Convolutional neuronal networks

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With Material from
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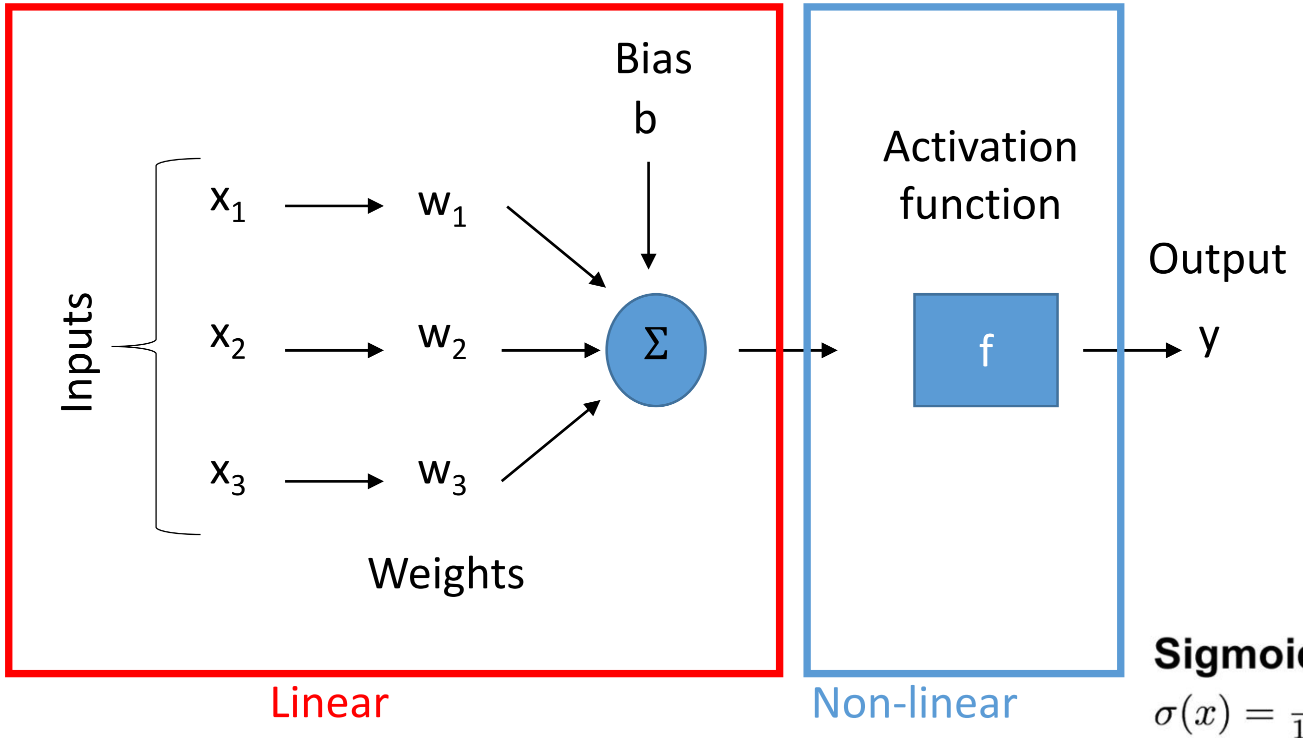
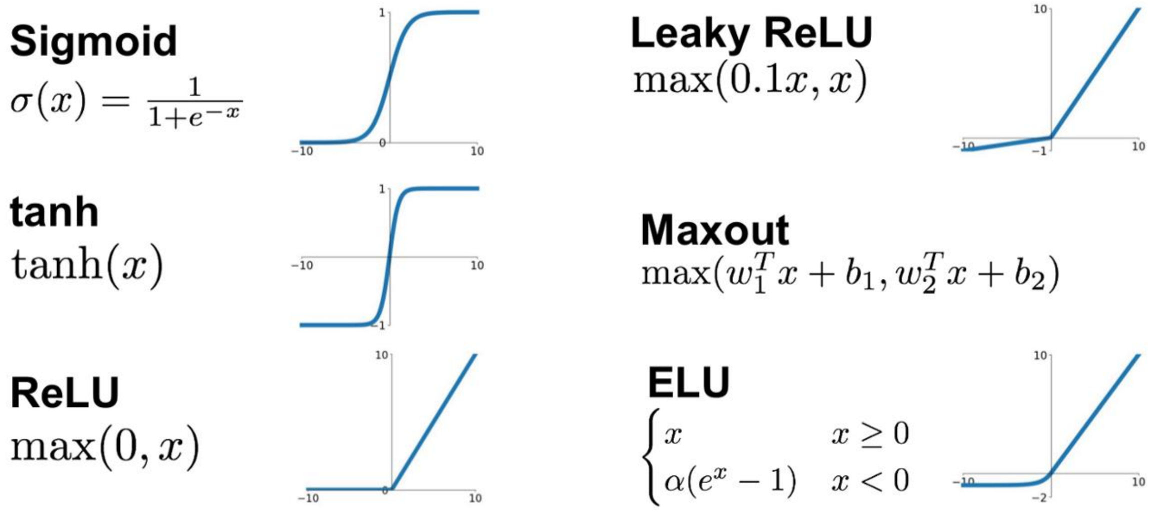
Convolutional neural networks



Single neuron output calculation

$$y = w_1x_1 + w_2x_2 + w_3x_3 + b = w^T x + b$$



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

- Pixel intensities
- Pixel coordinates
- Filter kernel entries

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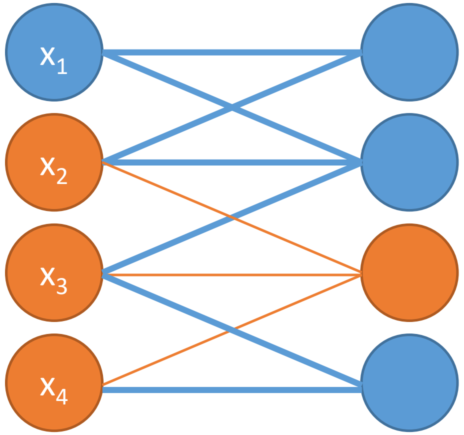
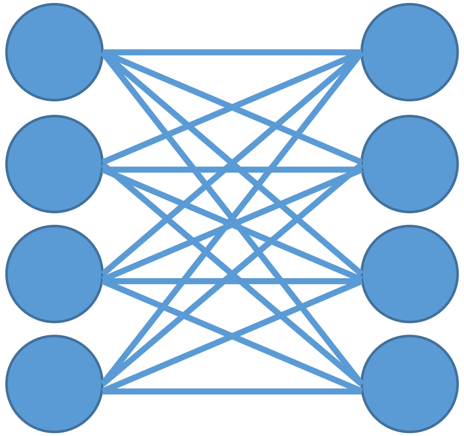
Convolutional neural networks

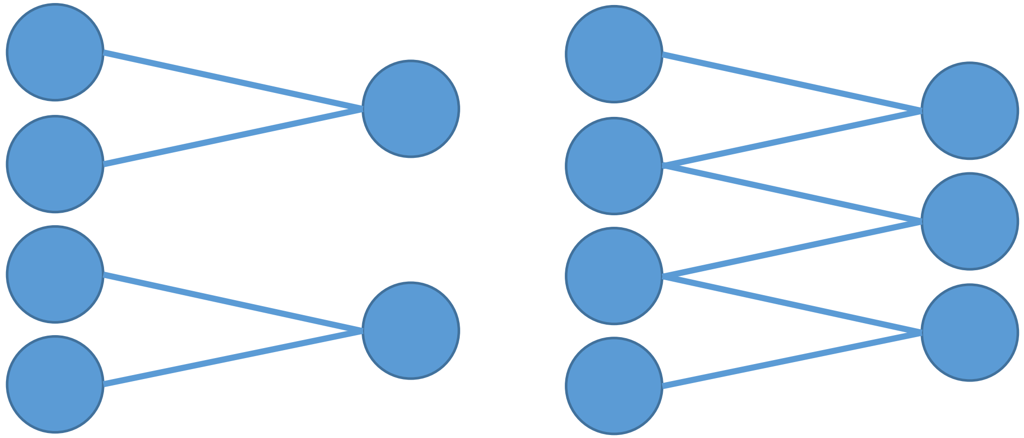
- Layers



Convolutional layer



Fully connected layer



Pooling layer
("Max pool", "Average pool")

Previously:
Defined filter kernels

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

Now:
Undefined filter kernels

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

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

Pooling maximal values

15	13
11	9

Averaging values

8.5	6.0
6.3	5.8

Learning: Back propagation

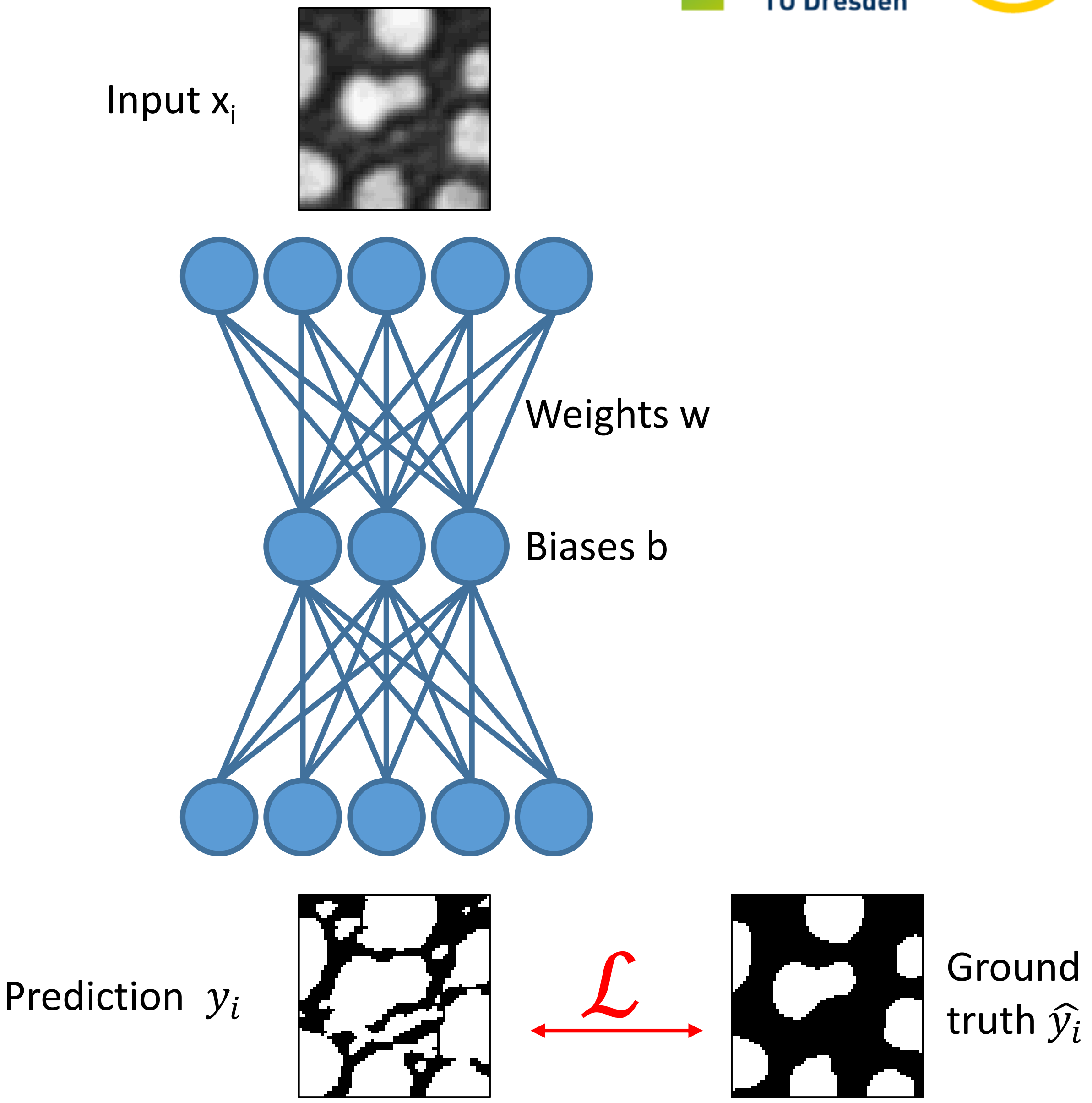
- Learning is an optimization problem

- 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:

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

- Step 3: Update weights



Slide adapted from: Mahmood Nazari, TU Dresde

Back-Propagation Algorithm

The loss function can be expanded from

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

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

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

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

Repeat this n times, each time update weights w

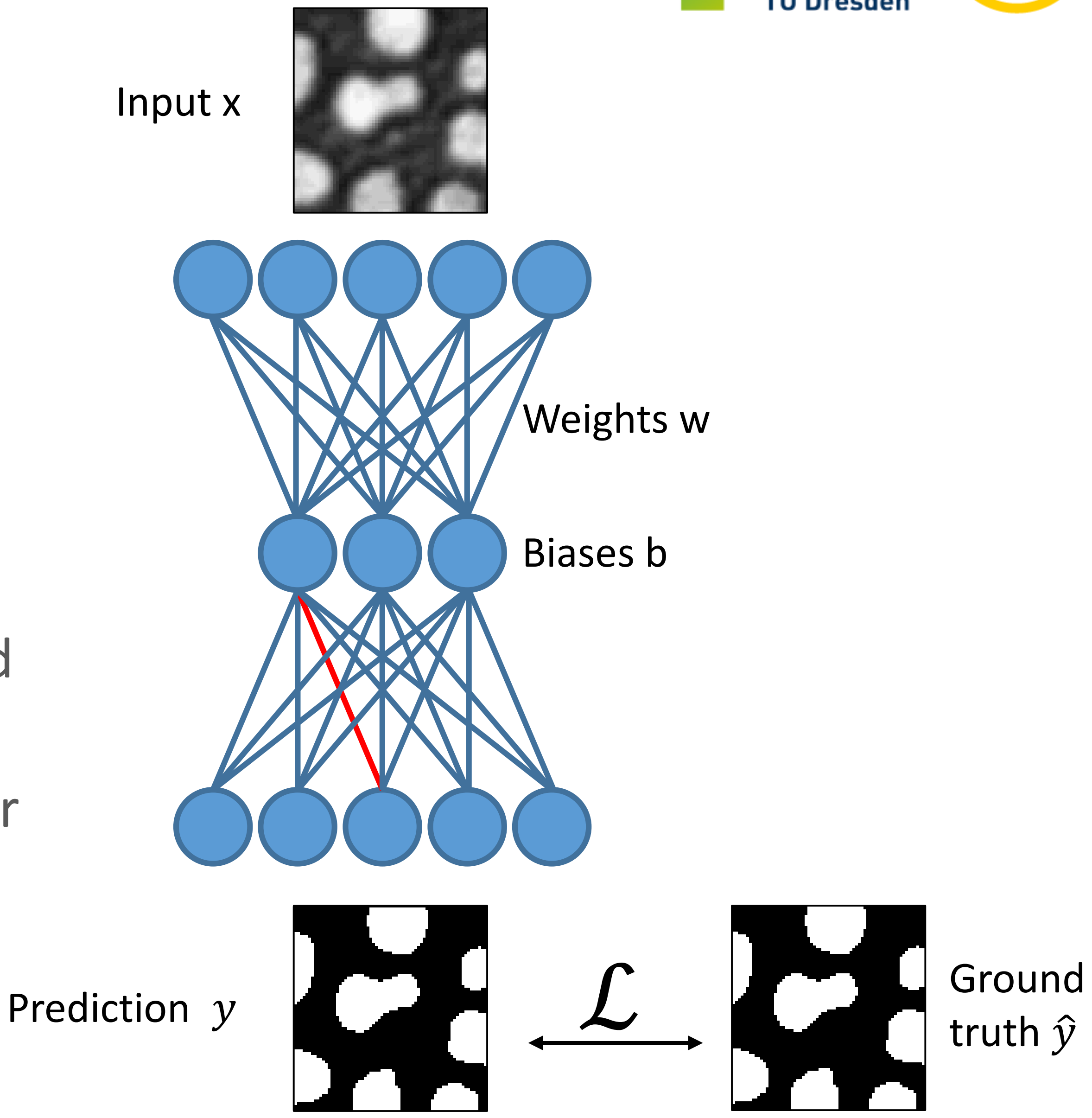
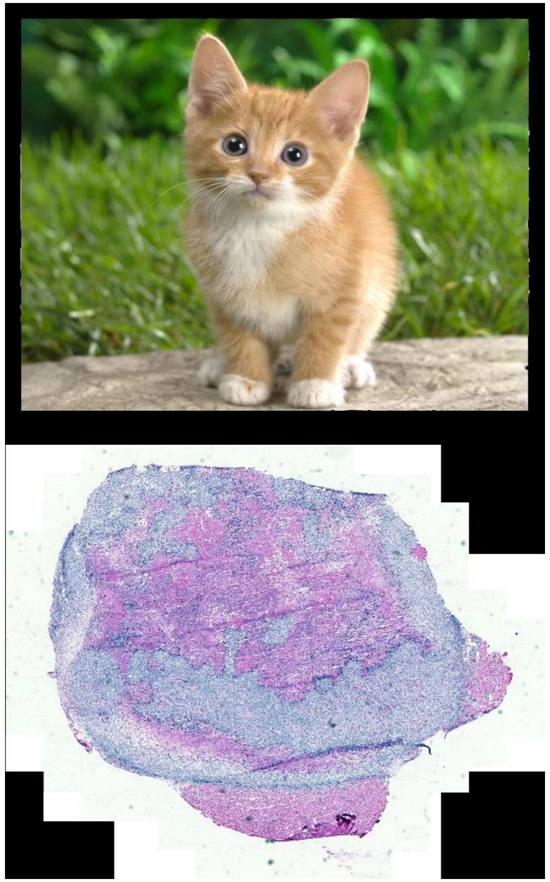
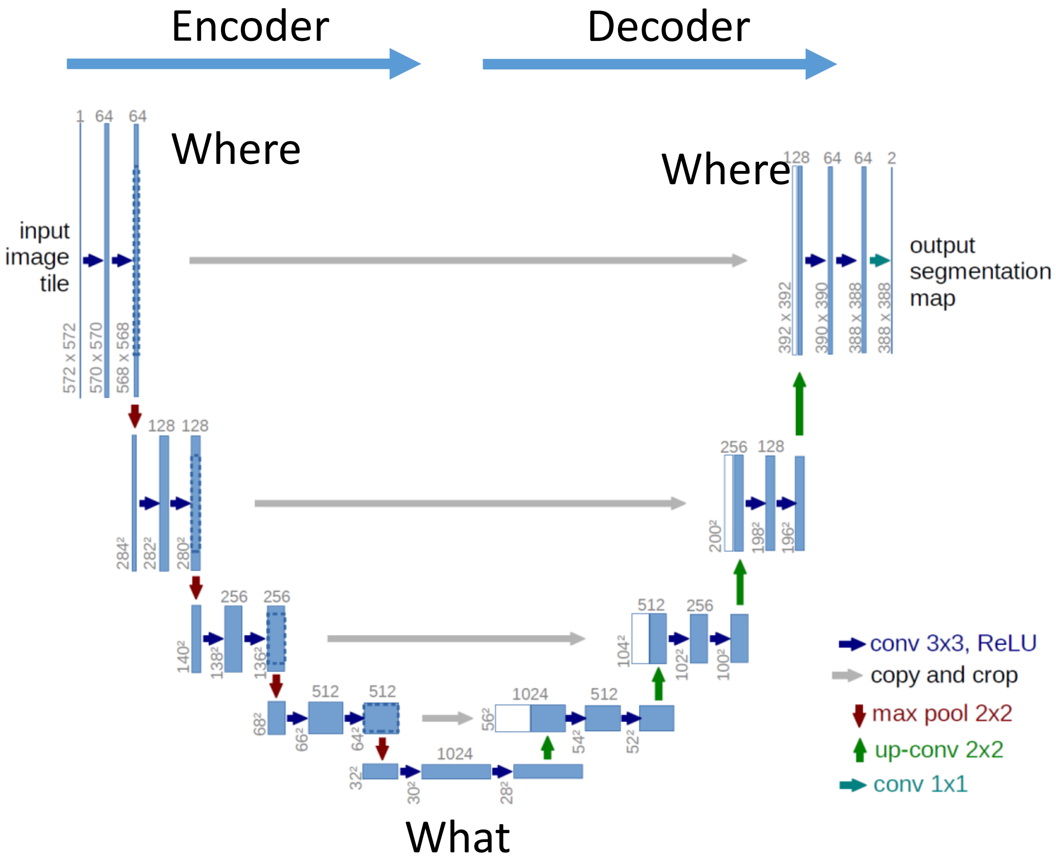
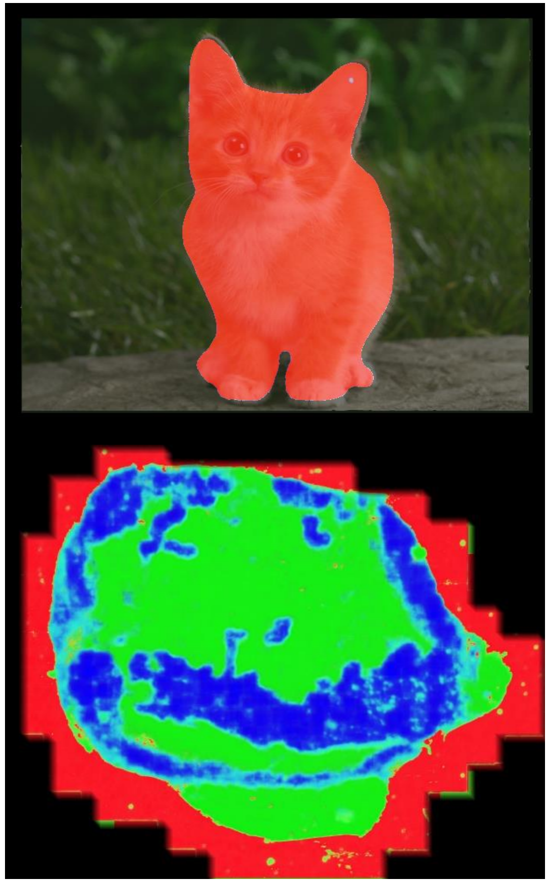


Image segmentation







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

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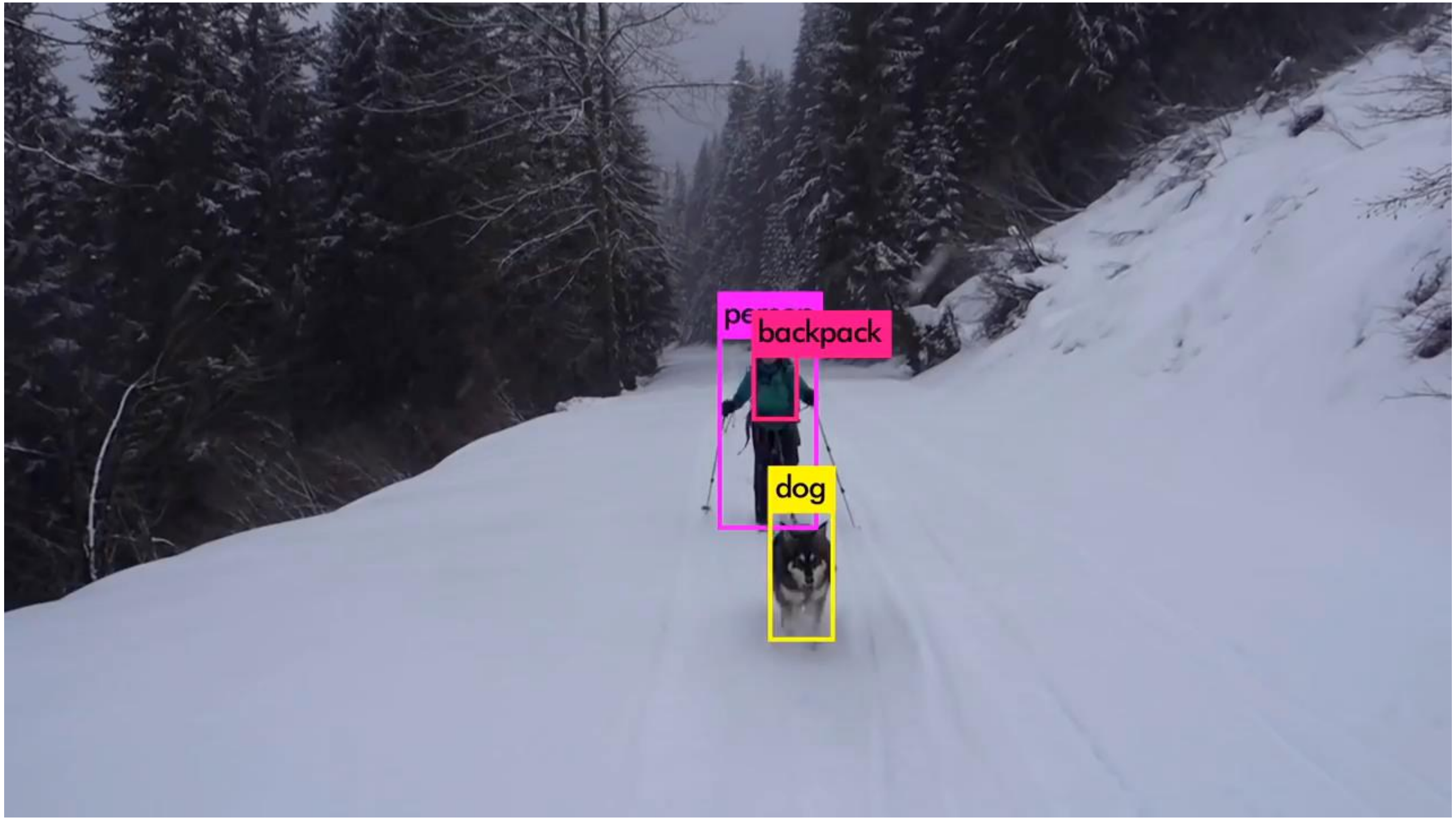
Ronneberger et al. (2015): U-Net: Convolutional Networks for Biomedical Image Segmentation

Object detection: YOLO

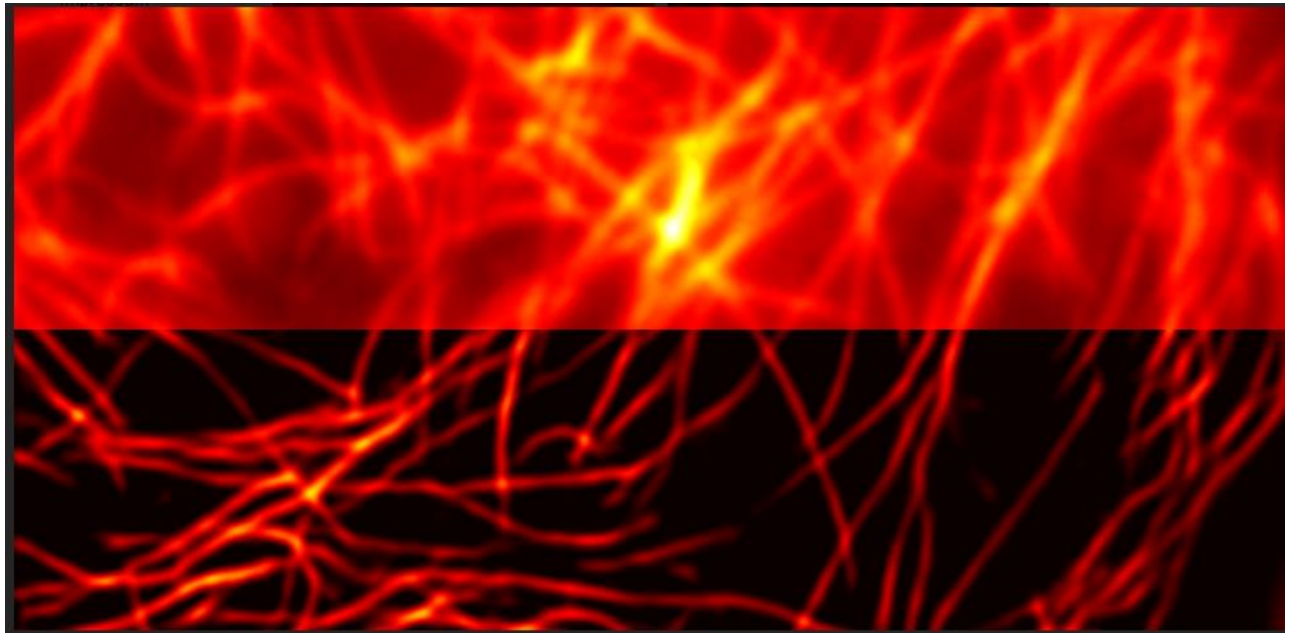
YOLO: You only look once



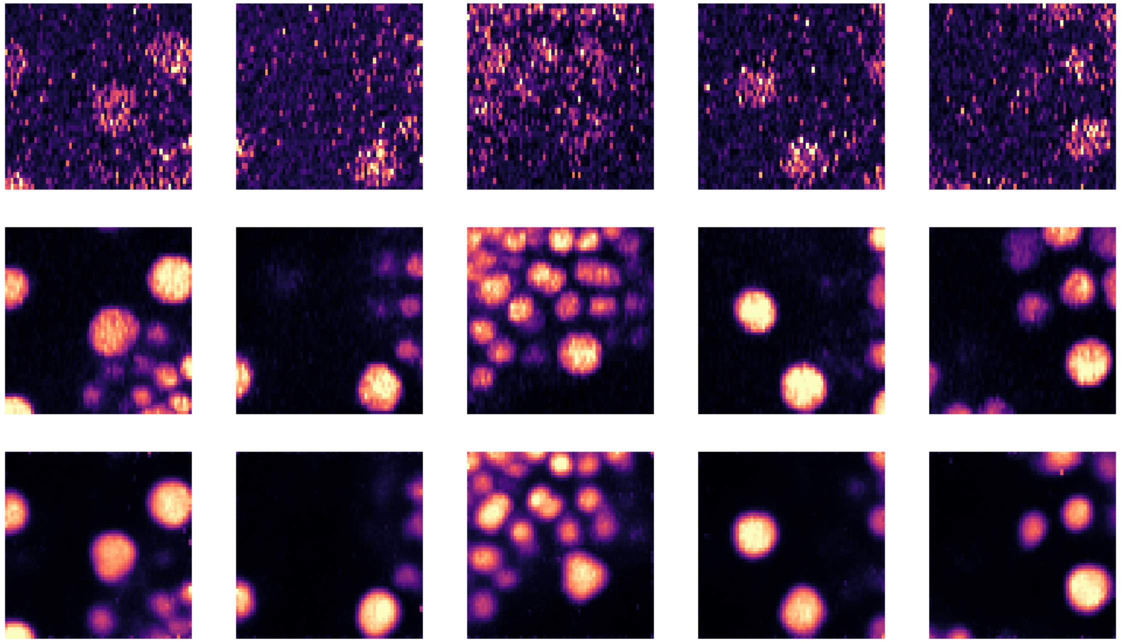
https://github.com/ultralytics/yolov5

Image denoising

- **CARE**: content-aware restoration
- Image acquisition of pairs of images: A high-quality and a low-quality image.
- Problem: Shot noise, Biology moves!
- Trained model only applicable to image data of the same conditions (biological system, microscope, etc)



5 example validation patches
top row: input (source), middle row: target (ground truth), bottom row: predicted from source



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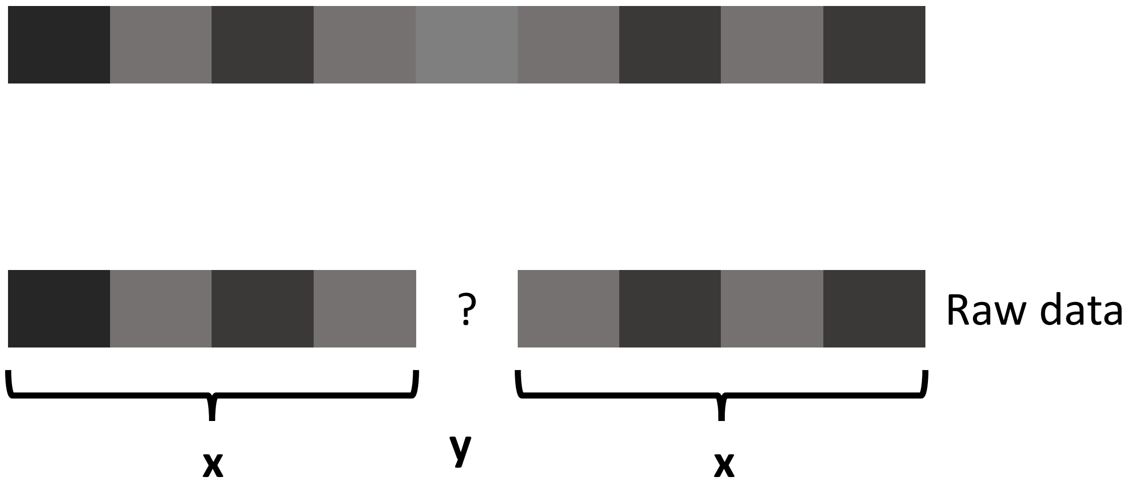
https://csbdeep.bioimagecomputing.com/

Image denoising

Raw data = signal + noise



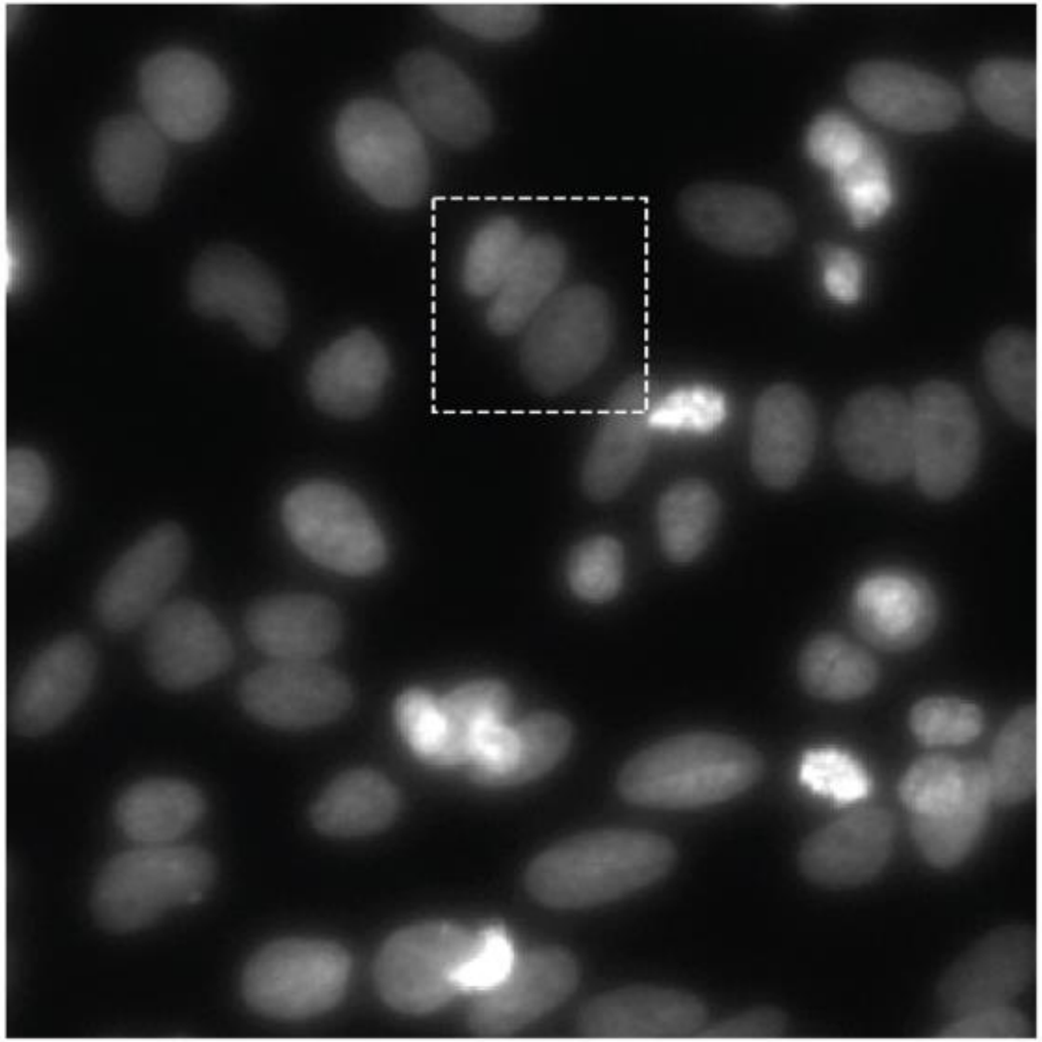
Strategy:

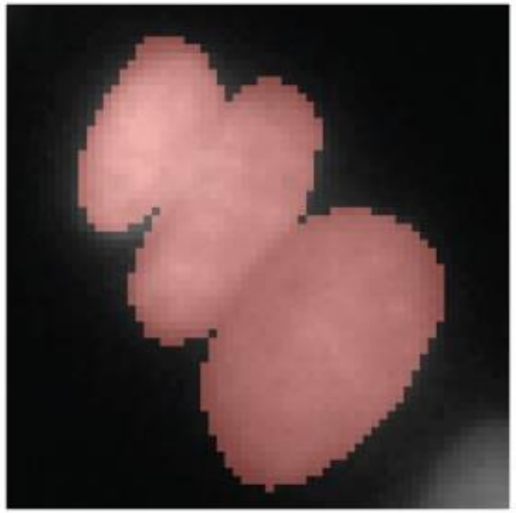
→ Try to predict intensity of pixel y from surrounding pixels x
→ CNN fails to predict noise component → N2V can only reproduce signal from the surroundings of **y**
→ Only **random** noise can be removed, otherwise artifacts occur

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

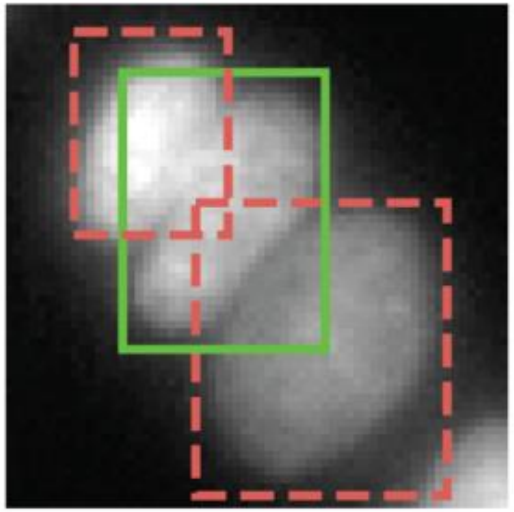
Stardist: Nucleus segmentation

Noisy images + Crowded cells = Common source of segmentation errors





Dense Segmentation
(e.g. U-Net)



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

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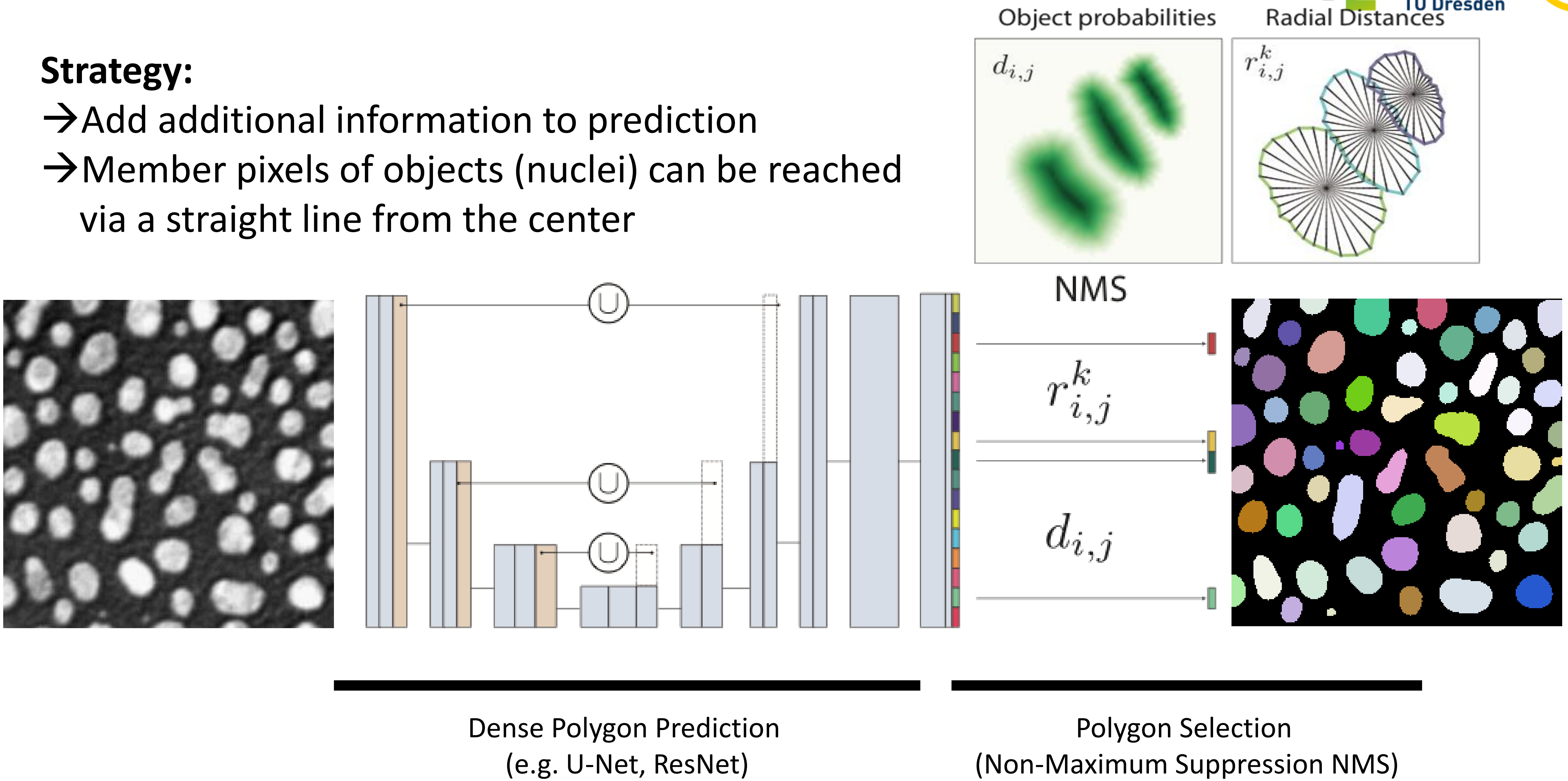
Schmid et al., MICCAI (2018)

Stardist: Nucleus segmentation

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



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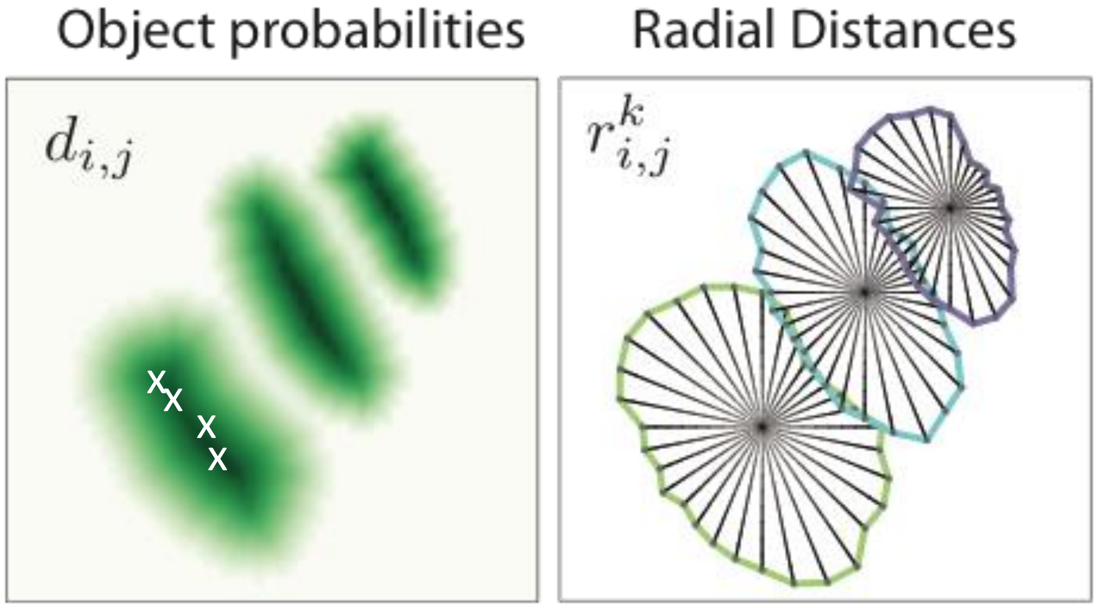
Schmid et al., MICCAI (2018)

Stardist: Nucleus segmentation



Problem:

→ Multiple candidate points for nucleus center

→ Overlapping instance predictions

Non-maximum-suppression (NMS):

→Intersection over Union (IoU) threshold τ determines „conservativeness“:

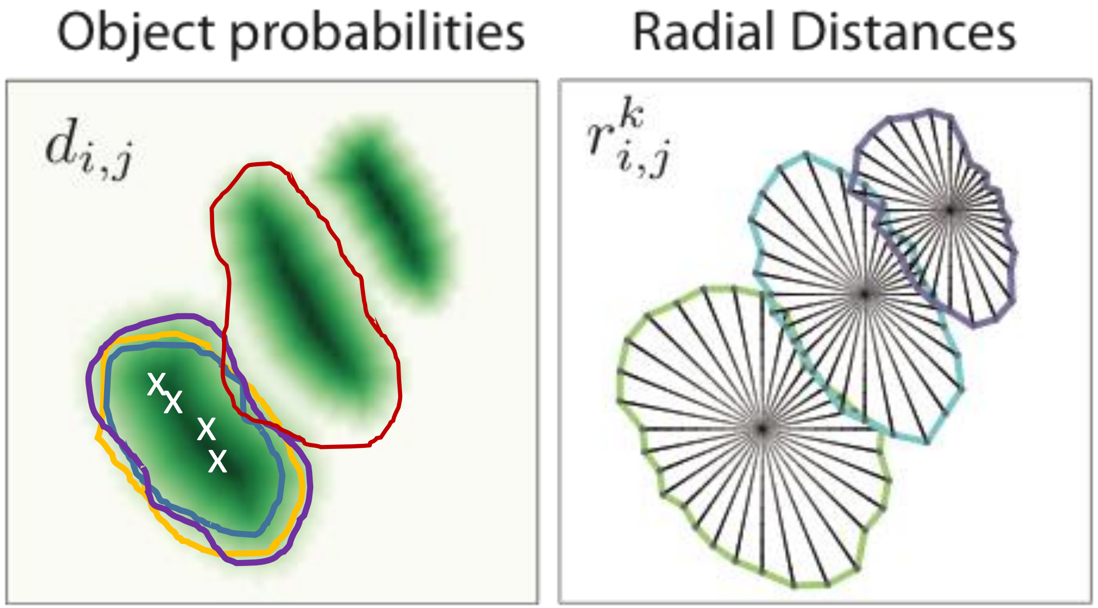
High τ: Objects tend to be considered as separate objects

Low τ: Objects tend to be considered as the same objects

https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

Schmid et al., MICCAI (2018)

Stardist: Nucleus segmentation



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?

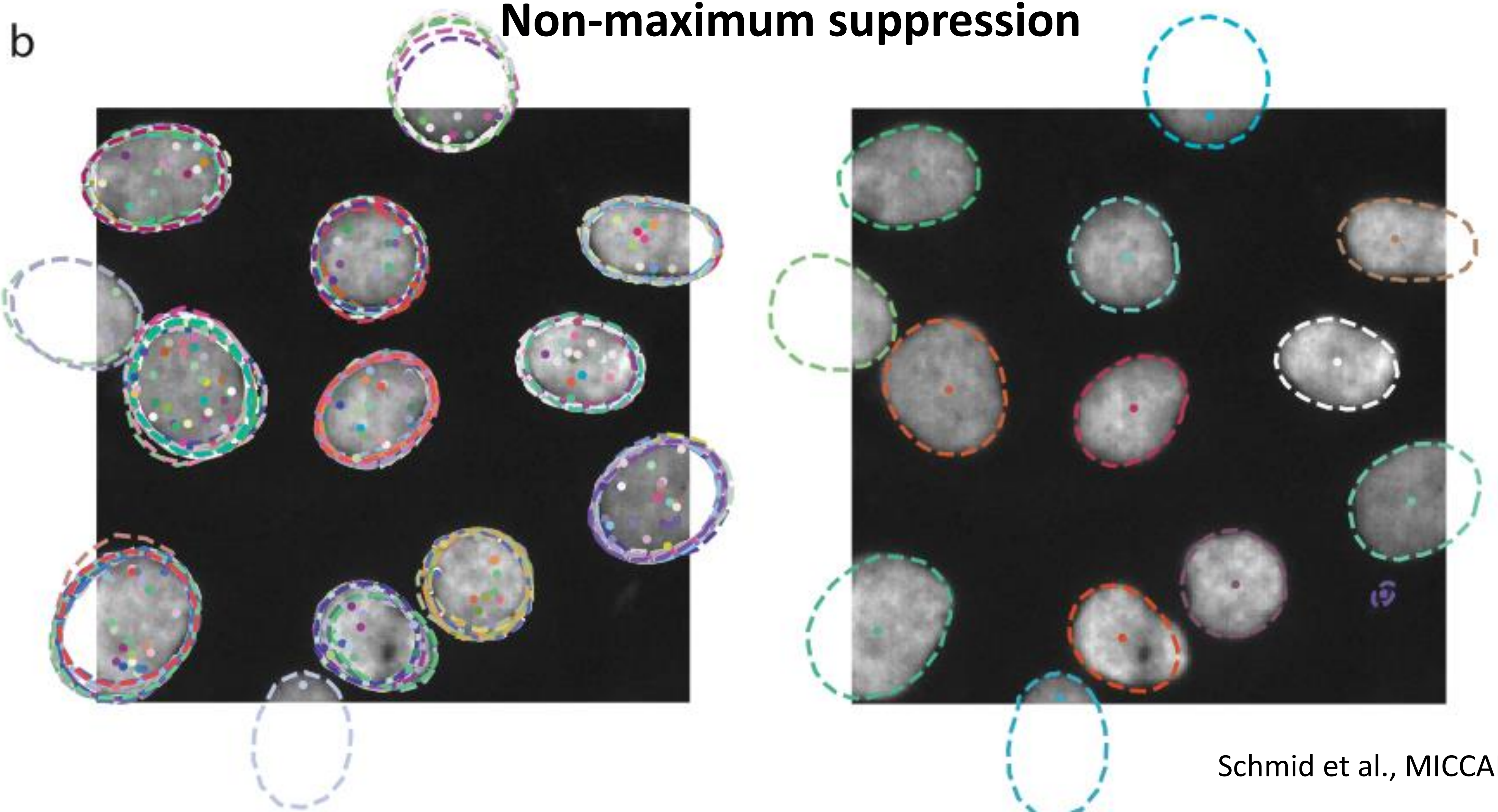
  → Yes: and are actually the same object, drop

  → No: and are separate nuclei

→ Setting τ very high leads to many false positives!

Stardist: Nucleus segmentation

Non-maximum suppression

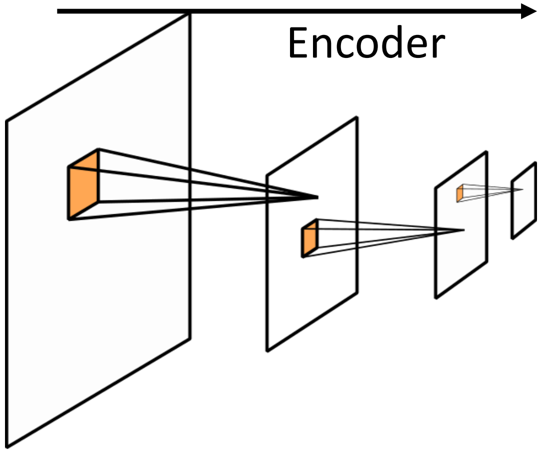


@jn

Schmid et al., MICCAI (2018)

Things to consider

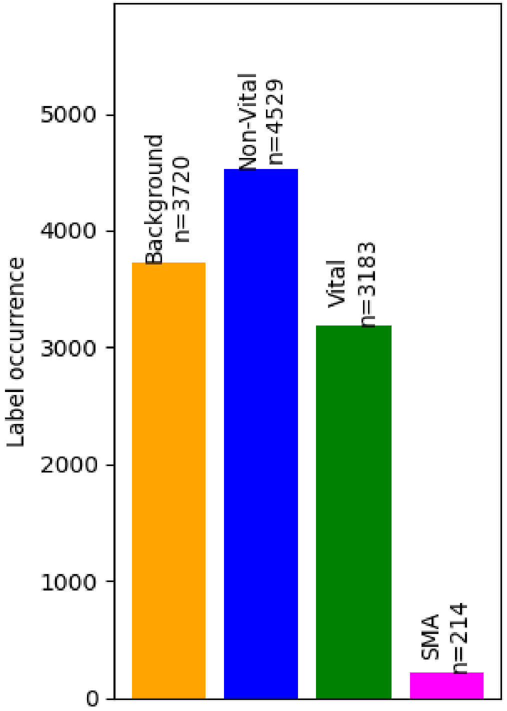
Many prediction frameworks use UNets – similar weak points

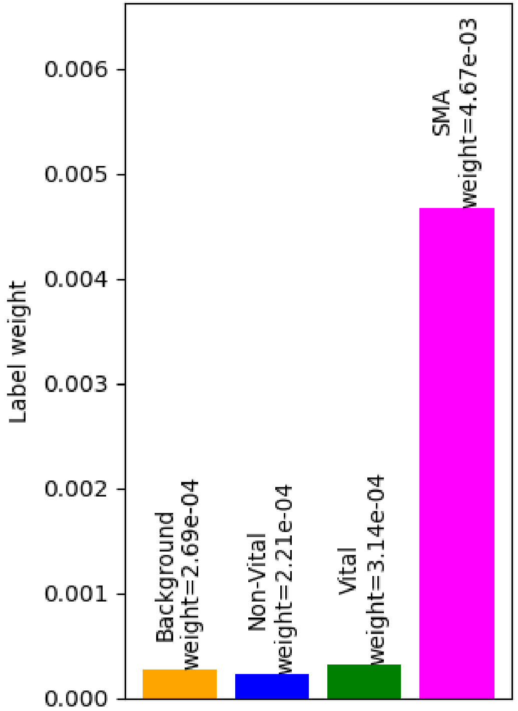


Receptive field:

→Neurons in deeper layers can only “see” parts of the raw image

→Objects must be smaller than receptive field to be detectable





Unbalanced training data:

→Heterogeneous occurrence of labels in training data

→Rare events will not be caught because they don’t harm accuracy much

→Weighted data sampling

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/

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Implementation aspects

Popular frameworks: https://www.tensorflow.org/ , https://www.pytorch.org/

PyTorch TensorFlow

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

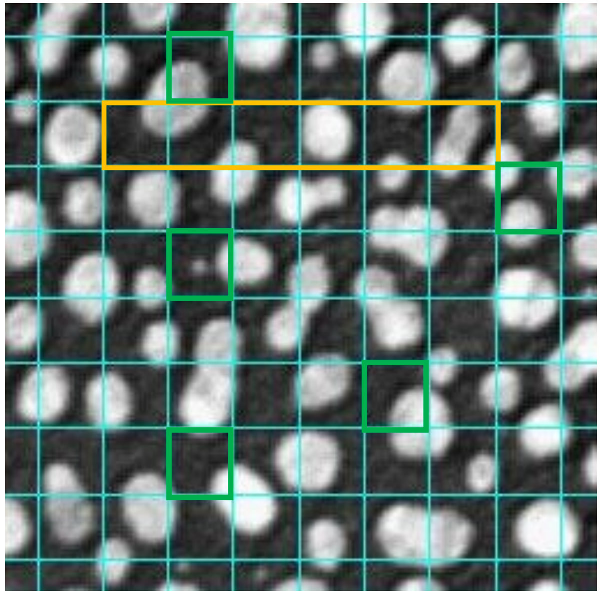
Memory: GPU memory limits < RAM memory → Images are tiled and passed through the network in *batches*

Batch-processing:

Batch dimension
Channel dimension

→For 2D multichannel image: data.shape = [B, C, Y, X]

→Batch normalization: Data in batch is normalized from [-σ, σ] → [-1, 1]
Higher batch size, smaller tiles → Better generalization of image statistics
Lower batch size, bigger tiles → Potentially larger receptive field



Tiles in batch   Tiles in batch

Train/test/validation split:

→During training: Measure performance (“*loss*”) of network, **update weights**

→During testing: Measure performance of updated network, **keep weights**

1 epoch

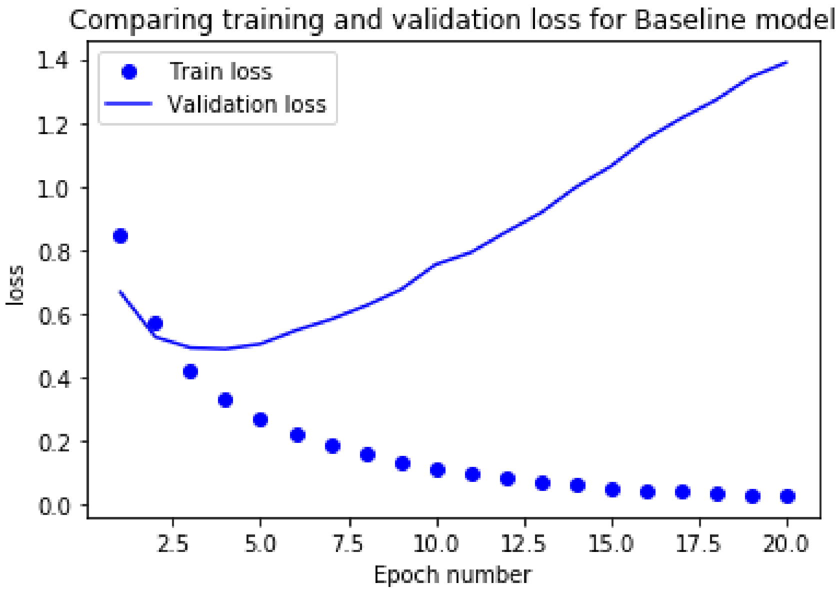
→Validation: Measure performance in **unseen** validation dataset

Implementation aspects

Training loss: Binary cross-entropy (Measure for information in image A contained in image B)

Test loss: Label-wise accuracy

→ We use different metrics in training/testing!

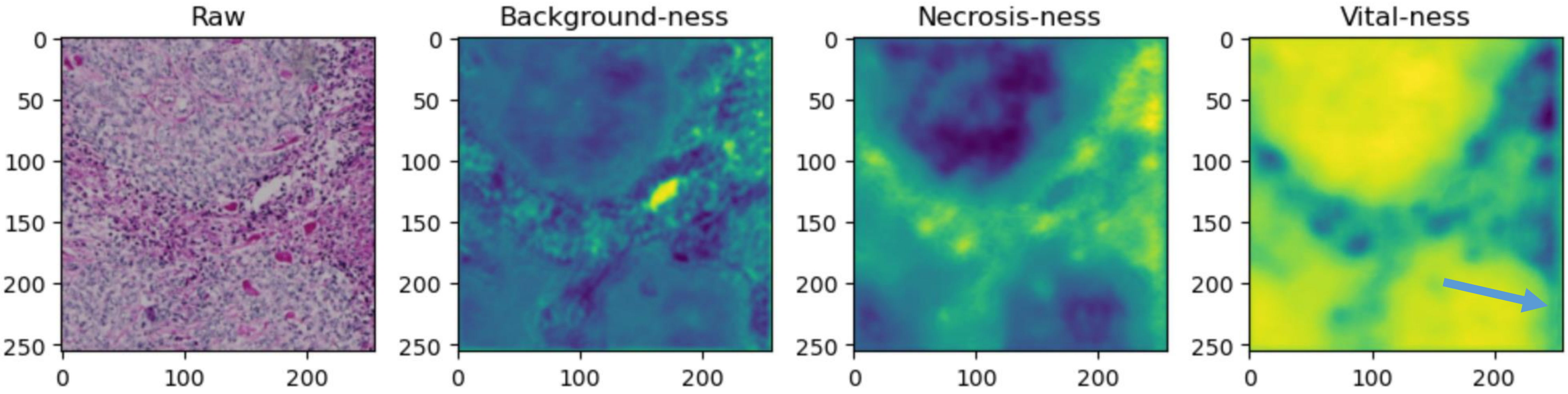


Overfitting:

→ Network is learning things „by heart“

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

Implementation aspects



0^{th}-batch

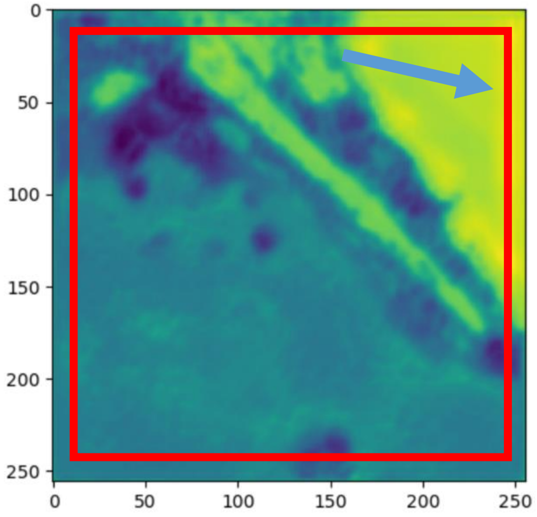
```
data['image'][0].shape
```

```
torch.Size([3, 256, 256])
```

```
data['prediction'][0,0]
```

```
data['prediction'][0,1]
```

```
data['prediction'][0,2]
```

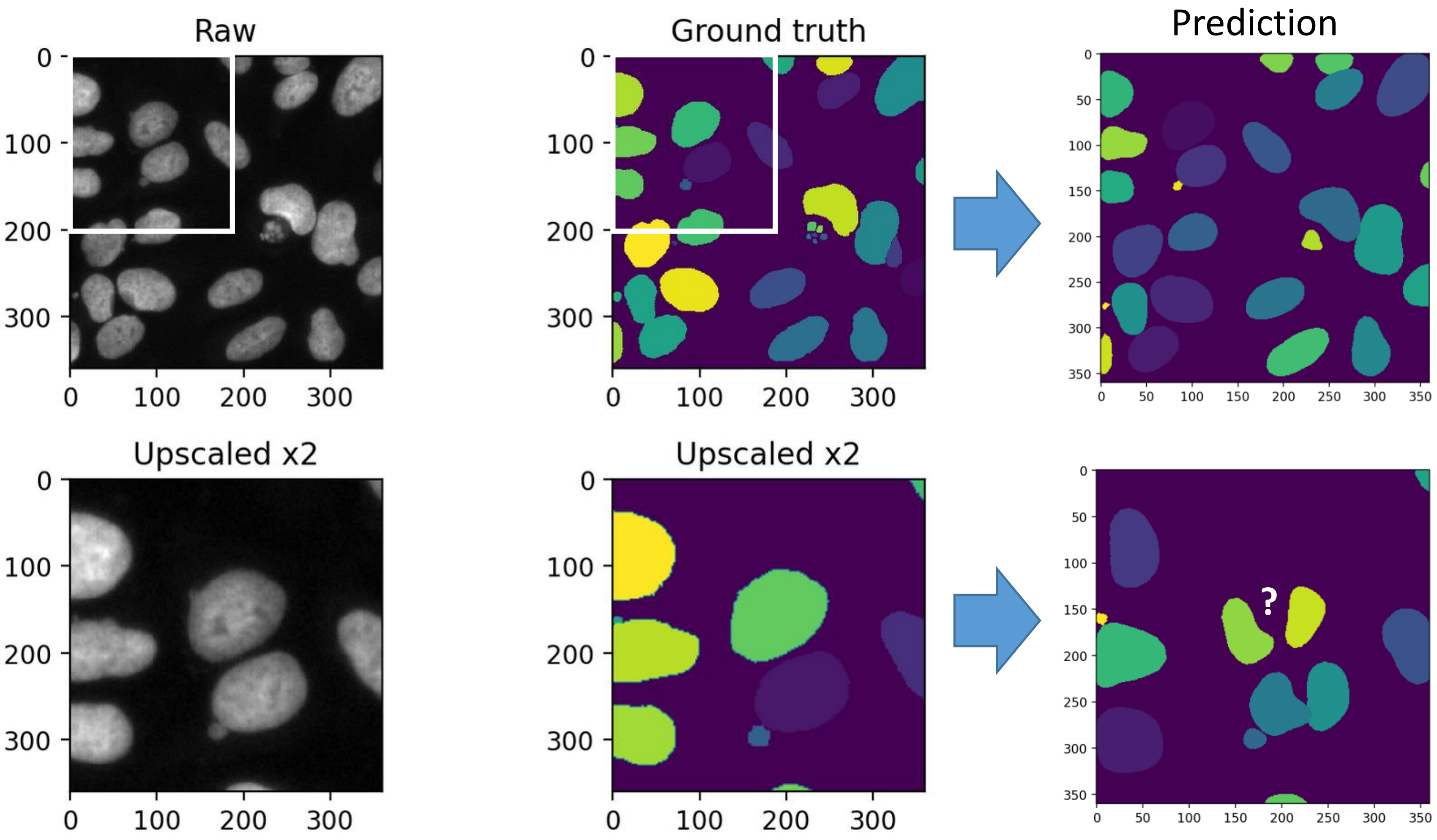


Stride:

→ Network can not predict accurately at image edges

→ We throw away a X-pixel wide margin at the image edge

Example



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 > better model