Regression and Image Restoration

Image based ML Tasks

Classification

$\mathbb{R}^N$

Cat, Dog, …

$[1, \ldots, K]$

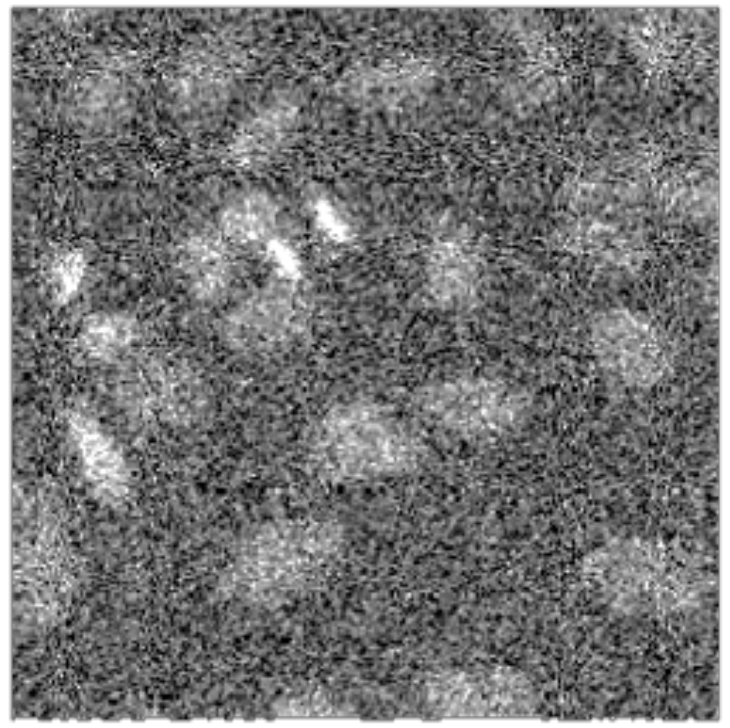
Detection/Segmentation

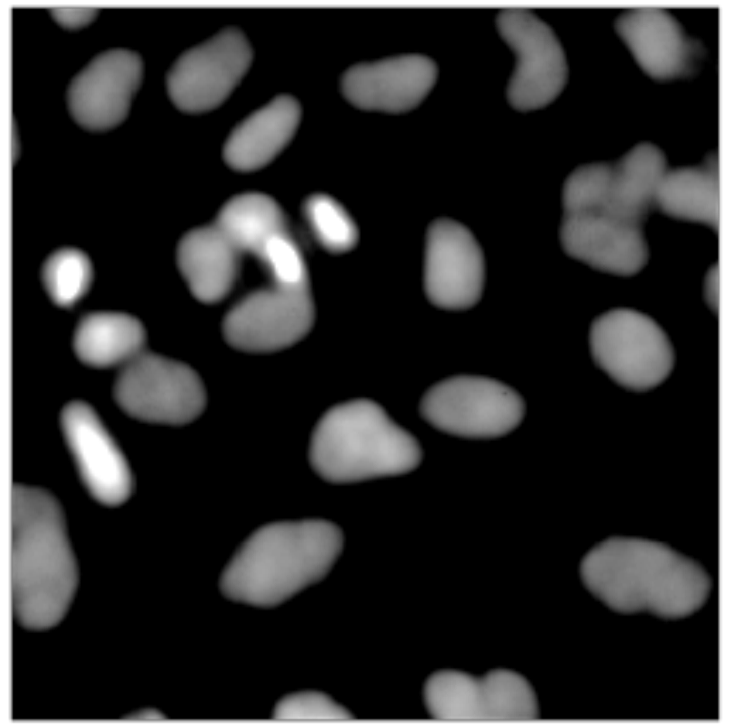
$\mathbb{R}^N$

$[1, \ldots, K]^N$

(Dense) Regression

$\mathbb{R}^N$

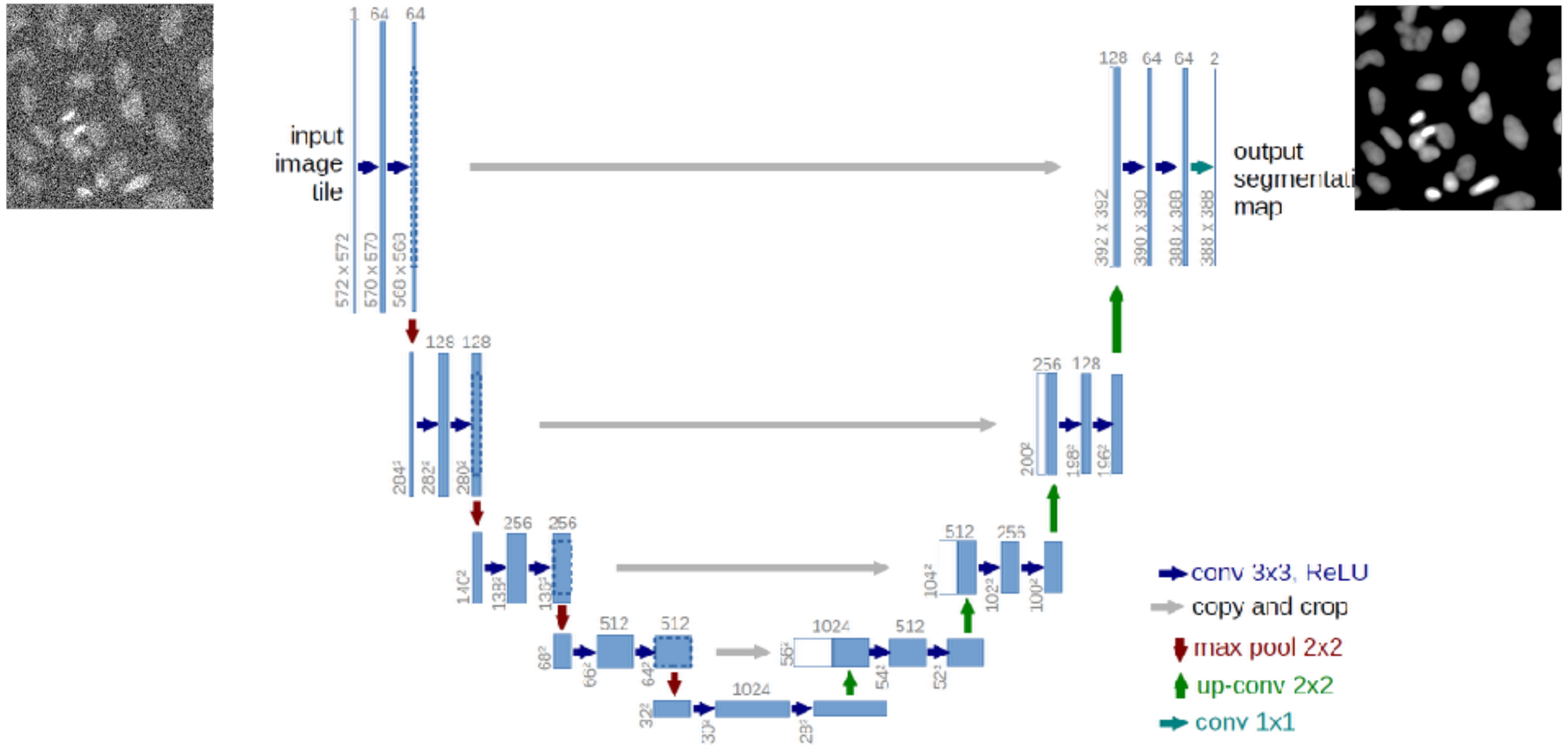




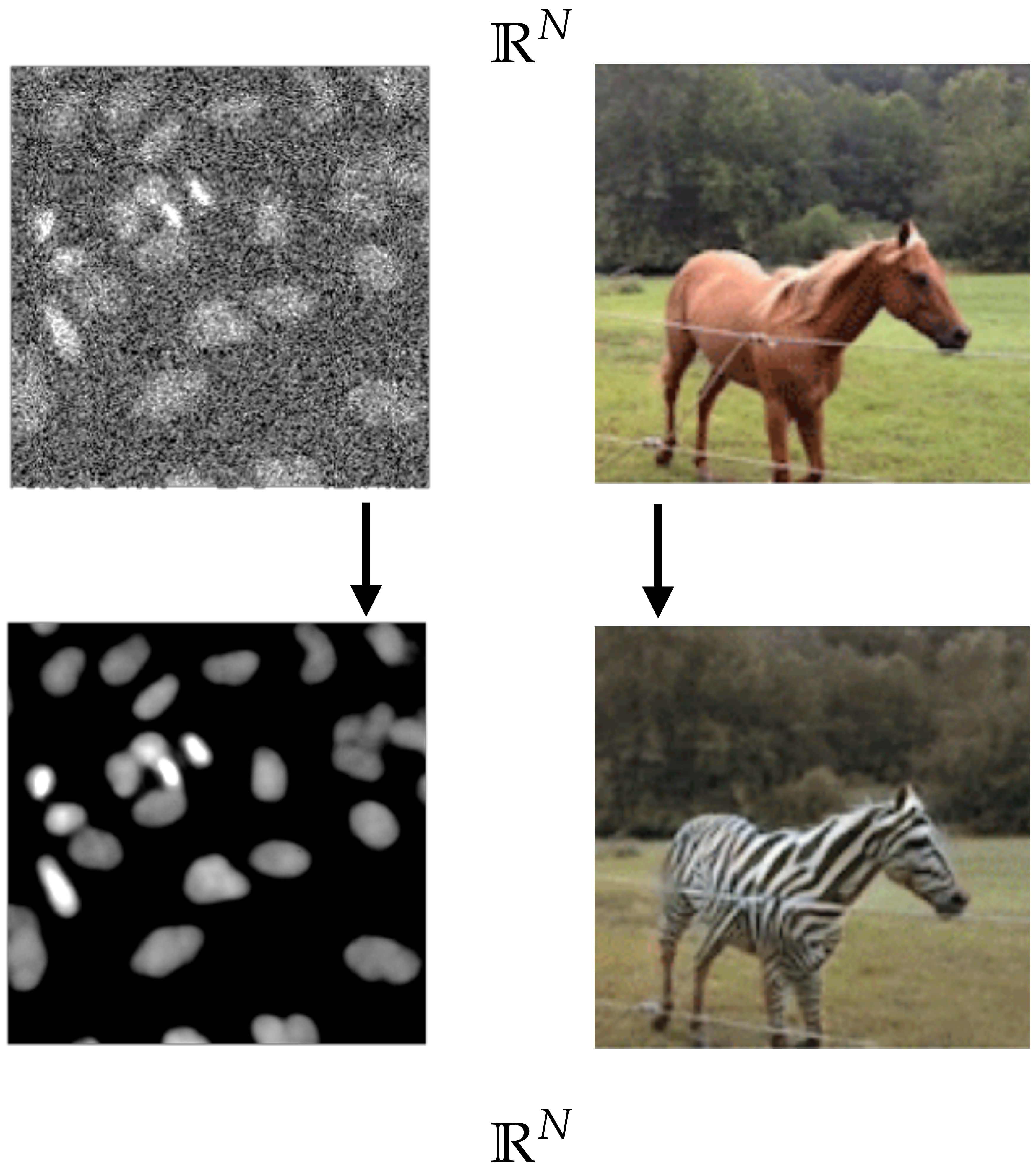
$\mathbb{R}^N$

(Dense) Regression

- Input and Output are real valued images (or scalars, sequences)
- We can use almost the same architectures as for dense segmentation, only have to change last activation function (e.g. linear, instead of sigmoid/softmax)

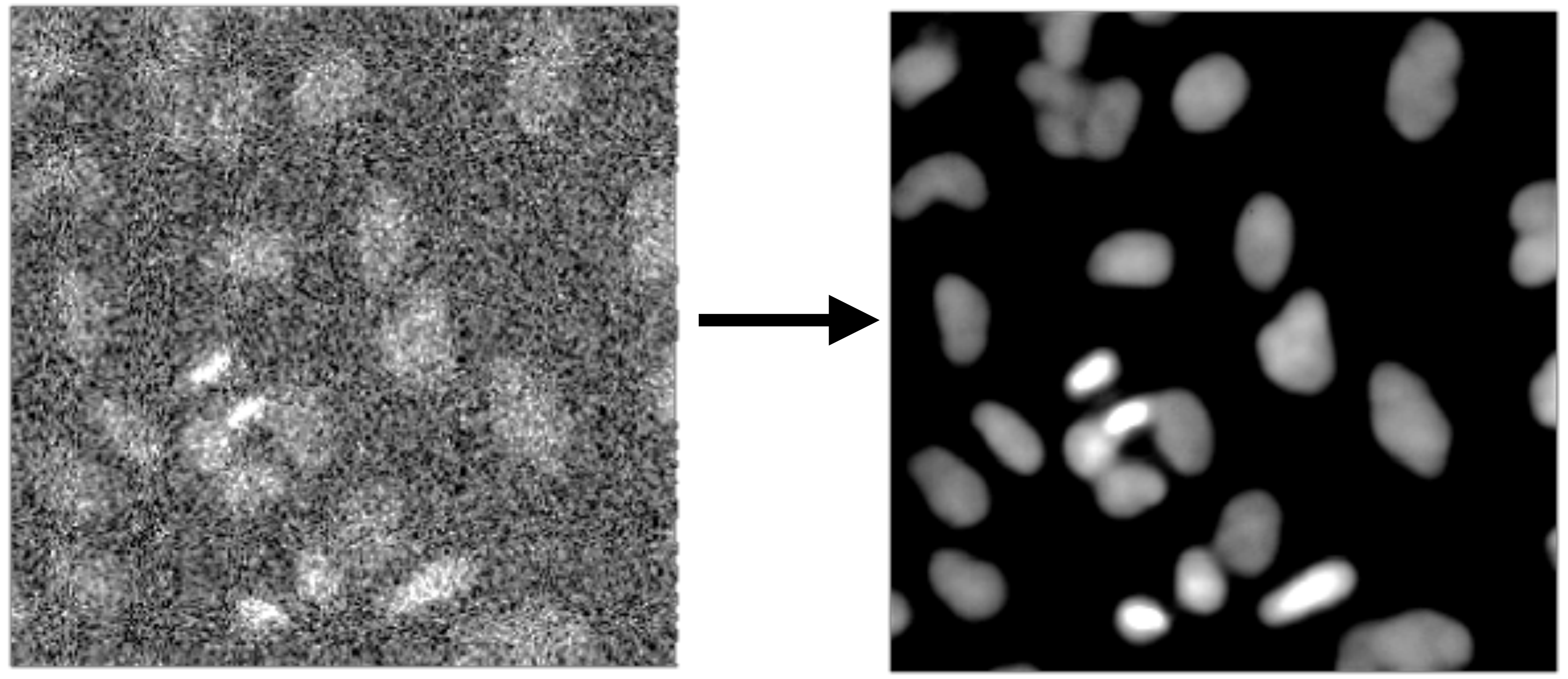


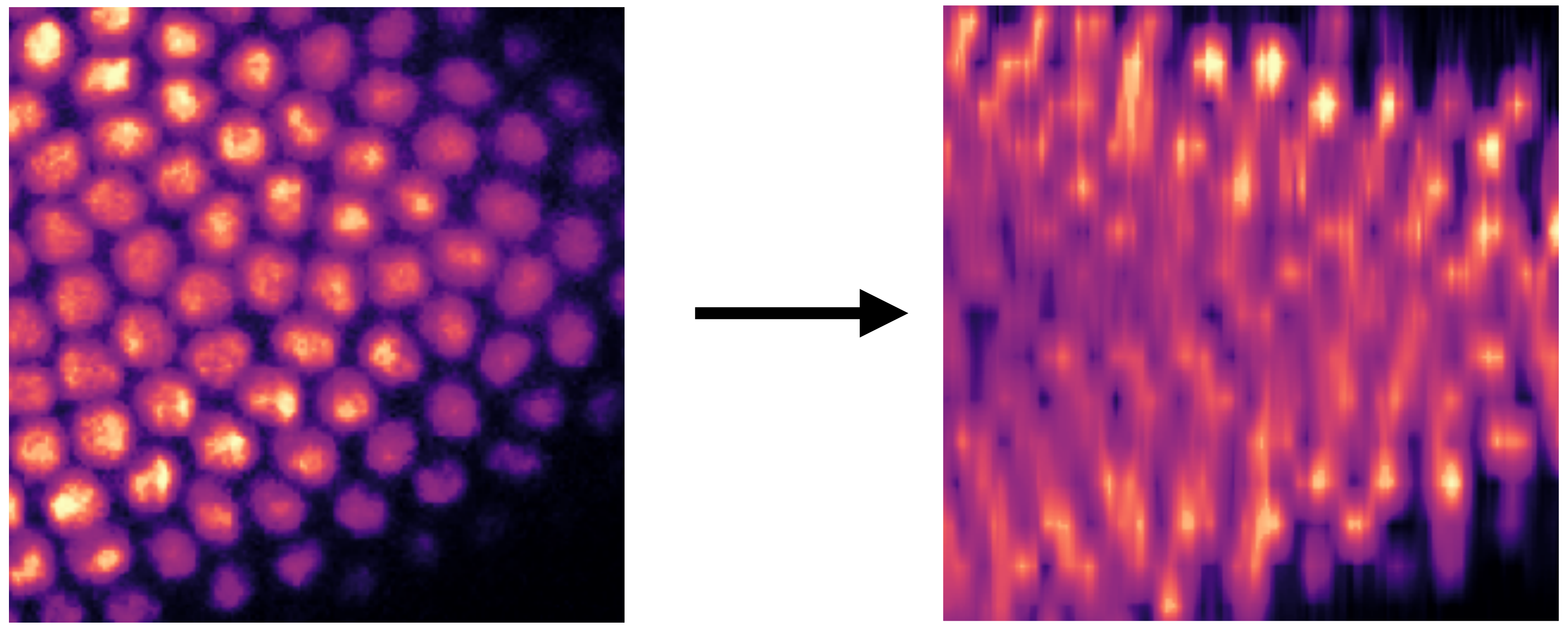
(Dense) Regression



Examples - Image Restoration

- Denoising, Upsampling (Mao 2016, CARE 2017)
- typically with pixel-wise loss, e.g. mean squared error (MSE, L2) $\frac{1}{N}\sum_{i=1}^{N}\|\tilde{y}_i - y_i\|^2$
  or mean absolute error (MAE, L1)

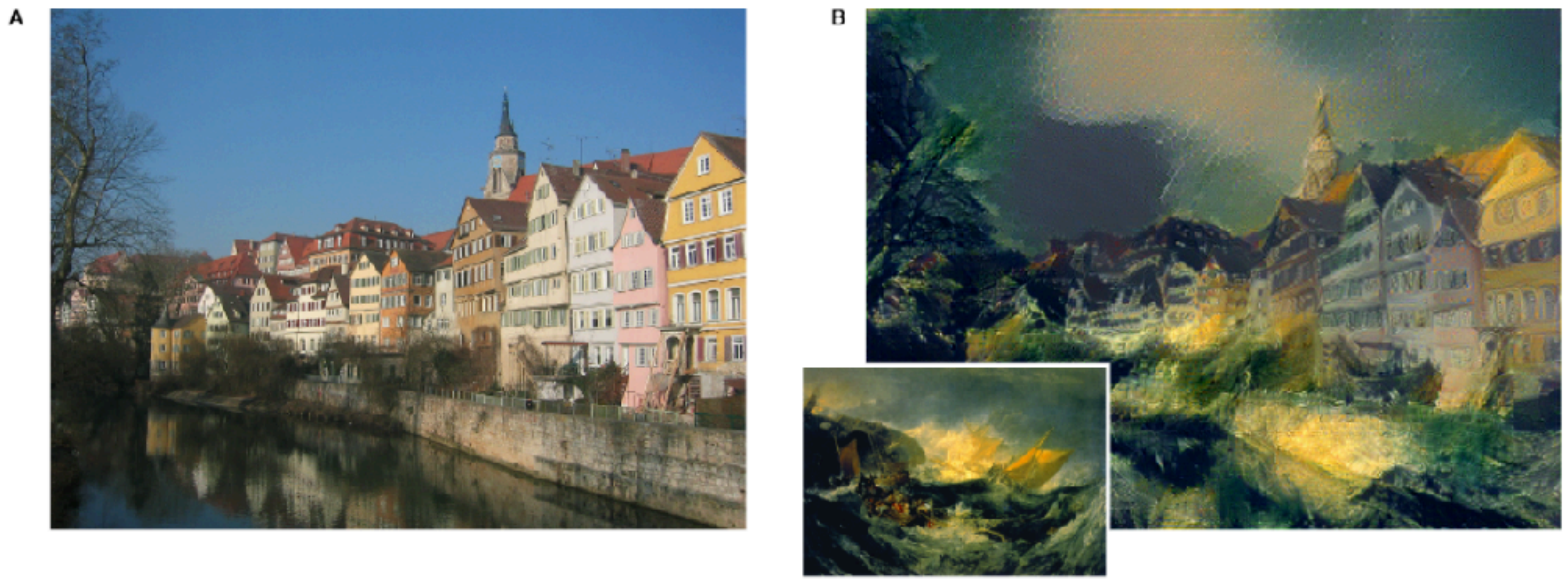




Examples - Style Transfer

- E.g. Gatys 2016, Johnson 2016

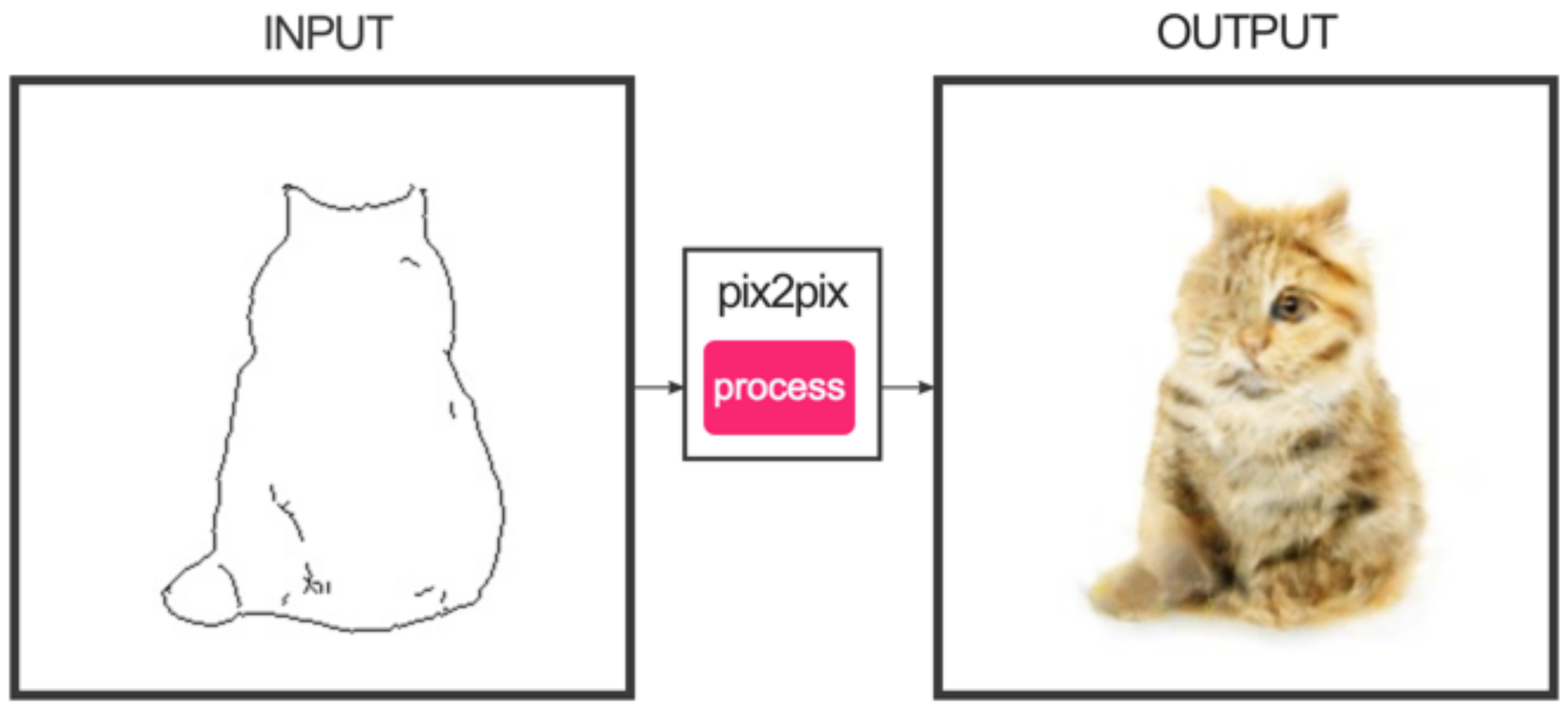
- Perceptual loss: Compare intermediate feature responses of a classification network



Examples - Image2Image Translation

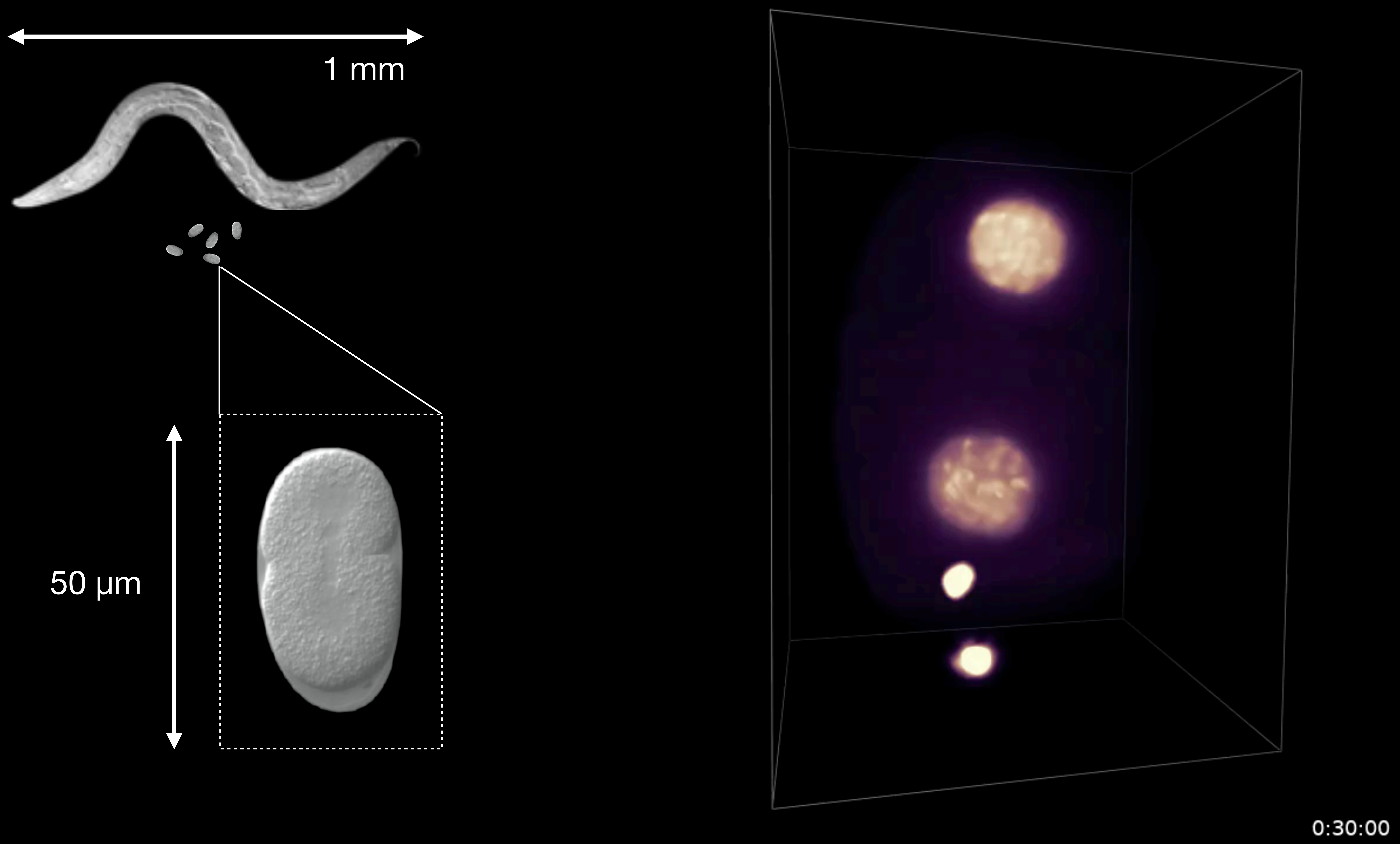
- E.g. pix2pix (Isola 2017), CycleGAN (Zhu/Park 2016)

- Adversarial loss: Using a discriminator (cf GANs)



https://affinelayer.com/pixsrv/

Case Study: Image Restoration for Fluorescence Microscopy


1 mm
50 µm
0:30:00

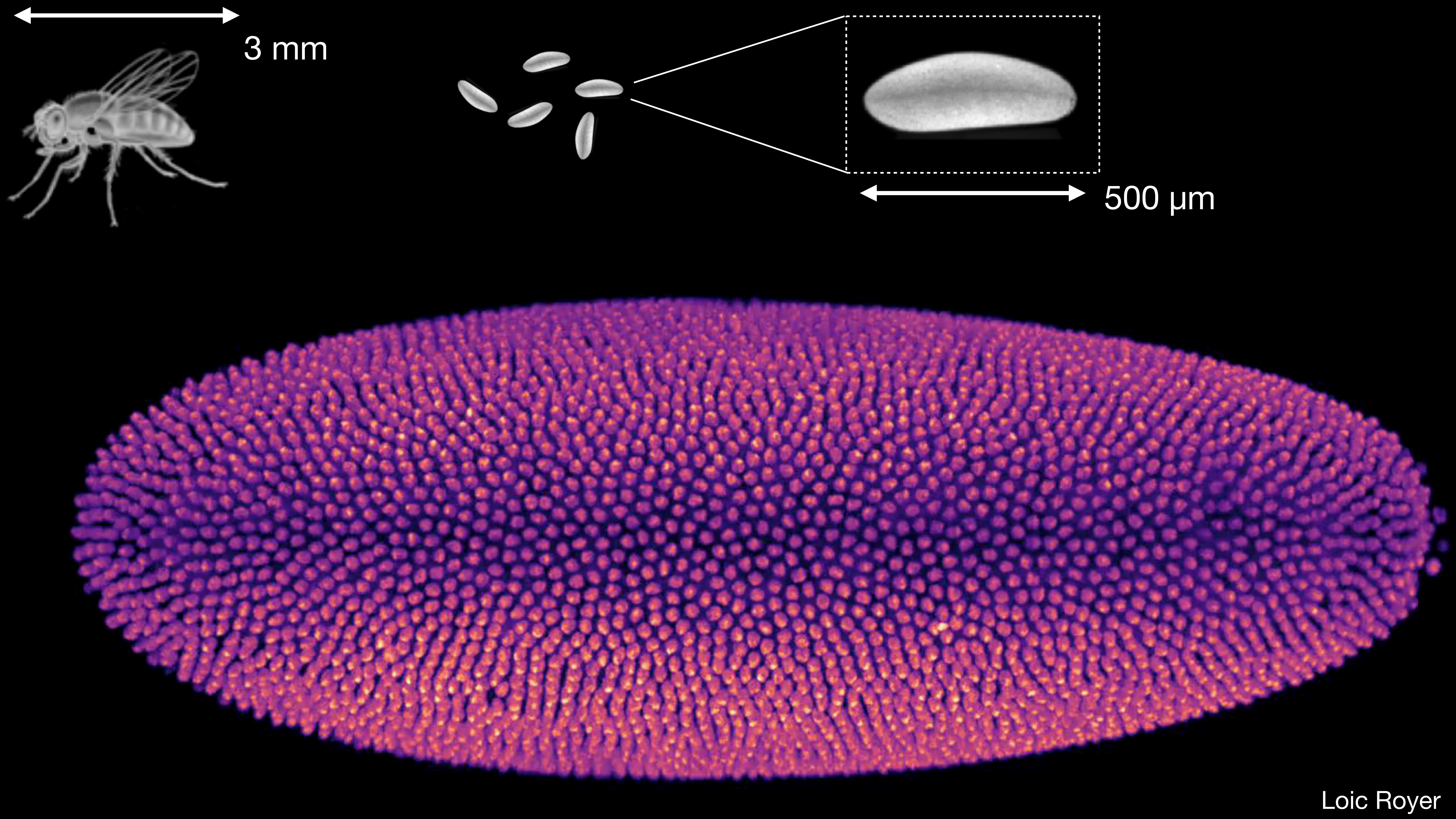
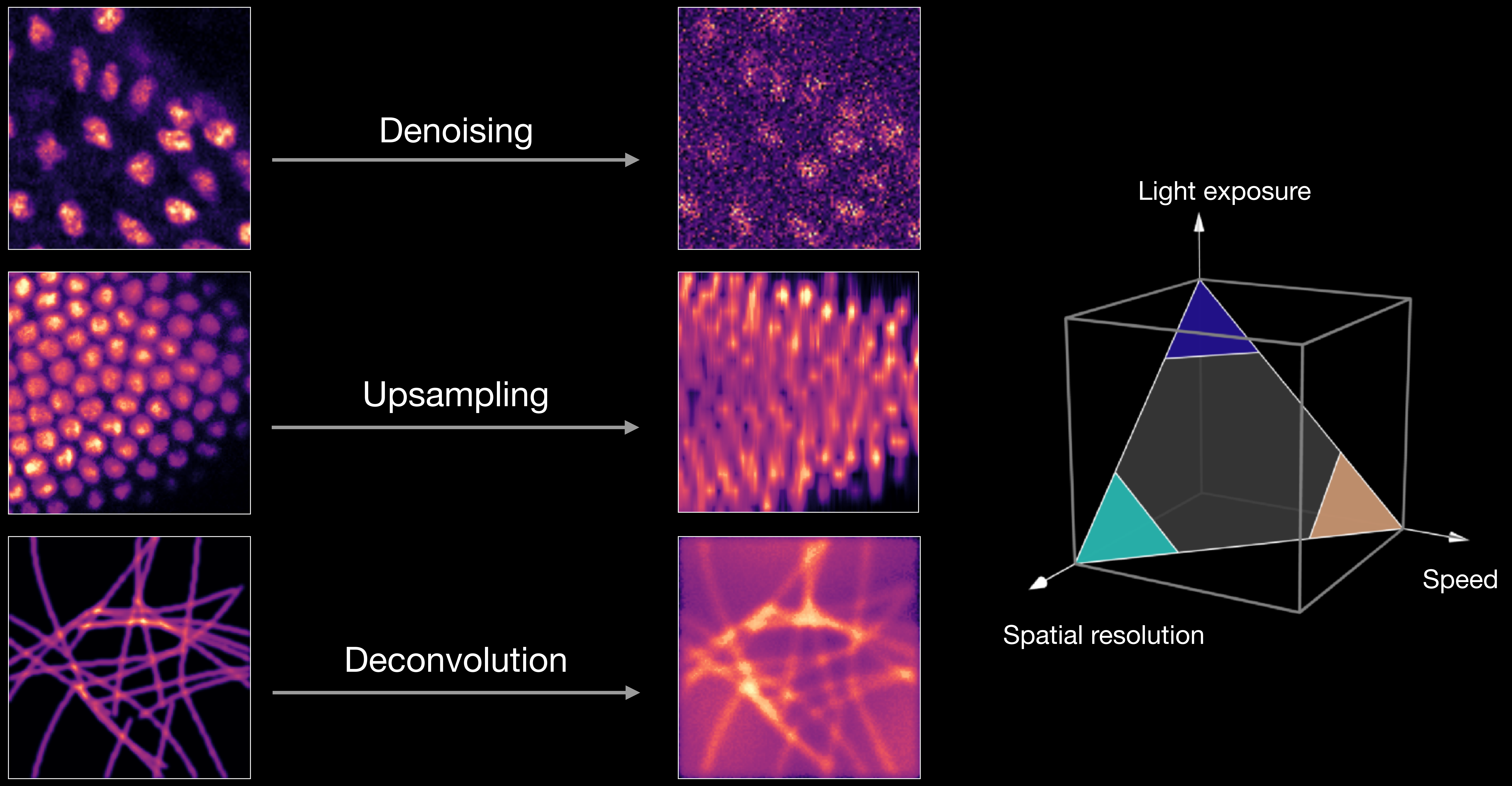

3 mm
500 µm
Loic Royer

Image Restoration for Fluorescence Microscopy

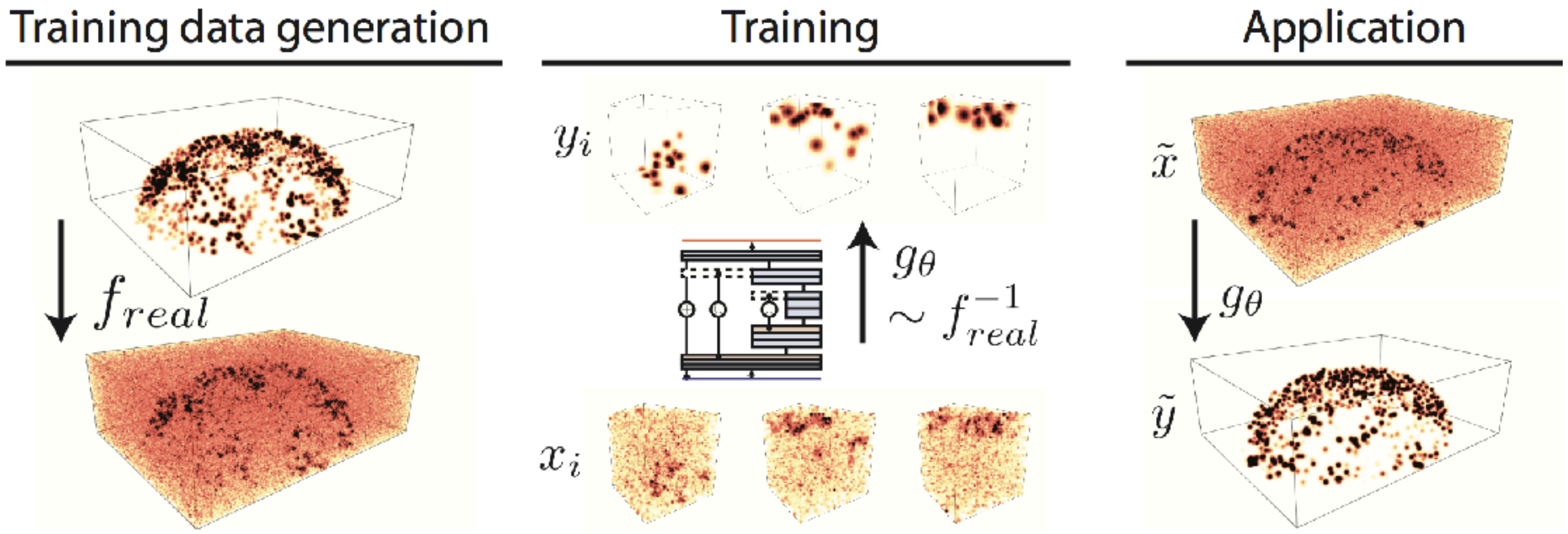


Imaging with low light

Imaging with low light

Content-Aware Image Restoration

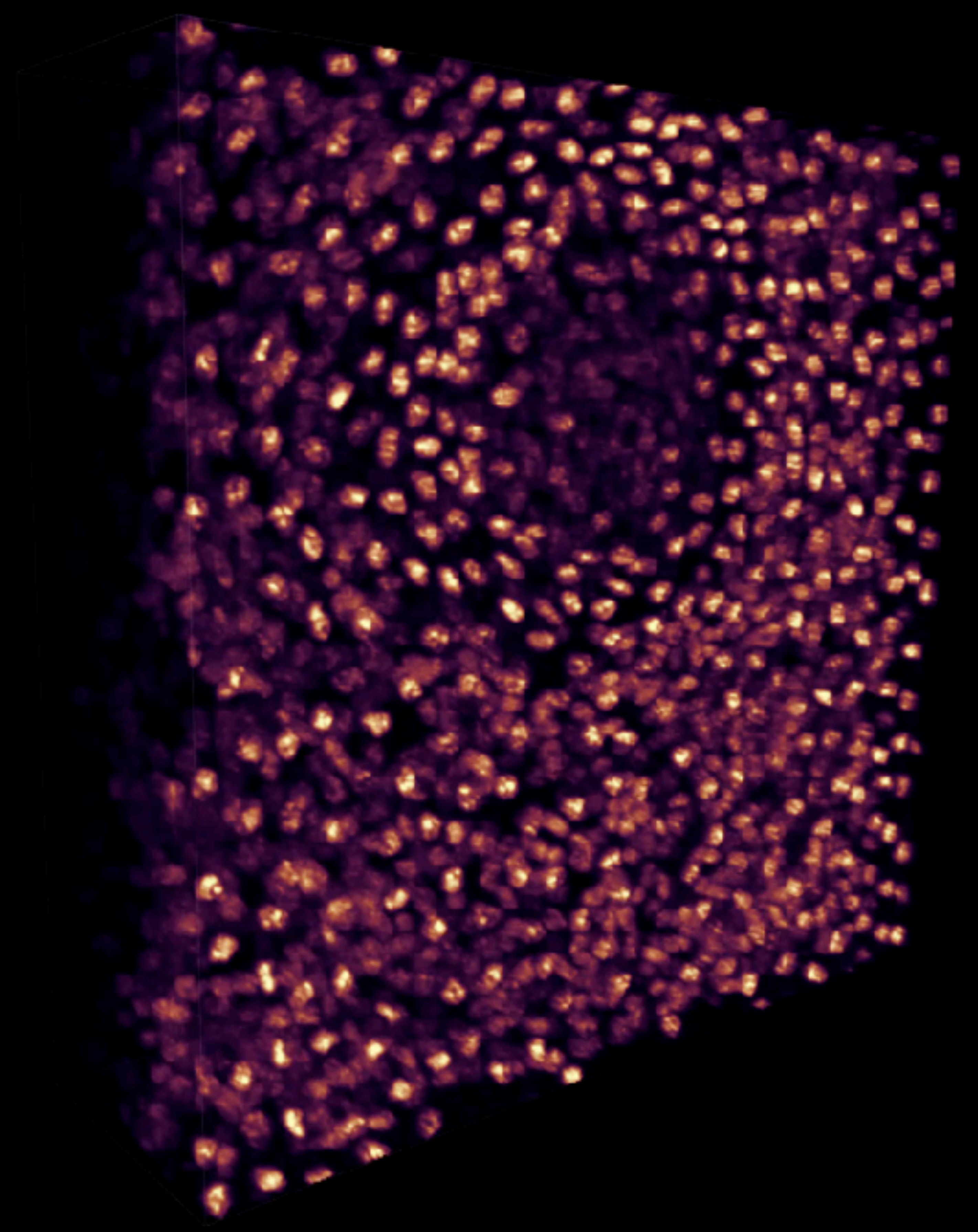
- Supervised regression based on a specific experiment/organism/imaging modality
- Training data generation via physically acquired data, semi-synthetic imaging models, or fully-synthetic data
- Using simple but robust residual versions of the U-Net in 2D and 3D
- Trade training time for inference time (super fast!)
- Provide intuitive code for training data generation and network training -> CSBDeep



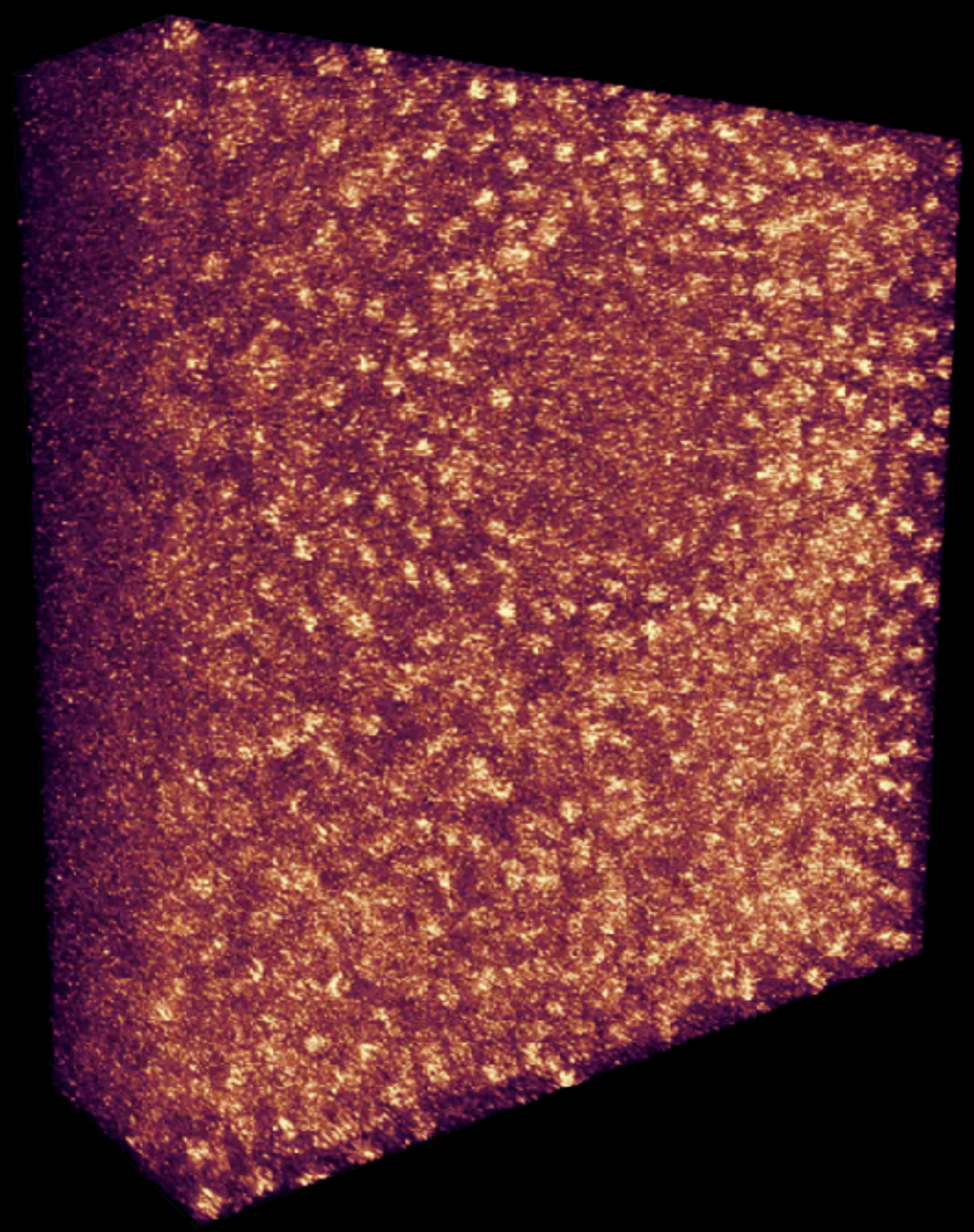
http://csbdeep.bioimagecomputing.com/

Imaging with low light

High

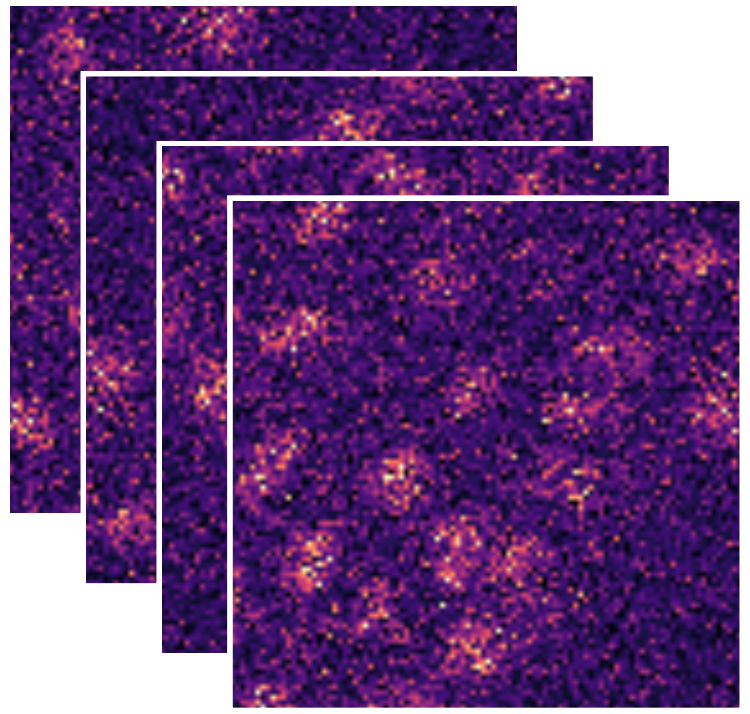


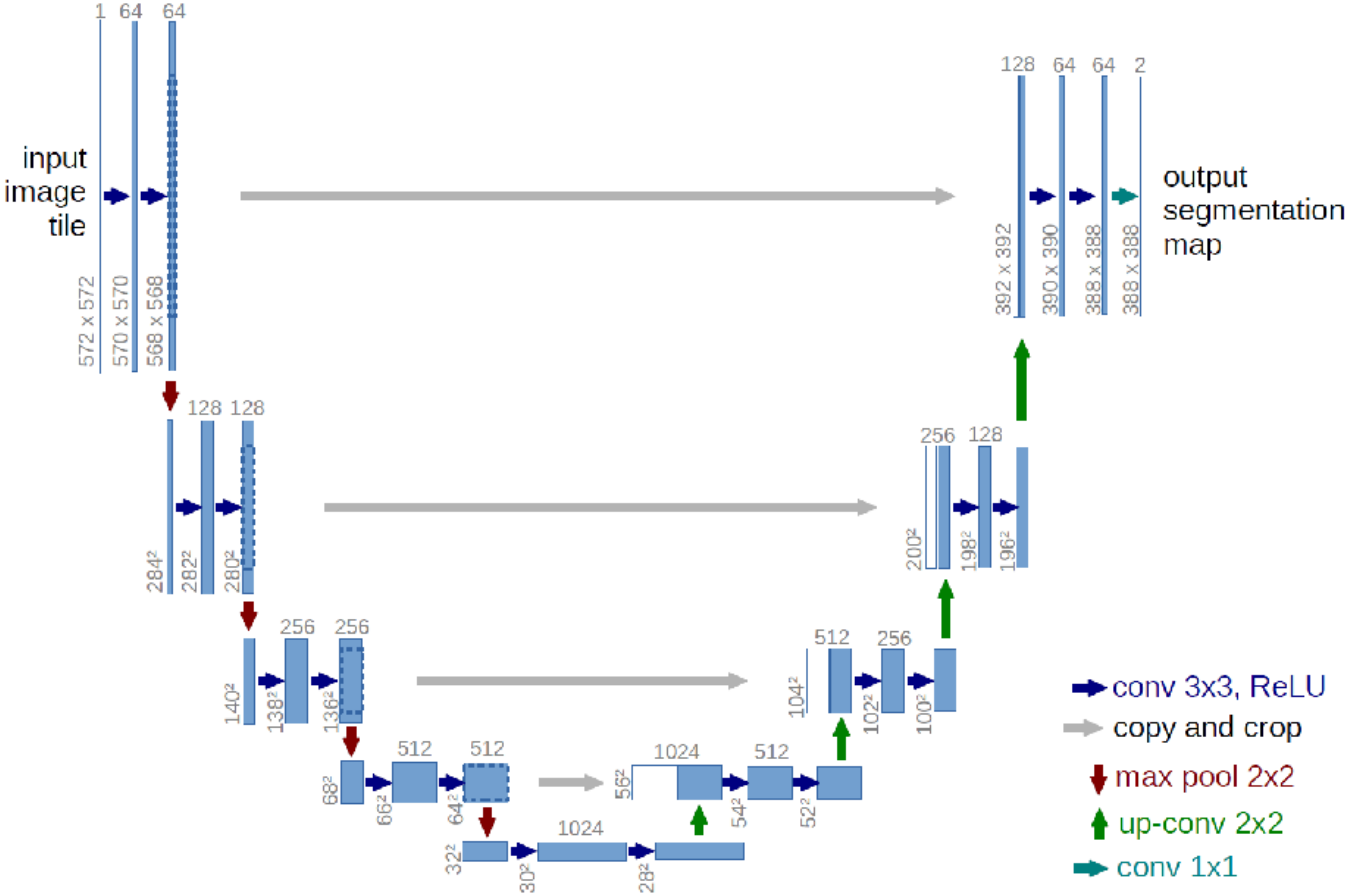
Low



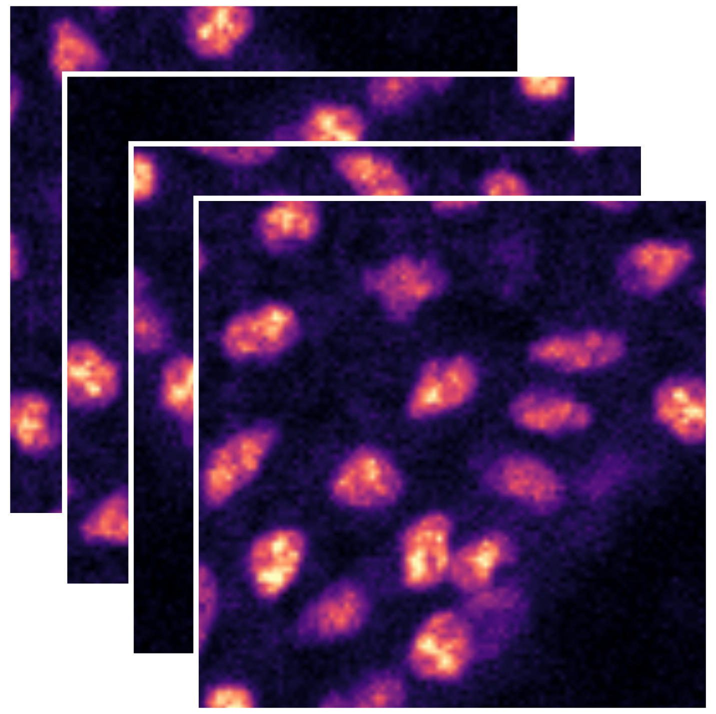
Imaging with low light

Low

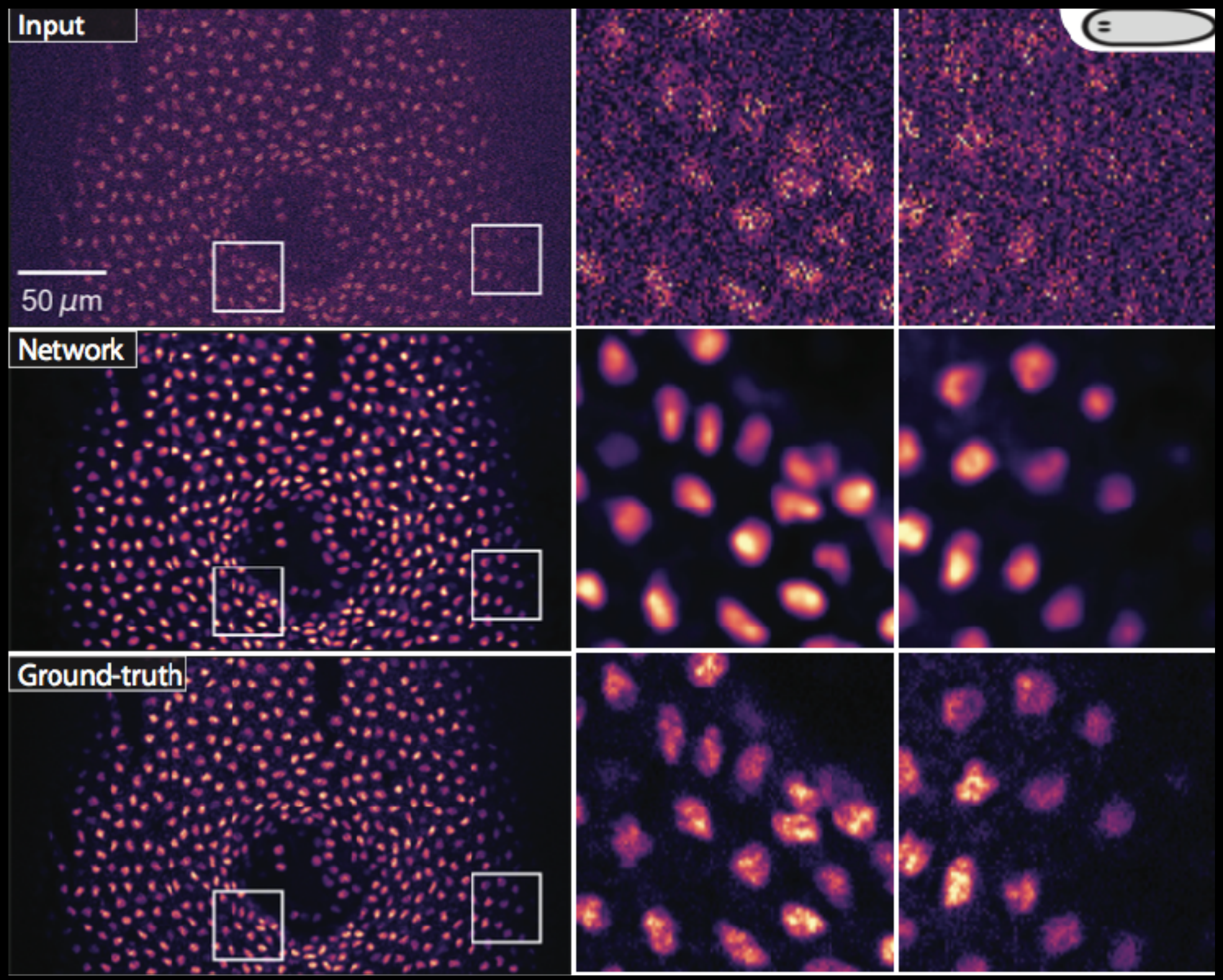


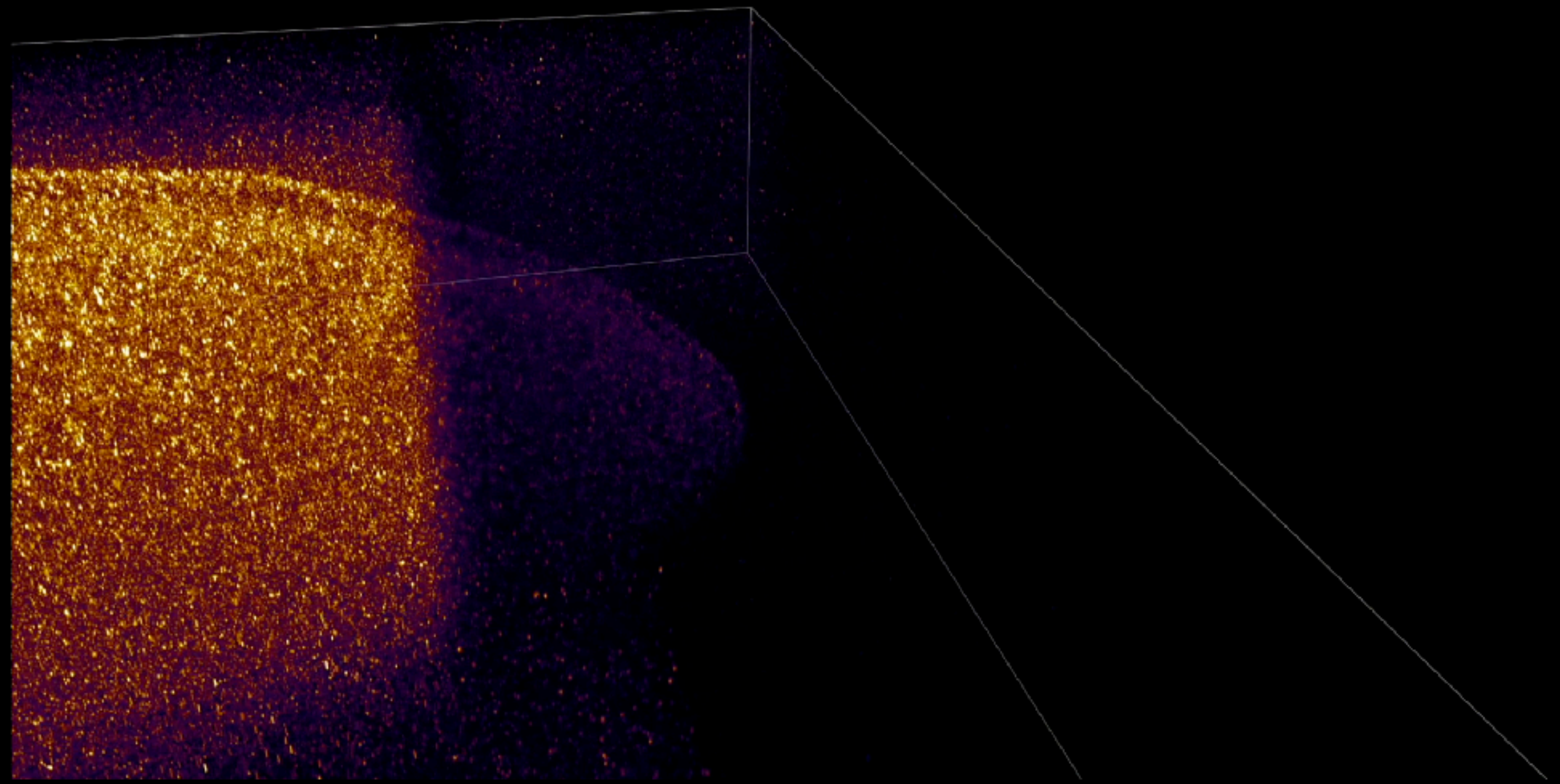


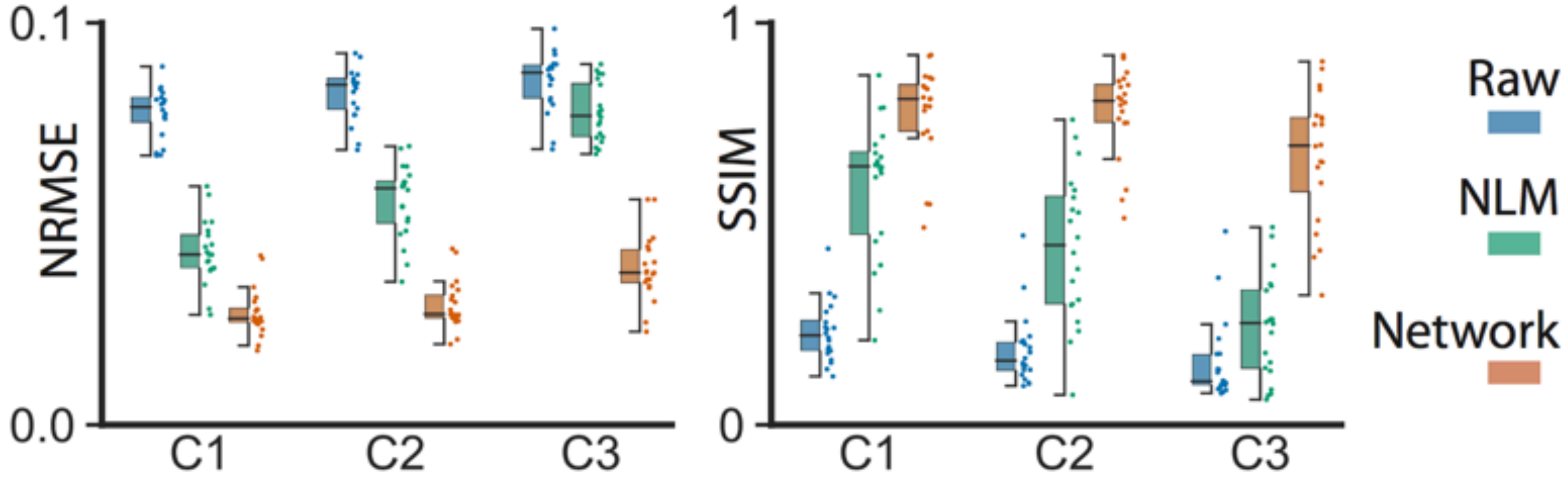
High



Imaging with low light



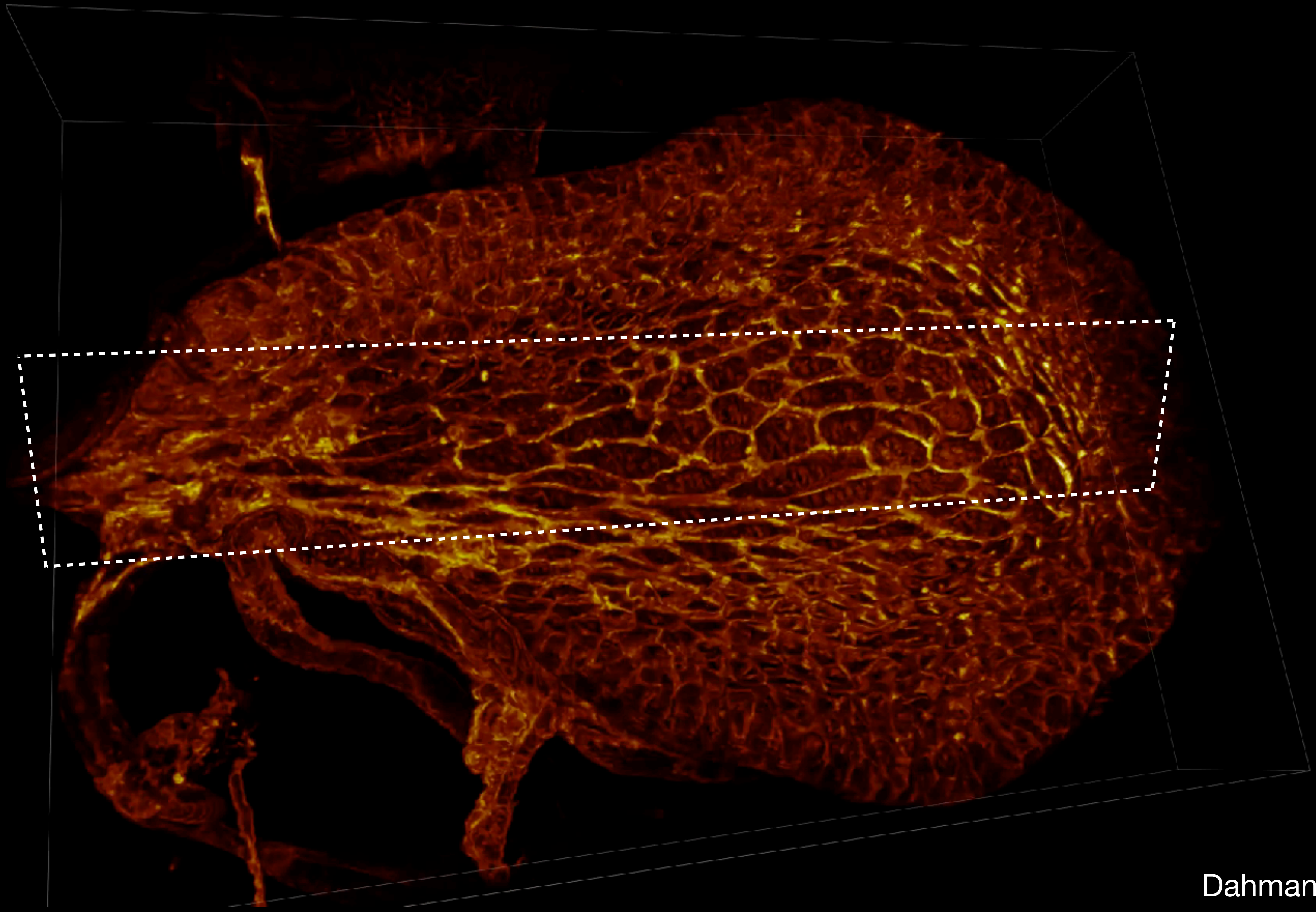




Challenges - Data Preprocessing and Normalisation

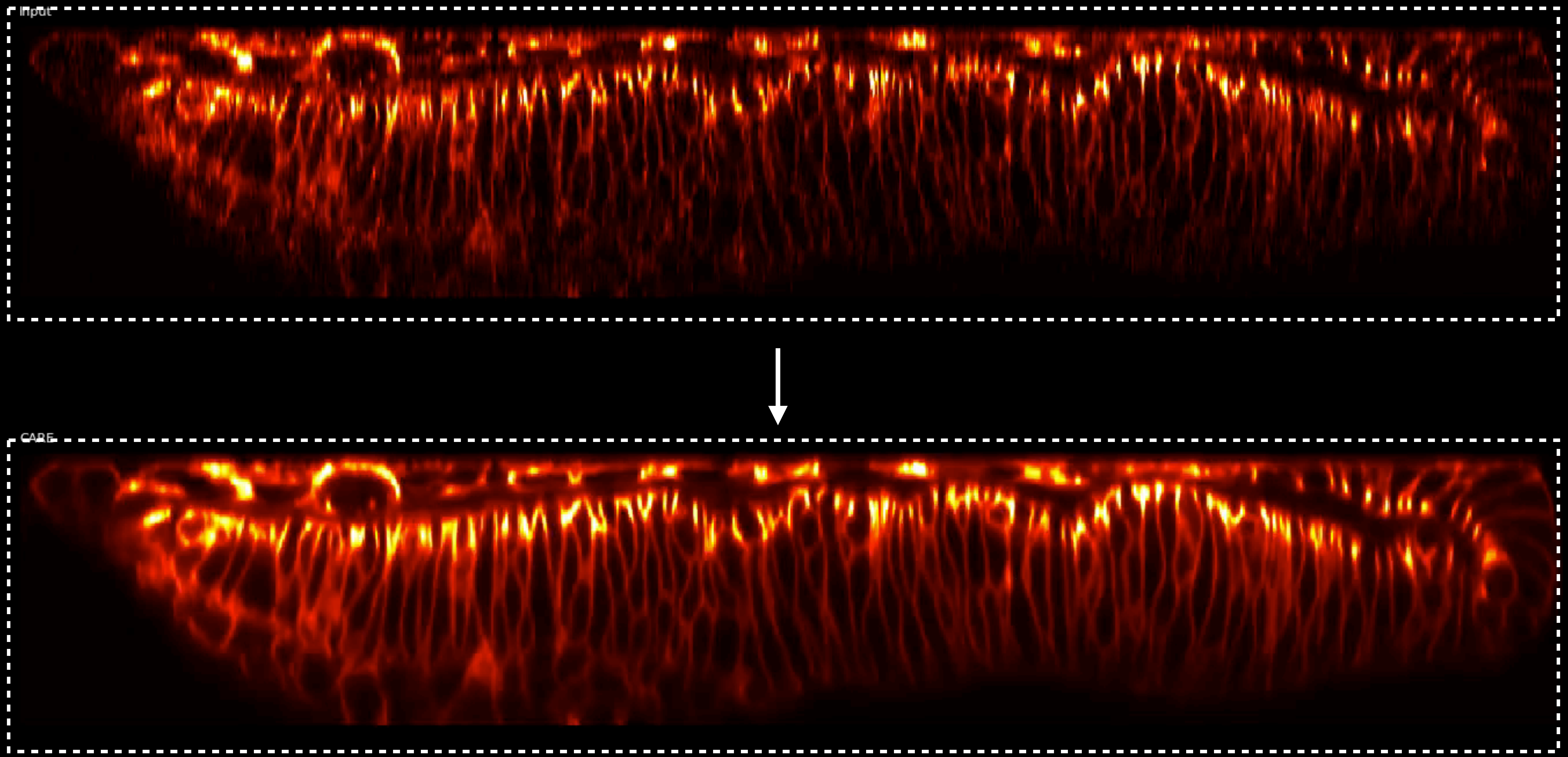
- All about getting good training data
- Typically >50% of all the work :)
- Dynamic range of network input should be ~ (-1,1) or (0,1)
  -> We typically choose a robust percent normalisation of input/output images
- Domain Knowledge!
- Beware of outliers (e.g. hot pixels, detector read errors)
- Input-Output volumes have to be pixel-perfect registered, beware of sample movement, stage jittering, etc

Works for upsampling too

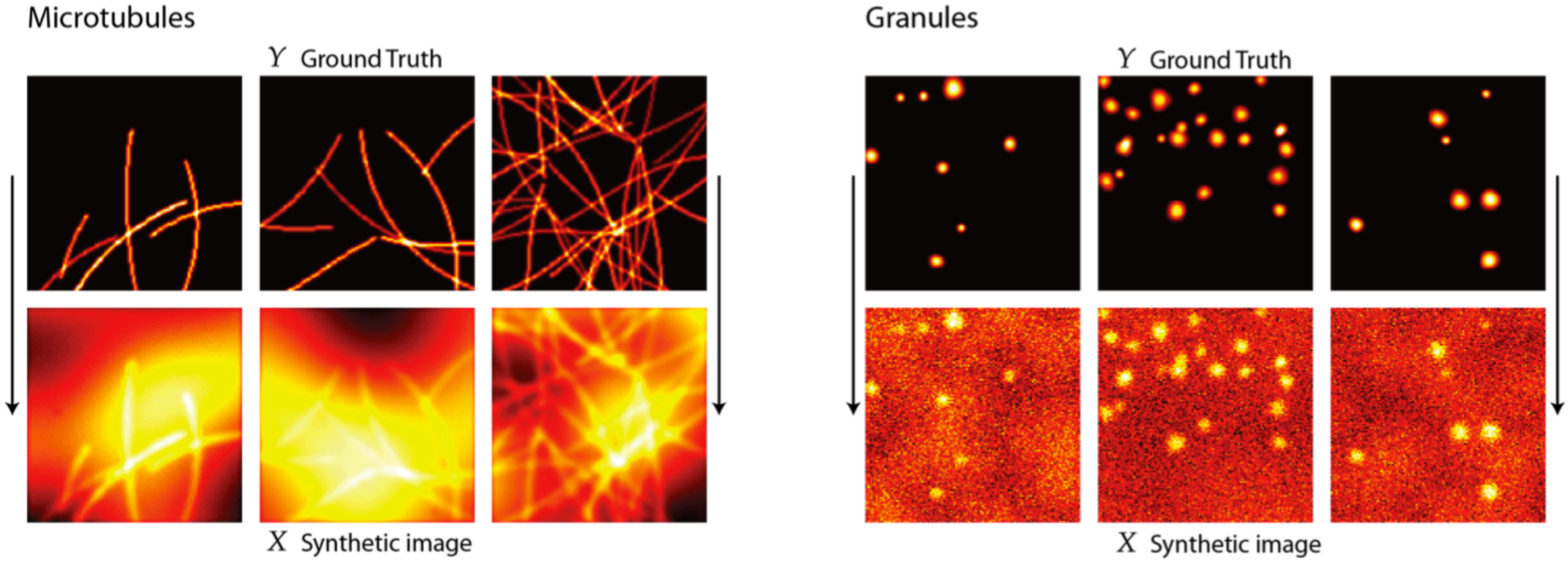


Dahmann Lab (TU-Dresden)

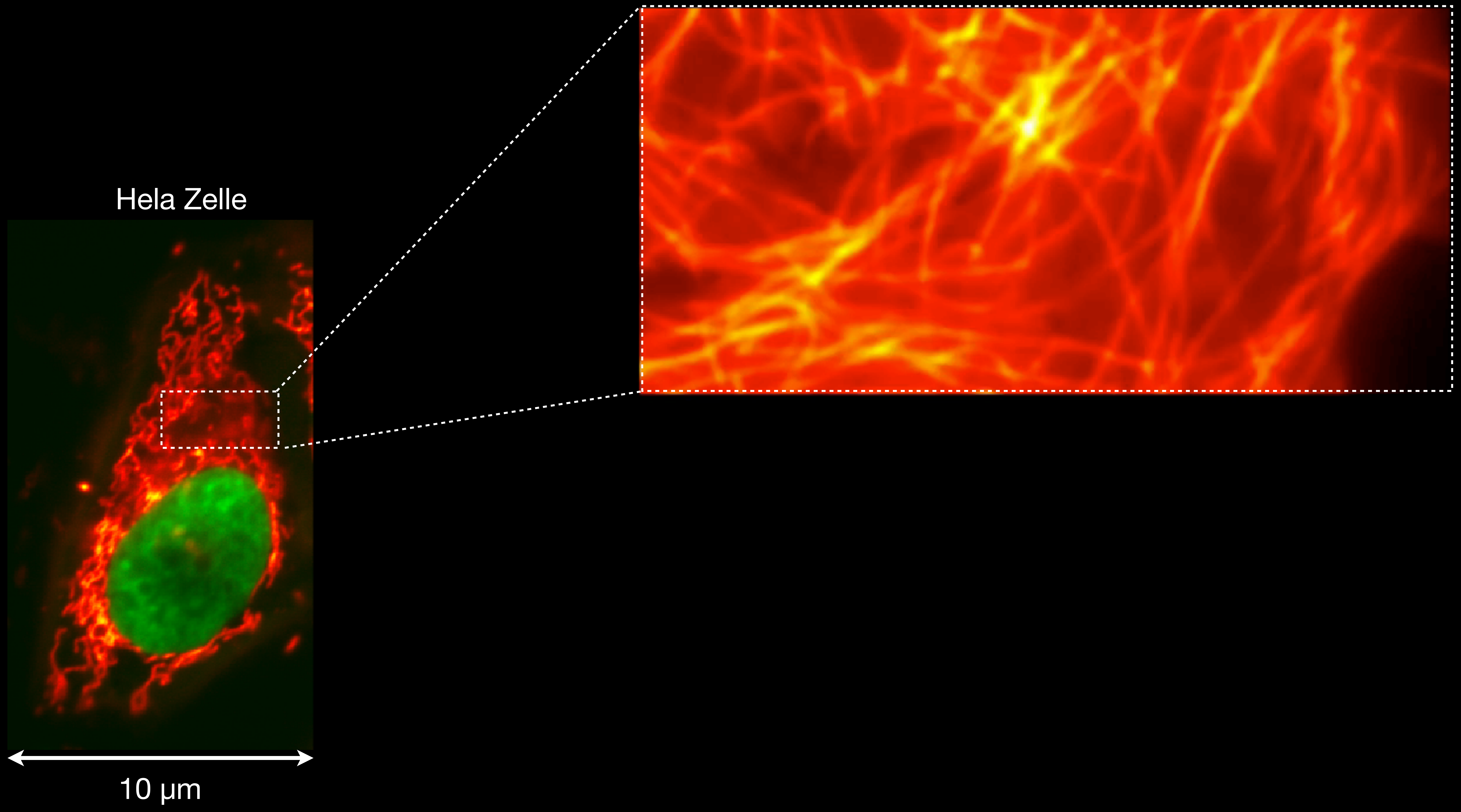
Works for upsampling too



Learning with synthetic models

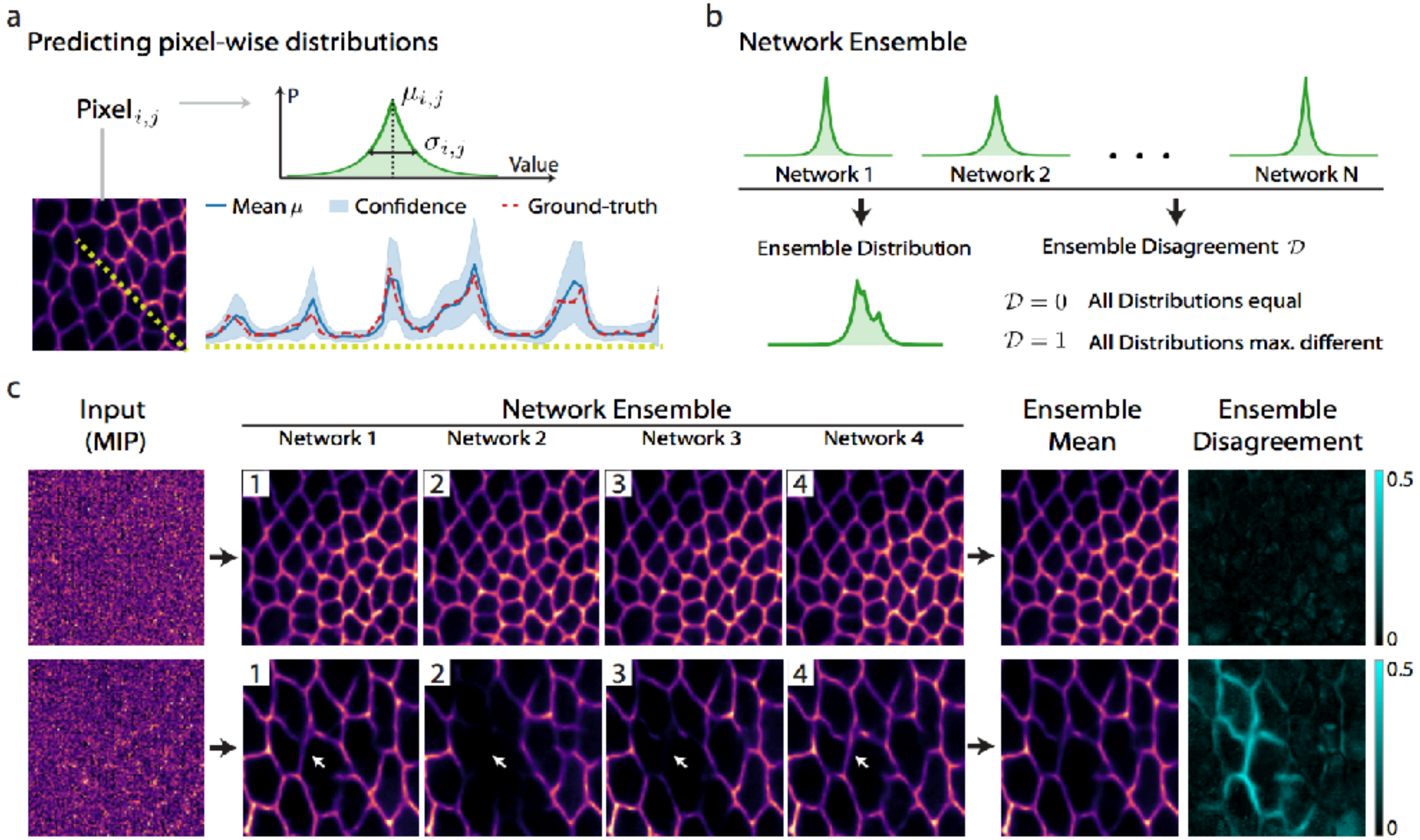


Learning with synthetic models



Challenges

- Interpretability (black box)
- Uncertainty quantification
- Out-of-Distribution detection



Recent Developments

- Analyzing Inverse Problems with Invertible Neural Networks (Ardizzone, 2018)
- Noise2Noise: Learning Image Restoration without Clean Data (Lehtinen, 2018)
- Deep Image Prior (Ulyanov, 2017)

Notebooks

day4/care/

- **denoising2D**
- denoising3D
- upsampling3D
- isotropic_reconstruction