YOLOv4: Optimal Speed and Accuracy of Object Detection

[Paper Link](#)

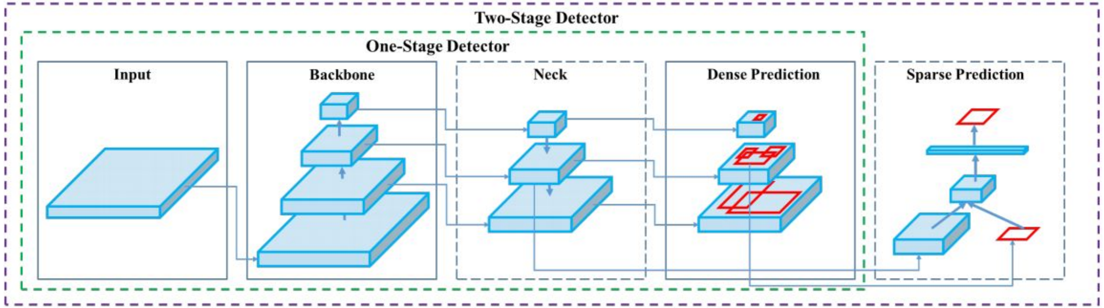
Reading notes
Hao Tsui

Agenda

- Object detector architecture breakdown
    - Backbone, neck, head
- Bag of freebies (BoF)
- Bag of specials (BoS)
- YOLOv4 architecture selection
- YOLOv4 BoF and BoS selection
- Experiments and results

Architecture - breakdown

Common object detector



- **Input**: Image, Patches, Image Pyramid
- **Backbones**: VGG16 [68], ResNet-50 [26], SpineNet [12], EfficientNet-B0/B7 [75], CSPResNeXt50 [81], CSPDarknet53 [81]
- **Neck**:
  - **Additional blocks**: SPP [25], ASPP [5], RFB [47], SAM [85]
  - **Path-aggregation blocks**: FPN [44], PAN [49], NAS-FPN [17], Fully-connected FPN, BiFPN [77], ASFF [48], SFAM [98]
- **Heads:**:
  - **Dense Prediction (one-stage)**:
    - RPN [64], SSD [50], YOLO [61], RetinaNet [45] (anchor based)
    - CornerNet [37], CenterNet [13], MatrixNet [60], FCOS [78] (anchor free)
  - **Sparse Prediction (two-stage)**:
    - Faster R-CNN [64], R-FCN [9], Mask R-CNN [23] (anchor based)
    - RepPoints [87] (anchor free)

Backbone / Feature extractor

Executing on different HW

GPU	CPU
VGG	SqueezeNet
ResNet	MobileNet
ResNeXt	ShuffleNet
DenseNet	
EfficientNet-B0/B7	
CSPResNeXt50	
CSPDarkNet53	

Neck (subset of bag of specials)

Collect feature maps from different stages

Additional block

- SPP
- ASPP
- RFB
- SAM

Path-aggregation blocks

- FPN
- PAN
- NAS-FPN
- Fully-connected FPN
- BiFPN
- ASFF
- SFAM

Head / Object detector

Region-based or Anchor-based

Two-stage / Sparse prediction

- RCNN
- Fast RCNN
- Faster RCNN
- R-FCN

Anchor-free

- RepPoints

One-stage / dense prediction

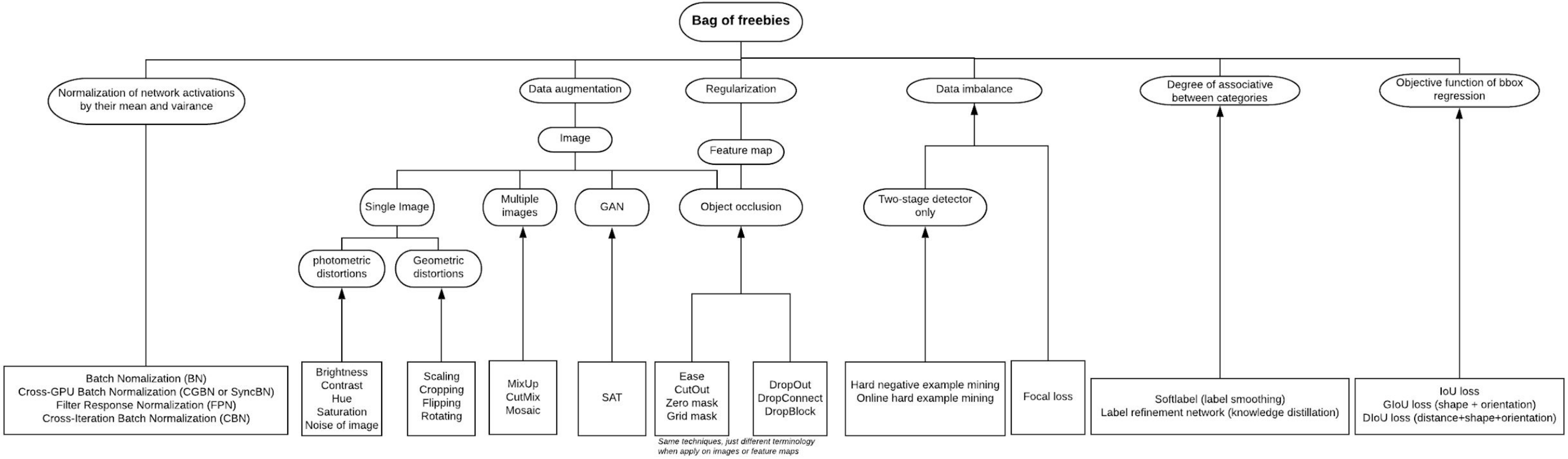
- YOLO
- SSD
- RetinaNet

Anchor-free

- CenterNet
- CornerNet
- MatrixNet
- FCOS

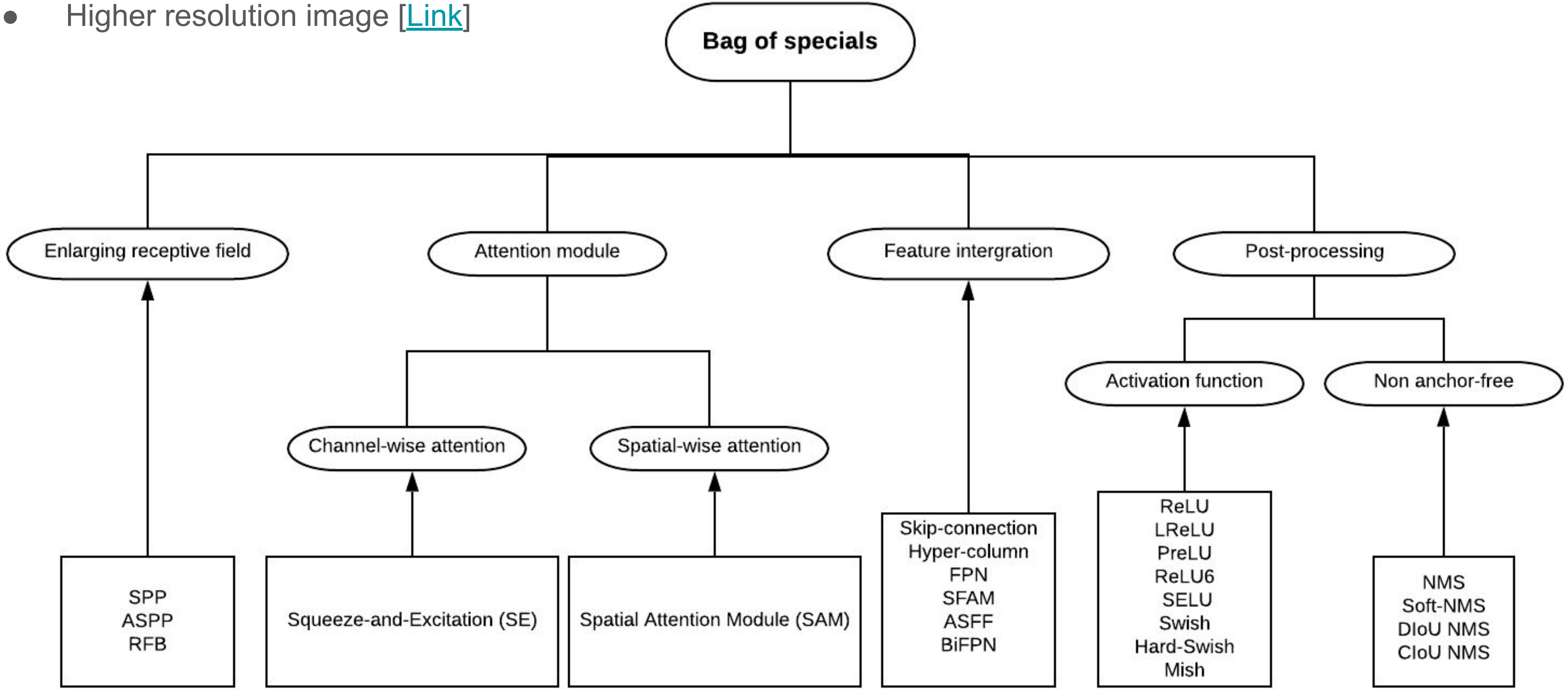
Bag of freebies

- ***Methods that only change the training strategy or only increase the training cost (nothing to do with inference)***
- Higher resolution image [Link]



Bag of specials

- *Plugin modules and post-processing methods that only increase the inference cost by a small amount but can significantly improve the accuracy*
- Higher resolution image [Link]



Architecture selection criteria

- Optimal **balance** among
  - Input network resolution (input image size)
  - Number of convolution layers
  - Number of parameters
  - Number of output layers (filters)
- Additional blocks for
  - increase receptive field (bag of specials)
  - Best method for parameter aggregation from diff. Backbone levels to diff. Detector levels (Necks)

Final architecture

- Optimal **balance** among
  - Input network resolution
  - Number of convolution layers
  - Number of parameters
  - Number of output layers (filters)
- Additional blocks for
  - increase receptive field (bag of specials)
  - Best method for parameter aggregation from diff. Backbone levels to diff. Detector levels (Necks)

Backbone: CSPDarknet53

Neck: SPP + PANet

Head: YOLOv3

Table 1: Parameters of neural networks for image classification.

Backbone model	Input network resolution	Receptive field size	Parameters	Average size of layer output (WxHxC)	BFLOPs (512x512 network resolution)	FPS (GPU RTX 2070)
CSPResNext50	512x512	425x425	20.6 M	**1058 K**	31 (15.5 FMA)	62
CSPDarknet53	512x512	725x725	**27.6 M**	950 K	52 (26.0 FMA)	**66**
EfficientNet-B3 (ours)	512x512	**1311x1311**	12.0 M	668 K	11 (5.5 FMA)	26

Why higher resolution?

- In contrast to the classifier, **detector** requires
  - Higher input network size: for detecting multiple small-sized objects
  - More layers: for a higher receptive field to cover the increase size of input network
  - More parameters: for greater capacity of a model to detect multiple objects of different sizes in a single images

The impact of receptive field size

- The influence of the receptive field with different size
  - Up to the object size - allows viewing the entire object
  - Up to the network size - allows viewing the context around the object
  - Exceeding the network size - increases the number of connections between the image point and the final activation

Selection of BoF and BoS

Backbone

BoF:

- Data augmentation
  - Mosaic, CutMix
- Regularization
  - DropBlock
- Class label smoothing

BoS:

- Mish activation
- Cross-stage partial connections (CSP)
- Multi-input weighted residual connections (MiWRC)

Detector

BoF:

- Data augmentation
  - Mosaic
  - Self-Adversarial Training
- CIoU-loss
- CmBN
- Eliminate grid sensitivity
- Multiple anchors for a single ground truth
- Cosine annealing scheduler
- Optimal hyper-parameters
- Random training shapes

BoS:

- Mish activation
- SPP-block
- SAM-block
- PAN path-aggregation block
- DIoU-NMS

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BoS:
- Mish activation
- SPP-block
- SAM-block
- PAN path-aggregation block
- DIoU-NMS

Mish

BoS - Backbone

$$f(x) = x \cdot tanh(\varsigma(x)) \quad (1)$$

where, $\varsigma(x) = \ln(1 + e^x)$ is the softplus activation [10] function. The graph of Mish is shown in Figure 1.

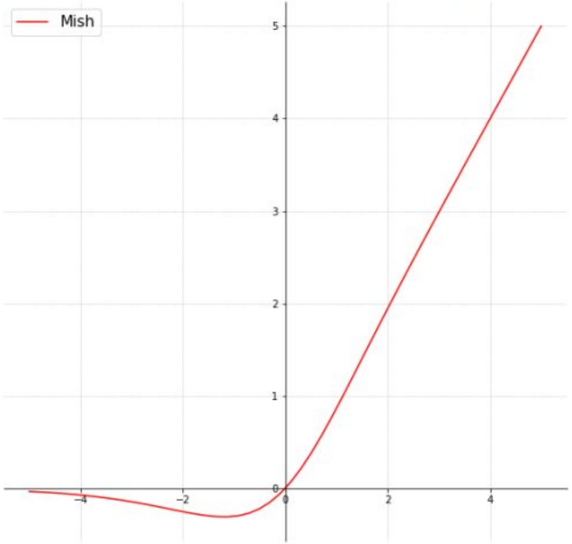
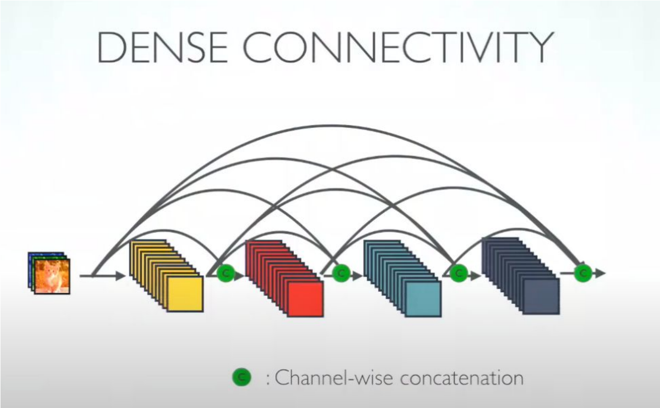


Figure 1. Mish Activation Function

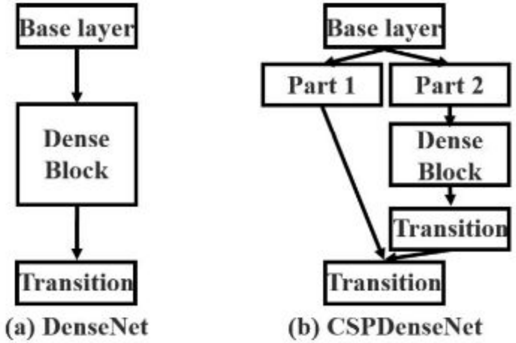
CSP: Cross-Stage Partial Connection

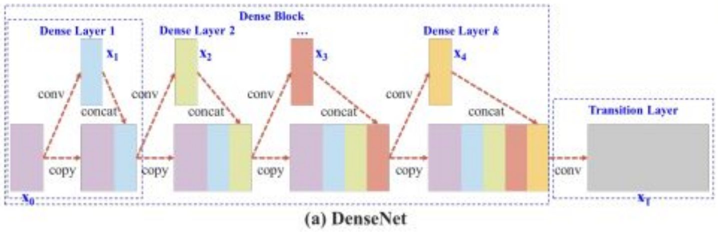
BoS - Backbone

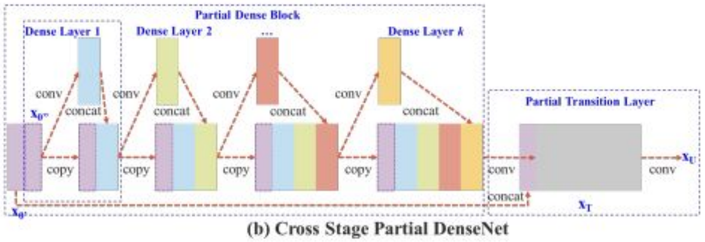
DenseNet



CSPDenseNet

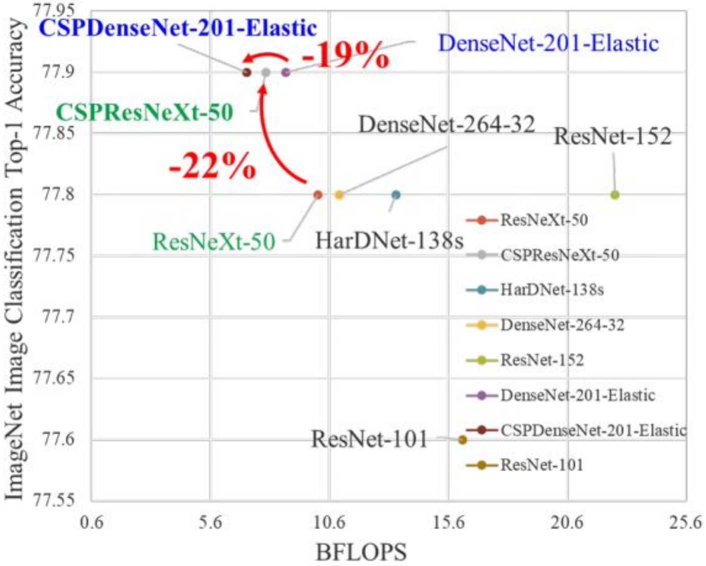


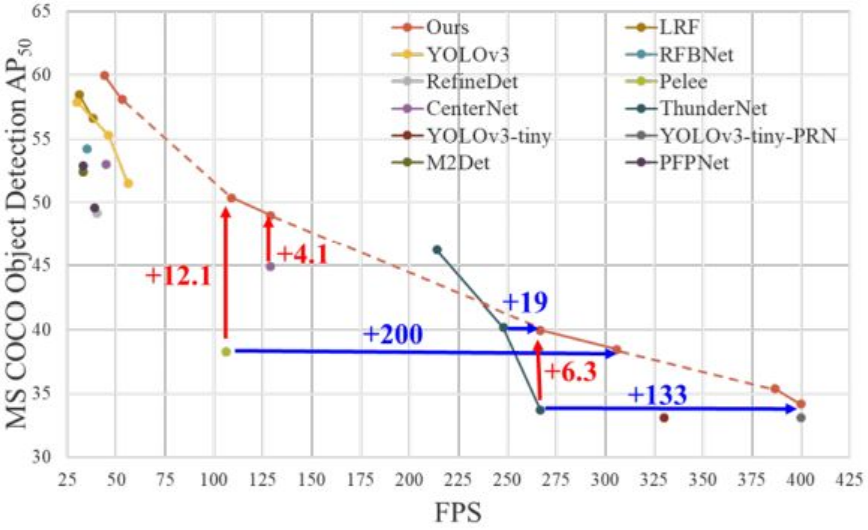




CSP: Cross-Stage Partial Connection

BoS - Backbone





YOLOv4 data augmentation

- Mosaic (new)
  - Allows detection of objects outside their normal context
  - Batch normalization calculates activation statistics from 4 different images -> <u>reduce need for large mini-batch size</u>

Figure 3: Mosaic represents a new method of data augmentation.

CutMix mixes 2, Mosaic mixes 4

- Self-Adversarial Training (SAT)
  - 2 forward backward stage
    - 1. Altering the original image
    - 2. Normal altering weights

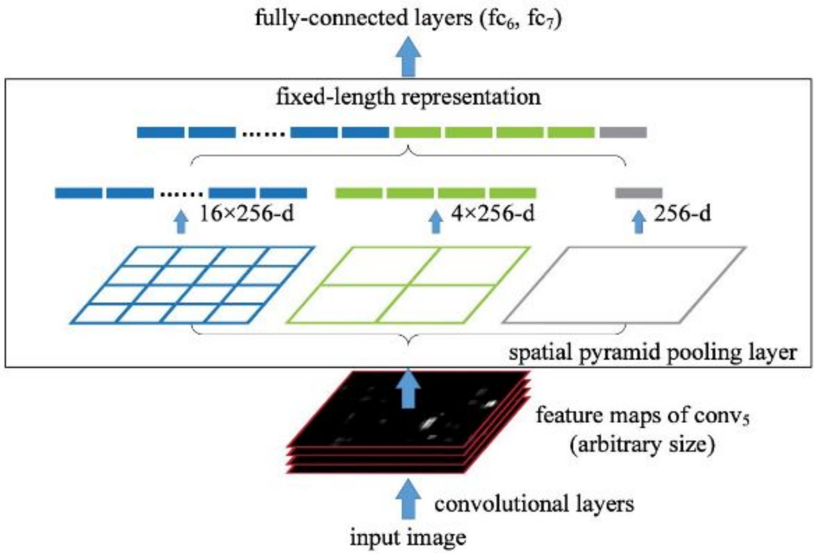
YOLOv4 modified stuffs

- Modified
  - Spatial Pyramid Pool (SPP)
  - Spatial Attention Module (SAM)
  - Path Aggregation Network (PAN)
  - Cross-Iteration Batch Normalization (CBN)

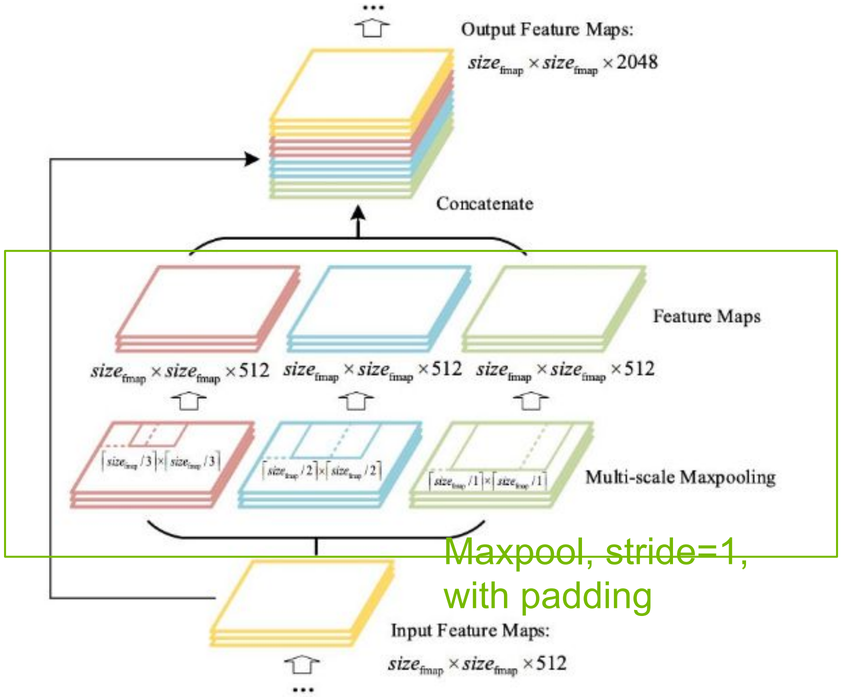
SPP: Spatial Pyramid Pooling

BoS - Neck

Original SPP



Modified SPP

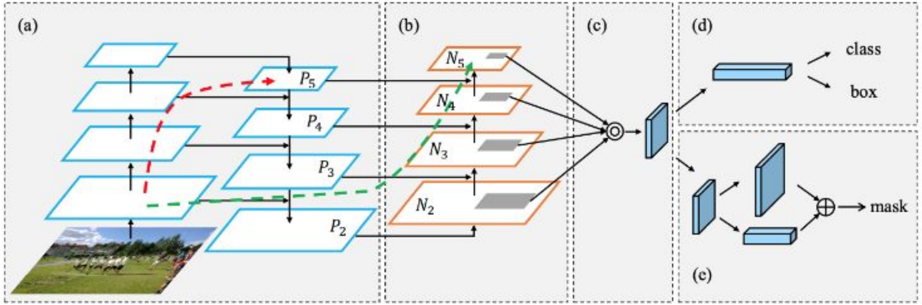


Maxpool, stride=1, with padding

PAN: Path Aggregation Network

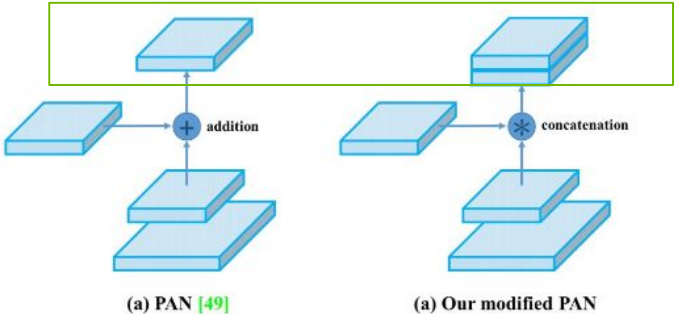
BoS - Neck

Original PAN



Modified PAN

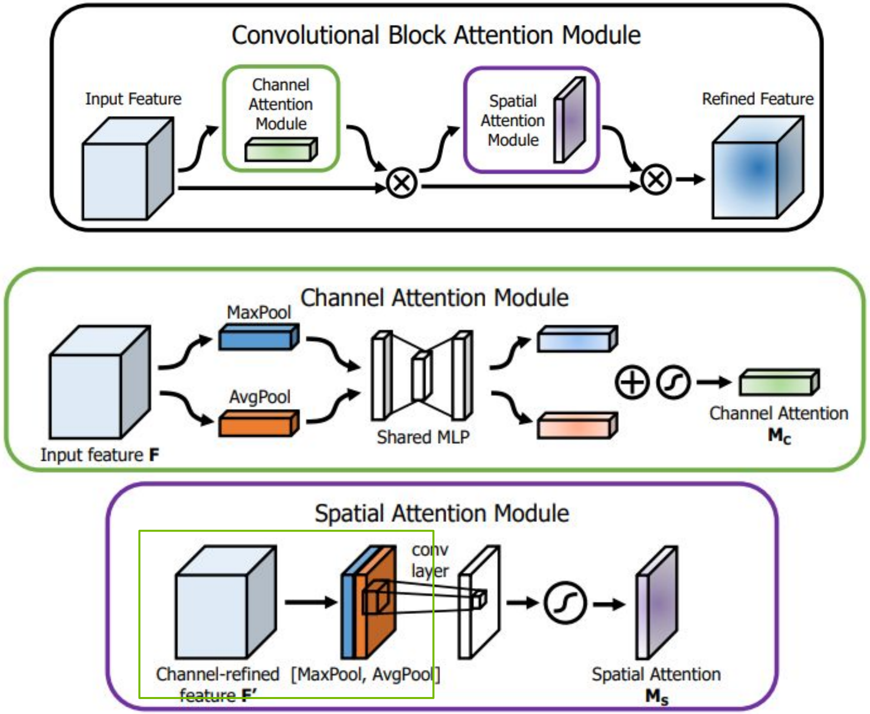
concatenation



SAM: Spatial Attention Module

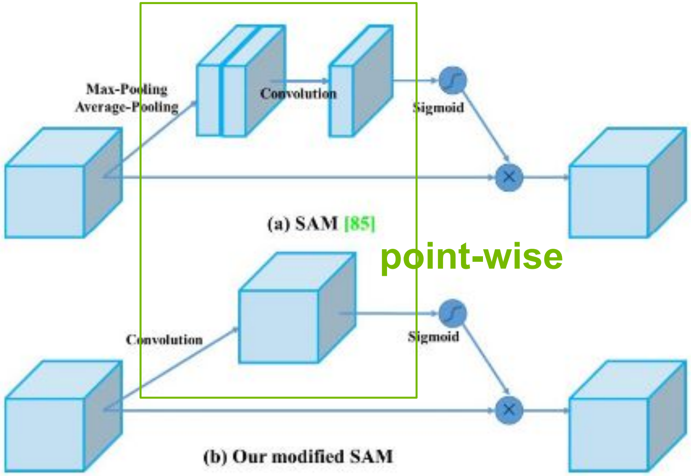
BoS - Neck

Original *CBAM

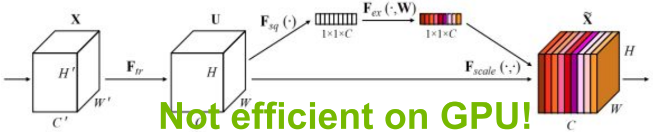


Along the channel

Modified SAM



Original SE



Not efficient on GPU!

CBN: Cross-Iteration Batch Normalization

BoF

Original CBN

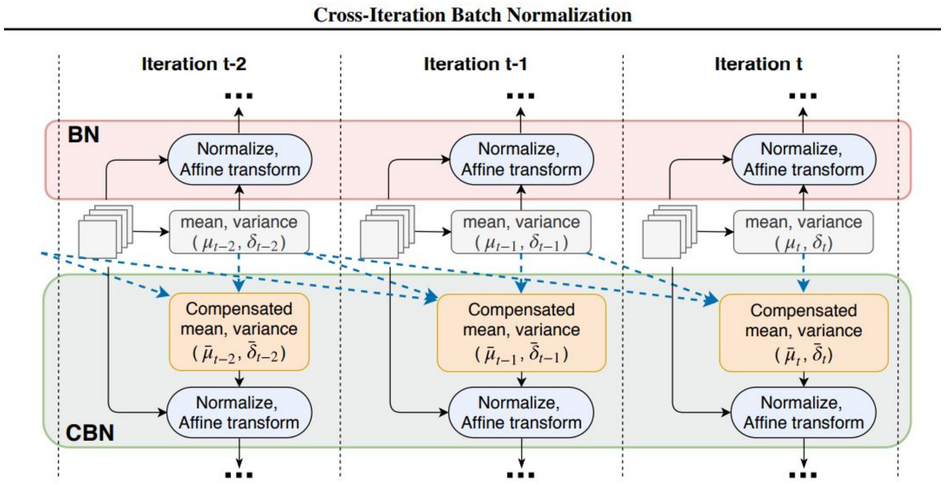


Figure 2. Illustration of BN and the proposed Cross-Iteration Batch Normalization (CBN).

Modified CBN

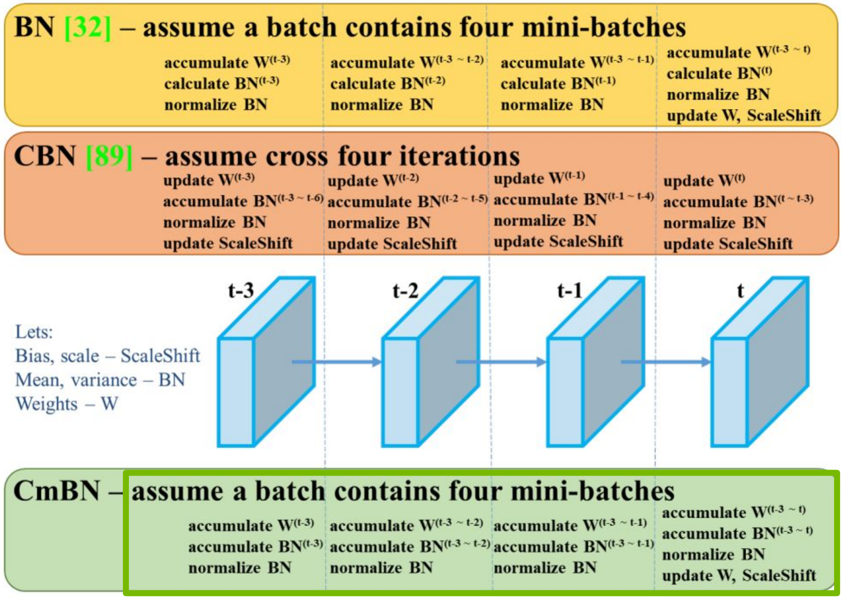


Figure 4: Cross mini-Batch Normalization.

Collects statistics only between mini-batches within a single batch

Dataset

- ImageNet -> Classifier
- MS COCO 2017 -> Detector

Influence of BoF and Activation on Classifier

Table 2: Influence of BoF and Mish on the CSPResNeXt-50 classifier accuracy.

MixUp	CutMix	Mosaic	Bluring	Label Smoothing	Swish	Mish	Top-1	Top-5
							77.9%	94.0%
✓							77.2%	**94.0%**
	✓						**78.0%**	**94.3%**
		✓					**78.1%**	**94.5%**
			✓				77.5%	93.8%
				✓			**78.1%**	**94.4%**
					✓		64.5%	86.0%
						✓	**78.9%**	**94.5%**
	✓	✓		✓			**78.5%**	**94.8%**
	✓	✓		✓		✓	**79.8%**	**95.2%**

Table 3: Influence of BoF and Mish on the CSPDarknet-53 classifier accuracy.

MixUp	CutMix	Mosaic	Bluring	Label Smoothing	Swish	Mish	Top-1	Top-5
							77.2%	93.6%
	✓	✓		✓			**77.8%**	**94.4%**
	✓	✓		✓		✓	**78.7%**	**94.8%**

CSPResNeXt outperform CSPDarkNet on classifier

Influence of BoF on Detector

Table 4: Ablation Studies of Bag-of-Freebies. (CSPResNeXt50-PANet-SPP, 512x512).

S	M	IT	GA	LS	CBN	CA	DM	OA	loss	AP	AP_{50}	AP_{75}
									MSE	38.0%	60.0%	40.8%
✓									MSE	37.7%	59.9%	40.5%
	✓								MSE	**39.1%**	**61.8%**	**42.0%**
		✓							MSE	36.9%	59.7%	39.4%
			✓						MSE	**38.9%**	**61.7%**	**41.9%**
				✓					MSE	33.0%	55.4%	35.4%
					✓				MSE	**38.4%**	**60.7%**	**41.3%**
						✓			MSE	**38.7%**	**60.7%**	**41.9%**
							✓		MSE	35.3%	57.2%	38.0%
✓									GIoU	**39.4%**	59.4%	**42.5%**
✓									DIoU	**39.1%**	58.8%	**42.1%**
✓									CIoU	**39.6%**	59.2%	**42.6%**
✓	✓	✓	✓						CIoU	**41.5%**	**64.0%**	**44.8%**
	✓		✓					✓	CIoU	36.1%	56.5%	38.4%
✓	✓	✓	✓					✓	MSE	**40.3%**	**64.0%**	**43.1%**
✓	✓	✓	✓					✓	GIoU	**42.4%**	**64.4%**	**45.9%**
✓	✓	✓	✓					✓	CIoU	**42.4%**	**64.4%**	**45.9%**

S: *Eliminate grid sensitivity*
M: *Mosaic*
IT: *IoU threshold*
GA: *Genetic algorithms*
LS: *Class label smoothing*
CBN: *Cross mini-batch normalization*
CA: *Cosine annealing scheduler*
DM: *Dynamic mini-batch size*
OA: *Optimized anchors*
MSE: *Mean Square Error*
GIoU: *(shape+orientation)*
DIoU: *(distance + shape+ orientation)*

Influence of BoS on Detector

Table 5: Ablation Studies of Bag-of-Specials. (Size 512x512).

Model	AP	AP_{50}	AP_{75}
CSPResNeXt50-PANet-SPP	42.4%	64.4%	45.9%
CSPResNeXt50-PANet-SPP-RFB	41.8%	62.7%	45.1%
CSPResNeXt50-PANet-SPP-SAM	**42.7%**	**64.6%**	**46.3%**
CSPResNeXt50-PANet-SPP-SAM-G	41.6%	62.7%	45.0%
CSPResNeXt50-PANet-SPP-ASFF-RFB	41.1%	62.6%	44.4%

Influence of Backbone on Detector

CSPDarkNet53 is more suitable for detector

Table 6: Using different classifier pre-trained weightings for detector training (all other training parameters are similar in all models) .

Model (with optimal setting)	Size	AP	AP_{50}	AP_{75}
CSPResNeXt50-PANet-SPP	512x512	42.4	64.4	45.9
CSPResNeXt50-PANet-SPP (BoF-backbone)	512x512	42.3	64.3	45.7
CSPResNeXt50-PANet-SPP (BoF-backbone + Mish)	512x512	42.3	64.2	45.8
CSPDarknet53-PANet-SPP (BoF-backbone)	512x512	42.4	64.5	46.0
CSPDarknet53-PANet-SPP (BoF-backbone + Mish)	512x512	43.0	64.9	46.5

CSPDarkNet outperform
CSPResNeXt on detector

Note**: previously, table 4 shows CSPResNeXt outperform CSPDarkNet for **classifier

***Note**: previously, table 4 shows CSPResNeXt + BoF + Mish increase **classifier** accuracy. But here shows decreasing.*
***Note**: CSPDarkNet shows increasing applying BoF + Mish on **both** classifier and detector*

Influence of Mini-batch on Detector

No more additional GPU

4.5. Influence of different mini-batch size on Detector training

Finally, we analyze the results obtained with models trained with different mini-batch sizes, and the results are shown in Table 7. From the results shown in Table 7, we found that after adding BoF and BoS training strategies, the mini-batch size has almost no effect on the detector's performance. This result shows that after the introduction of BoF and BoS, it is no longer necessary to use expensive GPUs for training. In other words, anyone can use only a conventional GPU to train an excellent detector.

Table 7: Using different mini-batch size for detector training.

Model (without OA)	Size	AP	AP_{50}	AP_{75}
CSPResNeXt50-PANet-SPP (without BoF/BoS, mini-batch 4)	608	37.1	59.2	39.9
CSPResNeXt50-PANet-SPP (without BoF/BoS, mini-batch 8)	608	38.4	60.6	41.6
CSPDarknet53-PANet-SPP (with BoF/BoS, mini-batch 4)	512	41.6	64.1	45.0
CSPDarknet53-PANet-SPP (with BoF/BoS, mini-batch 8)	512	41.7	64.2	45.2

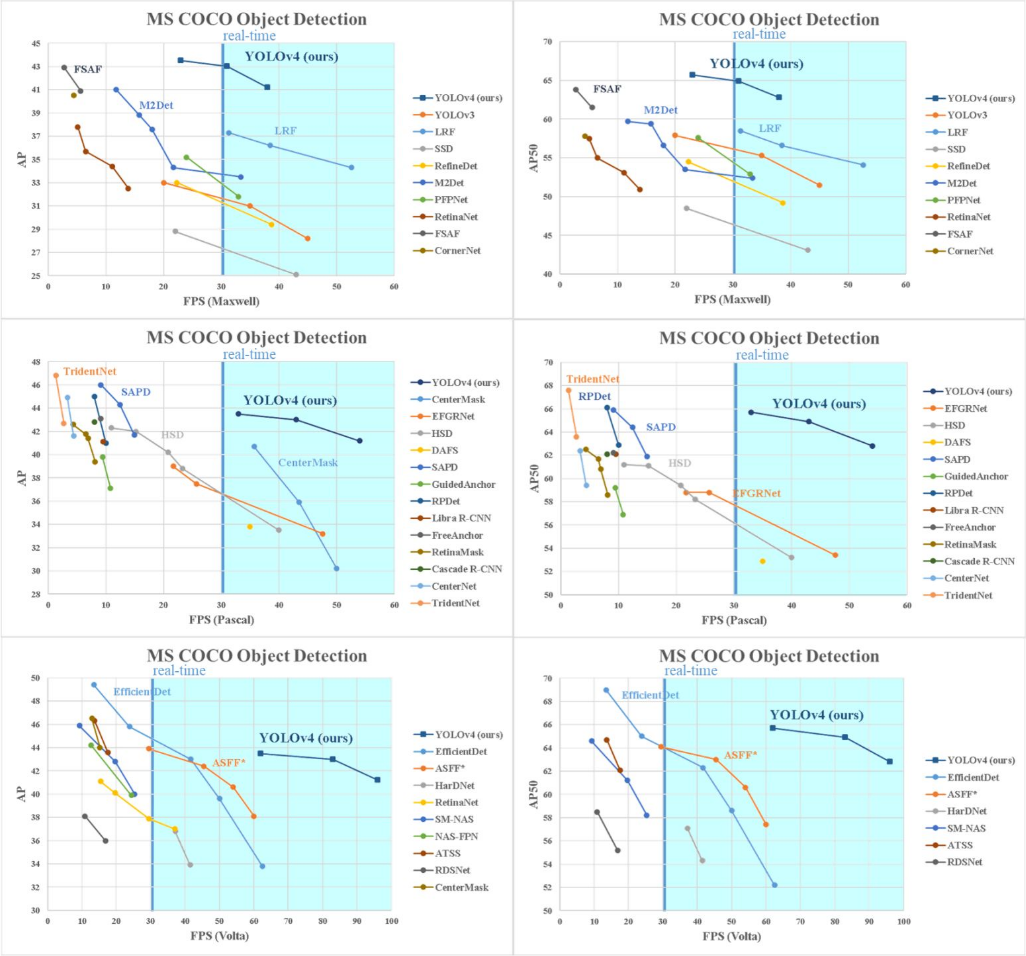


Figure 8: Comparison of the speed and accuracy of different object detectors. (Some articles stated the FPS of their detectors for only one of the GPUs: Maxwell/Pascal/Volta)

Maxwell

Table 8: Comparison of the speed and accuracy of different object detectors on the MS COCO dataset (test-dev 2017). (Real-time detectors with FPS 30 or higher are highlighted here. We compare the results with batch=1 without using tensorRT.)

Method	Backbone	Size	FPS	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
YOLOv4: Optimal Speed and Accuracy of Object Detection									
YOLOv4	CSPDarknet-53	416	38 (M)	41.2%	62.8%	44.3%	20.4%	44.4%	56.0%
YOLOv4	CSPDarknet-53	512	31 (M)	**43.0%**	**64.9%**	**46.5%**	**24.3%**	**46.1%**	**55.2%**
YOLOv4	CSPDarknet-53	608	23 (M)	43.5%	65.7%	47.3%	26.7%	46.7%	53.3%
Learning Rich Features at High-Speed for Single-Shot Object Detection [84]									
LRF	VGG-16	300	76.9 (M)	32.0%	51.5%	33.8%	12.6%	34.9%	47.0%
LRF	ResNet-101	300	52.6 (M)	34.3%	54.1%	36.6%	13.2%	38.2%	50.7%
LRF	VGG-16	512	38.5 (M)	36.2%	56.6%	38.7%	19.0%	39.9%	48.8%
LRF	ResNet-101	512	31.3 (M)	37.3%	58.5%	39.7%	19.7%	42.8%	50.1%
Receptive Field Block Net for Accurate and Fast Object Detection [47]									
RFBNet	VGG-16	300	66.7 (M)	30.3%	49.3%	31.8%	11.8%	31.9%	45.9%
RFBNet	VGG-16	512	33.3 (M)	33.8%	54.2%	35.9%	16.2%	37.1%	47.4%
RFBNet-E	VGG-16	512	30.3 (M)	34.4%	55.7%	36.4%	17.6%	37.0%	47.6%
YOLOv3: An incremental improvement [63]									
YOLOv3	Darknet-53	320	45 (M)	28.2%	51.5%	29.7%	11.9%	30.6%	43.4%
YOLOv3	Darknet-53	416	35 (M)	31.0%	55.3%	32.3%	15.2%	33.2%	42.8%
YOLOv3	Darknet-53	608	20 (M)	33.0%	57.9%	34.4%	18.3%	35.4%	41.9%
YOLOv3-SPP	Darknet-53	608	20 (M)	36.2%	60.6%	38.2%	20.6%	37.4%	46.1%
SSD: Single shot multibox detector [50]									
SSD	VGG-16	300	43 (M)	25.1%	43.1%	25.8%	6.6%	25.9%	41.4%
SSD	VGG-16	512	22 (M)	28.8%	48.5%	30.3%	10.9%	31.8%	43.5%
Single-shot refinement neural network for object detection [95]									
RefineDet	VGG-16	320	38.7 (M)	29.4%	49.2%	31.3%	10.0%	32.0%	44.4%
RefineDet	VGG-16	512	22.3 (M)	33.0%	54.5%	35.5%	16.3%	36.3%	44.3%
M2det: A single-shot object detector based on multi-level feature pyramid network [98]									
M2det	VGG-16	320	33.4 (M)	33.5%	52.4%	35.6%	14.4%	37.6%	47.6%
M2det	ResNet-101	320	21.7 (M)	34.3%	53.5%	36.5%	14.8%	38.8%	47.9%
M2det	VGG-16	512	18 (M)	37.6%	56.6%	40.5%	18.4%	43.4%	51.2%
M2det	ResNet-101	512	15.8 (M)	38.8%	59.4%	41.7%	20.5%	43.9%	53.4%
M2det	VGG-16	800	11.8 (M)	41.0%	59.7%	45.0%	22.1%	46.5%	53.8%
Parallel Feature Pyramid Network for Object Detection [34]									
PFPNet-R	VGG-16	320	33 (M)	31.8%	52.9%	33.6%	12%	35.5%	46.1%
PFPNet-R	VGG-16	512	24 (M)	35.2%	57.6%	37.9%	18.7%	38.6%	45.9%
Focal Loss for Dense Object Detection [45]									
RetinaNet	ResNet-50	500	13.9 (M)	32.5%	50.9%	34.8%	13.9%	35.8%	46.7%
RetinaNet	ResNet-101	500	11.1 (M)	34.4%	53.1%	36.8%	14.7%	38.5%	49.1%
RetinaNet	ResNet-50	800	6.5 (M)	35.7%	55.0%	38.5%	18.9%	38.9%	46.3%
RetinaNet	ResNet-101	800	5.1 (M)	37.8%	57.5%	40.8%	20.2%	41.1%	49.2%
Feature Selective Anchor-Free Module for Single-Shot Object Detection [102]									
AB+FSAF	ResNet-101	800	5.6 (M)	40.9%	61.5%	44.0%	24.0%	44.2%	51.3%
AB+FSAF	ResNeXt-101	800	2.8 (M)	42.9%	63.8%	46.3%	26.6%	46.2%	52.7%
CornerNet: Detecting objects as paired keypoints [37]									
CornerNet	Hourglass	512	4.4 (M)	40.5%	57.8%	45.3%	20.8%	44.8%	56.7%

Pascal

Table 9: Comparison of the speed and accuracy of different object detectors on the MS COCO dataset (test-dev 2017). (Real-time detectors with FPS 30 or higher are highlighted here. We compare the results with batch=1 without using tensorRT.)

Method	Backbone	Size	FPS	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
YOLOv4: Optimal Speed and Accuracy of Object Detection									
YOLOv4	CSPDarknet-53	416	54 (P)	41.2%	62.8%	44.3%	20.4%	44.4%	56.0%
YOLOv4	CSPDarknet-53	512	43 (P)	43.0%	64.9%	46.5%	24.3%	46.1%	55.2%
YOLOv4	CSPDarknet-53	608	33 (P)	**43.5%**	**65.7%**	**47.3%**	**26.7%**	**46.7%**	53.3%
CenterMask: Real-Time Anchor-Free Instance Segmentation [40]									
CenterMask-Lite	MobileNetV2-FPN	600×	50.0 (P)	30.2%	-	-	14.2%	31.9%	40.9%
CenterMask-Lite	VoVNet-19-FPN	600×	43.5 (P)	35.9%	-	-	19.6%	38.0%	45.9%
CenterMask-Lite	VoVNet-39-FPN	600×	35.7 (P)	40.7%	-	-	22.4%	43.2%	**53.5%**
Enriched Feature Guided Refinement Network for Object Detection [57]									
EFGRNet	VGG-16	320	47.6 (P)	33.2%	53.4%	35.4%	13.4%	37.1%	47.9%
EFGRNet	VG-G16	512	25.7 (P)	37.5%	58.8%	40.4%	19.7%	41.6%	49.4%
EFGRNet	ResNet-101	512	21.7 (P)	39.0%	58.8%	42.3%	17.8%	43.6%	54.5%
Hierarchical Shot Detector [3]									
HSD	VGG-16	320	40 (P)	33.5%	53.2%	36.1%	15.0%	35.0%	47.8%
HSD	VGG-16	512	23.3 (P)	38.8%	58.2%	42.5%	21.8%	41.9%	50.2%
HSD	ResNet-101	512	20.8 (P)	40.2%	59.4%	44.0%	20.0%	44.4%	54.9%
HSD	ResNeXt-101	512	15.2 (P)	41.9%	61.1%	46.2%	21.8%	46.6%	57.0%
HSD	ResNet-101	768	10.9 (P)	42.3%	61.2%	46.9%	22.8%	47.3%	55.9%
Dynamic anchor feature selection for single-shot object detection [41]									
DAFS	VGG16	512	35 (P)	33.8%	52.9%	36.9%	14.6%	37.0%	47.7%
Soft Anchor-Point Object Detection [101]									
SAPD	ResNet-50	-	14.9 (P)	41.7%	61.9%	44.6%	24.1%	44.6%	51.6%
SAPD	ResNet-50-DCN	-	12.4 (P)	44.3%	64.4%	47.7%	25.5%	47.3%	57.0%
SAPD	ResNet-101-DCN	-	9.1 (P)	46.0%	65.9%	49.6%	26.3%	49.2%	59.6%
Region proposal by guided anchoring [82]									
RetinaNet	ResNet-50	-	10.8 (P)	37.1%	56.9%	40.0%	20.1%	40.1%	48.0%
Faster R-CNN	ResNet-50	-	9.4 (P)	39.8%	59.2%	43.5%	21.8%	42.6%	50.7%
RepPoints: Point set representation for object detection [87]									
RPDet	ResNet-101	-	10 (P)	41.0%	62.9%	44.3%	23.6%	44.1%	51.7%
RPDet	ResNet-101-DCN	-	8 (P)	45.0%	66.1%	49.0%	26.6%	48.6%	57.5%
Libra R-CNN: Towards balanced learning for object detection [58]									
Libra R-CNN	ResNet-101	-	9.5 (P)	41.1%	62.1%	44.7%	23.4%	43.7%	52.5%
FreeAnchor: Learning to match anchors for visual object detection [96]									
FreeAnchor	ResNet-101	-	9.1 (P)	43.1%	62.2%	46.4%	24.5%	46.1%	54.8%
RetinaMask: Learning to Predict Masks Improves State-of-The-Art Single-Shot Detection for Free [14]									
RetinaMask	ResNet-50-FPN	800×	8.1 (P)	39.4%	58.6%	42.3%	21.9%	42.0%	51.0%
RetinaMask	ResNet-101-FPN	800×	6.9 (P)	41.4%	60.8%	44.6%	23.0%	44.5%	53.5%
RetinaMask	ResNet-101-FPN-GN	800×	6.5 (P)	41.7%	61.7%	45.0%	23.5%	44.7%	52.8%
RetinaMask	ResNeXt-101-FPN-GN	800×	4.3 (P)	42.6%	62.5%	46.0%	24.8%	45.6%	53.8%
Cascade R-CNN: Delving into high quality object detection [2]									

Volta

Table 10: Comparison of the speed and accuracy of different object detectors on the MS COCO dataset (test-dev 2017). (Real-time detectors with FPS 30 or higher are highlighted here. We compare the results with batch=1 without using tensorRT.)

Method	Backbone	Size	FPS	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
YOLOv4: Optimal Speed and Accuracy of Object Detection									
YOLOv4	CSPDarknet-53	416	96 (V)	41.2%	62.8%	44.3%	20.4%	44.4%	56.0%
YOLOv4	CSPDarknet-53	512	83 (V)	43.0%	64.9%	46.5%	24.3%	46.1%	55.2%
YOLOv4	CSPDarknet-53	608	62 (V)	**43.5%**	**65.7%**	47.3%	**26.7%**	46.7%	53.3%
EfficientDet: Scalable and Efficient Object Detection [77]									
EfficientDet-D0	Efficient-B0	512	62.5 (V)	33.8%	52.2%	35.8%	12.0%	38.3%	51.2%
EfficientDet-D1	Efficient-B1	640	50.0 (V)	39.6%	58.6%	42.3%	17.9%	44.3%	56.0%
EfficientDet-D2	Efficient-B2	768	41.7 (V)	43.0%	62.3%	46.2%	22.5%	**47.0%**	**58.4%**
EfficientDet-D3	Efficient-B3	896	23.8 (V)	45.8%	65.0%	49.3%	26.6%	49.4%	59.8%
Learning Spatial Fusion for Single-Shot Object Detection [48]									
YOLOv3 + ASFF*	Darknet-53	320	60 (V)	38.1%	57.4%	42.1%	16.1%	41.6%	53.6%
YOLOv3 + ASFF*	Darknet-53	416	54 (V)	40.6%	60.6%	45.1%	20.3%	44.2%	54.1%
YOLOv3 + ASFF*	Darknet-53	608×	45.5 (V)	42.4%	63.0%	**47.4%**	25.5%	45.7%	52.3%
YOLOv3 + ASFF*	Darknet-53	800×	29.4 (V)	43.9%	64.1%	49.2%	27.0%	46.6%	53.4%
HarDNet: A Low Memory Traffic Network [4]									
RFBNet	HarDNet68	512	41.5 (V)	33.9%	54.3%	36.2%	14.7%	36.6%	50.5%
RFBNet	HarDNet85	512	37.1 (V)	36.8%	57.1%	39.5%	16.9%	40.5%	52.9%
Focal Loss for Dense Object Detection [45]									
RetinaNet	ResNet-50	640	37 (V)	37.0%	-	-	-	-	-
RetinaNet	ResNet-101	640	29.4 (V)	37.9%	-	-	-	-	-
RetinaNet	ResNet-50	1024	19.6 (V)	40.1%	-	-	-	-	-
RetinaNet	ResNet-101	1024	15.4 (V)	41.1%	-	-	-	-	-
SM-NAS: Structural-to-Modular Neural Architecture Search for Object Detection [88]									
SM-NAS: E2	-	800×600	25.3 (V)	40.0%	58.2%	43.4%	21.1%	42.4%	51.7%
SM-NAS: E3	-	800×600	19.7 (V)	42.8%	61.2%	46.5%	23.5%	45.5%	55.6%
SM-NAS: E5	-	1333×800	9.3 (V)	45.9%	64.6%	49.6%	27.1%	49.0%	58.0%
NAS-FPN: Learning scalable feature pyramid architecture for object detection [17]									
NAS-FPN	ResNet-50	640	24.4 (V)	39.9%	-	-	-	-	-
NAS-FPN	ResNet-50	1024	12.7 (V)	44.2%	-	-	-	-	-
Bridging the Gap Between Anchor-based and Anchor-free Detection via Adaptive Training Sample Selection [94]									
ATSS	ResNet-101	800×	17.5 (V)	43.6%	62.1%	47.4%	26.1%	47.0%	53.6%
ATSS	ResNet-101-DCN	800×	13.7 (V)	46.3%	64.7%	50.4%	27.7%	49.8%	58.4%
RDSNet: A New Deep Architecture for Reciprocal Object Detection and Instance Segmentation [83]									
RDSNet	ResNet-101	600	16.8 (V)	36.0%	55.2%	38.7%	17.4%	39.6%	49.7%
RDSNet	ResNet-101	800	10.9 (V)	38.1%	58.5%	40.8%	21.2%	41.5%	48.2%
CenterMask: Real-Time Anchor-Free Instance Segmentation [40]									
CenterMask	ResNet-101-FPN	800×	15.2 (V)	44.0%	-	-	25.8%	46.8%	54.9%
CenterMask	VoVNet-99-FPN	800×	12.9 (V)	46.5%	-	-	28.7%	48.9%	57.2%