Understanding DNN-Based Object Detectors

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Presentation Overview

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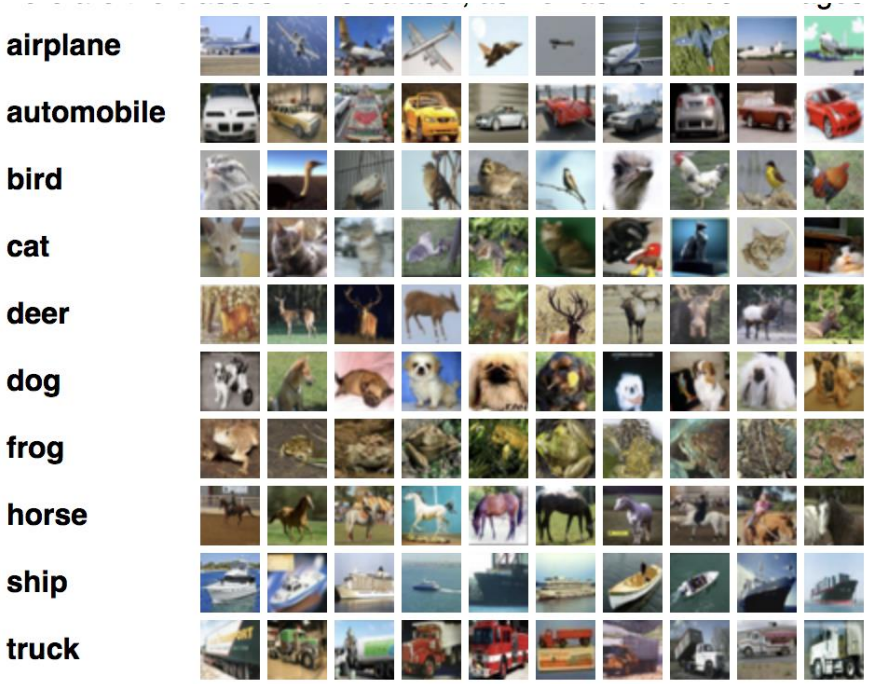
Problem Definition

Problem Definition

Image Classification (global- easier)



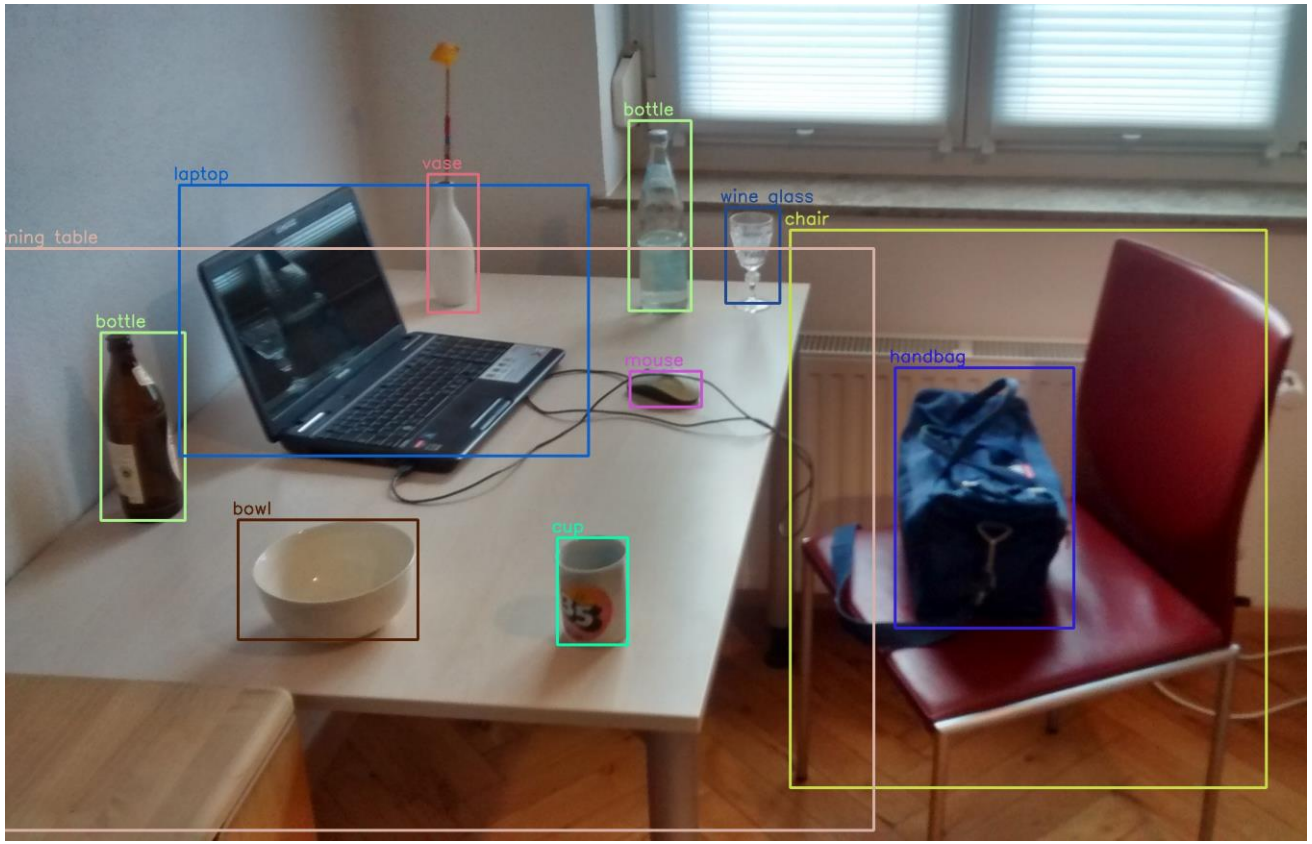
Ref: Example of Photographs of Objects From the CIFAR-10 Dataset

Object Segmentation (detailed- tougher)

Ref: https://medium.com/syncedreview/facebook-pointrend-rendering-image-segmentation-f3936d50e7f1

Problem Definition

Object Detection (Compromise):

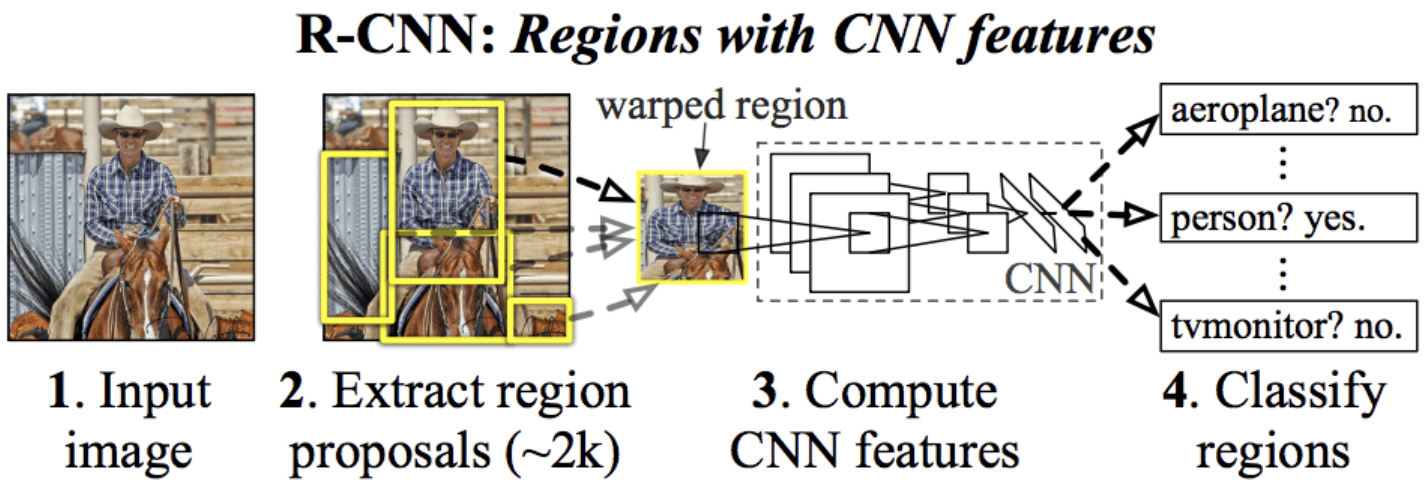


Ref: By (MTheiler) - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=75843378

1. Localize the object
   - Bounding box location
2. Estimate the size
   - Bounding box dimensions
3. Classify the object
   - Object label

Early Deep-Learning Based Approaches

Early Deep-Learning Based Approaches (R-CNN) 2014



"Rich feature hierarchies for accurate object detection and semantic segmentation"

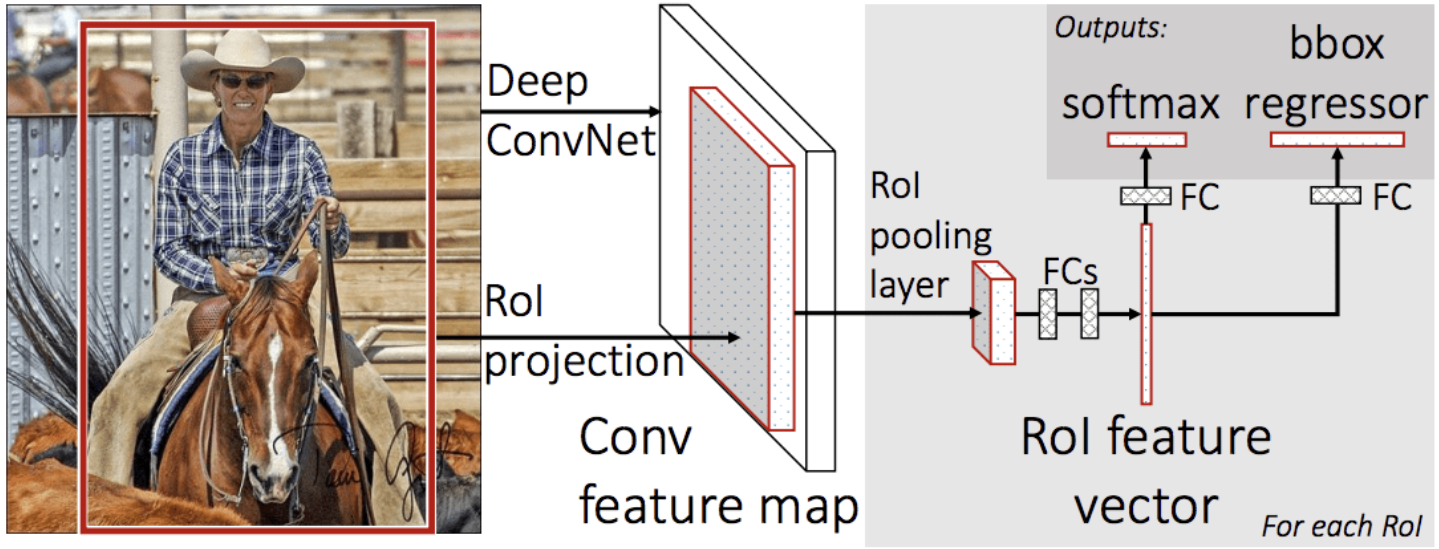
Issues:

1. Training is a multi-stage pipeline. Involves the preparation and operation of three separate models.
2. Training a deep CNN on so many region proposals per image is very slow.
3. Object detection is slow. Making predictions using a deep CNN on so many region proposals (~2000) is very slow.

Region Proposal: Generate and extract category independent region proposals, e.g. candidate bounding boxes. (Selective search)

Feature Extractor: Extract feature from each candidate region, e.g. using a deep CNN
Classifier. Classify features as one of the known class, e.g. linear SVM classifier model.

Early Deep-Learning Based Approaches (Fast R-CNN) 2015



Issue:
The model is significantly faster to train and to make predictions, yet still requires a set of candidate regions to be proposed along with each input image.

Fast R-CNN, ICCV 2015.

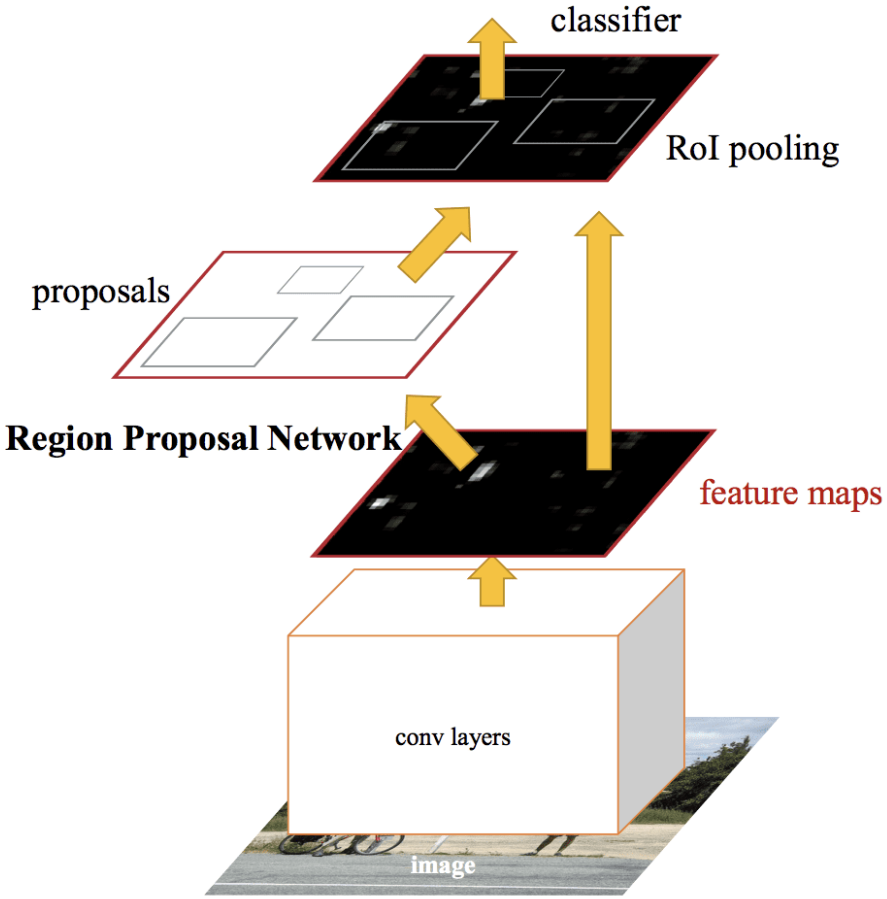
Region Proposal: Generate and extract category independent region proposals, e.g. candidate bounding boxes. (Selective search)

Classification and Bounding Box Combined: A single model instead of a pipeline to learn and output regions and classifications directly.

Early Deep-Learning Based Approaches (Faster R-CNN) 2016

Region Proposal Network: Convolutional neural network for proposing regions and the type of object to consider in the region.

Fast R-CNN: Convolutional neural network for extracting features from the proposed regions and outputting the bounding box and class labels.

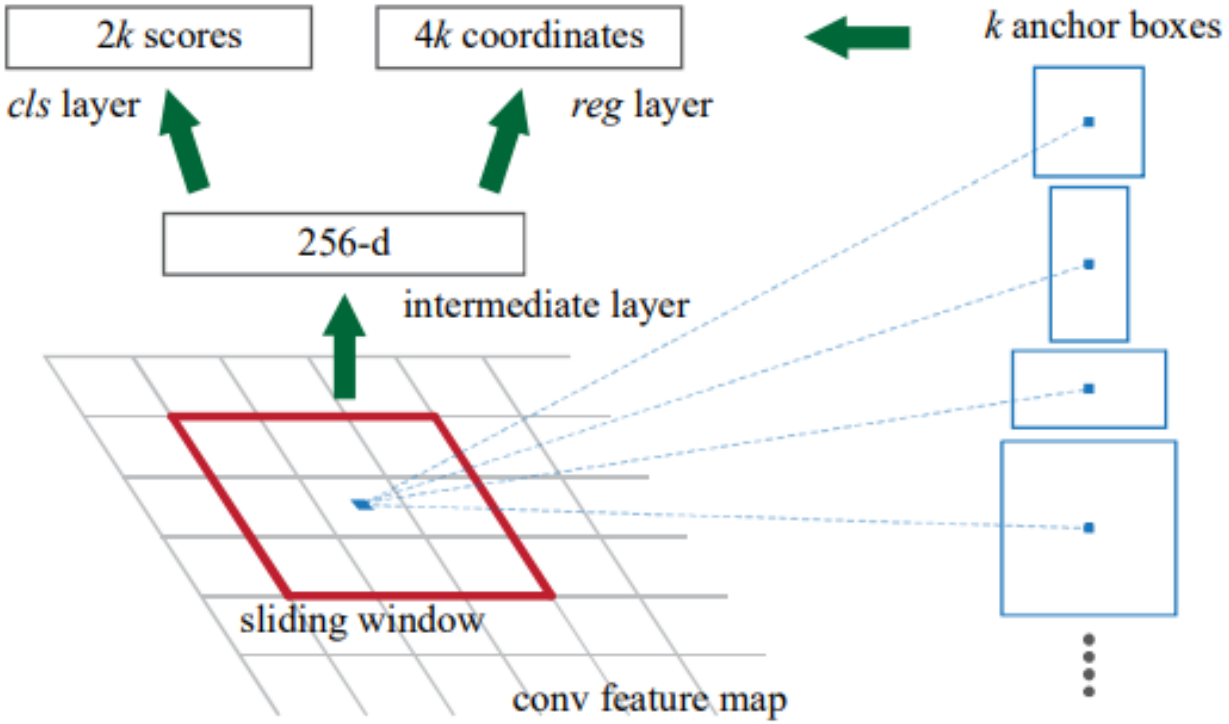


"Faster R-CNN: Towards Real-Time Object Detection Proposal Networks"

Early Deep-Learning Based Approaches (Faster R-CNN)

Region Proposal Network

- A procedure of alternating training is used where both sub-networks are trained at the same time. This allows the parameters in the feature detector deep CNN to be fine-tuned for both tasks simultaneously.
- For VGG-16 model, it has a frame rate of 5 fps on a K-40 GPU (**200 msec per image**).



"Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks"

Recent Advancements

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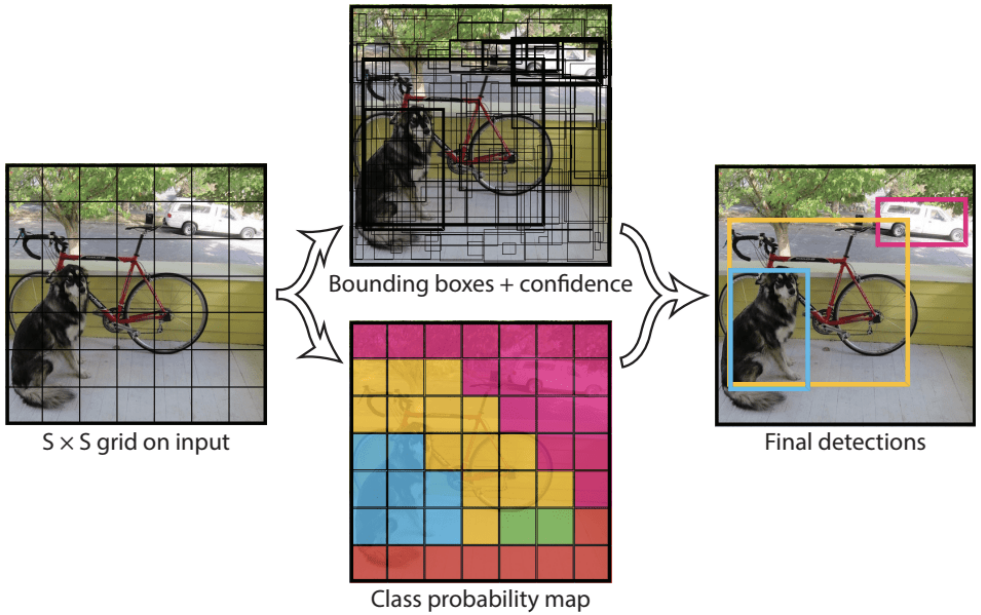
Recent Advancements (YOLO-V1) 2016

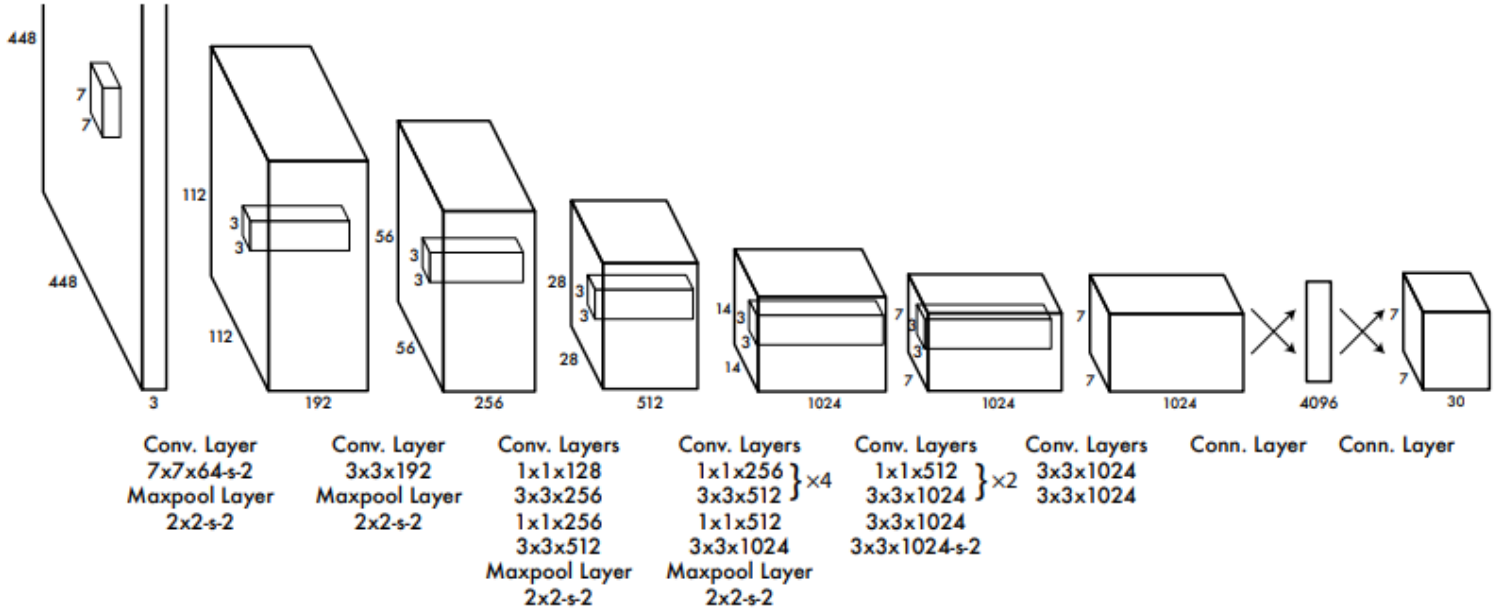


- Doesn't run network sequentially on regions.
- It divides the input image into an S × S grid. If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object.
- Each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities.
- These predictions are encoded as an S × S × (B ∗ 5 + C) tensor.
- On PASCAL VOC, S = 7, B = 2. PASCAL VOC has 20 labelled classes so C = 20. The final prediction is a 7 × 7 × 30 tensor

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

- **A single neural network predicts bounding boxes and class probabilities** directly from full images in one evaluation.
- Base YOLO model processes images on Titan X GPU in real-time at 45 fps, and up to 155 fps for a speed-optimized version of the model.
- YOLO makes more localization errors but is far less likely to predict false detections where nothing exists.

Recent Advancements (YOLO-v1: Network Architecture)



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

Limitations:

- YOLO imposes strong spatial constraints on bounding box predictions since each grid cell only predicts two boxes.
- It can only have one class in a cell. This model struggles with small objects that appear in groups, such as flocks of birds.
- This model uses relatively coarse features for predicting bounding boxes (it has multiple down-sampling layers).
- Finally, they train on a loss function that approximates detection performance.

- The network has 24 convolutional layers followed by 2 fully connected layers.
- Alternating 1 × 1 convolutional layers reduce the features space from preceding layers.
- The convolutional layers were pretrained on the ImageNet classification task.

Recent Advancements (YOLO-v3 and YOLO-v4)

V3 – 2018:

- The input image is divided into S x S grids at three different resolution scales (8x8, 16x16, 32x32) (large, medium and small)
- Each resolution scale is attended by each model output (3) and the output is conditioned by the input dimension H x W ([H/8, W/8, 3 * (5 + C)], [H/16, W/16, 3 * (5 + C)], [H/32, W/32, 3 * (5 + C)])
- Objects are learned based on the resolution and anchors. Each resolution has at least 3 anchors to define objects ratios at each cell.

V4 – 2020:

- Backbone: CSPDarknet53
- Head: YOLOv3

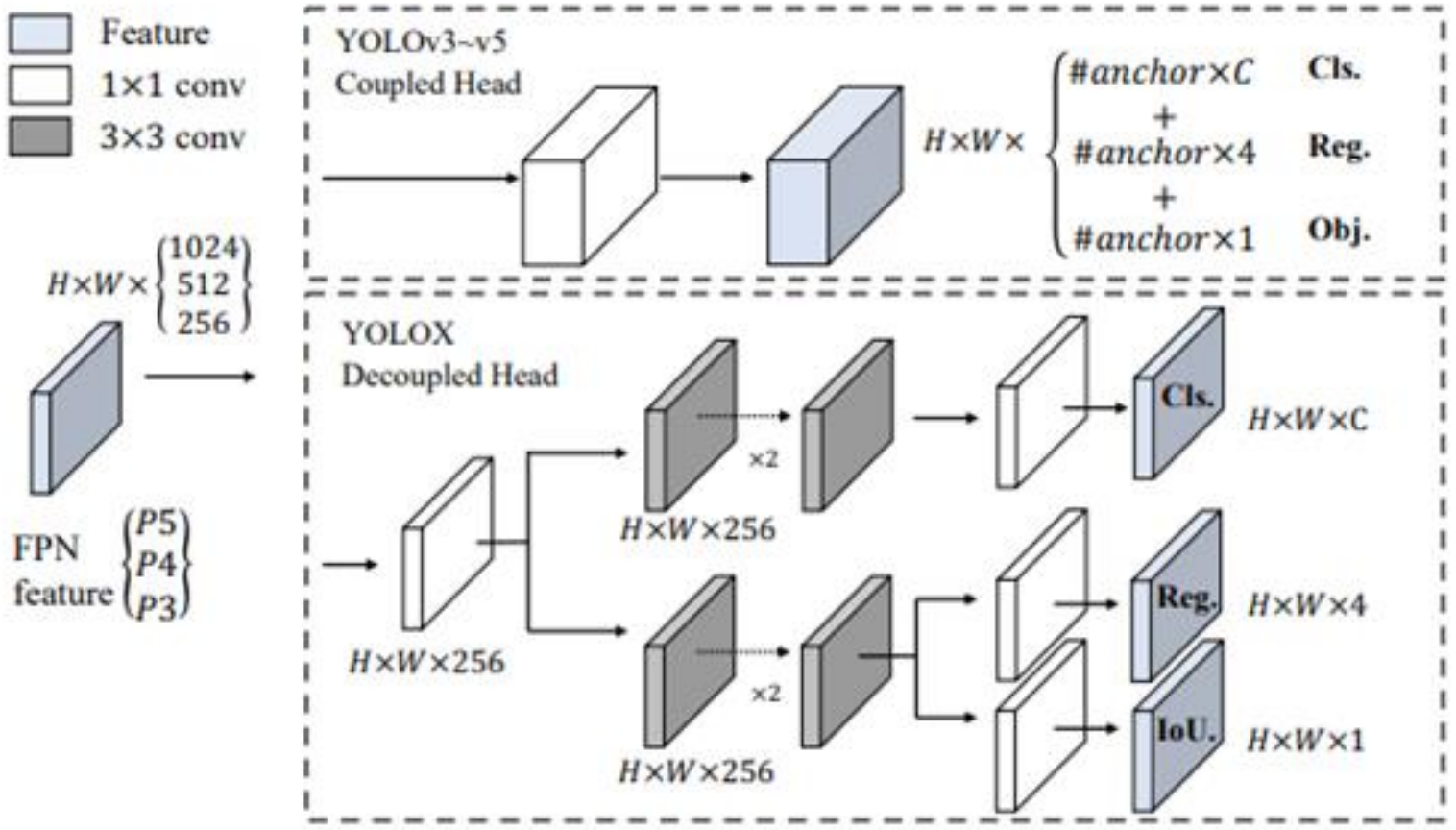
YOLO v4 utilizes:

- Bag of Freebies (BoF) for backbone: CutMix, 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
- Bag of Freebies (BoF) for detector: CIoU- loss, CmBN, DropBlock regularization, Mosaic data augmentation etc.

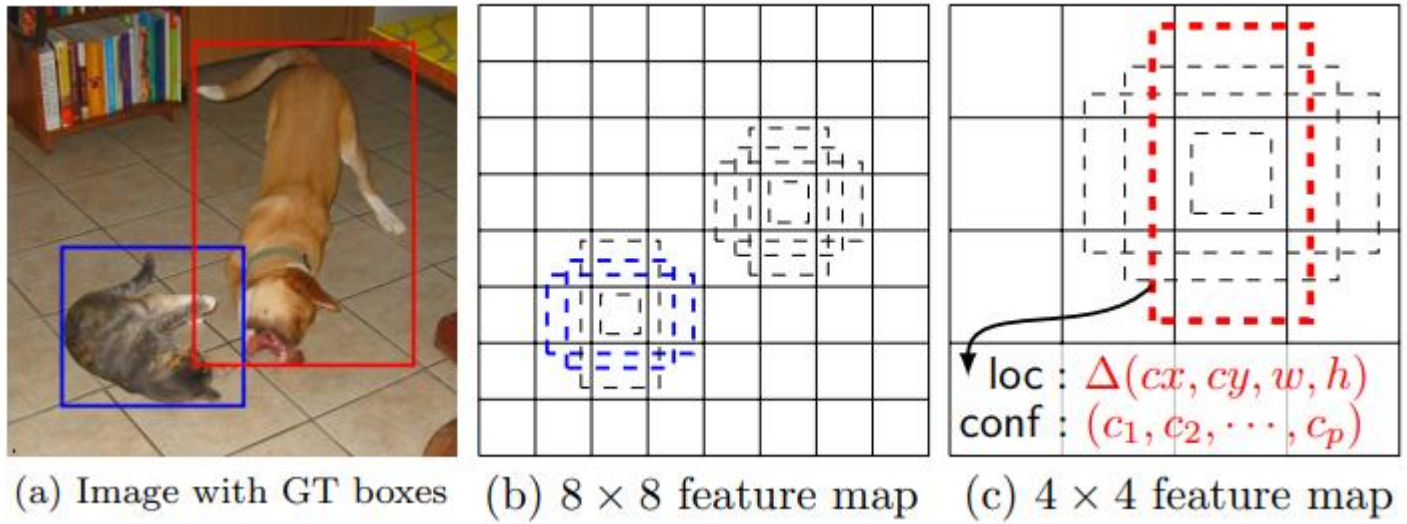
Recent Advancements (YOLOX) 2021

Anchor free, decoupled heads

- Feature channel is reduced to 256 using 1x1 conv.
- Add two parallel branches with two 3x3 conv layers (classification and regression)
- IoU branch is added to the regression branch.



Recent Advancements
SSD (Single Shot Detectors) 2016



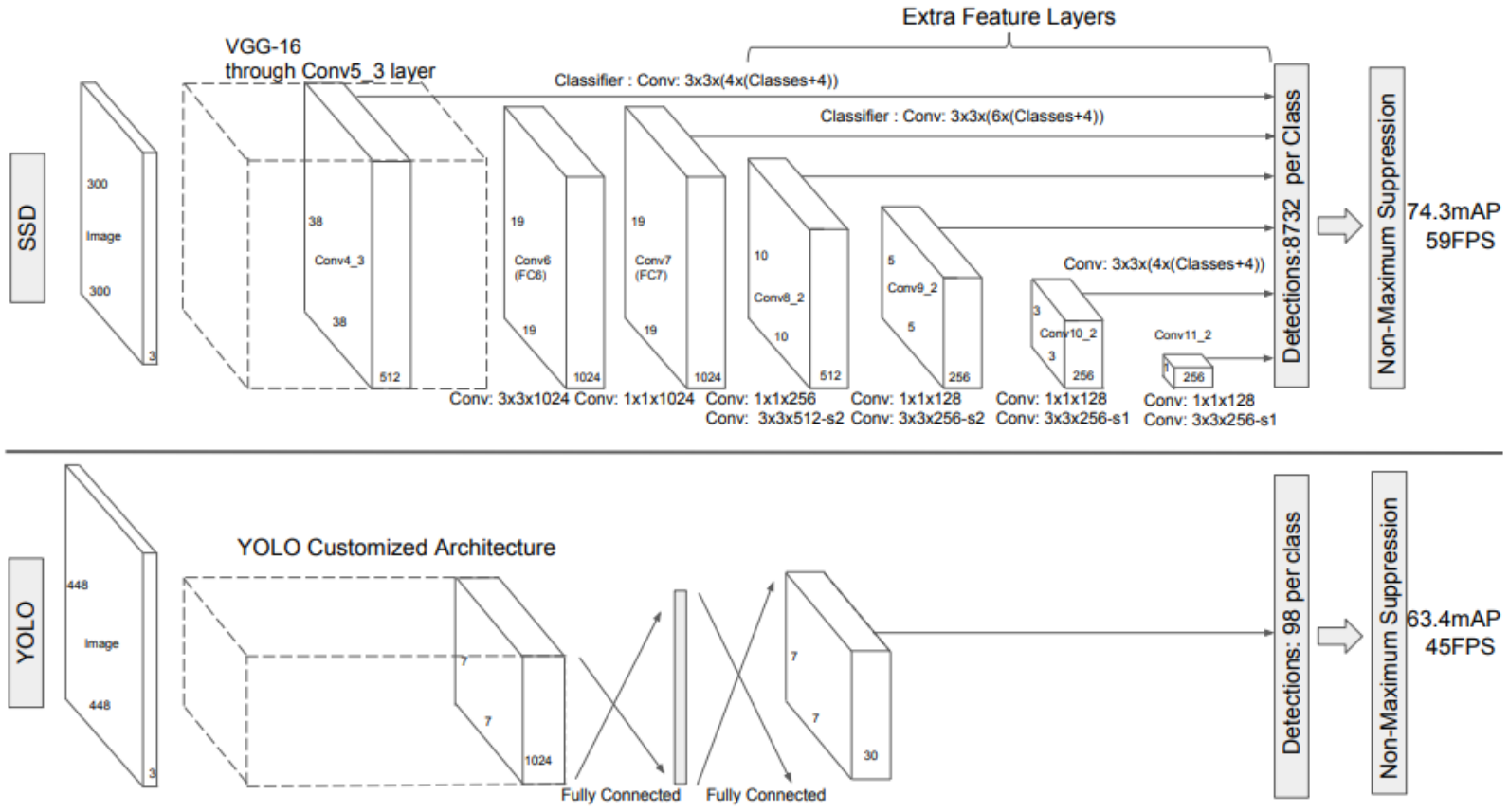
"SSD: Single Shot MultiBox Detector"

- In a convolutional fashion, it evaluates a small set of default boxes of different aspect ratios (anchor boxes) at each location in several feature maps with different scales (e.g. 8 × 8 and 4 × 4 in (b) and (c)).

- For each default box, it predicts both the shape offsets and the confidences for all object categories.

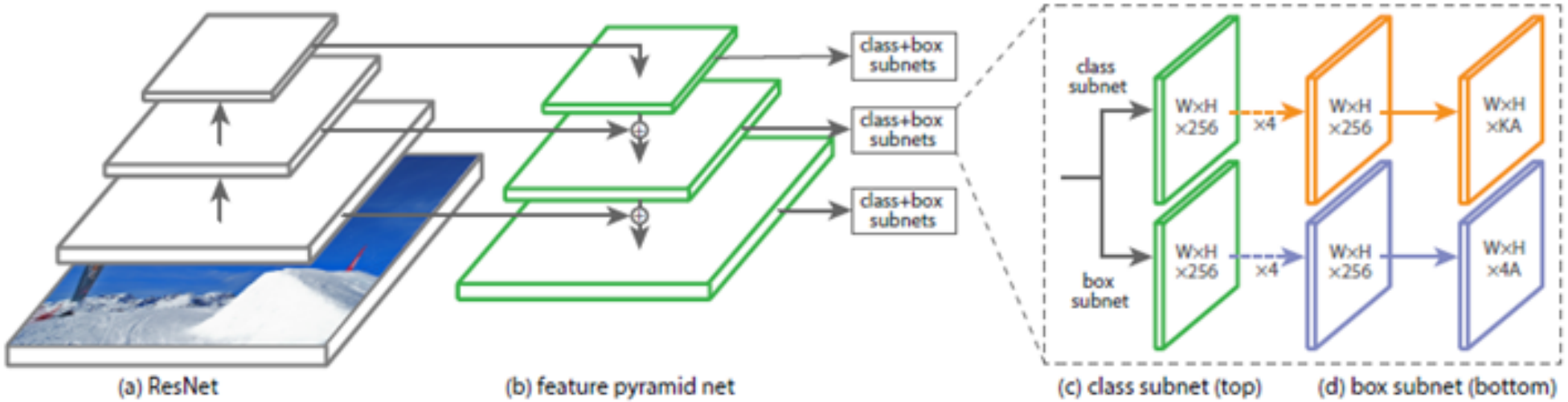
Recent Advancements (SSD – Network Architecture)

- SSD model adds several "feature scaler layers" to the end of a backbone network, which predict the offsets to default boxes of different scales and aspect ratios and their associated confidences.
- Inference frame rate (speed with batch size 8 using Titan X and cuDNN v4 with Intel Xeon E5-2667v3 @ 3.20 GHz) is 46 fps for SSD of 300x300 pixel images with mAP = 74.3%
- Whereas for YOLO (VGG-16) frame rate is 21 fps of 448x448 pixel images with mAP = 66.4%
- For SSD, candidate bounding boxes can be very large (~8732); NMS post-processing needs to be optimized.



"SSD: Single Shot MultiBox Detector"

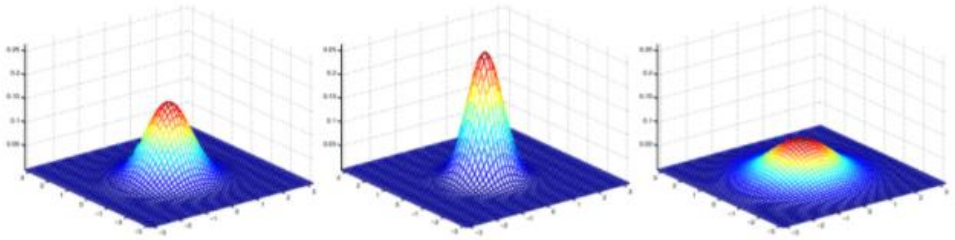
Recent Advancements (RetinaNet) 2017



'Focal Loss for Dense Object Detection〞

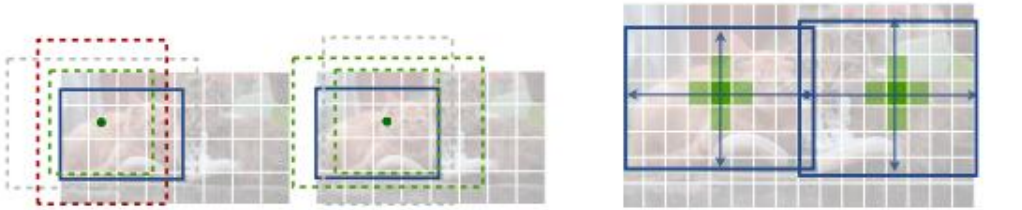
- Utilizes Feature Pyramid Network (FPN) backbone on top of feedforward ResNet architecture.
- Introduces Focal Loss to handle class imbalance in object detection dataset.
- RetinaNet with ResNet-101-FPN matches the accuracy of ResNet- 101-FPN Faster R-CNN [20],
- 172 msec on an Nvidia M40 GPU.
- At most 1k top-scoring predictions per FPN level, after thresholding detector confidence at 0.05.
- The top predictions from all levels are merged and non-maximum suppression (NMS) with a threshold of 0.5 is applied to yield the final detections.

Recent Advancements (CenterNet) 2019



https://sanjivgautamofficial.medium.com/generative-learning-algorithms-8a306976b9b1

- **Addresses the need for anchors and NMS post-processing**
- The backbone network generates heatmaps from the input image using CNNs.
- Object are localized by detecting the local maxima from the heatmaps.
- Single network predicts the keypoints (local maxima of heatmaps), offset, and size.
- The network predicts a total of C + 4 outputs at each location.



(a) Standard anchor based detection. Anchors count as positive with an overlap $IoU > 0.7$ to any object, negative with an overlap $IoU < 0.3$, or are ignored otherwise.

(b) Center point based detection. The center pixel is assigned to the object. Nearby points have a reduced negative loss. Object size is regressed.

"Objects as Points"

- Not best for accuracy but provides excellent accuracy-speed tradeoffs.
- Can easily be extended to 3D object detection, multi-object tracking and pose estimation etc.

Performance Metrics

Performance Metrics
How well the detector is doing?

Types of Errors:

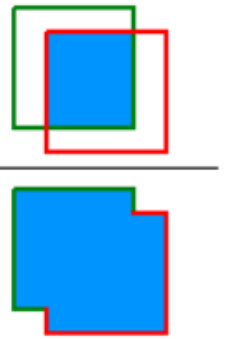
- True Positive (TP) — Correct detection made by the model.
- False Positive (FP) — Incorrect detection made by the detector.
- False Negative (FN) — A Ground-truth missed (not detected) by the object detector.
- True Negative (TN) — This is background region not detected by the model. This metric is not used in object detection because such regions are not explicitly annotated.
- Closeness or overlap of the detected bounding box with the ground truth (IoU).

Ref: https://towardsdatascience.com/on-object-detection-metrics-with-worked-example-216f173ed31e#:~:text=Average%20Precision%20(AP)%20and%20mean,COCO%20and%20PASCAL%20VOC%20challenges.

Intersection over Union (IoU):

IoU metric in object detection evaluates the degree of overlap between the ground (*gt*) truth and predicted (*pd*) bounding boxes. It is calculated as follows:

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} = \frac{\quad}{\quad}$$

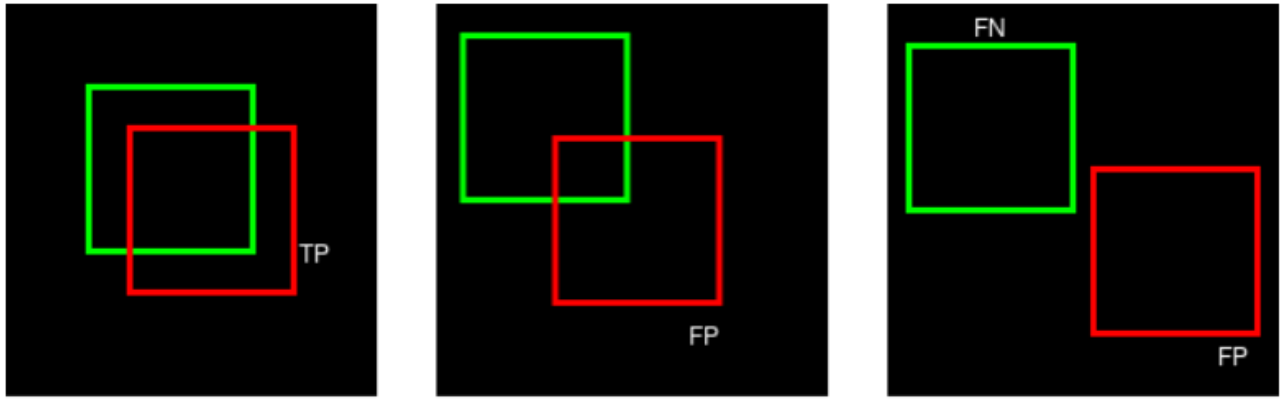


- IoU ranges between 0 and 1, where 0 shows no overlap and 1 means perfect overlap between *gt* and *pd*.
- IoU is used as a threshold (say, α), and using this threshold we can decide if a detection is correct or not.

Performance Metrics (IoU)

- True Positive (TP) is a detection for which IoU(*gt,pd*) ≥ α and
- False Positive (FP) is a detection for which IoU(*gt,pd*) < α.
- False Negative is a ground-truth (gt) missed together with gt for which IoU(*gt,pd*) < α.

Ref: https://towardsdatascience.com/on-object-detection-metrics-with-worked-example-216f173ed31e#:~:text=Average%20Precision%20(AP)%20and%20mean,COCO%20and%20PASCAL%20VOC%20challenges.



IoU = 0.86 IoU = 0.24 IoU = 0

Consider IoU threshold, α = 0.5, then TP, FP and FNs can be identified as shown in the figure above.

Note: If we raise the IoU threshold above 0.86, the first instance will be a FP, and if we lower the IoU threshold below 0.24, the second instance becomes TP.

Performance Metrics (Precision and Recall)

- **Precision** is the degree of exactness of the model in identifying only relevant objects. It is the ratio of TPs over all detections made by the model.
- **Recall** measures the ability of the model to detect all ground truths—TPs among all ground truths.
- A model is said to be a good model if it has high precision and high recall.

Ref: https://towardsdatascience.com/on-object-detection-metrics-with-worked-example-216f173ed31e#:~:text=Average%20Precision%20(AP)%20and%20mean,COCO%20and%20PASCAL%20VOC%20challenges.

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{TP}{\text{all detections}}$$

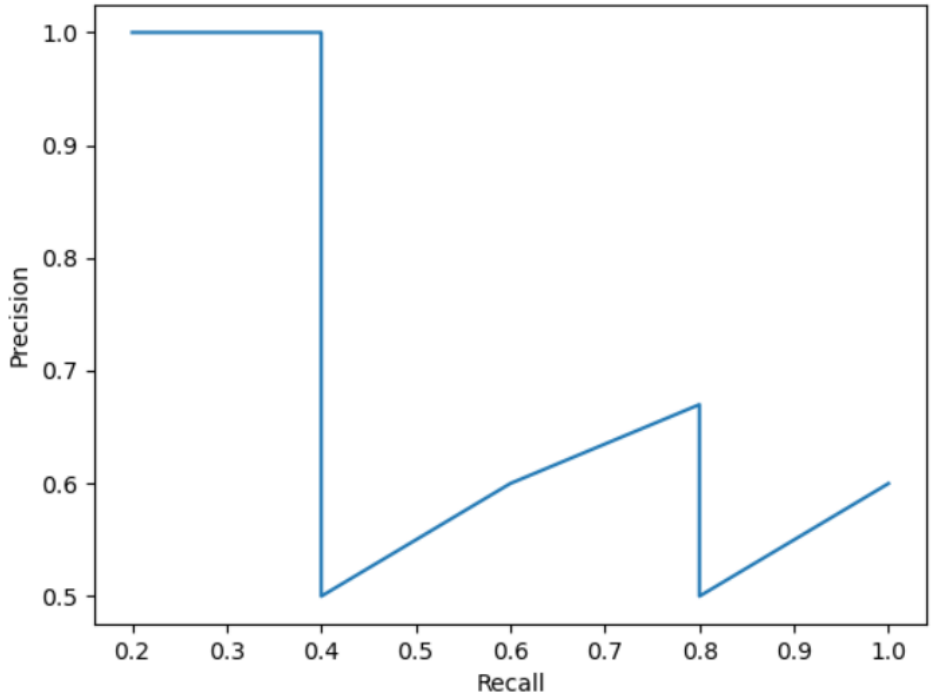
$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{TP}{\text{all ground-truths}}$$

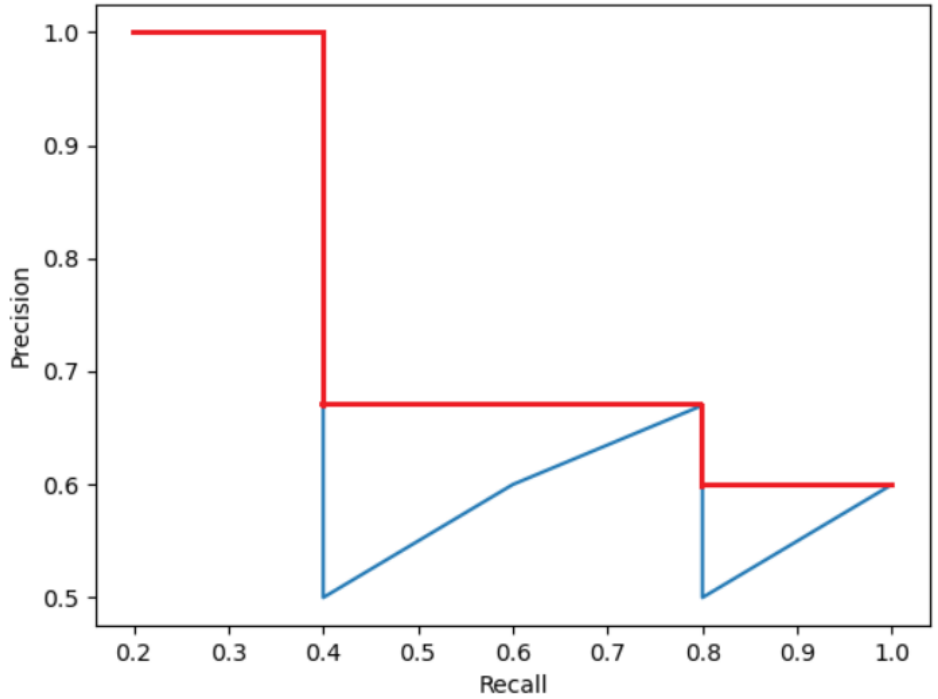
- Raising IoU threshold means that more objects will be missed by the model (more FNs and therefore low recall and high precision).
- Whereas a low IoU threshold will mean that the model gets more FPs (hence low precision and high recall).
- **For a good model, precision and recall stays high even when confidence score is varied.**

Performance Metrics (Precision-Recall Curve)

- The precision-recall (PR) curve is a plot of precision and recall at varying values of IoU thresholds.
- P-R curve is not monotonic, therefore smoothing is applied.

Ref: https://debuggercafe.com/evaluation-metrics-for-object-detection





Performance Metrics (mean Average Precision : mAP)

Average Precision (AP):

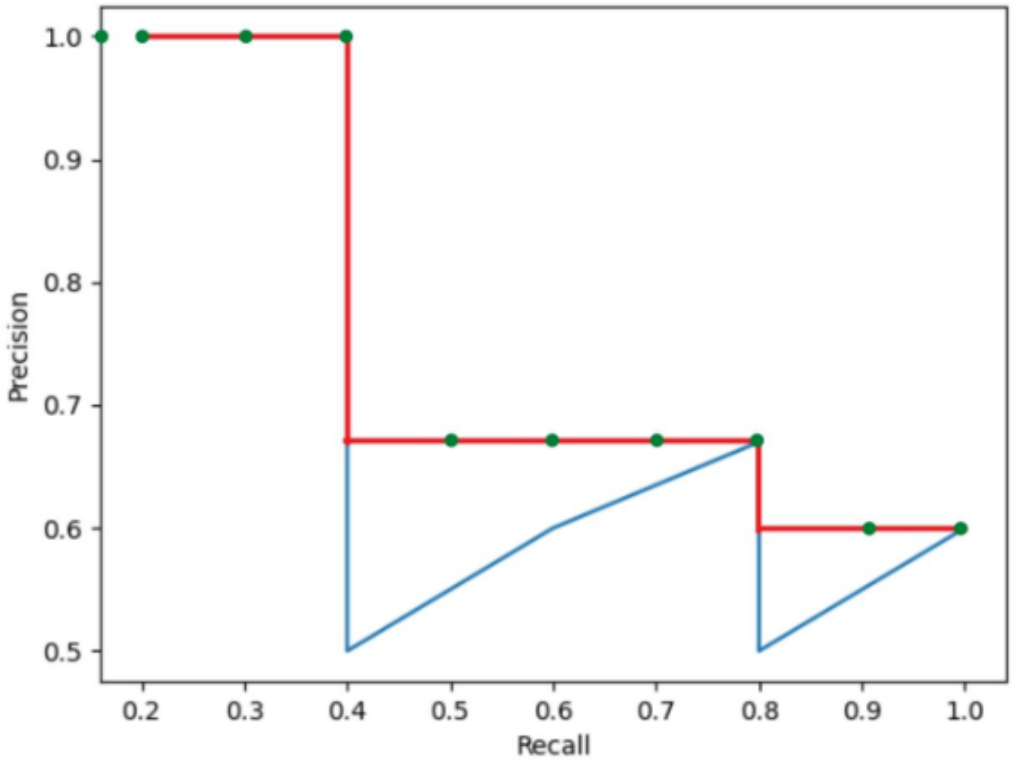
- AP@α is Area Under the Precision-Recall Curve (AUC-PR) evaluated at α IoU threshold.
- **AP50** and **AP75** mean AP calculated at IoU=0.5 and IoU=0.75, respectively.

Ref: https://towardsdatascience.com/on-object-detection-metrics-with-worked-example-216f173ed31e#:~:text=Average%20Precision%20(AP)%20and%20mean,COCO%20and%20PASCAL%20VOC%20challenges.

Ref: https://debuggercafe.com/evaluation-metrics-for-object-detection

Mean Average Precision (mAP):

- There are as many AP values as the number of classes.
- These AP values are averaged to obtain the metric - **mean Average Precision (mAP)**.
- **Pascal VOC benchmark** requires computing AP at 11 points - AP@[0,0.1,..., 1.0]



Performance Metrics (MS COCO Benchmark)

- MS COCO describes 12 evaluation metrics for submitting the results and determining the winners for the competition,
- The main evaluation metric is still the **mAP, or simply called AP**.

Ref: https://debuggercafe.com/evaluation-metrics-for-object-detection

Average Precision (AP):

AP	% AP at IoU=.50:.05:.95 **(primary challenge metric)**
$AP^{IoU=.50}$	% AP at IoU=.50 (PASCAL VOC metric)
$AP^{IoU=.75}$	% AP at IoU=.75 (strict metric)

AP Across Scales:

AP^{small}	% AP for small objects: area < 32^2
AP^{medium}	% AP for medium objects: 32^2 < area < 96^2
AP^{large}	% AP for large objects: area > 96^2

Average Recall (AR):

$AR^{max=1}$	% AR given 1 detection per image
$AR^{max=10}$	% AR given 10 detections per image
$AR^{max=100}$	% AR given 100 detections per image

AR Across Scales:

AR^{small}	% AR for small objects: area < 32^2
AR^{medium}	% AR for medium objects: 32^2 < area < 96^2
AR^{large}	% AR for large objects: area > 96^2

Comparisons

Comparisons (SSD, YOLO and Others)

Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	$\sim 1000 \times 600$
Fast YOLO	52.7	155	1	98	448×448
YOLO (VGG16)	66.4	21	1	98	448×448
SSD300	74.3	46	1	8732	300×300
SSD512	76.8	19	1	24564	512×512
SSD300	74.3	59	8	8732	300×300
SSD512	76.8	22	8	24564	512×512

Table 7: **Results on Pascal VOC2007 `test`.** SSD300 is the only real-time detection method that can achieve above 70% mAP. By using a larger input image, SSD512 outperforms all methods on accuracy while maintaining a close to real-time speed.

"SSD: Single Shot MultiBox Detector"

(With batch size 8 on Titan X and cuDNN v4 with Intel Xeon E5-2667v3 @ 3.20GHz.)

Comparisons (RetinaNet with Others)

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Two-stage methods							
Faster R-CNN+++ [16]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [20]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [17]	Inception-ResNet-v2 [34]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [32]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
One-stage methods							
YOLOv2 [27]	DarkNet-19 [27]	21.6	44.0	19.2	5.0	22.4	35.5
SSD513 [22, 9]	ResNet-101-SSD	31.2	50.4	33.3	10.2	34.5	49.8
DSSD513 [9]	ResNet-101-DSSD	33.2	53.3	35.2	13.0	35.4	51.1
RetinaNet (ours)	ResNet-101-FPN	39.1	59.1	42.3	21.8	42.7	50.2
RetinaNet (ours)	ResNeXt-101-FPN	**40.8**	**61.1**	**44.1**	**24.1**	**44.2**	51.2

Table 2. **Object detection** *single-model* results (bounding box AP), *vs.* state-of-the-art on COCO `test-dev`. We show results for our RetinaNet-101-800 model, trained with scale jitter and for 1.5× longer than the same model from Table 1e. Our model achieves top results, outperforming both one-stage and two-stage models. For a detailed breakdown of speed versus accuracy see Table 1e and Figure 2.

"Focal Loss with Dense Object Detection"

(RetinaNet with ResNet-101-FPN and a 600x600 pixel image size (*on nVidia M40 GPU) runs at 122 msec per image.)*

Comparisons (CenterNet and Others)

	Backbone	FPS	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
MaskRCNN [21]	ResNeXt-101	**11**	39.8	62.3	43.4	22.1	43.2	51.2
Deform-v2 [63]	ResNet-101	-	46.0	67.9	50.8	27.8	49.1	59.5
SNIPER [48]	DPN-98	*2.5*	46.1	67.0	51.6	29.6	48.9	58.1
PANet [35]	ResNeXt-101	-	47.4	67.2	51.8	30.1	**51.7**	60.0
TridentNet [31]	ResNet-101-DCN	0.7	**48.4**	**69.7**	**53.5**	**31.8**	51.3	**60.3**
YOLOv3 [45]	DarkNet-53	20	33.0	57.9	34.4	18.3	25.4	41.9
RetinaNet [33]	ResNeXt-101-FPN	5.4	40.8	61.1	44.1	24.1	44.2	51.2
RefineDet [59]	ResNet-101	-	36.4 / 41.8	57.5 / 62.9	39.5 / 45.7	16.6 / 25.6	39.9 / 45.1	51.4 / 54.1
CornerNet [30]	Hourglass-104	4.1	40.5 / 42.1	56.5 / 57.8	43.1 / 45.3	19.4 / 20.8	42.7 / 44.8	**53.9** / 56.7
ExtremeNet [61]	Hourglass-104	3.1	40.2 / 43.7	55.5 / 60.5	43.2 / 47.0	20.4 / 24.1	43.2 / 46.9	53.1 / 57.6
FSAF [62]	ResNeXt-101	*2.7*	**42.9** / 44.6	**63.8** / **65.2**	**46.3** / 48.6	**26.6** / **29.7**	**46.2** / **47.1**	52.7 / 54.6
CenterNet-DLA	DLA-34	**28**	39.2 / 41.6	57.1 / 60.3	42.8 / 45.1	19.9 / 21.5	43.0 / 43.9	51.4 / 56.0
CenterNet-HG	Hourglass-104	7.8	42.1 / **45.1**	61.1 / 63.9	45.9 / **49.3**	24.1 / 26.6	45.5 / **47.1**	52.8 / **57.7**

Table 2: State-of-the-art comparison on COCO test-dev. Top: two-stage detectors; bottom: one-stage detectors. We show single-scale / multi-scale testing for most one-stage detectors. Frame-per-second (FPS) were measured on the same machine whenever possible. Italic FPS highlight the cases, where the performance measure was copied from the original publication. A dash indicates methods for which neither code and models, nor public timings were available.

"Points as Objects"

(With Intel Core i7-8086K CPU, Titan Xp GPU, Pytorch 0.4.1, CUDA 9.0, and CUDNN 7.1.)

Choosing the Object Detector (High-Level, General Guidelines)

- High accuracy → More complex, larger models → lower speed
- High speed → Smaller, less complex models → lower accuracy
- Quantization → specific data types (fp16, int16, uint8) → lower accuracy
- Specific compute unit (GPU, NPU) → Highest speed → More effort

Model type	Accuracy	Speed	Model Size	Portability
Floating-point-32 bit (natively trained)	**Highest**	Lowest	Largest	**High**
Floating-point-16 bit	Low	Low	Small	Medium
Quantized (int16, uint8)	Lower	Fast	**Smaller**	Low (special math libraries)
Compute Unit (Not GPUs) (quantized models)	Lower	**Fastest**	Small	Lower

Conclusions

- Early DNN-based object detectors (R-CNN, Fast R-CNN, Faster R-CNN)
- Recent object detectors (YOLO, YOLOX, SSD, RetinaNet, CenterNet)
- Introduced metrics used for object detections
- Discussed performance and speed comparison
- General guidelines to choose object detectors (no free lunch!)

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References (Early Approaches)

Method	Bibliography	Link
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Questions?

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