THE UNIVERSITY OF TEXAS AT DALLAS

Object Detection

CS 4391 Introduction to Computer Vision
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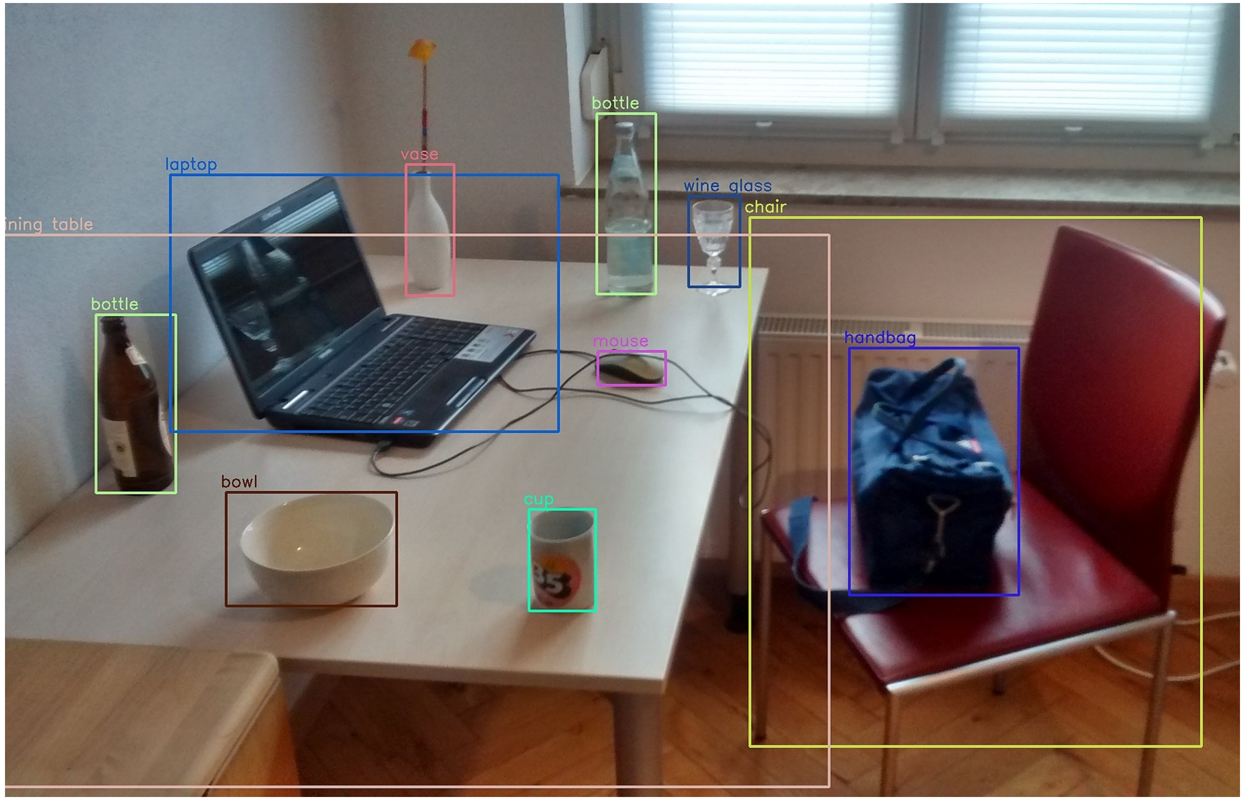
Department of Computer Science

Slides borrowed from Professor Yu Xiang

Object Detection

Localize objects in images and classify them



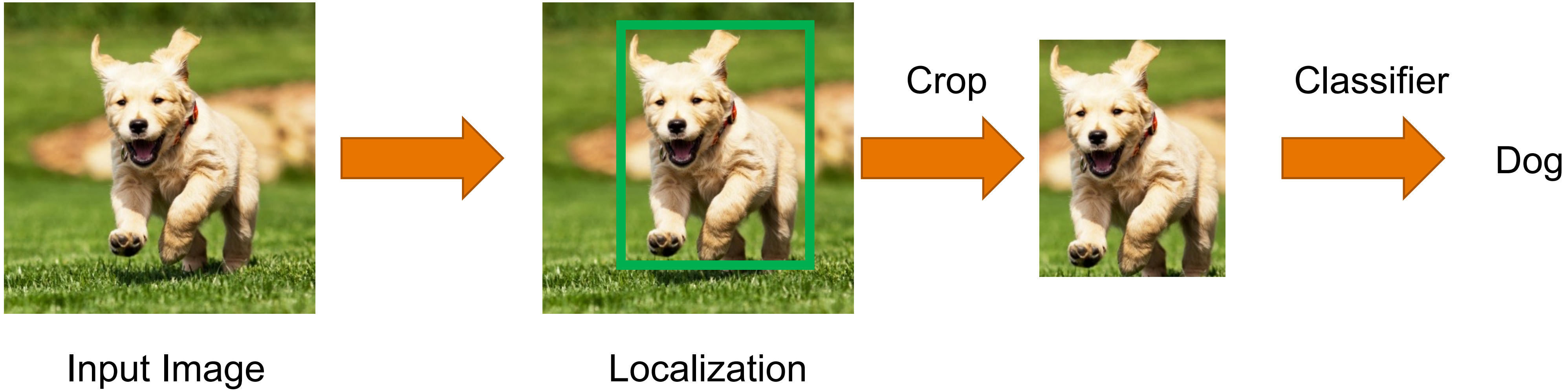
Wikipedia

Why using bounding boxes?

- Easy to store
    - (x, y, w, h): box center with width, height
    - (x1, y1, x2, y2): top left corner and bottom right corner
- Easy for image processing
    - Crop a region

Object Detection

Localization + Classification



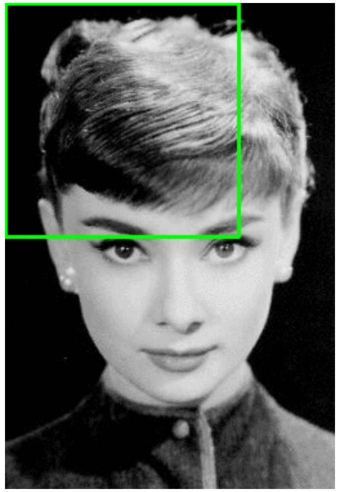
Localization: Sliding Window

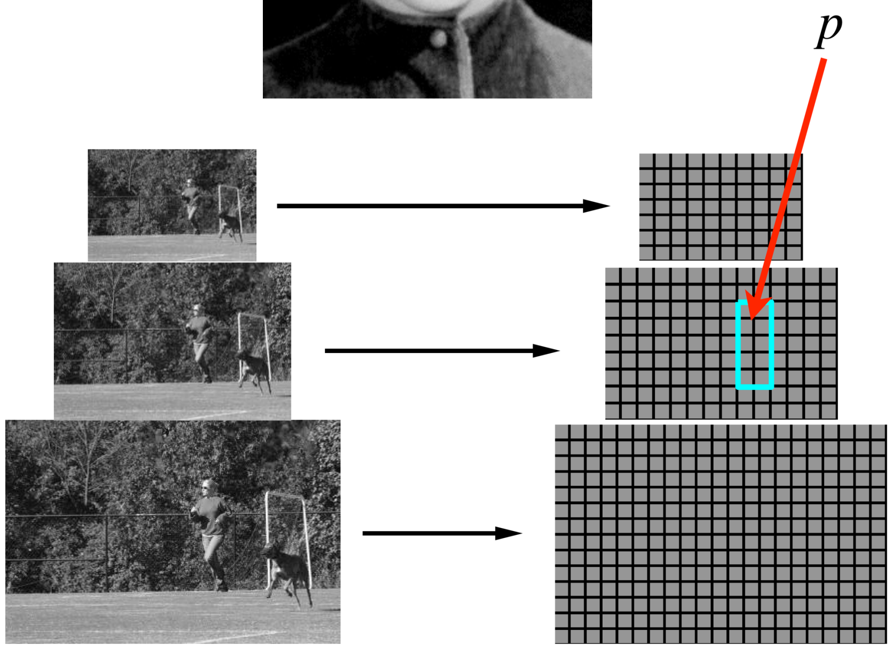
Select a window with a fixed size

Scan the input image with the window (bounding box)

How to deal with different object scales and aspect ratios?

- Use boxes with different aspect ratios
- Image pyramid



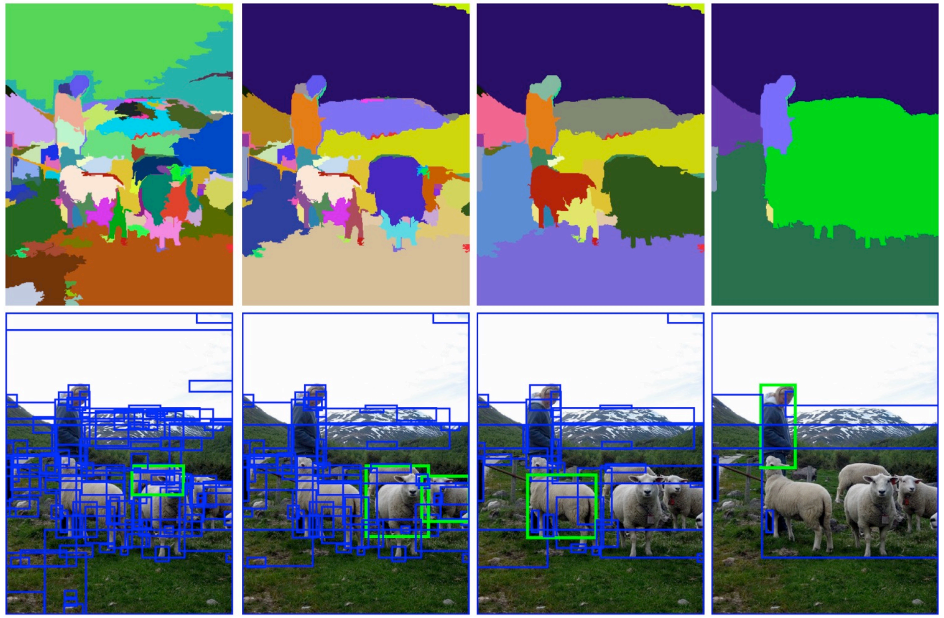


https://cvexplained.wordpress.com/tag/sliding-windows/

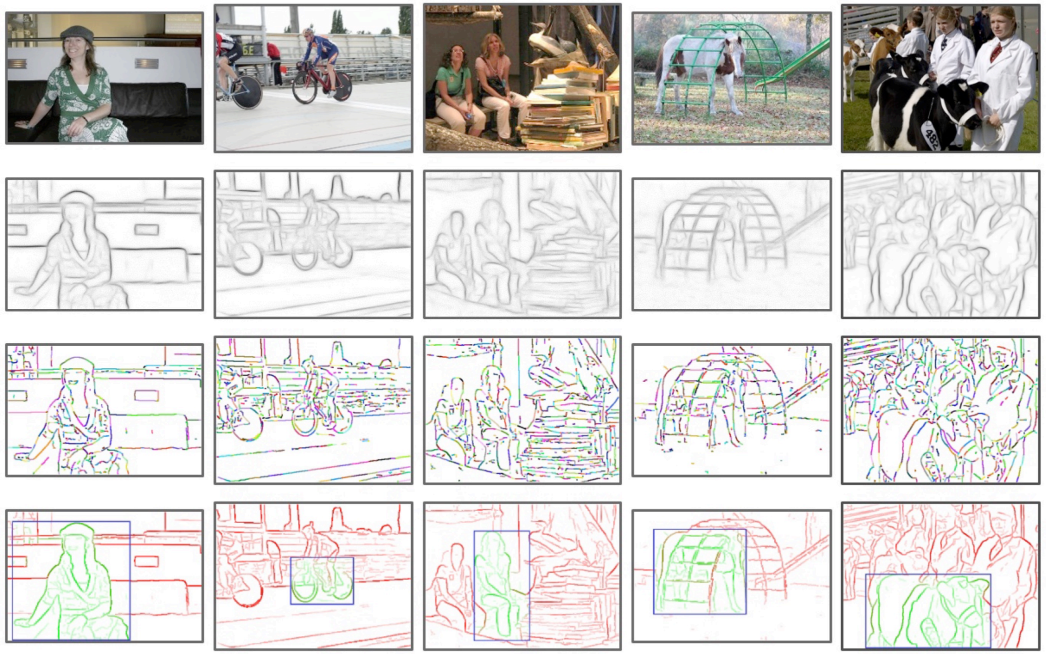
Localization: Region Proposal

Leverage methods that can generate regions with high likelihood of containing objects

- E.g., bottom-up segmentation methods, using edges



Selective Search, Sande et al., ICCV'11

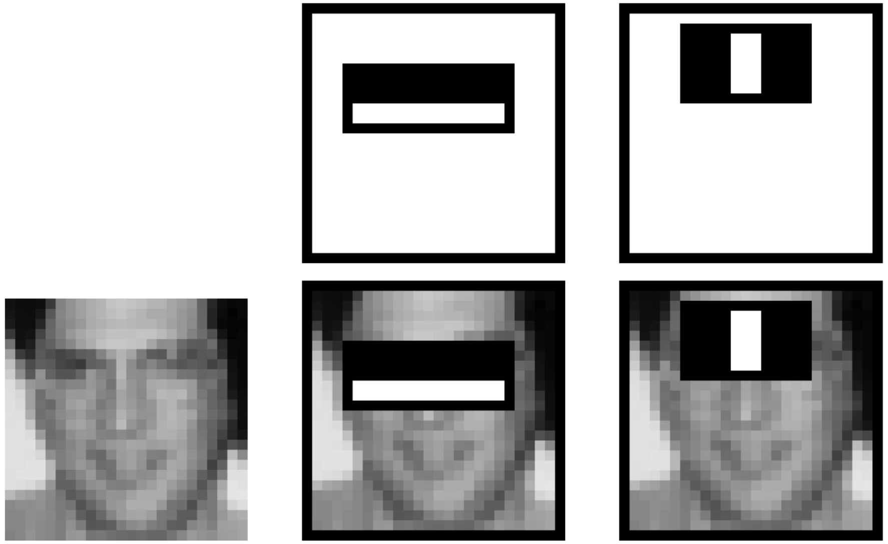


Edge Boxes. Zitnick & Dollar, ECCV'14

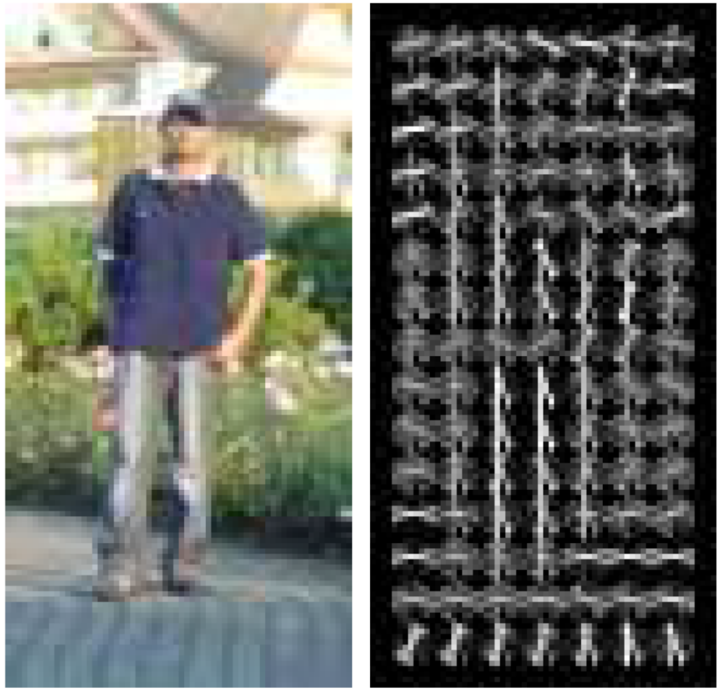
Classification: Features

Traditional methods: Hand-crafted features

Deep learning methods: learned features in the network



Viola and Jones: rectangle features



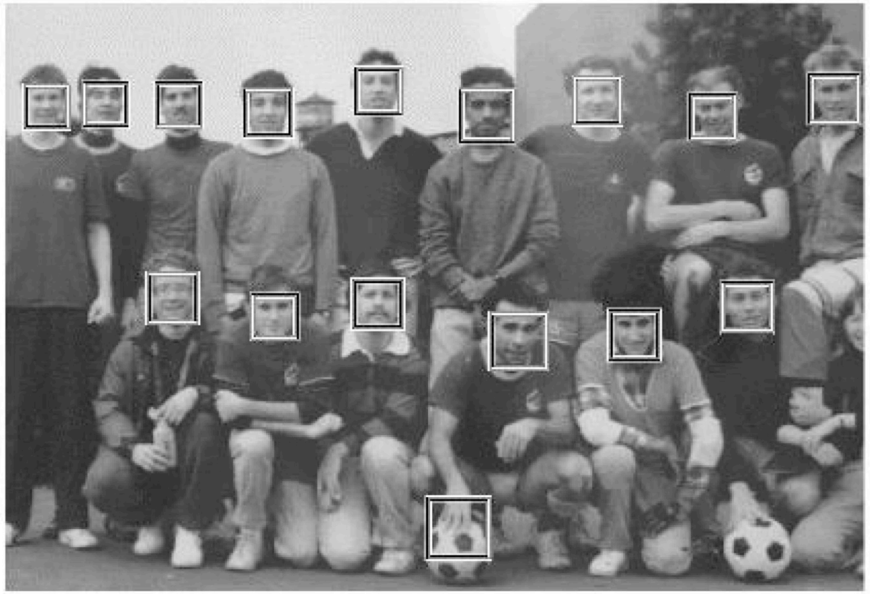
Dadal & Triggs: Histograms of Oriented Gradients

Classification: Classifiers

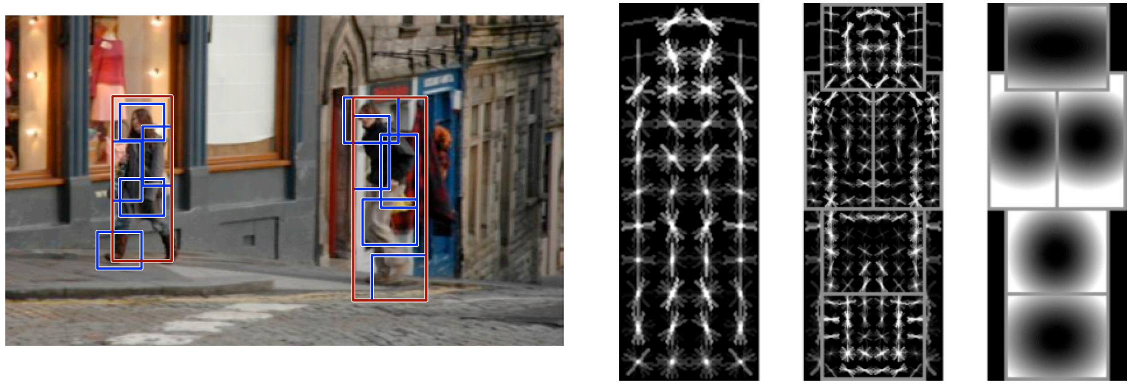
Traditional methods

- AdaBoost
- Support vector machines (SVMs)

- Deep learning methods
  - Neural networks

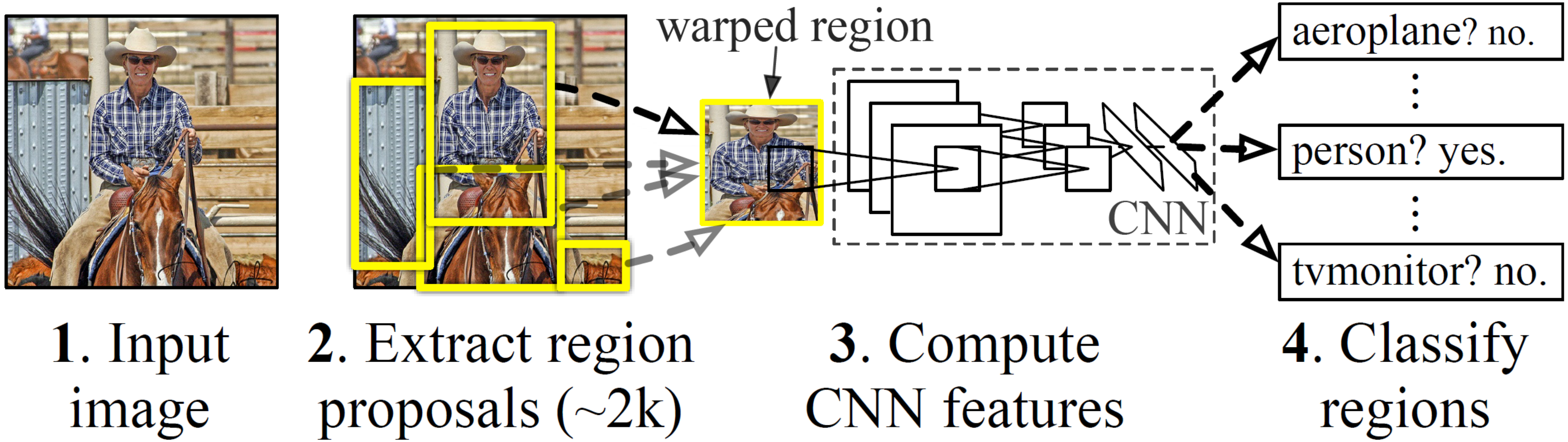


Viola and Jones: AdaBoost
Robust Real-time Object Detection. IJCV, 2001.



Felzenszwalb et al: SVM
Object detection with discriminatively trained part-based models . TPAMI, 2009.

R-CNN



Selective Search

SVM

Rich feature hierarchies for accurate object detection and semantic segmentation. Girshick et al., CVPR, 2014

R-CNN

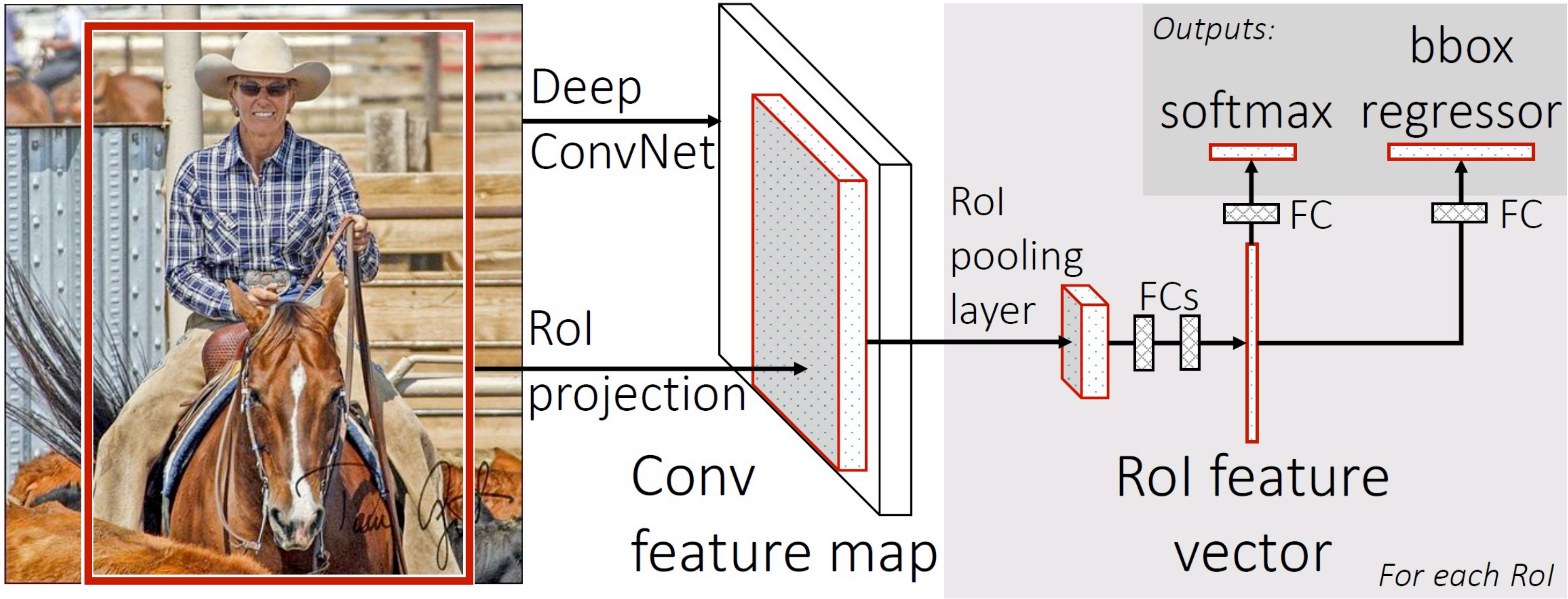
VOC 2007 test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
R-CNN pool$_5$	51.8	60.2	36.4	27.8	23.2	52.8	60.6	49.2	18.3	47.8	44.3	40.8	56.6	58.7	42.4	23.4	46.1	36.7	51.3	55.7	44.2
R-CNN fc$_6$	59.3	61.8	43.1	34.0	25.1	53.1	60.6	52.8	21.7	47.8	42.7	47.8	52.5	58.5	44.6	25.6	48.3	34.0	53.1	58.0	46.2
R-CNN fc$_7$	57.6	57.9	38.5	31.8	23.7	51.2	58.9	51.4	20.0	50.5	40.9	46.0	51.6	55.9	43.3	23.3	48.1	35.3	51.0	57.4	44.7
R-CNN FT pool$_5$	58.2	63.3	37.9	27.6	26.1	54.1	66.9	51.4	26.7	55.5	43.4	43.1	57.7	59.0	45.8	28.1	50.8	40.6	53.1	56.4	47.3
R-CNN FT fc$_6$	63.5	66.0	47.9	37.7	29.9	62.5	70.2	60.2	32.0	57.9	47.0	53.5	60.1	64.2	52.2	31.3	55.0	50.0	57.7	63.0	53.1
R-CNN FT fc$_7$	64.2	69.7	50.0	41.9	32.0	62.6	71.0	60.7	32.7	58.5	46.5	56.1	60.6	66.8	54.2	31.5	52.8	48.9	57.9	64.7	54.2
R-CNN FT fc$_7$ BB	**68.1**	**72.8**	**56.8**	**43.0**	**36.8**	**66.3**	**74.2**	**67.6**	**34.4**	**63.5**	**54.5**	**61.2**	**69.1**	**68.6**	**58.7**	**33.4**	**62.9**	**51.1**	**62.5**	**64.8**	**58.5**
DPM v5 [20]	33.2	60.3	10.2	16.1	27.3	54.3	58.2	23.0	20.0	24.1	26.7	12.7	58.1	48.2	43.2	12.0	21.1	36.1	46.0	43.5	33.7
DPM ST [28]	23.8	58.2	10.5	8.5	27.1	50.4	52.0	7.3	19.2	22.8	18.1	8.0	55.9	44.8	32.4	13.3	15.9	22.8	46.2	44.9	29.1
DPM HSC [31]	32.2	58.3	11.5	16.3	30.6	49.9	54.8	23.5	21.5	27.7	34.0	13.7	58.1	51.6	39.9	12.4	23.5	34.4	47.4	45.2	34.3

BB: bounding box regression

Features from AlexNet

Rich feature hierarchies for accurate object detection and semantic segmentation. Girshick et al., CVPR, 2014

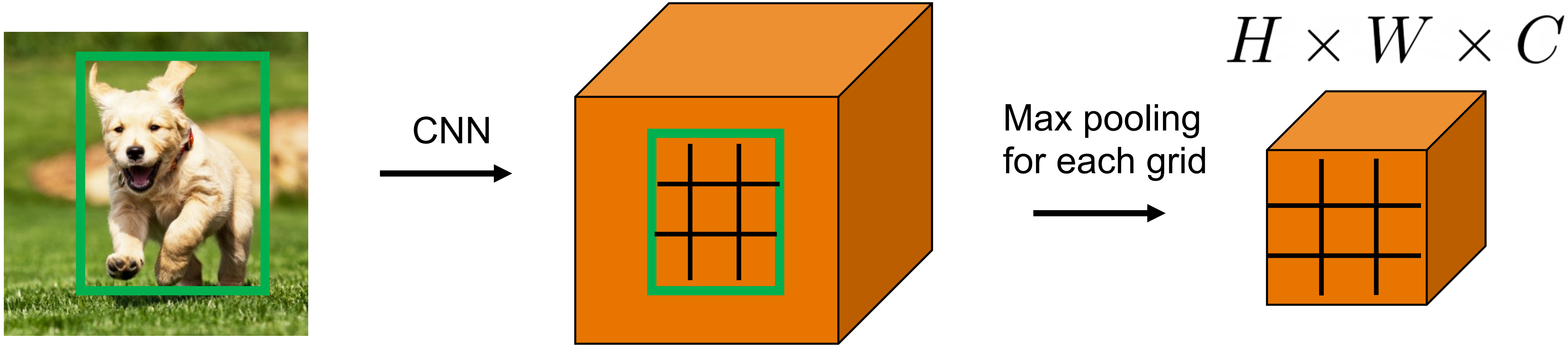
Fast R-CNN



Fast R-CNN. Girshick, ICCV, 2015

RoI Pooling

Divide the mapping RoI into H x W grids



RoI

$$(x, y, h, w)$$

RoI mapping to feature map

$$s \times (x, y, h, w)$$

$$s = \frac{1}{16}$$

7×7 RoI pooling in Fast R-CNN

Bounding Box Regression

Predict bounding box regression offset for K object classes

$$t^k = \left(t^k_{\mathrm{x}}, t^k_{\mathrm{y}}, t^k_{\mathrm{w}}, t^k_{\mathrm{h}}\right)$$

$$\begin{aligned} t_x &= (G_x - P_x)/P_w \\ t_y &= (G_y - P_y)/P_h \\ t_w &= \log(G_w/P_w) \\ t_h &= \log(G_h/P_h). \end{aligned}$$

$$\begin{aligned} \hat{G}_x &= P_w d_x(P) + P_x \\ \hat{G}_y &= P_h d_y(P) + P_y \\ \hat{G}_w &= P_w \exp(d_w(P)) \\ \hat{G}_h &= P_h \exp(d_h(P)). \end{aligned}$$

G: ground truth, P: input RoI

Fast R-CNN

Bounding box regress target

Loss function

$$L(p, u, t^u, v) = L_{\text{cls}}(p, u) + \lambda[u \geq 1] L_{\text{loc}}(t^u, v)$$

Softmax classification probabilities

$$p = (p_0, \ldots, p_K)$$

True class label

Bounding box regress prediction

$$t^u = (t^u_{\text{x}}, t^u_{\text{y}}, t^u_{\text{w}}, t^u_{\text{h}})$$

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

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

Fast R-CNN

	Fast R-CNN			R-CNN			SPPnet
	S	**M**	**L**	**S**	**M**	**L**	†**L**
train time (h)	**1.2**	2.0	9.5	22	28	84	25
train speedup	**18.3**×	14.0×	8.8×	1×	1×	1×	3.4×
test rate (s/im)	0.10	0.15	0.32	9.8	12.1	47.0	2.3
▷ with SVD	**0.06**	0.08	0.22	-	-	-	-
test speedup	98×	80×	146×	1×	1×	1×	20×
▷ with SVD	169×	150×	**213**×	-	-	-	-
VOC07 mAP	57.1	59.2	**66.9**	58.5	60.2	66.0	63.1
▷ with SVD	56.5	58.7	66.6	-	-	-	-

S: AlexNet, M: VGG, L: deep VGG

SVD for FCs layers

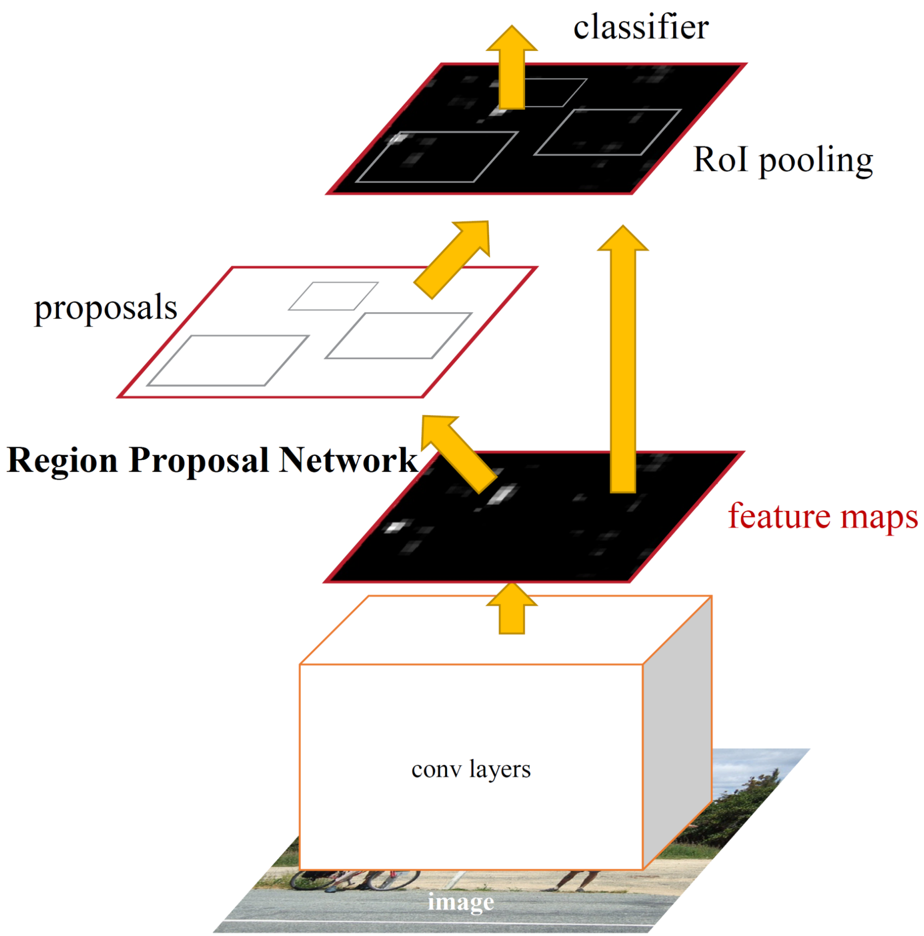
$$W \approx U \Sigma_t V^T$$

Fast R-CNN. Girshick, ICCV, 2015

Faster R-CNN

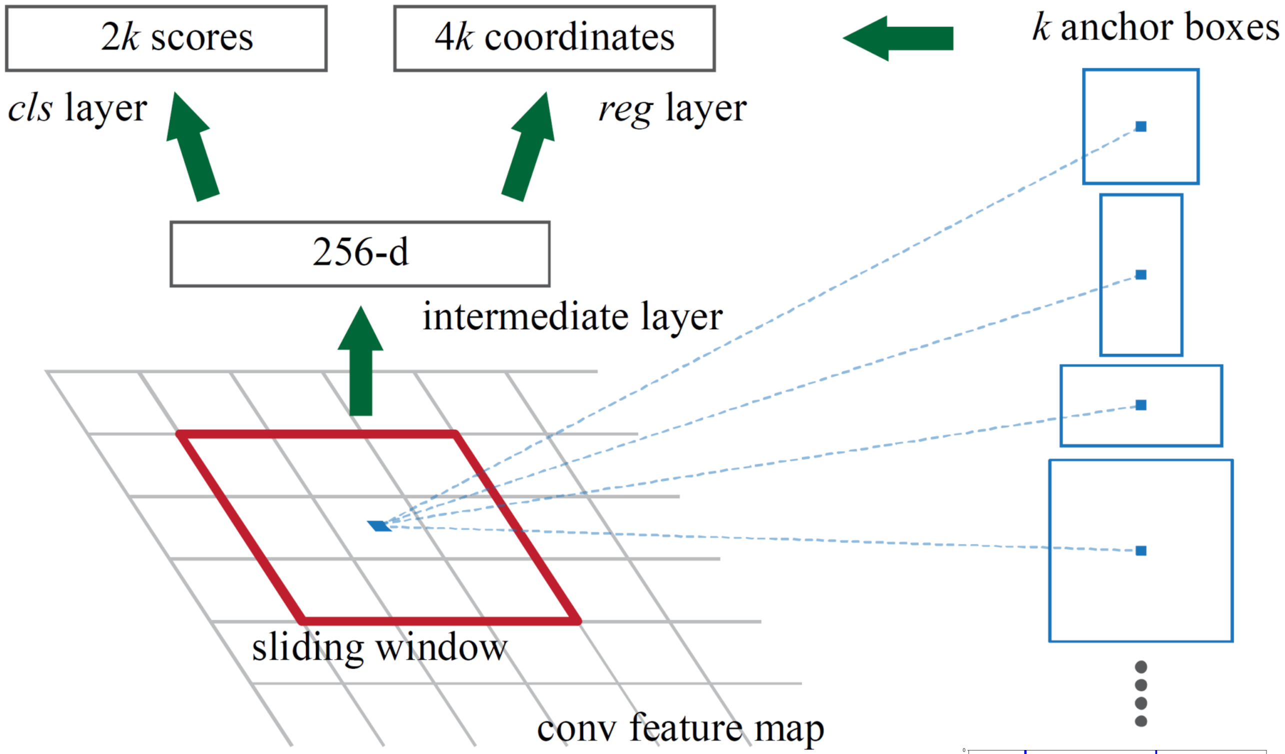
A single network for object detection

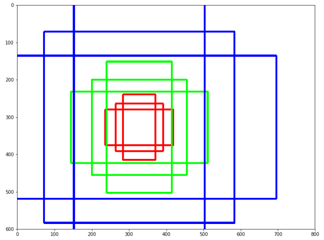
- Region proposal network
- Classification network



Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. Ren et al., NeurIPS, 2015

Region Proposal Network





3x3 conv layer to 256-d

```
layer {
  name: "rpn_conv/3x3"
  type: "Convolution"
  bottom: "conv5"
  top: "rpn/output"
  param { lr_mult: 1.0 }
  param { lr_mult: 2.0 }
  convolution_param {
    num_output: 256
    kernel_size: 3 pad: 1 stride: 1
    weight_filler { type: "gaussian" std: 0.01 }
    bias_filler { type: "constant" value: 0 }
  }
}
```

classification

```
layer {
  name: "rpn_cls_score"
  type: "Convolution"
  bottom: "rpn/output"
  top: "rpn_cls_score"
  param { lr_mult: 1.0 }
  param { lr_mult: 2.0 }
  convolution_param {
    num_output: 18   # 2(bg/fg) * 9(anchors)
    kernel_size: 1 pad: 0 stride: 1
    weight_filler { type: "gaussian" std: 0.01 }
    bias_filler { type: "constant" value: 0 }
  }
}
```

Bounding box regression

```
layer {
  name: "rpn_bbox_pred"
  type: "Convolution"
  bottom: "rpn/output"
  top: "rpn_bbox_pred"
  param { lr_mult: 1.0 }
  param { lr_mult: 2.0 }
  convolution_param {
    num_output: 36   # 4 * 9(anchors)
    kernel_size: 1 pad: 0 stride: 1
    weight_filler { type: "gaussian" std: 0.01 }
    bias_filler { type: "constant" value: 0 }
  }
}
```

Two stage vs One stage

Two stage detection methods

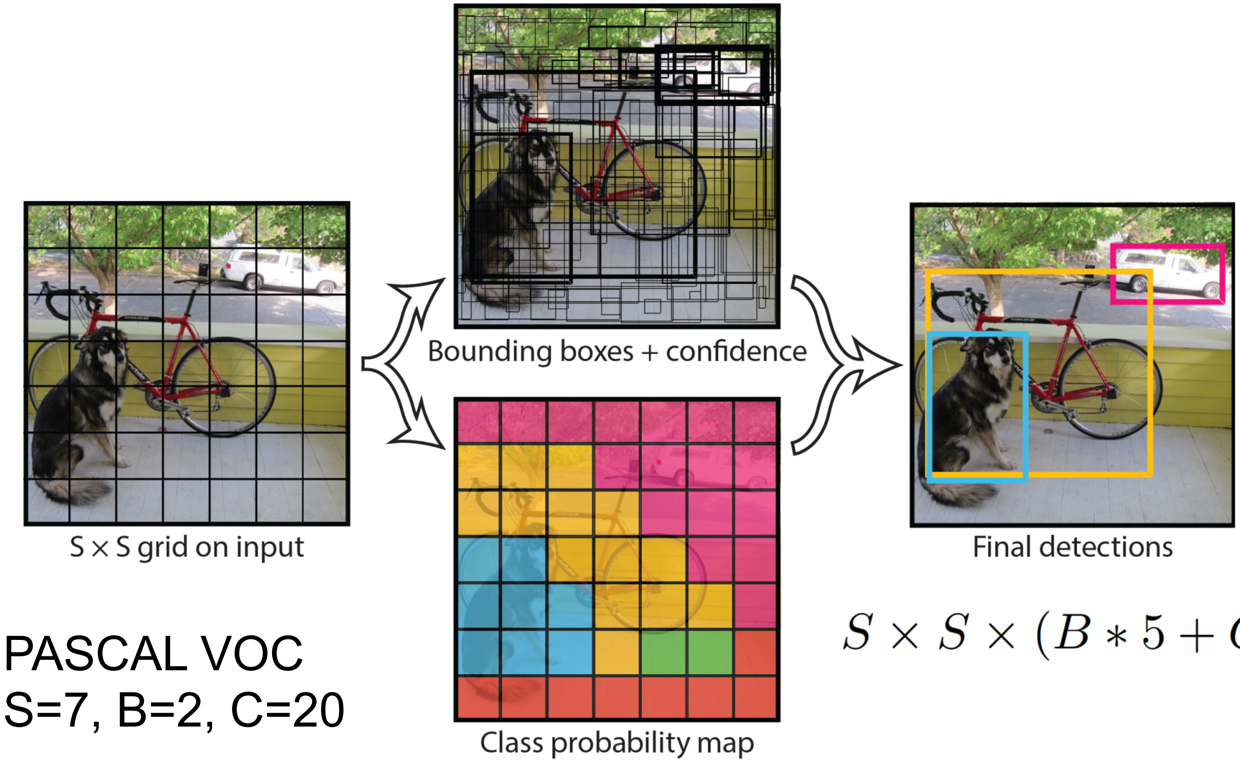
- Stage 1: generate region proposals
- Stage 2: classify region proposals and refine their locations
- E.g., R-CNN, Fast R-CNN, Faster R-CNN

One stage detection methods

- An end-to-end network for object detection
- E.g., YOLO

YOLO

Regress to bounding box locations and class probabilities



$$S \times S \times (B * 5 + C)$$

PASCAL VOC
S=7, B=2, C=20

- Each grid handles objects with centers (x, y) in it
- Each grid predicts B bounding boxes
- Each bounding box predicts (x, y, w, h) and confidence (IoU of box and ground truth box)

$$\Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}}$$

- Each grid also predicts C class probabilities

$$\Pr(\text{Class}_i | \text{Object})$$

- In testing

$$\Pr(\text{Class}_i | \text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}}$$

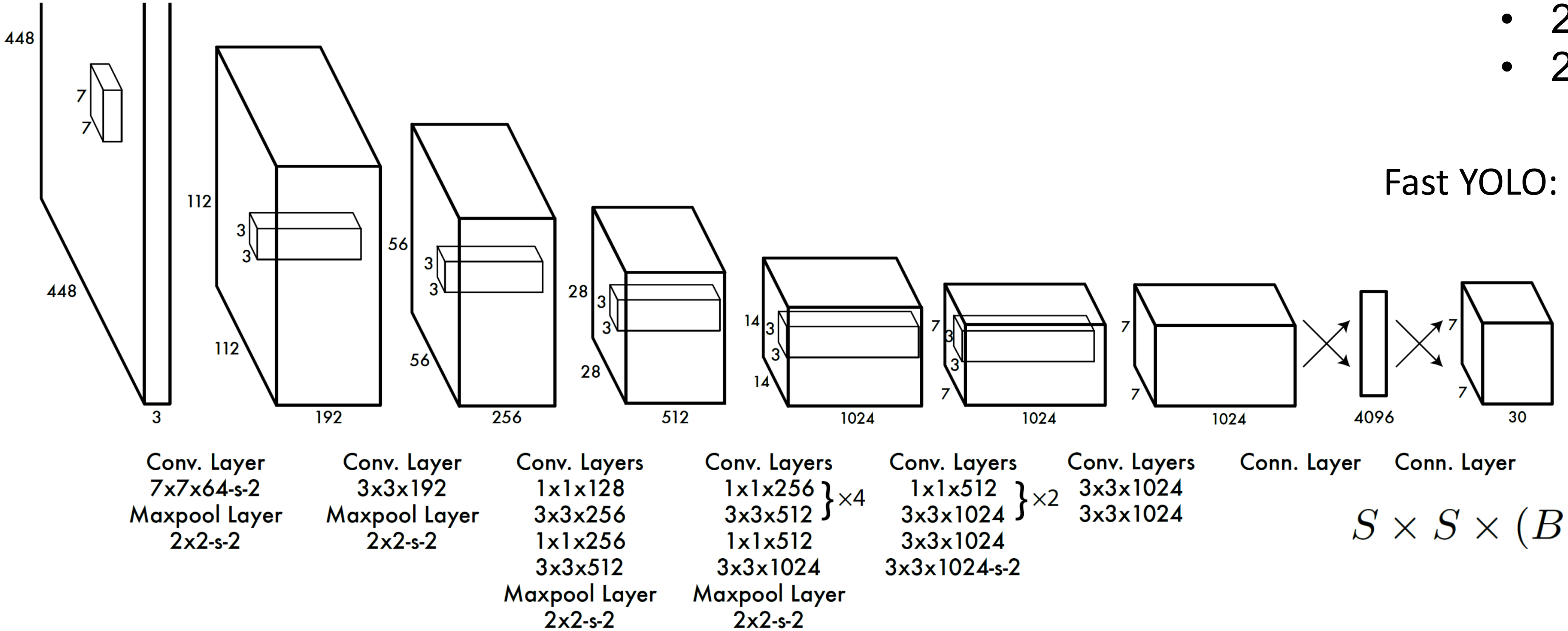
You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

YOLO

Regress to bounding box locations and class probabilities

- 24 convs
- 2 FCs

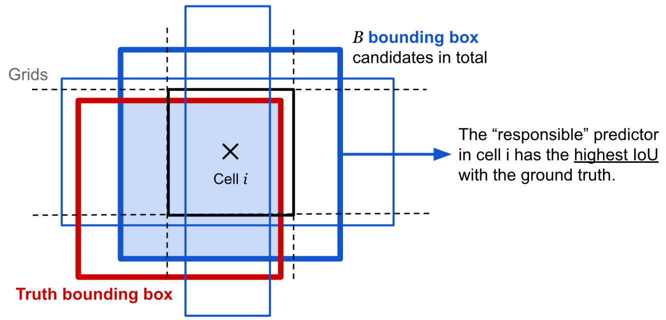
Fast YOLO: 9 convs, less filter



$$S \times S \times (B * 5 + C)$$

You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

YOLO



Training loss function

$$\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

Localization loss

$$+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence loss

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

Classification loss

$\mathbb{1}_{ij}^{\text{obj}}$ jth bounding box from cell i "responsible" for the prediction

highest current IOU with the ground truth

$\mathbb{1}_{i}^{\text{obj}}$ Object in cell i

$\lambda_{\text{coord}} = 5 \qquad \lambda_{\text{noobj}} = .5$

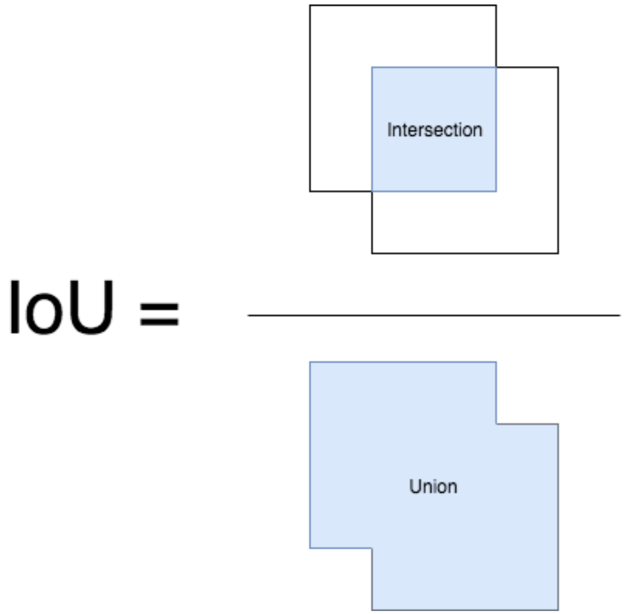
You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

Non-maximum Suppression

Keep the box with the highest confidence/score

Compute IoU between this box and other boxes

Suppress boxes with IoU > threshold



https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

YOLO

Real-Time Detectors	Train	mAP	FPS
100Hz DPM [31]	2007	16.0	100
30Hz DPM [31]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [38]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[28]	2007+2012	73.2	7
Faster R-CNN ZF [28]	2007+2012	62.1	18
YOLO VGG-16	2007+2012	66.4	21

You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

YOLOv2 and YOLOv3

YOLOv2

- Batch normalization (normalization of the layers' inputs by re-centering and re-scaling)
- High resolution classifier 416x416
- Convolutional with anchor boxes (remove FC layers)
- Dimension clustering to decide the anchor boxes
- Multi-scale training (change input image size)

YOLOv3

- Binary cross-entropy loss for the class predictions
- Prediction across scales

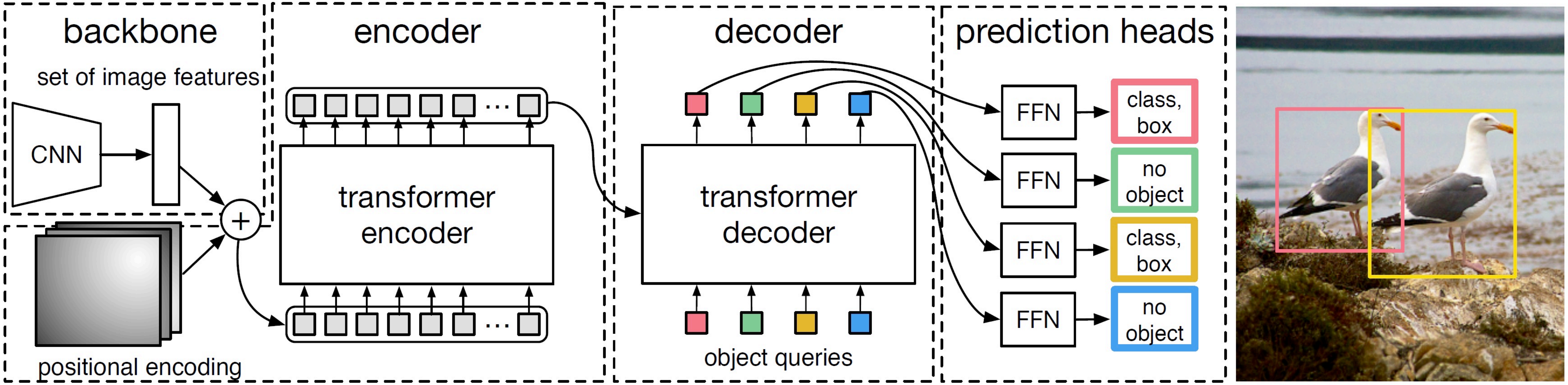
	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Table 1. **Darknet-53.**

YOLO9000: Better, Faster, Stronger. Redmon & Farhadi, CVPR, 2017
YOLOv3: An Incremental Improvement

DTER

Vision transformer-based object detection



End-to-End Object Detection with Transformers. Carion et al., ECCV, 2020

Summary

Two-stage detectors

- R-CNN, Fast R-CNN, Faster R-CNN
- Region proposal + classification
- Good performance, slow

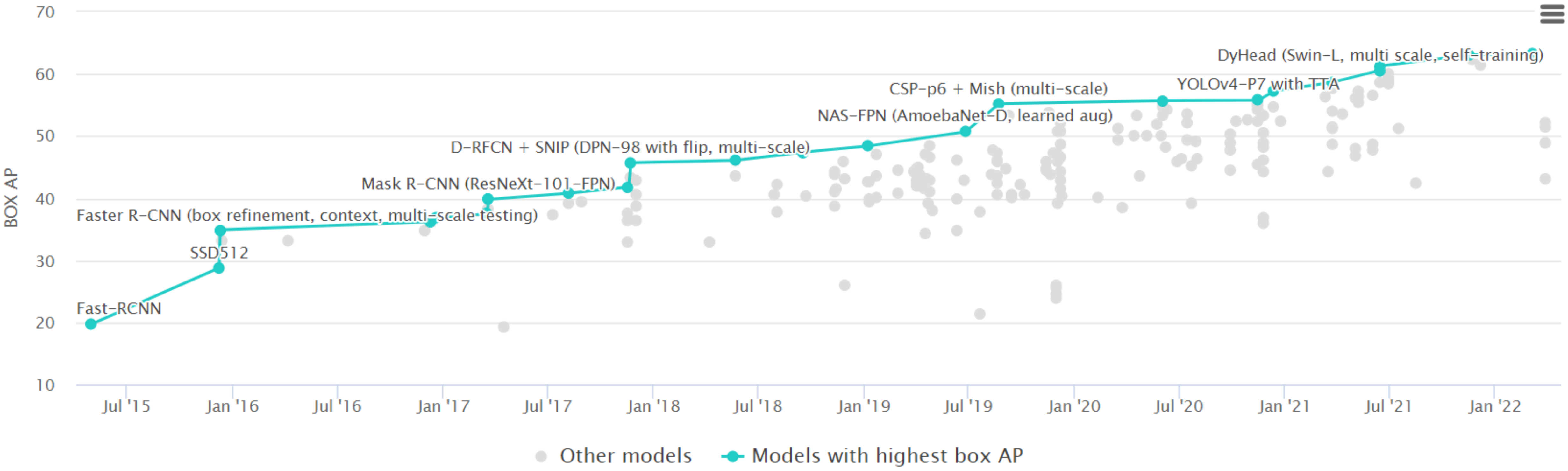
One-stage detectors

- YOLO, SSD
- End-to-end network to regress to bounding boxes
- Fast, comparable performance to two-stage detectors

Transformer-based detectors

- DTER
- Attention-based set prediction, using object queries

Object Detection on COCO test-dev



https://paperswithcode.com/sota/object-detection-on-coco

Further Reading

Viola–Jones object detection, 2001
https://www.cs.cmu.edu/~efros/courses/LBMV07/Papers/viola-cvpr-01.pdf
Deformable part model, 2010,
https://ieeexplore.ieee.org/document/5255236
R-CNN, 2014 https://arxiv.org/abs/1311.2524
Fast R-CNN, 2015 https://arxiv.org/abs/1504.08083
Faster R-CNN, 2015 https://arxiv.org/abs/1506.01497
YOLO, 2015 https://arxiv.org/abs/1506.02640
YOLOv2, 2016 https://arxiv.org/abs/1612.08242
Feature Pyramid Networks, 2017 https://arxiv.org/pdf/1612.03144.pdf
DTER, 2020 https://arxiv.org/abs/2005.12872