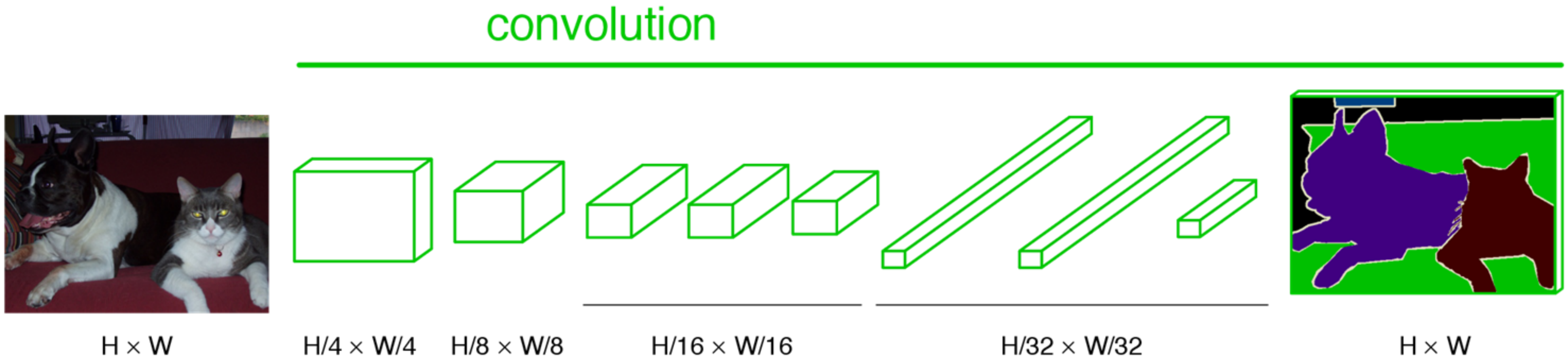
Structured Predictions with Deep Learning

James Hays

Outline – More complex outputs from deep networks

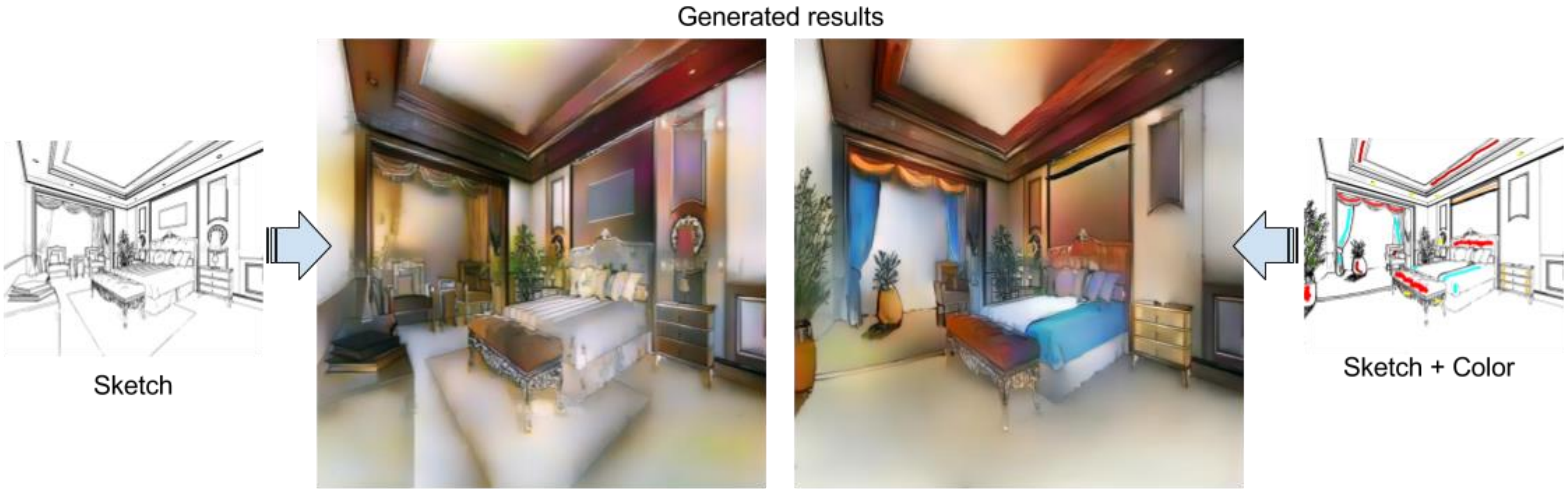
- Image Output (e.g. colorization, semantic segmentation, super-resolution, stylization, depth estimation…)
- Attributes
- Text Captions
- Semantic Keypoints
- Object Detection
  - Bounding boxes
  - Keypoint locations
  - Segmentation masks
  - 3D cuboids
  - 3D object coordinates

end-to-end, pixels-to-pixels network



What if we want other types of outputs?

- Easy*: Predict any fixed dimensional output



Scribbler: Controlling Deep Image Synthesis with Sketch and Color.
Sangkloy, Lu, Chen Yu, and Hays. CVPR 2017

*easy to design an architecture. Not necessarily easy to get working well.

What if we want other types of outputs?

- Easy: Predict a fixed number of labels. For *classification*, there will be just one best answer, but for other labels like *attributes,* dozens could be appropriate for an image.

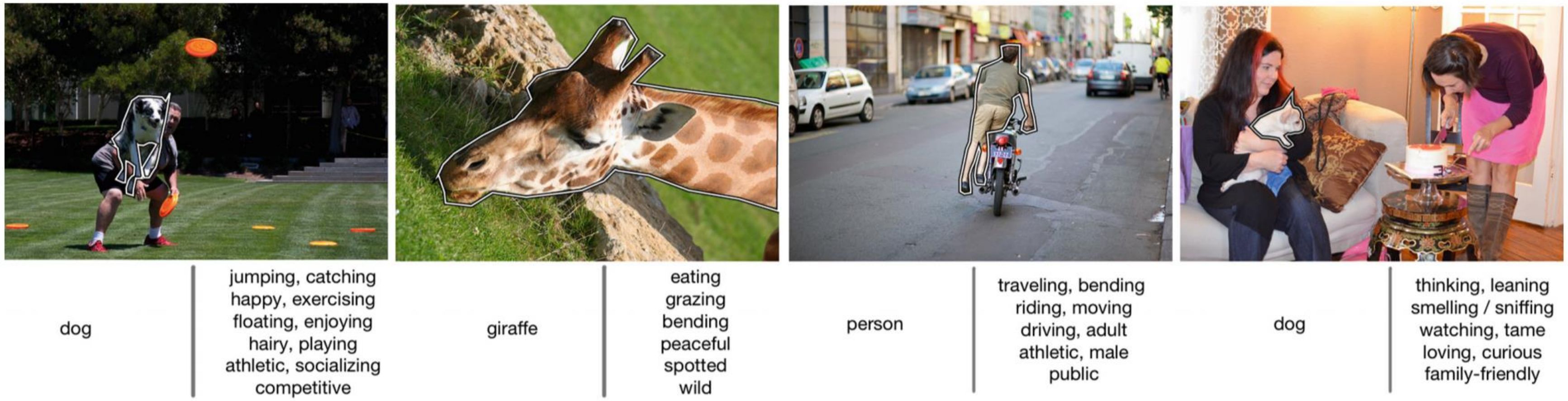


Fig. 1. *Examples from COCO Attributes.* In the figure above, images from the COCO dataset are shown with one object outlined in white. Under the image, the COCO object label is listed on the left, and the COCO Attribute labels are listed on the right.

What if we want other types of outputs?

- Hard: Outputs with varying dimensionality or cardinality
  - A natural language image caption
  - An arbitrary number of human keypoints (17 points each)
  - An arbitrary number of bounding boxes (4 parameters each) or segmentation masks (hundreds of parameters each)
- Today we will examine influential methods for keypoint prediction and object detection
  - The keypoint detection approach is *"bottom up"* and the object detection approach is *"top down"*.

Realtime Multi-Person Pose Estimation using Part Affinity Fields

Zhe Cao, Tomas Simon, Shih-En Wei, Yaser Sheikh
Carnegie Mellon University

CVPR 2017

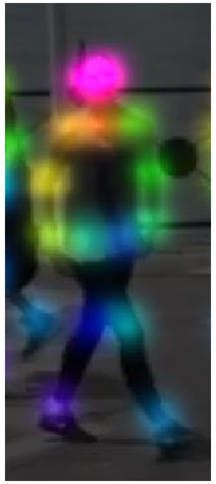
THE ROBOTICS INSTITUTE

Human Pose Estimation

Human Pose Estimation

Single-Person Pose Estimation

Single-Person Pose Estimation

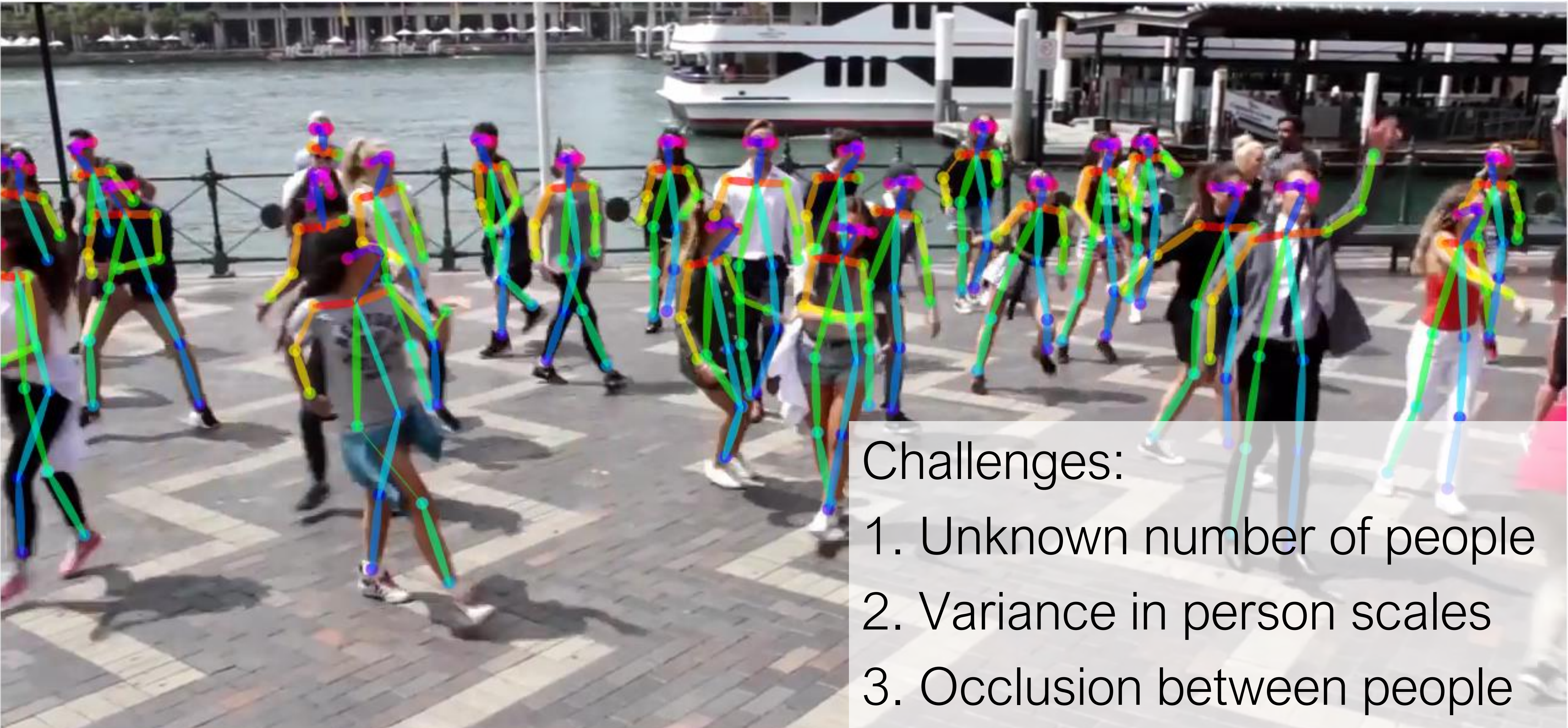


Multi-Person Pose Estimation

Multi-Person Pose Estimation

Major Challenge: Part-to-Person Association

Major Challenge: Part-to-Person Association



Challenges:

1. Unknown number of people
2. Variance in person scales
3. Occlusion between people

Major Challenge: Part-to-Person Association

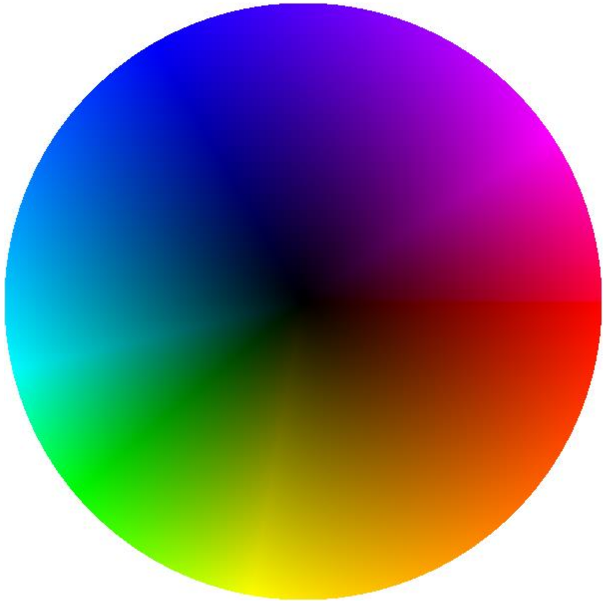
For 30 people and each with 17 joints, there are in total **1.3 x 10^5** pair-wise connection cost, NP-hard optimization

Unexpected Conclusion

Bottom-up

An **efficient** representation is **discriminative** enough that a greedy parse is sufficient to produce high-quality results

Novelty: Part Affinity Fields for Parts Association

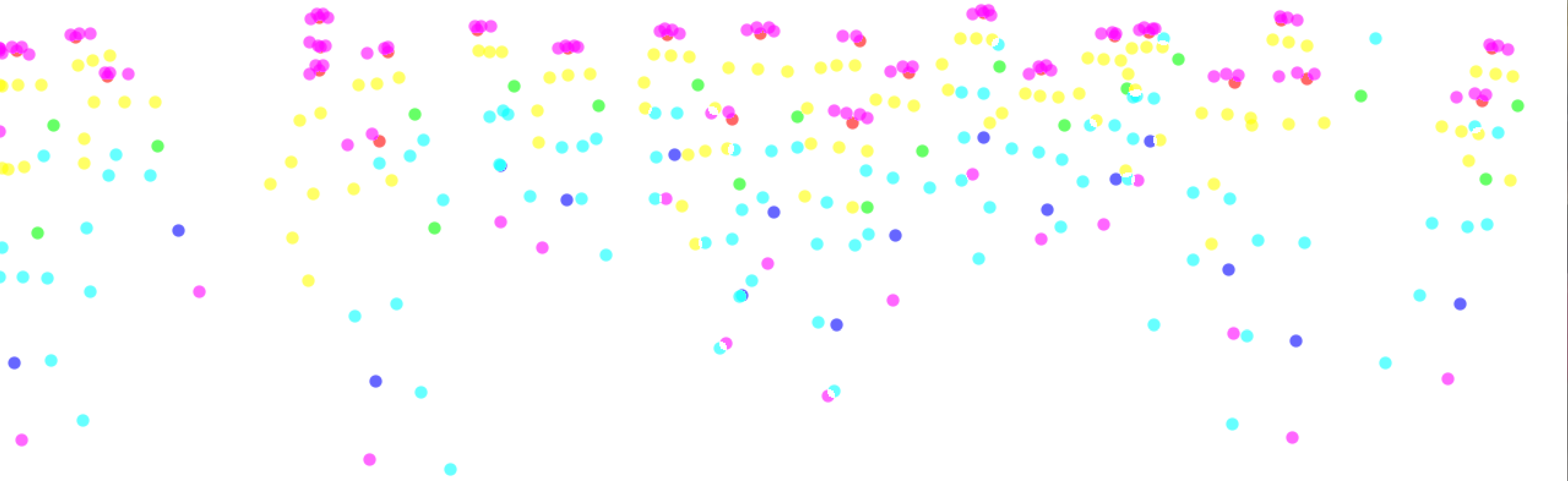


Part Affinity Field between right elbow and wrist

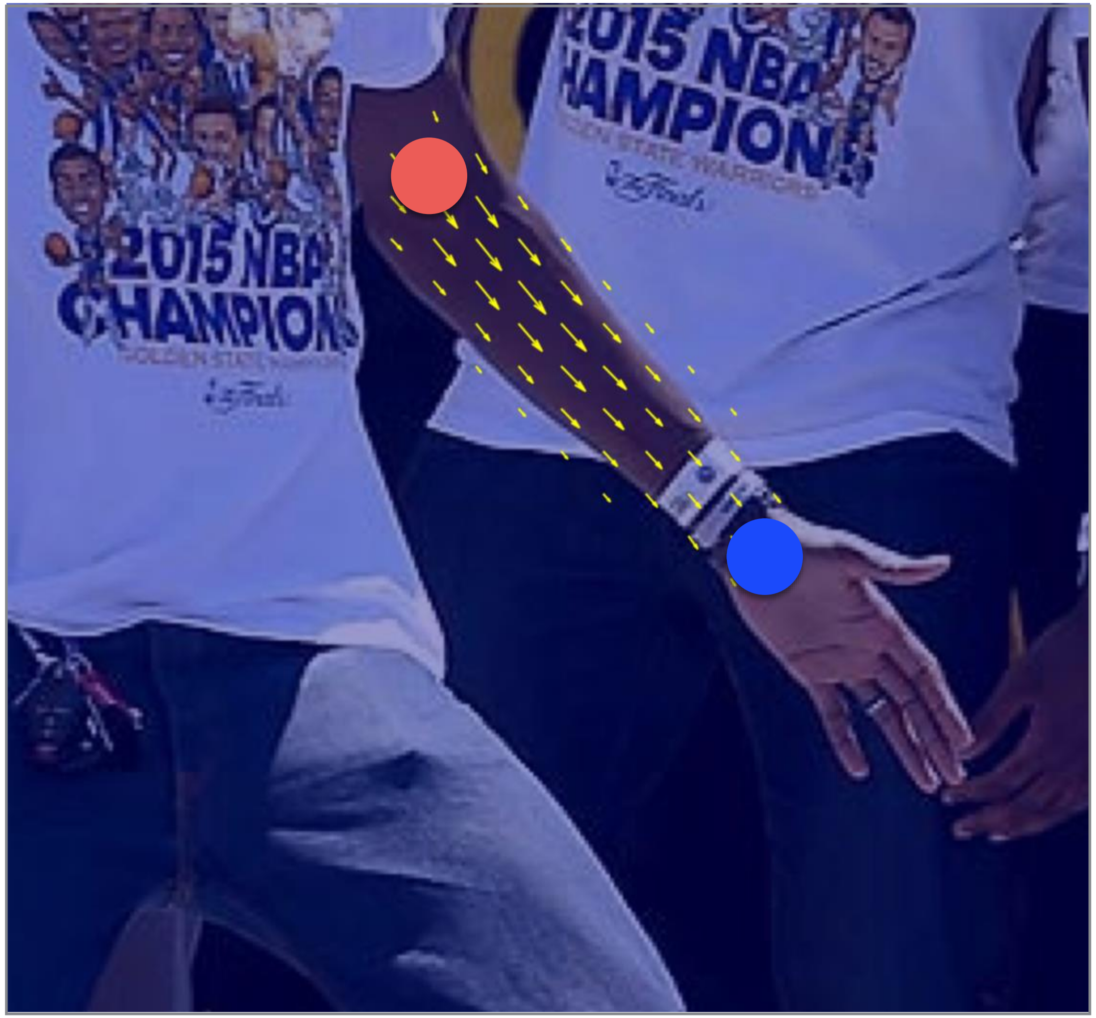
Novelty: Part Affinity Fields for Parts Association

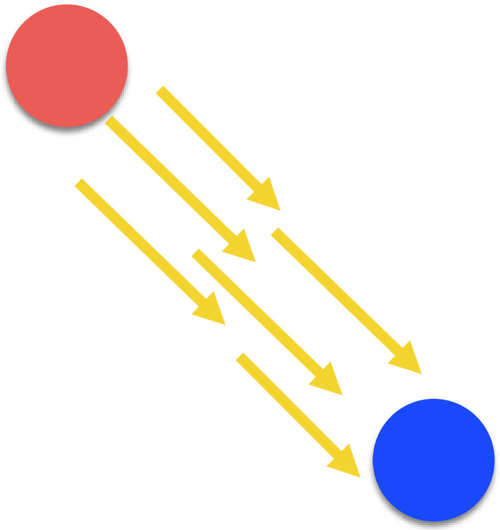
Part Affinity Field between right elbow and wrist

Novelty: Part Affinity Fields for Parts Association



Part Affinity Fields for Part-to-Part Association



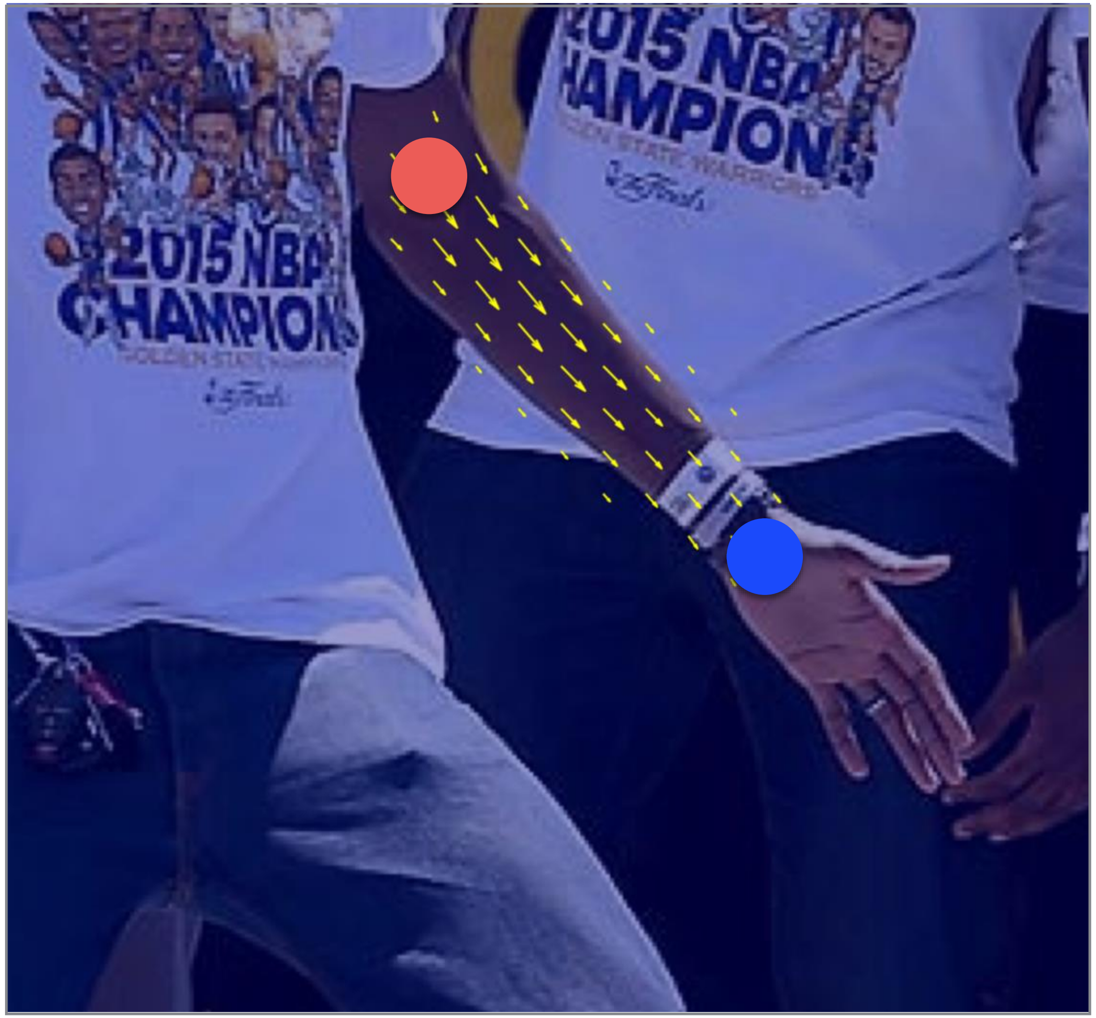


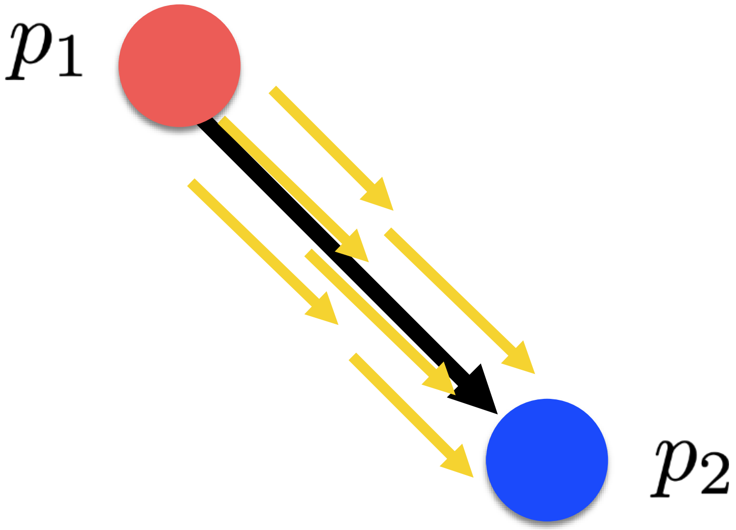
Direction vector in the PAFs

Part 1

Part 2

Part Affinity Fields for Part-to-Part Association

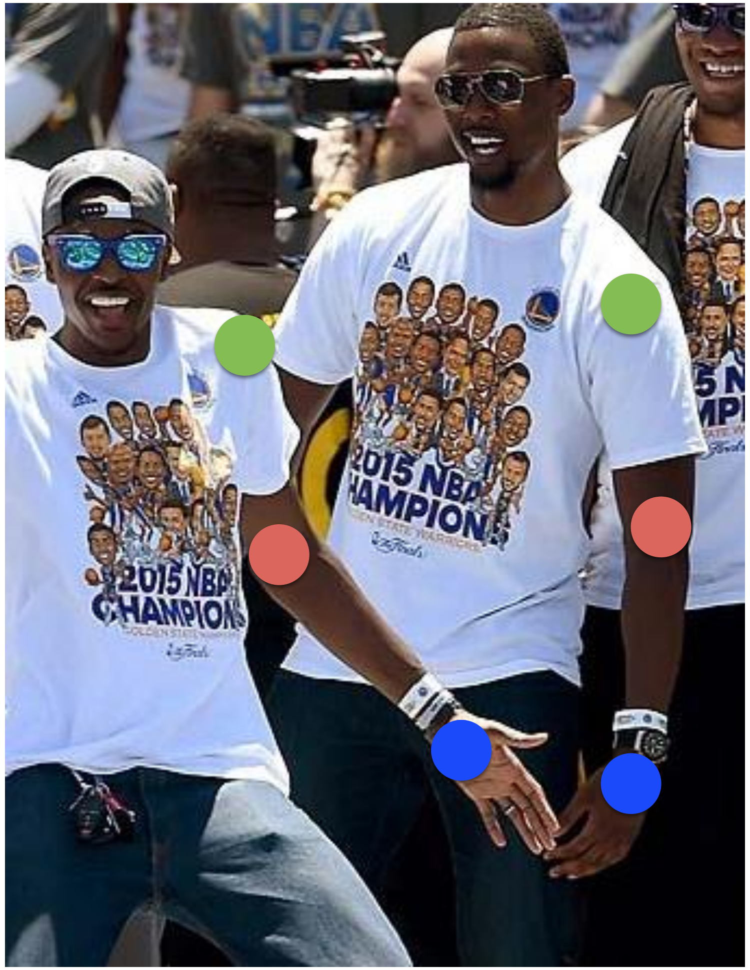




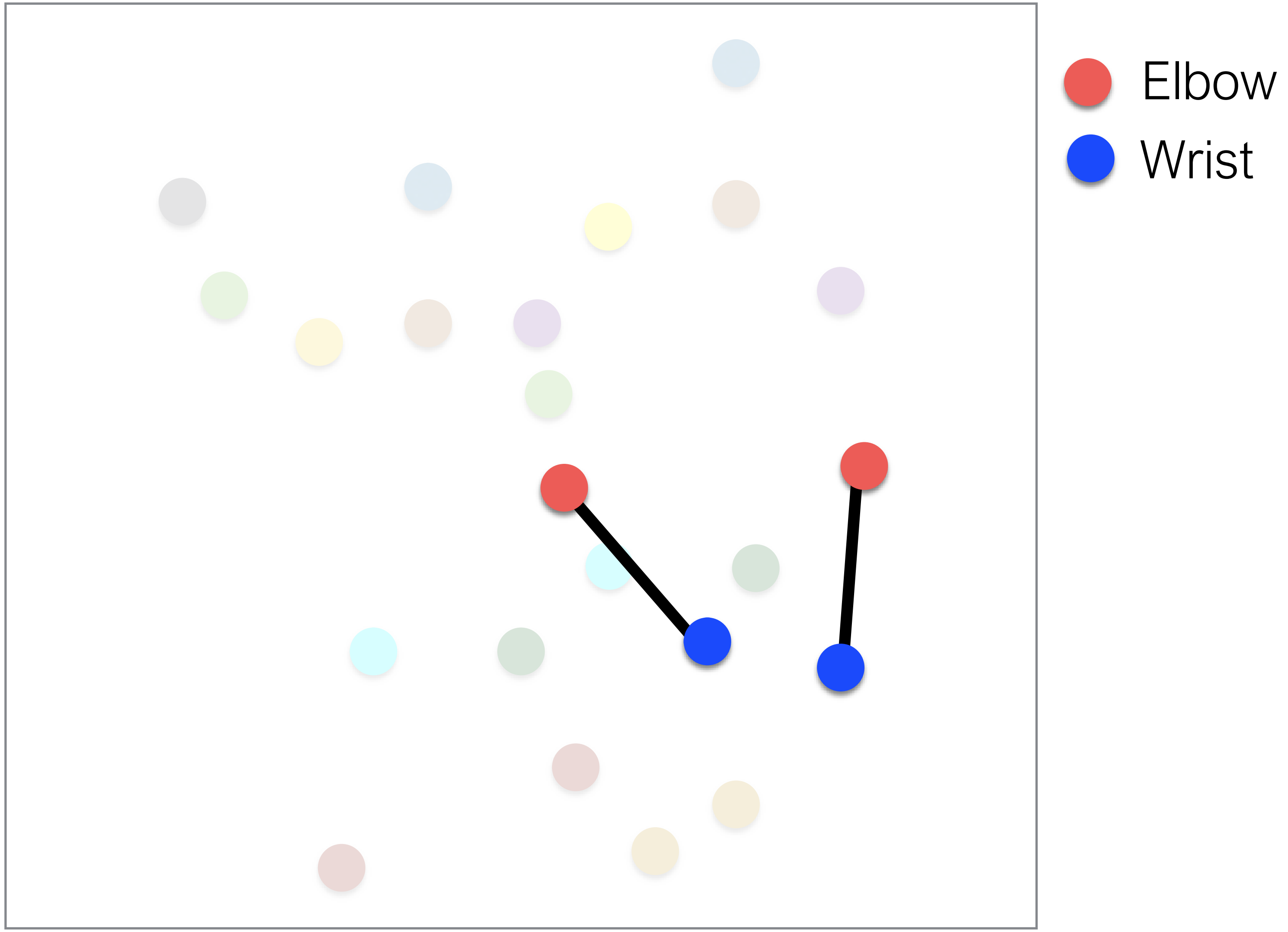
Affinity score between p_1 and p_2
$= \text{sum}(\vec{\mathbf{v}} \cdot \overrightarrow{p_1 p_2})$

Part Association for Full-body Pose

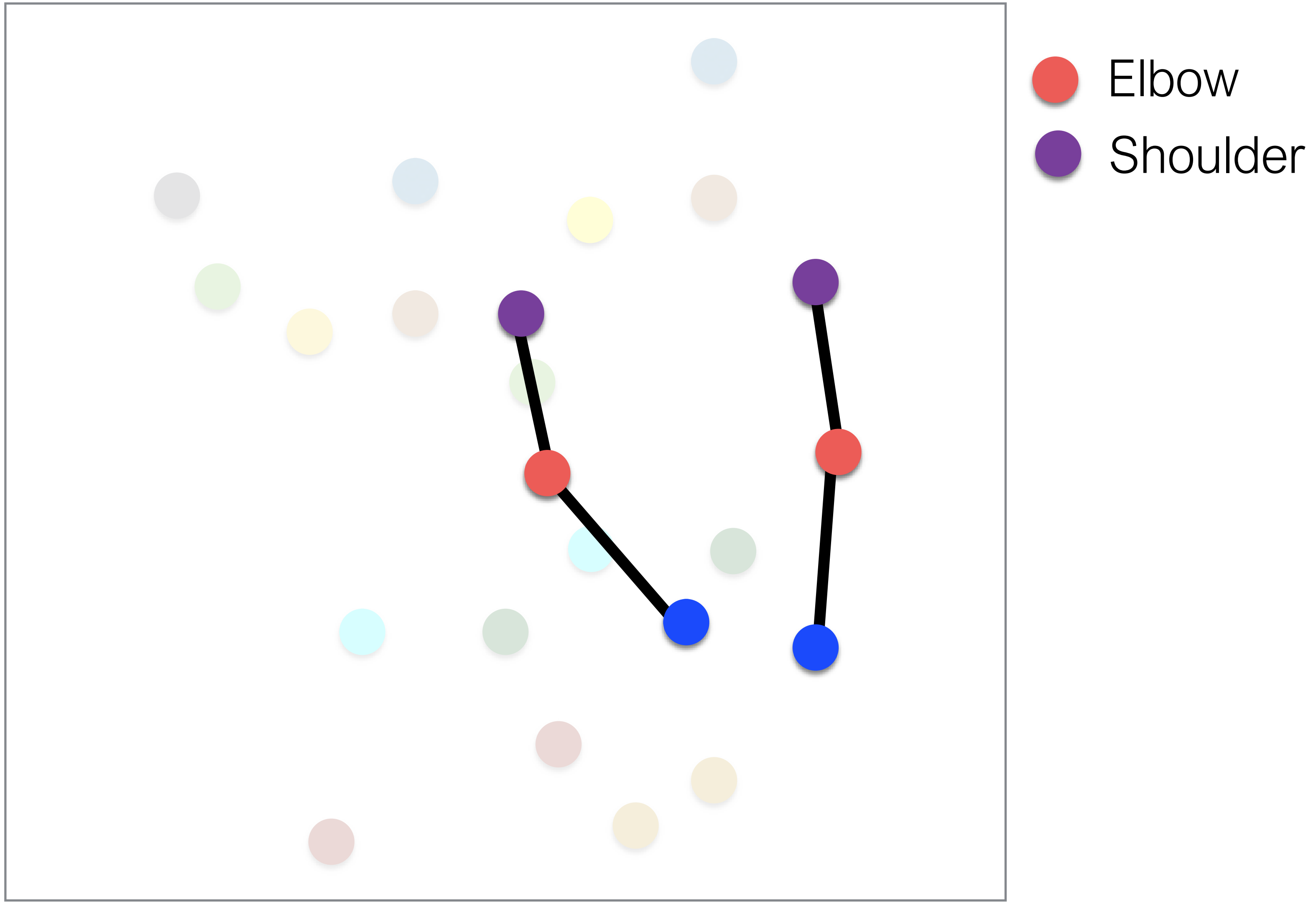
- Elbow
- Wrist
- Shoulder



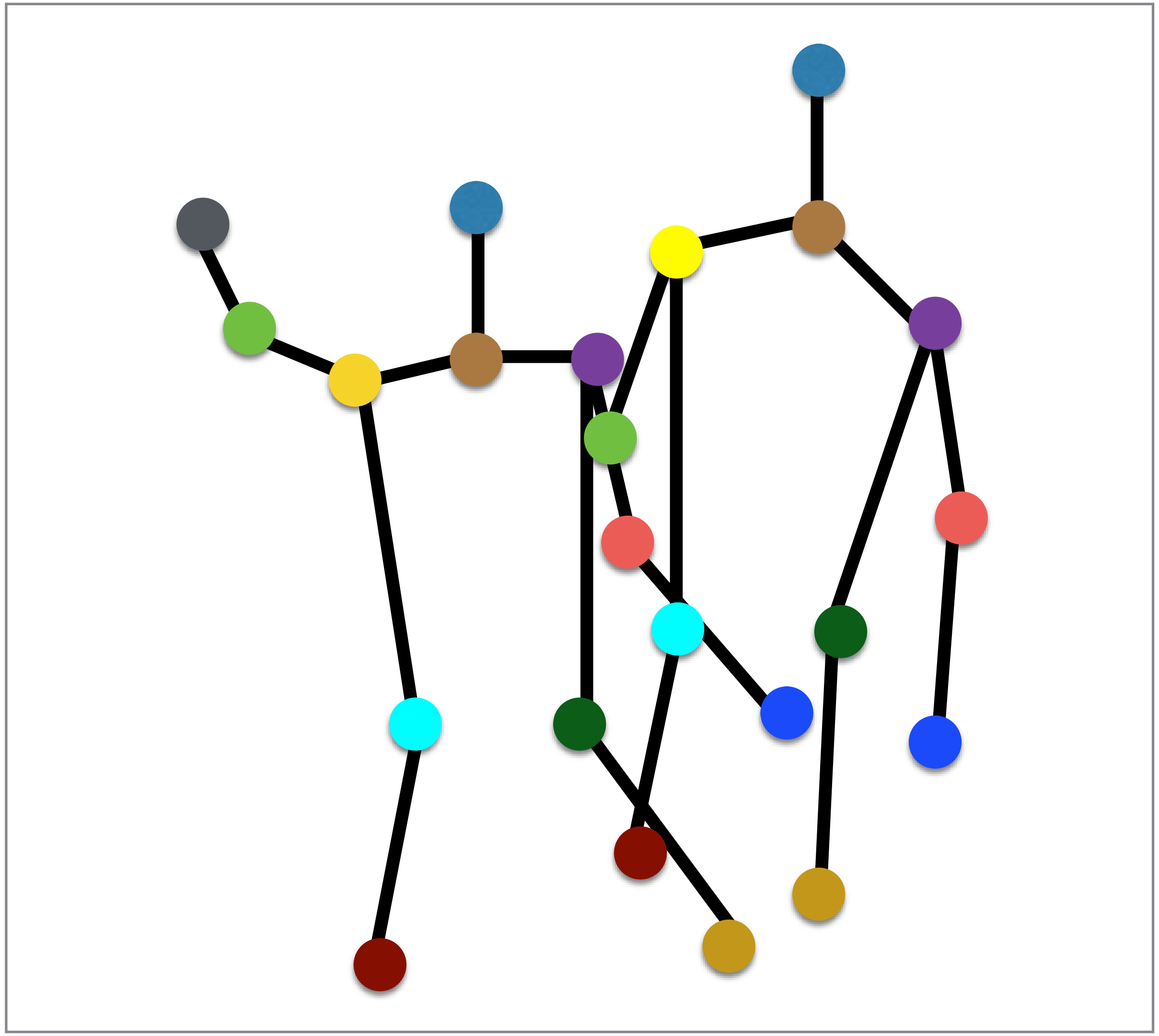
Greedy Algorithm for Body Parts Association



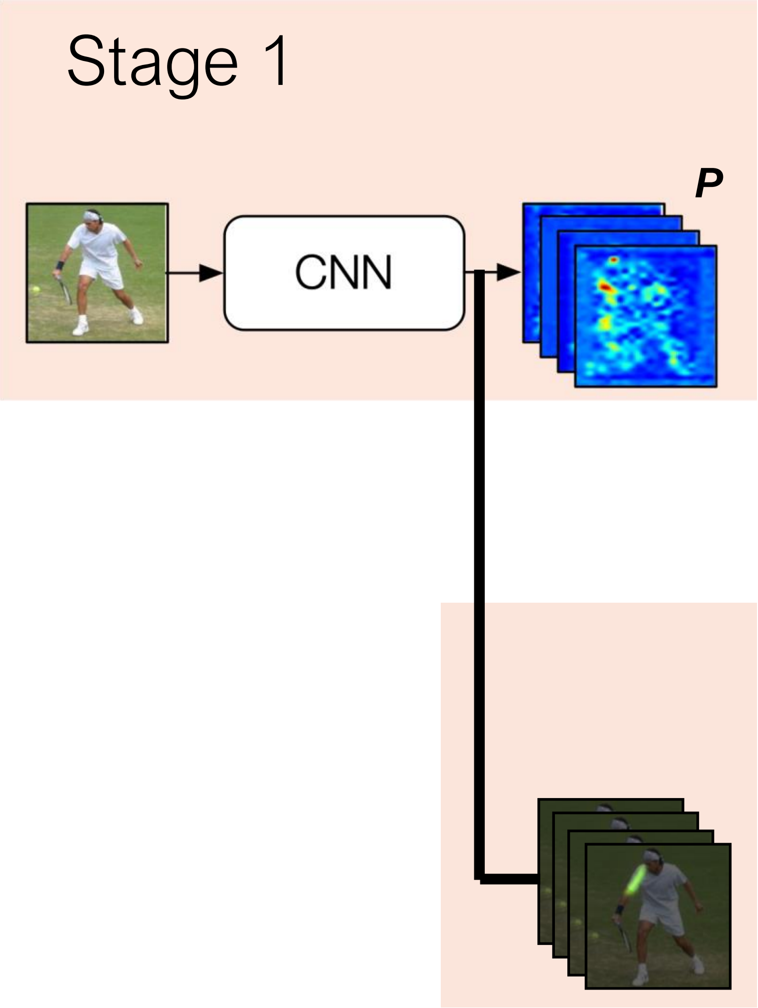
Greedy Algorithm for Body Parts Association



Greedy Algorithm for Body Parts Association



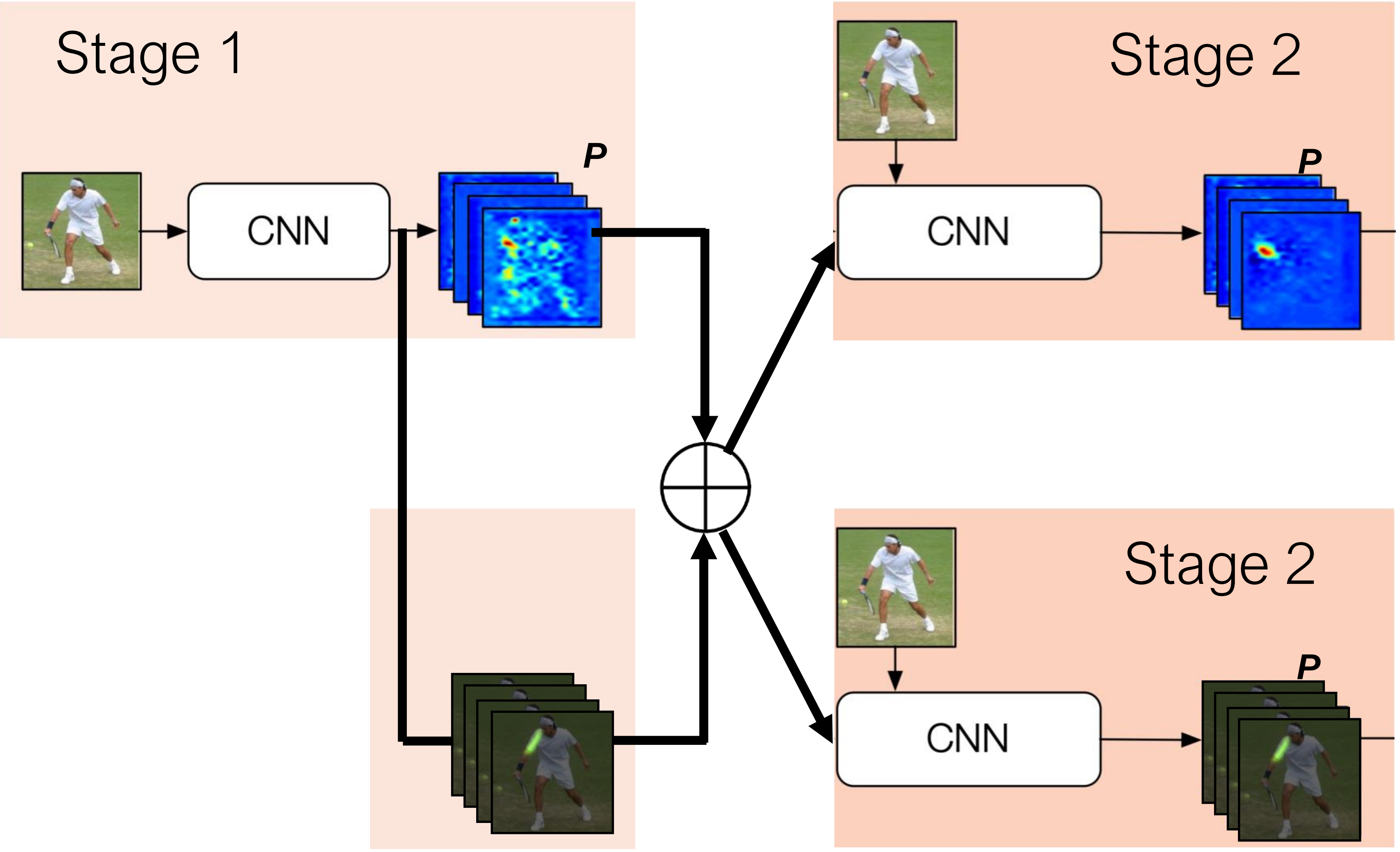
Jointly Learning Parts Detection and Parts Association



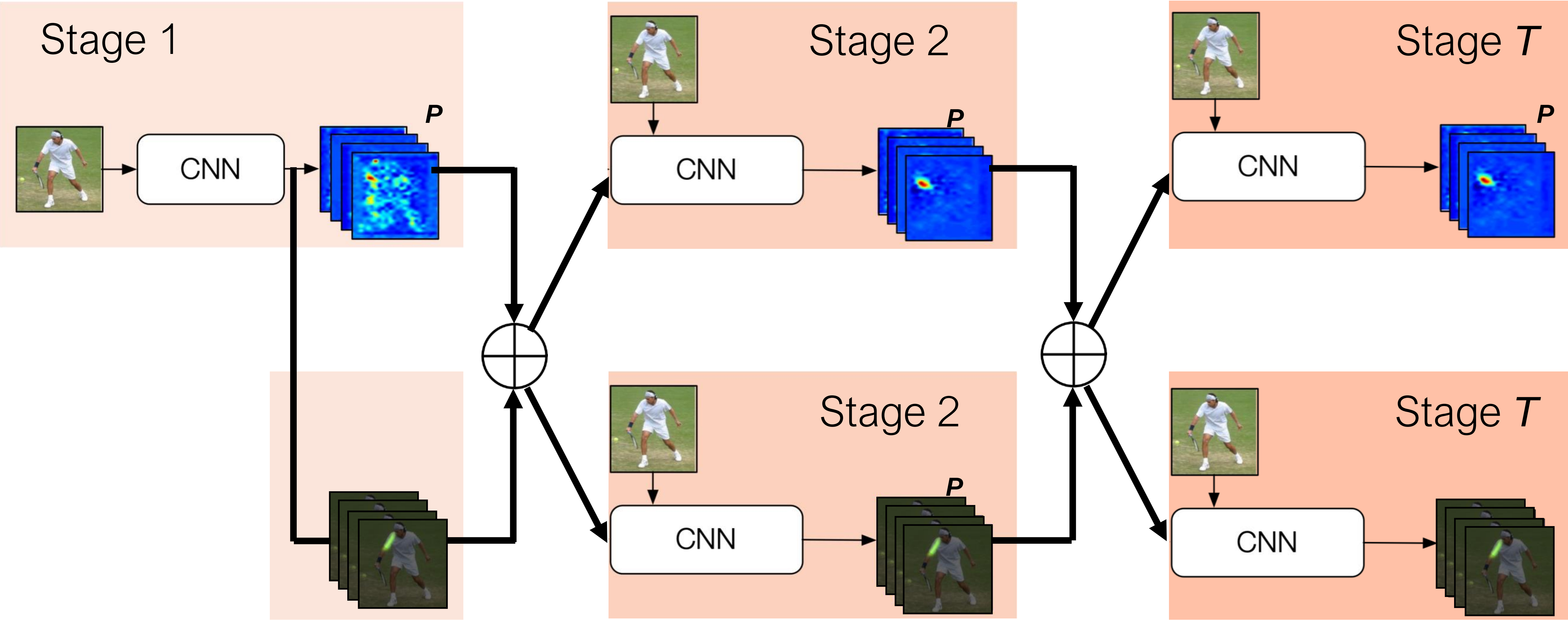
1st branch
part heatmaps

2nd branch
part affinity fields

Jointly Learning Parts Detection and Parts Association



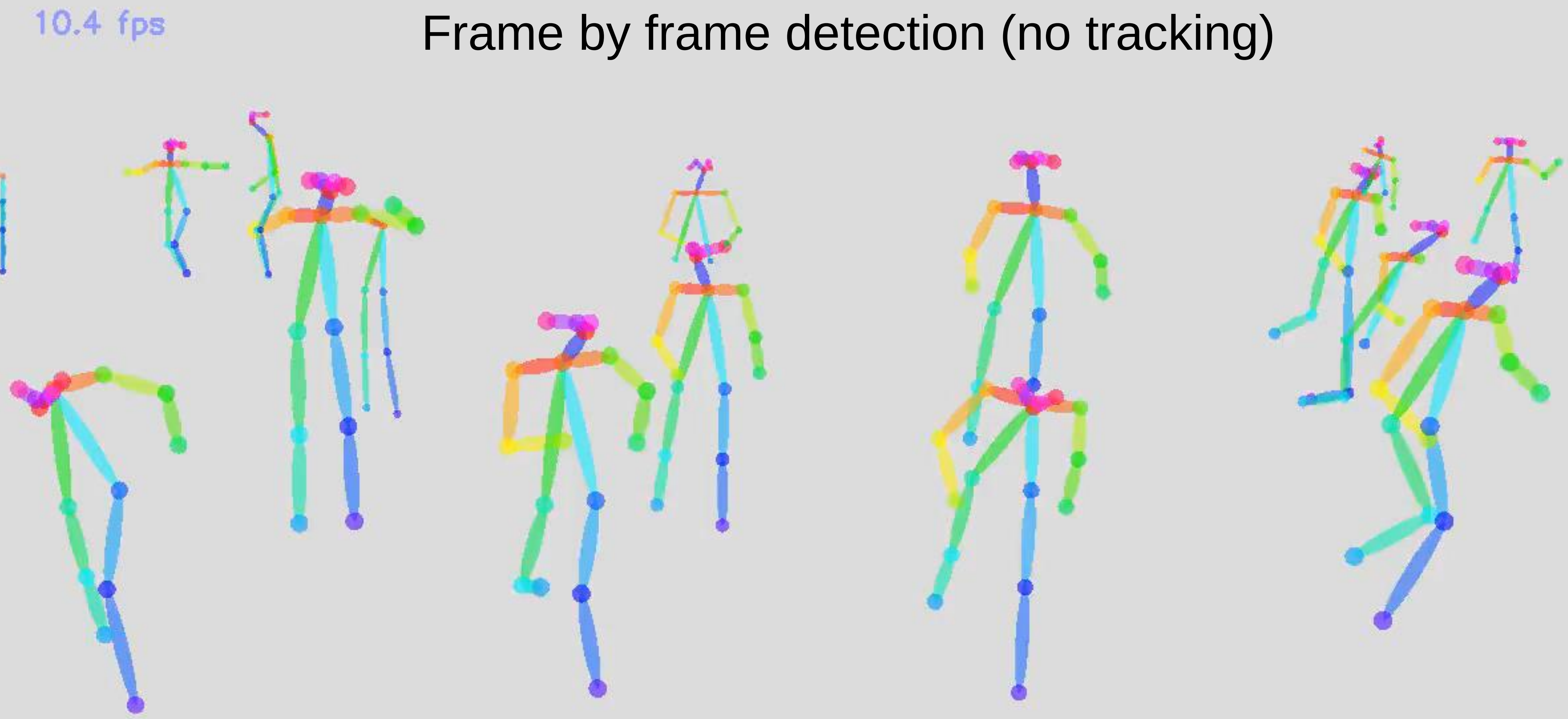
Jointly Learning Parts Detection and Parts Association




Bkg


PAFs

Frame by frame detection (no tracking)



Source: https://www.youtube.com/watch?v=2DiQUX11YaY

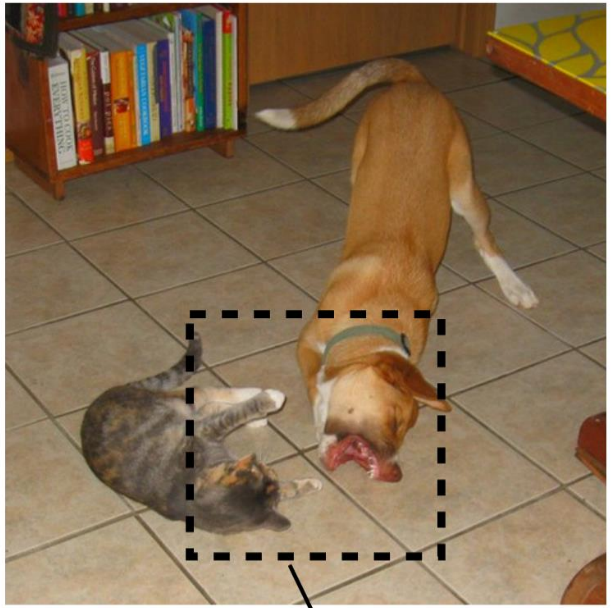
SSD: Single Shot MultiBox Detector

Wei Liu(1), **Dragomir Anguelov(2)**, Dumitru Erhan(3), Christian Szegedy(3), Scott Reed(4), Cheng-Yang Fu(1), Alexander C. Berg(1)

UNC Chapel Hill(1), **Zoox Inc.(2)**, Google Inc.(3), University of Michigan(4)

Bounding Box Prediction

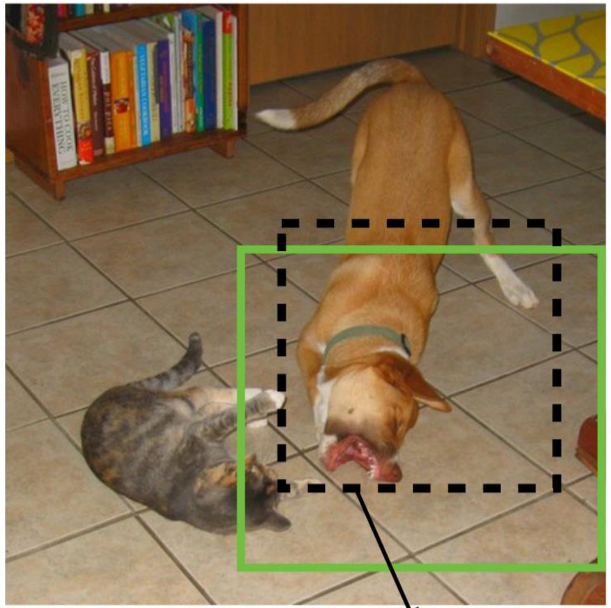
Classical sliding windows



Is it a cat? No

Discretize the box space **densely**

SSD and other deep approaches

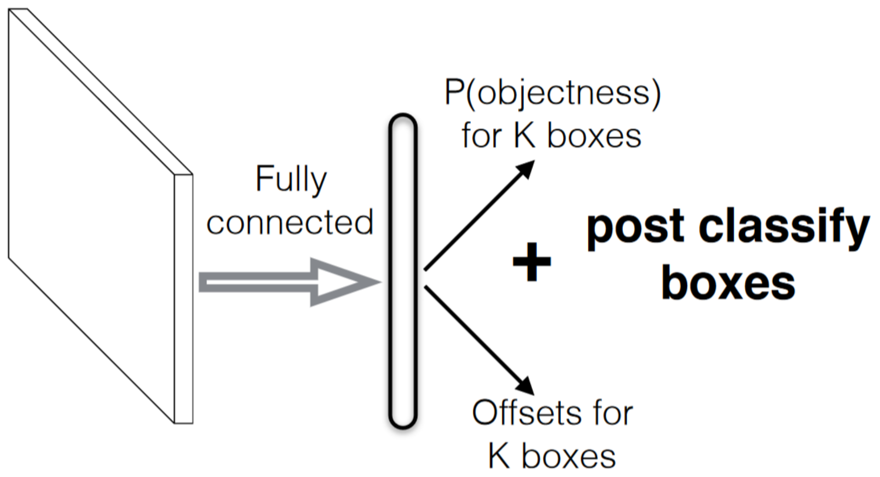


dog: 0.4 cat: 0.2

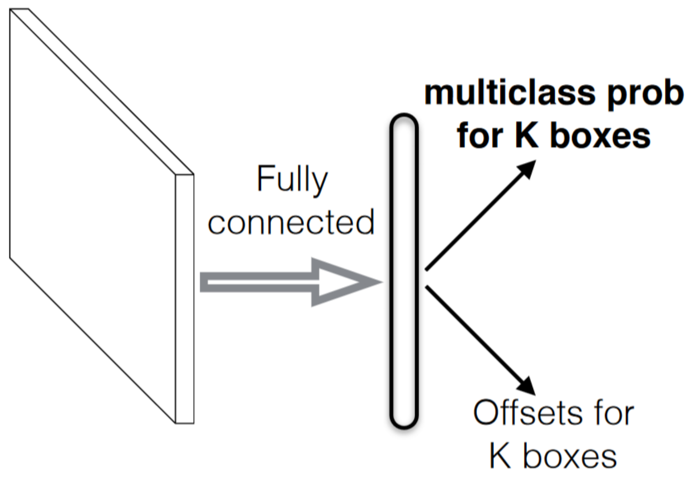
Discretize the box space more **coarsely**
Refine the coordinates of each box

Related Work

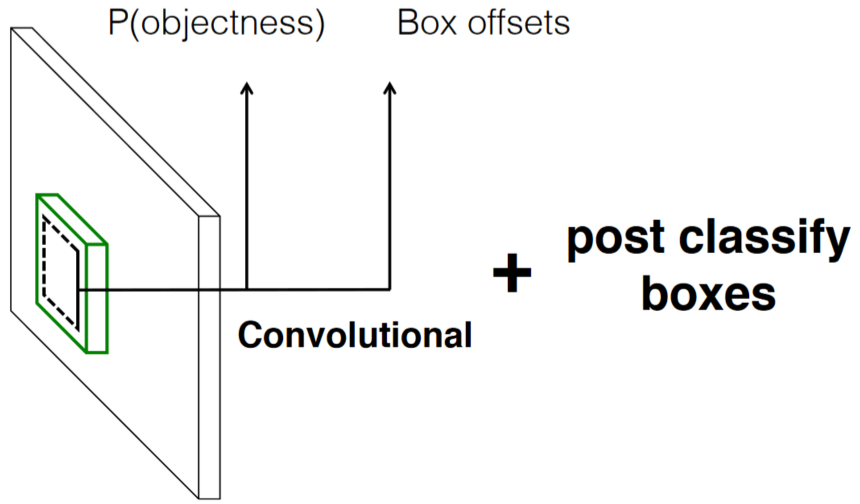
MultiBox [Erhan et al. CVPR14]



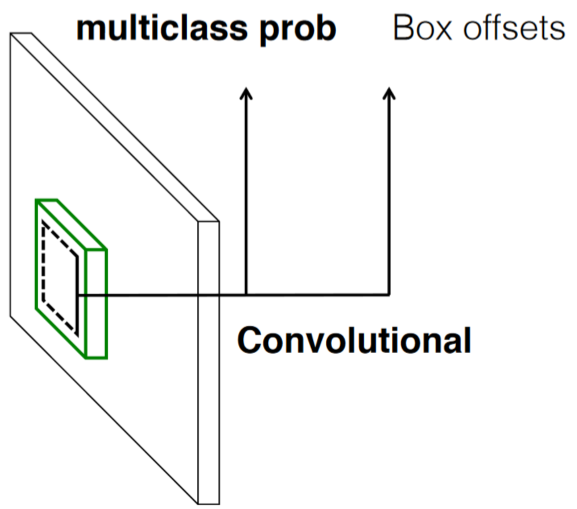
YOLO [Redmon et al. CVPR16]

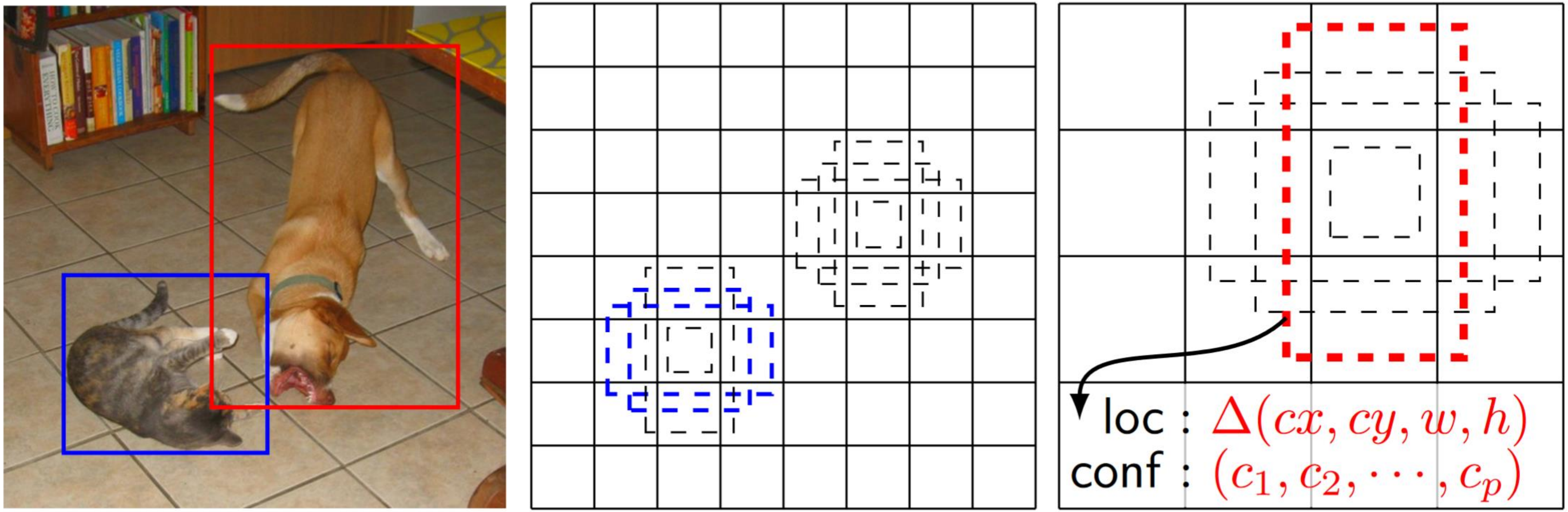


Faster R-CNN [Ren et al. NIPS15]



SSD

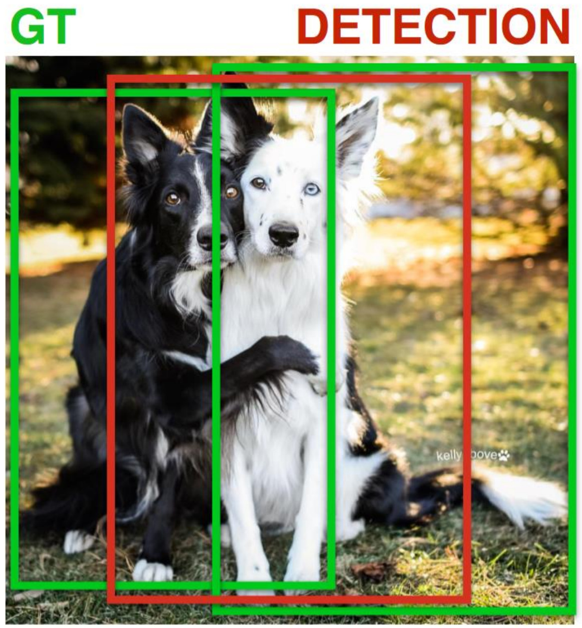




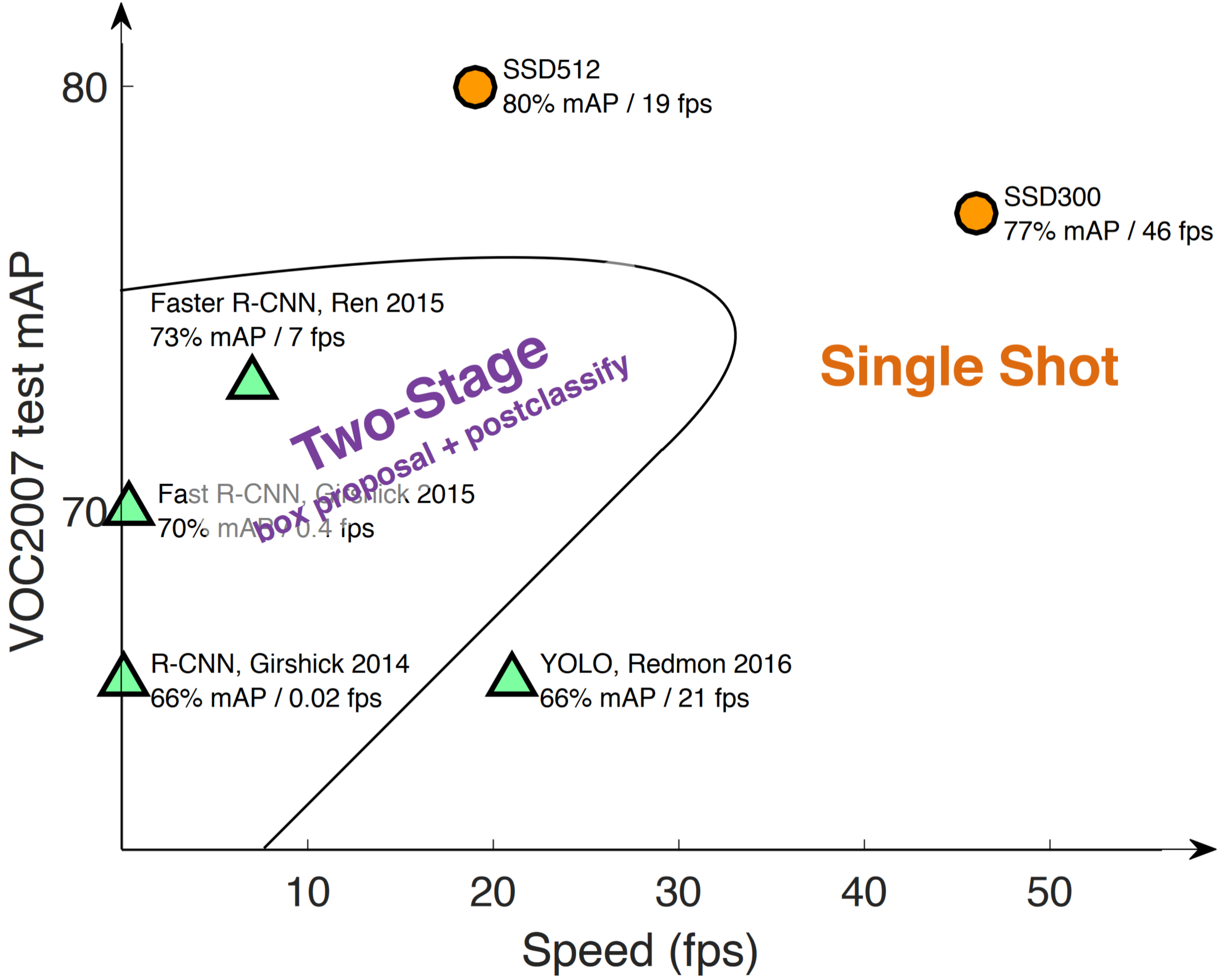
(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Why So Many Default Boxes?

	Faster R-CNN	YOLO	SSD300	SSD512
# Default Boxes	6000	98	8732	24564
Resolution	1000x600	448x448	300x300	512x512



- SmoothL1 or L2 loss for box shape averages among likely hypotheses
- Need to have enough default boxes (discrete bins) to do accurate regression in each
- General principle for regressing complex continuous outputs with deep nets



80
70
VOC2007 test mAP
SSD512
80% mAP / 19 fps
SSD300
77% mAP / 46 fps
Faster R-CNN, Ren 2015
73% mAP / 7 fps
Two-Stage
box proposal + postclassify
Single Shot
Fast R-CNN, Girshick 2015
70% mAP / 0.4 fps
R-CNN, Girshick 2014
66% mAP / 0.02 fps
YOLO, Redmon 2016
66% mAP / 21 fps
10
20
30
40
50
Speed (fps)

Mask R-CNN

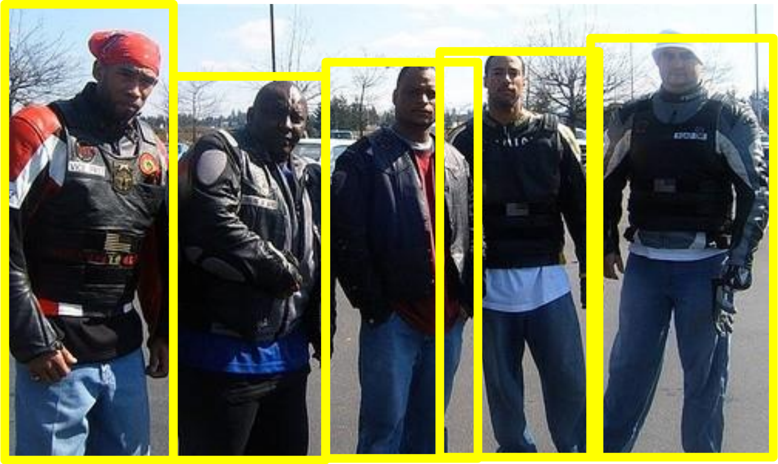
ICCV 2017

Kaiming He,

Georgia Gkioxari, Piotr Dollár, and Ross Girshick

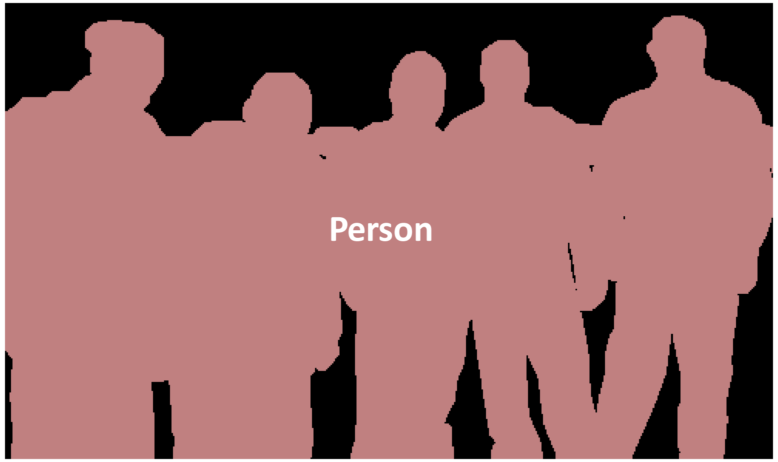
Facebook AI Research (FAIR)

Visual Perception Problems



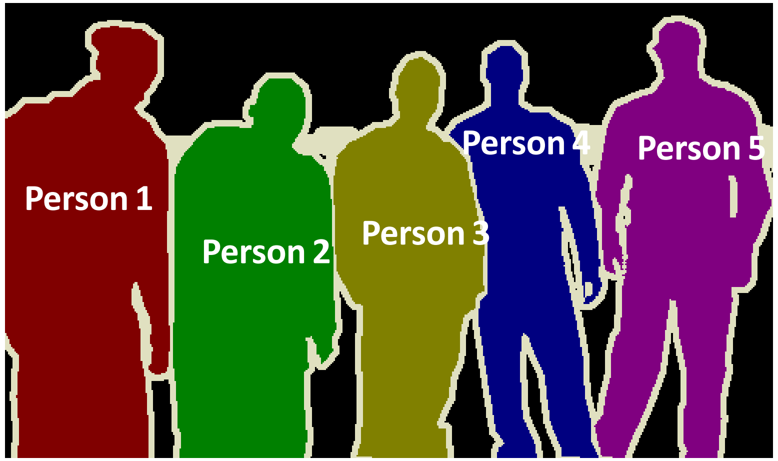
Object Detection

✓



Semantic Segmentation

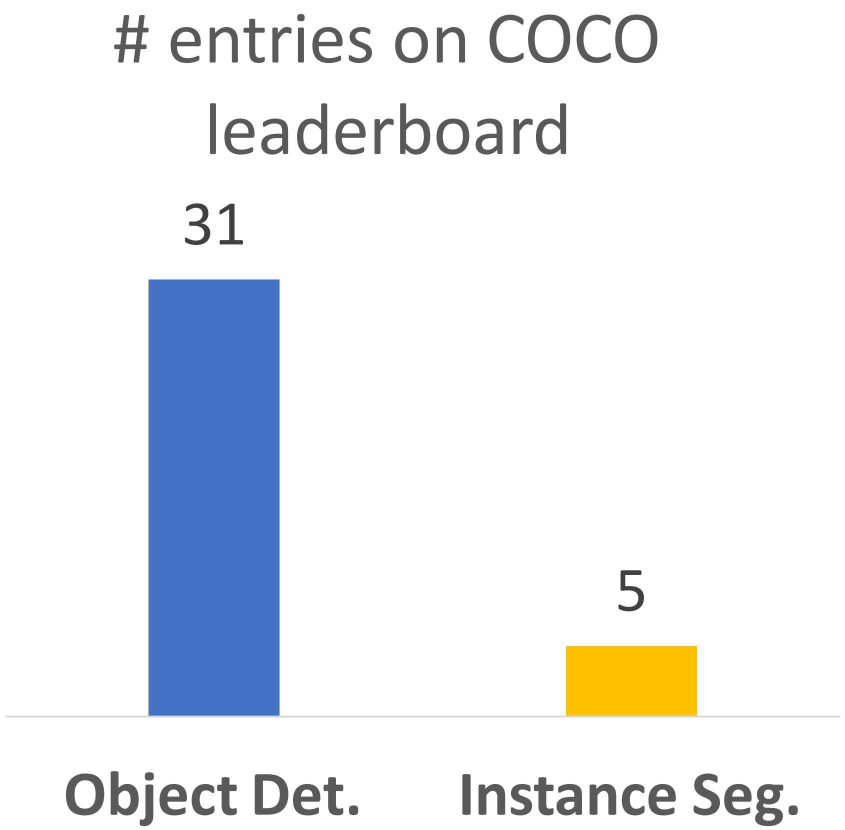
✓

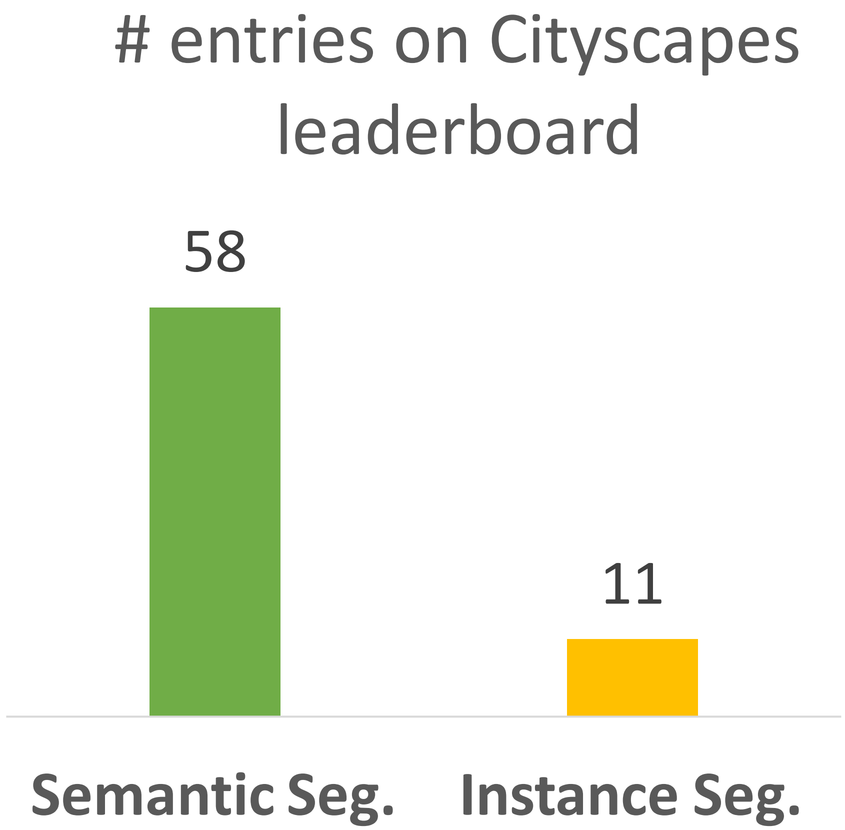


Instance Segmentation

?

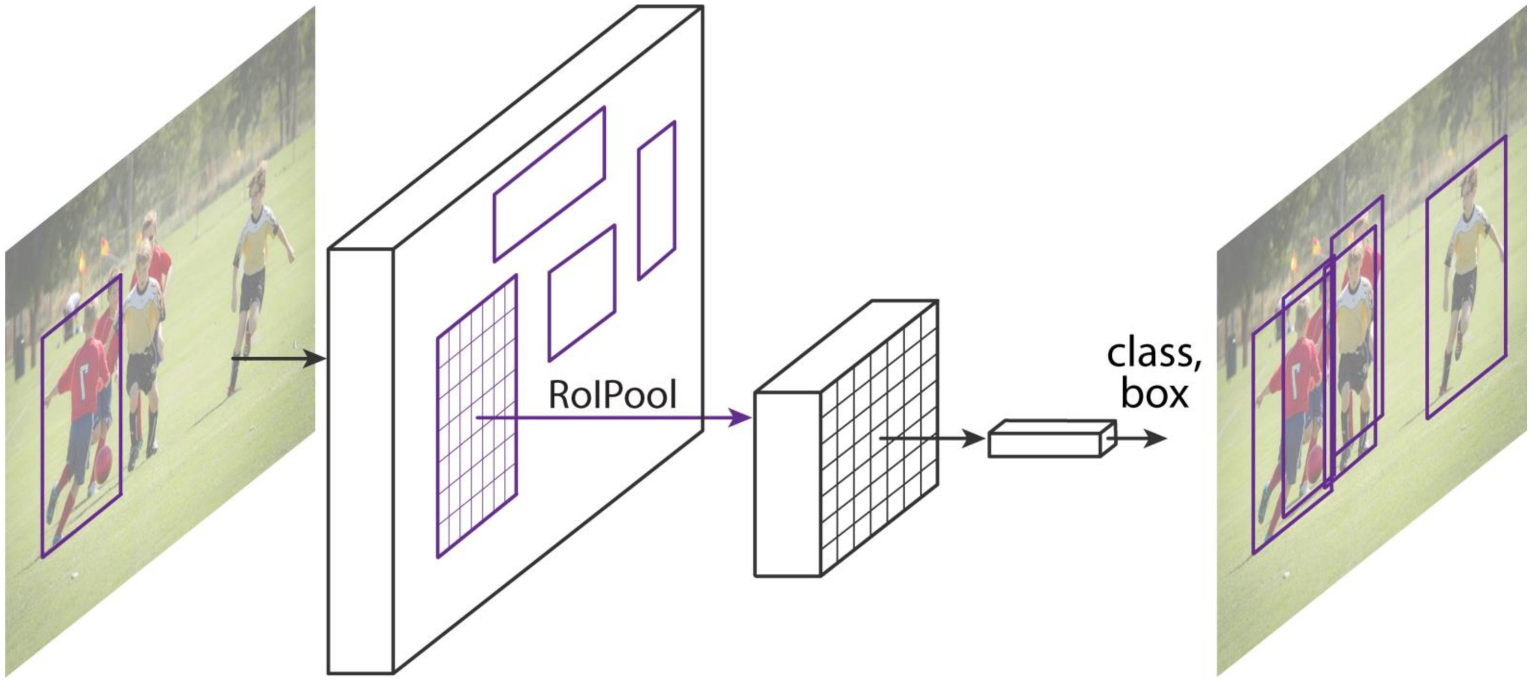
A Challenging Problem…





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

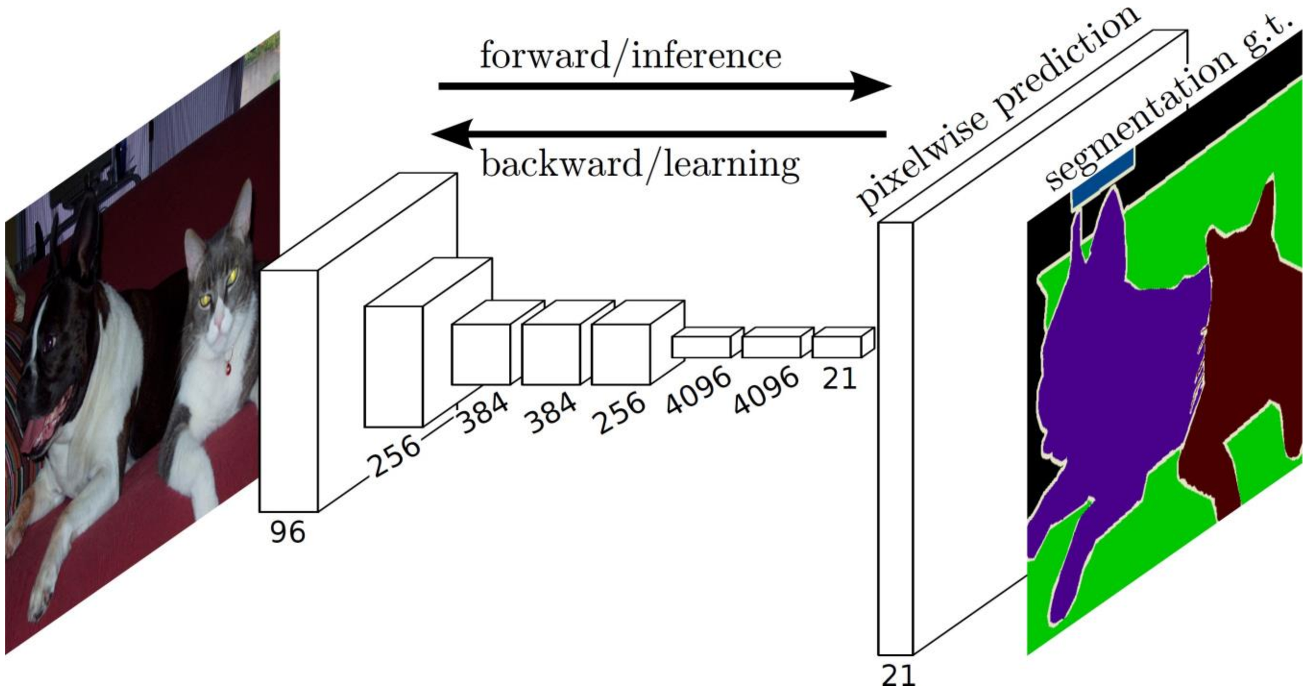
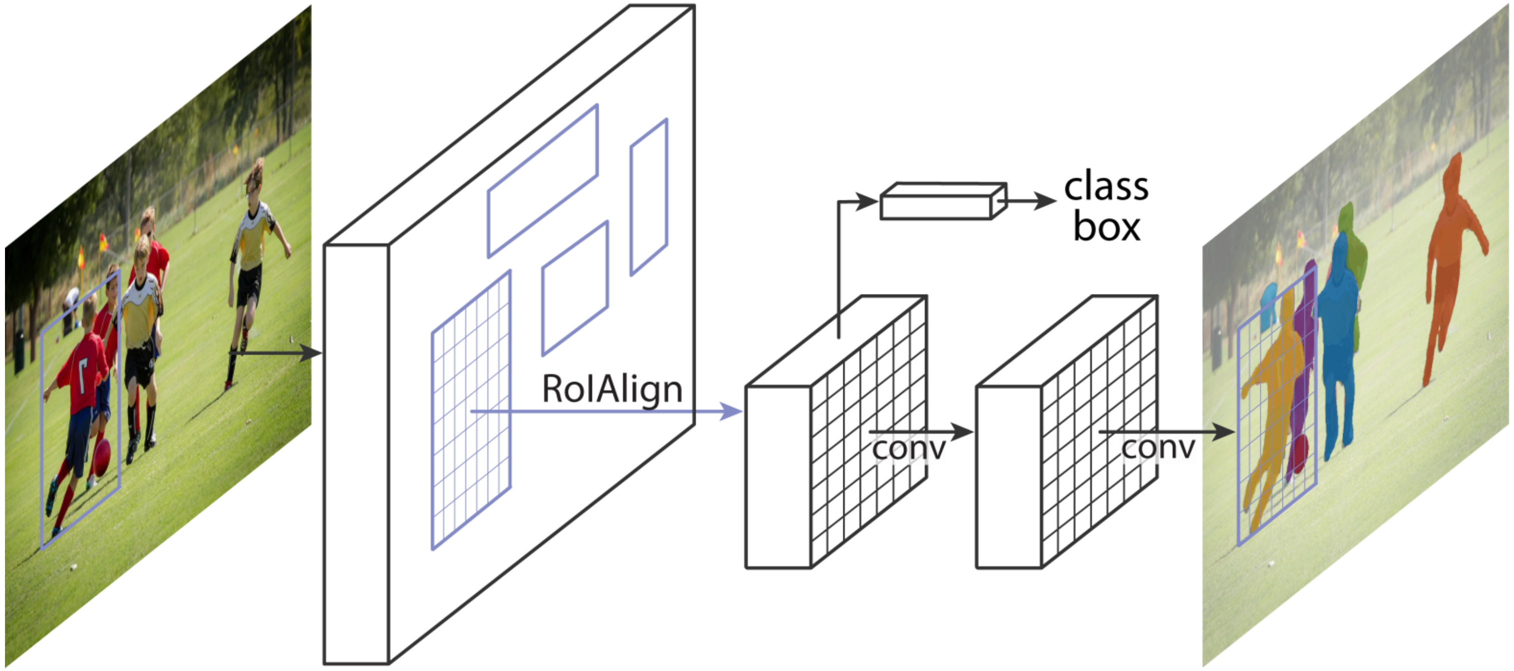


Figure credit: Long et al

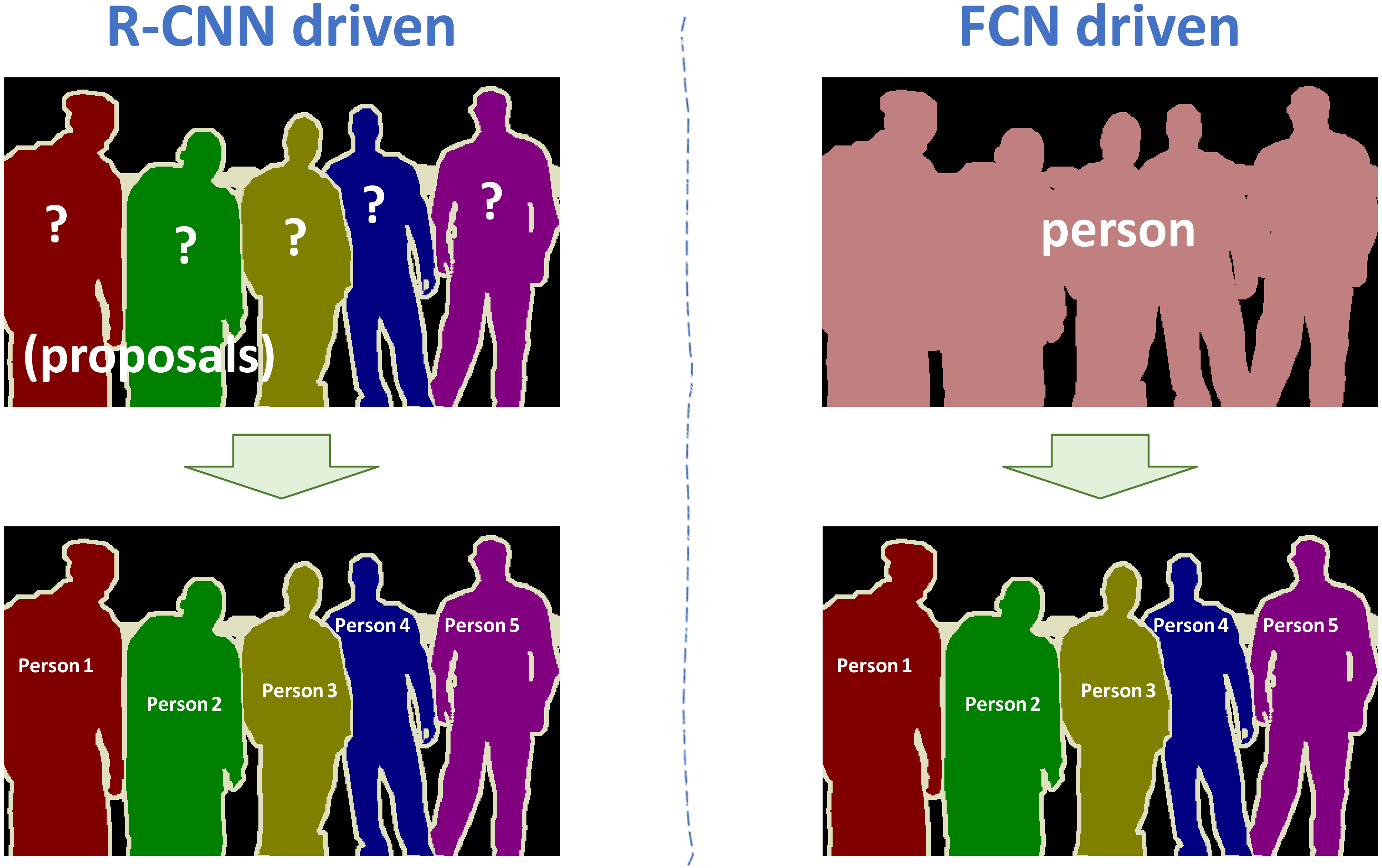
Jonathan Long, Evan Shelhamer, & Trevor Darrell. "Fully Convolutional Networks for Semantic Segmentation". CVPR 2015.

Instance Segmentation

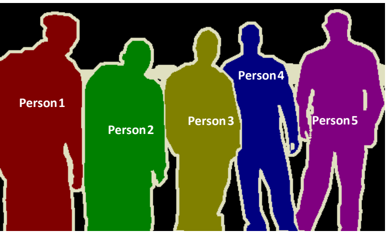
- **Goals** of Mask R-CNN
  - ✓Good speed
  - ✓Good accuracy
  - ✓Intuitive
  - ✓Easy to use



Instance Segmentation Methods

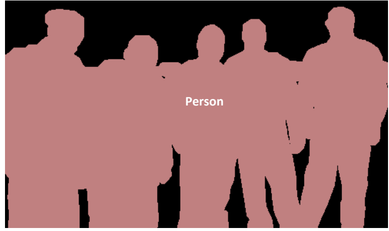


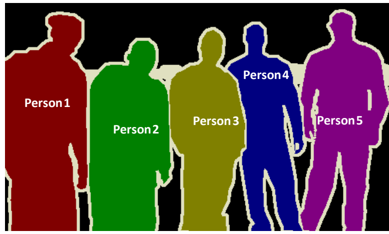
Instance Segmentation Methods



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]



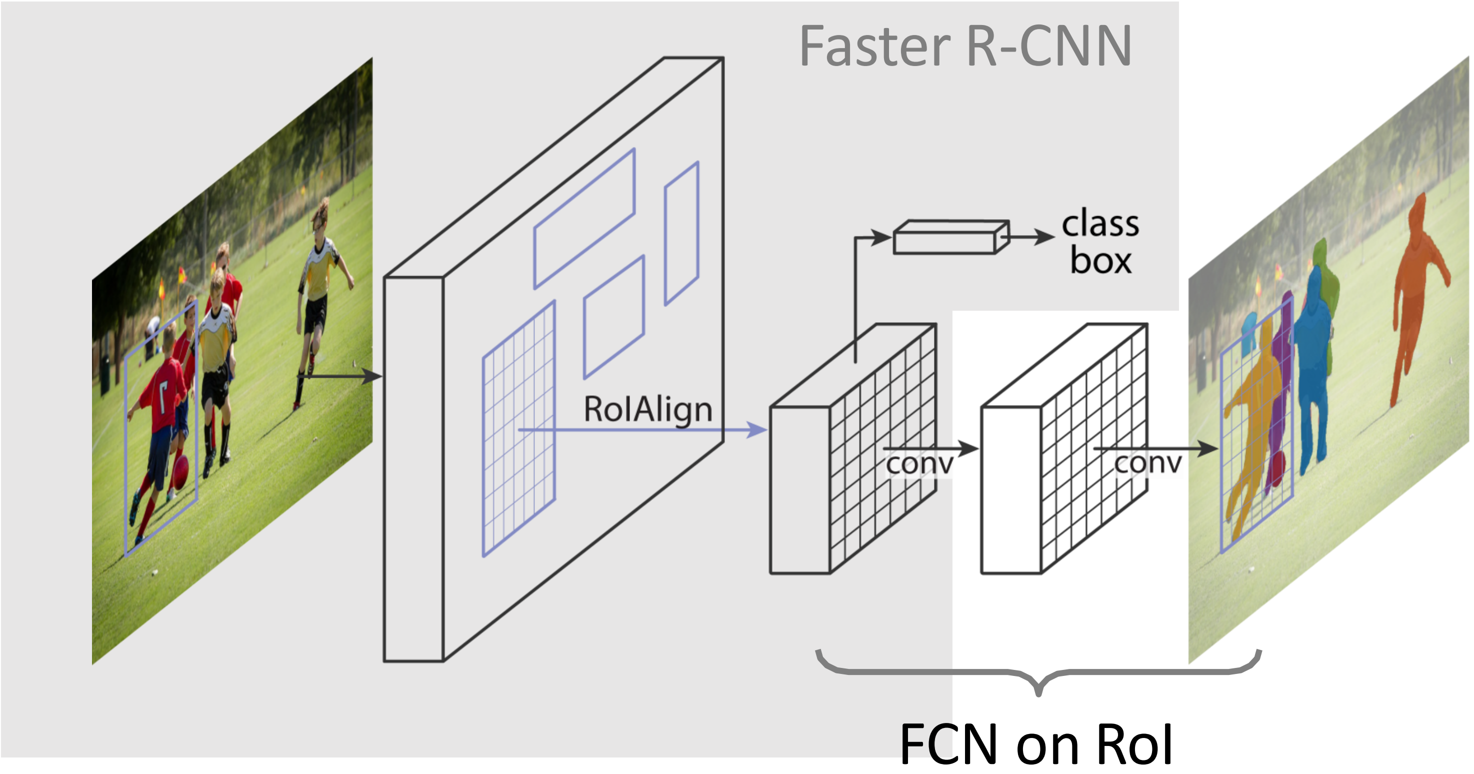


FCN-driven

- 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]

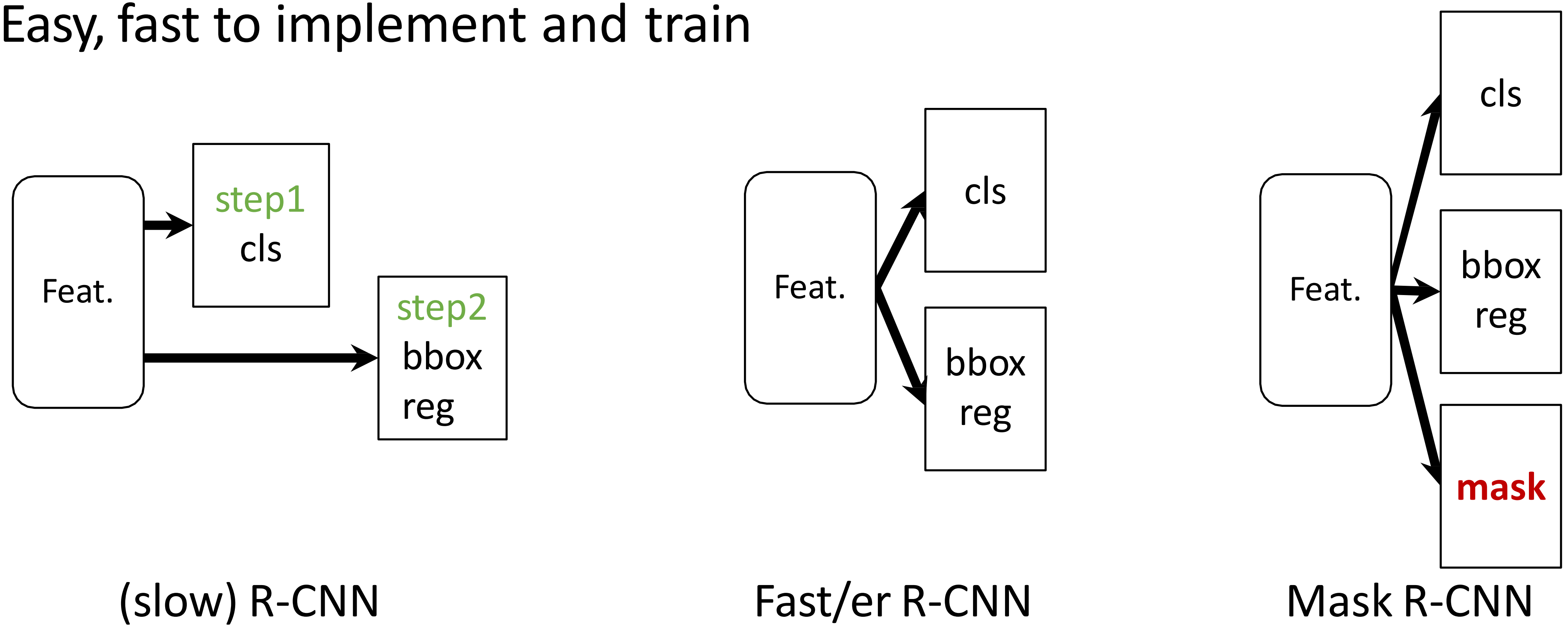
Mask R-CNN

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



Parallel Heads

- Easy, fast to implement and train

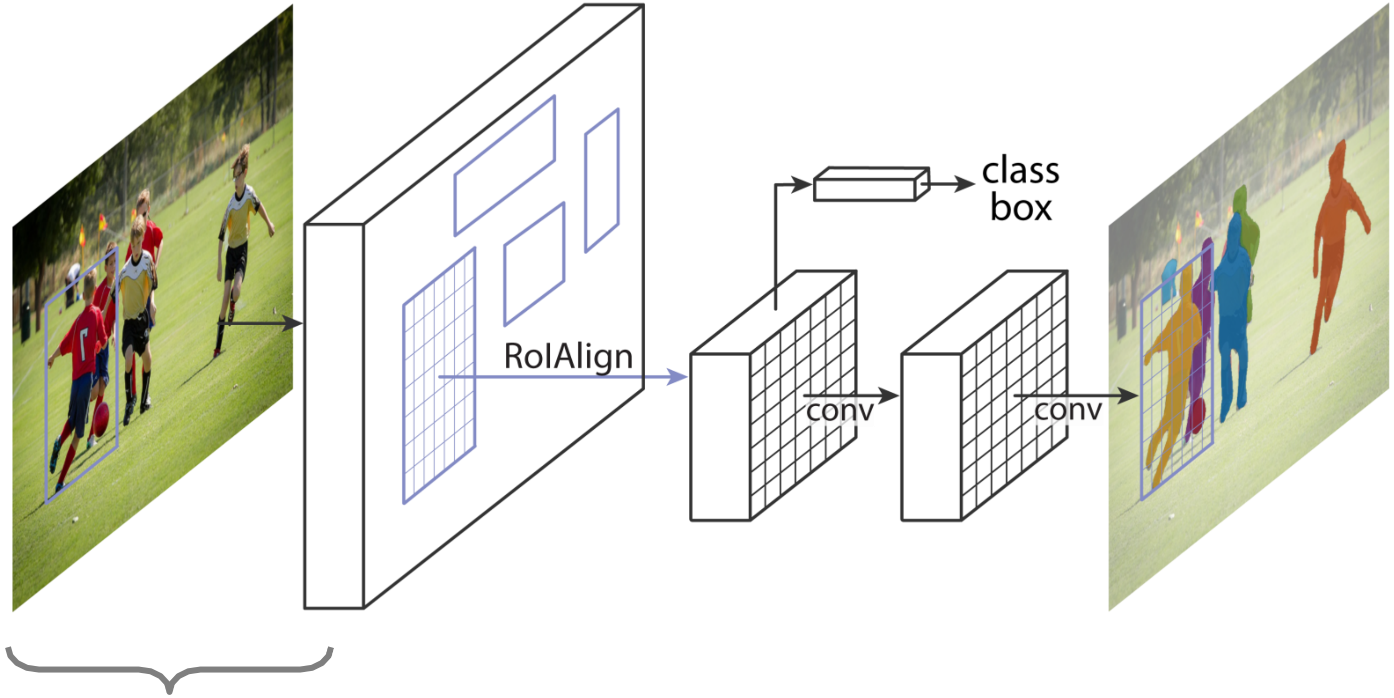


Invariance vs. Equivariance

- **Equivariance**: changes in input lead to corresponding changes in output

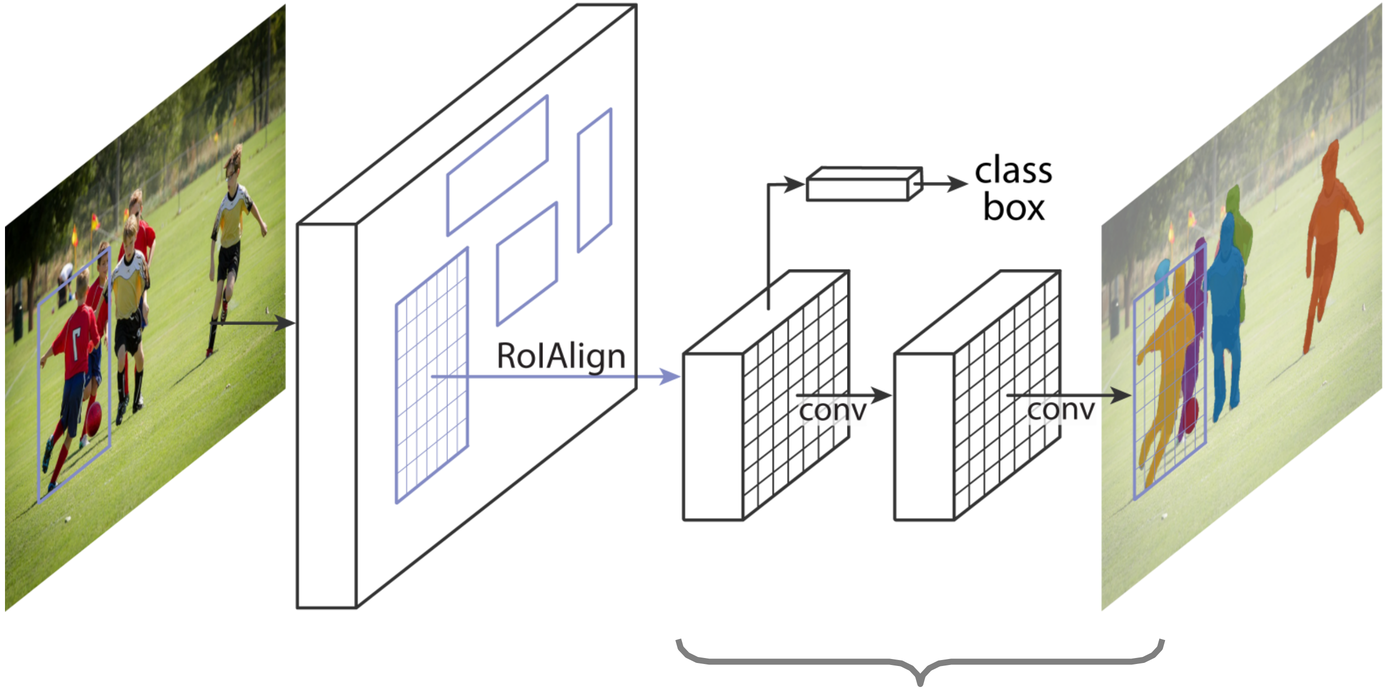
- *Classification* desires *invariant* representations: output a label
- *Instance Seg.* desires *equivariant* representations:
  - Translated object => translated mask
  - Scaled object => scaled mask
  - *Big and small* objects are equally important (due to AP metric)
    - unlike semantic seg. (counting pixels)

Equivariance in Mask R-CNN



1. Fully-Conv Features:
equivariant to global (image) translation

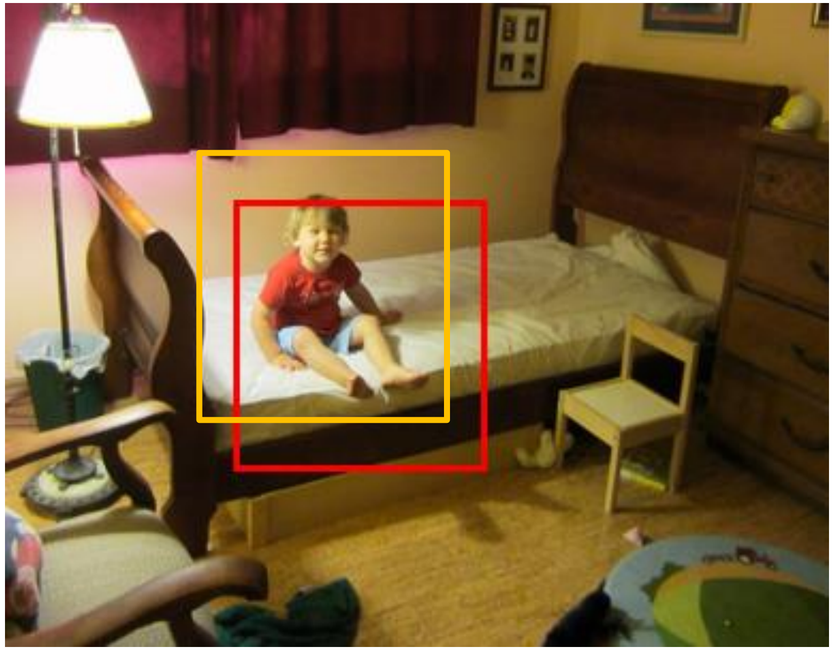
Equivariance in Mask R-CNN

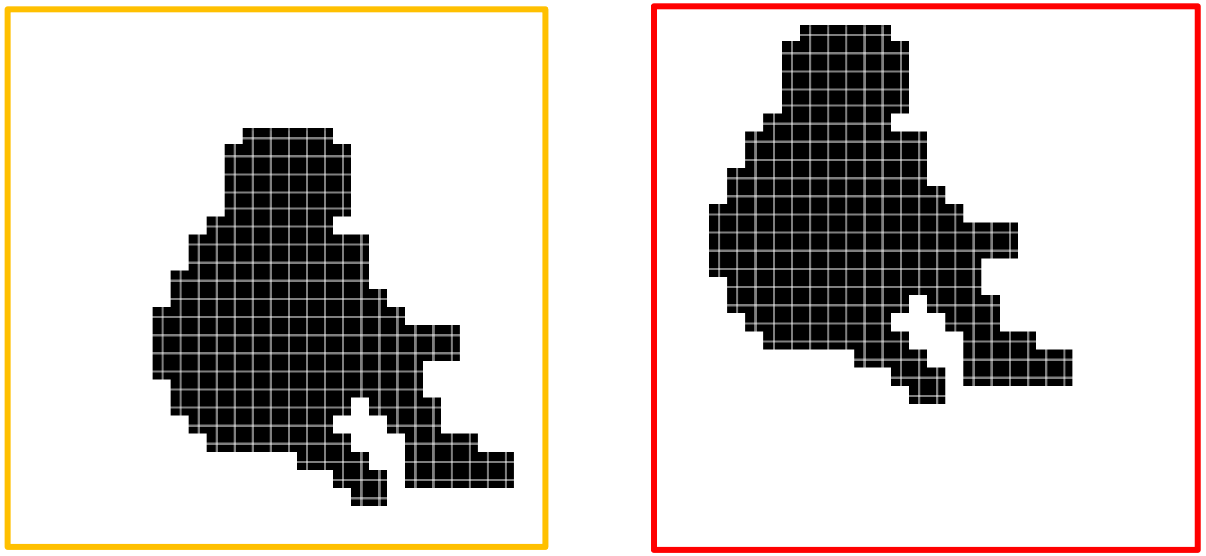


2. Fully-Conv on RoI:
equivariant to translation within RoI

Fully-Conv on RoI

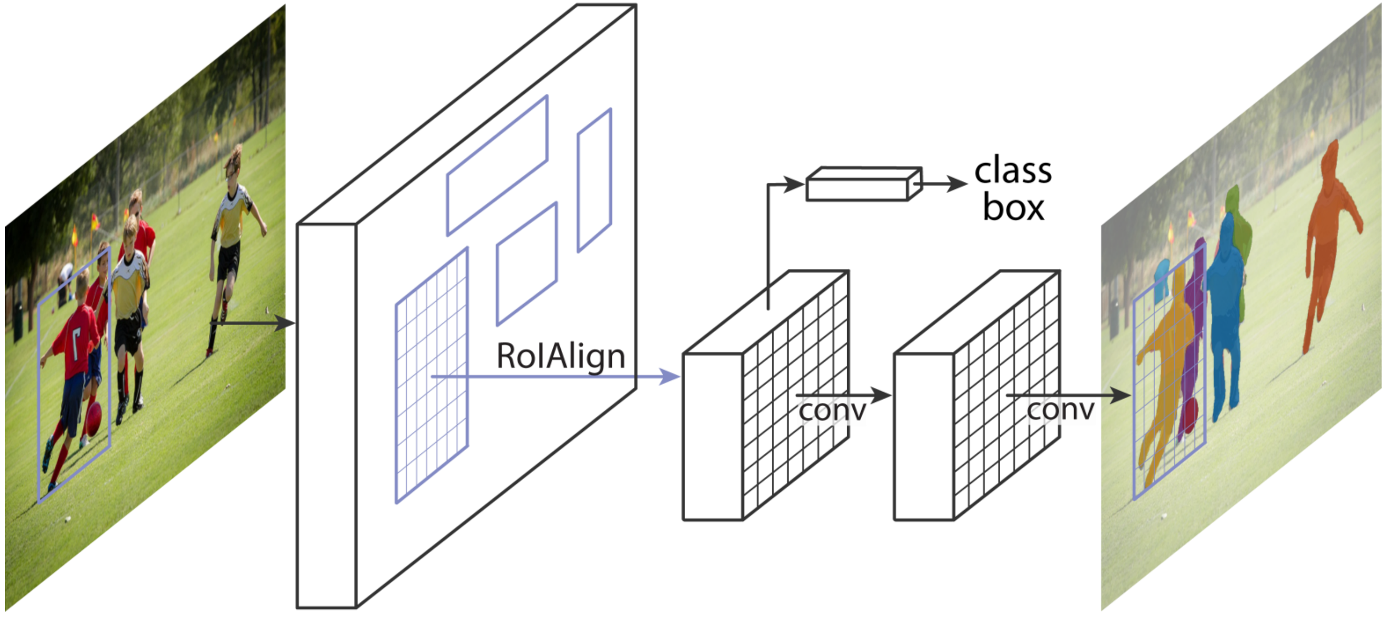
target masks on RoIs





Translation of object in RoI => Same translation of mask in RoI
- Equivariant to small translation of RoIs
- More robust to RoI's localization imperfection

Equivariance in Mask R-CNN



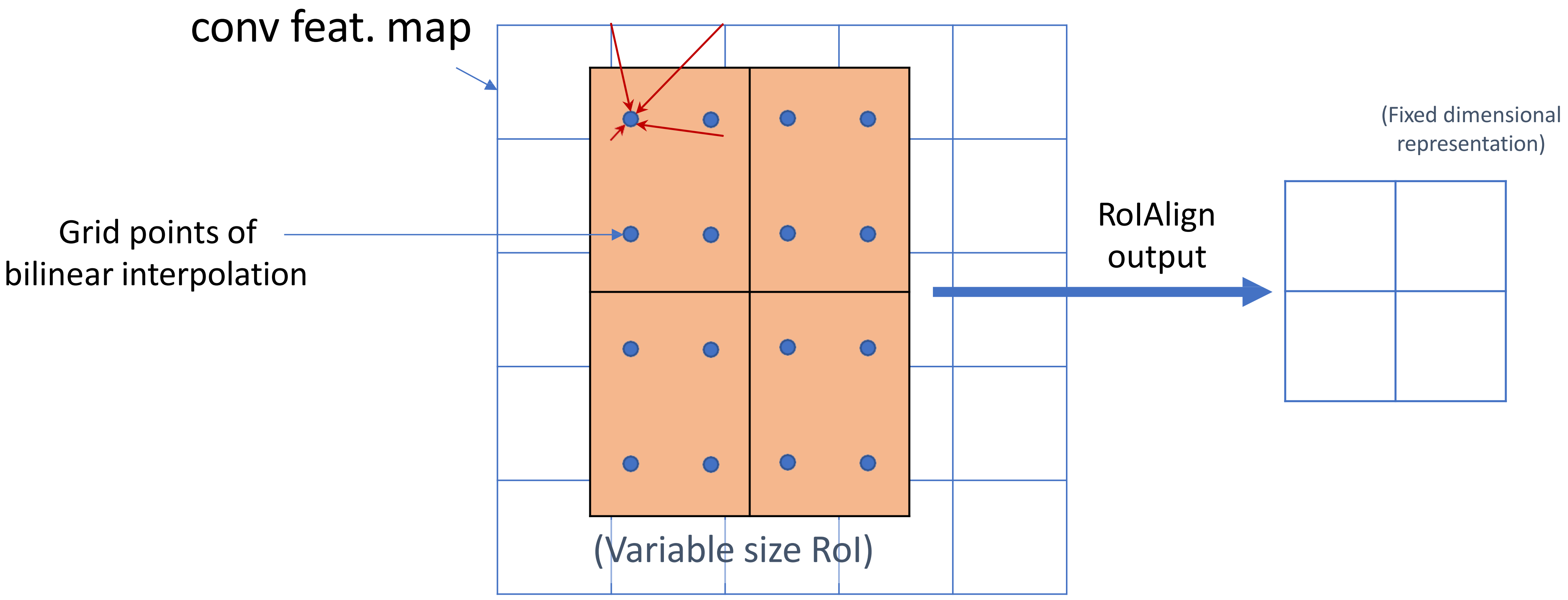
3. RoIAlign:

3a. maintain translation-equivariance before/after RoI

RoIAlign

FAQs: how to sample grid points within a cell?

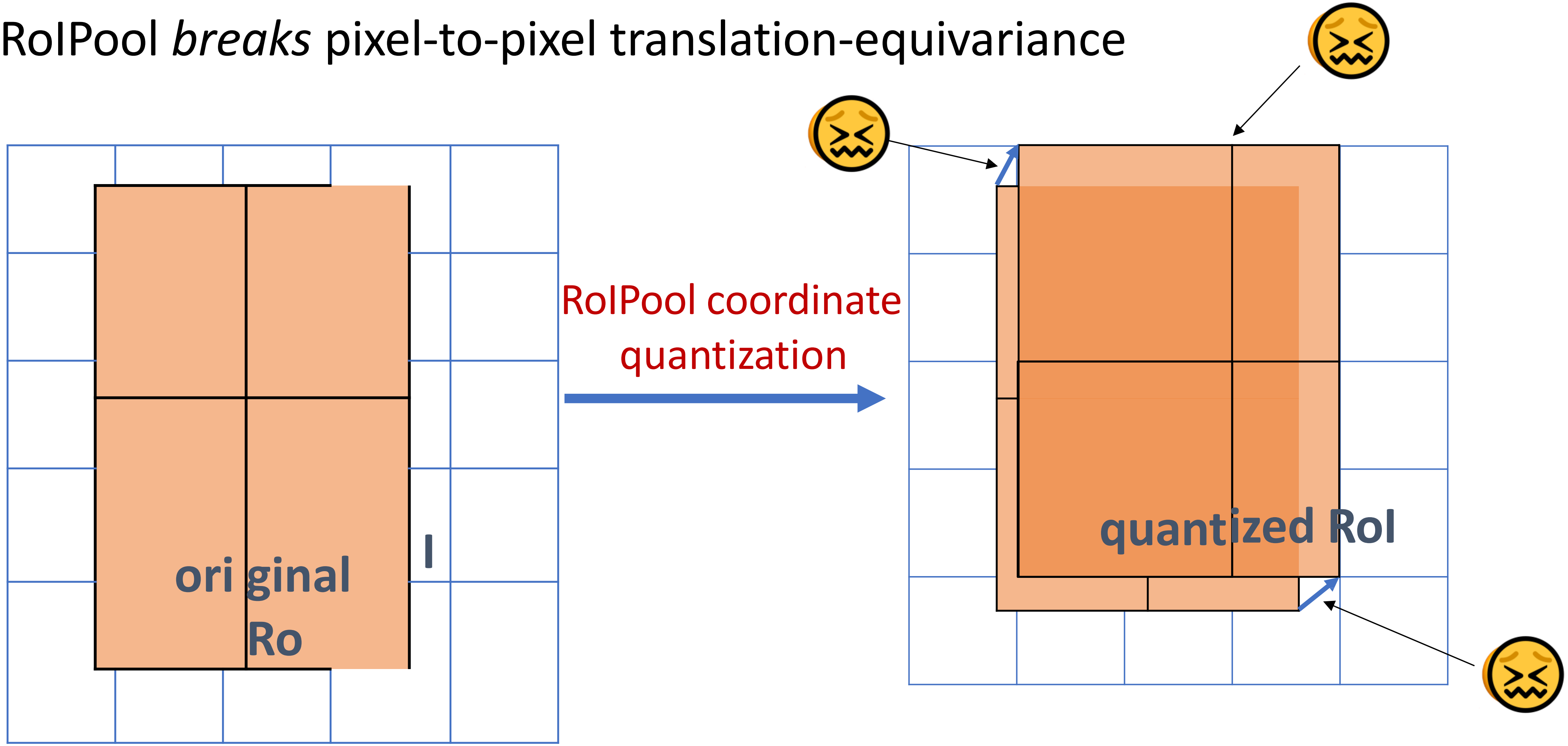
- 4 regular points in 2x2 sub-cells
- other implementation could work



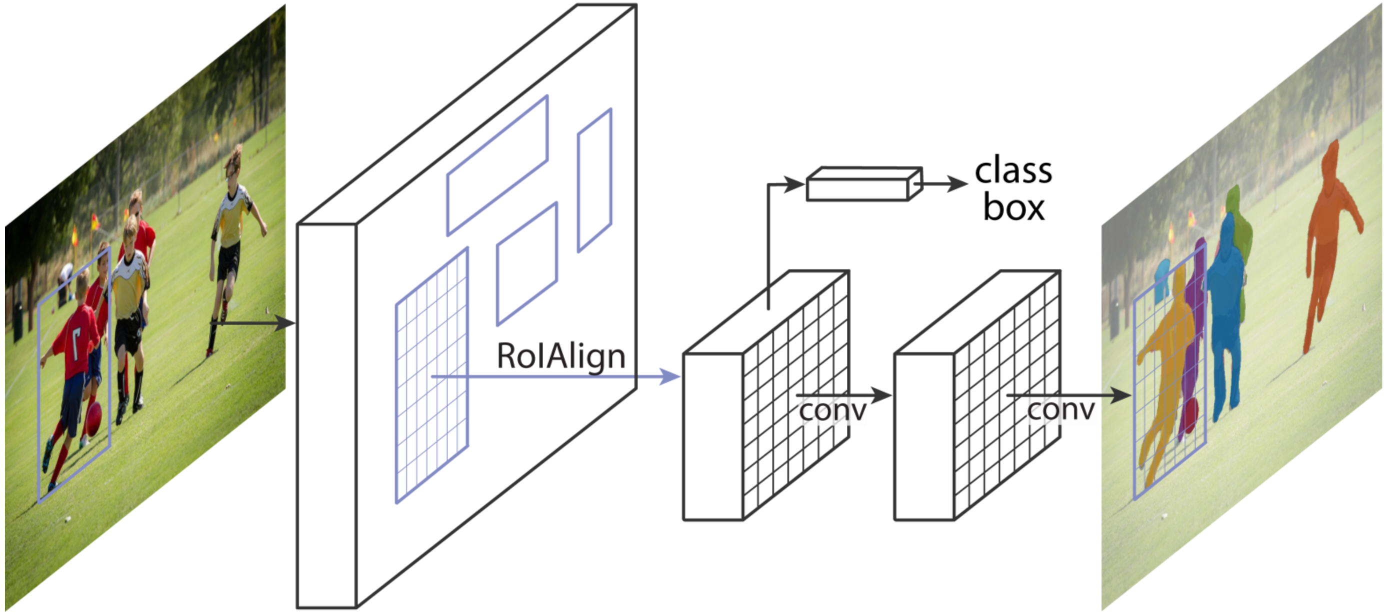
see also “What is wrong with convolutional neural nets?”, Geoffrey Hinton, 2017

RoIAlign vs. RoIPool

- RoIPool *breaks* pixel-to-pixel translation-equivariance



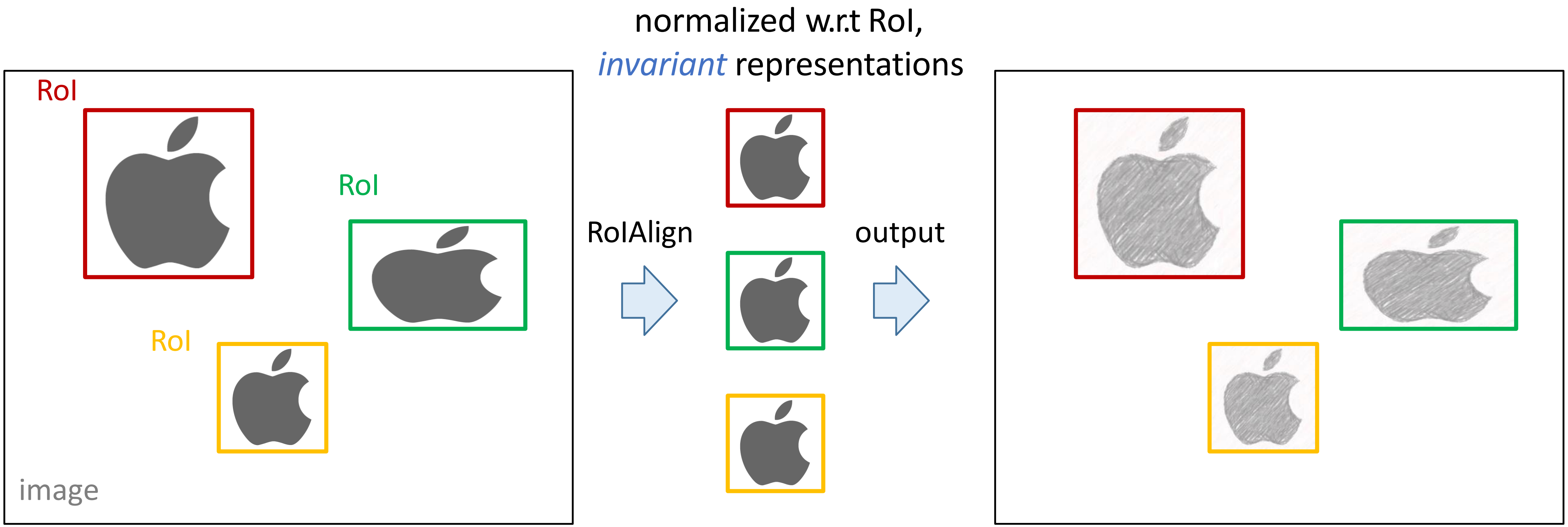
Equivariance in Mask R-CNN



3. RoIAlign:

3b. Scale-equivariant (and aspect-ratio-equivariant)

RoIAlign: Scale-Equivariance

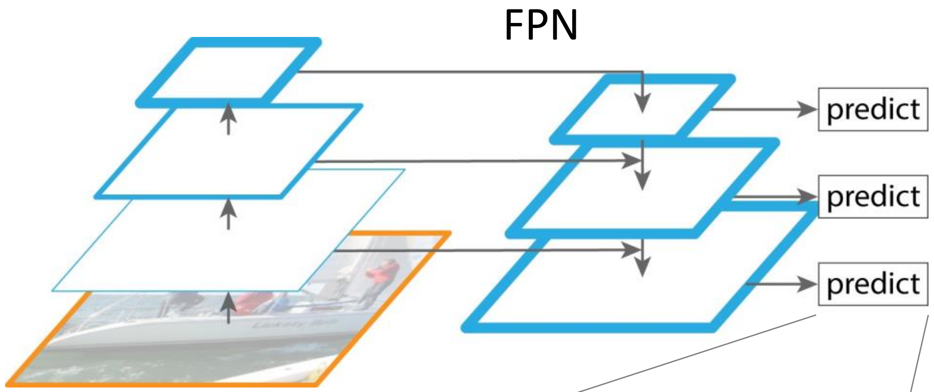


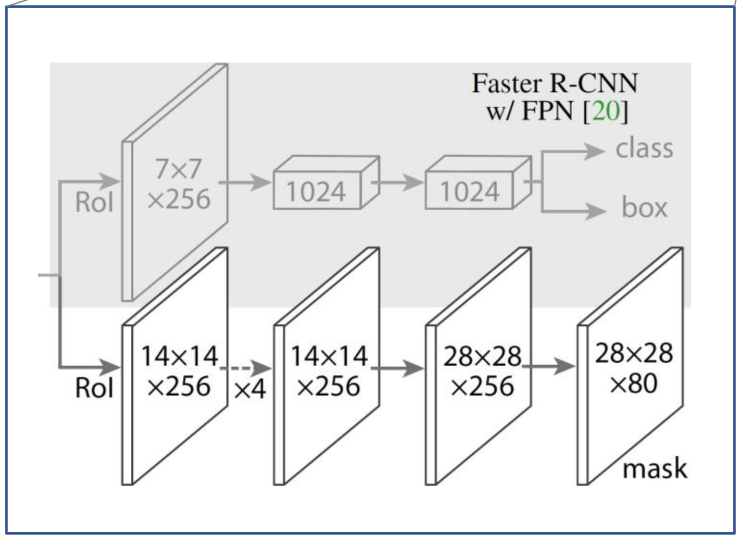
- RoIAlign creates *scale-invariant* representations
- RoIAlign + "output pasted back" provides *scale-equivariance*

More about Scale-Equivariance: FPN

- RoIAlign is scale-invariant if on raw pixels:
  - = (slow) R-CNN: crops and warps RoIs
- RoIAlign is scale-invariant if on scale-invariant feature maps

- Feature Pyramid Network (FPN) [Lin et al. CVPR'17] creates approx. scale-invariant features





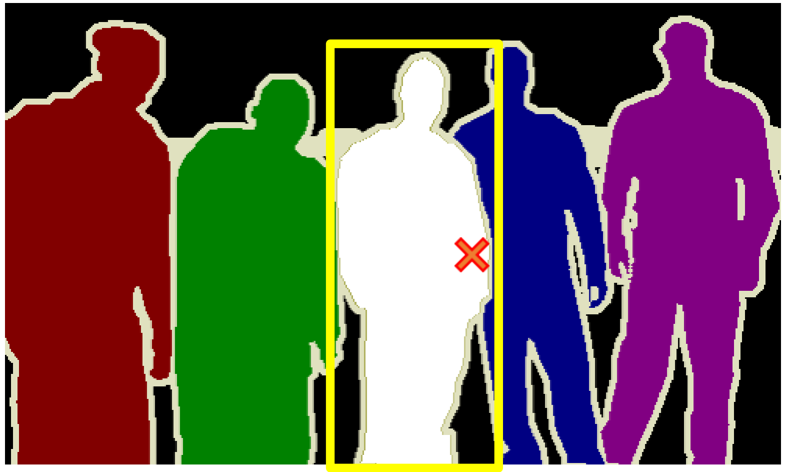
Equivariance in Mask R-CNN: Summary

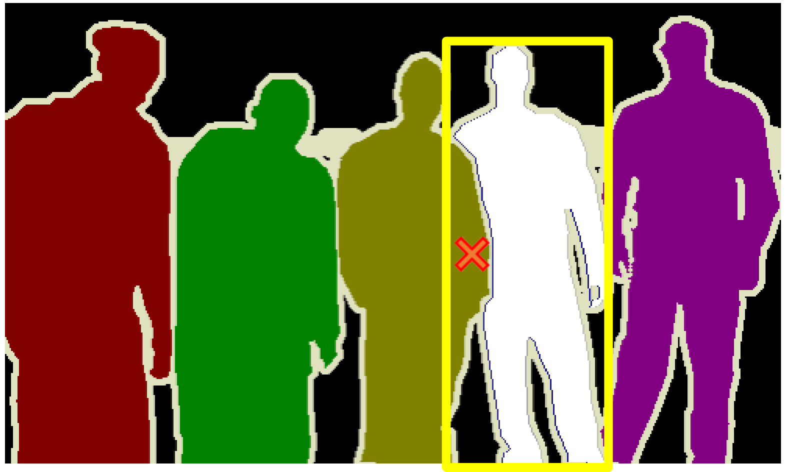
- Translation-equivariant
  - FCN features
  - FCN mask head
  - RoIAlign (pixel-to-pixel behavior)

- Scale-equivariant (and aspect-ratio-equivariant)
  - RoIAlign (warping and normalization behavior) + paste-back
  - FPN features

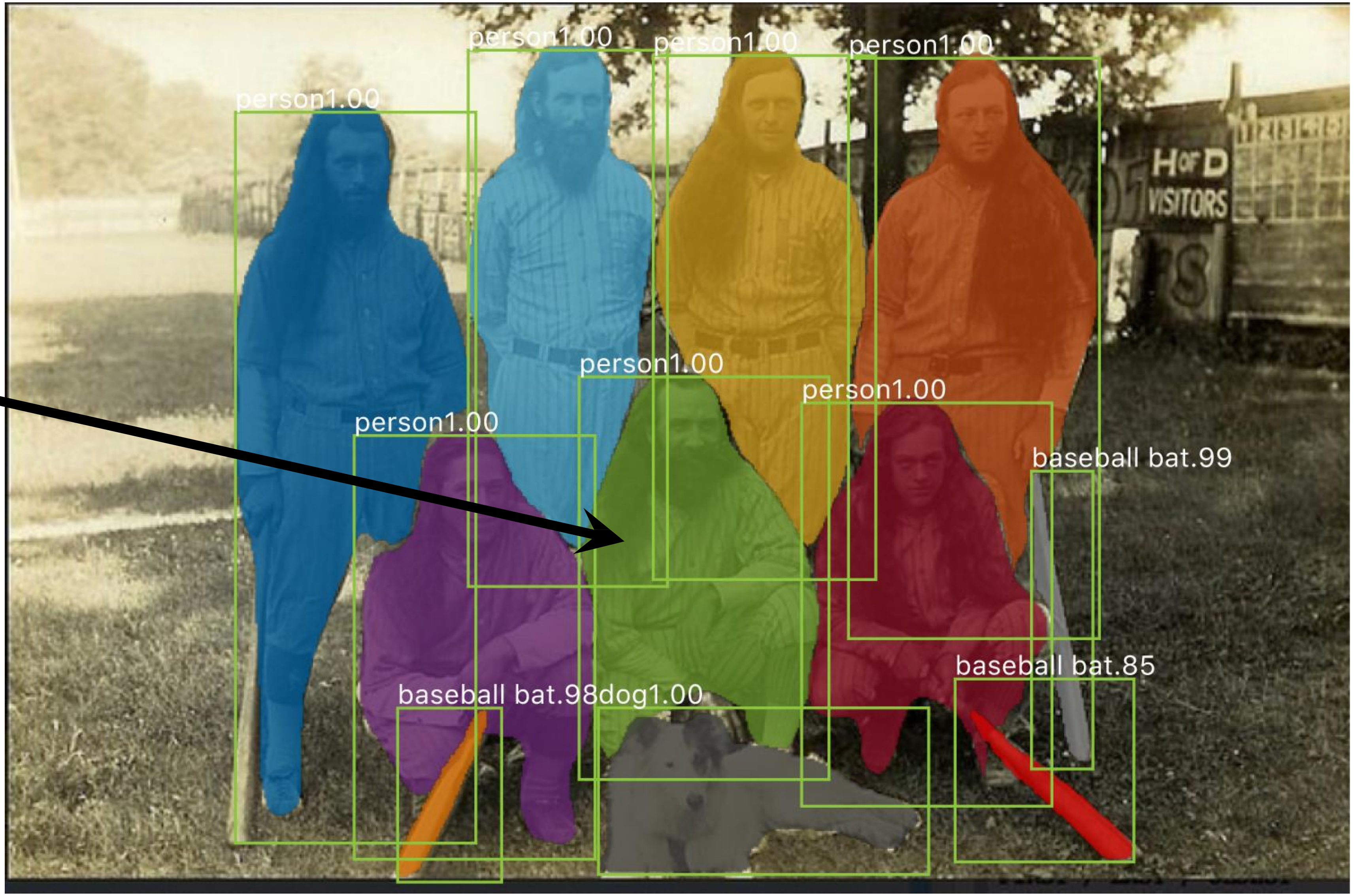
Instance Seg: When we don't want equivariance?

- A pixel x could have a different label w.r.t. different RoIs
  - zero-padding in RoI boundary breaks equivariance
  - outside objects are suppressed
  - only equivariant to small changes of RoIs (which is desired)





object surrounded by same-category objects



Mask R-CNN results on COCO

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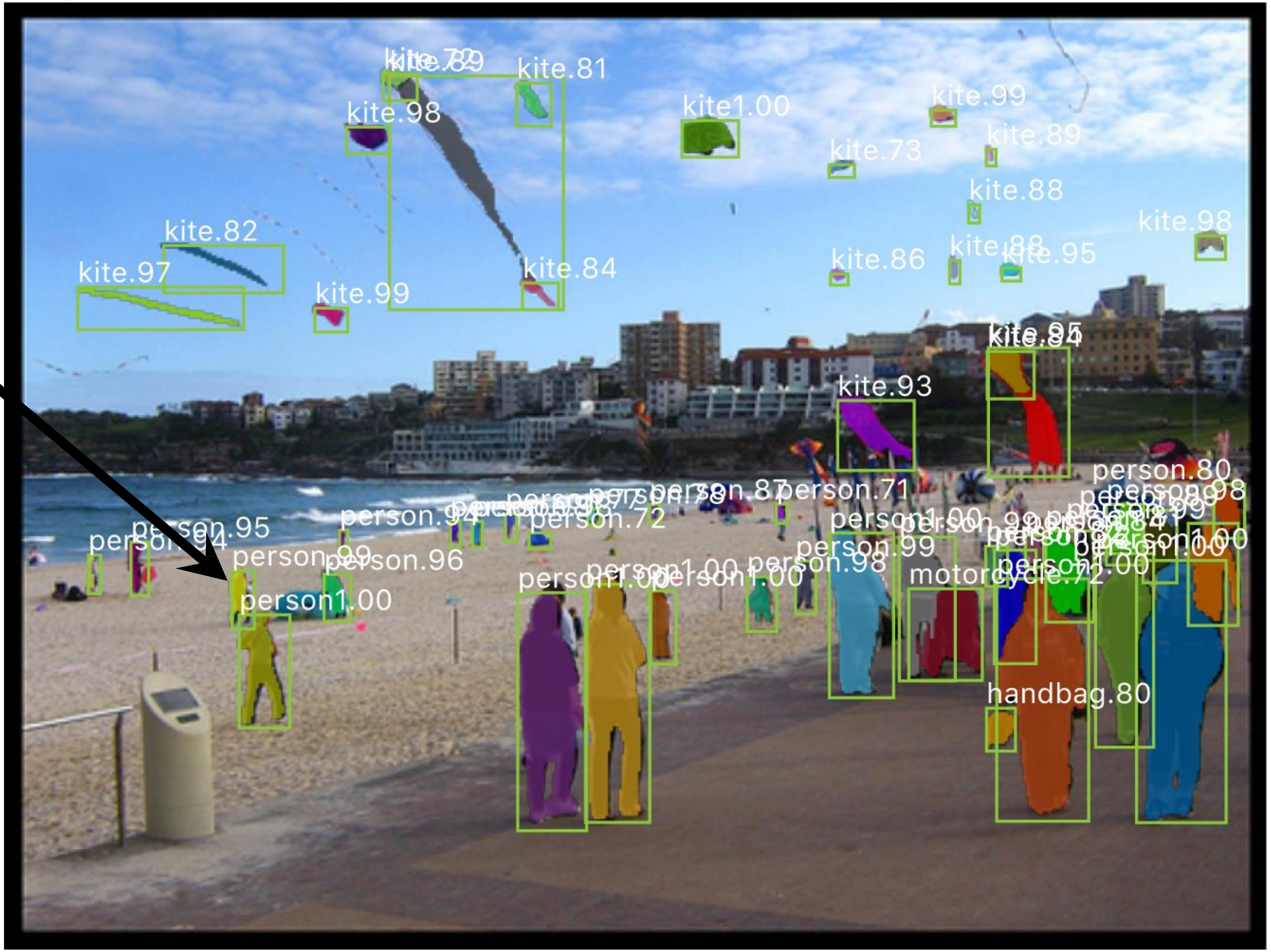
- benefit from better features (ResNeXt [Xie et al. CVPR'17])

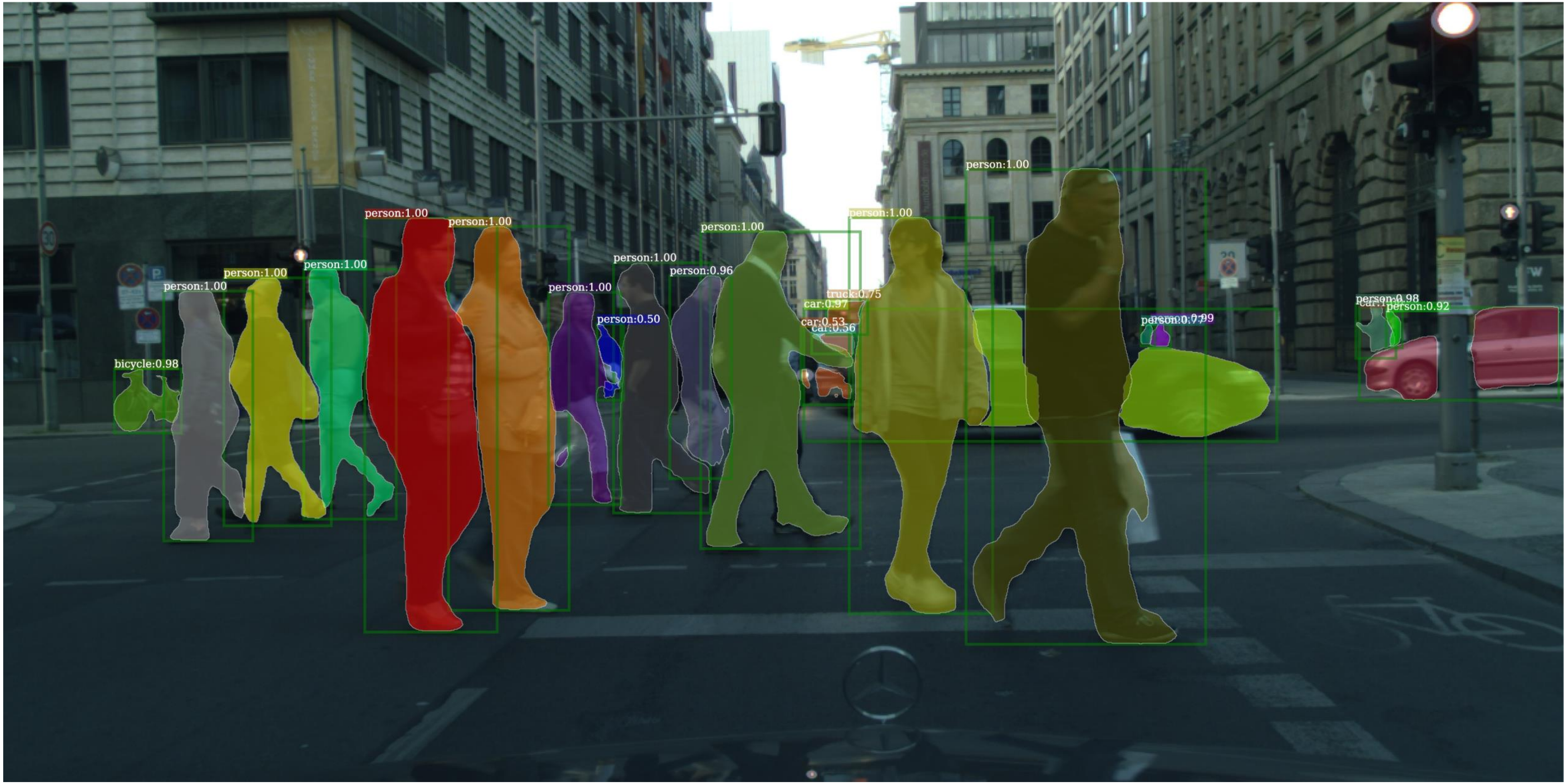
disconnected
object

Mask R-CNN results on COCO

small
objects



Mask R-CNN results on COCO

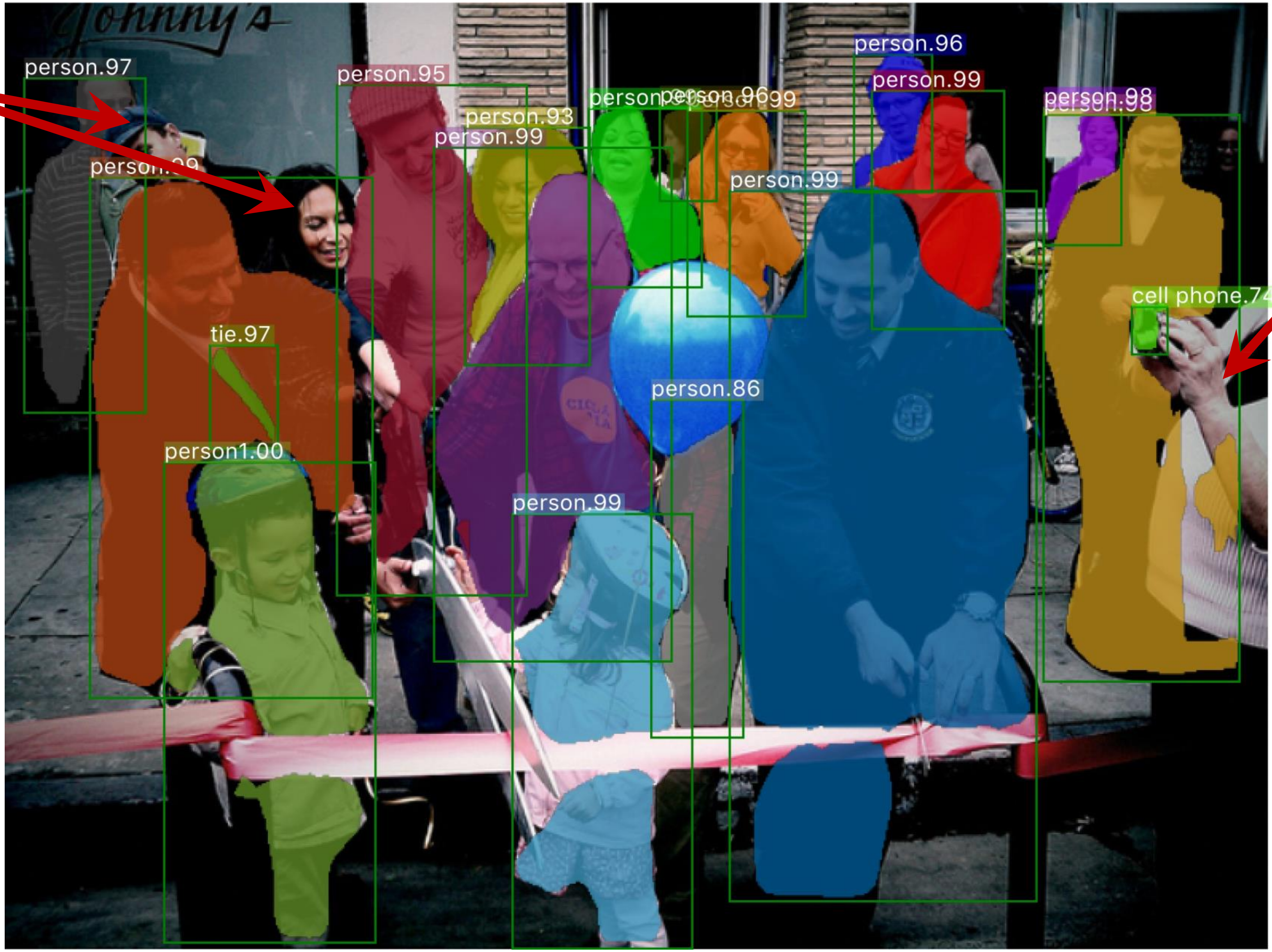


Mask R-CNN results on CityScapes

Failure case: detection/segmentation

missing

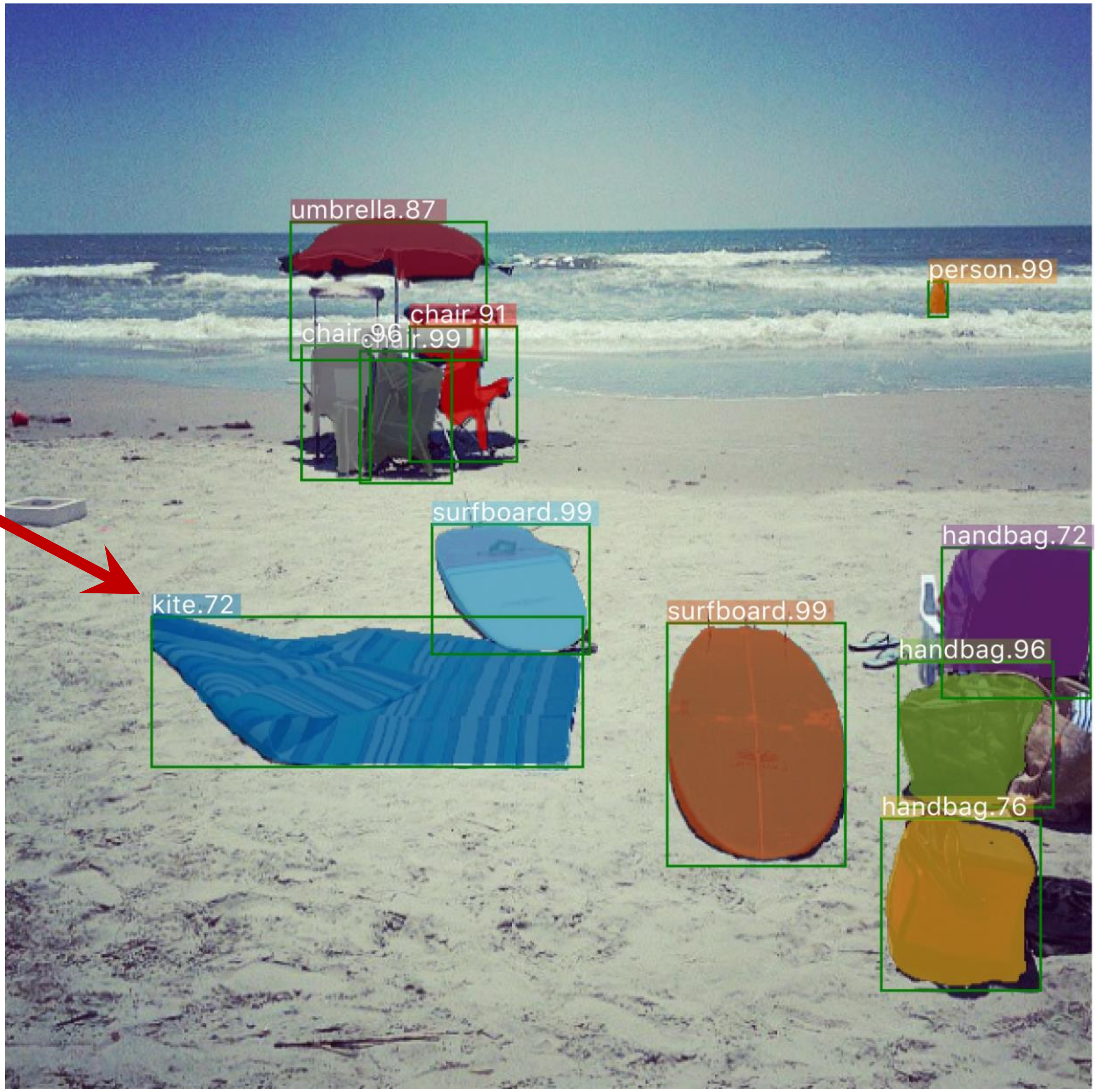
missing,
false mask



Mask R-CNN results on COCO

Failure case: recognition

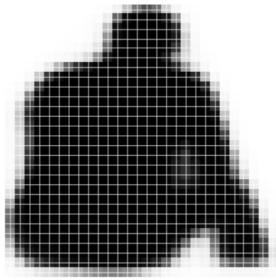
not a kite



Mask R-CNN results on COCO

28x28 soft prediction from Mask R-CNN

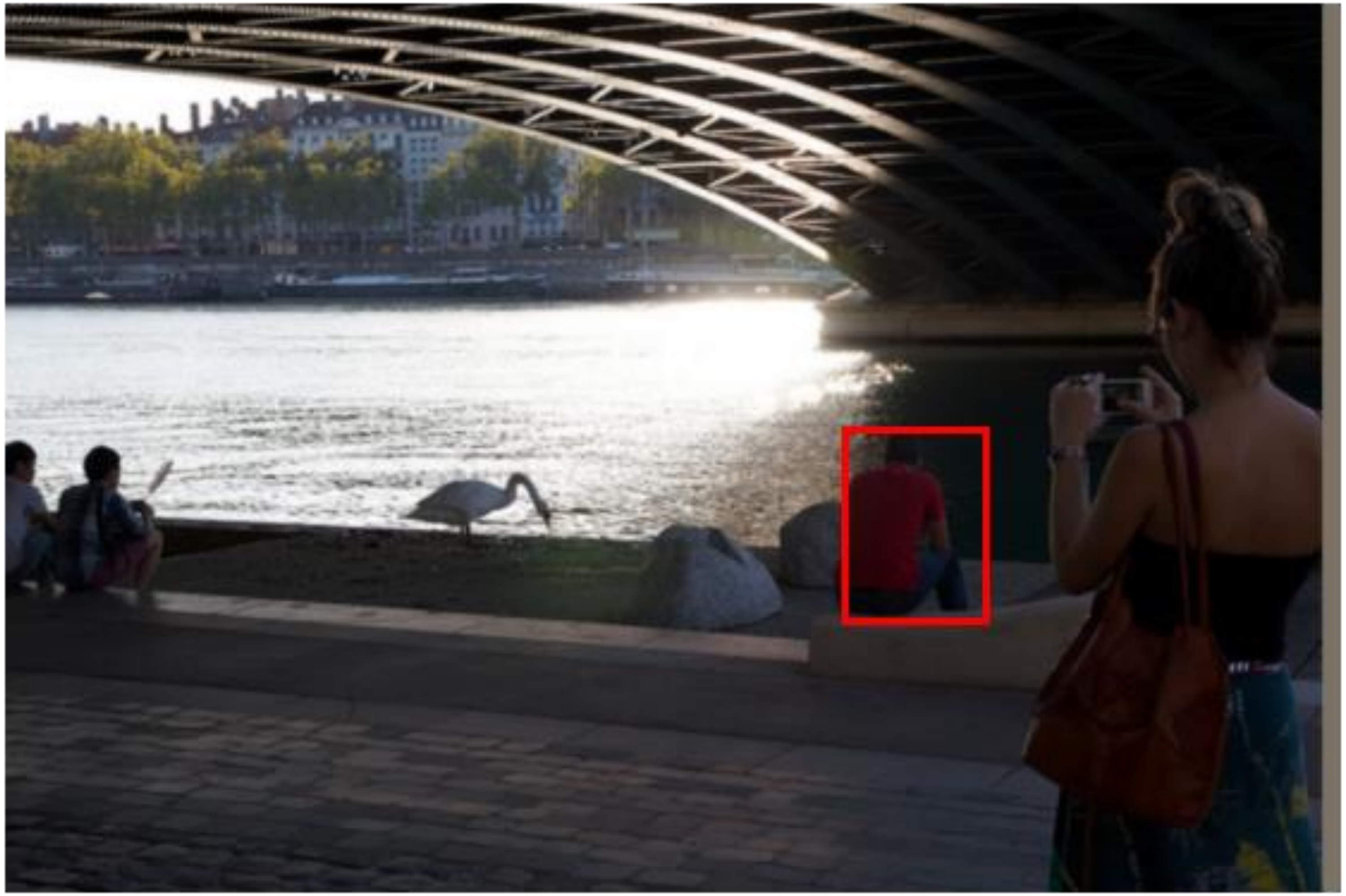
(enlarged)



Soft prediction resampled to image coordinates

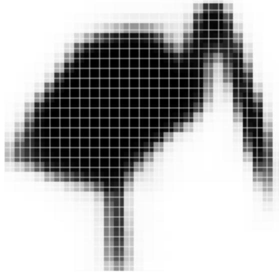
(bilinear and bicubic interpolation work equally well)

Final prediction (threshold at 0.5)



Validation image with box detection shown in red

28x28 soft prediction



Resized Soft prediction

Final mask

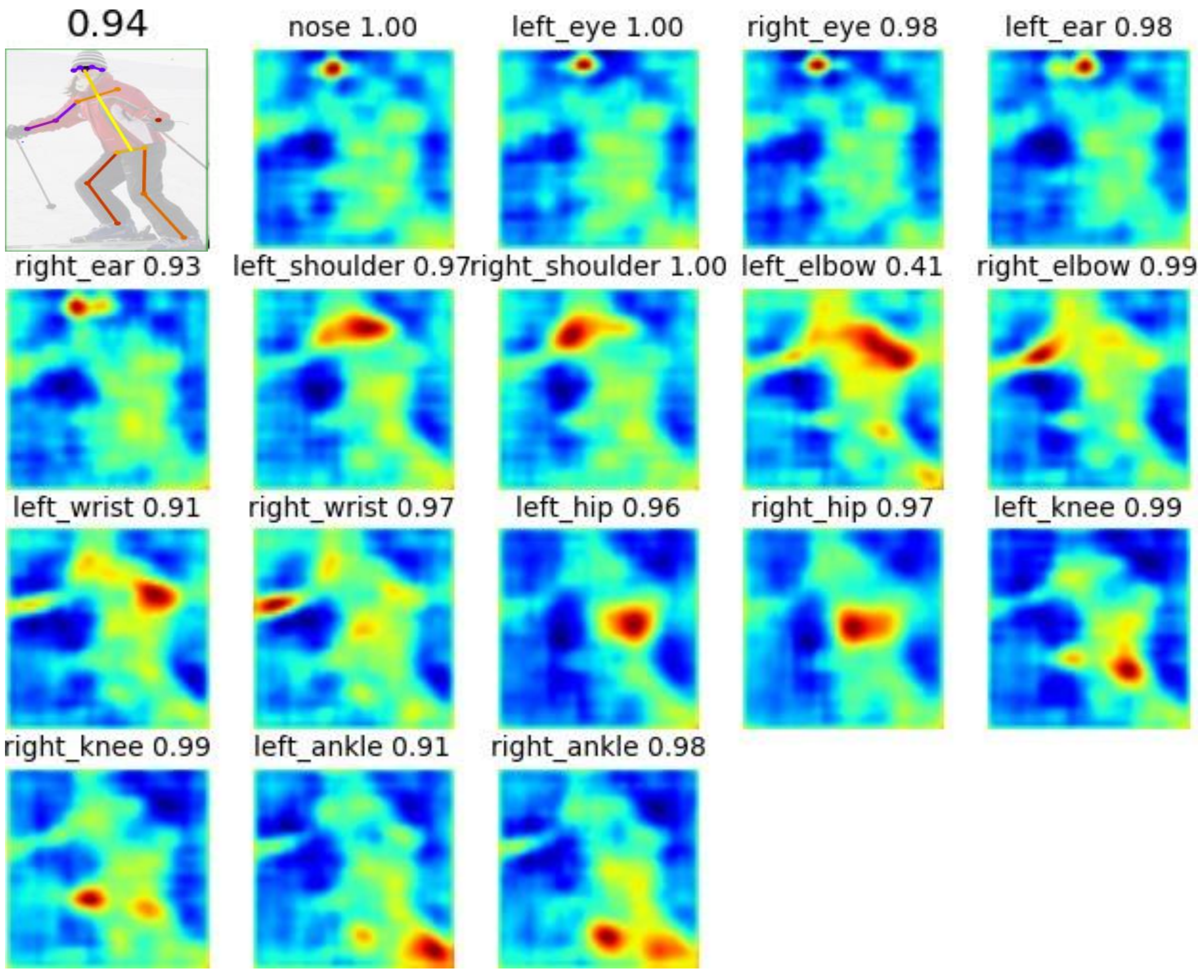
Validation image with box detection shown in red

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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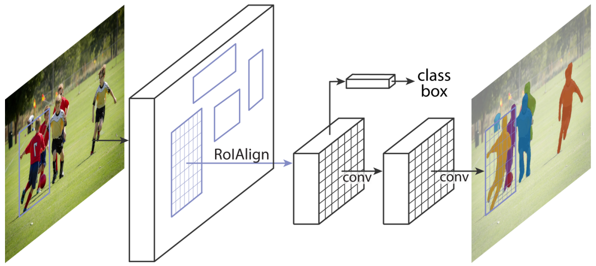
Conclusion

Mask R-CNN

- ✓Good speed
- ✓Good accuracy
- ✓Intuitive
- ✓Easy to use
- ✓Equivariance matters



Code open-sourced as Facebook AI Research's **Detectron** platform

Summary – More complex outputs from deep networks

- Image Output (e.g. colorization, semantic segmentation, super-resolution, stylization, depth estimation…)
- Attributes
- Text Captions
- Bottom up: Semantic Keypoints
- Top down: Object Detection
  - “single shot” vs “two stage”