Outline

Beyond ImageNet

1. Fully Convolutional Networks (FCNs)
2. Supervised Segmentation with Deep ConvNets

Outline

Beyond ImageNet

1. Fully Convolutional Networks (FCNs)
2. Supervised Segmentation with Deep ConvNets

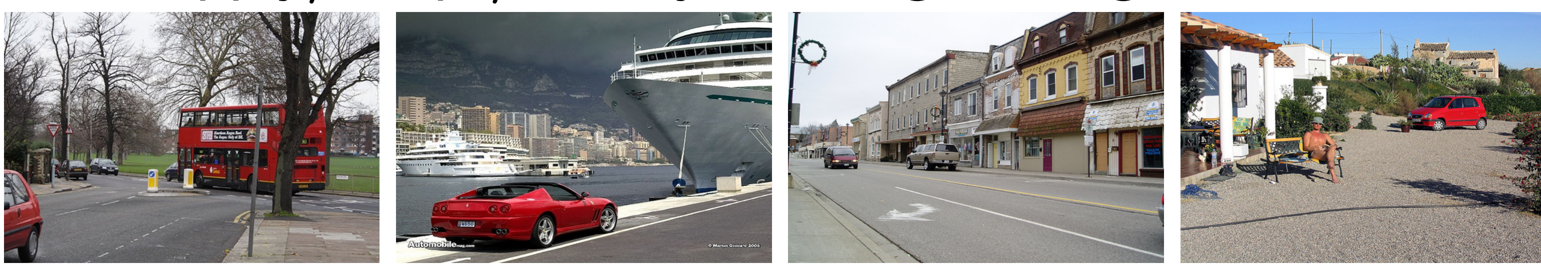
From ImageNet to complex scenes

- ImageNet: huge dataset (1.2M training images) with labels ... but centered objects

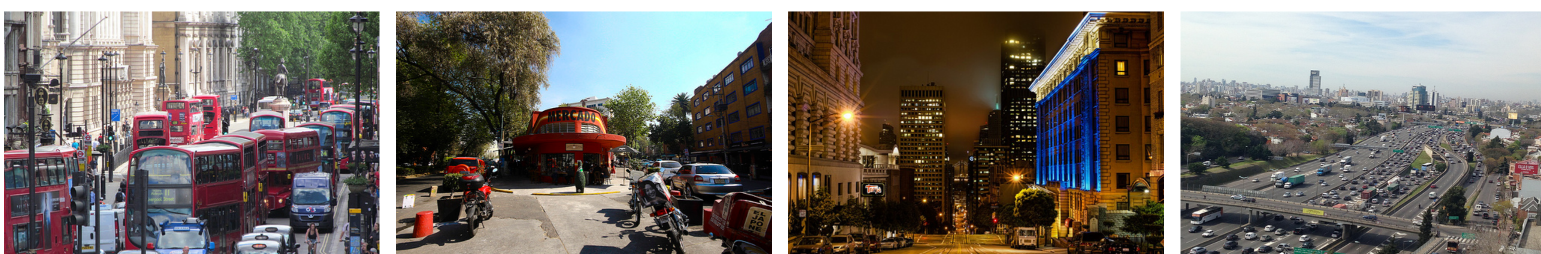
ImageNet

- How to apply/adapt/modify learning strategies to deal with:

VOC 2012



MS COCO



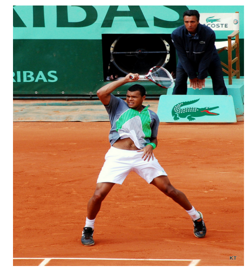
From ImageNet to complex scenes?

- Working on datasets with complex scenes (large and cluttered background), not centered objects, variable size, ...

VOC07/12

MIT67

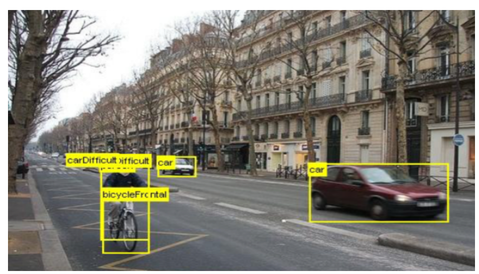
15 Scene



COCO

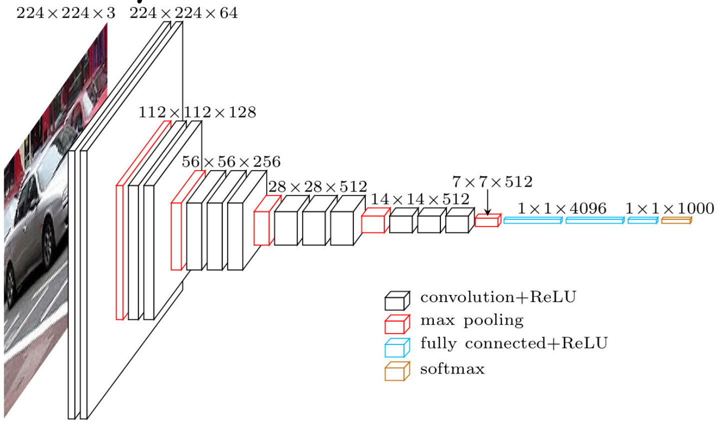
VOC12 Action

- Select relevant regions $\rightarrow$ better prediction



- Full annotations expensive $\Rightarrow$ training with weak supervision

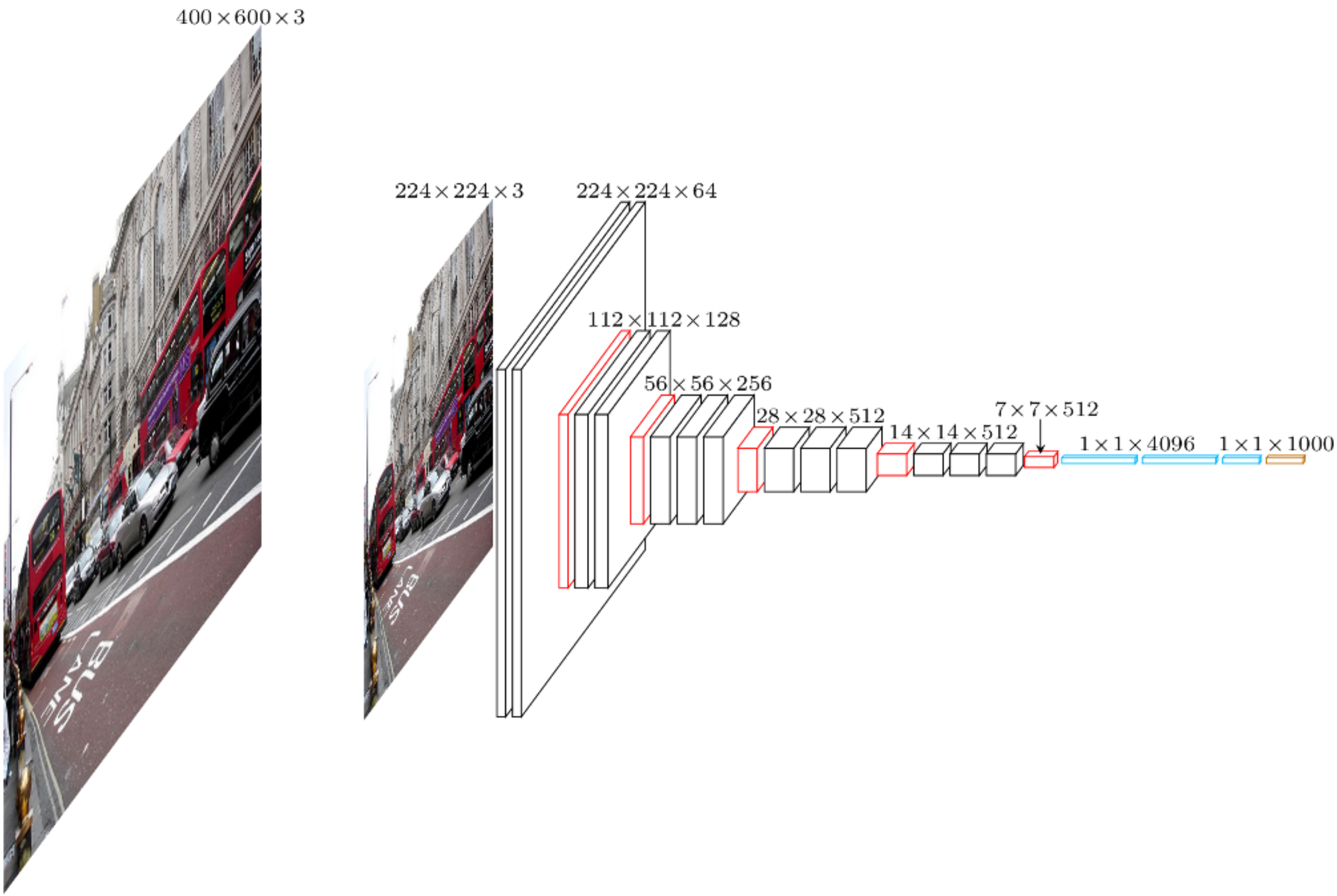
How to adapt VGG16 archi. for large/complex images?



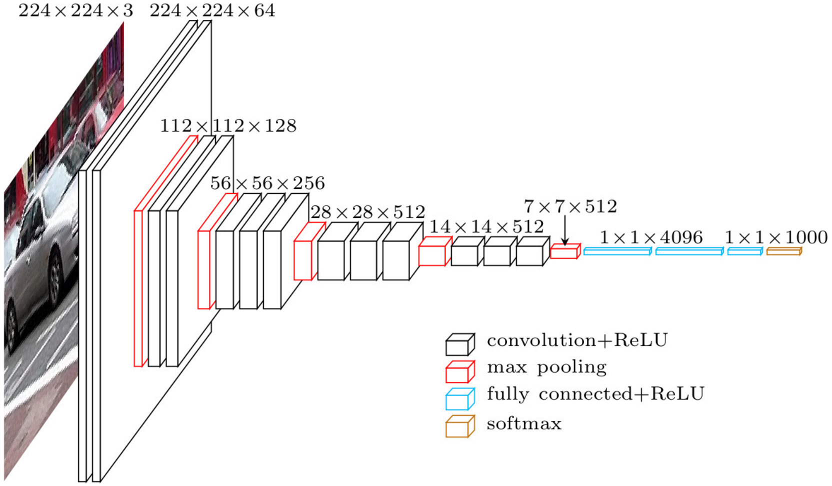
?

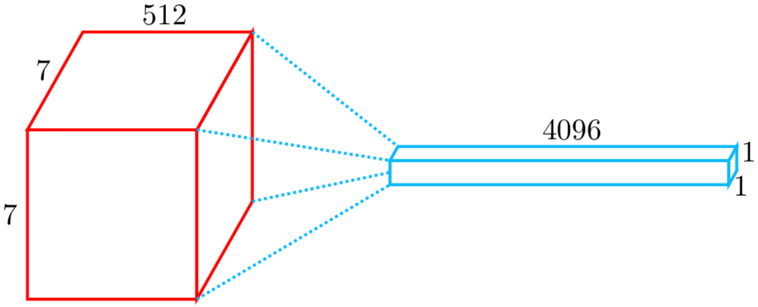
Naïve approach: brut transfer (next Section)

- Resize the image



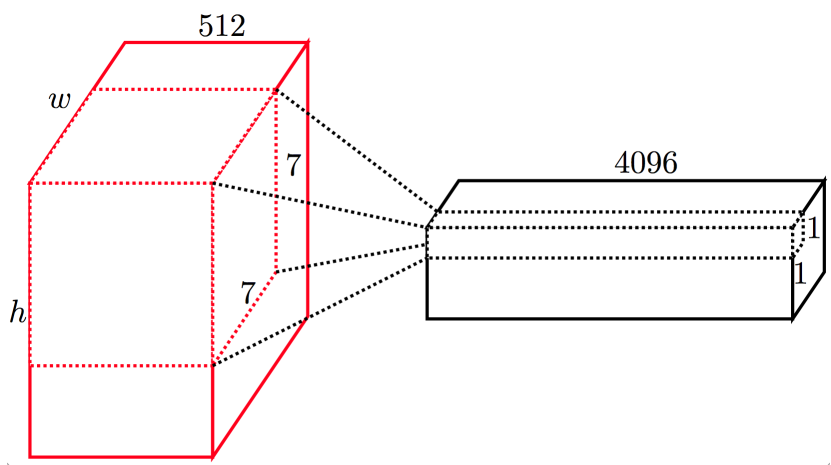
Sliding window ⇒ convolutional layers



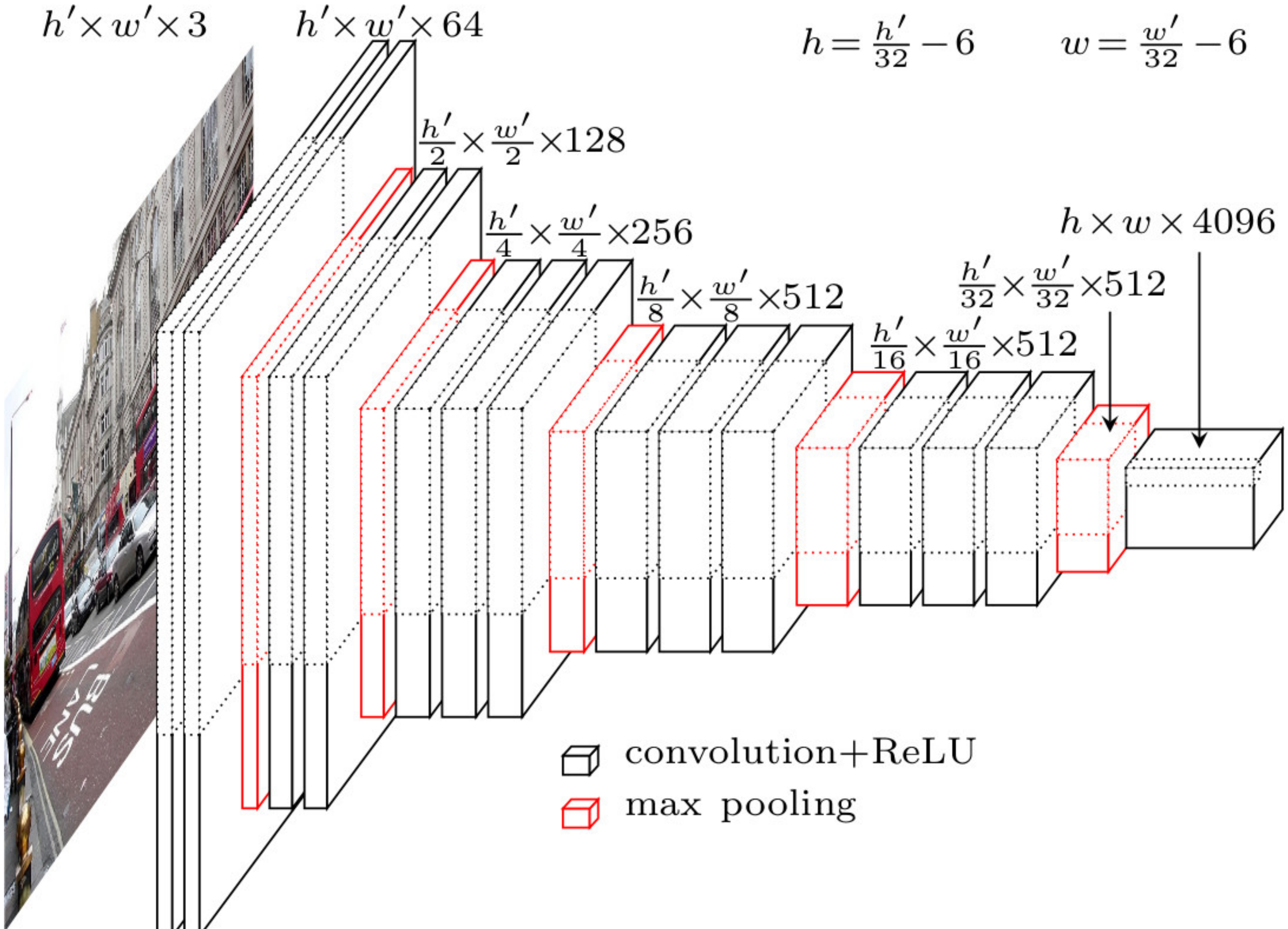


Sliding window $\Rightarrow$ convolutional layers

- Fully connected as convolutional layer (here 4096 conv. filters 7x7x512)



Sliding window ⇒ convolutional layers



Transfer – Pooling – Classification

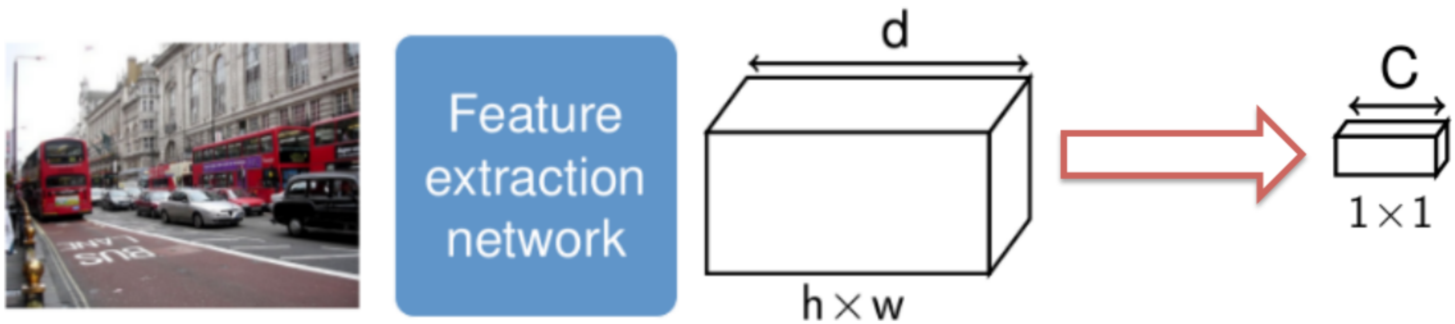
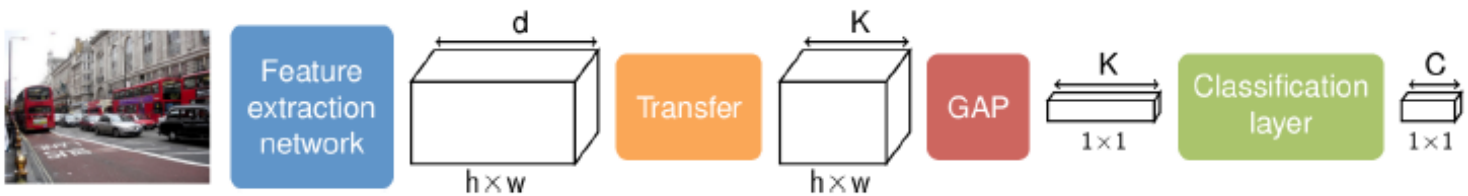


Image-based strategy

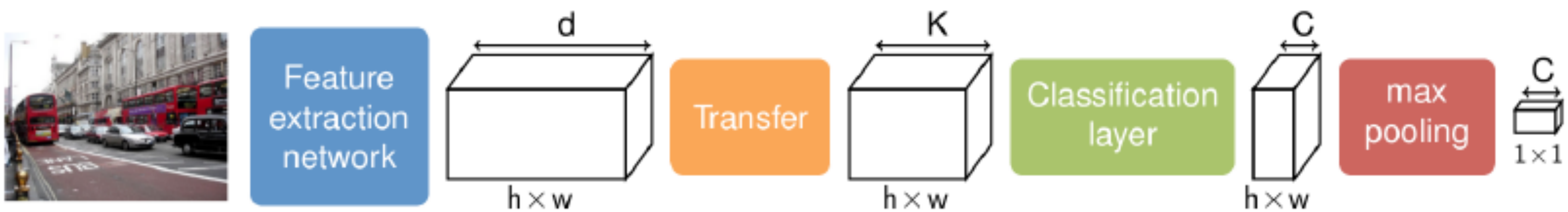
- Global Average Pooling (GoogLeNet, ResNet)



Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba
Learning Deep Features for Discriminative Localization.
In *CVPR*, 2016.

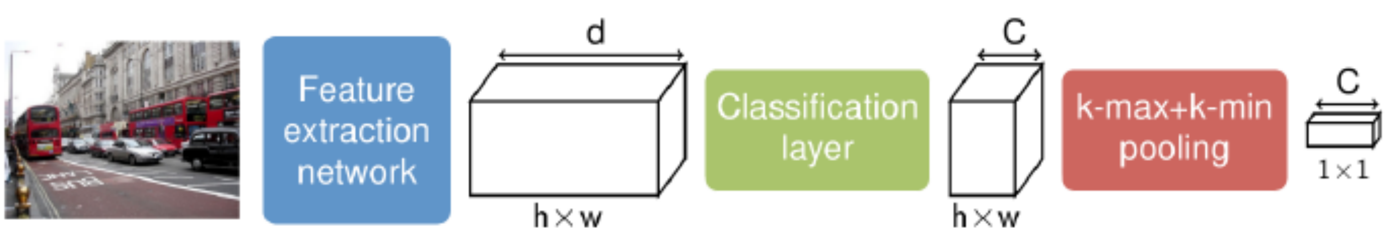
Region-based strategy

- Deep MIL



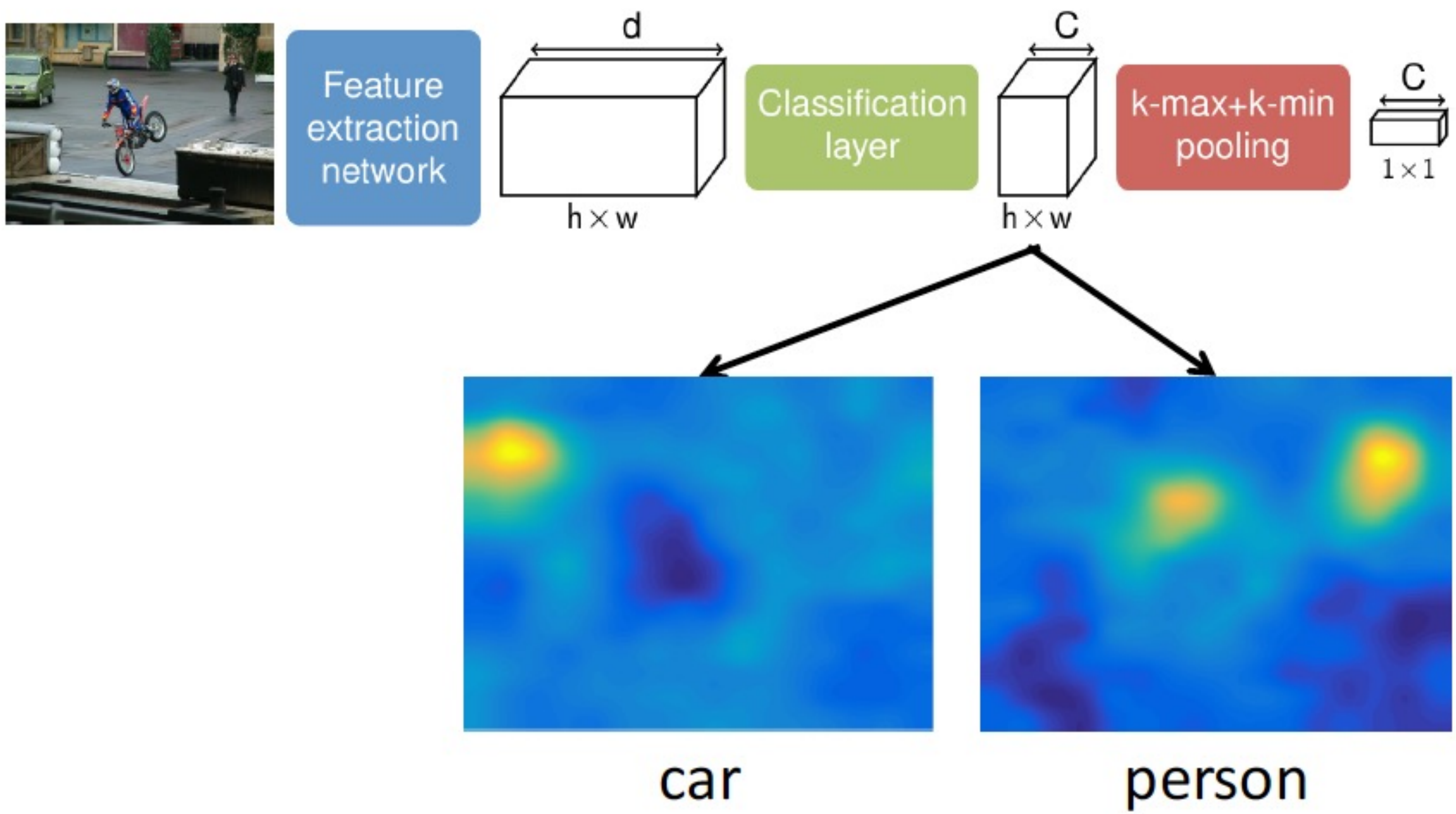
Maxime Oquab, Léon Bottou, Ivan Laptev and Josef Sivic
Is object localization for free? – Weakly-supervised learning with CNNs.
In *CVPR*, 2015.

- WELDON and ProNet [Sun, CVPR16]

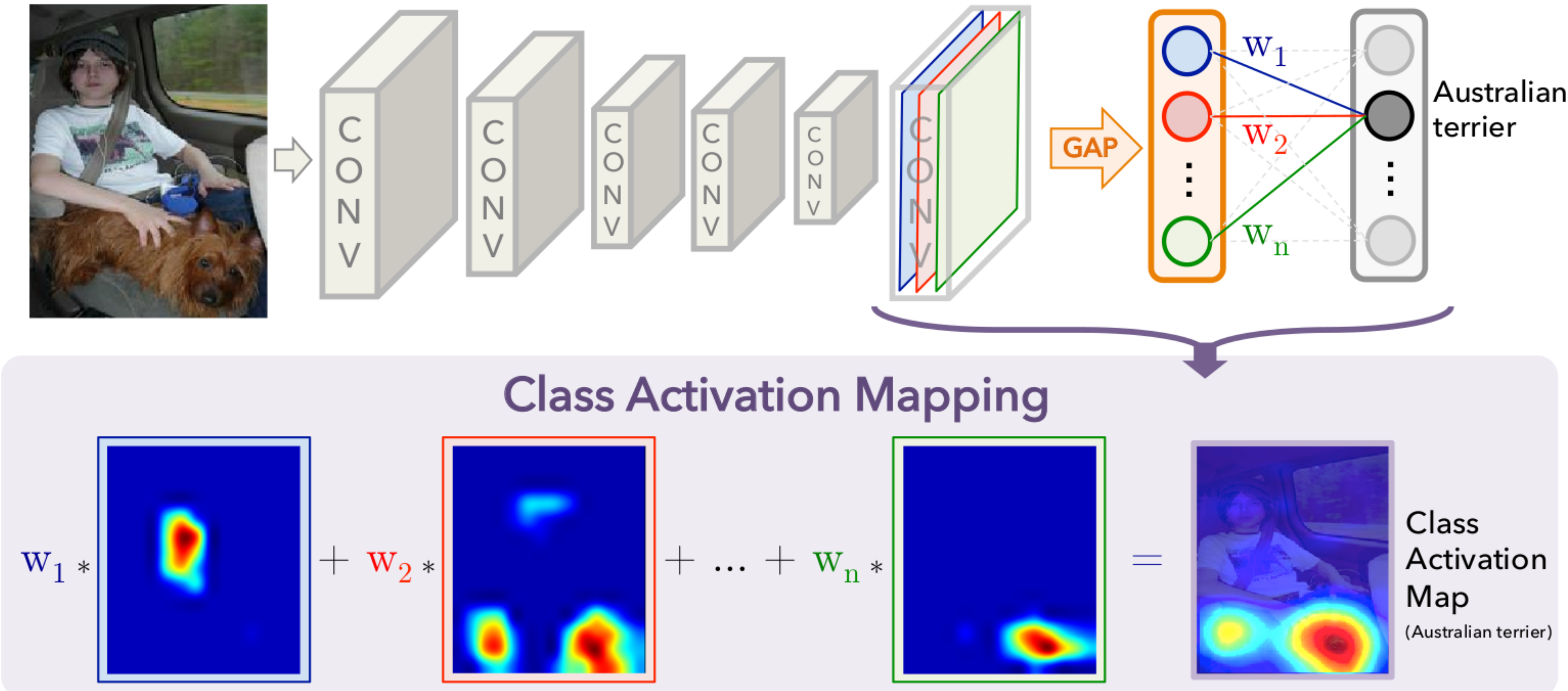


Thibaut Durand, Nicolas Thome, and Matthieu Cord
WELDON: Weakly Supervised Learning of Deep ConvNets.
In *CVPR*, 2016.

Pixel contribution to the classification

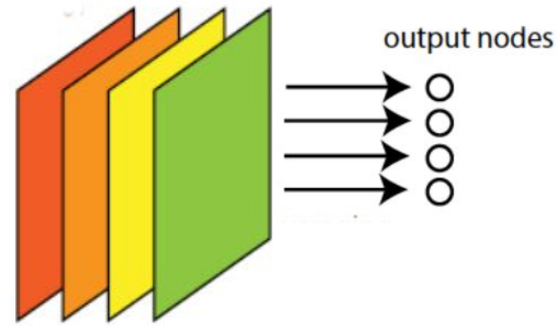


Pixel contribution to the classification



Pooling schemes

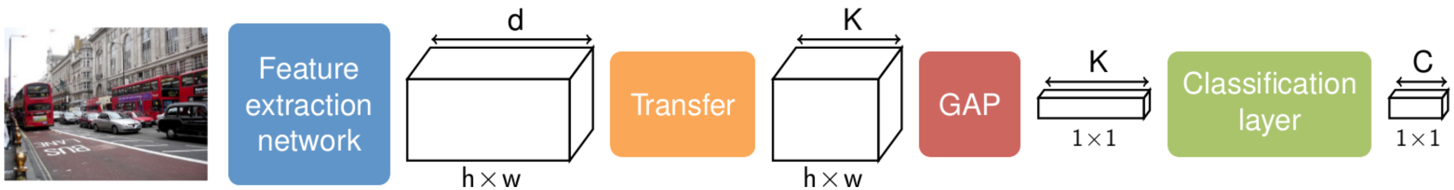
- Max [Oquab, CVPR15]



$$y^c = \max_{i,j} z_{ij}^c$$

- GAP [Zhou, CVPR16]

$$y^c = \frac{1}{N} \sum_{i,j} z_{ij}^c$$



- LSE [Pinheiro, CVPR15] / SPLeap [Kulkarni, ECCV16]

$$y^c = \frac{1}{\beta} \log \left(\frac{1}{N} \sum_{i,j} \exp(\beta \cdot z_{ij}^c) \right)$$

Max pooling limitation

- Classifying only with the max scoring region

- Loss of contextual information

Max pooling limitation

- Classifying only with the max scoring region

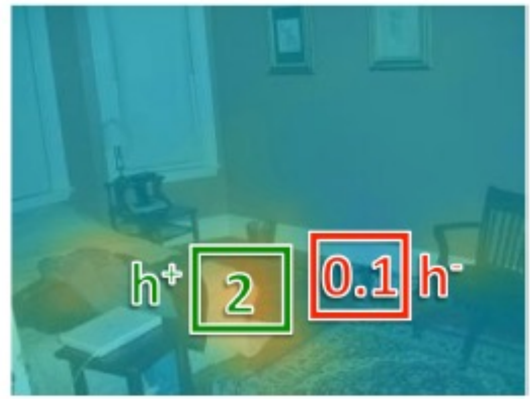
 

- Loss of contextual information

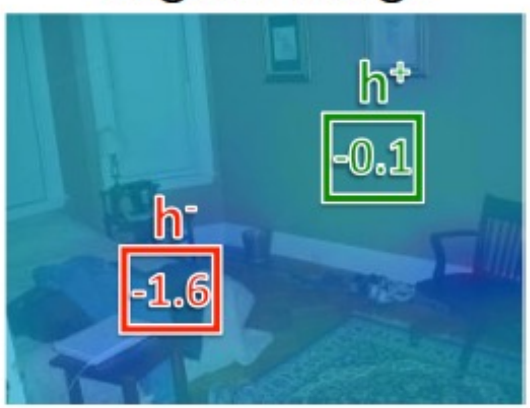
WELDON: `max+min` pooling

- $\mathbf{h}^+$: presence of the class $\rightarrow$ high $\mathbf{h}^+$
- $\mathbf{h}^-$: localized evidence of the absence of class

original image

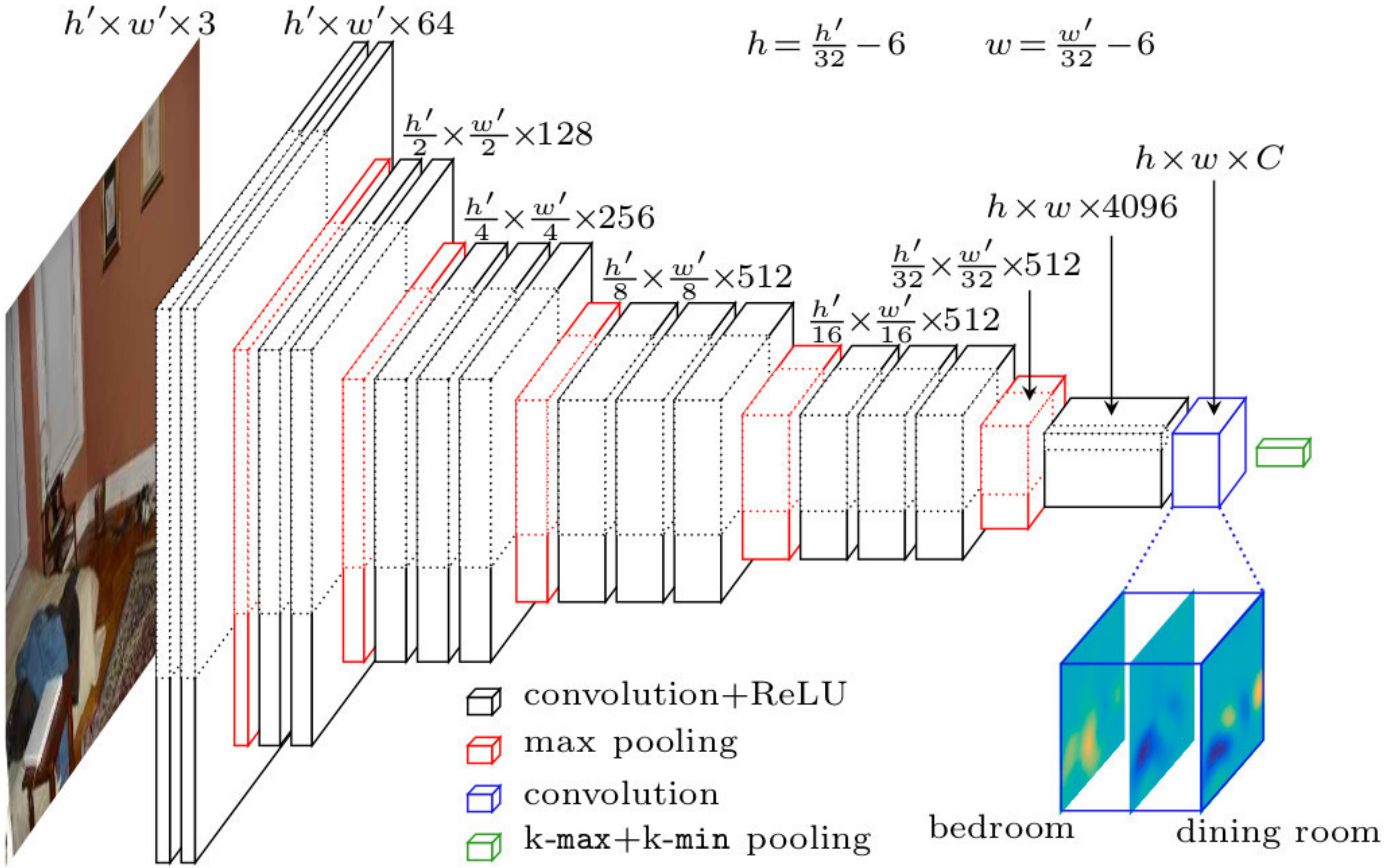


bedroom



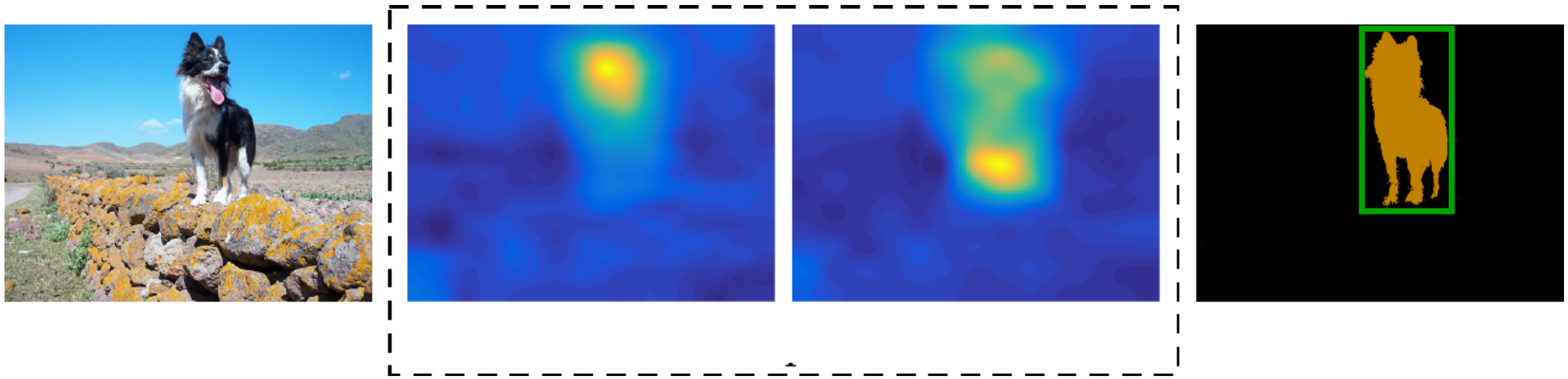
airport inside

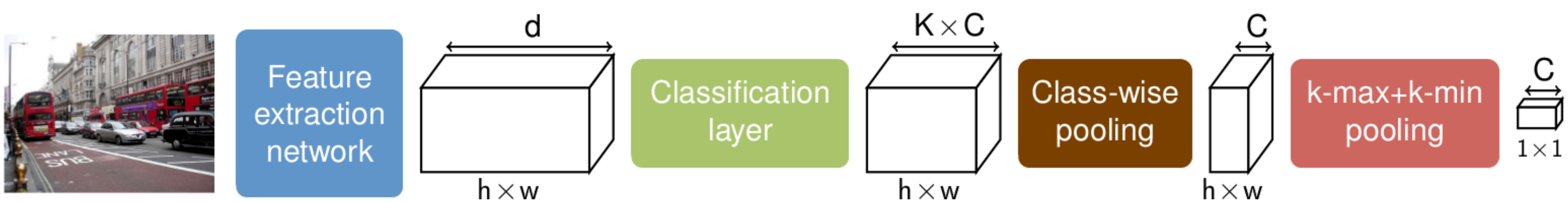
dining room

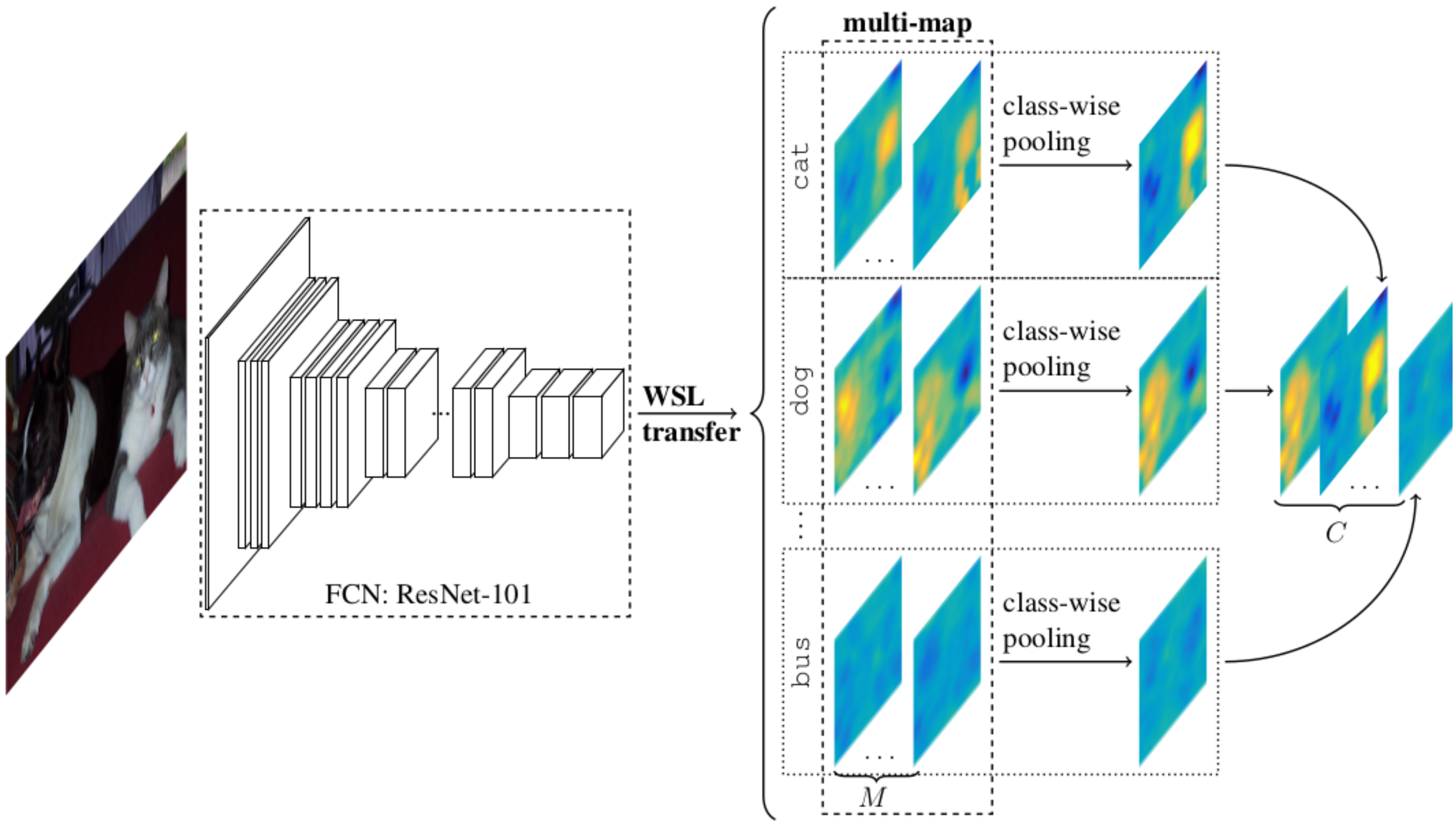


$h' \times w' \times 3$
$h' \times w' \times 64$
$h = \frac{h'}{32} - 6$
$w = \frac{w'}{32} - 6$
$\frac{h'}{2} \times \frac{w'}{2} \times 128$
$\frac{h'}{4} \times \frac{w'}{4} \times 256$
$\frac{h'}{8} \times \frac{w'}{8} \times 512$
$\frac{h'}{16} \times \frac{w'}{16} \times 512$
$\frac{h'}{32} \times \frac{w'}{32} \times 512$
$h \times w \times 4096$
$h \times w \times C$
convolution+ReLU
max pooling
convolution
k-max+k-min pooling
bedroom
dining room

- Generalization to K models per class
- Catch multiple class-related modalities

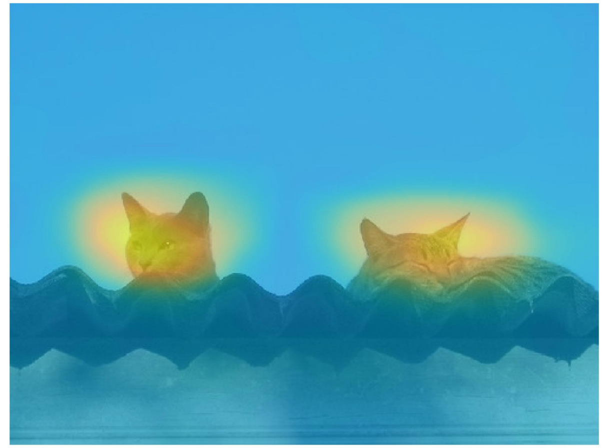




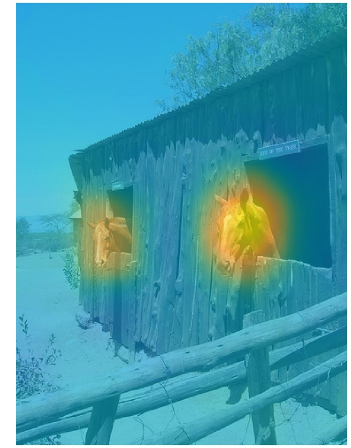

FCN: ResNet-101
WSL
transfer
multi-map
cat
dog
bus
class-wise
pooling
class-wise
pooling
class-wise
pooling
M
C

Class activation maps

bus



cat



horse

aeroplane

bottle

bicycle

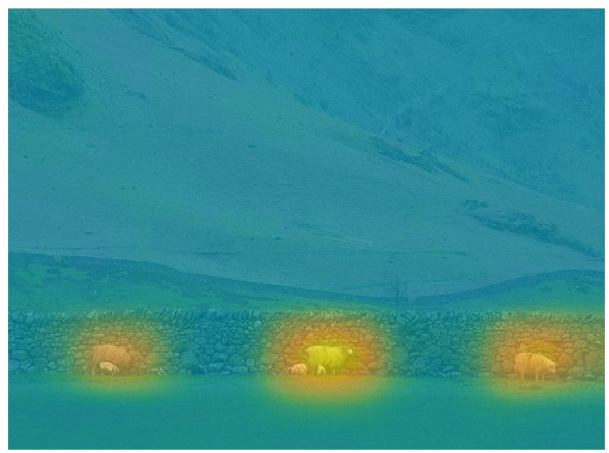
Class activation maps

bicycle

bird

motorbike

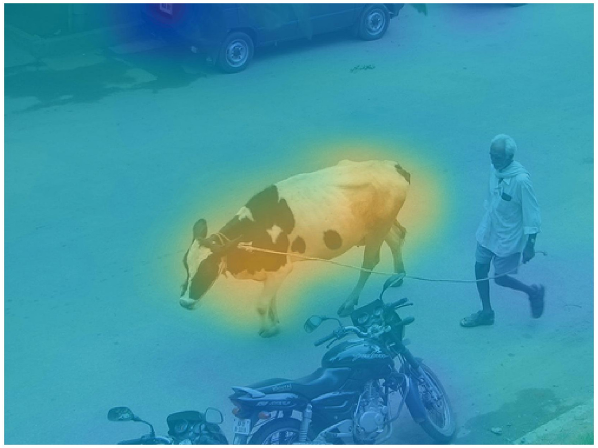
person



sheep

bird

Class activation maps



cow

motorbike

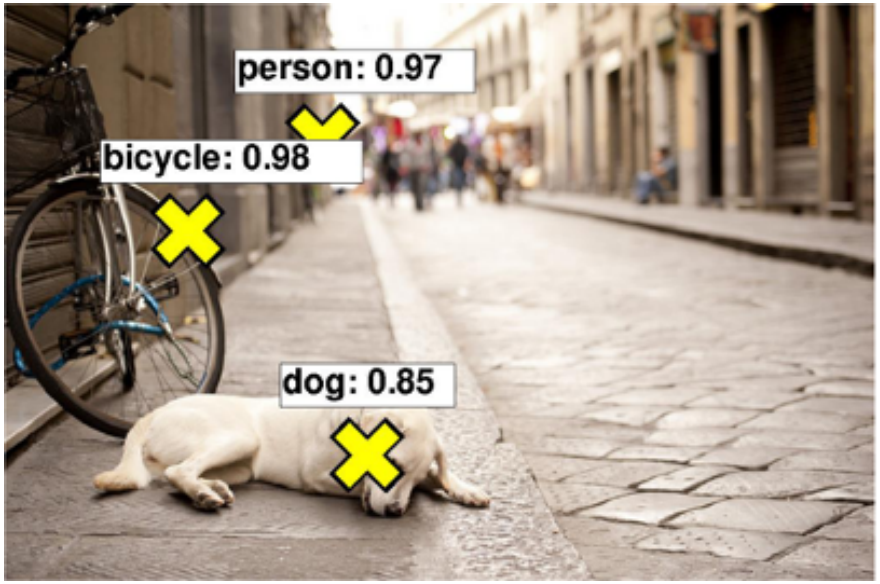
horse

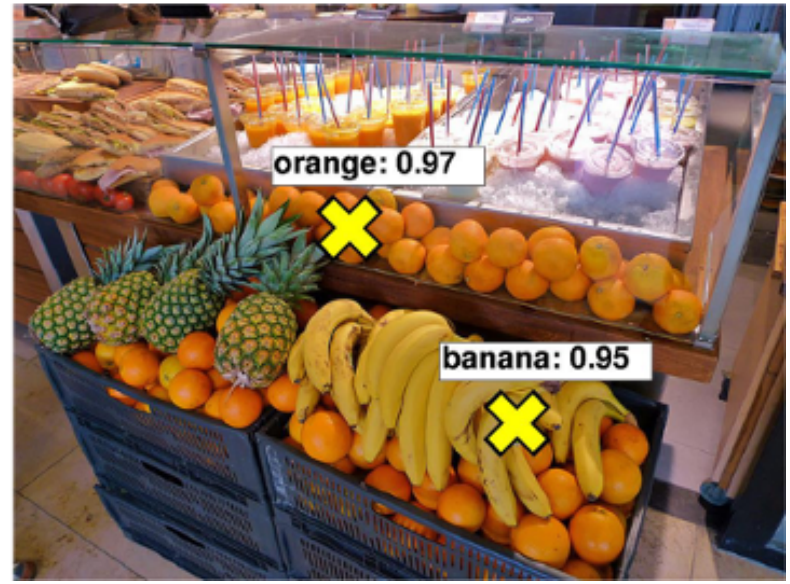
person

car

person

Visual recognition task: localization

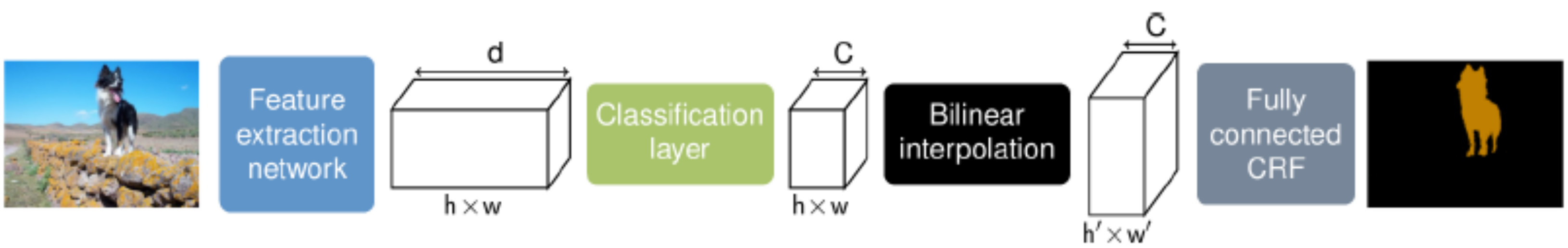




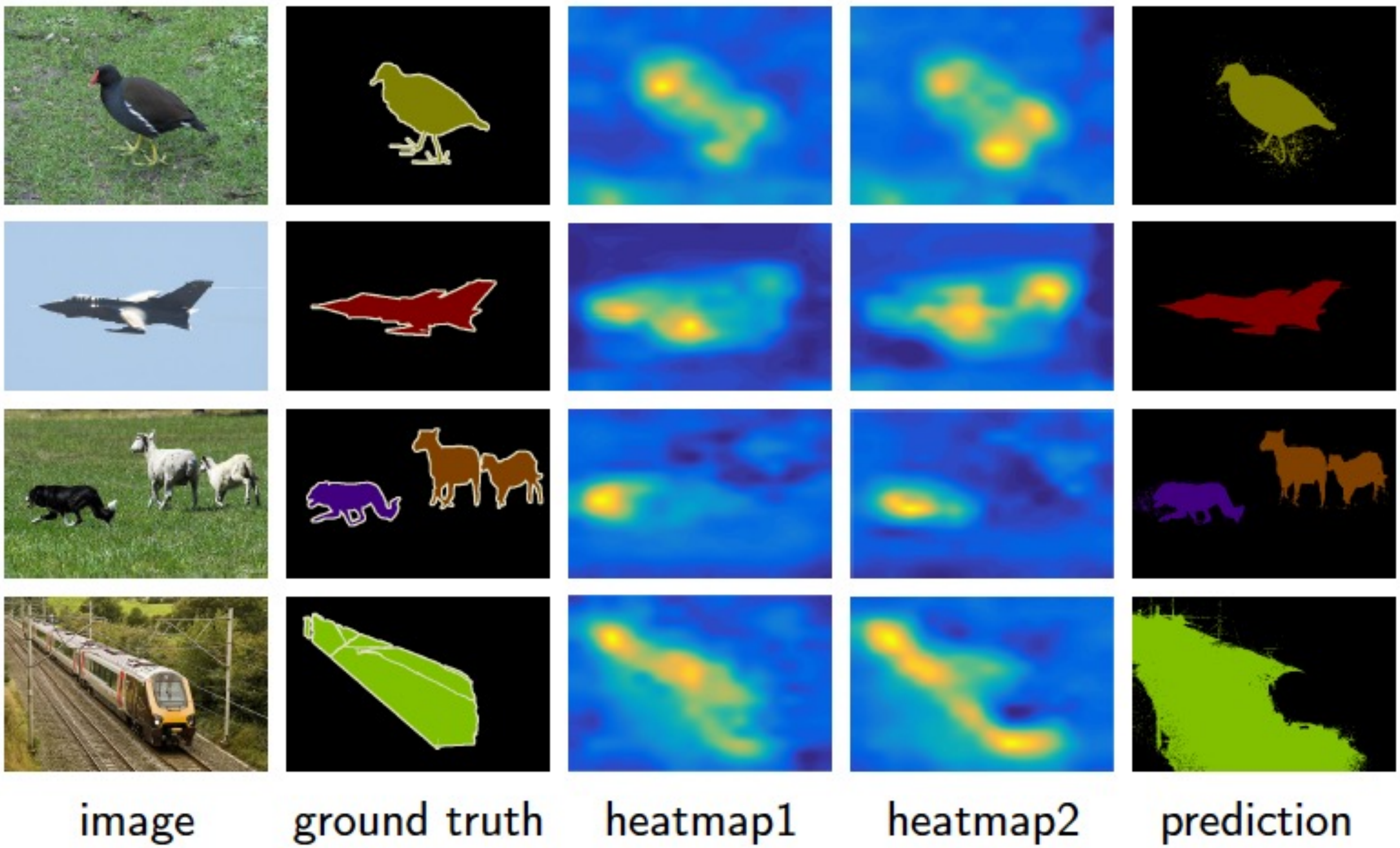
Method	VOC 2012	MS COCO
Deep MIL	74.5	41.2
ProNet	77.7	46.4
WSLocalization	79.7	49.2

In preview Segmentation

- WSL segmentation framework
  - Learning with image-level labels (presence/absence of the class)
  - Difficult task: no information about location and extend of objects
- Localized features in spatial maps
- Deep + fully connected CRFs



In preview Segmentation



Outline

Beyond ImageNet

1. Fully Convolutional Networks (FCNs)
2. **Supervised Segmentation with Deep ConvNets**
    1. F-CN Fully Convolutional Network
    2. DeepLab approach for supervised segmentation
    3. Deconvolution Networks

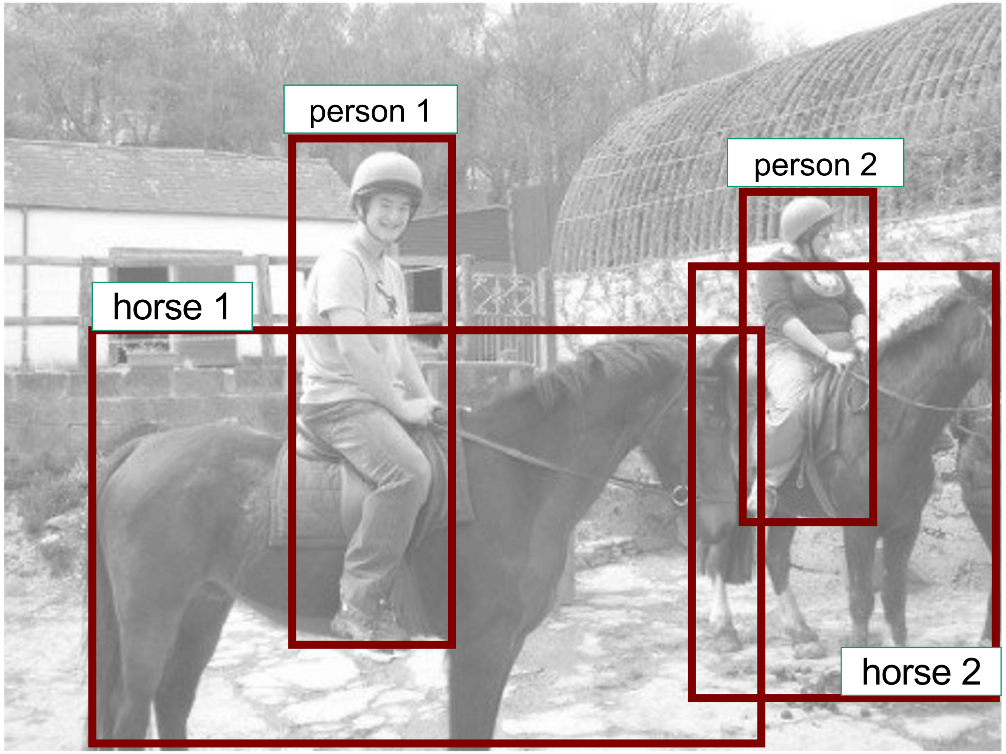
Segmentation: definitions

Def1: **Semantic** Segmentation

Label each pixel with a category label

Object Detection

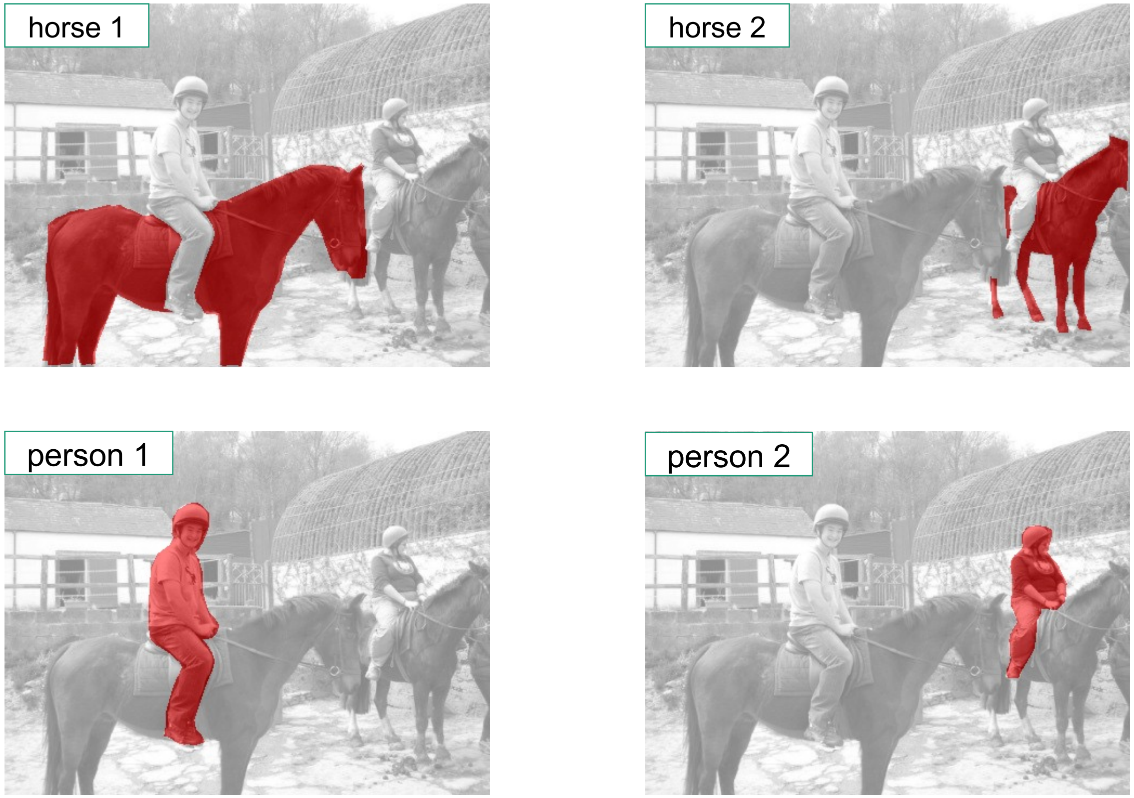
Detect every instance of the category and localize it with a bounding box.



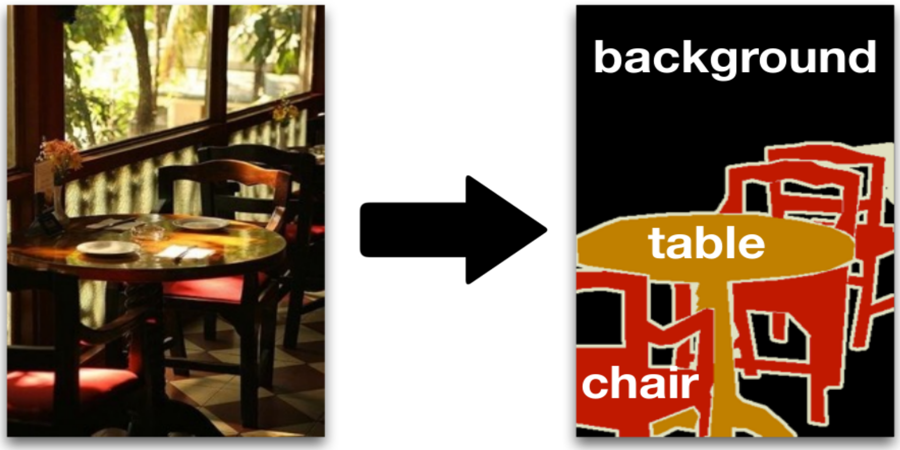
Def2: **Instance** segmentation

Simultaneous Detection and Segmentation

Detect and segment every instance of the category in the image



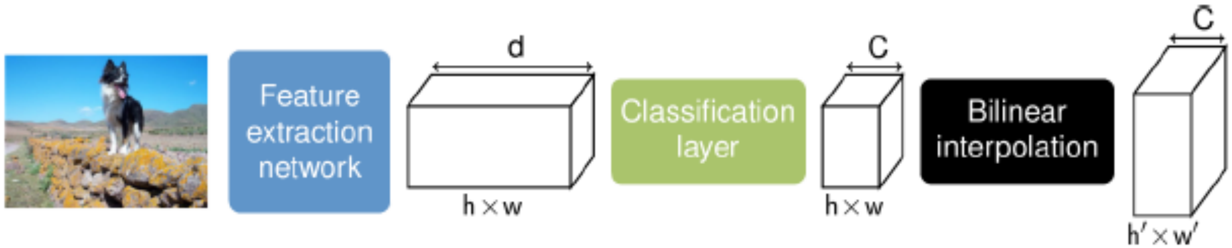
Supervised Segmentation with Deep ConvNets



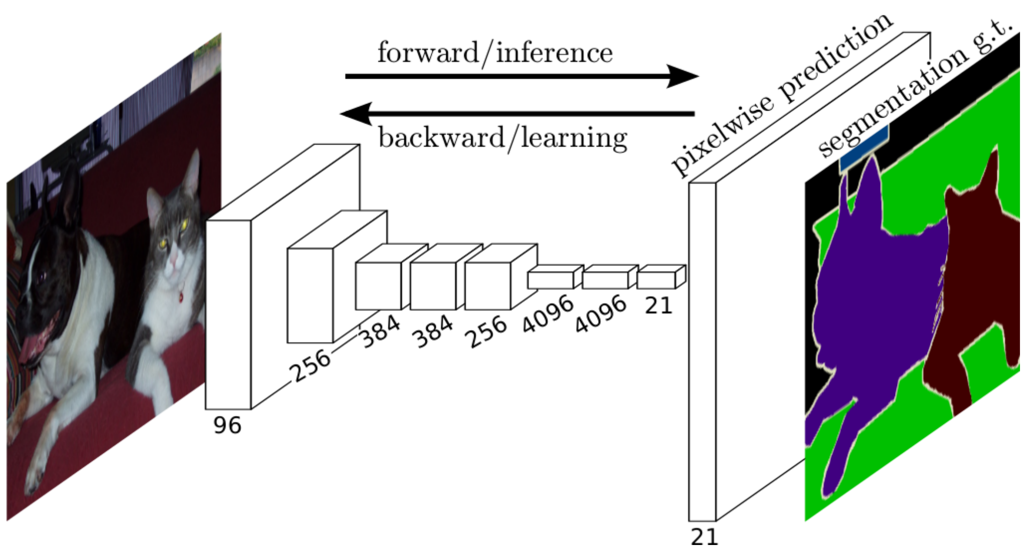
1. **F-CN Fully Convolutional Network**
2. DeepLab approach for supervised segmentation
3. Deconvolution Networks

Supervised Segmentation with Deep ConvNets

F-CN Fully Convolutional Network



- Fully-convolutional network: classify each "pixel"
- Upsampling output (bilinear interpolation + deconvolution)
- Network architecture: AlexNet, VGG16, GoogleNet
- Loss: soft-max per pixel



Supervised Segmentation with Deep ConvNets

F-CN Fully Convolutional Network

Learning process

1. Model pretrained on ImageNet
2. Decapitate each net by discarding the final classifier layer
3. Convert all fully-connected layers to convolutions
4. Append n^1 1×1 convolutions
5. Fine-tuning all layers by backpropagation

[1] n=number of classes

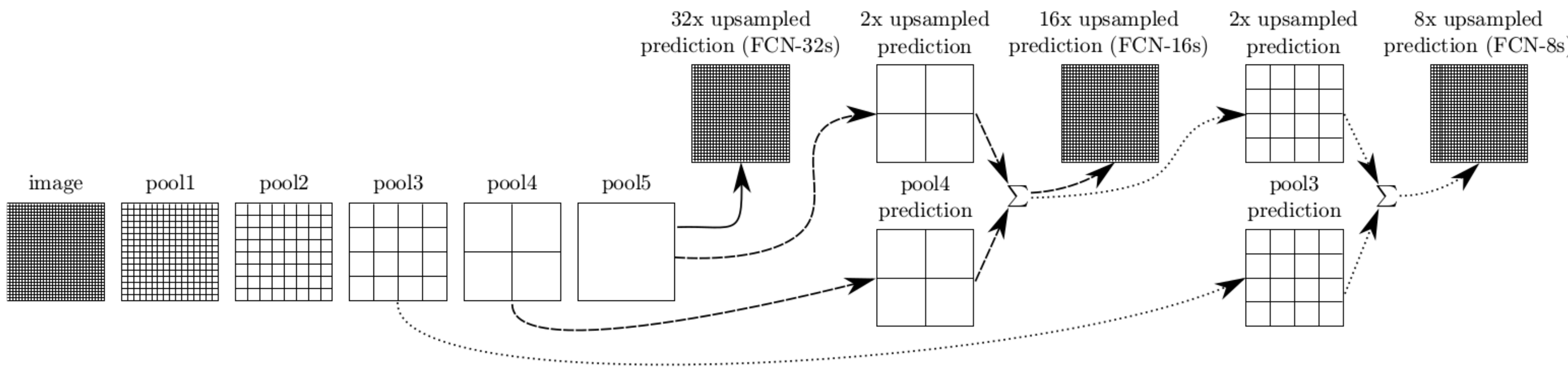
Supervised Segmentation with Deep ConvNets

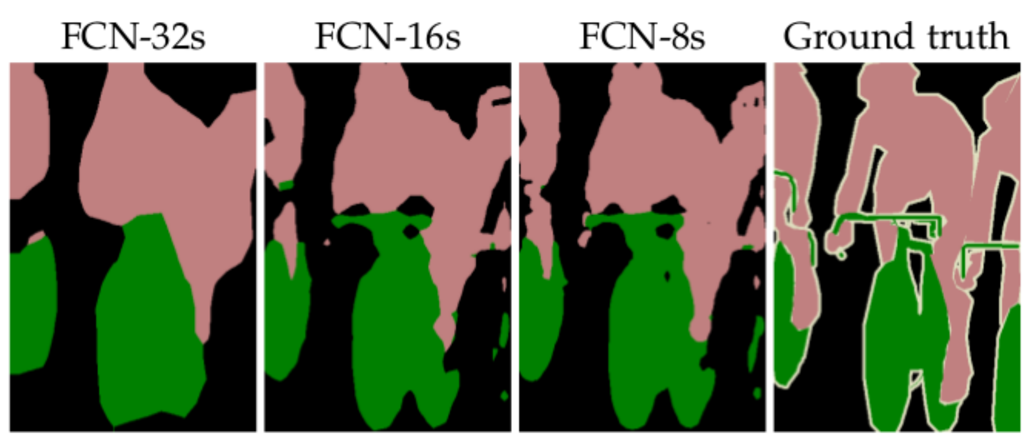
F-CN Fully Convolutional Network

- Problem: max pooling and striding reduces spatial resolution

Solution of the FCN approach

- Dense prediction: combines feature hierarchies
- Initialized with the parameters of coarse net
- Fine-tuning all layers by backpropagation





Supervised Segmentation with Deep ConvNets

1. F-CN Fully Convolutional Network
2. **DeepLab approach for supervised segmentation**
3. Deconvolution Networks

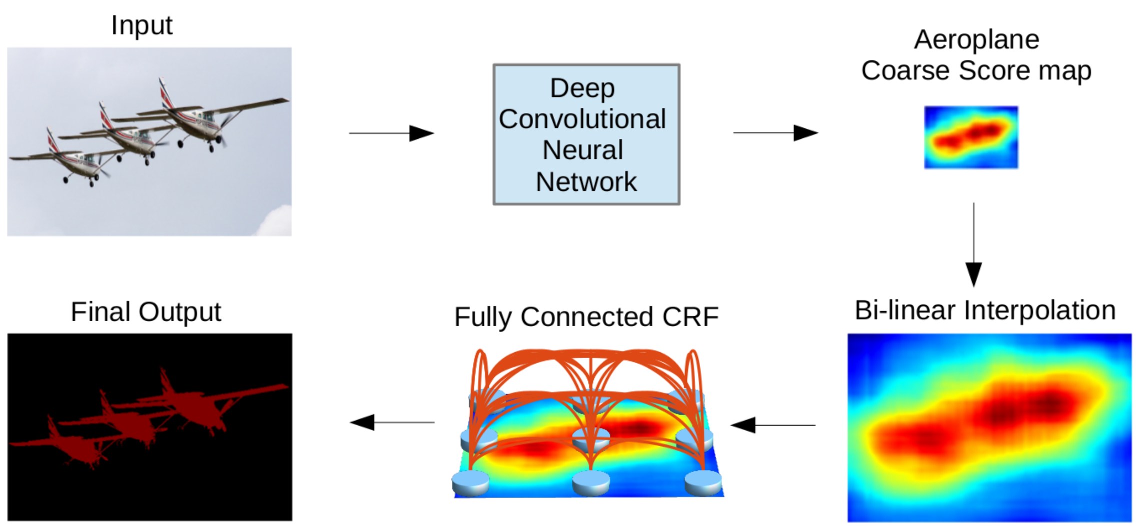
Supervised Segmentation with Deep ConvNets

DeepLab (v123) approach for supervised segmentation

Problem of the spatial resolution reduction

Solution of the DeepLab approach

1. Learn CNN for dense prediction tasks (Atrous)
2. Improve the localization of object boundaries with fully-connected CRF [?] (FC-CRF)



Supervised Segmentation with Deep ConvNets

DeepLab approach: **Atrous filtering** algo

- Remove the down-sampling from the last pooling layers.
- Up-sample the original filter by a factor of the strides:

  Atrous convolution for 1-D signal:

$$y[i] = \sum_{k=1}^{K} x[i + r \cdot k]w[k]$$

Introduce zeros between filter values

$x[i]$ 1-D input signal

$w[k]$ filter of length K

r *rate* parameter corresponds to the stride with which we sample the input signal.

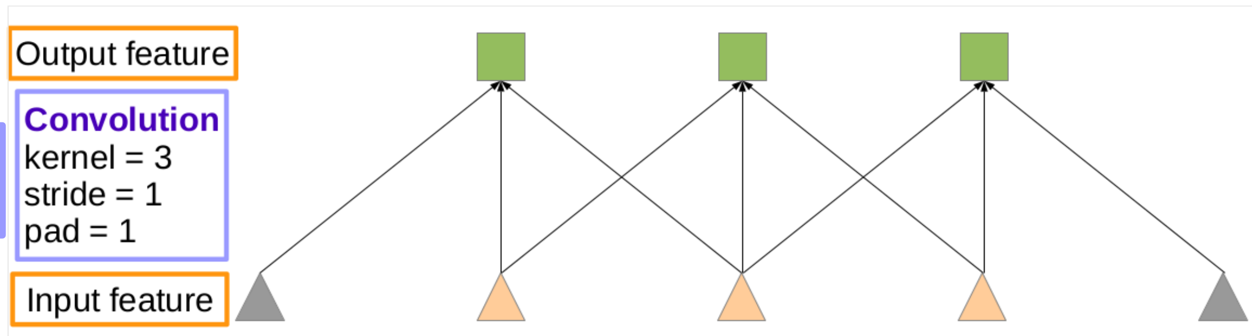
$y[i]$ output of atrous convolution.

- Note: standard convolution is a special case for *rate* r=1.

Supervised Segmentation with Deep ConvNets

Classical filtering/pooling/downsampling

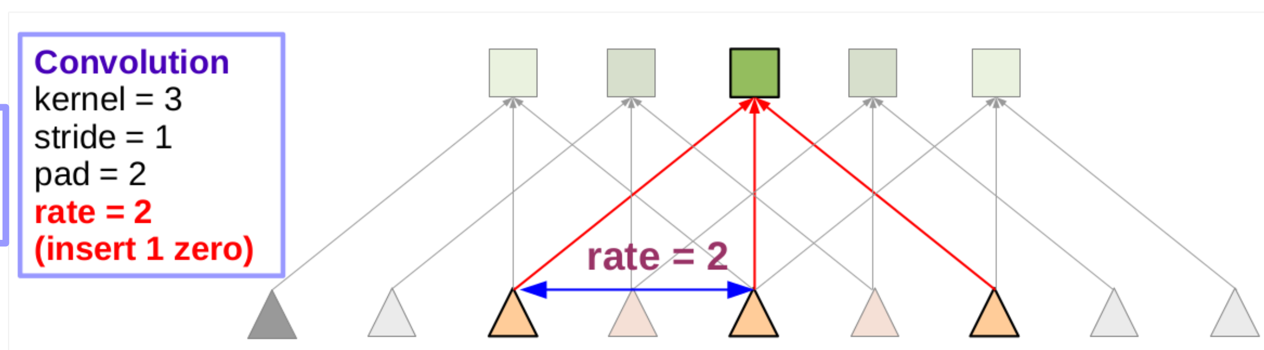
Downsampling
+



+
Upsampling

DeepLab approach: **Atrous filtering** algo

NO
downsampling



Supervised Segmentation with Deep ConvNets

DeepLab approach: **Atrous filtering** algo

Filters field-of-view

- **Small** field-of-view → accurate **localization**
- **Large** field-of-view → **context** assimilation
- 'Holes': Introduce zeros between filter values.
- **Effective filter size increases** (enlarge the **field-of-view** of filter): $k \times k$ filter to $k_e = k + (k-1)(r-1)$

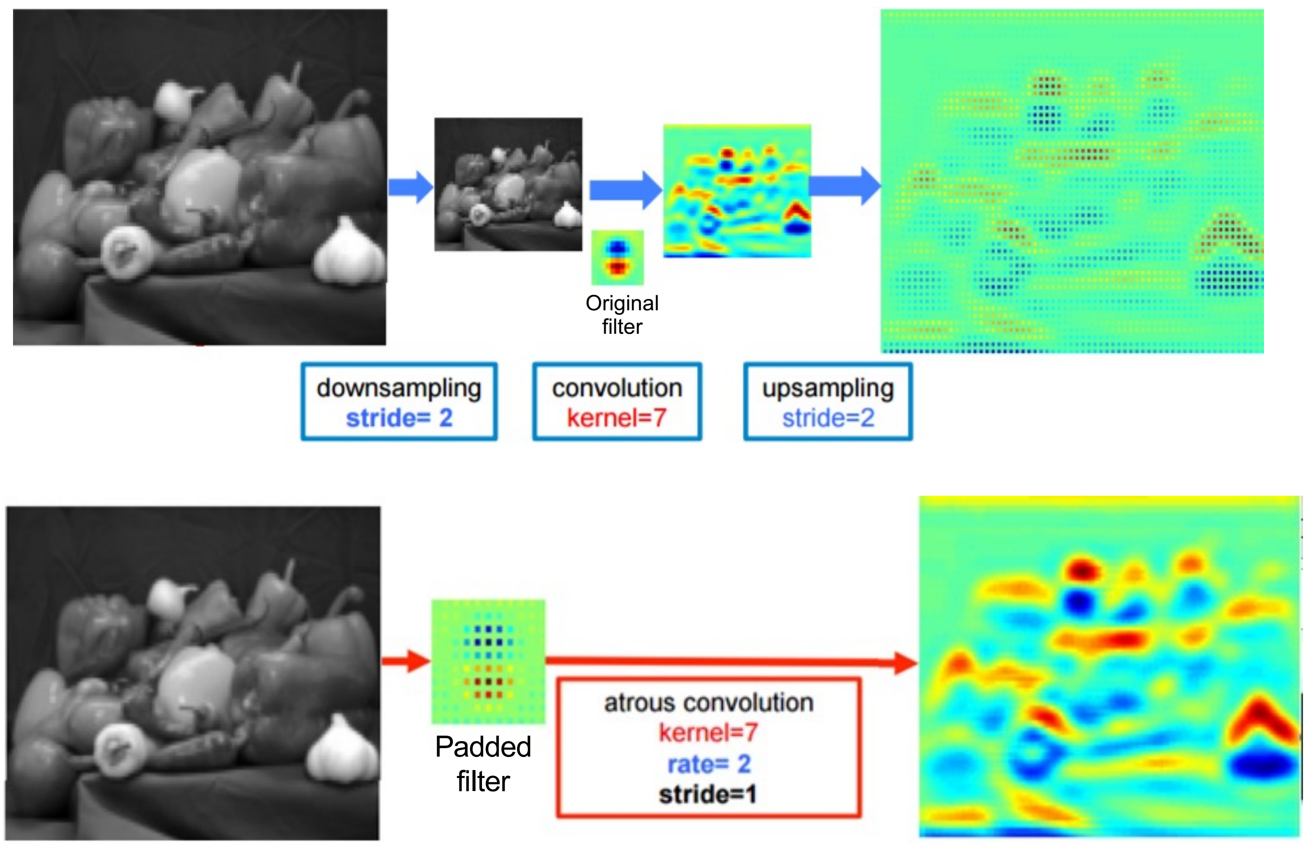
- However, we take into account **only** the **non-zero** filter values:
  - ✓ Number of filter parameters is the same.
  - ✓ Number of operations per position is the same.

Supervised Segmentation with Deep ConvNets

DeepLab approach: **Atrous filtering** algo

Standard convolution

Atrous convolution



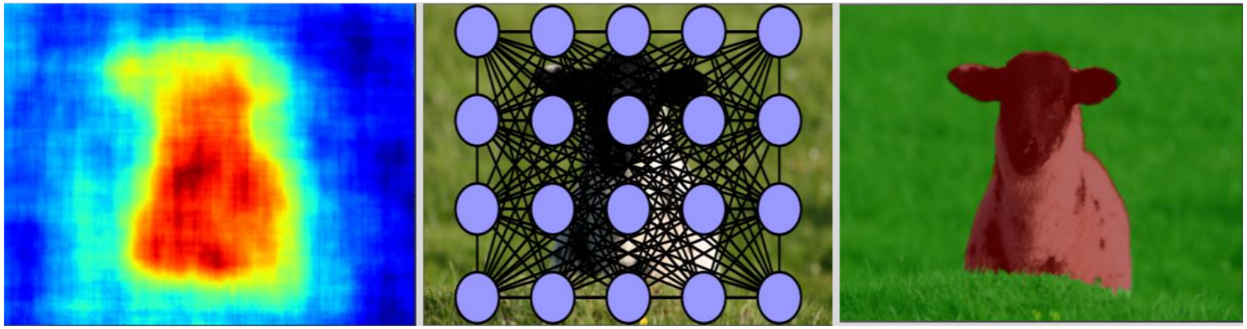
Supervised Segmentation with Deep ConvNets

DeepLab: Fully-Connected CRF

- Problem: poor object delineation (spatial and appearance consistency neglected)
- Solution: fully-connected CRF accounts for contextual information in the image

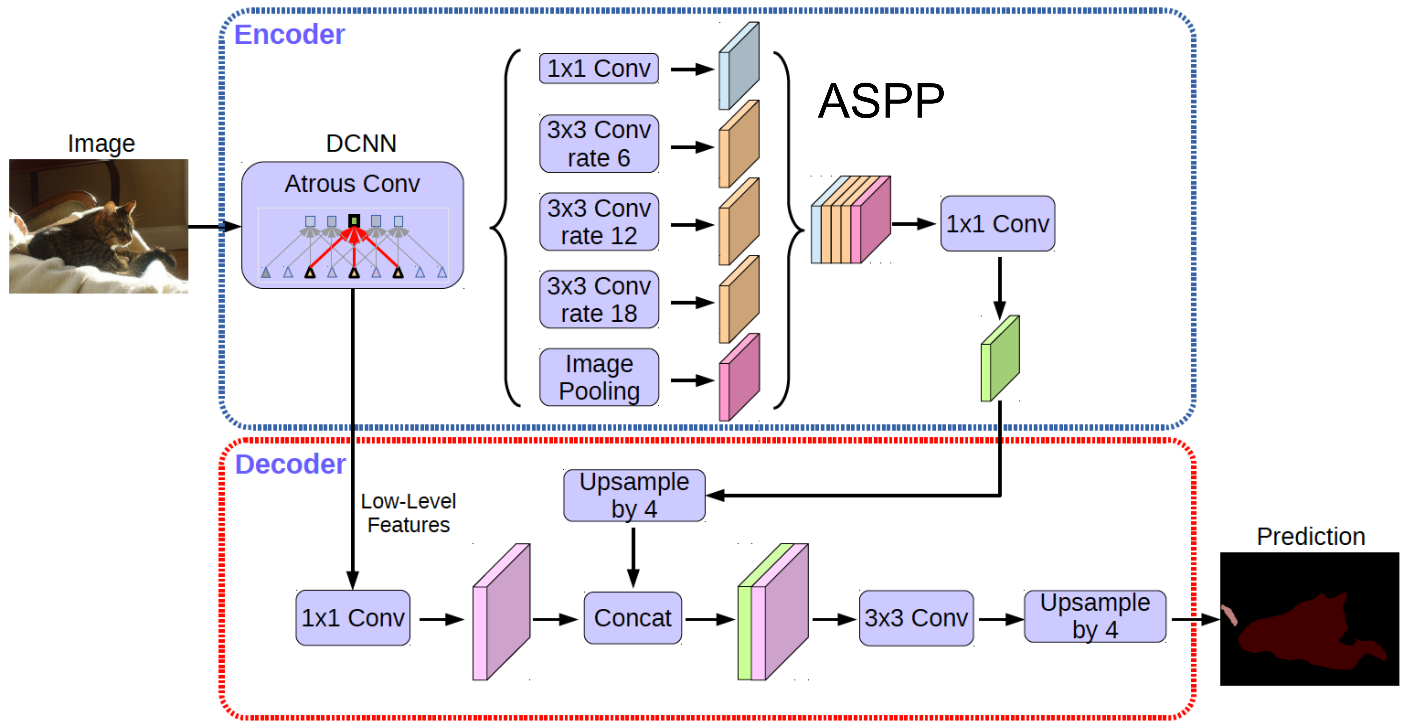
$$E(\mathbf{y}) = \sum_i \theta_i(y_i) + \sum_{i,j} \theta_{ij}(y_i, y_j)$$

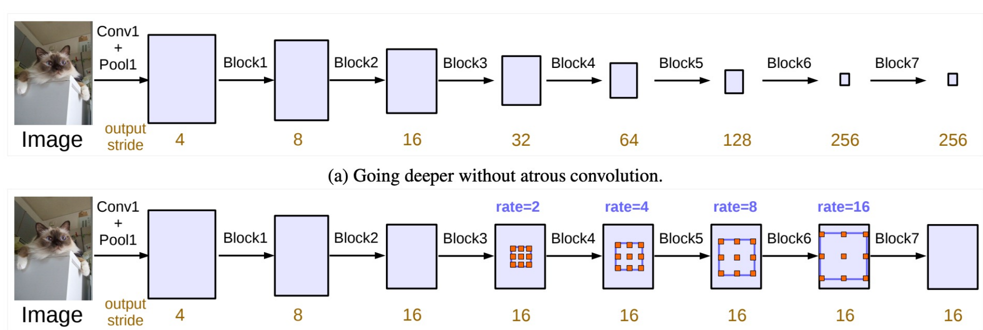
  - Unary term: output of FCN (upscaled)
  - Pairwise term: penalizes similar pixels having different labels



Supervised Segmentation with Deep ConvNets

- DeepLab V3+ [ECCV 2018]





(a) Going deeper without atrous convolution.

(b) Going deeper with atrous convolution. Atrous convolution with $rate > 1$ is applied after block3 when $output\_stride = 16$.

Figure 3. Cascaded modules without and with atrous convolution.

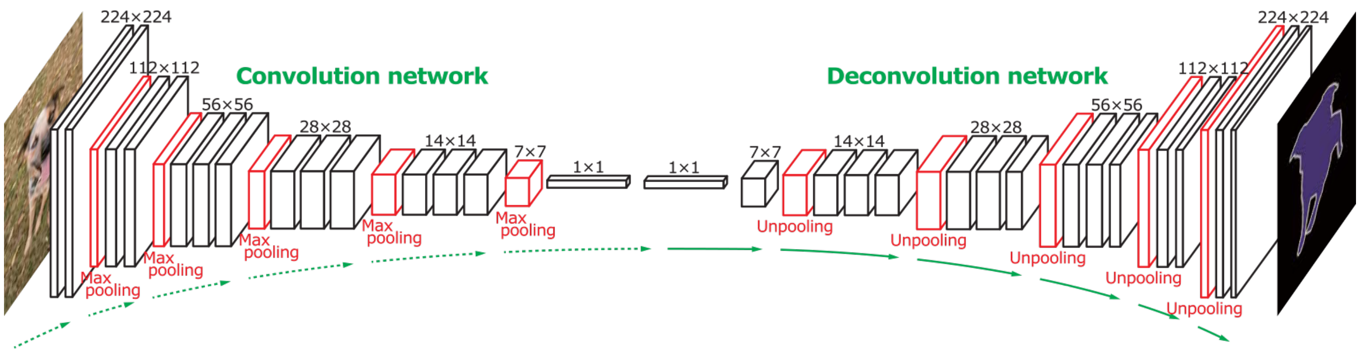
Supervised Segmentation with Deep ConvNets

1. F-CN Fully Convolutional Network
2. DeepLab approach for supervised segmentation
3. **Deconvolution Networks**

Supervised Segmentation with Deep ConvNets

Deconvolution Network

- Learn a multi-layer deconvolution network
- Network is composed of two parts:
  1. Convolution: feature extractor
  2. Deconvolution: shape generator that produces object segmentation from the feature extracted
- Deconvolution net is a mirrored version of the convolution net



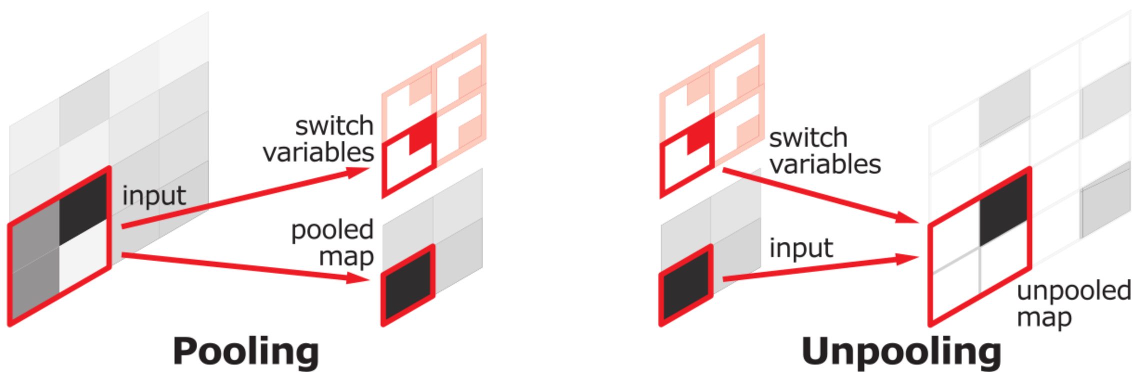
Hyeonwoo Noh, Seunghoon Hong, and Bohyung Han.
Learning deconvolution network for semantic segmentation.
In *ICCV*, 2015. [paper]

Supervised Segmentation with Deep ConvNets

Deconvolution Network

Unpooling

- Perform the reverse operation of pooling
- Reconstruct the original size of activations
- Useful to reconstruct the structure of input object
- Output: sparse activation map

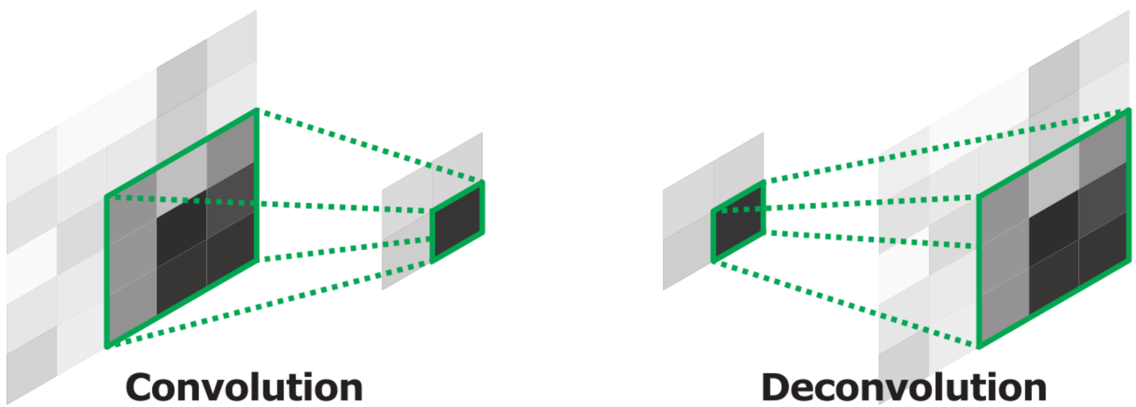


Supervised Segmentation with Deep ConvNets

Deconvolution Network

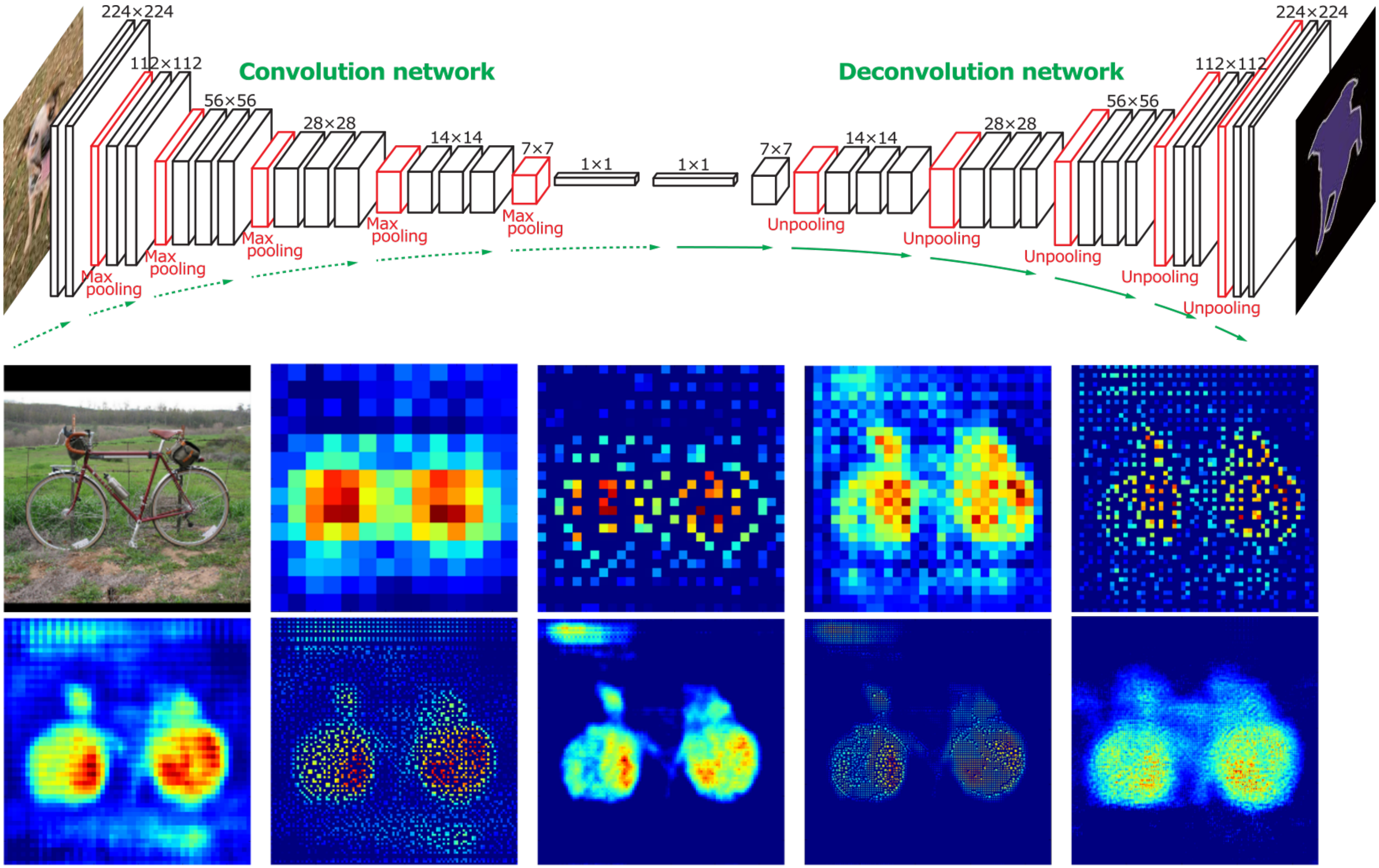
Deconvolution

- Connect single input activation to a multiple activations
- Learned filters correspond to bases to reconstruct shape of an input object
- Output: enlarged and dense activation map



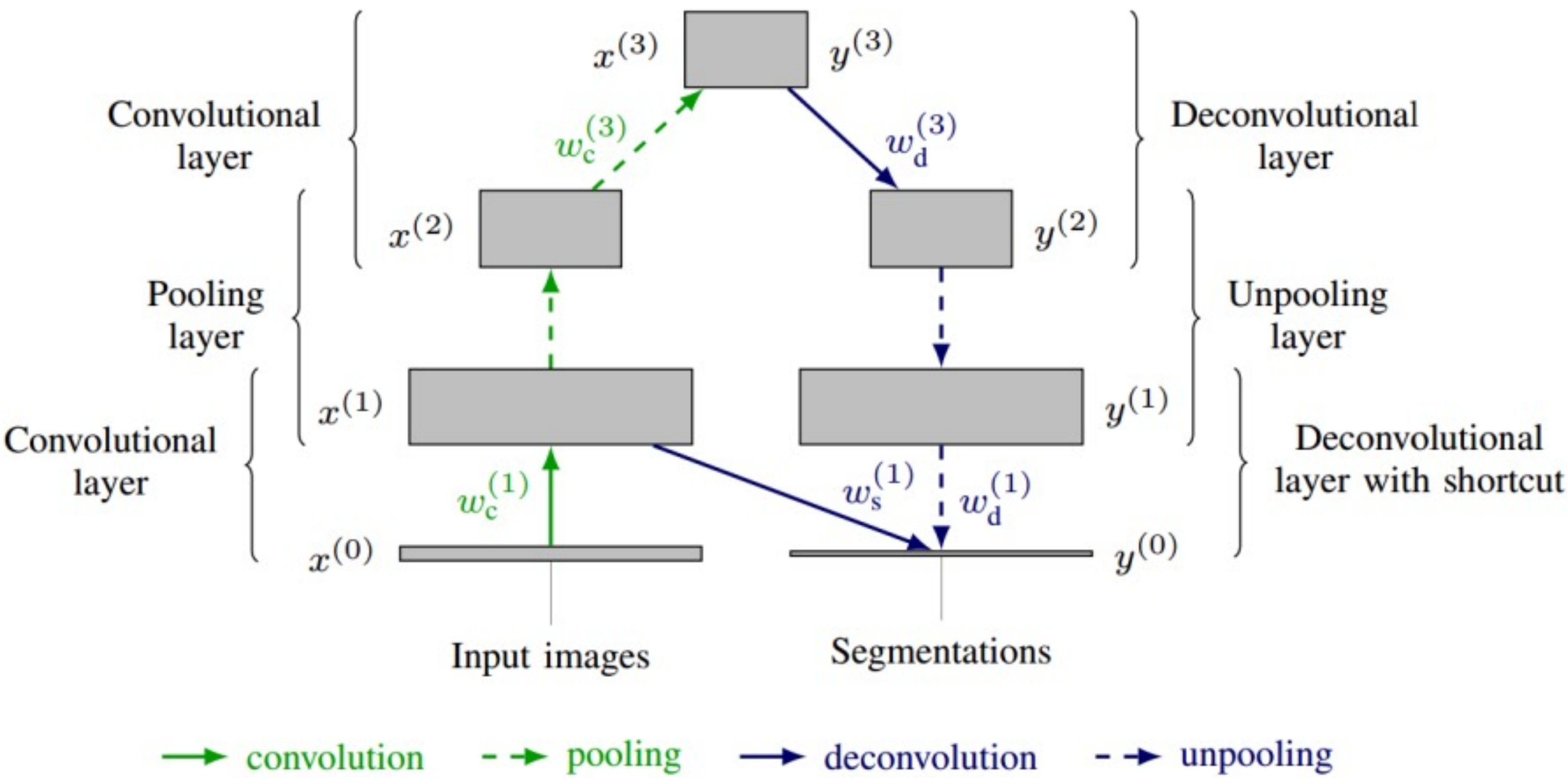
Supervised Segmentation with Deep ConvNets

Deconvolution Net: hourglass structure + unpooling switch variables



Supervised Segmentation with Deep ConvNets

Deconvolution Net + shortcut connection



Supervised Segmentation with Deep ConvNets

U-Net:
Hourglass/U shape Net
+ shortcut connection
by feature copies

Very popular in medical
Works well with low
training data

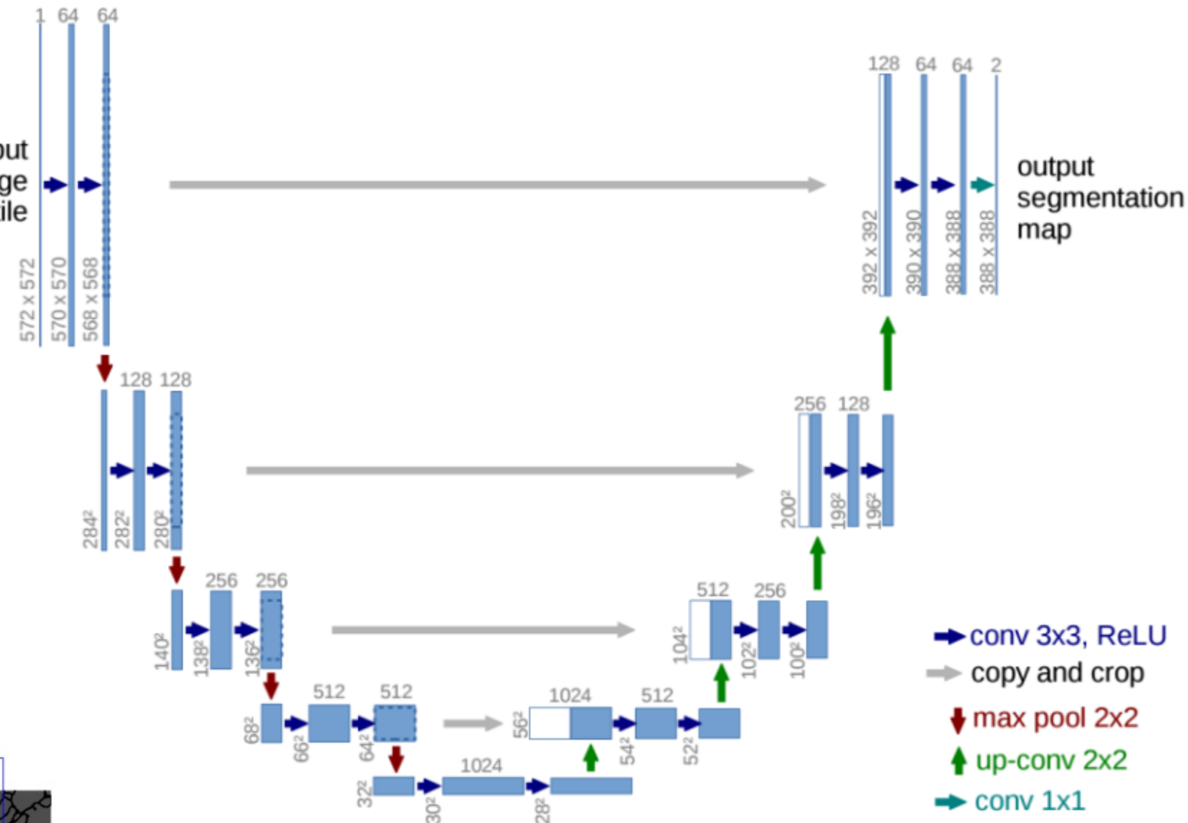


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

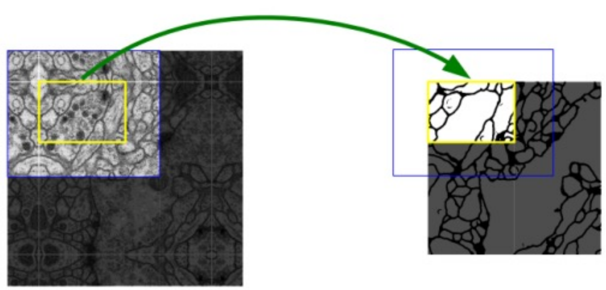


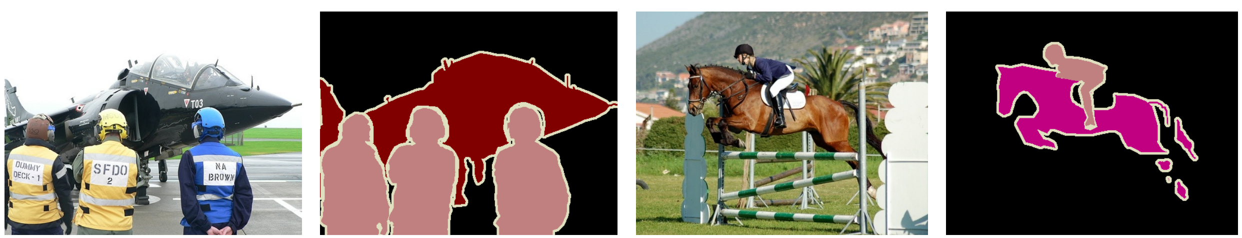
Fig. 2. Overlap-tile strategy for seamless segmentation of arbitrary large images (here segmentation of neuronal structures in EM stacks). Prediction of the segmentation in the yellow area, requires image data within the blue area as input. Missing input data is extrapolated by mirroring

http://deeplearning.net/tutorial/unet.html

Extra: Datasets

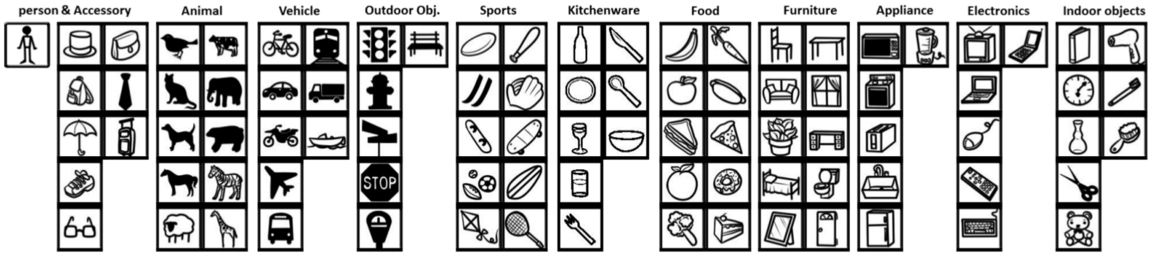
PASCAL VOC 12

- Train 1464 images / Val 1449 images / Test 1456 images
- 21 classes: *aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, dining table, dog, horse, motorbike, person, potted plant, sheep, sofa, train, tv/monitor* + background
- Evaluation: intersection-over-union metric
- Webpage: `http://host.robots.ox.ac.uk/pascal/VOC/voc2012/`



COCO

- Train 80k images / Val 20k images
- 91 classes, 11 super-categories:



- 3 challenges: detection, instance segmentation, captioning
- Webpage: `http://mscoco.org` [paper]

Extra: Weakly Supervised Segmentation

Supervised Image Segmentation Methods

Full supervision

- Precise annotation ☺
- Expensive and time consuming to obtain
  - "79s per label per image" [RBFL15] ☹
- Bottleneck for learning models at large scale ☹

Weakly Supervised Image Segmentation Methods

Weak supervision

- Reduce supervision: class labels (or tags) ☹ ☹
- Cheap to obtain
  - "1s per label per image" [RBFL15] ☺
- Scalable to large number of categories ☺

✓ background
✗ aeroplane
✗ cat
✓ chair
✗ dog
✗ person
✗ sheep
✓ table
✗ tvmonitor

Weakly supervised segmentation with CNN

Standard learning algorithms

- Maximize the likelihood of the observed training data

Problem

- Require full knowledge of the ground truth labeling
  - not available in the weakly supervised setting ☹

Solutions

1. Generation of segmentation mask

   George Papandreou, Liang-Chieh Chen, Kevin Murphy, and Alan L. Yuille. Weakly-and semi-supervised learning of a dcnn for semantic image segmentation. In *ICCV*, 2015.

2. Modified loss function: CNN optimized for classification

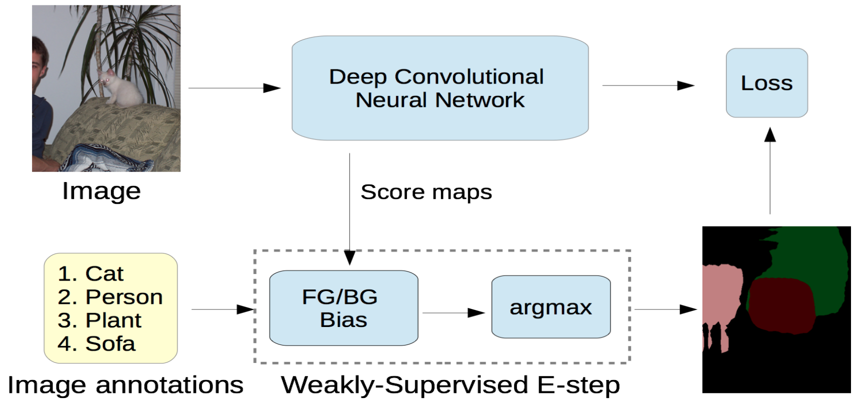
   Pedro O. Pinheiro and Ronan Collobert. From image-level to pixel-level labeling with convolutional networks. In *CVPR*, 2015.

Generation of segmentation mask

George Papandreou, Liang-Chieh Chen, Kevin Murphy, and Alan L. Yuille.
Weakly-and semi-supervised learning of a dcnn for semantic image segmentation.
In *ICCV*, 2015.

Idea: adaptive bias

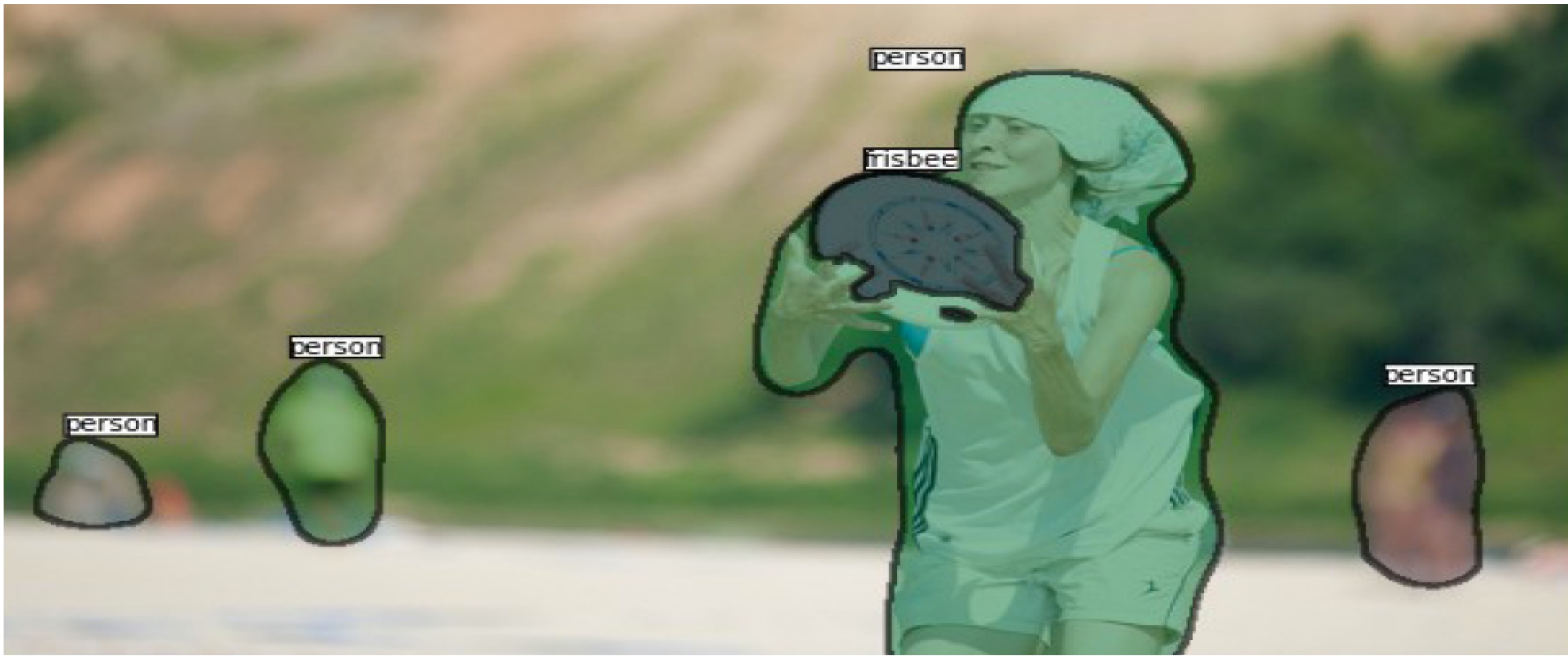
- Generated segmentation mask and train fully-supervised CNN
- Adaptive bias into the multi-instance learning framework
  - Boost classes known to be present
  - Suppress all others



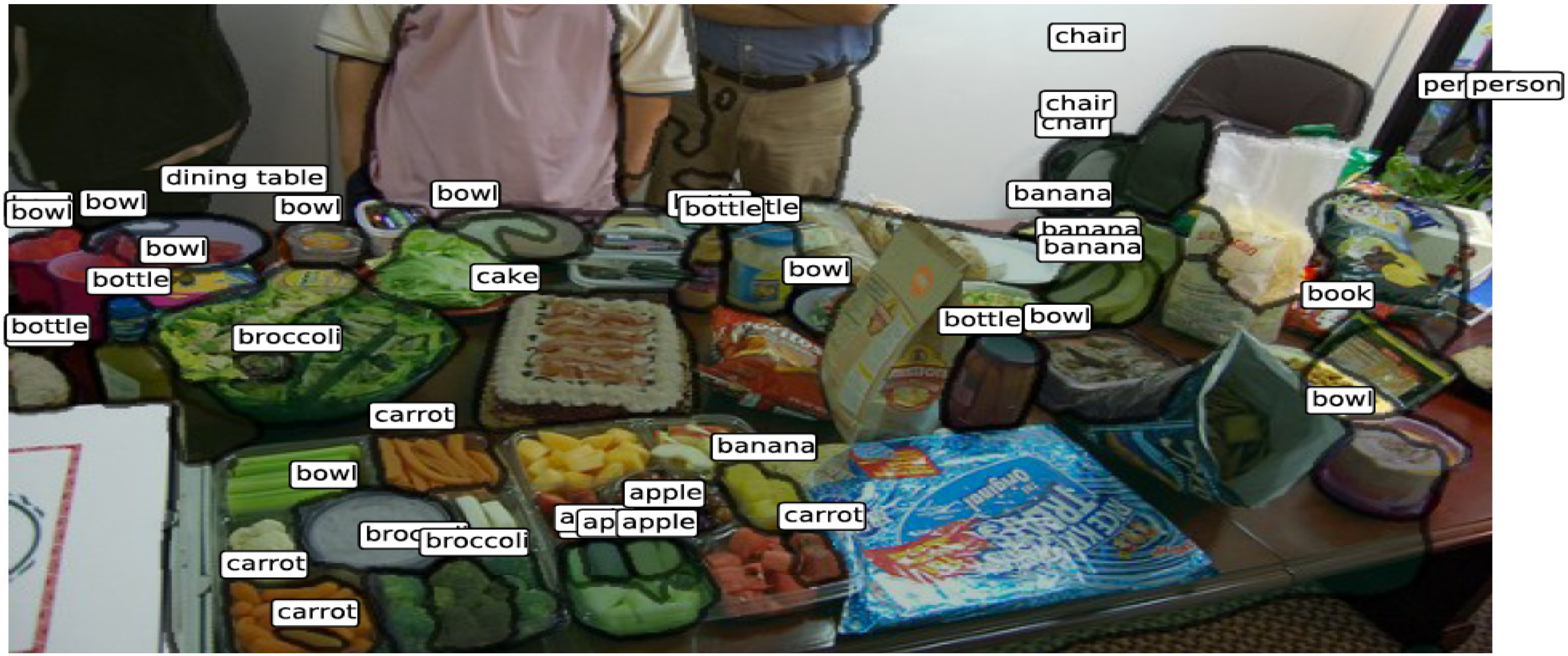
Segmentation Results

@Y. LeCun

Segmentation Results



Segmentation Results



@Y. LeCun

=> Mask-R-CNN