Fully convolutional neural networks

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Image definition

Definition

Here an image is a 2D array of size $p \times q$. Each array element belongs to $\mathbb{R}^d$. The dimension of the value space d, is often called the number of channels of the image.
The set of these images is $\mathcal{I}^d$.

Examples

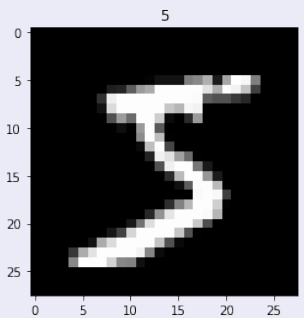
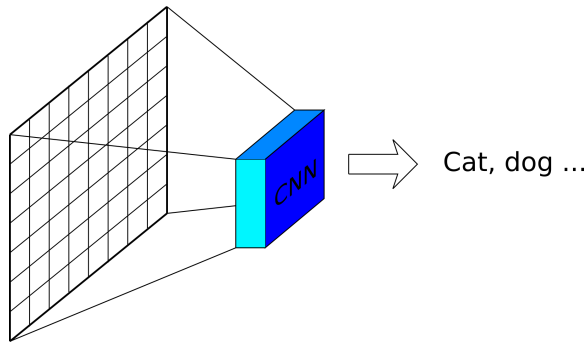


Figure: 28×28 grey level image $(d = 1)$ from the MNIST data set, and 481×321 colour image $(d = 3)$ from the Berkeley segmentation data set.

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

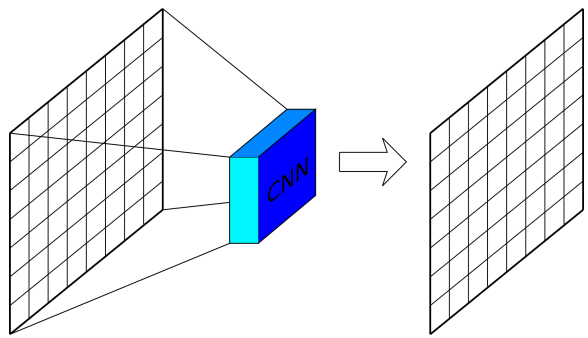


Image-to-image translation

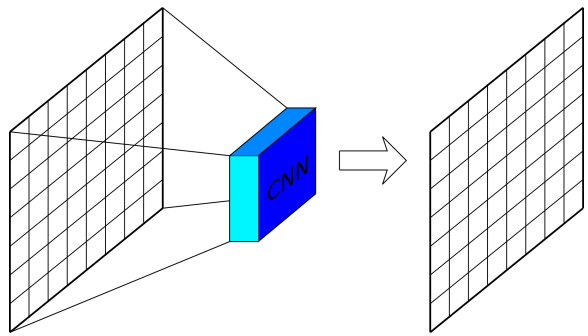
Definition: image-to-image translation

An image-to-image operator is a function that transforms an image into another image of same size:

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

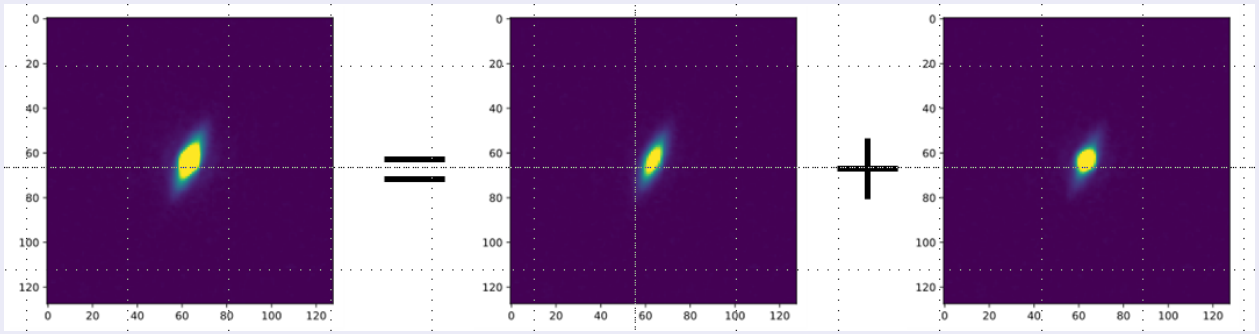
$$I \longmapsto J$$

Note that the number of channels of input and output images can be different.



Examples

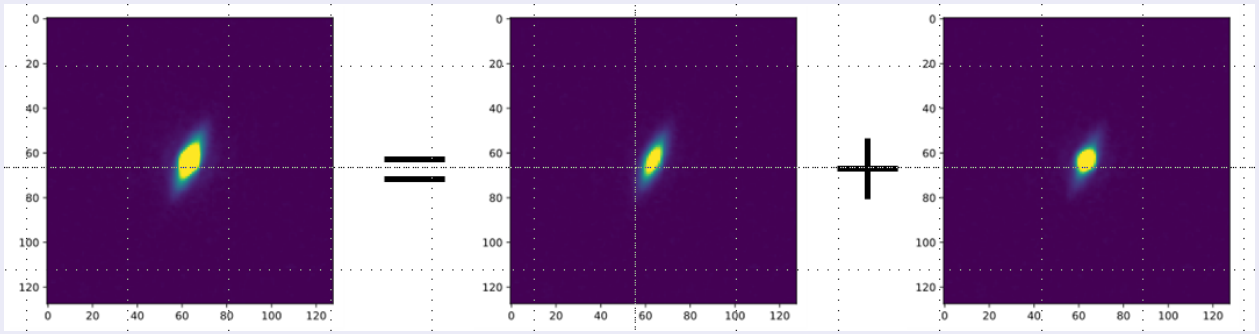
Bulge / disk decomposition



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

Examples

Bulge / disk decomposition



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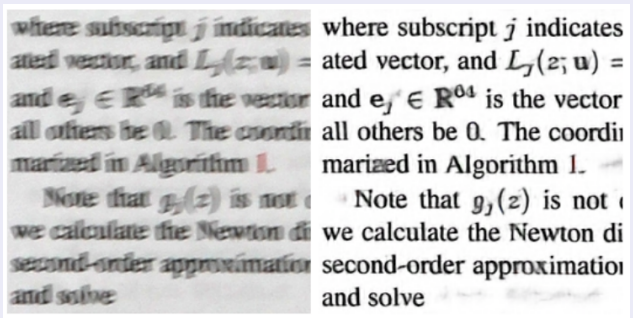
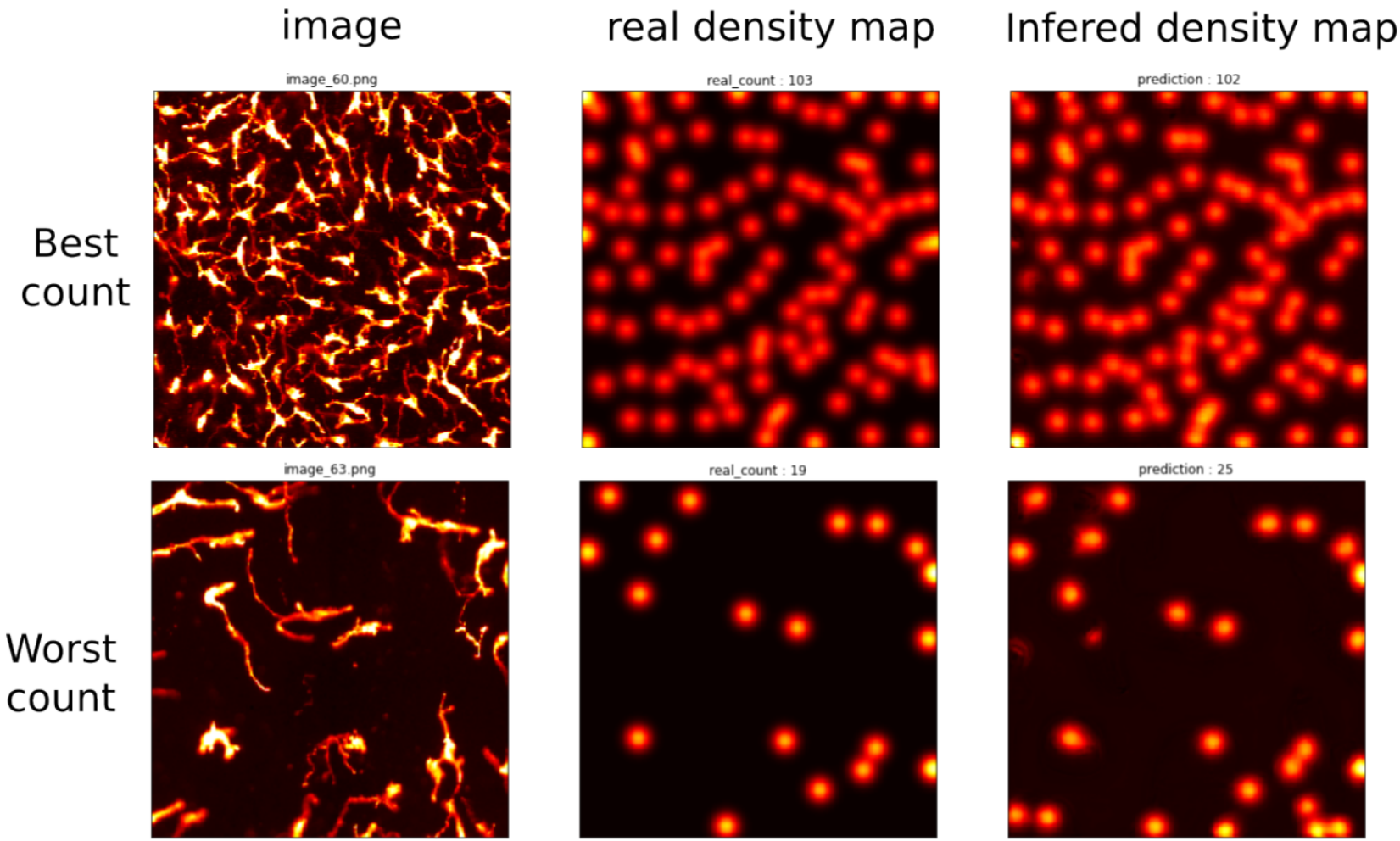
Deblurring network [Hradiš et al., 2015]



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.

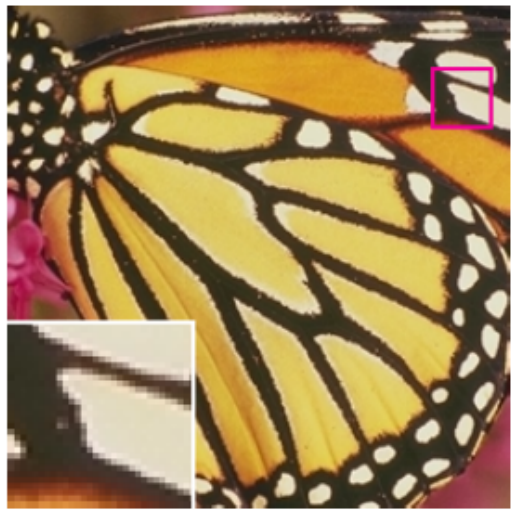
Note that $g_j(z)$ is not
we calculate the Newton di
second-order approximatio
and solve

Counting cells

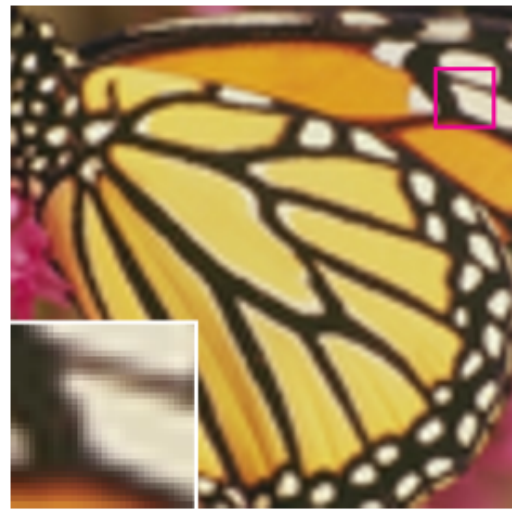


Credits: Tristan Lazard, master thesis

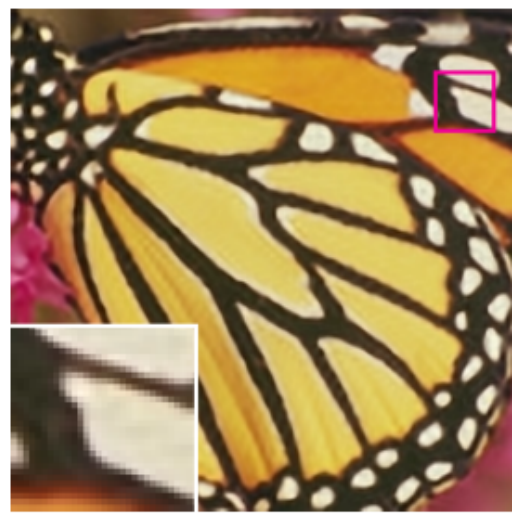
Super resolution



Original / PSNR



Bicubic / 24.04 dB



SRCNN / 27.95 dB

Credits:
http://mmlab.ie.cuhk.edu.hk/projects/SRCI

Microscopy cross-modality prediction[Ounkomol et al., 2018]

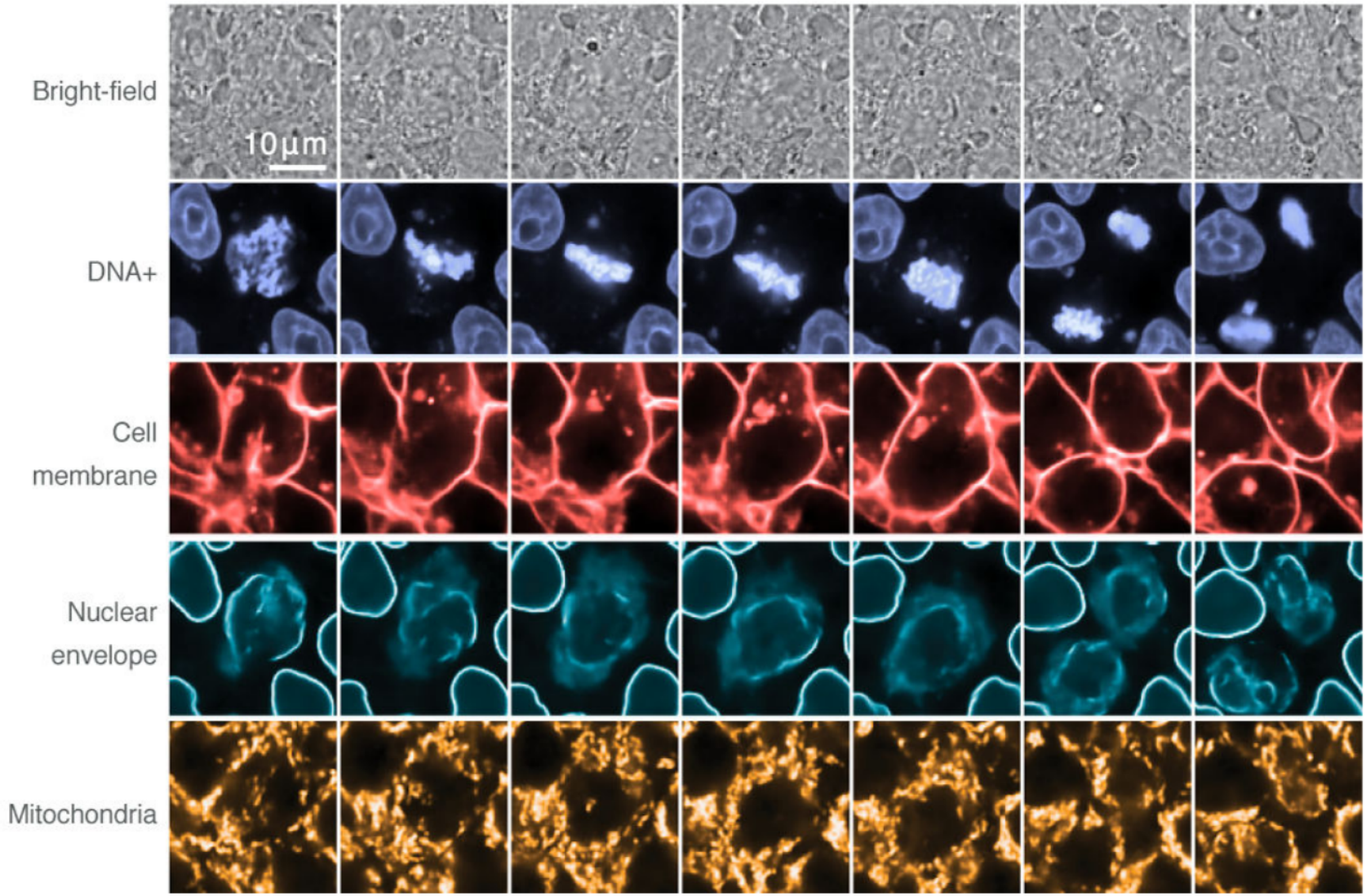


Image segmentation

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

Example

Credits: Pascal VOC database

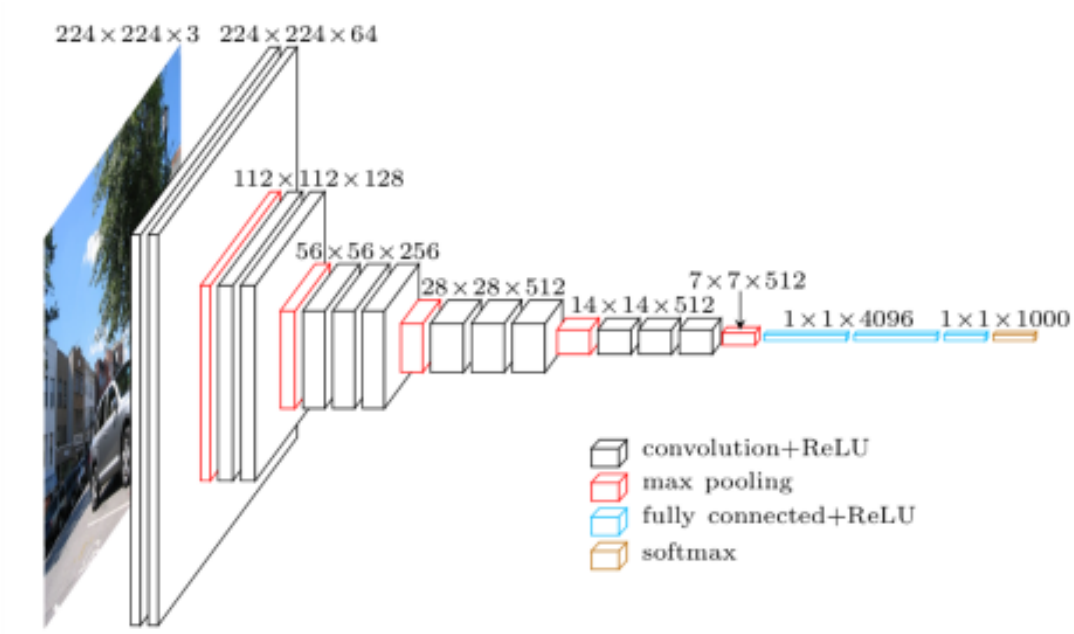
Other applications

- Image filtering
- High dynamic range
- Style modification
- Motion estimation

In the following, we will focus on image segmentation.

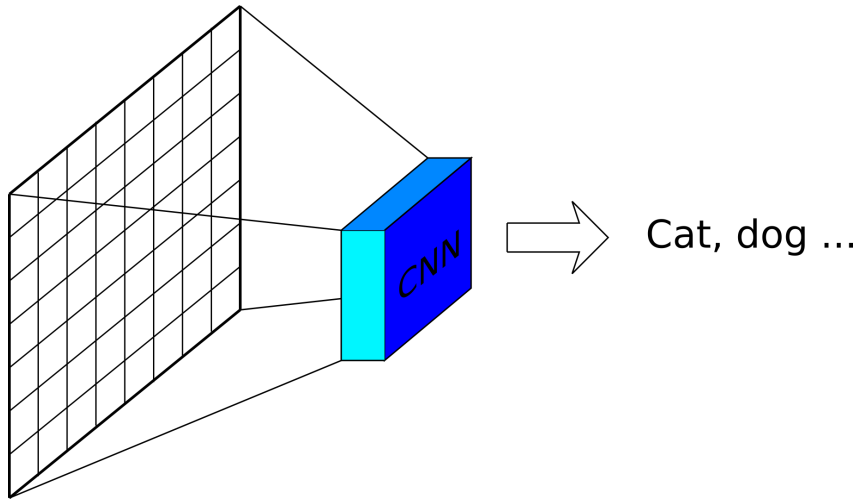
Contents

VGG16: an example network for image classification



Credits: VGG16 (From https://www.cs.toronto.edu/ frossard/post/

From classification nets to image-to-image nets



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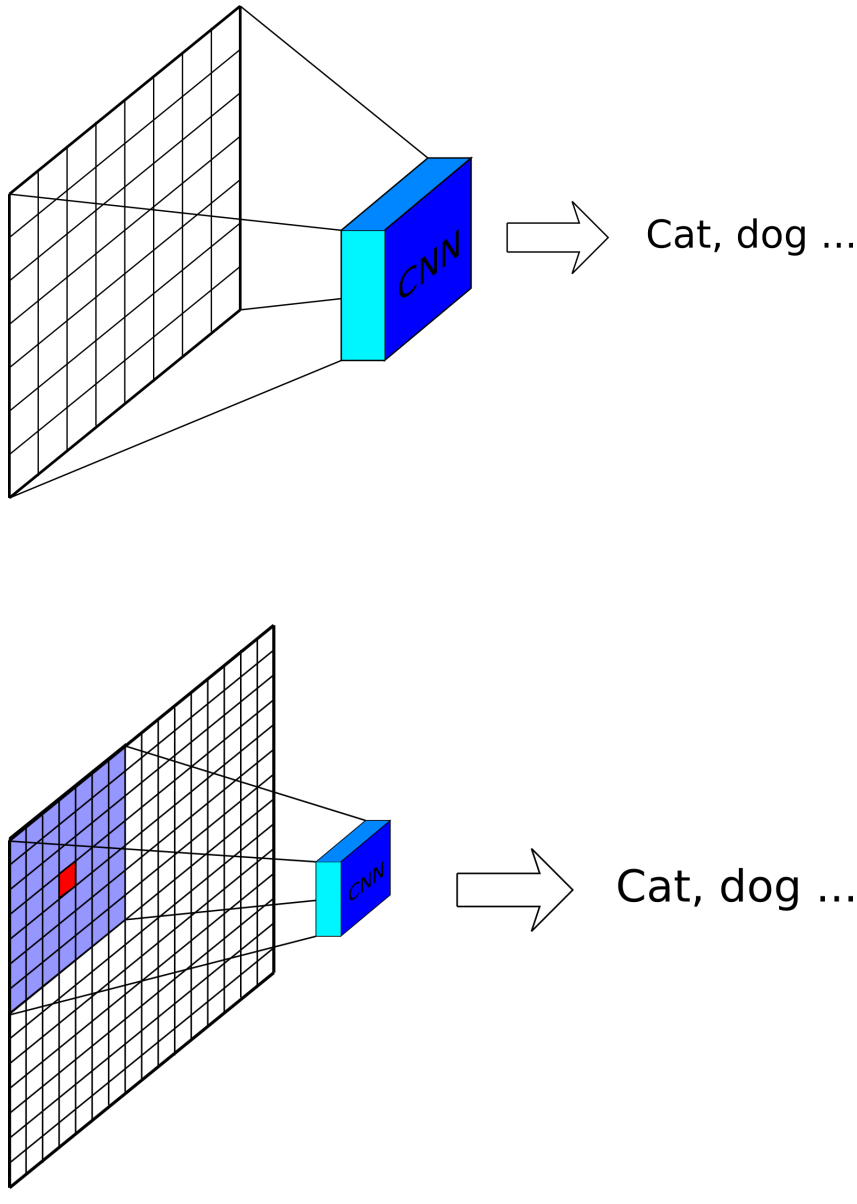

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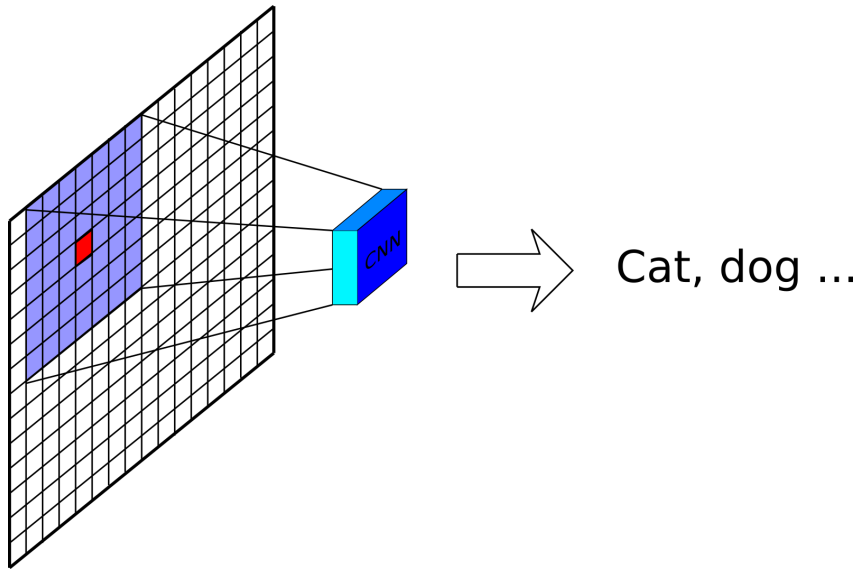

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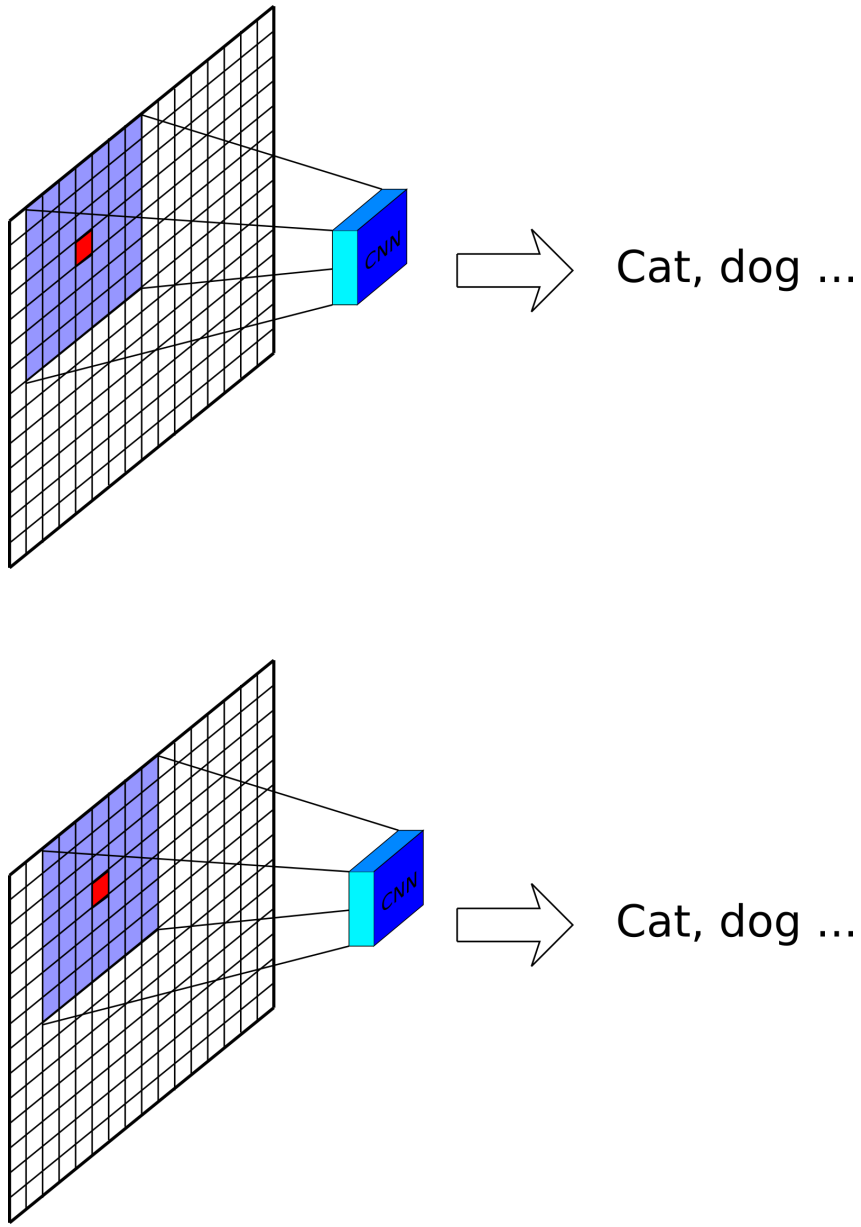
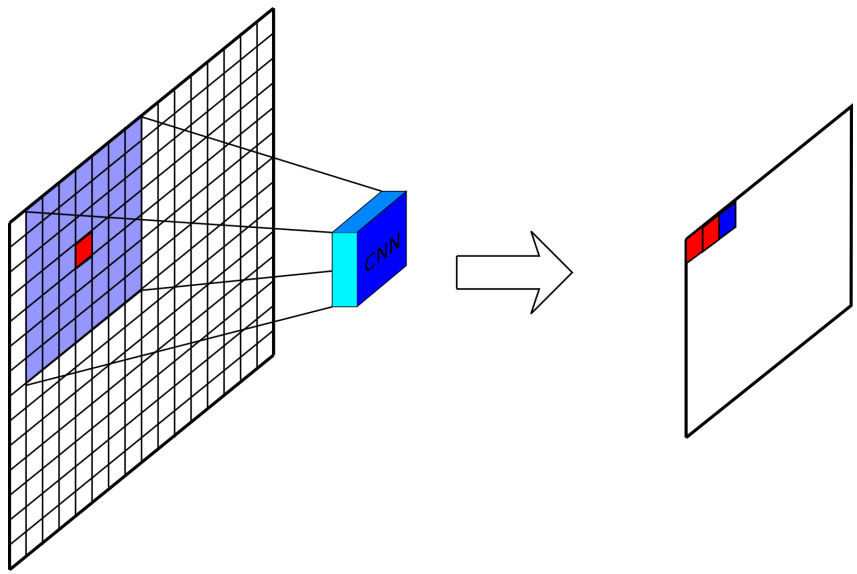


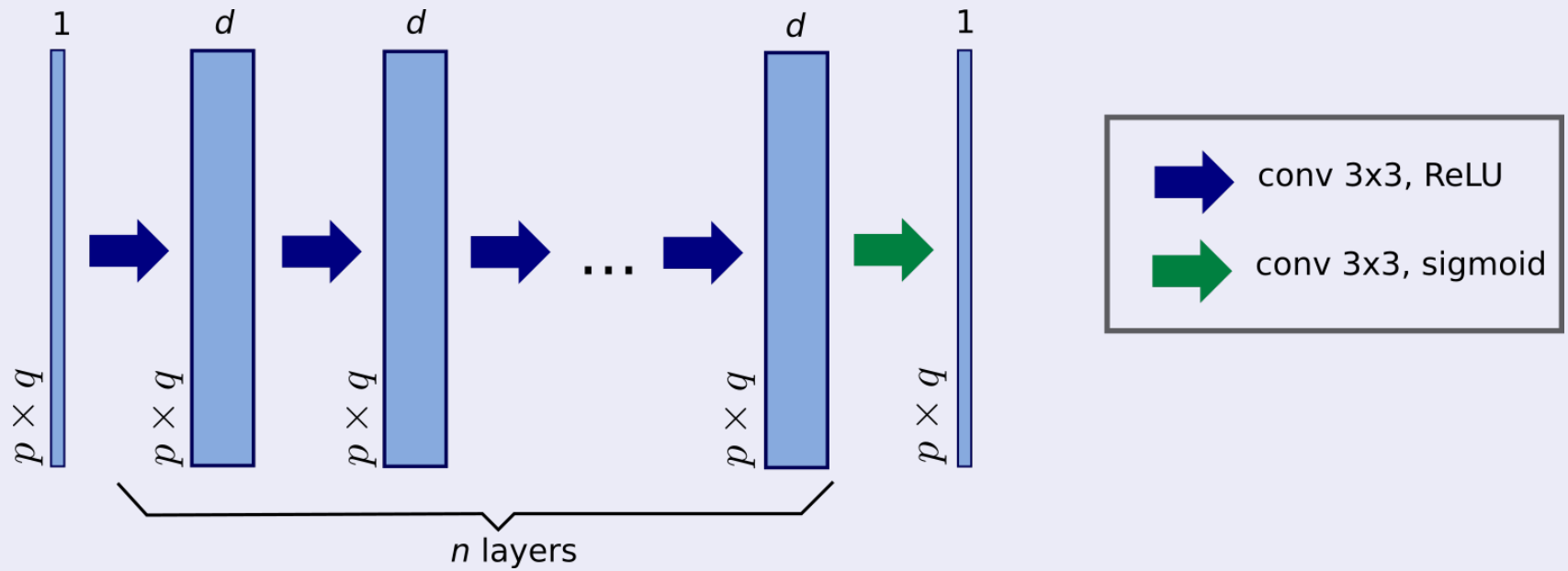
From classification nets to image-to-image nets



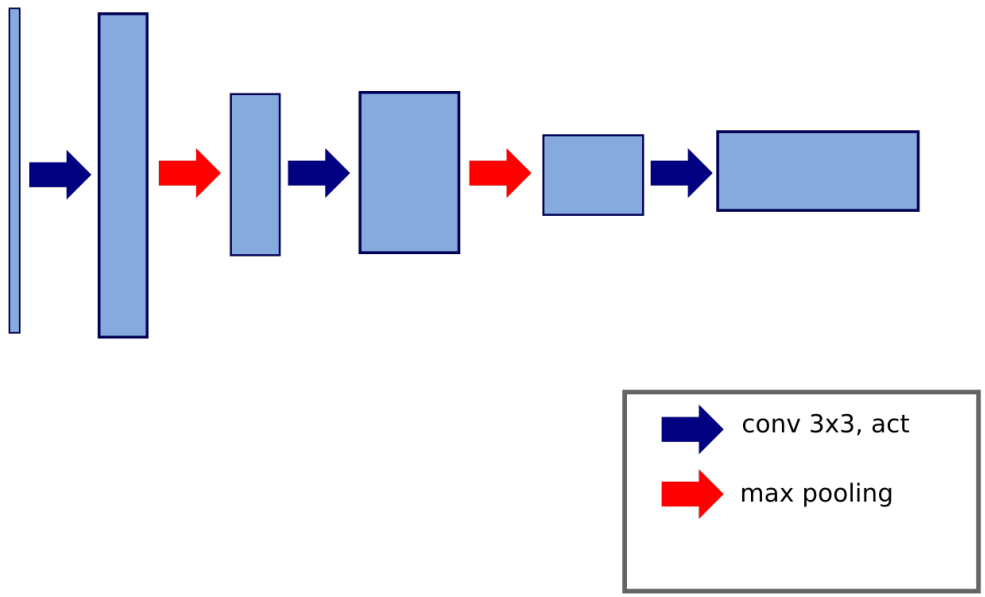
The neuron membrane segmentation challenge
winner [Ciresan et al., 2012] used this strategy. It is inefficient.

The simplest image-to-image architecture

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



Going back to the original image size



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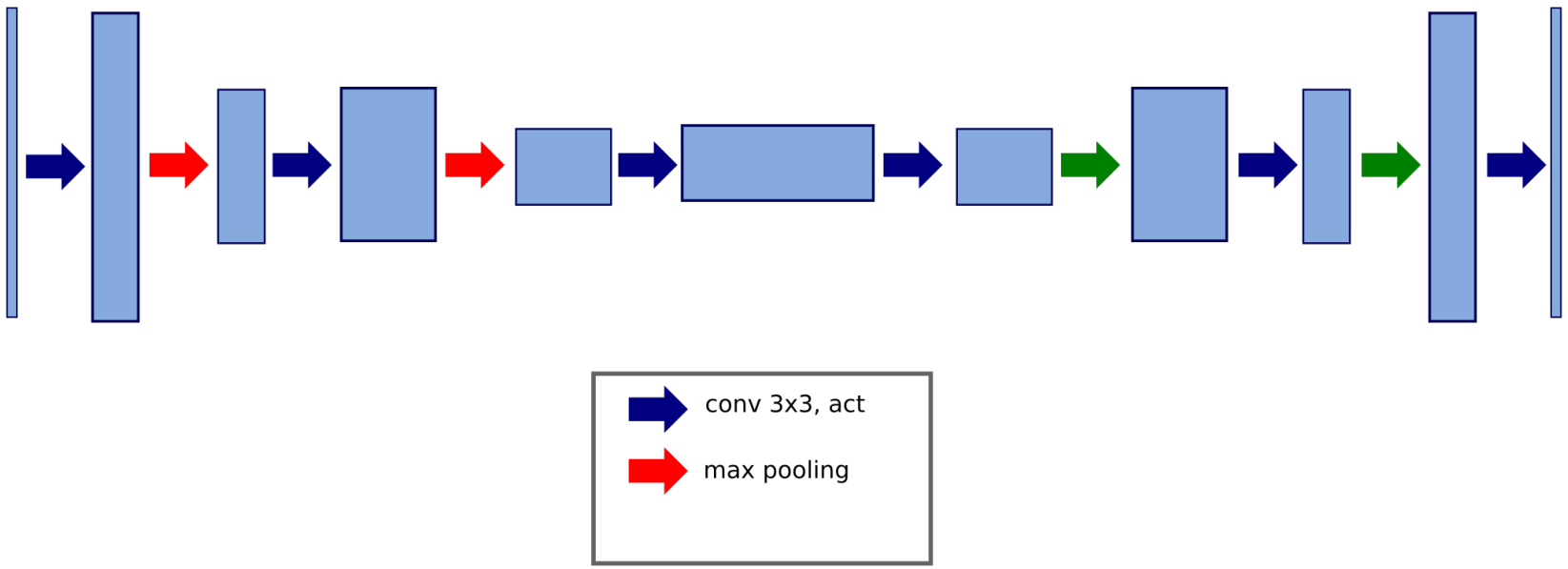

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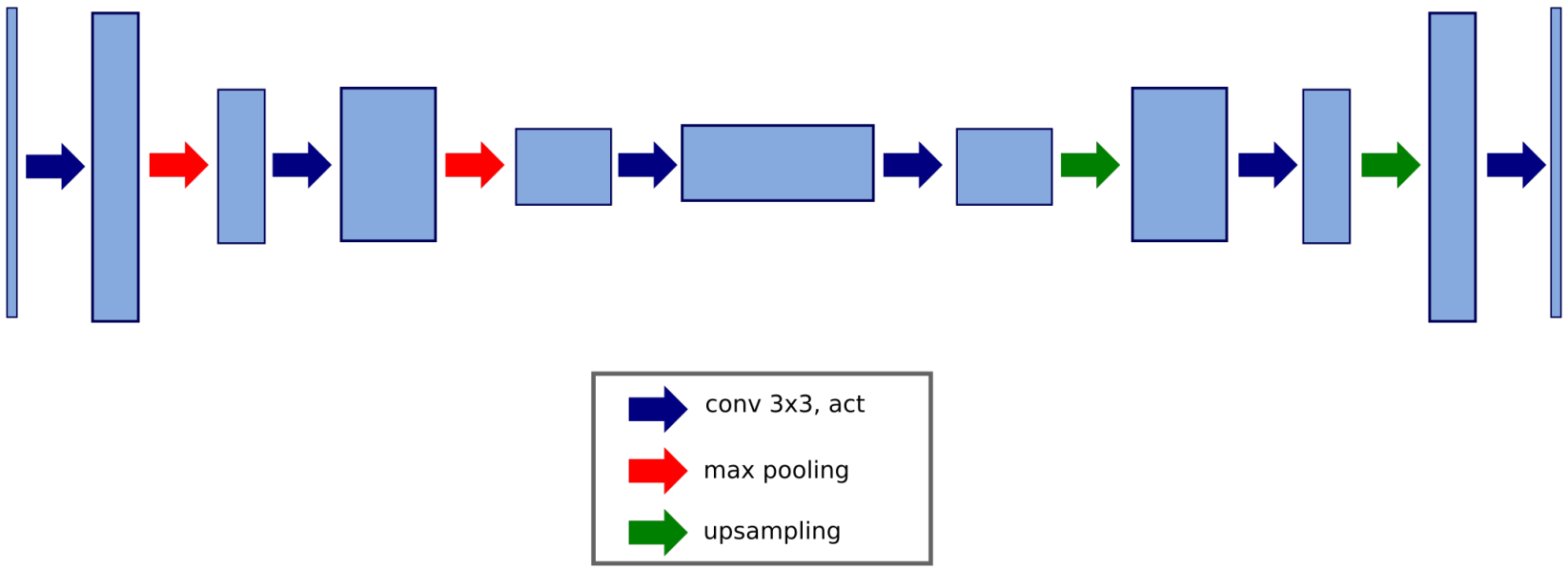
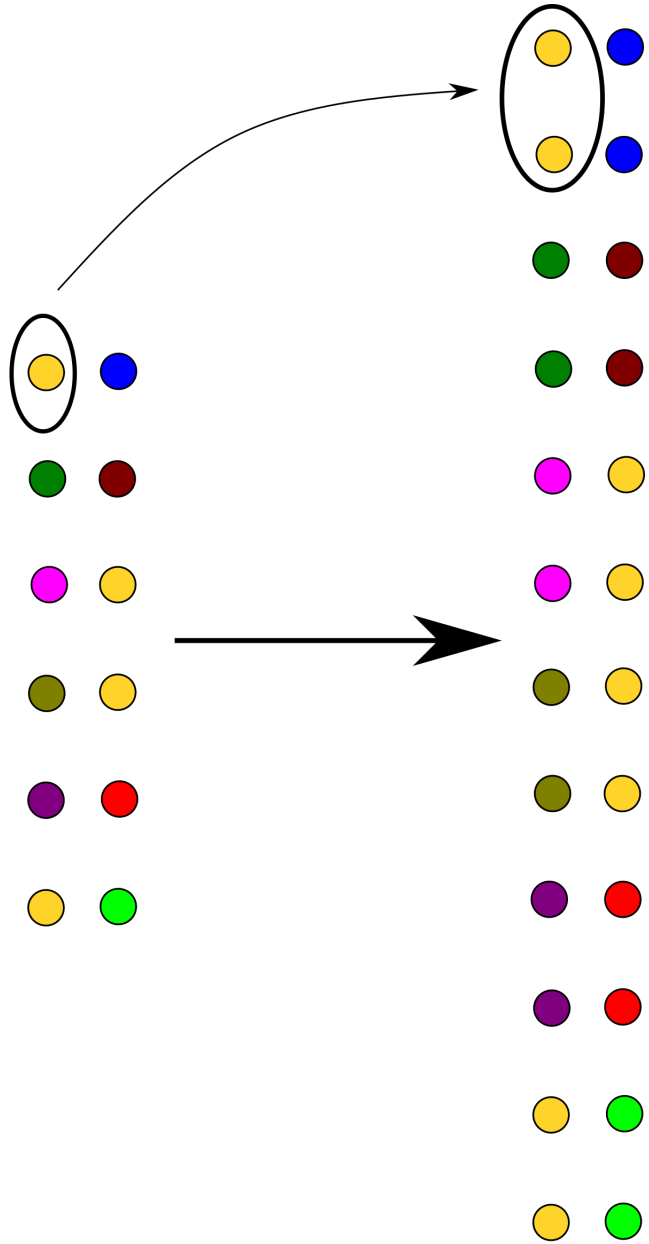


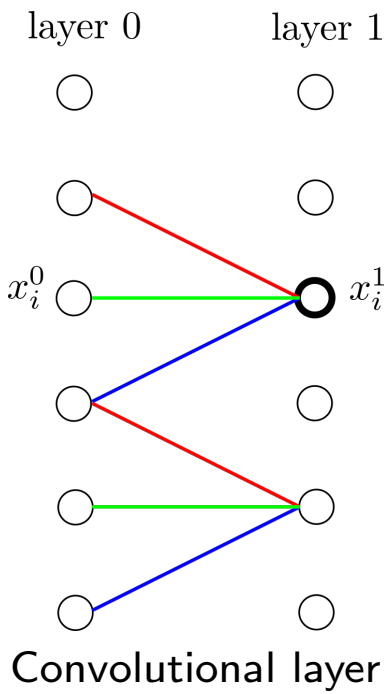
Upsampling techniques

- Replication
- Transposed convolution
- Pooling index memorization

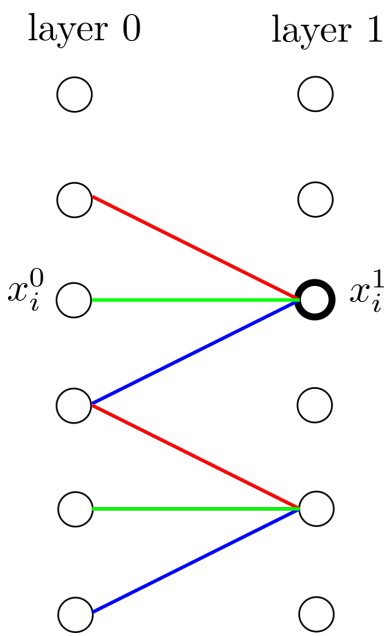
Upsampling through replication



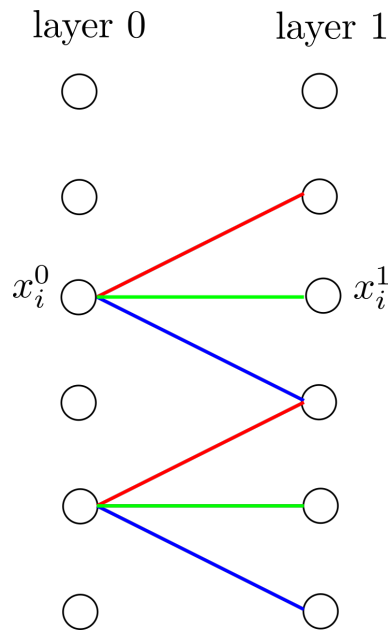
Transposed convolution



Transposed convolution

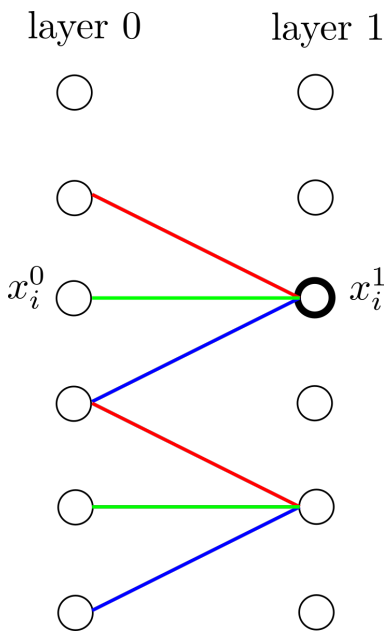


Convolutional layer



Transposed convolutional layer

Transposed convolution



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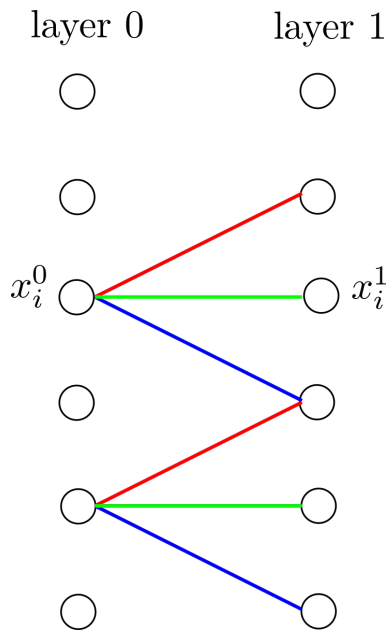
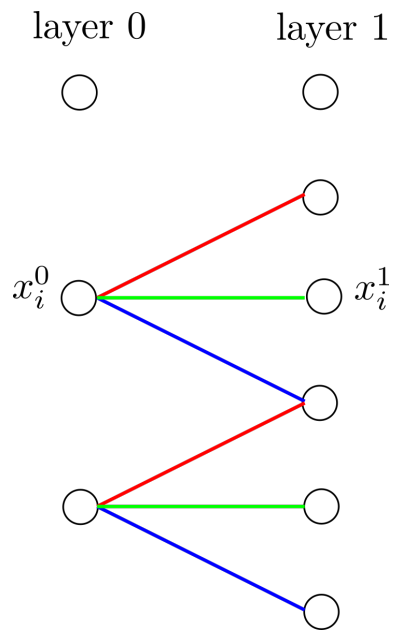


Transposed convolutional layer



Transposed convolutional layer with stride $= 2$

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Receptive field

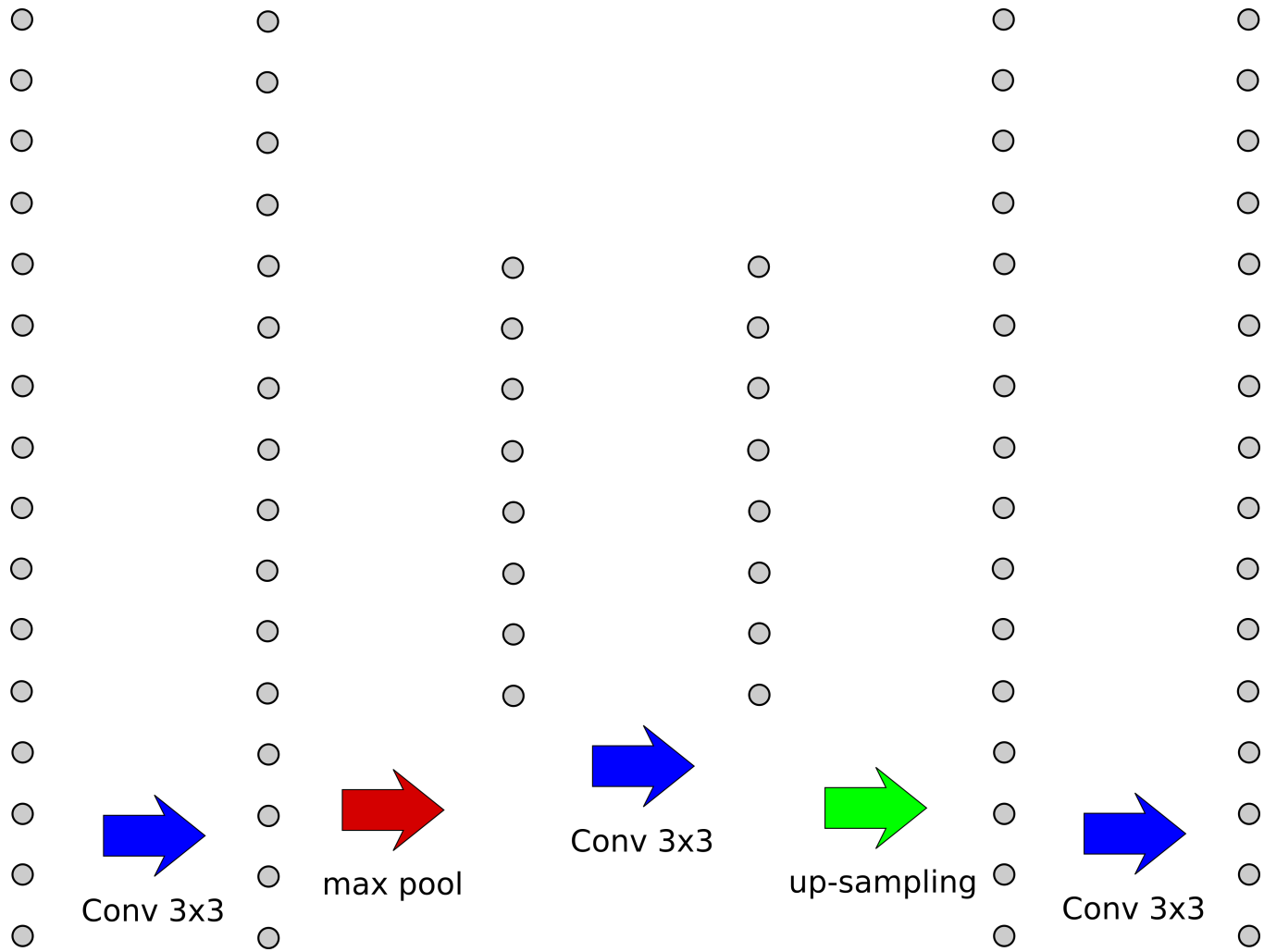
Definition: links between neurons

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



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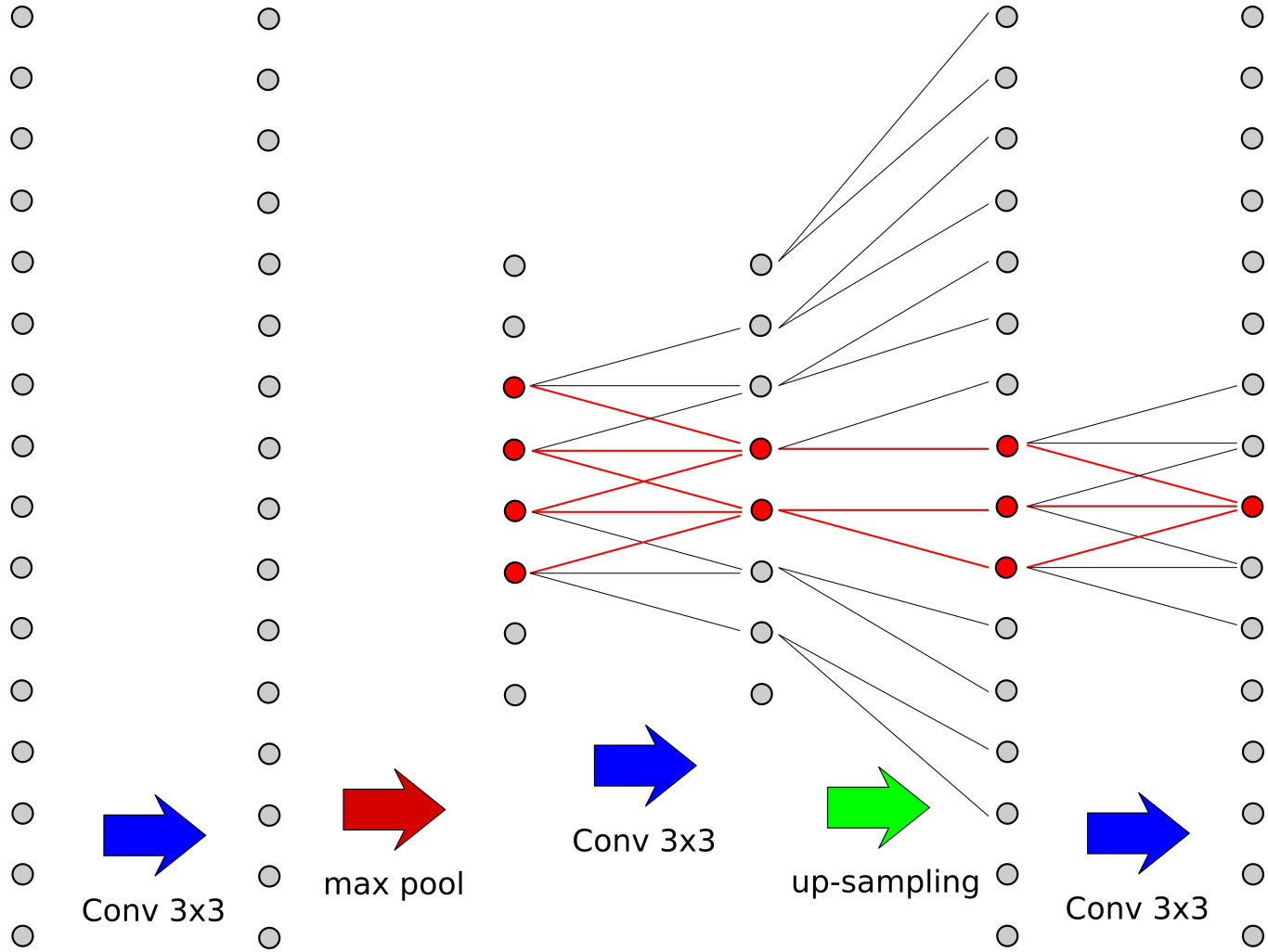
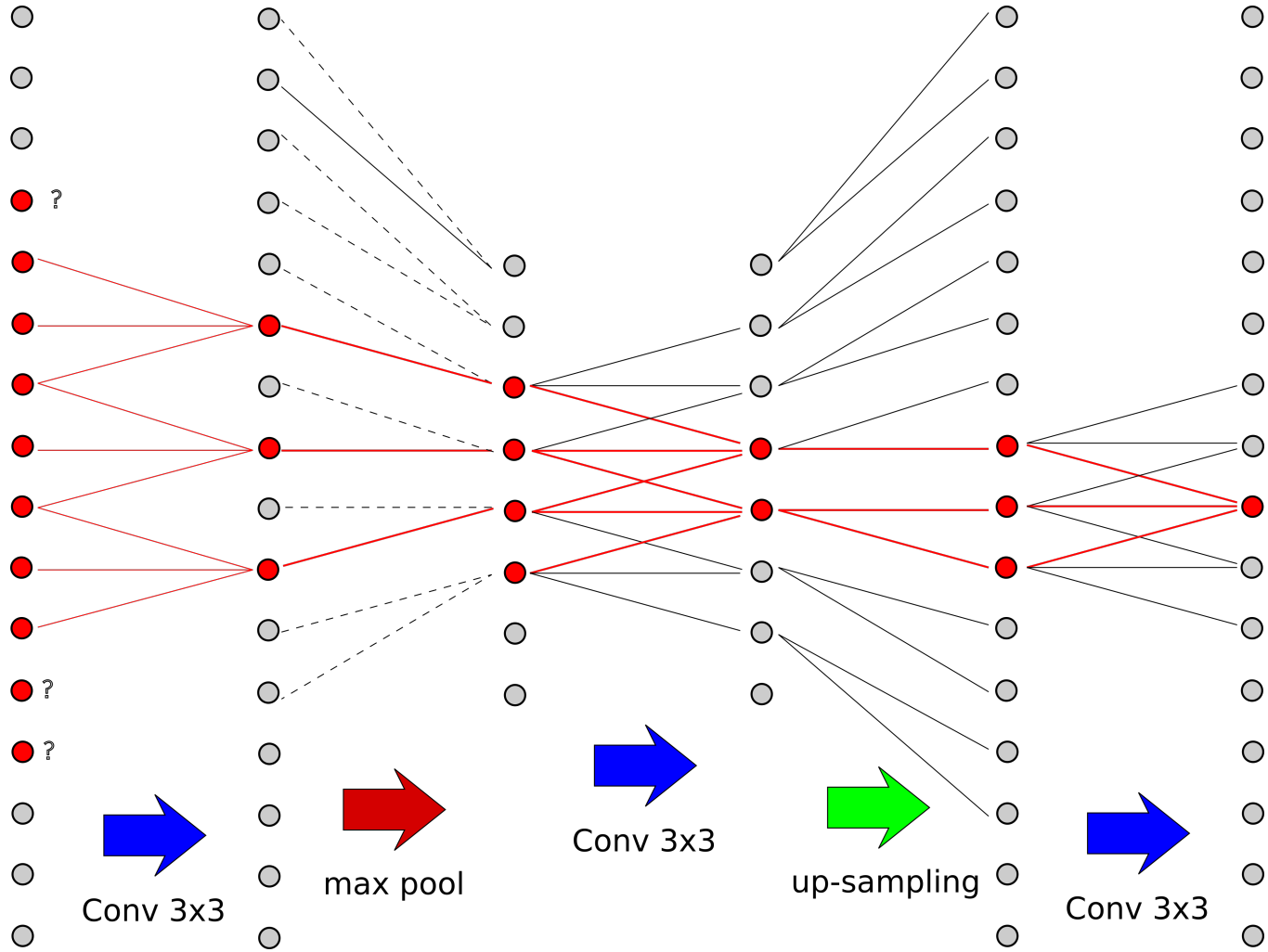
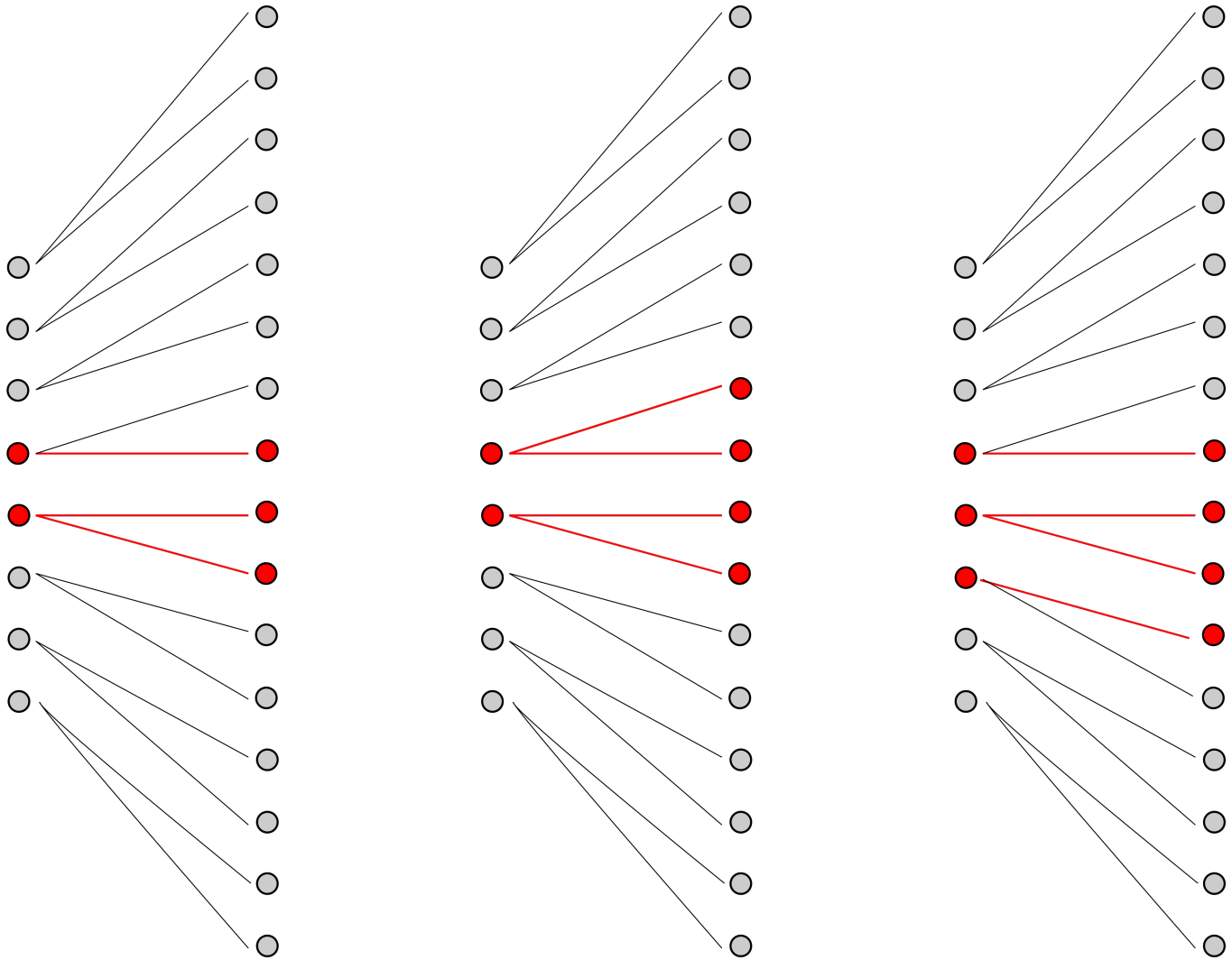


Illustration

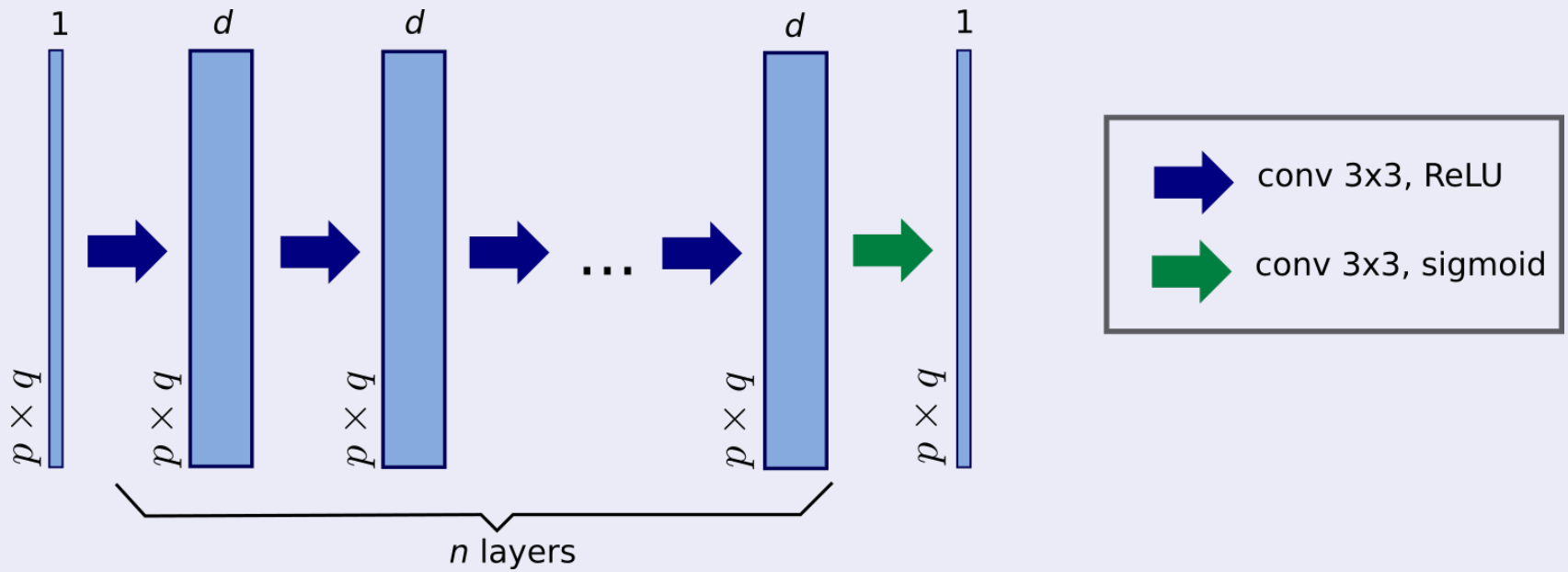


Receptive field evolution through an upsampling layer



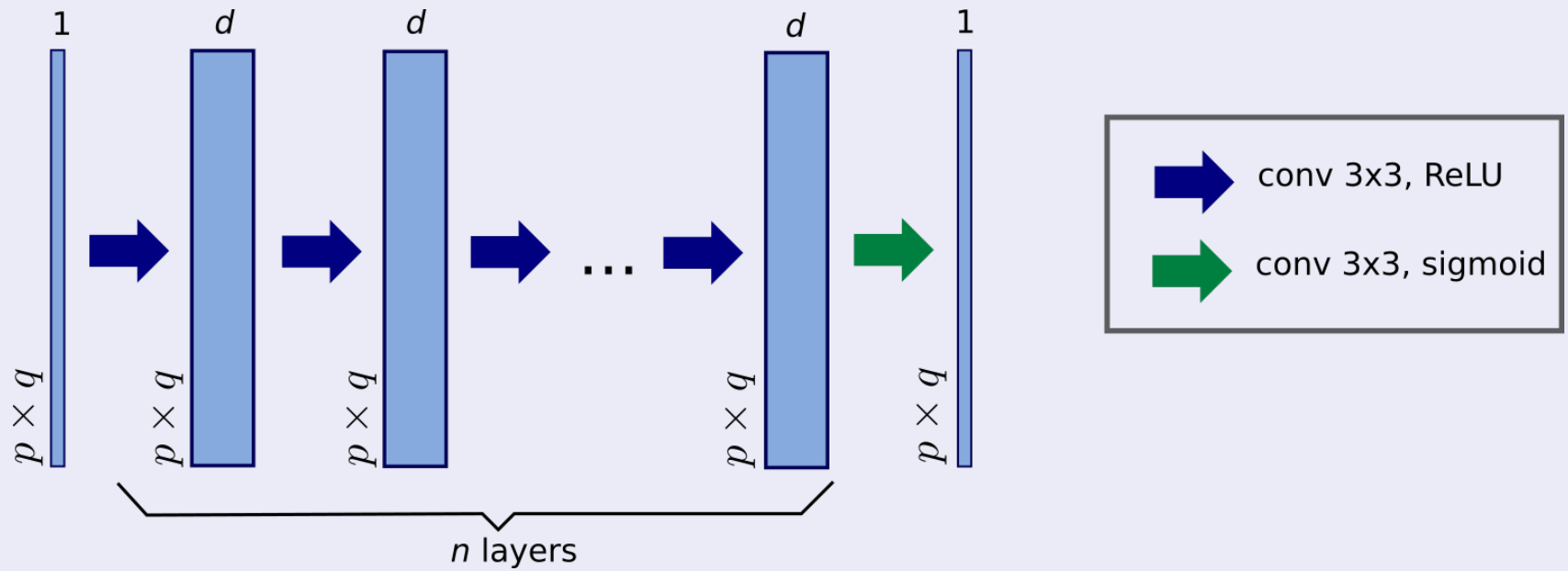
Example

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



Example

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



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

Contents

Equivariance

Definition

A function $f : E \longrightarrow F$ if equivariant with respect to the functions $t_E : E \longrightarrow E$ and $t_F : F \longrightarrow F$ iff $\forall x \in E$:

$$f(t_E(x)) = t_F(f(x))$$

Translation equivariance

- When $E = F$ and t_E and t_F are the same, any, translation, then we have *translation equivariance*.
- Translation equivariance is an often sought property for image processing operators.
- Note that we often abusively say *invariant* to translation instead of *equivariant* to translation.
- Given that in all practical cases images are defined on a bounded set, this property is only true "far enough" from the borders

Translation equivariance applied to neural networks

Definition

Let us consider an operator f between two layers L_1 and L_2 of a NN. Suppose that the receptive field of this operator for a given neuron p of L_2 is $R(p)$, a subset of neurons of L_1. Then f is said to be translation equivariant if, for any two neurons p and q of L_2, such that $L_1(R(p)) = L_1(R(q))$ (i.e. their receptive fields are identical) then $f(p) = f(q)$.

Simply put, the operator is translation equivariant if identical receptive fields produce identical values.

Translation equivariant operators

Operator	**Translation equivariant**
Convolution (stride$= 1$)	
Downsampling (stride > 1)	
Transposed convolution (stride> 1)	
Upsampling (stride> 1)	
Concatenation	
Addition	

Translation equivariant operators

Operator	**Translation equivariant**
Convolution (stride$= 1$)	yes
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- Position information can also be used in the network:
  - Through masks or segmentations

Translation equivariance: comments

Identical receptive fields produce identical outputs.

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

Illustration

Figure: Eye fundus / retina image

Credits: OPHDIAT database

Illustration

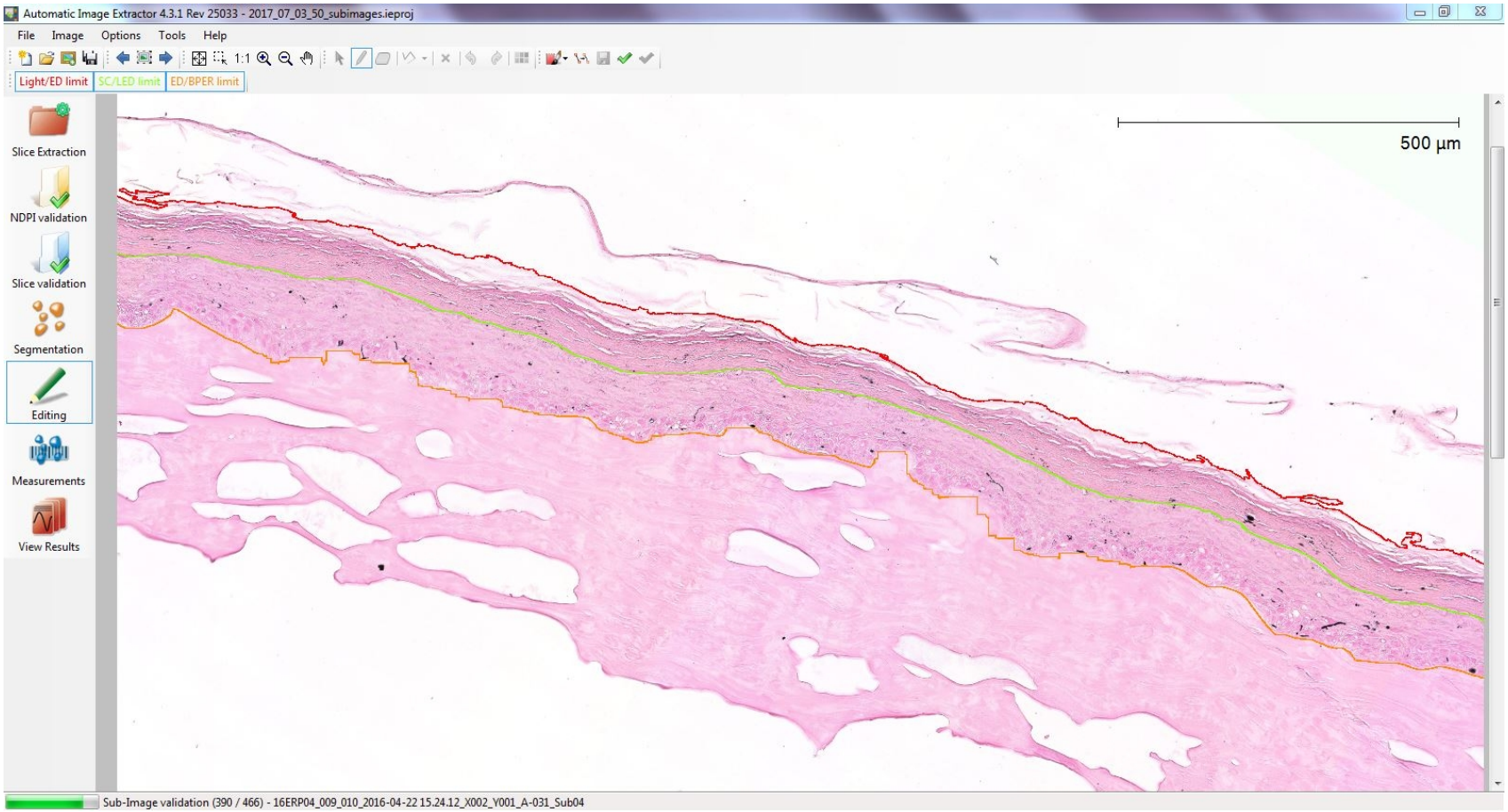


Figure: Histological image of reconstructed skin

Credits: L'Oréal

Contents

Image size flexibility

- A NN containing fully-connected layers can only process images of a given size
- A fully convolutional 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 fully convolutional 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

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

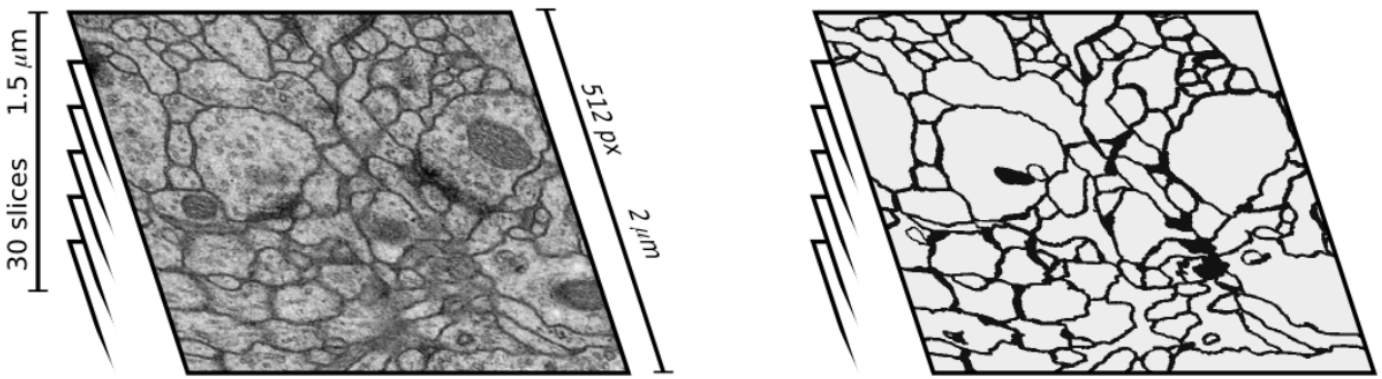
Some vocabulary on segmentation

- **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.

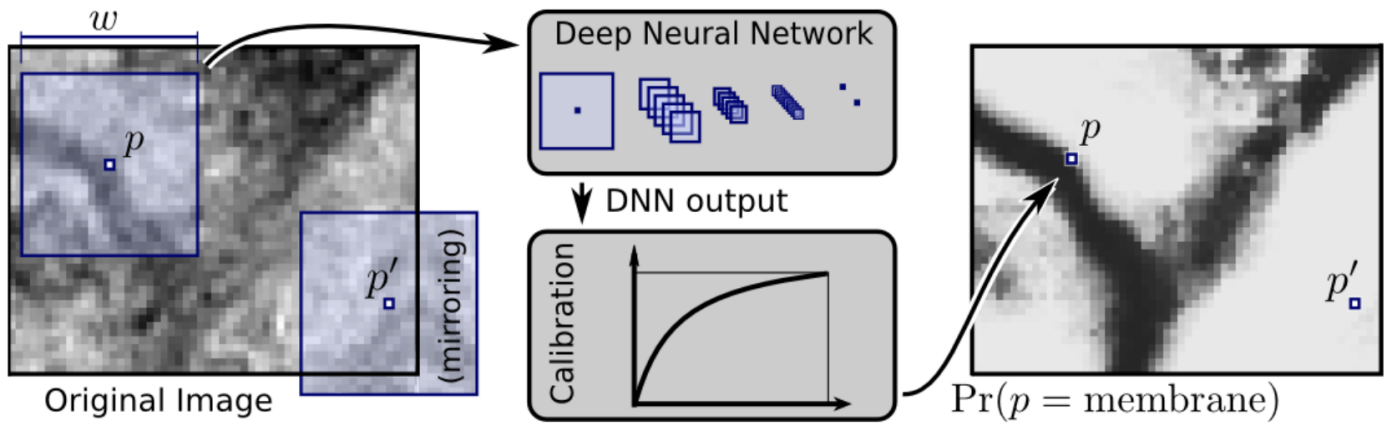
Contents

Neuron membrane segmentation challenge (ISBI 2012)

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



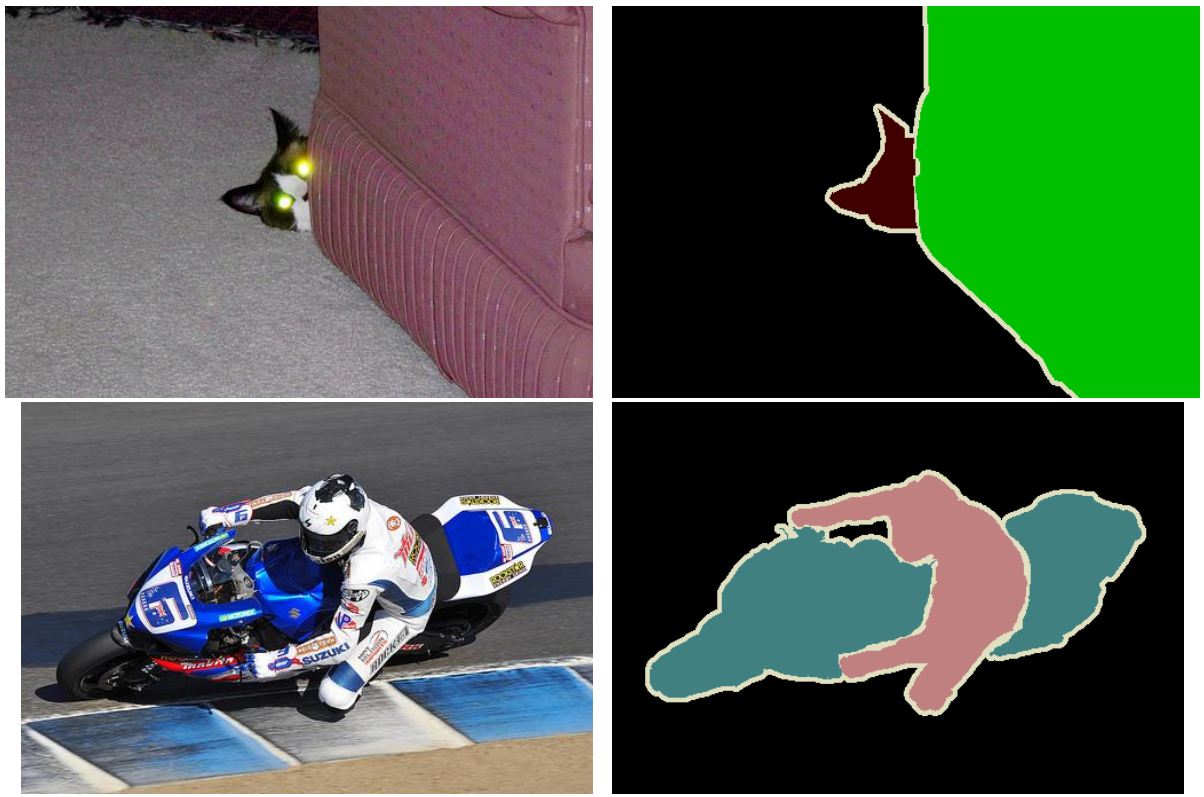
Neuron membrane segmentation challenge winner [Ciresan et al., 2012]



Contents

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.)

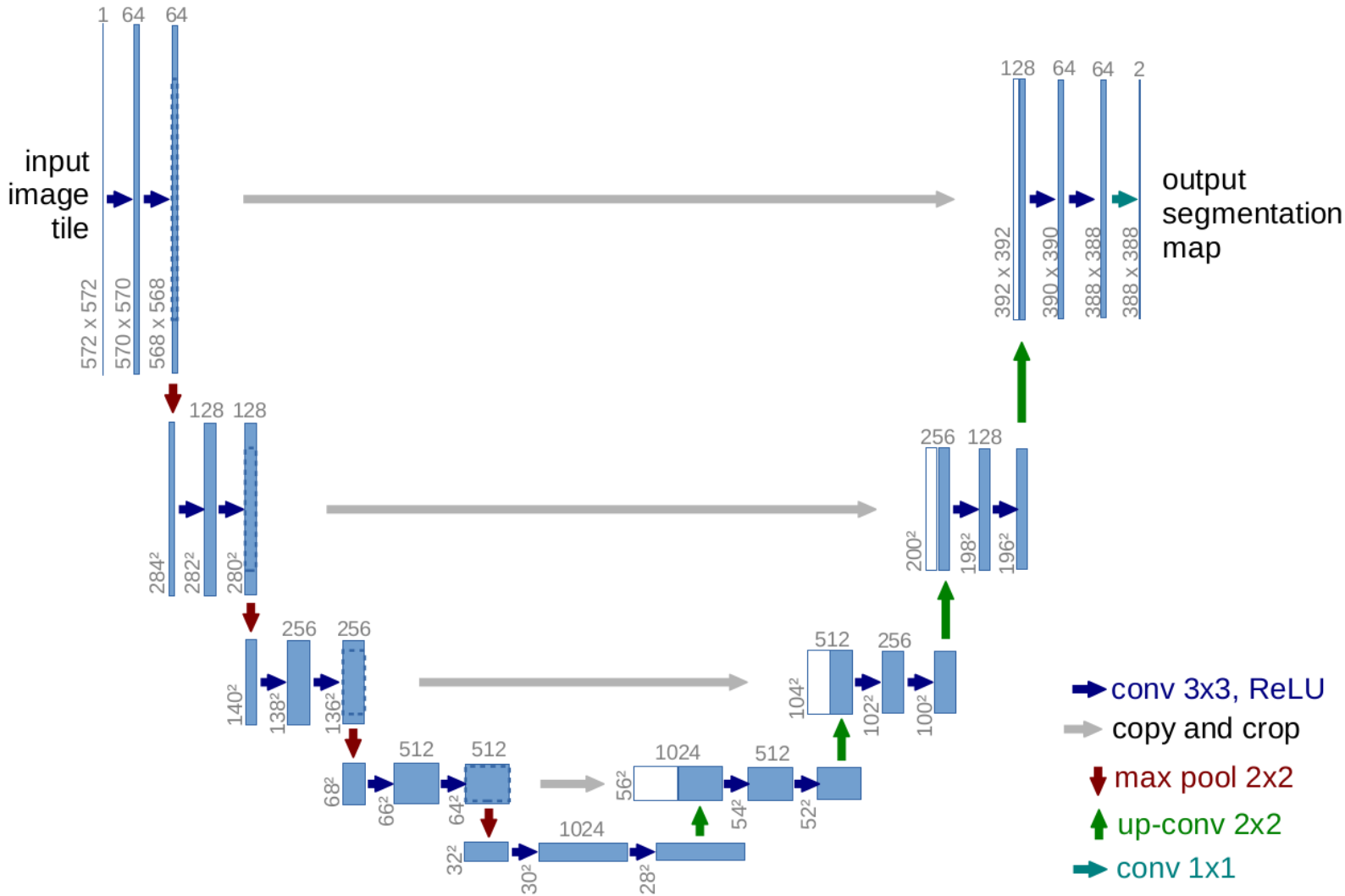


Convolutional nets for semantic image segmentation

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]



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
- But you can reduce the number of filters or the number of layers

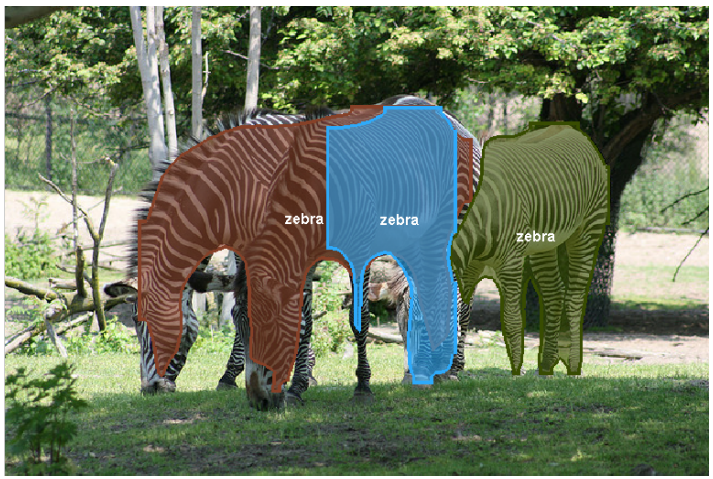
Contents

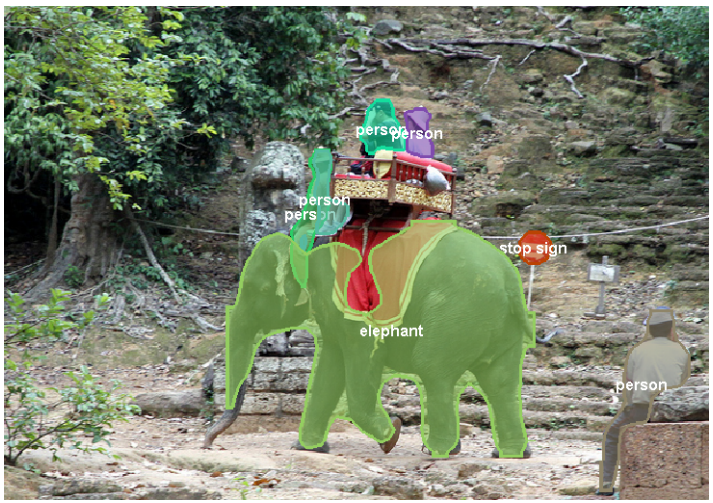
COCO: common objects in context [Lin et al., 2014]

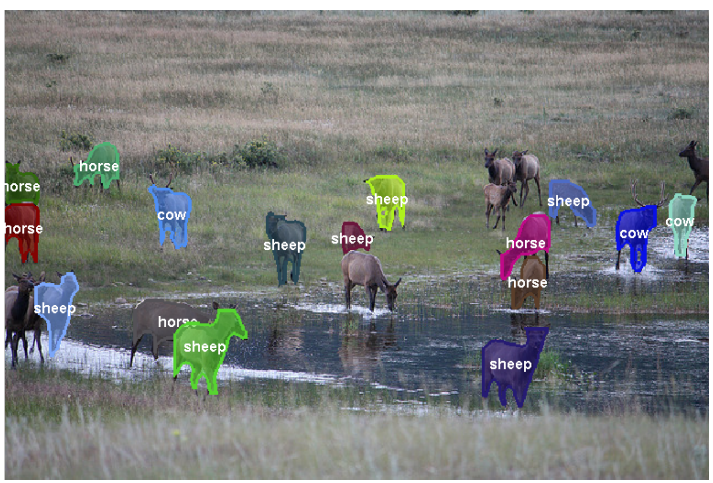
- 2 million objects, from 80 categories, in 300 000 images

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

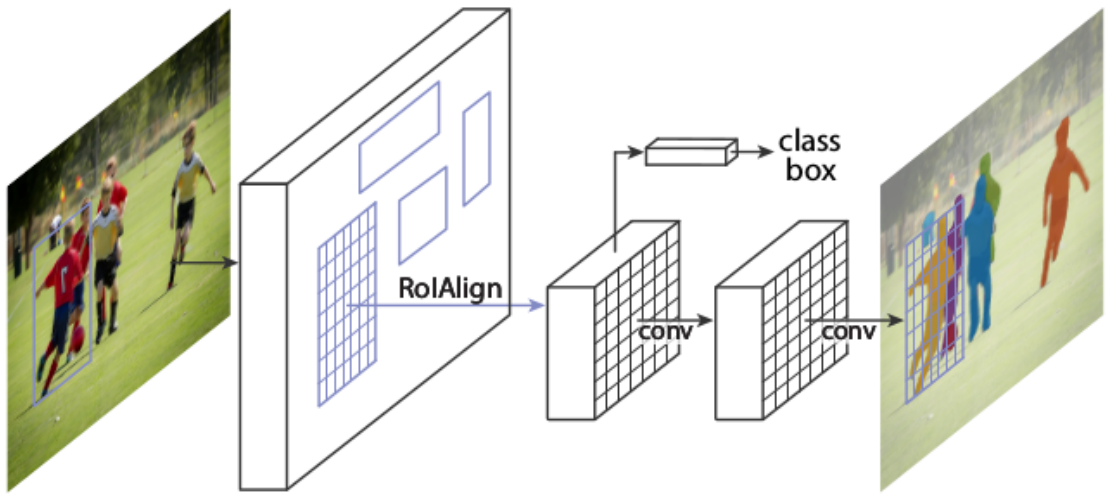
COCO instance segmentation challenge: examples of 2016 winner results



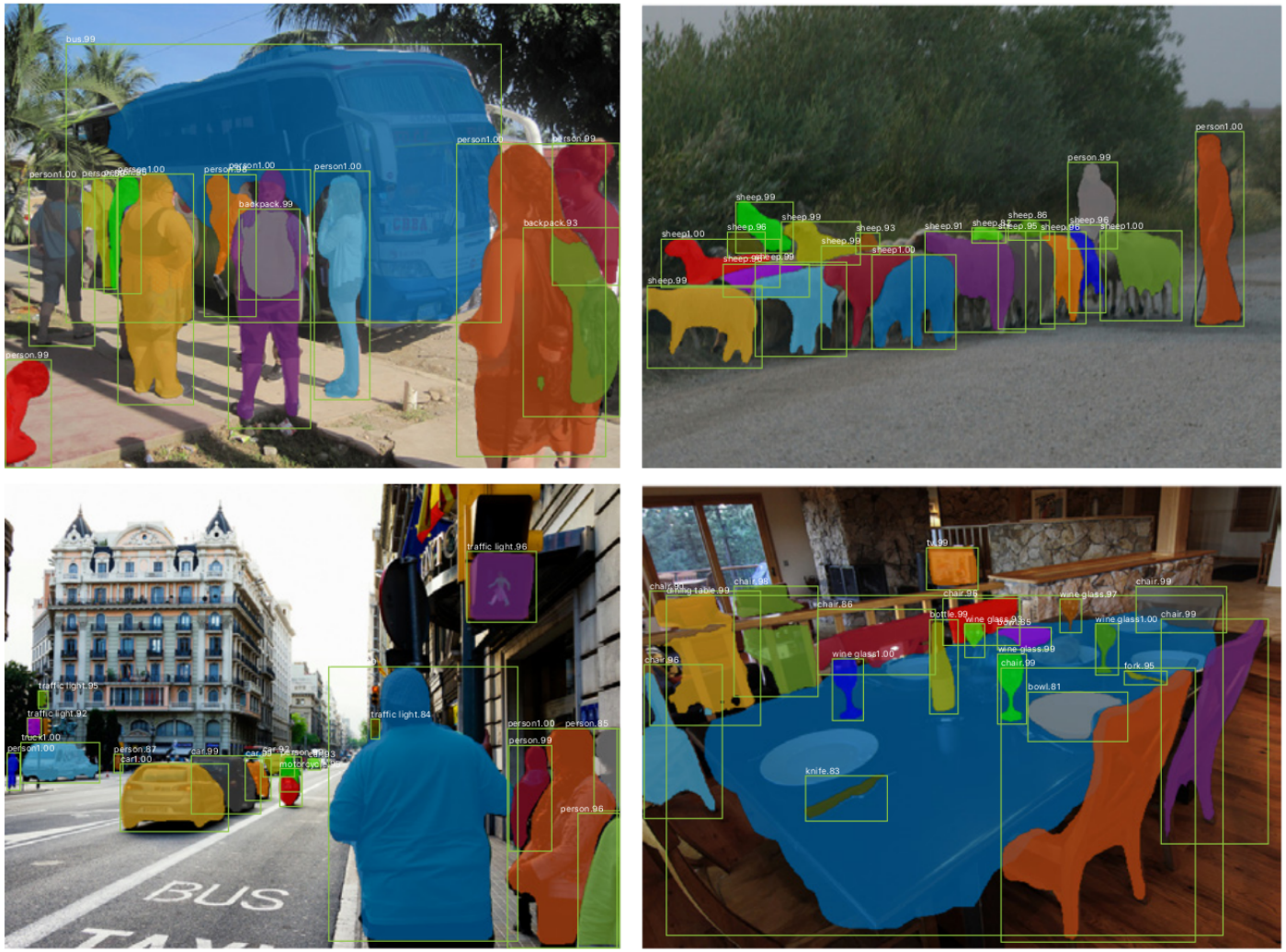




State of the art on the COCO database: Mask R-CNN [He et al., 2017]

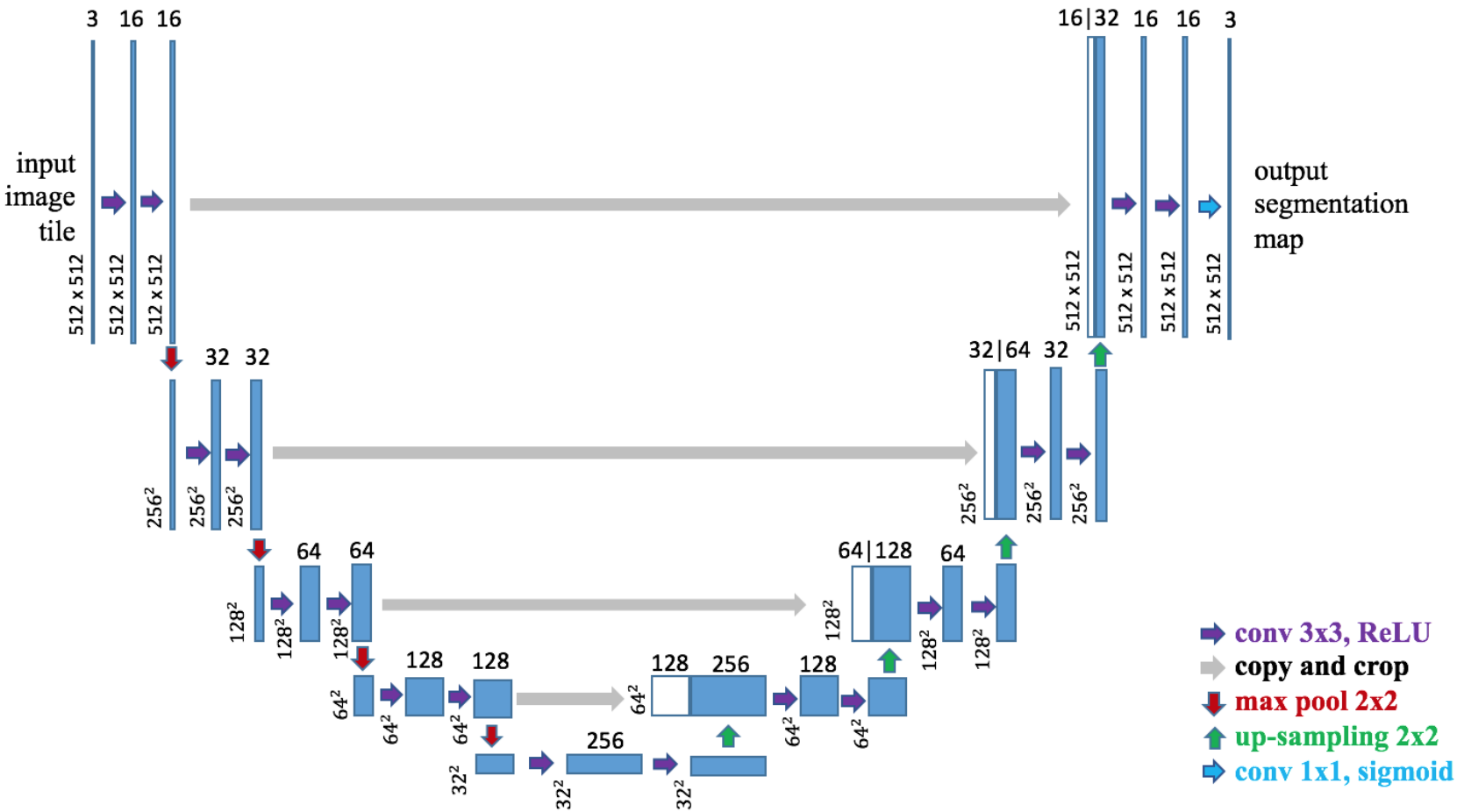


Mask R-CNN on the COCO database



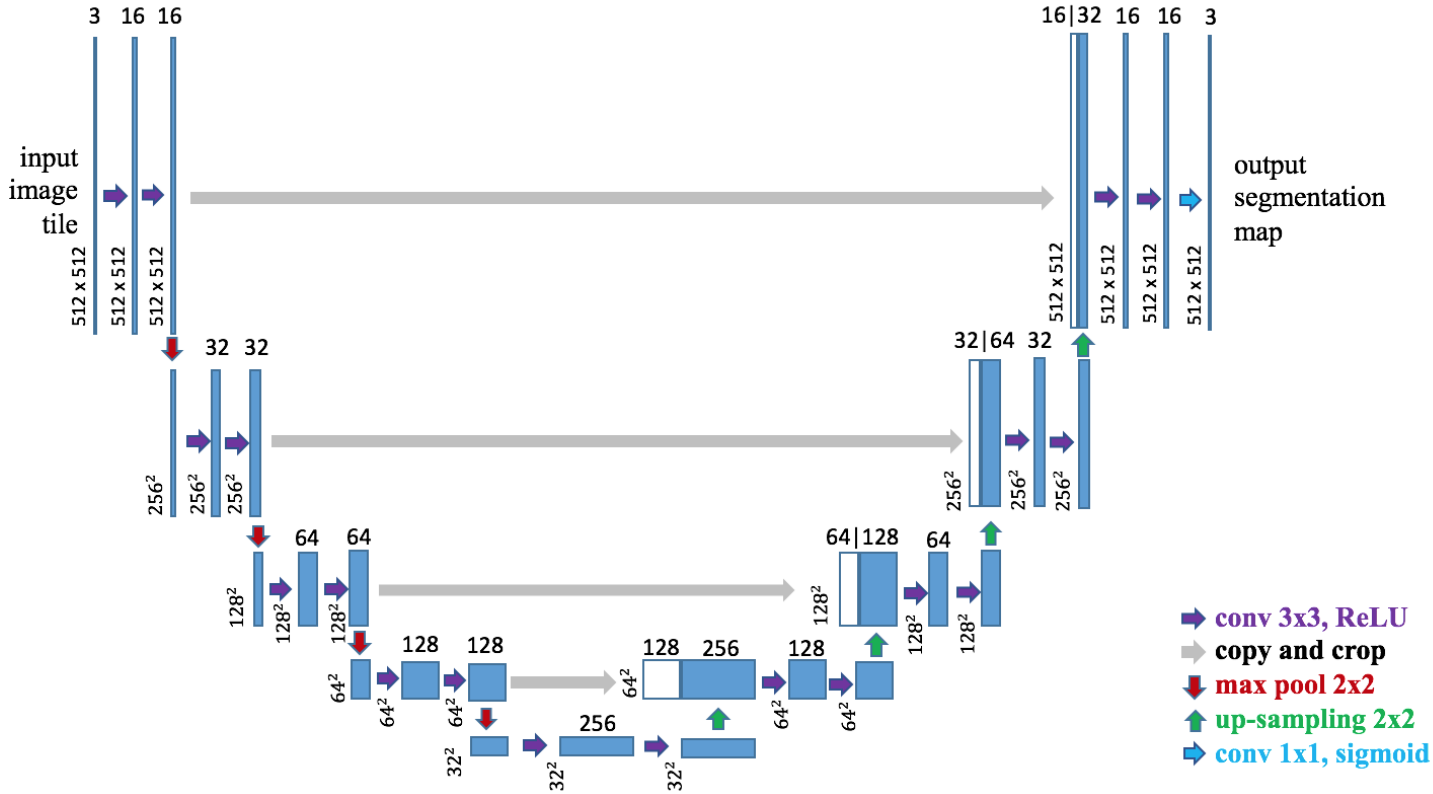
Contents

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



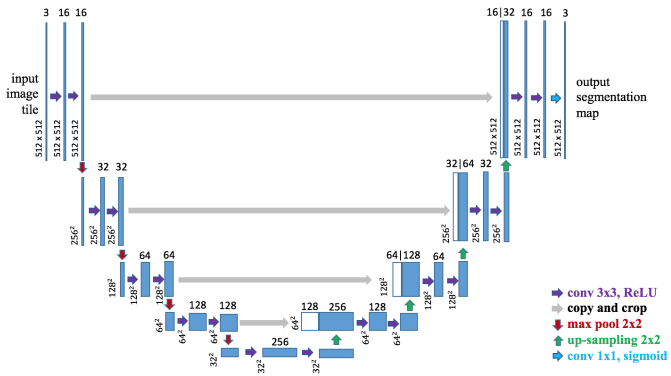
- Size and number of channels of input images?
- Segmentation into how many regions?

U-Net main ideas



- Encoding branch inspired by classification nets
- Decoding branch is symmetrical
- Skip connections

U-Net details



- 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:

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

U-Net improvements

- Convolutions with stride 2 instead of max-pooling in the encoder
- Transposed convolutions instead of simple up-sampling in the decoder
- Using an already optimized classification network as backbone for the encoder

Contents

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  - make them as large as possible, to reduce border effects
  - take a small batch size (1, 2, 4?)

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

A loss function inherited from image classification

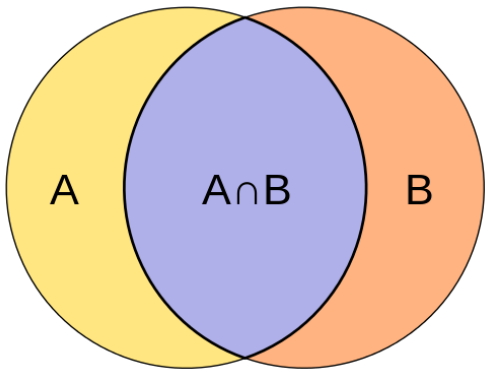
- Cross-entropy: $-\sum_i y_i \log(\hat{y}_i)$

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

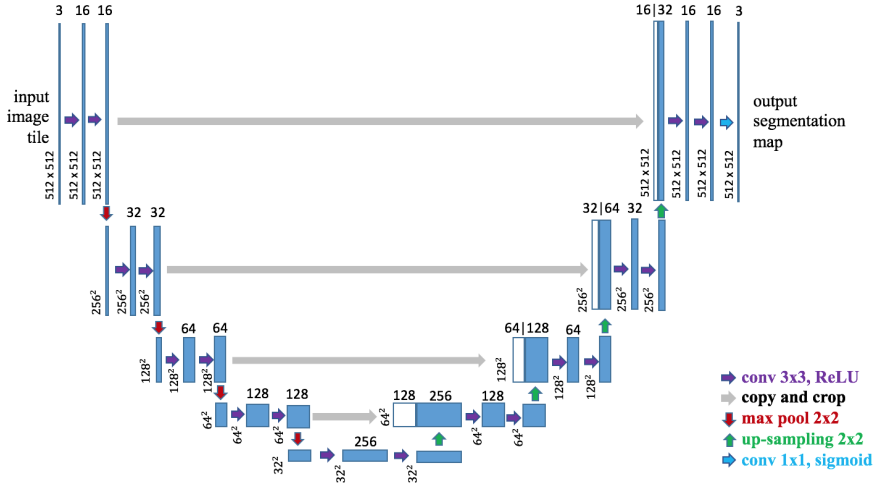
$$j(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{\sum_i y_i \hat{y}_i}{\sum_i y_i^2 + \sum_i \hat{y}_i^2 - \sum_i y_i \hat{y}_i + \epsilon}$$

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...

Applying fully-convolutional networks



Case study

Suppose that we have satisfactorily optimized this U-Net model, using images of size 512×512 during training. Now I want to apply this model to a new image, of size 1000×1000. How should I proceed?

- Resize the image?
- Cut it into 512×512 crops, predict and stitch the results together?

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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