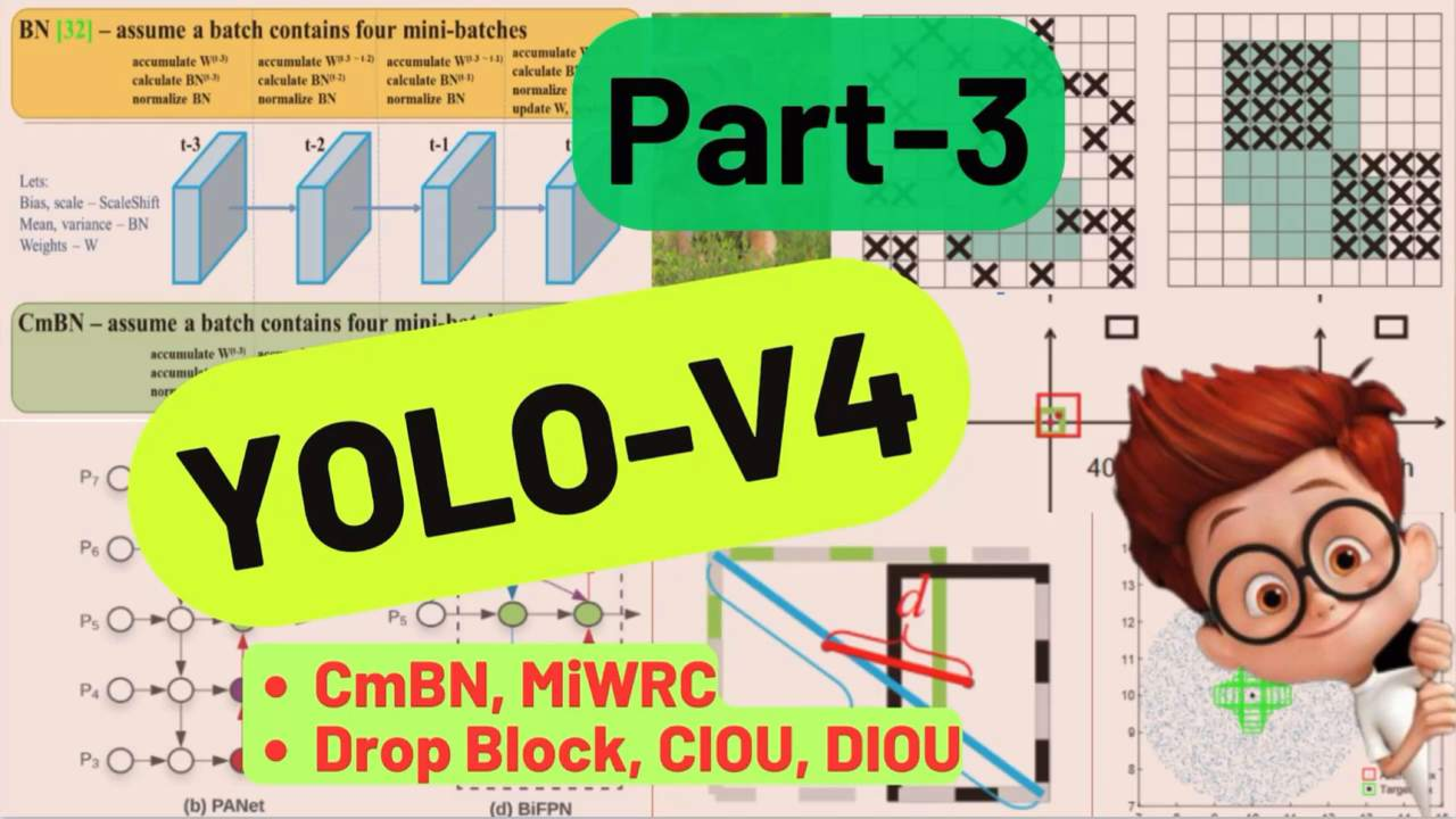

Part-3
YOLO-V4
• CmBN, MiWRC
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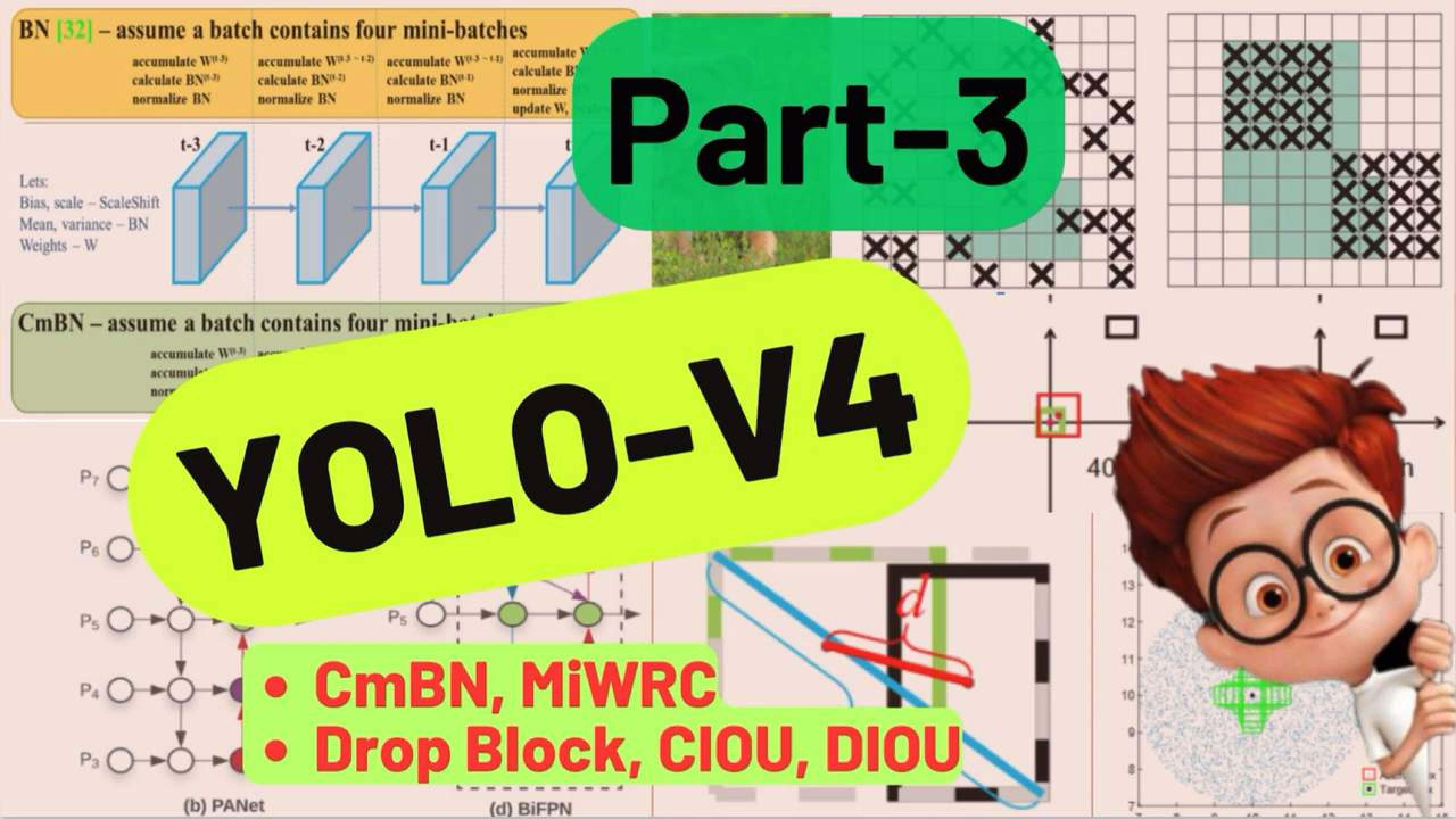
BN [32] – assume a batch contains four mini-batches
CmBN – assume a batch contains four mini-batches
Lets:
Bias, scale – ScaleShift
Mean, variance – BN
Weights – W
(b) PANet
(d) BiFPN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calculate $BN^{(t-3)}$
normalize BN
accumulate $W^{(t-3 \sim t-2)}$
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t-2
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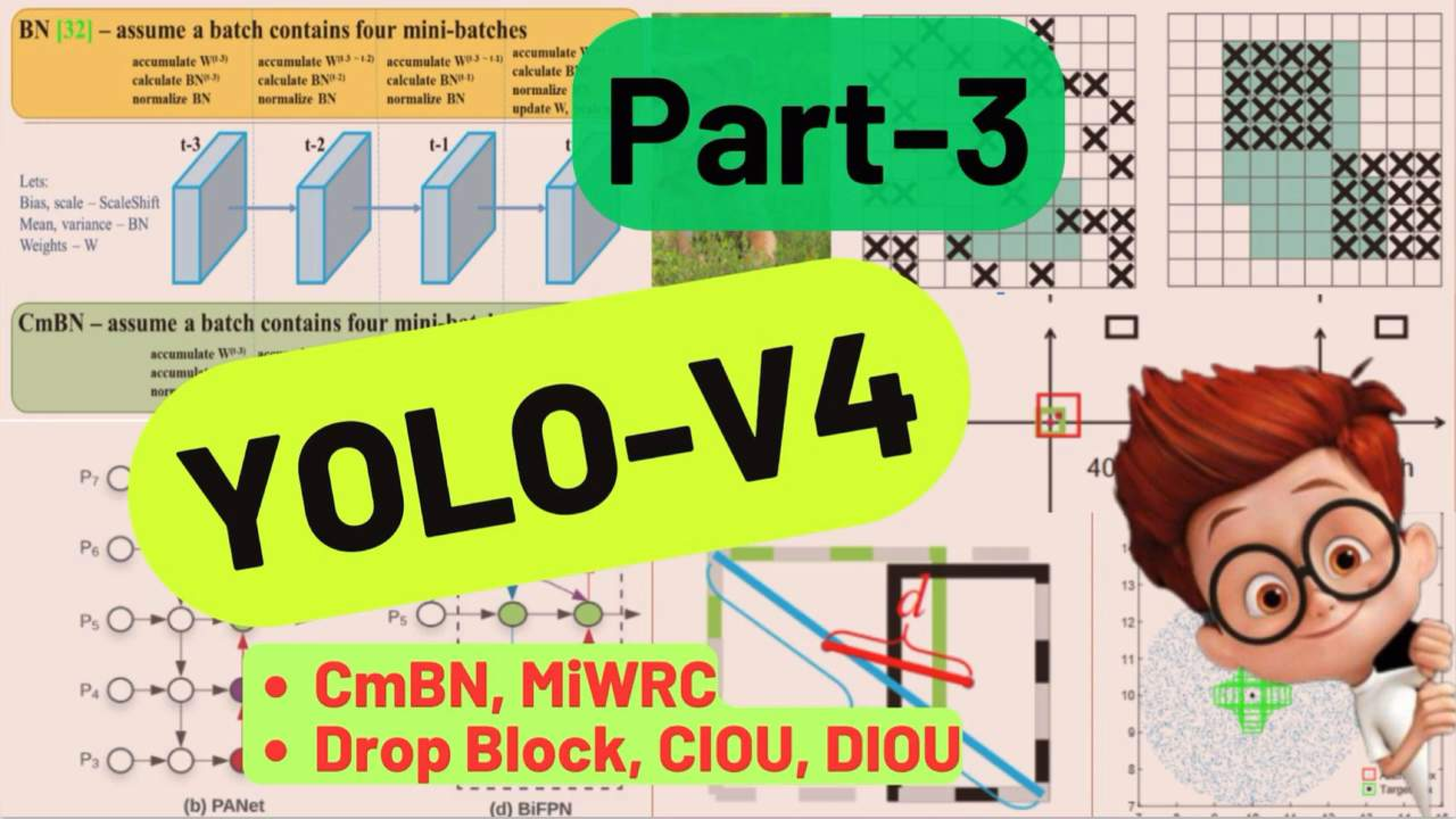
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  - **CSPNet**
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BoF & BoS - covered

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Batch Normalization:

- Mean (μ):

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- Normalize:

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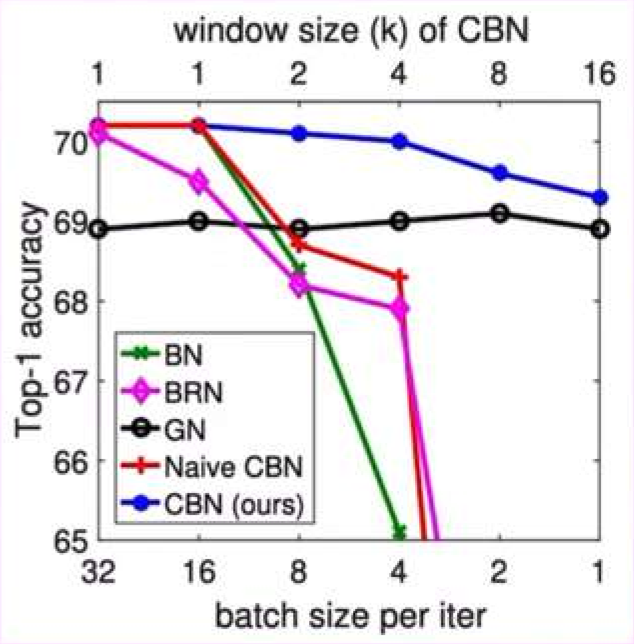
Drawbacks:

- Fails in case of small batch sizes (mean and variance are inaccurate)



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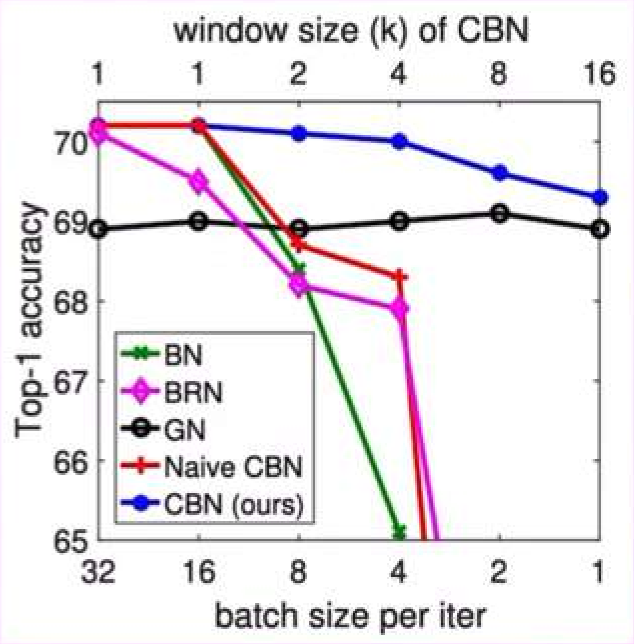

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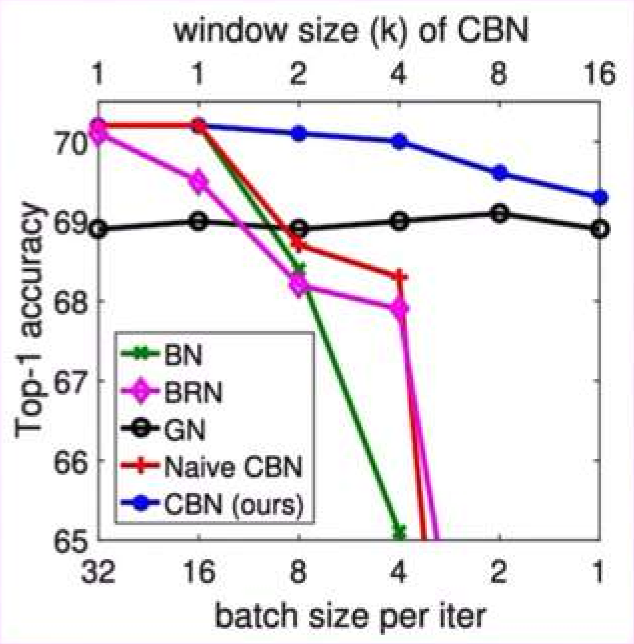

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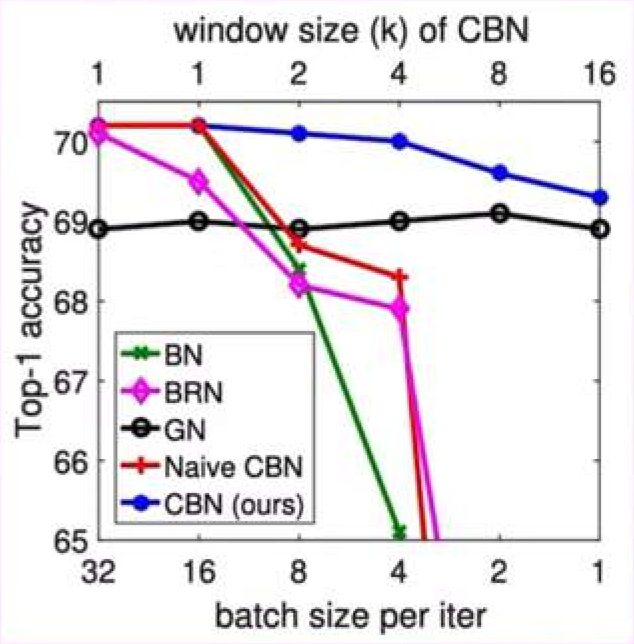

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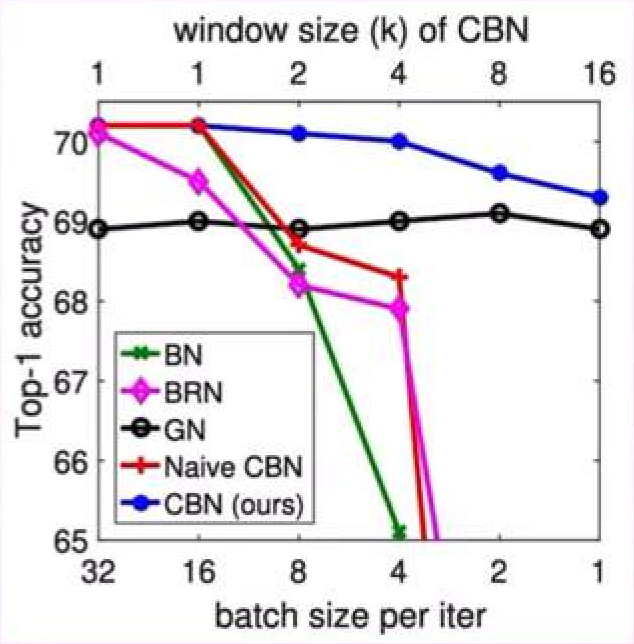

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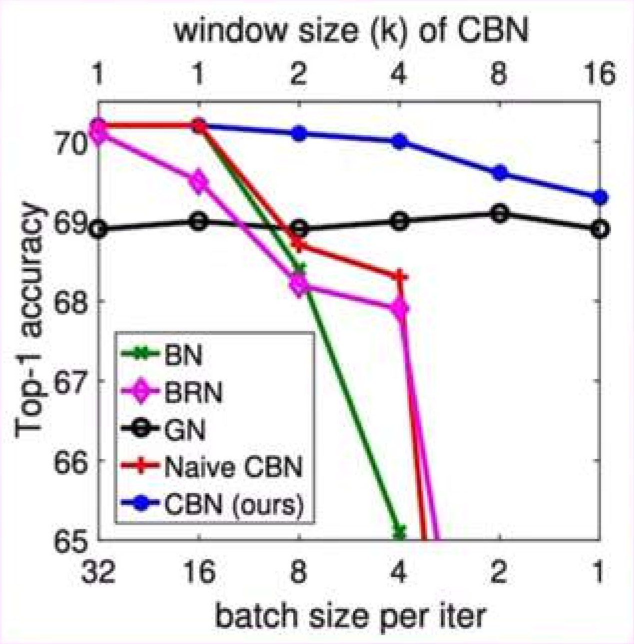

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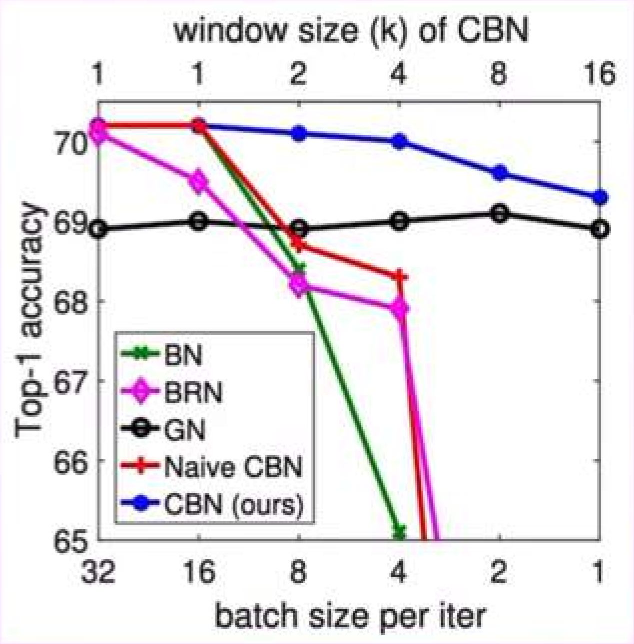

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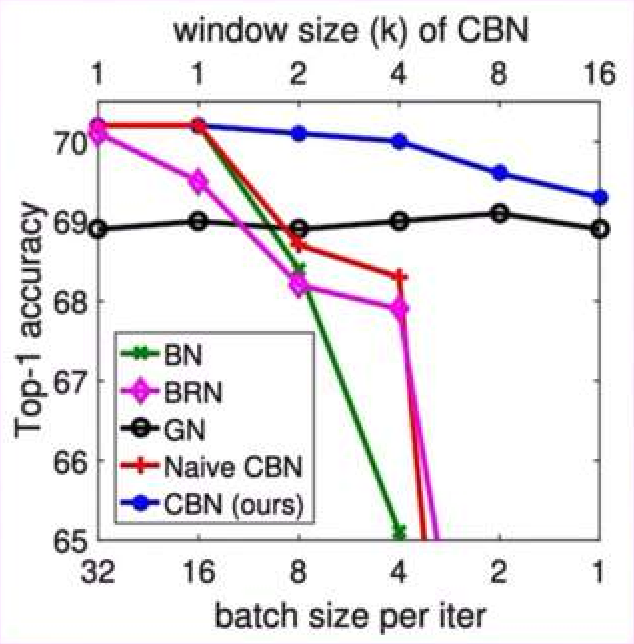

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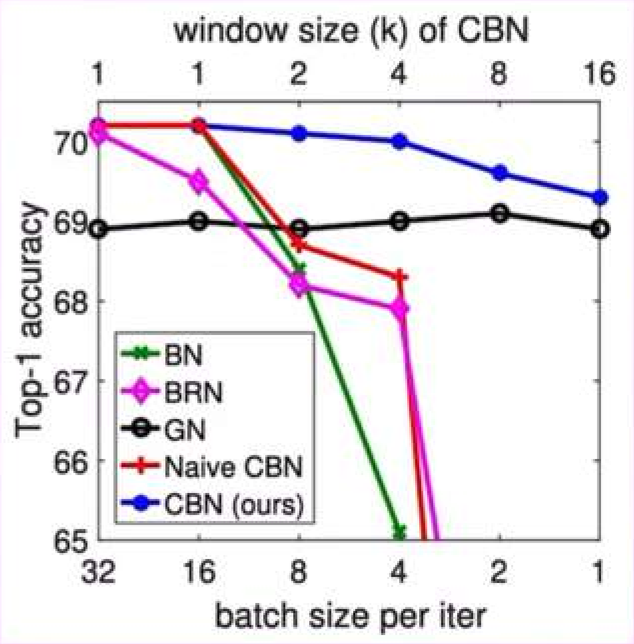

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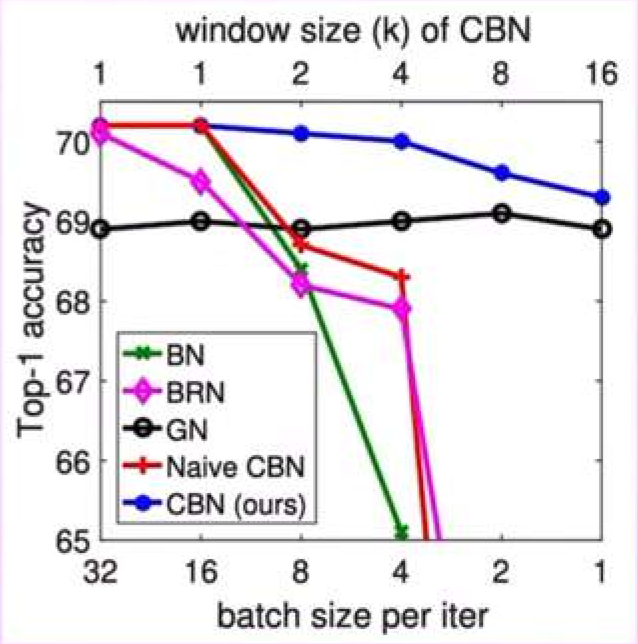

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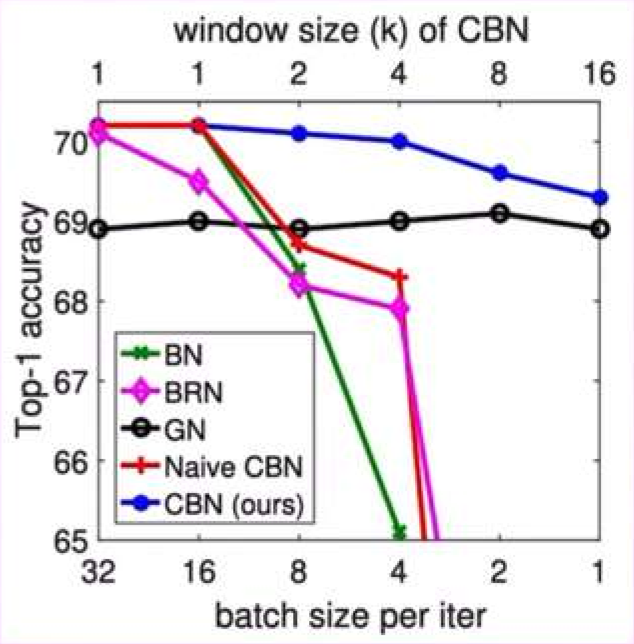

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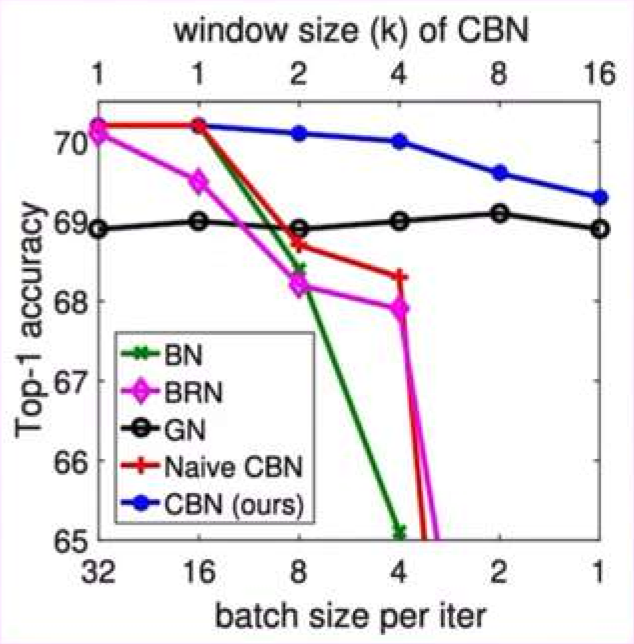

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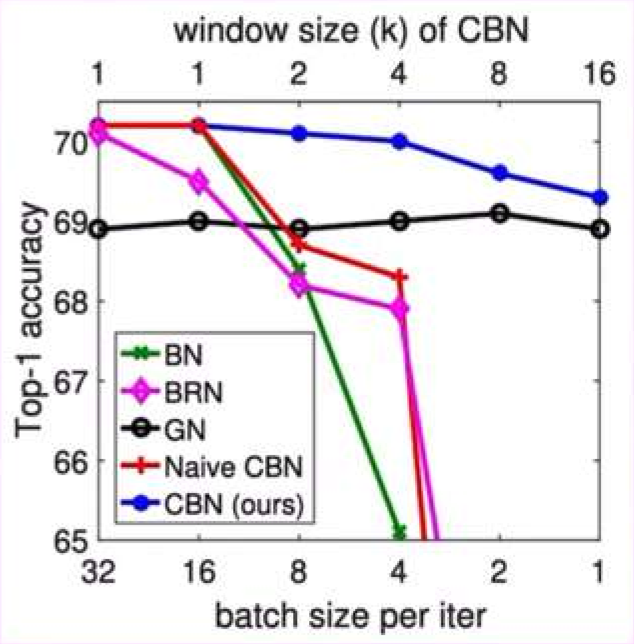

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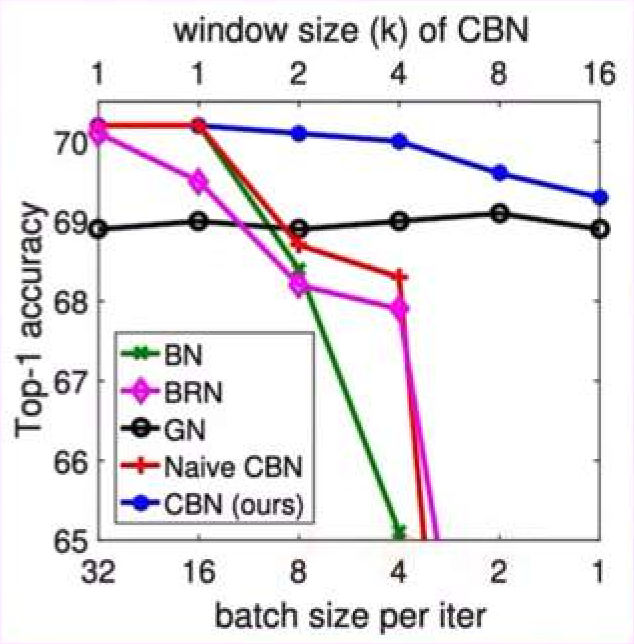

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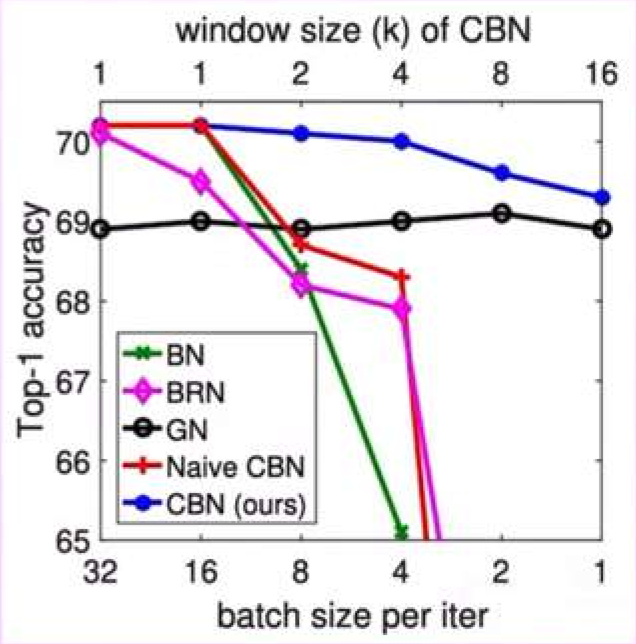

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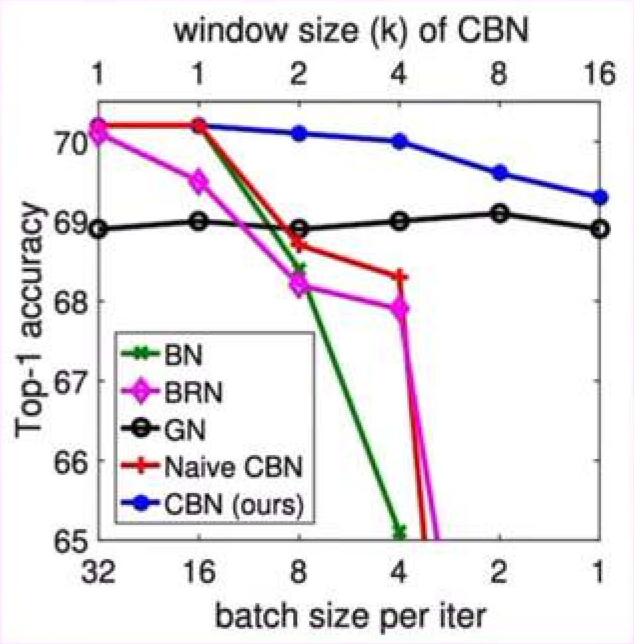

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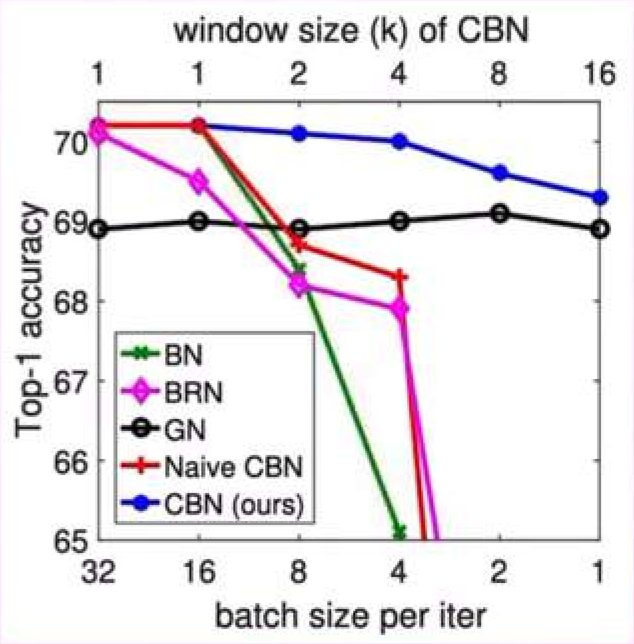

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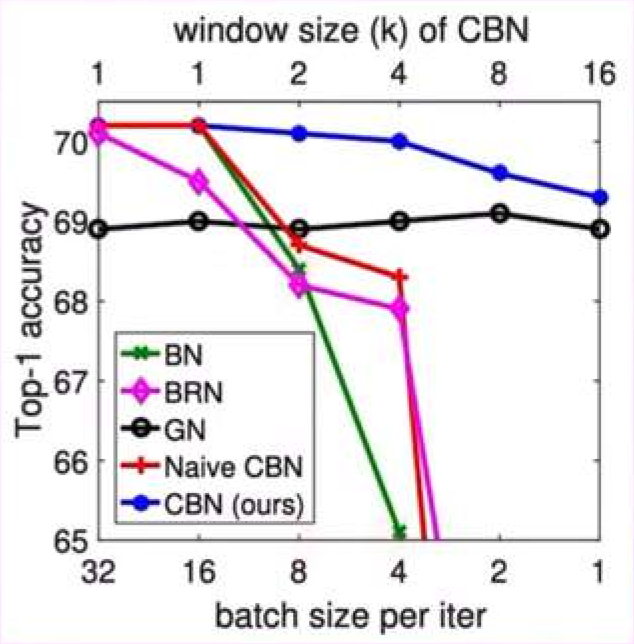

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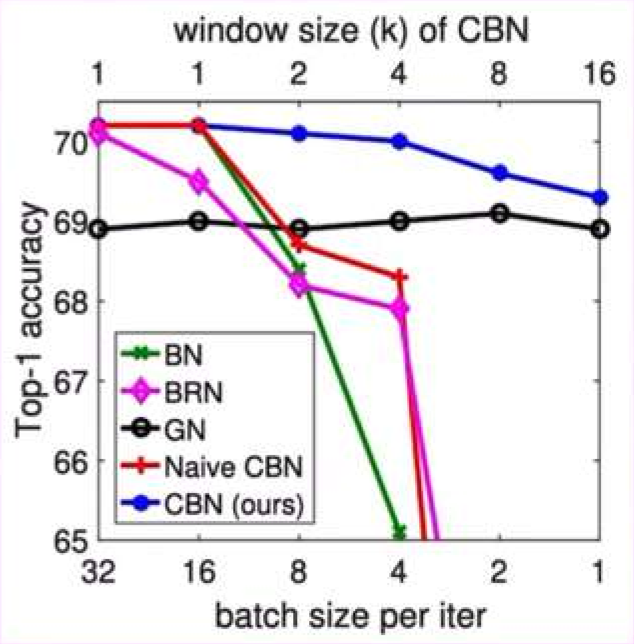

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- Collect statistics over the entire batch instead of mini-batches

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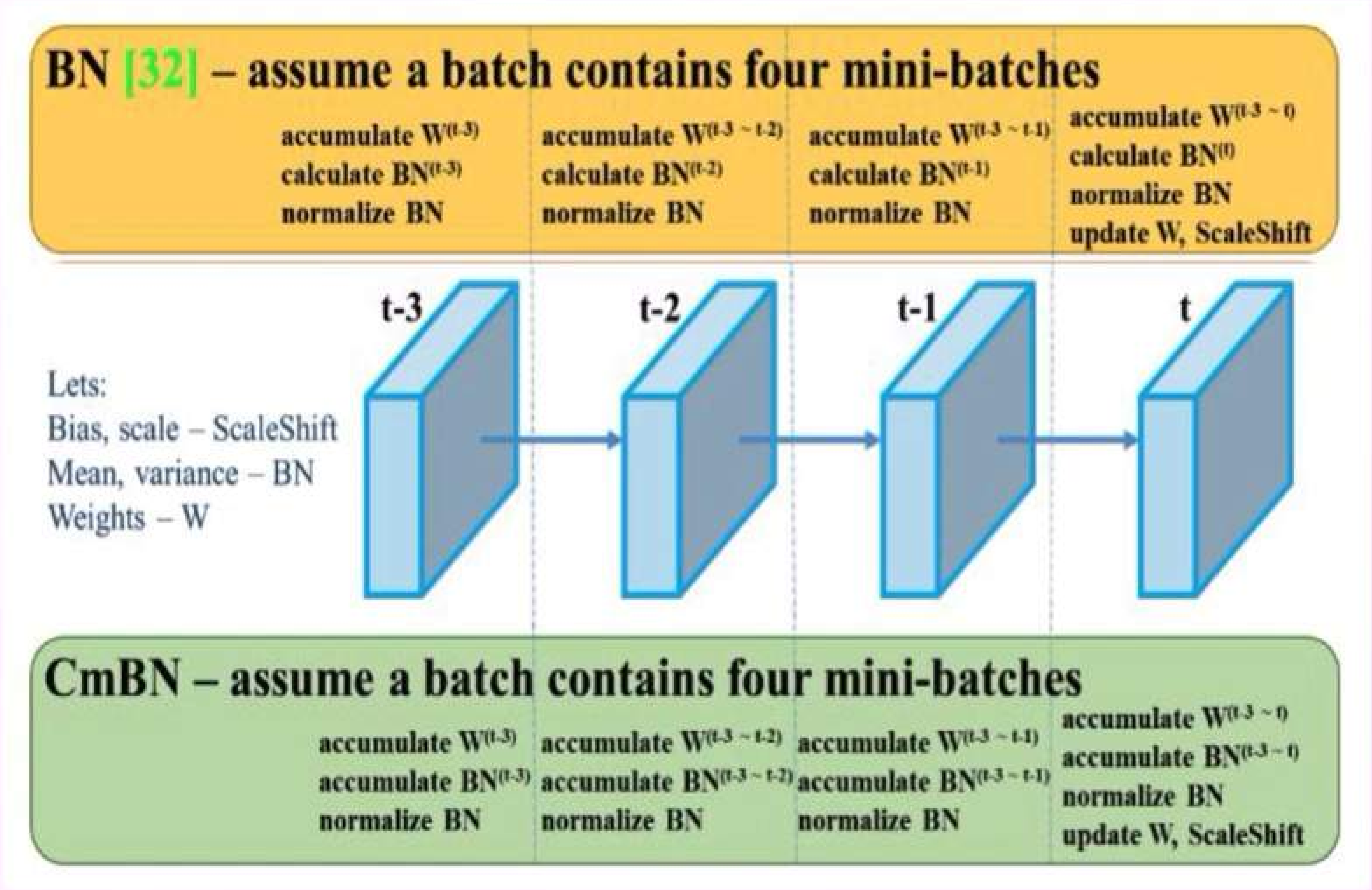

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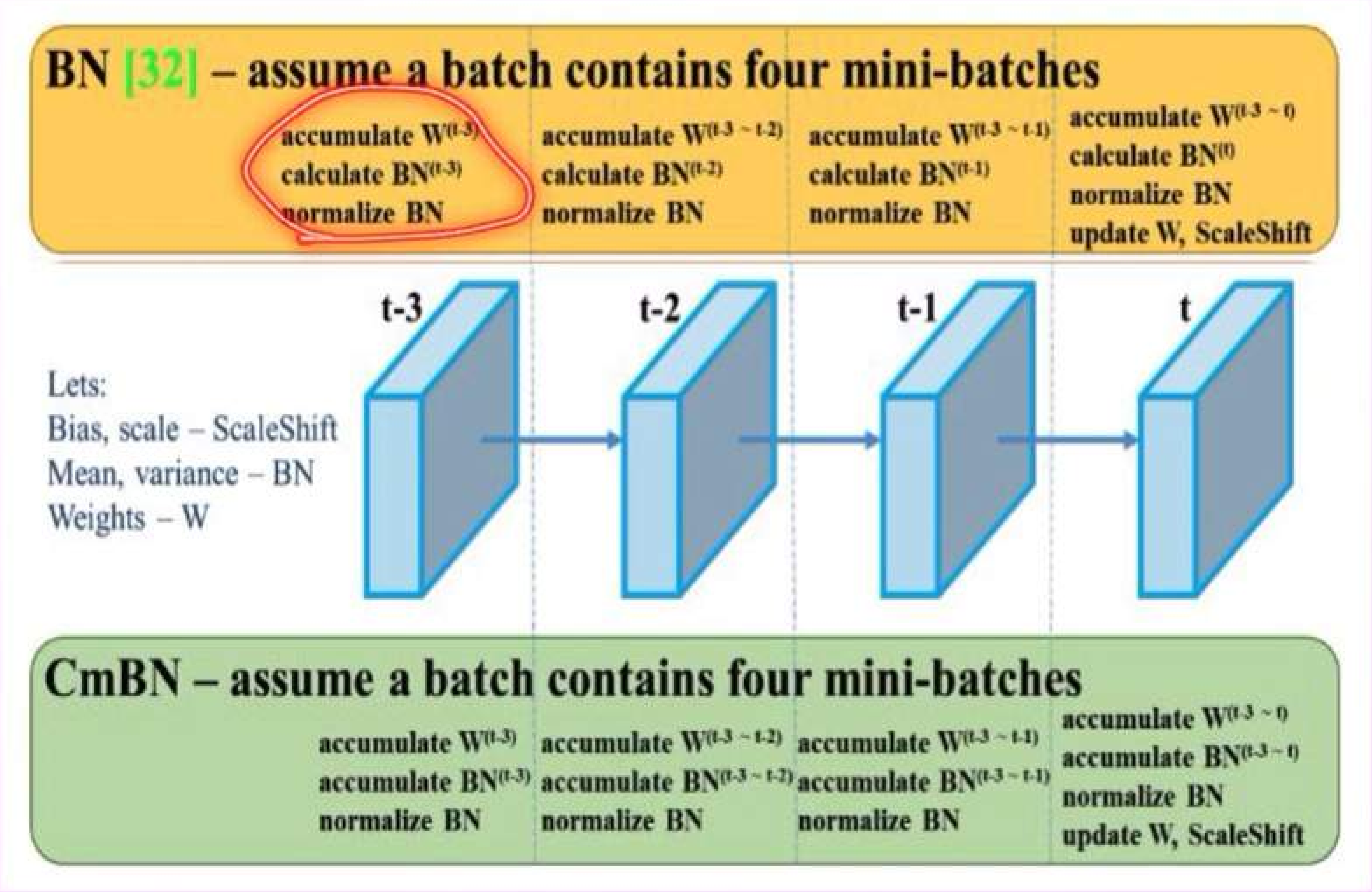

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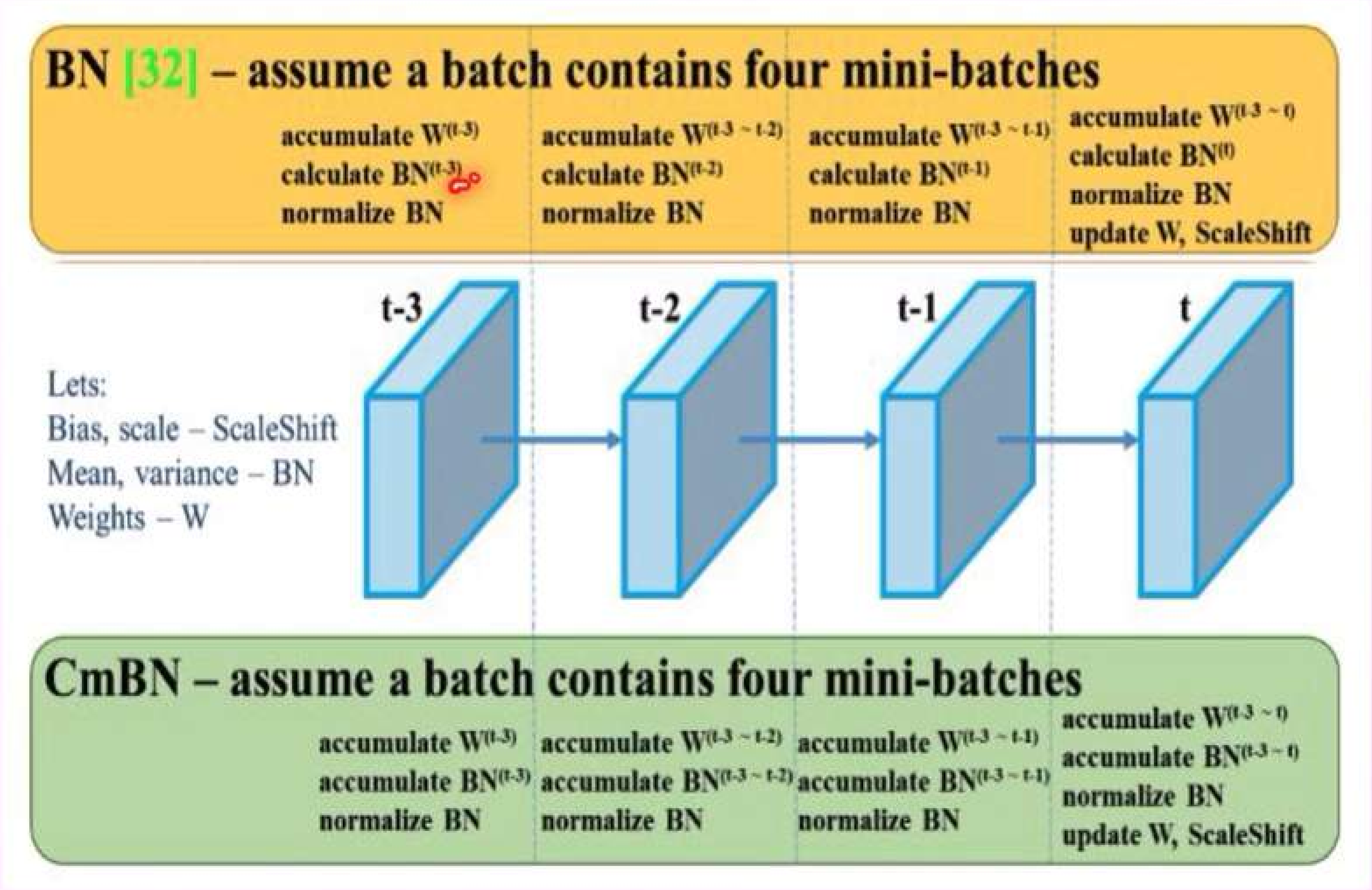

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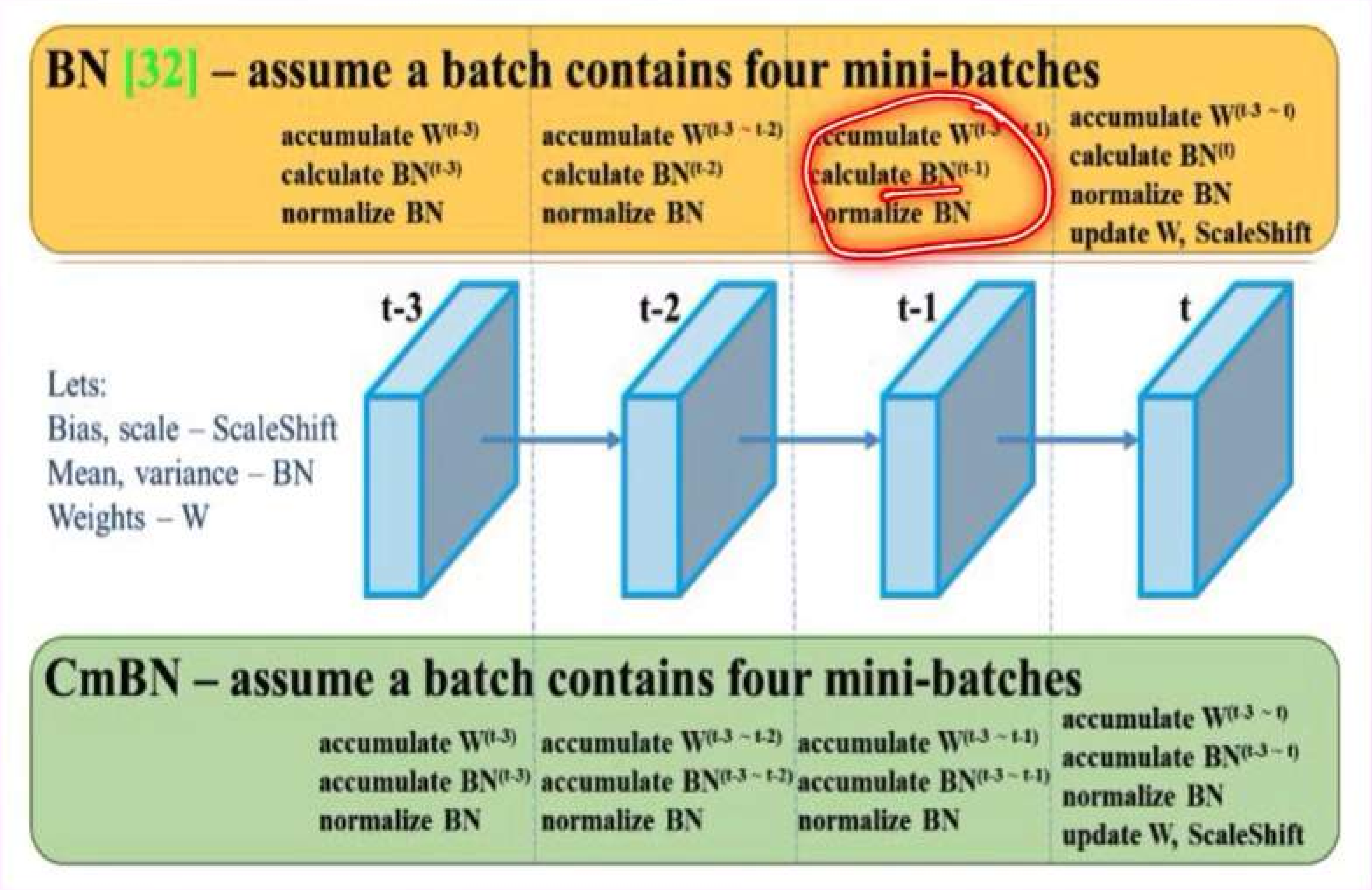
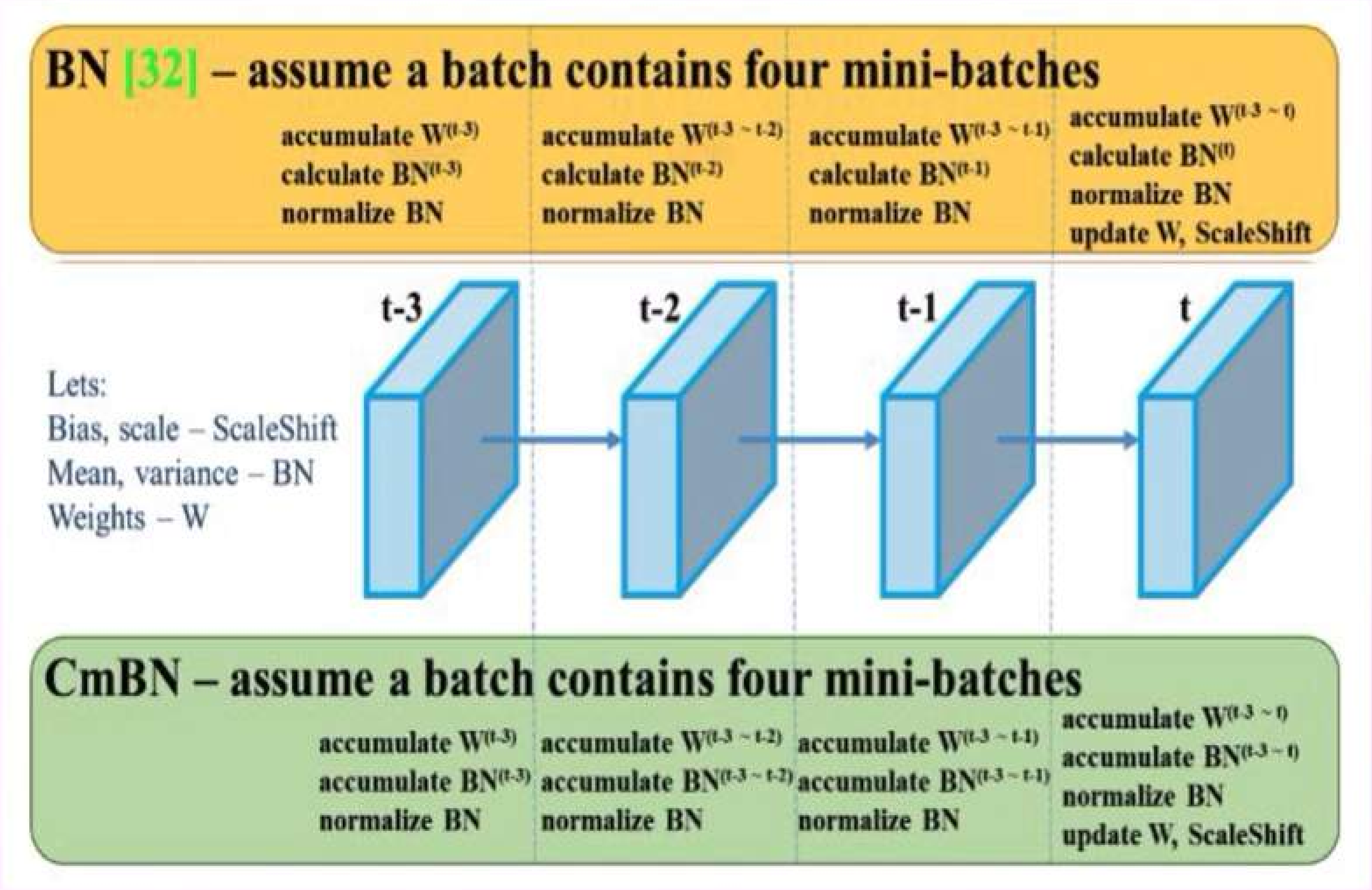
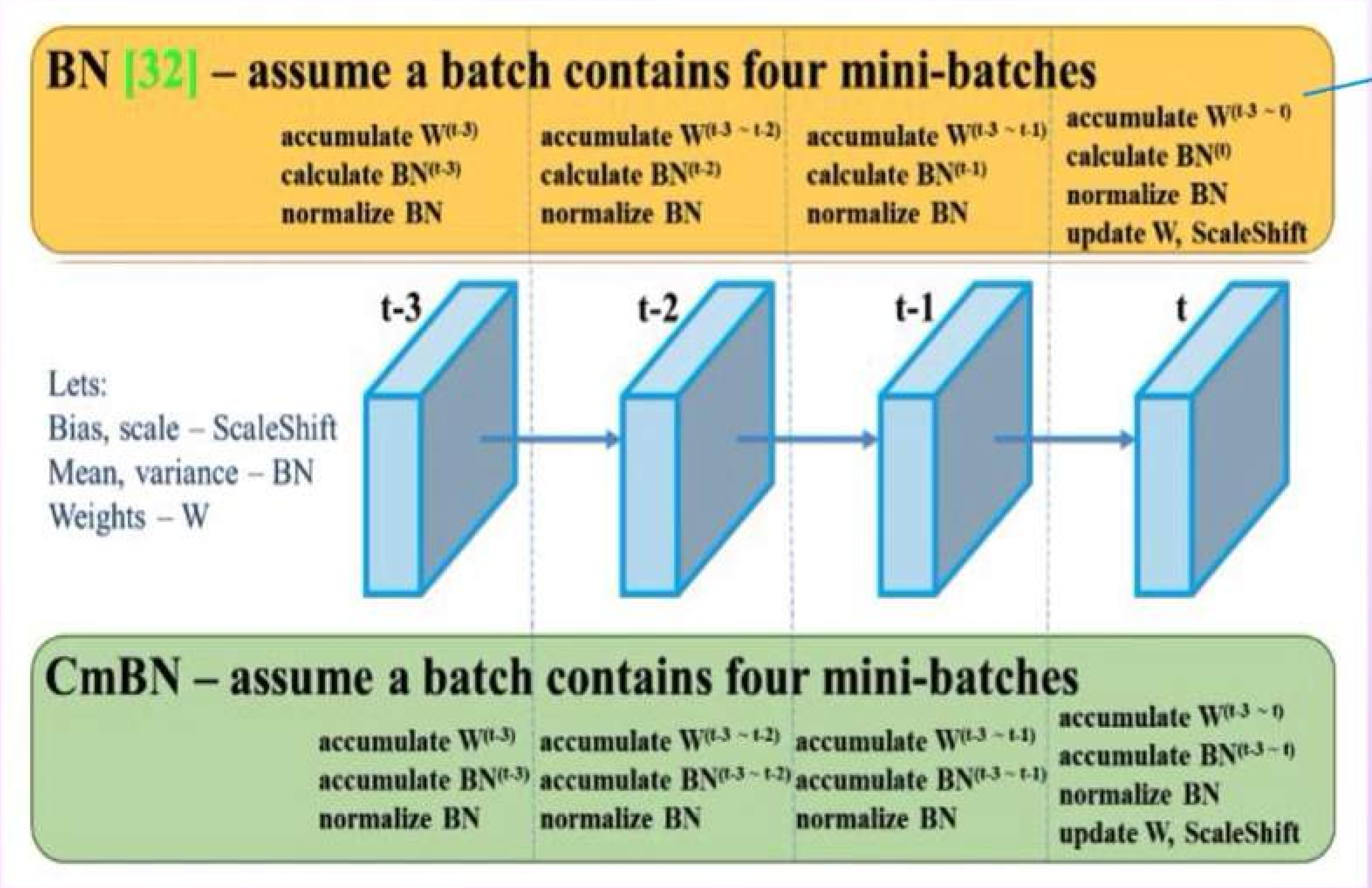


Cross Mini Batch Normalization

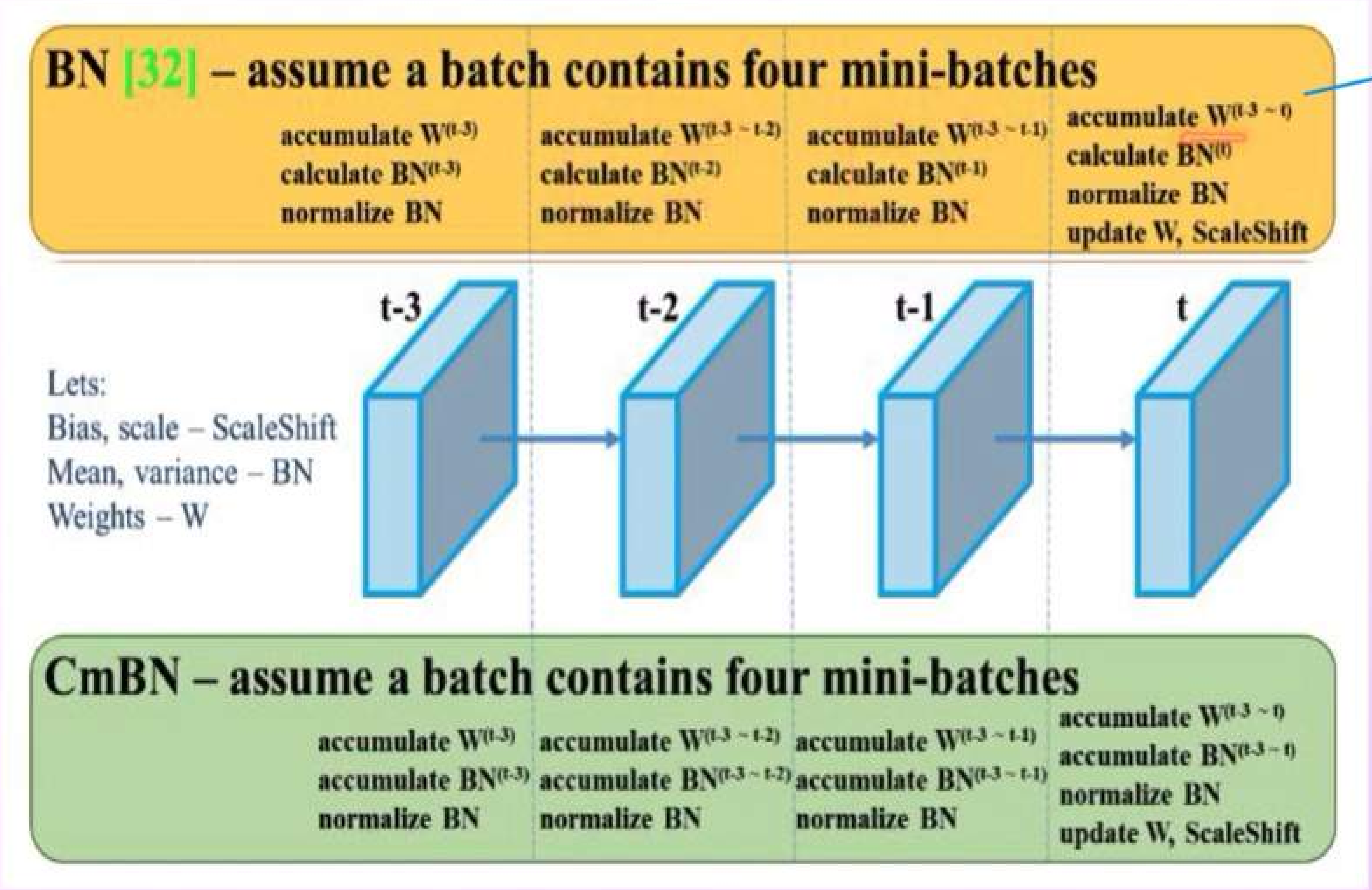


Cross Mini Batch Normalization



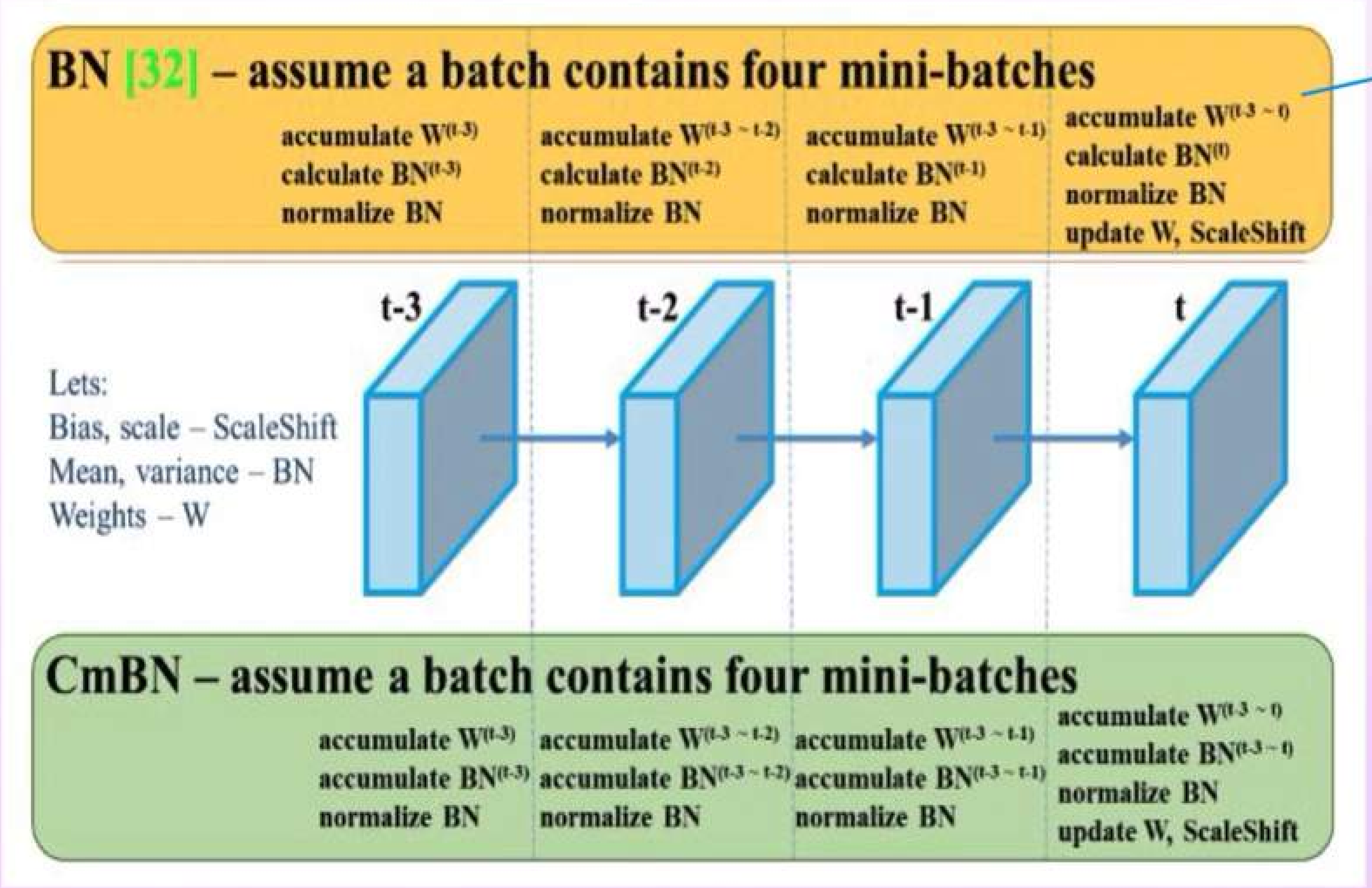
Gradient Accumulation

Cross Mini Batch Normalization



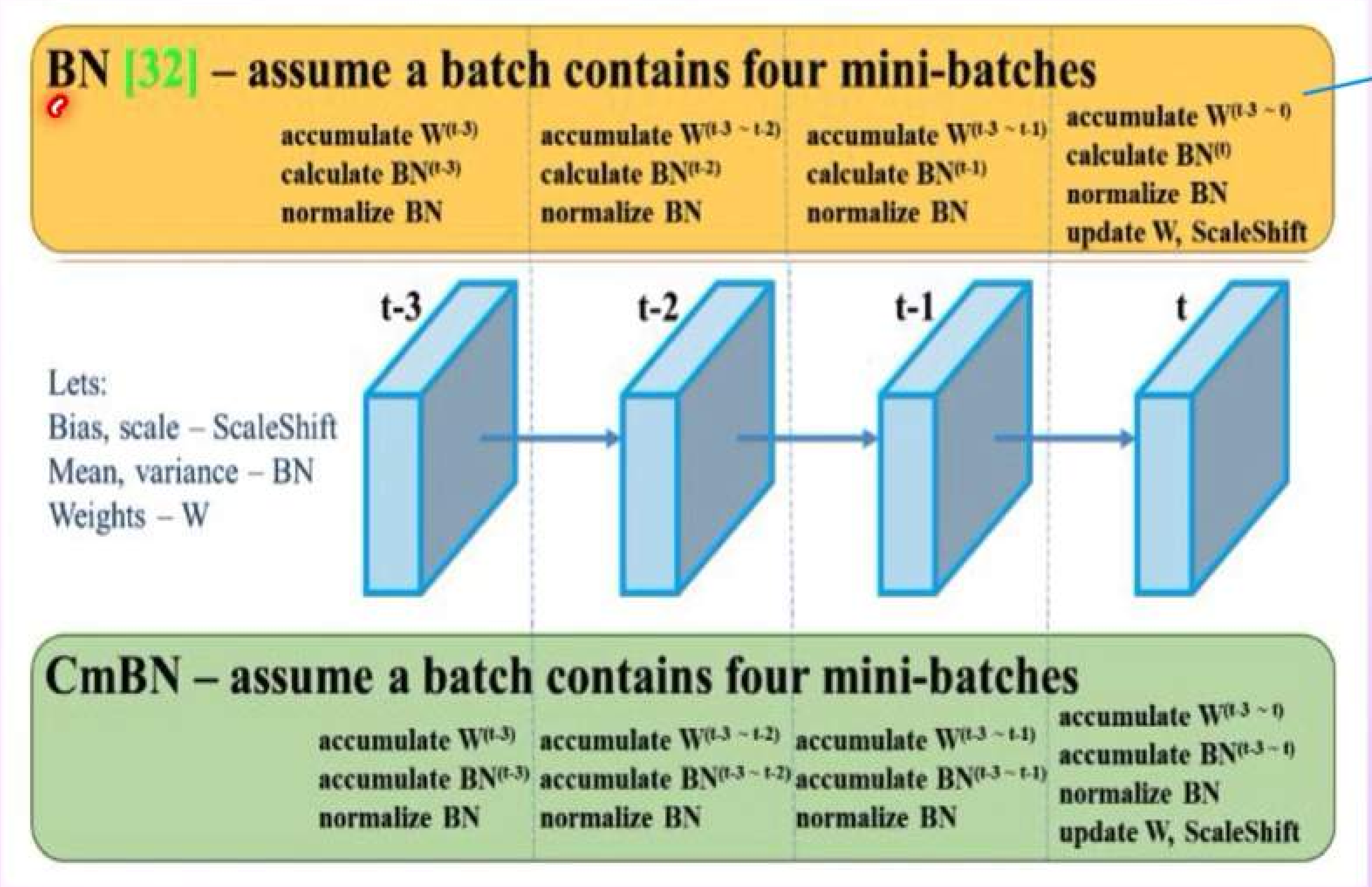
Gradient
Accumulation

Cross Mini Batch Normalization



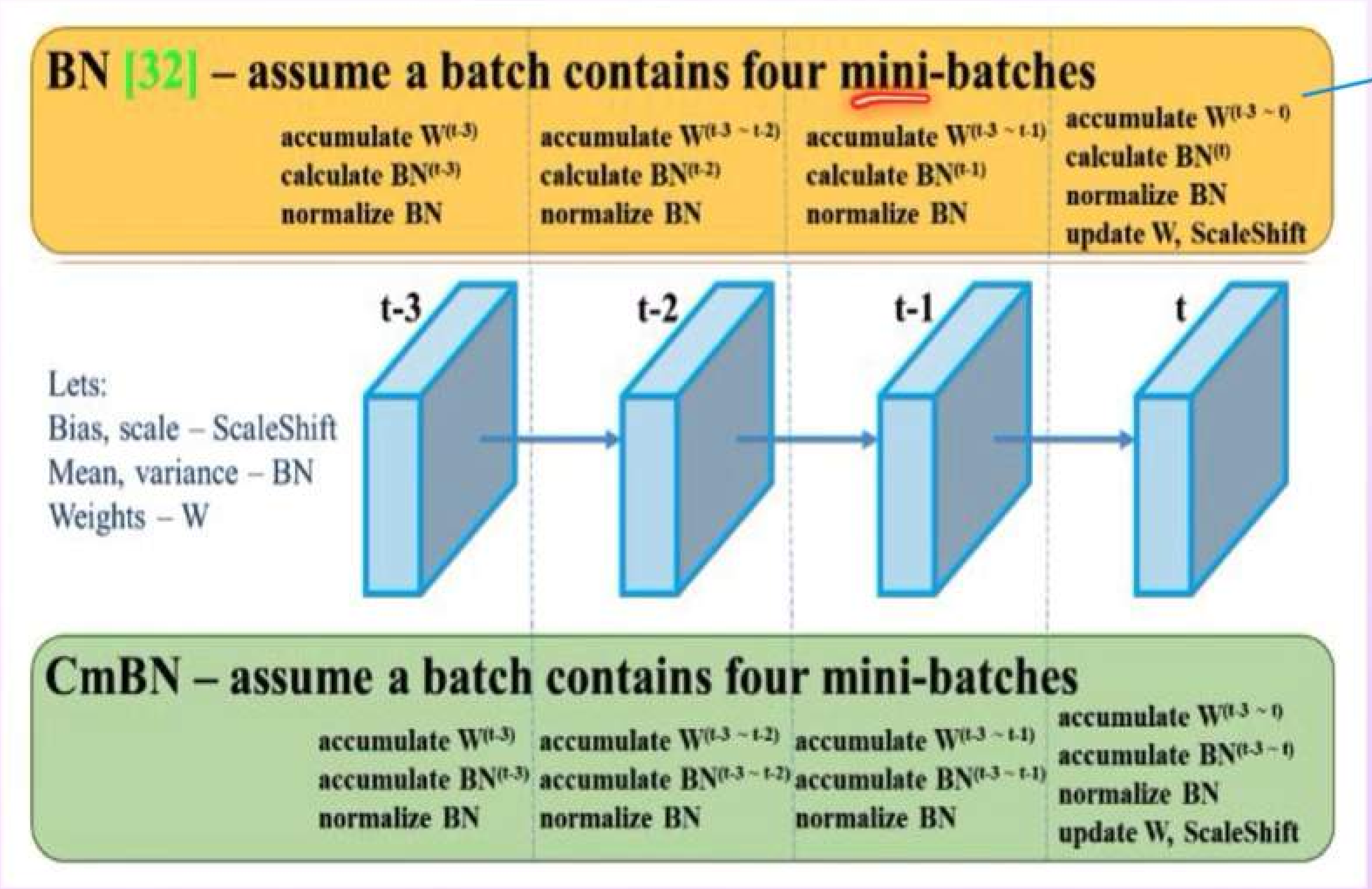
Gradient Accumulation

Cross Mini Batch Normalization



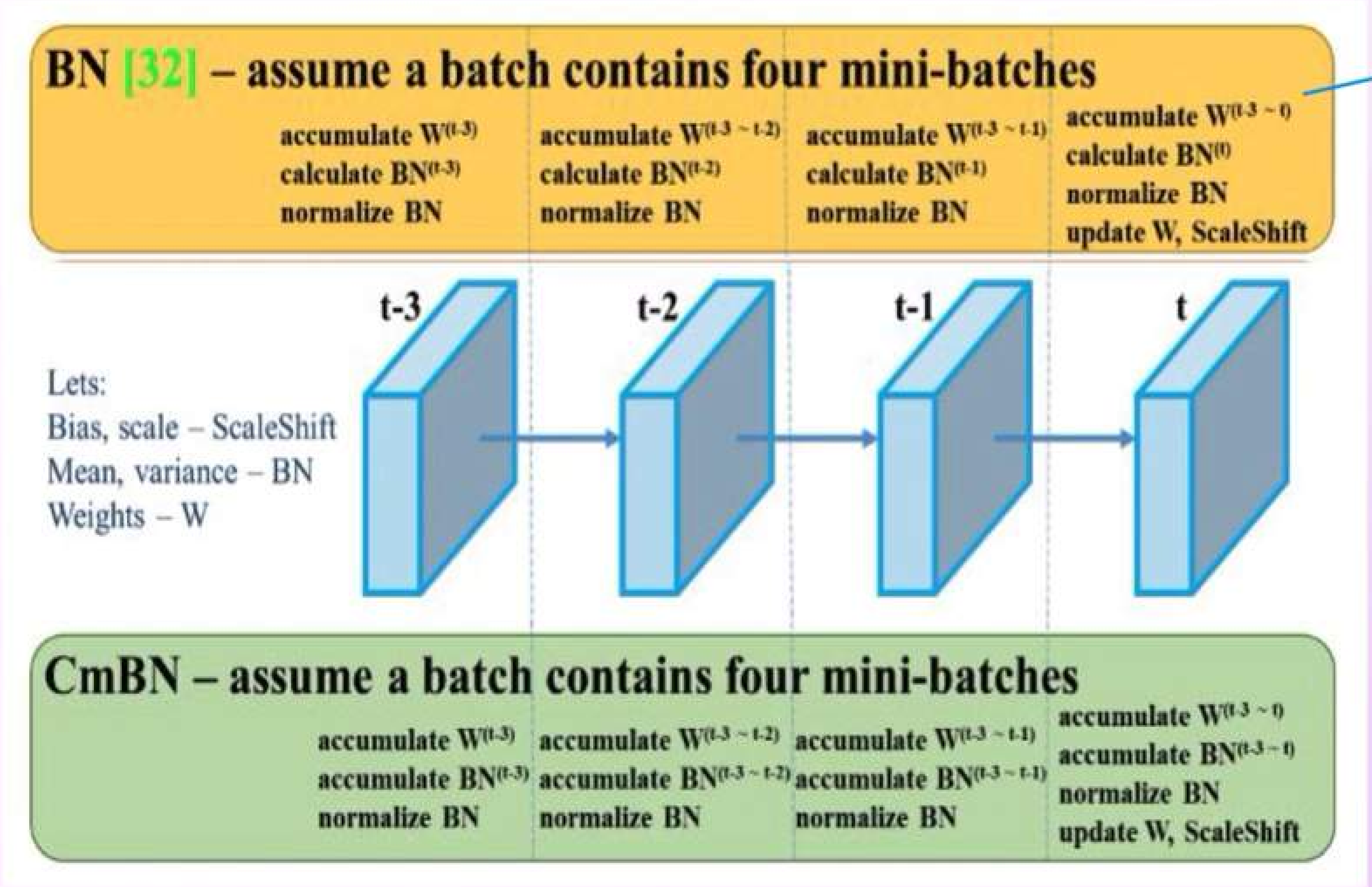
Gradient
Accumulation

Cross Mini Batch Normalization



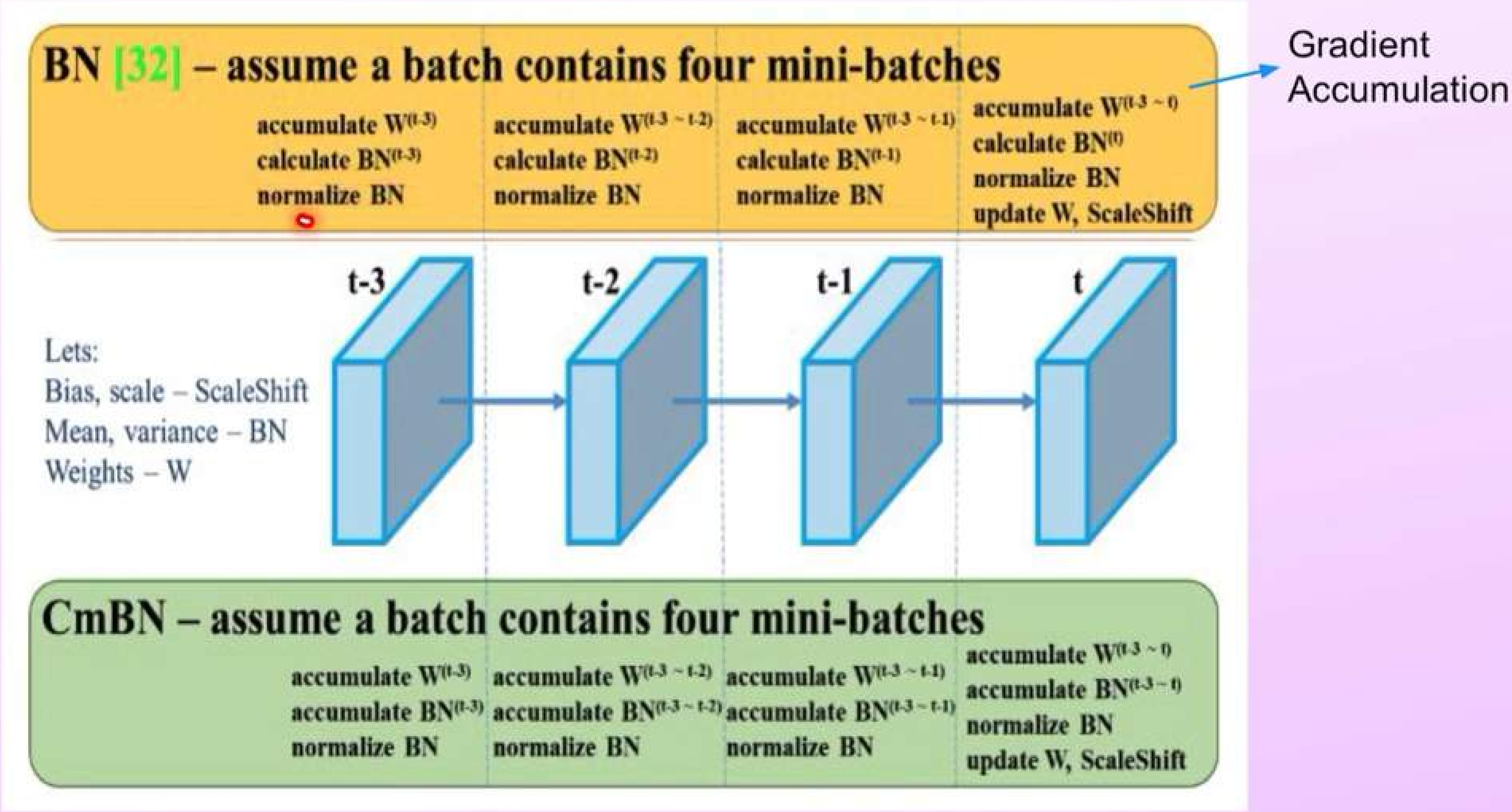
Gradient Accumulation

Cross Mini Batch Normalization



Gradient Accumulation

Cross Mini Batch Normalization



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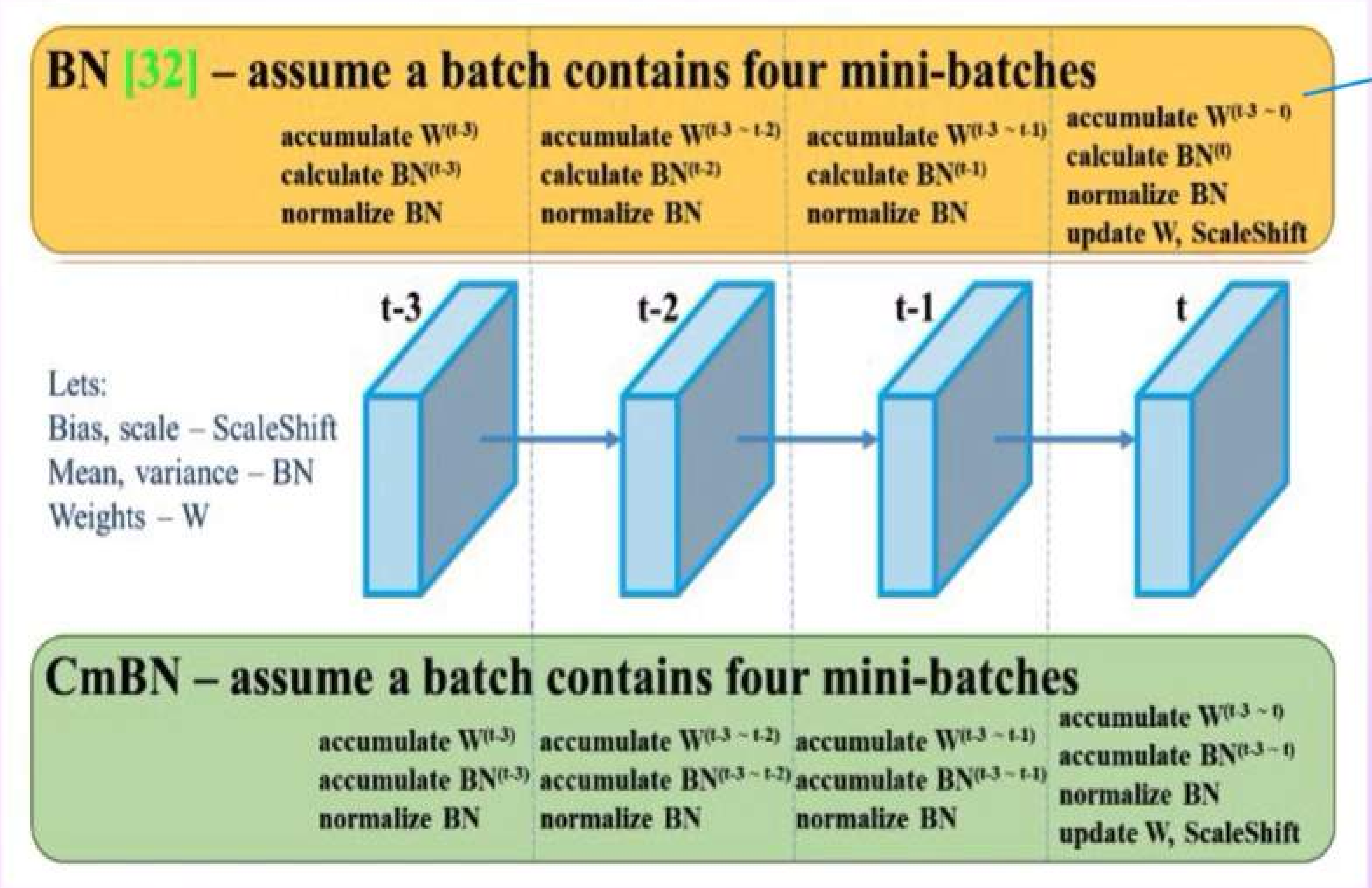

Gradient
Accumulation

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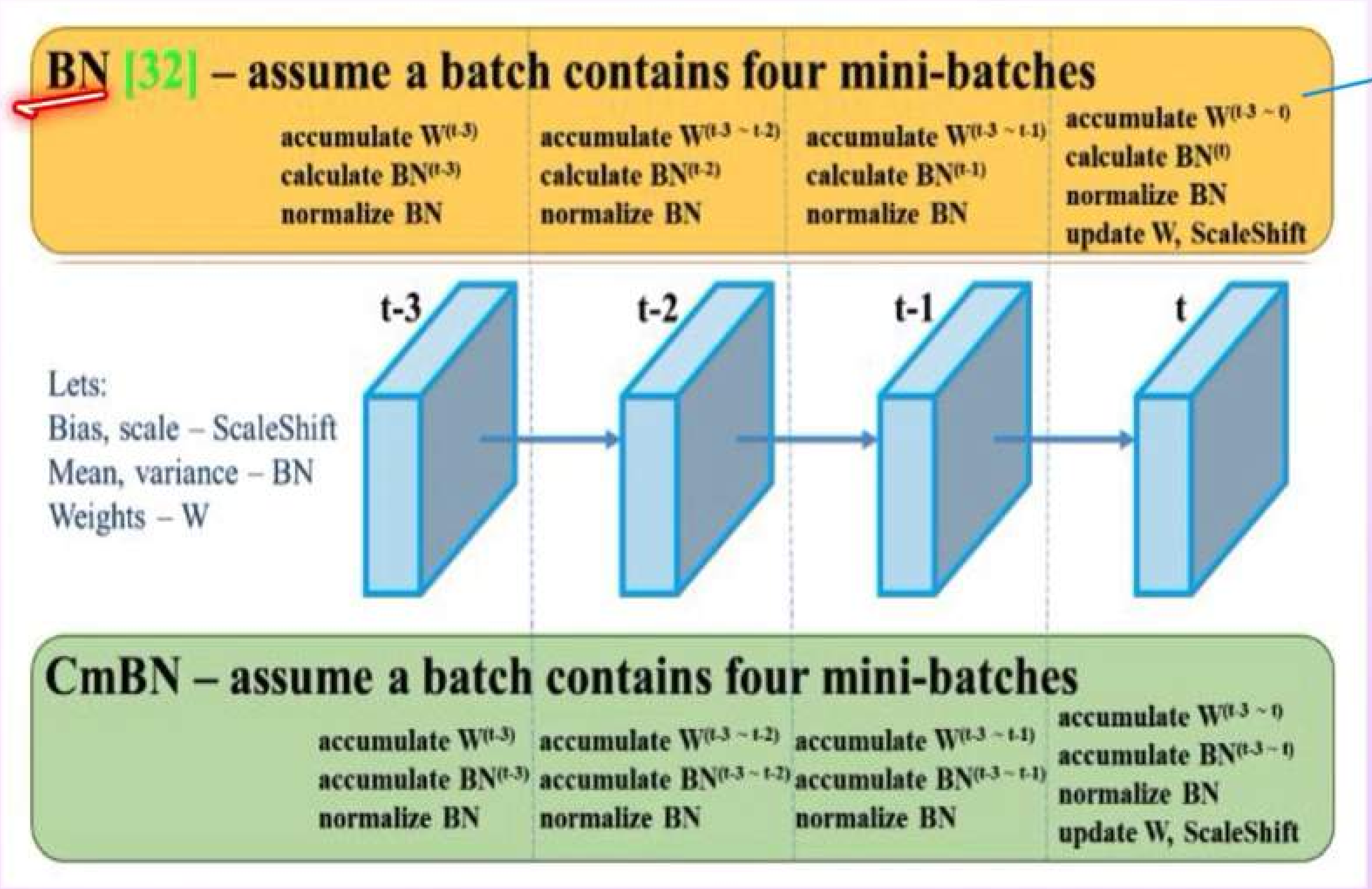
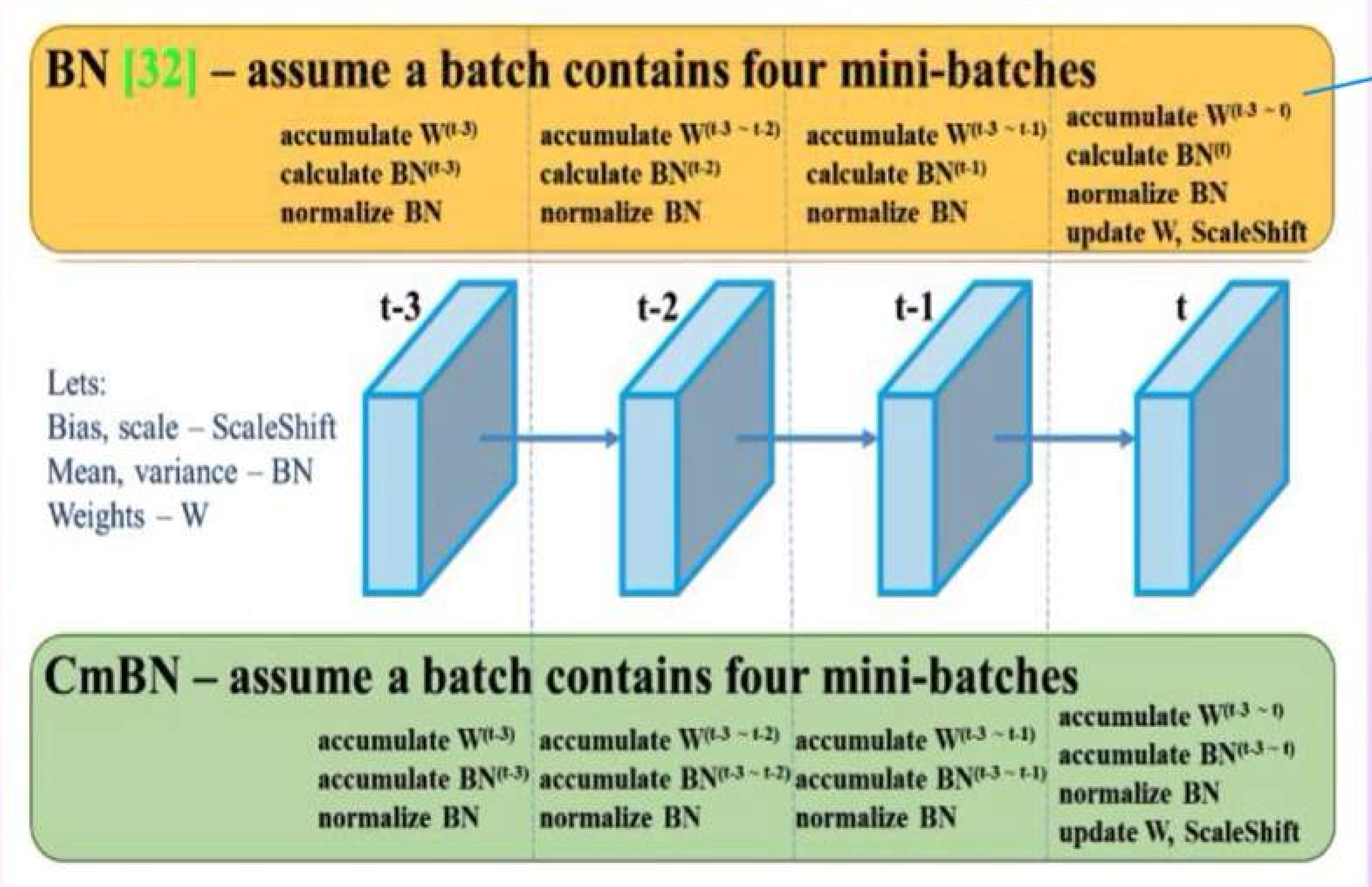


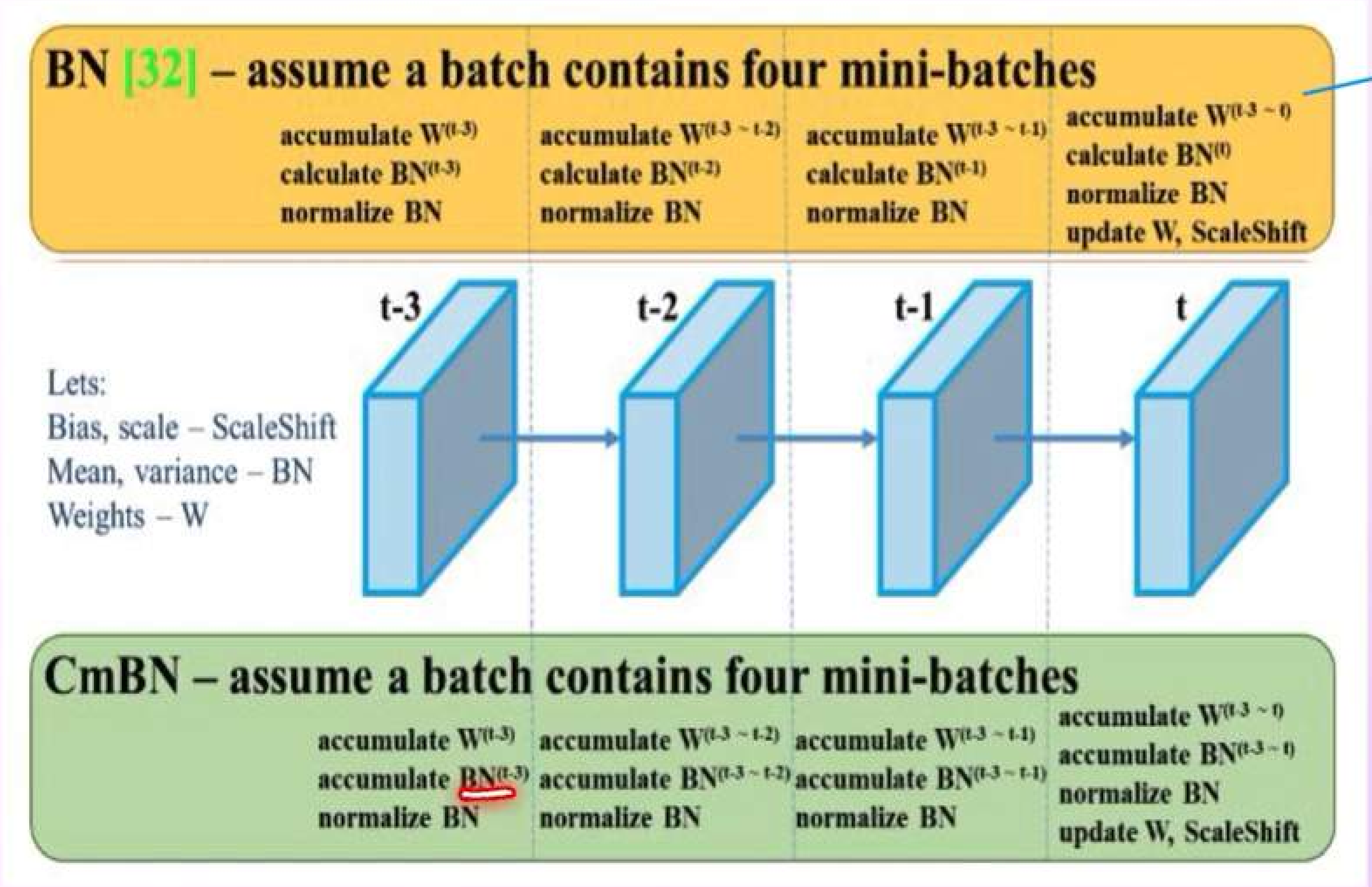
Gradient Accumulation

Cross Mini Batch Normalization



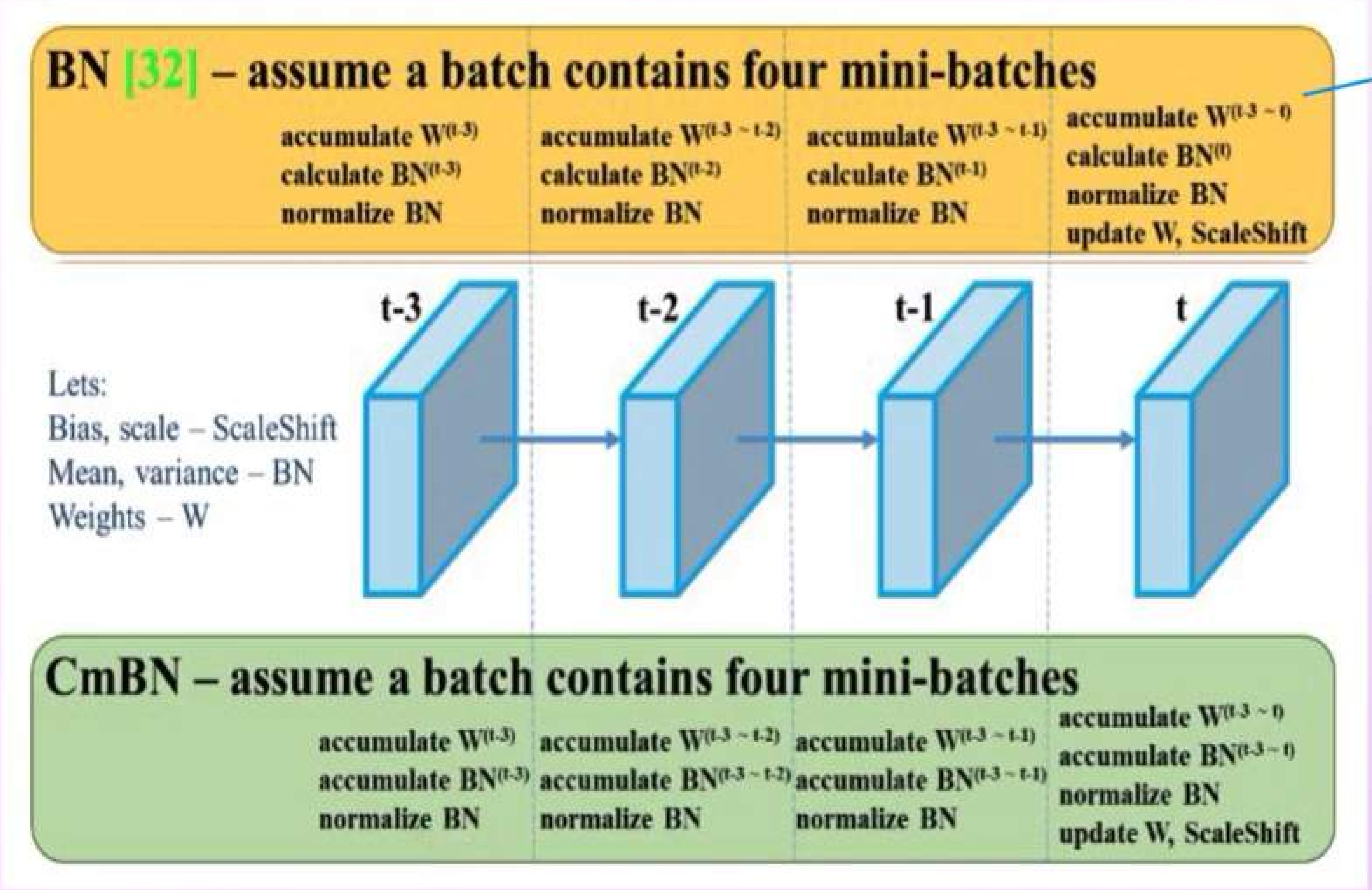
Gradient Accumulation

Cross Mini Batch Normalization



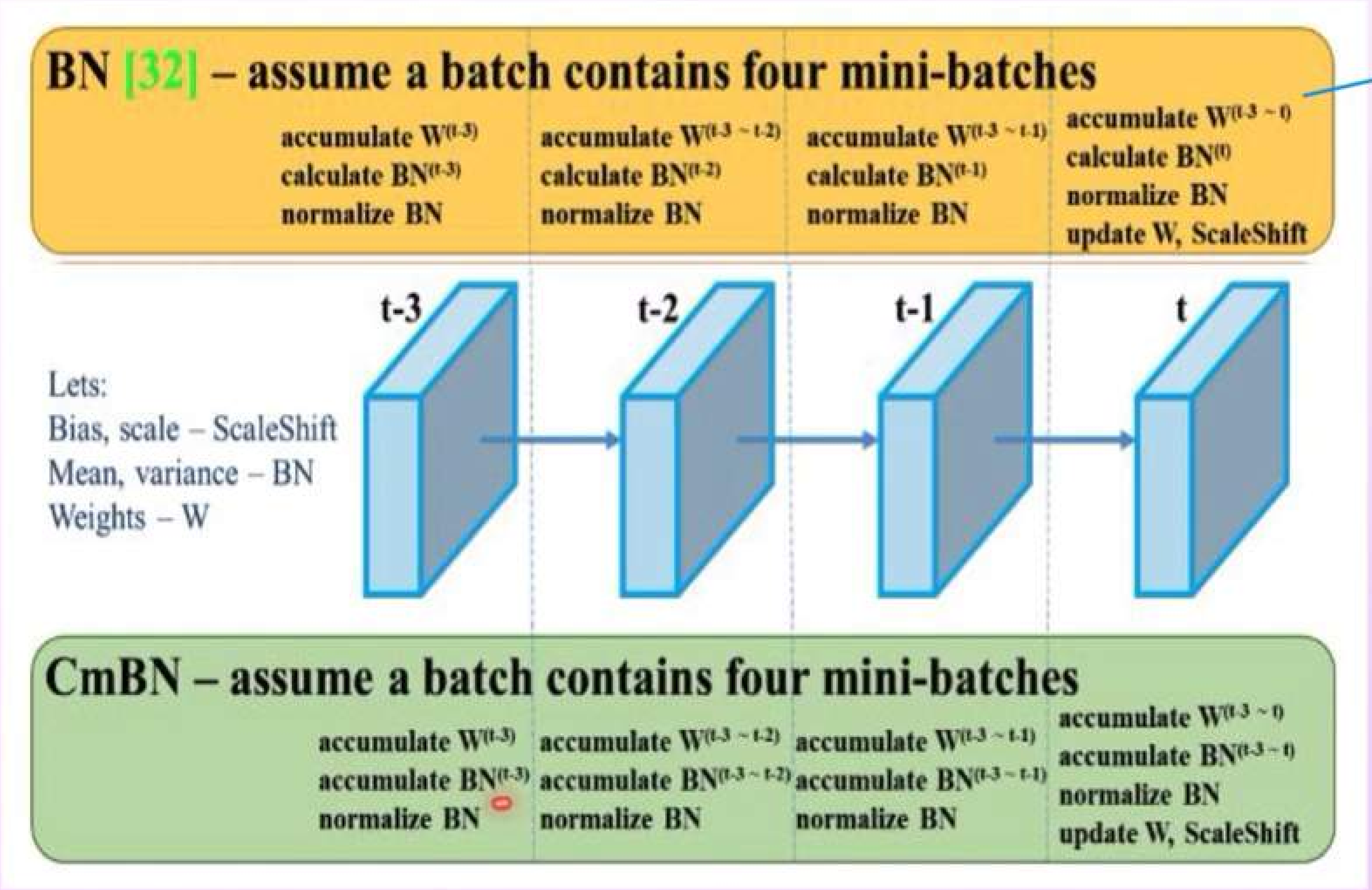
Gradient
Accumulation

Cross Mini Batch Normalization



Gradient Accumulation

Cross Mini Batch Normalization



Gradient
Accumulation

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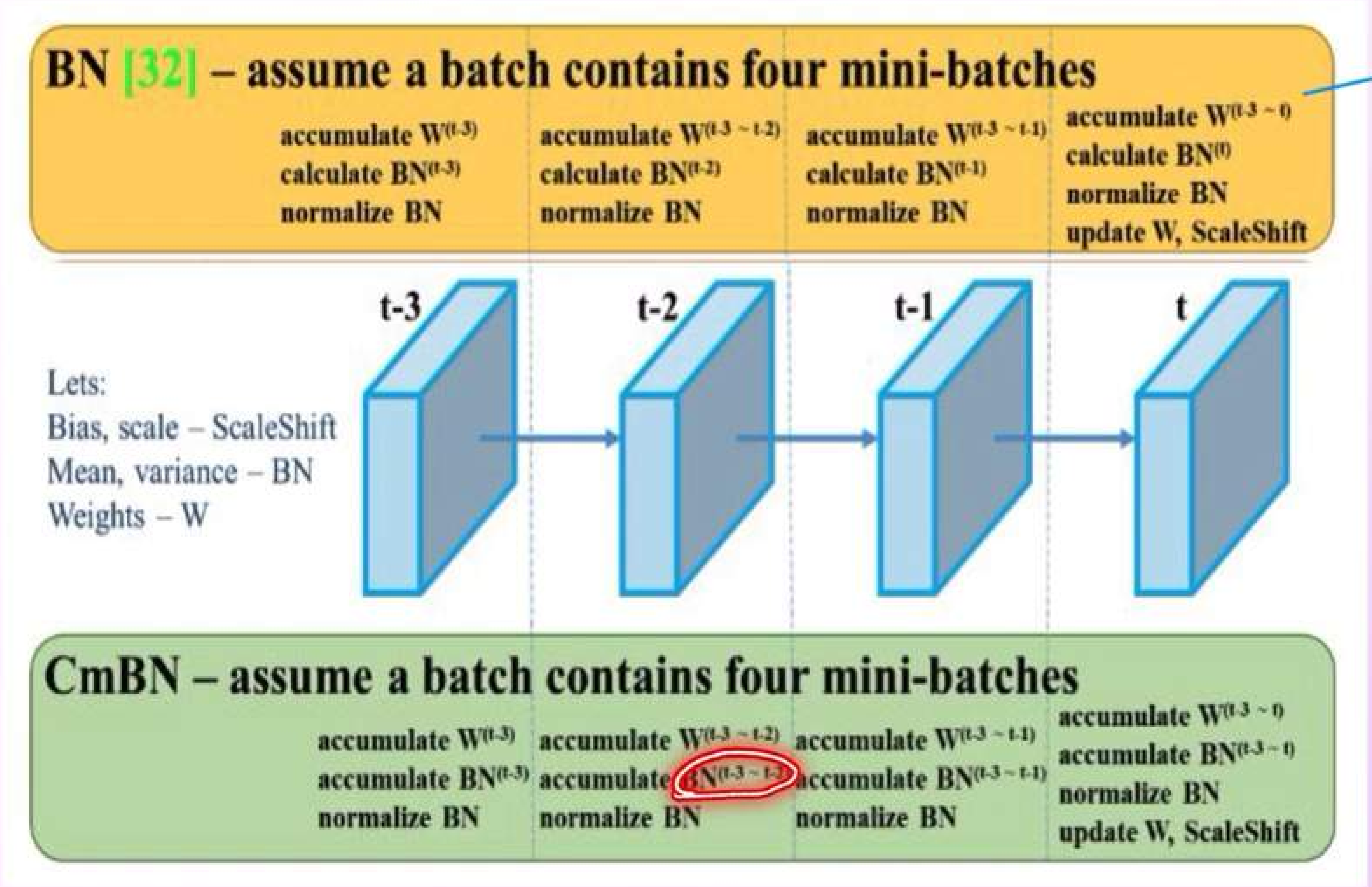
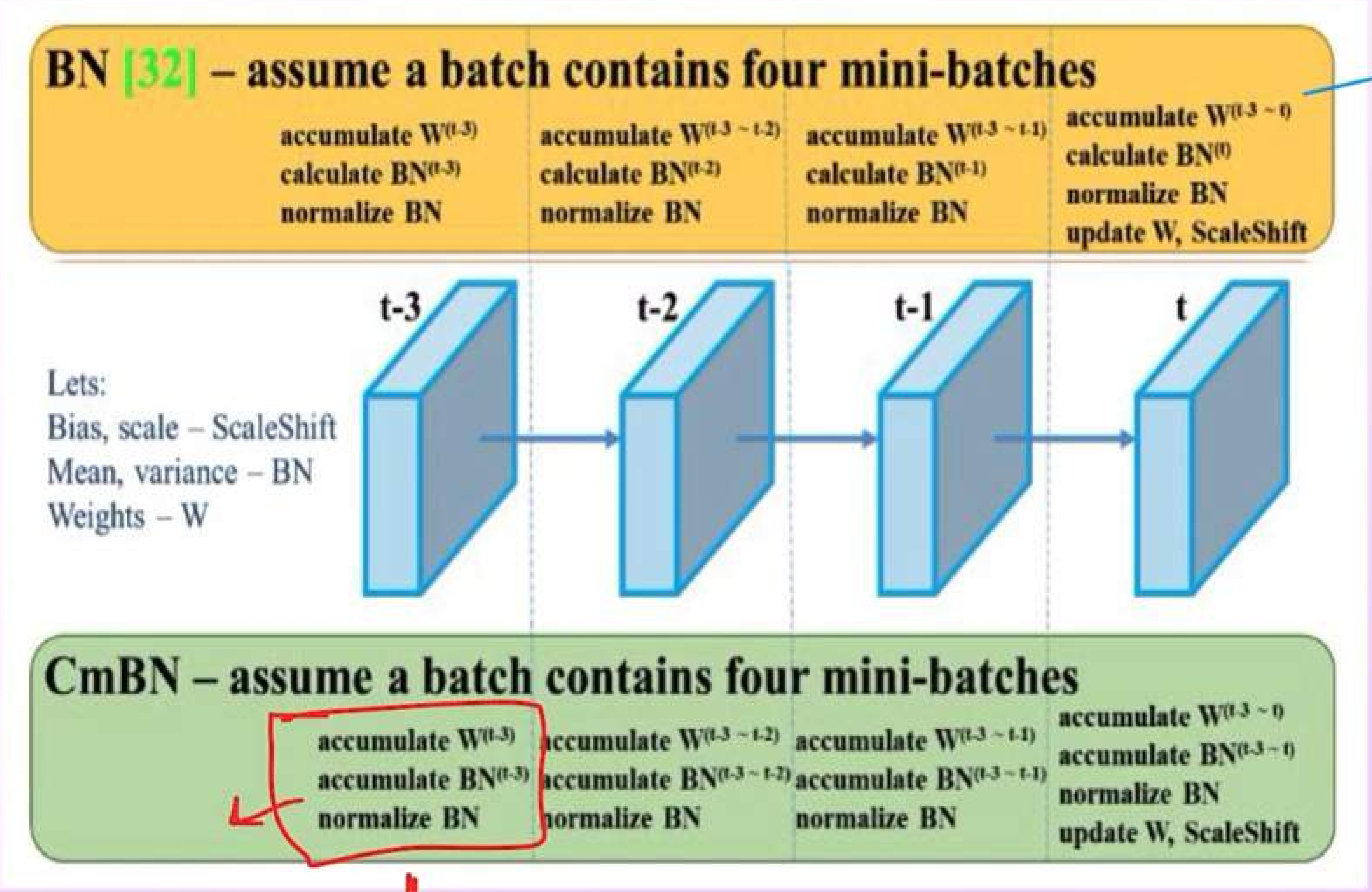


Gradient
Accumulation

Cross Mini Batch Normalization



Gradient Accumulation

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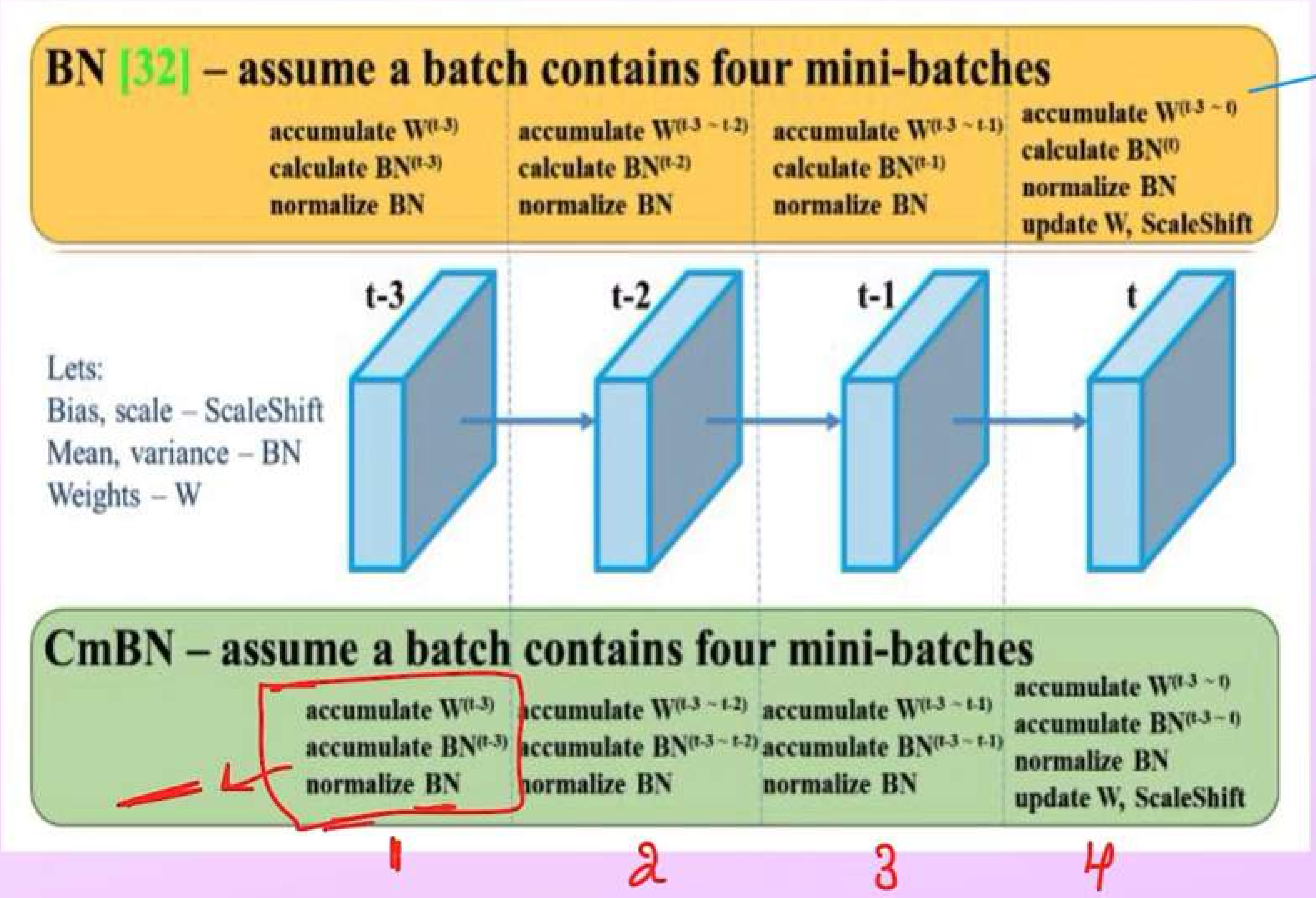

Gradient Accumulation

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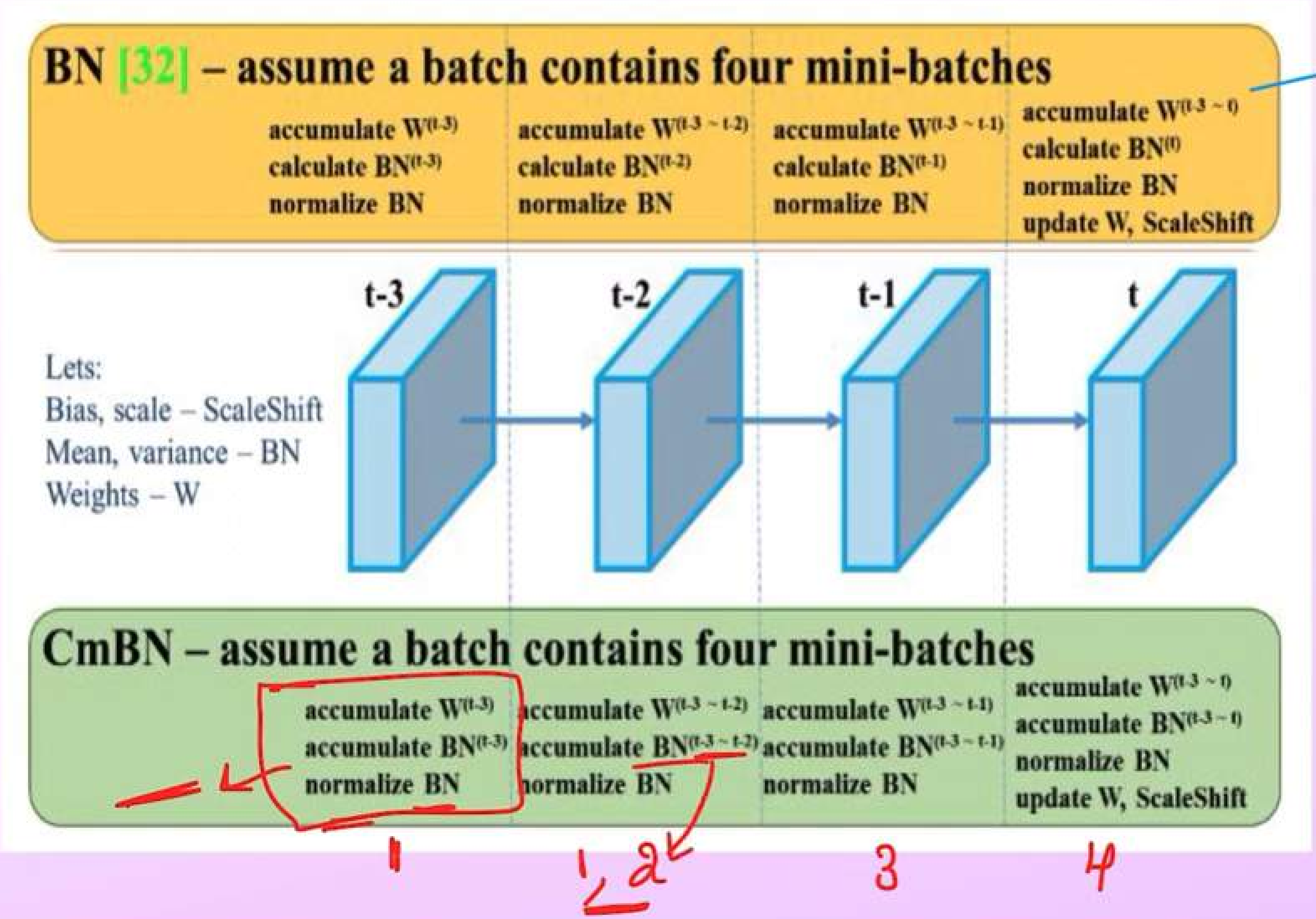
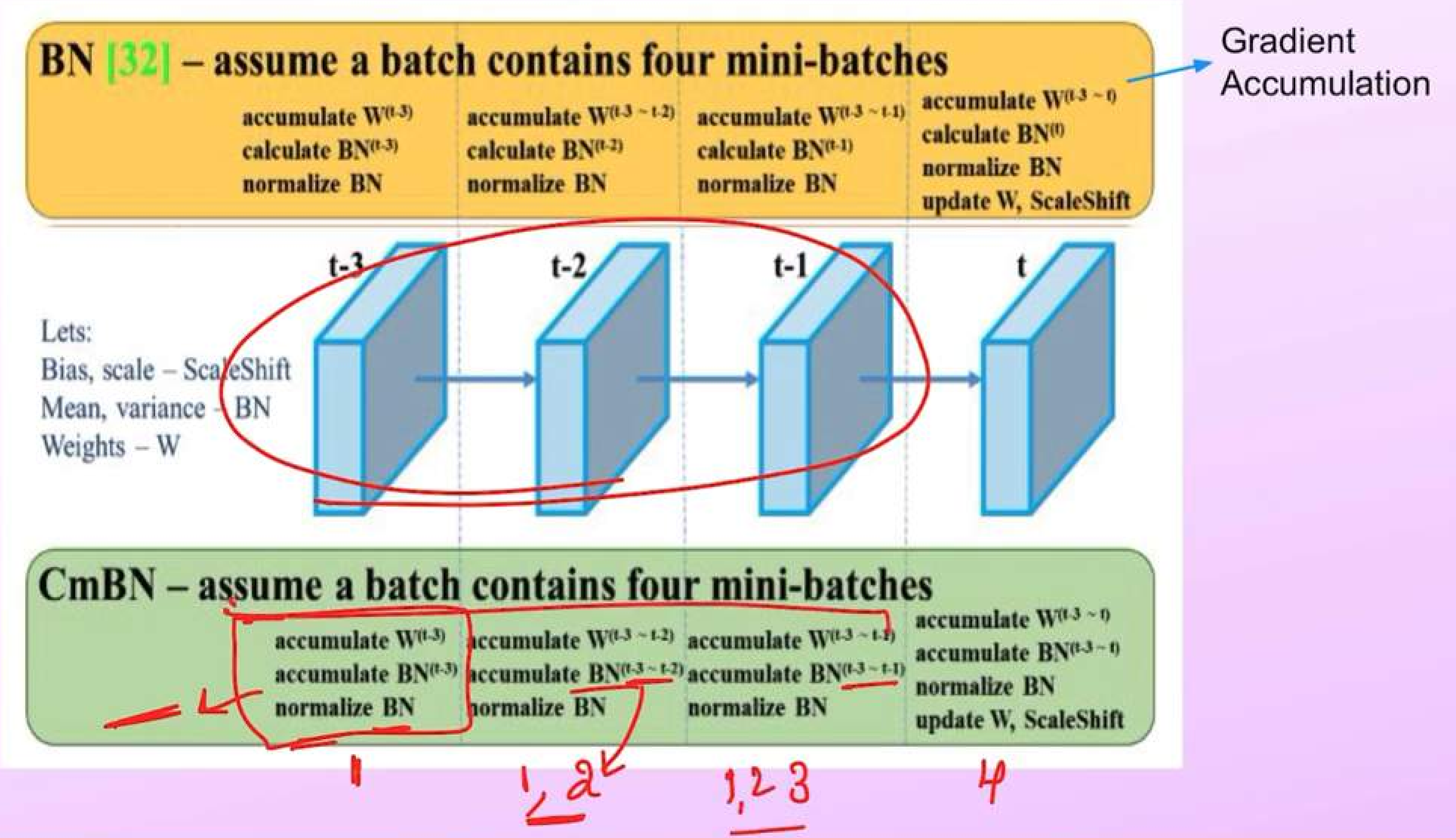
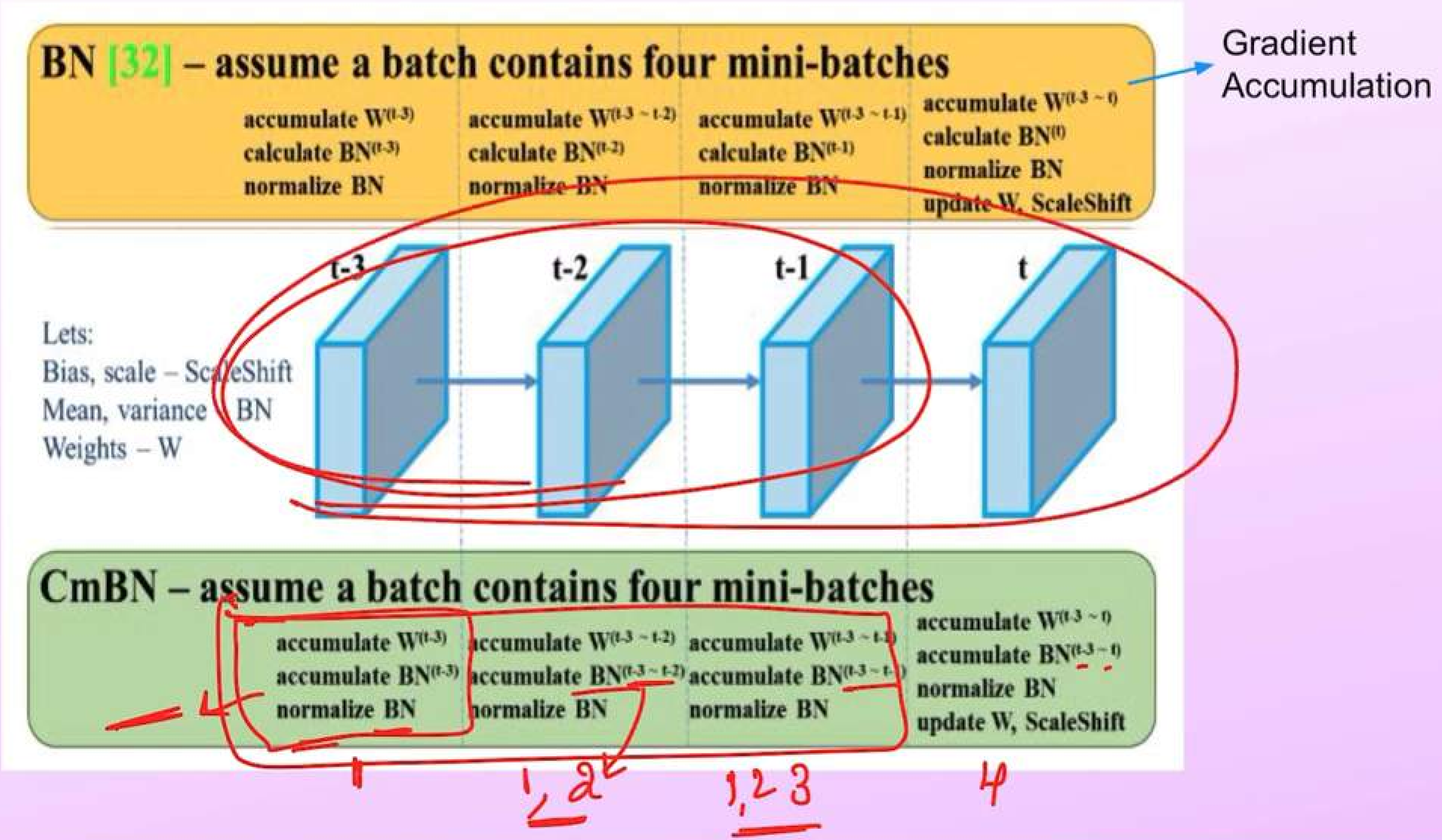


Gradient Accumulation

Cross Mini Batch Normalization



Cross Mini Batch Normalization



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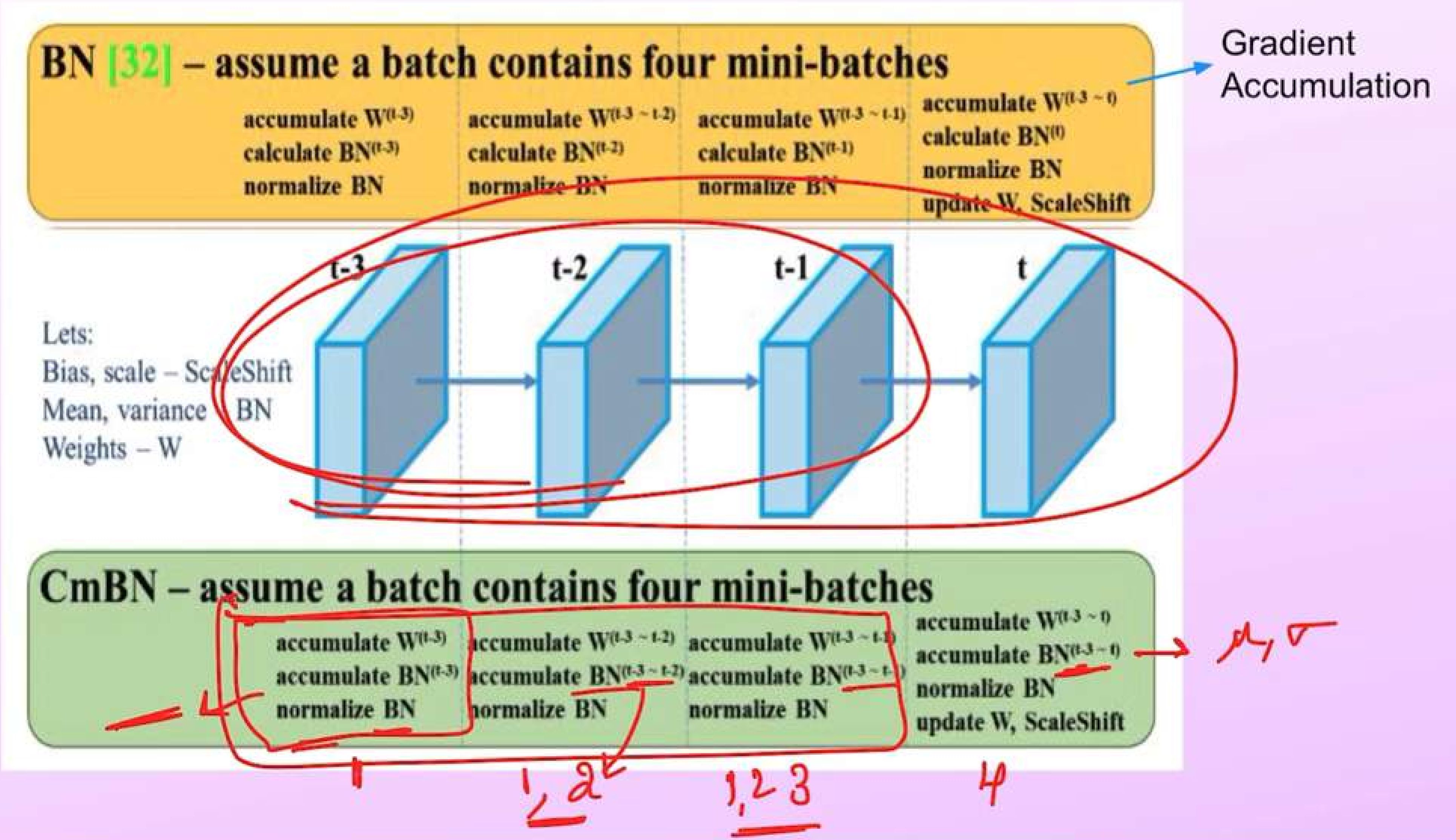
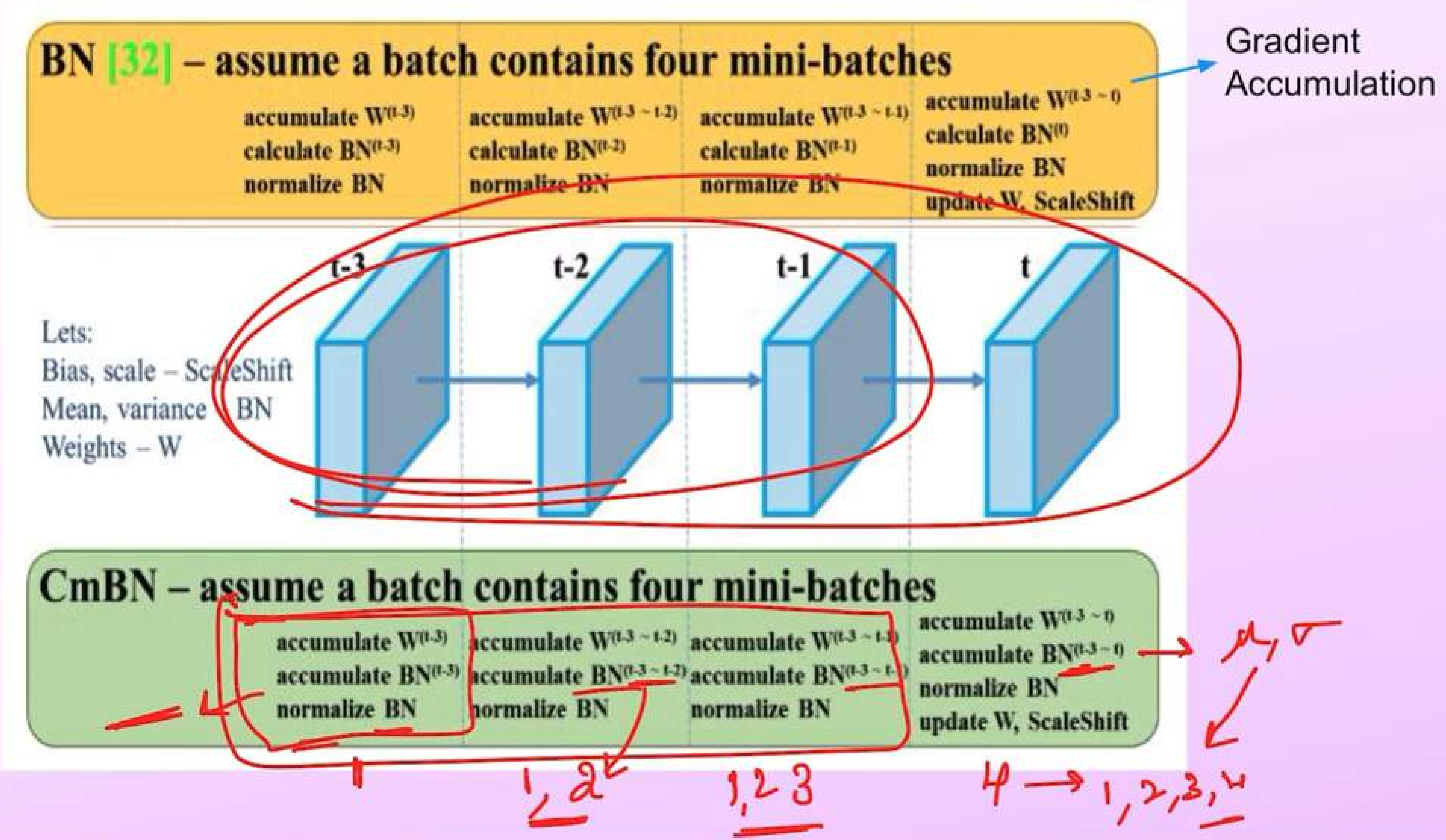


Cross Mini Batch Normalization



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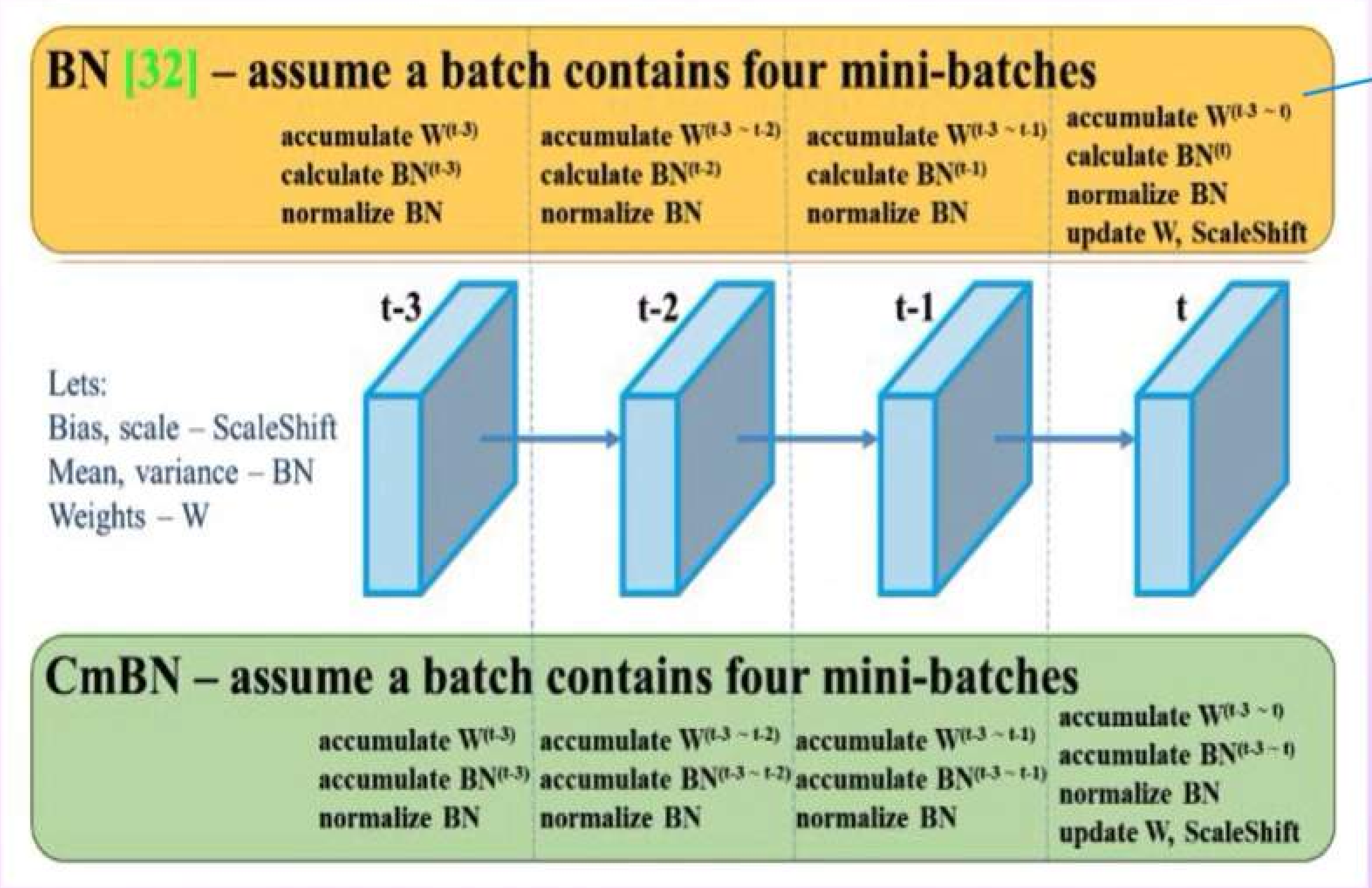
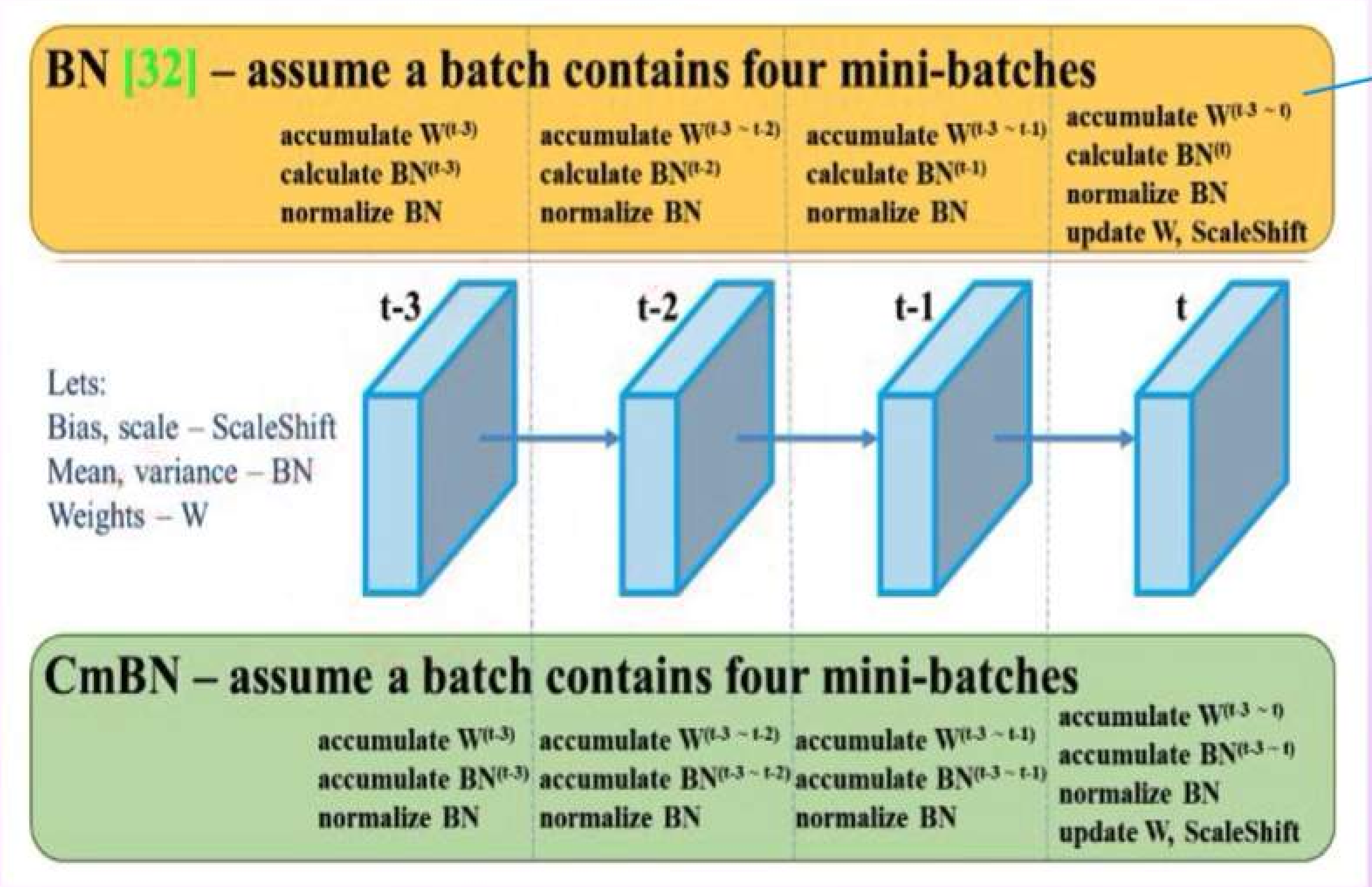


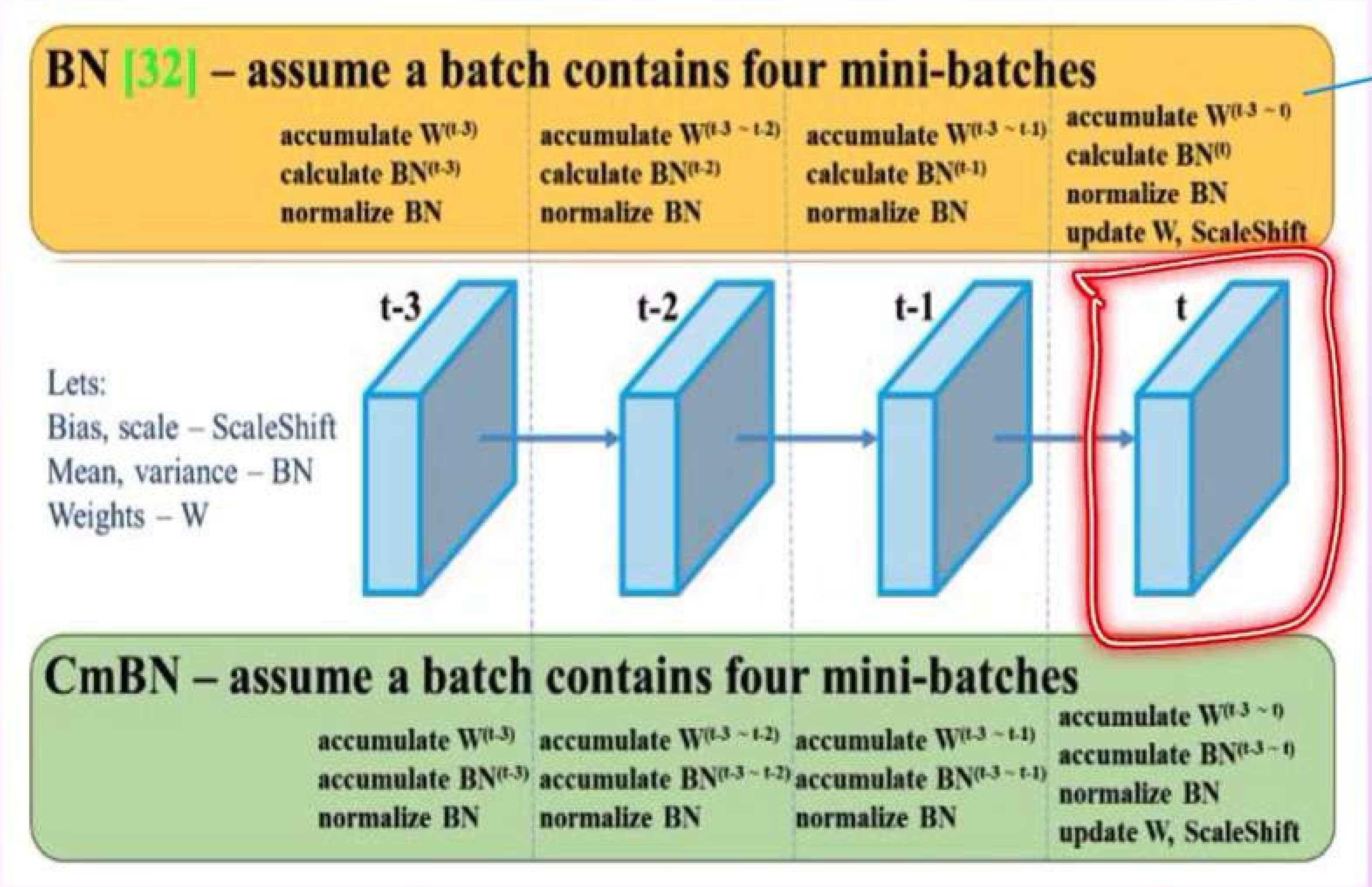
Gradient Accumulation

Cross Mini Batch Normalization



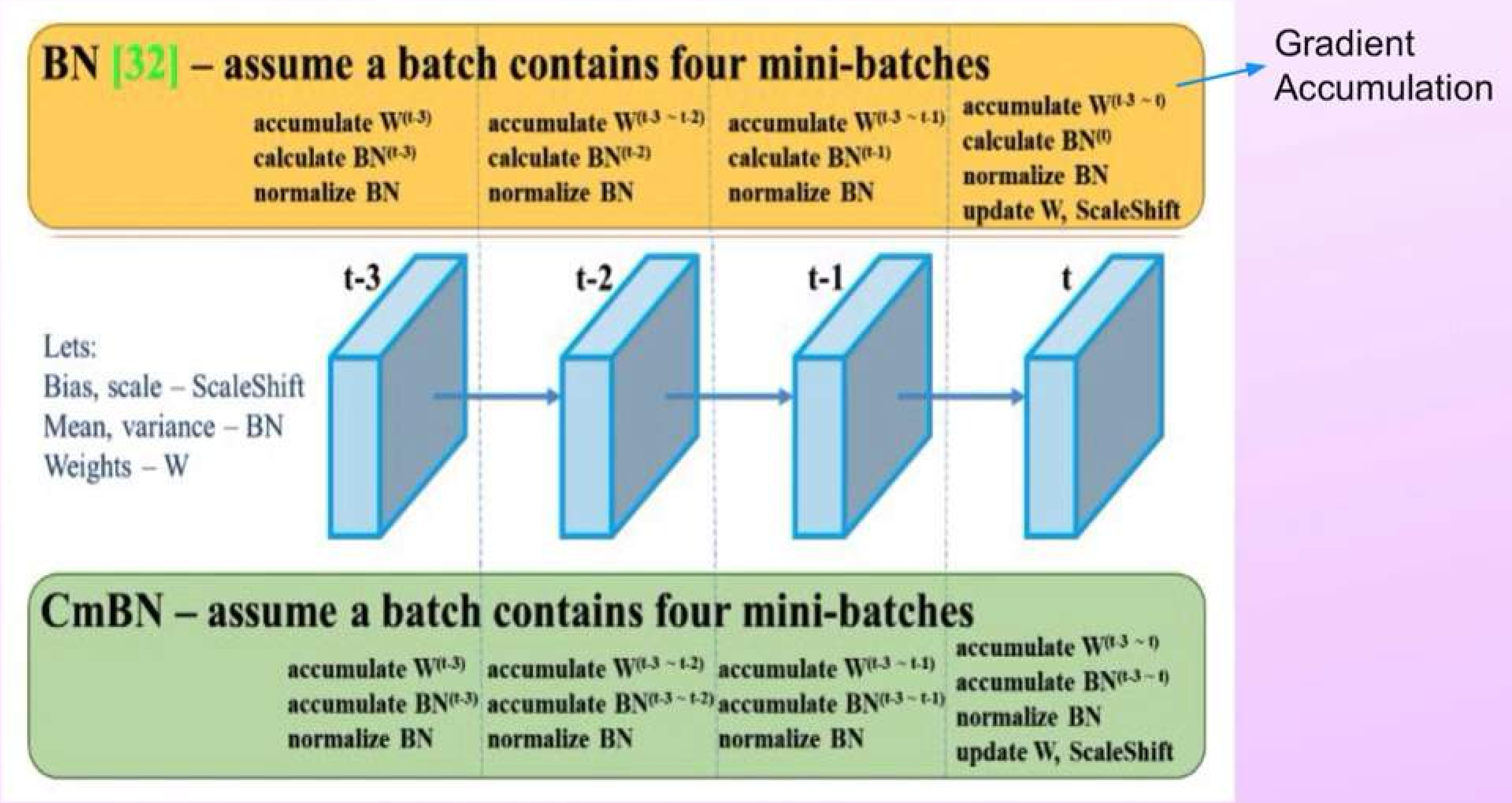
Gradient Accumulation

Cross Mini Batch Normalization



Gradient Accumulation

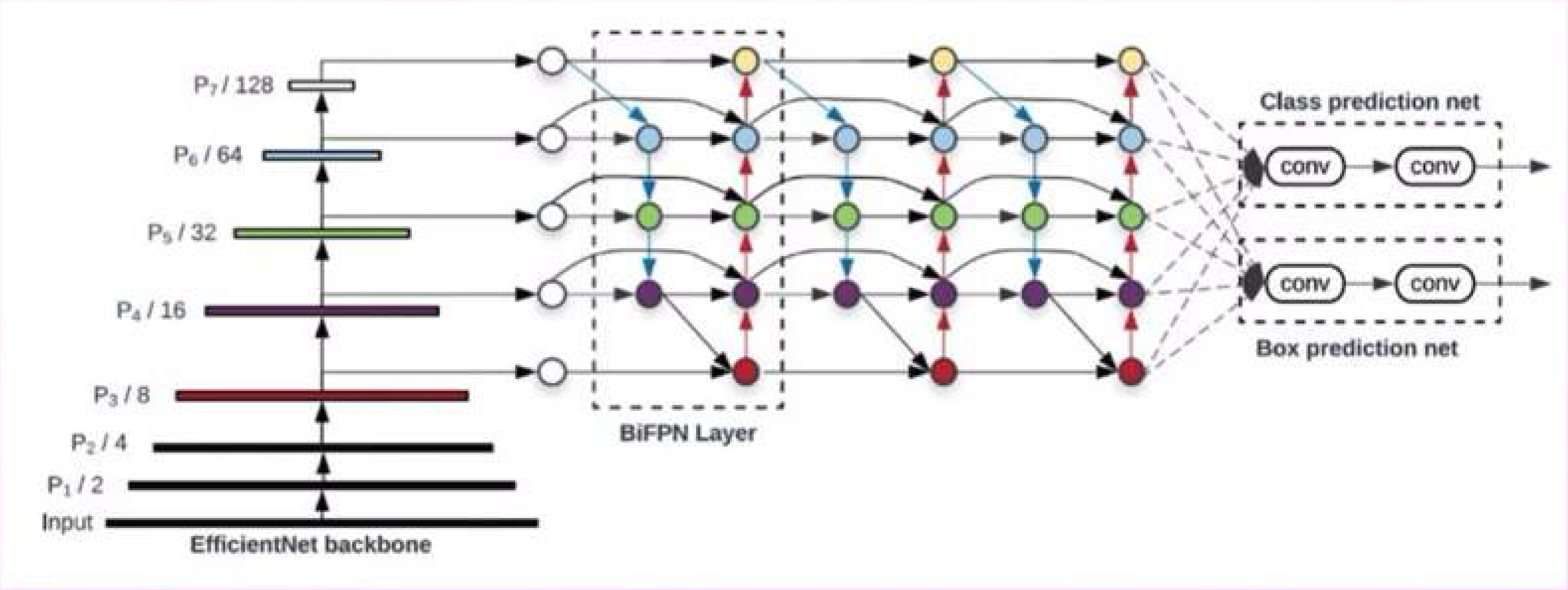
Cross Mini Batch Normalization



Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
- Stage: Neck

- EfficientDet —>



Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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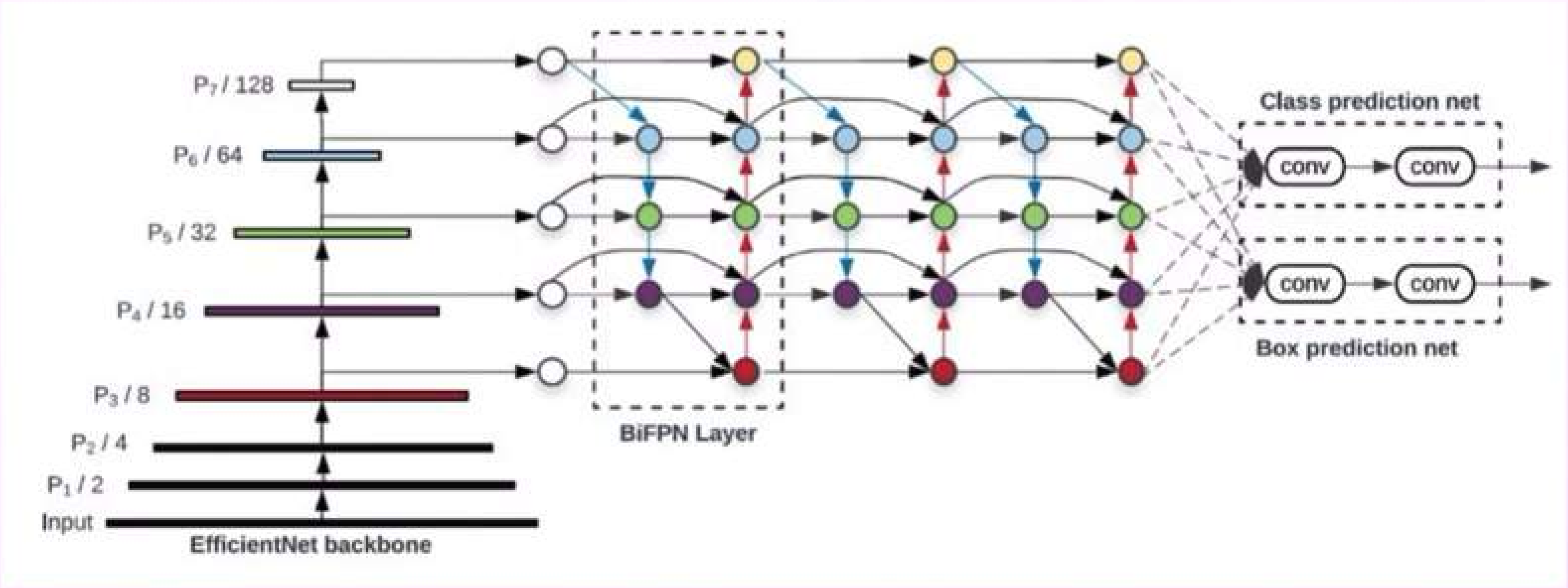

Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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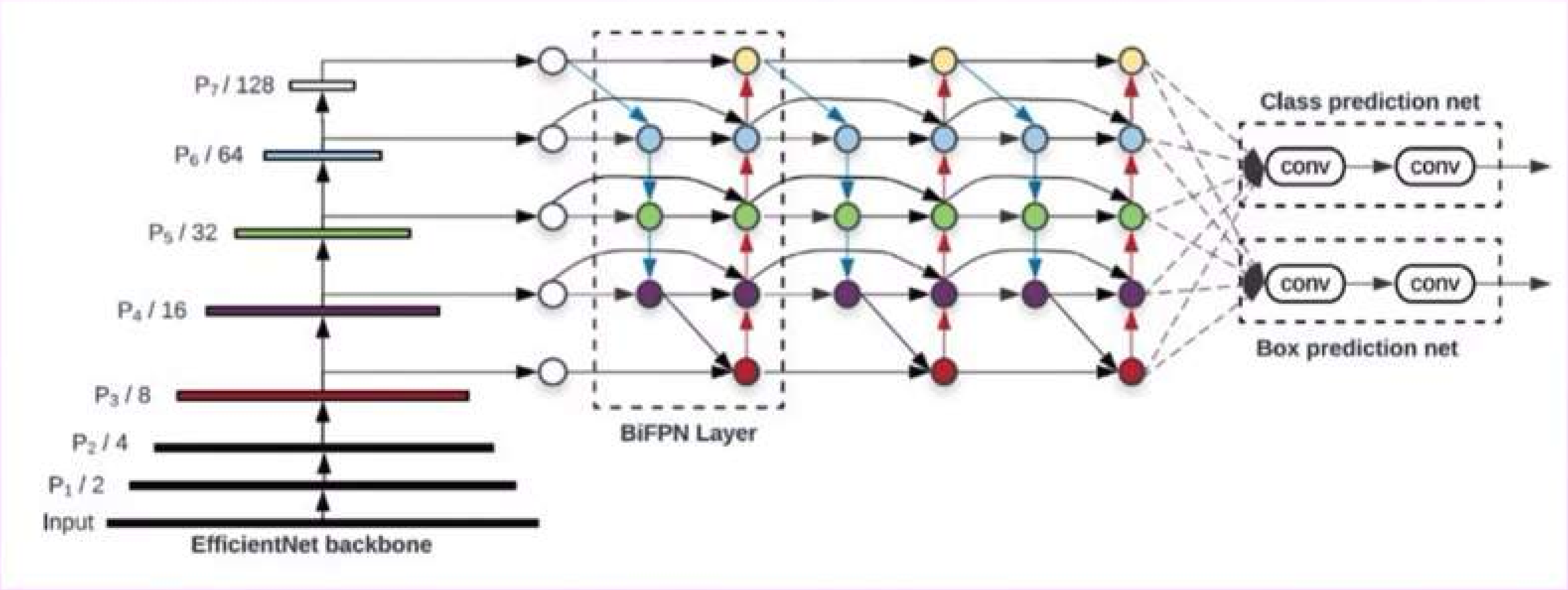
- EfficientDet —>



Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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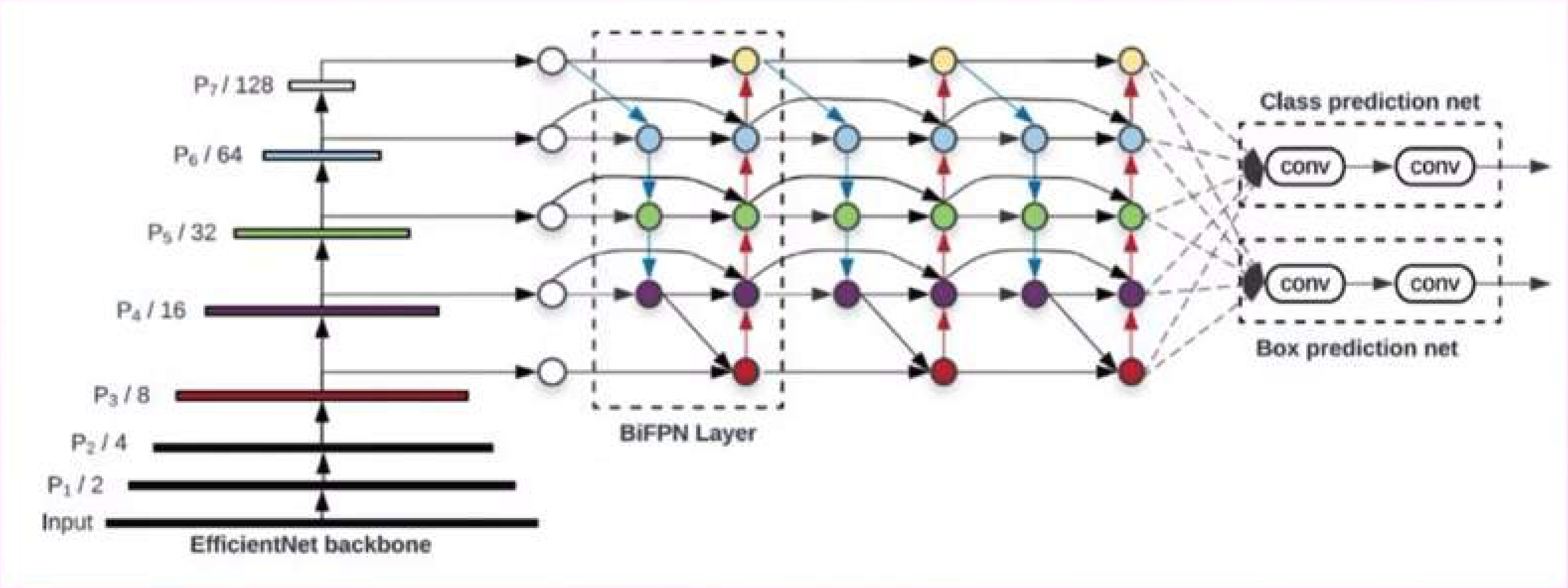
- EfficientDet —>



Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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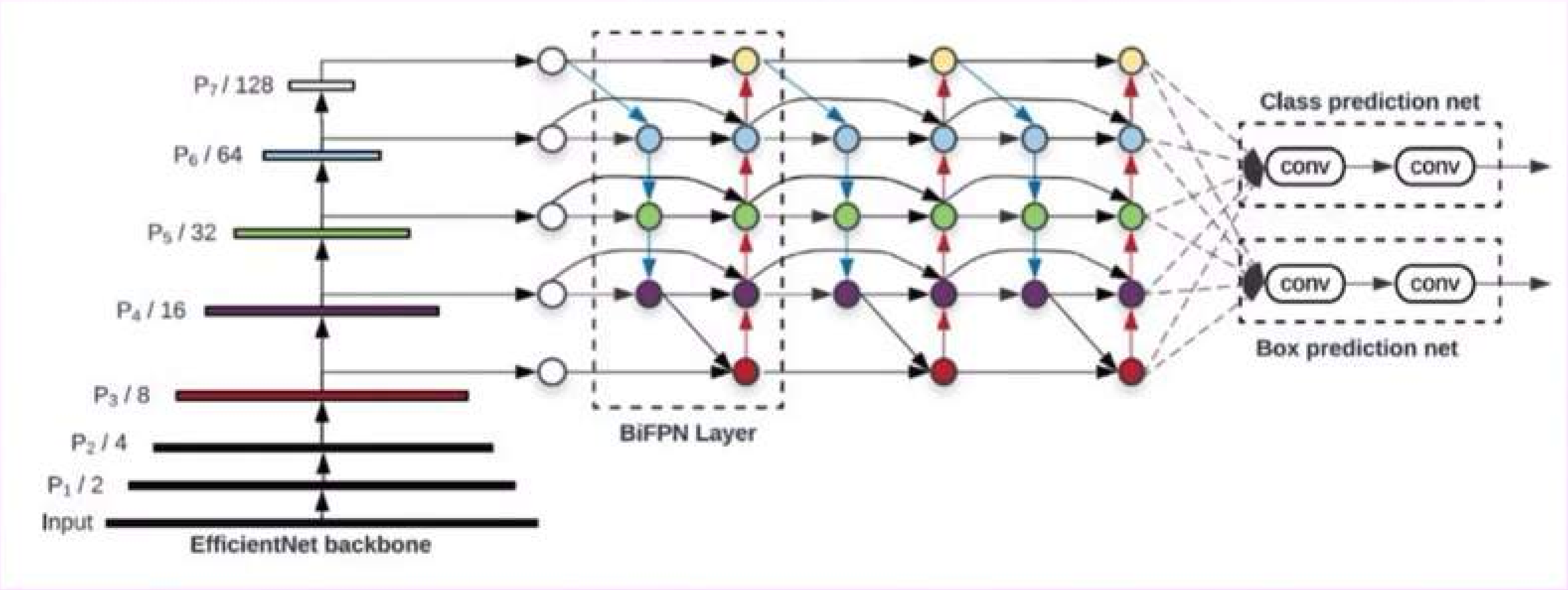

Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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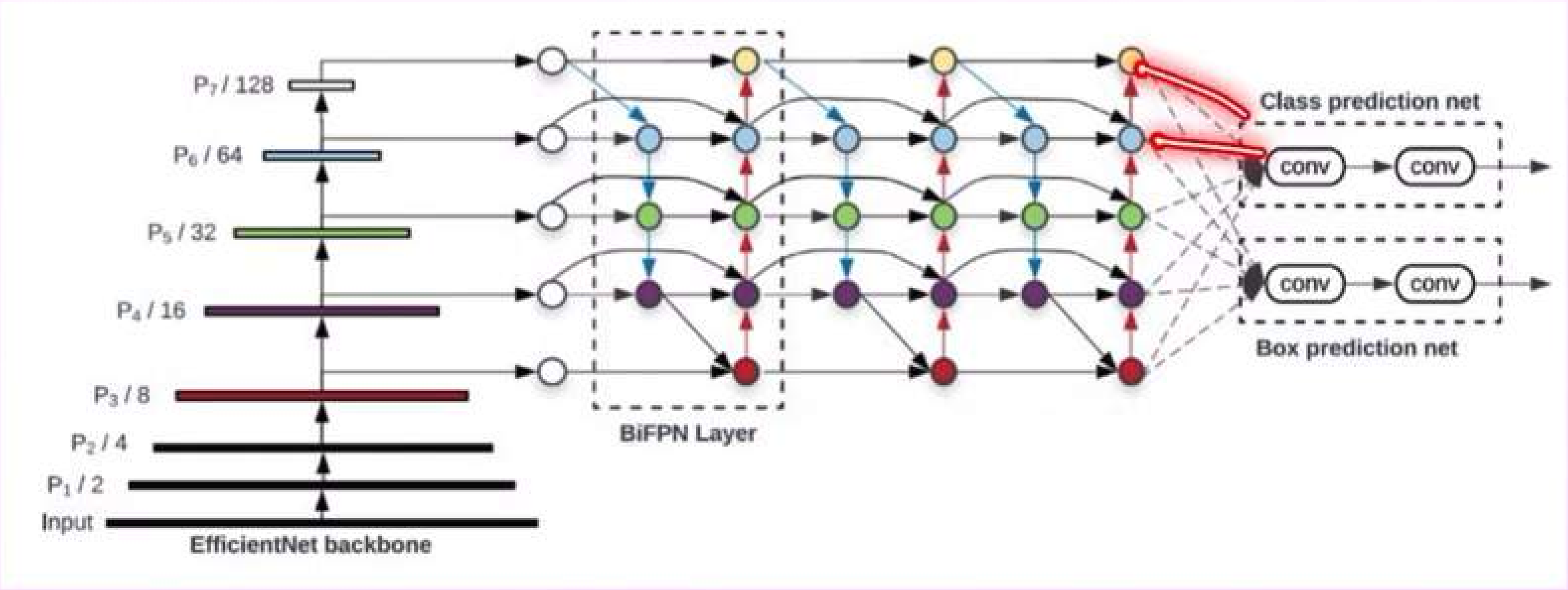

Multi-Input Weighted Residual Connections

- Idea from EfficientDet Paper
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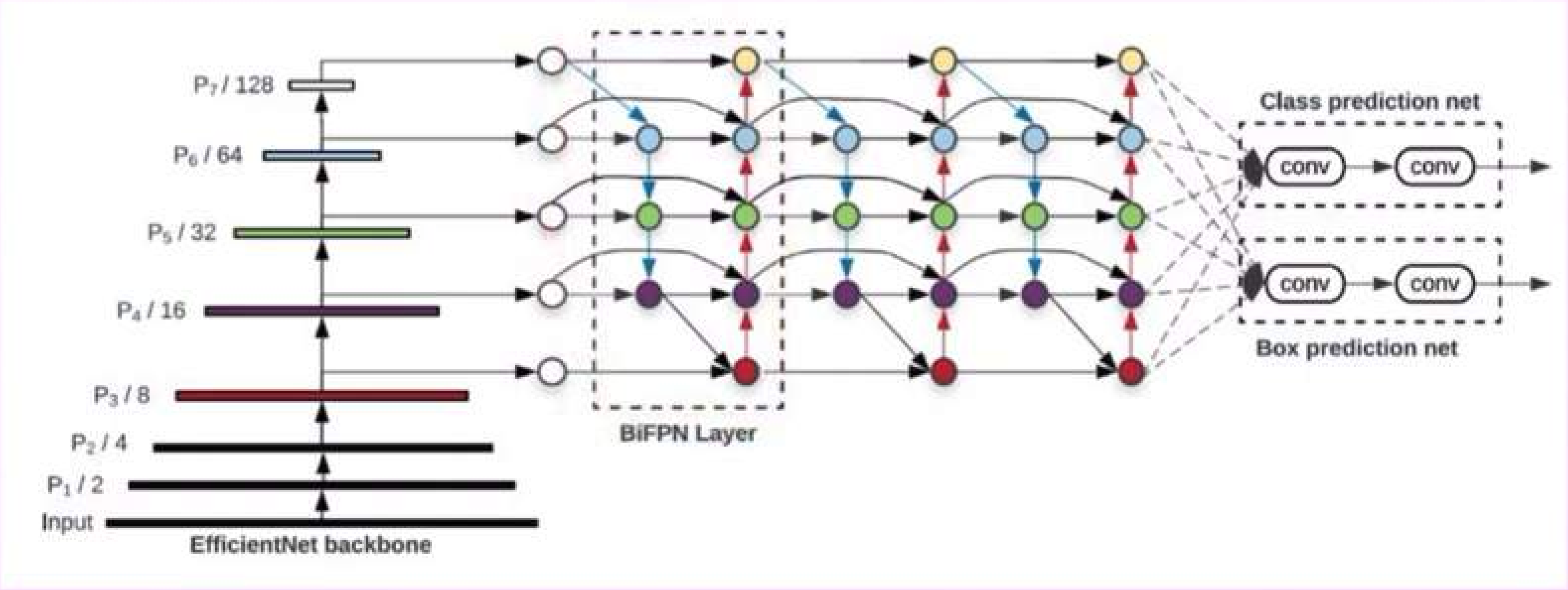
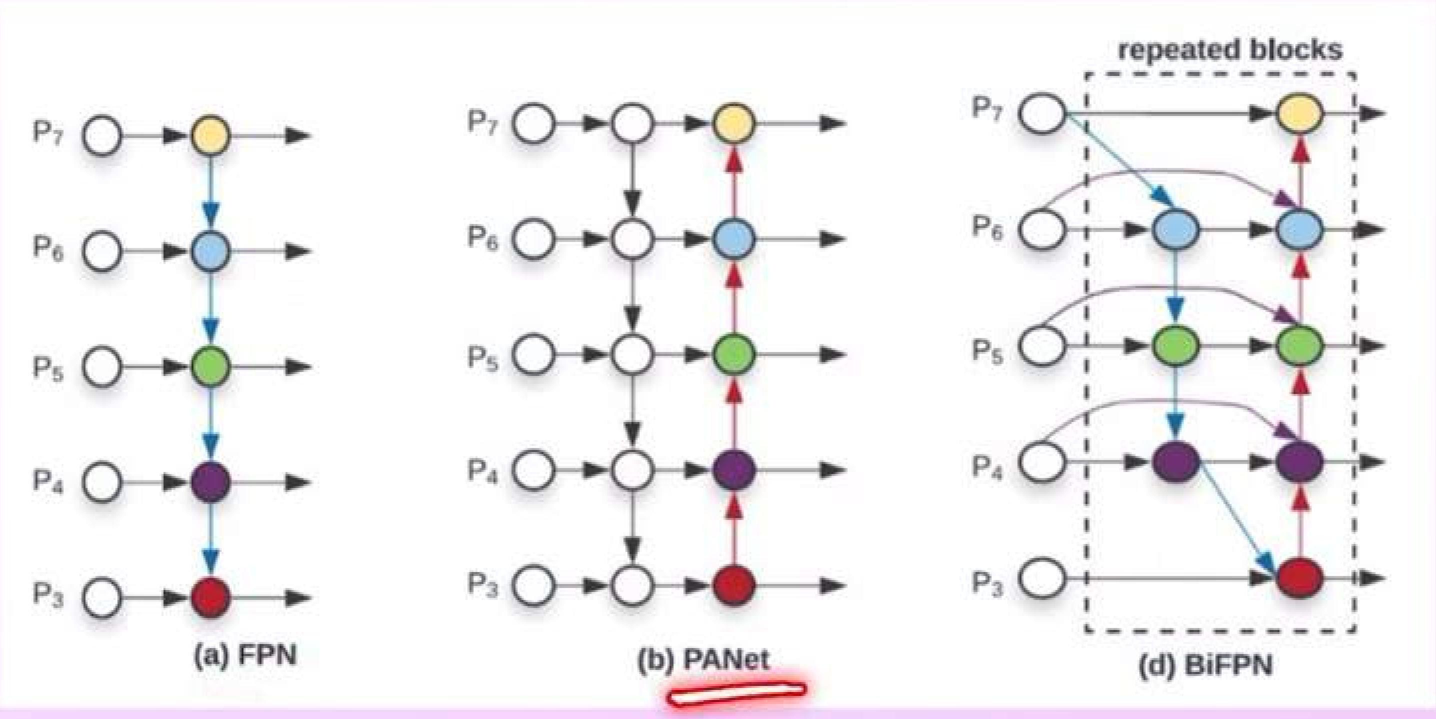
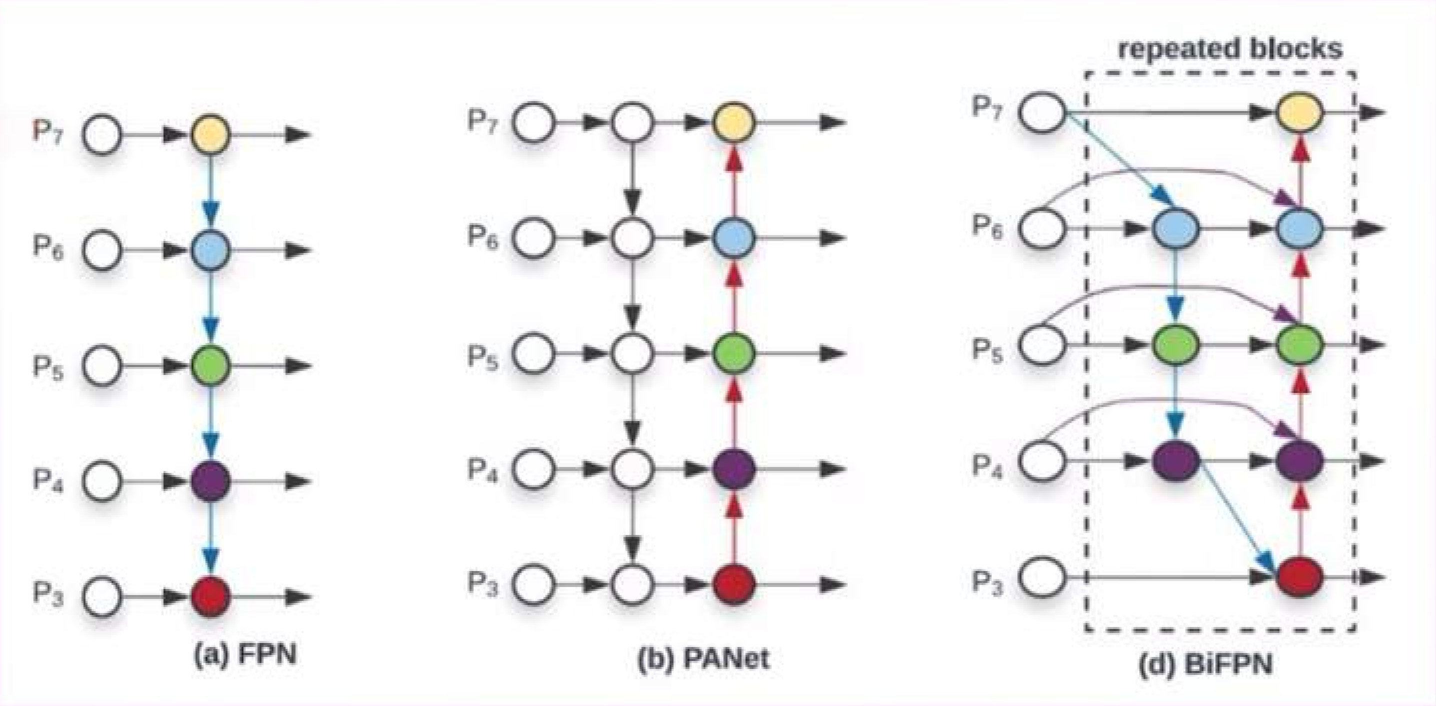
- EfficientDet —>



Multi-Input Weighted Residual Connections



Multi-Input Weighted Residual Connections



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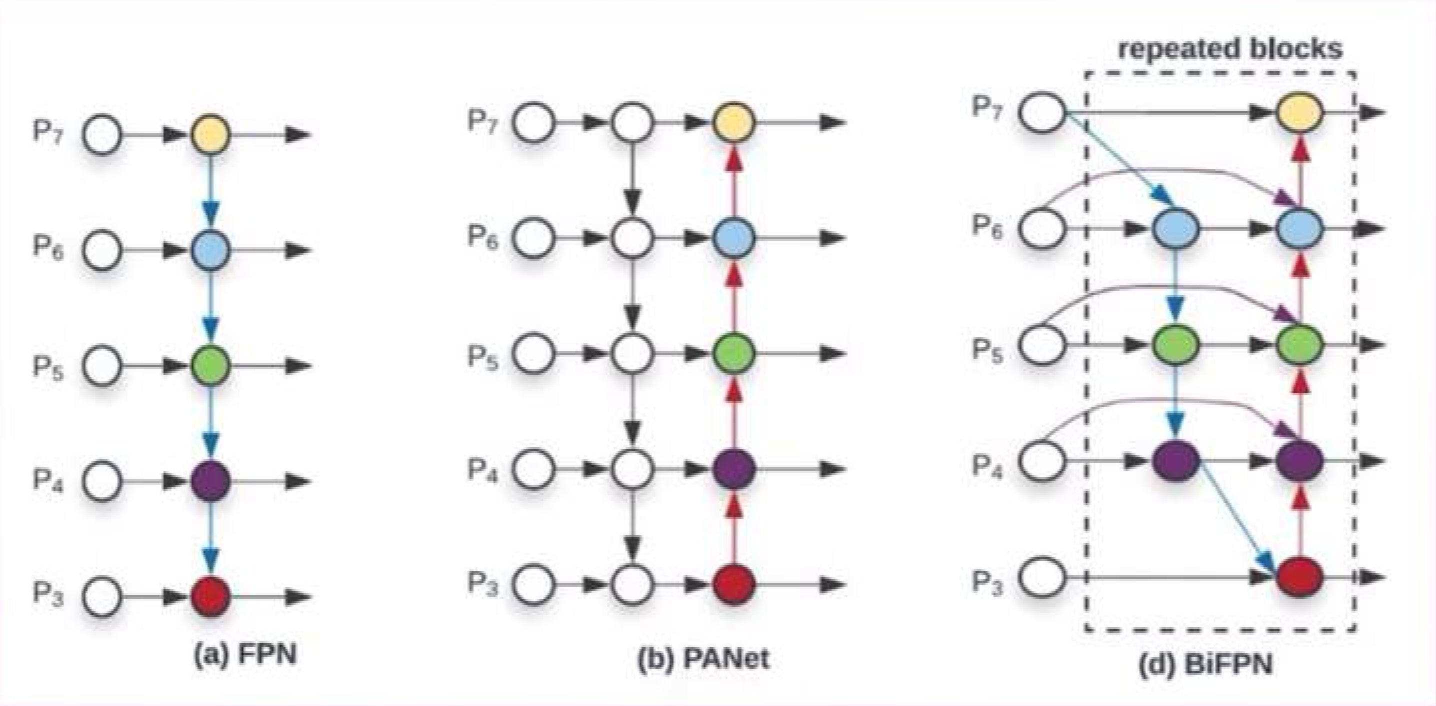

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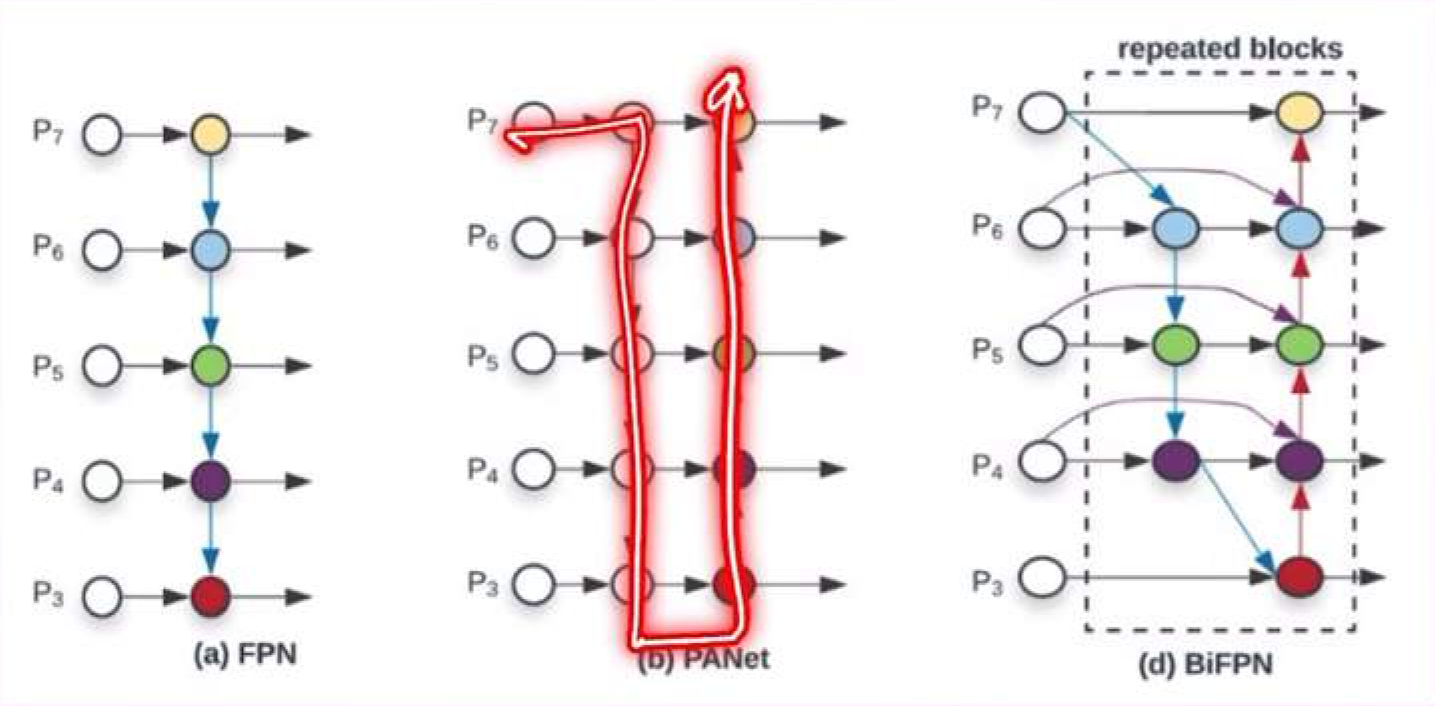

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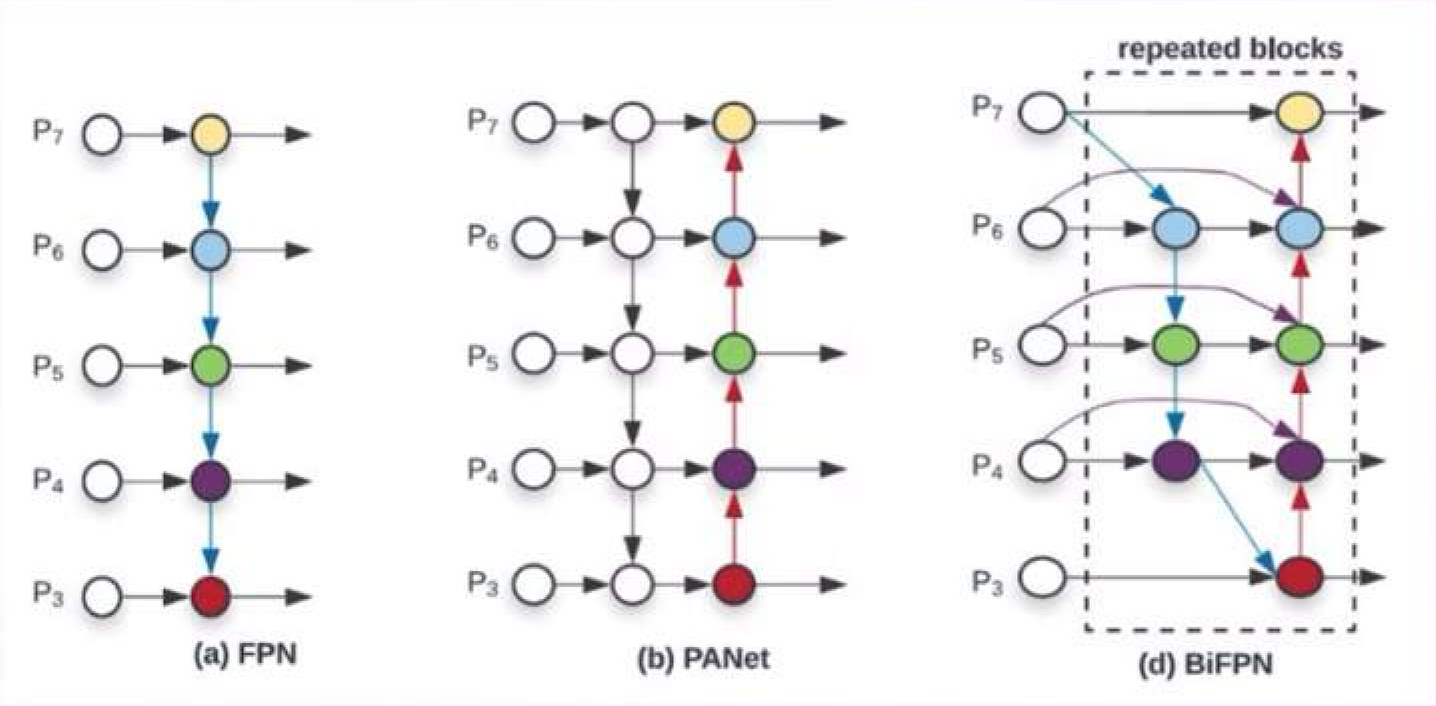
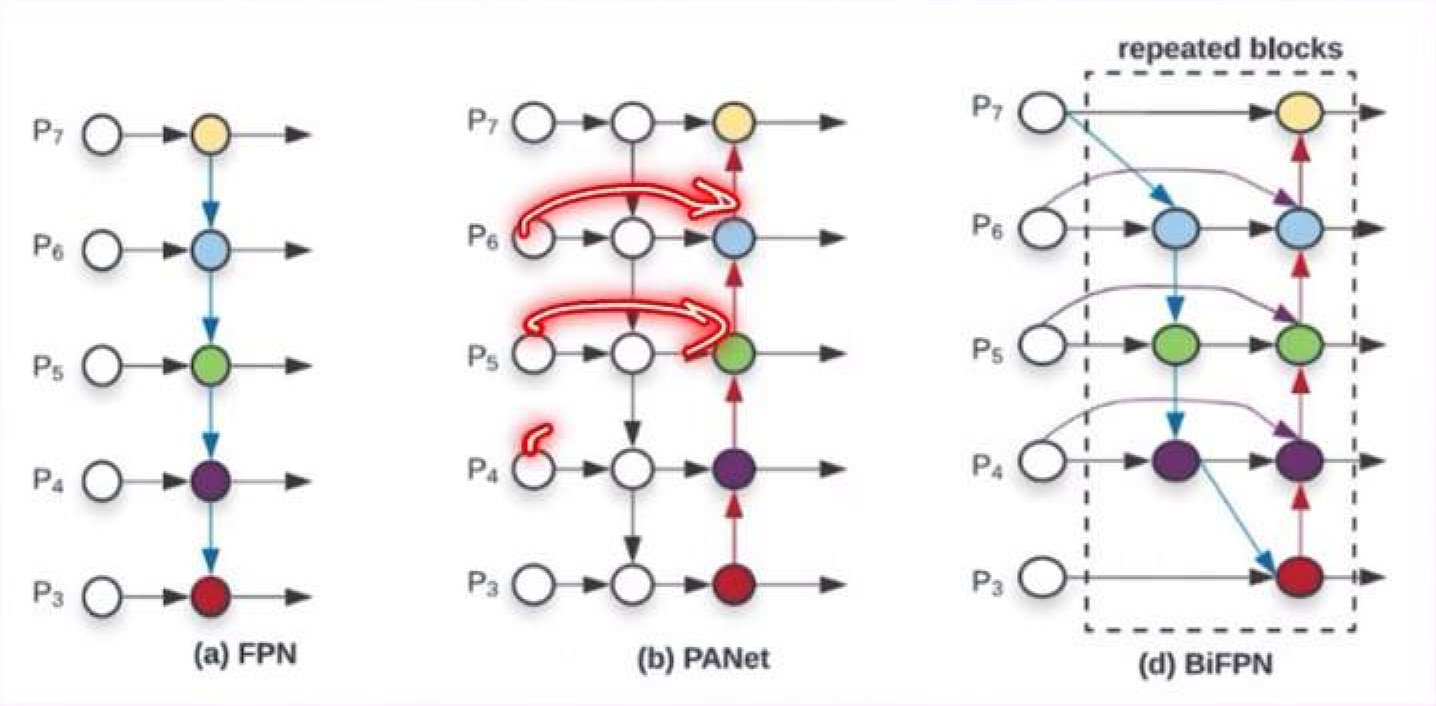
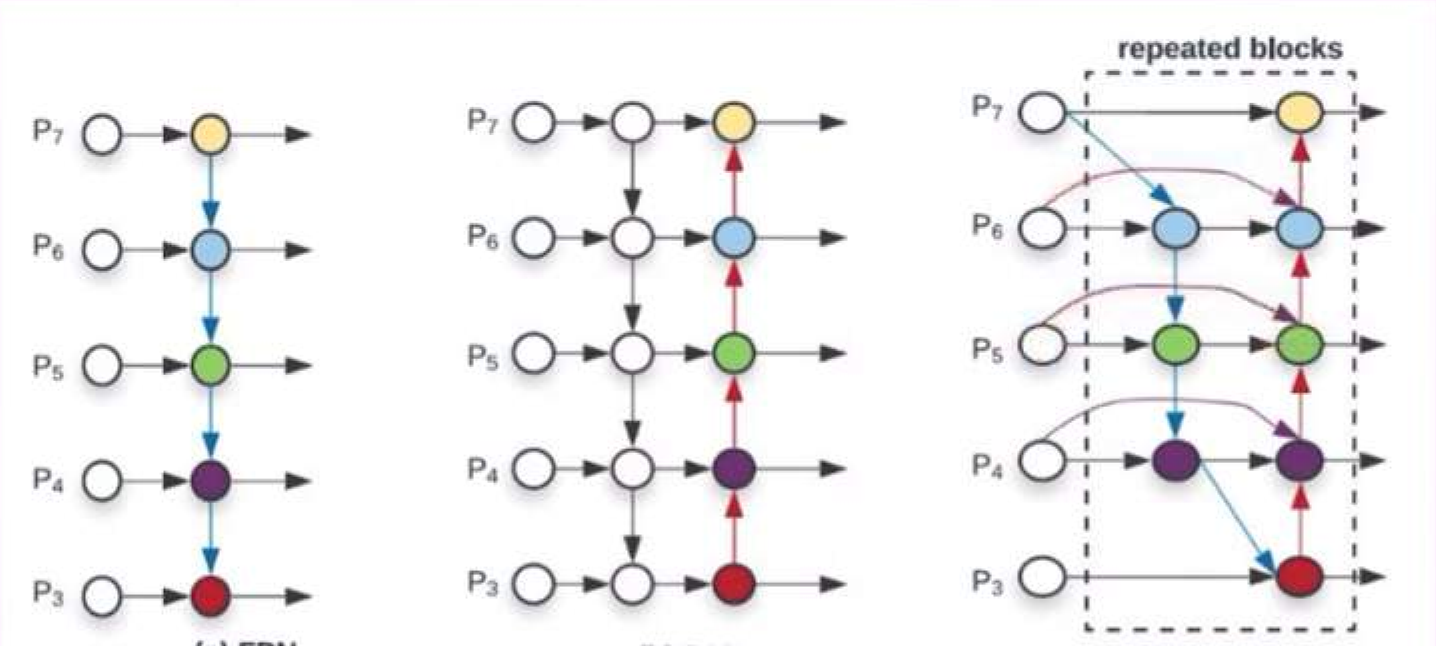


Multi-Input Weighted Residual Connections

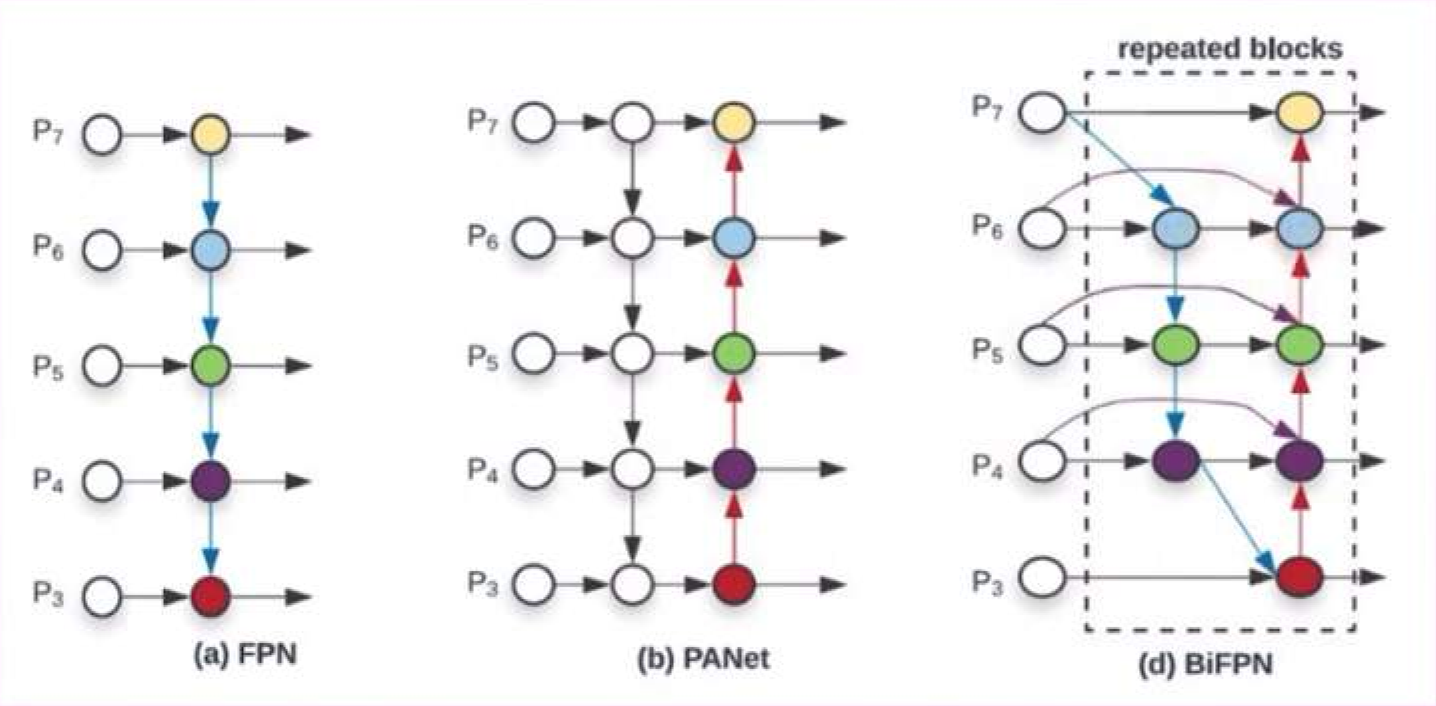


Multi-Input Weighted Residual Connections

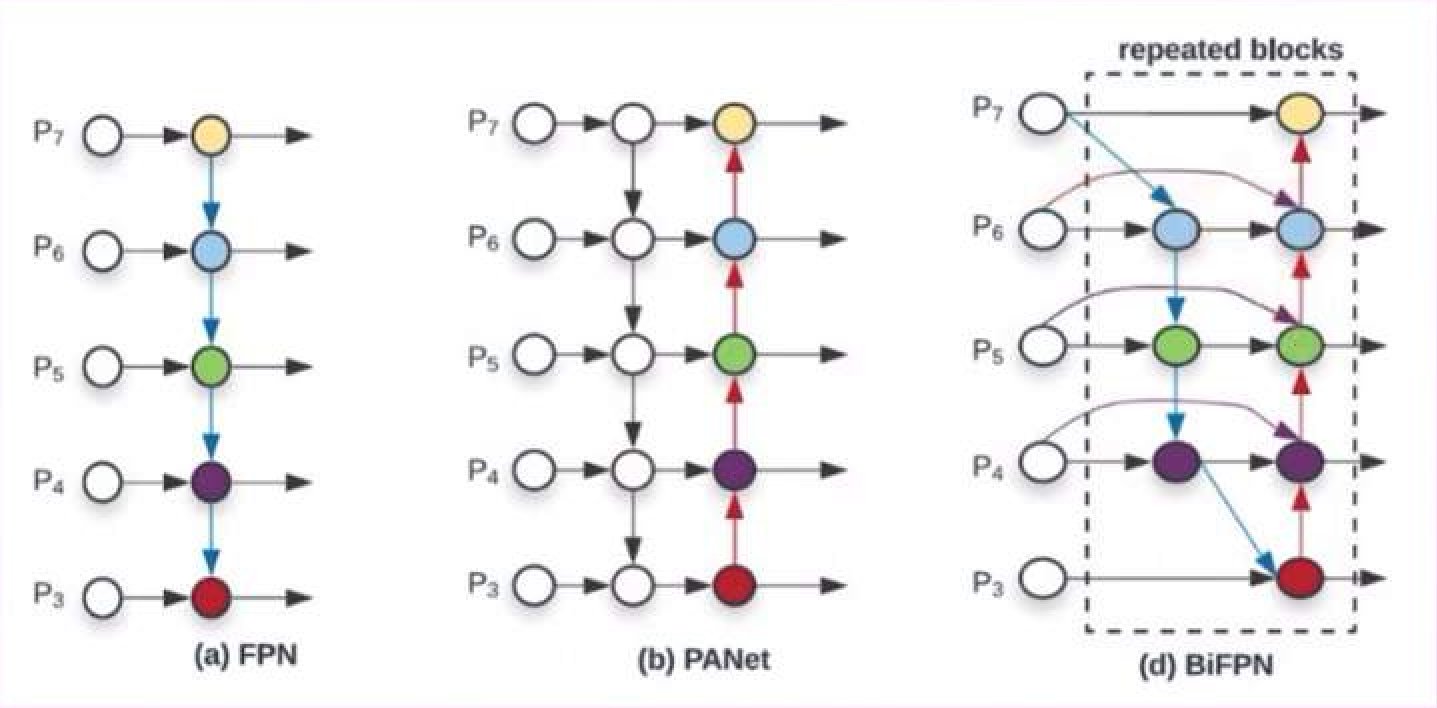


(a) FPN (b) PANet (d) BiFPN

Multi-Input Weighted Residual Connections



Multi-Input Weighted Residual Connections



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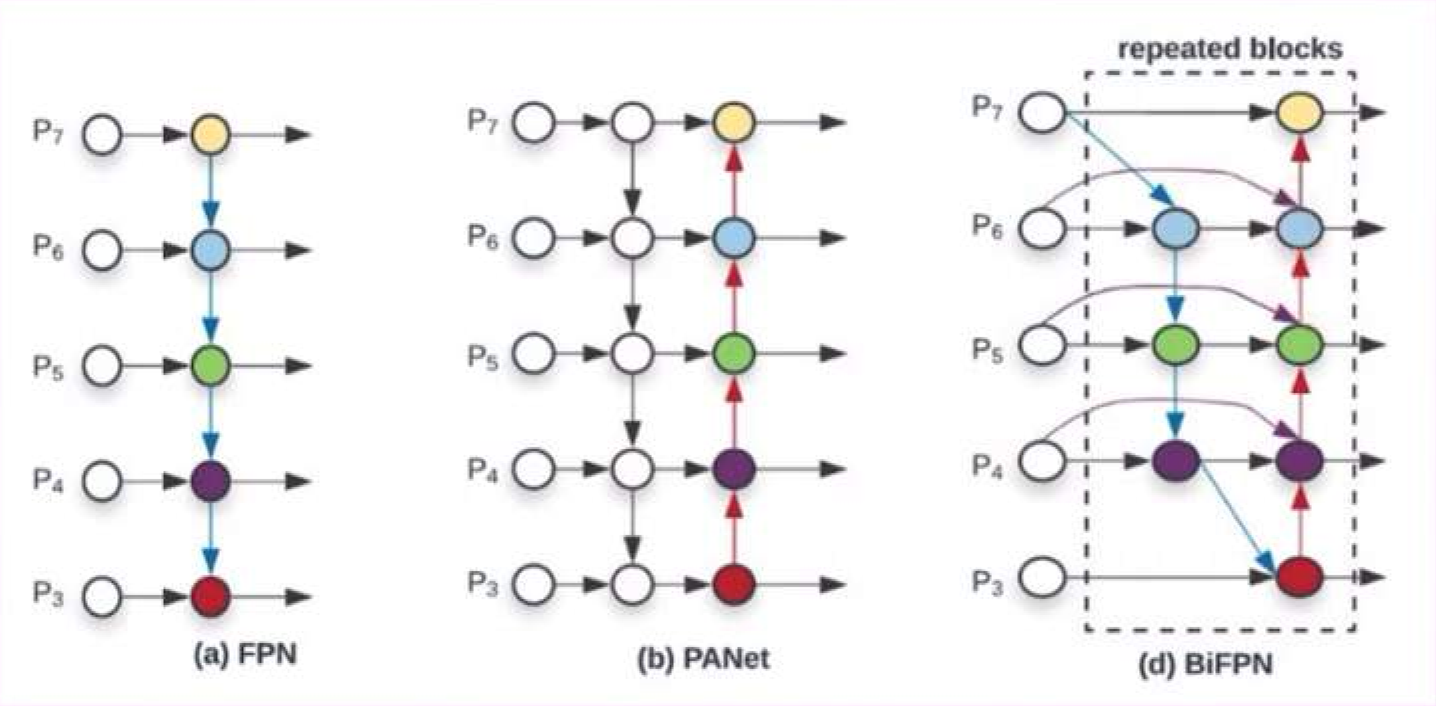

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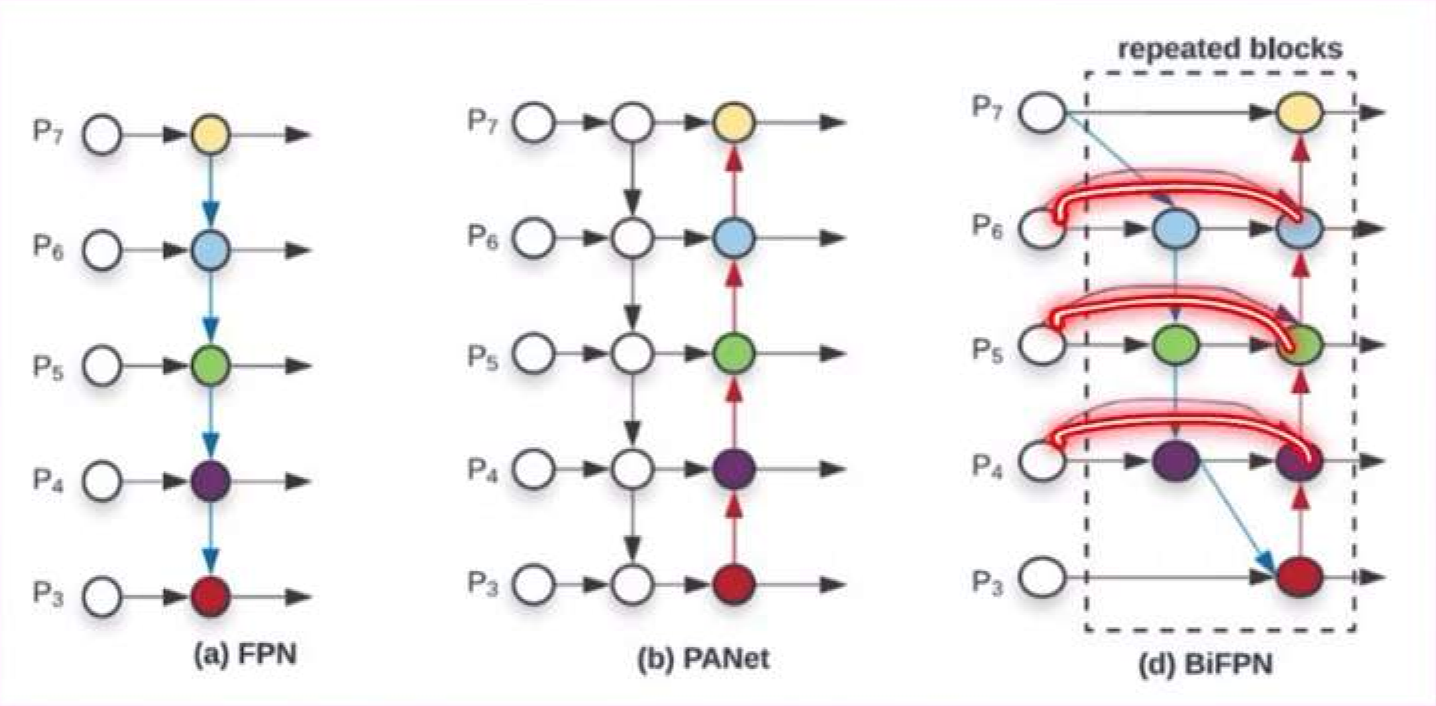
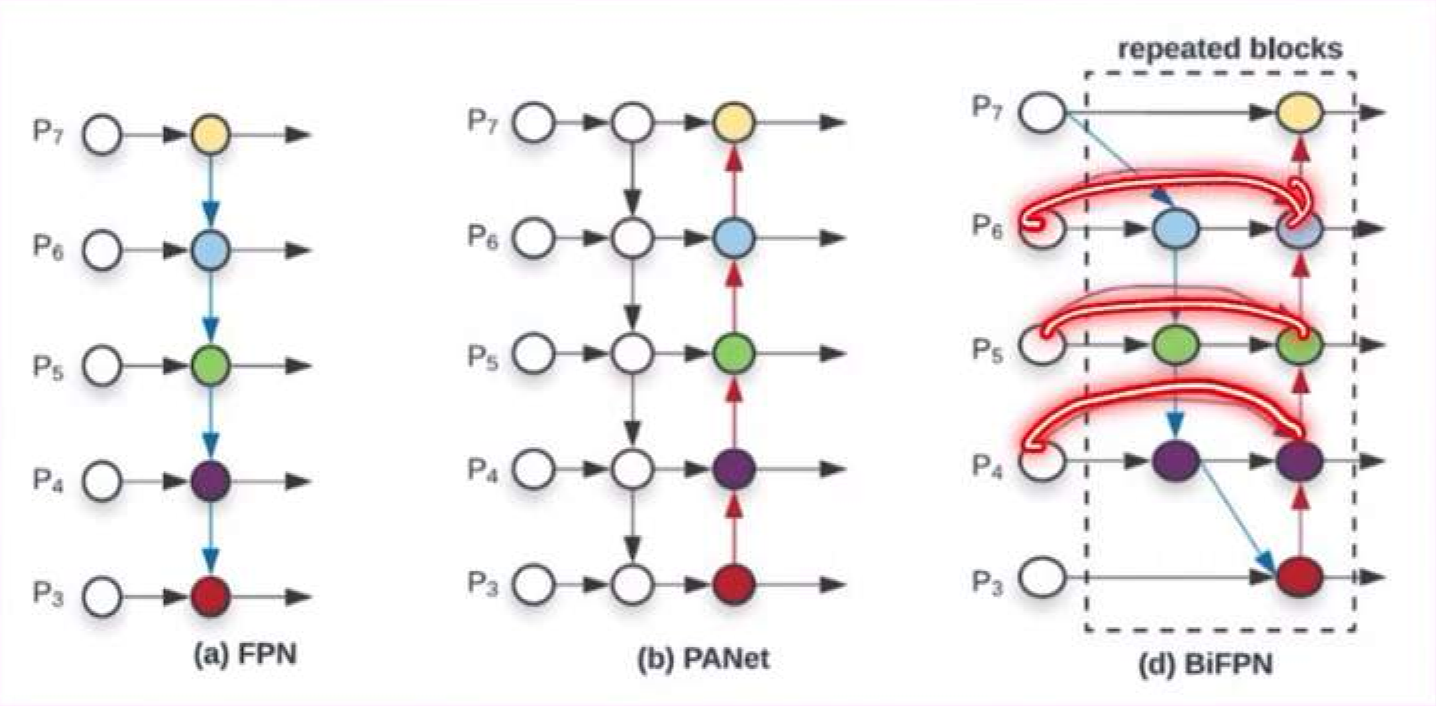
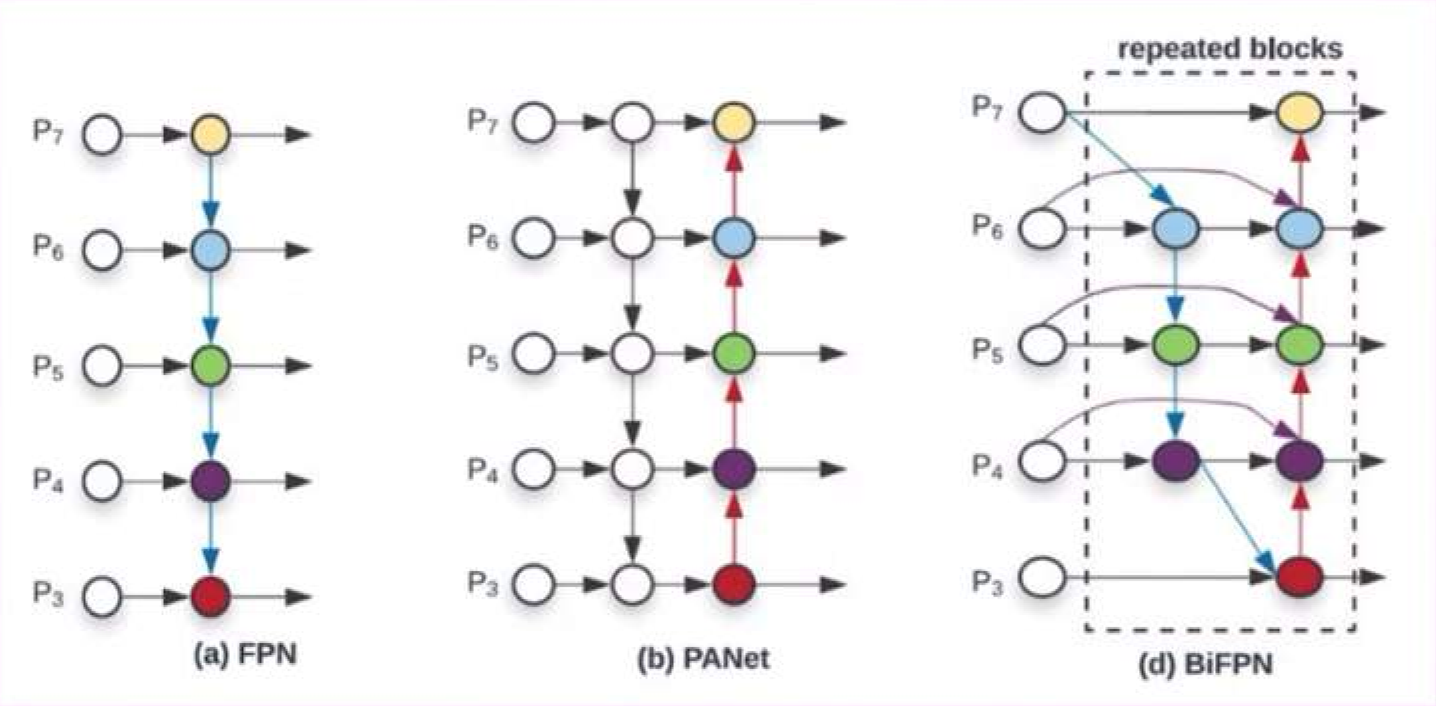


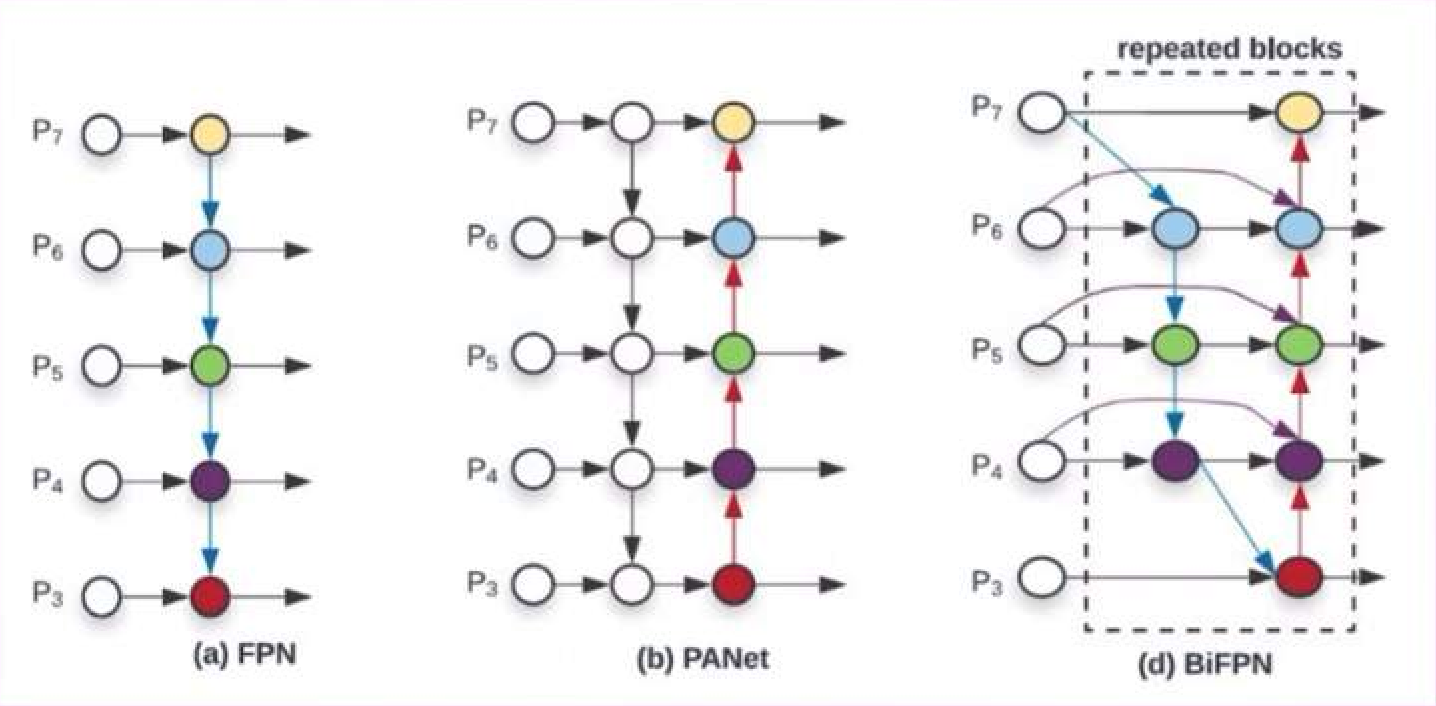
Multi-Input Weighted Residual Connections



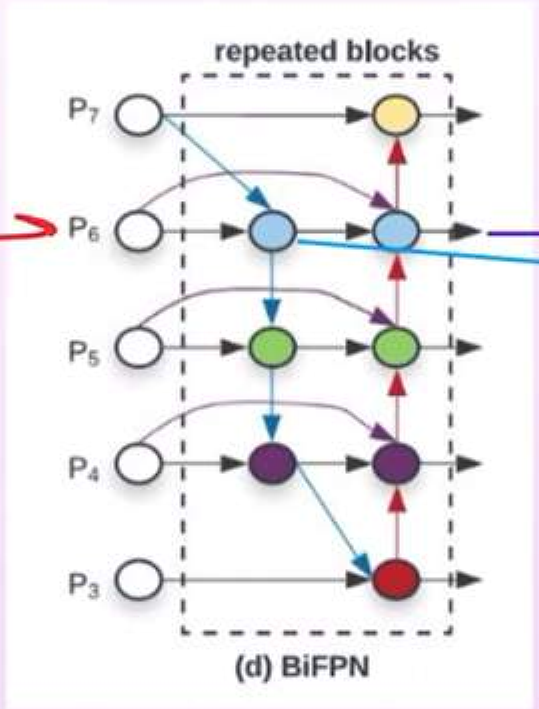
Multi-Input Weighted Residual Connections



Multi-Input Weighted Residual Connections



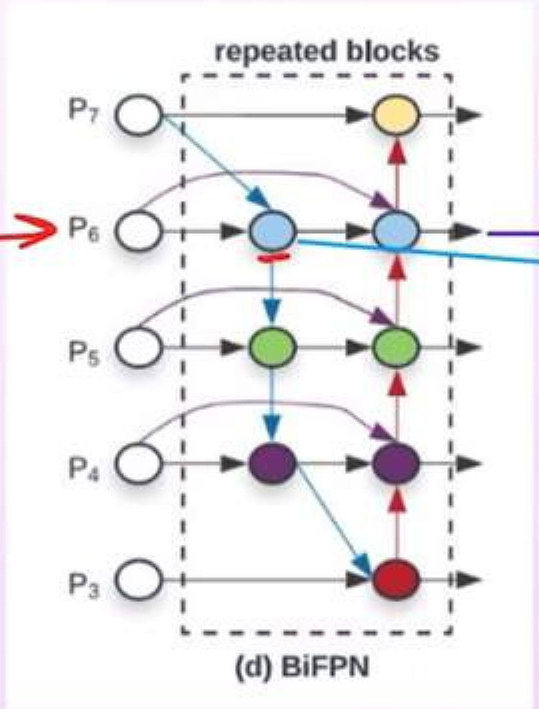
Multi-Input Weighted Residual Connections



$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

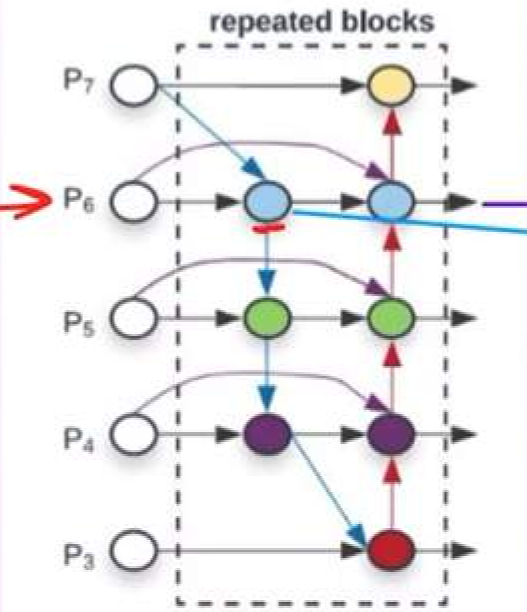
Multi-Input Weighted Residual Connections



$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

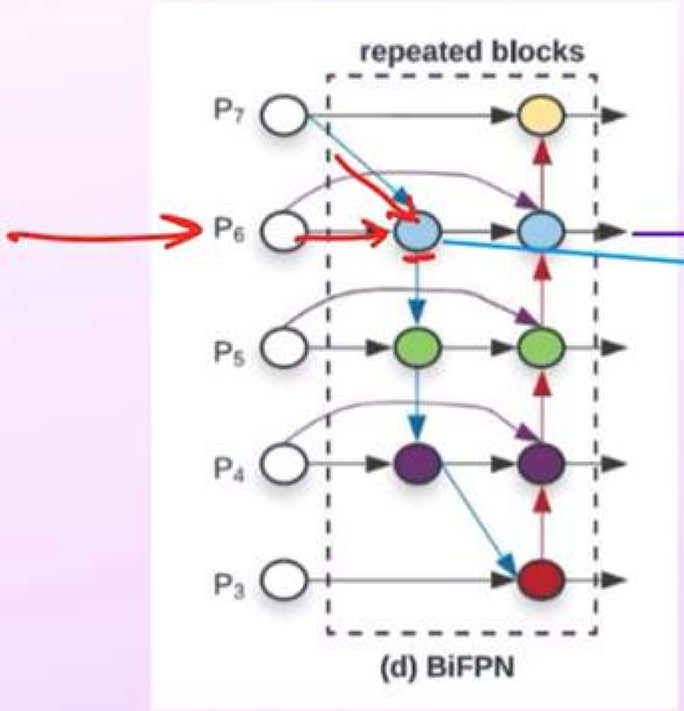


(d) BiFPN

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

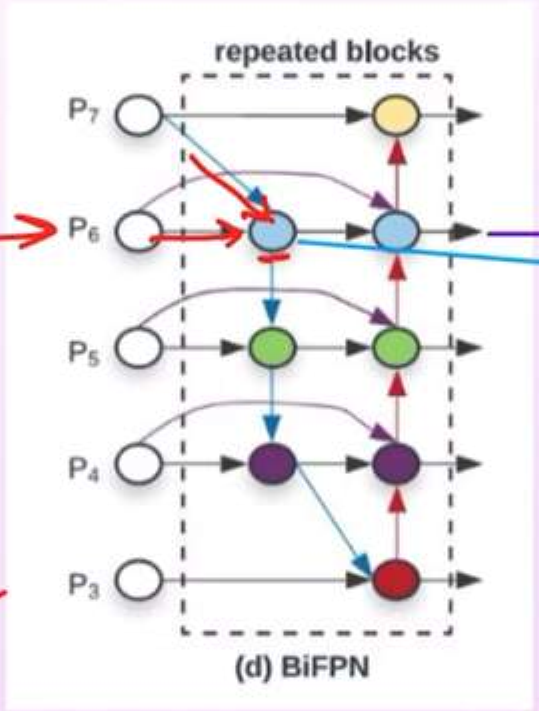


$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

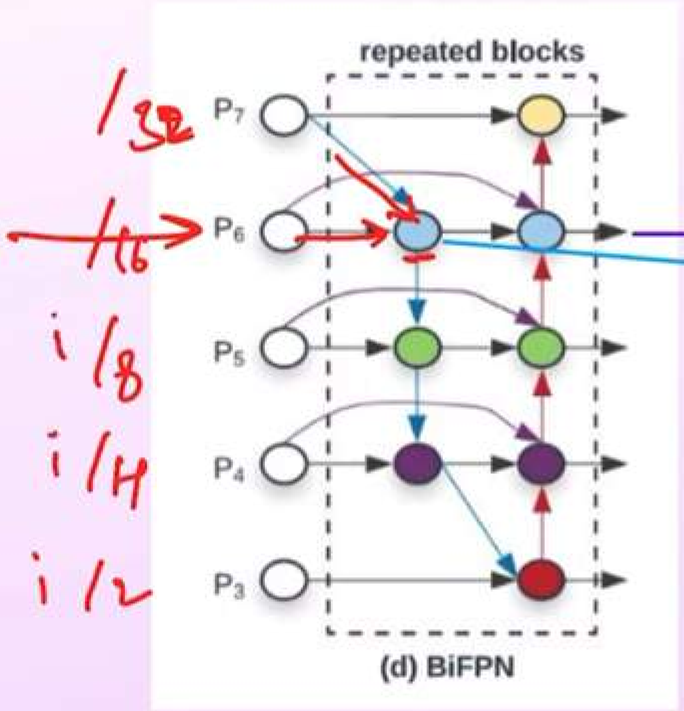
12



$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

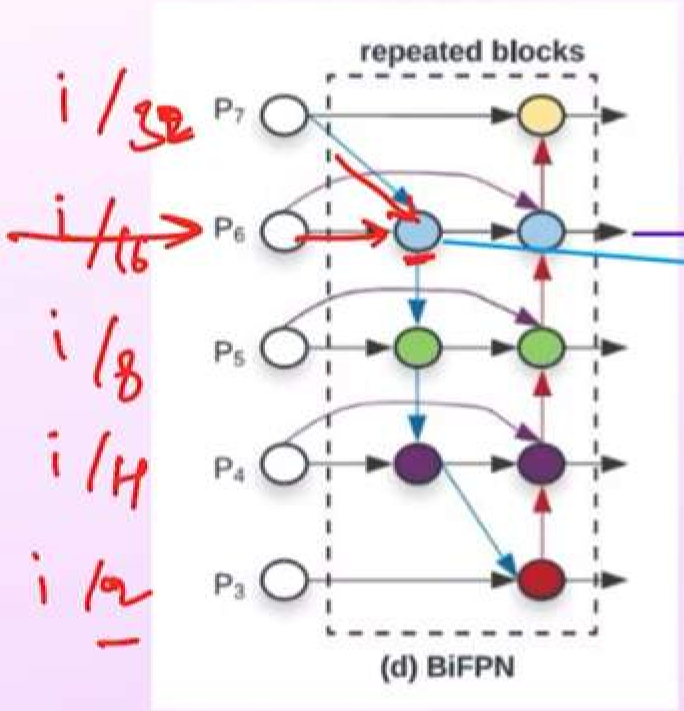
Multi-Input Weighted Residual Connections



$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

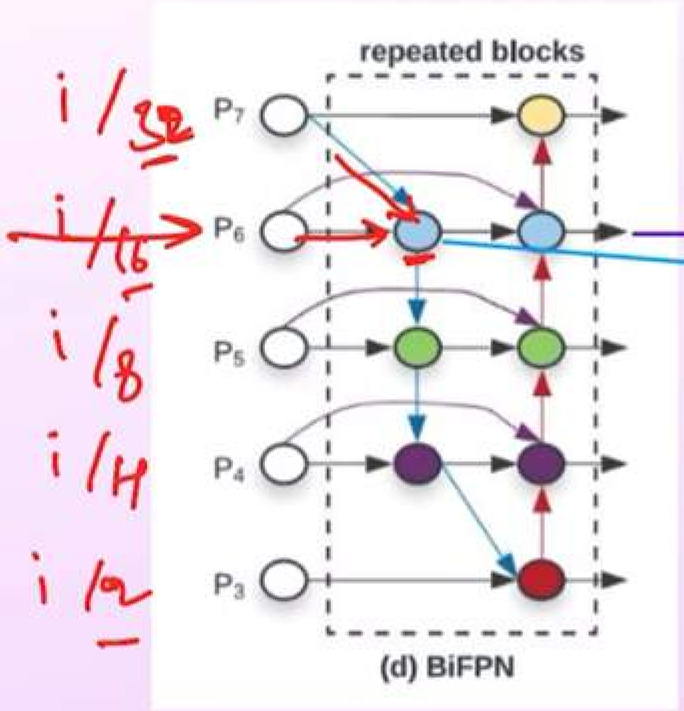
Multi-Input Weighted Residual Connections



$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w'_1 \cdot P_6^{in} + w'_2 \cdot P_6^{td} + w'_3 \cdot Resize(P_5^{out})}{w'_1 + w'_2 + w'_3 + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

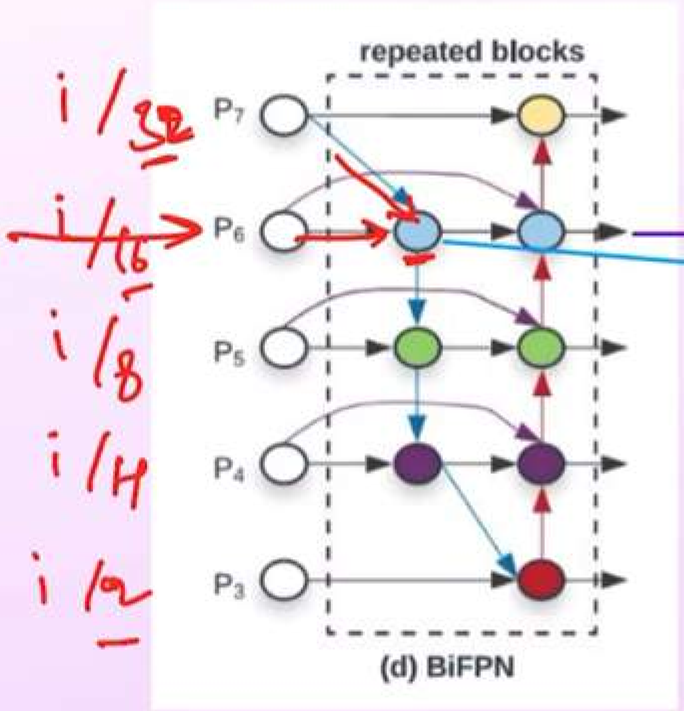


ups

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections



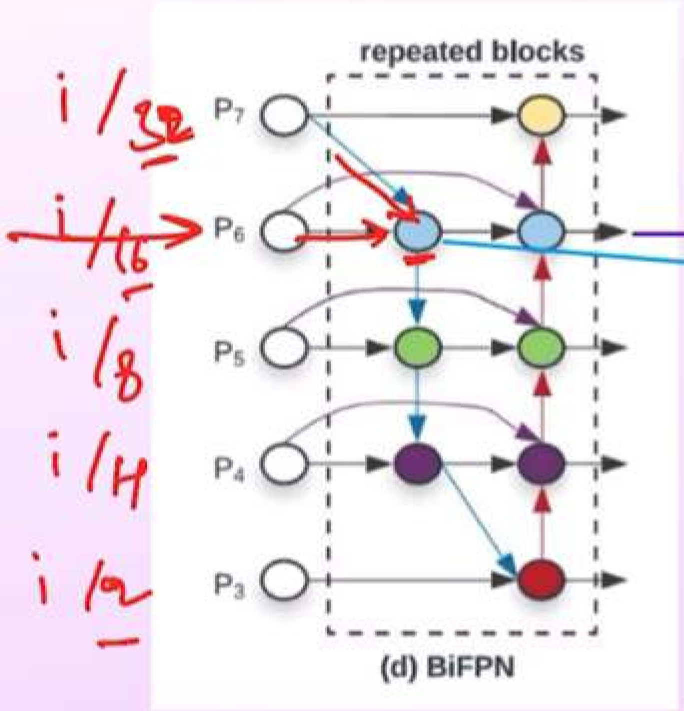
(d) BiFPN

upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections



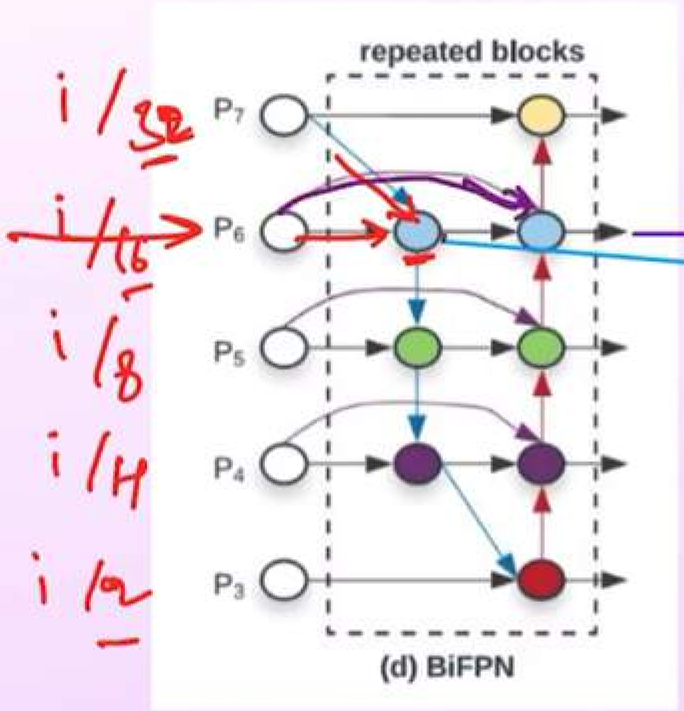
(d) BiFPN

upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

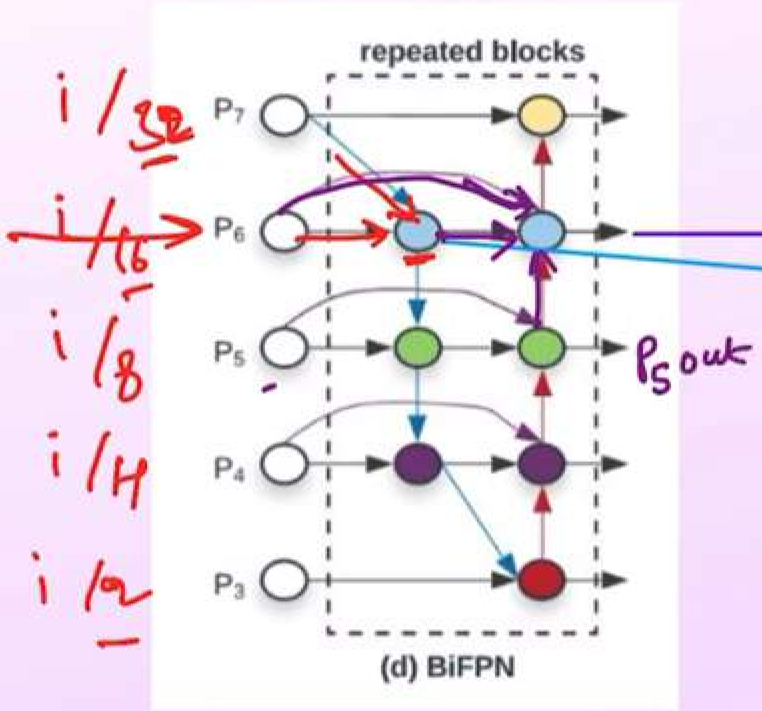


upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections



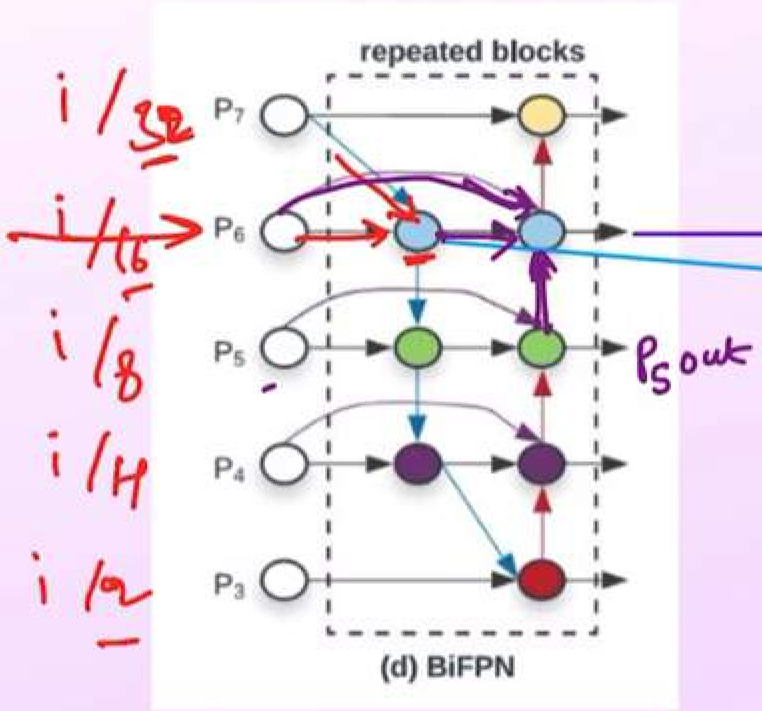
(d) BiFPN

upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w'_1 \cdot P_6^{in} + w'_2 \cdot P_6^{td} + w'_3 \cdot Resize(P_5^{out})}{w'_1 + w'_2 + w'_3 + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

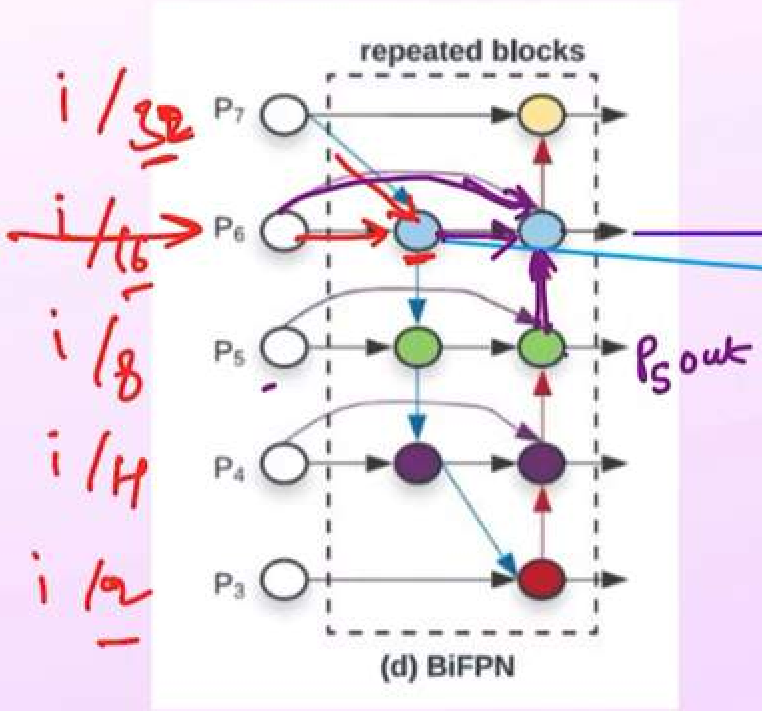


upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w'_1 \cdot P_6^{in} + w'_2 \cdot P_6^{td} + w'_3 \cdot Resize(P_5^{out})}{w'_1 + w'_2 + w'_3 + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

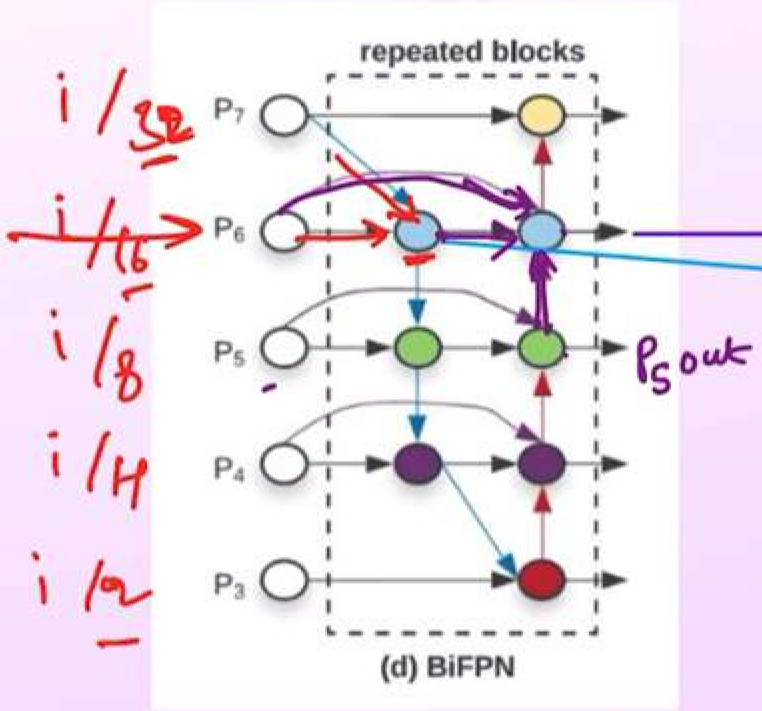


upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections



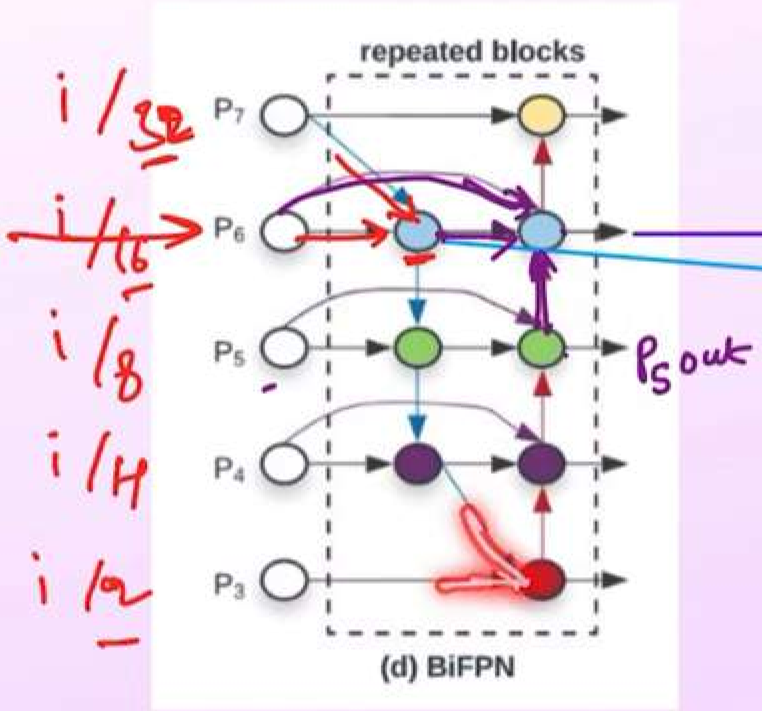
(d) BiFPN

upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections

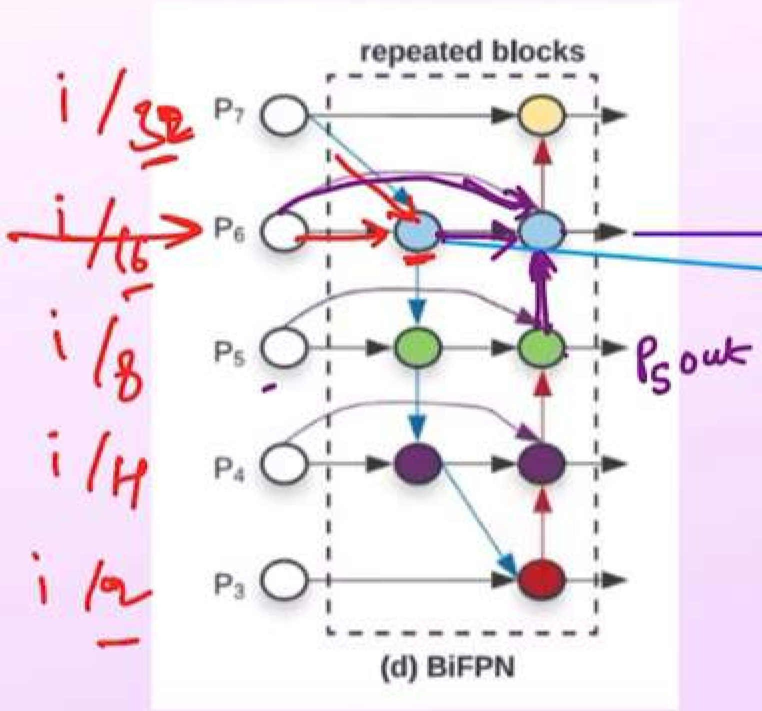


upsampling

$$P_6^{td} = Conv\left(\frac{w_1 \cdot P_6^{in} + w_2 \cdot Resize(P_7^{in})}{w_1 + w_2 + \epsilon}\right)$$

$$P_6^{out} = Conv\left(\frac{w_1' \cdot P_6^{in} + w_2' \cdot P_6^{td} + w_3' \cdot Resize(P_5^{out})}{w_1' + w_2' + w_3' + \epsilon}\right)$$

Multi-Input Weighted Residual Connections



(d) BiFPN

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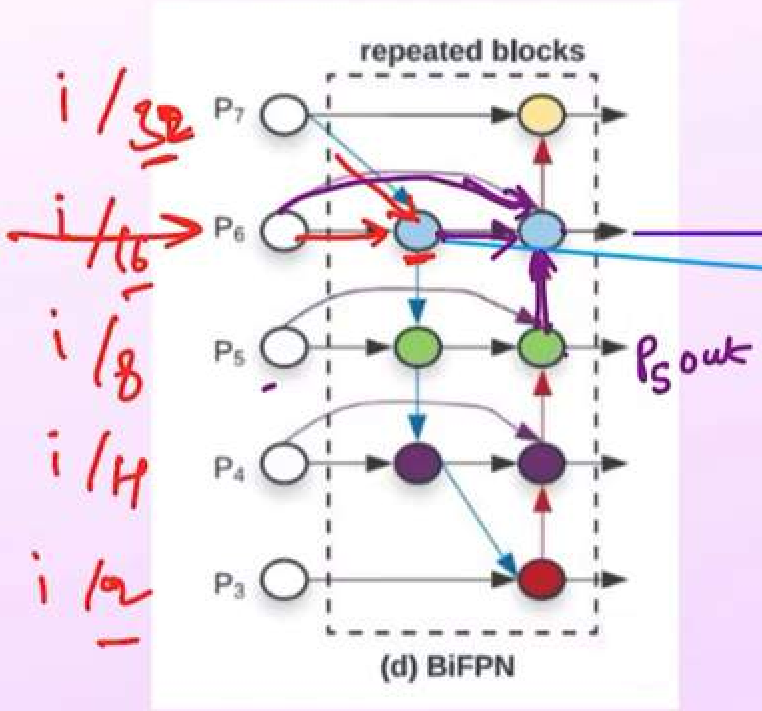
Multi-Input Weighted Residual Connections



upsampling

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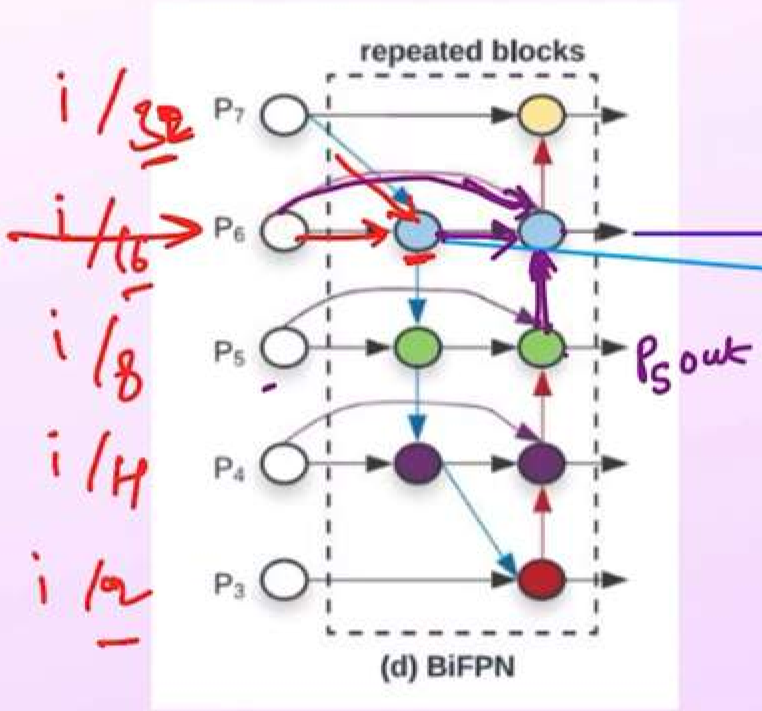
Multi-Input Weighted Residual Connections



upsampling

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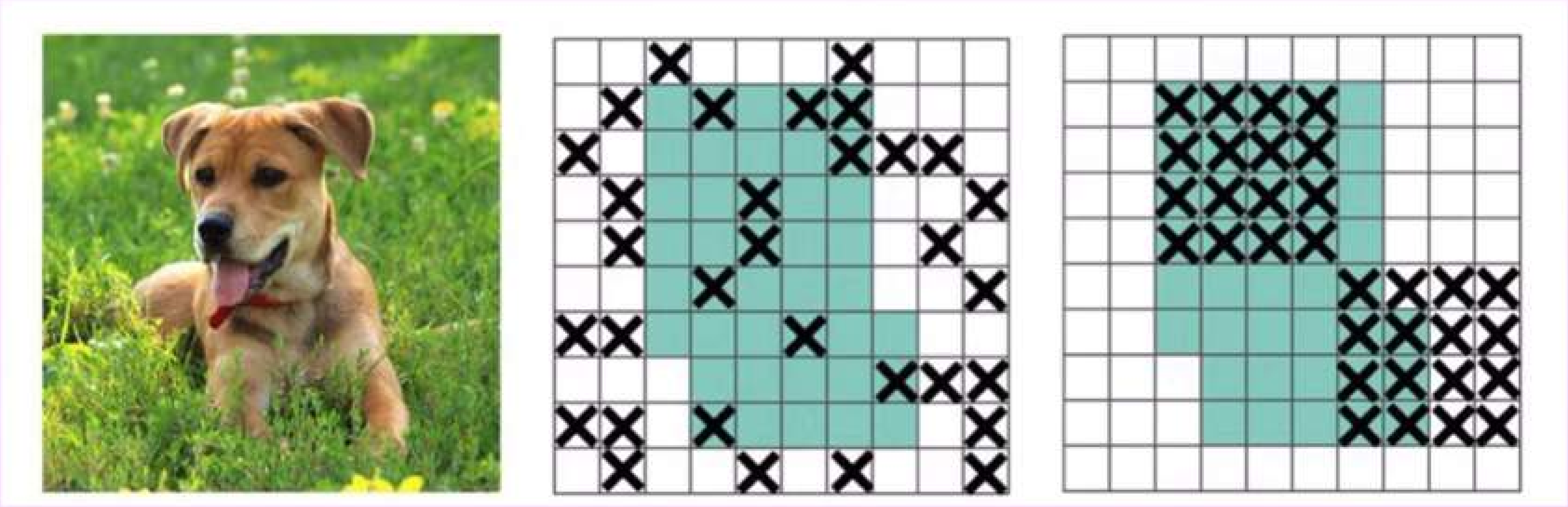
Drop Block Regularization

- Inspired from Dropout Layer
- Dropout works for dense layers
- Might not work well for convolution layers



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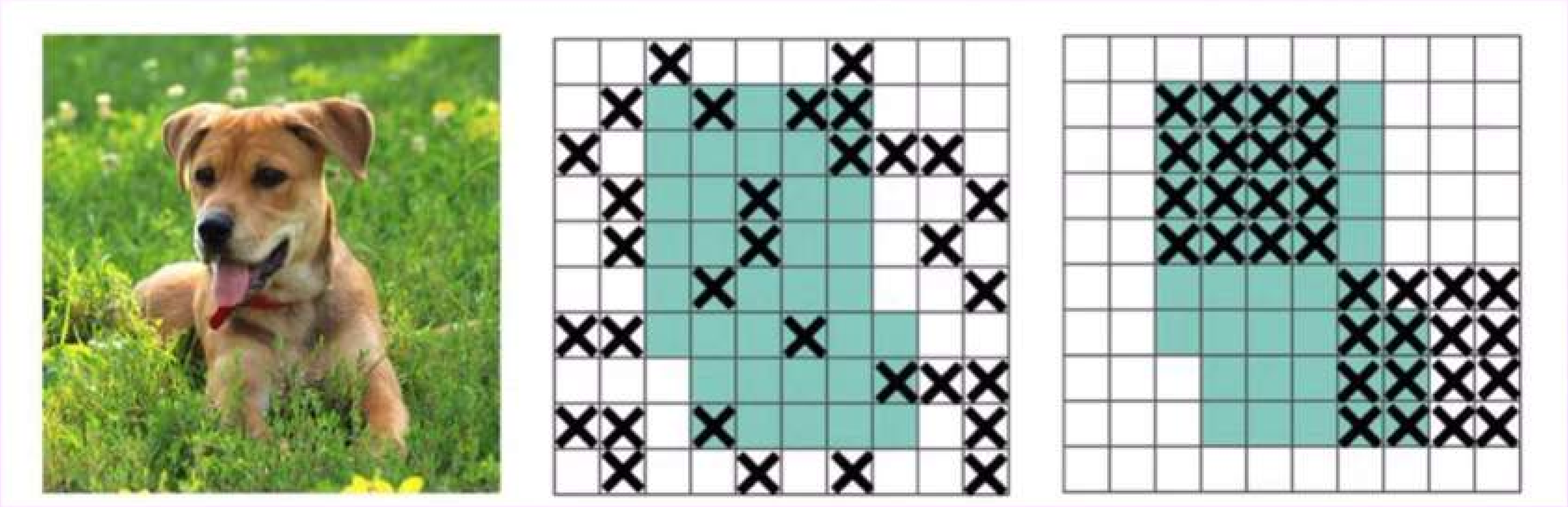

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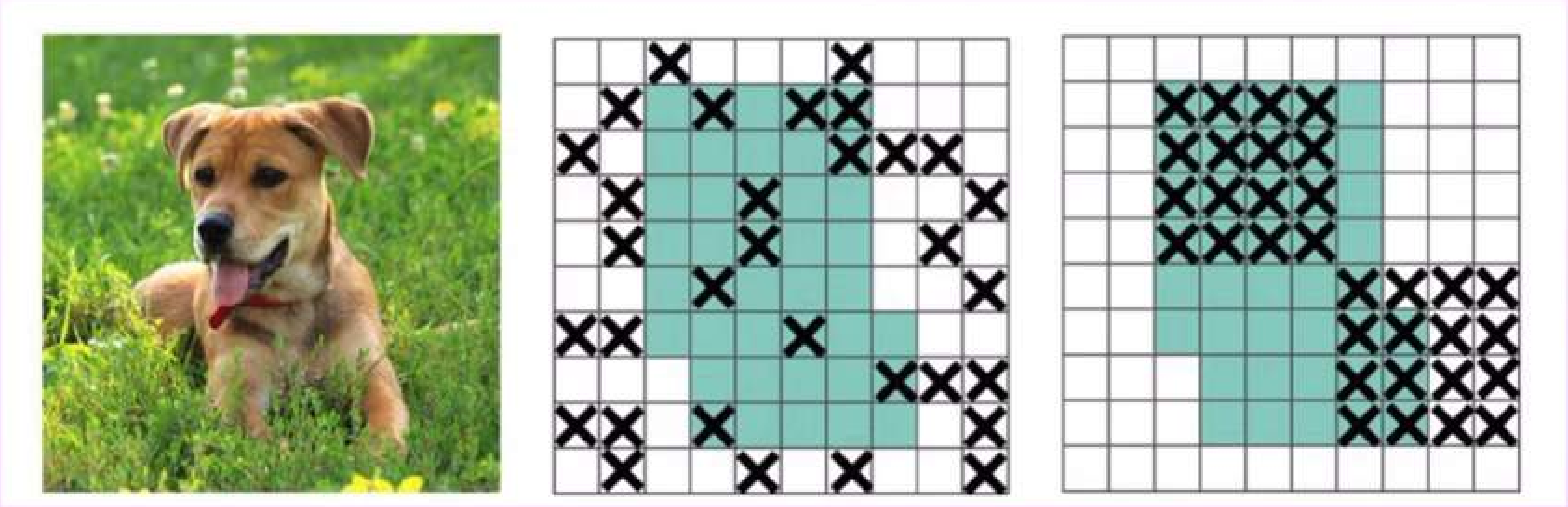

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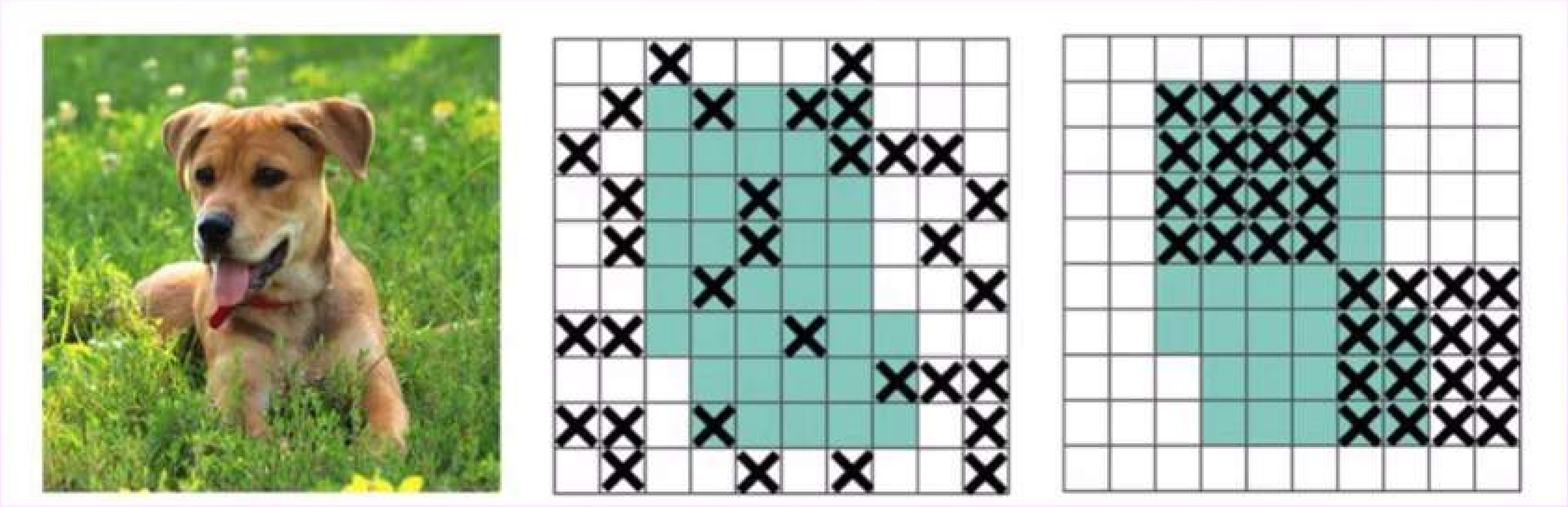

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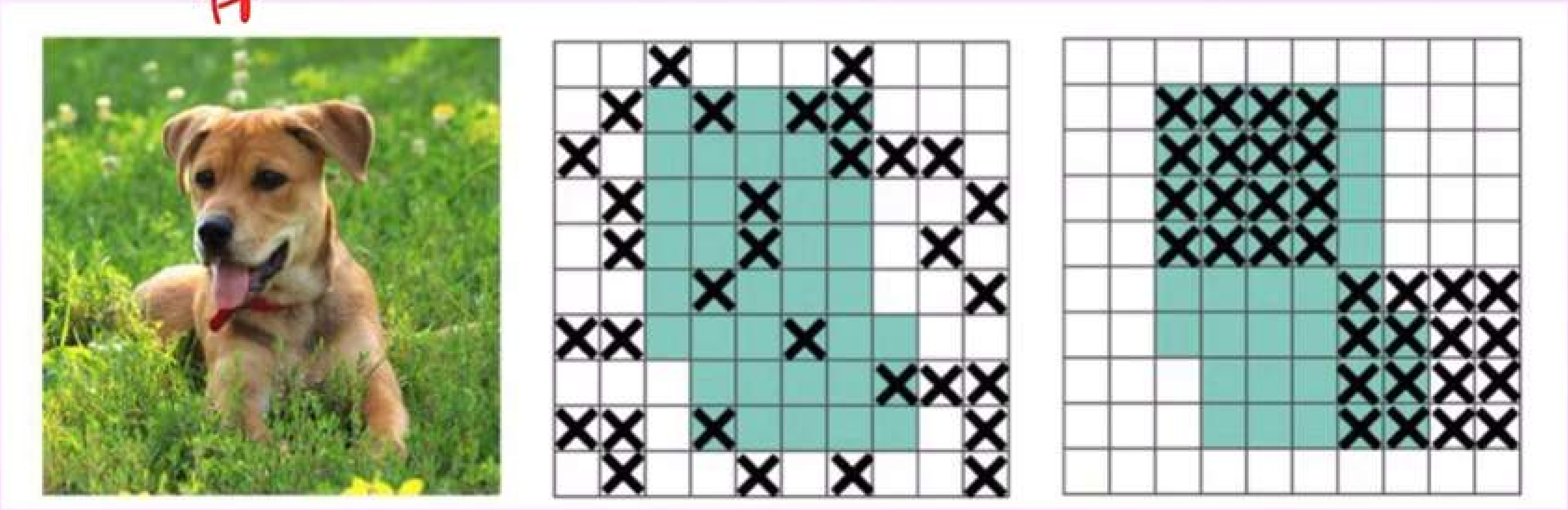
i/p

Feature map



Drop Block Regularization

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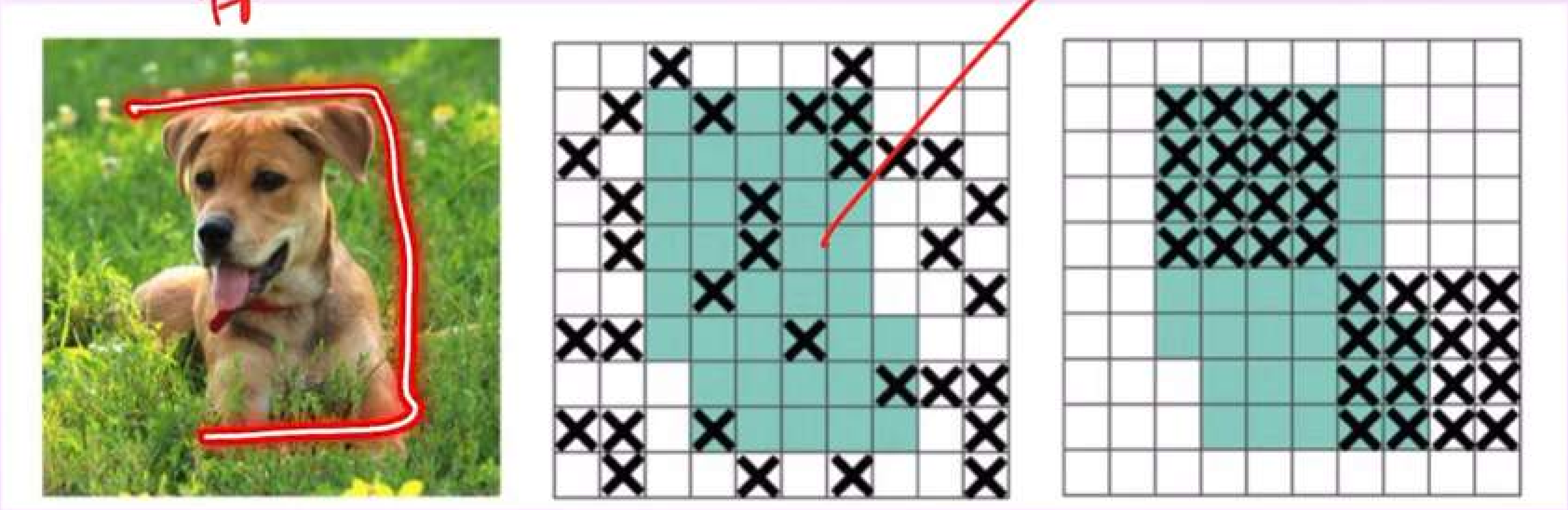
Activations

i/p

Feature map



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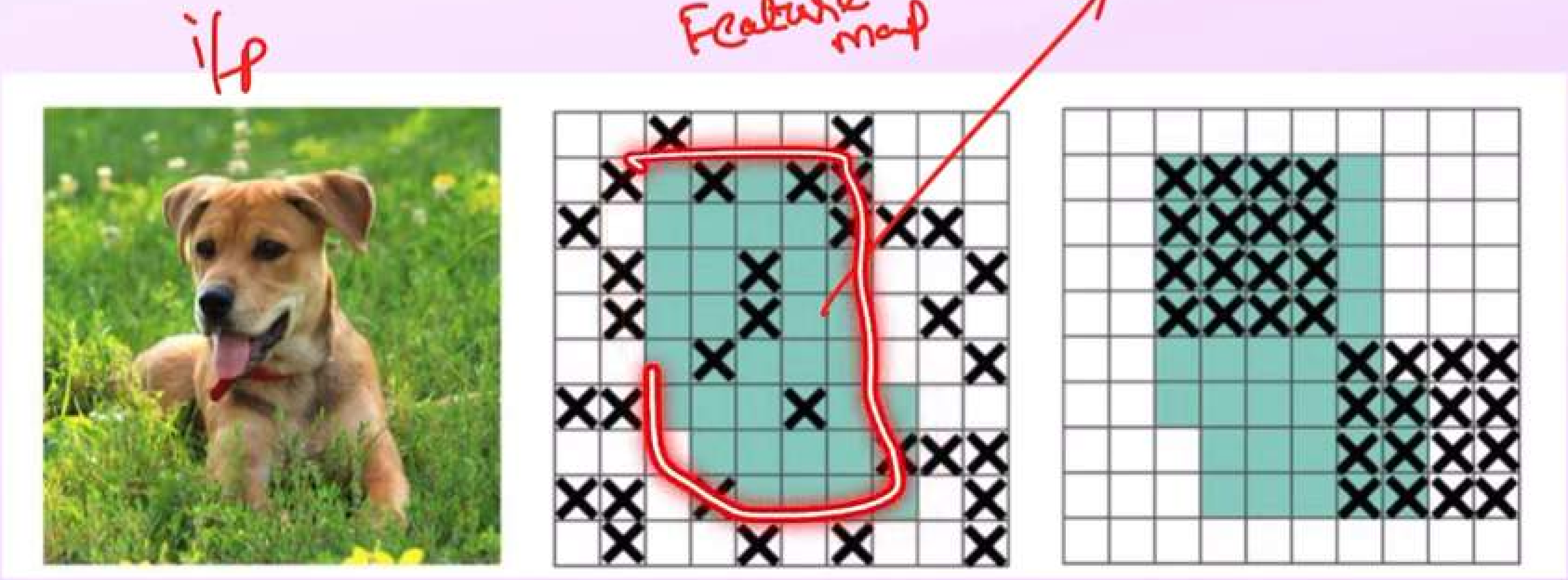

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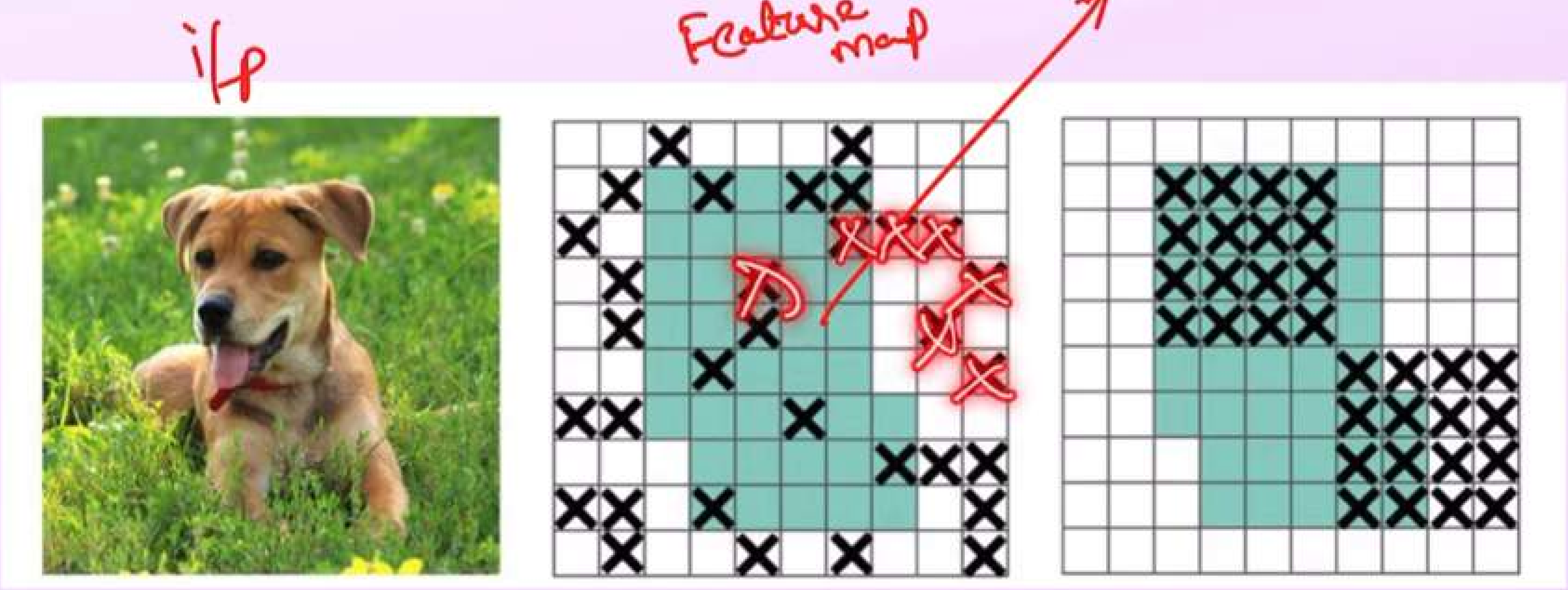

Drop Block Regularization

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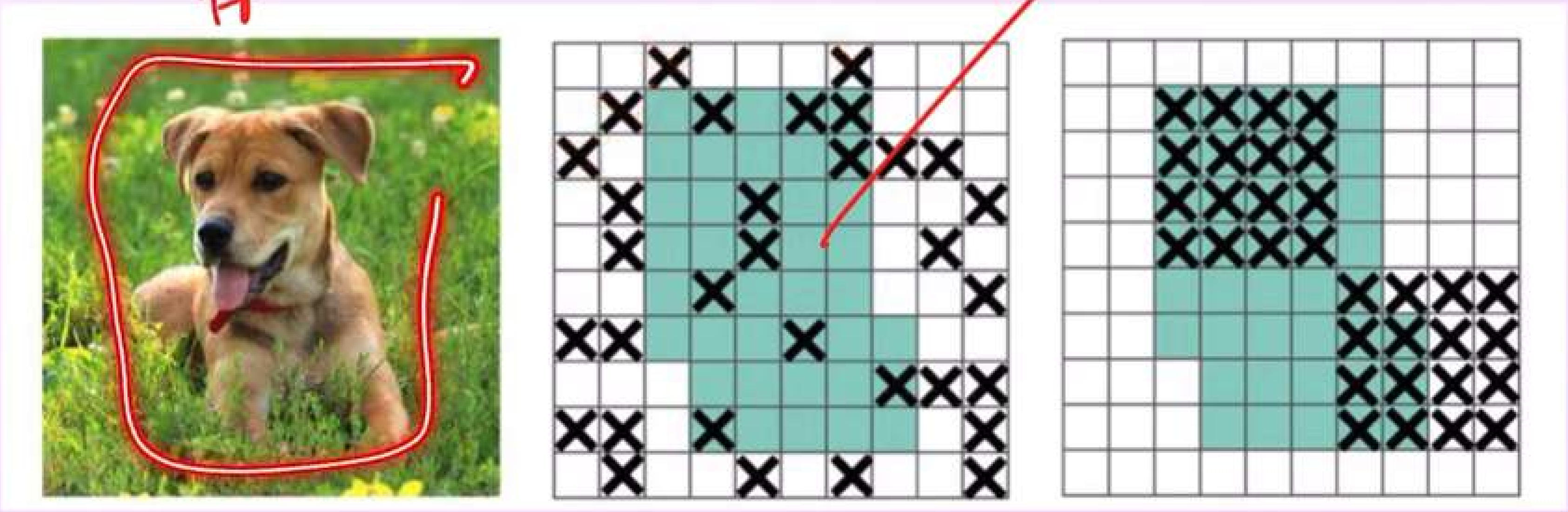
Activations

i/p Feature map



Drop Block Regularization

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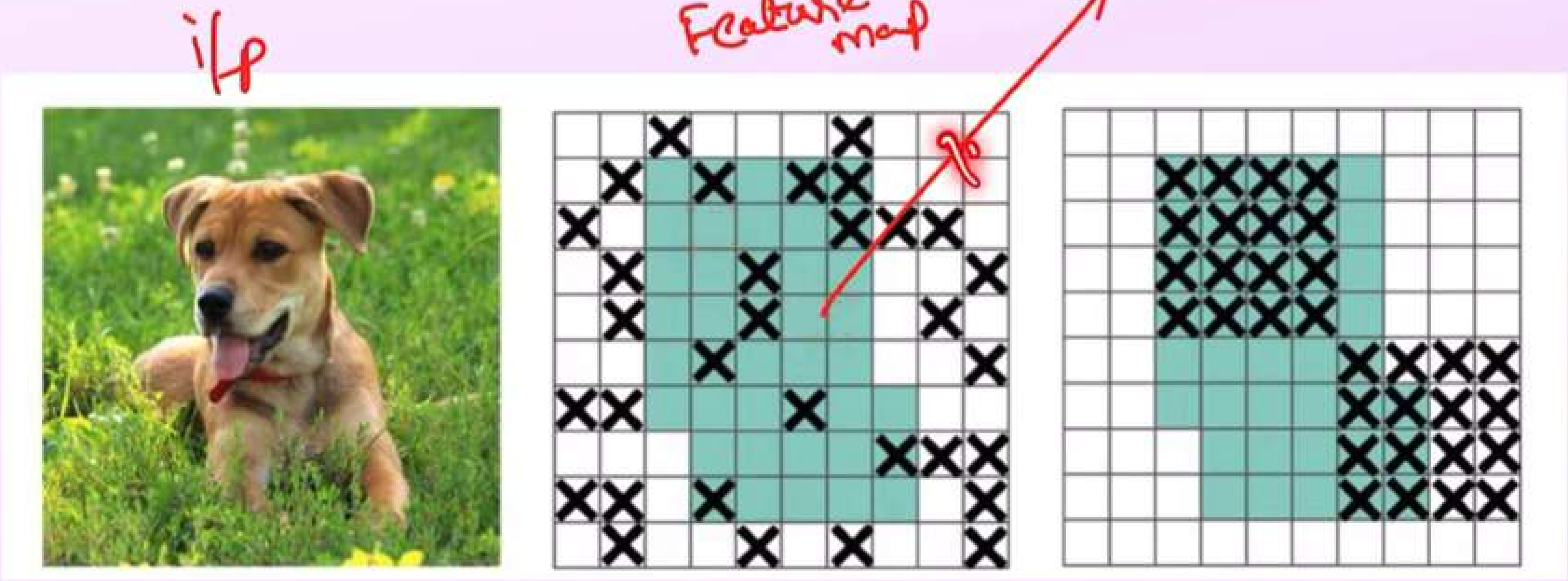
Activations



Drop Block Regularization

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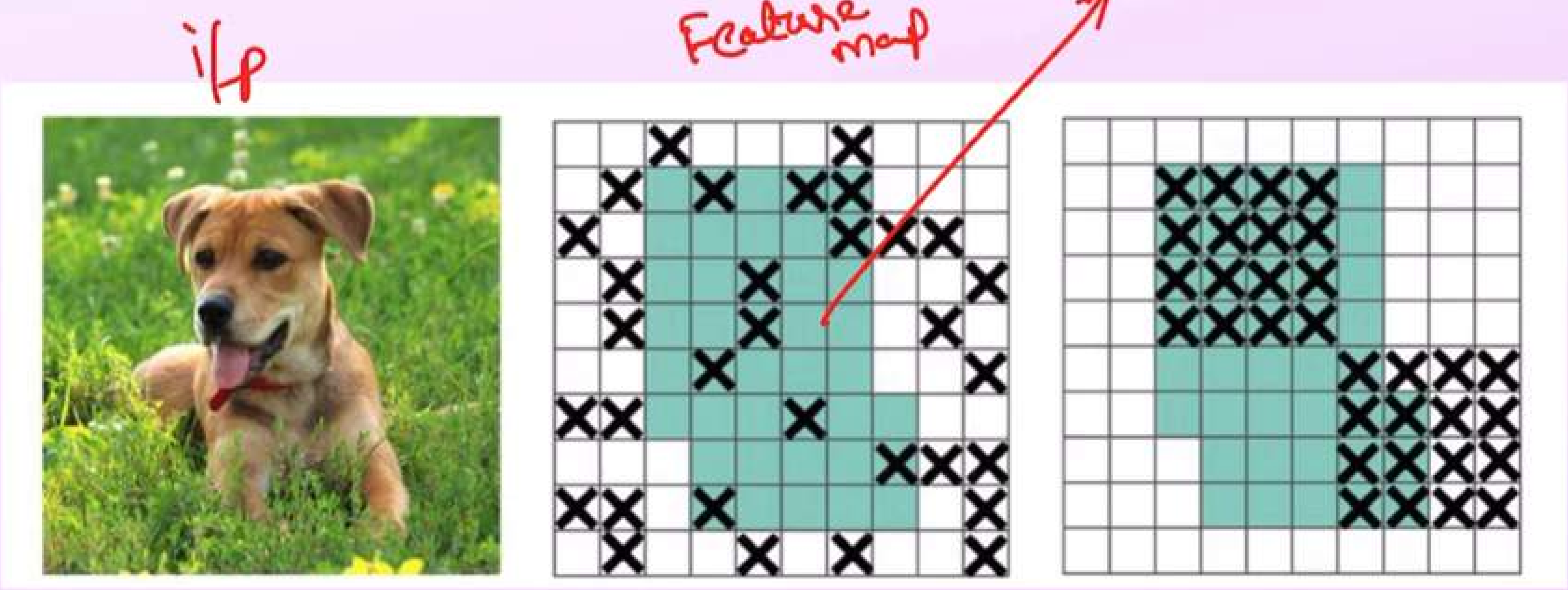
0.5



Drop Block Regularization

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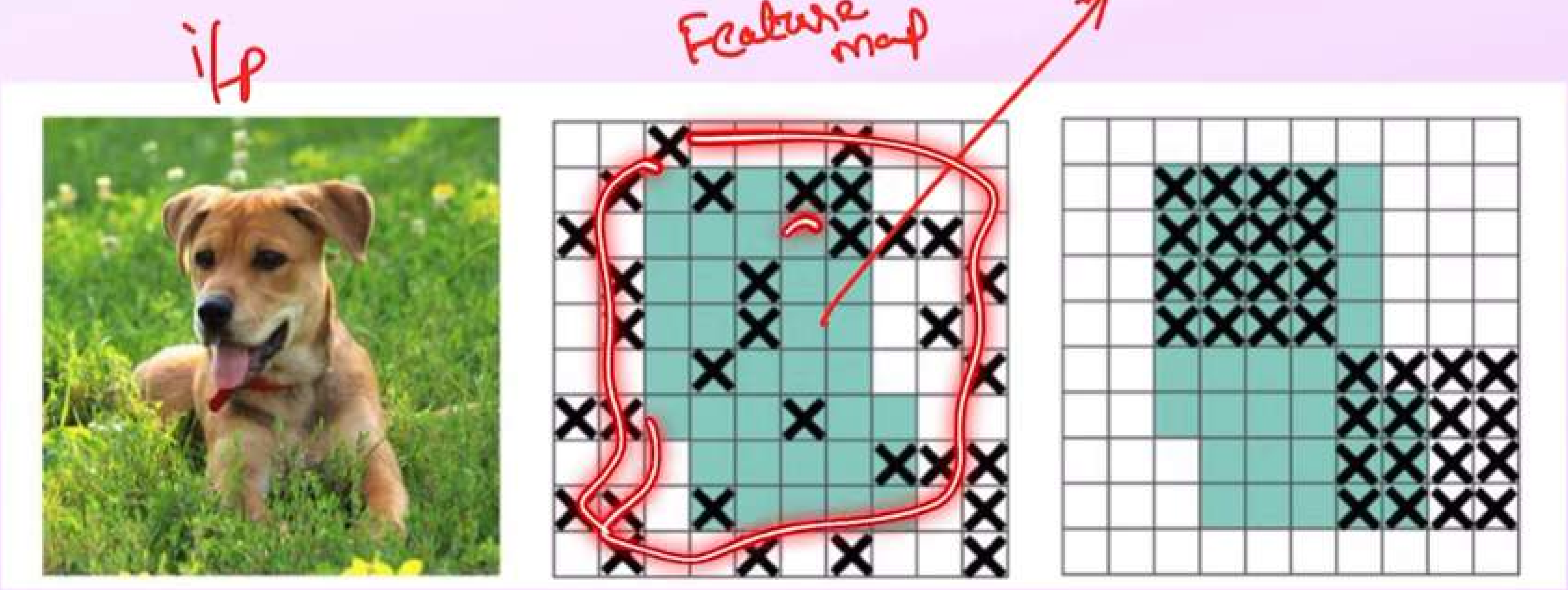

Drop Block Regularization

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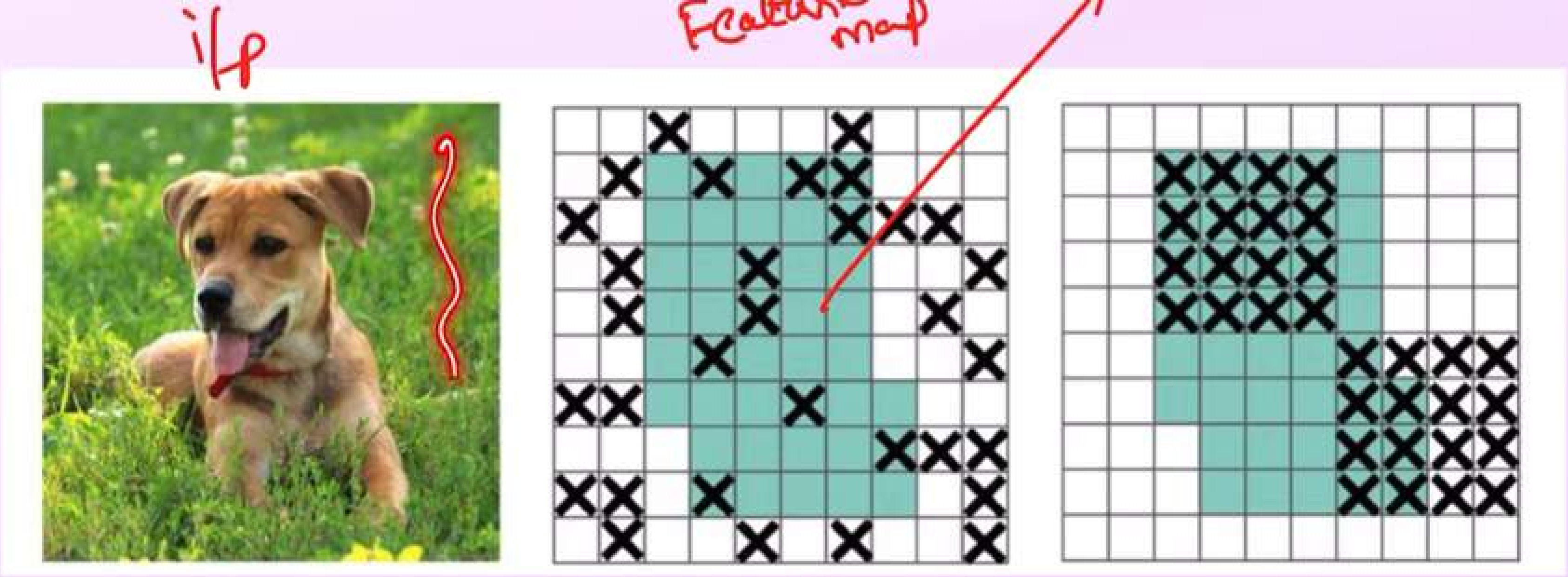
Activations



Drop Block Regularization

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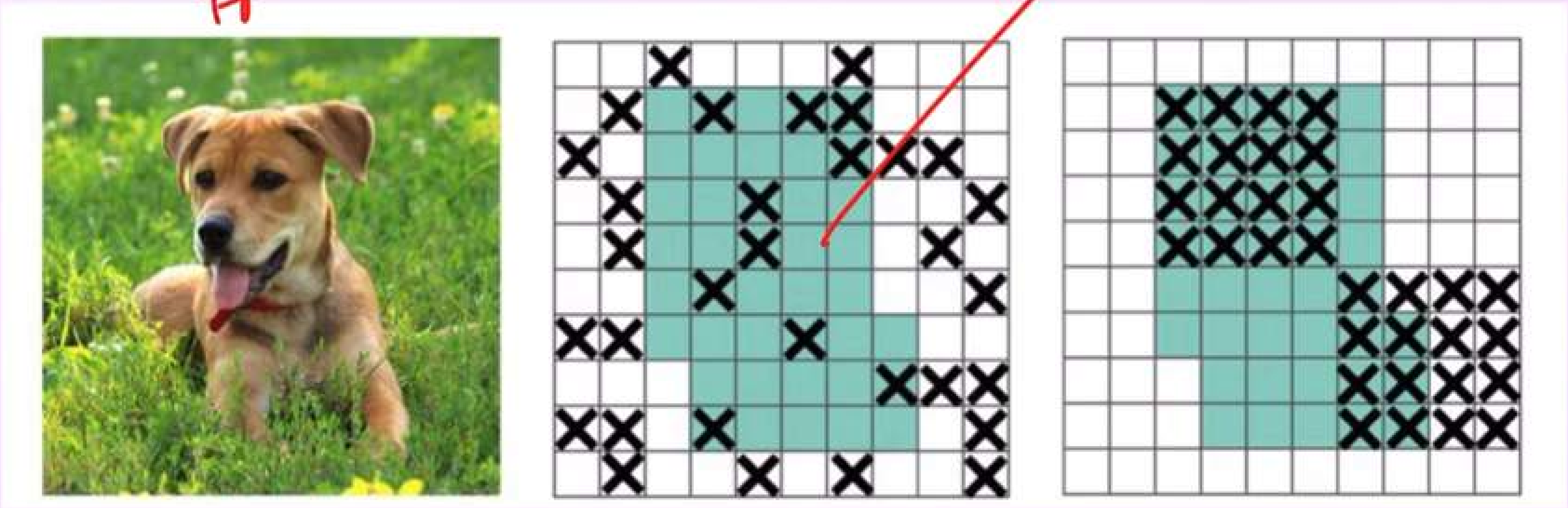
Activations

i/p

Feature map



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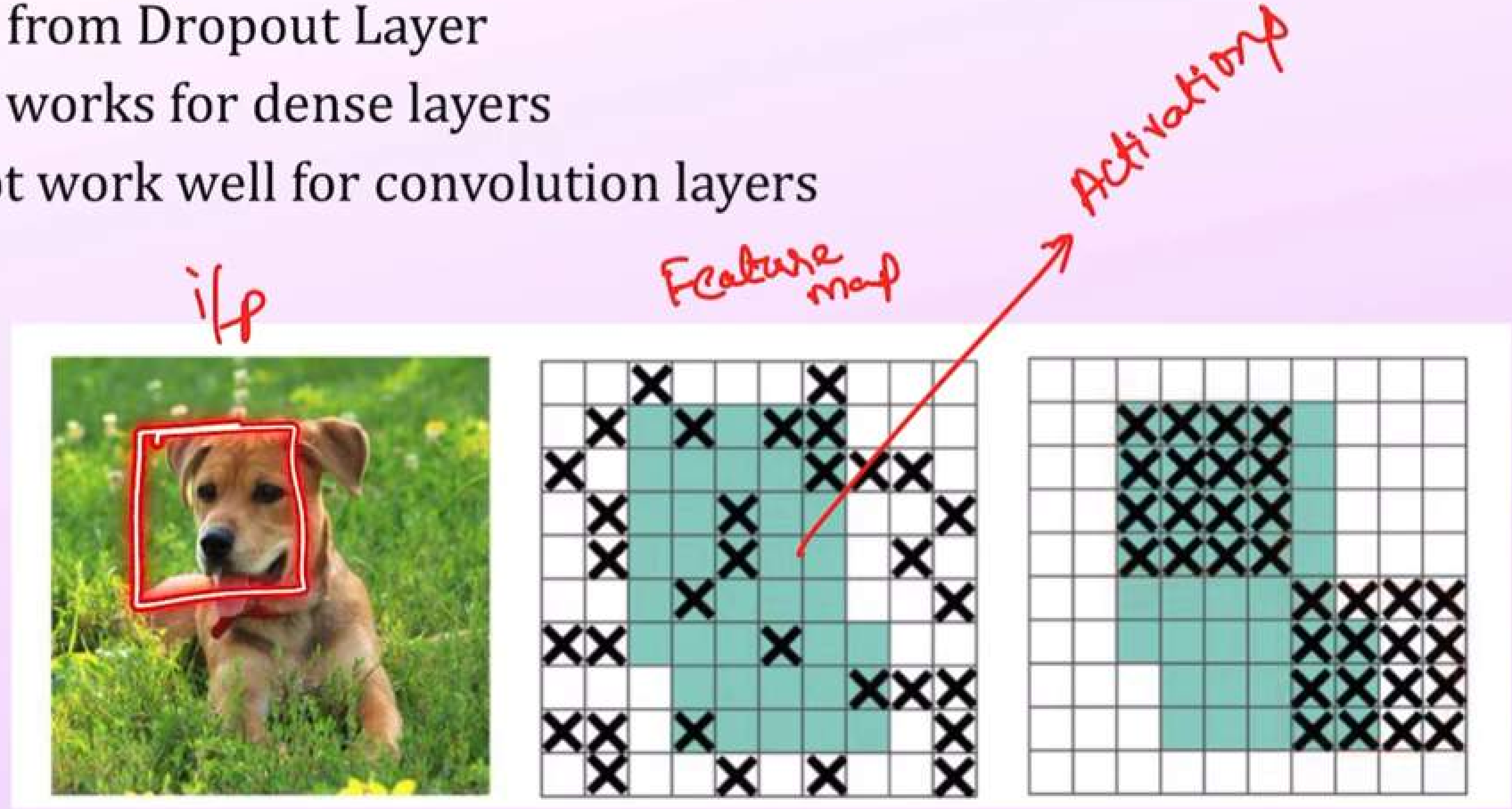

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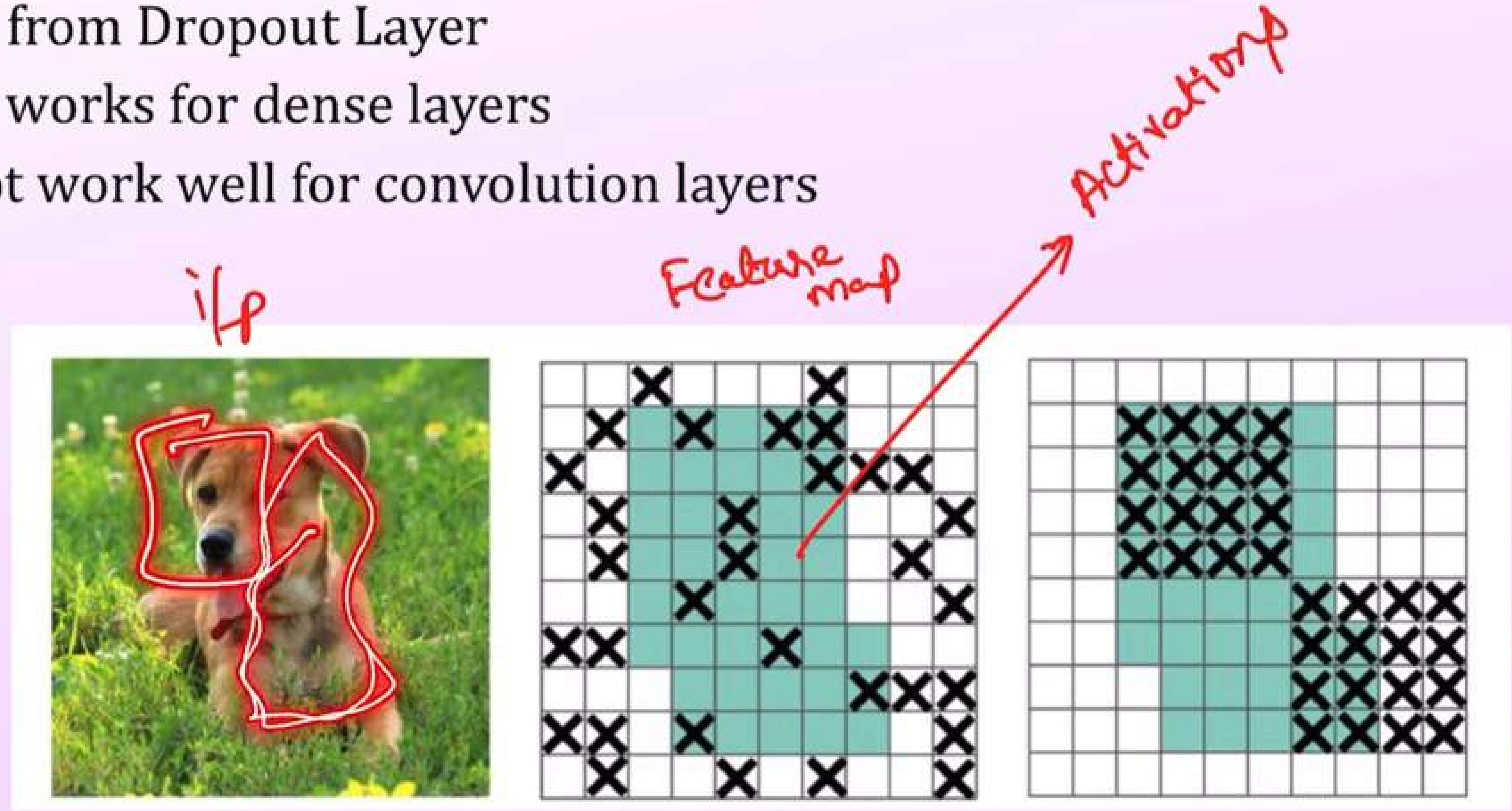

Drop Block Regularization

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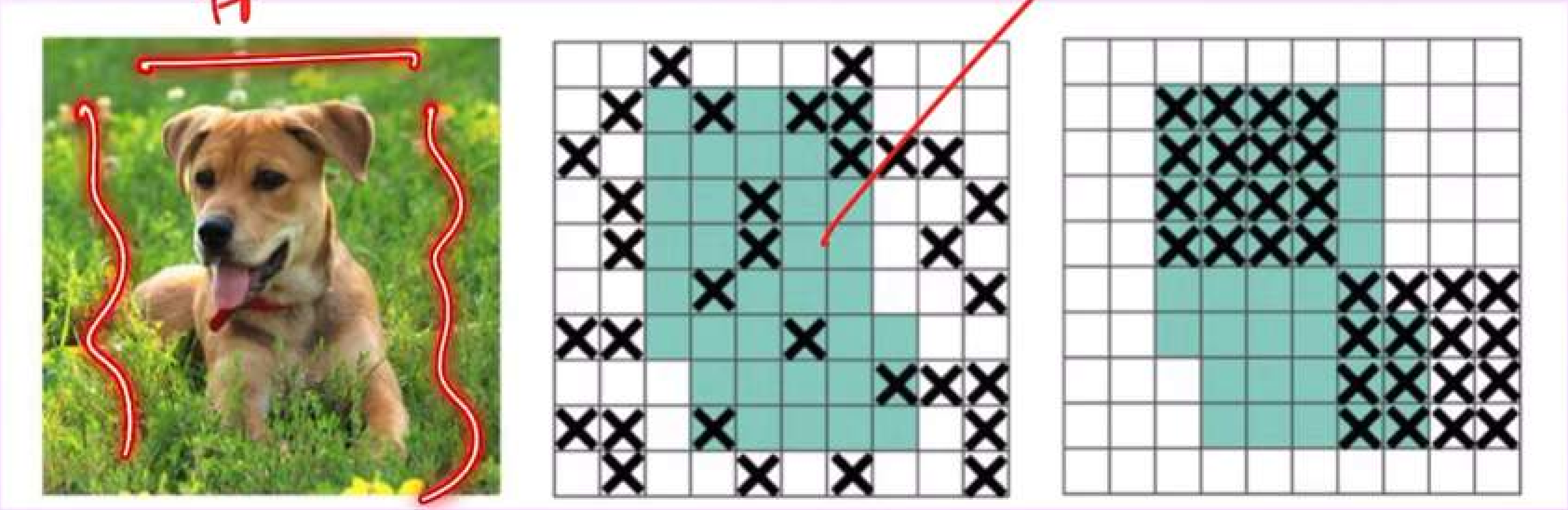
Activations

i/p

Feature map



Drop Block Regularization

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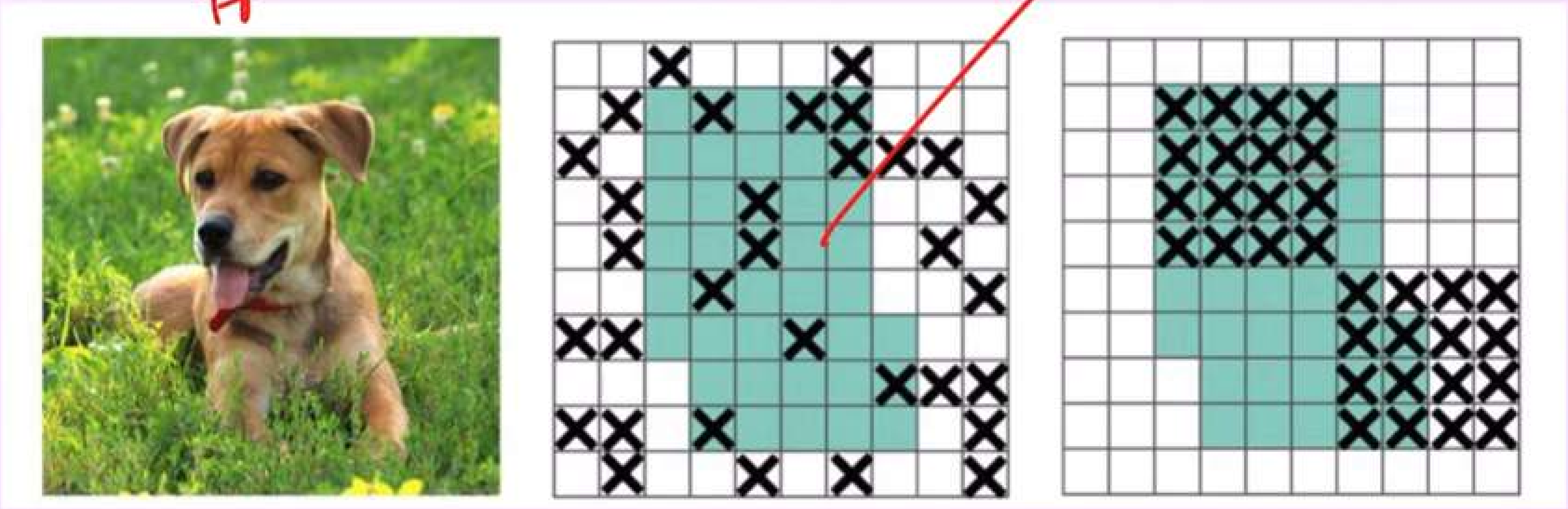
Activations

i/p Feature map



Drop Block Regularization

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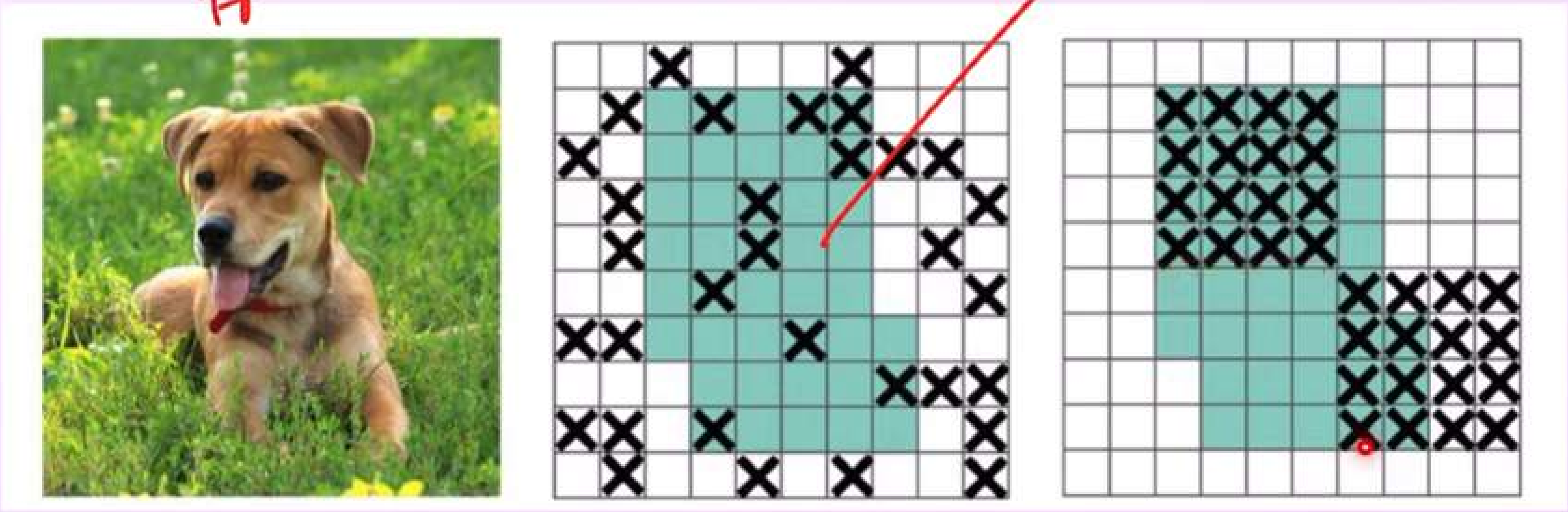
Activations

i/p Feature map



Drop Block Regularization

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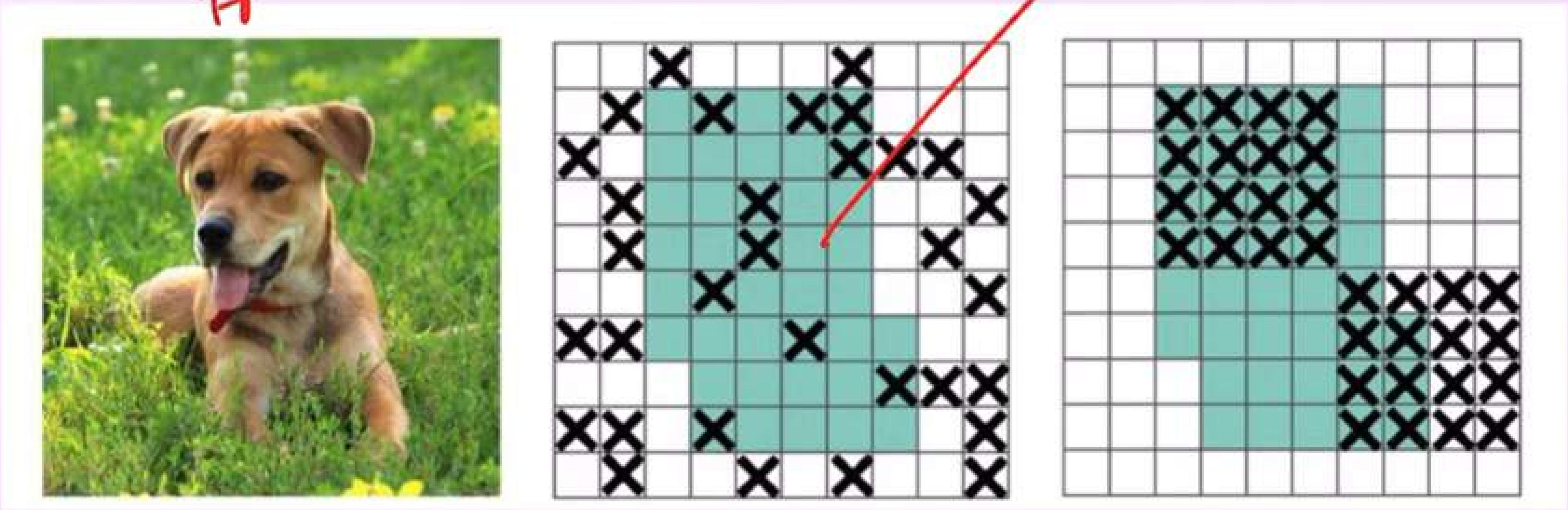
Activations

i/p Feature map



Drop Block Regularization

- Inspired from Dropout Layer
- Dropout works for dense layers
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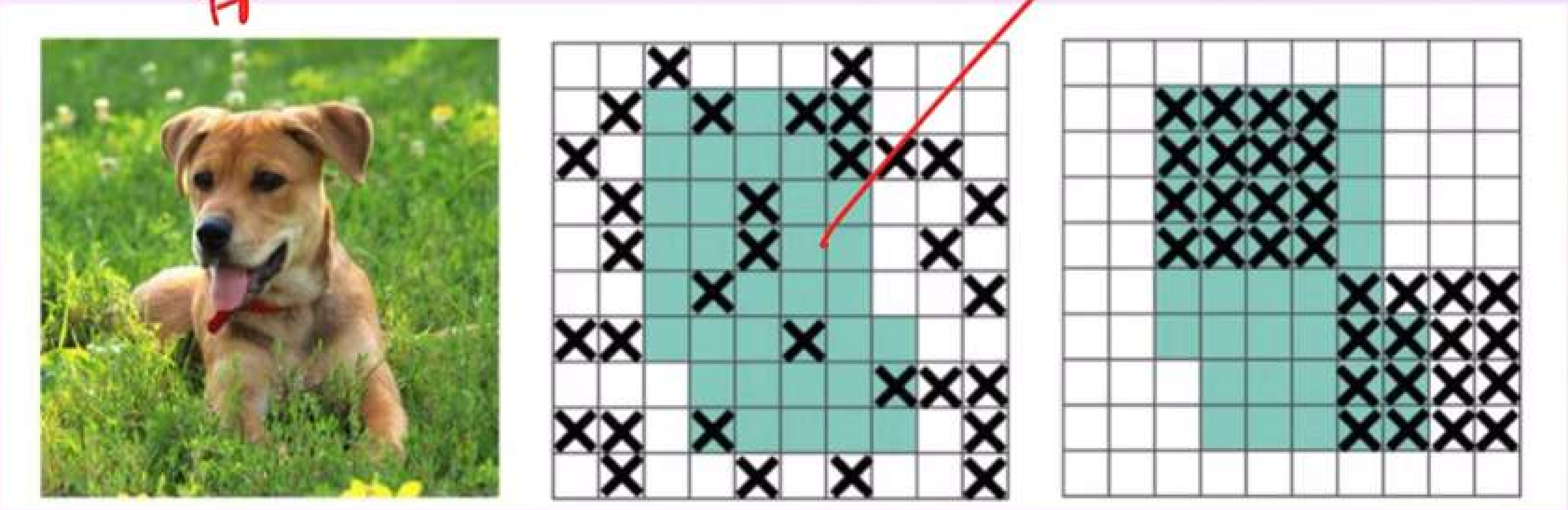
Activations

P=0.1 → 10%

i/p

Feature map



Drop Block Regularization

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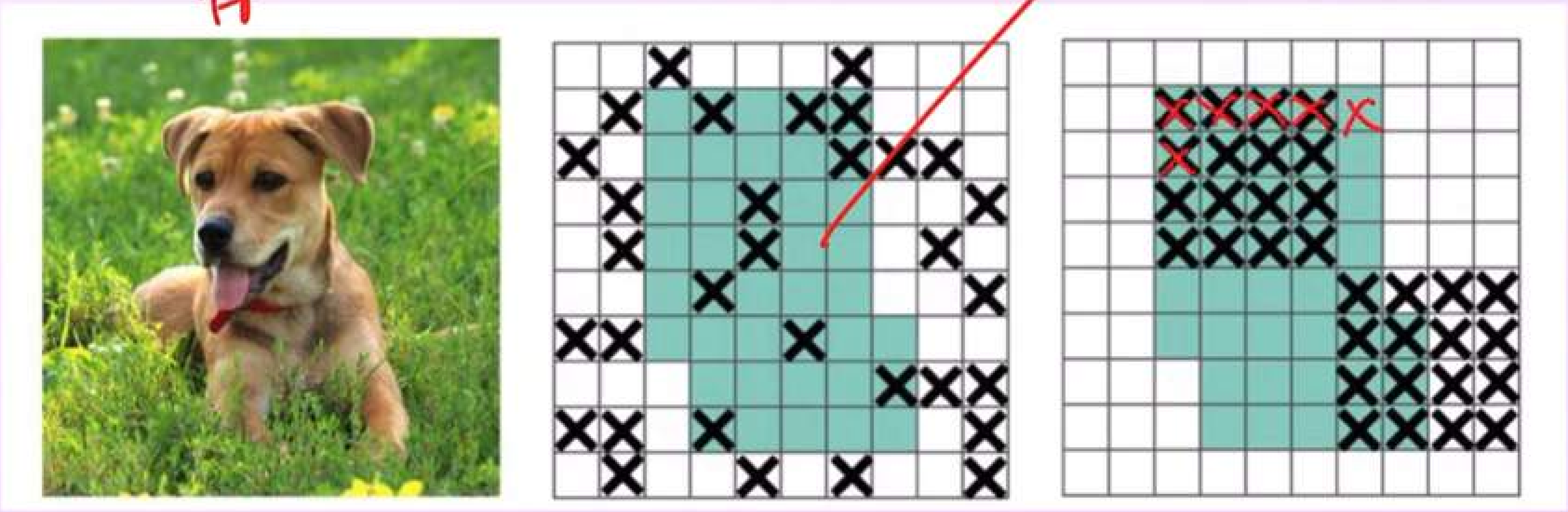
Activations

P=0.1 → 10%

i/p

Feature map



Drop Block Regularization

- Inspired from Dropout Layer
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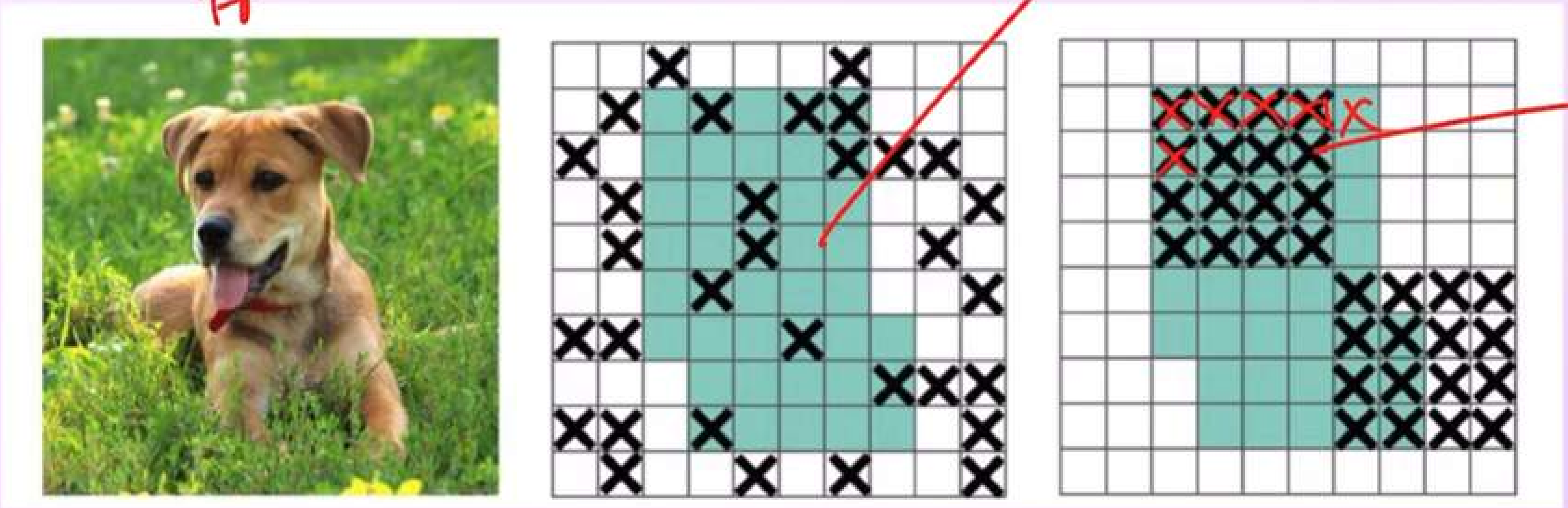
Activations

P=0.1

10%

i/p

Feature map



Block size

Drop Block Regularization

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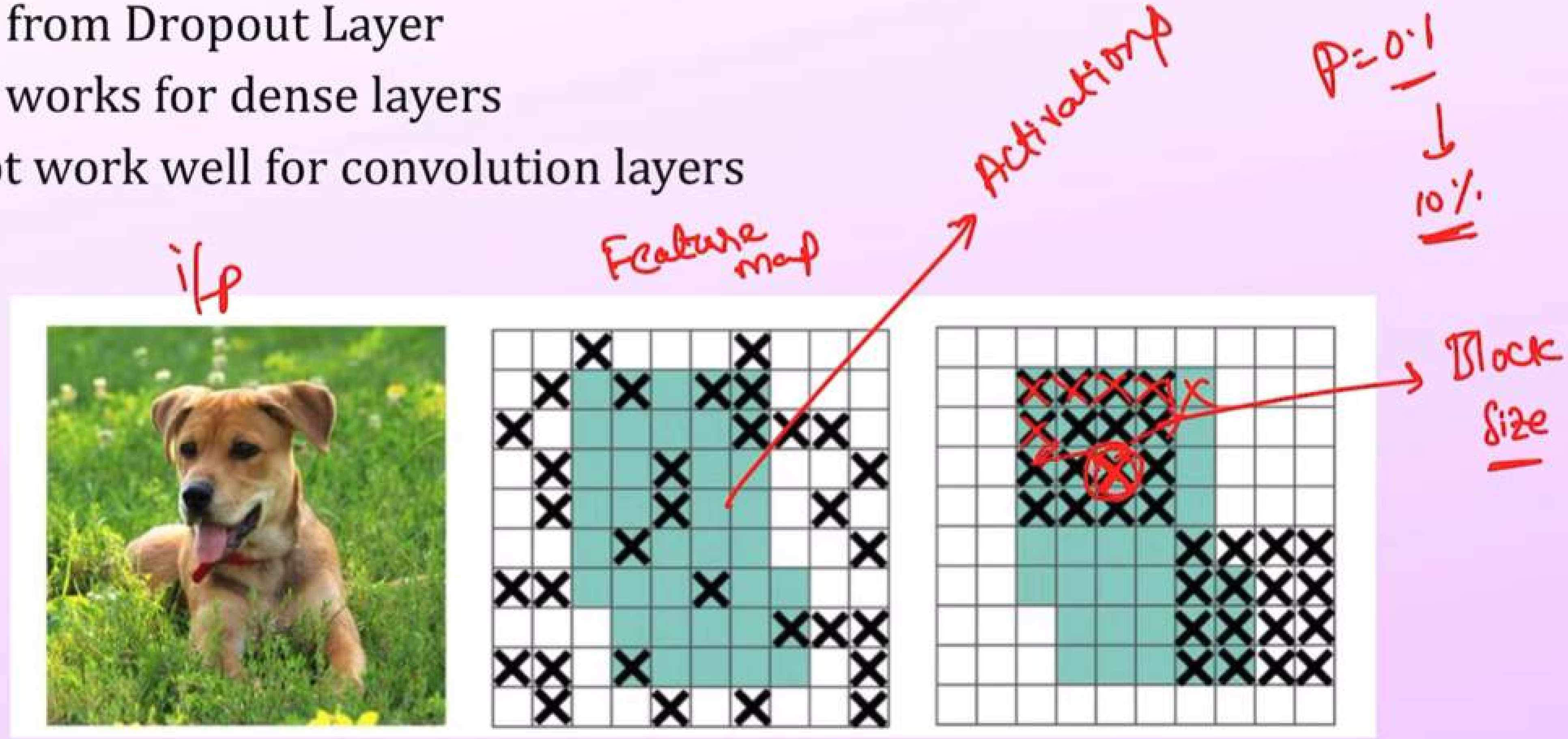
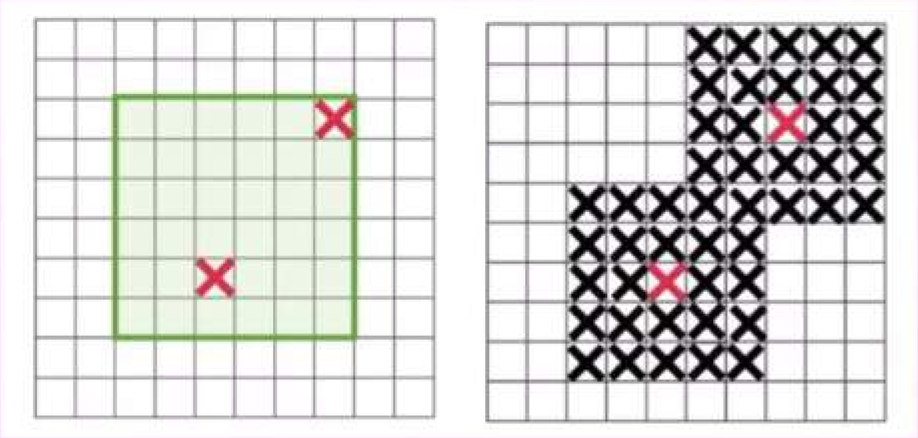


Drop Block Regularization

- Block_size
- γ - Probability of Keeping

Algorithm 1 DropBlock

Input:output activations of a layer (A), *block_size*, γ, *mode*
if *mode* == *Inference* **then**
  return A
end if
Randomly sample mask M: $M_{i,j} \sim Bernoulli(\gamma)$
For each zero position $M_{i,j}$, create a spatial square mask with the center being $M_{i,j}$, the width, height being *block_size* and set all the values of M in the square to be zero (see Figure 2).
Apply the mask: $A = A \times M$
Normalize the features: $A = A \times \mathbf{count}(M)/\mathbf{count\_ones}(M)$

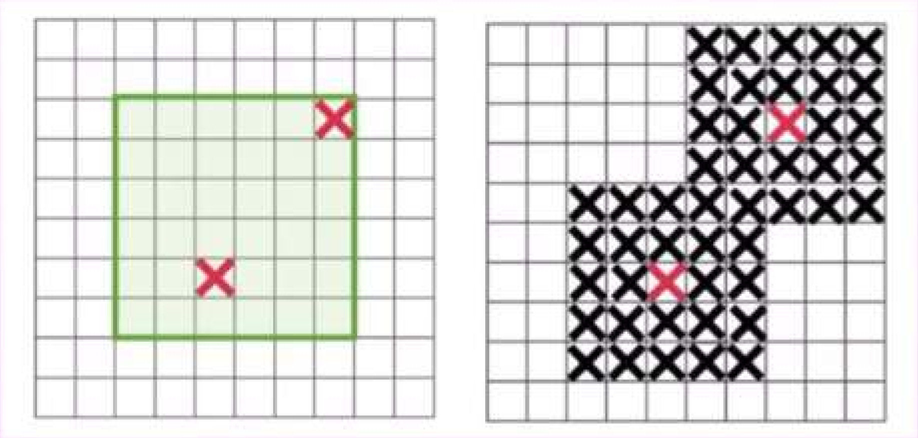


Drop Block Regularization

- Block_size
- γ - Probability of Keeping

Algorithm 1 DropBlock

```
Input:output activations of a layer (A), block_size, γ, mode
if mode == Inference then
    return A
end if
Randomly sample mask M: M_{i,j} ~ Bernoulli(γ)
For each zero position M_{i,j}, create a spatial square mask with the center being M_{i,j}, the width,
height being block_size and set all the values of M in the square to be zero (see Figure 2).
Apply the mask: A = A × M
Normalize the features: A = A × count(M)/count_ones(M)
```



Drop Block Regularization

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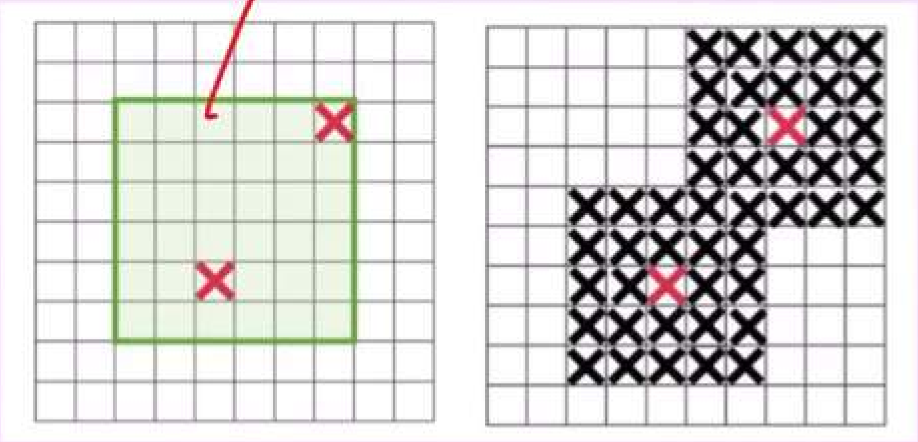

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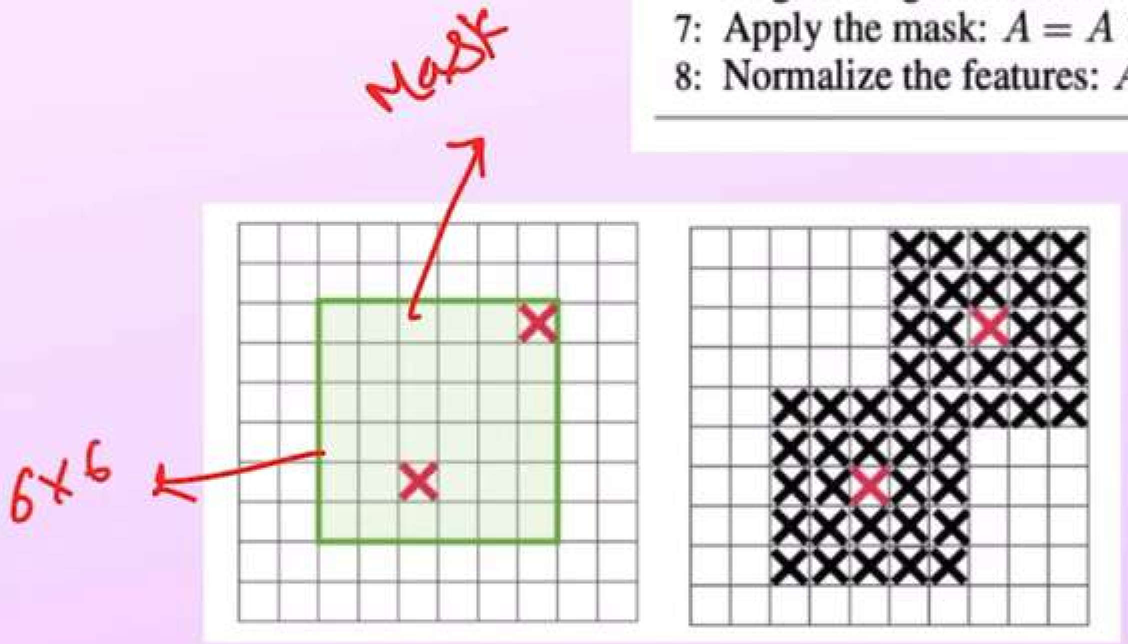

Drop Block Regularization

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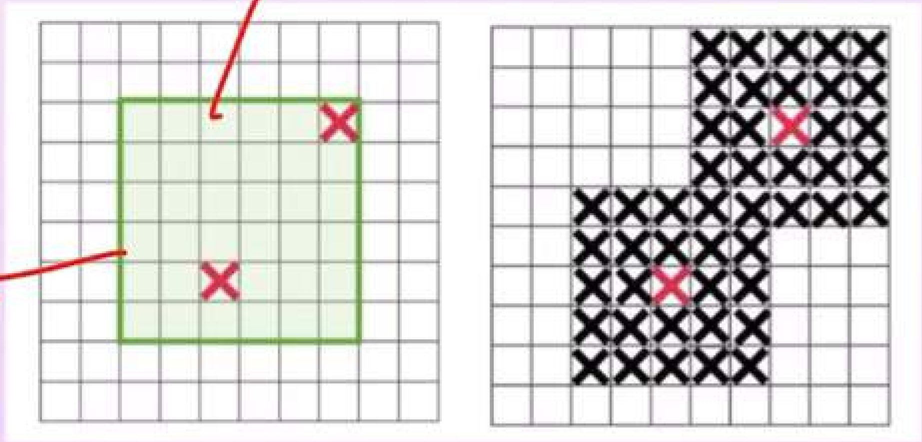
P
0.25

Mask

6x6



Drop Block Regularization

- Block_size
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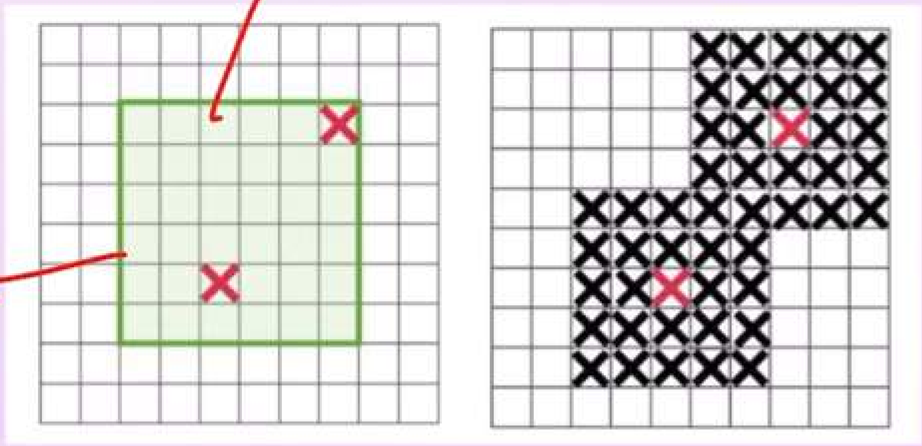
P
0.25

Mask

.9

6x6



Drop Block Regularization

- Block_size
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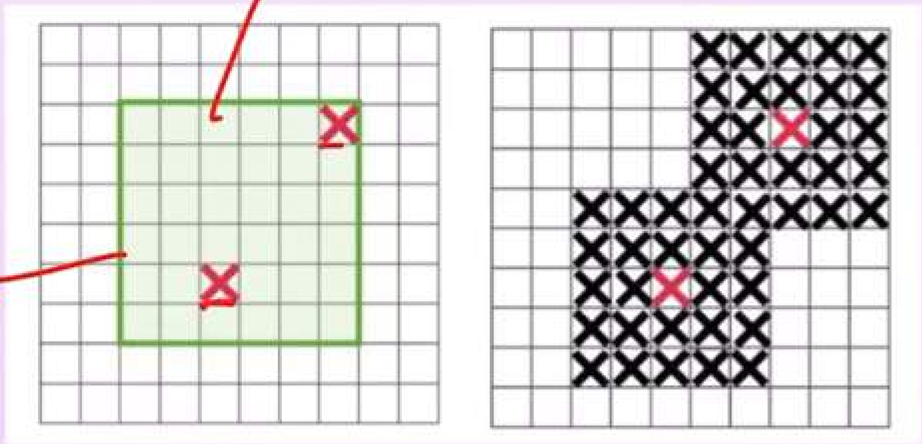
p
0.25

Mask

9

6x6



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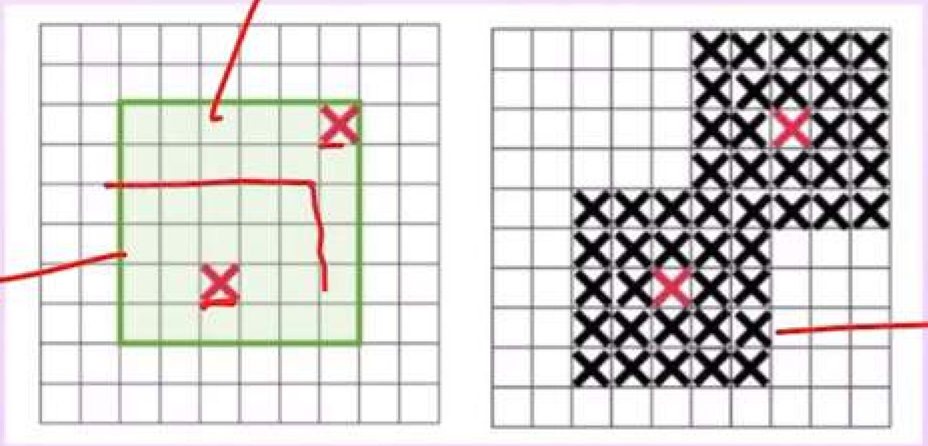
Apply the mask: $A = A \times M$
Normalize the features: $A = A \times \textbf{count}(M)/\textbf{count\_ones}(M)$

P
0.25

.9

6x6

Mask



5x5

Drop Block Regularization

- Block_size
- γ - Probability of Keeping

Algorithm 1 DropBlock

Input:output activations of a layer (A), *block_size*, γ, *mode*
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P
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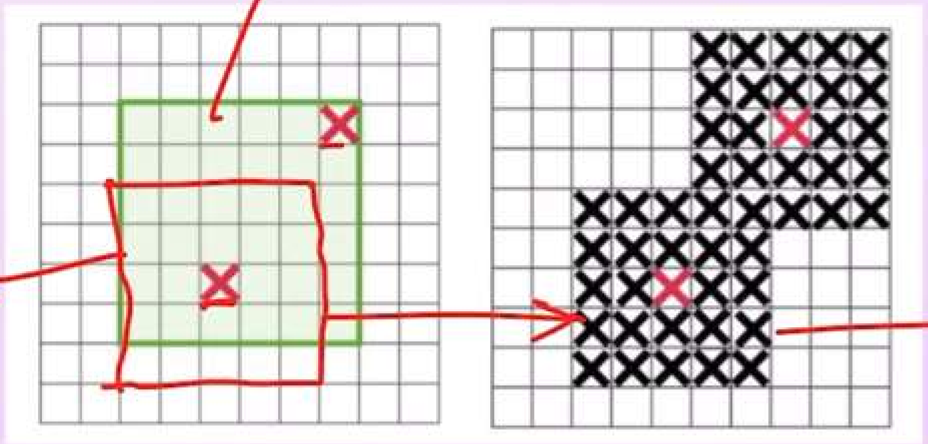
Mask

9

6x6



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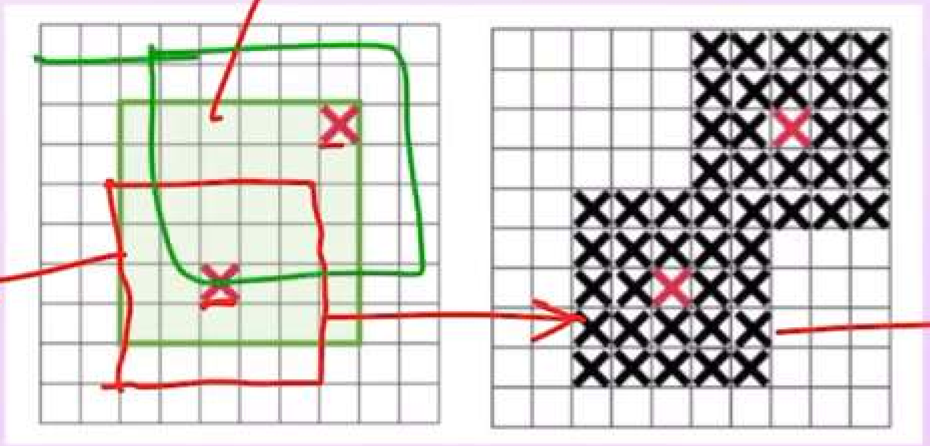

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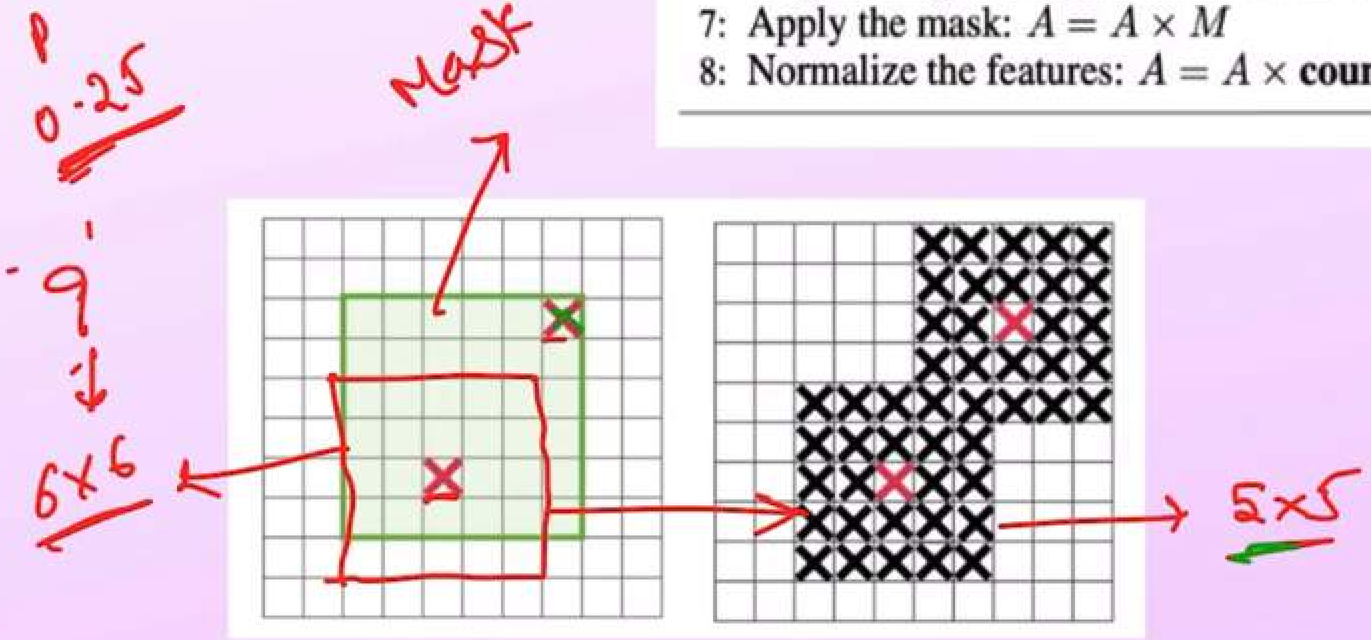

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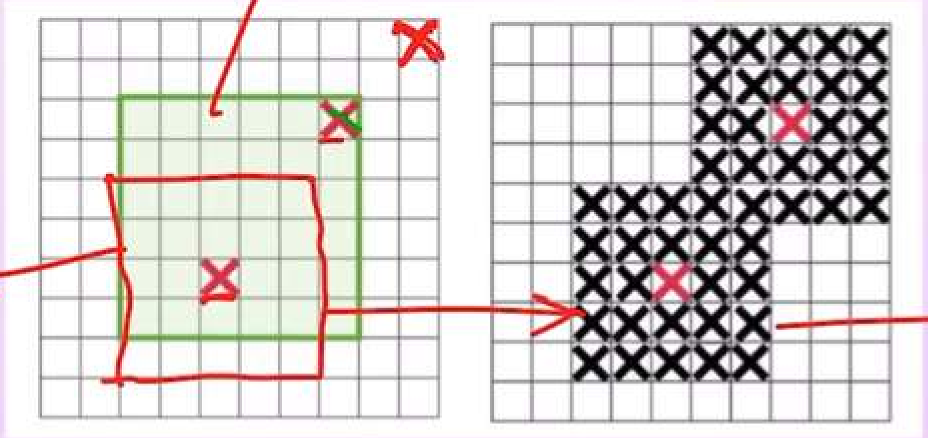
P
0.25

Mask

.9

6x6



5x5

Drop Block Regularization

- Block_size
- γ - Probability of Keeping

Algorithm 1 DropBlock

1: **Input:**output activations of a layer (A), *block_size*, γ, *mode*
2: **if** *mode* == *Inference* **then**
3: return A
4: **end if**
5: Randomly sample mask M: $M_{i,j} \sim Bernoulli(\gamma)$
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P
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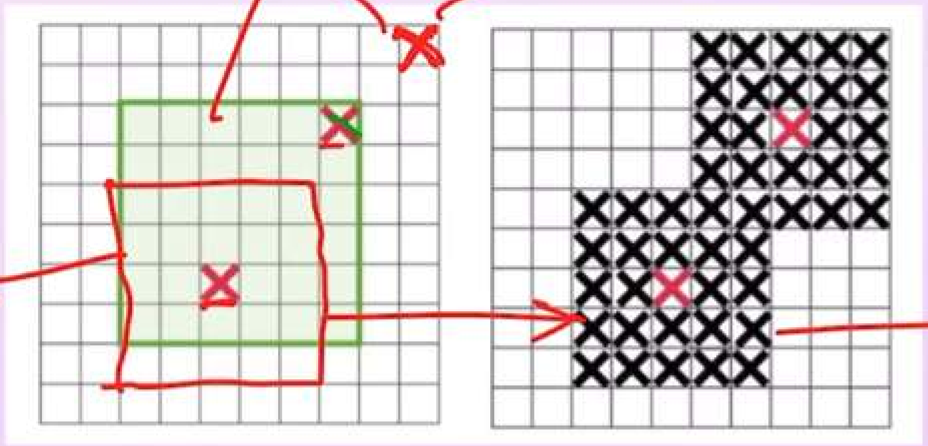

5x5

Drop Block Regularization

- Block_size
- γ - Probability of Keeping

Algorithm 1 DropBlock

```
Input: output activations of a layer (A), block_size, γ, mode
if mode == Inference then
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end if
Randomly sample mask M: M_{i,j} ~ Bernoulli(γ)
For each zero position M_{i,j}, create a spatial square mask with the center being M_{i,j}, the width,
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Apply the mask: A = A × M
Normalize the features: A = A × count(M)/count_ones(M)
```
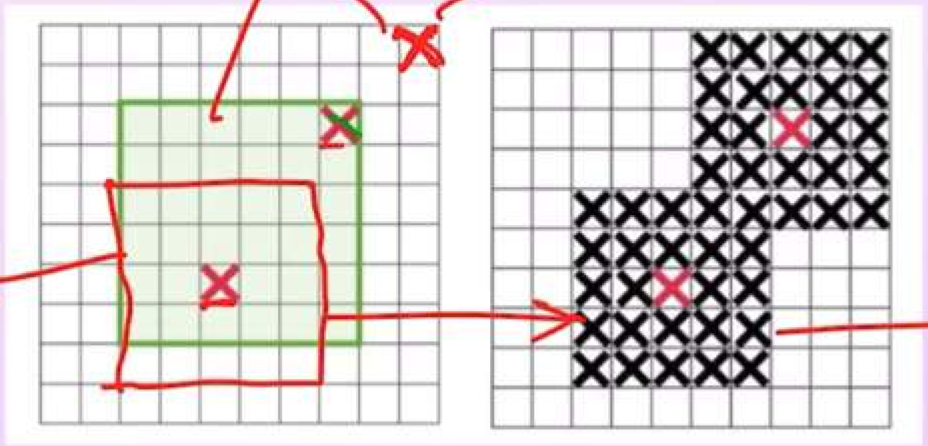

P 0.25

9



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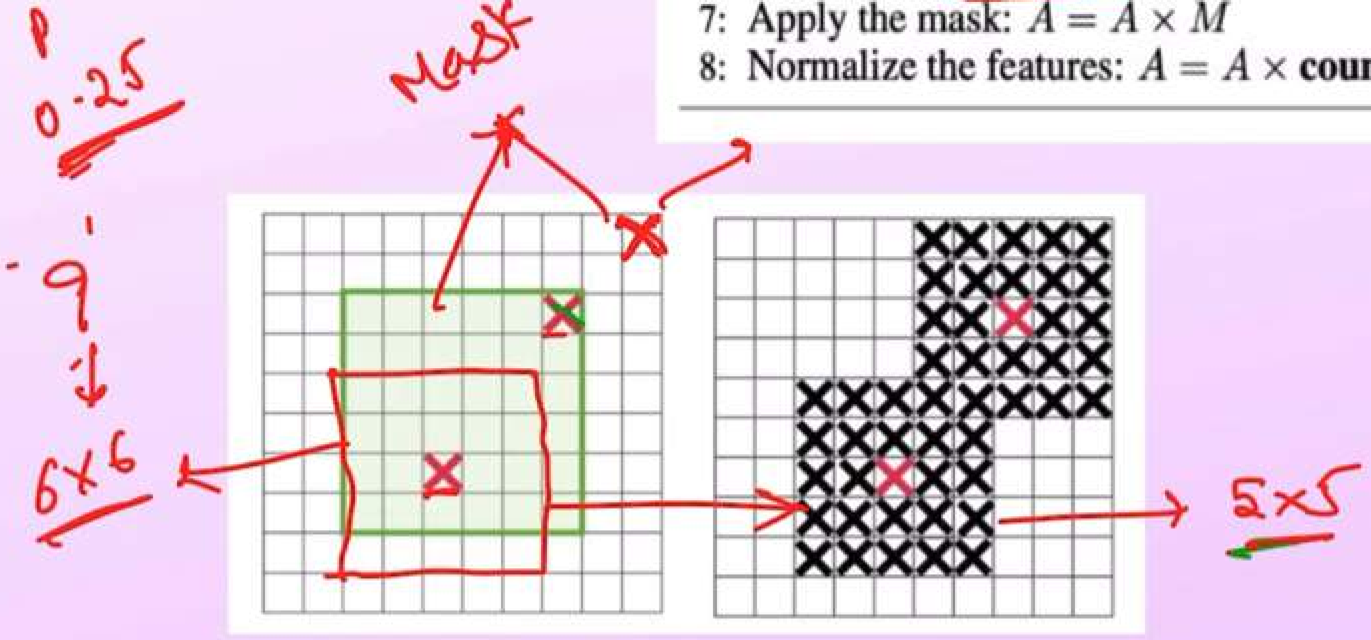

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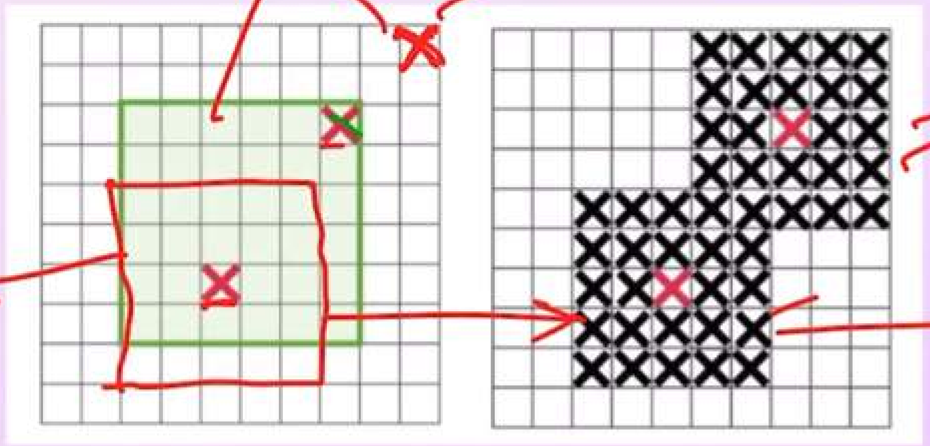
p
0.25

Mask

9

6x6



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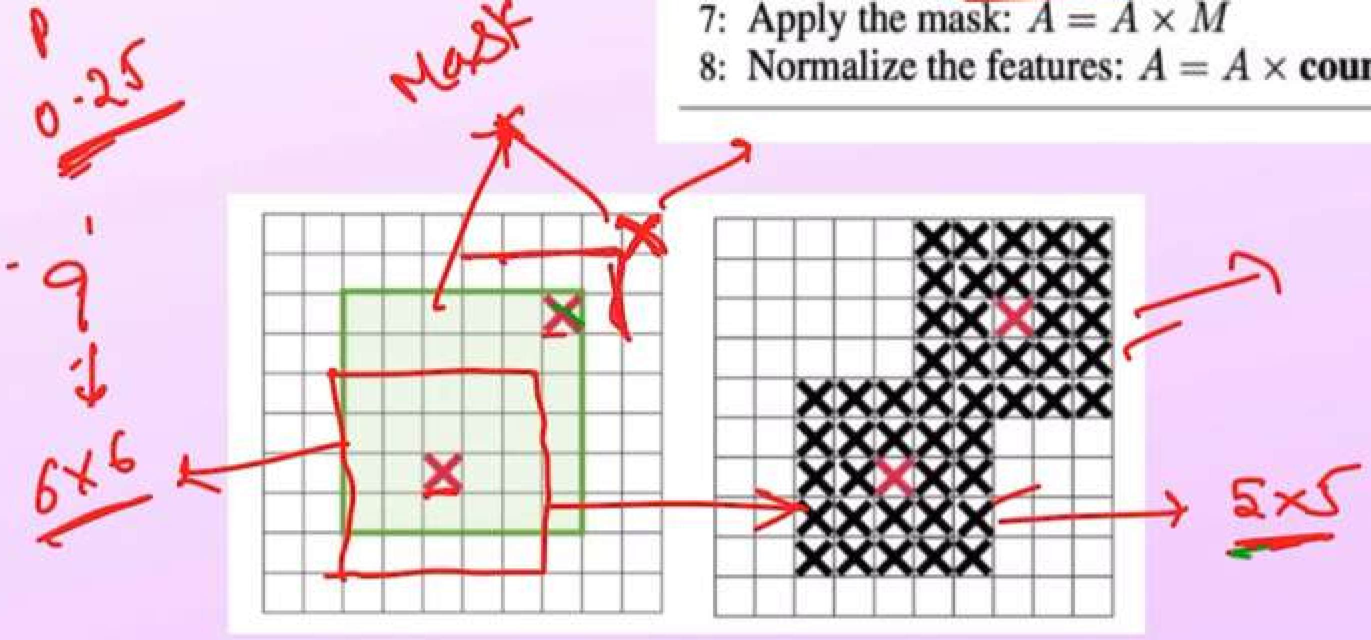

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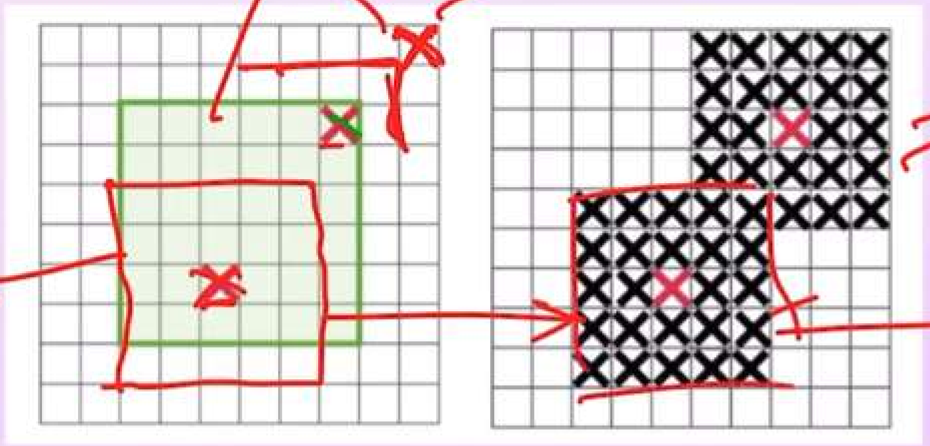

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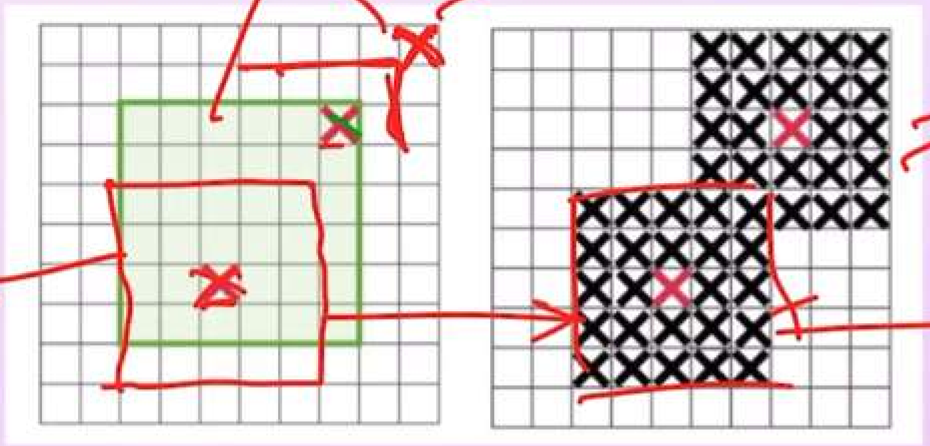
Mask

9

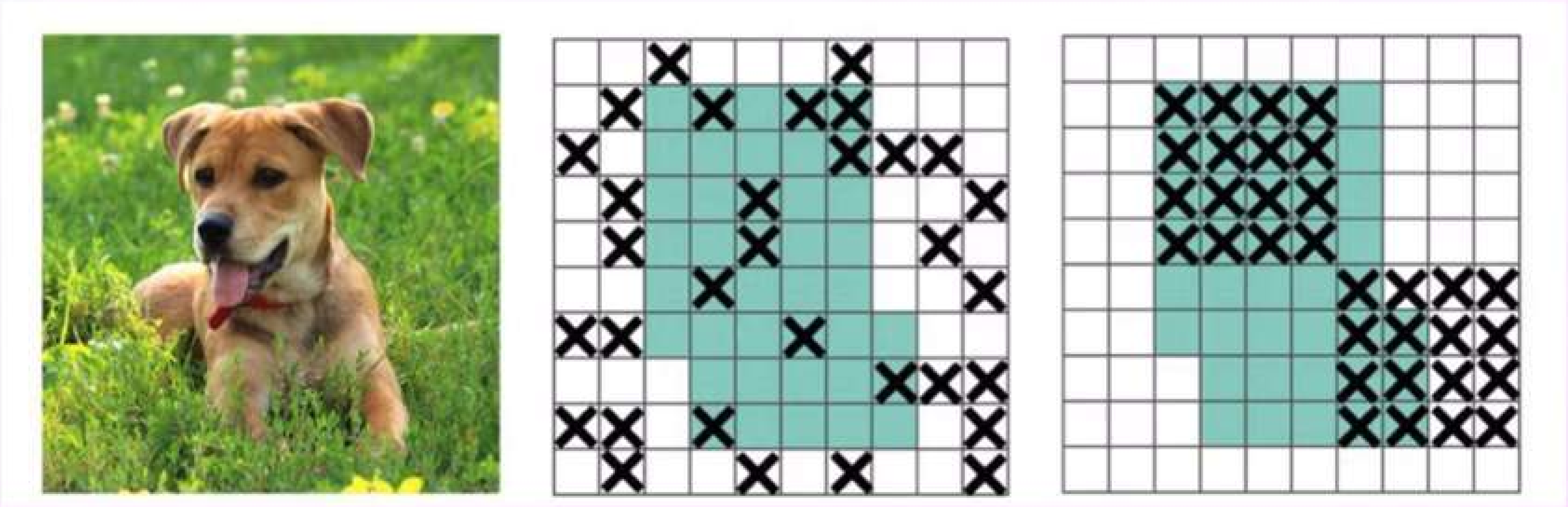
6x6



5x5

Drop Block Regularization

- ResNet-50 (Imagenet) - Improved accuracy from 76.51% to 78.13%
- RetinaNet (COCO) - 36.8% to 38.4%



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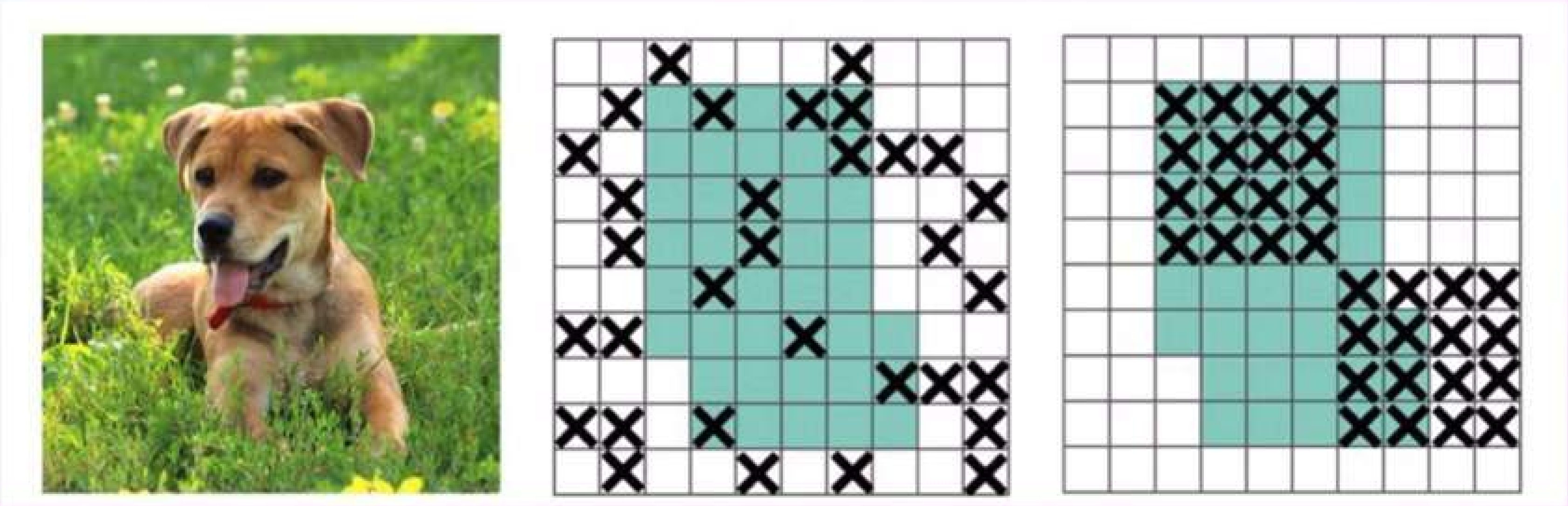

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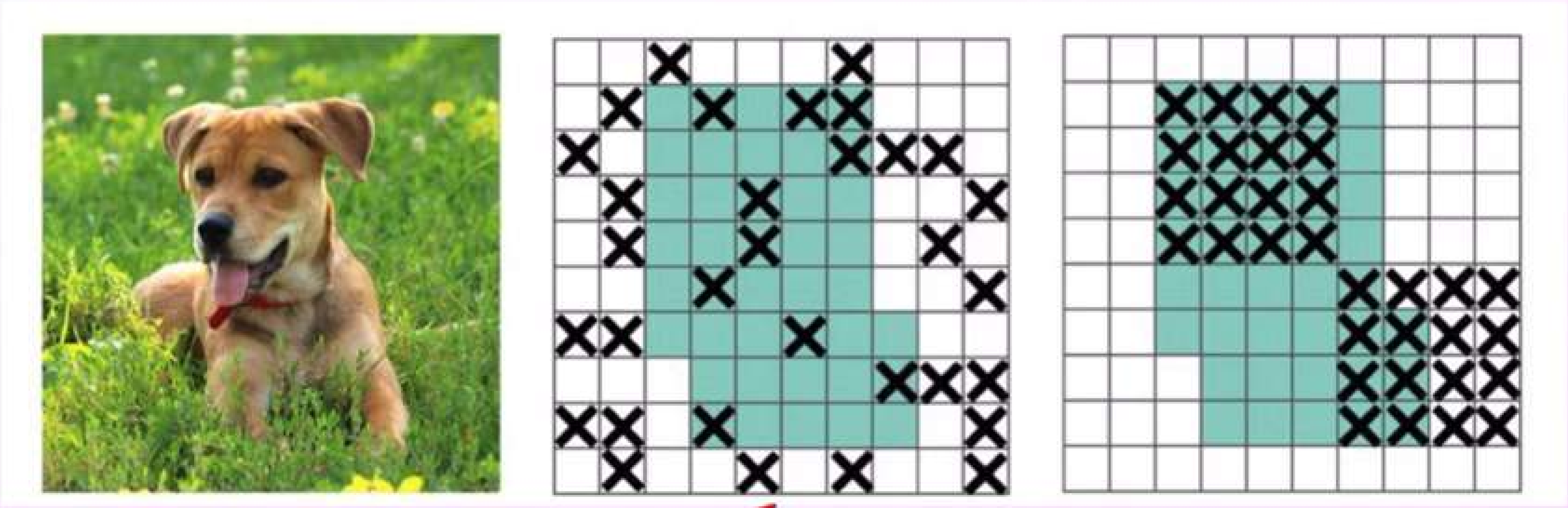

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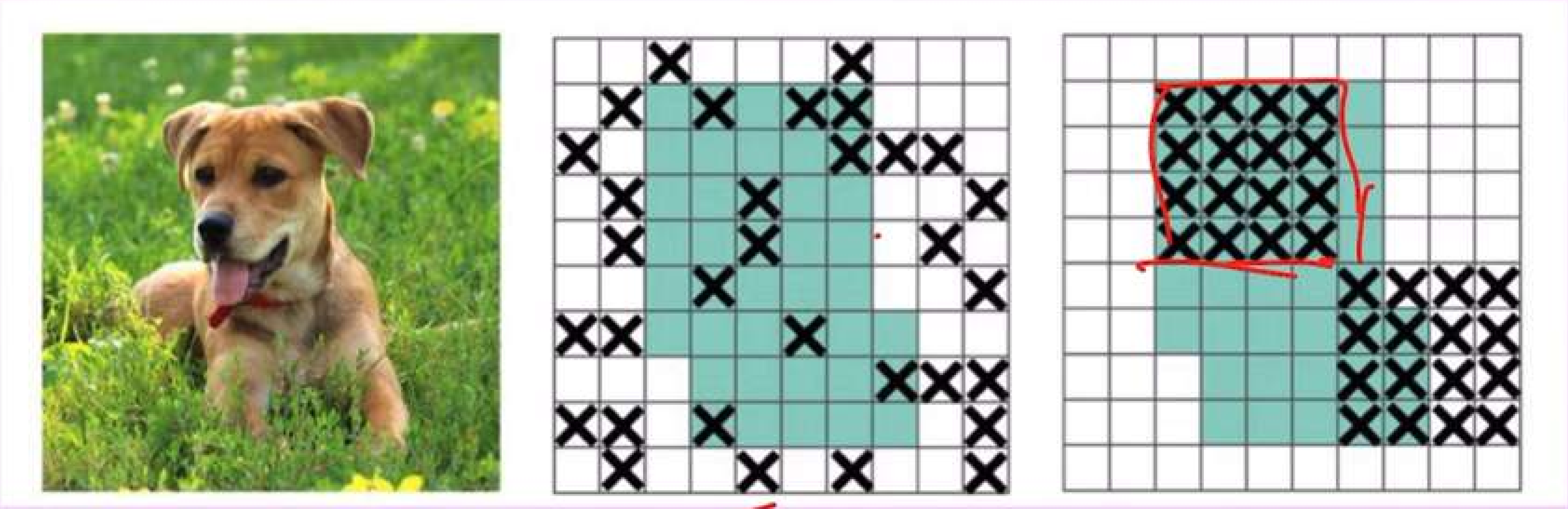

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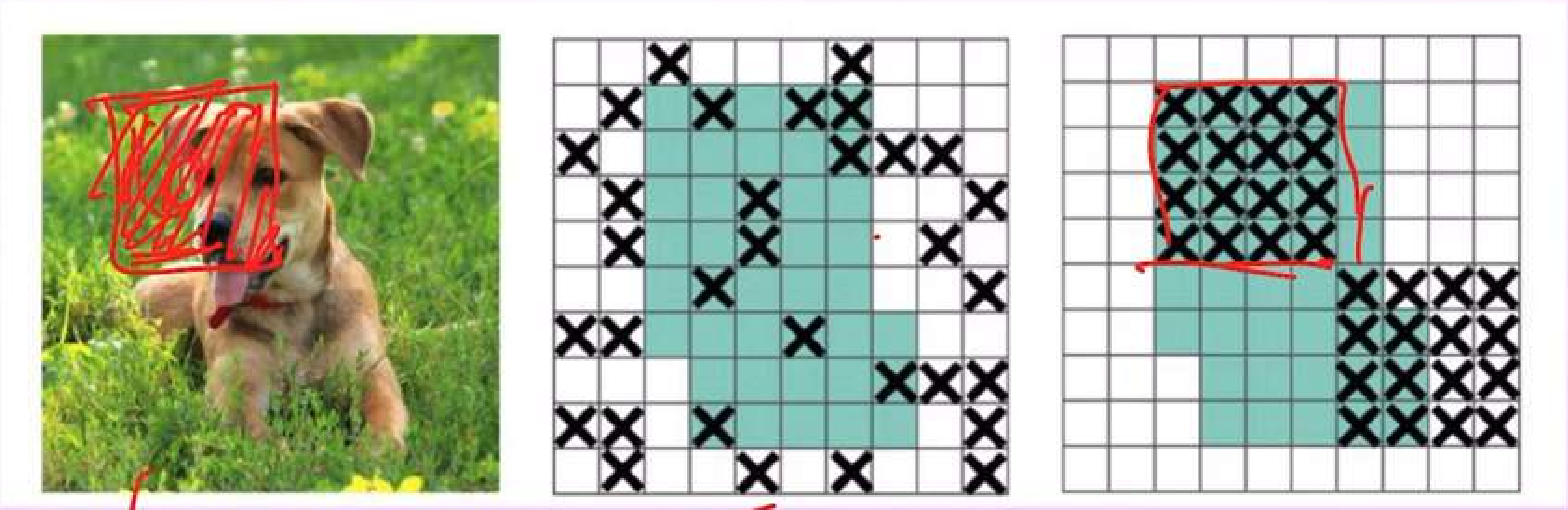

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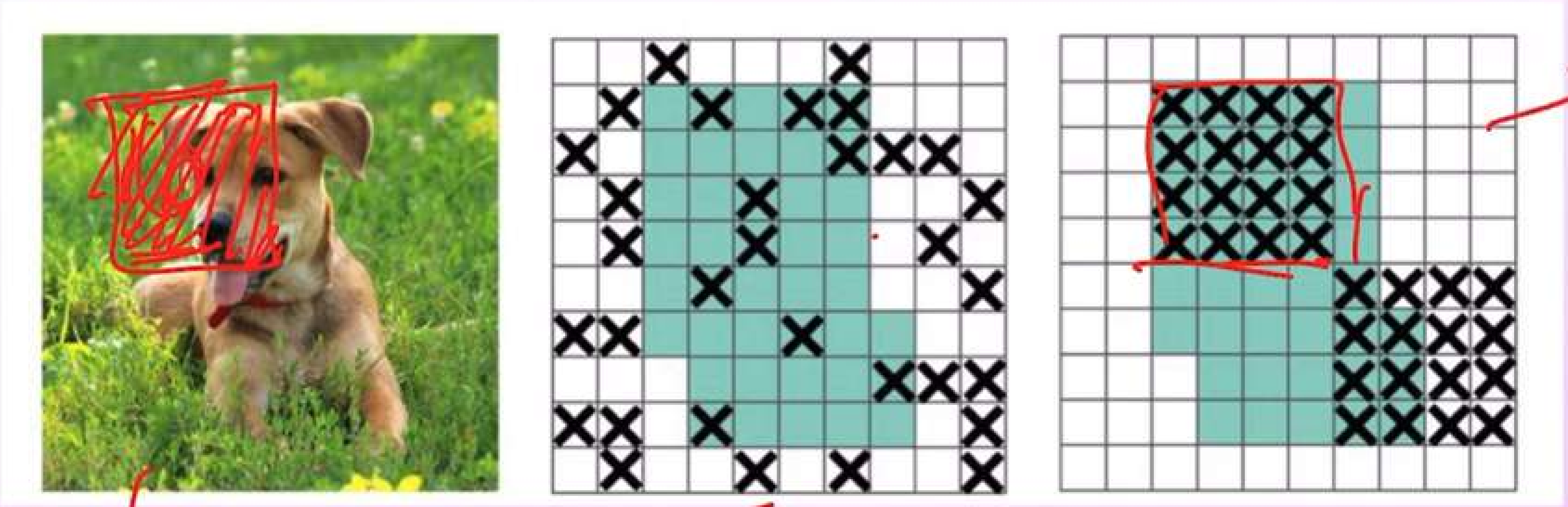
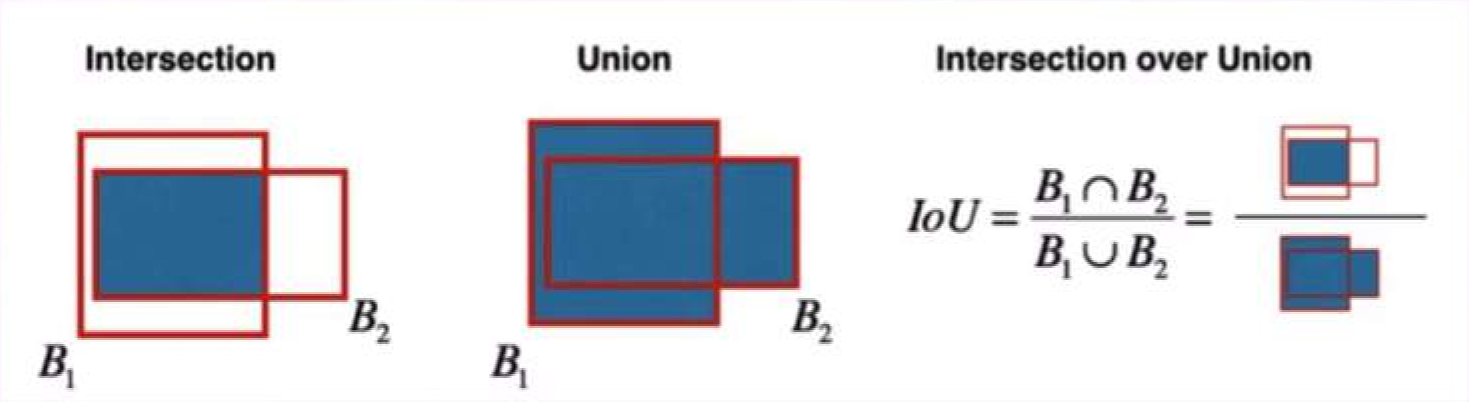


IOU Loss



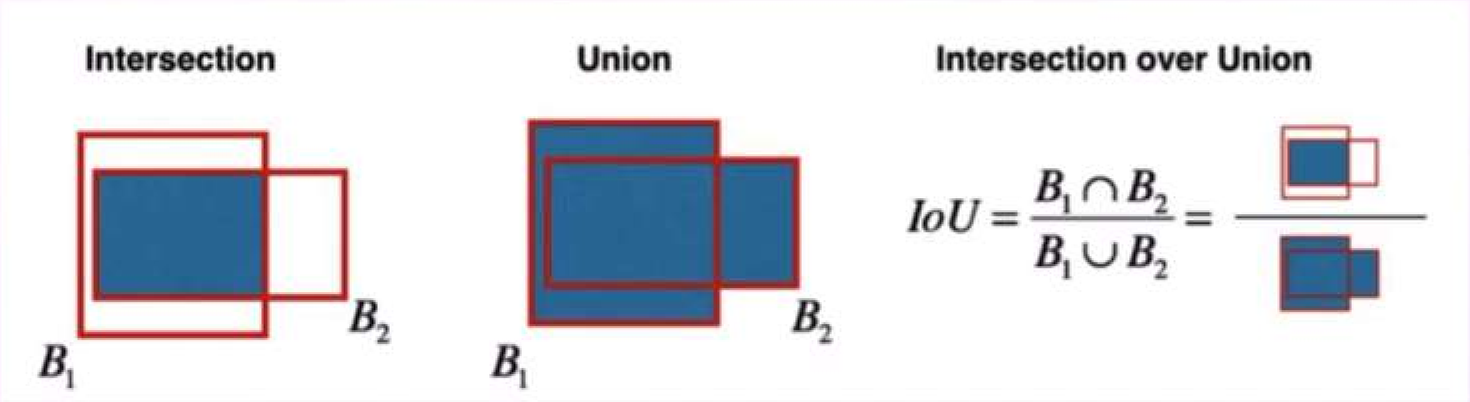
$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

IOU Loss



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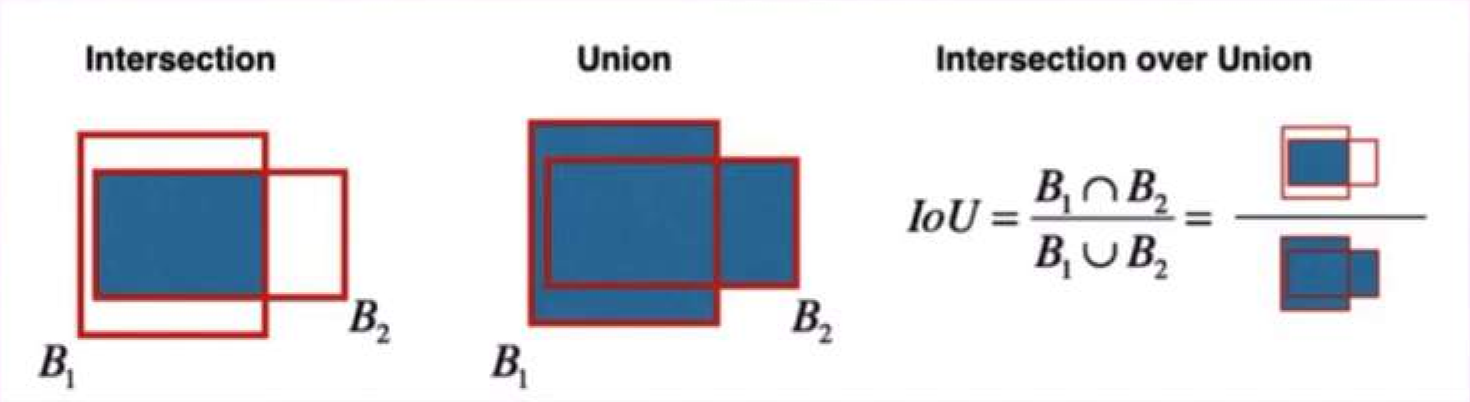

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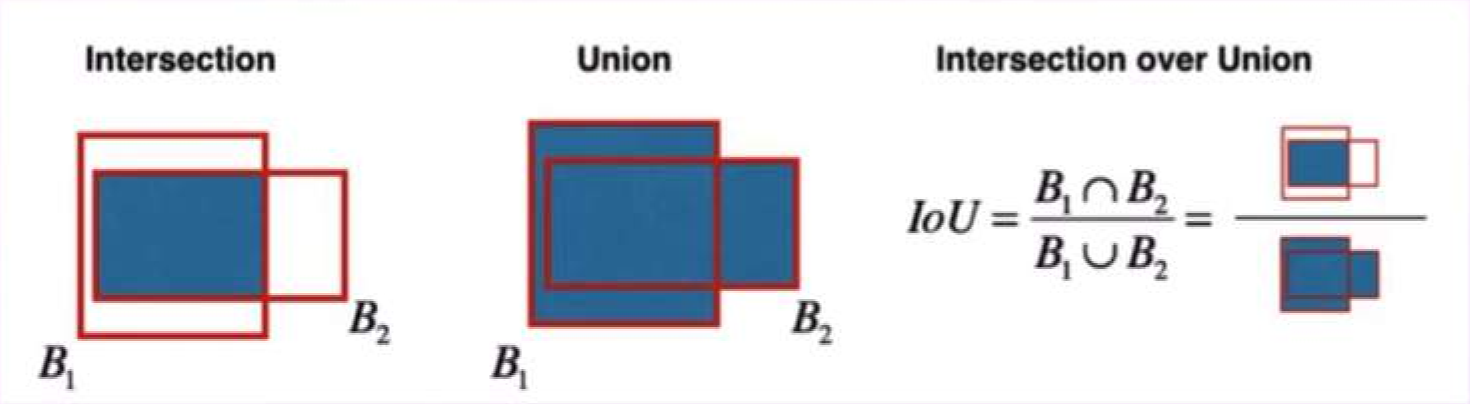

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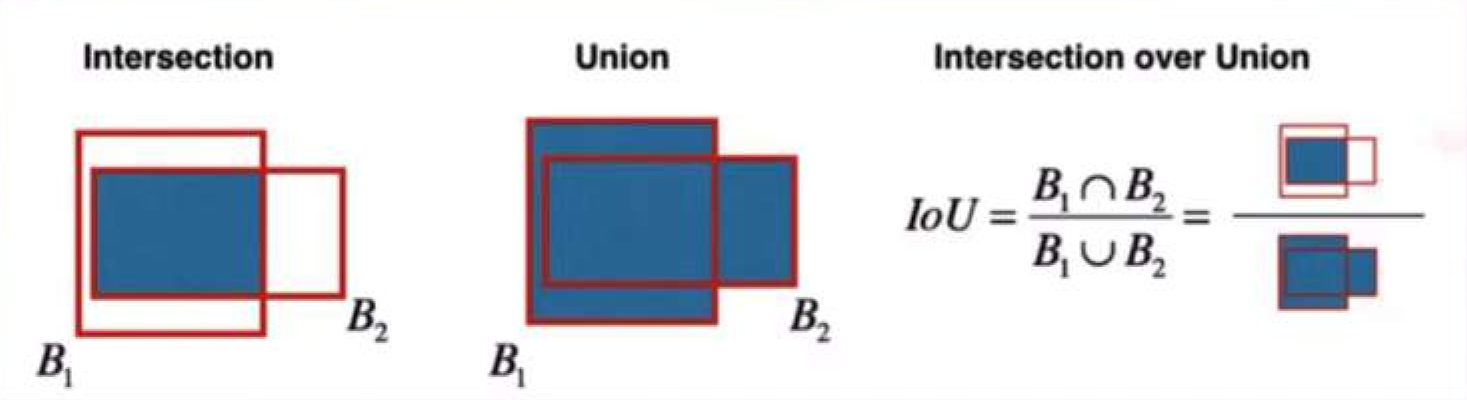

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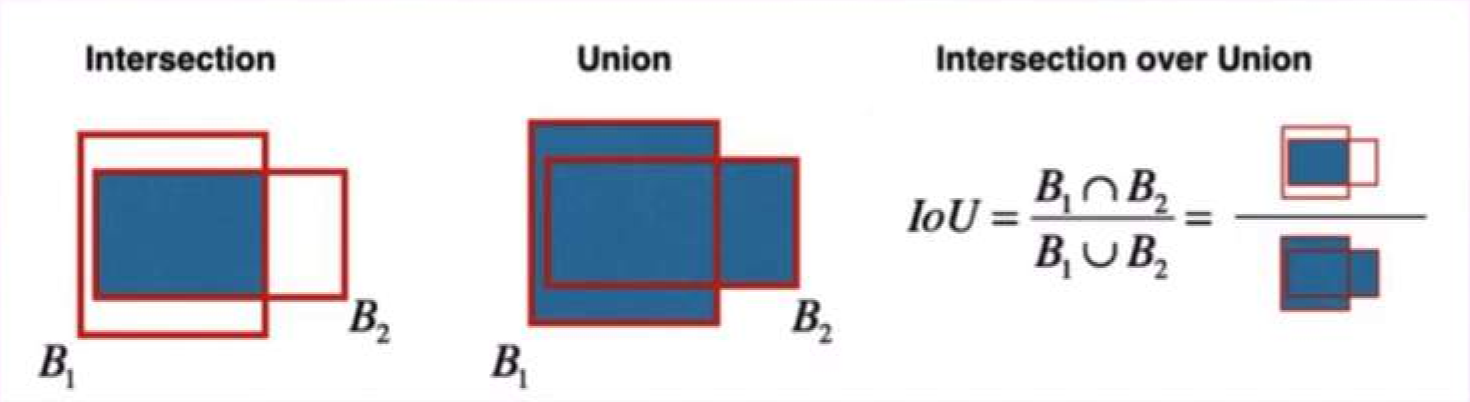

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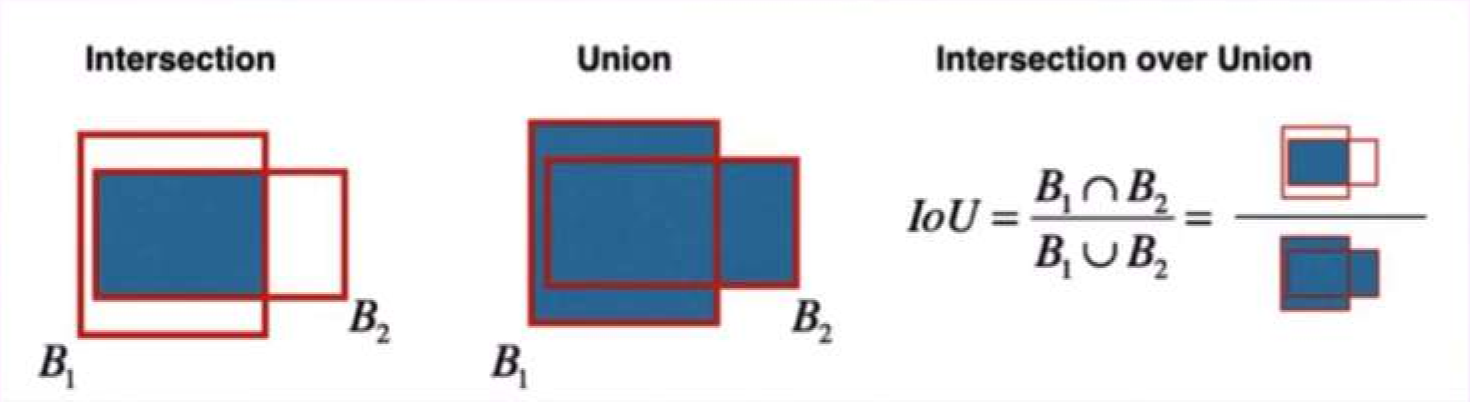

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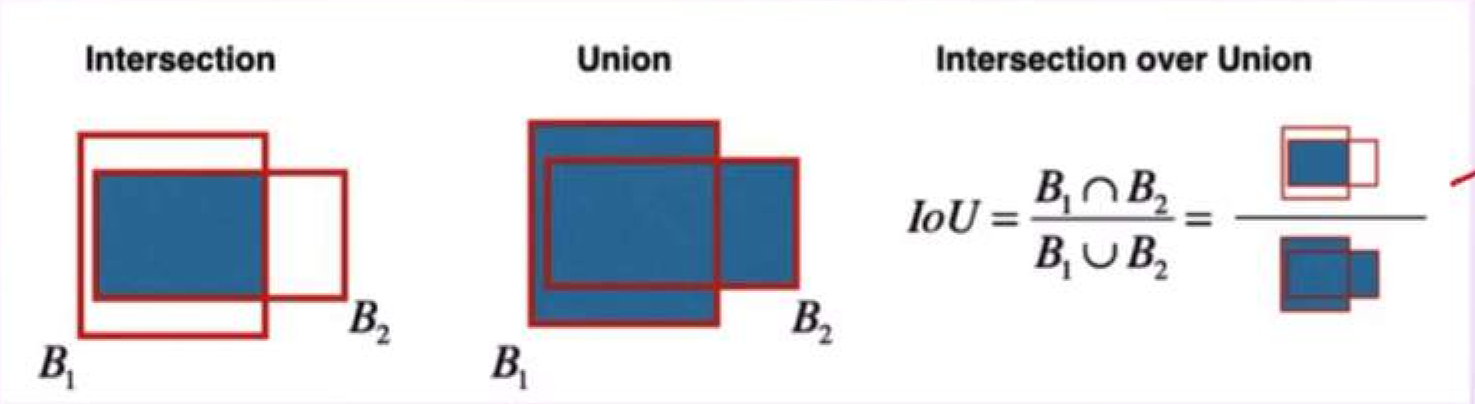

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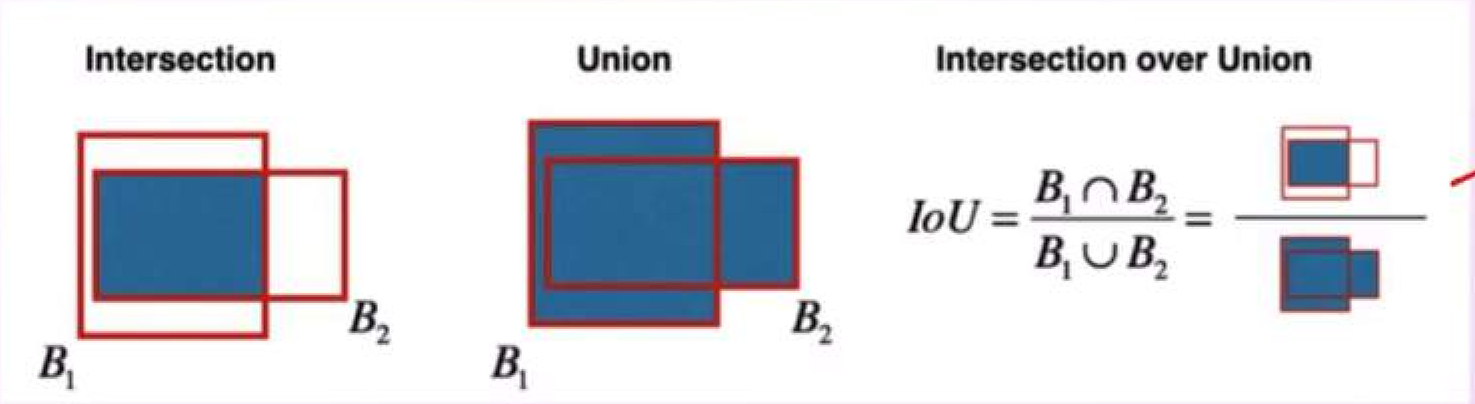
IOU Loss



1 → perfect overlap

0 → No overlap

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

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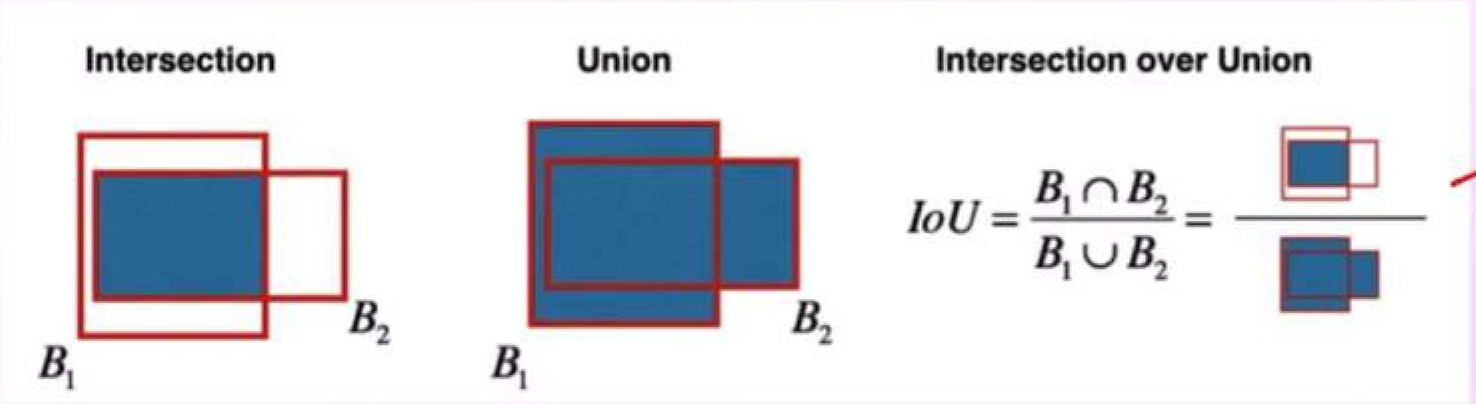

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IOU Loss

IOU ↑

1 → perfect overlap

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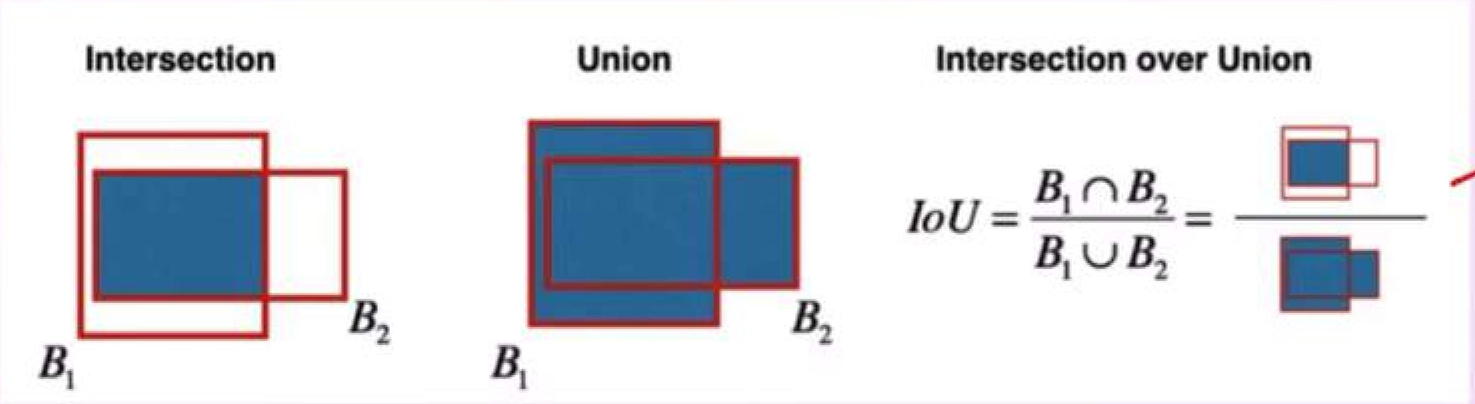

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IOU Loss

IOU ↑

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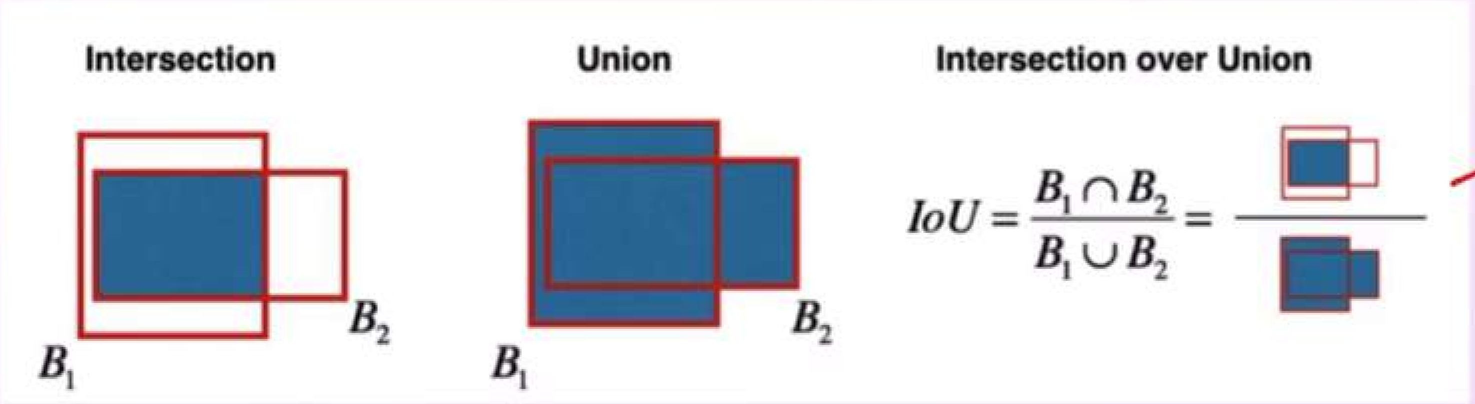

Loss ↓

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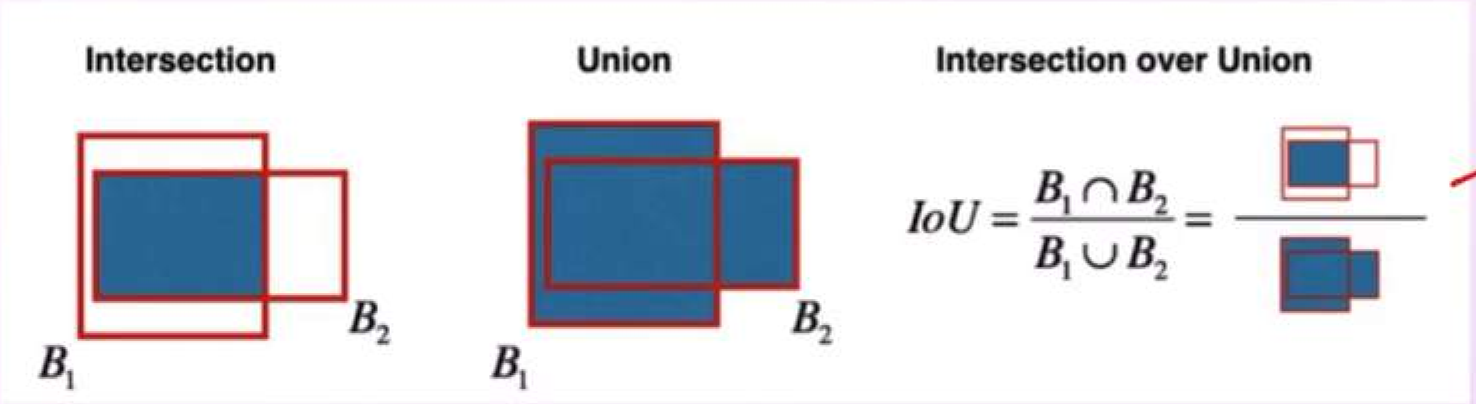
→ 1 − IOU → ↓

IOU Loss

IOU ↑

$1 \rightarrow$ perfect overlap

$0 \rightarrow$ No overlap



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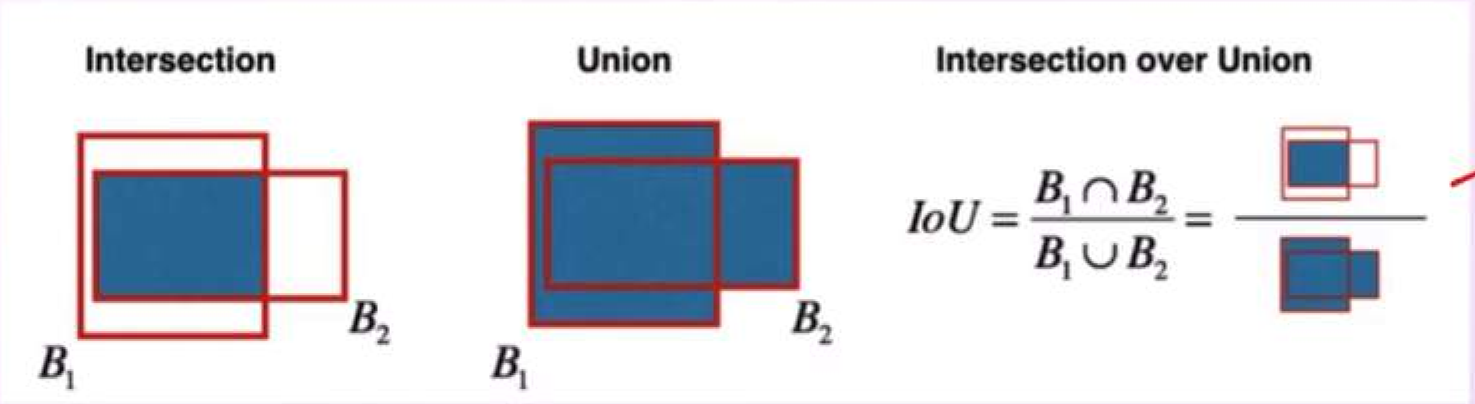
$\rightarrow 1 - \text{IOU} \rightarrow \Downarrow$

Loss ↓

IOU

0.7

IOU Loss



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$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - \text{IOU} \rightarrow \Downarrow$$

IOU ↑

1 → perfect overlap

0 → No overlap

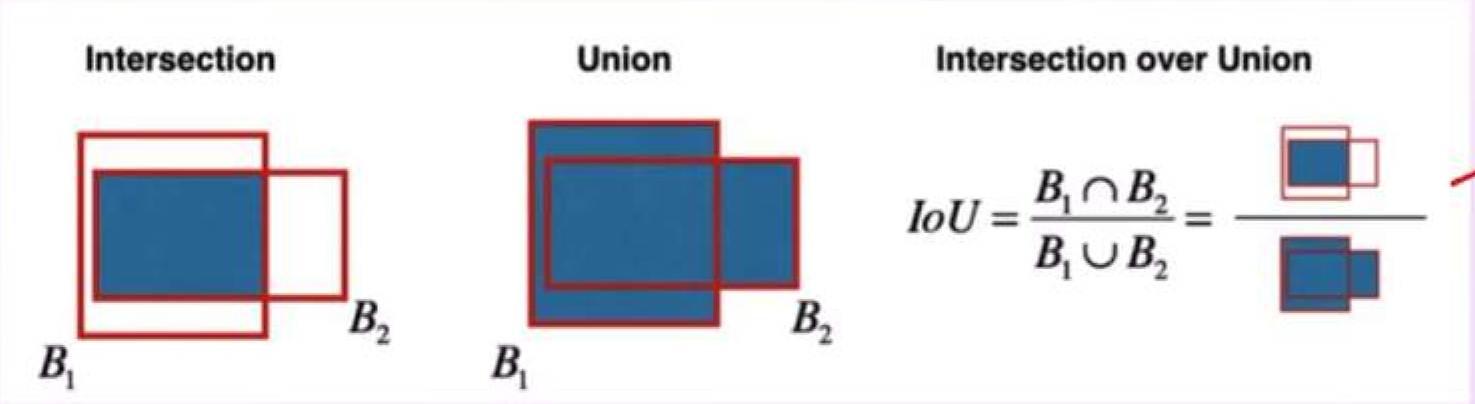
Loss ↓

IOU

0.7

→ 0.3 ↓

IOU Loss



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$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - IOU \rightarrow$$

IOU ↑

1 → perfect overlap

0 → No overlap

Loss ↓

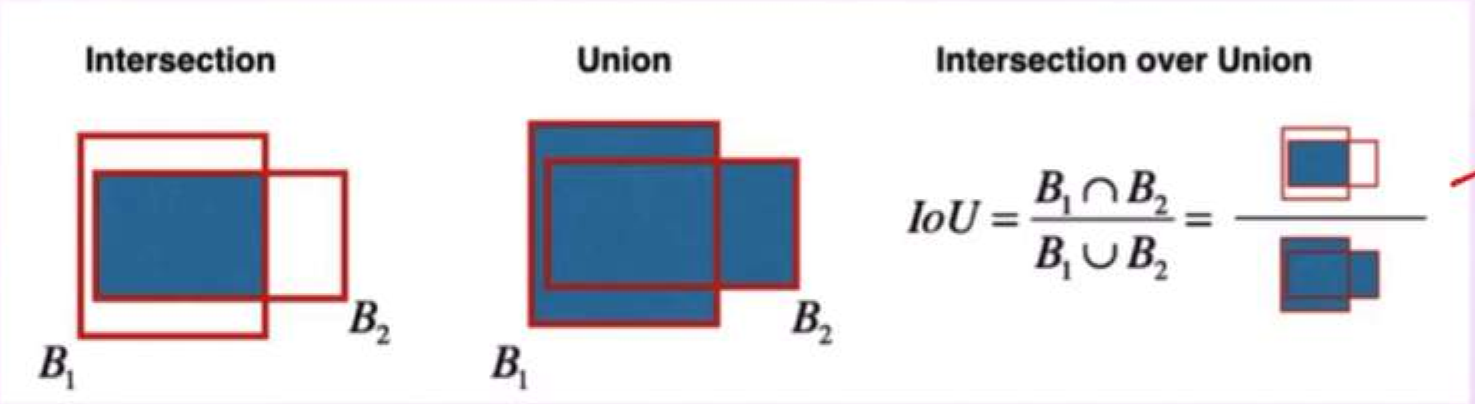
IOU

0.7

0.3 ↓ non overlapping

IOU Loss

IOU ↑



1 → perfect overlap

0 → No overlap

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

Loss ↓

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

IOU

0.7

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

→ 1 − IOU →

0.3 ↓ Non overlapping region

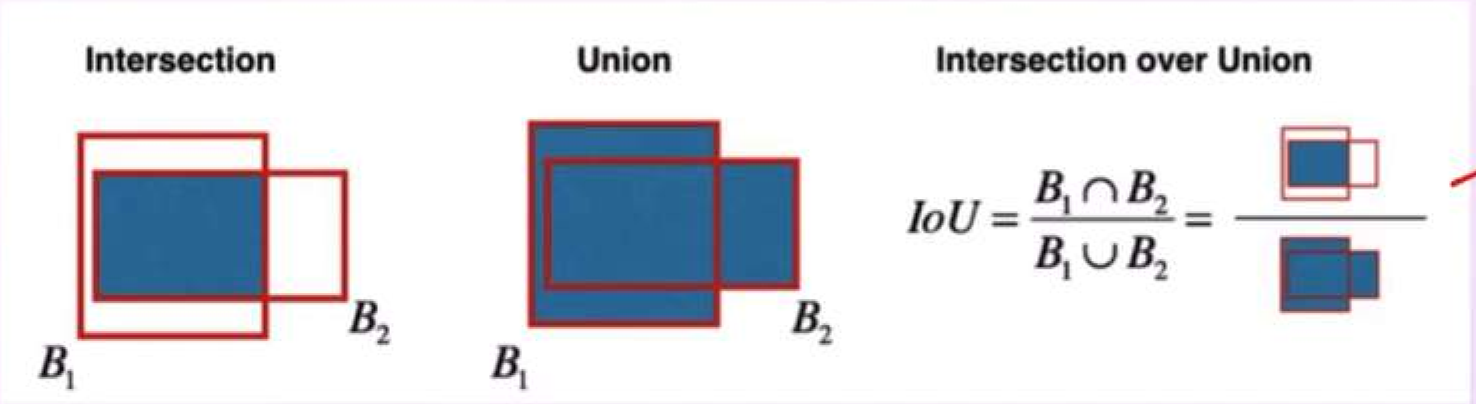
0.

IOU Loss

IOU ↑

1 → perfect overlap

0 → No overlap



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

Loss ↓

IOU

0.7

1 − IOU →

0.3 ↓

Non overlapping region

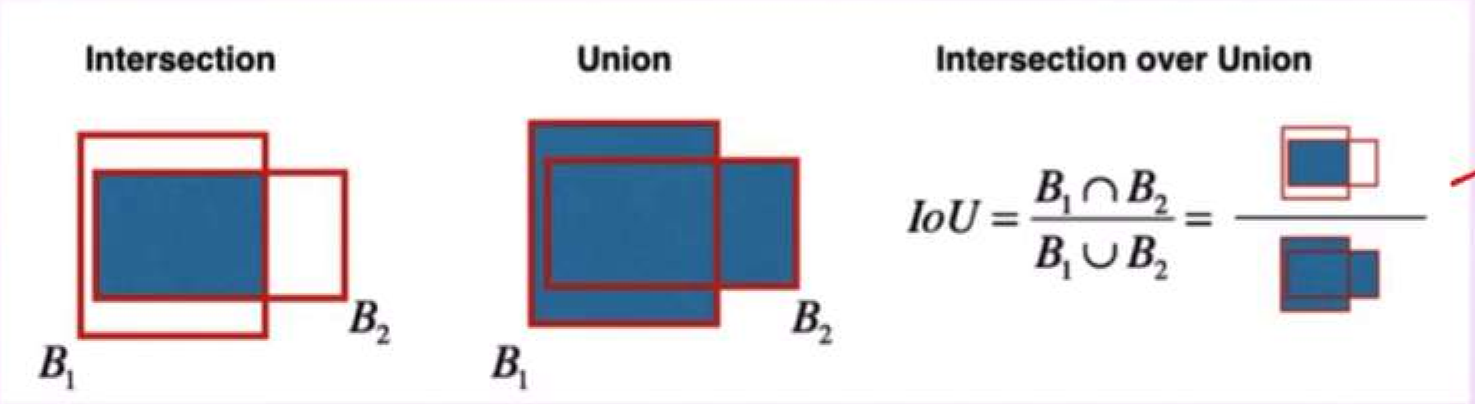
0.

IOU Loss

IOU ↑

1 → perfect overlap

0 → No overlap



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

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→ 1 − IOU →

Loss ↓

IOU

0.7

0.3 ↓

Non overlapping region

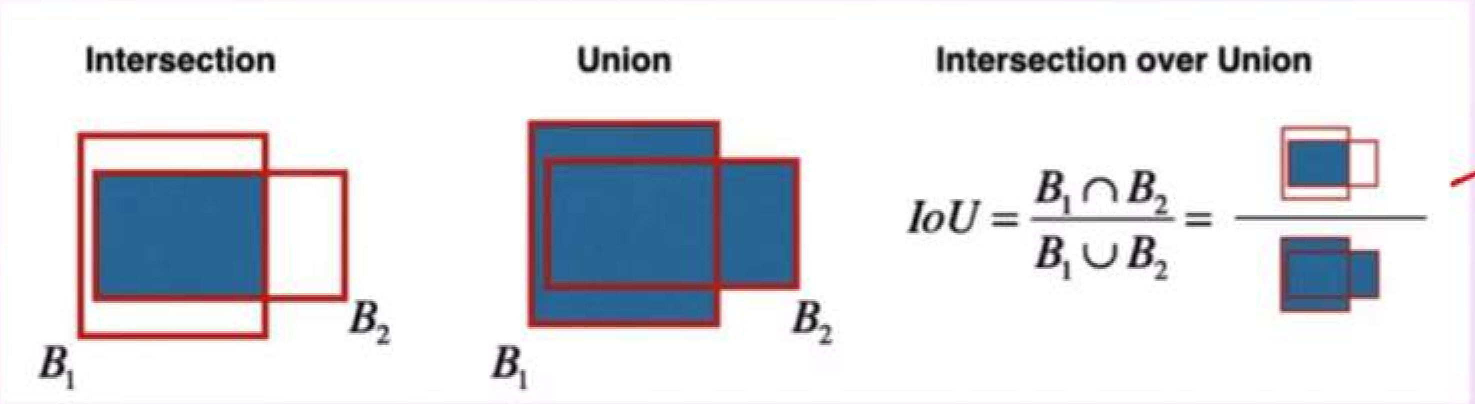
0.

IOU Loss

IOU ↑

1 → perfect overlap

0 → No overlap



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - IOU \rightarrow \Downarrow$$

Loss ↓

IOU

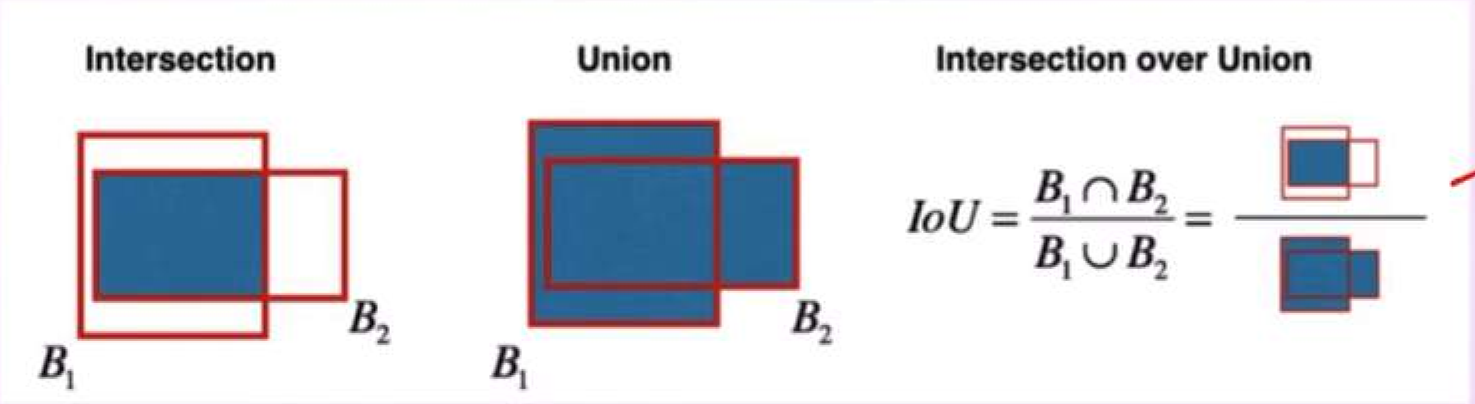
0.7

0.3 ↓

Non overlapping region

0.

IOU Loss



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - IOU \rightarrow$$

IOU ↑

1 → perfect overlap

0 → No overlap

Loss ↓

IOU 0.7 ↓

→ 0.3 ↓ Non overlapping region 0.

IOU Loss

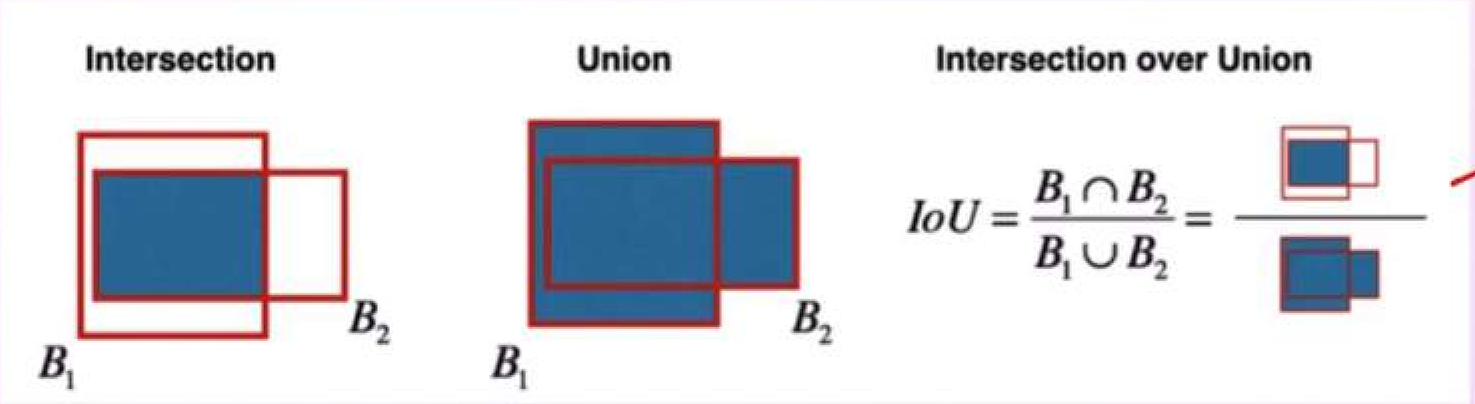
GT

1

IOU ↑

1 → perfect overlap

0 → No overlap



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - \text{IOU} \rightarrow$$

Logs ↓

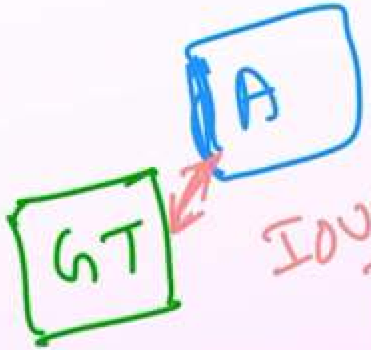
IOU

0.7

→ 0.3 ↓ Non overlapping region

0.

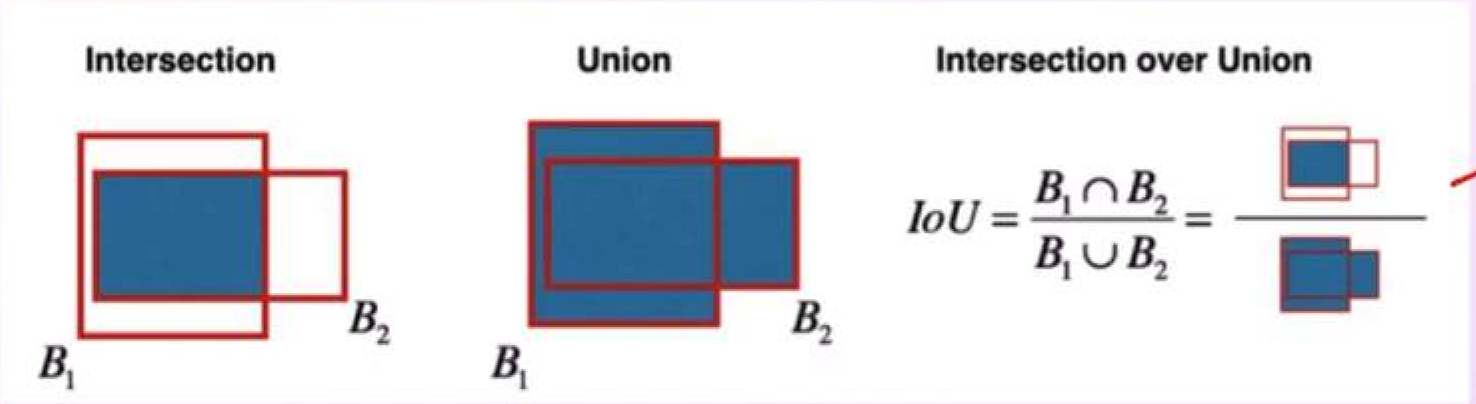
IOU Loss



IOU=0

IOU ↑

1 → perfect overlap



0 → No overlap

Loss ↓

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt}) \text{ is the ground-truth}$$

$$B = (x, y, w, h) \text{ is the predicted box}$$

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

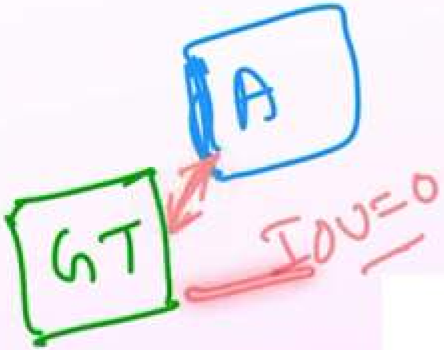
→ 1 − IOU →

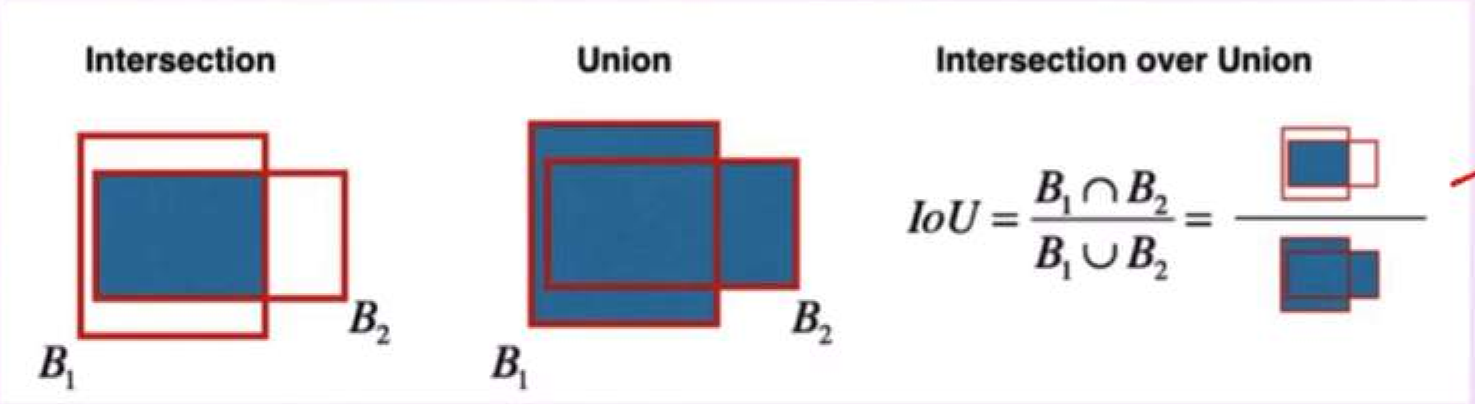
IOU 0.7

0.3 ↓ Non overlapping region

0.

IOU Loss





IOU ↑

1 → perfect overlap

0 → No overlap

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

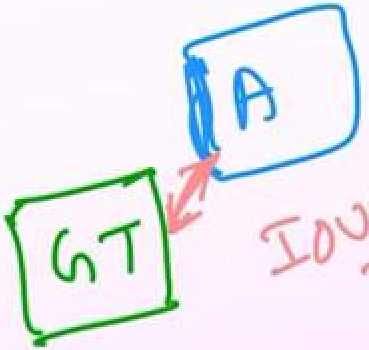
→ 1 − IOU →

Loss ↓

IOU 0.7

→ 0.3 ↓ Non overlapping region 0.

IOU Loss

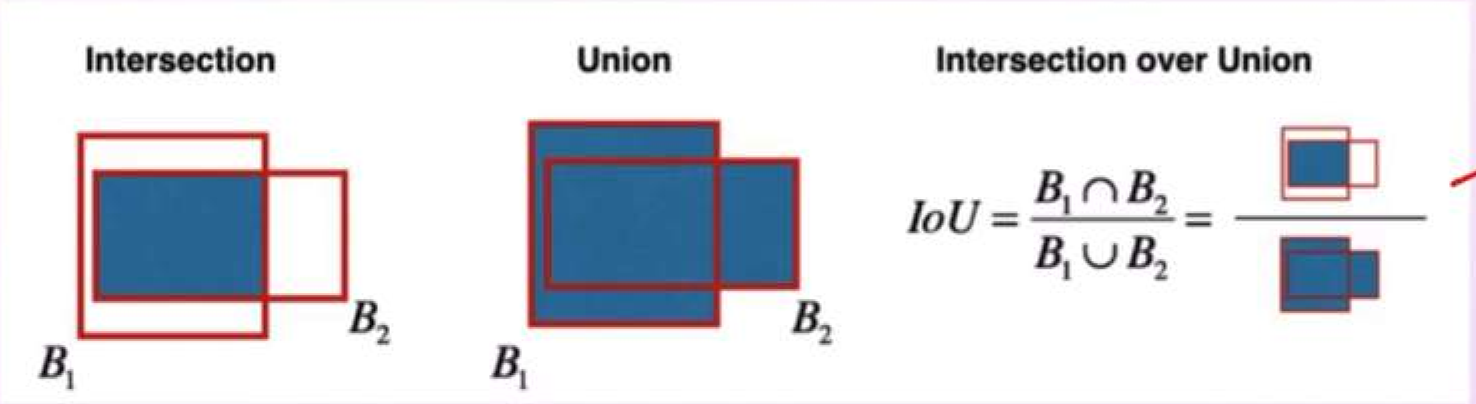


IOU=0

IOU ↑

1 → perfect overlap

0 → No overlap



$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - \mathrm{IOU} \rightarrow$$

Loss ↓

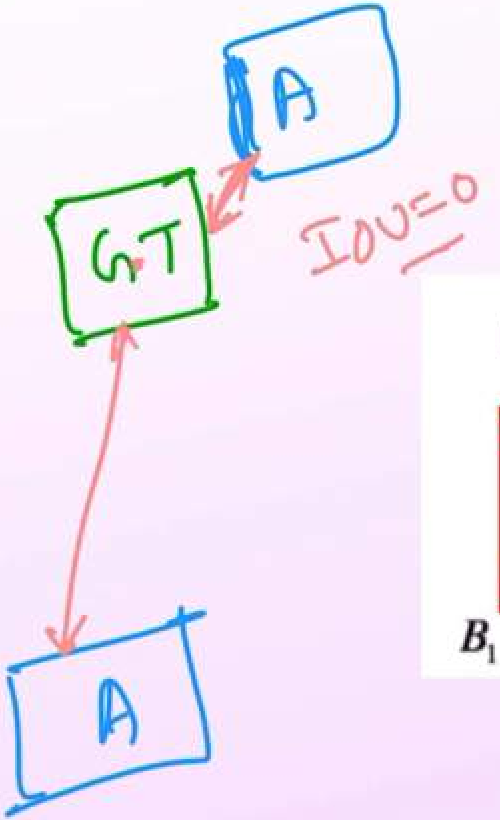
IOU 0.7 ⇓

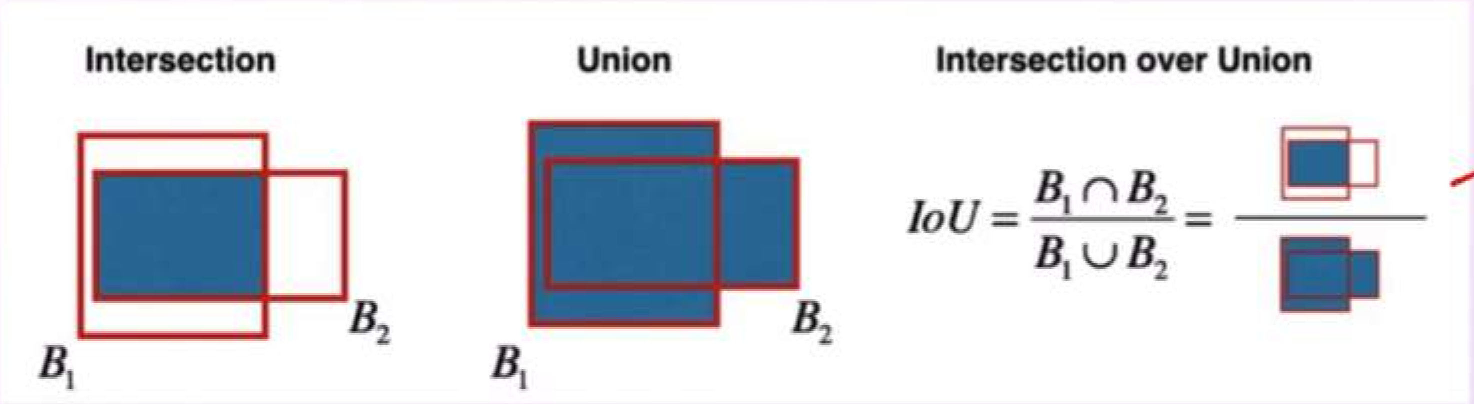
0.3 ↓

Non overlapping region

0.

IOU Loss





IOU ↑

1 → perfect overlap

0 → No overlap

Loss ↓

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

→ 1 − IOU →

IOU

0.7

0.3 ↓ non overlapping region

0.

IOU Loss

A

GT

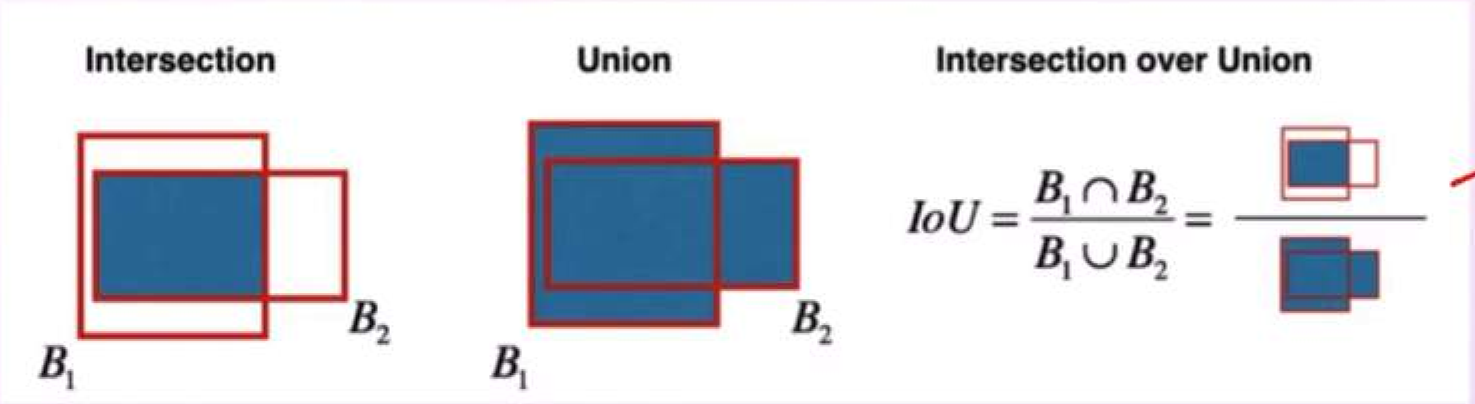
IOU=0

Loss = 1

A

IOU ↑

1 → perfect overlap



0 → No overlap

Loss ↓

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

→ 1 − IOU →

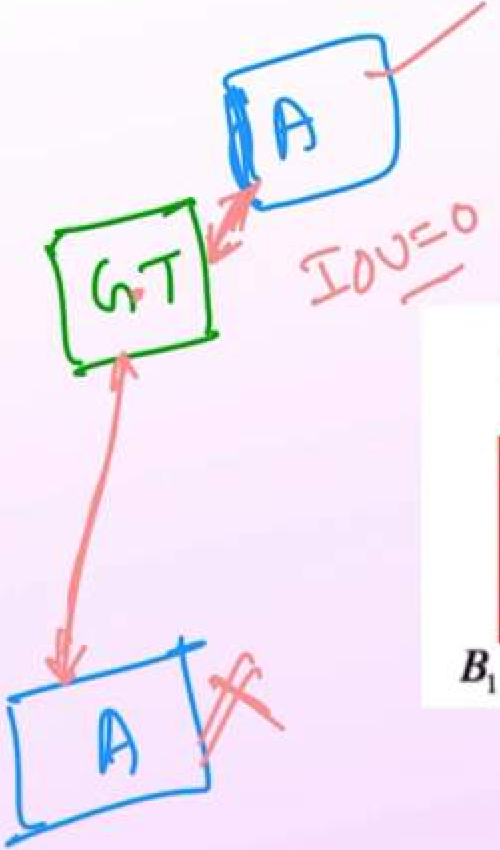
IOU

0.7

0.3 ↓ non overlapping region

0.

IOU Loss

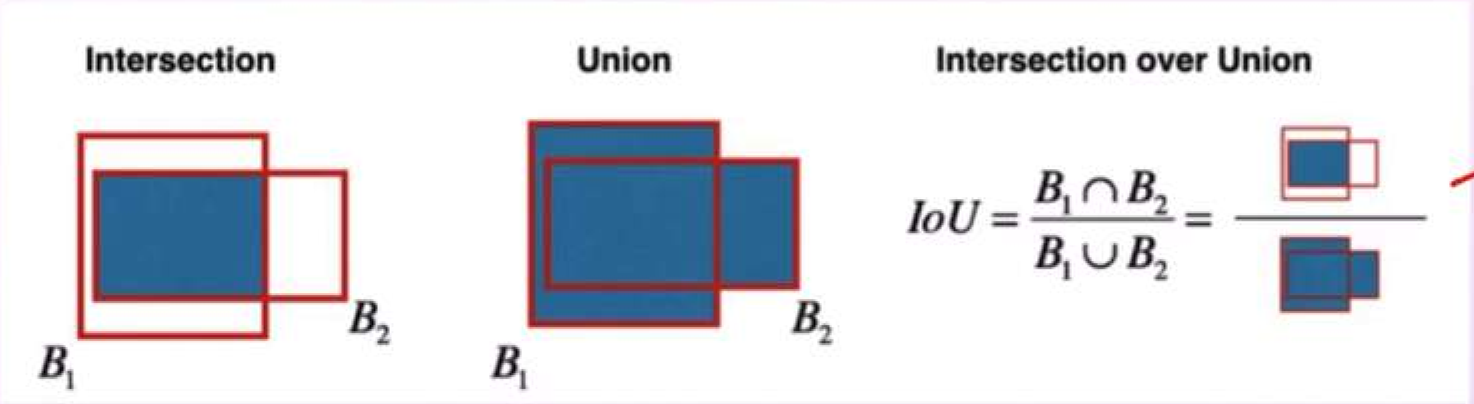


Loss = 0

IOU=0

IOU ↑

1 → perfect overlap



0 → No overlap

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}}$$

$B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth

$B = (x, y, w, h)$ is the predicted box

$$\mathcal{L}_{IoU} = 1 - \frac{B \cap B^{gt}}{B \cup B^{gt}} \rightarrow 1 - \text{IOU} \rightarrow$$

Loss ↓

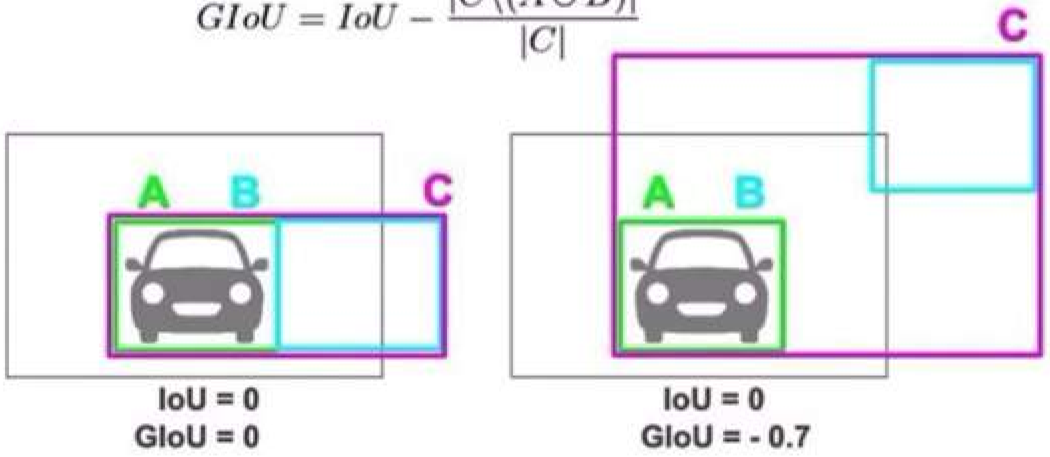
IOU 0.7

→ 0.3 ↓ Non overlapping region

0.

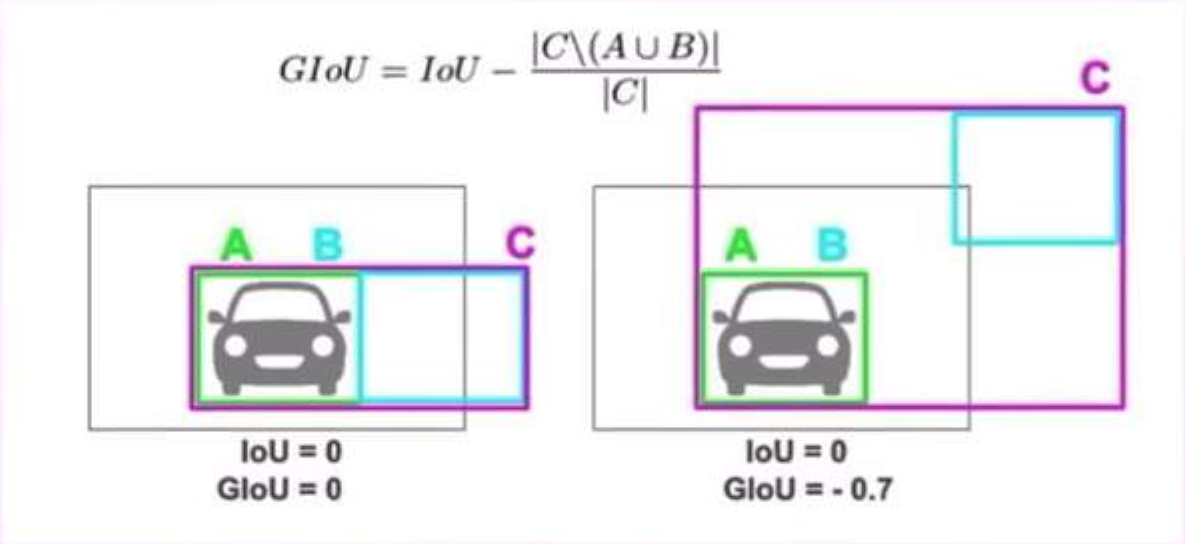
Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

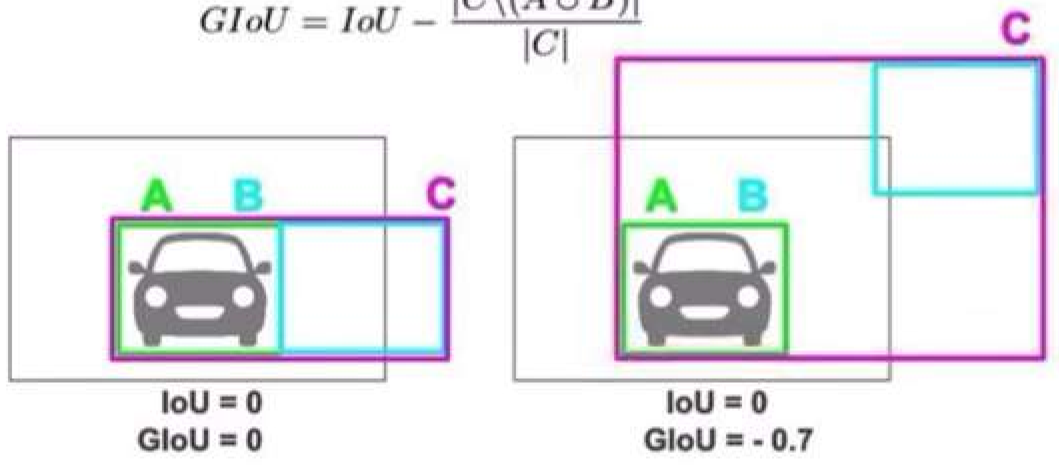
Generalized IOU Loss



$$\mathcal{L}_{GIoU} = \boxed{1 - IoU} + \frac{|C - B \cup B^{gt}|}{|C|}$$

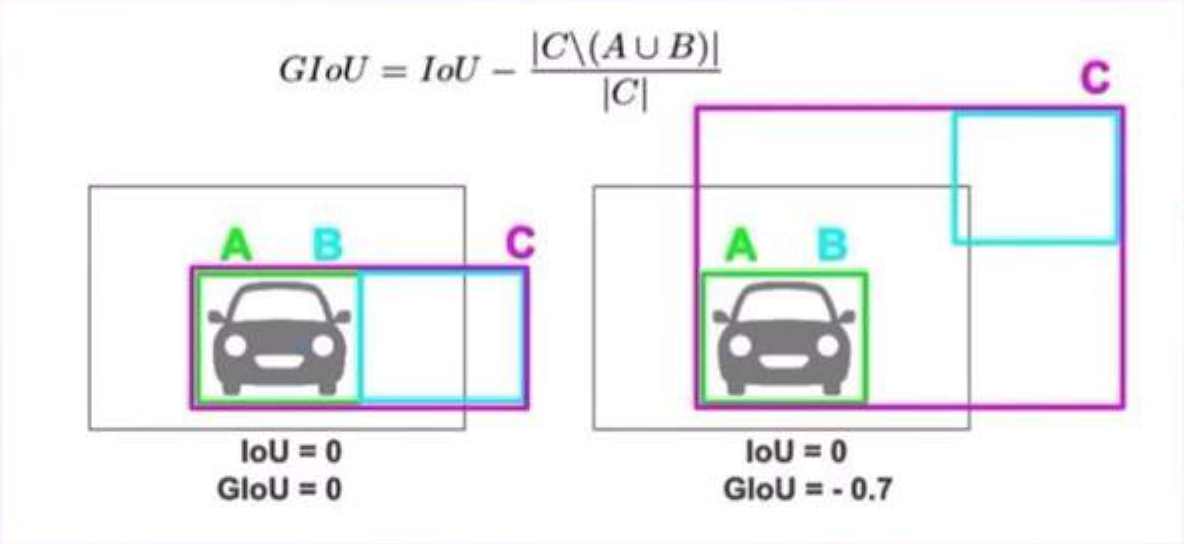
Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

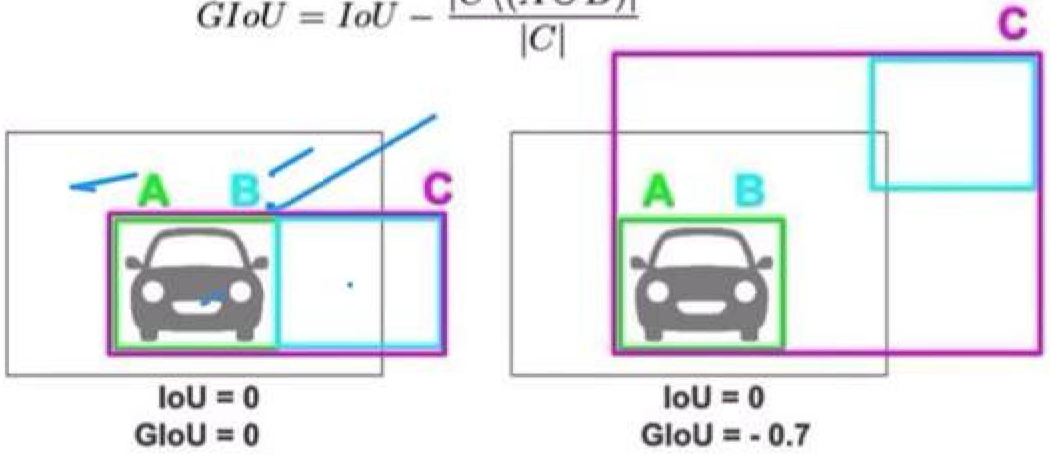


Minimum Enclosed Rectangle

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$

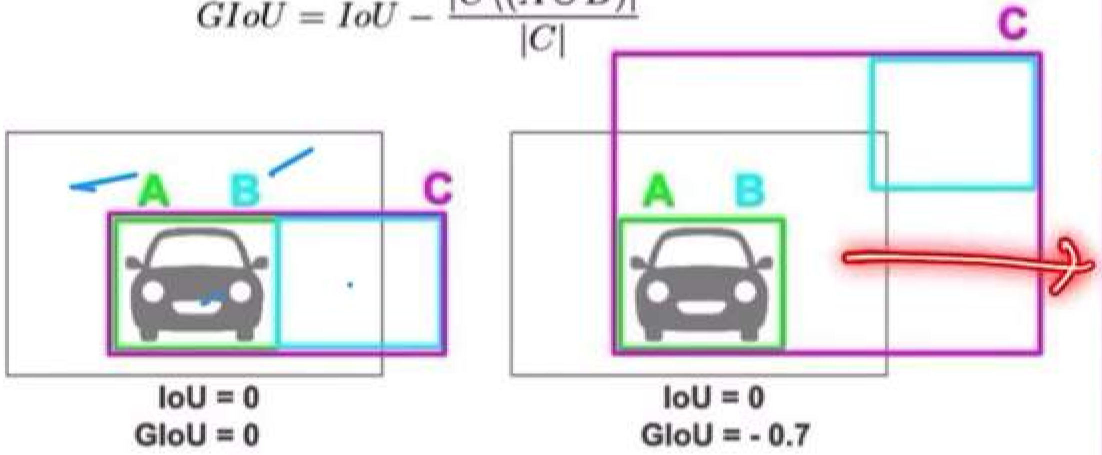


Minimum Enclosed Rectangle

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$

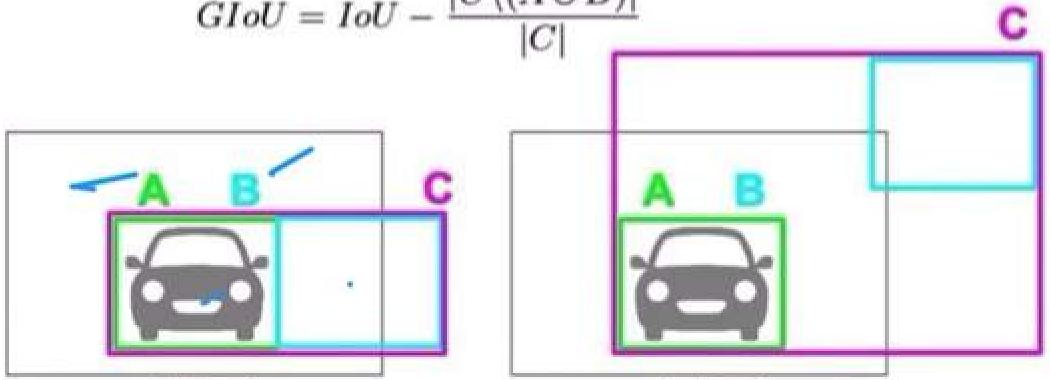


Minimum Enclosed Rectangle

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



IoU = 0
GIoU = 0

IoU = 0
GIoU = - 0.7

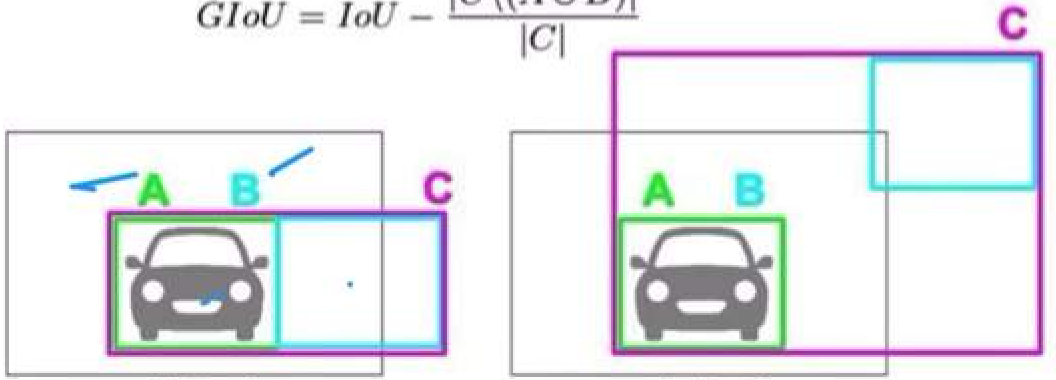
Minimum
Enclosed
Rectangle

Area

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C\backslash(A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

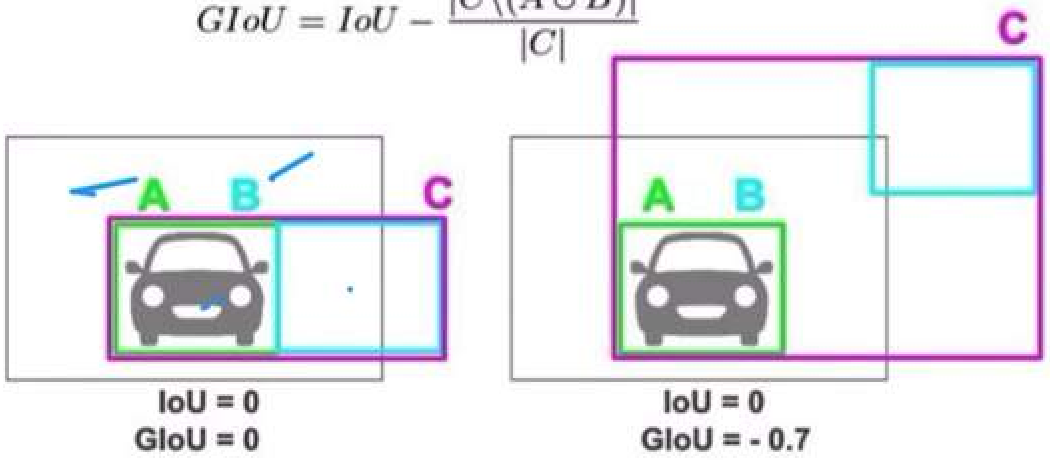
↓

↓

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C\backslash(A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

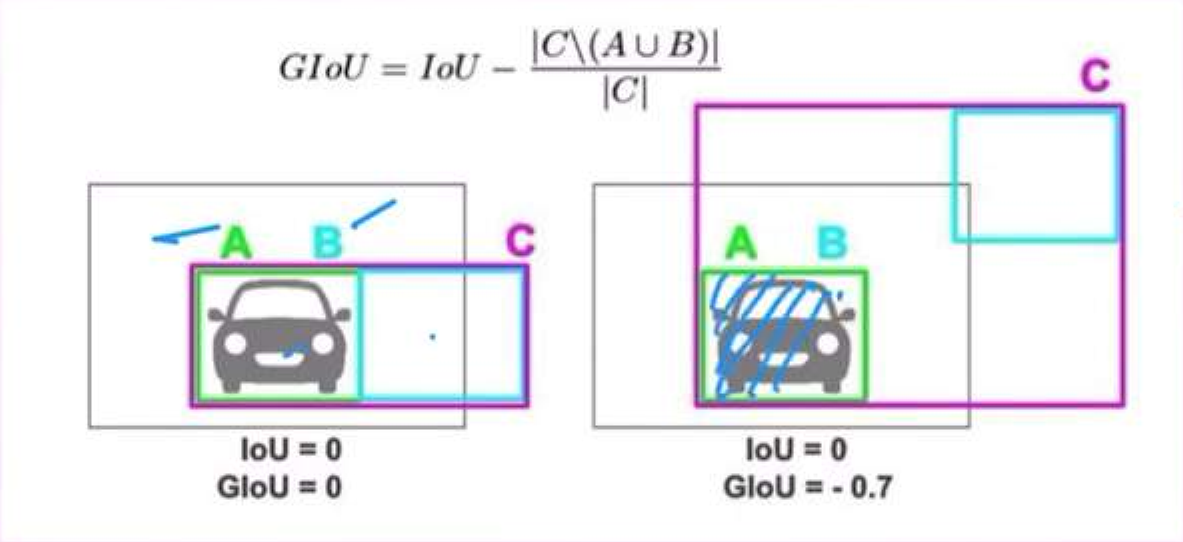
Area(C) > far

↓

Iou

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss



Minimum Enclosed Rectangle

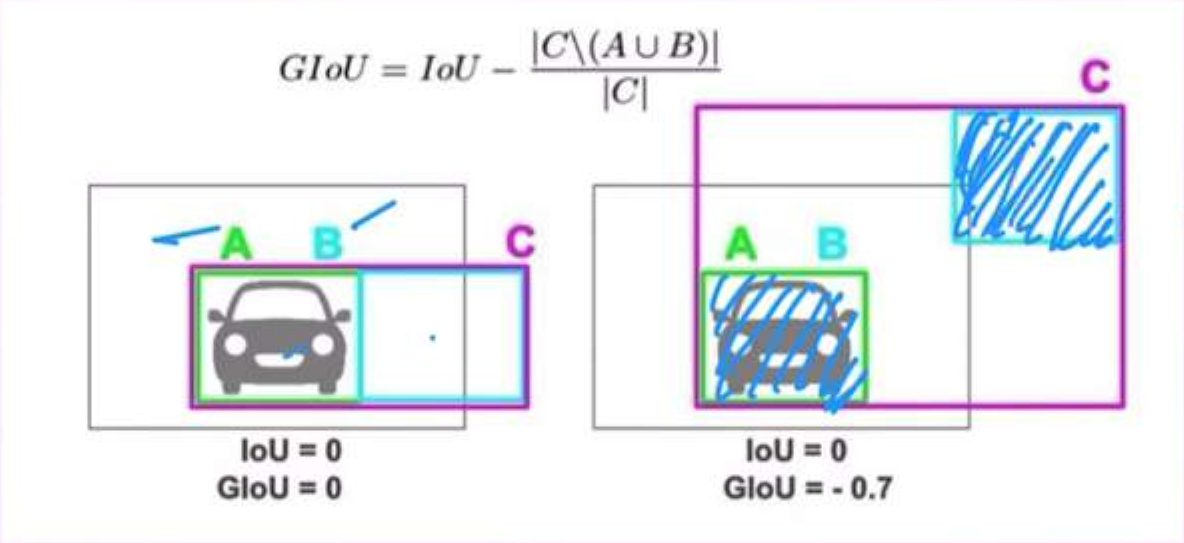
Area(C) > far

↓

loss

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss



Minimum Enclosed Rectangle

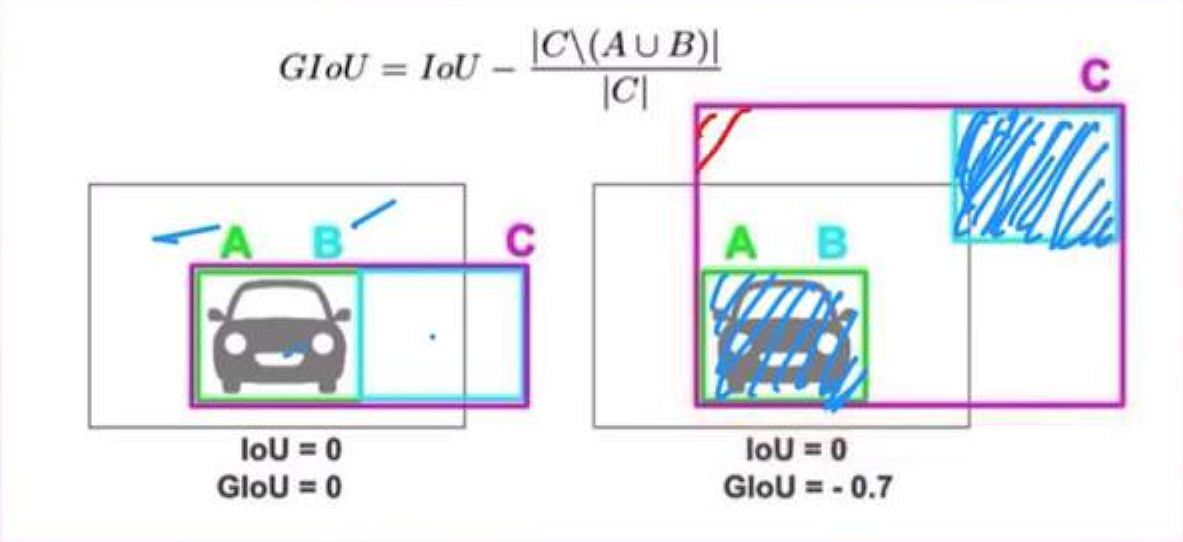
Area(C) > far

↓

Iou

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

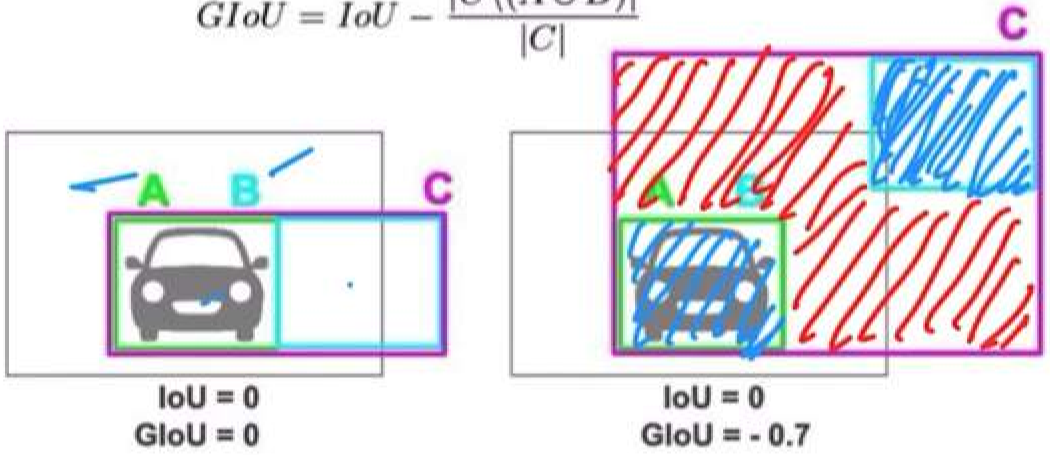
↓

low

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

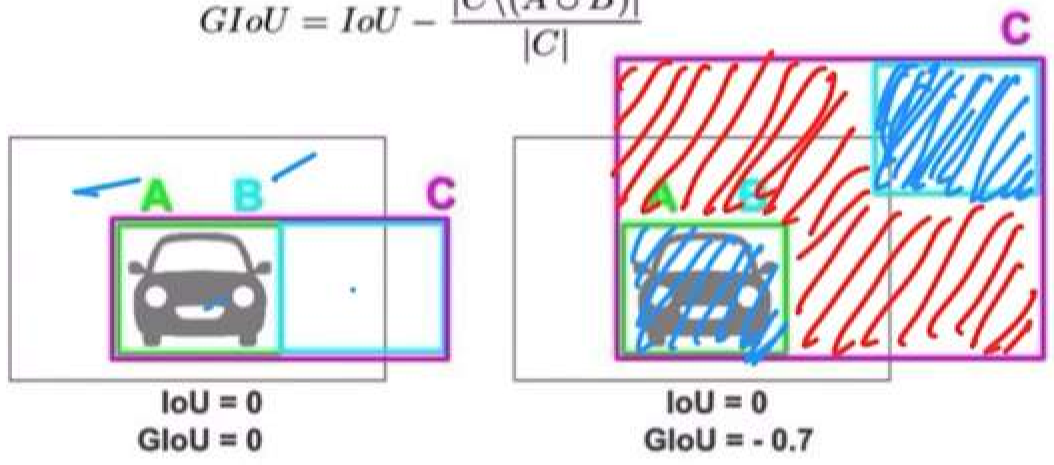
low

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

0, 1

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

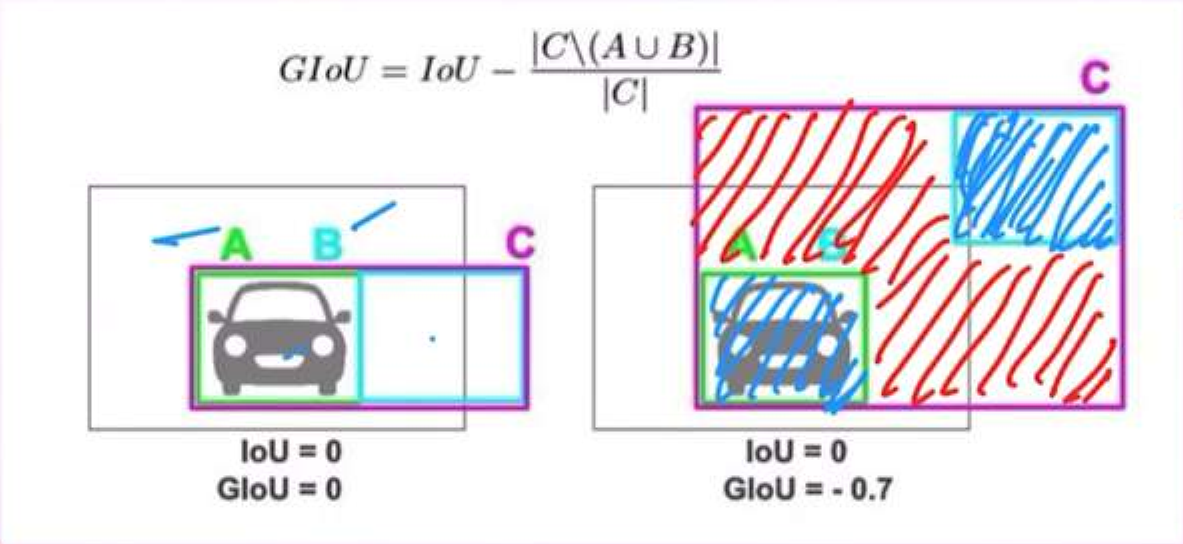
↓

low

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

↓

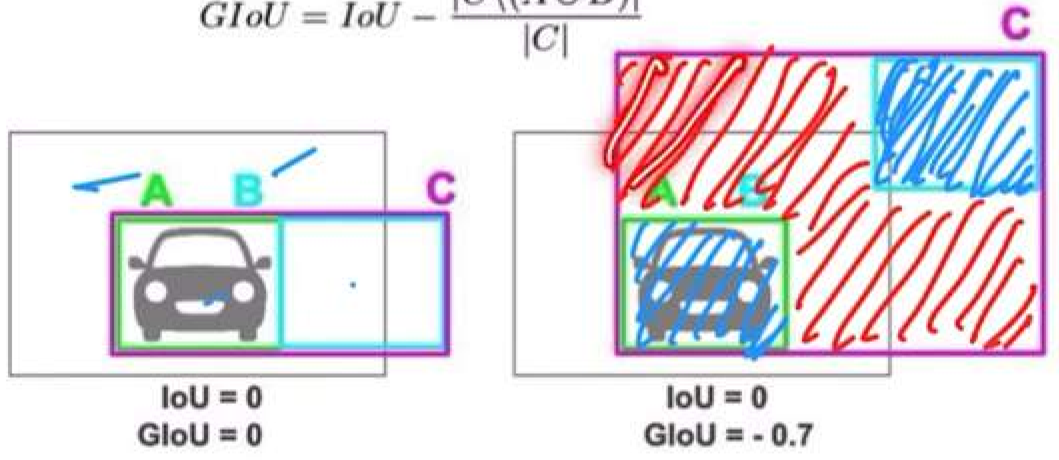
IoU

$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|} \rightarrow (0, 1)$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

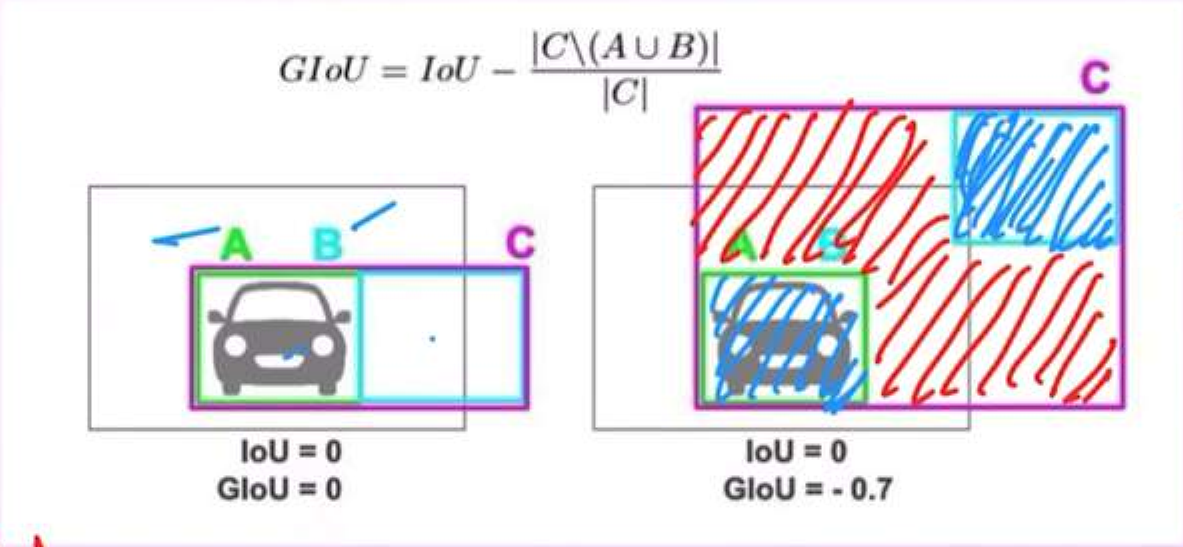
low

$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

↓

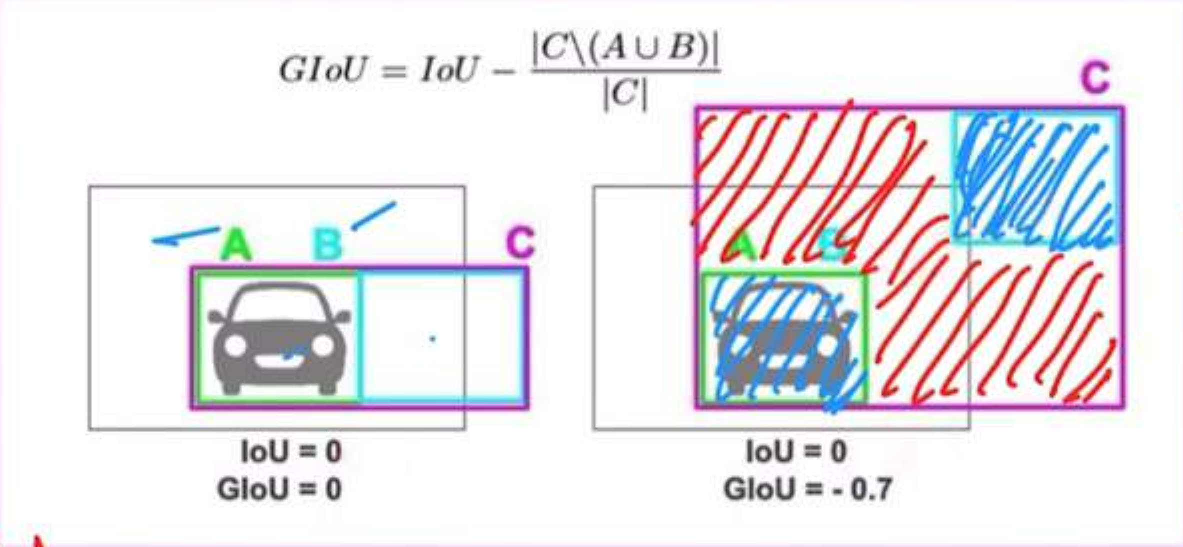
low

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

C − B ∪ B^gt

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

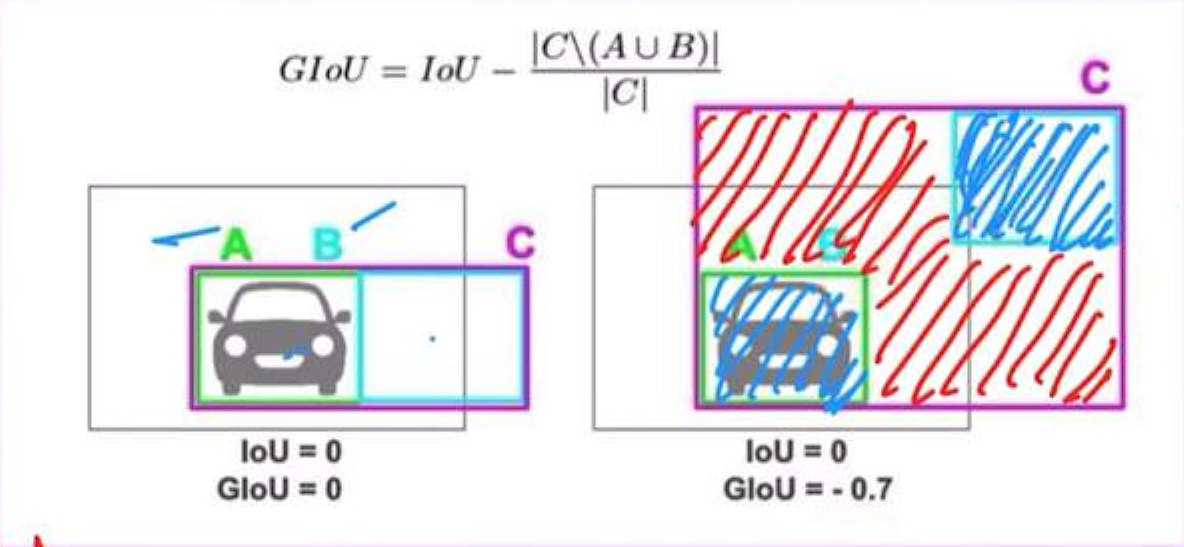
low

$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

↓

Iou

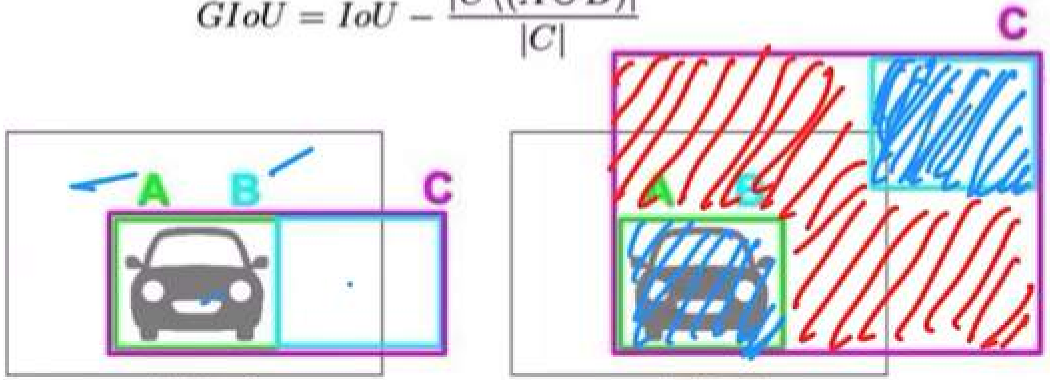
C − B ∪ B^gt

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



IoU = 0
GIoU = 0

IoU = 0
GIoU = - 0.7

Minimum Enclosed Rectangle

Area(C) > far

↓

loss

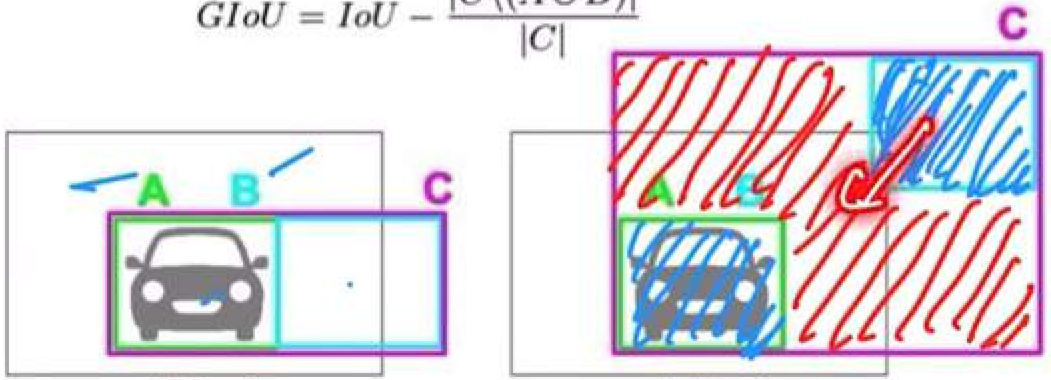
$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

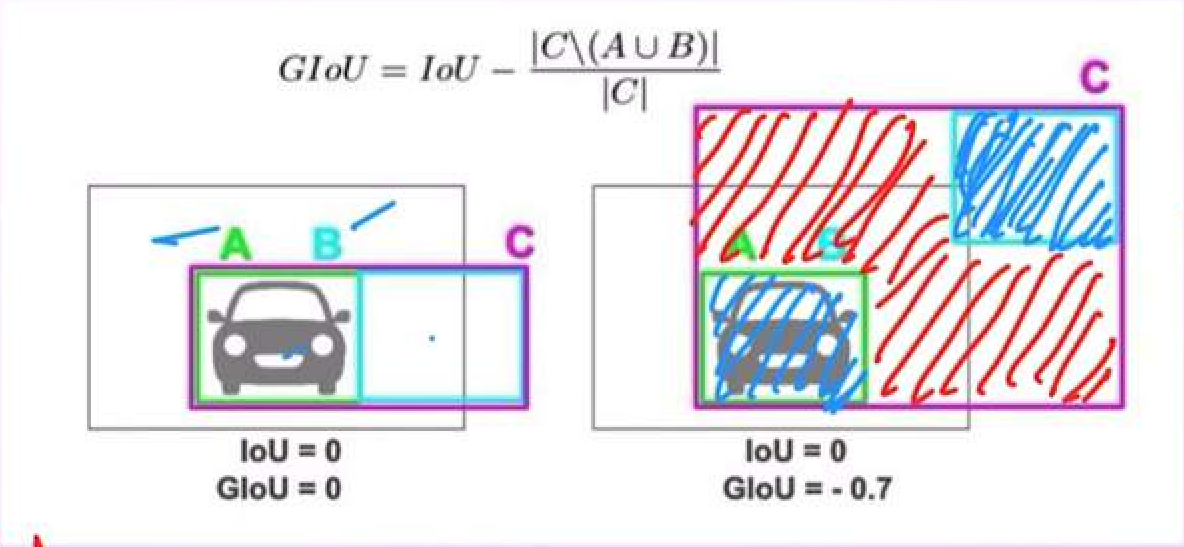
low

$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss



Minimum Enclosed Rectangle

Area(C) > far

↓

IoU

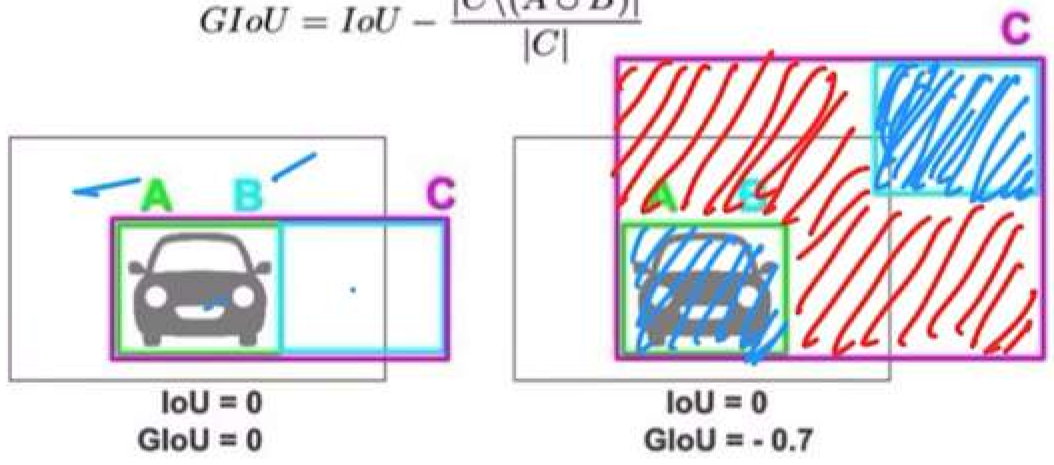
$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

IoU

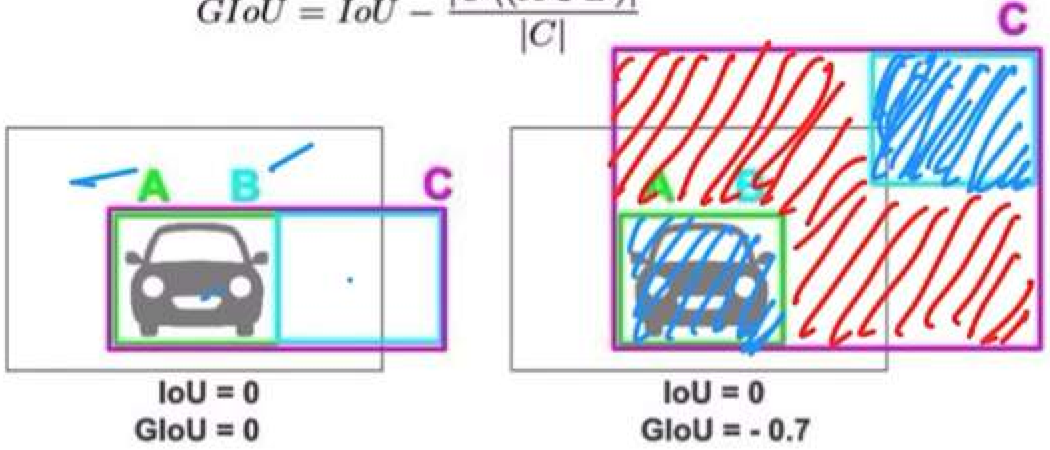
$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

low

$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

$(0,1)$

Distance IOU Loss

$$\mathcal{L}_{DIoU} = 1 - IoU + \underline{\frac{\rho^2(b, b^{gt})}{c^2}}$$

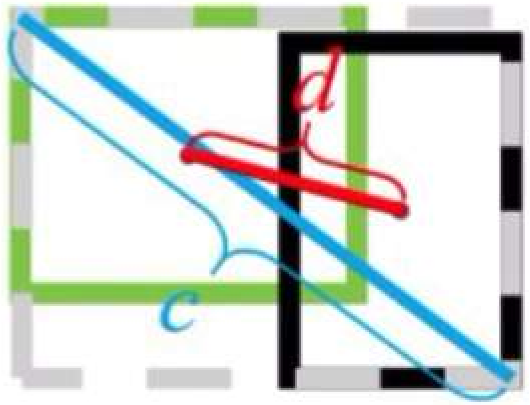


Figure 5: DIoU loss for bounding box regression, where the normalized distance between central points can be directly minimized. c is the diagonal length of the smallest enclosing box covering two boxes, and $d = \rho(\mathbf{b}, \mathbf{b}^{gt})$ is the distance of central points of two boxes.

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Distance IOU Loss

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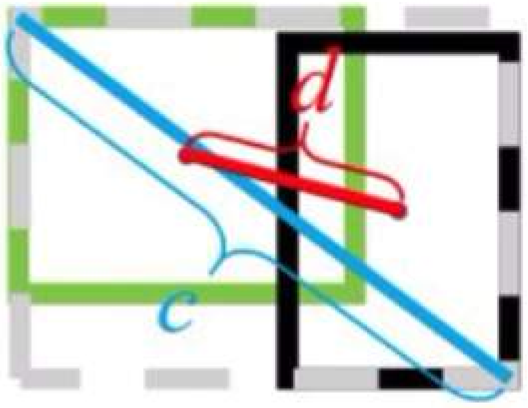

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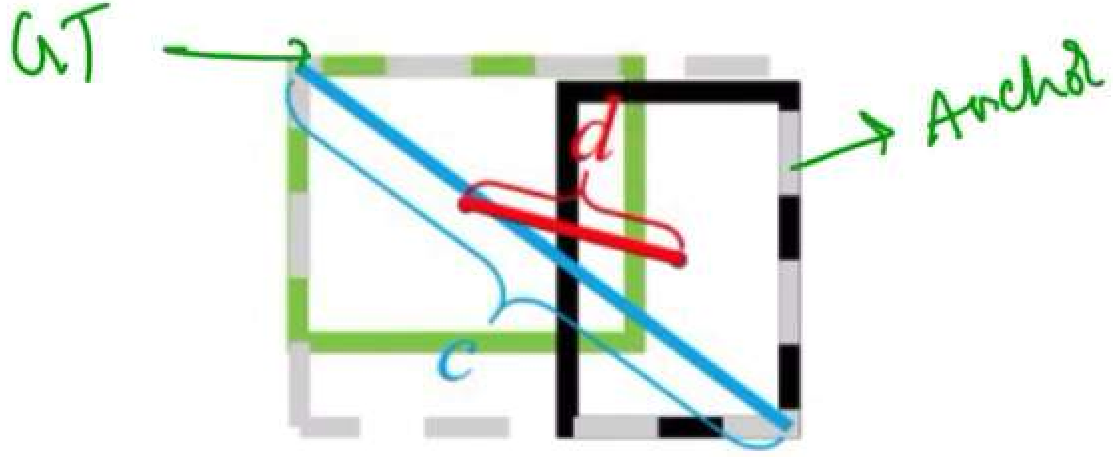

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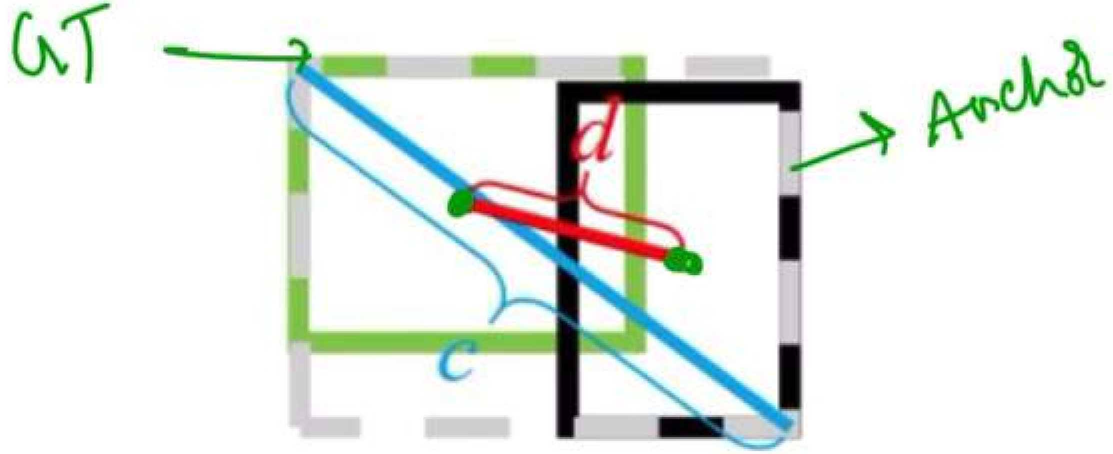

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Distance IOU Loss

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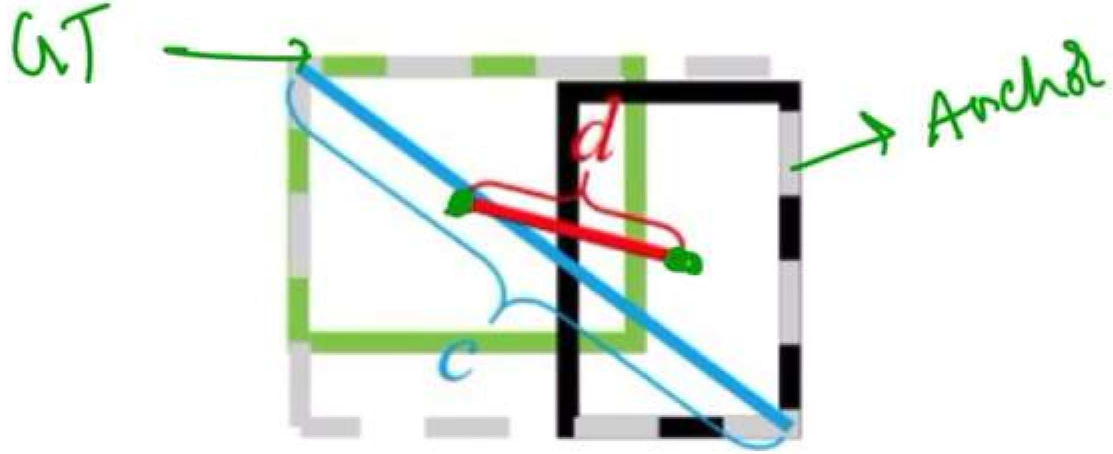

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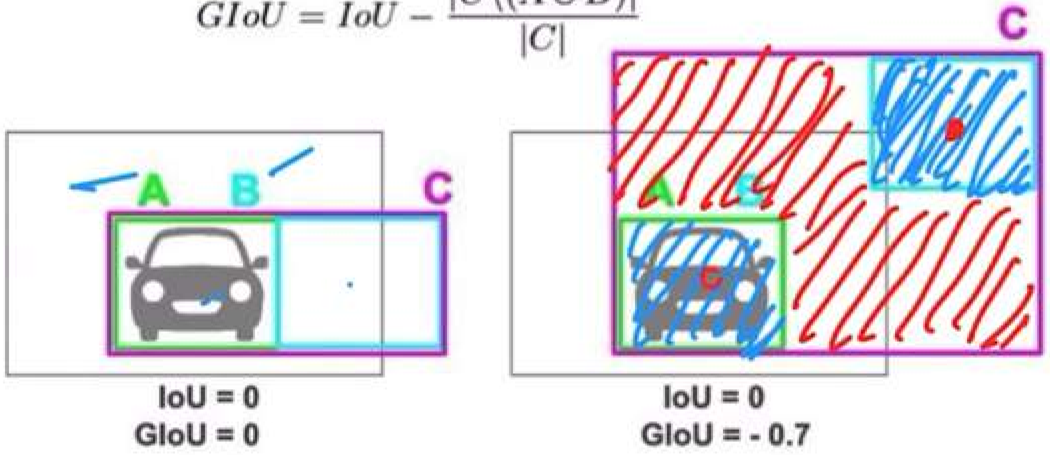
$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

loss

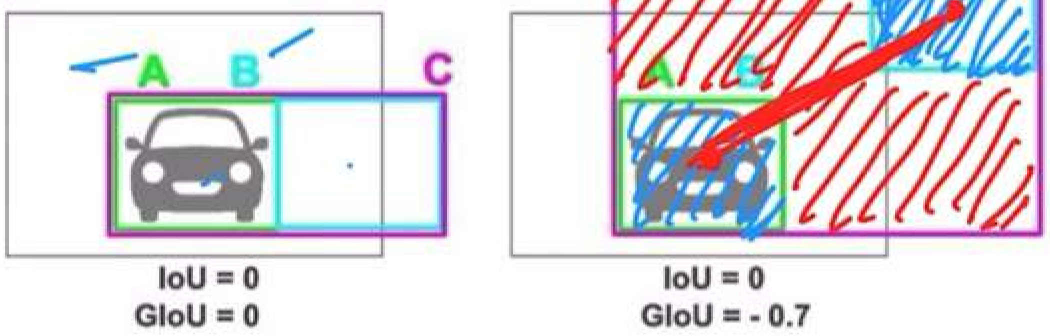
$C - B \cup B^{gt}$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

(0, 1)

Generalized IOU Loss

$$GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$$



Minimum Enclosed Rectangle

Area(C) > far

↓

low

$C - B \cup B^{gt}$

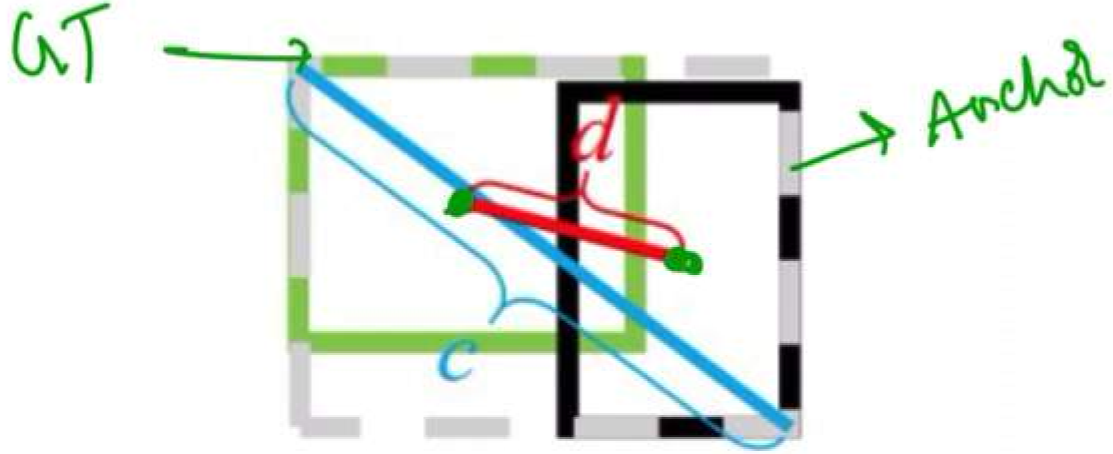
$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$

$(0, 1)$

Distance IOU Loss

$$\mathcal{L}_{DIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} \rightarrow d$$

$$\mathcal{L}_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|}$$



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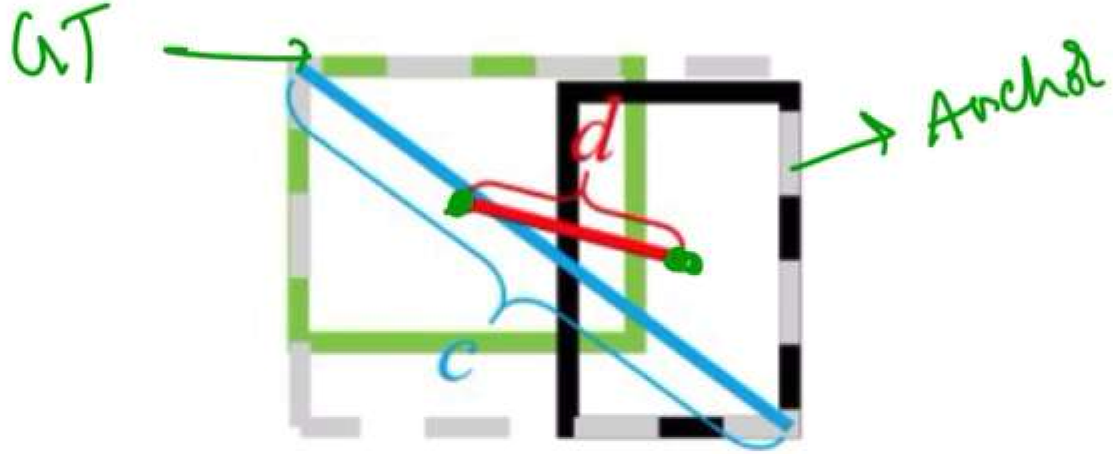

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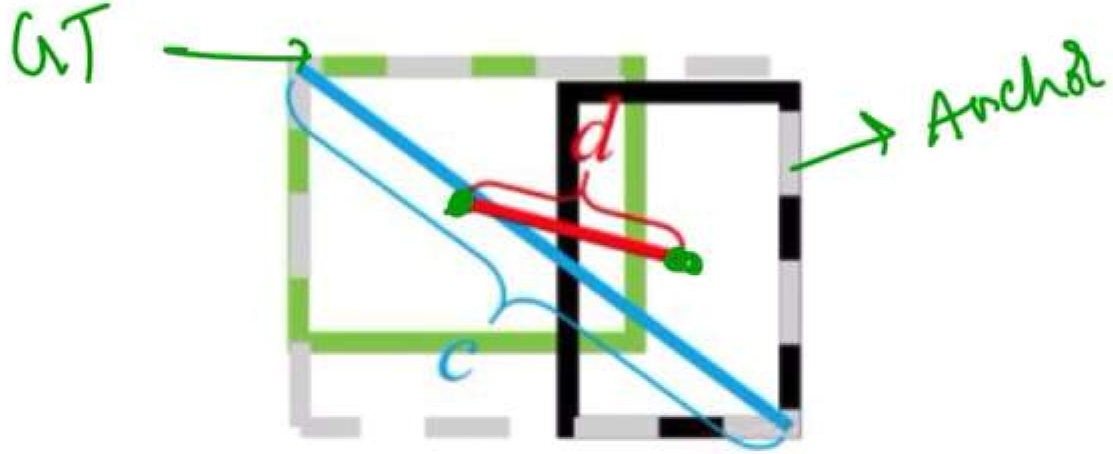

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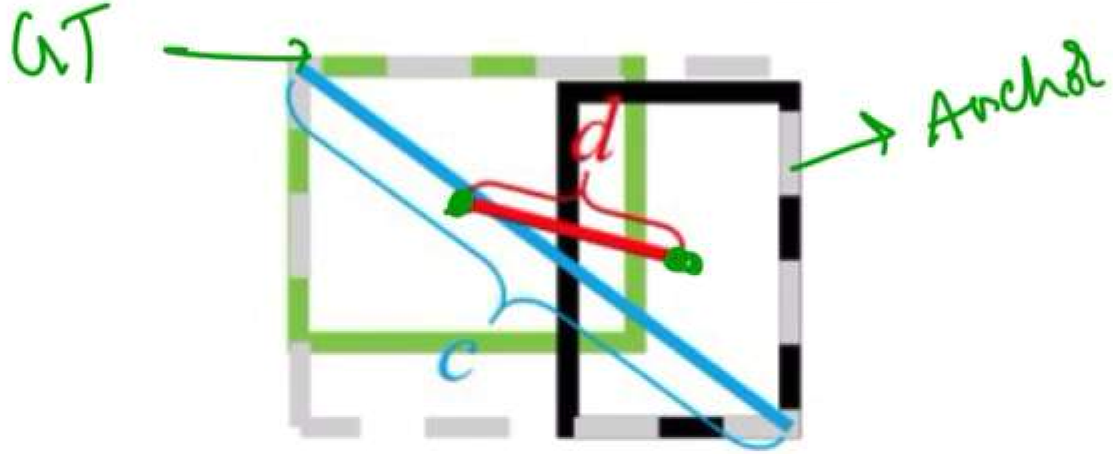

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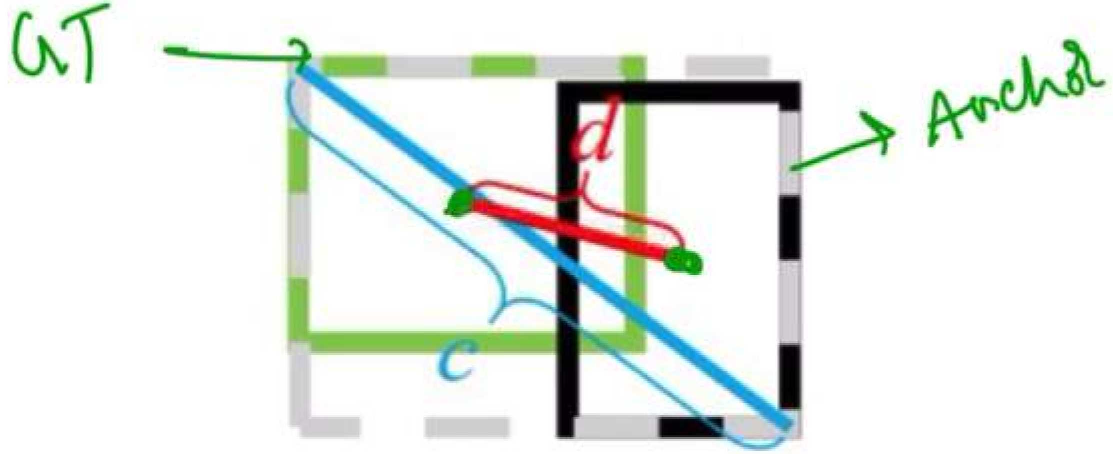
Distance IOU Loss

$$\mathcal{L}_{DIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2}$$

d



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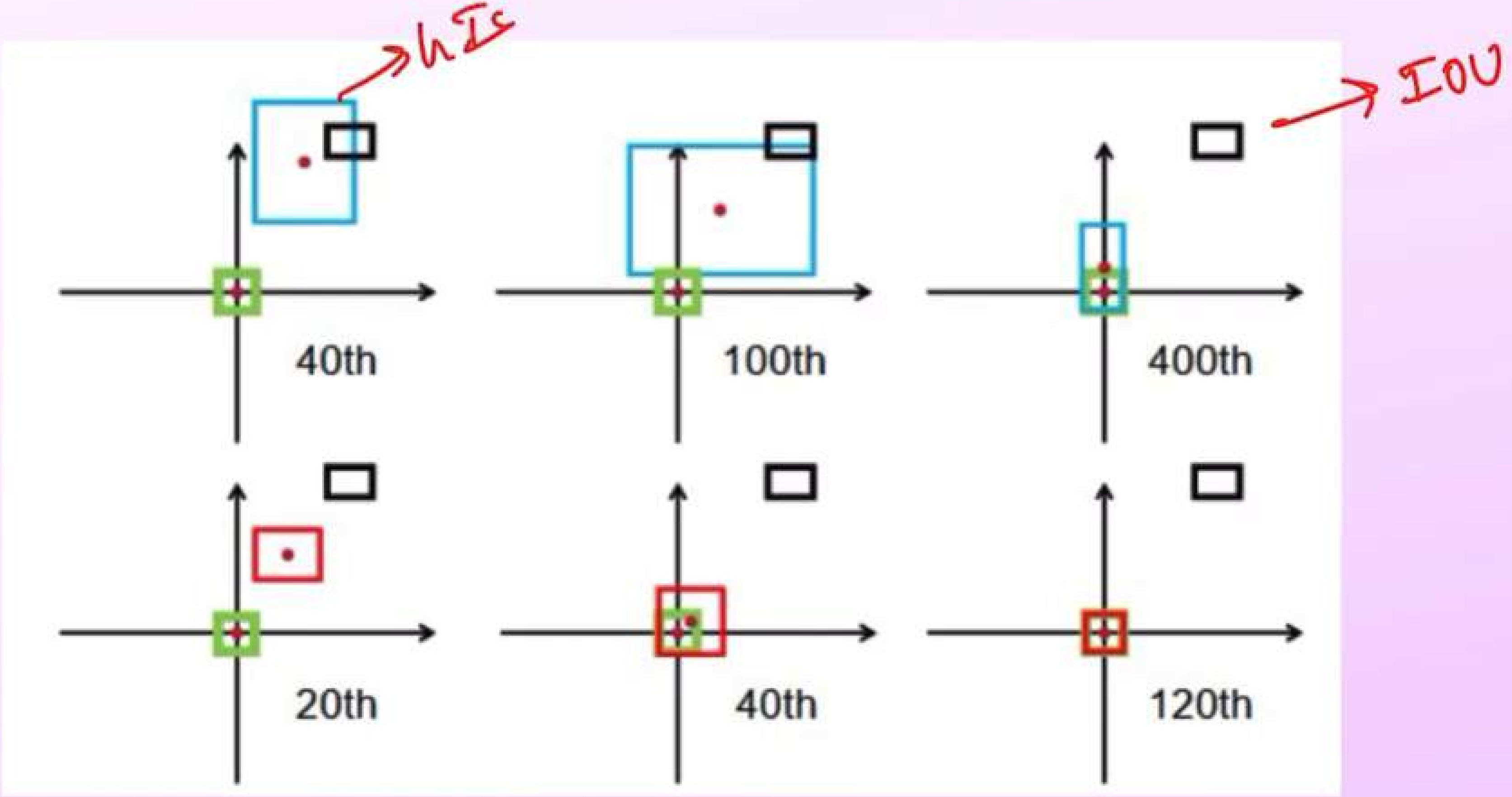
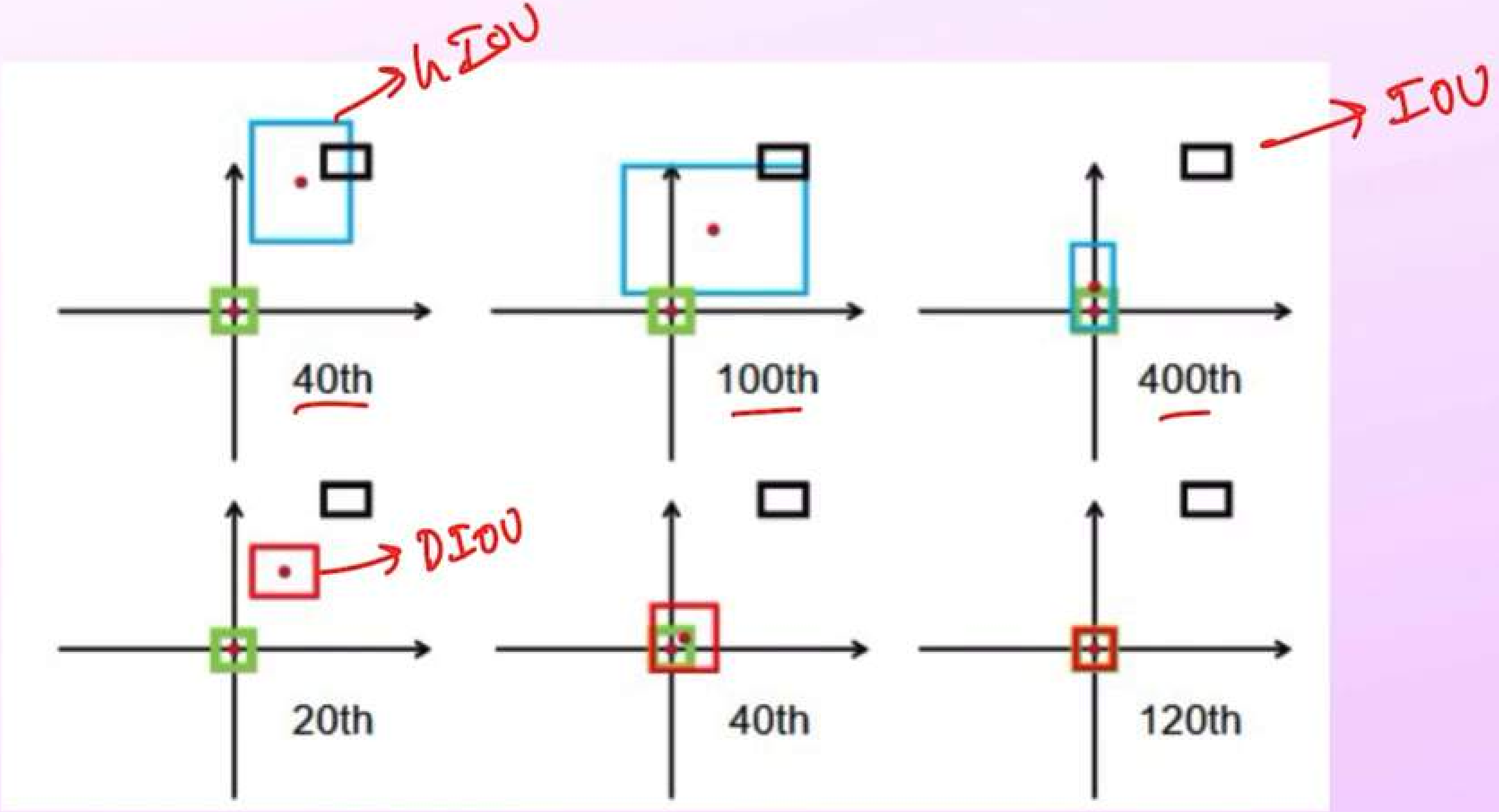


Distance IOU Loss



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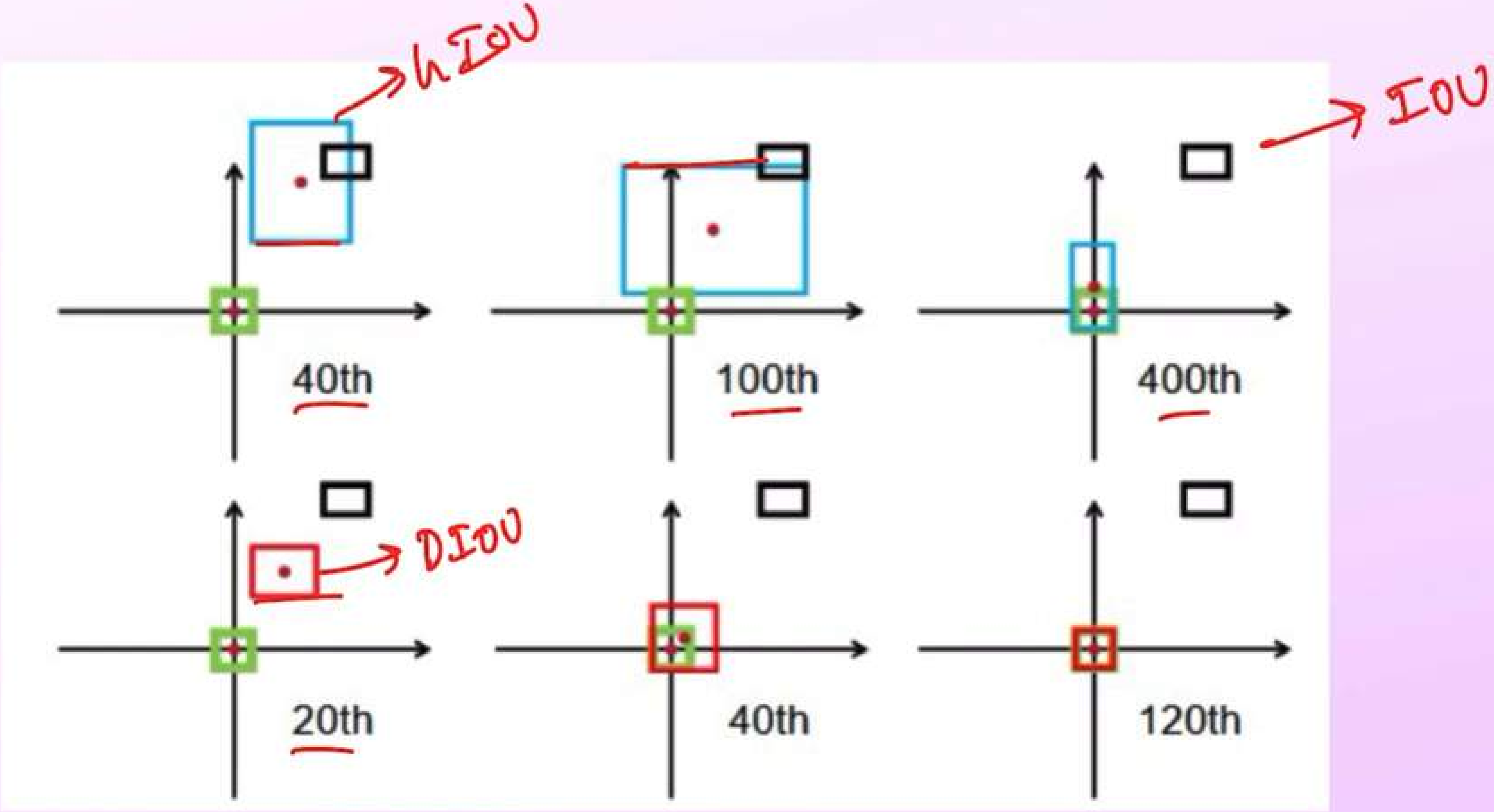

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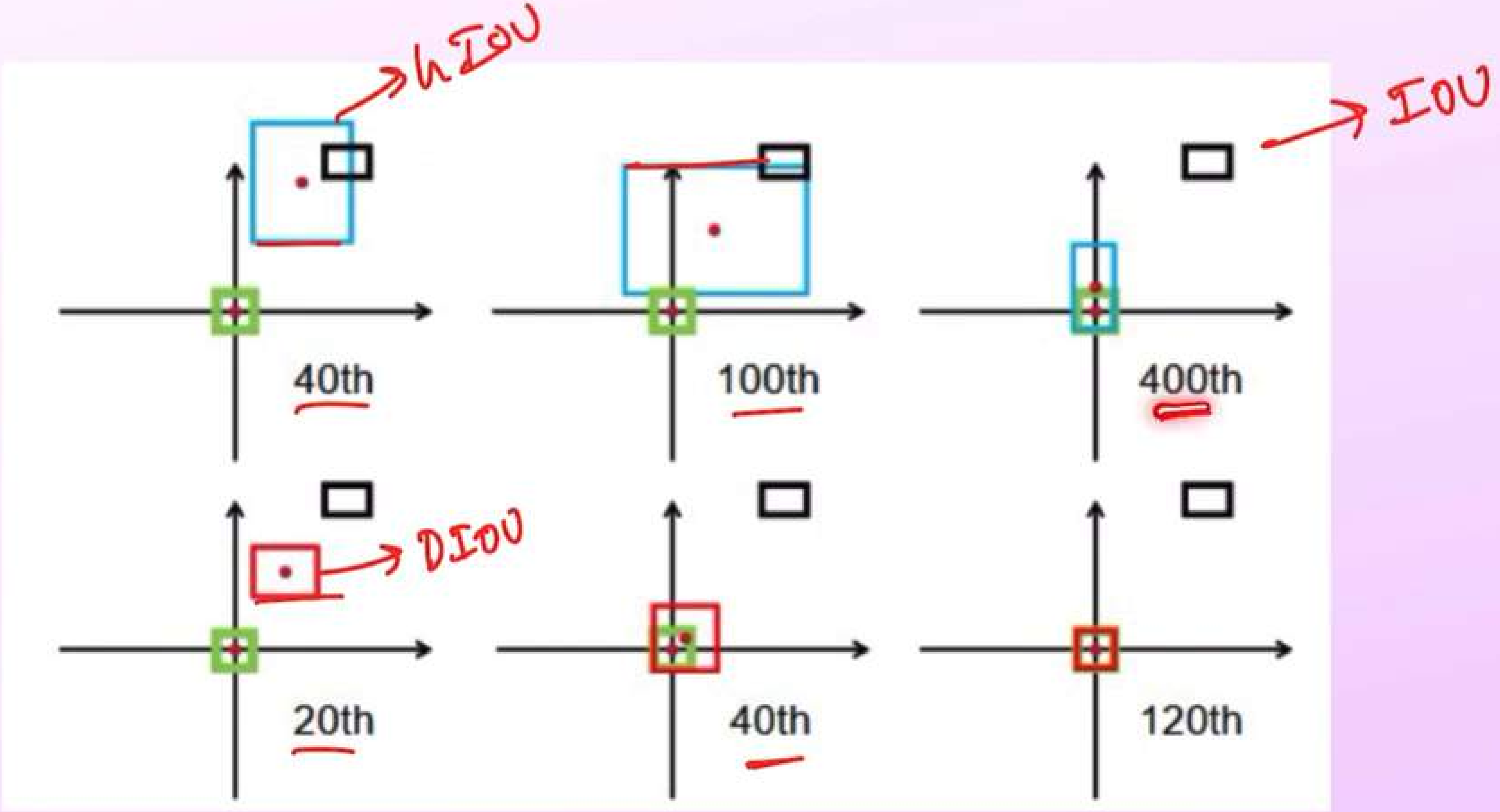

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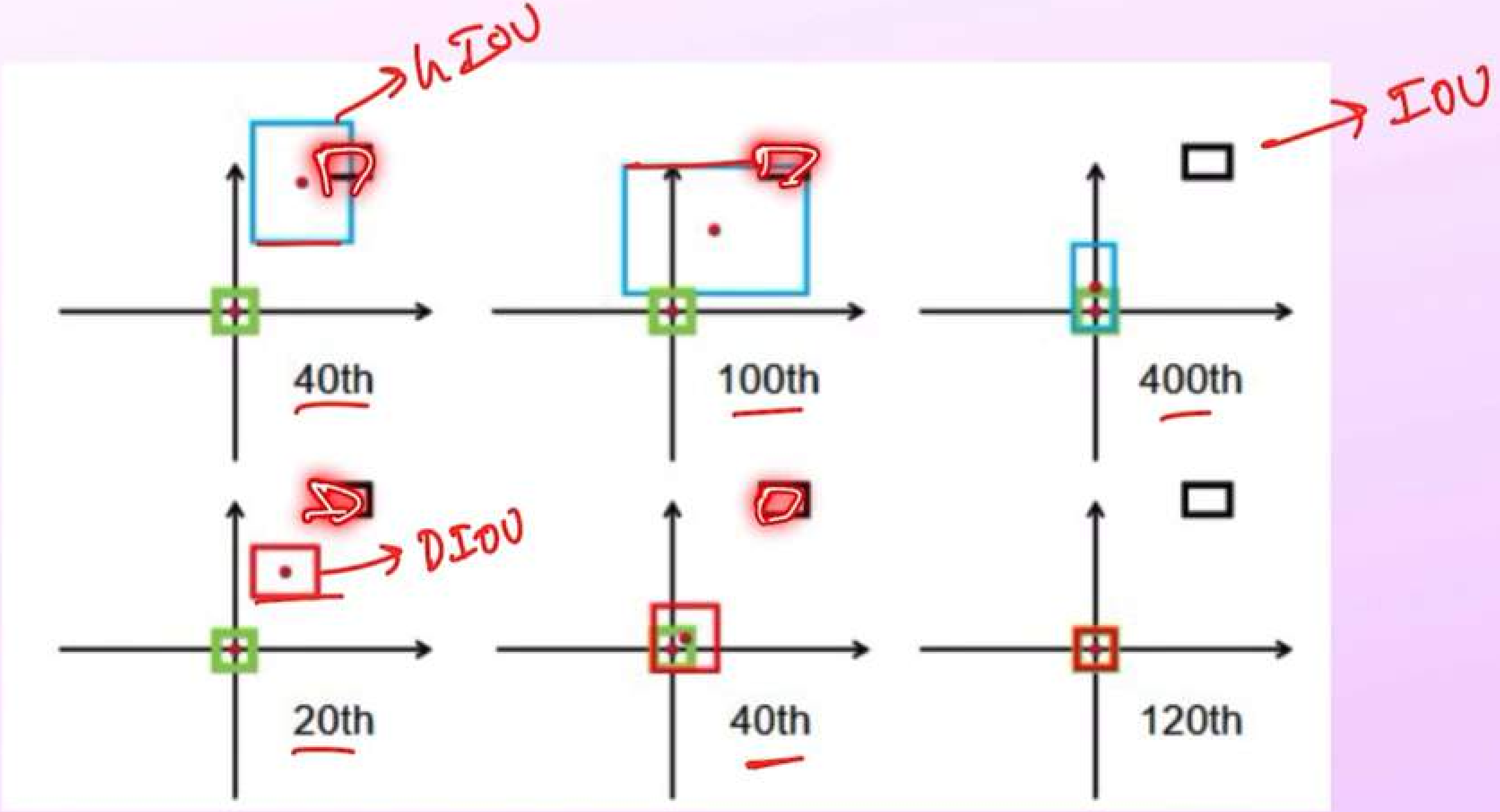

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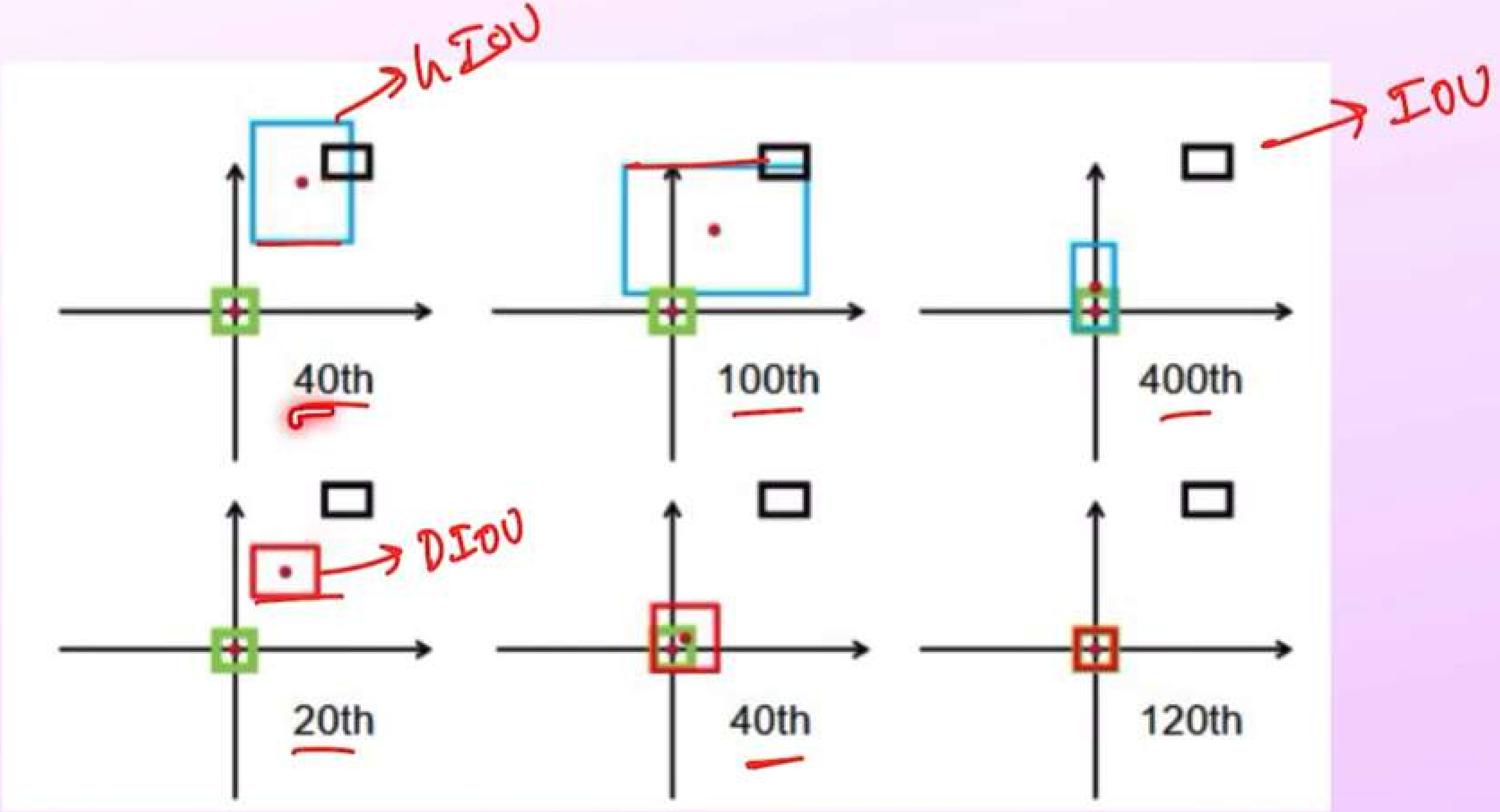

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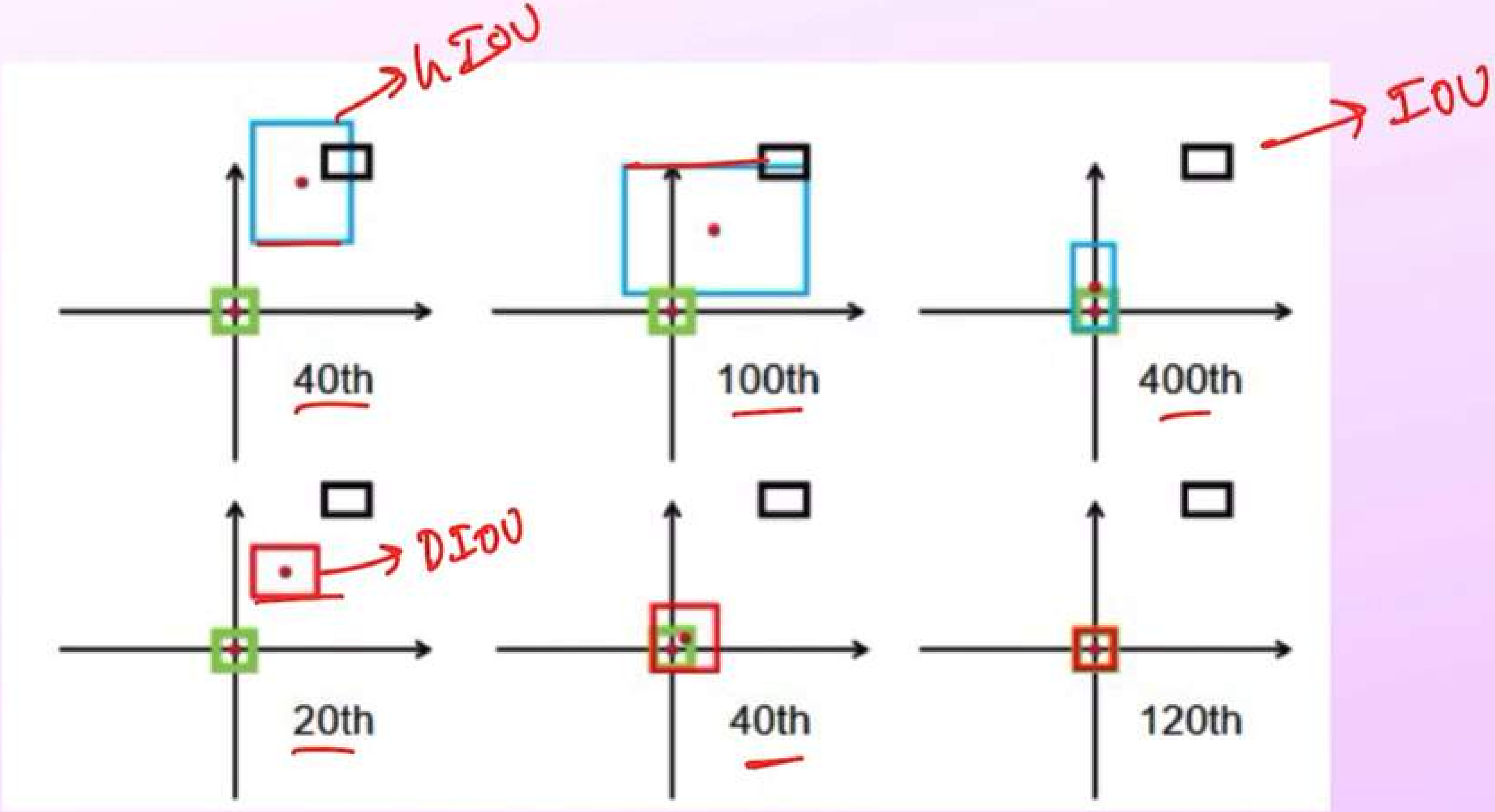

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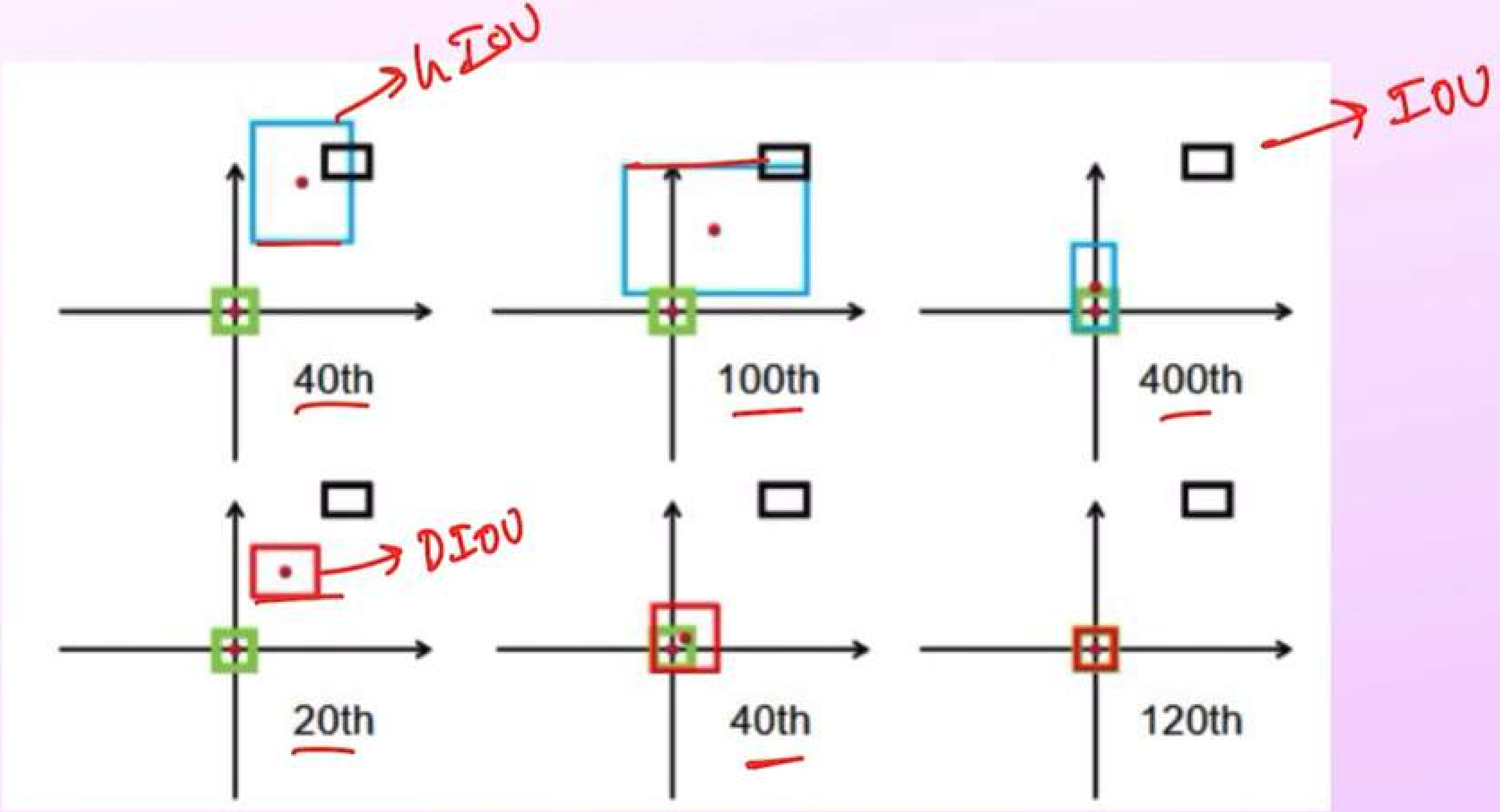

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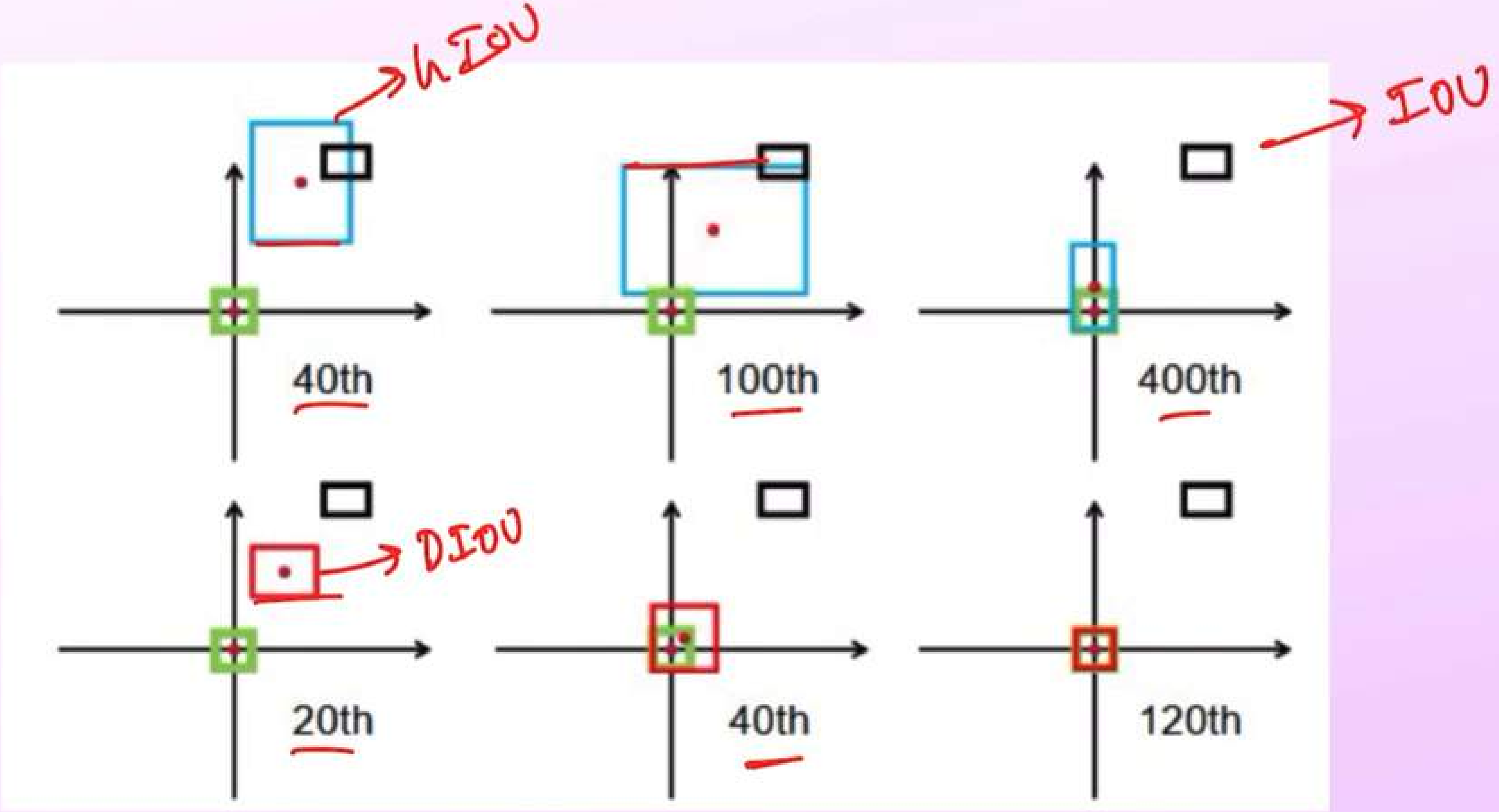

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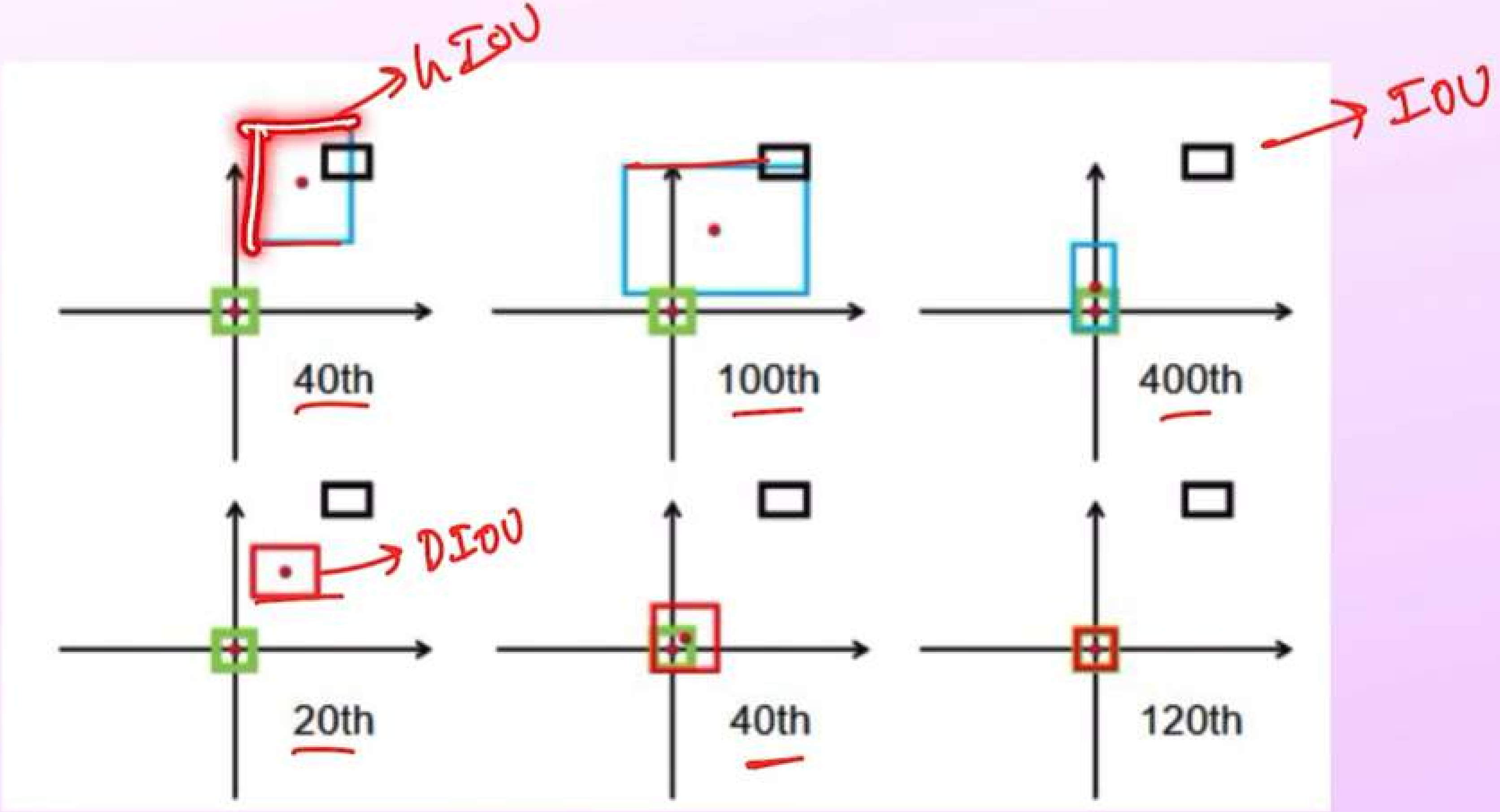

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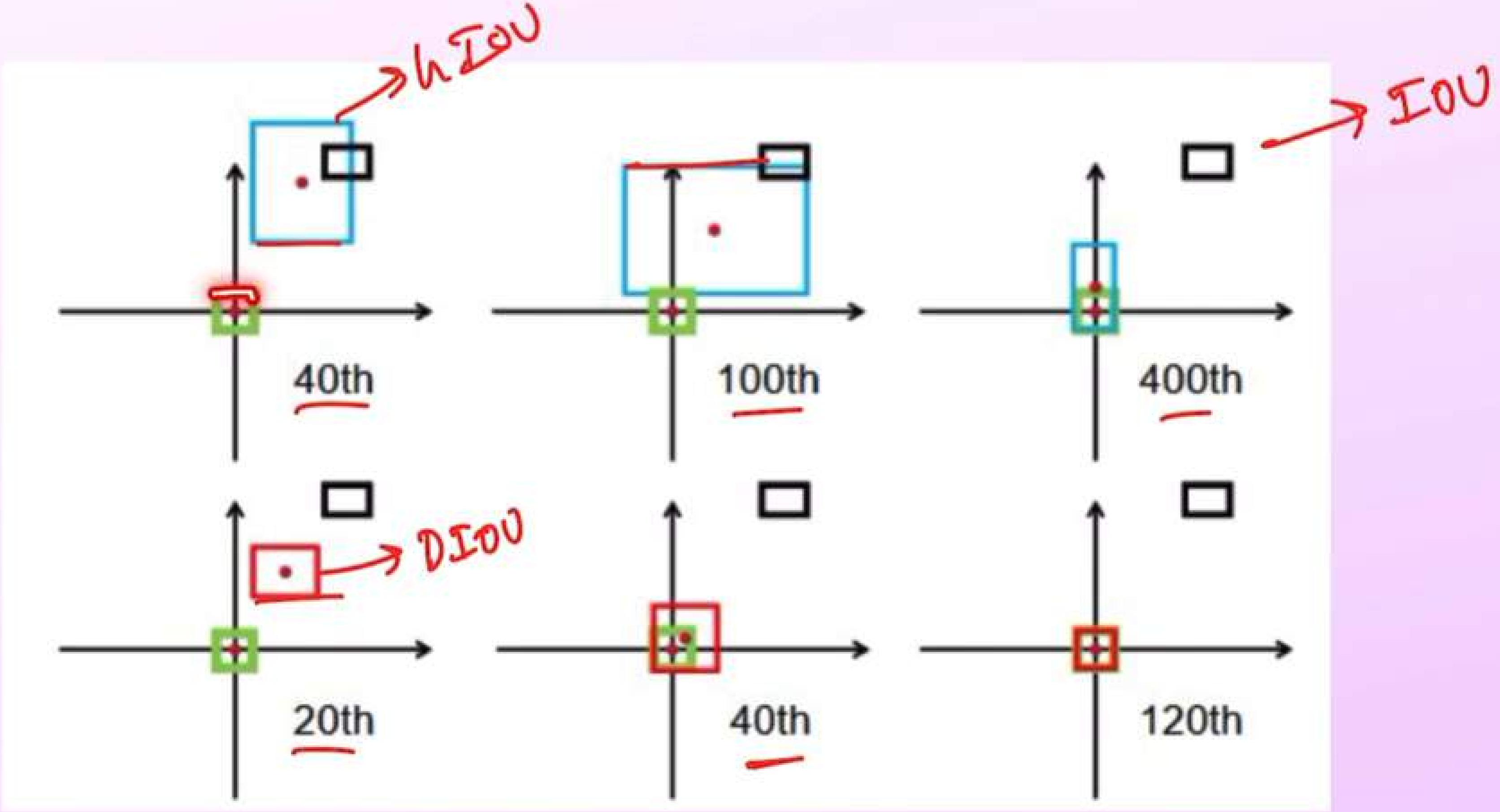

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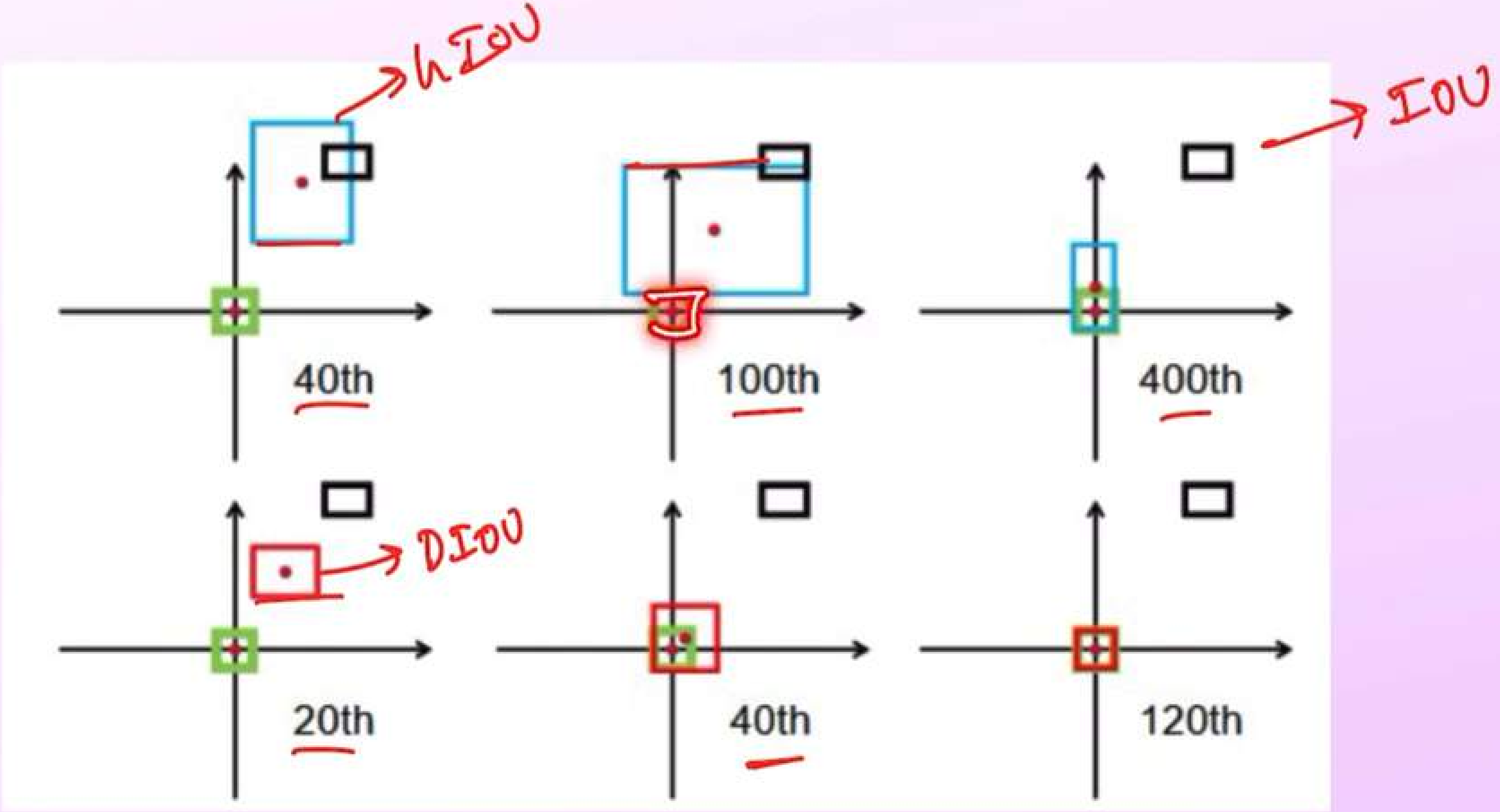

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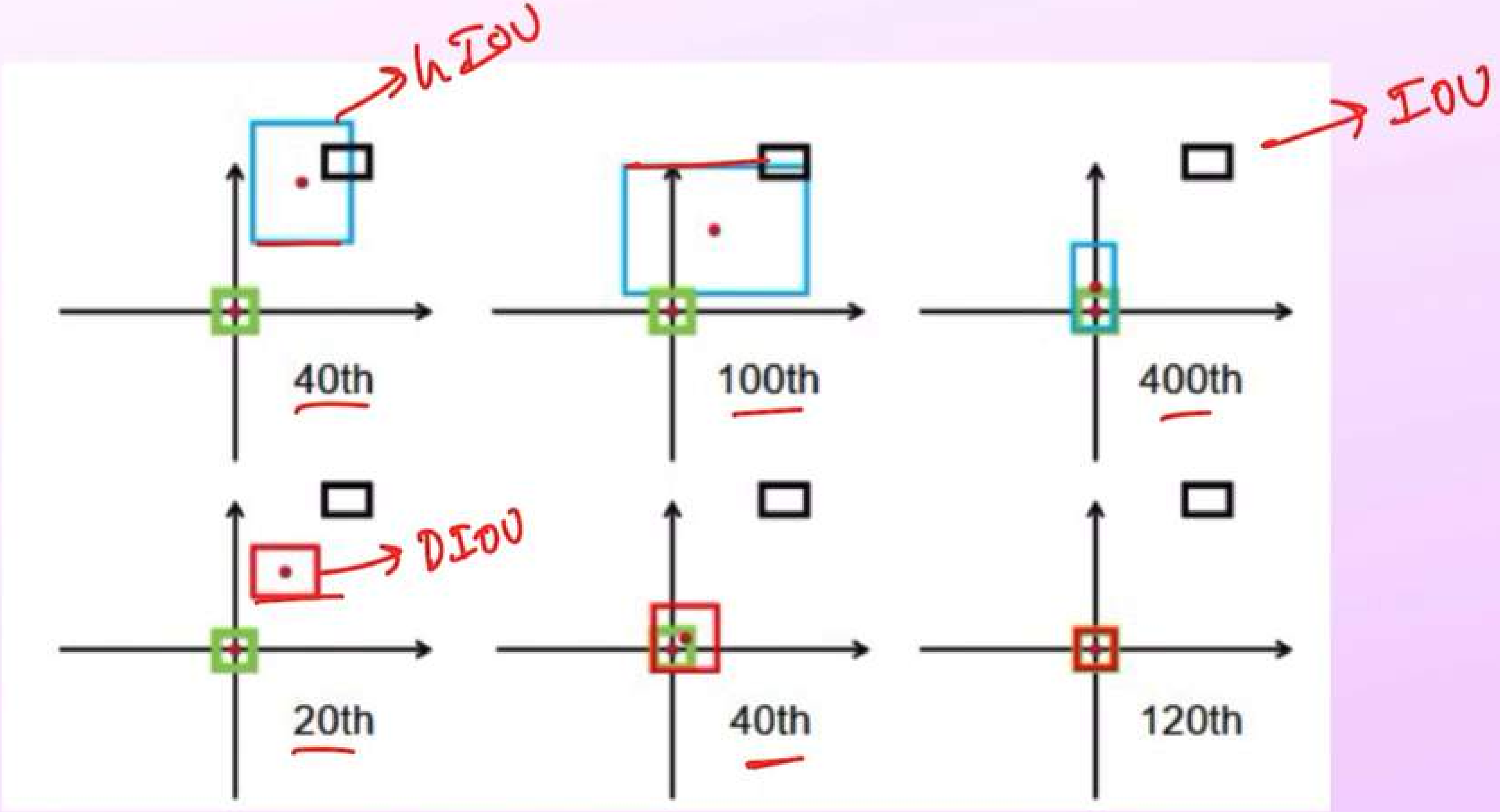

Complete IOU Loss

- Overlapping Area
- Distance between centers
- Aspect ratios

$$\mathcal{L}_{DIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2}$$

$$\mathcal{L}_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v$$

$$v = \frac{4}{\pi^2}(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h})^2$$

$$\alpha = \frac{v}{(1 - IoU) + v}$$

Complete IOU Loss

- Overlapping Area
- Distance between centers
- Aspect ratios

$$\mathcal{L}_{DIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2}$$

IOU

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Complete IOU Loss

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IOU Loss

Distance penalty

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Width Height

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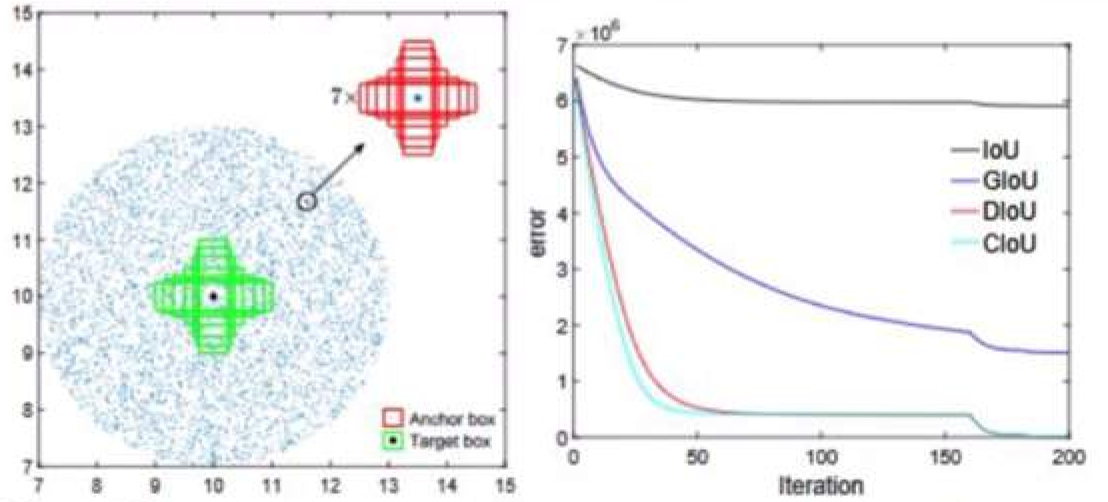

Figure 3: Simulation experiments: (a) 1,715,000 regression cases are adopted by considering different distances, scales and aspect ratios, (b) regression error sum (i.e., $\sum_n \mathbf{E}(t, n)$) curves of different loss functions at iteration t.

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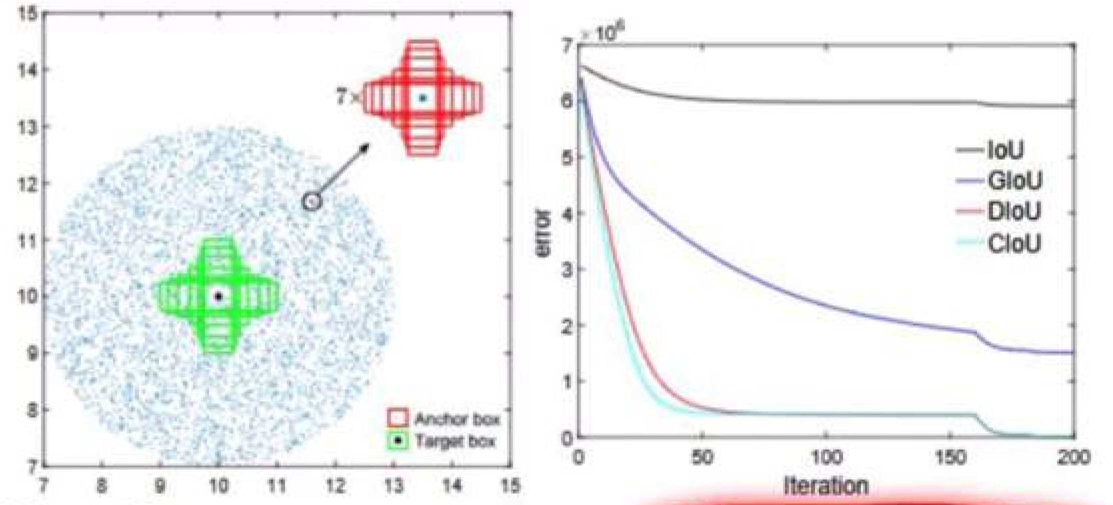

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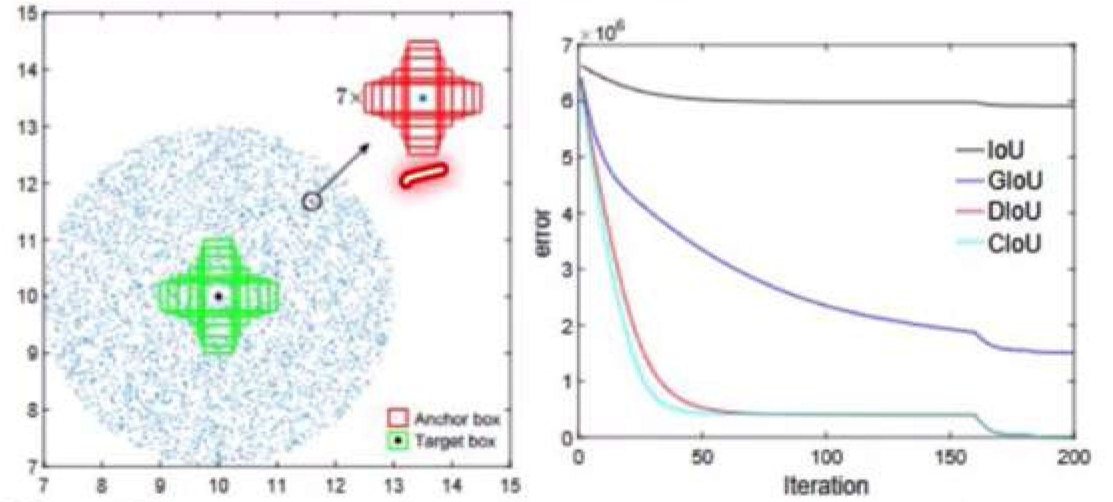

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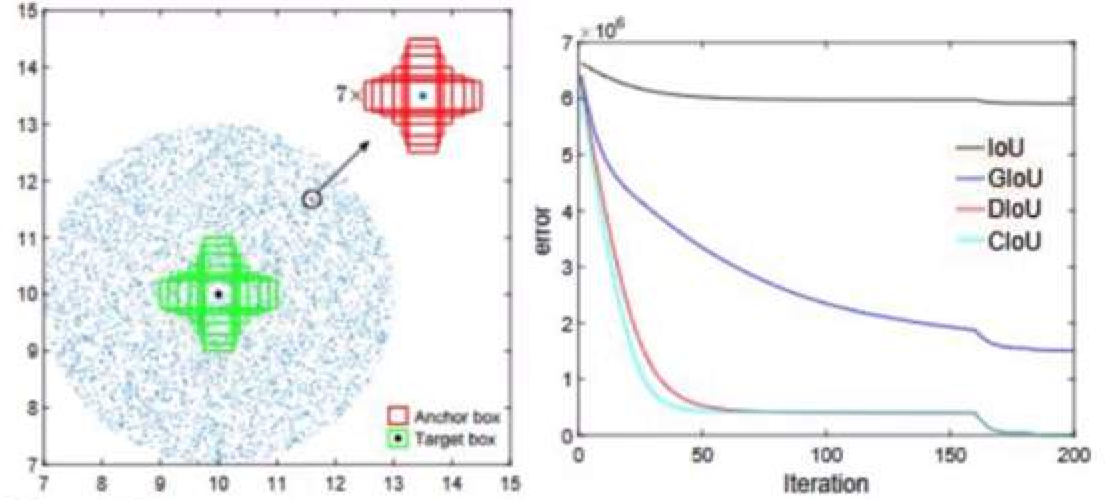

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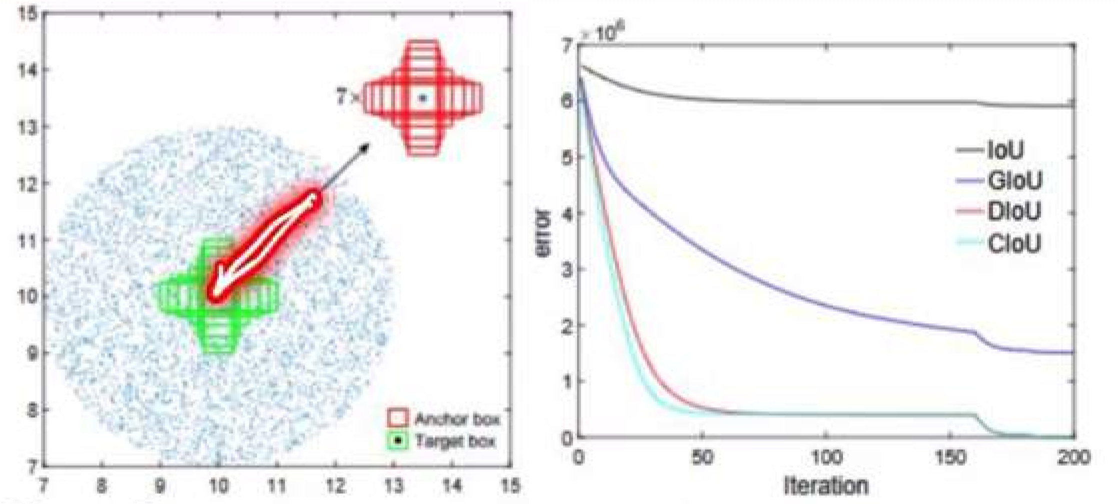

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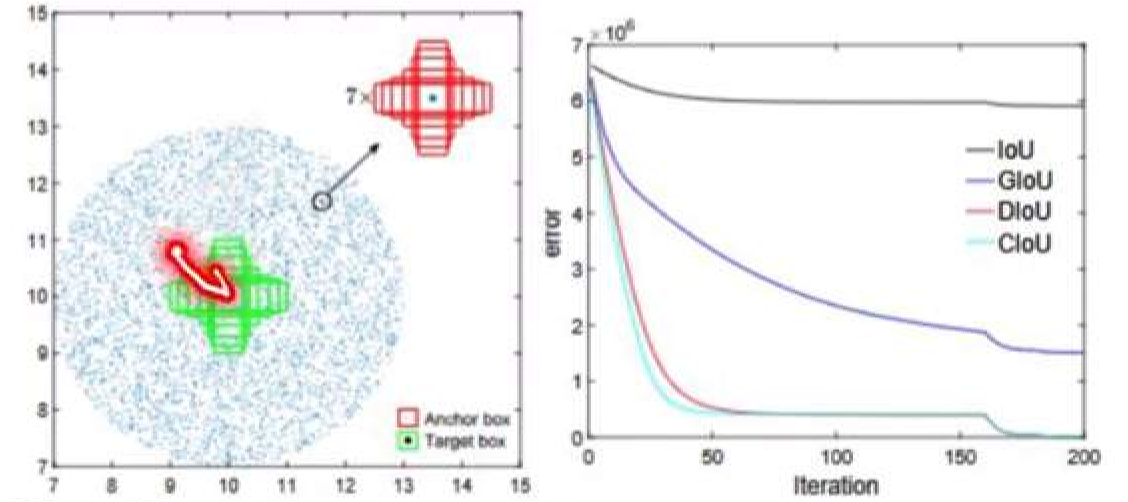

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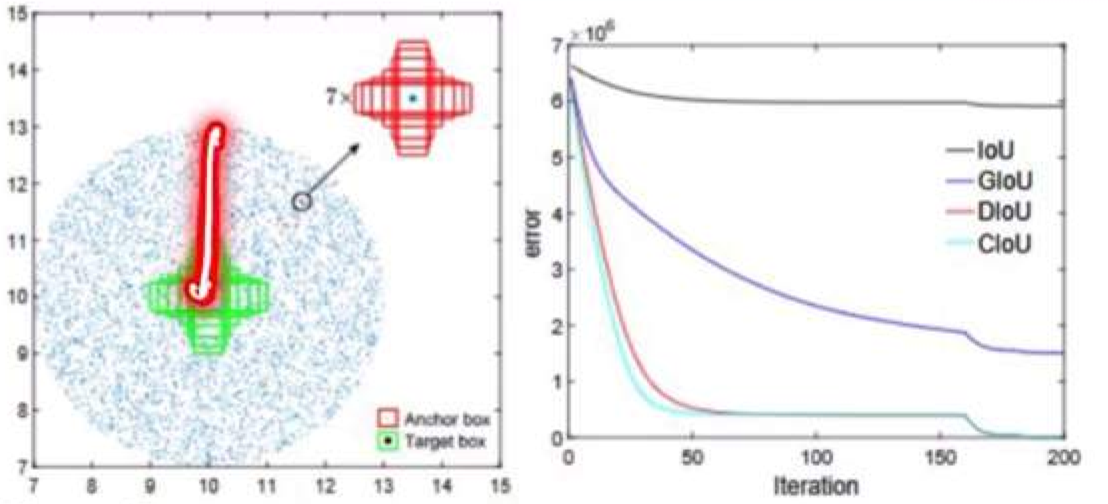

Figure 3: Simulation experiments: (a) 1,715,000 regression cases are adopted by considering different distances, scales and aspect ratios, (b) regression error sum (i.e., $\sum_n \mathbf{E}(t, n)$) curves of different loss functions at iteration t.

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- Distance between centers
- Aspect ratios

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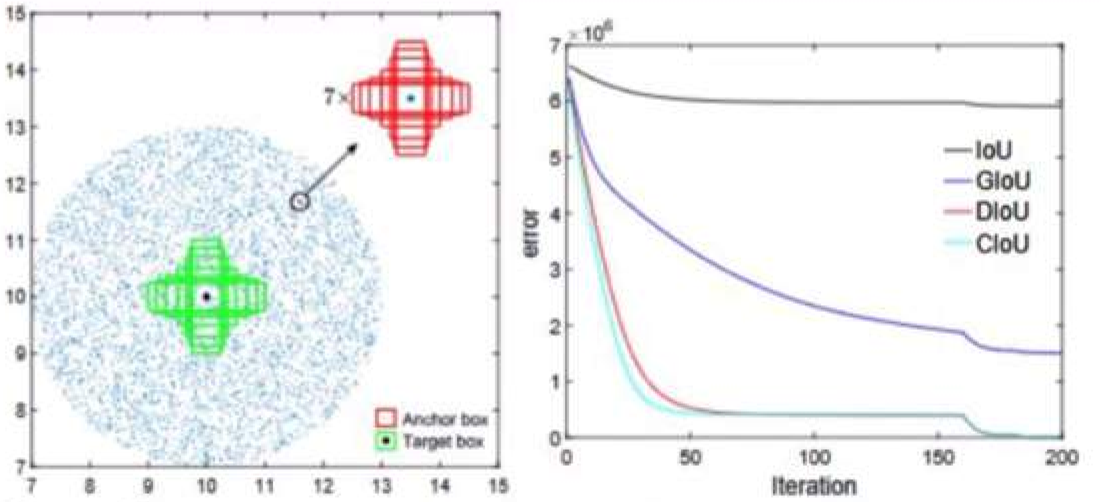

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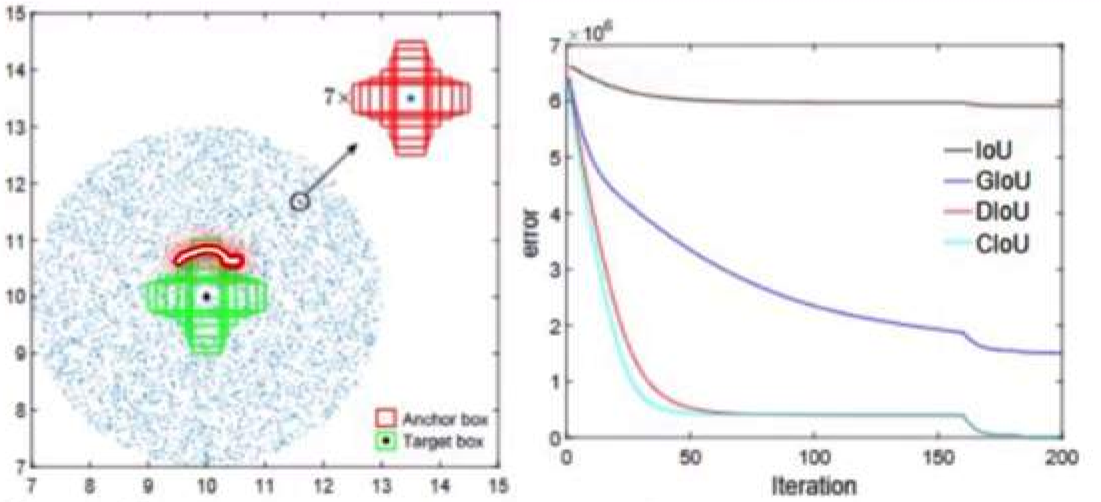

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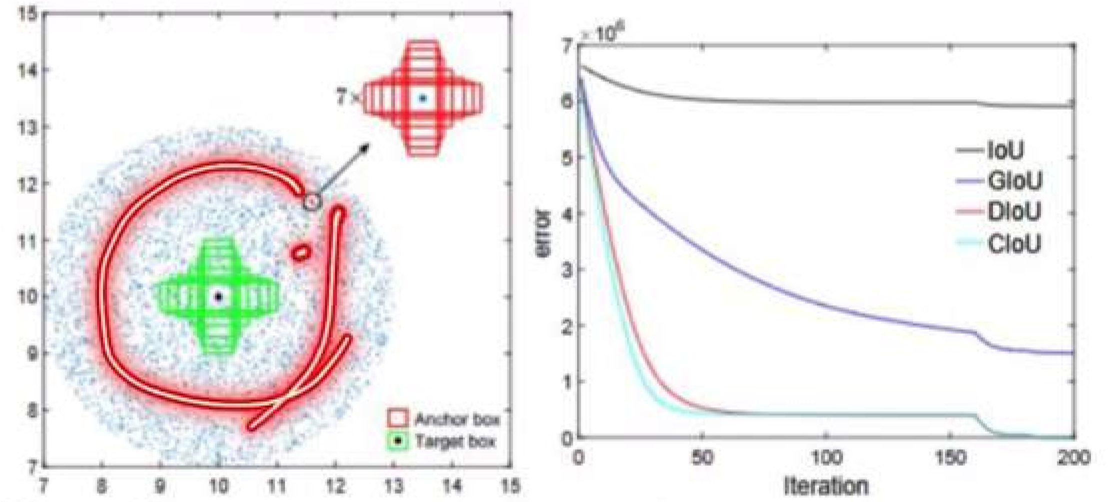

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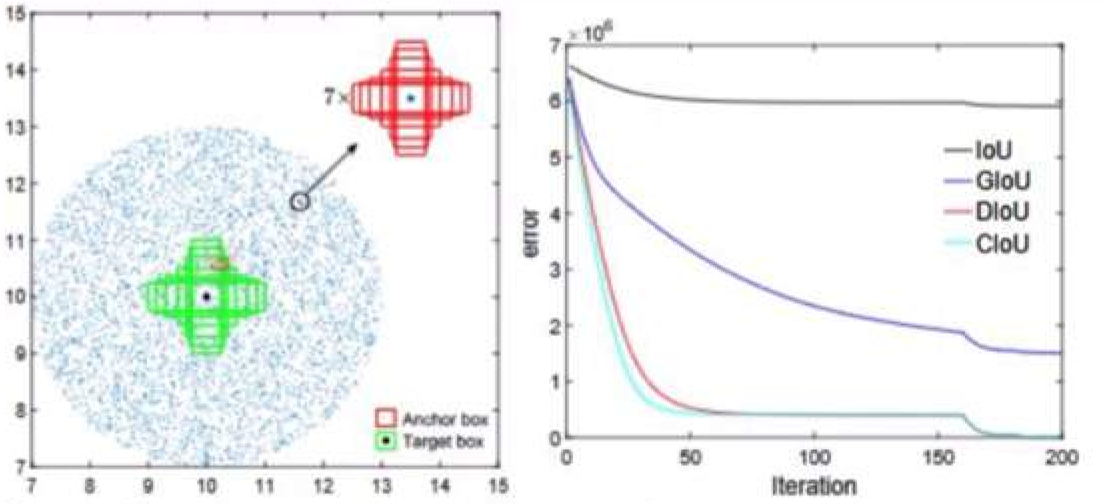

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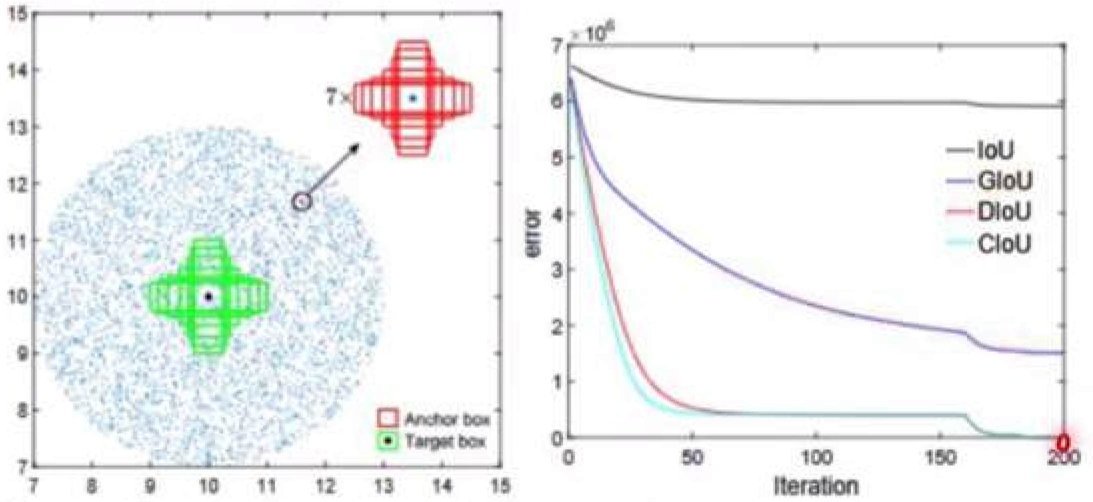

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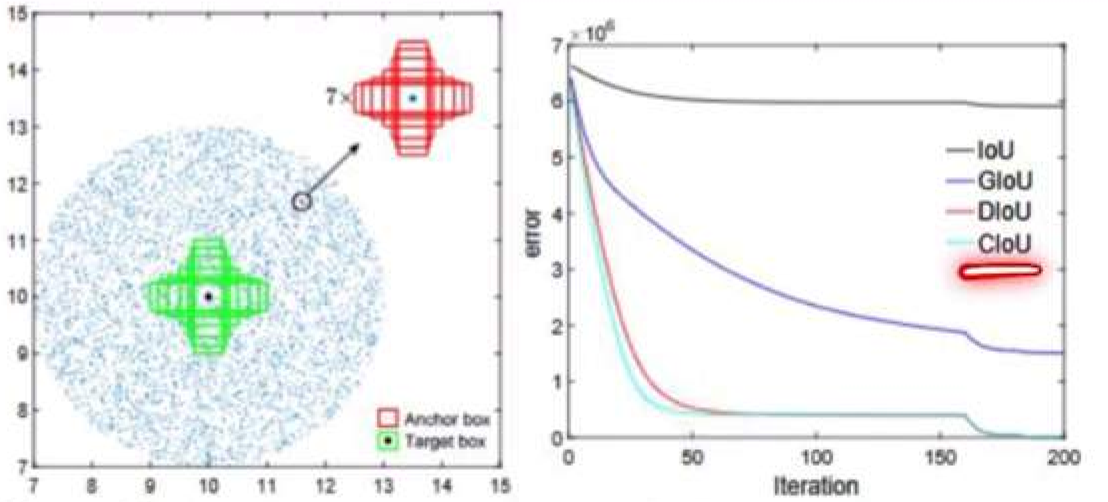

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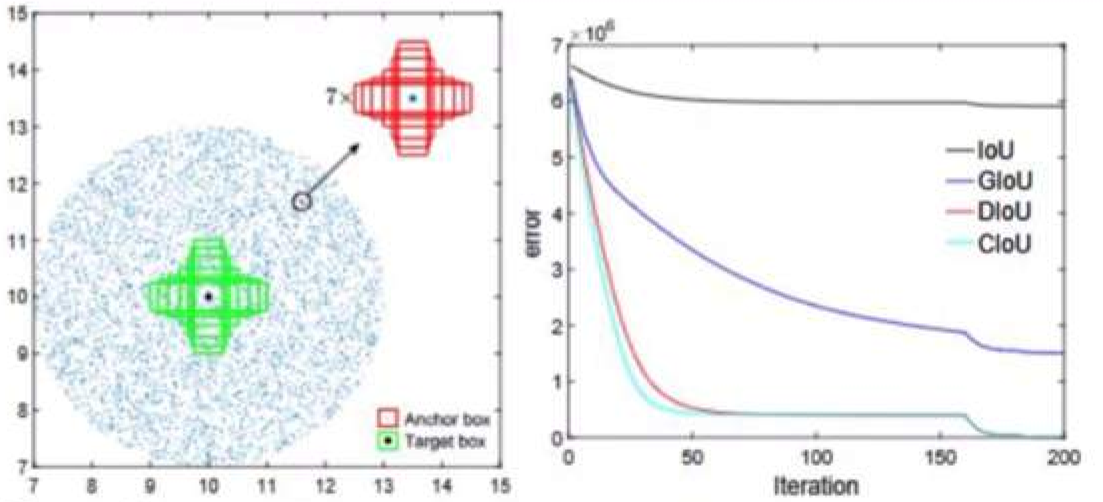

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Bag of Freebies (BoF)	• CutMix • Mosaic data augmentation • DropBlock • Class label smoothing	• CIoU-loss • Cross mini-Batch Normalization • DropBlock • Mosaic data augmentation • Self-Adversarial Training • Multiple anchors for a single ground truth • Cosine annealing scheduler • Optimal hyperparameters • Random training shapes
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