Convolutional neuronal networks

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With Material from

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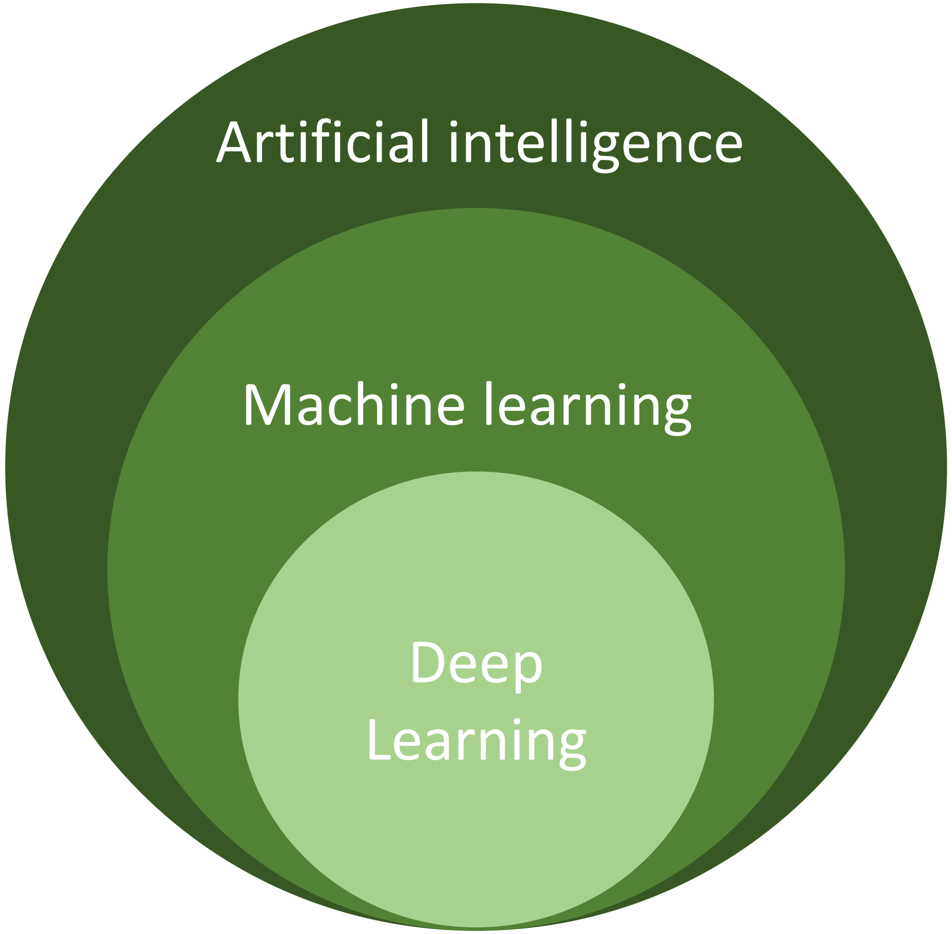
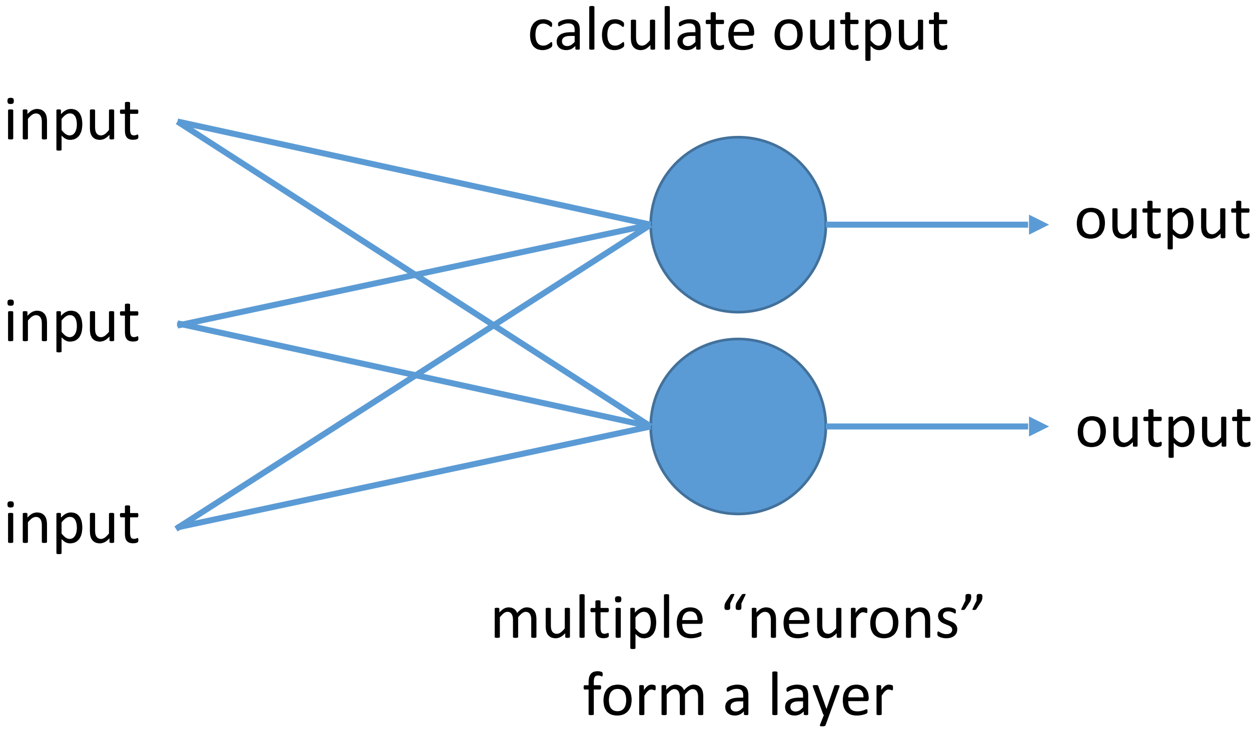
Neural networks are a form of machine learning



- Neural networks are composed of individual artificial "neurons"



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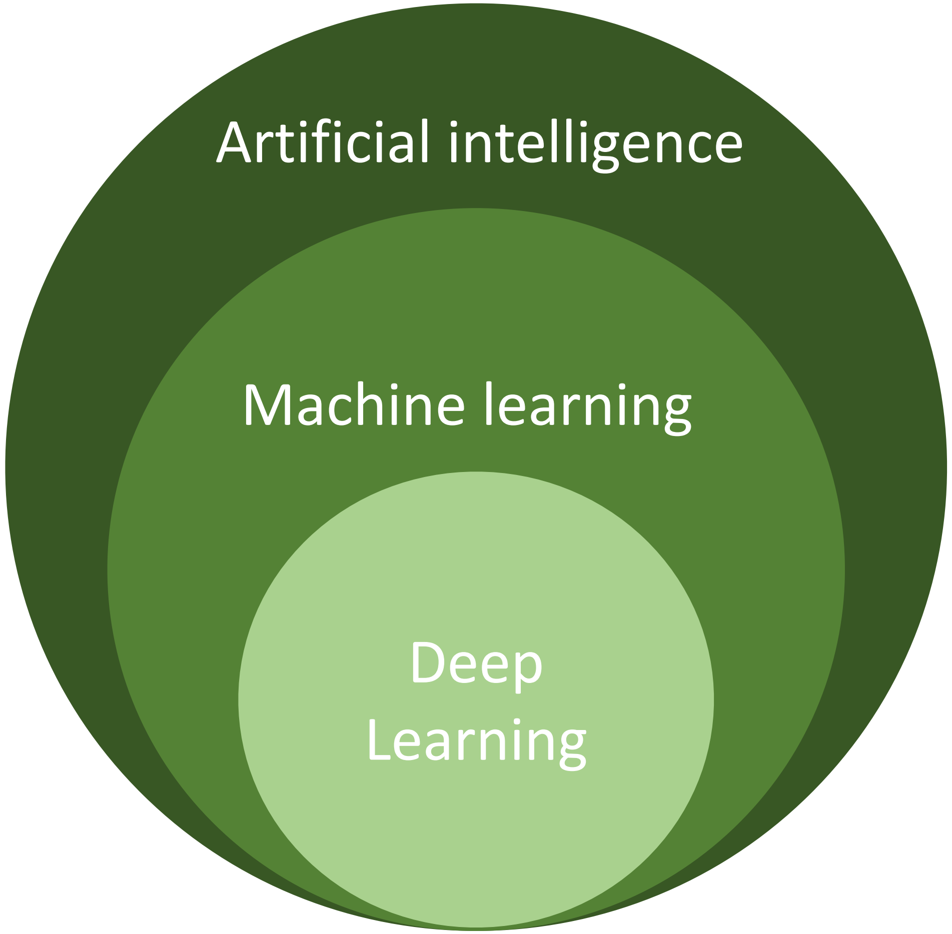
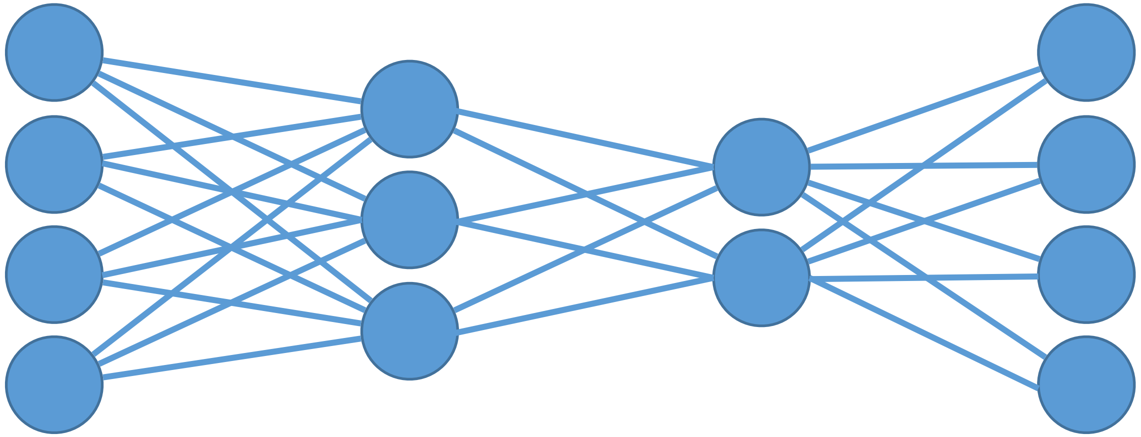
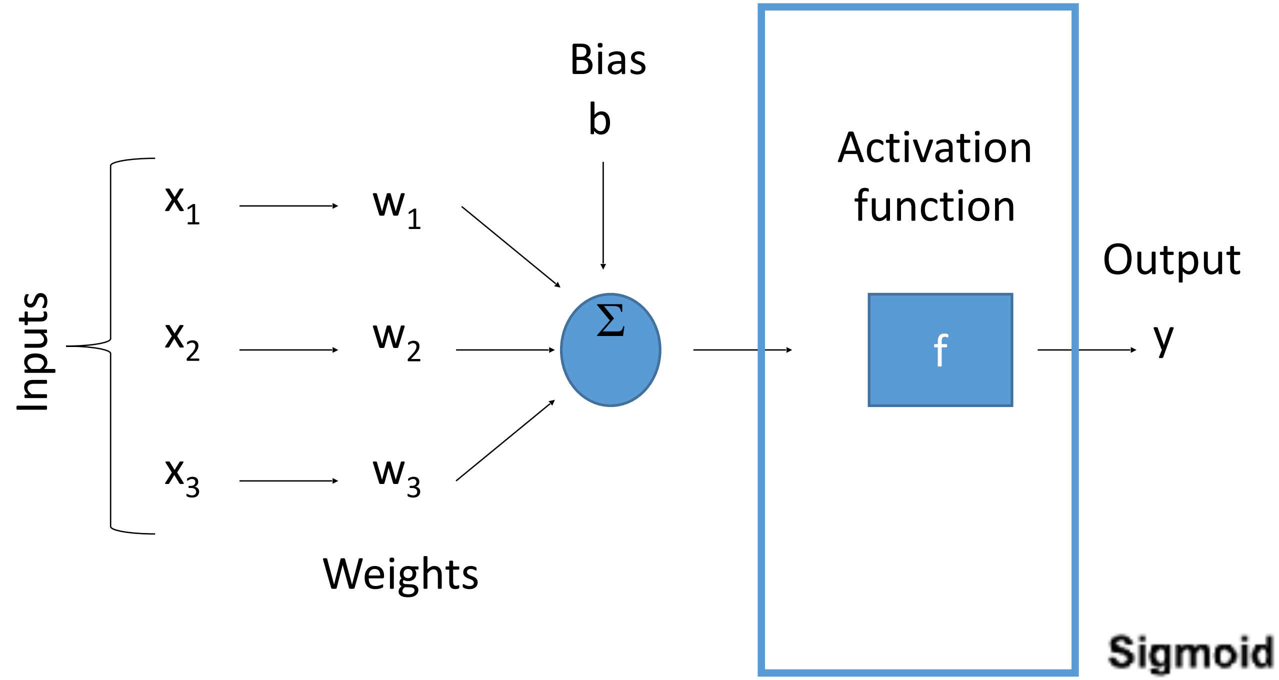


- Neural network: multiple layers of artificial "neurons"
- Deep neural network (DNN): neural network with more than one layer between input and output

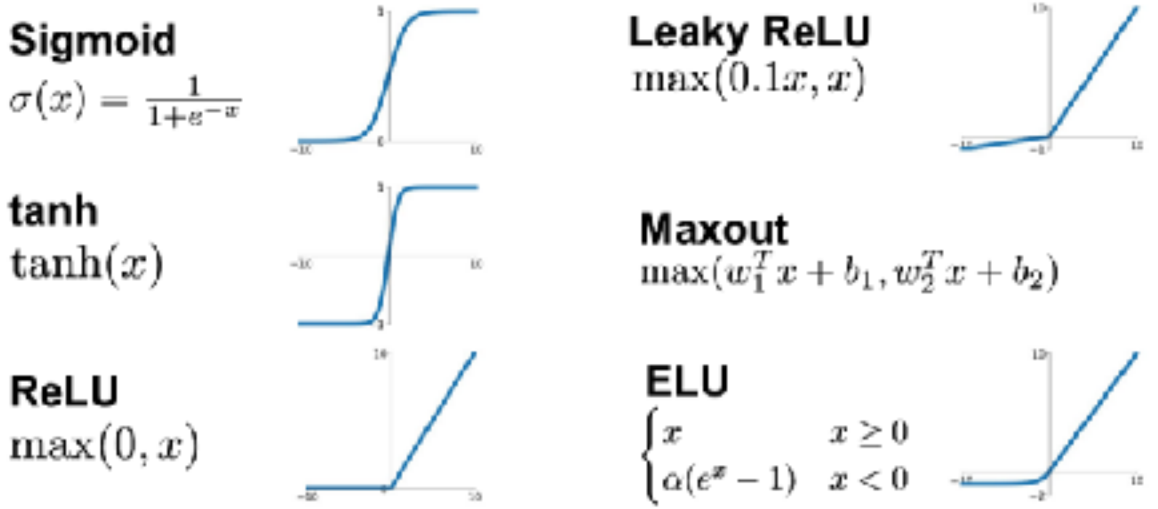


An artificial “neuron” is a mathematical function



Single neuron output calculation

$$y = w_1x_1 + w_2x_2 + w_3x_3 + b = w^Tx + b$$

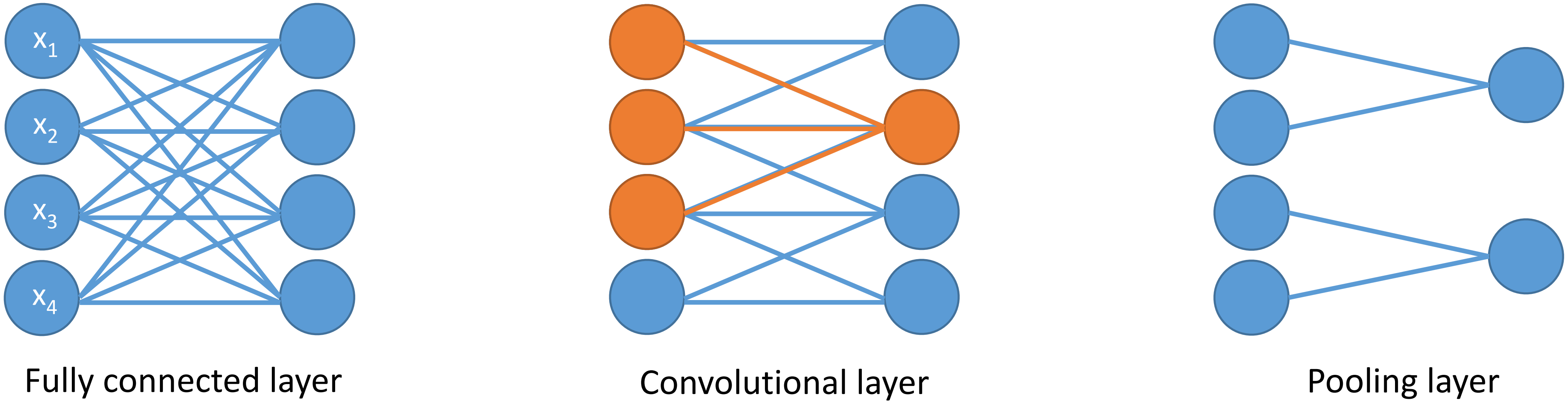


For image data, the values x_1, x_2,… would be

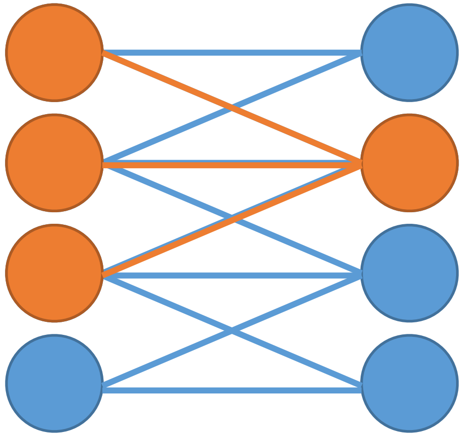
Pixel intensities

Pixel coordinates

Network layers can have different architectures



Convolutional layers perform convolution with learned kernels



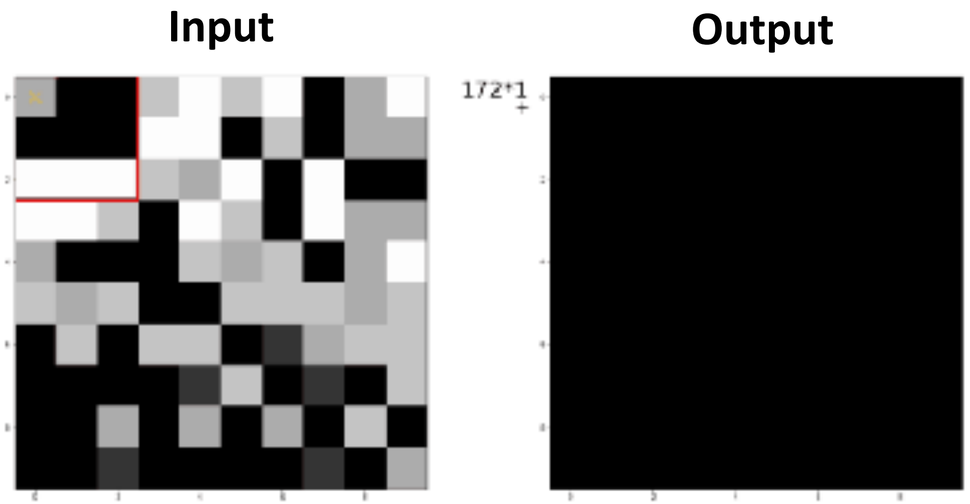
Convolutional layer

Previously:
Defined filter kernels

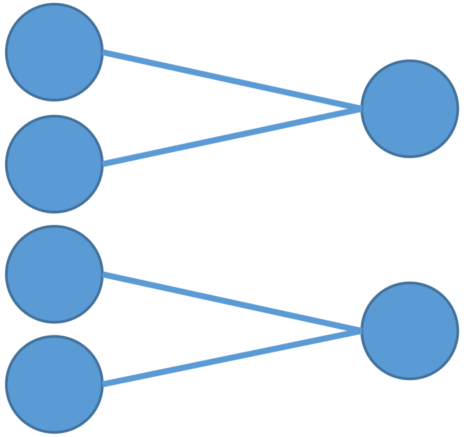
1/16	1/8	1/16
1/8	1/4	1/8
1/16	1/8	1/16

Now:
Learned filter kernels

w_{11}	w_{12}	w_{13}
w_{21}	w_{22}	w_{23}
w_{31}	w_{32}	w_{33}



Pooling layers reduce the layer size



Pooling layer

3	15	1	13
9	7	0	10
11	5	5	3
1	8	9	6

Maximal values

15	13
11	9

Average values

8.5	6.0
6.3	5.8

The network learns by minimizing a loss function

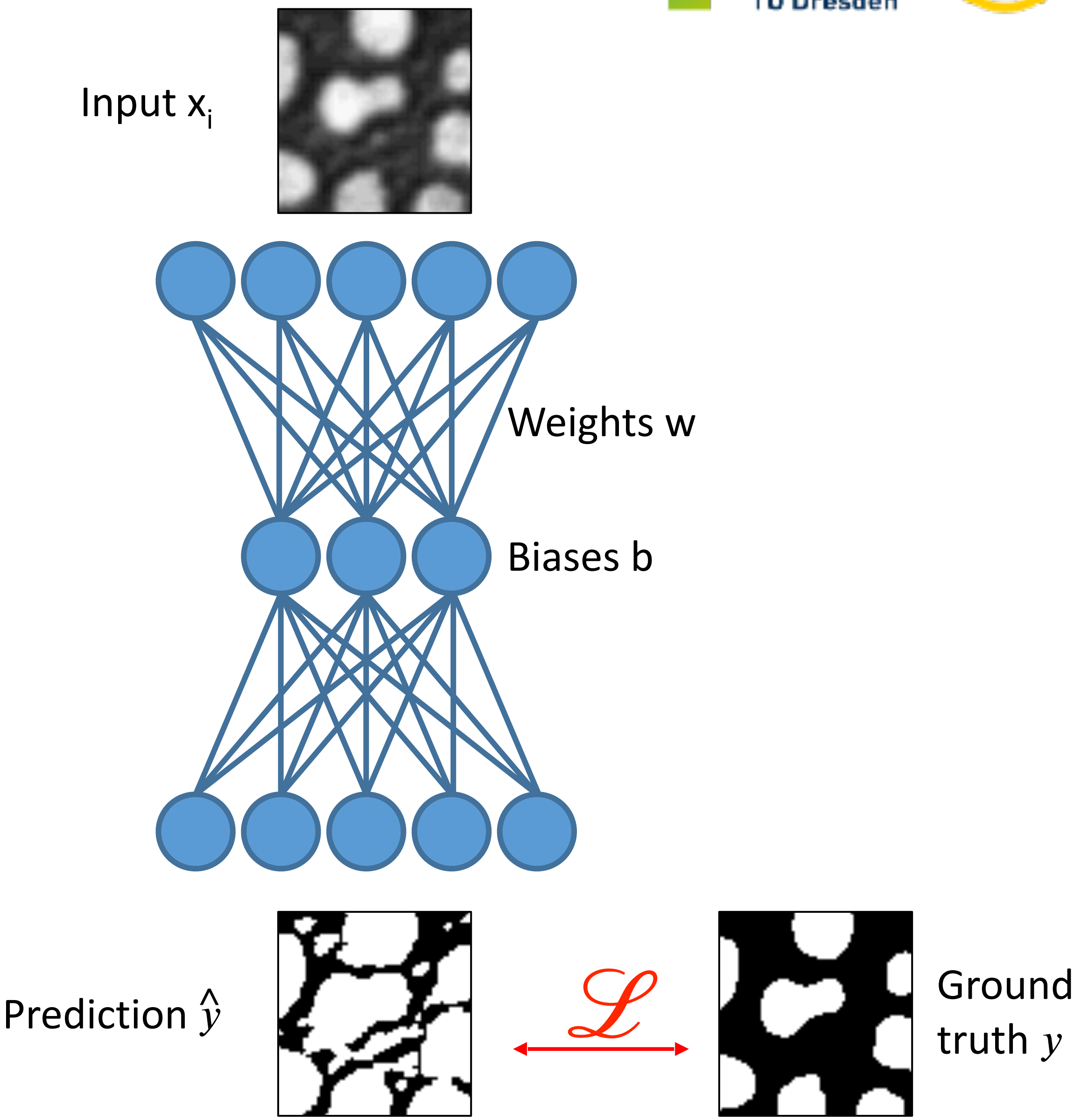
- Learning is an optimization problem

- Step 0: Initialize the network randomly
  - Weights
  - Bias
- Step 1: Forward pass the input through the network, get an initial prediction (Images 0…M)

- Step 2: Compare the output with the ground truth, computer the error (loss function)
  - The loss function can be freely defined.
  - Mean squared error:

$$\mathscr{L}(y, \hat{y}) = \frac{1}{M} \sum_{i=1}^{M} (\hat{y}_i - y_i)^2$$

- Step 3: Update weights



Slide adapted from: Mahmood Nazari, TU Dresden

Back-propagation: Minimize loss backwards from output

The loss function can be expanded from

$$\mathscr{L}(y, \hat{y}) = \frac{1}{M}\sum_{i=1}^{M}(\hat{y}_i - y_i)^2$$

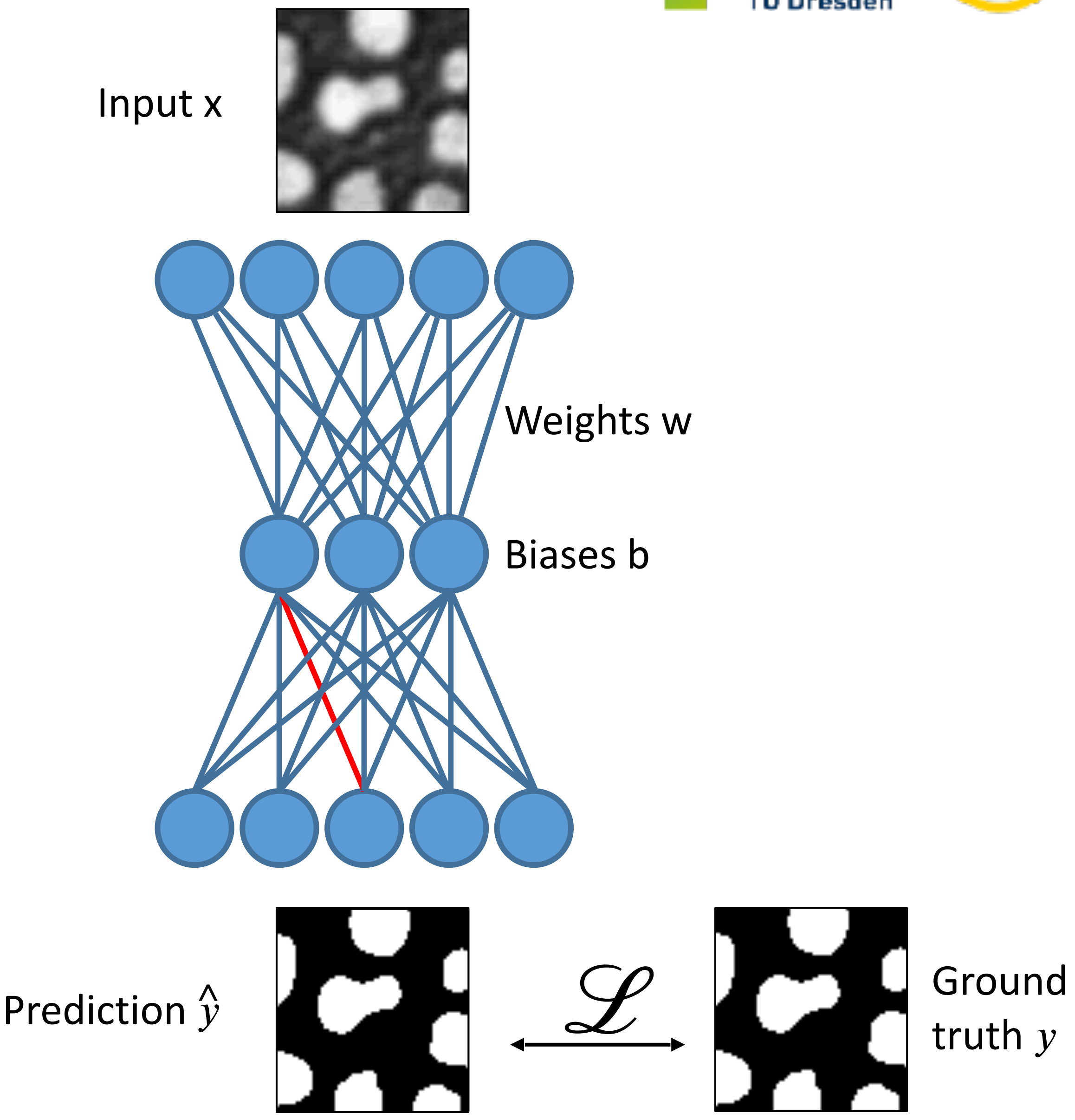
as the prediction depends on inputs x weights w and bias b

$$\mathscr{L}(\hat{y}, x, w) = \frac{1}{M}\sum_{i=1}^{M}((w^T x_i + b) - y_i)^2$$

We can calculate derivatives with respect to *w* and *b* to find their optimal values

→ Derivatives tell us how to change *w* & *b* in order to improve the prediction (i.e. minimize the loss function

Repeat this for each layer, update weights w



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What you need to train your own network

Popular frameworks:

https://www.tensorflow.org/

Google LLC, Public domain, via Wikimedia Commons

https://www.pytorch.org/

PyTorch, BSD, via Wikimedia Commons

Hardware requirements: Nvidia (CUDA-capable) graphics card (GPU)

Memory: The more GPU memory the better

Adam Kapetanakis, CC BY-SA 4.0, via Wikimedia Commons

Validation: Keep part of the data for testing and validation

Before you start training:

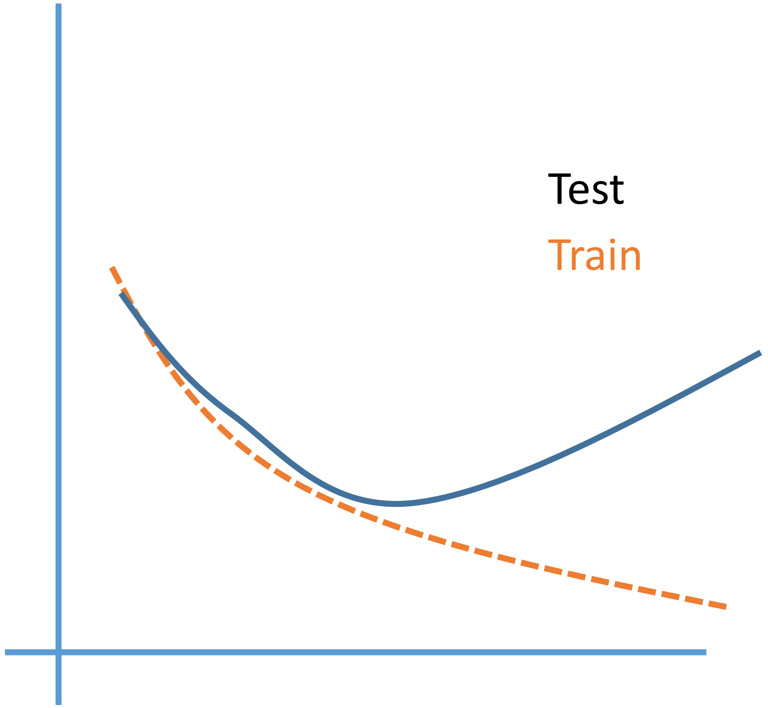
- Split data into three groups:
  - Training set
  - Testing set
  - Validation set

During training:

- Apply network to training set:
  - Measure performance (“loss”) of network, update weights
- Apply network to testing set:
  - Measure performance of updated network, keep weights unchanged
- Improve network architecture (optimize “hyperparameters”)

During validation:

- Measure performance in unseen validation dataset

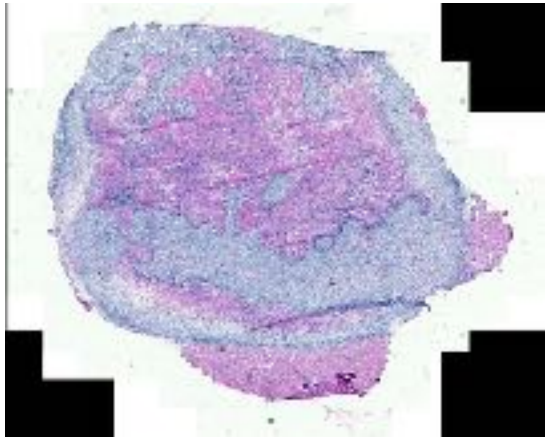


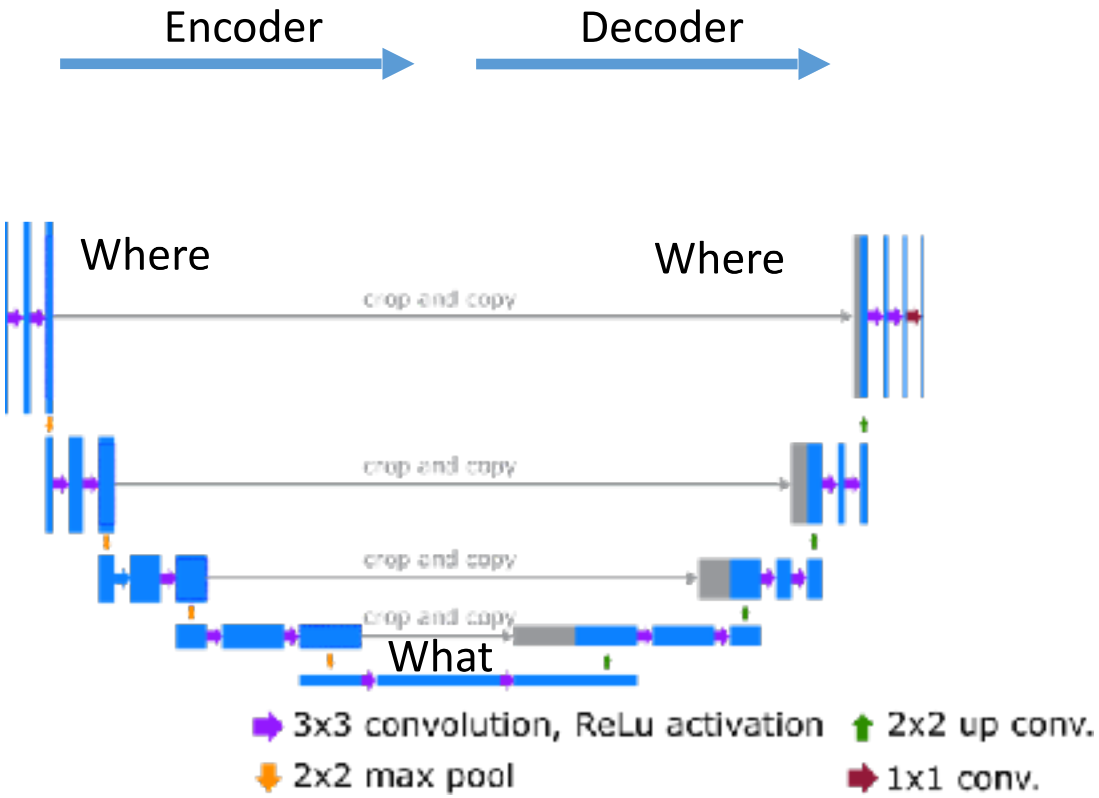
Overfitting:

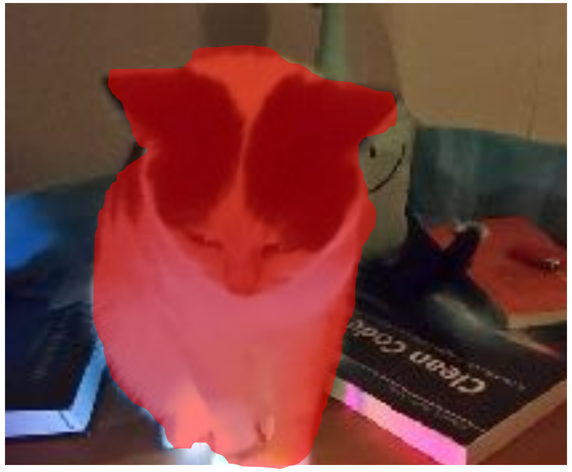
→ Network is learning things „by heart“

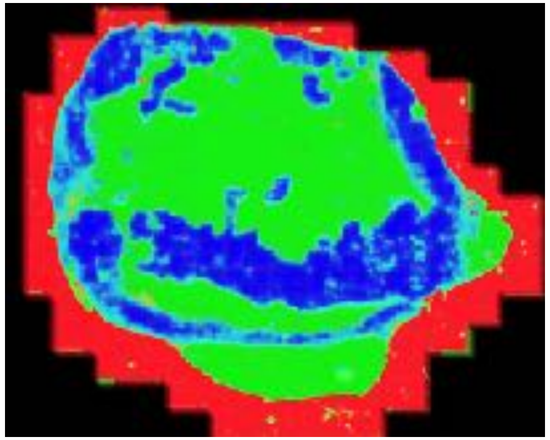
→ Hint at this happening: Updated weights from training fail to perform well in test

U-net: Image segmentation







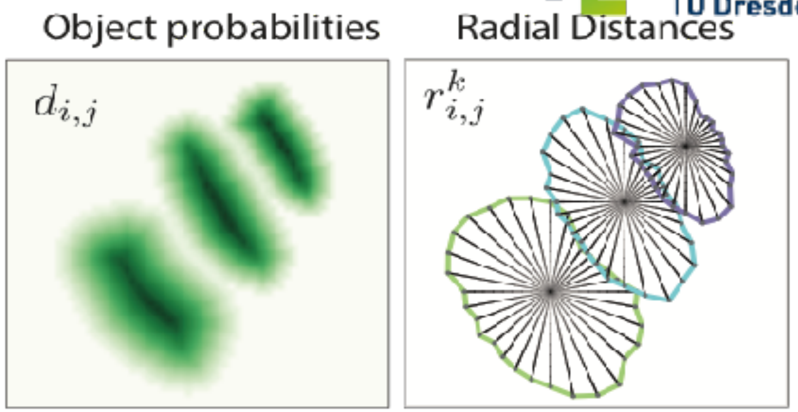


- The **U-net** is the most used network architecture in biological image processing using CNNs.
  - Encoder: Increase the “What”, decrease the “Where”
  - Decoder: Use the “What”, to identify the “Where”

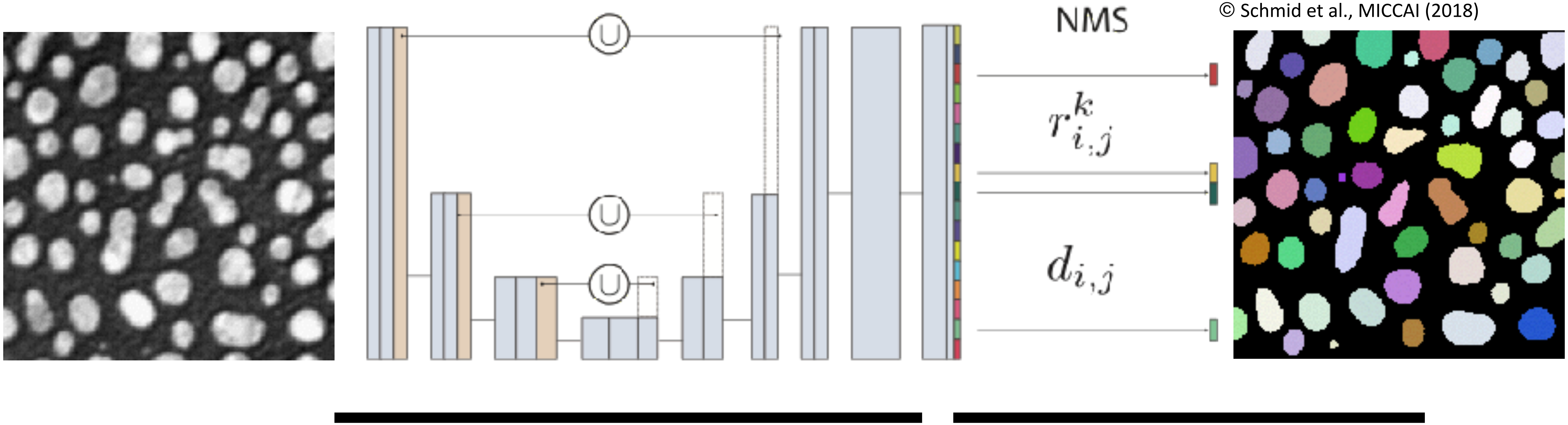
Ronneberger et al. (2015): U-Net: Convolutional Networks for Biomedical Image Segmentation

Stardist: Nucleus segmentation

Strategy:
→Add additional information to prediction
→Member pixels of objects (nuclei) can be reached via a straight line from the center



© Schmid et al., MICCAI (2018)



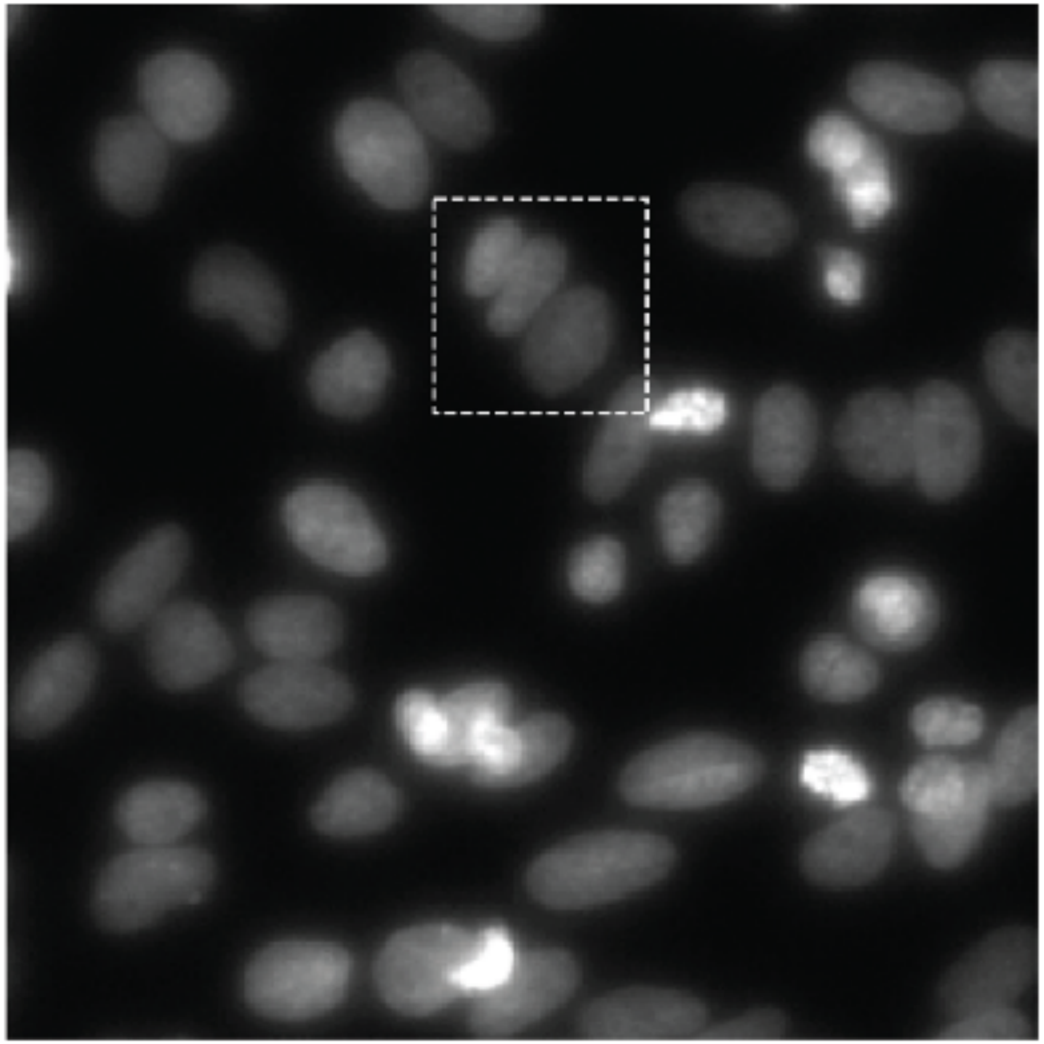
Dense Polygon Prediction
(e.g. U-Net, ResNet)

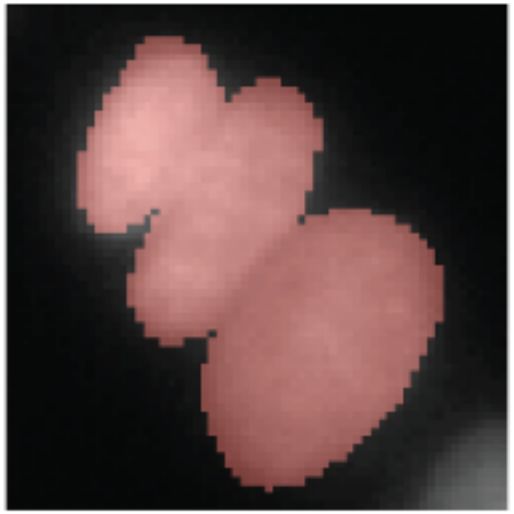
Polygon Selection
(Non-Maximum Suppression NMS)

Schmid et al., MICCAI (2018), https://github.com/stardist/stardist

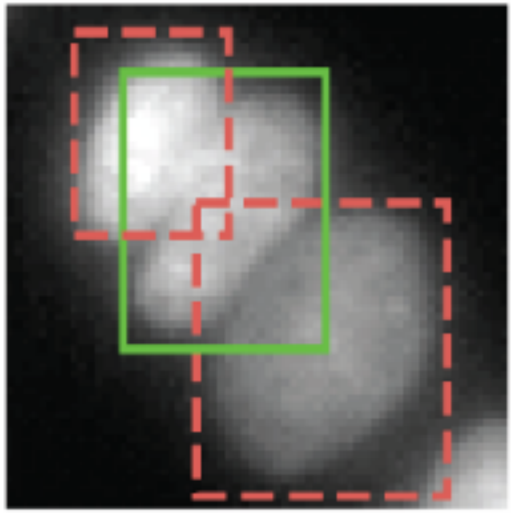
Other algorithms have problems with overlapping nuclei

Noisy images + Crowded cells = Common source of segmentation errors





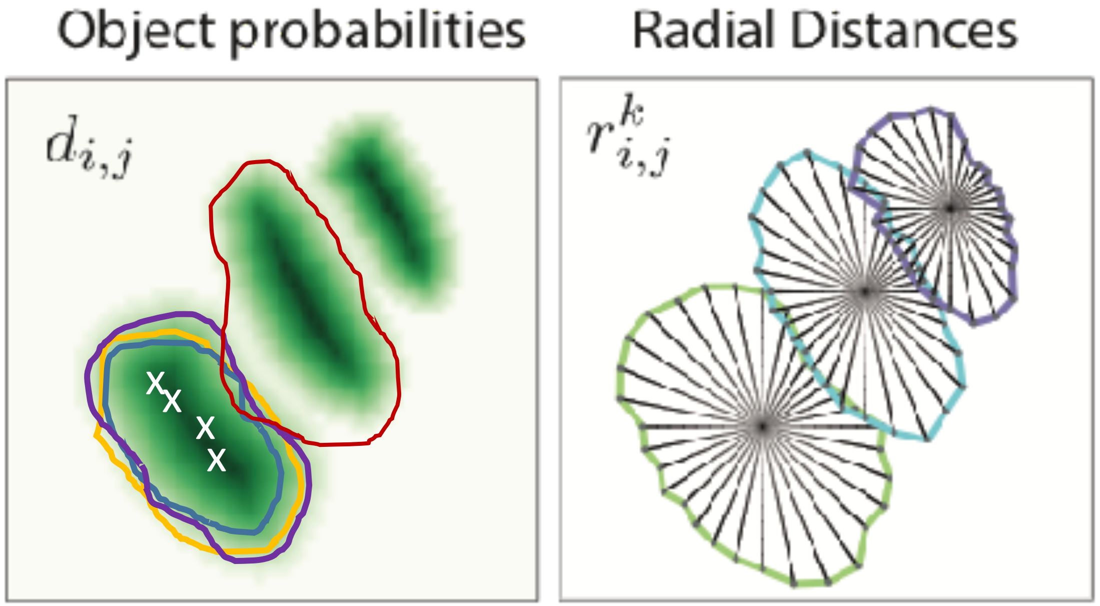
Dense Segmentation
(e.g. U-Net)



Bounding box based methods
(e.g. Mask-RCNN)

Schmid et al., MICCAI (2018), https://github.com/stardist/stardist

Stardist: Non-maximum-suppression resolves overlaps



Non-maximum-suppression (NMS):

→ Object probabilities: Probability that pixel belongs to class “nucleus”

→ Multiple maxima lead to multiple possible polygons for the same nucleus

Algorithm:

→ Select polygon with highest object probability inside:

→ Look at other polygons: Is the overlap of with larger than threshold τ?

  → Yes: and are actually the same object, drop

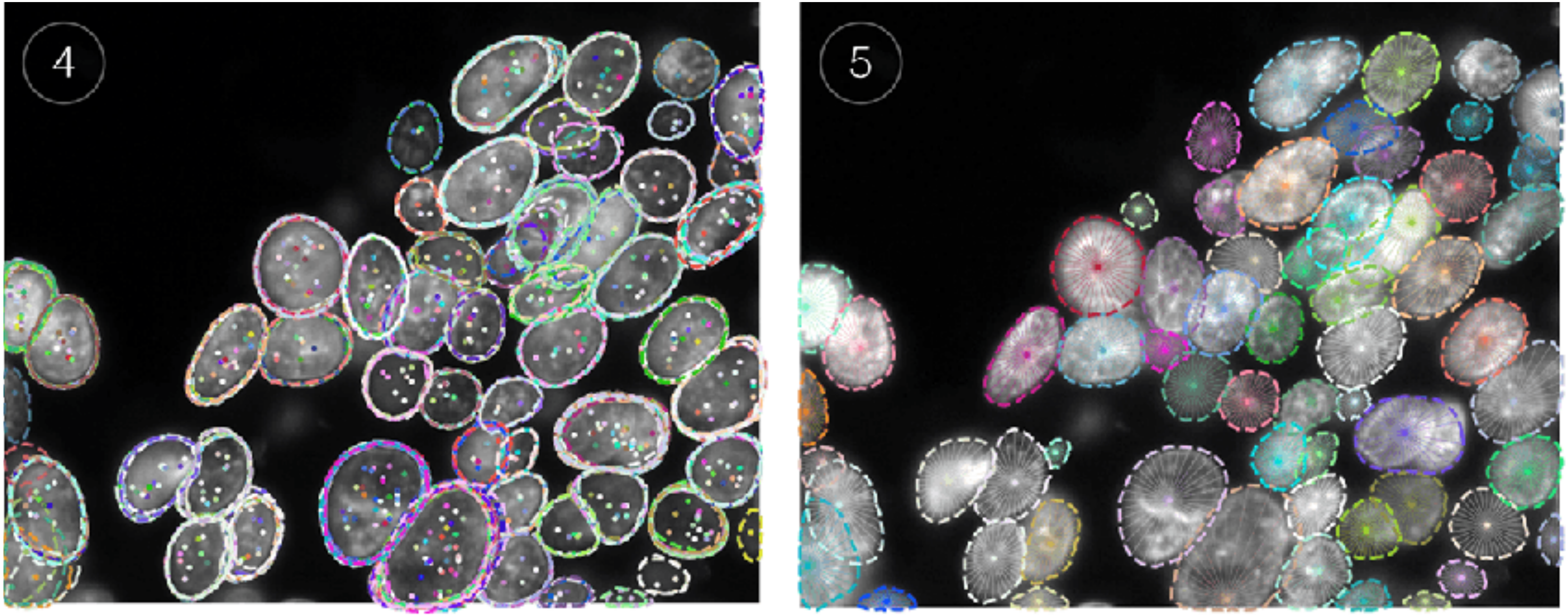
  → No: and are separate nuclei

→ Setting τ very high leads to many false positives!

Schmid et al., MICCAI (2018), https://github.com/stardist/stardist

Stardist: Non-maximum-suppression works well

Non-maximum suppression



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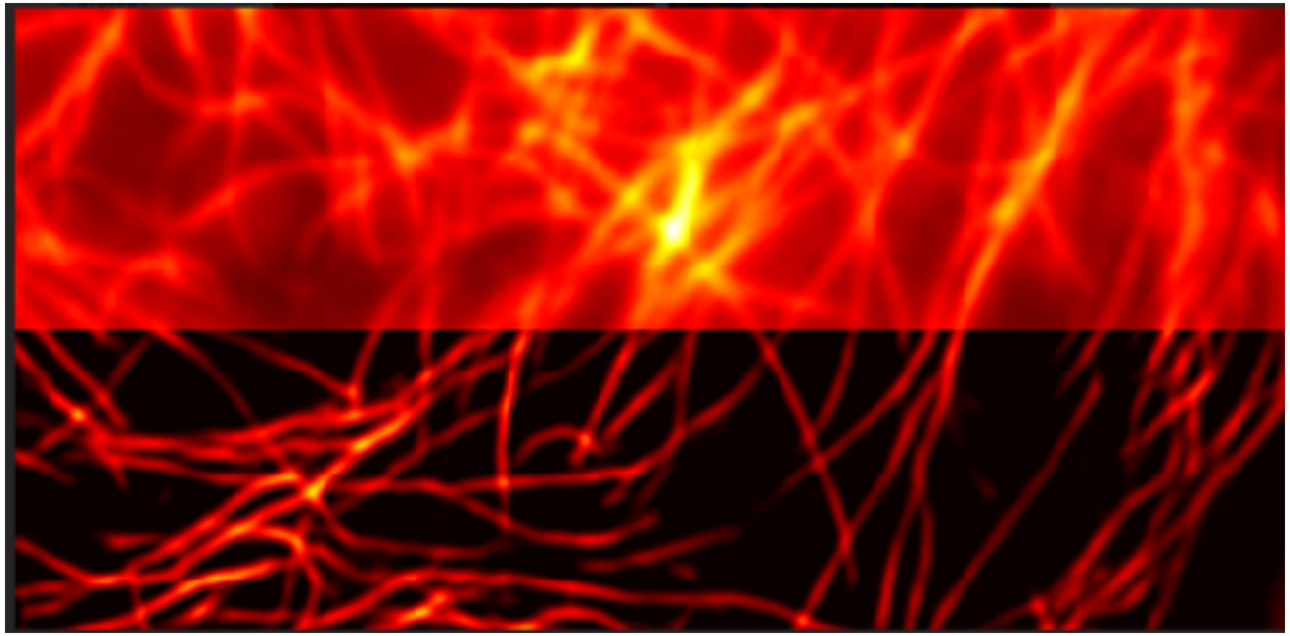
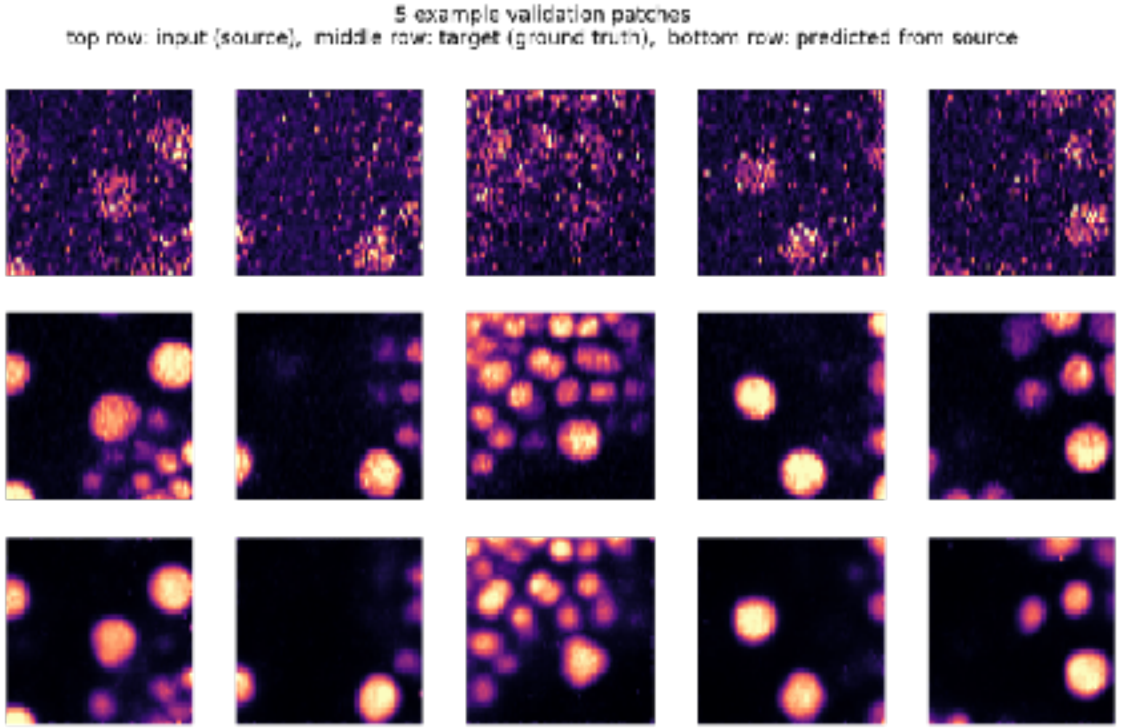
Schmid et al., MICCAI (2018), https://github.com/stardist/stardist

CARE: Improving resolution and denoising

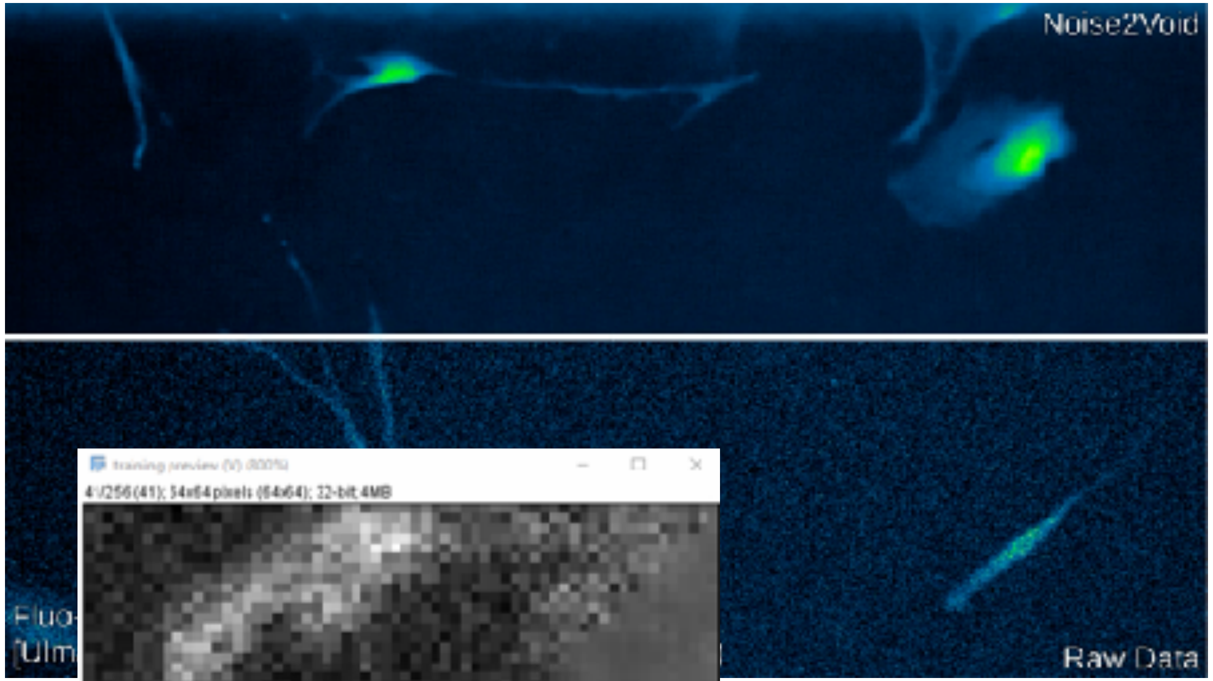
- **CARE**: content-aware restoration
- Image acquisition of pairs of images: A high-quality and a low-quality image.
- Caveats:
  - Reconstructs shot noise present in high quality training images
  - Trained model only applicable to image data of the same conditions (biological sample, microscope, etc)

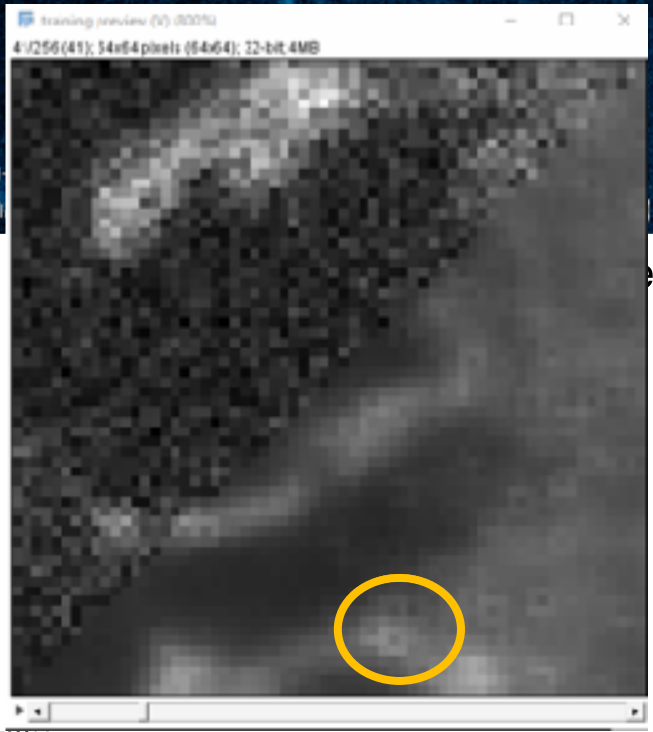


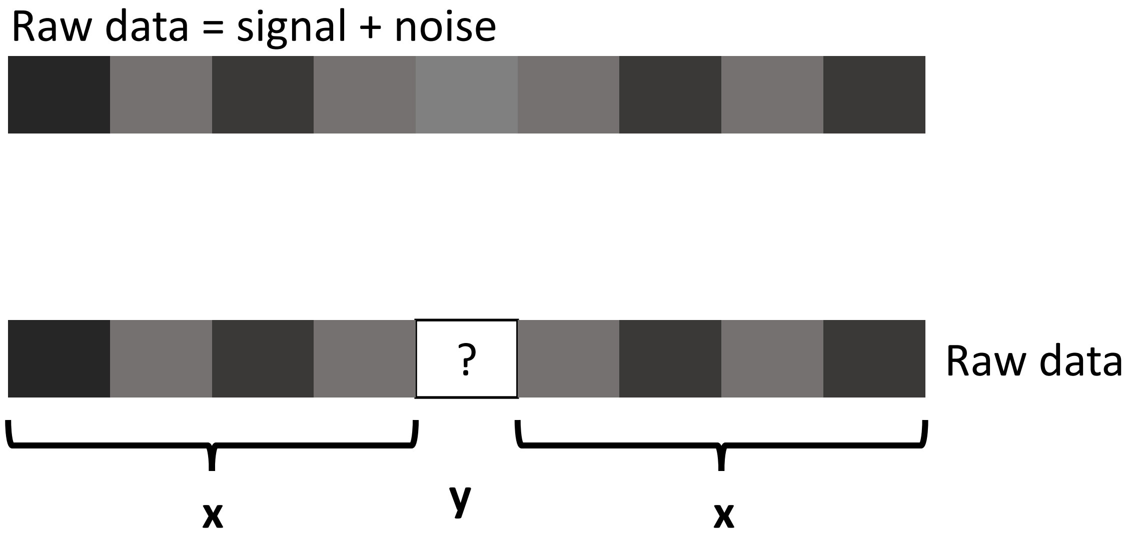


https://csbdeep.bioimagecomputing.com/

Noise to void: Image denoising







Strategy:

→ Try to predict intensity of pixel y from surrounding pixels x

→ CNN fails to predict noise component → N2V can only reproduce signal from the surroundings of **y**

Beware:

→ Only **random** noise can be removed, otherwise artifacts occur

https://github.com/juglab/n2v
https://forum.image.sc/t/n2v-artefacts-in-training-data/70686

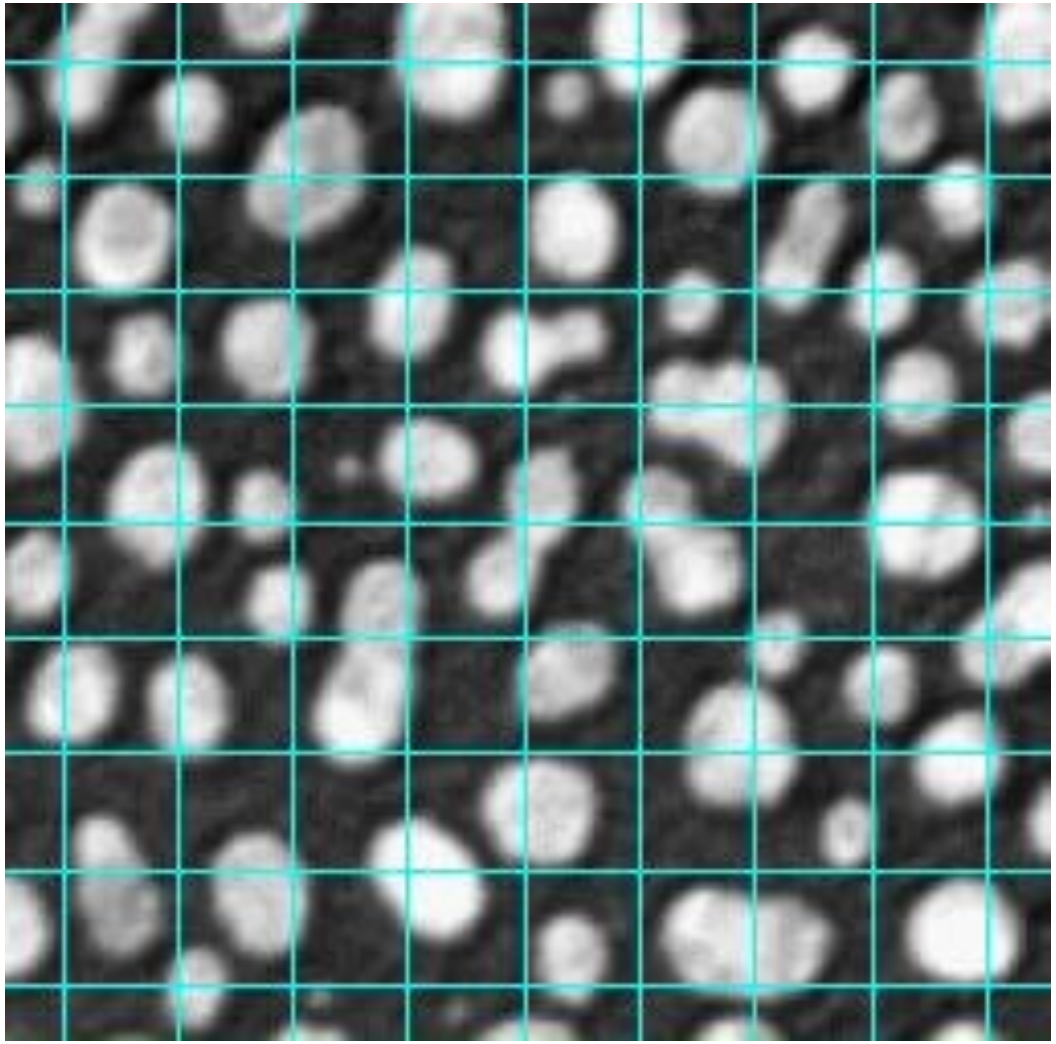
Caveats: GPU memory limits image size

→Images are tiled

→limited “receptive field of the network”

Receptive field:

→Objects must be smaller than receptive field to be detectable



Unbalanced training data leads to biased results

Unbalanced training data:

→Some labels appear more often in training data than others

→Rare events will not be learned because missing them doesn't harm accuracy much

→Weighted data sampling

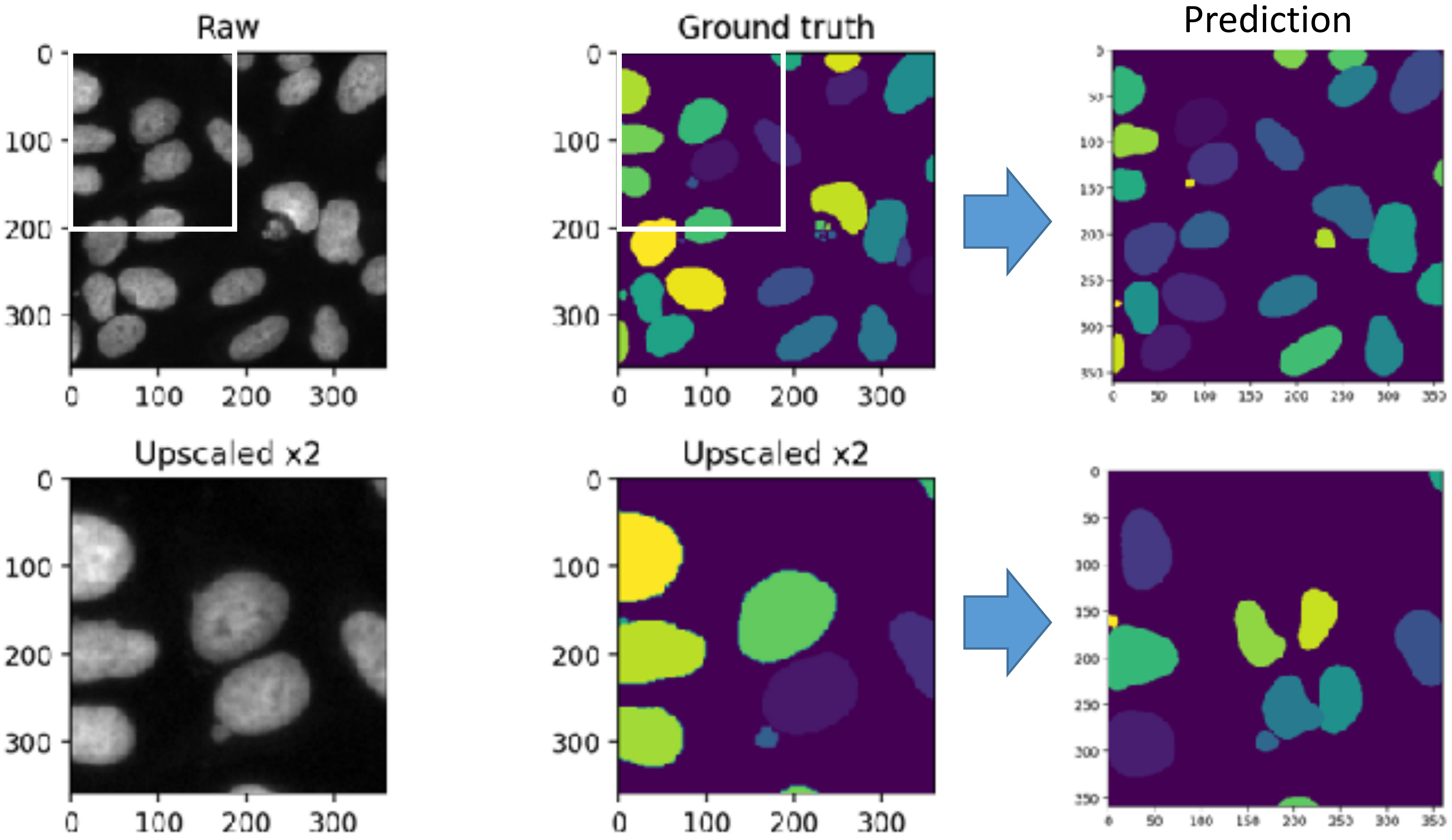
→**Biased results!!**

Is the iPhone racist? Chinese users claim iPhoneX face recognition can't tell them apart

APPLE has come under fire following numerous complaints from Chinese users who claim the iPhone X face recognition can't tell them apart.

https://www.news.com.au/technology/gadgets/mobile-phones/is-the-iphone-racist-chinese-users-claim-iphonex-face-recognition-cant-tell-them-apart/news-story/13814540e8c82ad466aca687e12af64c

When the input data does not fit to the training data



What happened here?

Receptive field too small

I used a different resolution than during training

Overfitting

Takeaways

- With great power comes great responsibility: **Validate your models well!**
- Better data more important than better model
- Often performs fantastic – *but you don't know why*
- Generative neural networks (like CARE) can dream up data – to a hammer everything looks like a nail!