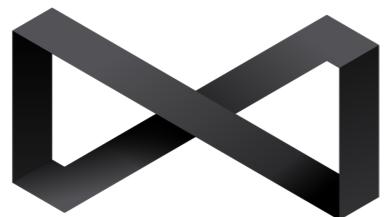
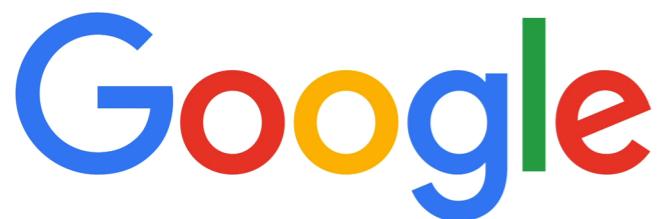


SSD: Single Shot MultiBox Detector

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)



THE UNIVERSITY
of NORTH CAROLINA
at CHAPEL HILL

FPS: 0.00

WR

1.53

OR

1.53

person: 0.83



Rio 2016

9

person: 0



person: (person: 0.37)



person: (person: 0.37)



person: (person: 0.37)



person: (person: 0.37)



person: (person: 0.37)



person: (person: 0.37)



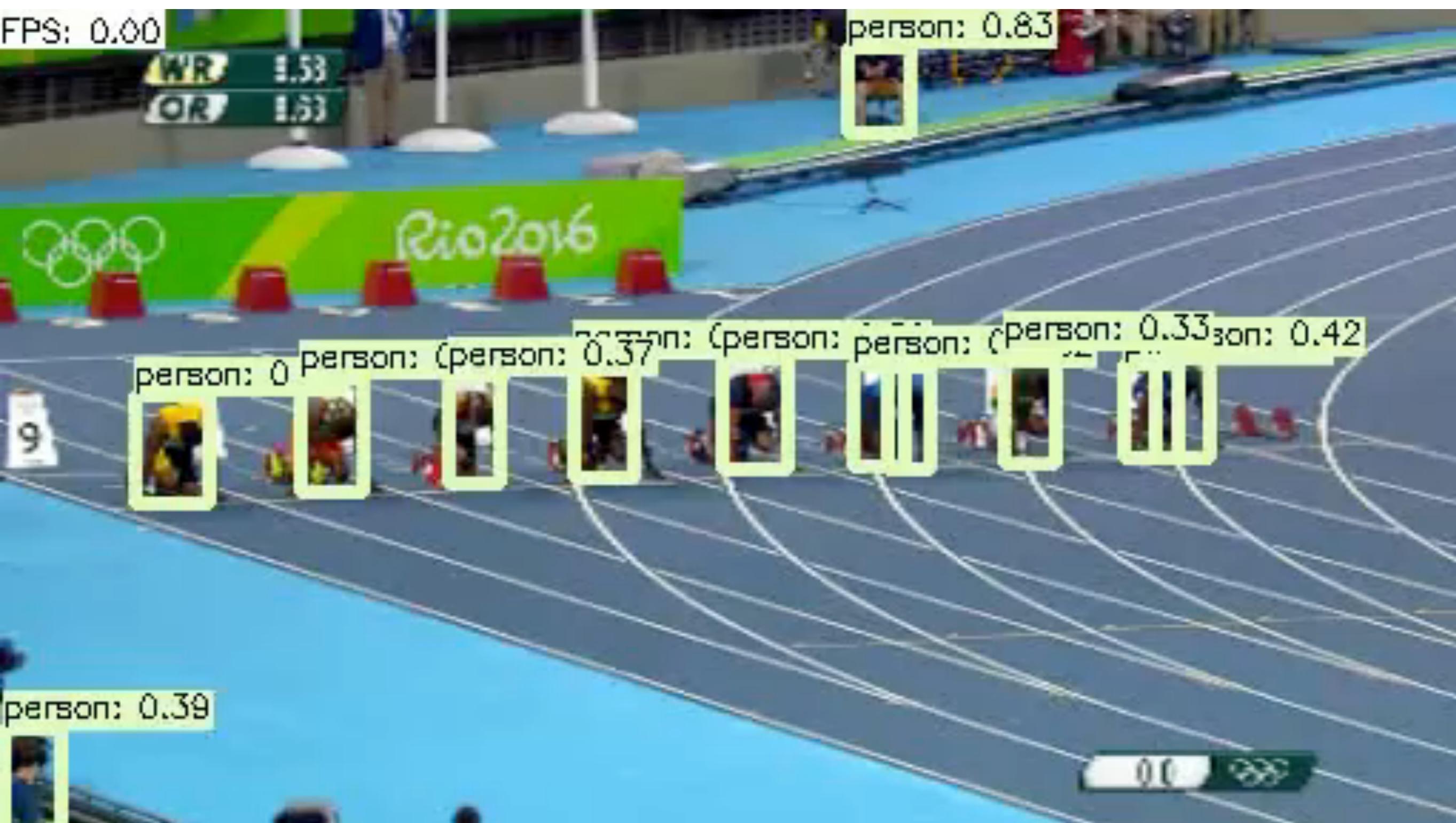
person: 0.39



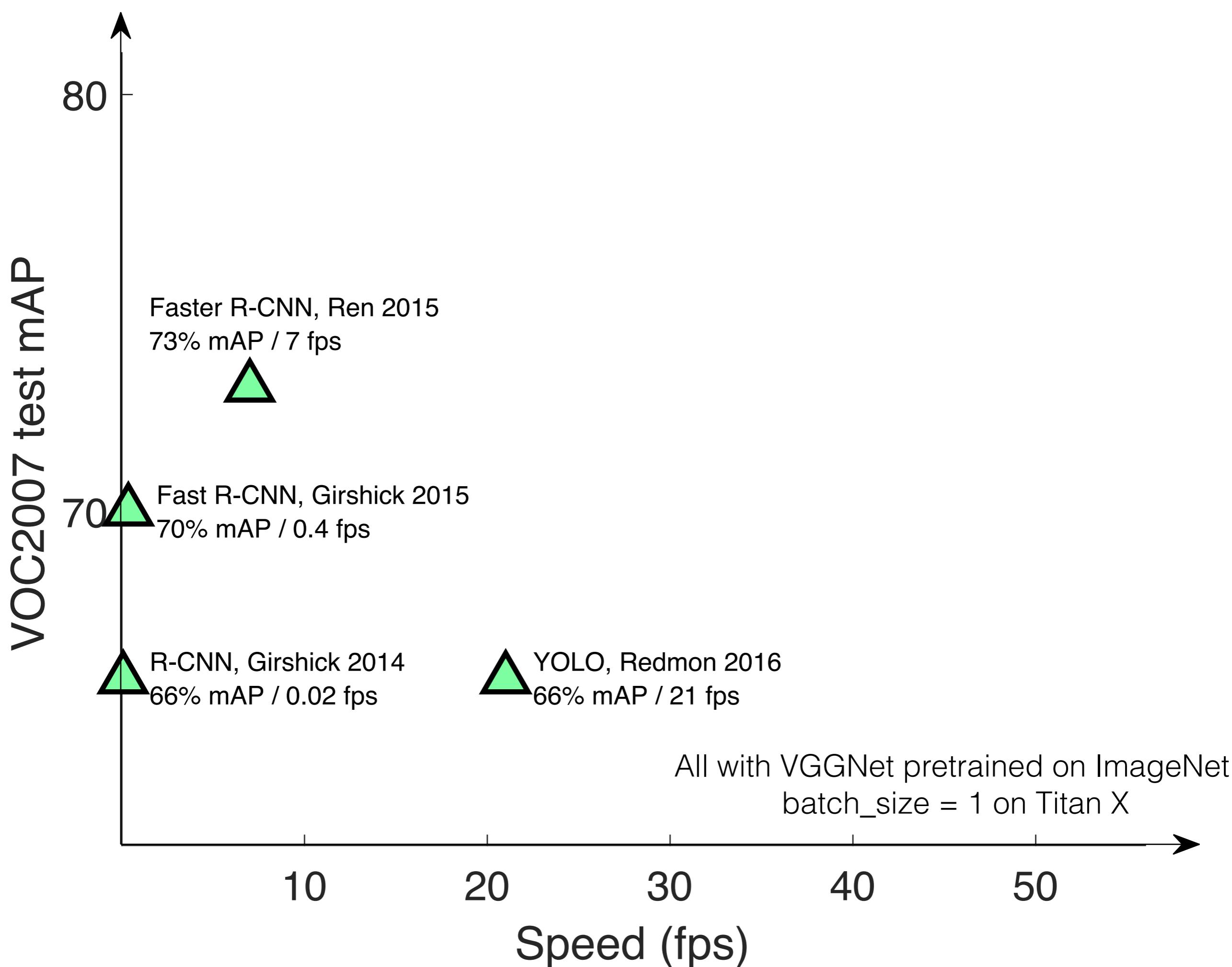
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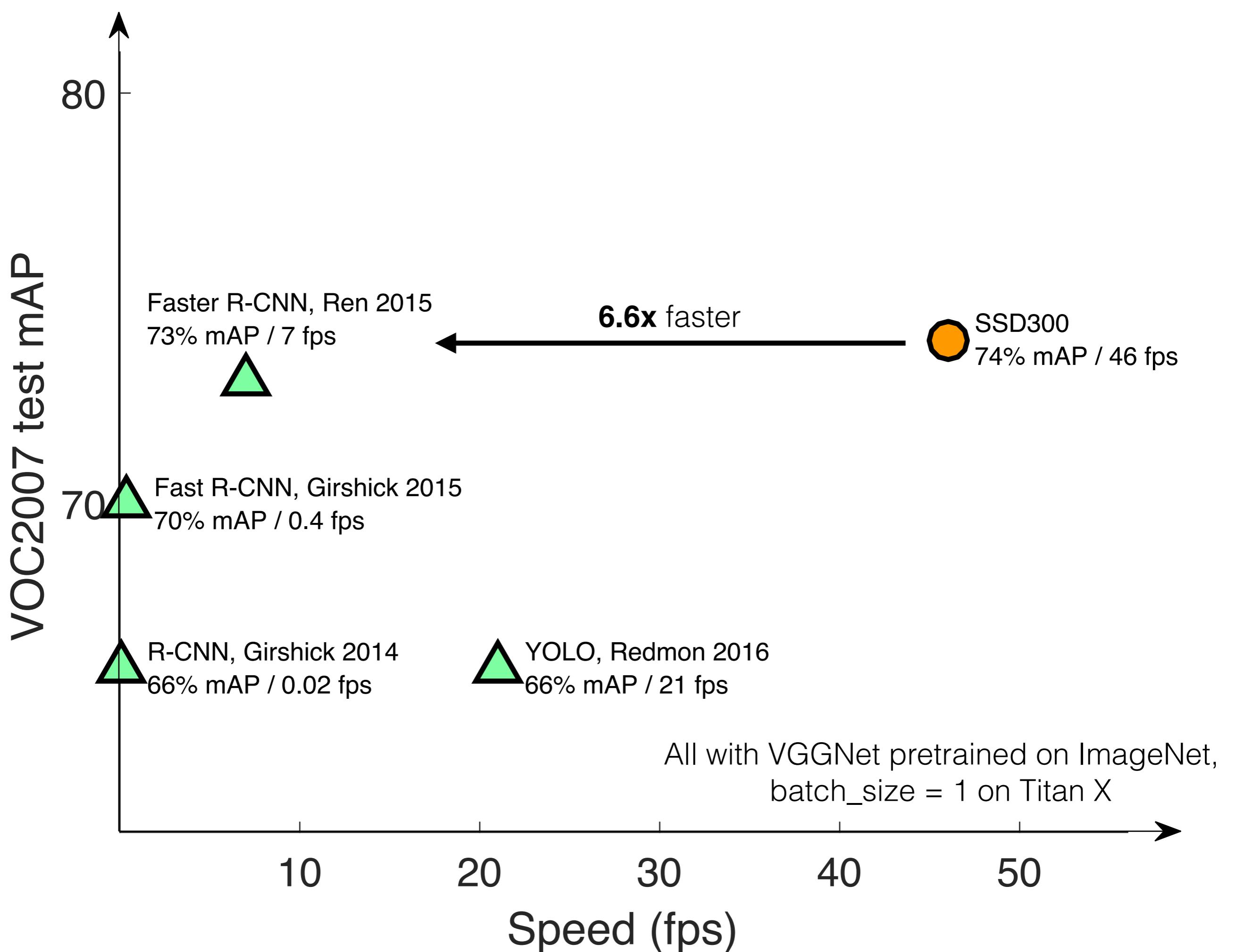


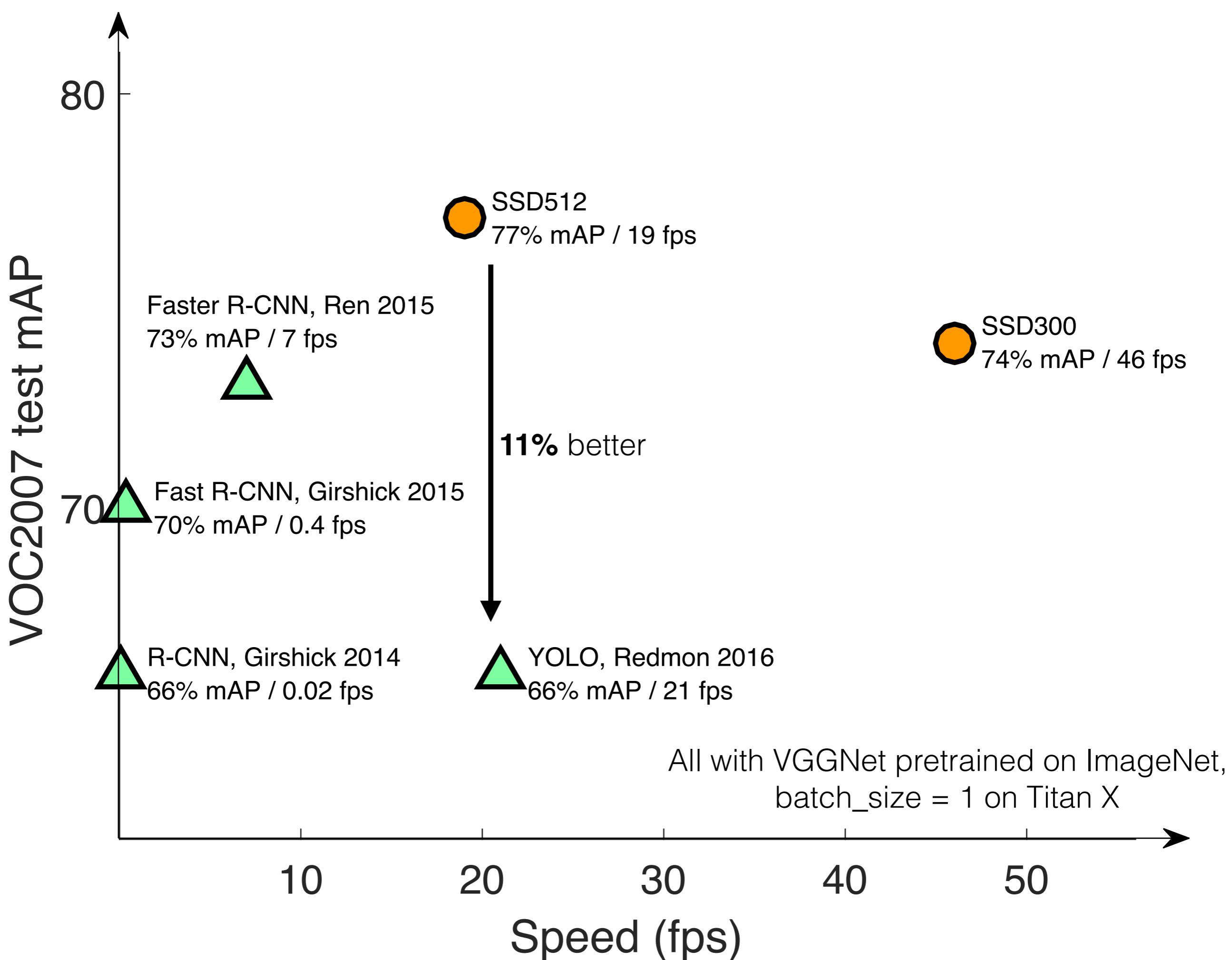
VGGNet
Titan X Pascal

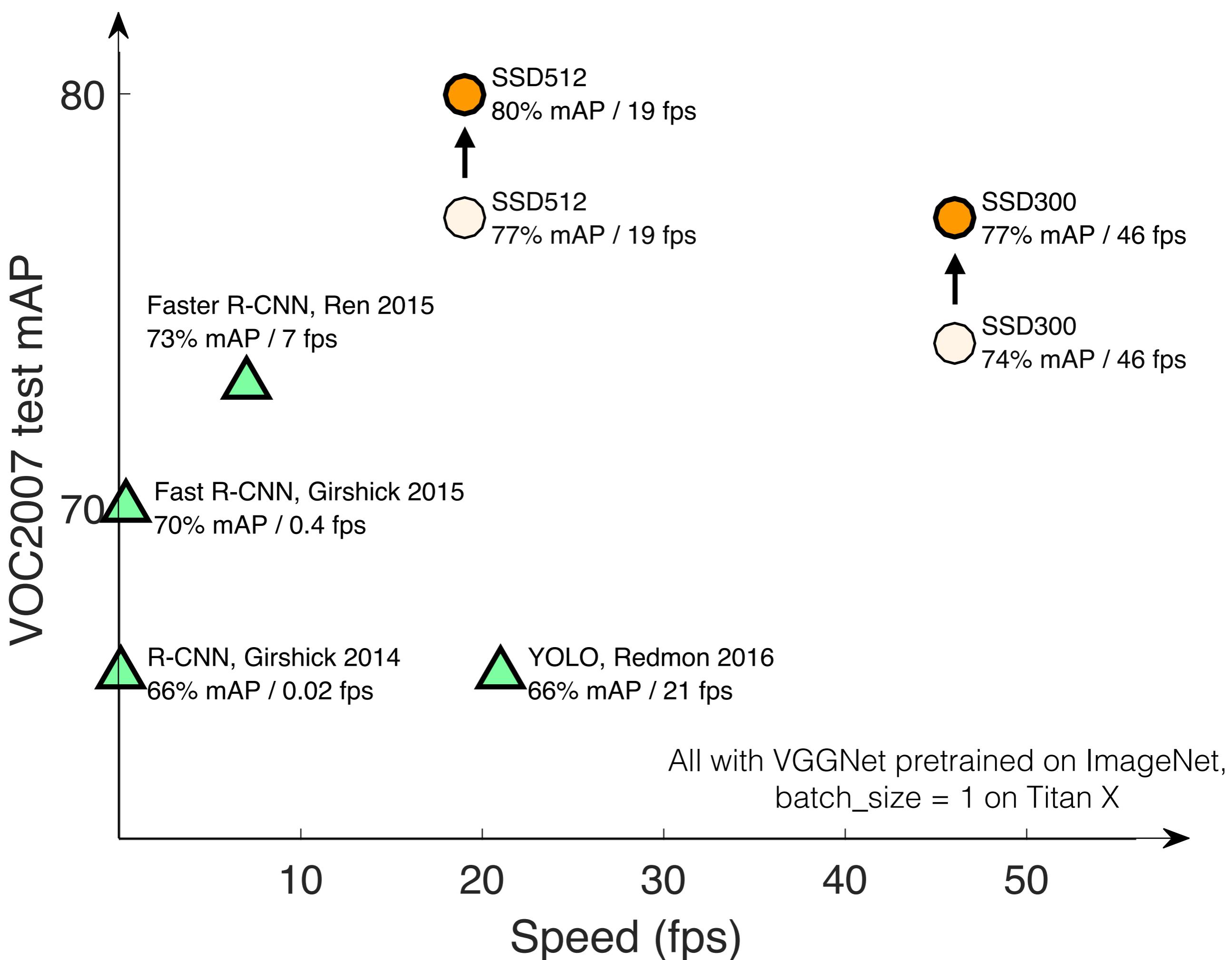


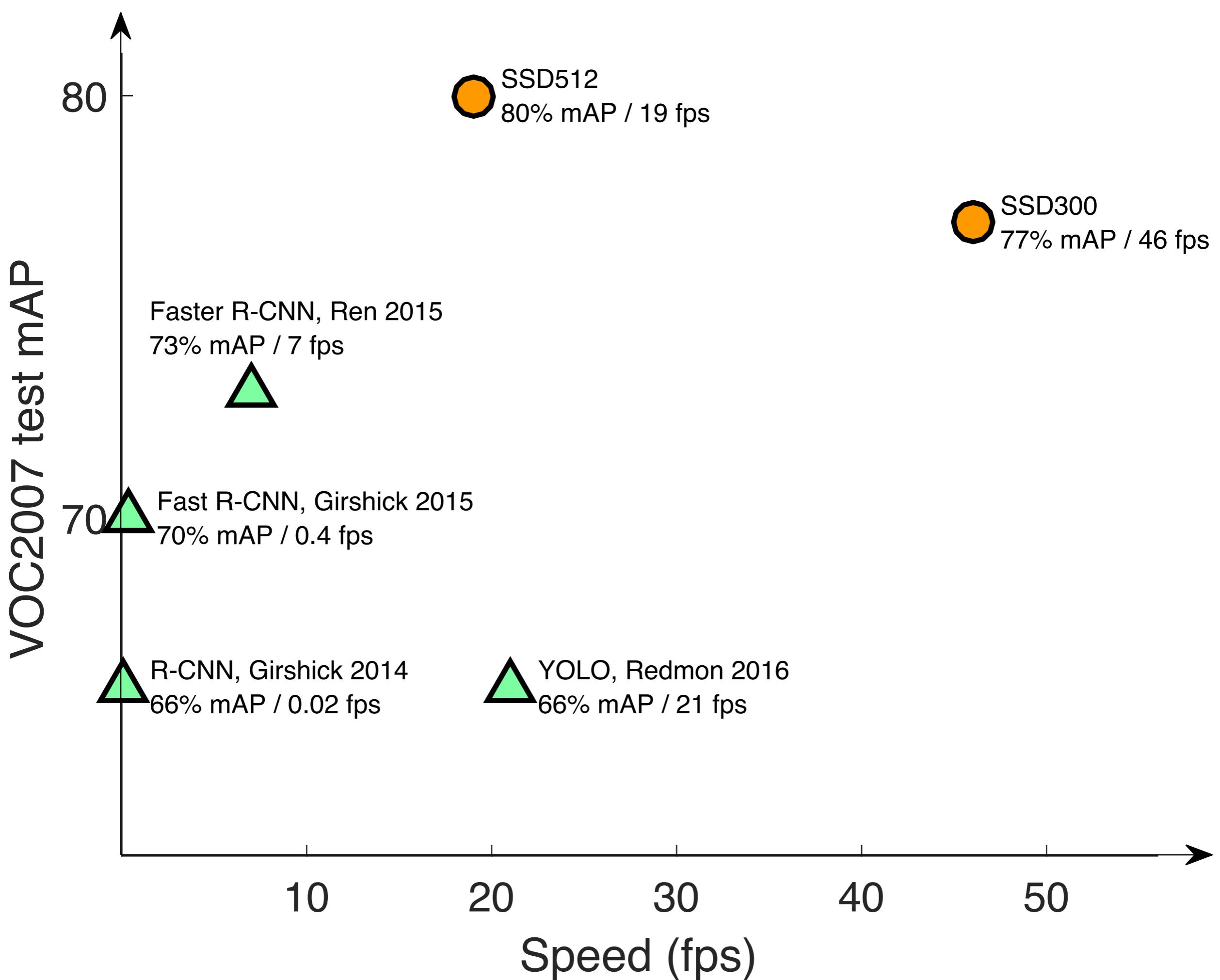
VGGNet
Titan X Pascal

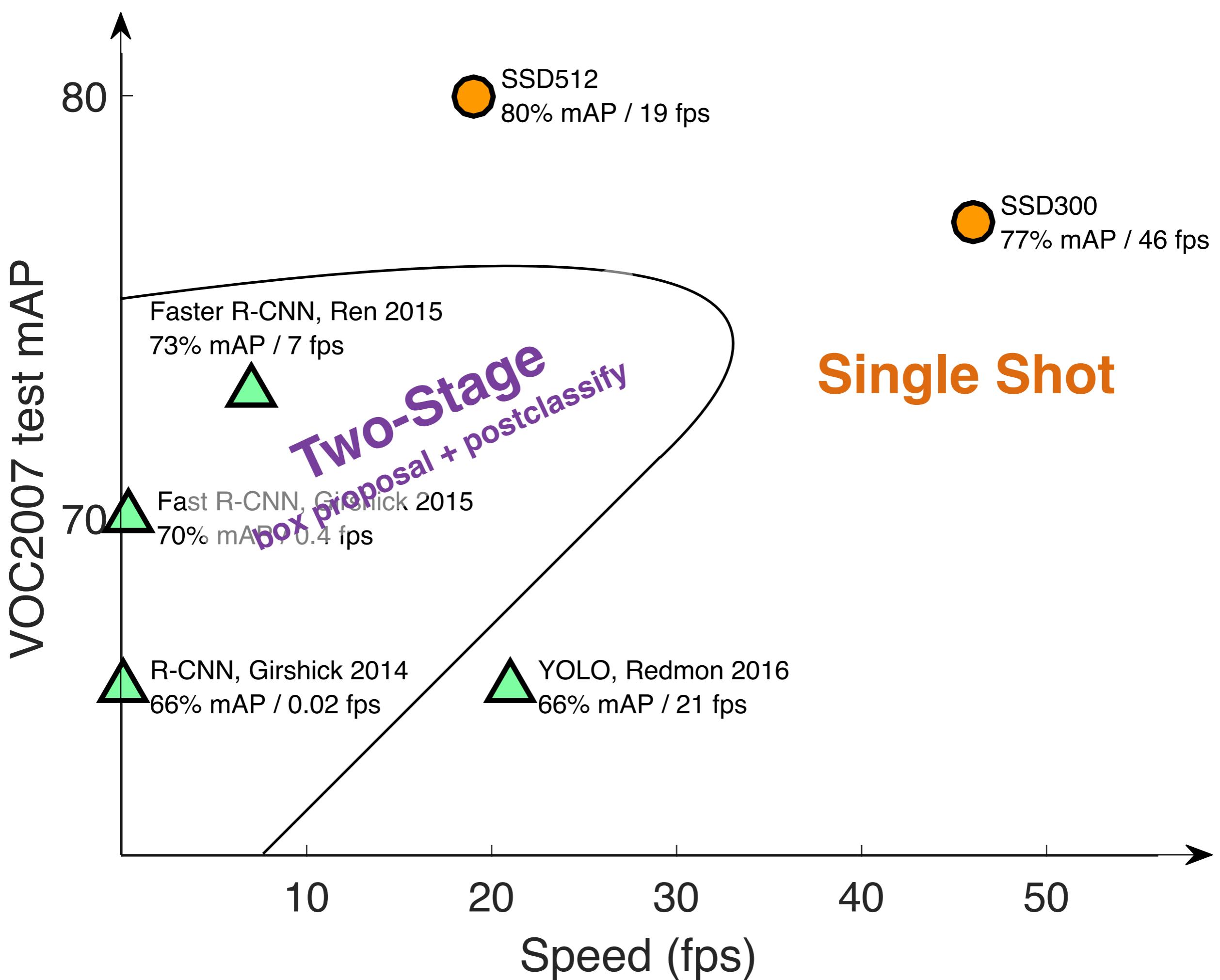






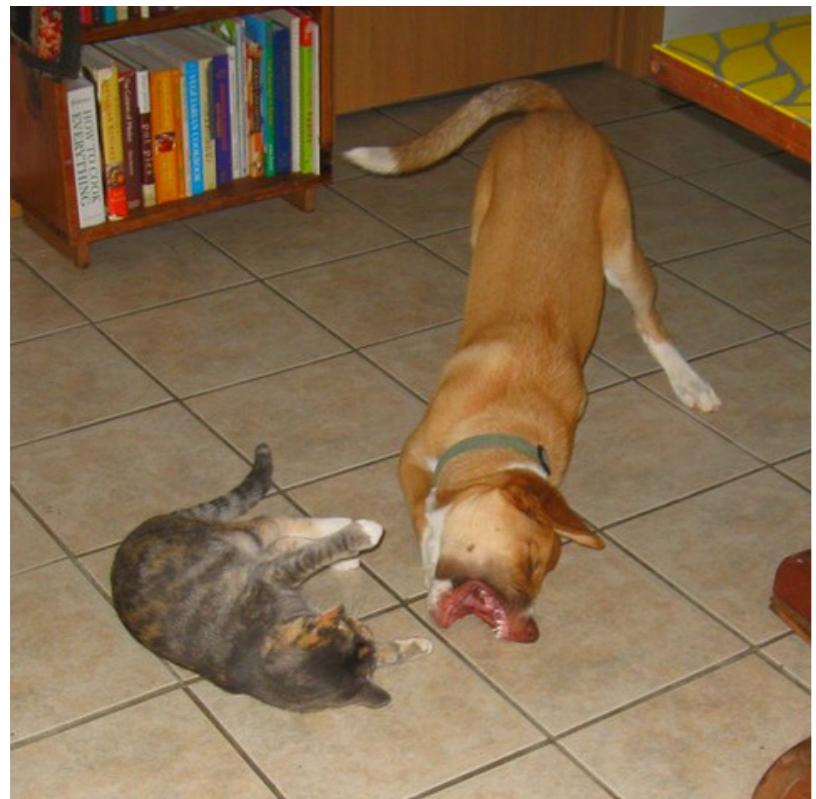






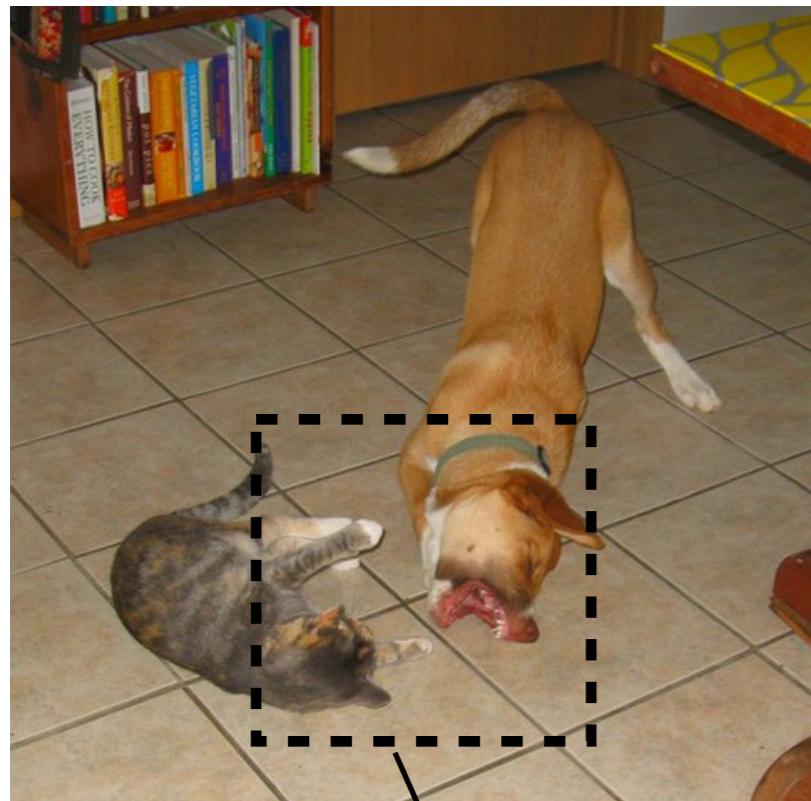
Bounding Box Prediction

Classical sliding
windows



Bounding Box Prediction

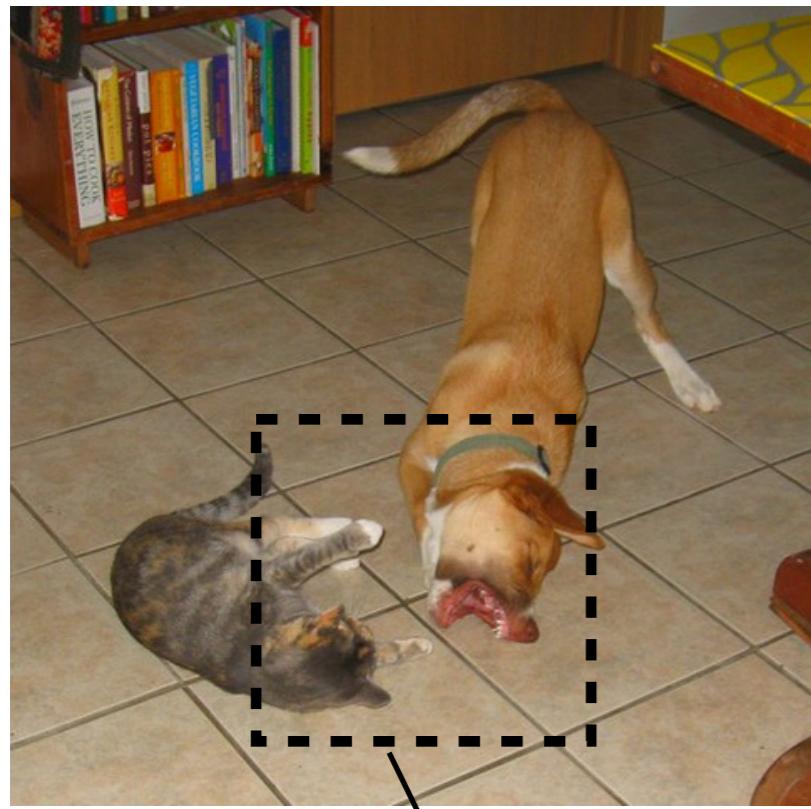
Classical sliding
windows



Is it a cat? **No**

Bounding Box Prediction

Classical sliding
windows

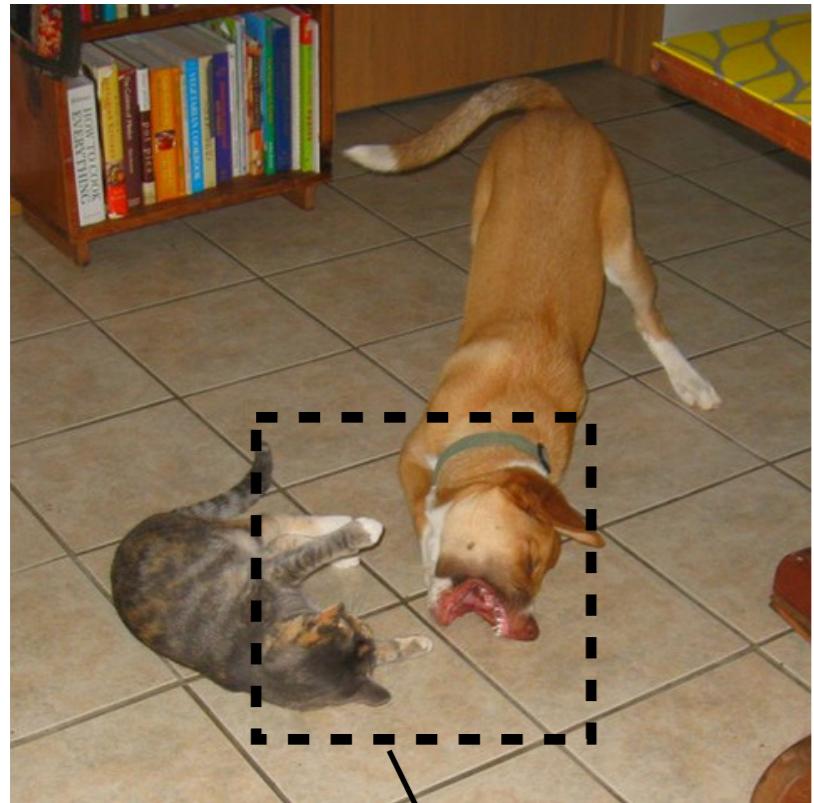


Is it a cat? **No**

Discretize the box space **densely**

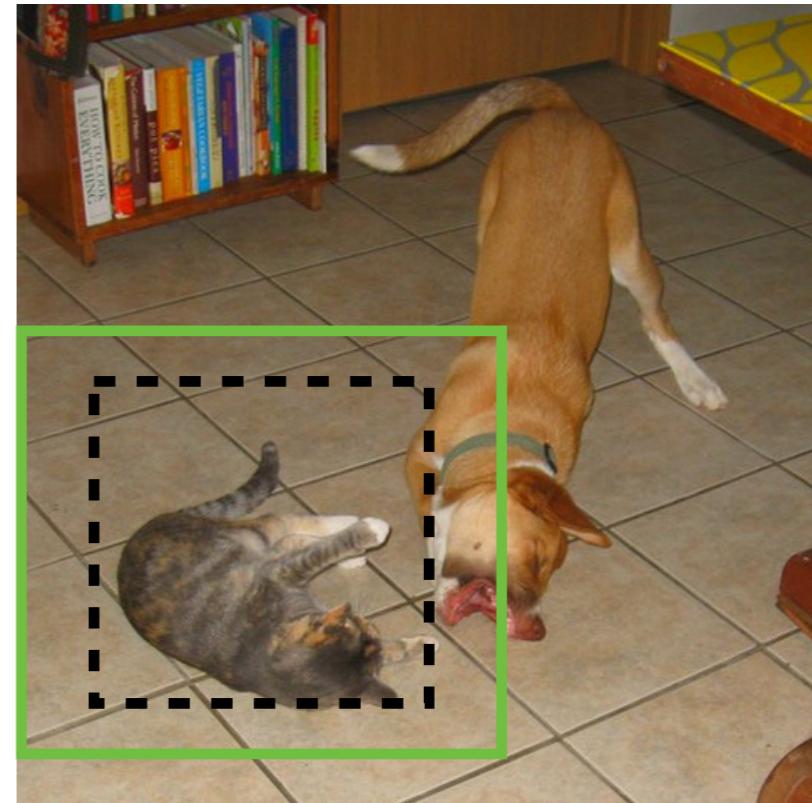
Bounding Box Prediction

Classical sliding windows



Is it a cat? **No**

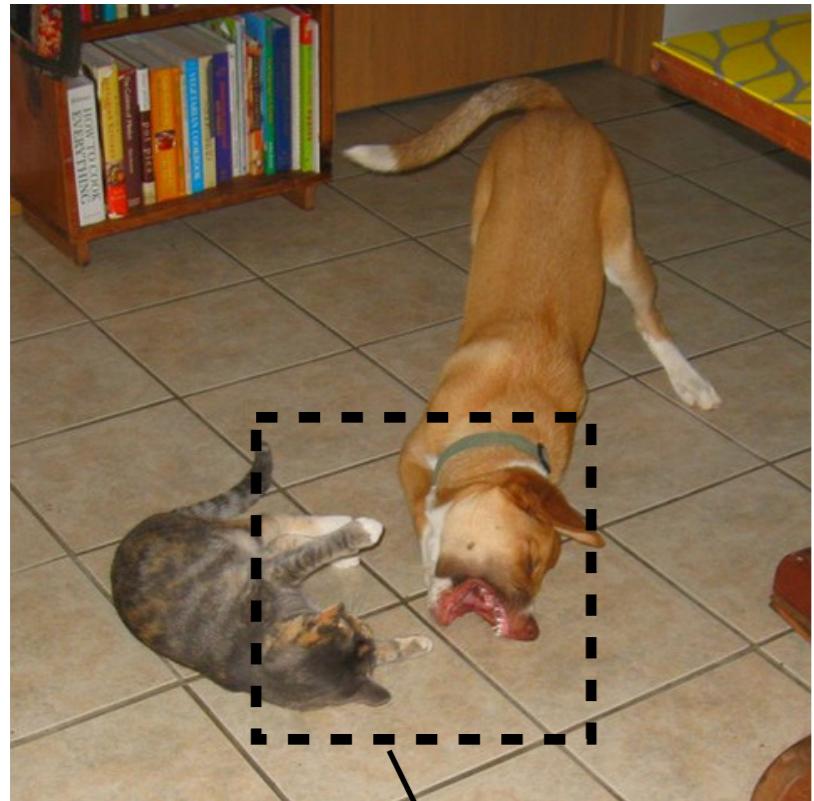
SSD and other deep approaches



Discretize the box space **densely**

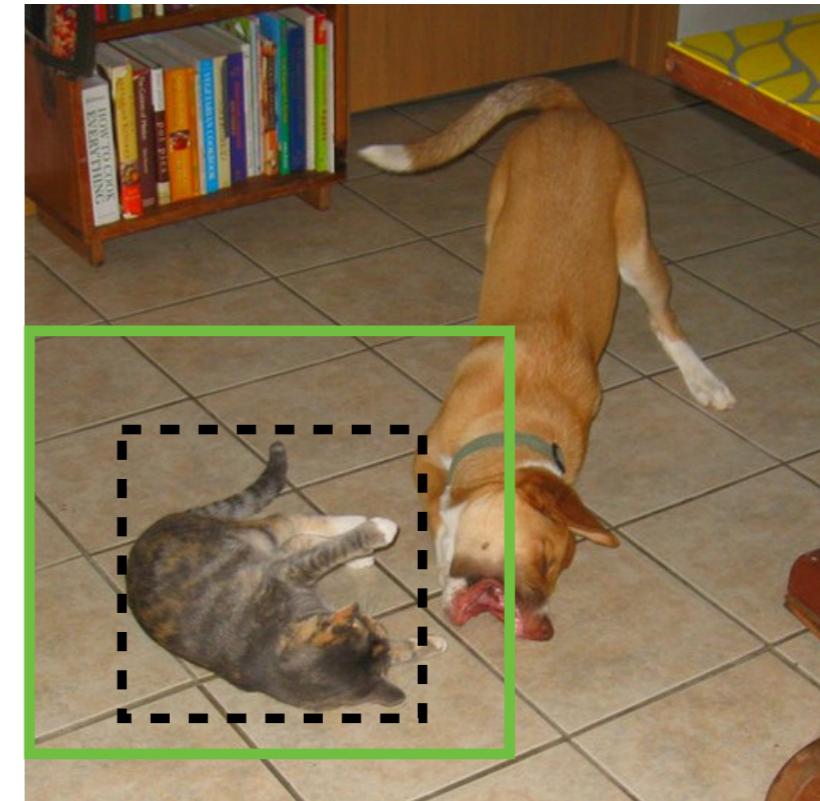
Bounding Box Prediction

Classical sliding
windows



Is it a cat? **No**

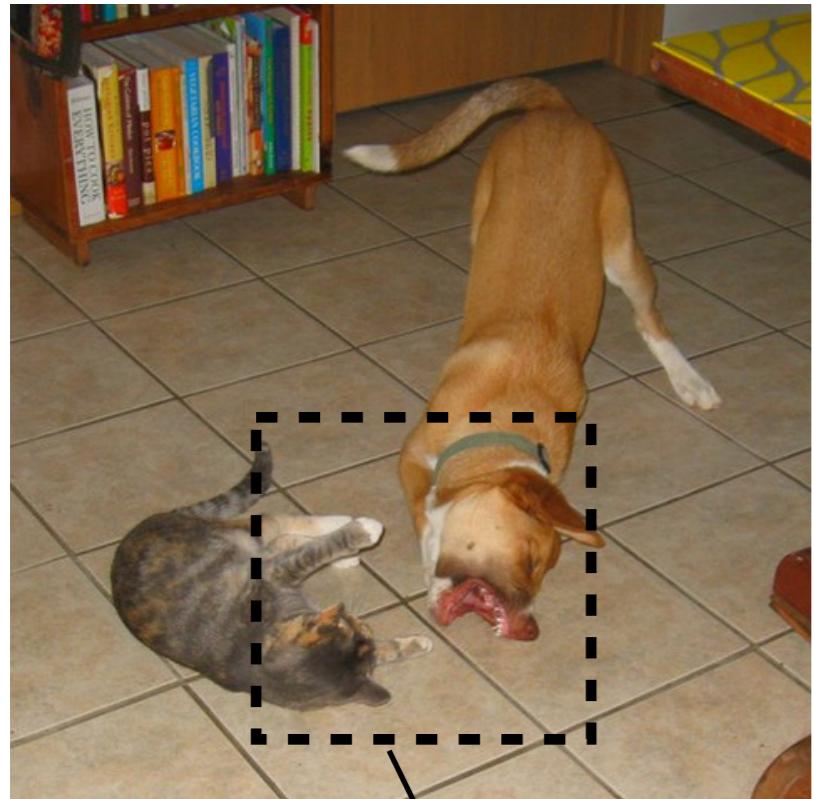
SSD and other deep
approaches



Discretize the box space **densely**

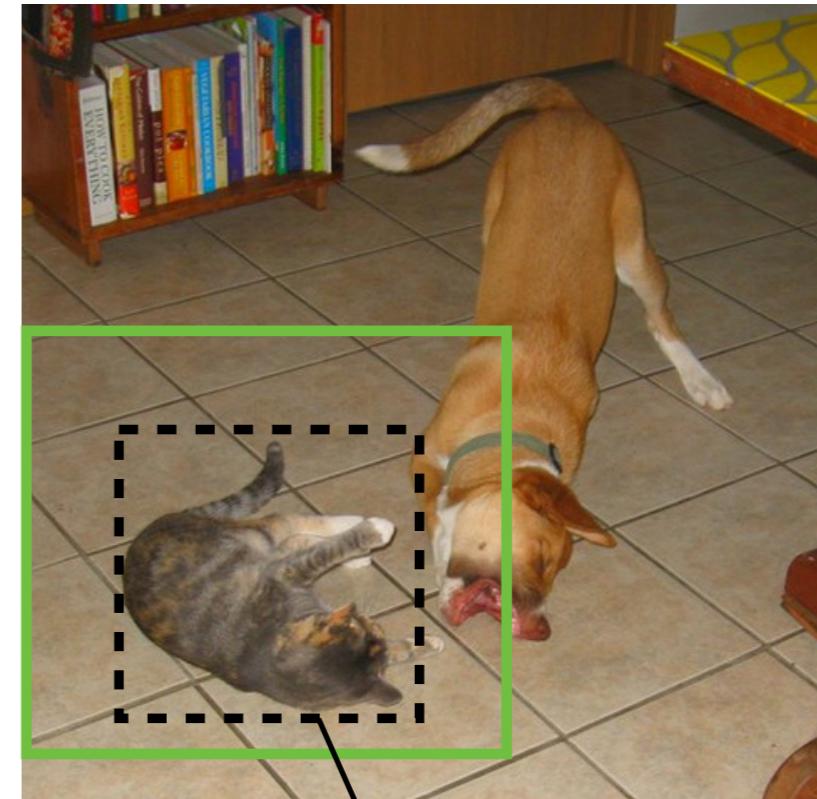
Bounding Box Prediction

Classical sliding windows



Is it a cat? **No**

SSD and other deep approaches

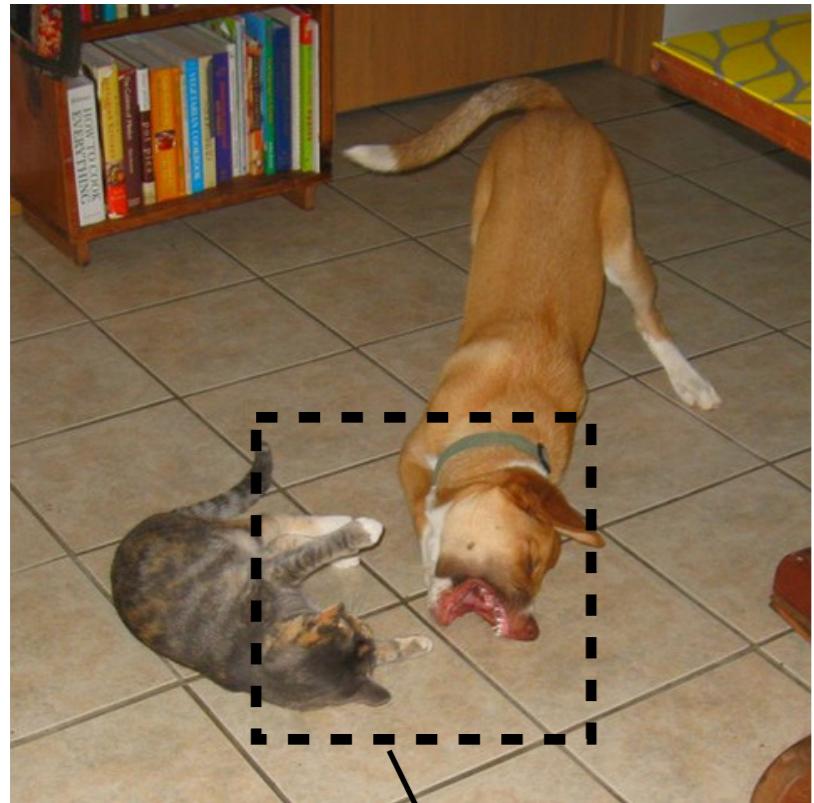


cat: 0.8 dog: 0.1

Discretize the box space **densely**

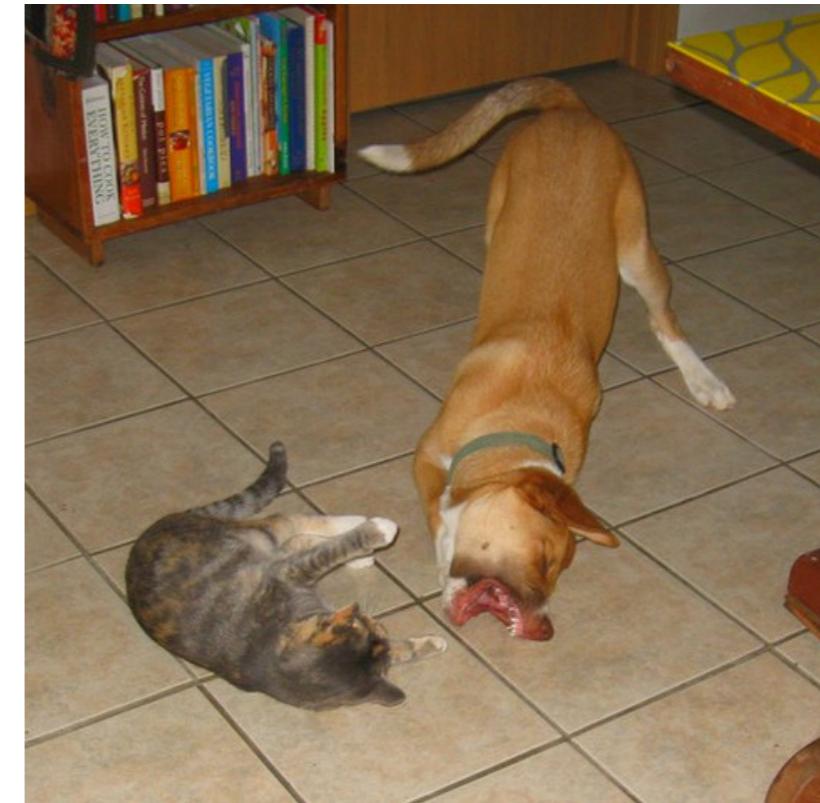
Bounding Box Prediction

Classical sliding
windows



Is it a cat? **No**

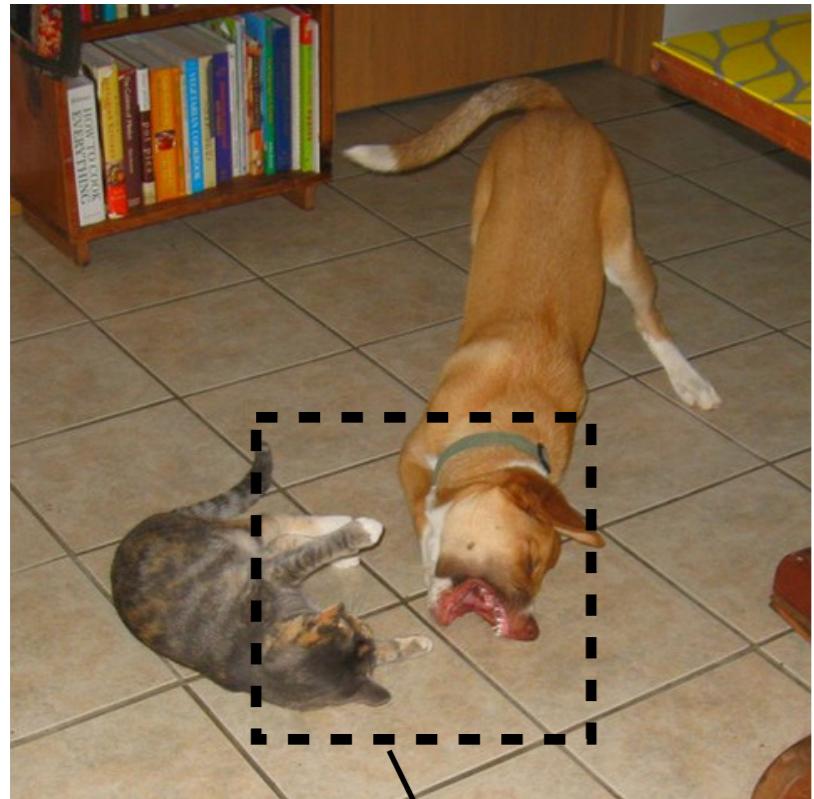
SSD and other deep
approaches



Discretize the box space **densely**

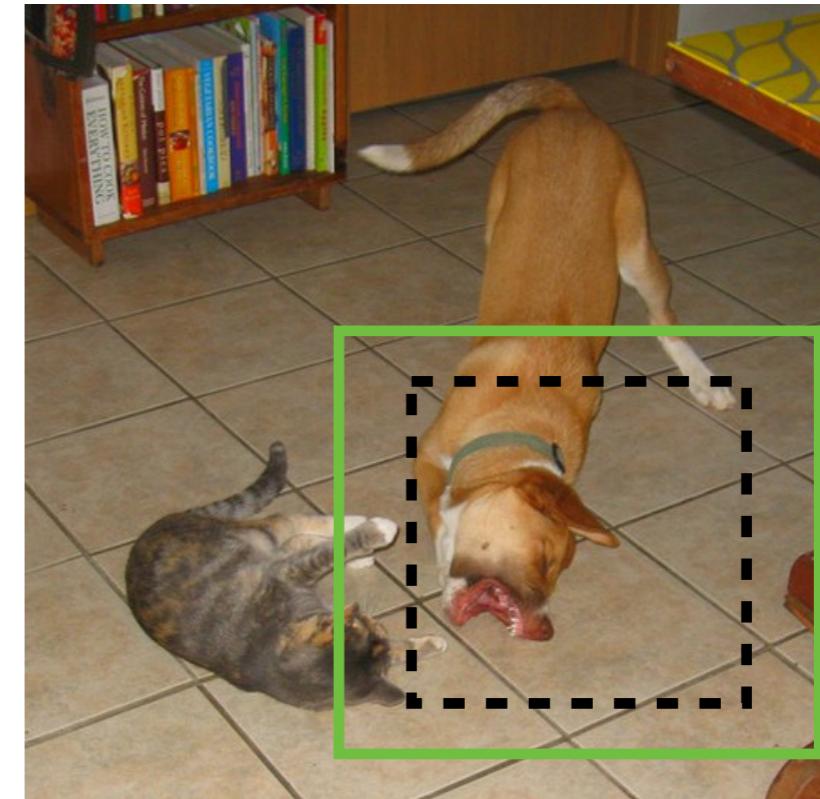
Bounding Box Prediction

Classical sliding
windows



Is it a cat? **No**

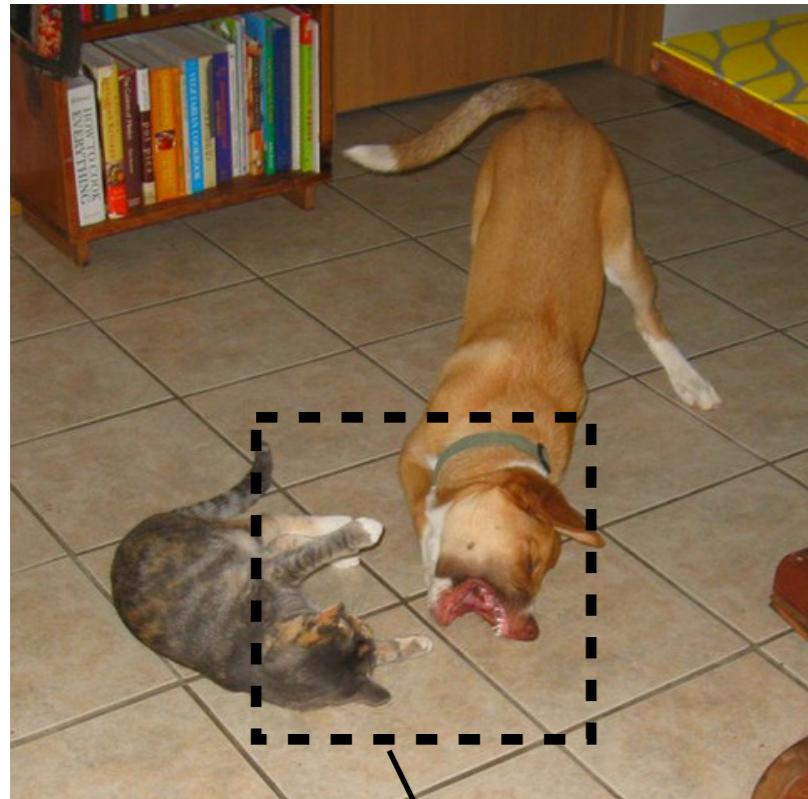
SSD and other deep
approaches



Discretize the box space **densely**

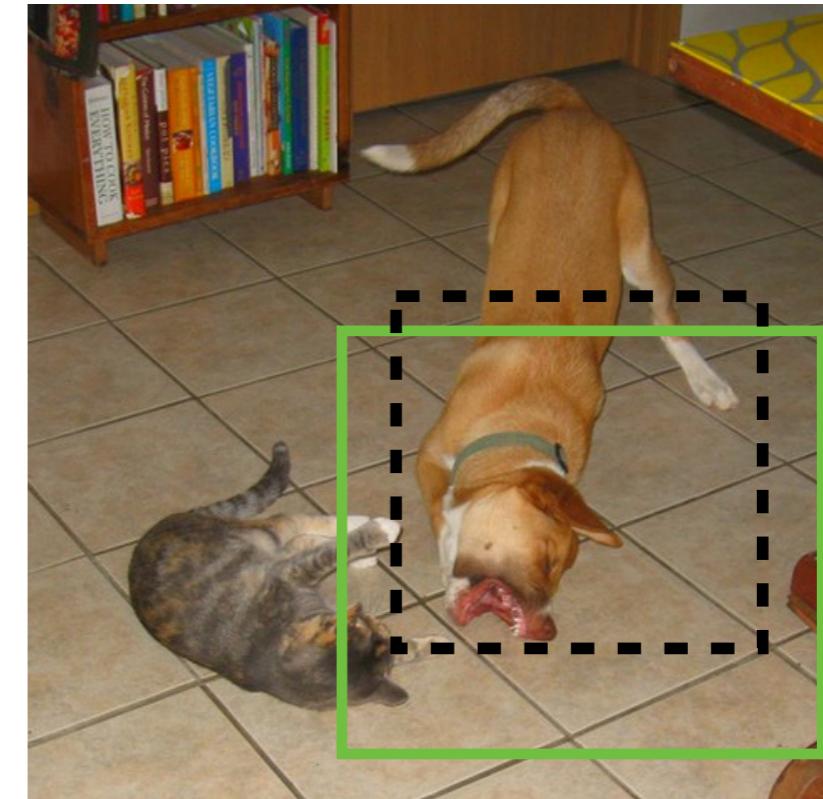
Bounding Box Prediction

Classical sliding windows



Is it a cat? **No**

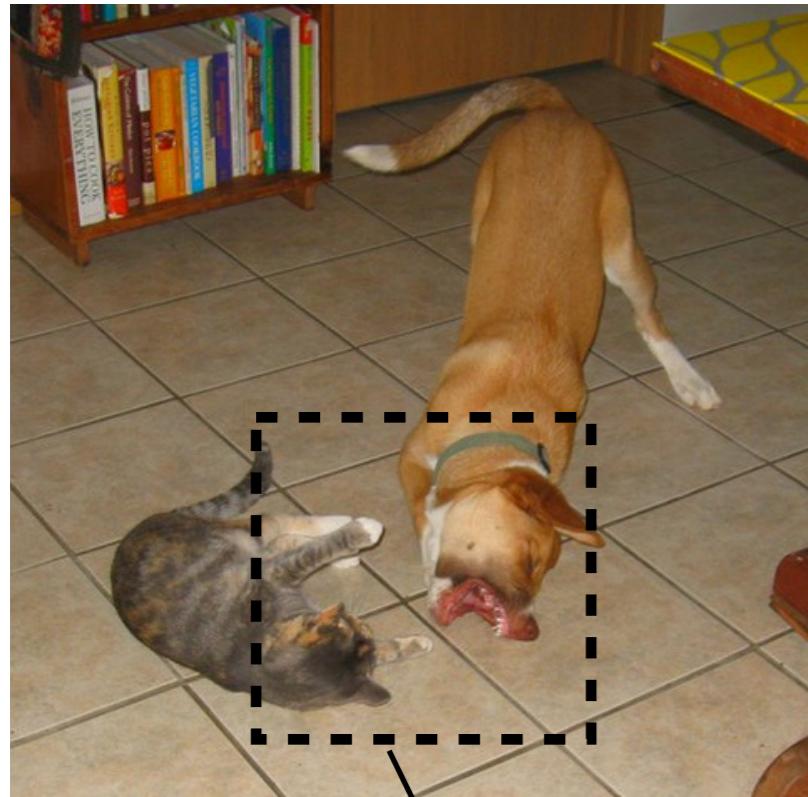
SSD and other deep approaches



Discretize the box space **densely**

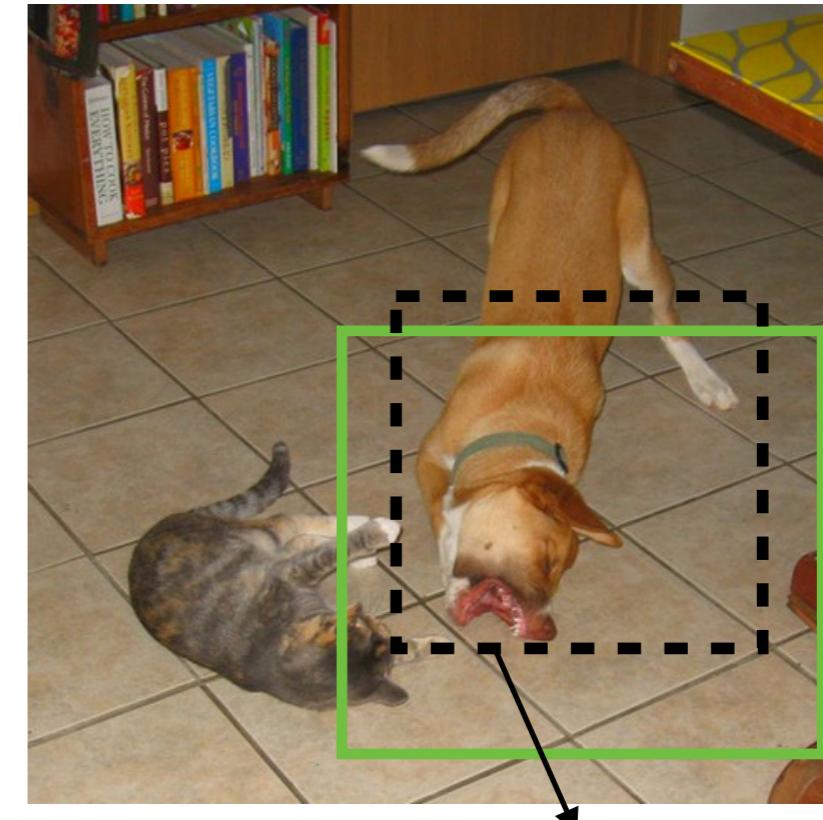
Bounding Box Prediction

Classical sliding windows



Is it a cat? **No**

SSD and other deep approaches

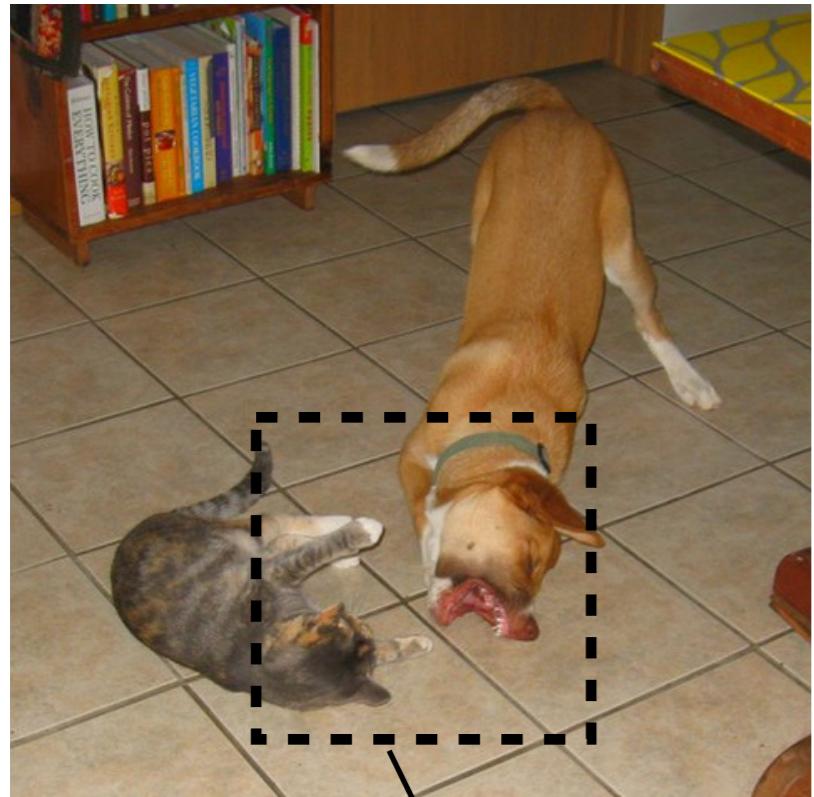


dog: 0.4 cat: 0.2

Discretize the box space **densely**

Bounding Box Prediction

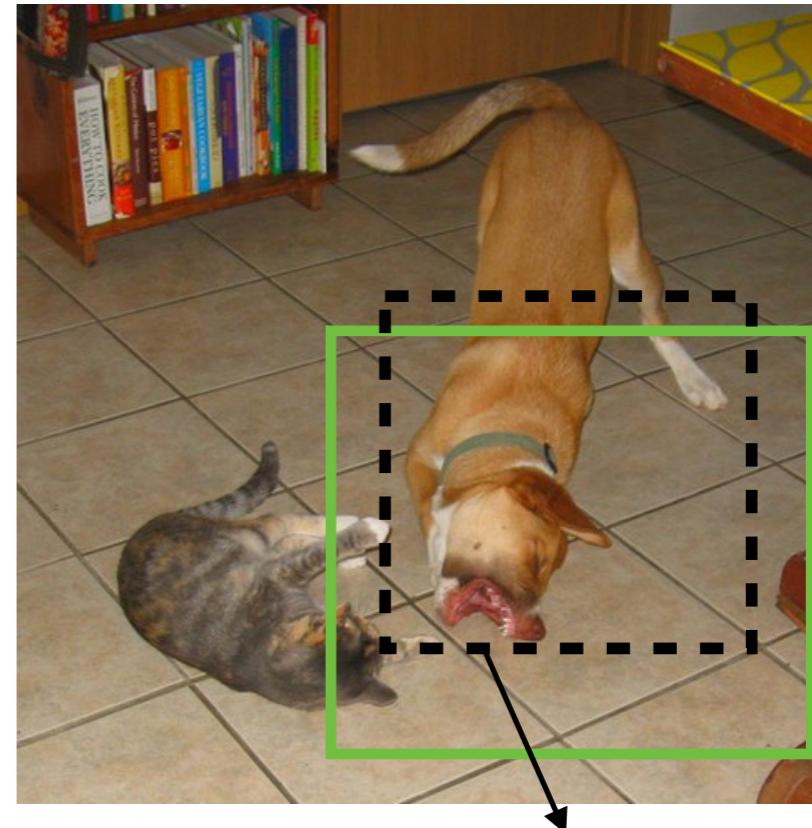
Classical sliding windows



Is it a cat? **No**

Discretize the box space **densely**

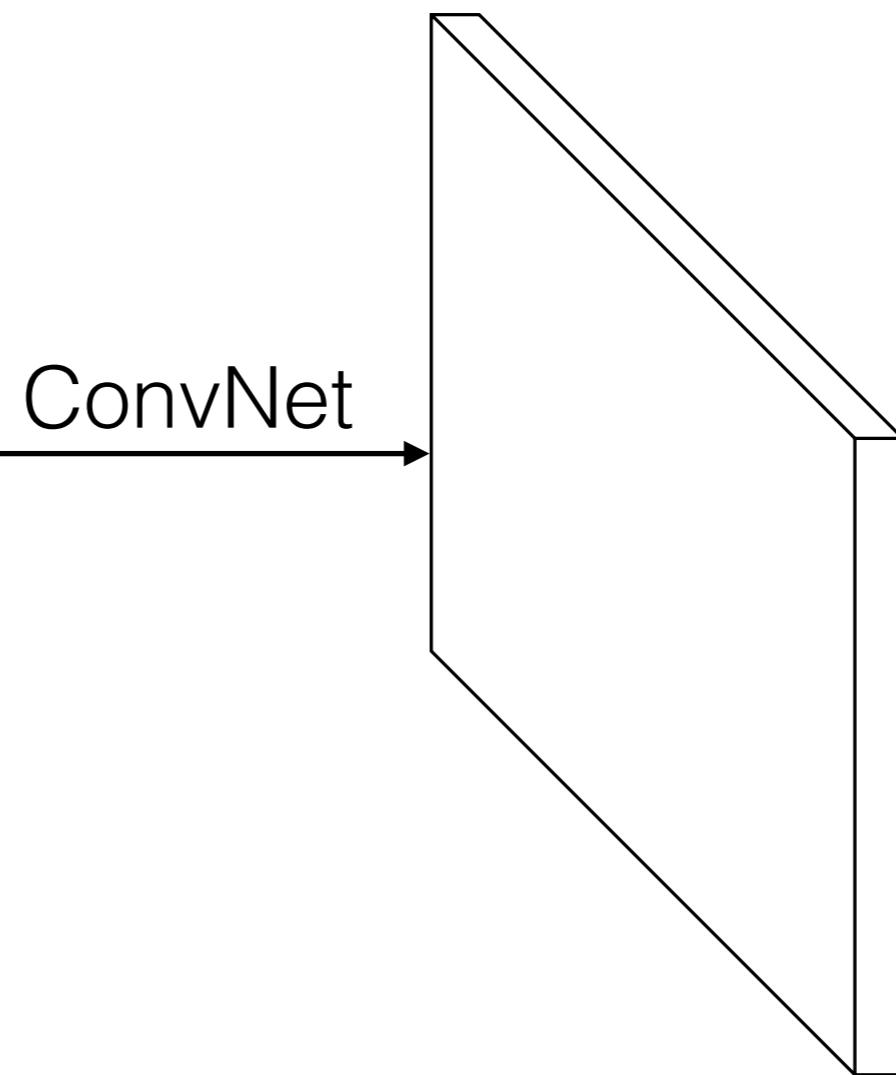
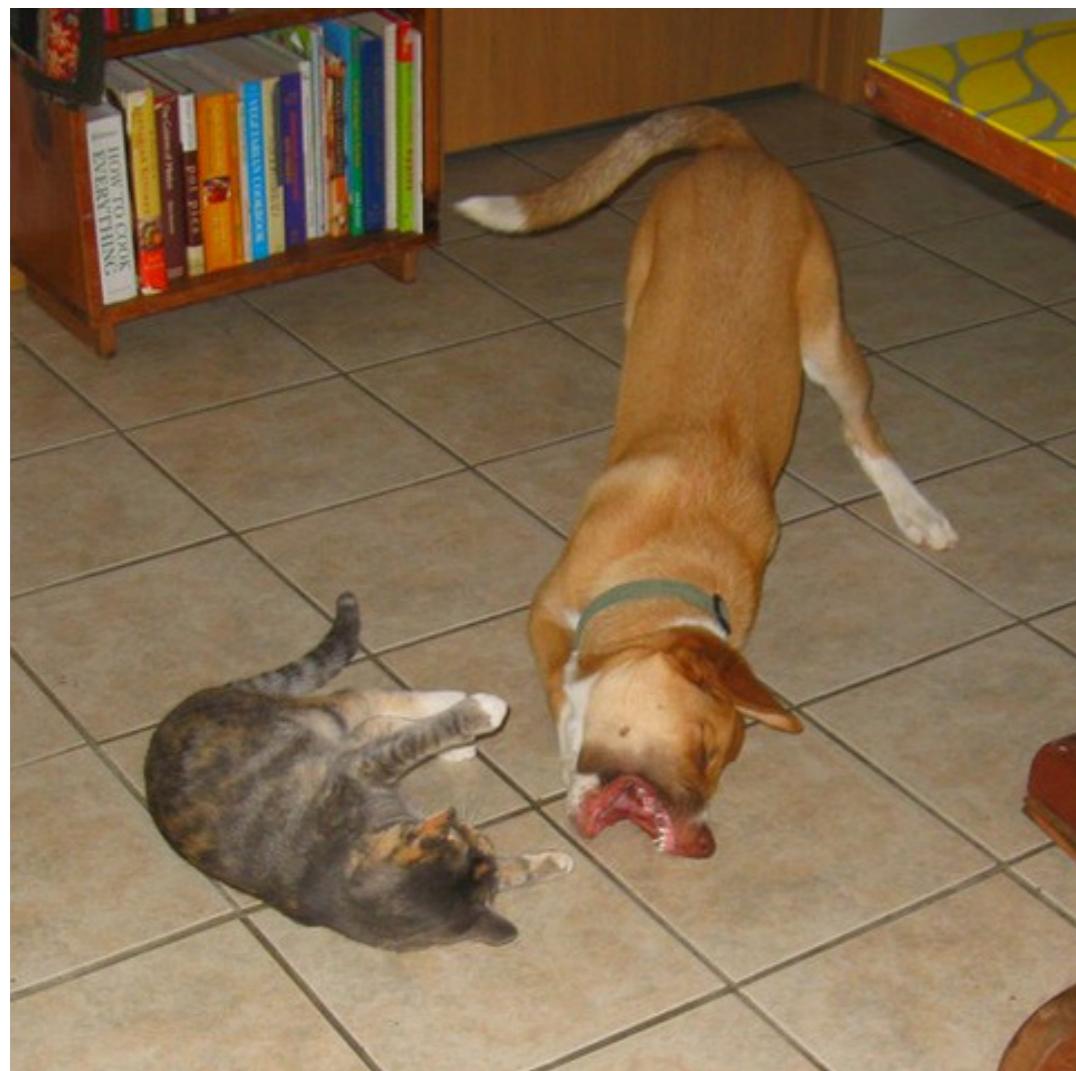
SSD and other deep approaches



dog: 0.4 cat: 0.2

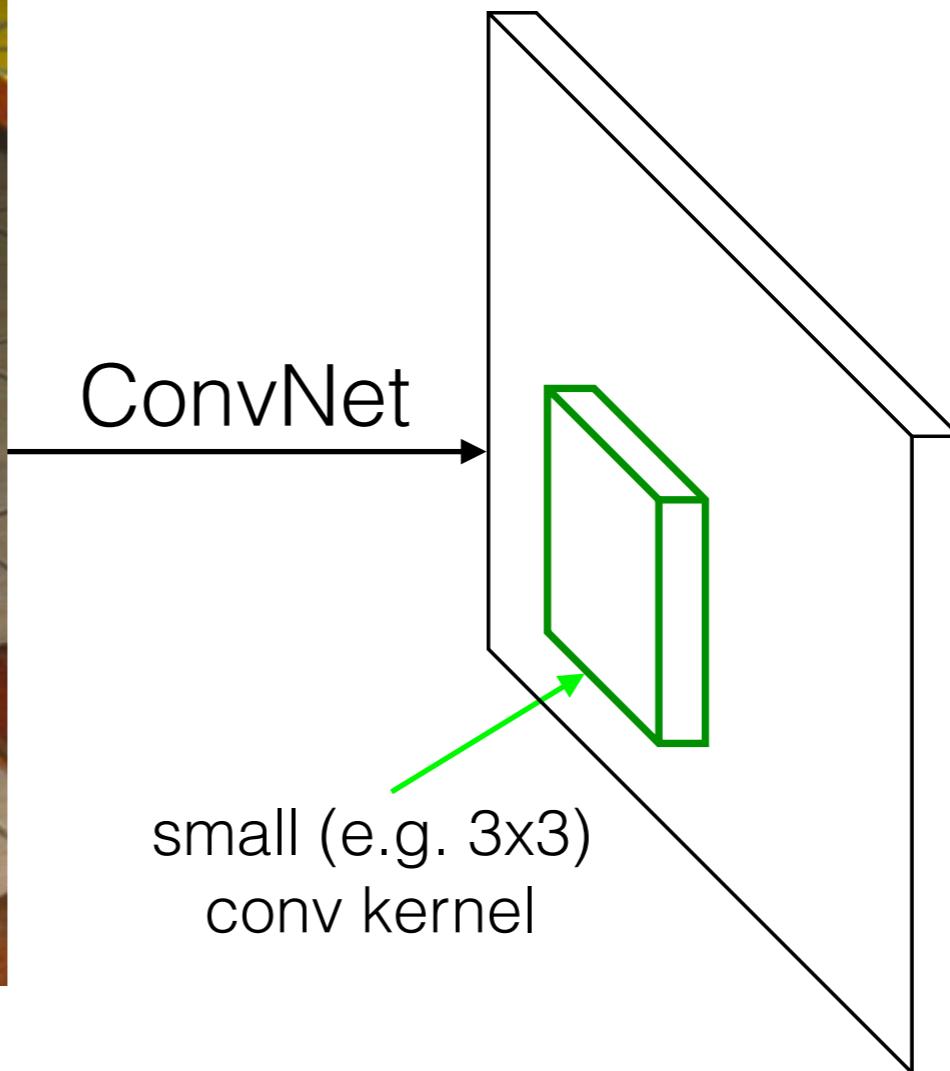
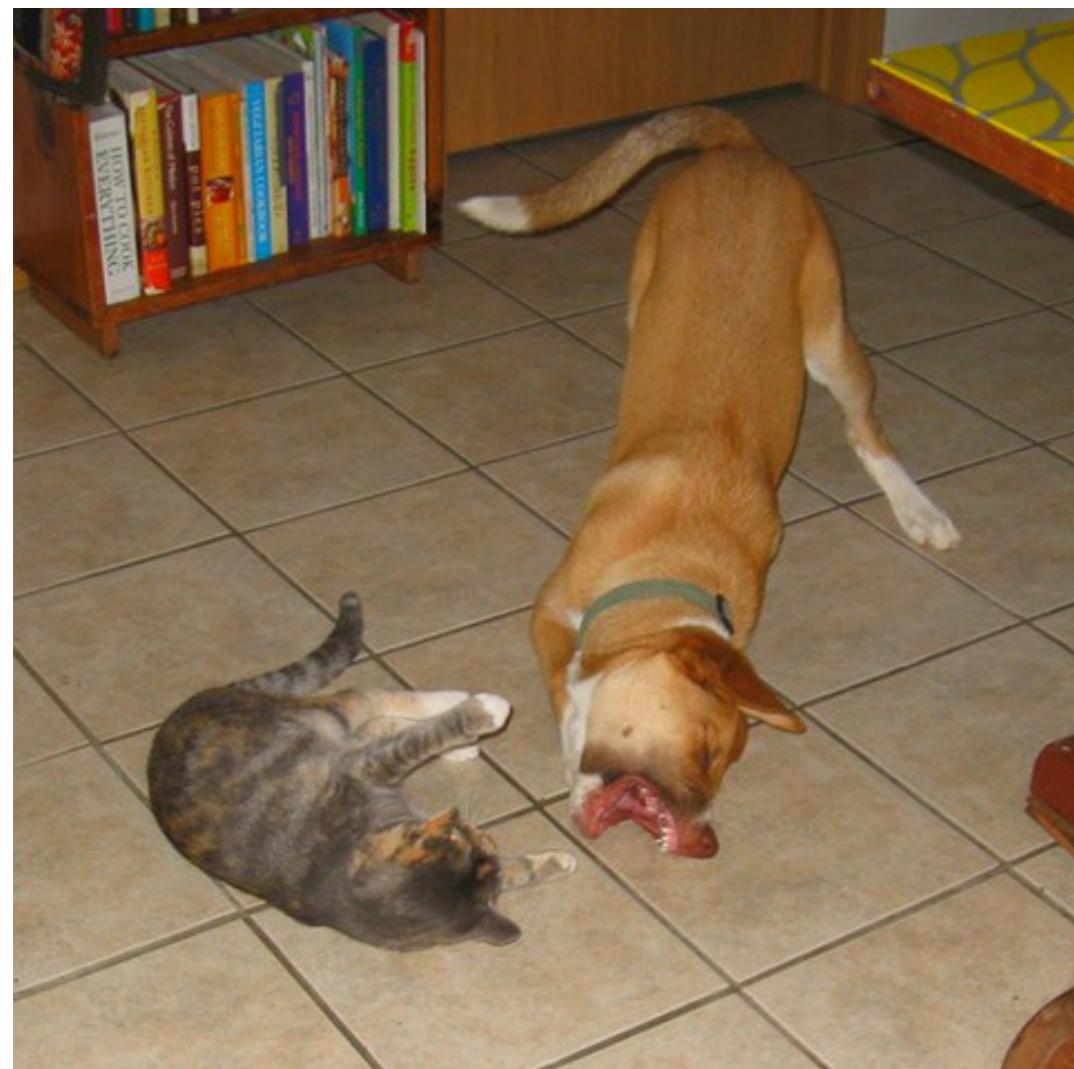
Discretize the box space more **coarsely**
Refine the coordinates of each box

SSD Output Layer



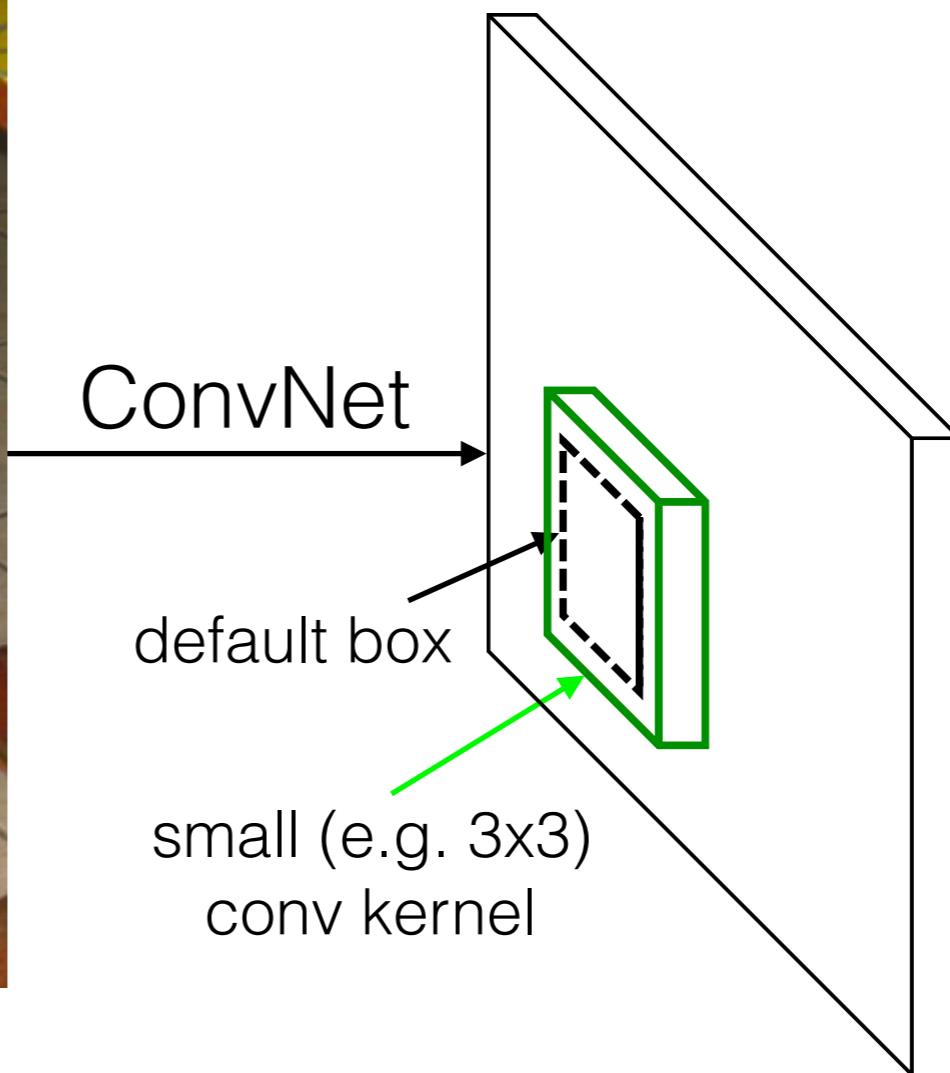
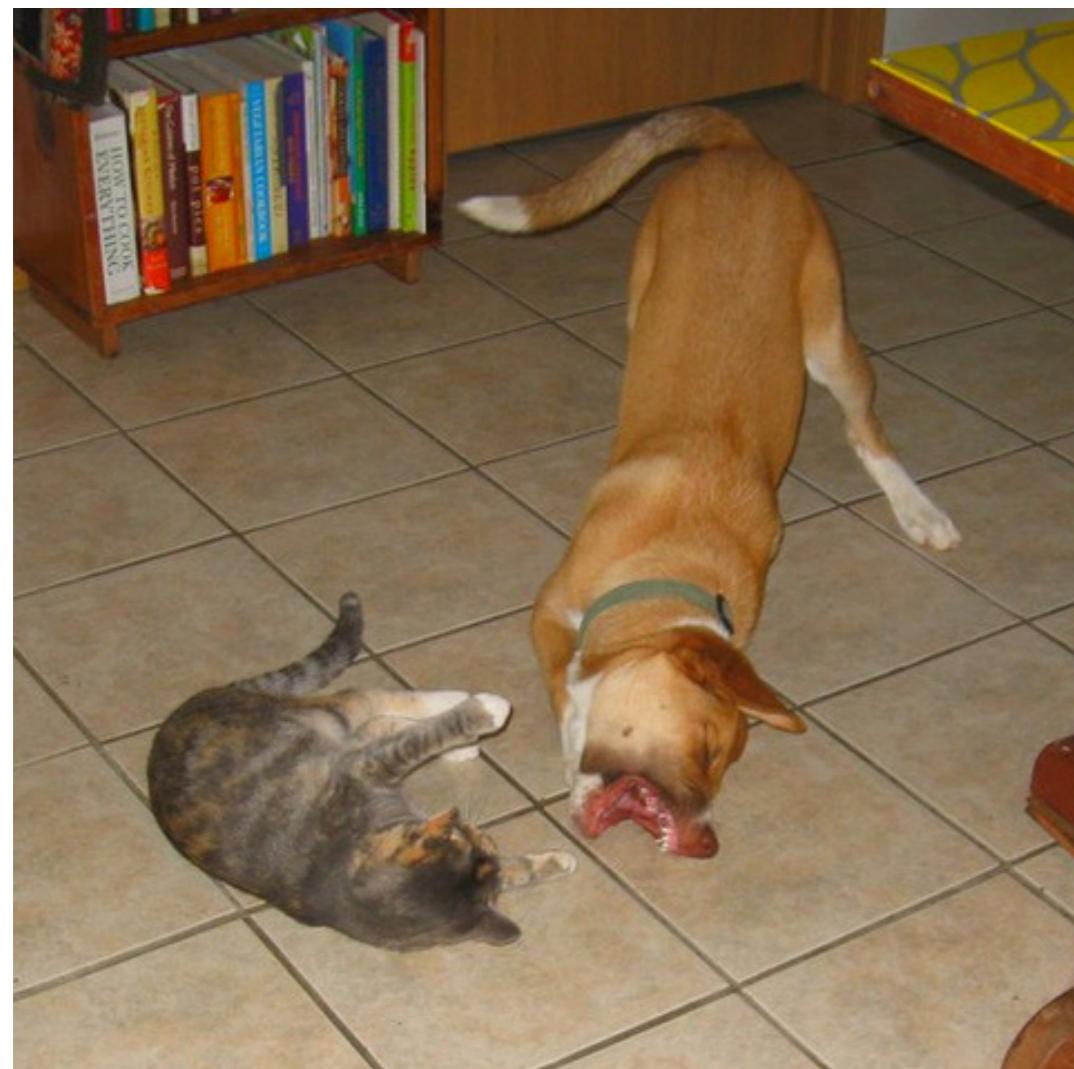
feature map

SSD Output Layer



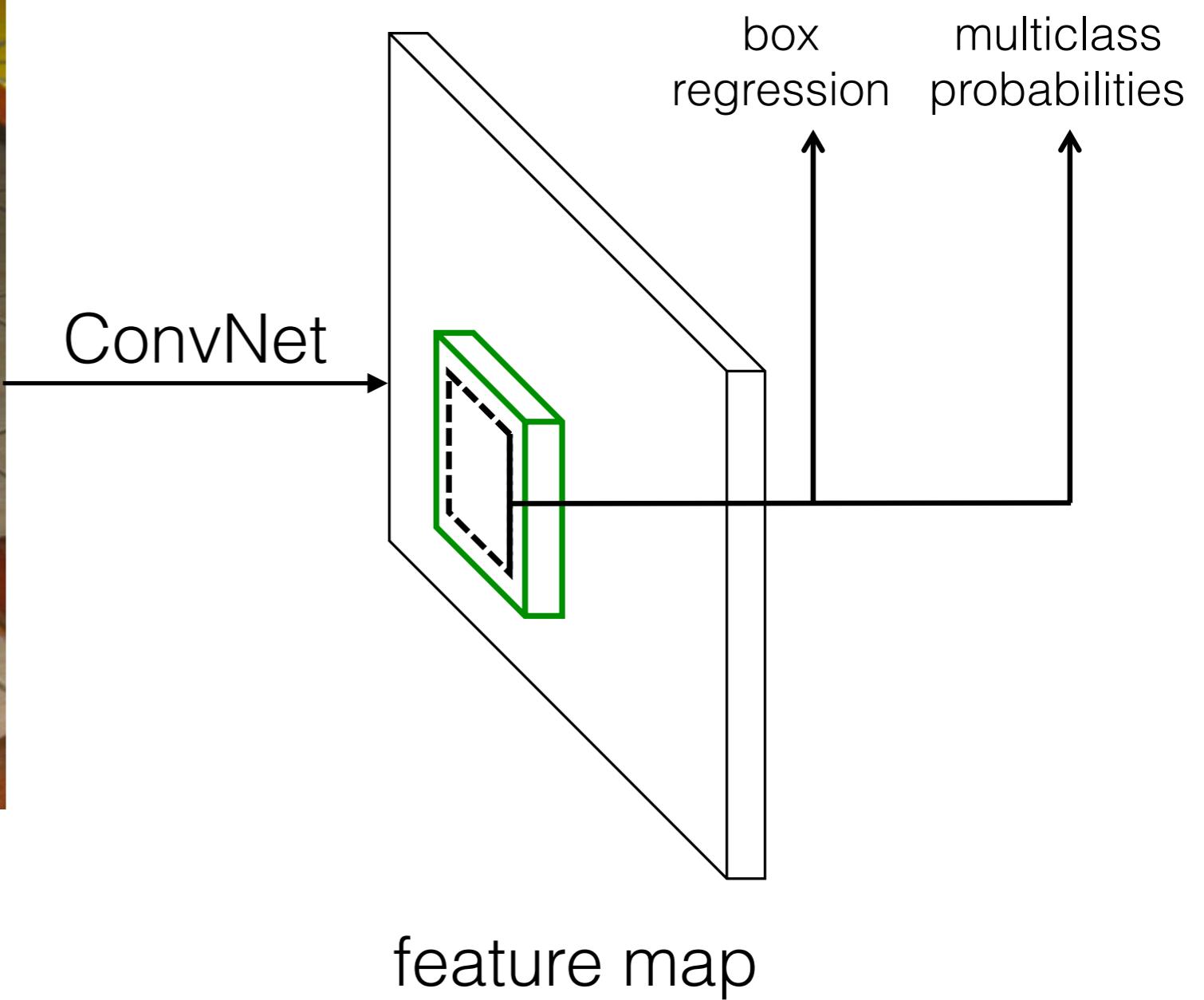
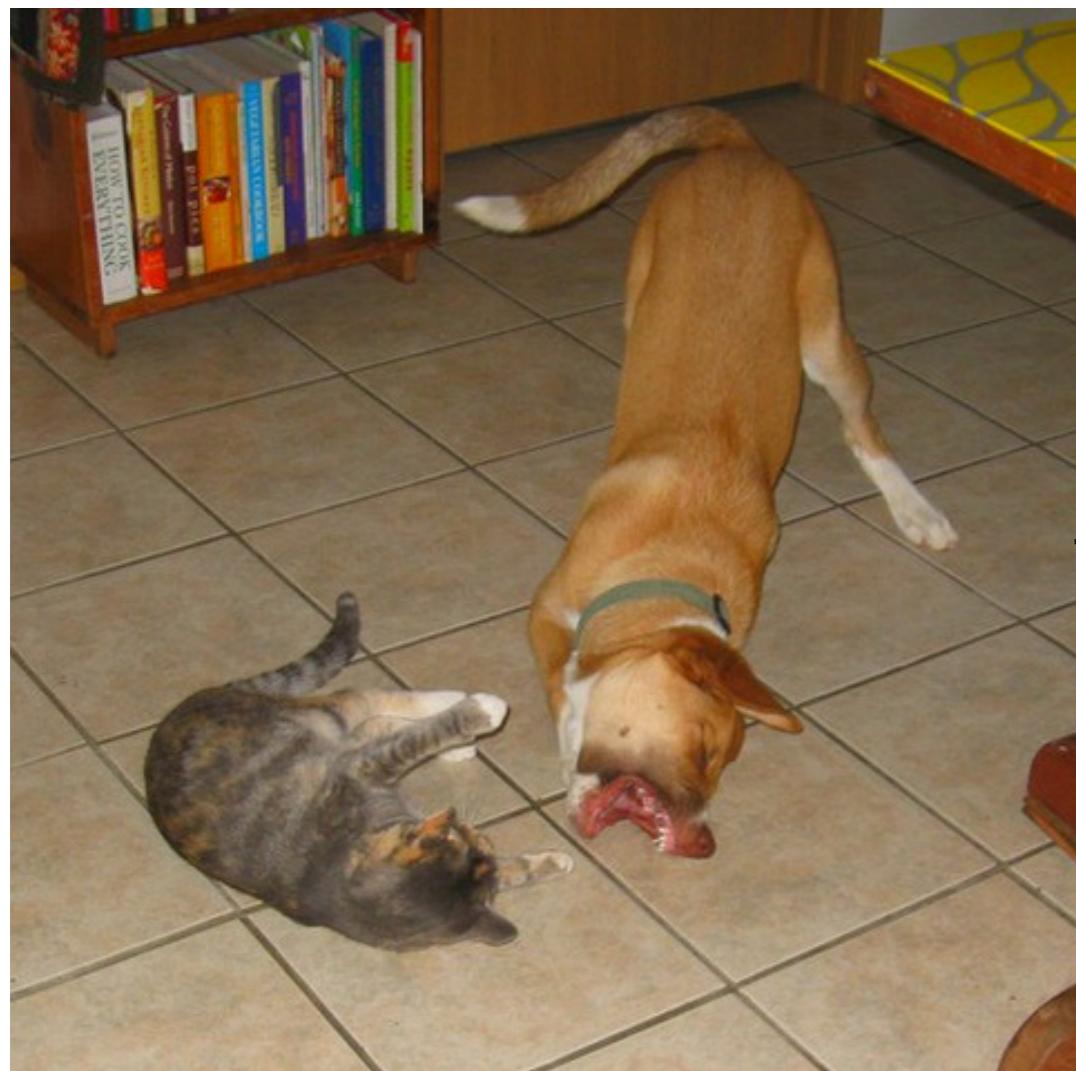
feature map

SSD Output Layer



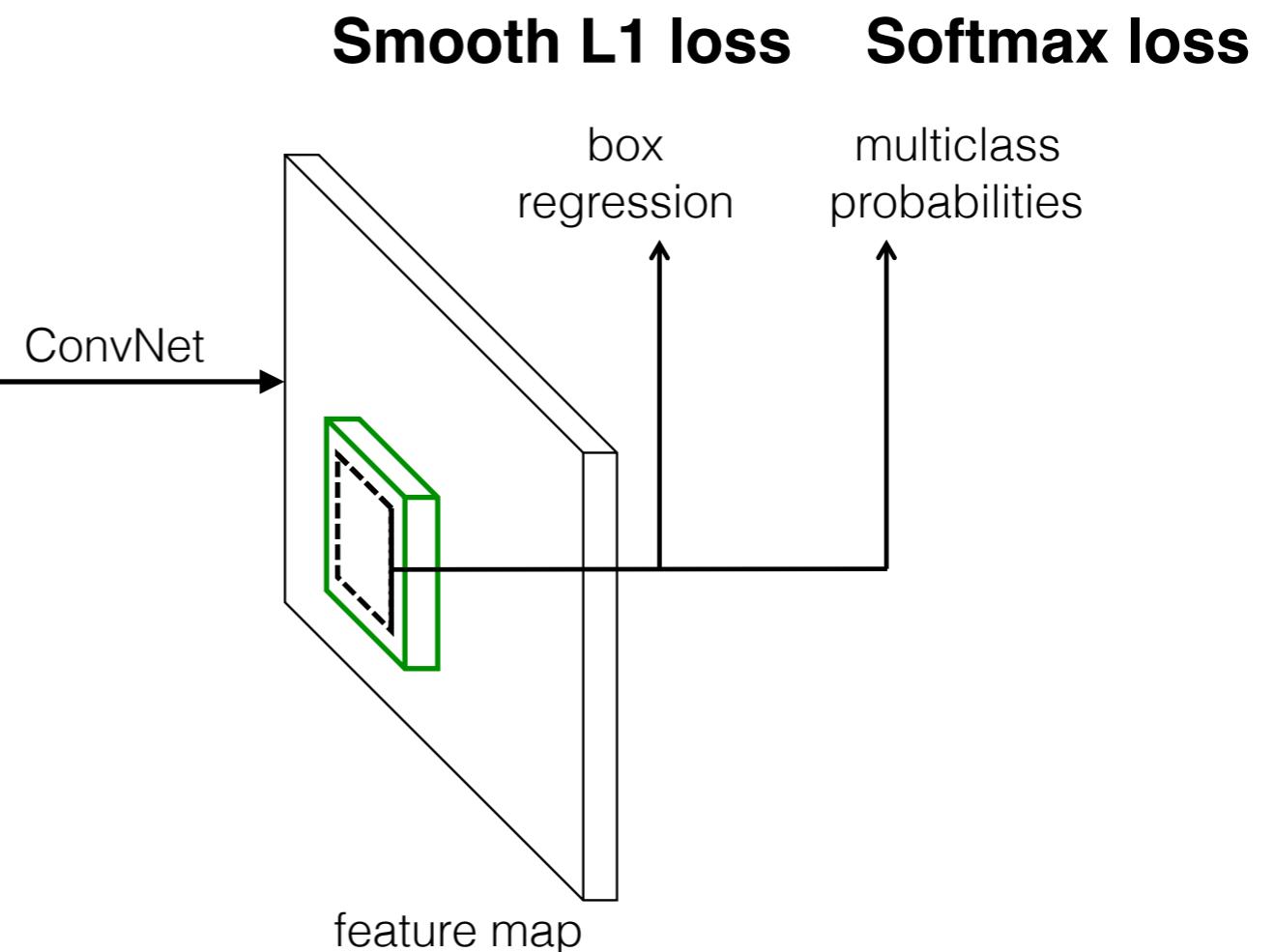
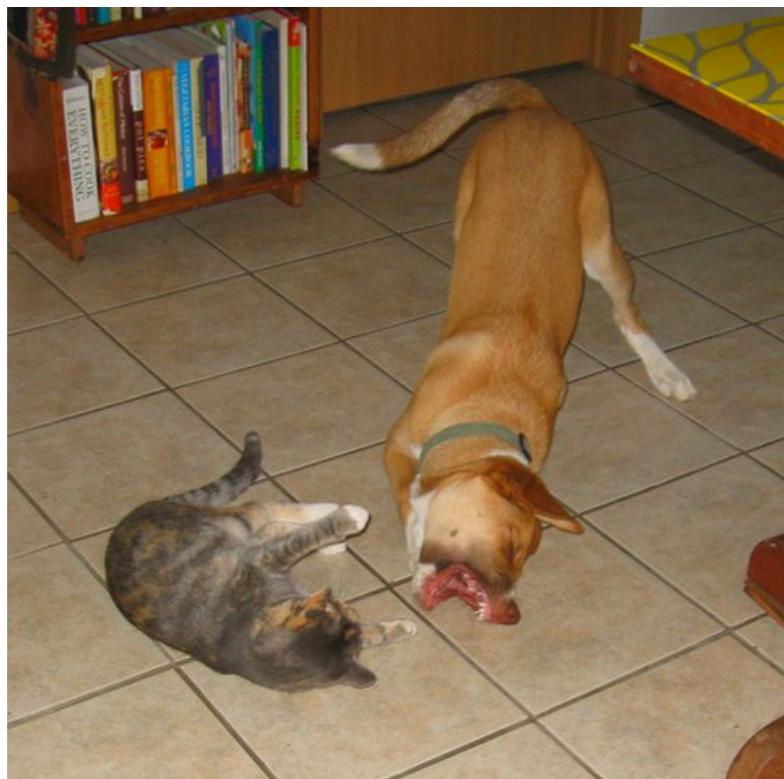
feature map

SSD Output Layer



SSD Training

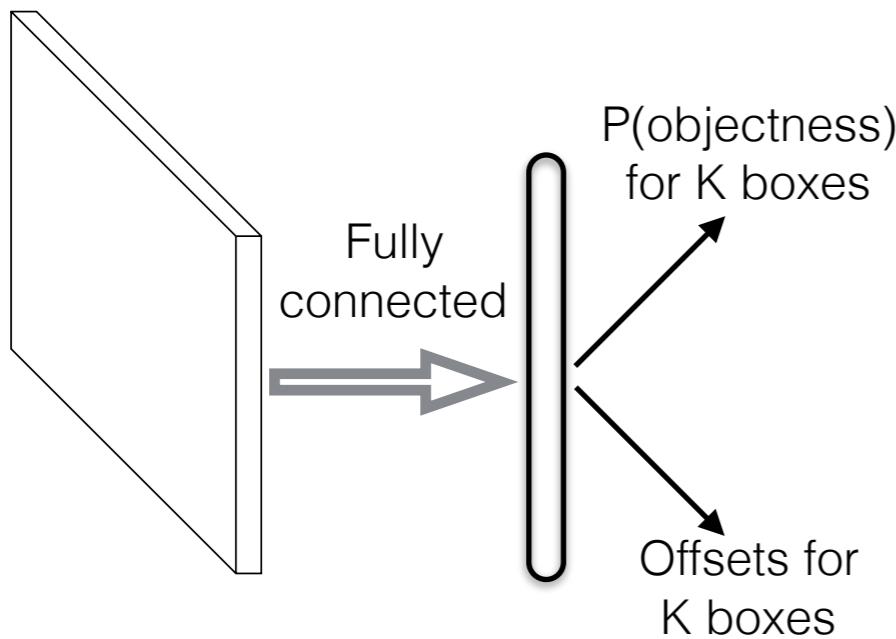
- Match default boxes to ground truth boxes to determine true/false positives.
- Loss = **SmoothL1**(box param) + **Softmax**(class prob)



Related Work

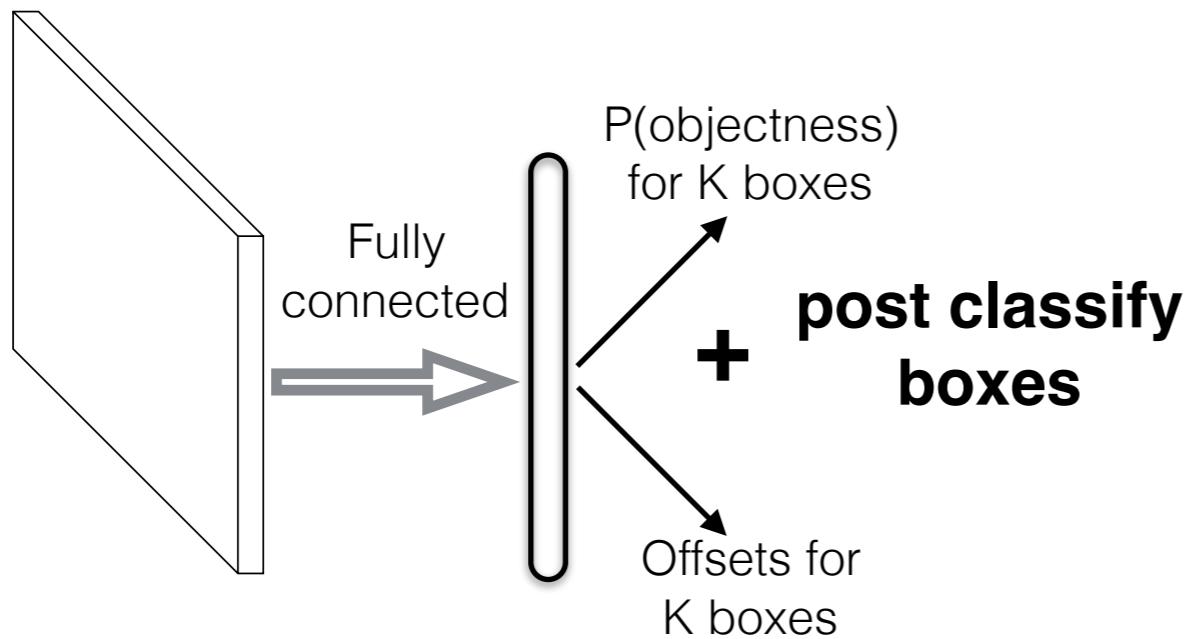
Related Work

MultiBox [Erhan et al. CVPR14]



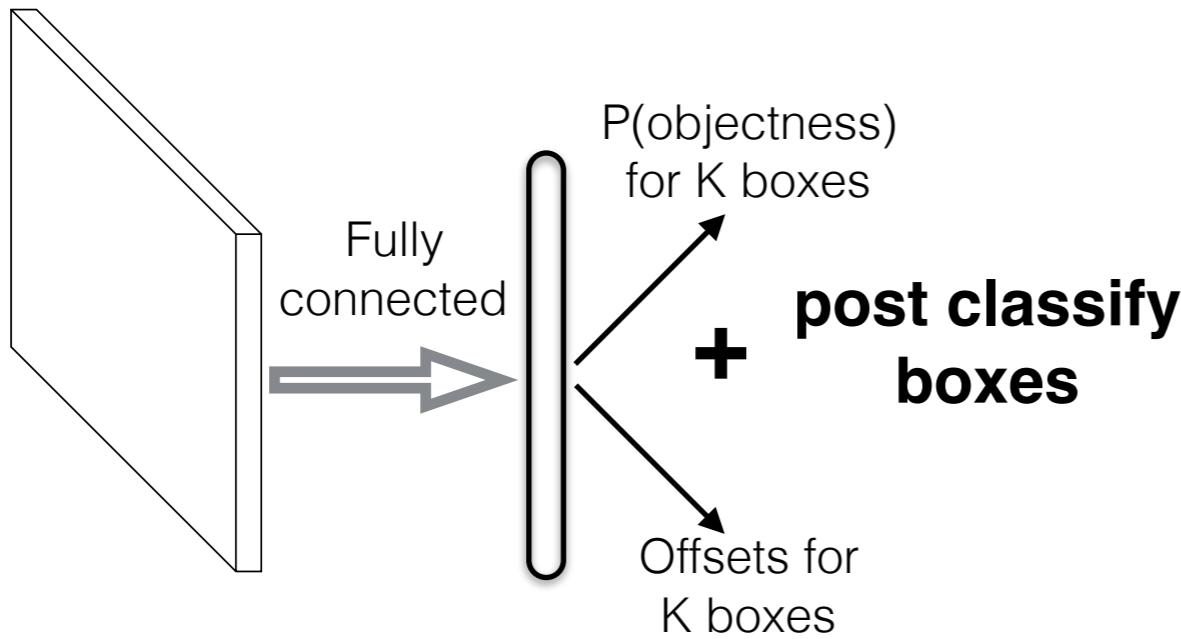
Related Work

MultiBox [Erhan et al. CVPR14]

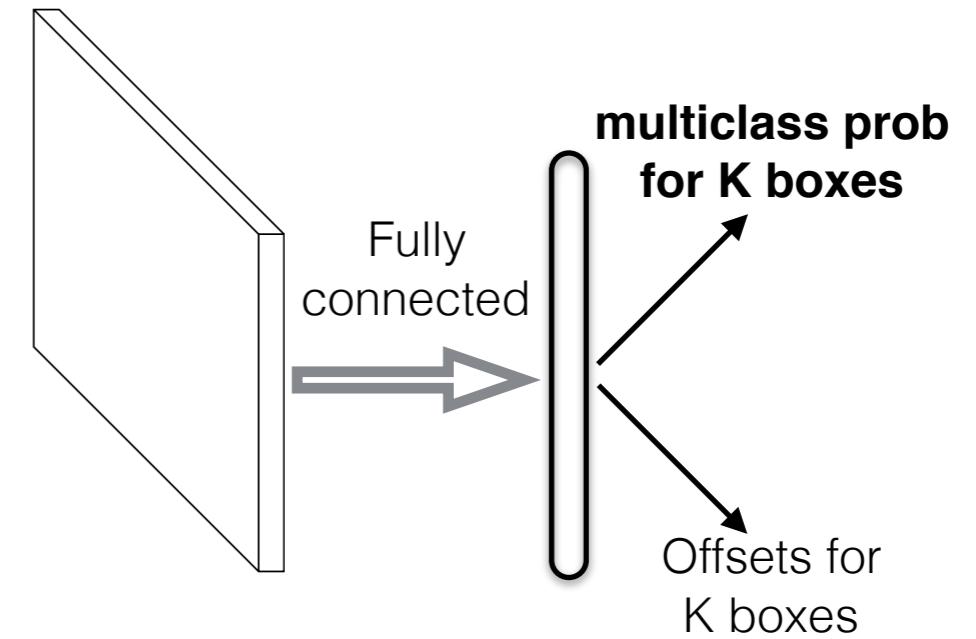


Related Work

MultiBox [Erhan et al. CVPR14]

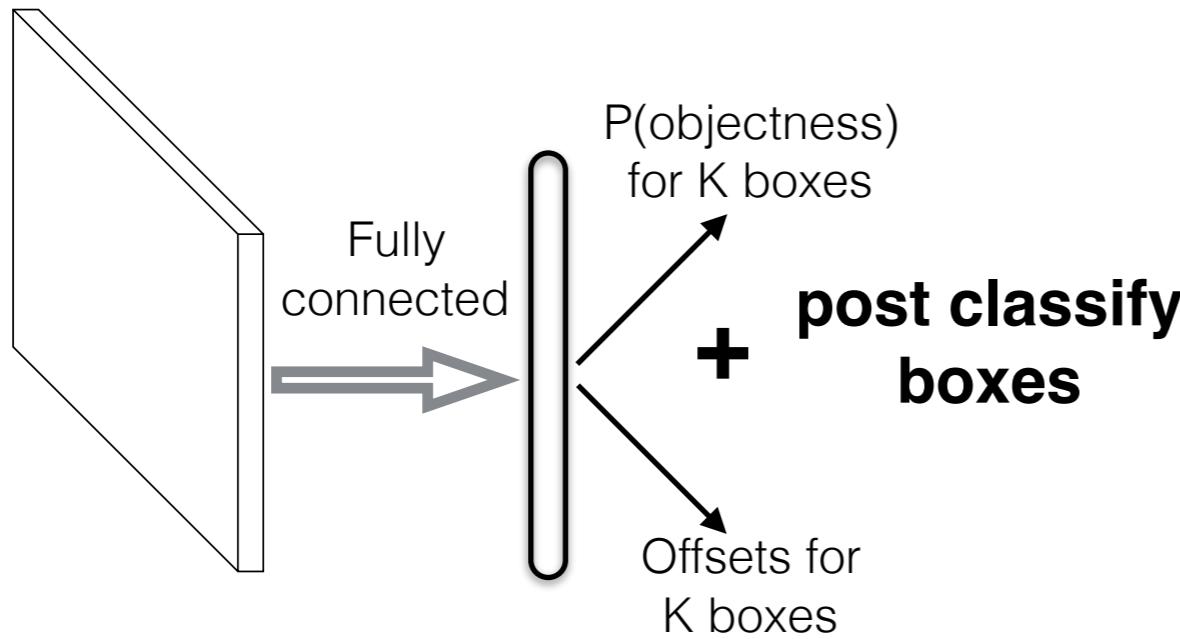


YOLO [Redmon et al. CVPR16]

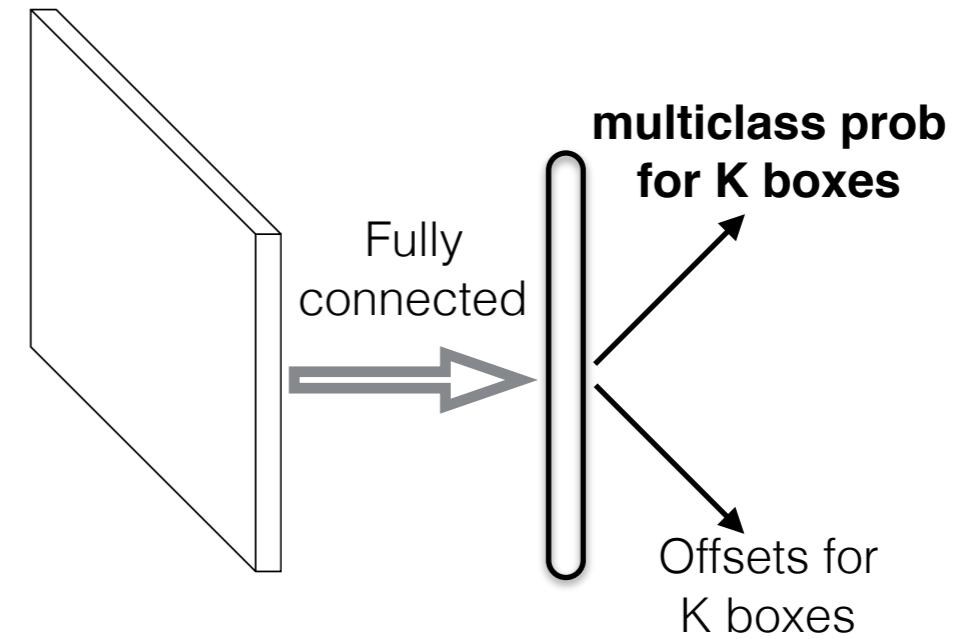


Related Work

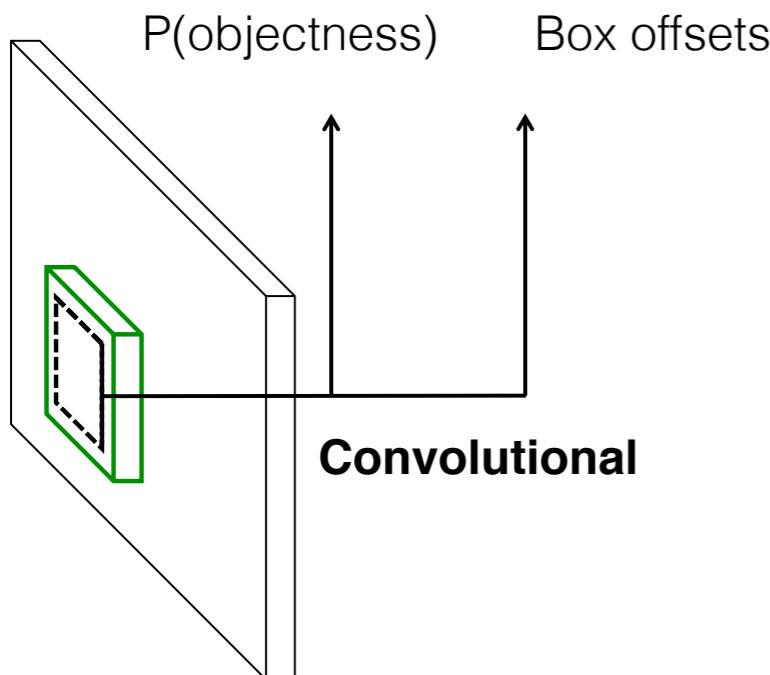
MultiBox [Erhan et al. CVPR14]



YOLO [Redmon et al. CVPR16]

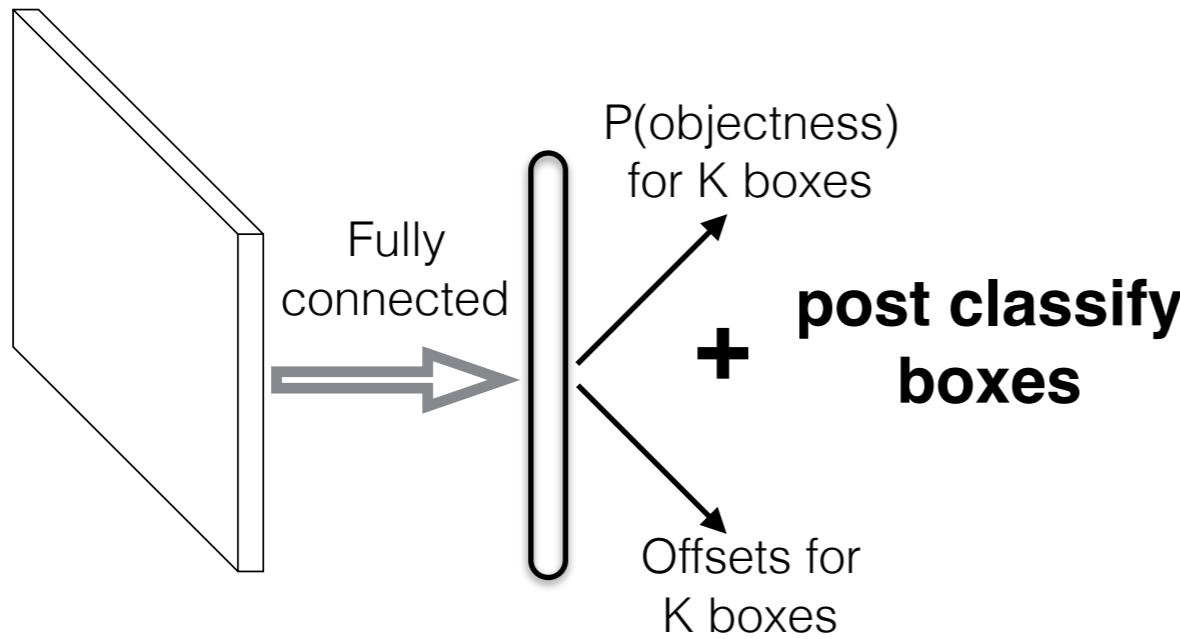


Faster R-CNN [Ren et al. NIPS15]

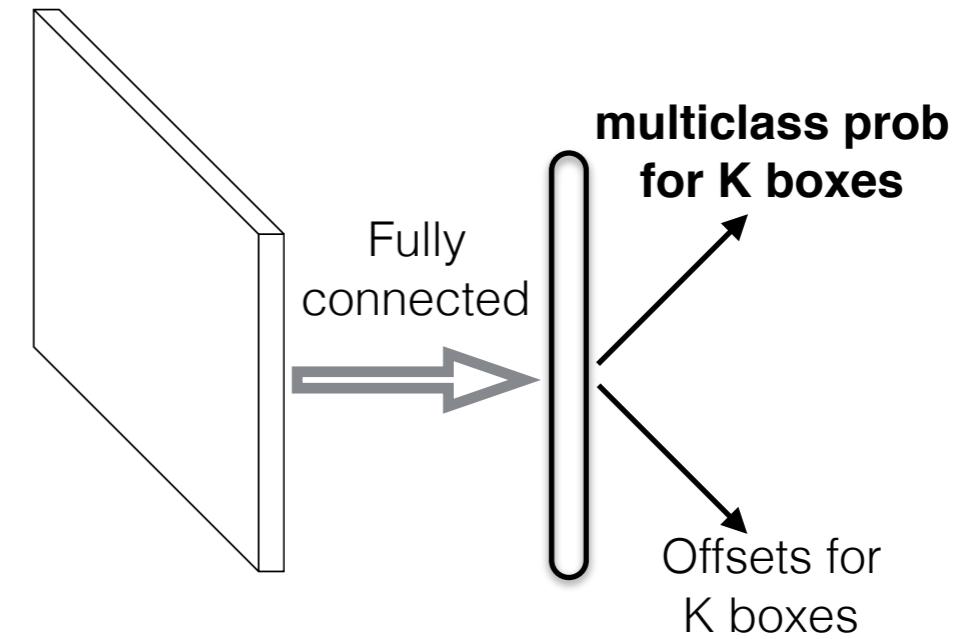


Related Work

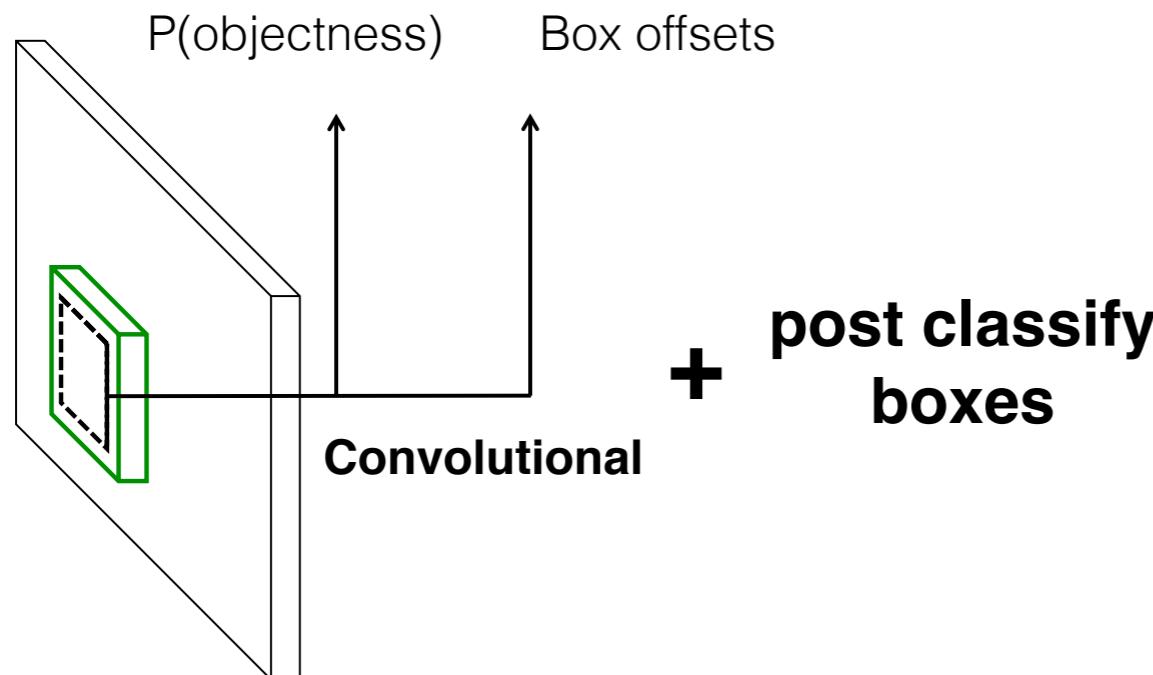
MultiBox [Erhan et al. CVPR14]



YOLO [Redmon et al. CVPR16]

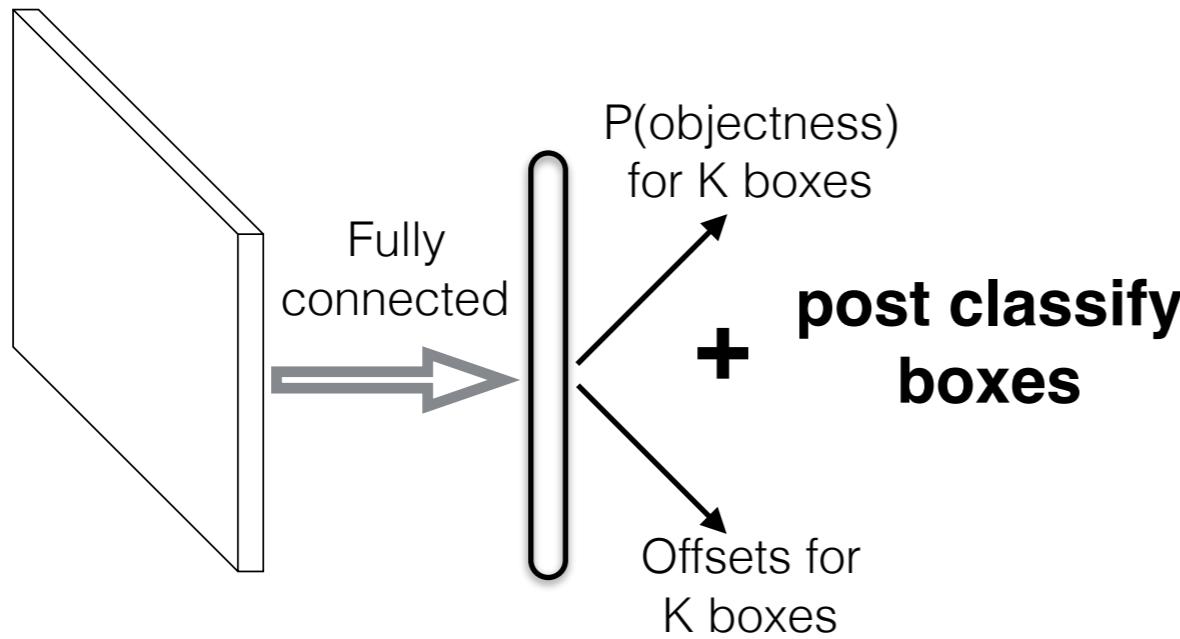


Faster R-CNN [Ren et al. NIPS15]

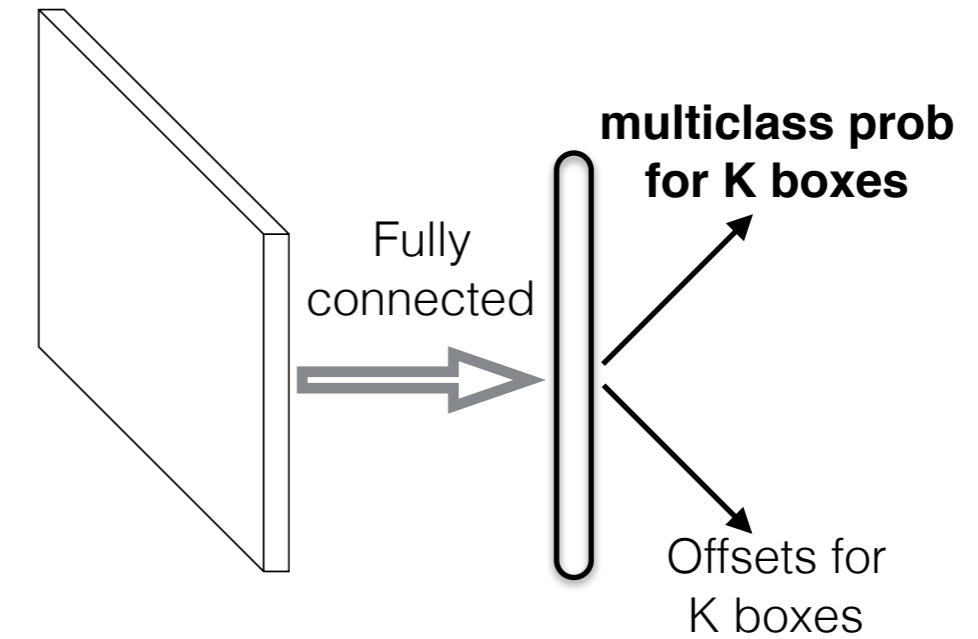


Related Work

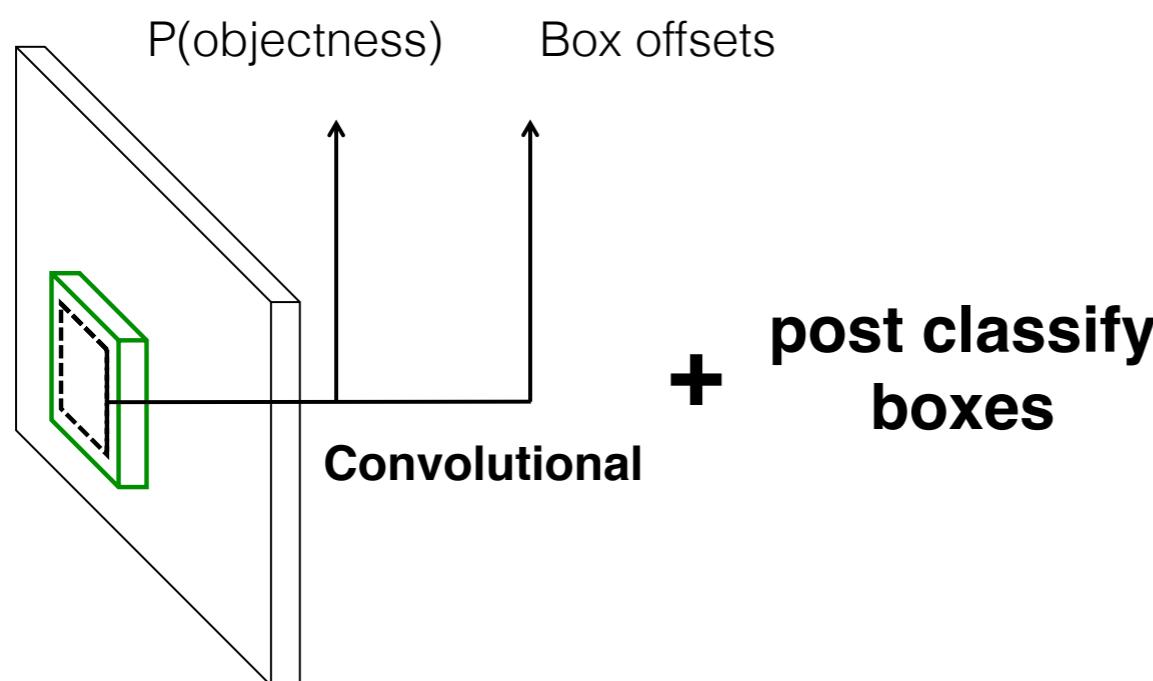
MultiBox [Erhan et al. CVPR14]



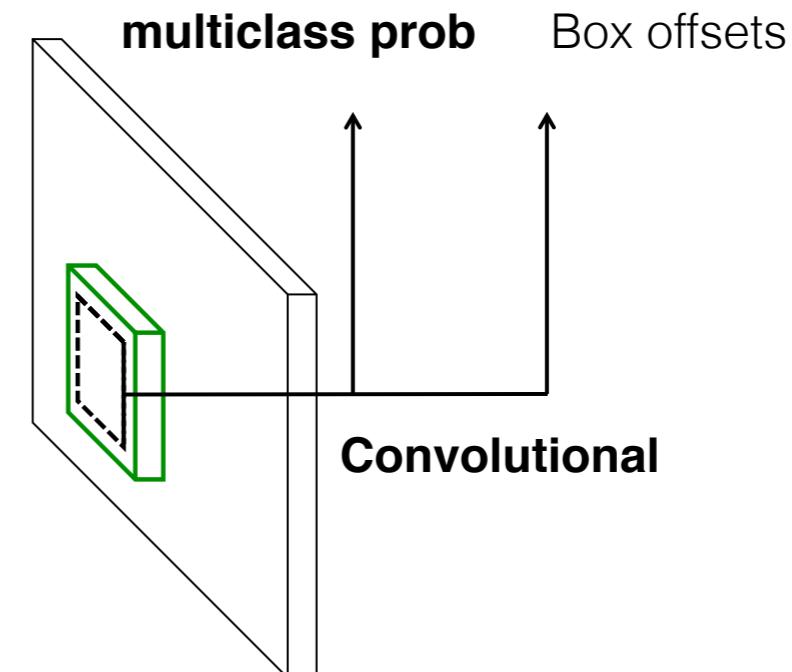
YOLO [Redmon et al. CVPR16]



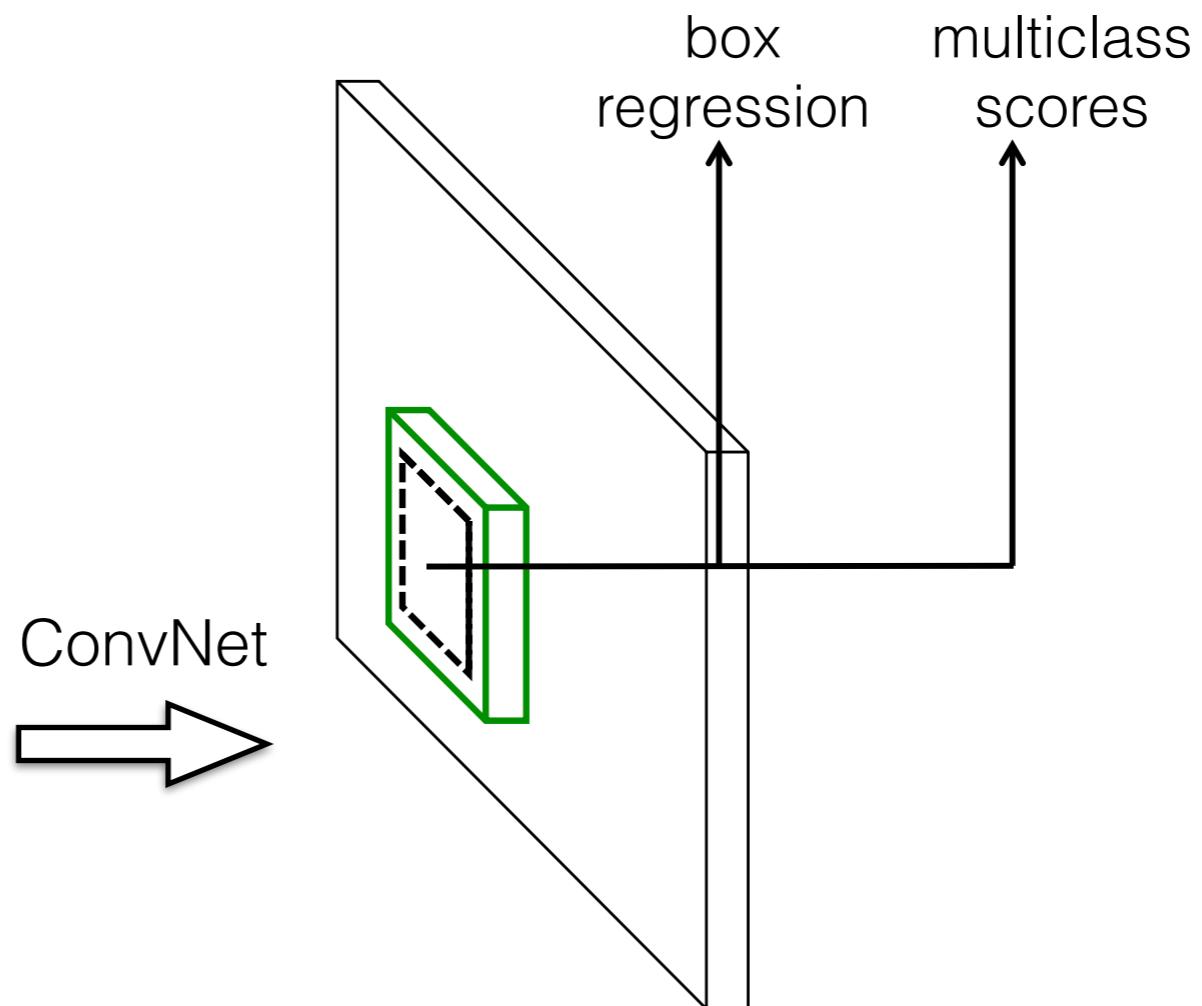
Faster R-CNN [Ren et al. NIPS15]



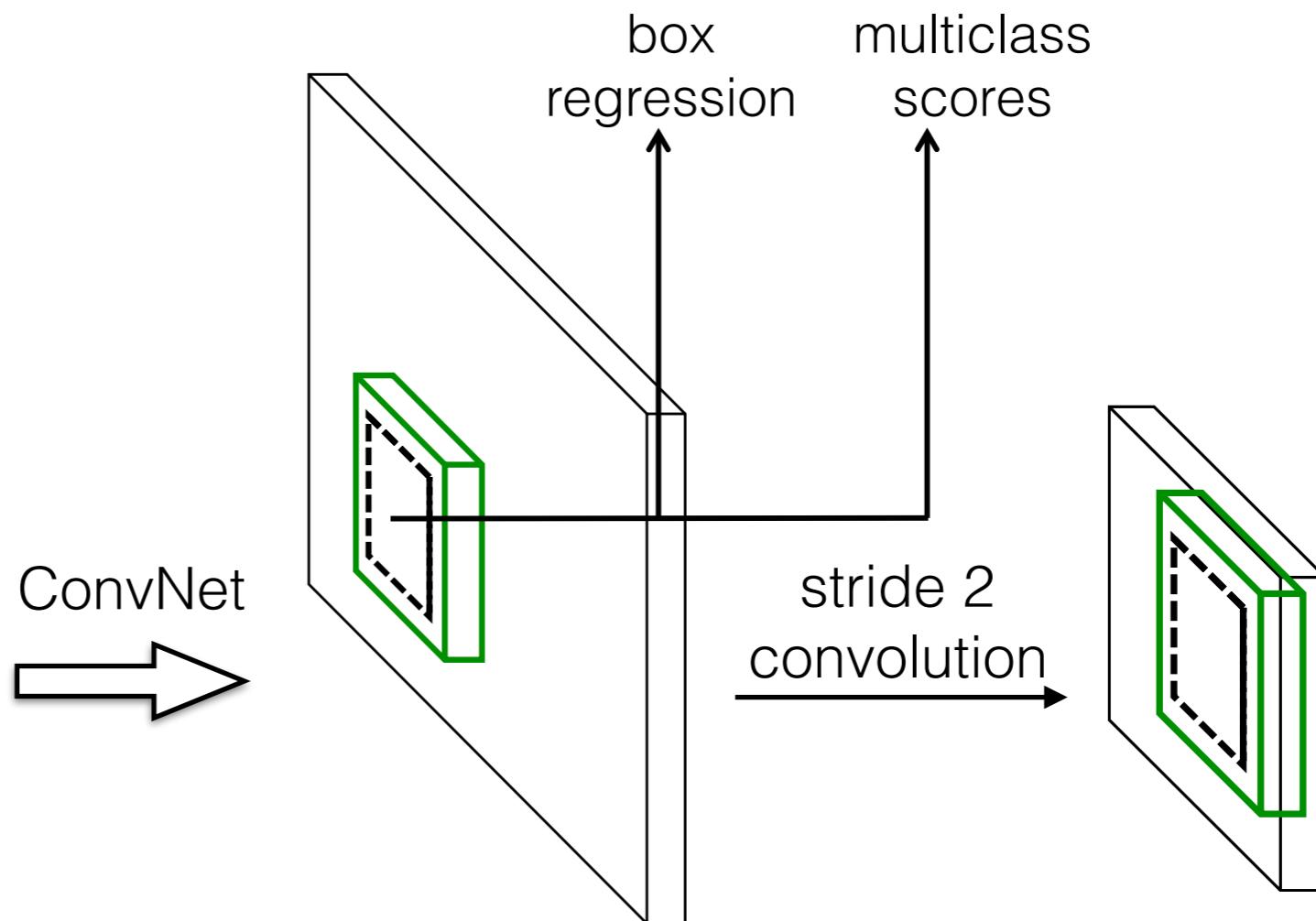
SSD



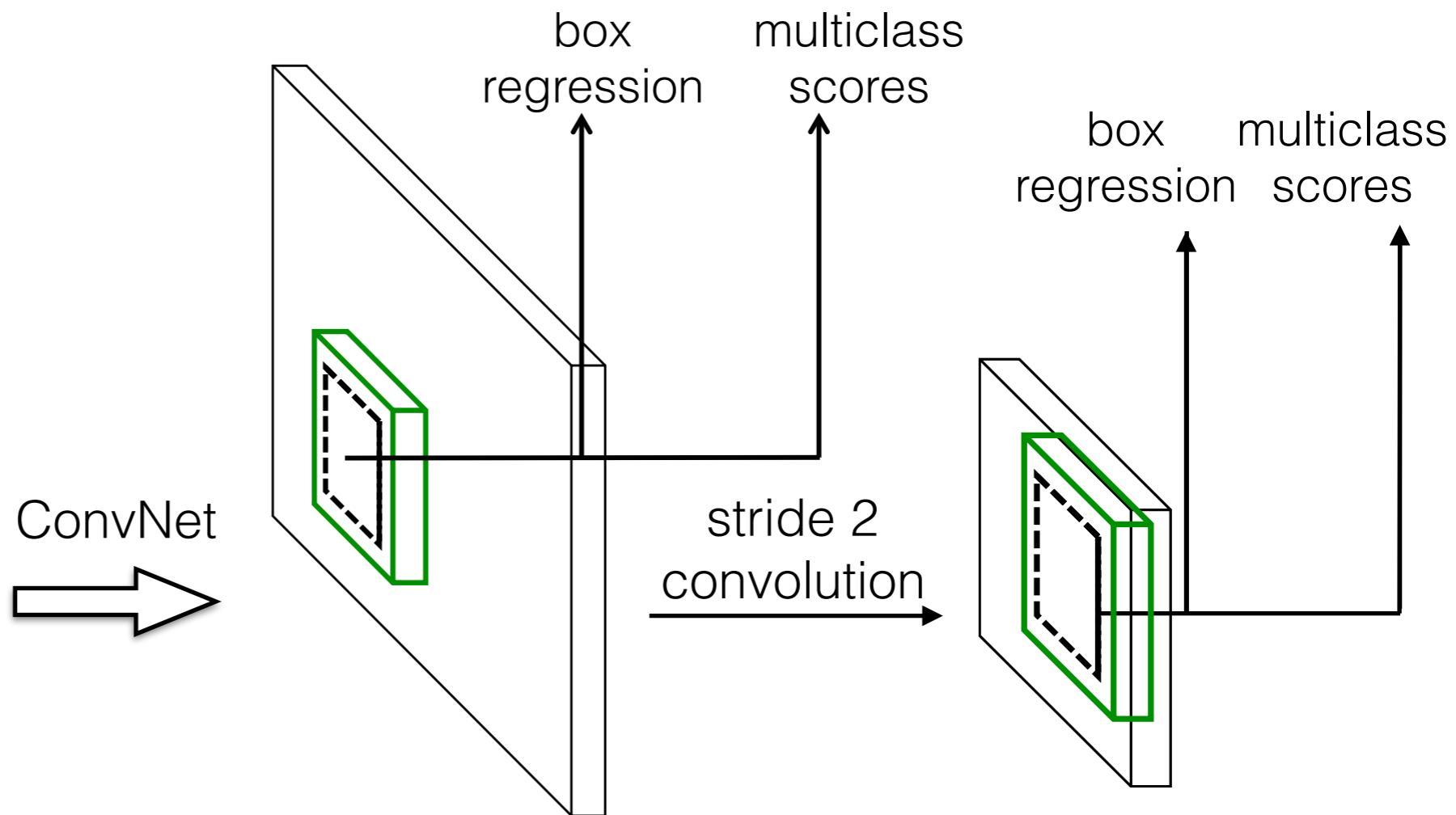
Contribution #1: Multi-Scale Feature Maps



Contribution #1: Multi-Scale Feature Maps

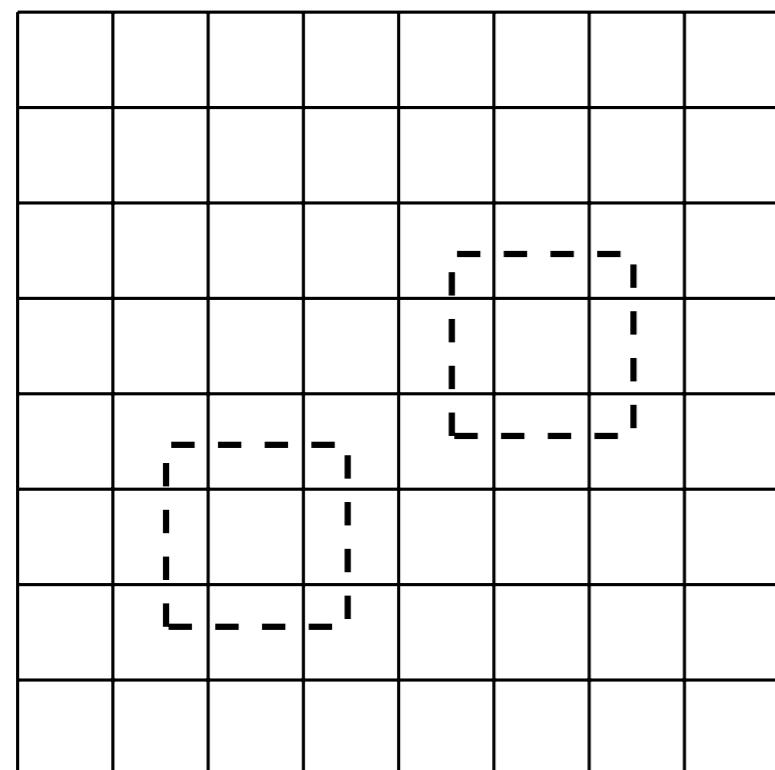


Contribution #1: Multi-Scale Feature Maps

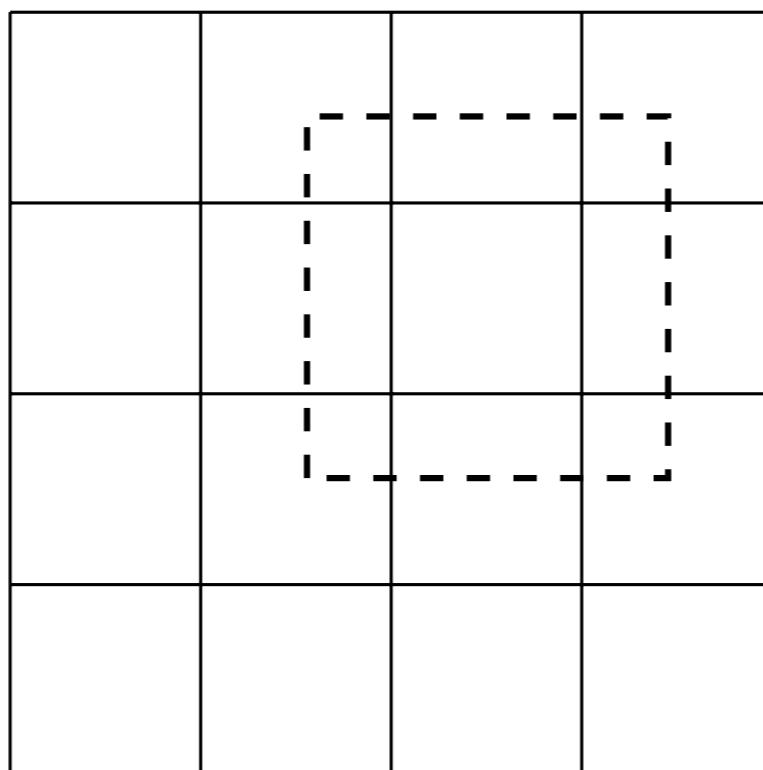


Multi-Scale Feature Maps

SSD



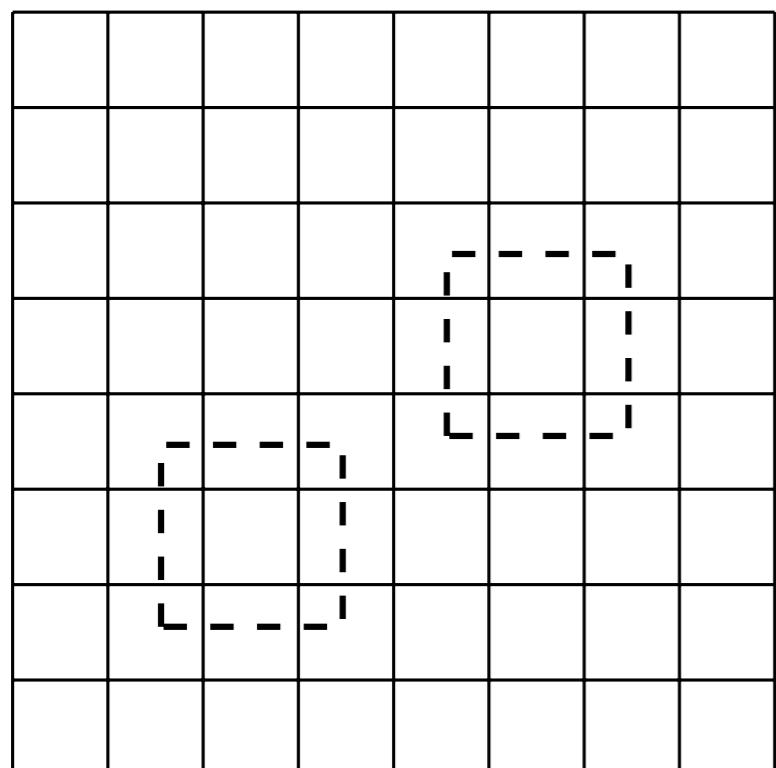
8×8 feature map



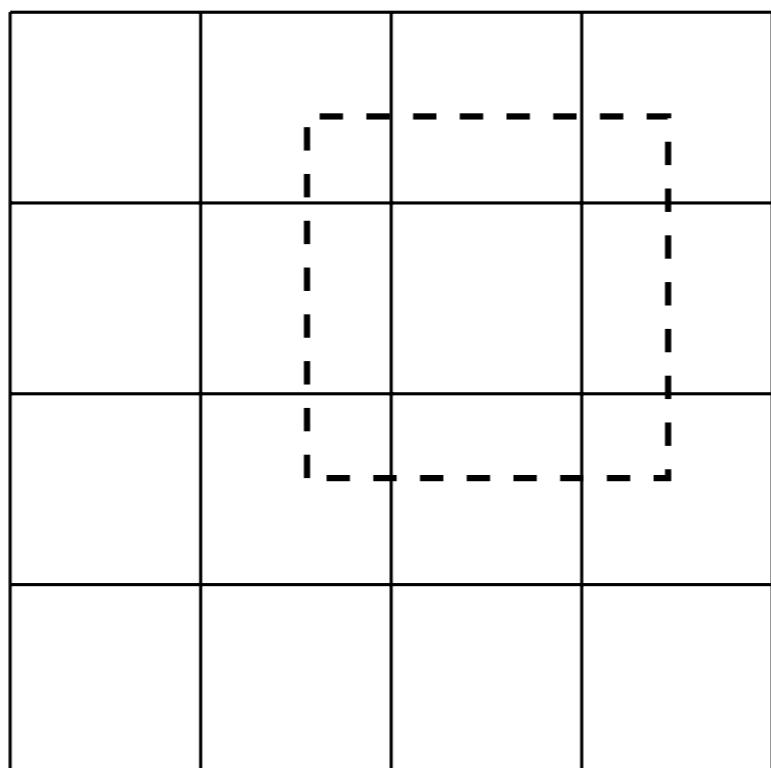
4×4 feature map

Multi-Scale Feature Maps

SSD



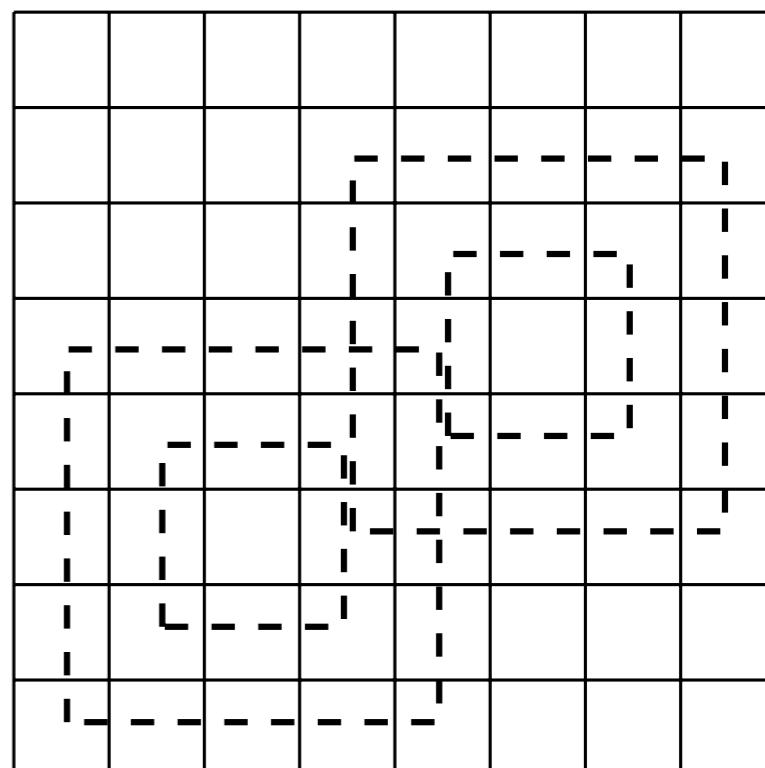
8×8 feature map



4×4 feature map

Faster R-CNN Objectness
Proposal, Ren 2015

vs.



8×8 feature map

Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP		# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
						74.3	63.4	8732
						70.7	69.2	9864
						62.4	64.0	8664

Multi-Scale Feature Maps Experiment

Prediction source layers from:						use boundary boxes?	mAP	# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1			
✓	✓	✓	✓	✓	✓	Yes	74.3	8732
✓	✓	✓				No	63.4	
✓						70.7	69.2	9864
						62.4	64.0	8664

Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP		# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
						74.3	63.4	8732
						70.7	69.2	9864
						62.4	64.0	8664

Multi-Scale Feature Maps Experiment

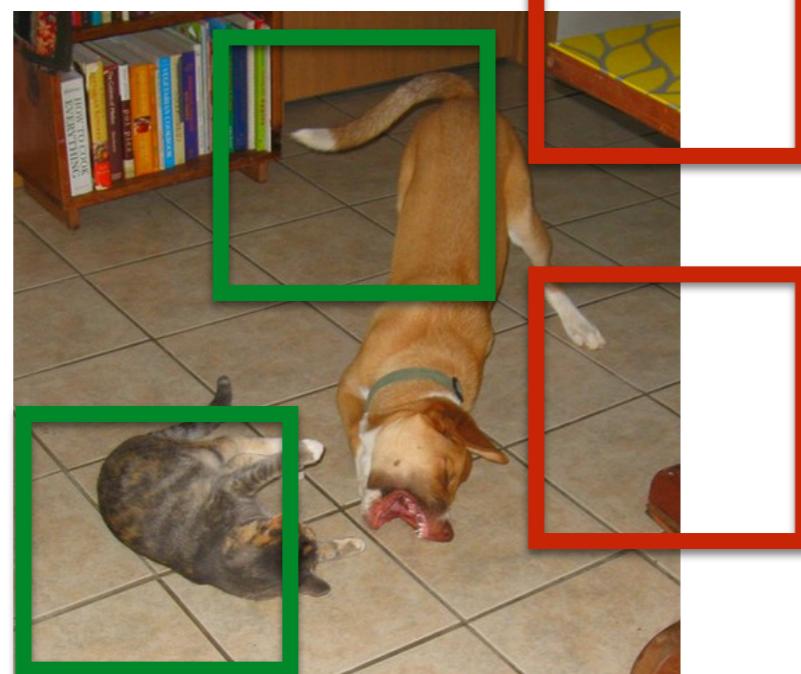
Prediction source layers from:						mAP		# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
						74.3	63.4	8732
						70.7	69.2	9864
						62.4	64.0	8664

Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP		# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
						74.3	63.4	8732
						70.7	69.2	9864
						62.4	64.0	8664

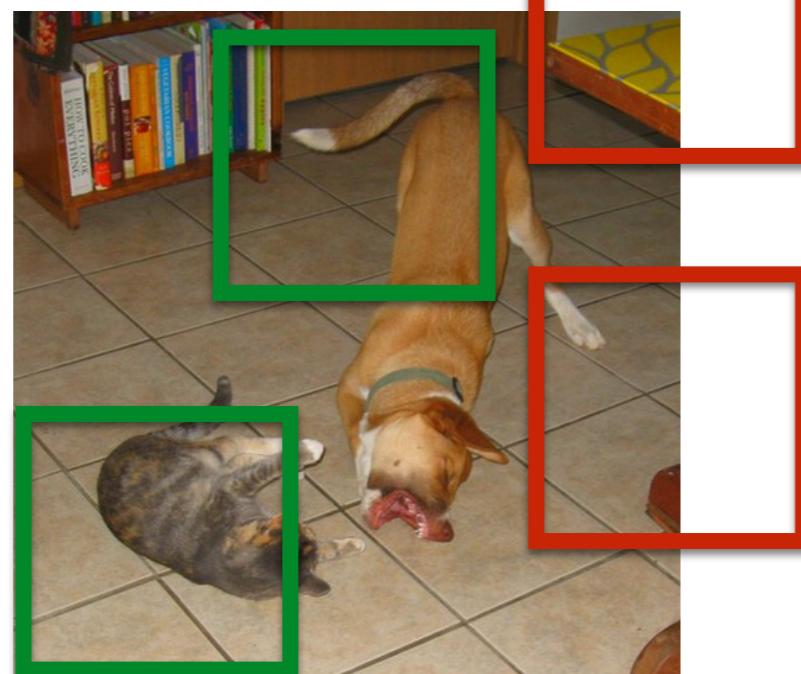
Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP		# Boxes
38×38	19×19	10×10	5×5	3×3	1×1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
✓	✓	✓	✓	✓	✓	74.3	63.4	8732
✓	✓	✓				70.7	69.2	9864
✓						62.4	64.0	8664



Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP		# Boxes
38×38	19×19	10×10	5×5	3×3	1×1	use boundary boxes?		
✓	✓	✓	✓	✓	✓	Yes	No	
						74.3	63.4	8732
						70.7	69.2	9864
						62.4	64.0	8664



boundary boxes

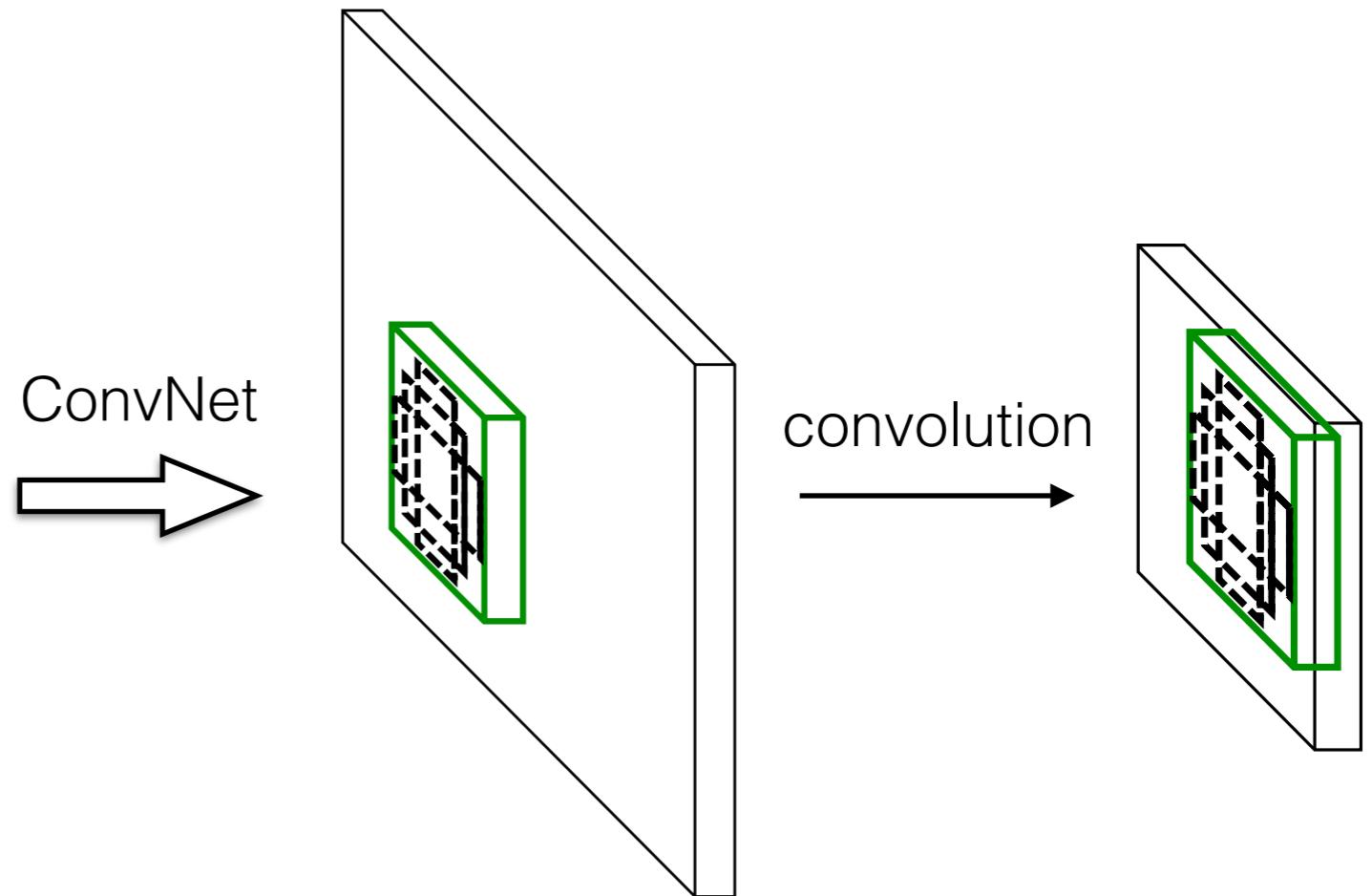
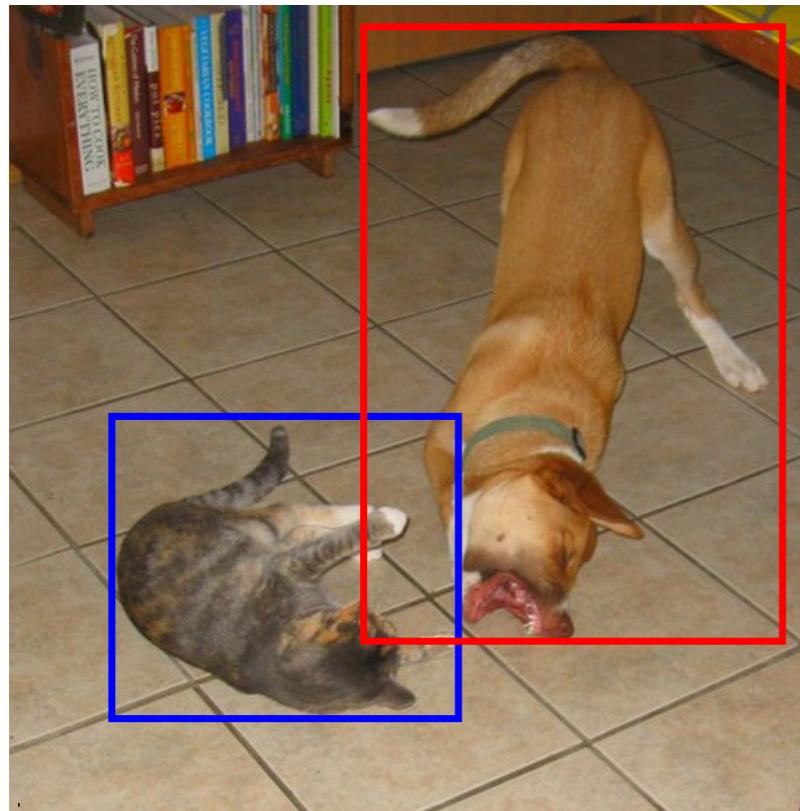
Multi-Scale Feature Maps Experiment

Prediction source layers from:						mAP	use boundary boxes?	# Boxes	
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1		Yes	No	
✓	✓	✓	✓	✓	✓	74.3	63.4	8732	
✓	✓	✓				70.7	69.2	9864	
✓						62.4	64.0	8664	

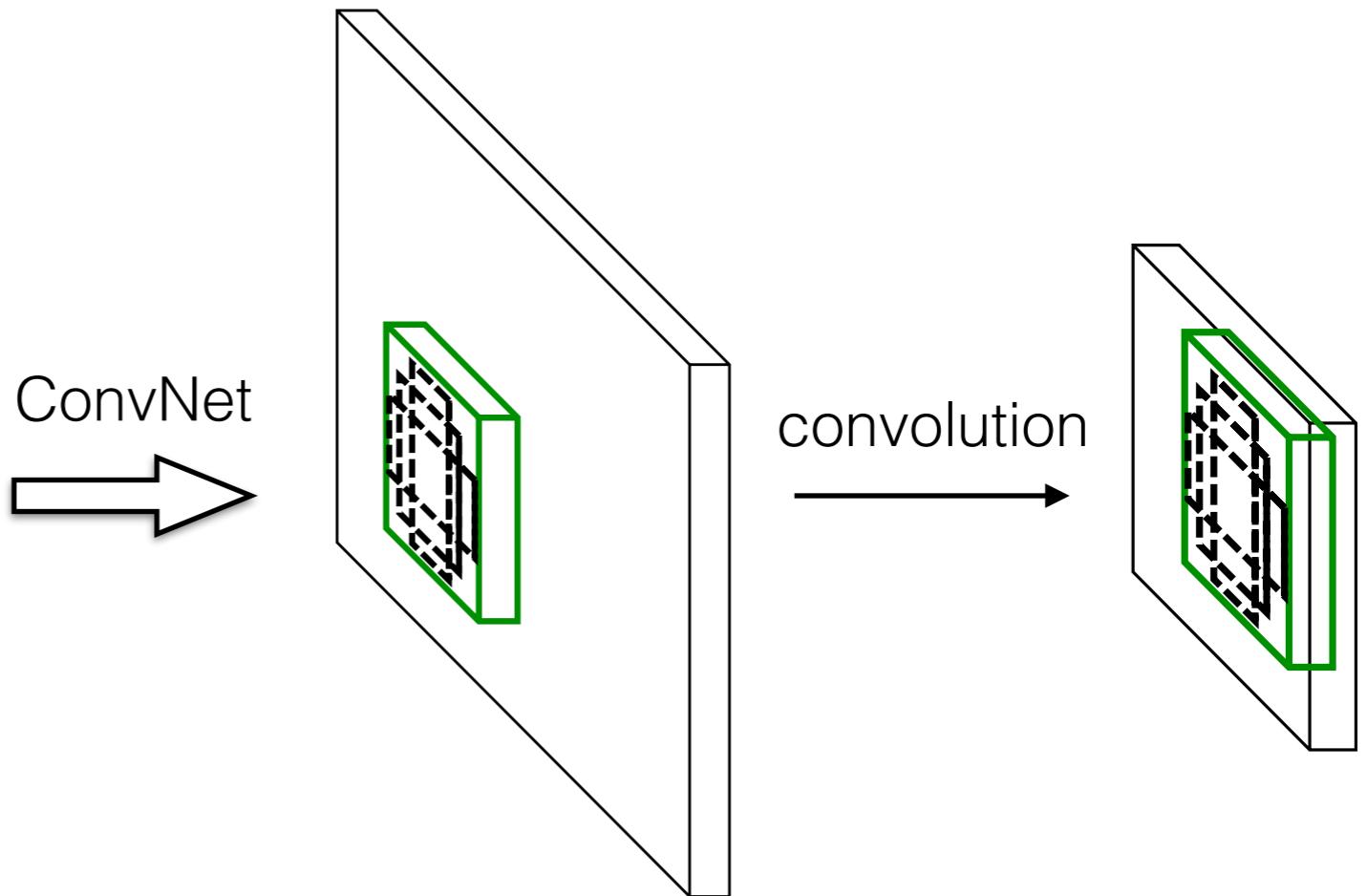
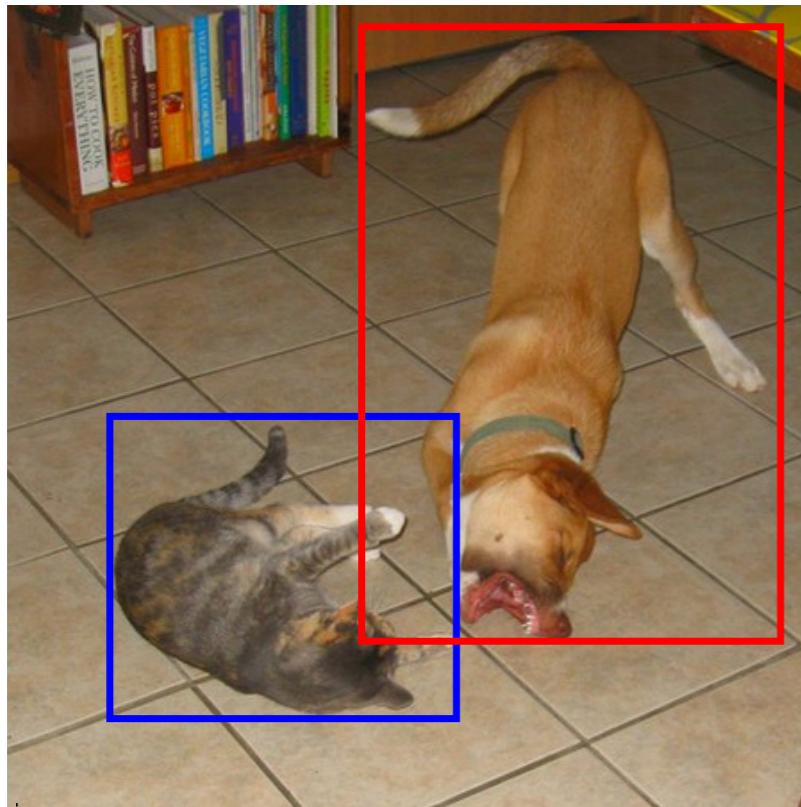
Multi-Scale Feature Maps Experiment

Prediction source layers from:						use boundary boxes?	mAP	# Boxes
38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1			
✓	✓	✓	✓	✓	✓	Yes	74.3	8732
✓	✓	✓				No	63.4	
						70.7	69.2	9864
						62.4	64.0	8664

Contribution #2: Splitting the Region Space

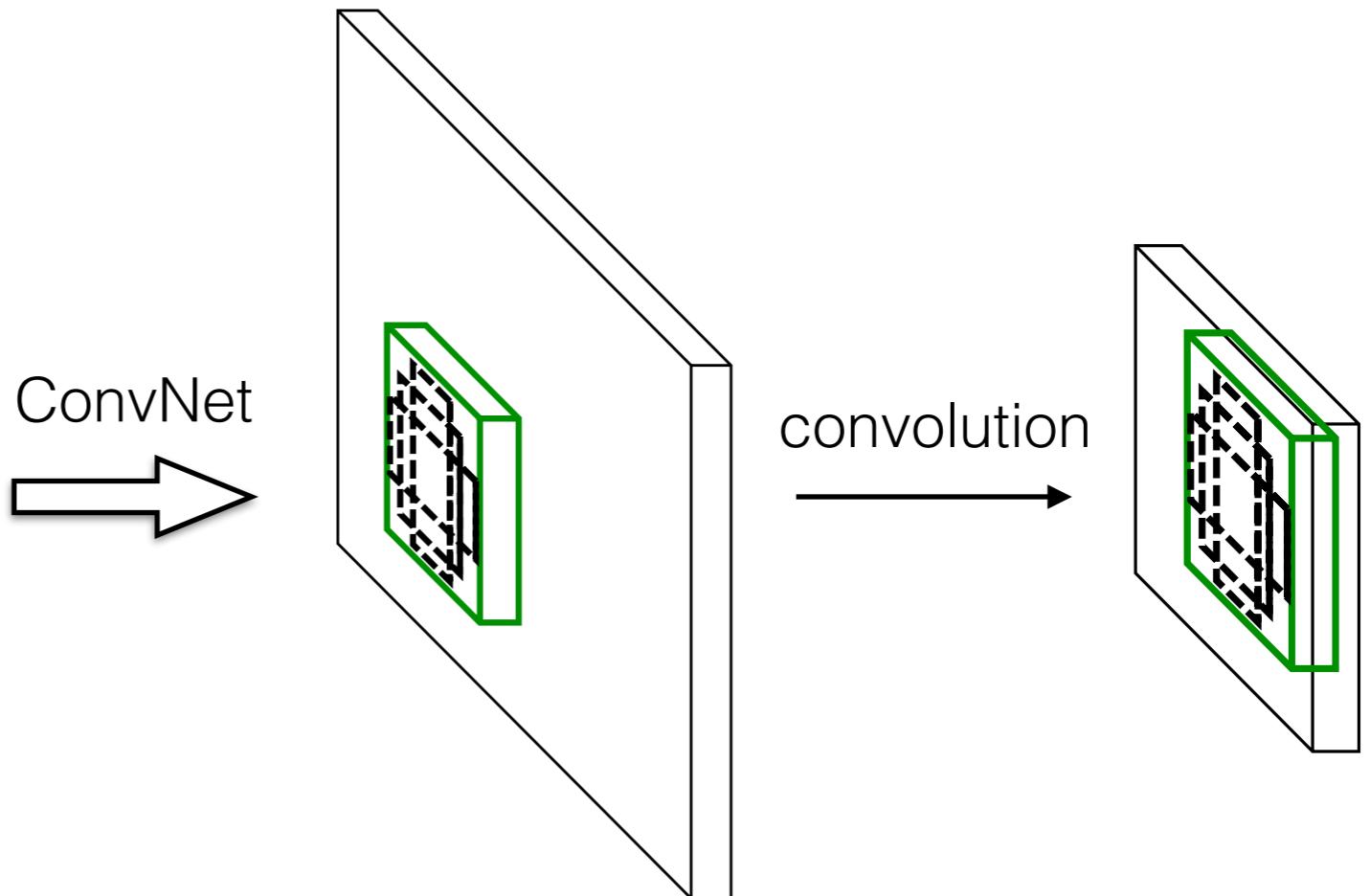
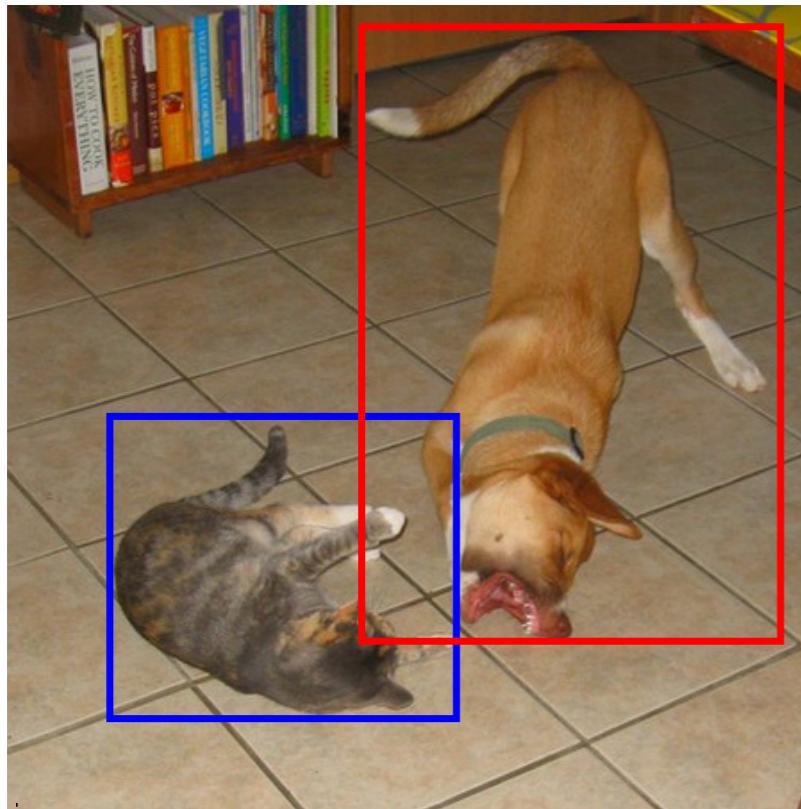


Contribution #2: Splitting the Region Space



	SSD300	
include $\{\frac{1}{2}, 2\}$ box?	✓	✓
include $\{\frac{1}{3}, 3\}$ box?		✓
number of Boxes	3880	7760
VOC2007 test mAP	71.6	73.7
		74.3

Contribution #2: Splitting the Region Space



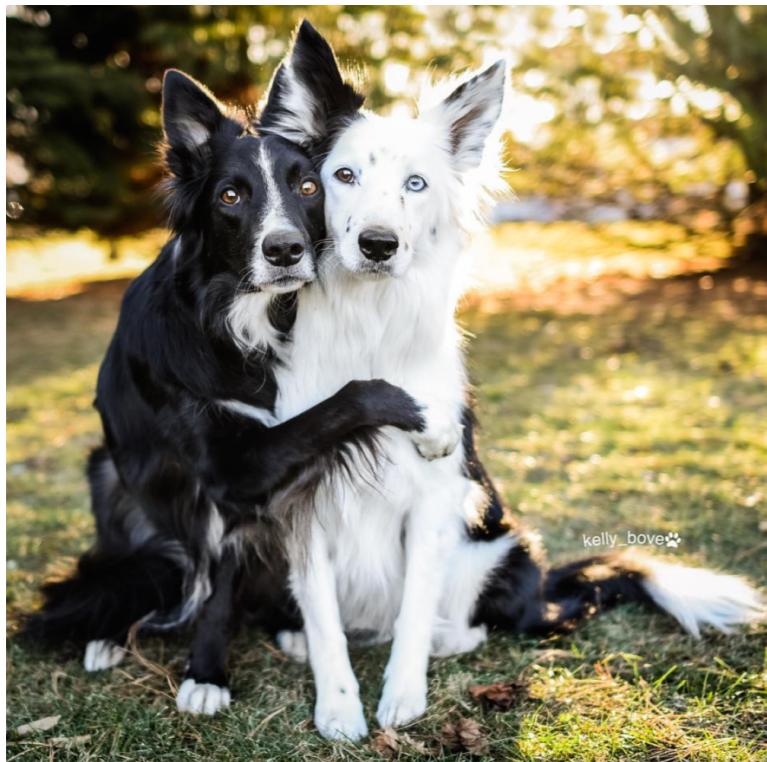
Use 38x38 feature map : **+2.5 mAP**
(conv4_3)

Why So Many Default Boxes?

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

Why So Many Default Boxes?

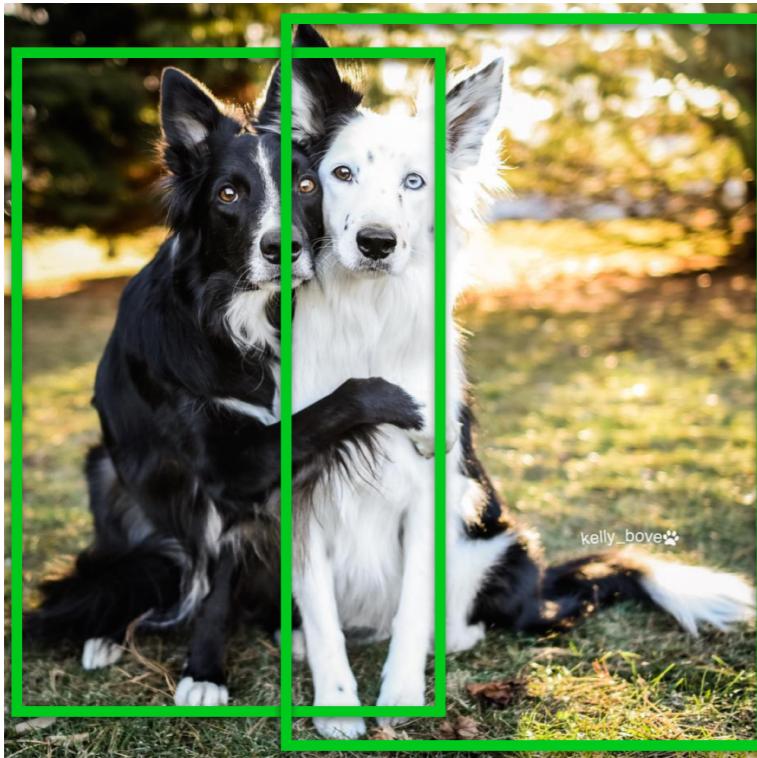
	Faster R-CNN	YOLO	SSD300	SSD512
# Default Boxes	6000	98	8732	24564
Resolution	1000x600	448x448	300x300	512x512



Why So Many Default Boxes?

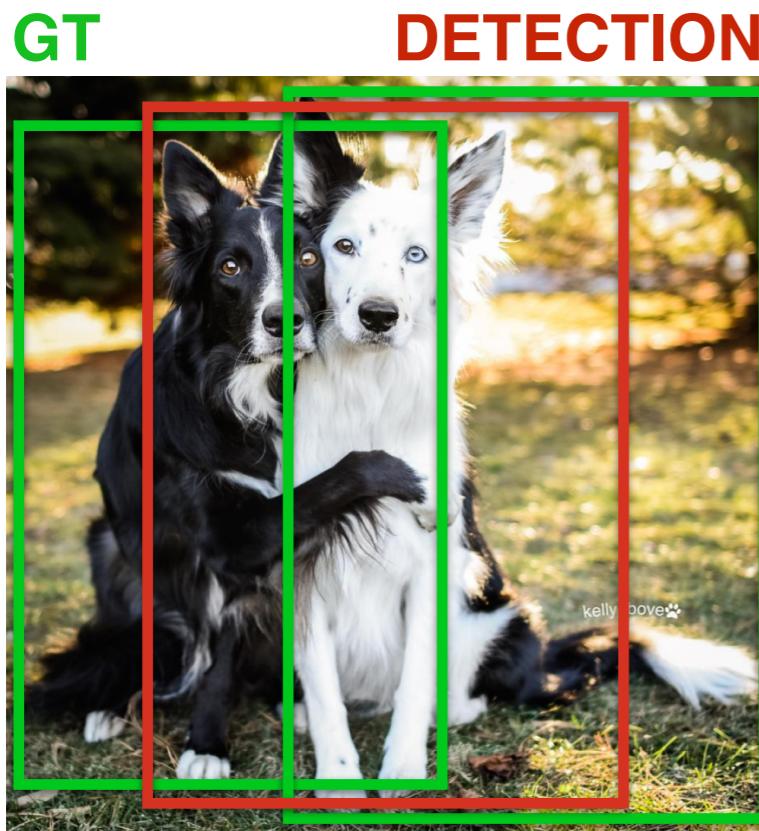
	Faster R-CNN	YOLO	SSD300	SSD512
# Default Boxes	6000	98	8732	24564
Resolution	1000x600	448x448	300x300	512x512

GT



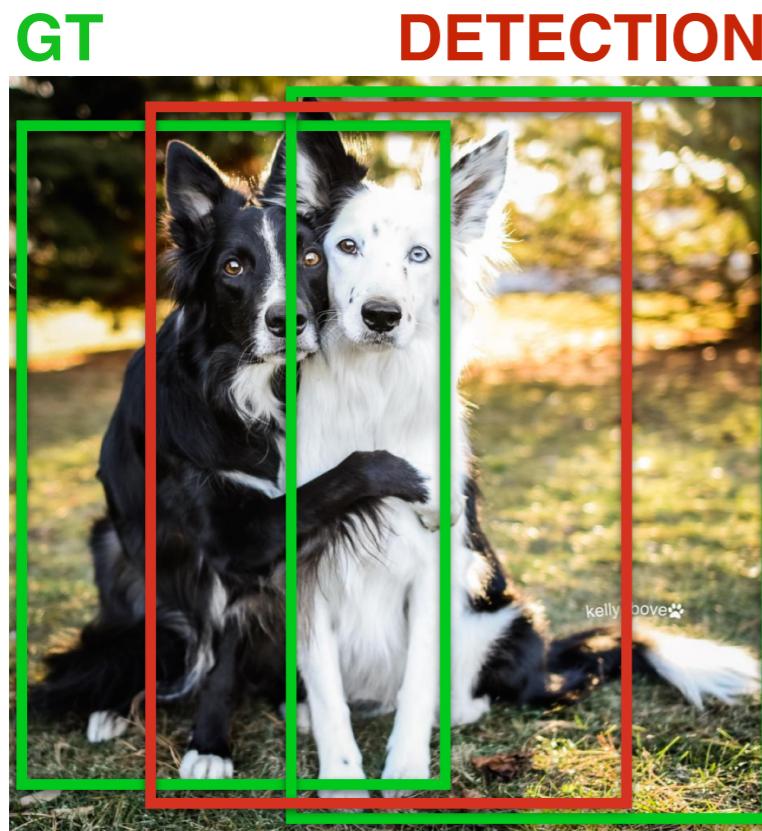
Why So Many Default Boxes?

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



Why So Many Default Boxes?

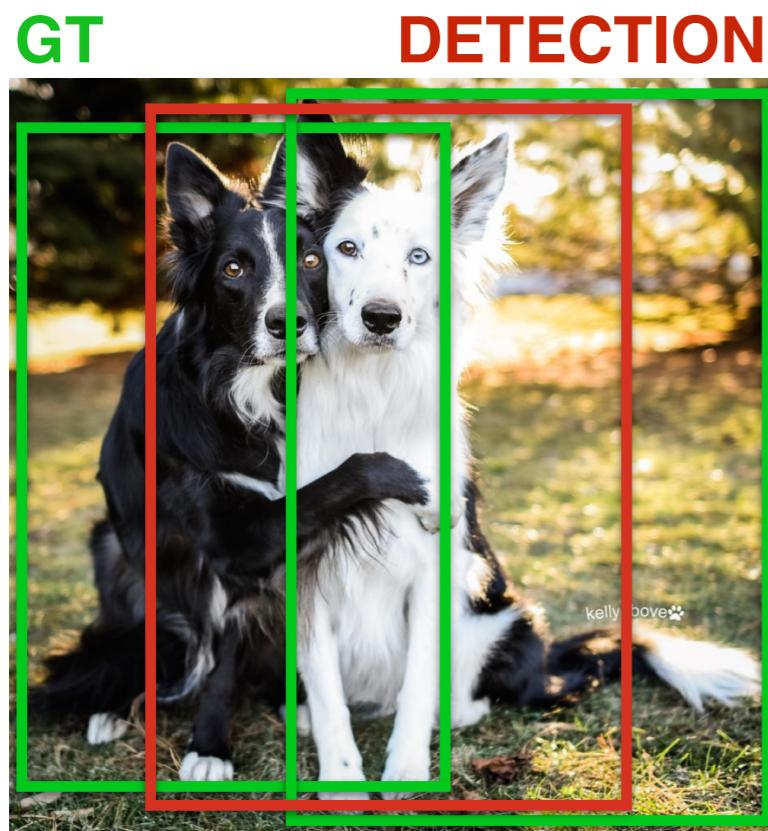
	Faster R-CNN	YOLO	SSD300	SSD512
# Default Boxes	6000	98	8732	24564
Resolution	1000x600	448x448	300x300	512x512



- SmoothL1 or L2 loss for box shape averages among likely hypotheses

Why So Many Default Boxes?

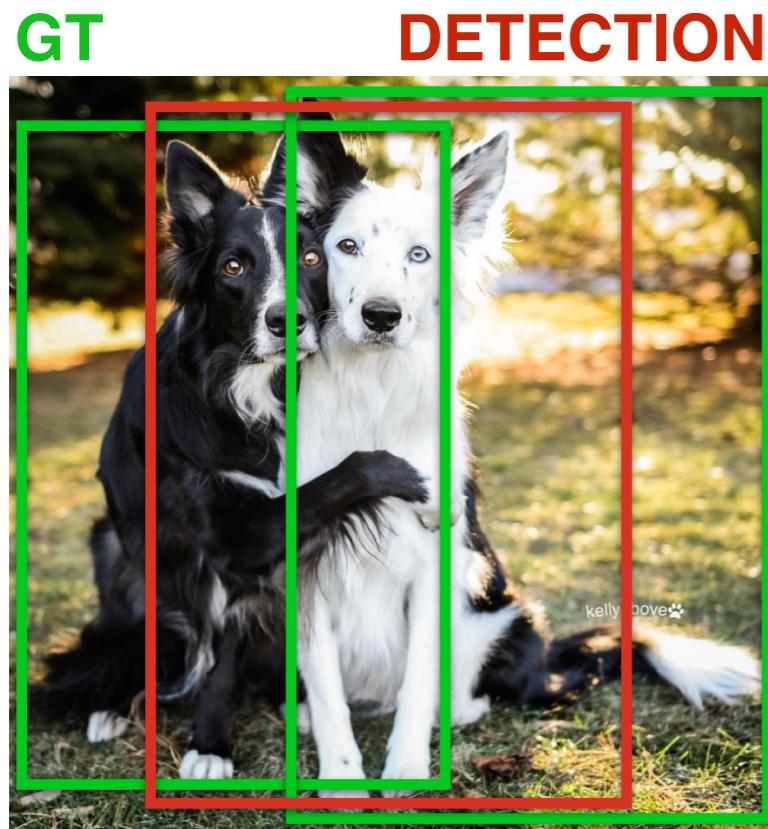
	Faster R-CNN	YOLO	SSD300	SSD512
# Default Boxes	6000	98	8732	24564
Resolution	1000x600	448x448	300x300	512x512



- 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

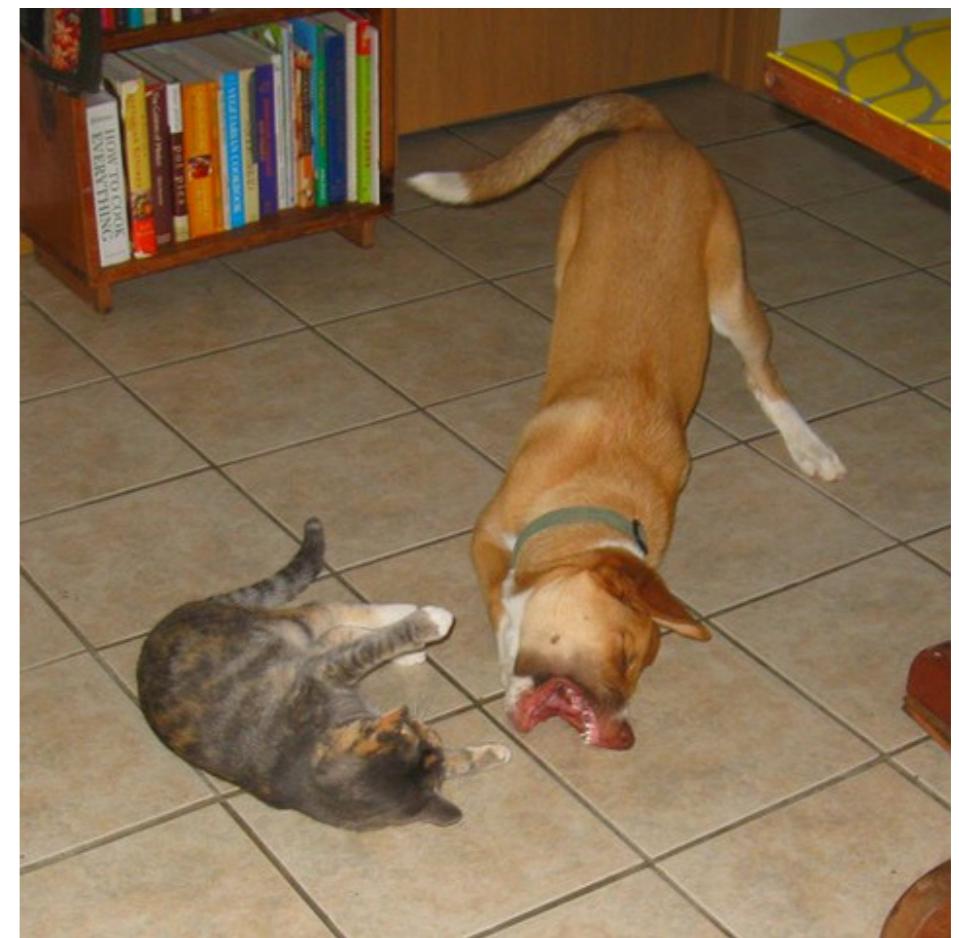
Why So Many Default Boxes?

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



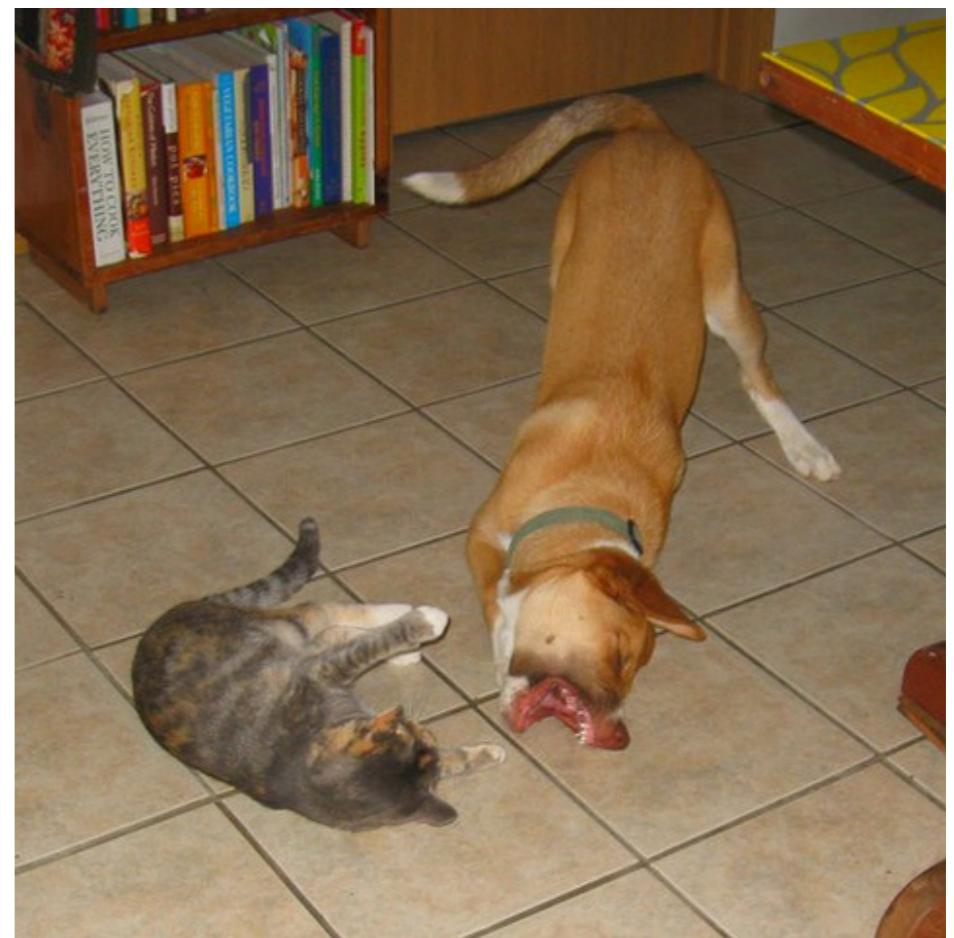
- SmoothL1 or L2 loss for box shape averages among likely hypotheses
- Need to have enough default boxes (discrete bins) to do accurate regression in each
- General principle for regressing complex continuous outputs with deep nets

Handling Many Default Boxes



Handling Many Default Boxes

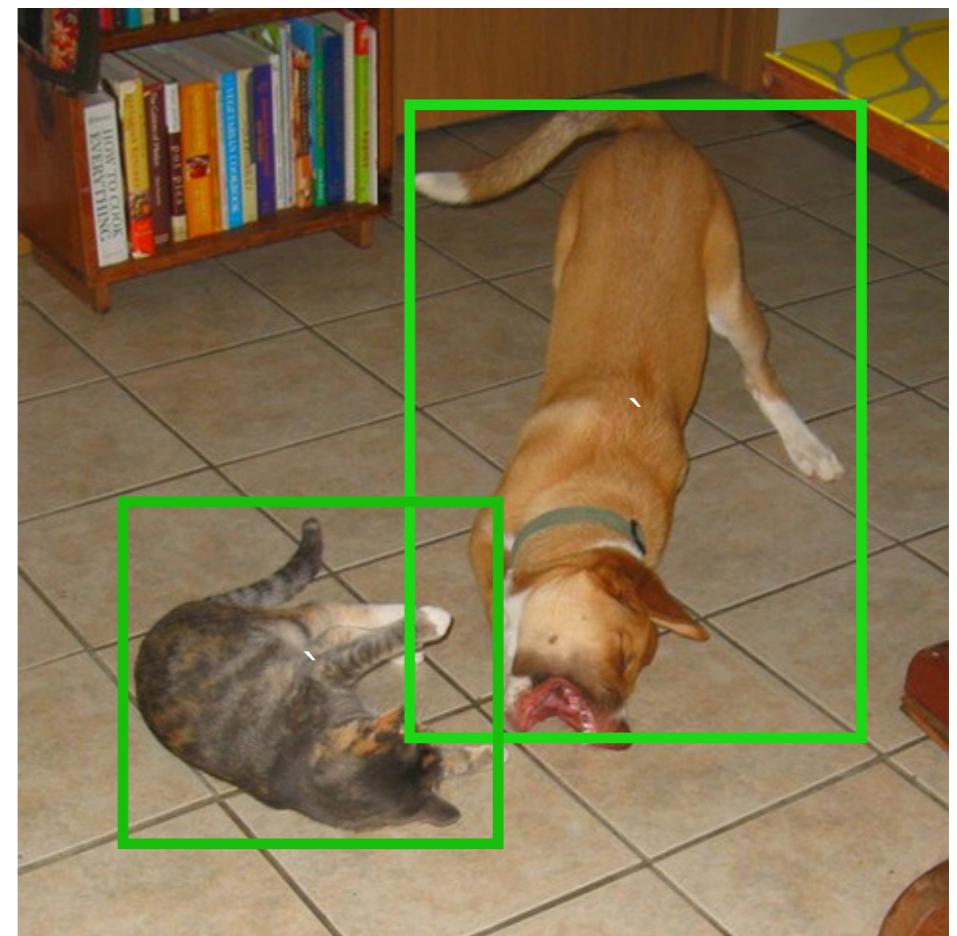
- Matching ground truth and default boxes



Handling Many Default Boxes

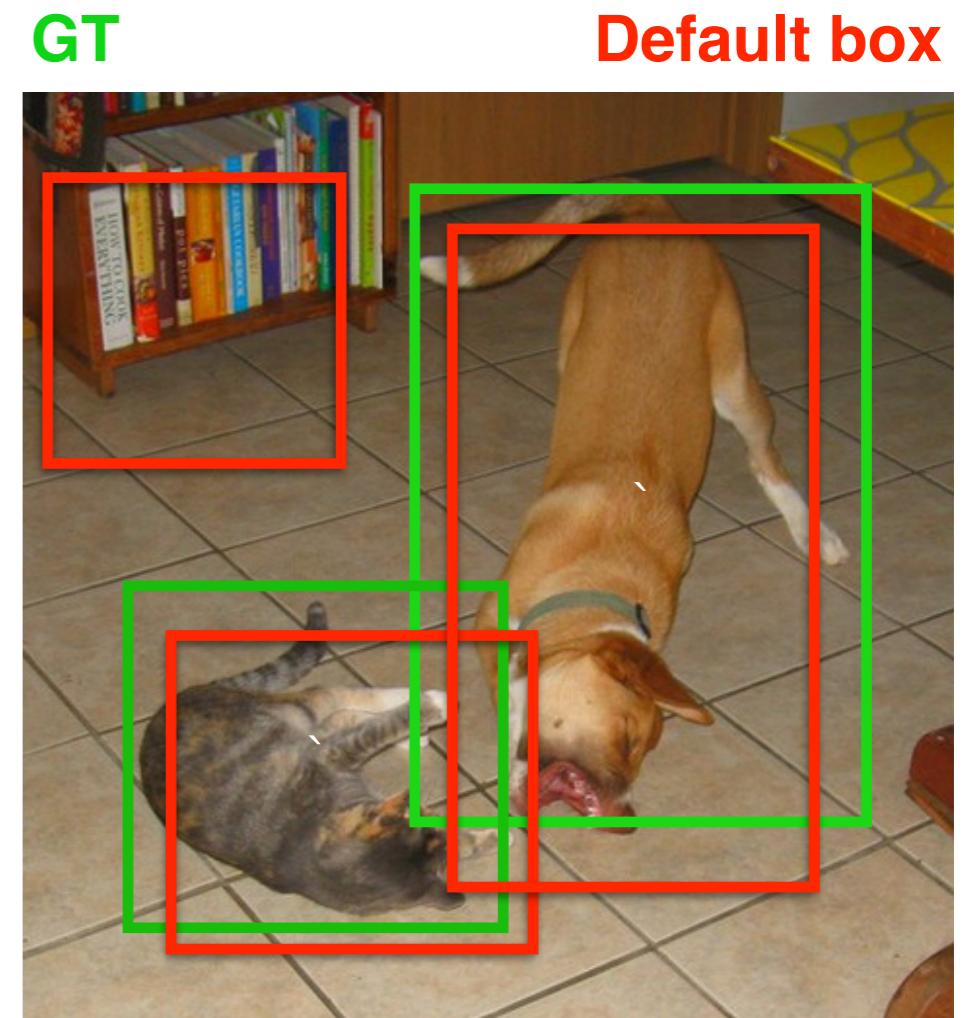
- Matching ground truth and default boxes

GT



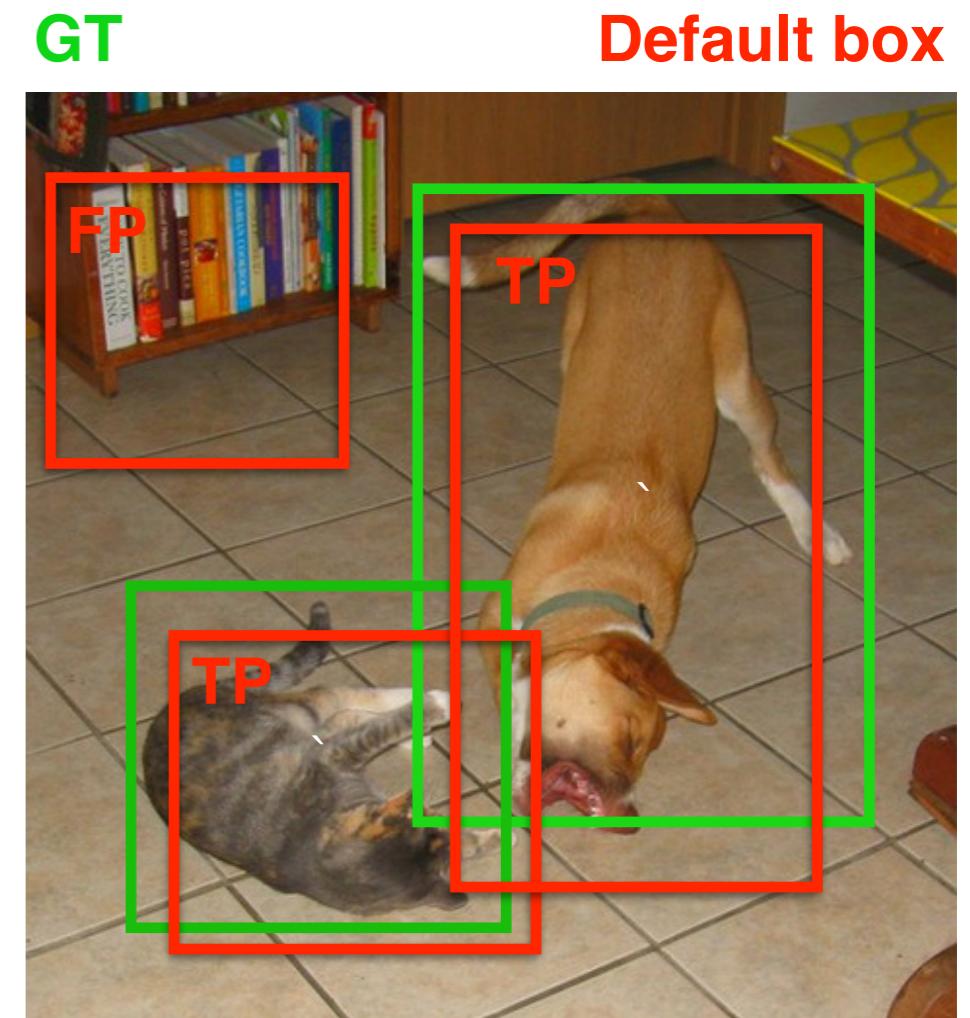
Handling Many Default Boxes

- Matching ground truth and default boxes



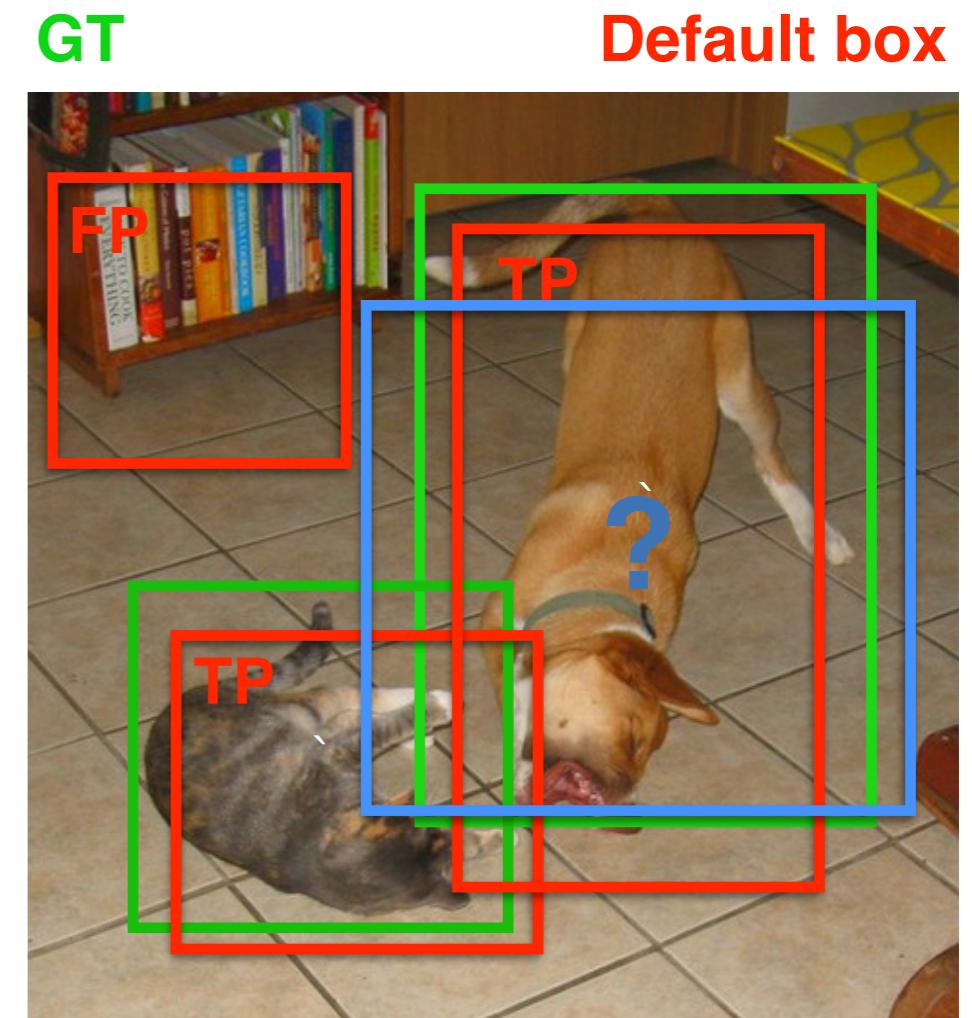
Handling Many Default Boxes

- Matching ground truth and default boxes



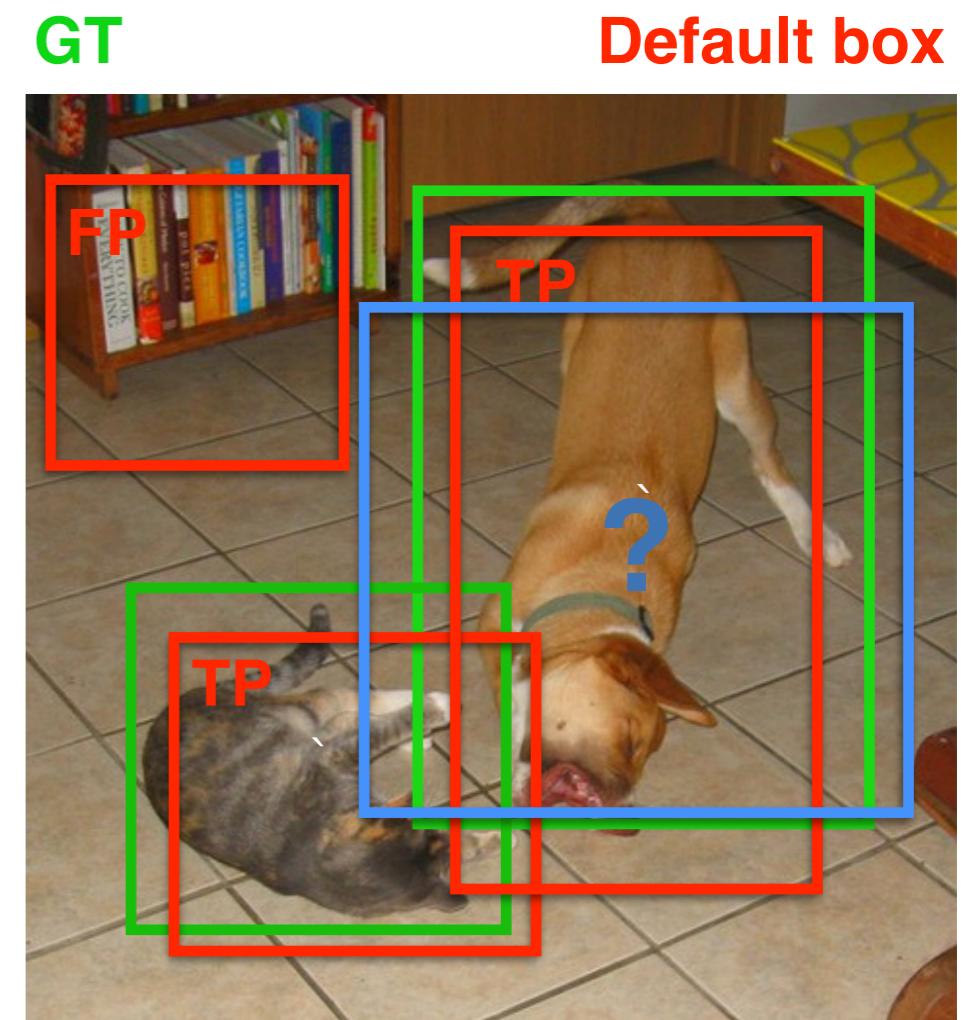
Handling Many Default Boxes

- Matching ground truth and default boxes



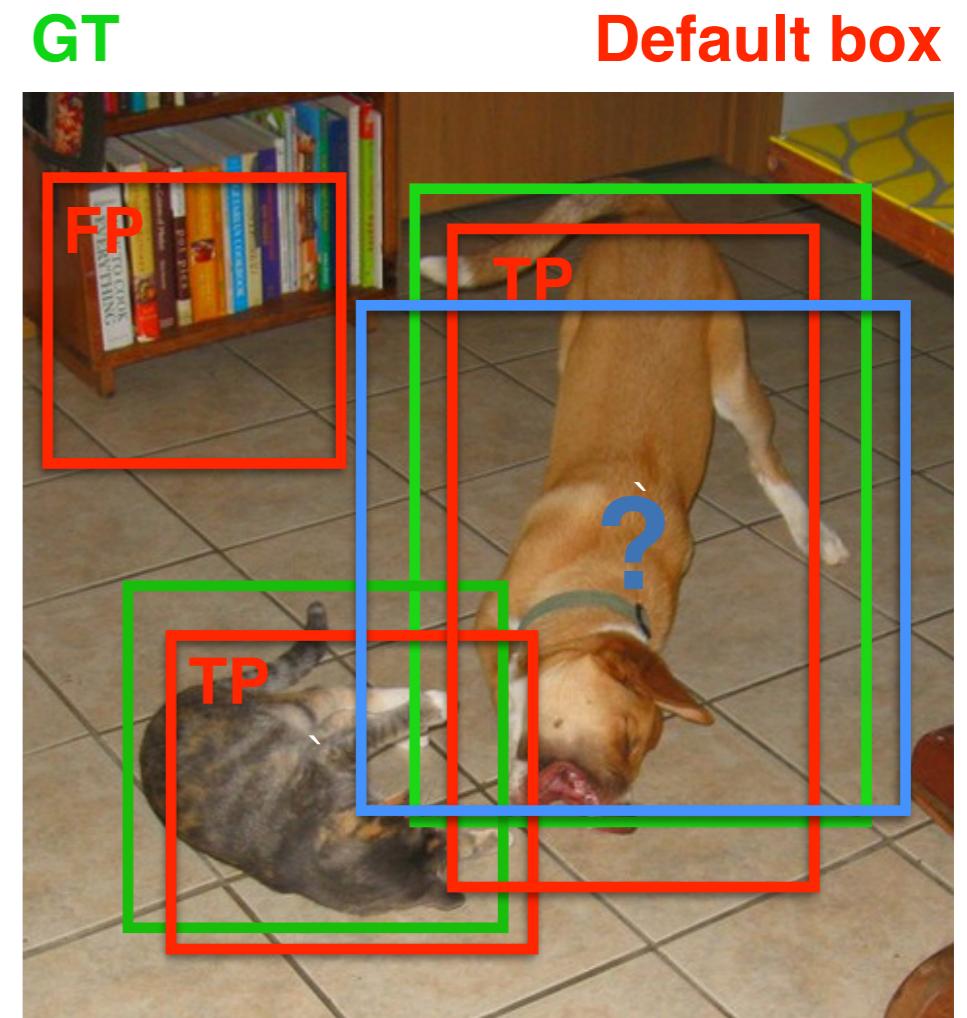
Handling Many Default Boxes

- Matching ground truth and default boxes
 - Match each GT box to closest default box



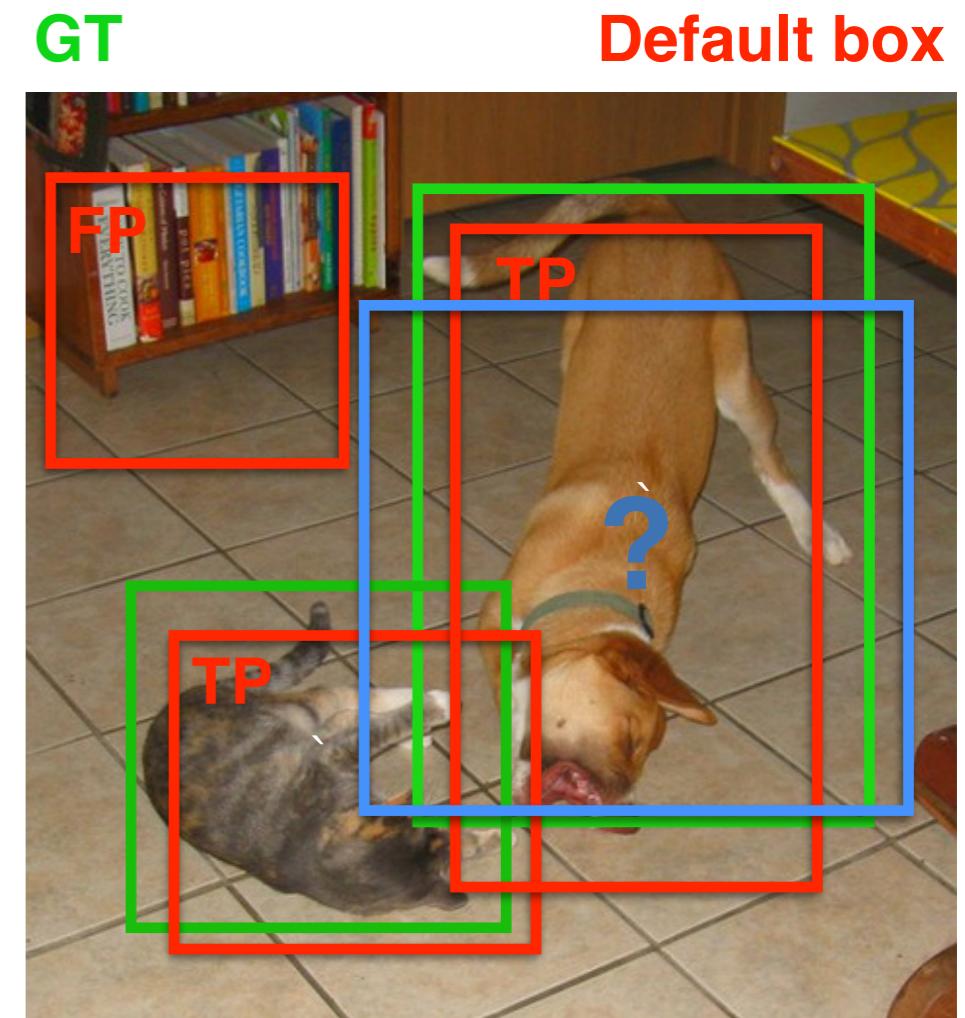
Handling Many Default Boxes

- Matching ground truth and default boxes
 - Match each GT box to closest default box
 - Also match each GT box to all unassigned default boxes with $\text{IoU} > 0.5$



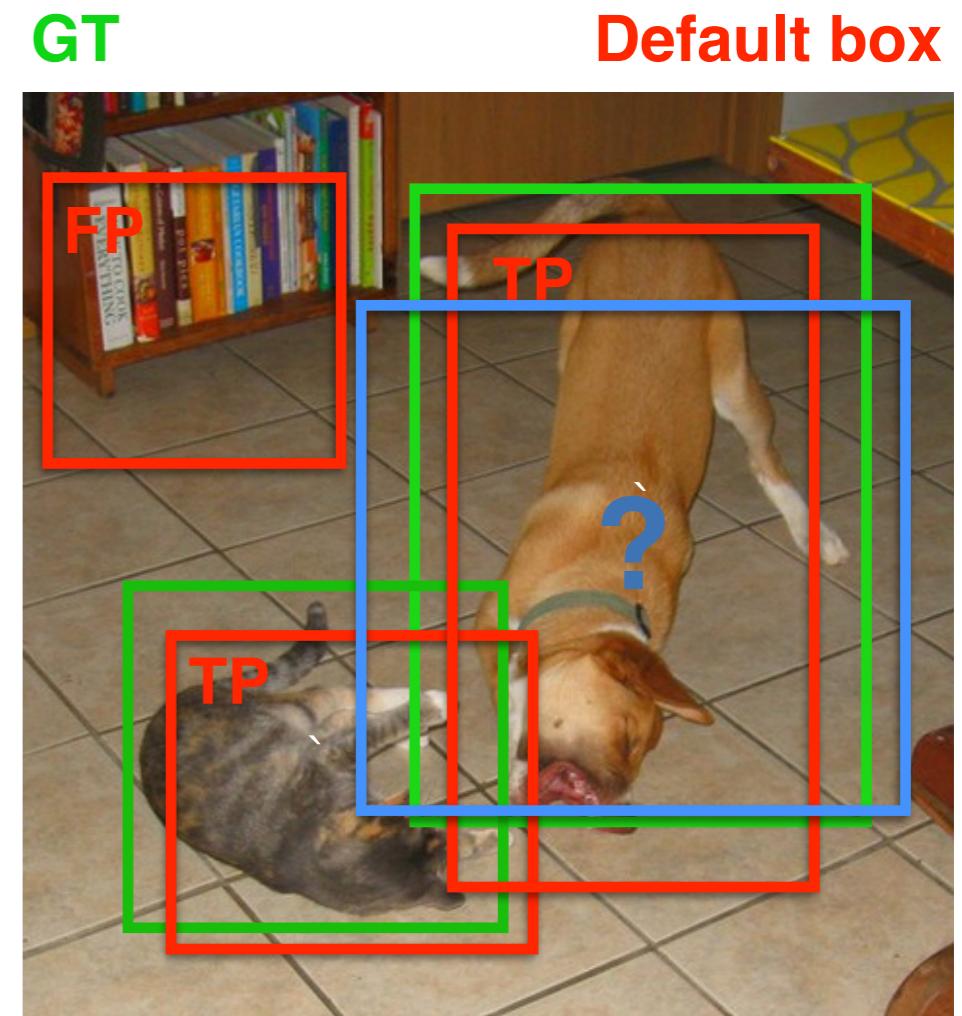
Handling Many Default Boxes

- Matching ground truth and default boxes
 - Match each GT box to closest default box
 - Also match each GT box to all unassigned default boxes with $\text{IoU} > 0.5$
- Hard negative mining



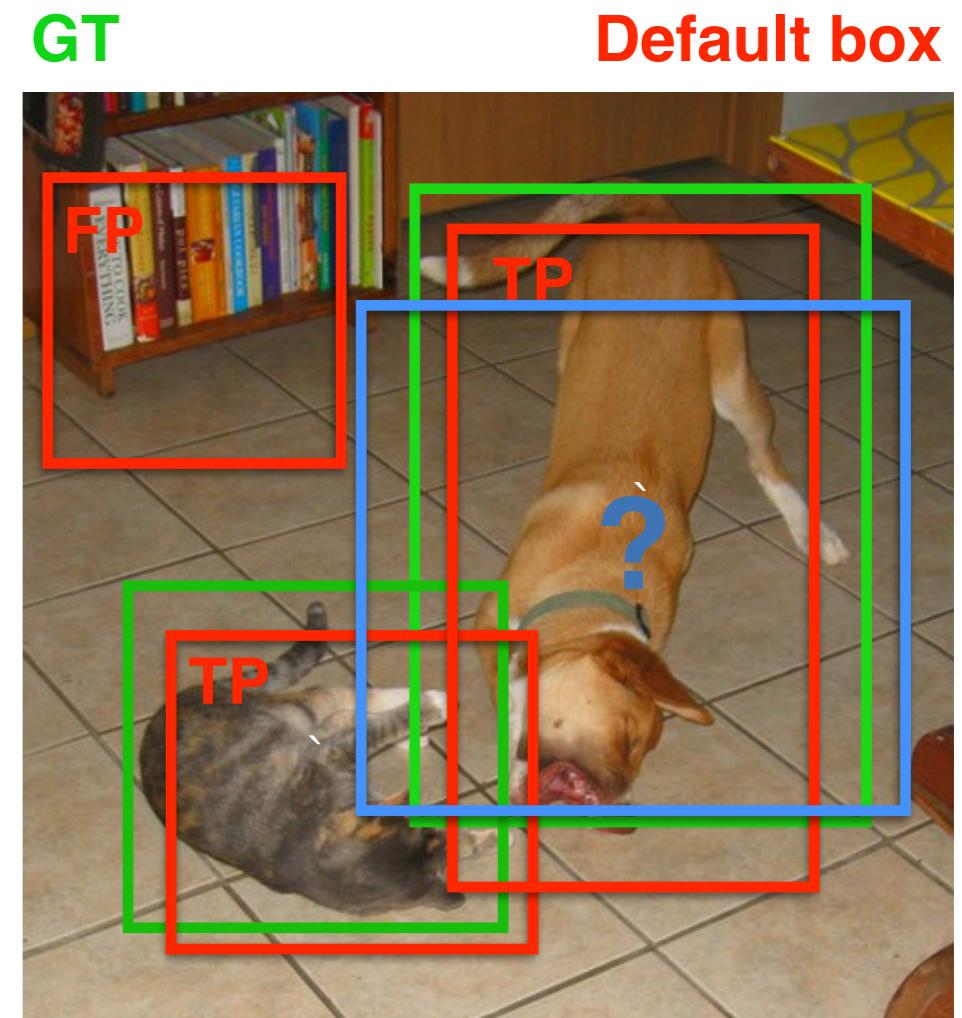
Handling Many Default Boxes

- Matching ground truth and default boxes
 - Match each GT box to closest default box
 - Also match each GT box to all unassigned default boxes with $\text{IoU} > 0.5$
- Hard negative mining
 - Unbalanced training: 1-30 TP, 8k-25k FP

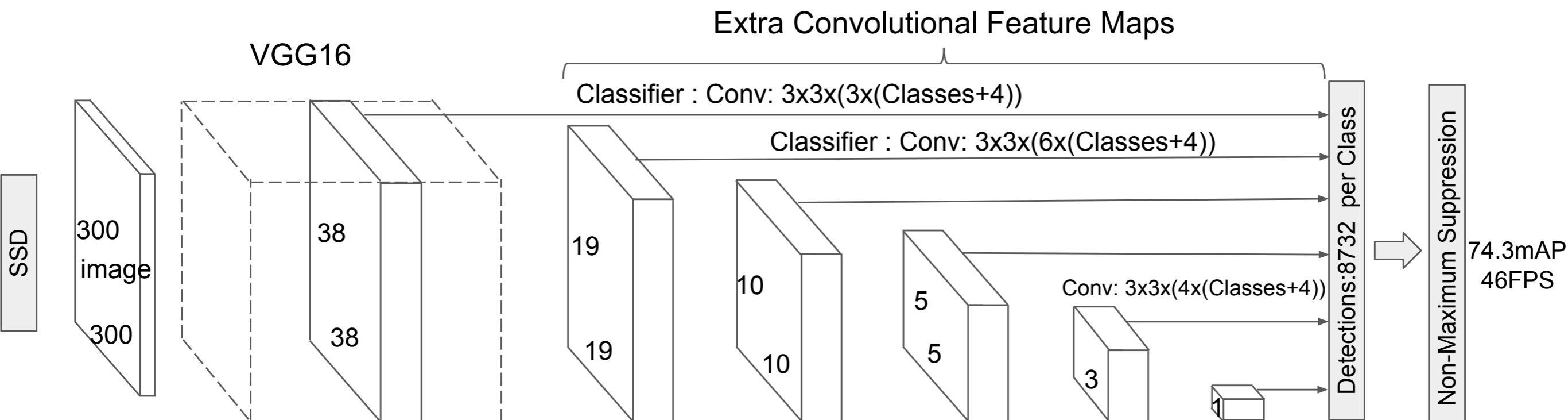


Handling Many Default Boxes

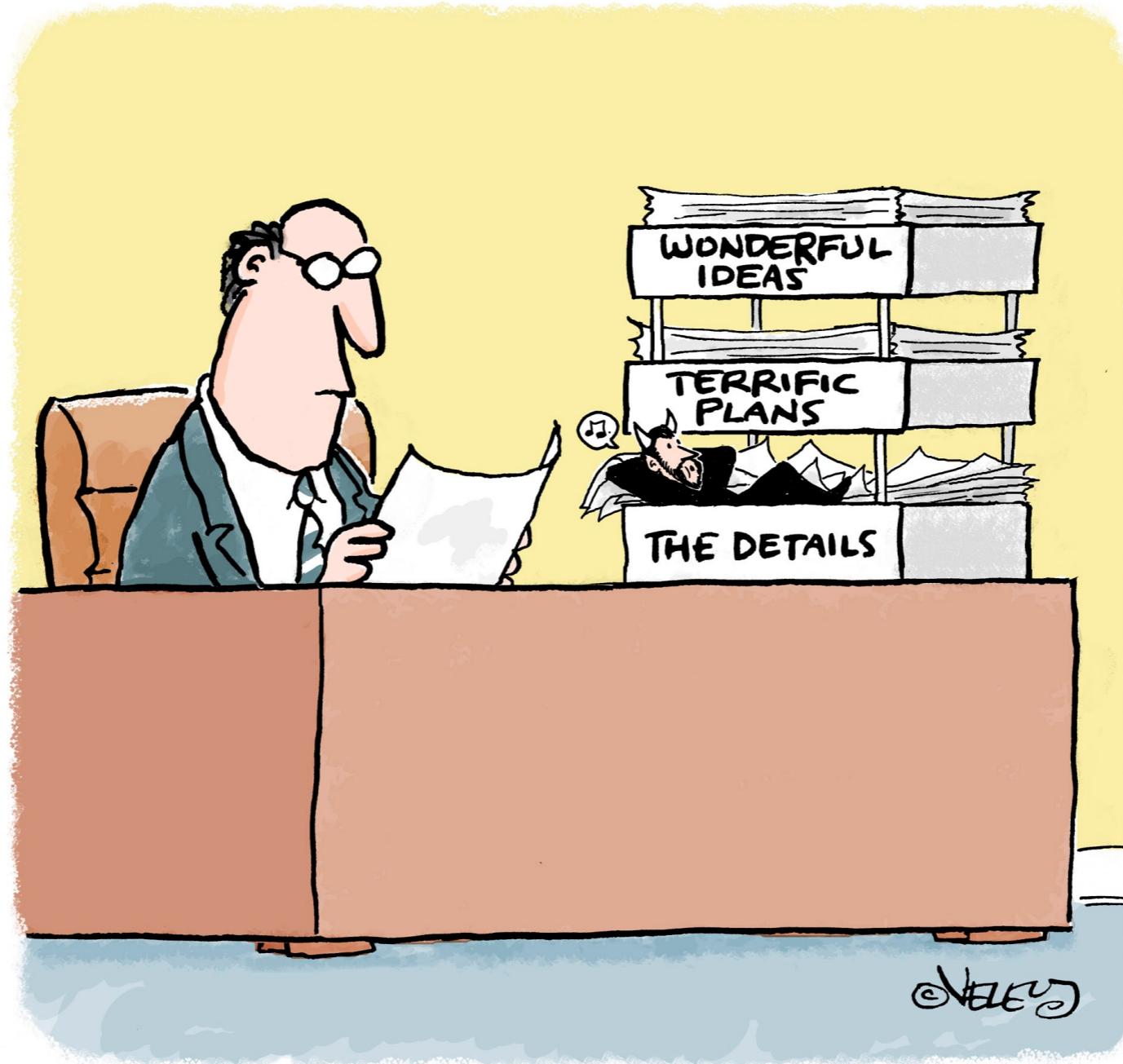
- Matching ground truth and default boxes
 - Match each GT box to closest default box
 - Also match each GT box to all unassigned default boxes with $\text{IoU} > 0.5$
- Hard negative mining
 - Unbalanced training: 1-30 TP, 8k-25k FP
 - Keep TP:FP ratio fixed (1:3), use worst-misclassified FPs.



SSD Architecture

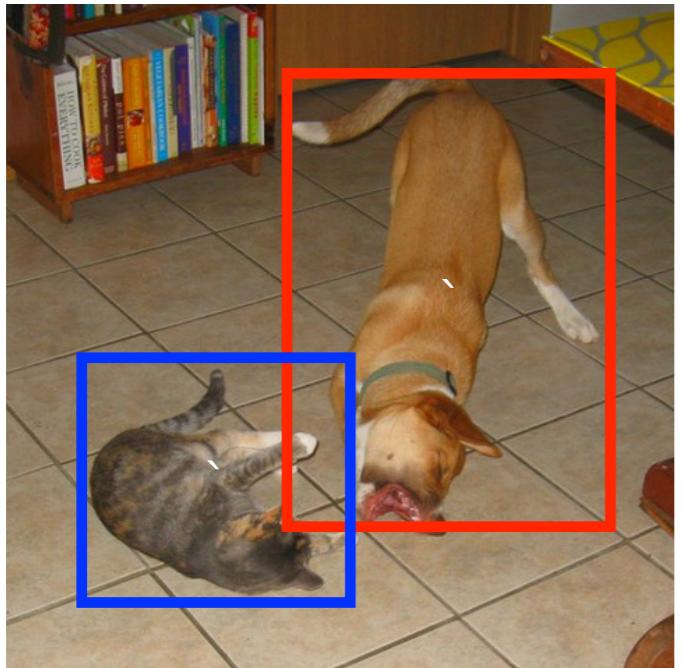


Contribution #3: The Devil is in the Details

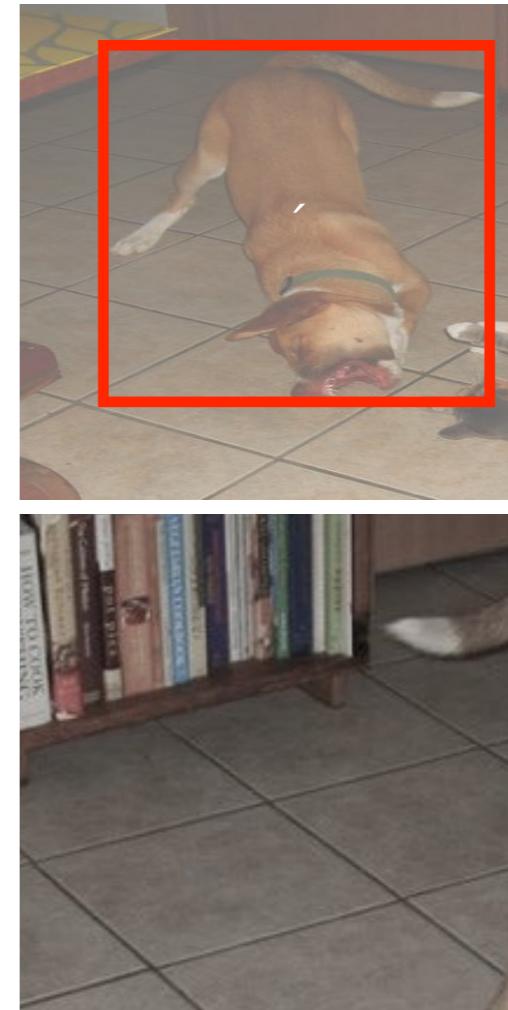
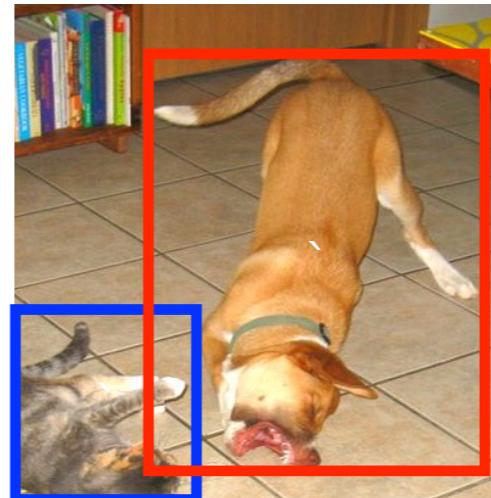
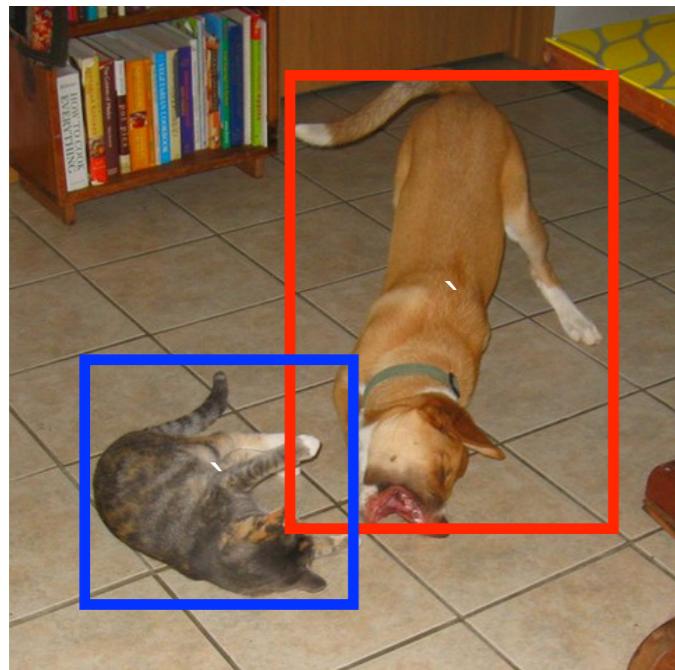


Data Augmentation

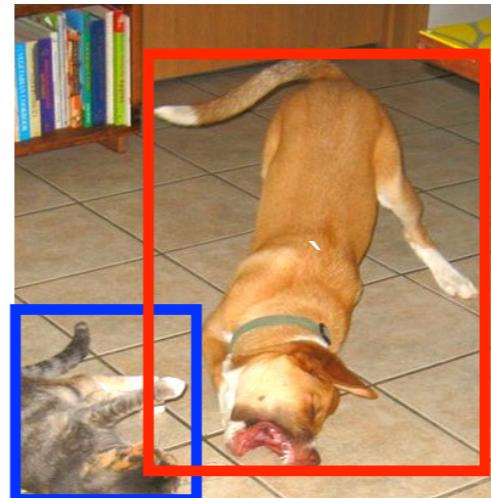
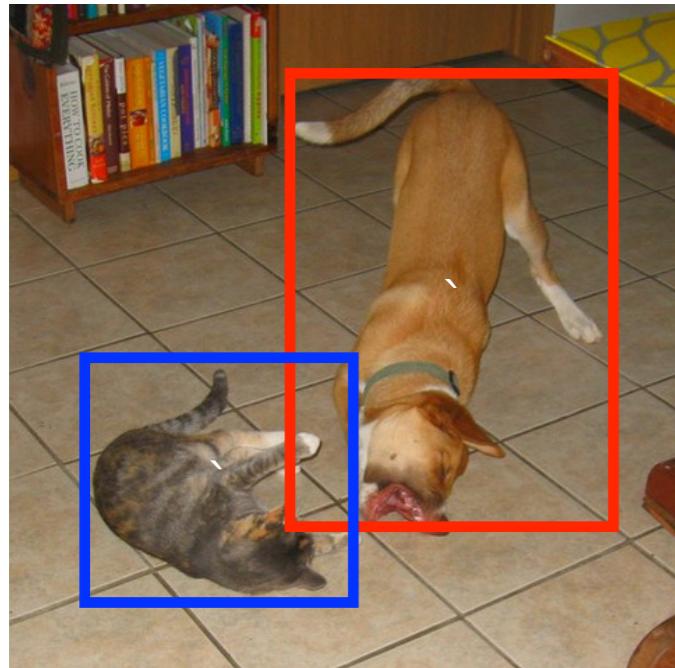
Data Augmentation



Data Augmentation



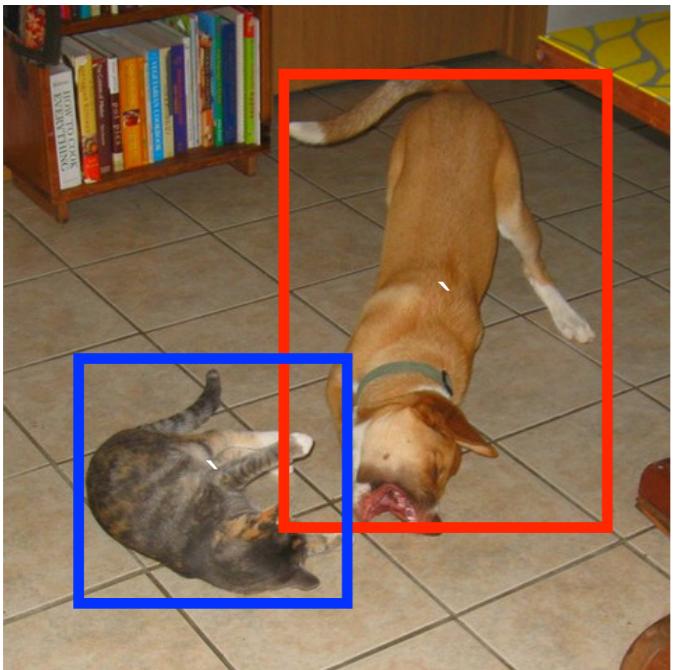
Data Augmentation



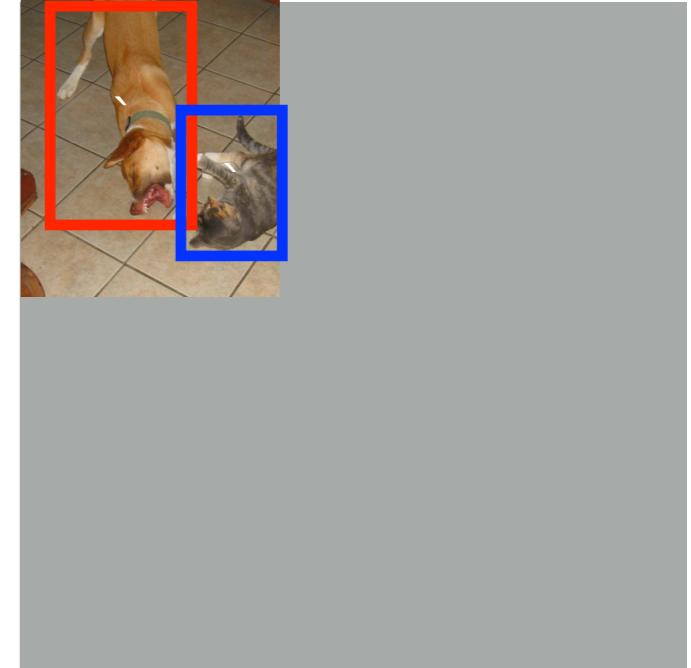
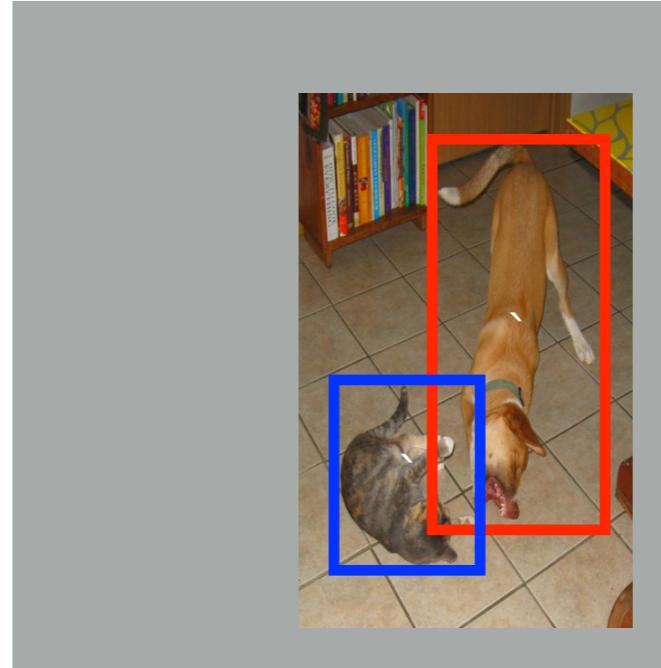
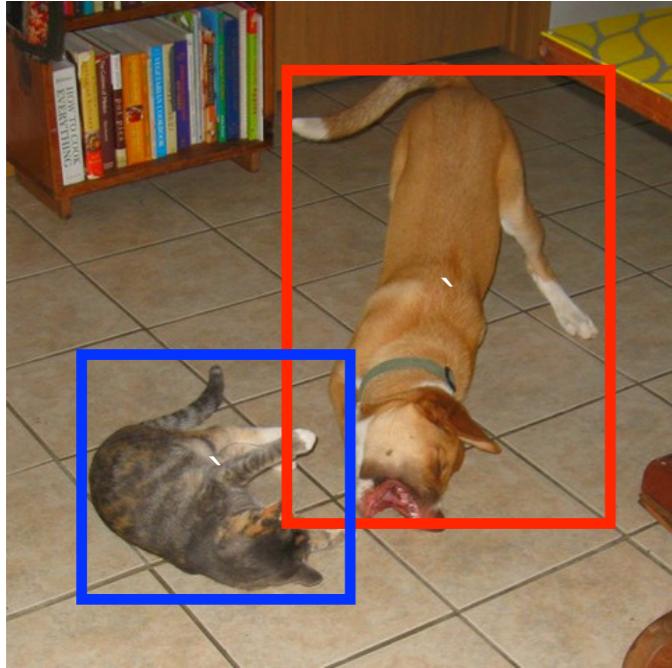
data augmentation	SSD300	
horizontal flip	✓	✓
random crop & color distortion		✓
VOC2007 test mAP	65.5	74.3

Data Augmentation

Data Augmentation

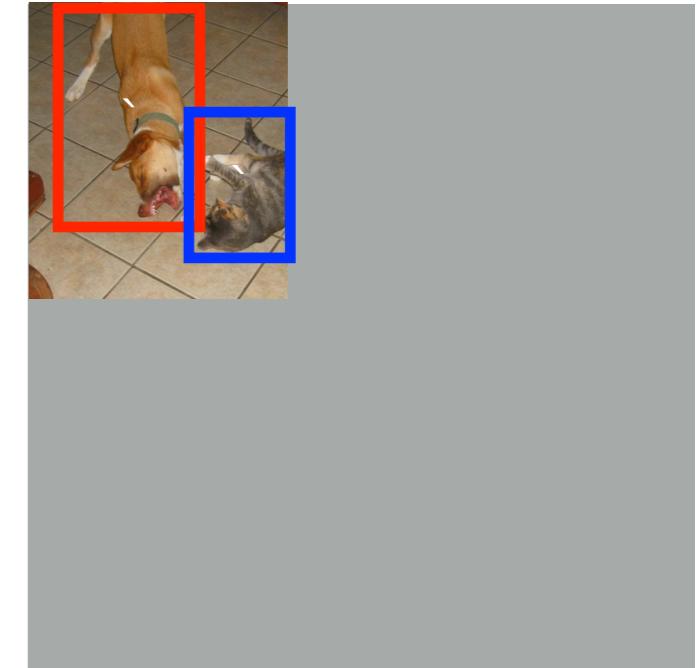
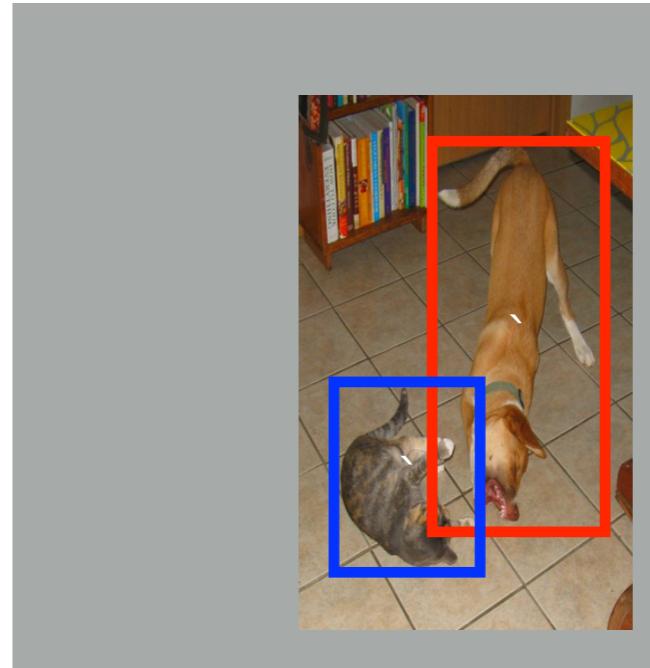
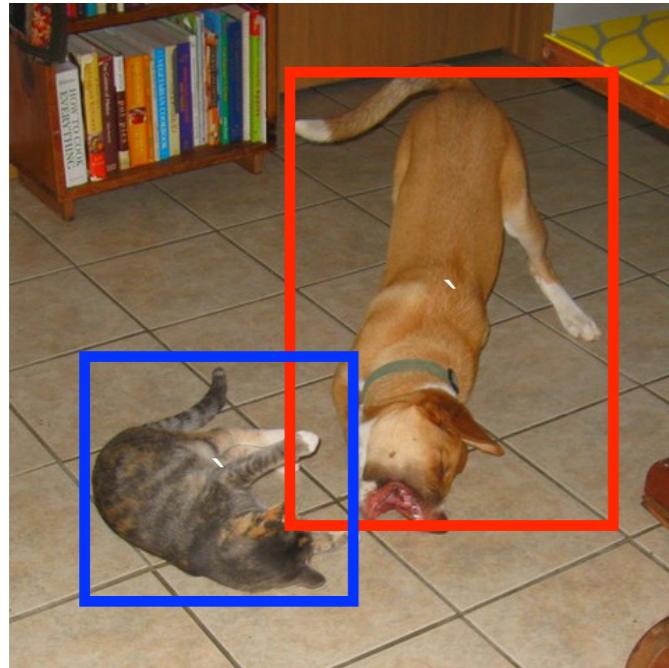


Data Augmentation



Random expansion creates more
small training examples

Data Augmentation



Random expansion creates more
small training examples

data augmentation	SSD300		
horizontal flip	✓	✓	✓
random crop & color distortion		✓	✓
random expansion			✓
VOC2007 test mAP	65.5	74.3	77.2

Results on VOC2007 test

Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	~ 1000 × 600
Fast YOLO	52.7	155	1	98	448 × 448
YOLO (VGG16)	66.4	21	1	98	448 × 448
SSD300	74.3	46	1	8732	300 × 300
SSD512	76.8	19	1	24564	512 × 512
SSD300	74.3	59	8	8732	300 × 300
SSD512	76.8	22	8	24564	512 × 512

Results on VOC2007 test

Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	~ 1000 × 600
Fast YOLO	52.7	155	1	98	448 × 448
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6.6x↑

Results on VOC2007 test

Method	mAP	FPS	batch size	# Boxes	Input resolution
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10%↑

Results on VOC2007 test

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SSD512	79.8	76.8	8	24564	512 × 512

Results on More Datasets

Results on More Datasets

Method	VOC2007	VOC2012	MS COCO	ILSVRC2014
	test	test	test-dev	val2
Fast R-CNN	70.0	68.4	19.7	N/A
Faster R-CNN	73.2	70.4	21.9	N/A
YOLO	63.4	57.9	N/A	N/A

Results on More Datasets

Method	VOC2007 test	VOC2012 test	MS COCO test-dev	ILSVRC2014 val2
Fast R-CNN	70.0	68.4	19.7	N/A
Faster R-CNN	73.2	70.4	21.9	N/A
YOLO	63.4	57.9	N/A	N/A
SSD300	74.3	72.4	23.2	43.4

Results on More Datasets

Method	VOC2007 test	VOC2012 test	MS COCO test-dev	ILSVRC2014 val2
Fast R-CNN	70.0	68.4	19.7	N/A
Faster R-CNN	73.2	70.4	21.9	N/A
YOLO	63.4	57.9	N/A	N/A
SSD300	74.3	72.4	23.2	43.4
SSD512	76.8	74.9	26.8	46.4

Results on More Datasets

Method	VOC2007 test	VOC2012 test	MS COCO test-dev	ILSVRC2014 val2
Fast R-CNN	70.0	68.4	19.7	N/A
Faster R-CNN	73.2	70.4	21.9	N/A
YOLO	63.4	57.9	N/A	N/A
SSD300*	77.2	75.8	25.1	N/A
SSD512*	79.8	78.5	28.8	N/A

COCO Bounding Box precision

COCO Bounding Box precision

mAP @ IoU	0.5	0.75	0.5:0.95
Faster R-CNN	45.3	23.5	24.2
SSD512*	48.5	30.3	28.8
gain	+3.2	+6.8	+4.6

Future Work

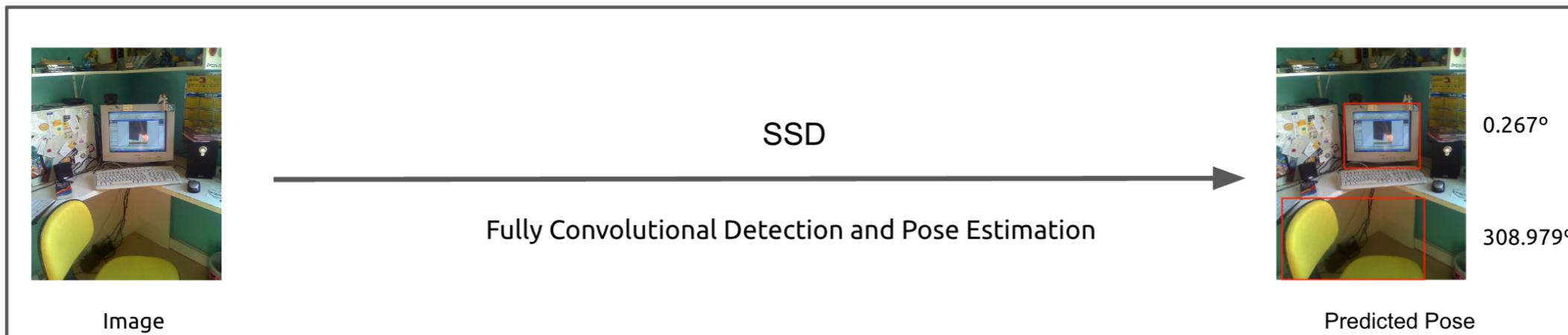
Future Work

- Object detection + pose estimation

Future Work

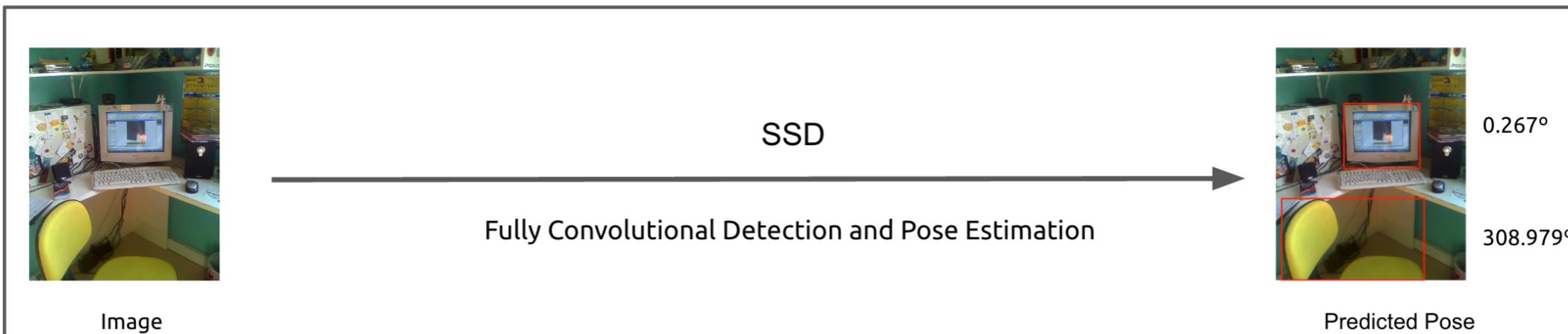
- Object detection + pose estimation

[Poirson et al, coming out at 3DV, 2016]



Future Work

- Object detection + pose estimation
[Poirson et al, coming out at 3DV, 2016]

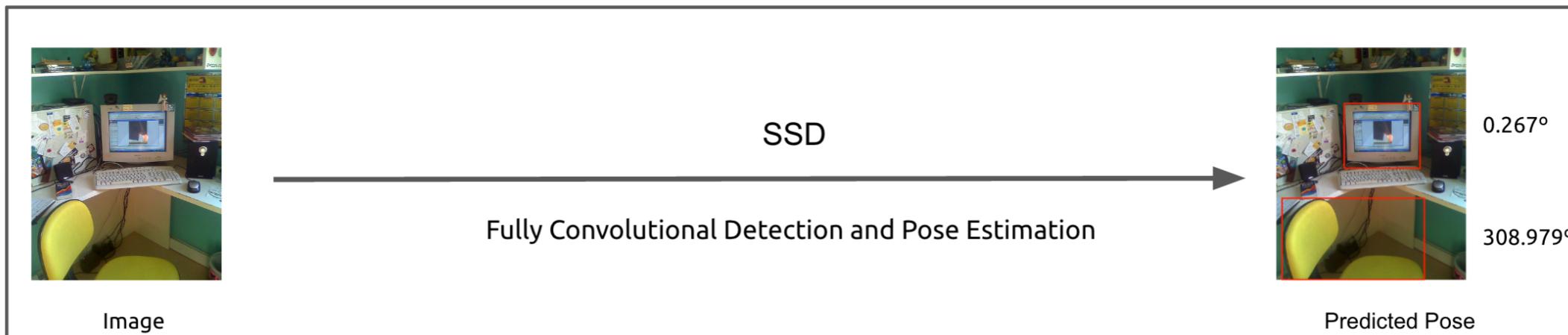


- Single shot 3D bounding box detection

Future Work

- Object detection + pose estimation

[Poirson et al, coming out at 3DV, 2016]



- Single shot 3D bounding box detection
- Joint object detection + tracking model

Check out the code/models



<https://github.com/weiliu89/caffe/tree/ssd>

Thank you!
Come by our poster O-1A-02