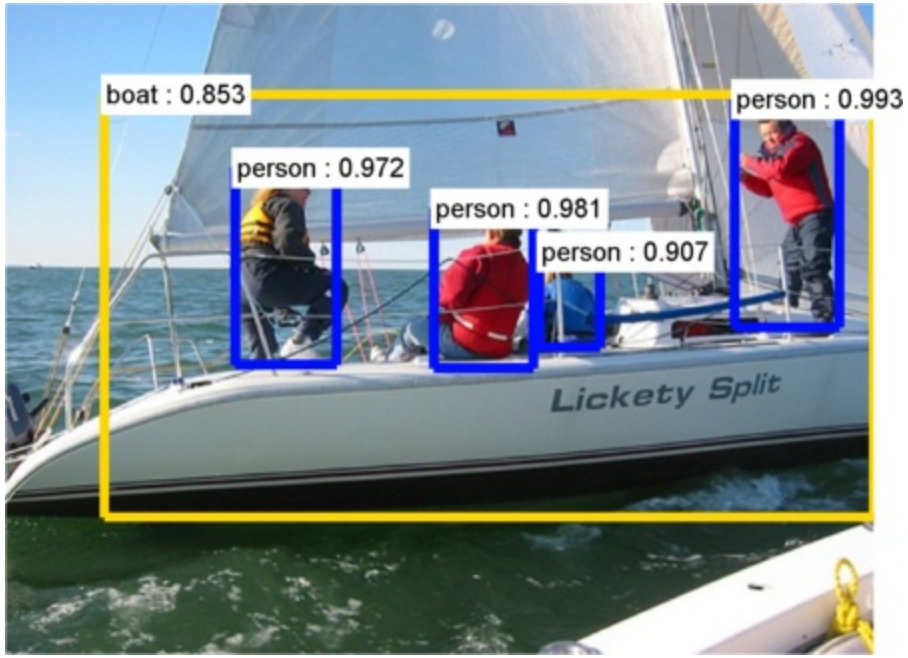
Object Detection

Lecture 9

Object Detection

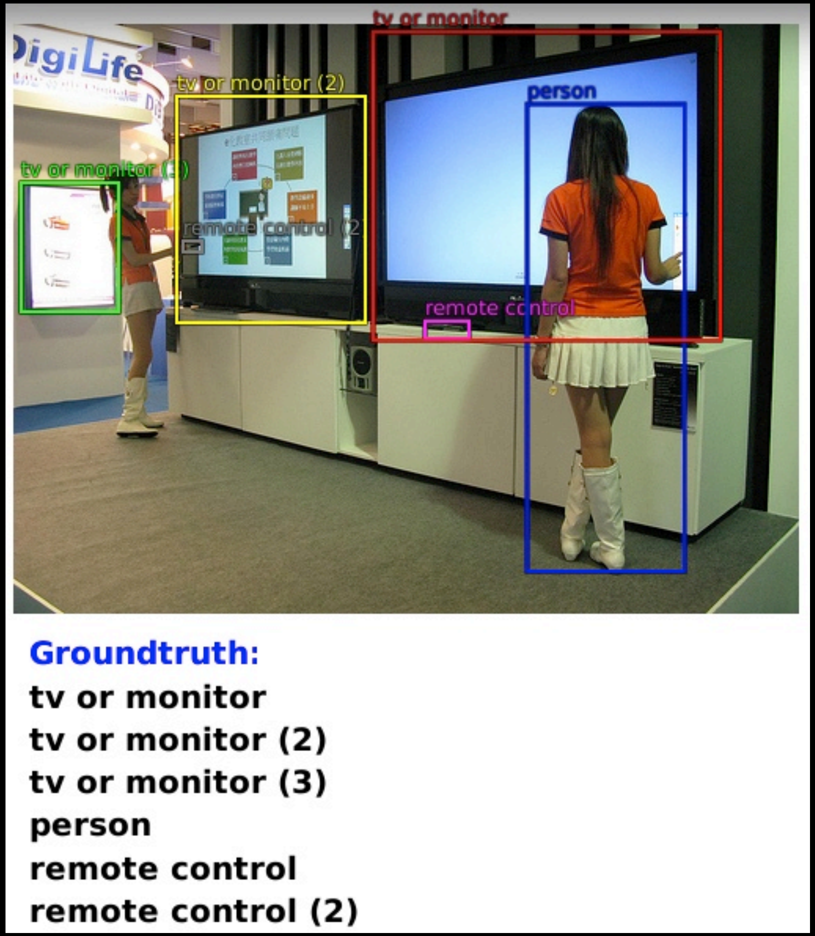
Image Classification
(what?)



Object Detection
(what + where?)

Detection with ConvNets

- So far, all about classification
- What about localizing objects within the scene?

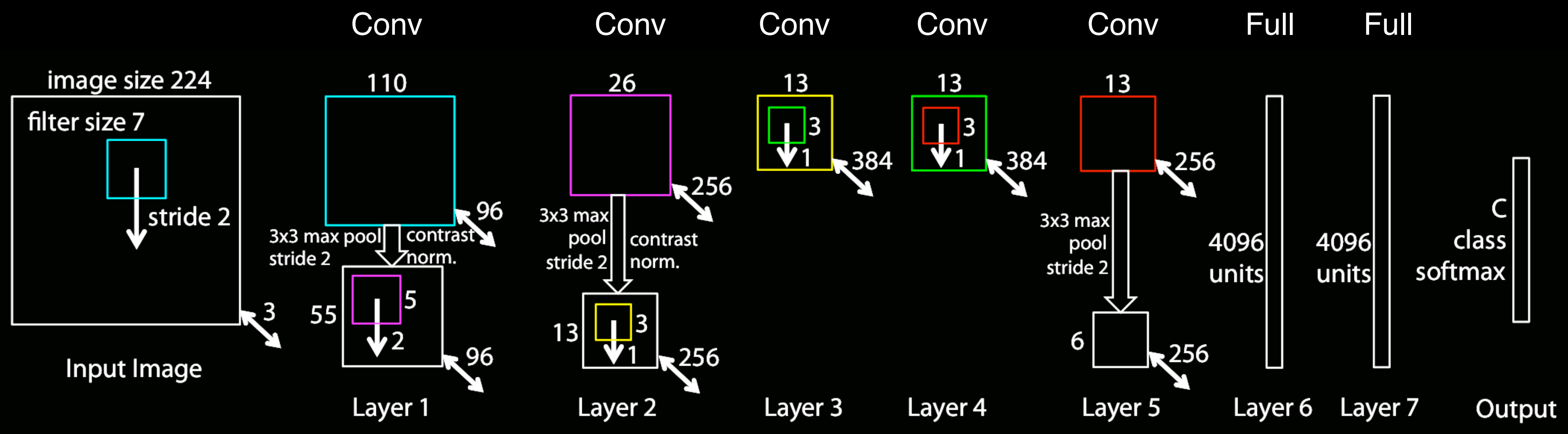


Two General Approaches

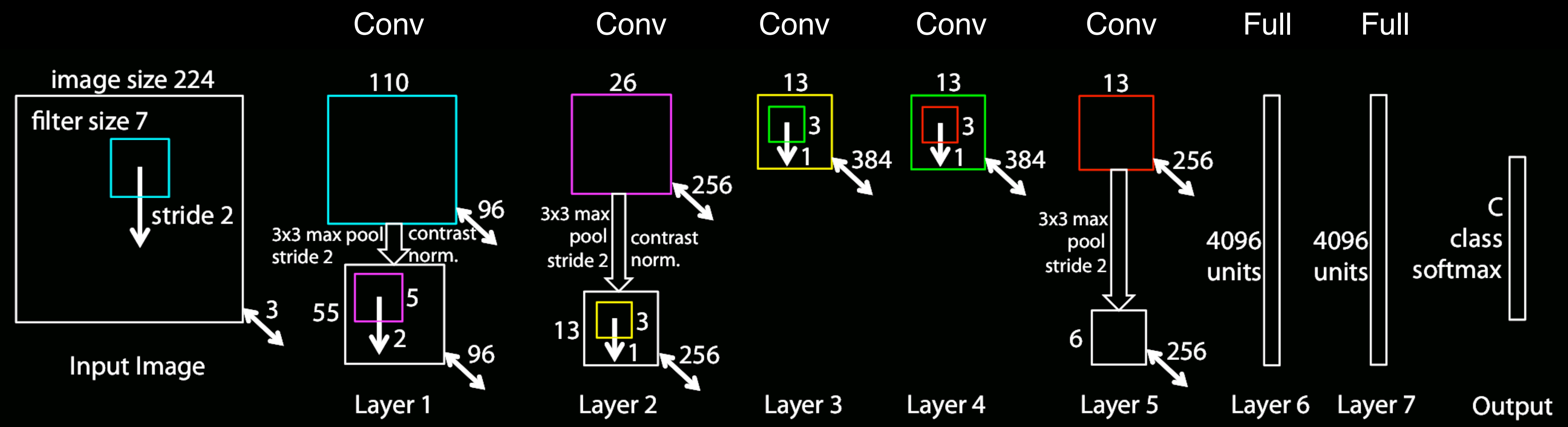
1. Examine very position / scale
   - E.g. Overfeat: Integrated recognition, localization and detection using convolutional networks, Sermanet et al., ICLR 2014

2. Use some kind of proposal mechanism to attend to a set of possible regions
   - E.g. Region-CNN [Rich feature hierarchies for accurate object detection and semantic segmentation, Girshick et al., CVPR 2014]

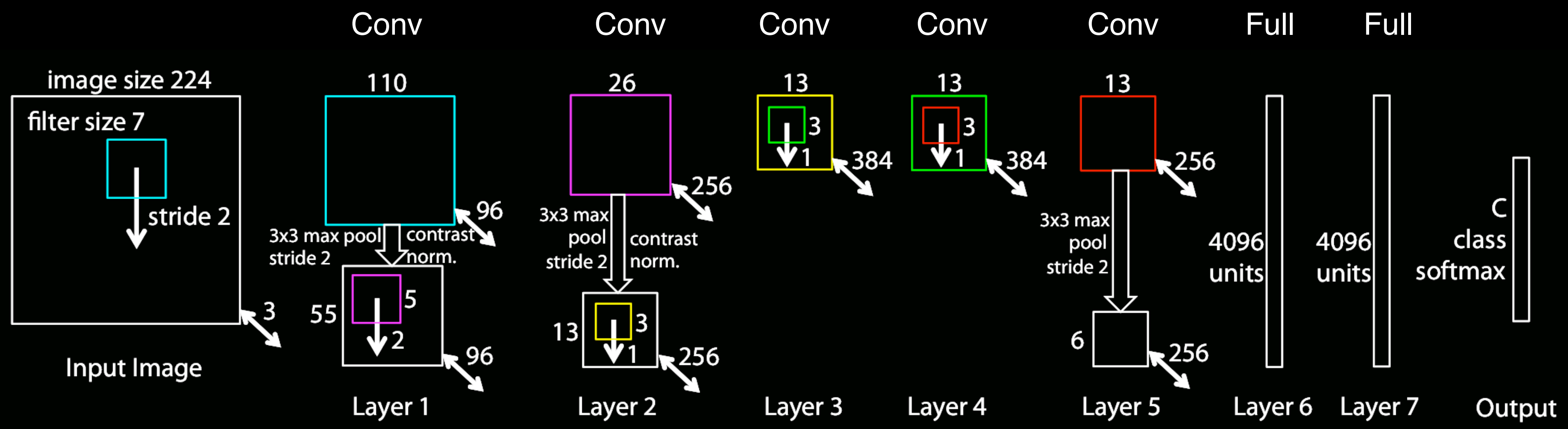
Sliding Window with ConvNet



Sliding Window with ConvNet



Sliding Window with ConvNet



Conv Conv Conv Conv Conv Full Full

image size 224
filter size 7
stride 2
3
Input Image

110
96
3x3 max pool
stride 2
contrast
norm.
55
5
2
96
Layer 1

26
256
3x3 max
pool
stride 2
contrast
norm.
13
3
1
256
Layer 2

13
3
1
384
Layer 3

13
3
1
384
Layer 4

13
256
3x3 max
pool
stride 2
6
256
Layer 5

4096
units
Layer 6

4096
units
Layer 7

C
class
softmax
Output

240
16
224
Input Window

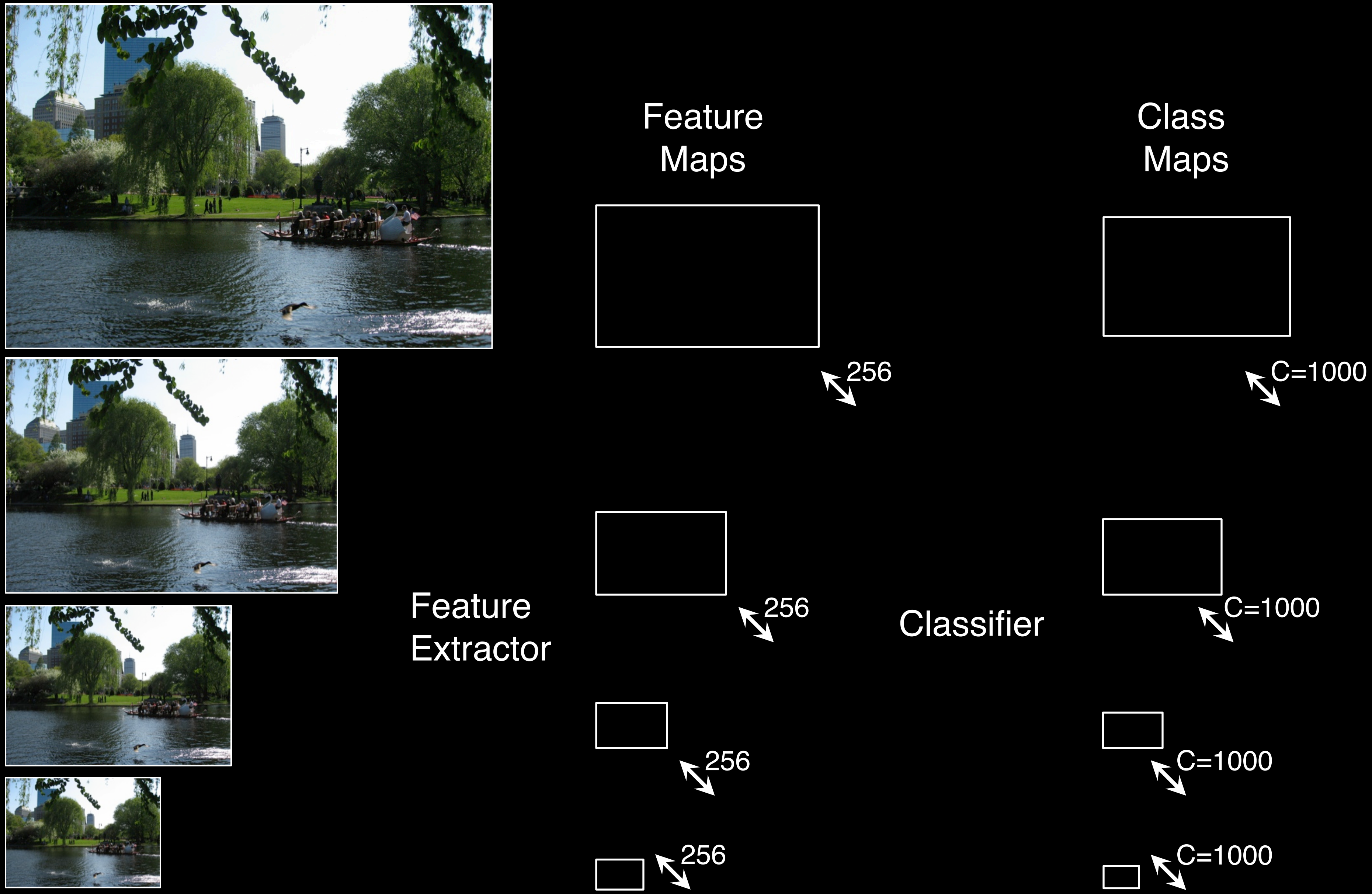
Feature Extractor

7
6
1
256

C
classes

No need to compute two separate windows --- Just one big input window

Multi-Scale Sliding Window ConvNet



Feature Maps

Class Maps

256

C=1000

Feature Extractor

256

Classifier

C=1000

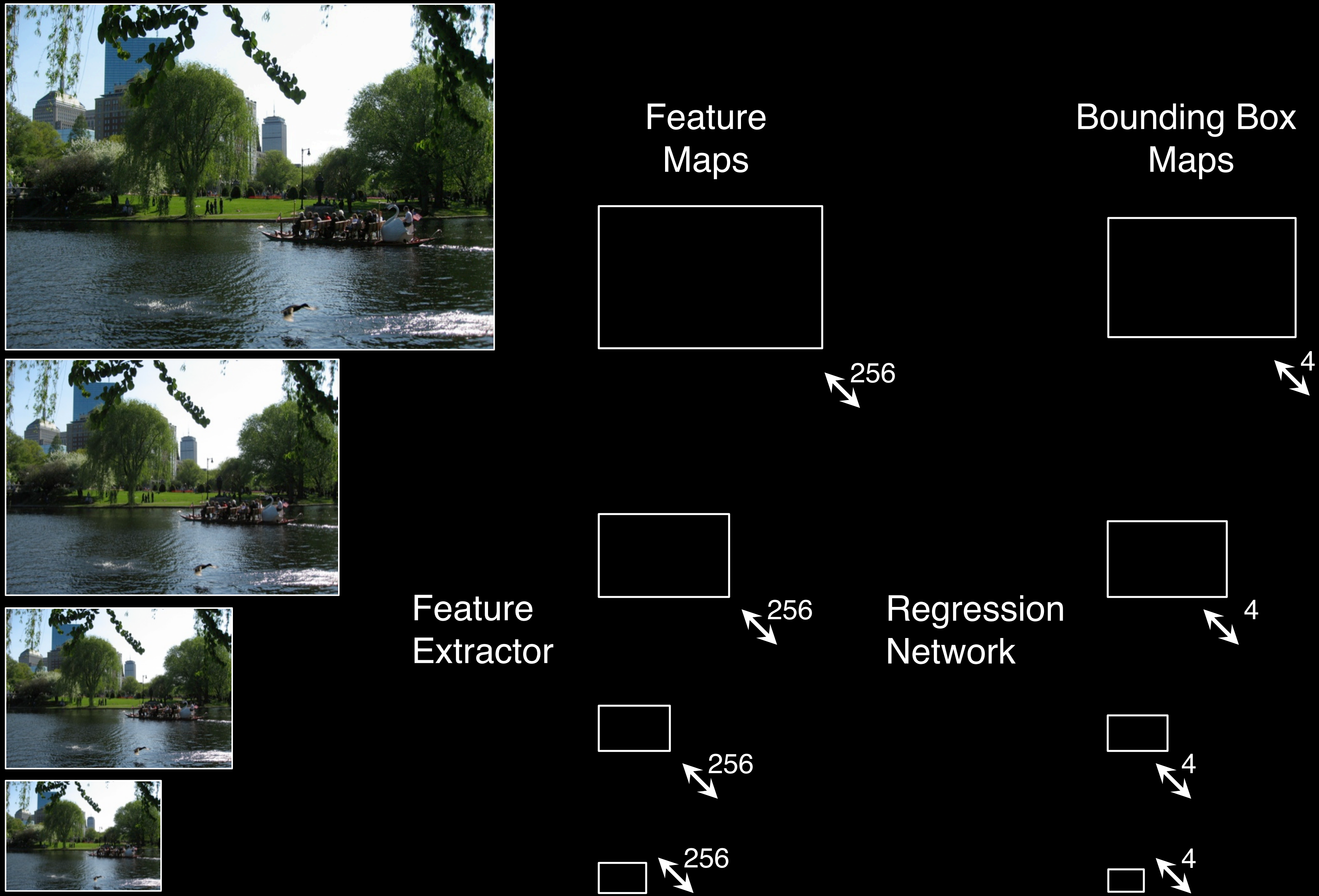
256

C=1000

256

C=1000

Multi-Scale Sliding Window ConvNet



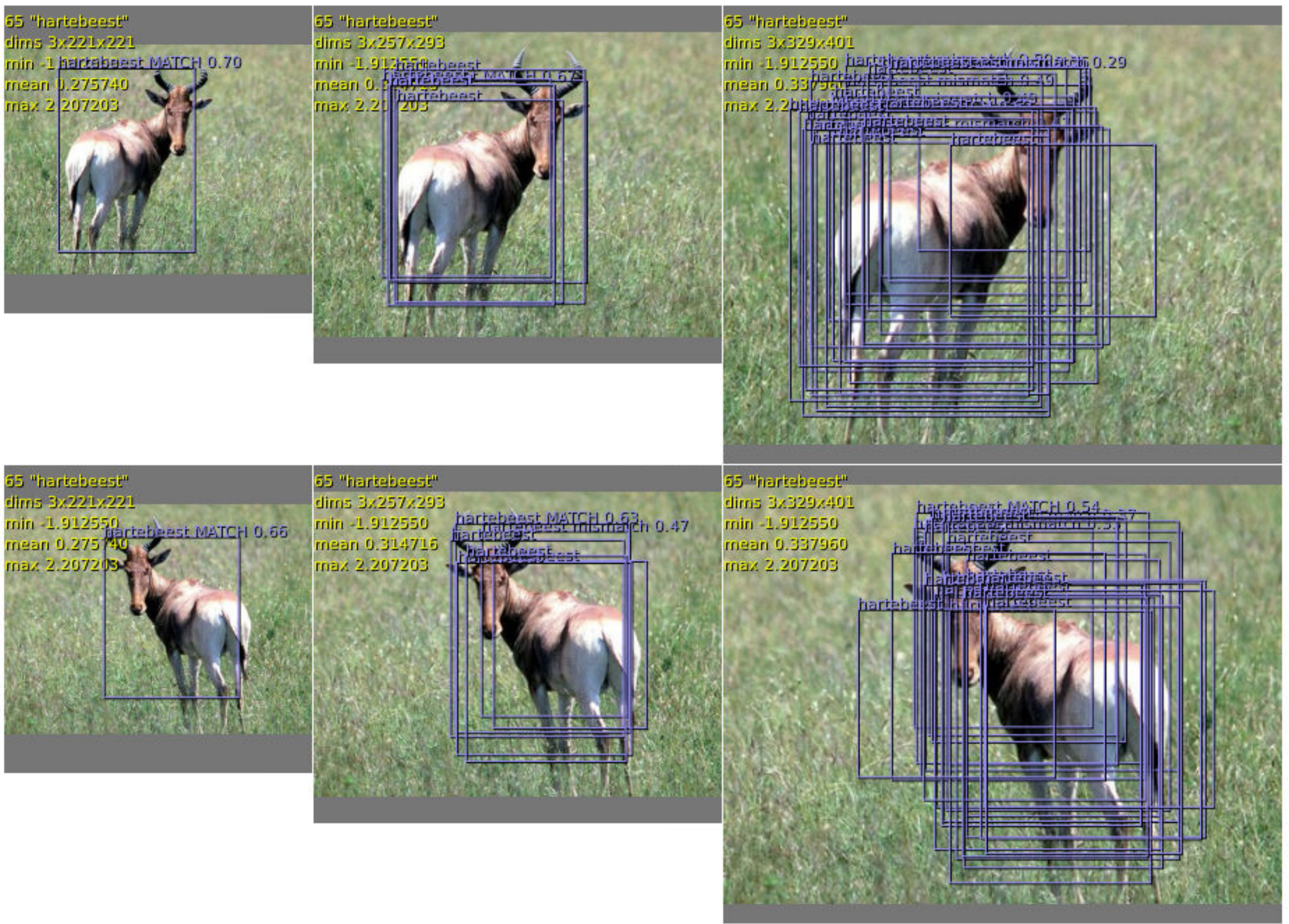
Feature Maps

Bounding Box Maps

Feature Extractor

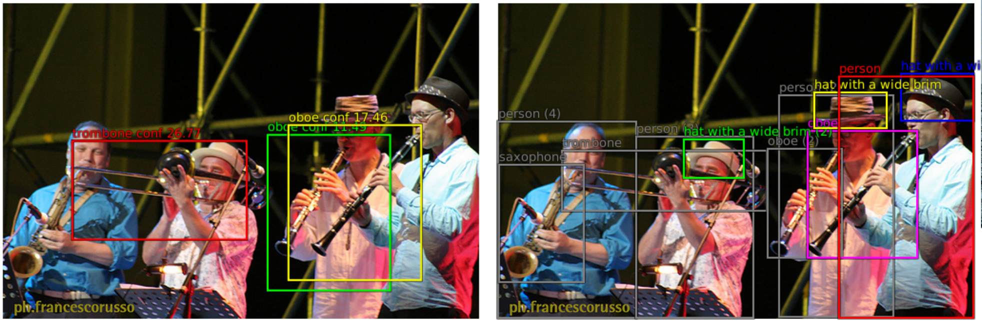
Regression Network

OverFeat – Output before NMS



Overfeat Detection Results

[Sermanet et al. ICLR 2014]



Top predictions:
trombone (confidence 26.8)
oboe (confidence 17.5)
oboe (confidence 11.5)

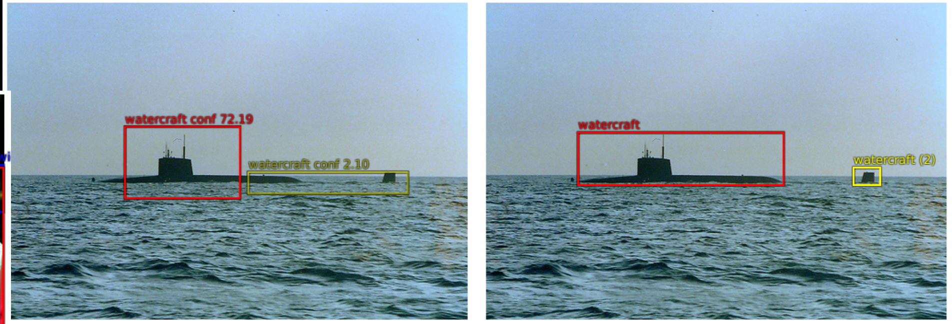
ILSVRC2012_val_00000614.JPEG

Groundtruth:
person
hat with a wide brim
hat with a wide brim (2)
hat with a wide brim (3)
oboe
oboe (2)
saxophone
trombone
person (2)
person (3)
person (4)

Top predictions:
microwave (confidence 5.6)
refrigerator (confidence 2.5)

ILSVRC2012_val_00000519.JPEG

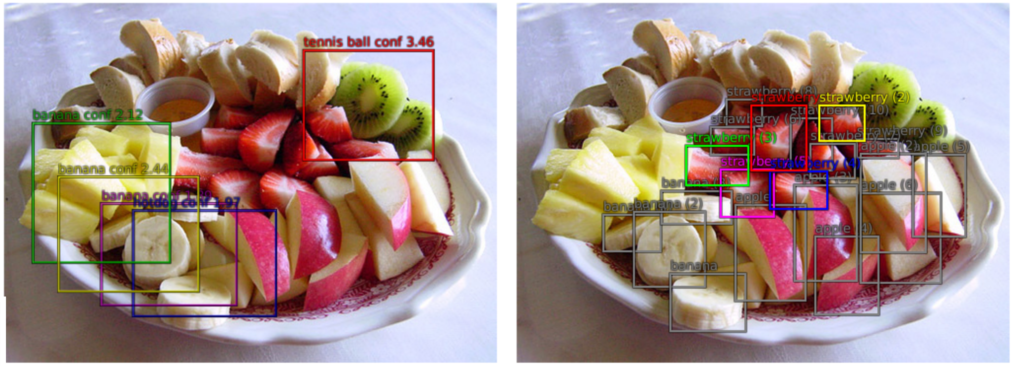
Groundtruth:
bowl
microwave



Top predictions:
watercraft (confidence 72.2)
watercraft (confidence 2.1)

ILSVRC2012_val_00000623.JPEG

Groundtruth:
watercraft
watercraft (2)



Top predictions:
tennis ball (confidence 3.5)
banana (confidence 2.4)
banana (confidence 2.1)
hotdog (confidence 2.0)
banana (confidence 1.9)

ILSVRC2012_val_00000320.JPEG

Groundtruth:
strawberry
strawberry (2)
strawberry (3)
strawberry (4)
strawberry (5)
strawberry (6)
strawberry (7)
strawberry (8)
strawberry (9)
strawberry (10)
apple
apple (2)
apple (3)

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Reproducible research – get the code!

http://git.io/vBqm5

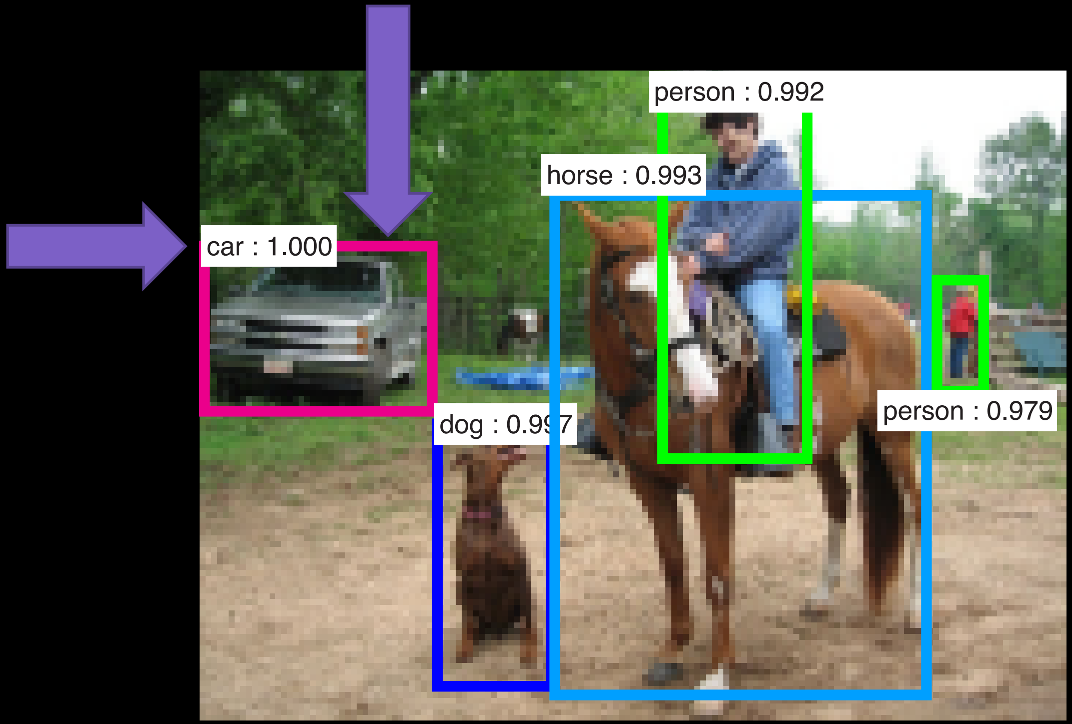
Fast R-CNN

Ross Girshick

Facebook AI Research (FAIR)

Work done at Microsoft Research

Fast Region-based ConvNets (R-CNNs) for Object Detection

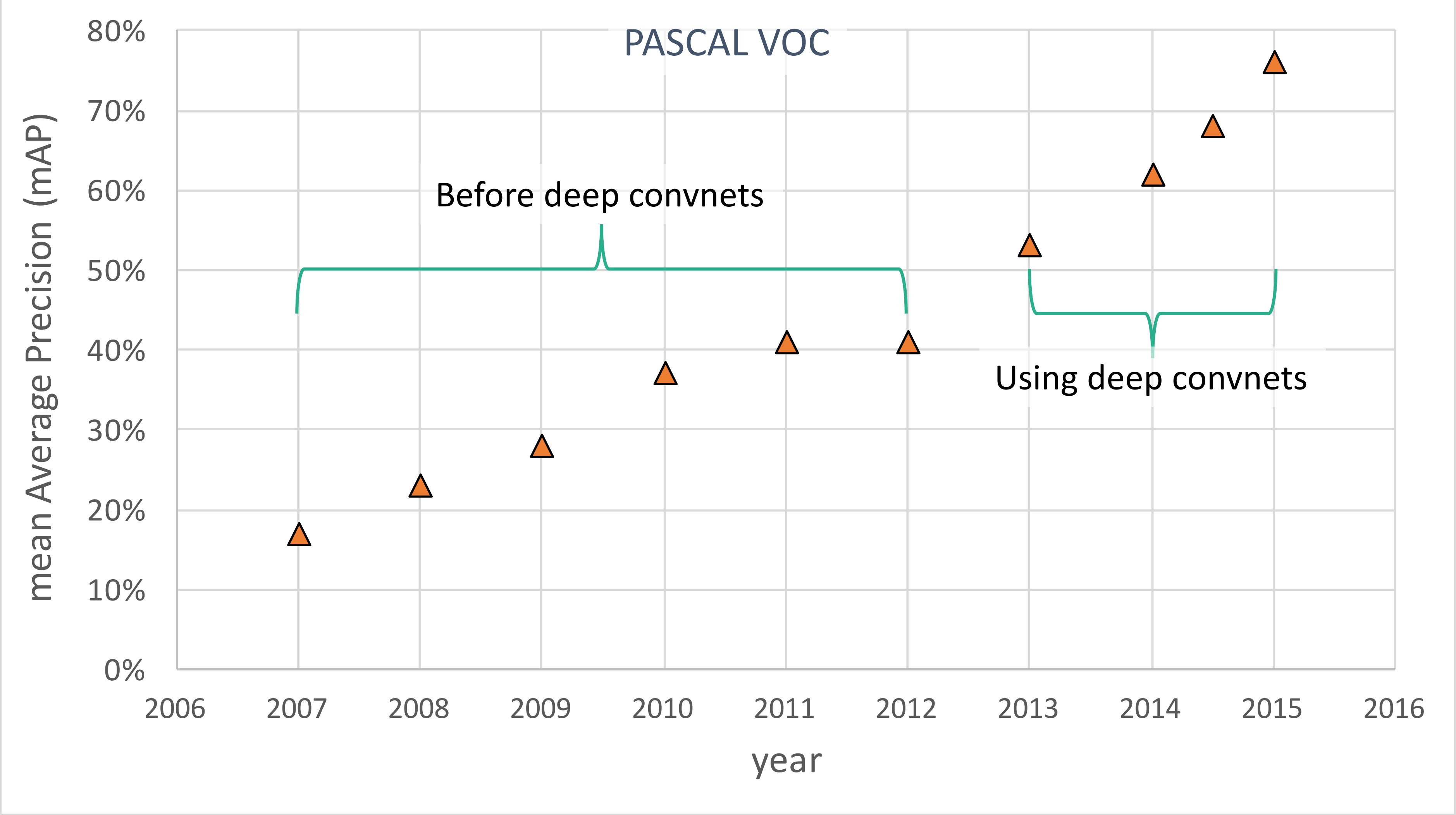


Localization
Where?

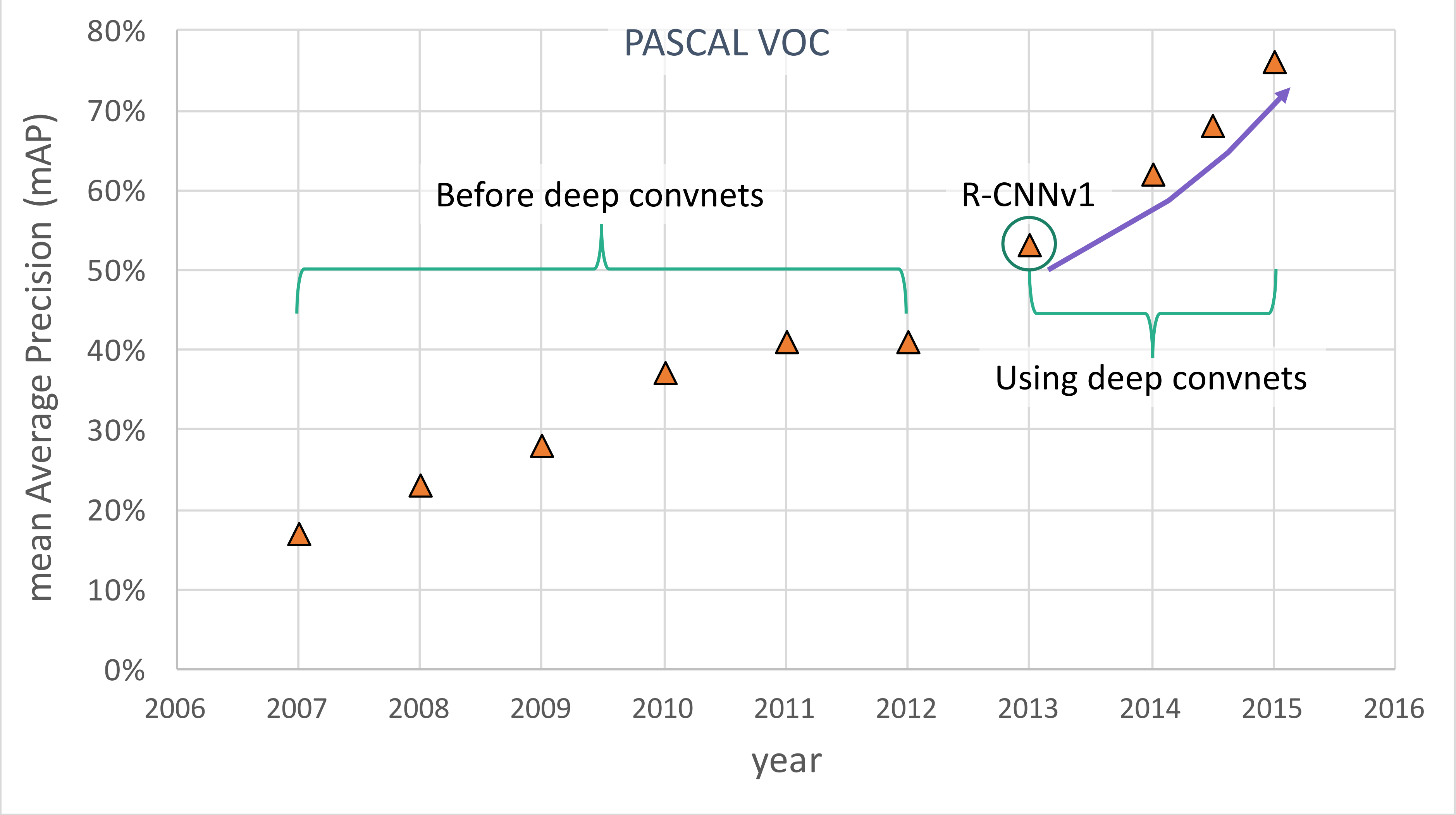
Recognition
What?

Figure adapted from Kaiming He

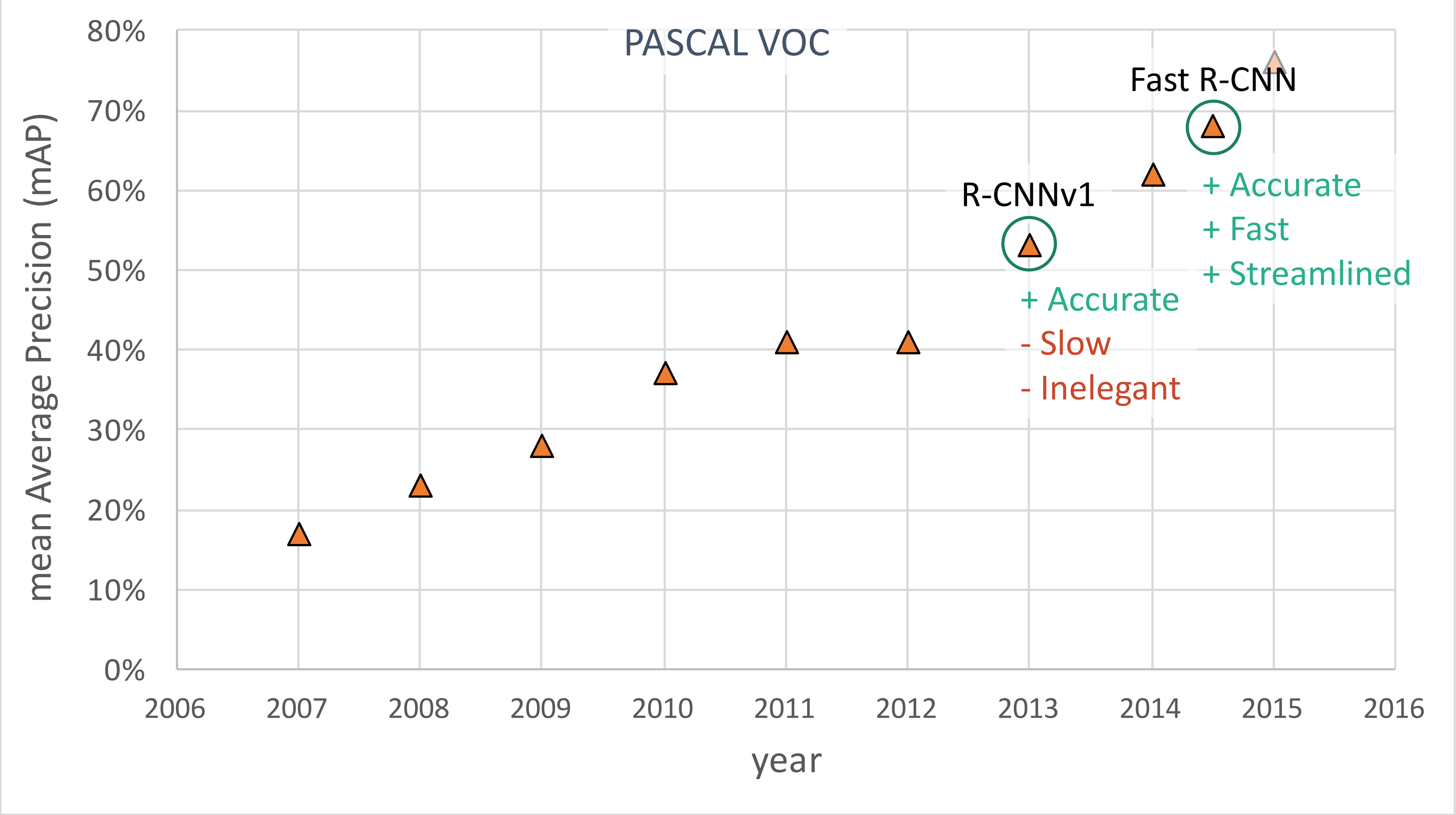
Object detection renaissance (2013-present)



Object detection renaissance (2013-present)



Object detection renaissance (2013-present)



Region-based convnets (R-CNNs)

- R-CNN (aka “slow R-CNN”) [Girshick et al. CVPR14]
- SPP-net [He et al. ECCV14]

Slow R-CNN

Input image

Girshick et al. CVPR14.

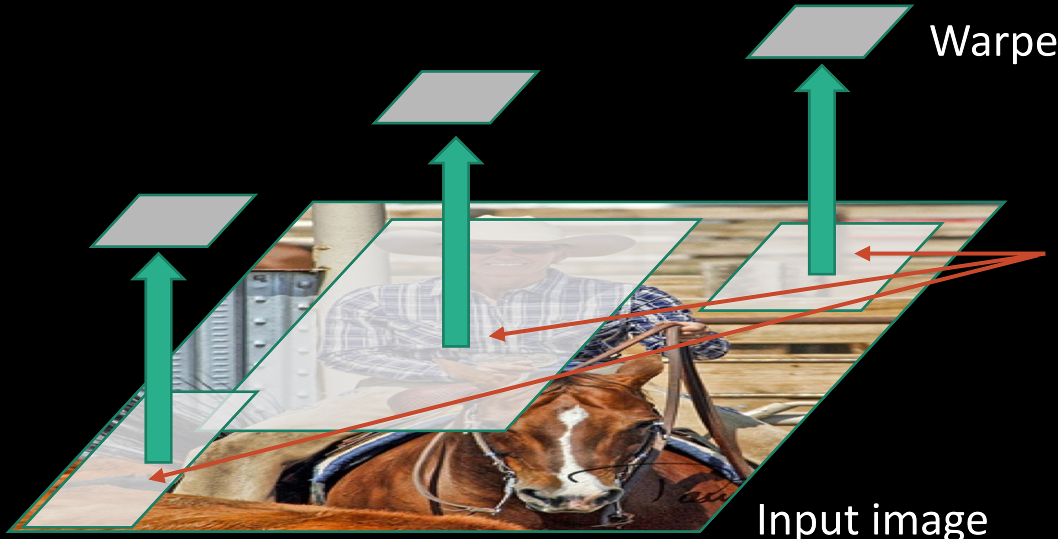
Slow R-CNN

Regions of Interest (RoI)
from a proposal method
(~2k)

Input image

Girshick et al. CVPR14.

Slow R-CNN



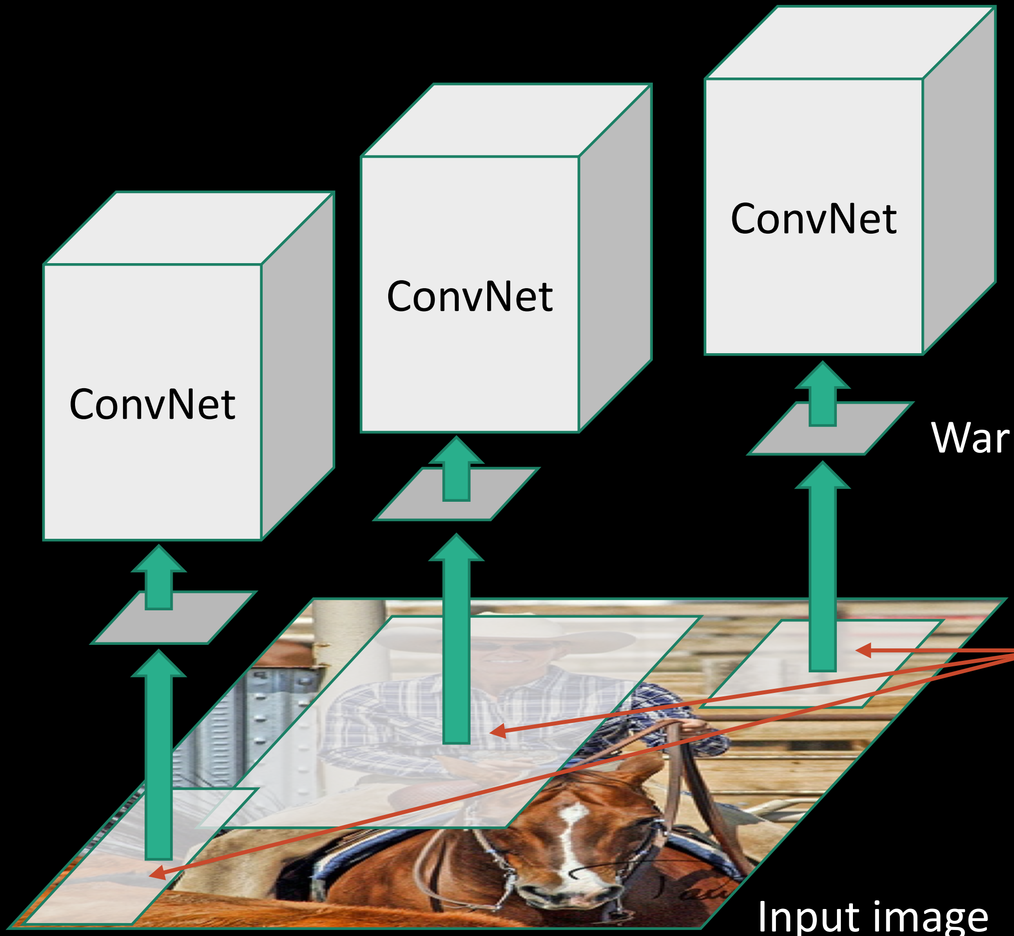
Warped image regions

Regions of Interest (RoI)
from a proposal method
(~2k)

Input image

Girshick et al. CVPR14.

Slow R-CNN



Forward each region through ConvNet

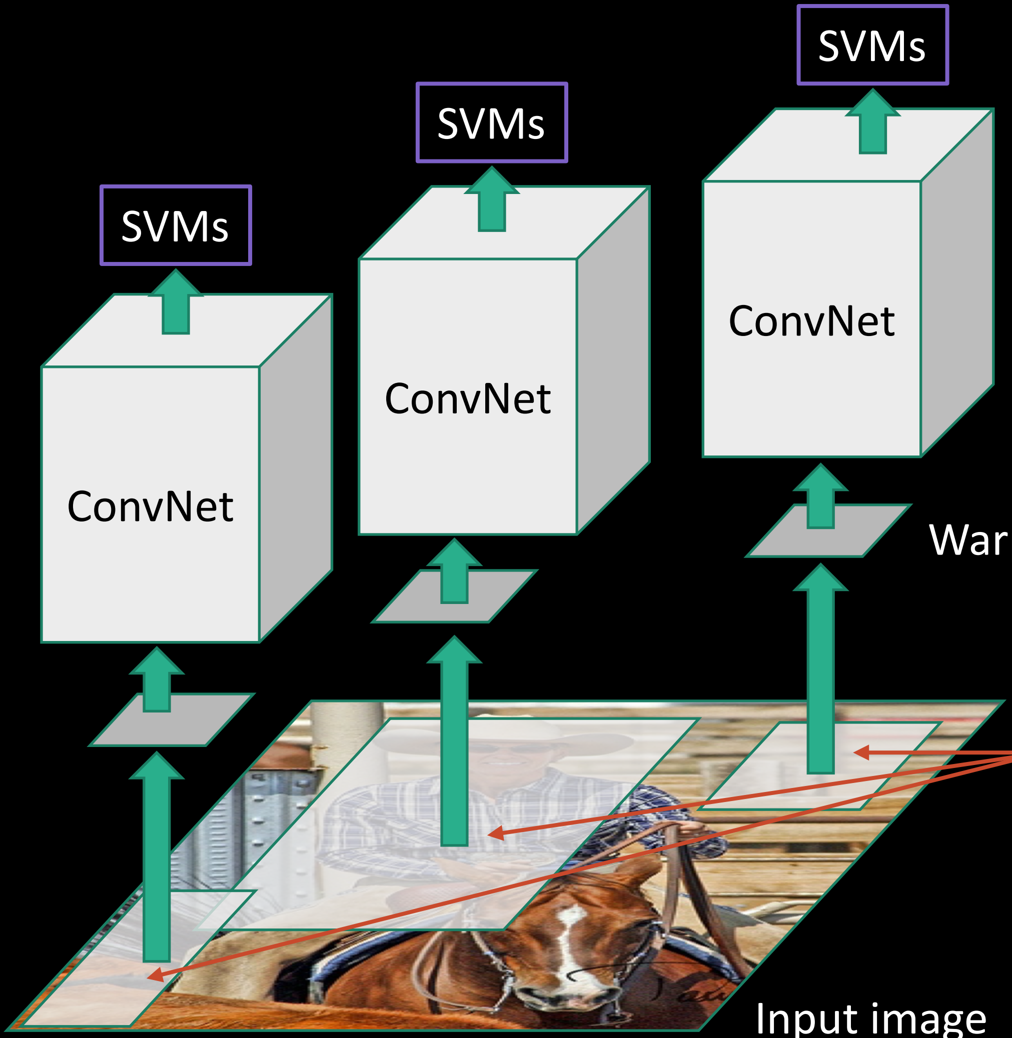
Warped image regions

Regions of Interest (RoI) from a proposal method (~2k)

Input image

Girshick et al. CVPR14.

Slow R-CNN



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

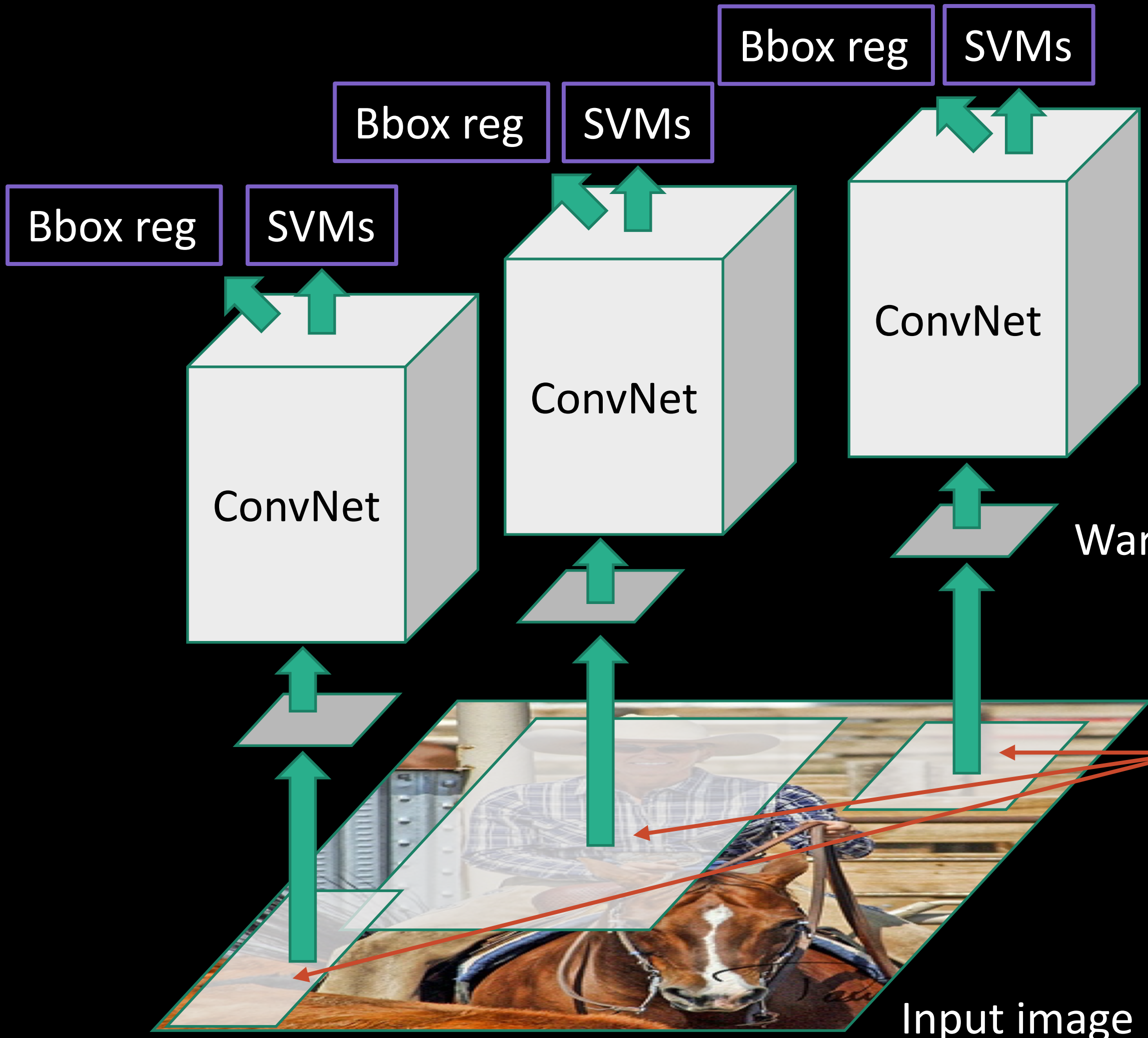
Regions of Interest (RoI) from a proposal method (~2k)

Input image

Girshick et al. CVPR14.

Post hoc component

Slow R-CNN



Apply bounding-box regressors

Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

Regions of Interest (RoI) from a proposal method (~2k)

Input image

Girshick et al. CVPR14.

Post hoc component

What’s wrong with slow R-CNN?

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- Ad hoc training objectives
    - Fine-tune network with softmax classifier (log loss)
    - Train post-hoc linear SVMs (hinge loss)
    - Train post-hoc bounding-box regressors (squared loss)

What’s wrong with slow R-CNN?

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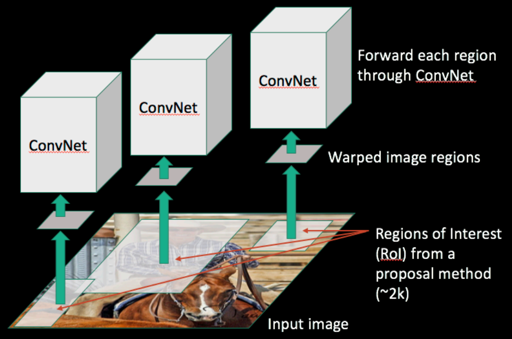
- Training is slow (84h), takes a lot of disk space

What’s wrong with slow R-CNN?

- Ad hoc training objectives
  - Fine-tune network with softmax classifier (log loss)
  - Train post-hoc linear SVMs (hinge loss)
  - Train post-hoc bounding-box regressions (least squares)
- Training is slow (84h), takes a lot of disk space
- Inference (detection) is slow
  - 47s / image with VGG16 [Simonyan & Zisserman. ICLR15]
  - Fixed by SPP-net [He et al. ECCV14]



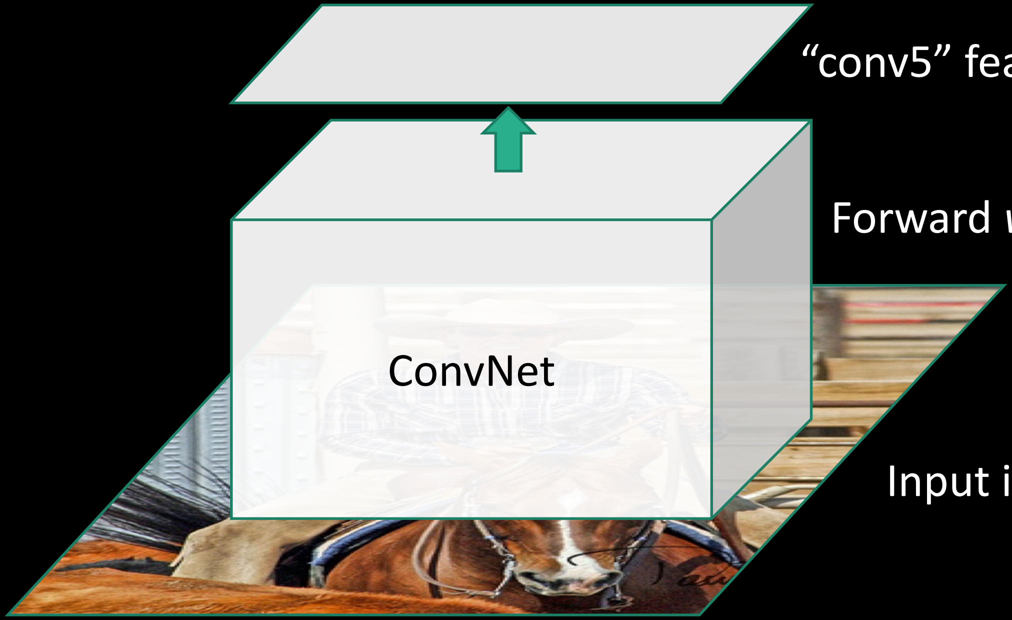
~2000 ConvNet forward passes per image

SPP-net

Input image

He et al. ECCV14.

SPP-net



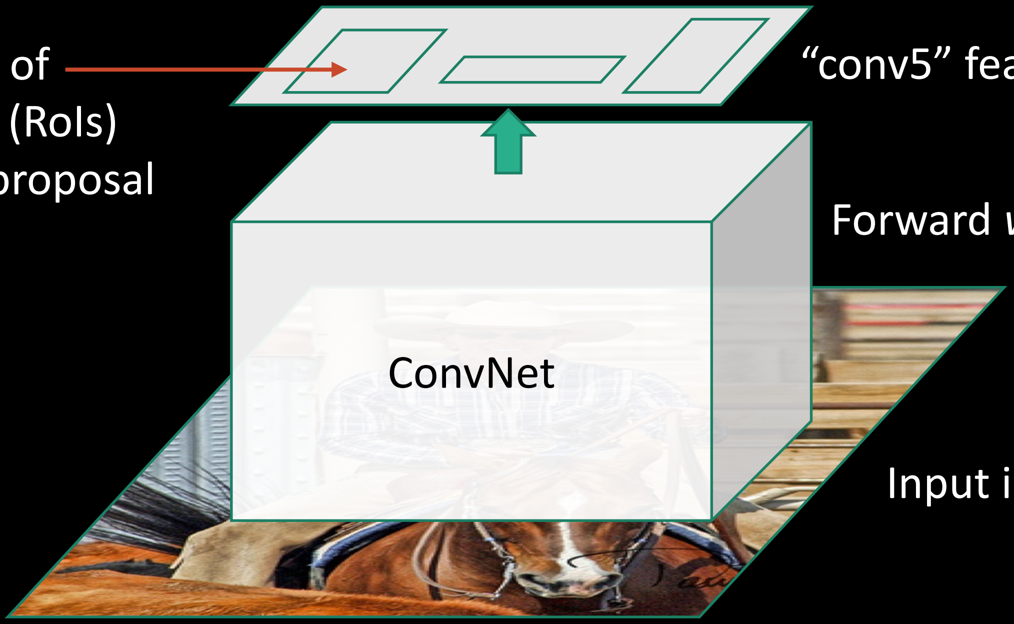
“conv5” feature map of image

Forward *whole* image through ConvNet

Input image

He et al. ECCV14.

SPP-net



Regions of Interest (RoIs) from a proposal method

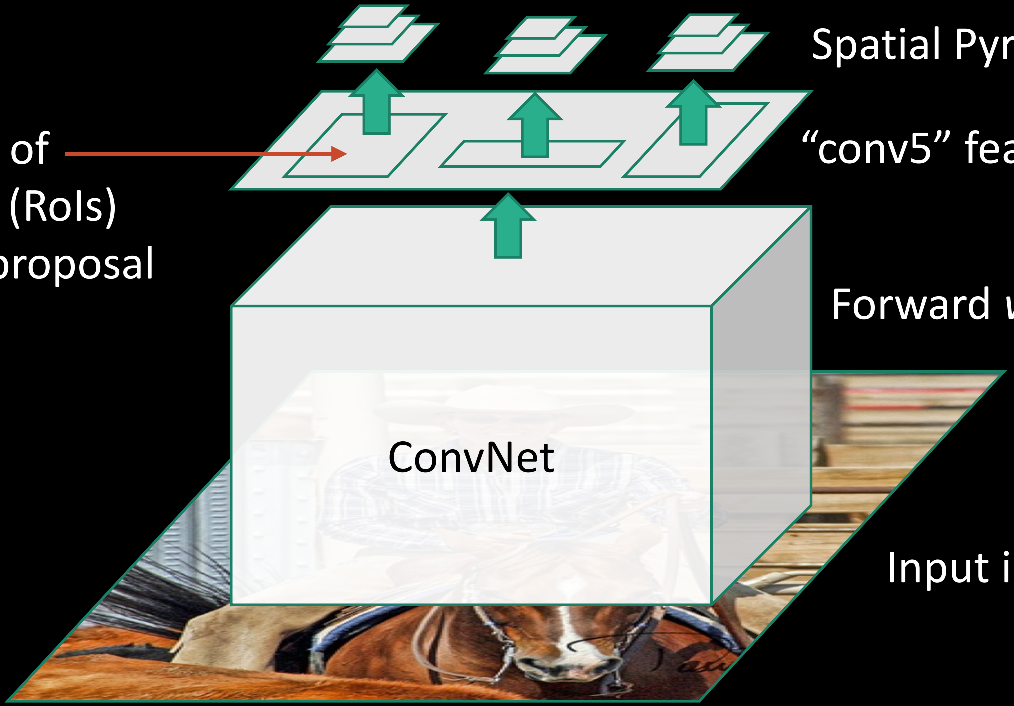
“conv5” feature map of image

Forward *whole* image through ConvNet

Input image

He et al. ECCV14.

SPP-net



Spatial Pyramid Pooling (SPP) layer

Regions of Interest (RoIs) from a proposal method

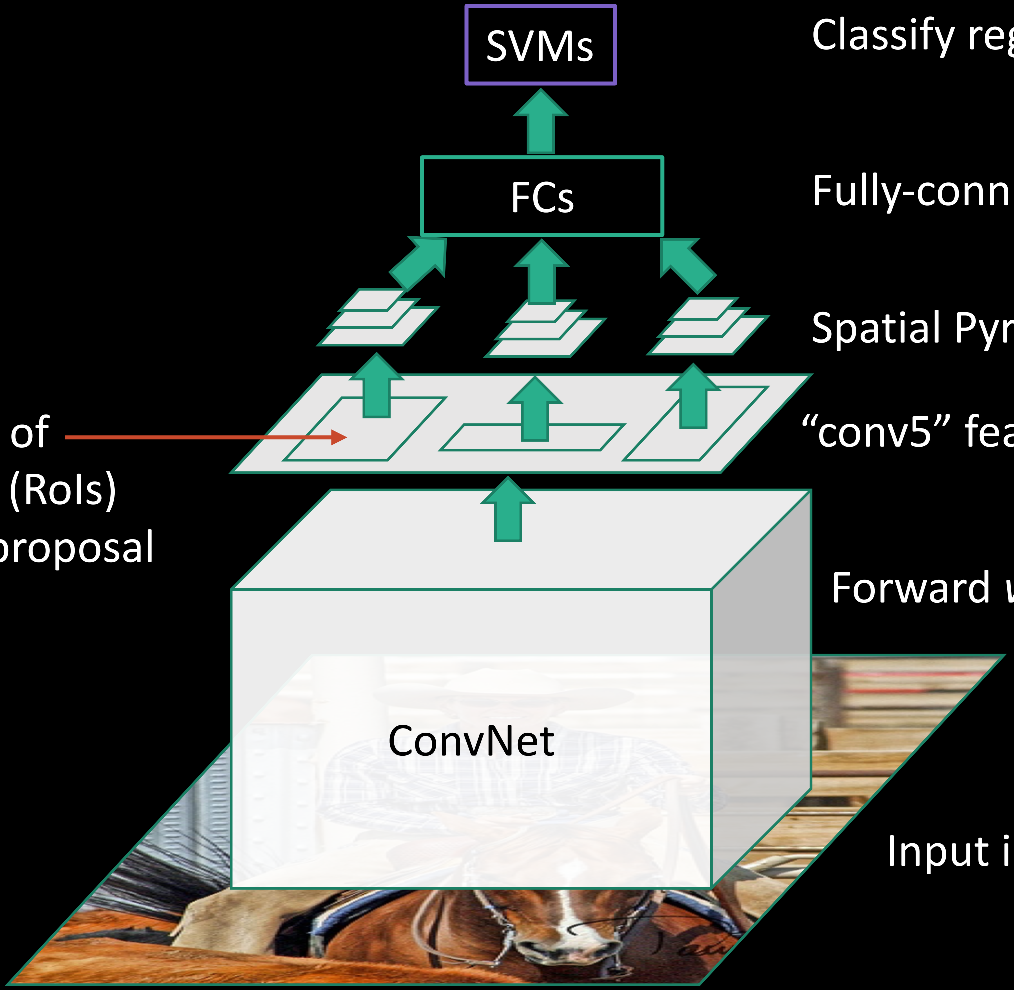
“conv5” feature map of image

Forward *whole* image through ConvNet

Input image

He et al. ECCV14.

SPP-net



Classify regions with SVMs

Fully-connected layers

Spatial Pyramid Pooling (SPP) layer

"conv5" feature map of image

Regions of
Interest (RoIs)
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Forward *whole* image through ConvNet

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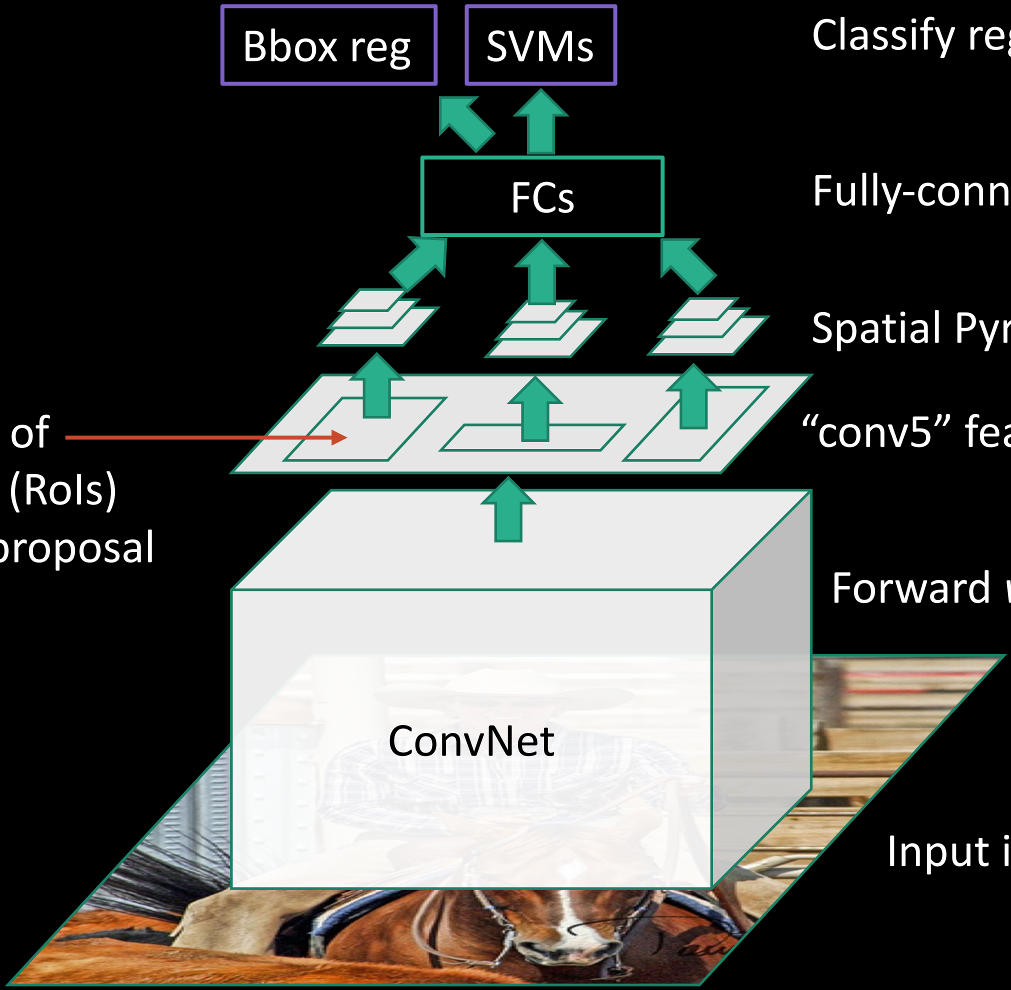
Post hoc component

SPP-net



Apply bounding-box regressors

Classify regions with SVMs

Fully-connected layers

Spatial Pyramid Pooling (SPP) layer

“conv5” feature map of image

Regions of Interest (RoIs) from a proposal method

Forward *whole* image through ConvNet

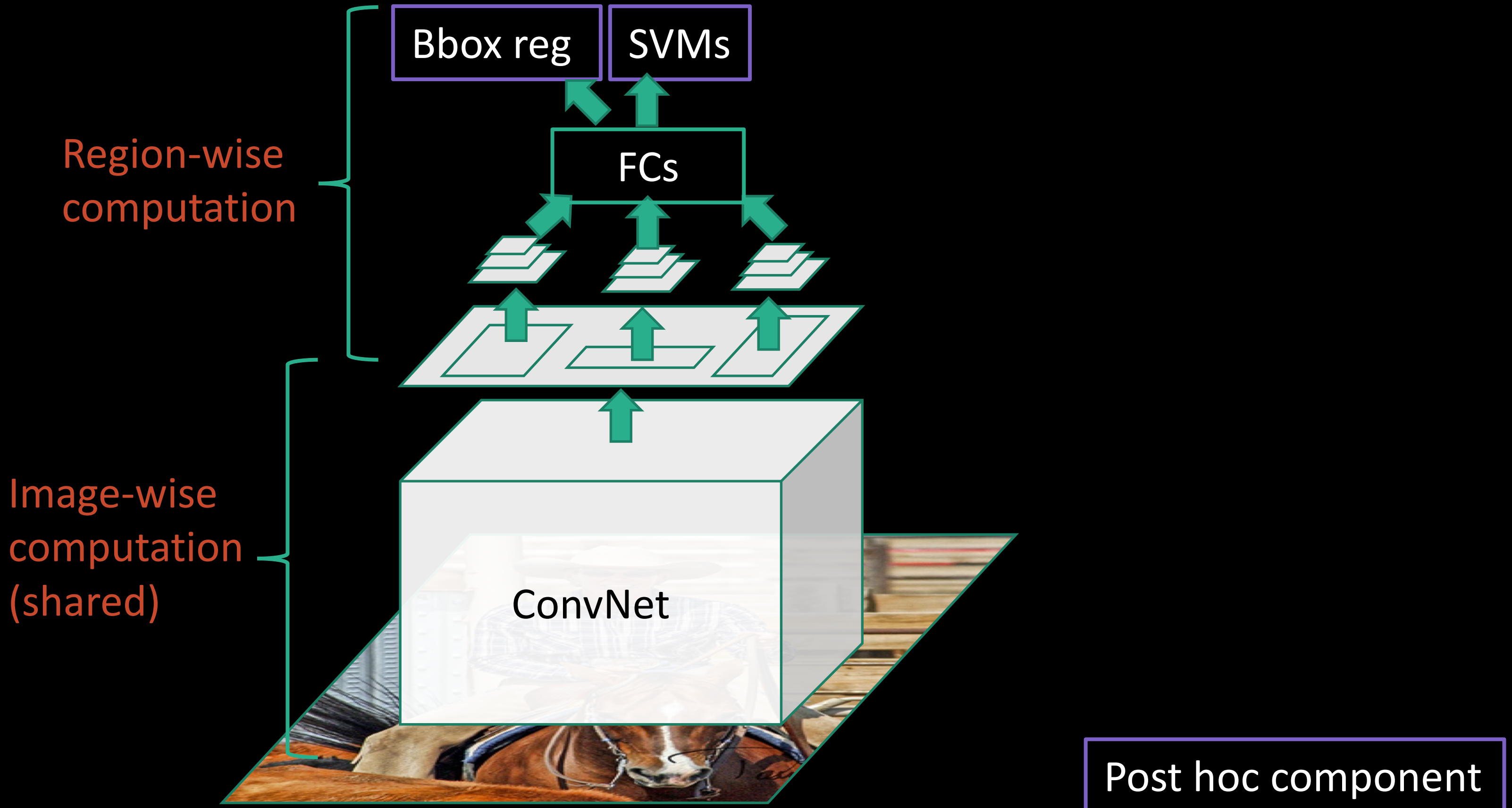
Input image

He et al. ECCV14.

Post hoc component

What's good about SPP-net?

- Fixes one issue with R-CNN: makes testing fast



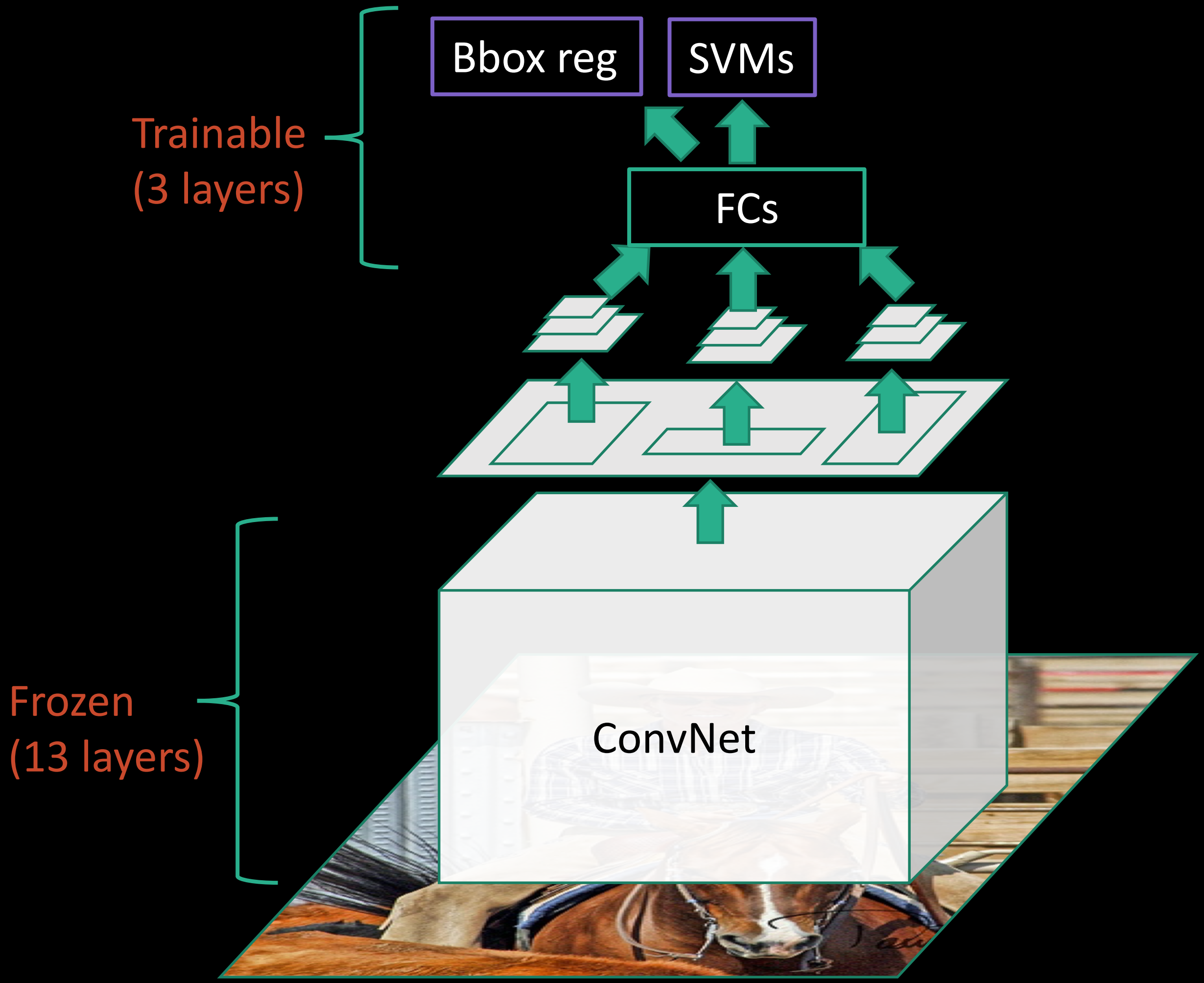
What’s wrong with SPP-net?

- Inherits the rest of R-CNN’s problems
  - Ad hoc training objectives
  - Training is slow (25h), takes a lot of disk space

What's wrong with SPP-net?

- Inherits the rest of R-CNN's problems
  - Ad hoc training objectives
  - Training is slow (though faster), takes a lot of disk space
- Introduces a new problem: cannot update parameters below SPP layer during training

SPP-net: the main limitation



He et al. ECCV14.

Post hoc component

Fast R-CNN

- Fast test-time, like SPP-net

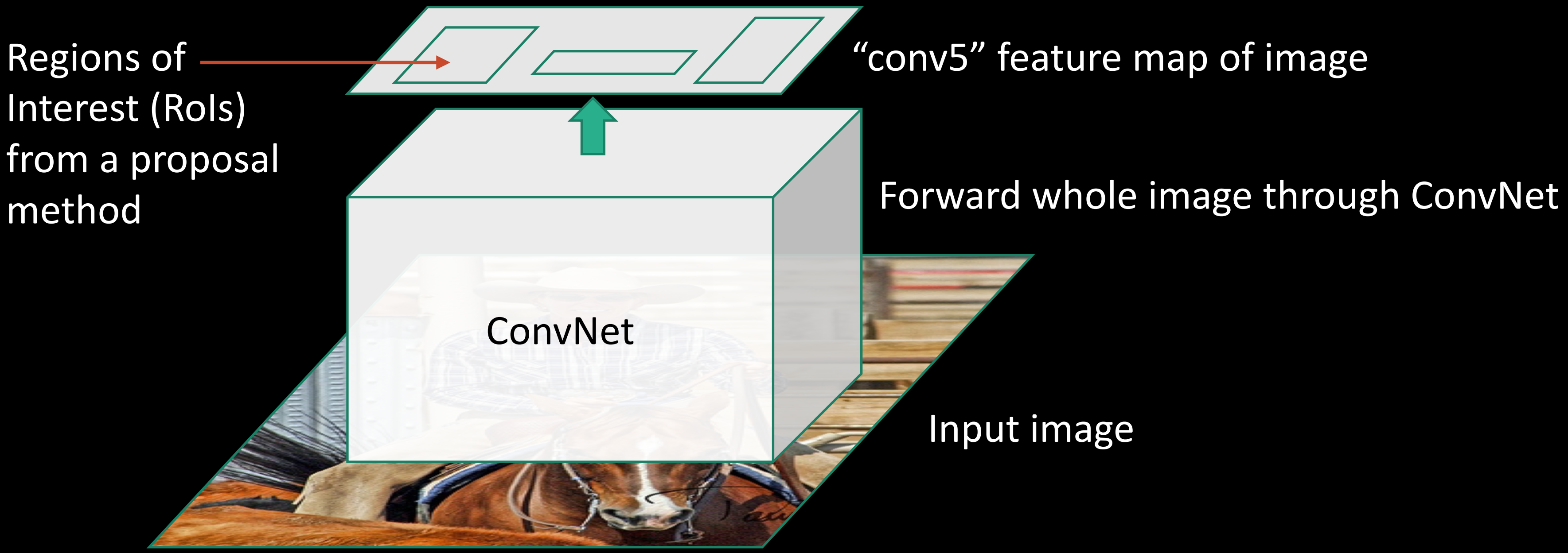
Fast R-CNN

- Fast test-time, like SPP-net
- One network, trained in one stage

Fast R-CNN

- Fast test-time, like SPP-net
- One network, trained in one stage
- Higher mean average precision than slow R-CNN and SPP-net

Fast R-CNN (test time)



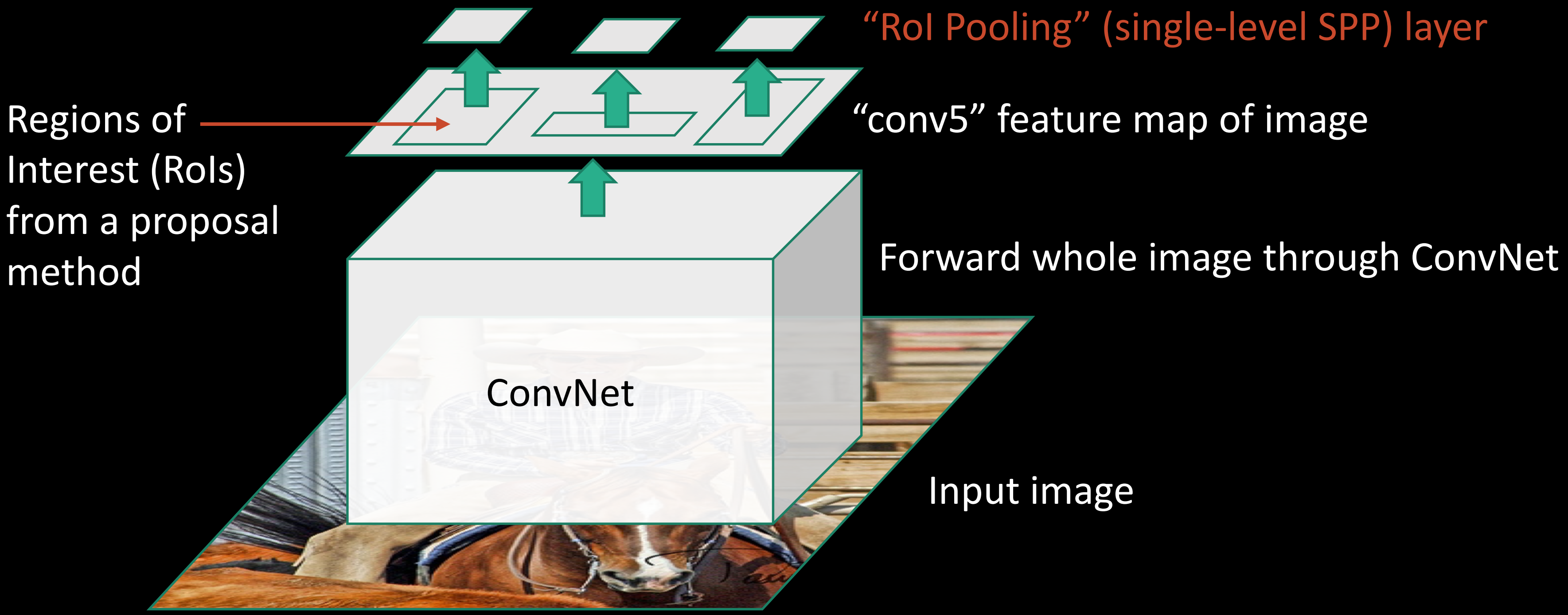
Regions of Interest (RoIs) from a proposal method

“conv5” feature map of image

Forward whole image through ConvNet

Input image

Fast R-CNN (test time)



“RoI Pooling” (single-level SPP) layer

“conv5” feature map of image

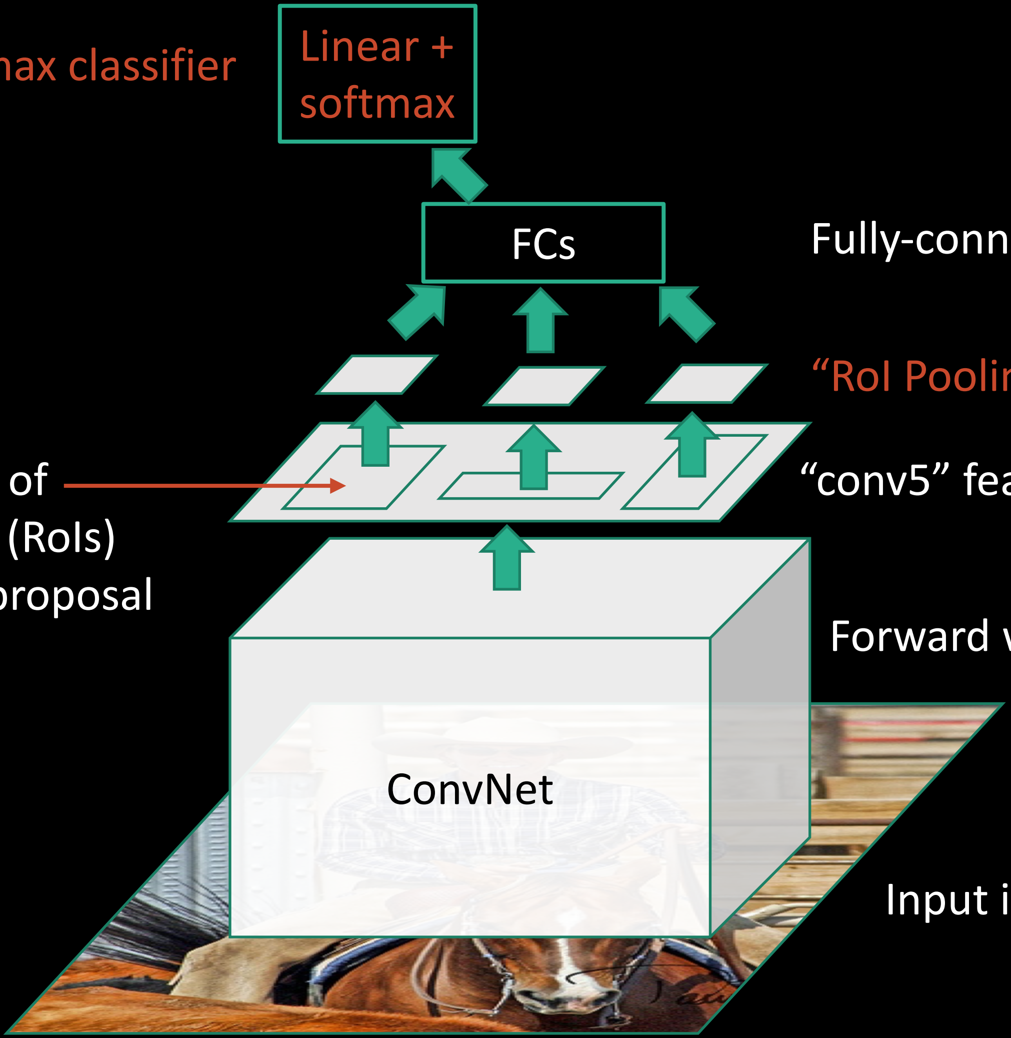
Regions of Interest (RoIs) from a proposal method

Forward whole image through ConvNet

ConvNet

Input image

Fast R-CNN (test time)



Softmax classifier

Linear + softmax

FCs

Fully-connected layers

“RoI Pooling” (single-level SPP) layer

Regions of Interest (RoIs) from a proposal method

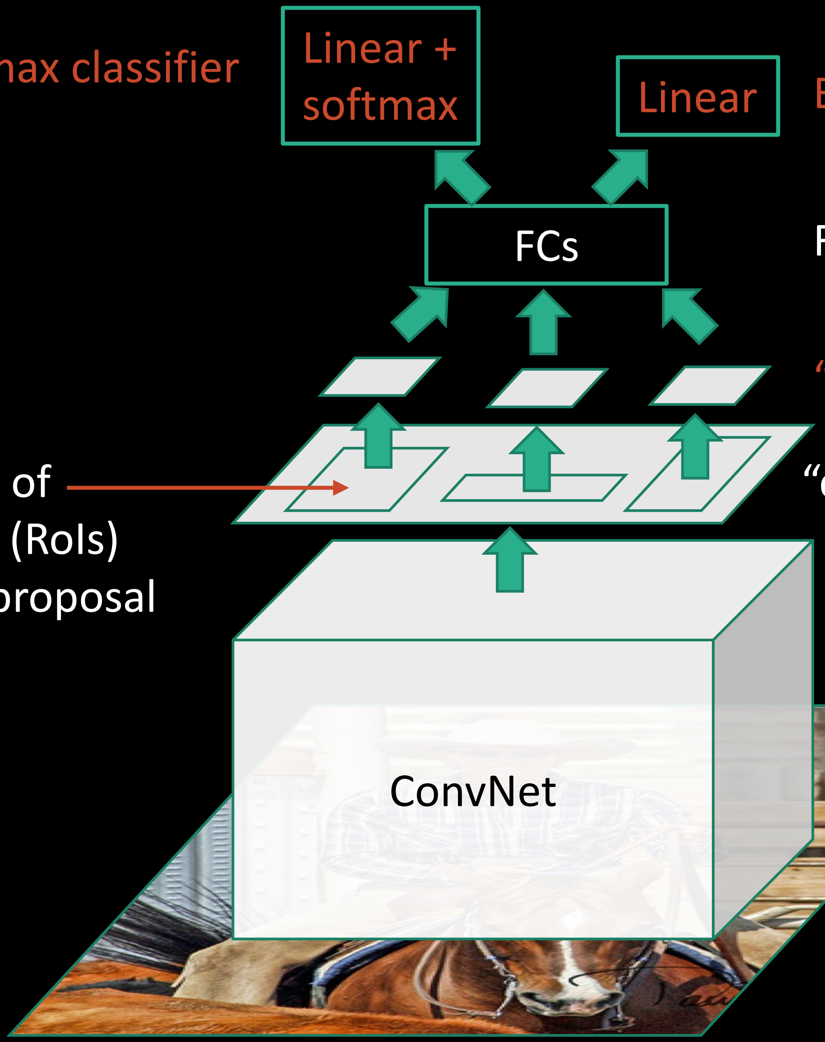
“conv5” feature map of image

Forward whole image through ConvNet

ConvNet

Input image

Fast R-CNN (test time)



Softmax classifier

Bounding-box regressors

Fully-connected layers

“RoI Pooling” (single-level SPP) layer

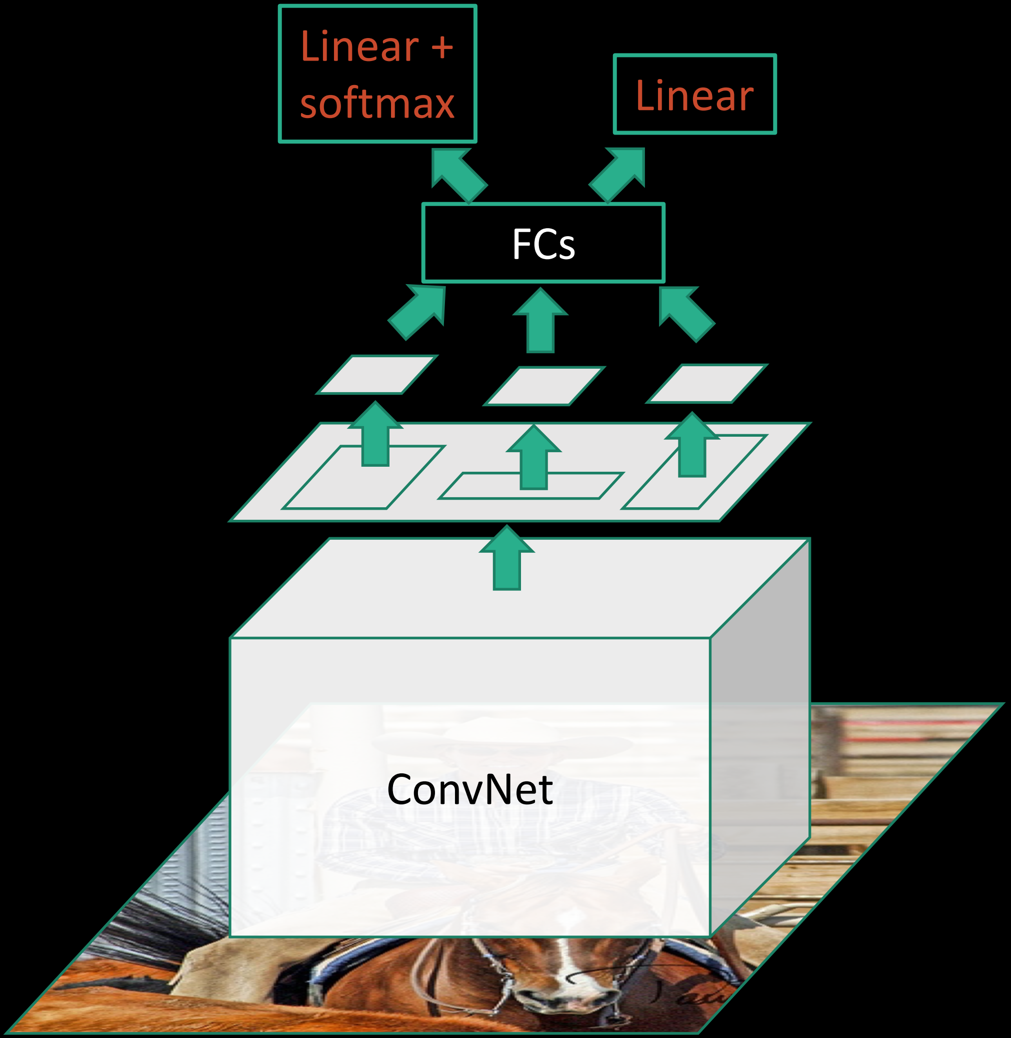
“conv5” feature map of image

Regions of Interest (RoIs) from a proposal method

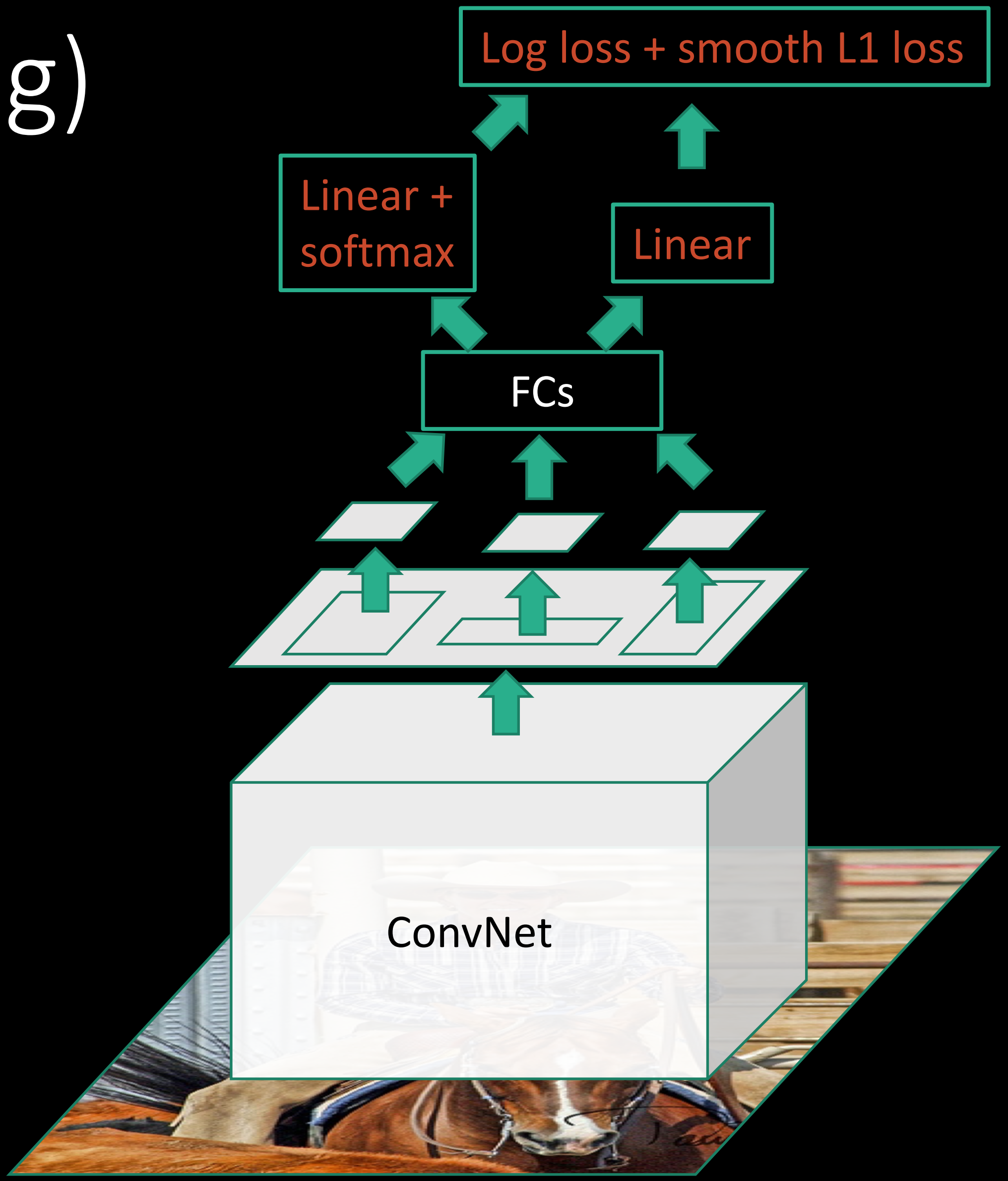
Forward whole image through ConvNet

Input image

Fast R-CNN (training)

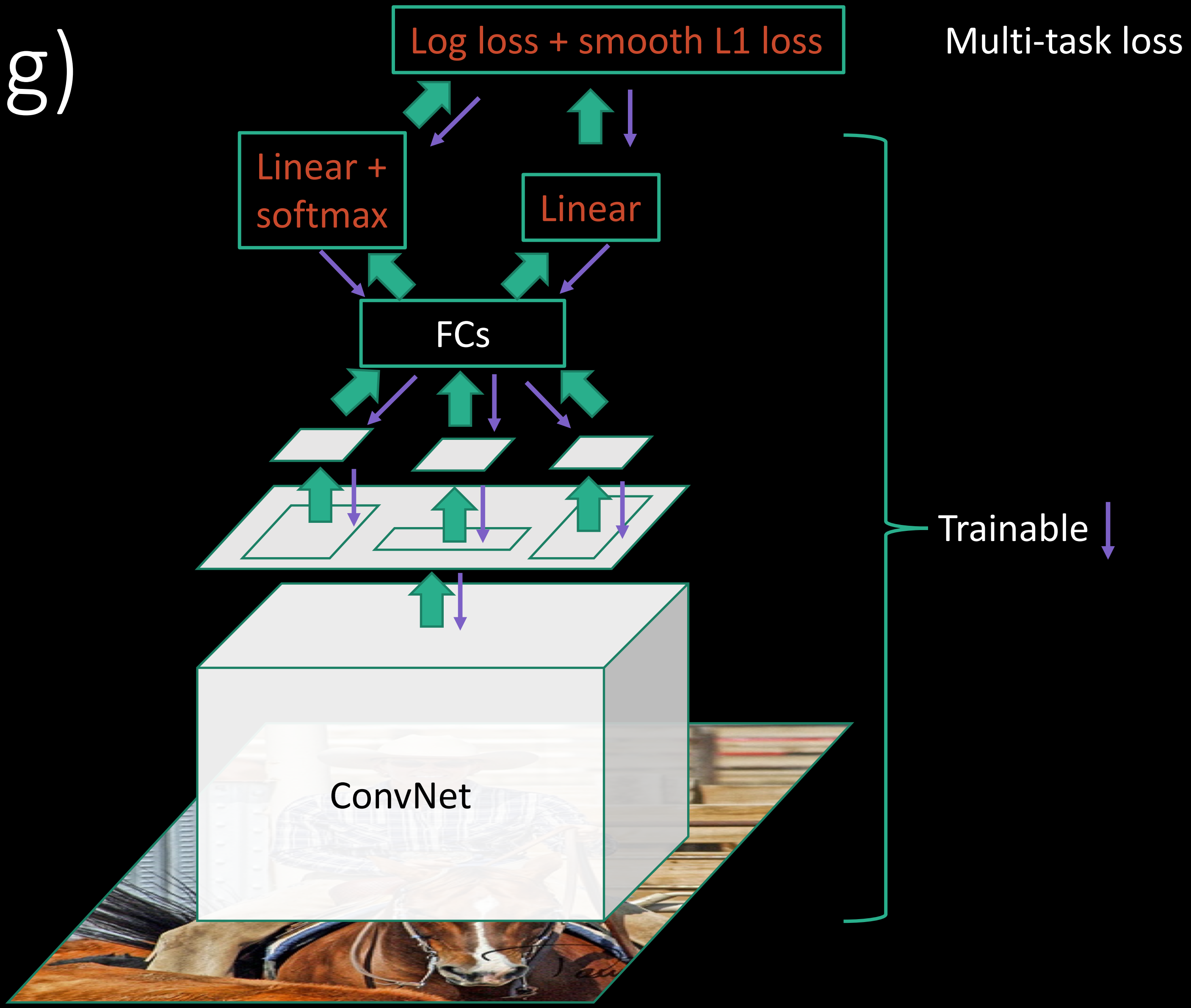


Fast R-CNN (training)



Multi-task loss

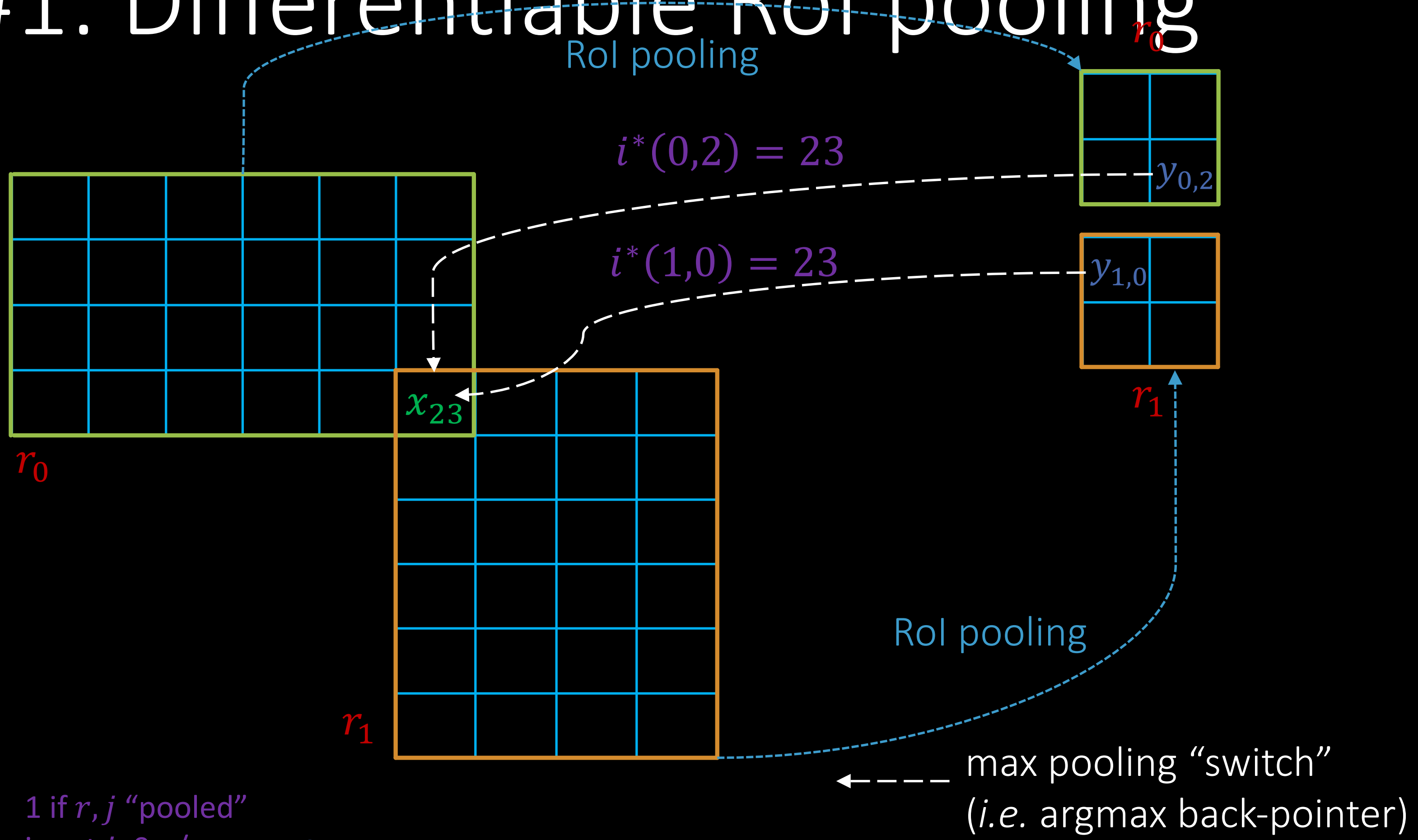
Fast R-CNN (training)



Obstacle #1: Differentiable RoI pooling

Region of Interest (RoI) pooling must be (sub-) differentiable to train conv layers

Obstacle #1: Differentiable RoI pooling



1 if r, j "pooled" input i; 0 o/w

$$\frac{\partial L}{\partial x_i} = \sum_r \sum_j [i = i^*(r, j)] \frac{\partial L}{\partial y_{rj}}$$

Partial for x_i

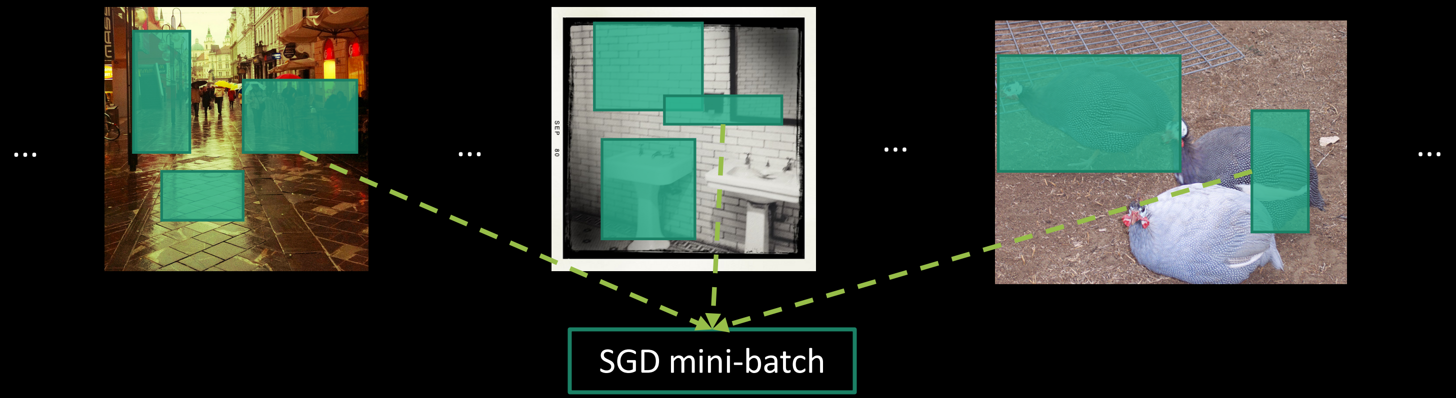
Over regions r, locations j

Partial from next layer

Obstacle #2: efficient SGD steps

Slow R-CNN and SPP-net use region-wise sampling to make mini-batches

- Sample 128 example RoIs uniformly at random
- Examples will come from different images with high probability



Obstacle #2: efficient SGD steps

Note the receptive field for one example RoI is often very large

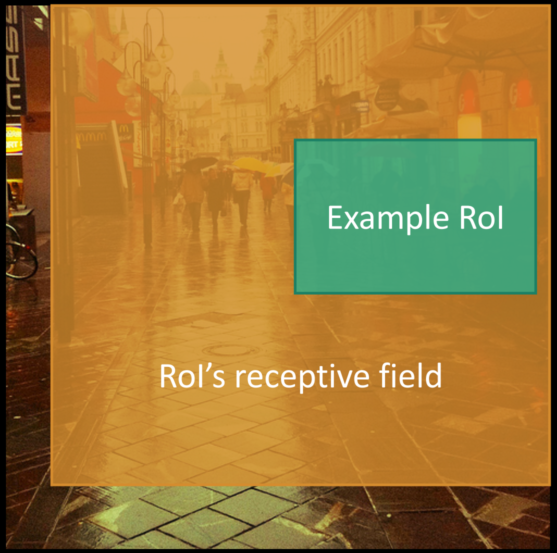
- Worst case: the receptive field is the entire image

Obstacle #2: efficient SGD steps

Worst case cost per mini-batch (crude model of computational complexity)

input size for Fast R-CNN input size for slow R-CNN

128*600*1000 / (128*224 *224) = 12x more computation than slow R-CNN



Obstacle #2: efficient SGD steps

Solution: use hierarchical sampling to build mini-batches

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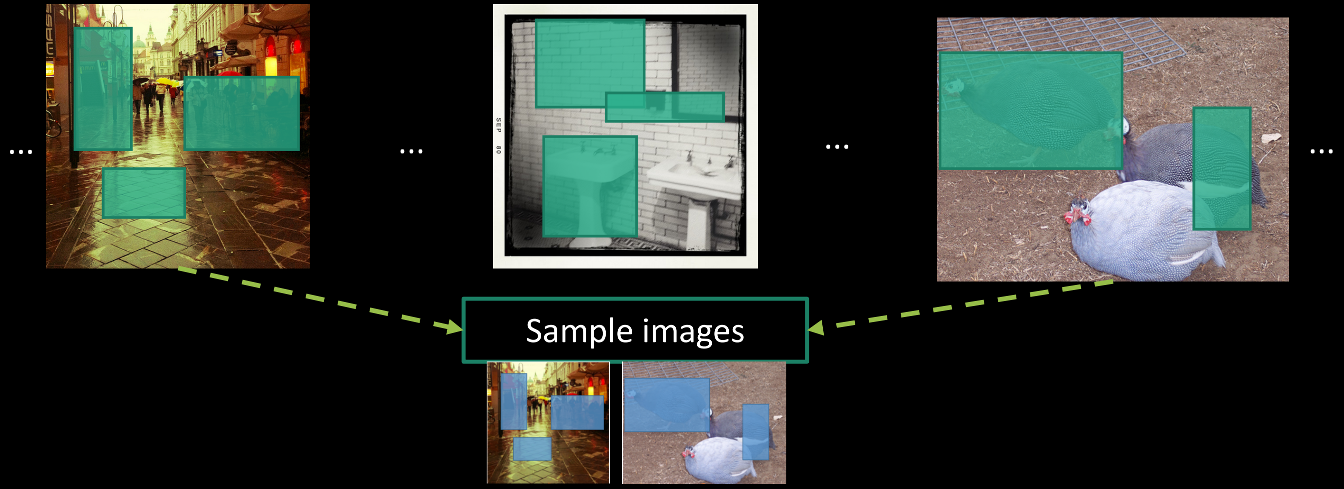


Sample images

- Sample a small number of images (2)

Obstacle #2: efficient SGD steps

Solution: use hierarchical sampling to build mini-batches

Sample images

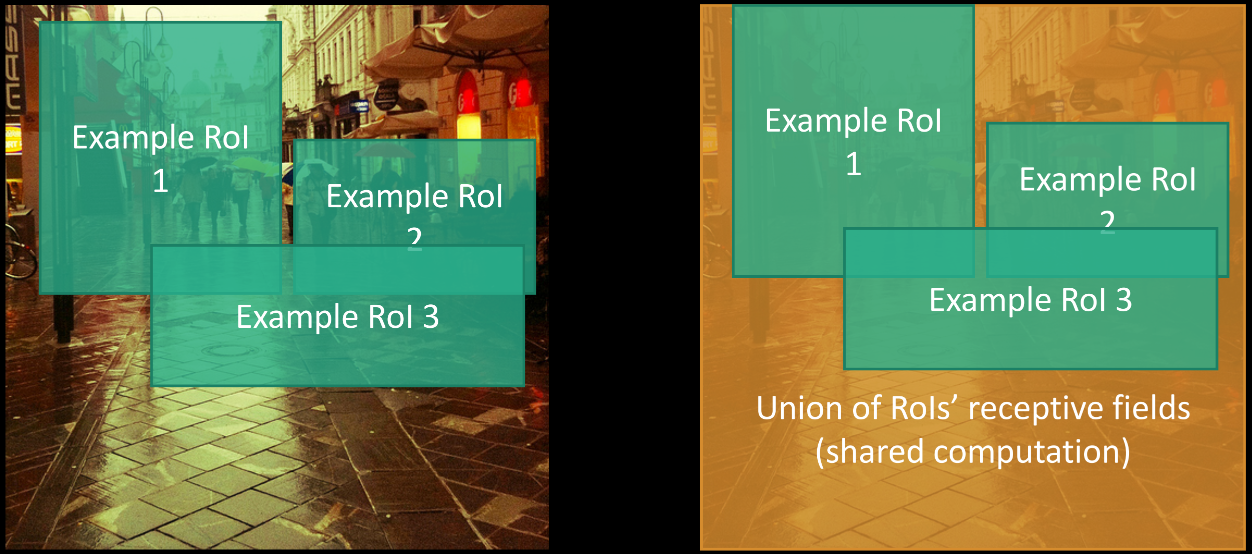
SGD mini-batch

- Sample a small number of images (2)
- Sample many examples from each image (64)

Obstacle #2: efficient SGD steps

Use the test-time trick from SPP-net during training

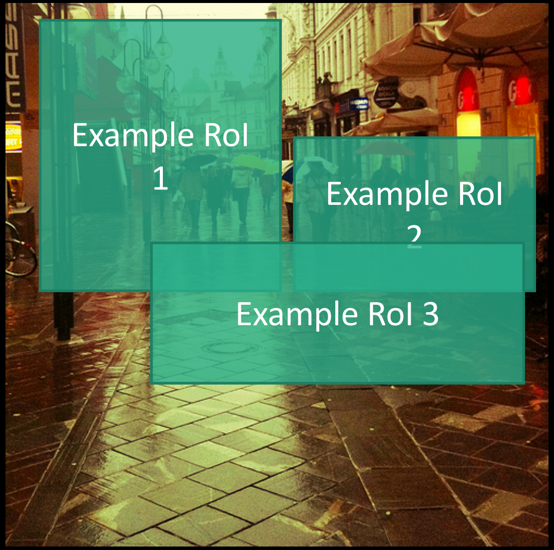
- Share computation between overlapping examples from the same image

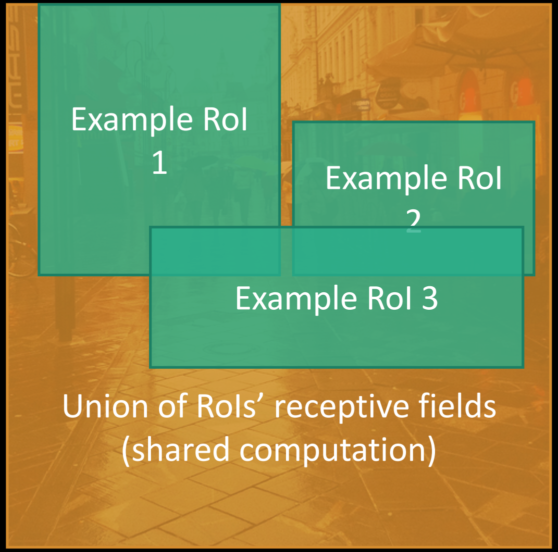


Obstacle #2: efficient SGD steps

Cost per mini-batch compared to slow R-CNN (same crude cost model)

- $\overset{\text{input size for Fast R-CNN}}{2*600*1000} / (\overset{\text{input size for slow R-CNN}}{128*224*224}) =$ 0.19x less computation than slow R-CNN





Main results

	Fast R-CNN	**R-CNN [1]**	**SPP-net [2]**
Train time (h)	**9.5**	84	25
- Speedup	**8.8x**	1x	3.4x
Test time / image	**0.32s**	47.0s	2.3s
Test speedup	**146x**	1x	20x
mAP	**66.9%**	66.0%	63.1%

Timings exclude object proposal time, which is equal for all methods.
All methods use VGG16 from Simonyan and Zisserman.

[1] Girshick et al. CVPR14.
[2] He et al. ECCV14.

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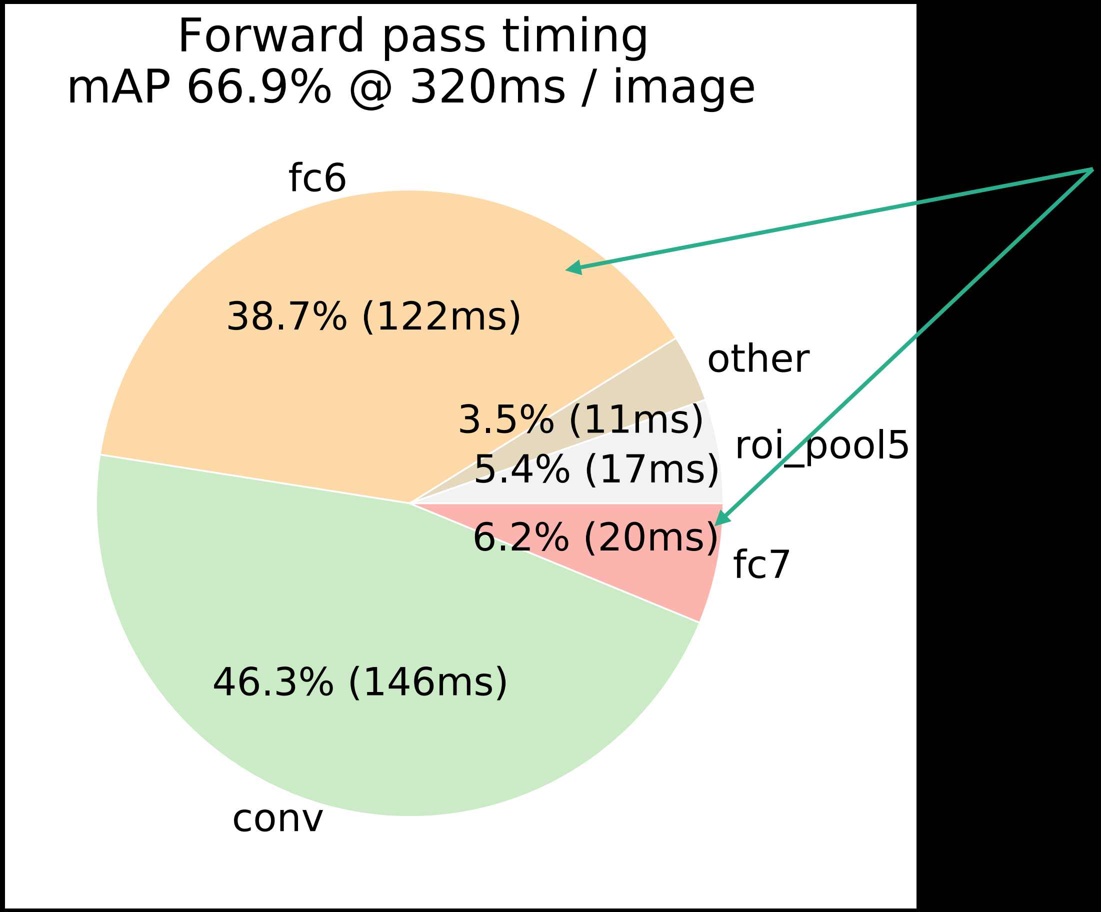
Main results

	Fast R-CNN	**R-CNN [1]**	**SPP-net [2]**
Train time (h)	**9.5**	84	25
- Speedup	**8.8x**	1x	3.4x
Test time / image	**0.32s**	47.0s	2.3s
Test speedup	**146x**	1x	20x
mAP	**66.9%**	66.0%	63.1%

Timings exclude object proposal time, which is equal for all methods.
All methods use VGG16 from Simonyan and Zisserman.

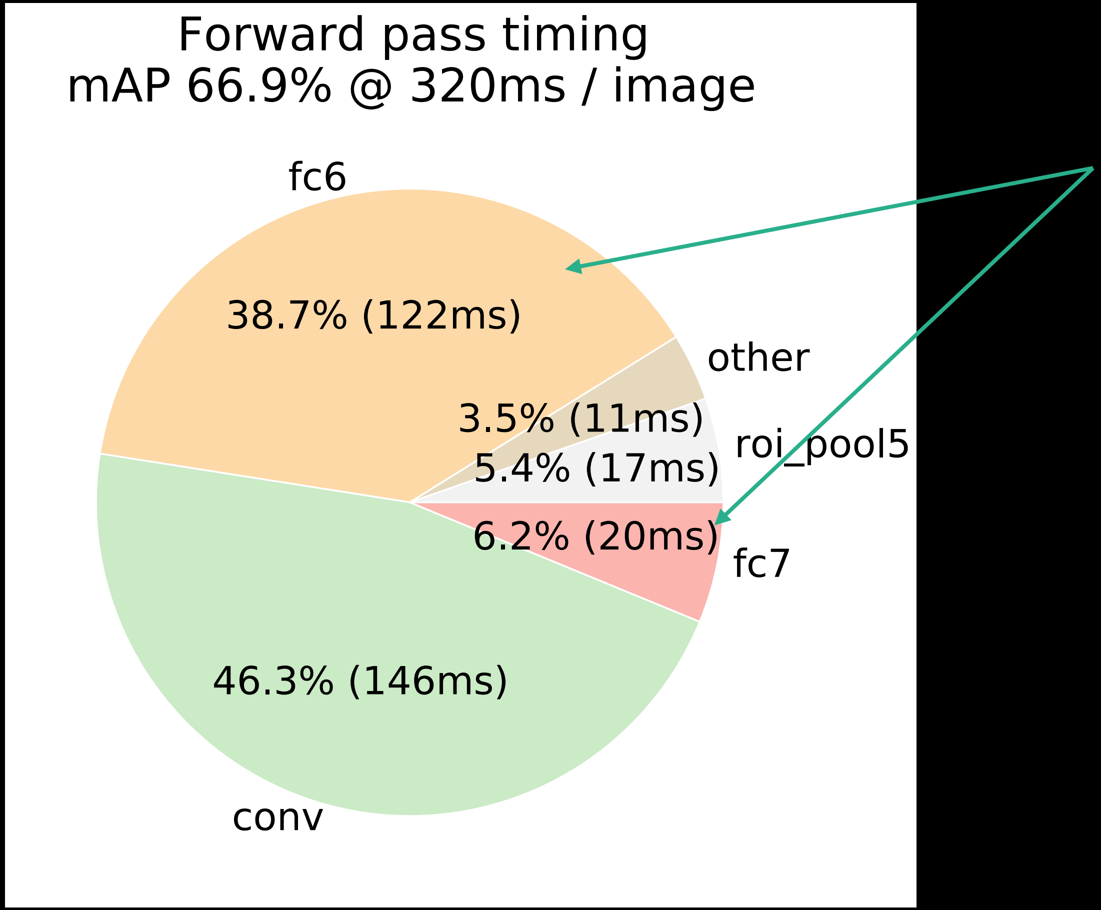
[1] Girshick et al. CVPR14.
[2] He et al. ECCV14.

Further test-time speedups



Fully connected layers take 45% of the forward pass time

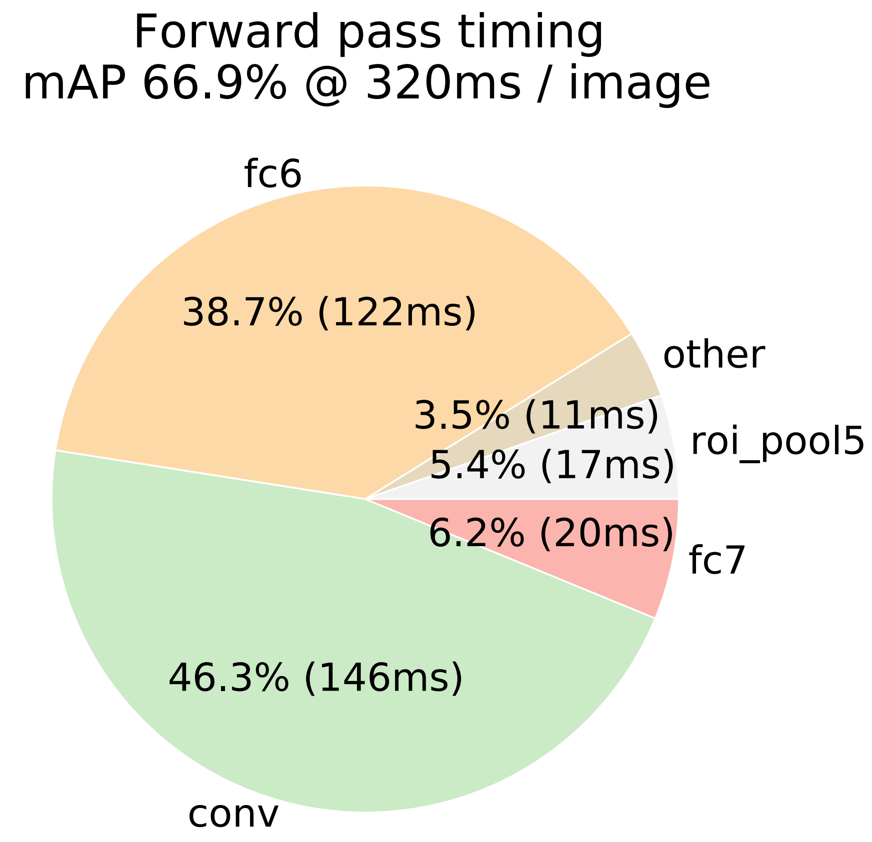
Further test-time speedups



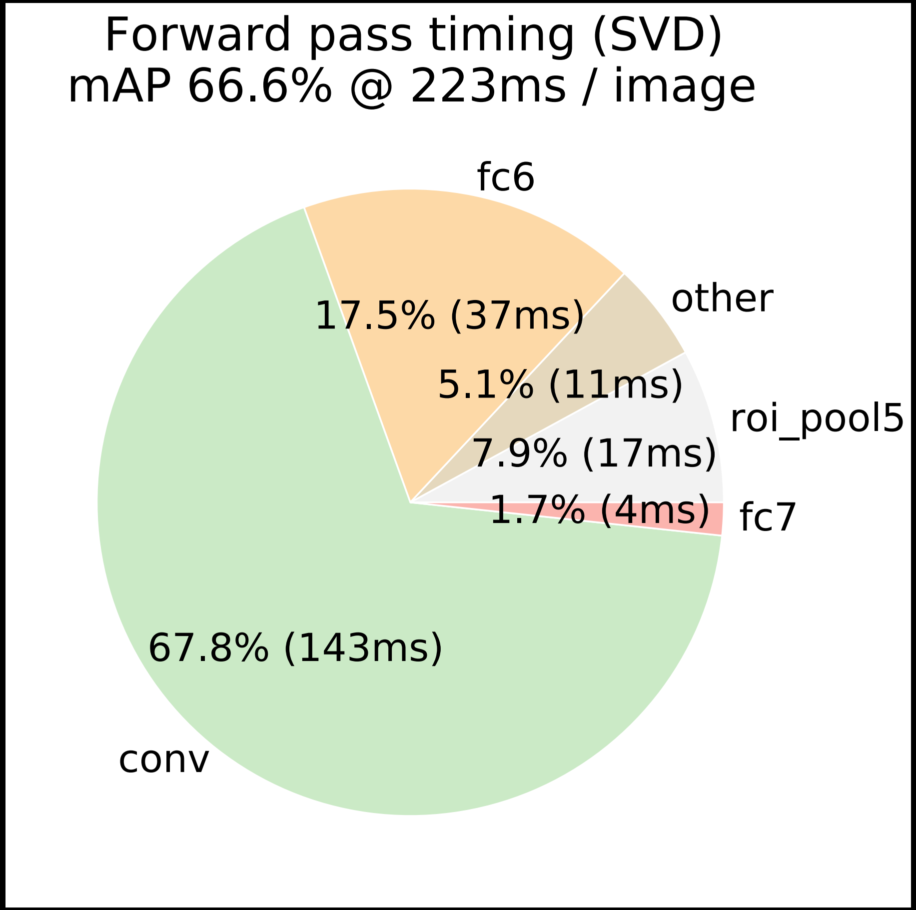
Compress these layers with truncated SVD

J. Xue, J. Li, and Y. Gong.
Restructuring of deep neural network acoustic models with singular value decomposition.
Interspeech, 2013.

Further test-time speedups



Without SVD



With SVD

Other findings

End-to-end training matters

	Fast R-CNN (VGG16)		
Fine-tune layers	≥ fc6	≥ conv3_1	≥ conv2_1
VOC07 mAP	61.4%	66.9%	67.2%
Test time per image	0.32s	0.32s	0.32s

1.4x slower training

Multi-task training helps

	Fast R-CNN (VGG16)			
Multi-task training?		Y		Y
Stage-wise training?			Y	
Test-time bbox reg.			Y	Y
VOC07 mAP	62.6%	63.4%	64.0%	66.9%

Multi-task training helps

	Fast R-CNN (VGG16)			
Multi-task training?		Y		Y
Stage-wise training?			Y	
Test-time bbox reg.			Y	Y
VOC07 mAP	62.6%	63.4%	64.0%	66.9%

Trained without
a bbox regressor

Multi-task training helps

	Fast R-CNN (VGG16)			
Multi-task training?		Y		Y
Stage-wise training?			Y	
Test-time bbox reg.			Y	Y
VOC07 mAP	62.6%	63.4%	64.0%	66.9%

Trained with
a bbox regressor,
but it’s disabled at
test time

Multi-task training helps

	Fast R-CNN (VGG16)			
Multi-task training?		Y		Y
Stage-wise training?			Y	
Test-time bbox reg.			Y	Y
VOC07 mAP	62.6%	63.4%	64.0%	66.9%

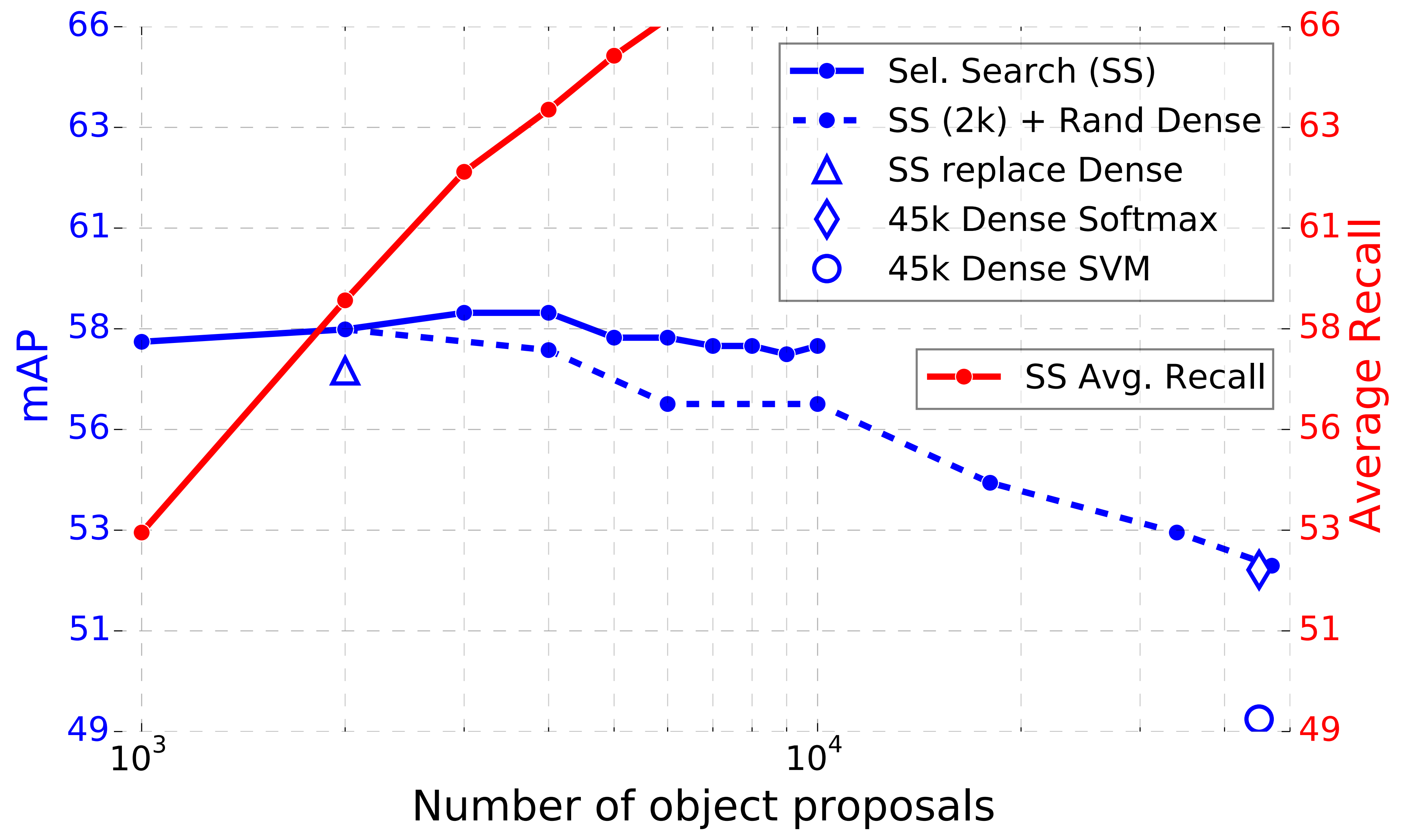
Post hoc bbox regressor, used at test time

Multi-task training helps

	Fast R-CNN (VGG16)			
Multi-task training?		Y		Y
Stage-wise training?			Y	
Test-time bbox reg.			Y	Y
VOC07 mAP	62.6%	63.4%	64.0%	66.9%

Multi-task objective,
using bbox regressors
at test time

More proposals is harmful



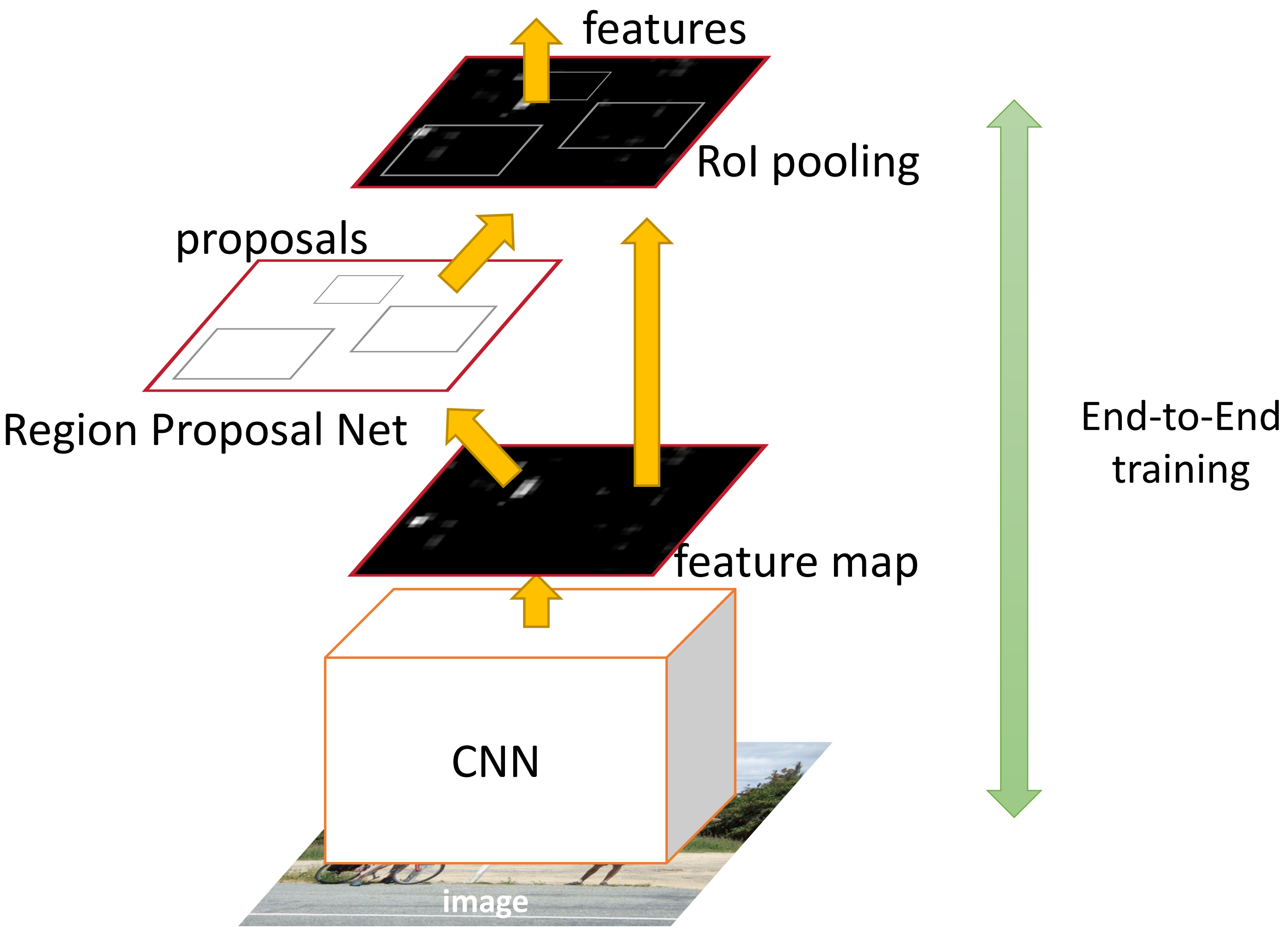
What’s still wrong?

- Out-of-network region proposals
  - Selective search: 2s / im; EdgeBoxes: 0.2s / im
- Fortunately, we have a solution
  - Our follow-up work was presented last week at NIPS

Shaoqing Ren, Kaiming He, Ross Girshick & Jian Sun.
“Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.” NIPS 2015.

Object Detection: Faster R-CNN

- Faster R-CNN
    - Solely based on CNN
    - No external modules
    - Each step is end-to-end



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Fast R-CNN take-aways

- End-to-end training of deep ConvNets for detection
- Fast training times
- Open source for easy experimentation
  “I think [the Fast R-CNN] code is average-somewhat above average for what it is.”
  – sporkles on r/MachineLearning
- A large number of ImageNet detection and COCO detection methods are built on Fast R-CNN
  Checkout the ImageNet / COCO Challenge workshop on Thursday!

Focal Loss for Dense Object Detection

Tsung-Yi Lin, Google Brain

Work done at Facebook AI Research with
Priya Goyal, Ross Girshick, Kaiming He, Piotr Dollár

Viola and Jones (2001)

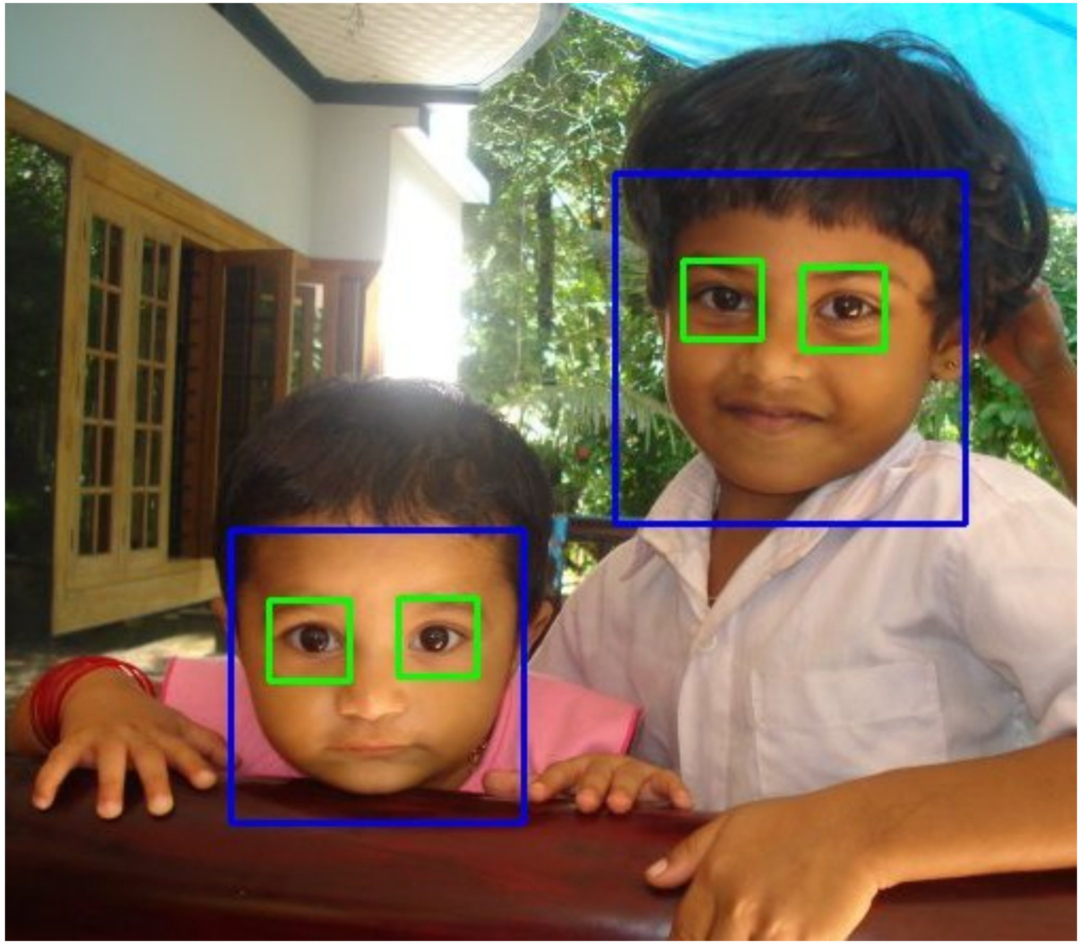
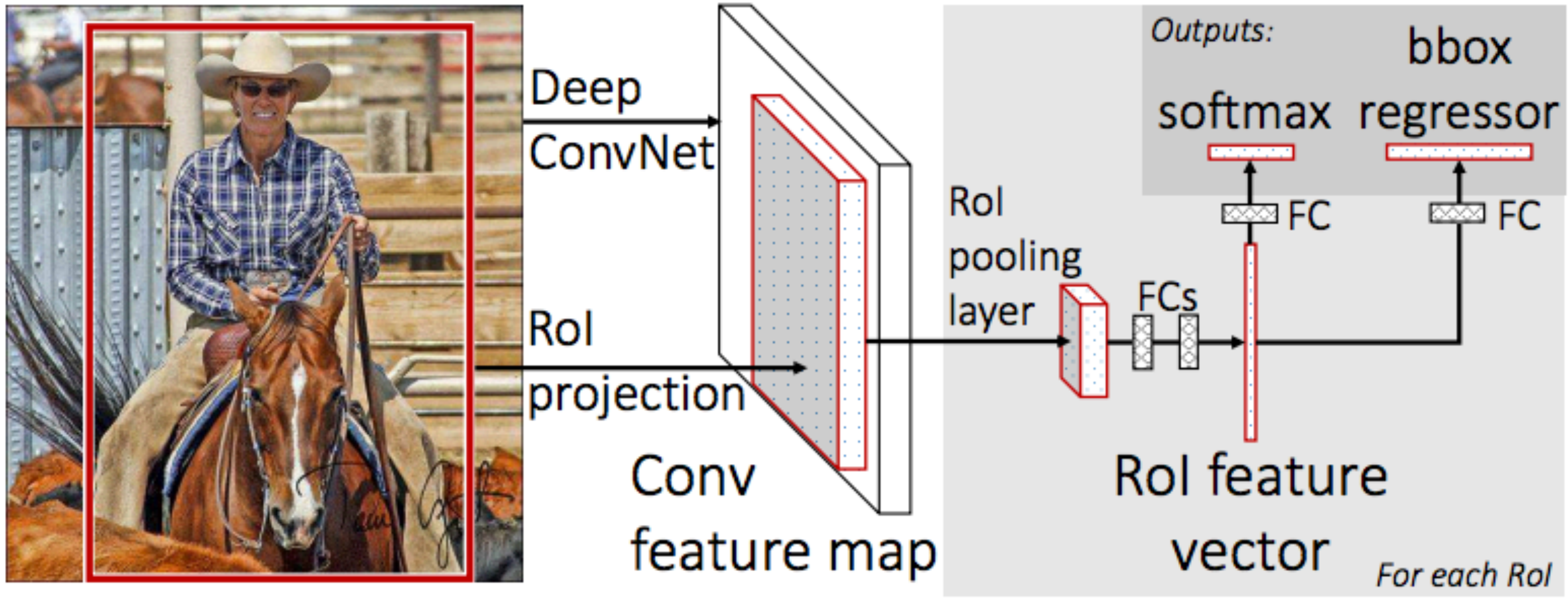


Image from OpenCV 3.3 website

Fast R-CNN

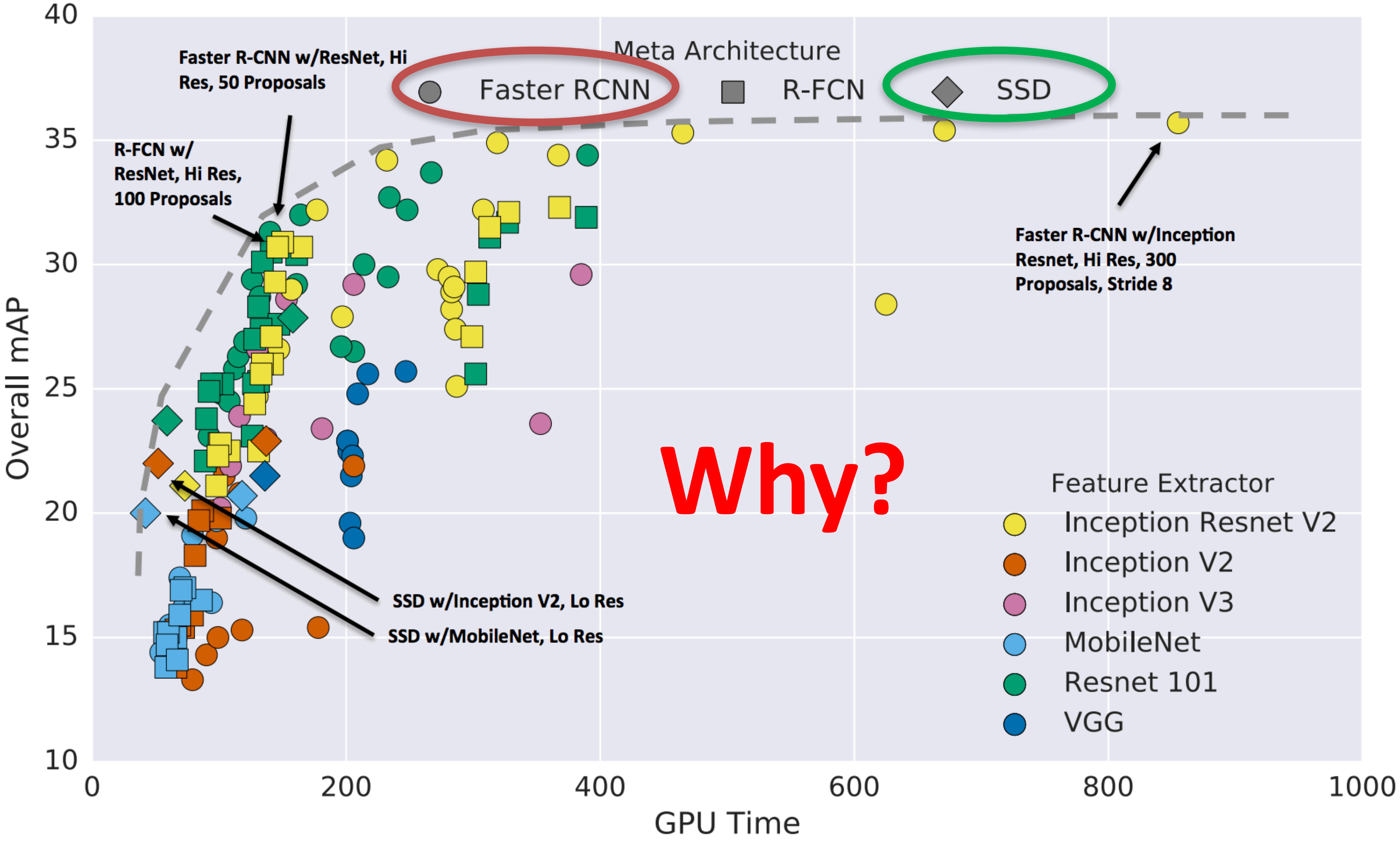


Fast R-CNN, Girshick

One-stage vs. Two-stage

- One-stage
  - Fast
  - Simple
- Two-stage
  - 10 - 40% better accuracy

One-stage vs. Two-stage



Speed/accuracy trade-offs for modern convolutional object detectors, Huang et al., CVPR 2017

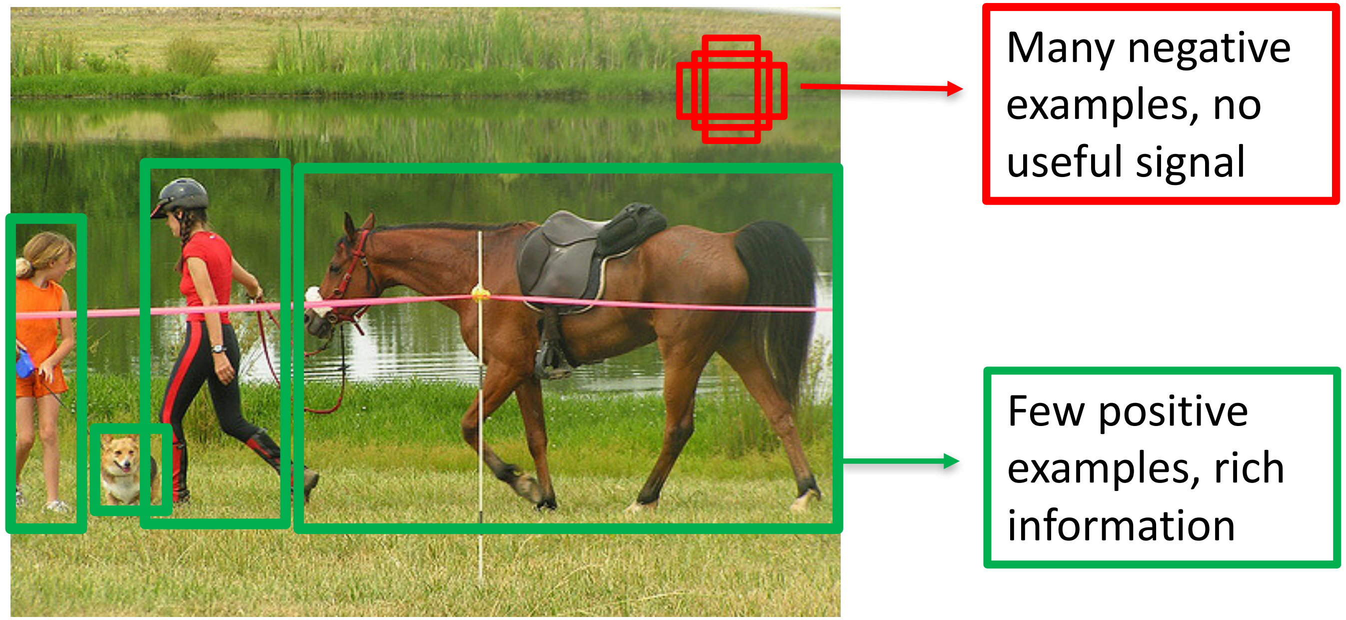
Toward dense detection

- YOLOv1 – 98 boxes
- YOLOv2 – ~1k
- OverFeat – ~1-2k
- SSD – ~8-26k

- This work – ~100k

Class Imbalance

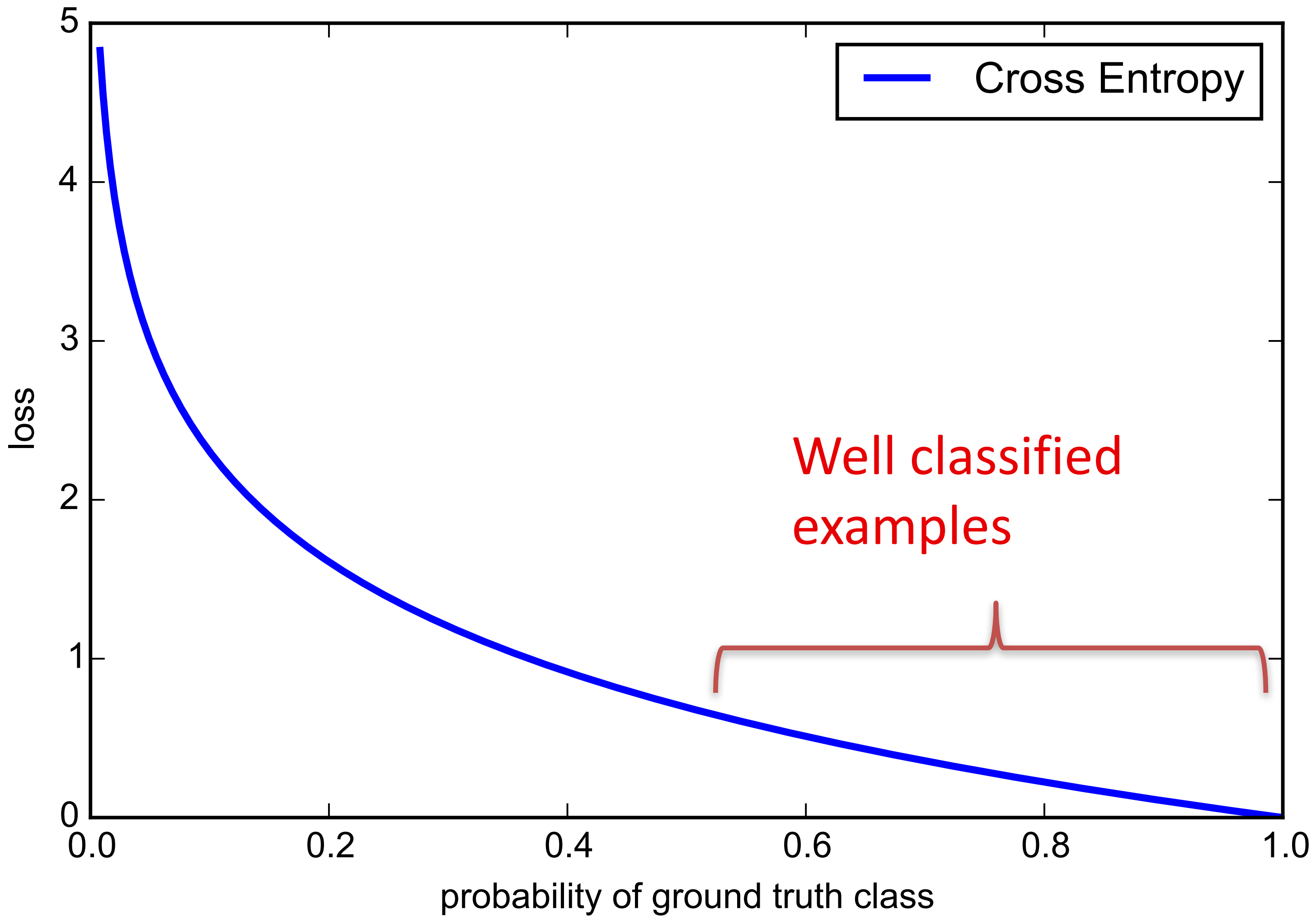
- Few training examples from foreground
- Most examples from background
  - Easy and uninformative
  - Distracting



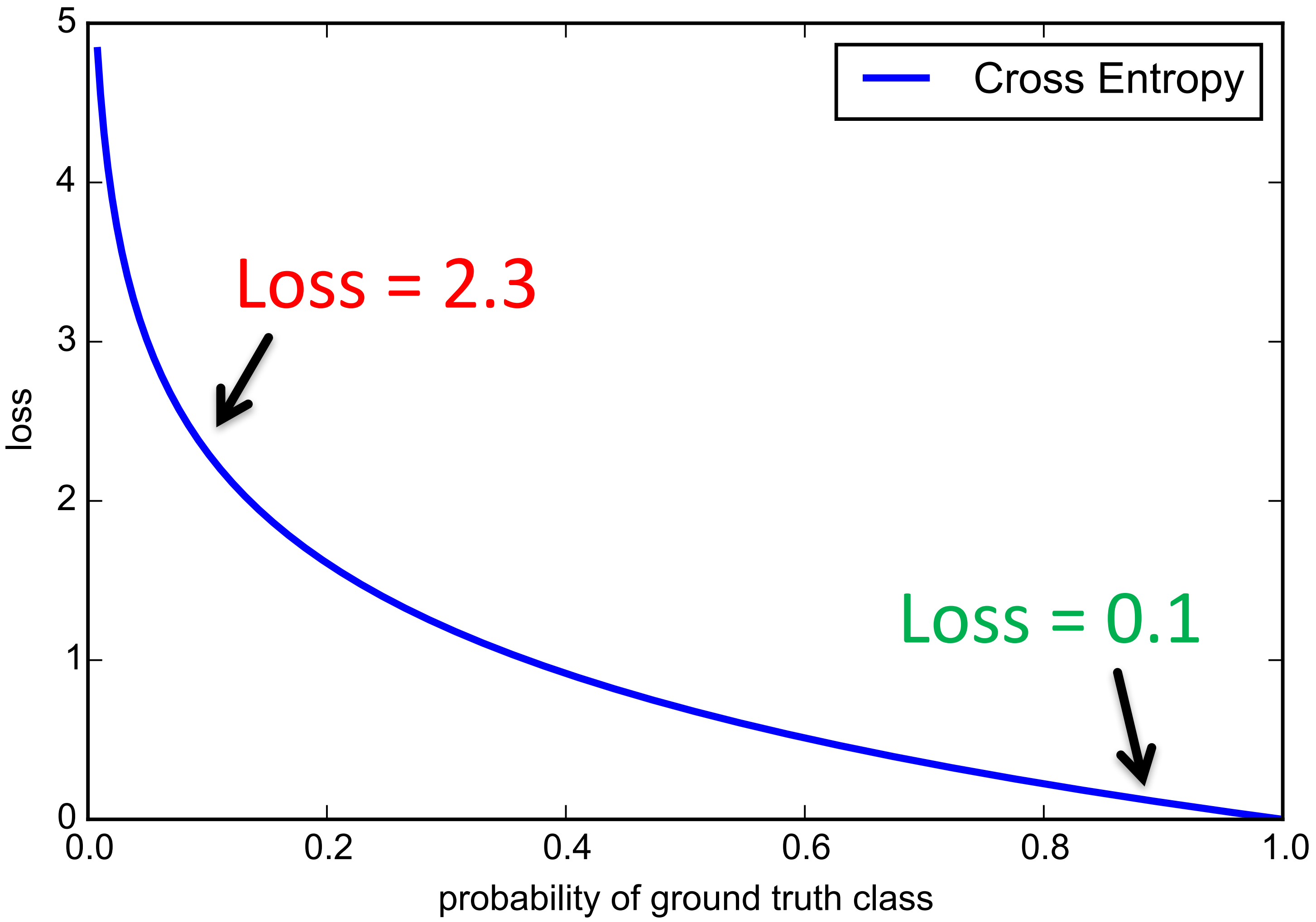
Many negative examples, no useful signal

Few positive examples, rich information

Cross Entropy

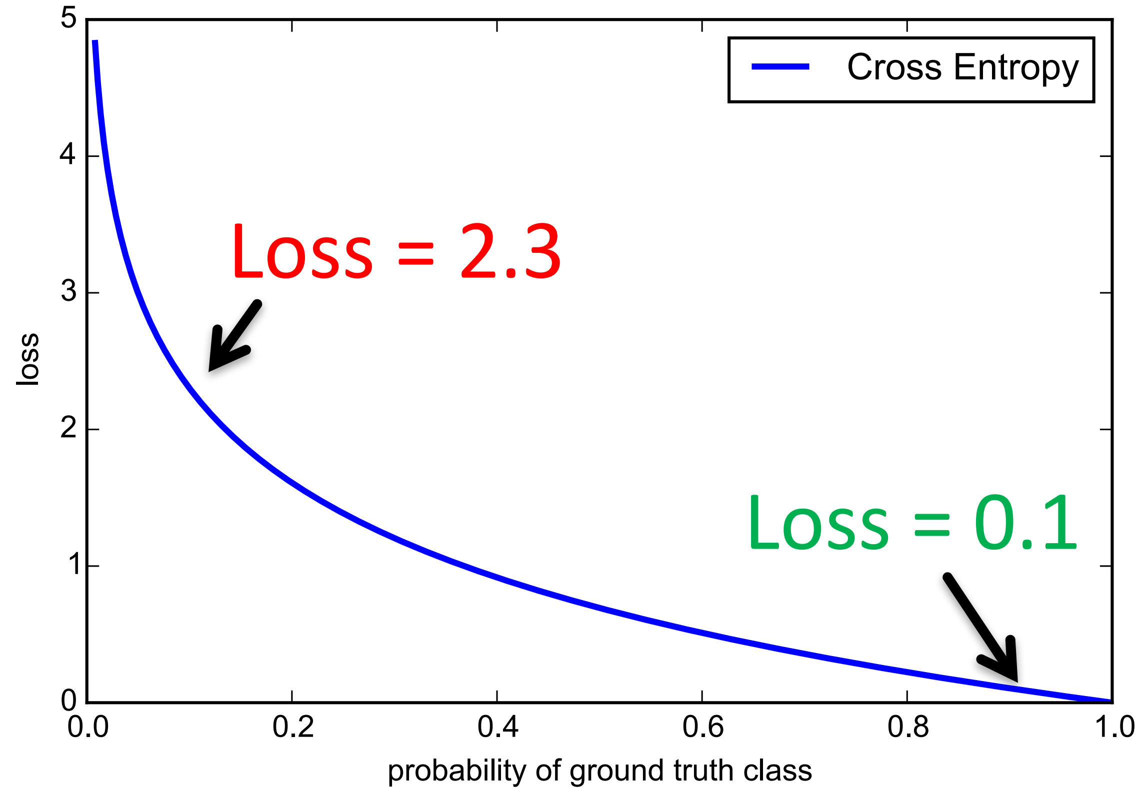


Cross Entropy



Cross Entropy with Imbalance Data

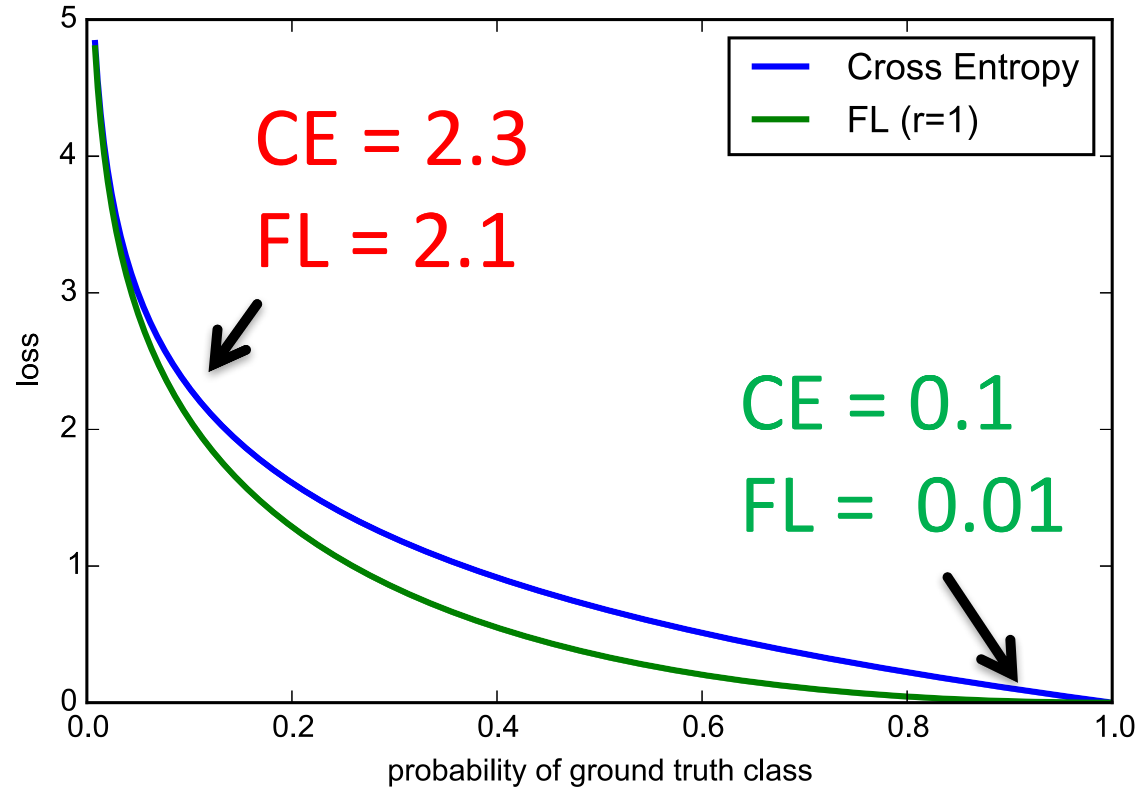
- 100000 easy : 100 hard examples
- **40x bigger loss** from easy examples



Focal Loss

$$\mathrm{CE}(p_\mathrm{t}) = -\log(p_\mathrm{t})$$

$$\mathrm{FL}(p_\mathrm{t}) = -\boxed{(1-p_\mathrm{t})^\gamma}\log(p_\mathrm{t})$$



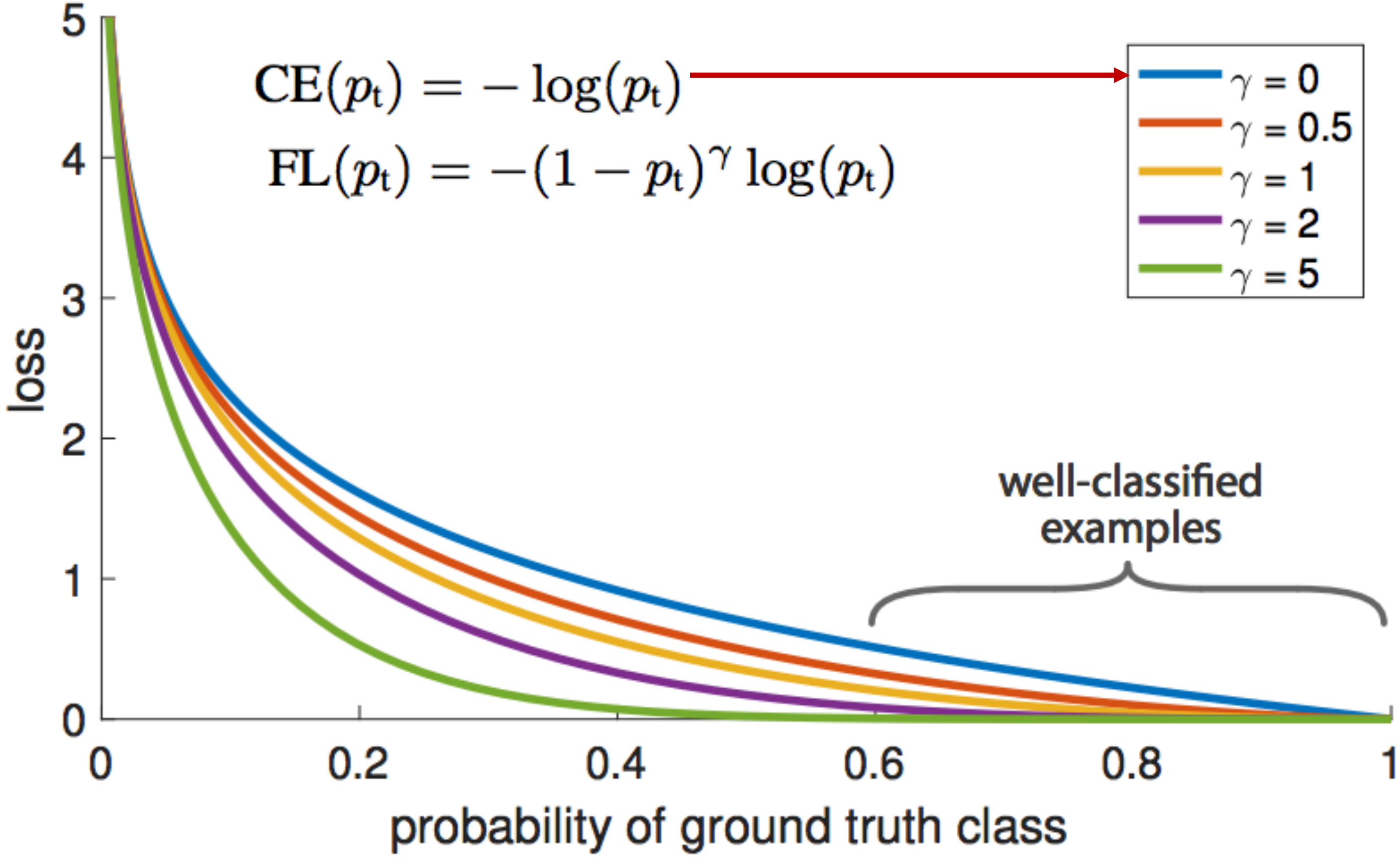
CE = 2.3

FL = 2.1

CE = 0.1

FL = 0.01

Focal Loss



$$\mathrm{CE}(p_t) = -\log(p_t)$$

$$\mathrm{FL}(p_t) = -(1-p_t)^{\gamma}\log(p_t)$$

Prior

- α-balanced Cross entropy

$$\mathrm{CE}(p_{\mathrm{t}}) = -\alpha_t \log(p_{\mathrm{t}})$$

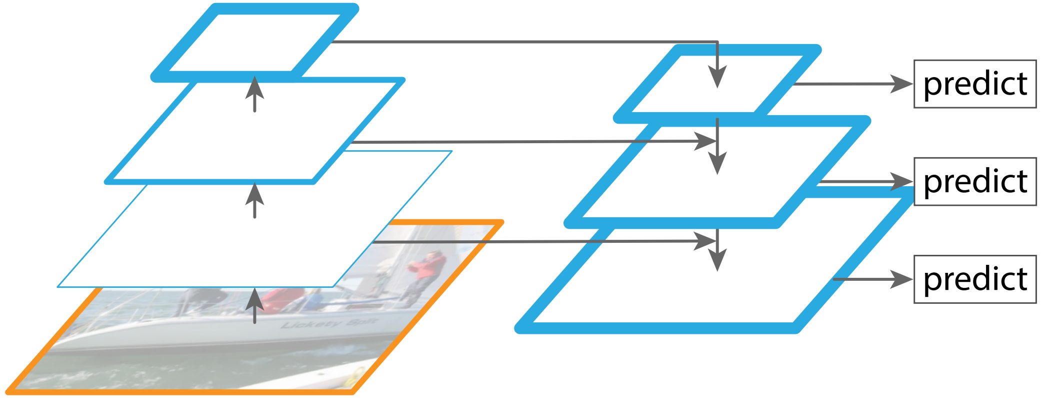
- α-balanced Focal Loss

$$\mathrm{FL}(p_{\mathrm{t}}) = -\alpha_t (1 - p_{\mathrm{t}})^{\gamma} \log(p_{\mathrm{t}})$$

- γ: focus more on hard examples
- α: offset class imbalance of number of examples

Feature Pyramid Network

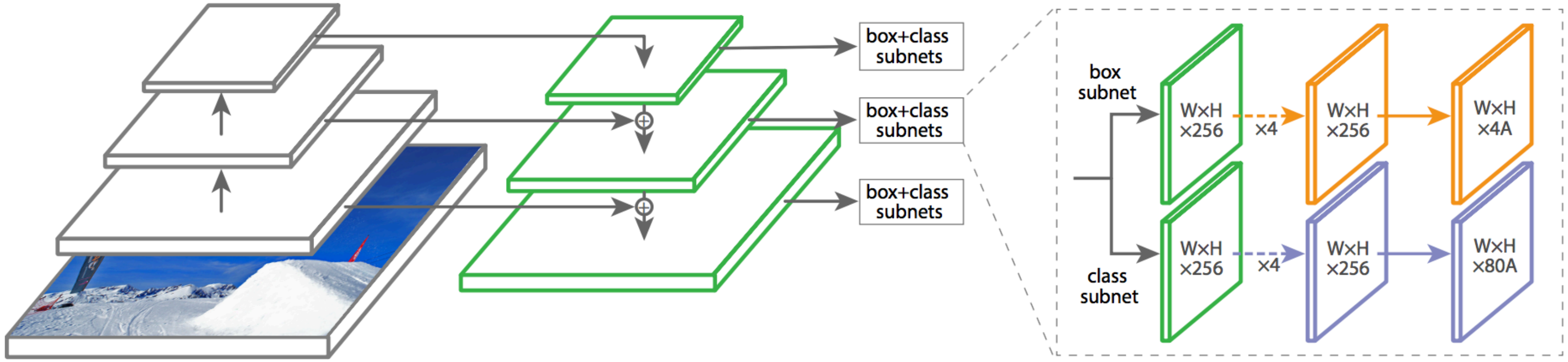
- Multiscale
- Semantically strong at all scales
- Fast to compute



Feature Pyramid Network for Object Detection, Lin et al., CVPR 2017

Architecture

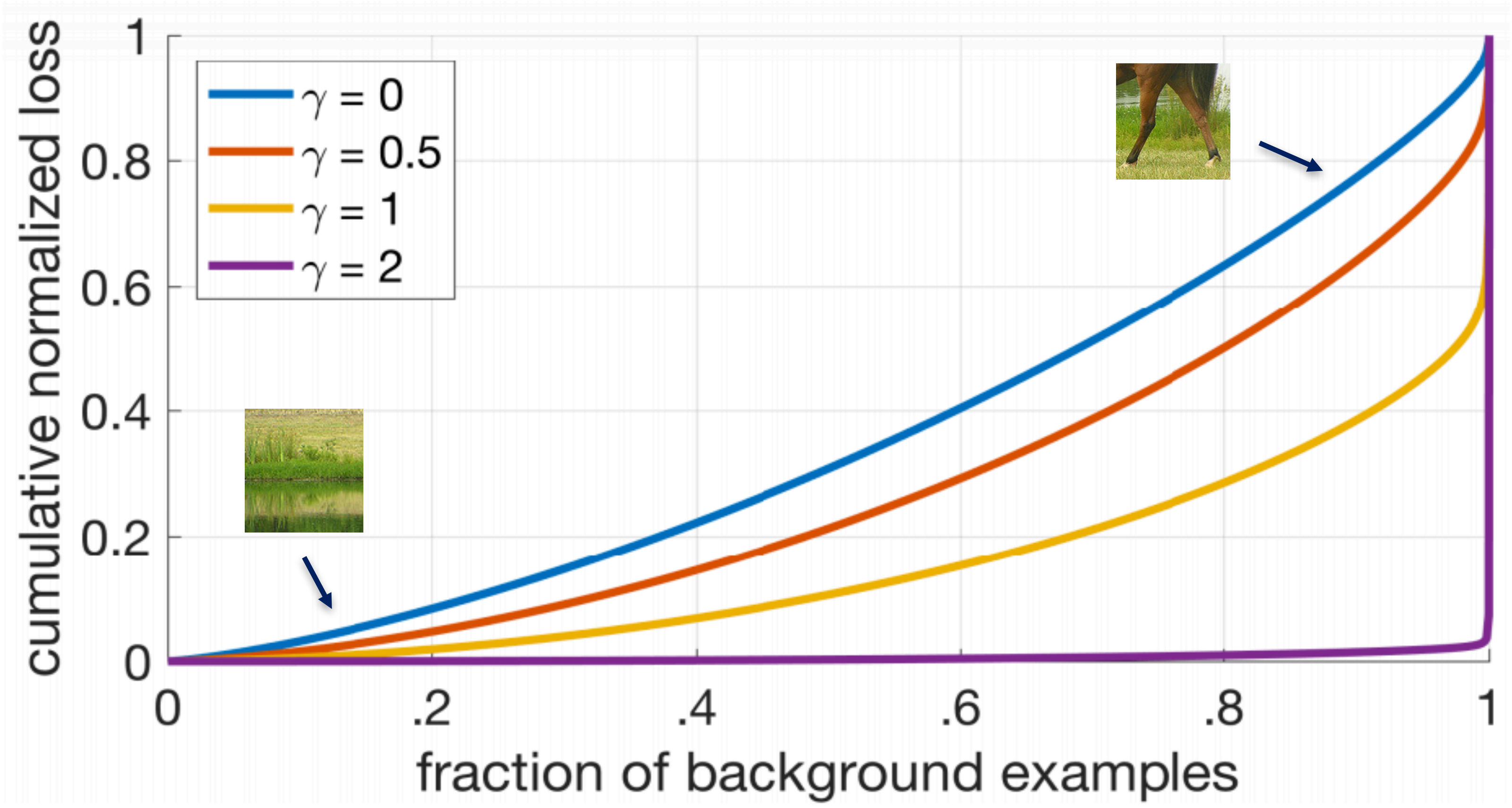
- RetinaNet
  - FPN + 100k boxes
  - Focal loss



(a) ResNet (b) feature pyramid net (c) box & class subnets

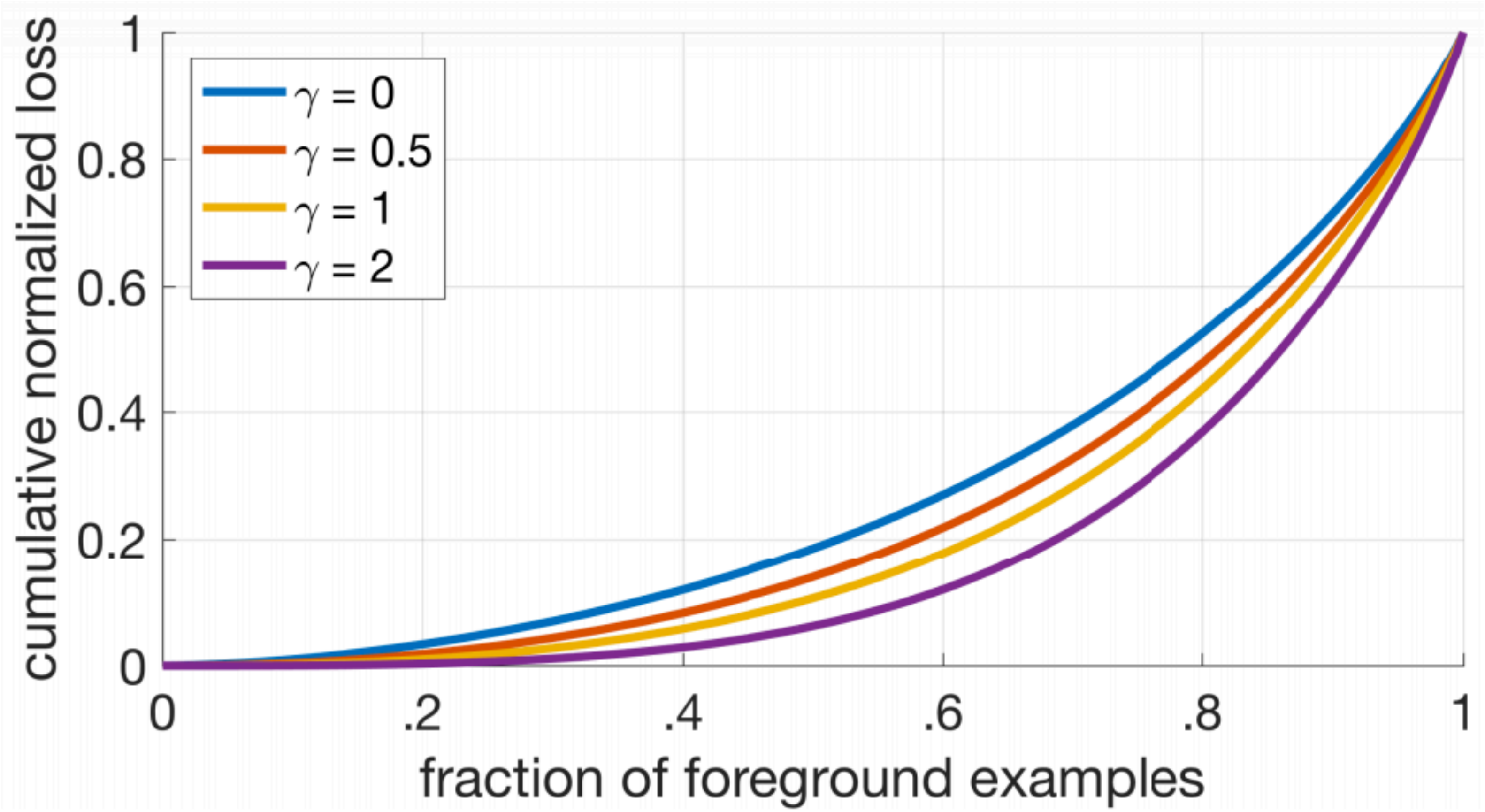
Loss Distribution under Focal Loss

Background Boxes



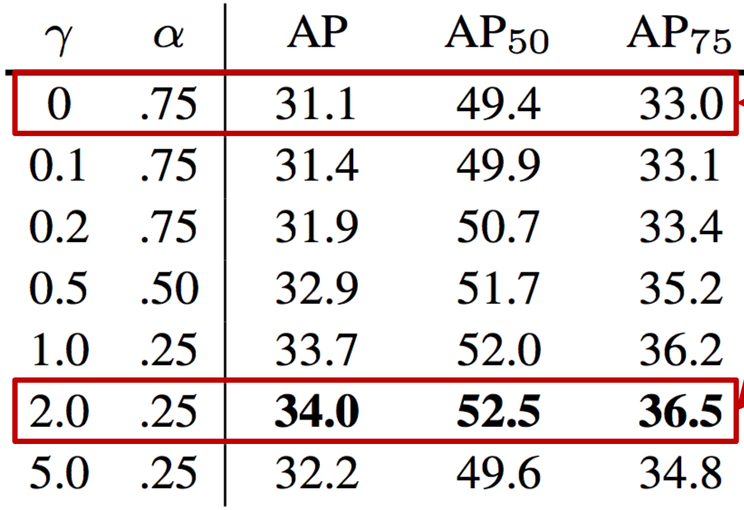
Loss Distribution under Focal Loss

Foreground Boxes



vs. Cross Entropy

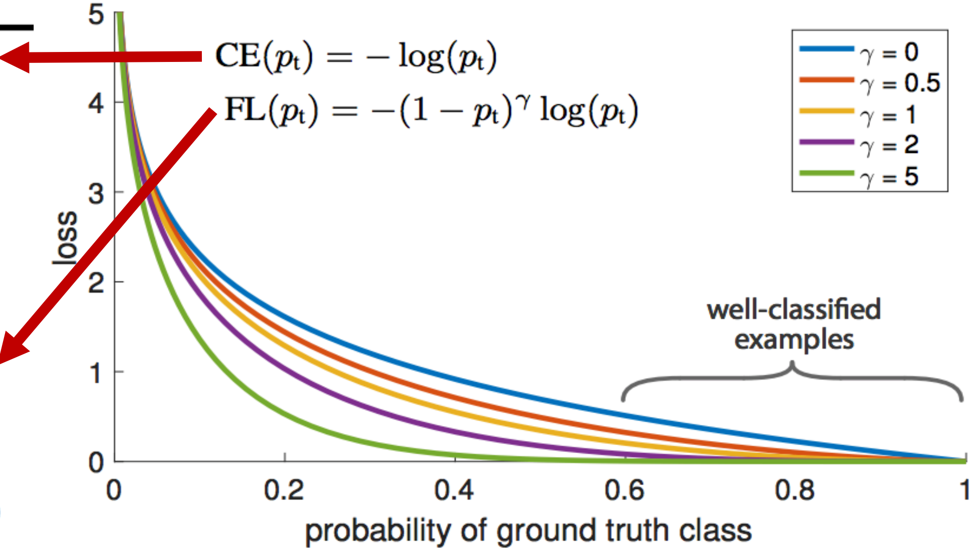
- + 2.9 AP to α-balanced cross entropy



γ	α	AP	AP_{50}	AP_{75}
0	.75	31.1	49.4	33.0
0.1	.75	31.4	49.9	33.1
0.2	.75	31.9	50.7	33.4
0.5	.50	32.9	51.7	35.2
1.0	.25	33.7	52.0	36.2
2.0	.25	**34.0**	**52.5**	**36.5**
5.0	.25	32.2	49.6	34.8

(b) **Varying γ for FL** (w. optimal α)

(ResNet-50-FPN 600px input image)

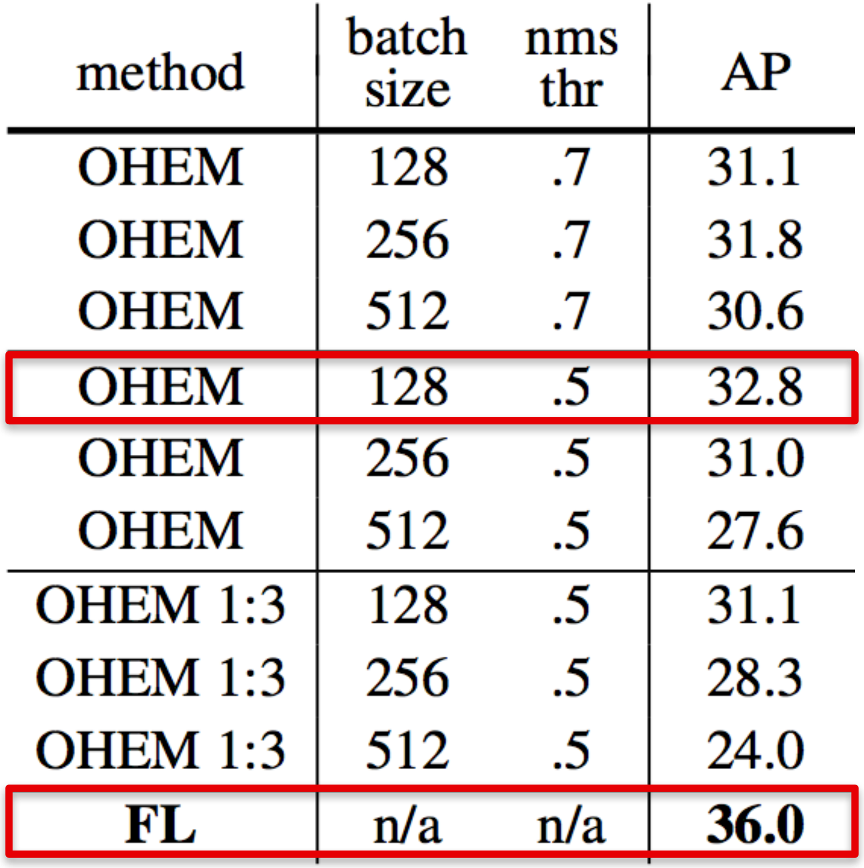


$\text{CE}(p_t) = -\log(p_t)$

$\text{FL}(p_t) = -(1-p_t)^\gamma \log(p_t)$

vs. OHEM

- +3.2 AP to best OHEM (ResNet-101 FPN)



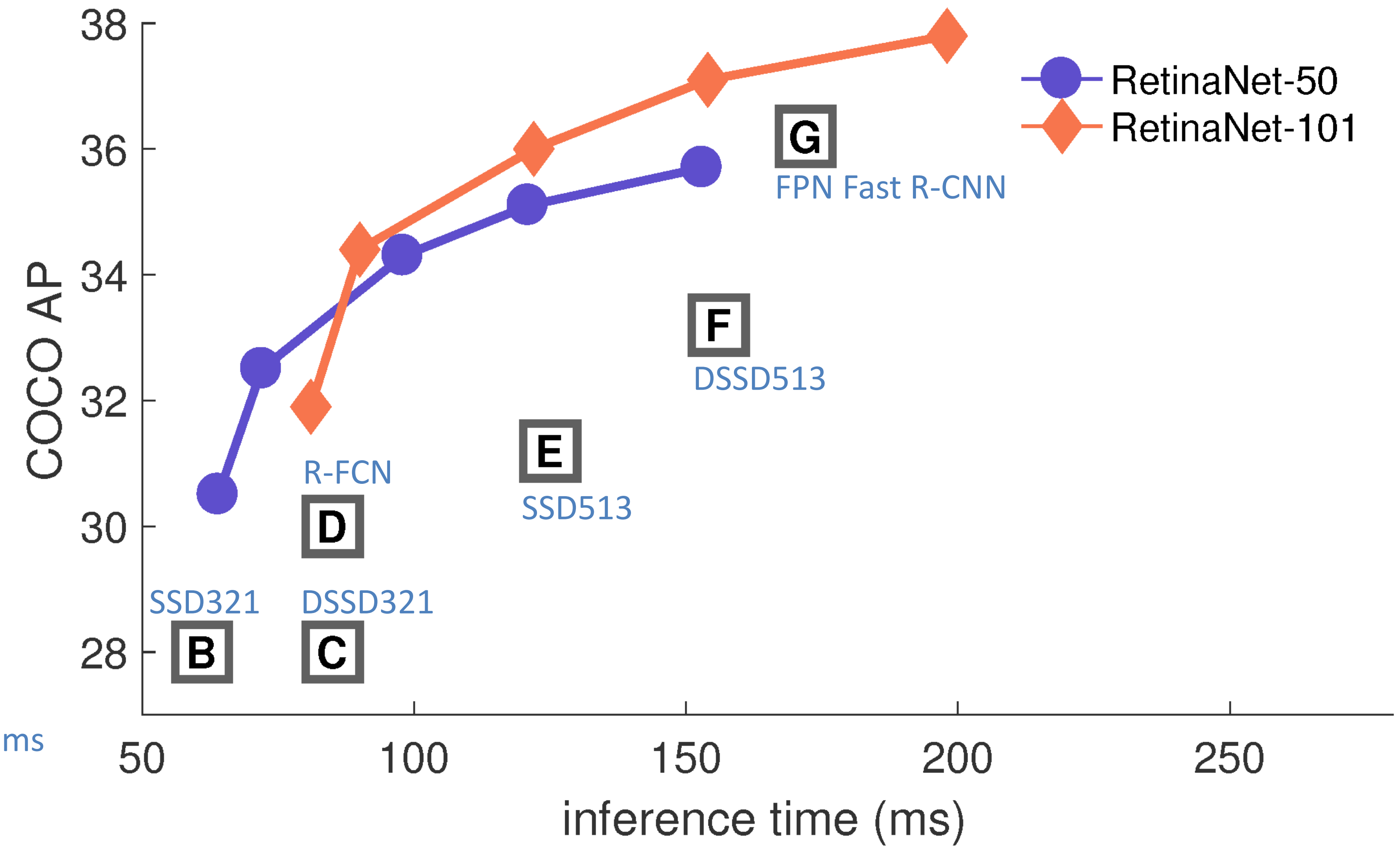
method	batch size	nms thr	AP
OHEM	128	.7	31.1
OHEM	256	.7	31.8
OHEM	512	.7	30.6
OHEM	128	.5	32.8
OHEM	256	.5	31.0
OHEM	512	.5	27.6
OHEM 1:3	128	.5	31.1
OHEM 1:3	256	.5	28.3
OHEM 1:3	512	.5	24.0
FL	n/a	n/a	**36.0**

→ **Best OHEM**

→ **Best Focal Loss**

Online Hard Example Mining, *Shrivastava et al., 2016*

RetinaNet performance



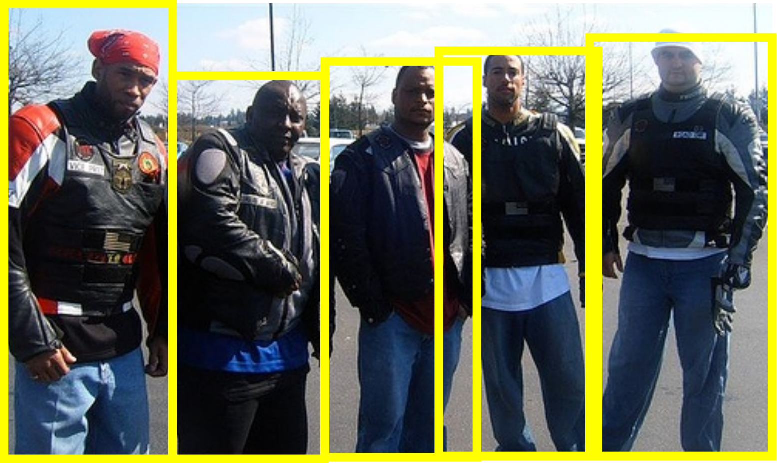
YOLOv2
AP 22 @ 25ms

Summary

- Identify **class imbalance** is the major issue for training one-stage dense detector
- Propose **Focal Loss** to address class imbalance
- Achieve state-of-the-art **accuracy** and **speed**

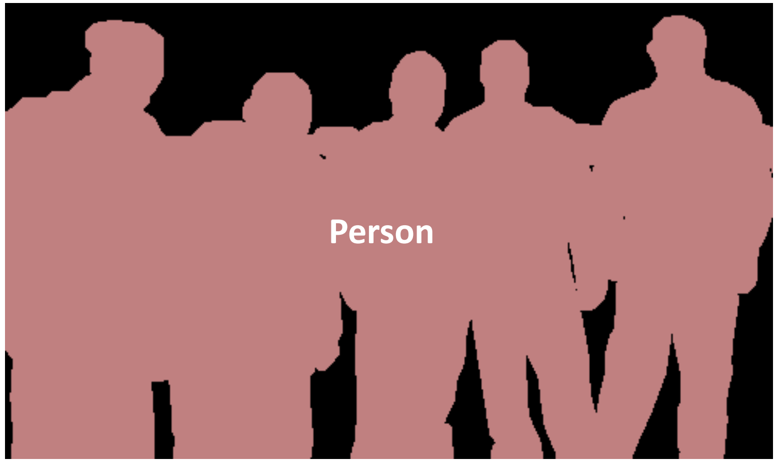
Mask R-CNN
Introduction

Visual Perception Problems



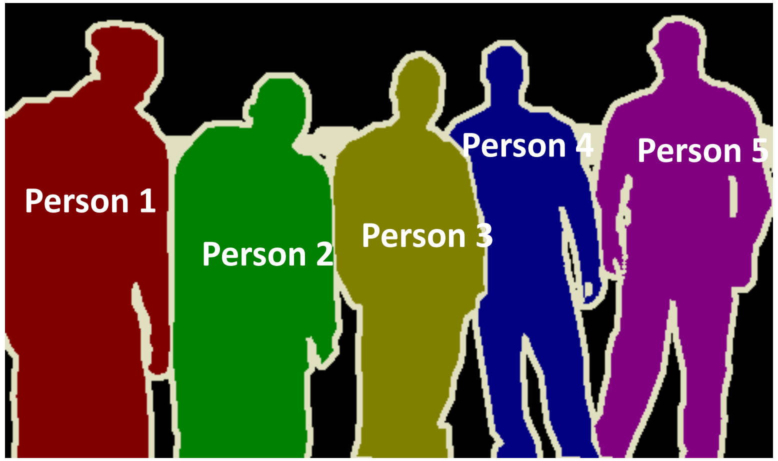
Object Detection

✓



Semantic Segmentation

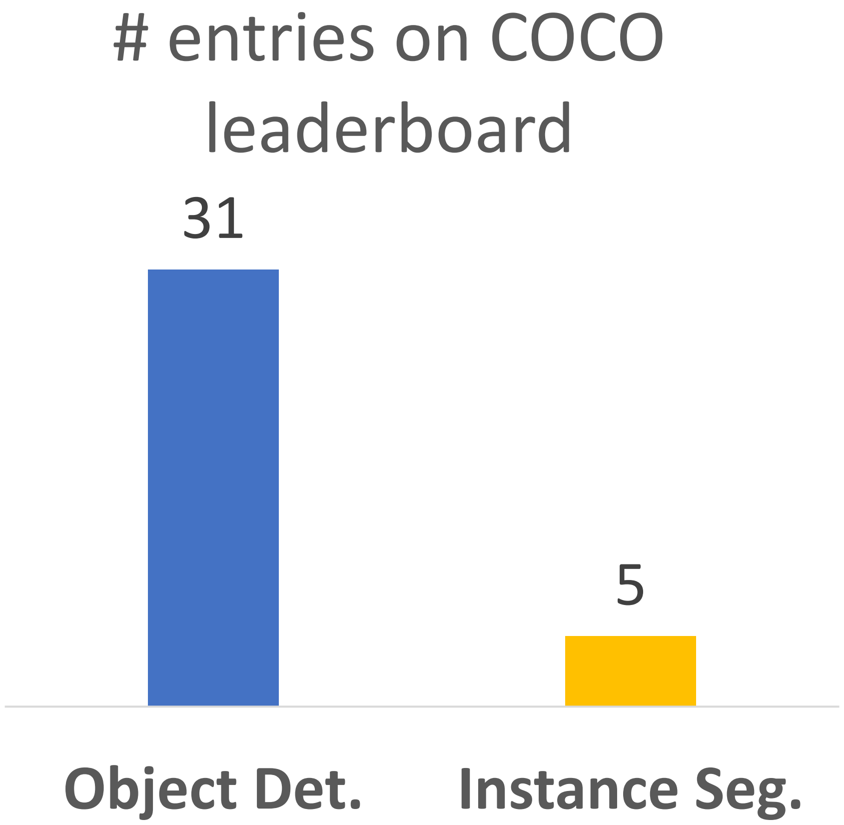
✓

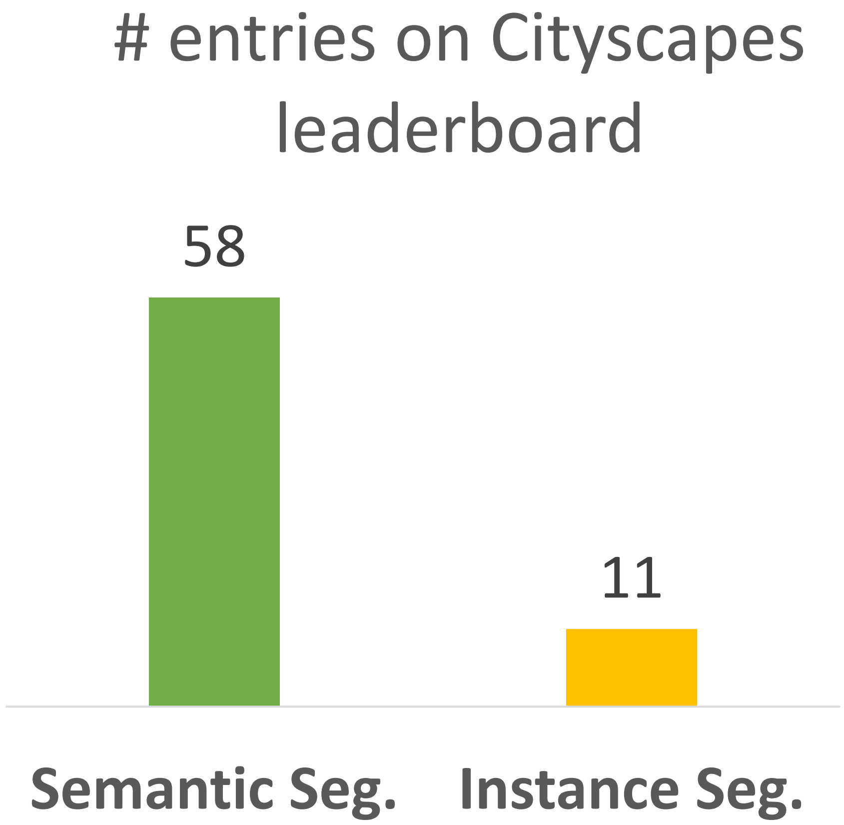


Instance Segmentation

?

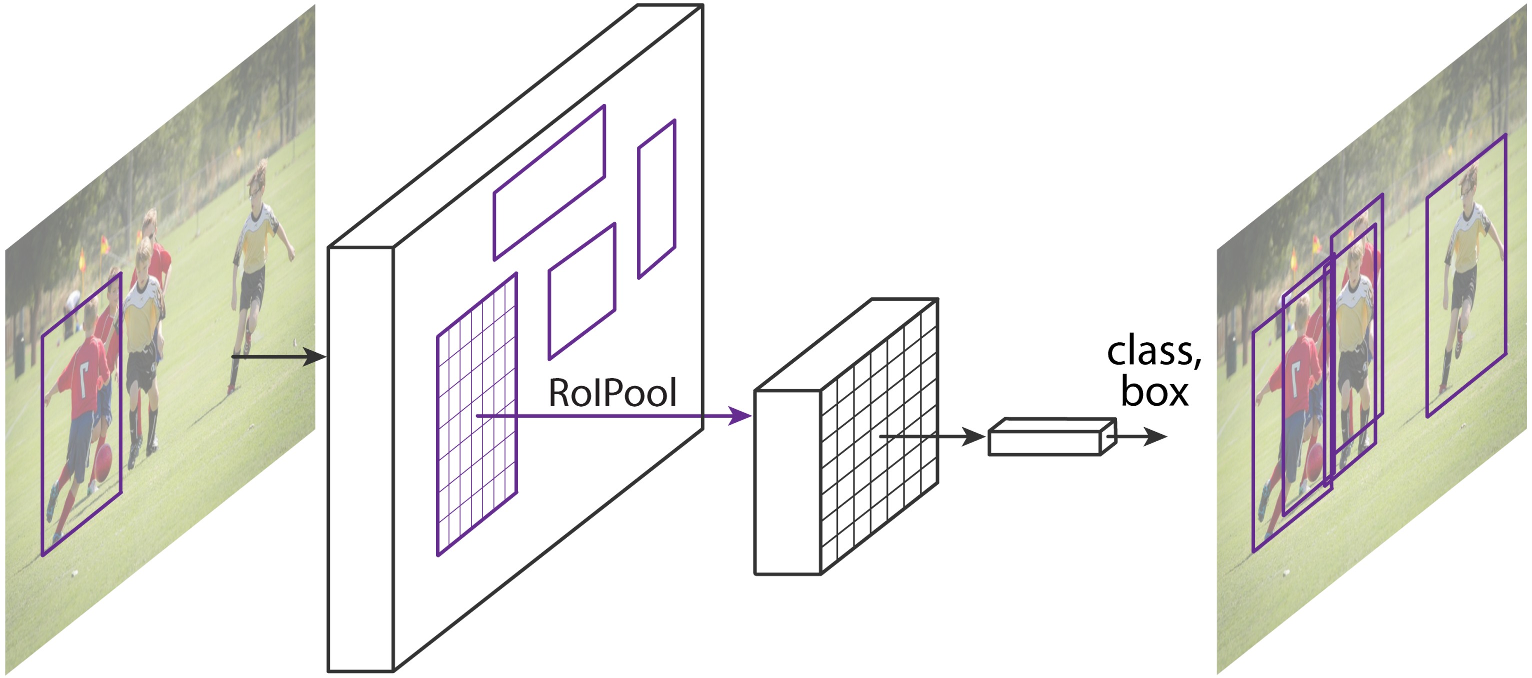
A Challenging Problem…





Object Detection

- Fast/Faster R-CNN
  - ✓Good speed
  - ✓Good accuracy
  - ✓Intuitive
  - ✓Easy to use



Ross Girshick. “Fast R-CNN”. ICCV 2015.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

Semantic Segmentation

- Fully Convolutional Net (FCN)
  - ✓Good speed
  - ✓Good accuracy
  - ✓Intuitive
  - ✓Easy to use

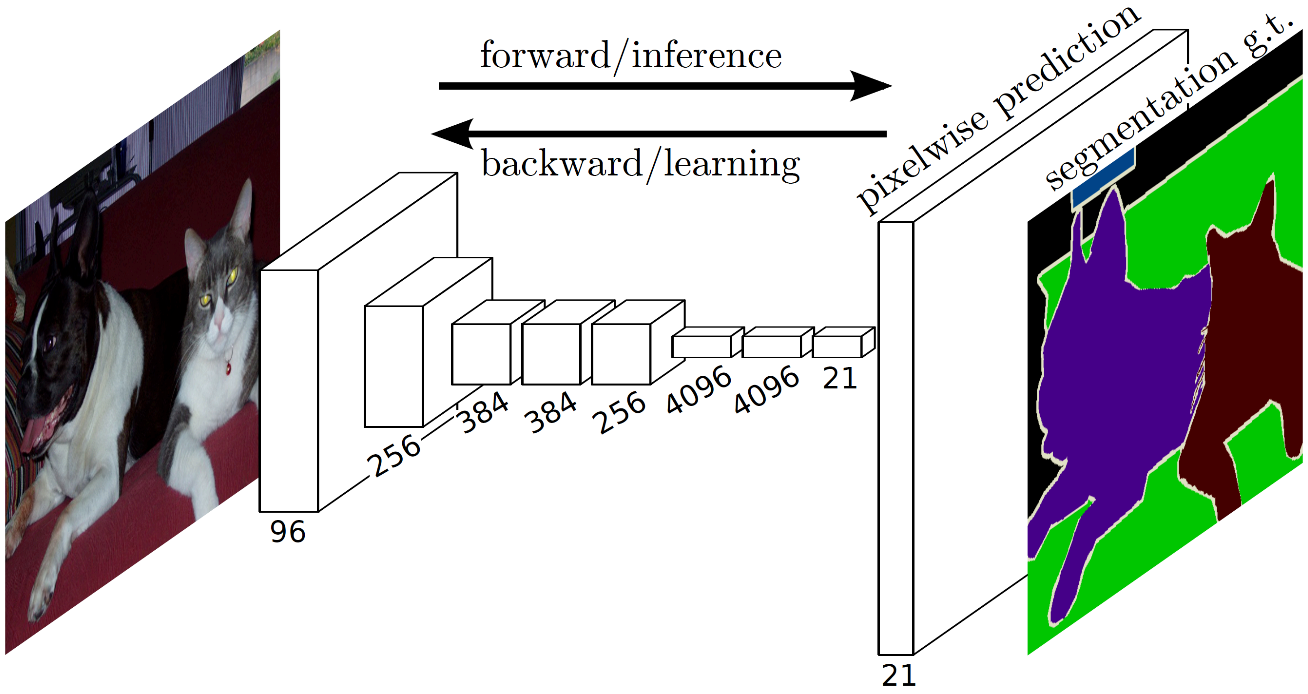
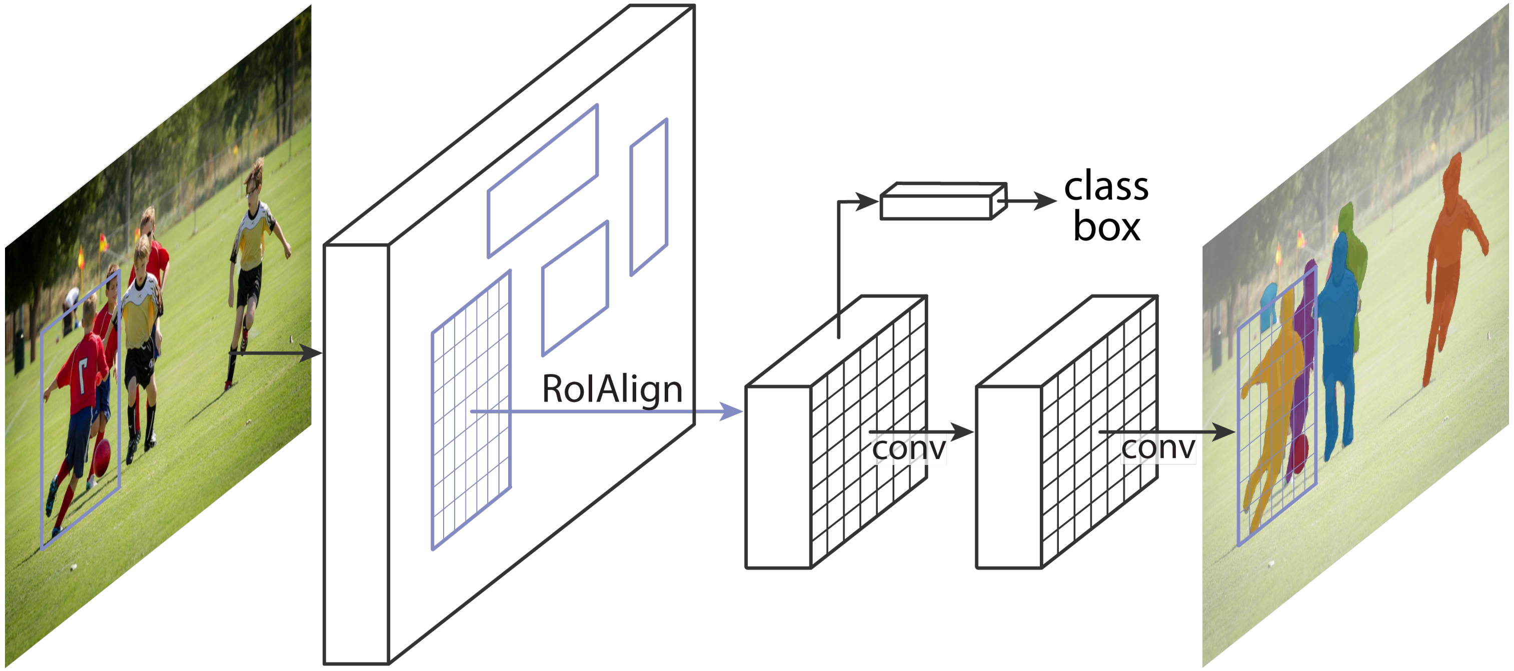


Figure credit: Long et al

Jonathan Long, Evan Shelhamer, & Trevor Darrell. “Fully Convolutional Networks for Semantic Segmentation”. CVPR 2015.

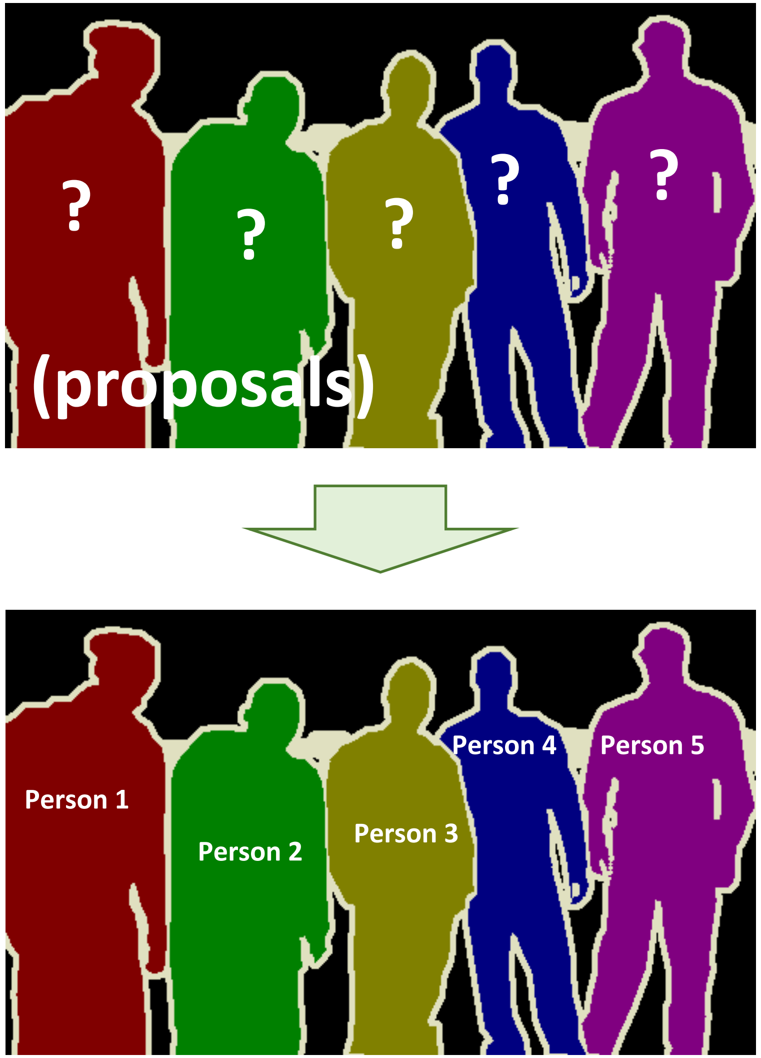
Instance Segmentation

- **Goals** of Mask R-CNN
  - ✓Good speed
  - ✓Good accuracy
  - ✓Intuitive
  - ✓Easy to use

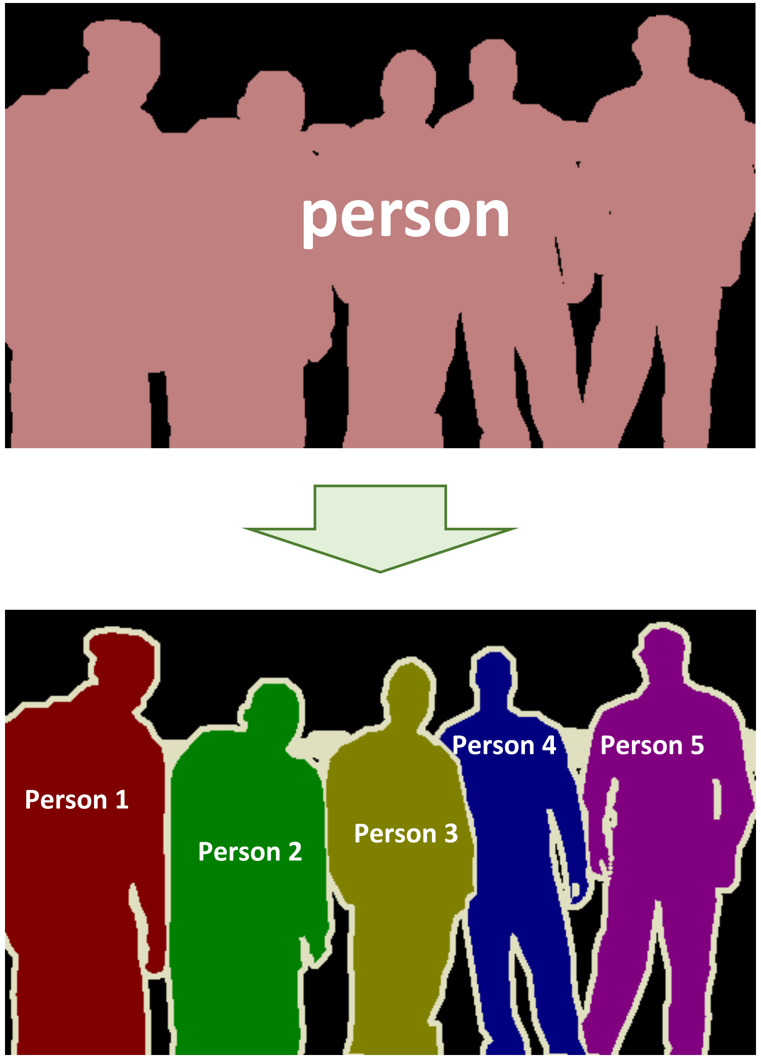


Instance Segmentation Methods

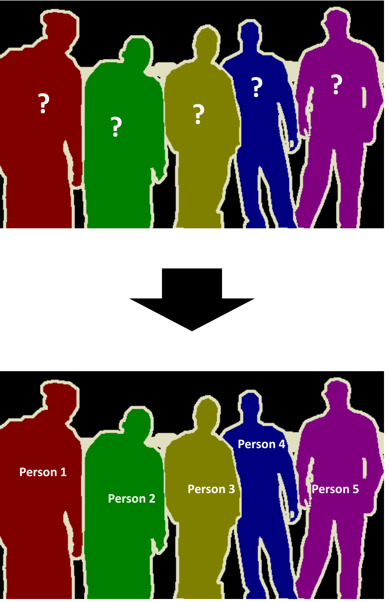
R-CNN driven



FCN driven

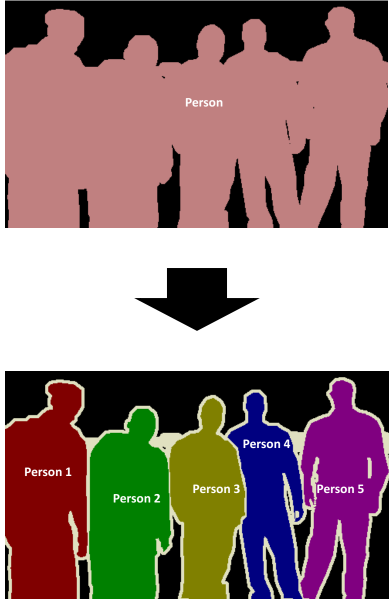


Instance Segmentation Methods



RCNN-driven

- SDS [Hariharan et al, ECCV’14]
- HyperCol [Hariharan et al, CVPR’15]
- CFM [Dai et al, CVPR’15]
- MNC [Dai et al, CVPR’16]



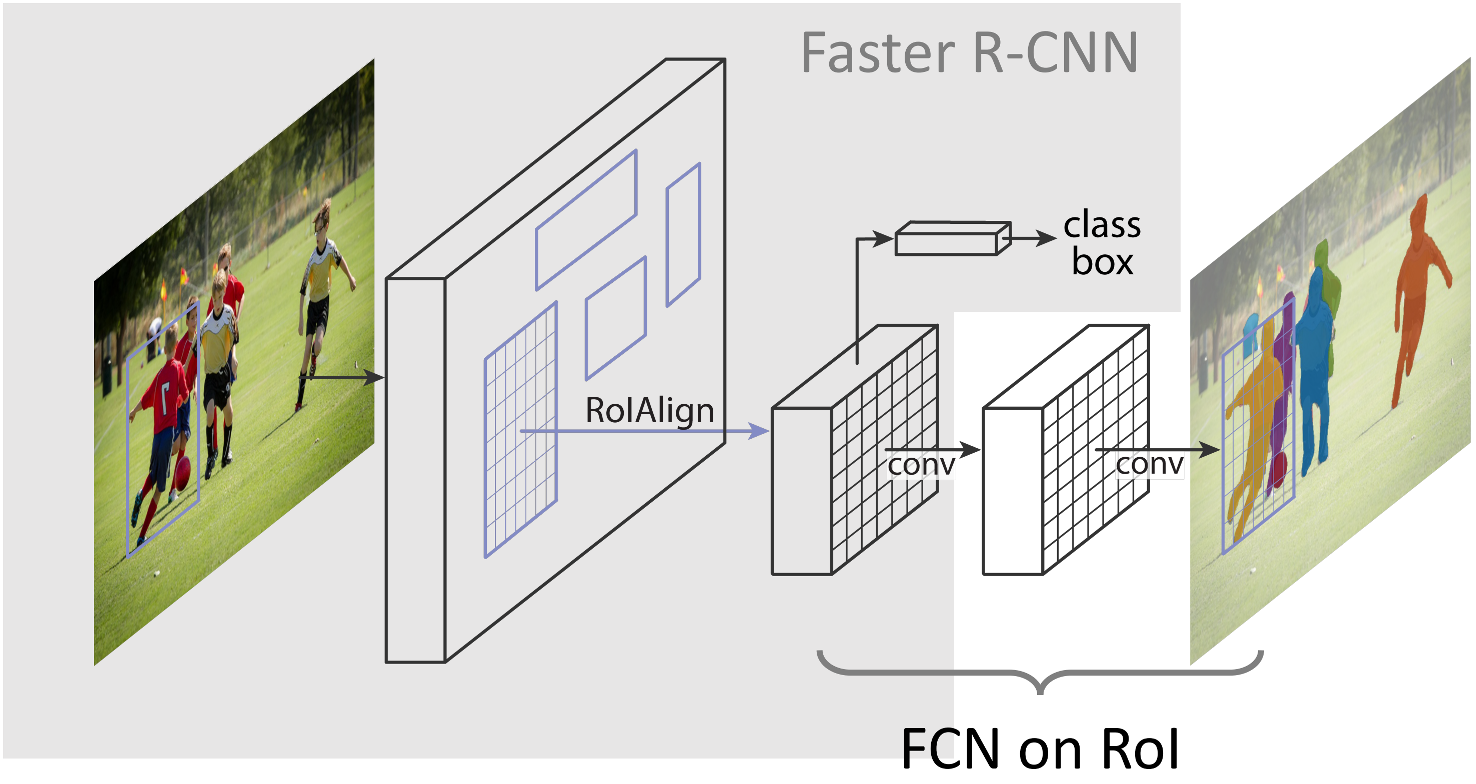
FCN-driven

- PFN [Liang et al, arXiv’15]
- InstanceCut [Kirillov et al, CVPR’17]
- Watershed [Bai & Urtasun, CVPR’17]

- FCIS [Li et al, CVPR’17]
- DIN [Arnab & Torr, CVPR’17]

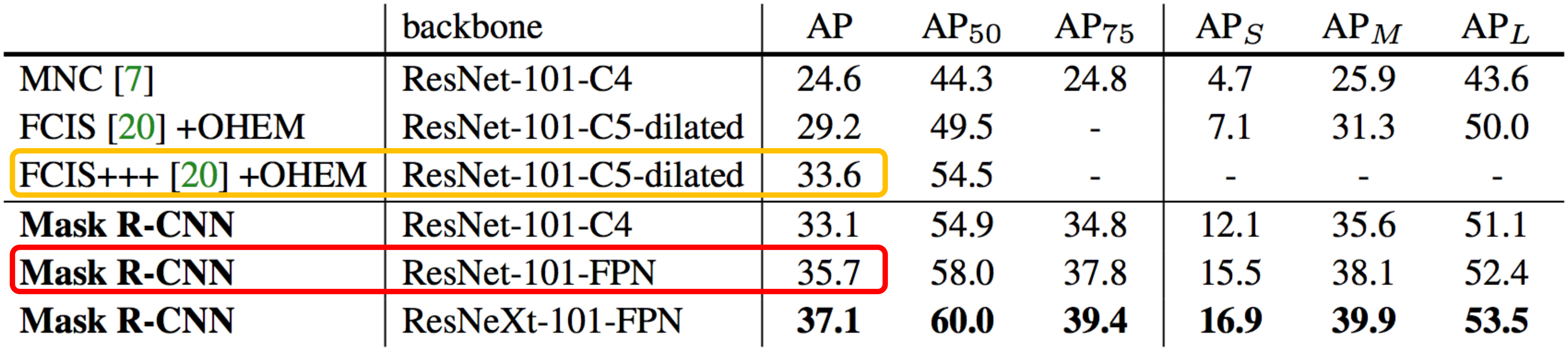
Mask R-CNN

- Mask R-CNN = **Faster R-CNN** with **FCN** on RoIs



Result Analysis

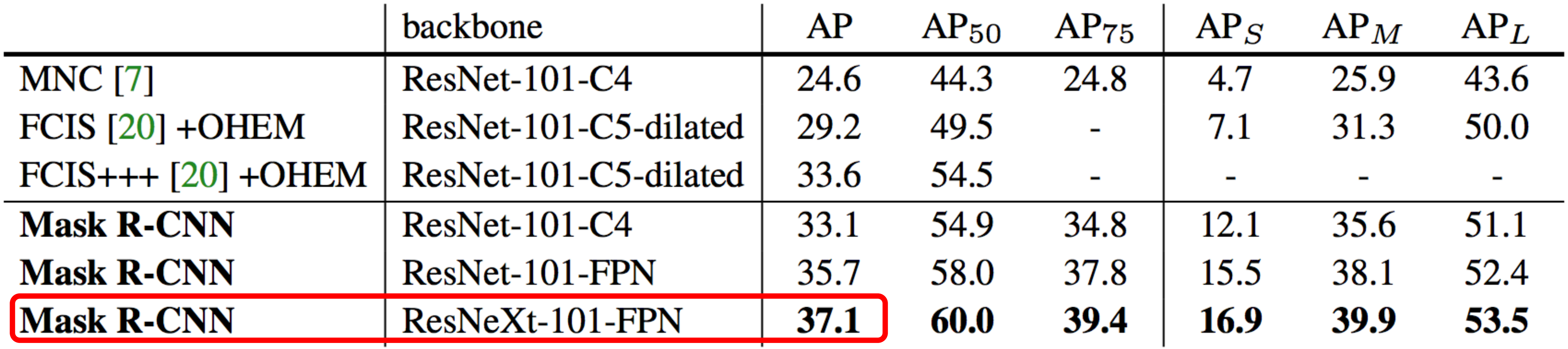
Instance Segmentation Results on COCO



	backbone	AP	AP$_{50}$	AP$_{75}$	AP$_S$	AP$_M$	AP$_L$
MNC [7]	ResNet-101-C4	24.6	44.3	24.8	4.7	25.9	43.6
FCIS [20] +OHEM	ResNet-101-C5-dilated	29.2	49.5	-	7.1	31.3	50.0
FCIS+++ [20] +OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN	ResNeXt-101-FPN	**37.1**	**60.0**	**39.4**	**16.9**	**39.9**	**53.5**

- **2 AP better** than SOTA w/ R101, without bells and whistles
- **200ms / img**

Instance Segmentation Results on COCO



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FCIS+++ [20] +OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
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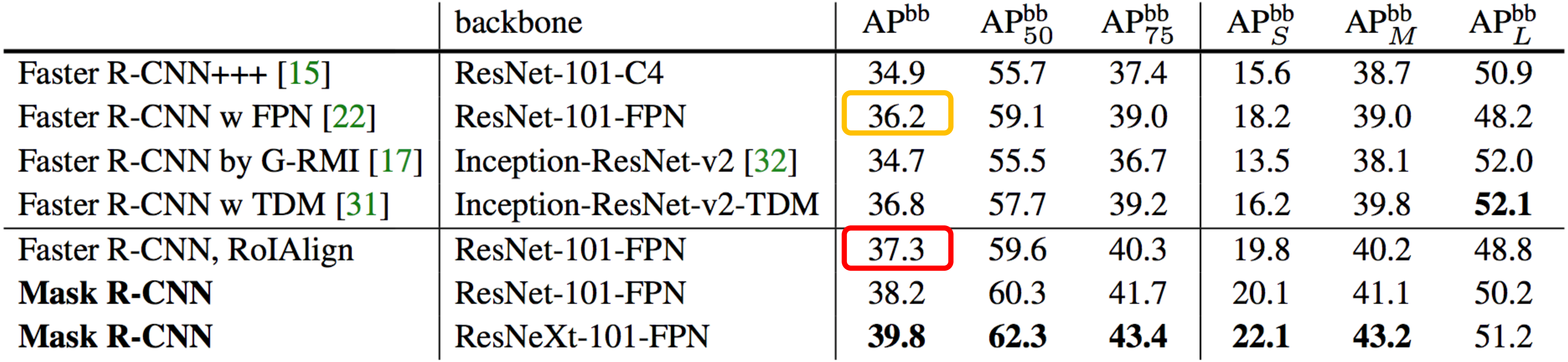
Mask R-CNN	ResNeXt-101-FPN	**37.1**	**60.0**	**39.4**	**16.9**	**39.9**	**53.5**

- benefit from better features (ResNeXt [Xie et al. CVPR’17])

Object Detection Results on COCO

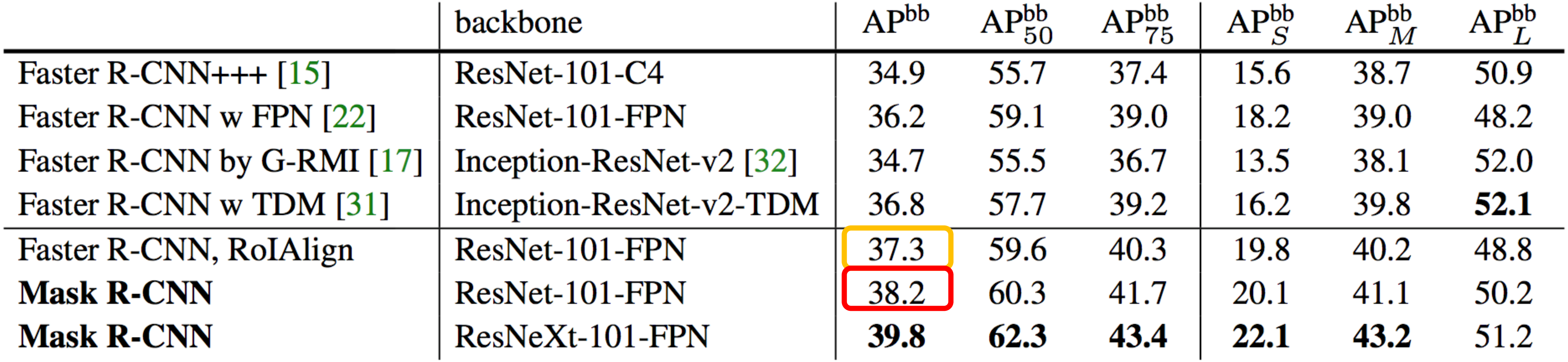


	backbone	AP^{bb}	$\text{AP}^{\text{bb}}_{50}$	$\text{AP}^{\text{bb}}_{75}$	$\text{AP}^{\text{bb}}_{S}$	$\text{AP}^{\text{bb}}_{M}$	$\text{AP}^{\text{bb}}_{L}$
Faster R-CNN+++ [15]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [22]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [17]	Inception-ResNet-v2 [32]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [31]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
Faster R-CNN, RoIAlign	ResNet-101-FPN	37.3	59.6	40.3	19.8	40.2	48.8
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7	20.1	41.1	50.2
Mask R-CNN	ResNeXt-101-FPN	**39.8**	**62.3**	**43.4**	**22.1**	**43.2**	51.2

bbox detection improved by:

- RoIAlign

Object Detection Results on COCO



	backbone	AP^{bb}	$\text{AP}^{\text{bb}}_{50}$	$\text{AP}^{\text{bb}}_{75}$	$\text{AP}^{\text{bb}}_{S}$	$\text{AP}^{\text{bb}}_{M}$	$\text{AP}^{\text{bb}}_{L}$
Faster R-CNN+++ [15]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [22]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [17]	Inception-ResNet-v2 [32]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [31]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
Faster R-CNN, RoIAlign	ResNet-101-FPN	37.3	59.6	40.3	19.8	40.2	48.8
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7	20.1	41.1	50.2
Mask R-CNN	ResNeXt-101-FPN	**39.8**	**62.3**	**43.4**	**22.1**	**43.2**	51.2

bbox detection improved by:

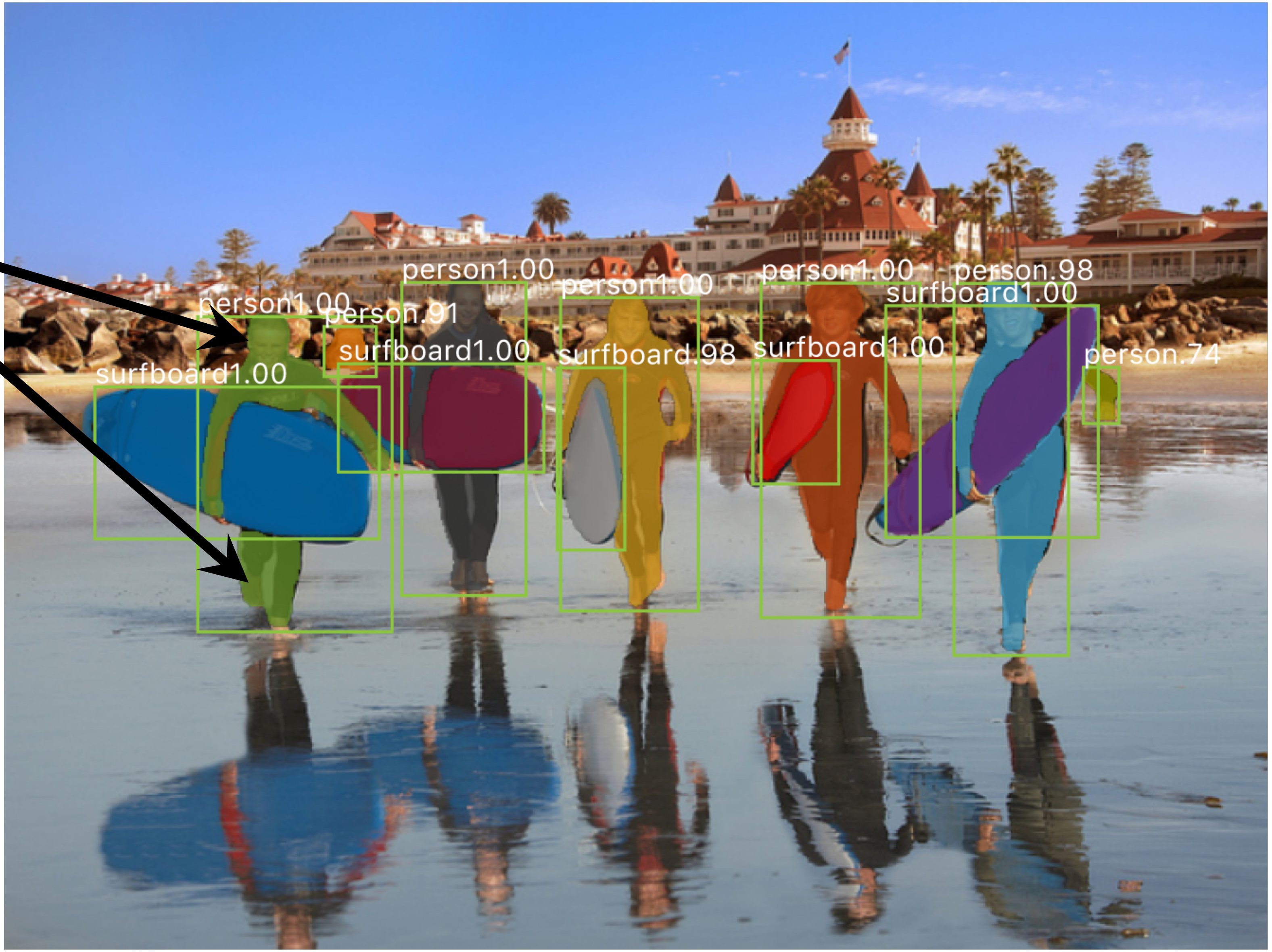
- RoIAlign
- Multi-task training w/ mask

COCO Competition

- Our Mask R-CNN achieves a single-model result of
  - 47.9 bbox AP
  - 43.5 mask AP

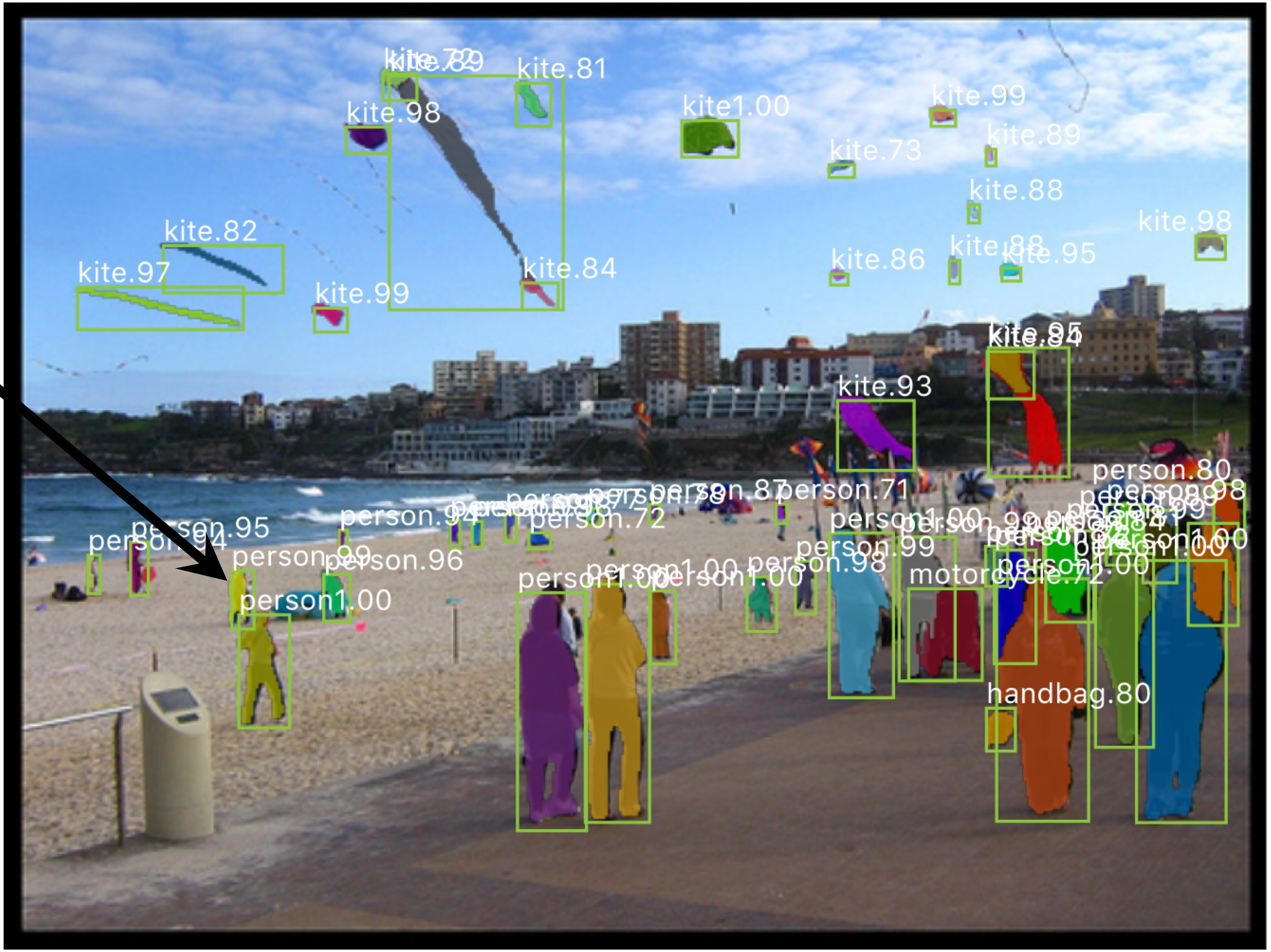
- More in our talk in COCO workshop (10/29, Sun)

disconnected
object

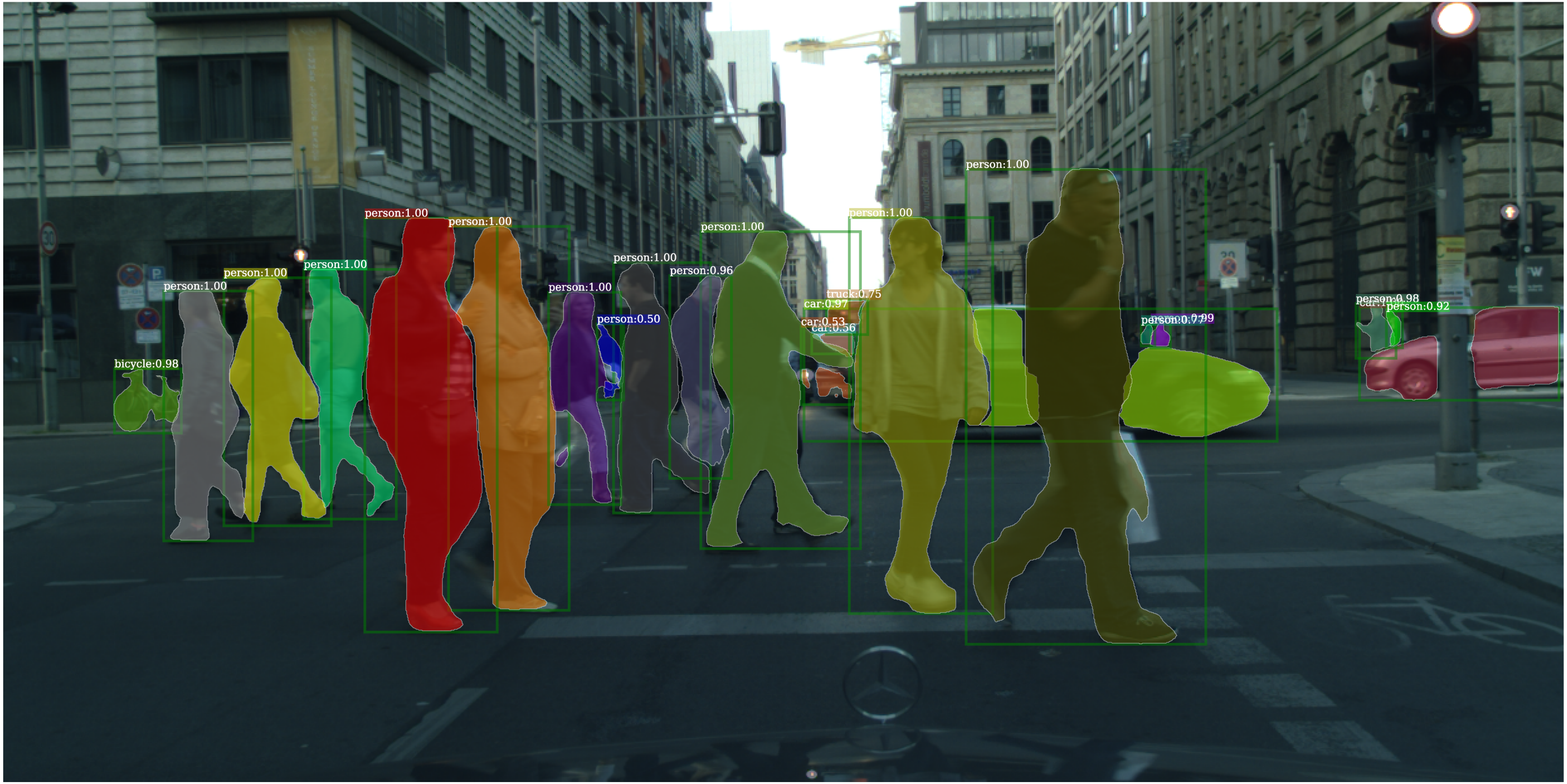


Mask R-CNN results on COCO

small
objects

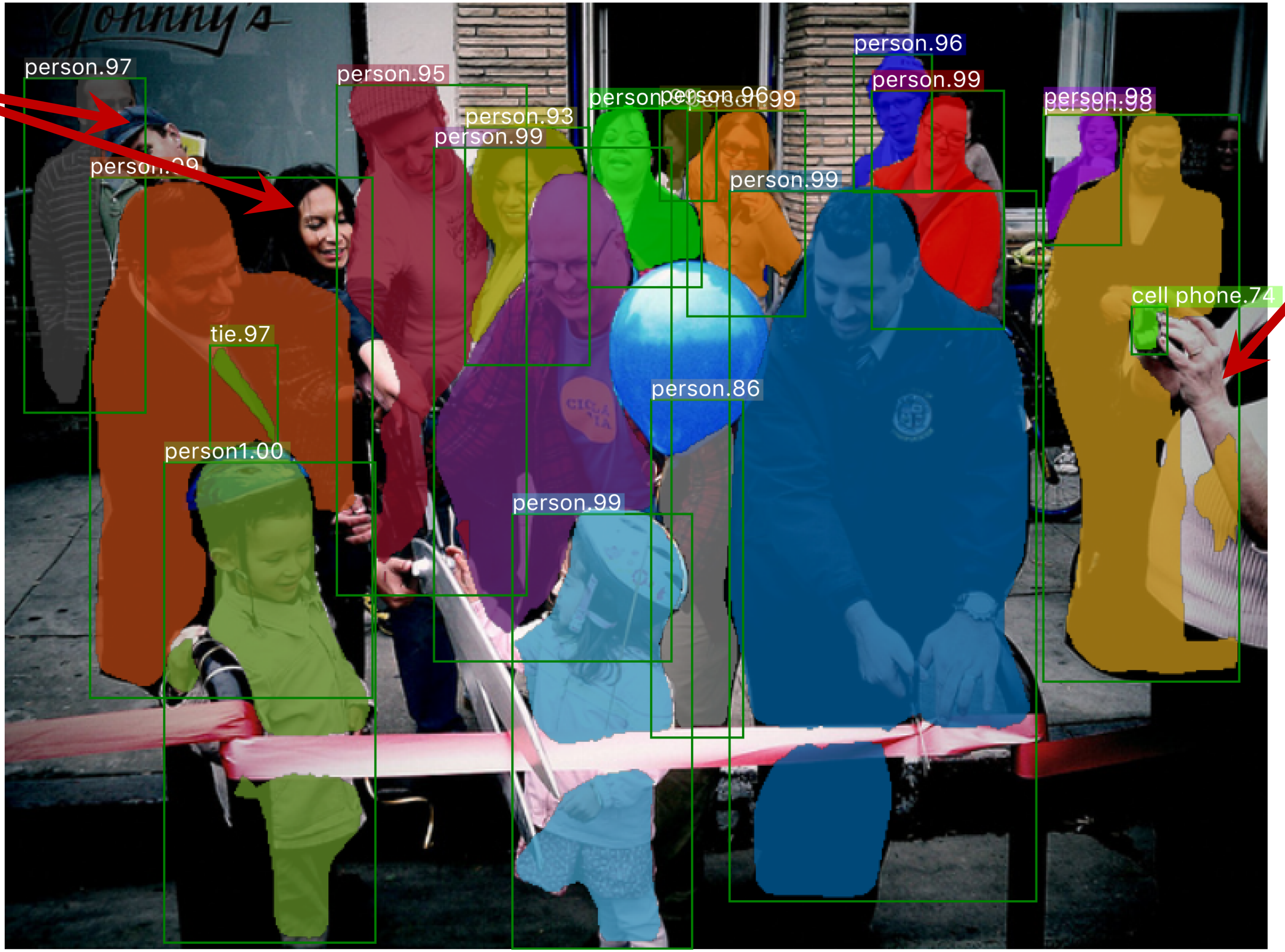


Mask R-CNN results on COCO



Mask R-CNN results on CityScapes

Failure case: detection/segmentation

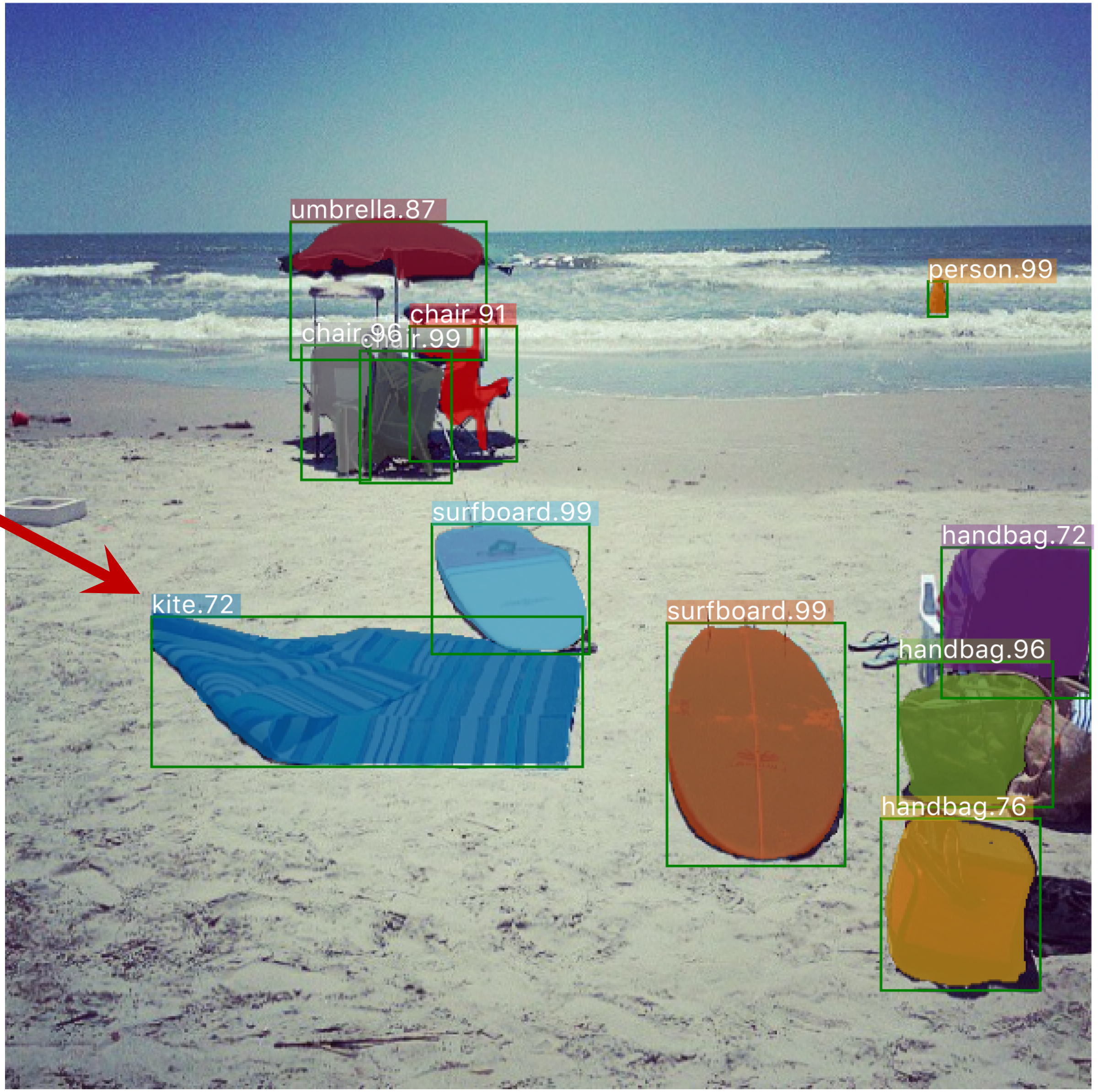


missing

missing,
false mask

Mask R-CNN results on COCO

Failure case: recognition



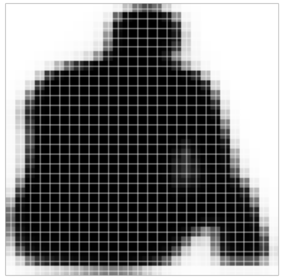
not a kite

Mask R-CNN results on COCO

Validation image with box detection shown in red

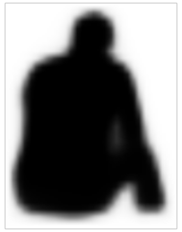
28x28 soft prediction from Mask R-CNN

(enlarged)



Soft prediction resampled to image coordinates

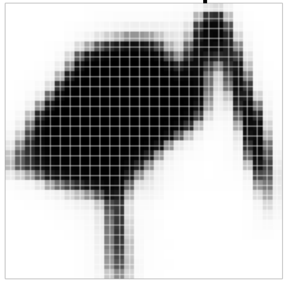
(bilinear and bicubic interpolation work equally well)



Final prediction (threshold at 0.5)

Validation image with box detection shown in red

28x28 soft prediction



Resized Soft prediction

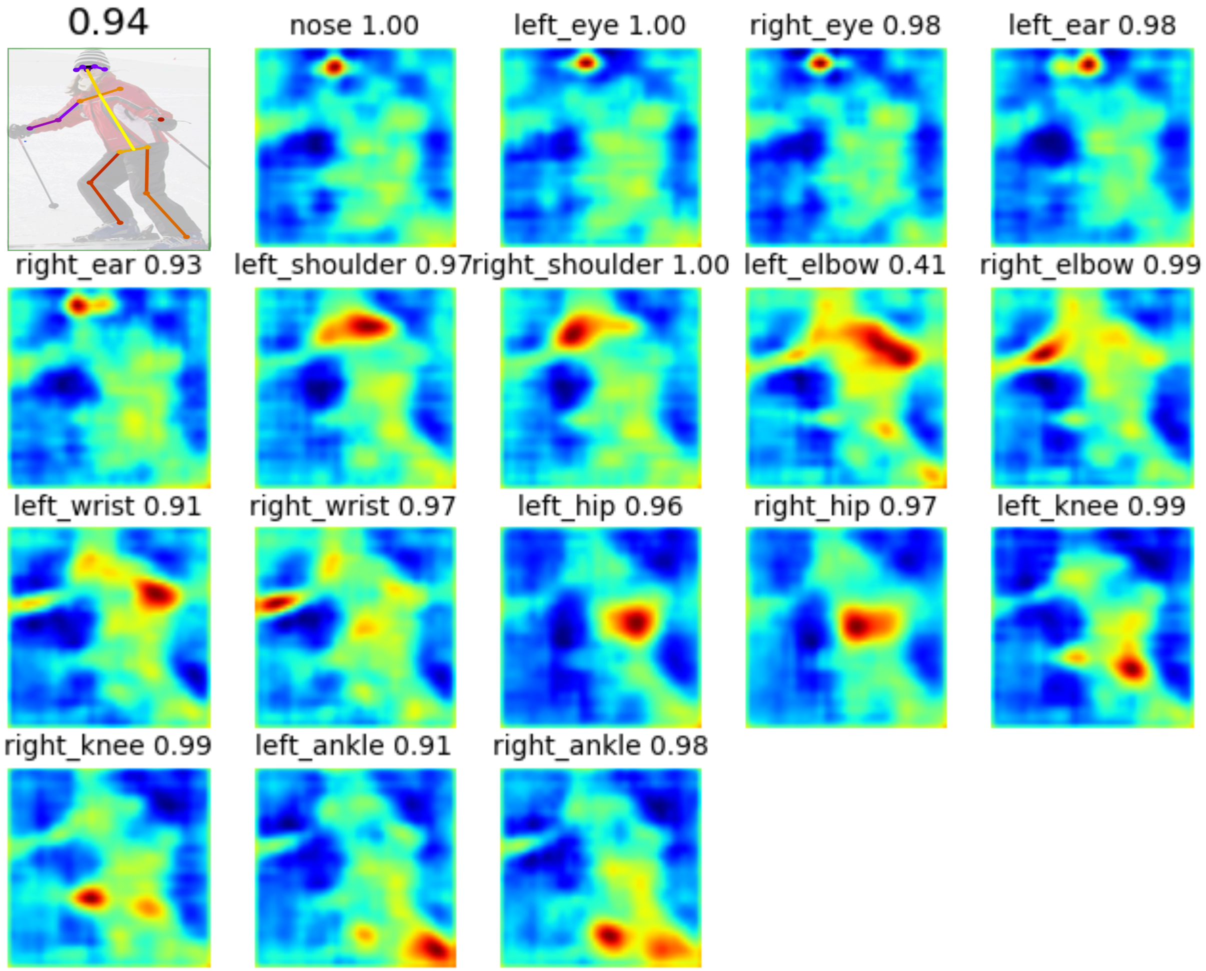
Final mask

Mask R-CNN: for Human Keypoint Detection

- 1 keypoint = 1-hot “mask”
- Human pose = 17 masks

- Softmax over spatial locations
  - e.g. 56^2-way softmax on 56x56

- Desire the same equivariances
  - translation, scale, aspect ratio

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Mask R-CNN frame-by-frame