

YOLO: You Only Look Once

Unified Real-Time Object Detection

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[\[Website\]](#) [\[Paper\]](#) [\[arXiv\]](#) [\[Reviews\]](#)

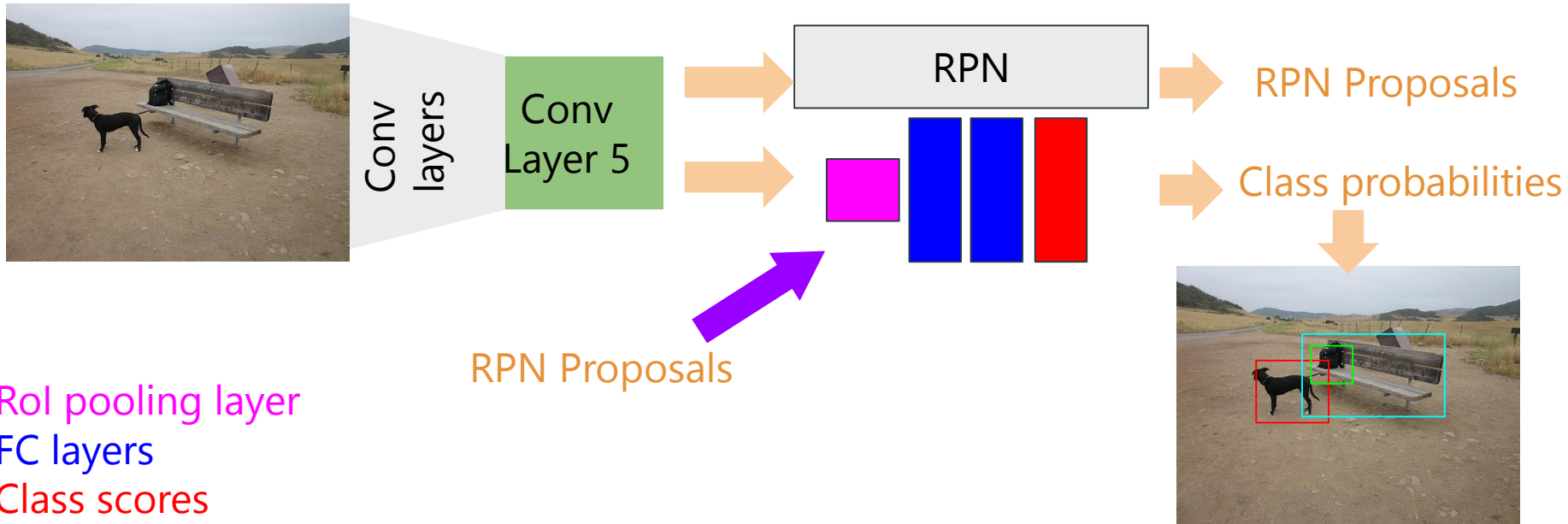




INTRODUCTION



Nowadays State of the Art approach, are so architected:



This complex pipeline means that:

- Slow Pipeline
- Single Pipelines Hard to Optimize
- Need Parallel Training for Components









WHAT'S NEW?

(In the architecture approach.)



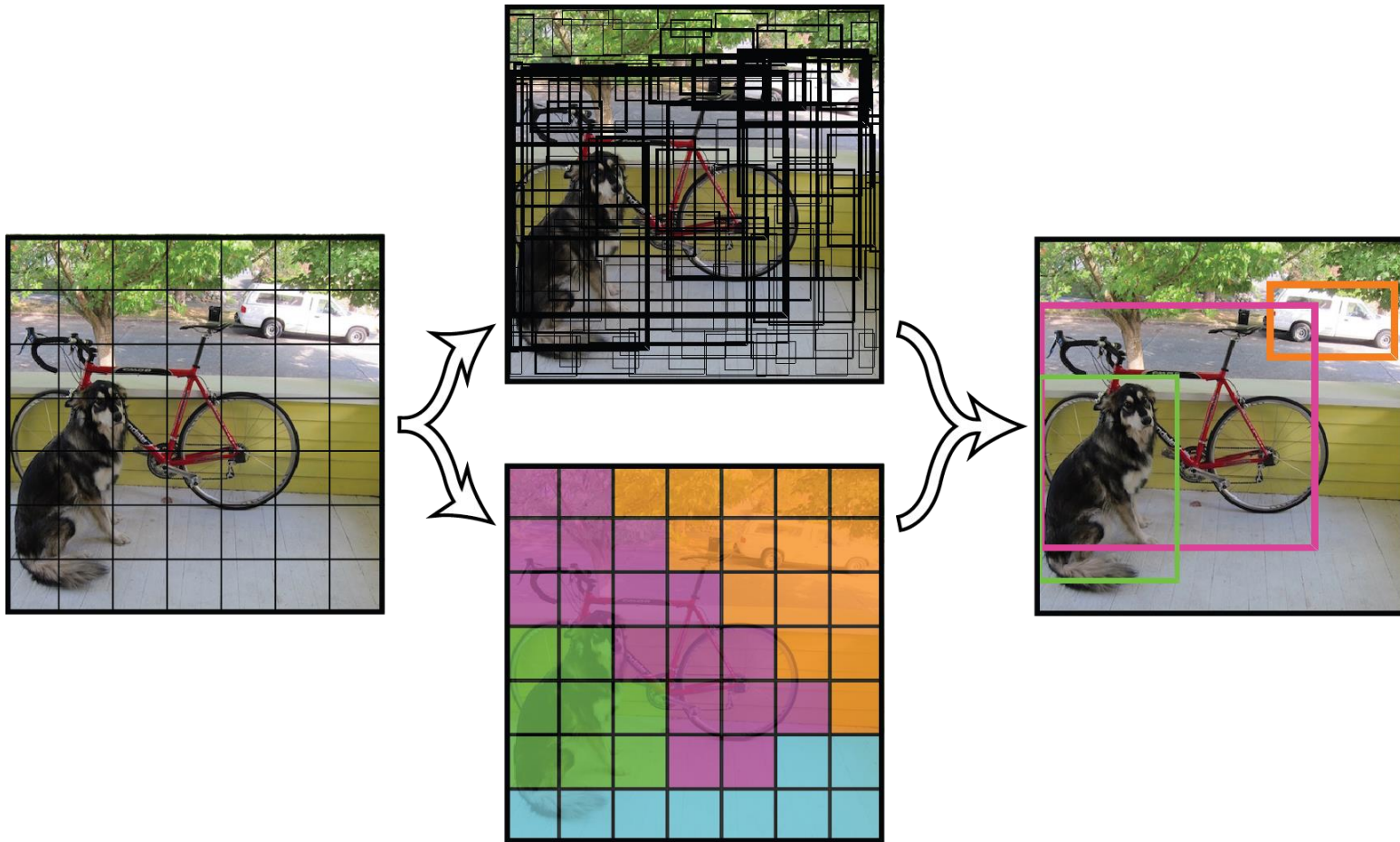
Concepts

-  Detection as Single Regression Problem
-  Developed as Single Convolutional Network
-  Reason Globally on the Entire Image
-  Learns Generalizable Representations

 **Easy & Fast**



Unified Detection



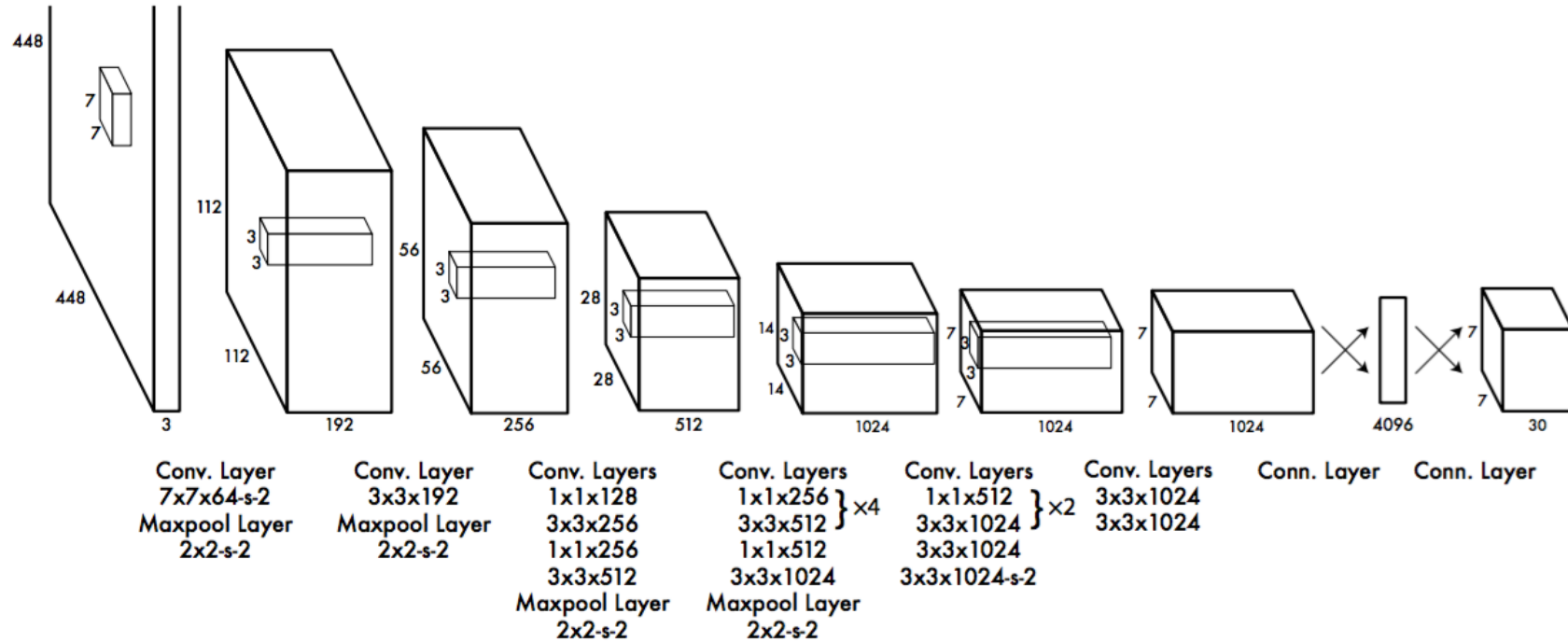
- Divide the image into a $S \times S$ grid.
 - If the center of an object fall into a grid cell, it will be the responsible for the object.
- Each grid cell predict:
 - B bounding boxes;
 - B confidence scores as $C = \Pr(\text{Obj}) * \text{IOU}$;
 - C cond. Class prob. as $P = \Pr(\text{Class}_i | \text{Object})$;
- Confidence Prediction is obtained as IOU of predicted box and any ground truth box.

➤ We obtain the class-specific confidence score as:

$$\Pr(\mathit{Class}_i | \mathit{Object}) * \Pr(\mathit{Object}) * \mathit{IOU} \\ = \\ \Pr(\mathit{Class}_i) * \mathit{IOU}$$



Design





Loss-Function

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

➤ *Limitations*

- Struggle with Small Object.
- Struggle with Different aspects and ratios of objects.
- Loss function is an approximation.
- Loss function threatens errors in different boxes ratio at the same.



EXPERIMENTS

(How performs?.)





General Comparison

Real-Time Detectors	Train	mAP	FPS
100Hz DPM [30]	2007	16.0	100
30Hz DPM [30]	2007	26.1	30
Fast YOLO	2007+2012	52.7	155
YOLO	2007+2012	63.4	45
<hr/>			
Less Than Real-Time			
Fastest DPM [37]	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[27]	2007+2012	73.2	7
Faster R-CNN ZF [27]	2007+2012	62.1	18



Fast R-CNN & YOLO

Fast R-CNN

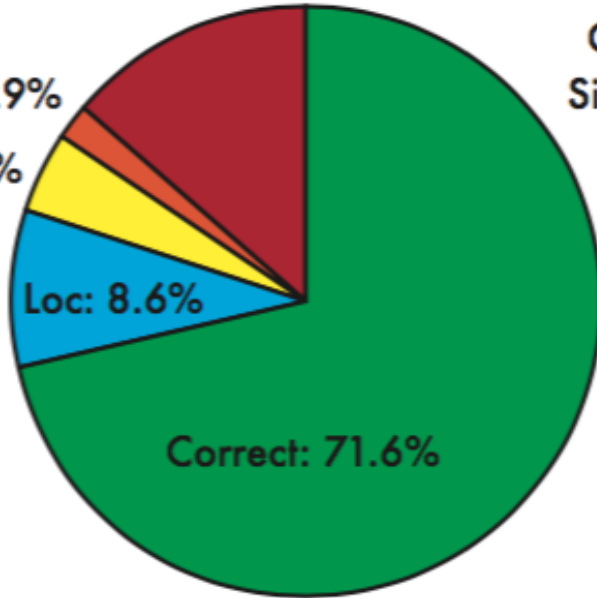
Background: 13.6%

Other: 1.9%

Sim: 4.3%

Loc: 8.6%

Correct: 71.6%



YOLO

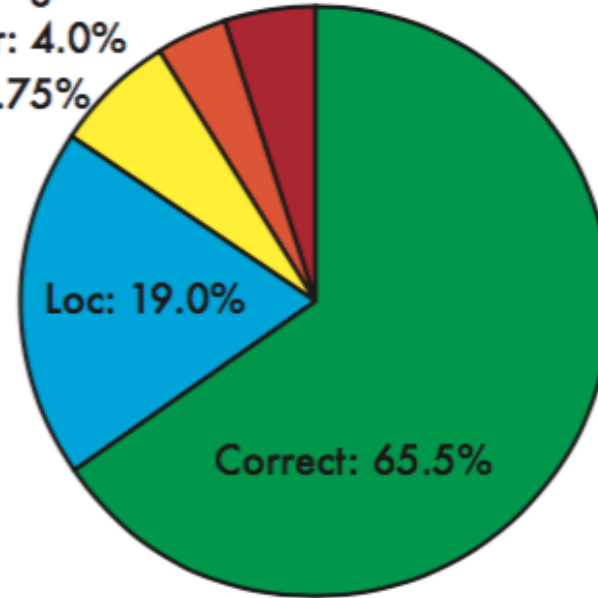
Background: 4.75%

Other: 4.0%

Sim: 6.75%

Loc: 19.0%

Correct: 65.5%



➤ *Fast R-CNN & YOLO*

Using YOLO accuracy for Big object to avoid detection mistakes into Fast R-CNN:

	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



Fast R-CNN & YOLO

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 [27]	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 [28]	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	22.7	68.3	55.9	81.4	36.2	60.8	48.5	77.2	72.3	71.3	63.5	28.9	52.2	54.8	73.9	50.8
Feature Edit [32]	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





SUMMARY

(Why is an interesting approach.)



➤ *Pros*

- Trained on a loss function that directly corresponds to detection performance.
- The entire model is trained jointly.
- The fastest general-purpose object detector in the literature.
- At least detection at 45fps.



References

- You Only Look Once: Unified, Real-Time Object Detection, Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi.



THANKS !!!

QUESTIONS?

