What can(’t) we do we ConvNets?

Pose regression + Object detection

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Outline

- Architectures of classification networks
- Architectures of segmentation networks
- Architectures of regression networks
- Architectures of detection networks

OpenPose [Cao, TPAMI, 2019]
https://arxiv.org/pdf/1812.08008.pdf

input

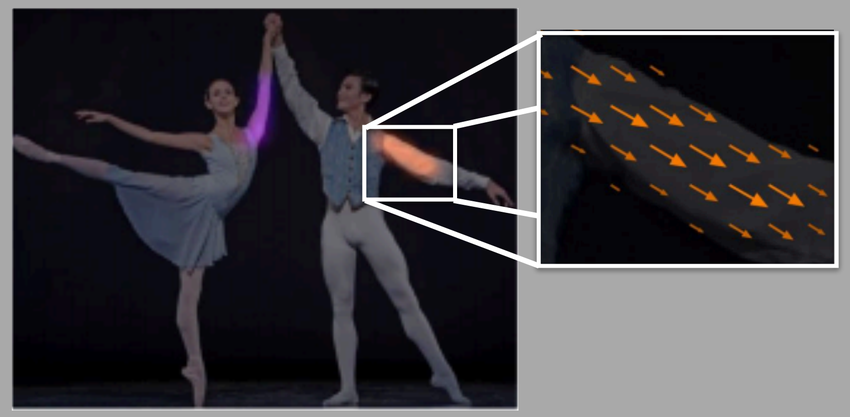
VGG-19

F

"Complicated stuff inside":

(1) detect joints

(2) estimate limbs directions



output

Out is two fold => how to find articulated structure?

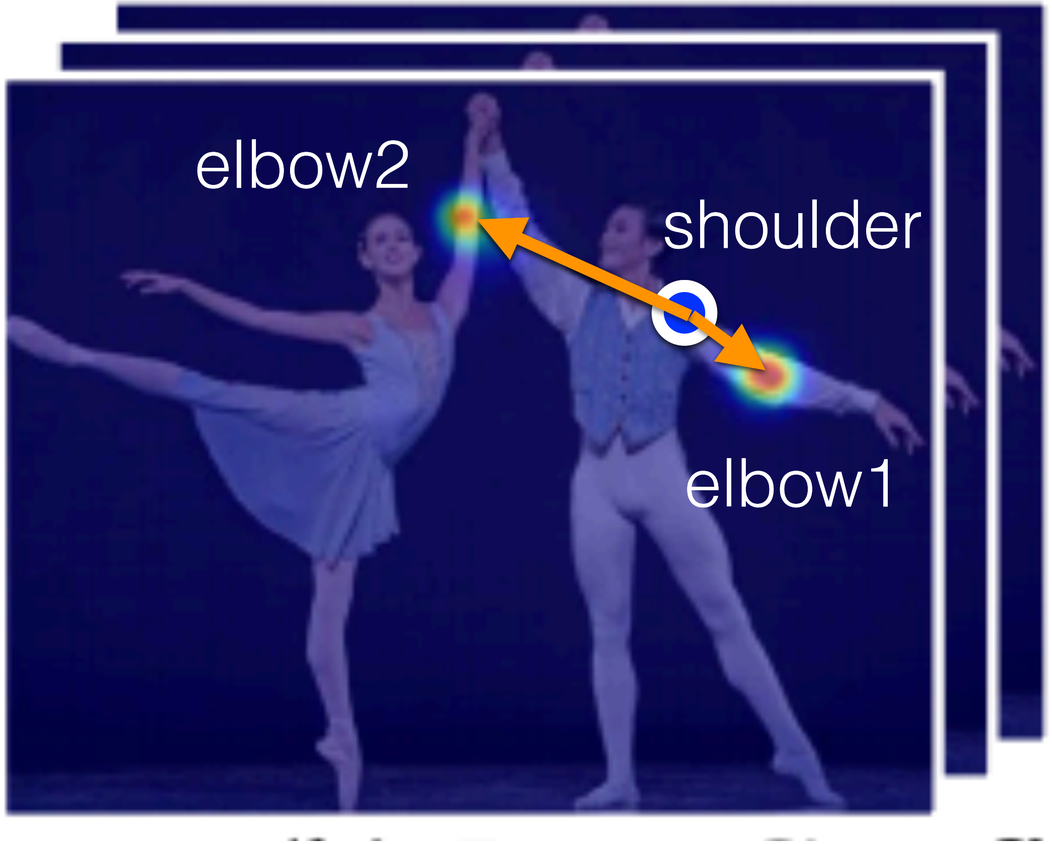
PAFs

joints

Out is two fold => how to find articulated structure?
Greedy matching that is consistent with PAF

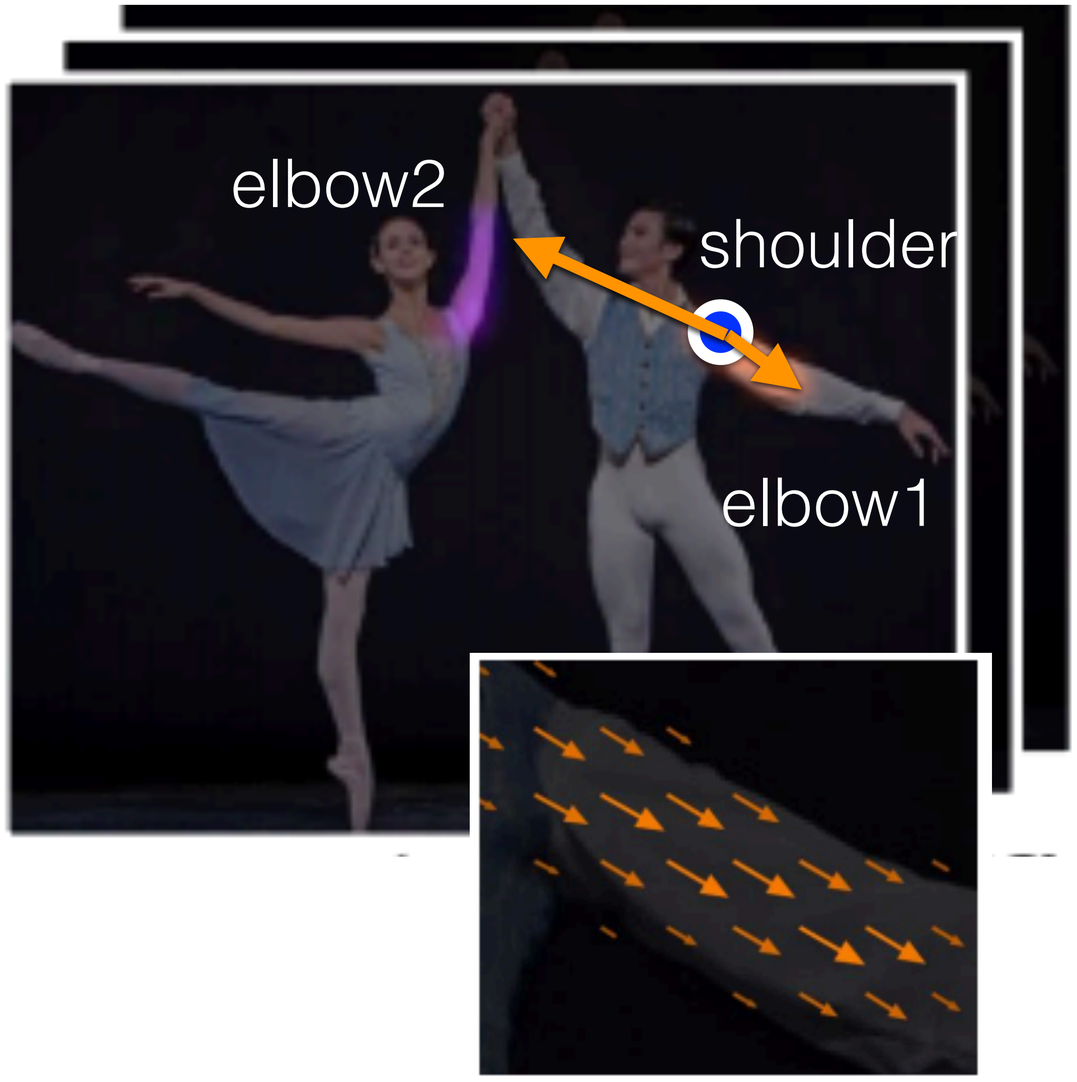
PAFs

joints

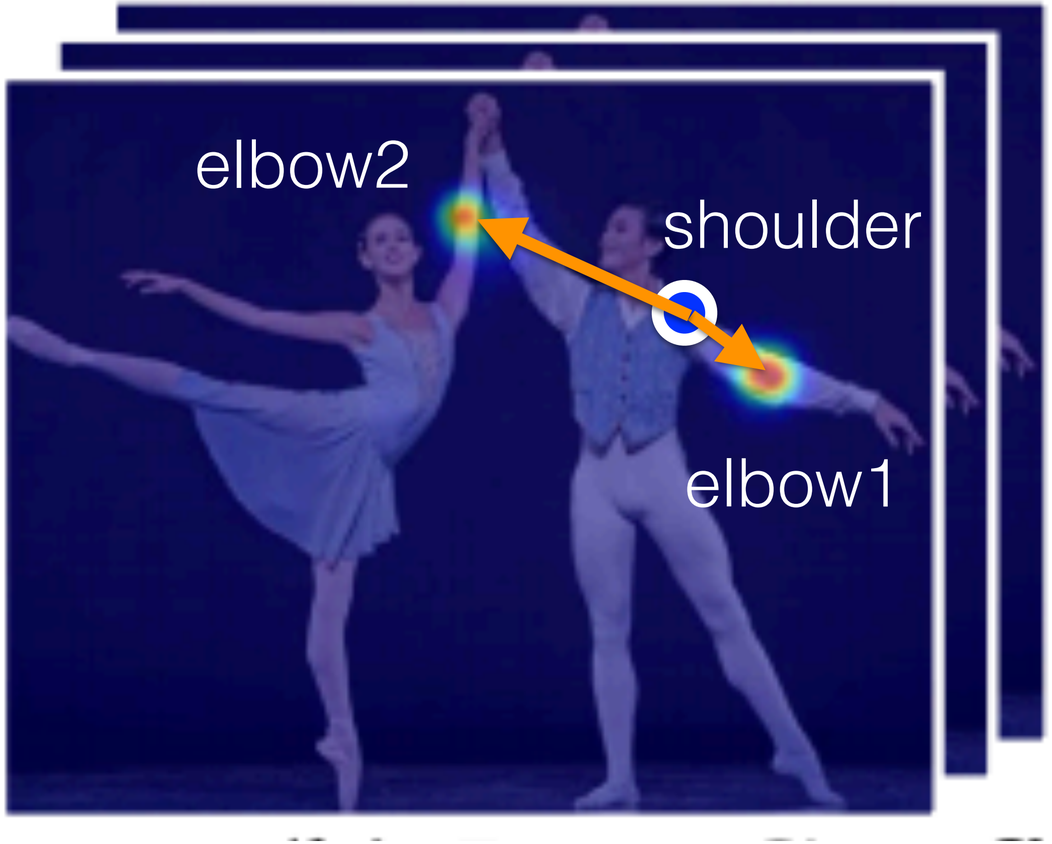


OpenPose [Cao, TPAMI, 2019]
https://arxiv.org/pdf/1812.08008.pdf

PAFs



joints



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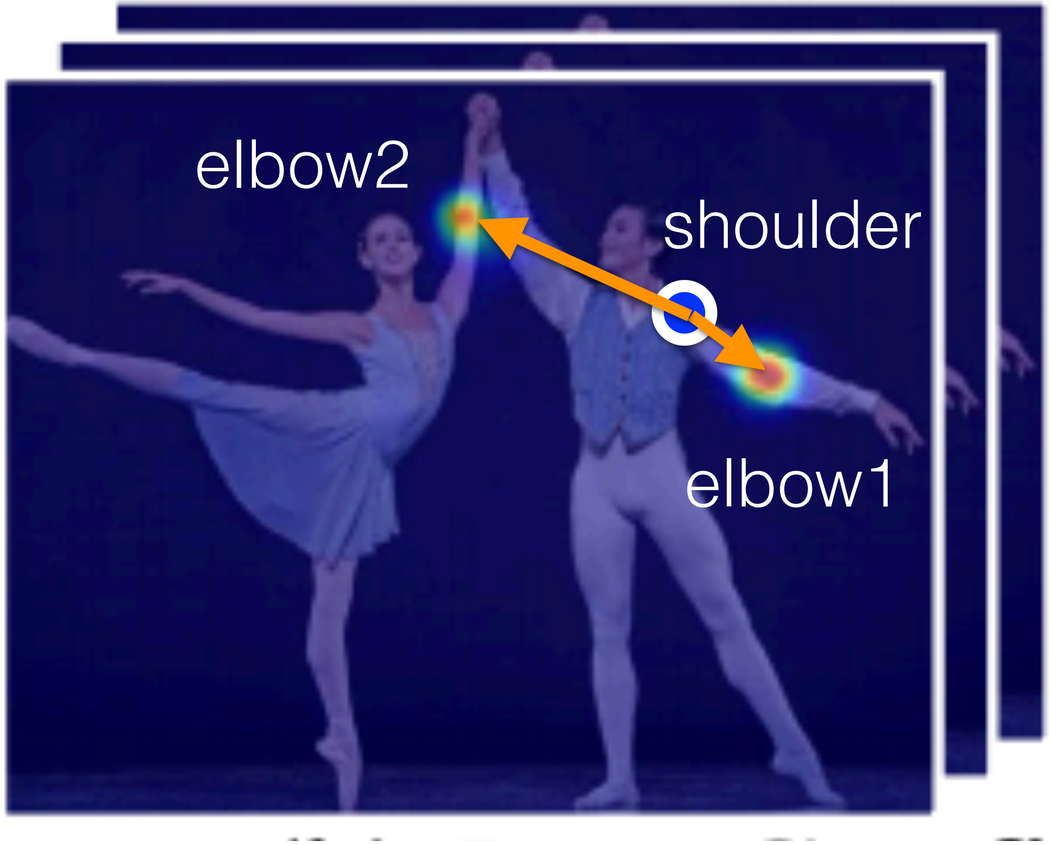
PAFs

joints

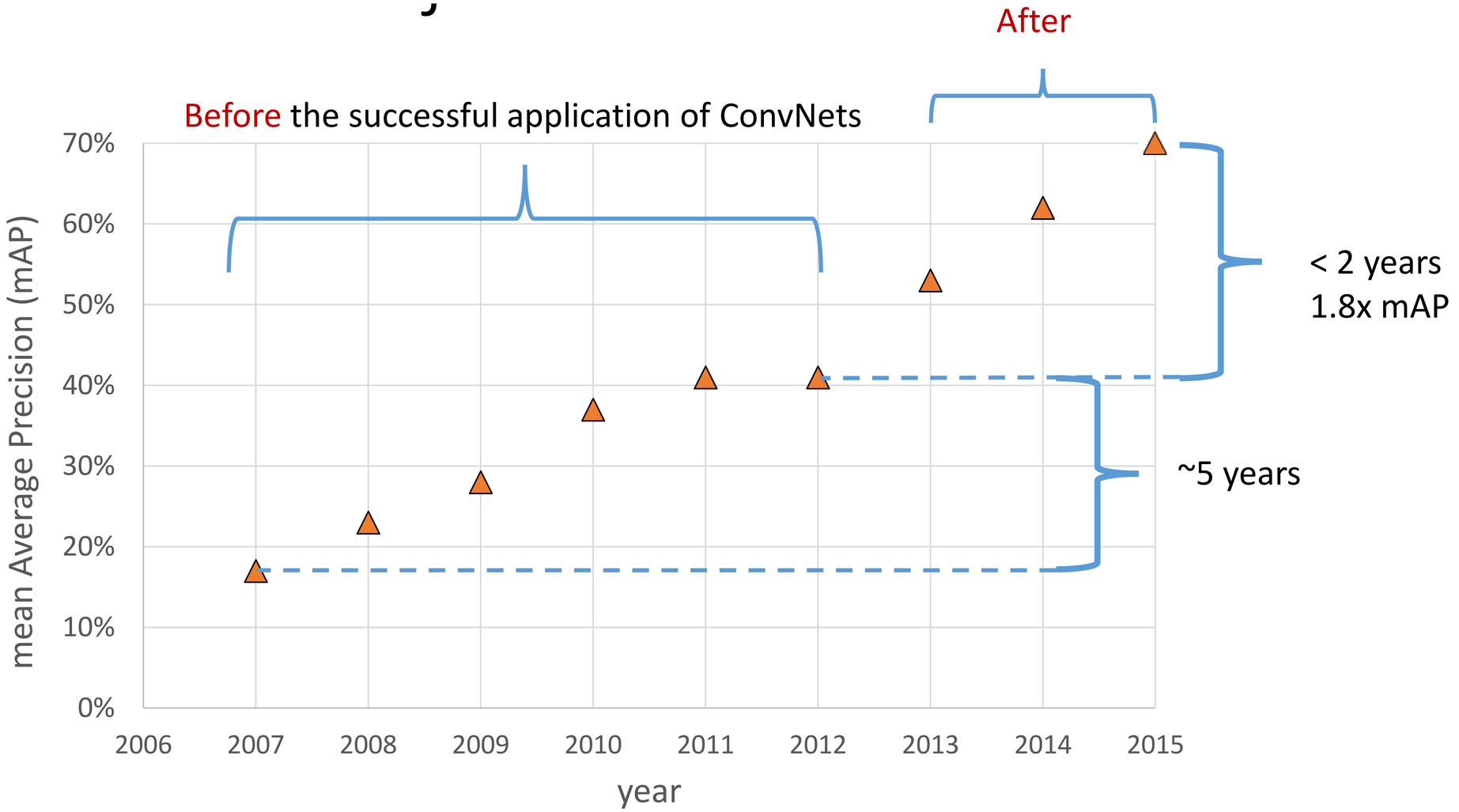


PoseTrack challenge (ICCV 2017/ECCV 2018)
https://posetrack.net

Outline

- Architectures of classification networks
- Architectures of segmentation networks
- Architectures of regression networks
- Architectures of detection networks
- Architectures of feature matching networks

Pascal VOC object detection challenge



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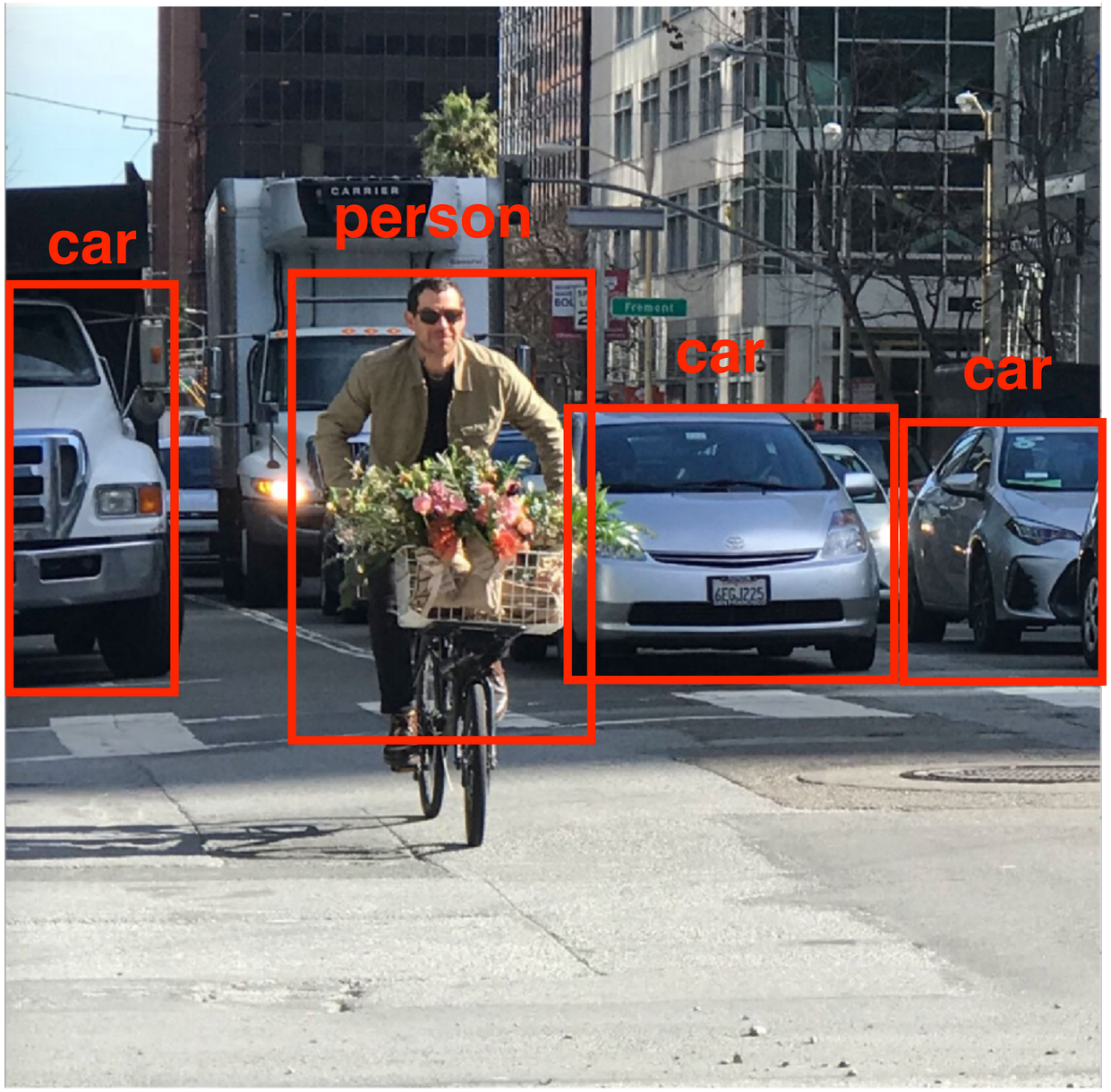
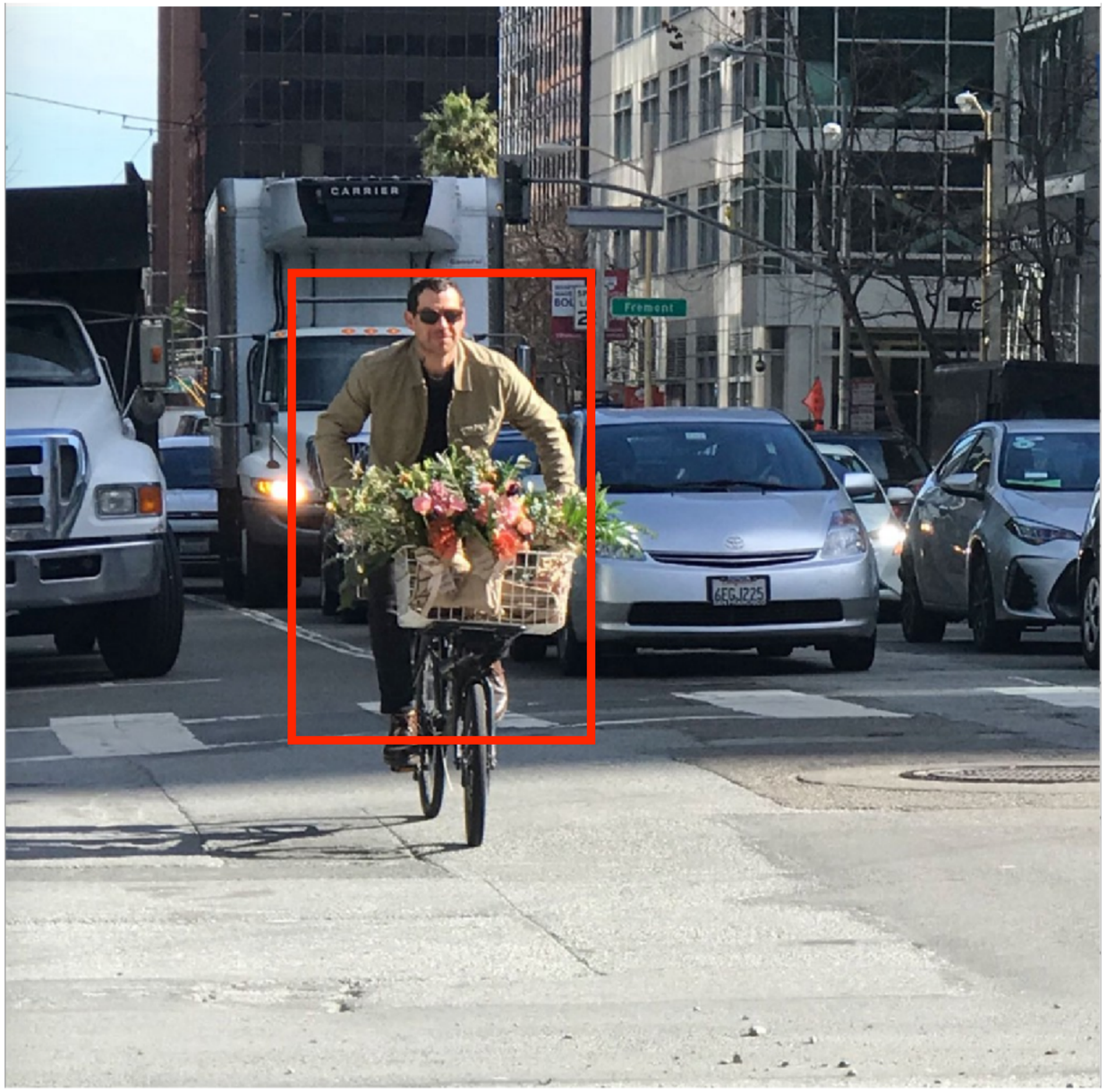
Object detection

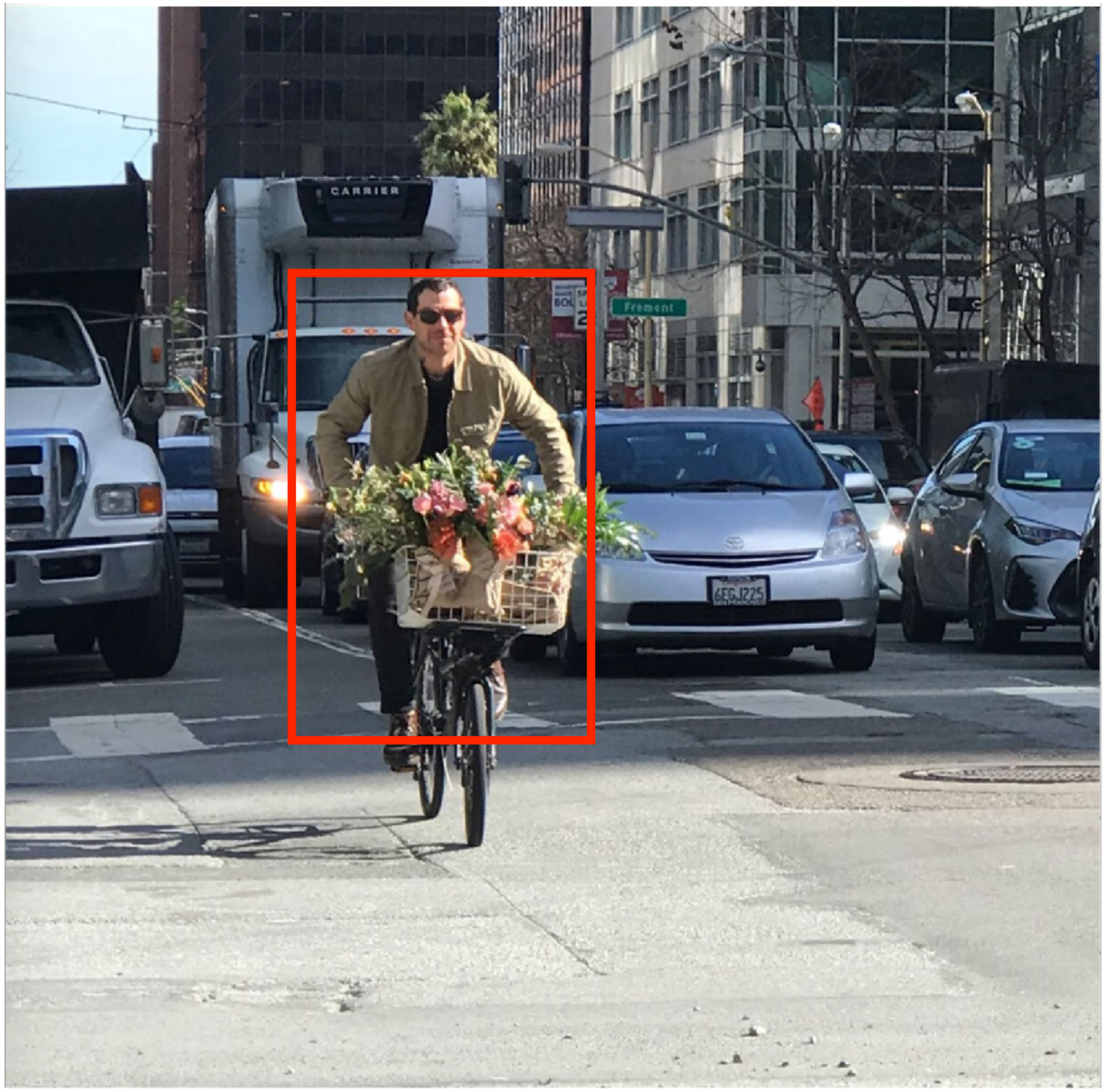
Object detection

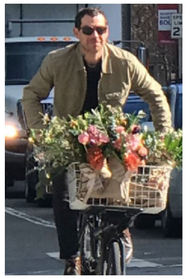


Object detection



Object detection

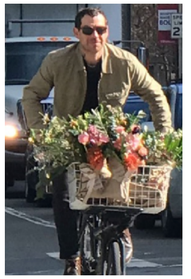




CNN

0.7	**person**
0.1	car
0.2	building
0.0	bckg

Object detection



CNN

0.7	**person**
0.1	car
0.2	building
0.0	bckg

Object detection

CNN

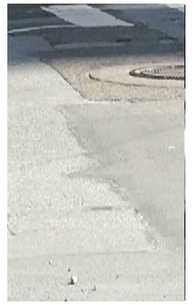
0.0	person
0.9	**car**
0.1	building
0.0	bckg

Object detection

CNN

0.0	person
0.9	**car**
0.1	building
0.0	bckg

Object detection



CNN

0.0	person
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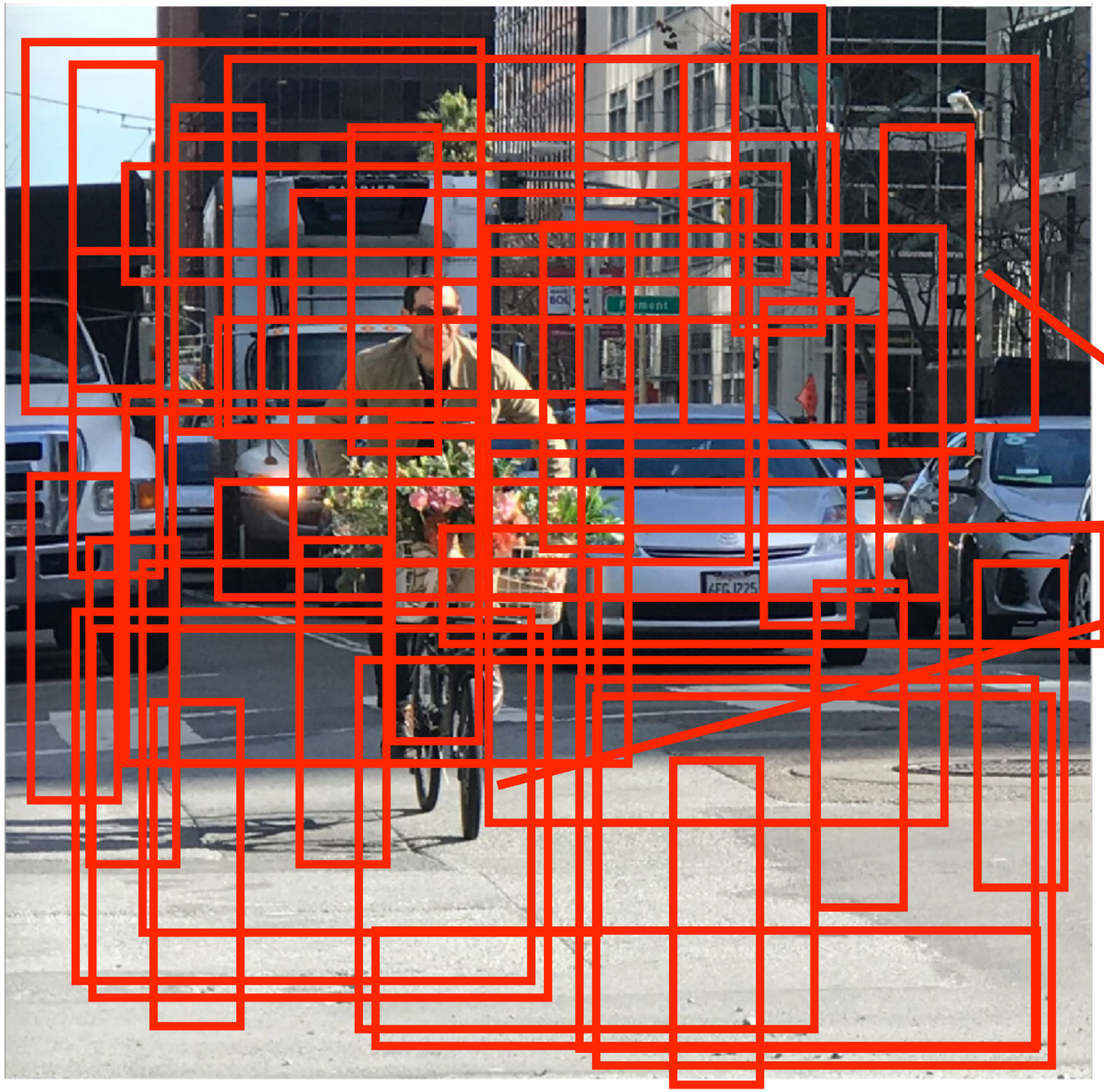
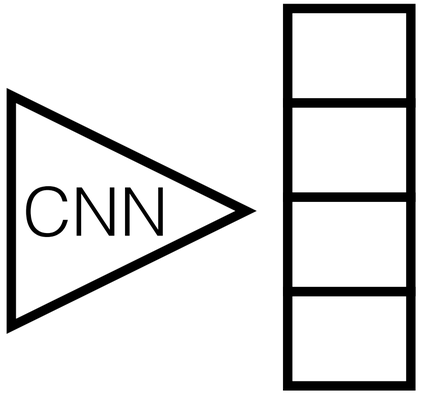
0.9	**bckg**

Object detection

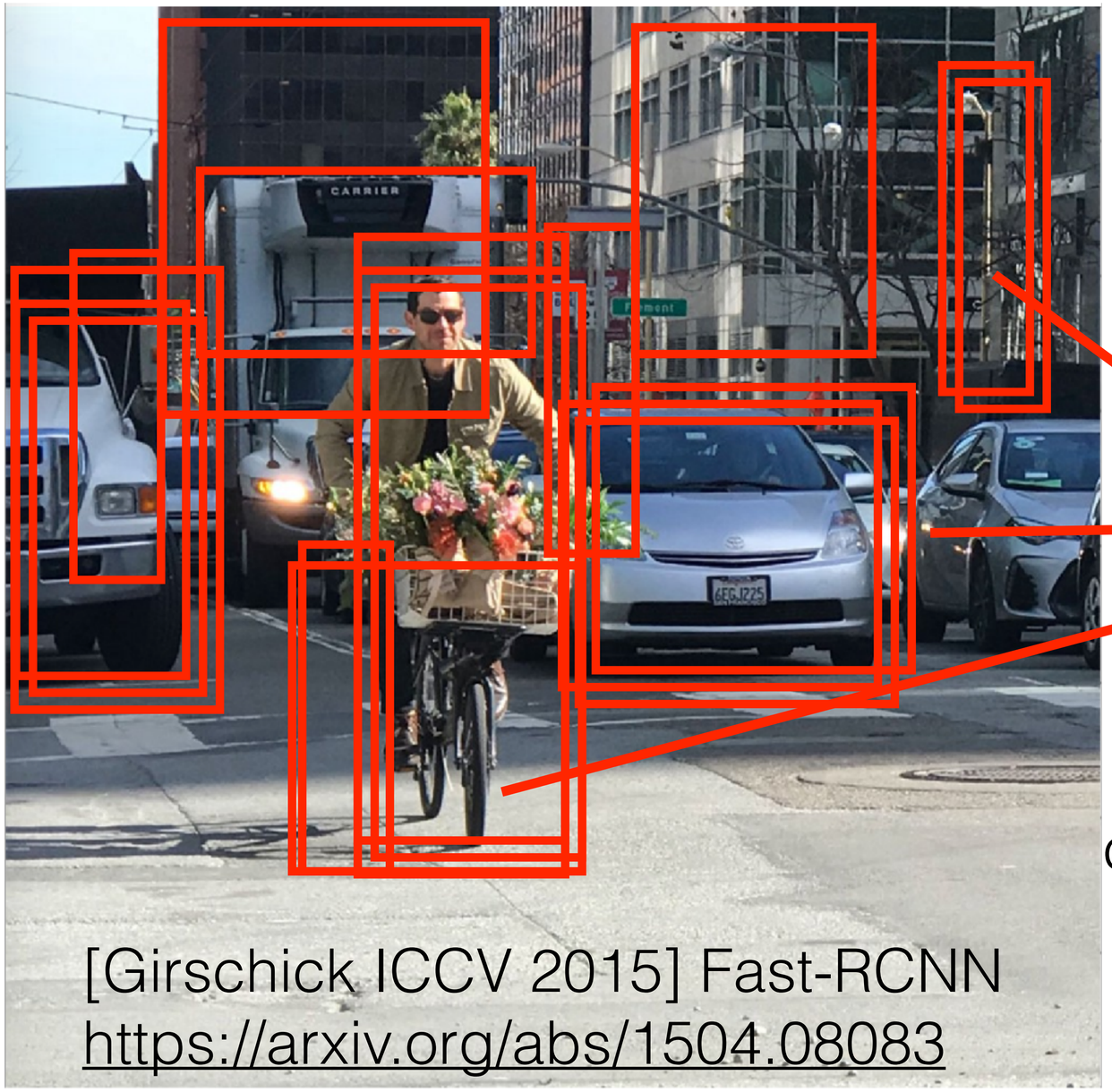




classify all rectangles

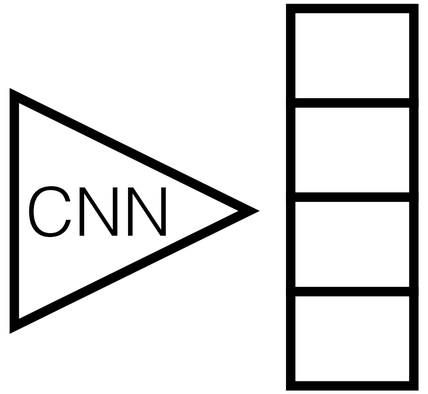
- H x W x Aspect_Ratio x Scales x 0.001 sec = **months**

Object detection



[Girschick ICCV 2015] Fast-RCNN
https://arxiv.org/abs/1504.08083

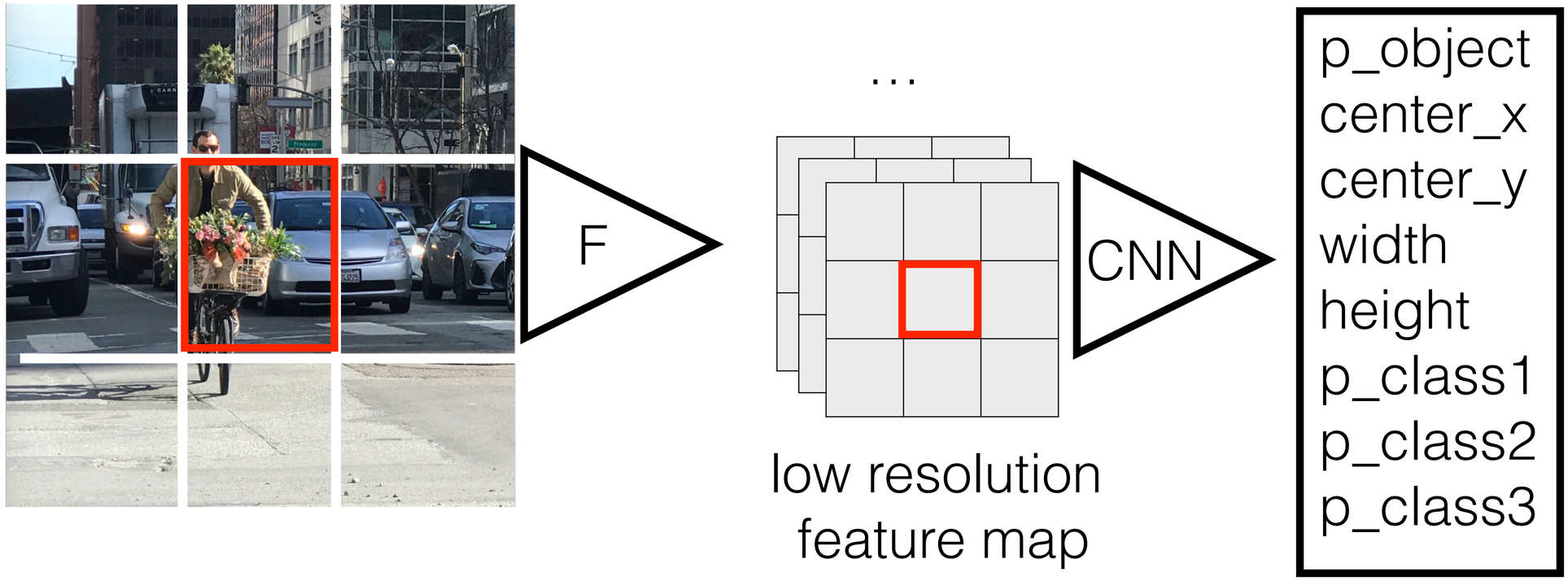
The selective search for region proposals is computational bottleneck !!!



classify + align only 2k region proposals

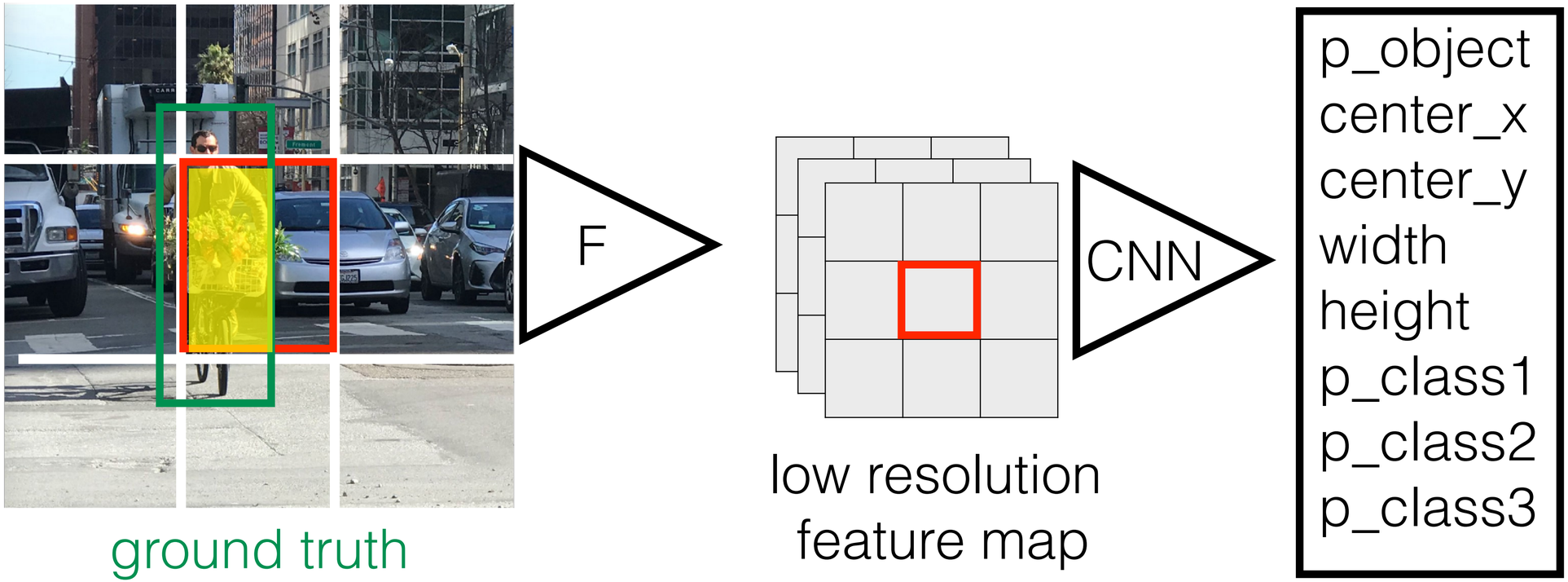
- (find 2k cand.) + (2k cand. x 0.001 sec) = **47+2 sec = 49 sec**

YOLO and Faster RCNN architectures
https://arxiv.org/abs/1506.01497



- divide image into 3x3 sub images (corresponding to its receptive fields)
- predict relative position, objectness, class for each sub-im

YOLO and Faster RCNN architectures
https://arxiv.org/abs/1506.01497



- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- learn from ground truth

YOLO and Faster RCNN architectures
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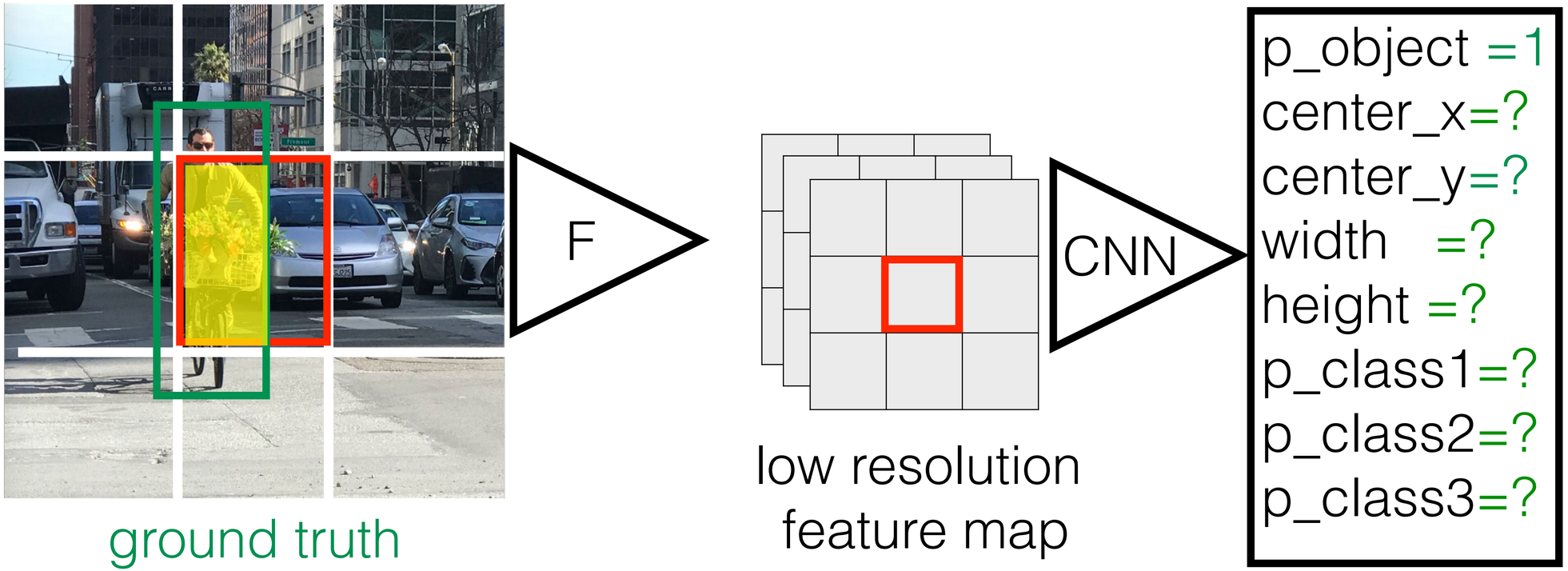

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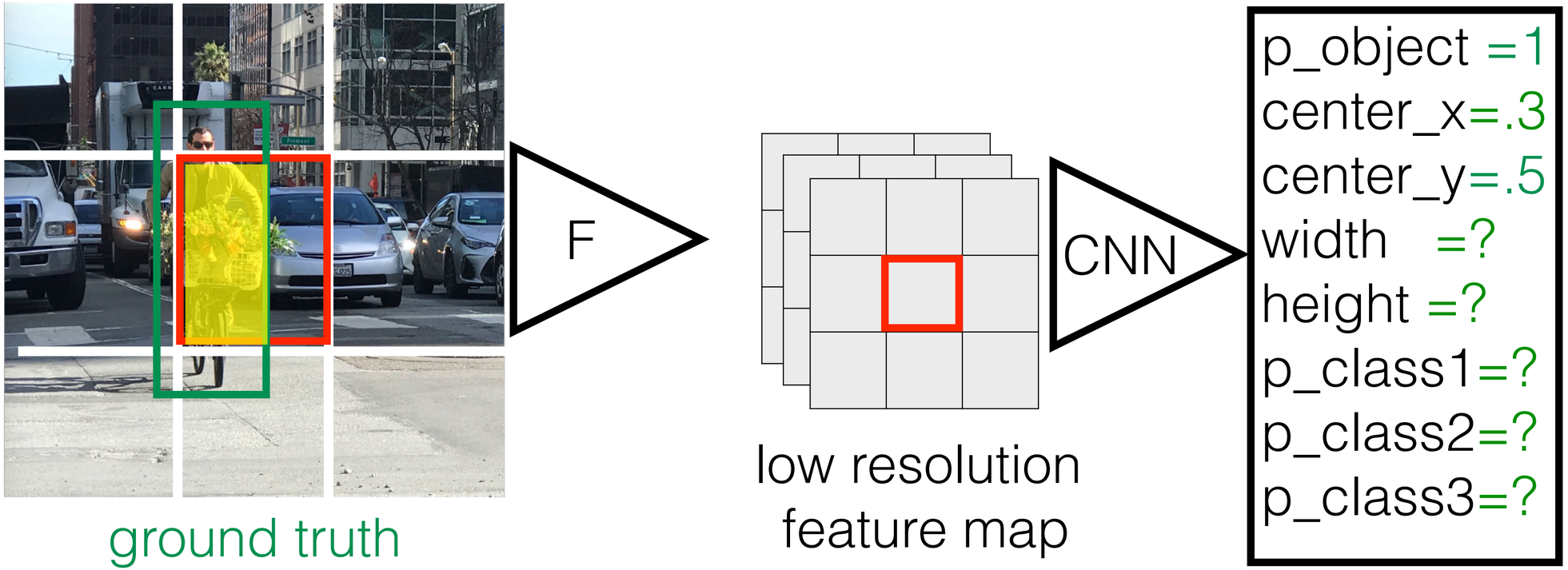

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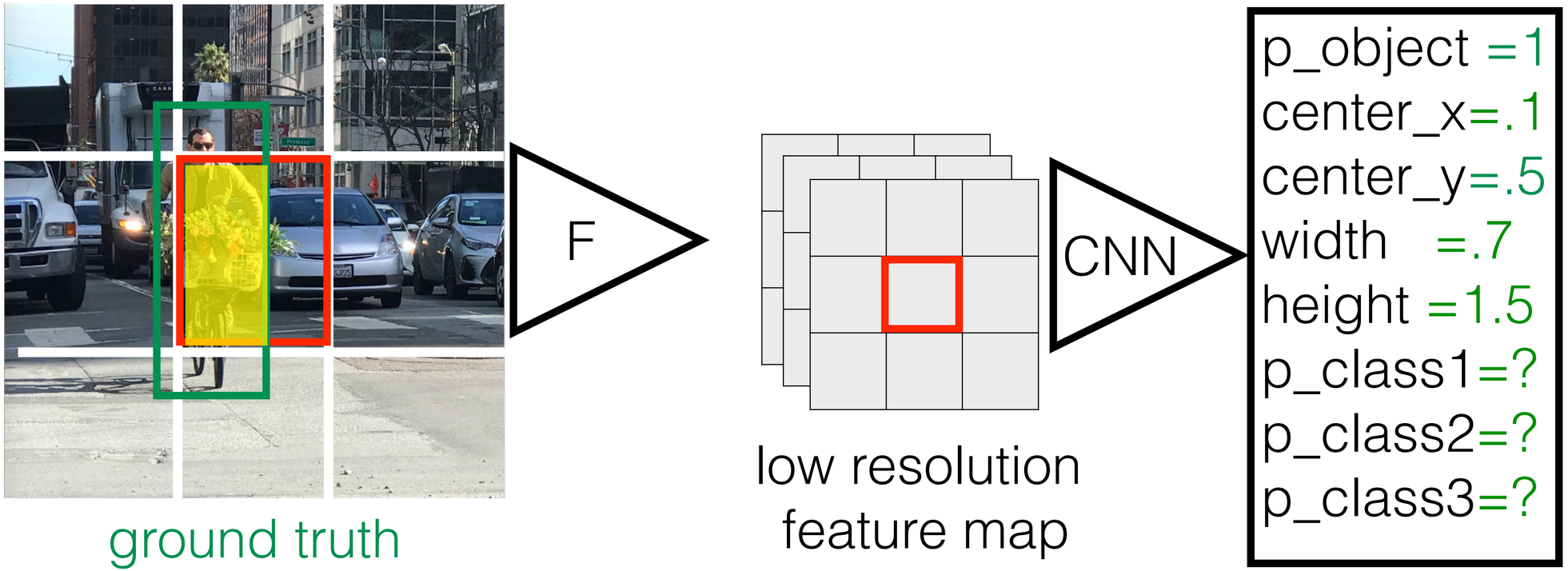

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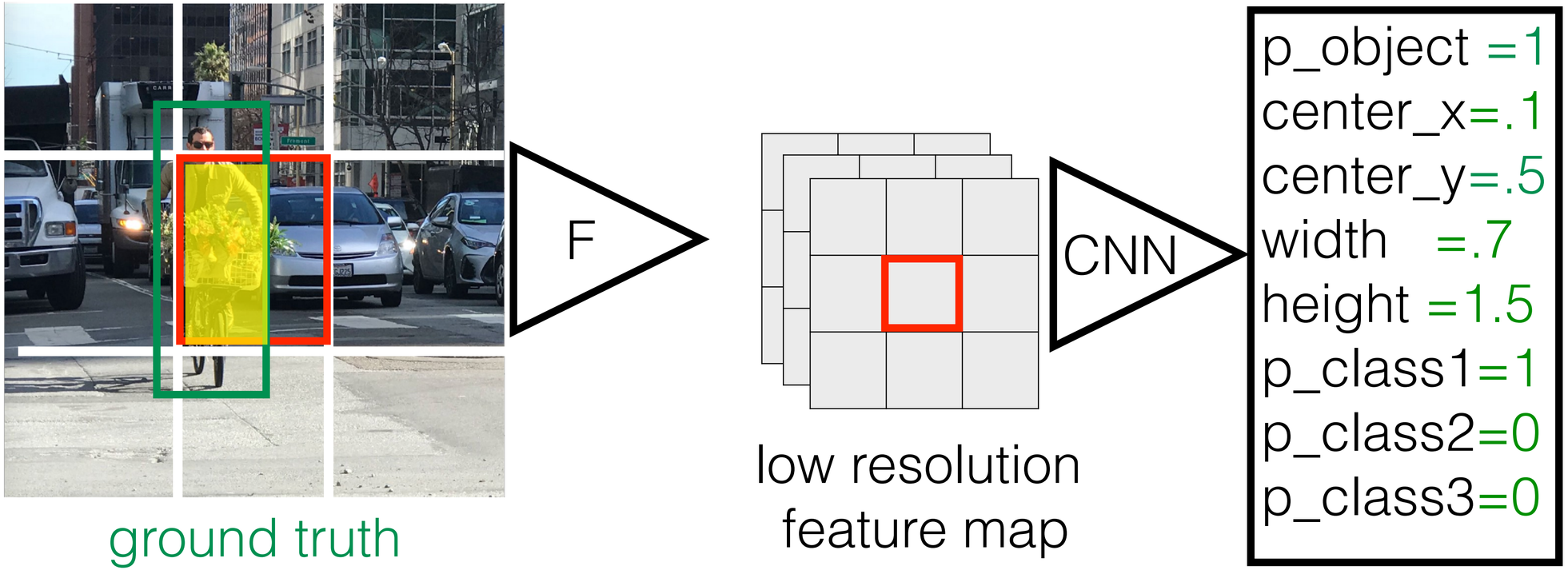

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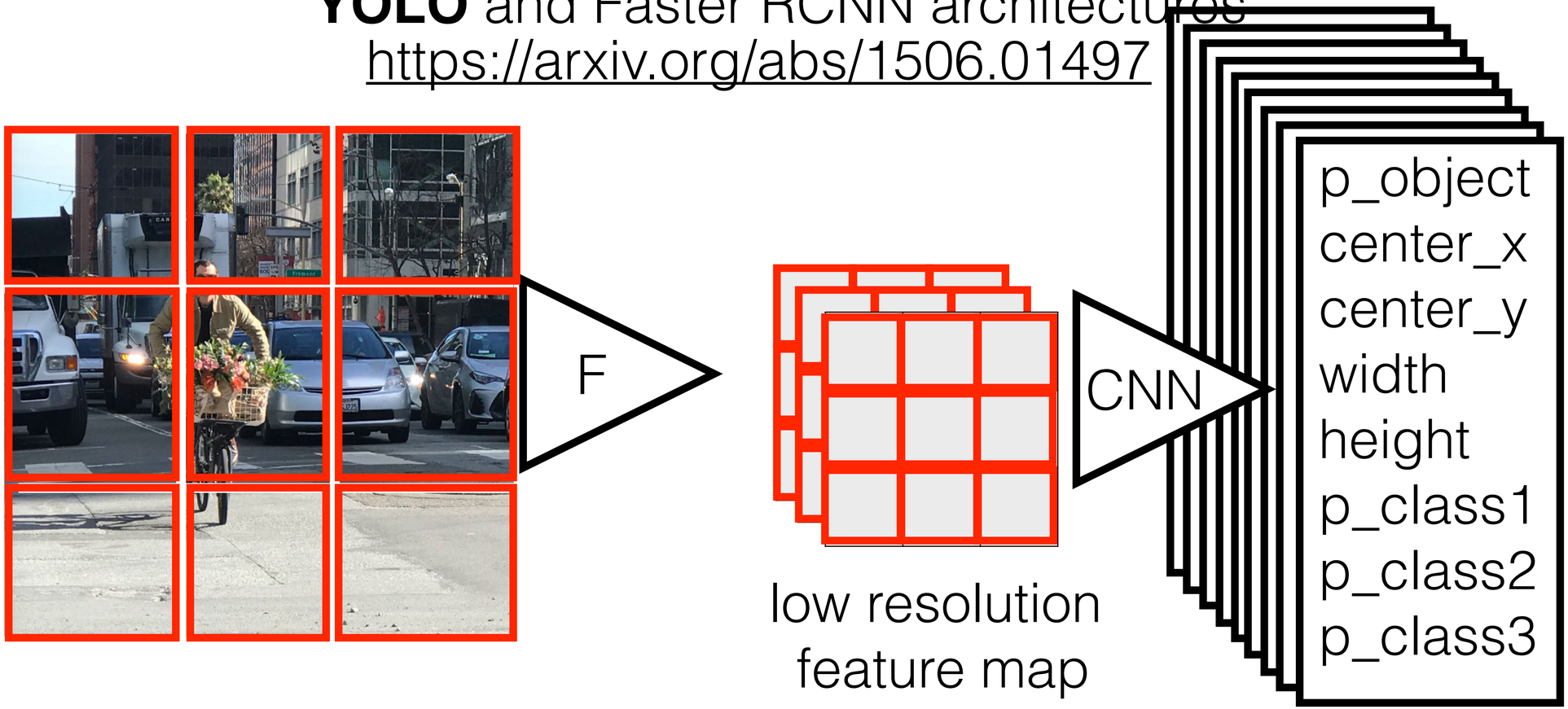
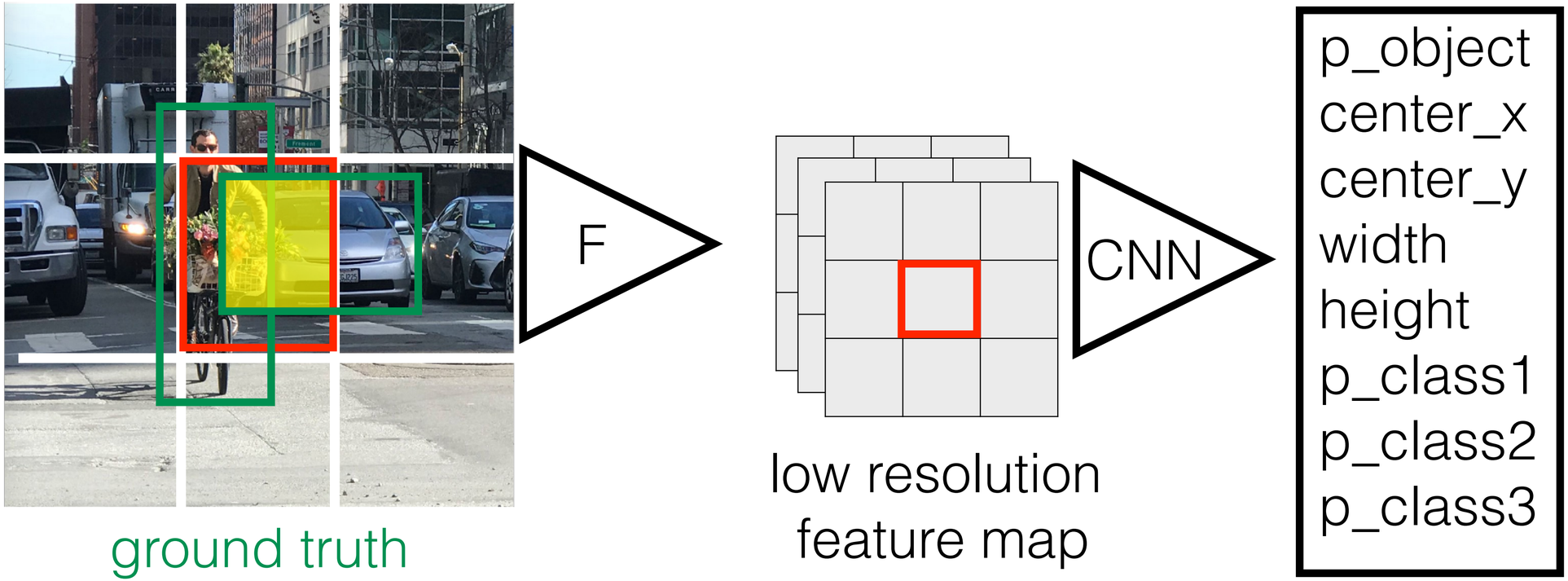


- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- each sub-image has its own output

Do you see any problem?

=> more obj in one sub-im

YOLO and Faster RCNN architectures
https://arxiv.org/abs/1506.01497



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Do you see any problem?

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YOLO and Faster RCNN architectures

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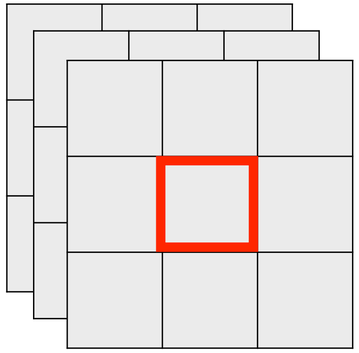
ground truth

F



low resolution
feature map

CNN

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

anchor bb1

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

anchor bb2

Introduce anchor bounding boxes

- Perform region proposal by CNN => **0.05-0.2 sec**

Object detection

- Approach works but it takes extremely long to compute response on all rectangular sub-windows:
  H x W x Aspect_Ratio x Scales x 0.001 sec = **months**
- Instead we can use elementary signal processing method to extract only 2k viable candidates: [Girschick ICCV 2015], Fast-RCNN https://arxiv.org/abs/1504.08083
  (find 2k cand.) + (2k cand. x 0.001 sec) = **47+2 sec = 49 sec**
- Perform region proposal by CNN => **0.05-0.2 sec**

[Faster RCNN 2017] https://arxiv.org/abs/1506.01497 (slower, works for smaller objs)

[Redmont CVPR 2018], https://arxiv.org/abs/1804.02767 (faster, small obj. problems)

How to report classifier quality?

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS

GT BKGD:

Binary classifier testing presence of potentially dangerous case:

Positive class

GT CARS


CLS CARS



Negative class

GT BKGD:




CLS BGGD:



Binary classifier testing presence of potentially dangerous case:

Positive class

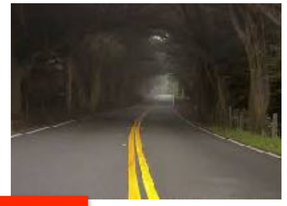
Negative class

GT CARS


CLS CARS



GT BKGD:

CLS BGGD:


false negative (FN) … classifier **falsely** indicates positive class (e.g. car) as a **negative** class => missed danger

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS


GT BKGD:




CLS CARS



CLS BGGD:



false negative (FN) … classifier **falsely** indicates positive class (e.g. car) as a **negative** class => missed danger

false positive (FP) … classifier **falsely** indicates negative class (e.g. background) as a **positive** class => false alarm

Binary classifier testing presence of potentially dangerous case:

false negative (FN) … classifier **falsely** indicates positive class (e.g. car) as a **negative** class => missed danger

false positive (FP) … classifier **falsely** indicates negative class (e.g. background) as a **positive** class => false alarm

true positive (TP) … classifier correctly indicate ground **truth** positive class (e.g. car) as a **positive** class => correctly found danger

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS


GT BKGD:




CLS CARS



CLS BGGD:



false negative (FN) … classifier **falsely** indicates positive class (e.g. car) as a **negative** class => missed danger

false positive (FP) … classifier **falsely** indicates negative class (e.g. background) as a **positive** class => false alarm

true positive (TP) … classifier correctly indicate ground **truth** positive class (e.g. car) as a **positive** class => correctly found danger

true negative (TN) … classifier correctly indicate ground **truth** negative class (e.g. bckg) as a **negative** class => correctly found safety

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS


GT BKGD:




CLS CARS



CLS BGGD:



false negative (FN) =1

false positive (FP) =2

true positive (TP) =1

true negative (TN) =2

"1/3 of of samples classified as CARS are actually CARS"

$$\text{Precision (P)} = \frac{TP}{TP + FP} = \frac{1}{1 + 2} = 1/3$$

What is their meaning?

$$\text{Recall (R)} = \frac{TP}{TP + FN} = \frac{1}{1 + 1} = 1/2$$

"1/2 of all CARS is discovered"

What is best classifier? Oracle: Precision = Recall = 1

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS

GT BKGD:

CLS CARS

CLS BGGD:

0.9 0.5 0.1 -0.1 -0.4 -0.6

false negative (FN) =1

false positive (FP) =2

true positive (TP) =1

true negative (TN) =2

$$\text{Precision (P)} = \frac{TP}{TP + FP} = \frac{1}{1 + 2} = 1/3$$

$$\text{Recall (R)} = \frac{TP}{TP + FN} = \frac{1}{1 + 1} = 1/2$$

Oracle: Precision = Recall = 1

Binary classifier testing presence of potentially dangerous case:

Positive class

Negative class

GT CARS

GT BKGD:

CLS CARS

CLS BGGD:

0.9 0.5 0.1 -0.1 -0.4 -0.6

false negative (FN) =0

false positive (FP) =2

true positive (TP) =2

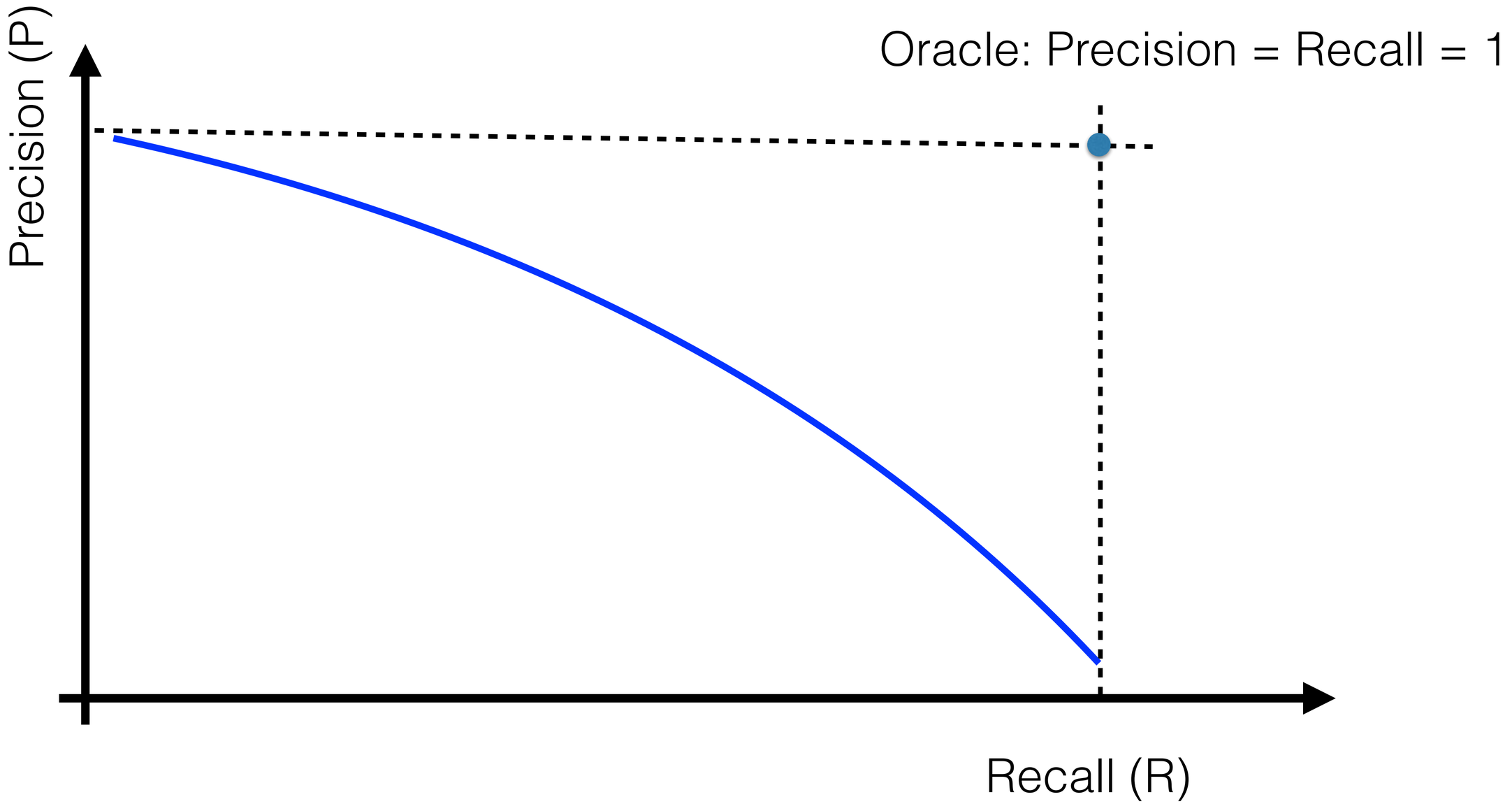
true negative (TN) =2

$$\text{Precision (P)} = \frac{TP}{TP + FP} = \frac{2}{2 + 2} = 1/2$$

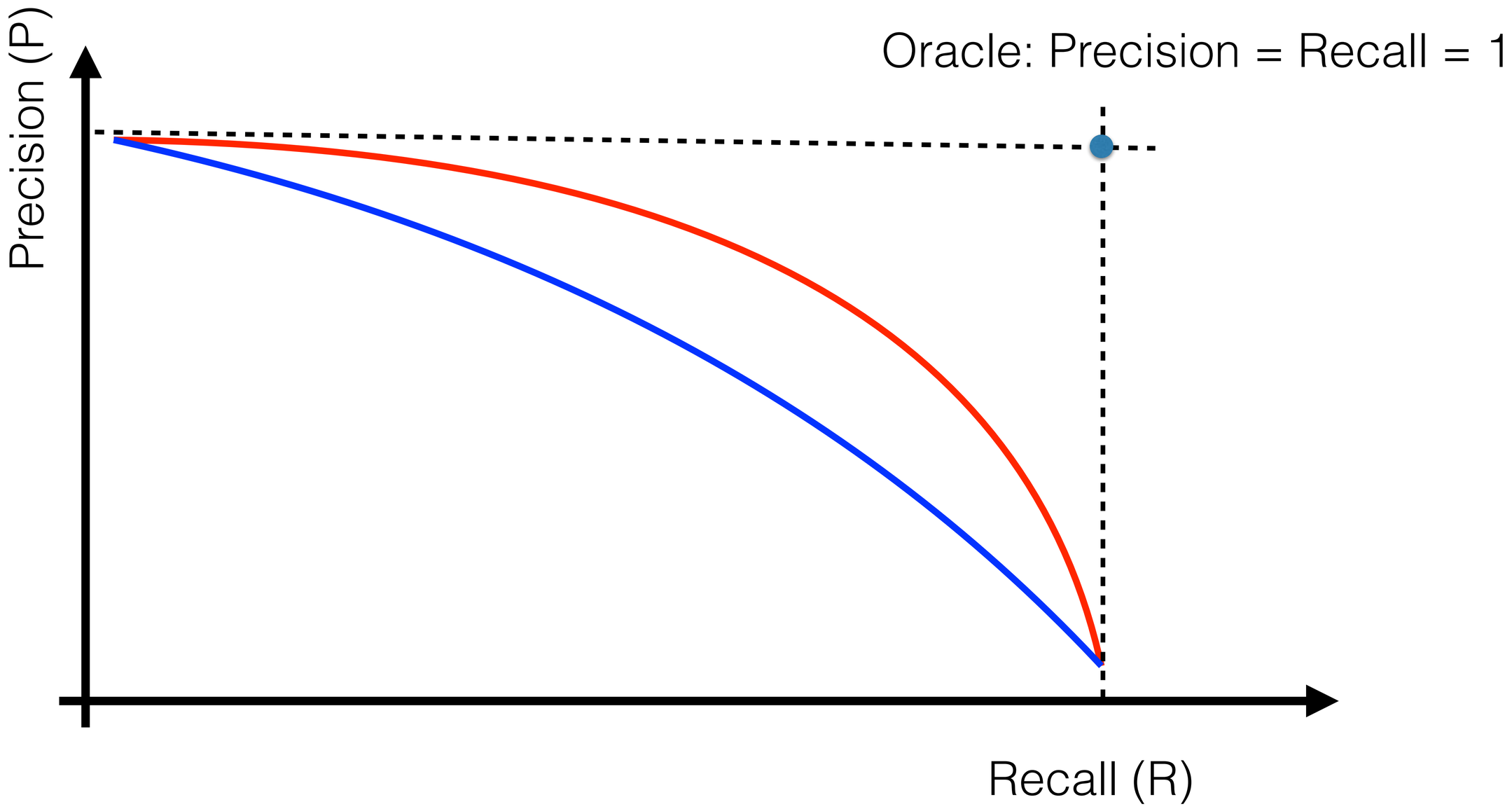
$$\text{Recall (R)} = \frac{TP}{TP + FN} = \frac{2}{2 + 0} = 1$$

Oracle: Precision = Recall = 1

Smoothed Precision-Recall curve



Smoothed Precision-Recall curve



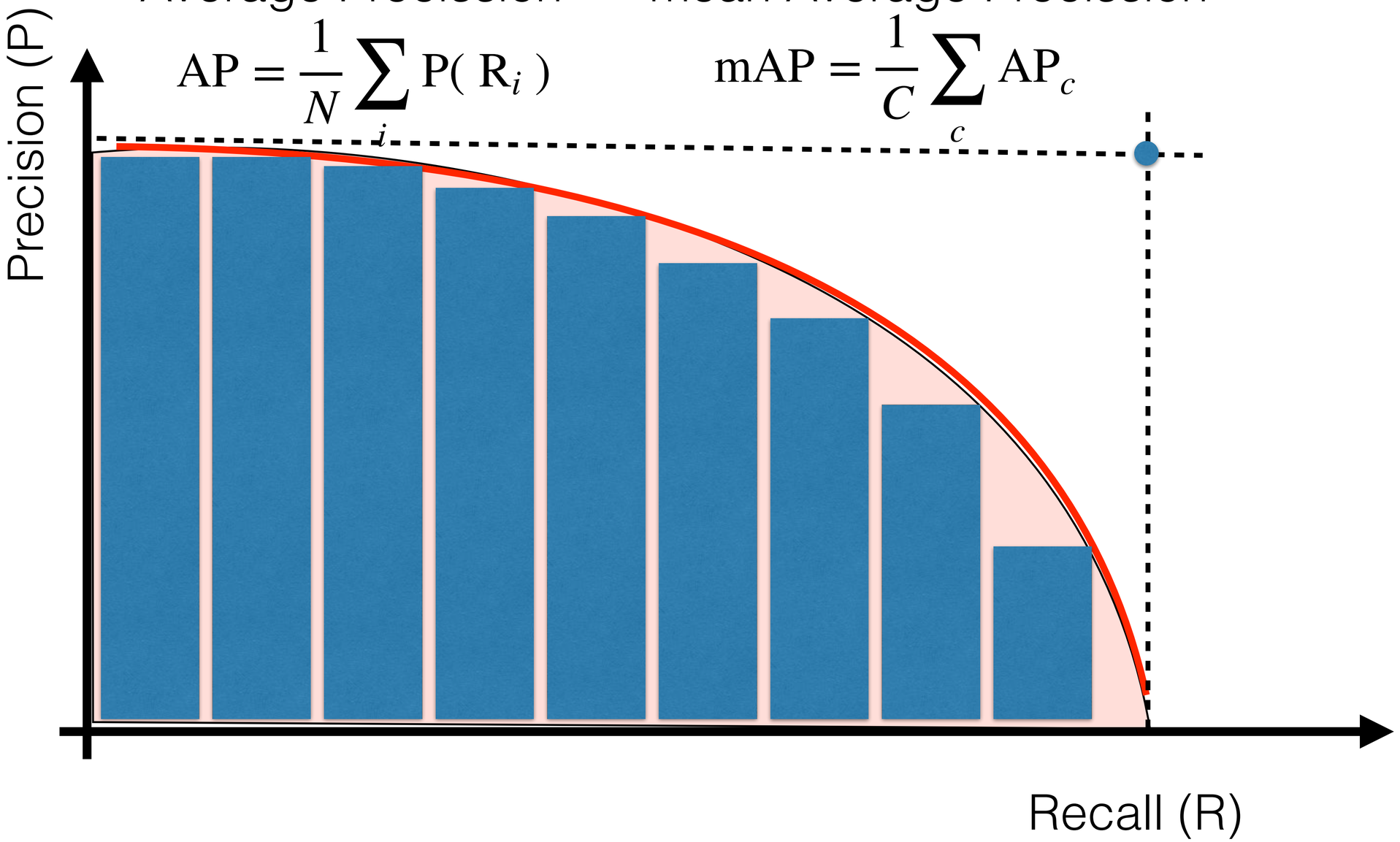
Smoothed Precision-Recall curve

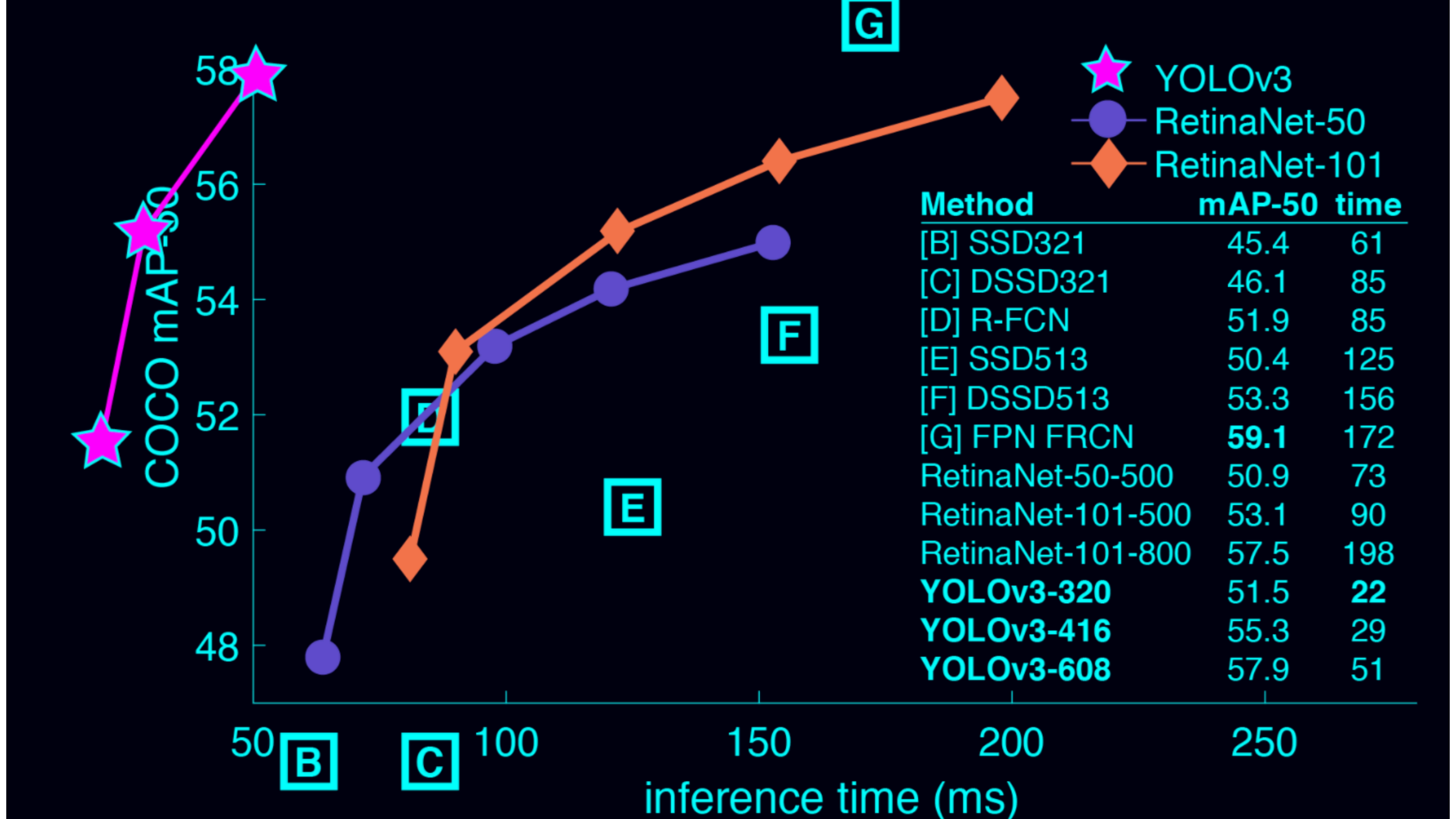
Average Precission

$$\mathrm{AP} = \frac{1}{N} \sum_{i} \mathrm{P}(\mathrm{R}_i)$$

mean Average Precission

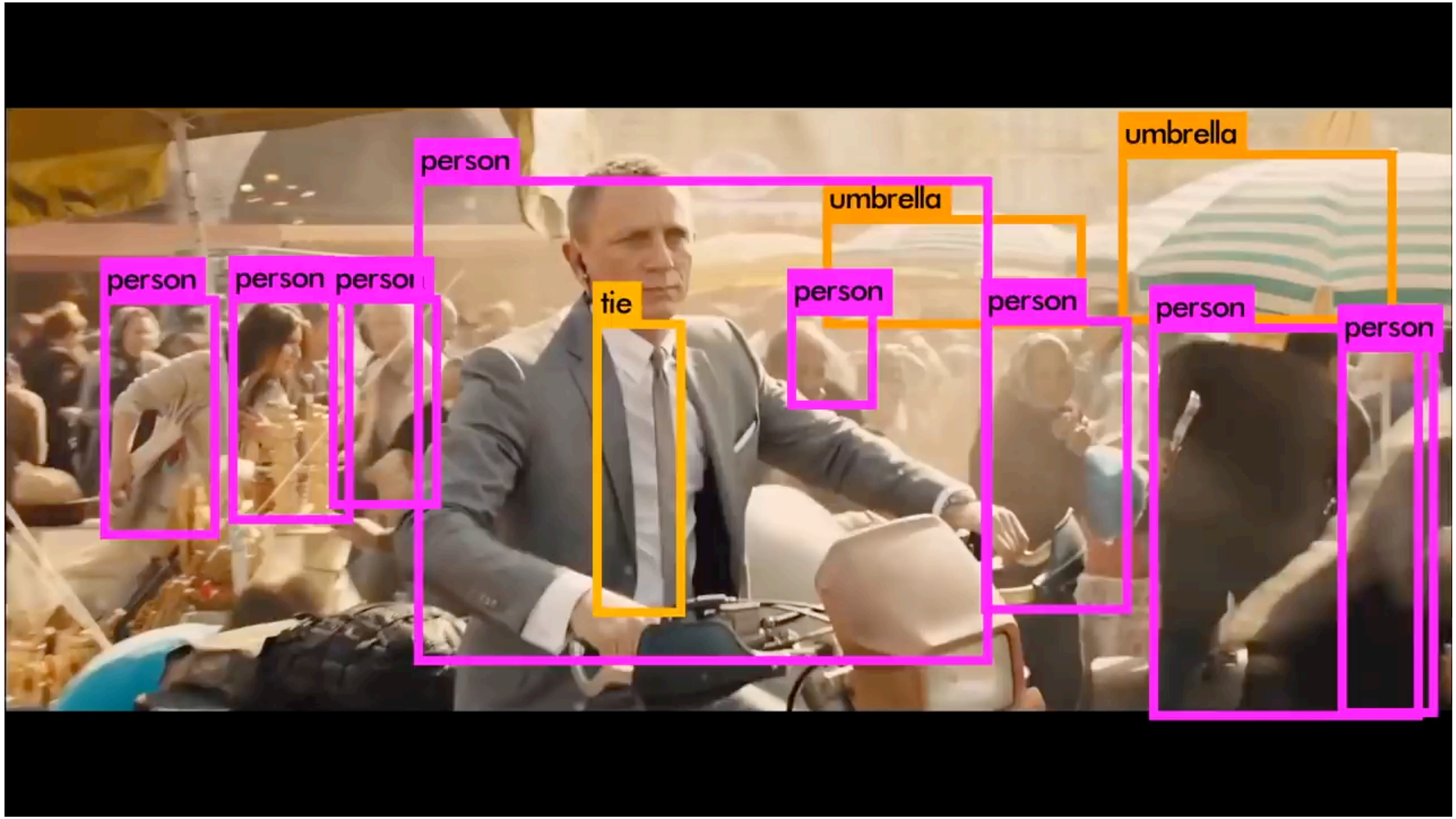
$$\mathrm{mAP} = \frac{1}{C} \sum_{c} \mathrm{AP}_c$$





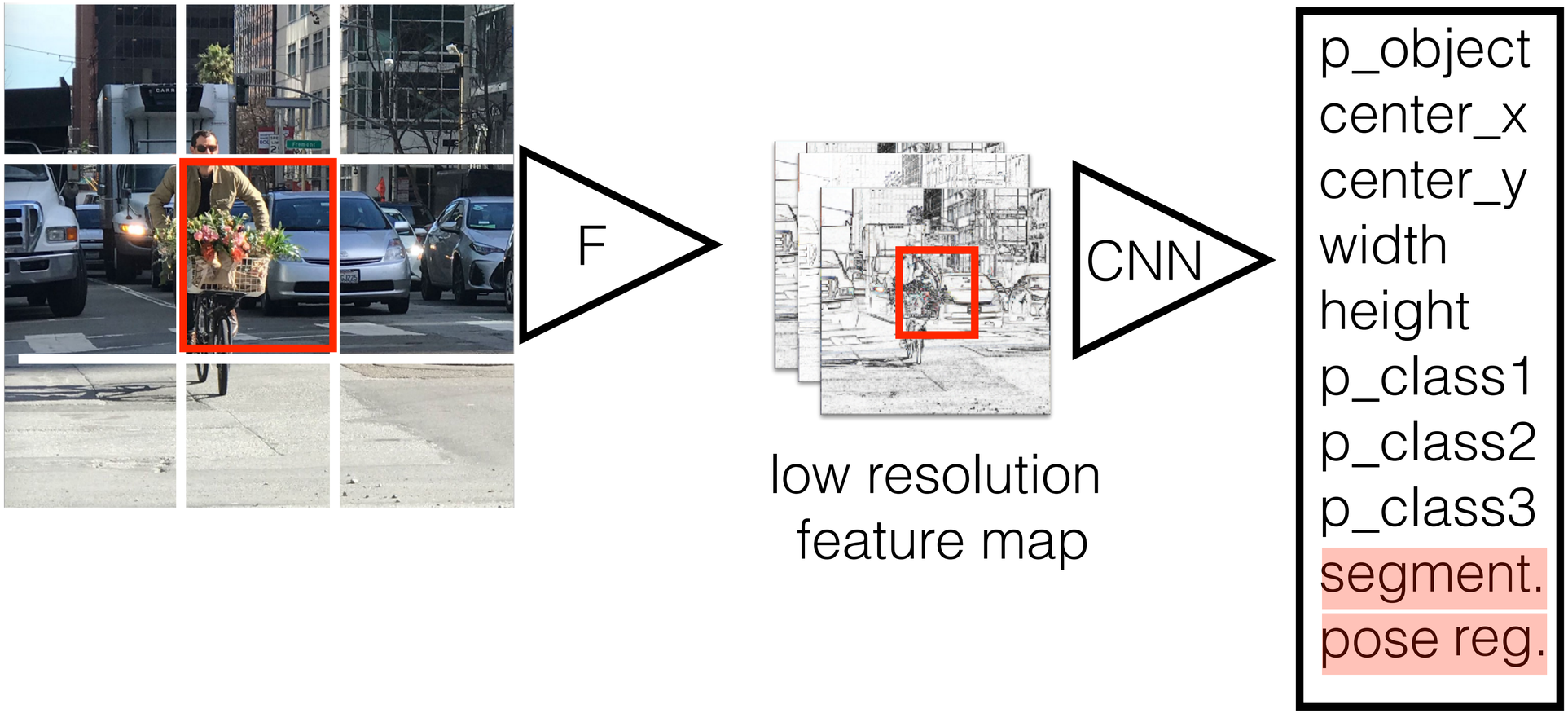
Method	mAP-50	time
[B] SSD321	45.4	61
[C] DSSD321	46.1	85
[D] R-FCN	51.9	85
[E] SSD513	50.4	125
[F] DSSD513	53.3	156
[G] FPN FRCN	**59.1**	172
RetinaNet-50-500	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.5	198
YOLOv3-320	51.5	**22**
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51

Deep convolutional - object detection



[Redmont CVPR 2018], https://arxiv.org/abs/1804.02767
code: https://pjreddie.com/darknet/yolo/

YOLO and Faster RCNN architectures
https://arxiv.org/abs/1506.01497



[He et al CVPR 2017] Mask-RCNN
https://arxiv.org/abs/1703.06870

Mask RCNN - results

[He et al CVPR 2017] Mask-RCNN
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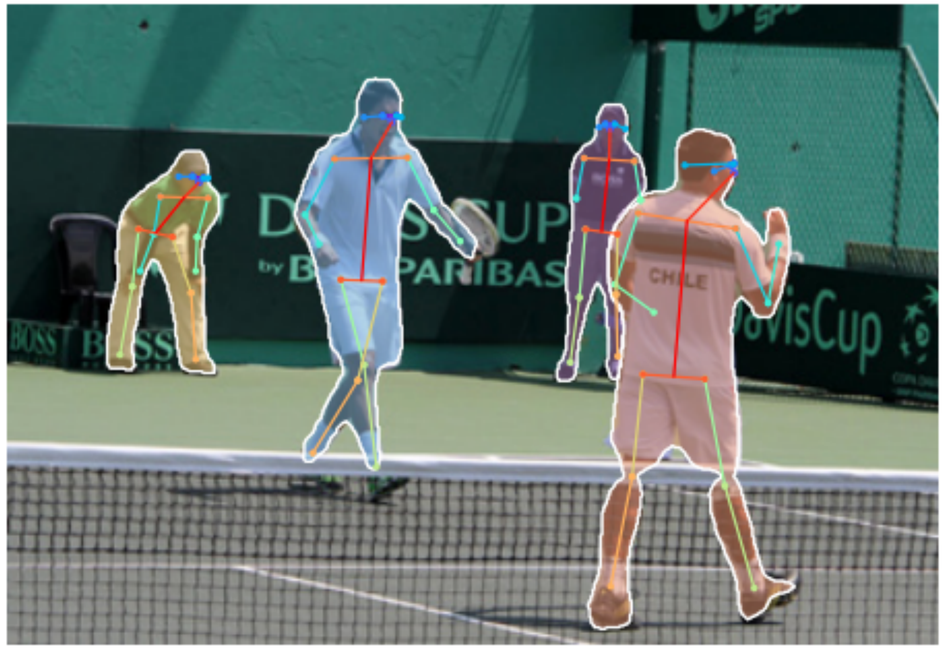
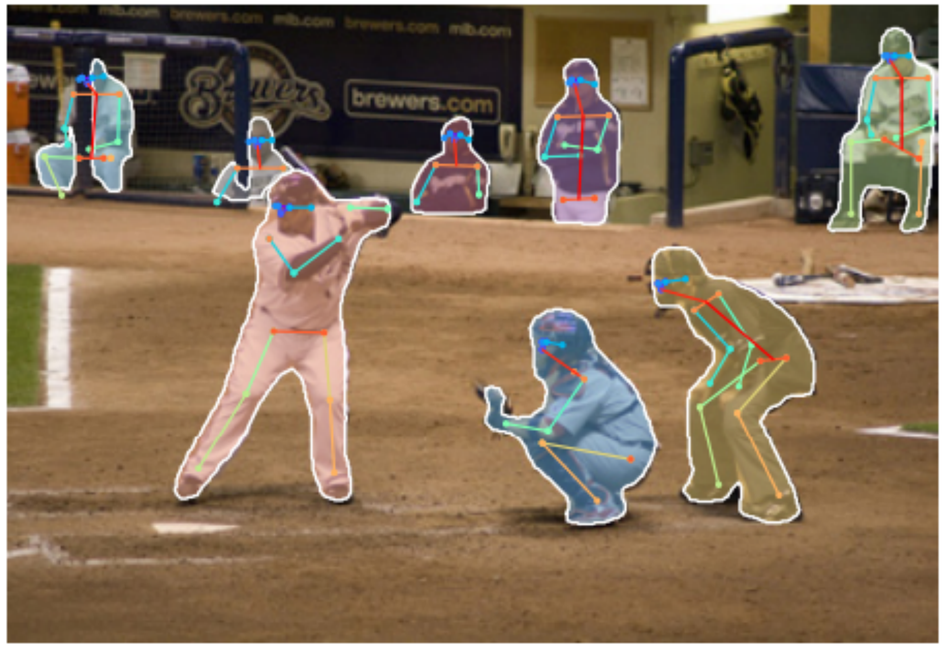
Mask RCNN - results

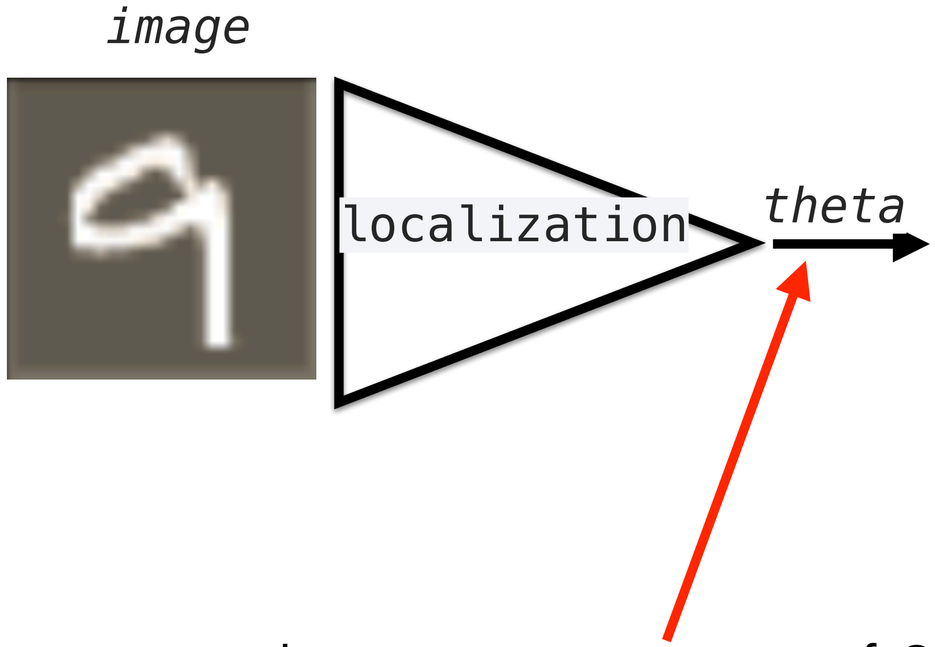




Outline

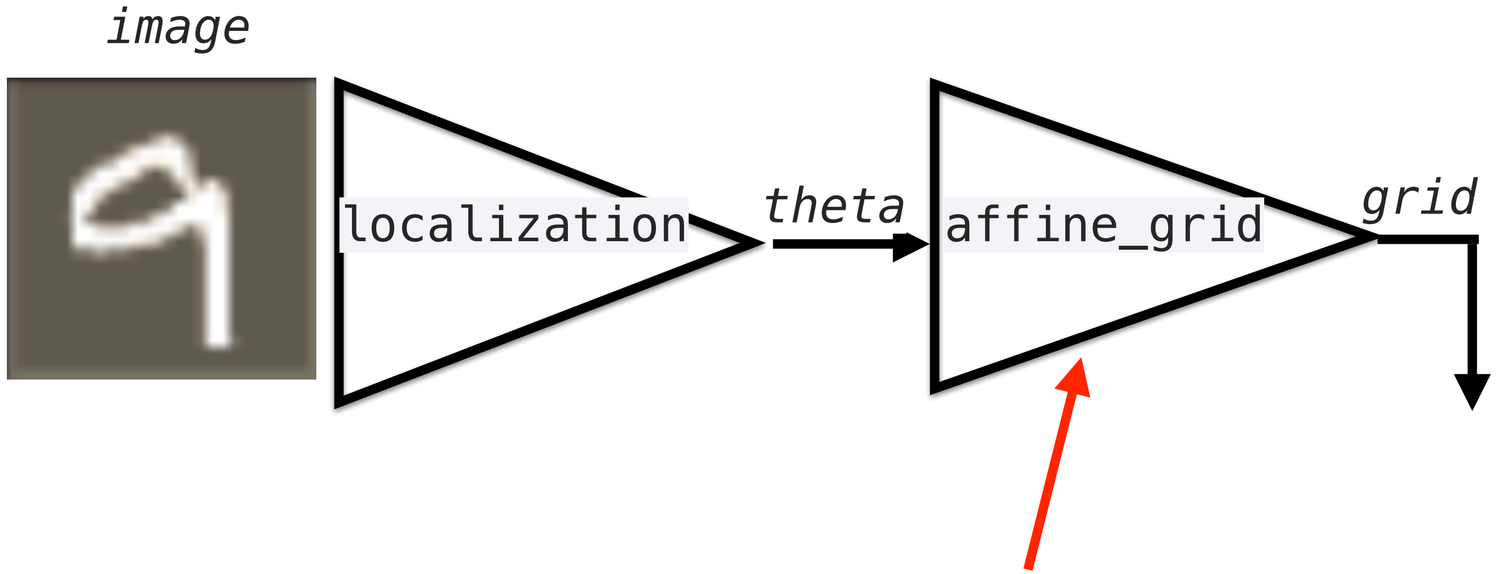
- Architectures of classification networks
- Architectures of segmentation networks
- Architectures of regression networks
- Architectures of detection networks
- Spatial Transformer networks
- Architectures of feature matching networks

Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf



estimate parameters of 2D similarity transformation

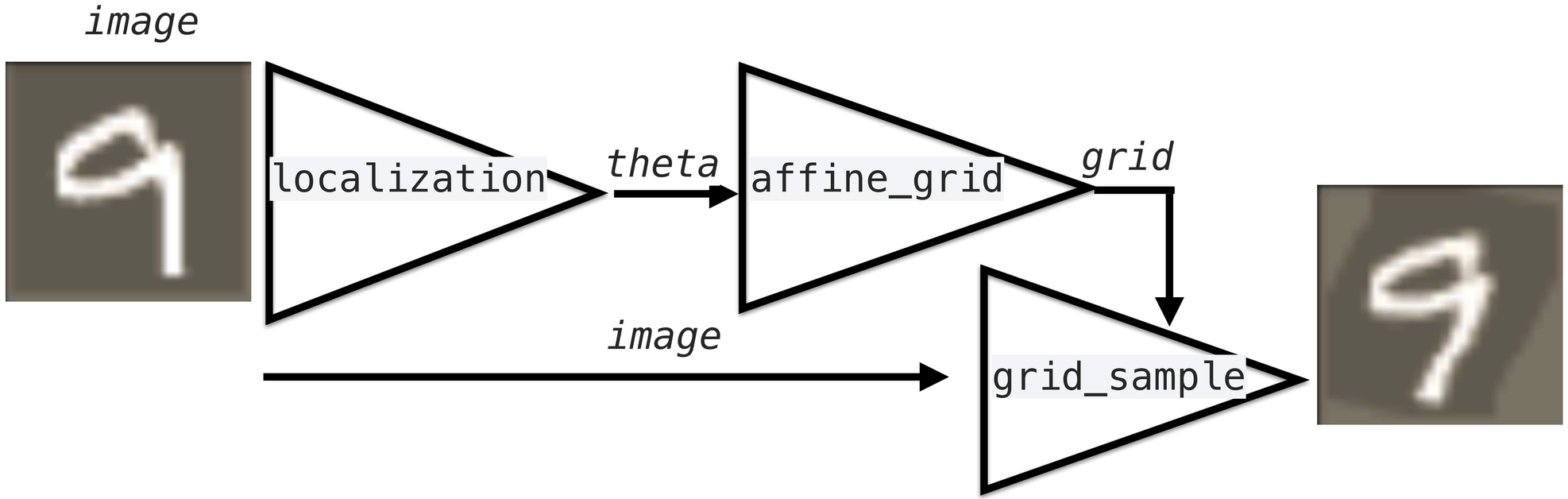
Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf



estimate pixel-wise correspondences of
the 2D similarity transformation

`torch.nn.functional.affine_grid(theta, size, align_corners=None)`

Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf

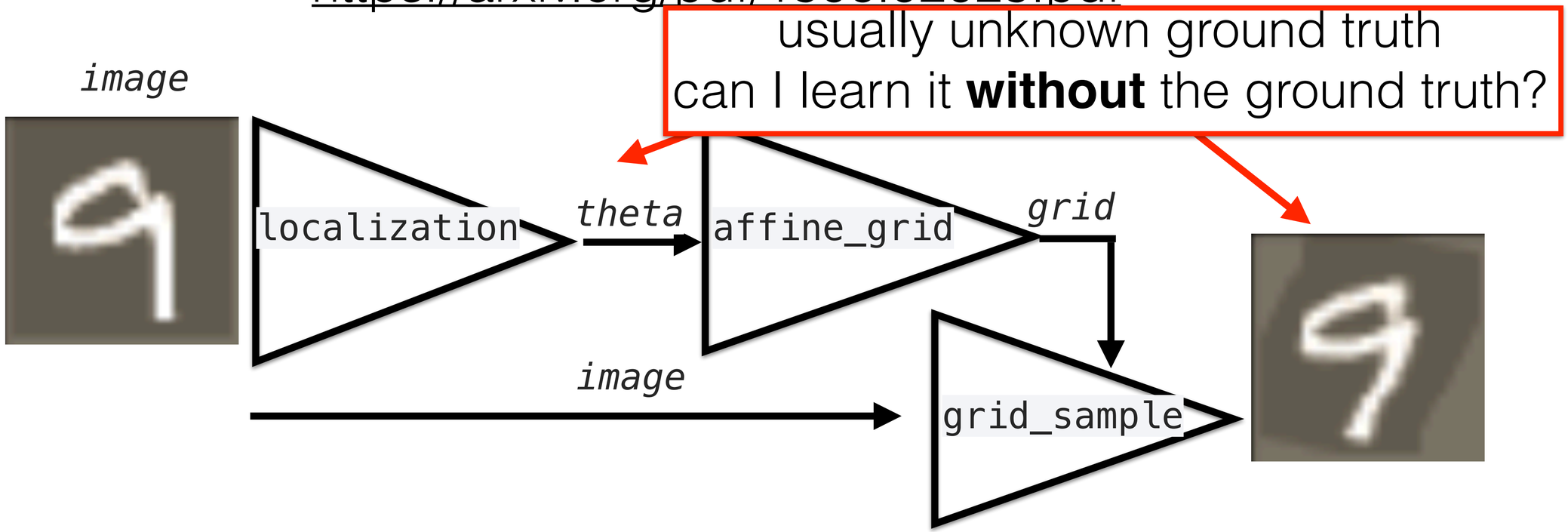



```
torch.nn.functional.affine_grid(theta, size, align_corners=None)

torch.nn.functional.grid_sample(input, grid, mode='bilinear',
                                padding_mode='zeros', align_corners=None)
```

Spatial Transformer networks [Jaderberg 2016]

https://arxiv.org/pdf/1506.02025.pdf

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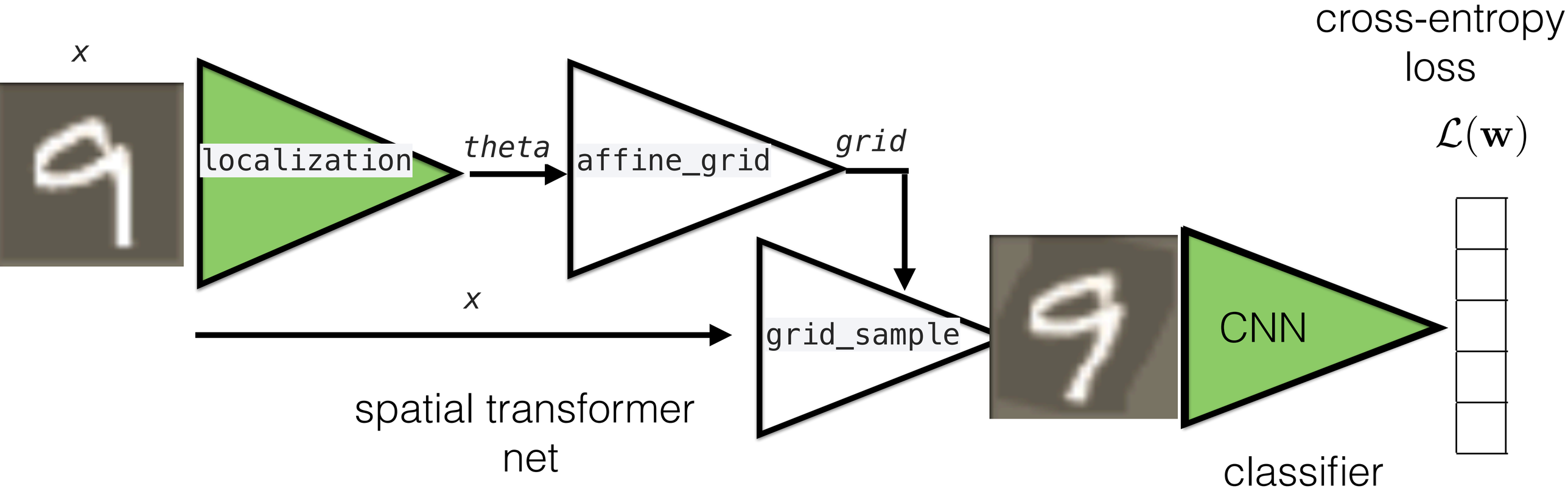
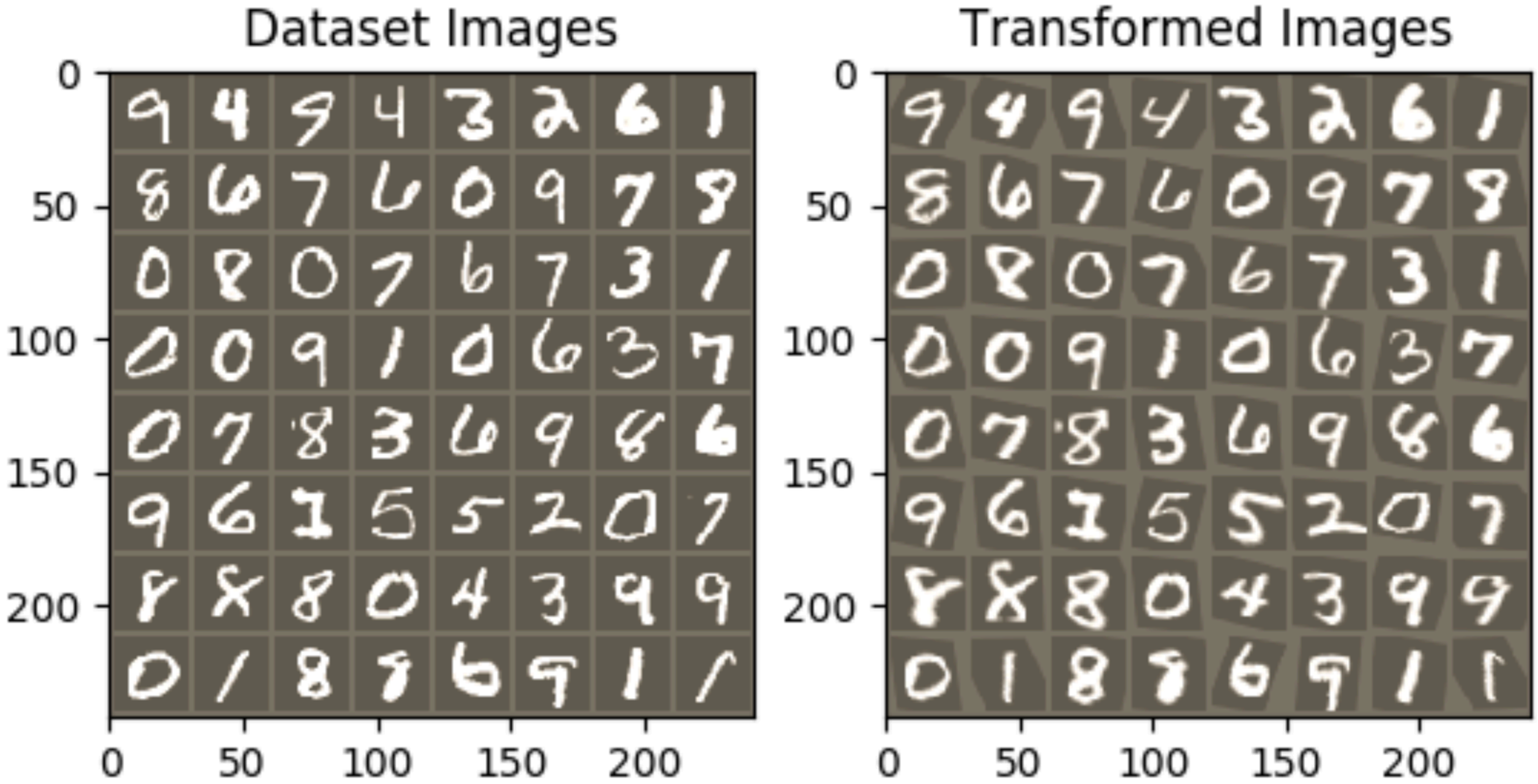


Jointly learn CNN + STN weights, which perform the most suitable transformation for the classification task

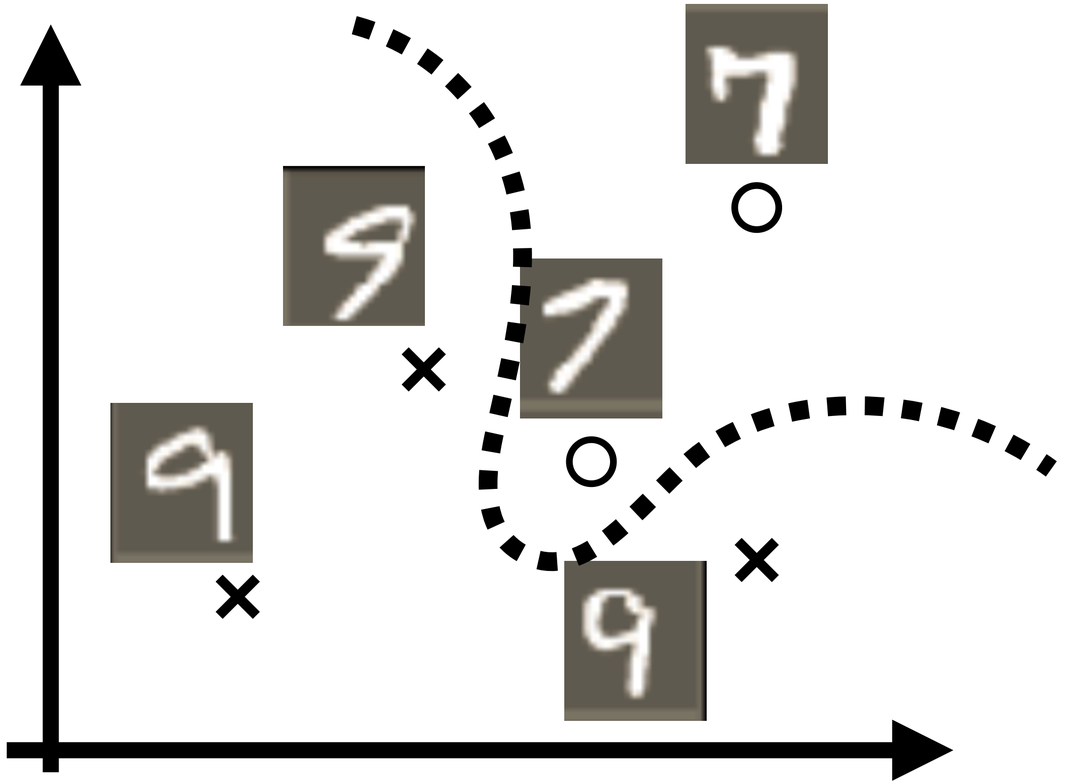
Spatial Transformer networks

https://pytorch.org/tutorials/intermediate/spatial_transformer_tutorial.html

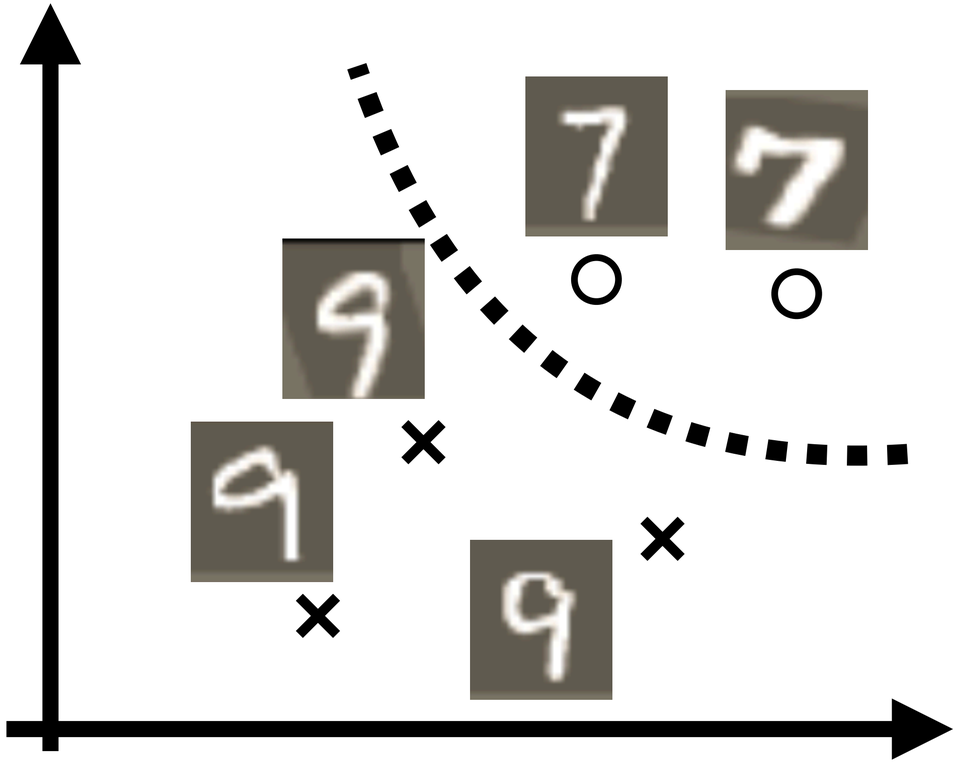


Spatial Transformer networks

I works better, because correctly-aligned numbers has smaller within-class scatter



“9” vs “7”
no handwritinf style compensation



“9” vs “7” compensated rot+transl
enforced strong prior about nature of the scatte

[Zimmermann et al TPAMI 2014]