Fully convolutional neural networks

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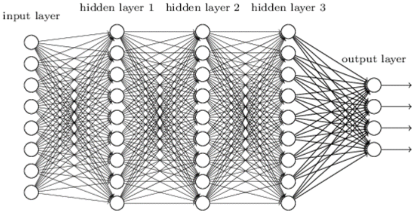
Contents

1. Introduction
2. Image segmentation
3. Properties of fully-convolutional neural networks
4. Using fully-convolutional networks
5. Conclusion

Contents

1. Introduction
2. Image segmentation
3. Properties of fully-convolutional neural networks
4. Using fully-convolutional networks
5. Conclusion

Recall from yesterday: image classification with NN



Simple fully-connected neural network

Cross-entropy loss function used for classification tasks:

$$L(\boldsymbol{\theta}) = -\sum_{i=1}^{n} y_i \log(f(\mathbf{x}_i, \theta))$$

Learning image transformations

- An image classification task is a function from the set of considered images into a set of labels
- In many applications, we want to transform an image into another image

Image definition

Definition: image

An 2-dimensional image I of size $p \times q$ $(p, q \in \mathbb{N}^*)$ is a function:

$$[0, \dots p-1] \times [0, \dots q-1] \longmapsto \mathbb{R}^d \quad (d \in \mathbb{N}^*)$$

The set of these images is $\mathcal{I}^d$.

Examples

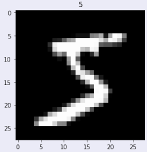


Figure: 28×28 grey level image $(d = 1)$ from the MNIST data set, and 481×321 colour image $(d = 3)$ from the Berkeley segmentation data set.

Image-to-image NN

Definition: image-to-image neural network

An image-to-image NN F is a NN that transforms an image into an image of same size[a]:

$$\begin{aligned} F : \mathcal{I}^{d_1} &\longrightarrow \mathcal{I}^{d_2} \\ I &\longmapsto F(I) \end{aligned}$$

Note that the dimensions d_1 and d_2 of the value spaces can be different.

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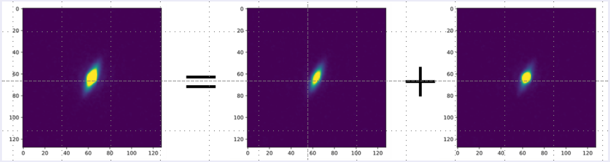
[a] In some applications the output size is different from the input size, but for the sake of simplicity we will not consider this case here

Examples

Bulge / disk decomposition



(Credits: Tuccillo, Huertas-Company, Velasco-Forero, Decencière)

Deblurring network [Hradiš et al., 2015]

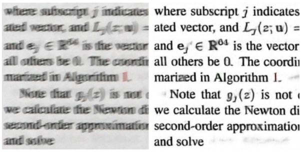


Image Segmentation with NNs

- Image segmentation often is an important step in an image processing work flow
- Image segmentation has been a very active deep learning research field

Image segmentation example

Credits: Pascal VOC database

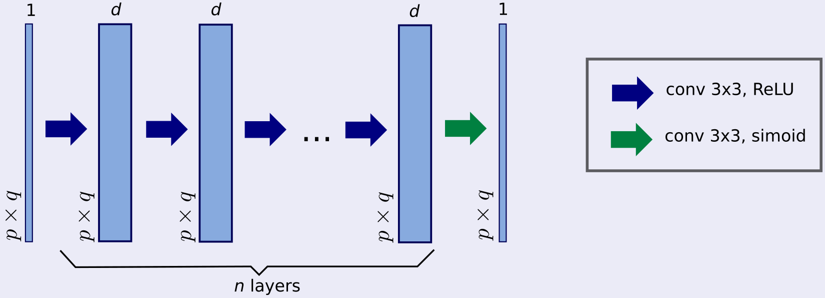
Other applications

- Image filtering
- High dynamic range
- Style modification
- Super-resolution (image size increases)
- Motion estimation

Image-to-image NNs architecture

- Image-to-image NNs are based on convolutional layers
- If downsampling is used, the corresponding upsampling is needed

Example: plain CNN [Pang et al., 2010]



Receptive field

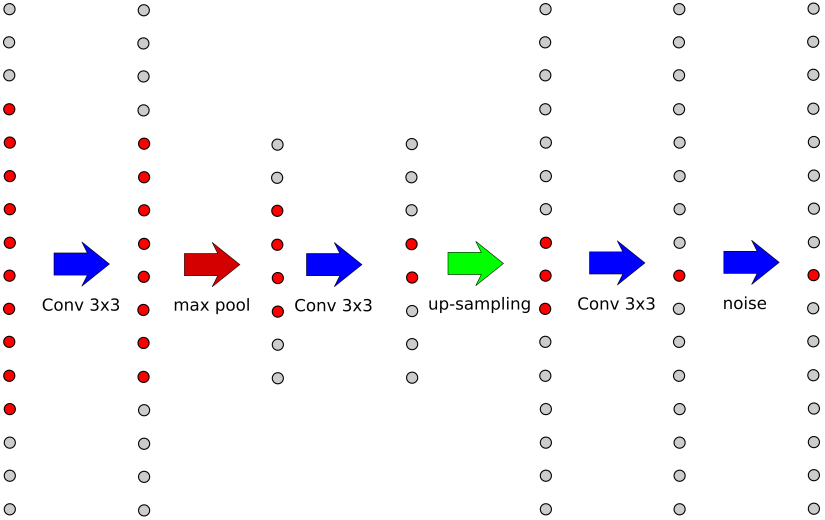
Definition: links between neurons

In a NN, we say that neuron a is linked to neuron b if there is an oriented path in the corresponding graph going from a to b.

Definition

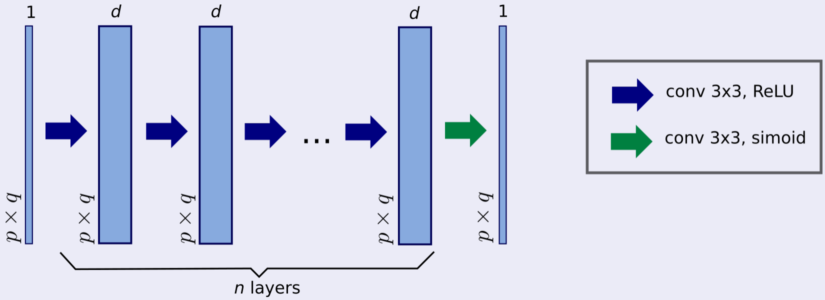
The receptive field of a neuron in a NN is the set of *input neurons* that are linked to that neuron.
The size of the receptive field is an essential property when designing a fully-convolutional NN architecture.

Illustration



Example

What is the size of the receptive field of the neurons in the last layer?



Answer: $1 + 2 \times (n + 1)$

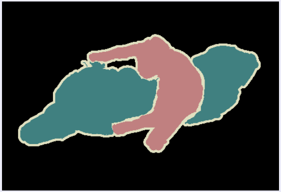
The specific case of image segmentation

Definition: image segmentation

Let I be an image defined on D. A segmentation of I is a partition of D. In practice the regions of the segmentation should correspond to the objects in I, which is application dependant.

- A partition is often represented as a labelled image
- In order to make the segments symmetric, each one is represented by a different channel

Image segmentation example



Credits: Pascal VOC database

Some vocabulary on segmentation

- **Object detection / localization**: bounding box around the object(s).
- **Binary segmentation**: segmentation in 2 classes, background and object.
- **Semantic segmentation**: a label is given to each pixel, according to the object it belongs to.
- **Instance segmentation**: identify each separate object, even if they belong to the same class.

Contents

1 Introduction

2 Image segmentation
- Binary segmentation
- Semantic segmentation
- Instance segmentation

3 Properties of fully-convolutional neural networks

4 Using fully-convolutional networks

5 Conclusion

Contents

1 Introduction

2 Image segmentation
- Binary segmentation
- Semantic segmentation
- Instance segmentation

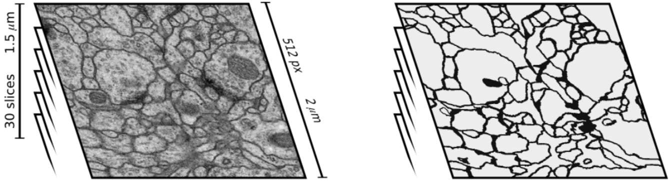
3 Properties of fully-convolutional neural networks

4 Using fully-convolutional networks

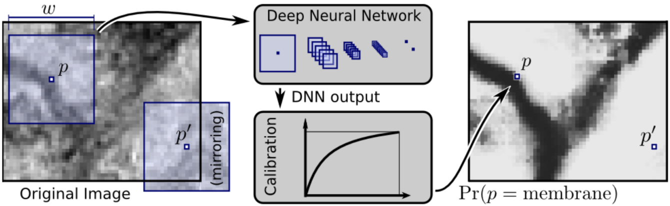
5 Conclusion

Neuron membrane segmentation challenge (ISBI 2012)

- Train: single stack of size $30 \times 512 \times 512$.
- Test: a second stack of same size.



Neuron membrane segmentation challenge winner [Ciresan et al., 2012]

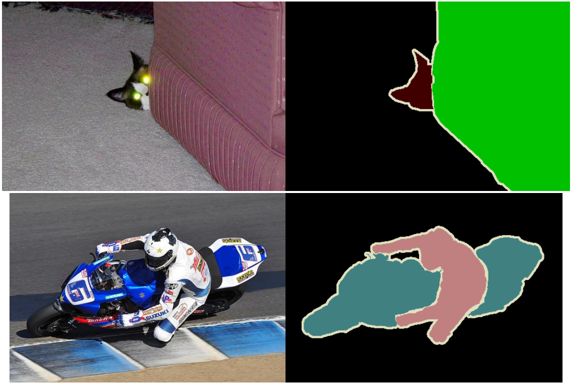


Contents

1. Introduction
2. Image segmentation
   - Binary segmentation
   - Semantic segmentation
   - Instance segmentation
3. Properties of fully-convolutional neural networks
4. Using fully-convolutional networks
5. Conclusion

Pascal visual object classes segmentation challenge 2012 [Everingham et al., 2014]

- 1464 training and 1449 validation images
- automatic online test, with unknown images
- 20 image categories (cat, sofa, motorbike, person, etc.)

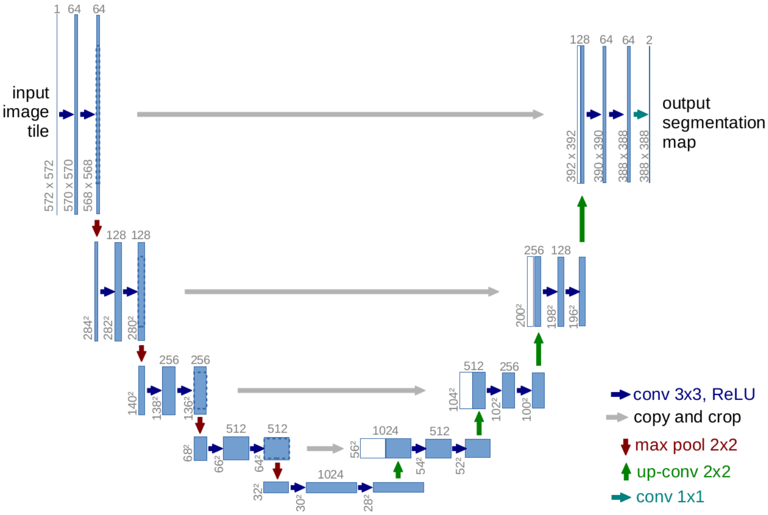


Convolutional nets for semantic image segmentation

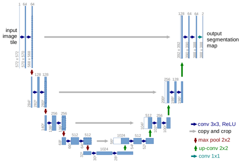
Three papers in 2015:

- Fully convolutional networks for semantic segmentation [Long et al., 2015]
- U-Net: convolutional networks for biomedical image segmentation [Ronneberger et al., 2015]
- SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation [Badrinarayanan et al., 2015]

Example: U-Net architecture [Ronneberger et al., 2015]



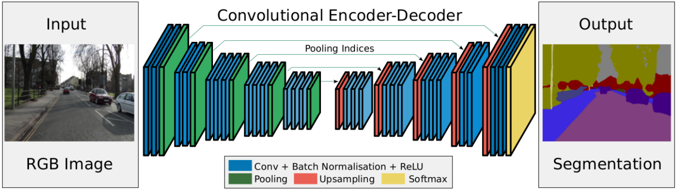
Notes on the U-Net architecture [Ronneberger et al., 2015]



- Activation of the last layer: soft-max
- Other activations: ReLU
- Loss used in the original publication: cross entropy with a weight map w to favor some pixels:

$$L(\boldsymbol{\theta}) = \sum_{M \in D} w(M) \log\big(\hat{y}_{l(M)}(M)\big)$$

Example: SegNet architecture [Badrinarayanan et al., 2015]



Remarks

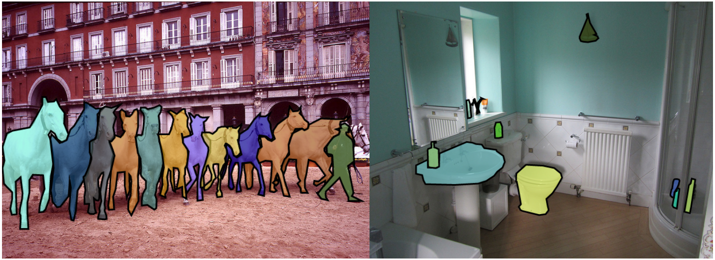
- These architectures easily contain a number of parameters of the order of 10^7 (28 million for U-Net)
- Their optimization might be difficult
- For many segmentation applications, they are overkill
  - But you can reduce the number of filters or the number of layers

Contents

1. Introduction
2. Image segmentation
   - Binary segmentation
   - Semantic segmentation
   - Instance segmentation
3. Properties of fully-convolutional neural networks
4. Using fully-convolutional networks
5. Conclusion

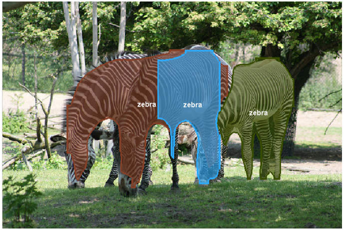
COCO: common objects in context [Lin et al., 2014]

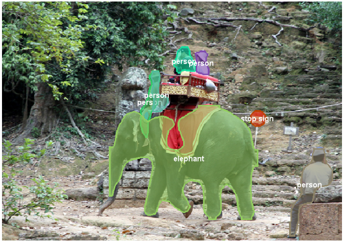
- 2 million objects, from 80 categories, in $300\,000$ images

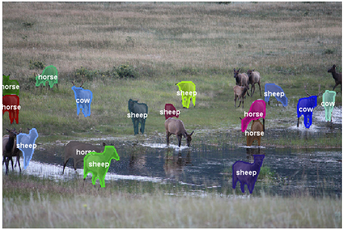


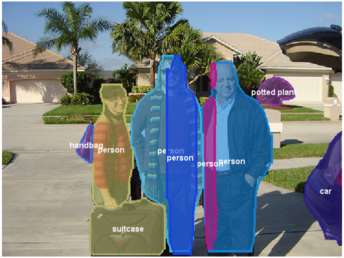
Winner 2016: Fully Convolutional Instance-aware Semantic Segmentation (Microsoft) [Li et al., 2016]

COCO instance segmentation challenge: examples of 2016 winner results

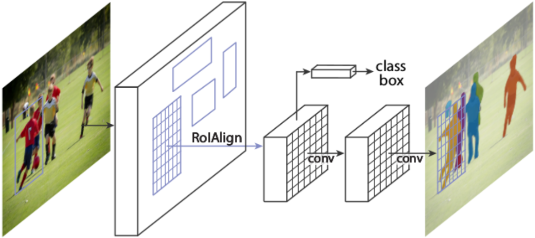




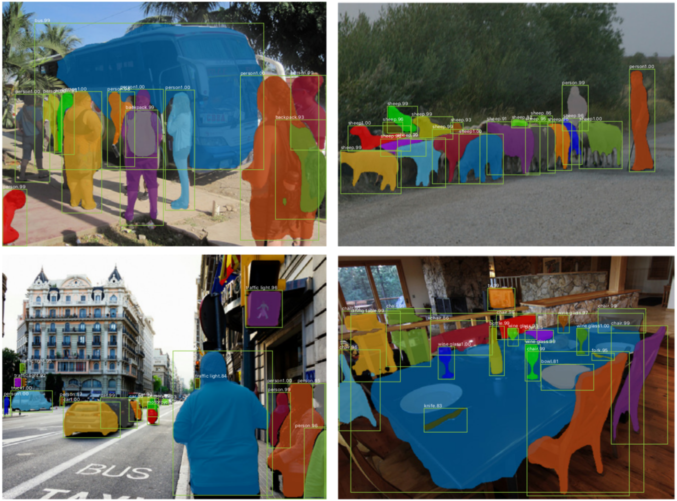




State of the art on the COCO database: Mask R-CNN [He et al., 2017]

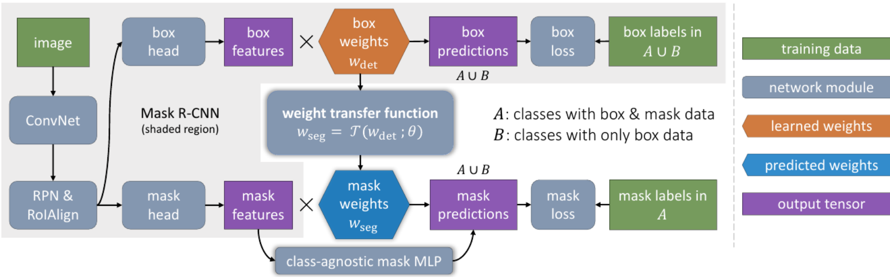


Mask R-CNN on the COCO database



Partially supervised segmentation - [Hu et al., 2017]

- 80 segmented categories from COCO database
- 3000 visual concepts using box annotations from the Visual Genome data set (100k images)



Current (?) trends for instance segmentation

- Region proposal +
- Fully convolutional (very deep) network +
- (Post-processing)

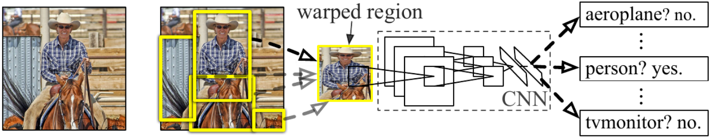


Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

Meanwhile, on the object detection field...

- YOLO: you look only once [Redmon and Farhadi, 2016]
- SSD: single shot detector [Liu et al., 2016]

Contents

1 Introduction

2 Image segmentation

3 Properties of fully-convolutional neural networks

4 Using fully-convolutional networks

5 Conclusion

Translation invariance

Identical receptive fields produce identical outputs.

- If padding is used in the network, border effects can be important.
- Translation invariance is not always welcome!
- Position information can also be used in the network:
  - Through masks or segmentations
  - Through pixel coordinates

Image size flexibility

- A NN containing fully-connected layers can only process images of a given size
- A translation invariant NN can be applied to images of any size, as long as its dimensions are compatible with the subsampling steps of the network
- Practical limit: the memory of the system
- Note that as the input image gets larger, border effects become proportionally less present

Robustness with respect to ground-truth errors

This is more an empirical observation than a mathematical property, but fully-convolutional NNs tend to be robust with respect to errors in the contours position on the ground-truth.

Contents

1. Introduction
2. Image segmentation
3. Properties of fully-convolutional neural networks
4. Using fully-convolutional networks
5. Conclusion

Dealing with image sizes during training

- In segmentation applications, original images are often of different sizes and possibly very large.
- In theory, given the translation invariance of fully-convolutional NN, we could use them directly as input. In practice, we are limited by memory size.
- Solution: extract fixed-sized crops from your training set:
  - make them as large as possible, to reduce border effects
  - take a small batch size (1, 2, 4?)

Post-processing for segmentation

- Superpixels (e.g. [Farabet et al., 2013])
- Conditional random fields
- Mathematical morphology

Loss functions for image segmentation

- $\hat{\mathbf{y}} = (\hat{\mathbf{y}}_i)$: network output
- $\mathbf{y} = (\mathbf{y}_i)$: binary expected output
- We suppose that all $\hat{\mathbf{y}}_i$ are in $[0, 1]$
- We want the $\hat{\mathbf{y}}$ to be *as close as possible* to $\mathbf{y}$

Loss functions for image segmentation

Most commonly used loss functions

- Mean squared error (MSE): $\sum_i (\hat{y}_i - y_i)^2$
- Cross-entropy: $-\sum_i y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$

Measures used in image processing

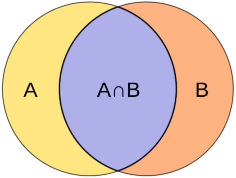
Let A and B be two sets, not simultaneously empty.

Dice coefficient

$$D(A,B) = \frac{2|A \cap B|}{|A| + |B|}$$

Jaccard index

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$



Properties

- $\forall A, B : 0 \leq J(A,B) \leq D(A,B) \leq 1$
- If $A = B$, then $D(A,B) = J(A,B) = 1$
- If $A \cap B = \emptyset$, then $D(A,B) = J(A,B) = 0$

Credits: Public domain (Wikipedia.org)

Generalization to $[0, 1]$

$\mathbf{y}$ and $\hat{\mathbf{y}}$ are in $[0, 1]^n$, not simultaneously equal to 0.

Dice similarity

$$D(\mathbf{y}, \hat{\mathbf{y}}) = \frac{2 \sum_i y_i \hat{y}_i}{\sum_i y_i + \sum_i \hat{y}_i}$$

Jaccard similarity

$$J(\mathbf{y}, \hat{\mathbf{y}}) = \frac{\sum_i y_i \hat{y}_i}{\sum_i y_i + \sum_i \hat{y}_i - \sum_i y_i \hat{y}_i}$$

Corresponding loss functions

$\mathbf{y}$ and $\hat{\mathbf{y}}$ are in $[0,1]^n$, not simultaneously equal to 0.

Dice loss

$$d(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{2\sum_i y_i \hat{y}_i}{\sum_i y_i + \sum_i \hat{y}_i}$$

Jaccard loss

$$j(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{\sum_i y_i \hat{y}_i}{\sum_i y_i + \sum_i \hat{y}_i - \sum_i y_i \hat{y}_i}$$

In practice, these two losses give similar results.

Corresponding loss functions - variants

$\mathbf{y}$ and $\hat{\mathbf{y}}$ are in $[0,1]^n$, not simultaneously equal to 0.
Constant ϵ, which is typically "small", keeps the denominator "far enough" from zero.

Dice loss

$$d(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{2\sum_i y_i \hat{y}_i}{\sum_i y_i^2 + \sum_i \hat{y}_i^2 + \epsilon}$$

Jaccard loss

$$j(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{\sum_i y_i \hat{y}_i}{\sum_i y_i^2 + \sum_i \hat{y}_i^2 - \sum_i y_i \hat{y}_i + \epsilon}$$

These variants seem to work similarly to the original version. To the extent of my knowledge, there have been no studies on their respective merits.

Conclusion on loss functions

- Use the Jaccard loss as base line for segmentation problems
- Note that these losses compute their values pixel-wise: they do not take into account any structure (for example, continuity)
- Working on specific losses enforcing structure might be an interesting research path...

Contents

1 Introduction

2 Image segmentation

3 Properties of fully-convolutional neural networks

4 Using fully-convolutional networks

5 Conclusion

Image segmentation: a solved problem?

- Progress in image segmentation since 2012 has been enormous
- Several complex problems have now satisfactory solutions
- Training can be a problem (large annotated databases, difficult optimization)
- There are still challenges ahead...

Some research subjects

- Optimization - a very general, and essential, subject
- Making training databases as small as possible
- Specific losses
- Taking *a priori* structural information into account

References I

[Badrinarayanan et al., 2015] Badrinarayanan, V., Kendall, A., and Cipolla, R. (2015). SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *arXiv:1511.00561 [cs]*. arXiv: 1511.00561.

[Ciresan et al., 2012] Ciresan, D., Giusti, A., Gambardella, L. M., and Schmidhuber, J. (2012). Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images. In Pereira, F., Burges, C. J. C., Bottou, L., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 25*, pages 2843–2851. Curran Associates, Inc.

[Everingham et al., 2014] Everingham, M., Eslami, S. M. A., Gool, L. V., Williams, C. K. I., Winn, J., and Zisserman, A. (2014). The Pascal Visual Object Classes Challenge: A Retrospective. *International Journal of Computer Vision*, 111(1):98–136.

[Farabet et al., 2013] Farabet, C., Couprie, C., Najman, L., and LeCun, Y. (2013). Learning Hierarchical Features for Scene Labeling. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8):1915–1929.

[Girshick et al., 2014] Girshick, R., Donahue, J., Darrell, T., and Malik, J. (2014). Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In *Proceedings CVPR*, pages 580–587.

[He et al., 2017] He, K., Gkioxari, G., Dollár, P., and Girshick, R. (2017). Mask R-CNN. *arXiv:1703.06870 [cs]*. arXiv: 1703.06870.

References II

[Hradiš et al., 2015] Hradiš, M., Kotera, J., Zemcík, P., and Šroubek, F. (2015). Convolutional neural networks for direct text deblurring. In *Proceedings of BMVC*, volume 10.

[Hu et al., 2017] Hu, R., Dollár, P., He, K., Darrell, T., and Girshick, R. (2017). Learning to Segment Every Thing. *arXiv:1711.10370 [cs]*. arXiv: 1711.10370.

[Li et al., 2016] Li, Y., Qi, H., Dai, J., Ji, X., and Wei, Y. (2016). Fully Convolutional Instance-aware Semantic Segmentation. *arXiv:1611.07709 [cs]*. arXiv: 1611.07709.

[Lin et al., 2014] Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C. L., and Dollár, P. (2014). Microsoft COCO: Common Objects in Context. *arXiv:1405.0312 [cs]*. arXiv: 1405.0312.

[Liu et al., 2016] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., and Berg, A. C. (2016). SSD: Single Shot MultiBox Detector. *arXiv:1512.02325 [cs]*, 9905:21–37. arXiv: 1512.02325.

[Long et al., 2015] Long, J., Shelhamer, E., and Darrell, T. (2015). Fully Convolutional Networks for Semantic Segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3431–3440.

References III

[Pang et al., 2010] Pang, B., Zhang, Y., Chen, Q., Gao, Z., Peng, Q., and You, X. (2010). Cell Nucleus Segmentation in Color Histopathological Imagery Using Convolutional Networks. In *2010 Chinese Conference on Pattern Recognition (CCPR)*, pages 1–5.

[Redmon and Farhadi, 2016] Redmon, J. and Farhadi, A. (2016). YOLO9000: Better, Faster, Stronger. *arXiv:1612.08242 [cs]*. arXiv: 1612.08242.

[Ronneberger et al., 2015] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In Navab, N., Hornegger, J., Wells, W. M., and Frangi, A. F., editors, *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, number 9351 in Lecture Notes in Computer Science, pages 234–241. Springer International Publishing.