



TEACHING CONVOLUTIONAL NEURAL NETWORKS

Till Korten

With Material from

Johannes Müller, Robert Haase: PoL

Alex Krull, Uwe Schmidt: MPI CBG

Martin Weigert: EPFL Lausanne

Ignacio Arganda-Carreras: Universidad del País Vasco

WHAT TO EXPECT

- 30 min presentation:
 - Teaching methods
 - Fundamentals of CNNs
- 60 min flipped classroom session
- 30 min break
- 60 min pair programming session
- 30 min feedback and discussion

CLASSICAL LECTURE

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- Lecture given by teacher (this presentation)
- Learners prepare exercises on their own
- Teaching assistants grade exercises
- Pro:
 - Familiar for teachers and learners
- Con:
 - One speed for all (too slow for some, too fast for others)
 - Once learners lose track, they remain lost
 - Wasted opportunity of being in a group

FLIPPED CLASSROOM

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- Learners individually study materials (before course)
- Exercises solved by group in class
- Materials must be suited for self-study
- Pro:
 - Learners study at their own pace
 - Learner explain exercises to each other: they still remember what was the key information for them to understand
 - Time efficient
- Con:
 - Puts more responsibility on the learners: Learners that do not study will be completely lost

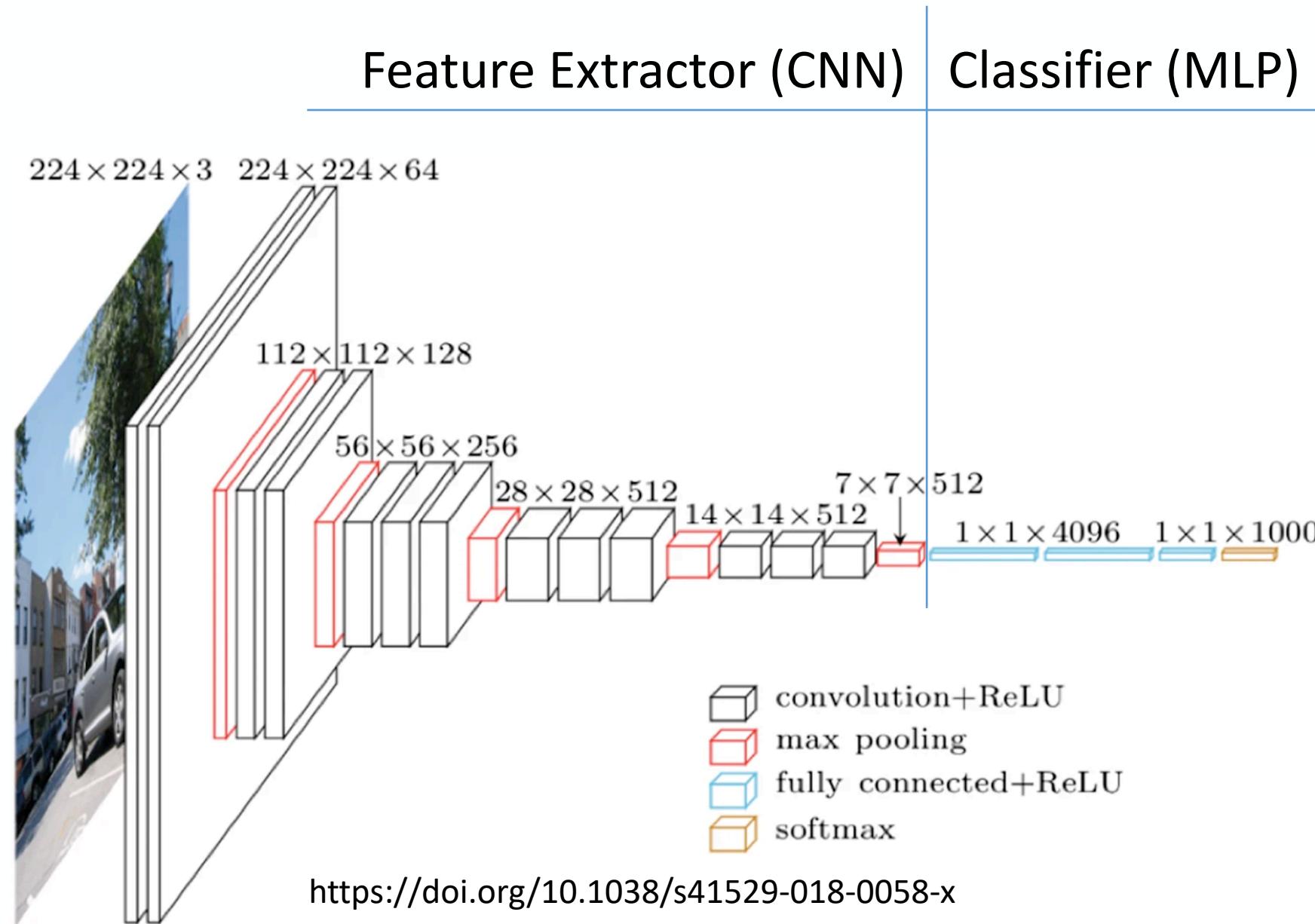
PAIR PROGRAMMING

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- Learners study materials and prepare exercises in small groups
- Materials and exercises are discussed in class
- Works very well online (breakout rooms)
- For coding:
 - One person writes code (=driver, attention to detail)
 - The others advise and consult (=navigators, high level attention)
 - IMHO hands down the best method for teaching to code
- Pro:
 - Learning is more fun and more efficient in small groups
- Con:
 - Logistics in presence: Noise in large classrooms / Needs a lot of space

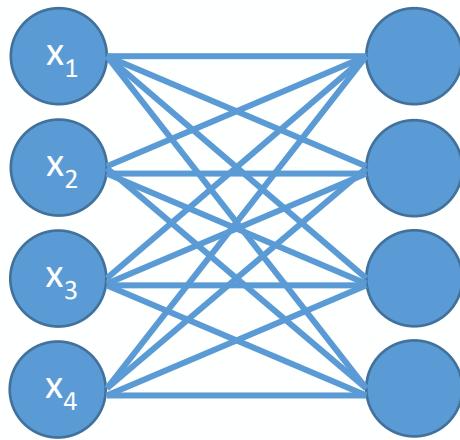
CNN EXTRACT FEATURES FROM IMAGES

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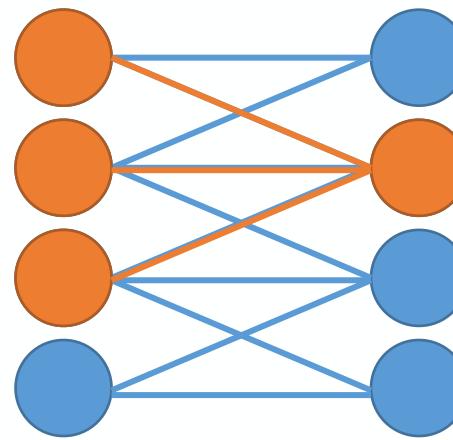


NETWORK LAYER ARCHITECTURES

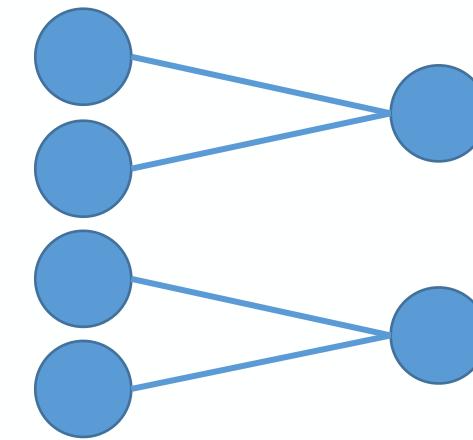
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Fully connected layer



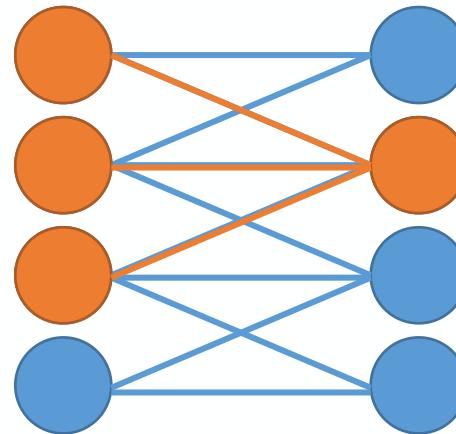
Convolutional layer



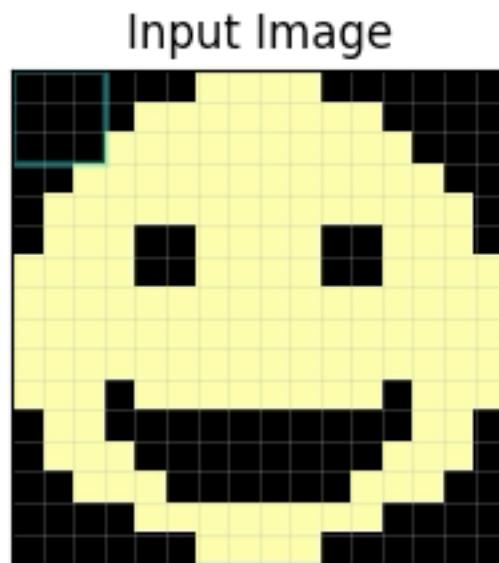
Pooling layer

CNN - CONVOLUTION WITH LEARNED KERNELS

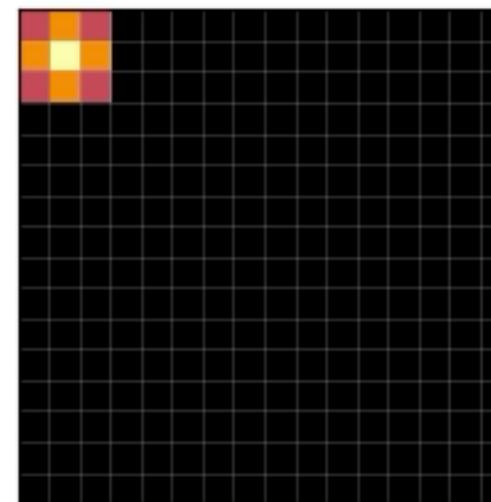
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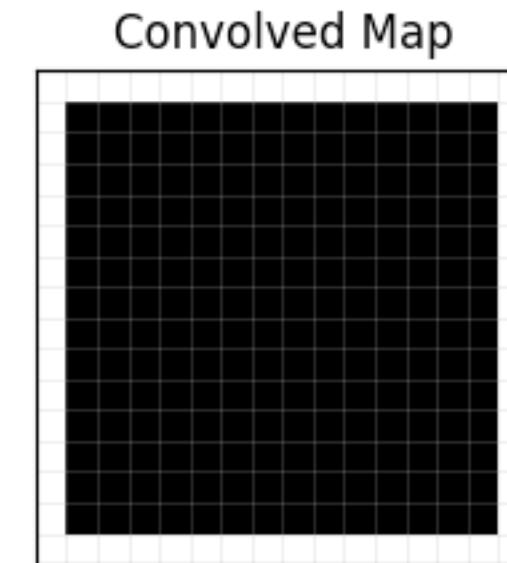
Convolutional layer



Input Image



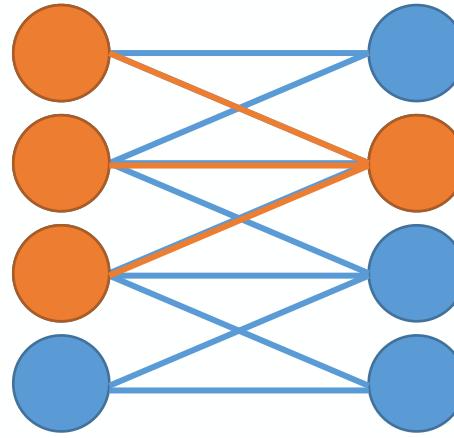
Kernel Position



Convolved Map

CNN - CONVOLUTION WITH LEARNED KERNELS

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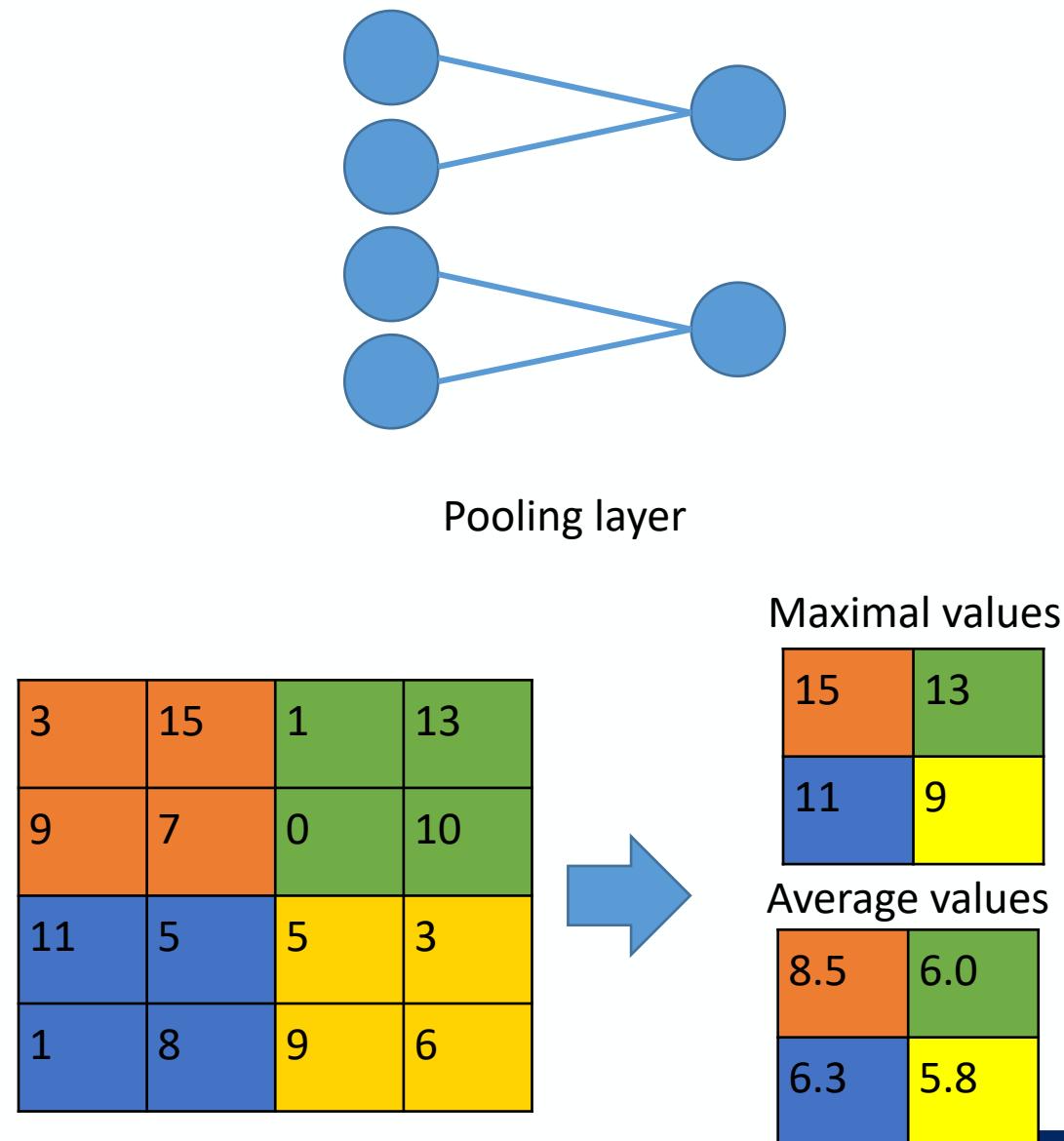


Convolutional layer

- Convolution operation enforces spatial invariance in the network architecture
- Reduces number of parameters
- Makes networks much more computationally and data efficient

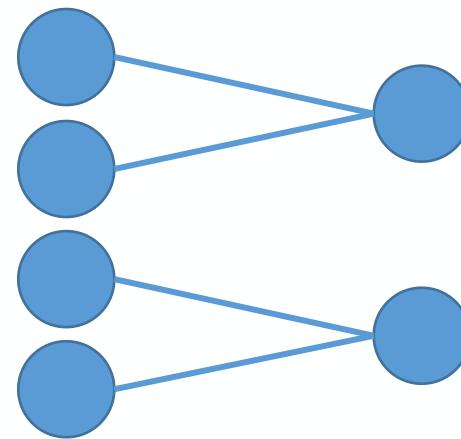
POOLING LAYERS REDUCE THE LAYER SIZE

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POOLING LAYERS REDUCE THE LAYER SIZE

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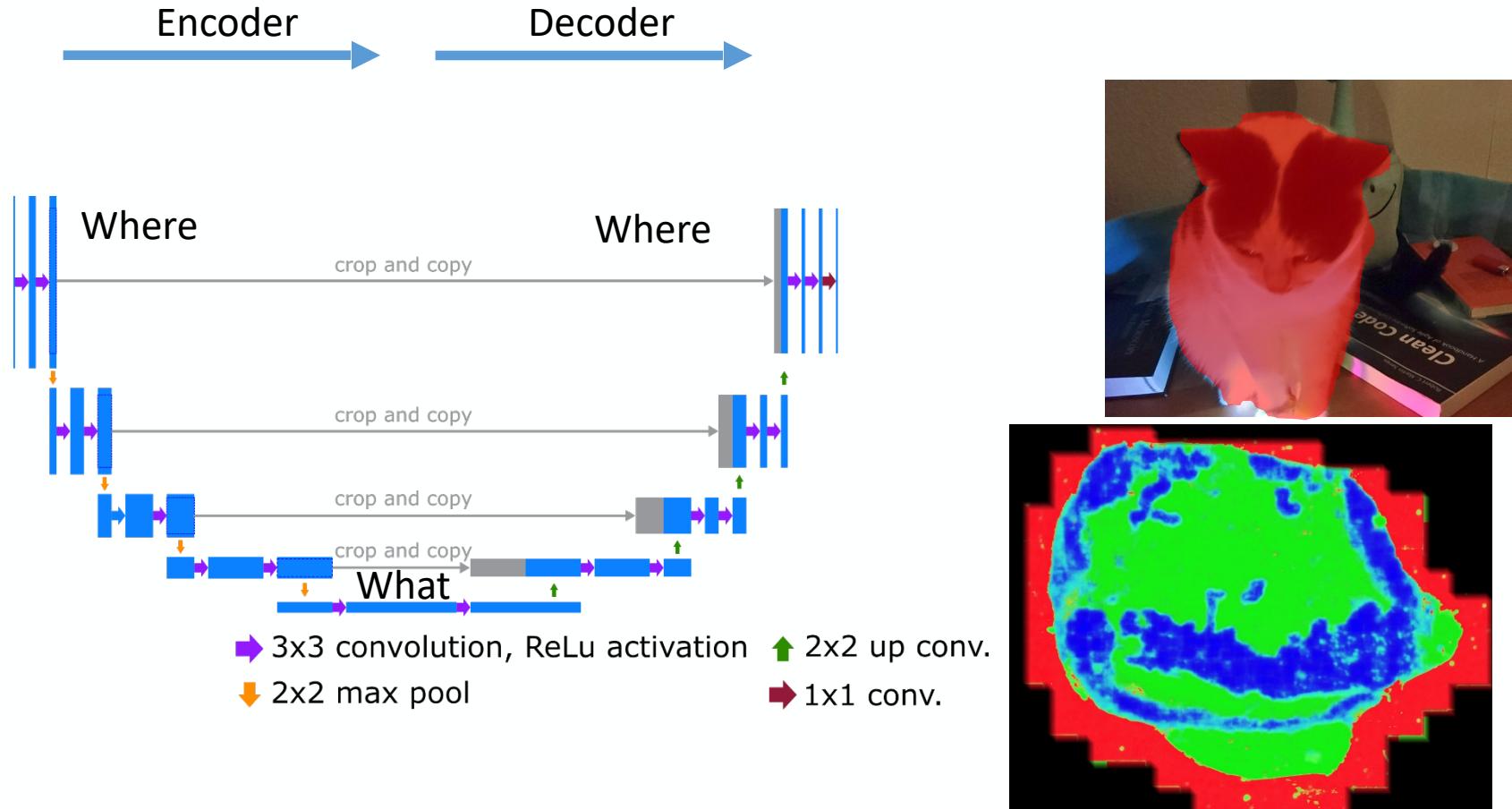
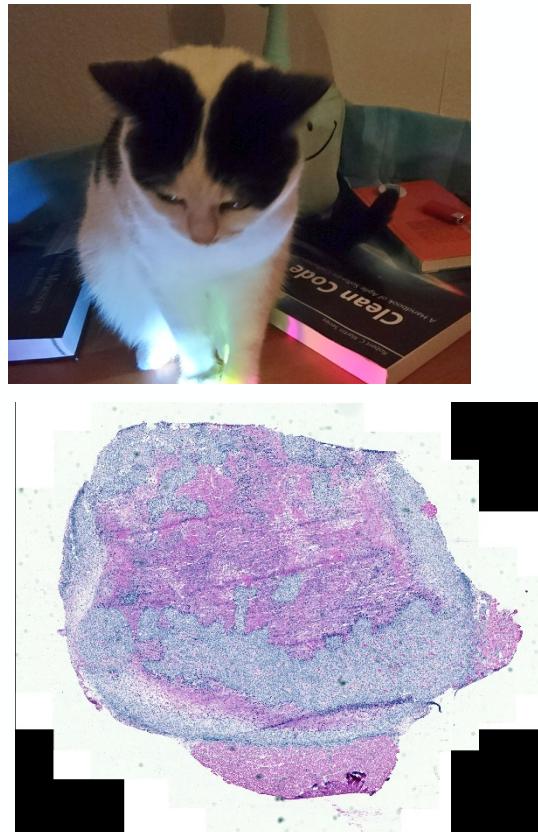


Pooling layer

- Halves input image width/height
- Usually combined with increased size of feature dimension (depth)
- Often followed by batch normalisation to reduce risk of exploding weights
- Helps network to learn more complex features
- Doubles perceptive field

U-NET: IMAGE SEGMENTATION

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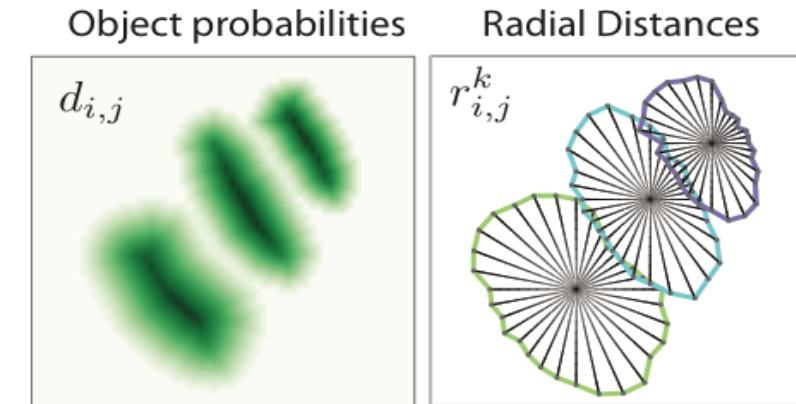
- The U-net is the most used network architecture in biological image processing using CNNs.
 - Encoder: Increase the “What”, decrease the “Where”
 - Decoder: Use the “What”, to identify the “Where”

STARDIST: NUCLEUS SEGMENTATION

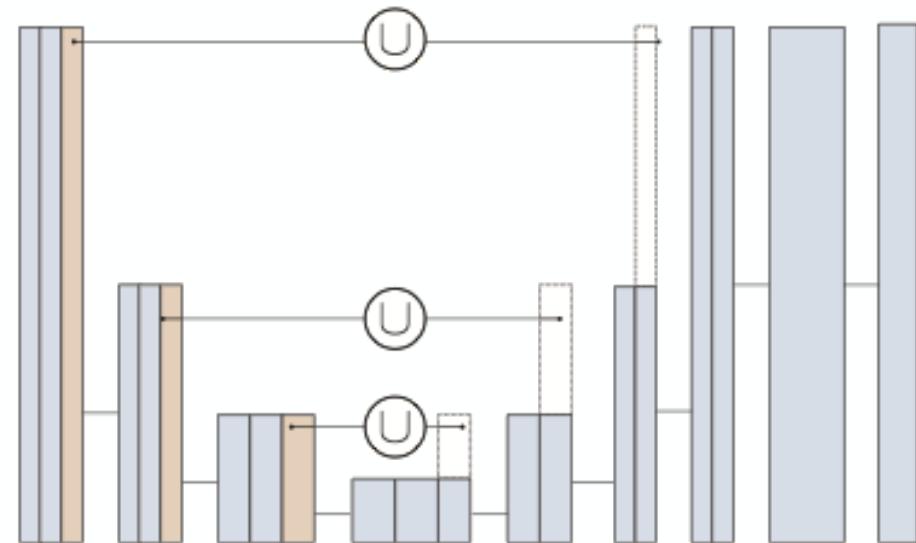
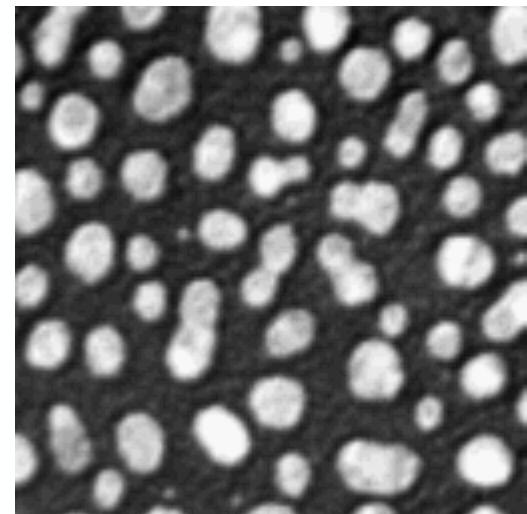
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Strategy:

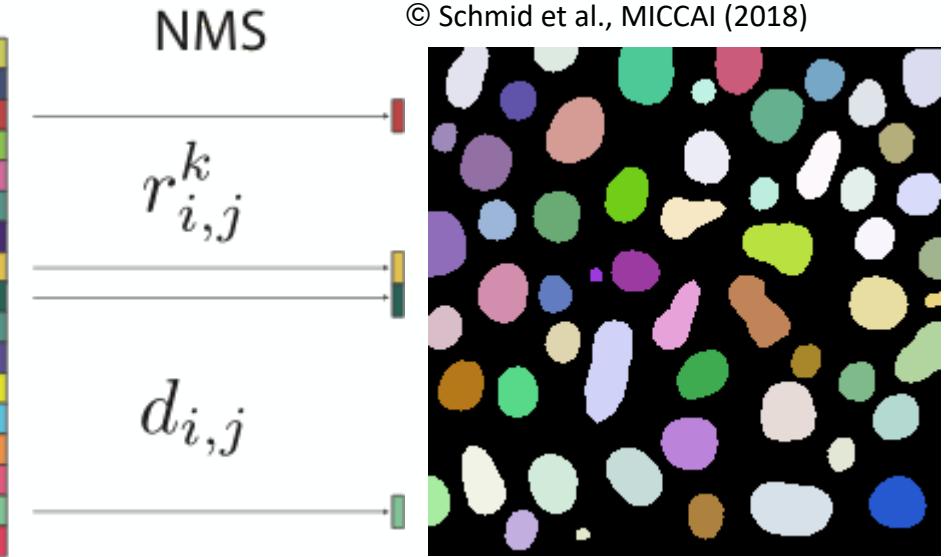
- Add additional information to prediction
- Member pixels of objects (nuclei) can be reached via a straight line from the center



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

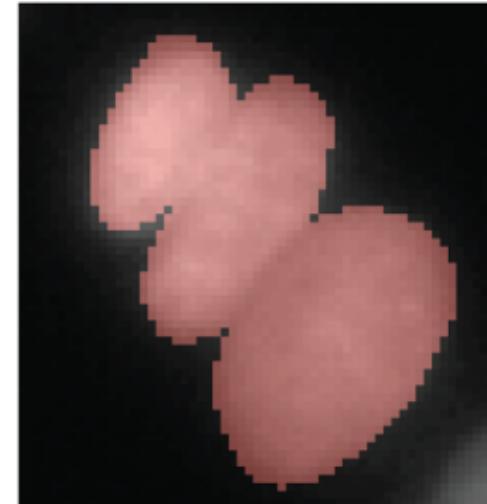
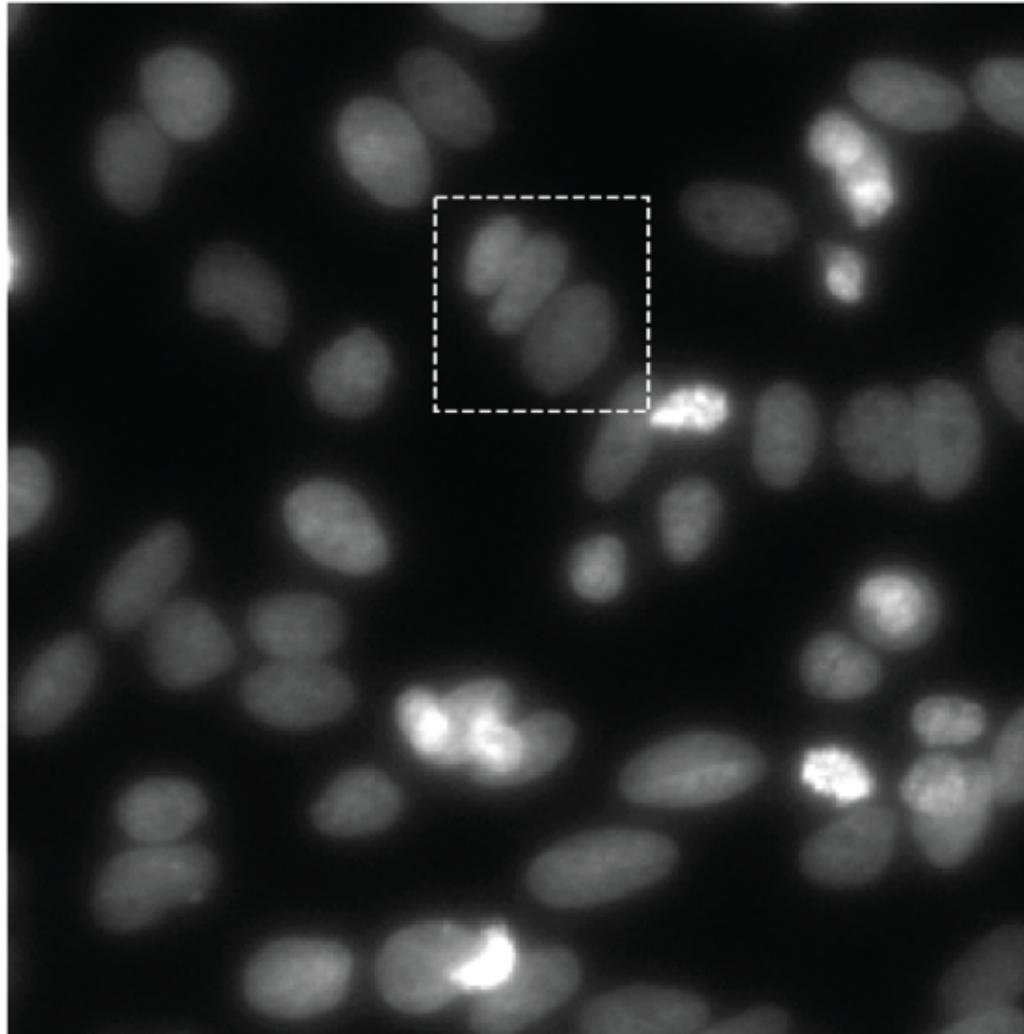


Polygon Selection
(Non-Maximum Suppression NMS)

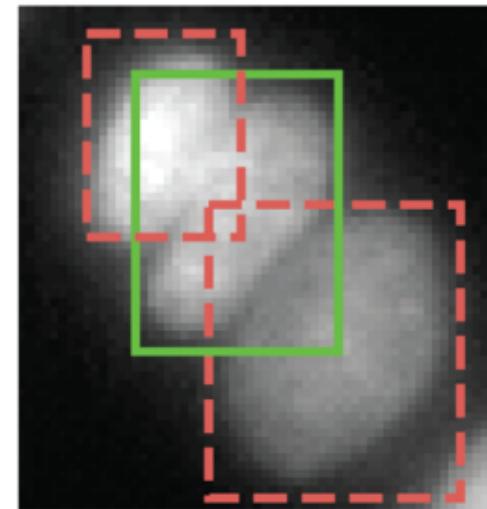
OTHER ALGORITHMS HAVE PROBLEMS WITH OVERLAPPING NUCLEI

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Noisy images + Crowded cells = Common source of segmentation errors



Dense Segmentation
(e.g. U-Net)

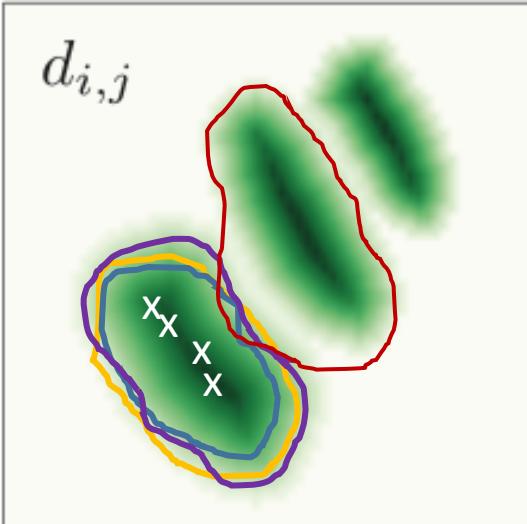


Bounding box based methods
(e.g. Mask-RCNN)

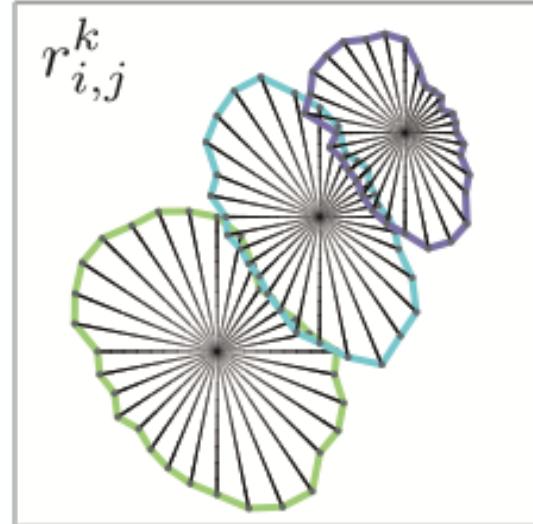
STARDIST: NON-MAXIMUM-SUPPRESSION RESOLVES OVERLAPS

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Object probabilities



Radial Distances



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Non-maximum-suppression (NMS):

- Object probabilities: Probability that pixel belongs to class “nucleus”
- Multiple maxima lead to multiple possible polygons for the same nucleus

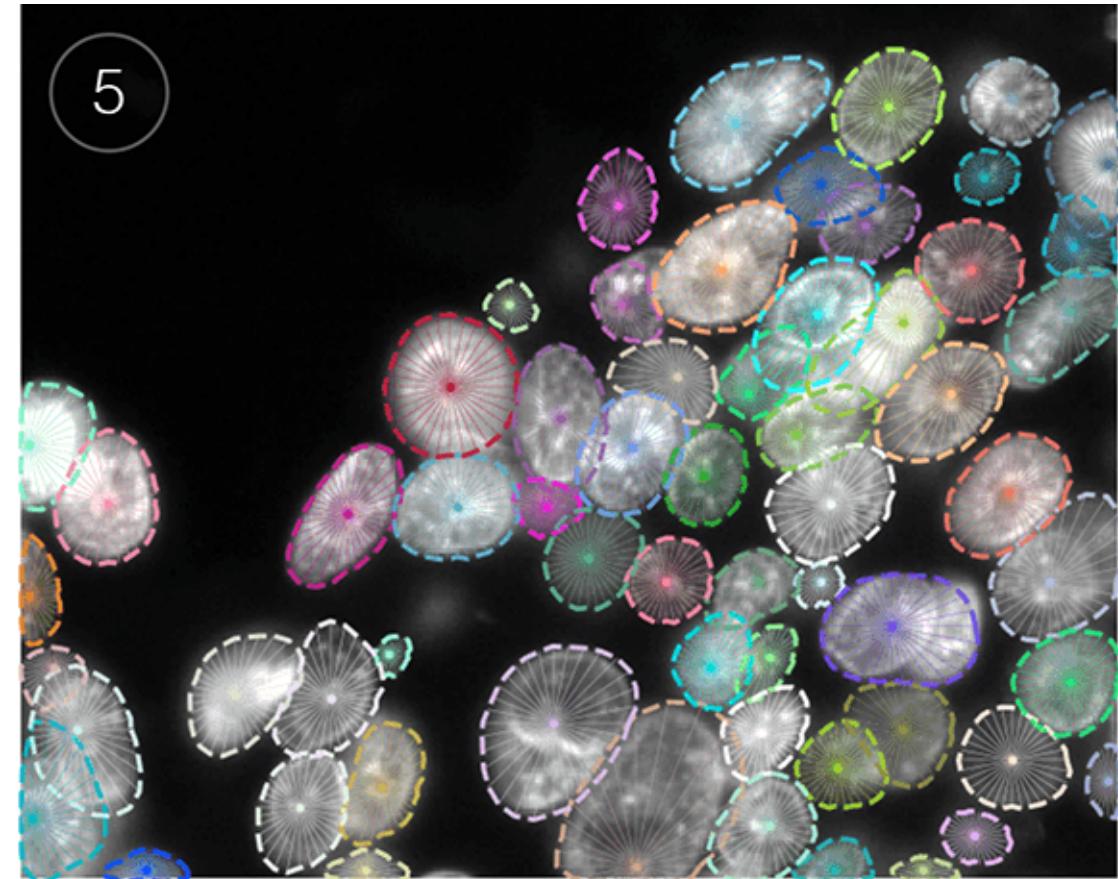
Algorithm:

- 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: NON-MAXIMUM-SUPPRESSION WORKS WELL

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Non-maximum suppression

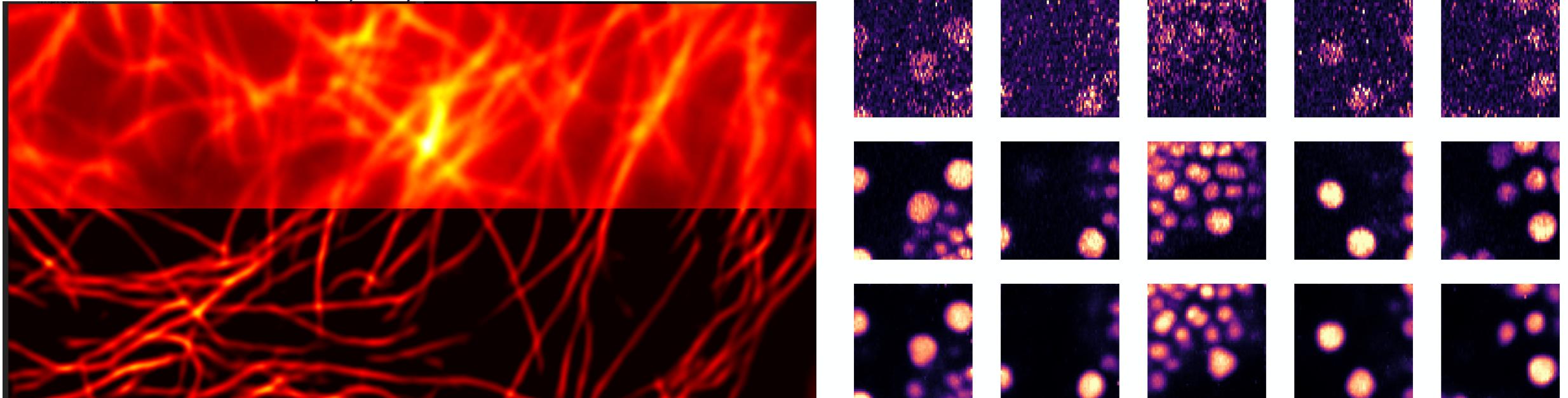


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CARE: IMPROVING RESOLUTION AND DENOISING

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- 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)



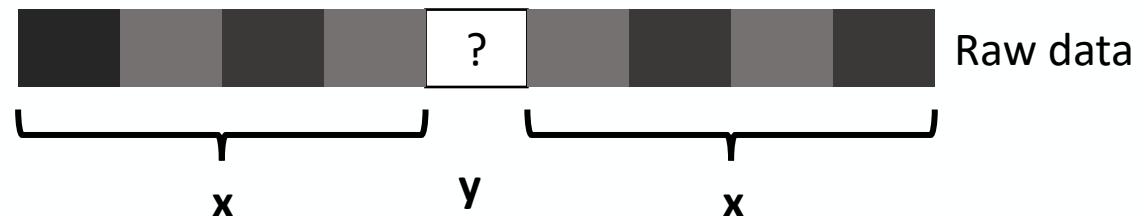
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NOISE TO VOID: IMAGE DENOISING

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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

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>

HELMHOLTZAI

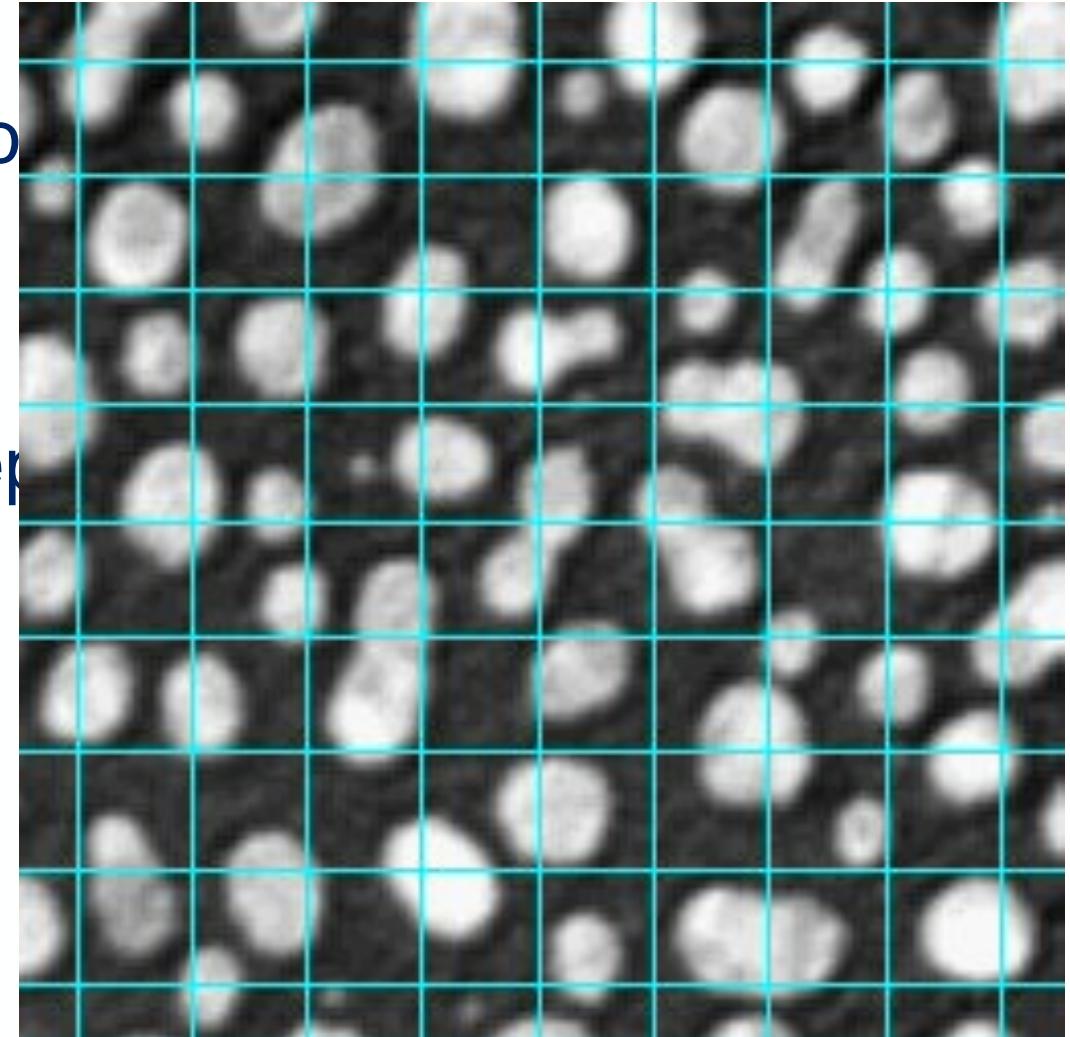
CAVEATS: GPU MEMORY LIMITS IMAGE SIZE

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- Images are tiled
- limited “receptive field of the network”

Receptive field:

- Objects must be smaller than receptive field



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!!

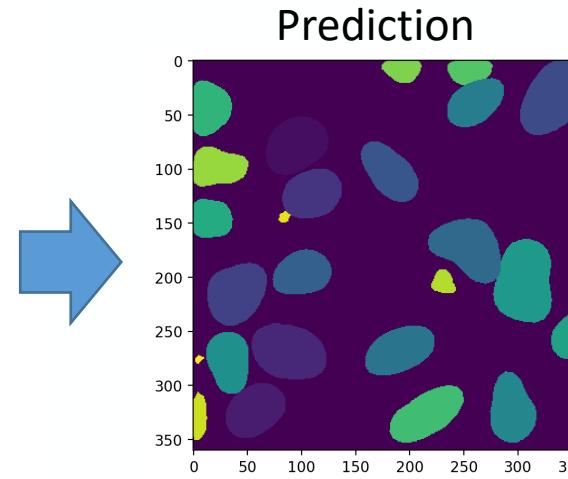
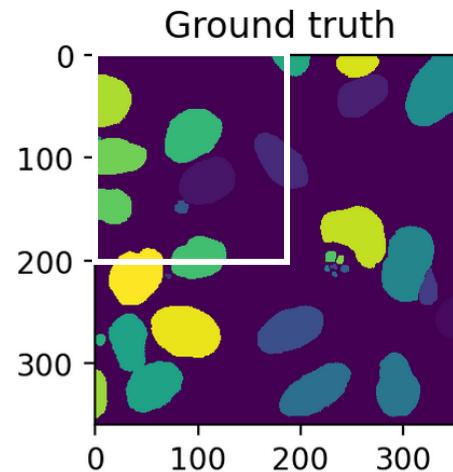
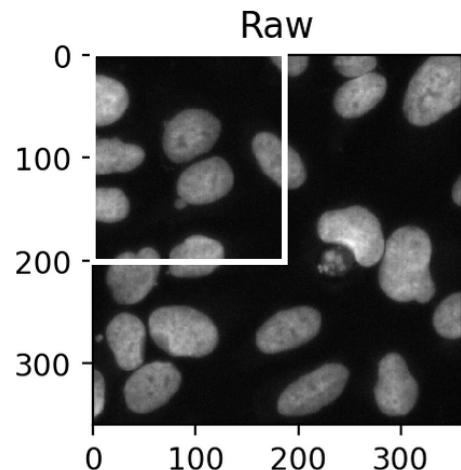
Is the iPhone racist? Chinese users claim iPhoneX face recognition can't tell them apart

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>

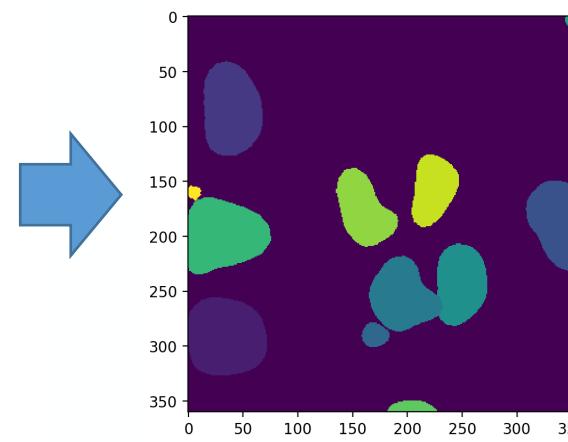
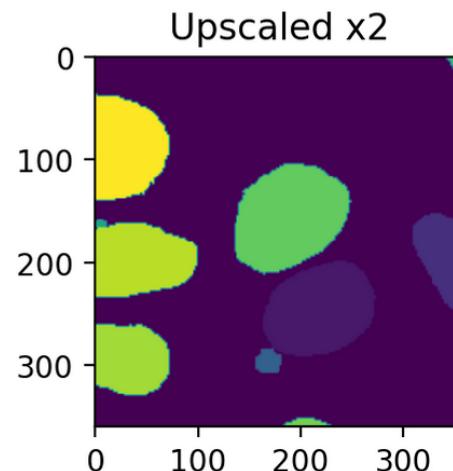
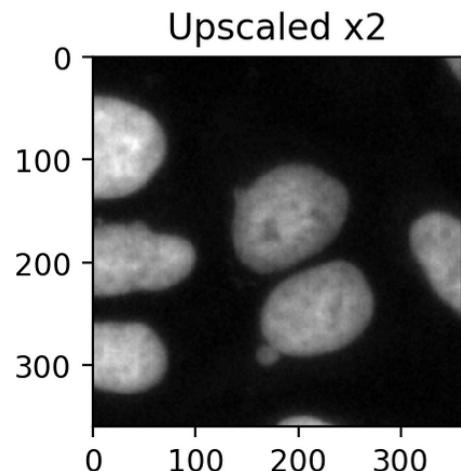
WHEN THE INPUT DATA DOES NOT FIT TO THE TRAINING DATA

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What happened here?

Receptive field too small



I used a different resolution than during training

Overfitting

TAKEAWAYS

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- 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!