CMP717
Image Processing

Semantic Segmentation

Erkut Erdem
Hacettepe University
Computer Vision Lab (HUCVL)

Semantic Segmentation

- Joint recognition & segmentation
  - segmenting all the objects in a given image and identifying their visual categories
- aka scene parsing or image parsing
- Early studies aim at segmenting out a single object of a known category
  - Borenstein & Ullman, 2002, Liebe & Schiele, 2003, etc.
- More recent work depends on CNNs
  - Farabet et al., 2013, Pinheiro and Collobert, 2014, Long et al., 2015, Noh et al., 2015

Computer Vision Tasks

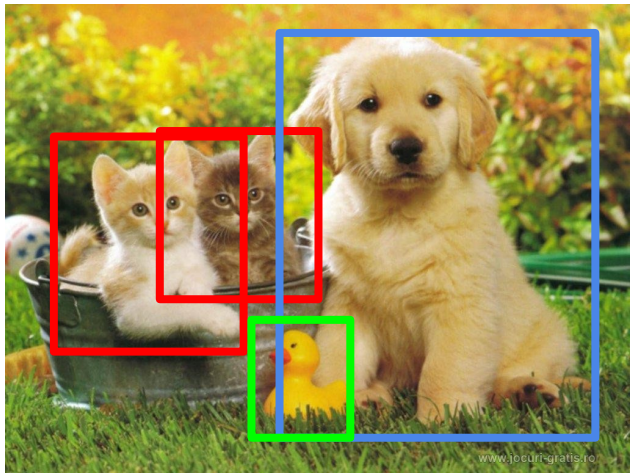
Classification

CAT

Classification
+ Localization

CAT

Object
Detection



CAT, DOG, DUCK

Semantic
Segmentation

CAT, DOG, DUCK

Single
object

Multiple
objects

F.-F. Li, A. Karpathy and J. Johnson

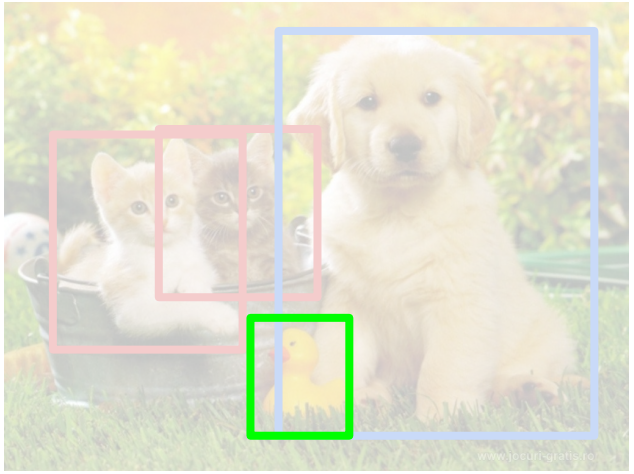
Computer Vision Tasks

Classification

Classification + Localization

Object Detection

Semantic Segmentation



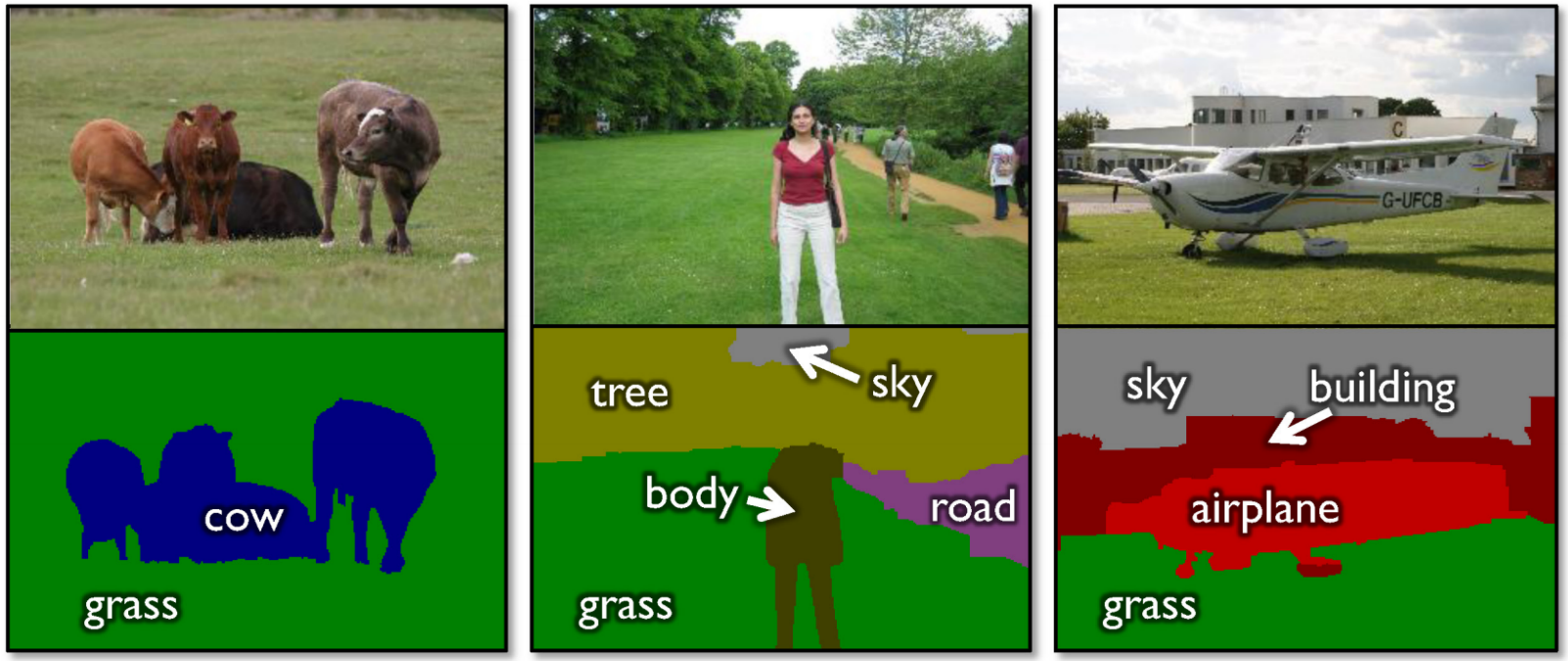
Today

Semantic Segmentation

Label every pixel in the image with a category label

Don't differentiate instances (cows)

Classic computer vision problem



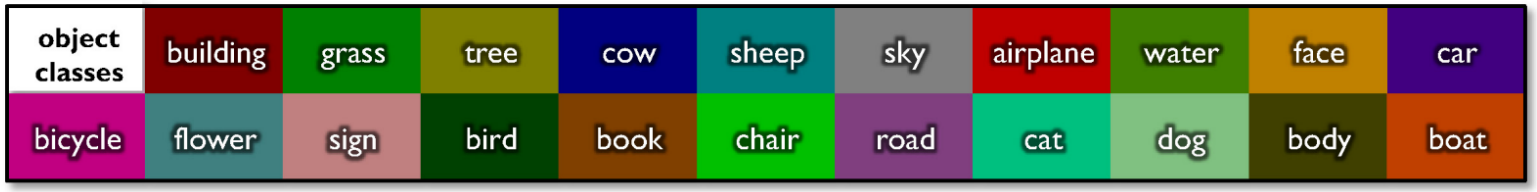


Figure credit: Shotton et al, "TextonBoost for Image Understanding: Multi-Class Object Recognition and Segmentation by Jointly Modeling Texture, Layout, and Context", IJCV 2007

Instance Segmentation

Detect instances, give category, label pixels

"simultaneous detection and segmentation" (SDS)

Lots of recent work (MS-COCO)

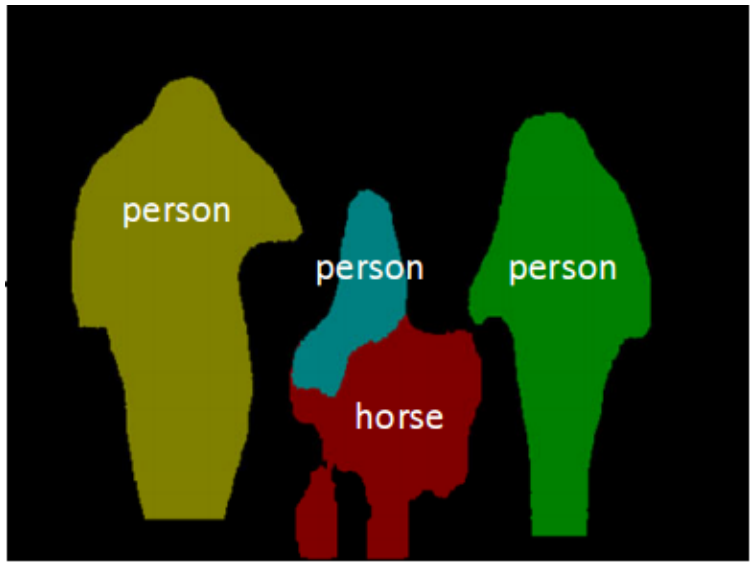
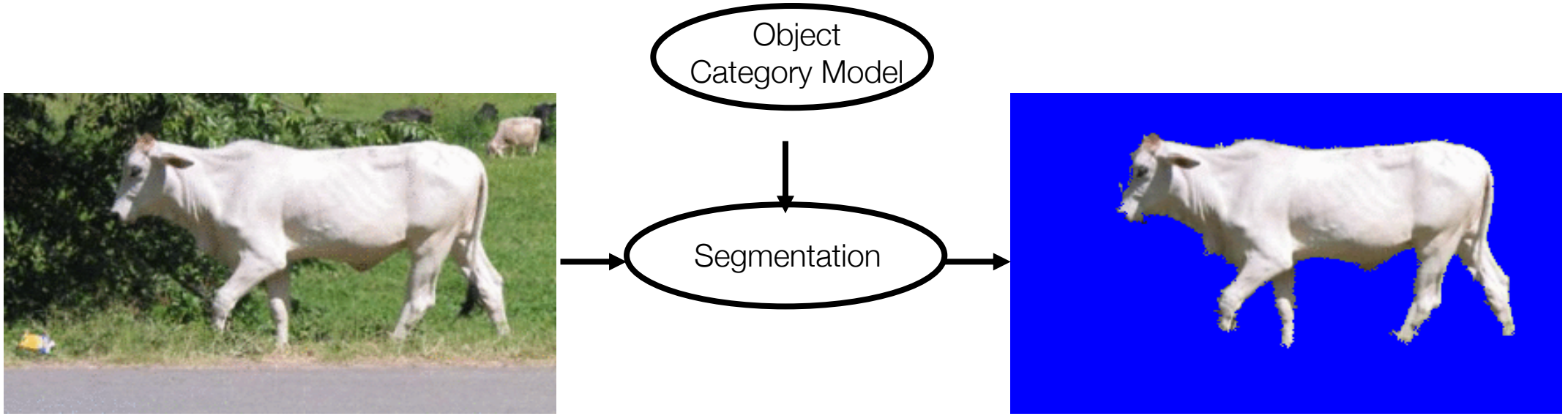


Figure credit: Dai et al, "Instance-aware Semantic Segmentation via Multi-task Network Cascades", arXiv 2015

Early Studies of Semantic Segmentation

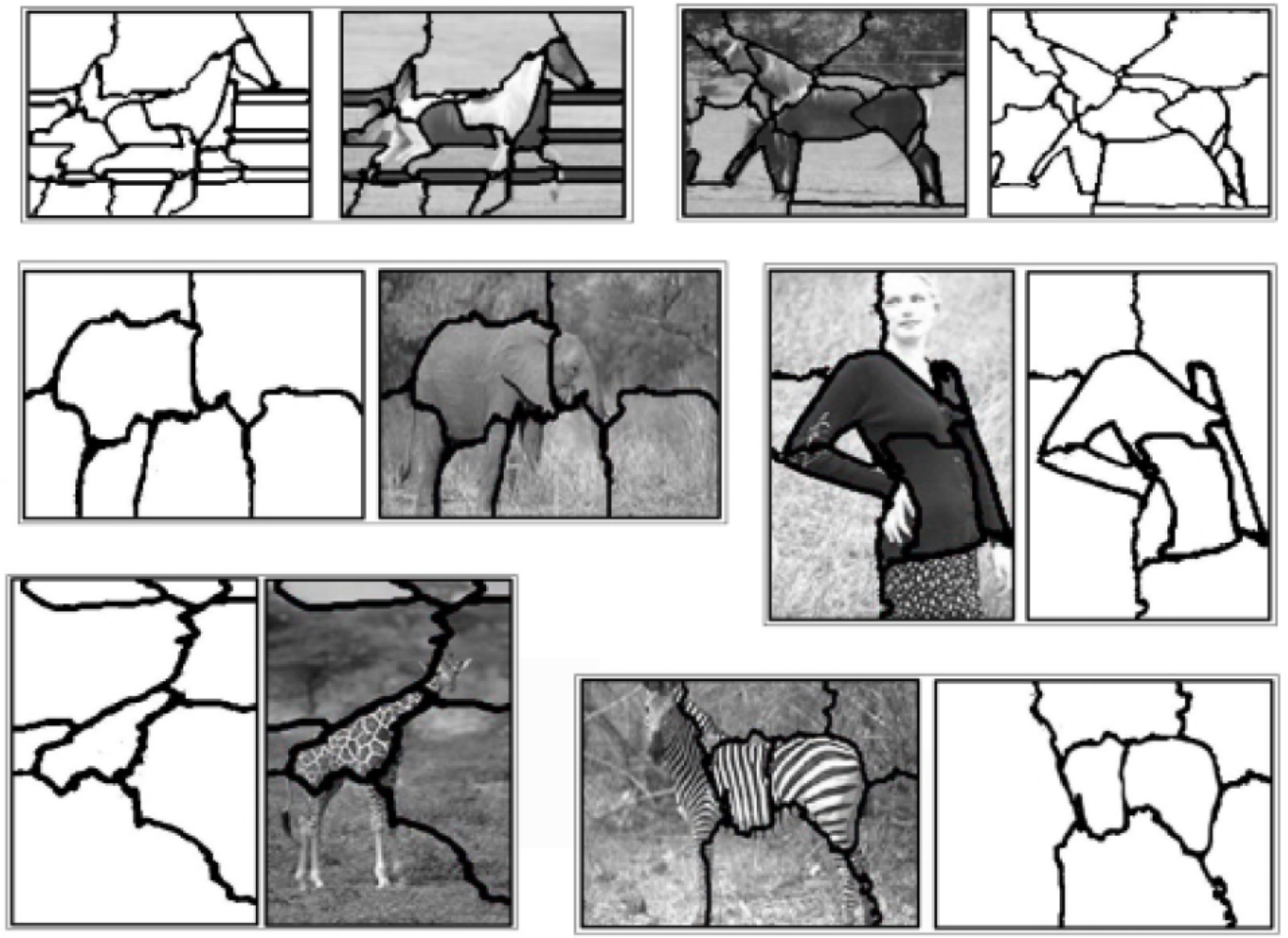
- Given an image and object category, to segment the object



- Segmentation should (ideally) be
  - shaped like the object e.g. cow-like
  - obtained efficiently in an unsupervised manner
  - able to handle self-occlusion

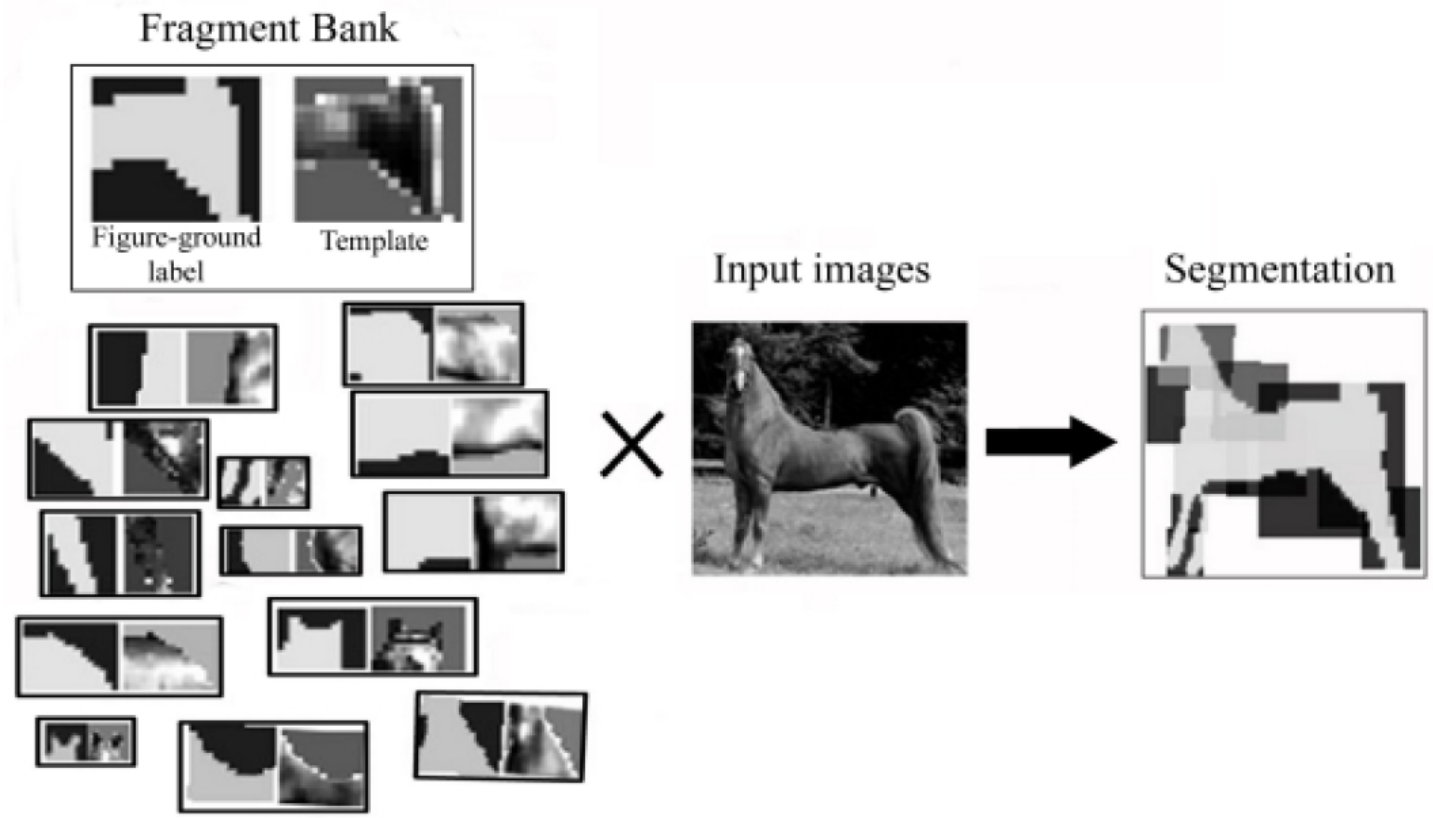
Examples of Bottom-up Segmentation

Using Normalized Cuts, Shi & Malik, 1997



R. Fergus

Jigsaw approach: Borenstein and Ullman, 2002



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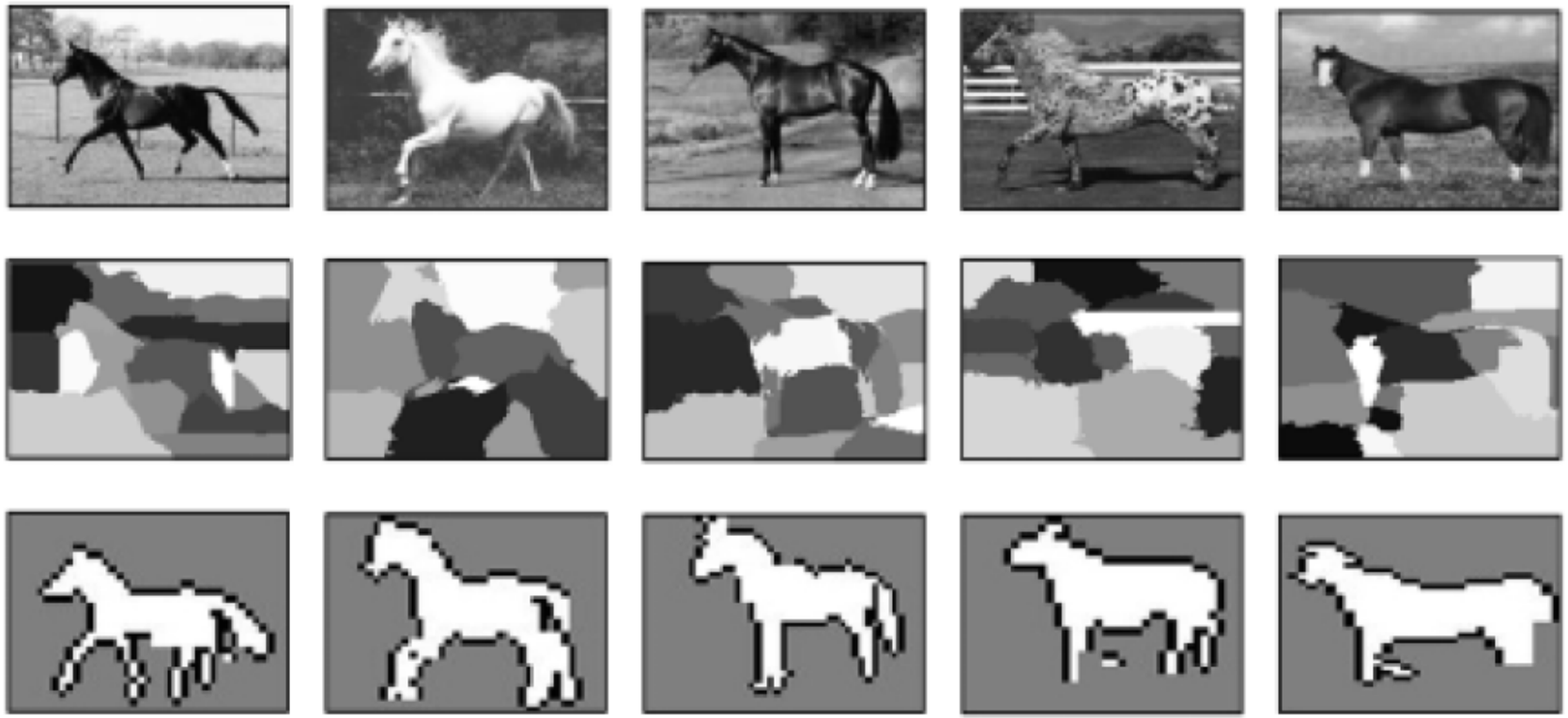
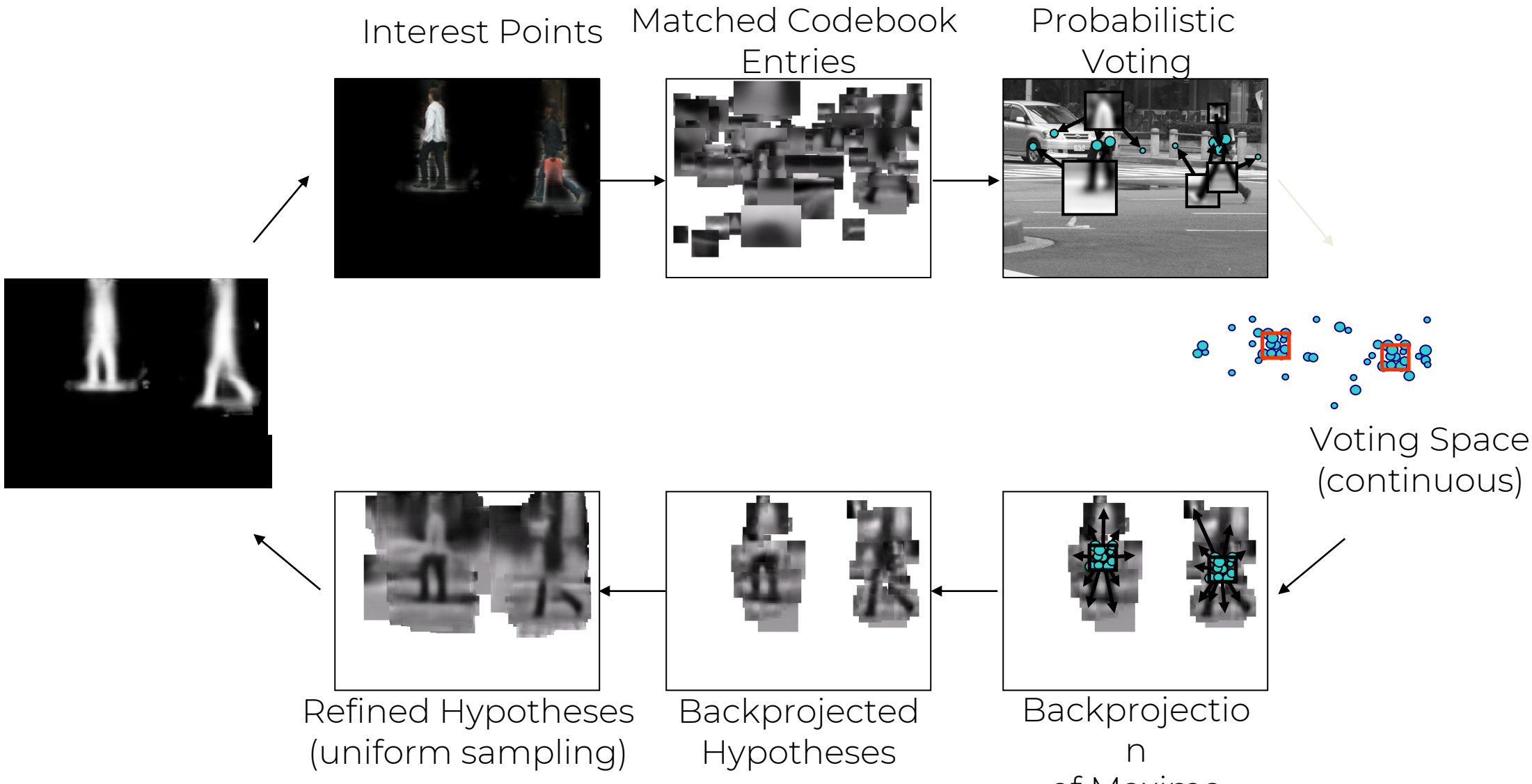


Implicit Shape Model - Liebe and Schiele, 2003



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Random Fields for segmentation

I = Image pixels (observed)
h = foreground/background labels (hidden) – one label per pixel
θ = Parameters

$$\underbrace{p(h \mid I, \theta)}_{\text{Posterior}}$$

Random Fields for segmentation

I = Image pixels (observed)
h = foreground/background labels (hidden) – one label per pixel
θ = Parameters

$$\underbrace{p(h \mid I, \theta)}_{\text{Posterior}} \propto \underbrace{p(I, h \mid \theta)}_{\text{Joint}} = \underbrace{p(I \mid h, \theta)}_{\text{Likelihood}} \underbrace{p(h \mid \theta)}_{\text{Prior}}$$

1. Generative approach models joint
   → Markov random field (MRF)

2. Discriminative approach models posterior directly
   → Conditional random field (CRF)

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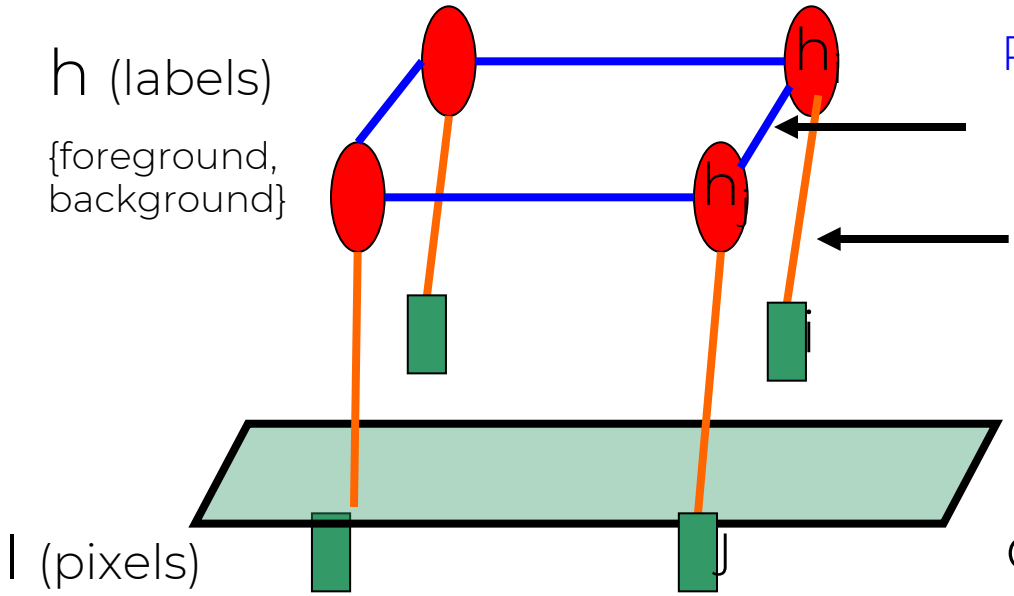
Generative Markov Random Field

$$p(h, I \mid \theta) = p(I \mid h, \theta)\, p(h \mid \theta)$$

$$= \frac{1}{Z(\theta)} \left[\prod_i \phi_i(I \mid h_i, \theta_i) \prod_{ij} \psi_{ij}(h_i, h_j \mid \theta_{ij}) \right]$$

Likelihood

MRF Prior



Pairwise Potential (MRF)

$\Psi_{ij}(h_i, h_j \mid \theta_{ij})$

Unary Potential

$\phi_i(I \mid h_i, \theta_i)$

Prior has no dependency on I

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Conditional Random Field

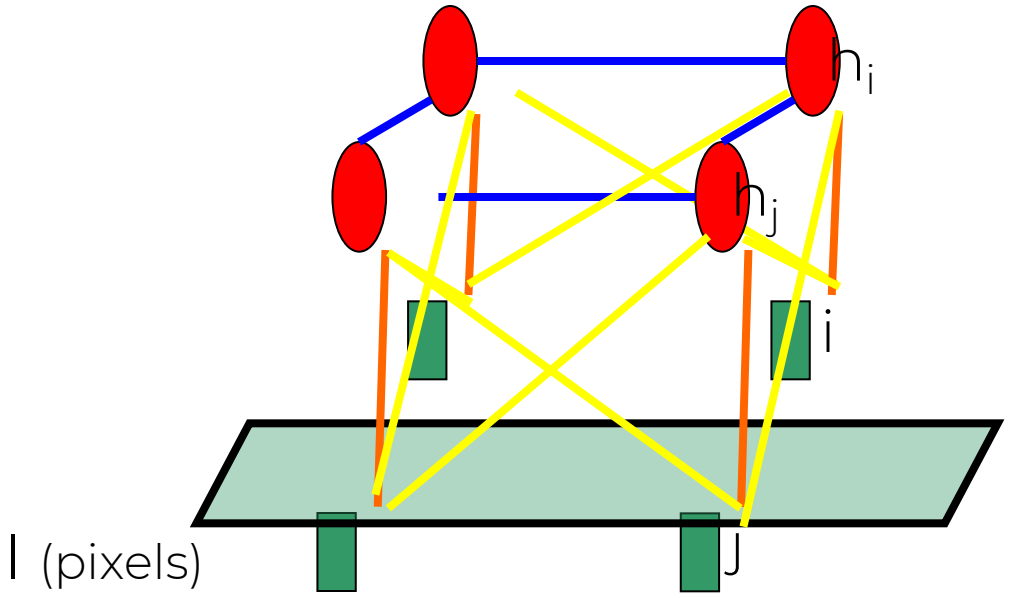
Discriminative approach

Lafferty, McCallum and Pereira 2001

$$p(h \mid I, \theta) = \frac{1}{Z(I,\theta)} \left[\prod_i \underbrace{\phi_i(h_i, I \mid \theta_i)}_{\text{Unary}} \prod_{ij} \underbrace{\psi_{ij}(h_i, h_j, I \mid \theta_{ij})}_{\text{Pairwise}} \right]$$

- Dependency on I allows introduction of pairwise terms that make use of image.
- For example, neighboring labels should be similar only if pixel colors are similar → Contrast term

e.g Kumar and Hebert 2003



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Conditional Random Fields for Segmentation

- Segmentation map x
- Image I

$$E(x;I) = \nu \sum_{i,j} w_{ij}|x(i) - x(j)| + \sum_{k} \lambda_k |x - x_{F_k,I}|$$

Low-level pairwise term

High-level local term

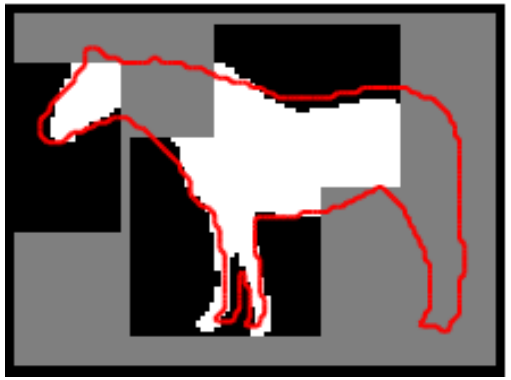
Pixel-wise similarity

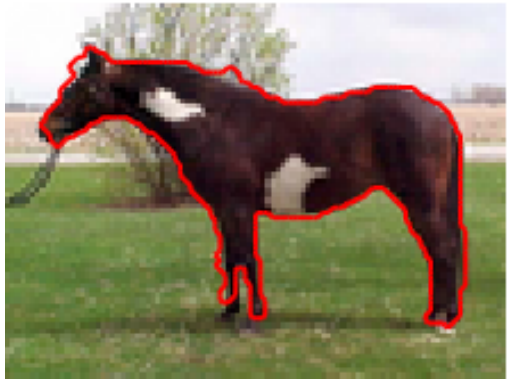
Levin & Weiss [ECCV 2006]

$$E(h;I) = \sum_i \lambda_i \left| h - h_{F_i,I} \right| + \sum_{ij} w(i,j) \left| h_i - h_j \right|$$

Consistency with fragments segmentation

Segmentation alignment with image edges





Resulting min-cut segmentation

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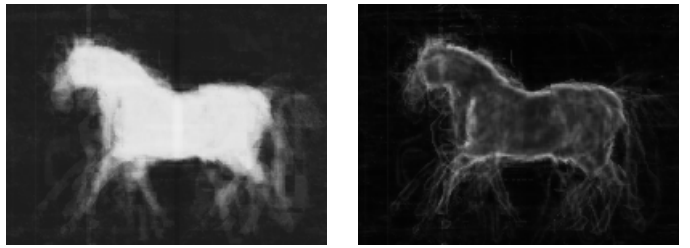
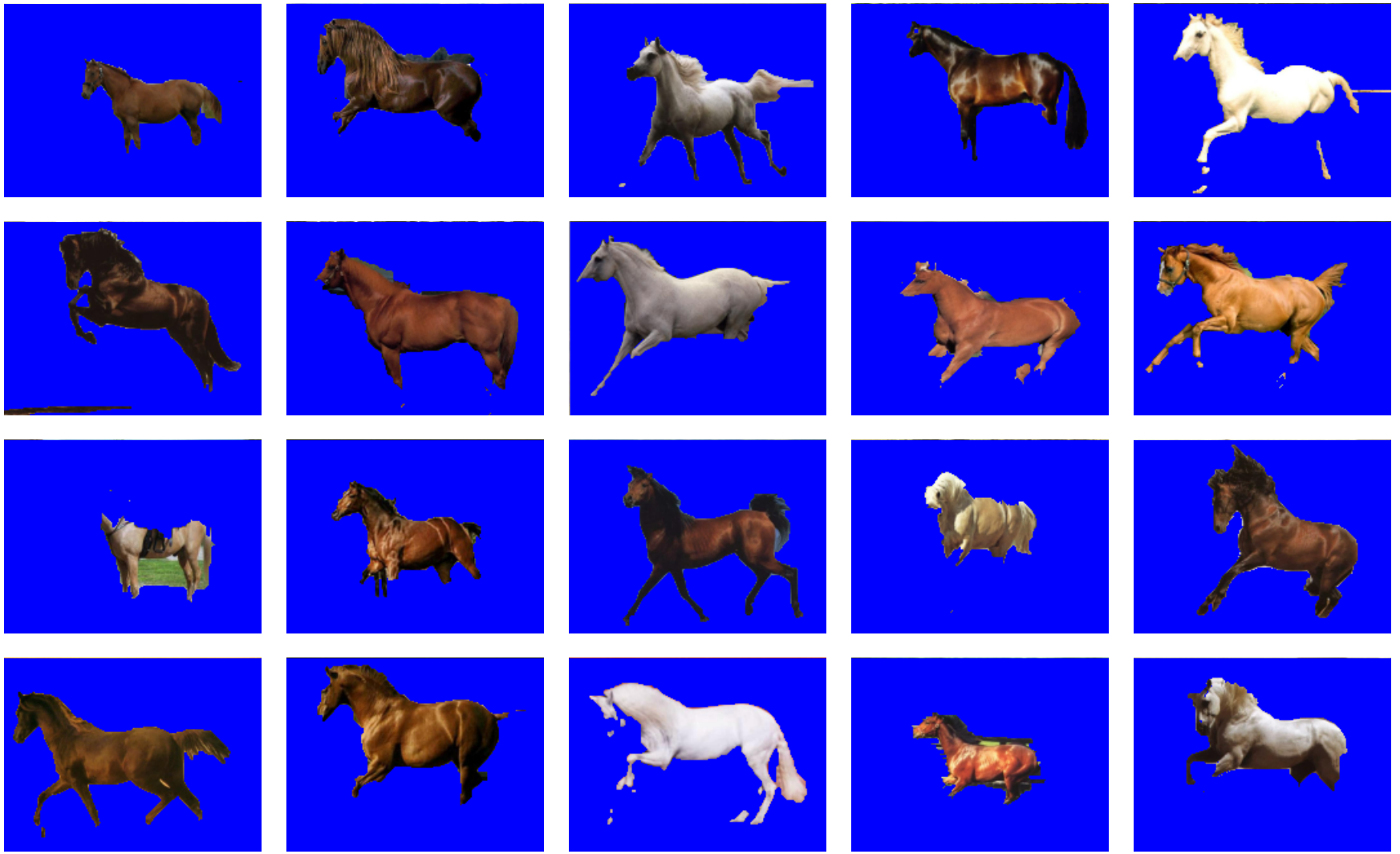
Levin & Weiss [ECCV 2006]

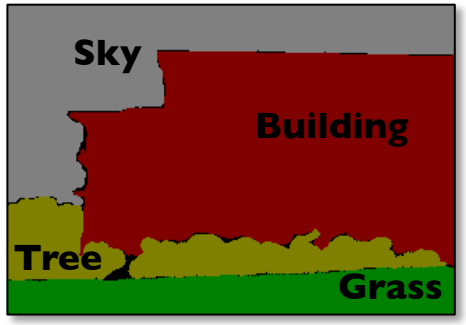
Levin & Weiss [ECCV 2006]





Semantic Segmentation

Joint Object recognition & segmentation

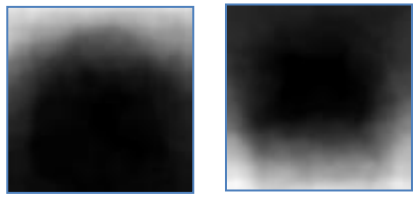


$$E(x,\omega) = \sum_i \theta_i(\omega, x_i) + \sum_i \theta_i(x_i) + \sum_i \theta_i(x_i) + \sum_{i,j} \theta_{ij}(x_i,x_j)$$

(color) (location) (class) (edge aware Ising prior)

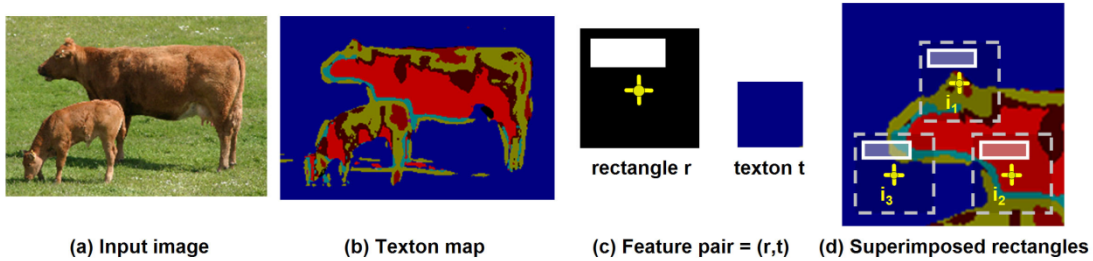
$x_i \in \{1,\ldots,K\}$ for K object classes

Location



sky grass

Class (boosted textons)



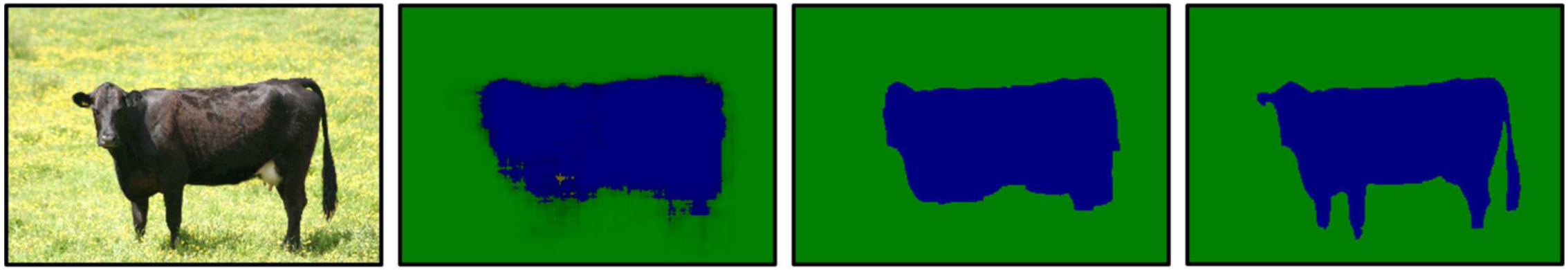
(a) Input image (b) Texton map (c) Feature pair = (r,t) (d) Superimposed rectangles

[TextonBoost; Shotton et al, '06]

C. Rother

Semantic Segmentation

Joint Object recognition & segmentation



(a) (b) 69.6% (c) 70.3% (d) 72.2%

Class + location

\+ edges

\+ color

[TextonBoost; Shotton et al, '06]

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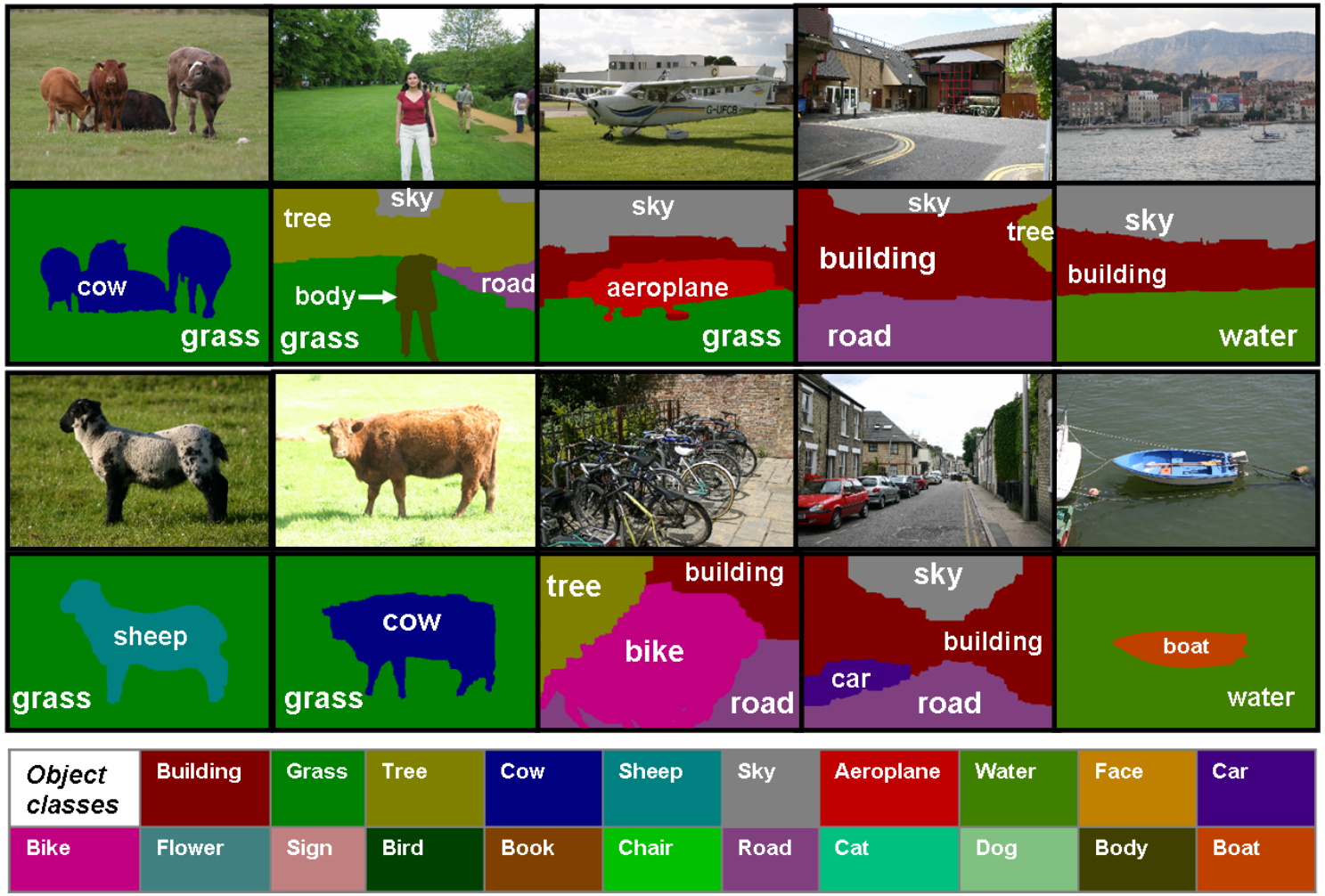
Semantic Segmentation

Joint Object recognition & segmentation

Good results …



[TextonBoost; Shotton et al, '06]

C. Rother

Semantic Segmentation

Joint Object recognition & segmentation

Failure cases…

[TextonBoost; Shotton et al, '06]

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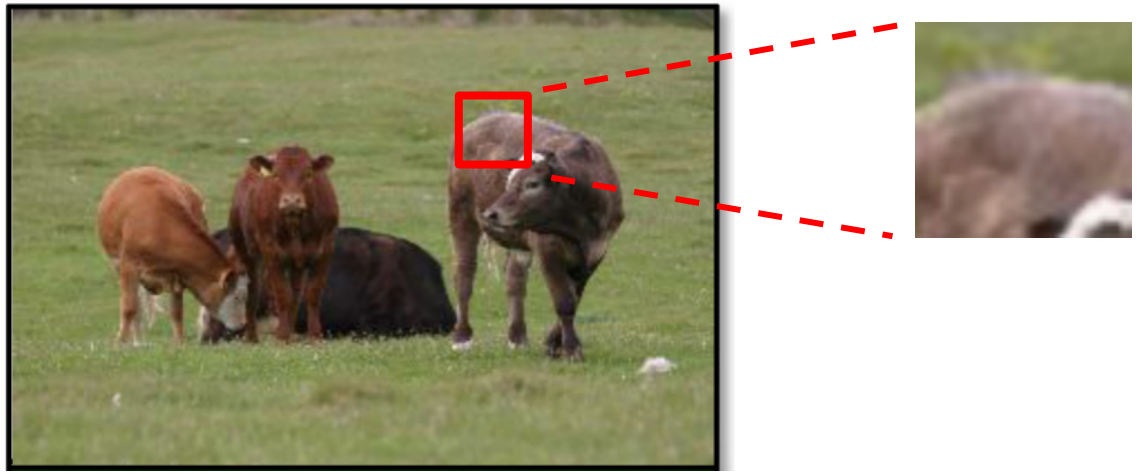
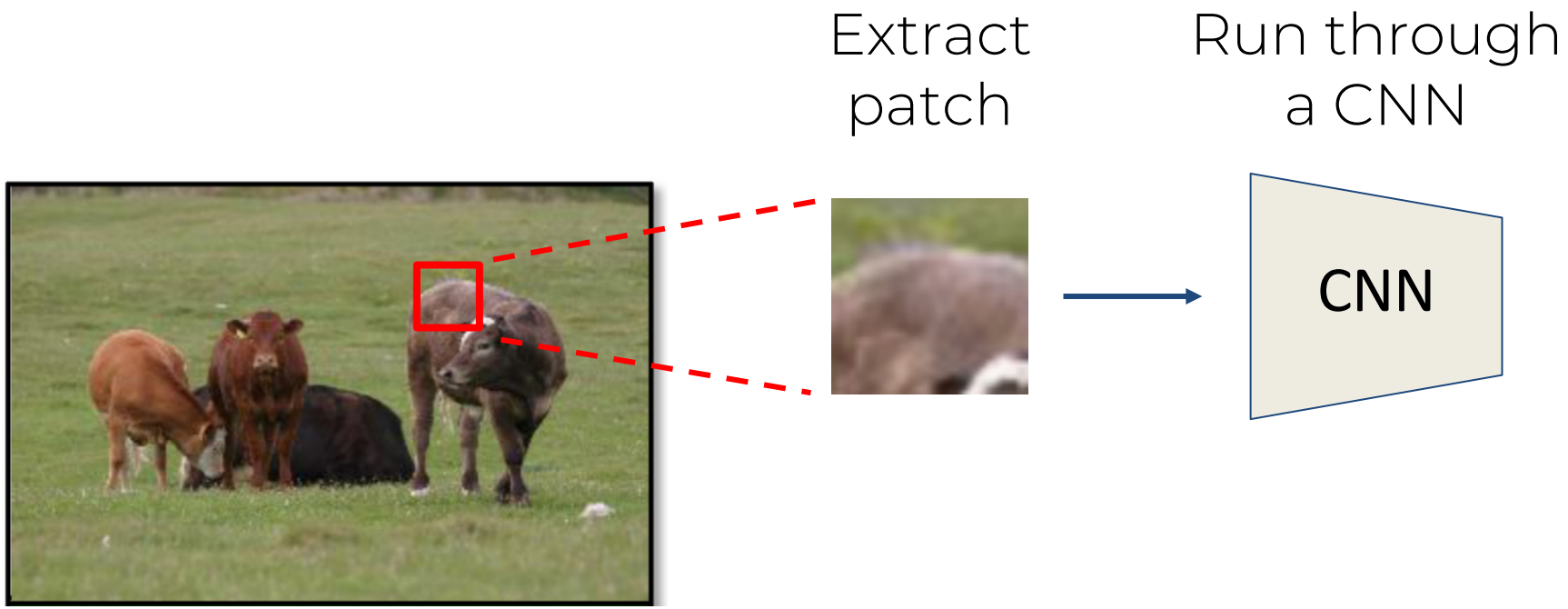
Deep Semantic Segmentation

Deep Semantic Segmentation

Extract patch



Deep Semantic Segmentation



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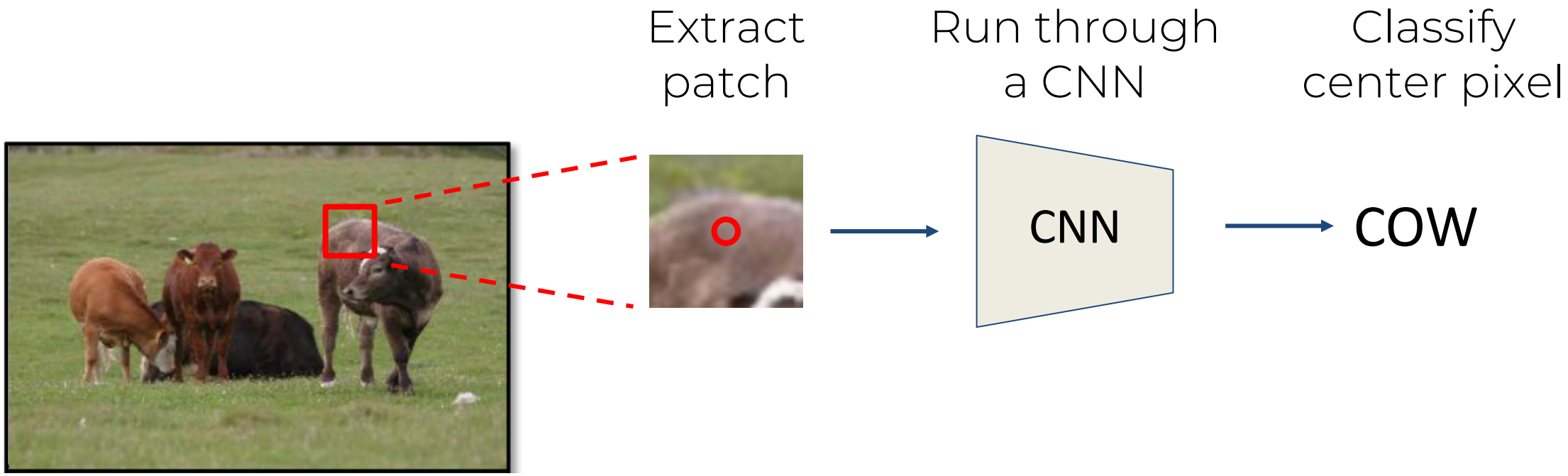

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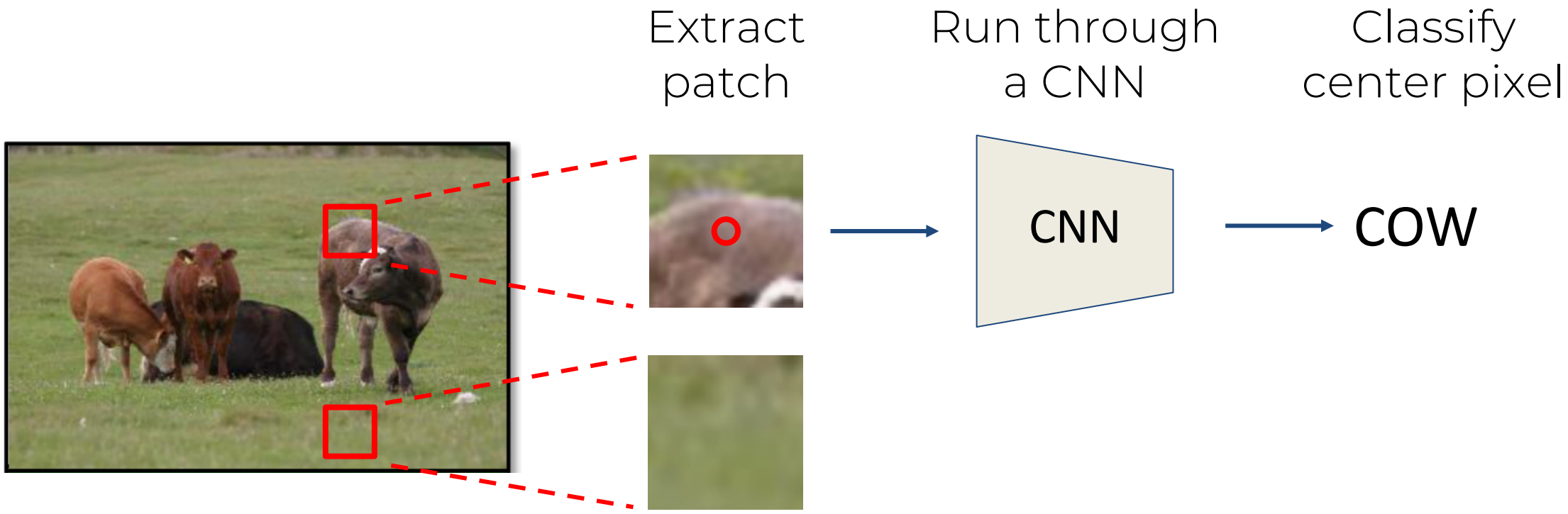

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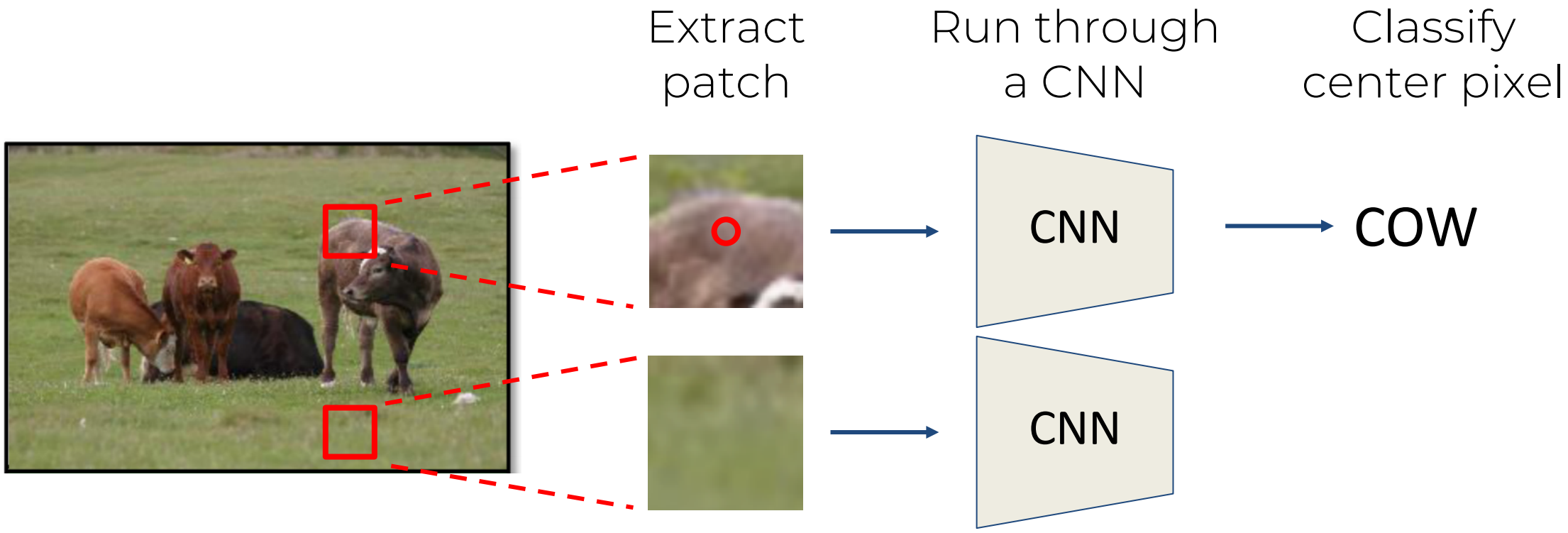

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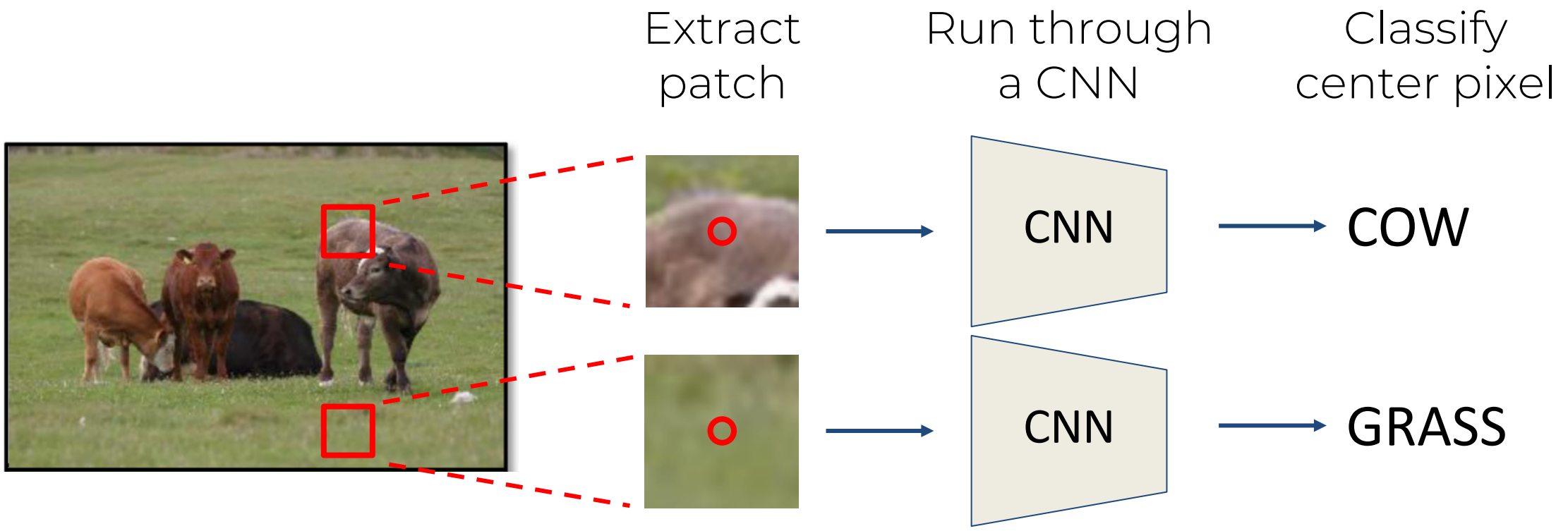

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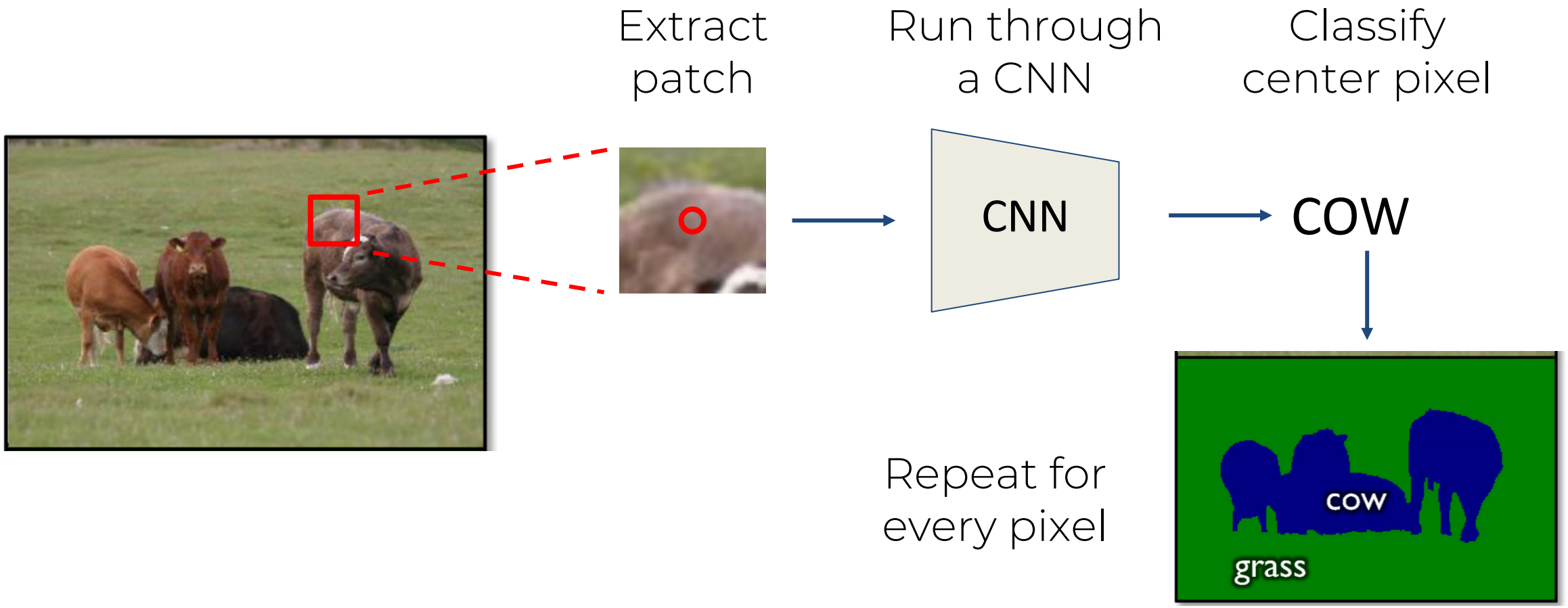
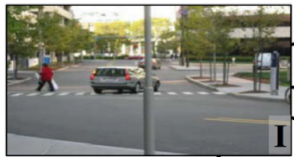


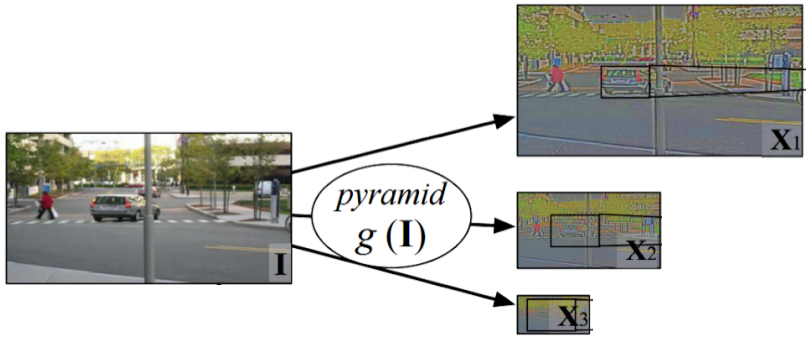
Semantic Segmentation: Multi-Scale



Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013

Semantic Segmentation: Multi-Scale

Resize image to multiple scales



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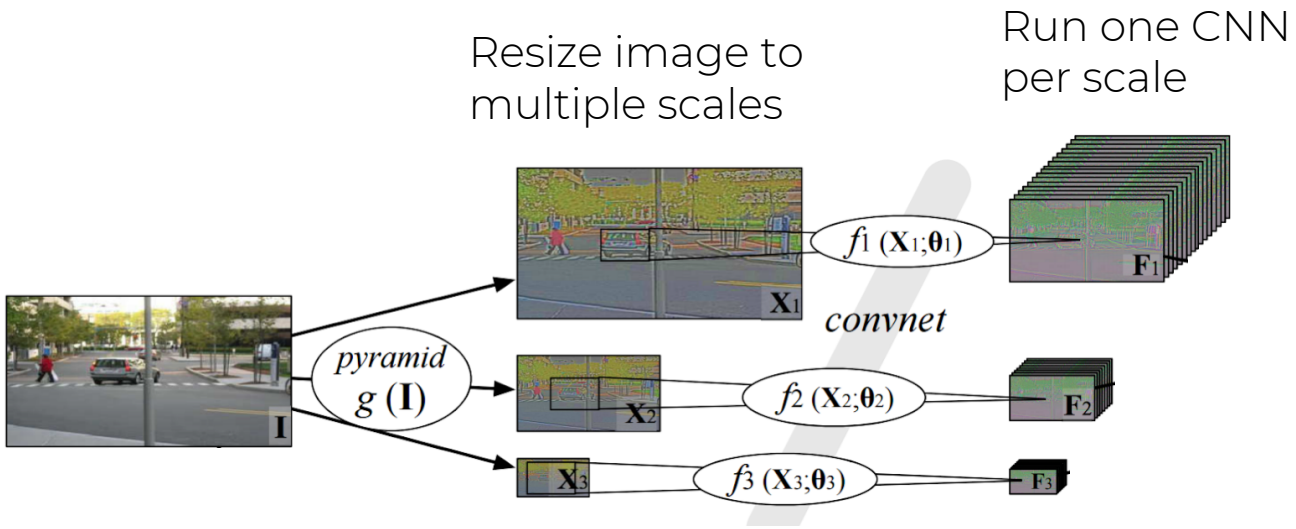

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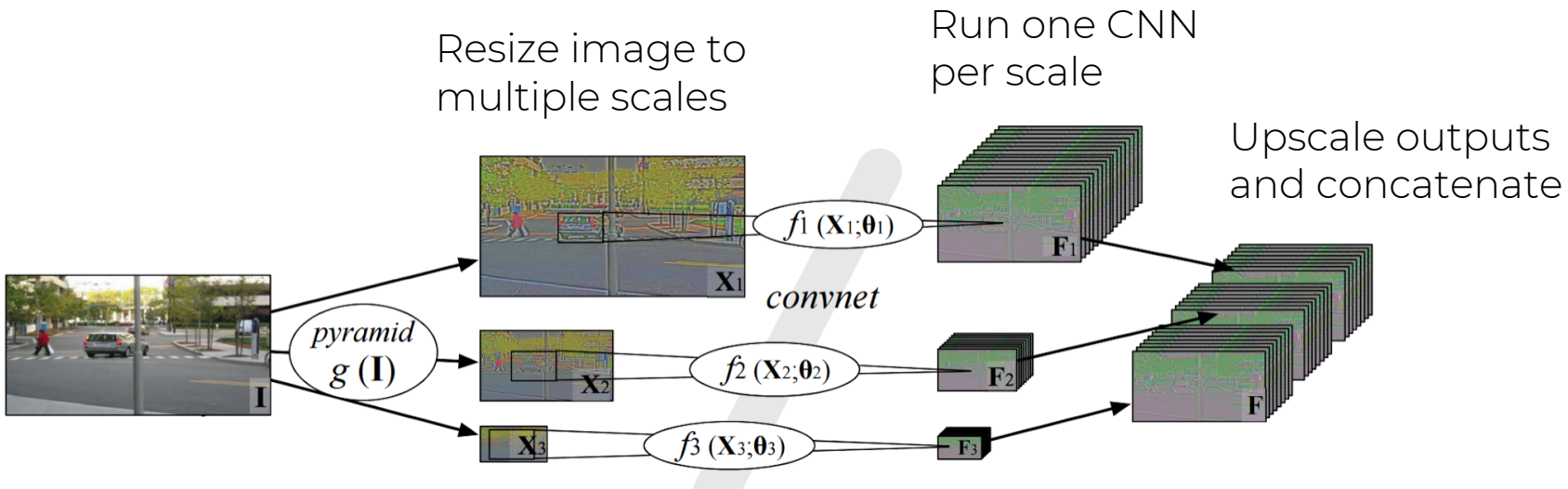

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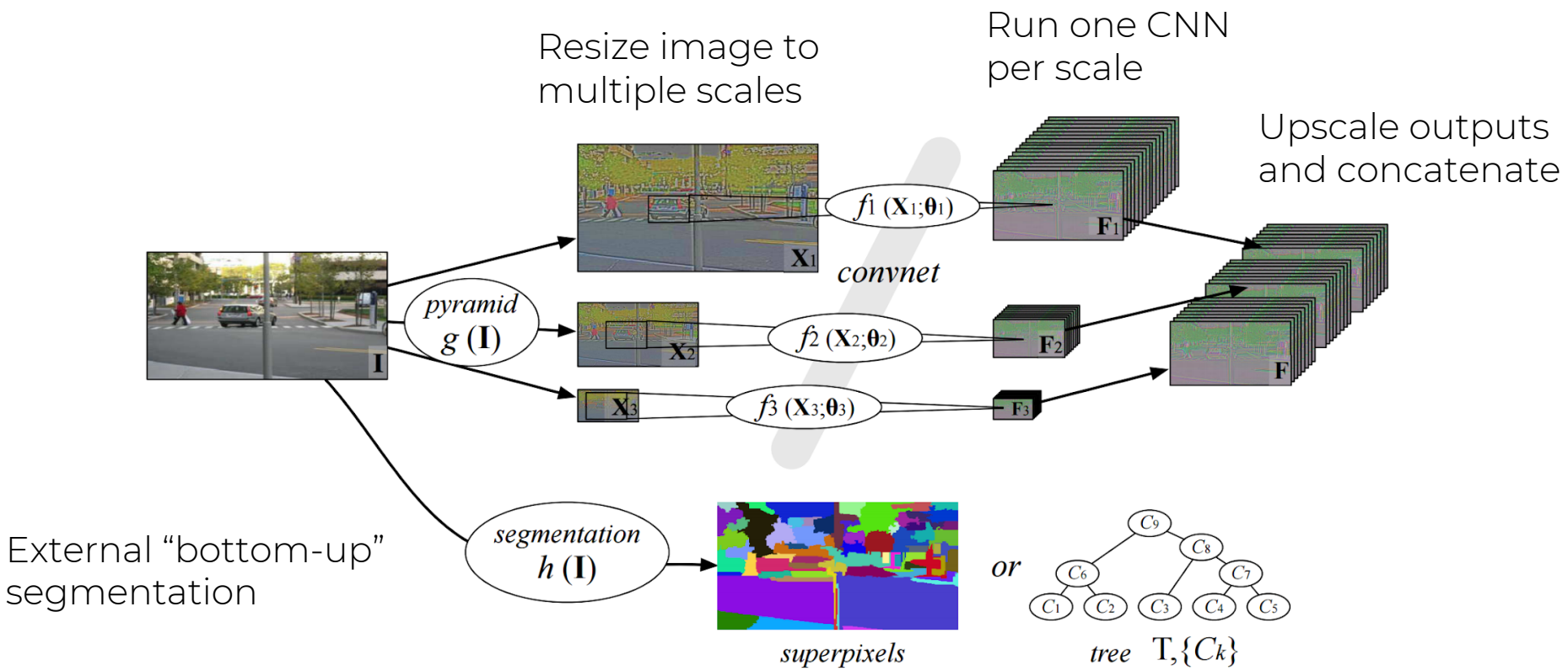

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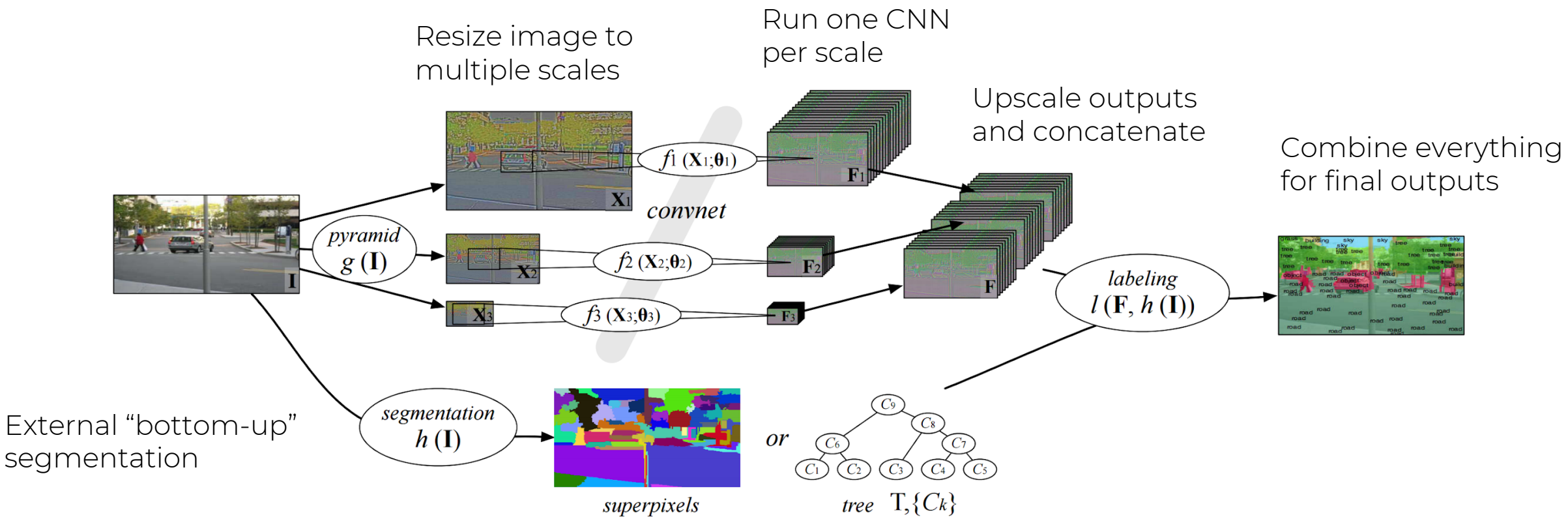
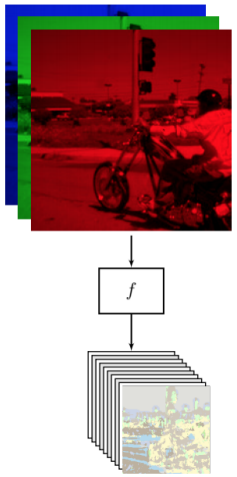


Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

Semantic Segmentation: Refinement

Apply CNN once to get labels

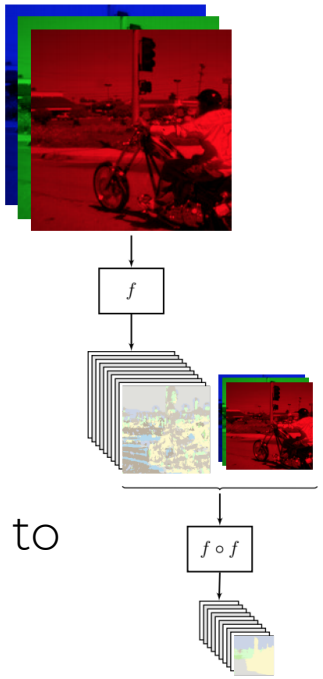


Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Semantic Segmentation: Refinement

Apply CNN once to get labels

Apply AGAIN to refine labels



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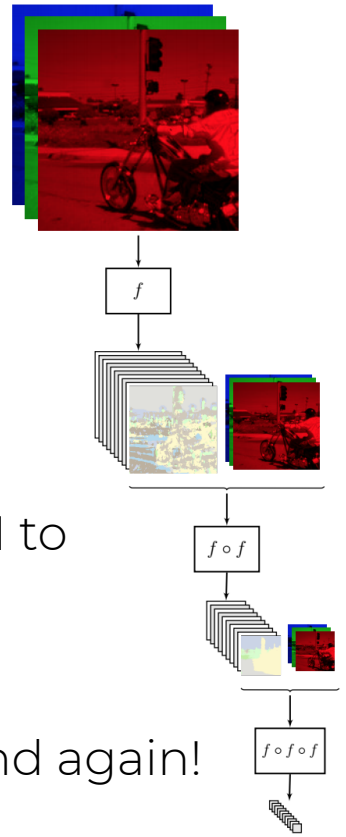
Semantic Segmentation: Refinement

Apply CNN once to get labels

Apply AGAIN to refine labels

And again!



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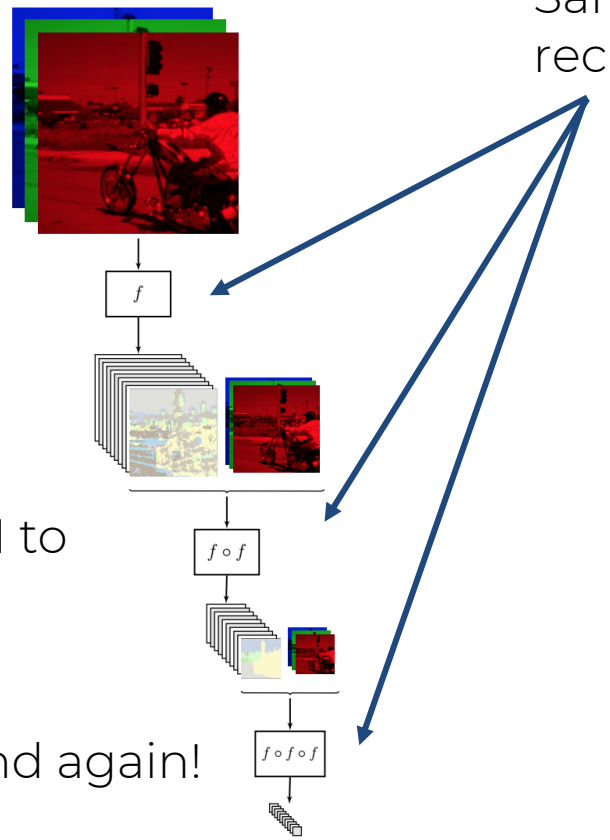
Semantic Segmentation: Refinement

Same CNN weights:
recurrent convolutional network

Apply CNN once to get labels

Apply AGAIN to refine labels

And again!



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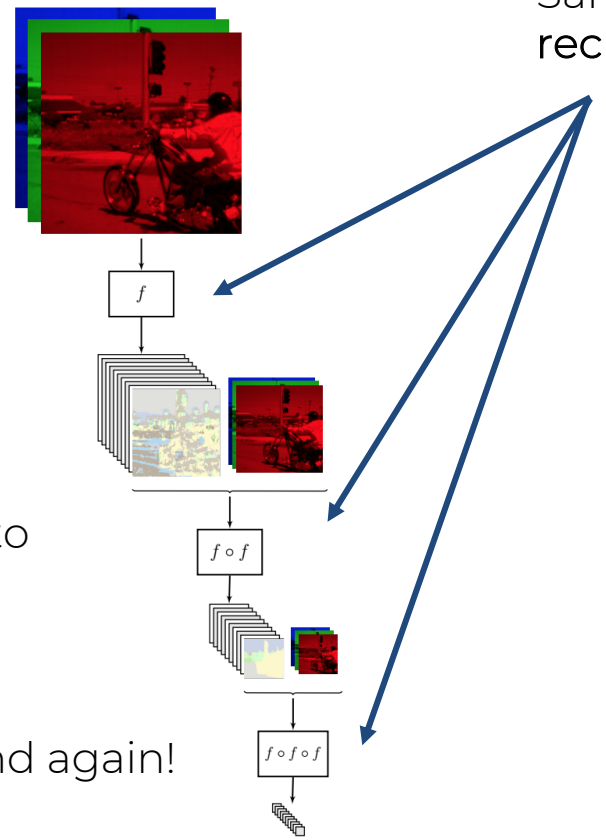
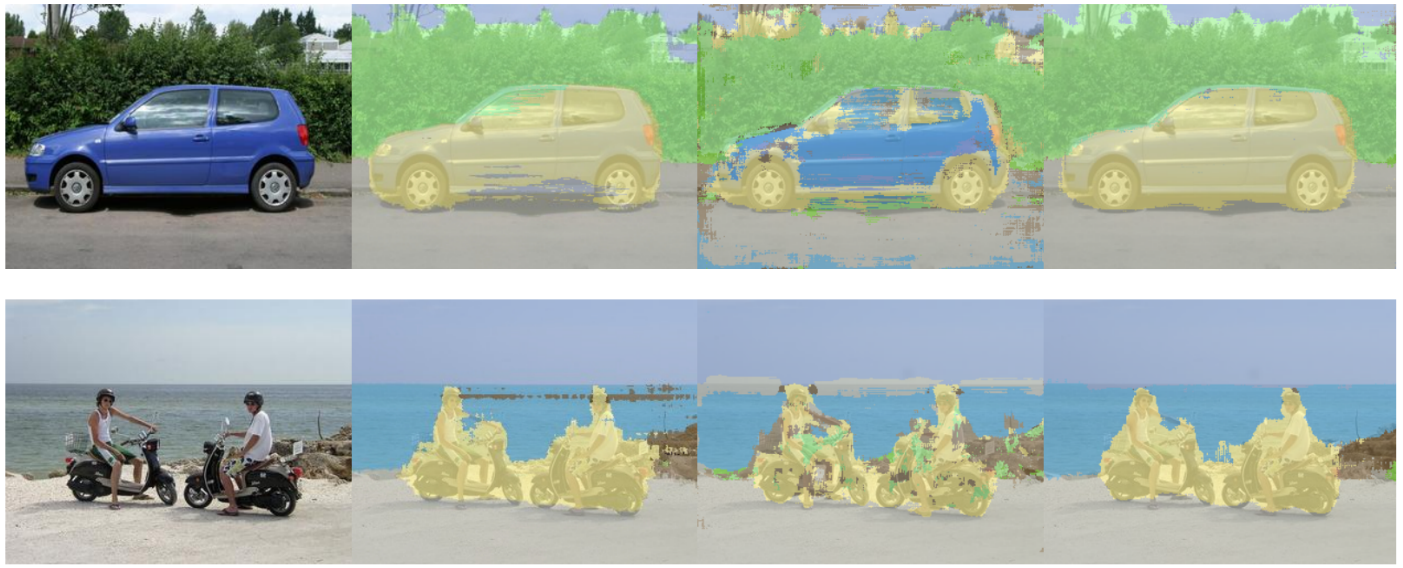
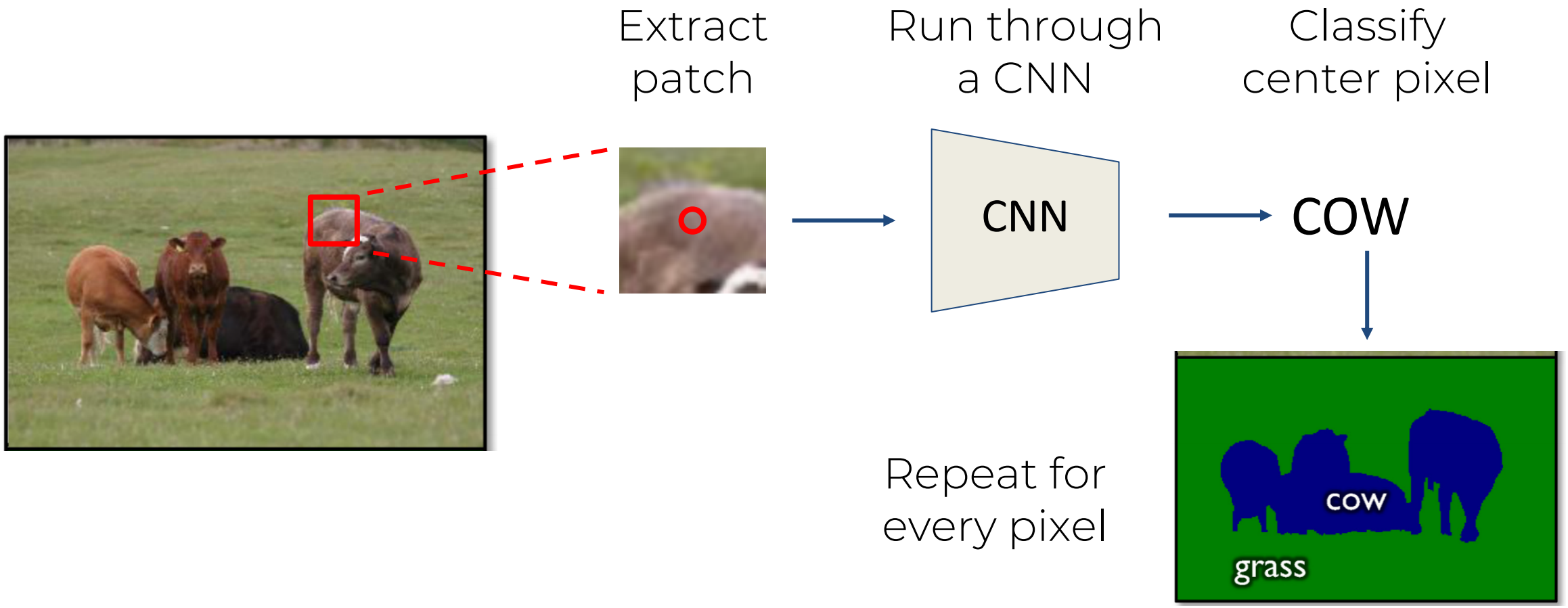




More iterations improve results

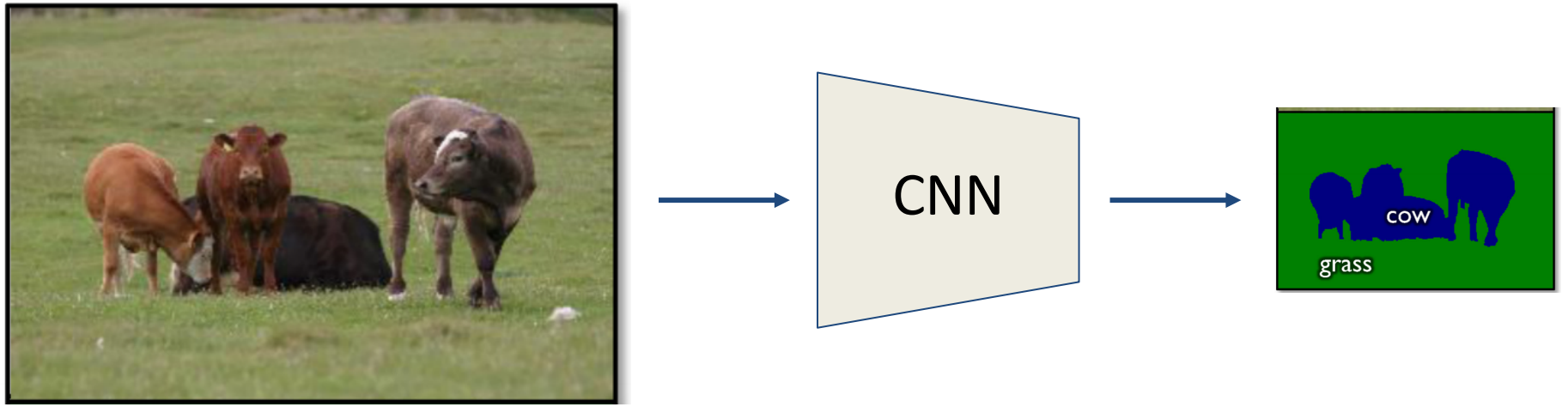
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Deep Semantic Segmentation



Semantic Segmentation Idea: Fully Convolutional

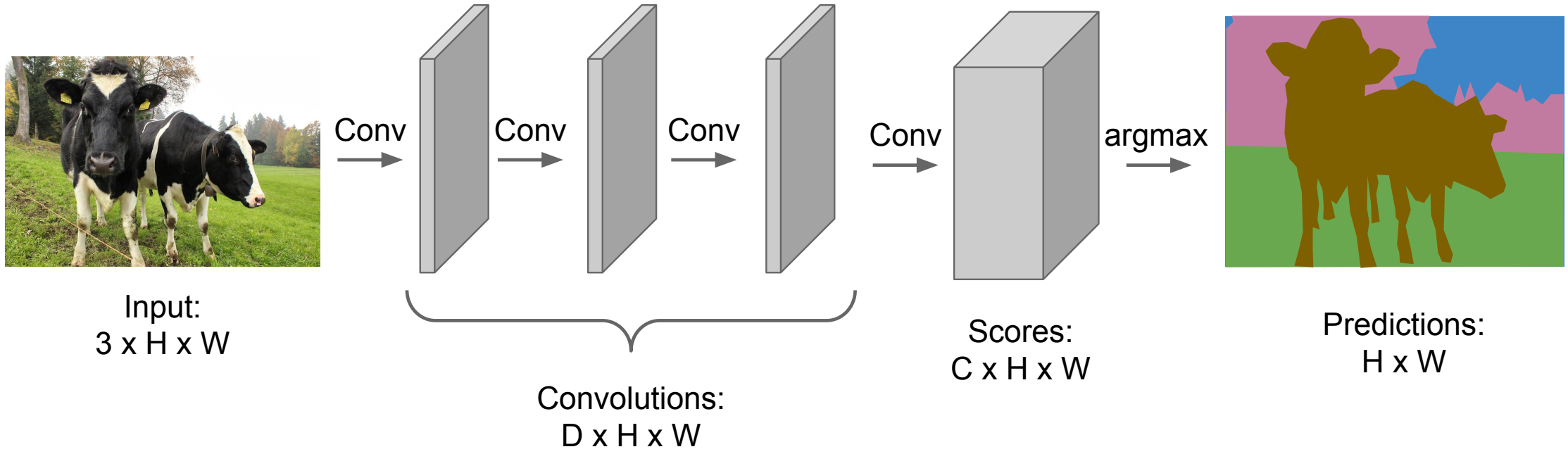
Run “fully convolutional” network to get all pixels at once



Smaller output due to pooling

Semantic Segmentation Idea: Fully Convolutional

- Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



Semantic Segmentation Idea: Fully Convolutional

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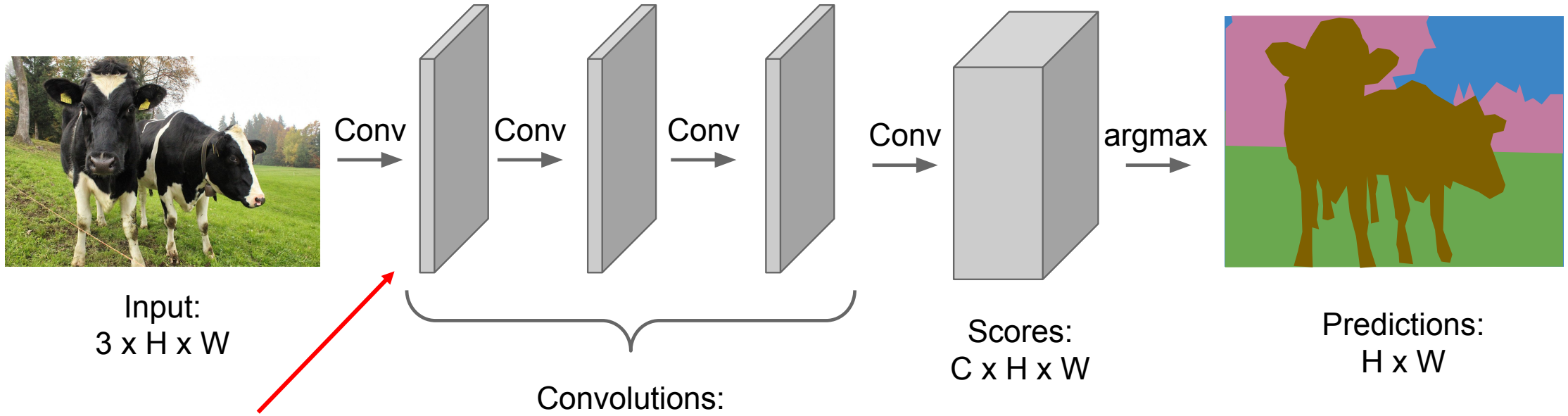
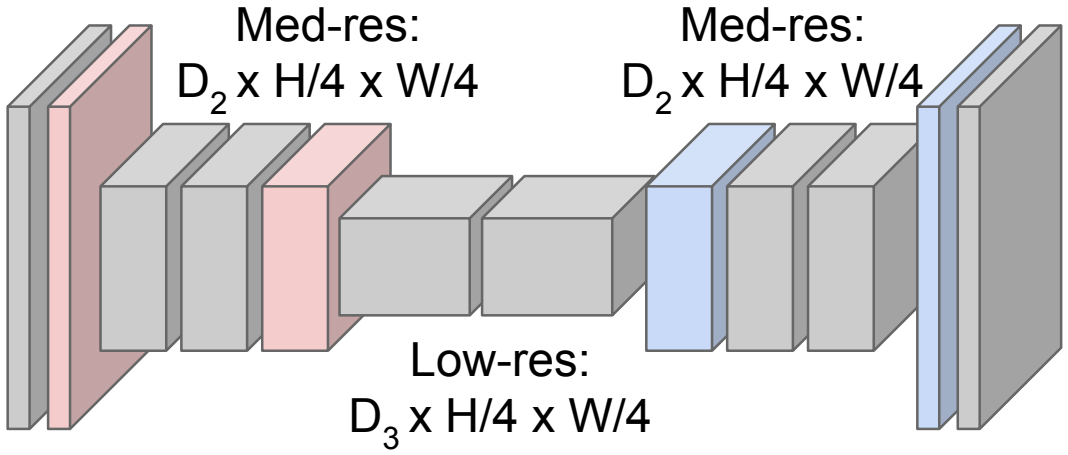


Semantic Segmentation Idea: Fully Convolutional

- Design network as a bunch of convolutional layers, with downsampling and upsampling inside the network!

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

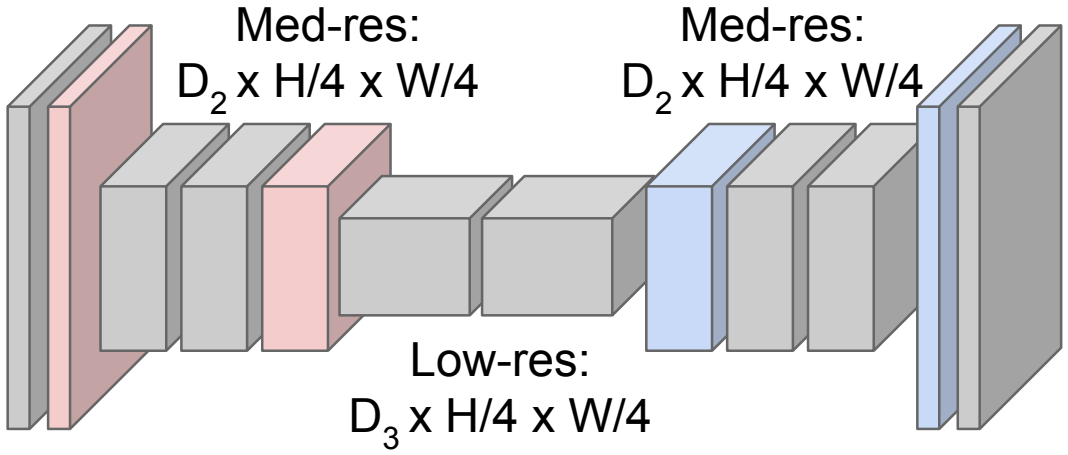
High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Semantic Segmentation Idea: Fully Convolutional

- Design network as a bunch of convolutional layers, with downsampling and upsampling inside the network!

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

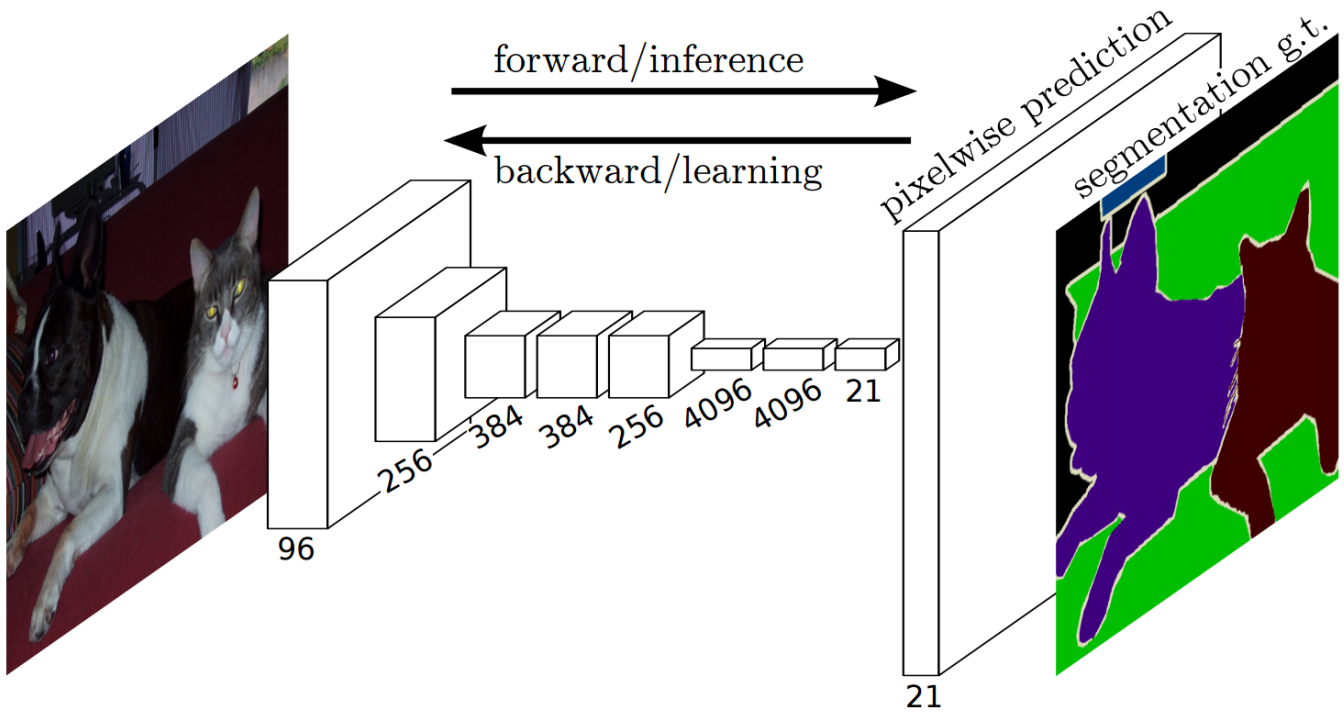
High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Downsampling:
Pooling, strided convolution

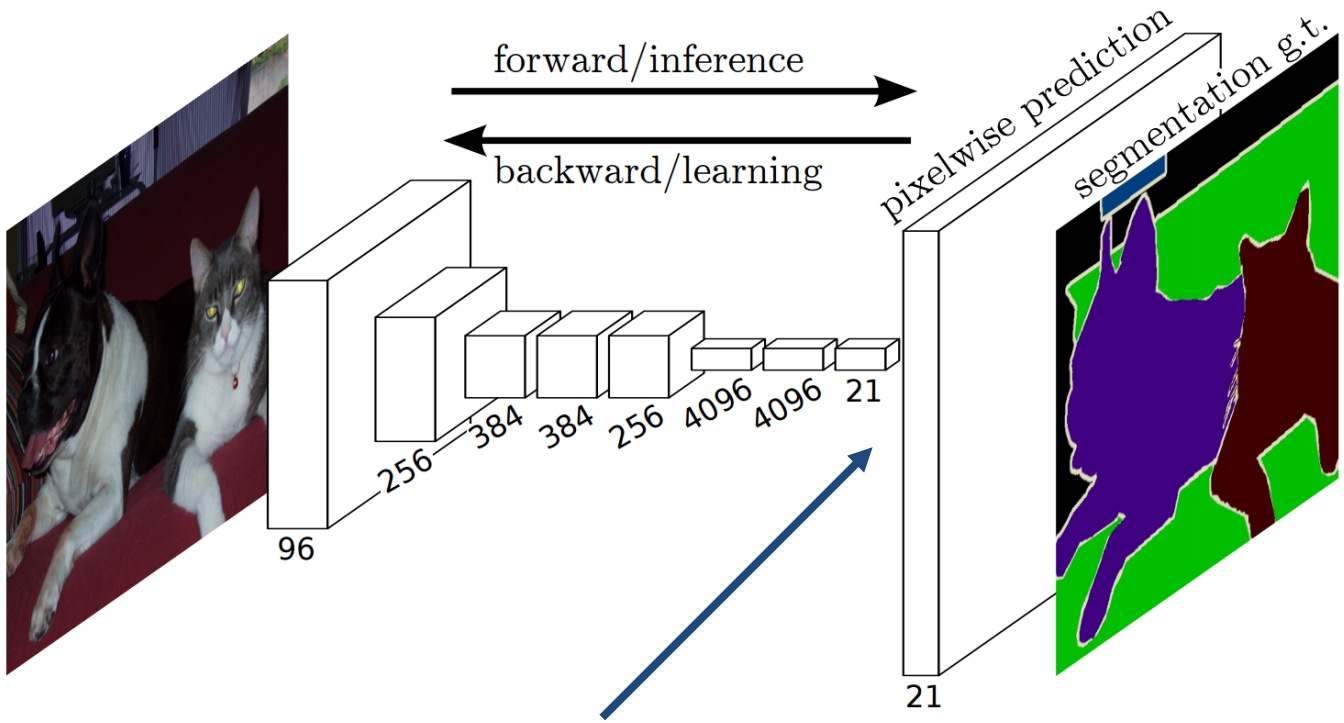
Upsampling: ???

Semantic Segmentation: Upsampling



Long, Shelhamer, and Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015

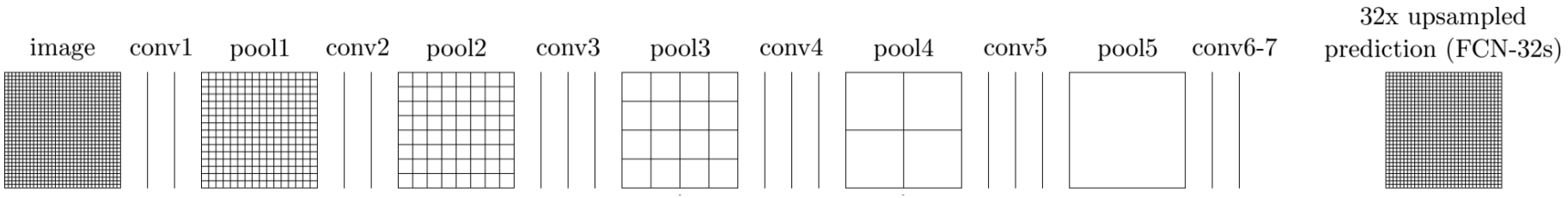
Semantic Segmentation: Upsampling



Learnable upsampling!

Long, Shelhamer, and Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015

Semantic Segmentation: Upsampling



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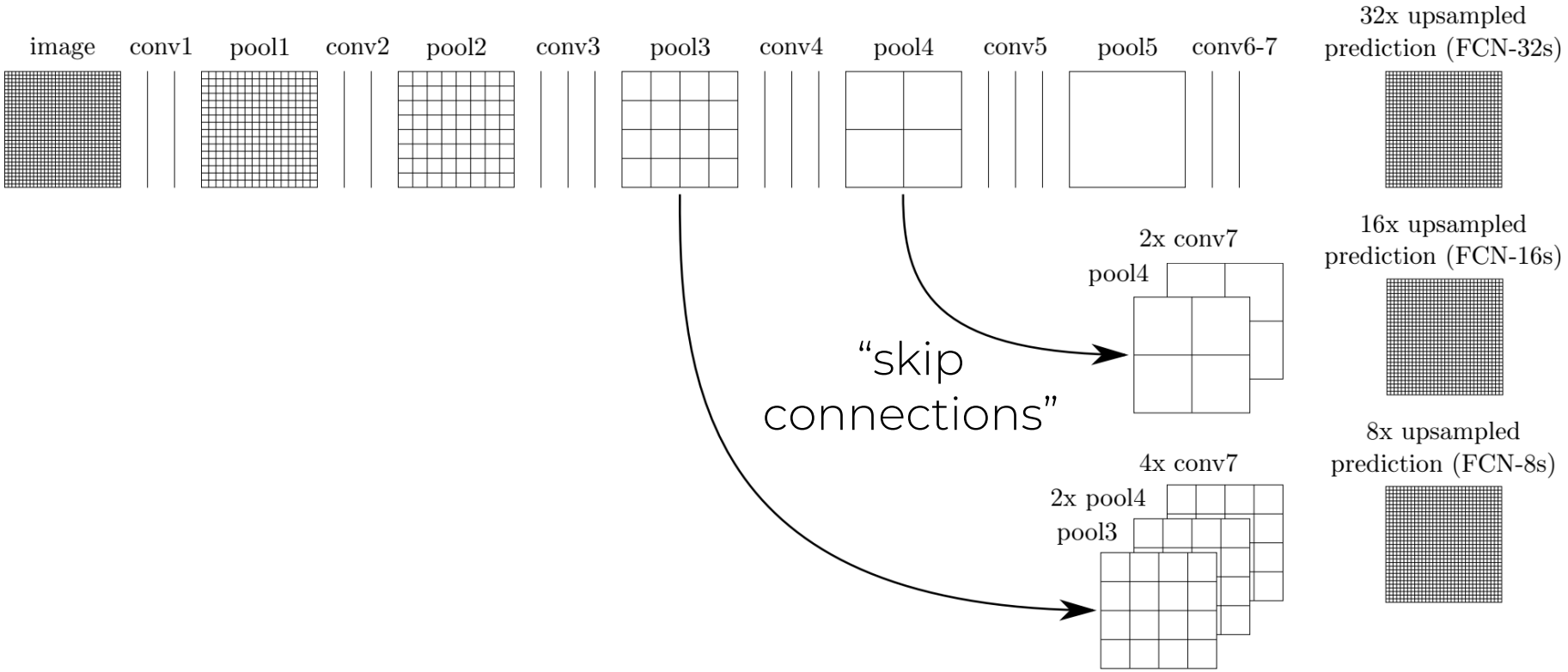

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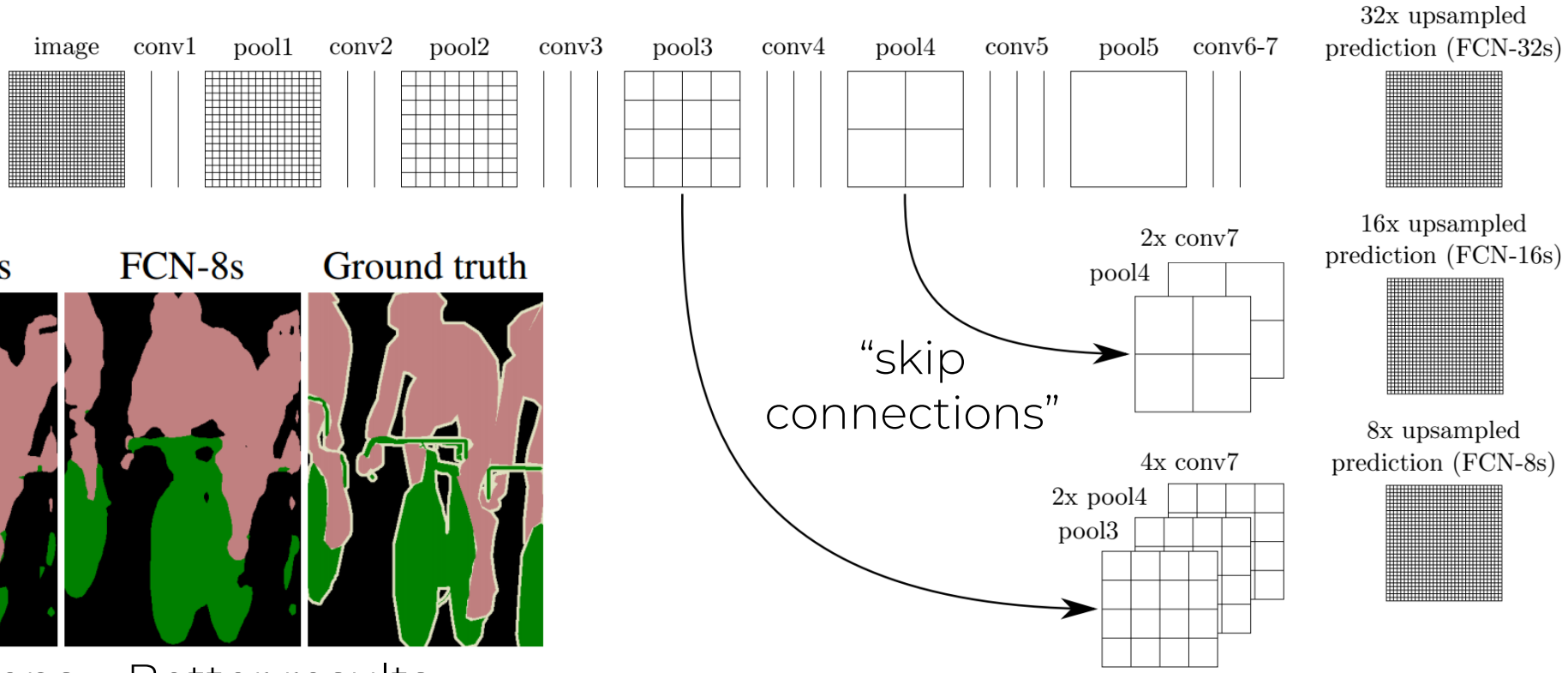
Semantic Segmentation: Upsampling

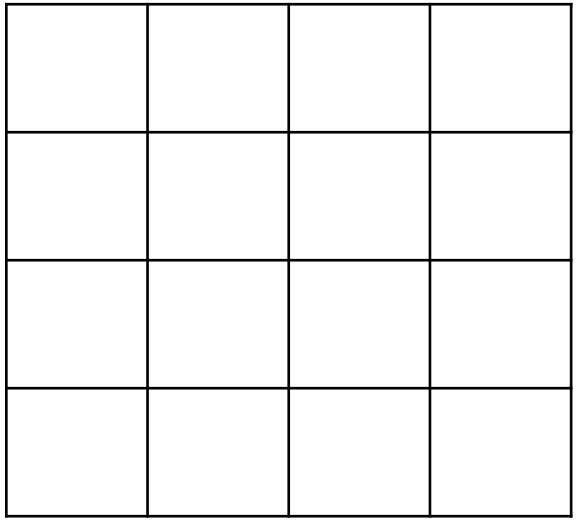


Skip connections = Better results

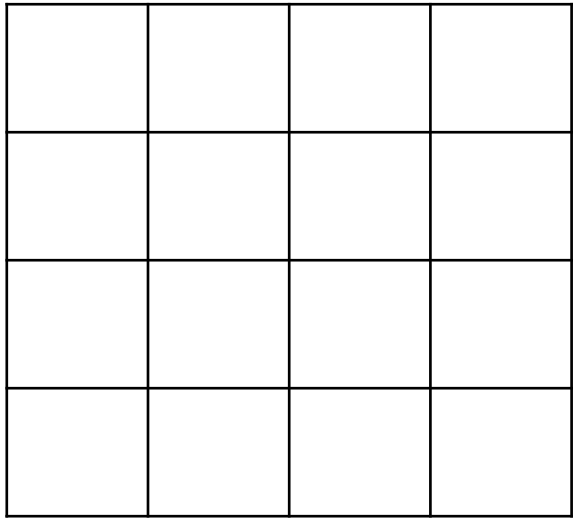
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Learnable Upsampling: “Deconvolution”

Typical 3 x 3 convolution, stride 1 pad 1

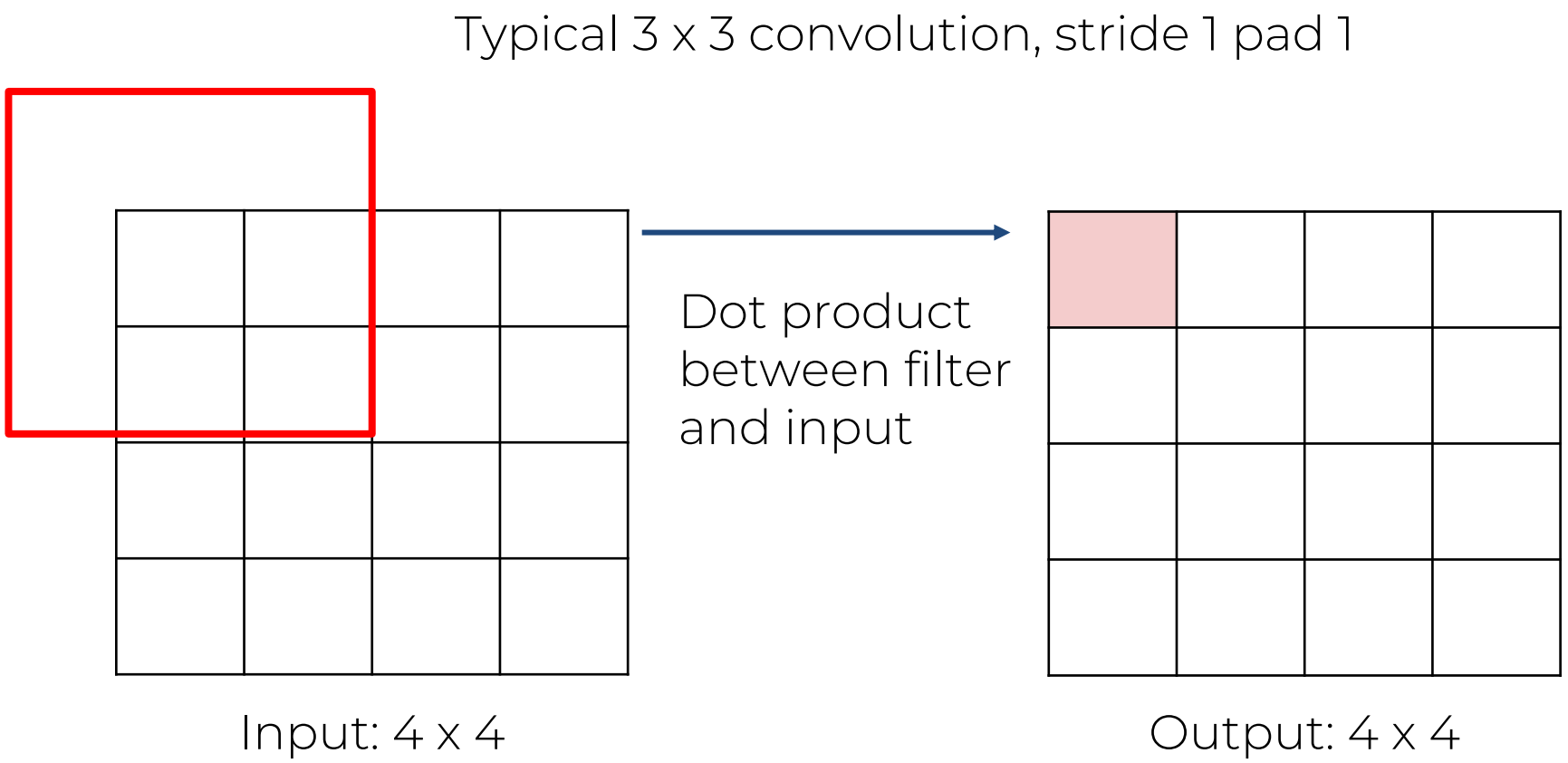


Input: 4 x 4



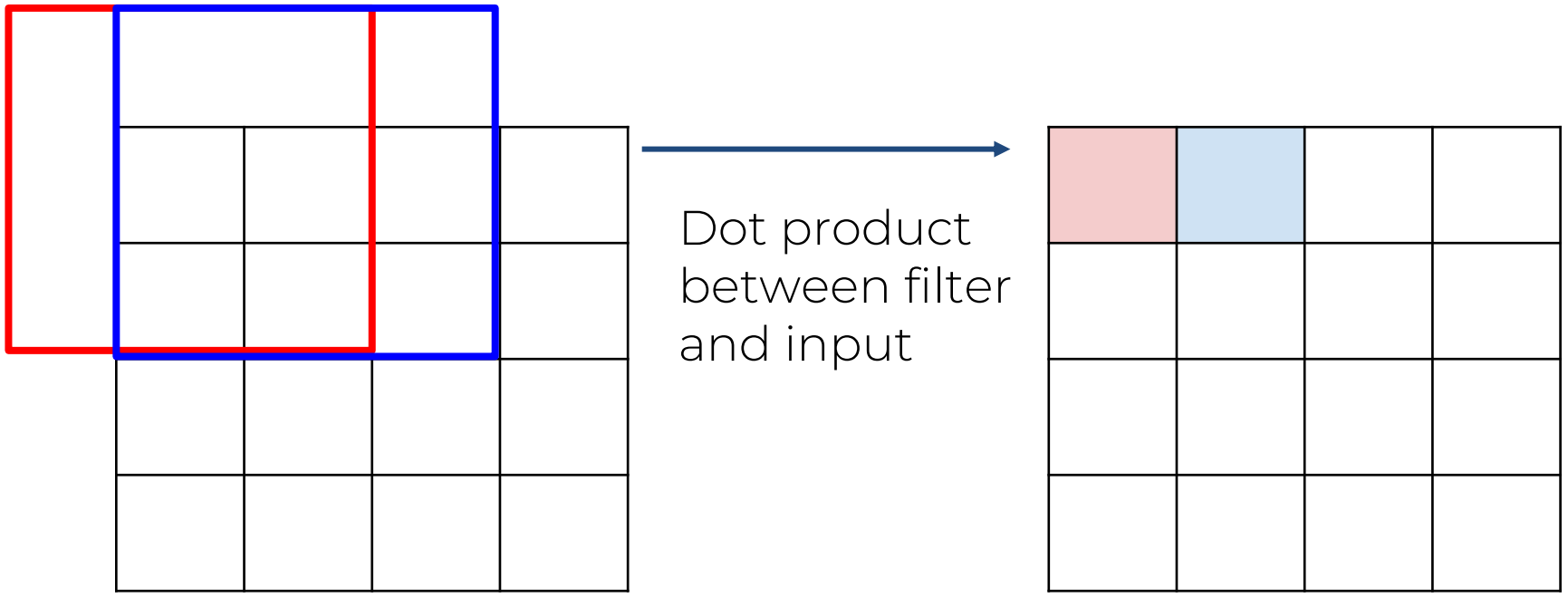
Output: 4 x 4

Learnable Upsampling: "Deconvolution"



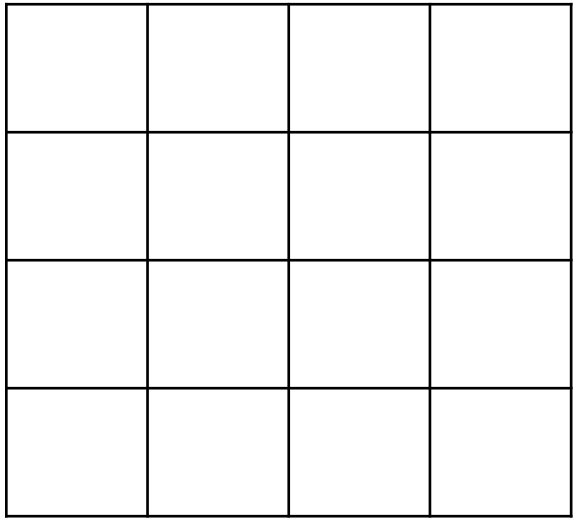
Learnable Upsampling: “Deconvolution”

Typical 3 x 3 convolution, stride 1 pad 1

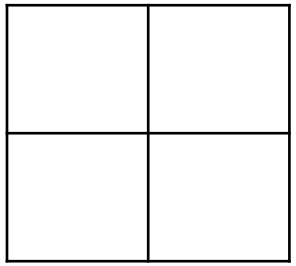


Learnable Upsampling: “Deconvolution”

Typical 3 x 3 convolution, **stride 2** pad 1

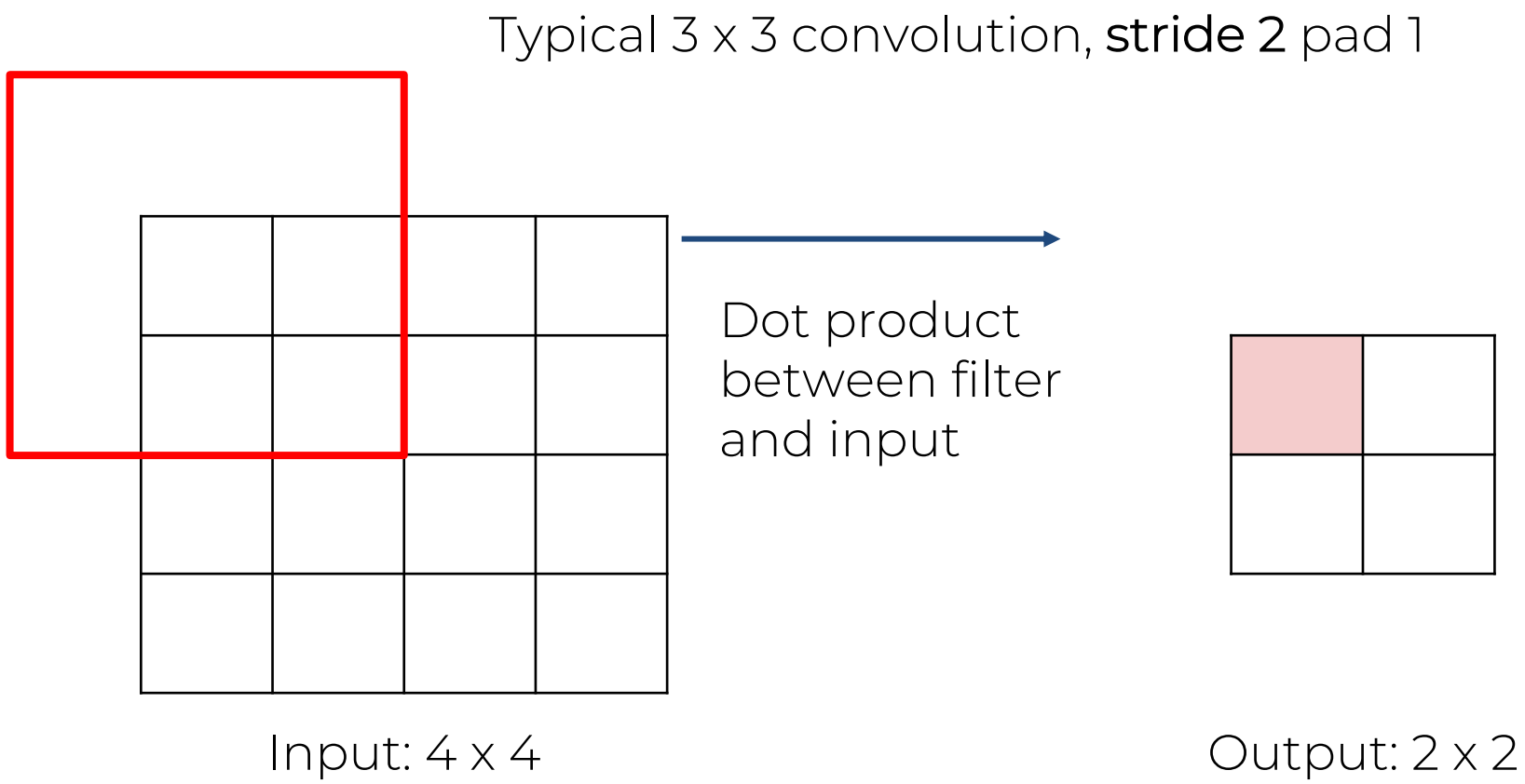


Input: 4 x 4

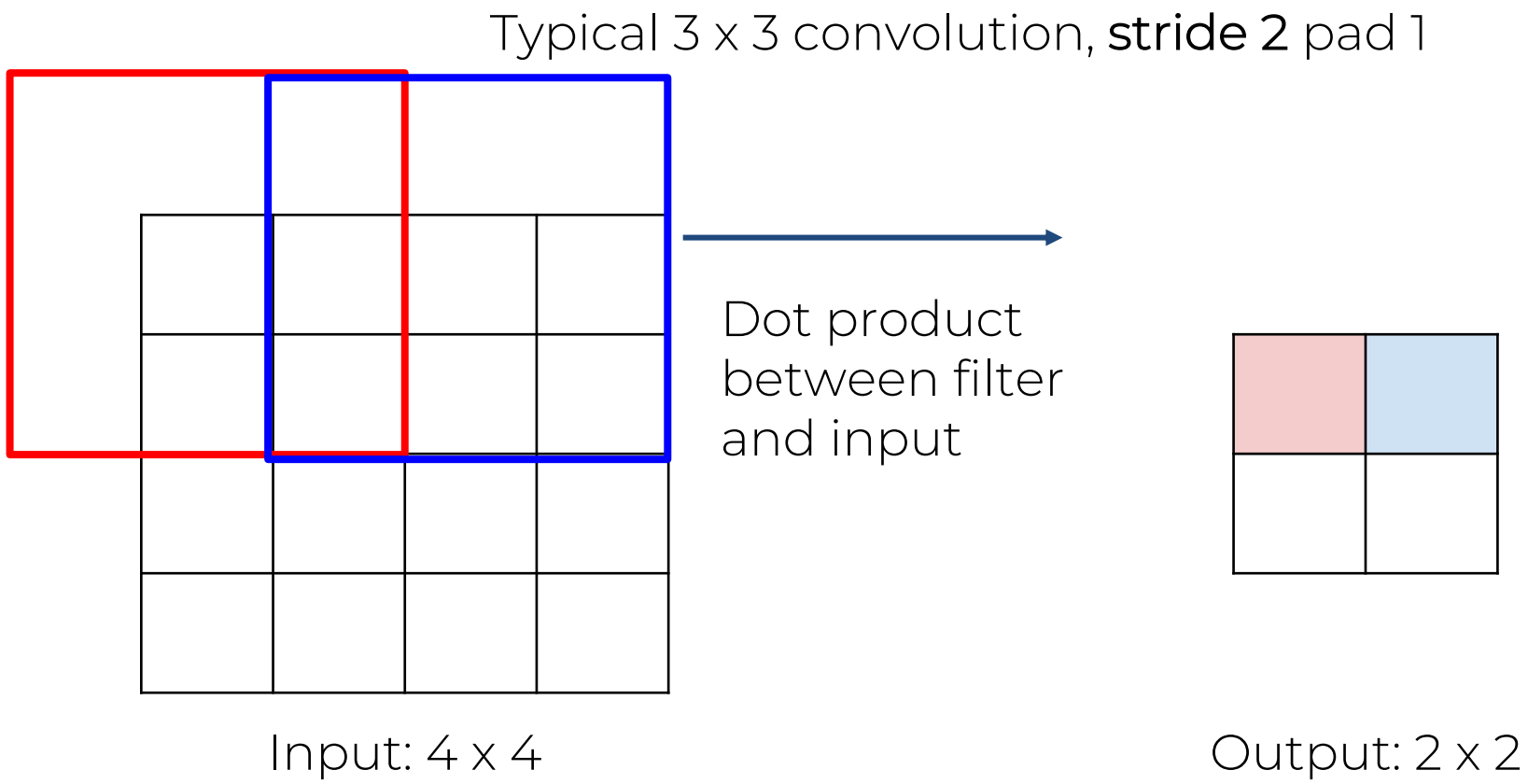


Output: 2 x 2

Learnable Upsampling: "Deconvolution"

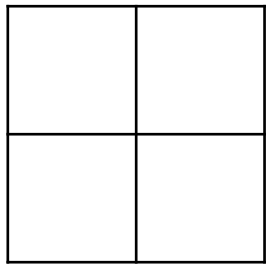


Learnable Upsampling: "Deconvolution"

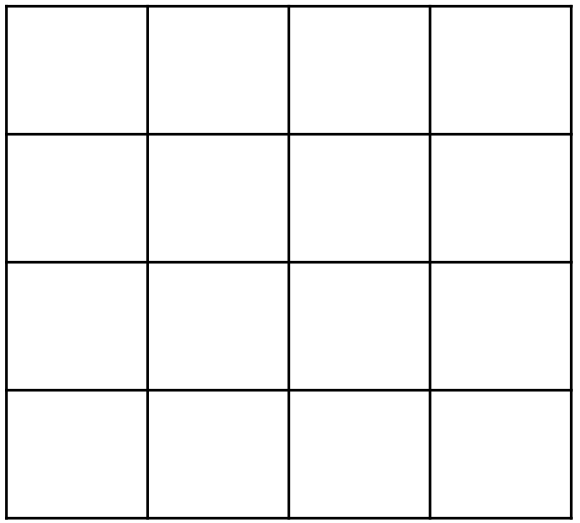


Learnable Upsampling: “Deconvolution”

3 x 3 deconvolution, stride 2 pad 1

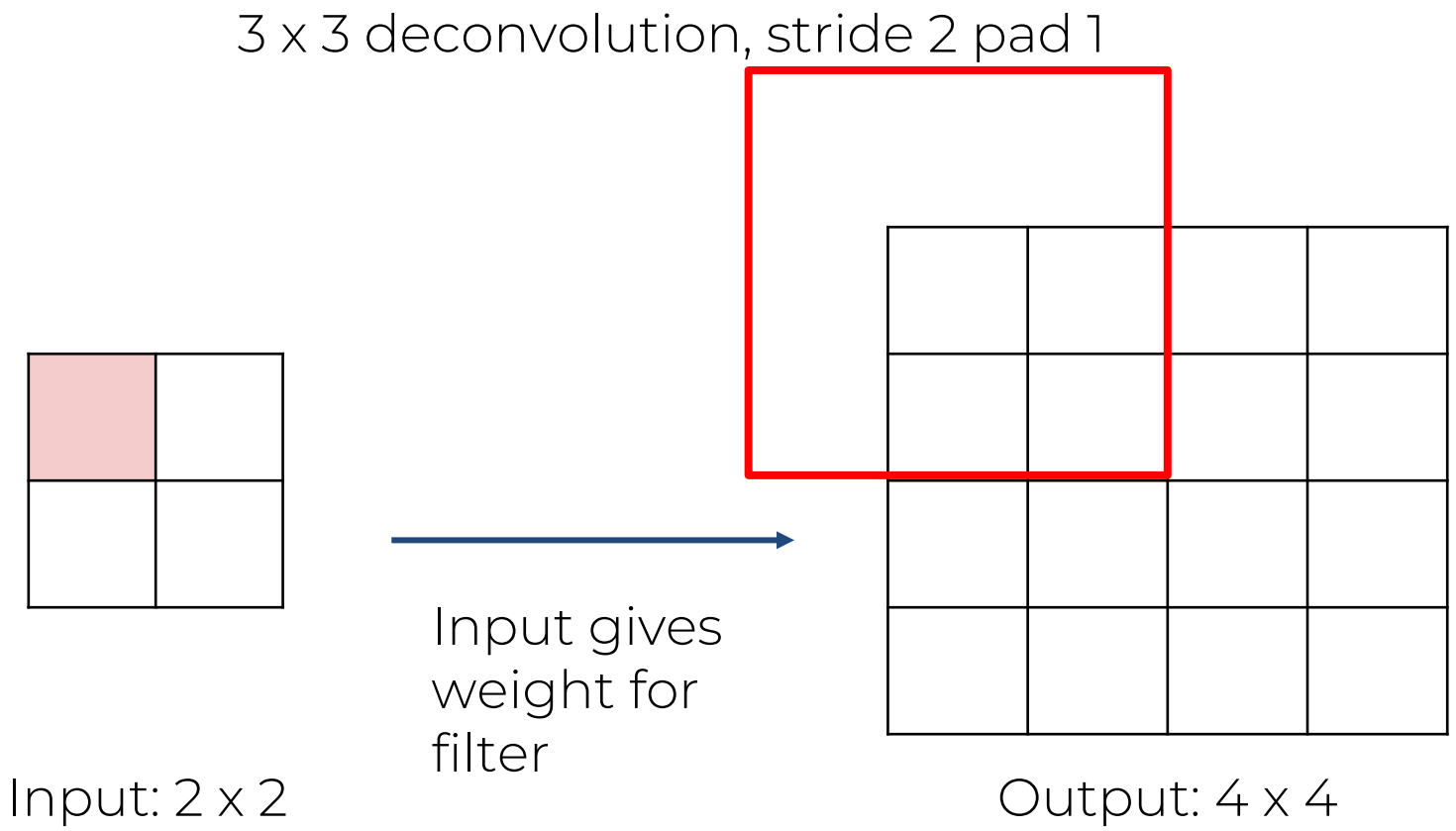


Input: 2 x 2

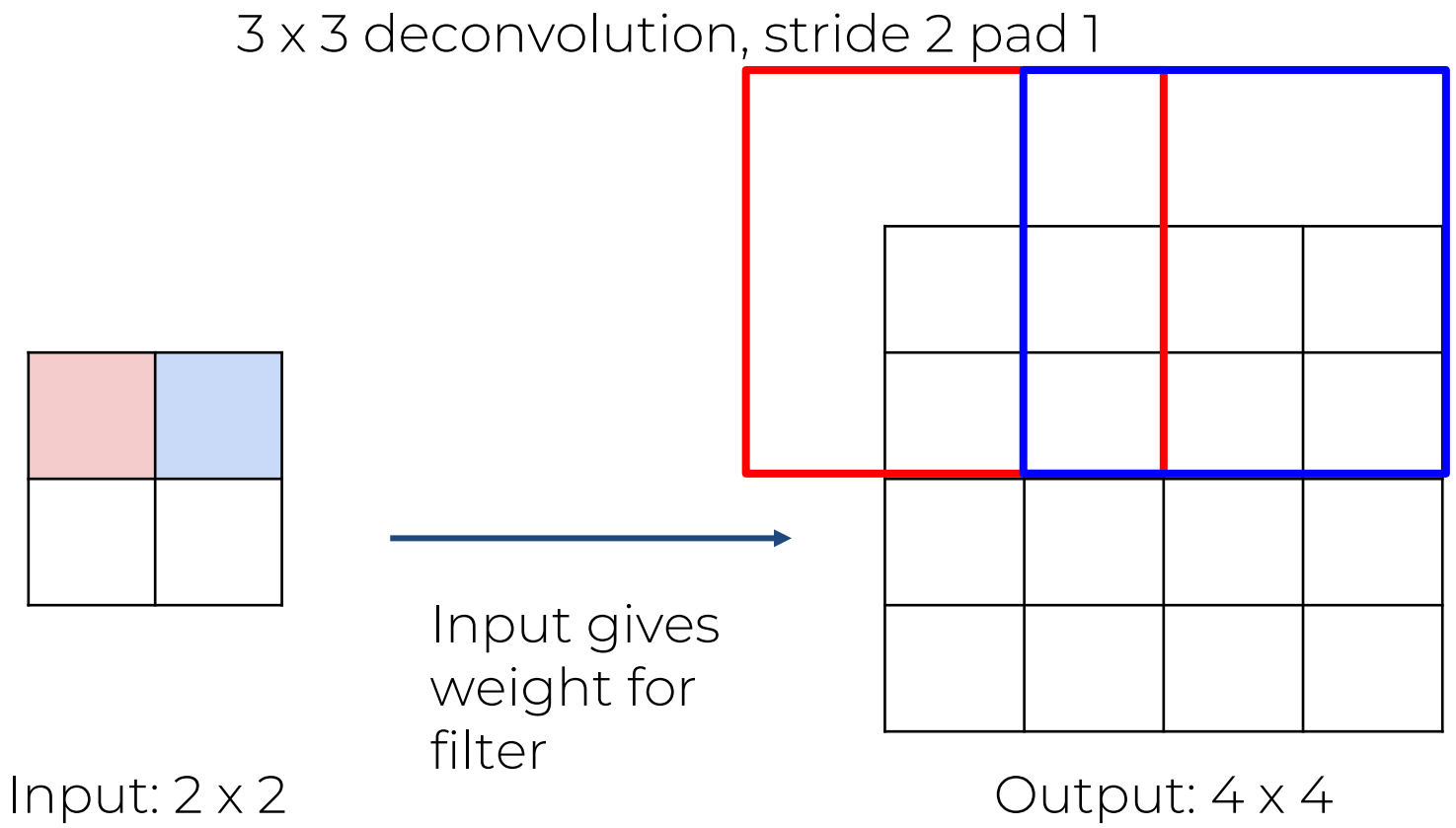


Output: 4 x 4

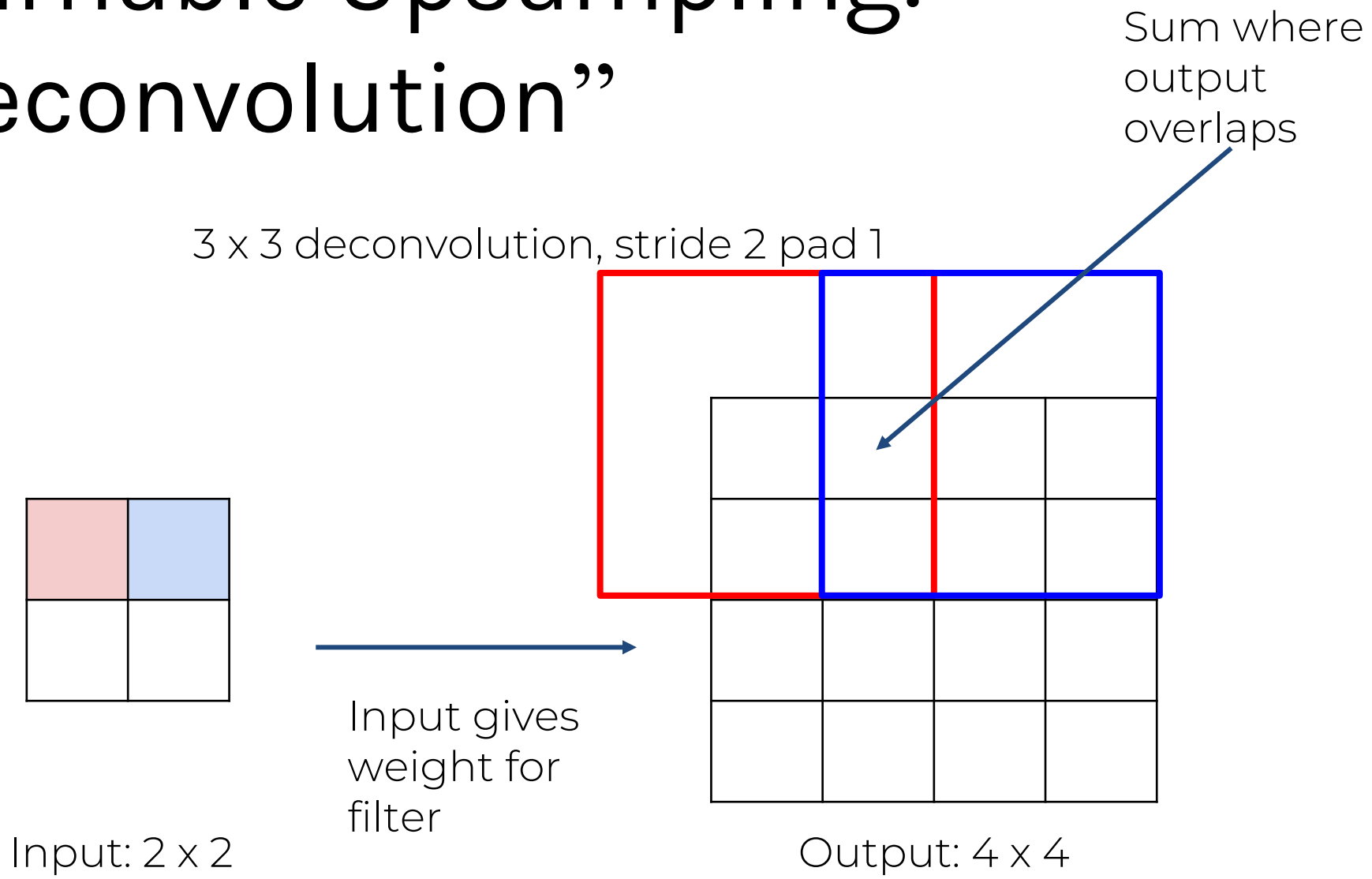
Learnable Upsampling: "Deconvolution"



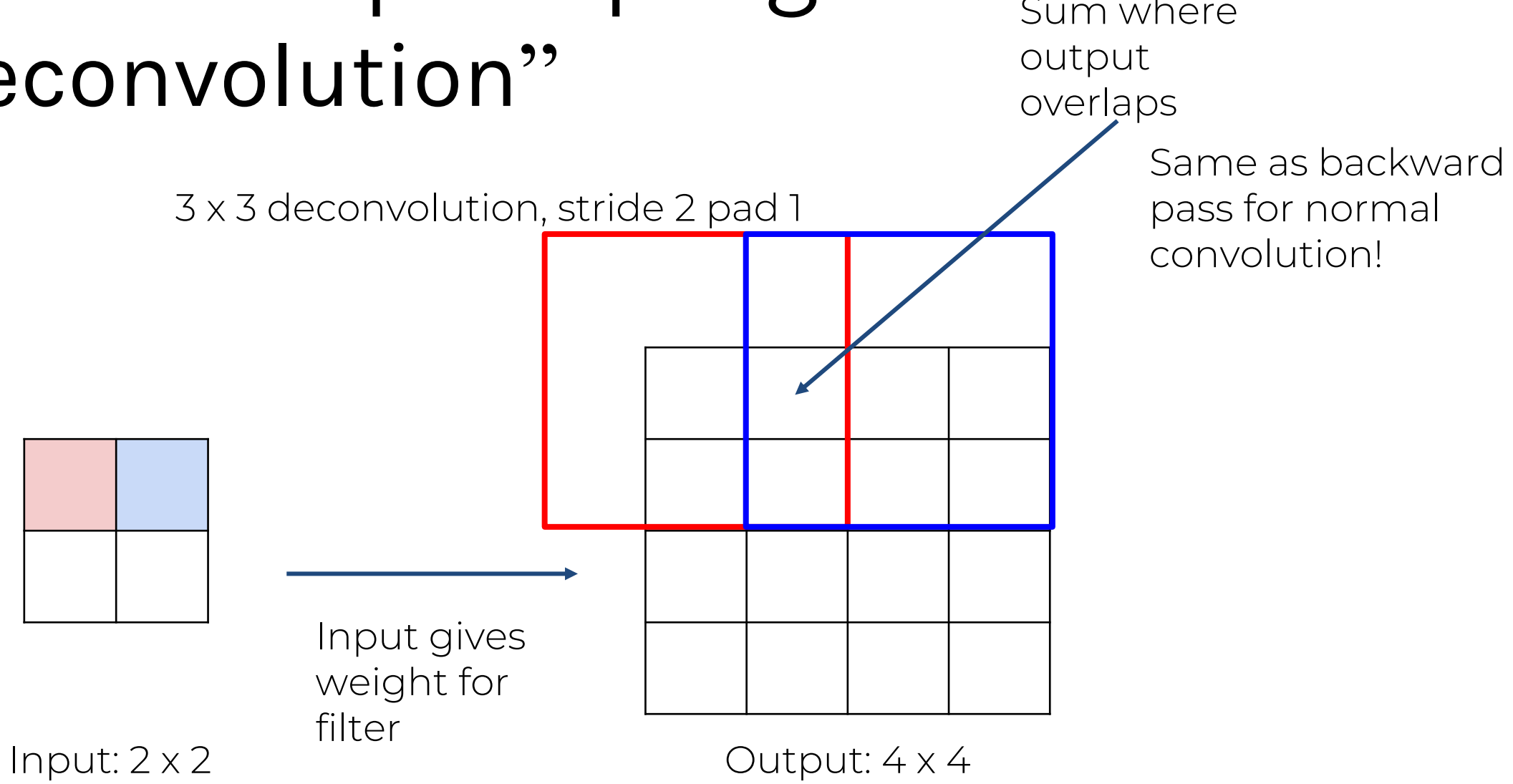
Learnable Upsampling: "Deconvolution"



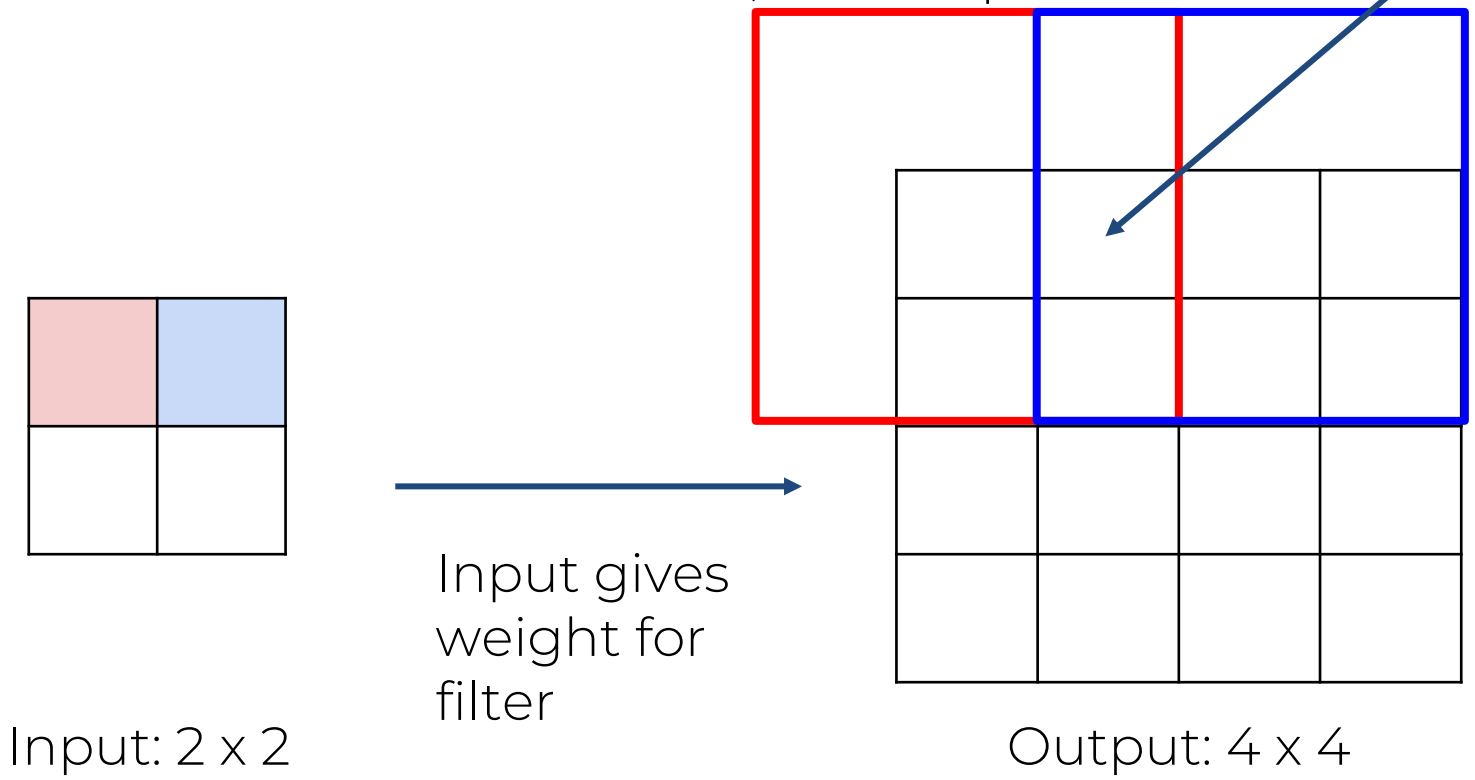
Learnable Upsampling: "Deconvolution"



Learnable Upsampling: "Deconvolution"



Learnable Upsampling: "Deconvolution"



"Deconvolution" is a bad name, already defined as "inverse of convolution"

Better names:
convolution transpose,
backward strided convolution,
1/2 strided convolution,
upconvolution

Learnable Upsampling: "Deconvolution"

[1]It is more proper to say "convolutional transpose operation" rather than "deconvolutional" operation. Hence, we will be using the term "convolutional transpose" from now.

Im et al, "Generating images with recurrent adversarial networks", arXiv 2016

A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

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Great explanation in appendix

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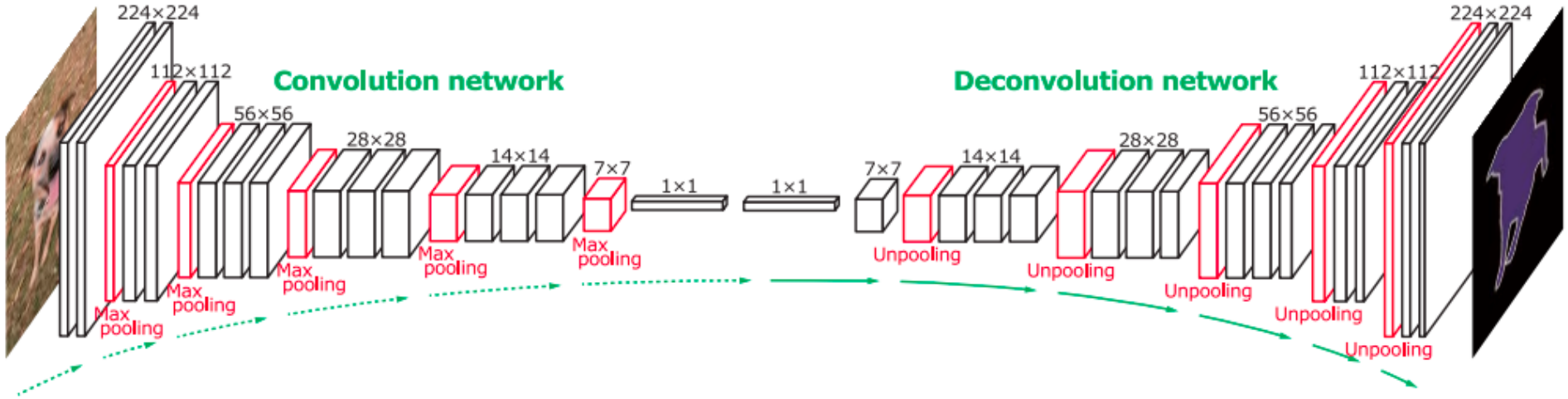
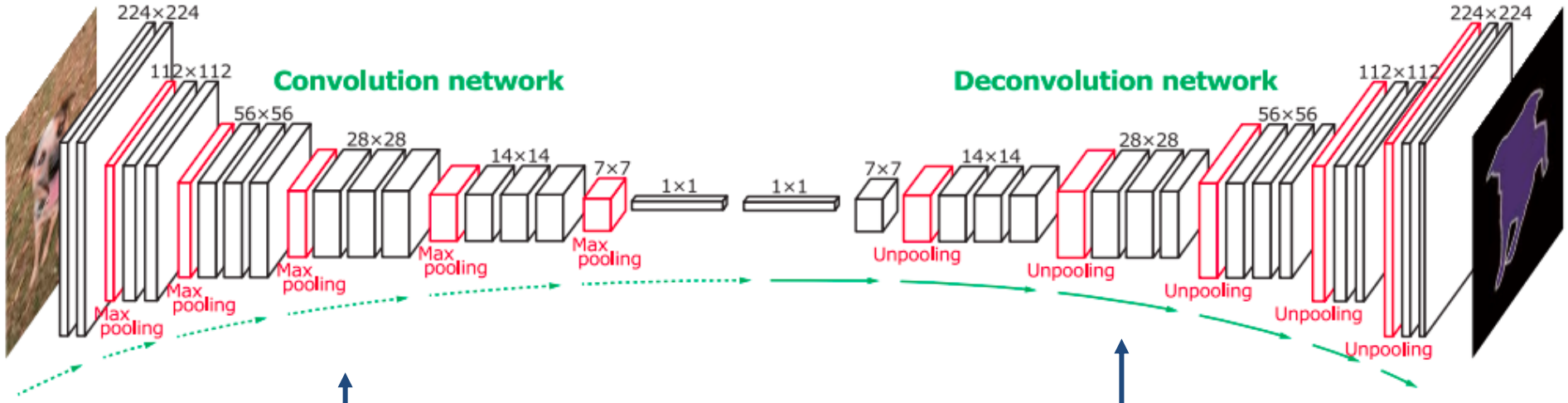
Semantic Segmentation: Upsampling



Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Semantic Segmentation: Upsampling



Normal VGG

"Upside down" VGG

6 days of training on Titan X...

Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Instance Segmentation

Detect instances, give category, label pixels

"simultaneous detection and segmentation" (SDS)

Lots of recent work (MS-COCO)

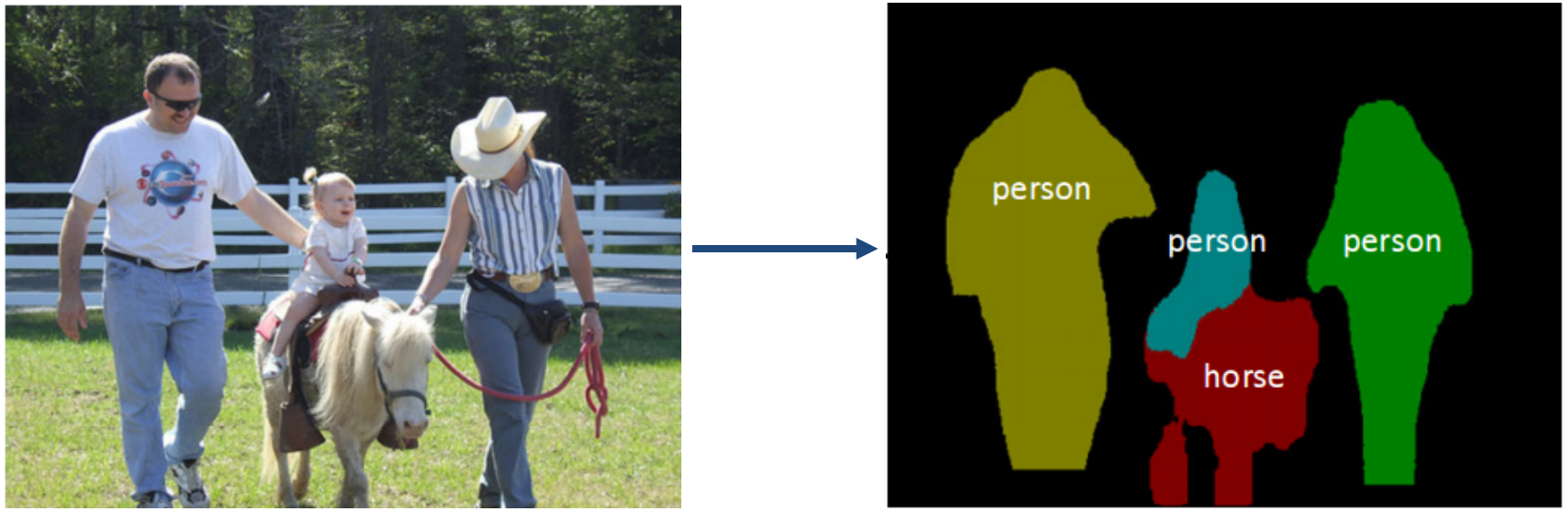
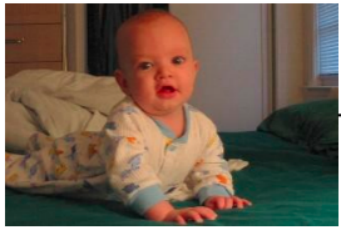


Figure credit: Dai et al, "Instance-aware Semantic Segmentation via Multi-task Network Cascades", arXiv 2015

Instance Segmentation

Similar to R-CNN,
but with segments



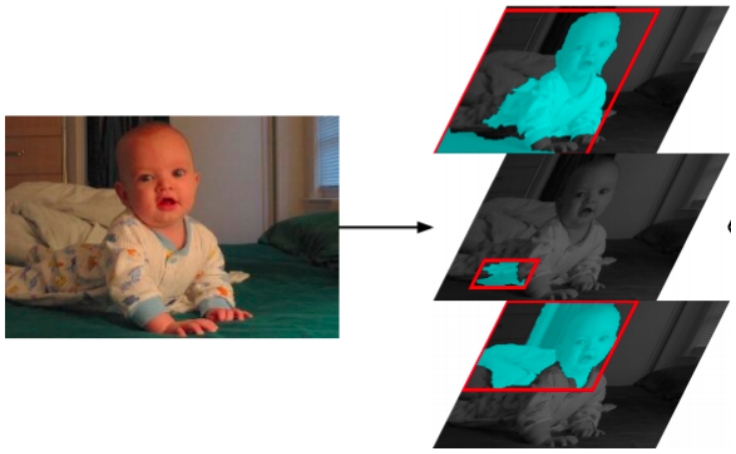
Hariharan et al, “Simultaneous Detection and Segmentation”, ECCV 2014

Instance Segmentation

Similar to R-CNN,
but with segments

Proposal Generation

External Segment proposals



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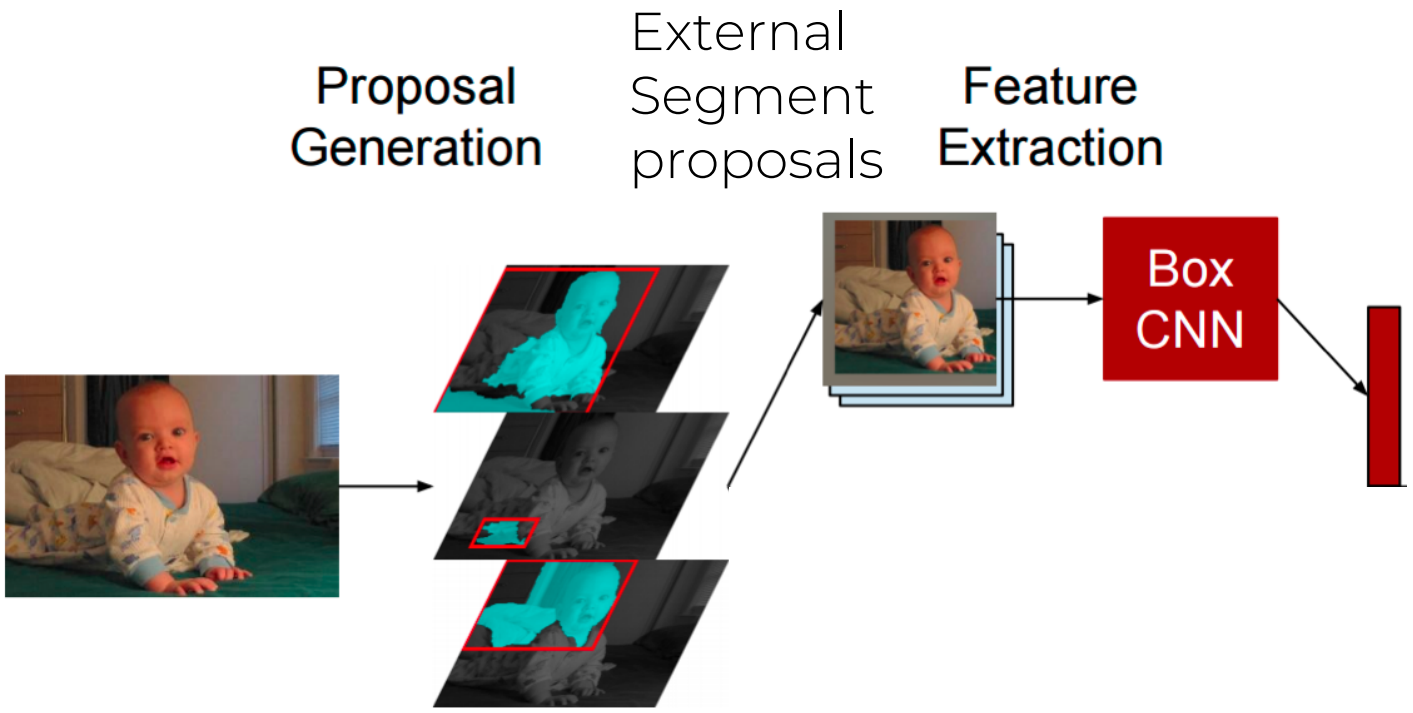

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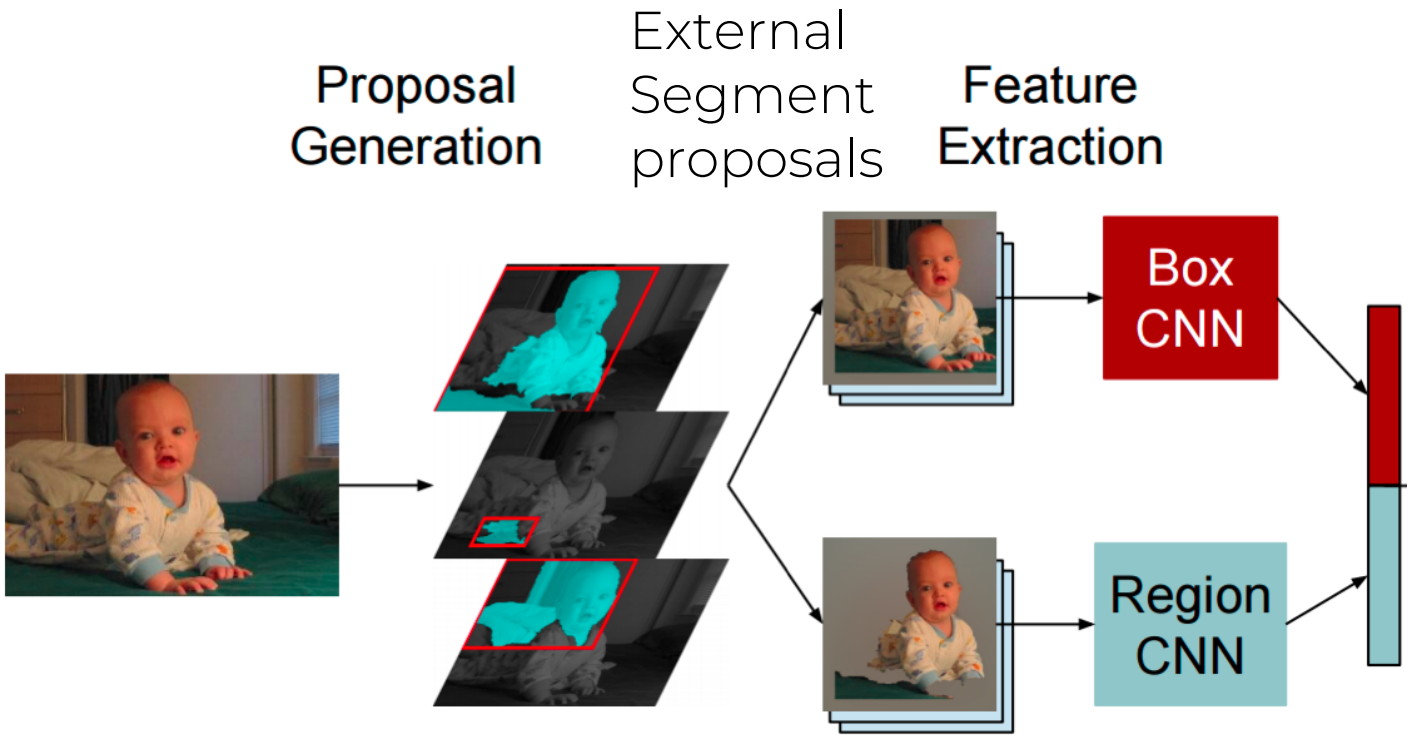

Mask out background
with mean image

Hariharan et al, “Simultaneous Detection and Segmentation”, ECCV 2014

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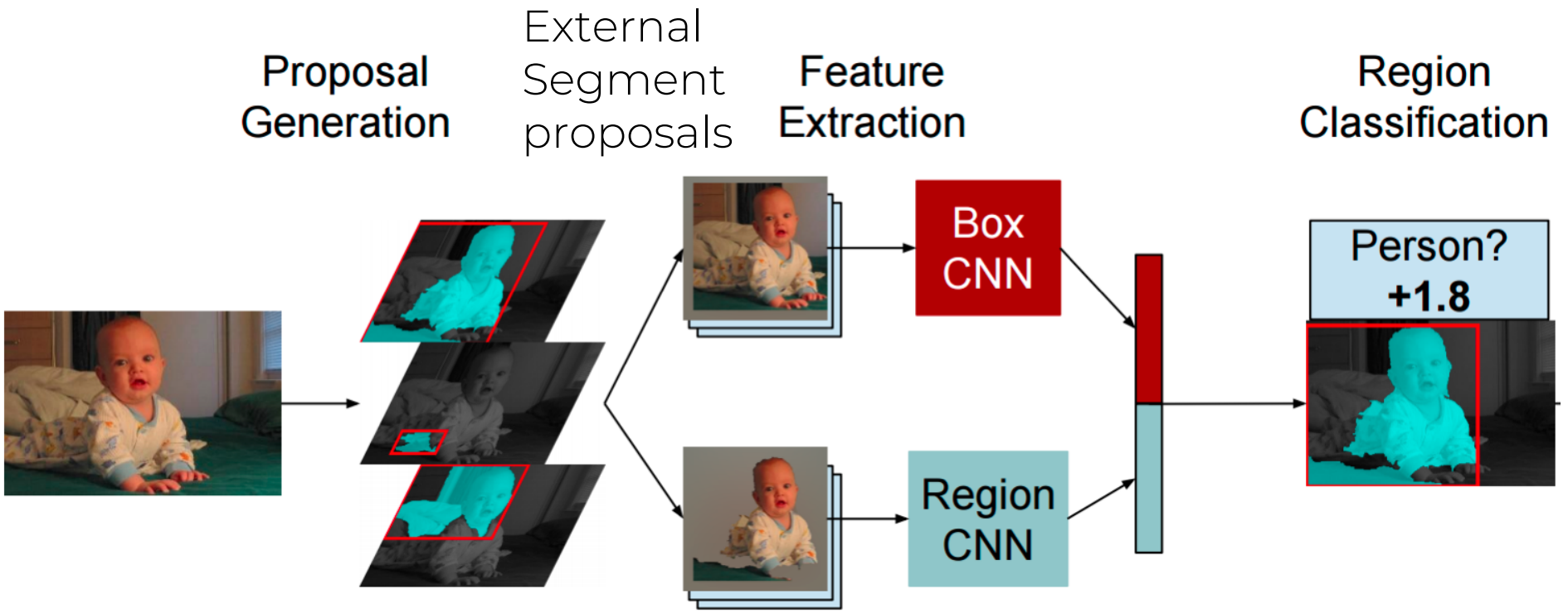

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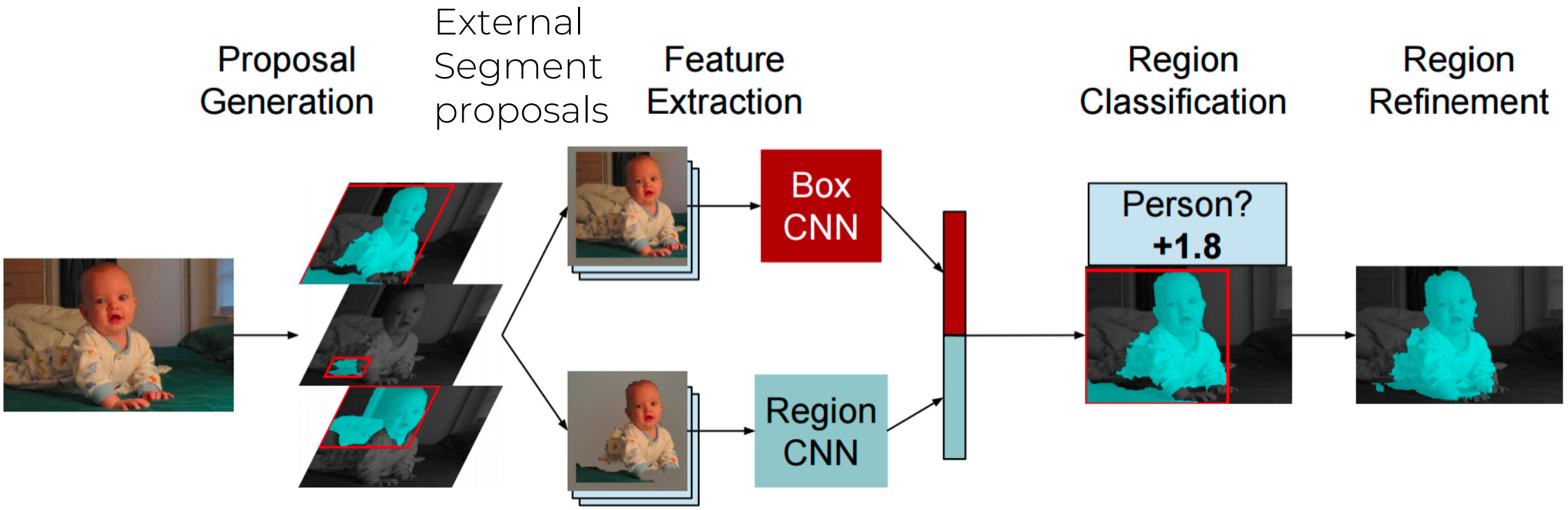
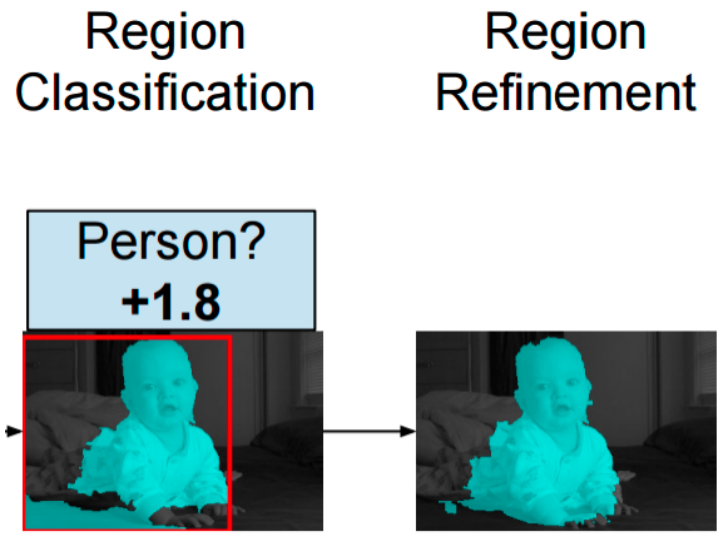


Mask out background
with mean image

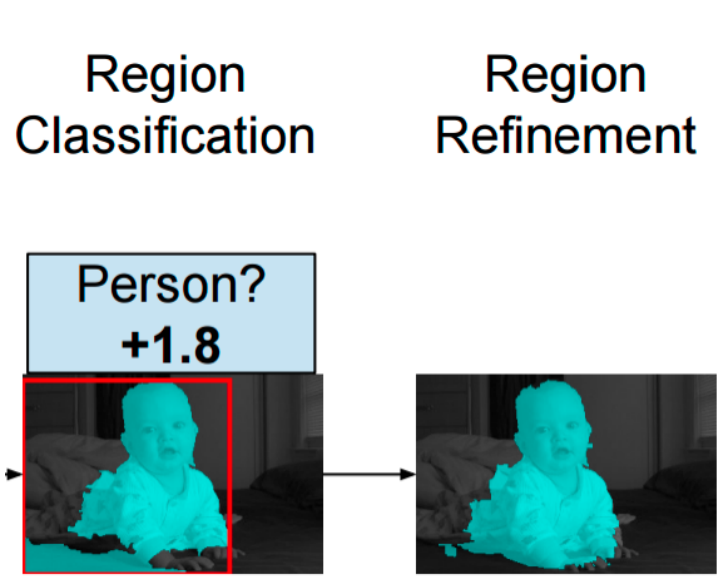
Hariharan et al, "Simultaneous Detection and Segmentation", ECCV 2014

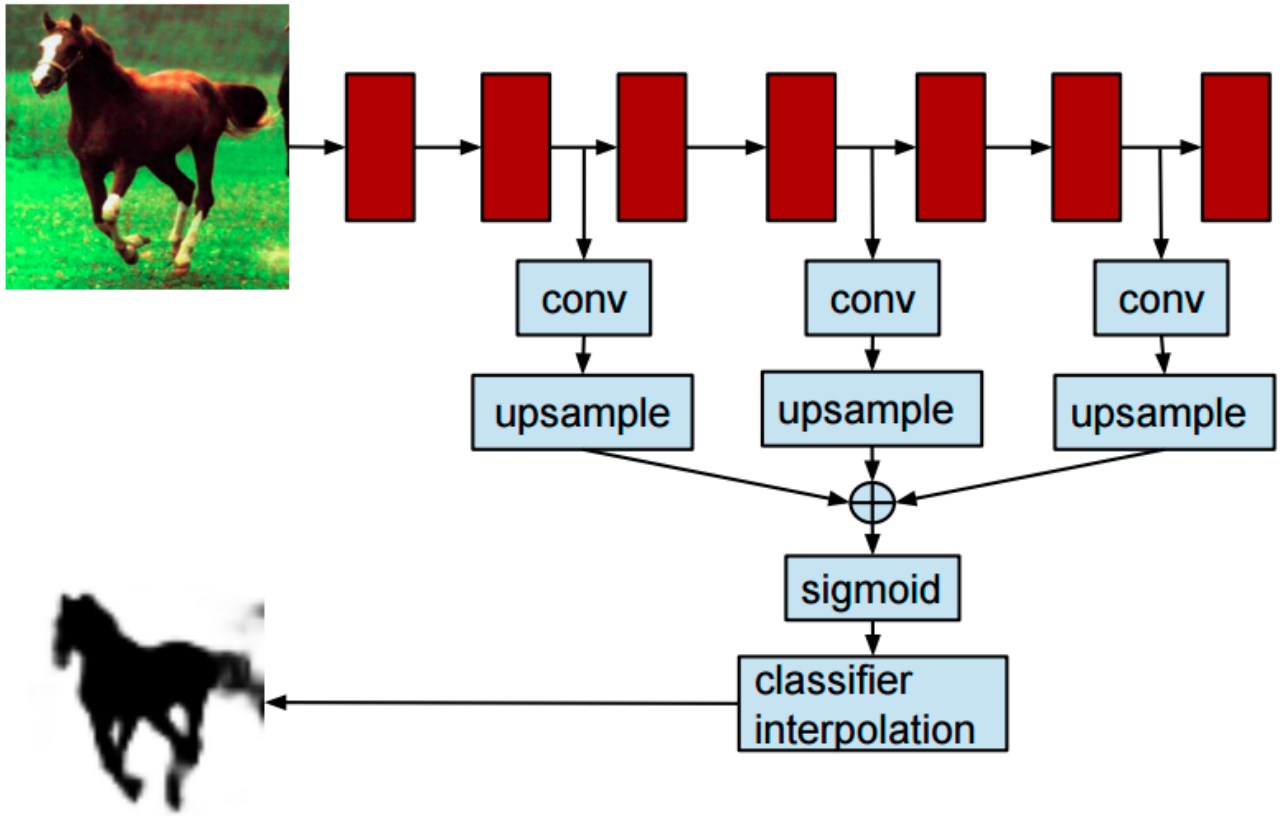
Instance Segmentation: Hypercolumns



Hariharan et al, “Hypercolumns for Object Segmentation and Fine-grained Localization”, CVPR 2015

Instance Segmentation: Hypercolumns





Hariharan et al, "Hypercolumns for Object Segmentation and Fine-grained Localization", CVPR 2015

Instance Segmentation: Cascades

Similar to
Faster R-CNN

Won COCO 2015
challenge
(with ResNet)

Dai et al, "Instance-aware Semantic Segmentation via Multi-task Network Cascades", arXiv 2015

Instance Segmentation: Cascades

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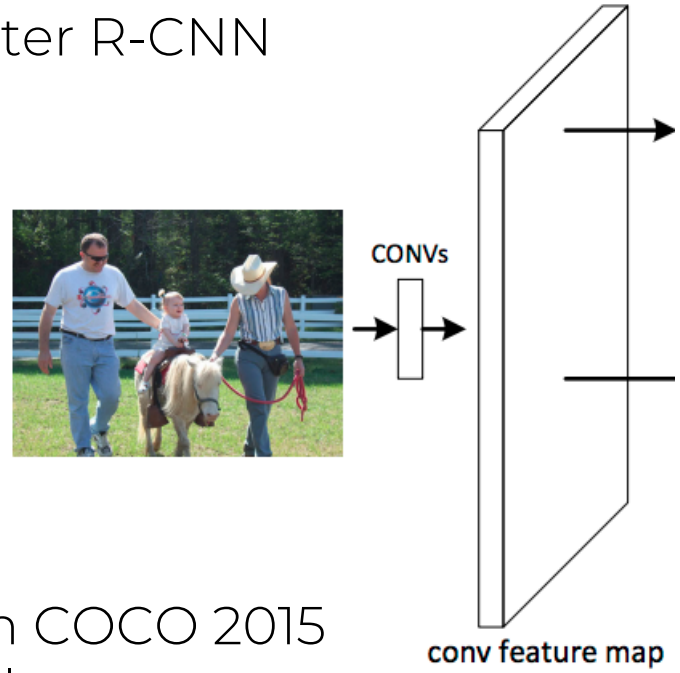

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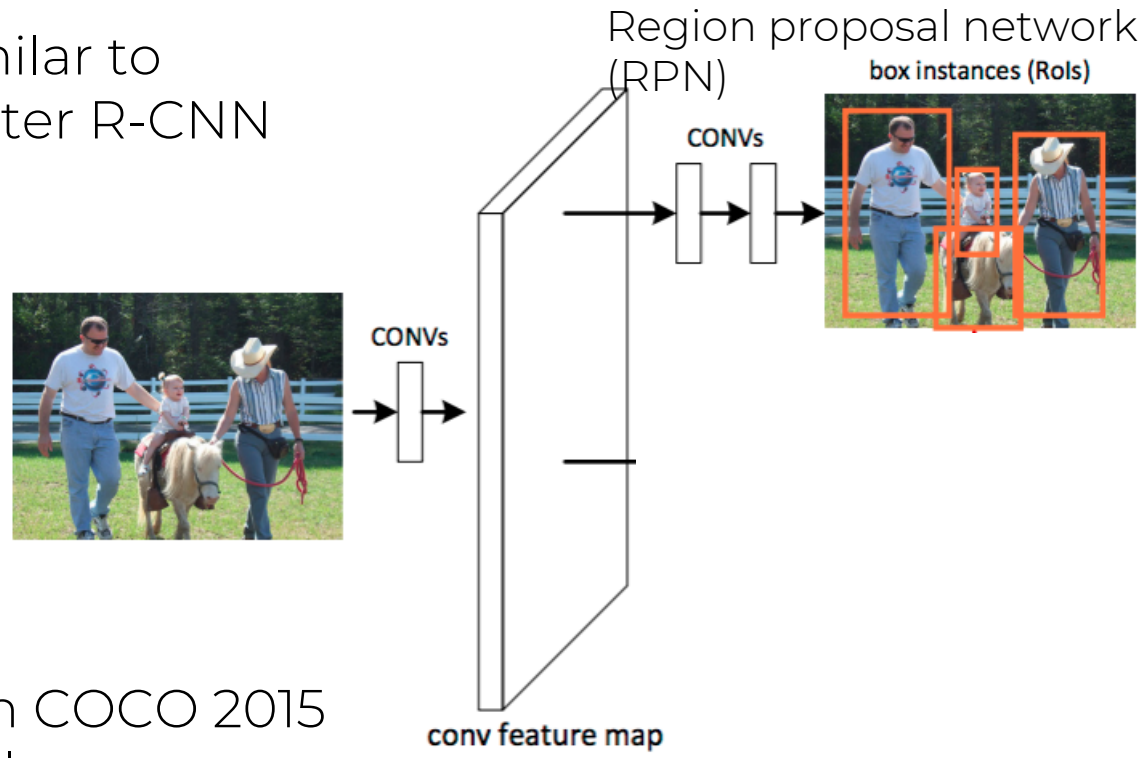

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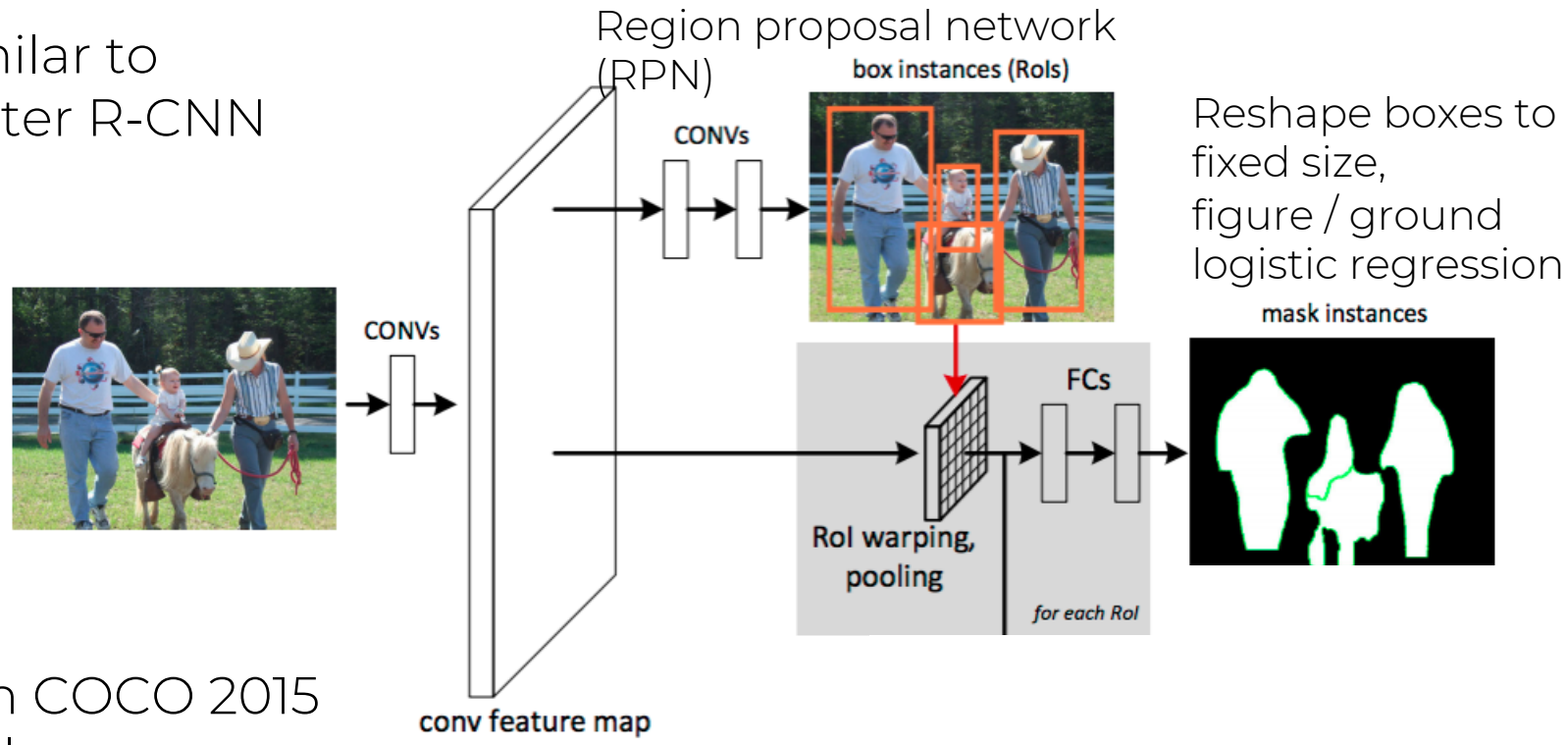

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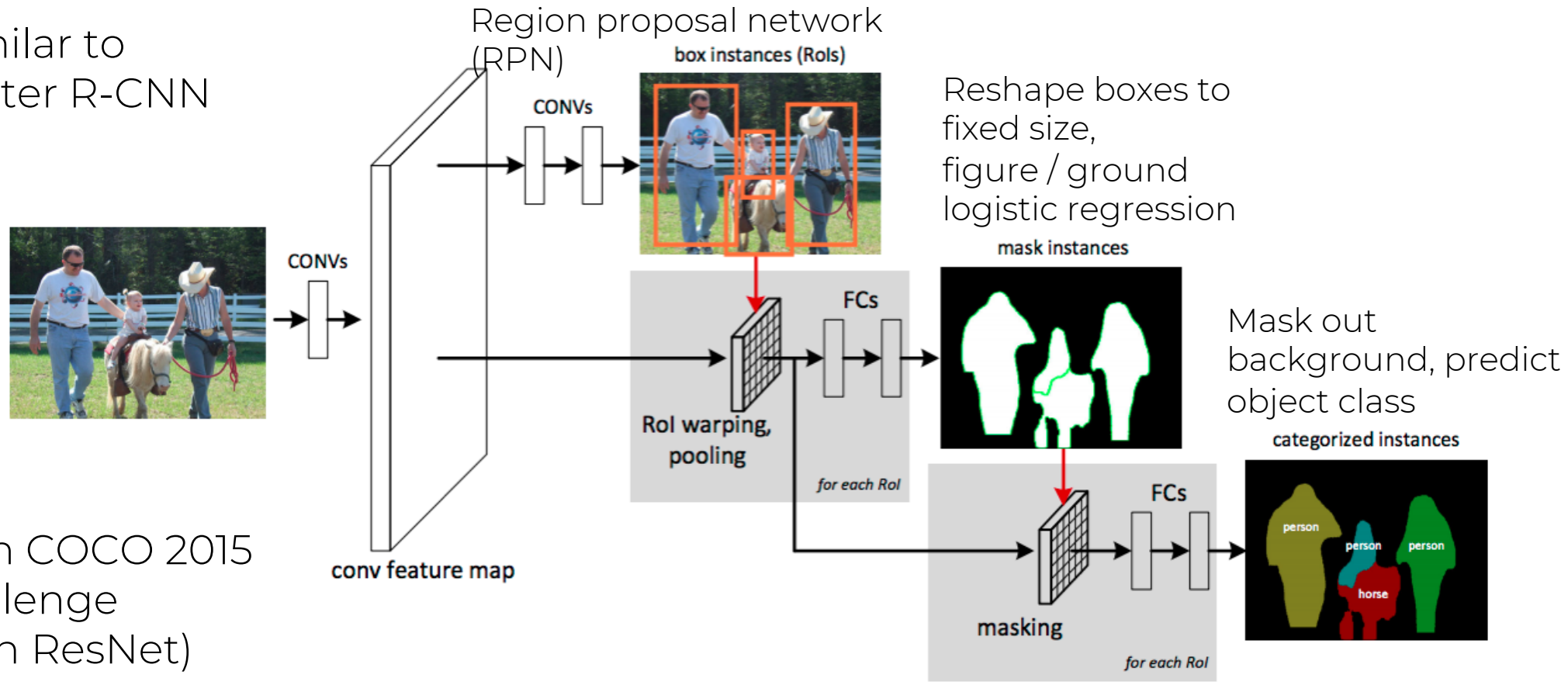

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challenge
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Instance Segmentation: Cascades

Similar to
Faster R-CNN

Region proposal network
(RPN)

box instances (RoIs)

Reshape boxes to
fixed size,
figure / ground
logistic regression

Learn entire model
end-to-end!

CONVs

CONVs

conv feature map

RoI warping,
pooling

FCs

for each RoI

mask instances

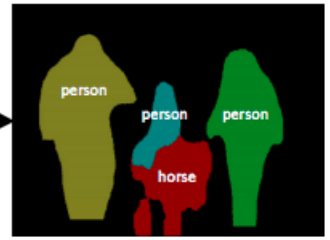
Mask out
background, predict
object class

masking

FCs

for each RoI

categorized instances



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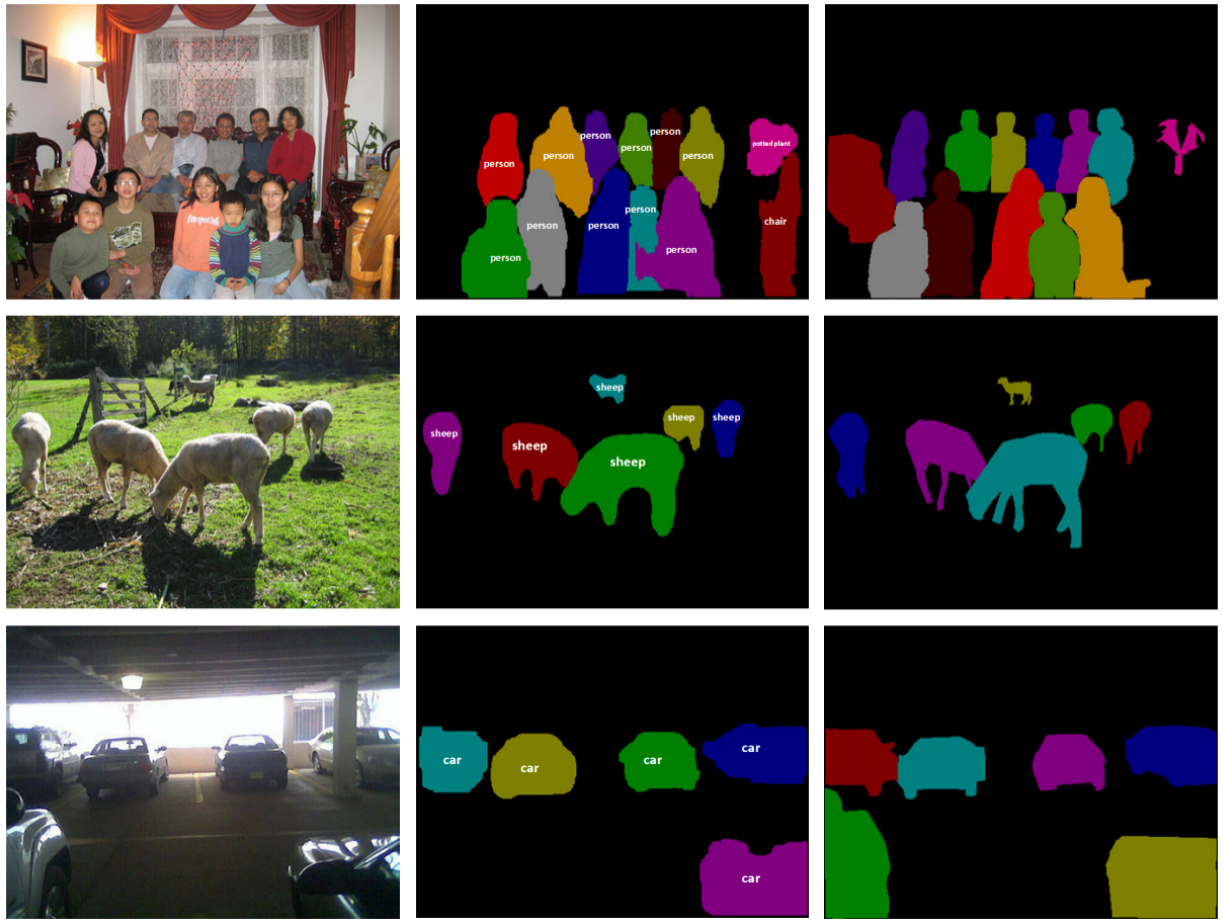
Instance Segmentation: Cascades



Predictions Ground truth

Dai et al, "Instance-aware Semantic Segmentation via Multi-task Network Cascades", arXiv 2015

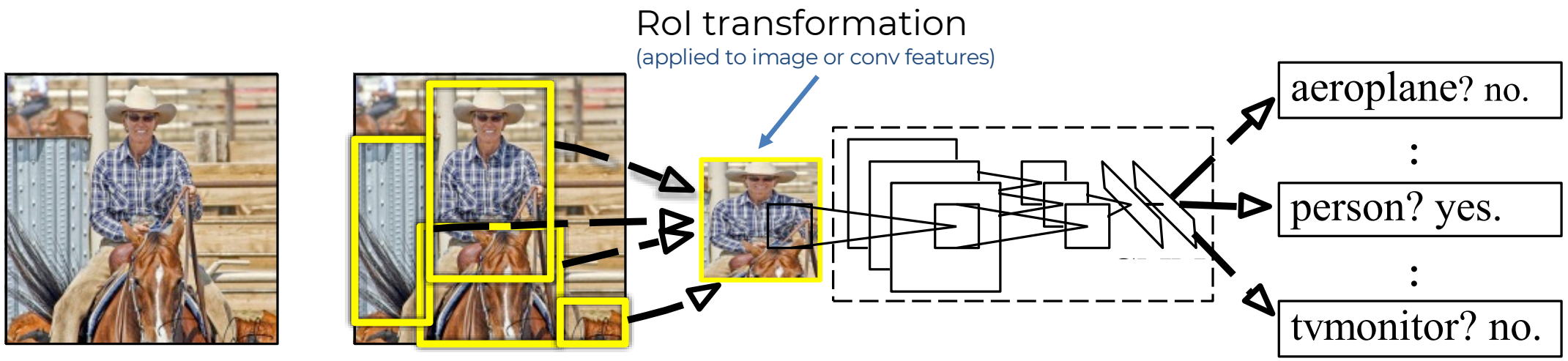
Mask R-CNN: Model Overview

R-CNN-style detection system

1. Backbone architecture
2. Feature Pyramid Network (FPN)
3. Region Proposal Network (RPN)
4. Region of interest feature alignment (RoIAlign)
5. Multi-task network head
   - Box classifier
   - Box regressor
   - Mask predictor
   - Keypoint predictor

Modular composition of many recent ideas

0. R-CNN-style Approach to Object Detection



Input image

Object / region proposals (RoIs)
(external or internal to network)

Deep Learning-based region classifier

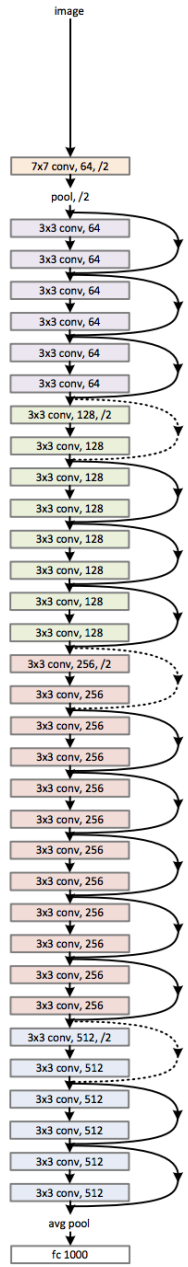
Detection = Region classification + box regression + ...

General formula for **R**egion-based **CNN** models

Girshick, Donahue, Darrell, Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. CVPR 2014
Uijlings, van de Sande, Gevers, Smeulders. Selective Search for Object Recognition. IJCV 2013

1. Backbone ConvNet

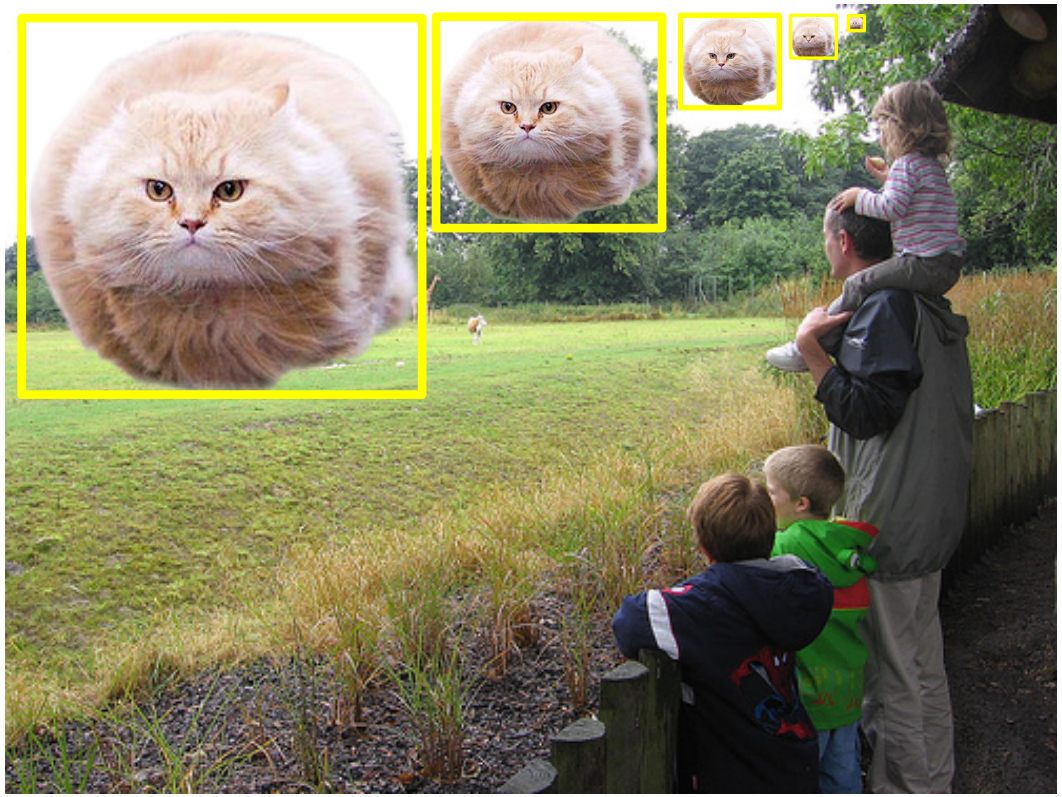
Example:
ResNet-34

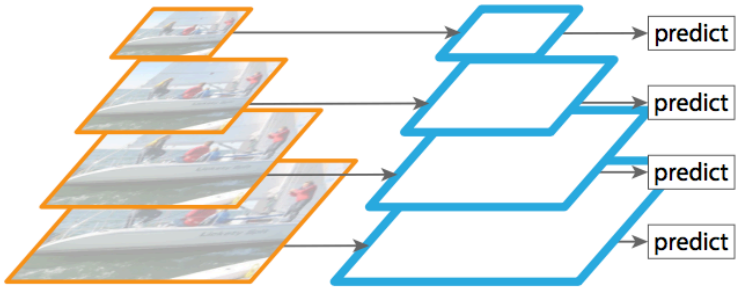


Use any standard ConvNet as a “backbone architecture”

- AlexNet, VGG, ResNet, Inception, Inception-ResNet, ResNeXt, …
- Use “same” padding everywhere (preserves integer scales)
- Prefer fully convolutional networks (ignoring cls head; see next slide)
- Pre-train on ImageNet classification (or similar)

2. Scale Invariant Detection

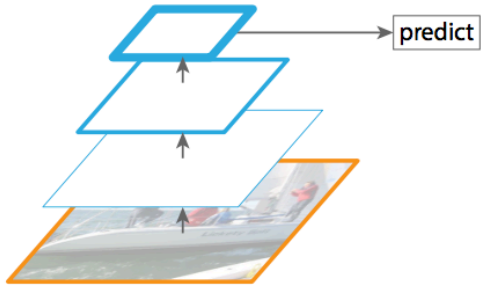




(a) Featurized image pyramid

SLOW!

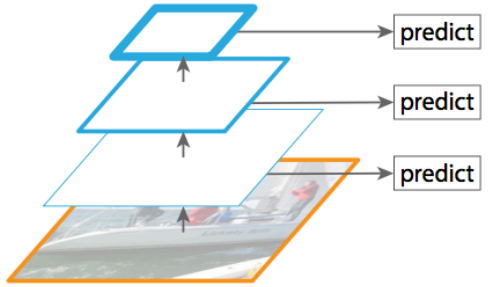
(Viola & Jones, HOG, DPM, multiscale Fast R-CNN, …)



(b) Single feature map

Do nothing; give up; Fast

(Fast R-CNN, YOLO, …)



(c) Pyramidal feature hierarchy

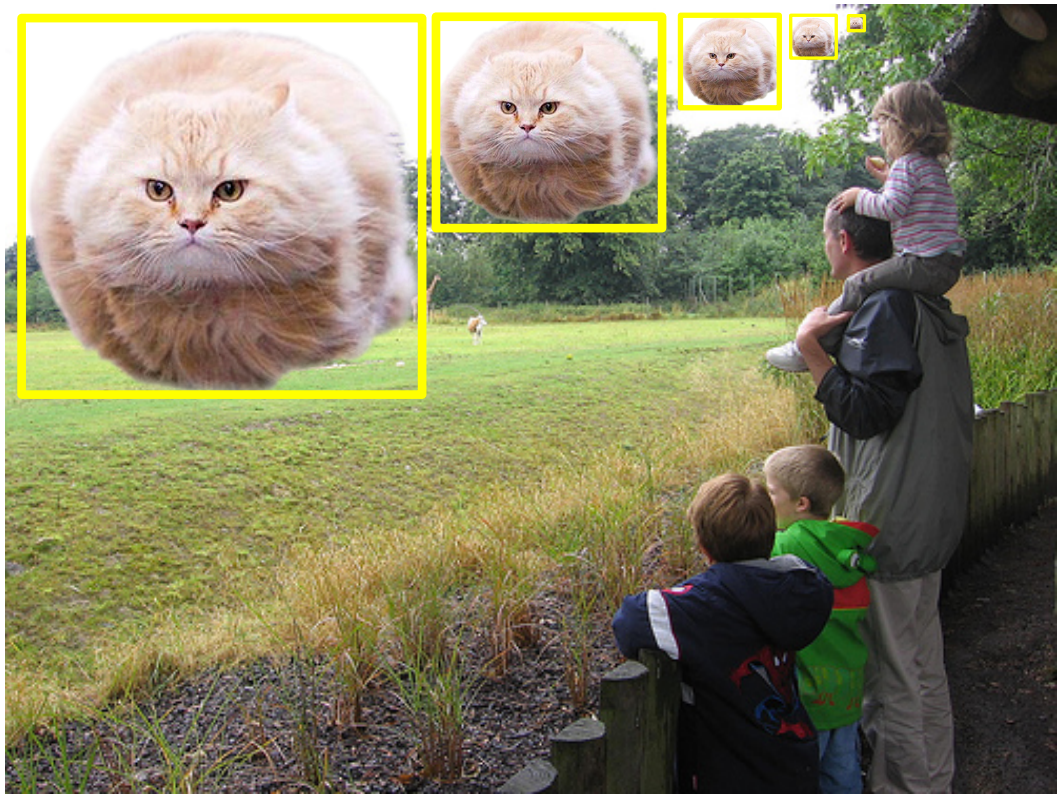
Fast!

(≈ SSD, …)

Popular strategies for detecting objects over large scale changes

R. Girshick

2. Scale Invariant Detection



(a) Featurized image pyramid

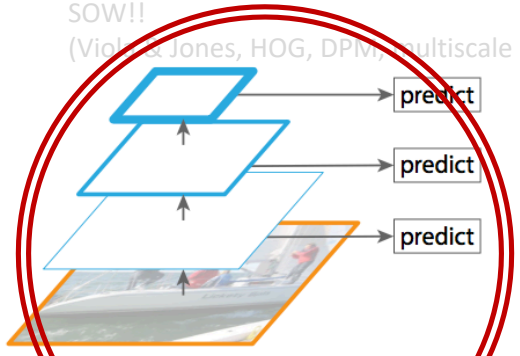
SOW!!

(Viola & Jones, HOG, DPM, Multiscale Fast R-CNN, …)

(b) Single feature map

Do nothing; give up; Fast!

(Fast R-CNN, YOLO, …)



(c) Pyramidal feature hierarchy

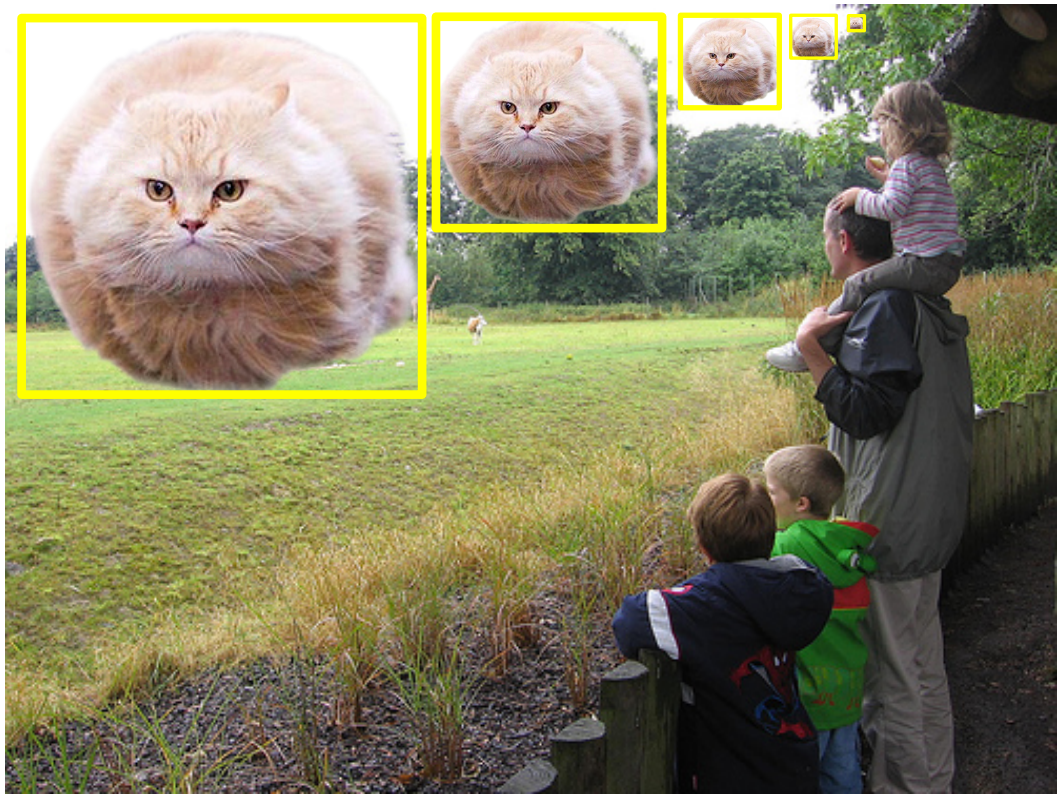
Fast!

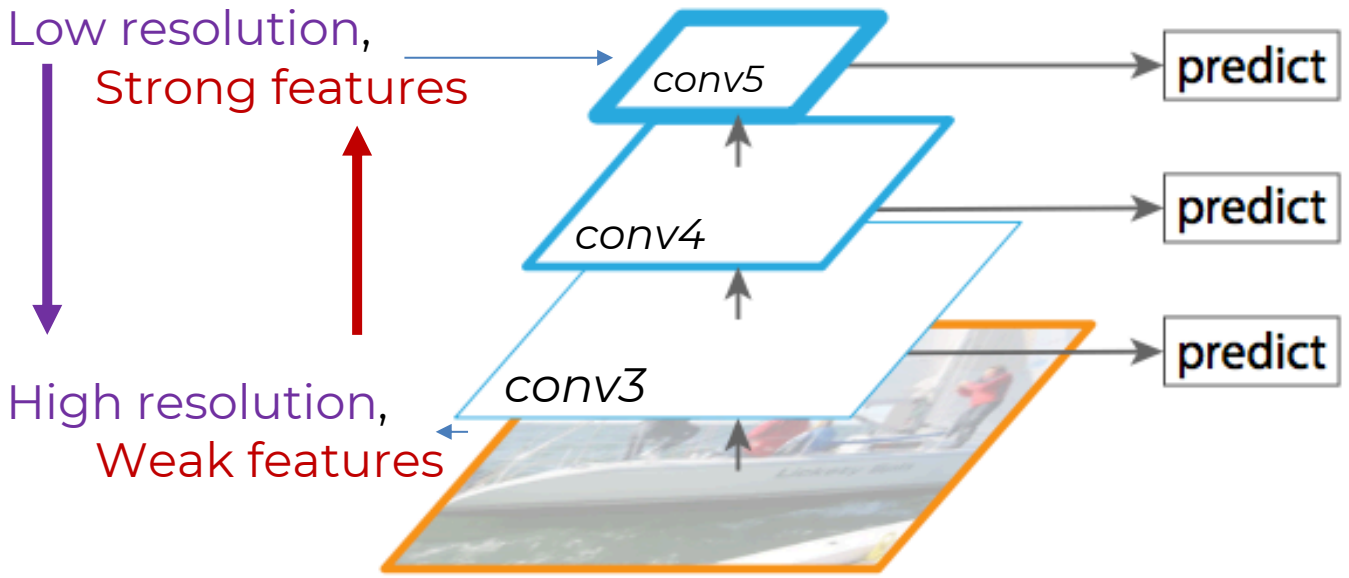
(≈ SSD, …)

Let's examine this one

R. Girshick

Compromise Feature Quality, but Fast (“Free”)



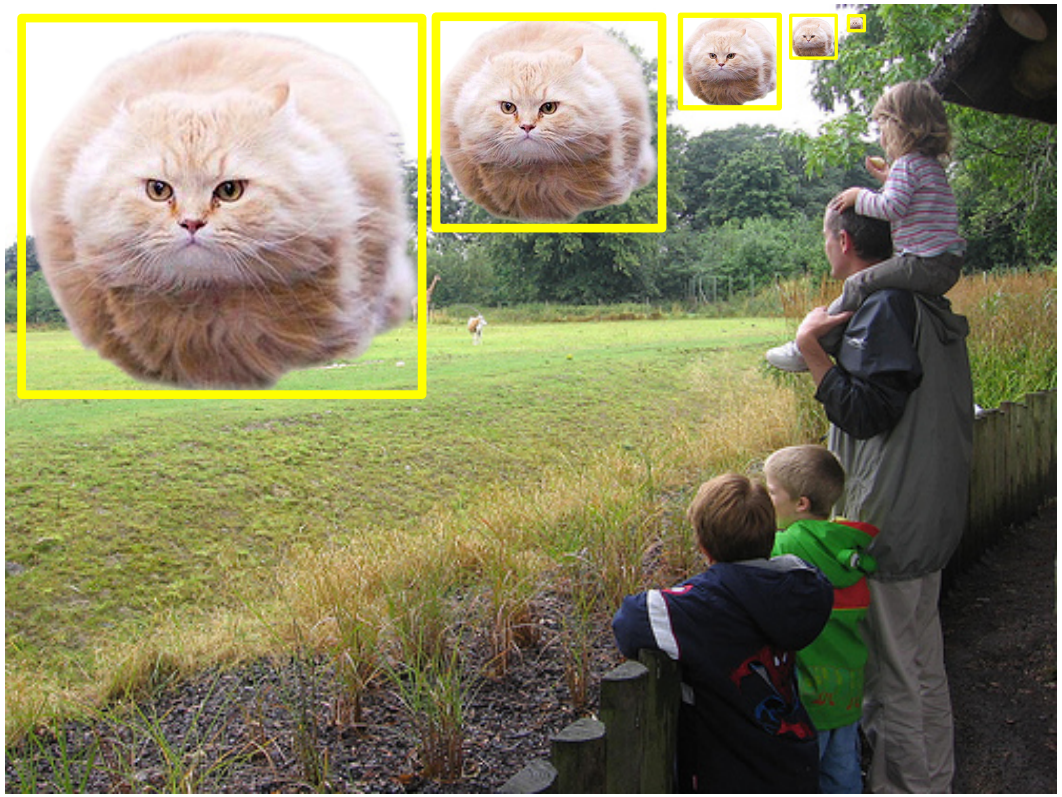


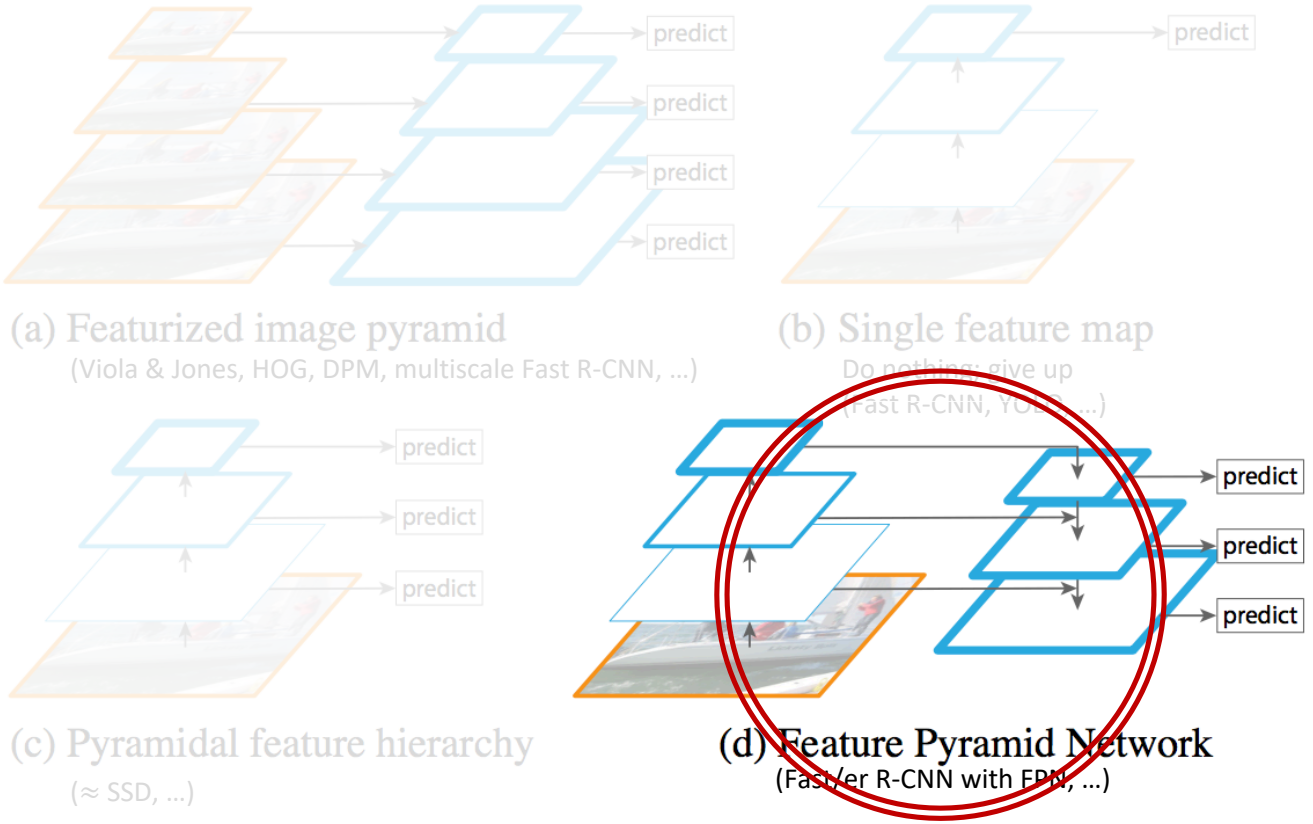
The “native” in-network feature pyramid poses an inherent tradeoff

R. Girshick

2. … + Feature Pyramid Network (FPN)

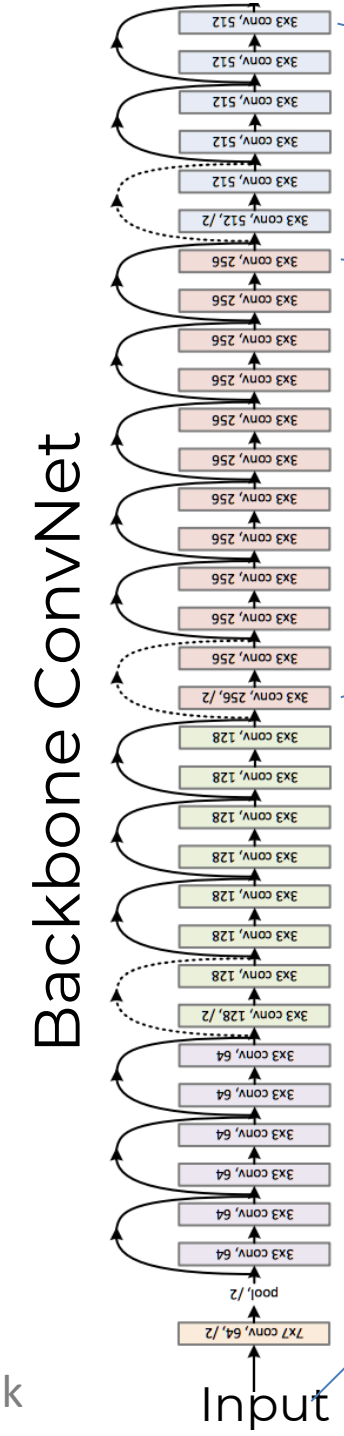
[Optional, but recommended]





Lin et al. Feature Pyramid Networks for Object Detection. In CVPR 2017.

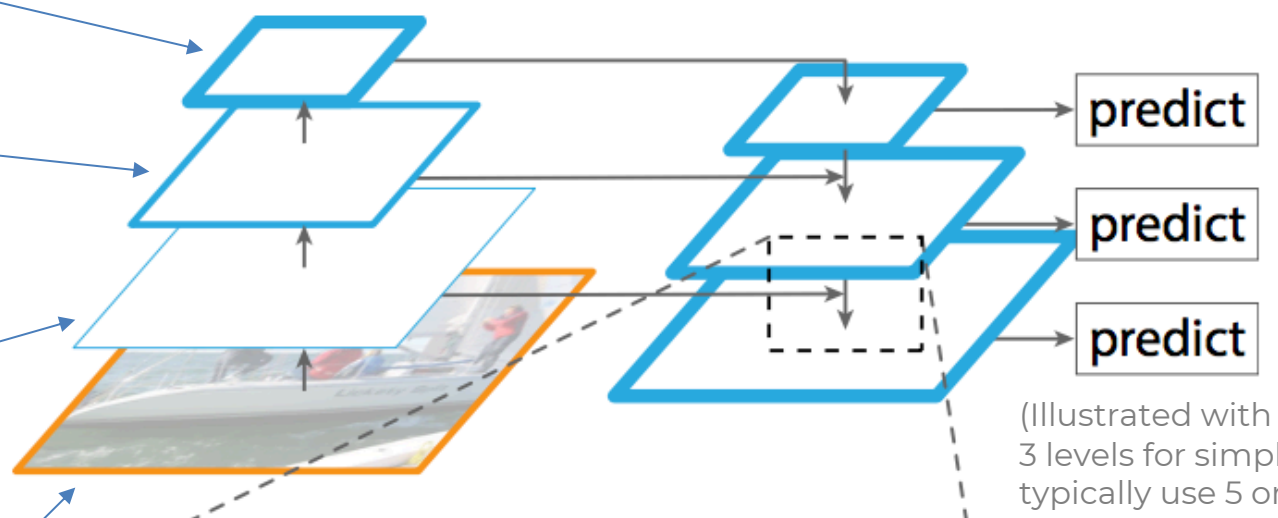
FPN



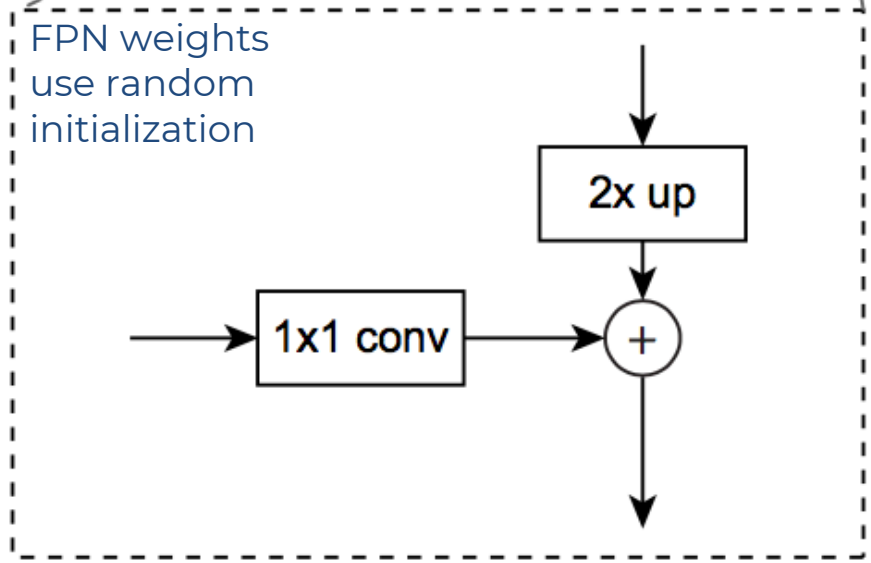
1/16 image resolution
Res4 stage output

1/8 image resolution
Res3 stage output

1/4 image resolution
Res2 stage output



(Illustrated with
3 levels for simplicity;
typically use 5 or 6)



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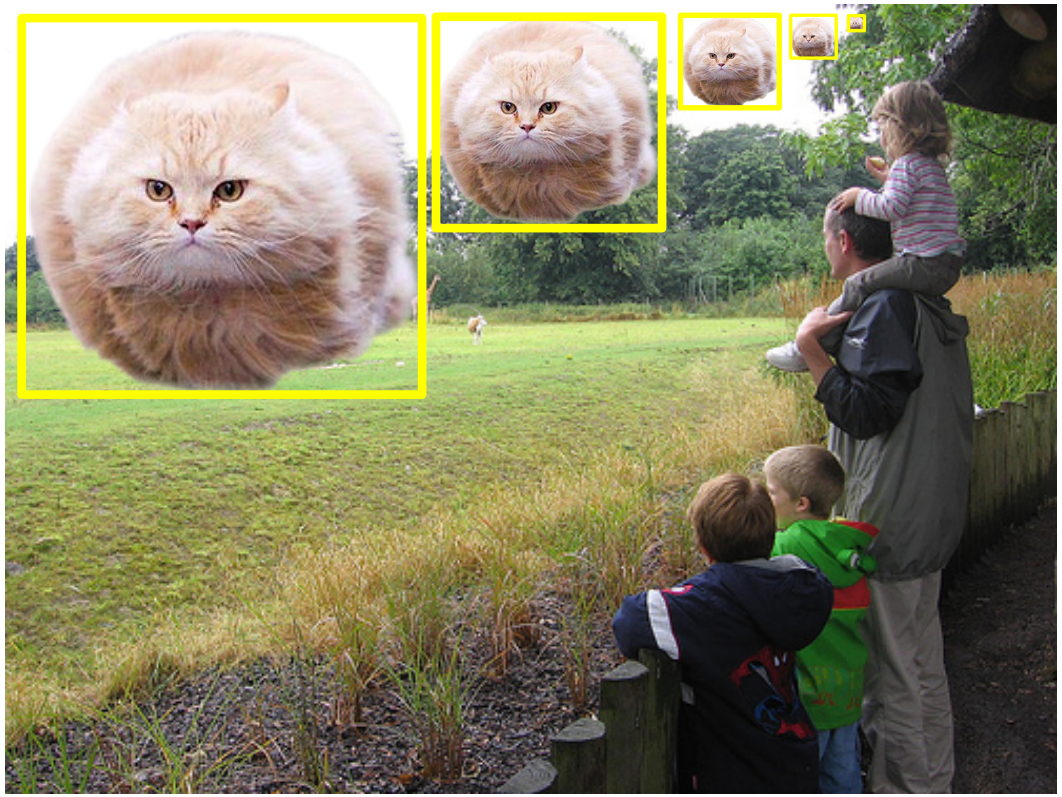
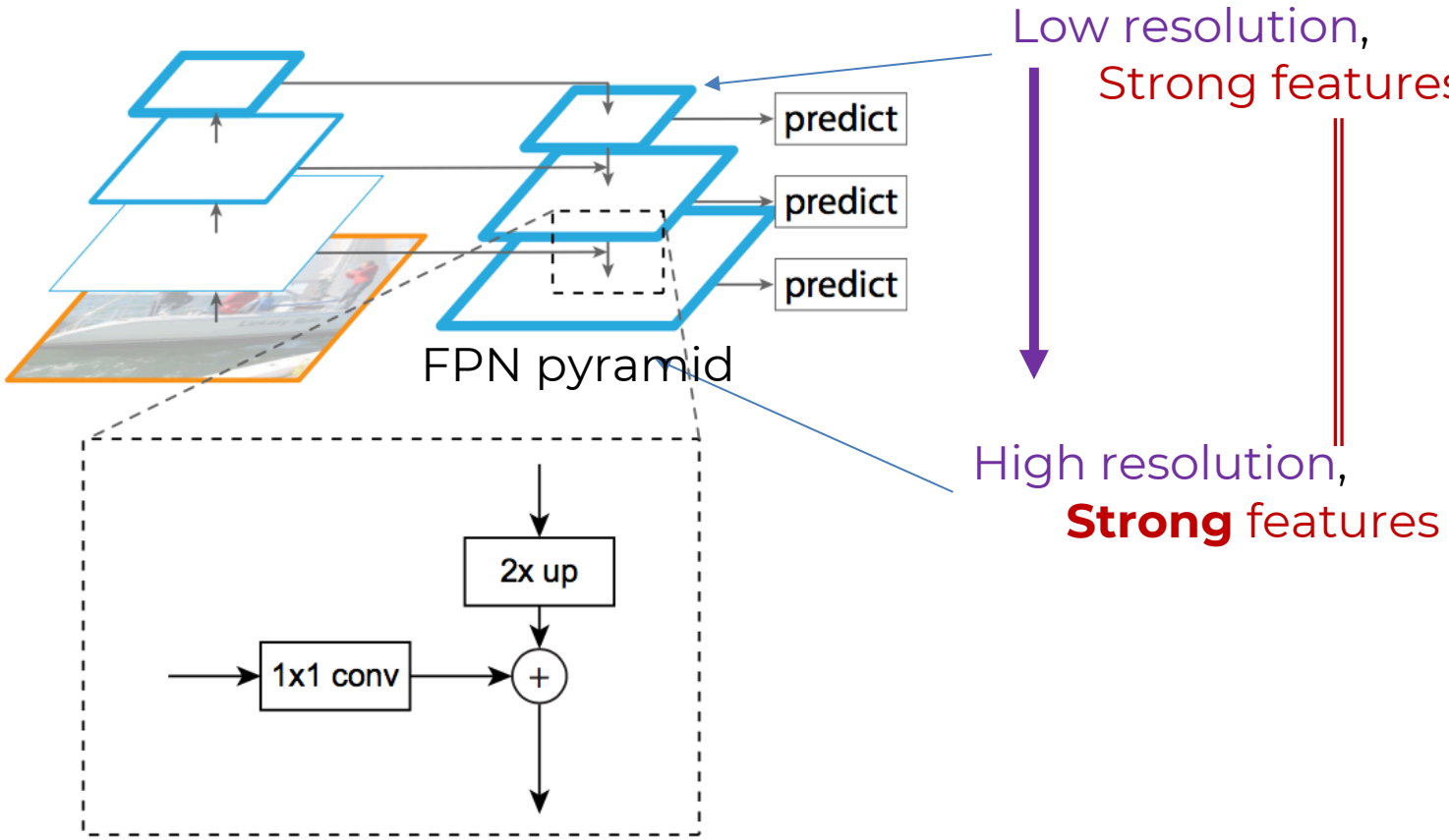
Lin et al. Feature Pyramid Networks for Object Detection. In CVPR 2017.

No Compromise on Feature Quality, still Fast

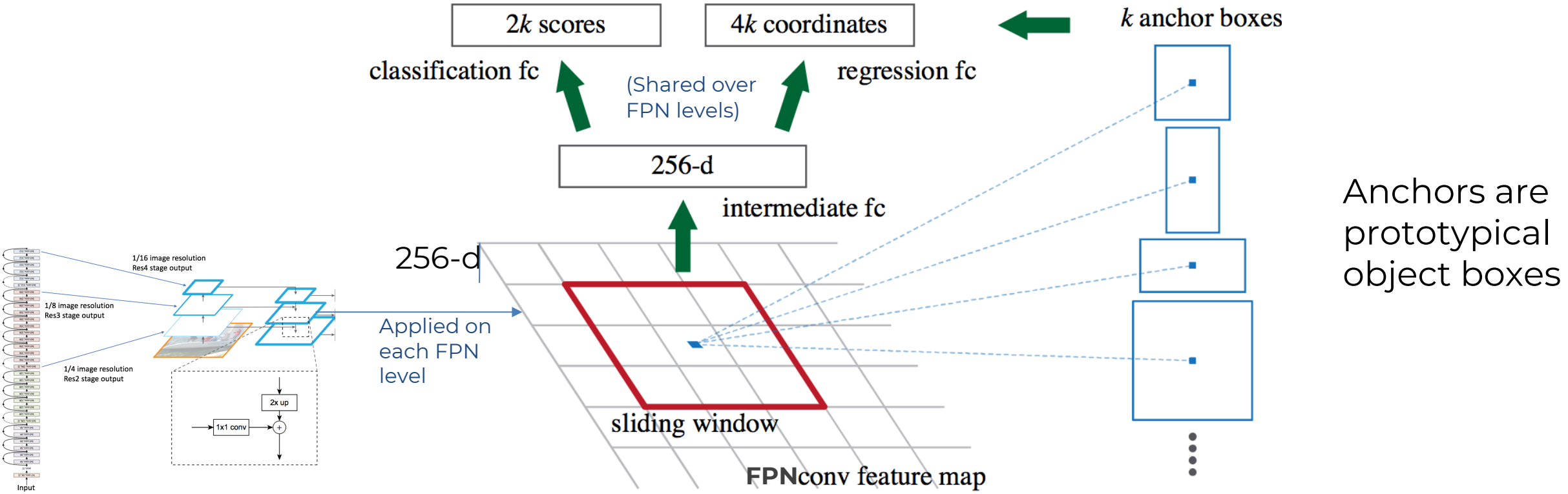




Lin et al. Feature Pyramid Networks for Object Detection. In CVPR 2017.

3. … + Region Proposal Network (RPN)

Proposals = sliding window object/not-object classifier
+ box regression *inside the same network*

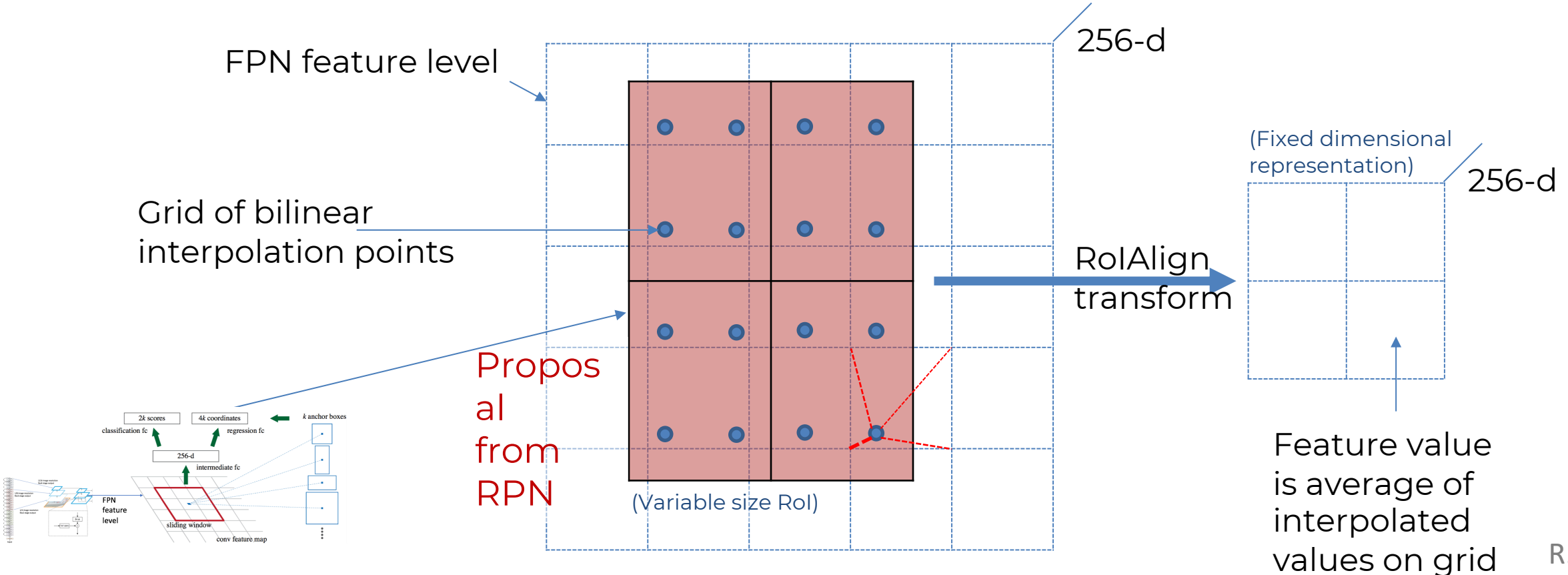


Anchors are prototypical object boxes

Ren et al. Faster R-CNN: Region Proposal Networks for Real-Time Object Detection. In NIPS 2015

4. … + RoIAlign Transform (on each Proposal)

Smoothly normalize features and predictions into coordinate frame
free of scale and aspect ratio



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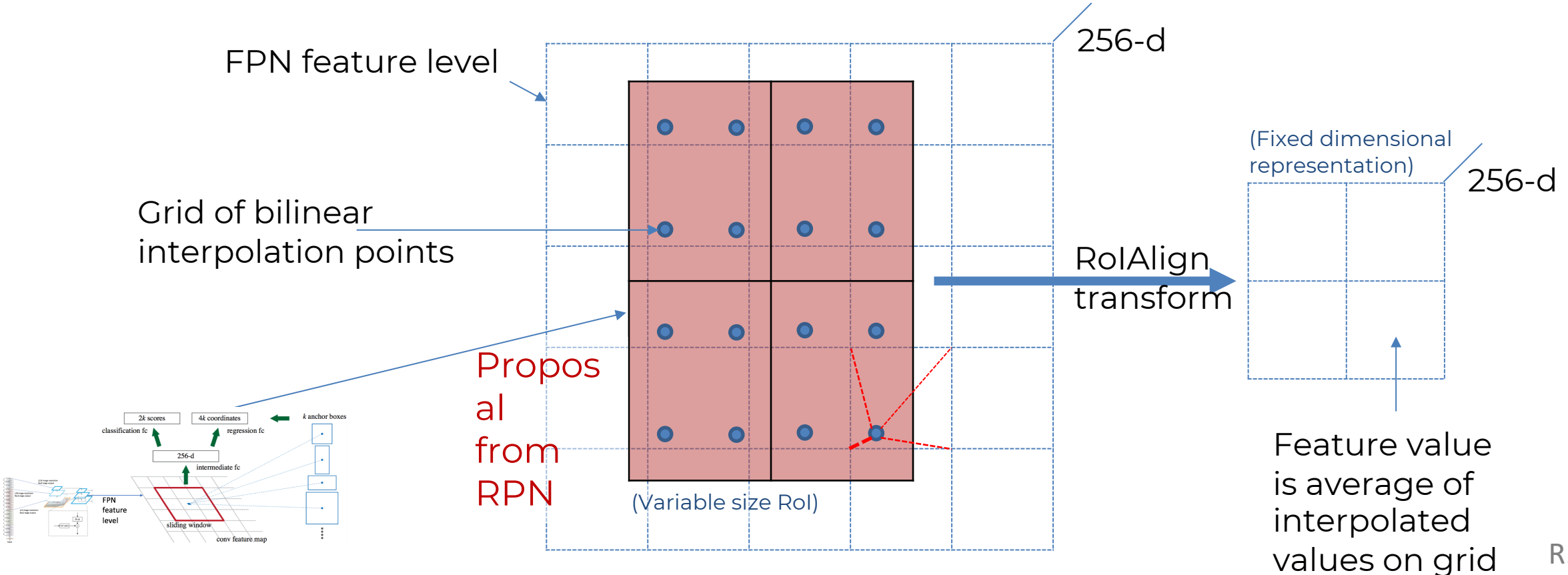
4. … + RoIAlign Transform (on each Proposal)

Key: No coordinate quantization
(cf. RoIPool in Fast R-CNN, etc.)



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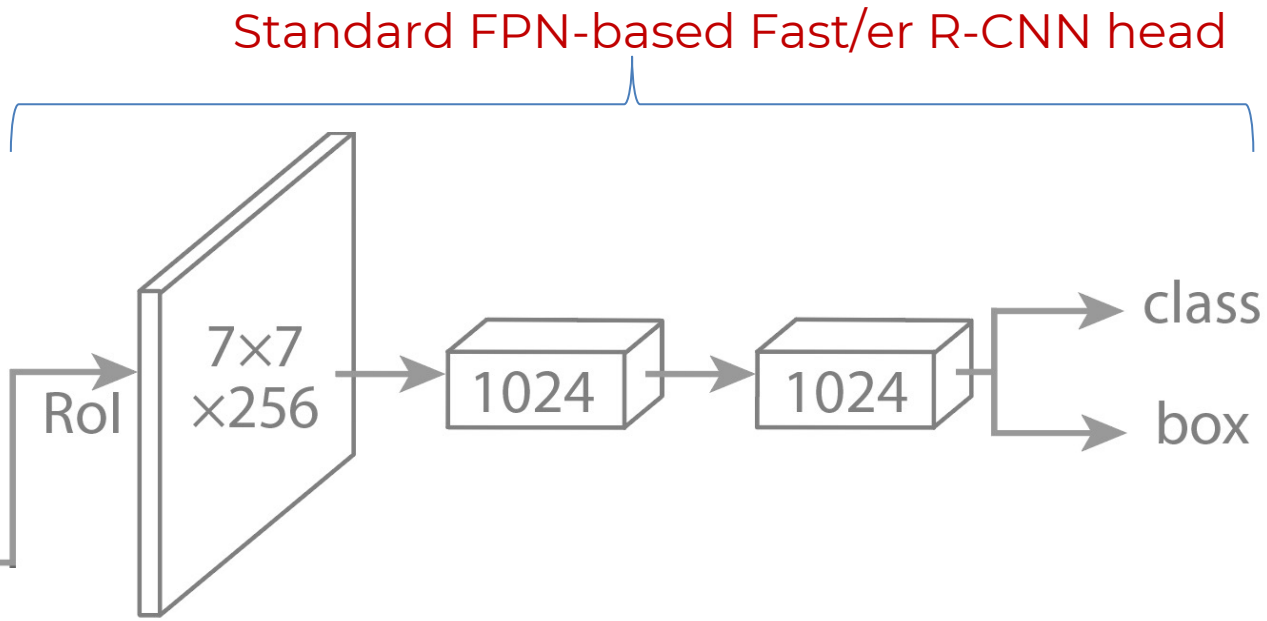
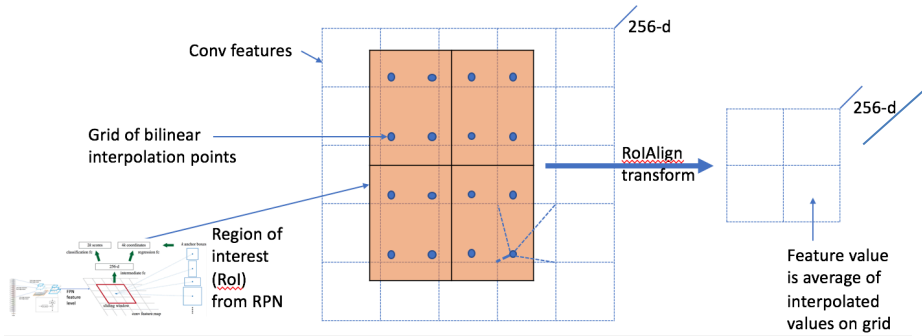
5. … + Task-specific Heads (on each Proposal)

Task specific heads for …

- Bounding box detection
- Object classification
- Instance mask prediction
- Human keypoint prediction



RoIAlign transformed features



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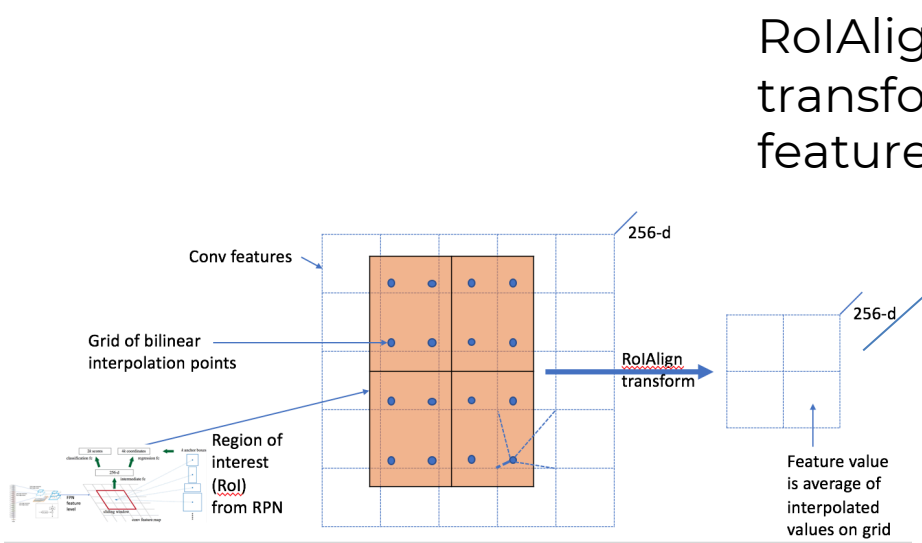
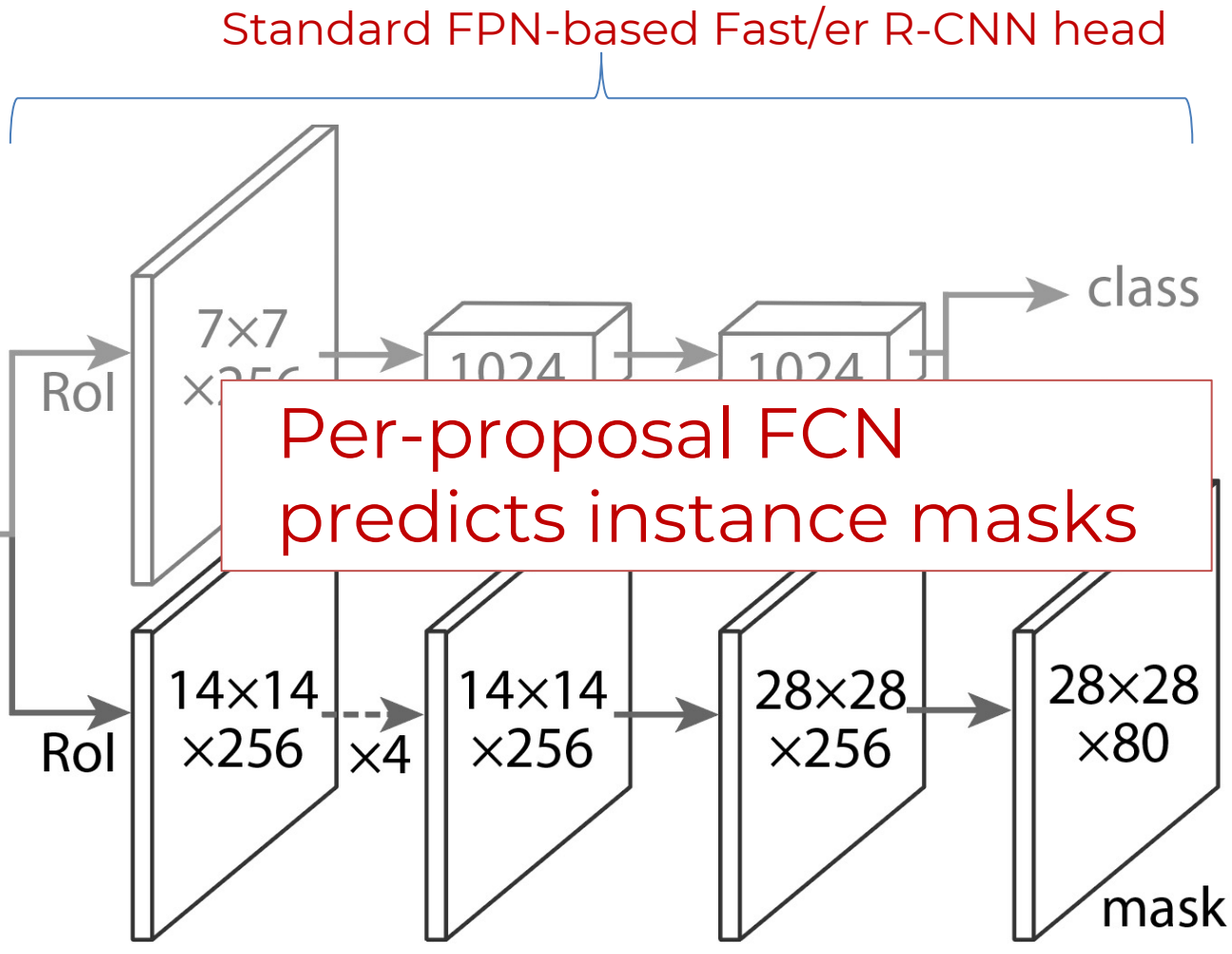
5. … + Task-specific Heads (on each Proposal)

Task specific heads for …

- Bounding box detection
- Object classification
- Instance mask prediction
- Human keypoint prediction





Mask R-CNN: Training

Same as “image centric” Fast/er R-CNN training

- Use precomputed proposals for faster experimentation
- Use joint / end-to-end training for sharing features

But with training targets for masks

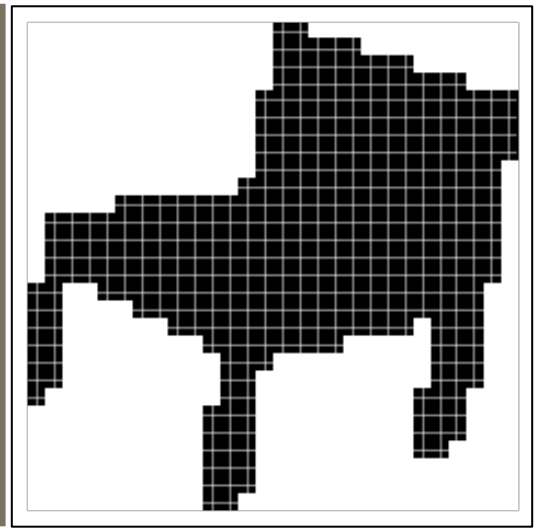
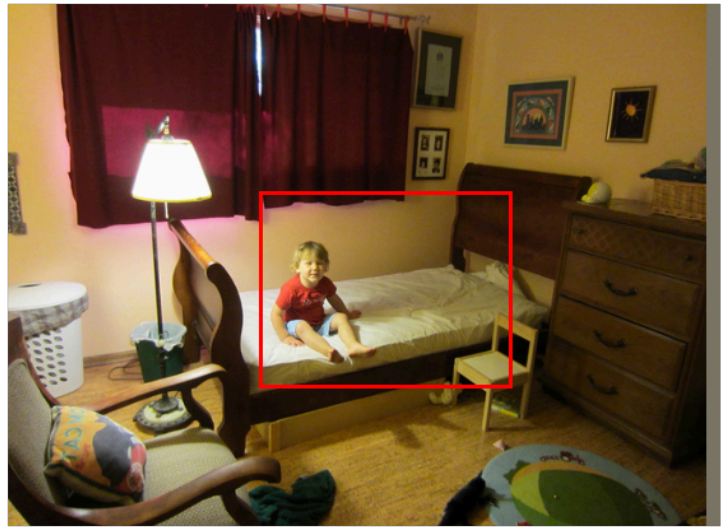
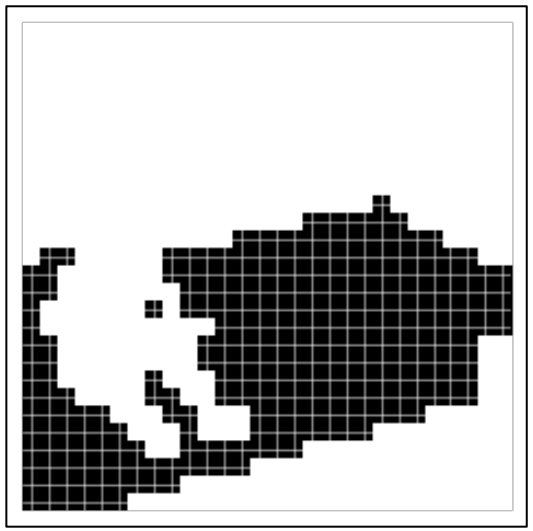
Example Mask Training Targets

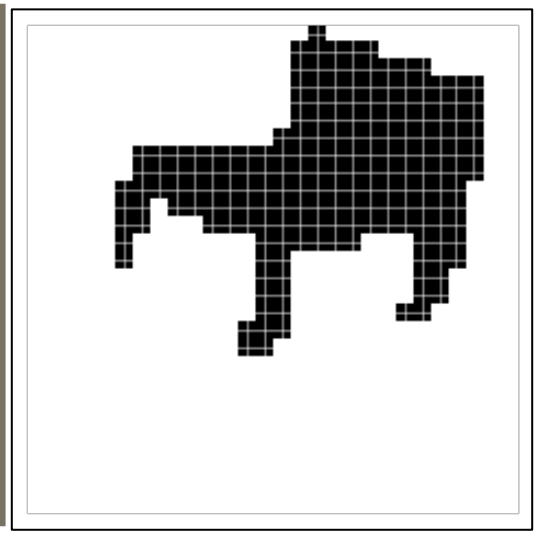
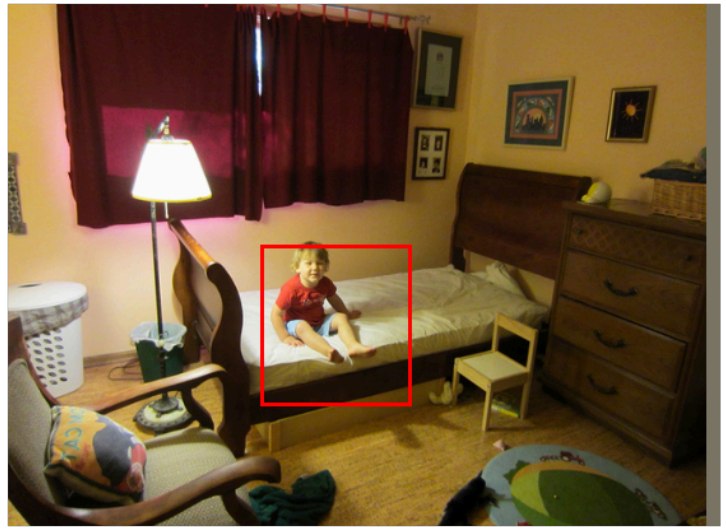
Image with training proposal

28x28 mask target

Image with training proposal

28x28 mask target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Mask R-CNN: Inference

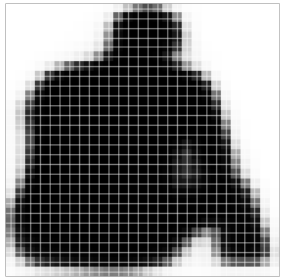
1. Perform Faster R-CNN inference
   - Generate proposals (RPN)
   - Score the proposals
   - Regress from proposals to refined detection boxes
   - Apply NMS and take the top *K* (= 100, e.g.)

2. Run RoIAlign and mask head on top-*K* refined, post-NMS boxes
   - Fast (only compute masks for top-*K* detections)
   - Improves accuracy (uses *refined* detection boxes, not proposals)

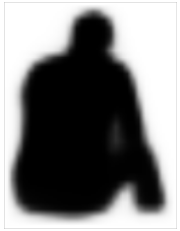
Mask Prediction

Validation image with box detection shown in red

28x28 soft prediction from Mask R-CNN
(enlarged)



Soft prediction resampled to image coordinates
(bilinear and bicubic interpolation work equally well)



Final prediction (threshold at 0.5)

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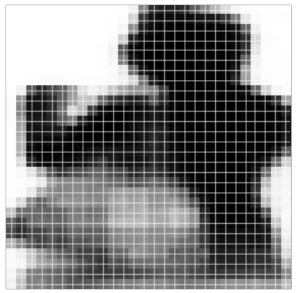
Mask Prediction

Validation image with box detection shown in red

28x28 soft prediction



Resized soft prediction

Final mask

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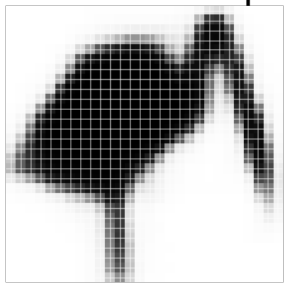
Mask Prediction

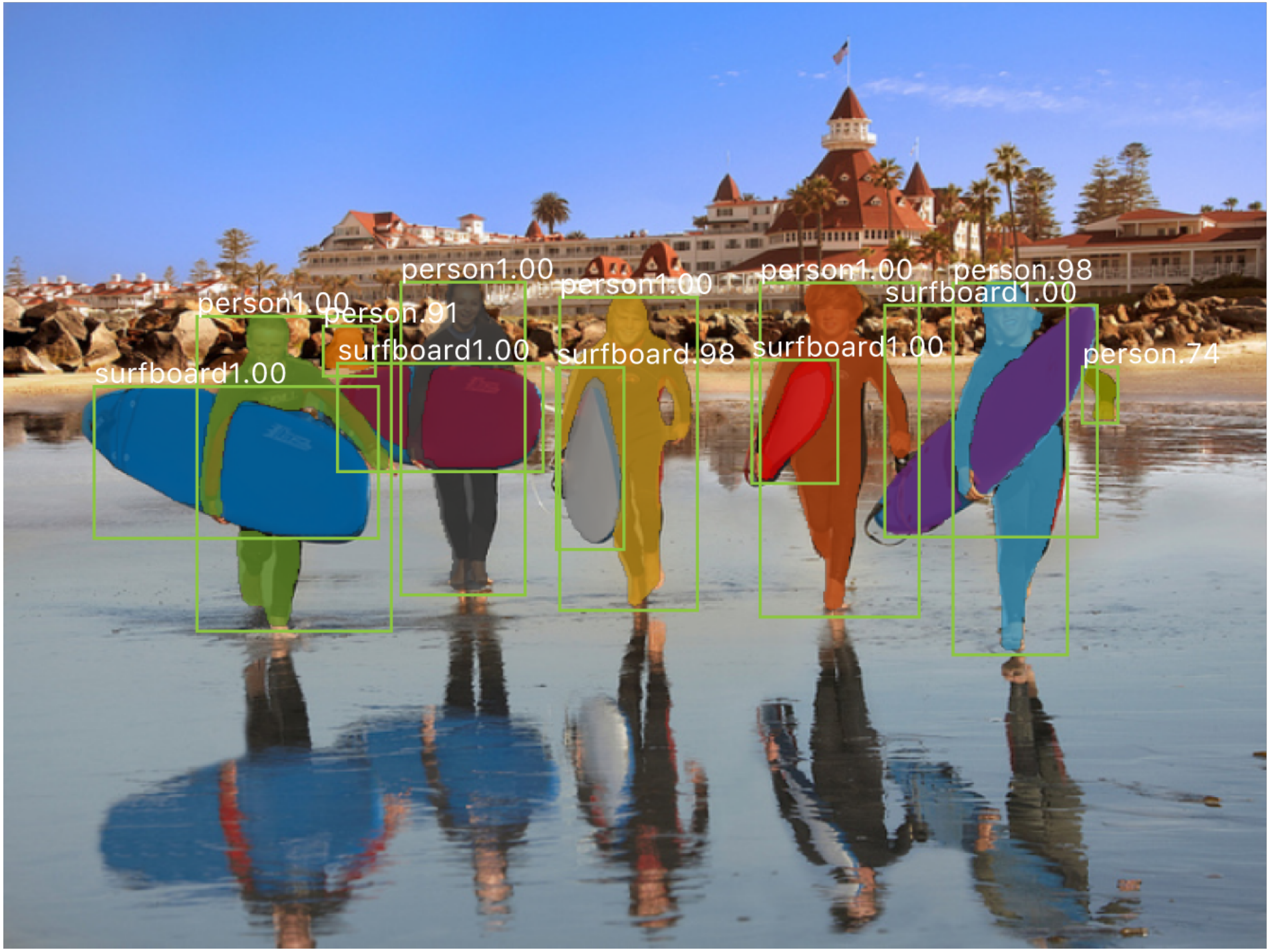
Validation image with box detection shown in red

28x28 soft prediction



Resized Soft prediction

Final mask


person1.00
person1.00
person1.00
person1.00
person.98
surfboard1.00
person1.00
person.91
surfboard1.00
surfboard.98
surfboard1.00
person.74
surfboard1.00

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person1.00
person.88
tv.98
tv.84
person1.00
person1.00
bottle.97
wine glass.99
dining table.95
wine glass1.00
wine glass1.00

R. Girshick

Segmentation Overview

- Semantic segmentation
  - Classify all pixels
  - Fully convolutional models, downsample then upsample
  - Learnable upsampling: fractionally strided convolution
  - Skip connections can help

- Instance Segmentation
  - Detect instance, generate mask
  - Similar pipelines to object detection