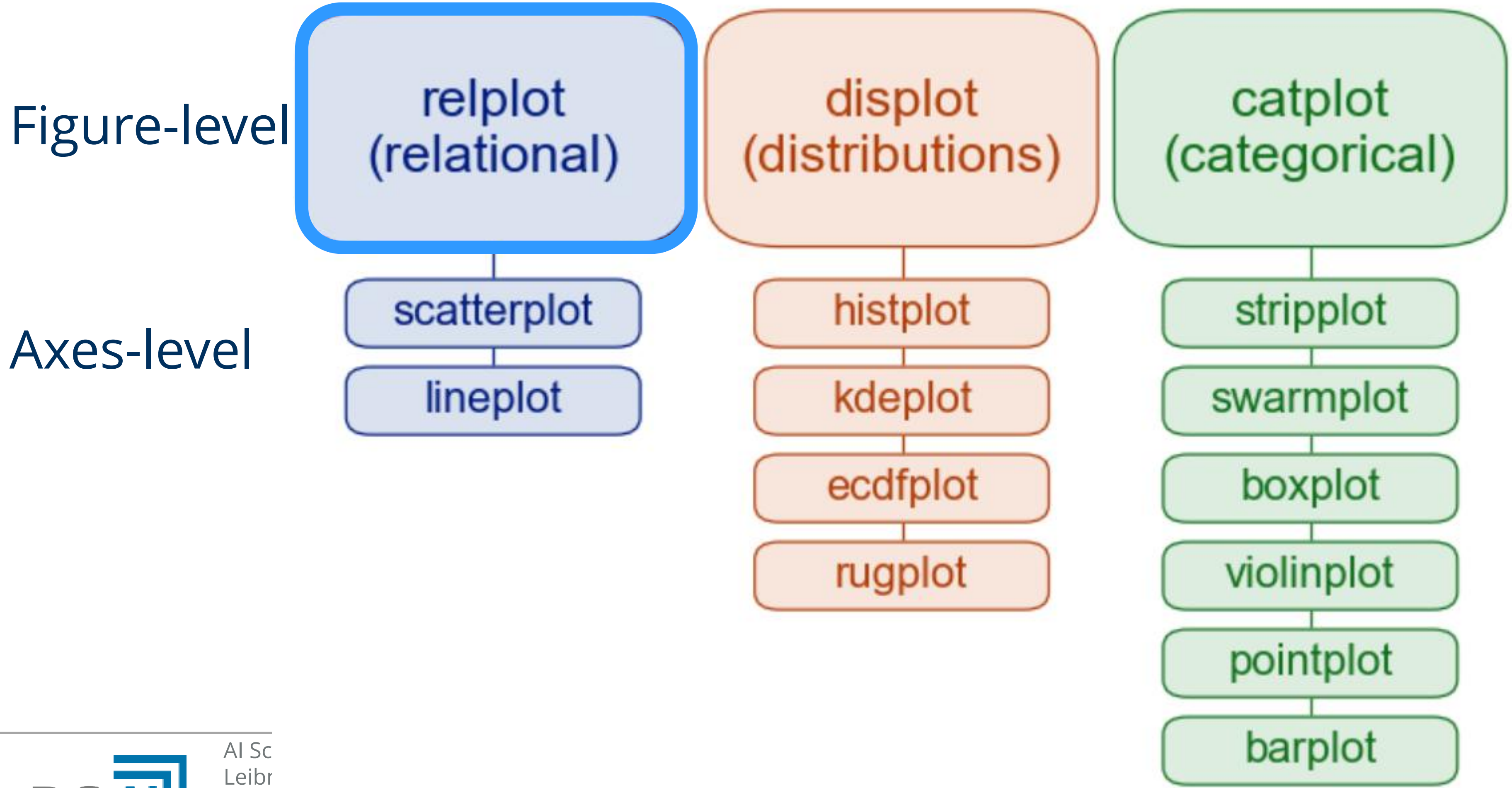



```
sns.displot(data=data, x='value',
            hue='series', kind="ecdf")
```

Axes level



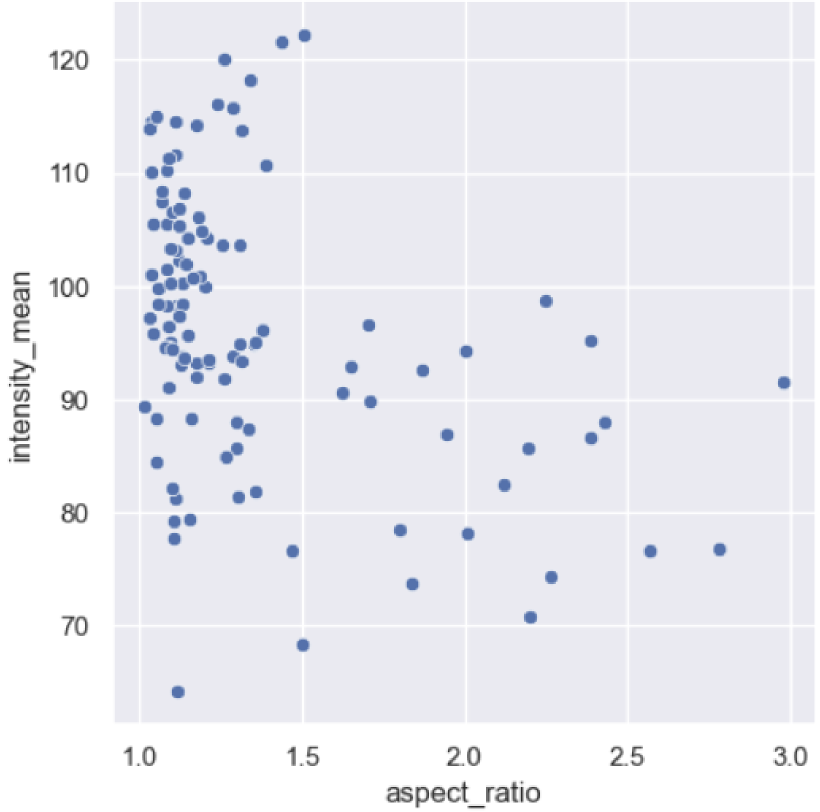
Concepts behind seaborn



Relationships

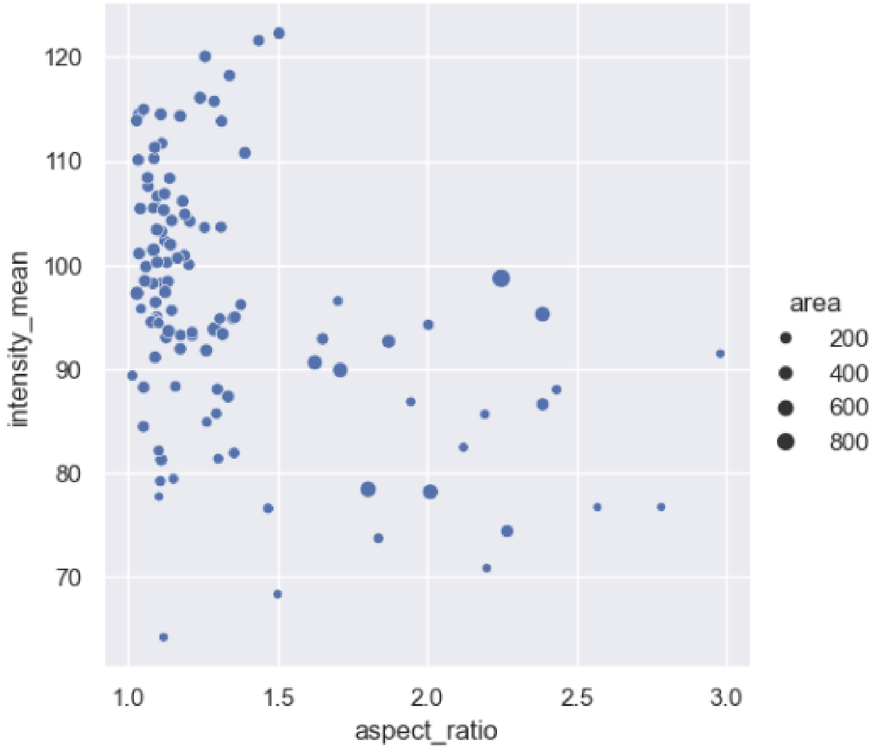
```
sns.relplot(data=df,
            x="aspect_ratio",
            y="intensity_mean");
```

area	intensity_mean	major_axis_length	minor_axis_length	aspect_ratio	file_name
139	96.546763	17.504104	10.292770	1.700621	20P1_POS0010_D_1UL
360	86.613889	35.746808	14.983124	2.385805	20P1_POS0010_D_1UL
43	91.488372	12.967884	4.351573	2.980045	20P1_POS0010_D_1UL
140	73.742857	18.940508	10.314404	1.836316	20P1_POS0010_D_1UL
144	89.375000	13.639308	13.458532	1.013432	20P1_POS0010_D_1UL



Relationships

```python
sns.relplot(data=df,
            x="aspect_ratio",
            y="intensity_mean",
            size="area");
```



area	intensity_mean	major_axis_length	minor_axis_length	aspect_ratio	file_name
139	96.546763	17.504104	10.292770	1.700621	20P1_POS0010_D_1UL
360	86.613889	35.746808	14.983124	2.385805	20P1_POS0010_D_1UL
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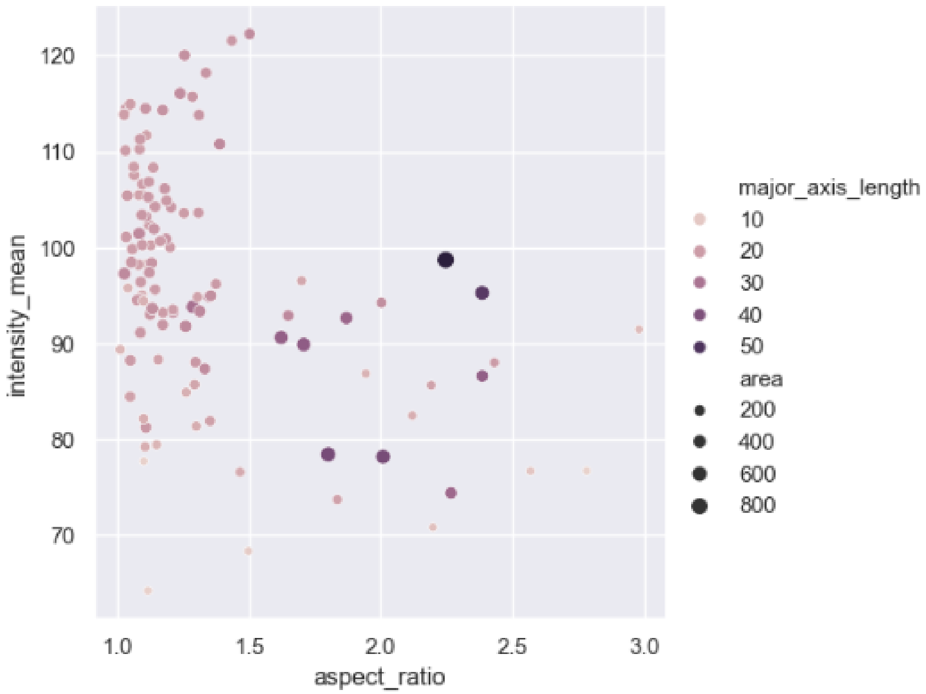
144	89.375000	13.639308	13.458532	1.013432	20P1_POS0010_D_1UL

Relationships

```
sns.relplot(data=df,
            x="aspect_ratio",
            y="intensity_mean",
            size="area",
            hue="major_axis_length");
```

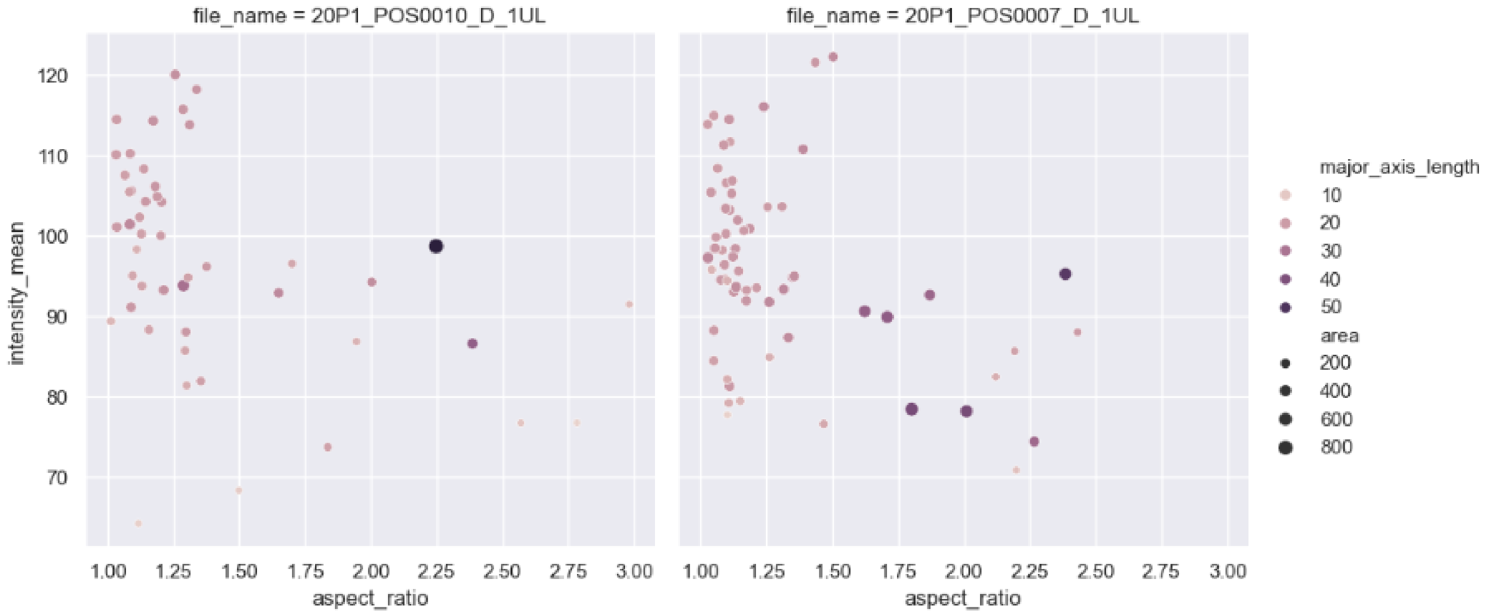
area	intensity_mean	major_axis_length	minor_axis_length	aspect_ratio	file_name
139	96.546763	17.504104	10.292770	1.700621	20P1_POS0010_D_1UL
360	86.613889	35.746808	14.983124	2.385805	20P1_POS0010_D_1UL
43	91.488372	12.967884	4.351573	2.980045	20P1_POS0010_D_1UL
140	73.742857	18.940508	10.314404	1.836316	20P1_POS0010_D_1UL
144	89.375000	13.639308	13.458532	1.013432	20P1_POS0010_D_1UL



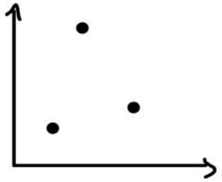
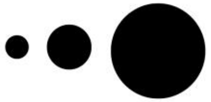
Relationships

```python
sns.relplot(data=df,
            x="aspect_ratio",
            y="intensity_mean",
            size="area",
            hue="major_axis_length",
            col="file_name");
```

area	intensity_mean	major_axis_length	minor_axis_length	aspect_ratio	file_name
139	96.546763	17.504104	10.292770	1.700621	20P1_POS0010_D_1UL
360	86.613889	35.746808	14.983124	2.385805	20P1_POS0010_D_1UL
43	91.488372	12.967884	4.351573	2.980045	20P1_POS0010_D_1UL
140	73.742857	18.940508	10.314404	1.836316	20P1_POS0010_D_1UL
144	89.375000	13.639308	13.458532	1.013432	20P1_POS0010_D_1UL

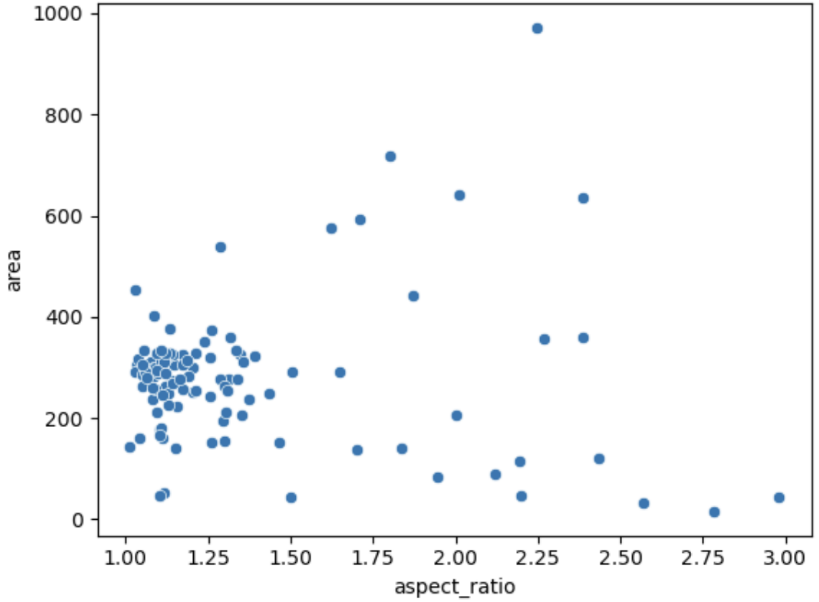


Basic elements of data visualization

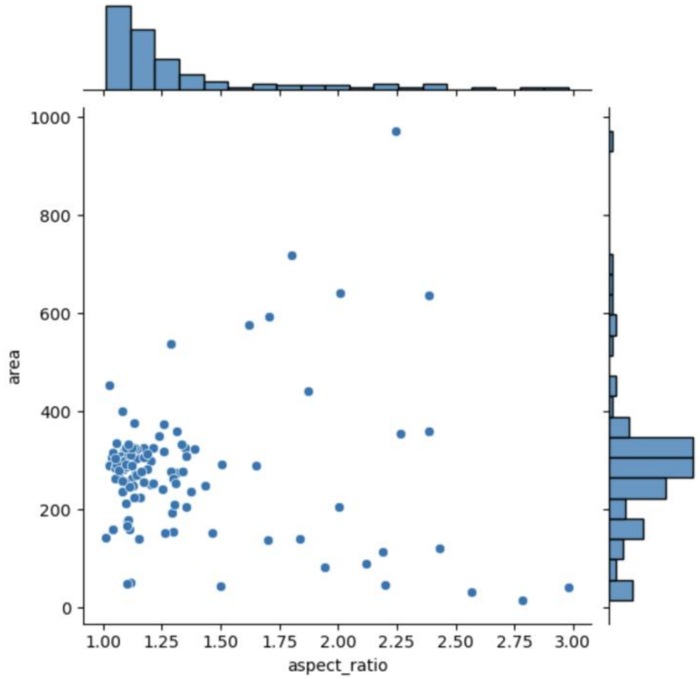
			Characteristics				
			Selective	Associative	Quantitative	Or der	Length
Visual Variables	Position		yes	yes	yes	yes	infinite
	Size		yes	no	partially	yes	Selection: ~ 5 Distinction: ~ 20

Relationships

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




```
sns.jointplot(data=df, x="aspect_ratio", y="area");
```



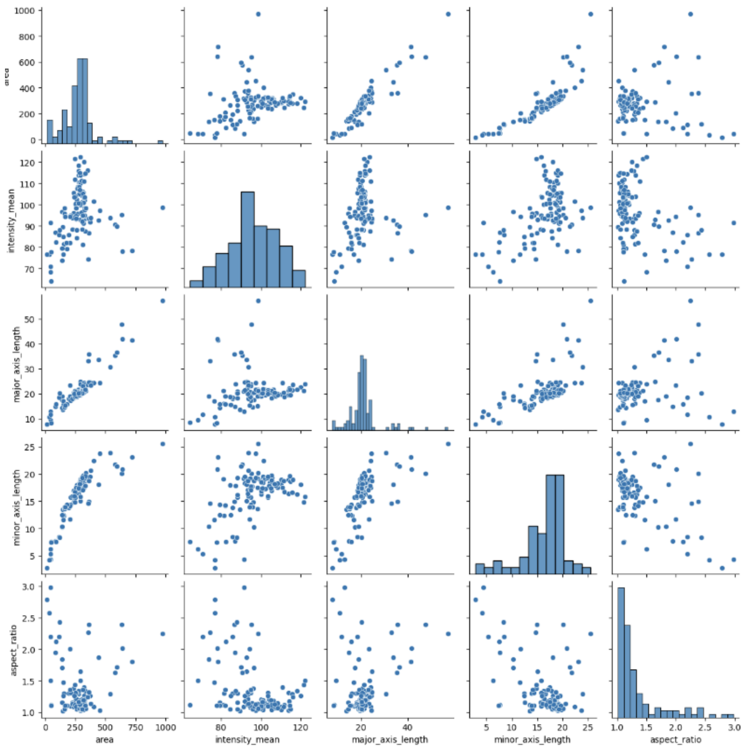
Relationships

Pairplots are great for getting an overview

	area	intensity_mean	major_axis_length	minor_axis_length	aspect_ratio	file_name
0	139	96.546763	17.504104	10.292770	1.700621	20P1_POS0010_D_1UL
1	360	86.613889	35.746808	14.983124	2.385805	20P1_POS0010_D_1UL
2	43	91.488372	12.967884	4.351573	2.980045	20P1_POS0010_D_1UL
3	140	73.742857	18.940508	10.314404	1.836316	20P1_POS0010_D_1UL
4	144	89.375000	13.639308	13.458532	1.013432	20P1_POS0010_D_1UL
...	...	...	...	...	...	...
106	305	88.252459	20.226532	19.244210	1.051045	20P1_POS0007_D_1UL
107	593	89.905565	36.508370	21.365394	1.708762	20P1_POS0007_D_1UL
108	289	106.851211	20.427809	18.221452	1.121086	20P1_POS0007_D_1UL
109	277	100.664260	20.307965	17.432920	1.164920	20P1_POS0007_D_1UL
110	46	70.869565	11.648895	5.298003	2.198733	20P1_POS0007_D_1UL

111 rows × 6 columns

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

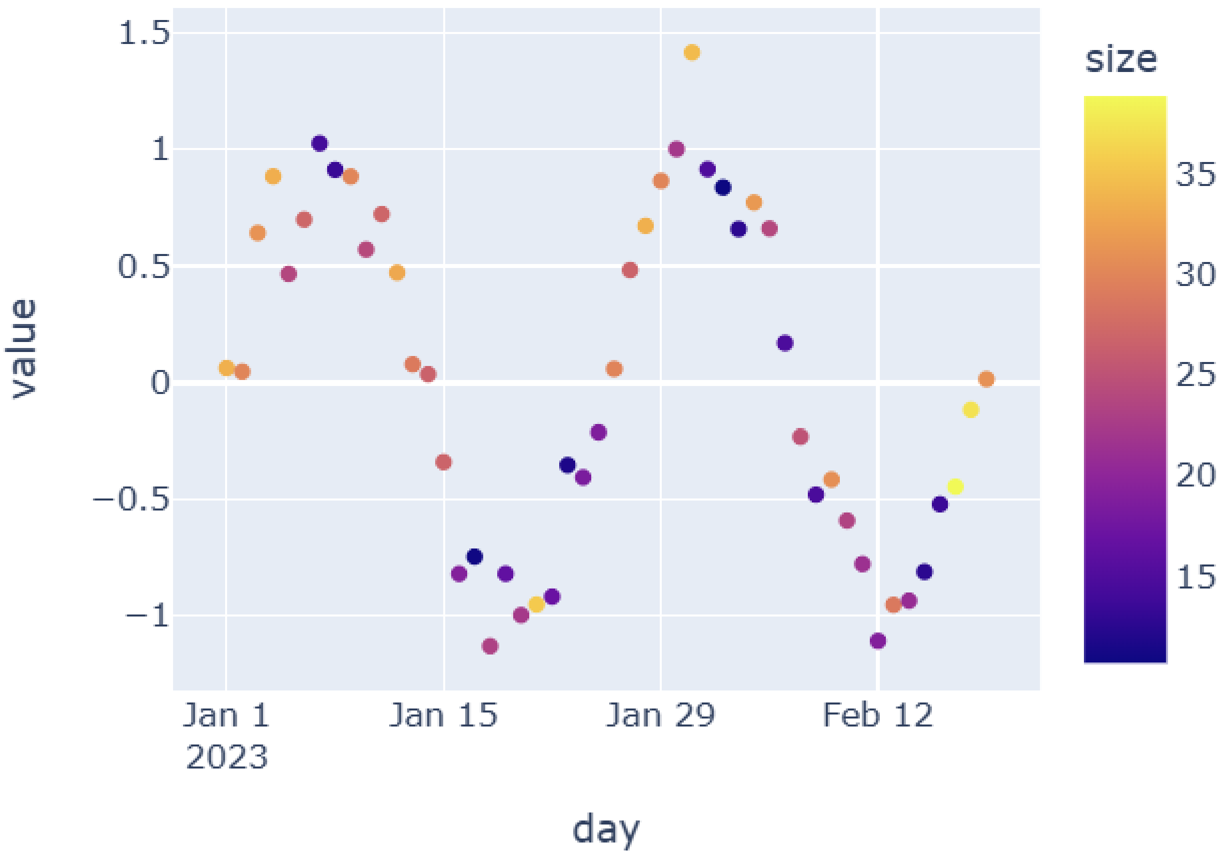


Interactive plotting

The plotly library aims at a similar API like seaborn and brings interactive plots.

```
import plotly.express as px
```

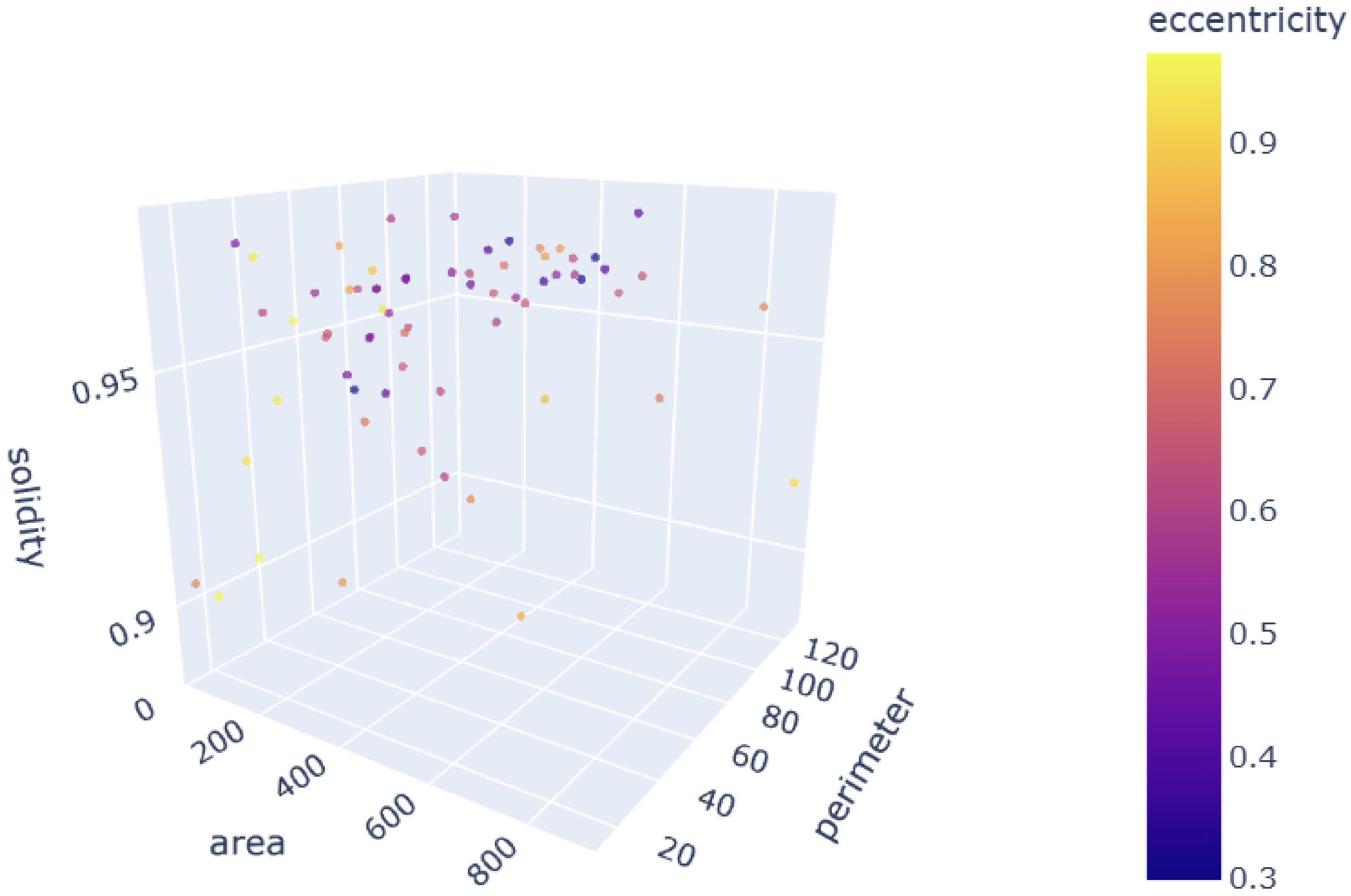
```
px.scatter(
    df,
    x="day",
    y="value",
    color="size"
)
```



Plotting in 3D with plotly

```python
import plotly.express as px
```

```python
fig = px.scatter_3d(df,
                    x="area",
                    y="perimeter",
                    z="solidity",
                    color="eccentricity")
```



Plotting higher dimensional data

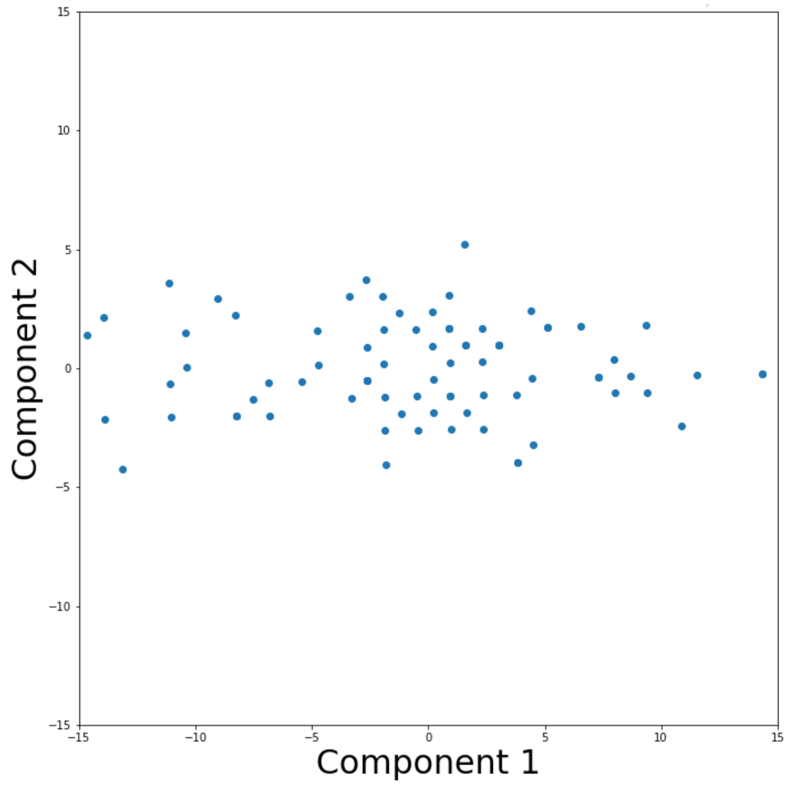
Using Dimensionality reduction (a.k.a. unsupervised machine learning)

-> Embeddings

	count	mean	std
label	44.0	22.500000	12.845233
area	44.0	401.863636	202.852288
bbox_area	44.0	542.750000	295.106376
equivalent_diameter	44.0	21.781085	6.174086
convex_area	44.0	423.295455	216.613747
max_intensity	44.0	234.909091	17.517856
mean_intensity	44.0	190.116971	15.034153
min_intensity	44.0	128.000000	0.000000
extent	44.0	0.758804	0.063276
local_centroid-0	44.0	11.439824	4.126230
local_centroid-1	44.0	10.138666	3.491815
solidity	44.0	0.953153	0.024749
feret_diameter_max	44.0	26.382434	8.915046
major_axis_length	44.0	25.876797	9.591558
minor_axis_length	44.0	18.872898	5.158791
orientation	44.0	0.053057	0.691430
eccentricity	44.0	0.600434	0.165688
standard_deviation_intensity	44.0	29.556705	5.507399
aspect_ratio	44.0	1.374342	0.397611
roundness	44.0	0.762889	0.156695
circularity	44.0	0.918858	0.133288

Many dimensions

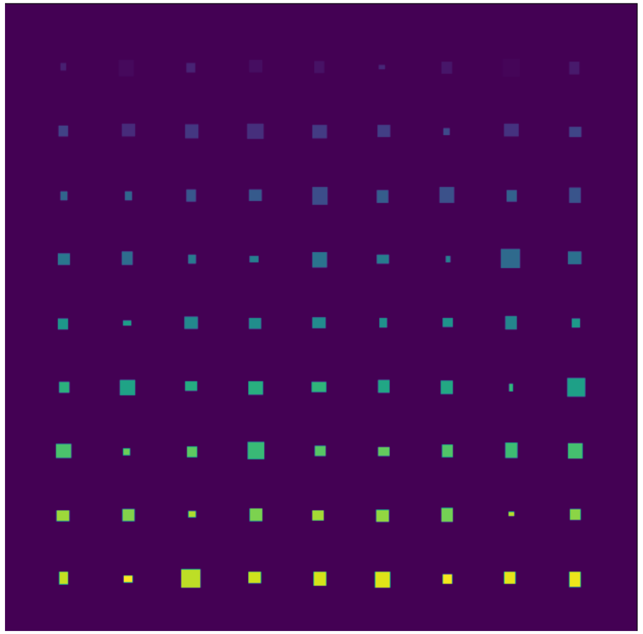
Dimensionality reduction

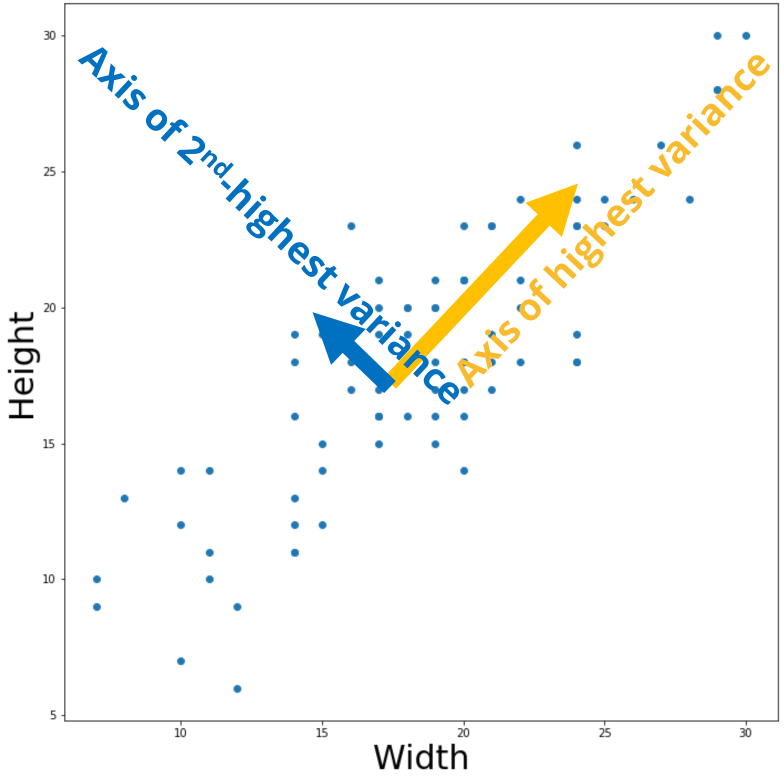


PCA: Principal Component Analysis

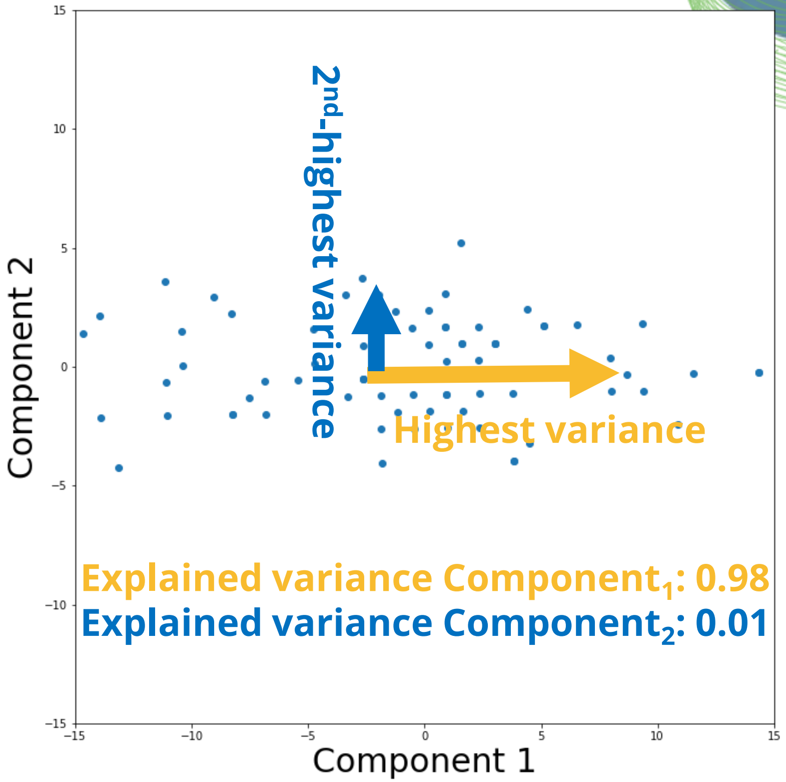
Decomposes data into linear combinations of features that explain the highest variance

Example: Squares of different size





PCA



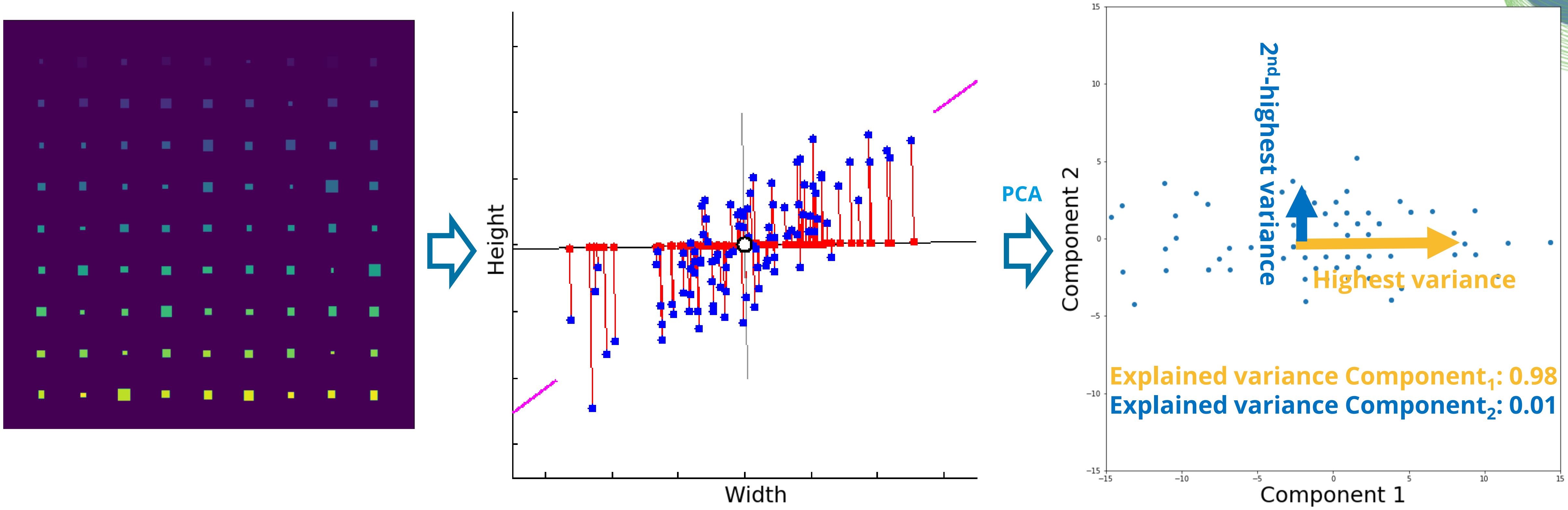
→ PCA transforms width/height measurements into a coordinate system that explains existing variance better

Slide adapted from Johannes Soltwedel, PoL TU-Dresden (licensed [CC-BY 4.0](CC-BY 4.0))

PCA: Principal Component Analysis

Decomposes data into linear combinations of features that explain the highest variance

Example: Squares of different size



→ PCA transforms width/height measurements into a coordinate system that explains existing variance better

PCA in Python: `sklearn.decomposition.PCA`

- Import package

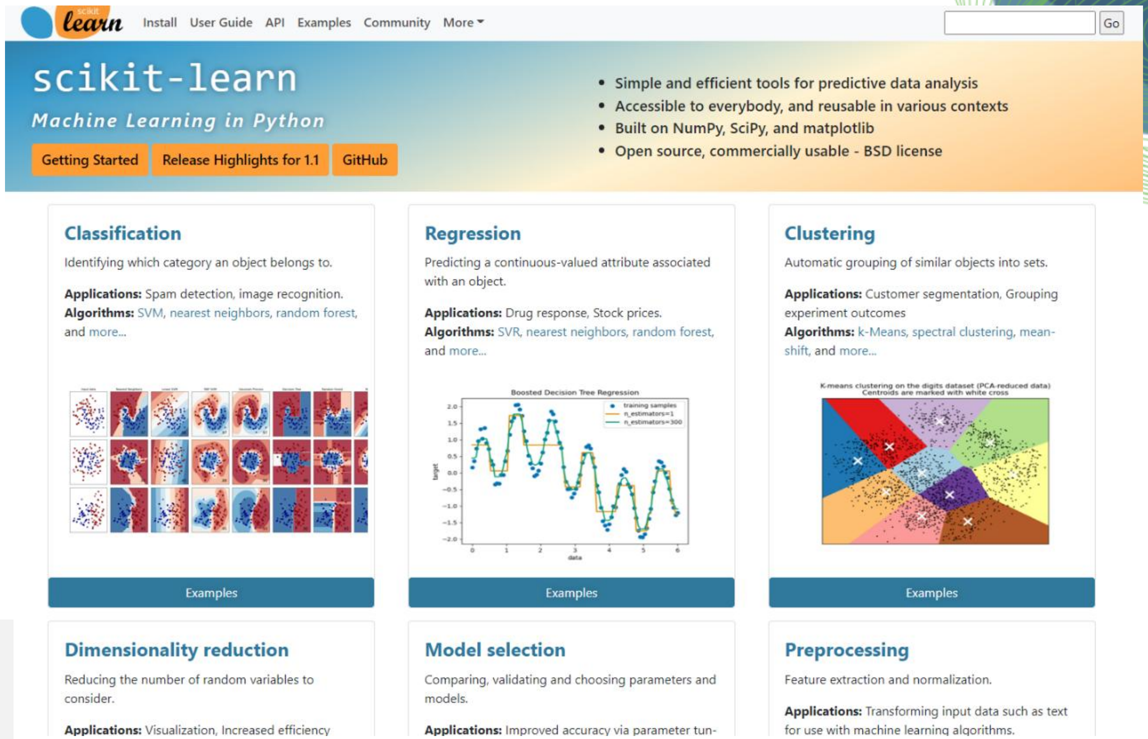
```
from sklearn.decomposition import PCA
```

- Apply PCA

```
pca = PCA(n_components=2)
pca.fit(standardized_data)
```

- Transform data into new coordinate system

```
transformed_data = pca.transform(data)
```



Important!

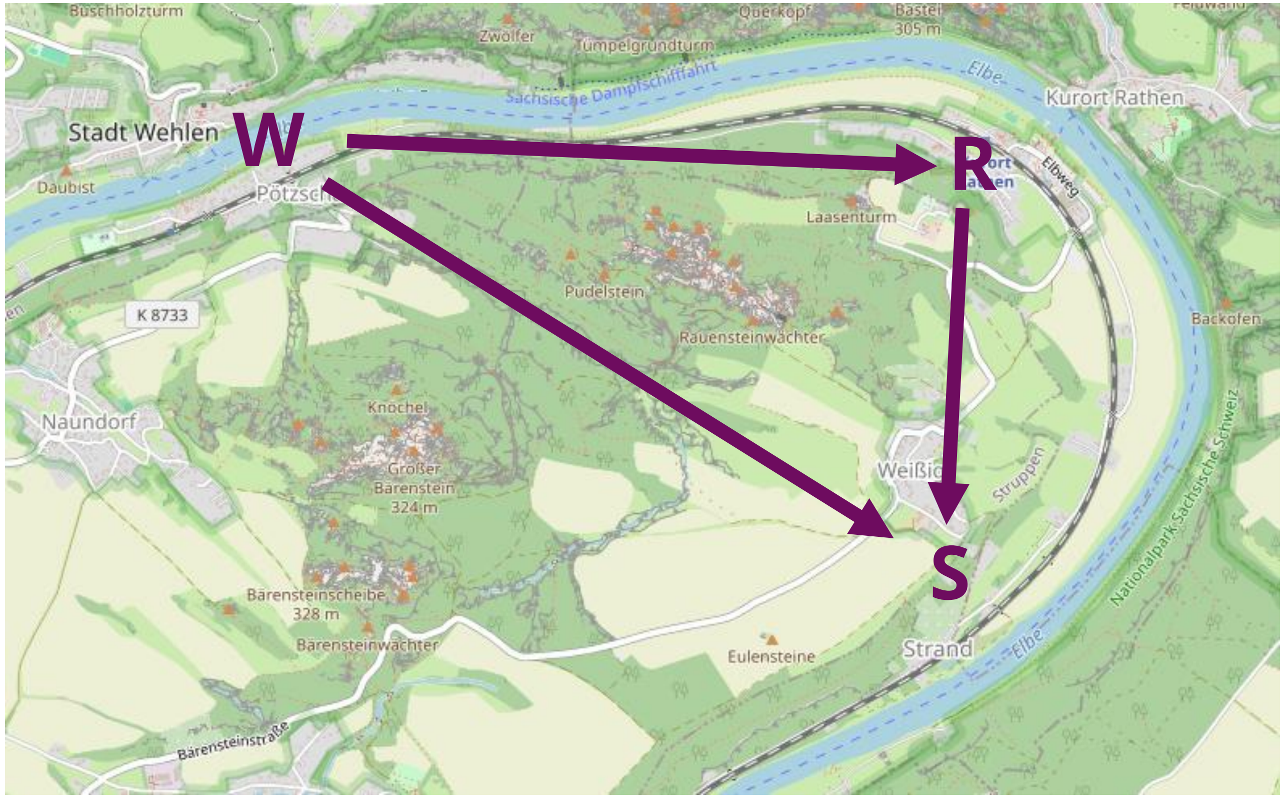
Always check the explained variance along the PCA component axes!

```
pca.explained_variance_ratio_
```

```
array([0.98773142, 0.01226858])
```

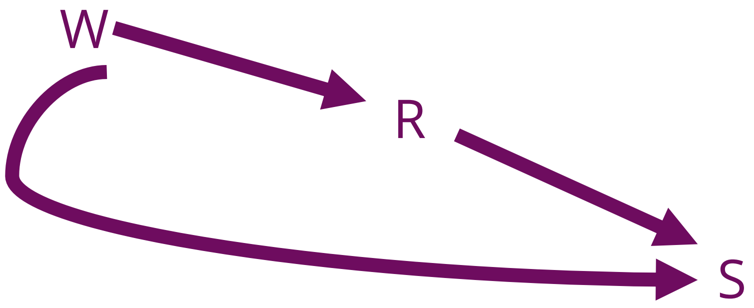
Non-Euclidian spaces

Not all features might be distances in space



Use travel time between W and S as metric for distance

→ Travelling from **W**ehlen to **S**trand by bike is probably faster if you make a detour through **R**athen



Slide adapted from Johannes Soltwedel, PoL TU-Dresden (licensed CC-BY 4.0)
Map source: OpenStreetMap (license ODbL), https://www.openstreetmap.org/#map=14/50.9500/14.0666

32

Uniform Manifold Approximation Projection (UMAP)

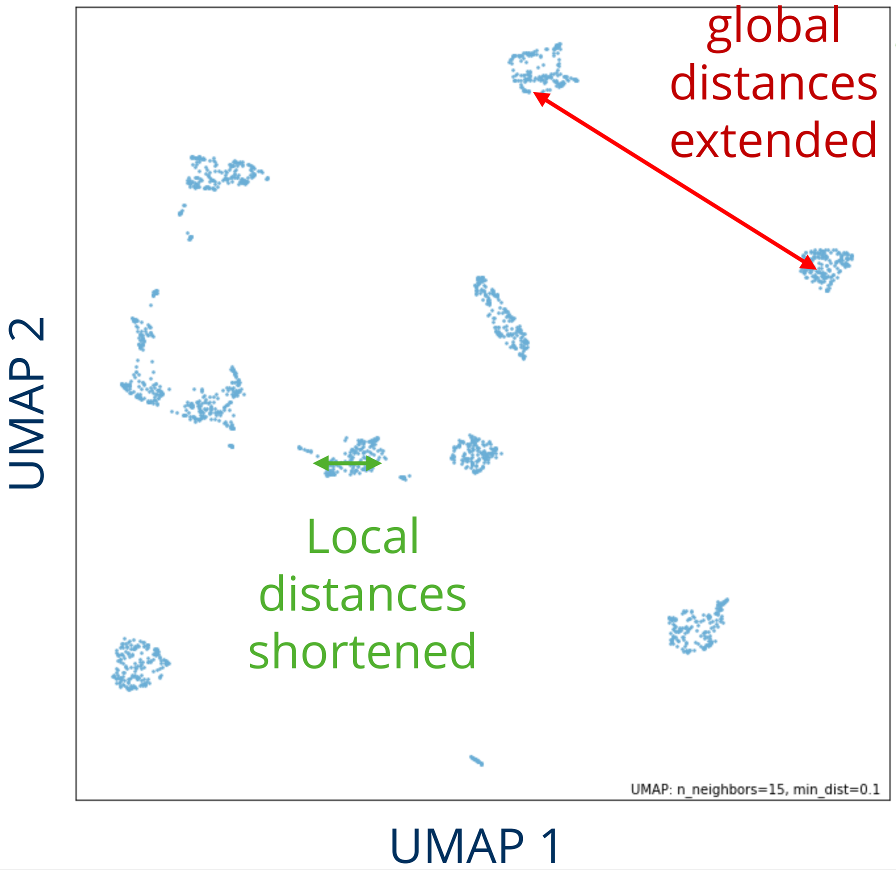
Structural, hierarchical, non-linear transformation

Modifies density of data points.

	count	mean	std
label	44.0	22.500000	12.845233
area	44.0	401.863636	202.852288
bbox_area	44.0	542.750000	295.106376
equivalent_diameter	44.0	21.781085	6.174086
convex_area	44.0	423.295455	216.613747
max_intensity	44.0	234.909091	17.517856
mean_intensity	44.0	190.116971	15.034153
min_intensity	44.0	128.000000	0.000000
extent	44.0	0.758804	0.063276
local_centroid-0	44.0	11.439824	4.126230
local_centroid-1	44.0	10.138666	3.491815
solidity	44.0	0.953153	0.024749
feret_diameter_max	44.0	26.382434	8.915046
major_axis_length	44.0	25.876797	9.591558
minor_axis_length	44.0	18.872898	5.158791
orientation	44.0	0.053057	0.691430
eccentricity	44.0	0.600434	0.165688
standard_deviation_intensity	44.0	29.556705	5.507399
aspect_ratio	44.0	1.374342	0.397611
roundness	44.0	0.762889	0.156695
circularity	44.0	0.918858	0.133288

Many dimensions

UMAP



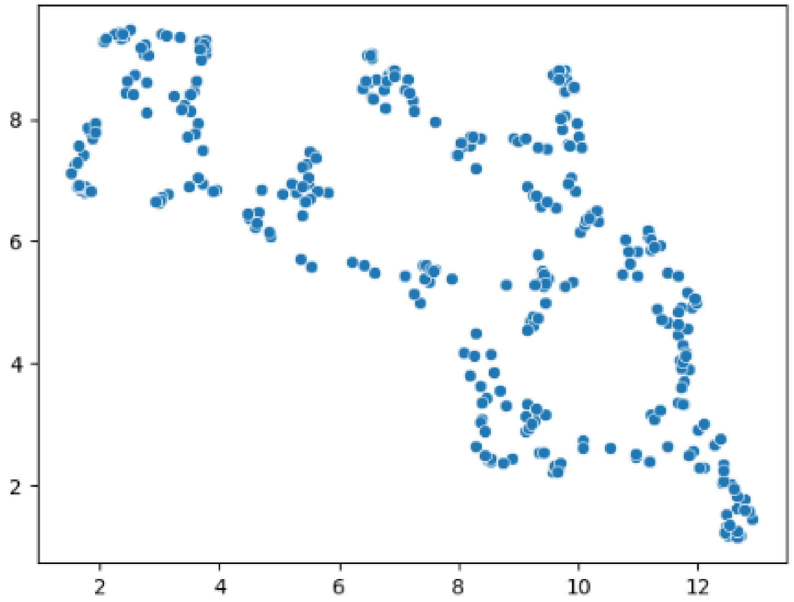
Uniform Manifold Approximation Projection (UMAP)

Non-deterministic algorithm: You execute it twice, you get different results.

[11]:
```
reducer = umap.UMAP()
embedding2 = reducer.fit_transform(scaled_statistics)

seaborn.scatterplot(x=embedding2[:, 0],
                    y=embedding2[:, 1])
```

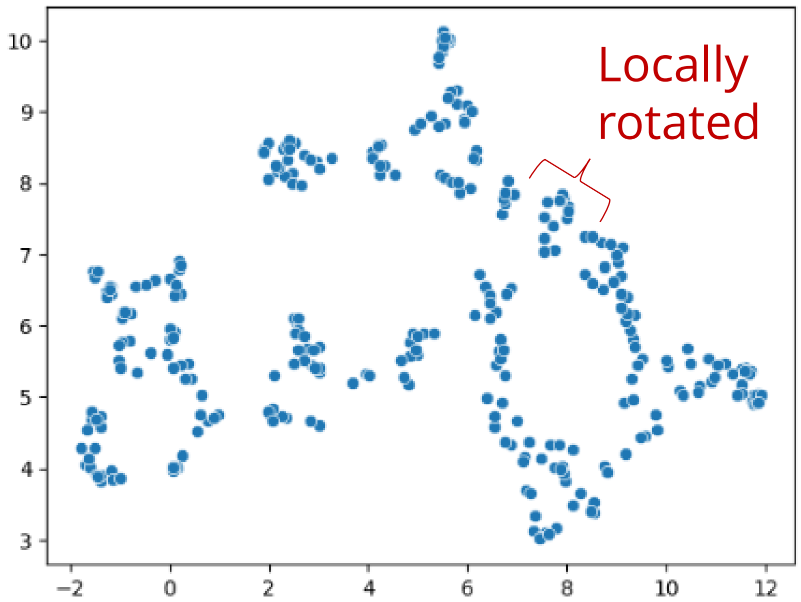
[11]: <AxesSubplot: >



[12]:
```
reducer = umap.UMAP()
embedding2 = reducer.fit_transform(scaled_statistics)

seaborn.scatterplot(x=embedding2[:, 0],
                    y=embedding2[:, 1])
```

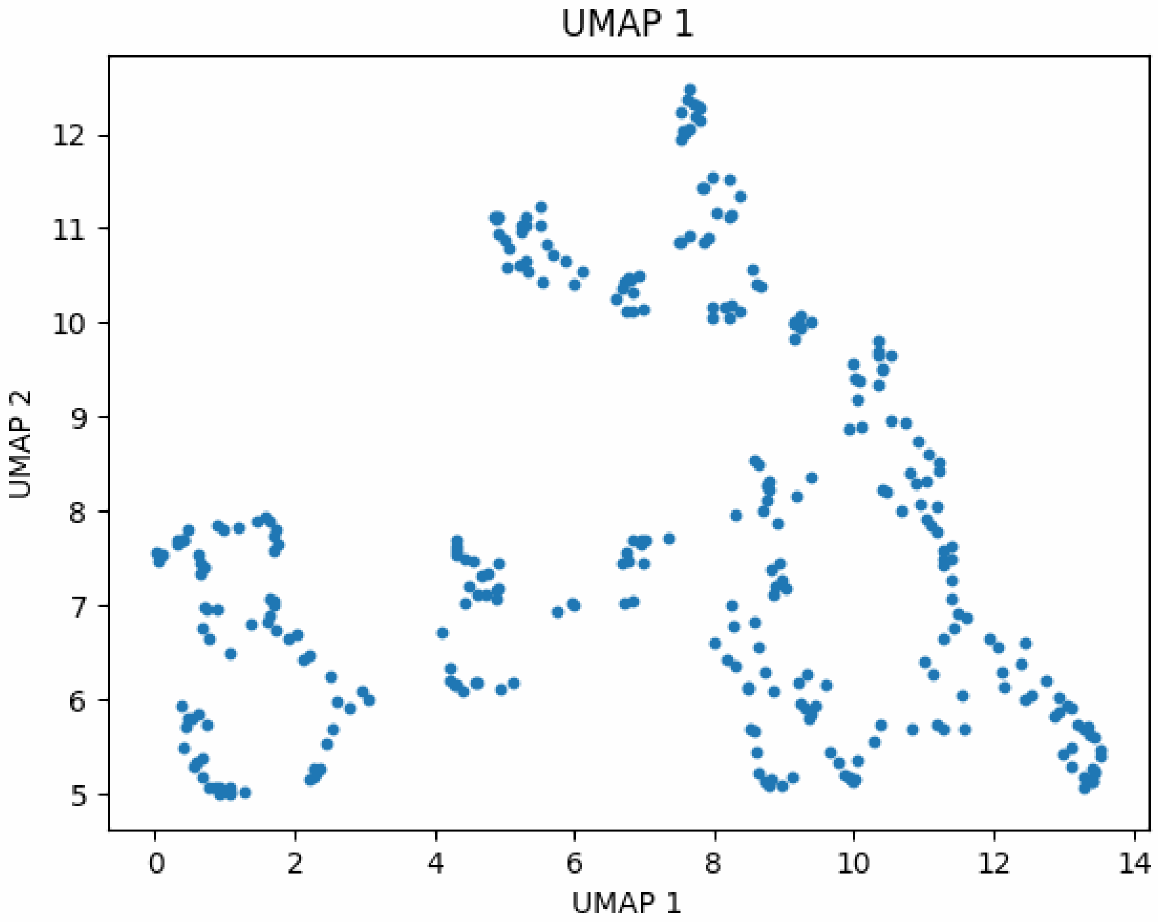
[12]: <AxesSubplot: >



Globally rotated

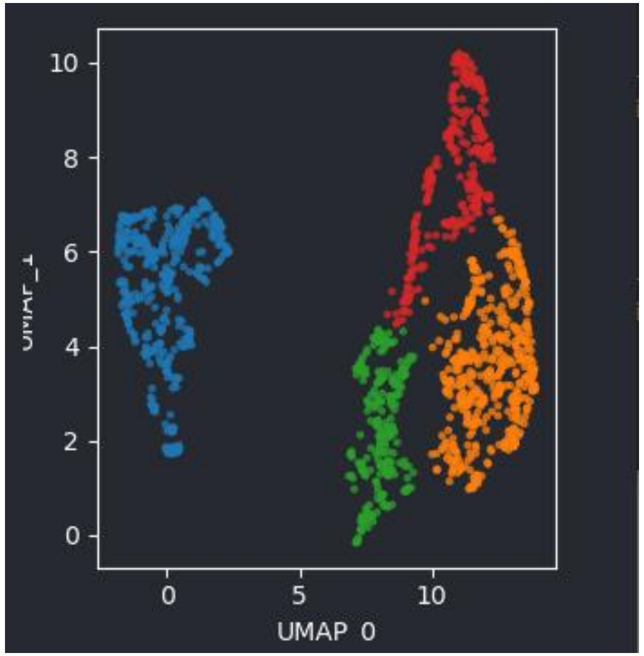
Uniform Manifold Approximation Projection (UMAP)

Non-deterministic algorithm: You execute it twice, you get different results.

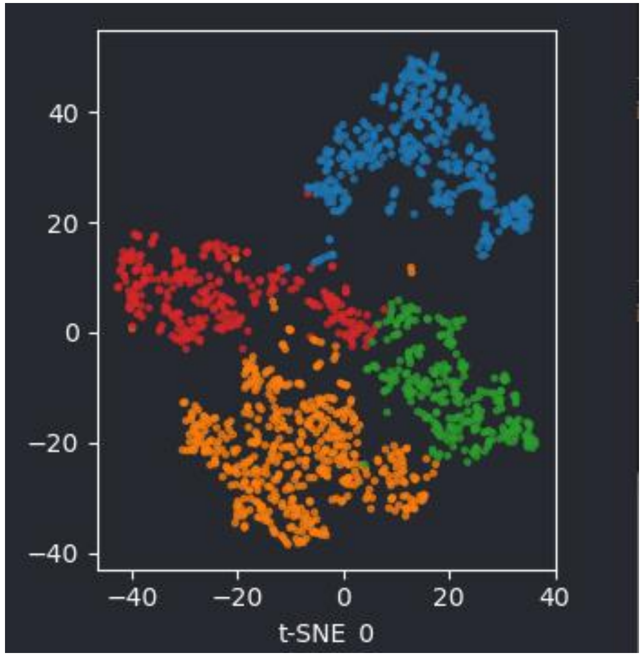


Dimensionality reduction

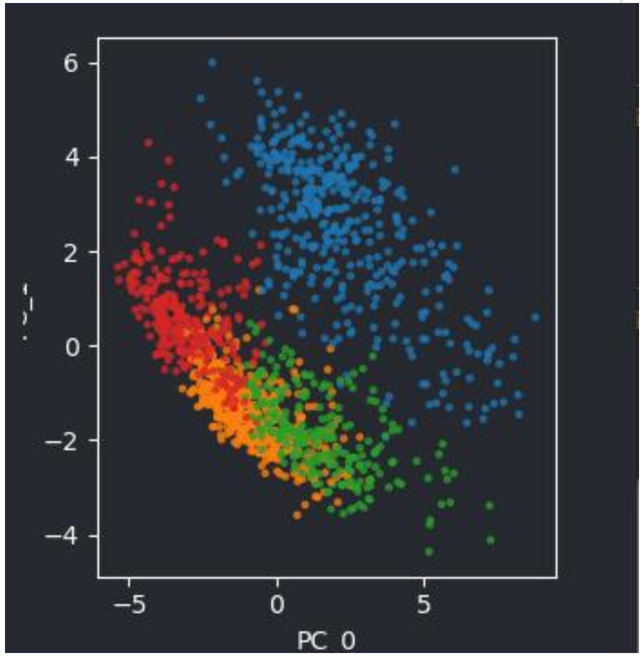
Visual comparison of different methods



Uniform manifold approximation and projection (UMAP)



t-distributed stochastic neighbor embedding (t-SNE)



Principal component analysis (PCA)

Visualizing images

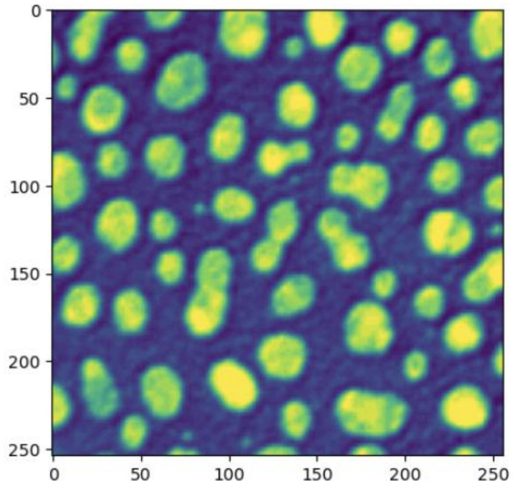
`imshow` originates from Matlab and has been implemented many times.

```
[1]: import matplotlib.pyplot as plt
     import stackview
     from skimage import io
```

matplotlib

```
[3]: plt.imshow(image)
```

```
[3]: <matplotlib.image.AxesImage at 0x1fa5b5145d0>
```

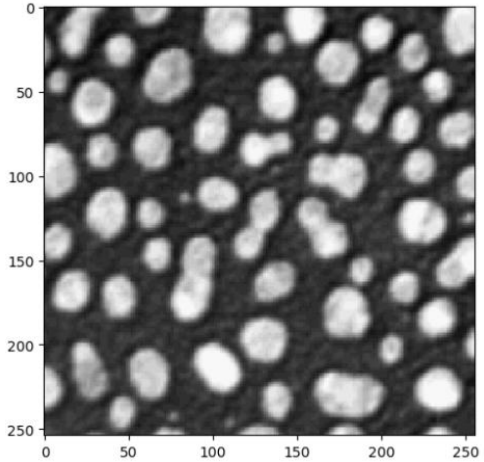


scikit-image

```
[4]: io.imshow(image)
```

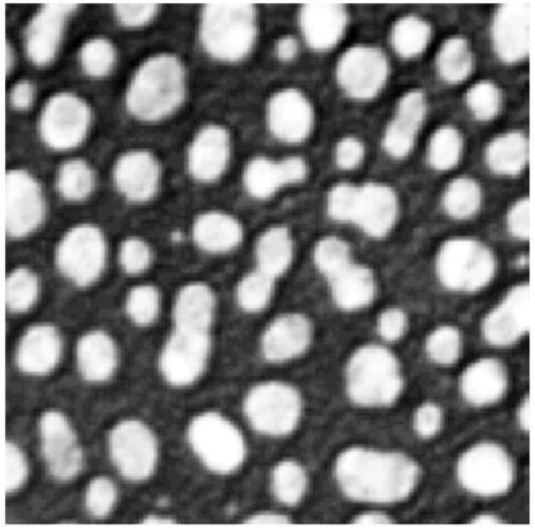
```
C:\Users\rober\AppData\Local\Temp\ipykernel_46732\2038164919.py:1: FutureWarning: `imshow` is deprecated since version 0.25 and will be removed in version 0.27. Please use `matplotlib`, `napari`, etc. to visualize images.
  io.imshow(image)
```

```
[4]: <matplotlib.image.AxesImage at 0x1fa580cbc50>
```



stackview

```
[5]: stackview.imshow(image)
```



Visualizing images

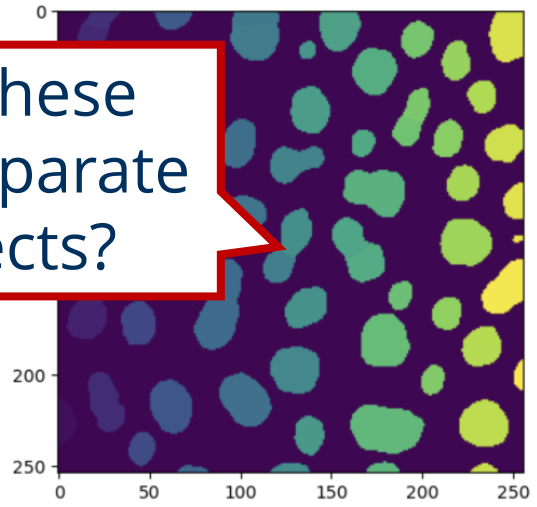
`imshow` originates from Matlab and has been implemented many times.

```
[1]: import matplotlib.pyplot as plt
     import stackview
     from skimage import io
```

matplotlib

```
[6]: plt.imshow(labels)
```

```
[6]: <matplotlib.image.AxesImage at 0x1fa5b6df210>
```



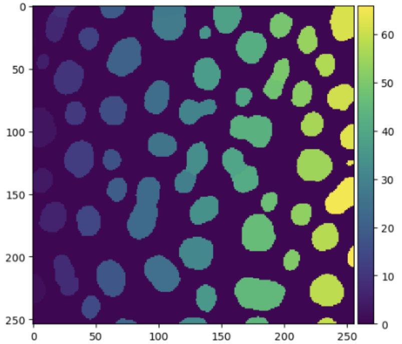
Are these two separate objects?

scikit-image

```
[7]: io.imshow(labels)
```

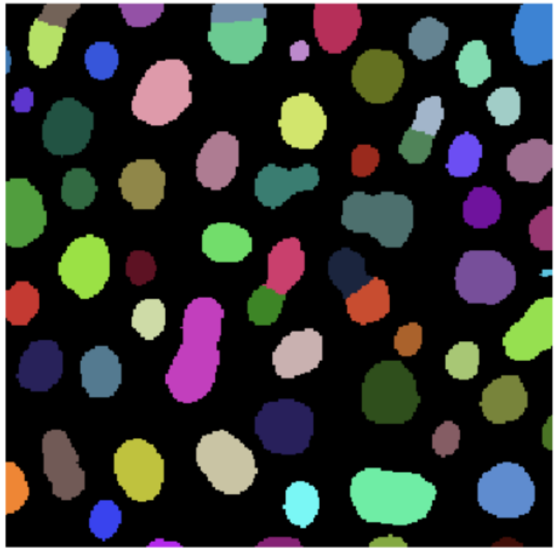
```
C:\Users\rober\AppData\Local\Temp\ipykernel_46732\28416559.py:1: FutureWarning: `imshow` is deprecated since version 0.25 and will be removed in version 0.27. Please use `matplotlib`, `napari`, etc. to visualize images.
  io.imshow(labels)
C:\Users\rober\miniforge3\envs\bob-env\Lib\site-packages\skimage\io\_plugins\matplotlib_plugin.py:158: UserWarning: Low image data range; displaying image with stretched contrast.
  lo, hi, cmap = _get_display_range(image)
```

```
[7]: <matplotlib.image.AxesImage at 0x1fa5b67b410>
```



stackview

```
[8]: stackview.imshow(labels)
```

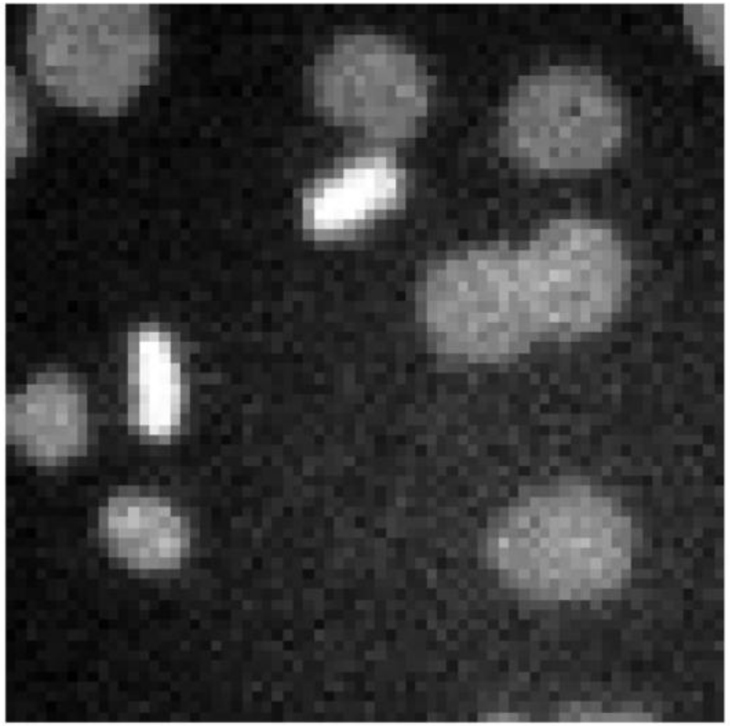


Visualizing images

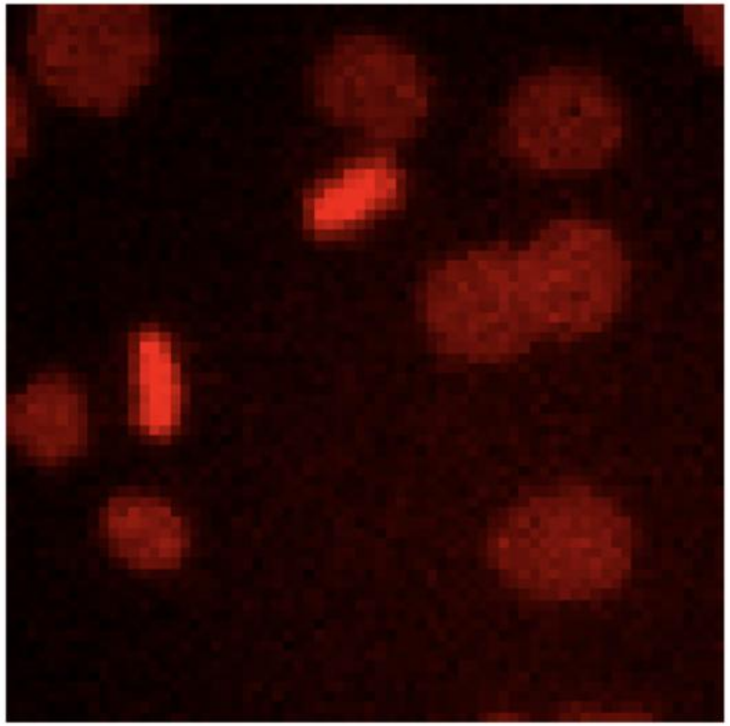
… using *stackview*

Disclosure: I maintain this

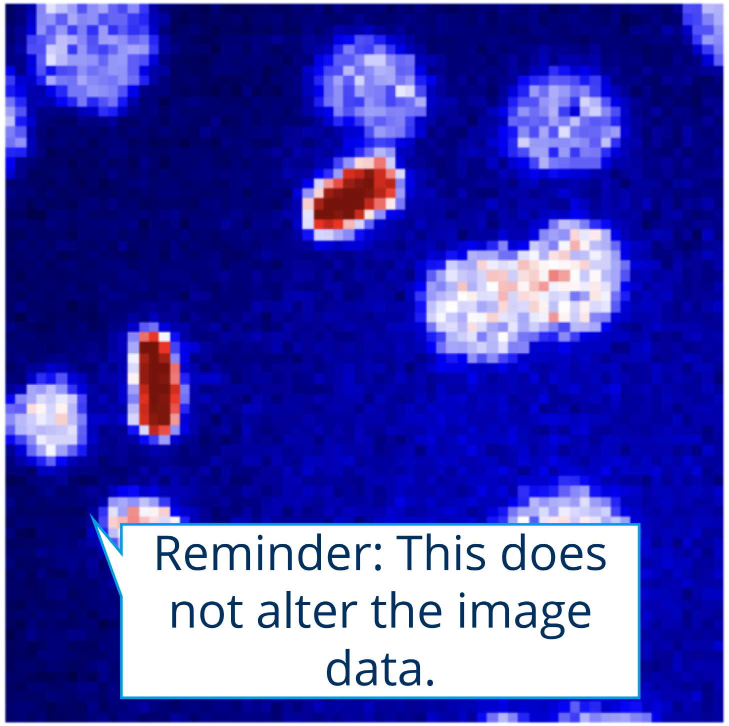
[3]:
```python
import stackview
stackview.imshow(image)
```



[5]:
```python
stackview.imshow(image, colormap="pure_red")
```



[6]:
```python
stackview.imshow(image, colormap="seismic")
```



Reminder: This does not alter the image data.

https://github.com/haesleinhuepf/stackview
https://github.com/ScaDS/BIDS-lecture-2025/blob/main/02a_image_processing/02_opening_visualizing_images.ipynb

Visualizing images

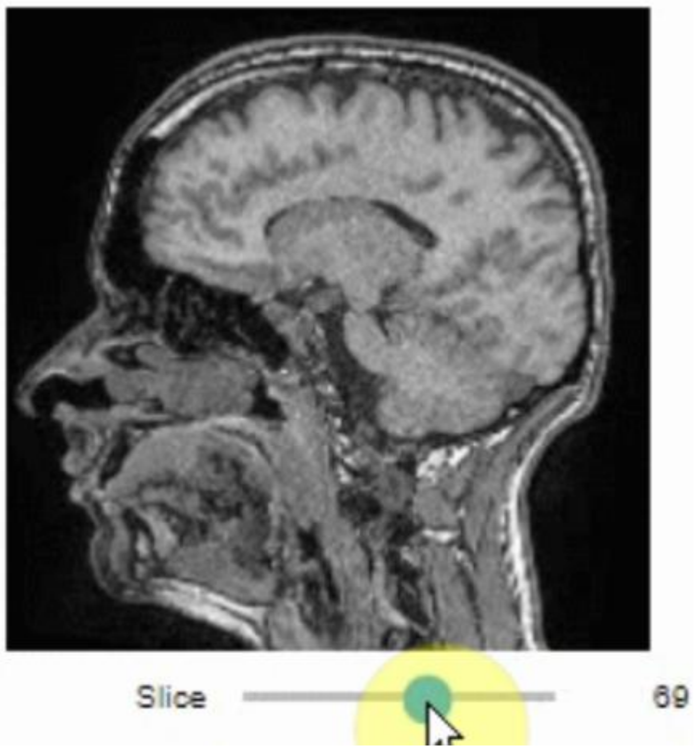
… using *stackview*

```
[6]: stackview.slice(mri_image)
```

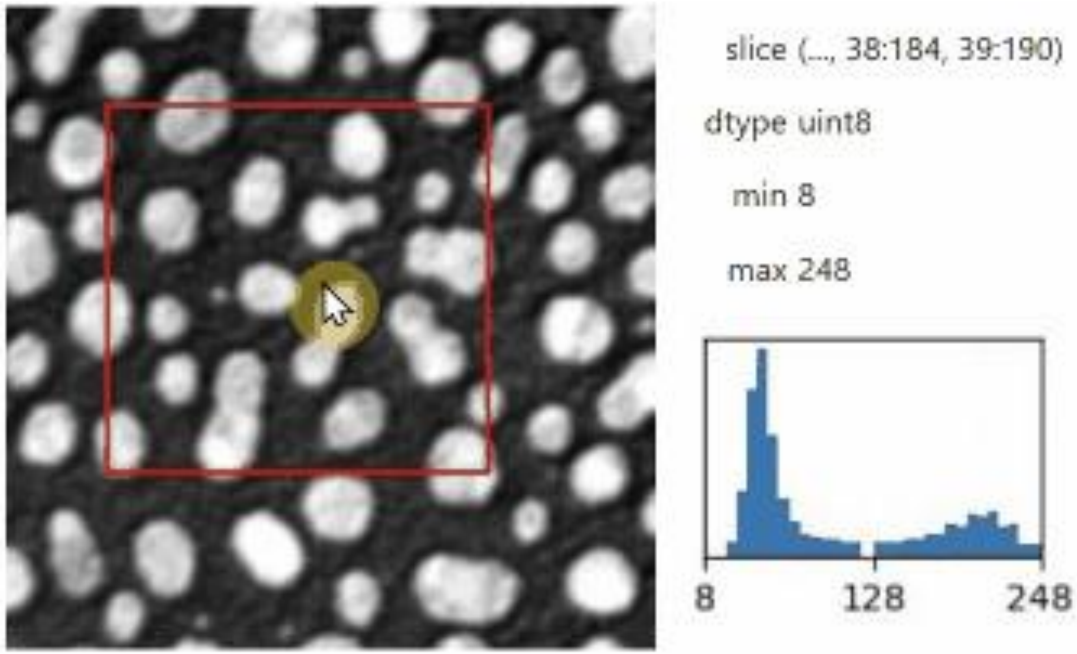
Visualizing images

... using *stackview*

```
[6]: stackview.slice(mri_image)
```




```
[8]: stackview.histogram(image)
```

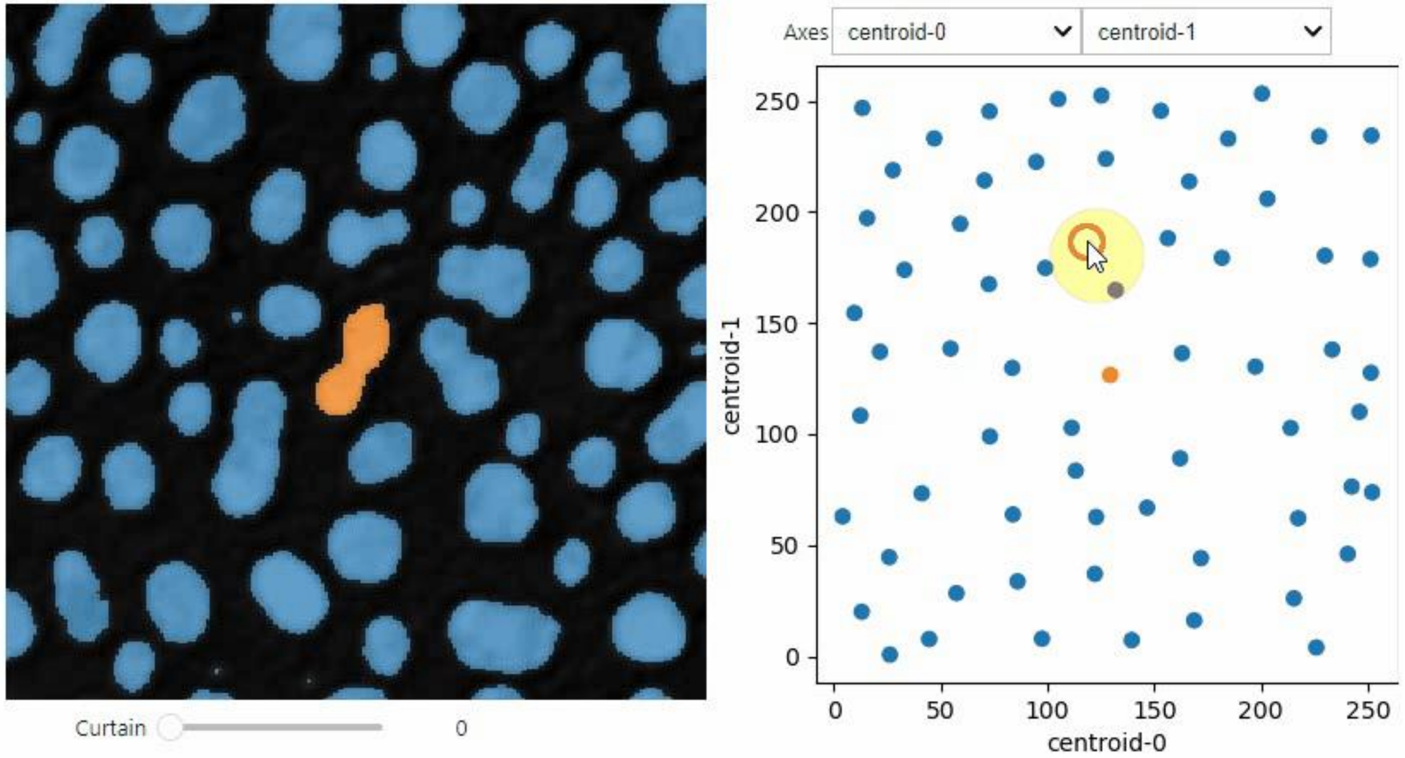


Selecting objects according to their properties

Understanding what certain measurements *mean* may require interactive user interfaces

```
[6]: stackview.clusterplot(image=image,
                          labels=labeled_image,
                          df=df,
                          column_x="area",
                          column_y="aspect_ratio",
                          zoom_factor=1.6,
                          alpha=0.7)
```

[6]:



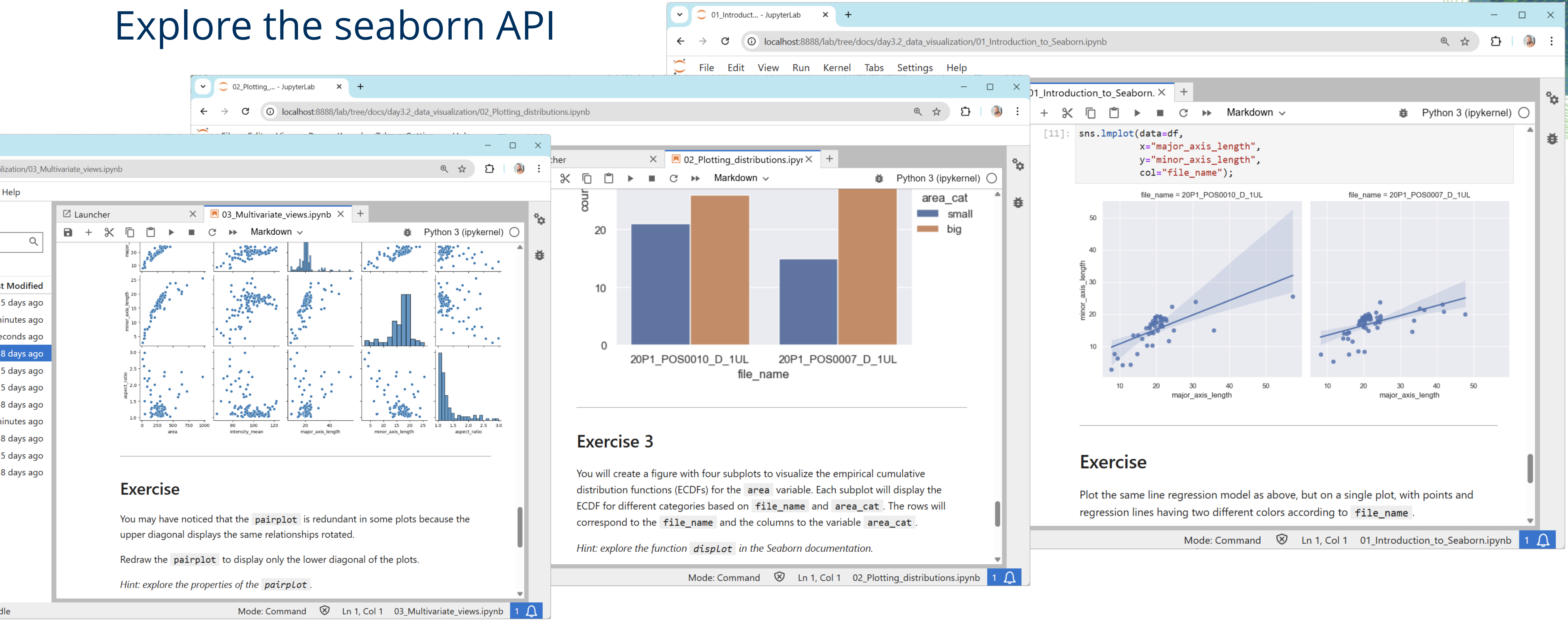
CENTER FOR SCALABLE DATA ANALYTICS
AND ARTIFICIAL INTELLIGENCE

Exercises

Robert Haase

Plotting: seaborn

Explore the seaborn API



Plotting: plotly

Explore interactive plotting using plotly

Note: This will only work on the jupyter4nfdi system.

```
!pip install plotly pandas
```

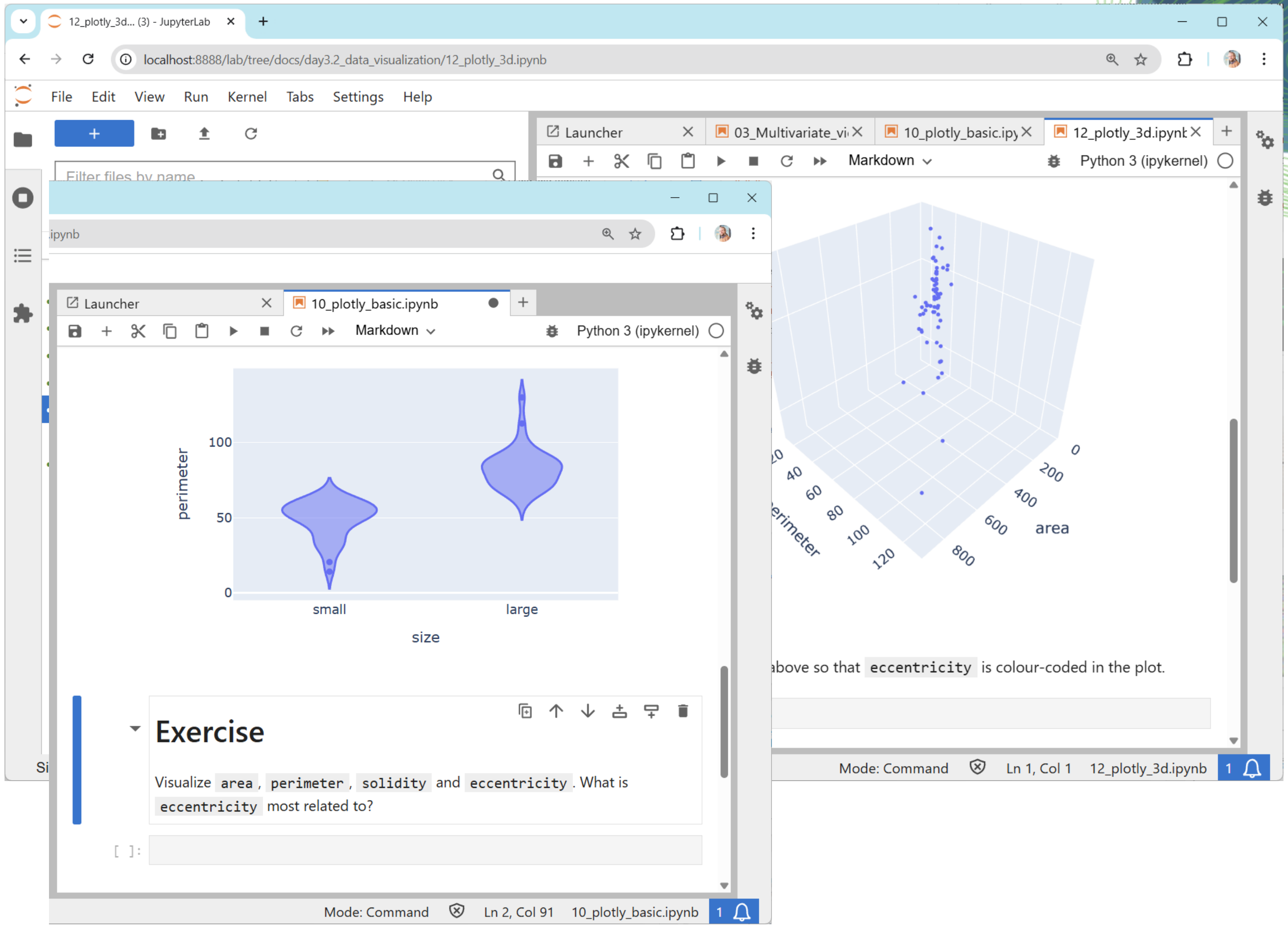


Image visualization

Note: This will only work on the jupyter4nfdi system.

You will need to install stackview by executing this from a code cell:

```
!pip install stackview pandas
```