

Neural Object Detection

Ilya Zakharkin | Deep Learning School

About

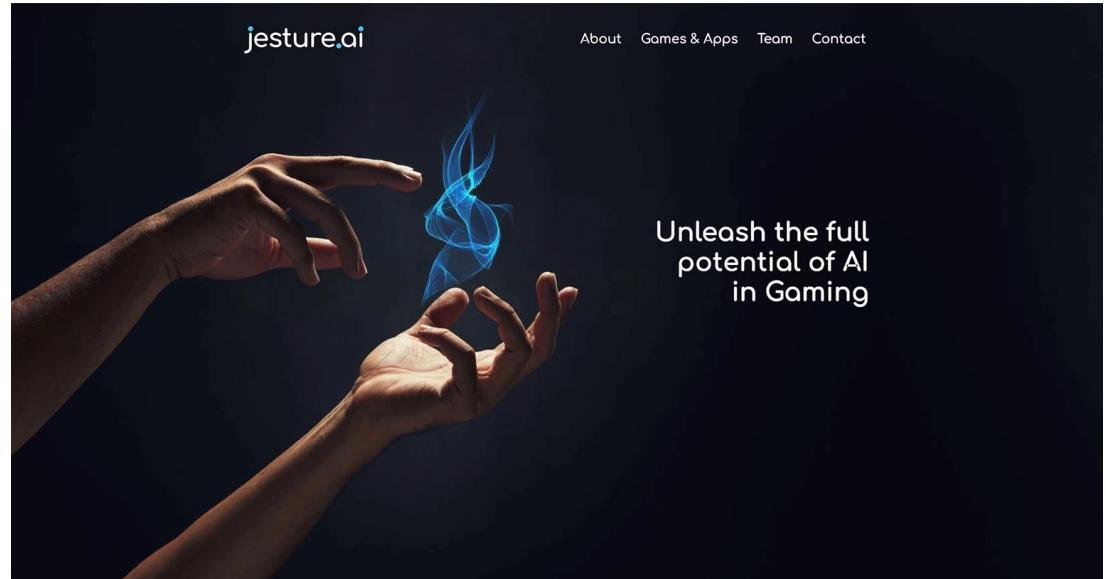


ШКОЛА АНАЛИЗА ДАННЫХ



About

SAMSUNG



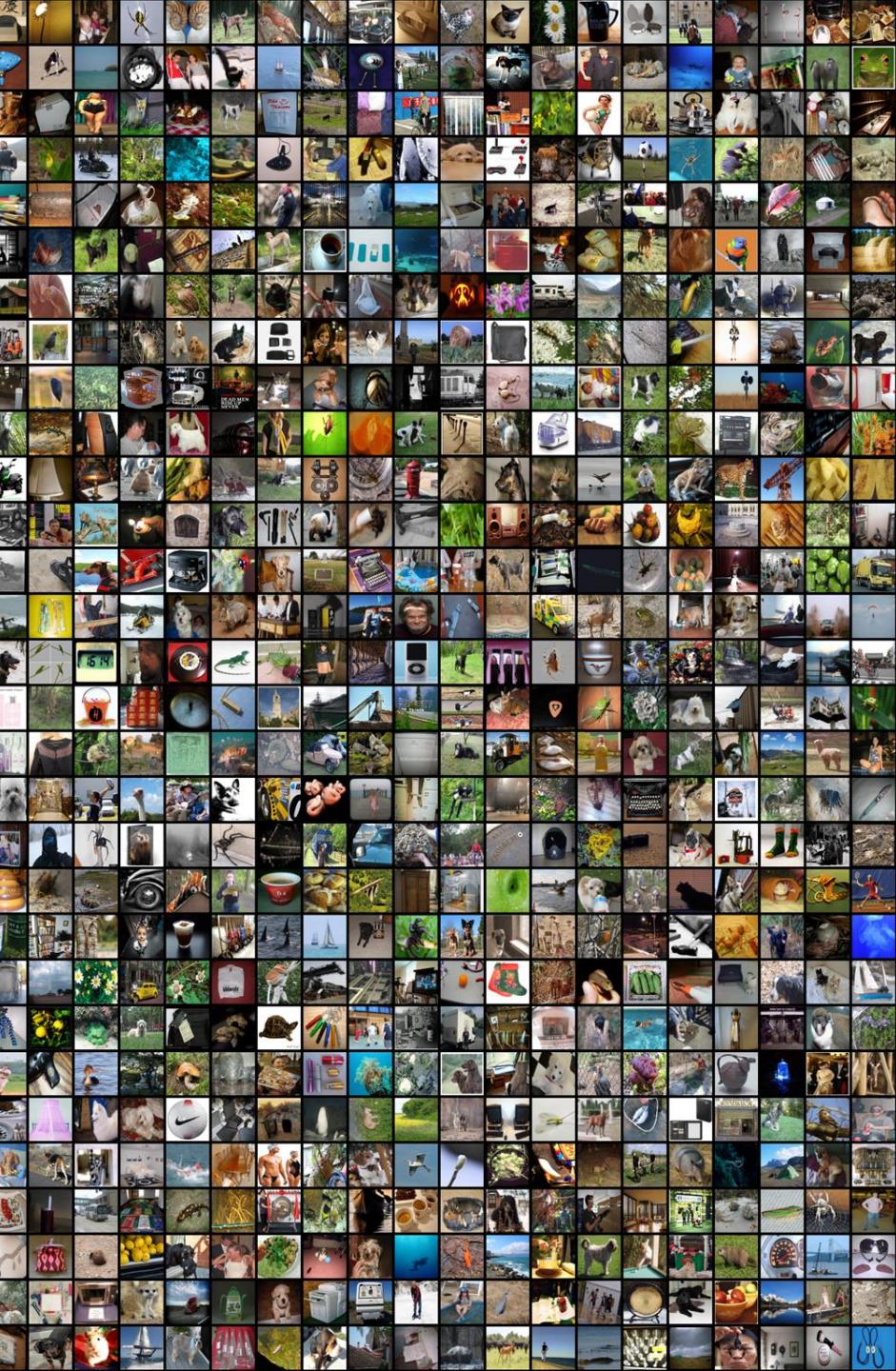
<https://www.gesture.ai/>

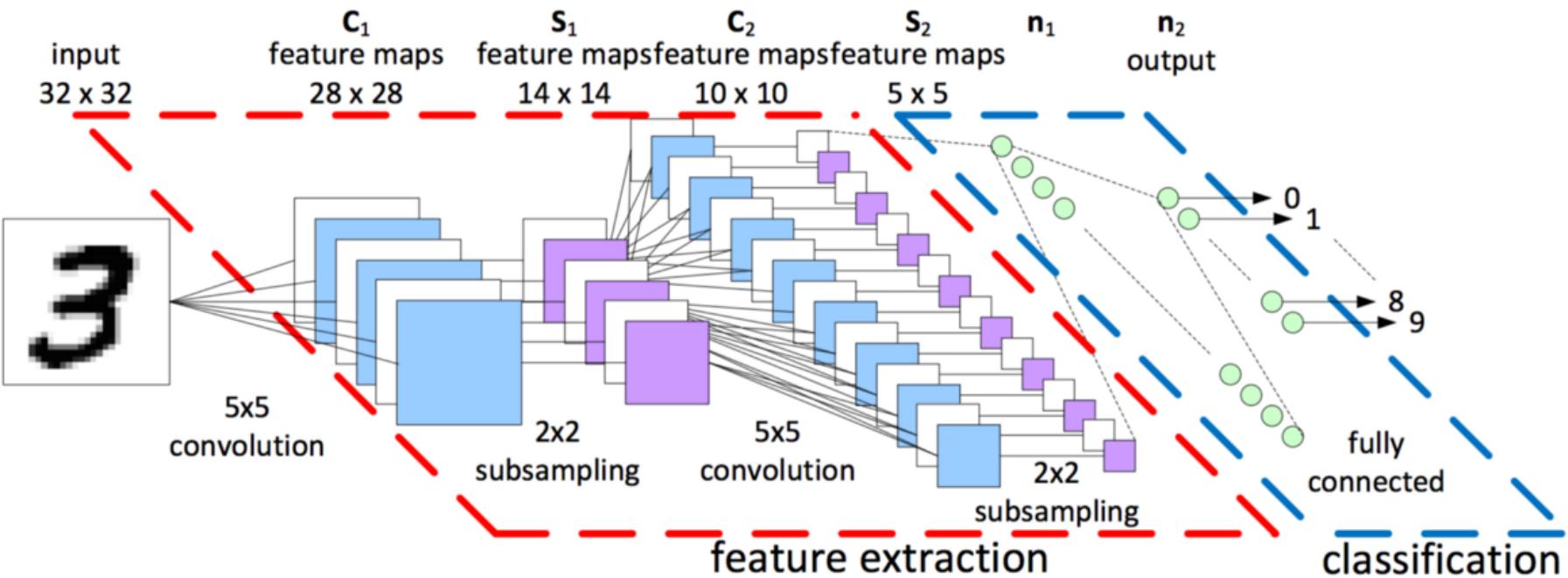
Lecture plan

1. Classification recap
2. Object Detection basics
3. Two-stage (proposal-based) methods
4. One-stage (single-shot) methods
5. Modern approaches & tasks

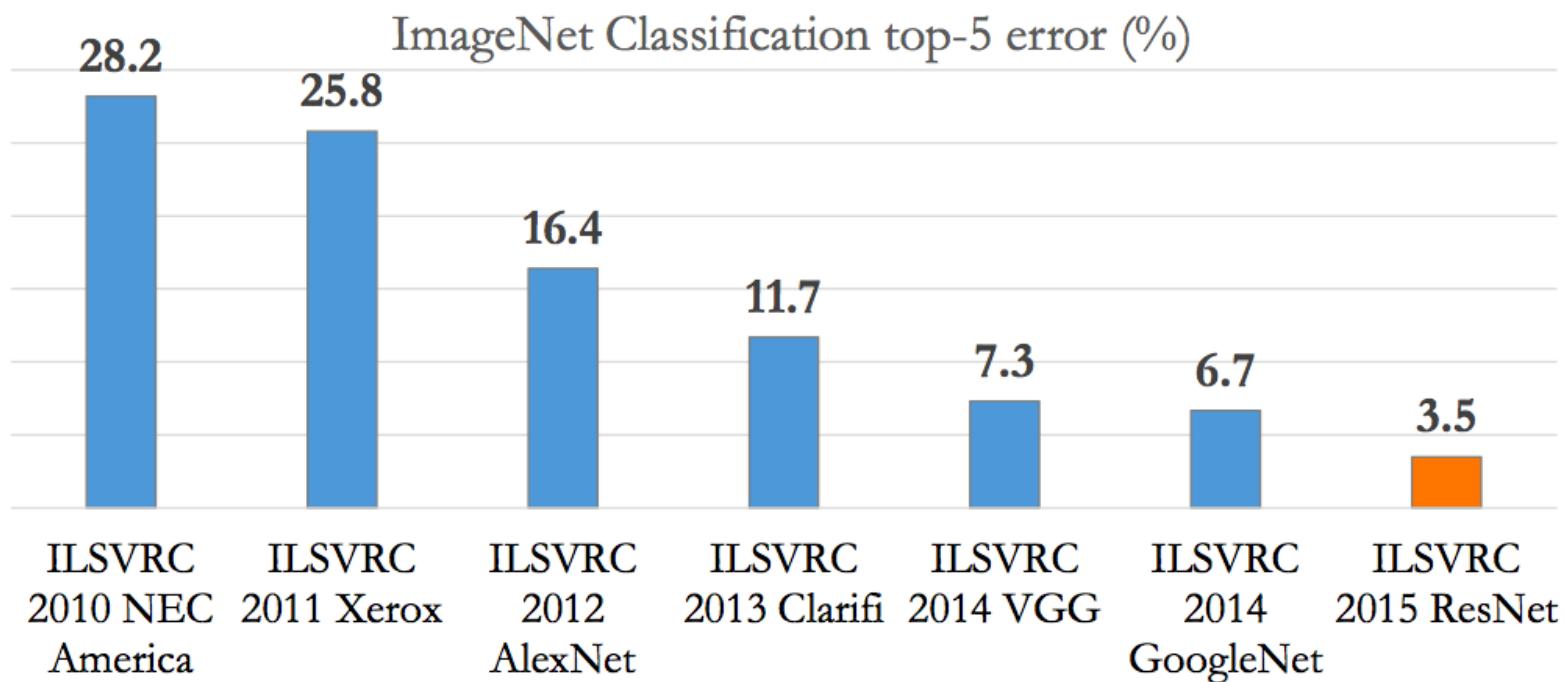
Image Classification

Recap





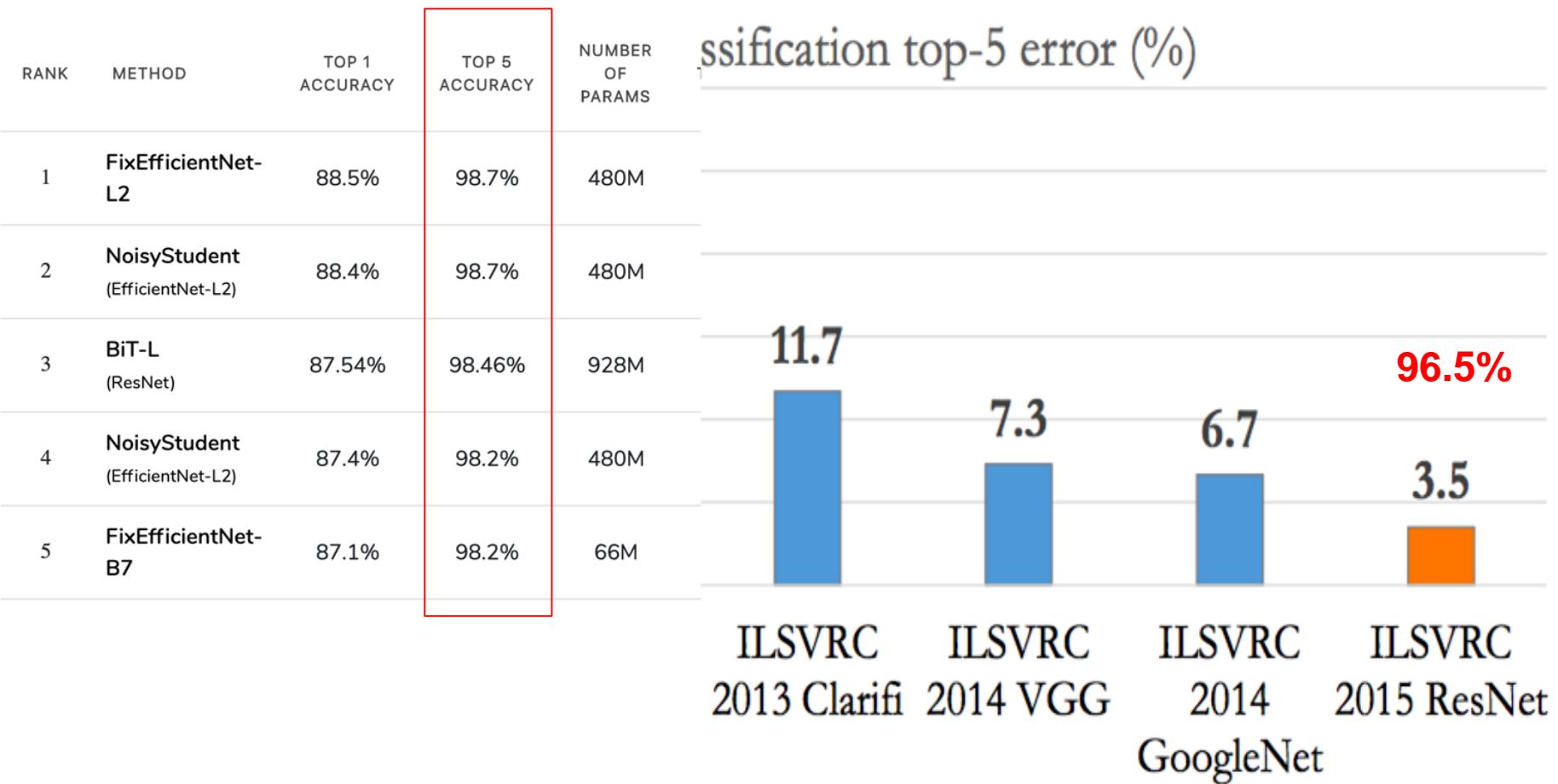
Classification: ILSVRC



Classification: ILSVRC

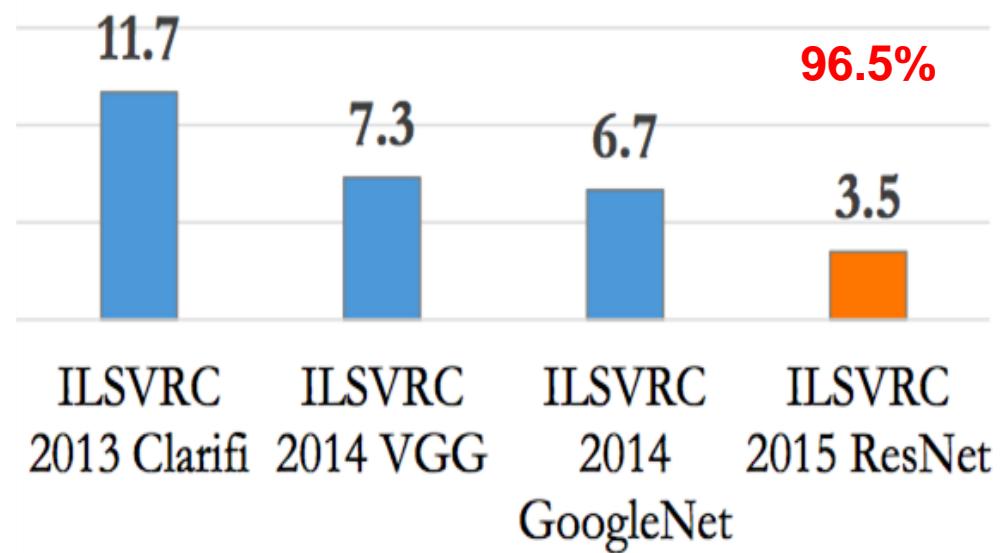
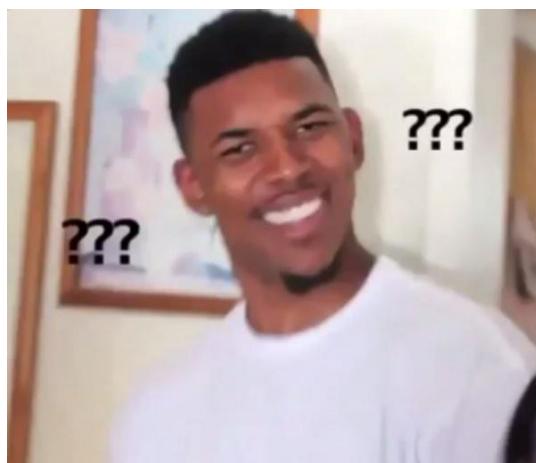
RANK	METHOD	TOP 1 ACCURACY	TOP 5 ACCURACY	NUMBER OF PARAMS	EXTRA TRAINING DATA	PAPER TITLE	YEAR	PAPER	CODE
1	FixEfficientNet-L2	88.5%	98.7%	480M	✓	Fixing the train-test resolution discrepancy: FixEfficientNet	2020		
2	NoisyStudent (EfficientNet-L2)	88.4%	98.7%	480M	✓	Self-training with Noisy Student improves ImageNet classification	2020		
3	BiT-L (ResNet)	87.54%	98.46%	928M	✓	Big Transfer (BiT): General Visual Representation Learning	2019		
4	NoisyStudent (EfficientNet-L2)	87.4%	98.2%	480M	✓	Self-training with Noisy Student improves ImageNet classification	2019		
5	FixEfficientNet-B7	87.1%	98.2%	66M	✓	Fixing the train-test resolution discrepancy: FixEfficientNet	2020		

Classification: ILSVRC



Classification: ILSVRC

		(320x320)						
66	ResNet-152	80.62%	95.51%		Deep Residual Learning for Image Recognition	2015		
67	ResNet-200	80.60%	95.20%		East AutoAugment	2018		



Classification: ILSVRC

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43 [†]
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	19.38	4.49

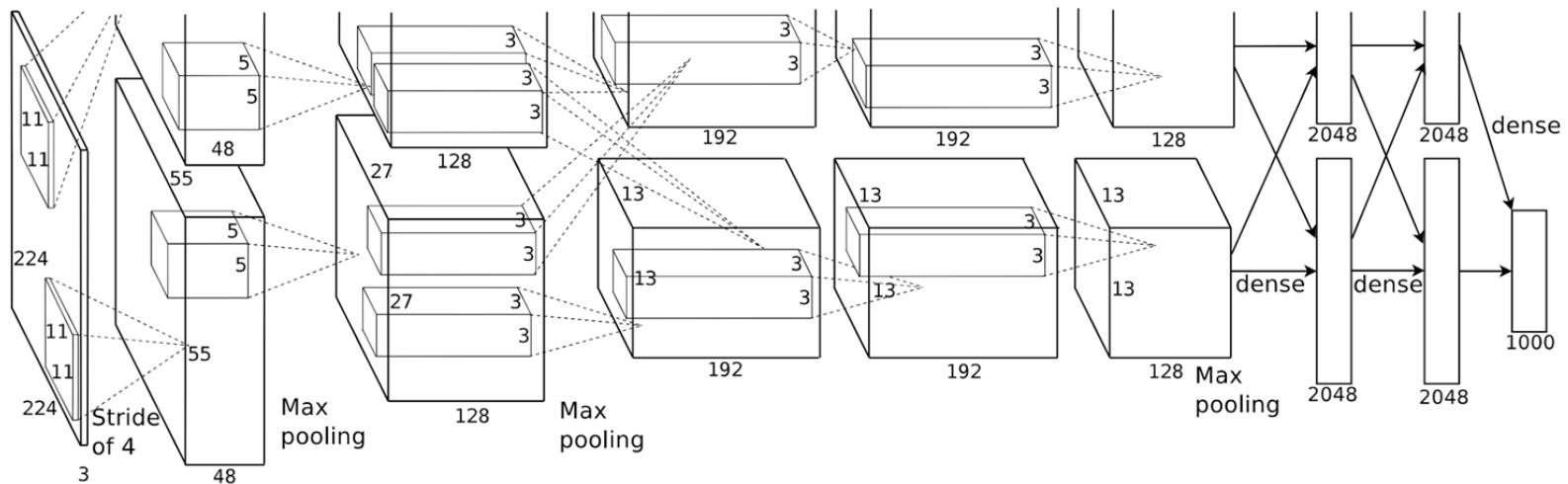
Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except [†] reported on the test set).

method	top-5 err. (test)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	3.57

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

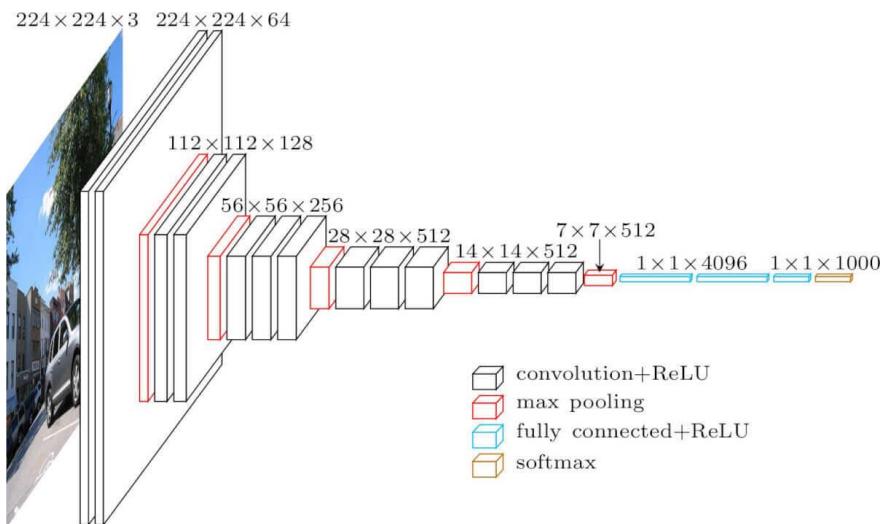
Classification: AlexNet

- Idea: Conv -> Conv (= ConvBlock) + Deeper + GPU
- [Paper](#)
- Code: available in every framework



Classification: VGG

- Idea: Several conv blocks (deeper net)
- [Paper](#)
- Code: available in every framework



ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224×224 RGB image)					
conv3-64	conv3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv1-256	conv3-256 conv3-256 conv3-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096	FC-4096	FC-4096	FC-1000	soft-max	

Classification: Inception (v1)

- Idea: Inception-block + 1x1 conv + deep supervision
- [Paper](#)
- Code: available in every framework

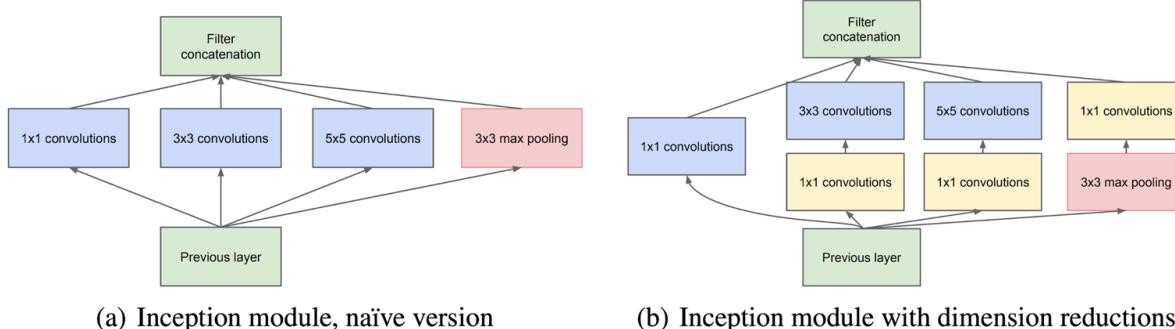
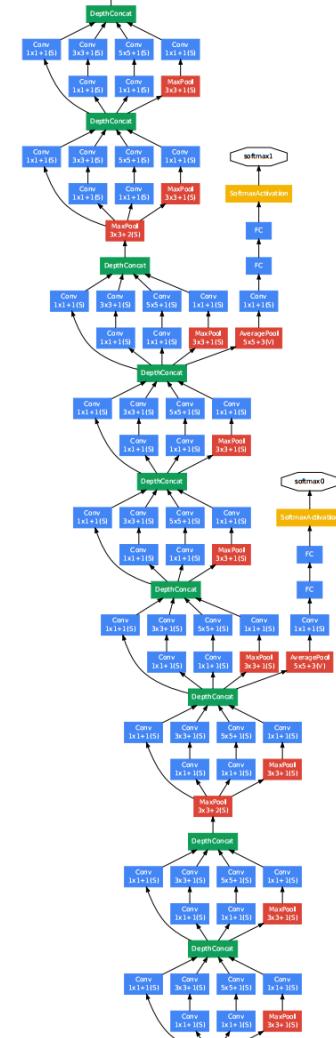


Figure 2: Inception module



Classification: ResNet

- Idea: Residual connections (Shortcuts)
- [Paper](#)
- Code: available in every framework

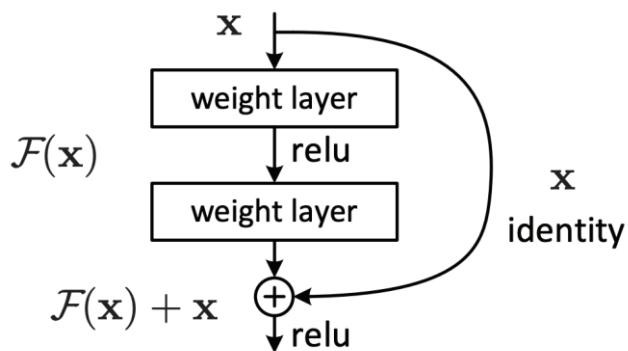
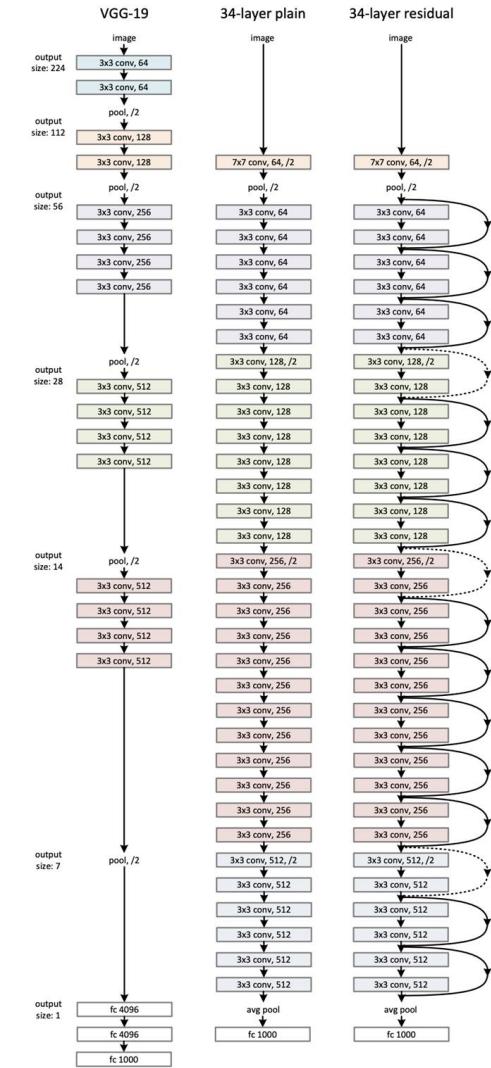
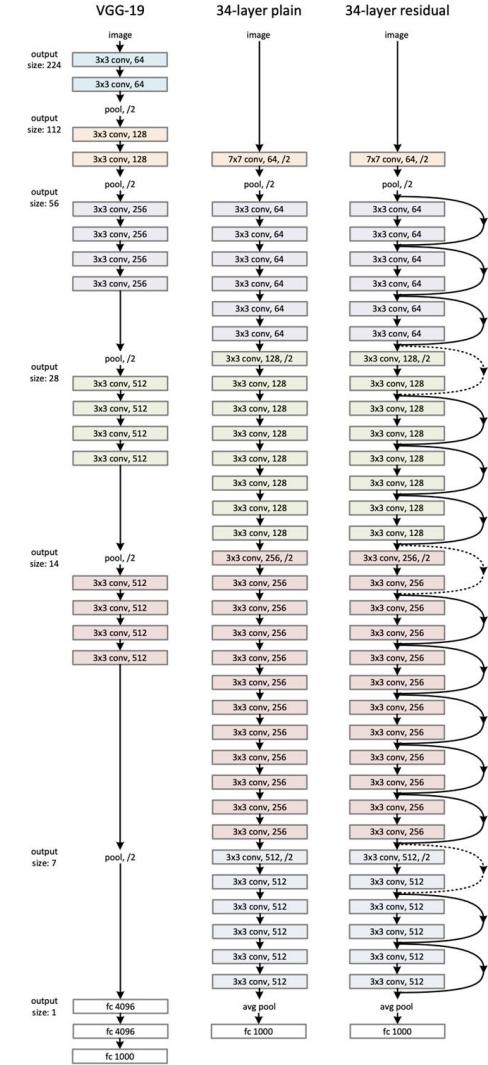
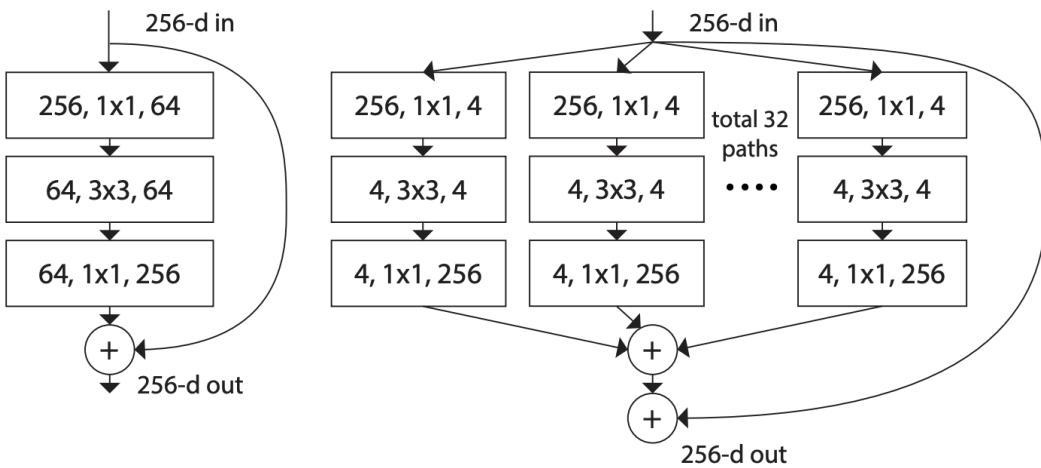


Figure 2. Residual learning: a building block.



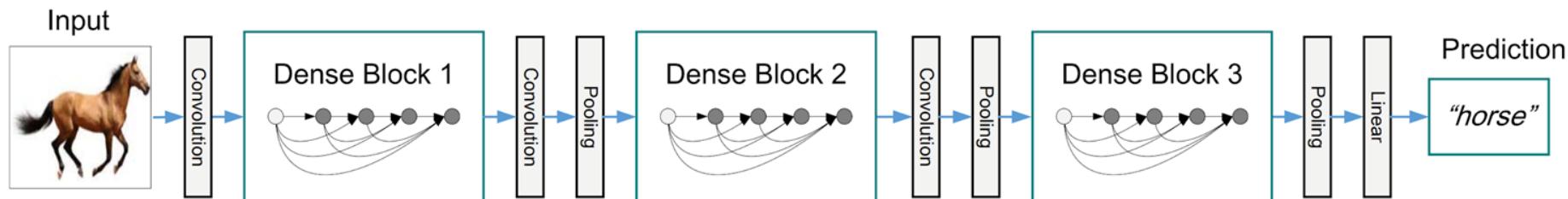
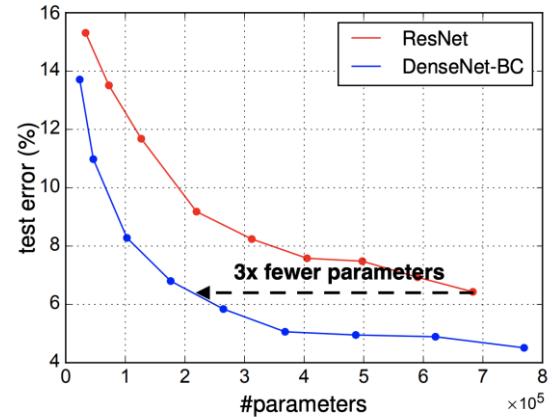
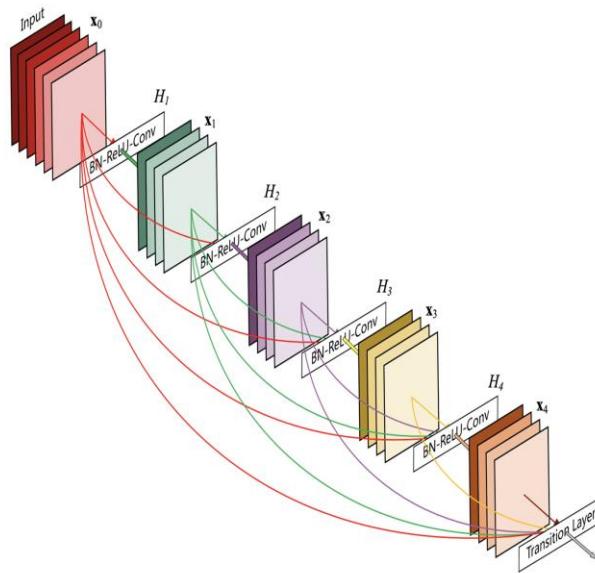
Classification: ResNeXt

- Idea: Aggregated residual blocks
- [Paper](#)
- [Code](#)
- Bottom: Cardinality (C) = 32, d = 4



Classification: DenseNet

- Idea: Dense block
- [Paper](#)
- Code:
torchvision / tf.models



Classification: Squeeze-and-Excitation Net (SENet)

- Idea: SE-block
- [Paper](#)
- [Code](#)

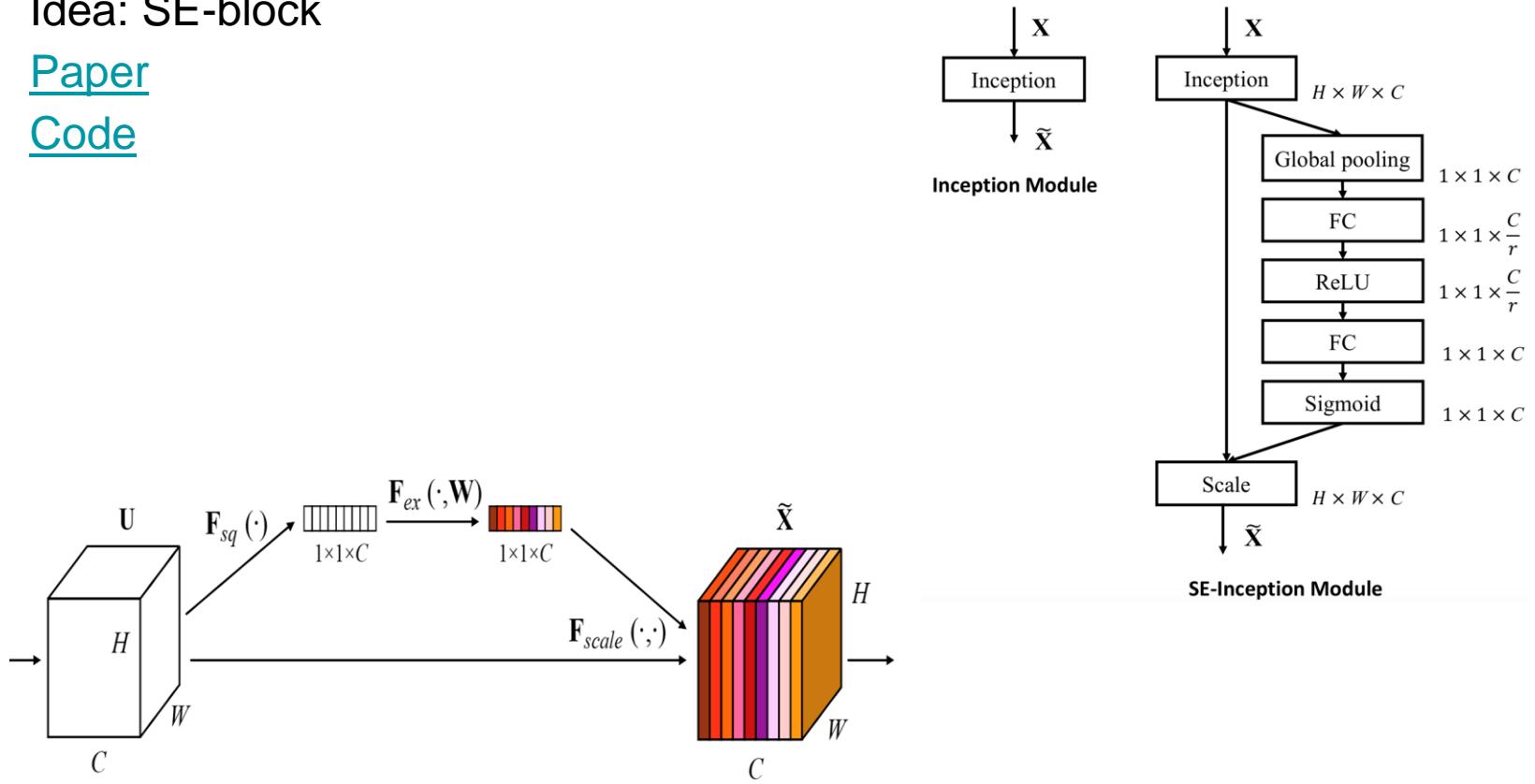
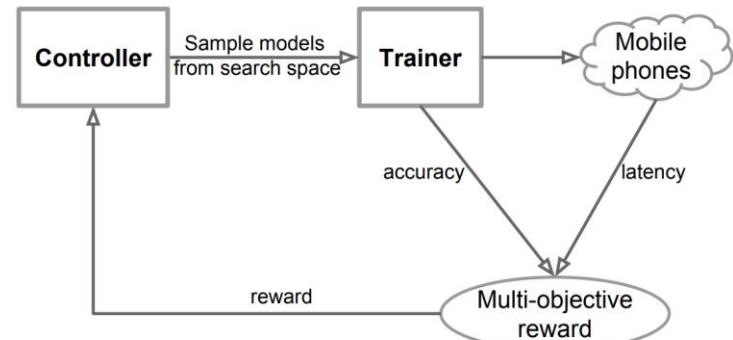
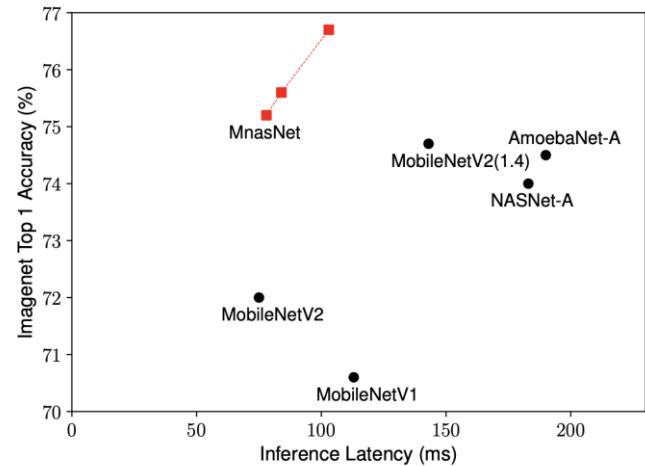
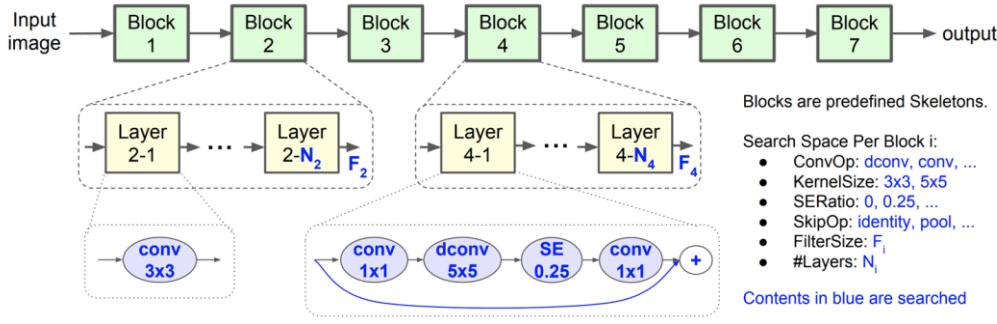


Figure 1: A Squeeze-and-Excitation block.

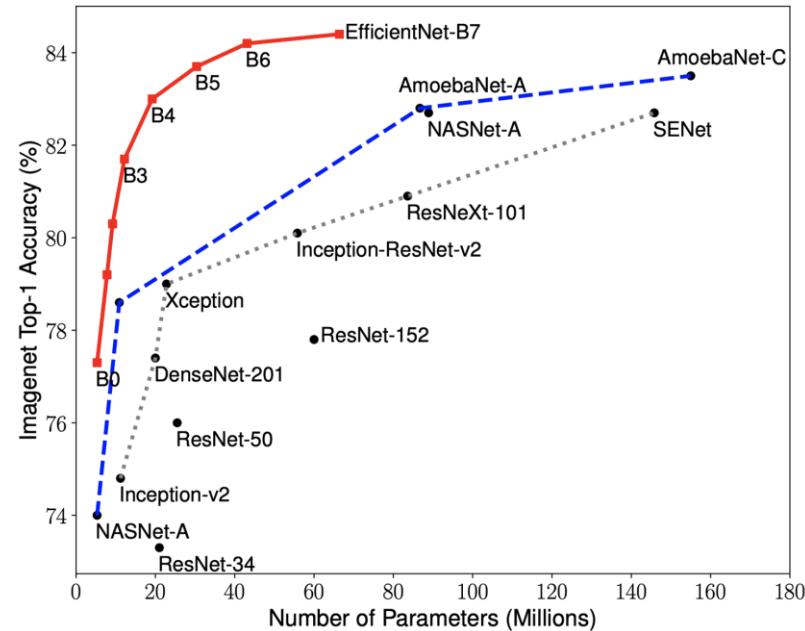
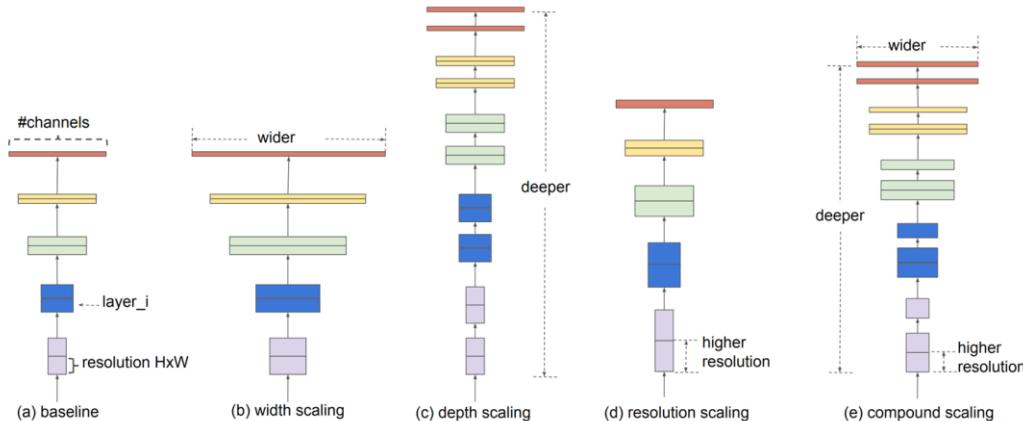
Classification: MnasNet

- Idea: [AutoML](#)
(Neural Architecture Search, NAS)
- [Paper](#)
- [Code](#)
- Speed ~100ms on Mobile CPU (Pixel)



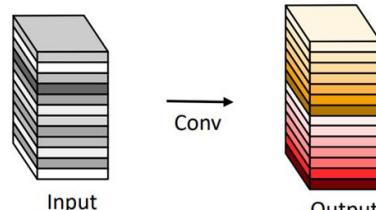
Classification: EfficientNet (2019)

- Idea: [AutoML](#) + Compound scaling
- [Paper](#)
- [Code](#)

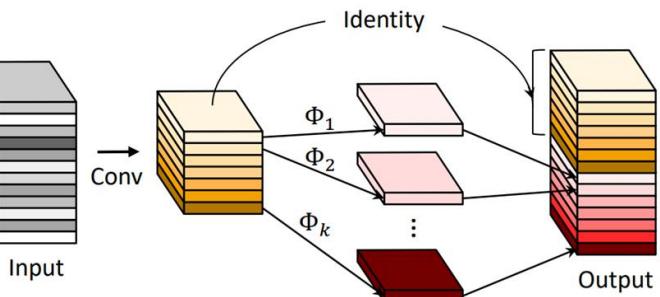


Classification: GhostNet (2019-2020)

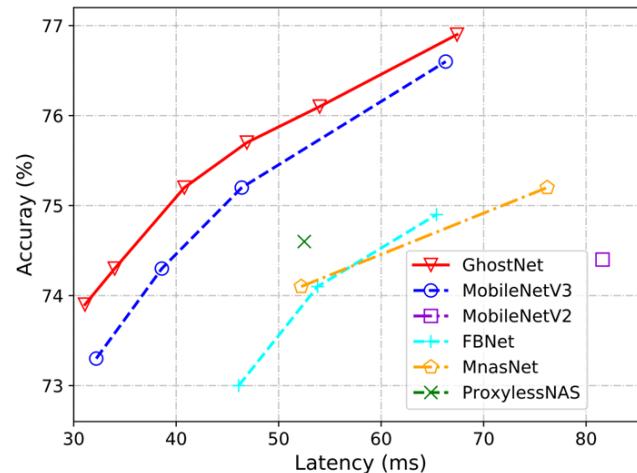
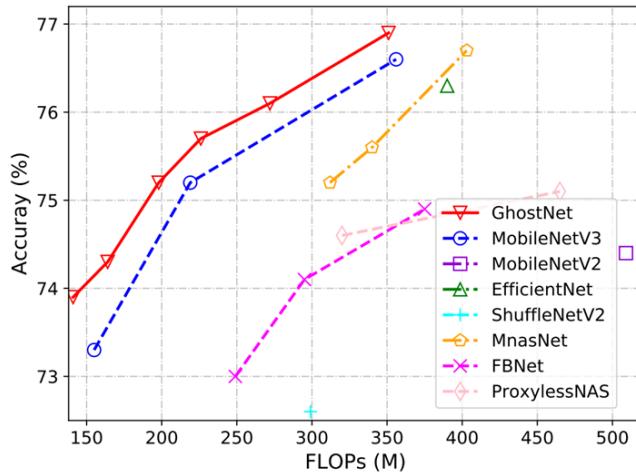
- Idea: Ghost module
- [Paper](#)
- [Code](#)

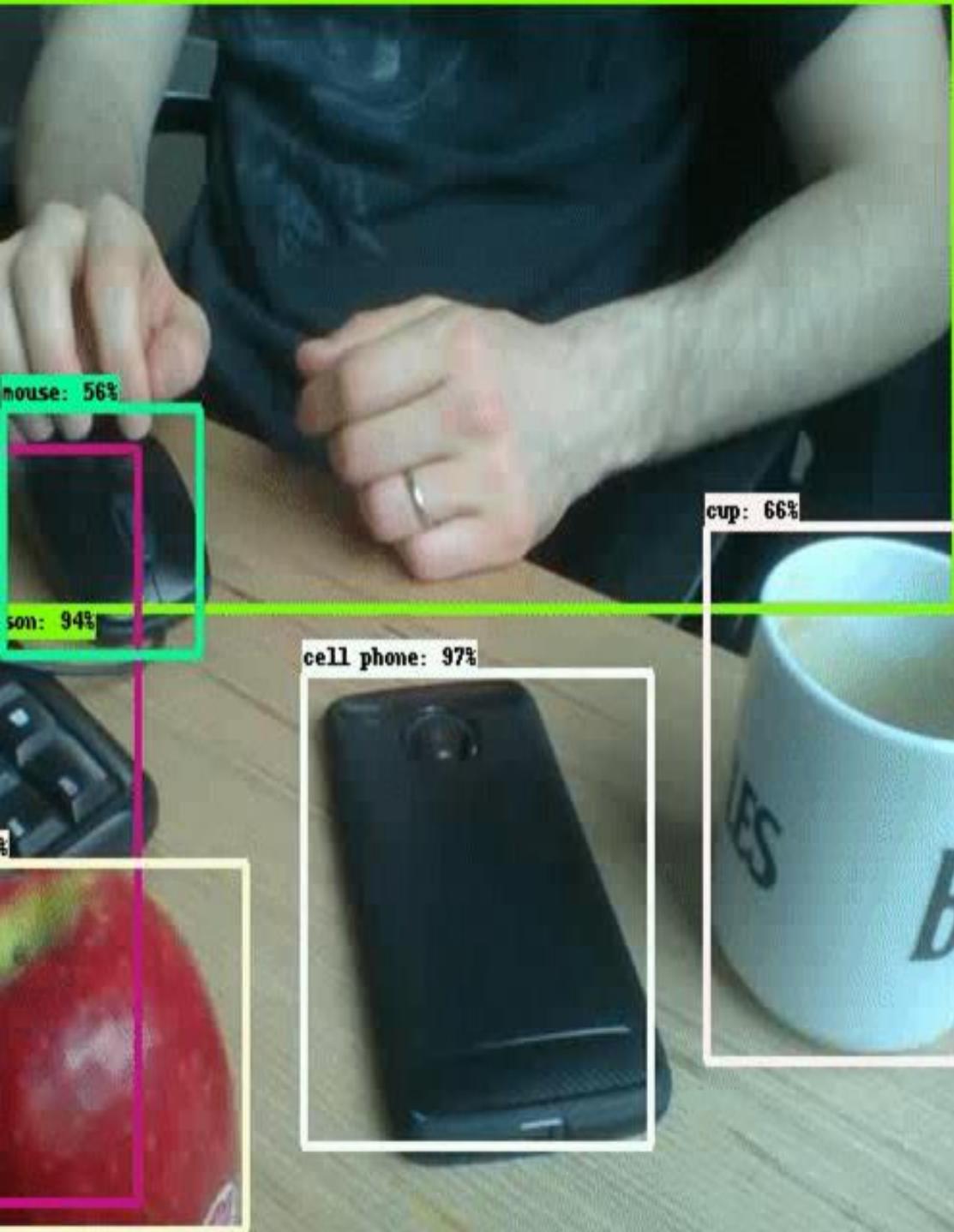


(a) The convolutional layer.



(b) The Ghost module.





Detection

Datasets & Metrics

Object Detection: Task statement

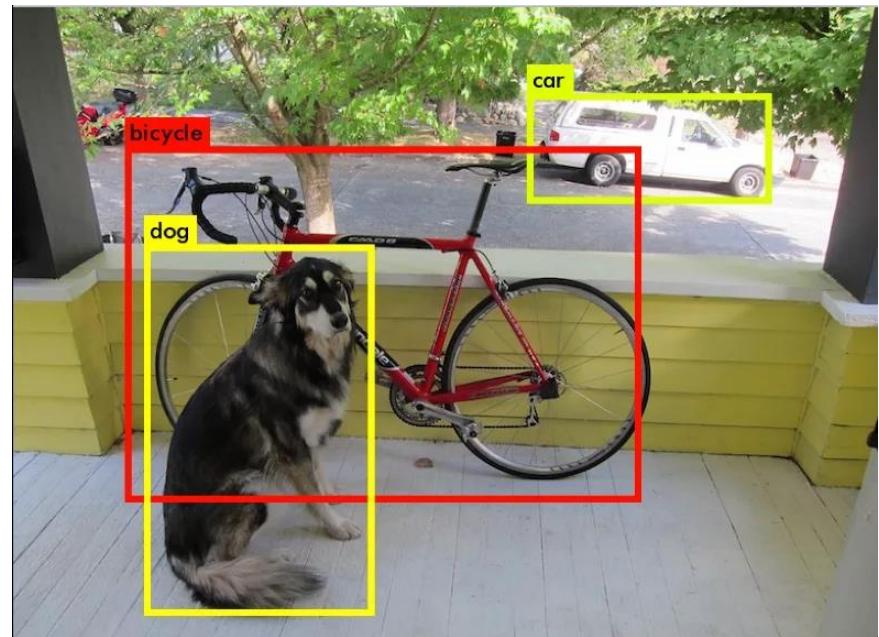
Input: Image (np.array)

Output: “bounding boxes with class labels”

Each BBox is:

- Top-Left corner: (x_{tl}, y_{tl})
- Bottom-Right corner: (x_{br}, y_{br})
- Class name
- Confidence (probability of this class)

⇒ 6 numbers per each box



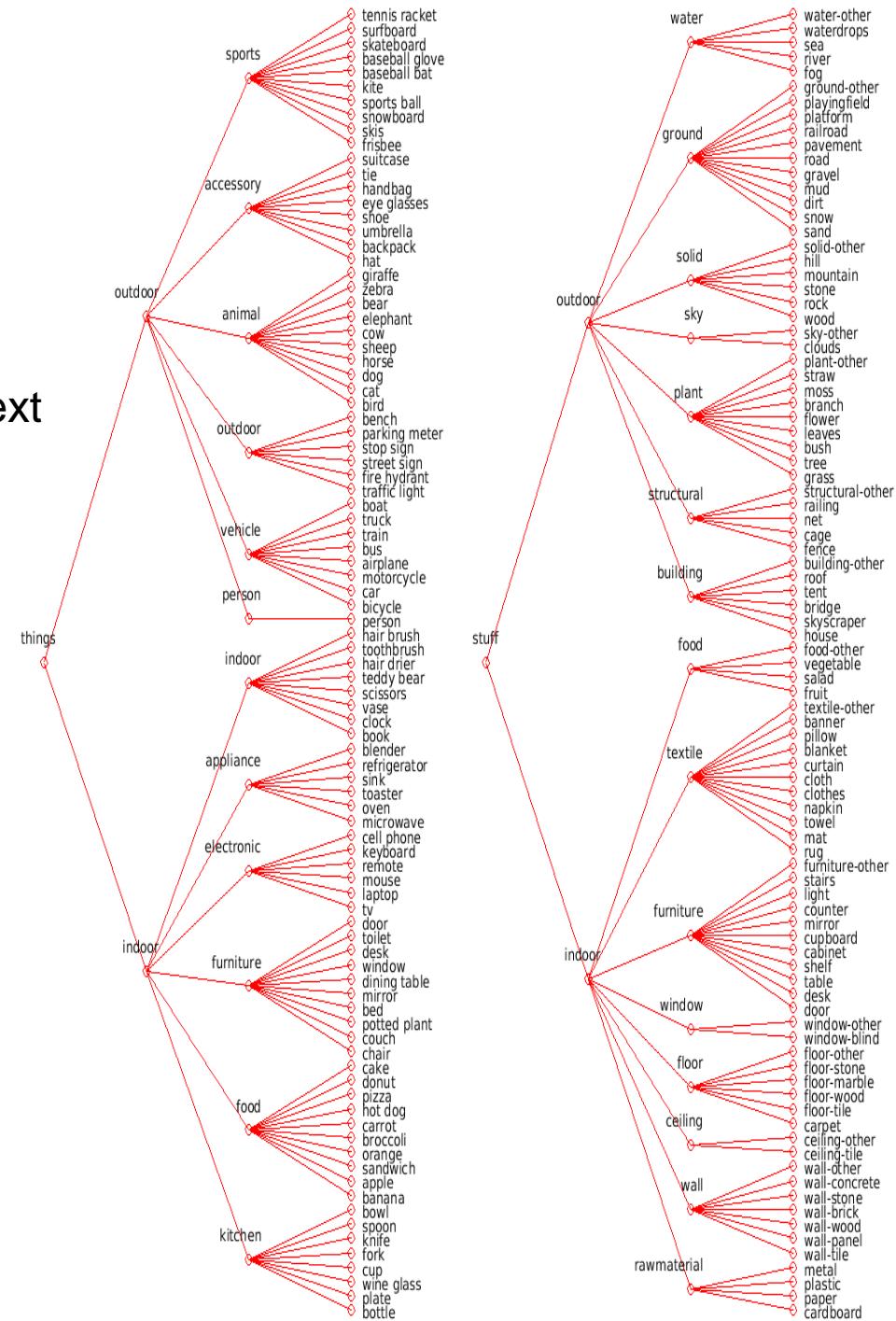
Object Detection: Data

1. PASCAL VOC 2012
 2. MS COCO 2017
 3. ImageNet
 4. Google Open Images v6
 5. Epic Kitchens



MS COCO 2017

- MicroSoft Common Objects in COnText
- 80 classes
- Train: ~120k images ~18GB
- Val: ~5k images ~1GB
- Test: ~40k images ~6GB
- Vary in size and quality
- [Paper](#)



Google Open Images v6

Table 2: Boxes.

	Train	Validation	Test	# Classes
Images	1,743,042	41,620	125,436	-
Boxes	14,610,229	303,980	937,327	600

Details:

<https://storage.googleapis.com/openimages/web/factsfigures.html>

Kaggle:

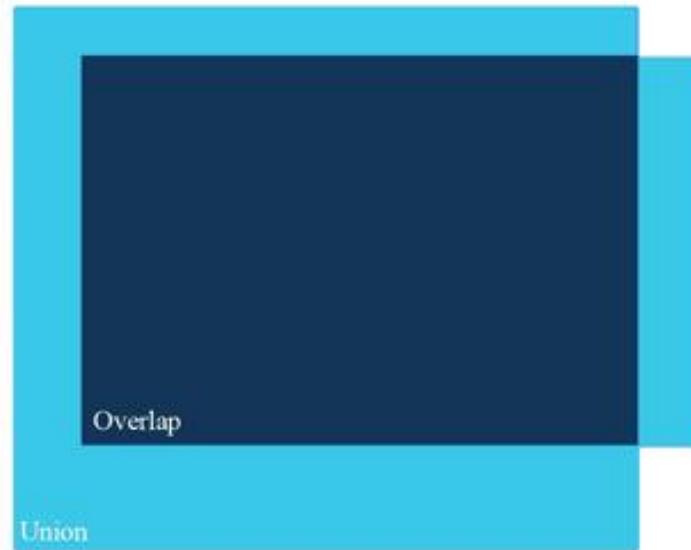
<https://www.kaggle.com/c/open-images-object-detection-rvc-2020>

Intersection over Union (IoU, Jaccard index)



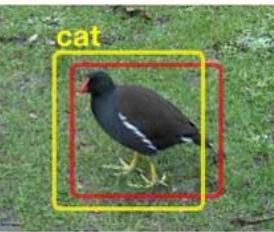
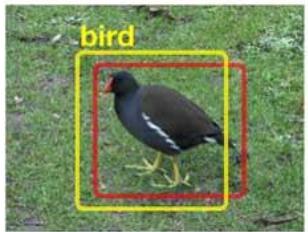
- Ground truth
- Prediction

$$IoU = \frac{\text{area of overlap}}{\text{area of union}}$$



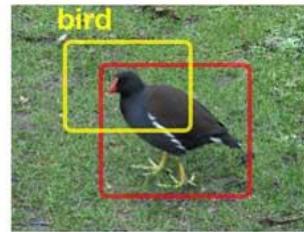
Positives & Negatives

TP

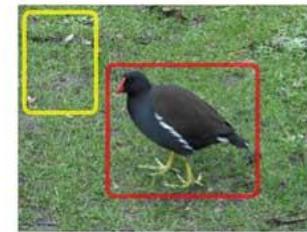


wrong class

FP

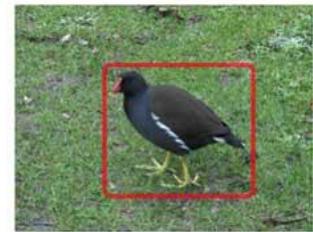


IOU < 0.5



no overlap

FN



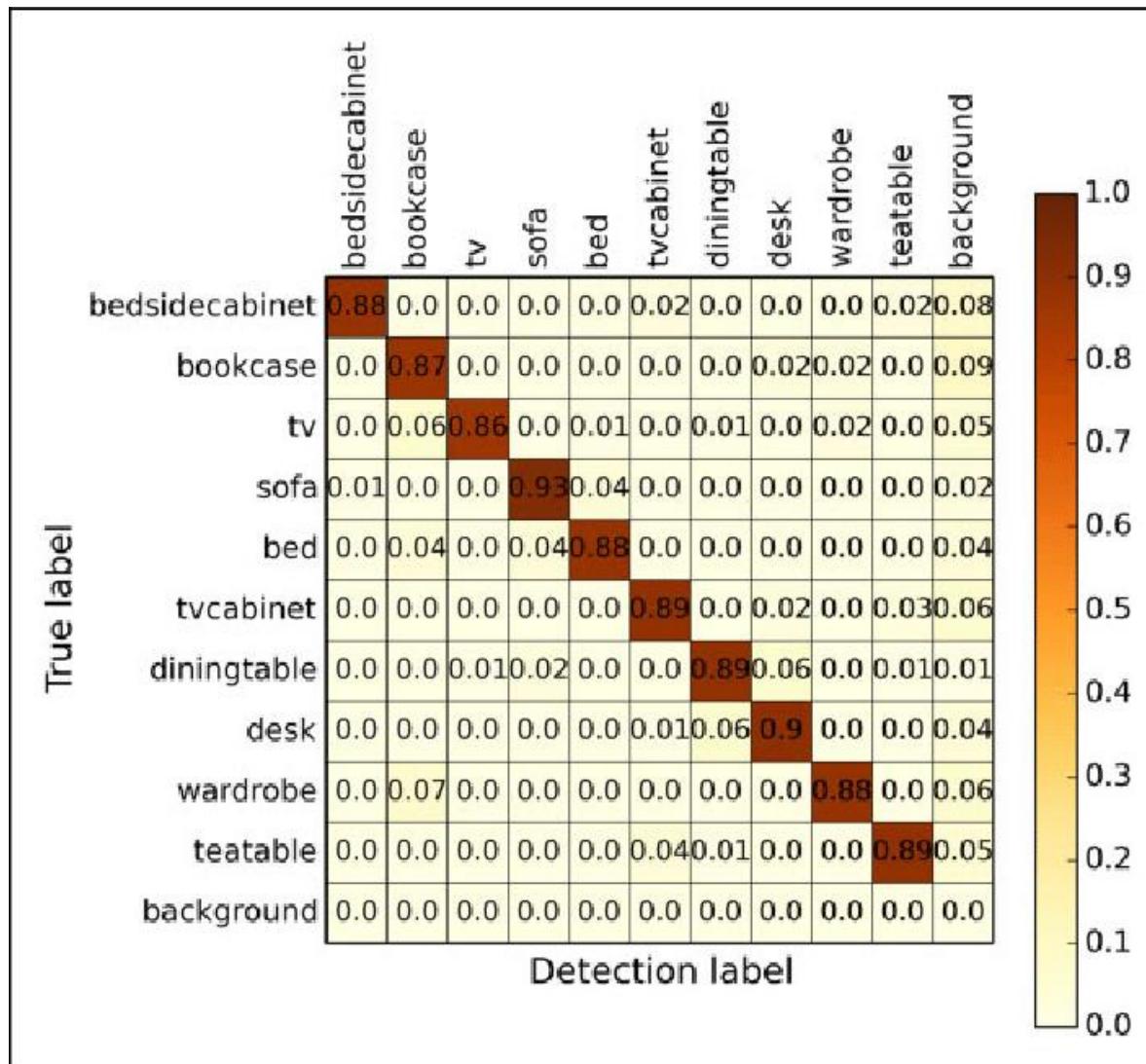
no prediction

Precision, recall

$$\textbf{Precision} = \frac{\textit{True Positives}}{\textit{True Positives} + \textit{False Positives}}$$

$$\textbf{Recall} = \frac{\textit{True Positives}}{\textit{True Positives} + \textit{False Negatives}}$$

Confusion matrix



mean Average Precision (mAP)

$$AP = \frac{1}{11} \times (AP_r(0) + AP_r(0.1) + \dots + AP_r(1.0))$$

Good explanation

Let's invent our own detector

Let's invent our own detector

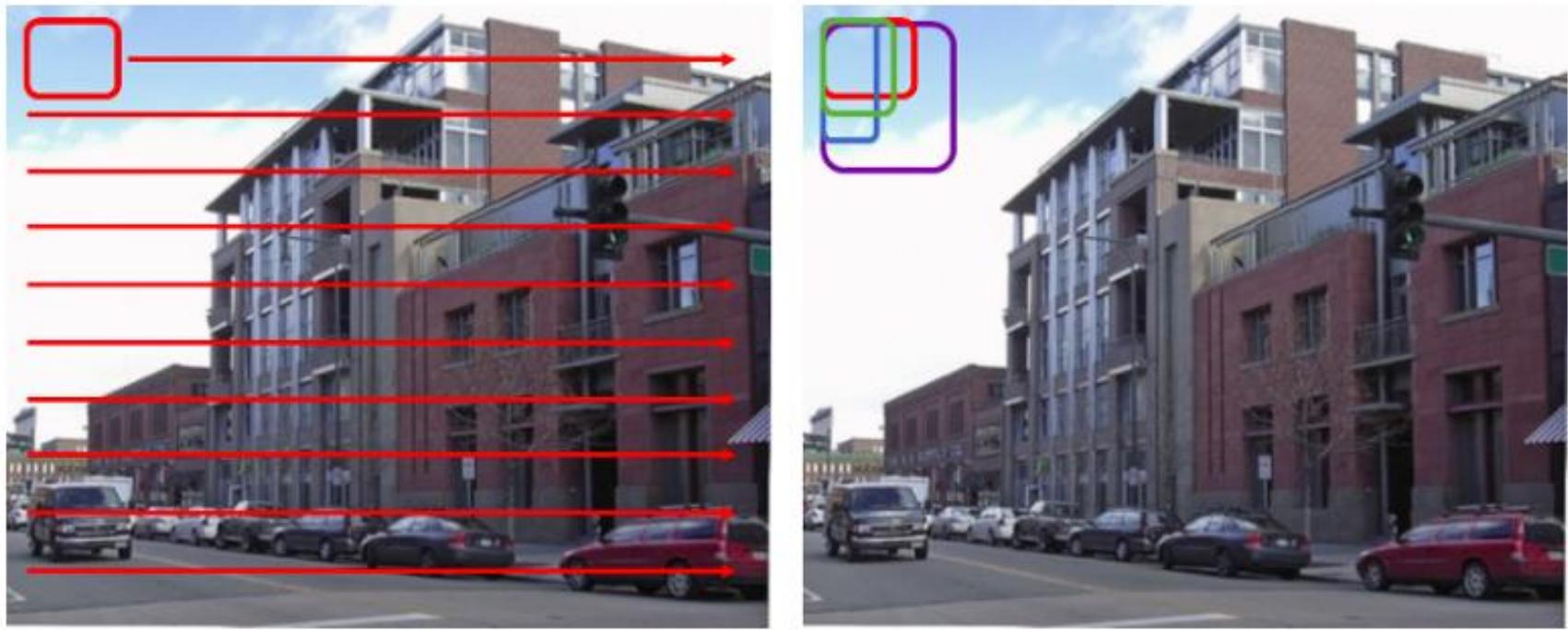


Illustration of Sliding Window (Left) with Different Aspect Ratios and Sizes (Right)

Summary

1. Detection task is not easy
2. Datasets are quite large and accessible
3. Metrics are specific, but reasonable
4. Simple object detector invented

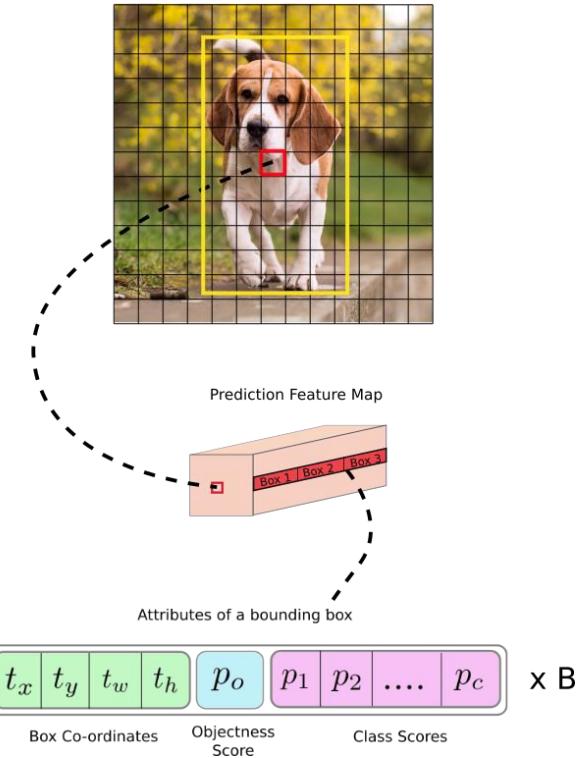
Two-stage detectors

RCNN, Fast-RCNN, Faster-RCNN

Detection: Core idea

1. Make default boxes assumptions
2. Regress their corners coordinates
3. Predict class inside each box
4. Filter not confident predictions

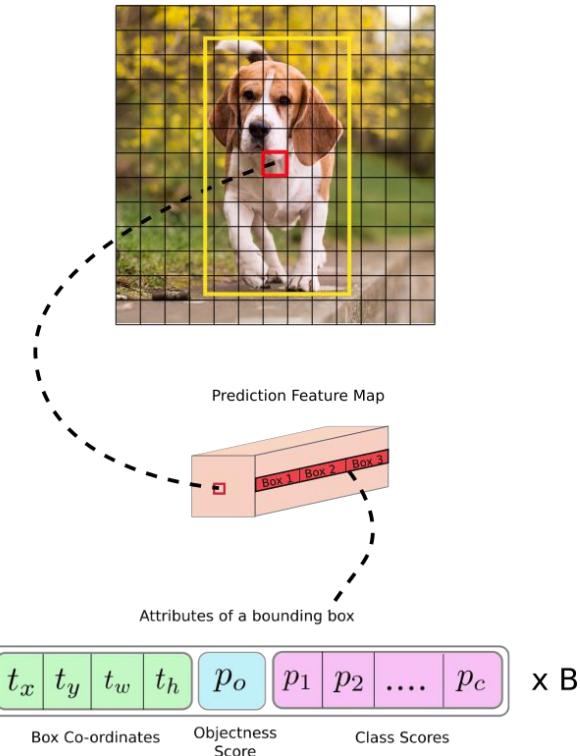
Image Grid. The Red Grid is responsible for detecting the dog



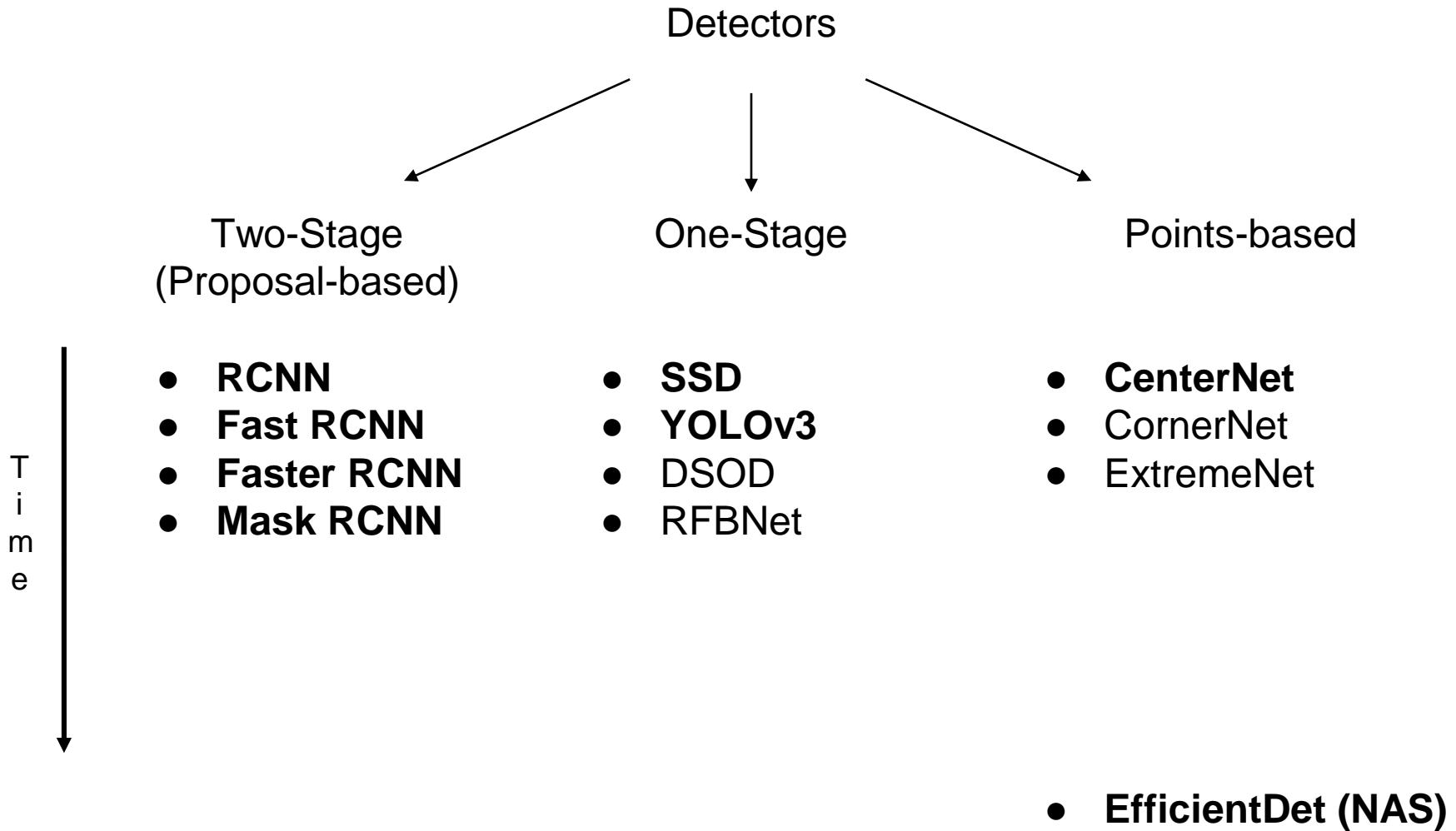
Detection: Core idea

1. Make default boxes assumptions
“Anchor boxes”
2. **Regress** their corners coordinates
Simultaneously ↑↓
3. Predict **class** inside each box
4. Filter not confident predictions
Non-max suppression (NMS)

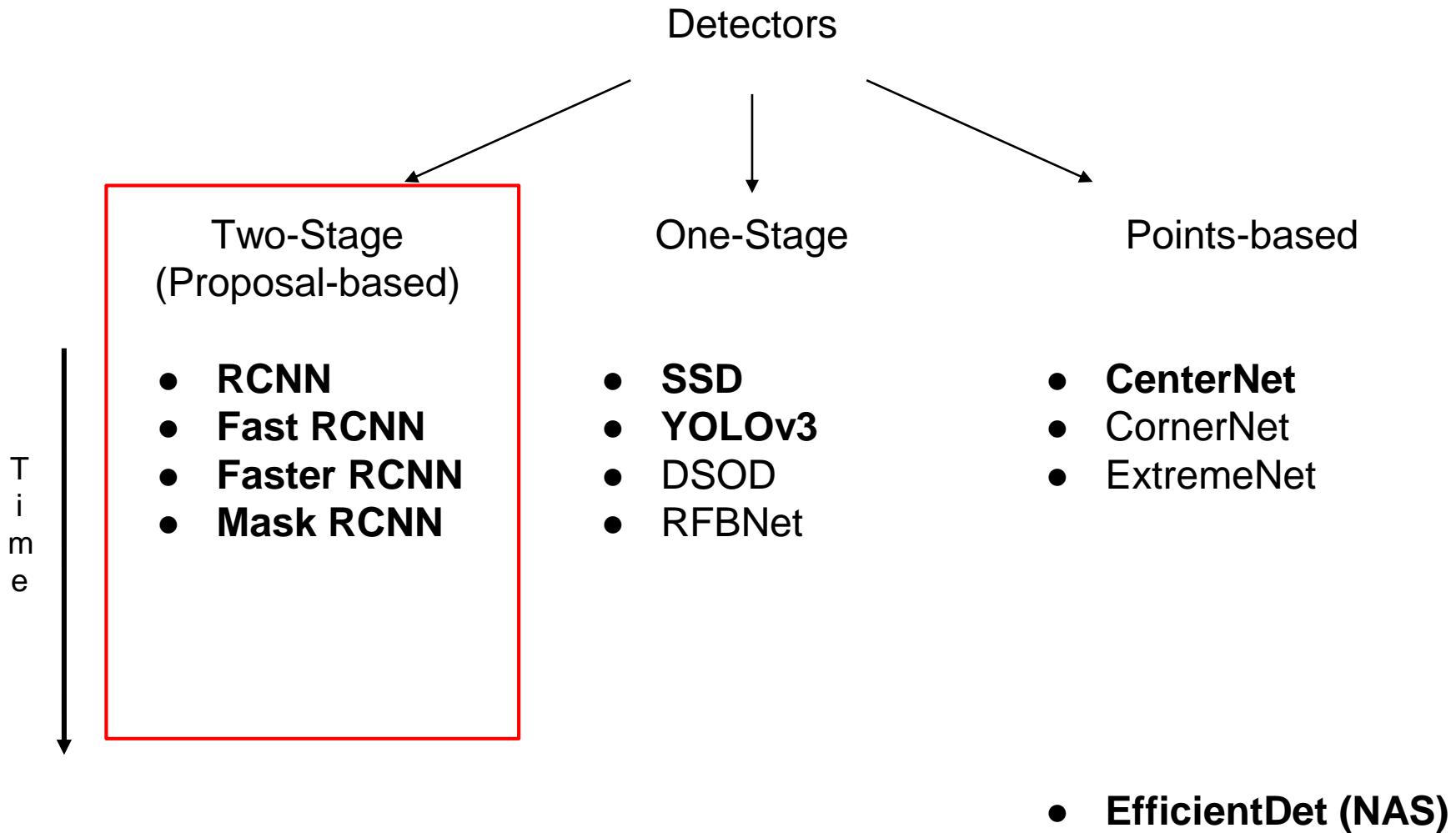
Image Grid. The Red Grid is responsible for detecting the dog



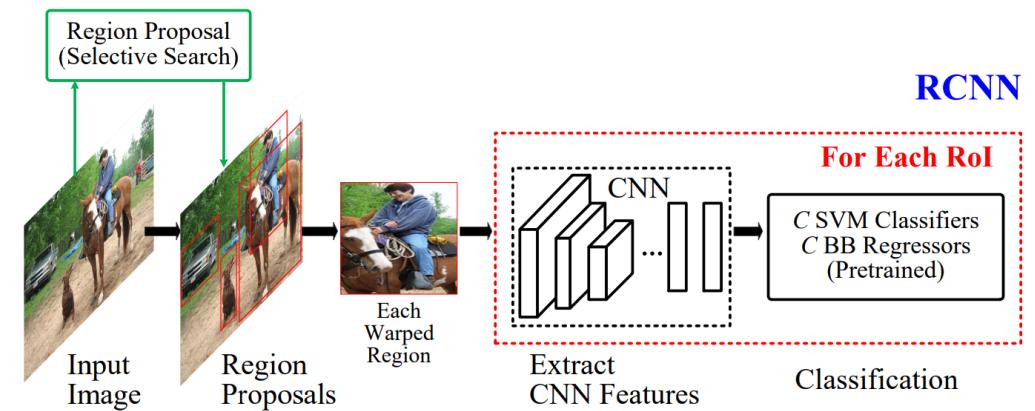
Detection: Taxonomy



Detection: Taxonomy

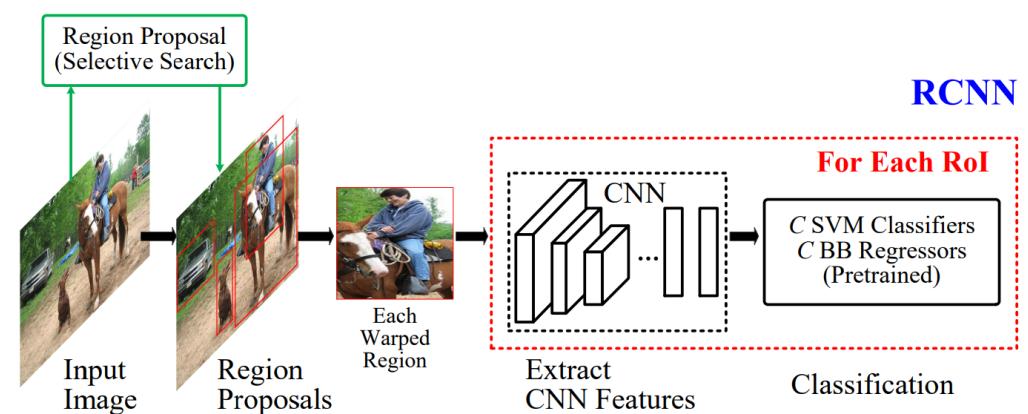


Detection: Two-stage (proposal-based)



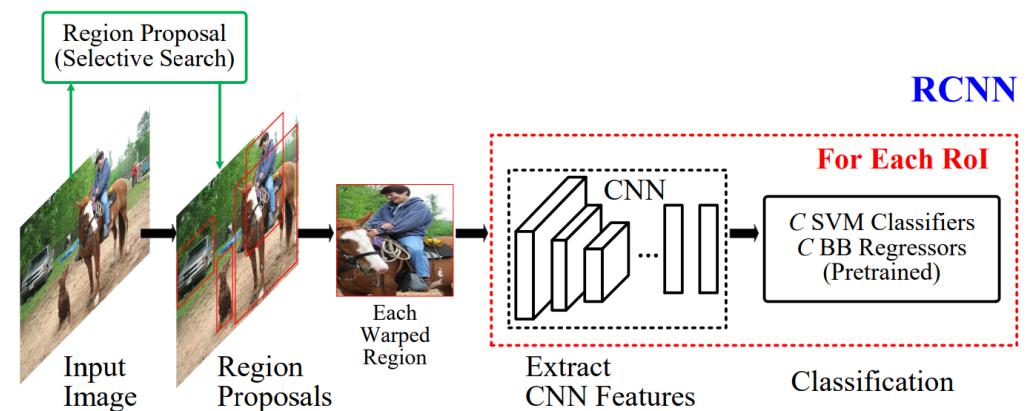
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)



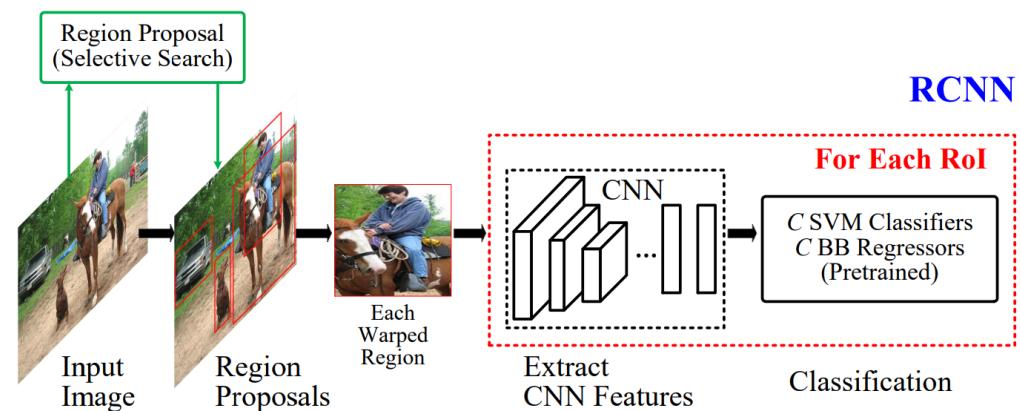
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape



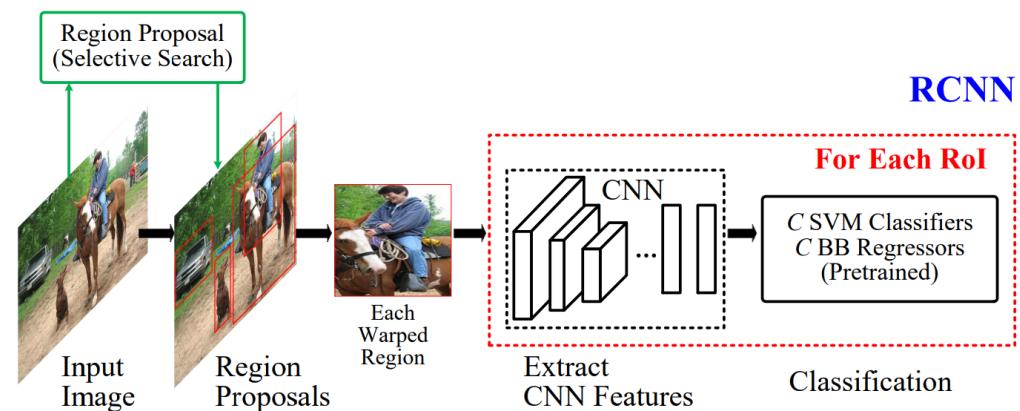
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)



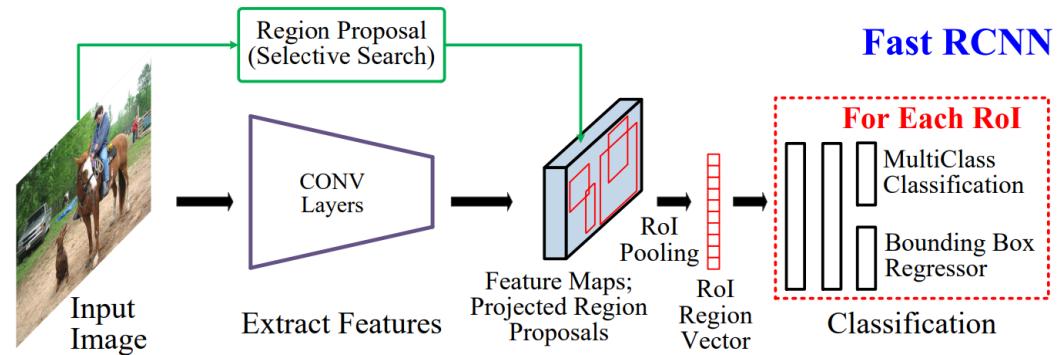
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)
4. Post-process predictions



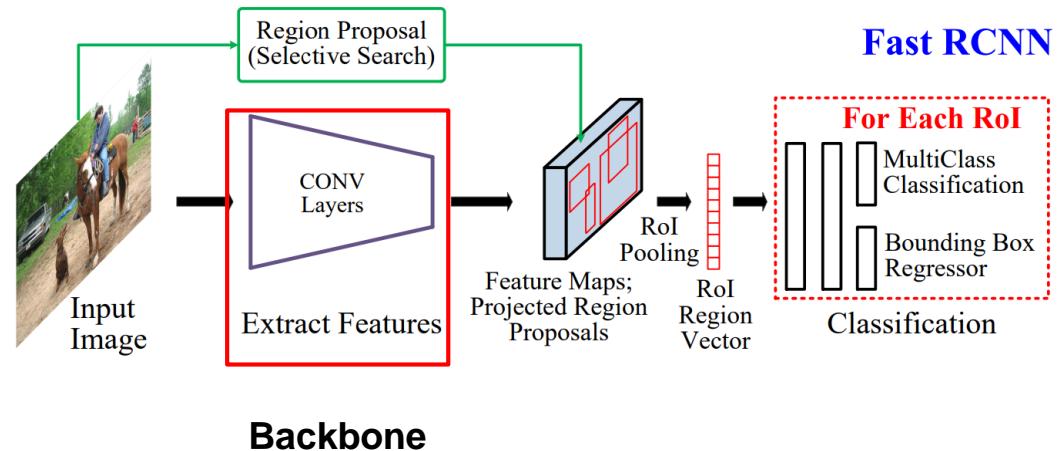
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)
4. Post-process predictions



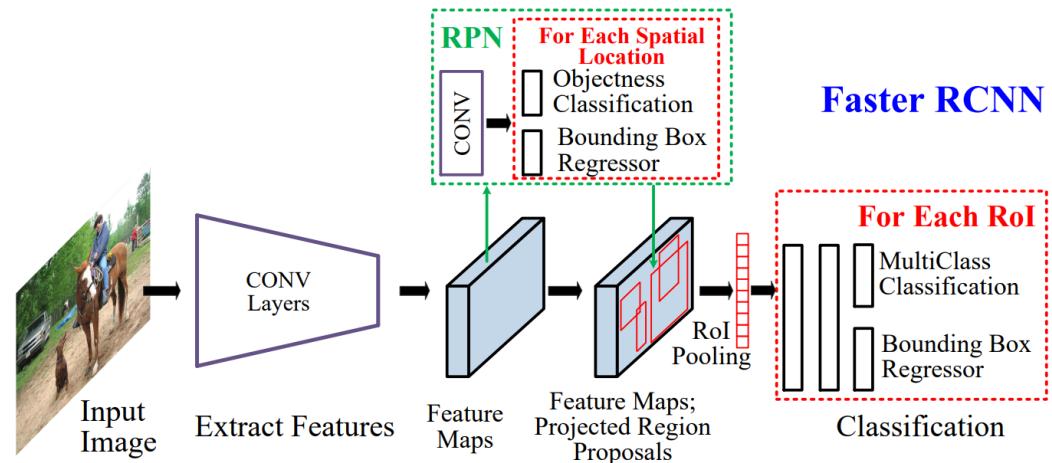
Detection: Backbone

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)
4. Post-process predictions



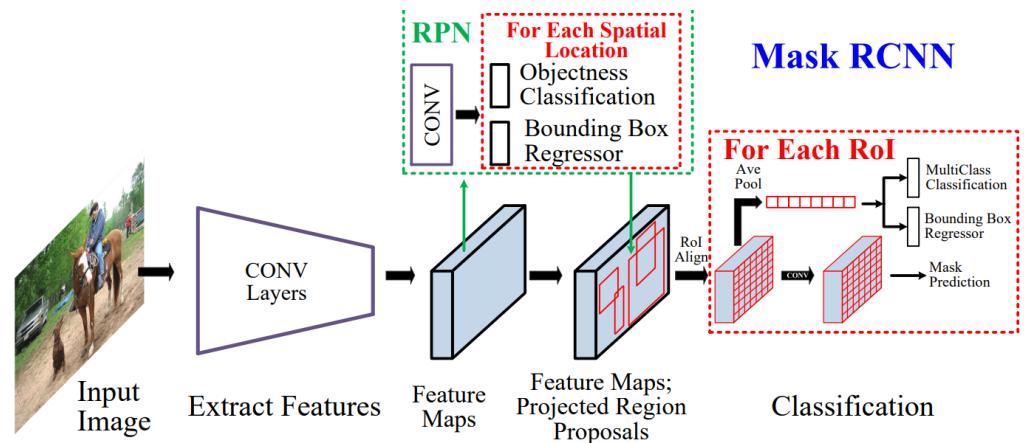
Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)
4. Post-process predictions



Detection: Two-stage (proposal-based)

1. Generate boxes proposals
(with separate algorithm / net)
2. Warp them to one shape
3. Regress and classify them
(with another algorithm)
4. Post-process predictions



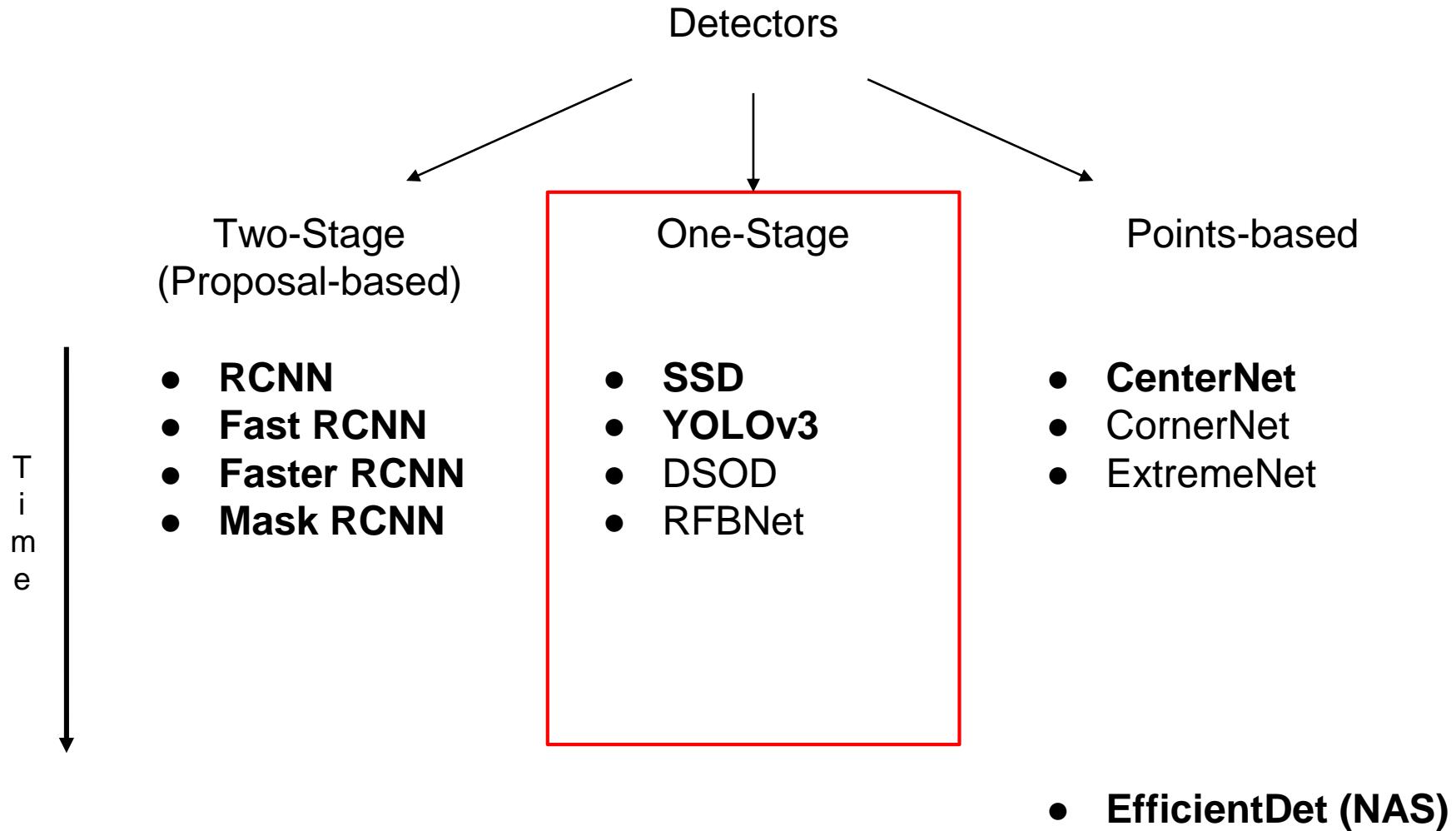
Summary

1. Core ideas
2. Two-stage detectors

One-stage detectors

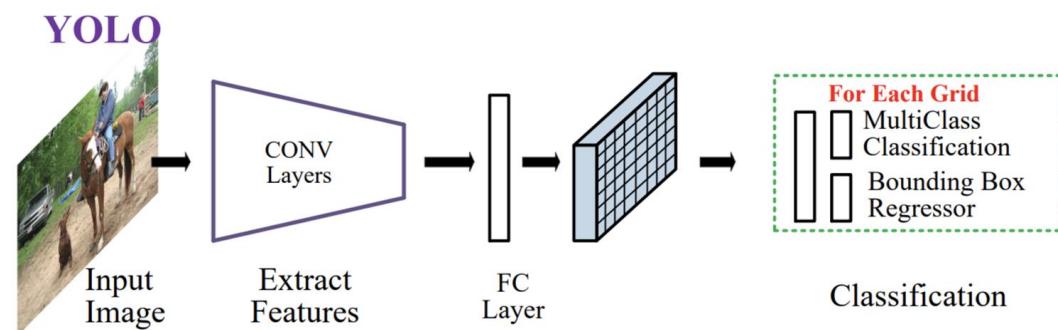
SSD, YOLO

Detection: Taxonomy



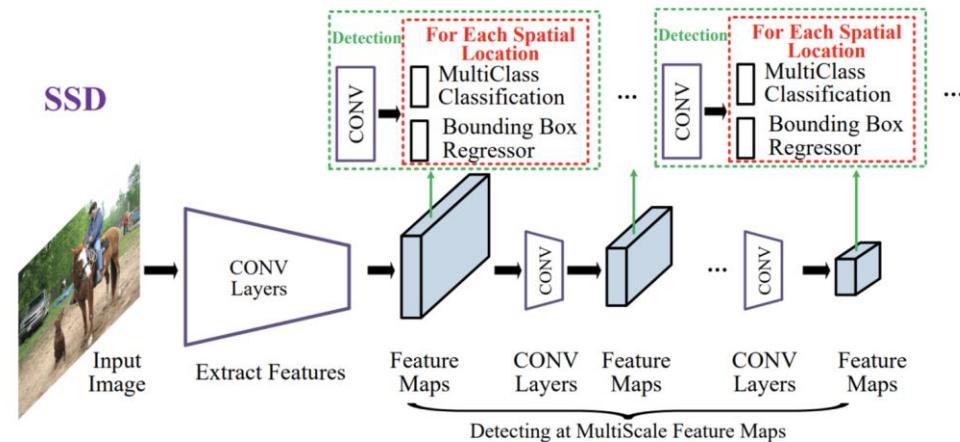
Detection: You Only Look Once

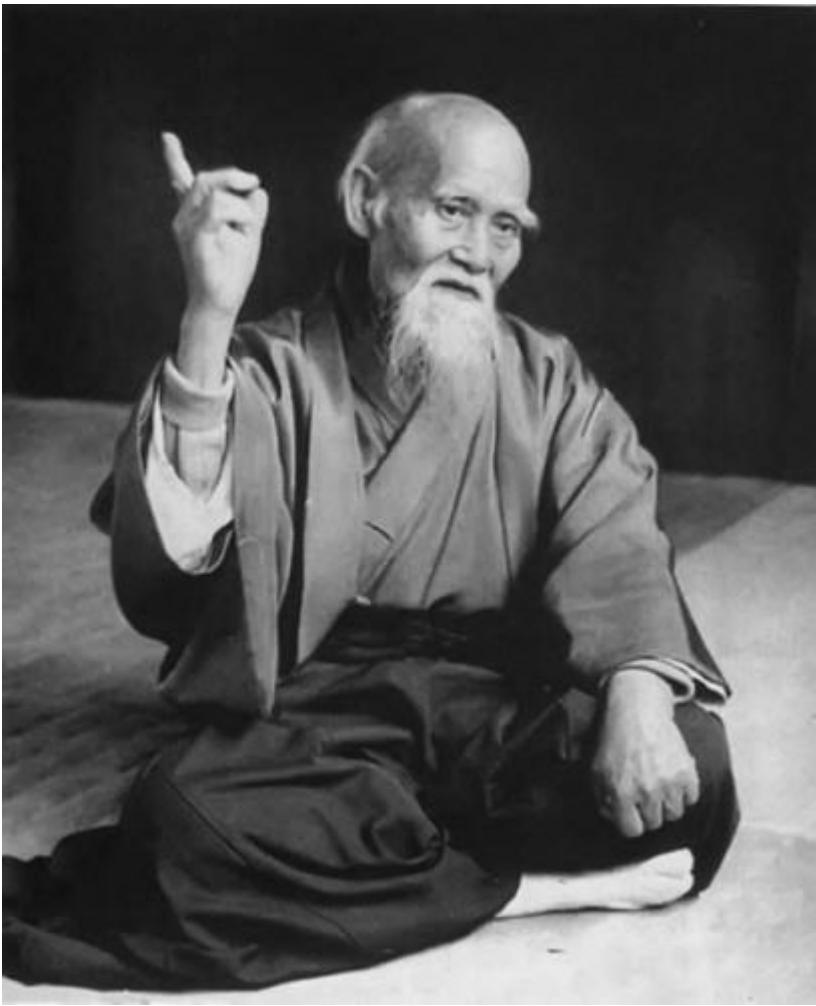
1. Get features from a **Backbone Network**
2. Predict feature map (“grid”)
3. Predict boxes from grid
4. Post-process predictions



Detection: Single-Shot Multibox Detector (SSD)

1. Get features from a **Backbone Network**
2. Predict feature map (“grid”)
3. Predict boxes from grid
4. Post-process predictions

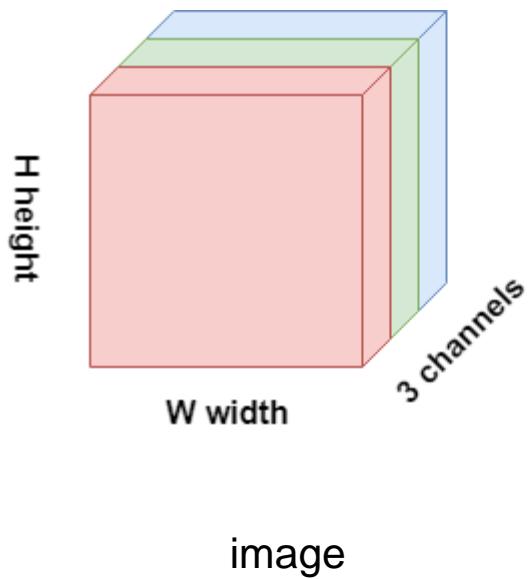




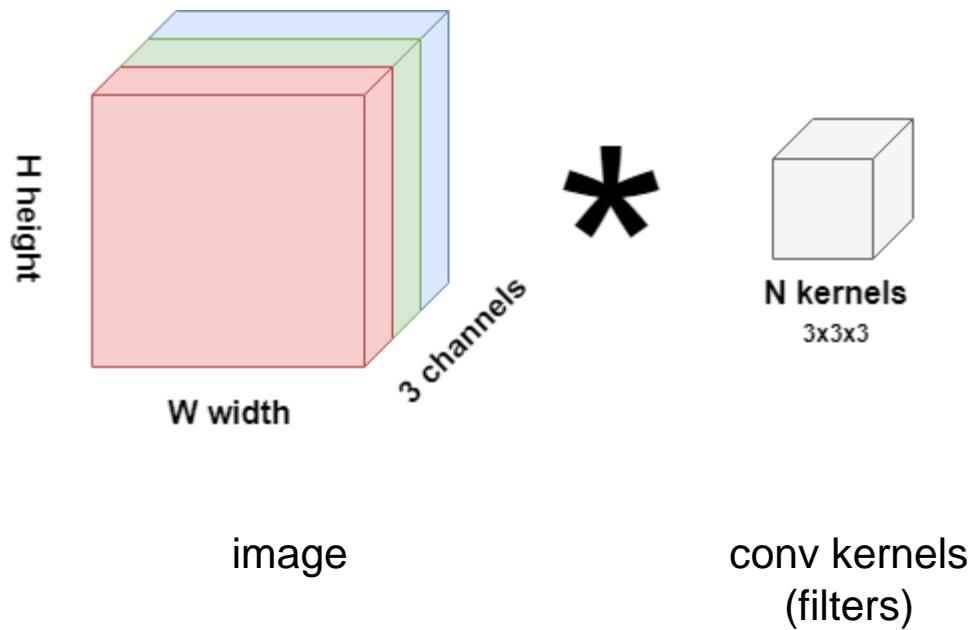
“Hone one thing,
but to the ideal”

Some clever person

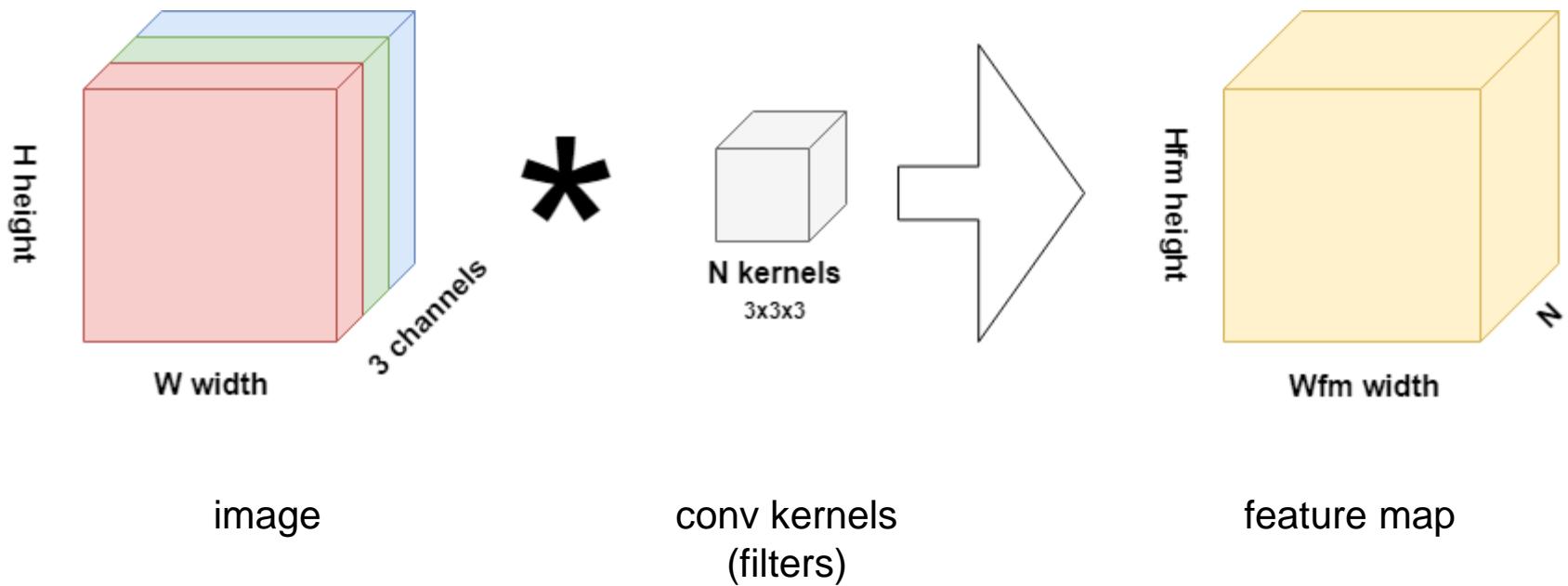
Convolutions: recap



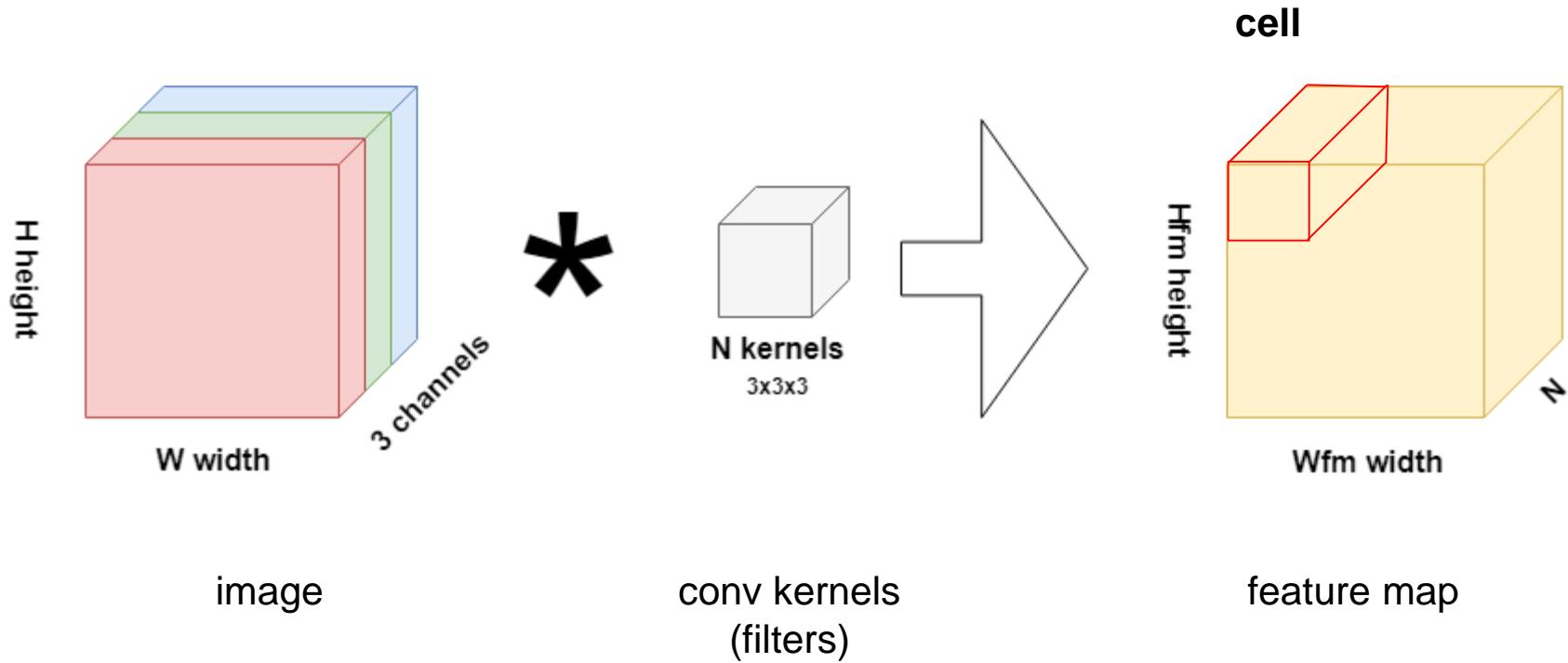
Convolutions: recap



Convolutions: recap



Convolutions: recap



SSD: up-to-bottom explanation

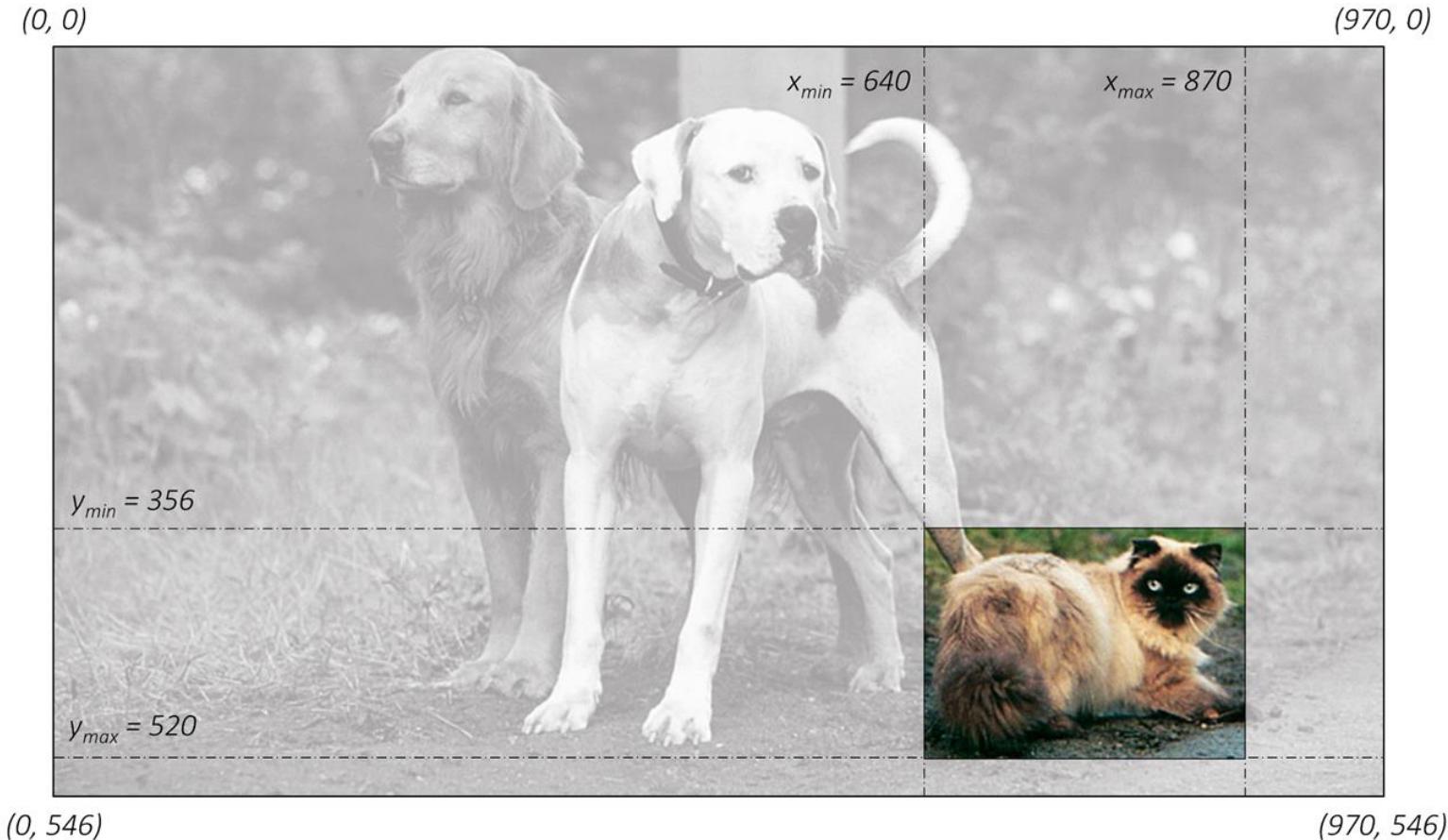
SSD pipeline

1. Input: image (h,w,3) → Backbone
2. Backbone → feature map
3. Feature map → boxes locations and classes inside of them

Detection task

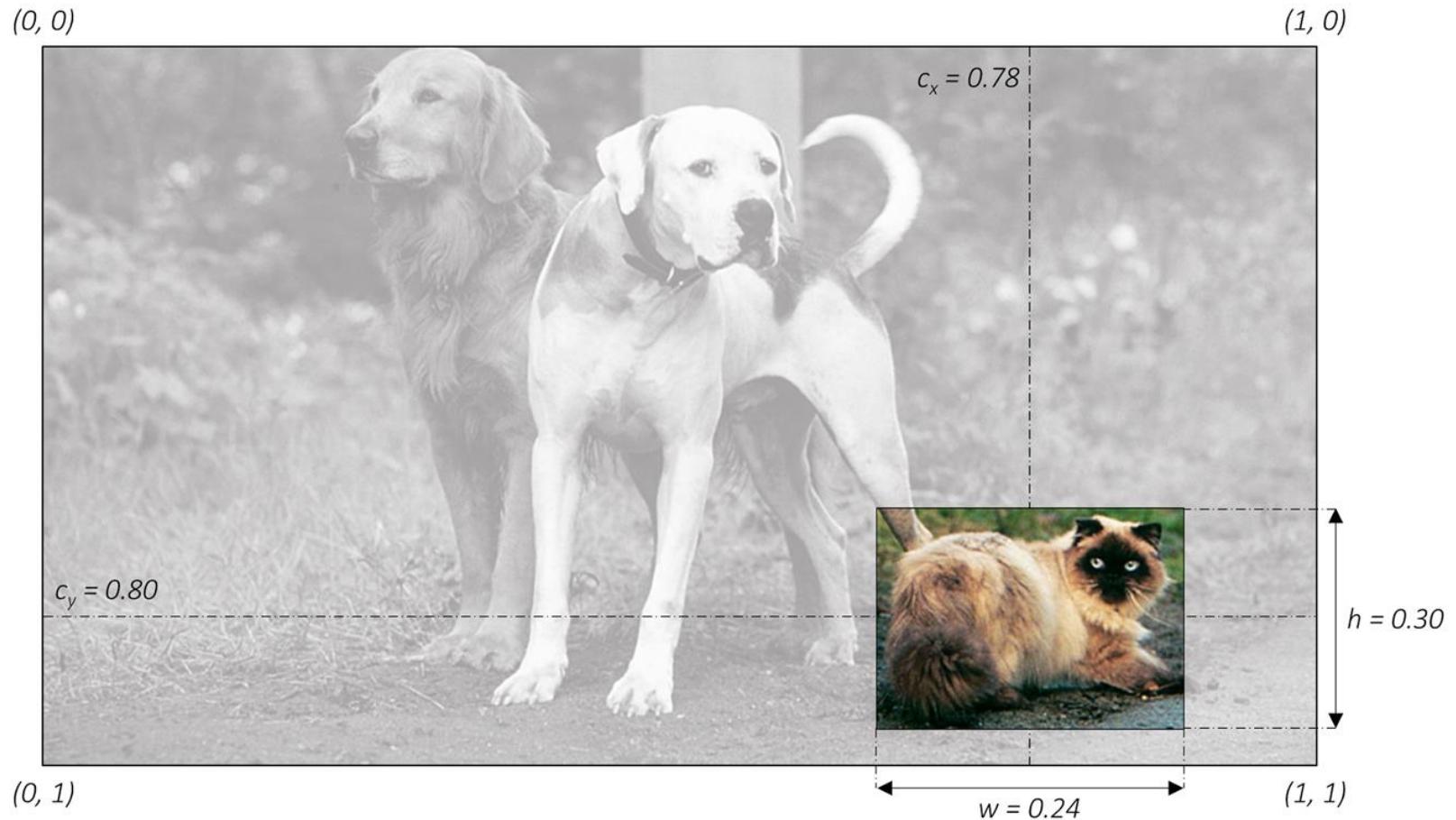
1. How many boxes?
2. What should be the size of an input image?
3. How to train? (~ how to make it differentiable?)

SSD: tlrb format



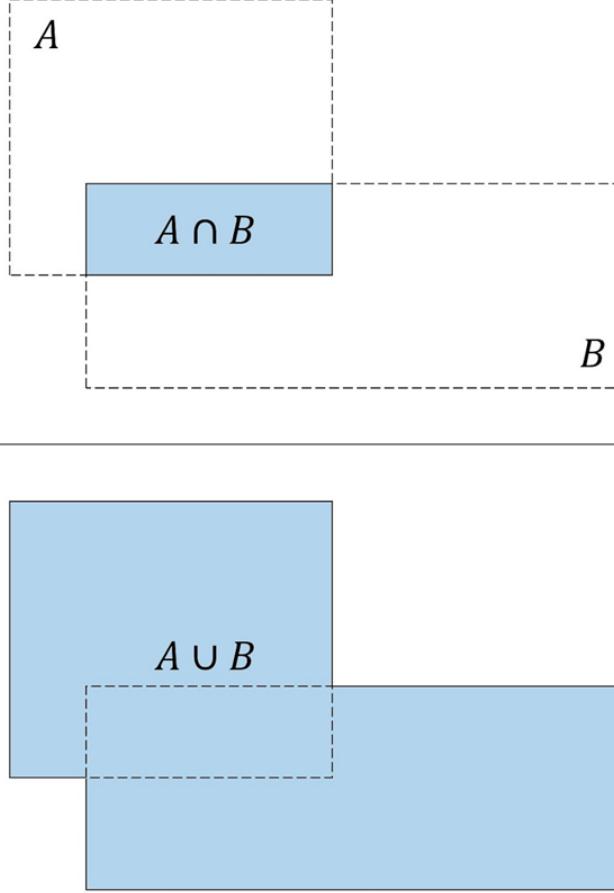
Boundary Coordinates $(x_{min}, y_{min}, x_{max}, y_{max}) = (640, 356, 870, 520)$

SSD: xywh format

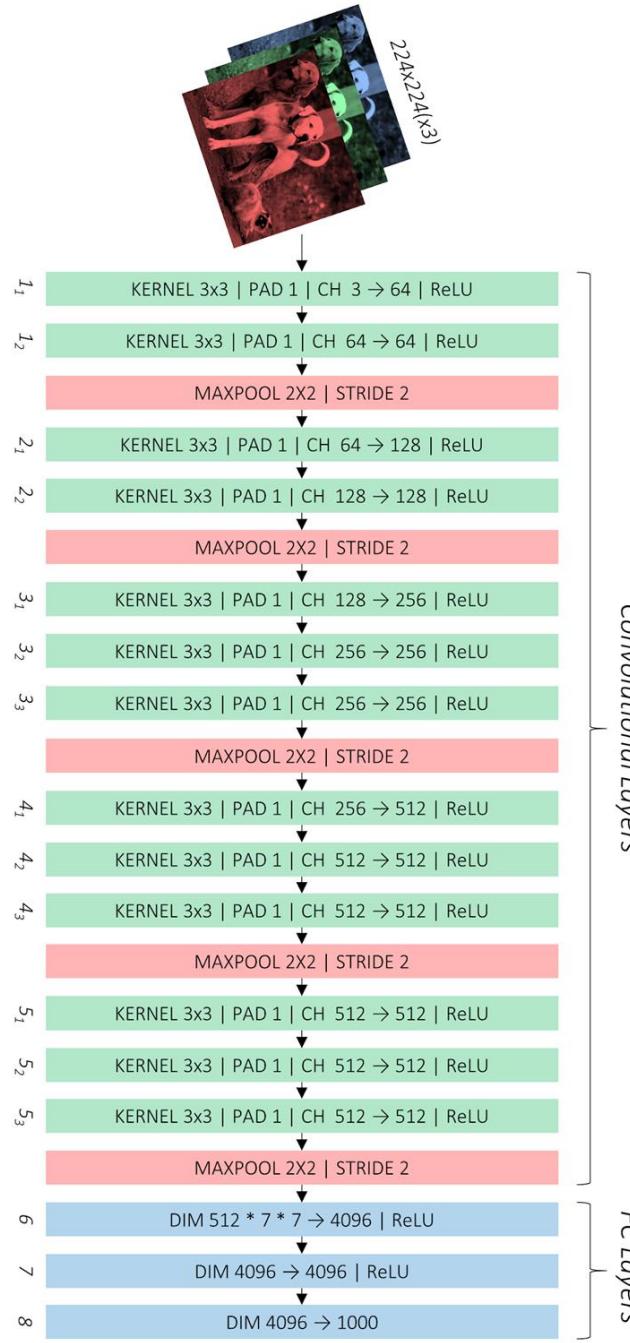


$$\text{Center-Size Coordinates } (c_x, c_y, w, h) = (0.78, 0.8, 0.24, 0.30)$$

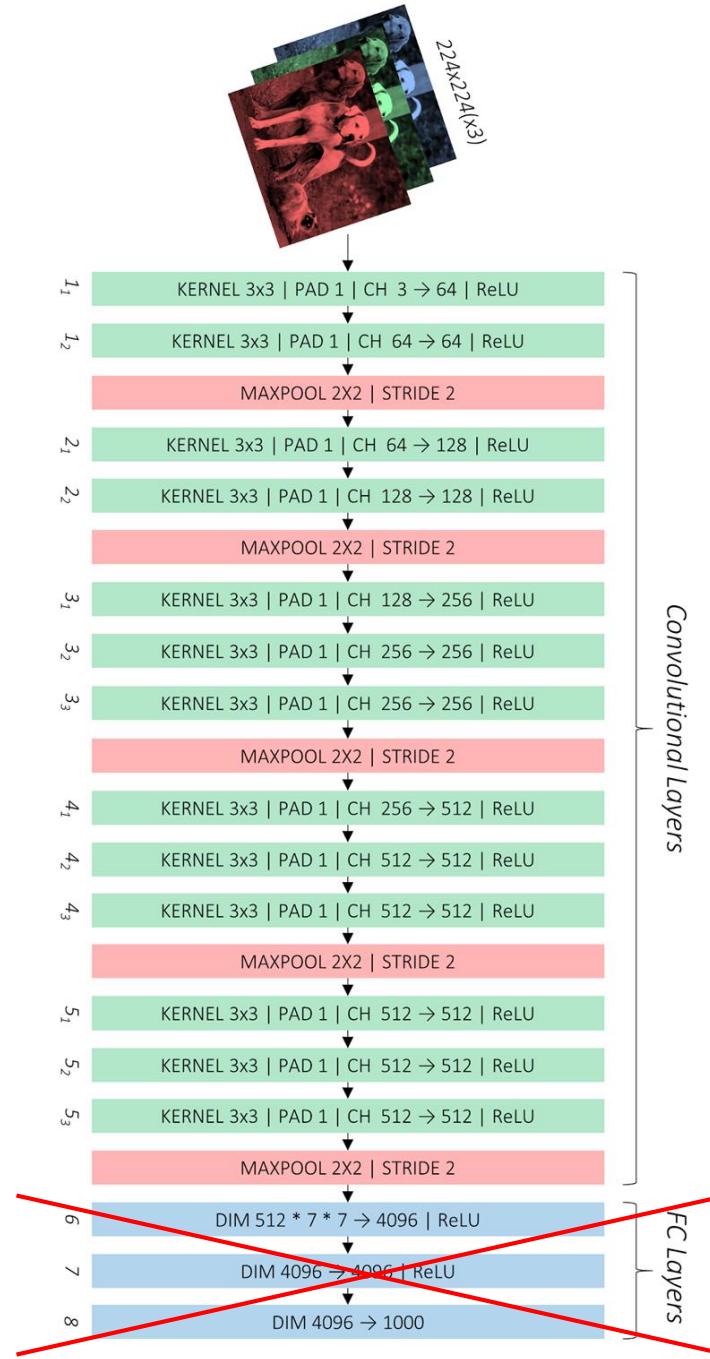
SSD: Intersection over Union

$$Jaccard\ Index = \frac{A \cap B}{A \cup B} = \frac{\text{Area of } A \cap B}{\text{Area of } A \cup B}$$


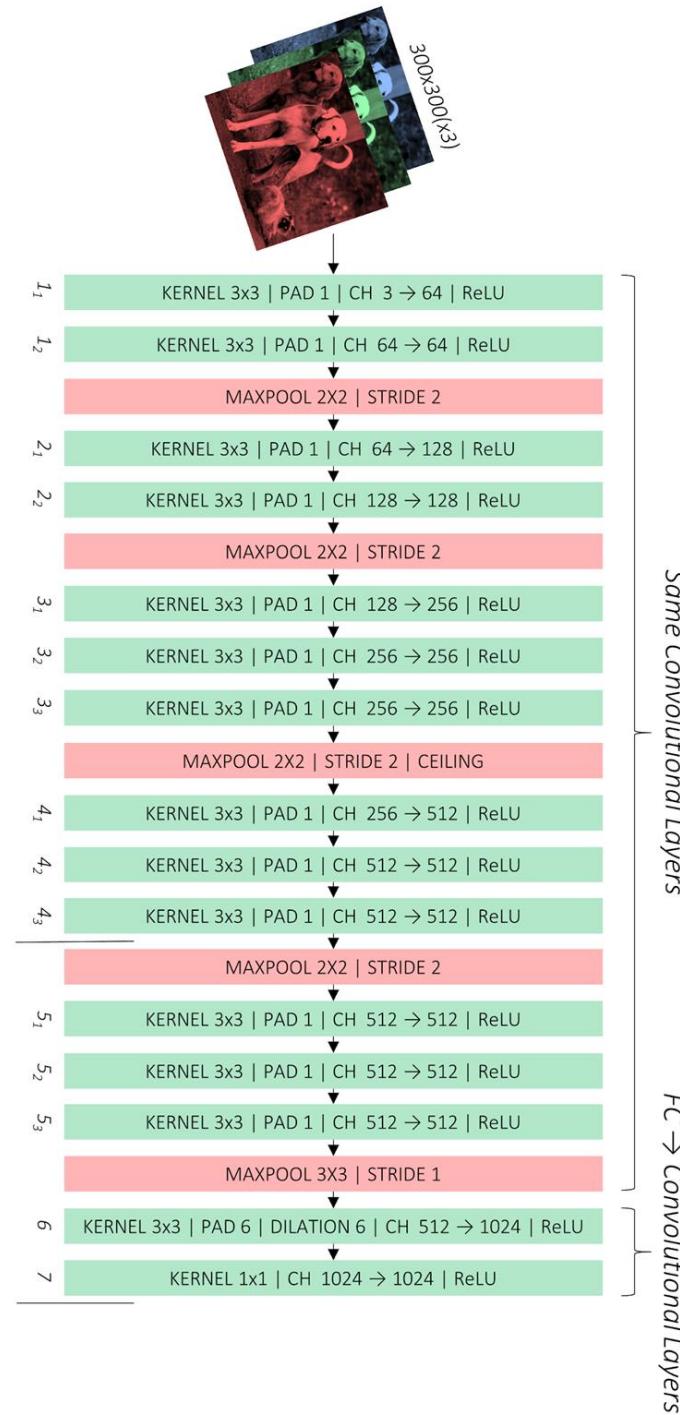
SSD: VGG



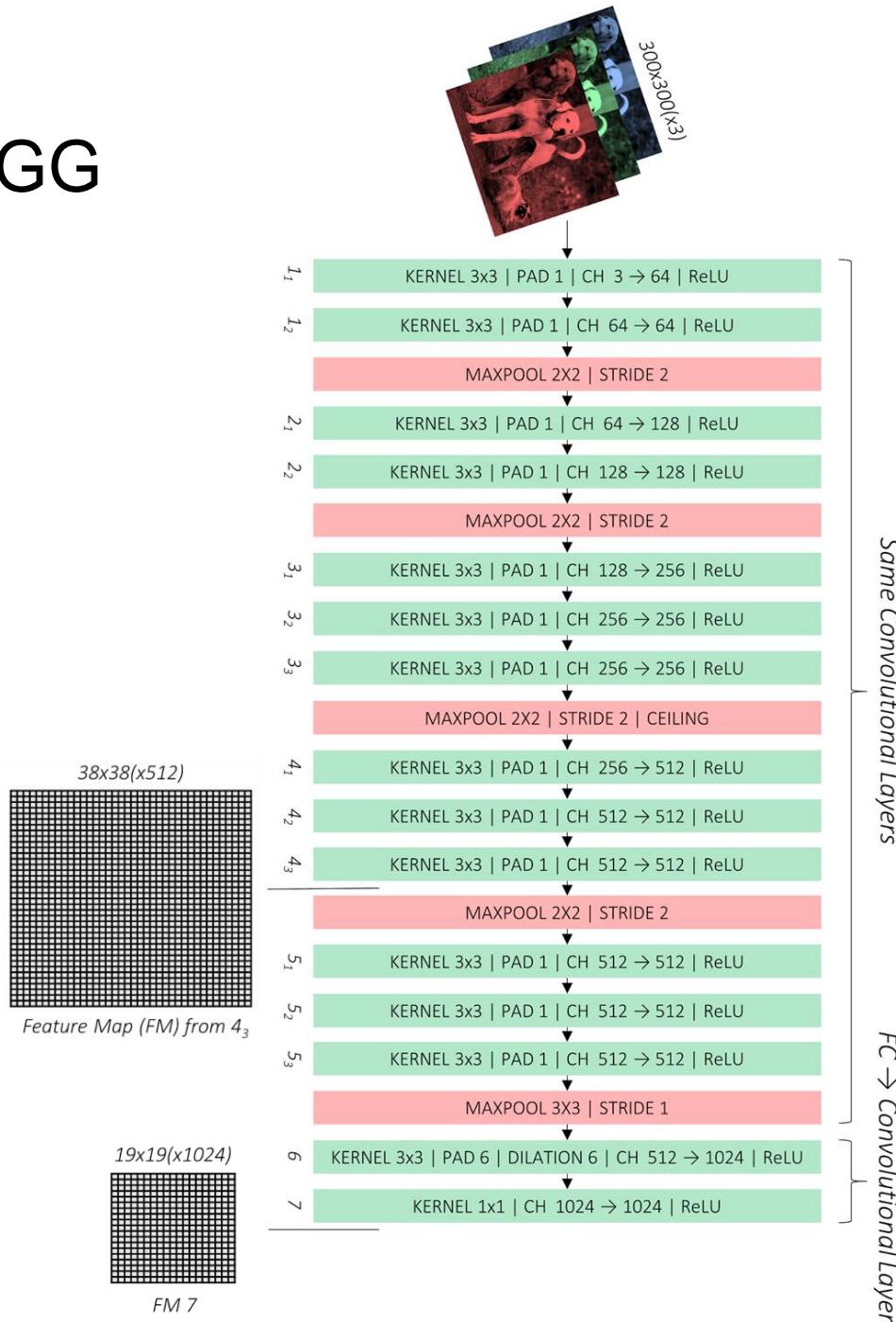
SSD: VGG



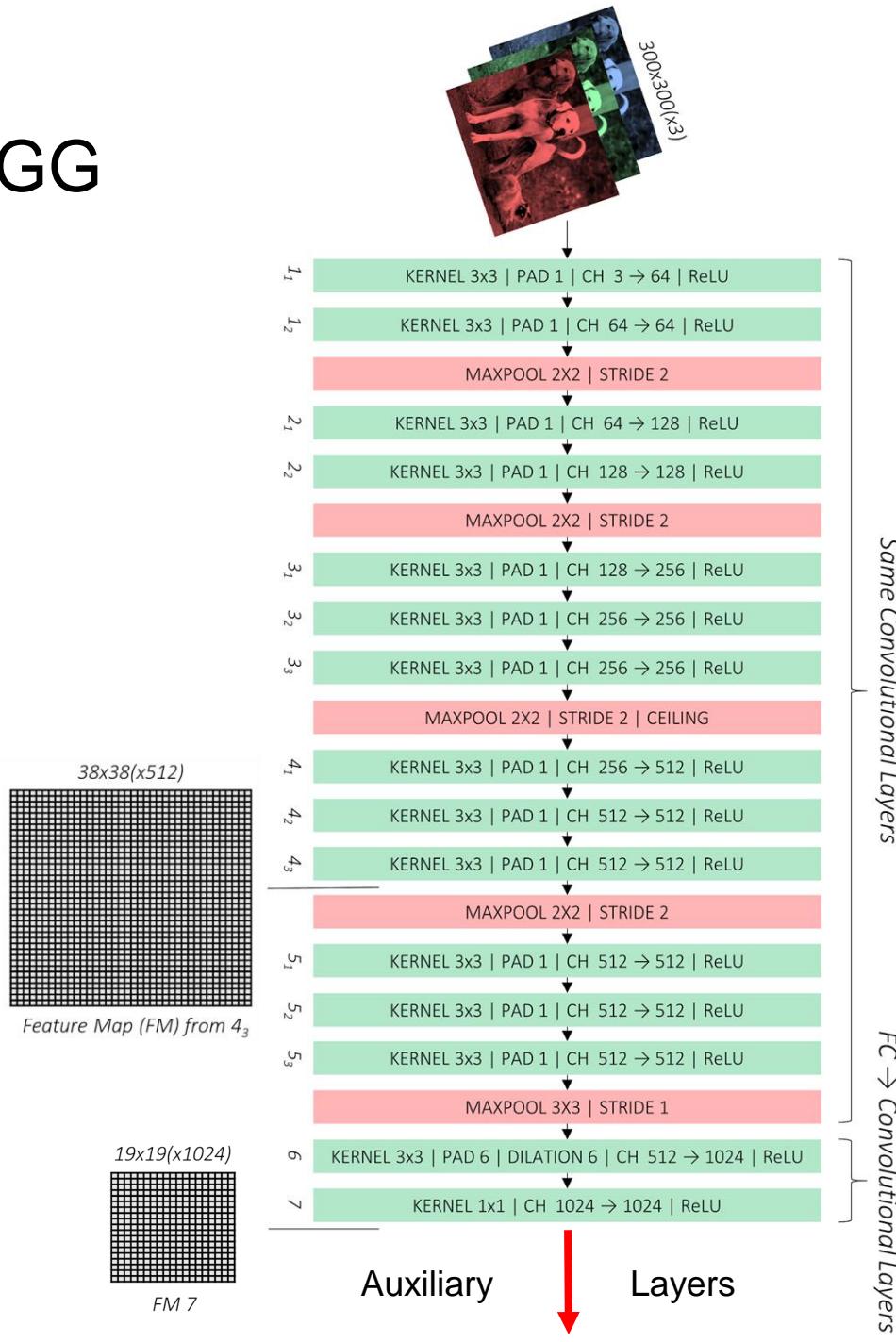
SSD



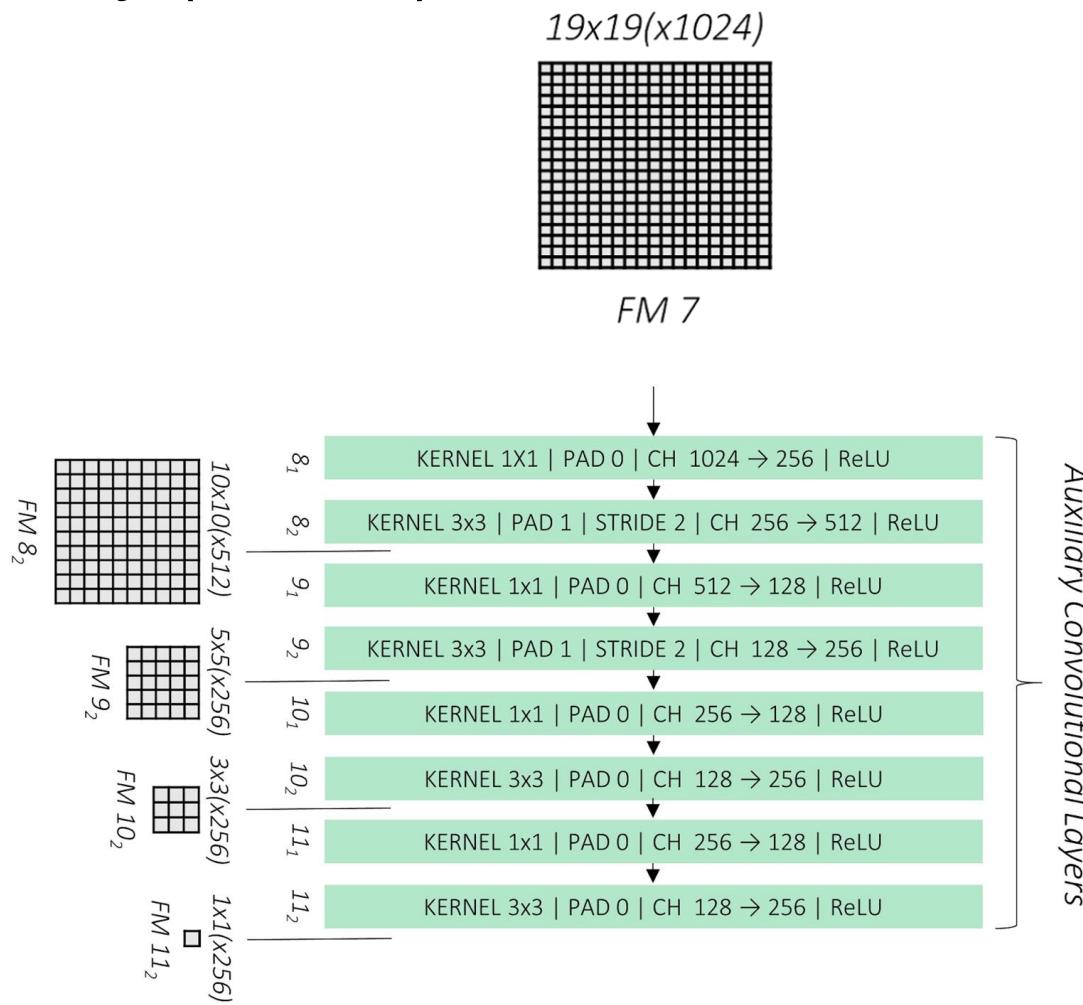
SSD: VGG



SSD: VGG

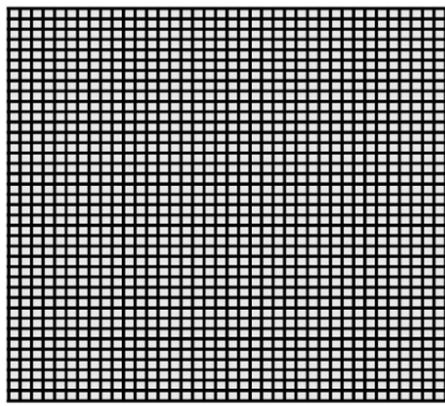


SSD: auxiliary (“extra”) layers



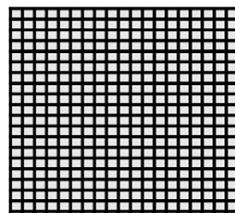
SSD: feature maps

$38 \times 38(x512)$



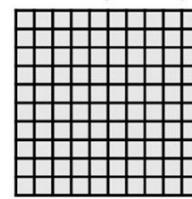
Feature Map (FM) from 4_3

$19 \times 19(x1024)$



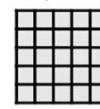
FM 7

$10 \times 10(x512)$



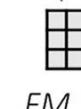
FM 8₂

$5 \times 5(x256)$



FM 9₂

$3 \times 3(x256)$



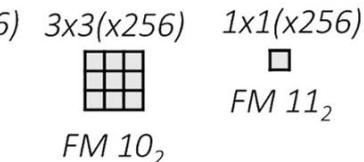
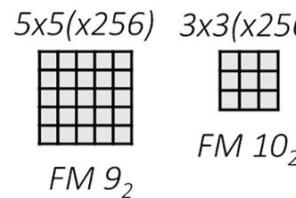
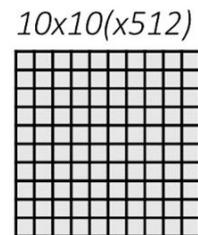
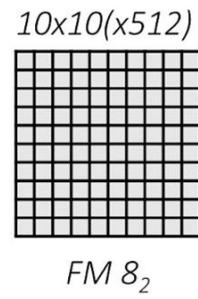
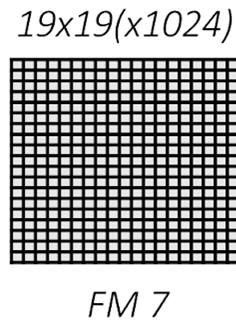
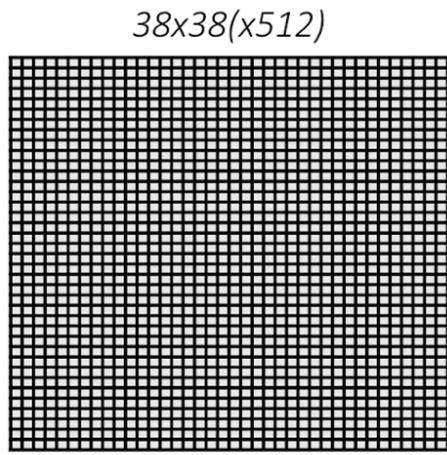
FM 10₂

$1 \times 1(x256)$



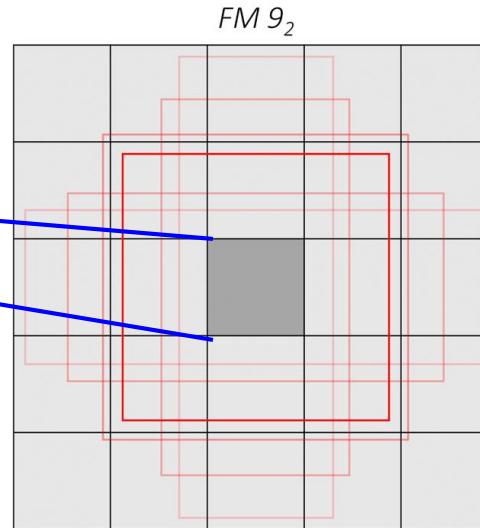
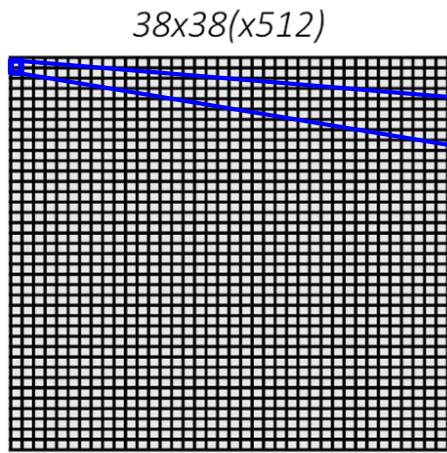
FM 11₂

SSD



Each of these feature maps' cells has 4-6 “default boxes”

SSD: “default boxes” of one cell

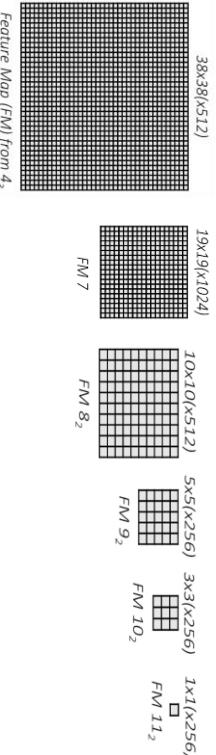


At each location, there are 5 priors with aspect ratios 1, 2, 3, $\frac{1}{2}$, $\frac{1}{3}$ and areas equal to that of a square of side 0.55

Also, a 6th prior with aspect ratio 1 and of side 0.63

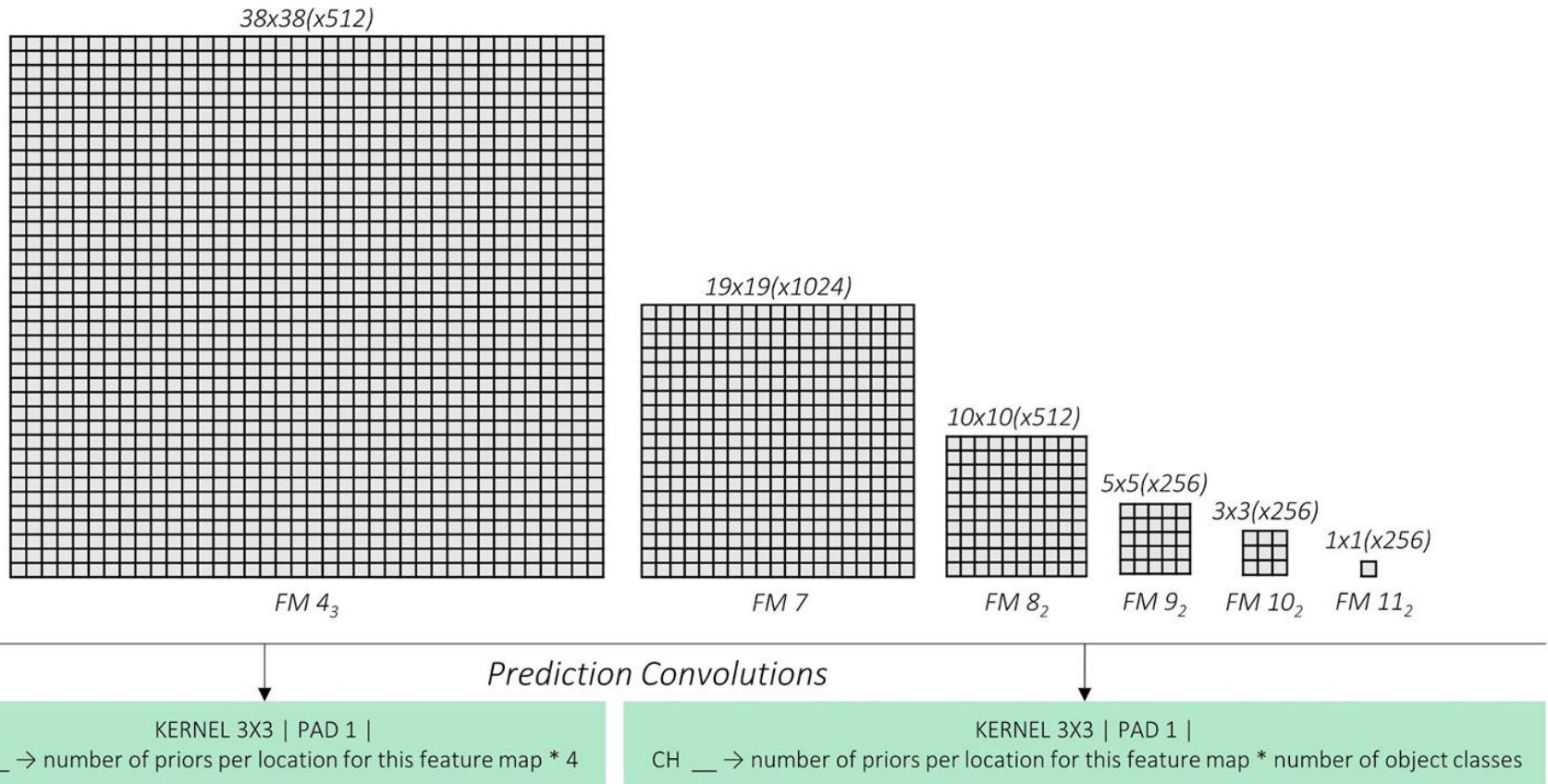
Each of these feature maps' cells has 4-6 “default boxes”

SSD: number of default boxes



Feature Map From	Feature Map Dimensions	Prior Scale	Aspect Ratios	Number of Priors per Position	Total Number of Priors on this Feature Map
conv4_3	38, 38	0.1	1:1, 2:1, 1:2 + an extra prior	4	5776
conv7	19, 19	0.2	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	2166
conv8_2	10, 10	0.375	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	600
conv9_2	5, 5	0.55	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	150
conv10_2	3, 3	0.725	1:1, 2:1, 1:2 + an extra prior	4	36
conv11_2	1, 1	0.9	1:1, 2:1, 1:2 + an extra prior	4	4
Grand Total	-	-	-	-	8732 priors

SSD: prediction convolutions

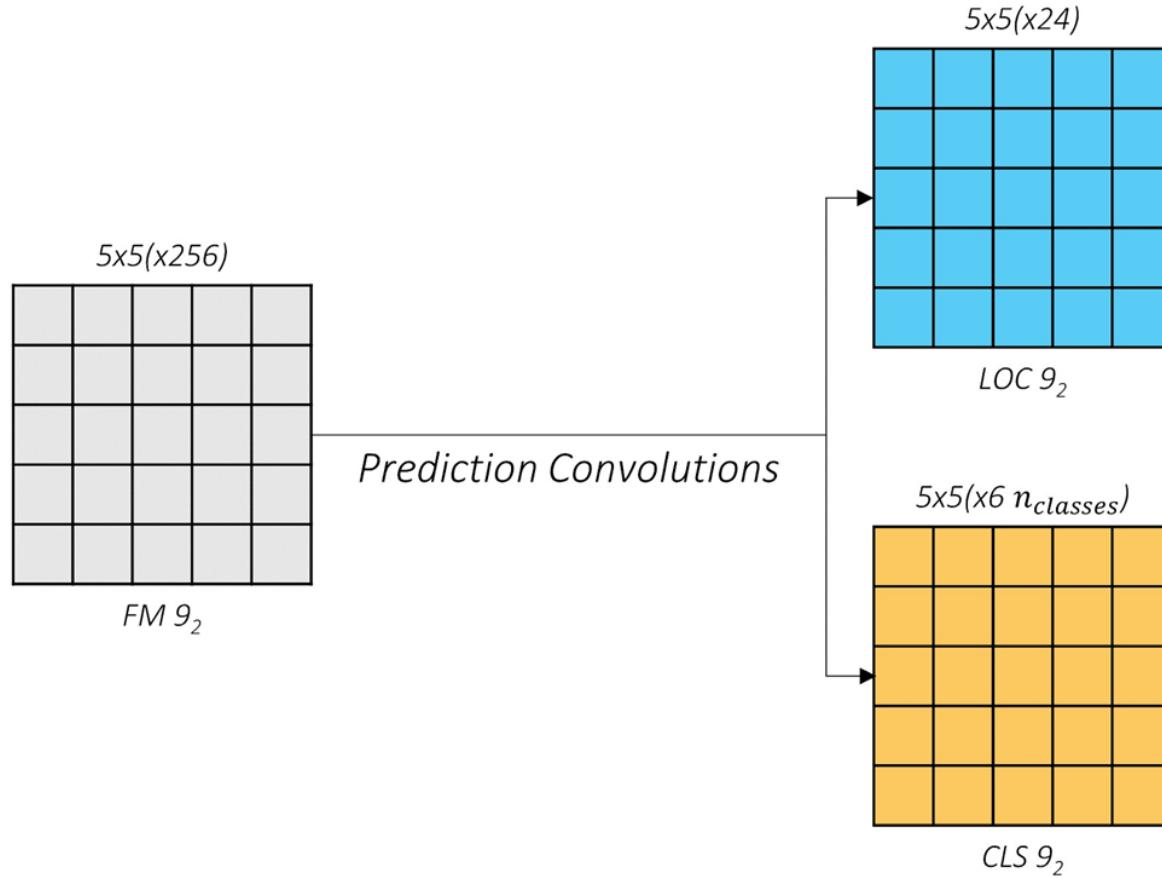


A convolutional layer for each feature map predicting localization boxes in the form of offsets (g_{c_x} , g_{c_y} , g_w , g_h) from each prior at each location in the feature map.

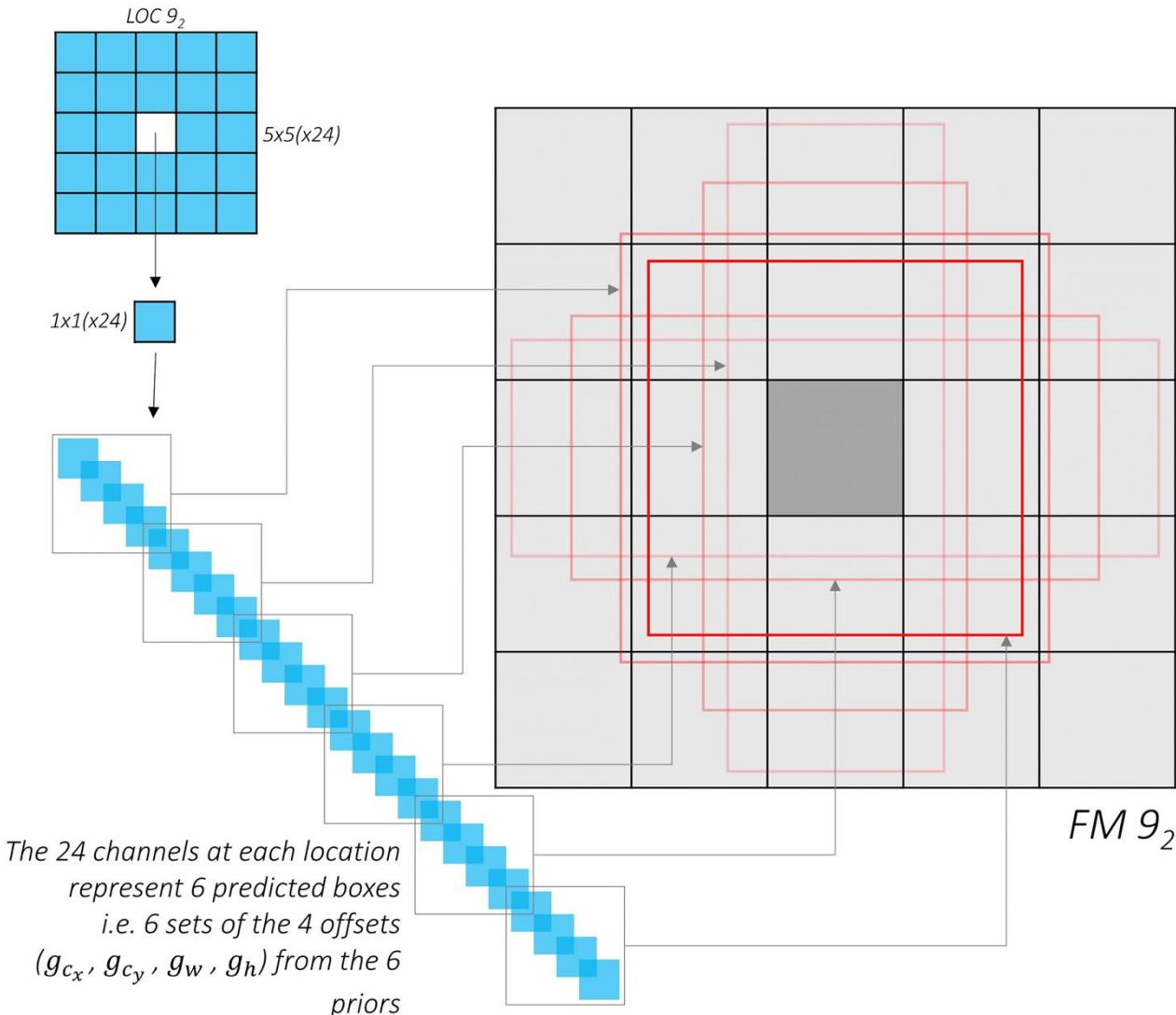
A convolutional layer for each feature map predicting class scores for each prior at each location in the feature map.

This indicates the type of object in the corresponding localization box. If the class predicted is 'background', there is no object.

SSD: prediction scheme

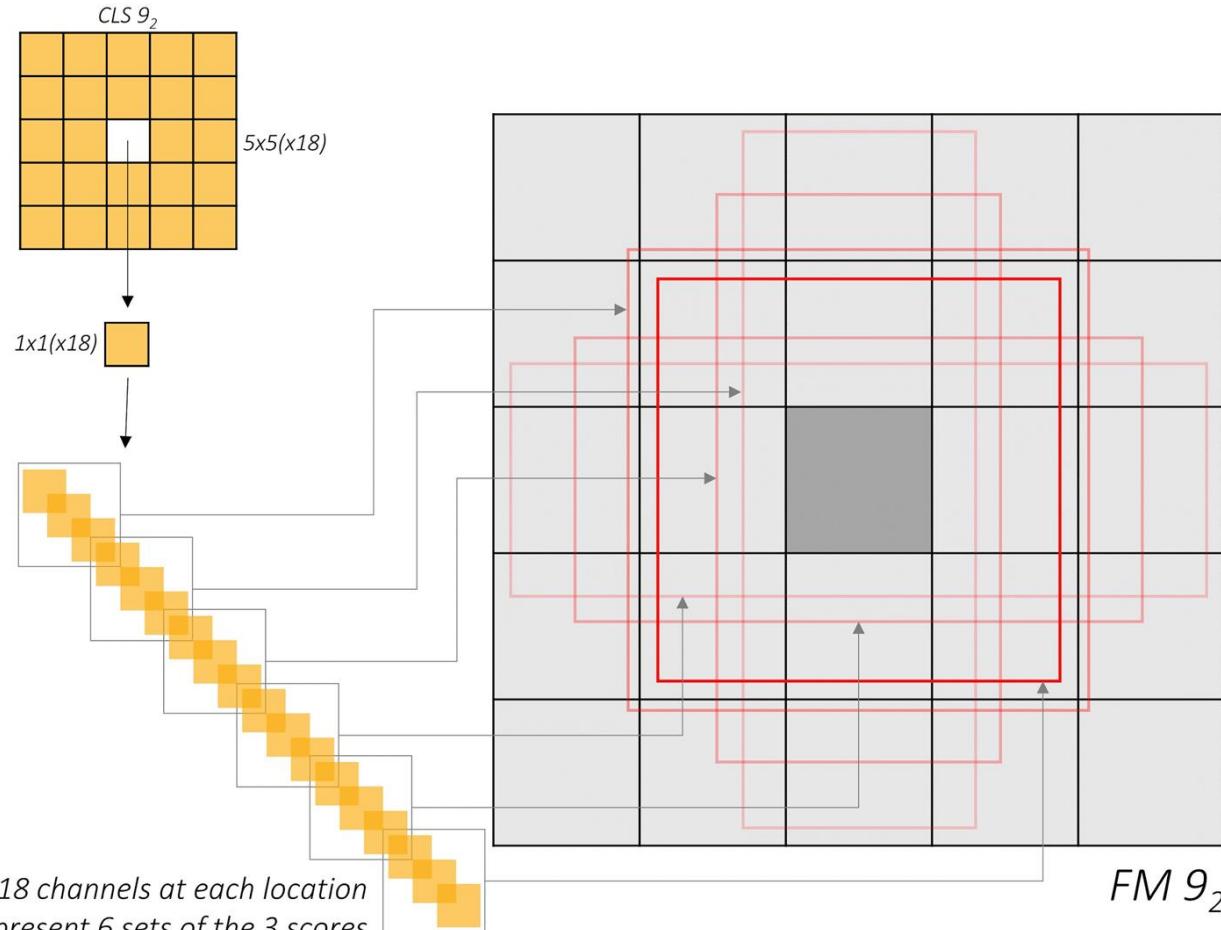


SSD: location coordinates channels



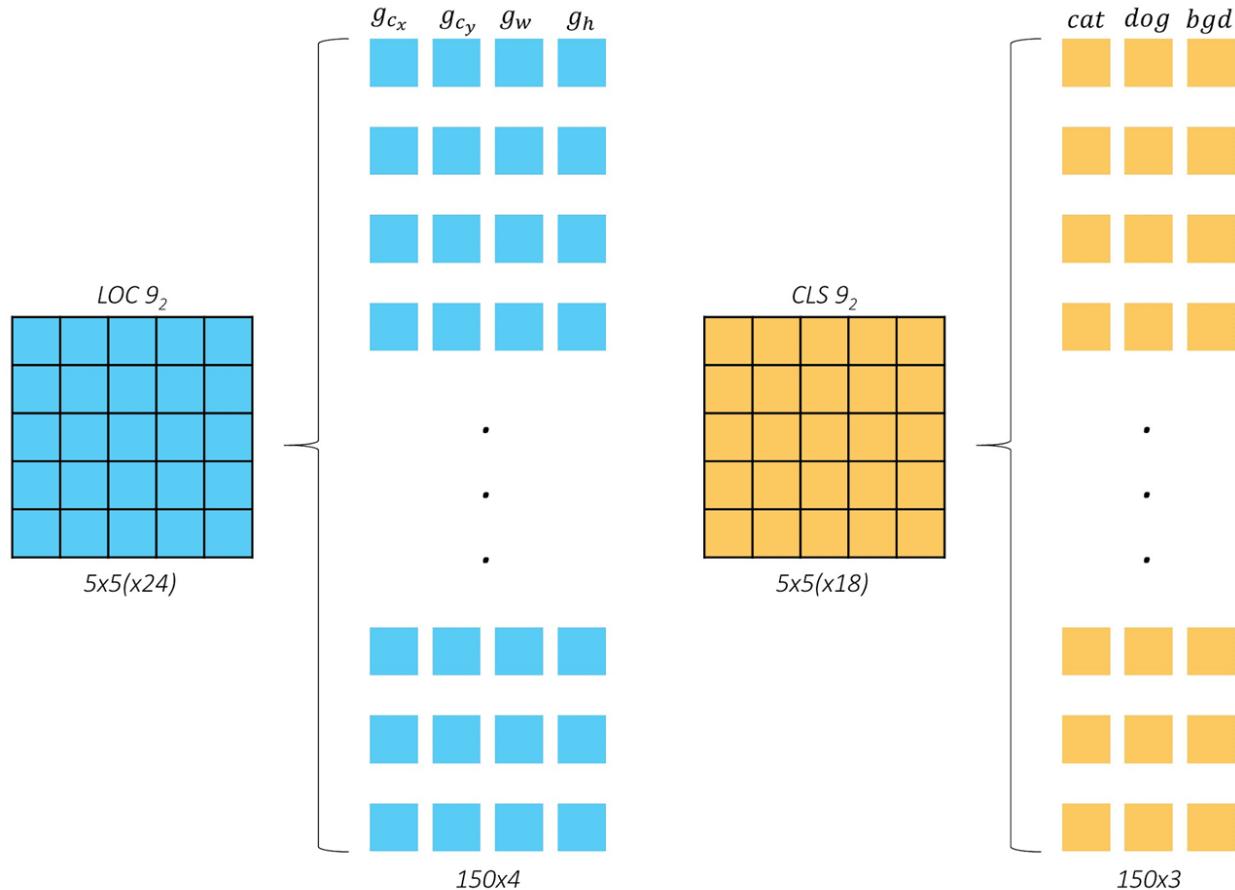
SSD: classification score channels

Assume $n_{classes} = 3$ (cat, dog, background)



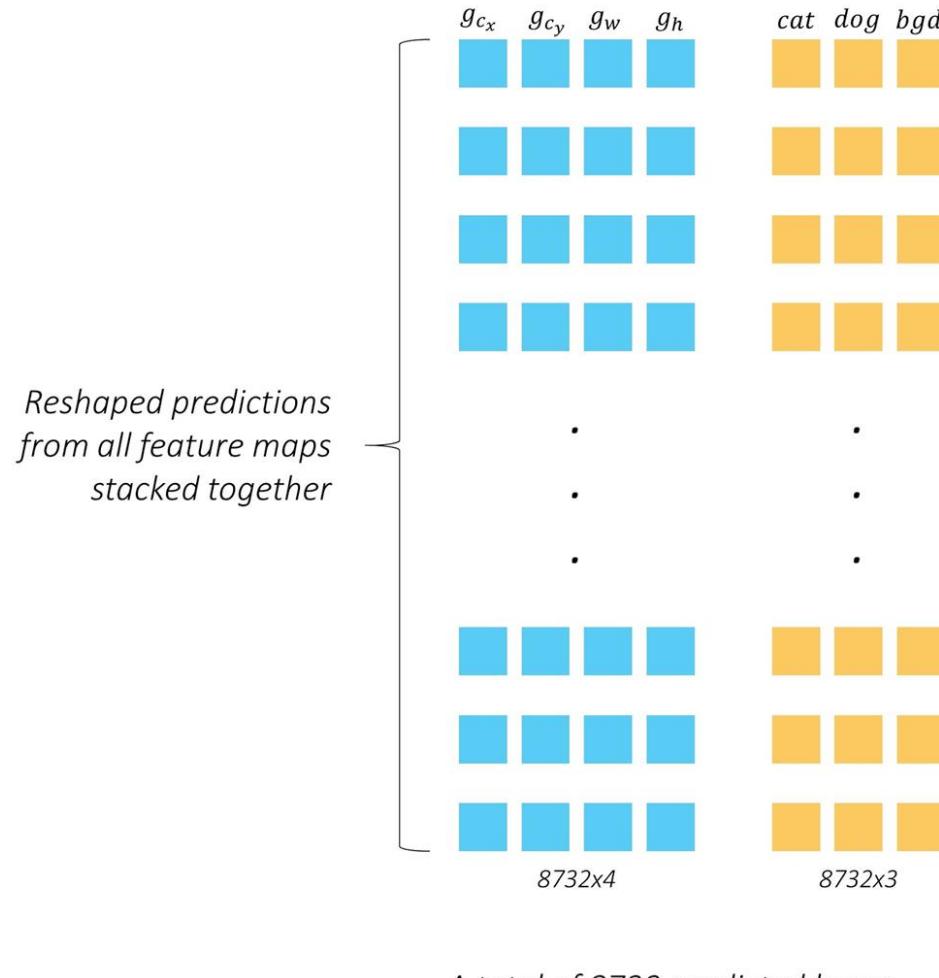
The 18 channels at each location
represent 6 sets of the 3 scores
(cat, dog, bgd) for the 6 priors

SSD: boxes of FM 9

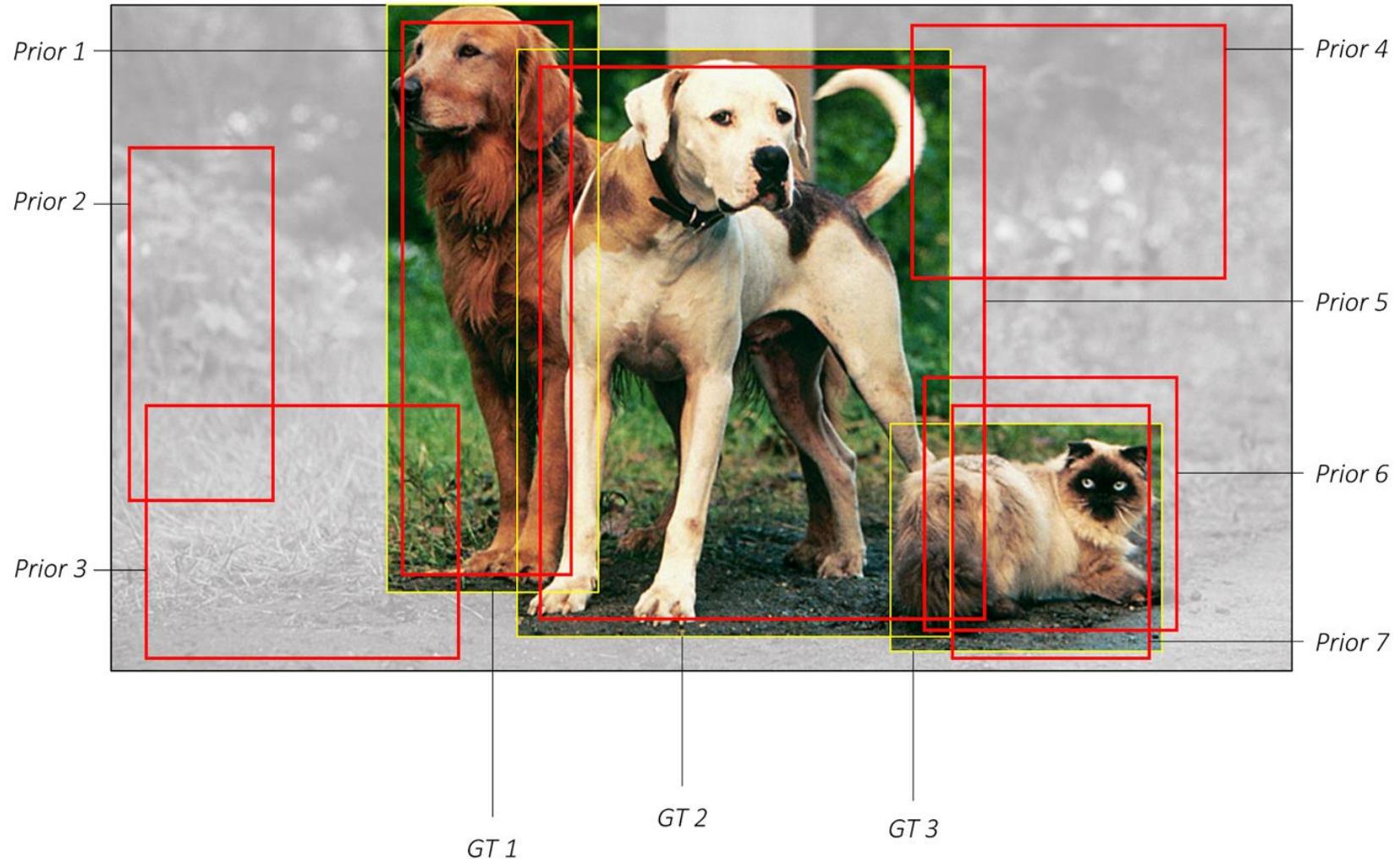


*Reshape predictions from FM 9_2 to represent offsets and class scores
for the 150 predicted boxes*

SSD: all predicted boxes



SSD: predictions



SSD: matching

IoU	GT 1	GT 2	GT 3
Prior 1	0.75	0.07	0
Prior 2	0	0	0
Prior 3	0.05	0	0
Prior 4	0	0.03	0
Prior 5	0.05	0.88	0.06
Prior 6	0	0.03	0.65
Prior 7	0	0	0.68

Match each prior to the ground truth that has the best Jaccard overlap.

	Matched GT	Type	Label	Coordinates
Prior 1	GT 1	Positive	dog	of GT 1
Prior 2	GT 1	Negative	bgd	-
Prior 3	GT 1	Negative	bgd	-
Prior 4	GT 2	Negative	bgd	-
Prior 5	GT 2	Positive	dog	of GT 2
Prior 6	GT 3	Positive	cat	of GT 3
Prior 7	GT 3	Positive	cat	of GT 3

If a prior has a Jaccard overlap greater than 0.5 with its matched ground truth object, then it really contains this object, and is a positive match.

Otherwise, it is a negative match, and is assigned a 'background' label.

SSD: coordinate regression loss

$$L_{loc} = \frac{1}{n_{positives}} \left(\sum_{positives} Smooth L_1 Loss \right)$$

SSD: coordinate regression loss

$$L_{loc} = \frac{1}{n_{positives}} \left(\sum_{positives} Smooth L_1 Loss \right)$$

$$L_{loc}(t, v) = \sum_{i \in \{x, y, w, h\}} \text{smooth}_{L_1}(t_i - v_i),$$

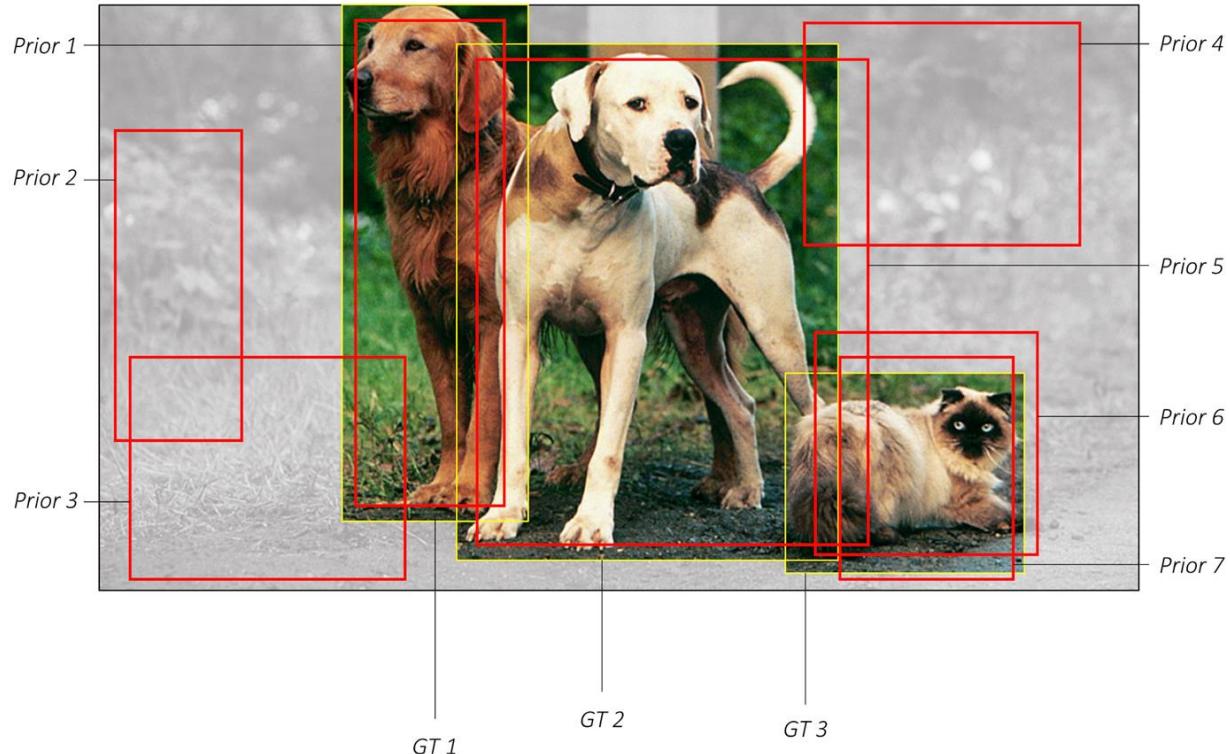
in which

$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases}$$

SSD: classification loss + hard negative mining

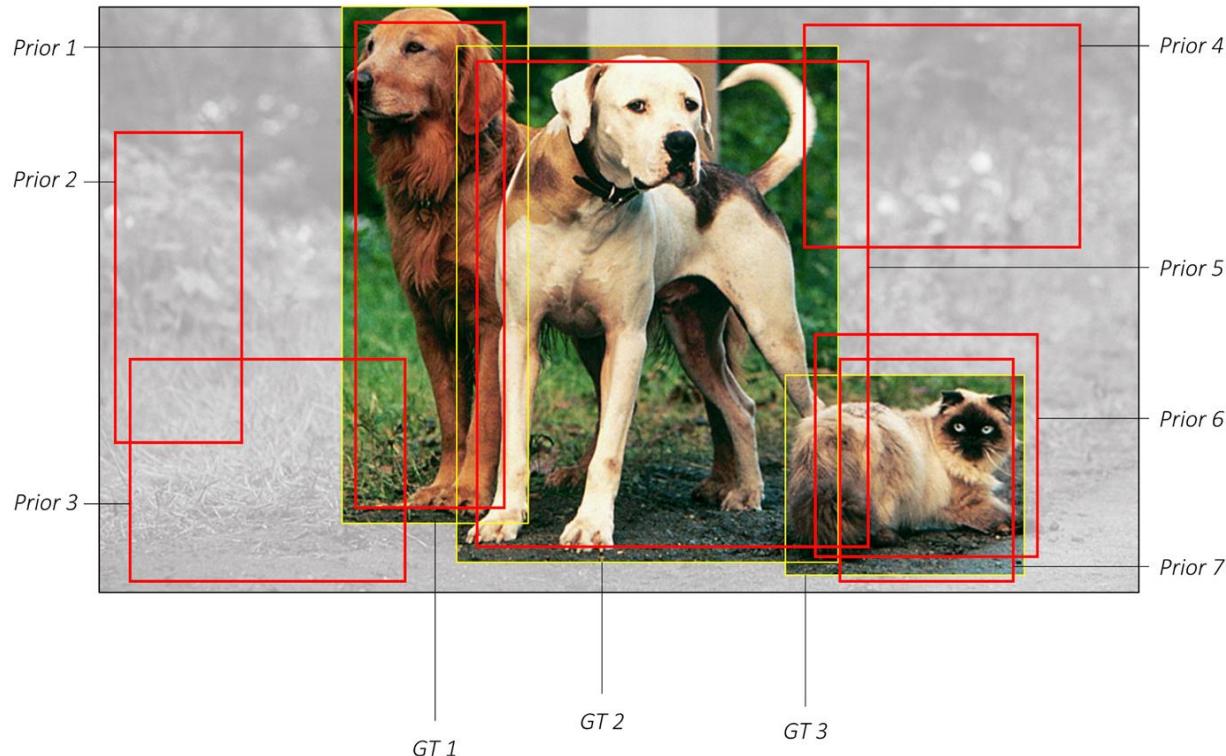
$$L_{conf} = \frac{1}{n_{positives}} \left(\sum_{positives} CE\ Loss + \sum_{hard\ negatives} CE\ Loss \right)$$

SSD: classification loss + hard negative mining



$$L_{conf} = \frac{1}{n_{positives}} \left(\sum_{positives} CE\ Loss + \sum_{hard\ negatives} CE\ Loss \right)$$

SSD: classification loss + hard negative mining



$$L_{conf} = \frac{1}{n_{positives}} \left(\sum_{positives} CE\ Loss + \sum_{hard\ negatives} CE\ Loss \right)$$

$$N_{hard_negatives} = 3 * N_{positives}$$

SSD: full multibox loss

$$L_{loc} = \frac{1}{n_{positives}} \left(\sum_{positives} Smooth\ L_1\ Loss \right)$$

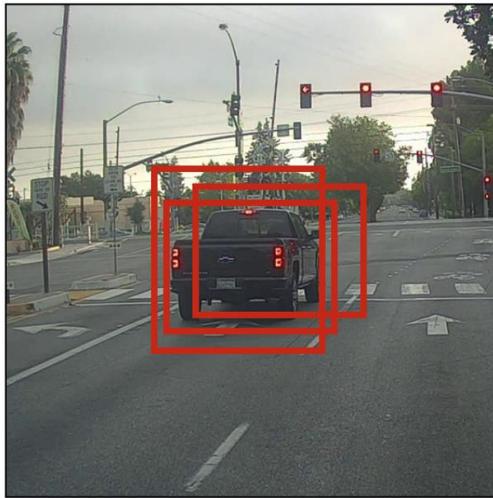
$$L_{conf} = \frac{1}{n_{positives}} \left(\sum_{positives} CE\ Loss + \sum_{hard\ negatives} CE\ Loss \right)$$

$$N_{hard_negatives} = 3 * N_{positives}$$

$$L = L_{conf} + \alpha \cdot L_{loc}$$

Detection: non-max suppression

Before non-max suppression



Non-Max
Suppression



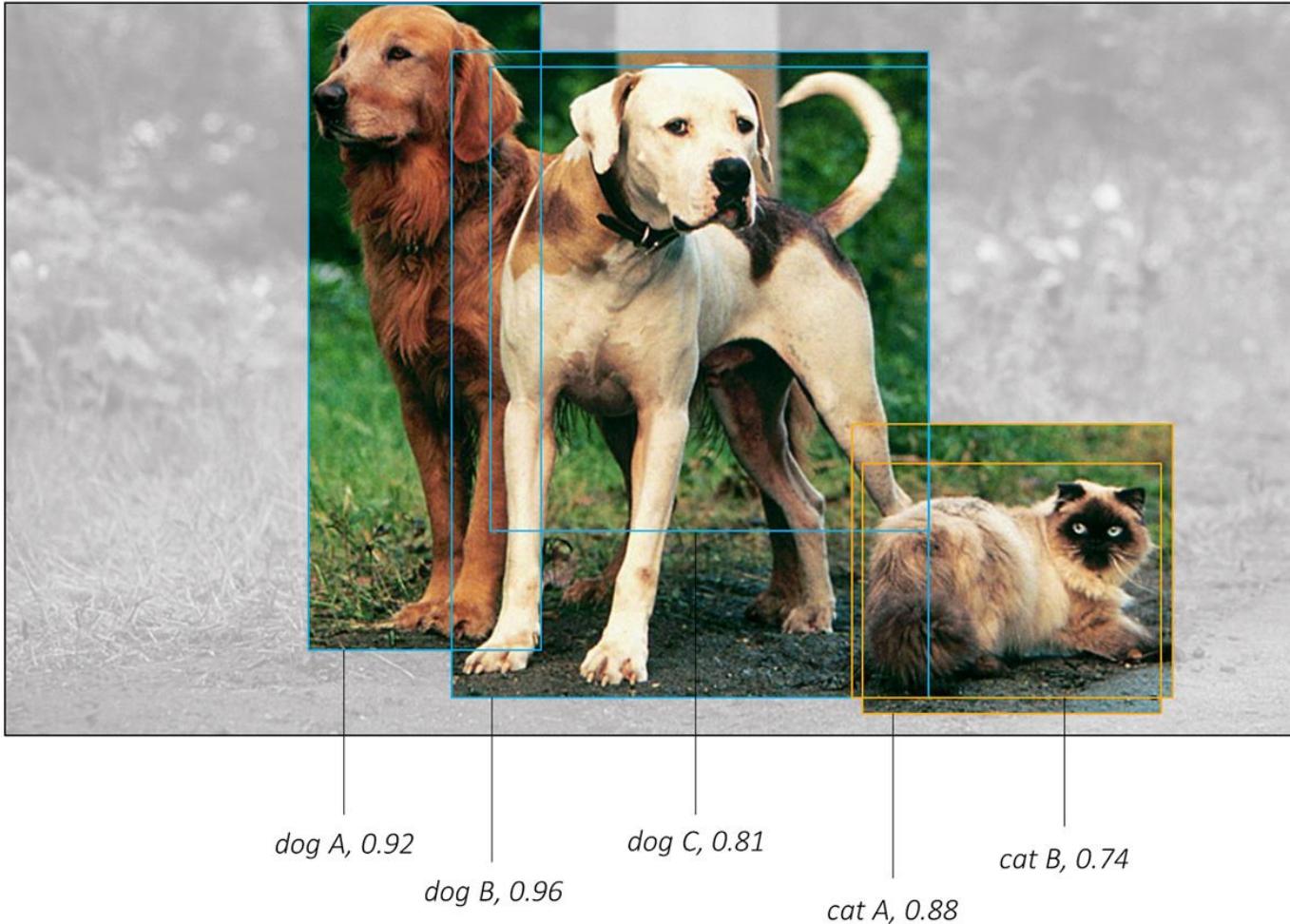
After non-max suppression



For each class separately!

Detection: non-max suppression

There are usually multiple predictions for the same object



Detection: non-max suppression



dog, 0.92

dog, 0.96

cat, 0.88

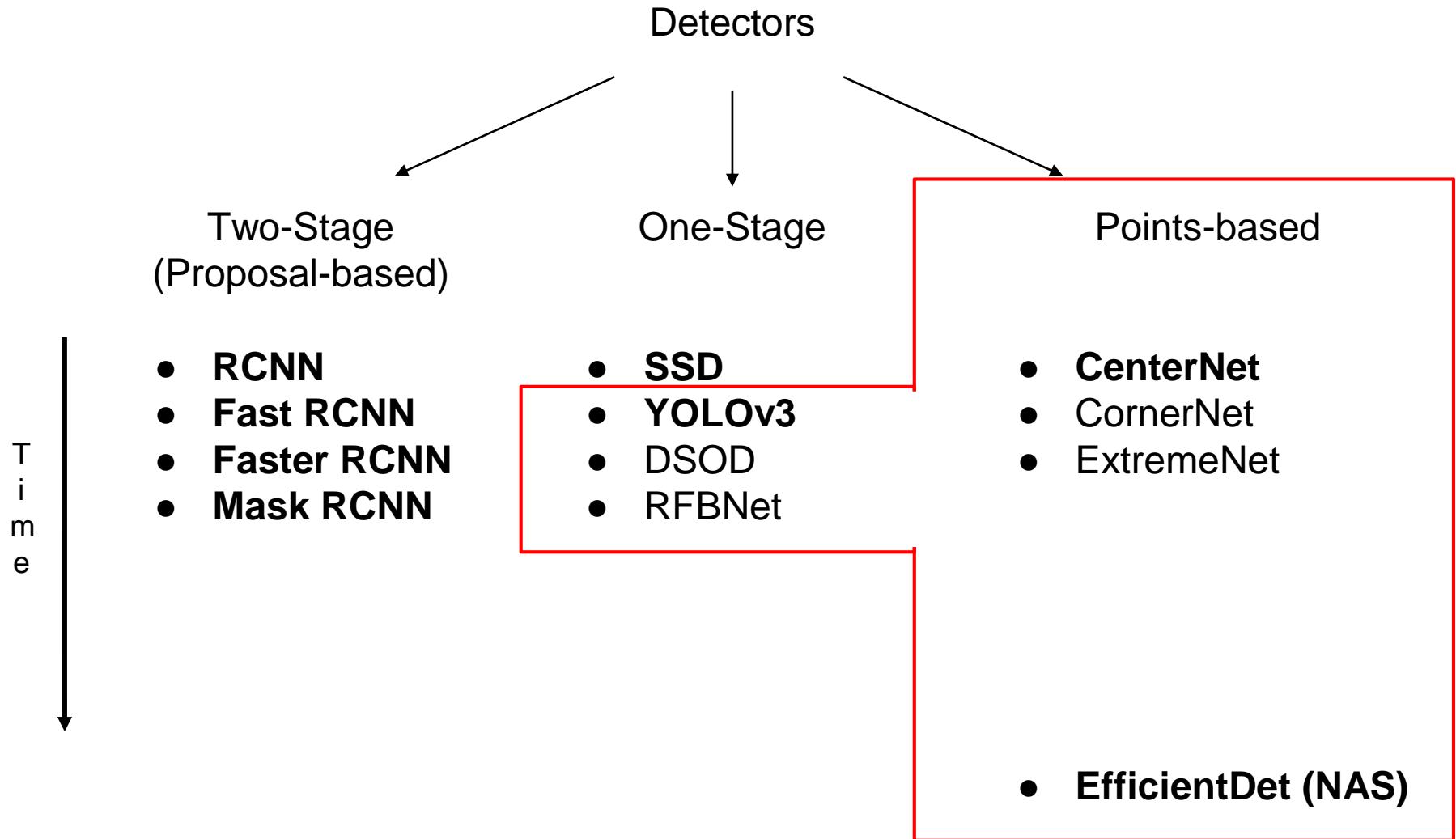
Summary

1. One-stage detectors
2. In-depth SSD architecture

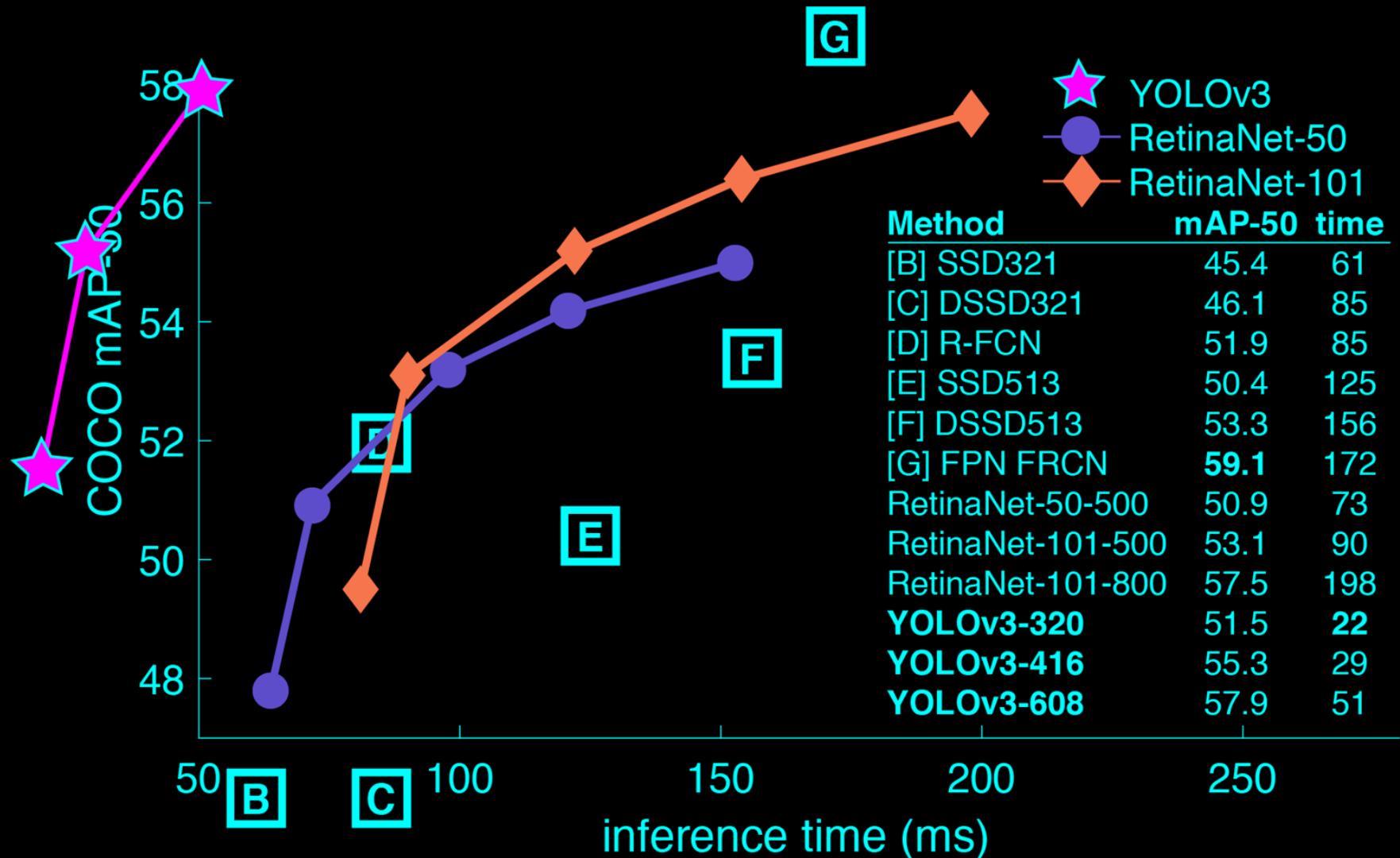
Modern approaches

State-of-the-Art

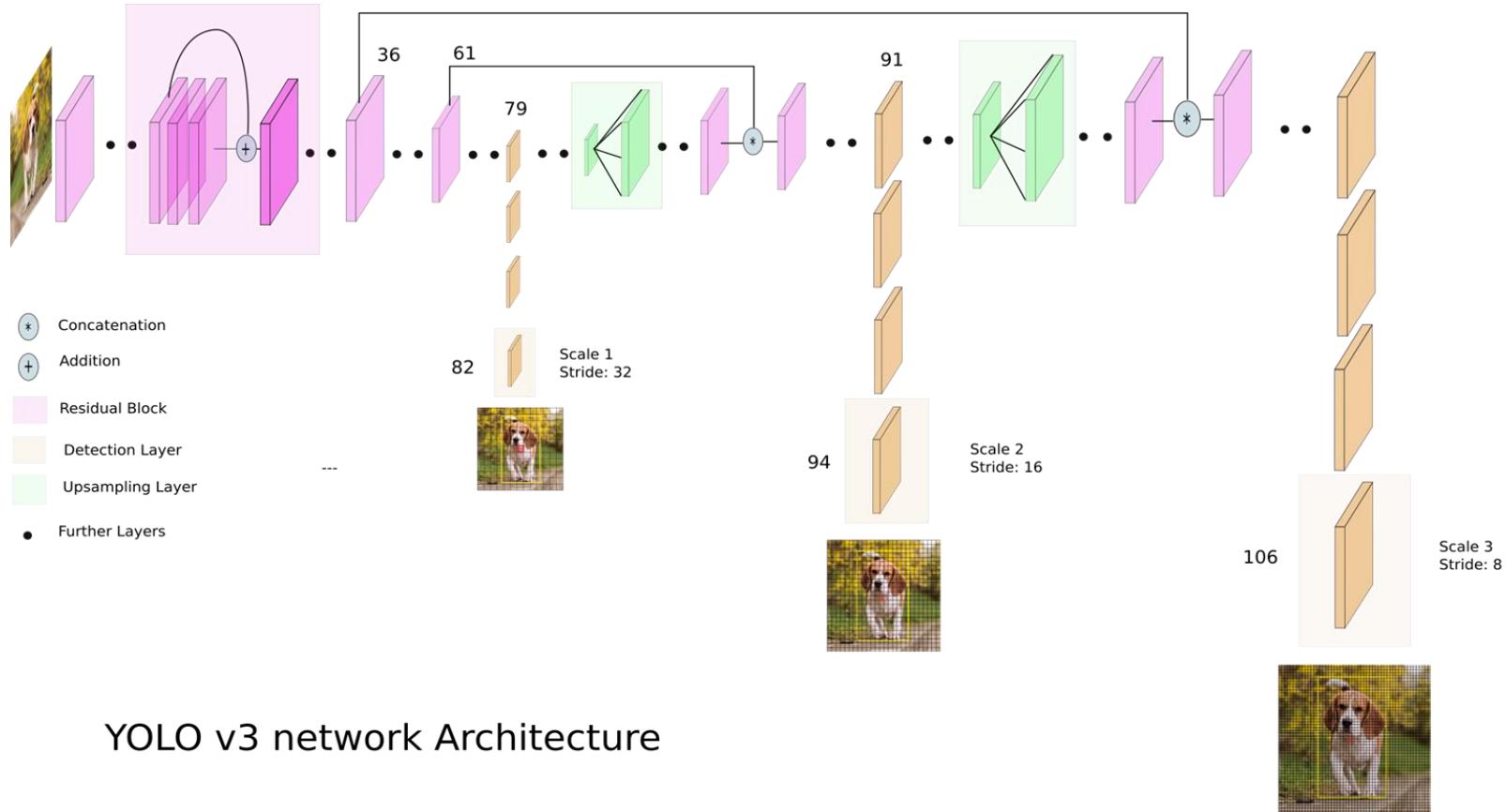
Detection: Taxonomy



Incremental improvement: YOLOv3 (2018)



Incremental improvement: YOLOv3 (2018)



Optimal detection: YOLOv4 (2020)

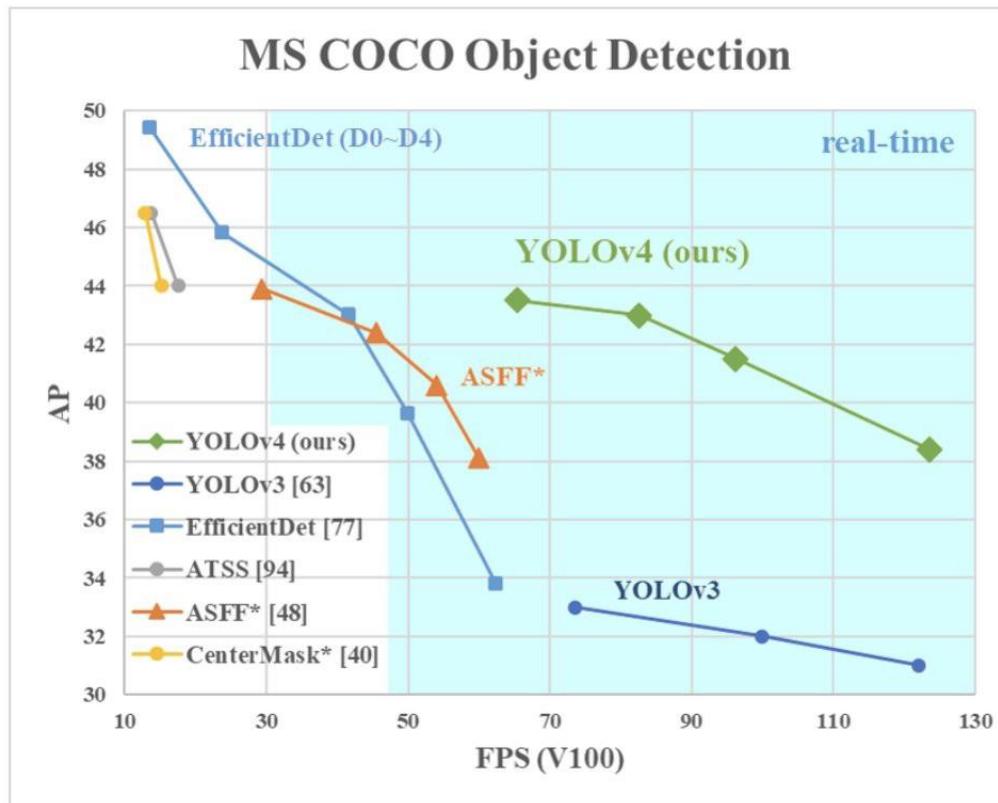


Figure 1: Comparison of the proposed YOLOv4 and other state-of-the-art object detectors. YOLOv4 runs twice faster than EfficientDet with comparable performance. Improves YOLOv3's AP and FPS by 10% and 12%, respectively.

Optimal detection: YOLOv4 (2020)

3.4. YOLOv4

In this section, we shall elaborate the details of YOLOv4.

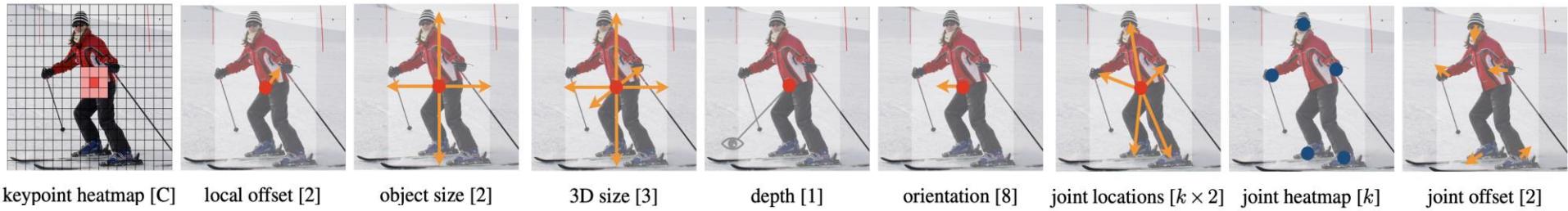
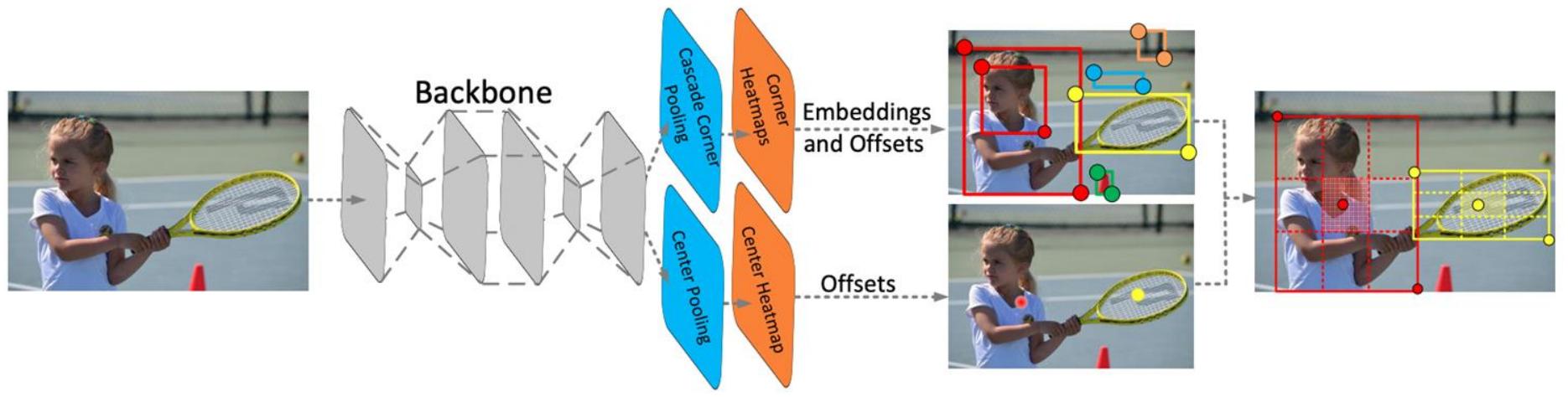
YOLOv4 consists of:

- Backbone: CSPDarknet53 [81]
- Neck: SPP [25], PAN [49]
- Head: YOLOv3 [63]

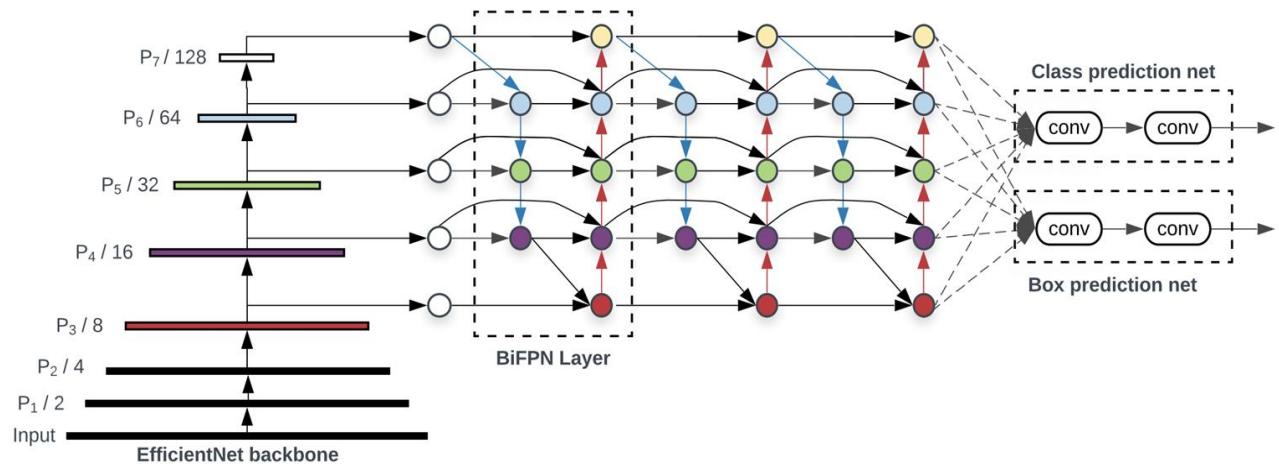
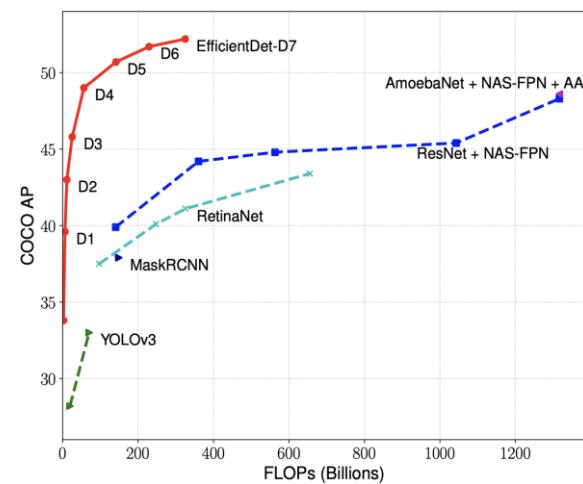
YOLO v4 uses:

- Bag of Freebies (BoF) for backbone: CutMix and Mosaic data augmentation, DropBlock regularization, Class label smoothing
- Bag of Specials (BoS) for backbone: Mish activation, Cross-stage partial connections (CSP), Multi-input weighted residual connections (MiWRC)
- Bag of Freebies (BoF) for detector: CIoU-loss, CmBN, DropBlock regularization, Mosaic data augmentation, Self-Adversarial Training, Eliminate grid sensitivity, Using multiple anchors for a single ground truth, Cosine annealing scheduler [52], Optimal hyper-parameters, Random training shapes
- Bag of Specials (BoS) for detector: Mish activation, SPP-block, SAM-block, PAN path-aggregation block, DIoU-NMS

Objects as Points: CenterNet (2019)



NAS in Detection: EfficientDet (2019-2020)



Idea: EfficientNet + BiFPN

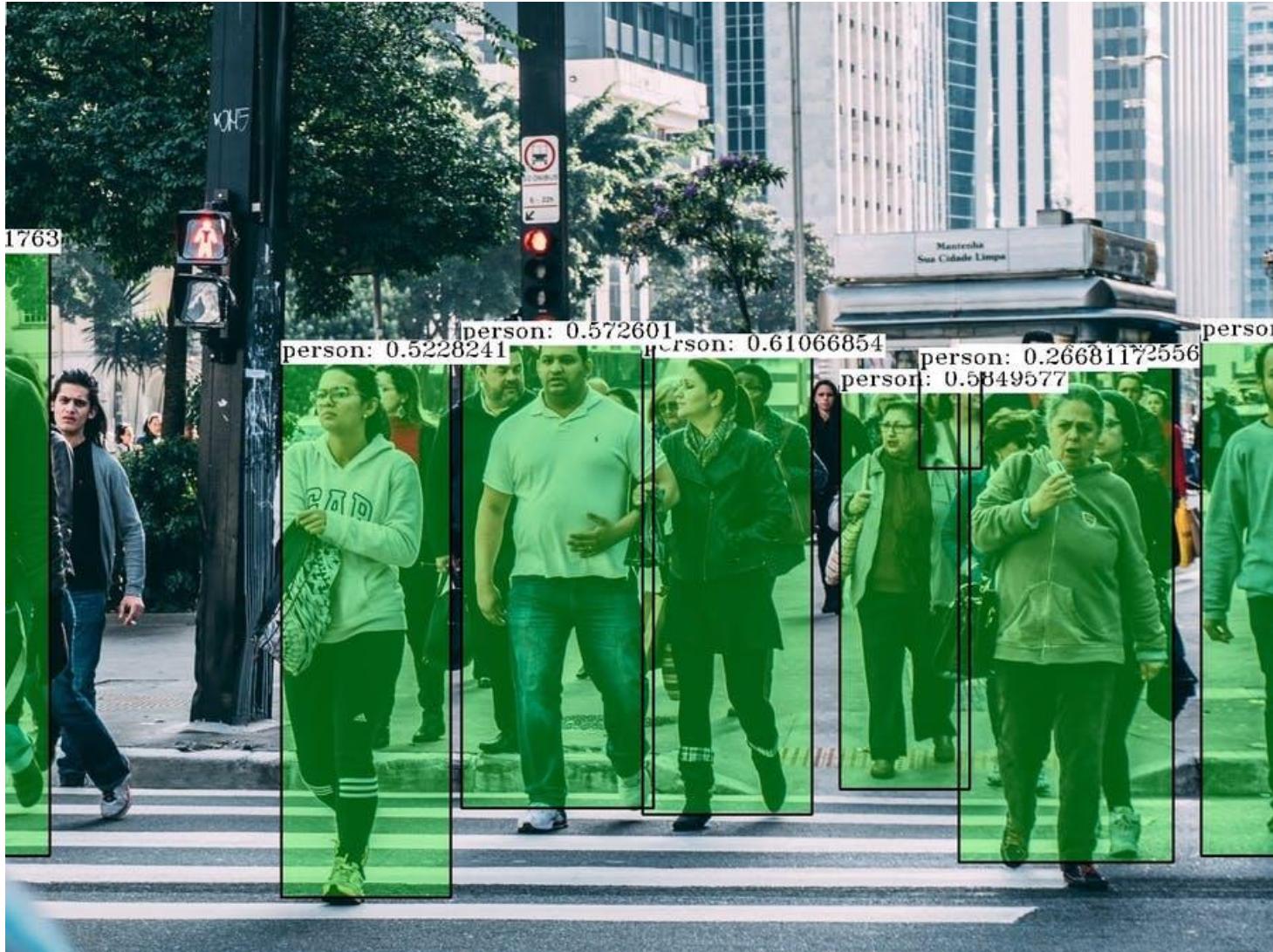
Modern tasks

Specific detection applications

In real life we need to

1. Detect **people**
2. Detect **faces**
3. Detector **text**
4. Do **tracking** through the video (time), not only image
5. Recognize **actions**: proxy, end-to-end
6. Detect in **3D**: self-driving, robotics, VR/AR

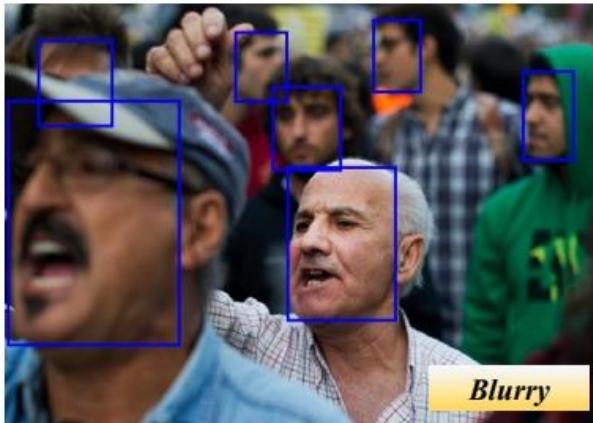
In real life we need to: detect people



In real life we need to: detect faces



Scale



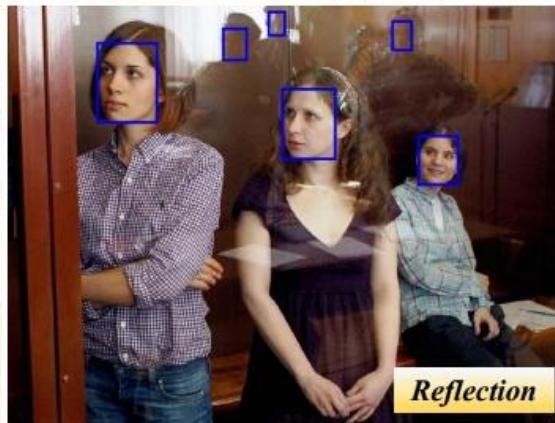
Blurry



Illumination



Pose & Occlusion



Reflection

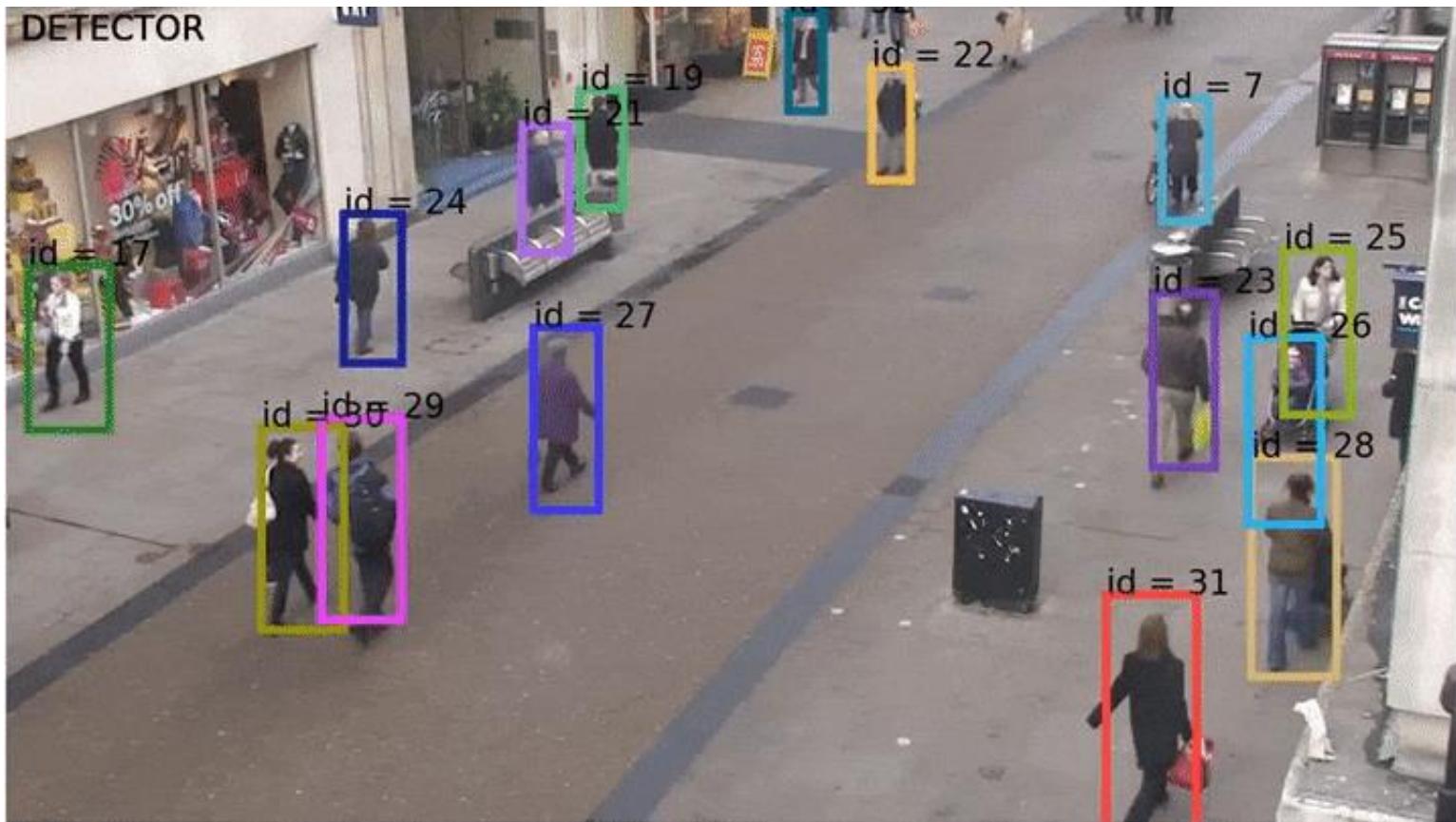


Makeup

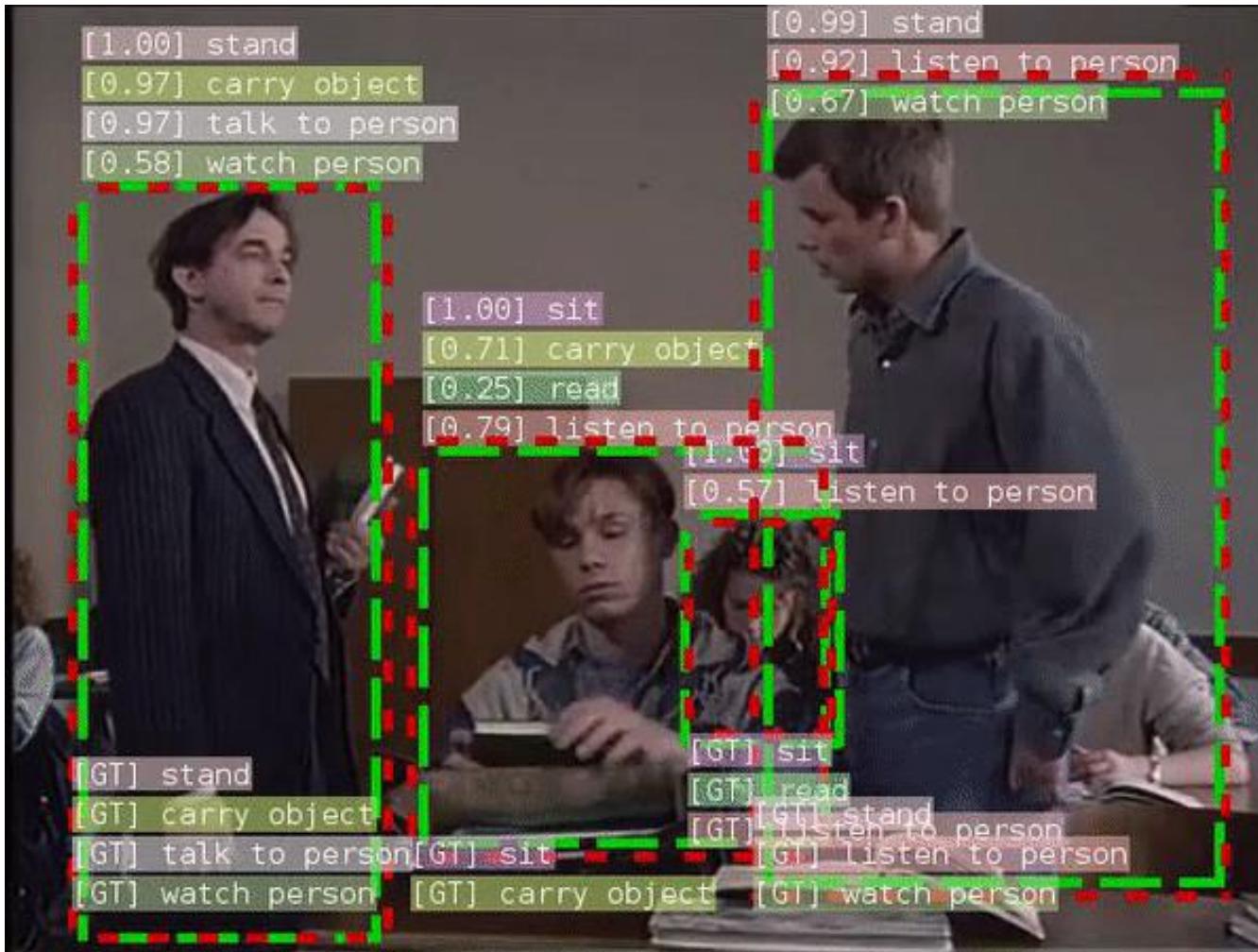
In real life we need to: detect text



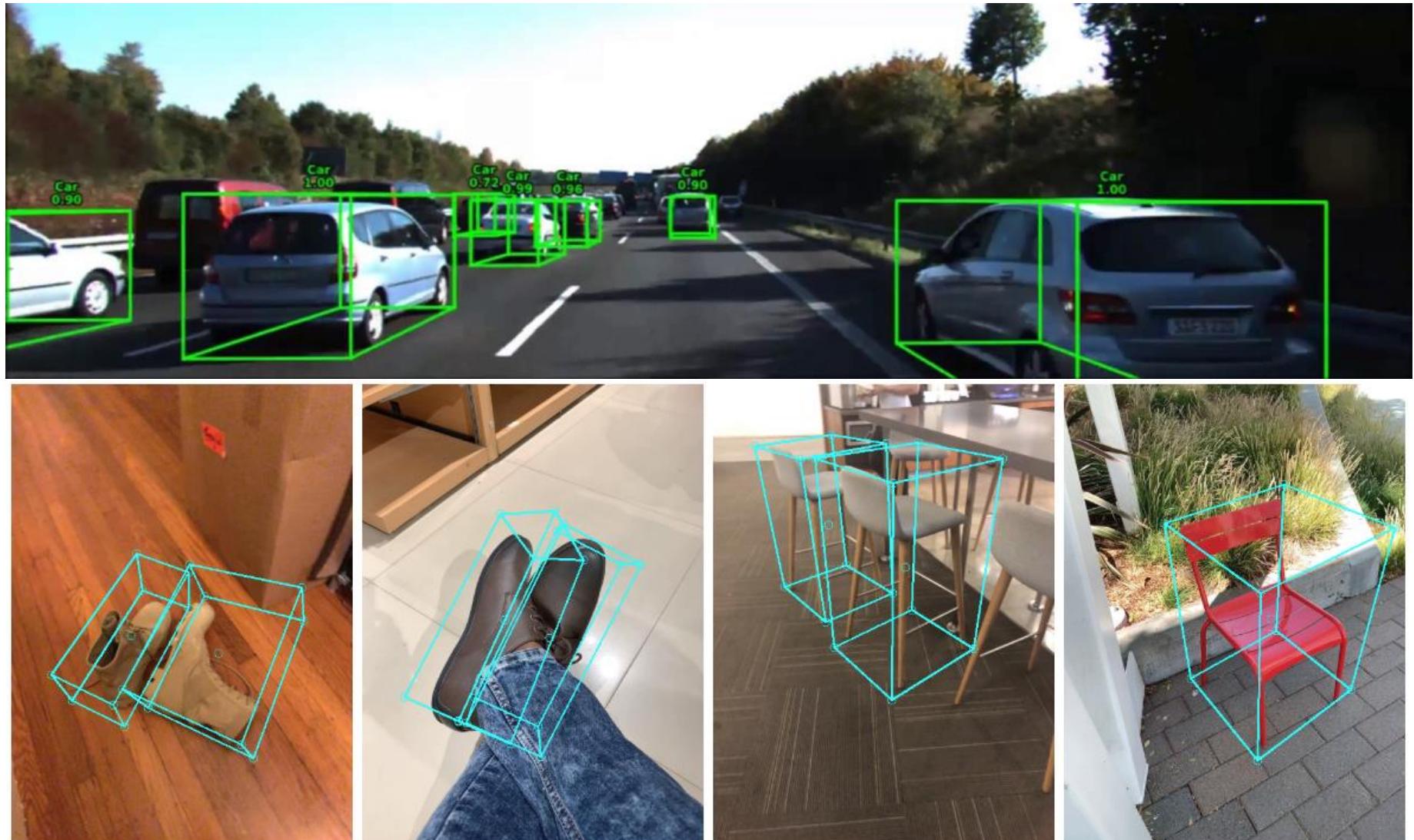
In real life we need to: do tracking



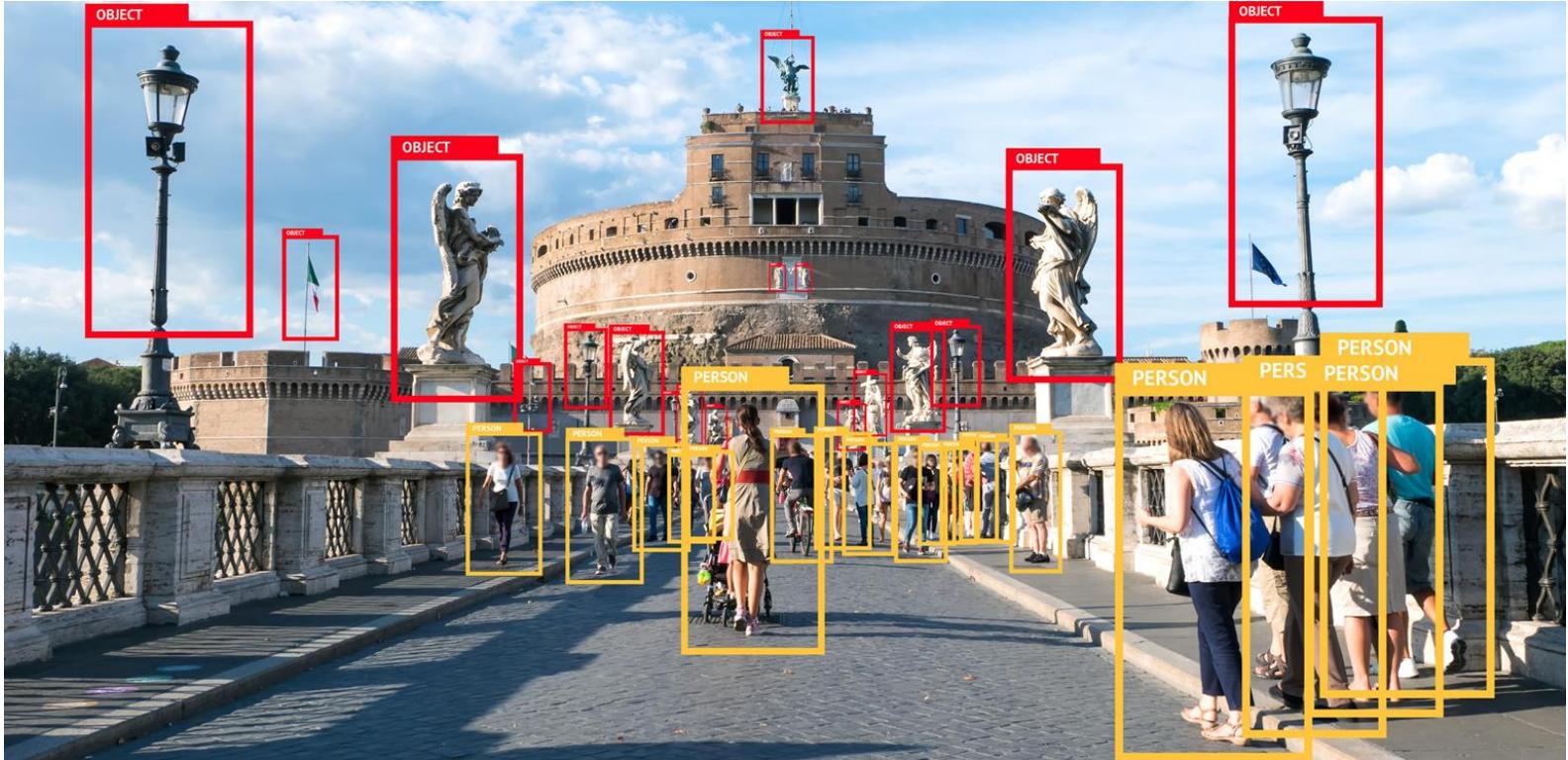
In real life we need to: recognize actions



In real life we need to: detect in 3D



Solutions to these tasks



<https://habr.com/ru/company/mipt/blog/458190/>

Lecture summary

1. Classification recap
2. Object Detection basics
3. Two-stage (proposal-based) methods
4. One-stage (single-shot) methods
5. Modern approaches & tasks

