

Image Processing and Filtering

Till Korten

With material from

Marcelo Leomil Zoccoler and Robert Haase, PoL TU Dresden

Mauricio Rocha Martins, Norden lab, MPI CBG

Dominic Waithe, Oxford University

Alex Bird, Dan White, MPI CBG

April 2023

- Image Data Analysis workflows
- Goal: **Quantify observations, substantiate conclusions with numbers**

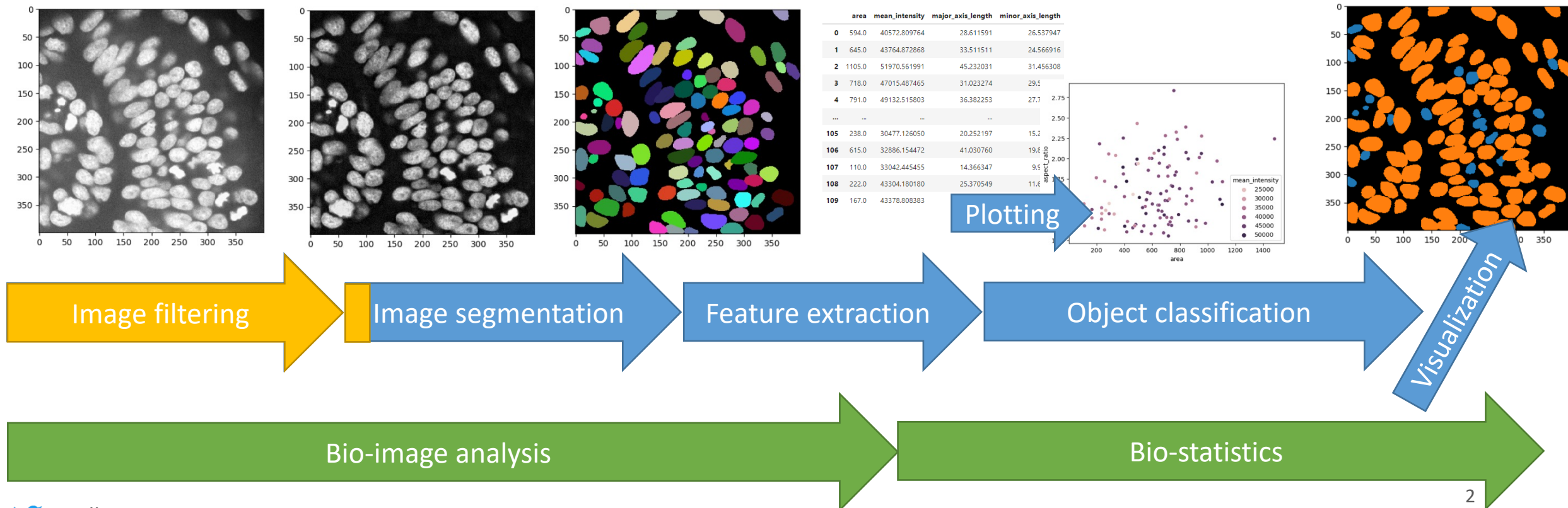


Image Filtering

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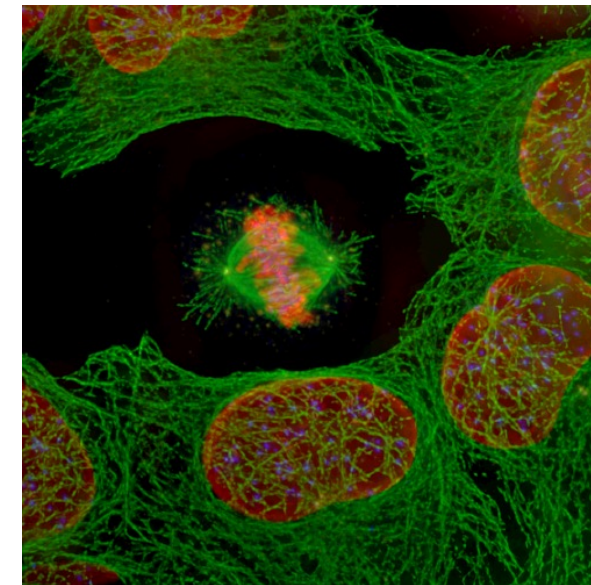
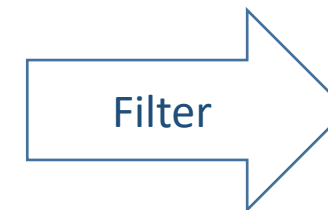
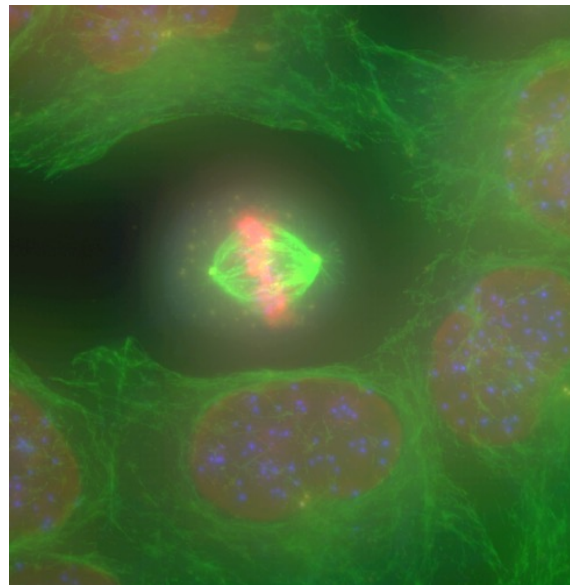
With material from

Robert Haase and Marcelo Leomil Zoccoler, PoL, TU Dresden

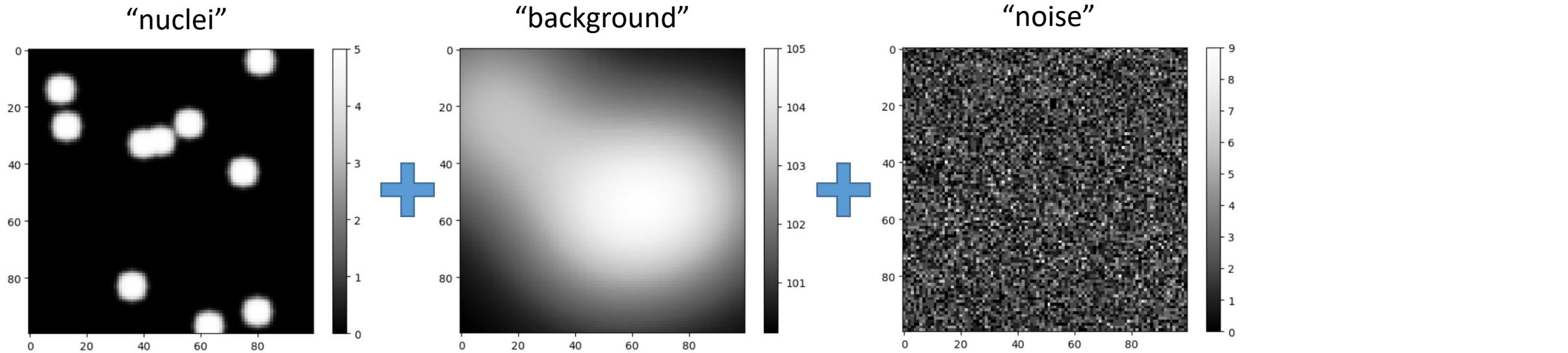
September 2023

- 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



- Image formation (simulated)



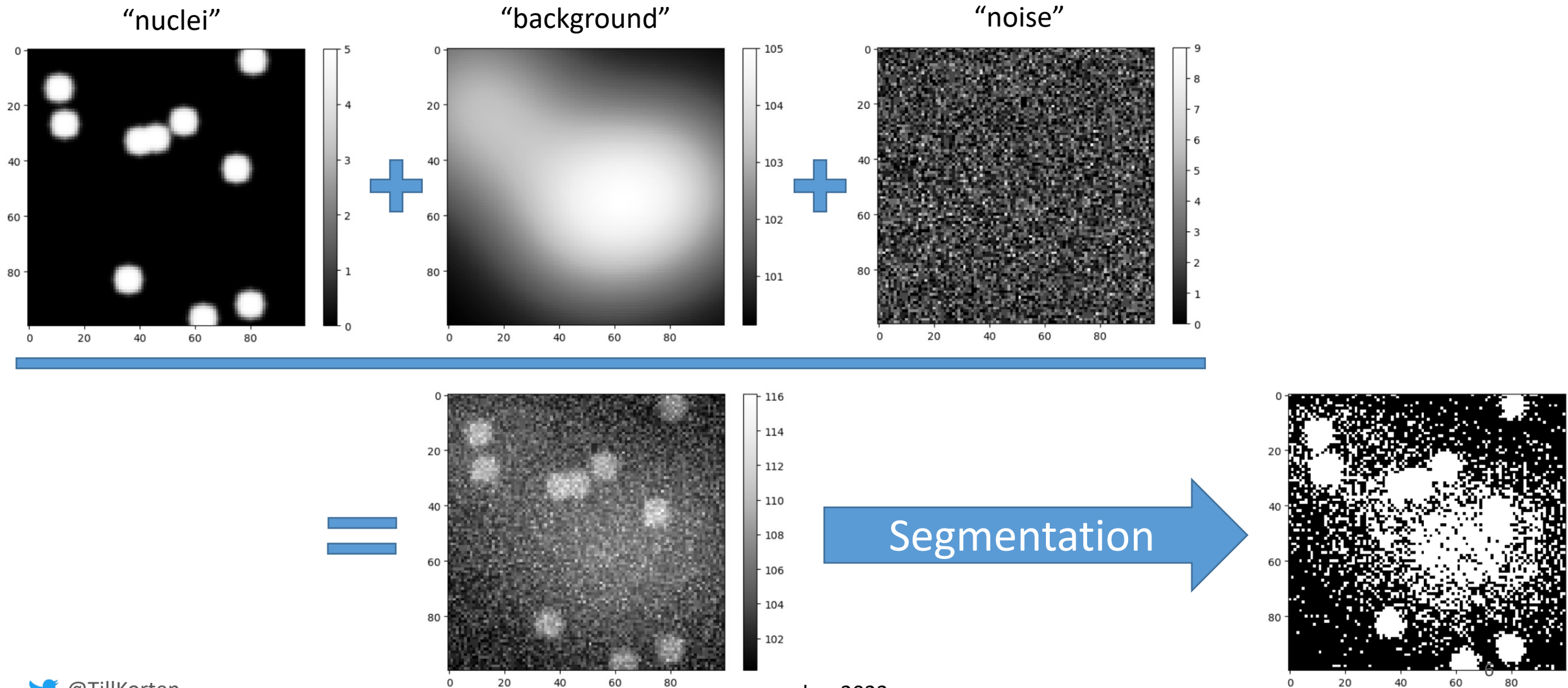
- Aberrations, defocus
- Motion blur

- Light from objects behind and in front of the scene (out-of-focus light)
- Dirt on the object slide
- Camera offset

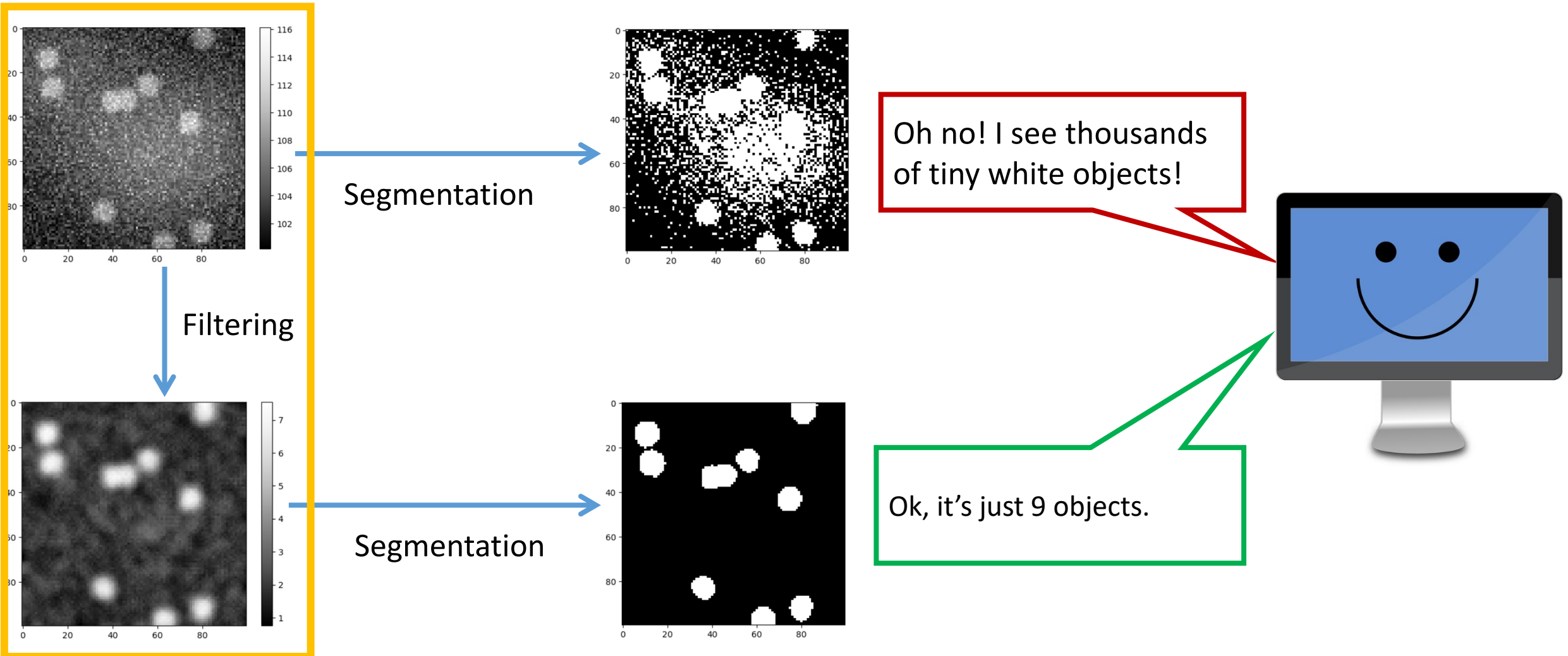
- Shot noise (arriving photons)
- Dark noise (electrons made from photons)
- Read-out-noise (electronics)

Effects harming image quality

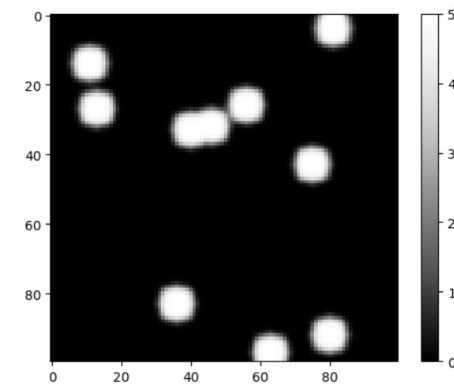
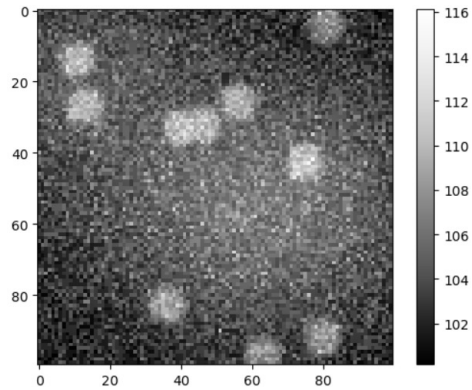
- Image formation (simulated)



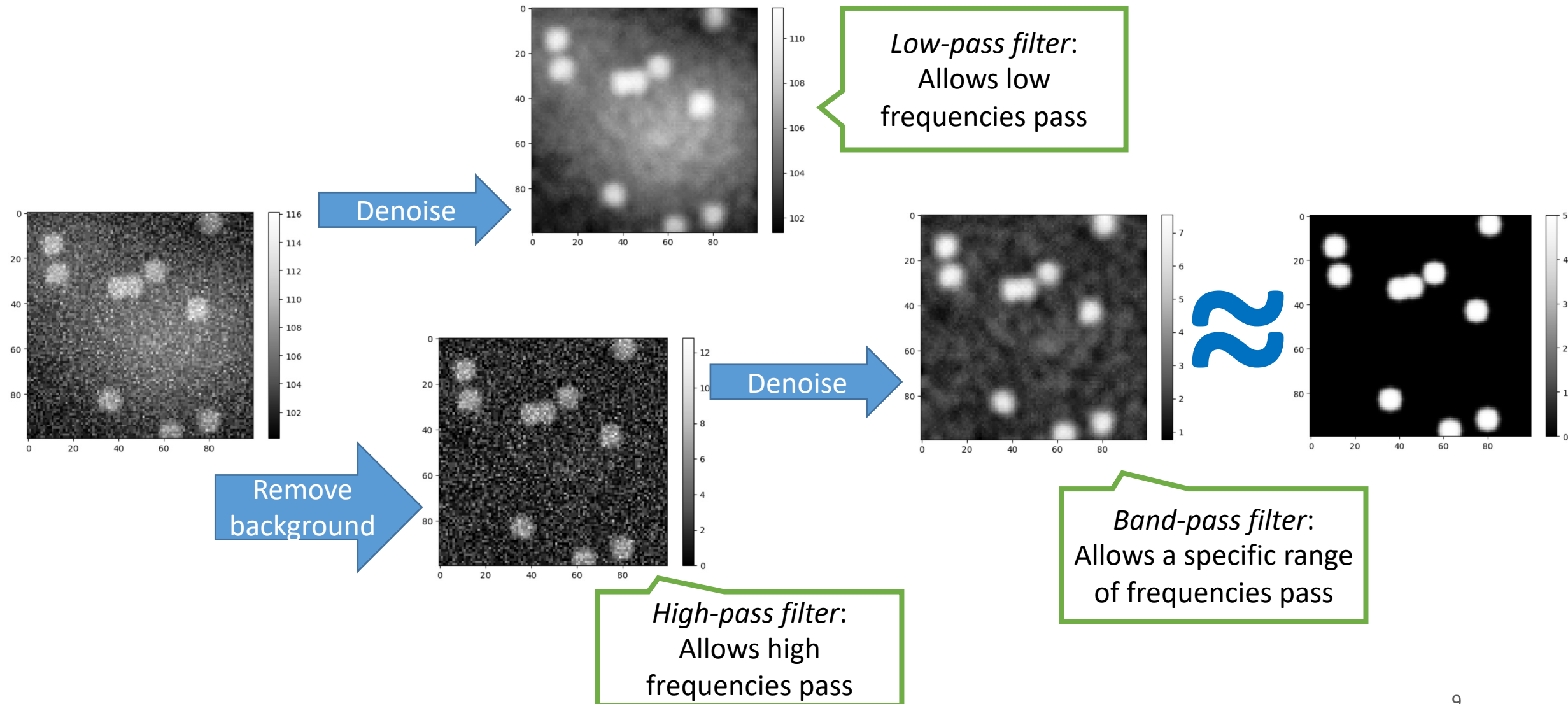
- We need to remove the noise to help the computer *interpreting* the image



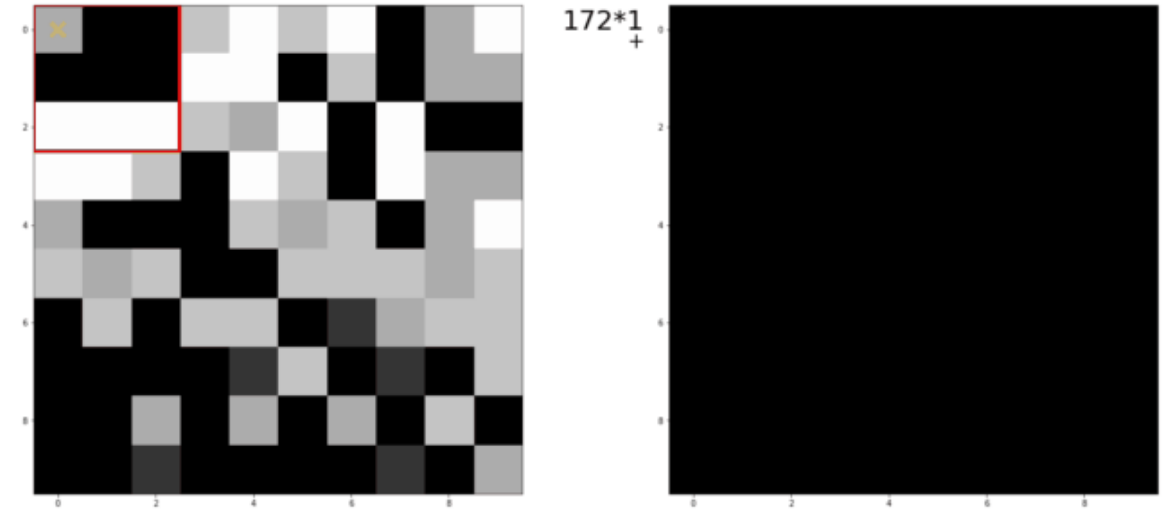
- Attempt to invert / “undo” processes disturbing image quality



- Attempt to invert / “undo” processes disturbing image quality



- *Linear filters* replace each pixel value with a weighted linear combination of surrounding pixels
- Filter *kernels* are matrices describing a linear filter
- This multiplication of surrounding pixels according to a matrix is called *convolution*



Mean filter, 3x3 kernel

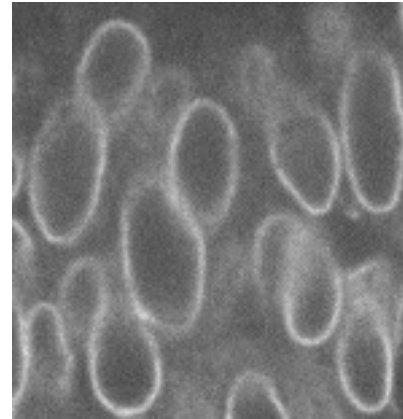
$$\begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix}$$

- Terminology:

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

- Examples

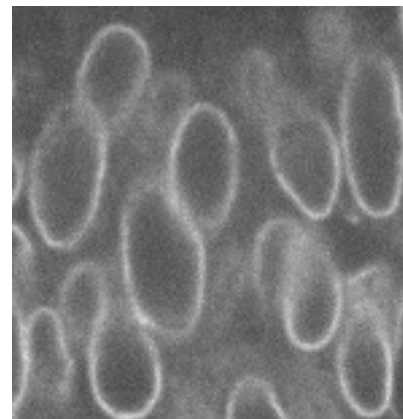
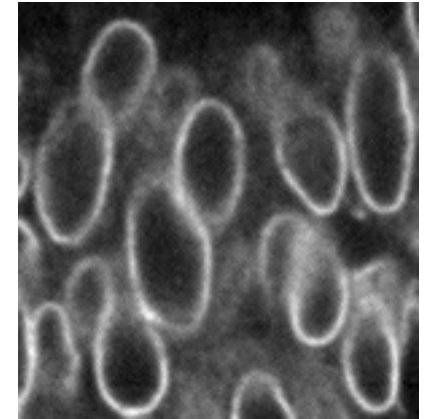
- Mean
- Gaussian blur
- Sobel-operator
- Laplace-filter



*

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

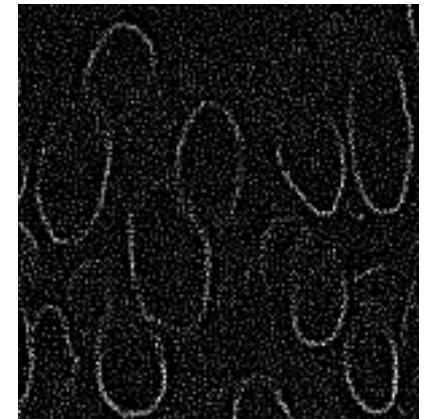
=



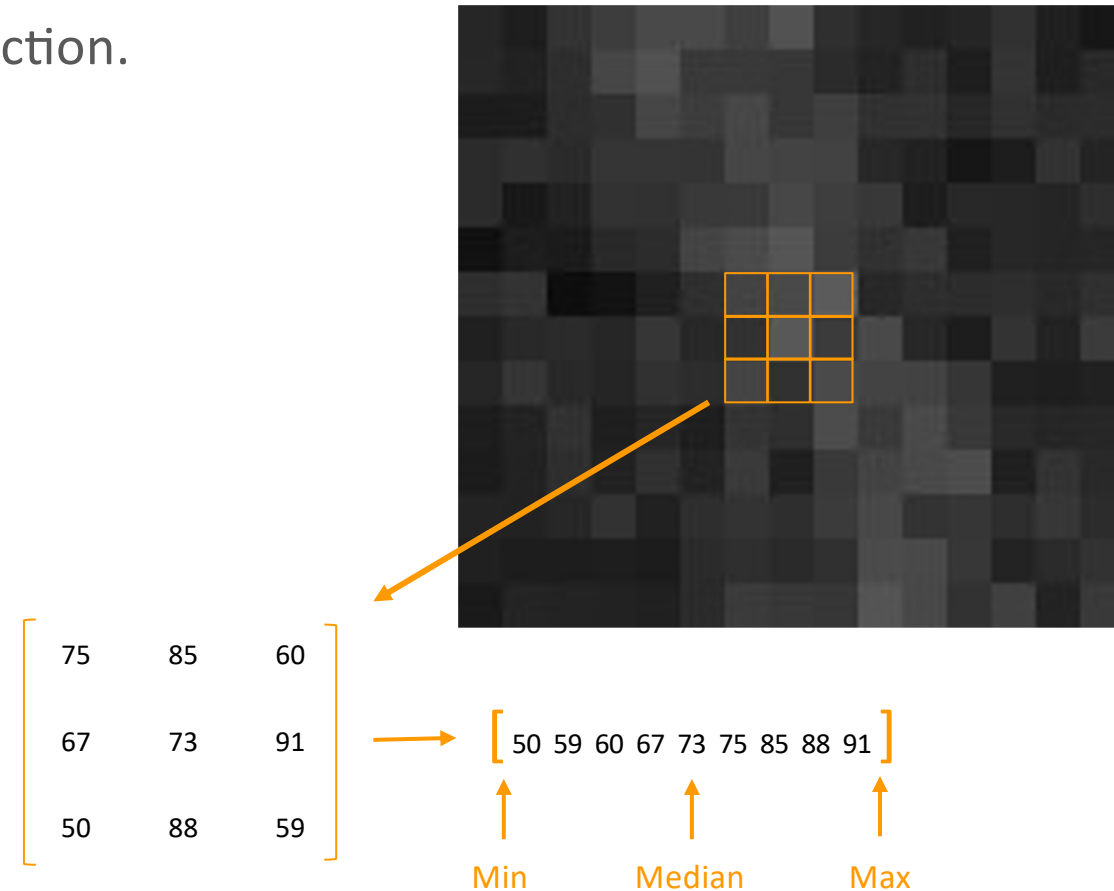
*

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

=



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



- Gaussian filter
- Median filter (computationally expensive)

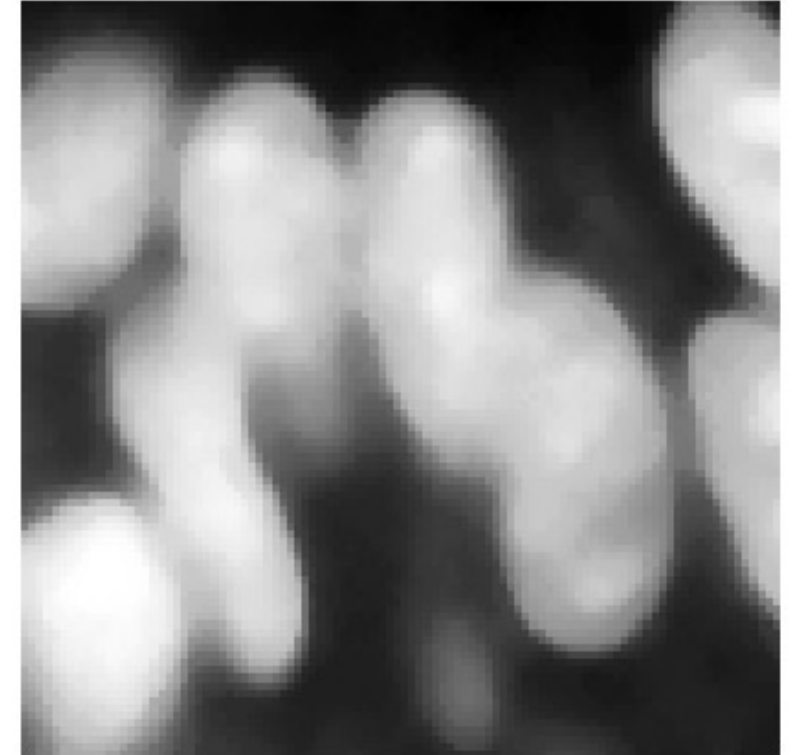
Original



Gaussian

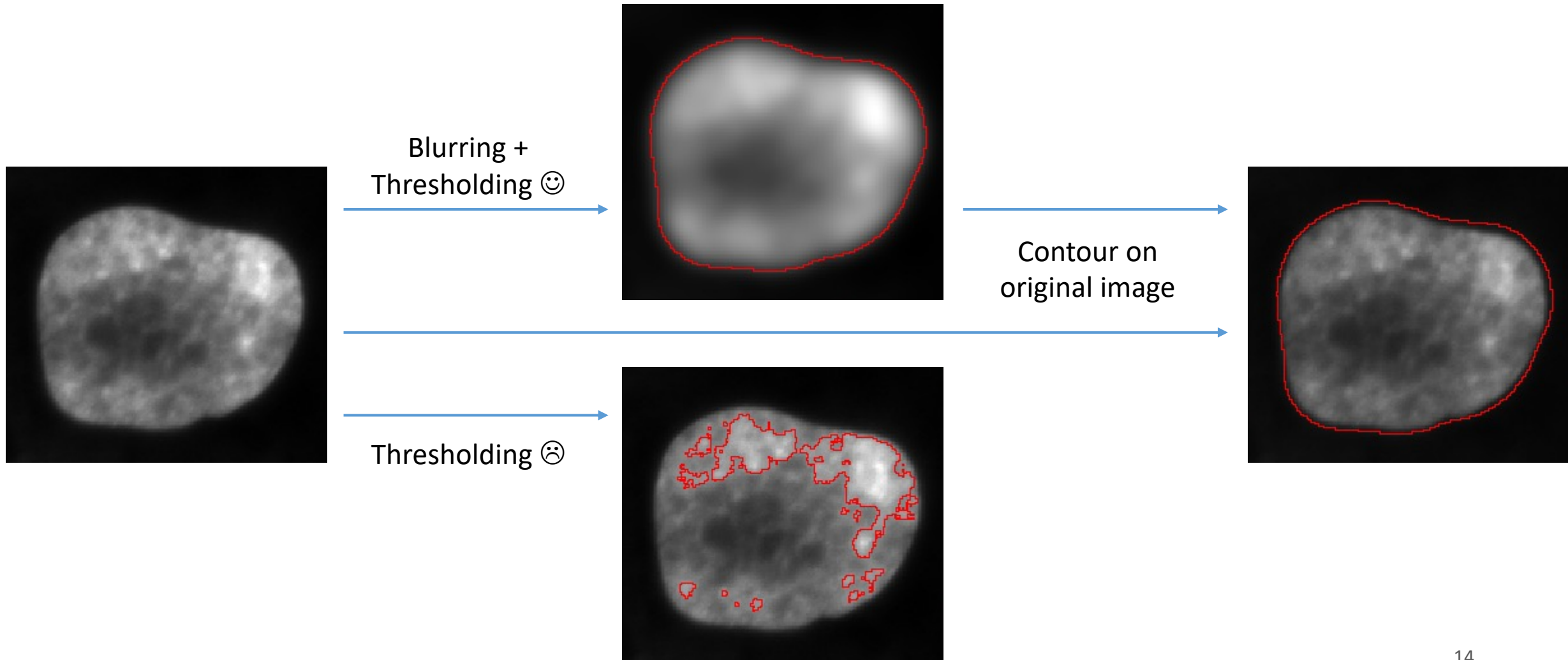


Median

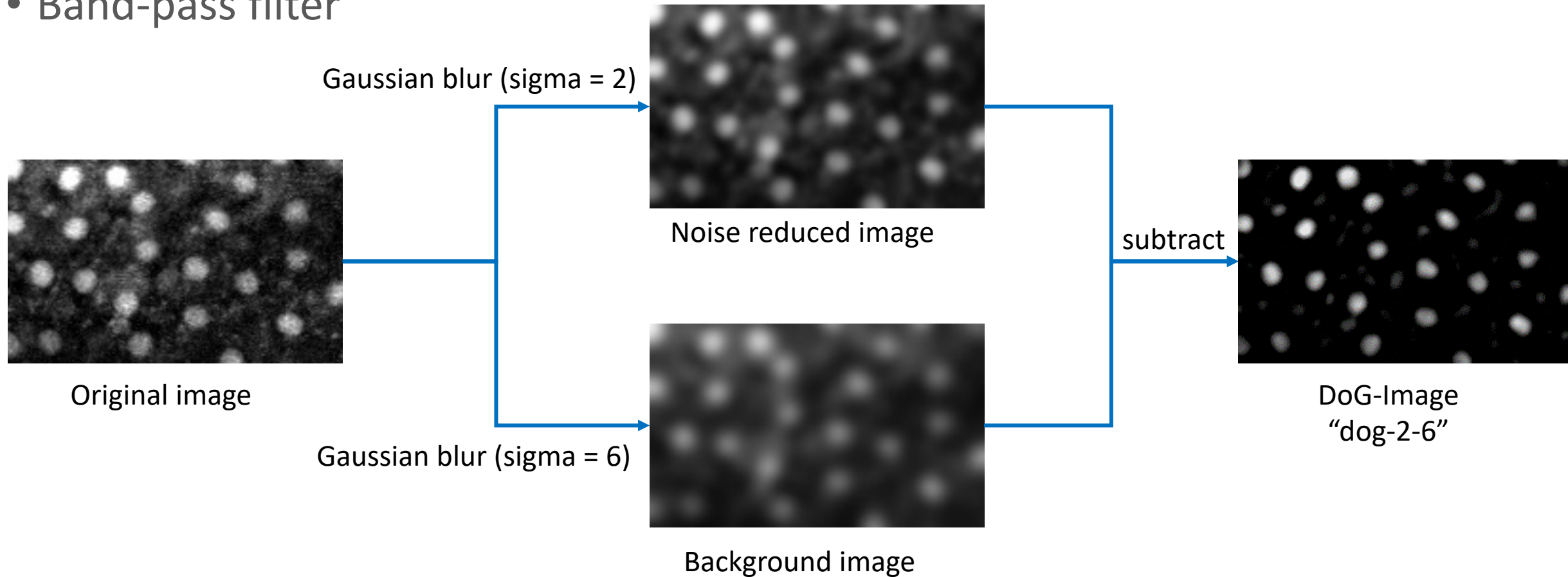


Filtering for improving thresholding results

- In case thresholding algorithms outline the wrong structure, blurring in advance may help.
- However: **Do not** continue processing the blurred image, continue with the original!



- Improve image in order to detect bright objects.
- Band-pass filter

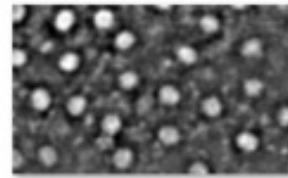


Difference-of-Gaussian (DoG)

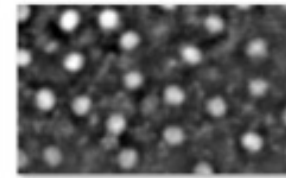
- Example DoG images



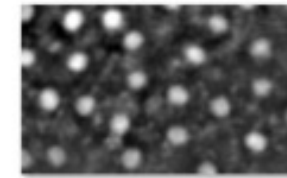
dog-1-1



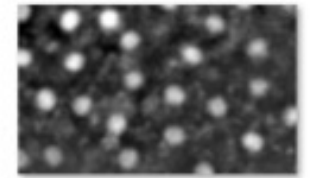
dog-1-4



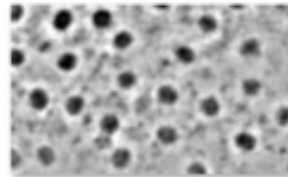
dog-1-7



dog-1-10



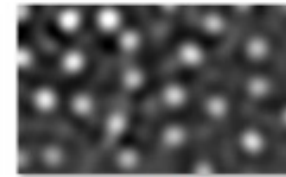
dog-1-13



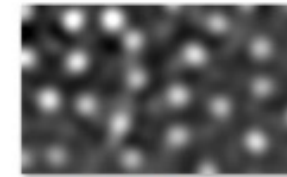
dog-4-1



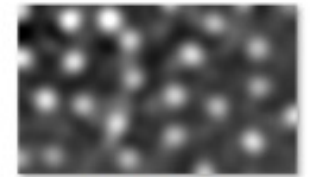
dog-4-4



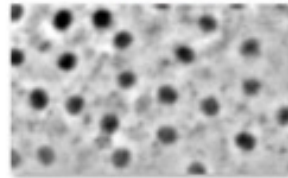
dog-4-7



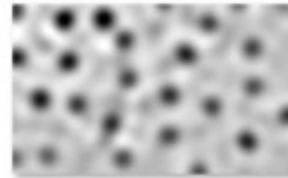
dog-4-10



dog-4-13



dog-7-1



dog-7-4



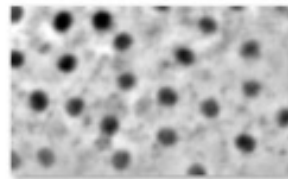
dog-7-7



dog-7-10



dog-7-13



dog-10-1



dog-10-4



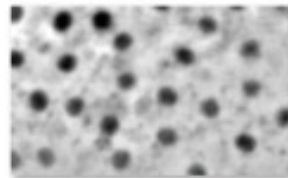
dog-10-7



dog-10-10



dog-10-13



dog-13-1



dog-13-4



dog-13-7

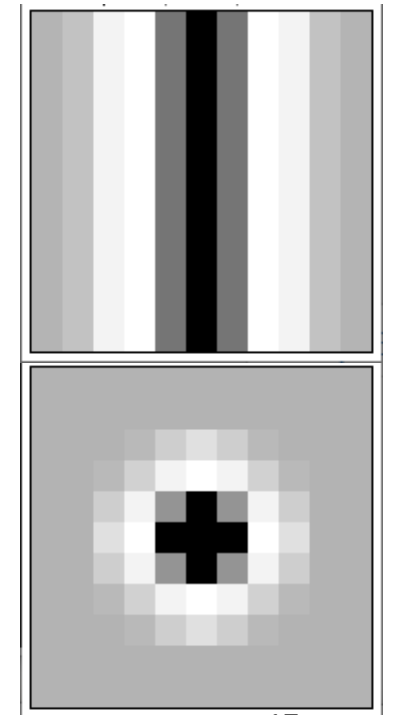
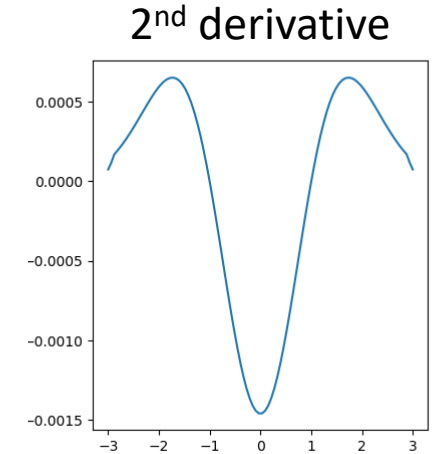
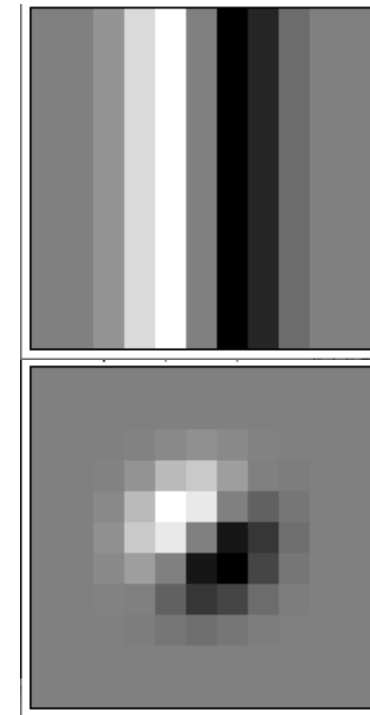
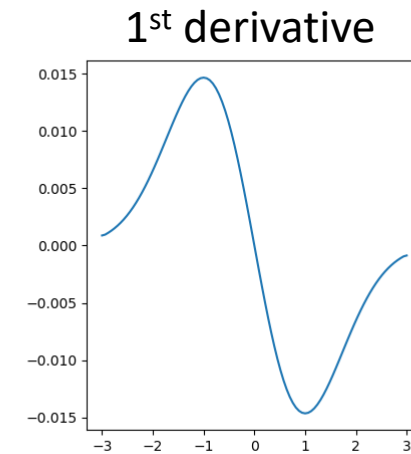
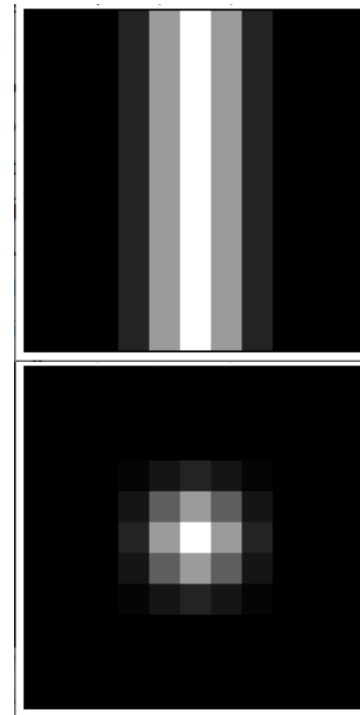
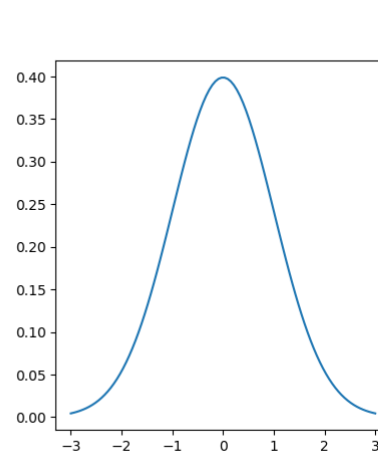
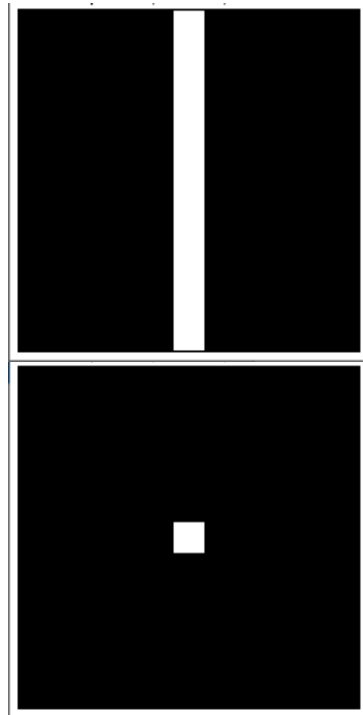


dog-13-10

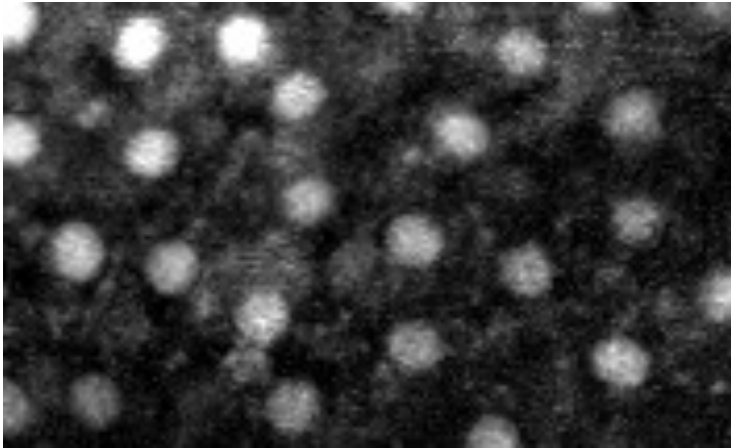


dog-13-13

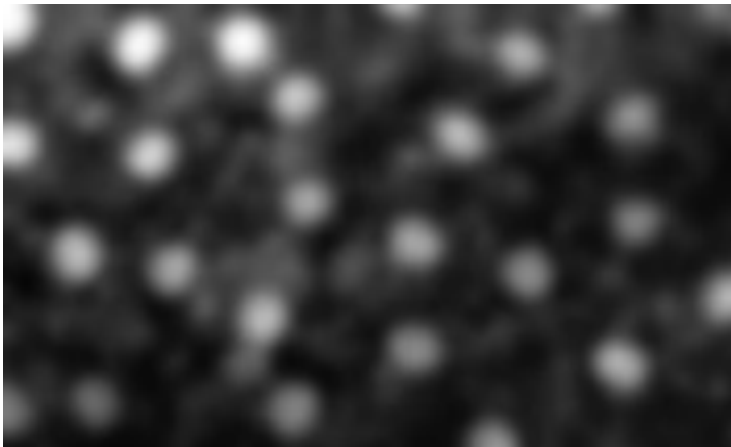
- *Second derivative of a Gaussian blur filter*
- Used for edge-detection and edge enhancement
- Also known as the *Mexican-hat-filter*



Laplace filter

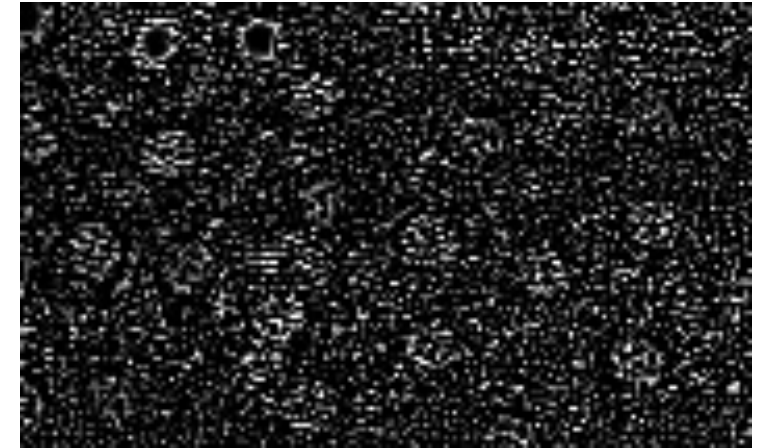


Gaussian filter



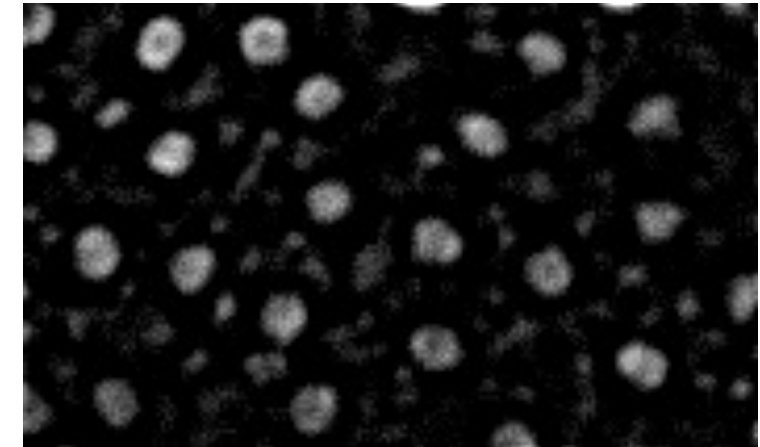
Laplacian of Gaussian filter

$$* \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} =$$



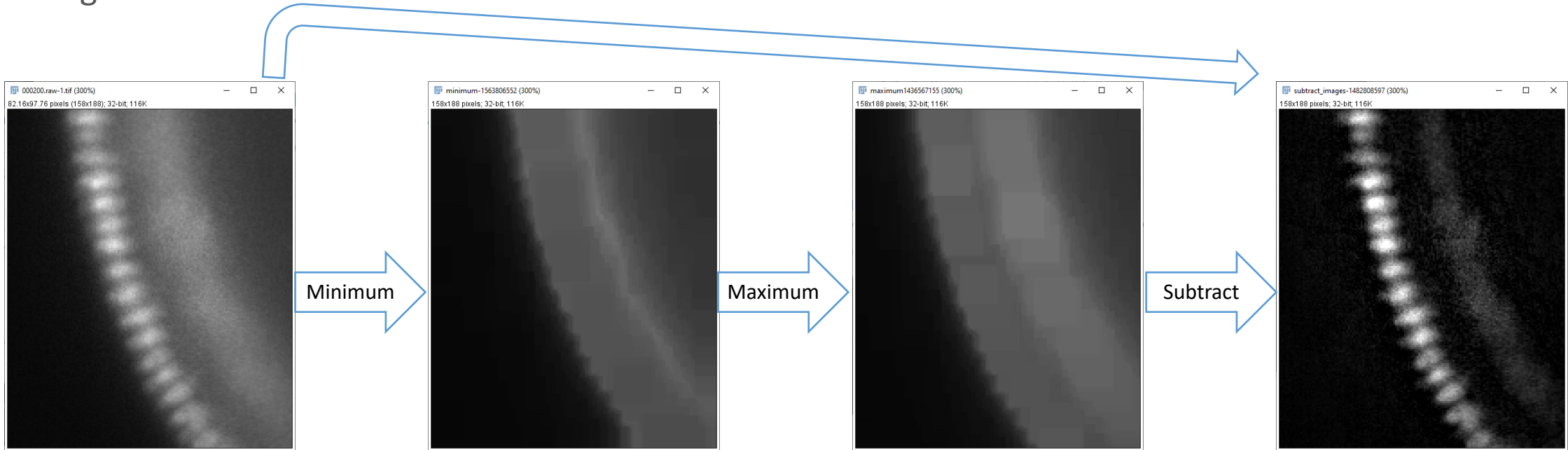
Laplace filtered image

$$* \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} =$$

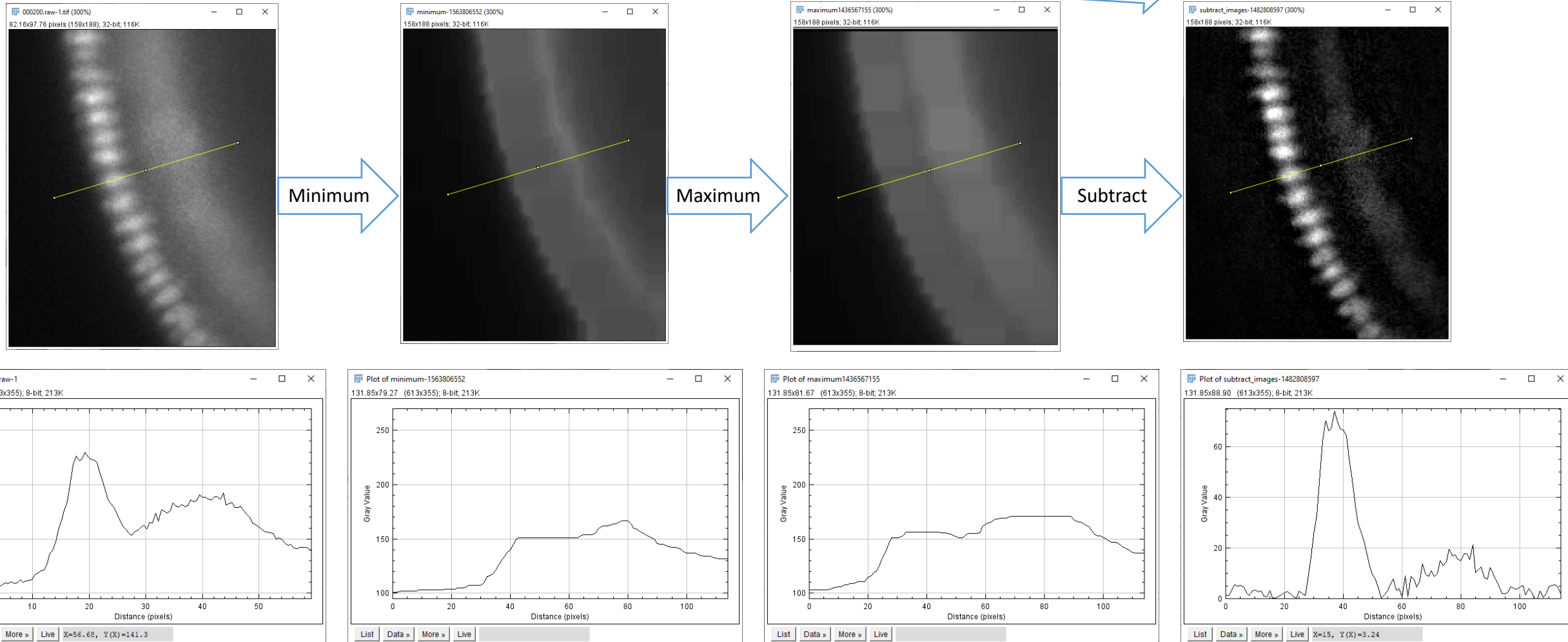


LoG image

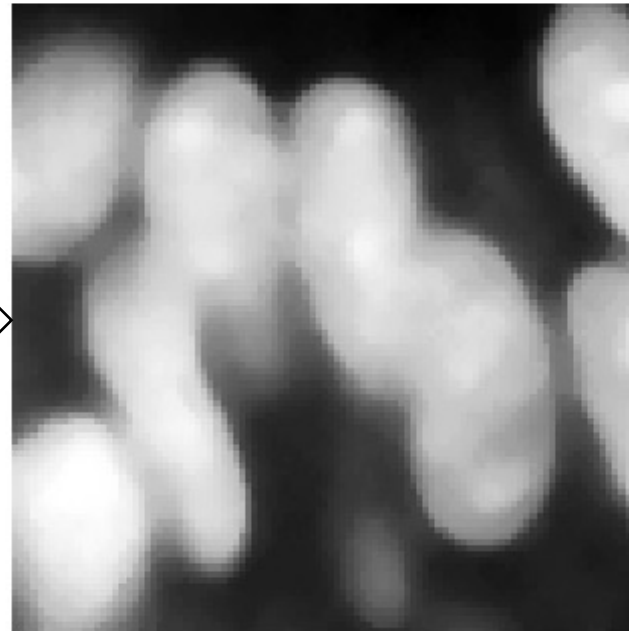
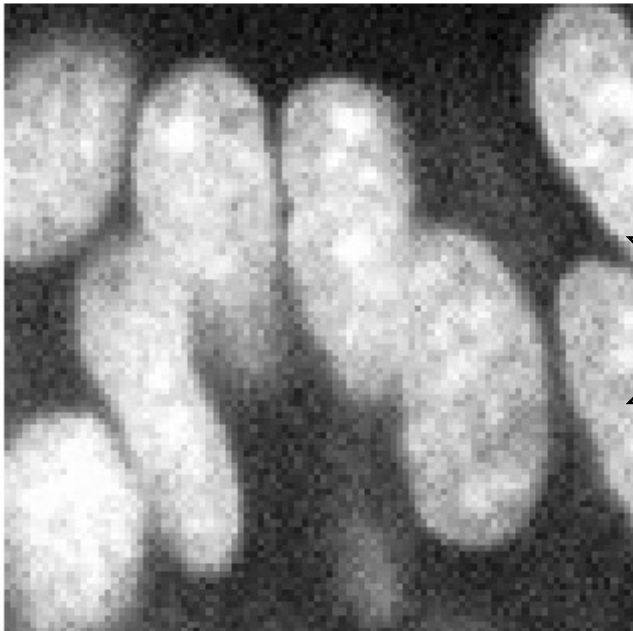
- Background subtraction



- Background subtraction



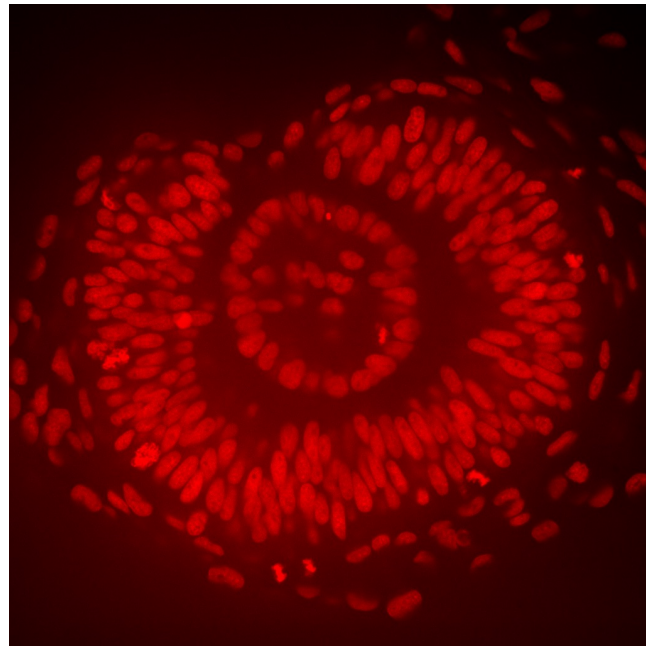
- The median filter is a ...



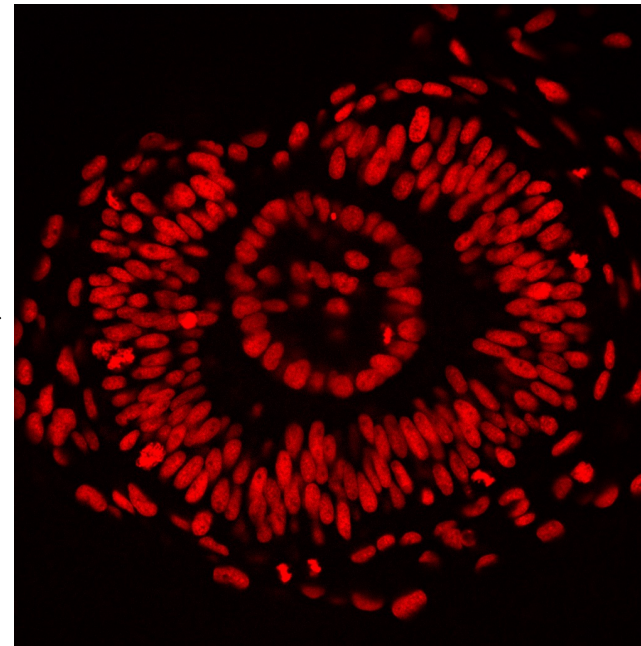
Linear filter

Non-linear filter

- Removing background from an image is a ... ?



Subtract
background



Low-pass
filter

High-pass
filter

Image segmentation

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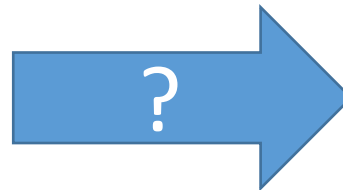
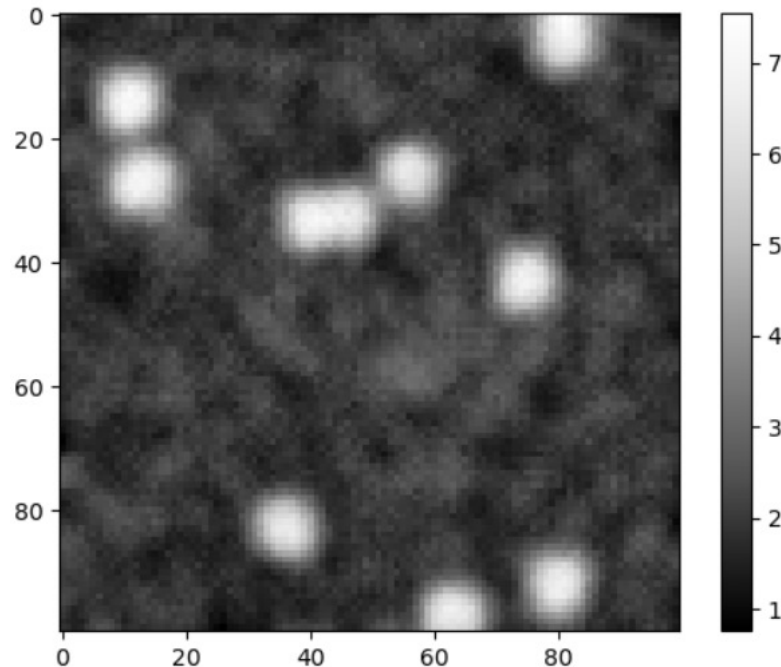
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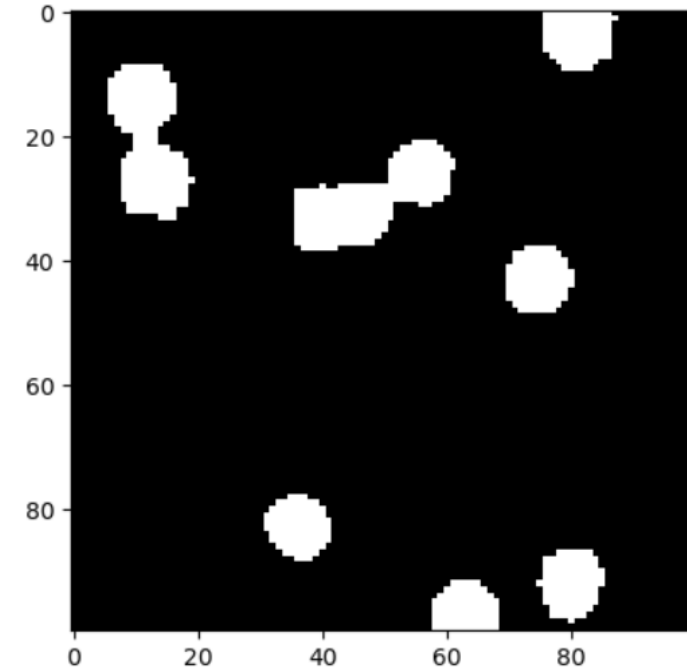
Thresholding

- Very basic and yet efficient segmentation technique
- Histogram based, to determine an intensity threshold
- Not state-of-the-art in many fields (anymore)

Intensity image



Binary image



- Searching for a threshold where the variance in both classes (above/below threshold) becomes minimal.

$$Var(I) = \sum_{i \in I} g_i - \bar{g}_I$$

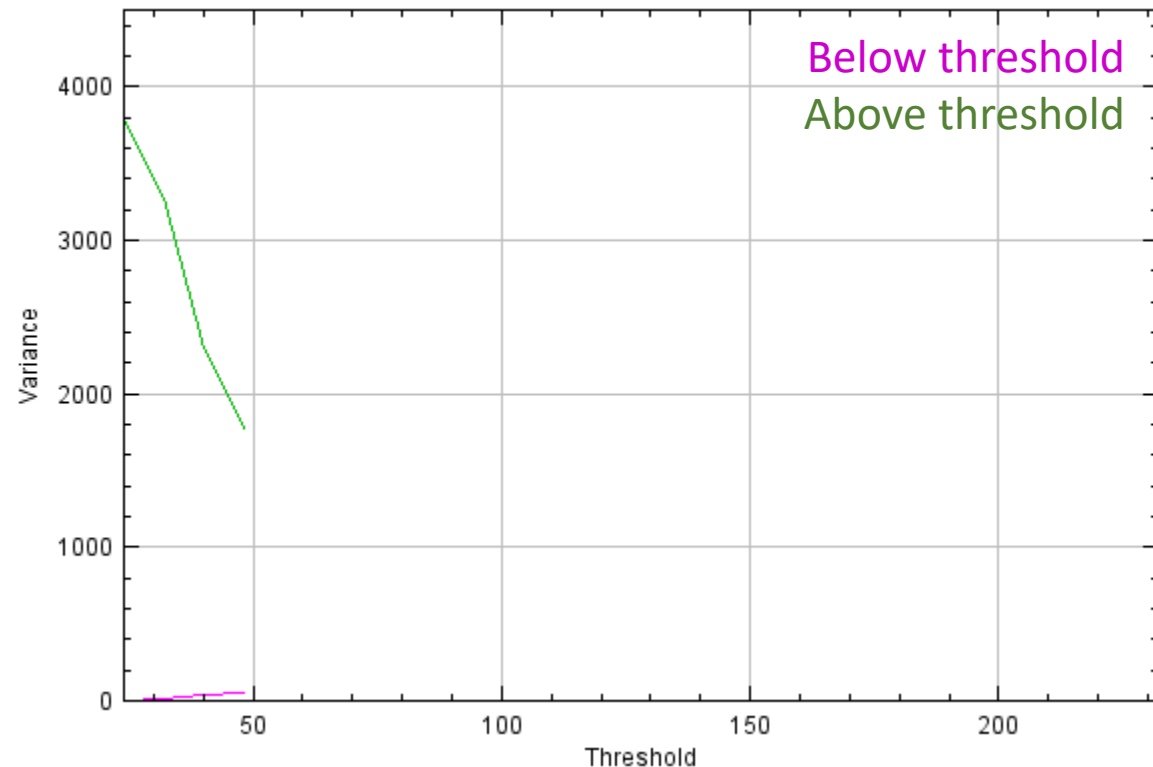
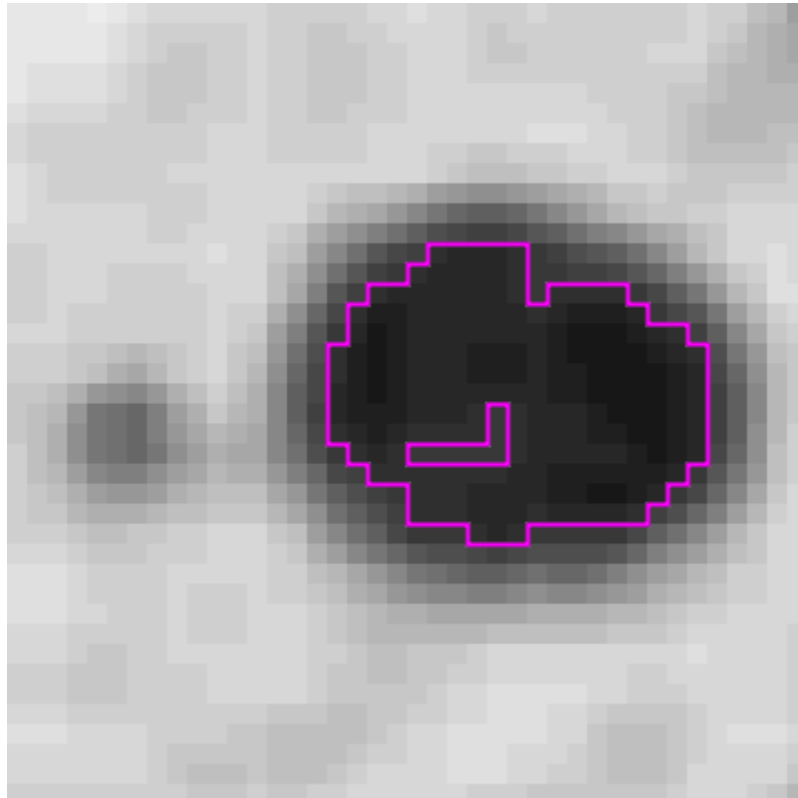
$$\bar{g}_I = \sum_{i \in I} \frac{g_i}{n_I}$$

$Var(I)$... Variance in image I

g_i ... grey value of a pixel i

\bar{g}_I ... mean grey value of the whole image I

n_I ... number of pixels in Image I



- Searching for a threshold where the variance in both classes (above/below threshold) becomes minimal.

$$Var(I) = \sum_{i \in I} g_i - \bar{g}_I$$

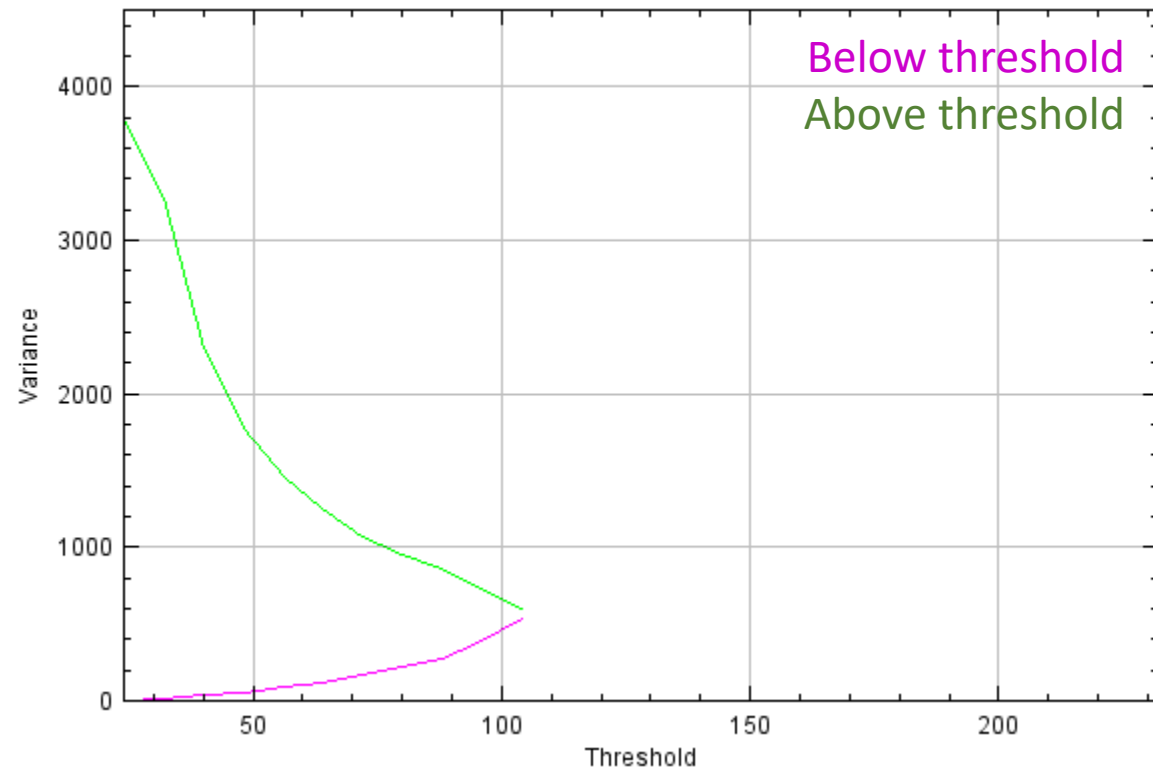
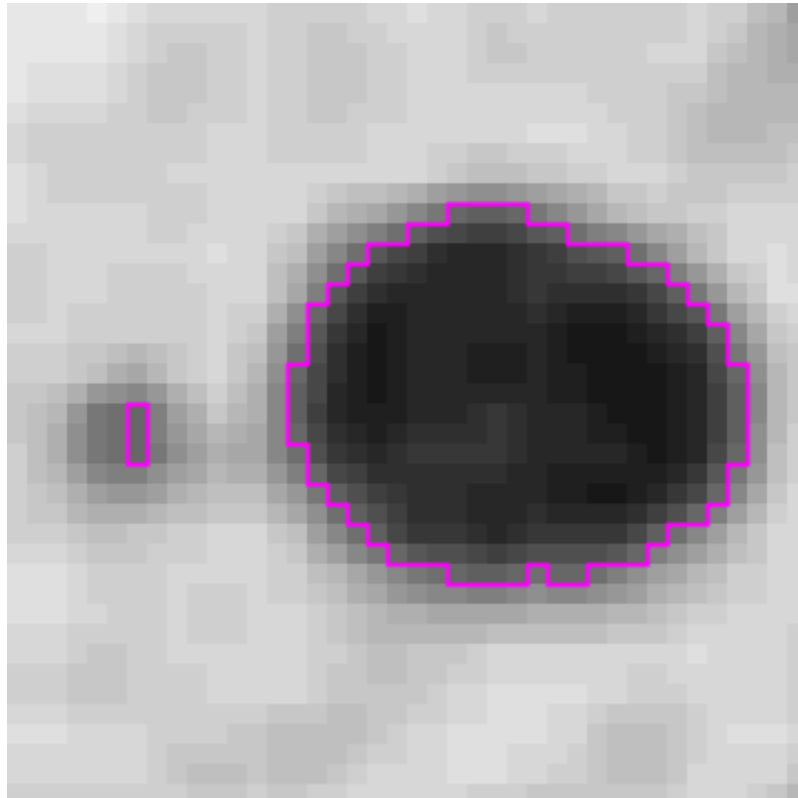
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$$Var(I) = \sum_{i \in I} g_i - \bar{g}_I$$

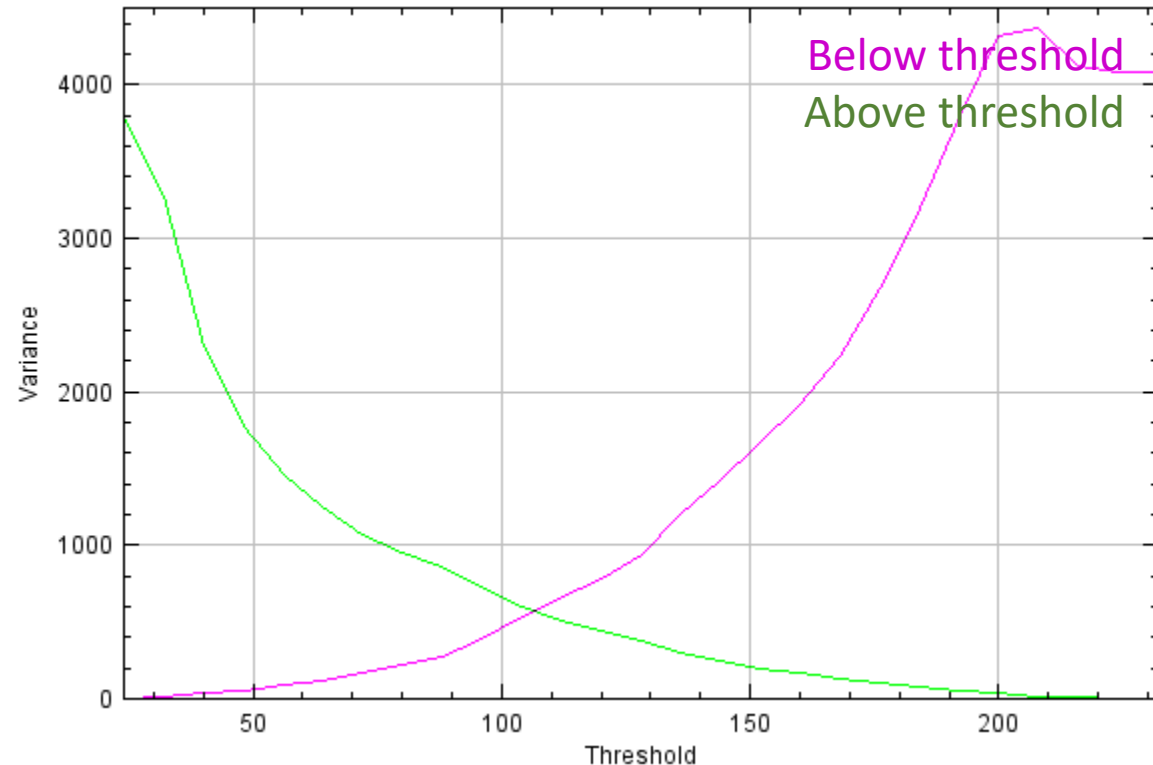
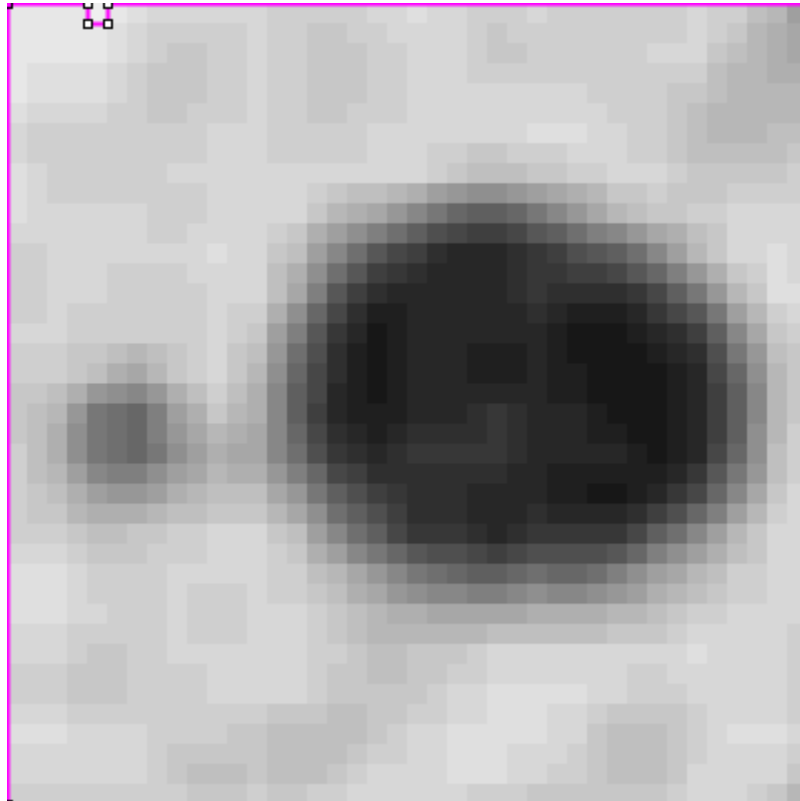
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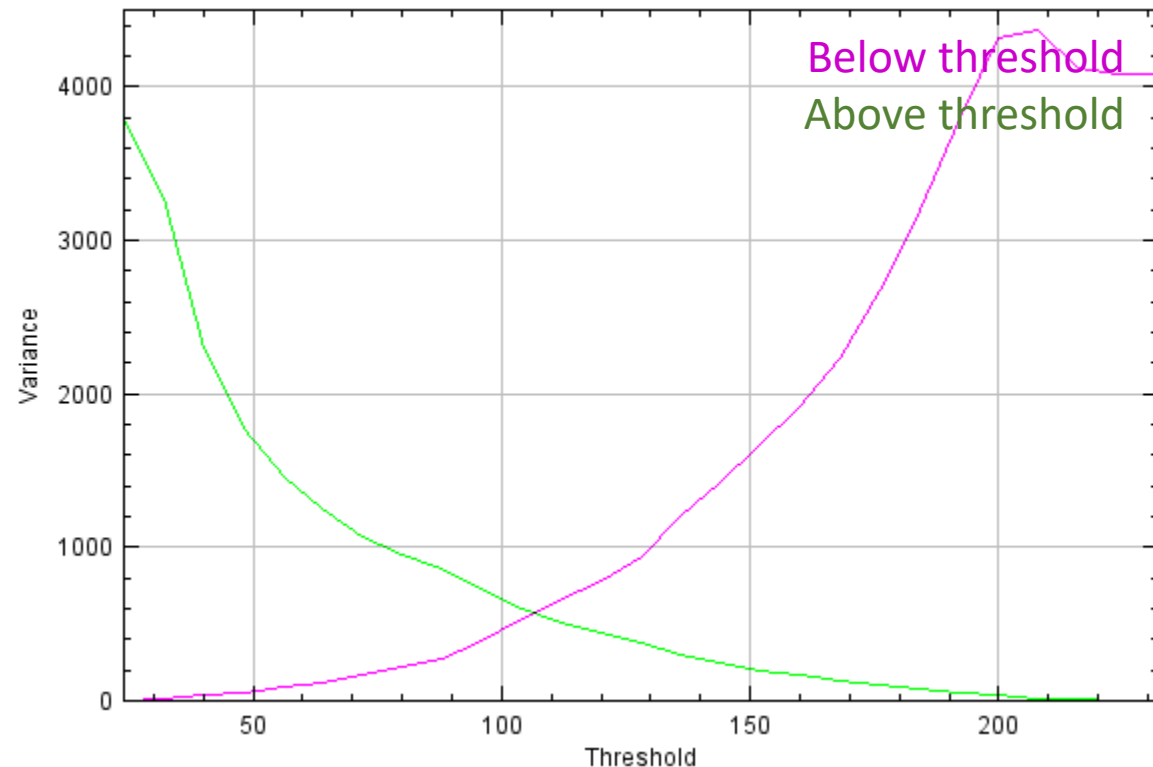
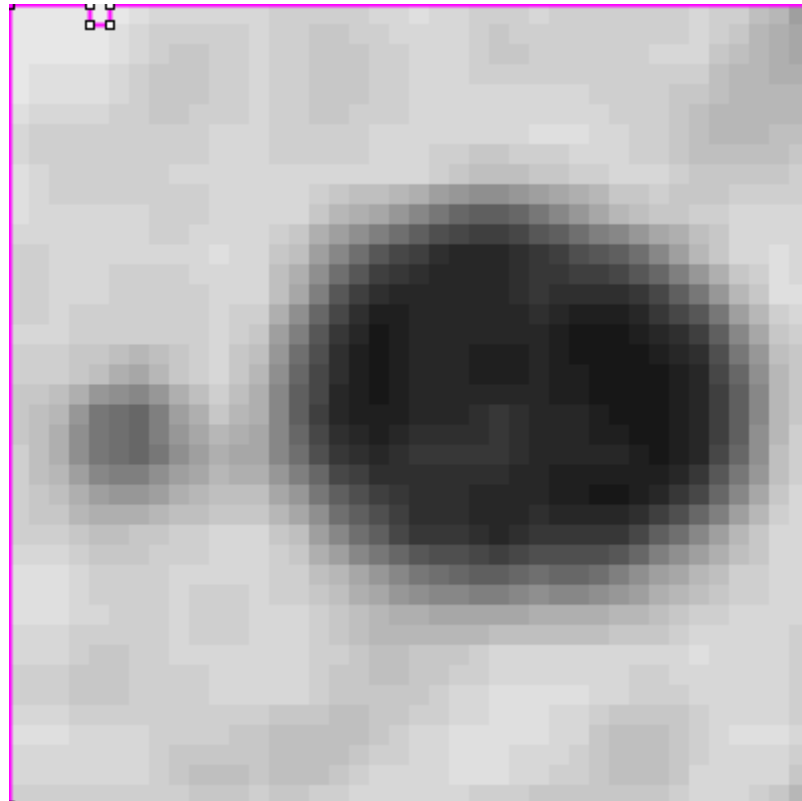
n_I ... number of pixels in Image I



- Searching for a threshold where the variance in both classes (above/below threshold) becomes minimal.
- Weighted (!) sum variance

$$Var'(I) = \frac{n_A}{n_I} Var(A) + \frac{n_B}{n_I} Var(B)$$

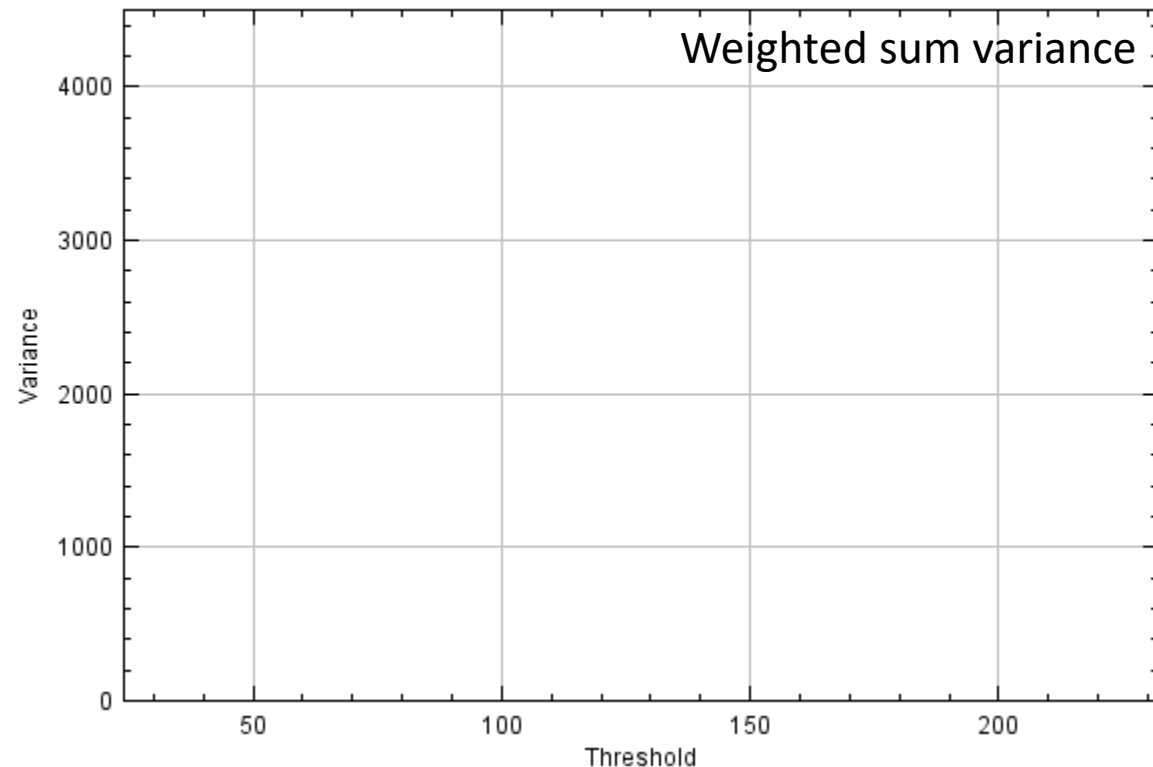
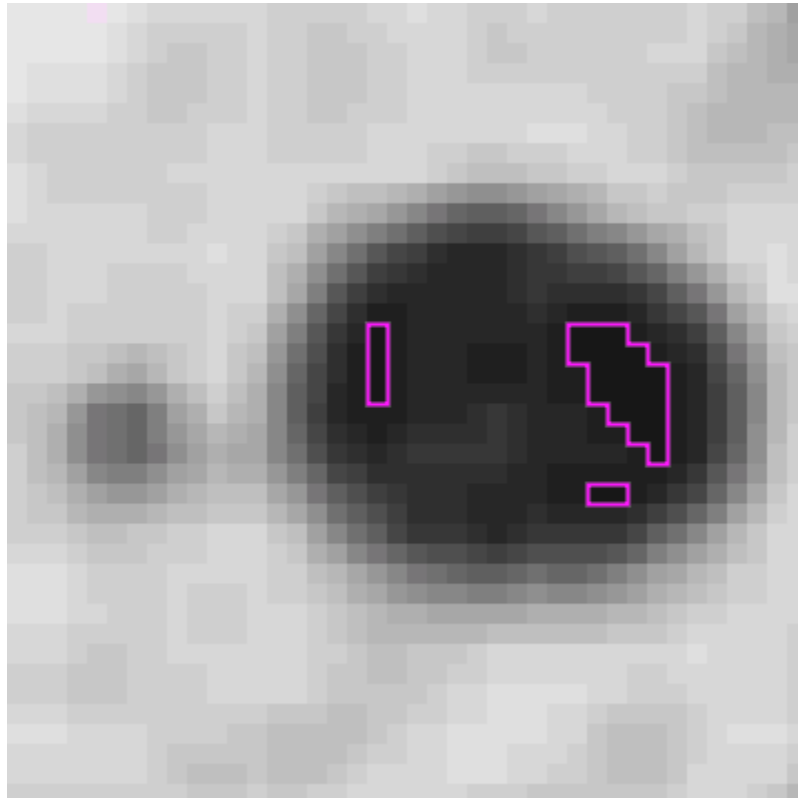
$$I = A \cup B$$



- Searching for a threshold where the variance in both classes (**above/below** threshold) becomes minimal.
- Weighted (!) sum variance

$$Var'(I) = \frac{n_A}{n_I} Var(A) + \frac{n_B}{n_I} Var(B)$$

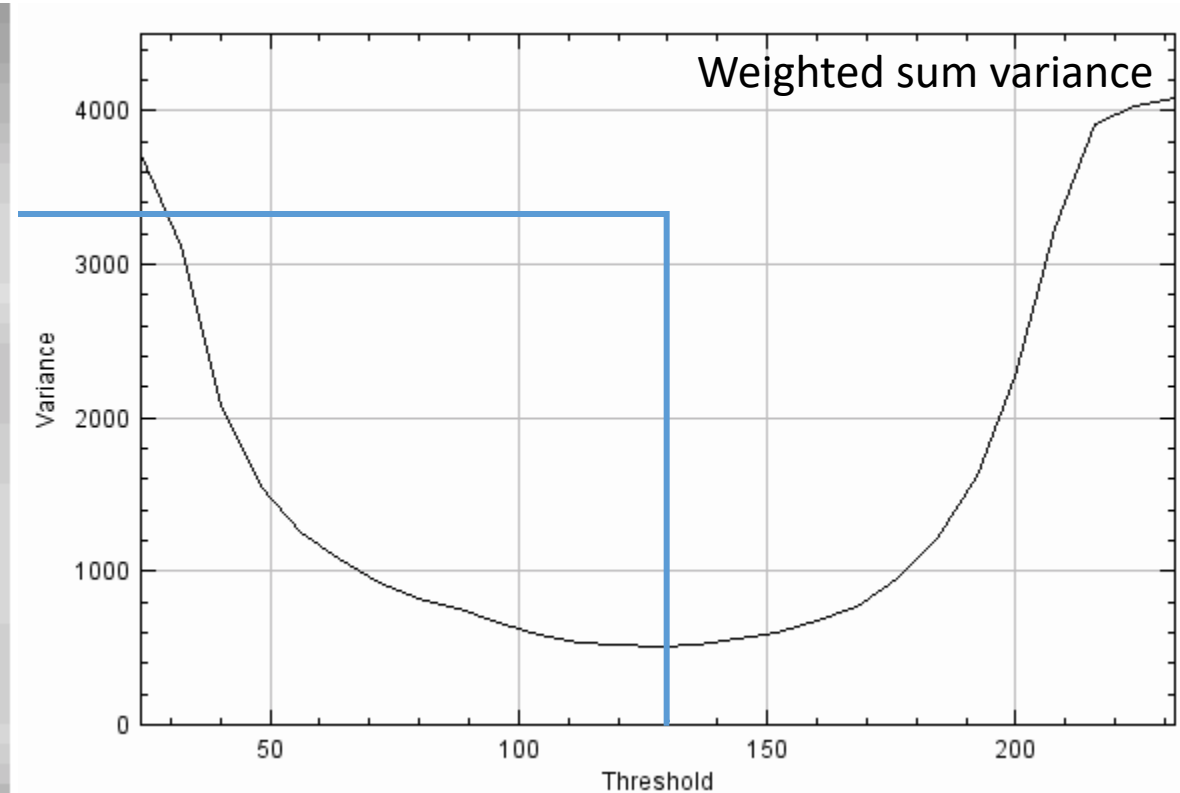
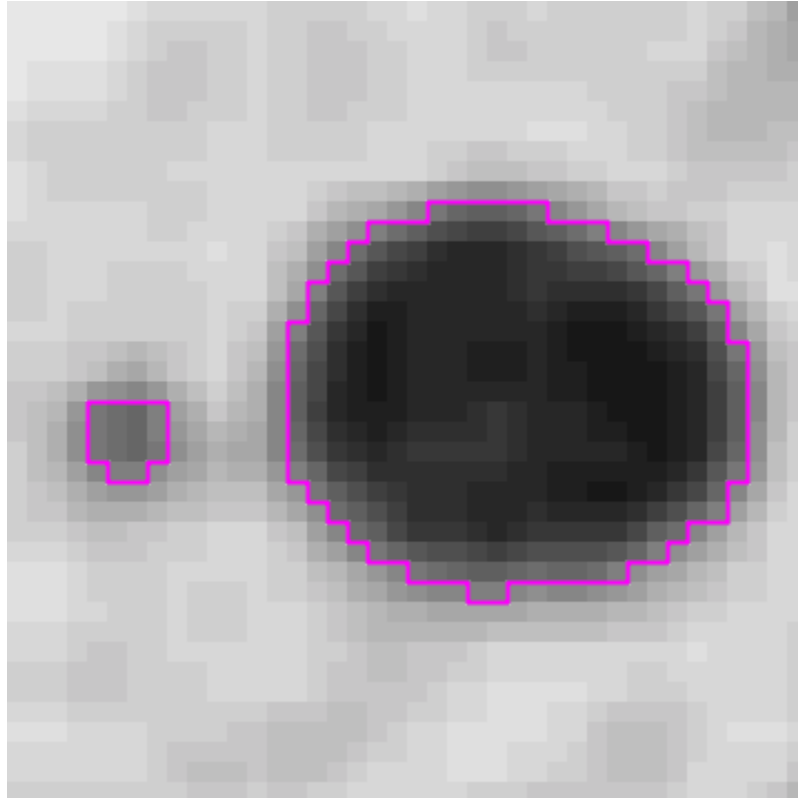
$$I = A \cup B$$



- Searching for a threshold where the variance in both classes (above/below threshold) becomes minimal.
- Weighted (!) sum variance

$$Var'(I) = \frac{n_A}{n_I} Var(A) + \frac{n_B}{n_I} Var(B)$$

$$I = A \cup B$$



See also: <http://www.labbookpages.co.uk/software/imgProc/otsuThreshold.html>

- Cite the thresholding method of your choice properly

“We segmented the cell nuclei in the images using Otsu’s thresholding method (Otsu et Al. 1979) implemented in scikit-image (van der Walt et al. 2014).”

IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, VOL. SMC-9, NO. 1, JANUARY 1979

A Threshold Selection Method from Gray-Level Histograms

NOBUYUKI OTSU

Abstract—A nonparametric and unsupervised method of automatic threshold selection for picture segmentation is presented. An optimal threshold is selected by the discriminant criterion, namely, so as to maximize the separability of the resultant classes in gray levels. The procedure is very simple, utilizing only the zeroth- and the first-order cumulative moments of the gray-level histogram. It is straightforward to extend the method to multithreshold problems. Several experimental results are also presented to support the validity of the method.

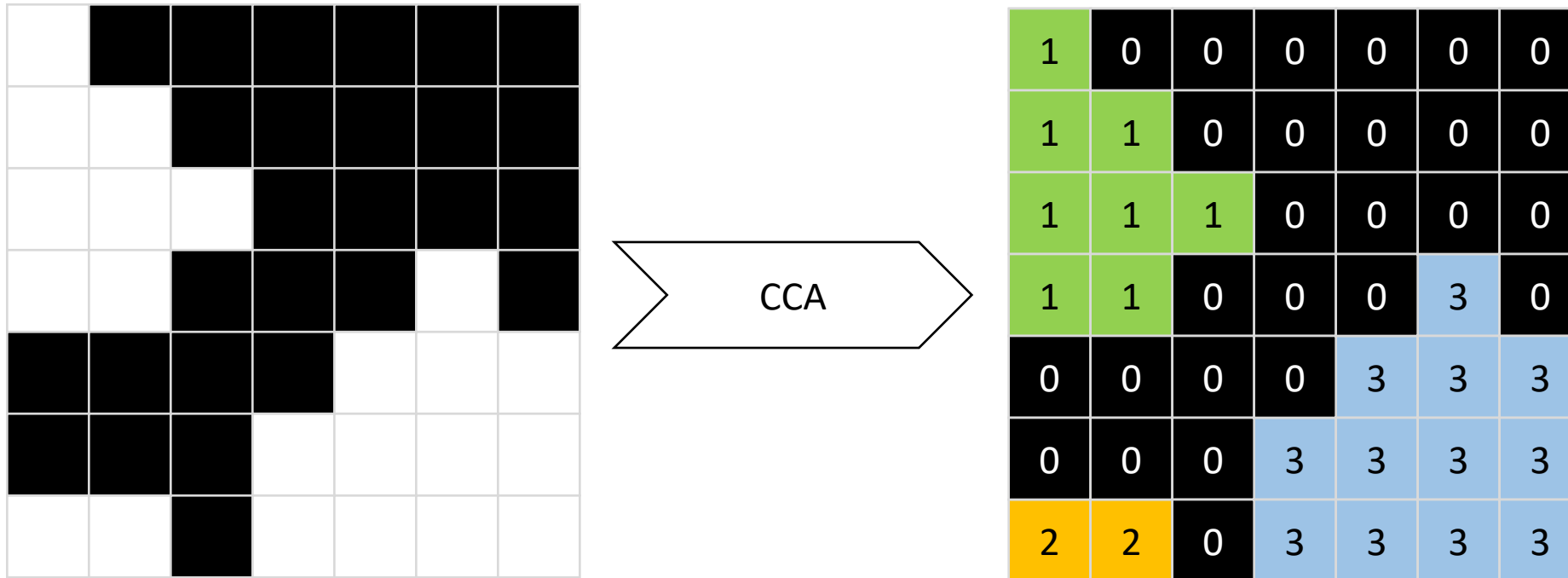
Instance segmentation

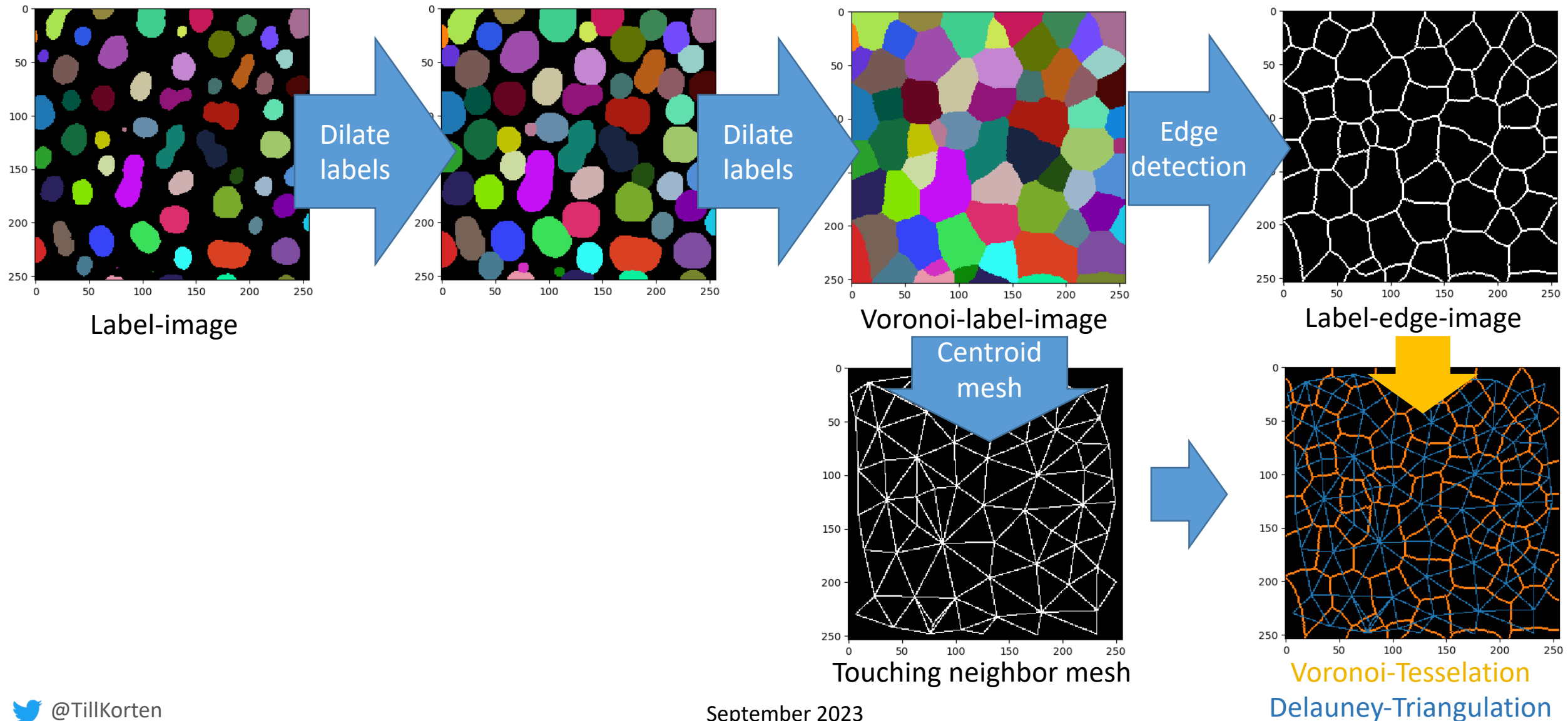
Till Korten

With material from
Robert Haase, PoL, TU Dresden

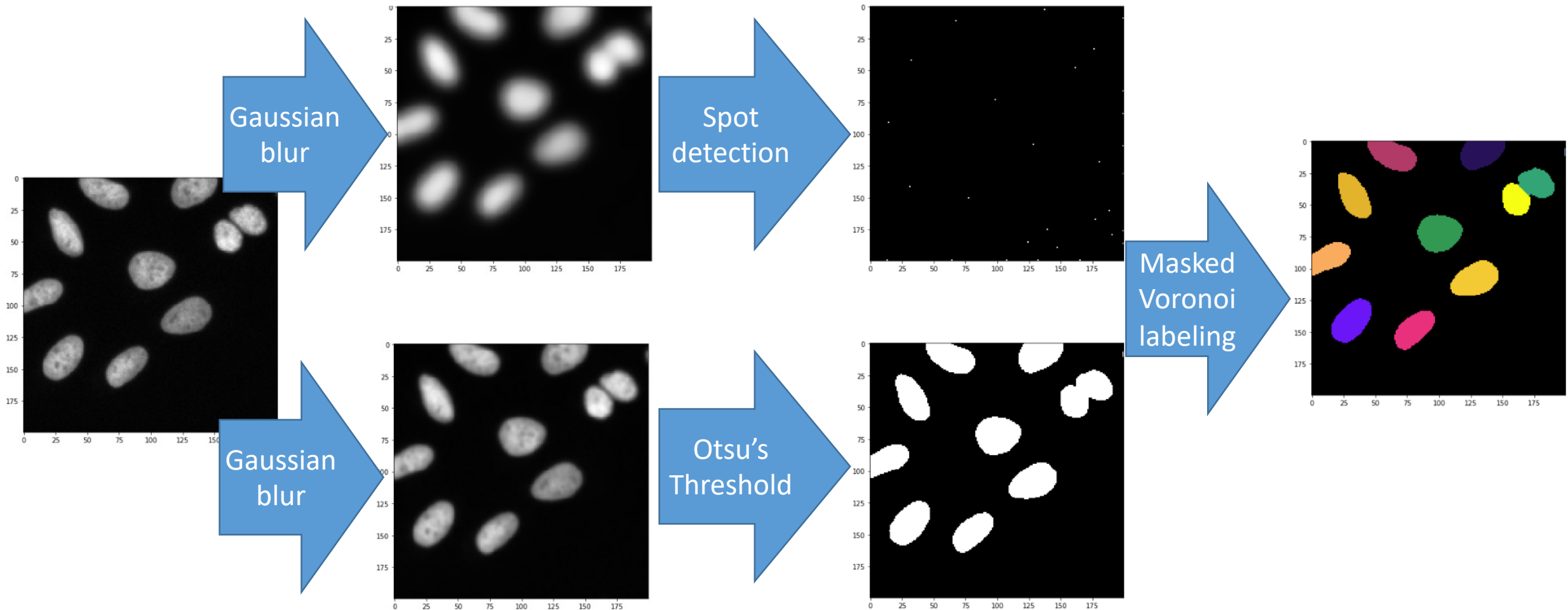
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- In order to allow the computer differentiating objects, connected component analysis (CCA) is used to mark pixels belonging to different objects with different numbers
- Background pixels are marked with 0.
- The maximum intensity of a labelled map corresponds to the number of objects.

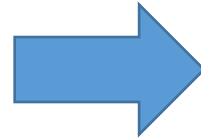




- Combination of Gaussian blur, Otsu's Threshold and Voronoi-labeling

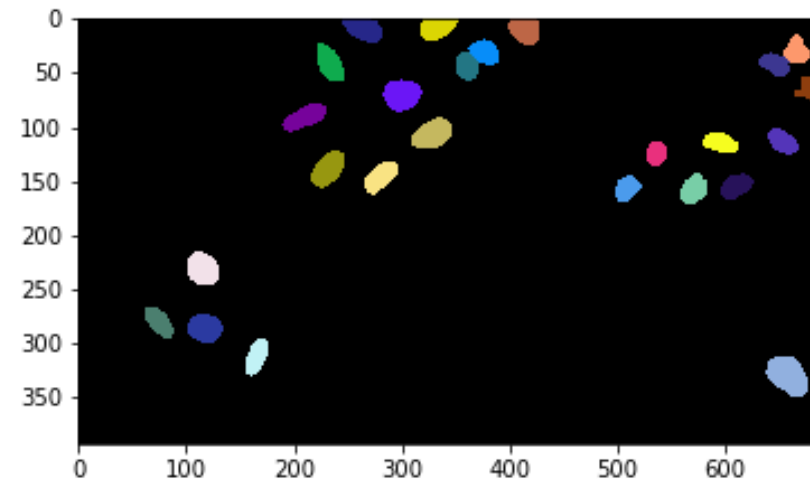
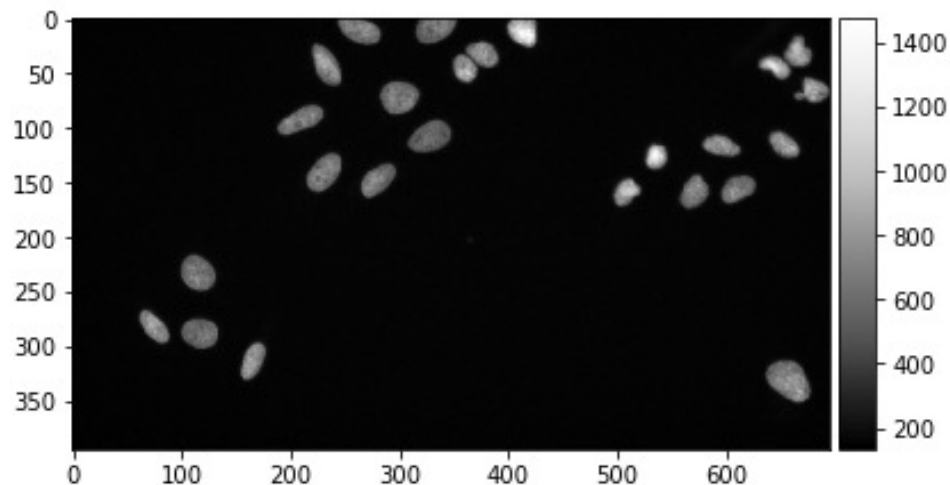


- Gaussian-Blur
- Otsu-Thresholding
- Spot-detection
- Watershed on the binary image



... in a single line of code:

```
segmented = nsbatwm.voronoi_otсу_labeling(input_image,  
                                           spot_sigma=5,  
                                           outline_sigma=1  
                                           )  
segmented
```



nsbatwm made image

shape (395, 695)

dtype int32

size 1.0 MB

min 0

max 25