THE UNIVERSITY OF TEXAS AT DALLAS

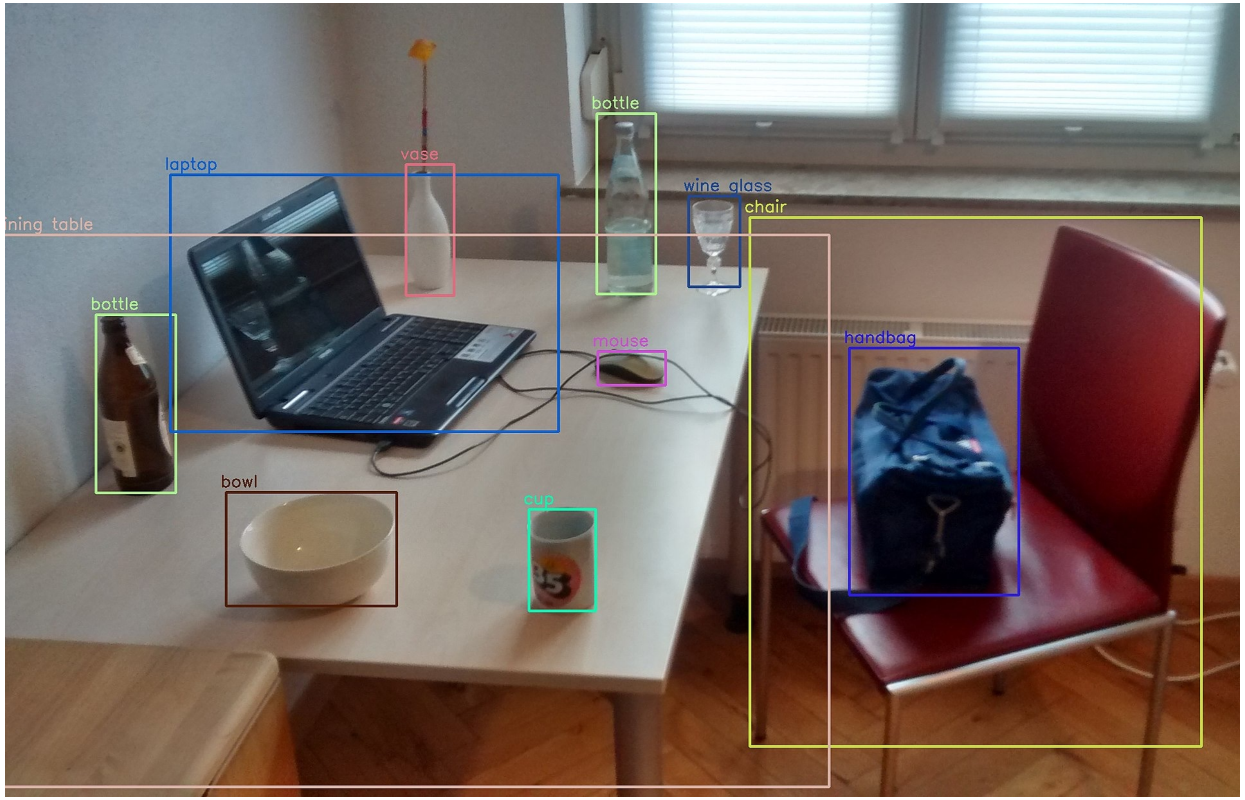
Object Detection

CS 6384 Computer Vision
Professor Yapeng Tian
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

Input Image

Localization

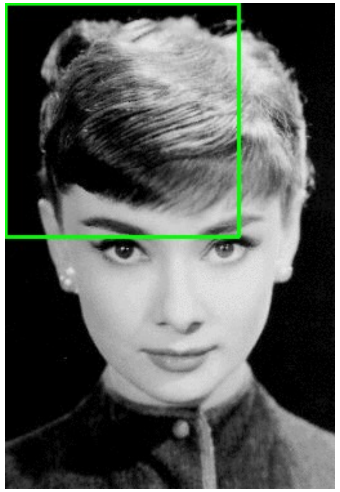
Localization: Sliding Window

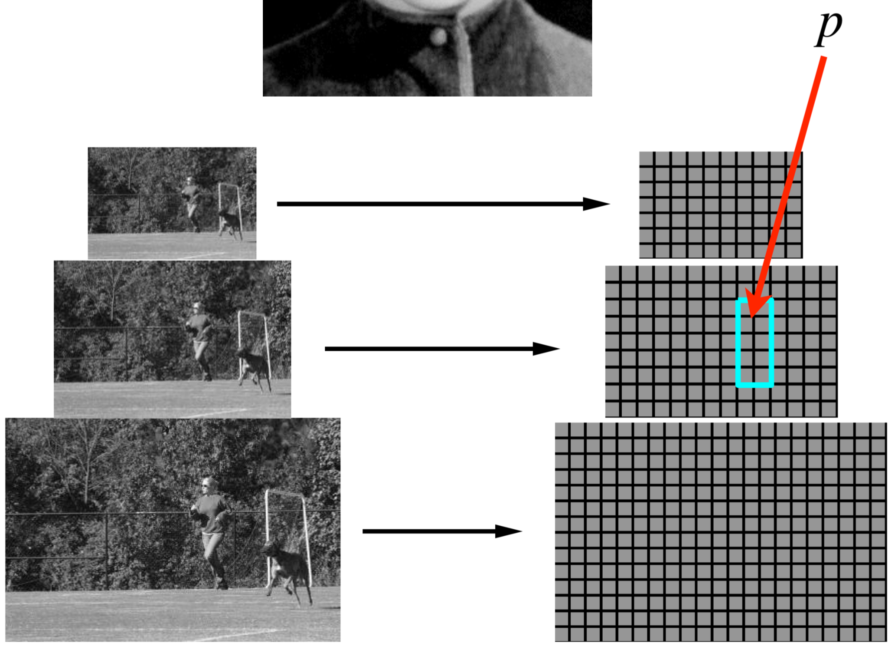
Select a window with a fixed size

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



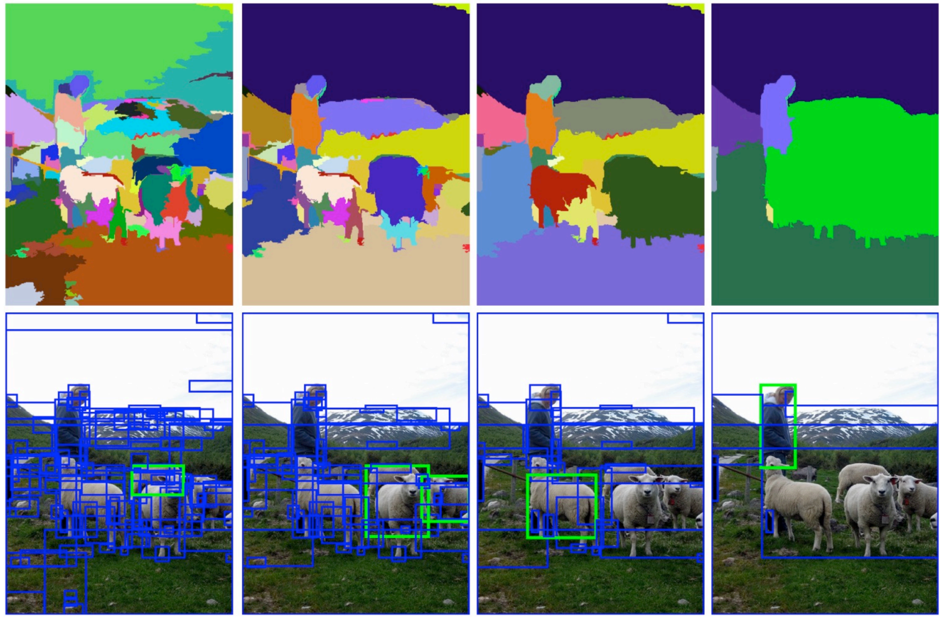


https://cvexplained.wordpress.com/tag/sliding-windows/

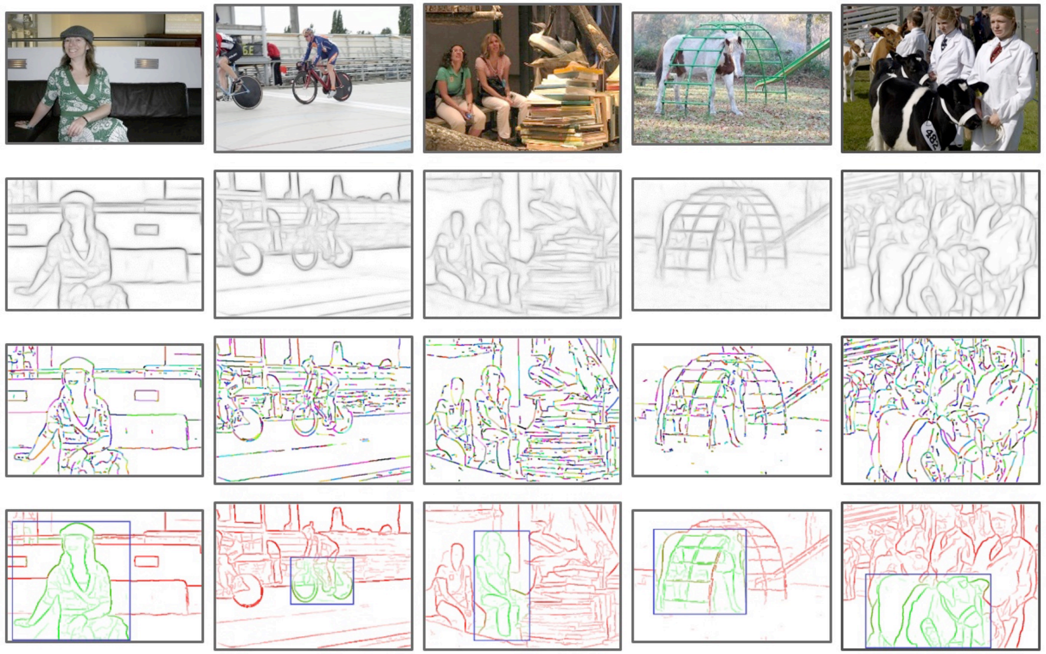
Localization: Region Proposal

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

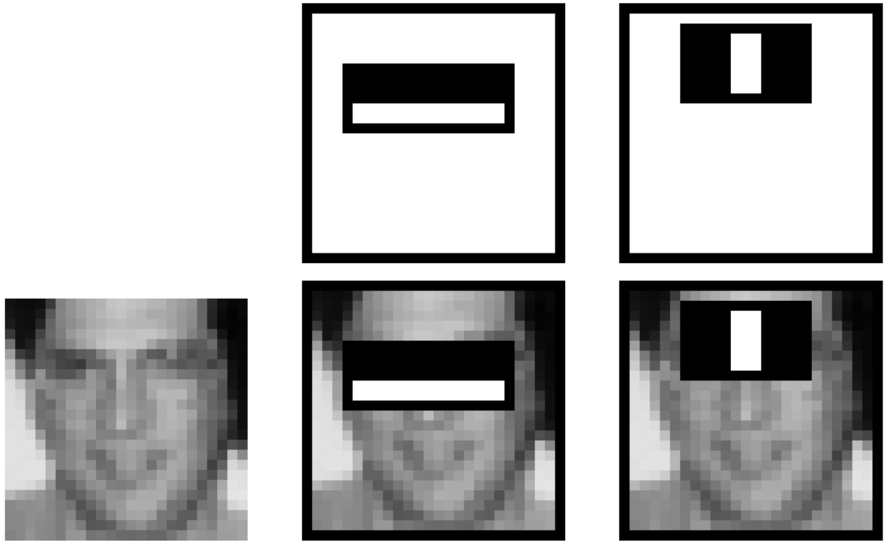


Edge Boxes. Zitnick & Dollar, ECCV'14

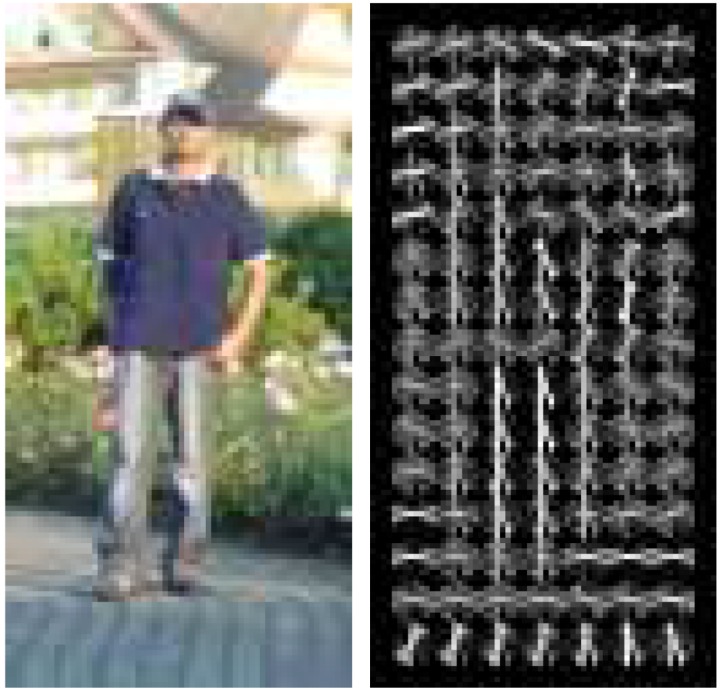
Classification: Features

Traditional methods: Hand-crafted features

Deep learning methods: learned features in the network



Viola and Jones: rectangle features



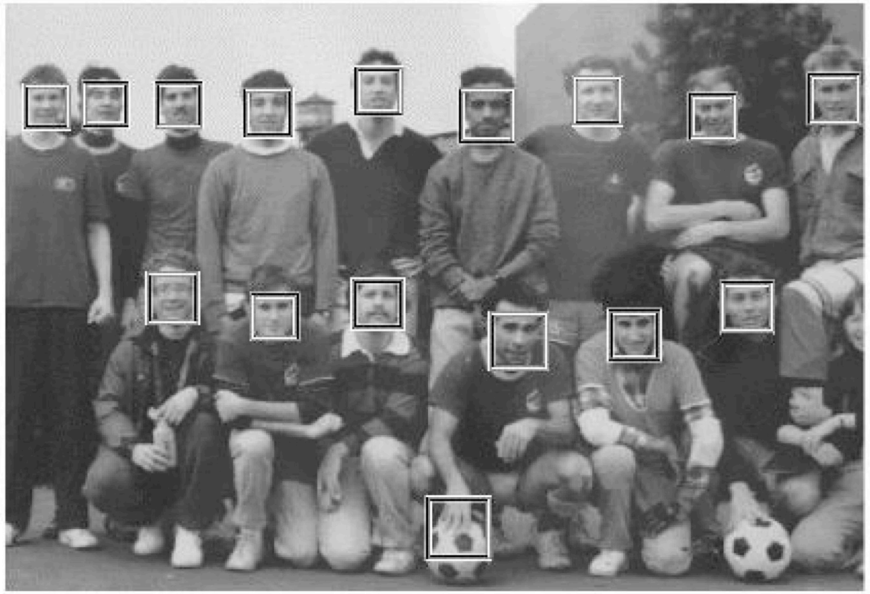
Dadal & Triggs: Histograms of Oriented Gradients

Classification: Classifiers

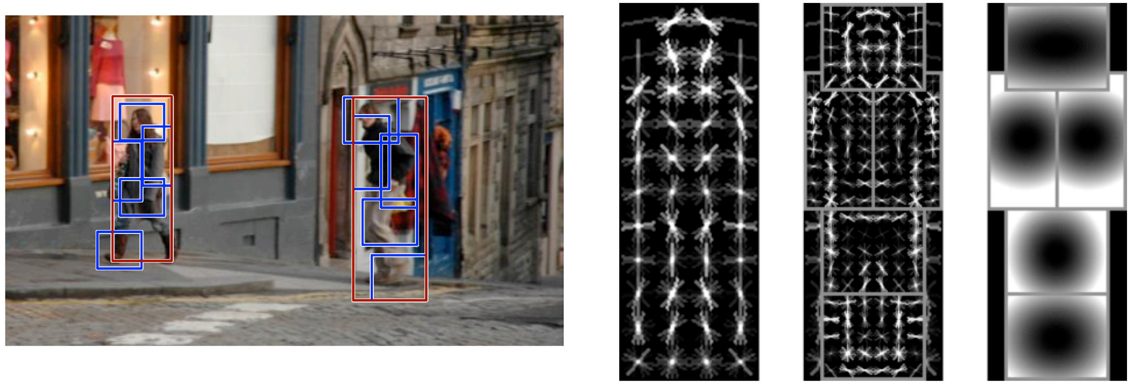
Traditional methods

- AdaBoost
- Support vector machines (SVMs)

- Deep learning methods
  - Neural networks

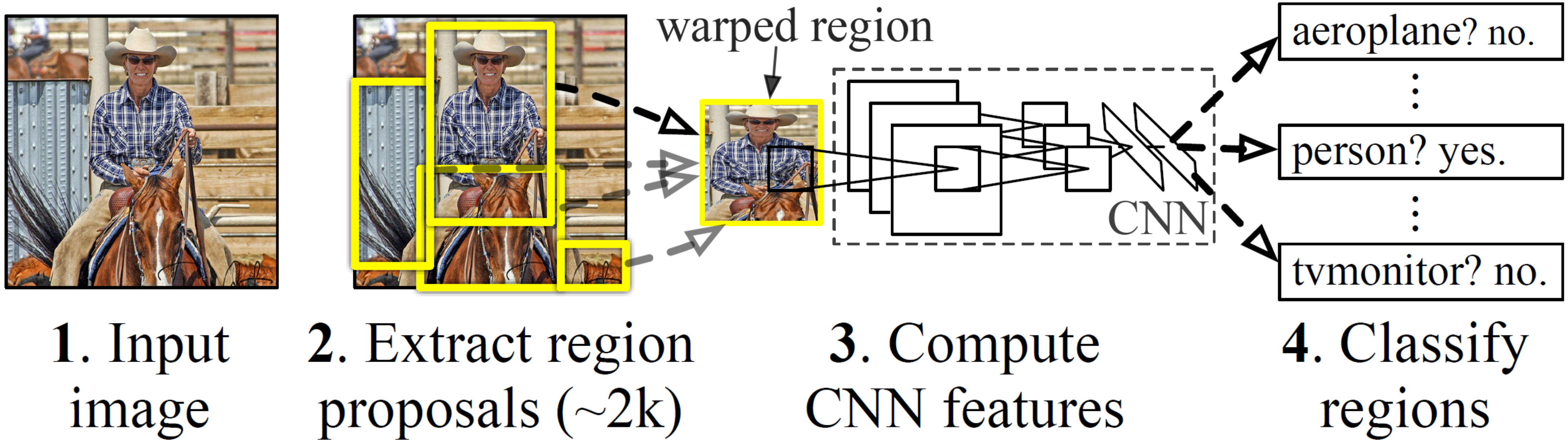


Viola and Jones: AdaBoost
Robust Real-time Object Detection. IJCV, 2001.



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

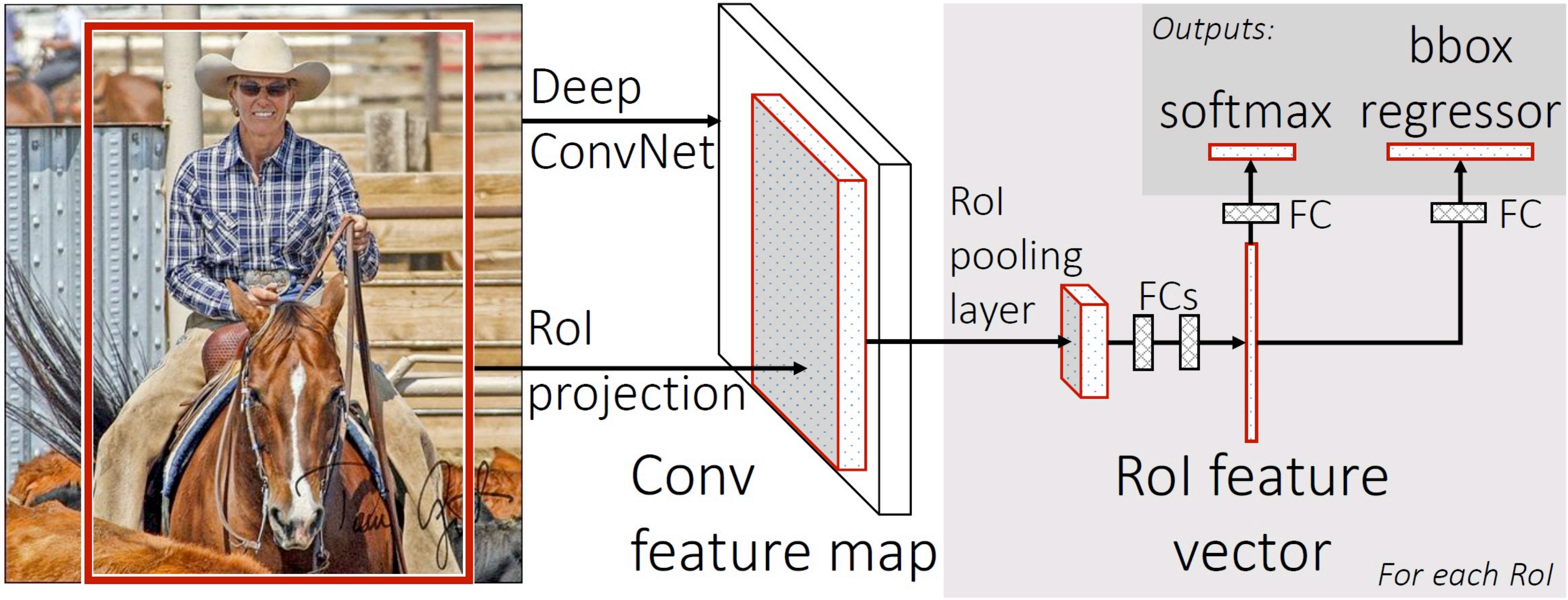
VOC 2007 test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
R-CNN $pool_5$	51.8	60.2	36.4	27.8	23.2	52.8	60.6	49.2	18.3	47.8	44.3	40.8	56.6	58.7	42.4	23.4	46.1	36.7	51.3	55.7	44.2
R-CNN fc_6	59.3	61.8	43.1	34.0	25.1	53.1	60.6	52.8	21.7	47.8	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

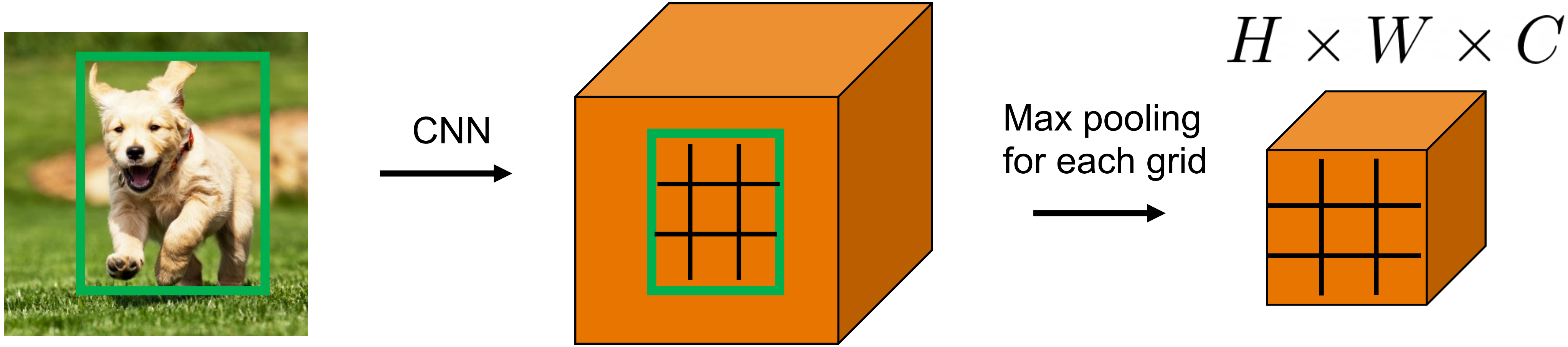
Fast R-CNN



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

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

$$t_x = (G_x - P_x)/P_w$$
$$t_y = (G_y - P_y)/P_h$$
$$t_w = \log(G_w/P_w)$$
$$t_h = \log(G_h/P_h).$$

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

G: ground truth, P: input RoI

Fast R-CNN

Loss function

Bounding box regress target

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

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

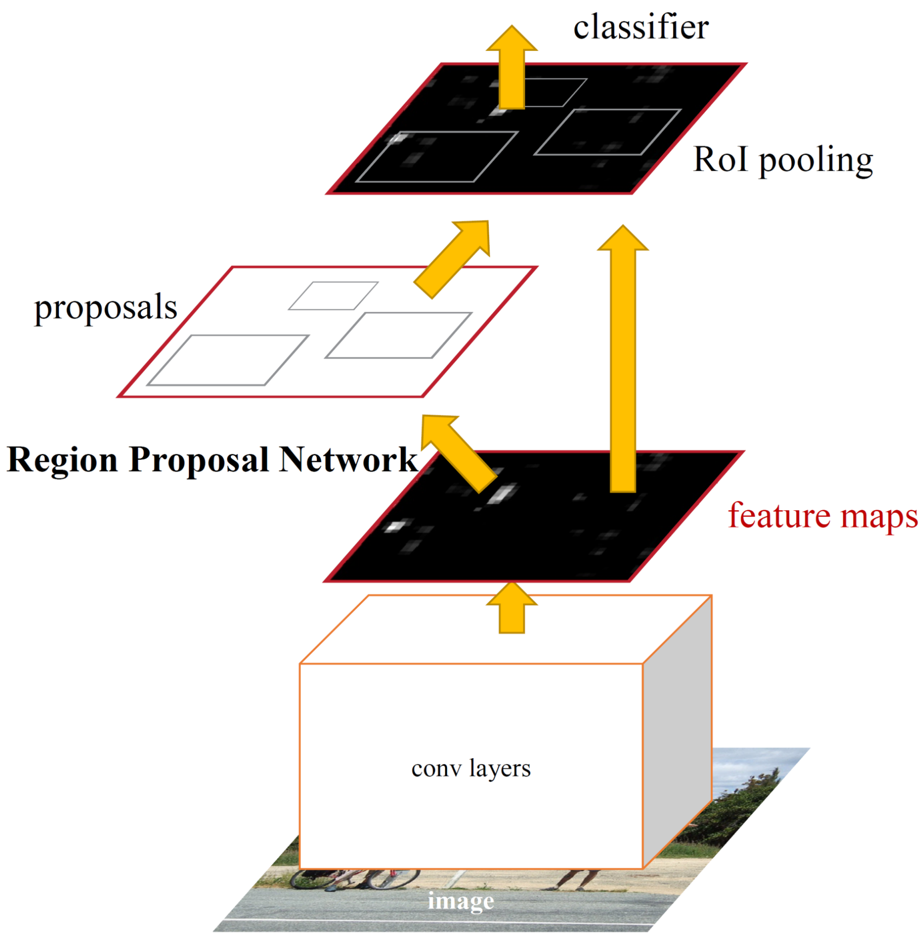
$$W \approx U\Sigma_t V^T$$

Fast R-CNN. Girshick, ICCV, 2015

Faster R-CNN

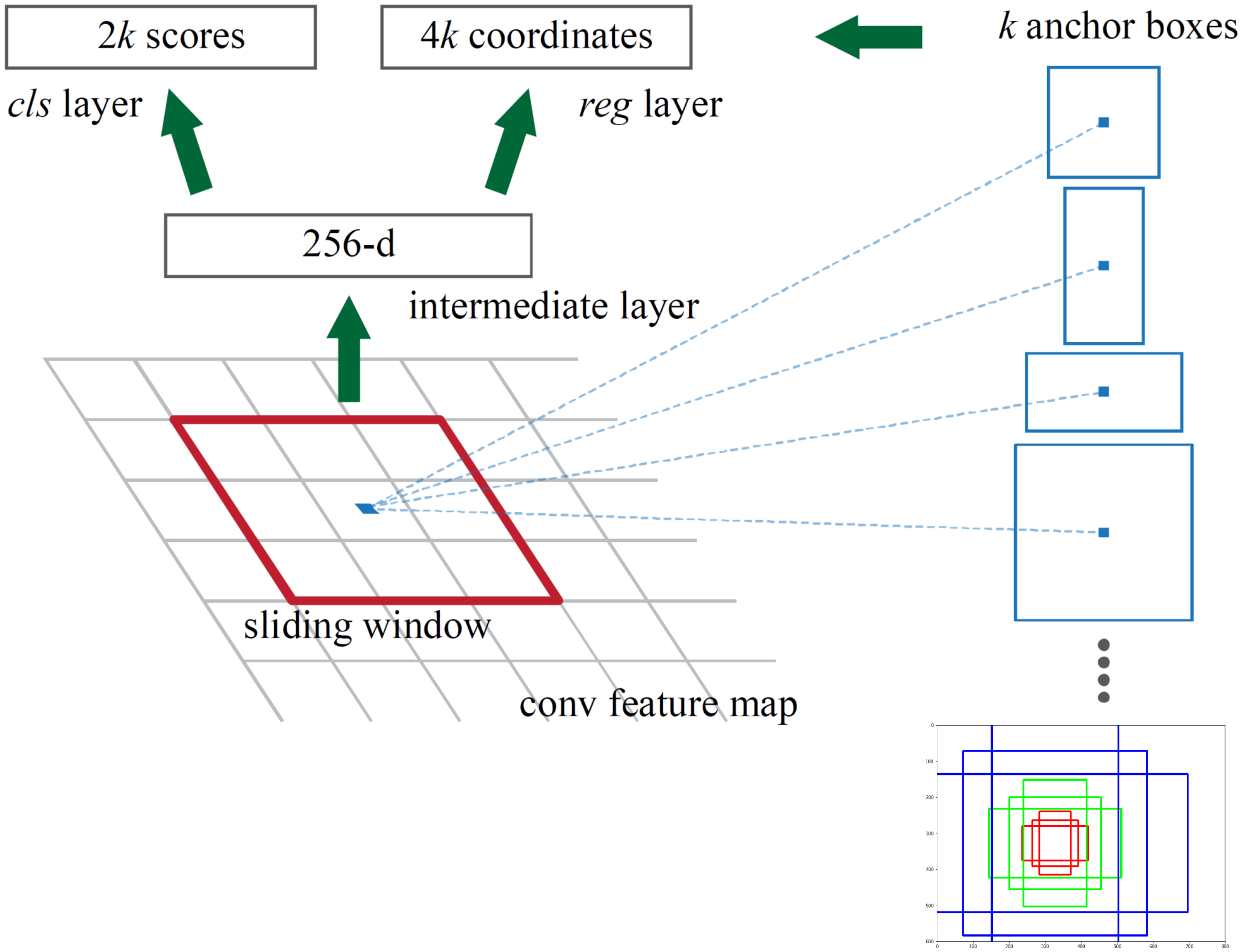
A single network for object detection

- 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

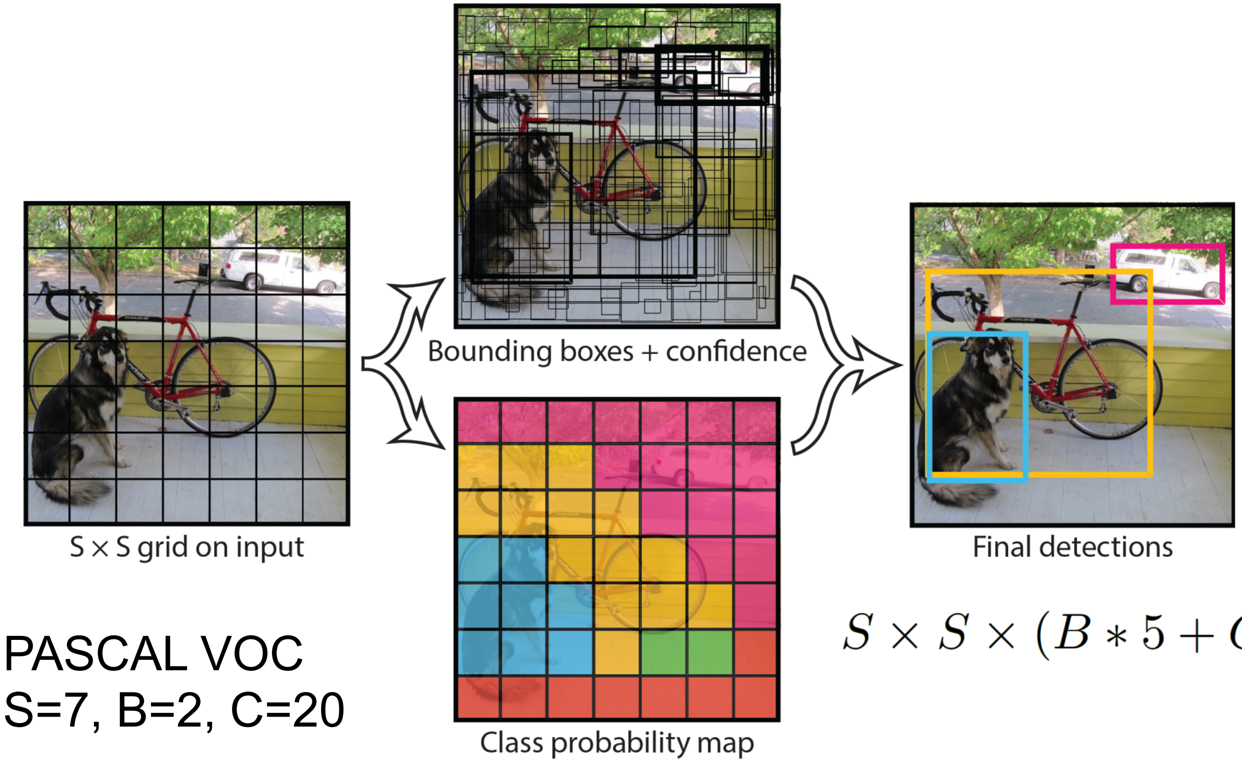
- Stage 1: generate region proposals
- Stage 2: classify region proposals and refine their locations
- E.g., R-CNN, Fast R-CNN, Faster R-CNN

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

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

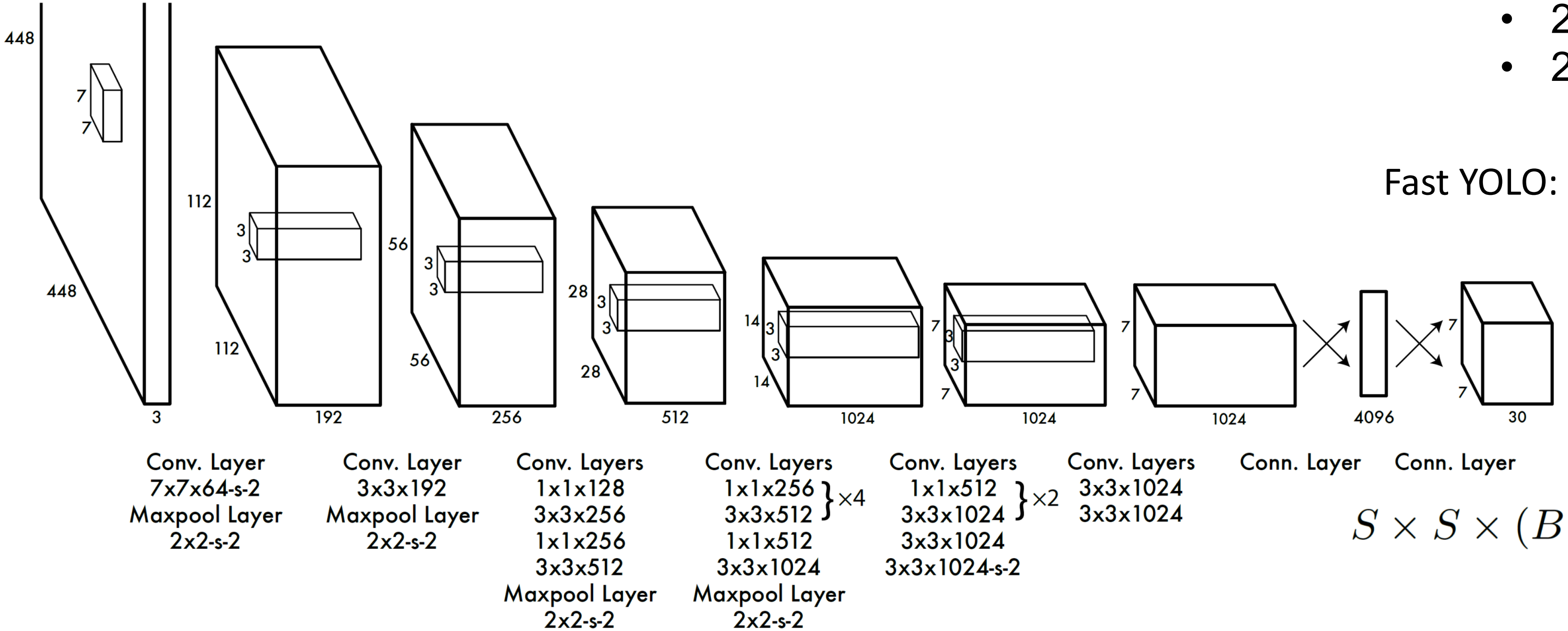
You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

YOLO

Regress to bounding box locations and class probabilities

- 24 convs
- 2 FCs

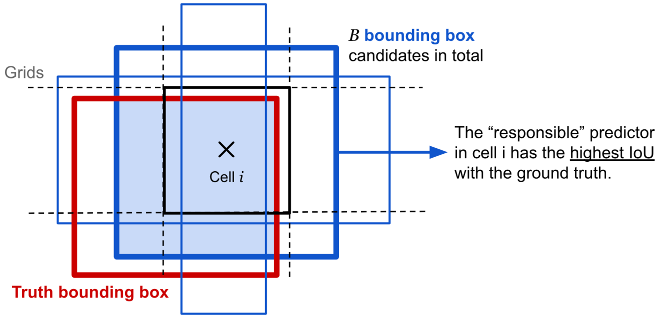
Fast YOLO: 9 convs, less filter



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

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

YOLO



Training loss function

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

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

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

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

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

$\mathbb{1}_{ij}^{\text{obj}}$ 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

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

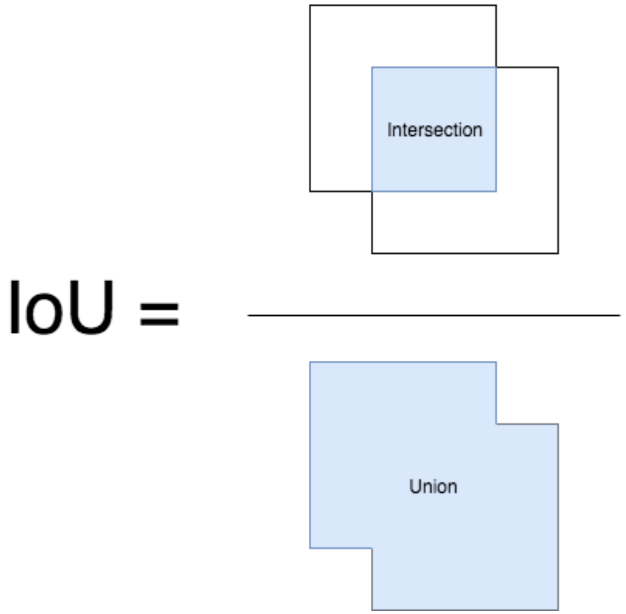
You Only Look Once: Unified, Real-Time Object Detection. Redmon et al., CVPR, 2016

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

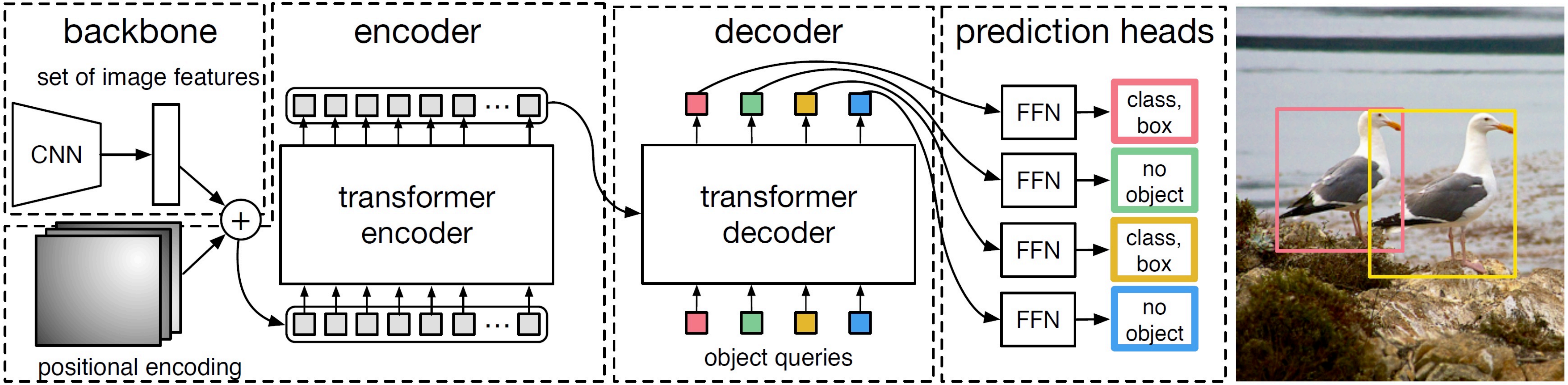
	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 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

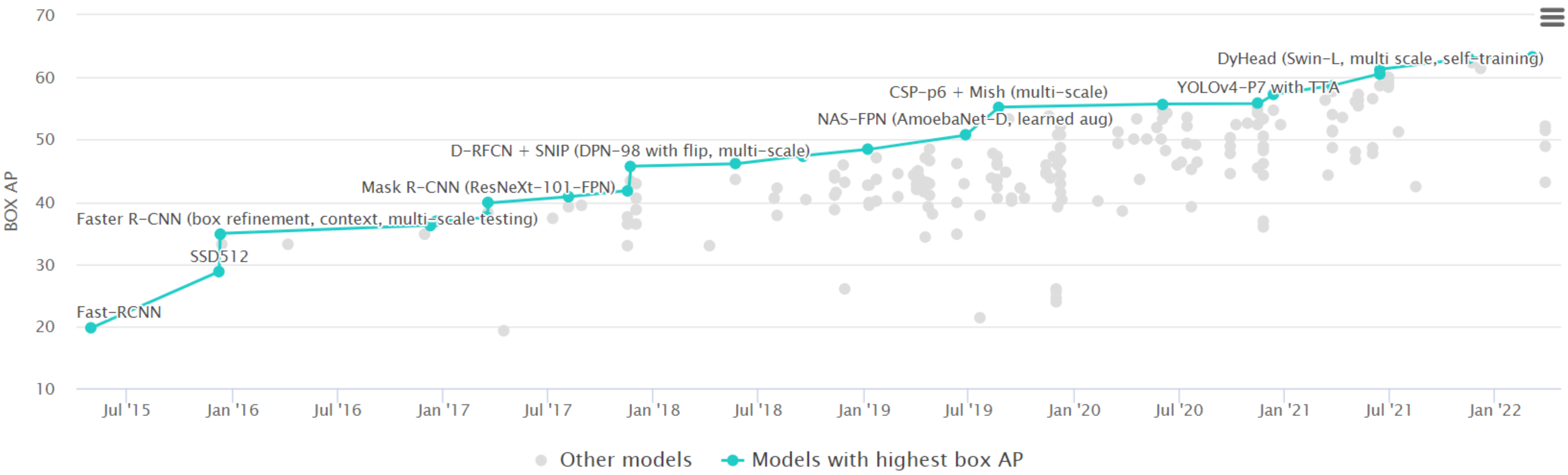
One-stage detectors

- 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