Convolutional Neural Networks for Semantic Segmentation

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Artificial Neural Networks and Deep Learning

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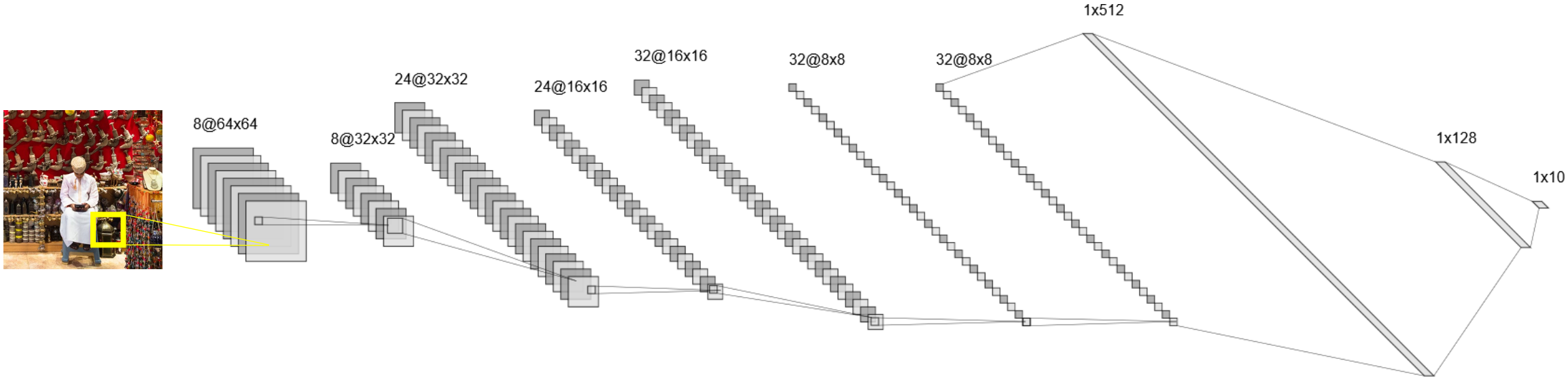
Fully Convolutional Networks

What happens when feeding the network with an image having different size?

Convolutional Neural Networks (CNN)

The typical architecture of a convolutional neural network



CNNs are meant to process input of a fixed size (e.g. 200 x 200).

The **convolutional and subsampling layers** operate in a sliding manner over image having arbitrary size

The **fully connected** layer constrains the input to a fixed size.

Convolutional Neural Networks (CNN)

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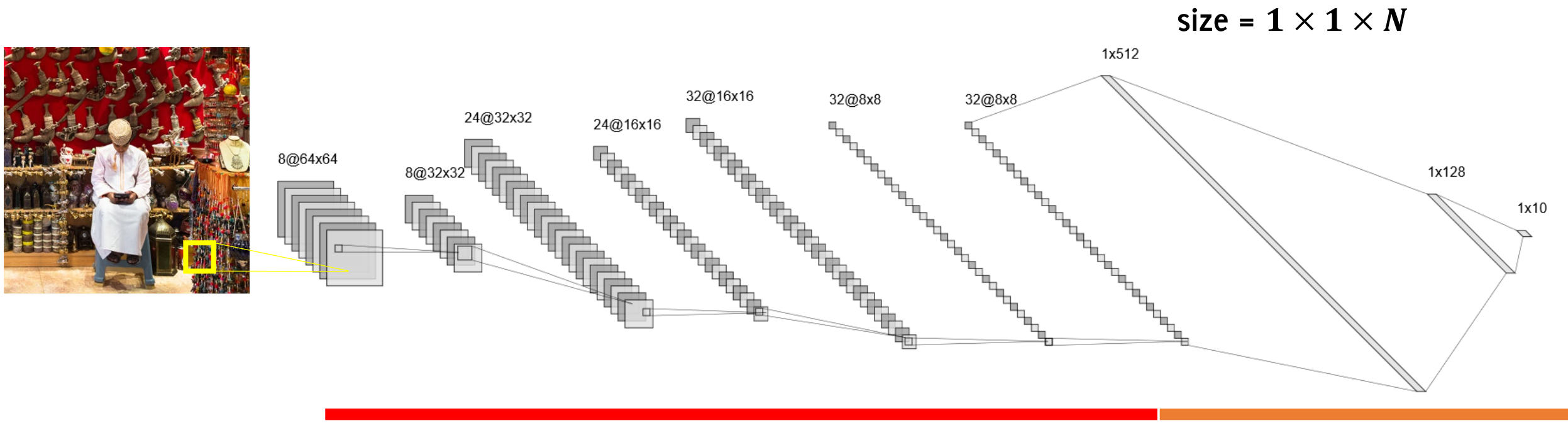


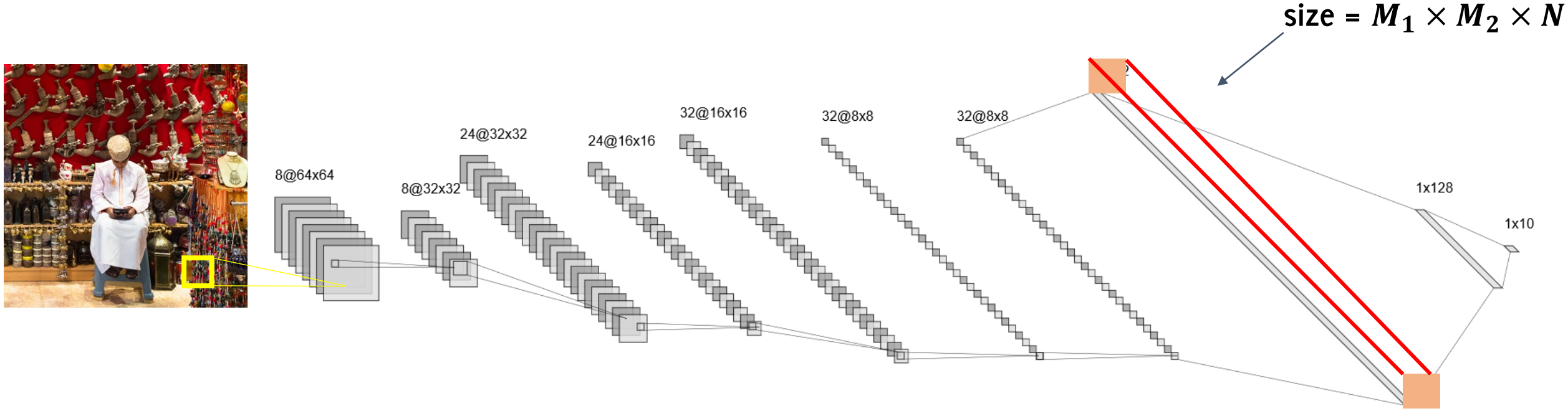
What happens when we feed a larger image to the network?

Convolutional Neural Networks (CNN)

Convolutional filters can be applied to volumes of any size, yielding larger volumes in the network until the FC layer.

The **FC network however does require a fixed input size**

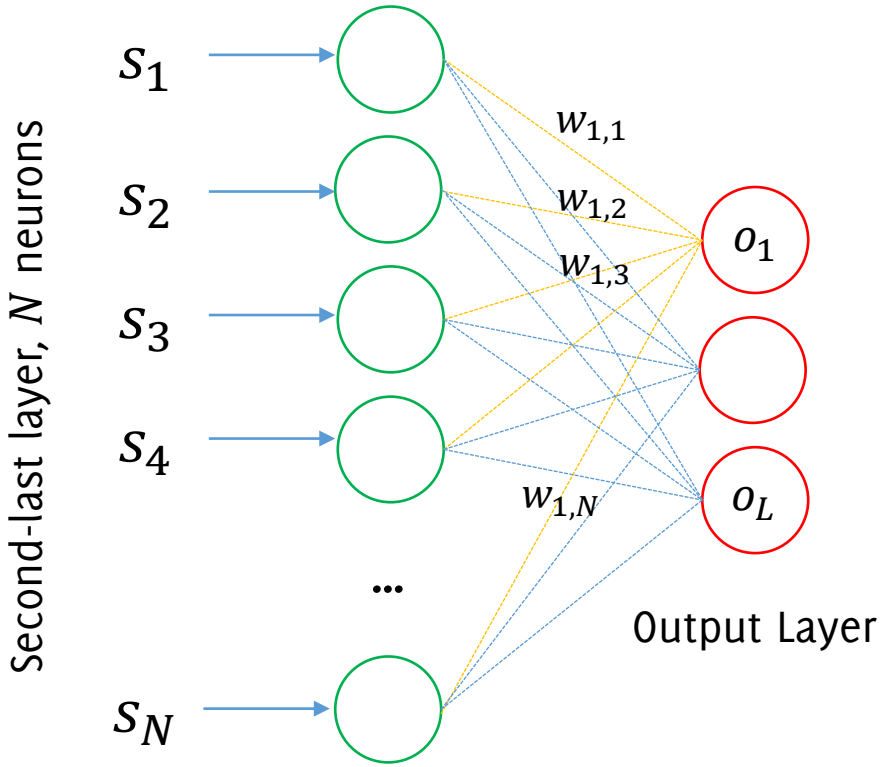
Thus, CNN cannot compute class scores, yet can extract features!



Fully Convolutional Neural Networks (FC-CNN)

However, **since the FC is linear, it can be represented as convolution!**

Weights associated to output neuron i : $\boldsymbol{w_i} = \left[w_{i,j}\right]_{j=1:N}$



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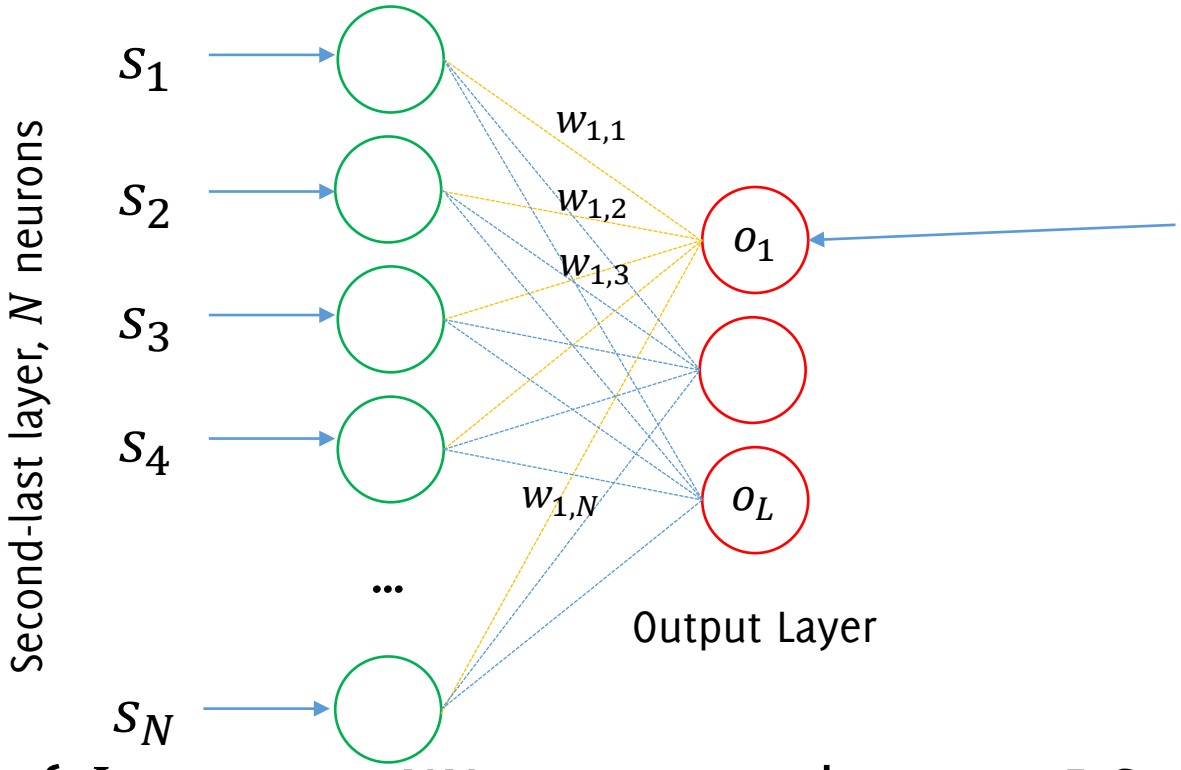

$$o_i = \sum_{j=1:N} w_{i,j} s_j + b_i$$

$$o_i = (\boldsymbol{w_i})' \, \boldsymbol{s} + b_i$$

$$o_i = (\boldsymbol{w_i} \circledast \boldsymbol{s})(0,0) + b_i$$

A FC layer of L outputs NN corresponds to a 2DConv layer having **$\boldsymbol{L}$ filters with size $\boldsymbol{1 \times 1 \times N}$**

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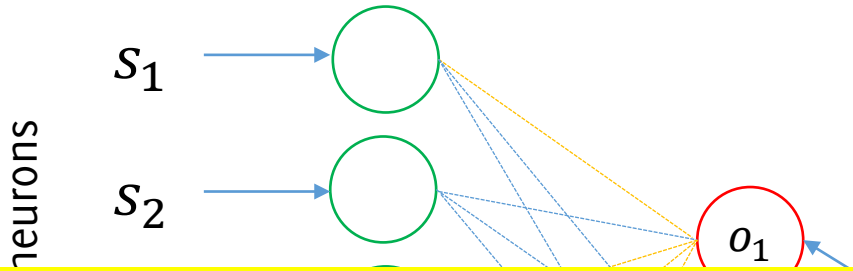


$$o_i = \sum w_{i,j} s_j + b_i$$

This transformation can be applied to each hidden layer of a FC network placed at the CNN top

This transformation consists in reading weights from the neuron in the dense layer end recycling together with bias in the new convolutional layer.

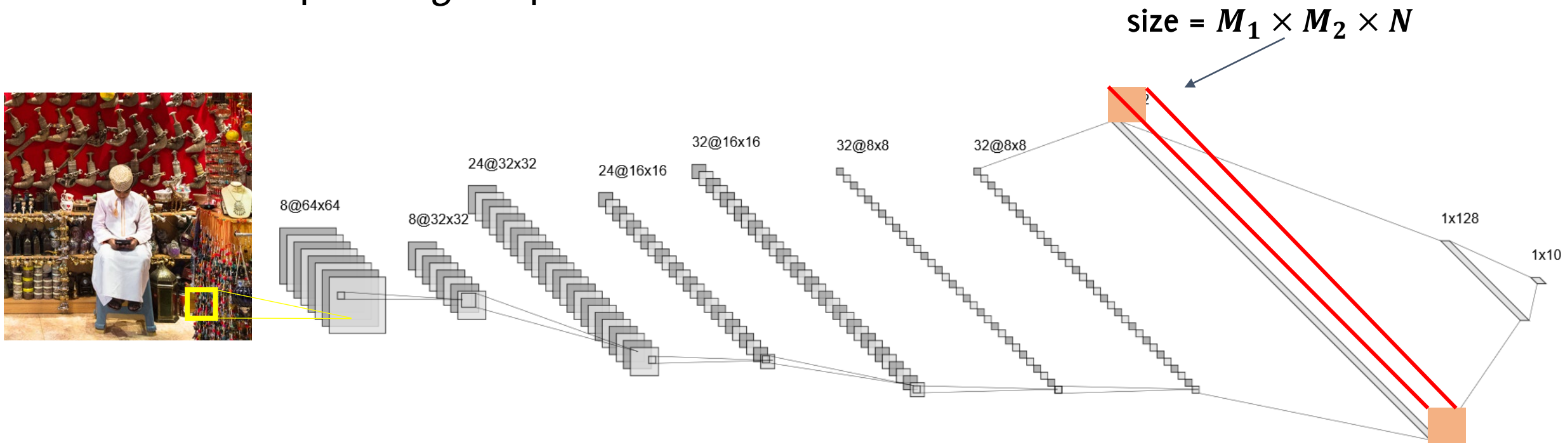
A FC layer

L filters with size $1 \times 1 \times N$

Fully Convolutional Neural Networks (FC-CNN)

However, since the FC is linear, it can be represented as convolution against L filters of size $1 \times 1 \times N$

Each of **these convolutional filters contains the weights of the FC** for the corresponding output neuron

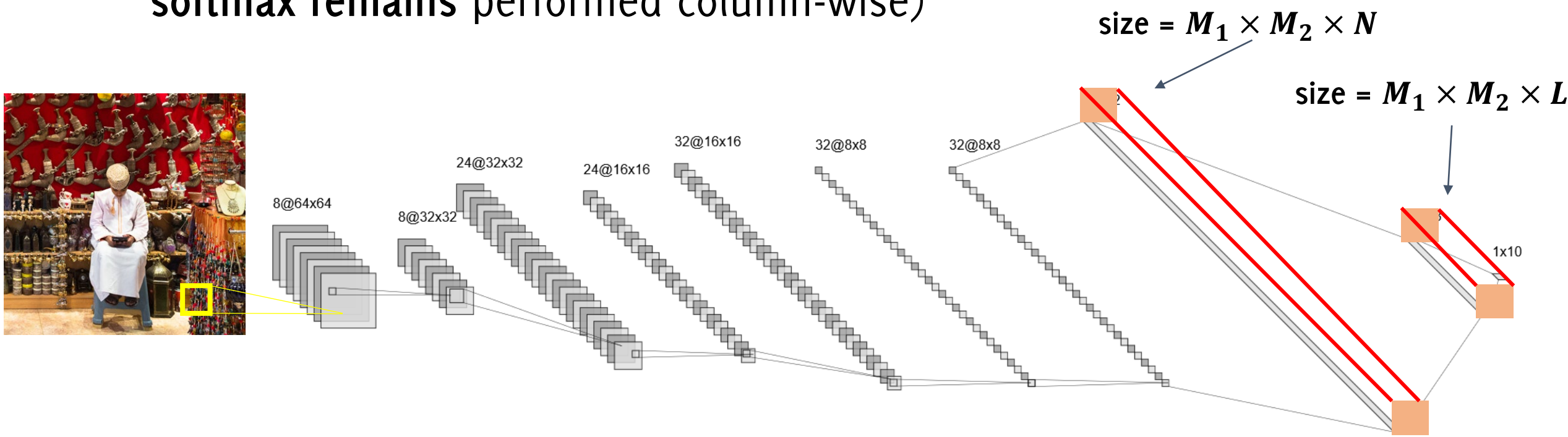


Long, J., Shelhamer, E., Darrell, T. "Fully convolutional networks for semantic segmentation". CVPR 2015

Fully Convolutional Neural Networks (FC-CNN)

For each output class we obtain an image, having:

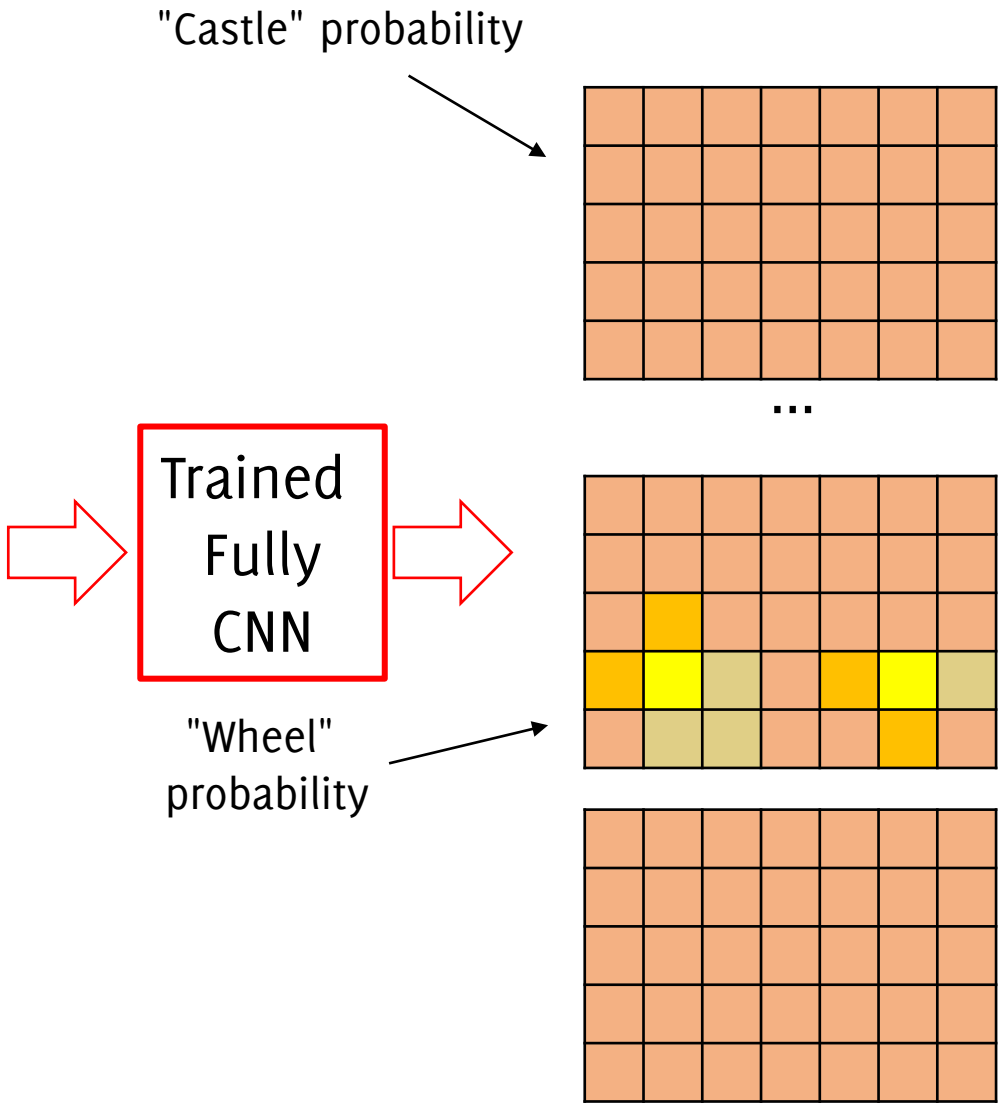
- **Lower resolution** than the input image
- **Class probabilities** for the receptive field of each pixel (assuming **softmax remains** performed column-wise)



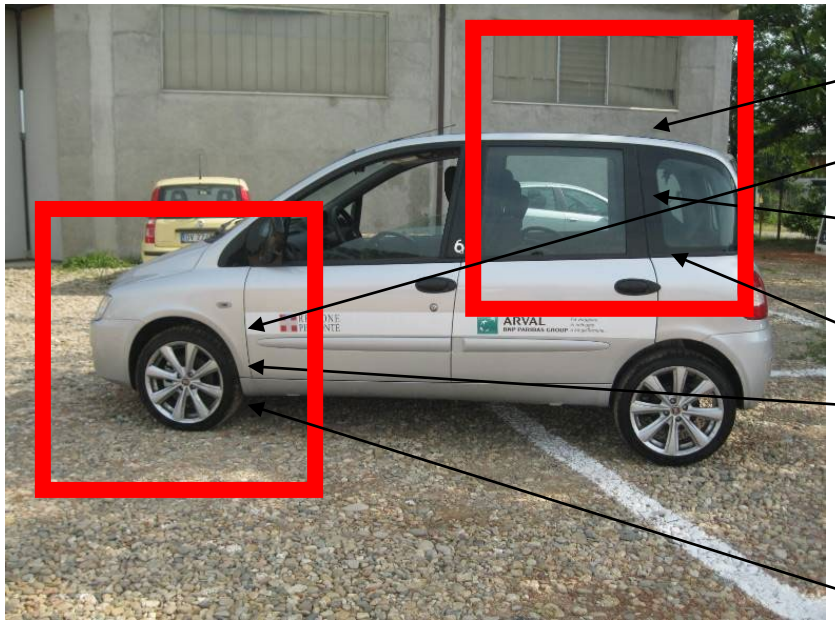
Long, J., Shelhamer, E., Darrell, T. "Fully convolutional networks for semantic segmentation". CVPR 2015

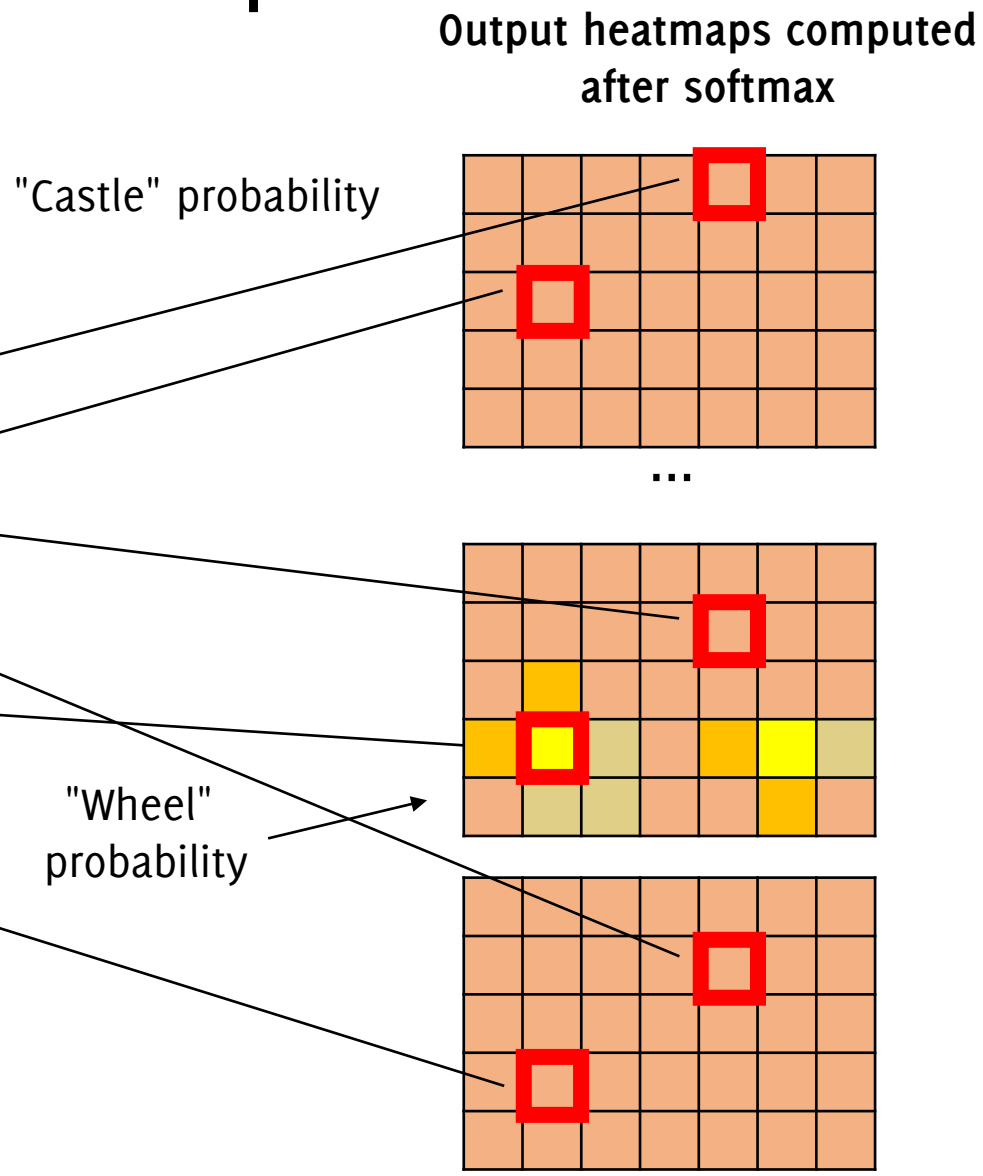
Output of a FC-CNN as heatmaps

A larger image than those used for training the network



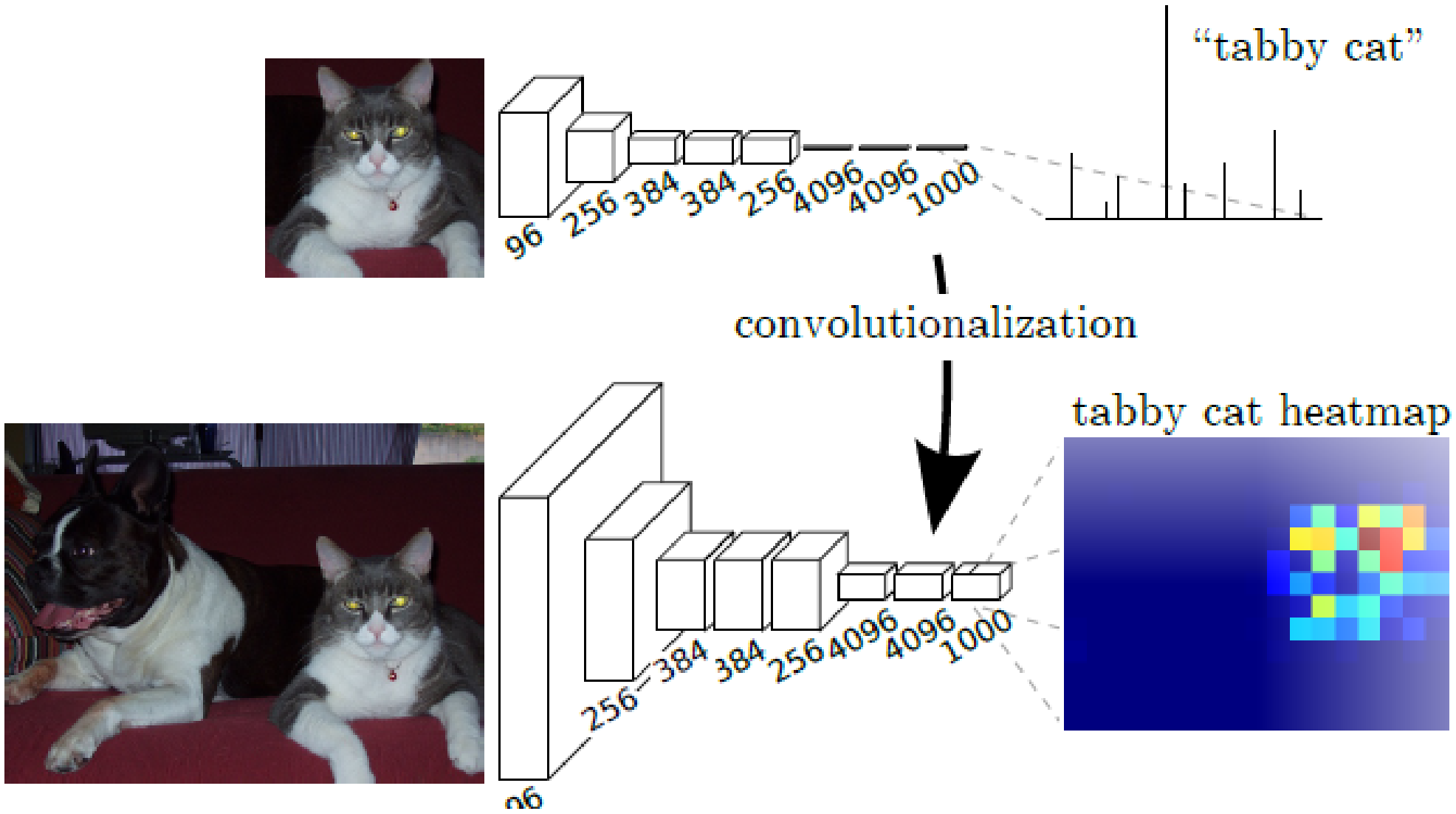
Output of a FCNN as heatmaps





Each pixel in the heatmap corresponds to a "*receptive field*" in the input image

Migration to FCNN of a pretrained model

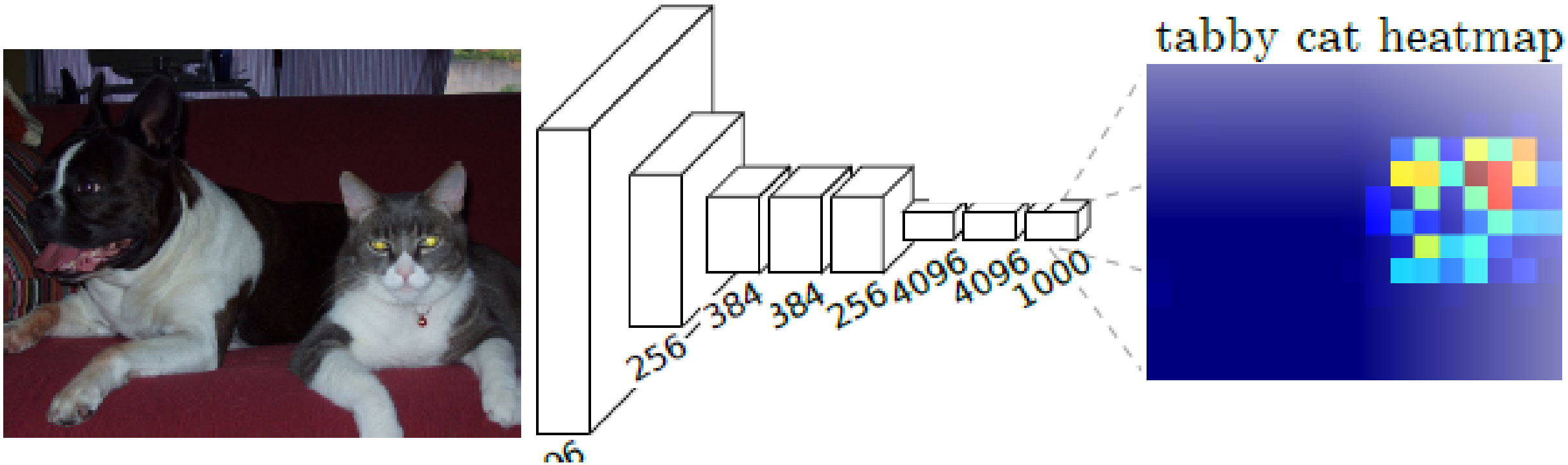


Long, Jonathan, *Evan* Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Migration to FCNN of a pretrained model

This stack of convolutions operates on the whole image as a **powerful, nonlinear, filter** which operates as a **classifier sliding on the latent space**.

Significantly more efficient than patch extraction and classification: this avoids multiple repeated computations within overlapping patches



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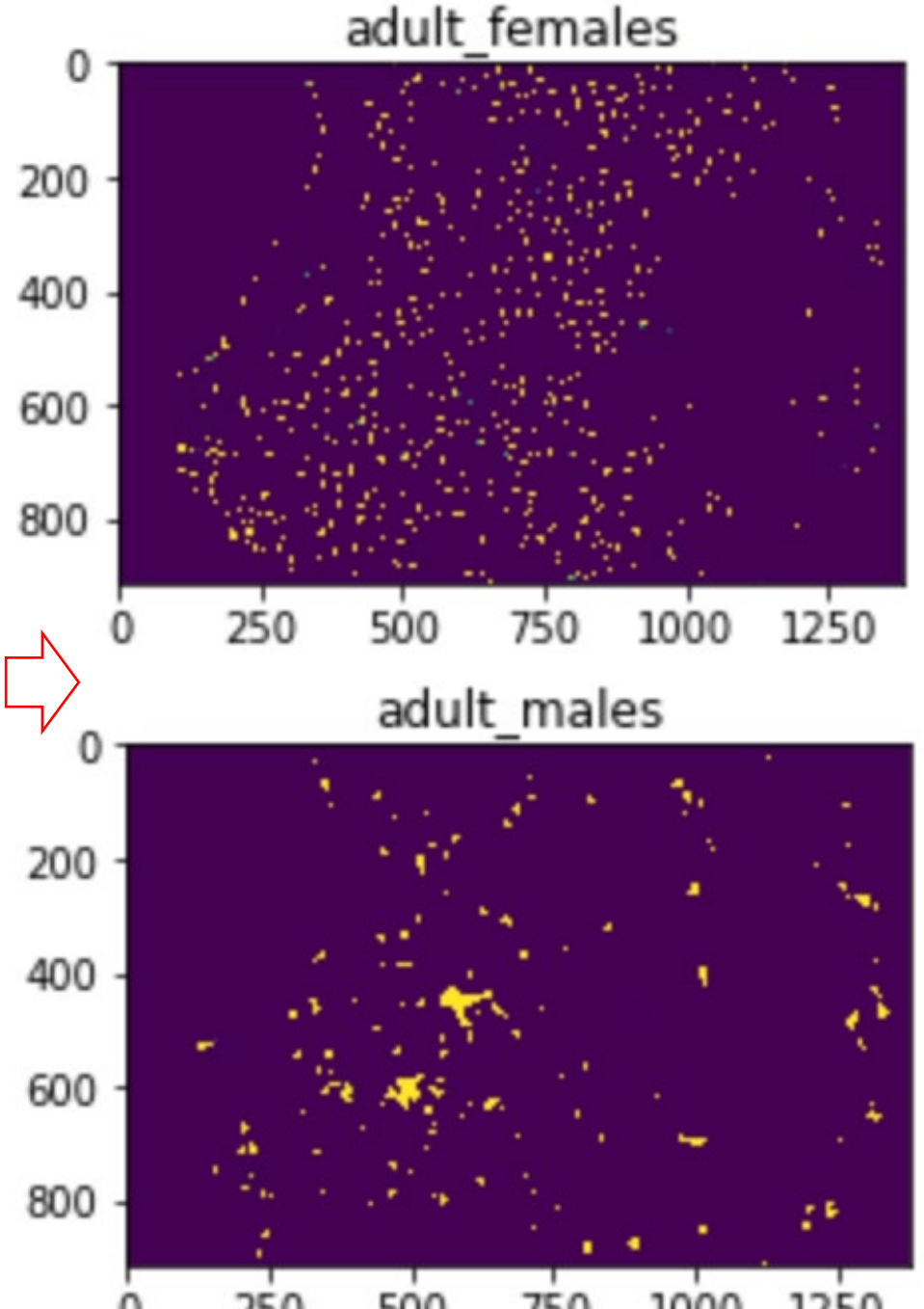
Sealion HeatMaps

FCNN



Credits Yinan Zhou
https://github.com/marioZYN/FC-CNN-Demo

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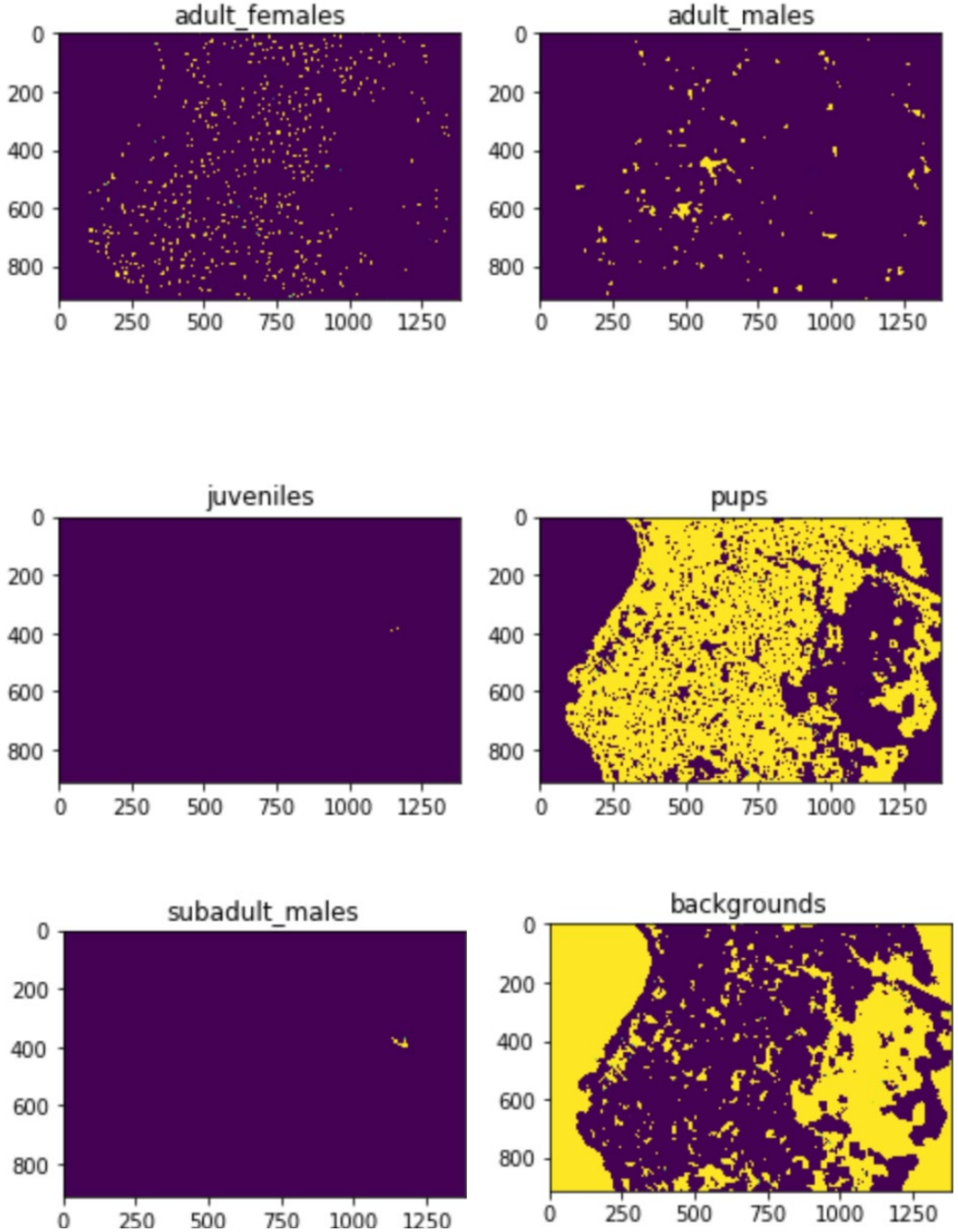

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Fully convolutional networks in keras

It is necessary to get and set the weights of networks by means of the methods **`get_weights`** and **`set_weights`**

- get the weights of the trained CNN

```
w7, b7 = model.layers[7].get_weights()
```

- reshape these weights to become ten 1x1 convolutional filters having depth equal to 256 (these sizes are dictated by the sizes of the dense layer in the “traditional” CNN)

```
w7.reshape(1, 1, 256, 10)
```

- assign these weights to the FCNN architecture

```
model2.layers[7].set_weights(w7, b7)
```

Fully convolutional networks in kears

What happens when the classification network has a flattening layer?

Layer (type)	Output Shape	Param #
Input (InputLayer)	[(None, 96, 96, 3)]	0
preprocessing (Sequential)	(None, 96, 96, 3)	0
conv1 (Conv2D)	(None, 96, 96, 16)	448
mp1 (MaxPooling2D)	(None, 48, 48, 16)	0
conv2 (Conv2D)	(None, 48, 48, 32)	4640
mp2 (MaxPooling2D)	(None, 24, 24, 32)	0
conv3 (Conv2D)	(None, 24, 24, 64)	18496
mp3 (MaxPooling2D)	(None, 12, 12, 64)	0
conv4 (Conv2D)	(None, 12, 12, 128)	73856
flatten (Flatten)	(None, 18432)	0
dropout_12 (Dropout)	(None, 18432)	0
dense2 (Dense)	(None, 256)	4718848
Output (Dense)	(None, 6)	1542

Fully convolutional networks in kears

Include a **convolutional layer** having the **same spatial size** as the activation before flattening

```
fully_conv_1 = tfkl.Conv2D(
        filters=256,
        kernel_size=(12,12),
        padding='valid',
        activation='relu',
        name='fully_conv_1'
    )(conv4)
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Convolution options need ot be valid to give a single response

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Convolution options need ot be valid to give a single response

The number of filters corresponds to the number of output neurons of the filter

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Fully convolutional networks in kears

Make sure each convolutional layer have the same number of parameters as the dense layer it is replacing

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Fully convolutional networks in kears

Build the network to take as input any spatial size

```
fc_input_shape = (None,None,3)
fc_output_shape = (None,None,6)
input_layer = tfkl.Input(shape=input_s
hape, name='Input')
…
output_layer = tfkl.Conv2D(
        filters=output_shape[-1],
        kernel_size=(1,1),
        padding='valid',
        activation='softmax',
        name='fully_conv_2'
    )(fully_conv_1)
```

Layer (type)	Output Shape	Param #
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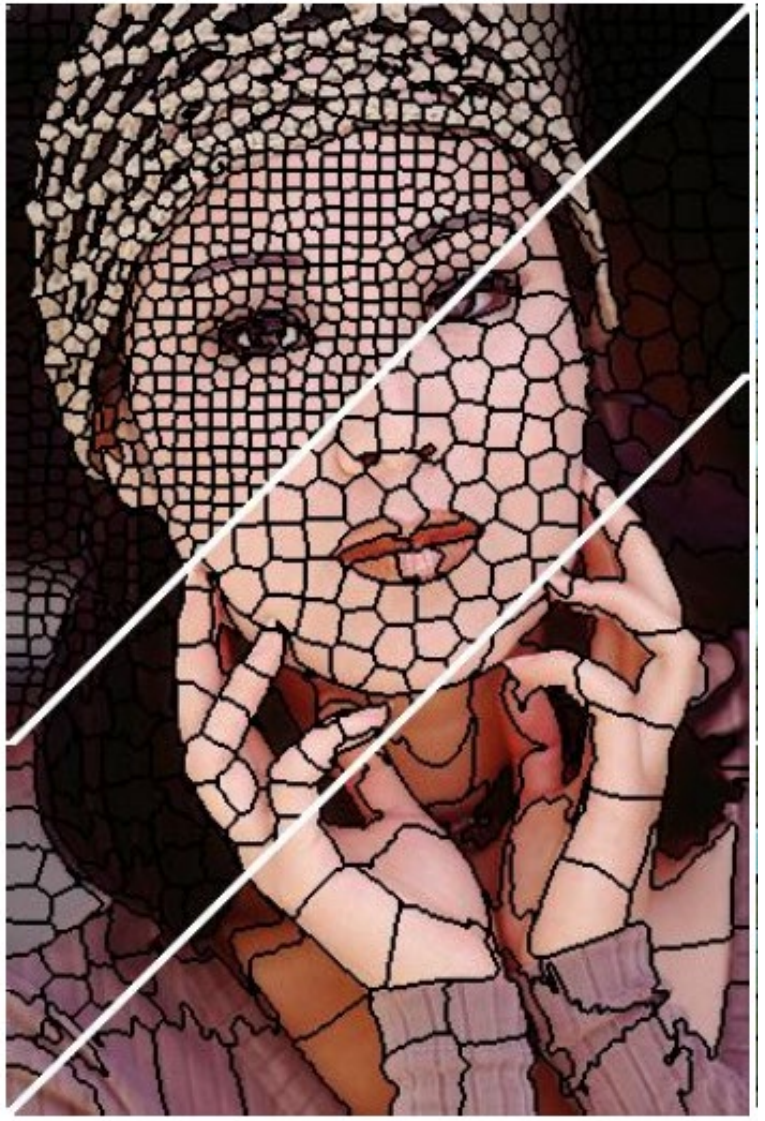
Image Segmentation

Image Segmentation

Goal: identify groups of pixel that "go together"

- Group together similar-looking pixel for efficiency
- Separate images into coherent objects

One way of looking at segmentation is **clustering**



Achanta, et al S*LIC superpixels compared to state-of-the-art superpixel methods*. TPAMI 2012

Problem Formulation: Image Segmentation

Given an image $I \in \mathbb{R}^{R \times C \times 3}$, having as domain $\mathcal{X}$, the goal of image segmentation consists in estimating a partition $\{R_i\}$ such that

$$\bigcup_i R_i = \mathcal{X}$$

and $R_i \cap R_j = \emptyset, \quad i \neq j$

There are two types of sementation:

- Unsupervised (what we address here)
- Supervised (or Semantic)

Semantic Segmentation

Zheng et al. “Conditional Random Fields as Recurrent Neural Networks”, ICCV 2015

Semantic Segmentation, the problem

The goal of semantic segmentation is:

Given an image I, **associate to each pixel** (r, c) **a label** from Λ.

The **result of segmentation is a map of labels** containing in each pixel the estimated class.

Remark: In this image there is no distinction among persons.
Segmentation **does not separate different instances belonging to the same class**.
That would be instance segmentation.

http://www.robots.ox.ac.uk/~szheng/crfasrnndemo

Semantic Segmentation, the problem

Assign **to each pixel** of an image $I \in \mathbb{R}^{R \times C \times 3}$:

- a label $\{l_i\}$ from a fixed set of categories
  $\Lambda = \{\text{"wheel"}, \text{"cars"}, \ldots, \text{"castle"}, \text{"baboon"}\}$,

$$I \rightarrow S \in \Lambda^{R \times C}$$

where $S(x, y) \in \Lambda$ denotes the class associated to the pixel (x, y)

To this purpose, you are given a training set

$$TR = \{(I, GT)_i\}$$

Which have been (manually) annotated and that can be used for training

Semantic Segmentation by Fully Convolutional Neural Networks

Predicting dense outputs for arbitrary-sized inputs

From Classification to Segmentation

Setup:

- You are given a pre-trained CNN for classification
- You possibly performed transfer learning to the problem at hand
- You have «convolutionalized» it to extract heatmaps

Limitation:

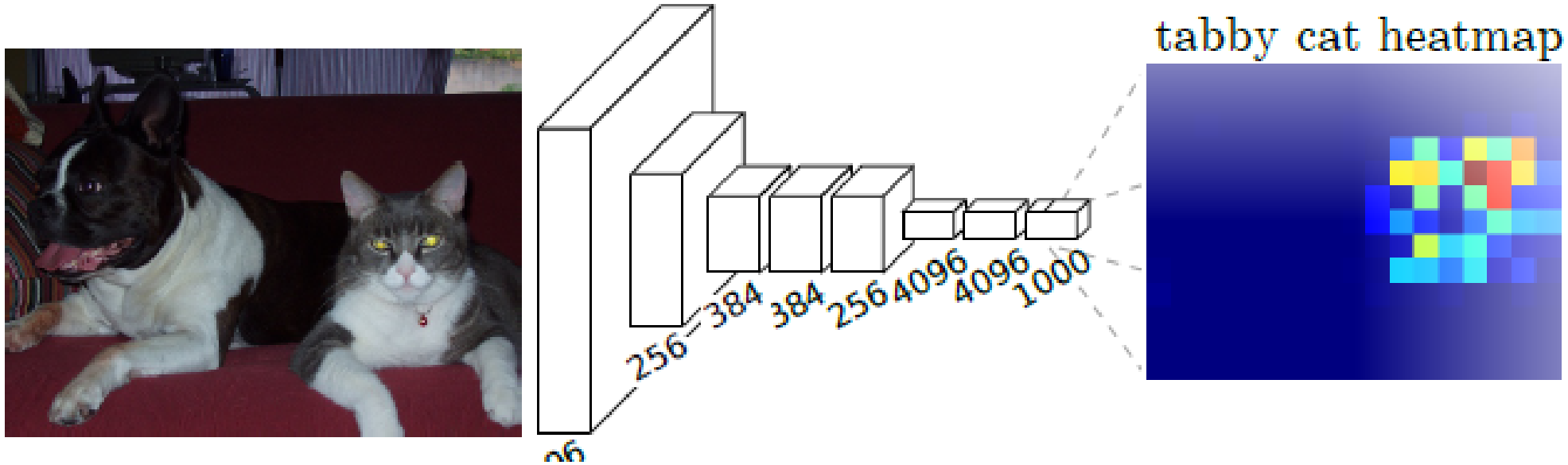
- Heatmaps are very low-resolution

Goal:

- Obtain a Semantic Segmentation network for images of arbitrary size

Simple Solution (1): Direct Heatmap Predictions

We can assign the predicted label in the heatmap to the whole receptive field, however that would be a **very coarse estimate**

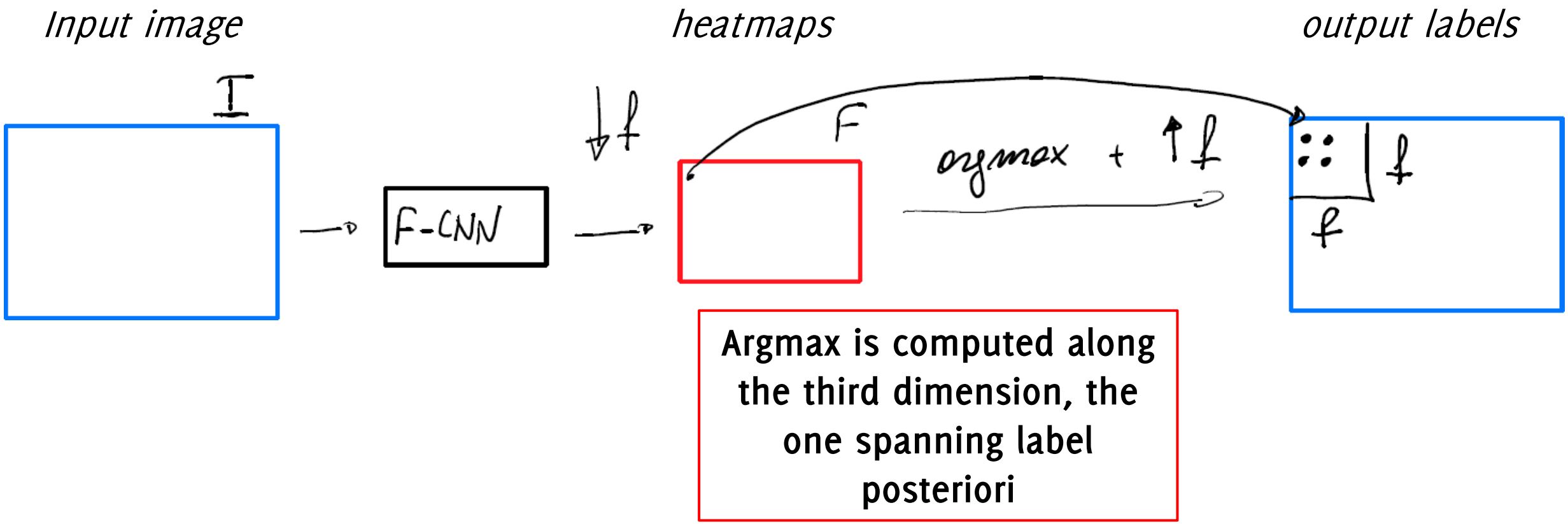


We need to upsample the estimated map!

Long, Jonathan, *Evan* Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Simple Solution (1): Direct Heatmap Upsampling

Very coarse estimates

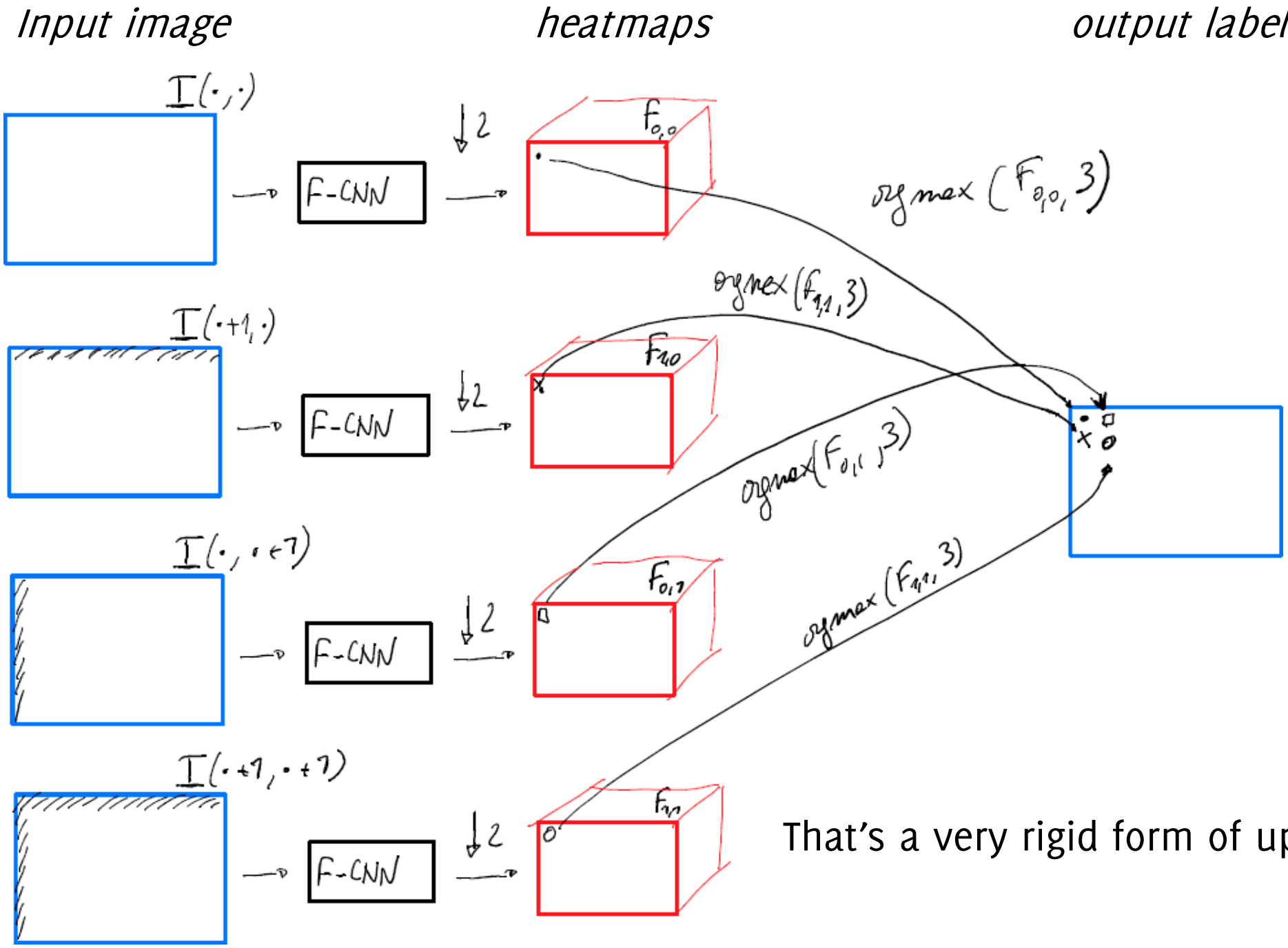


Argmax is computed along the third dimension, the one spanning label posteriori

Simple Solution (2): The Shift and Stich

Shift and Stich: Assume there is a downsampling ratio f between the size of input and of the output heatmap

Long, Jonathan, *Evan* Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015



That's a very rigid form of upsamling!

Simple Solution (2): The Shift and Stich

Shift and Stich: Assume there is a downsampling ratio f between the size of input and of the output heatmap

- Compute **heatmaps** for all $\boldsymbol{f^2}$ possible shifts of the input $(0 \leq r, c < f)$
- **Map predictions from the $\boldsymbol{f^2}$** heatmaps to the image: each pixel in the heatmap **provides prediction of the central pixel of the receptive field**
- **Interleave the heatmaps** to form an image as large as the input

Shift and Stitch

- **exploits the whole depth of the network**

- **efficient implementation** via the à trous algorithm as in Wavelets (dilating filters rather than repeating operations)

However, **the upsampling method is very rigid**

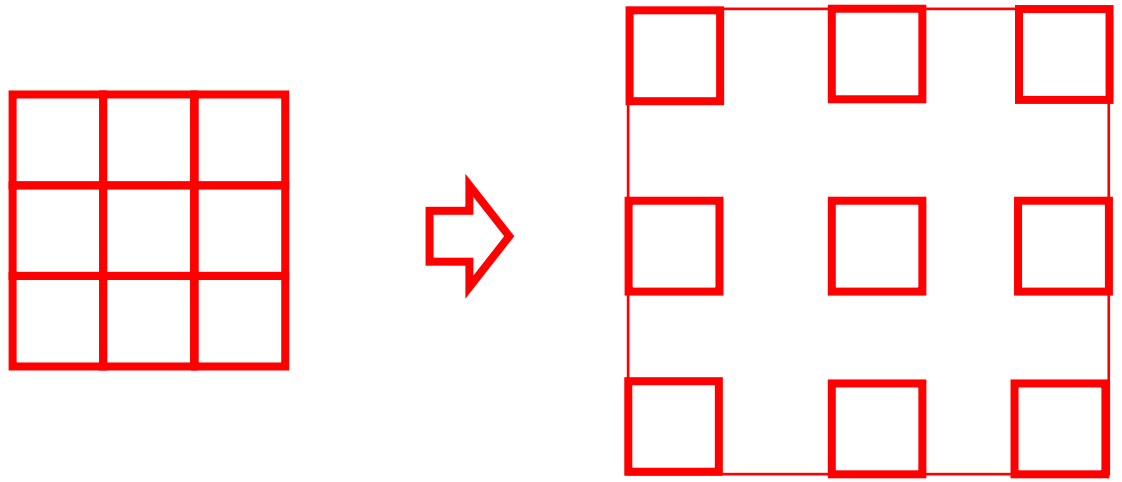
Long, Jonathan, *Evan* Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Simple Solution (2): The Shift and Stich

The same effect as shift and stich can be obtained by

- Remove strides in pooling layer (conv or mp). This is equivalent as computing the output of all the shifted versions at once
- *Rarefy* the filters of the following convolution layer by upsamping and zero padding

$$f'_{ij} = \begin{cases} f_{i/s,j/s} & \text{if } s \text{ divides both } i \text{ and } j; \\ 0 & \text{otherwise,} \end{cases}$$



- Repeat the same operation along each channel dimension
- Repeat for each subsampling layer

Long Jonathan, Evan Shelhamer and Trevor Darrel, «Fully convolutional networks for semantic segmentation» CVPR 2015

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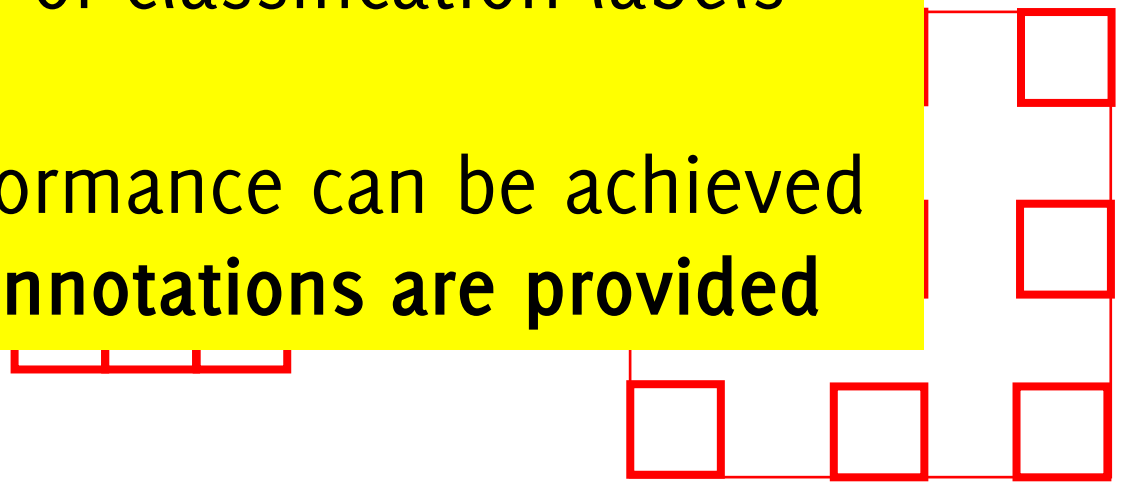
- *Rarefy* the … nd zero padd…

$$f'_{ij} = \begin{cases} \\ \end{cases}$$

This is a good option when annotations are provided in the form of classification labels

However, superior performance can be achieved when **segmentation annotations are provided**



- Repeat the same operation along each channel dimension
- Repeat for each subsampling layer

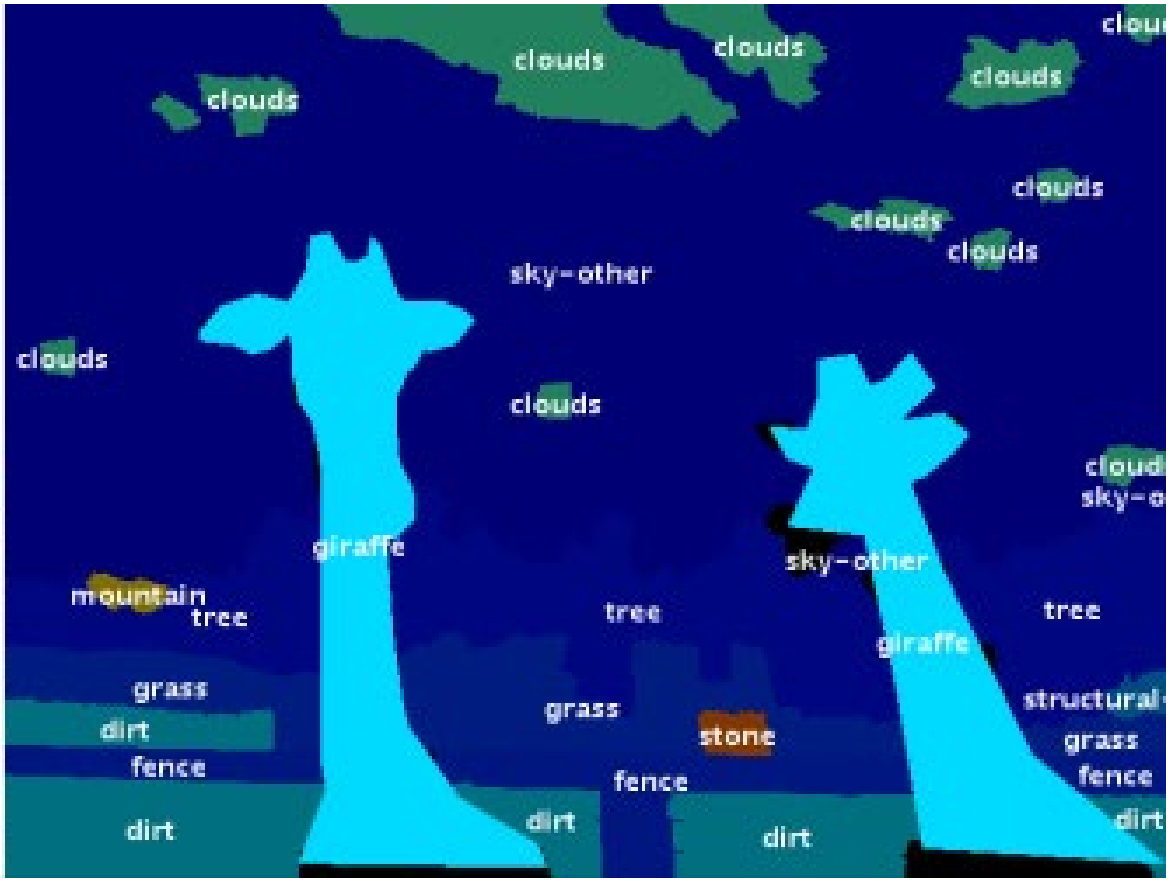
Long Jonathan, Evan Shelhamer and Trevor Darrel, «Fully convolutional networks for semantic segmentation» CVPR 2015

Training Semantic Segmentation Networks

Training Set

The training set is made of pairs (I, GT), where the GT is a pixel-wise annotated image over the categories in Λ

I



GT

http://cocodataset.org/

The Training Set

COCO
Common Objects in Context

COCO Explorer

COCO 2017 train/val browser (123,287 images, 886,284 instances). Crowd labels not shown.

Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

The Training Set $TR = \{(I, GT)_i\}$

I is the input image
GT is the annotation
(shown in overlays)

Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

The Training Set $TR = \{(I, GT)_i\}$

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(shown in overlays)

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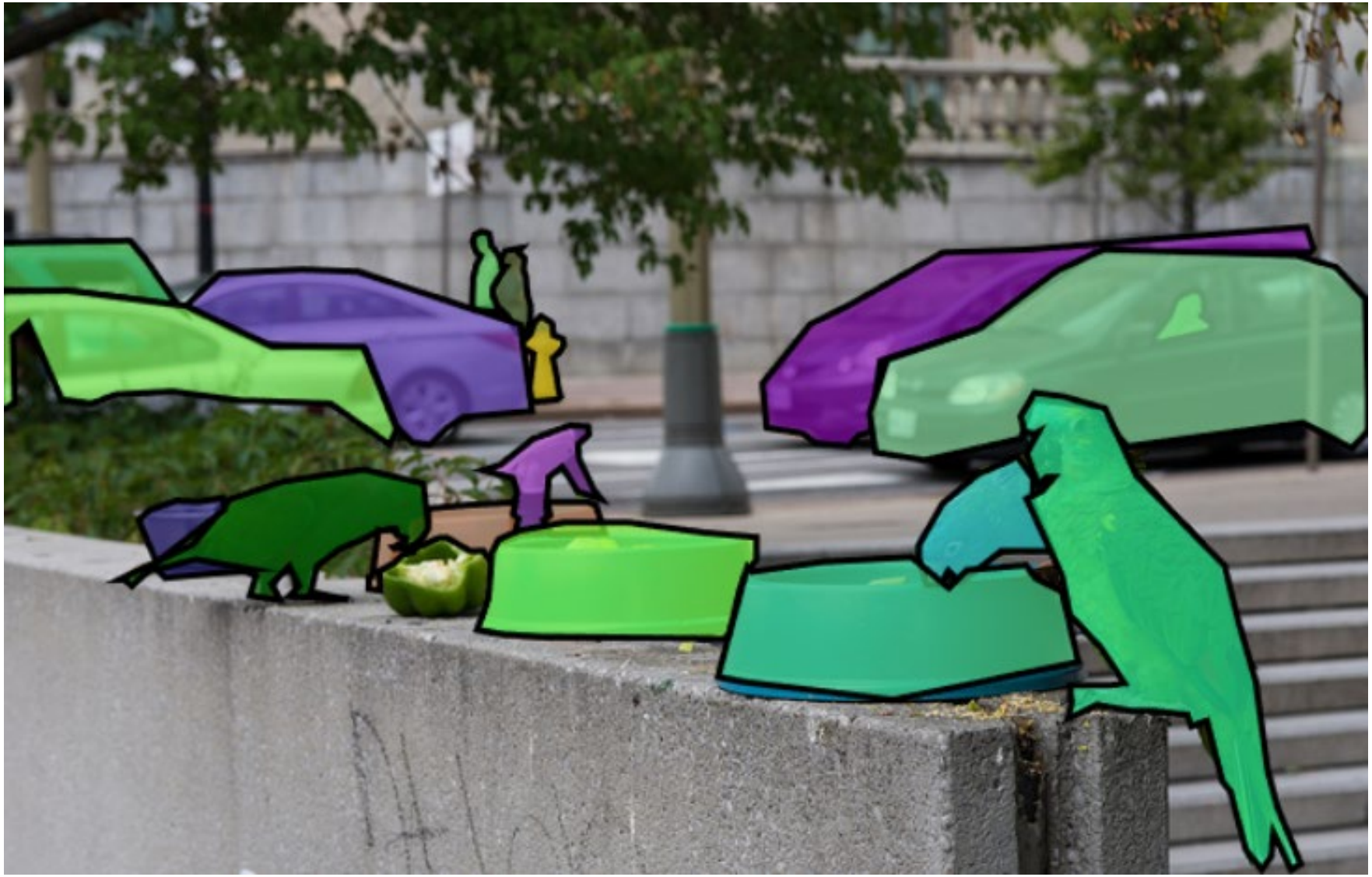
(shown in overlays)



Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

The Training Set

COCO
Common Objects in Context

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- **Object segmentation**
- **Recognition in context**
- **Superpixel stuff segmentation**
- **330K images (>200K labeled)**
- **1.5 million object instances**
- **80 object categories**
- **91 stuff categories**
- **5 captions per image**
- **250,000 people with keypoints**

Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

The Training Set

COCO
Common Objects in Context

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- Object segmentation
- ...text
- ...gmentation
- ...K labeled)
- ...nstances
- ...es
- ...ge
- ...h keypoints

Training set very difficult to annotate ☺

Microsoft COCO dataset provides 200.000 annoated images over 80 categories

(humans have joints annotated as well)

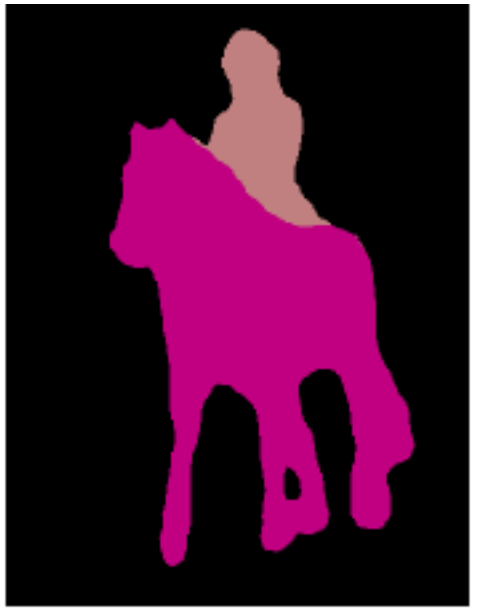
Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

Training a Segmentation Network

Assume you already have a suitable architecture able to perform segmentation (see next the technical aspects)

I

Segmentation Network (trained)



S

$\approx$

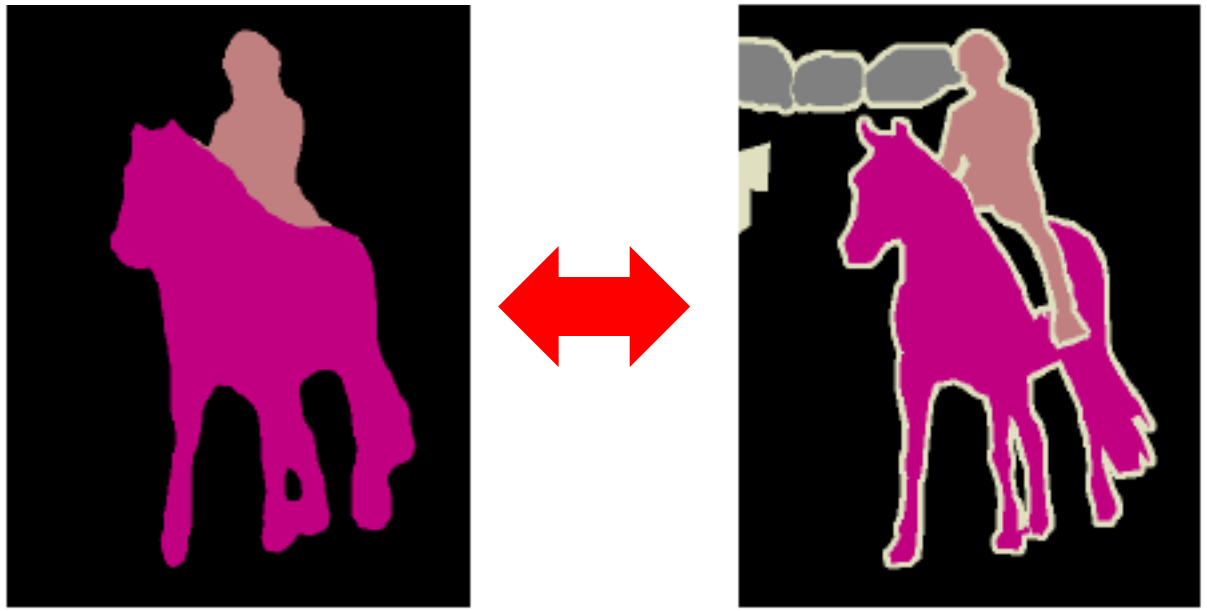
GT

How to compare S and GT to assess network performance and compute the loss?

FC-CNN Training Options: The «full-image» way

We can compute the segmentation loss as the sum of classification losses at each pixel $\boldsymbol{x_j}$ of the image (or a region $\boldsymbol{R}$)

$$\hat{\theta} = \underset{x_j \in I}{\operatorname{argmin}} \sum_{x_j \in R} \ell\left(\boldsymbol{x_j}, \theta\right)$$



S GT

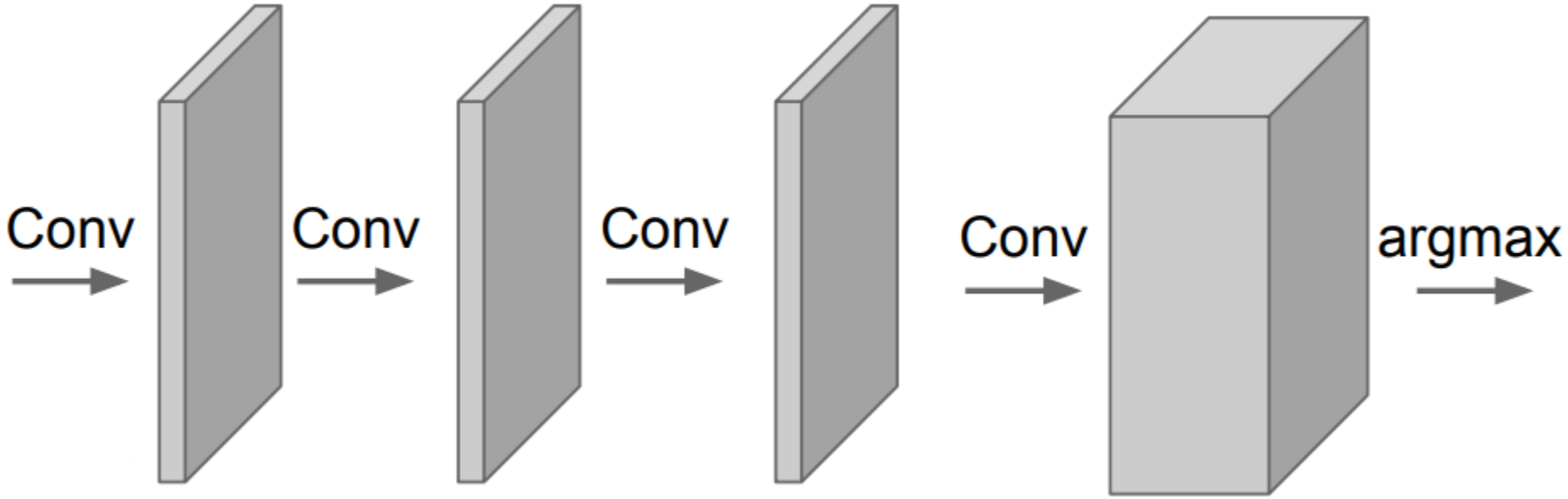
$\ell\left(\boldsymbol{x_j}, \theta\right)$ is the loss of the classifier (e.g. categorical cross entropy) when comparing $S(\boldsymbol{x_j})$ against $GT(\boldsymbol{x_j})$

Semantic Segmentation Networks

Simple Solution (3): Only Convolutions

What if we avoid any pooling (just conv2d and activation layers)?

- Very small receptive field
- Very inefficient



CS231n: Convolutional Neural Networks for Visual Recognition http://cs231n.github.io/

Drawbacks of convolutions only

- On the one hand **we need to "go deep" to extract high level information** on the image
- On the other hand **we want to stay local not to loose spatial resolution** in the predictions

Semantic segmentation faces an inherent tension between semantics and location:

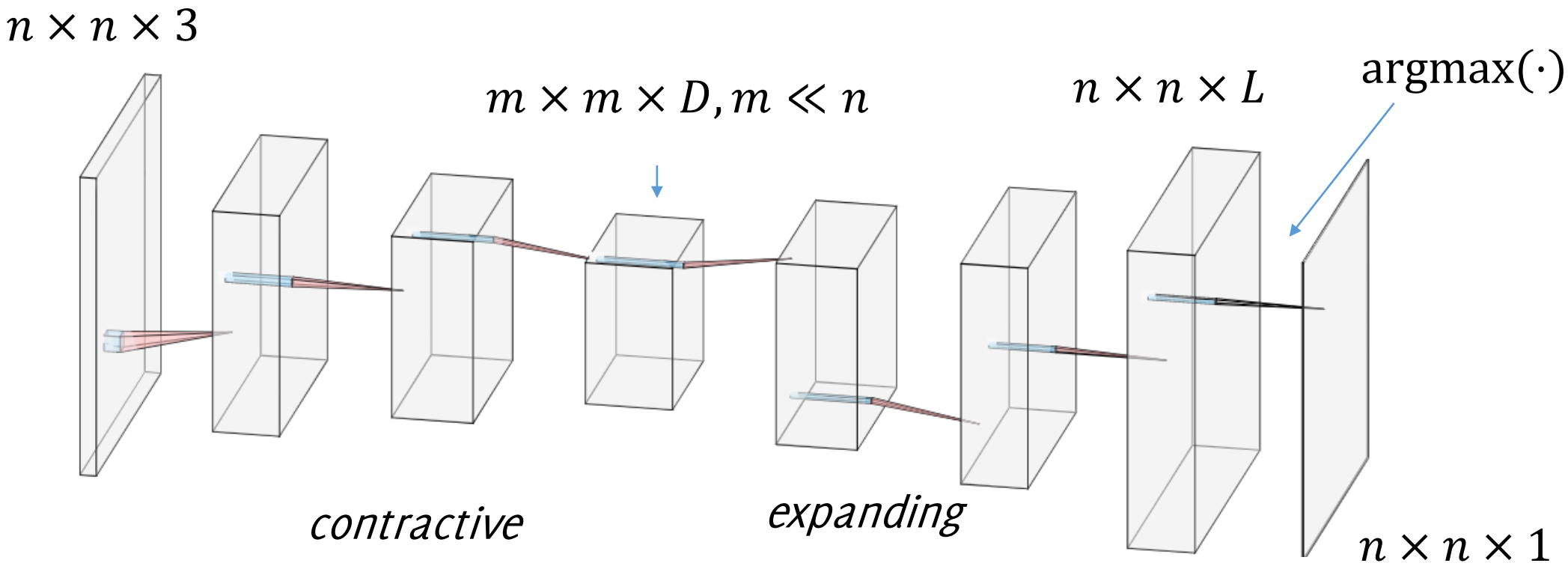
- ***global information resolves what****, while*
- ***local information resolves where***

Combining fine layers and coarse layers *lets the model make local predictions that respect global structure.*

Long, Jonathan, *Evan* Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Low-dimensional representation and upsampling

An architecture like the following would probably be more suitable for semantic segmentation

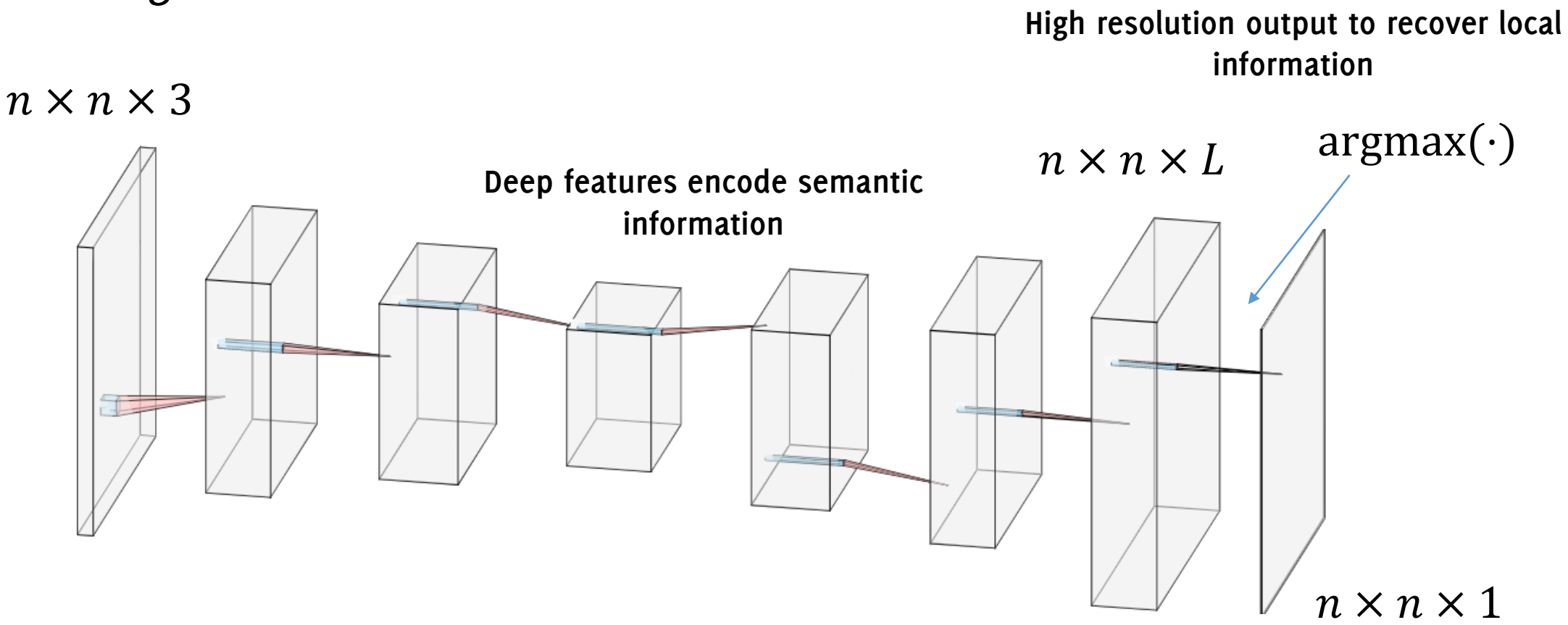


Conv + pooling / downsampling

Conv + upsampling

Low-dimensional representation and upsampling

An architecture like the following would probably be more suitable for semantic segmentation



Conv + pooling / downsampling

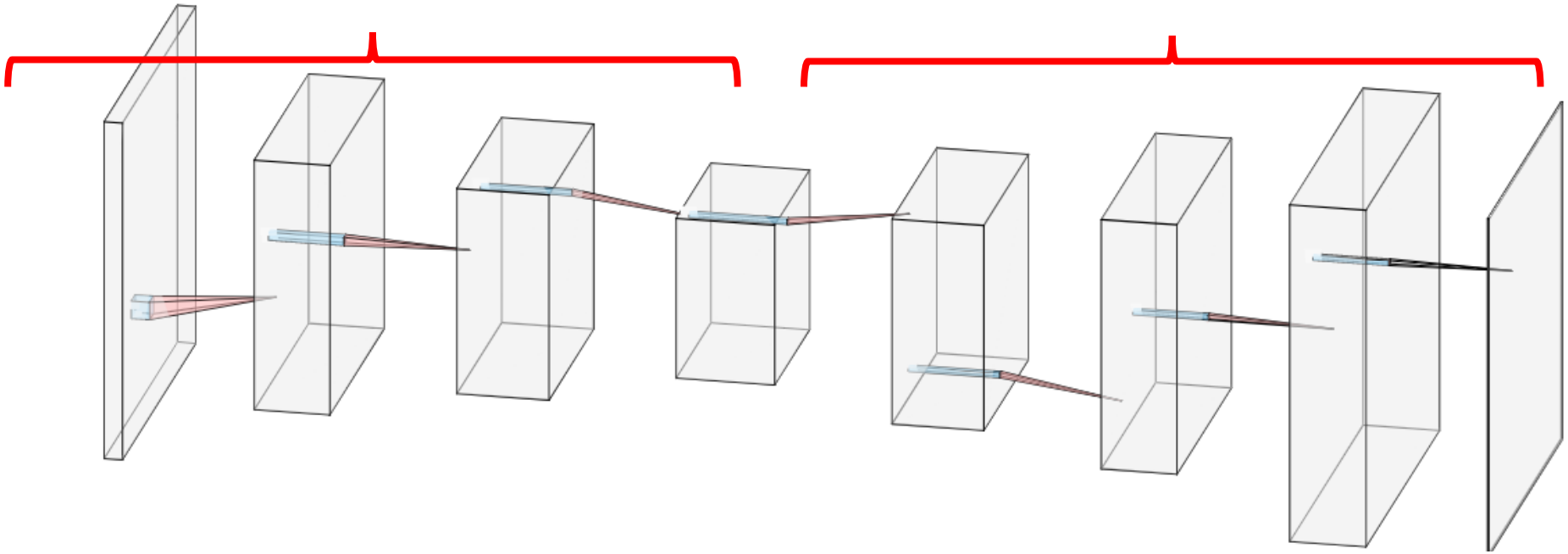
Conv + upsampling

Low-dimensional representation and upsampling

An architecture like the following would probably be more suitable for semantic segmentation

The first half is the same of a classification network

The second half is meant to upsample the predictions to cover each pixel in the image

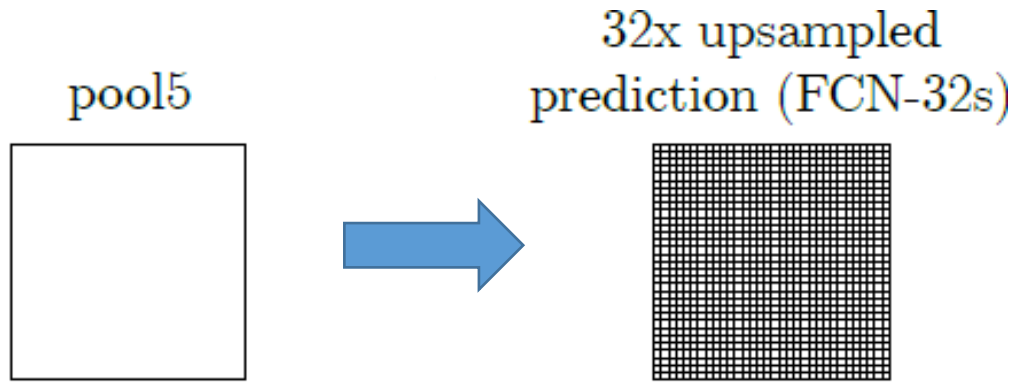


Increasing the image size is necessary to obtain sharp contours and spatially detailed class predictions

Conv + pooling / downsampling

Conv + upsampling

How to perform upsampling?



Nearest Neighbor

1	2
3	4

→

1	1	2	2
1	1	2	2
3	3	4	4
3	3	4	4

Input: 2 x 2 Output: 4 x 4

"Bed of Nails"

1	2
3	4

→

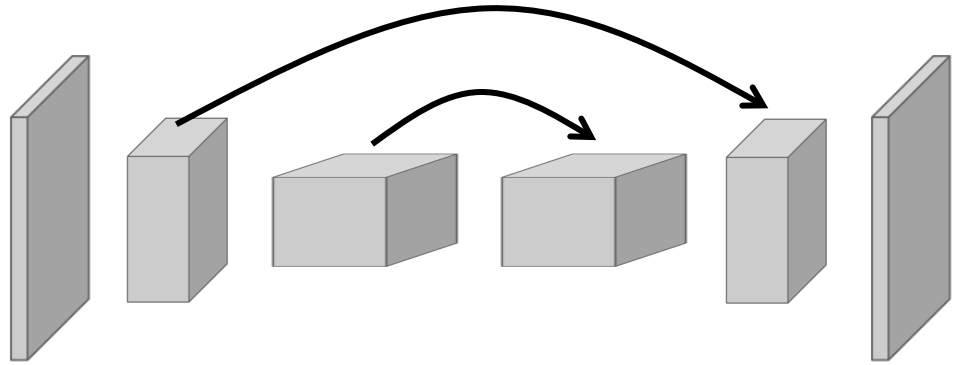
1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

Input: 2 x 2 Output: 4 x 4

CS231n: Convolutional Neural Networks for Visual Recognition http://cs231n.github.io/

Max Unpooling

You have to keep track of the locations of the max during maxpooling



Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

Rest of the network

Max Unpooling
Use positions from pooling layer

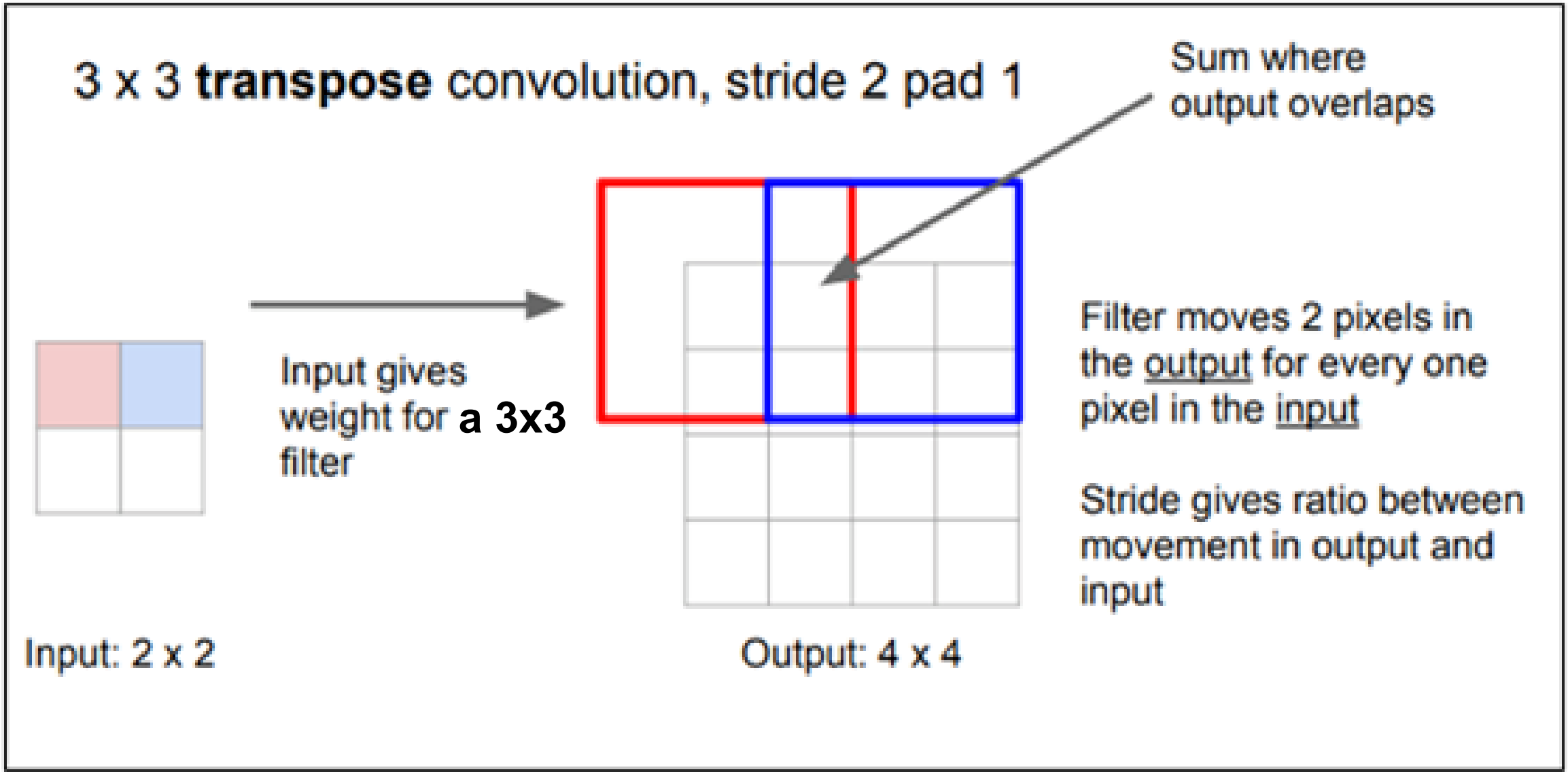
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

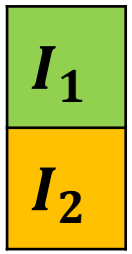
Transpose Convolution



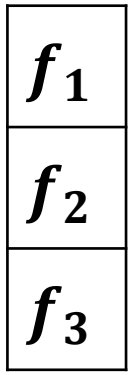
Transpose Convolution

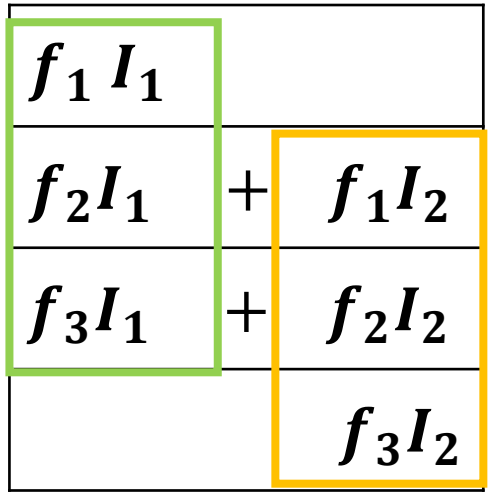
Transpose convolution with stride 1

Input 2 x 1



Filter 3 x 1

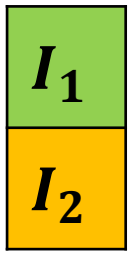




Transpose Convolution

Transpose convolution with stride 2, even larger expansion

Input 2 x 1



Filter 3 x 1

f_1
f_2
f_3

$f_1 I_1$		
$f_2 I_1$		
$f_3 I_1$	+	$f_1 I_2$
		$f_2 I_2$
		$f_3 I_2$

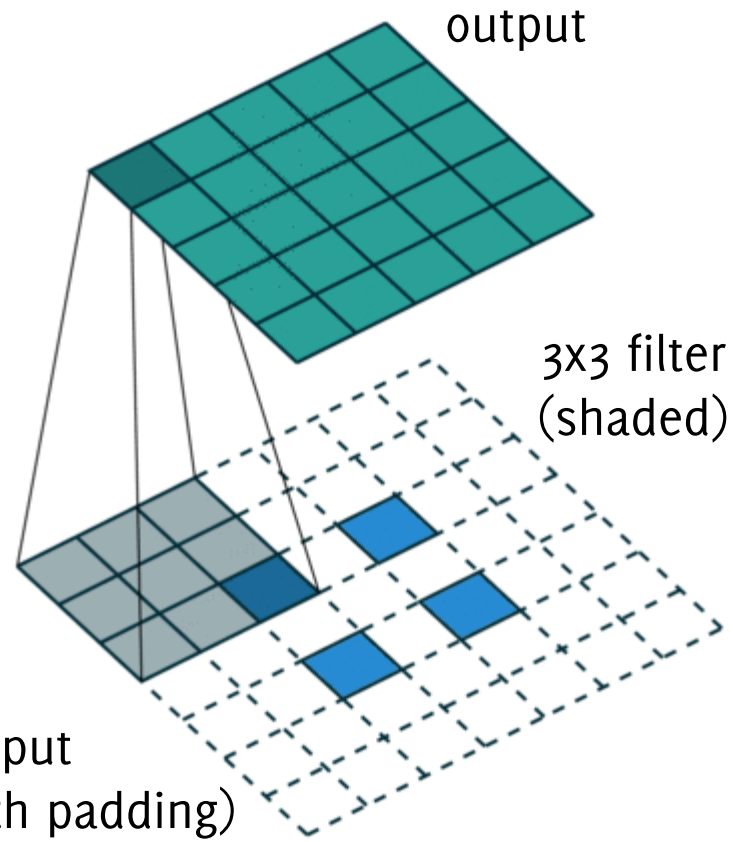
Transpose Convolution

Transpose Convolution and upsampling:

Transpose Convolution can be seen as a traditional convolution after having upsampled the input image

All in all

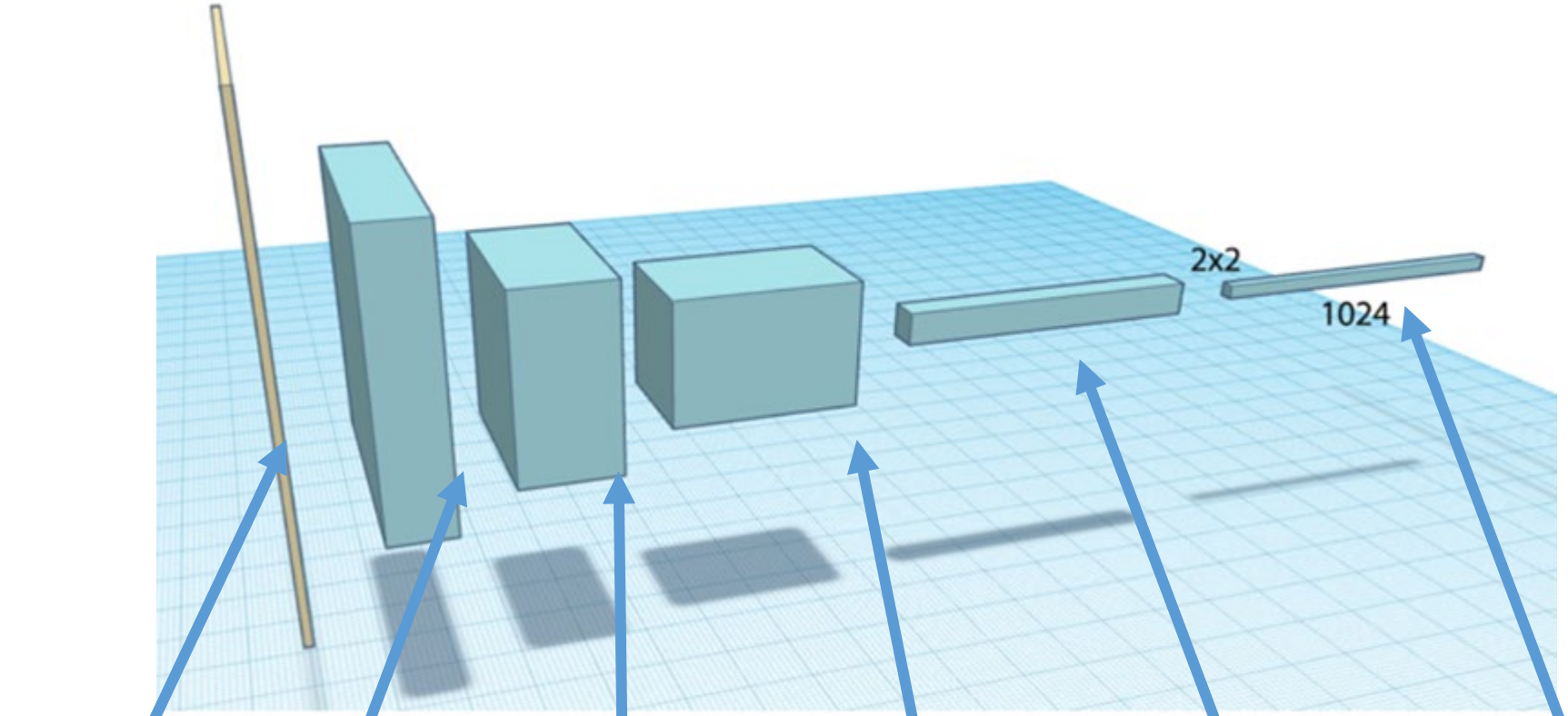
- **Upsamping based on convolution** gives more degrees of freedom, since the **filters can be learned**
- Many names for transpose convolution: fractional strided convolution, backward strided convolution, deconvolution (very misleading!!!)



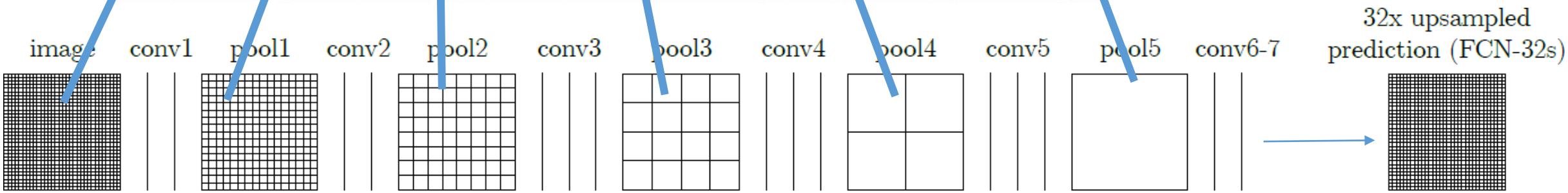
https://github.com/vdumoulin/conv_arithmetic

Dumoulin, Vincent, and Francesco Visin. "A guide to convolution arithmetic for deep learning." *arXiv preprint arXiv:1603.07285* (2016).

Low-dimensional representation and upsampling

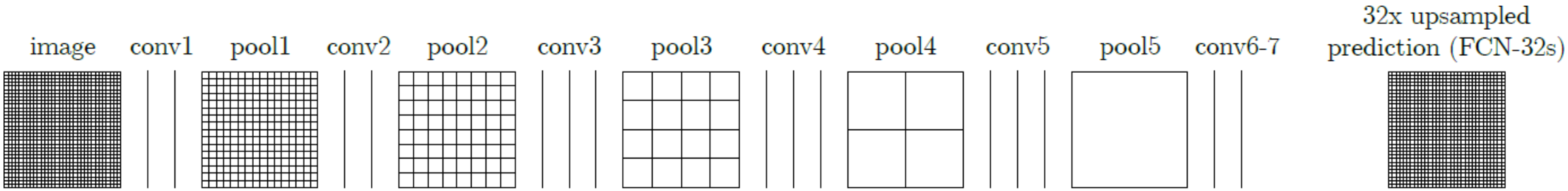


Upsampling



Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

FC-CNN Upsampling



- Data-driven upsampling of the coarse outputs to pixel-dense outputs
- These filters are initialized as bilinear upsampling filters
- This upsampling is mandatory to compute the loss against the GT (which is at full resolution)

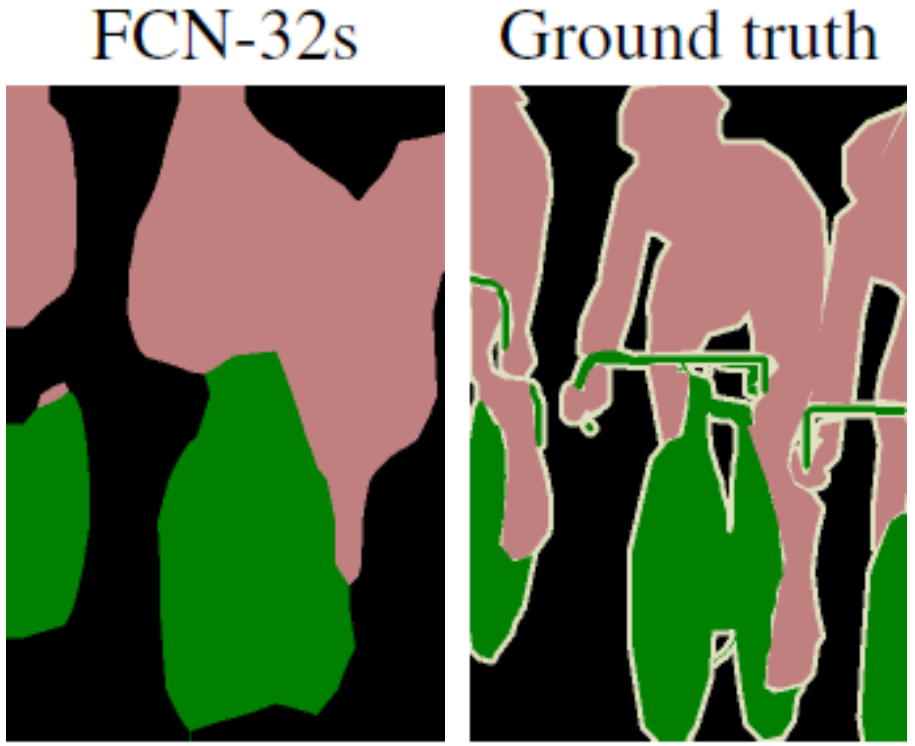
Prediction Upsampling

Linear upsampling of a factor f can be implemented as a convolution against a filter with a fractional stride $1/f$.

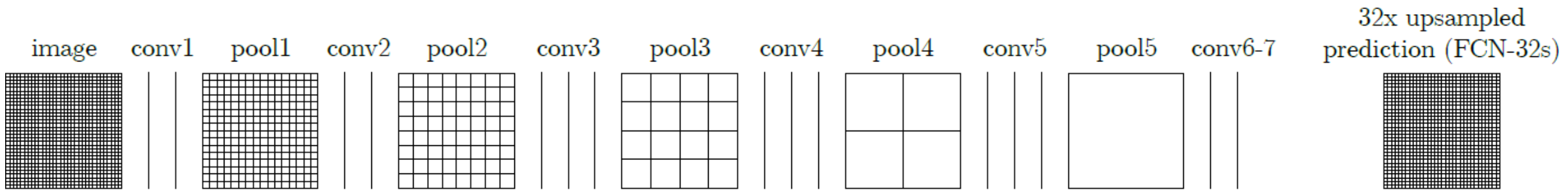
Upsampling filters can thus be learned during network training.

These **predictions** however are **very coarse**

Upsampling filters are learned with initialization equal to the bilinear interpolation

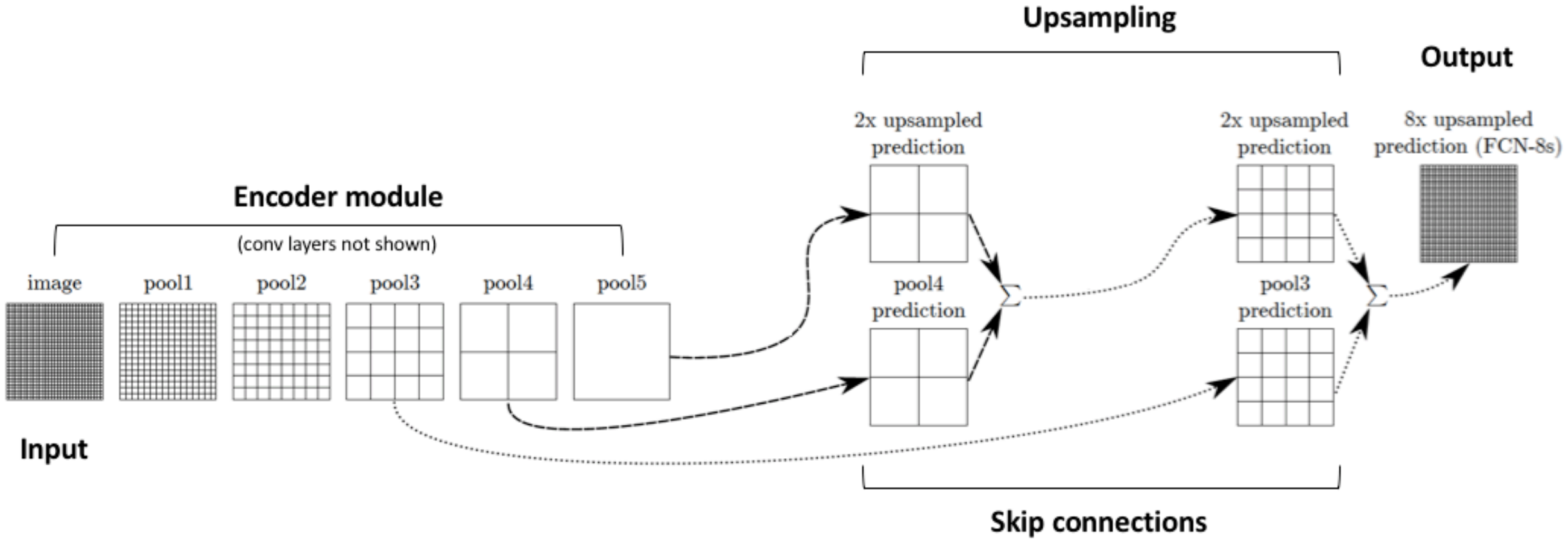


Upsampling filters



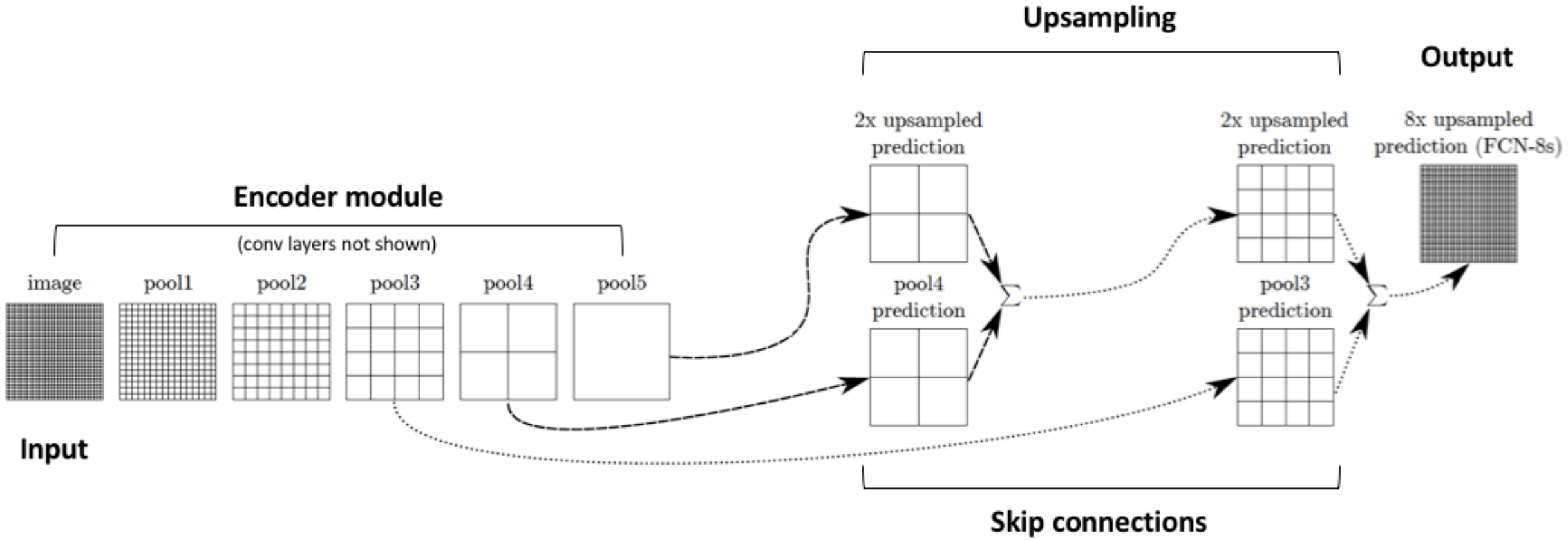
Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Improve segmentation: Skip Connections!



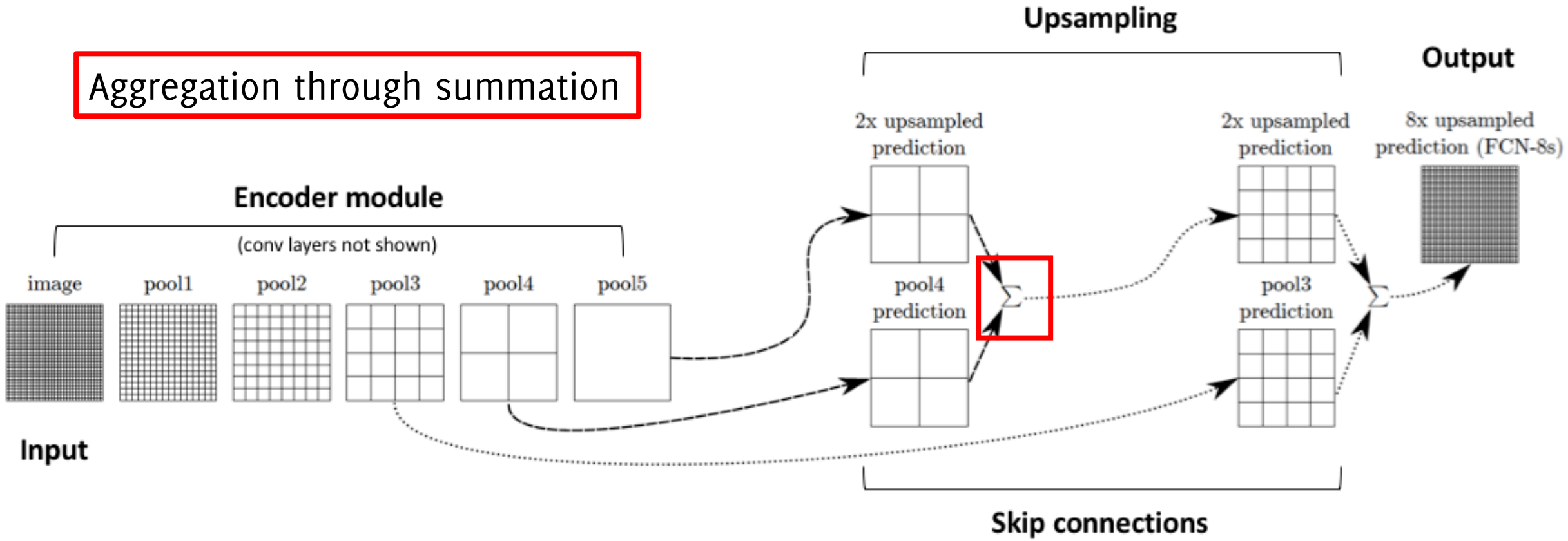
https://www.jeremyjordan.me/semantic-segmentation/

Improve segmentation: Skip Connections!



https://www.jeremyjordan.me/semantic-segmentation/

Solution: Skip Connections!



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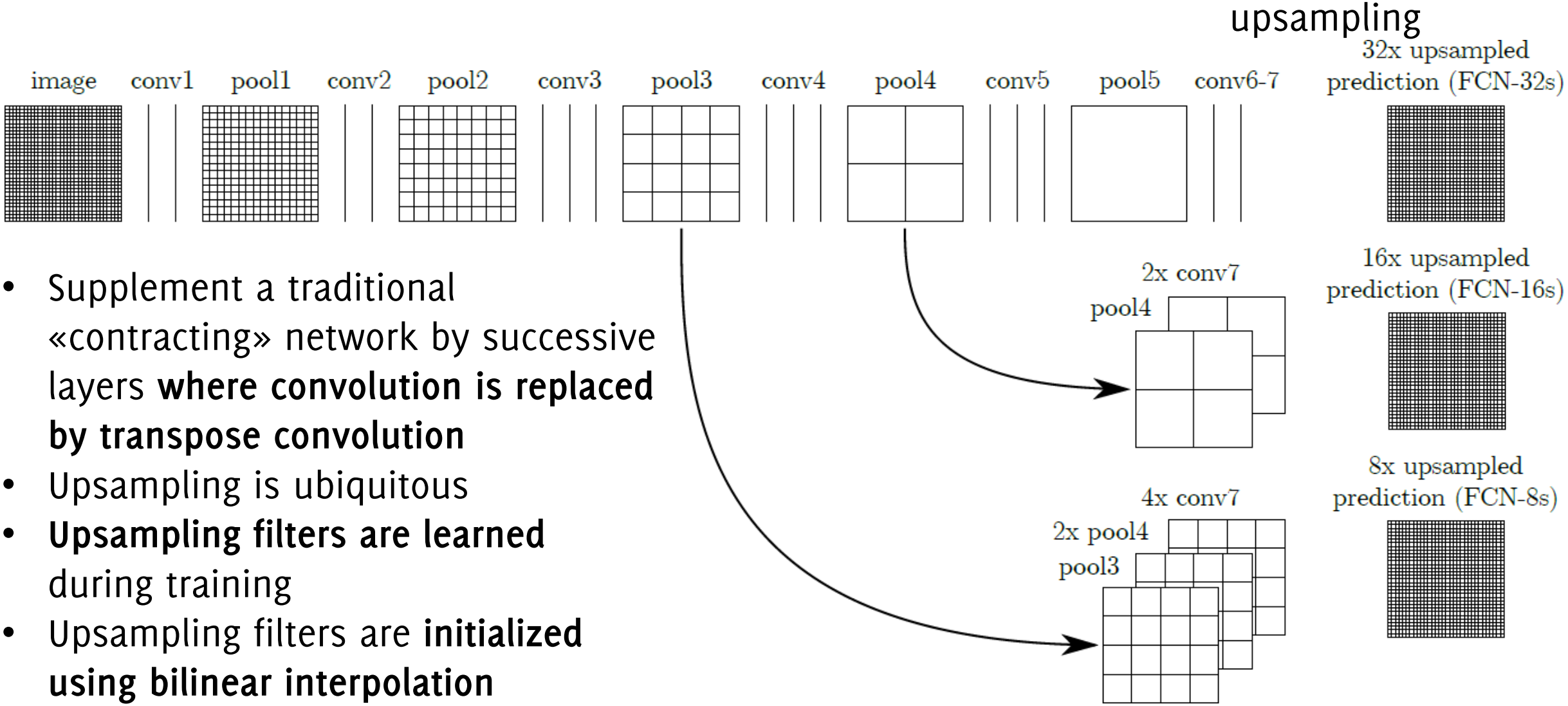
Solution: Skip Connections!



- Supplement a traditional «contracting» network by successive layers **where convolution is replaced by transpose convolution**
- Upsampling is ubiquitous
- **Upsampling filters are learned** during training
- Upsampling filters are **initialized using bilinear interpolation**

Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Solution: Skip Connections!

- Supplement a traditional «contracting» network by successive layers **where convolution is replaced by transpose convolution**
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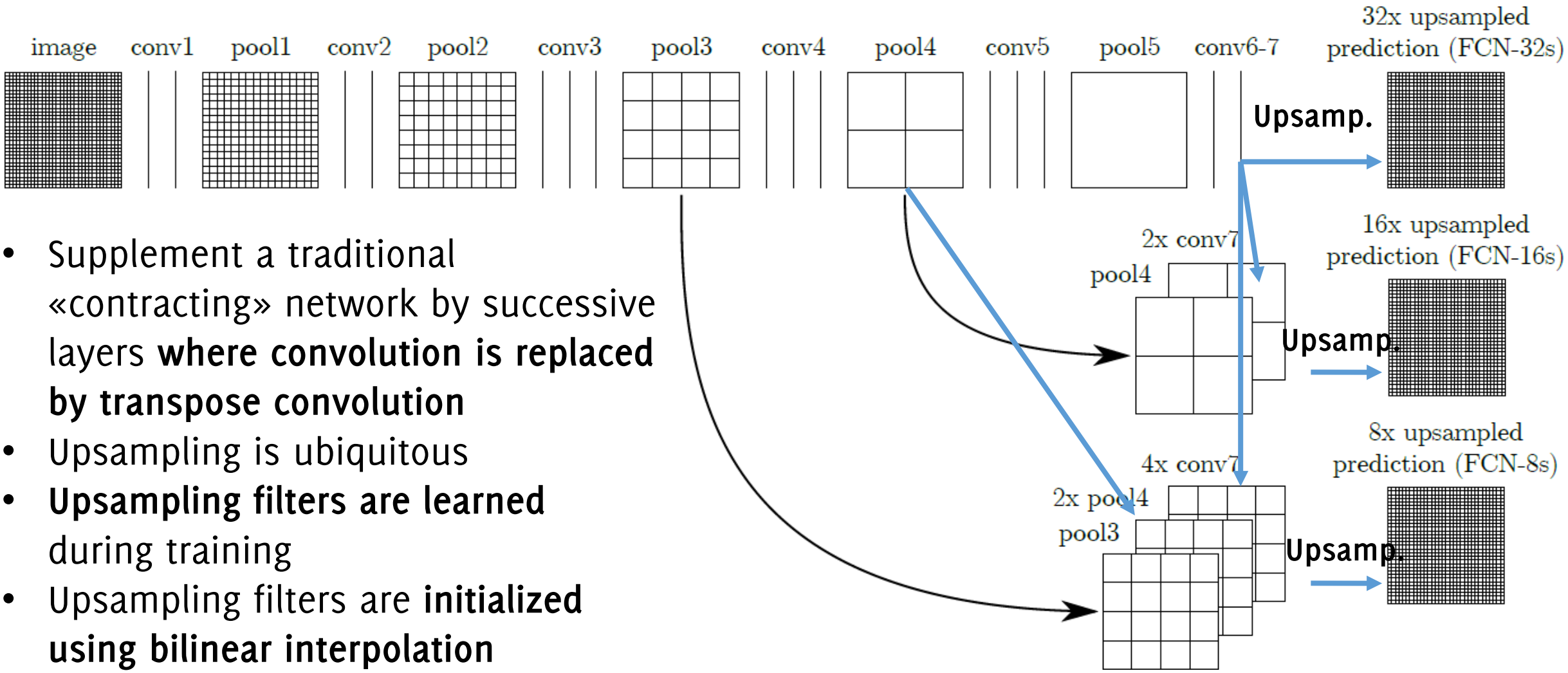
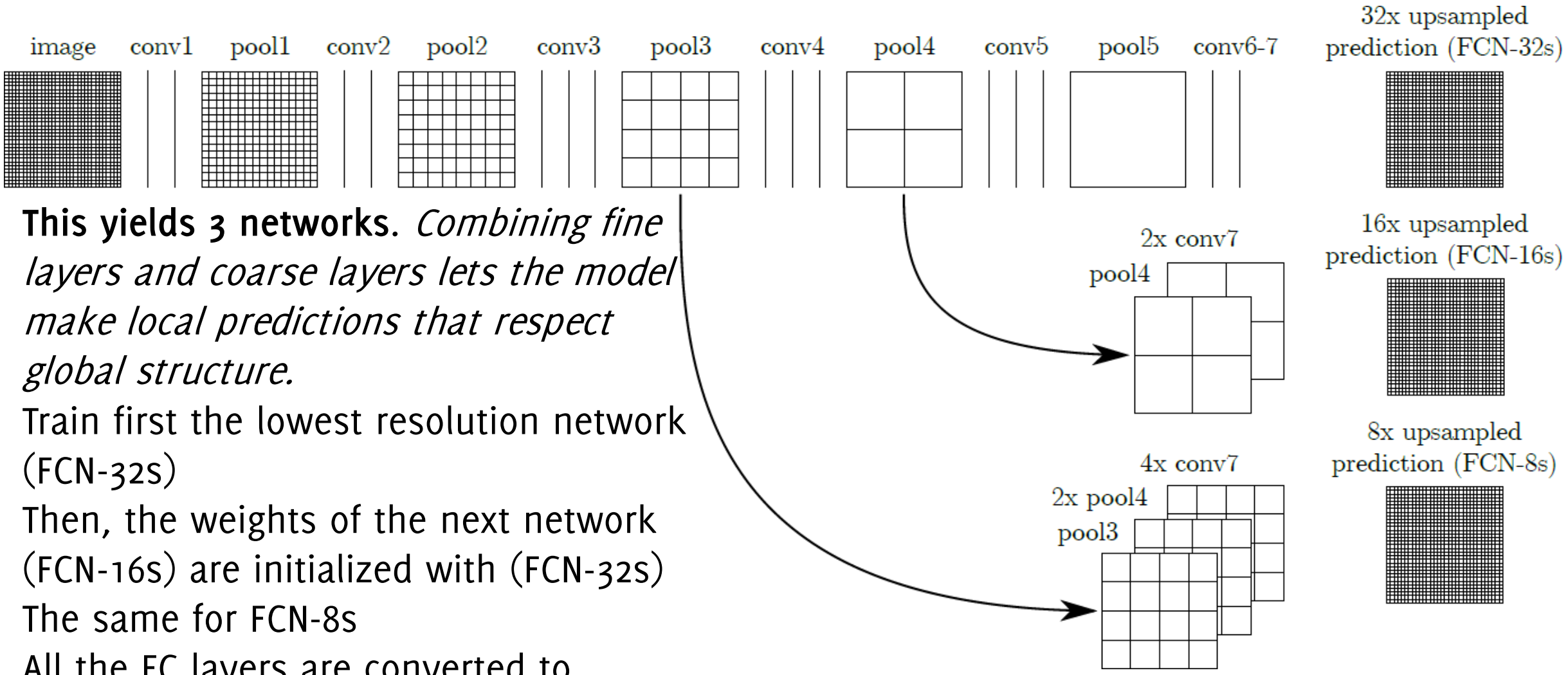


Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Solution: Skip Connections!

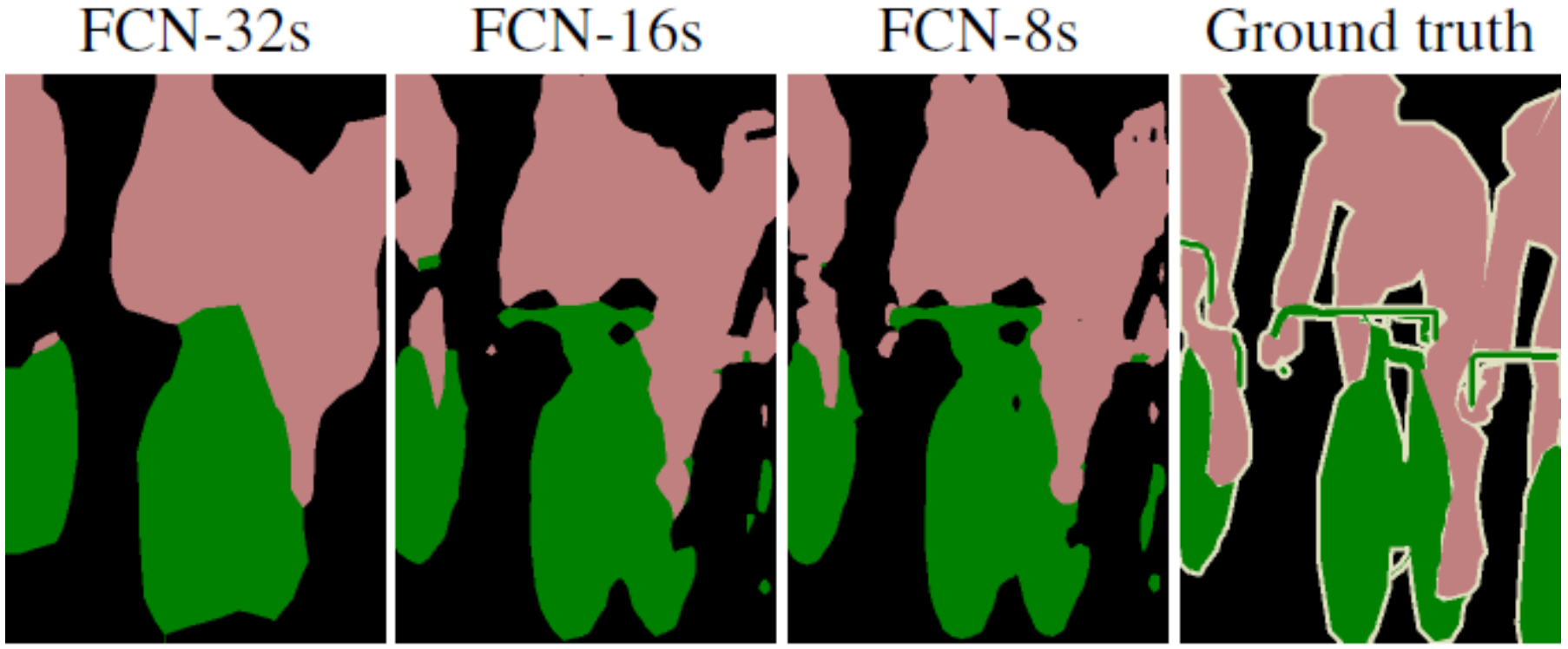


- **This yields 3 networks.** *Combining fine layers and coarse layers lets the model make local predictions that respect global structure.*
- Train first the lowest resolution network (FCN-32s)
- Then, the weights of the next network (FCN-16s) are initialized with (FCN-32s)
- The same for FCN-8s
- All the FC layers are converted to convolutional layers 1x1

Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Semantic Segmentation

Retaining intermediate information is beneficial, the deeper layers contribute to provide a better refined estimate of segments



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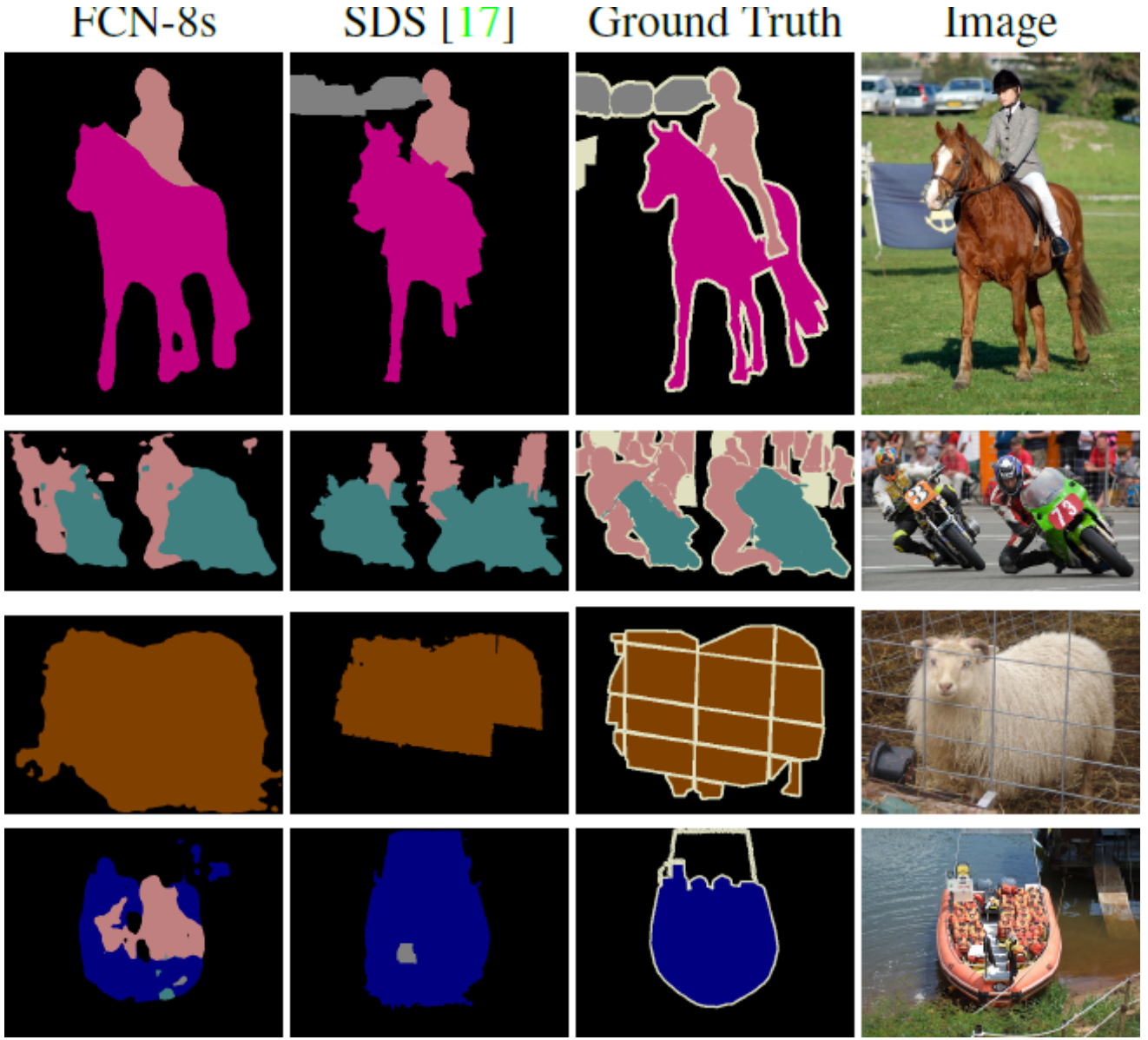
Semantic Segmentation Results



Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." CVPR 2015

Comments

- Both learning and inference can be performed on the whole-image-at-a-time
- It is possible to **perform transfer learning/fine tuning** of **pre-trained classification models** (segmentation typically requires fewer labels than classification)
- **Accurate pixel-wise prediction** is achieved by upsampling layers
- Outperforms state-of the art in 2015
- Being fully convolutional, this network **handles arbitrarily sized input**

U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, and Thomas Brox

Computer Science Department and BIOSS Centre for Biological Signalling Studies,
University of Freiburg, Germany
ronneber@informatik.uni-freiburg.de,
WWW home page: http://lmb.informatik.uni-freiburg.de/

U-Net

Network formed by:

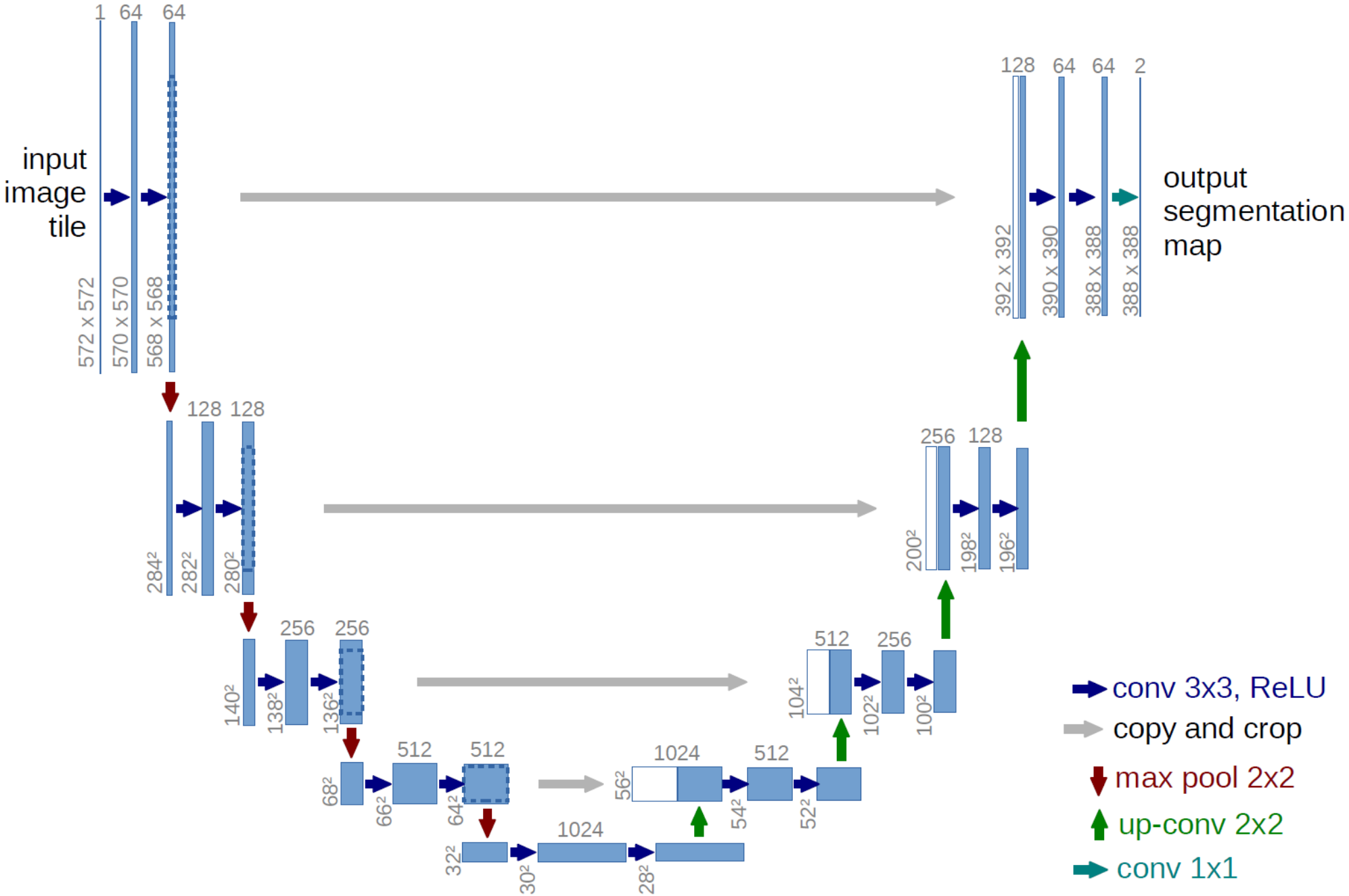
- A contracting path
- An expansive path

No fully connected layers

Major differences w.r.t. (Long et al. 2015):

- use **a large number of feature channels** in the upsampling part, while in (long et al. 2015) there were a few upsampling. The network become symmetric
- **Use excessive data-augmentation** by applying elastic deformations to the training images

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *MICCAI*, 2015.



Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *MICCAI*, 2015.

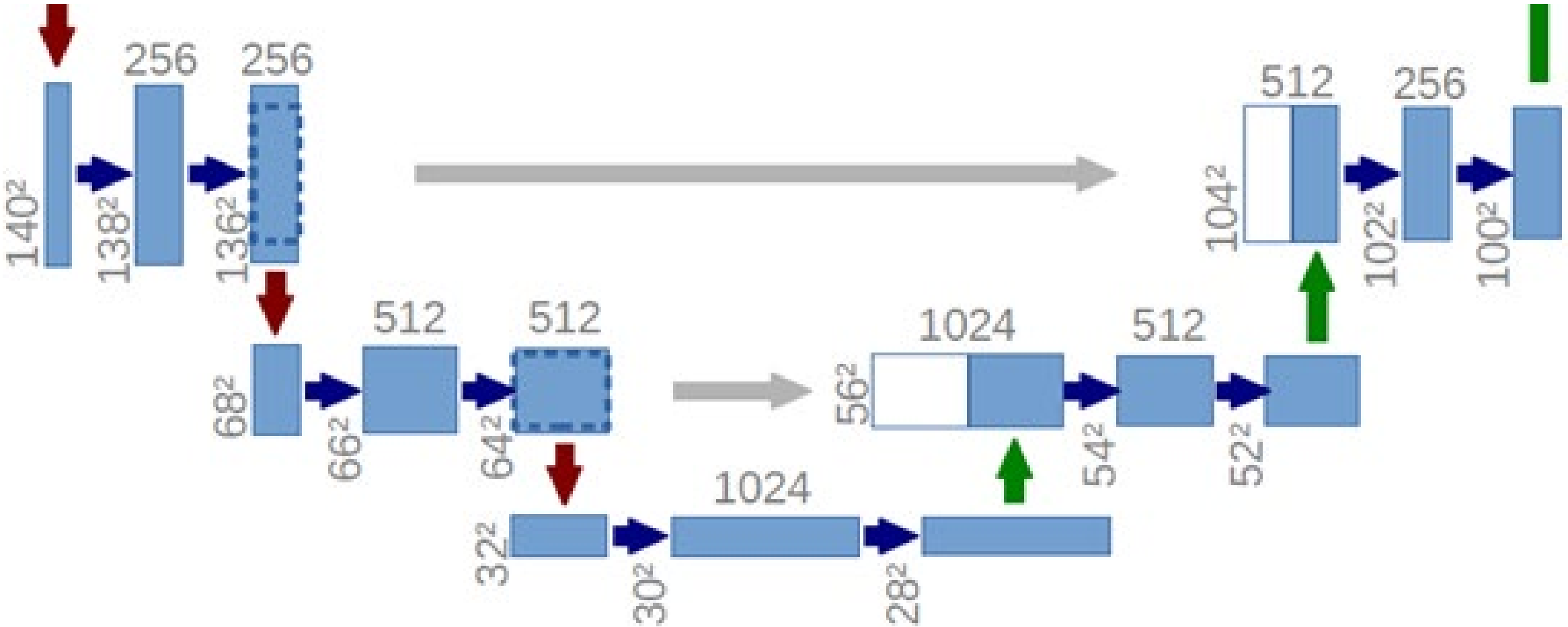
U-Net: Contracting path

Repeats blocks of:

- 3×3 convolution + ReLU ('valid' option, no padding)
- 3×3 convolution + ReLU ('valid' option, no padding)
- Maxpooling 2×2

At each downsampling the number of feature maps is doubled

U-Net: Skip connections



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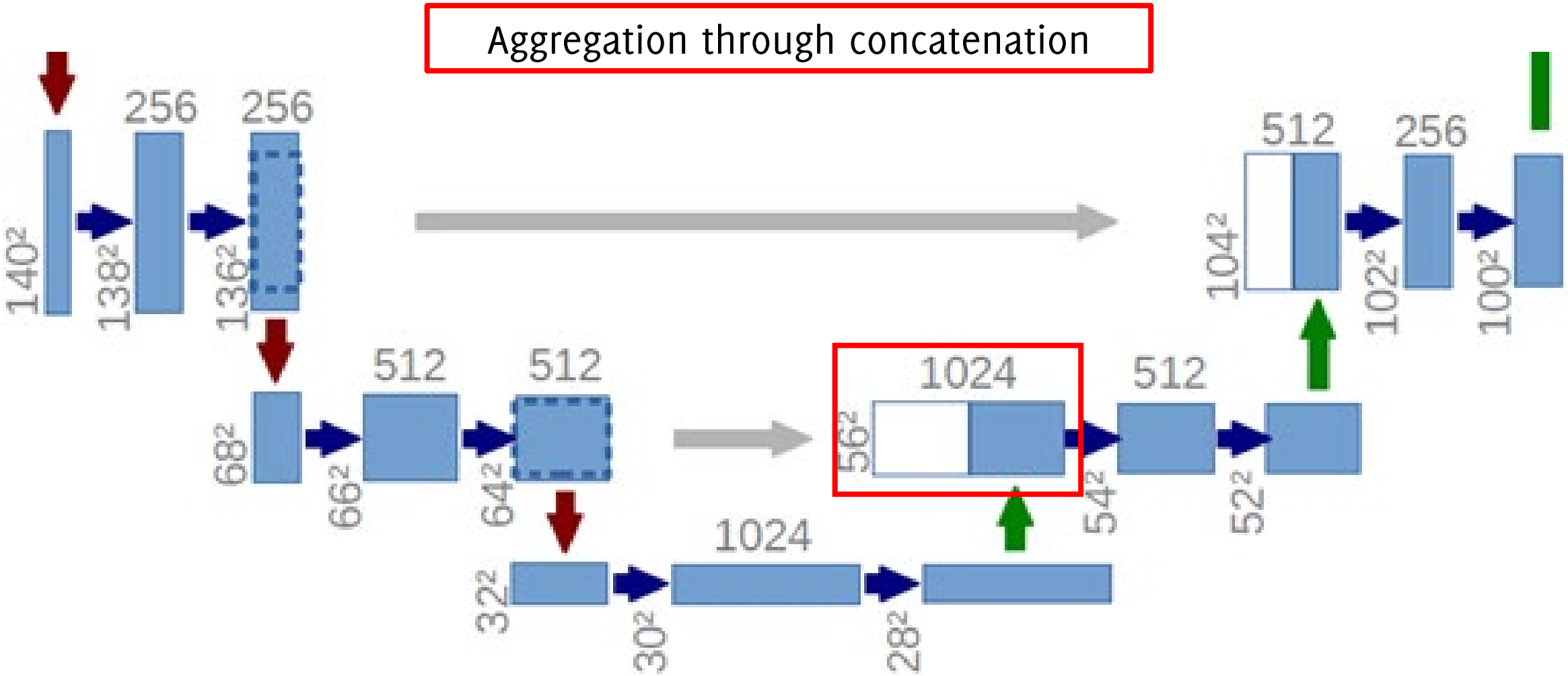
U-Net: Skip connections



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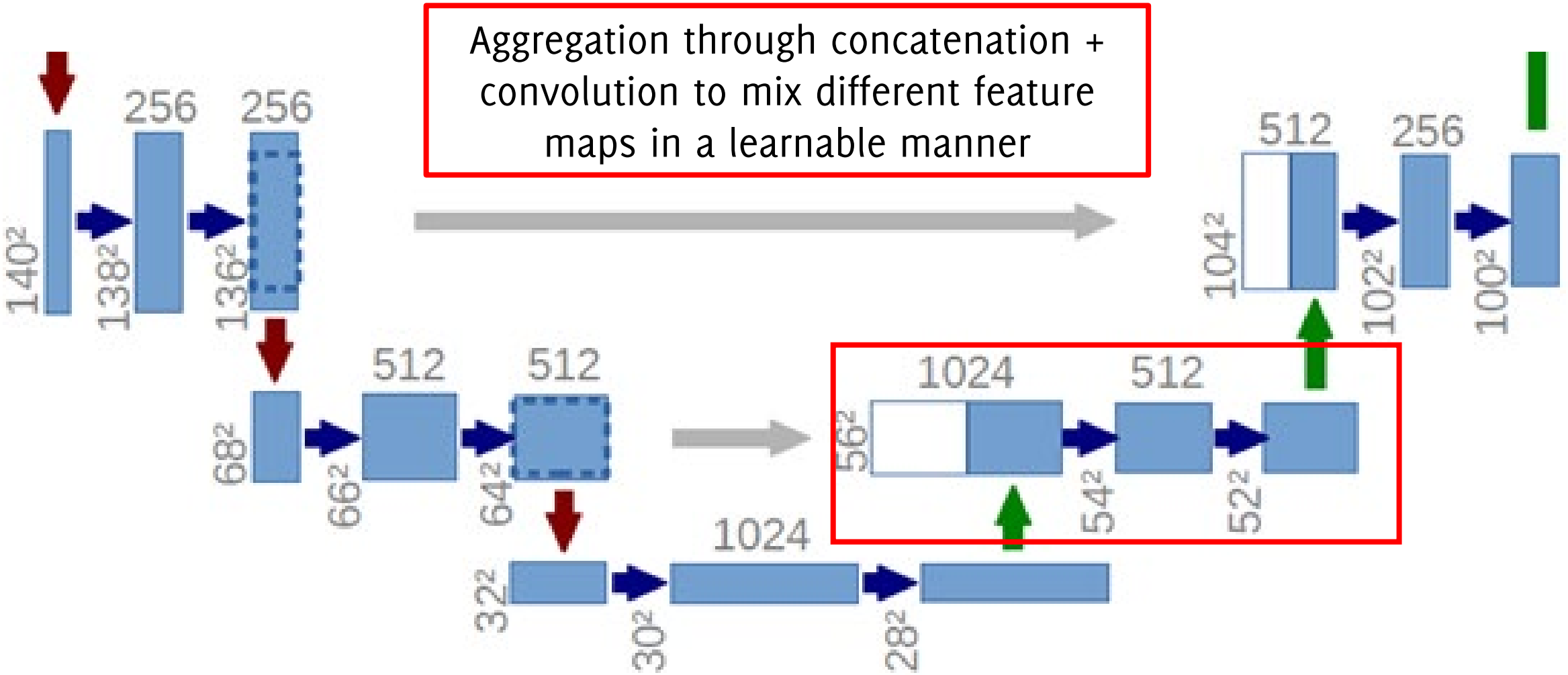
U-Net: Skip connections



Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *MICCAI*, 2015.

U-Net: Expanding path

Repeats blocks of:

- 2×2 transpose convolution, halving the number of feature maps (but doubling the spatial resolution)
- Concatenation of corresponding cropped features
- 3×3 convolution + ReLU
- 3×3 convolution + ReLU

Aggregation during upsampling

U-Net: Network Top

No fully connected layers: there are L convolutions against filters $1 \times 1 \times N$, to yield predictions out of the convolutional feature maps

Output image is smaller than the input image by a constant border

U-Net: Training

Full-image training by a weighted loss function

$$\hat{\theta} = \min_{\theta} \sum_{\boldsymbol{x_j}} w(\boldsymbol{x}_j)\ell(\boldsymbol{x_j}, \theta)$$

where the weight

$$w(\boldsymbol{x}) = w_c(\boldsymbol{x}) + w_0\, e^{-\frac{(d_1(\boldsymbol{x})+d_2(\boldsymbol{x}))^2}{2\sigma^2}}$$

- w_c is used to balance class proportions (remember no patch resampling in full-image training)
- d_1 is the distance to the border of the closest cell
- d_2 is the distance to the border of the second closest cell

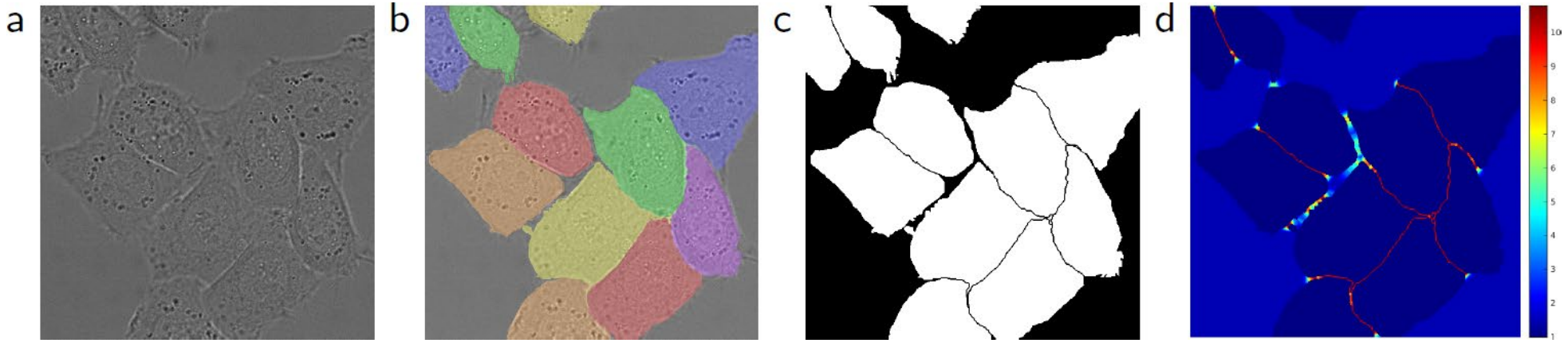
U-Net: Training

Full-image training by a weighted loss function

$$w(\boldsymbol{x}) = w_c(\boldsymbol{x}) + w_0\, e^{-\frac{\left(d_1(\boldsymbol{x})+d_2(\boldsymbol{x})\right)^2}{2\sigma^2}}$$

- w_c is used to balance class proportions (remember no patch resampling in full-image training)
- d_1 is the distance to the border of the closest cell
- d_2 is the distance to the border of the second closest cell

Weights are large when the distance to the first two closest cells is small



Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *MICCAI*, 2015.

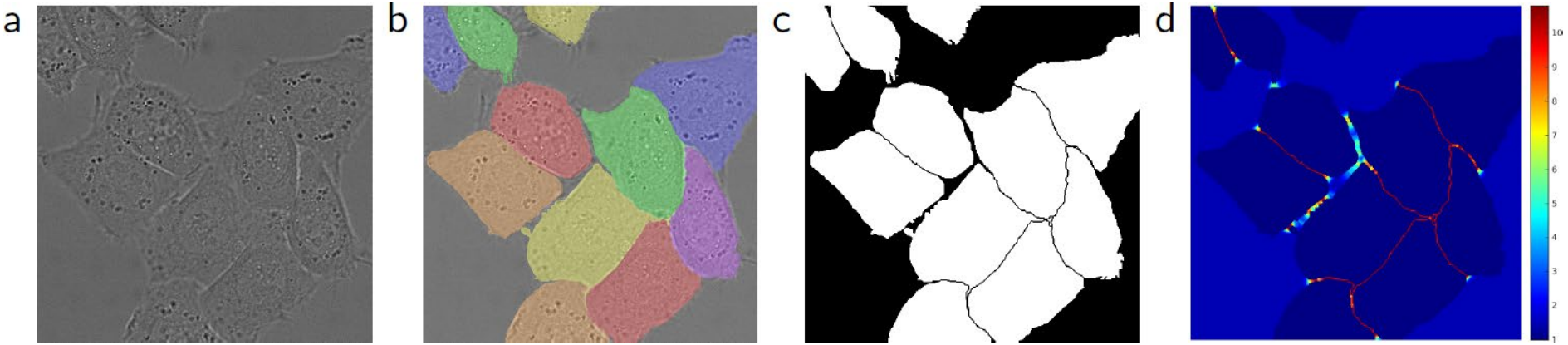
U-Net: Training

Full-image training by a weighted loss function

$$w(\boldsymbol{x}) = w_c(\boldsymbol{x}) + w_0\, e^{-\frac{\left(d_1(\boldsymbol{x})+d_2(\boldsymbol{x})\right)^2}{2\sigma^2}}$$

Takes into account class unbalance in the training set

Enhances classification performance at borders of different objects



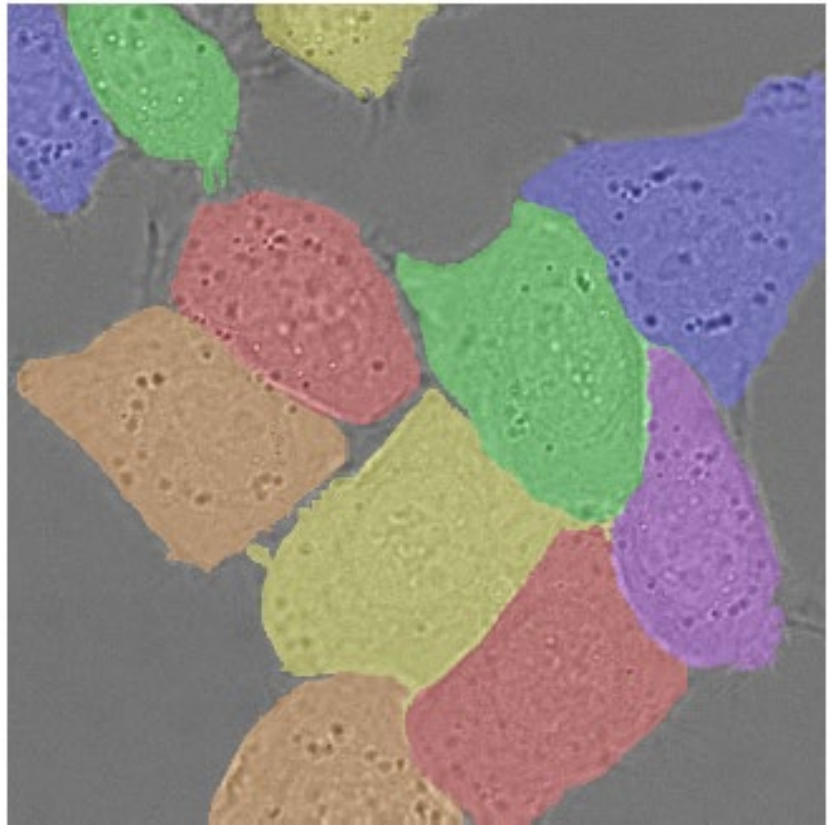
Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *MICCAI*, 2015.

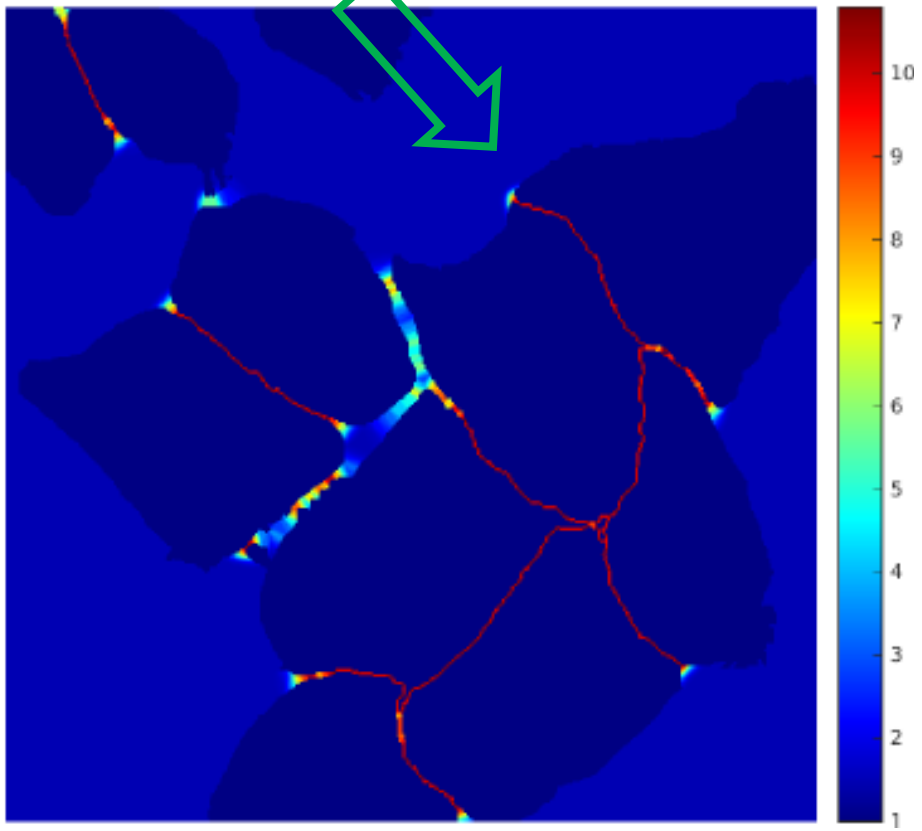
U-Net: Training

This term is large at pixels close to borders delimiting objects of different cells (note that thin borders are red, maximum score)

Full-image training by a weighted loss function

$$w(\boldsymbol{x}) = w_c(\boldsymbol{x}) + w_0\, e^{-\frac{\left(d_1(\boldsymbol{x})+d_2(\boldsymbol{x})\right)^2}{2\sigma^2}}$$





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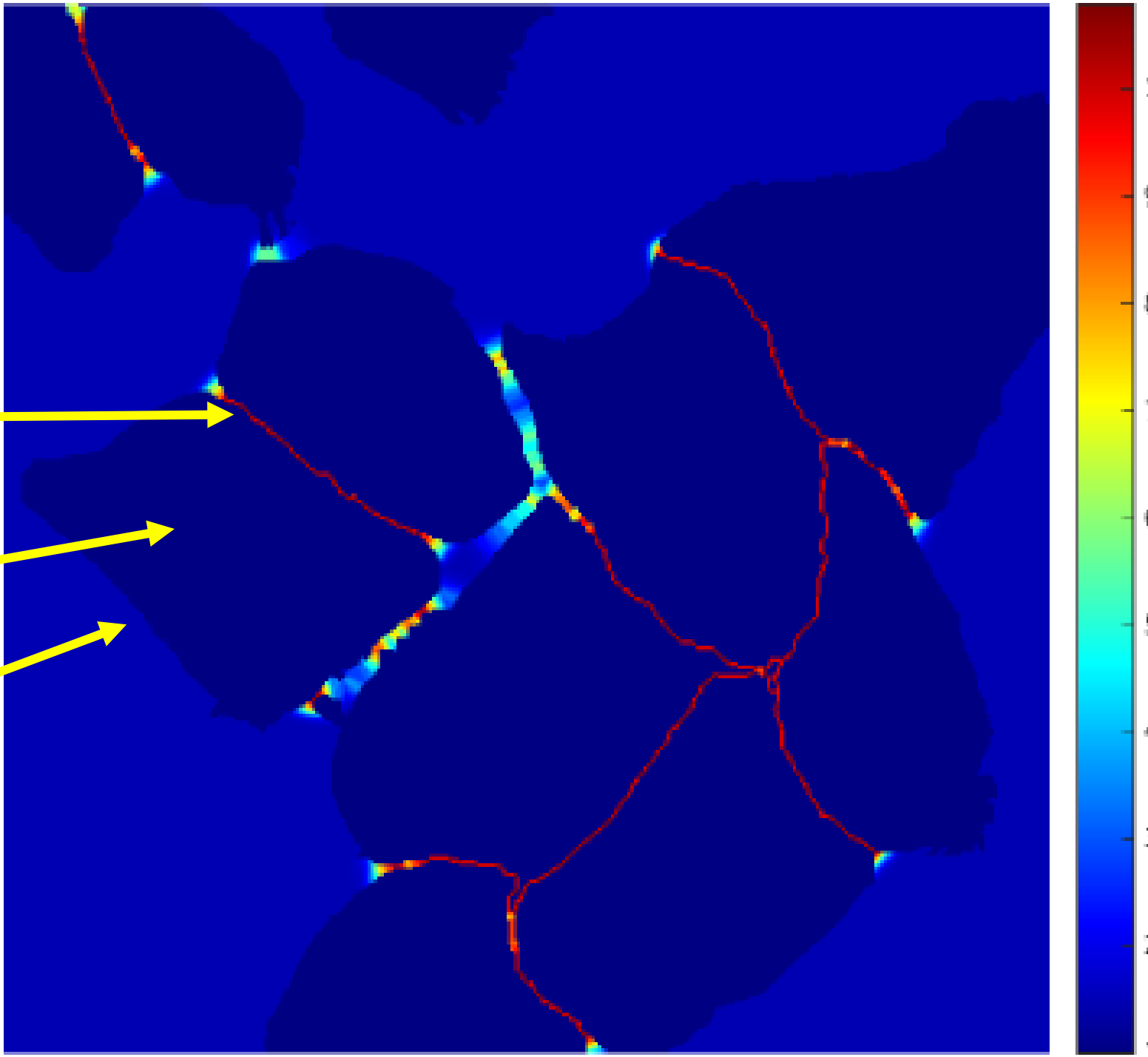
U-Net: Training

$$w(\boldsymbol{x}) = w_c(\boldsymbol{x}) + w_0\, e^{-\frac{\left(d_1(\boldsymbol{x})+d_2(\boldsymbol{x})\right)^2}{2\sigma^2}}$$

small $d_1(\boldsymbol{x})$ and small $d_2(\boldsymbol{x})$

large $d_1(\boldsymbol{x})$ and $d_2(\boldsymbol{x})$

small $d_1(\boldsymbol{x})$ and large $d_2(\boldsymbol{x})$



U-Net Block in Keras

```
# make sure that within this block spatial sizes are preserved
def unet_block(input_tensor, filters, kernel_size=3, activation='relu', name=''):
    # 2D convolution
    x = tfkl.Conv2D(filters, kernel_size=3, padding='same', name=name+'conv1')(input_tensor)
    # batch normalization (optional)
    x = tfkl.BatchNormalization(name=name+'bn1')(x)
    # activation after batchnorm (this is kind of debated)
    x = tfkl.Activation(activation, name=name+'activation1')(x)
    # 2D convolution
    x = tfkl.Conv2D(filters, kernel_size=3, padding='same', name=name+'conv2')(x)
    # batch normalization (optional)
    x = tfkl.BatchNormalization(name=name+'bn2')(x)
    # activation
    x = tfkl.Activation(activation, name=name+'activation2')(x)
    return x
```

U-Net Block in Keras

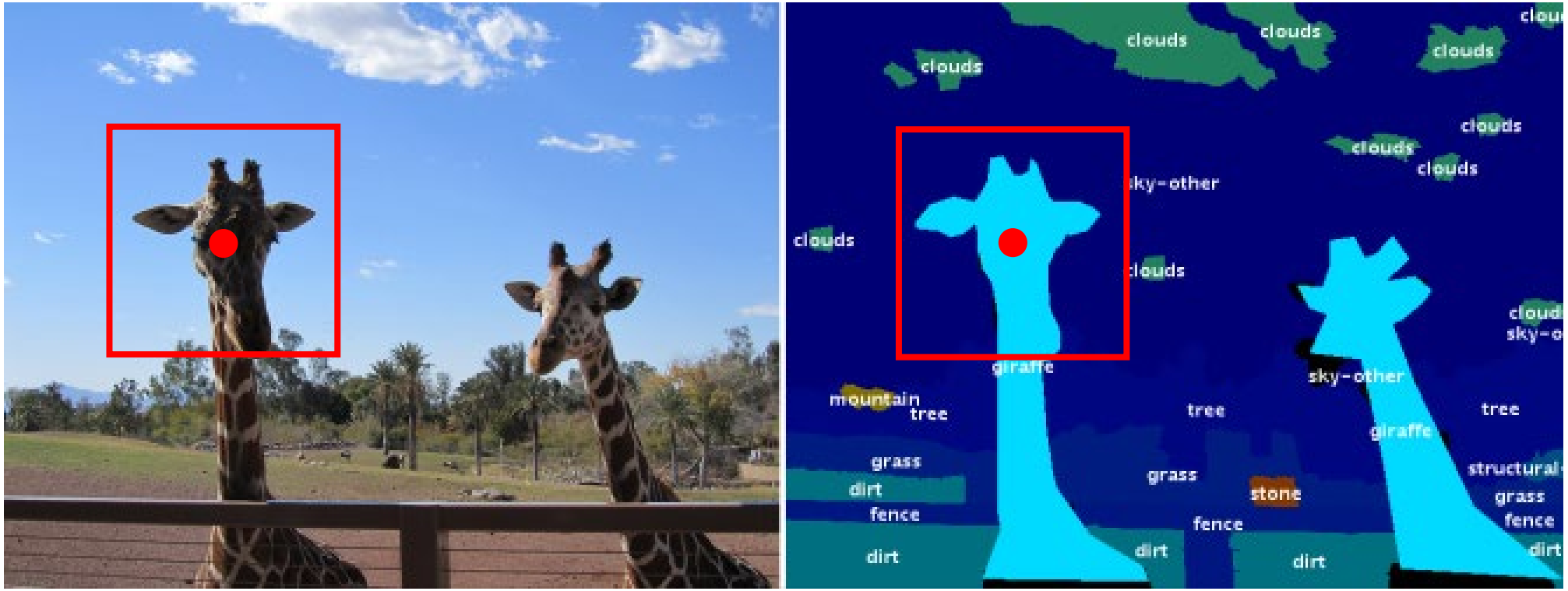
```
# Forth Downsampling
    down_block_4 = unet_block(d3, 256, name='down_block4_')
    d4 = tfkl.MaxPooling2D()(down_block_4)
    d4 = tfkl.Dropout(0.2, seed=seed)(d4)
# Bottleneck
    bottleneck = unet_block(d4, 512)
# First Upsampling layer
    # add 2D upsampling layer (this has learnable weights)
    u1 = tfkl.UpSampling2D()(bottleneck)
    # add dropout
    u1 = tfkl.Dropout(0.2, seed=seed)(u1)
    # concatenate the output of down_block_4 (the deepest layer in the contractive path) wit
h the first layer in the expanding path.
    # Spatial sizes need to be consistent, otherwise it is not possible to concatenate
    u1 = tfkl.Concatenate()([u1,down_block_4])
    # add a convolutional block (Exactly same architecture as in the contractive path)
    u1 = unet_block(u1, 256, name='up_block1_')
```

Concatenation is meant along the channel dimension, then values are mixed by forthcoming convolutional layers

Patch-wise Training vs Full-image Training

«Patch-based» training

- Prepare a training set for a classification network
- Crop as many patches $\boldsymbol{x_i}$ from annotated images and assign to each patch, the label corresponding to the patch center



FC-CNN Training Options

The «patch-based» way:

- Prepare a training set for a classification network
- Crop as many patches $\boldsymbol{x_i}$ from annotated images and assign to each patch, **the label corresponding to the patch center**
- **Train a CNN for classification** from scratches, or
  fine tune a pre-trained model over the segmentation classes
- **Convolutionalization:** once trained the network, **move the FC layers to 1x1 convolutions**
- **(Design and train the upsampling side of the network)**

FC-CNN Training Options

The «patch-based» way:

- The classification network is trained to minimize the classification loss ℓ over a mini-batch $\boldsymbol{B}$

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{\boldsymbol{x_j} \in \boldsymbol{B}} \ell\left(\boldsymbol{x_j}, \theta\right)$$

  where $\boldsymbol{x_j}$ belongs to a mini-batch $\boldsymbol{B}$

- Batches of patches are **randomly assembled during training**
- **It is possible to resample patches for solving** class imbalance
- It is **very inefficient**, since convolutions on overlapping patches are repeated multiple times

FC-CNN Training Options: The «full-image» way

When full-image annotations are provided, $\boldsymbol{x_j}$ **are all the pixels in a region** $\boldsymbol{R}$ **of the input image** and the loss is evaluated over the corresponding labels in the annotation for semantic segmentation.

$$\hat{\theta} = \underset{\boldsymbol{x_j} \in I}{\operatorname{argmin}} \sum_{\boldsymbol{x_j} \in \boldsymbol{R}} \ell\left(\boldsymbol{x_j}, \theta\right)$$

Therefore, **each region provides already a mini-batch estimate for computing gradient**.

Whole image fully convolutional training is identical to patchwise training where each batch consists of all the receptive fields of the units below the loss for an image [...]. While this is more efficient than uniform sampling of patches, it reduces the number of possible batches

FCNN Training Options

The «full-image» way:

- **FCNN are trained in an end-to-end manner to predict the segmented output** $S(\cdot,\cdot)$.
- This loss is the sum of losses over different pixels. Derivatives can be easily computed through the whole network, and this can be trained through backpropagation.
- No need to pass through a classification network first.
- Takes **advantage of FC-CNN efficiency**, does not have to re-compute convolutional features in overlapping regions.
- **End-to-end training is more efficient** than patch-wise training

Limitations and solutions

Limitations of full-image training and solutions:

- **Minibatches in patch-wise training are assambled randomly.** Image regions in full-image training are not. To make the estimated loss a bit stochastic, adopt random mask

$$\text{minimize} \sum_{x_j} M(\boldsymbol{x_j}) \ell\left(\boldsymbol{x_j}, \theta\right)$$

  being $M(\boldsymbol{x_j})$ a binary random variable

- **It is not possible to perform patch resampling** to compensate for class imbalance. One should go **for weighting the loss over different labels**

$$\text{minimize} \sum_{x_j} w(\boldsymbol{x_j}) \ell\left(\boldsymbol{x_j}, \theta\right)$$

  being $w(\boldsymbol{x_j})$ a weight that depends on the true label of $\boldsymbol{x_j}$

Example of Research Projects on Semantic Segmentation

Credits Sebastiano Rossi

Looking for Champions to to address next challenges…

In collaboration with

ISTITUTO DI RICERCHE FARMACOLOGICHE MARIO NEGRI · IRCCS

PERIVALLON

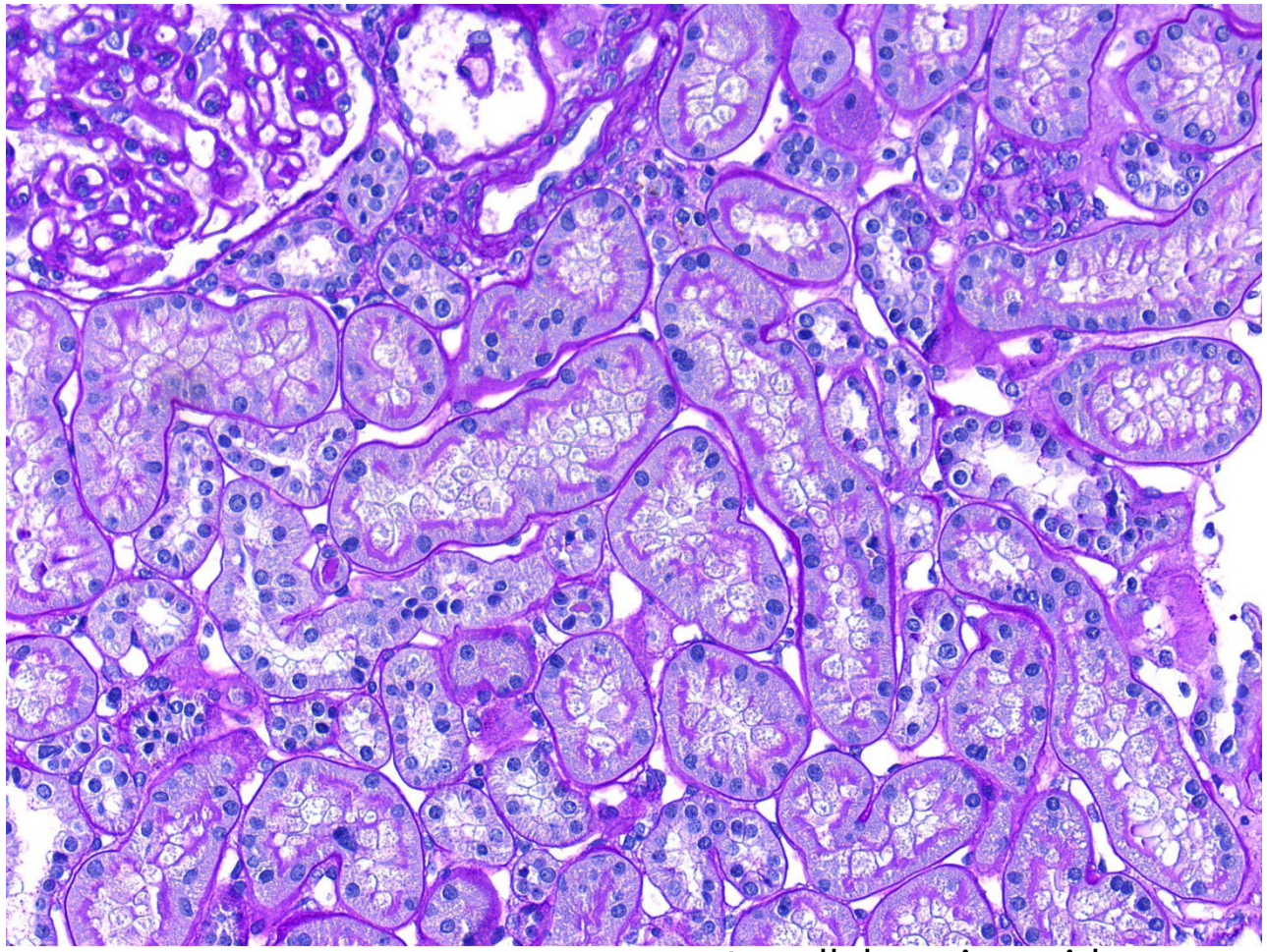
Semantic Segmentation in Medical Images

In medical images (more than natural images) it is often important to quantitatively assess areas (nr of pixels) covered by a specific class.

Here, we want to assess **renal peritubular interstitium** volume in **kidney's biopsies.**

Why?

- Area is correlated with the kidney's chronic pathologies evolution.
- Could be considered as a biomarker to monitor the effectiveness of some drug on kidney's diseases.



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Semantic Segmentation in Medical Images

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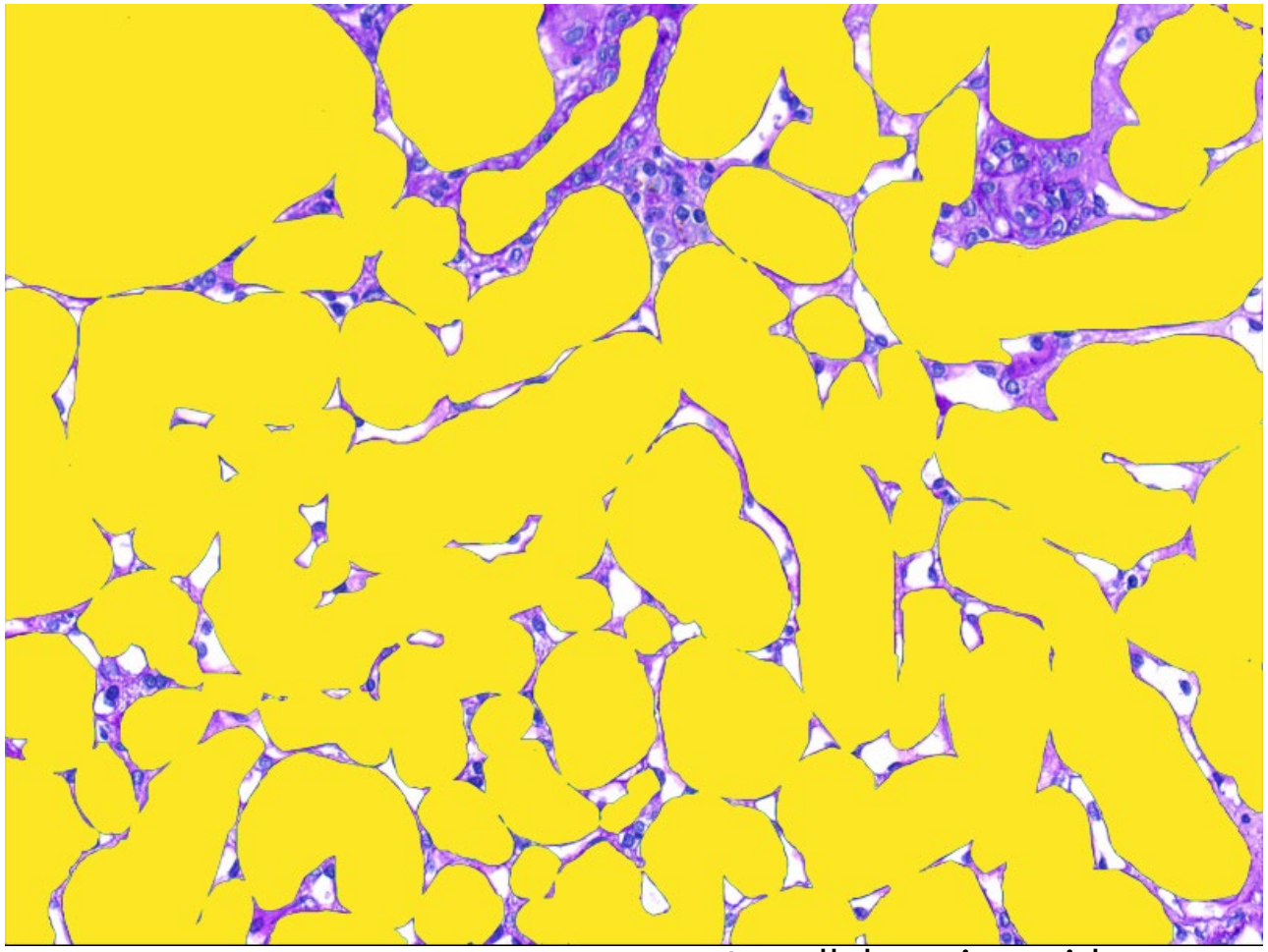

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Problem

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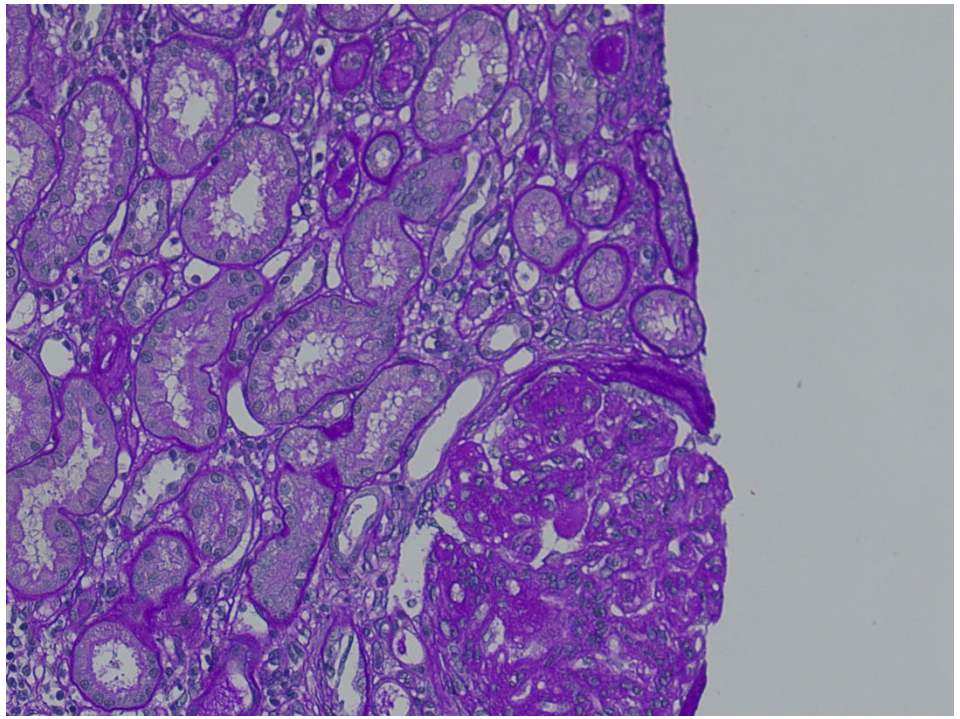
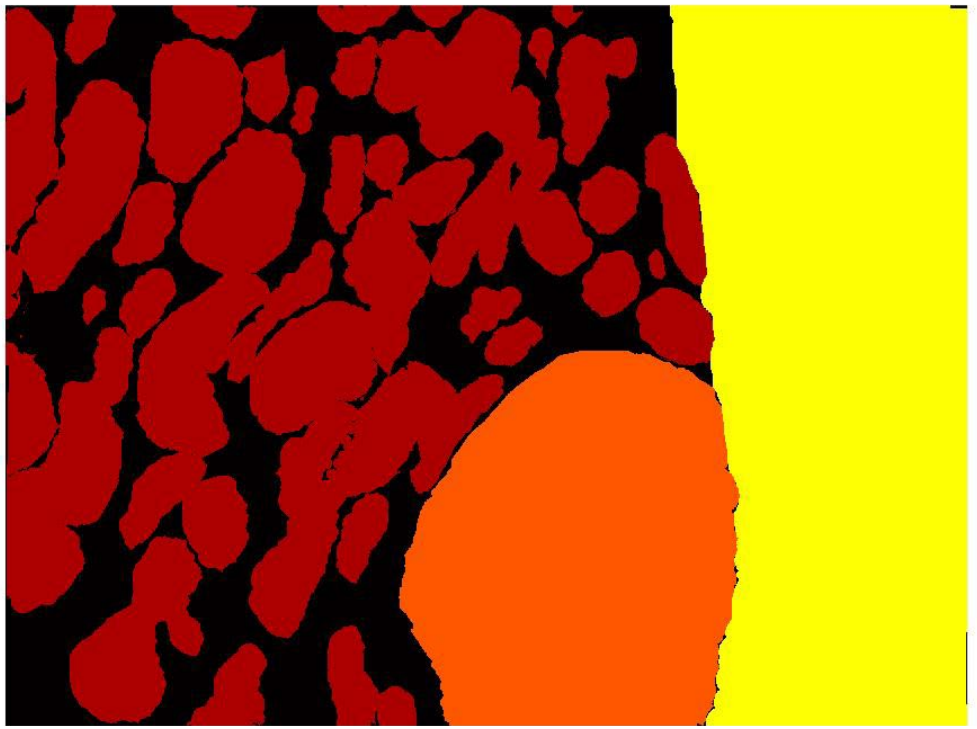
- Semantic segmentatation of kidney biopsises (1920 x 2560 x 3 images)
- 4 classes: *'Interstitial' (black), 'Tubules' (red), 'Glomerolus' (orange), 'Other' (yellow)*

Original image



Ground truth

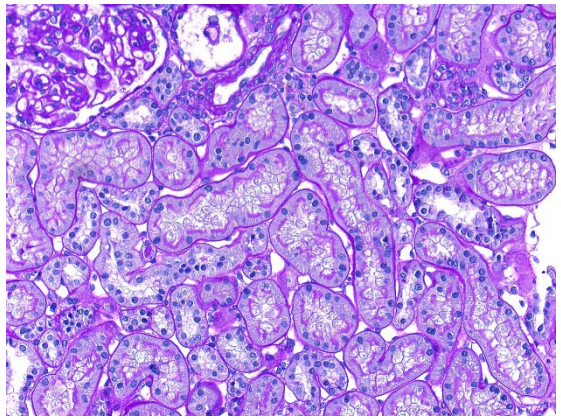


Intrinsic Challenges

SCARSE ANNOTATIONS

Few images available with the correspondent **dense annotations**.
In our application the average **annotation time** is 2 hours for each image.

Image

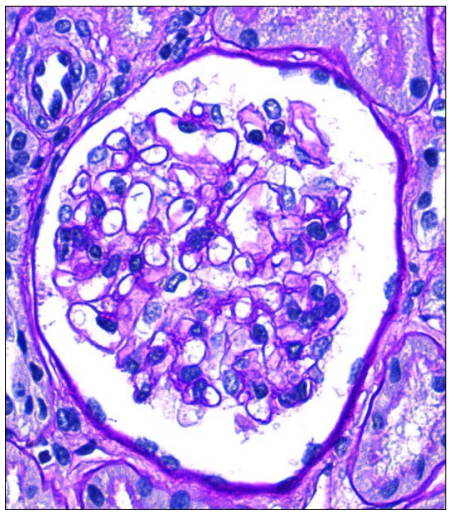


Dense Annotations

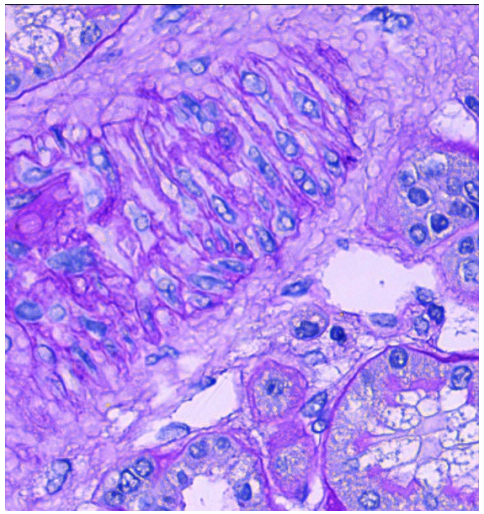
HIGH ANATOMICAL VARIABILITY

Different patients suffering from **different pathologies**, great **anatamical variability** even within the **same group**.

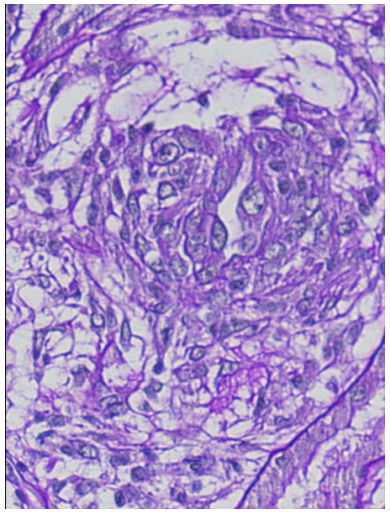
Healthy Subject



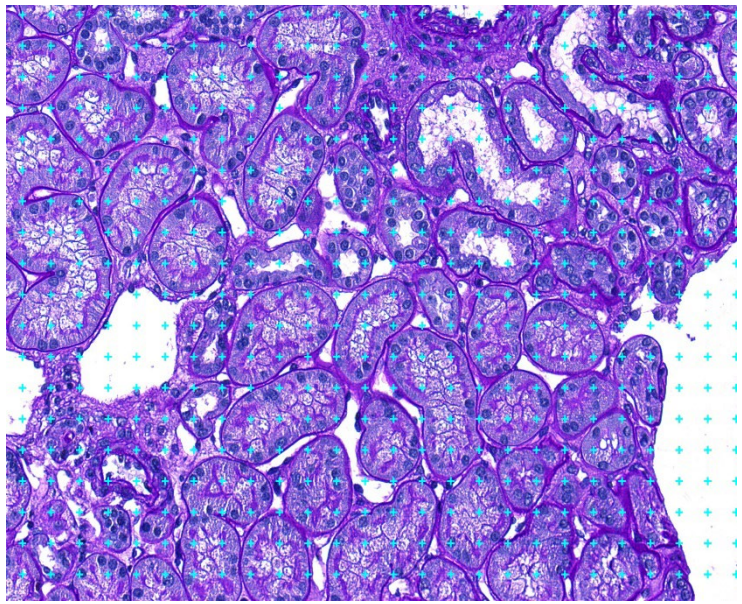
Healthy Subject

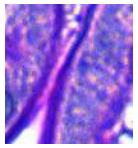


Patient

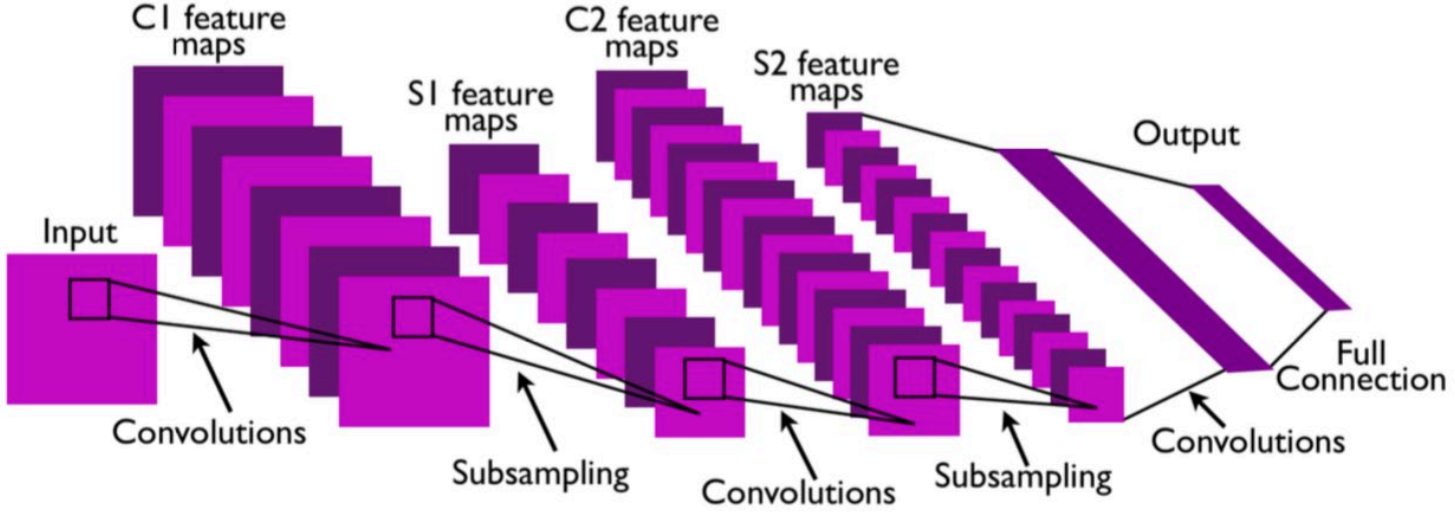


Fully Convolutional CNN from Grid annotations





- Crop the image around the grid points and assign to each patch the class of the central pixel
- Train a classification network with the patches



Credits: Sebastiano Rossi

Fully Convolutionalization

In collaboration with
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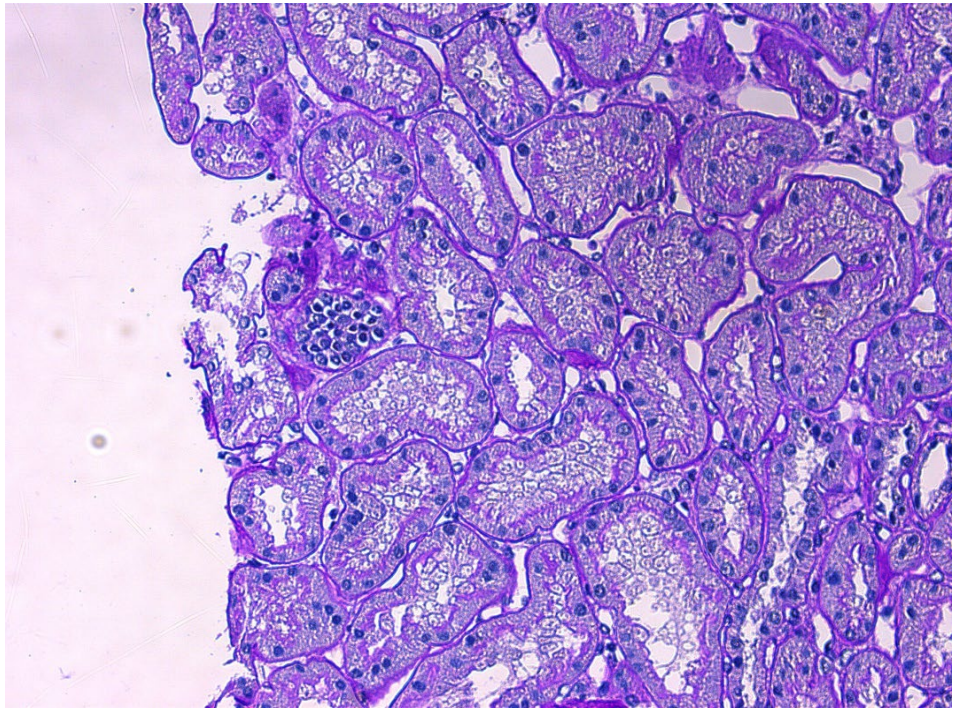
- Modify the network to make it fully convolutional (substitute the dense layers with 1x1 convolutions)
- It is now possible to feed the network with images of any size, receiving in output an heatmap instead of a simple class prediction
- Apply a technique to upsample the heatmap and get a segmentation mask of the same size of the original image (for example shift and stitch)

Credits: Sebastiano Rossi

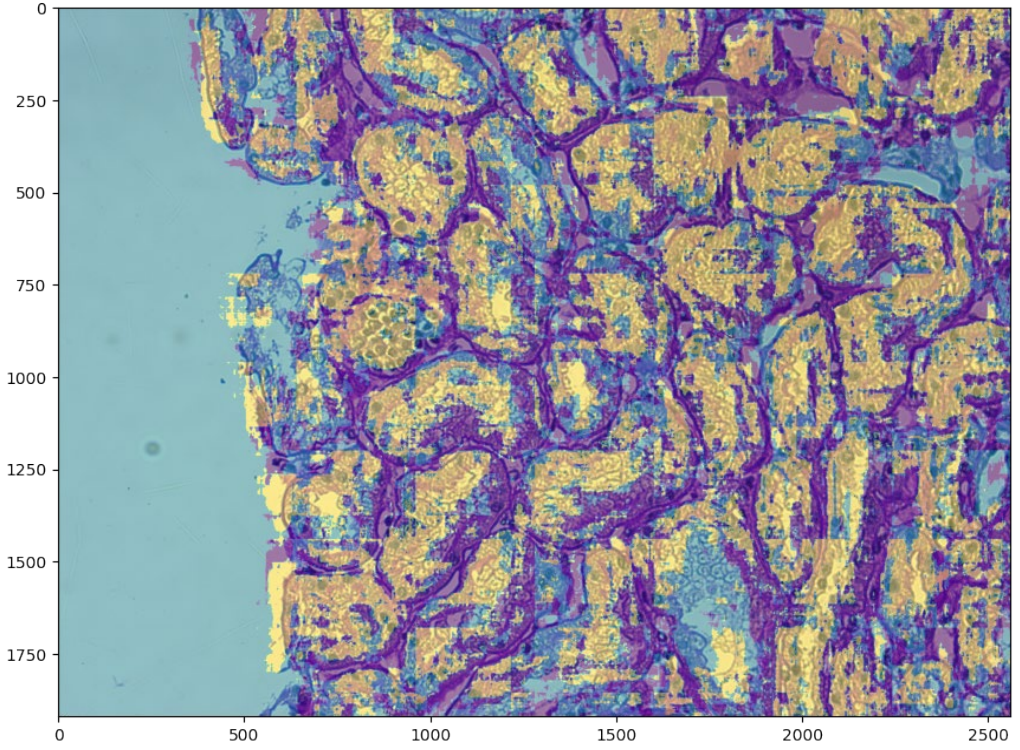
Shift and Stitch Results

Efficient inference by a vanilla classification network trained on 30917 patches of size 200x200

Original image



Shift and stitch result



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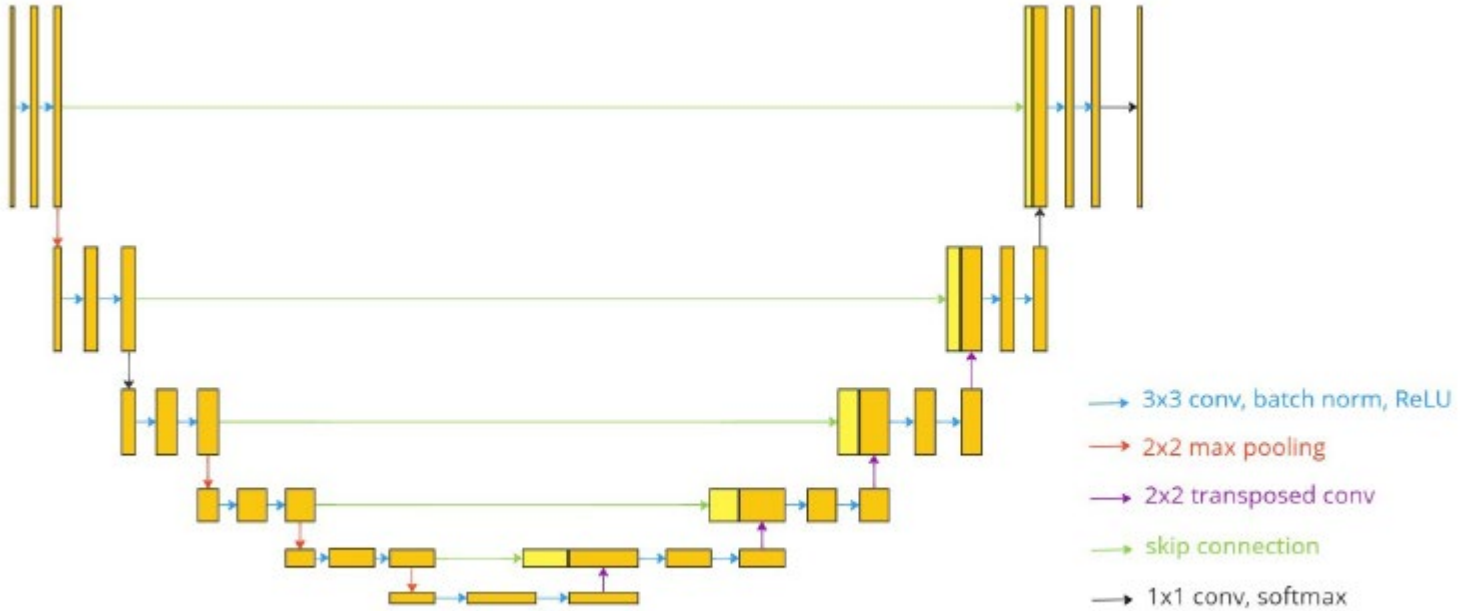
Semantic Segmentation Network

Training a semantic segmentation model can be very demaning when it comes to prepare the annotations



Credits: Sebastiano Rossi

Sparse Annotations

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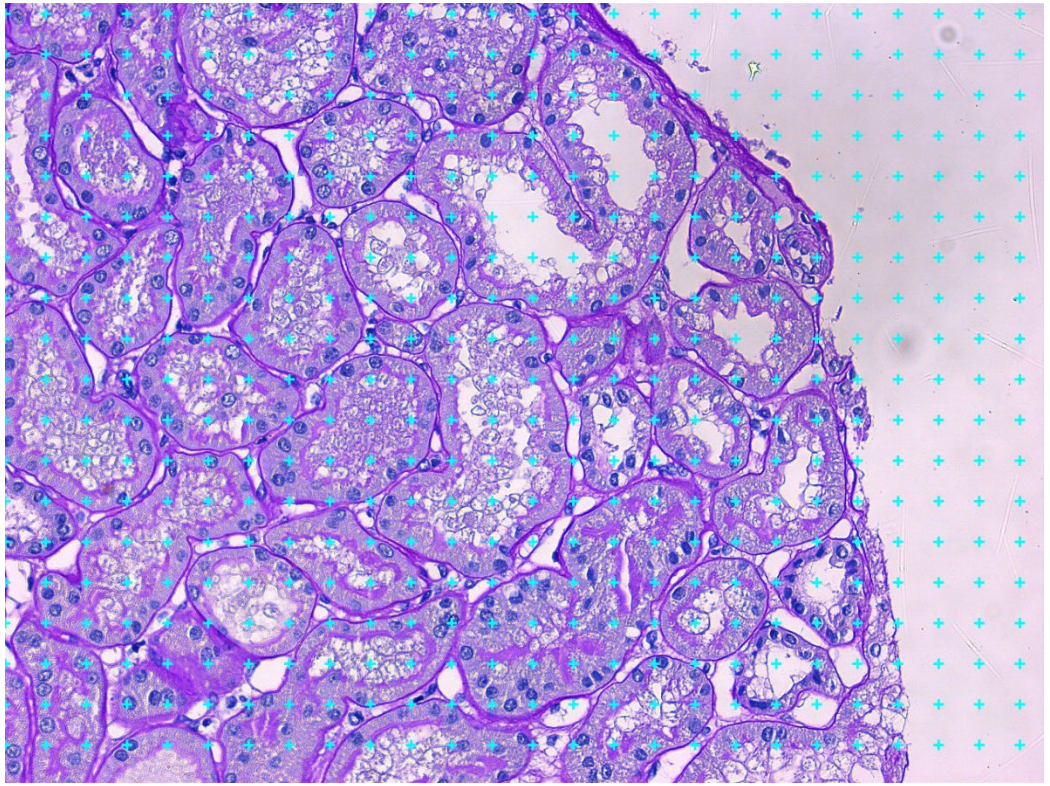
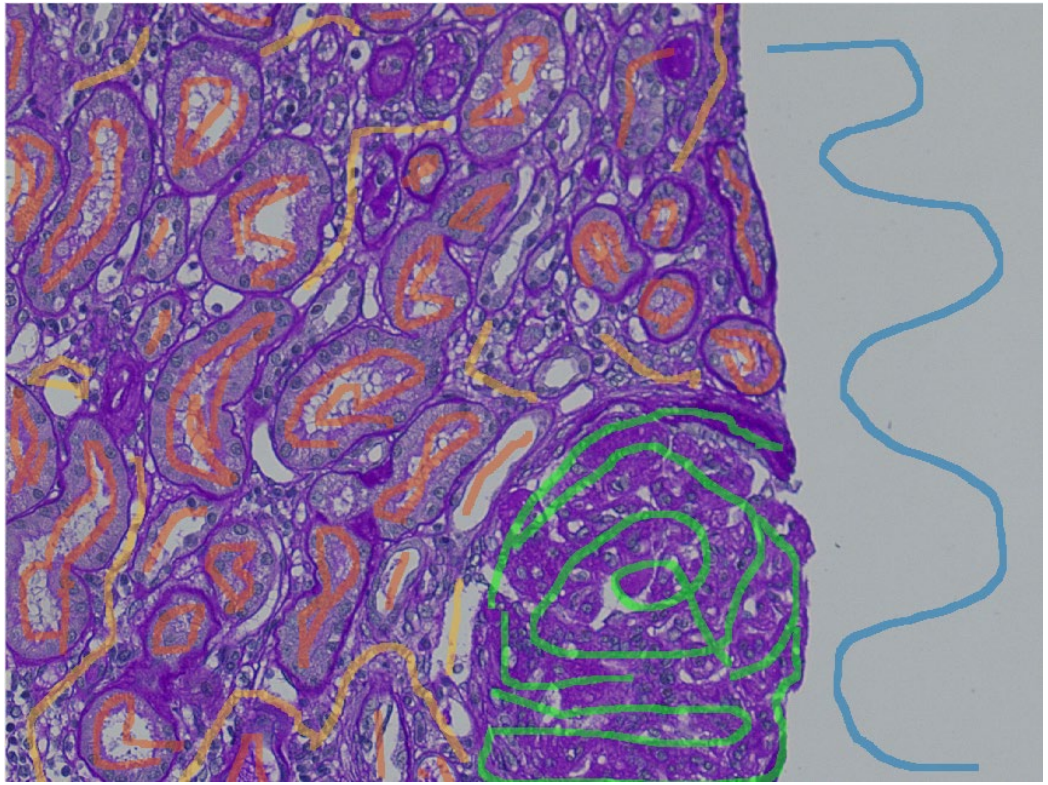
For training rely only on sparse annotations like the following ones:

Grid annotations

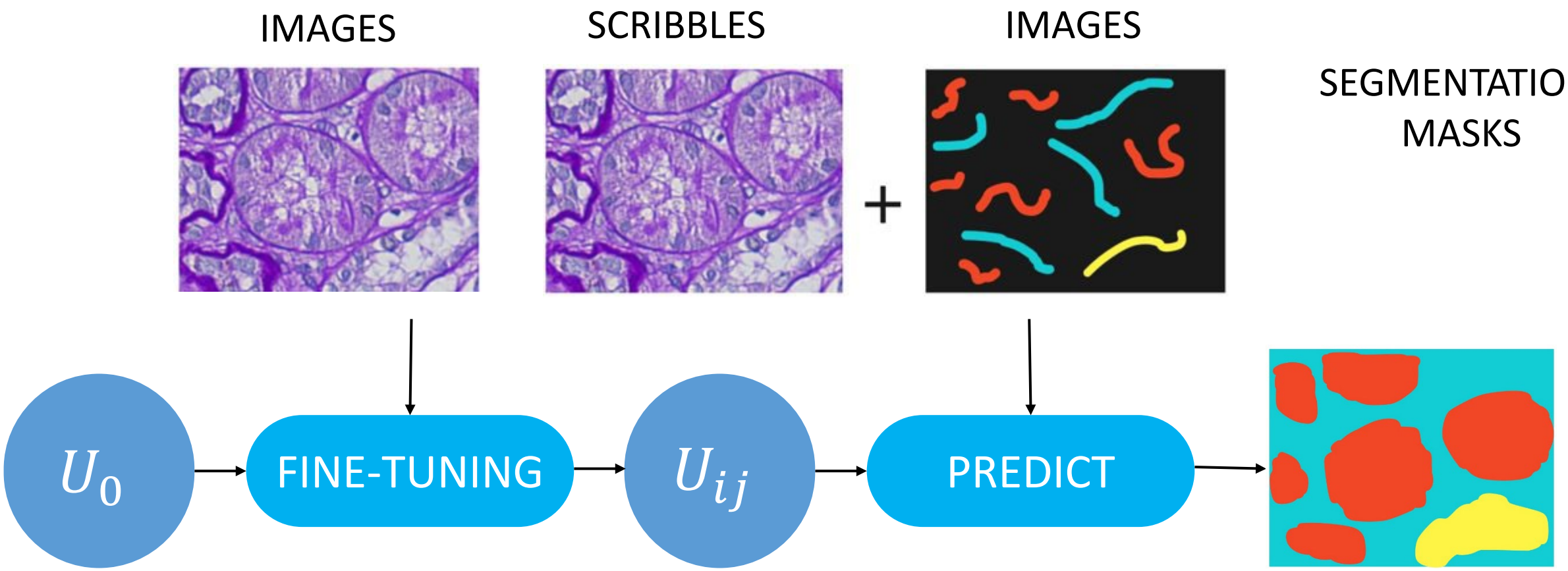


Scribble annotations



Credits: Sebastiano Rossi

Fine tuning on Sparse Annotations

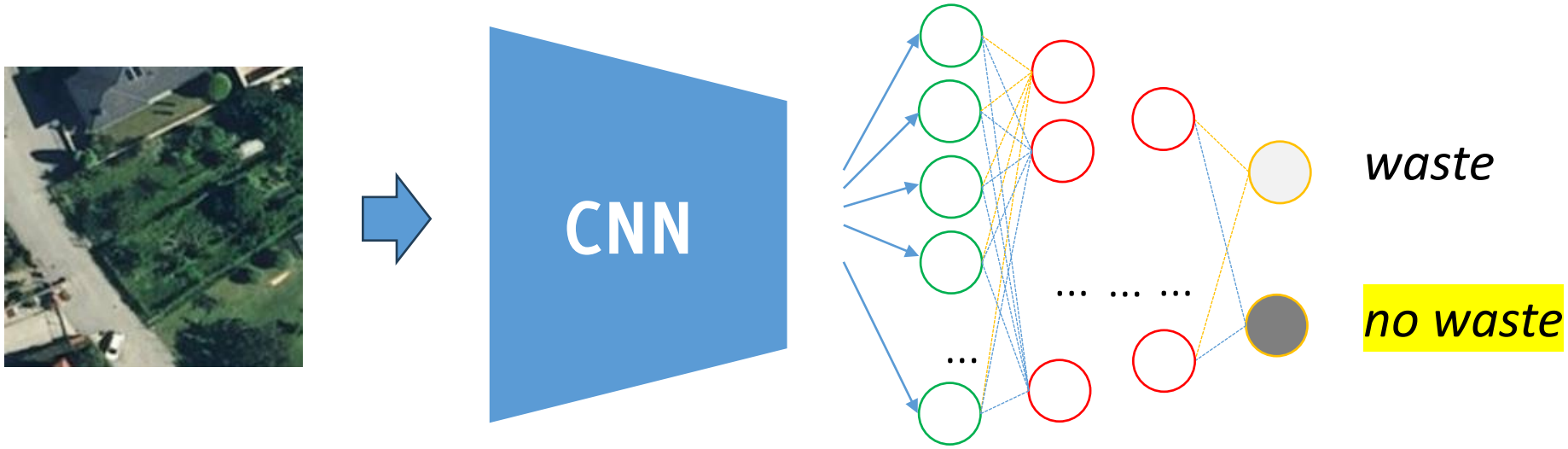


Credis Sebastiano Rossi

Deep Learning to inspect Remote Sensing Images

EU funded project aiming at fighting environmental crime

- Illegal landfills detection by DL models analyzing remote sensing images (VHR satellite images)
- Sparse annotations provided (landfills locations)

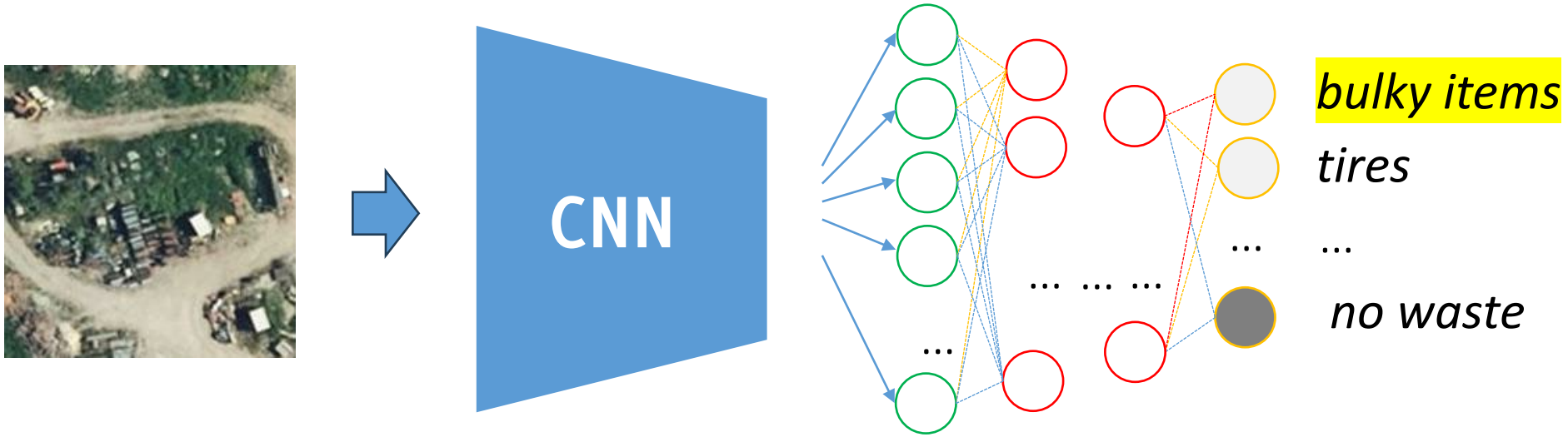


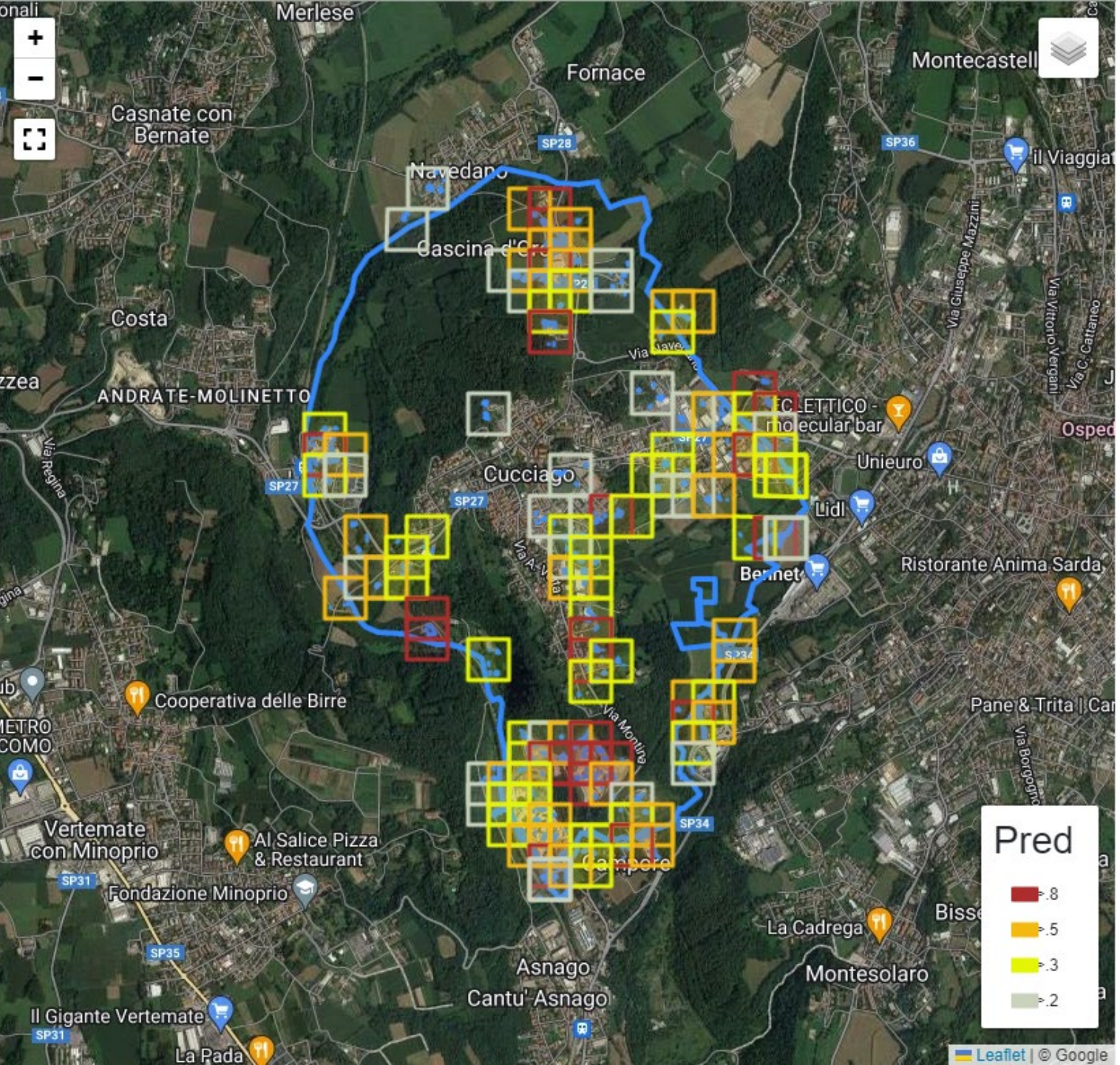
Collaboration with Prof. Fraternali

Deep Learning to inspect Remote Sensing Images

Addressing classification waste detection by patch classification

- extensions to segmentation by shift and stitch and *saliency maps (see next lecture)*

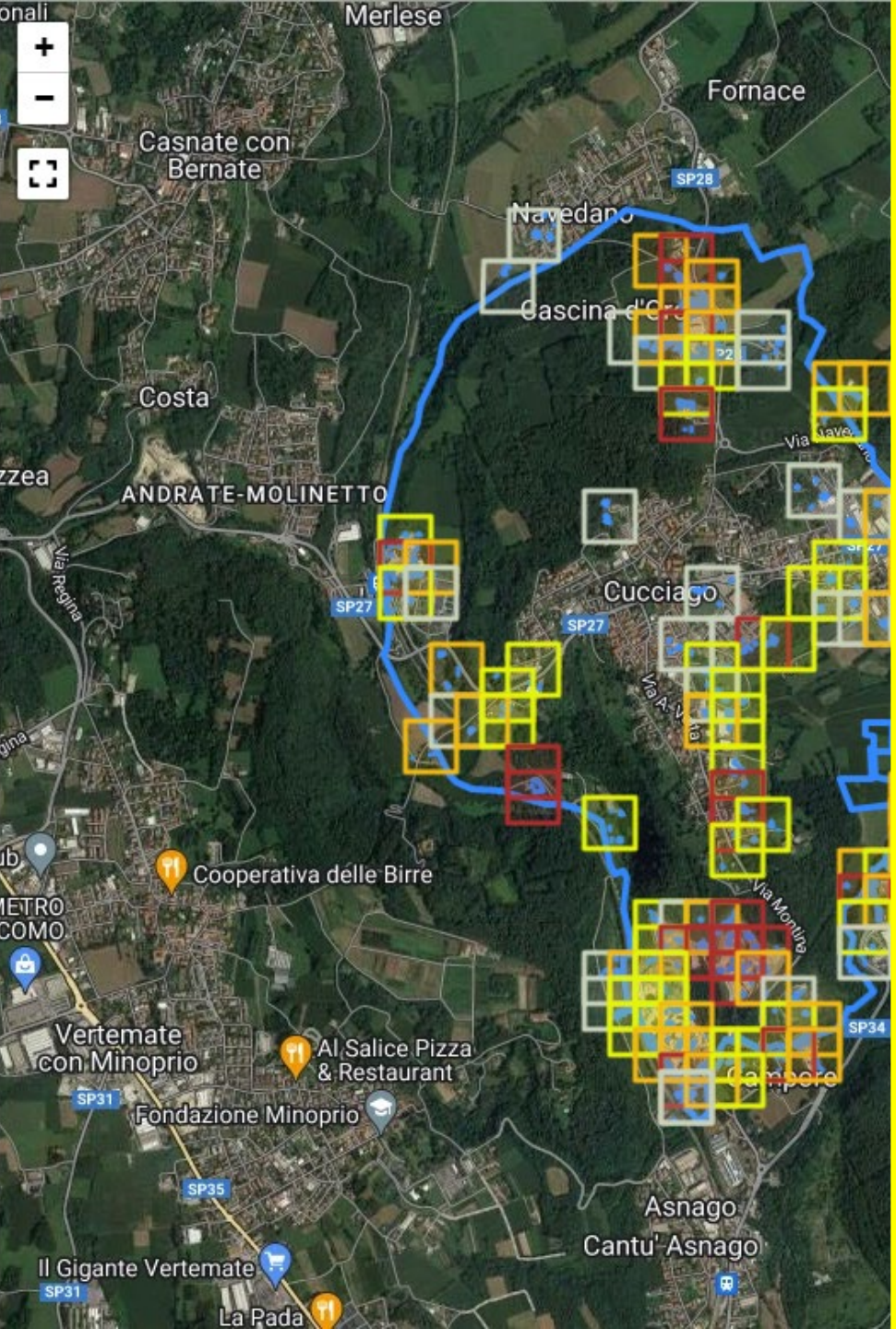


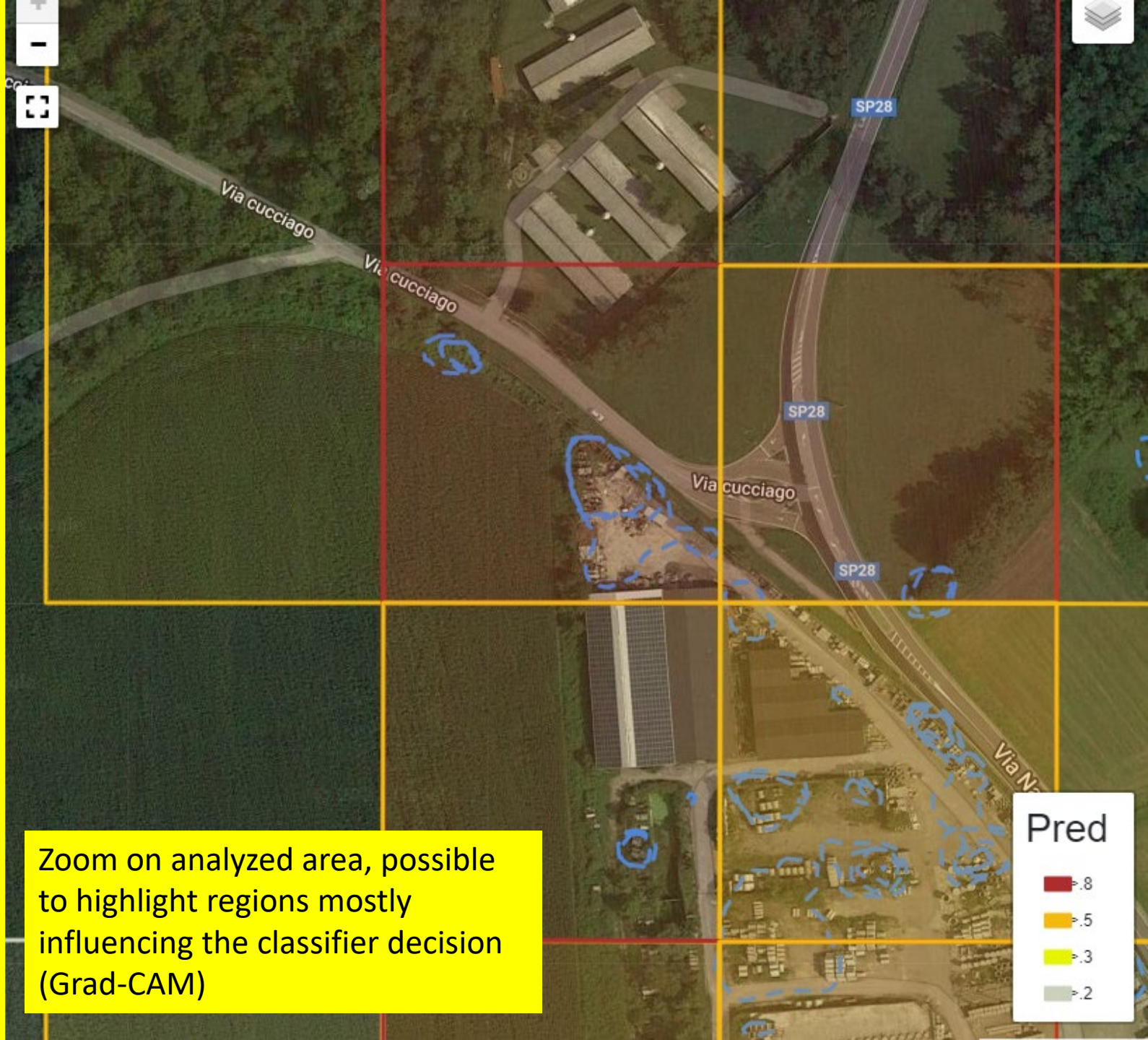


The ODIN Platform within Perivallon

- Tight collaboratio with ARPA Lombardia to get annotations
- 100+ municipalities automatically scanned by our system on Google Earth images
- Regular surveys are planned to detect both existing and new waste disposal sites

T. R. Nahime, F. Milani, and P. Fraternali. "ODIN: Pluggable Meta-annotations and Metrics for the Diagnosis of Classification and Localization." *Int. Conf. on Machine Learning, Optimization, and Data Science*.





Zoom on analyzed area, possible to highlight regions mostly influencing the classifier decision (Grad-CAM)

Examples of segmentation