

# Image Processing and Filtering

Marcelo Leomil Zoccoler

With material from

Robert Haase, PoL

Mauricio Rocha Martins, Norden lab, MPI CBG

Dominic Waithe, Oxford University

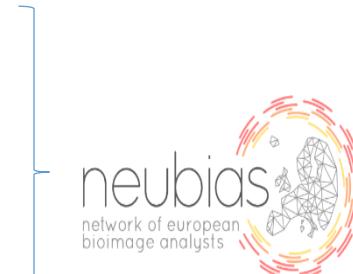
Nuno P Martins, IGC Lisbon

Paulo Aguiar, INEB, Porto

Sebastian Tosi, IRB Barcelona

Benoit Lombardot, Scientific Computing Facility, MPI CBG

Alex Bird, Dan White, MPI CBG



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# Last week: Python algorithms

- Conditions: if-else statement:

```
if condition :  
    # do something if  
    # condition is true  
  
else :  
    # do something else if  
    # condition is false  
  
    # do in any case
```

- Loops: for, while
  - Generate arrays within for loops

```
# for loops  
for i in range(0, 5):  
    print(i)  
  
0  
1  
2  
3  
4
```

```
# we start with an empty list  
numbers = []  
  
# and add elements  
for i in range(0, 5):  
    numbers.append(i * 2)  
  
print(numbers)  
  
[0, 2, 4, 6, 8]
```

- Functions:

```
def sum_numbers(a, b):  
  
    result = a + b  
  
    return result
```

name (parameters)

body commands

return statement  
(optional)

- Libraries:

```
from my_library import square  
  
square(5)
```

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-  08\_loops.ipynb
-  09\_custom\_functions.ipynb
-  10\_custom\_libraries.ipynb
-  my\_library.py

# Lecture overview

Today

- Image Visualization
  - Pixels, Voxels
  - Resolution versus pixel size
  - Lookup tables/ Colormaps
  - Histograms
  - Brightness and Contrast
  - Introduction to napari
- Image Processing
  - Filters
  - Morphological Operations
  - Noise Removal
  - Background Subtraction
- Practicals

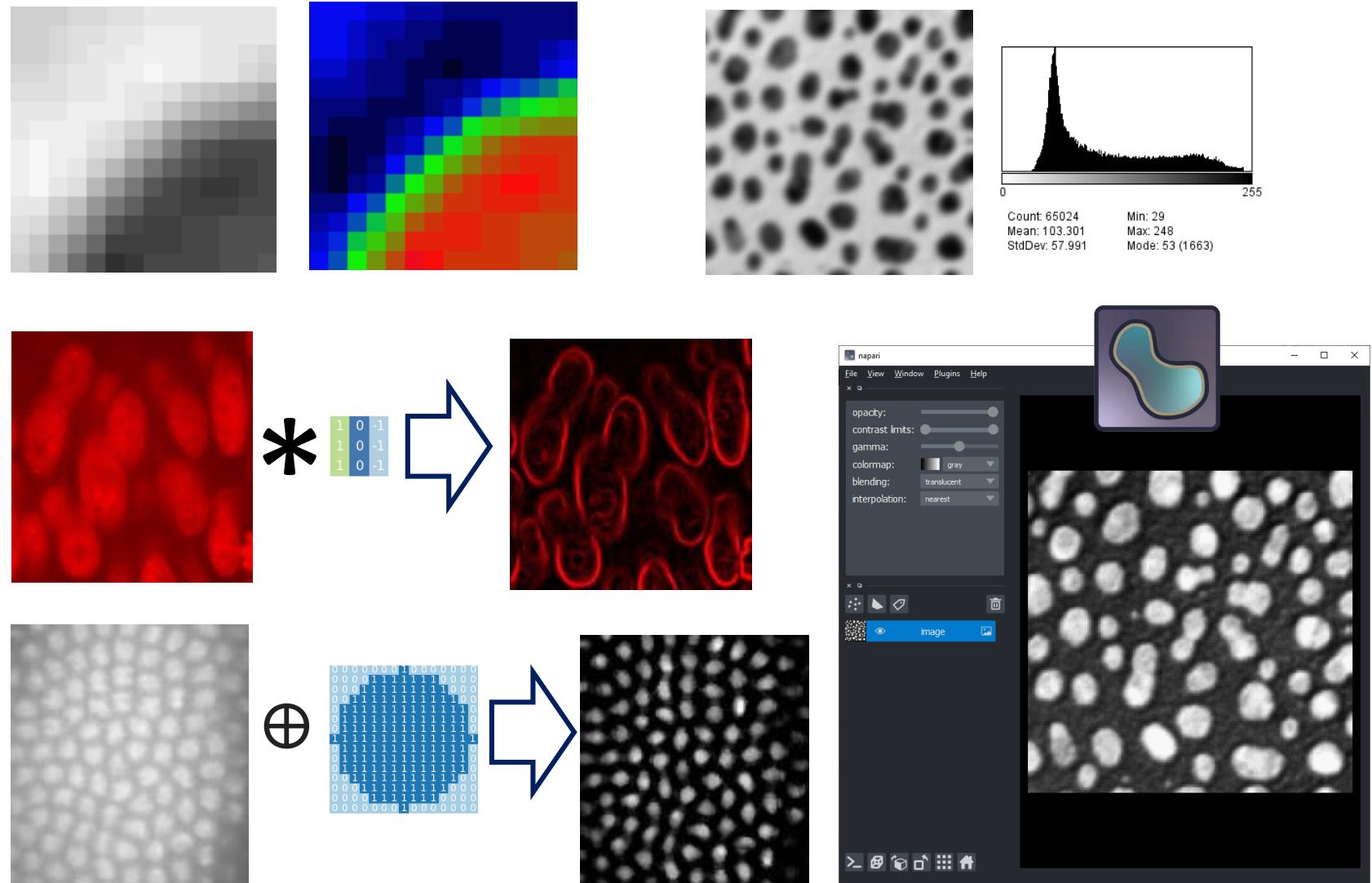




Image by [Pezibear](#) from [Pixabay](#),  
[Pixabay License](#) - Free for commercial use - No attribution required

# Image Visualization

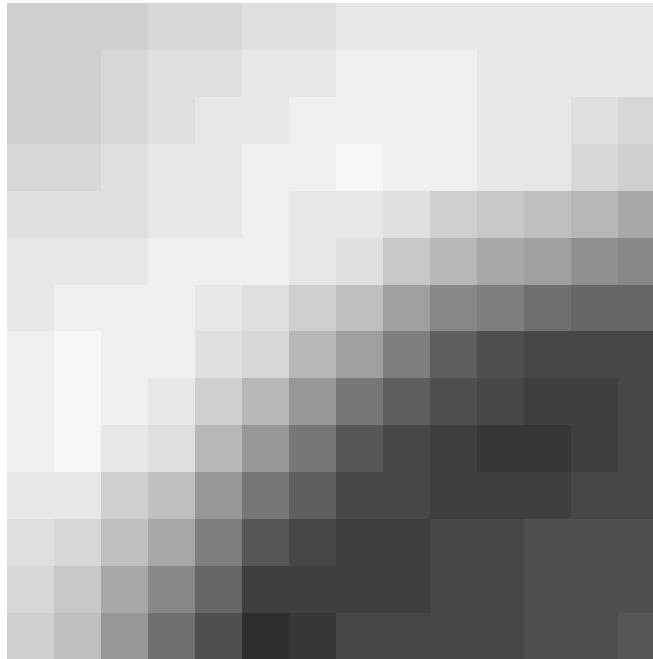
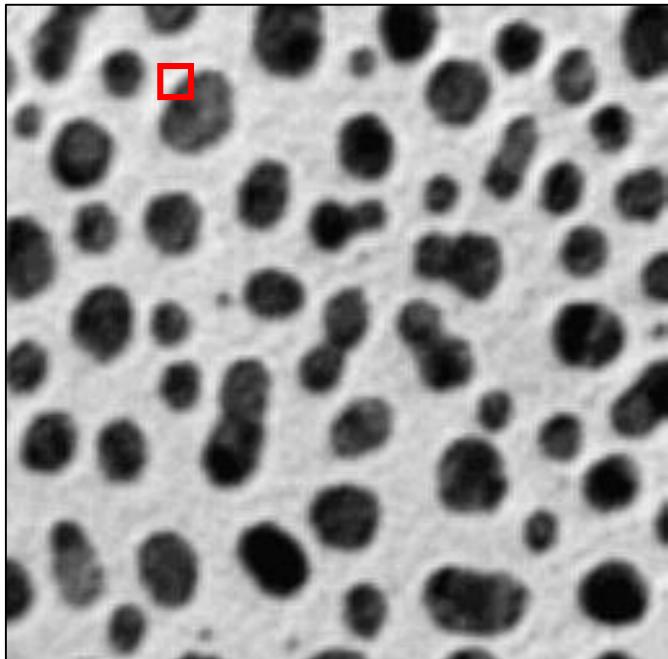
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Robert Haase, PoL

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# Images and pixels

- An image is just a matrix of numbers
- Pixel: “picture element”
- The edges between pixels are an artefact. In reality, they don’t exist!



|    |    |     |     |     |     |     |     |     |     |     |     |     |     |     |
|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 48 | 48 | 48  | 40  | 40  | 32  | 32  | 24  | 24  | 24  | 24  | 24  | 24  | 24  | 24  |
| 48 | 48 | 40  | 32  | 32  | 24  | 24  | 16  | 16  | 16  | 16  | 24  | 24  | 24  | 24  |
| 48 | 48 | 40  | 32  | 24  | 24  | 16  | 16  | 16  | 16  | 16  | 24  | 24  | 32  | 40  |
| 40 | 40 | 32  | 24  | 24  | 16  | 16  | 16  | 8   | 16  | 16  | 24  | 24  | 40  | 48  |
| 32 | 32 | 32  | 24  | 24  | 16  | 24  | 24  | 32  | 48  | 56  | 64  | 72  | 88  |     |
| 24 | 24 | 24  | 16  | 16  | 16  | 24  | 32  | 56  | 72  | 88  | 96  | 112 | 120 |     |
| 24 | 16 | 16  | 16  | 24  | 32  | 48  | 64  | 96  | 120 | 128 | 144 | 152 | 152 |     |
| 16 | 8  | 16  | 16  | 32  | 40  | 72  | 96  | 128 | 160 | 176 | 184 | 184 | 184 |     |
| 16 | 8  | 16  | 24  | 48  | 72  | 104 | 136 | 160 | 176 | 184 | 192 | 192 | 192 | 184 |
| 24 | 24 | 48  | 64  | 104 | 136 | 160 | 184 | 184 | 192 | 192 | 192 | 192 | 184 | 184 |
| 32 | 40 | 64  | 88  | 128 | 168 | 184 | 192 | 192 | 184 | 184 | 176 | 176 | 176 | 176 |
| 40 | 56 | 88  | 120 | 152 | 192 | 192 | 192 | 184 | 184 | 184 | 176 | 176 | 176 | 176 |
| 48 | 64 | 104 | 144 | 176 | 208 | 200 | 184 | 184 | 184 | 184 | 176 | 176 | 176 | 168 |

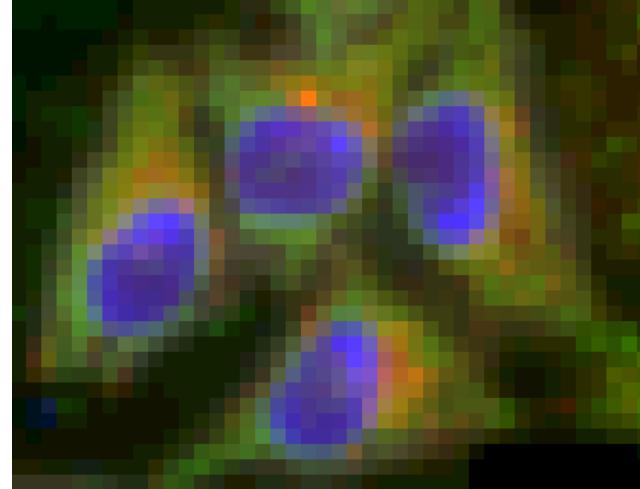


# Pixel size versus resolution

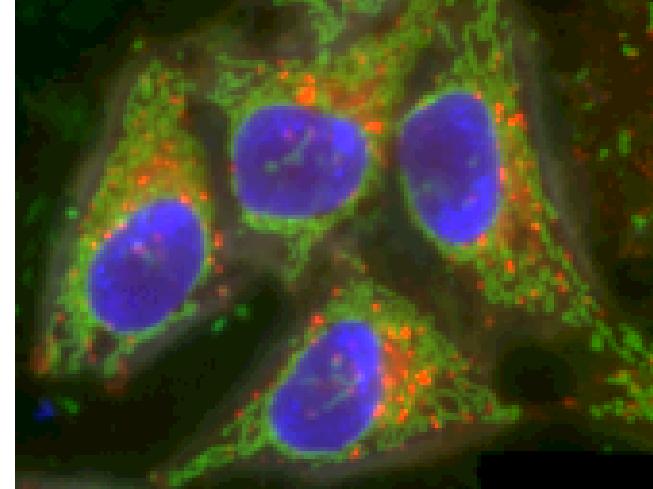
- Pixel size is a digital property of an image.
- You configure it during the imaging session at the microscope.



Pixel size: 3.3  $\mu\text{m}$



Pixel size: 0.8  $\mu\text{m}$

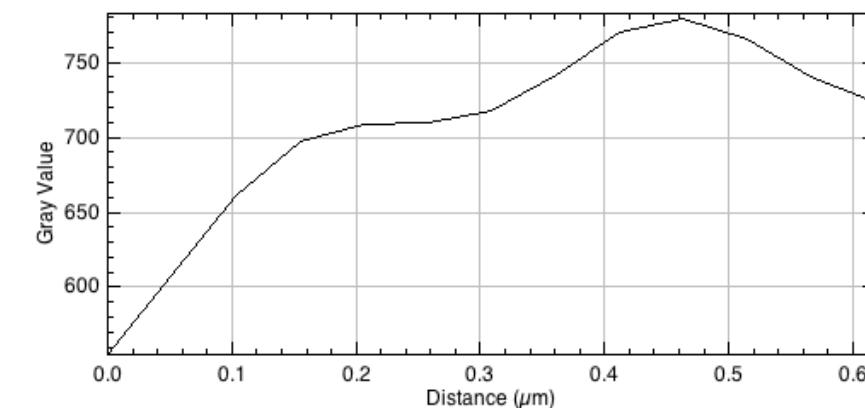
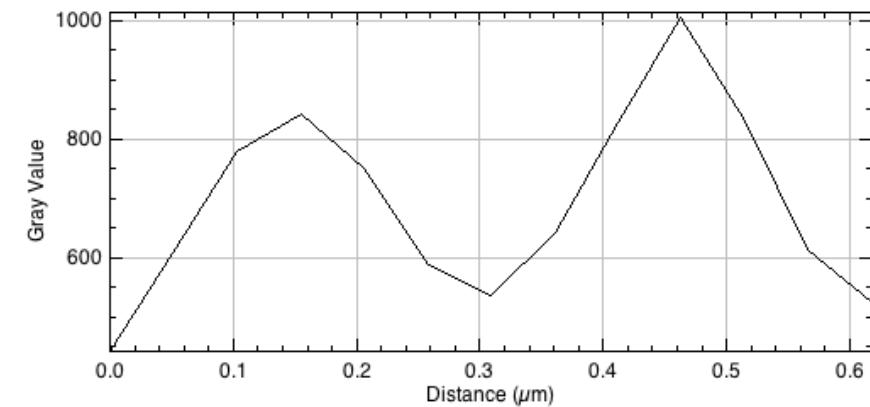
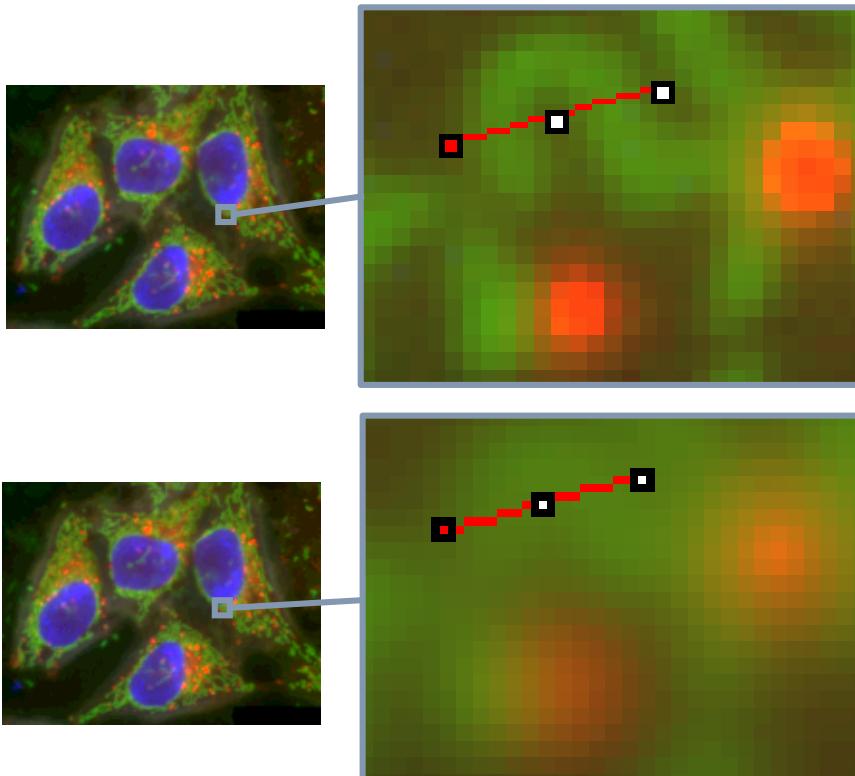


Pixel size: 0.05  $\mu\text{m}$

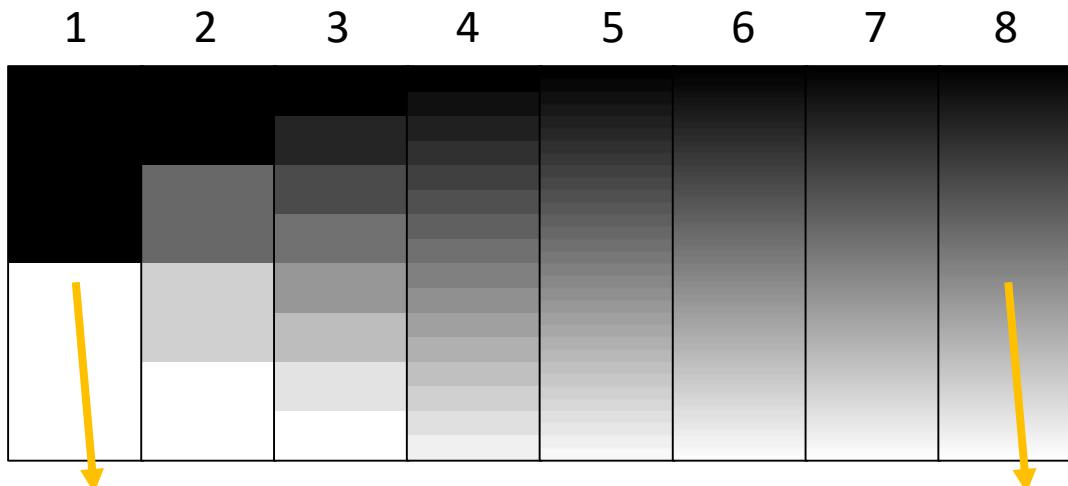
- We are not talking about resolution!

# Pixel size versus resolution

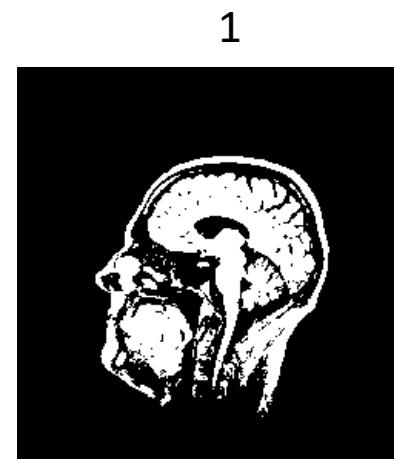
- Resolution is a property of your imaging system.
- The measure of how close object can be in an image while still being differentiable, is called spatial resolution.



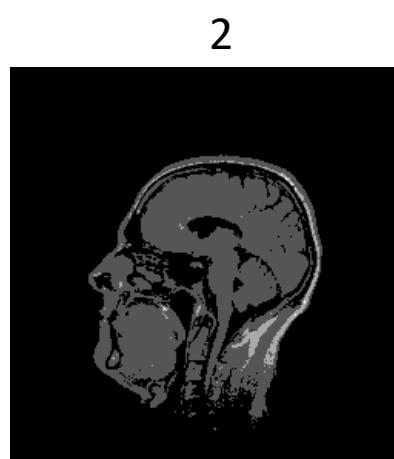
- A bits is the smallest memory unit in computers, *atomic data*.
- The bit-depth  $n$  enumerates how many different intensity values are present in an image:
  - $2^n$  grey values
- In microscopy, images are usually stored as 8, 12 or 16-bit images.



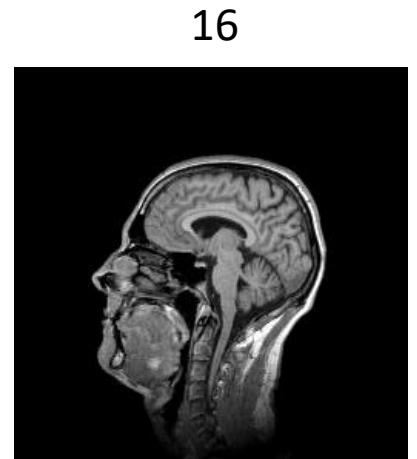
```
image.dtype  
dtype('bool')
```



```
image.dtype  
dtype('uint8')
```



```
image_16bit = image.astype('uint16')
```

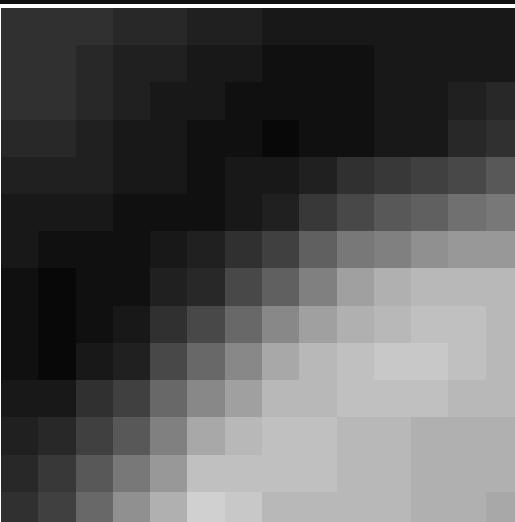


# Lookup tables / Colormaps

- The lookup table decides how the image is displayed on screen.
- Applying a different lookup table doesn't change the image. All pixel values stay the same, they just appear differently

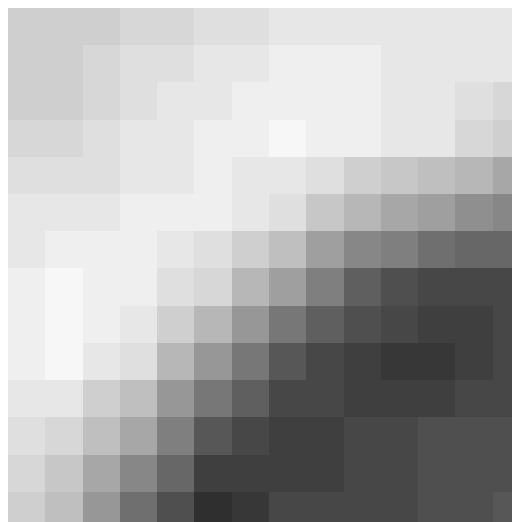
| Pixel value | Display color |
|-------------|---------------|
| 0           | Black         |
| 1           | Dark gray     |
| 2           | Medium gray   |
| ...         |               |
| 255         | White         |

```
plt.imshow(image, cmap='gray')
```



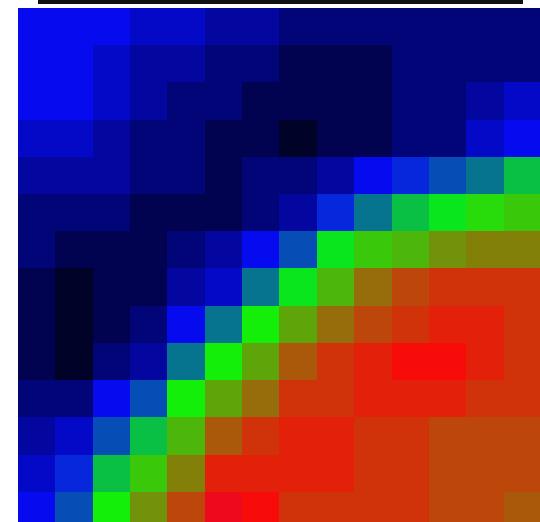
| Pixel value | Display color |
|-------------|---------------|
| 0           | Black         |
| 1           | Dark gray     |
| 2           | Medium gray   |
| ...         |               |
| 255         | White         |

```
plt.imshow(image, cmap='gray_r')
```



| Pixel value | Display color |
|-------------|---------------|
| 0           | Red           |
| 1           | Orange        |
| 2           | Yellow        |
| ...         |               |
| 255         | Blue          |

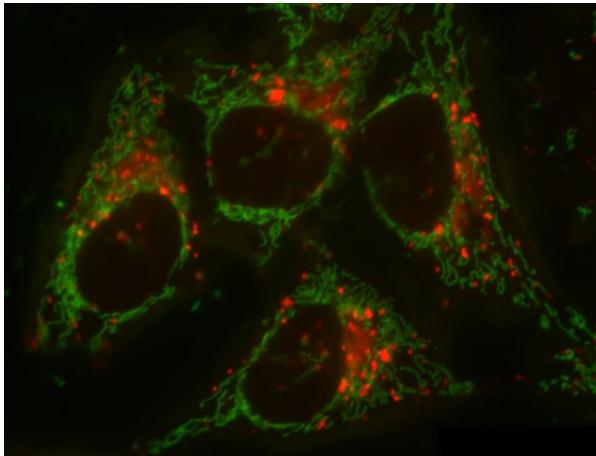
```
plt.imshow(image, cmap='jet')
```



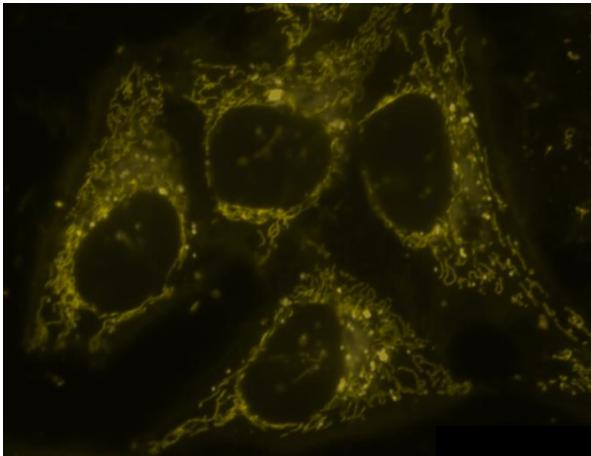
# Lookup tables

- Choose visualization of your color tables wisely!
- Think of people with red/green blindness!

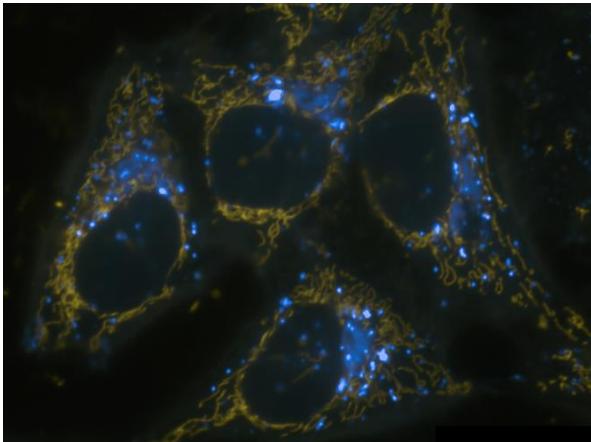
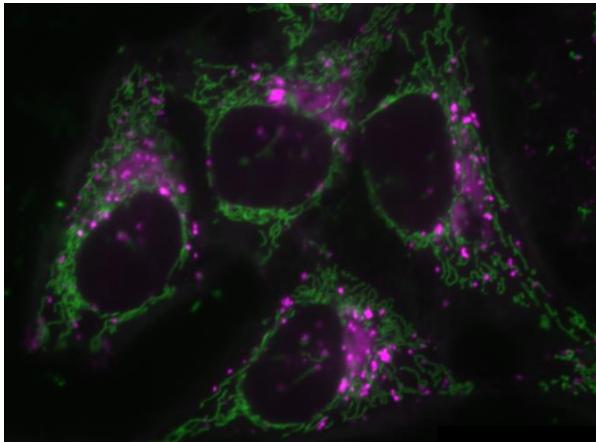
Default view



Red/green blind people see it like this

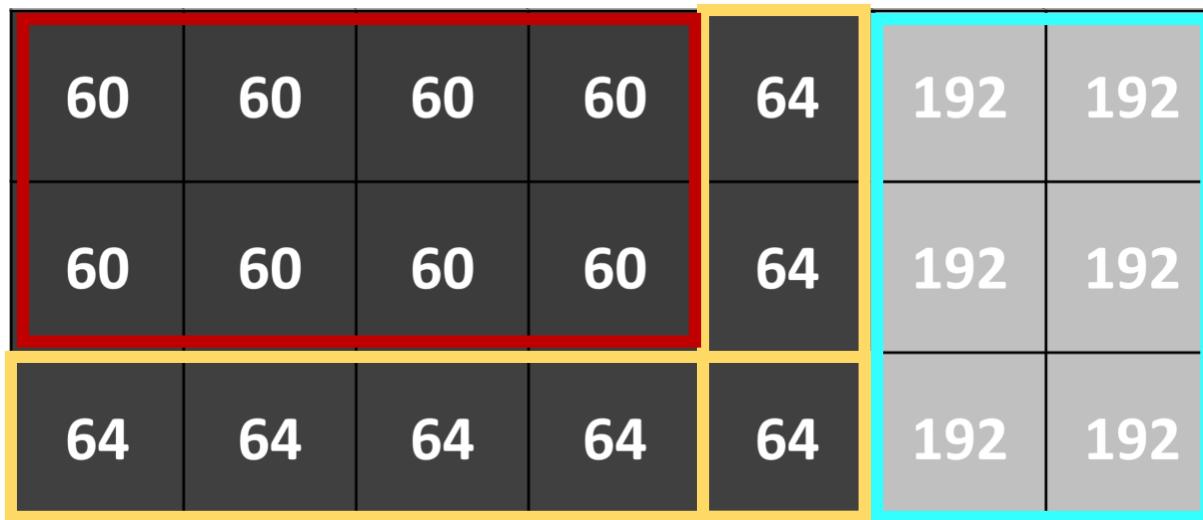


Replace red with  
magenta!



# Histogram

Consider the following image:



How many elements does it have?

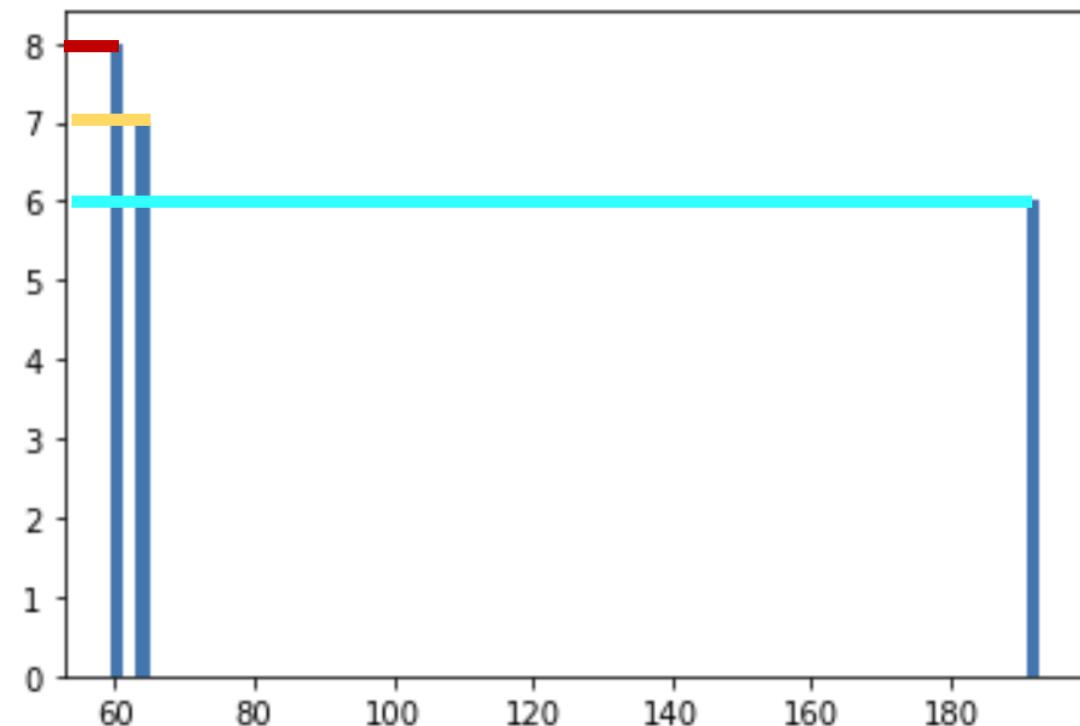
Which pixel value occurs more often?

If we may be mistaken in such a small image,  
imagine for big images!

The histogram answers these questions at a  
glance!

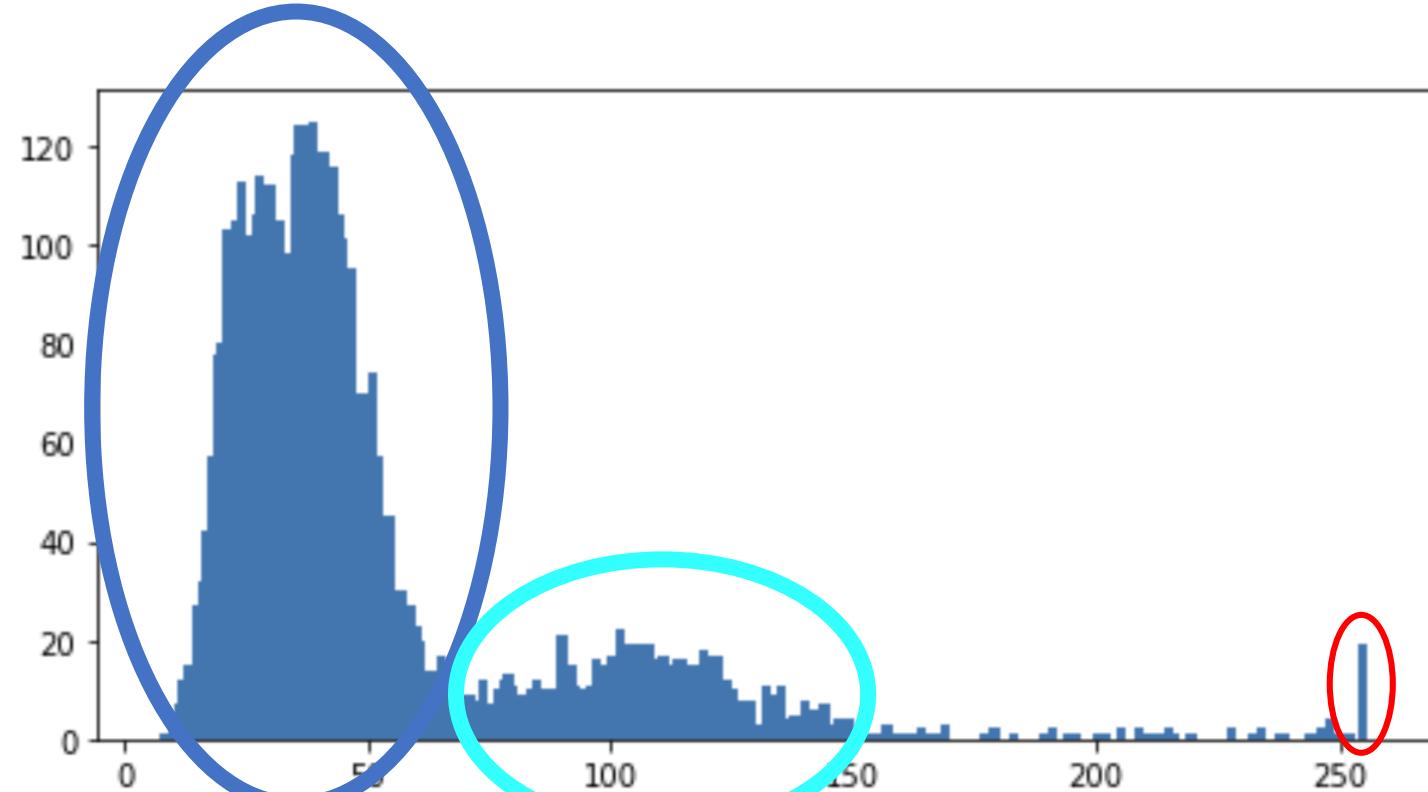
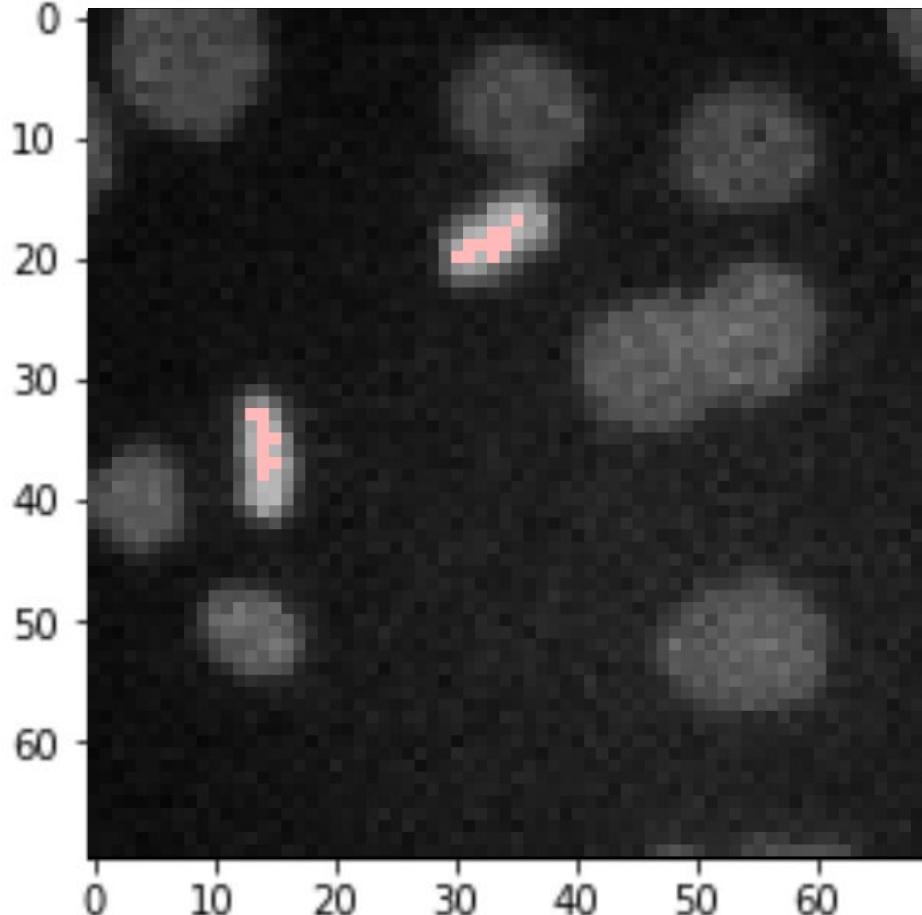
Histogram: a graph that shows how frequent values are in an array/image

```
from skimage.exposure import histogram  
  
pixel_counts, pixel_values = histogram(array)  
  
plt.bar(pixel_values, pixel_counts)
```



# Image Histogram

Example with a slightly larger image:

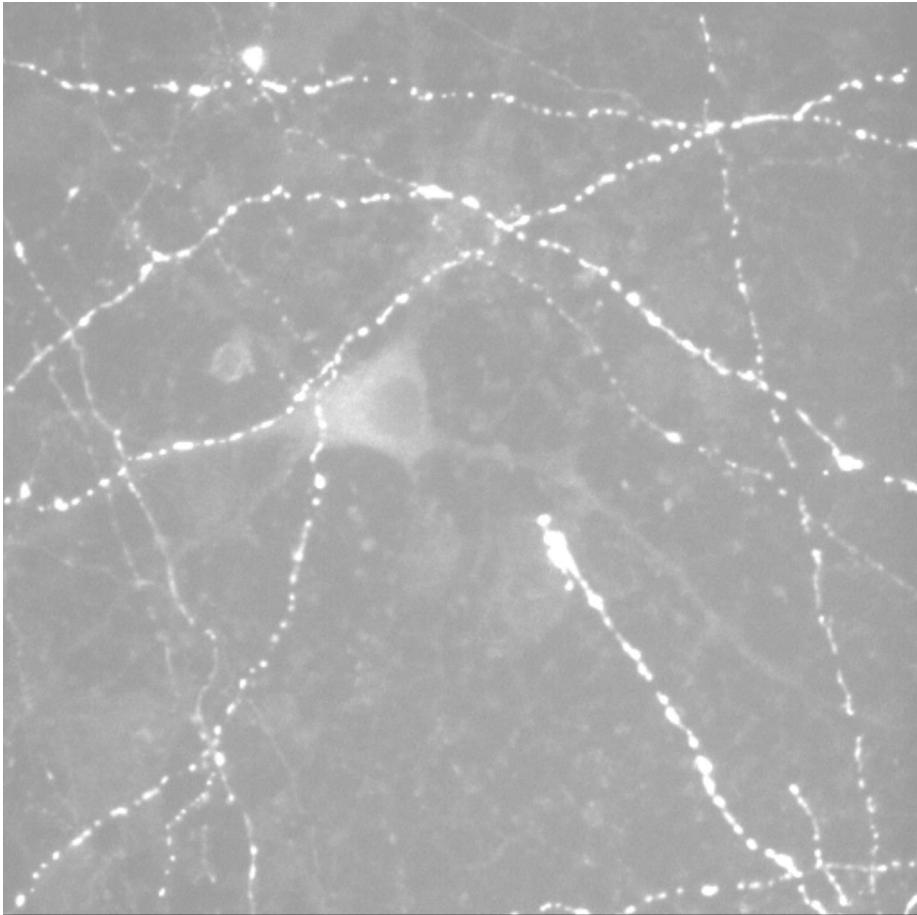


# Visualisation: brightness / contrast

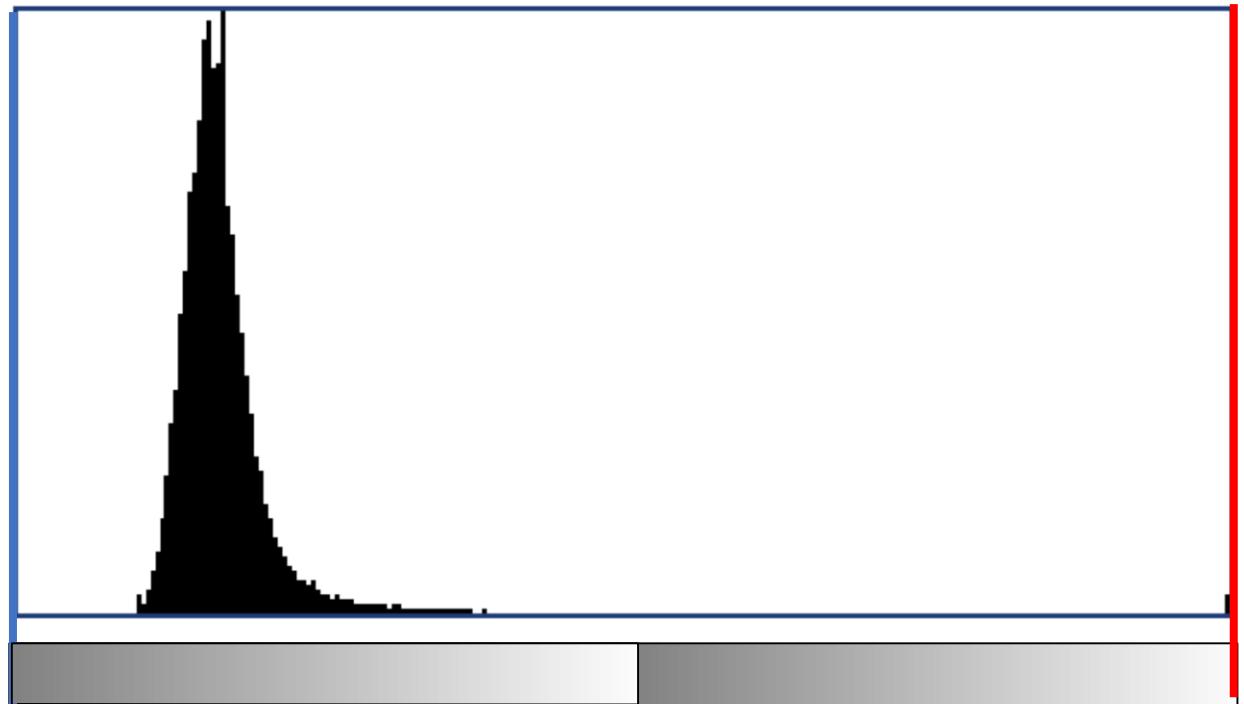
**Brightness:** a relative attribute that represents how much light a source is emitting.

**Contrast:** refers to the amount of color or grayscale differentiation that exists between various image features.

- Is this image bright?
- Does it have good contrast?



Decrease vmin and vmax:  
Brightness Increased



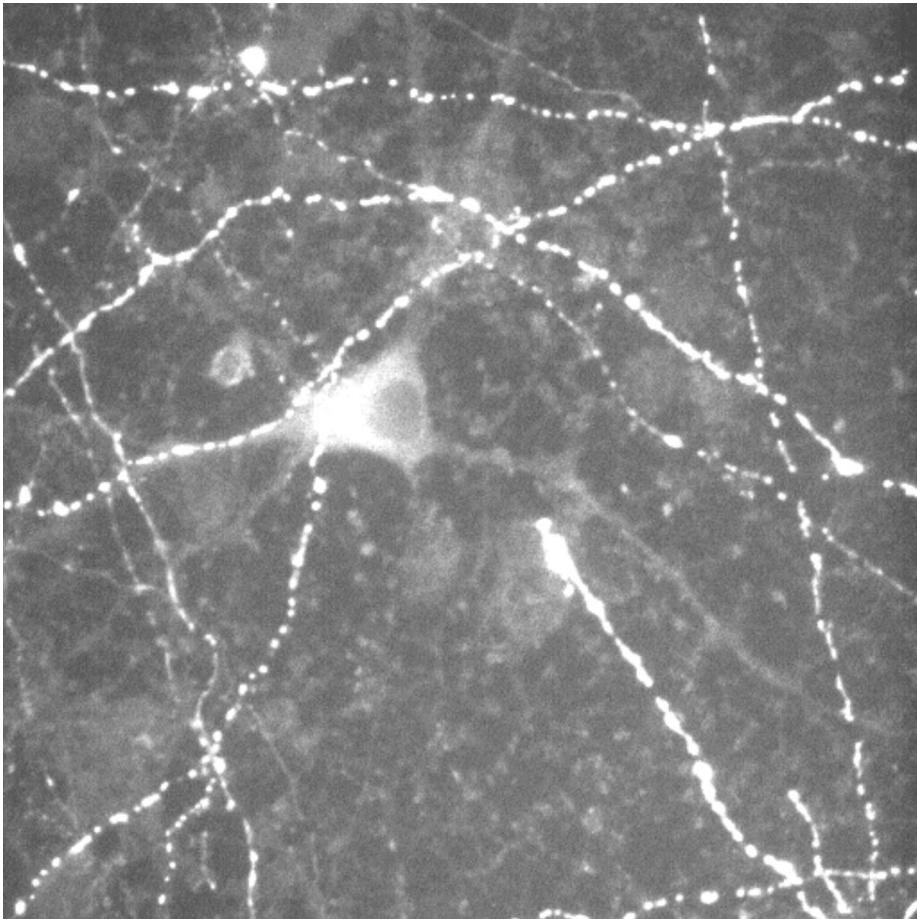
```
plt.imshow(image, cmap='gray', vmin=0, vmax=255)
```

# Visualisation: brightness / contrast

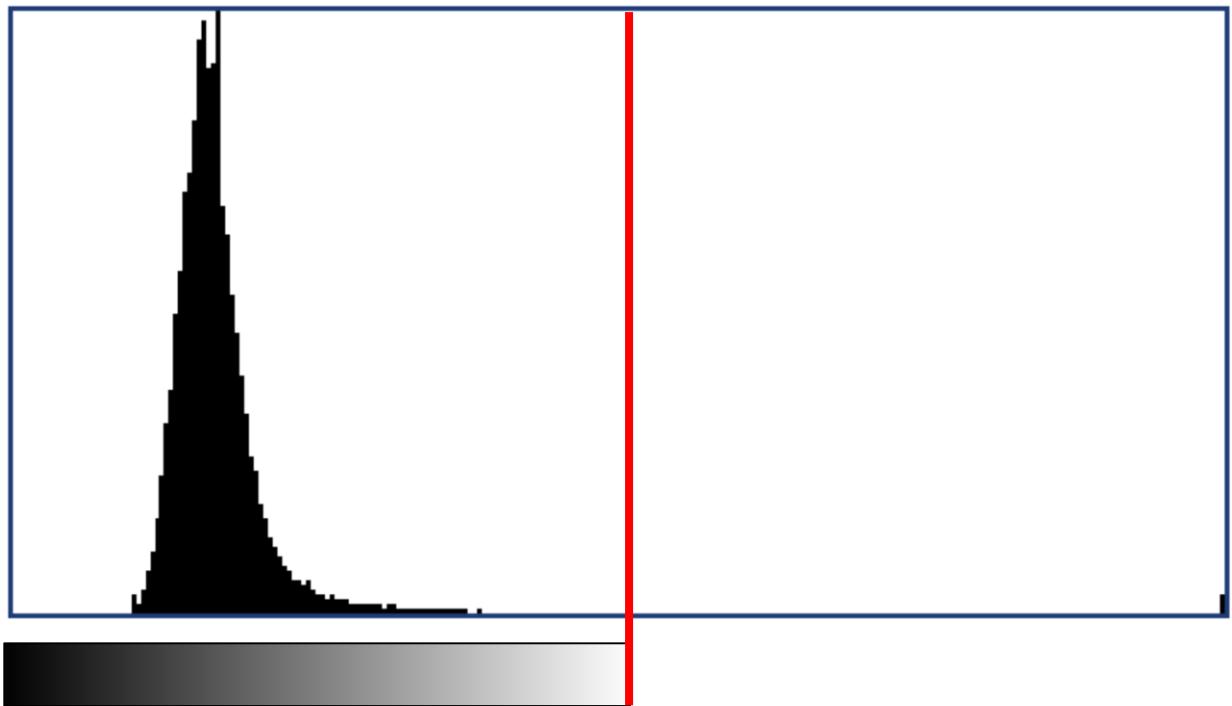
**Brightness:** a relative attribute that represents how much light a source is emitting.

**Contrast:** refers to the amount of color or grayscale differentiation that exists between various image features.

- Is this image bright?
- Does it have good contrast?



Decrease only vmax:  
Contrast Increased

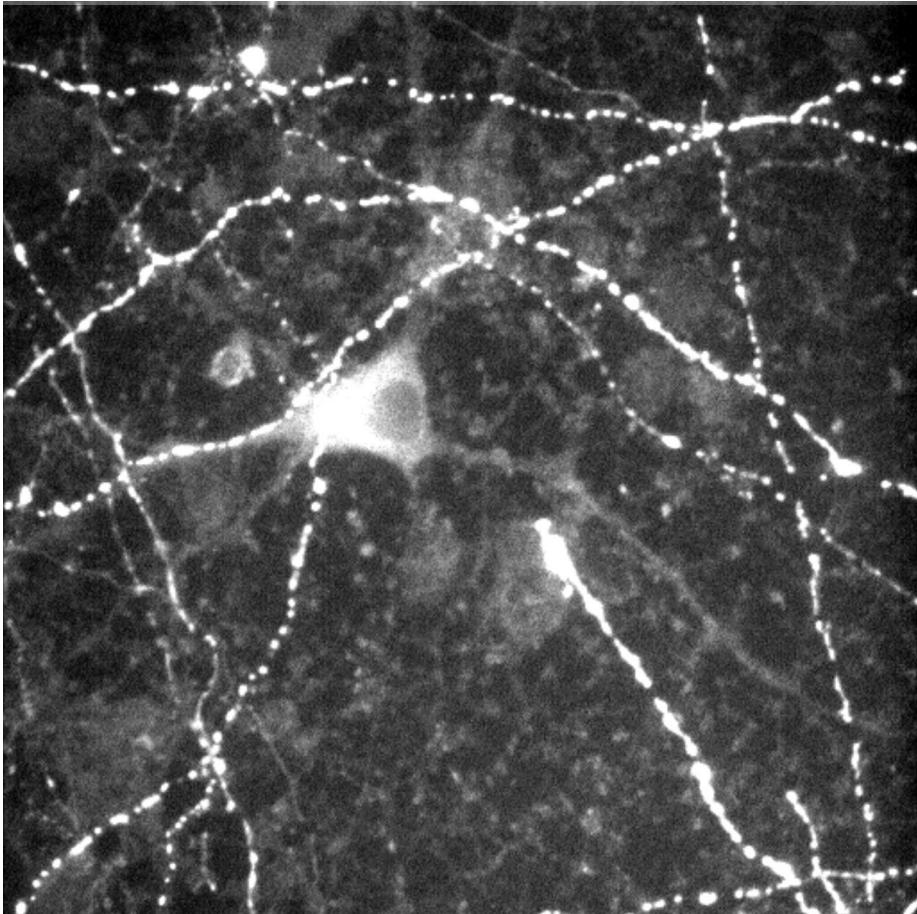


# Visualisation: brightness / contrast

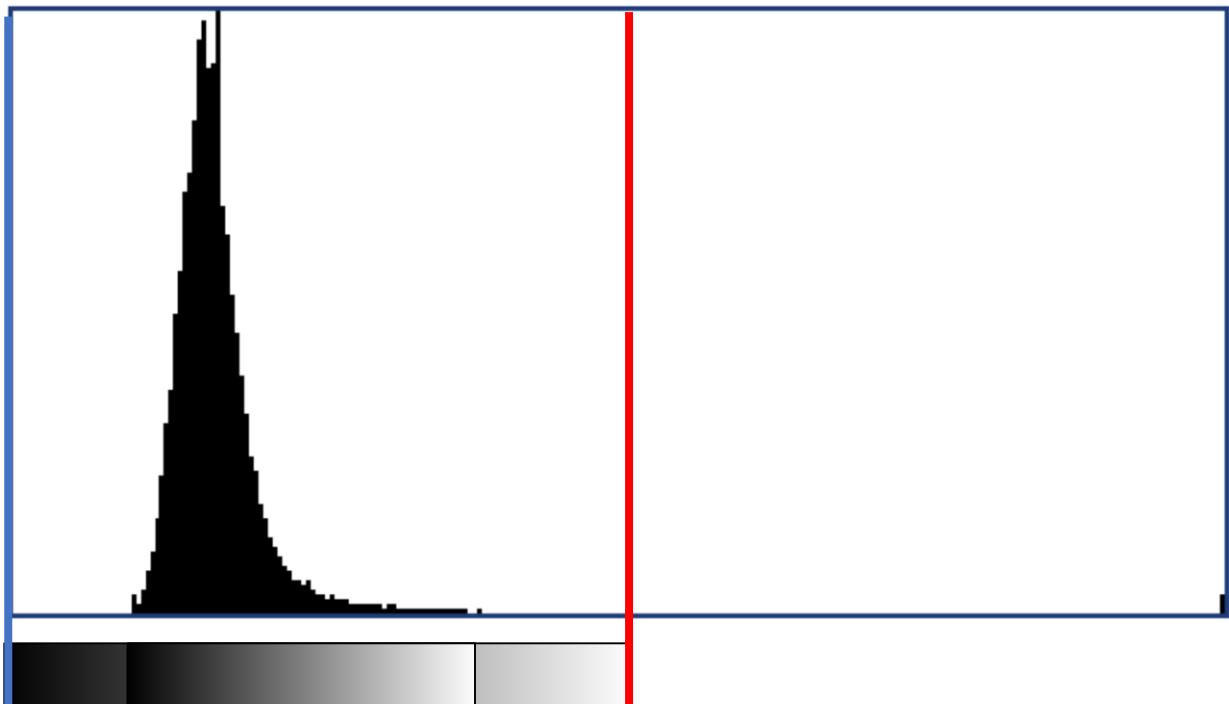
**Brightness:** a relative attribute that represents how much light a source is emitting.

**Contrast:** refers to the amount of color or grayscale differentiation that exists between various image features.

- Is this image bright?
- Does it have good contrast?



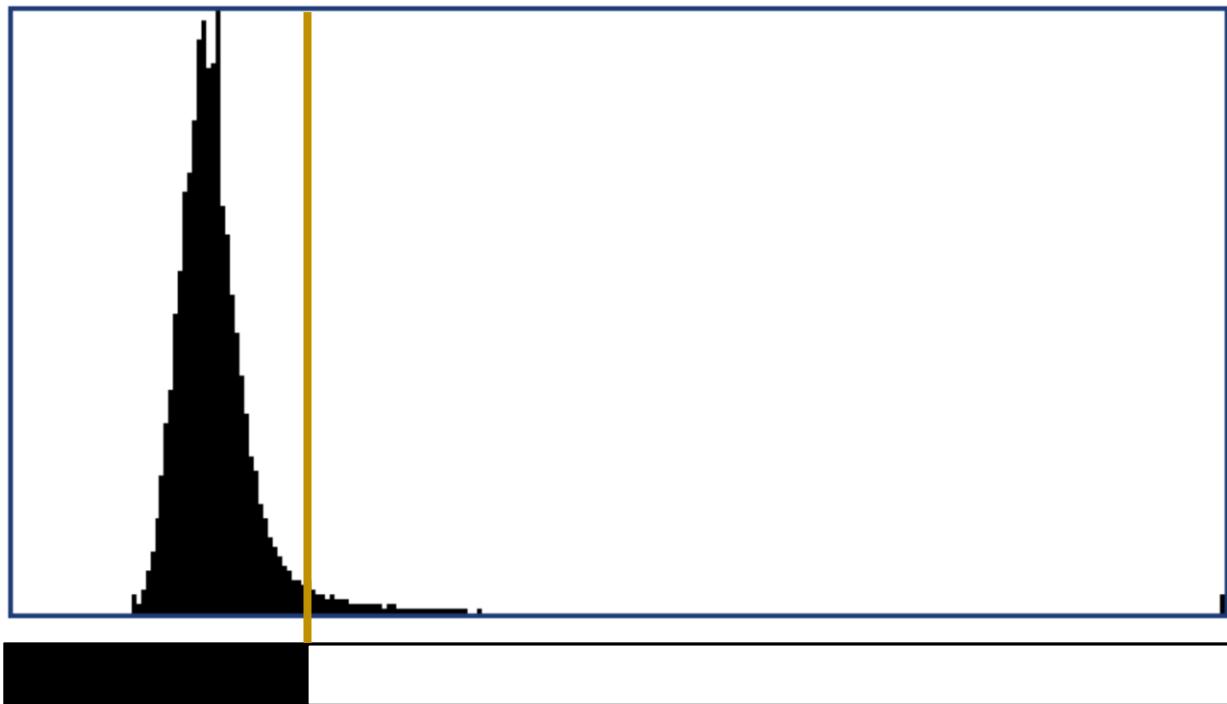
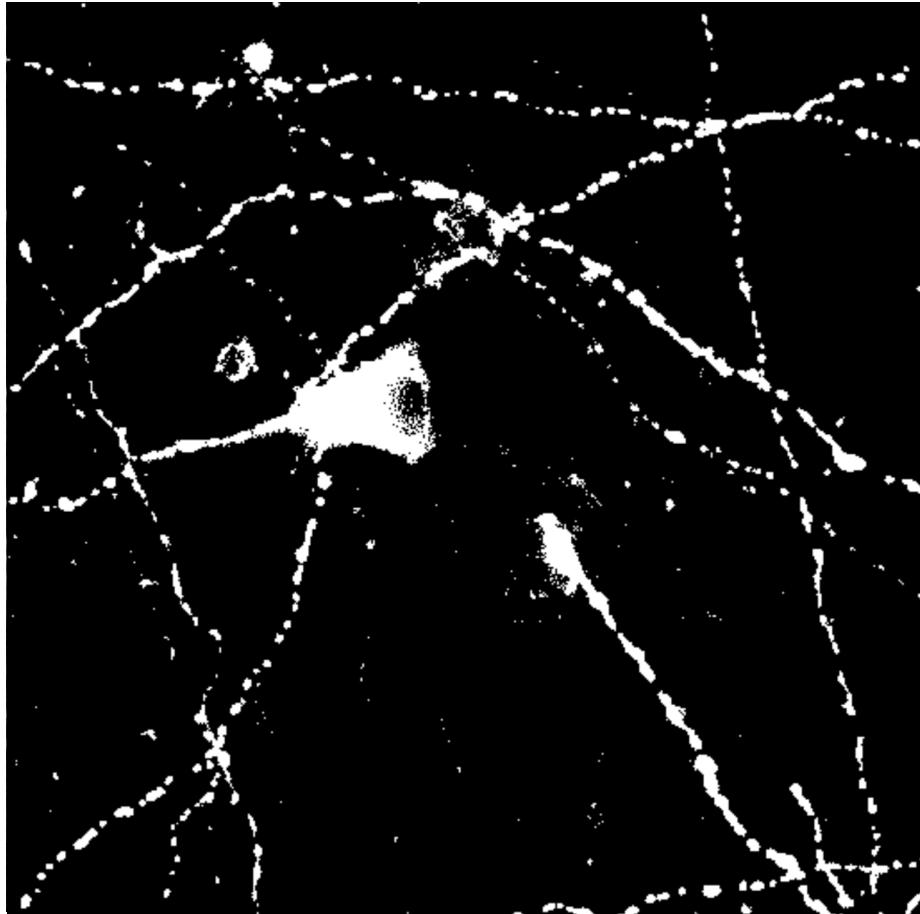
Window  $v_{min}$  and  $v_{max}$  around histogram:  
Contrast Increased



Don't do such a narrow window right before acquisition!  
If your signal changes over time/sample, you will lose information.

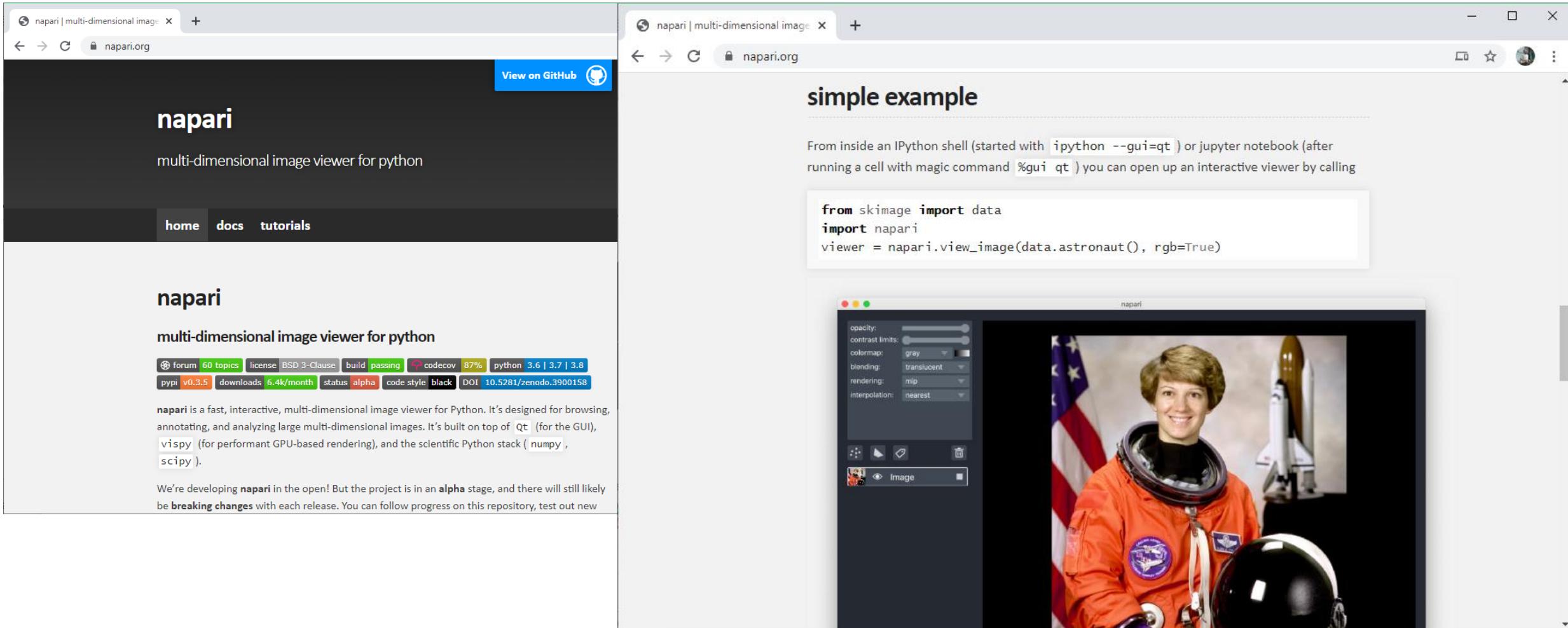
# Binarization: a quick peek

Values above a threshold value are replaced by 1 (or True).  
Values below or equal threshold are replaced by 0 (or False)



```
image_binary = image > value
```

- Multi-dimensional image viewer in python
- <https://napari.org/>

The image shows two browser windows side-by-side. The left window displays the official napari website at napari.org. It features a dark header with the word "napari" in white, followed by "multi-dimensional image viewer for python". Below this is a navigation bar with "home", "docs", and "tutorials" links. The main content area contains a large "napari" logo, the text "multi-dimensional image viewer for python", and a "View on GitHub" button. At the bottom, there's information about the project's status on forums, pypi, and GitHub, along with a brief description of what napari is and its dependencies. The right window shows a "simple example" page from the same site. It includes instructions for running the code in an IPython shell or Jupyter notebook to open an interactive viewer. A code block shows how to import skimage and napari, and then use napari.view\_image to display an astronaut image. Below the code is a screenshot of the napari application interface. The interface has a dark theme with a central image of an astronaut in an orange suit. To the left of the image is a control panel with sliders for "opacity", "contrast limits", "colormap" (set to "gray"), "blending" (set to "translucent"), "rendering" (set to "mip"), and "interpolation" (set to "nearest"). There are also buttons for zooming and other image manipulation.

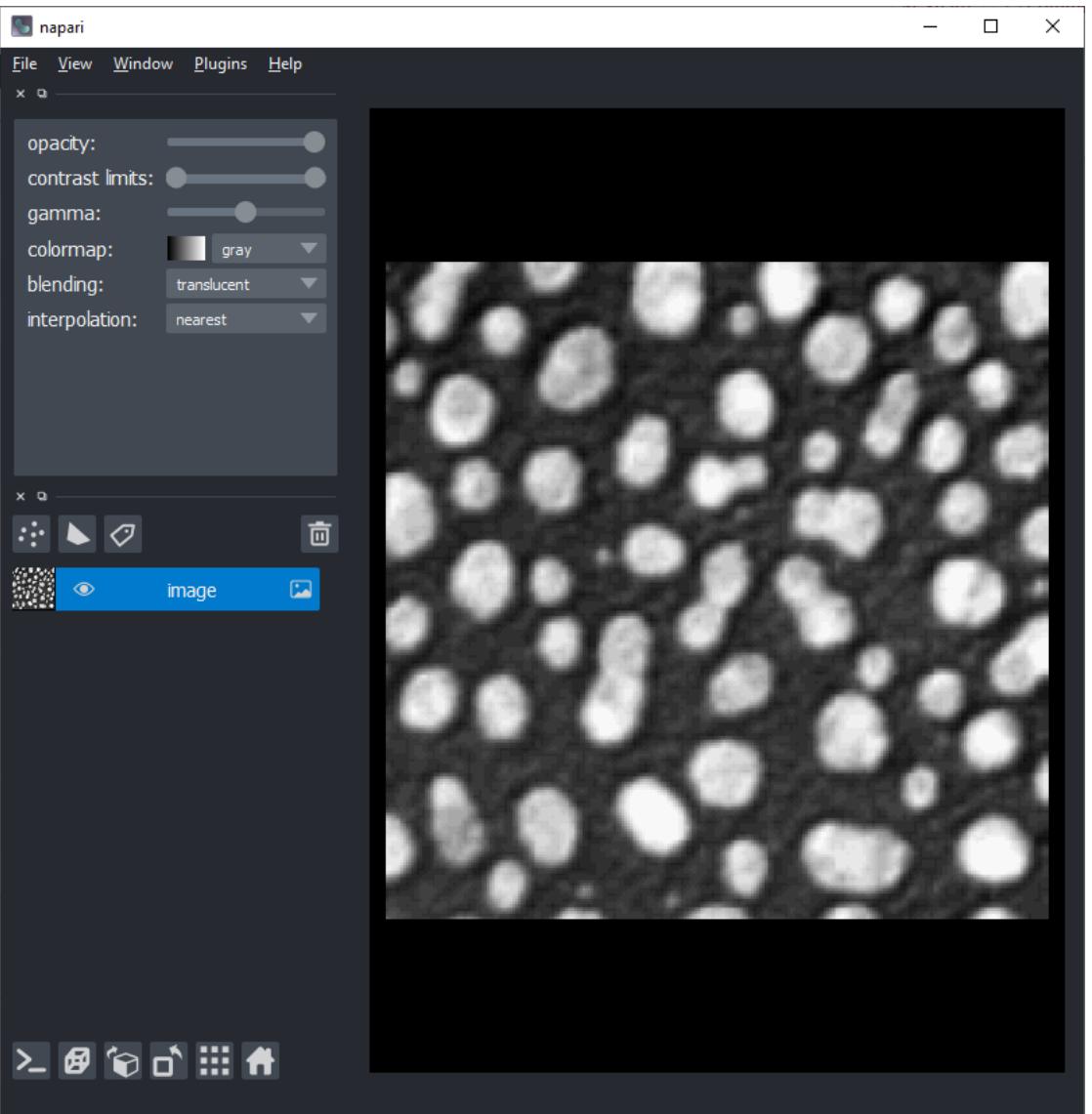
- Open a window

```
import napari

# Create an empty viewer
viewer = napari.Viewer()
```

- Add an image (layer)

```
# Add a new Layer containing an image
viewer.add_image(image)
```



# Add multiple images as layers

- Add layers to napari to visualize intermediate processing results on top of each other or side by side.

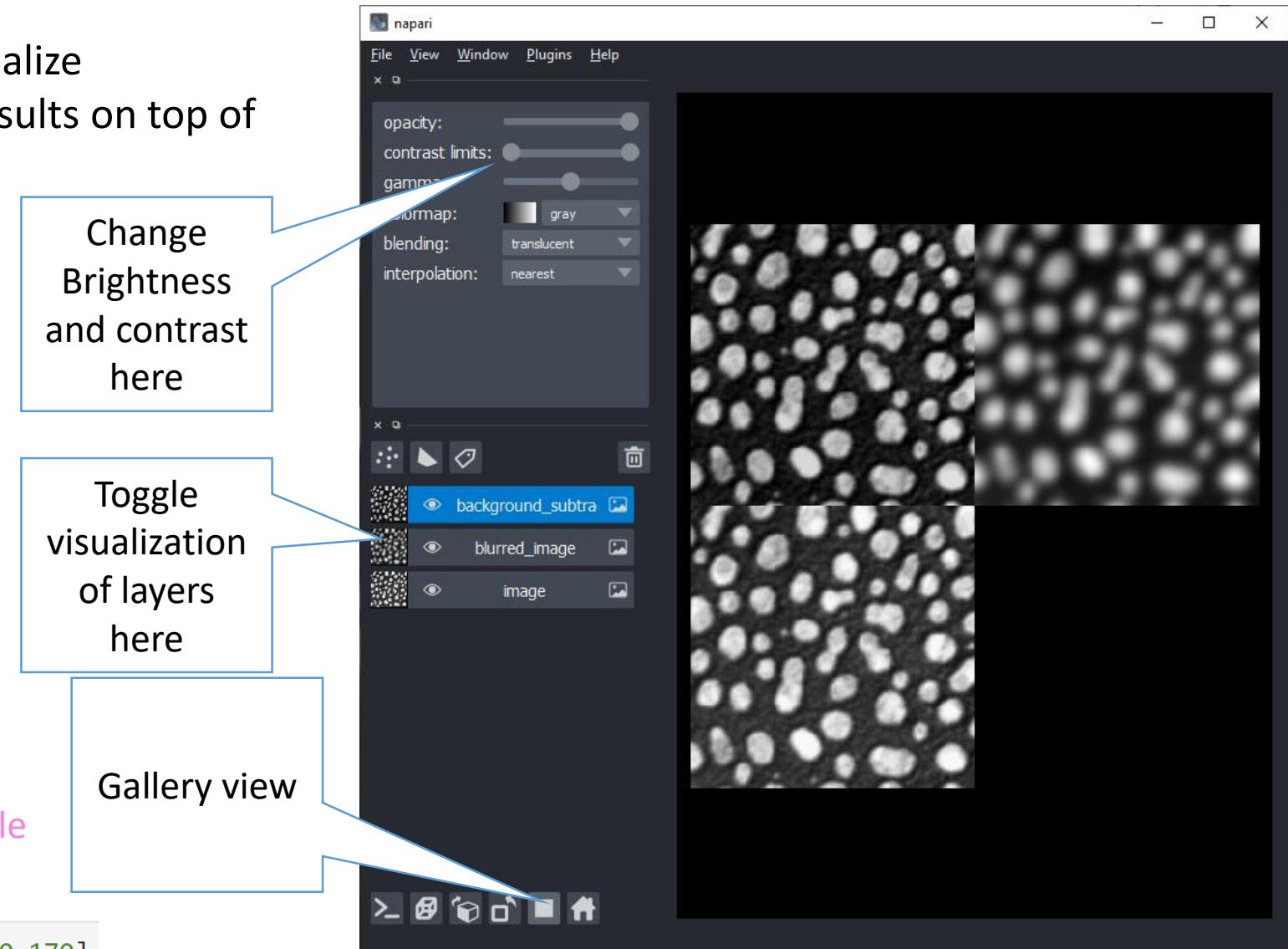
- Change layer visualization within napari...

... or via code in a jupyter notebook:

```
viewer.layers[0].contrast_limits  
[0, 255]
```

1. Access the viewer
2. Access the layers
3. Choose a layer (by index or name)
4. “Press TAB” and check out available properties

```
viewer.layers[0].contrast_limits = [30,170]
```



Find more image layer attributes here:

April 2022 <https://napari.org/api/napari.layers.Image.html#napari.layers.Image>

# Image Processing: Filters

Marcelo Leomil Zoccoler

With material from

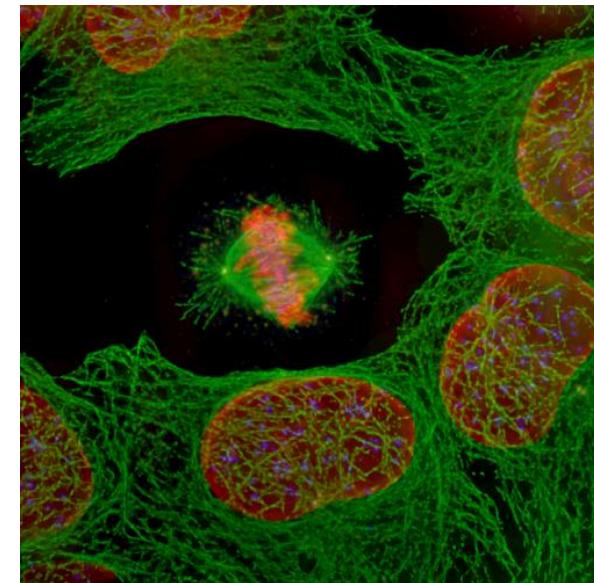
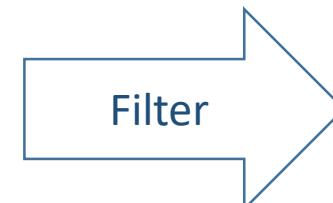
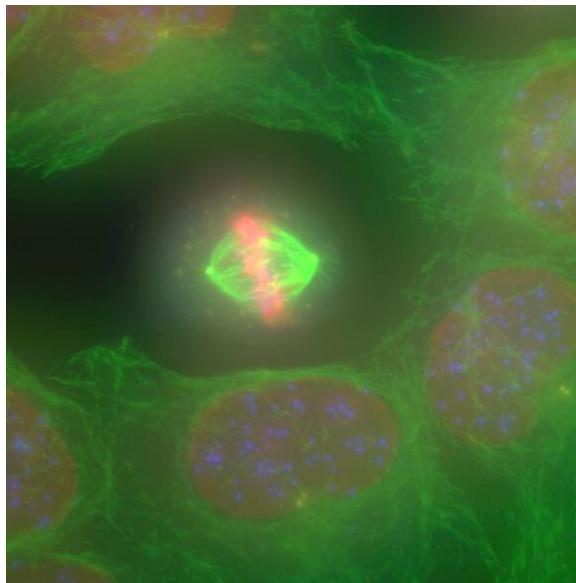
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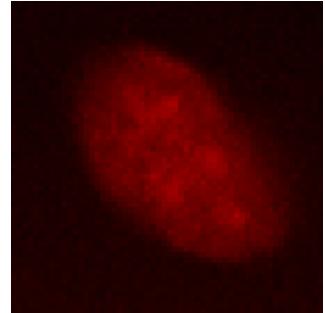
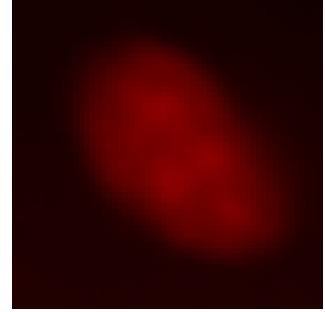
- An image processing filter is an operation on an image.
- It takes an image and produces a new image out of it.
- Filters change pixel values.
- There is no “best” filter. Which filter fits your needs, depends on the context.
- Filters do not do magic. They can not make things visible which are not in the image.

- Application examples
  - Noise-reduction
  - Artefact-removal
  - Contrast enhancement
  - Correct uneven illumination

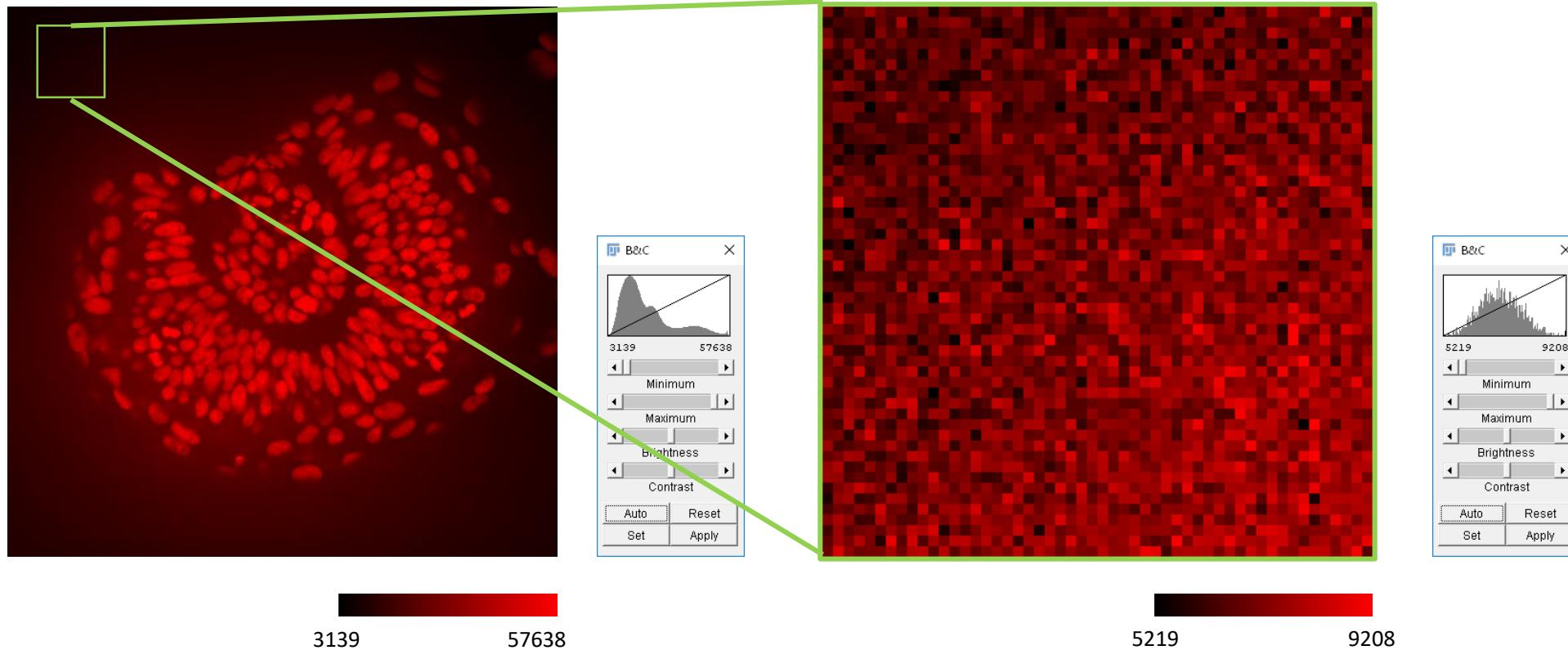


# Effects harming image quality

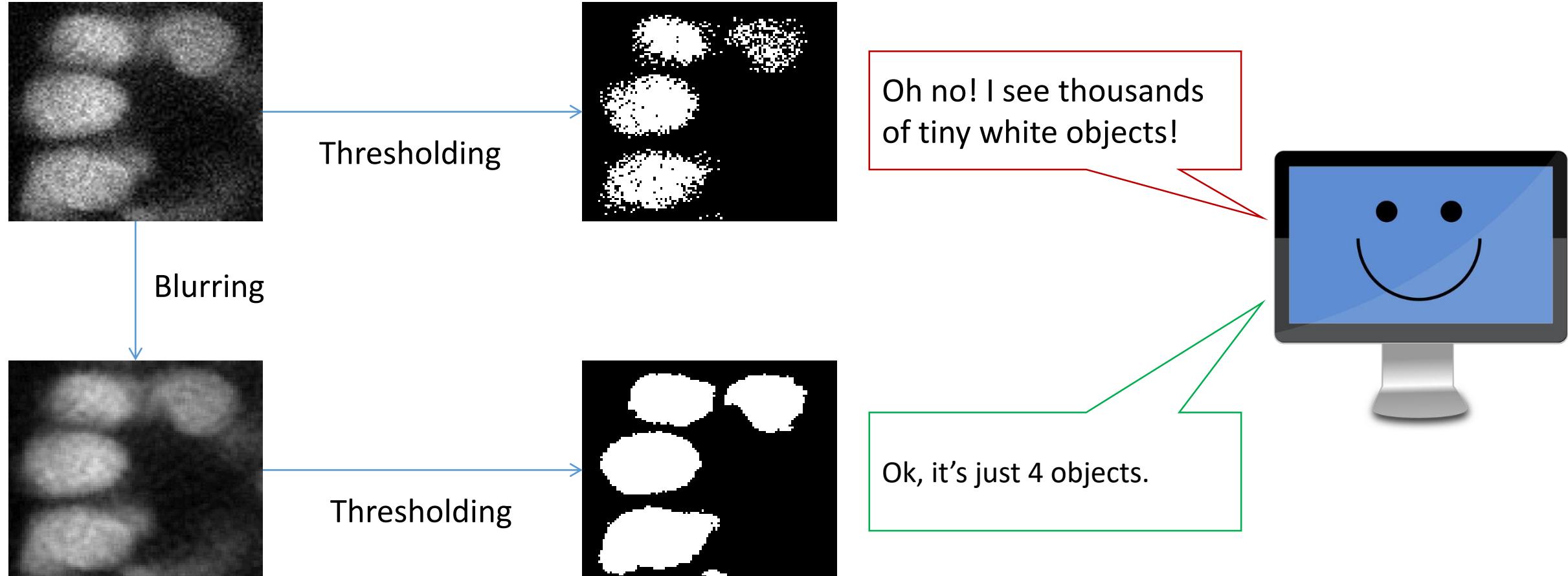
- Noise is a general term for unwanted modifications that a signal may suffer during capture, storage, transmission, processing, or conversion.
- In microscopy, image quality suffers from
  - shot noise: Statistical variation of the photons arriving at the camera
  - dark noise: Statistical variation of how many electrons are generated if a photon arrives in a camera pixel (temperature dependent).
  - read out noise: introduced by the electronics, especially the analog-digital-converter
  - Physical/optical effects: aberrations, defocus
  - Biological/physiological/structural effects: motion, diffusion



- When dealing with noise in microscopic image processing, we mostly mean the noise visible in the images.

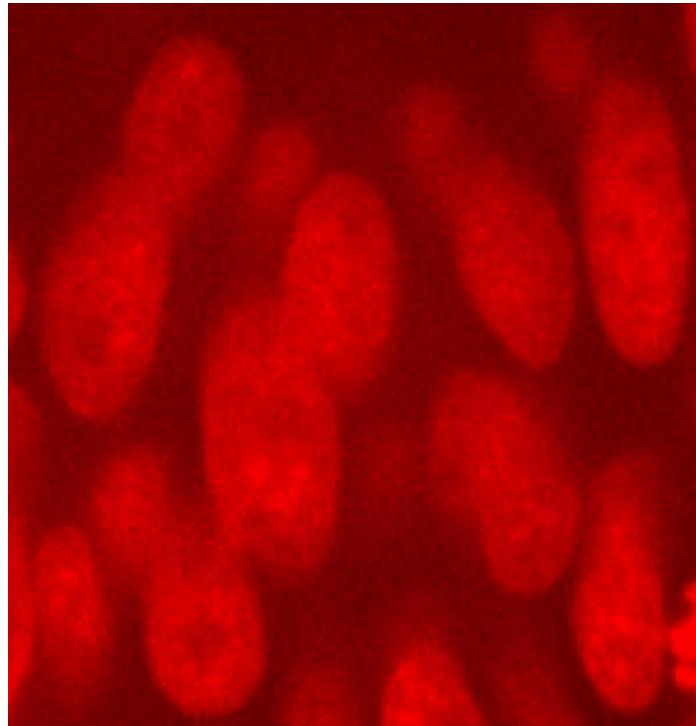


- We need to remove the noise to help the computer *interpreting* the image

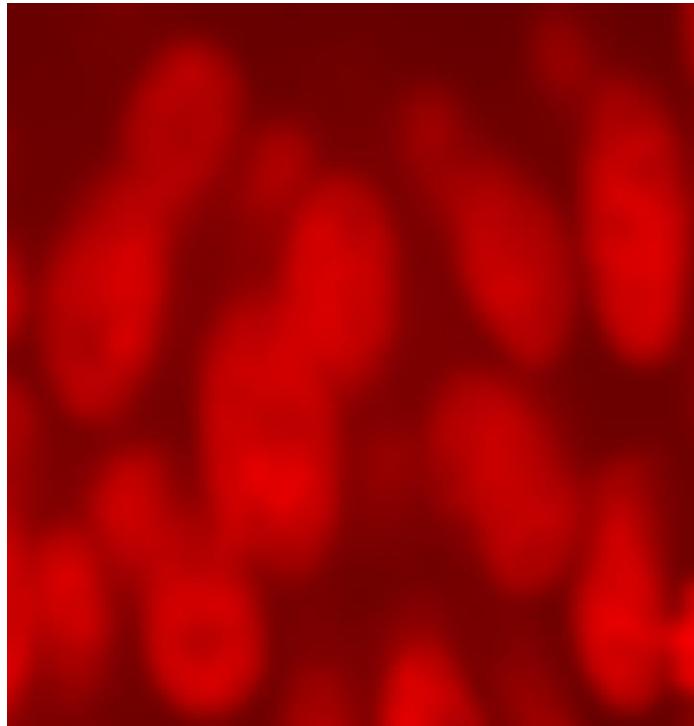


# Image correction / noise removal

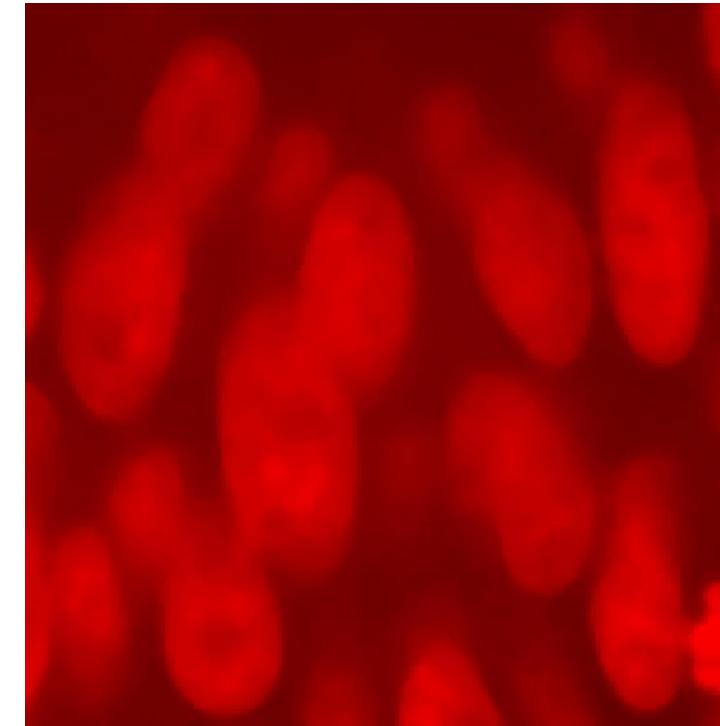
- Noise removal using *filters*



Original image



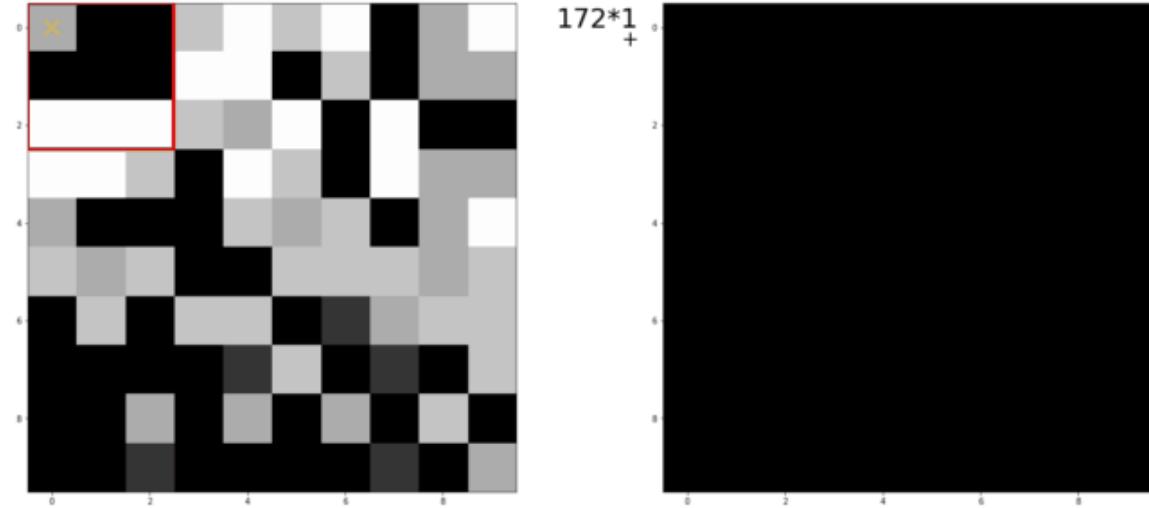
Gaussian blur filtered



Median filtered

# Linear Filters

- Linear filters replace each pixel value with a linear combination of surrounding pixels
  - Basically, linear filtering is a Convolution
  - It needs a kernel (weight template)
  - Result: new image where each pixel is replaced by the weighted sum of pixel values in the neighbourhood.
- Kernels are matrices describing a linear filter

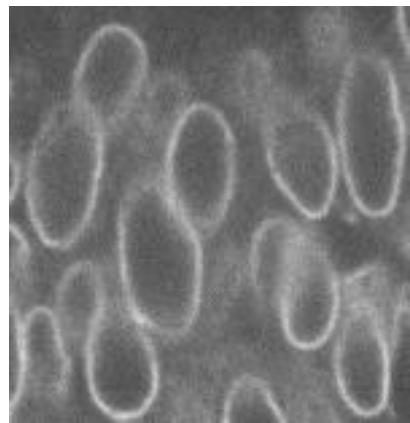


Mean filter, 3x3 kernel

$$\begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix}$$

- Terminology:
  - “We convolve an image with a kernel.”
  - Convolution operator: \*

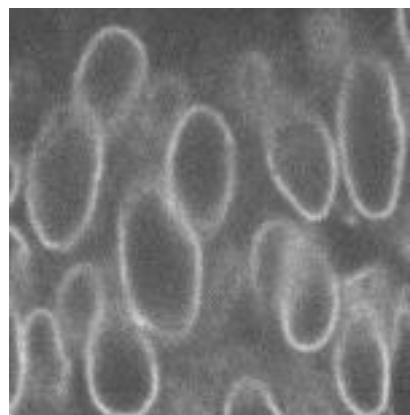
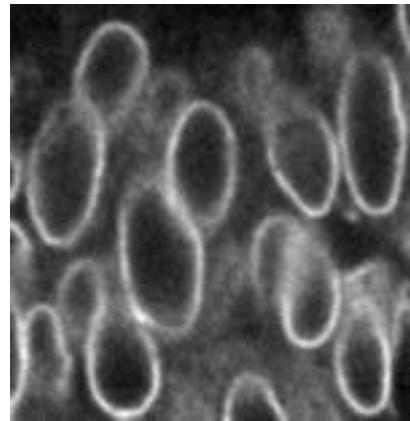
- Examples
  - Mean
  - Gaussian blur
  - Sobel-operator
  - Laplace-filter



\*

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

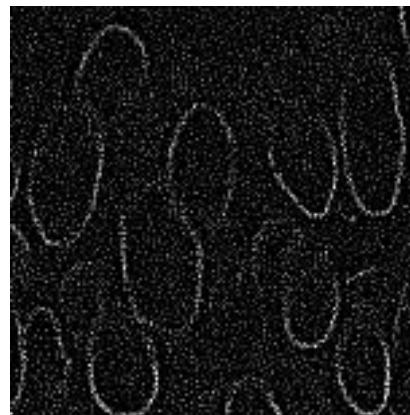
=



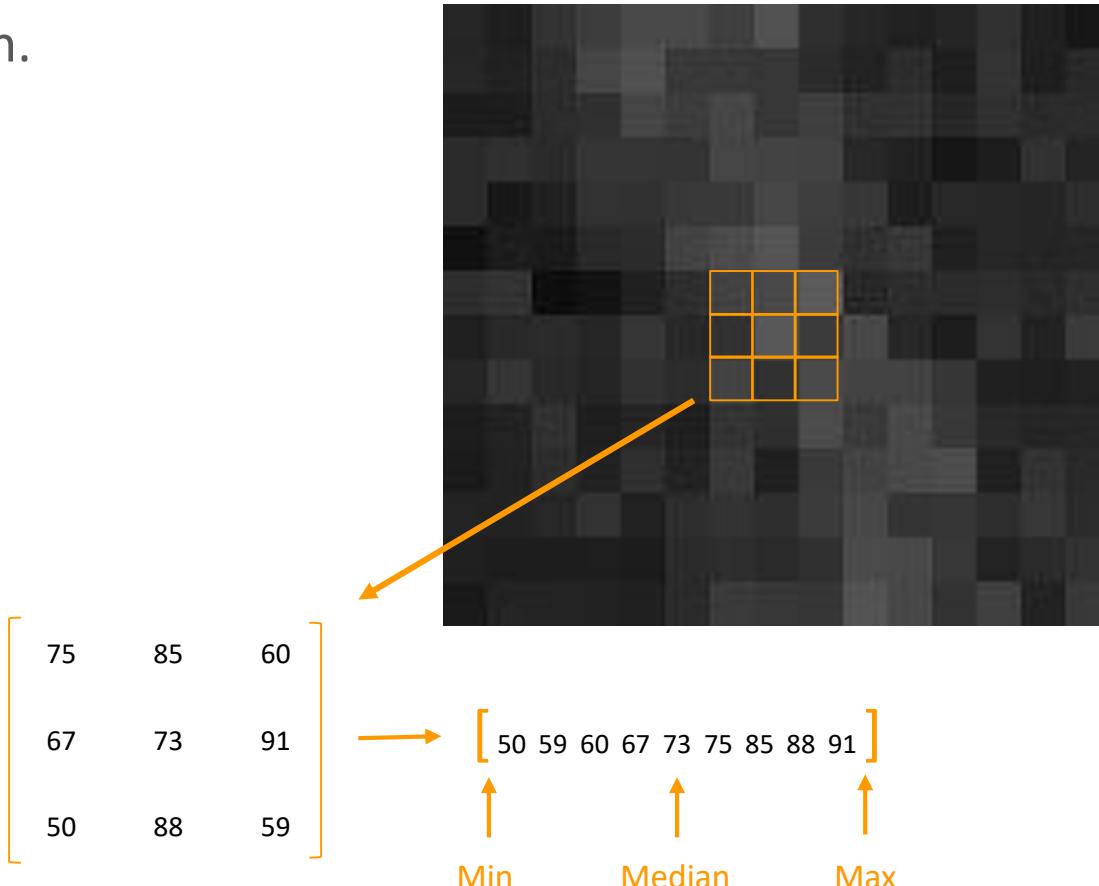
\*

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

=



- Non linear filters also replace pixel value inside a rolling window but in a non linear function.
- Examples: order statistics filters
  - Min
  - Median
  - Max
  - Variance
  - Standard deviation



In python, for linear filters, we could apply a kernel to an image like this:

```
kernel = np.array(  
    [[1/9, 1/9, 1/9],  
     [1/9, 1/9, 1/9],  
     [1/9, 1/9, 1/9]])
```

```
from scipy.ndimage import convolve  
  
output = convolve(image, kernel)
```

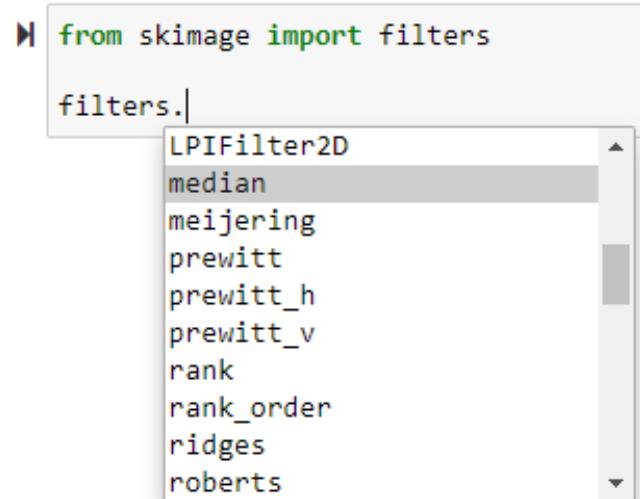
But scikit-image already has several of these filters implemented and optimized.

```
from skimage.filters import gaussian  
  
output = gaussian(image, sigma = 1)
```

Then there is no need to provide a kernel. And you can also directly apply non-linear filters.

```
from skimage.filters import median  
  
output = median(image)
```

Available filters can be searched like this:



# Image Processing: Morphological Operations

Marcelo Leomil Zoccoler

With material from

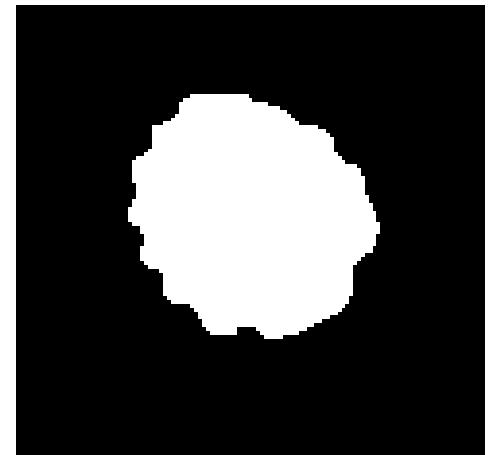
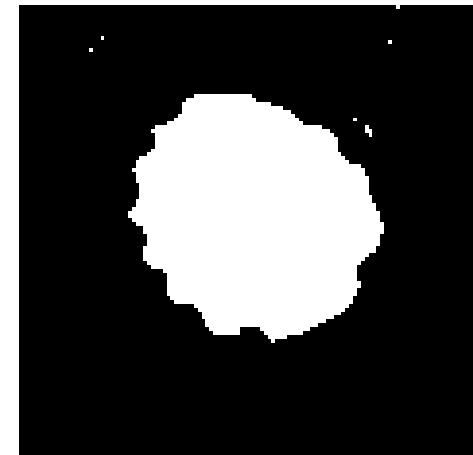
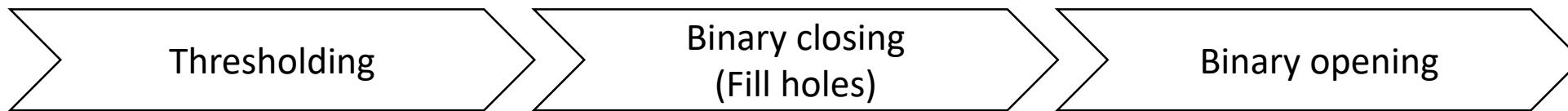
Robert Haase, PoL

Mauricio Rocha Martins, Norden lab, MPI CBG

April 2022

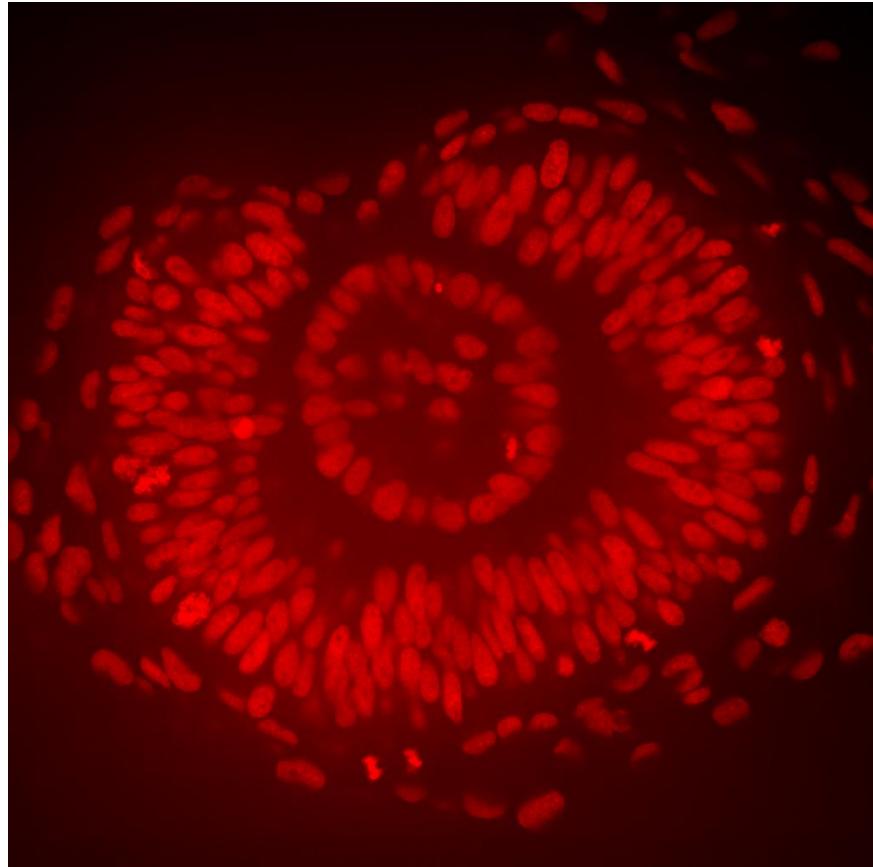
# Refining masks

- Binary mask images may not be perfect immediately after thresholding.
- There are ways of refining them

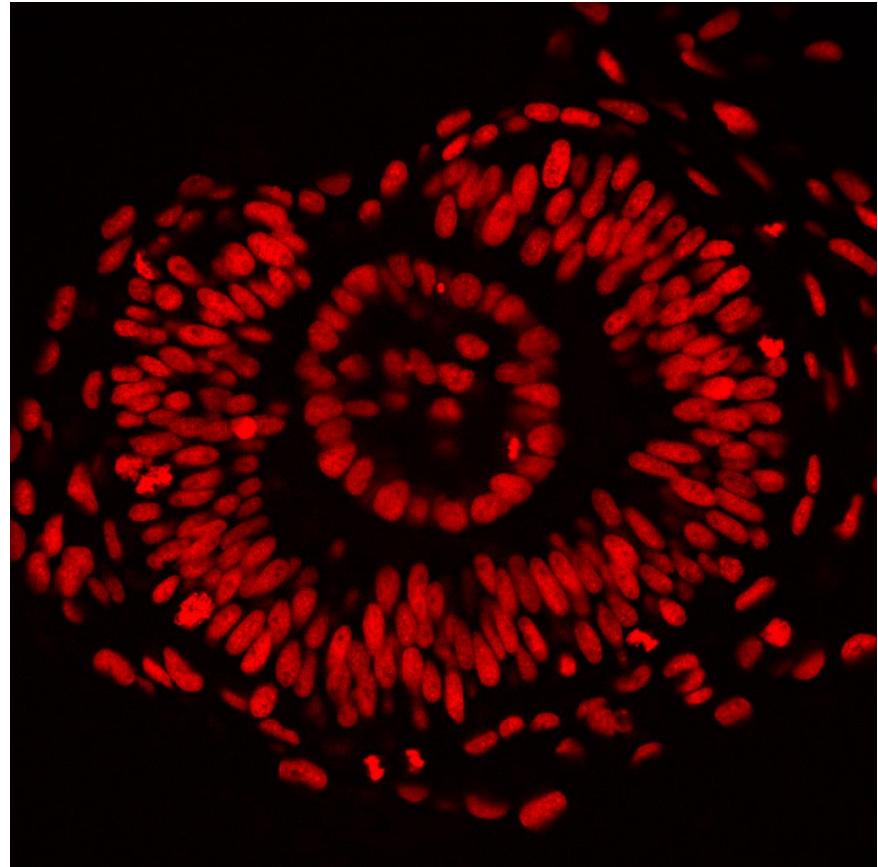


# Background removal

- Differentiating objects is easier if their background intensity is equal.

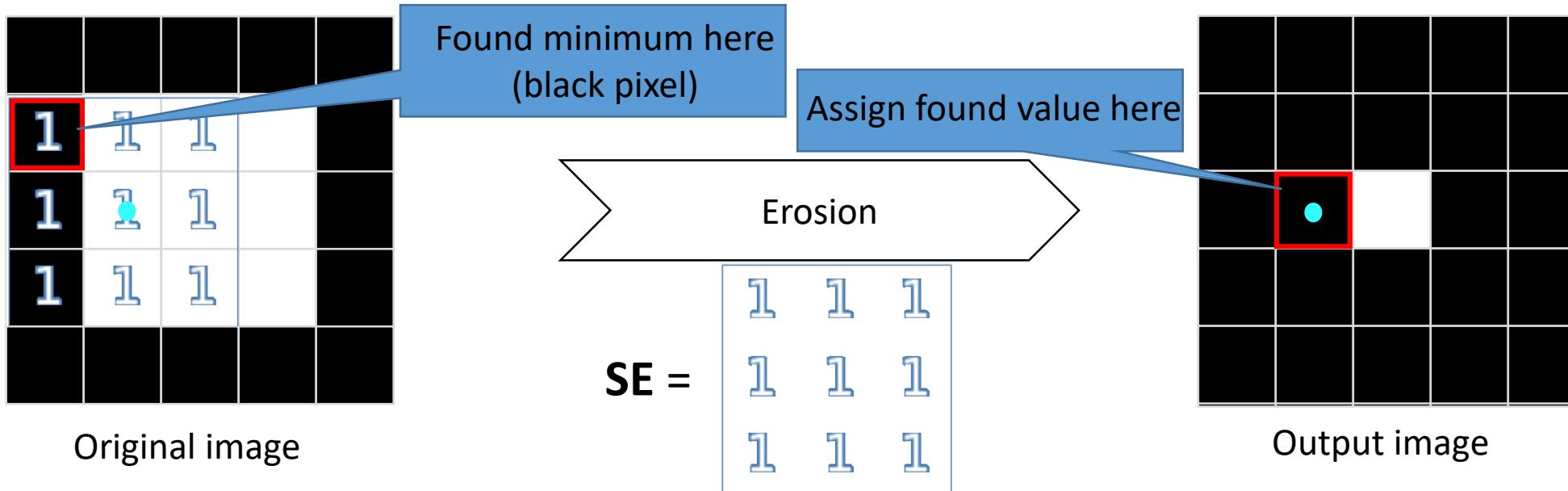


Subtract  
background



# Refining masks: Erosion

- Erosion: Every pixel with at least one black neighbor becomes black.



Erosion is essentially a minimum filter whose extent is defined by the kernel (structural element or **SE**) size and shape.

Dilation is essentially a maximum filter whose extent is defined by the kernel (structural element or **SE**) size and shape.

For an example with a grayscale image, check out this gif:  
[https://en.wikipedia.org/wiki/Erosion\\_\(morphology\)#/media/File:Grayscale\\_Morphological\\_Erosion.gif](https://en.wikipedia.org/wiki/Erosion_(morphology)#/media/File:Grayscale_Morphological_Erosion.gif)

# Refining masks: Dilation

- Dilation: Every pixel with at least one white neighbor becomes white.

|   |   |   |  |  |
|---|---|---|--|--|
| 1 | 1 | 1 |  |  |
| 1 | 1 | 1 |  |  |
| 1 | 1 | 1 |  |  |
|   |   |   |  |  |
|   |   |   |  |  |



8-connected neighborhood  
*Moore-Neighborhood*

|   |   |   |  |  |
|---|---|---|--|--|
| 0 | 1 | 0 |  |  |
| 1 | 1 | 1 |  |  |
| 0 | 1 | 0 |  |  |
|   |   |   |  |  |
|   |   |   |  |  |



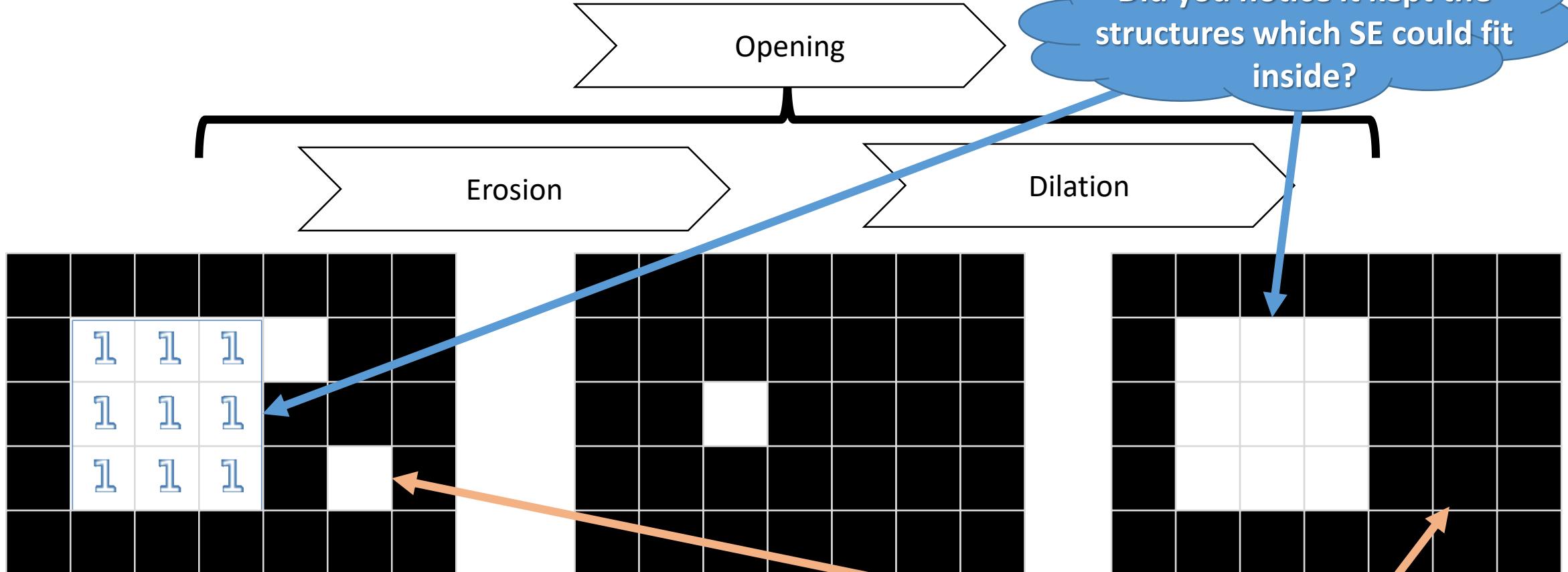
4-connected neighborhood  
*von-Neumann-Neighborhood*

|  |  |  |  |  |
|--|--|--|--|--|
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
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|--|--|--|--|--|
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|  |  |  |  |  |
|  |  |  |  |  |

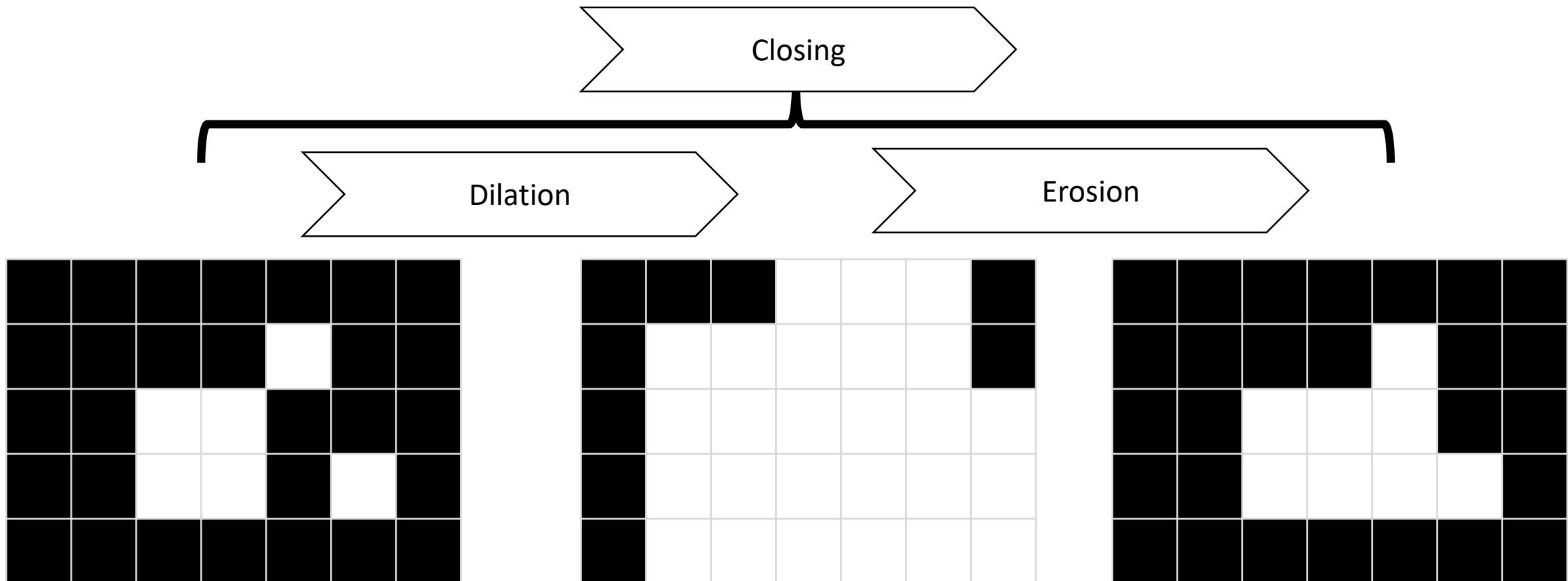
# Refining masks: Erosion & Dilation

- Erosion and dilation combined allow correcting outlines.



- It can separate white (high intensity) structures that are weakly connected
- It may erase small white structures
- It tends to better preserve area of structures

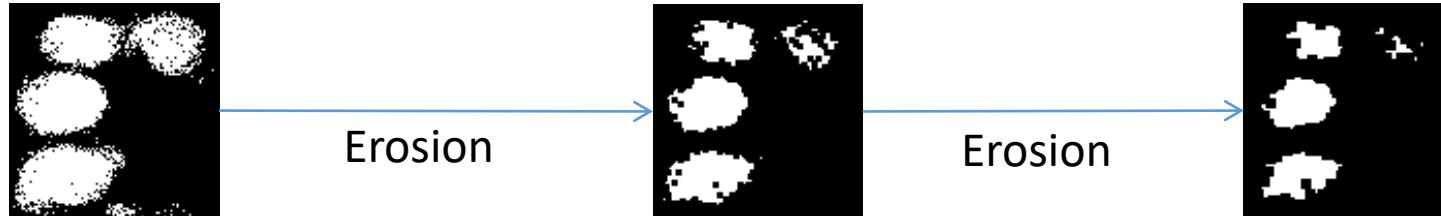
# Refining masks: Erosion & Dilation



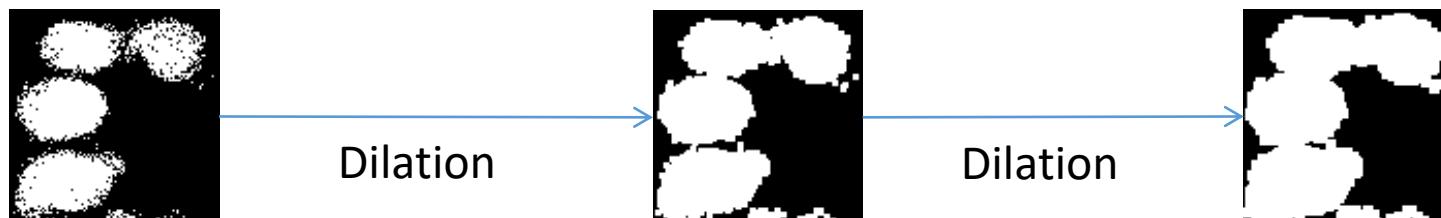
- It can connect white (high intensity) structures that are nearby
- It may close small holes inside structures
- It tends to better preserve area of structures

# Refining masks: Erosion / dilation

- Erosion: Set all pixels to black which have at least one black neighbor.



- Dilation: Set all pixels to white which have at least one white neighbor.



- Closing: Dilation + Erosion



- Opening: Erosion + Dilation



# Morphological Operations in Python

Scikit-image has a sub-package called morphology

```
from skimage import morphology
```

You must define a SE first (also called footprint):

```
SE = morphology.square(3)
SE

array([[1, 1, 1],
       [1, 1, 1],
       [1, 1, 1]], dtype=uint8)
```

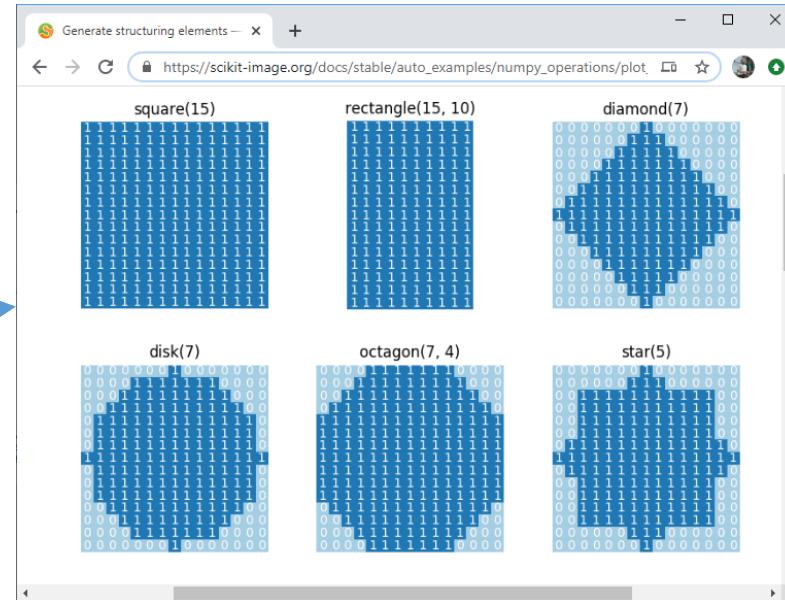
For a binary image, you apply it like this:

```
output = morphology.binary_dilation(binary_image, SE)
```

For a grayscale image, you apply it like this:

```
output = morphology.dilation(image, SE)
```

It can have other shapes/sizes:



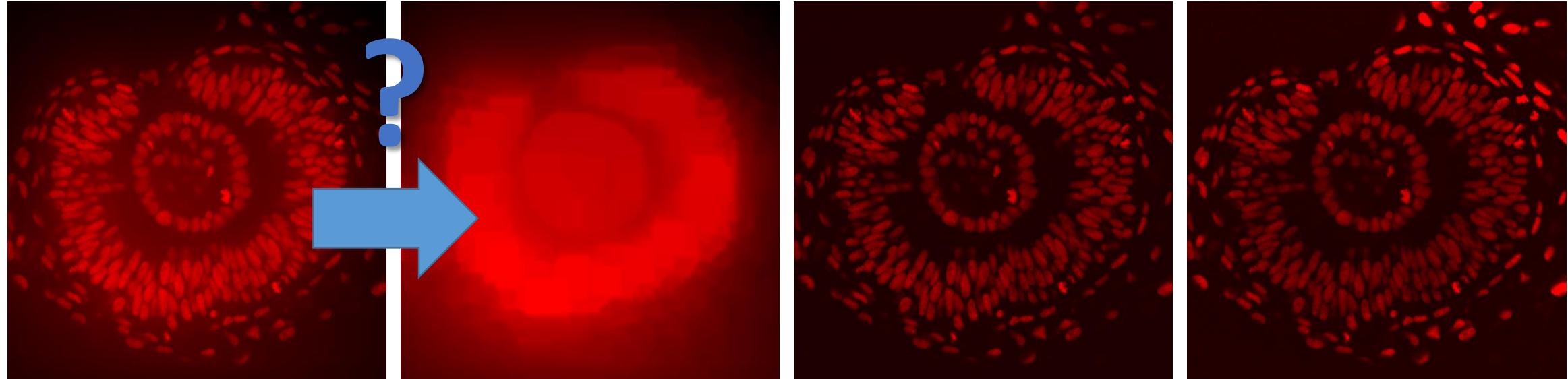
[https://scikit-image.org/docs/stable/auto\\_examples/numpy\\_operations/plot\\_structuring\\_elements.html#sphx-glr-auto-examples-numpy-operations-plot-structuring-elements-py](https://scikit-image.org/docs/stable/auto_examples/numpy_operations/plot_structuring_elements.html#sphx-glr-auto-examples-numpy-operations-plot-structuring-elements-py)

# Background removal

- Depending on the effect we want to correct for, it might make sense to divide an image by its background.

Do you remember that opening  
kept the structures which the SE  
could fit inside?

And do you remember that  
opening deletes structures smaller  
than SE?

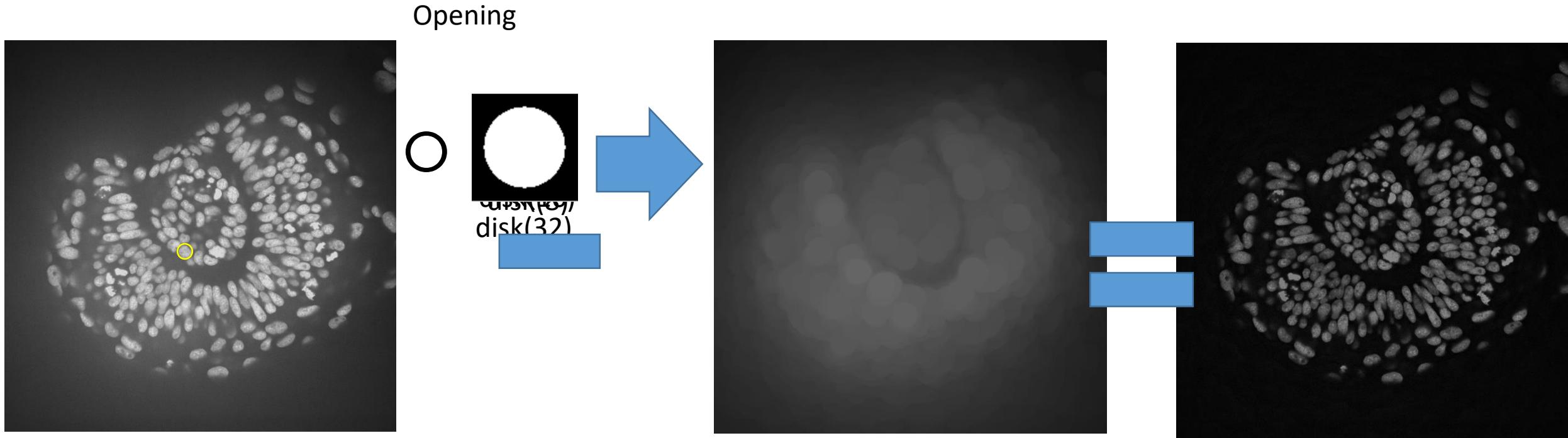


Original image

Extracted  
background

Subtracted  
background

Image divided by  
background



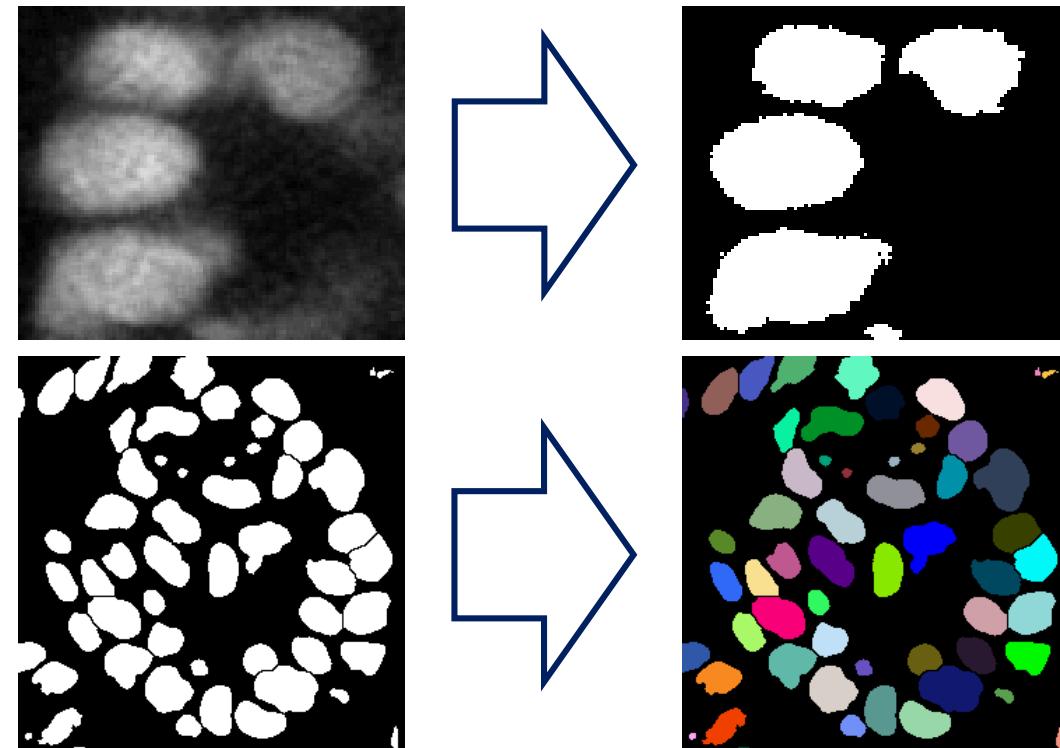
Original image

Structures have a radius  $\approx 12$

This is a good estimation of the background

You have just learned the white tophat filter!

- Image visualization
  - Pixel size, colormaps, bit-depth
  - Image histogram
  - Brightness/Contrast
  - Binarization
  - Napari
- Image Filtering
  - Noise Removal
  - Edge Detection
- Morphological Operations
  - Mask Refinement
  - Background subtraction
- Tools
  - Python
    - Scikit-image
    - Napari



## Coming up next

- Image Segmentation
  - Thresholding
  - Connected component analysis
  - Feature extraction

# Extra: Image visualization: subplots with matplotlib

- Use matplotlib to put images side-by-side

```
median_filtered = filters.median(noisy_mri, disk(1))
mean_filtered = filters.rank.mean(noisy_mri, disk(1))
gaussian_filtered = filters.gaussian(noisy_mri, sigma=1)

fig, axs = plt.subplots(2, 3, figsize=(15,10))

# first row
axs[0, 0].imshow(median_filtered)
axs[0, 0].set_title("Median")
axs[0, 1].imshow(mean_filtered)
axs[0, 1].set_title("Mean")
axs[0, 2].imshow(gaussian_filtered)
axs[0, 2].set_title("Gaussian")
```

```
# second row
axs[1, 0].imshow(median_filtered[50:100, 50:100])
axs[1, 1].imshow(mean_filtered[50:100, 50:100])
axs[1, 2].imshow(gaussian_filtered[50:100, 50:100])
```

row      column

[https://matplotlib.org/stable/api/\\_as\\_gen/matplotlib.pyplot.subplots.html](https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.subplots.html)

