# Feature extraction and working with tables

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With material from

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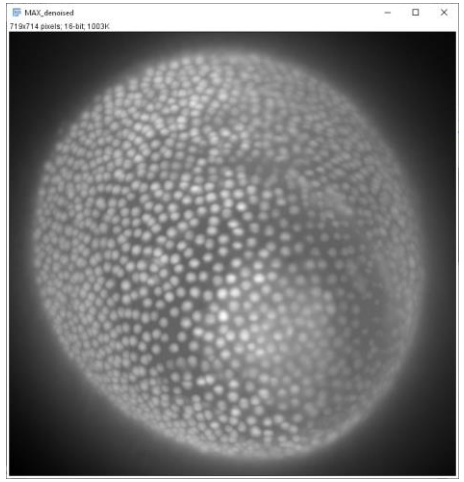
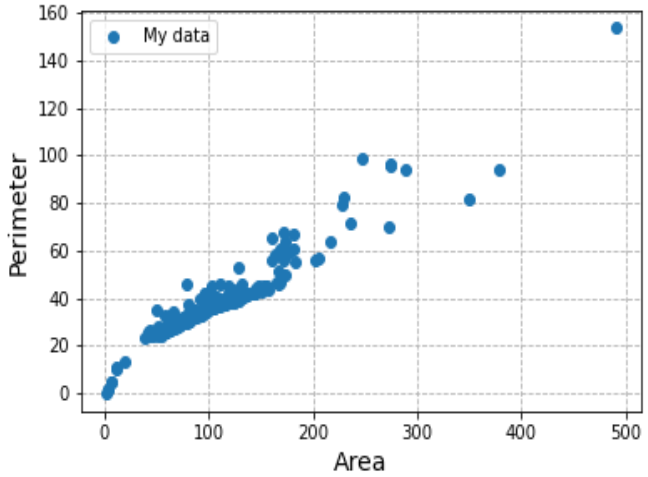
# Feature extraction

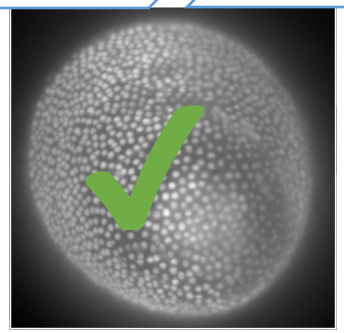
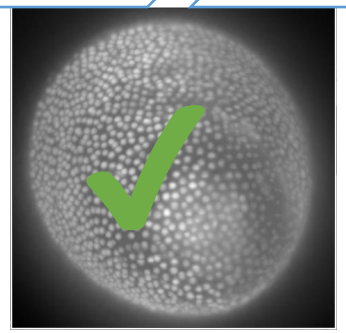
- Feature extraction is a *late* processing step in image analysis.
- It can be used for images, or segmented/labelled images

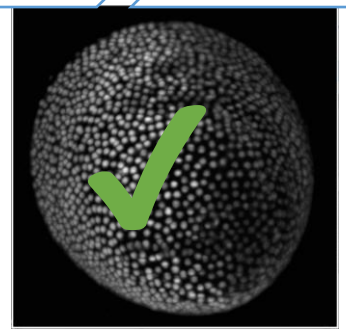


Feature Extraction




Acquisition → Denoising → Background subtraction → Segmentation → Labeling → Feature Extraction



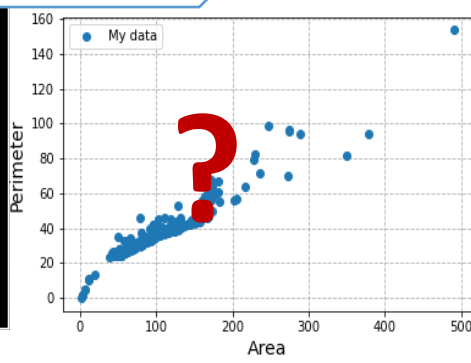






Image data source: Daniela Vorkel, Myers lab, MPI CBG

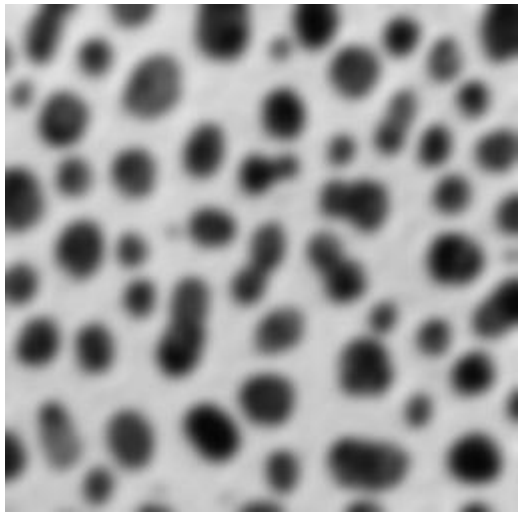
# Feature extraction

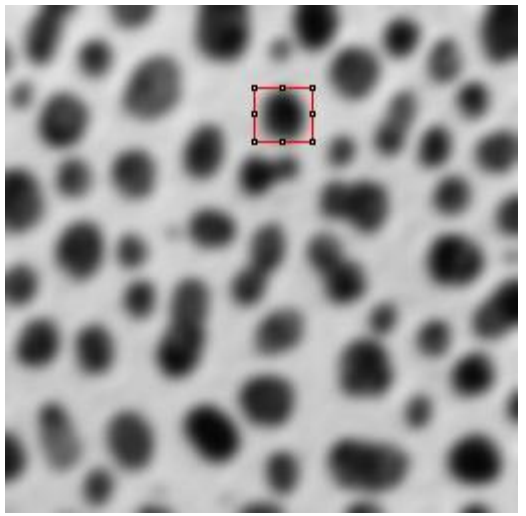
- A *feature* is a countable or measurable property of an image or object.
- Goal of feature extraction is finding a minimal set of features to describe an object well enough to differentiate it from other objects.

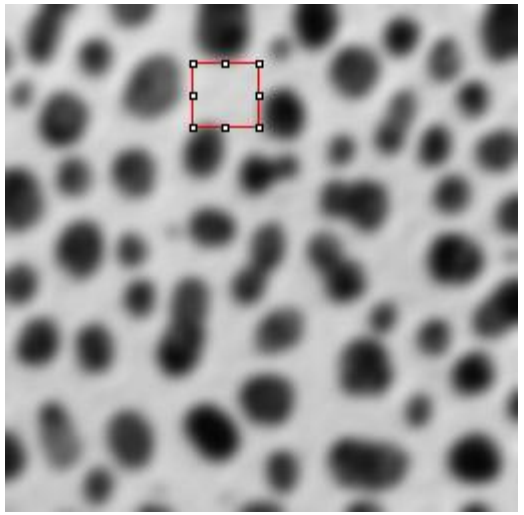
- **Intensity based**
  - Mean intensity
  - Standard deviation
  - Total intensity
  - Textures
- **Shape based /spatial**
  - Area / Volume
  - Roundness
  - Solidity
  - Circularity / Sphericity
  - Elongation
  - Centroid
  - Bounding box
- **Spatio-temporal**
  - Displacement,
  - Speed,
  - Acceleration
- **Others**
  - Overlap
  - Colocalization
  - Neighborhood
- **Mixed features**
  - Center of mass
  - Local minima / maxima

# Intensity based features

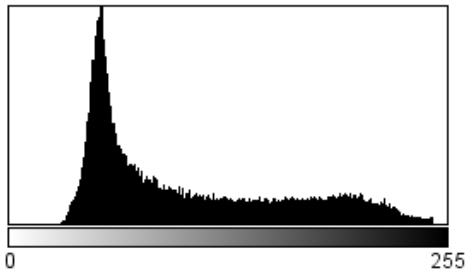
- Min / max
- Median
- Mean
- Mode
- Variance
- Standard deviation



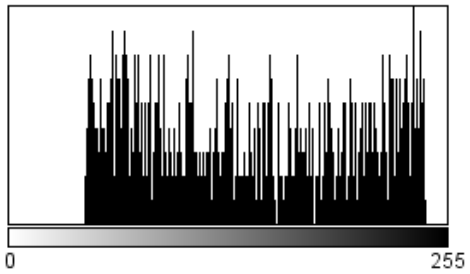




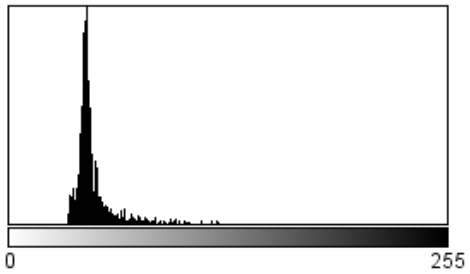
- Can be derived from pixel values
- Don’t take spatial relationship of pixels into account




Count: 65024
Mean: 103.301
StdDev: 57.991
Min: 29
Max: 248
Mode: 53 (1663)




Count: 783
Mean: 141.308
StdDev: 61.876
Min: 44
Max: 243
Mode: 236 (9)



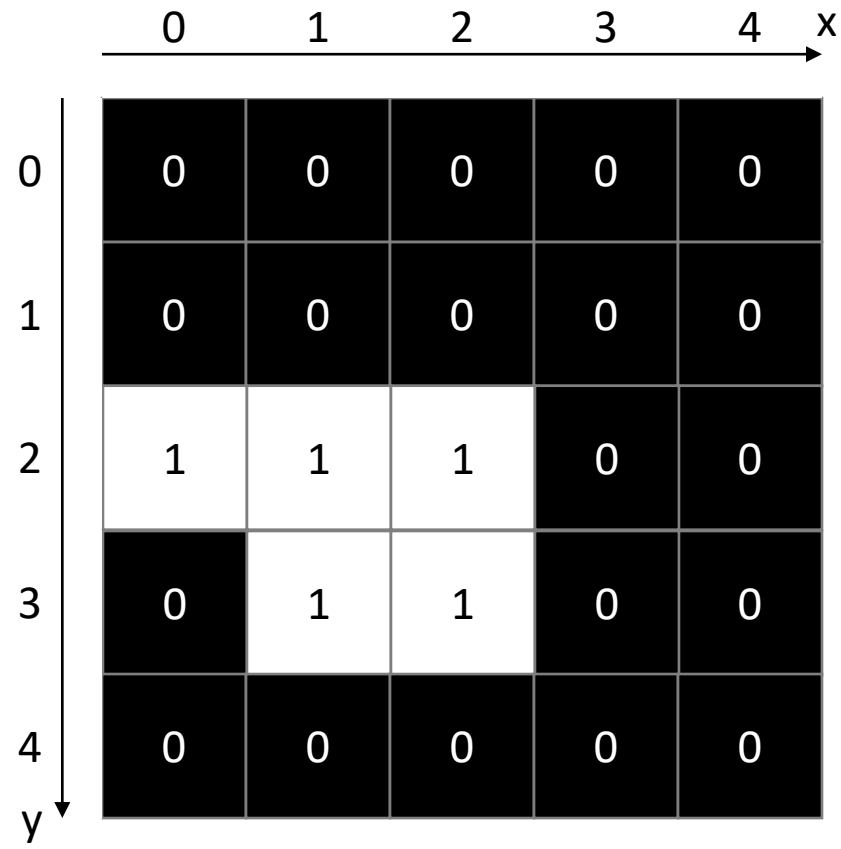

Count: 1056
Mean: 49.016
StdDev: 12.685
Min: 34
Max: 122
Mode: 45 (120)

- See also:
  - descriptive statistics
  - histogram

# Bounding rectangle / bounding box

- Position and size of the smallest rectangle containing all pixels of an object
  - $x_b$, $y_b$ … position of the bounding box
  - $w_b$ … width of the bounding box
  - $h_b$ … height of the bounding box

| variable | value |
|---|---|
| $x_b$ | 0 |
| $y_b$ | 2 |
| $w_b$ | 3 |
| $h_b$ | 2 |



# Center of mass

- Relative position in an image weighted by pixel intensities

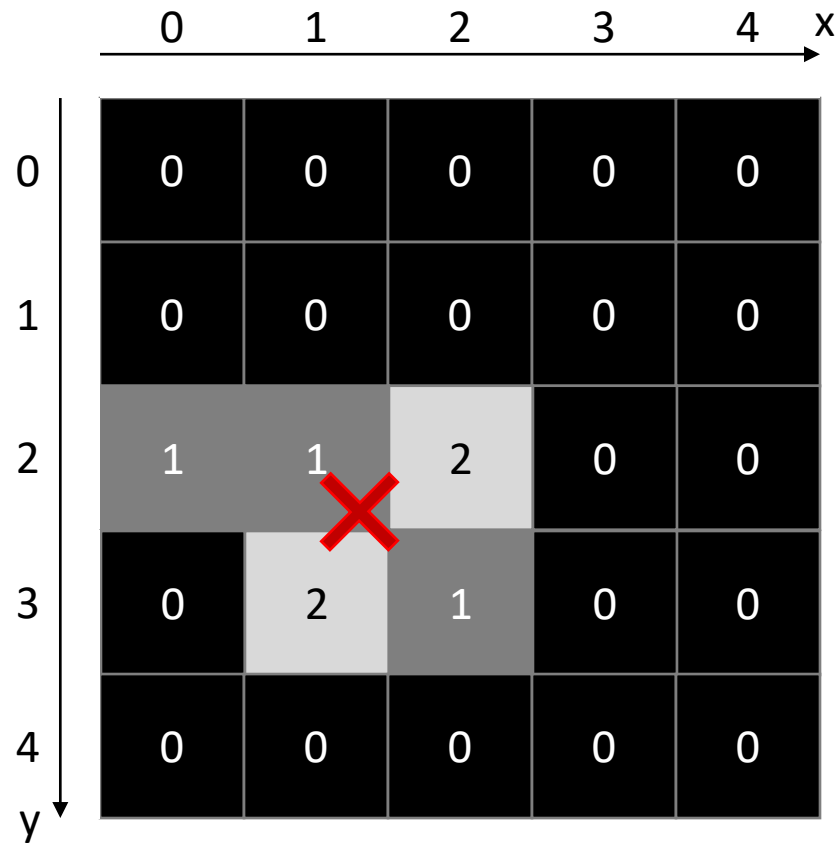
  - x, y … pixel coordinates
  - w … image width
  - h … image height
  - μ … mean intensity
  - $g_{x,y}$ … pixel grey value
  - $x_m$, $y_m$ … center of mass coordinates

$$\mu = \frac{1}{wh} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} g_{x,y}$$

$$x_m = \frac{1}{wh\mu} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} x \, g_{x,y}$$

$$y_m = \frac{1}{wh\mu} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} y \, g_{x,y}$$

"sum intensity"
"total intensity"




$x_m$ = 1/7 (1·0 + 1·1 + 2·2 + 2·1 + 1·2) = 1.3

$y_m$ = 1/7 (1·2 + 1·2 + 2·3 + 2·2 + 1·3) = 2.4

# Center of geometry / centroid

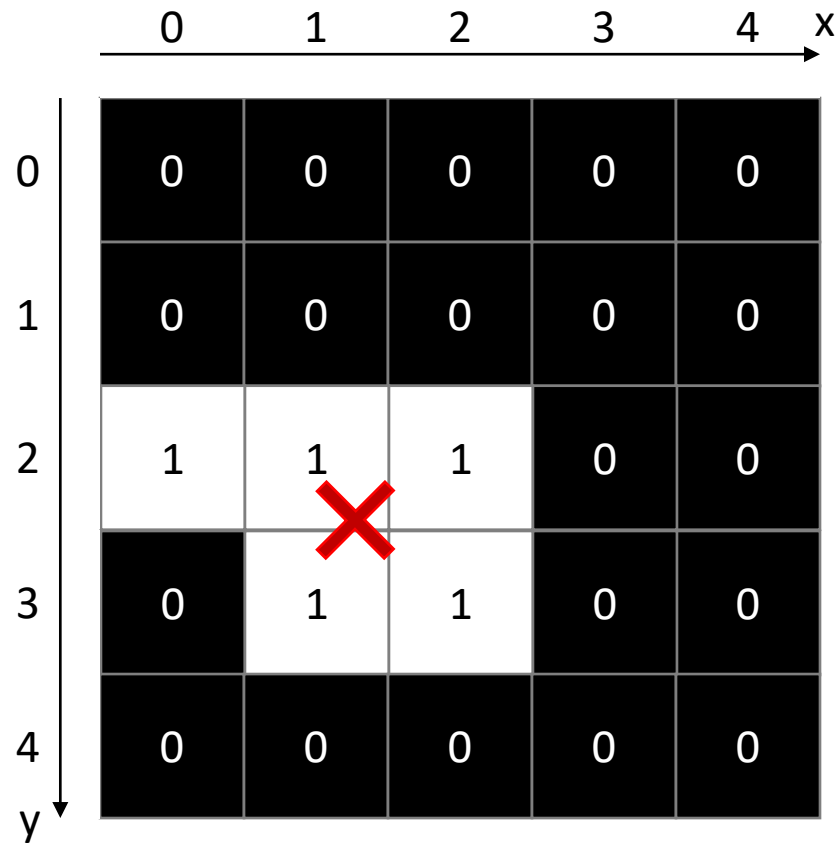
- Relative position in an image weighted by pixel intensities
- Special case of center of mass for binary images
  - x, y … pixel coordinates
  - w … image width
  - h … image height
  - μ … mean intensity
  - $g_{x,y}$ … pixel grey value, integer in range [0;1]
  - $x_m$, $y_m$ … center of mass coordinates

$$\mu = \frac{1}{wh} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} g_{x,y}$$

$$x_m = \frac{1}{wh\mu} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} x \, g_{x,y}$$

$$y_m = \frac{1}{wh\mu} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} y \, g_{x,y}$$

Number of white pixels

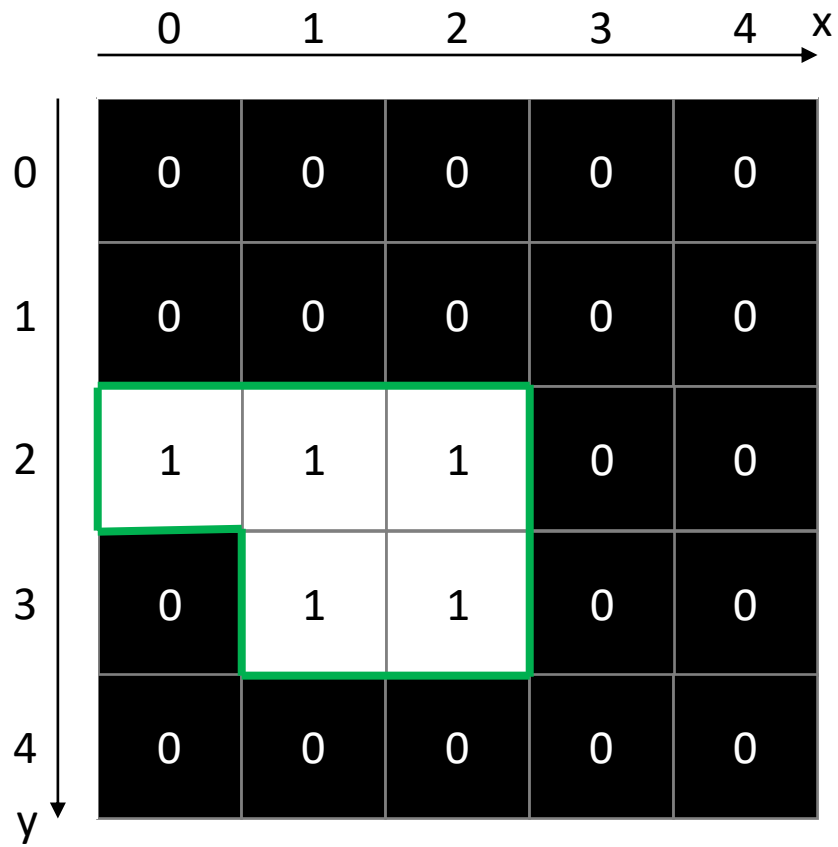


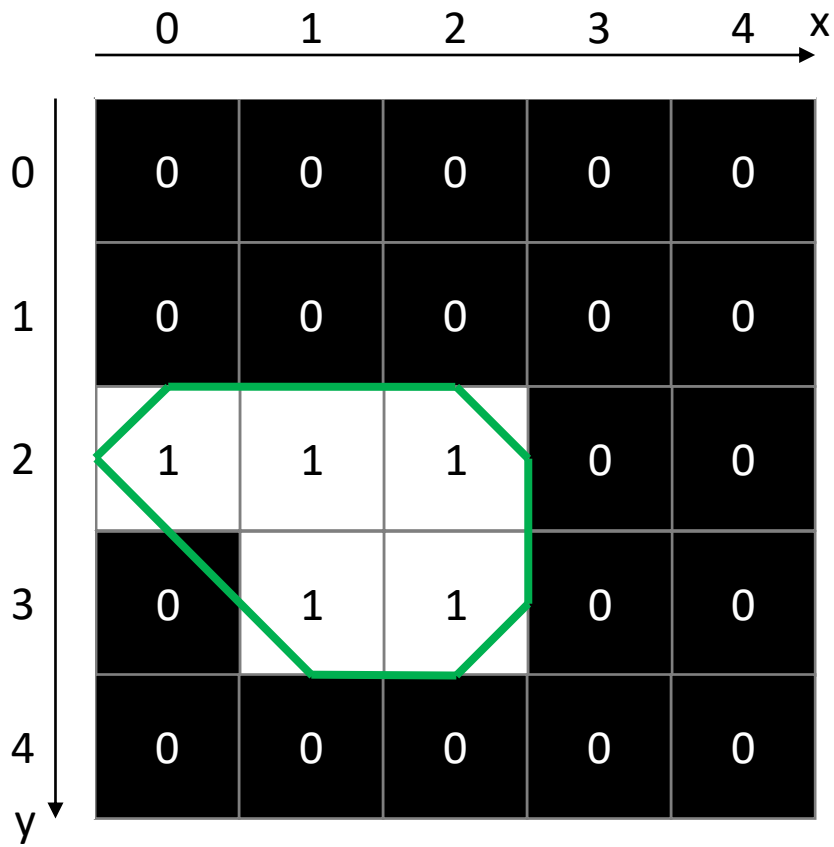

$x_m$ = 1/5 (1·0 + 1·1 + 1·2 + 1·1 + 1·2) = 1.2

$y_m$ = 1/5 (1·2 + 1·2 + 1·3 + 1·2 + 1·3) = 2.4

# Perimeter

- Length of the outline around an object
- Depends on the actual implementation



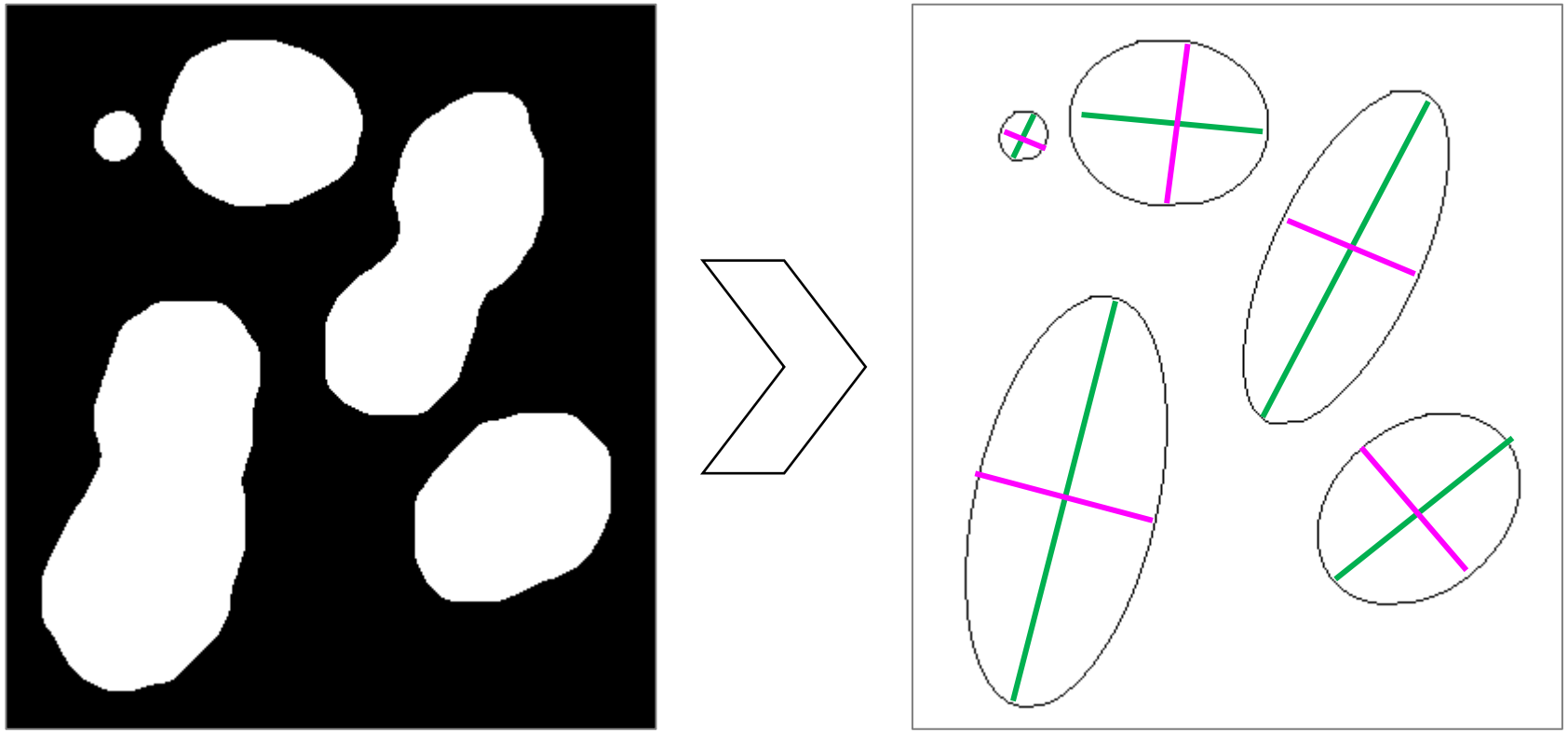



# Fit ellipse

- For every object, find the optimal ellipse simplifying the object.

- Major axis … long diameter
- Minor axis … short diameter

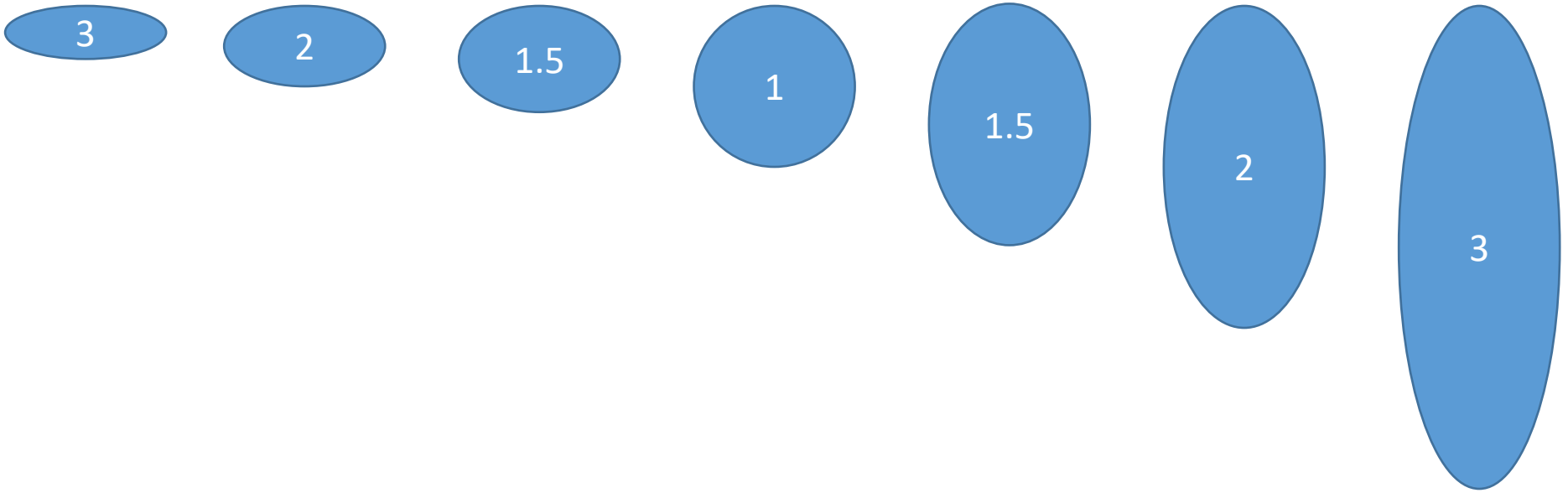
- Major and minor axis are perpendicular to each other



# Aspect ratio

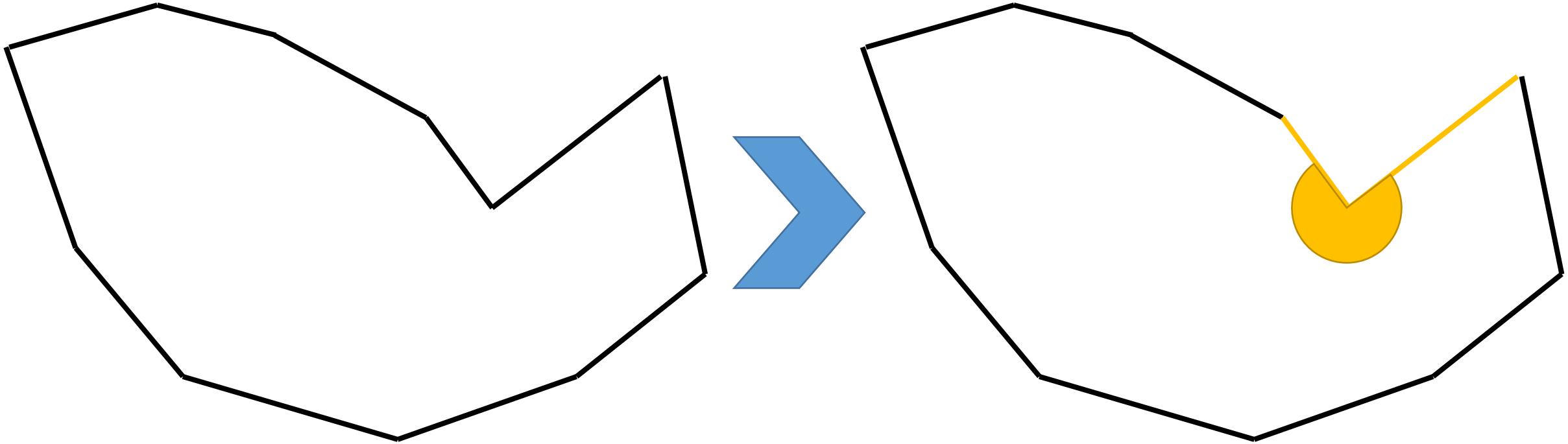
- The aspect ratio describes the elongation of an object.

AR = major / minor



# Convex hull

- By removing all concave corners of an object, we retrieve its convex hull.



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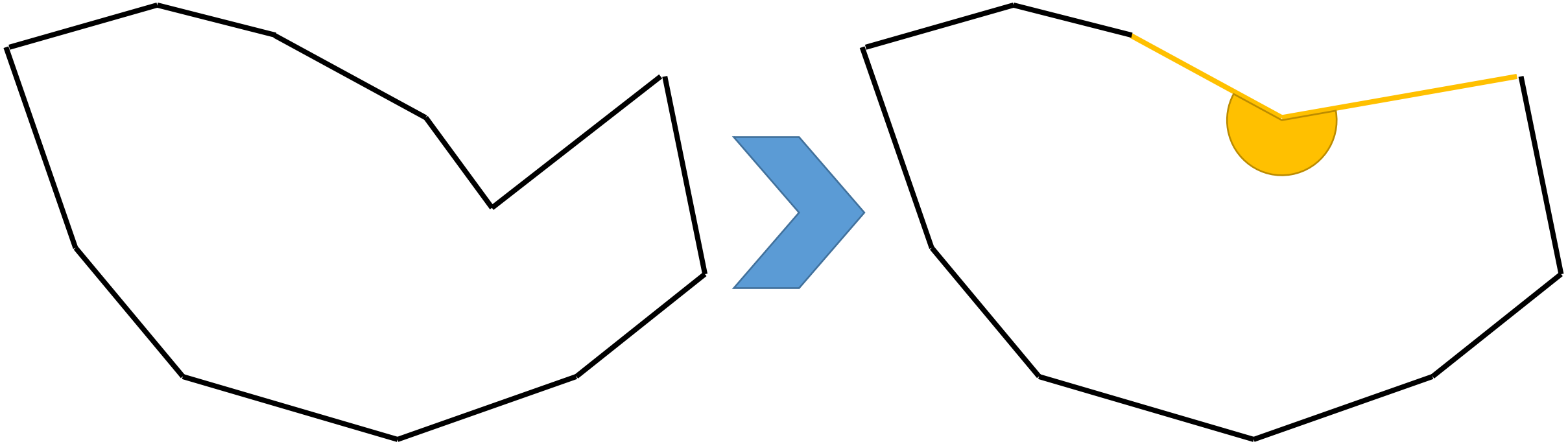

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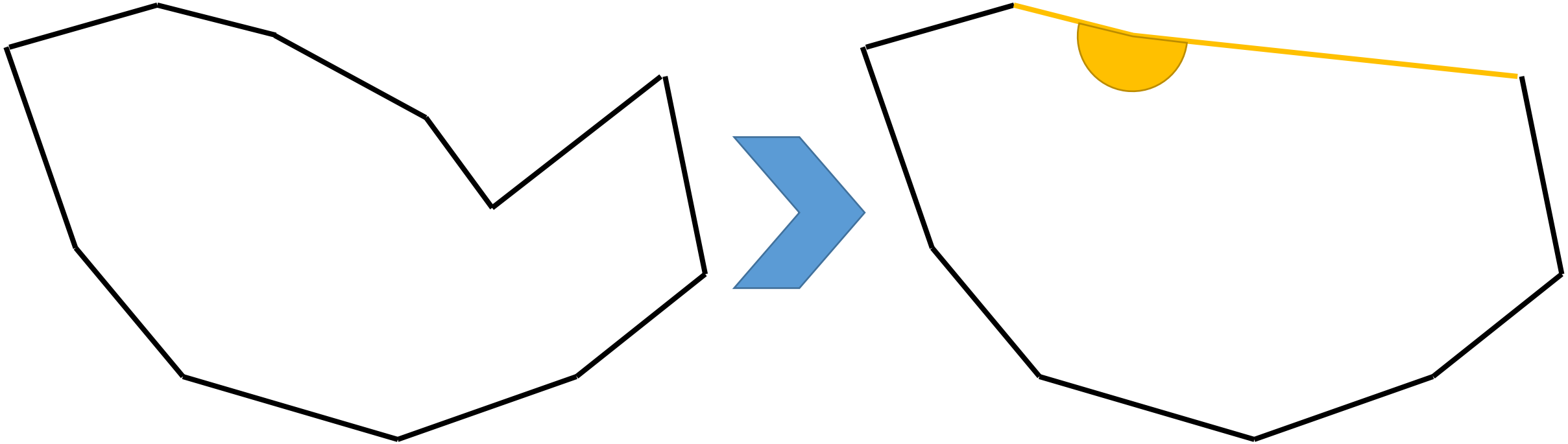

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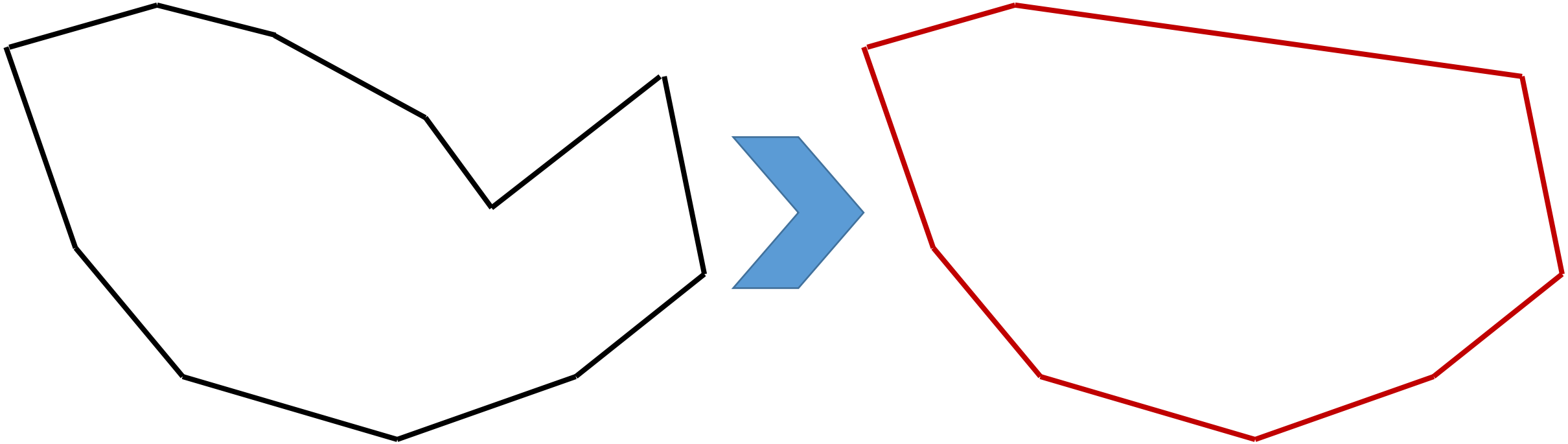


$$solidity = \frac{A}{A_{convexHull}}$$

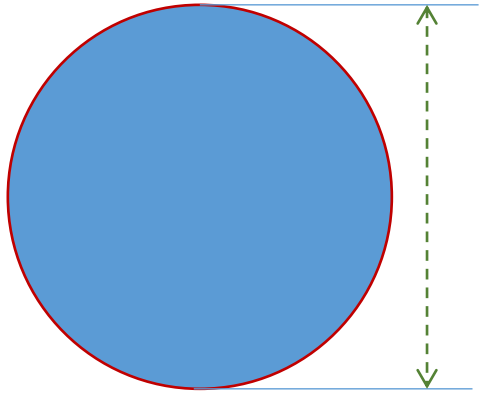
# Roundness and circularity

- The definition of a circle leads us to measurements of circularity and roundness.
- In case you use these measures, define them correctly. They are not standardized!

Diameter $d$

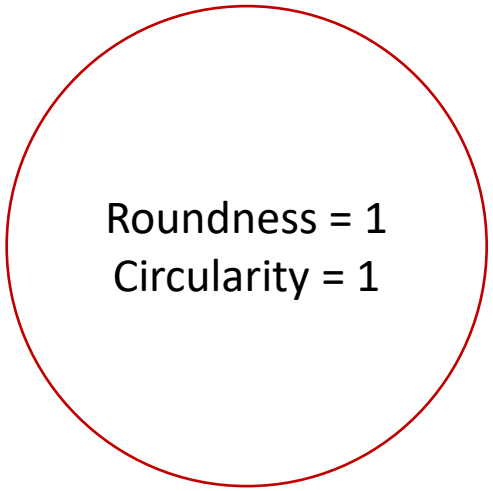
Circumference $C = \pi d$

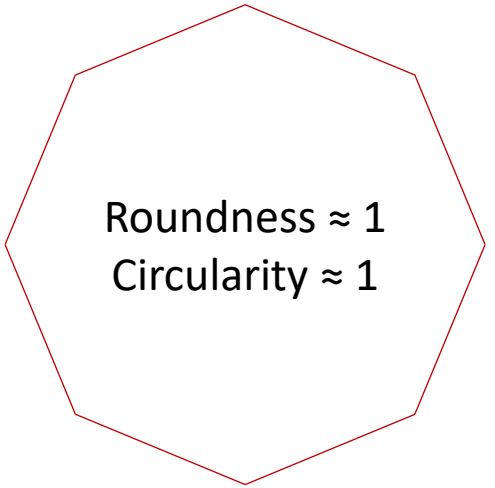
Area $A = \frac{\pi d^2}{4}$

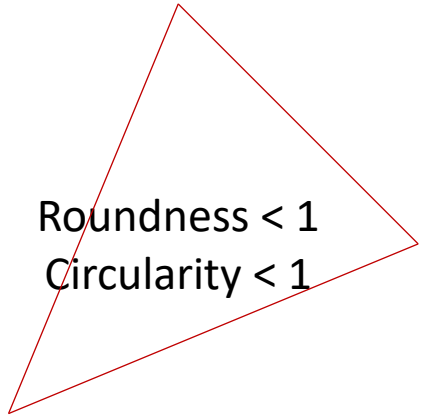


$$roundness = \frac{4 * A}{\pi\, major^2}$$

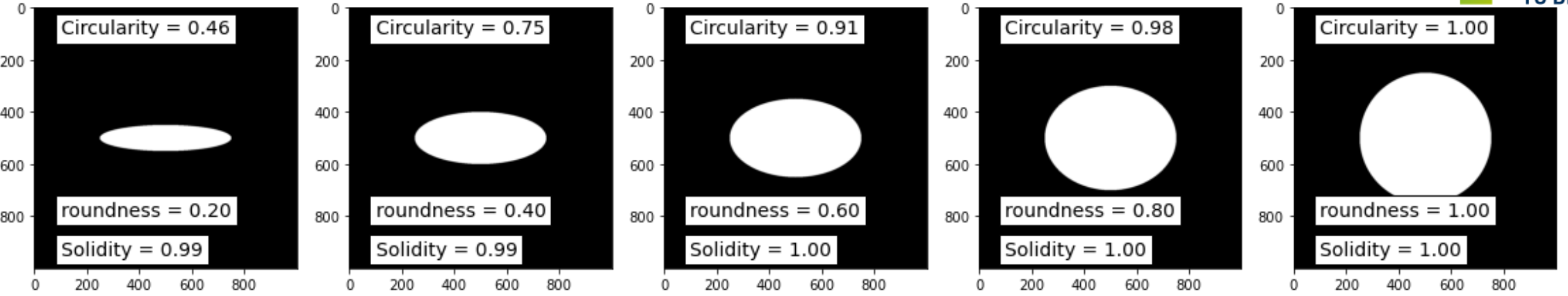
$$circularity = \frac{4\pi * A}{perimeter^2}$$



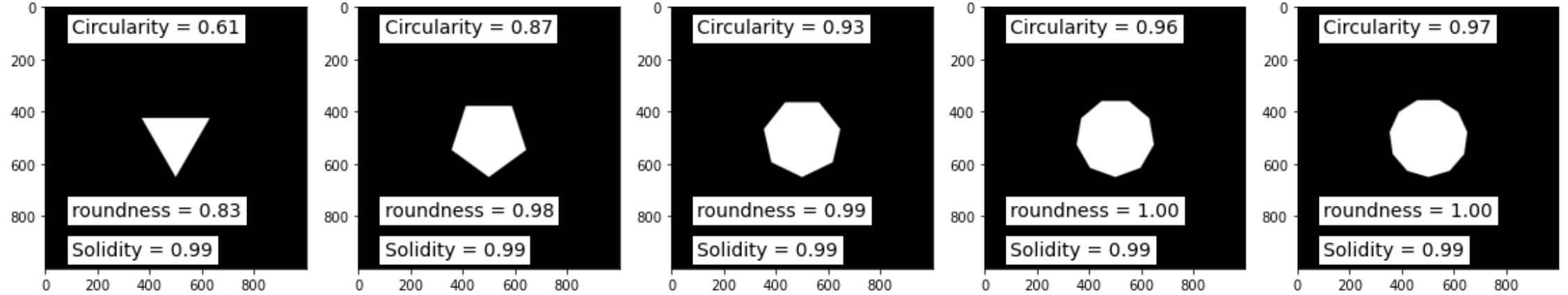



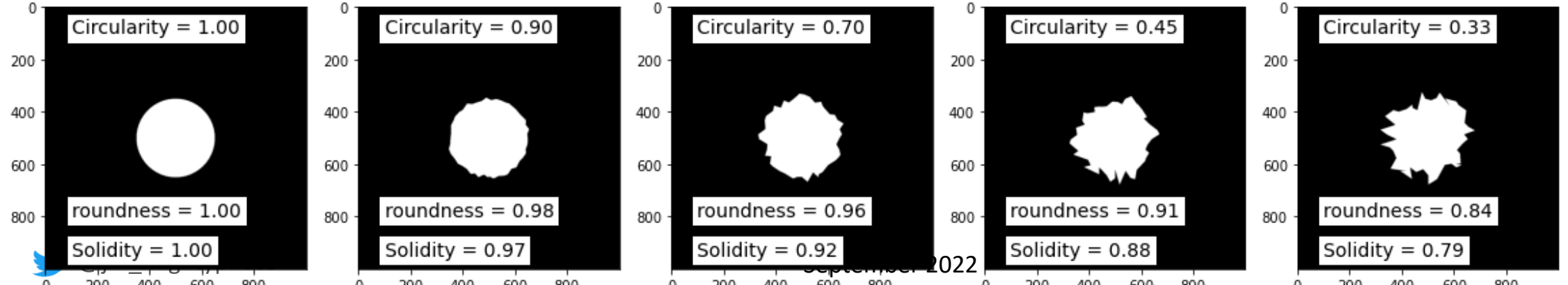
# Roundness and circularity




$$roundness = \frac{4 * A}{\pi\, major^2}$$




$$circularity = \frac{4\pi * A}{perimeter^2}$$




$$solidity = \frac{A}{A_{convexHull}}$$

# Feature extraction in Python

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- **In Fiji**: *Analyze > Analyze Particles…*
- **In Python:**

```
from skimage import measure
```

https://scikit-image.org/docs/stable/api/skimage.measure.html

| | |
|---|---|
| `skimage.measure.blur_effect` (image[, h_size, …]) | Compute a metric that indicates the strength of blur in an image (0 for no blur, 1 for maximal blur). |
| `skimage.measure.euler_number` (image[, …]) | Calculate the Euler characteristic in binary image. |
| `skimage.measure.find_contours` (image[, …]) | Find iso-valued contours in a 2D array for a given level value. |
| `skimage.measure.grid_points_in_poly` (shape, verts) | Test whether points on a specified grid are inside a polygon. |
| `skimage.measure.inertia_tensor` (image[, mu]) | Compute the inertia tensor of the input image. |
| `skimage.measure.inertia_tensor_eigvals` (image) | Compute the eigenvalues of the inertia tensor of the image. |
| `skimage.measure.label` (label_image[, …]) | Label connected regions of an integer array. |
| `skimage.measure.regionprops` (label_image[, …]) | Measure properties of labeled image regions. |
| `skimage.measure.regionprops_table` (label_image) | Compute image properties and return them as a pandas-compatible table. |

**area** : int

Number of pixels of the region.

**area_bbox** : int

Number of pixels of bounding box.

**area_convex** : int

Number of pixels of convex hull image, which is the smallest convex polygon that e

**area_filled** : int

Number of pixels of the region will all the holes filled in. Describes the area of the i

**axis_major_length** : float

The length of the major axis of the ellipse that has the same normalized second ce
the region.

**axis_minor_length** : float

The length of the minor axis of the ellipse that has the same normalized second ce
the region.

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# Processing tables with Python

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June 2021

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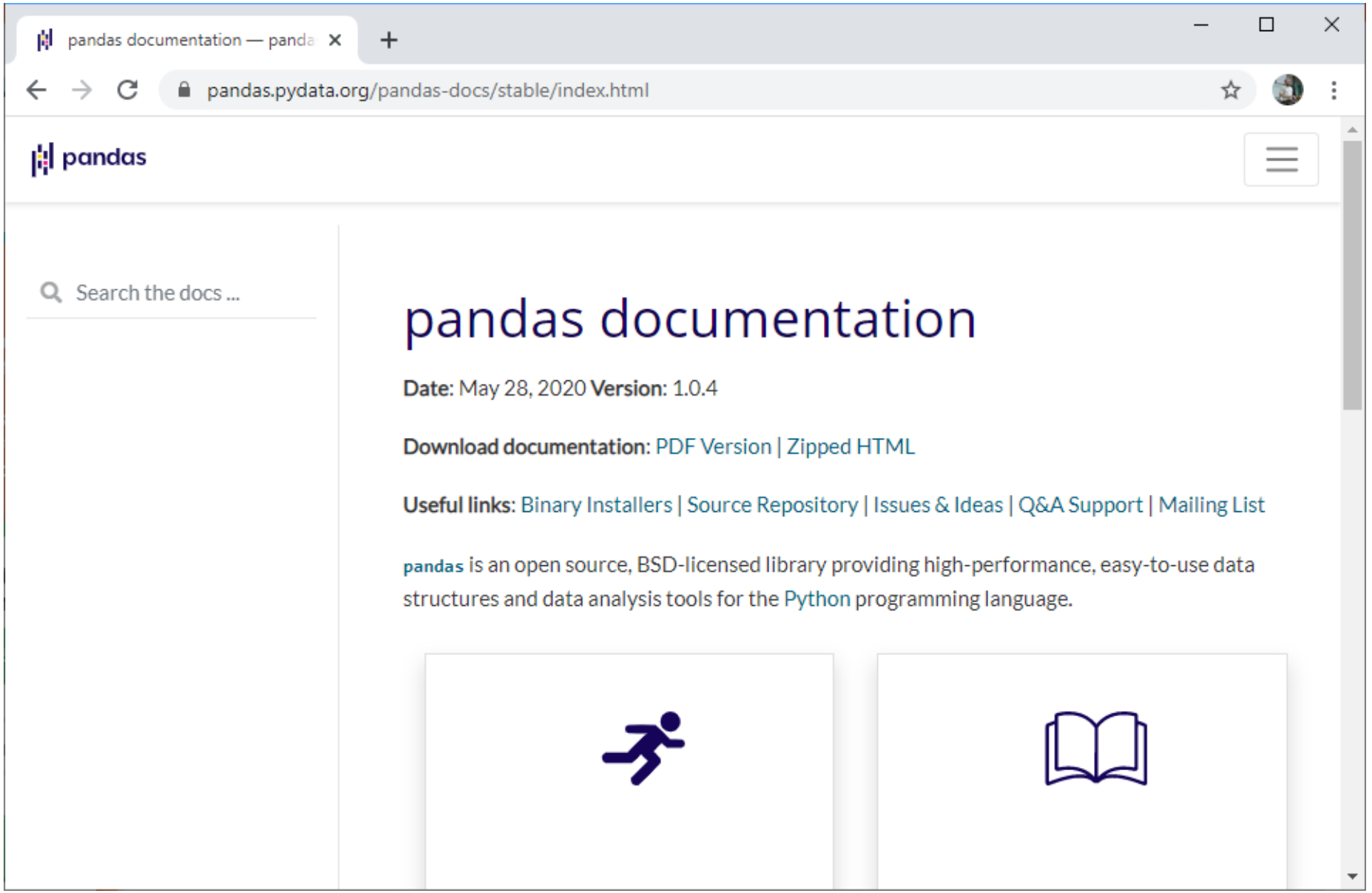
# Pandas

- pandas is a library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.

```
conda install pandas
```



# Processing tables with pandas

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- Typical use-case:
  - You get data from a colleague in form of a table.
  - Using pandas, you can analyze it in python.

- Loading a table in python using pandas:

```
import pandas as pd

data_frame = pd.read_csv("Measurements_ImageJ.csv", delimiter=',')
data_frame
```

| | | Area | Mean | Circ. | AR | Round | Solidity |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 2610 | 96.920 | 0.773 | 1.289 | 0.776 | 1.0 |
| 1 | 2 | 2100 | 90.114 | 0.660 | 2.333 | 0.429 | 1.0 |
| 2 | 3 | 27 | 110.222 | 0.108 | 27.000 | 0.037 | 1.0 |

# Processing tables with pandas

PoL Physics of Life TU Dresden

- Typical use-case:
  - You get data from a colleague in form of a table.
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| | | Area | Mean | Circ. | AR | Round | Solidity |
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| 1 | 2 | 2100 | 90.114 | 0.660 | 2.333 | 0.429 | 1.0 |
| 2 | 3 | 27 | 110.222 | 0.108 | 27.000 | 0.037 | 1.0 |

- Accessing a column

```
data_frame["Mean"]
```

```
0     96.920
1     90.114
2    110.222
Name: Mean, dtype: float64
```

- Determining mean of a column

```
import numpy as np
np.mean(data_frame["Mean"])
```

```
99.08533333333332
```

- Accessing an individual cell

```
data_frame["Mean"][0]
```

```
1.2890000000000001
```

# Processing tables with pandas

- Creating tables with pandas

- Creating a new table

```
header = ['A', 'B', 'C']

data = [
    [1, 2, 3],  # this will later be colum A
    [4, 5, 6],  #                          B
    [7, 8, 9]   #                          C
]

# convert the data and header arrays in a pandas data frame
data_frame = pd.DataFrame(data, header)

# show it
data_frame
```

| | 0 | 1 | 2 |
|---|---|---|---|
| A | 1 | 2 | 3 |
| B | 4 | 5 | 6 |
| C | 7 | 8 | 9 |

- *Rotate* a table

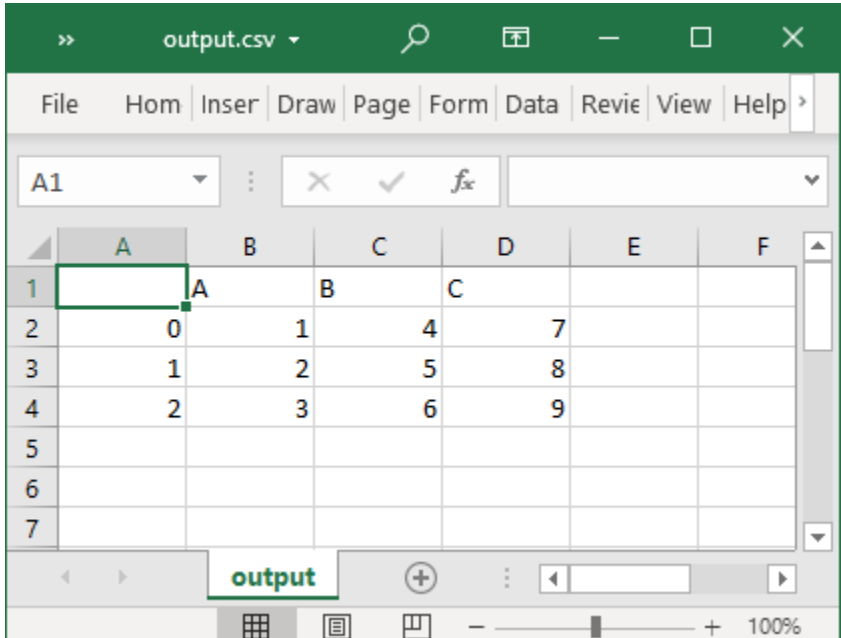
```
# rotate/flip it
data_frame = data_frame.transpose()

# show it
data_frame
```

| | A | B | C |
|---|---|---|---|
| 0 | 1 | 4 | 7 |
| 1 | 2 | 5 | 8 |
| 2 | 3 | 6 | 9 |

- Save it to disc

```
# save a dataframe to a CSV
data_frame.to_csv("output.csv")
```



# Selecting rows and columns

| | City | Country | Population | Area_km2 |
|---|---|---|---|---|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

- Selecting columns

```
cities[['City', 'Country']]
```

| | City | Country |
|---|---|---|
| 0 | Tokyo | Japan |
| 1 | Delhi | India |
| 2 | Shanghai | China |
| 3 | Sao Paulo | Brazil |
| 4 | Mexico City | Mexico |

- Selecting rows

```
cities[cities['Area_km2'] > 2000]
```

| | City | Country | Population | Area_km2 |
|---|---|---|---|---|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 2 | Shanghai | China | 24183000 | 6341 |

# Combining tables

- The big art in data science is the ability of combining information from multiple sources to gain new insights.

| | Country | Population |
|---|---|---|
| 0 | Japan | 127202192 |
| 1 | India | 1352642280 |
| 2 | China | 1427647786 |
| 3 | Brazil | 209469323 |
| 4 | Mexico | 126190788 |

| | City | Country | Population | Area_km2 |
|---|---|---|---|---|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

```
combined = countries.merge(cities, on='Country', suffixes=['_country', '_city'])
combined
```

| | Country | Population_country | City | Population_city | Area_km2 |
|---|---|---|---|---|---|
| 0 | Japan | 127202192 | Tokyo | 13515271 | 2191 |
| 1 | India | 1352642280 | Delhi | 16753235 | 1484 |
| 2 | China | 1427647786 | Shanghai | 24183000 | 6341 |
| 3 | Brazil | 209469323 | Sao Paulo | 12252023 | 1521 |
| 4 | Mexico | 126190788 | Mexico City | 9209944 | 1485 |

```
# compute ratio
combined['City_Country_population_ratio'] = combined['Population_city'] / combined['Population_country']

# only show selected columns
combined[['City', 'City_Country_population_ratio']]
```

| | City | City_Country_population_ratio |
|---|---|---|
| 0 | Tokyo | 0.106250 |
| 1 | Delhi | 0.012386 |
| 2 | Shanghai | 0.016939 |
| 3 | Sao Paulo | 0.058491 |
| 4 | Mexico City | 0.072984 |