YOLO

You Only Look Once:
Unified, Real-Time Object Detection

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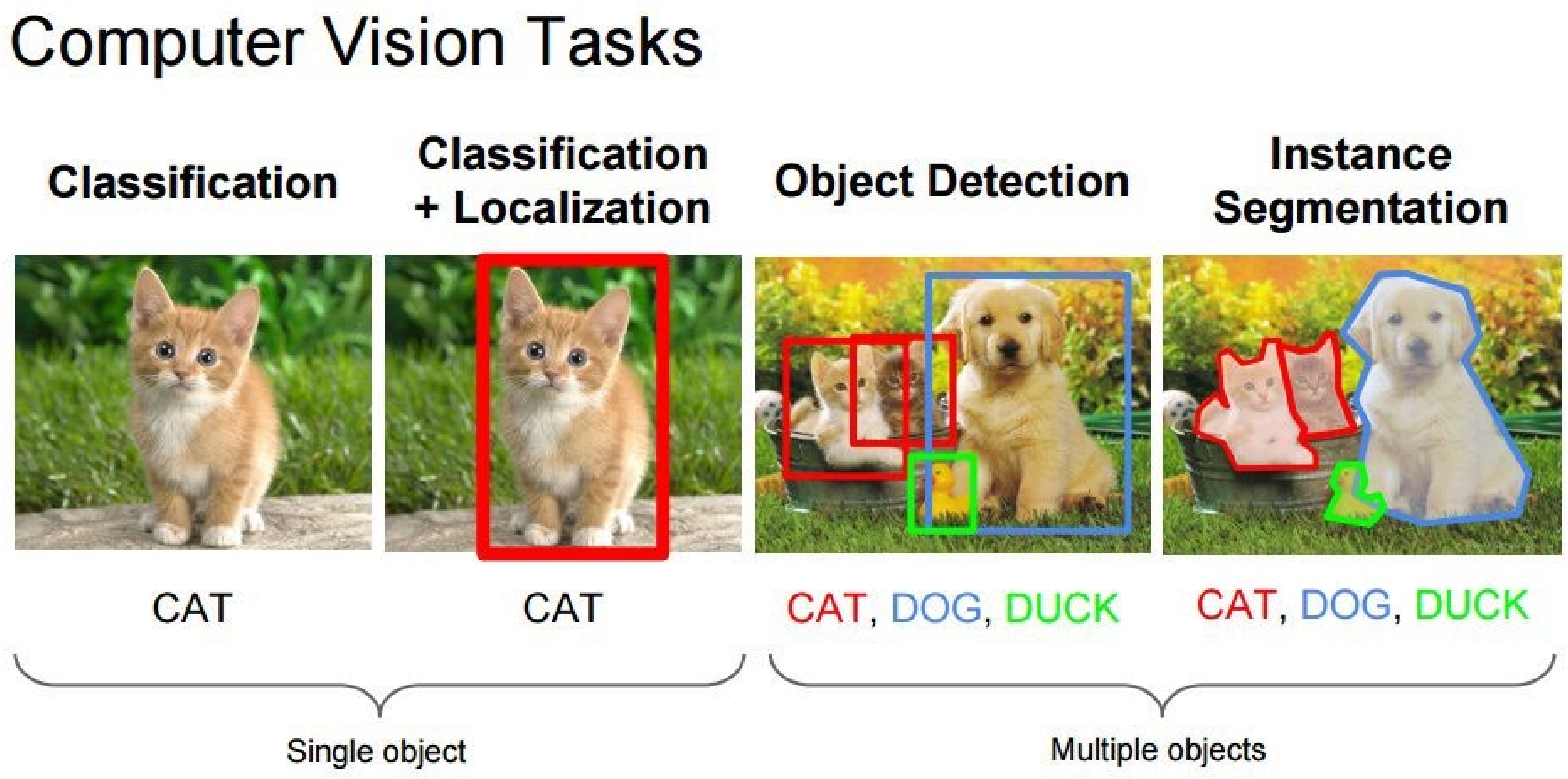
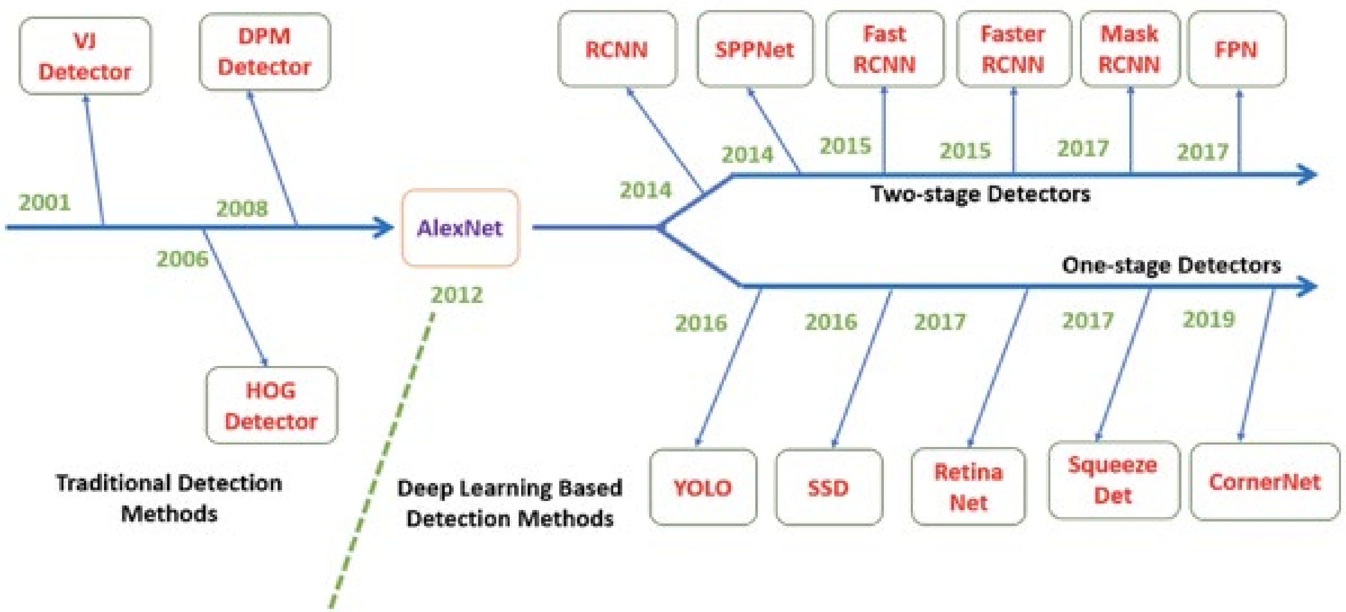
Computer Vision

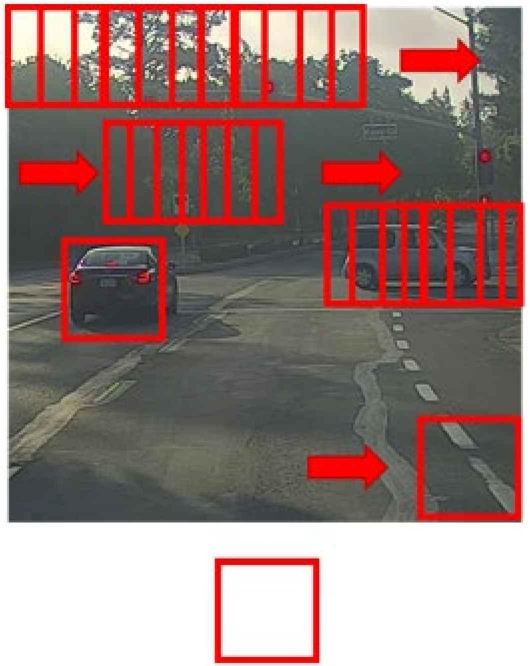


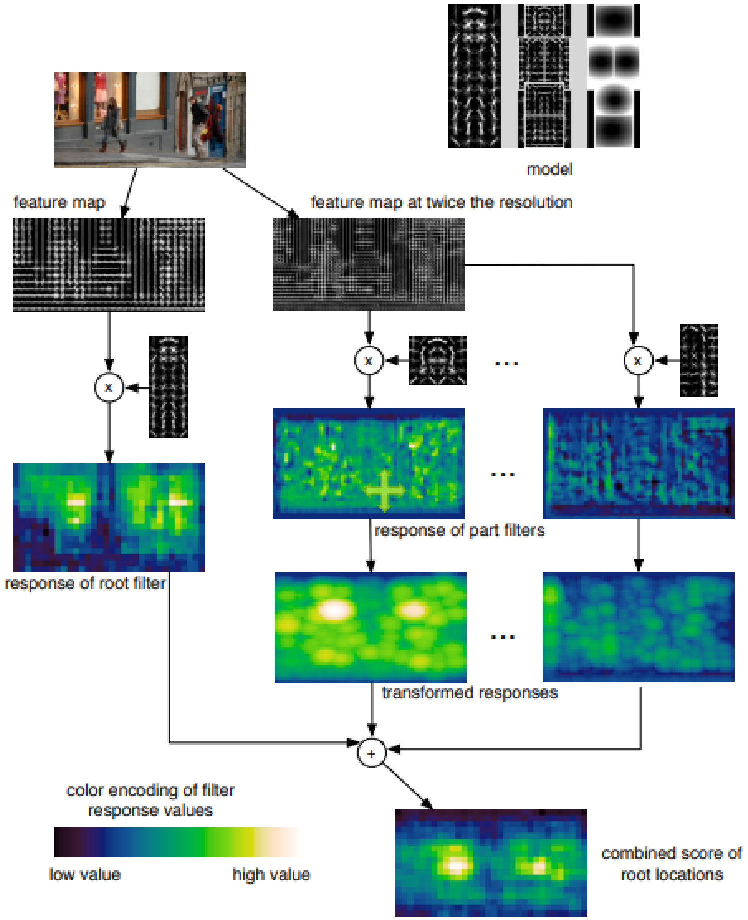
Obejct Detection -> (Multi-Labeled) Classification + Localization

Object Detection

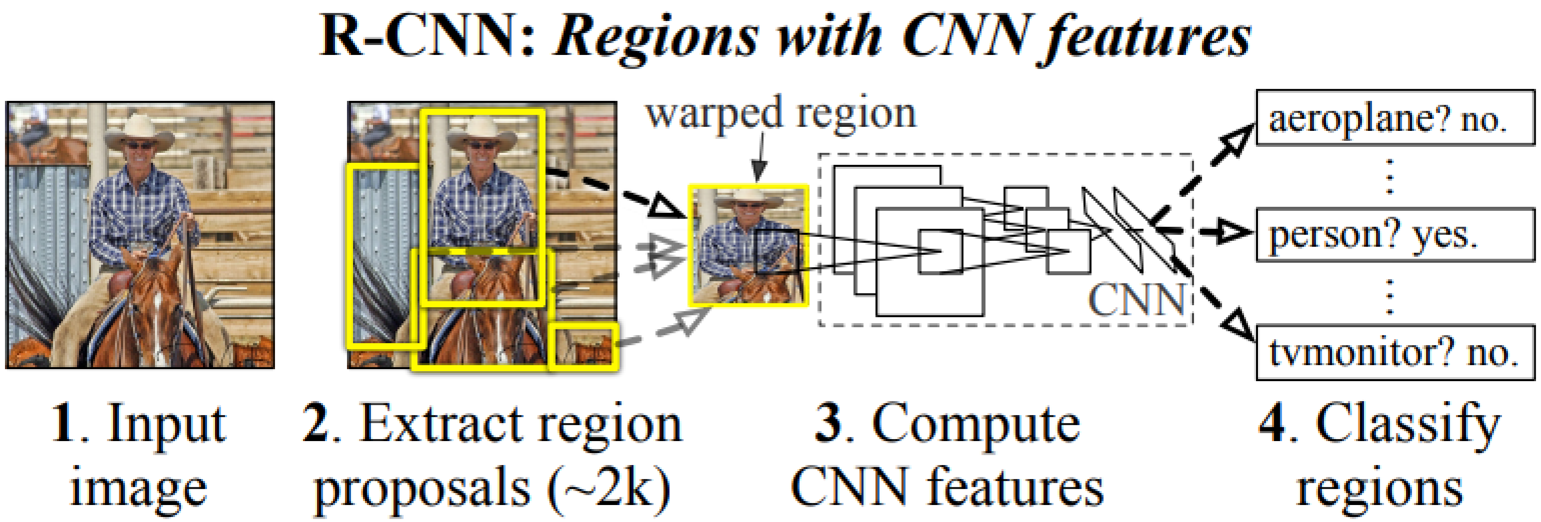


Deformable parts models (DPM)





R-CNN (Regions Based Convolutional Neural Networks)



Region propsals

Region Classification

Real-time object detection

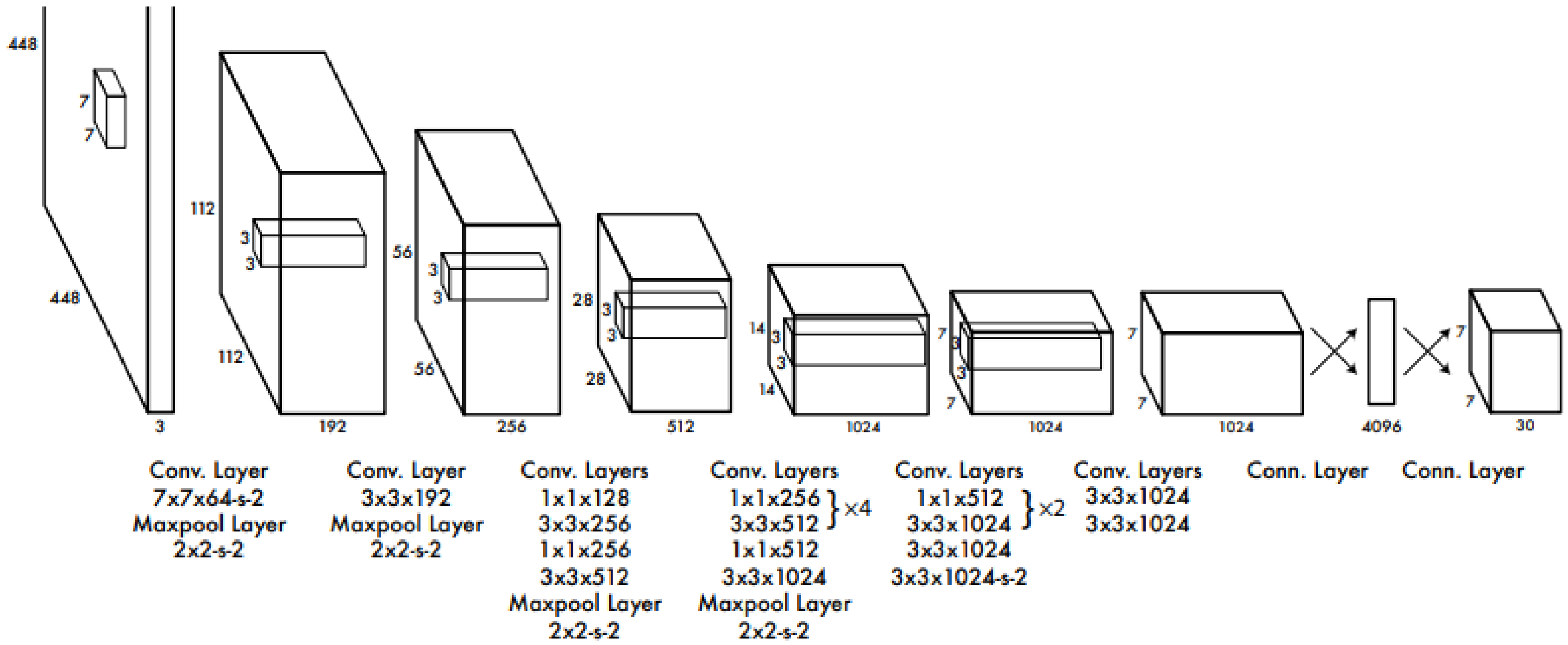
https://www.youtube.com/watch?v=MPU2HistivI

ImageNet

ImageNet 2012
Top-5 Accuracy : 88%

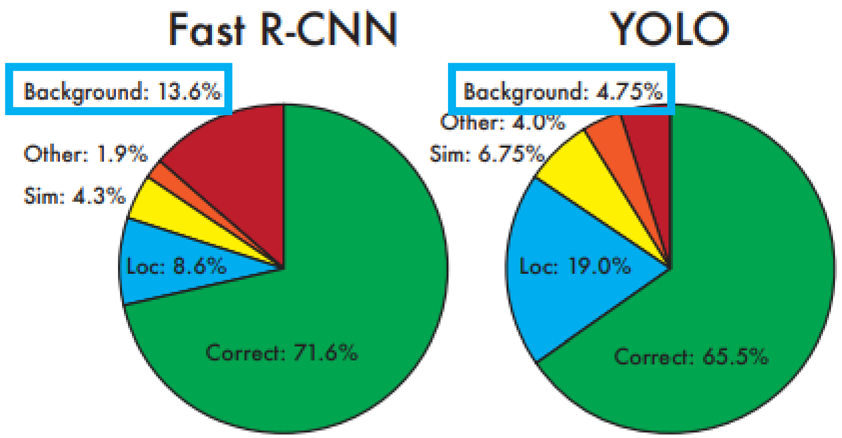
YOLO – Unified Detection

One-state Detector



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



- **FPS** mean Frame Rate
- GPU : TITAN X

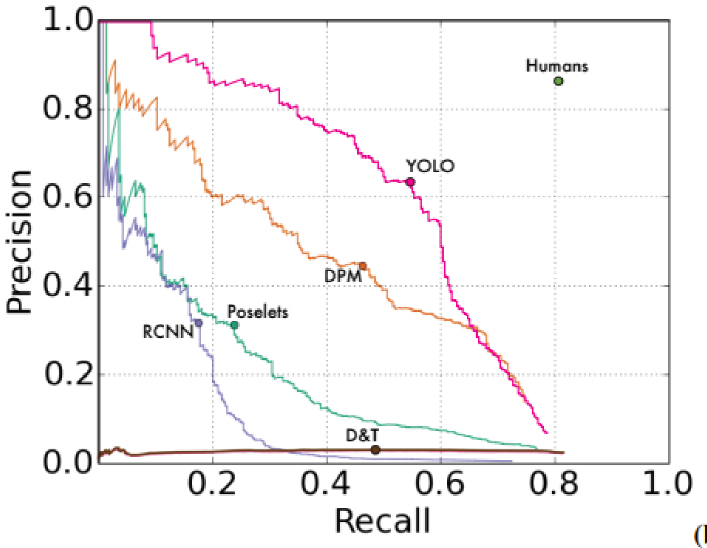
Confusion Matrix

		Predicted Class: Positive	Predicted Class: Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

Positive -> True
Negative -> False
Predicted Class -> 모델의 예측
Actual Class -> 원래 Class(정답)
Specificity -> 특이도
Negative Predictive Value -> 음성 예측도
Precision -> 정밀도
Sensitivity (Recall) -> 재현율(민감도)

Precision : 모델이 True라 예측했을 때 실제 True의 비율
Recall : 실제 값이 True일 때 모델이 True라 예측한 비율
AUC Curve : Precision & Recall Trade off
-> 우측 상단으로 갈 수록 높은 점수

YOLO



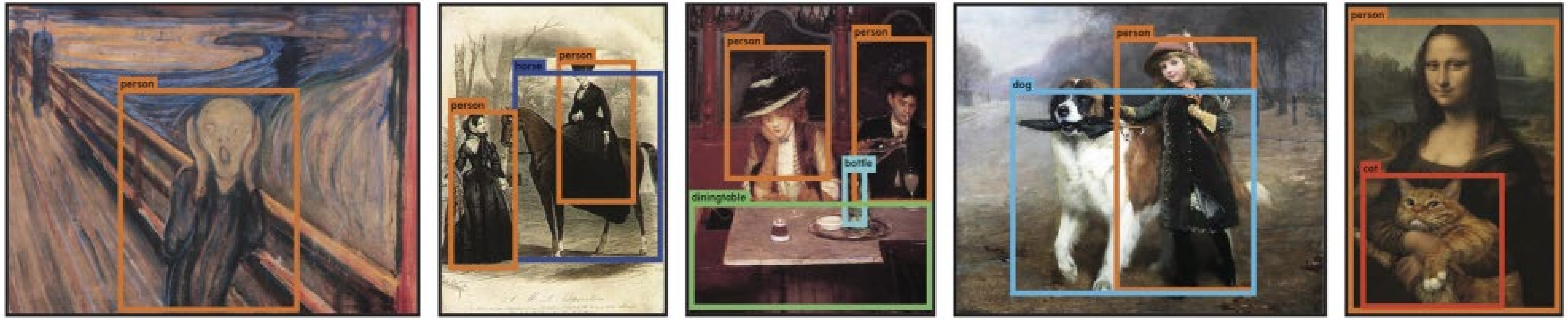
(a) Picasso Dataset precision-recall curves.

Train Data : PASCAL VOC 2007

	VOC 2007	Picasso		People-Art
	AP	AP	Best F_1	AP
YOLO	**59.2**	**53.3**	**0.590**	**45**
R-CNN	54.2	10.4	0.226	26
DPM	43.2	37.8	0.458	32
Poselets [2]	36.5	17.8	0.271	
D&T [4]	-	1.9	0.051	

(b) Quantitative results on the VOC 2007, Picasso, and People-Art Datasets. The Picasso Dataset evaluates on both AP and best F_1 score.

Figure 5: Generalization results on Picasso and People-Art datasets.



YOLO – Unified Detection

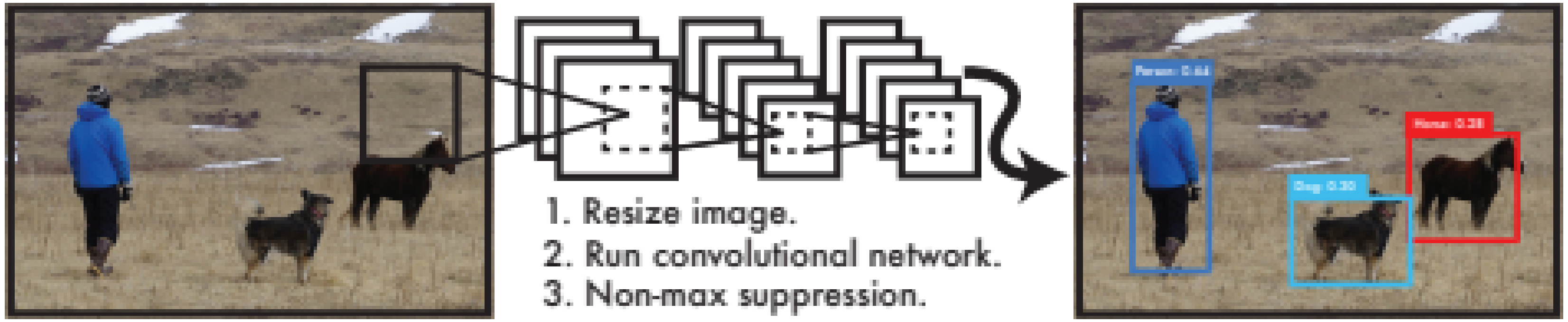


Figure 1: The YOLO Detection System. Processing images with YOLO is simple and straightforward. Our system (1) resizes the input image to 448 × 448, (2) runs a single convolutional network on the image, and (3) thresholds the resulting detections by the model's confidence.

YOLO

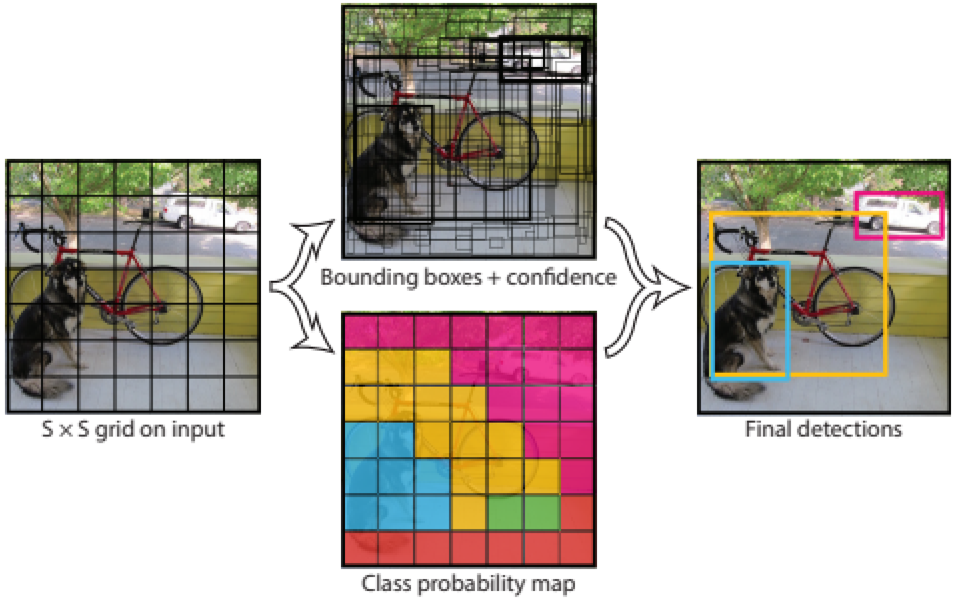
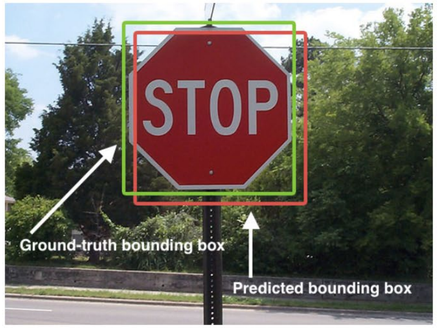
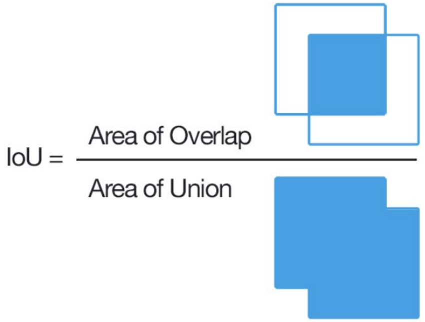


Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

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

$\boxed{x,\ y,\ w,\ h,\ \text{confidence}}$





YOLO

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

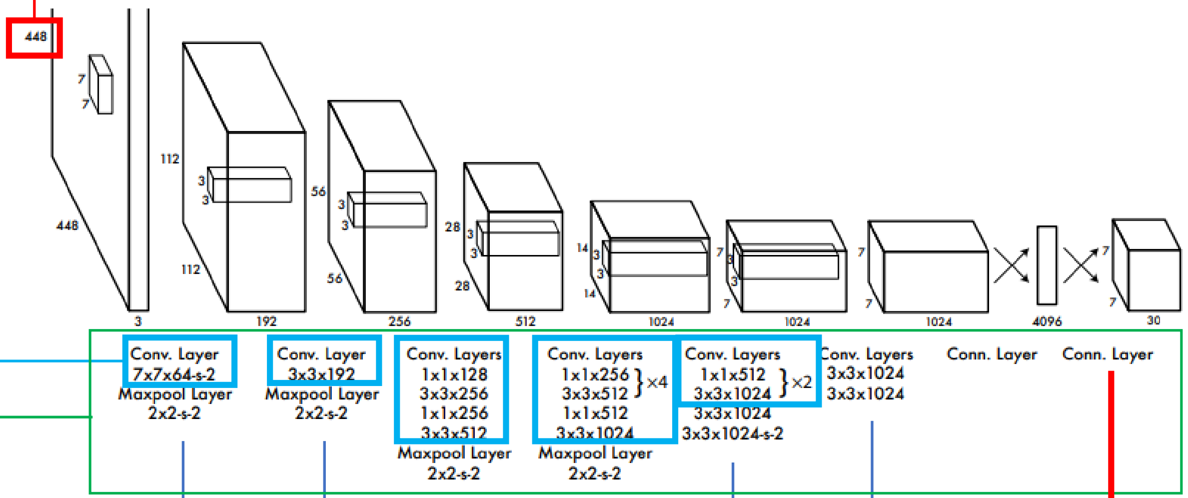
If contain object: Pr(object) = 1
else : Pr(object) = 0

Unified Detection - Training

Pretrain : ImageNet 1000-Classification dataset (224x224)

Fine-tuning : VOC dataset 2007 and 2012

Detection : 448x448

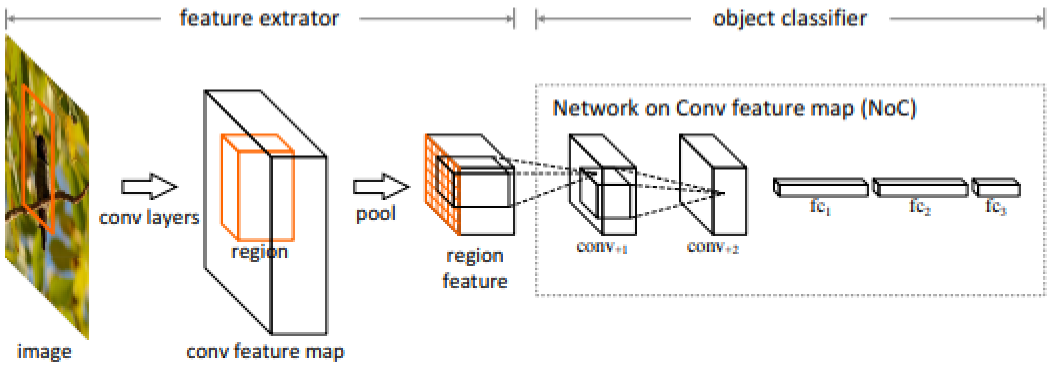


1	1	4	10	6	2

Conv Layer : 24

Linear Layer : 2

S. Ren, K. He, R. B. Girshick, X. Zhang, and J. Sun.
Object detection networks on convolutional feature maps. CoRR, abs/1504.06066, 2015.



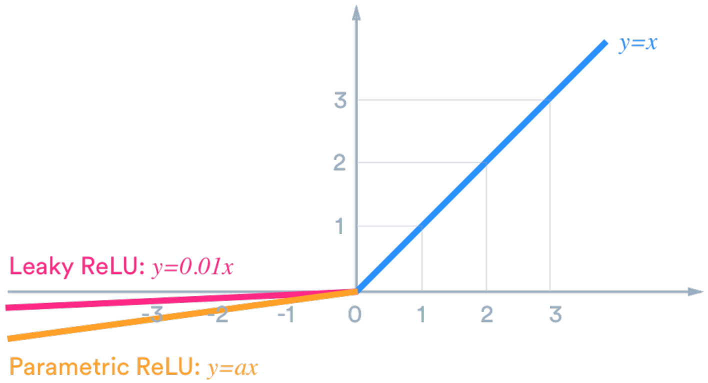
Class probabilities (C = 20)

Bounding box coordinates((x,y,w,h,c) = 5 x (B = 2))

Hyperparater

Linear Activation
-> leaky rectified linear activation

$$\phi(x) = \begin{cases} x, & \text{if } x > 0 \\ 0.1x, & \text{otherwise} \end{cases}$$



Loss Function
-> Sum-Squared-Error

$$\mathrm{SSR} = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

1. **Easy to optimize**
2. **Weights localization equally with classification error**
3. **Training diverge early on**
   - **Confidence score will be zero (not contain object)**
   - **Overpowering the gradient (contain object)**
4. **Weight errors in large box equally small box**

Hyperparater

Loss Function

To solve the problem of equally reflecting weight errors
in large and small boxes

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$
$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$
$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$
$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$
$$+ \sum_{i=0}^{S^2} 1_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

λ_{coord} **Increase loss from bounding box coordinates predictions**
Default = 5

λ_{noobj} **Decrease loss from Confidence predictions that don't contain objects for bounding boxes**
Default = 0.5

$\mathbb{1}_{i}^{\text{obj}}$ **Objects appears in cell I**

$\mathbb{1}_{ij}^{\text{obj}}$ **Jth bounding box predictor in cell i**

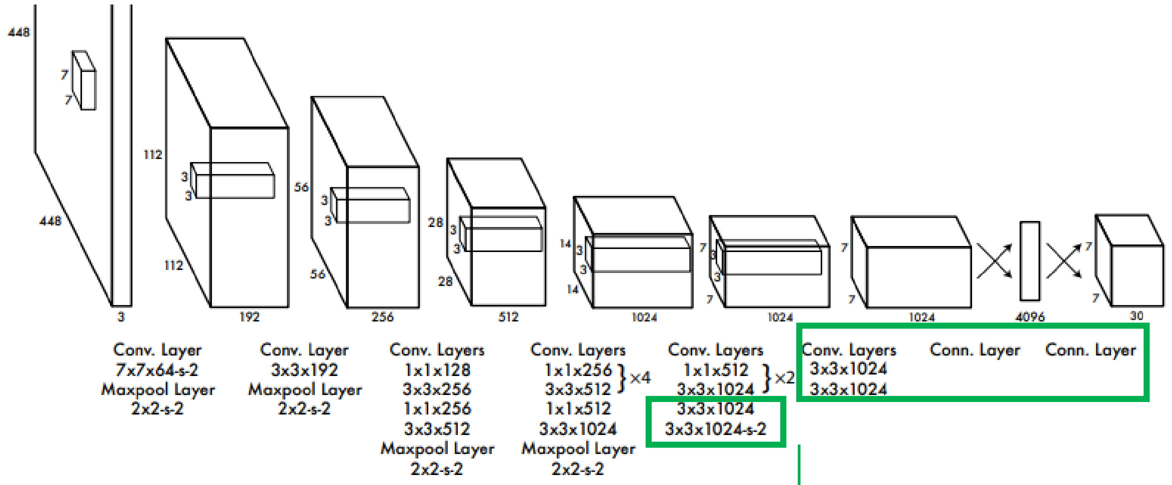
Hyperparater

Pretrain : ImageNet 1000-Classification dataset (224x224)

Fine-tuning : VOC dataset 2007 and 2012

Test : VOC dataset 2012 (also include 2007)

Detection : 448x448



Randomly initialized weighted

Epoch = 135
Batch size = 64
Momentum = 0.9
Weight decay = 0.0005
Dropout = 0.5

Learning Rate Schedule

Default = 0.001
~ 75 epochs = 0.001 -> 0.01
~ 105 epochs = 0.001
~ 135 epochs = 0.0001

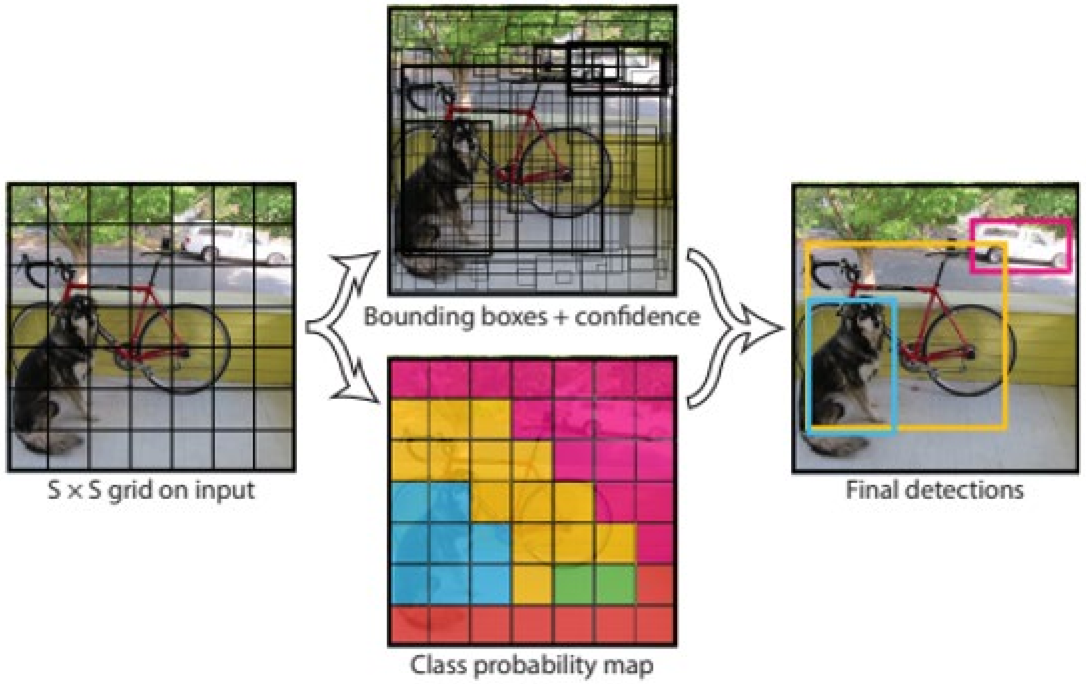
Image Augmentation

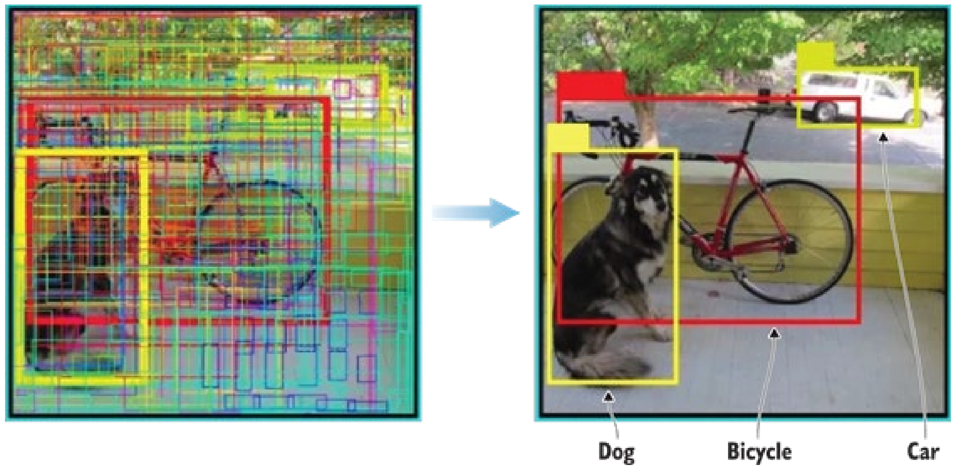
Translations +
scaling = up to 20%
Random adjust
exposure/saturation
= factor of 1.5 HSV

Inference

- Testing on PASCAL VOC, predict on 98 bounding boxes
- YOLO -> Fast
- Only requires a single network

- Some large objects or objects near of the boarder of multiple cell
- **Non-Maximal Suppression**



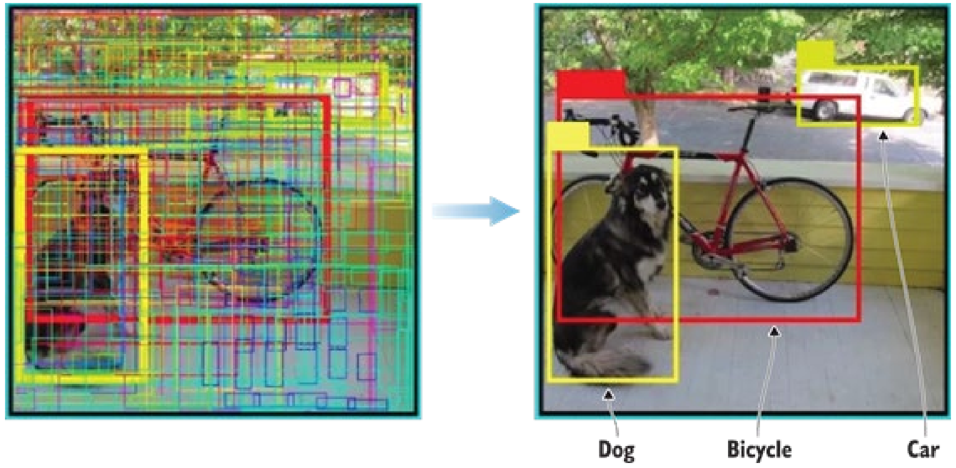


Non-Maximal Suppression

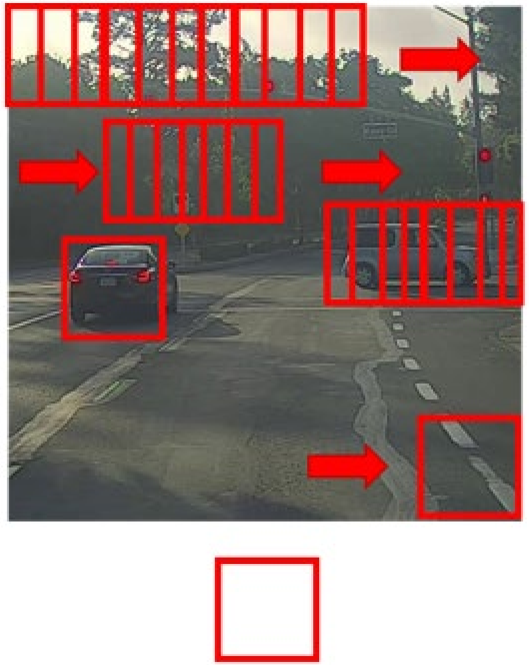
Execution process of NMS

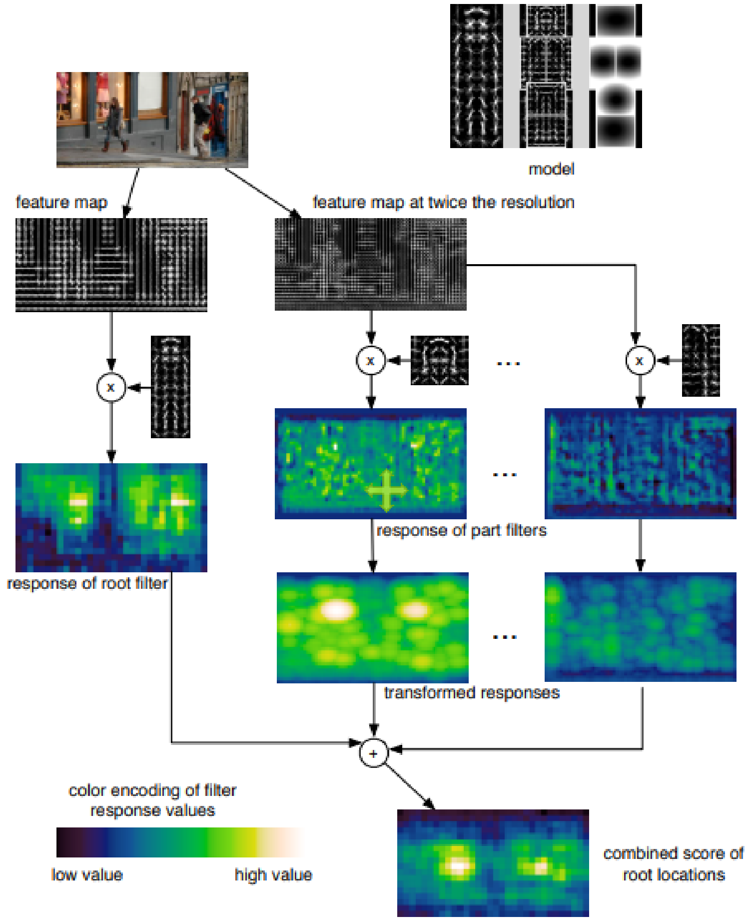
1. If “Confidence Score” less then threshold -> remove
2. Descending sort for “Confidence Score”
3. Select the box with highest “Confidence Score”
4. Compare the IOU this box with other boxes
5. Remove the bounding boxes with IOU higher then threshold(0.5)
6. Select the next box and Repeat 4-6

- NMS adds 2-3% in mAP (Mean Average Precision)

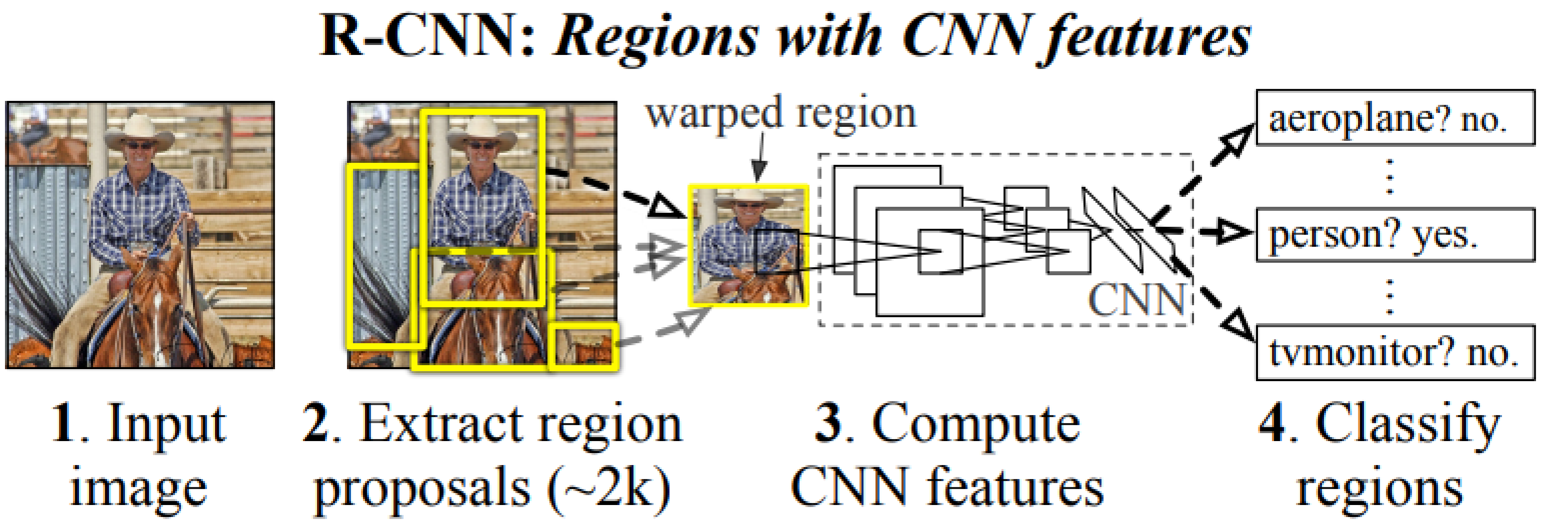


YOLO versus DPM



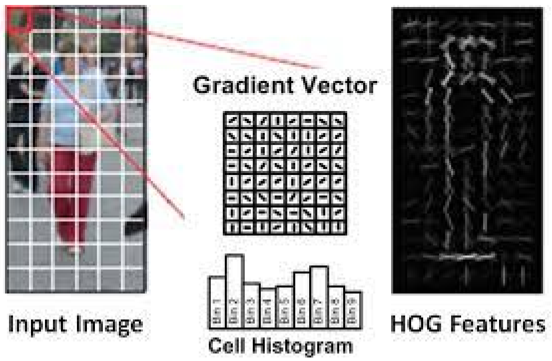


YOLO versus R-CNN



Selective Search

YOLO versus Fast Detectors



“HOG Computation” for speeding up the DPM

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			
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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
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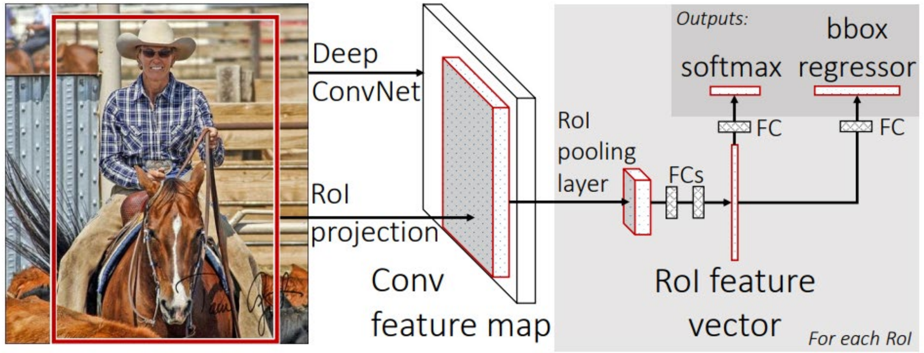
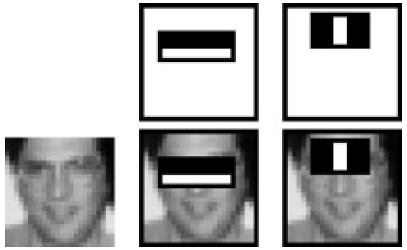


Fast, Faster R-CNN

- Using Neural Network instead Selective Search
- Sharing computation



Robust Real-Time Face Detection

Comparison to Other Real-Time Systems

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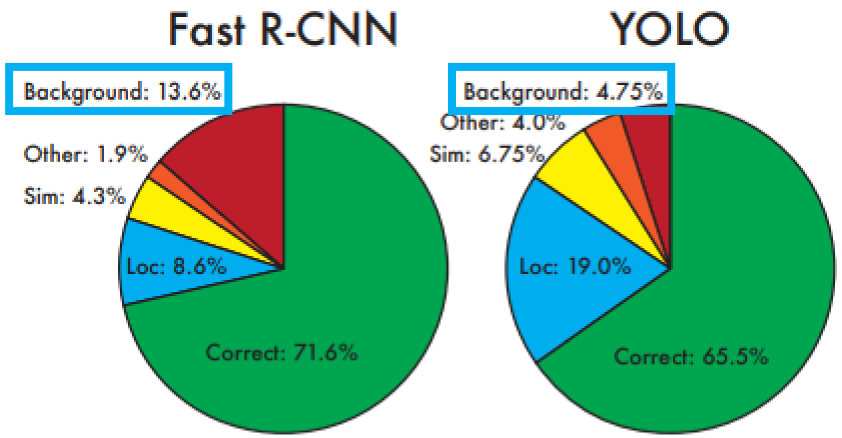


- **FPS** mean Frame Rate
- GPU : TITAN X

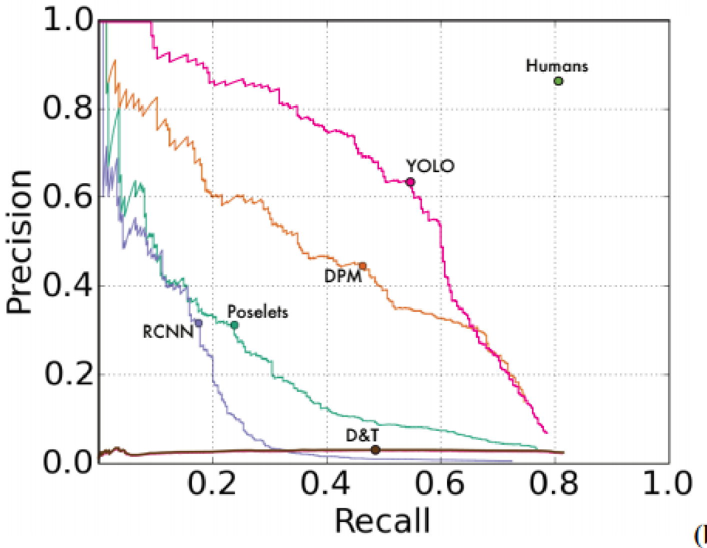
- Correct: correct class and IOU > .5
- Localization: correct class, .1 < IOU < .5
- Similar: class is similar, IOU > .1
- Other: class is wrong, IOU > .1
- Background: IOU < .1 for any object

Combining Fast R-CNN and YOLO

	mAP	Combined	Gain
Fast R-CNN	71.8	-	-
Fast R-CNN (2007 data)	**66.9**	72.4	.6
Fast R-CNN (VGG-M)	59.2	72.4	.6
Fast R-CNN (CaffeNet)	57.1	72.1	.3
YOLO	63.4	**75.0**	**3.2**

VOC 2012 test	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
MR_CNN_MORE_DATA [11]	**73.9**	**85.5**	**82.9**	**76.6**	**57.8**	**62.7**	**79.4**	77.2	86.6	**55.0**	**79.1**	**62.2**	87.0	**83.4**	**84.7**	78.9	45.3	73.4	65.8	80.3	74.0
HyperNet_VGG	71.4	84.2	78.5	73.6	55.6	53.7	78.7	**79.8**	87.7	49.6	74.9	52.1	86.0	81.7	83.3	**81.8**	**48.6**	**73.5**	59.4	79.9	65.7
HyperNet_SP	71.3	84.1	78.3	73.3	55.5	53.6	78.6	79.6	87.5	49.5	74.9	52.1	85.6	81.6	83.2	81.6	48.4	73.2	59.3	79.7	65.6
Fast R-CNN + YOLO	70.7	83.4	78.5	73.5	55.8	43.4	79.1	73.1	**89.4**	49.4	75.5	57.0	**87.5**	80.9	81.0	74.7	41.8	71.5	68.5	**82.1**	67.2
MR_CNN_S_CNN [11]	70.7	85.0	79.6	71.5	55.3	57.7	76.0	73.9	84.6	50.5	74.3	61.7	85.5	79.9	81.7	76.4	41.0	69.0	61.2	77.7	72.1
Faster R-CNN [28]	70.4	84.9	79.8	74.3	53.9	49.8	77.5	75.9	88.5	45.6	77.1	55.3	86.9	81.7	80.9	79.6	40.1	72.6	60.9	81.2	61.5
DEEP_ENS_COCO	70.1	84.0	79.4	71.6	51.9	51.1	74.1	72.1	88.6	48.3	73.4	57.8	86.1	80.0	80.7	70.4	46.6	69.6	**68.8**	75.9	71.4
NoC [29]	68.8	82.8	79.0	71.6	52.3	53.7	74.1	69.0	84.9	46.9	74.3	53.1	85.0	81.3	79.5	72.2	38.9	72.4	59.5	76.7	68.1
Fast R-CNN [14]	68.4	82.3	78.4	70.8	52.3	38.7	77.8	71.6	89.3	44.2	73.0	55.0	**87.5**	80.5	80.8	72.0	35.1	68.3	65.7	80.4	64.2
UMICH_FGS_STRUCT	66.4	82.9	76.1	64.1	44.6	49.4	70.3	71.2	84.6	42.7	68.6	55.8	82.7	77.1	79.9	68.7	41.4	69.0	60.0	72.0	66.2
NUS_NIN_C2000 [7]	63.8	80.2	73.8	61.9	43.7	43.0	70.3	67.6	80.7	41.9	69.7	51.7	78.2	75.2	76.9	65.1	38.6	68.3	58.0	68.7	63.3
BabyLearning [7]	63.2	78.0	74.2	61.3	45.7	42.7	68.2	66.8	80.2	40.6	70.0	49.8	79.0	74.5	77.9	64.0	35.3	67.9	55.7	68.7	62.6
NUS_NIN	62.4	77.9	73.1	62.6	39.5	43.3	69.1	66.4	78.9	39.1	68.1	50.0	77.2	71.3	76.1	64.7	38.4	66.9	56.2	66.9	62.7
R-CNN VGG BB [13]	62.4	79.6	72.7	61.9	41.2	41.9	65.9	66.4	84.6	38.5	67.2	46.7	82.0	74.8	76.0	65.2	35.6	65.4	54.2	67.4	60.3
R-CNN VGG [13]	59.2	76.8	70.9	56.6	37.5	36.9	62.9	63.6	81.1	35.7	64.3	43.9	80.4	71.6	74.0	60.0	30.8	63.4	52.0	63.5	58.7
YOLO	57.9	77.0	67.2	57.7	38.3	$\boxed{22.7}$	68.3	55.9	81.4	$\boxed{36.2}$	60.8	48.5	77.2	72.3	71.3	63.5	$\boxed{28.9}$	52.2	54.8	73.9	50.8
Feature Edit [33]	56.3	74.6	69.1	54.4	39.1	33.1	65.2	62.7	69.7	30.8	56.0	44.6	70.0	64.4	71.1	60.2	33.3	61.3	46.4	61.7	57.8
R-CNN BB [13]	53.3	71.8	65.8	52.0	34.1	32.6	59.6	60.0	69.8	27.6	52.0	41.7	69.6	61.3	68.3	57.8	29.6	57.8	40.9	59.3	54.1
SDS [16]	50.7	69.7	58.4	48.5	28.3	28.8	61.3	57.5	70.8	24.1	50.7	35.9	64.9	59.1	65.8	57.1	26.0	58.8	38.6	58.9	50.7
R-CNN [13]	49.6	68.1	63.8	46.1	29.4	27.9	56.6	57.0	65.9	26.5	48.7	39.5	66.2	57.3	65.4	53.2	26.2	54.5	38.1	50.6	51.6

Generalizability



(a) Picasso Dataset precision-recall curves.

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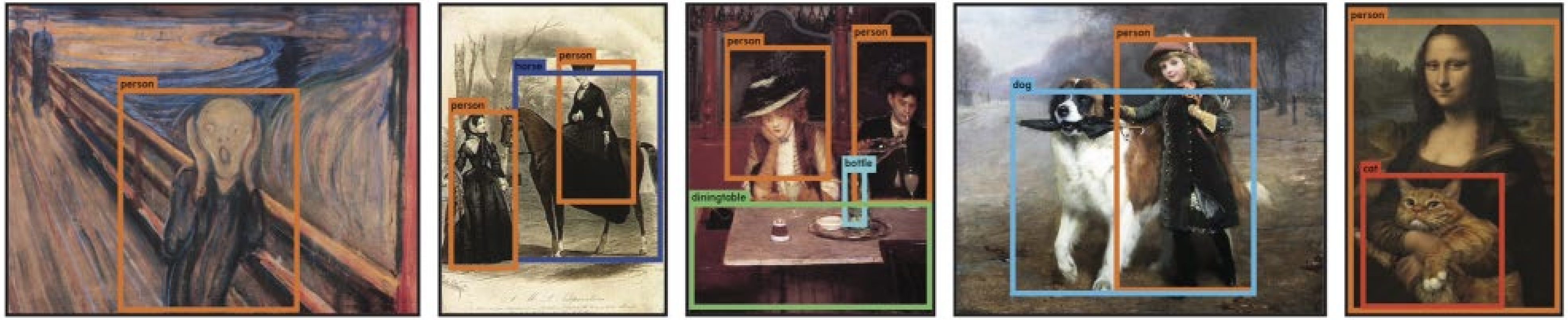
YOLO	**59.2**	**53.3**	**0.590**	**45**
R-CNN	54.2	10.4	0.226	26
DPM	43.2	37.8	0.458	32
Poselets [2]	36.5	17.8	0.271	
D&T [4]	-	1.9	0.051	

(b) Quantitative results on the VOC 2007, Picasso, and People-Art Datasets. The Picasso Dataset evaluates on both AP and best F_1 score.

Figure 5: Generalization results on Picasso and People-Art datasets.



Generalizability

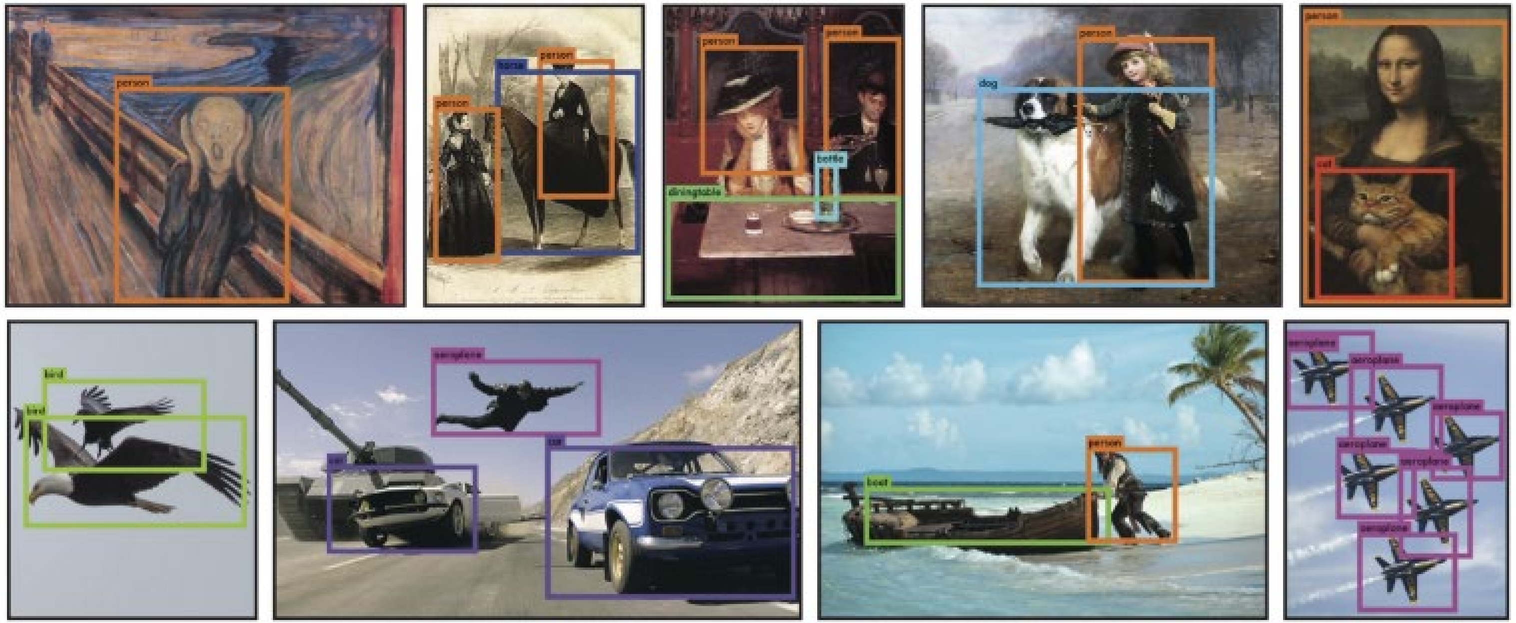


Figure 6: Qualitative Results. YOLO running on sample artwork and natural images from the internet. It is mostly accurate although it does think one person is an airplane.

Limitations of YOLO

- Since each grid cell only predicts number of B boxes and only have one class
  -> struggles with small objects that appear in groups

- model learns to predict bounding boxes
  -> struggles to generalize to objects in new or unusual aspect ratios or configurations

- Our loss function treats errors the same in small boxes versus large bounding boxes
  -> incorrect error about localizations

Conclusion

- YOLO is simple and fast (Unified detection)
- YOLO enables real-time detection
- YOLO generalizes well to new domains