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

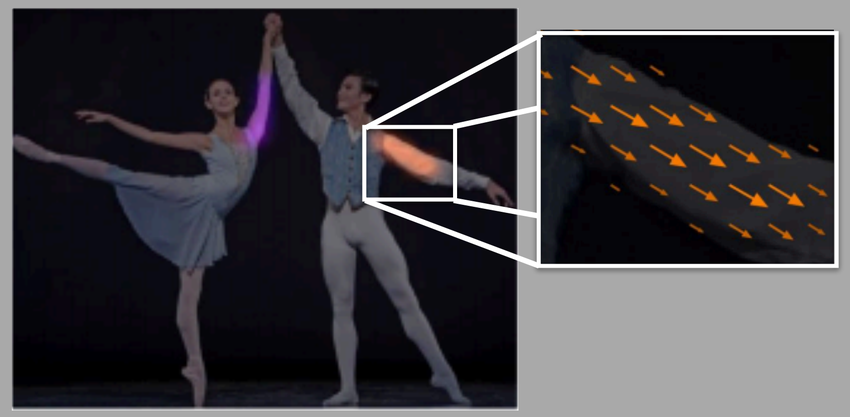
VGG-19

F

"Complicated stuff inside":

(1) detect joints

(2) estimate limbs directions



output

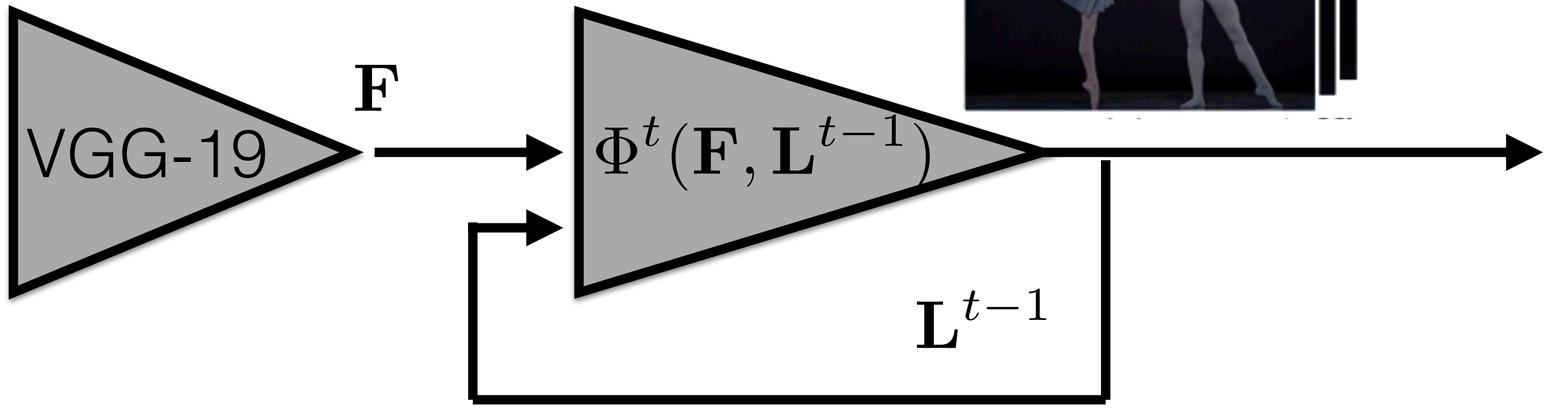
OpenPose [Cao, TPAMI, 2019]
https://arxiv.org/pdf/1812.08008.pdf

VGG-19

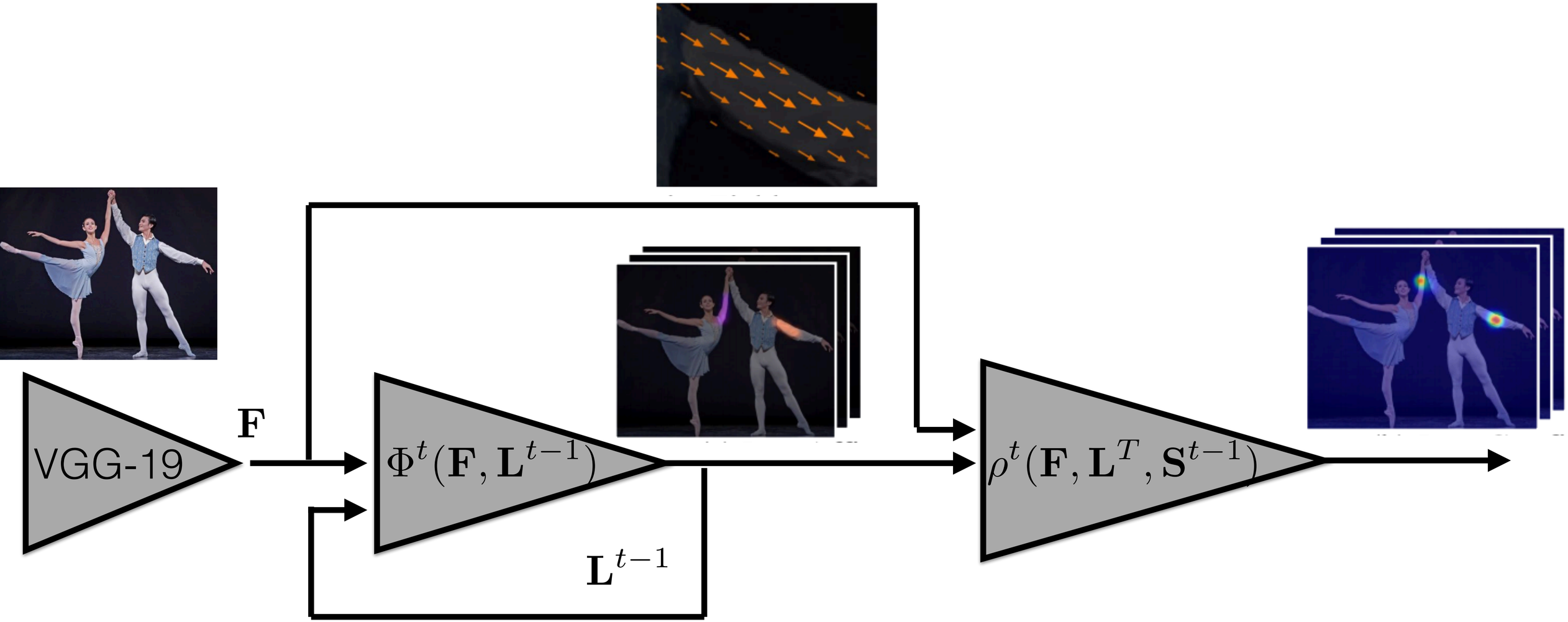
$\mathbf{F}$

$\Phi^t(\mathbf{F}, \mathbf{L}^{t-1})$

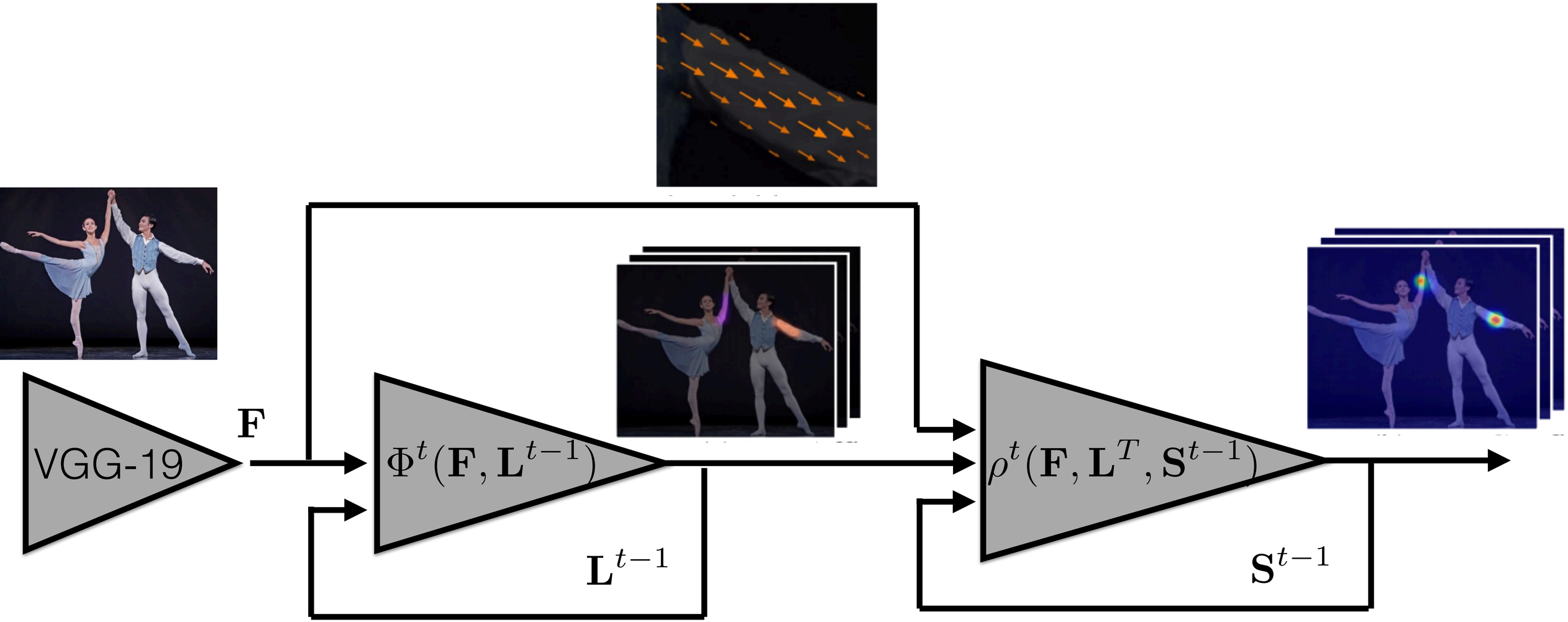
OpenPose [Cao, TPAMI, 2019]
https://arxiv.org/pdf/1812.08008.pdf



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



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



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

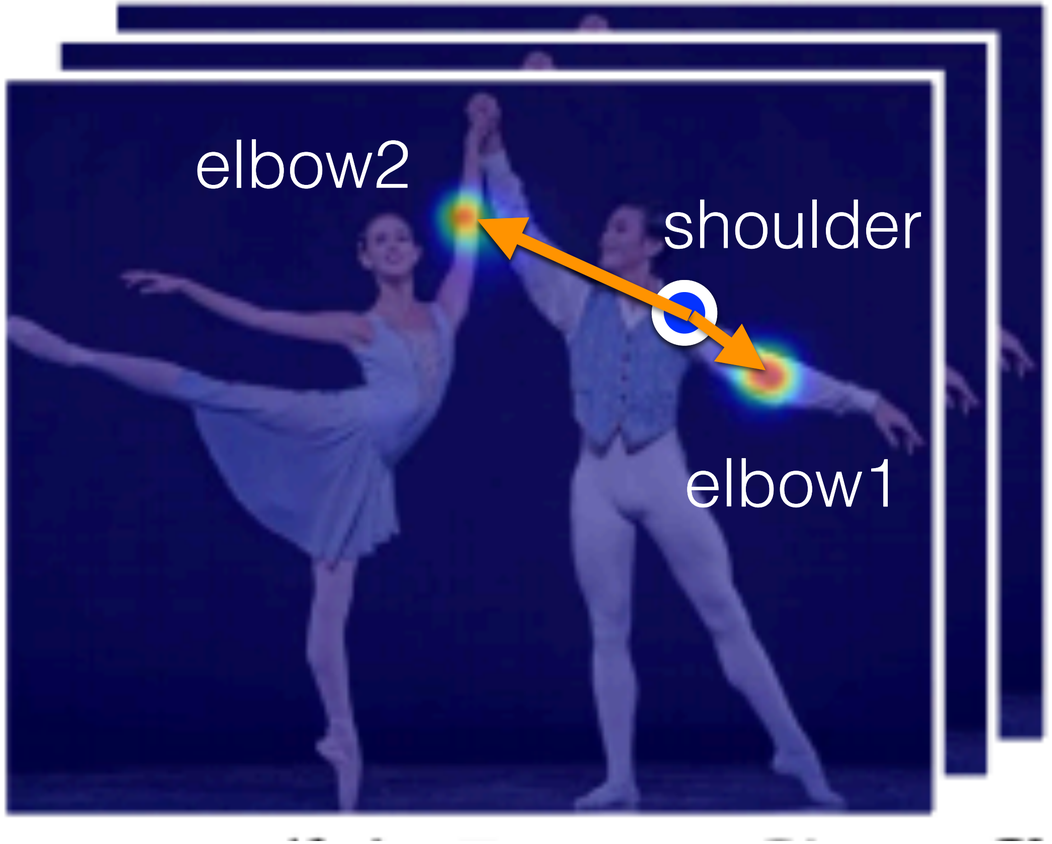
PAFs

joints

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

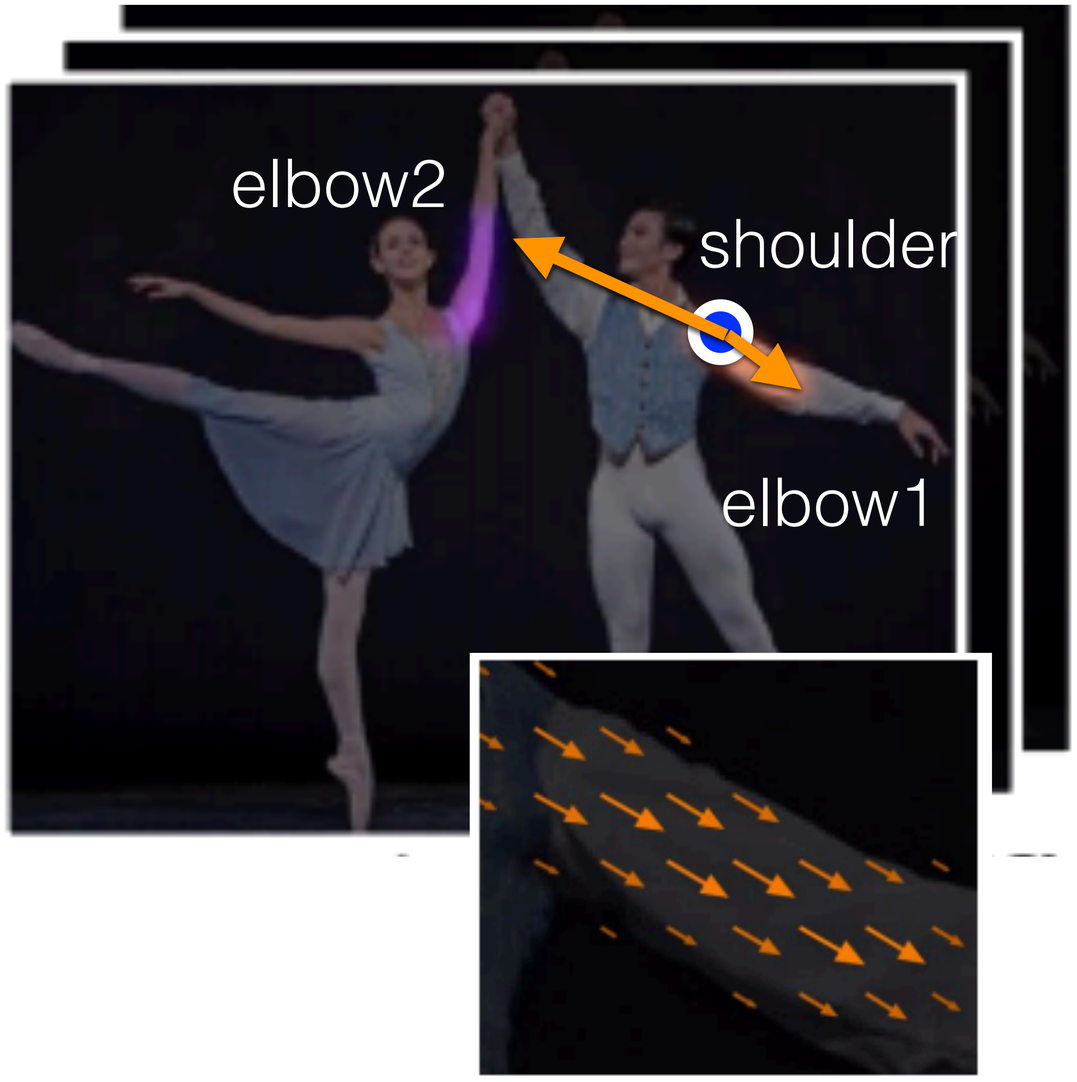
PAFs

joints

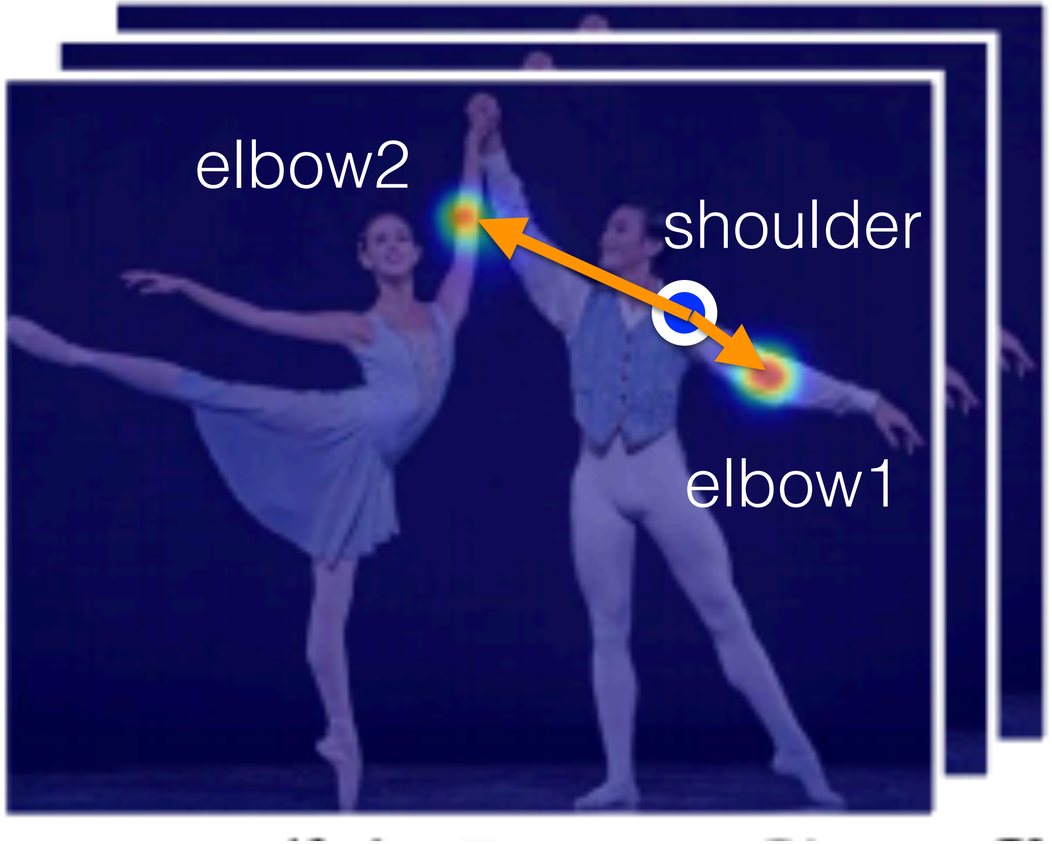


OpenPose [Cao, TPAMI, 2019]
https://arxiv.org/pdf/1812.08008.pdf

PAFs



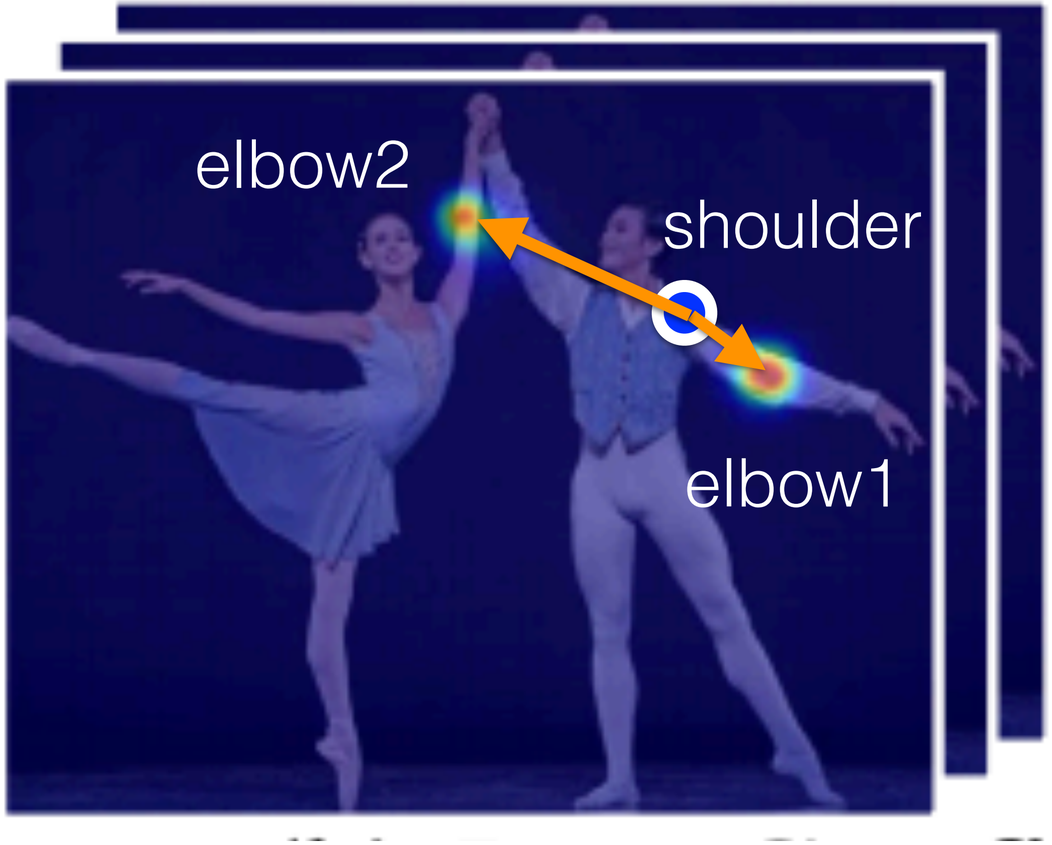
joints



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

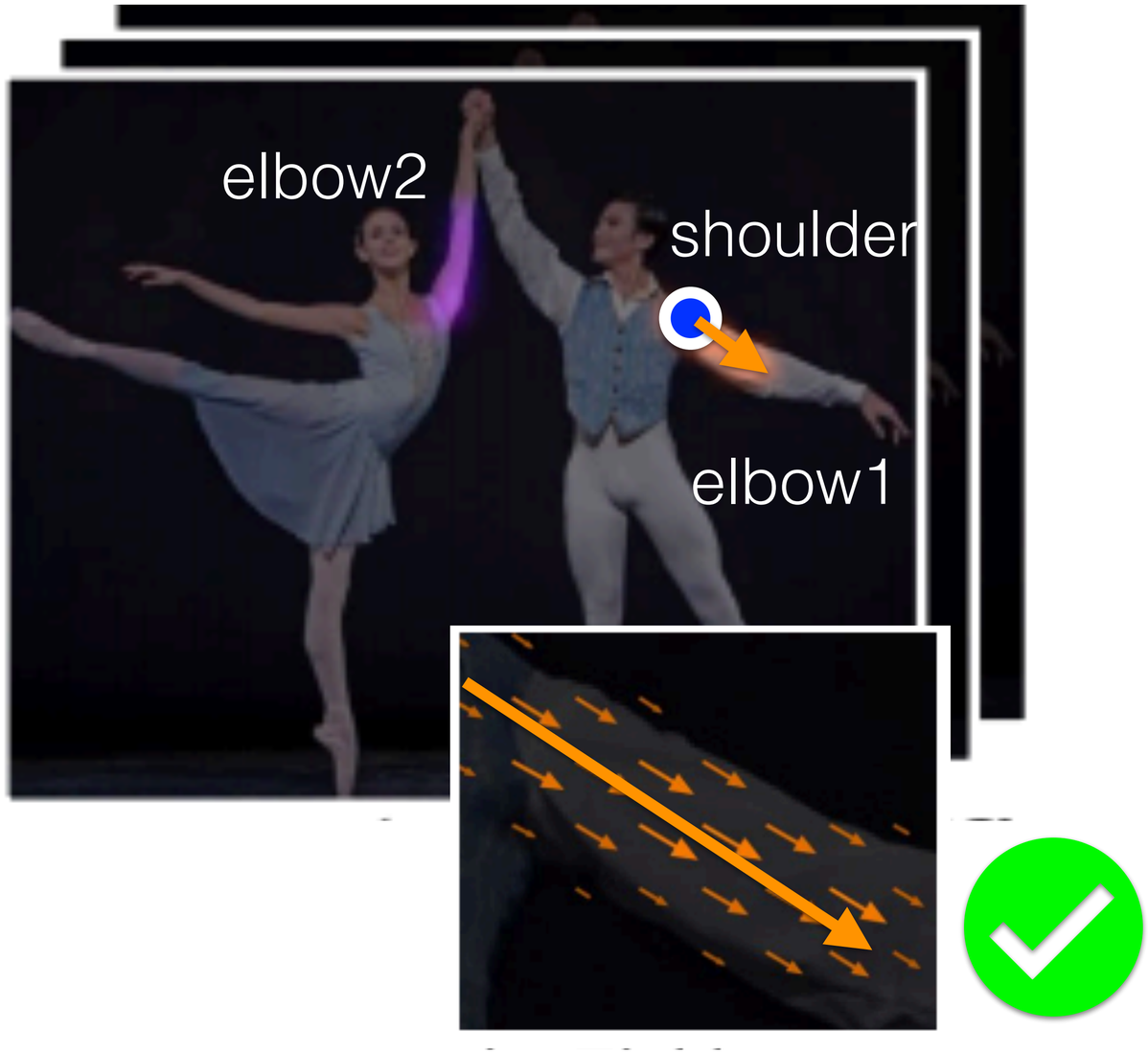
PAFs

joints



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

PAFs



output

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

Pose regression references

- PoseTrack benchmark a datasets
  https://posetrack.net

- Guler et al. (Facebook Research), DensePose
  https://arxiv.org/abs/1802.00434
  https://github.com/facebookresearch/Densepose
  https://www.youtube.com/watch?v=EMjPqgLX14A&feature=youtu.be

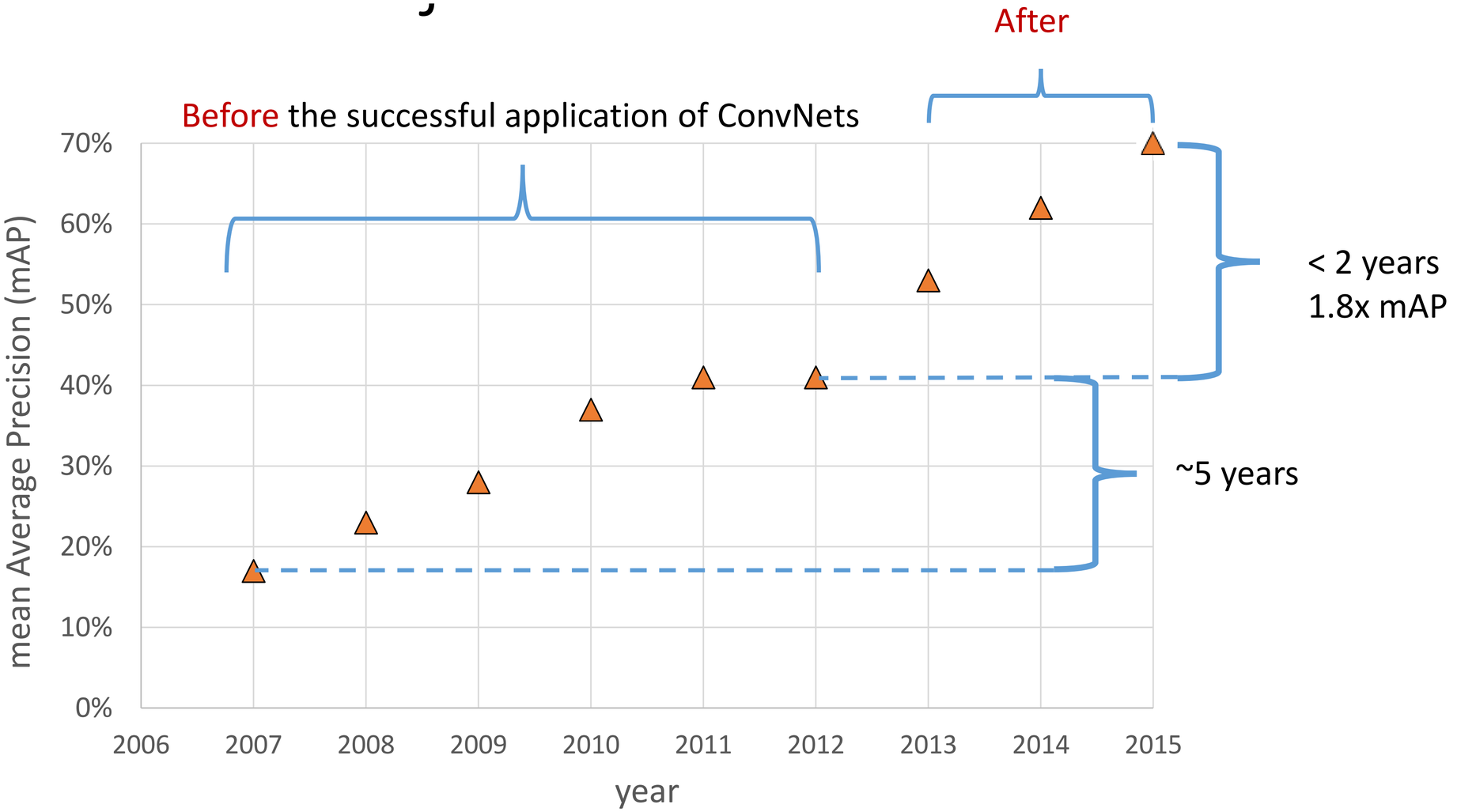
- Realtime Multi-Person 2D Human Pose Estimation using Part Affinity Fields, CVPR 2017 Oral
  https://www.youtube.com/watch?v=pW6nZXeWlGM

- Integral Human Pose Regression [Sun ECCV 2018]
  Microsoft Research
  https://arxiv.org/abs/1711.08229
  https://github.com/JimmySuen/integral-human-pose

Outline

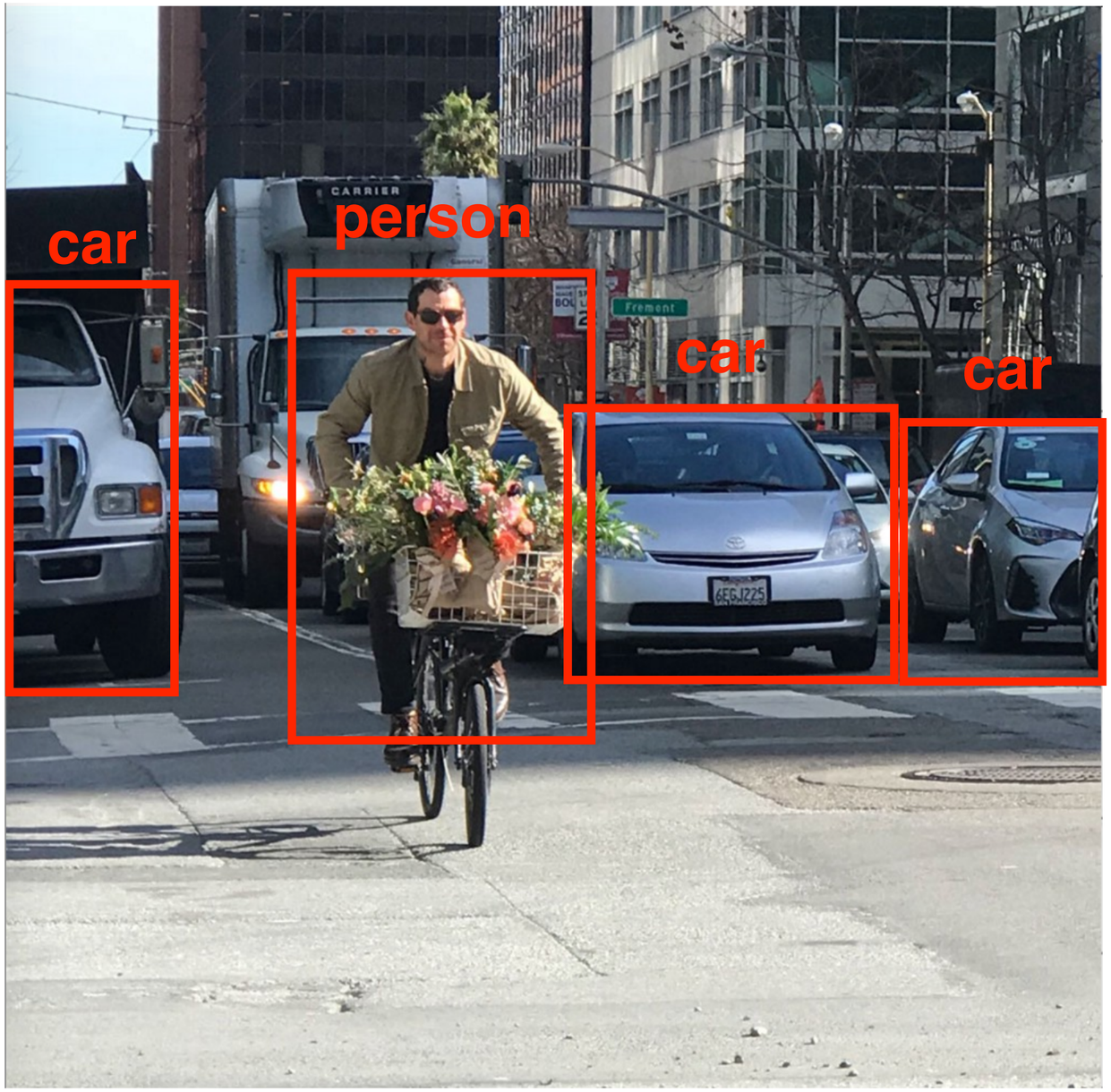
- Architectures of classification networks
- Architectures of segmentation networks
- Architectures of regression networks
- Architectures of detection networks
- Architectures of feature matching networks

Pascal VOC object detection challenge

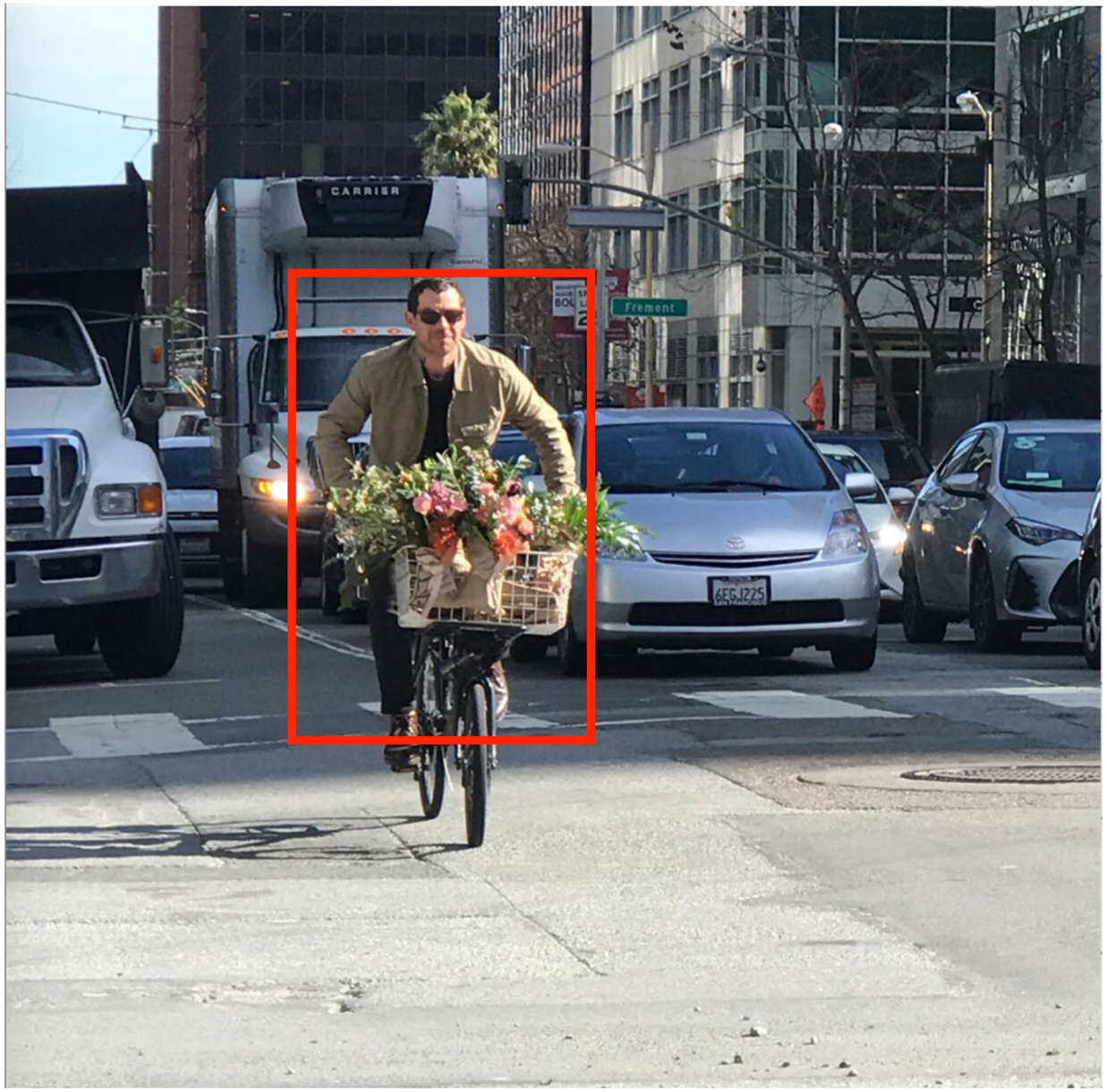


Object detection

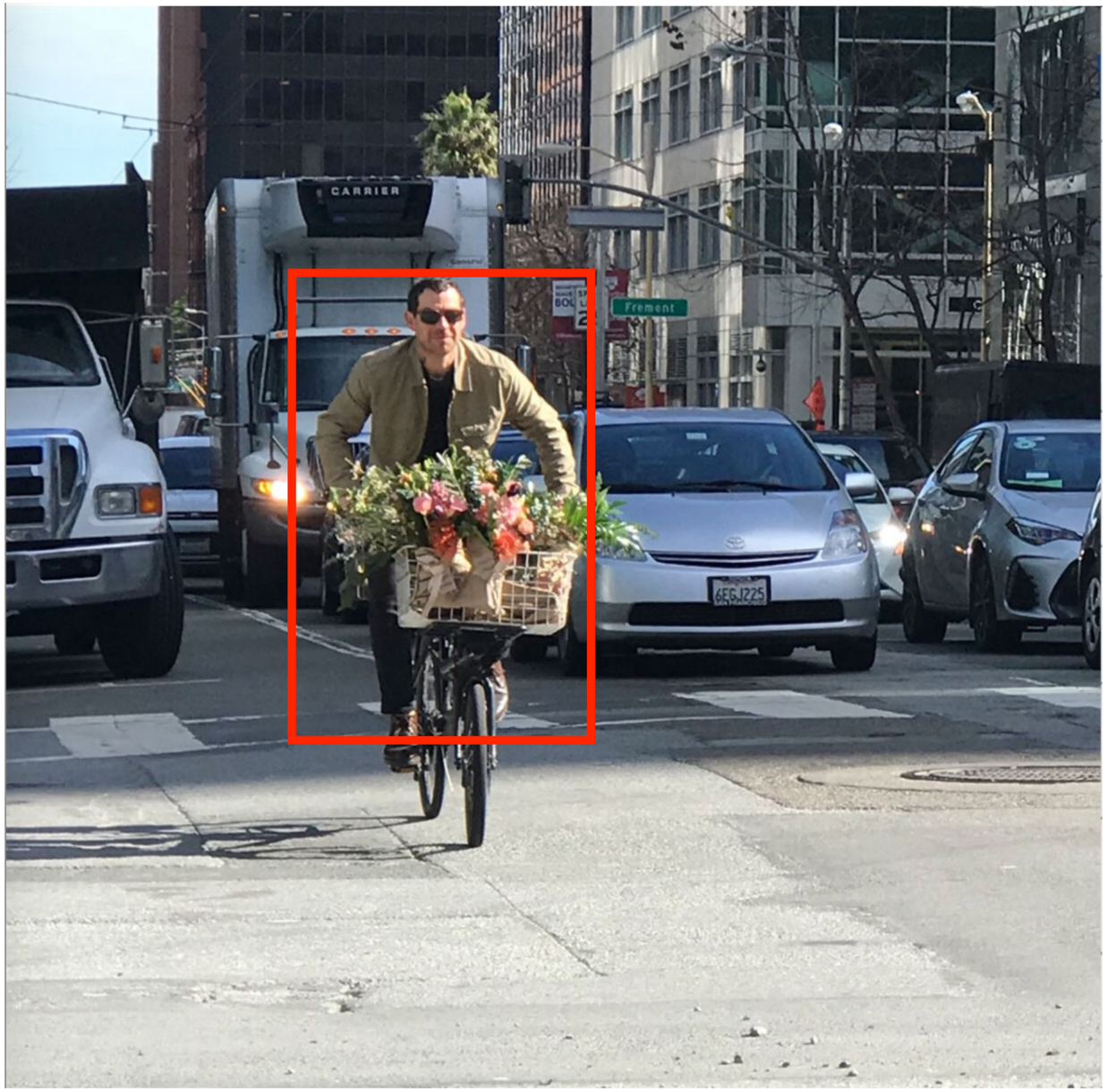
Object detection

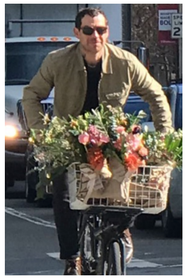


Object detection



Object detection



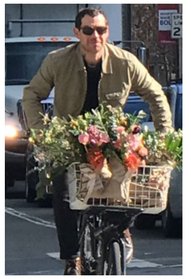


CNN

0.7
0.1
0.2
0.0

class: person

Object detection



CNN

0.7
0.1
0.2
0.0

Object detection

CNN

0.0
0.9
0.1
0.0

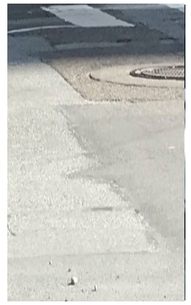
class: car

Object detection

CNN

0.0
0.9
0.1
0.0

Object detection

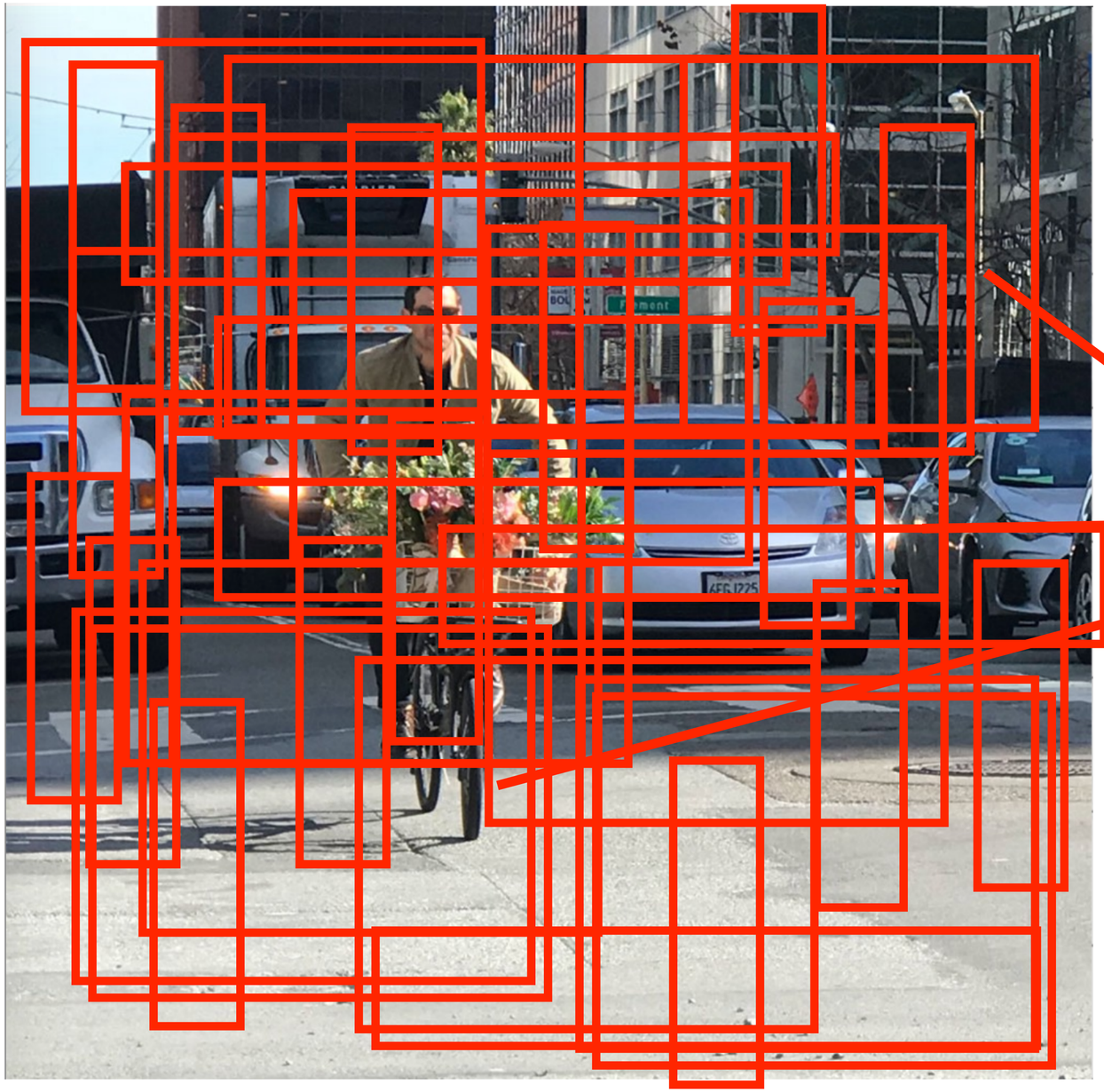


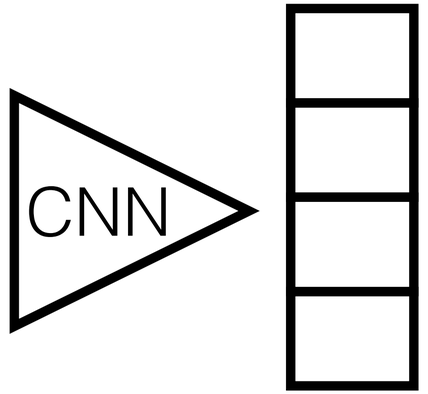
CNN

0.0
0.1
0.0
0.9

class: background

Object detection



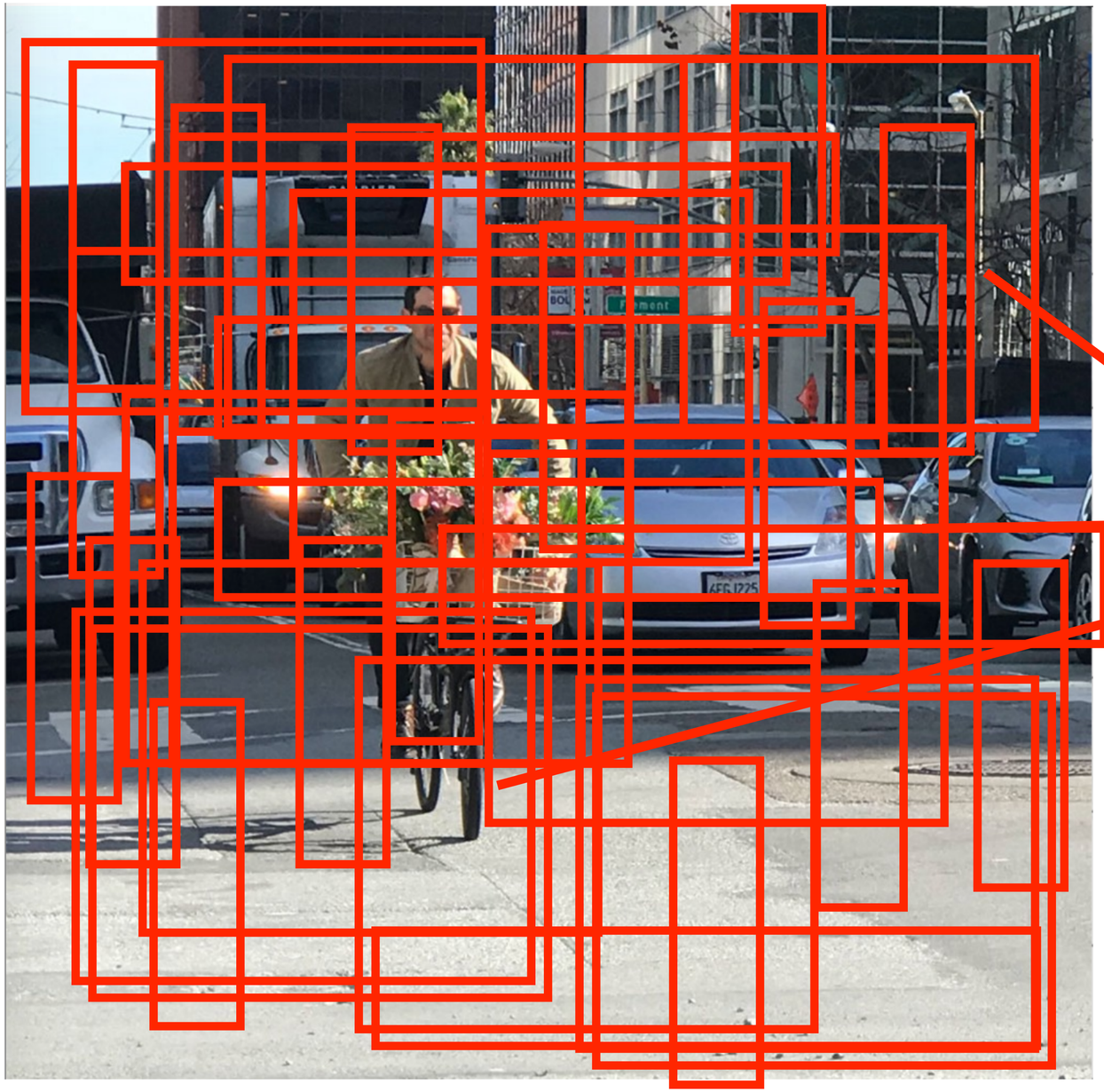


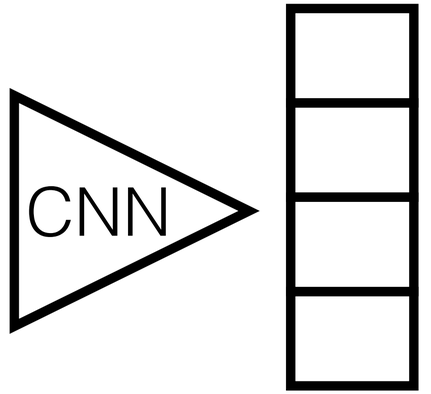
classify all rectangles

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**

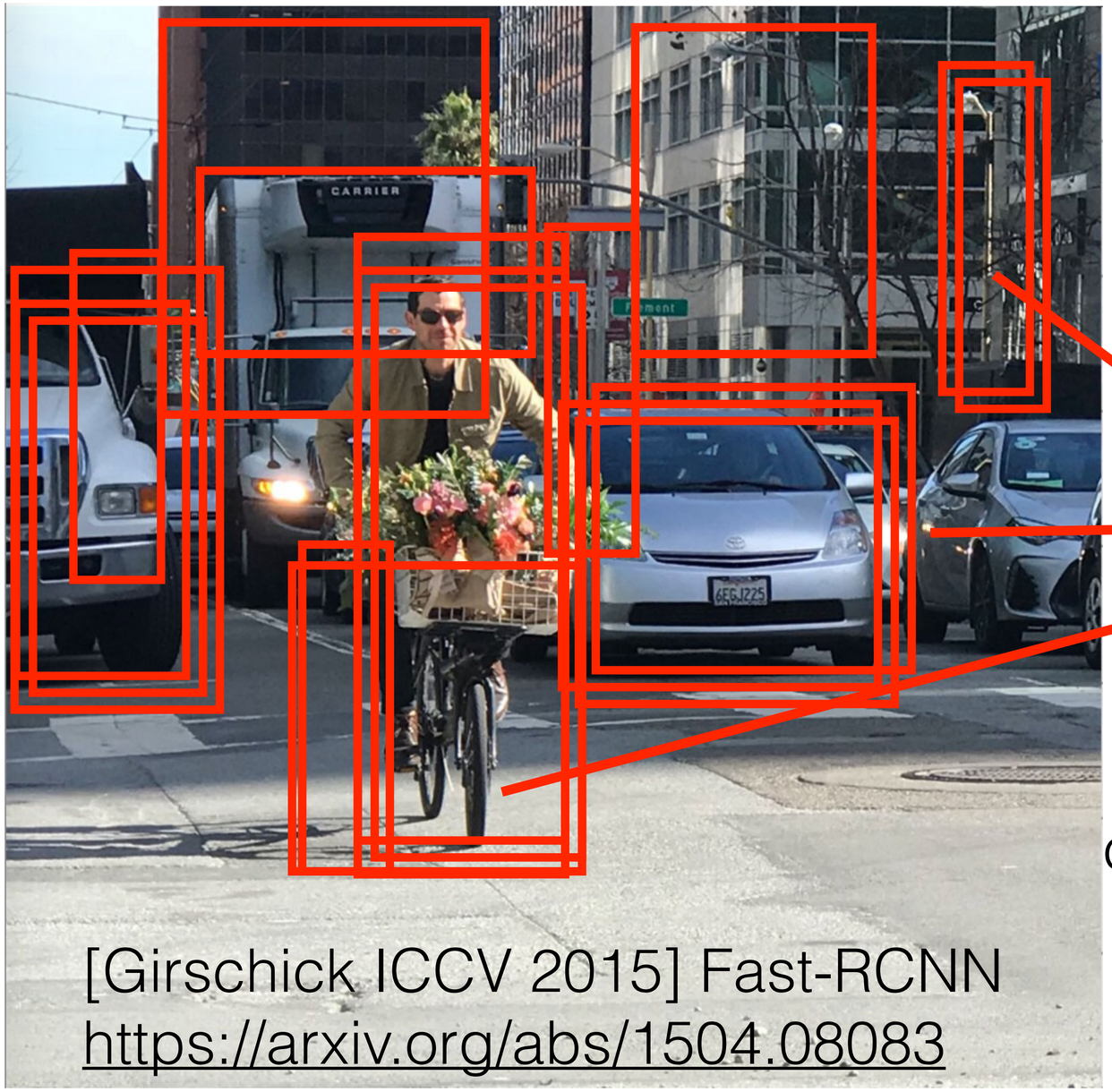
Object detection





classify all rectangles

Object detection



CNN

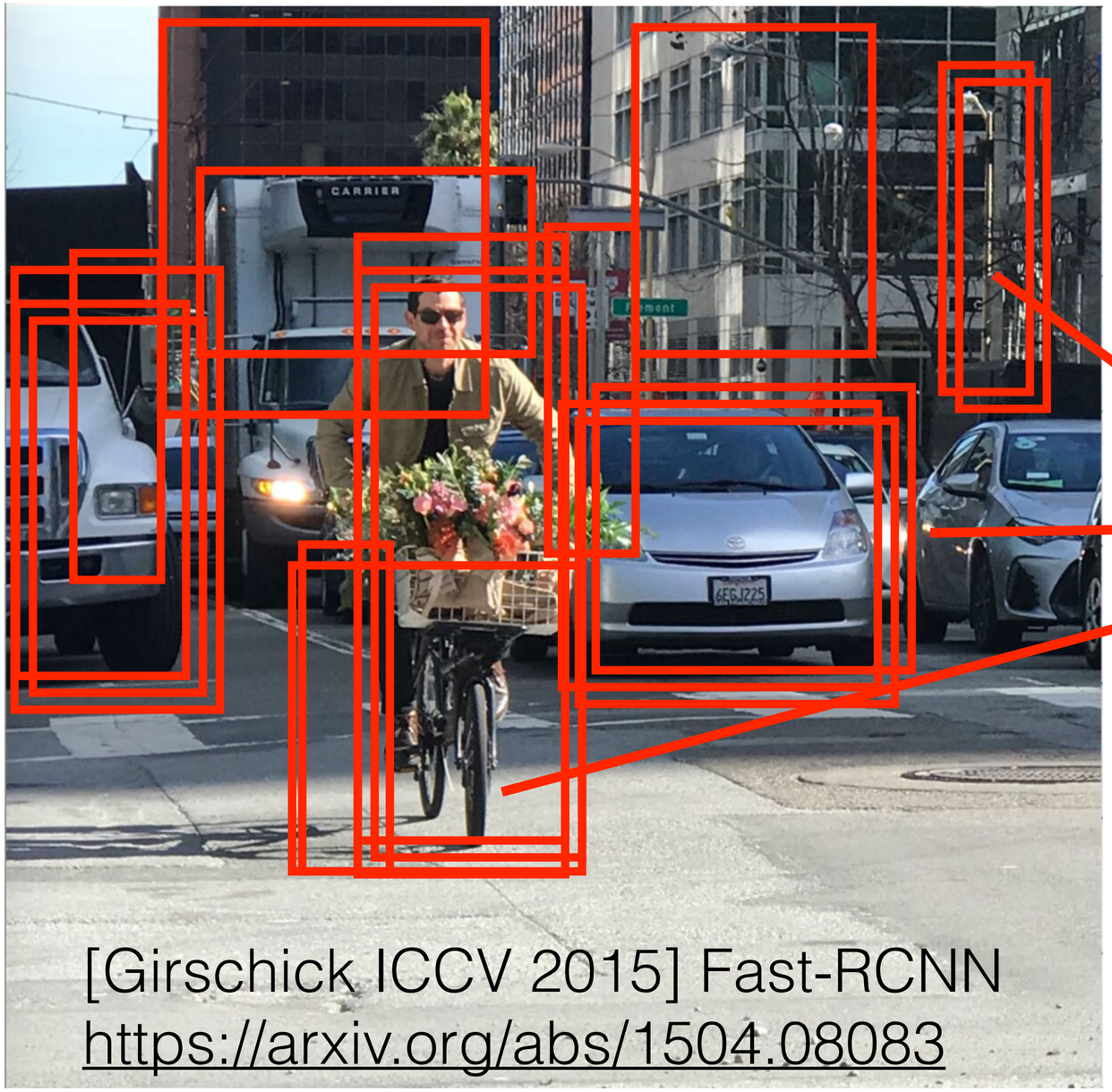
classify + align only 2k region proposals

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

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**

Object detection



[Girschick ICCV 2015] Fast-RCNN
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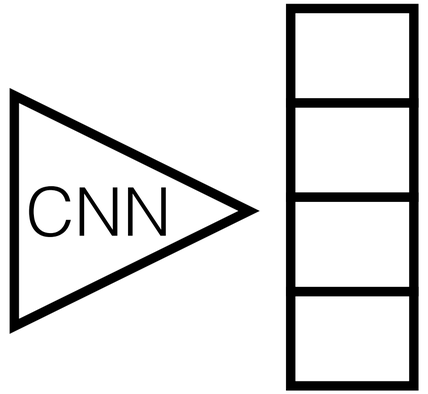
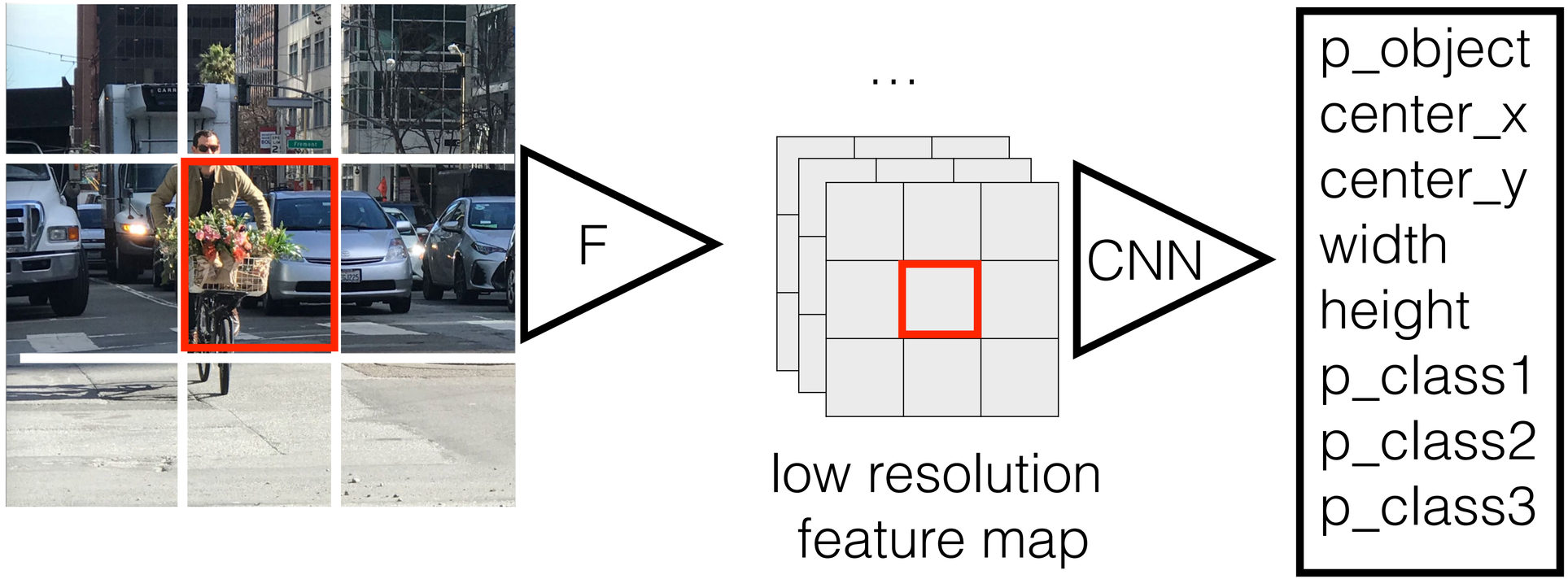


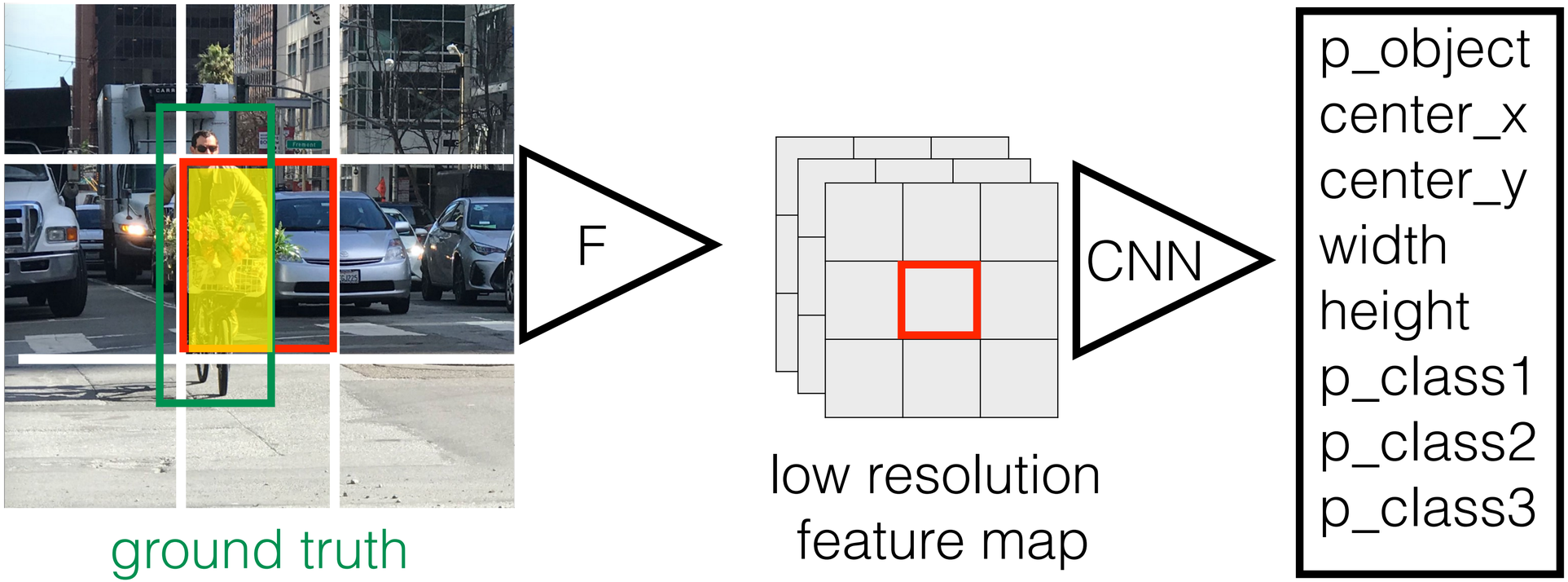
The selective search for region proposals is computational bottleneck !!!

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



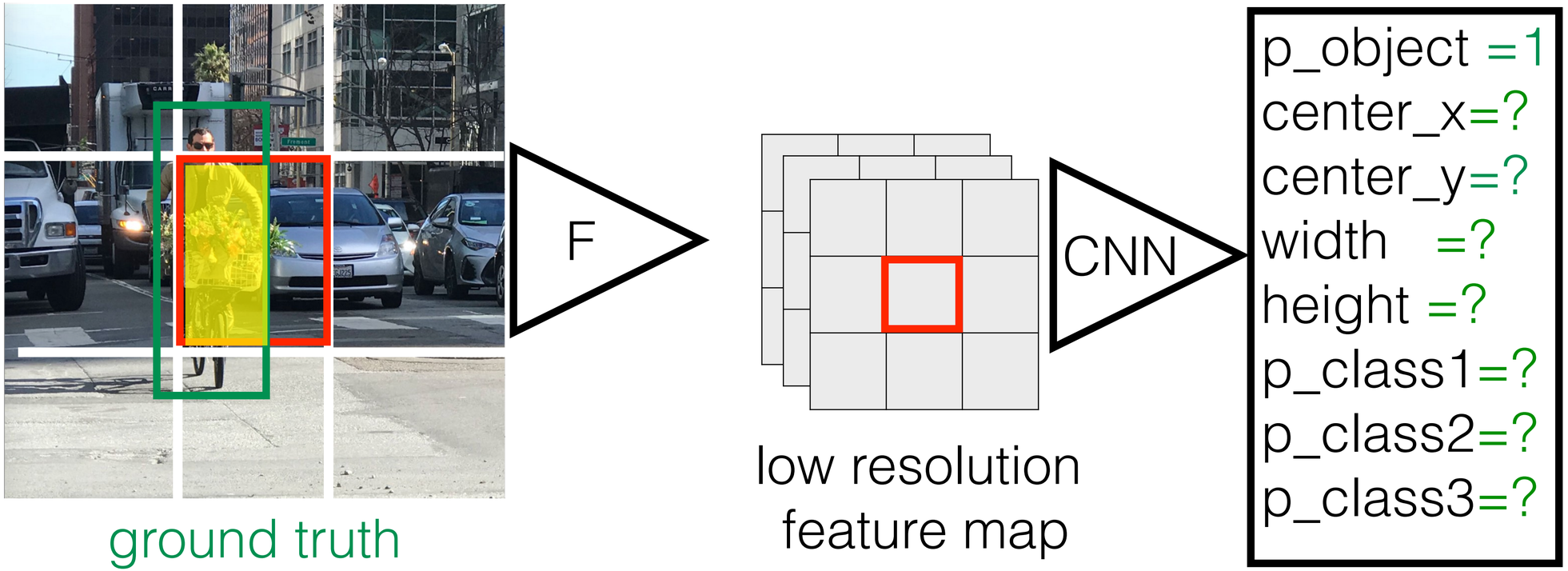
- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im

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



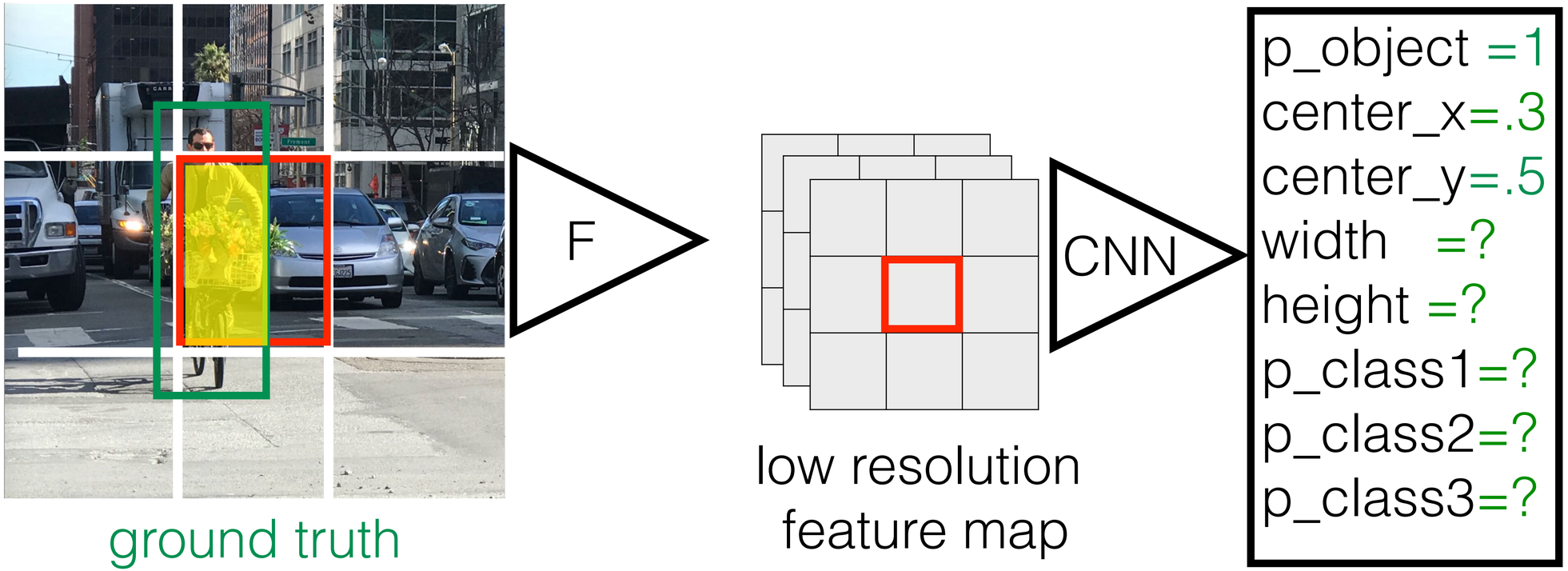
- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- learn from ground truth

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



- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- ground truth: bbs with IoU>0.7 are objects,
  bbs with IoU<0.3 not objects

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



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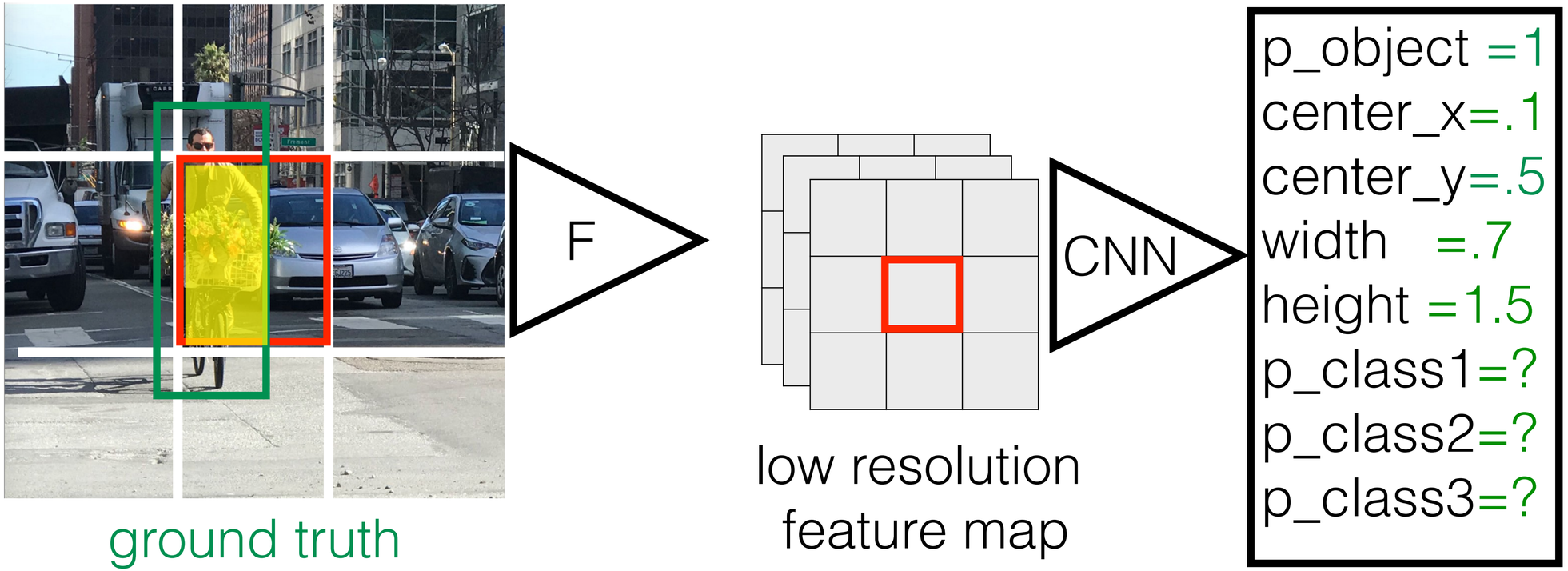

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- predict relative position, objectness, class for each sub-im
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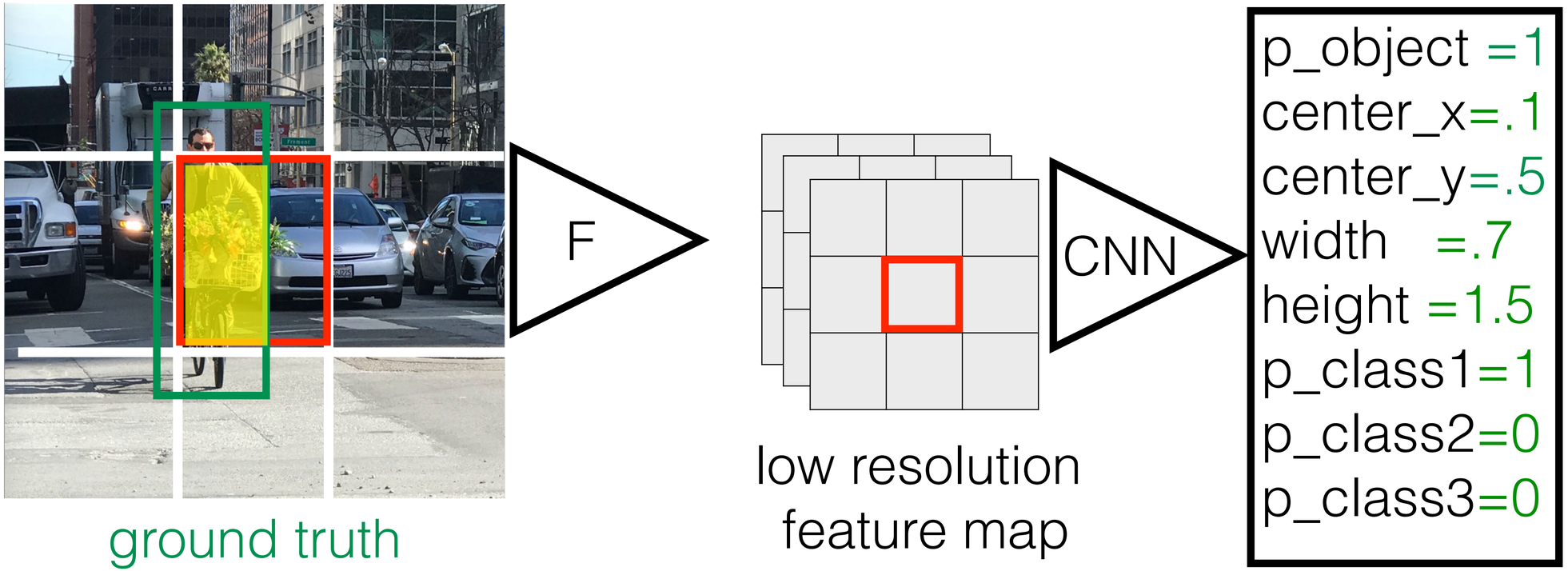

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YOLO and Faster RCNN architectures

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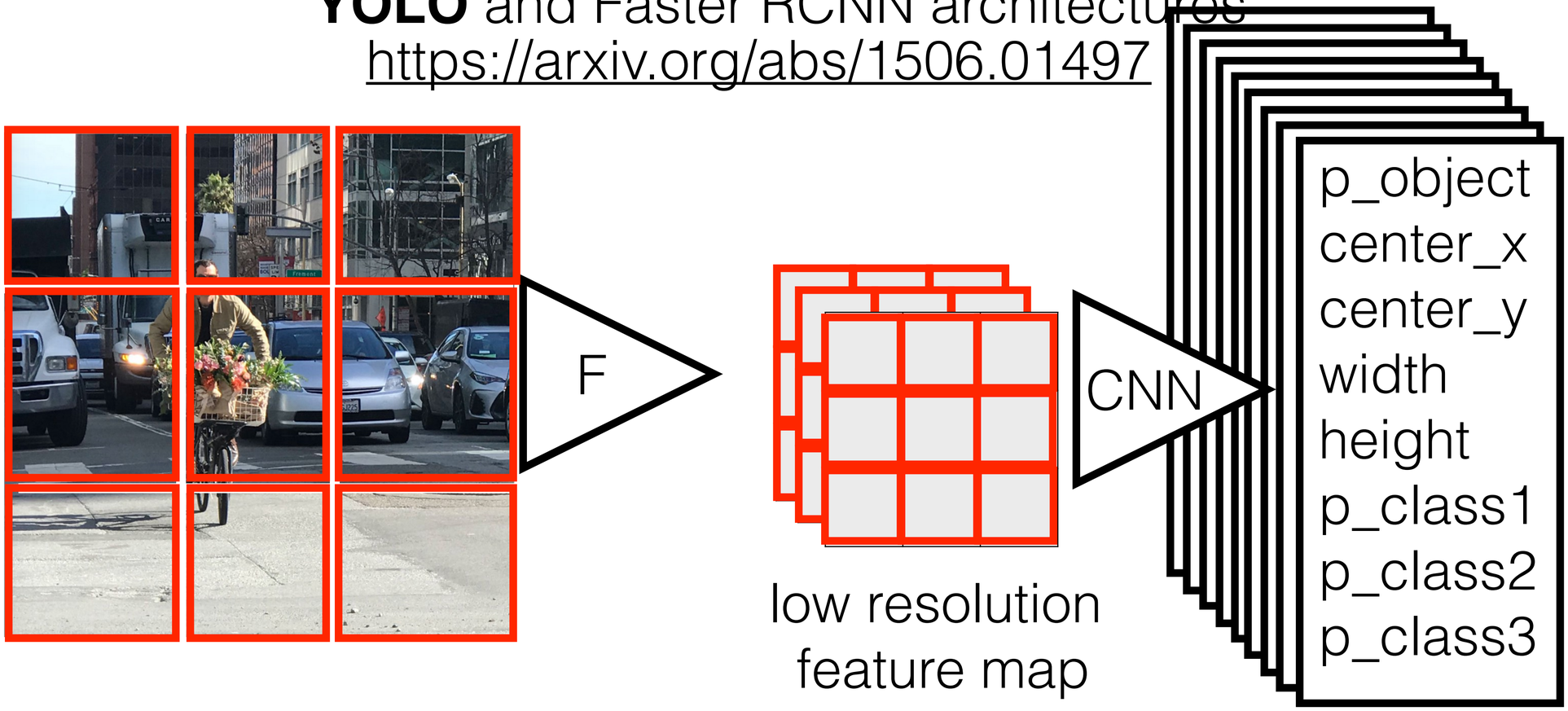
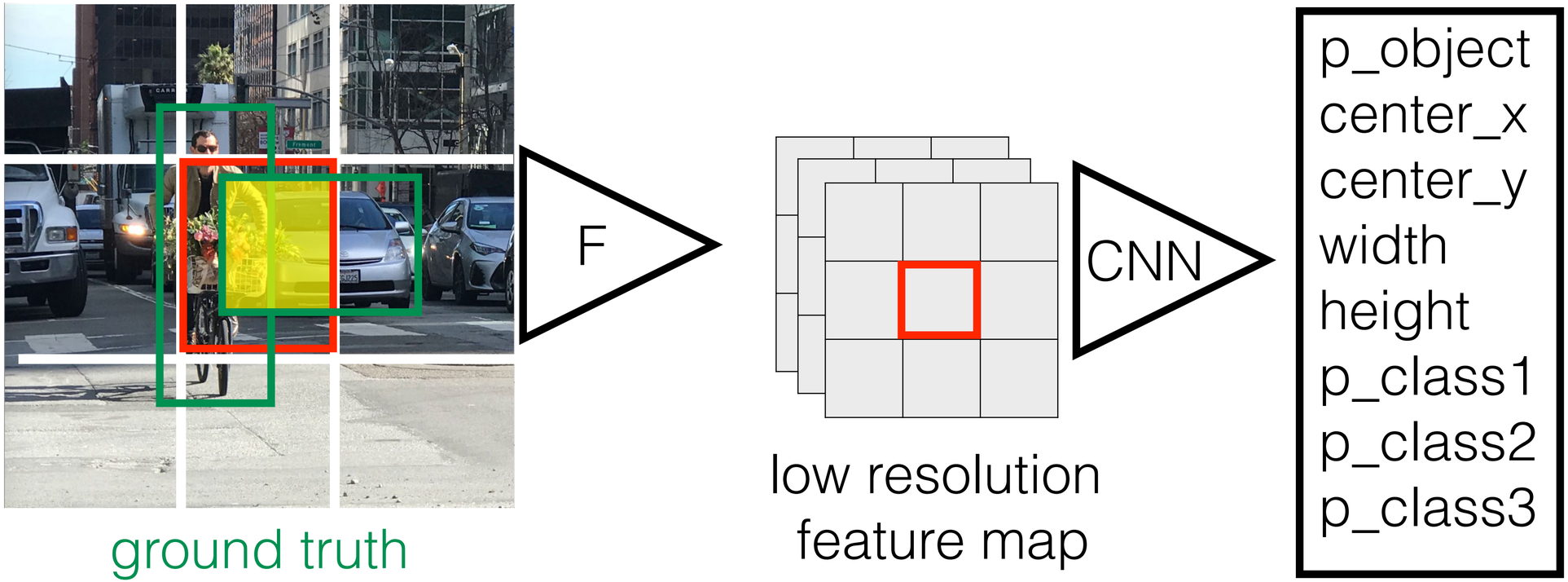


- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- each sub-image has its own output

Do you see any problem?

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



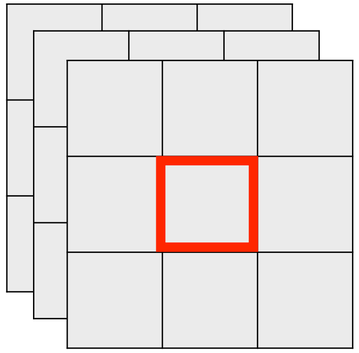
- divide image into 3x3 sub images
- predict relative position, objectness, class for each sub-im
- ground truth: bbs with IoU>0.7 are objects, => more obj in one sub-im
  bbs with IoU<0.3 not objects

YOLO and Faster RCNN architectures

https://arxiv.org/abs/1506.01497

ground truth

F



low resolution feature map

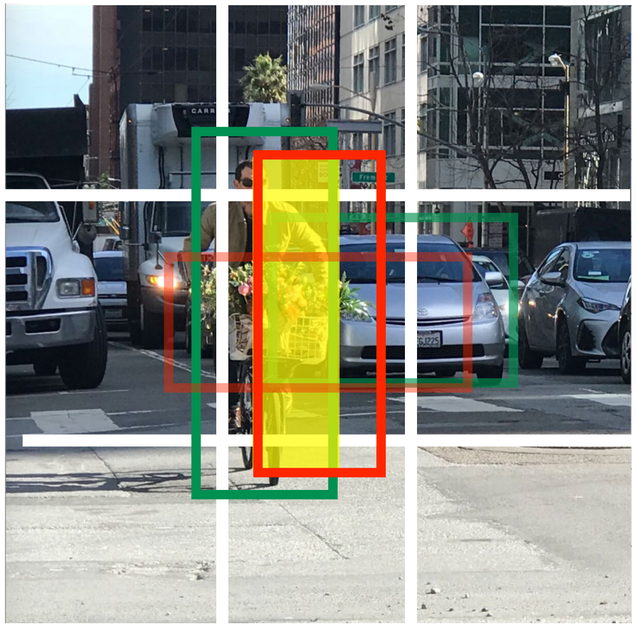
CNN

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

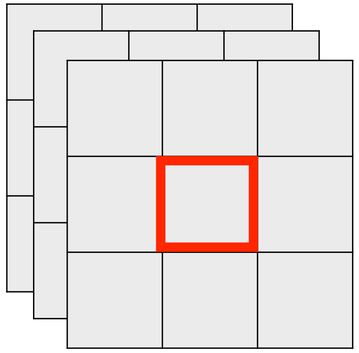
Introduce anchor bounding boxes

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



ground truth

F



low resolution
feature map

CNN

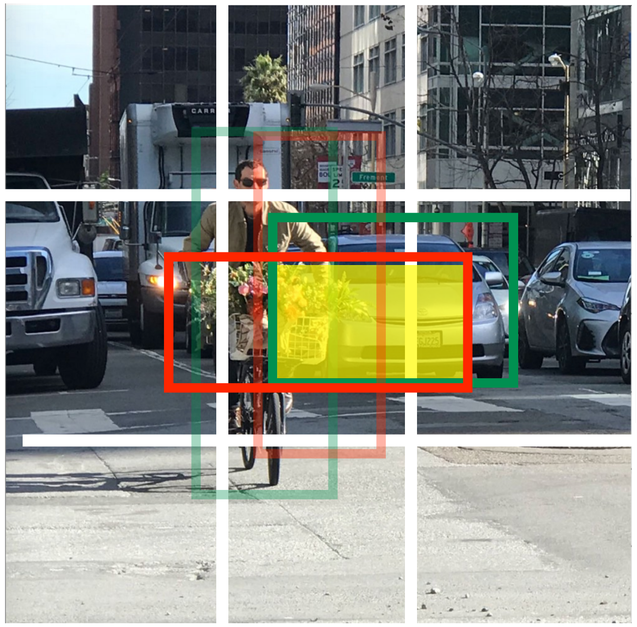
p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

Introduce anchor bounding boxes

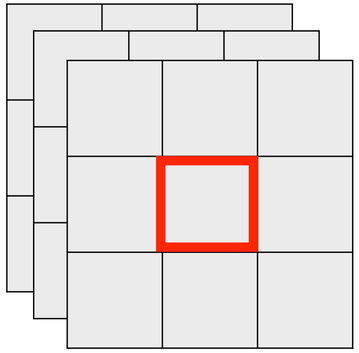
- for each anchor bb CNN predicts:
  - its “alignment with gt” (regression loss)
  - its “objectness”+”class” (classification loss)

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



ground truth

F



low resolution
feature map

CNN

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

p_object
center_x
center_y
width
height
p_class1
p_class2
p_class3

Introduce anchor bounding boxes

- for each anchor bb CNN predicts:
  - its “alignment with gt” (regression loss)
  - its “objectness”+”class” (classification loss)

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

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:

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

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


CLS CARS



GT BKGD:




CLS BGGD:



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) =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

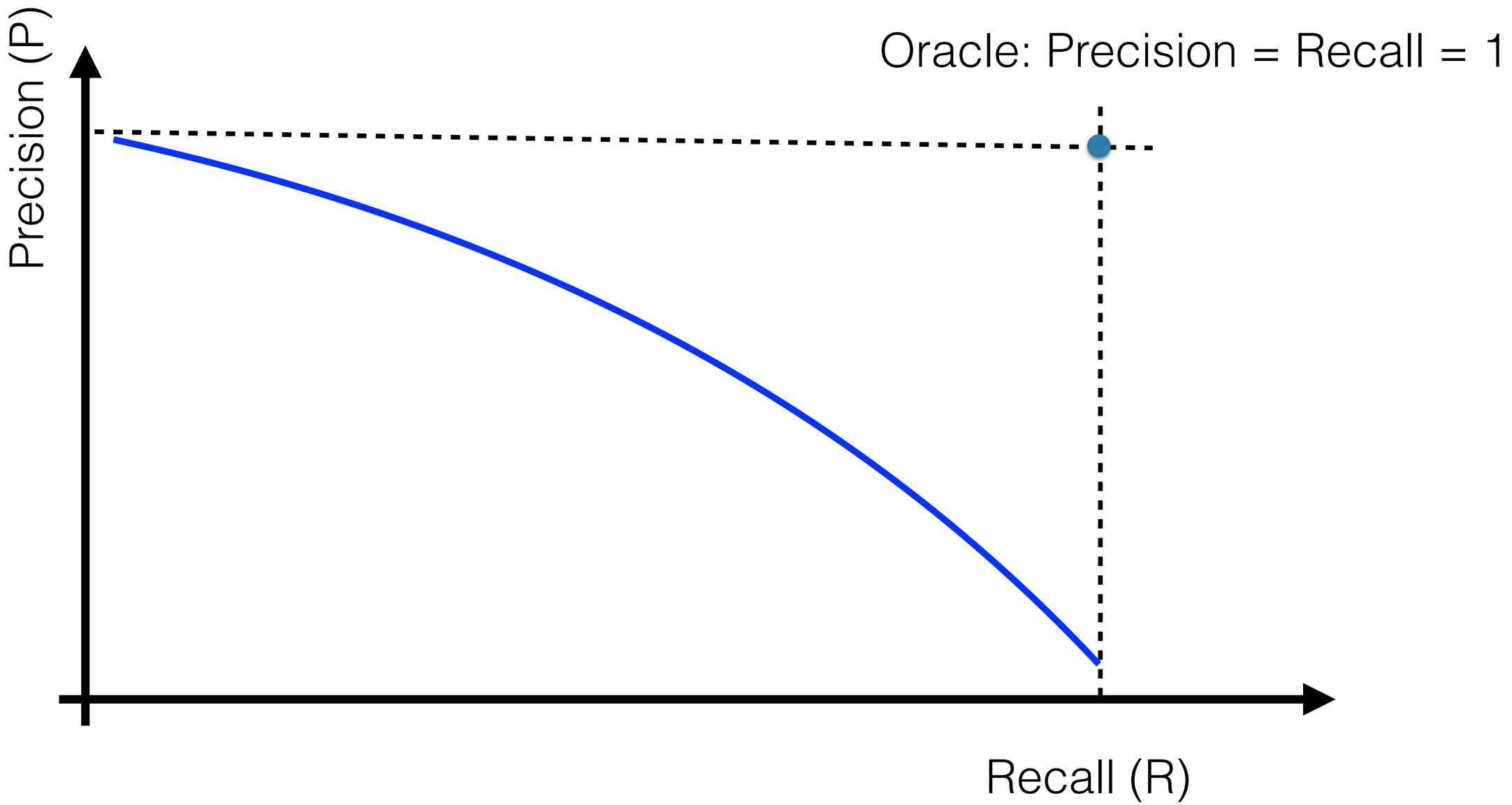
true negative (TN) =2

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

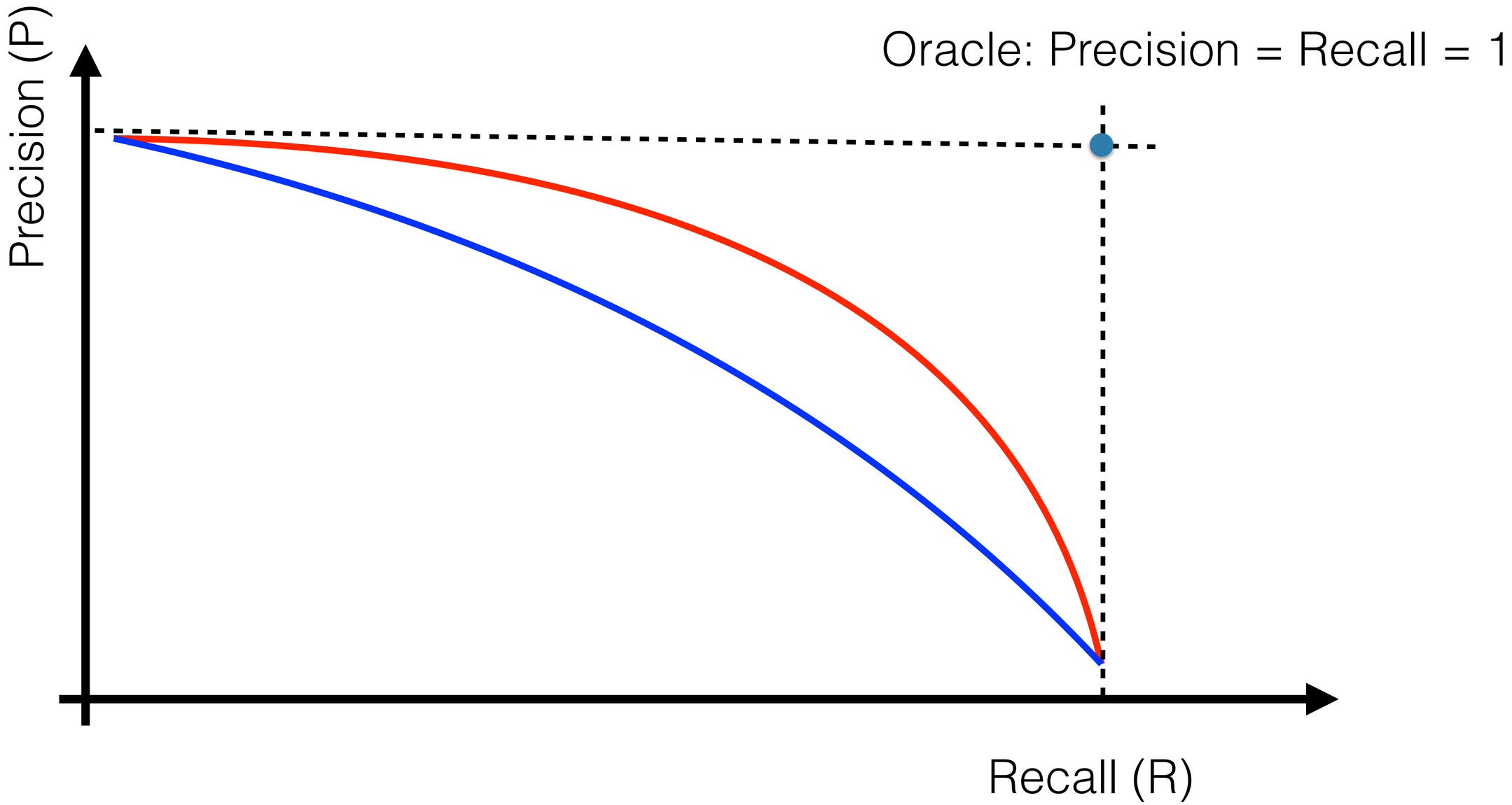
$$\text{Recall (R)} = \frac{TP}{TP + FN} = \frac{2}{2 + 0} = 1$$

Oracle: Precision = Recall = 1

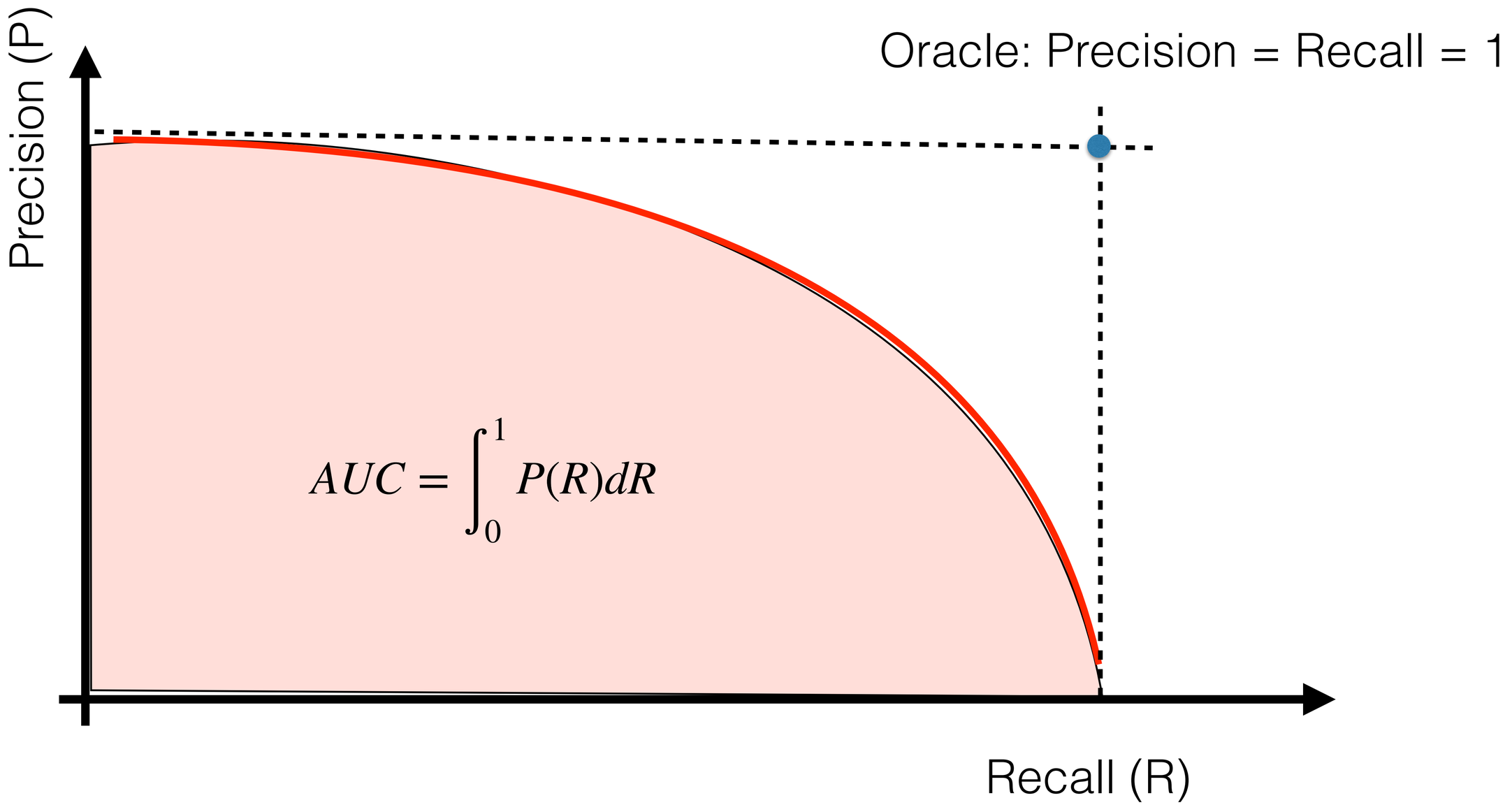
Smoothed Precision-Recall curve



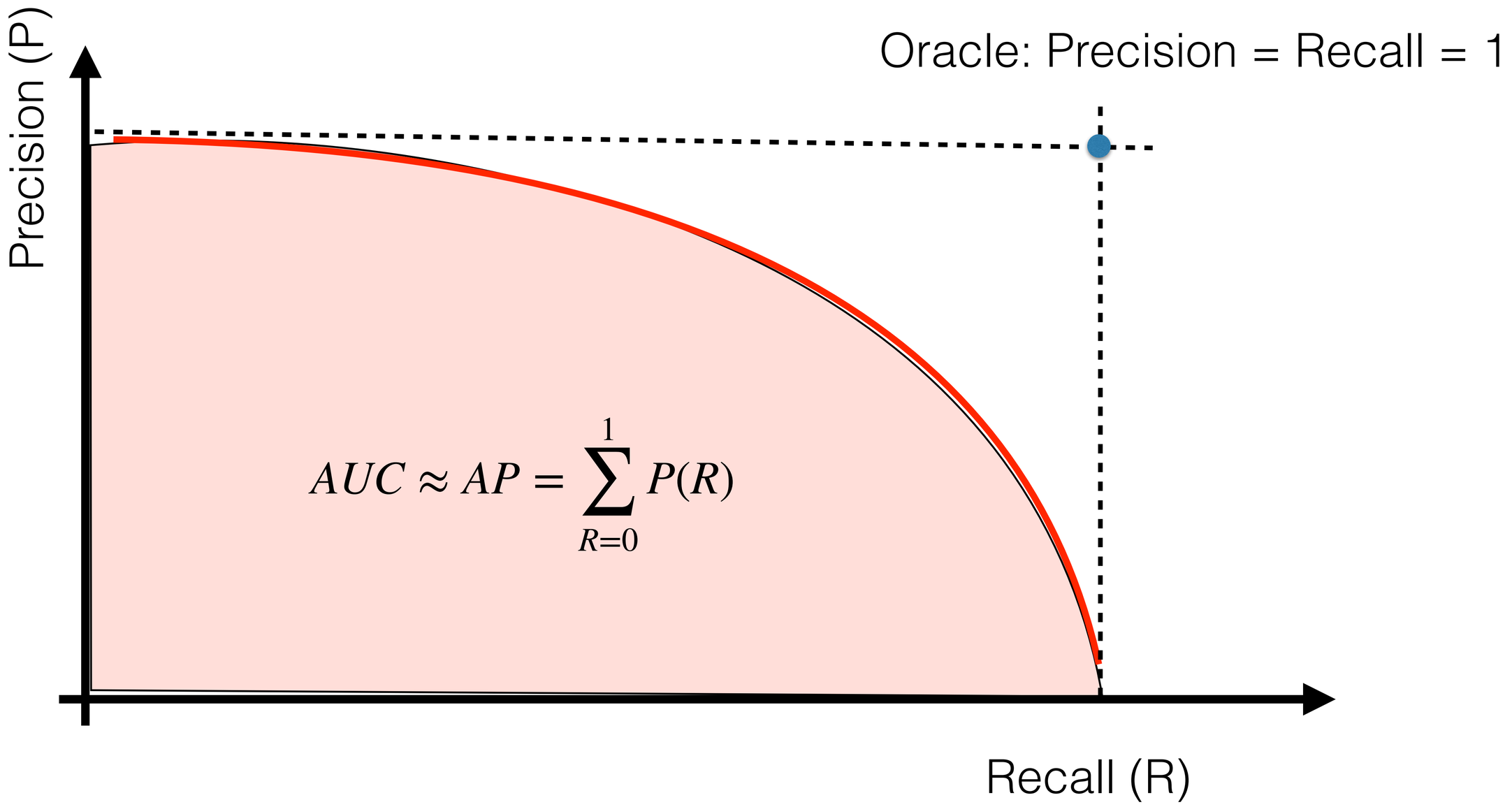
Smoothed Precision-Recall curve

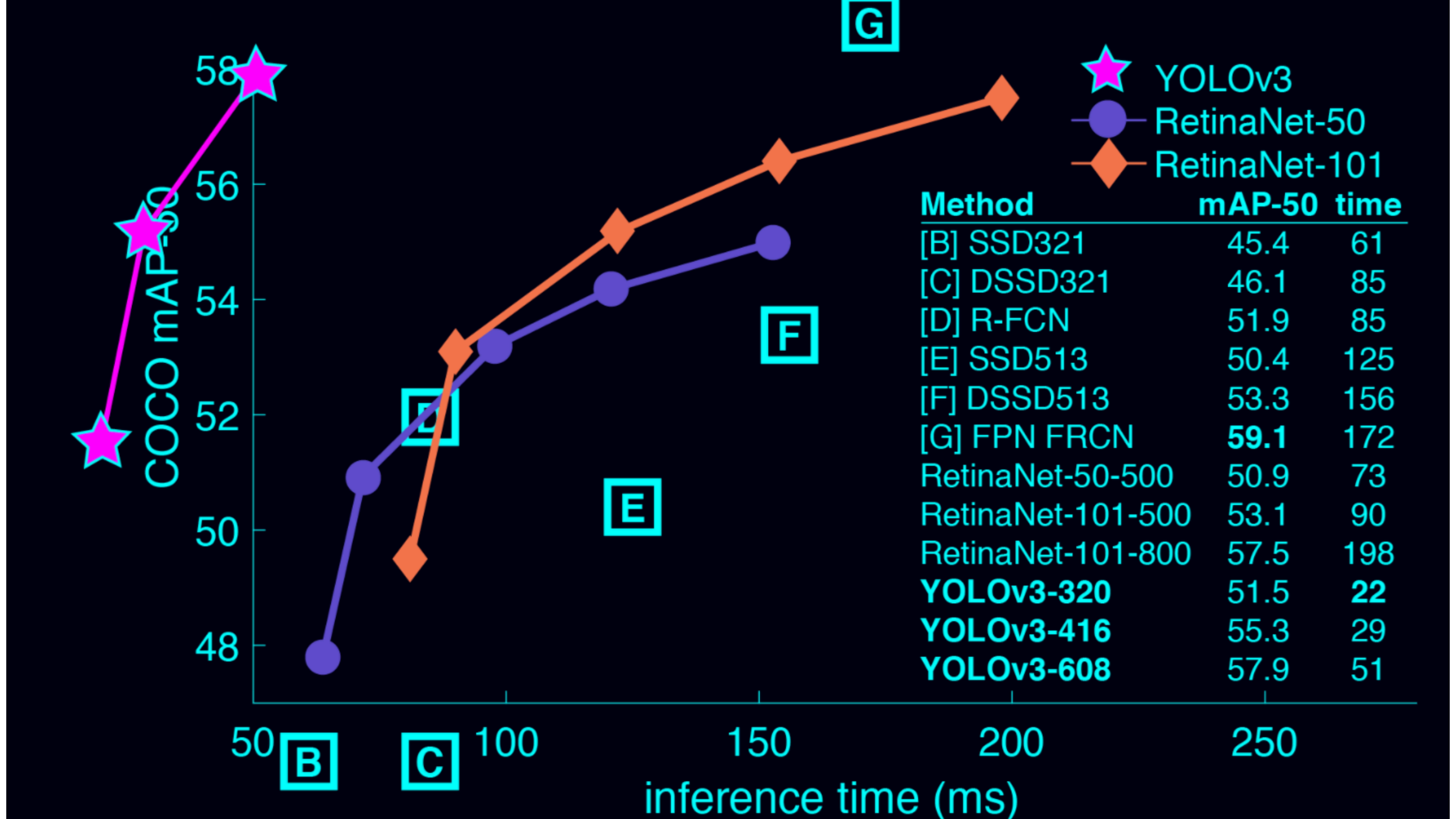


Smoothed Precision-Recall curve



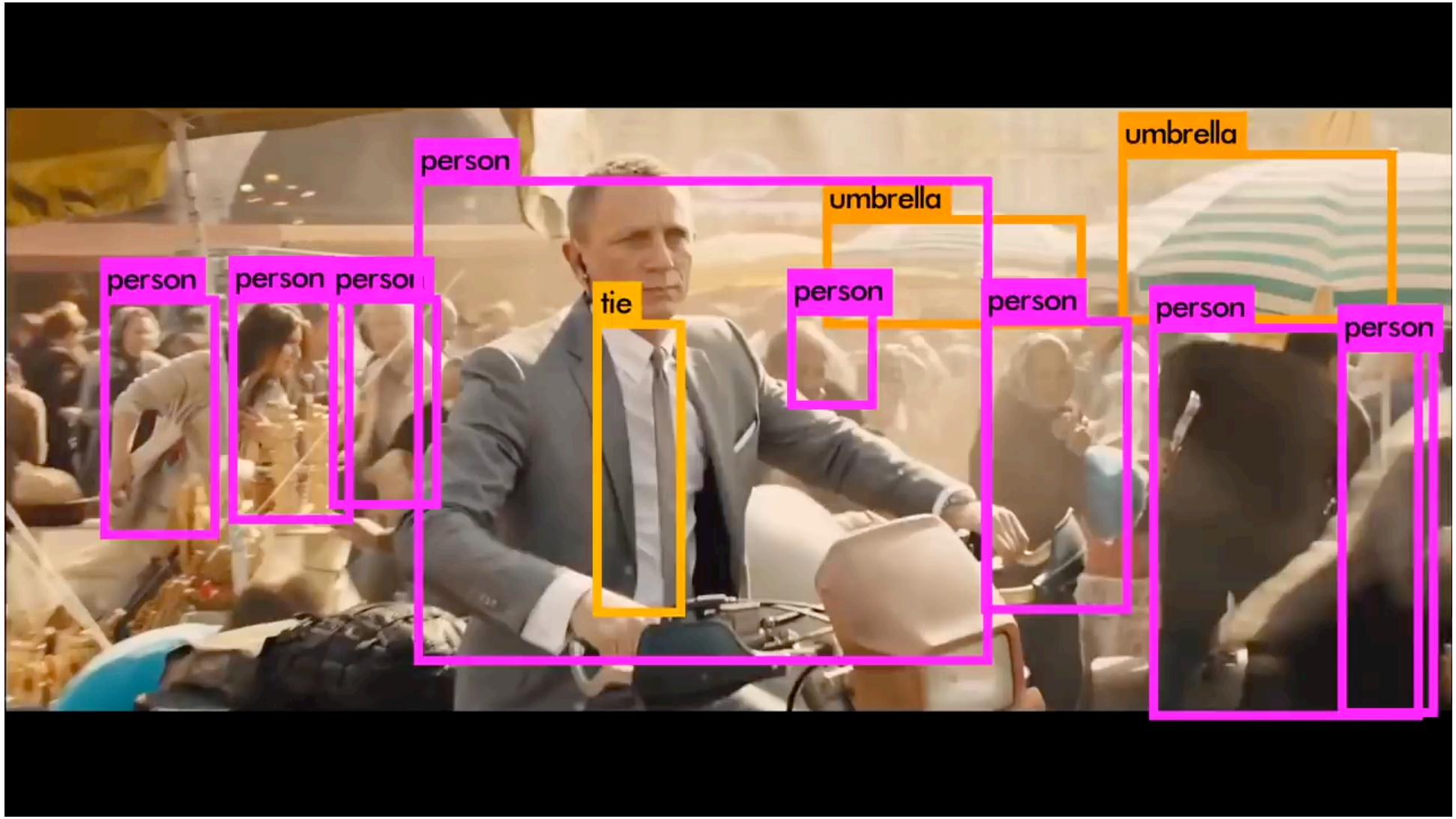
Smoothed Precision-Recall curve





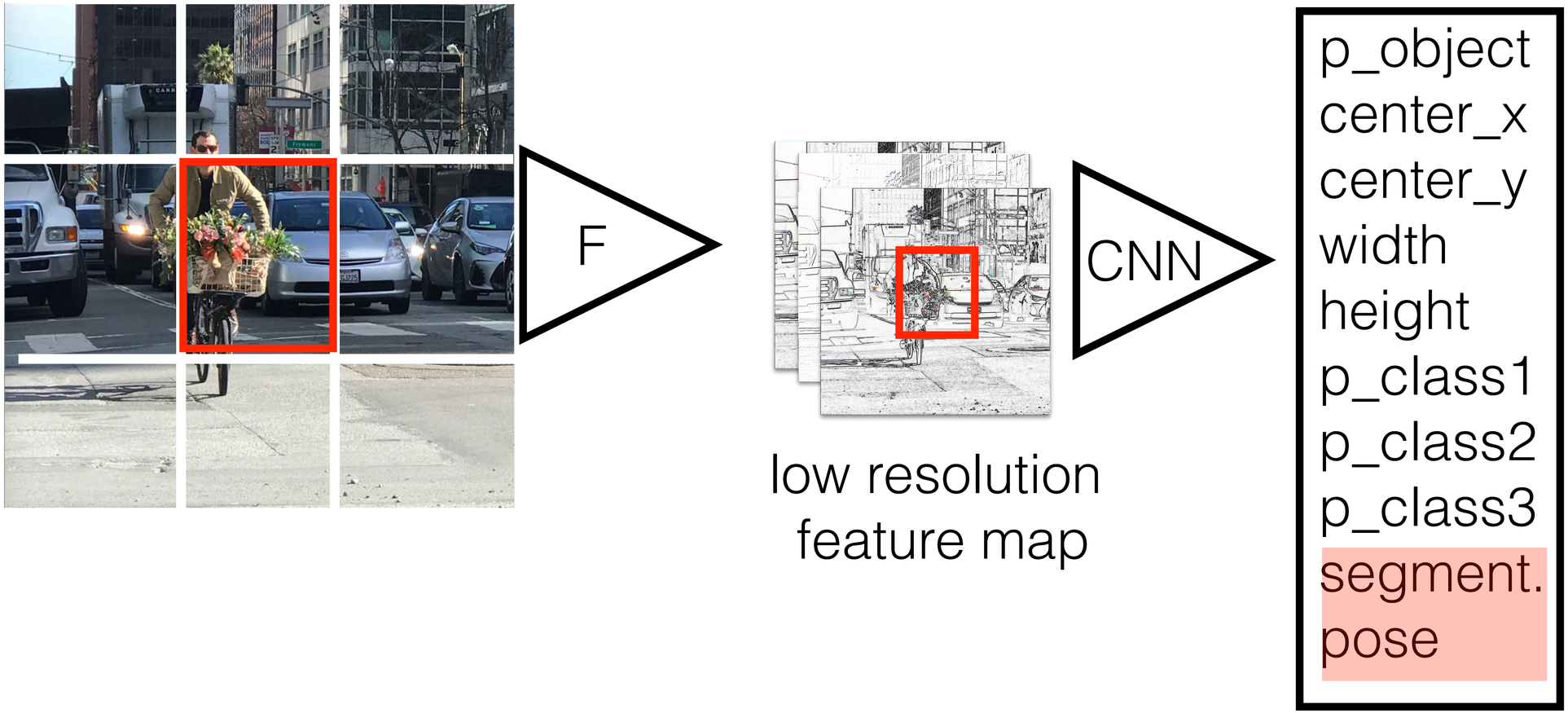
Method	mAP-50	time
[B] SSD321	45.4	61
[C] DSSD321	46.1	85
[D] R-FCN	51.9	85
[E] SSD513	50.4	125
[F] DSSD513	53.3	156
[G] FPN FRCN	**59.1**	172
RetinaNet-50-500	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.5	198
YOLOv3-320	51.5	**22**
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51

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

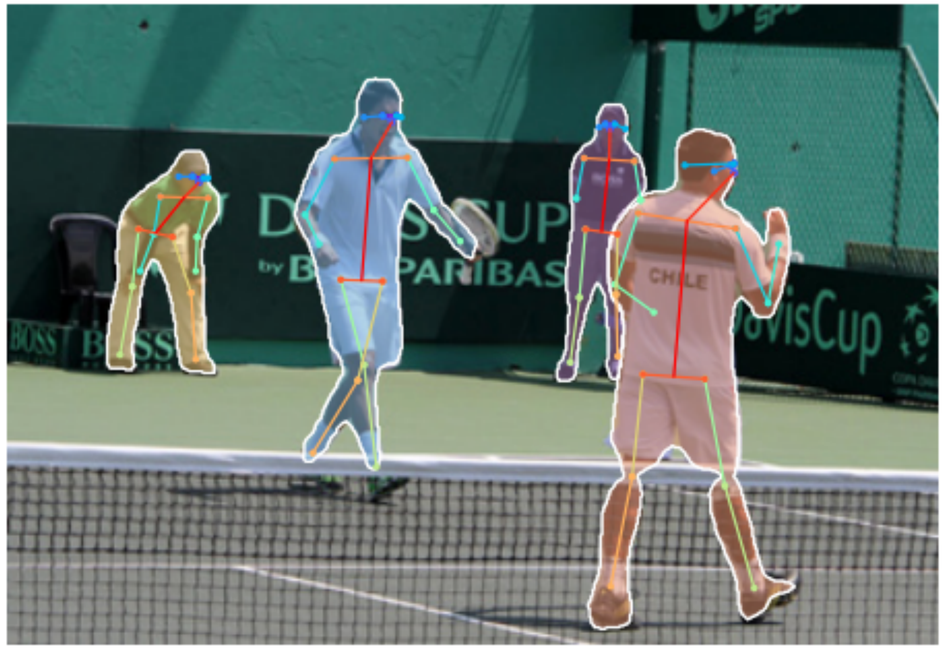


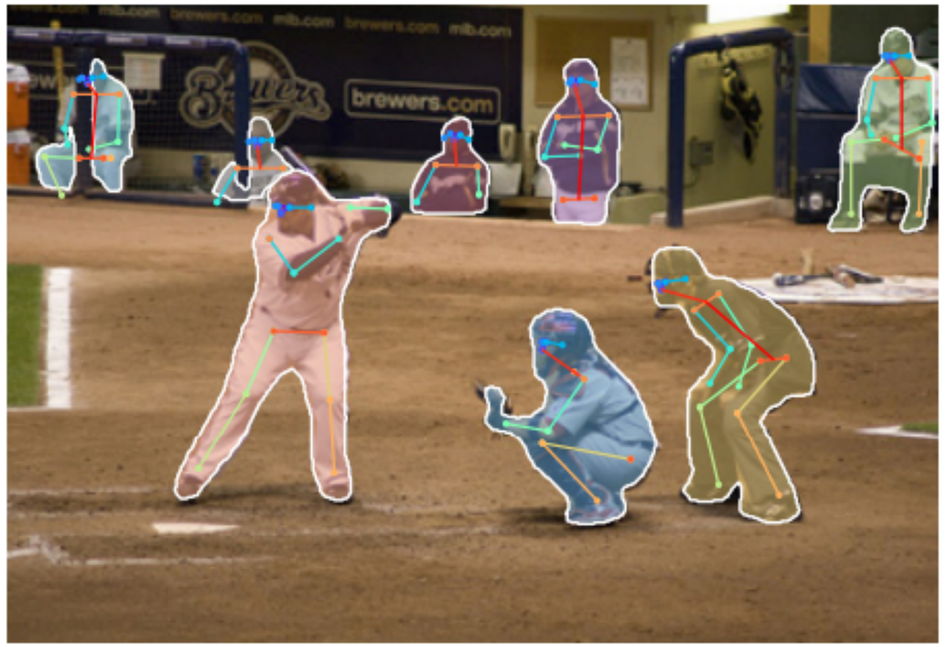
[He et al CVPR 2017] Mask-RCNN
https://arxiv.org/abs/1703.06870

Mask RCNN - results

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

Mask RCNN - results

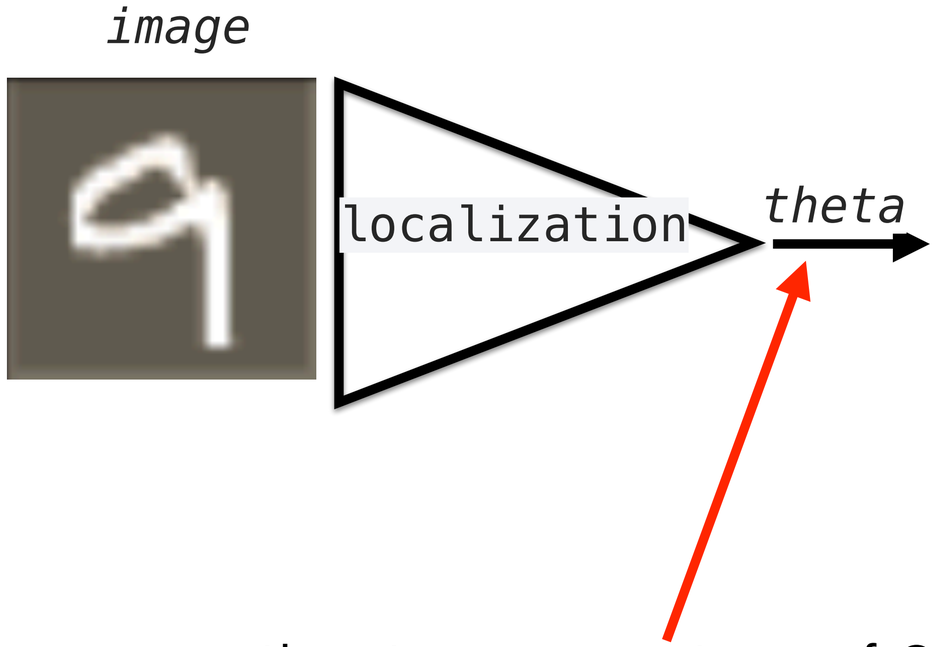




Outline

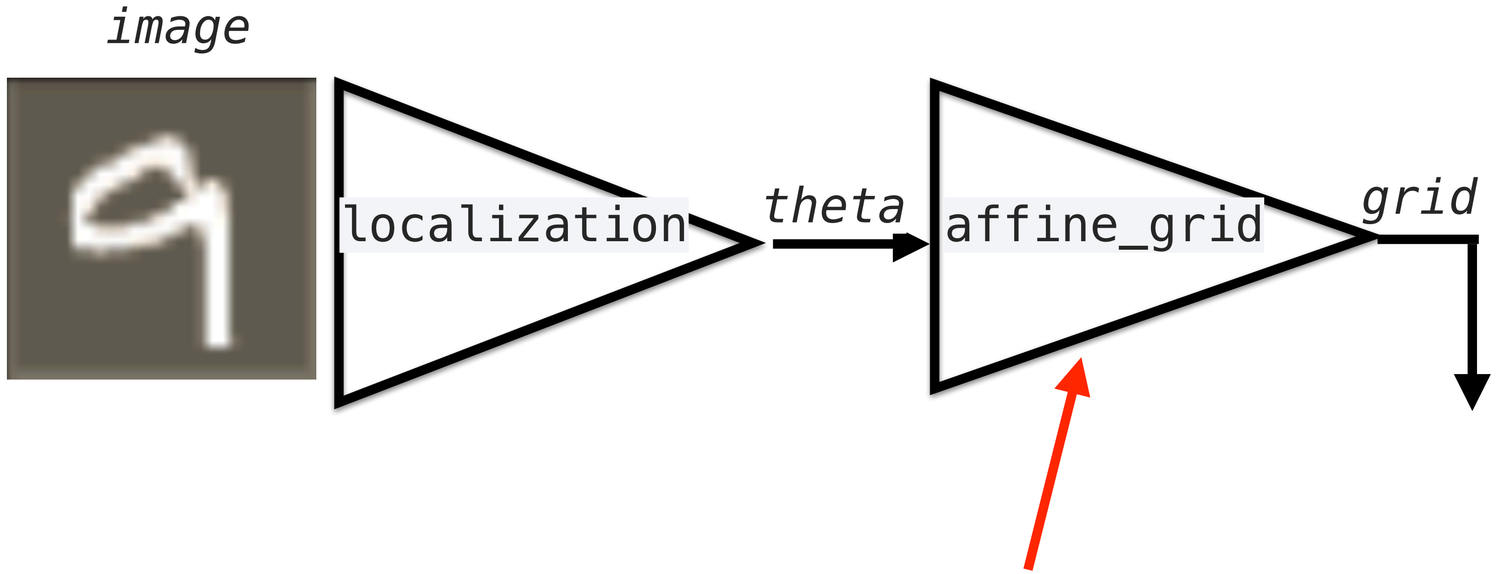
- Architectures of classification networks
- Architectures of segmentation networks
- Architectures of regression networks
- Architectures of detection networks
- Spatial Transformer networks
- Architectures of feature matching networks

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



estimate parameters of 2D similarity transformation

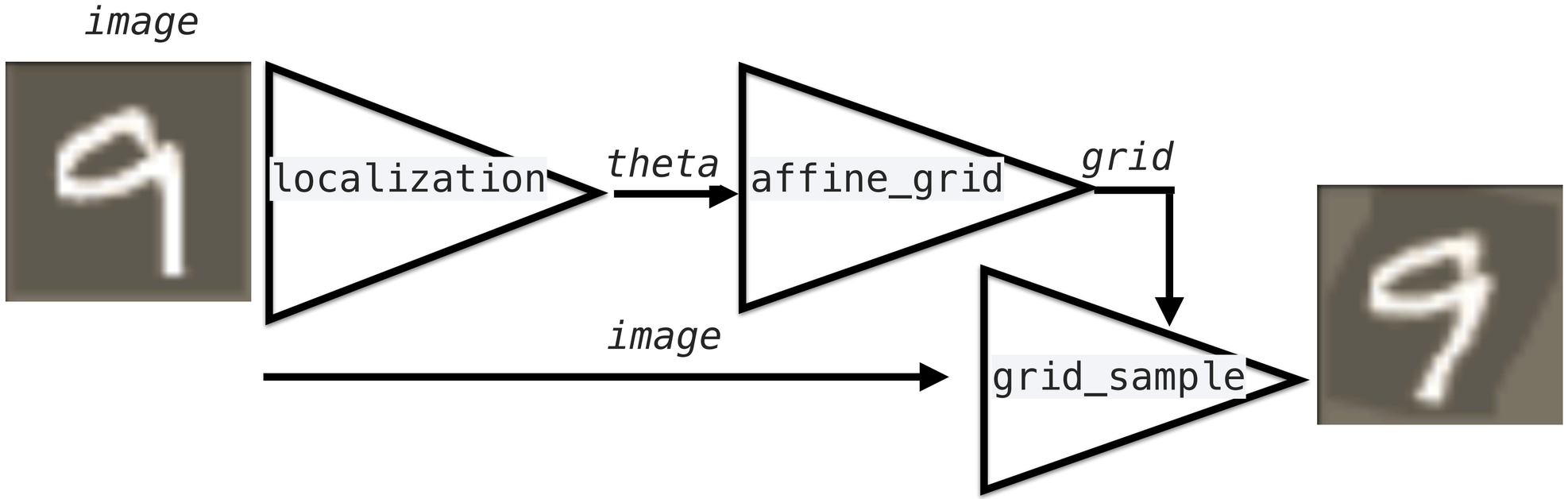
Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf



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

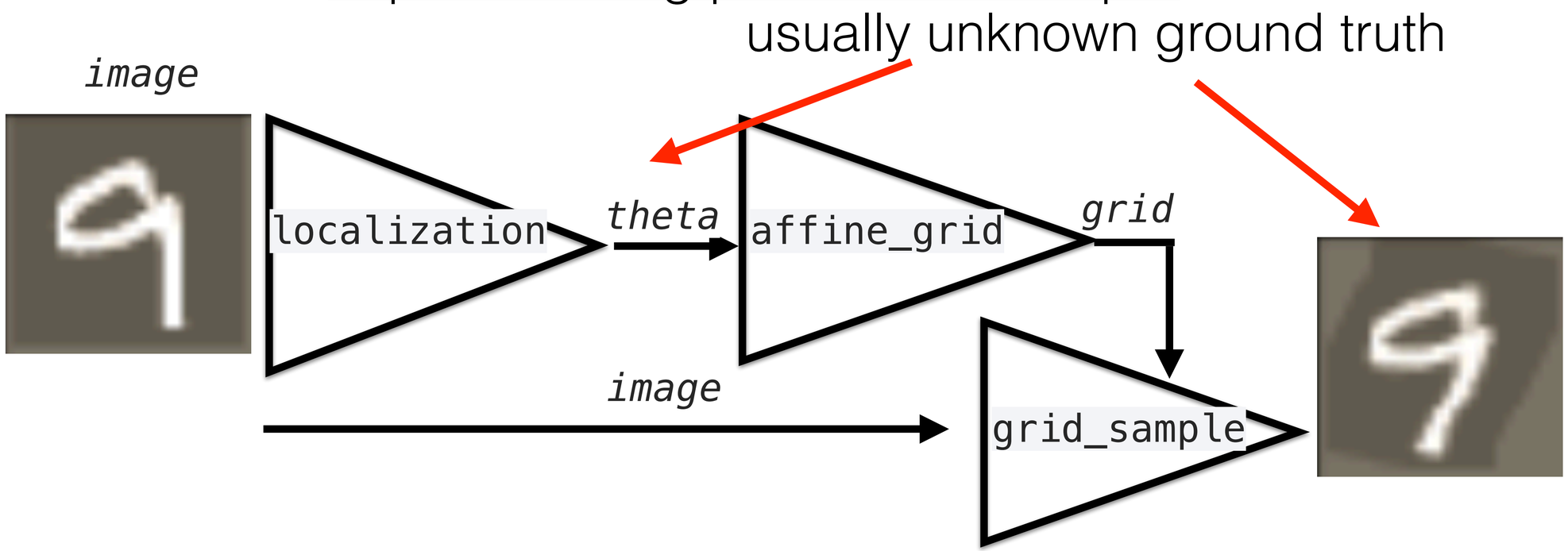



```
torch.nn.functional.affine_grid(theta, size, align_corners=None)

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




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

torch.nn.functional.grid_sample(input, grid, mode='bilinear',
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```

Spatial Transformer networks [Jaderberg 2016]
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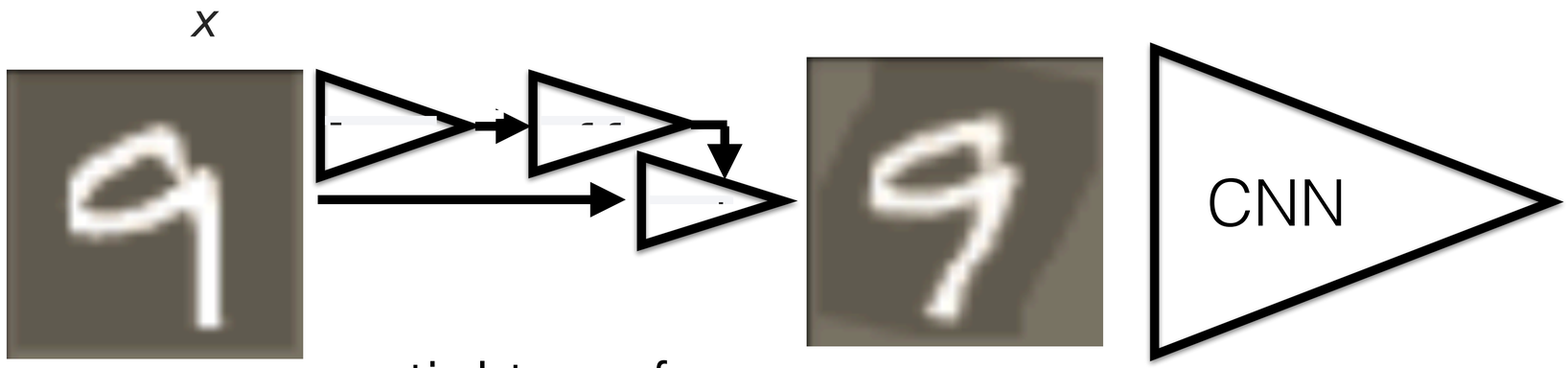
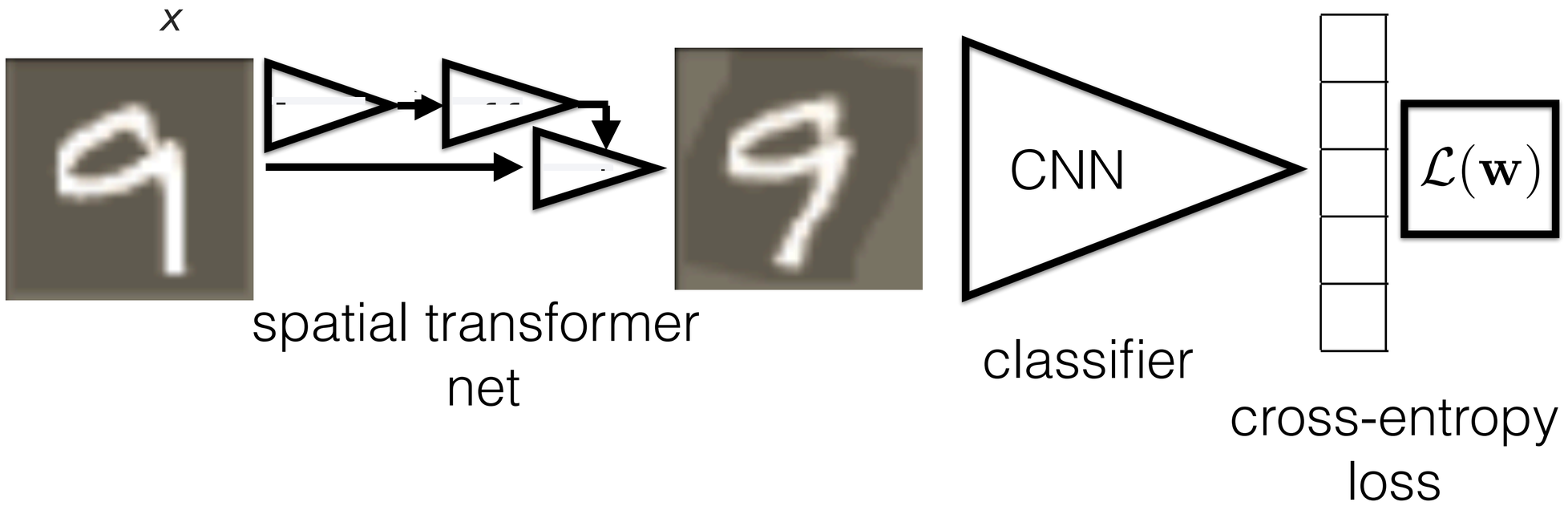


spatial transformer net

classifier

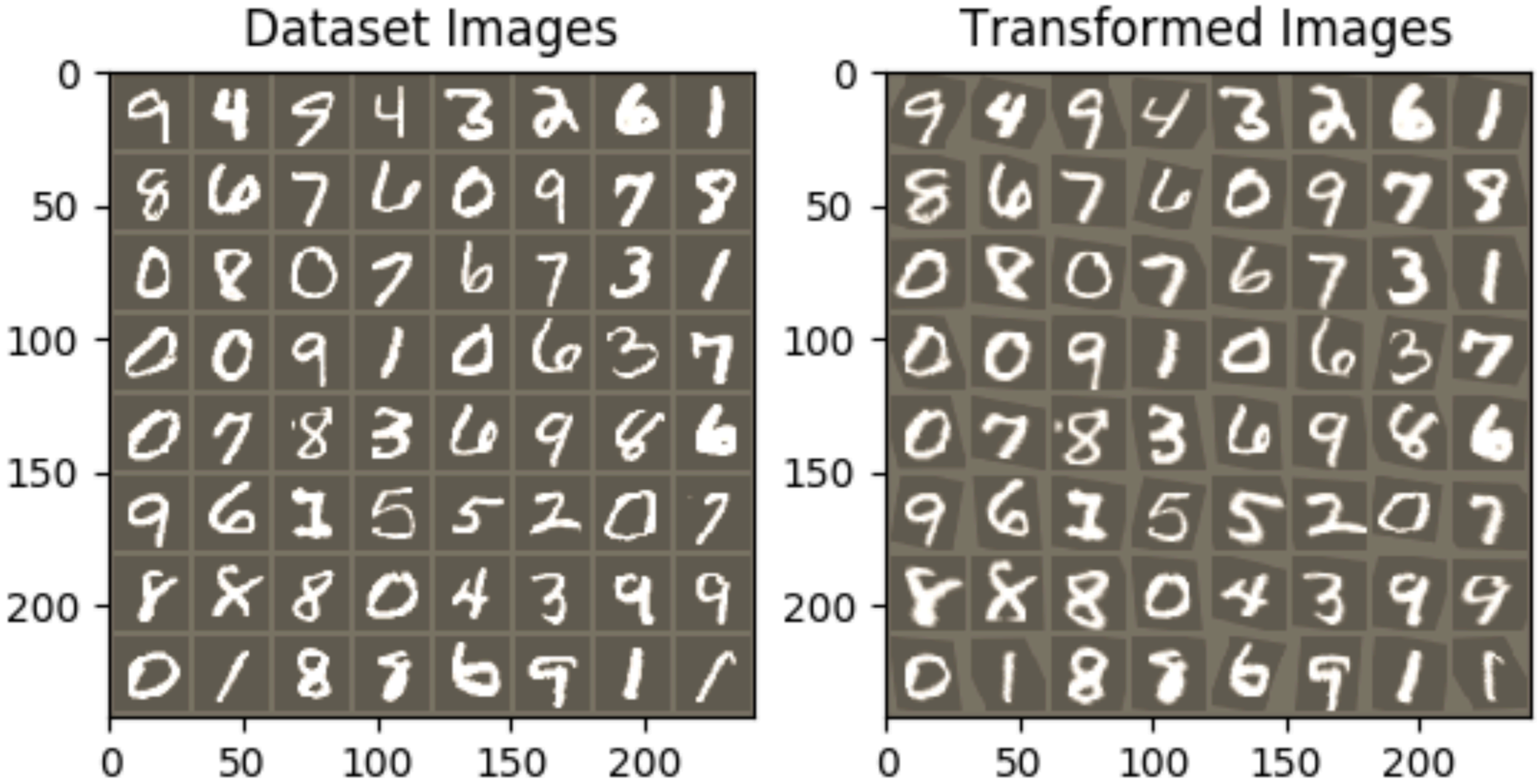
Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf



Backpropagation learns also STN weights, which perform the most suitable transformation for the classification task

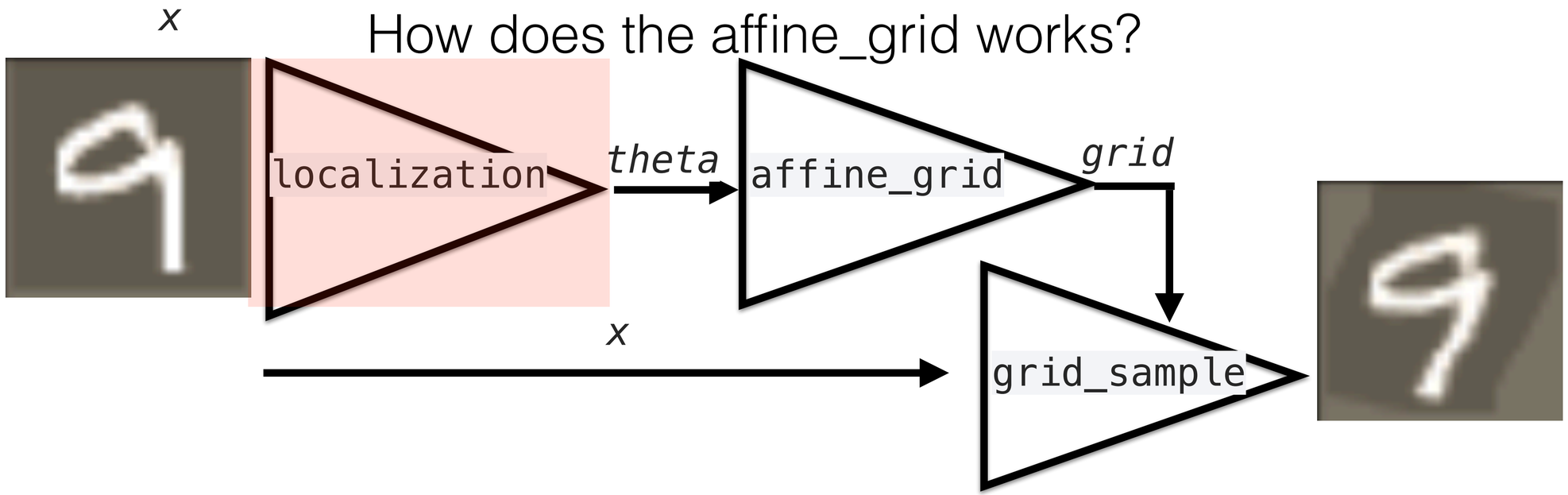
Spatial Transformer networks

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



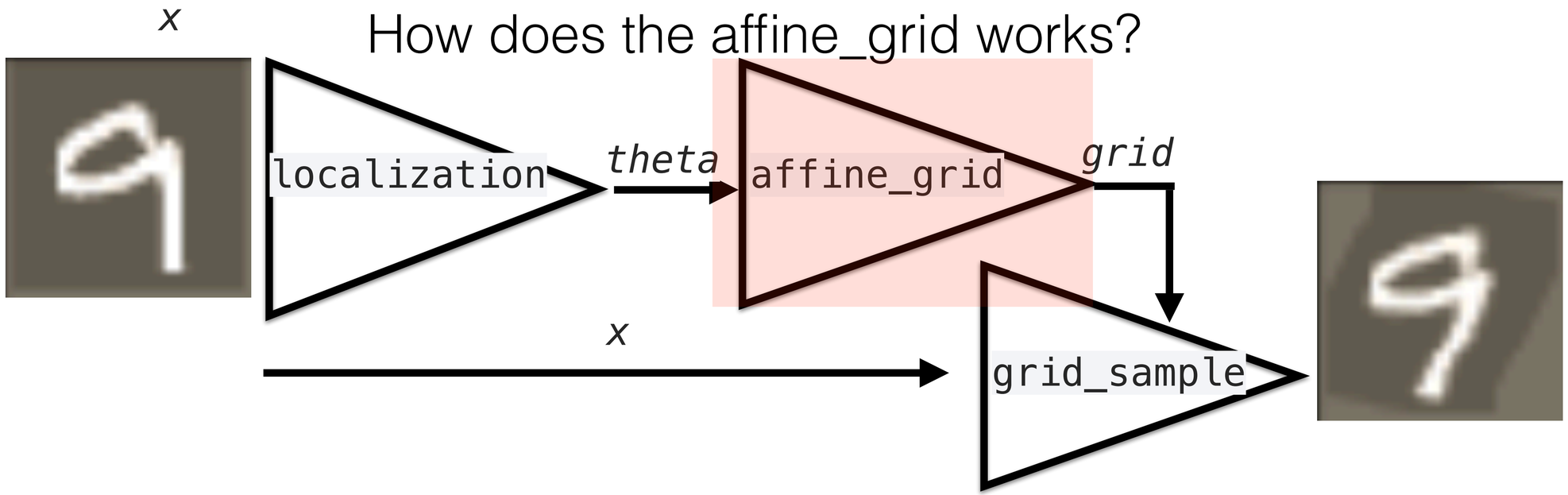
Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf

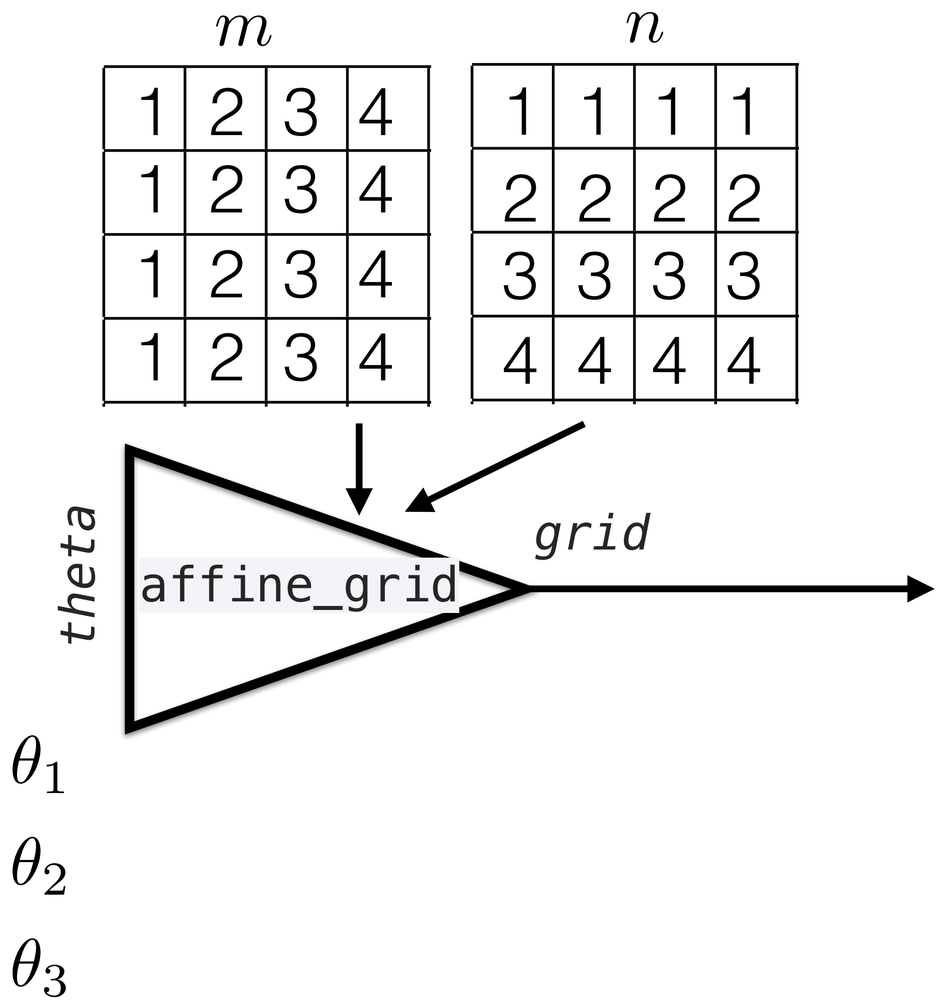
How does the affine_grid works?

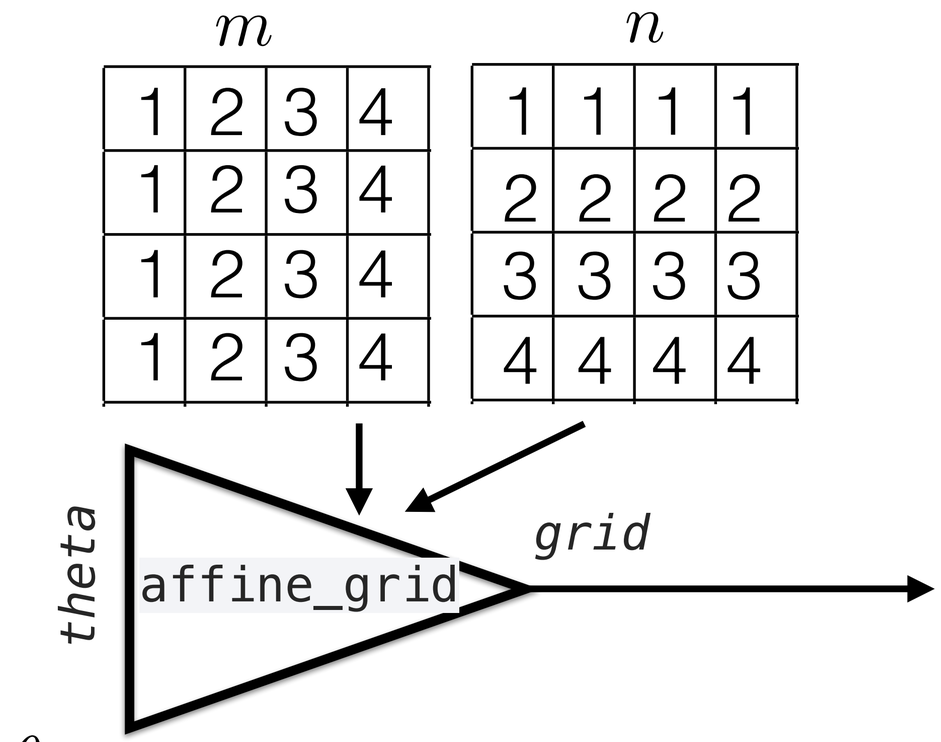


Spatial Transformer networks [Jaderberg 2016]
https://arxiv.org/pdf/1506.02025.pdf

How does the affine_grid works?




m
n
1 2 3 4
1 2 3 4
1 2 3 4
1 2 3 4
1 1 1 1
2 2 2 2
3 3 3 3
4 4 4 4
theta
affine_grid
grid
θ_1
θ_2
θ_3

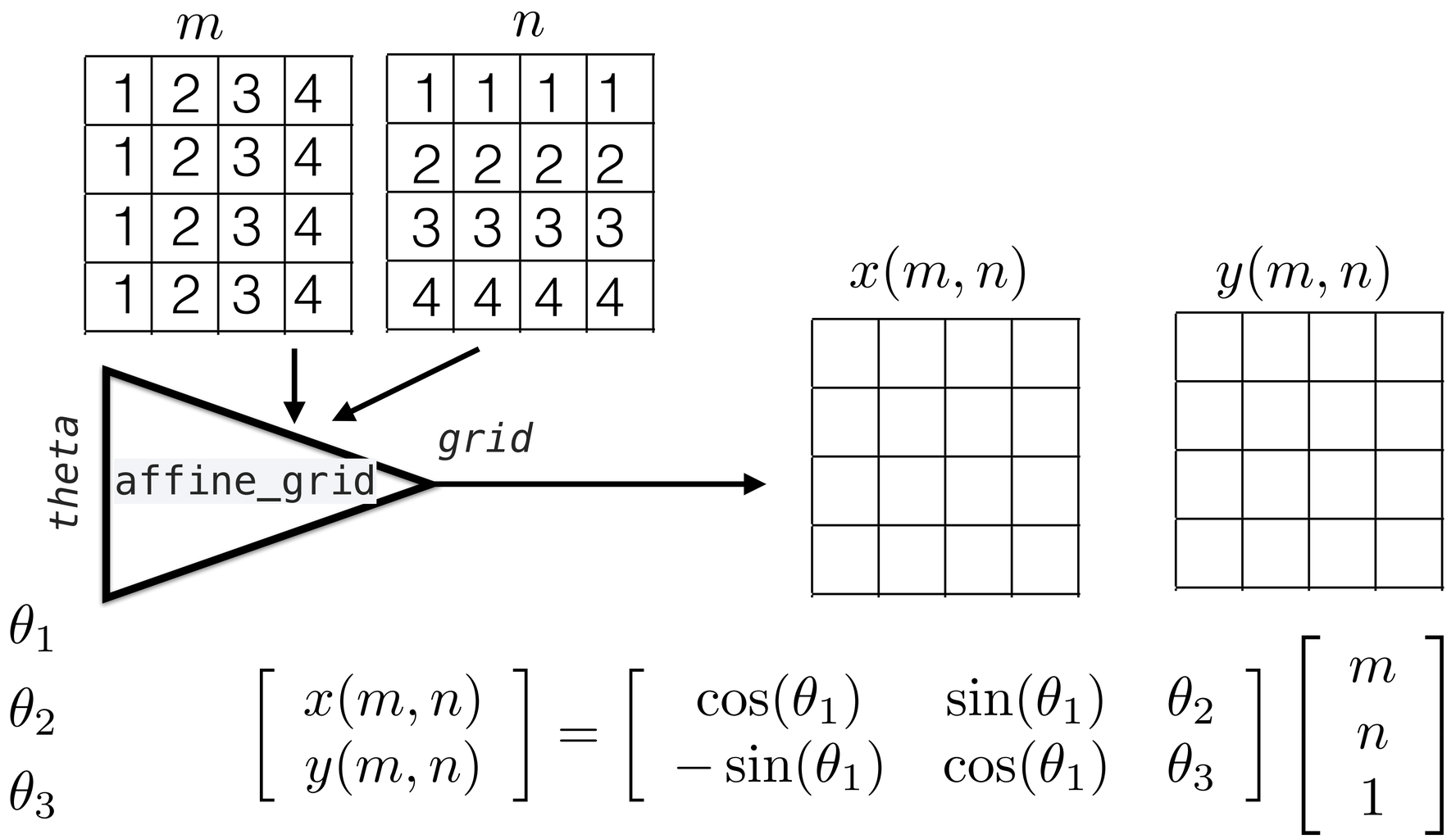


θ_1

θ_2

θ_3

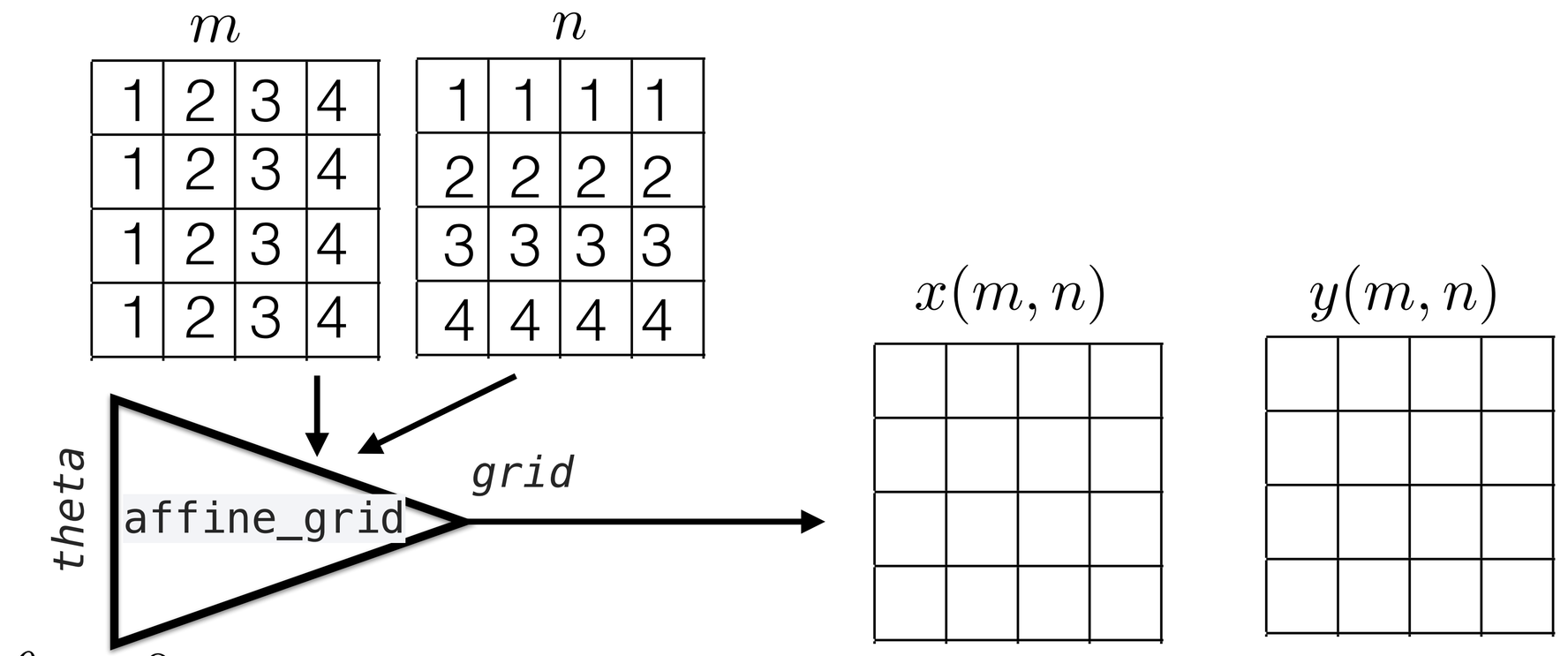
$$\begin{bmatrix} x(m,n) \\ y(m,n) \end{bmatrix} = \begin{bmatrix} \cos(\theta_1) & \sin(\theta_1) & \theta_2 \\ -\sin(\theta_1) & \cos(\theta_1) & \theta_3 \end{bmatrix} \begin{bmatrix} m \\ n \\ 1 \end{bmatrix}$$



Output arrays x(m,n) and y(m,n) say:

where should we read the output (m,n)-pixel from the original image

Can we translate image by 1 pixel up?



$$\theta_1 = 0$$
$$\theta_2 = 0$$
$$\theta_3 = 1$$

$$\begin{bmatrix} x(m,n) \\ y(m,n) \end{bmatrix} = \begin{bmatrix} \cos(\theta_1) & \sin(\theta_1) & \theta_2 \\ -\sin(\theta_1) & \cos(\theta_1) & \theta_3 \end{bmatrix} \begin{bmatrix} m \\ n \\ 1 \end{bmatrix}$$

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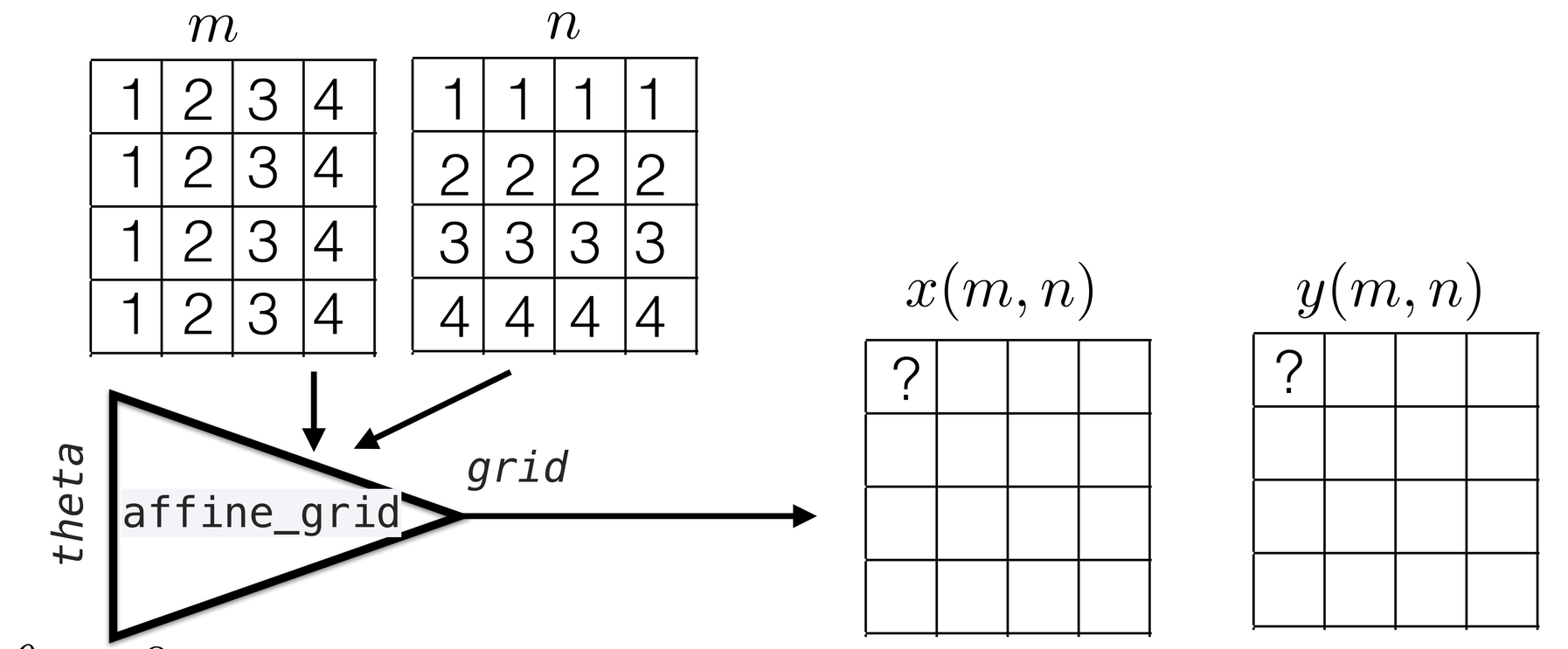


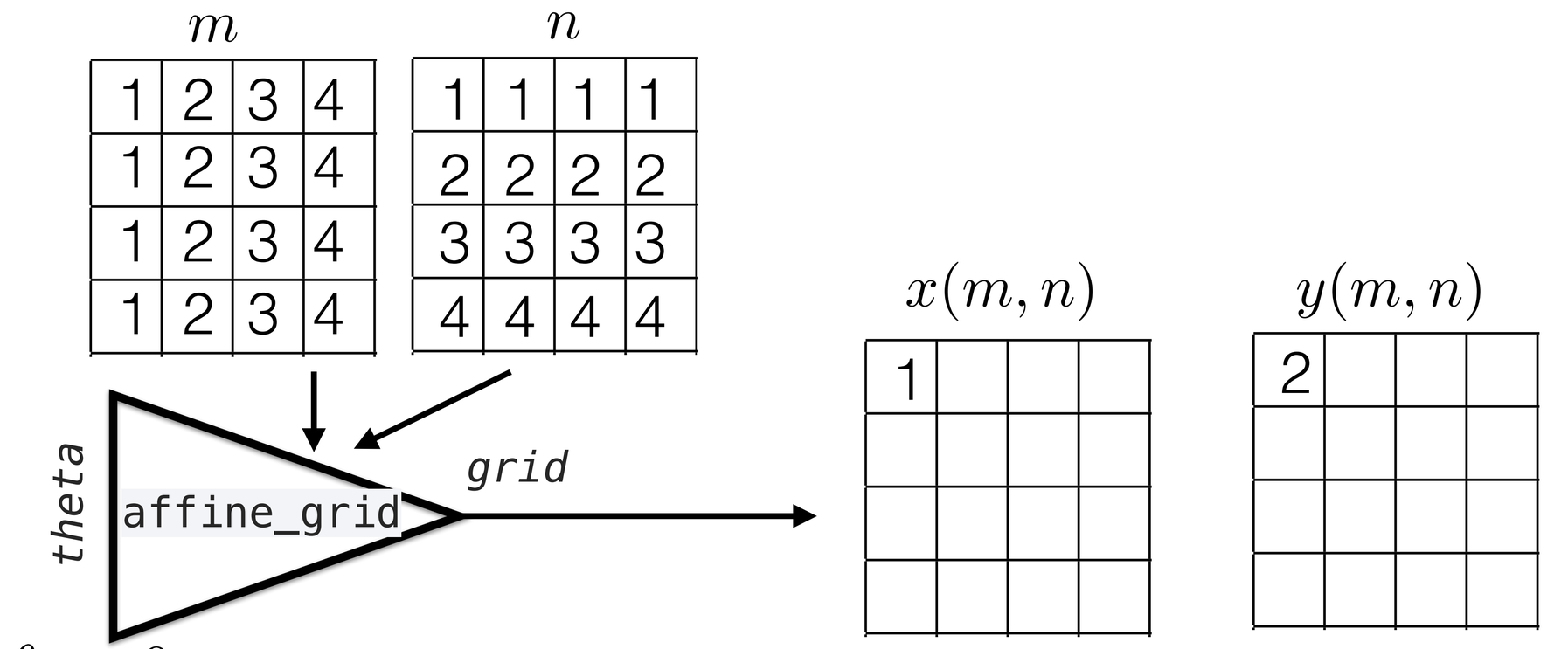
$$\theta_1 = 0$$
$$\theta_2 = 0$$
$$\theta_3 = 1$$

$$\begin{bmatrix} x(m,n) \\ y(m,n) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} m \\ n \\ 1 \end{bmatrix}$$

Output arrays x(m,n) and y(m,n) say:

where should we read the output (m,n)-pixel from the original image

Can we translate image by 1 pixel up?



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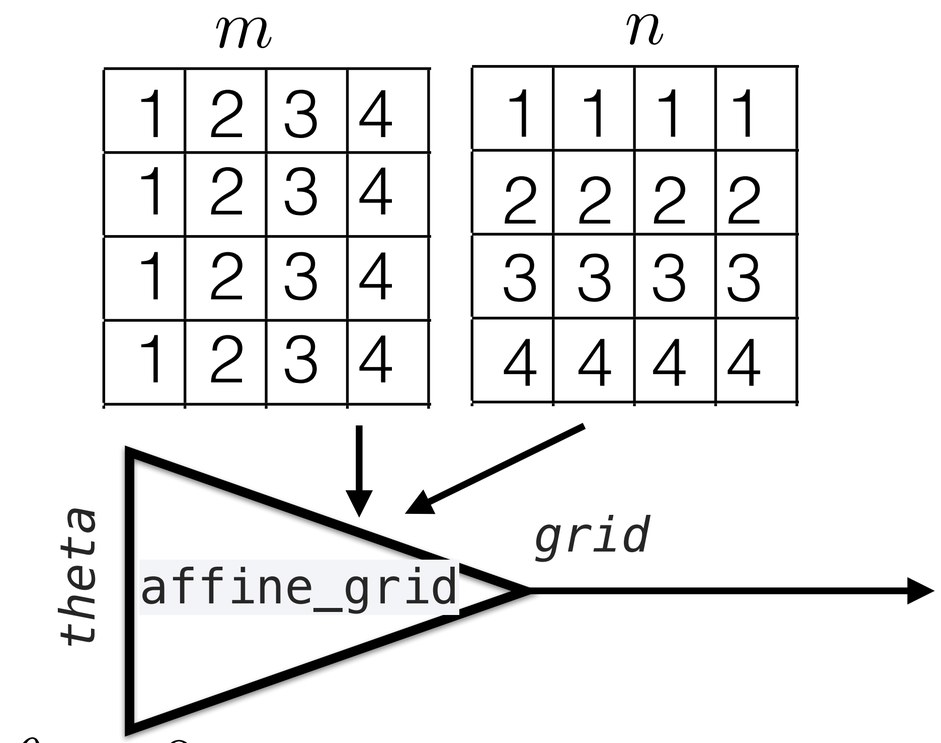

$x(m,n)$

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

$y(m,n)$

2	2	2	2
3	3	3	3
4	4	4	4
5	5	5	5

$$\theta_1 = 0$$
$$\theta_2 = 0$$
$$\theta_3 = 1$$

$$\begin{bmatrix} x(m,n) \\ y(m,n) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} m \\ n \\ 1 \end{bmatrix}$$

Output arrays x(m,n) and y(m,n) say:

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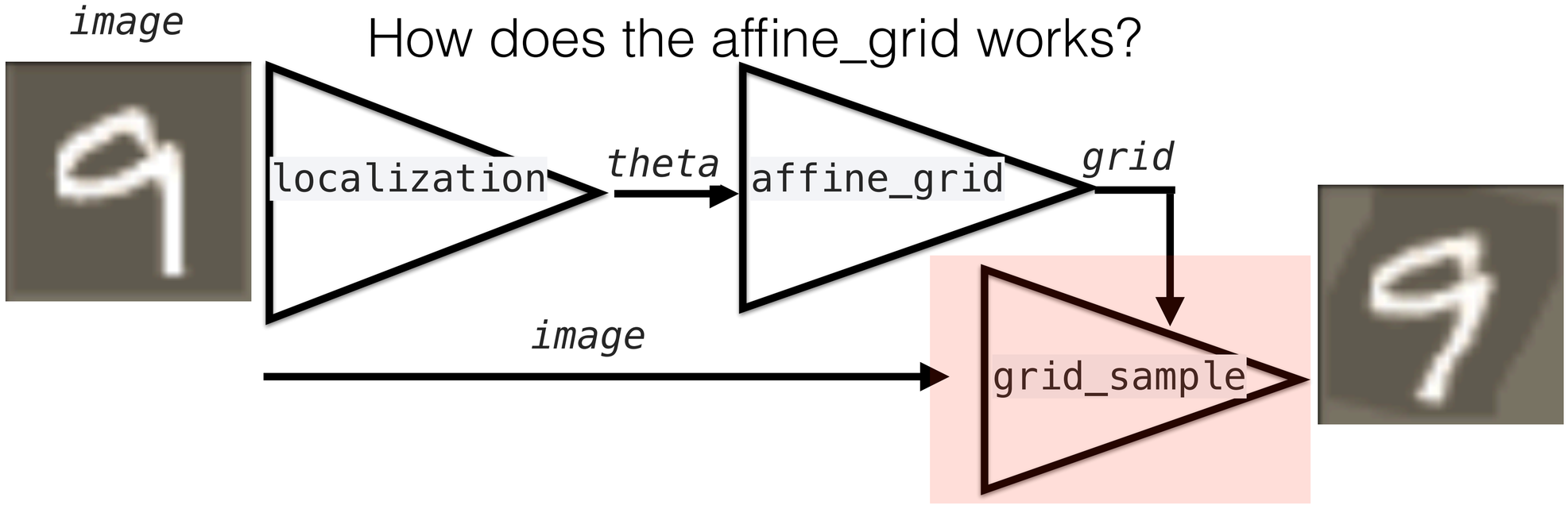
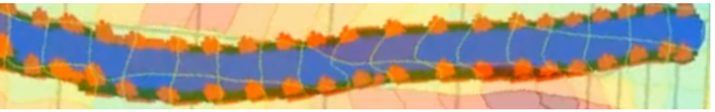


Trajectory optimization

backprop

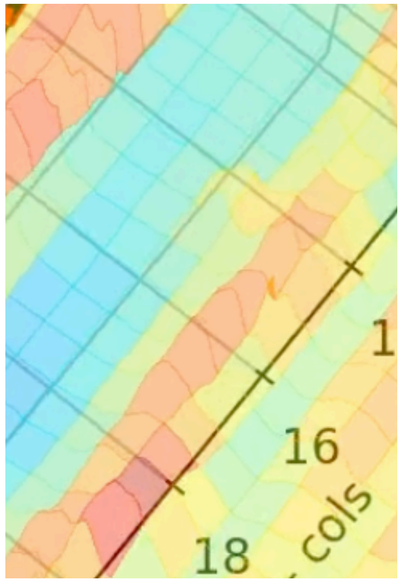
robot's *trajectory*



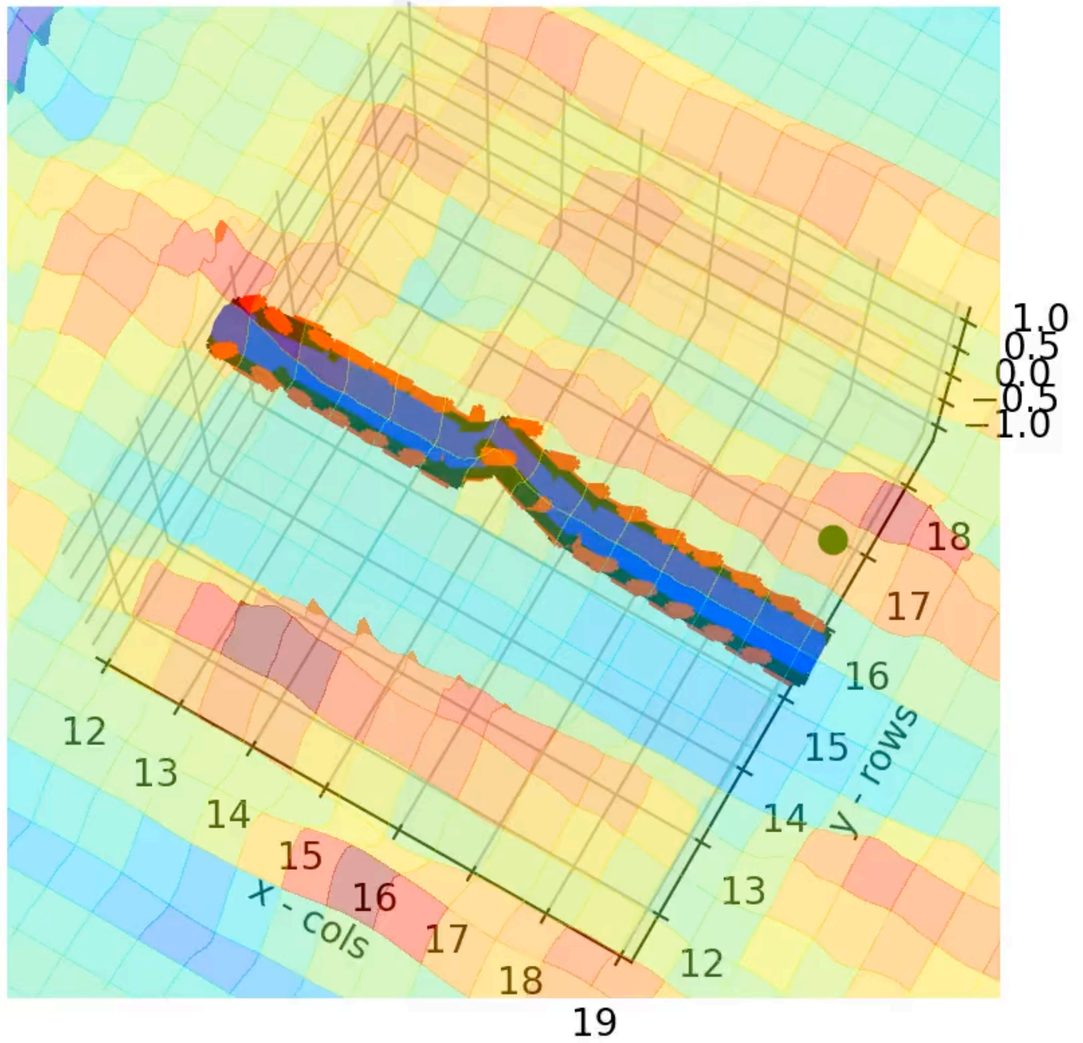
costmap

grid_sample

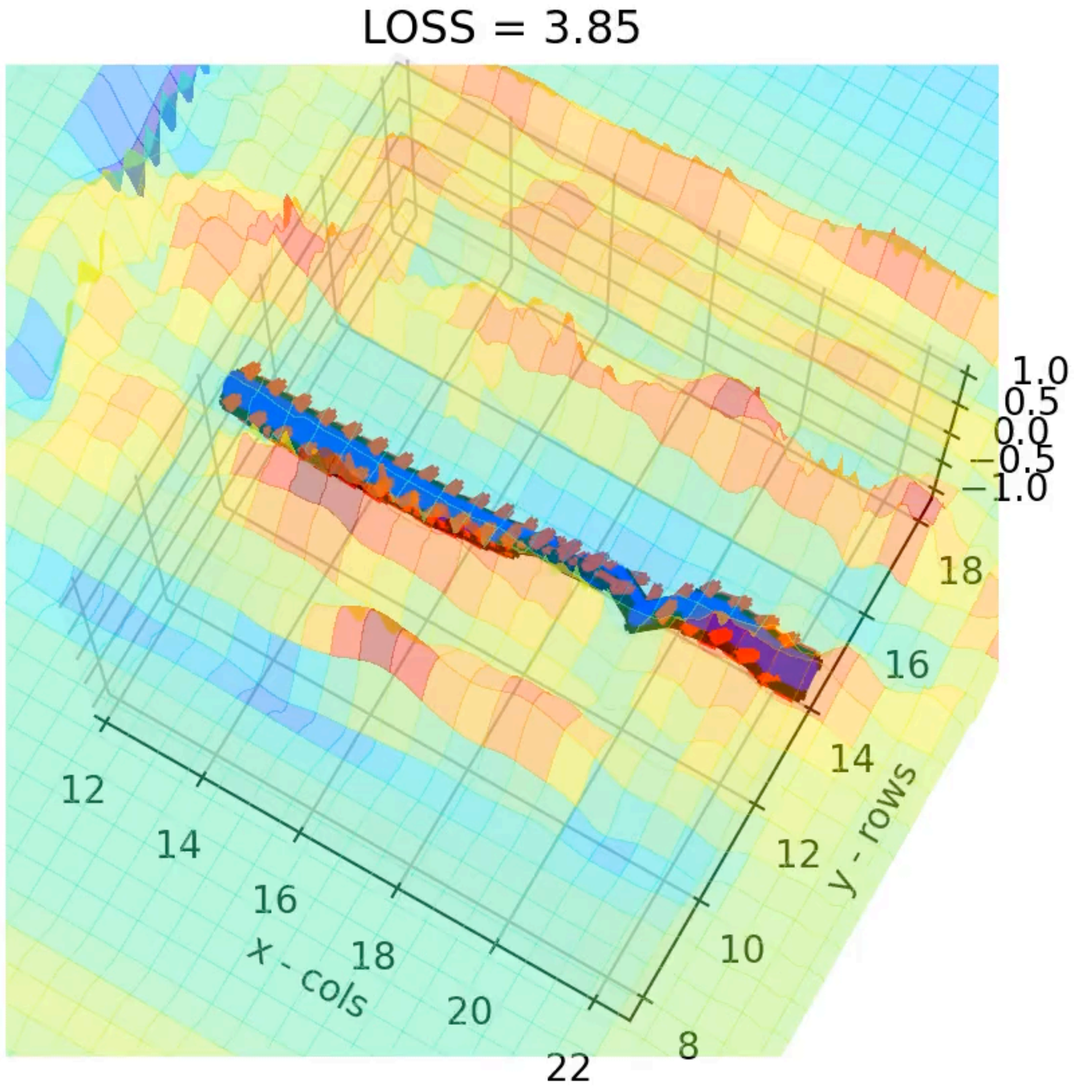
LOSS



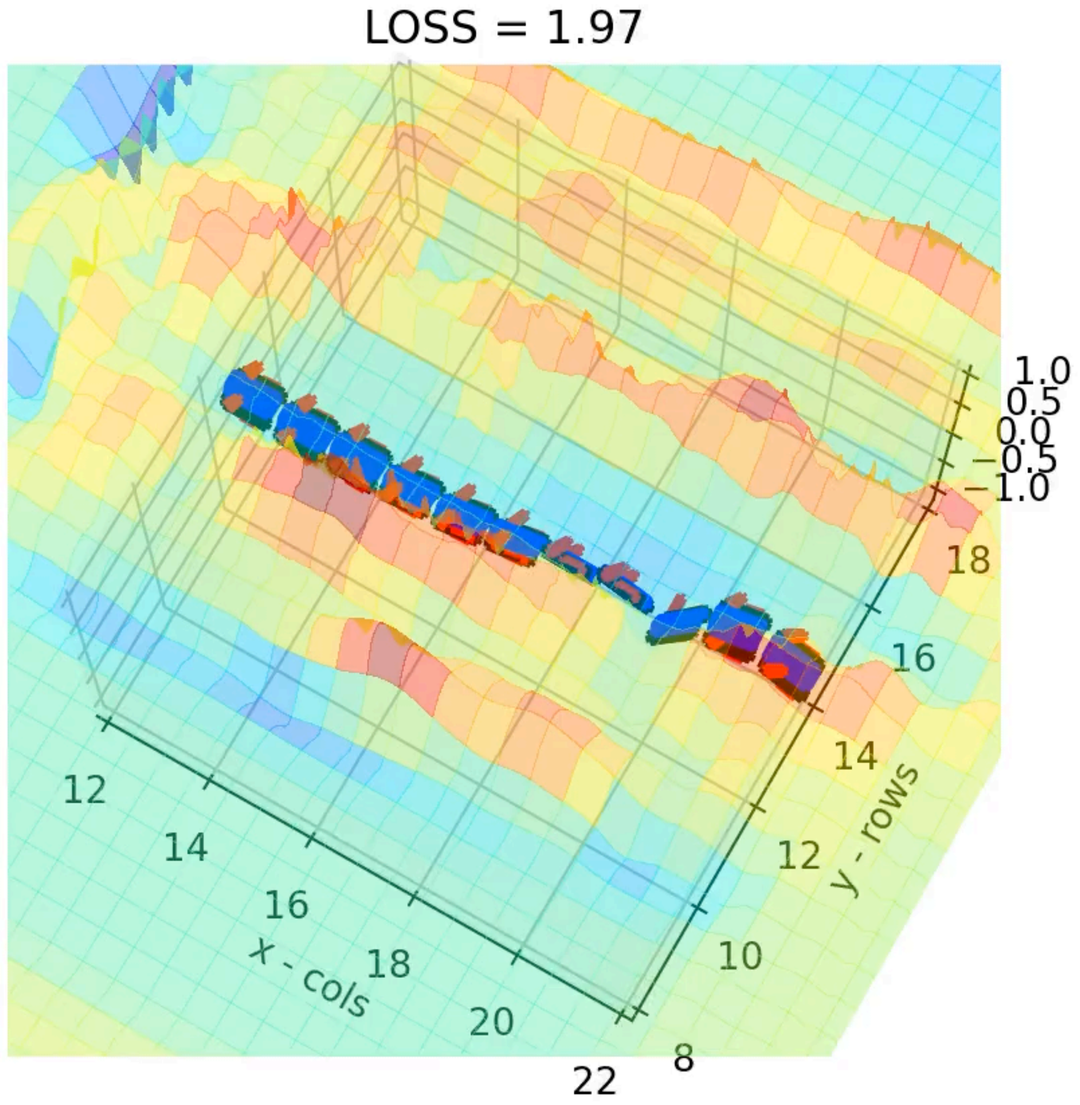
LOSS = 104.24



Trajectory optimization



dense trajectory (21 samples)



sparse trajectory (11 samples)

Summary architectures

- Deeper architectures, with small kernels, skip-connections and batch-norms (e.g. ResNet, DenseNet) seems reasonable.
- Reception field of pixels in a feature map determine their ability to infer from spatial context.
- Atrous spatial pyramid seems to be viable replacement for max-pooling
- Spatial Transform Layer allows to end-to-end differentiable spatial transformation (e.g. interpolation, cropping, projective/euclidean transformation of rigid bodies)
- A lot of dark-magic needed for successful training