Fully convolutional neural networks

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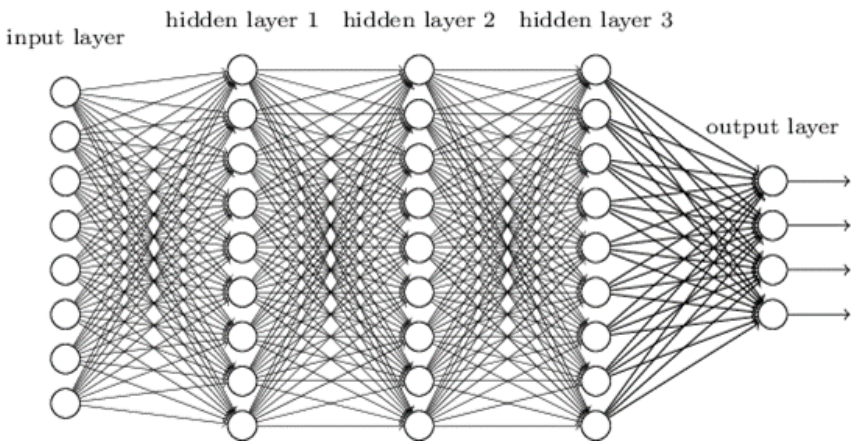
Recall from yesterday: image classification with NN



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

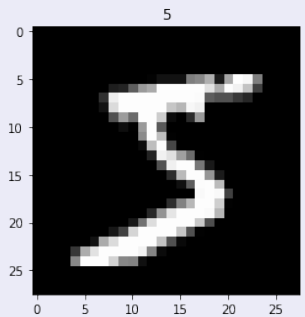


Figure: 28×28 grey level image $(d = 1)$ from the MNIST data set, and 481×321 colour image $(d = 3)$ from the Berkeley segmentation data set.

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]:

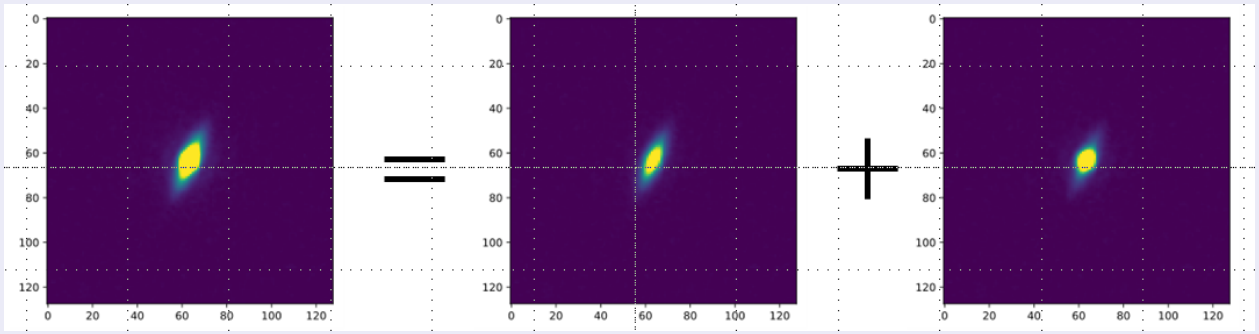
$$F : \mathcal{I}^{d_1} \longrightarrow \mathcal{I}^{d_2}$$
$$I \longmapsto F(I)$$

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

[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

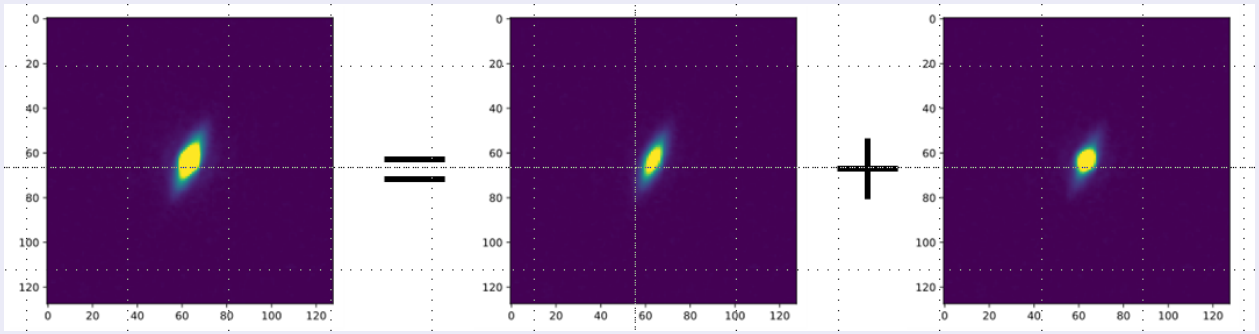
Bulge / disk decomposition



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

Examples

Bulge / disk decomposition



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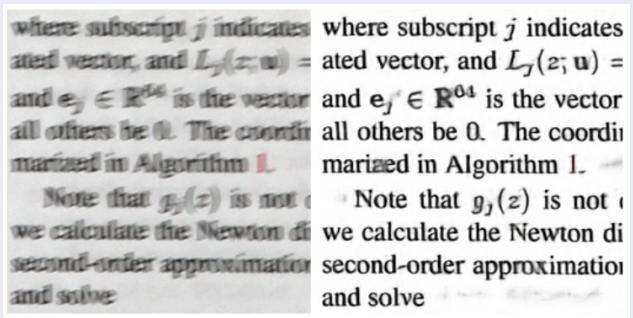
Deblurring network [Hradiš et al., 2015]



where subscript j indicates
ated vector, and $L_j(z; \mathbf{u}) =$
and $\mathbf{e}_j \in \mathbb{R}^{64}$ is the vector
all others be 0. The coordi
marized in Algorithm 1.

Note that $g_j(z)$ is not
we calculate the Newton di
second-order approximatio
and solve

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

Image-to-image NNs architecture

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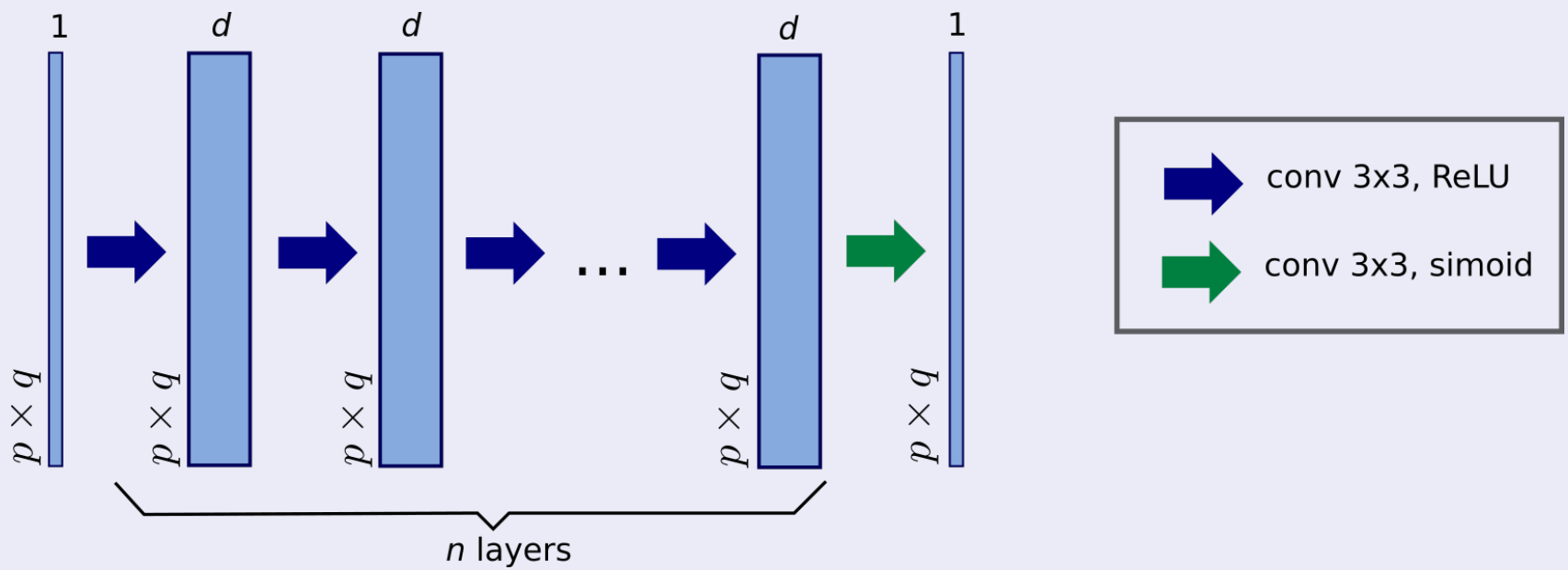
Example: plain CNN [Pang et al., 2010]



Receptive field

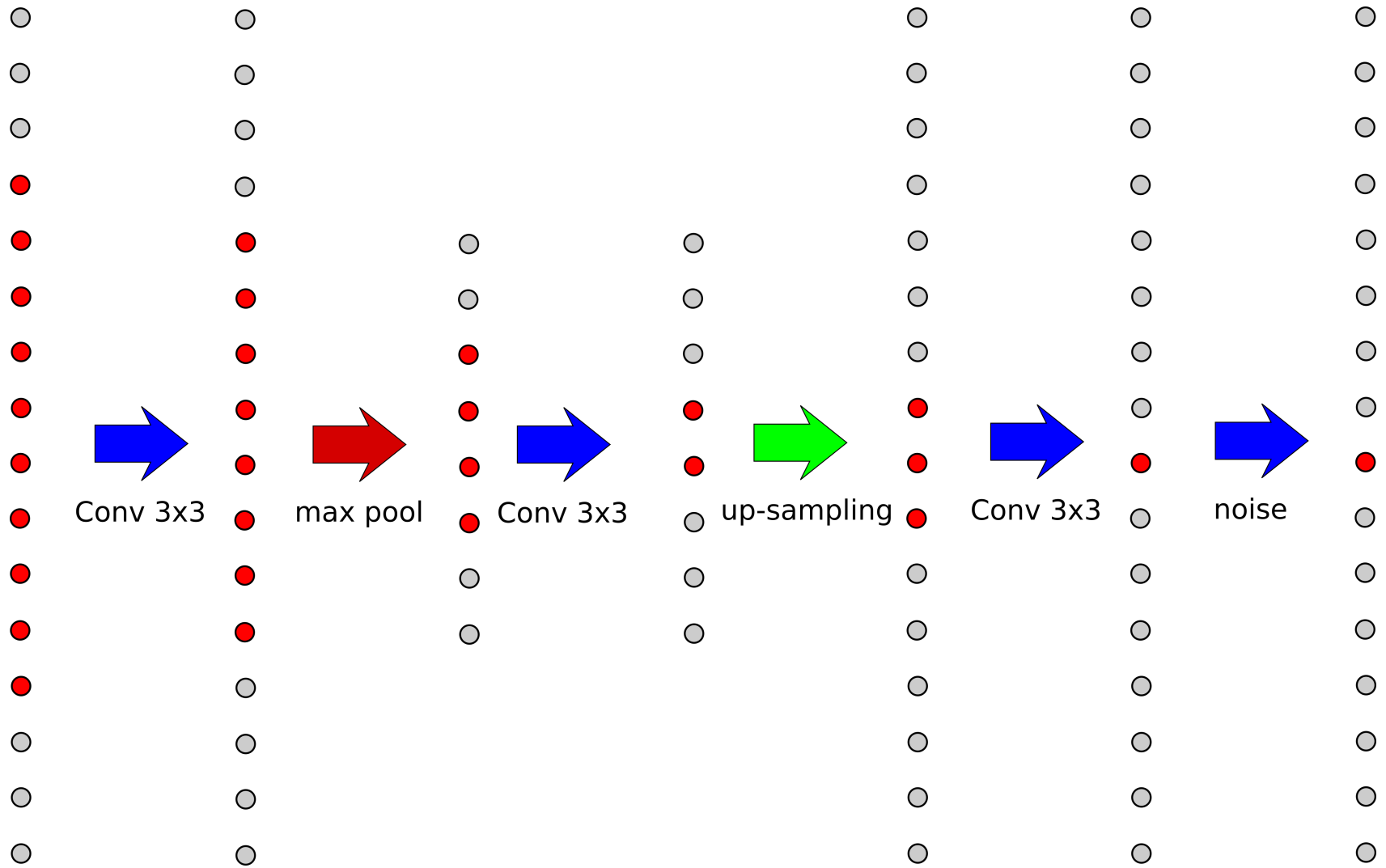
Definition: links between neurons

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

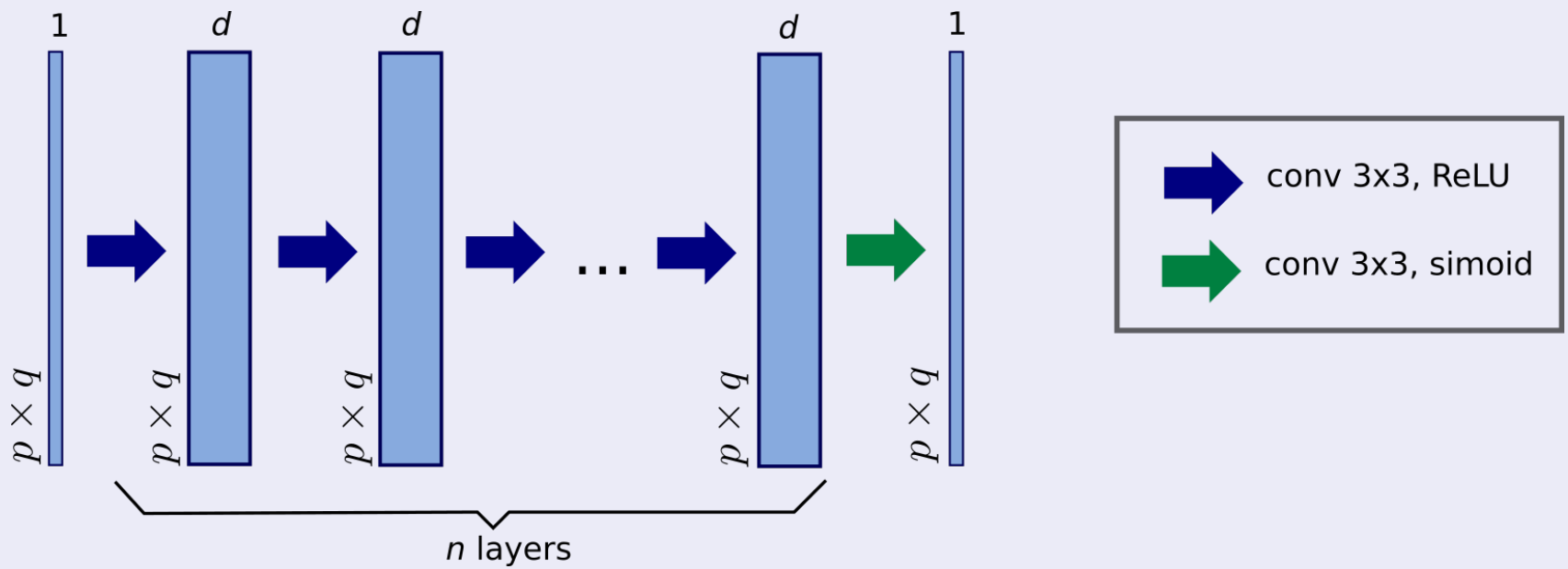
The receptive field of a neuron in a NN is the set of *input neurons* that are linked to that neuron.
The size of the receptive field is an essential property when designing a fully-convolutional NN architecture.

Illustration



Example

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



Example

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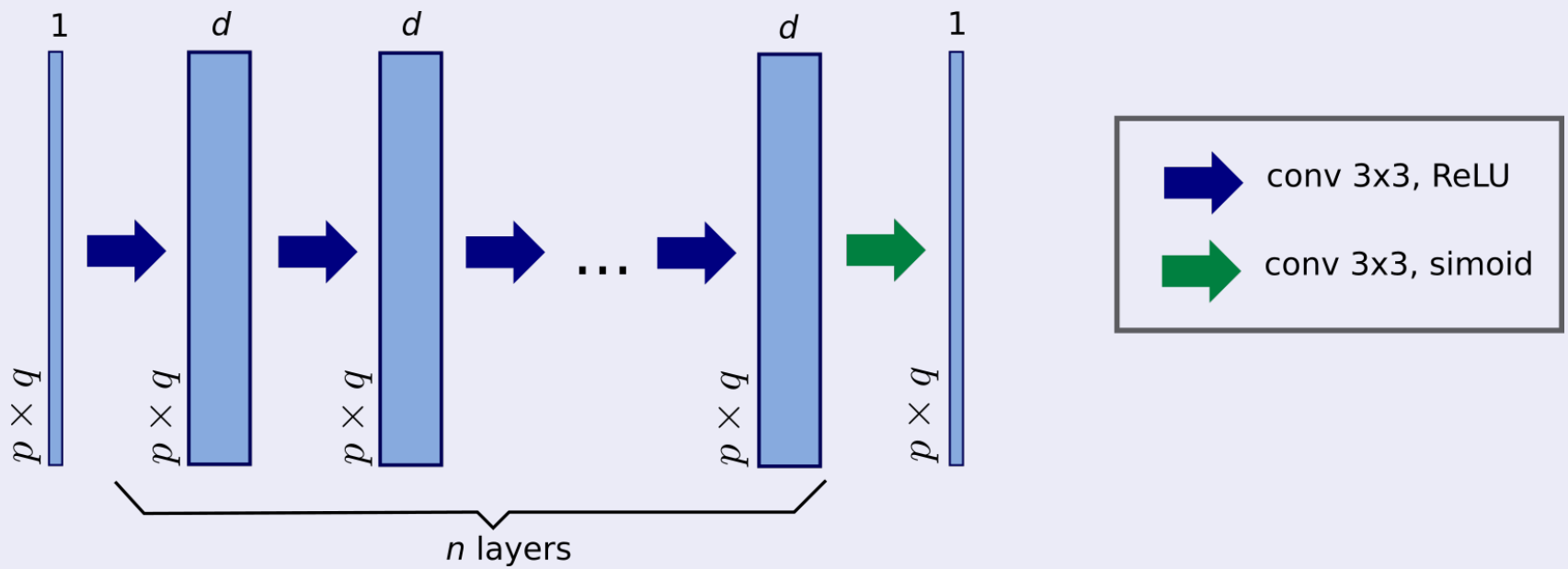

Answer: $1 + 2 \times (n + 1)$

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.

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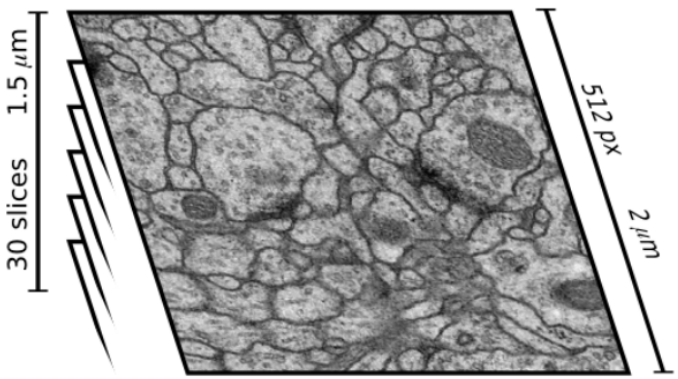
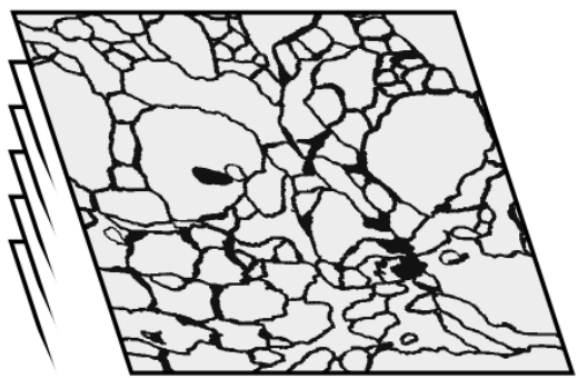
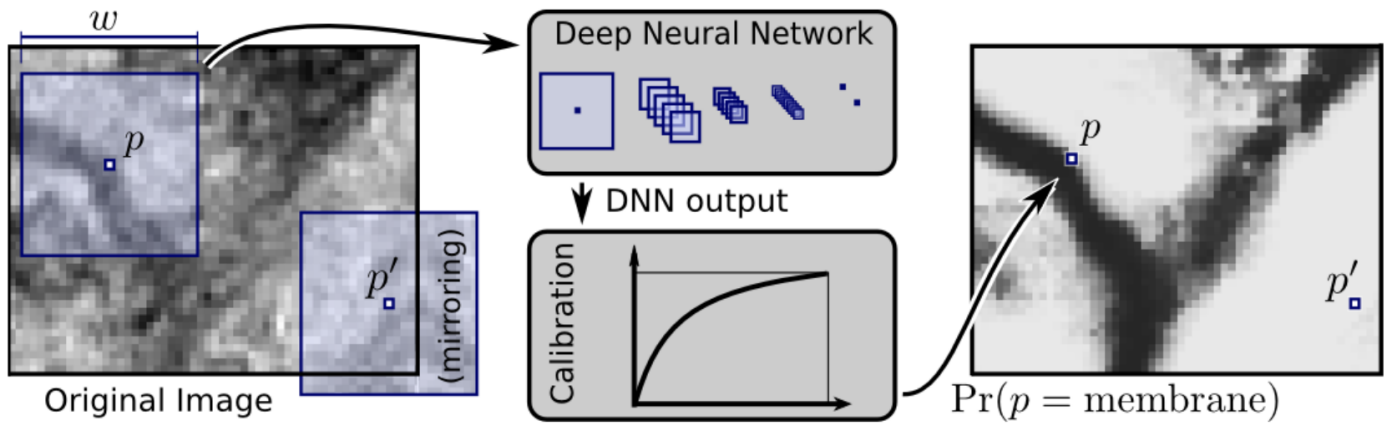
Neuron membrane segmentation challenge (ISBI 2012)

- 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]



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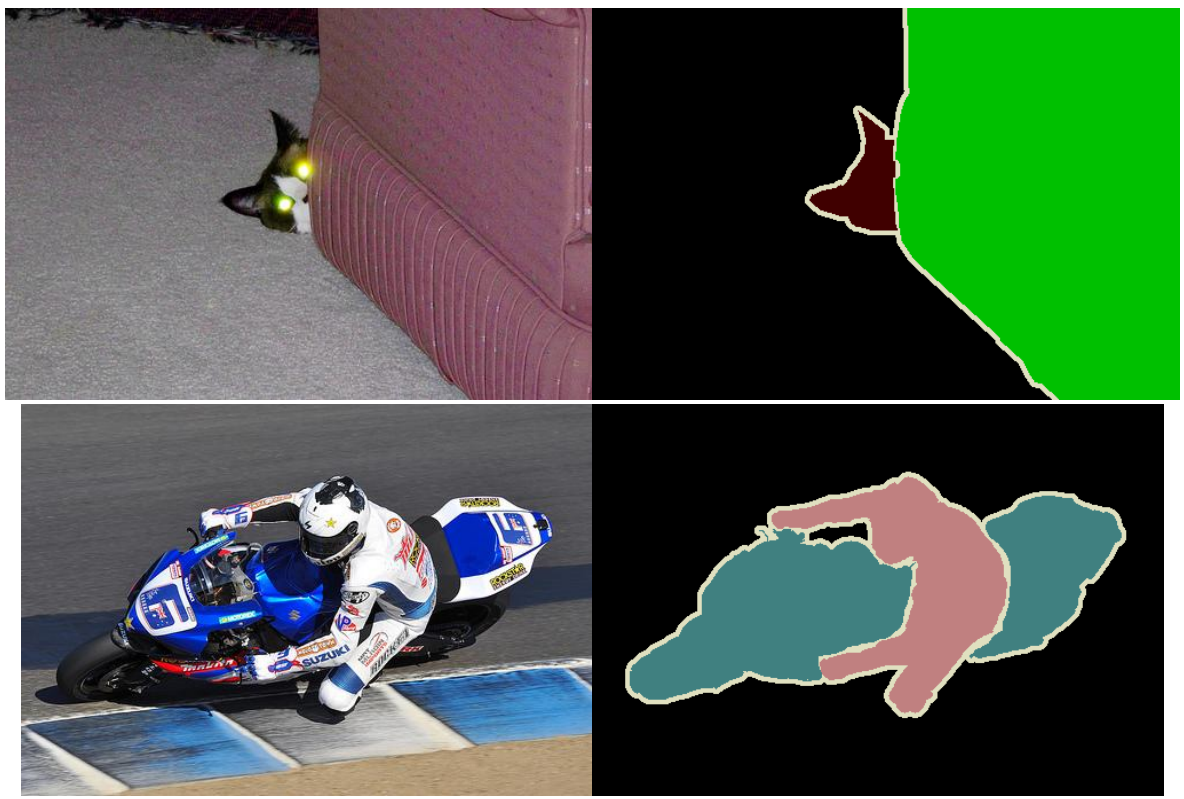
Pascal visual object classes segmentation challenge 2012 [Everingham et al., 2014]

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

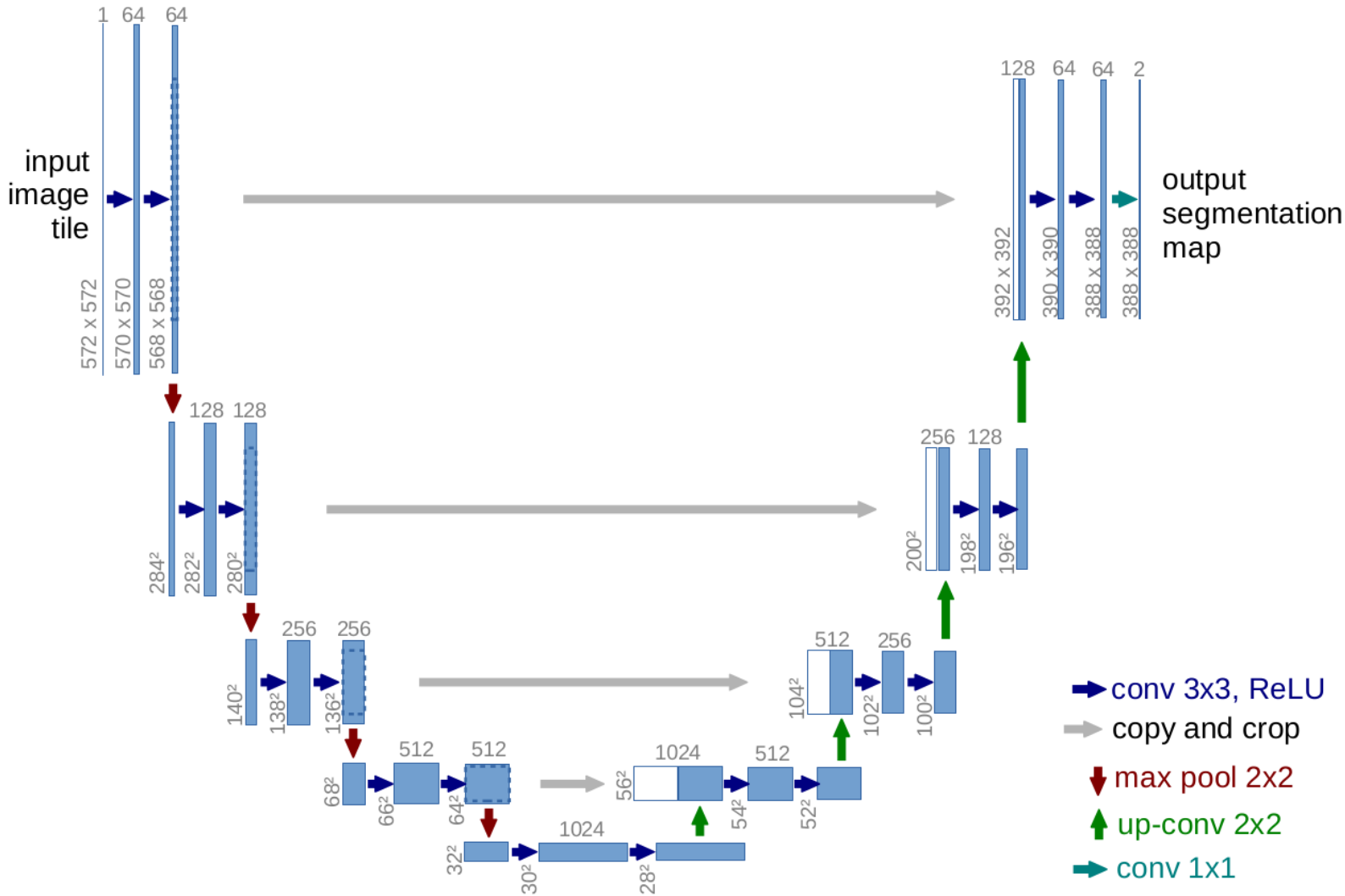


Convolutional nets for semantic image segmentation

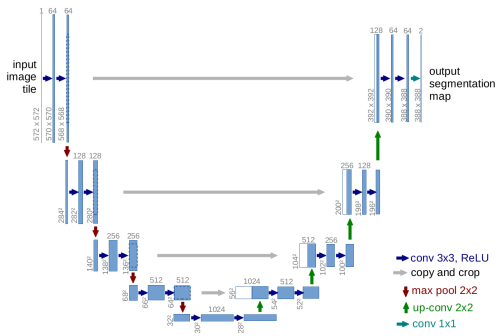
Three papers in 2015:

- 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]



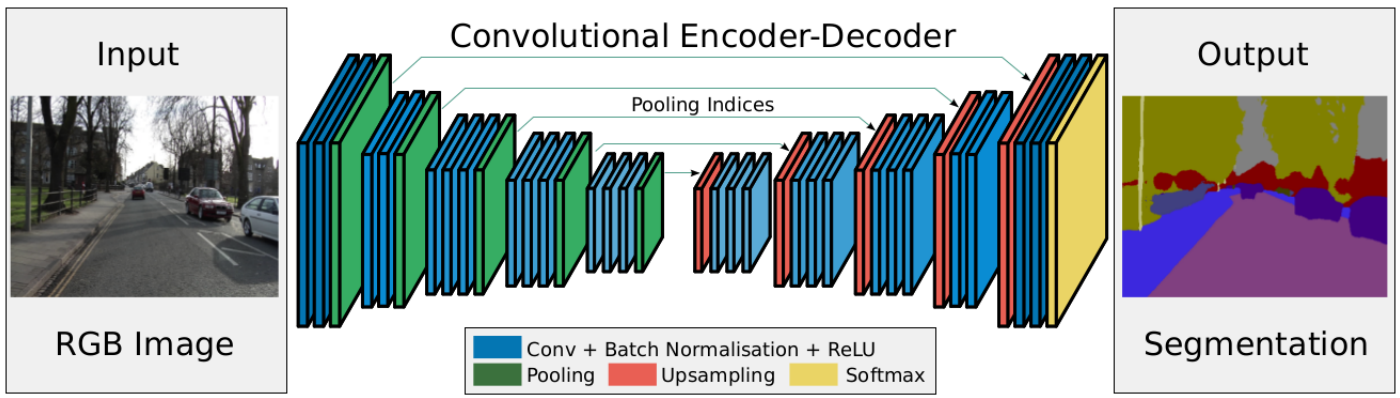
Notes on the U-Net architecture [Ronneberger et al., 2015]



- 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

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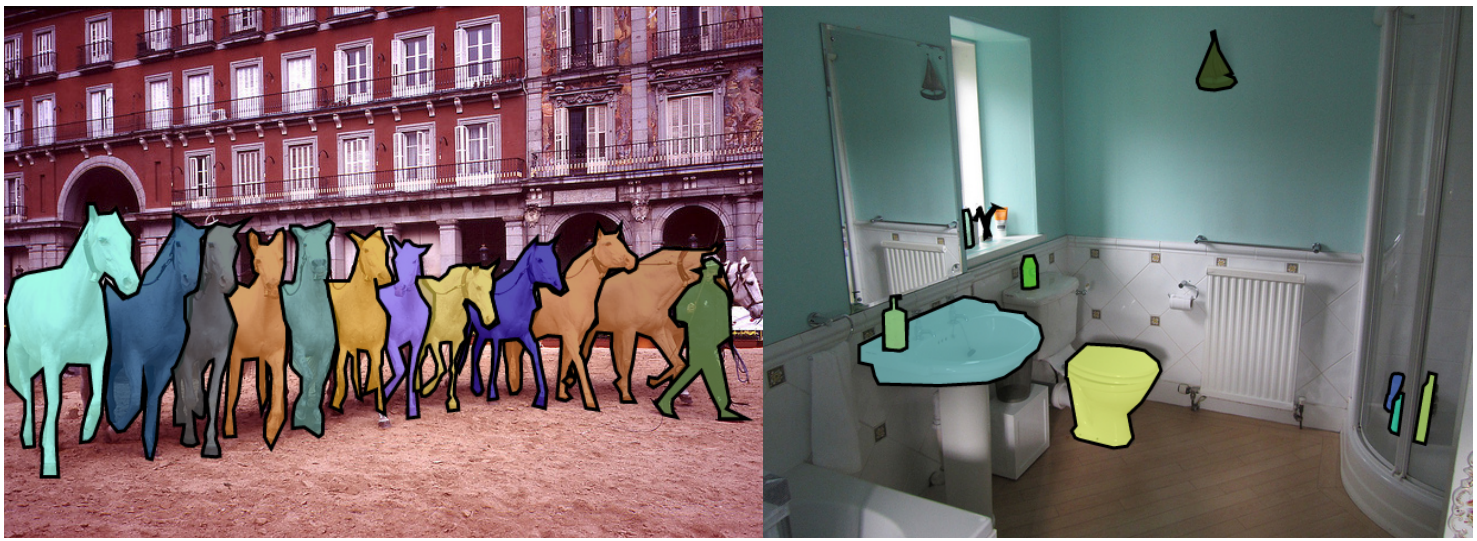
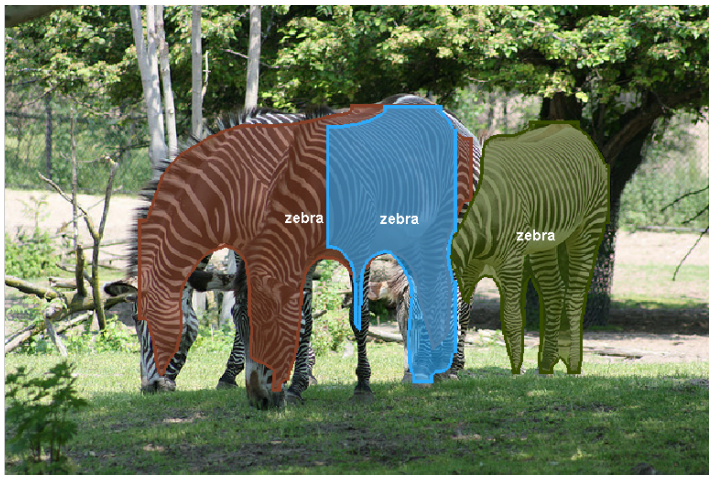
COCO: common objects in context [Lin et al., 2014]

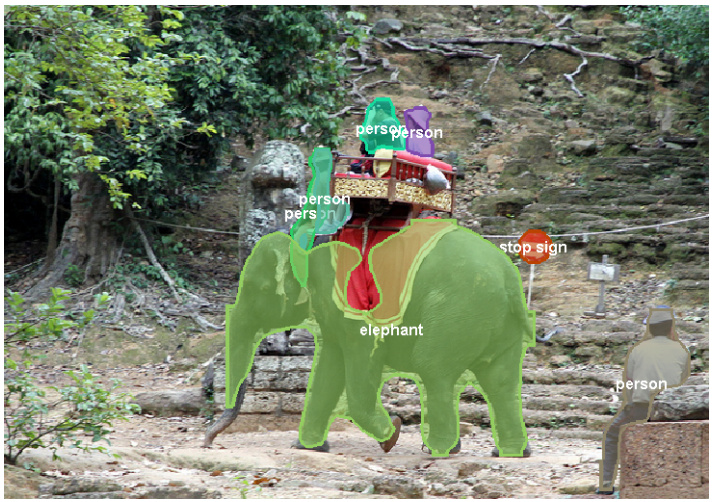
- 2 million objects, from 80 categories, in $300\,000$ images

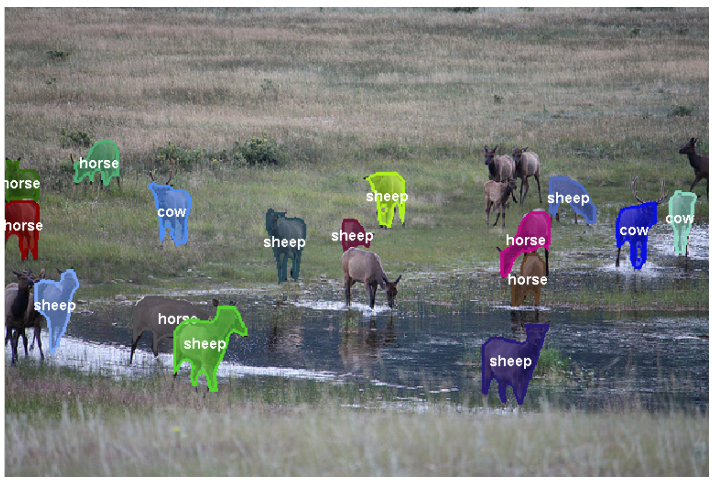


Winner 2016: Fully Convolutional Instance-aware Semantic Segmentation (Microsoft) [Li et al., 2016]

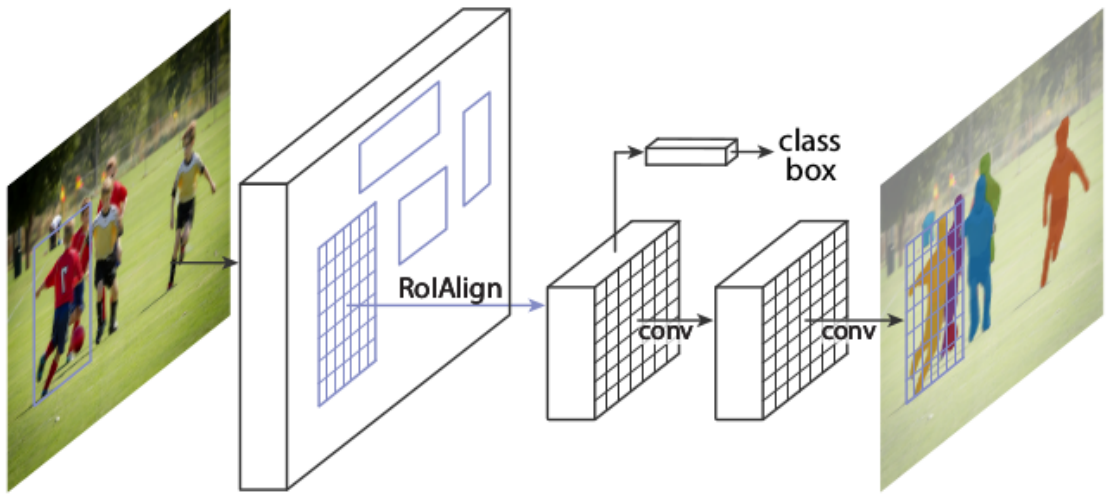
COCO instance segmentation challenge: examples of 2016 winner results



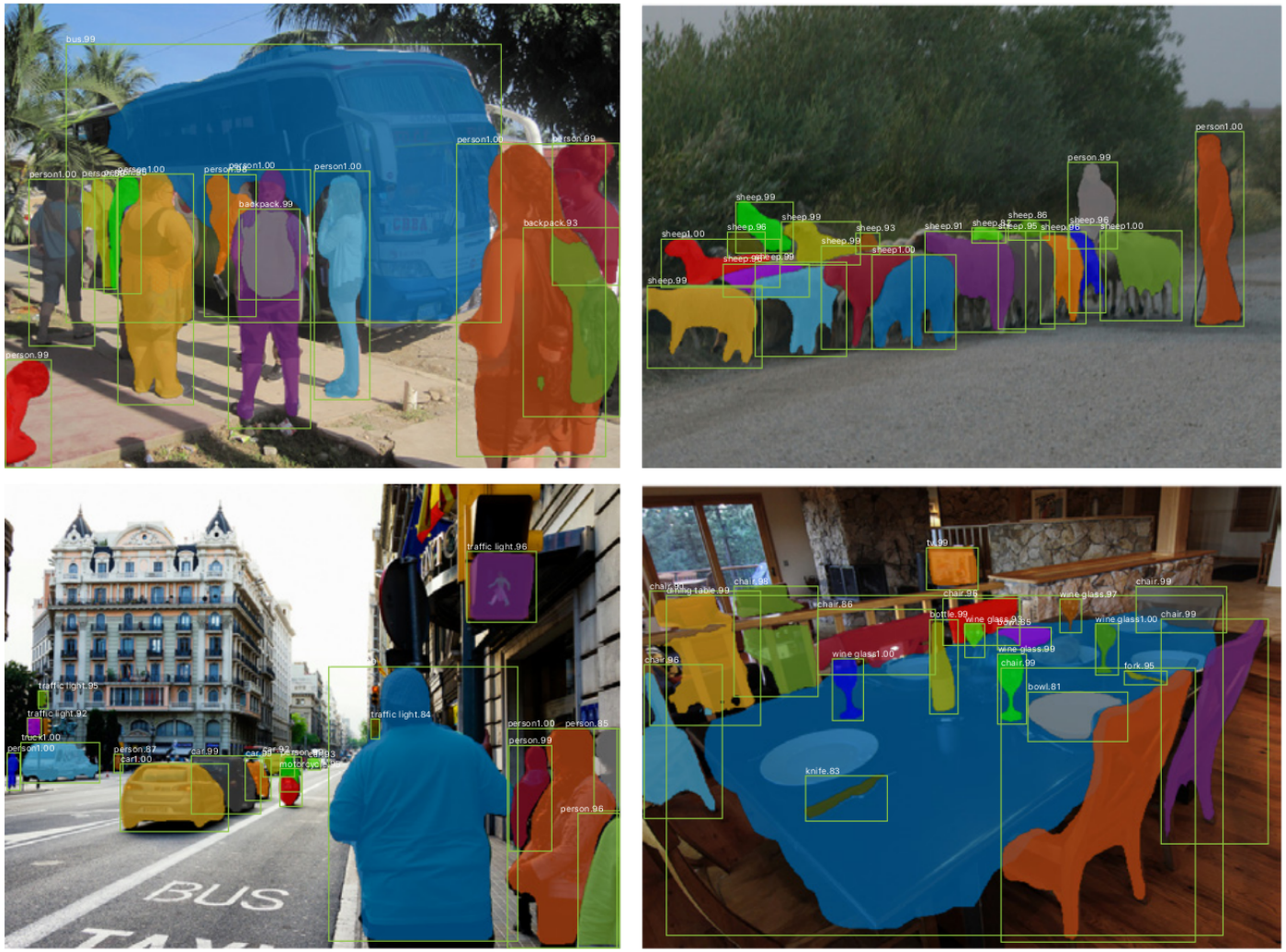




State of the art on the COCO database: Mask R-CNN [He et al., 2017]

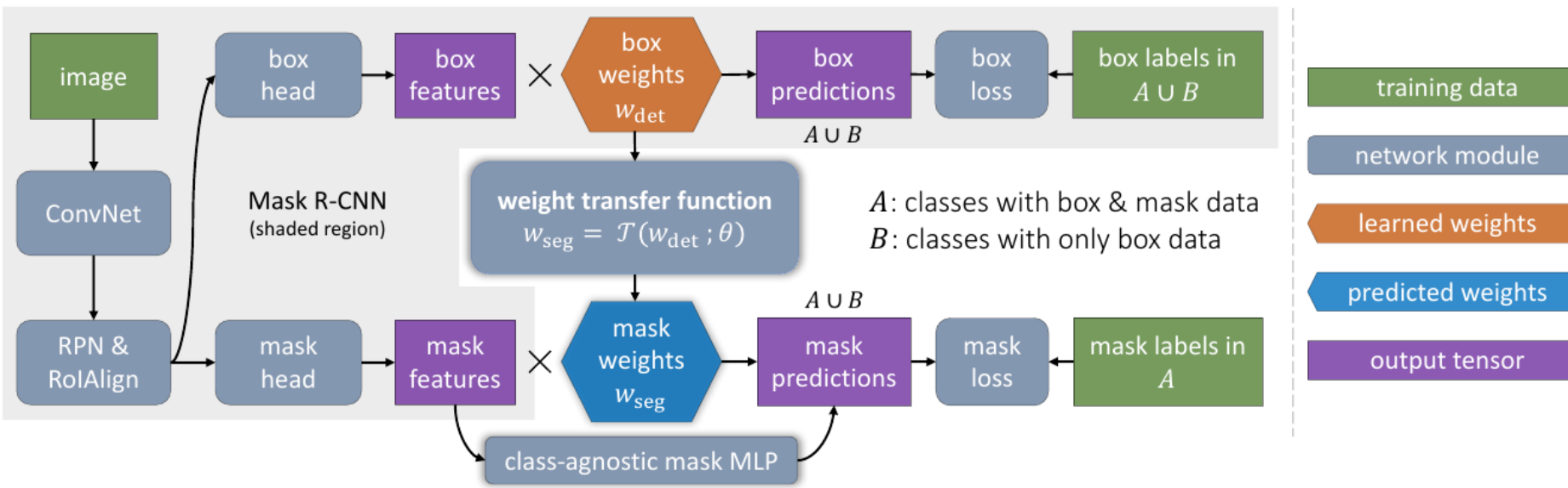


Mask R-CNN on the COCO database



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)

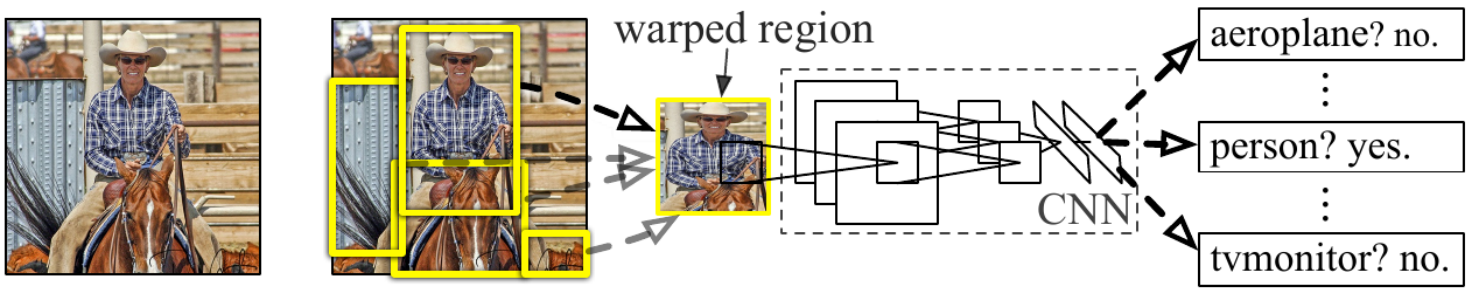


Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

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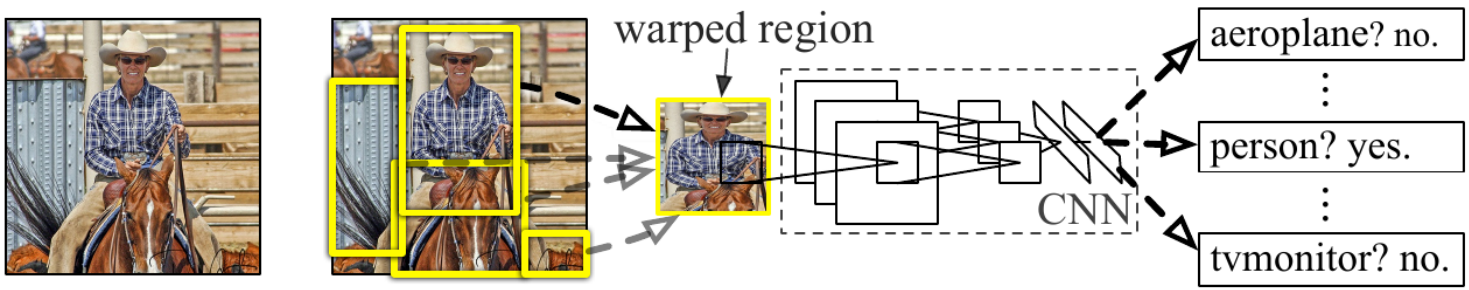

Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

Meanwhile, on the object detection field...

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

Contents

Translation invariance

Identical receptive fields produce identical outputs.

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Translation invariance

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  - 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

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.

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Dealing with image sizes during training

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- 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

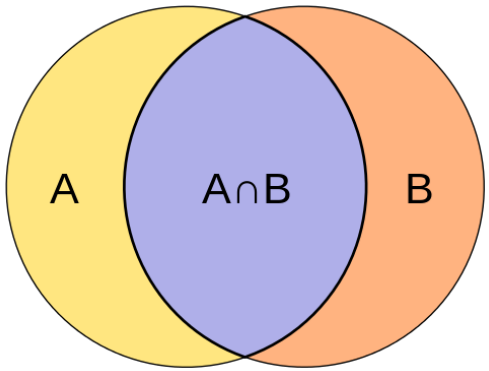
- Mean squared error (MSE): $\sum_i (\hat{y}_i - y_i)^2$
- Cross-entropy: $-\sum_i y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$

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

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

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