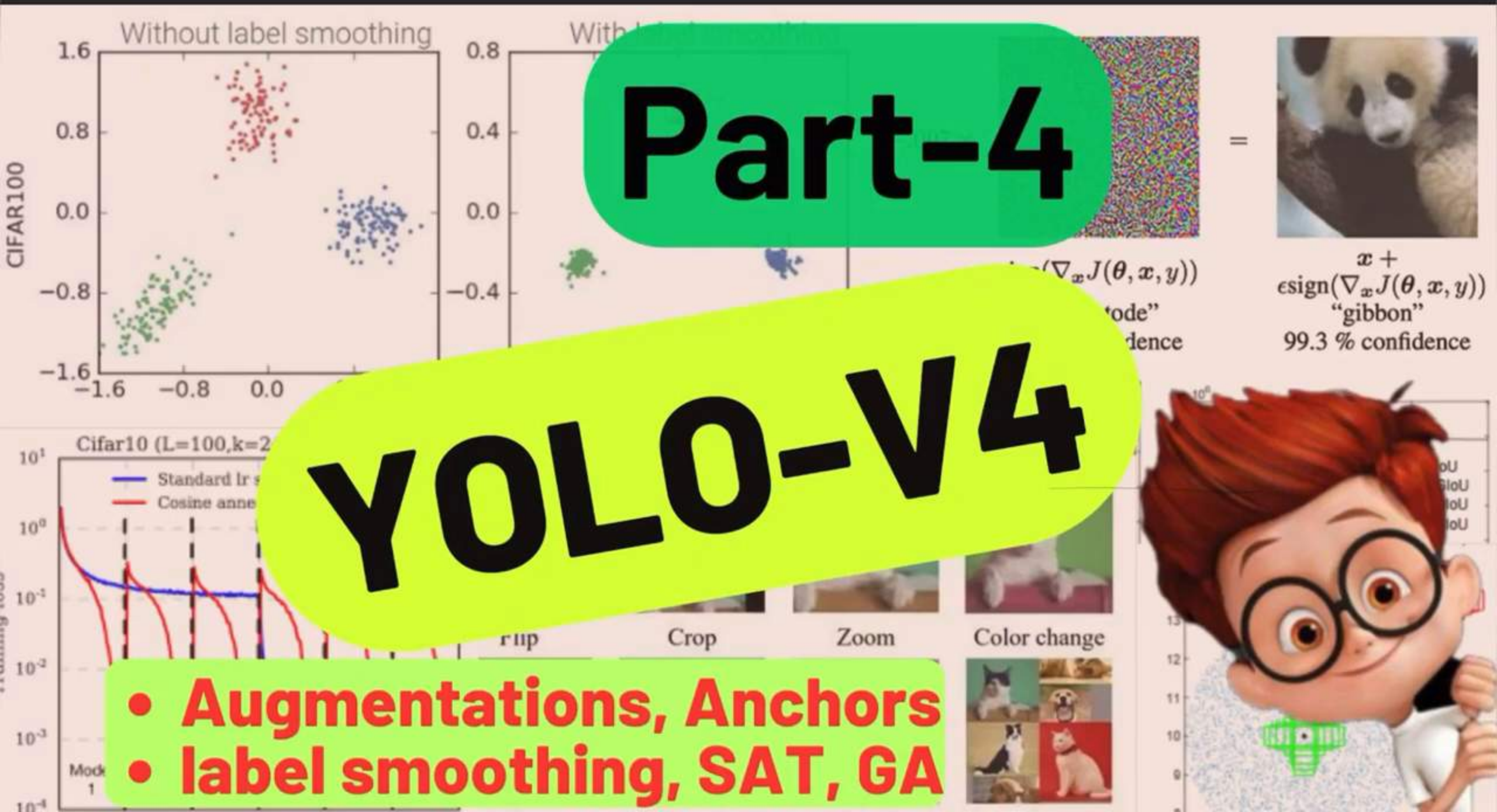
Without label smoothing
CIFAR100
Part-4
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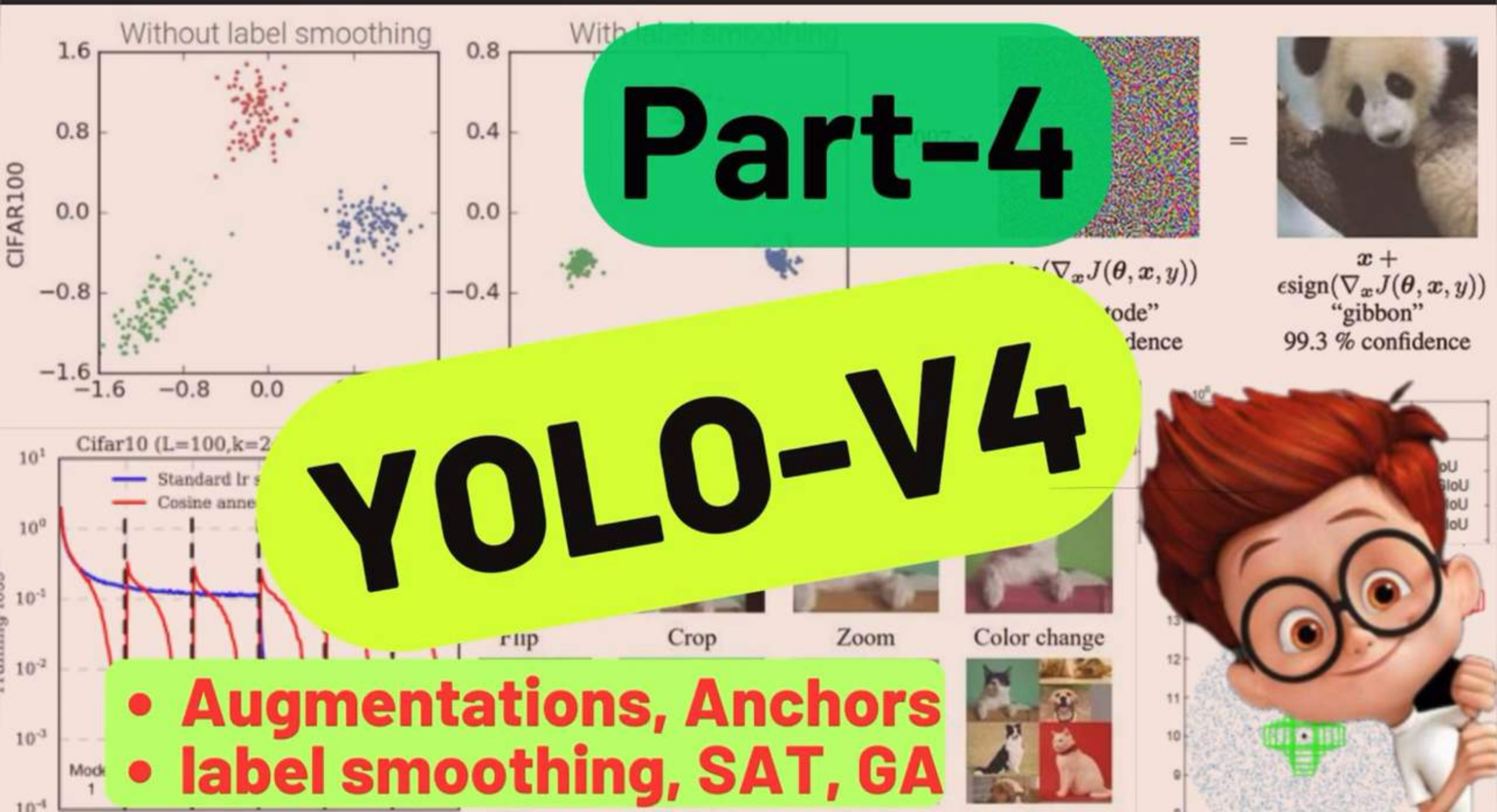
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BoF & BoS - covered

	Backbone	Detector
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
Bag of Specials (BoS)	• Mish activation • Cross-stage partial connections (CSP) • Multi-input weighted residual connections (MiWRC)	• Mish activation • SPP-block • SAM-block • PAN path-aggregation block • DIoU-NMS

Data Augmentations

- Methods to increase data
  - Volume
  - Variations

- Methods:
  - Photometrics Distortions:
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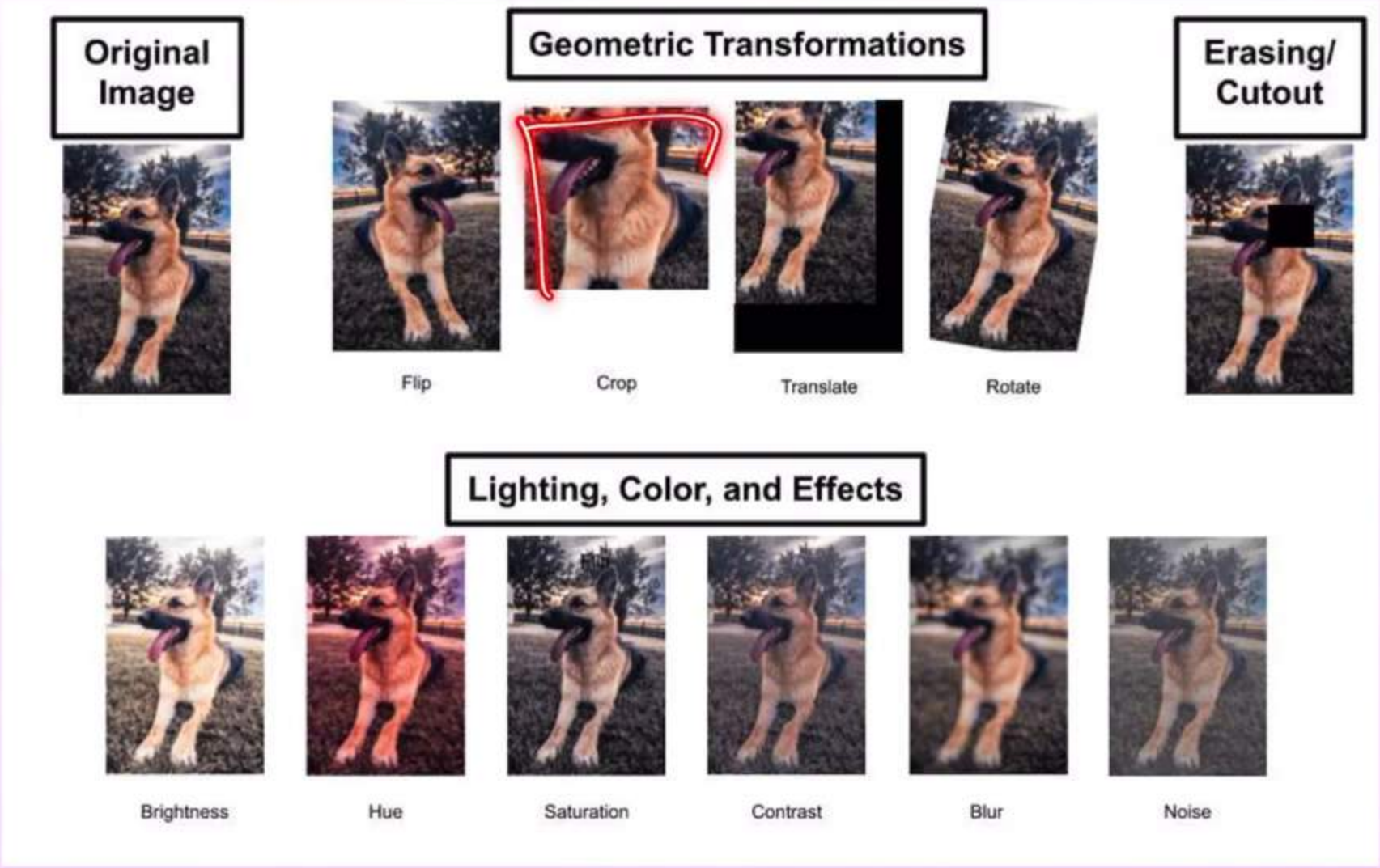

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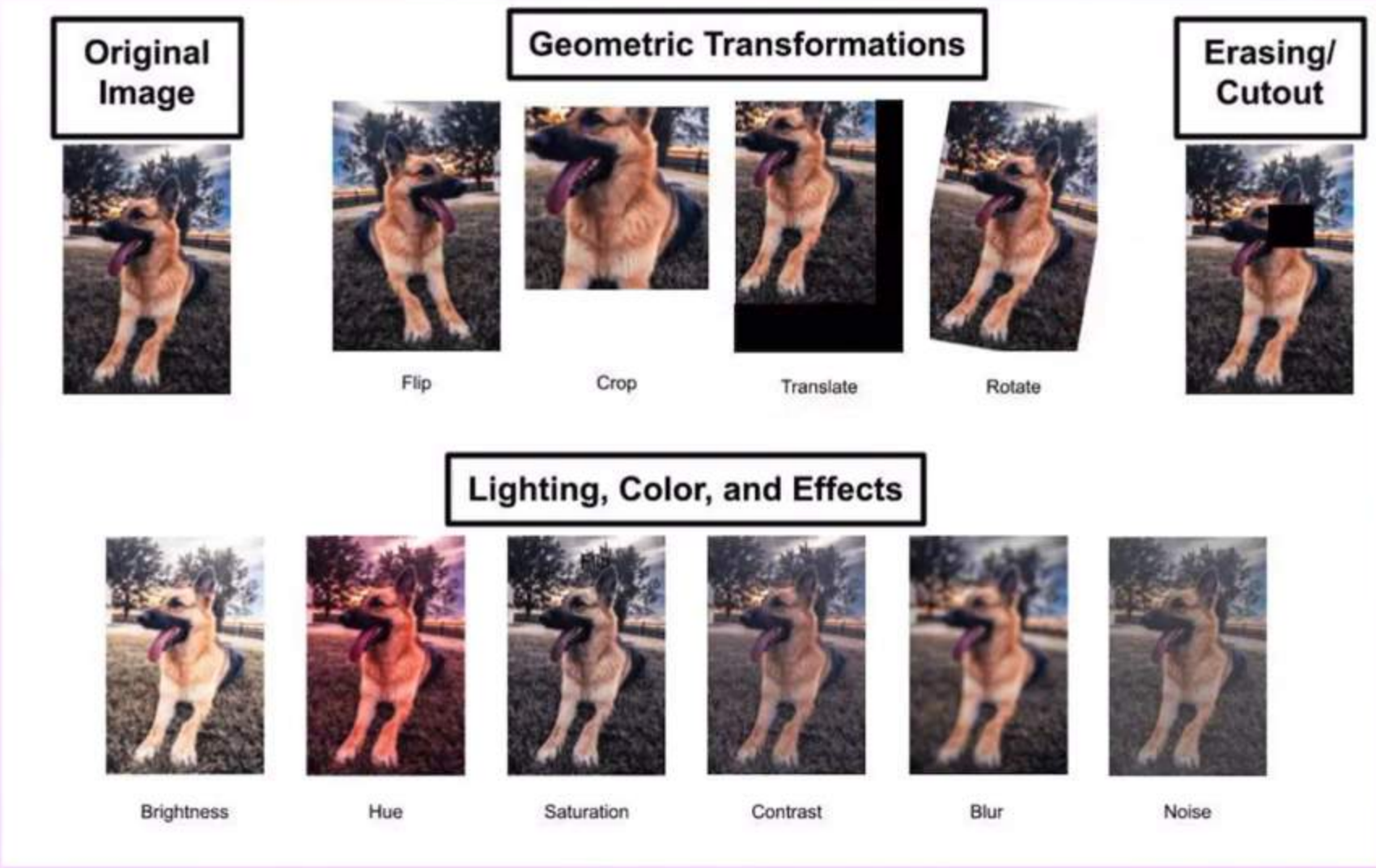

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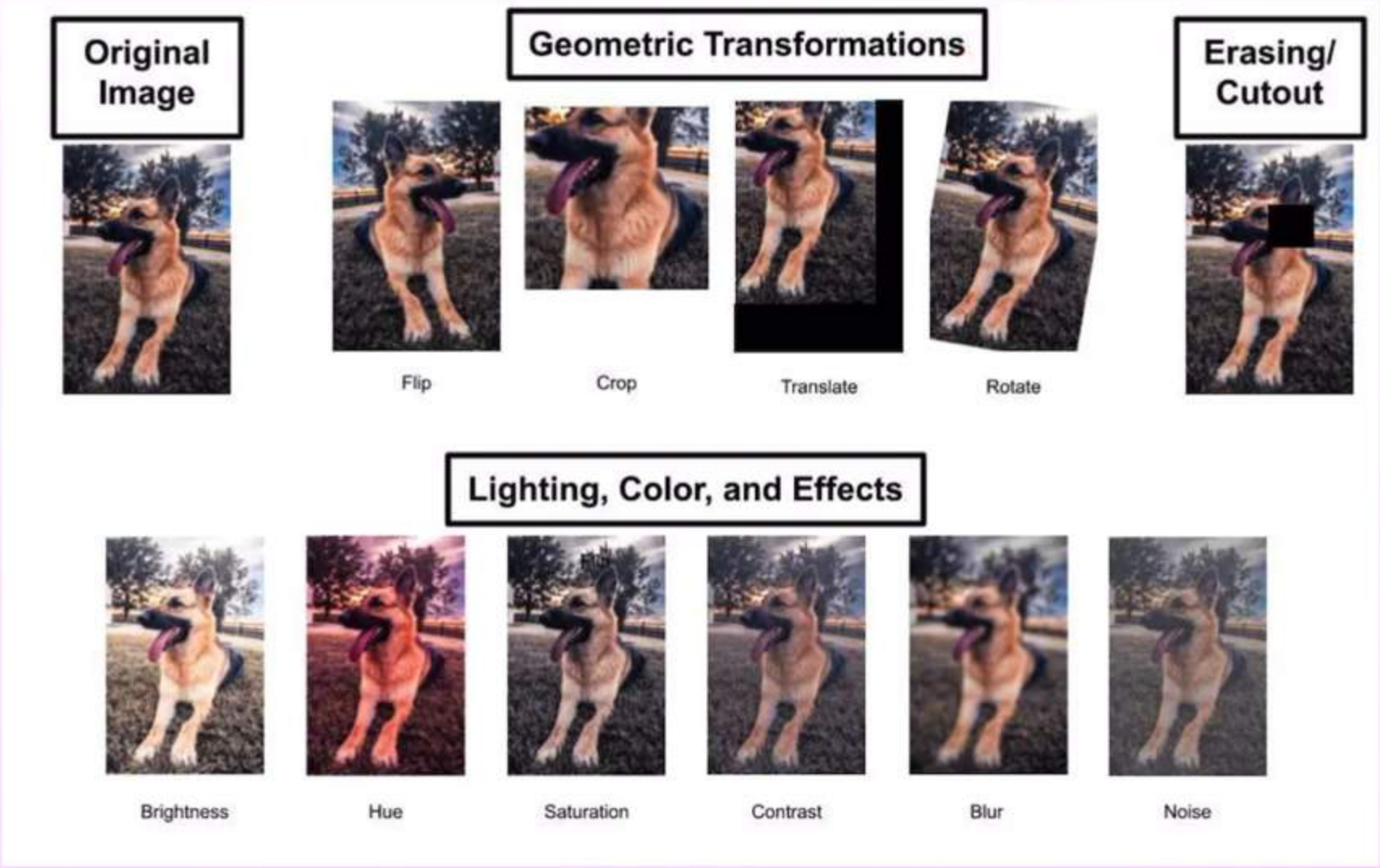

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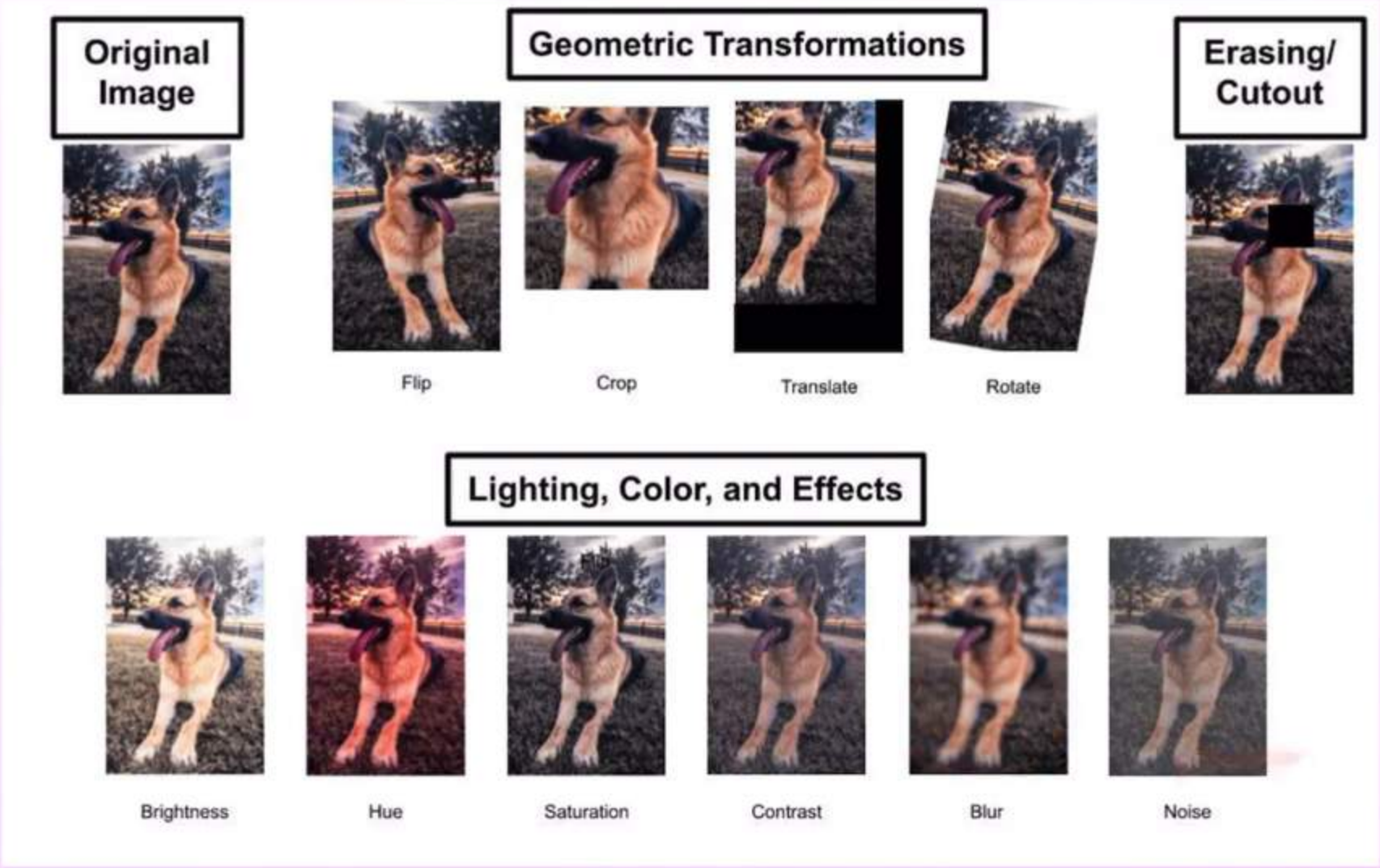

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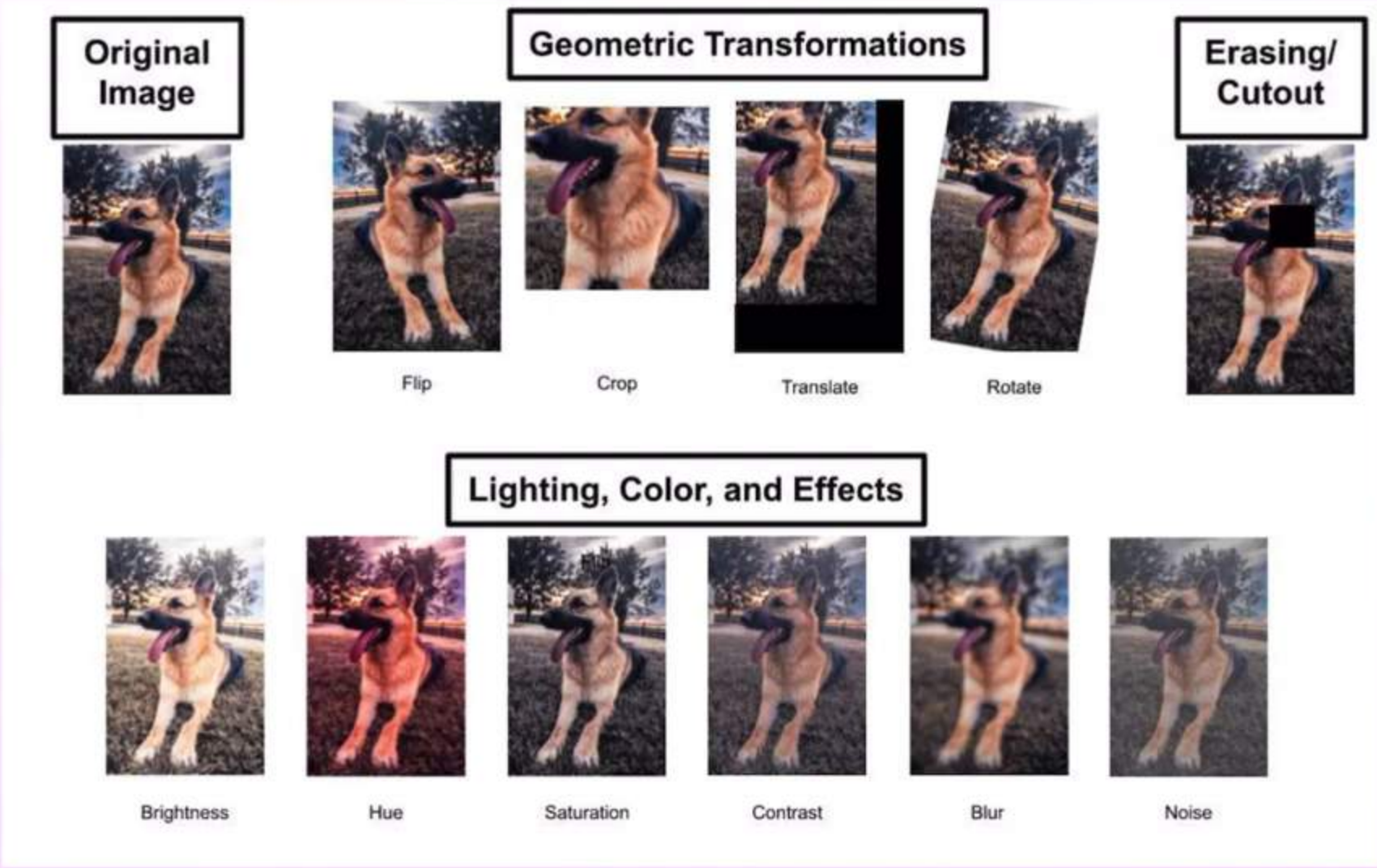

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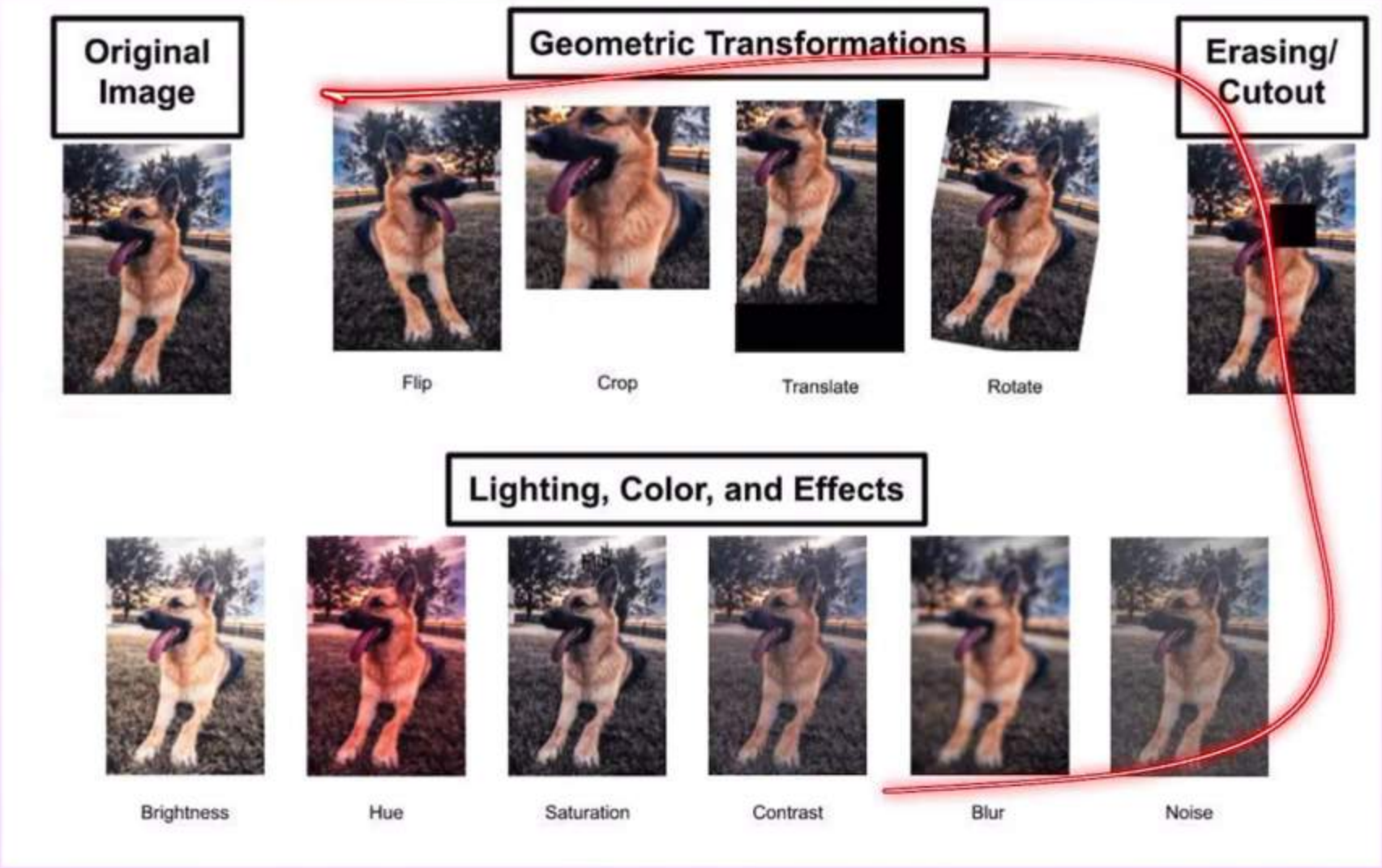

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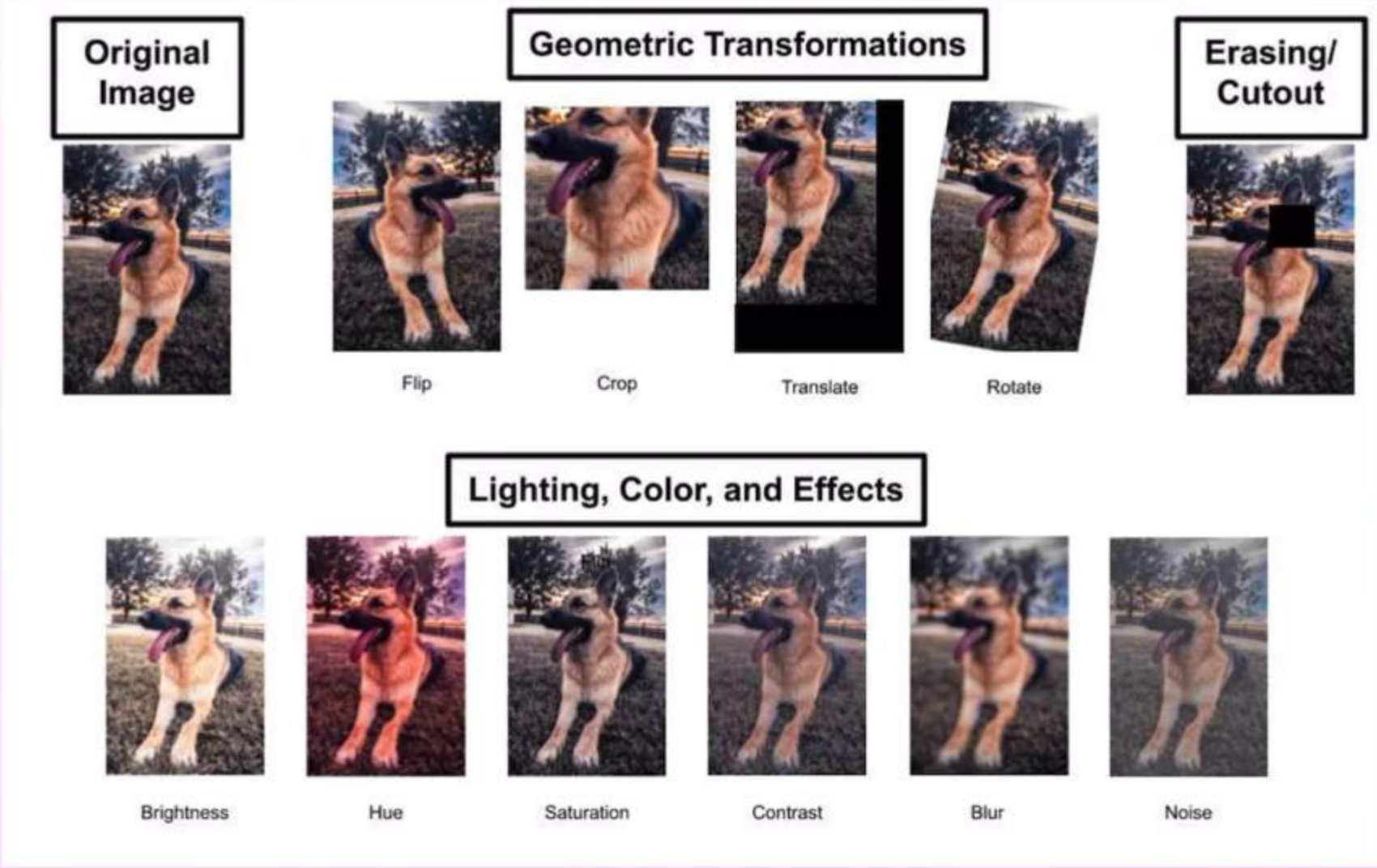

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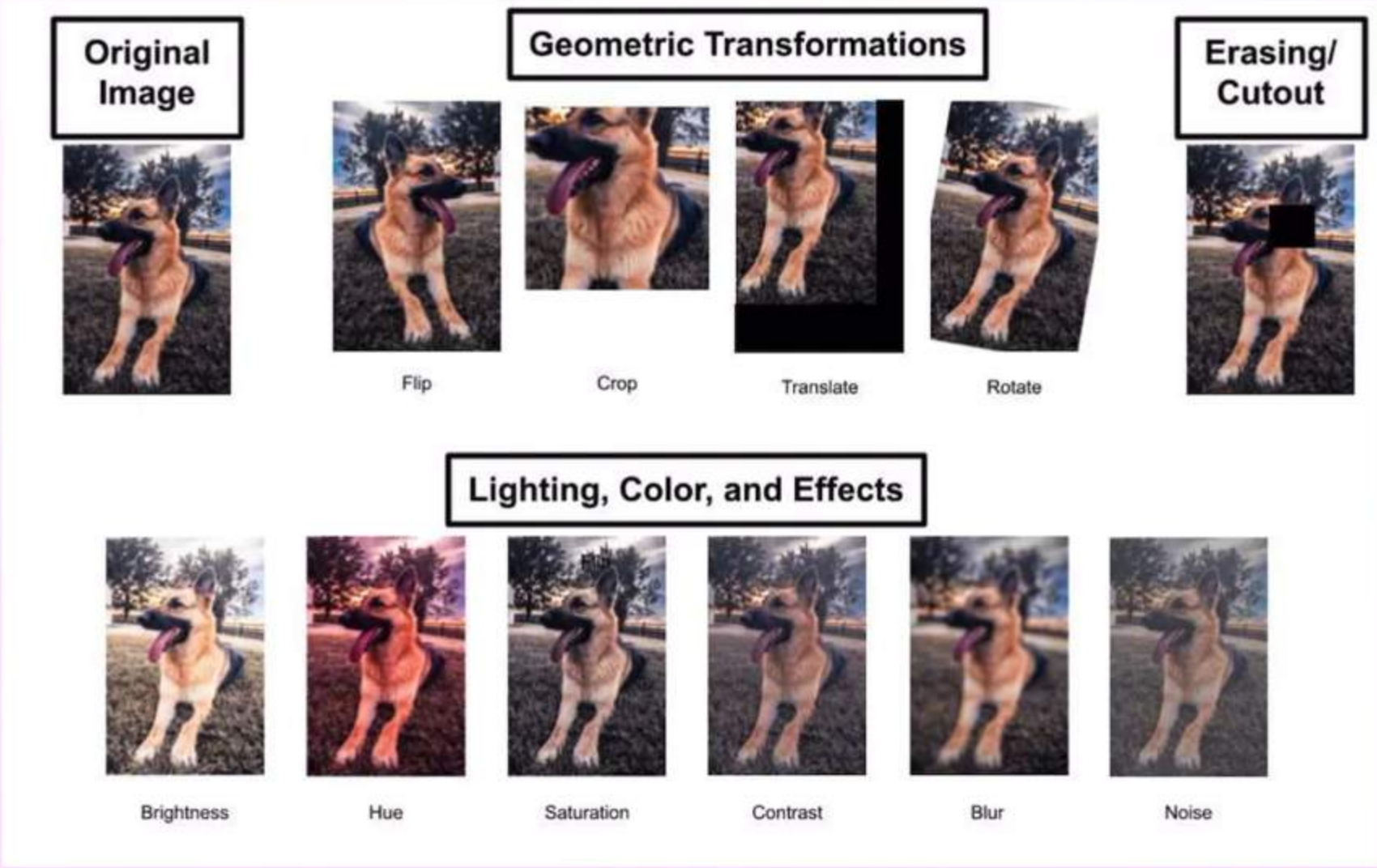

Mixup Augmentation

$$\begin{aligned} \hat{x} &= \lambda x_i + (1-\lambda)x_j, \\ \hat{y} &= \lambda y_i + (1-\lambda)y_j, \end{aligned}$$

where $\lambda \in [0, 1]$ is a random number

x0.52

x0.48

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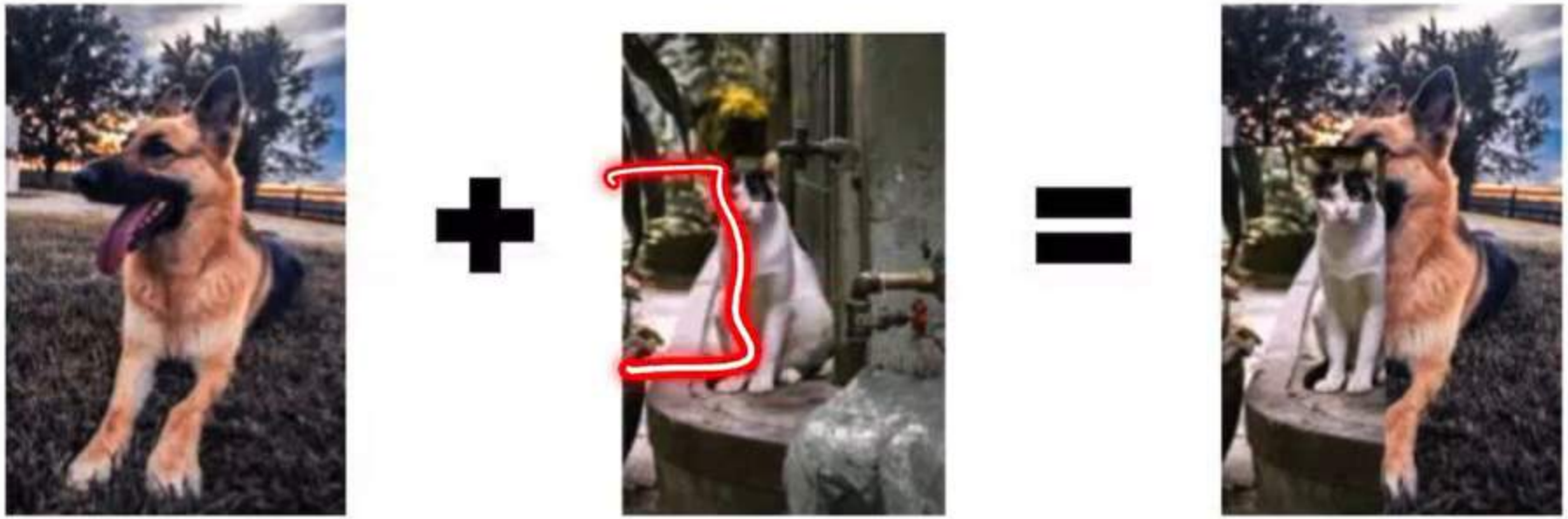

Cutmix Augmentation

Cutmix Augmentation

Mosaic Augmentation

aug_-319215602_0_-238783579.jpg

aug_-1271888501_0_-749611674.jpg

aug_1462167959_0_-1659206634.jpg

aug_1474493600_0_-45389312.jpg

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Mosaic Augmentation

4 images

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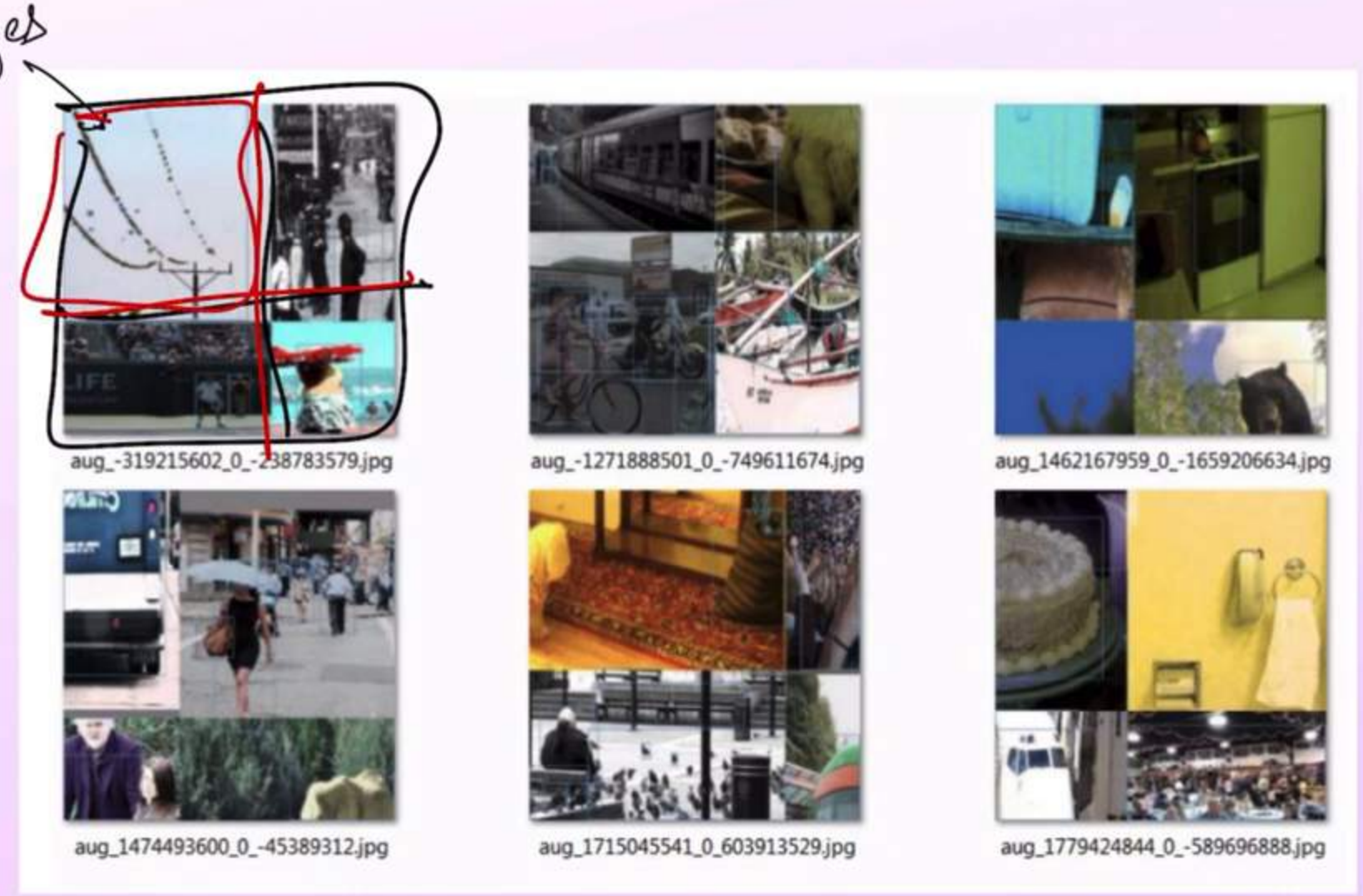

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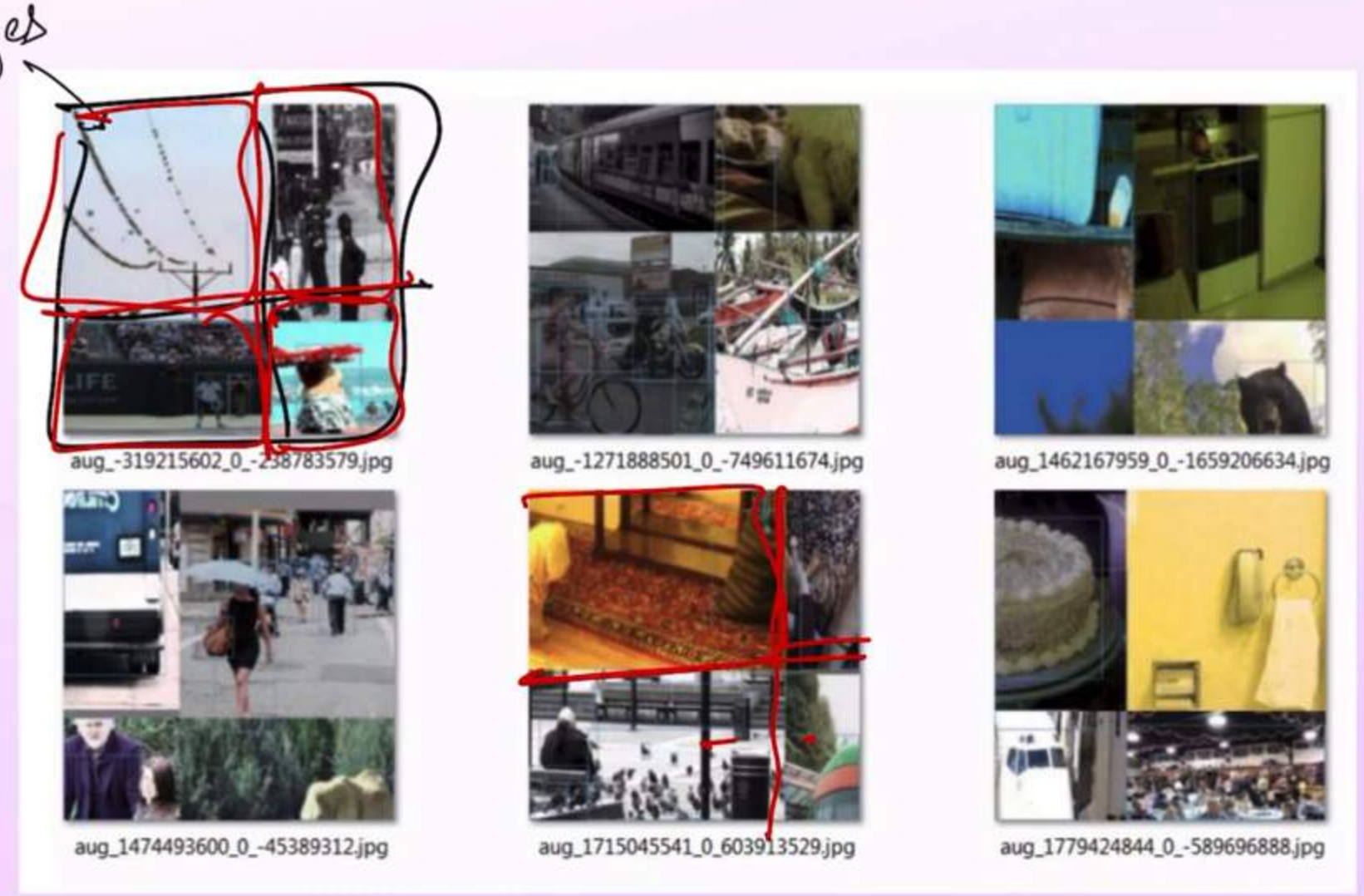

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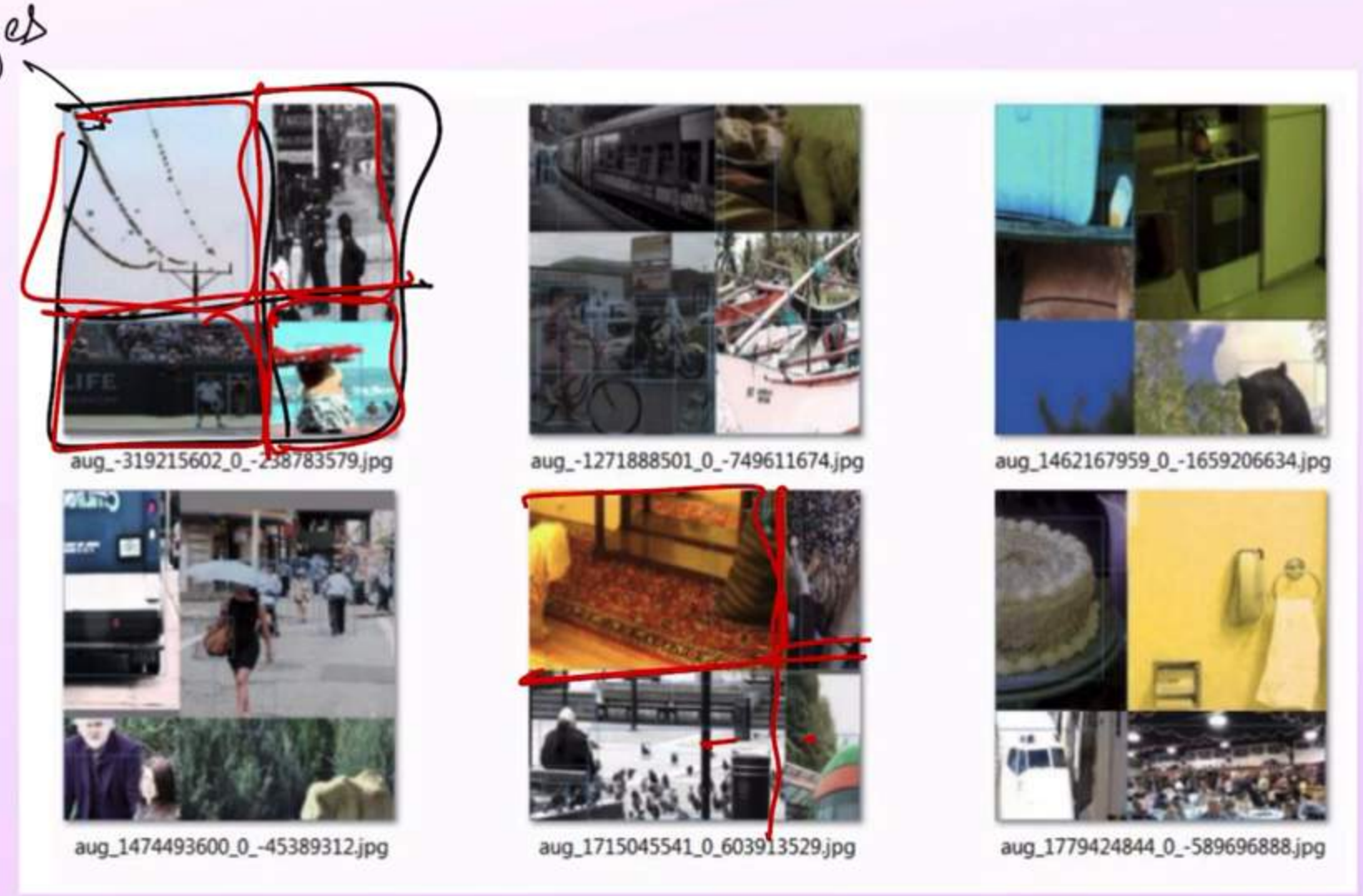

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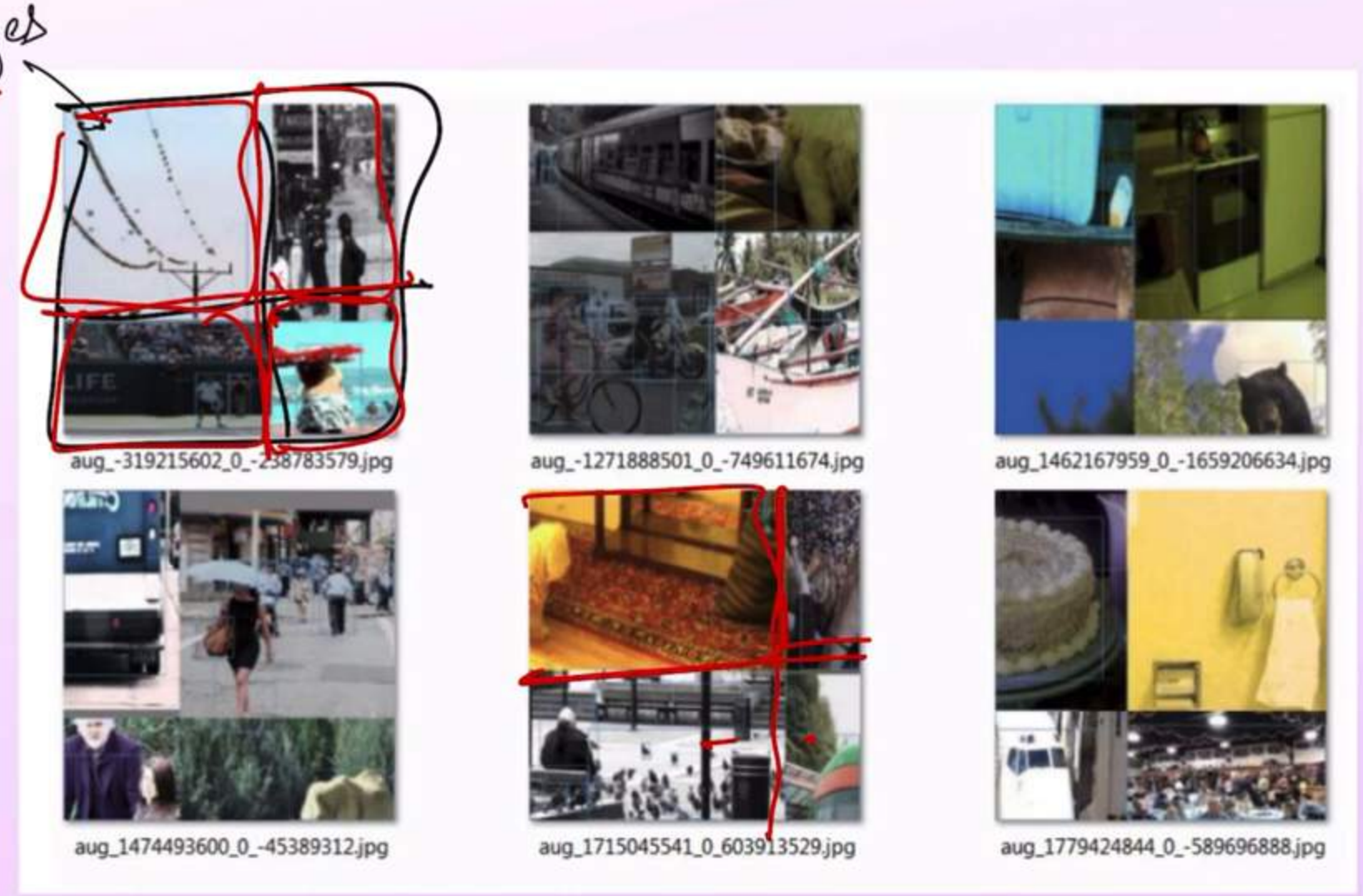

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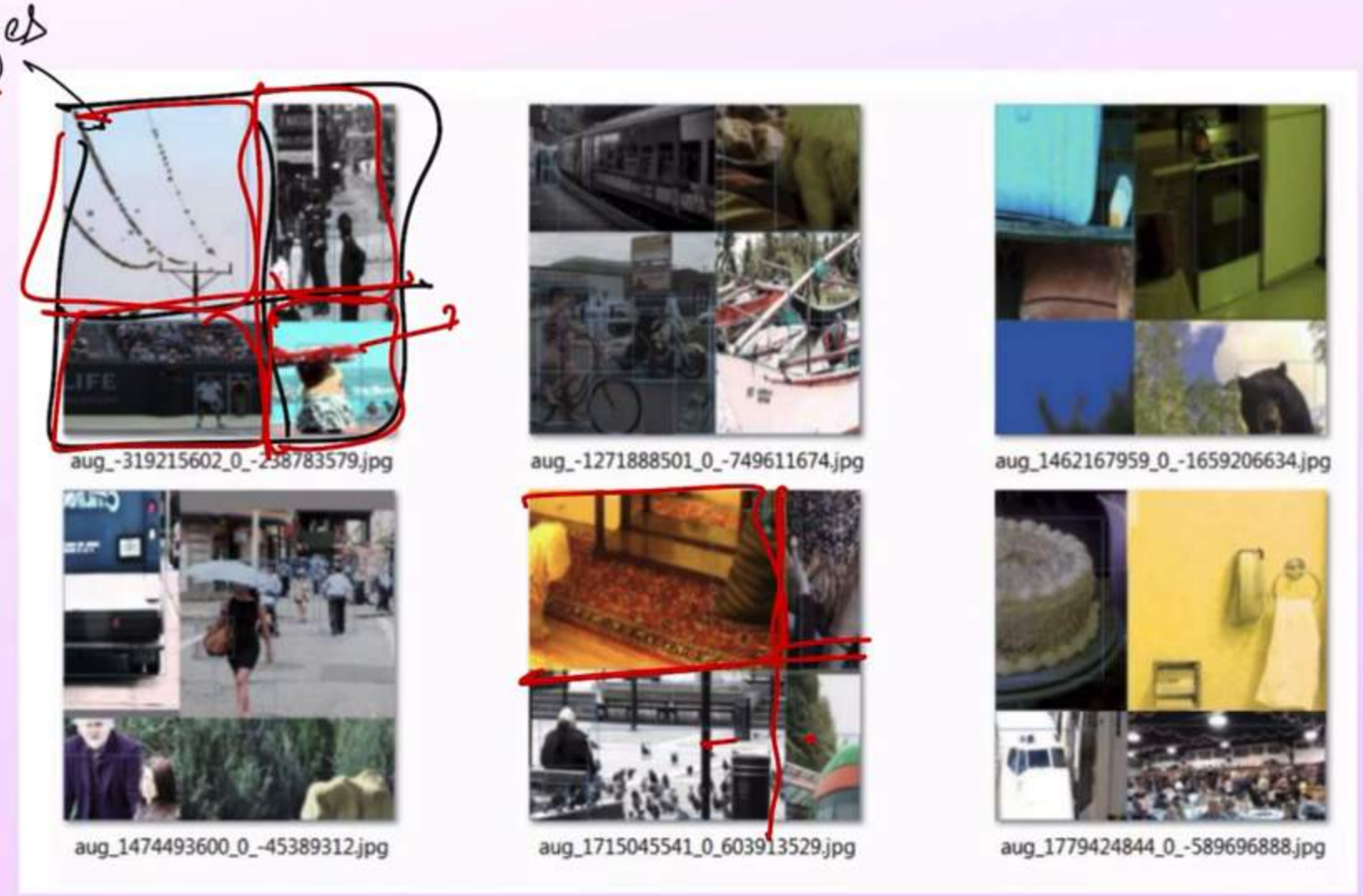

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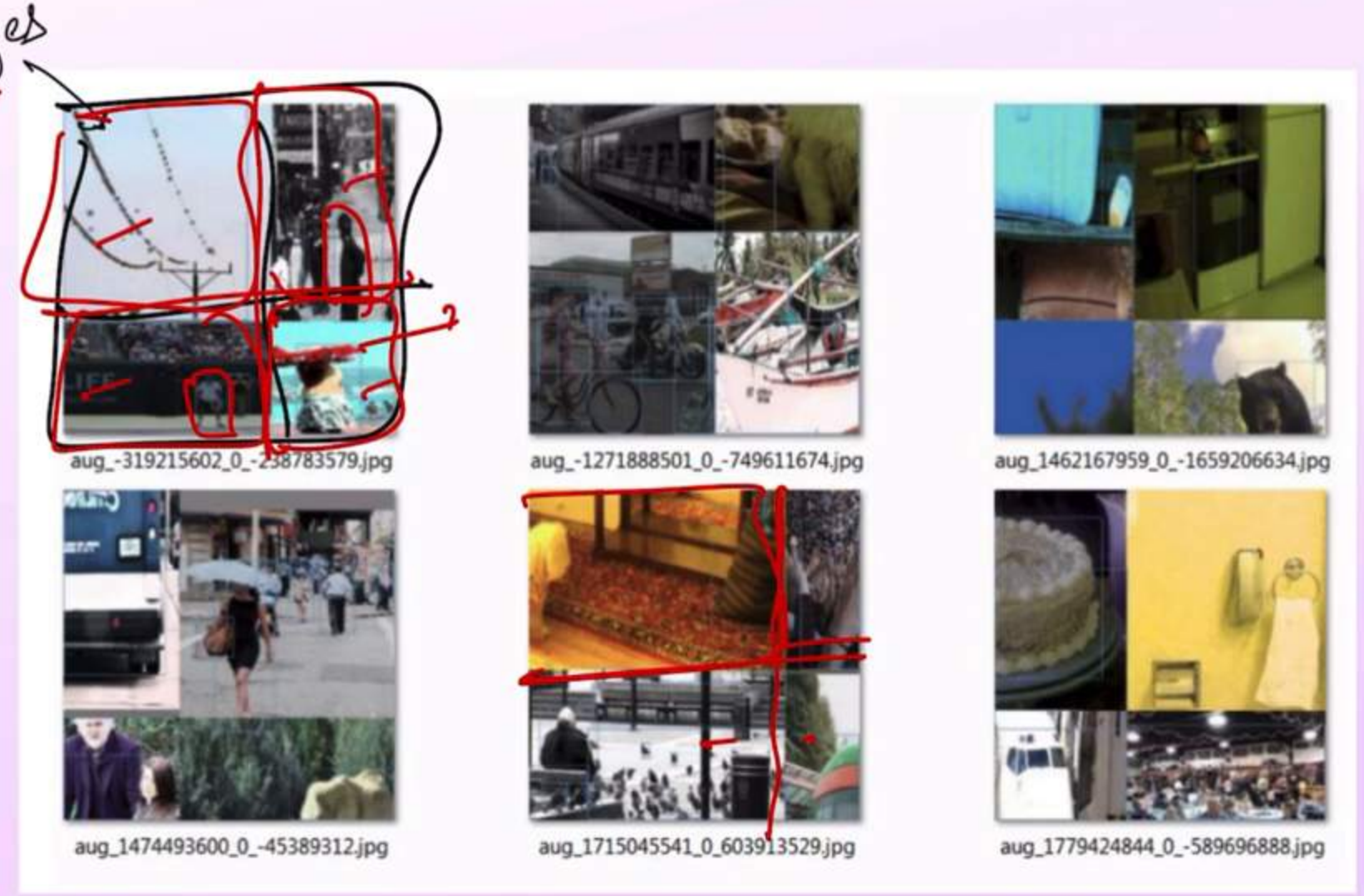

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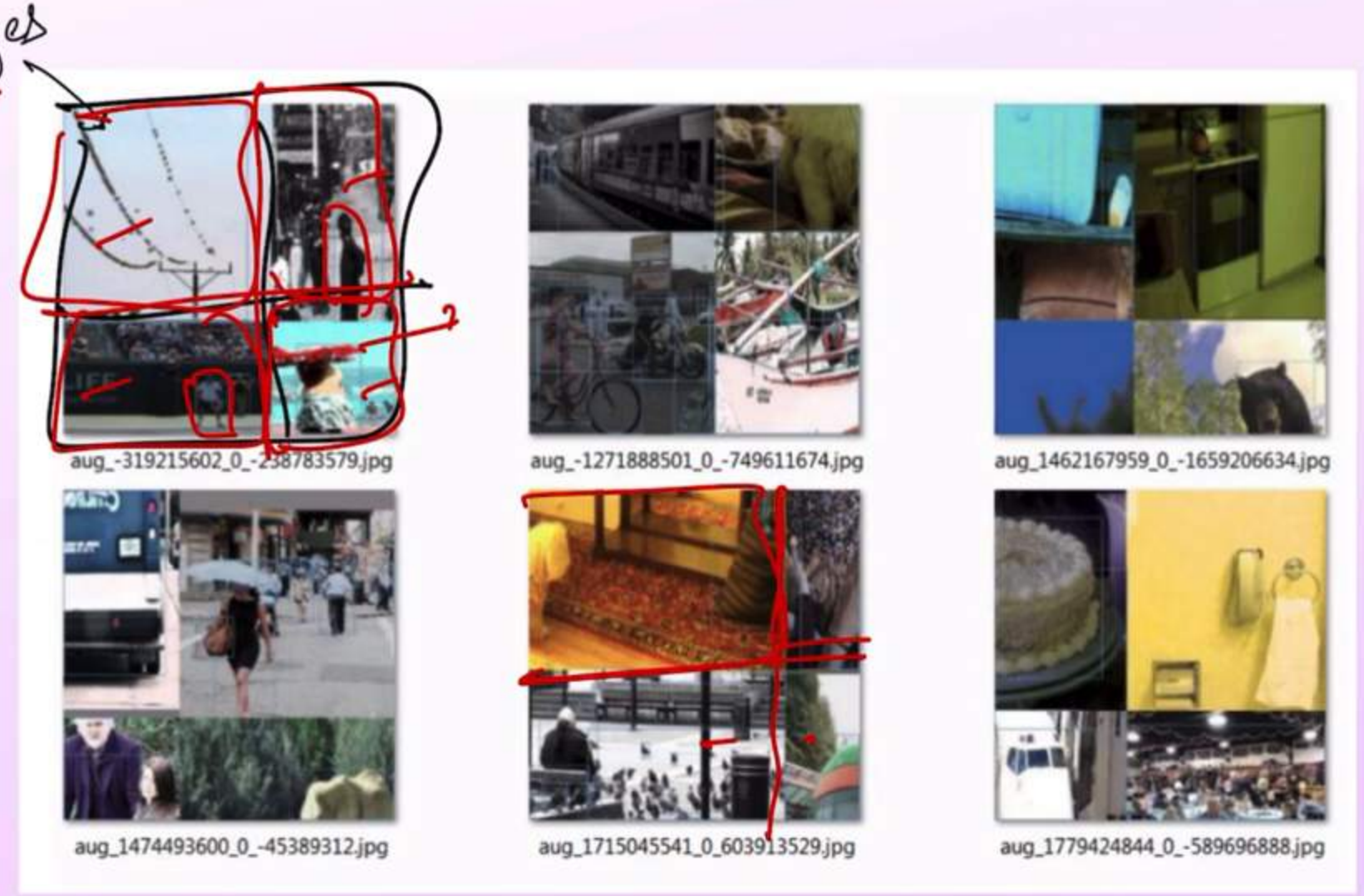

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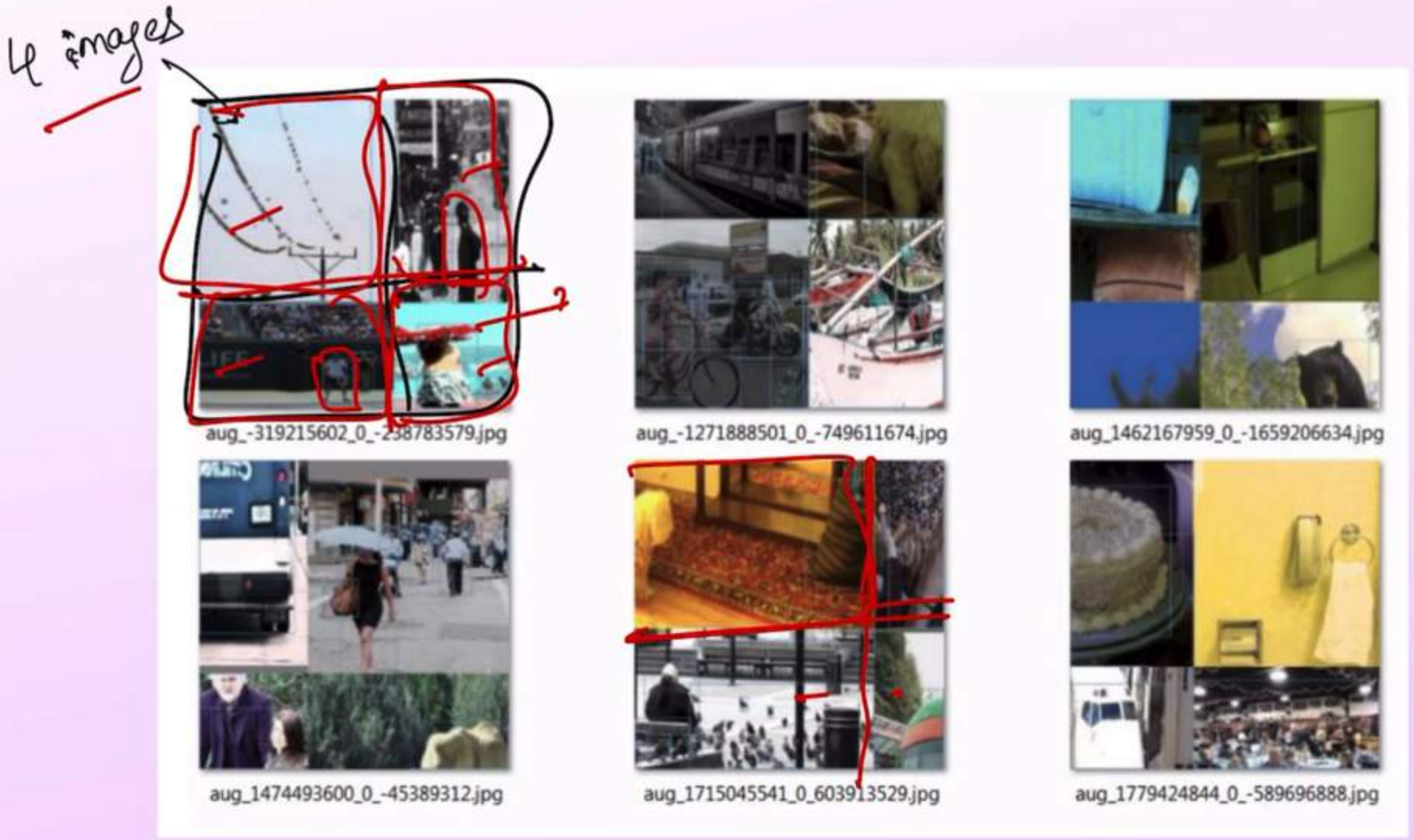

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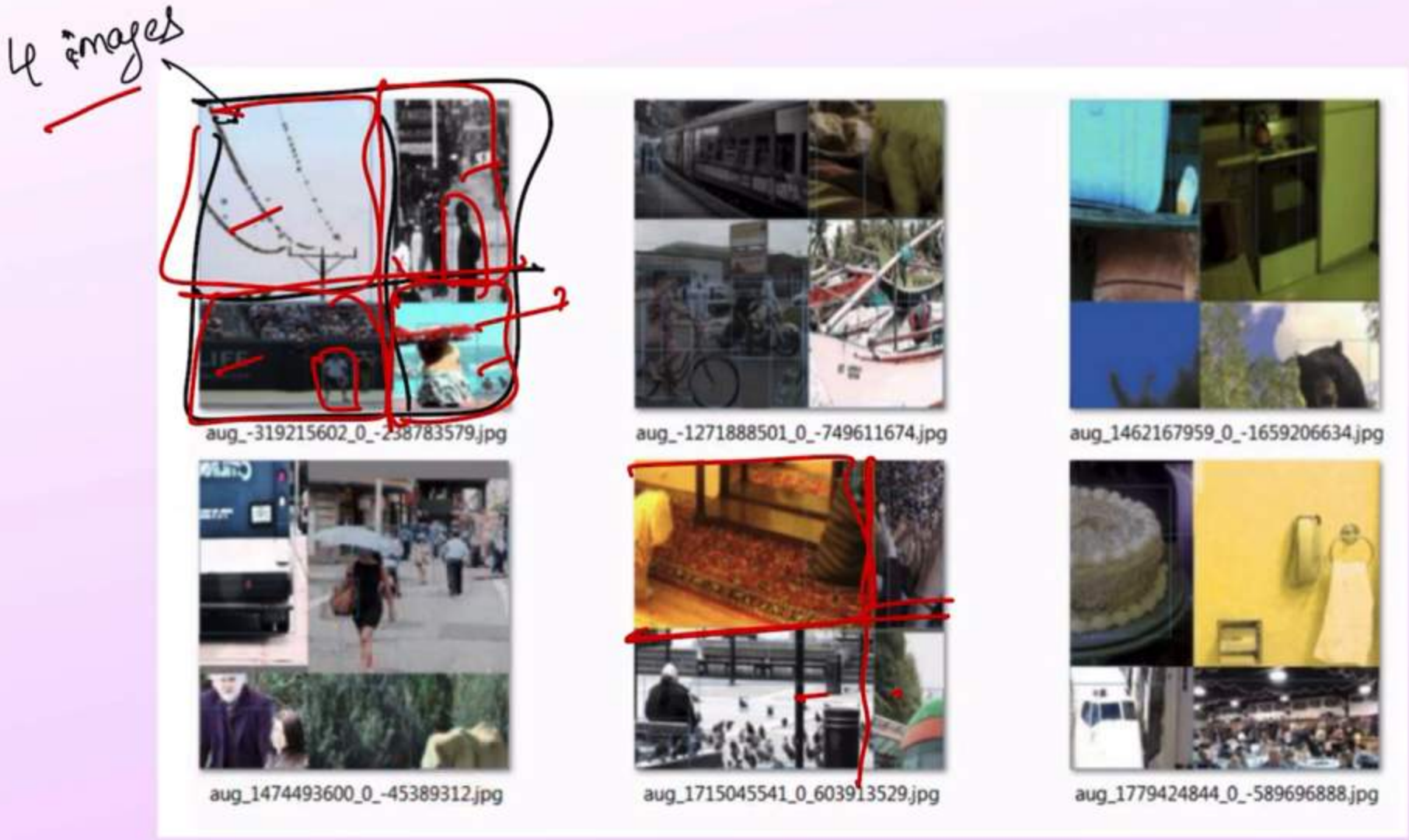

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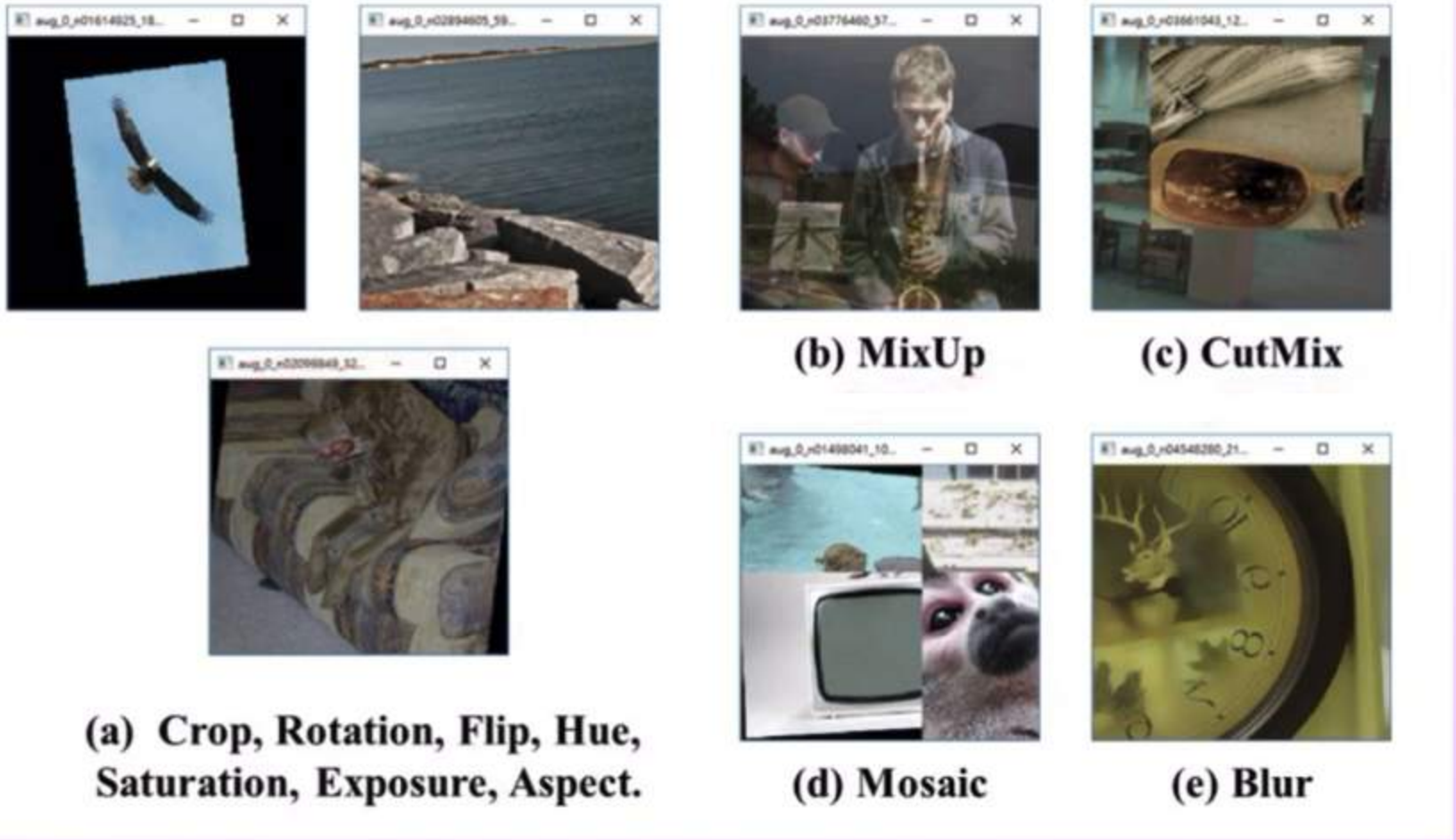

(a) Crop, Rotation, Flip, Hue, Saturation, Exposure, Aspect.

(b) MixUp

(c) CutMix

(d) Mosaic

(e) Blur

Random Training Shapes

- Randomly selecting the shape of the images during training
- Similar to multi-scale training
- Example Range - [320, 416, 512, 608]
- **Dynamic Batching**
  - Dynamically decide the batch size based on the image sizes

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320 x 320

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10 images

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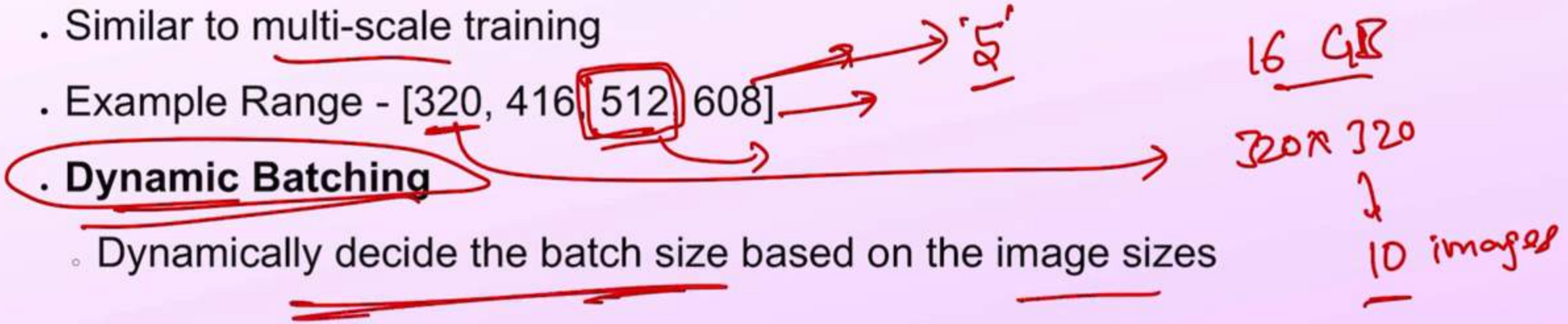

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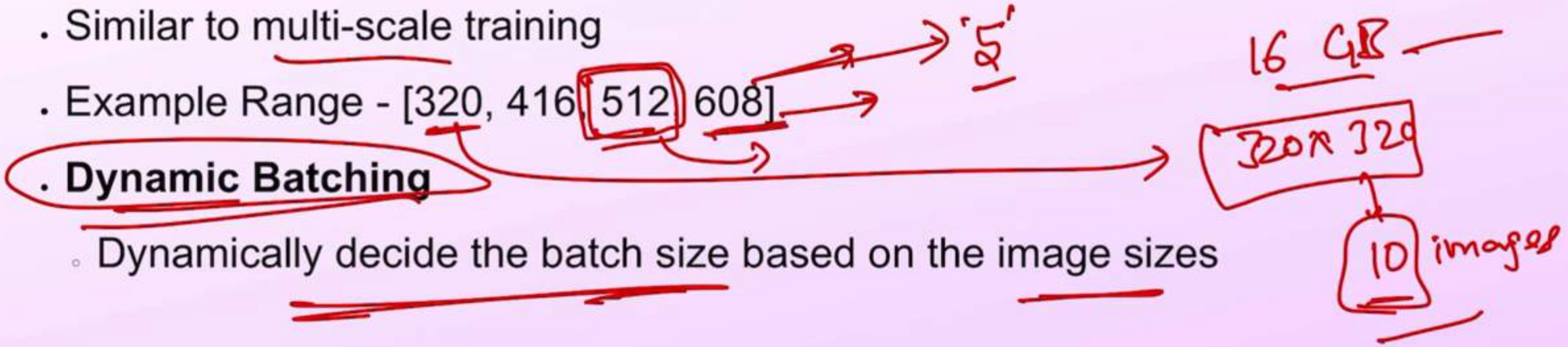

Random Training Shapes

Example:

Suppose the predefined image sizes are [320, 416, 512, 608].

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- Multiple Anchor boxes for a single Groundtruth
- Usually one anchor box is assigned to groundtruth based on IOU
- In YOLOV4:
  - Take an IOU threshold
  - keep all the anchors which has IOU greater than the threshold
  - Calculate predictions and loss for all of these

- Improves the learning capability of the model and speedup the learning process
- Better handling of different object sizes

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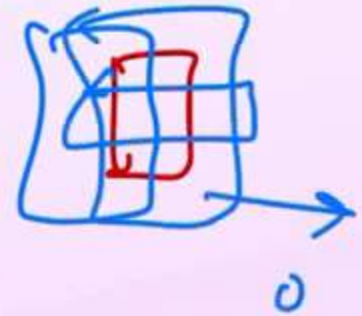

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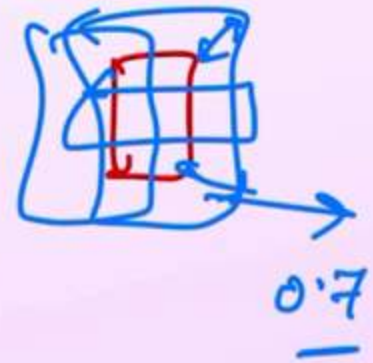

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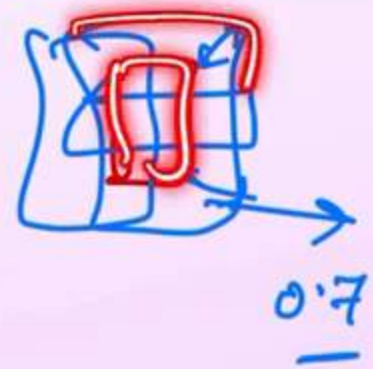

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Label Smoothing

- Example:
  - 5 classes - cat, dog, horse, tiger, lion
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- But why do we need this?

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Label Smoothing

- Prevents overconfidence
- Improves calibration
- Enhances Regularization
- Mitigates the Impact of Noisy Labels

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Label Smoothing

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0.9 → 90%

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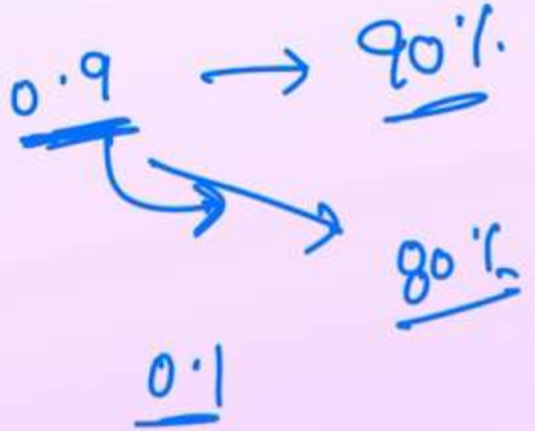

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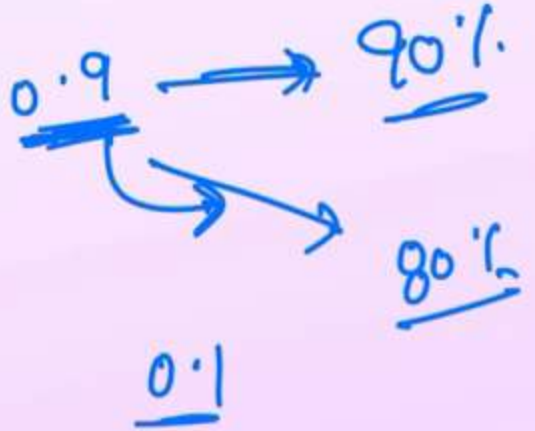

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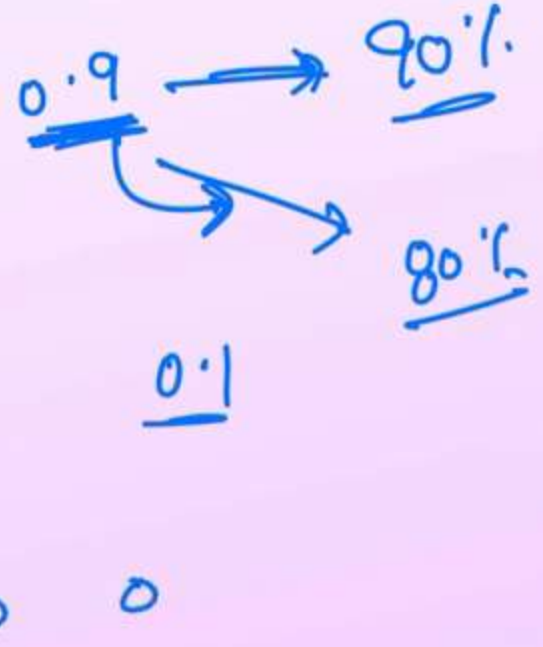

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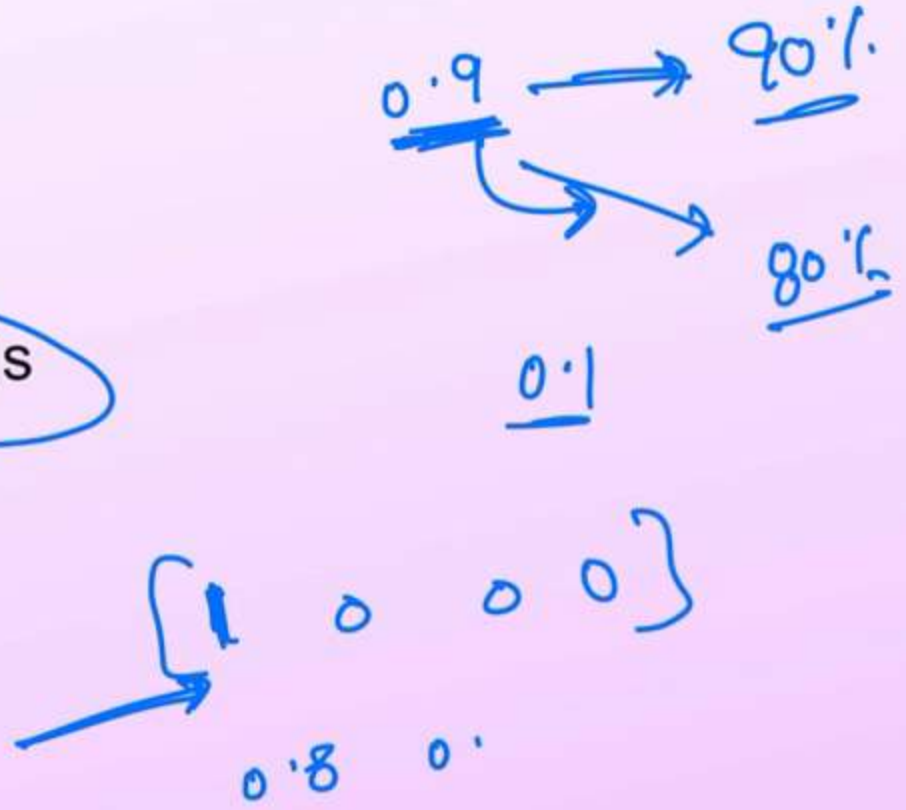

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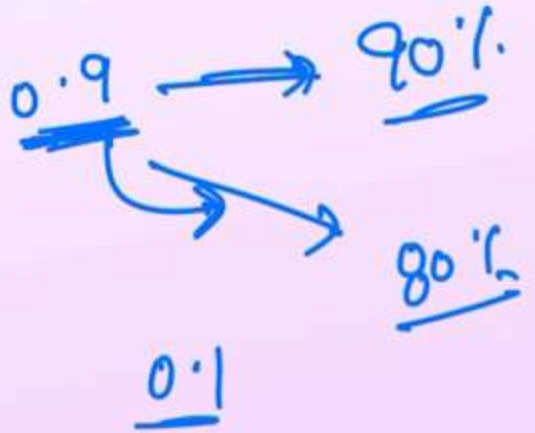

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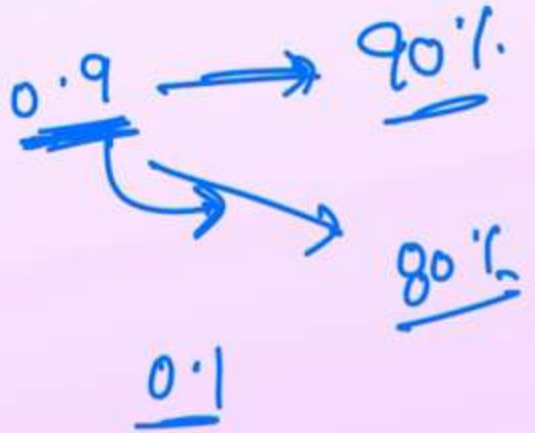

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- How to do this? - [0.025, 0.025, 0.025, 0.9, 0.025]

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- α - smoothing parameter
- C - total classes
- smoothed label:
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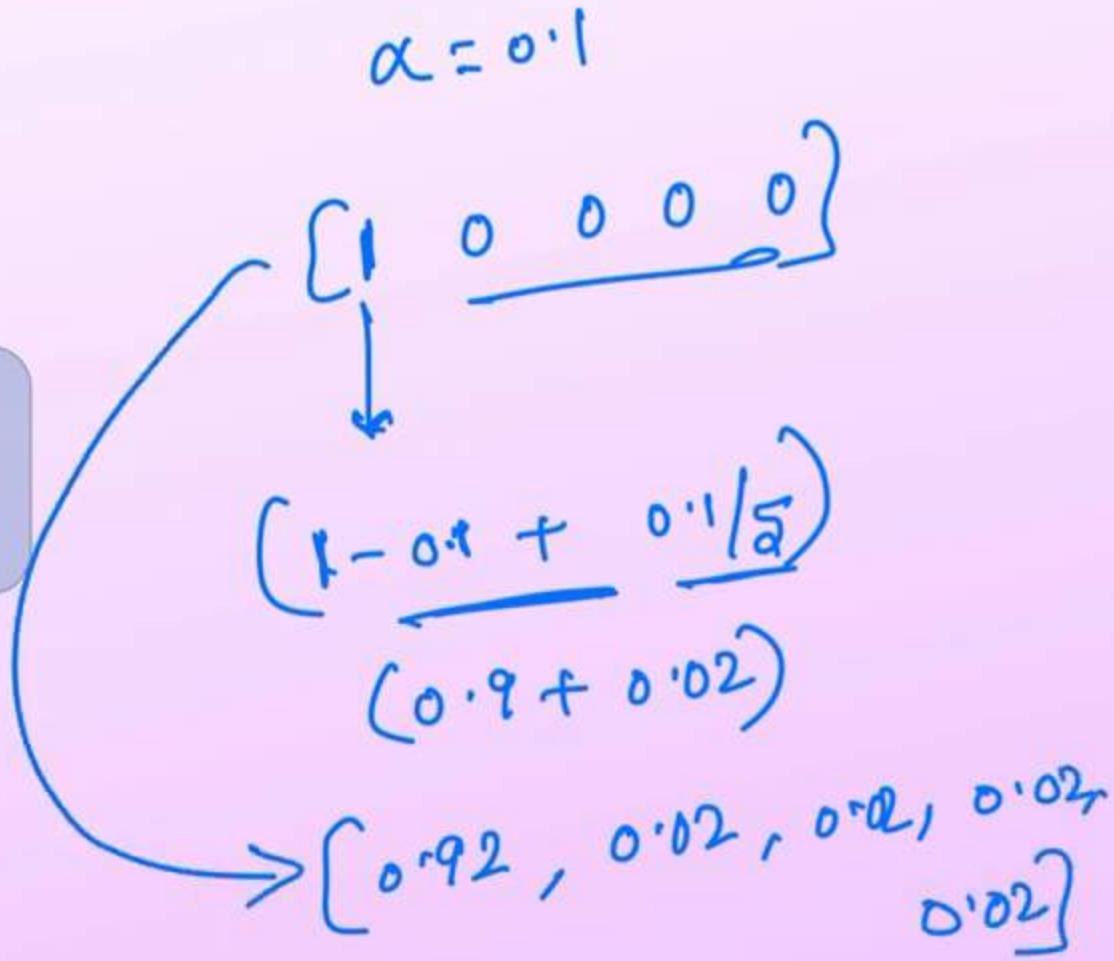

Label Smoothing

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from tensorflow.keras.losses import CategoricalCrossentropy

# Define label smoothing factor
label_smoothing = 0.1

# Initialize the loss function with label smoothing
loss_fn = CategoricalCrossentropy(label_smoothing=label_smoothing)

# Example true labels and predictions
y_true = tf.constant([[1.0, 0.0, 0.0]])  # One-hot encoded label for class A
y_pred = tf.constant([[0.8, 0.1, 0.1]])  # Model's predictions

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Cosine Annealing Lr Scheduler

- Lr Scheduler - adjusts the learning rate during training
- Starts with high value and decreases over time
- Cosine Annealing scheduler

  - follows cosine wave pattern of reducing values

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CosineAnnealingWarmupRestarts(optimizer, first_cycle_steps=10, cycle_mult=1.0, max_lr=0.1, min_lr=0.001, gamma=0.7)
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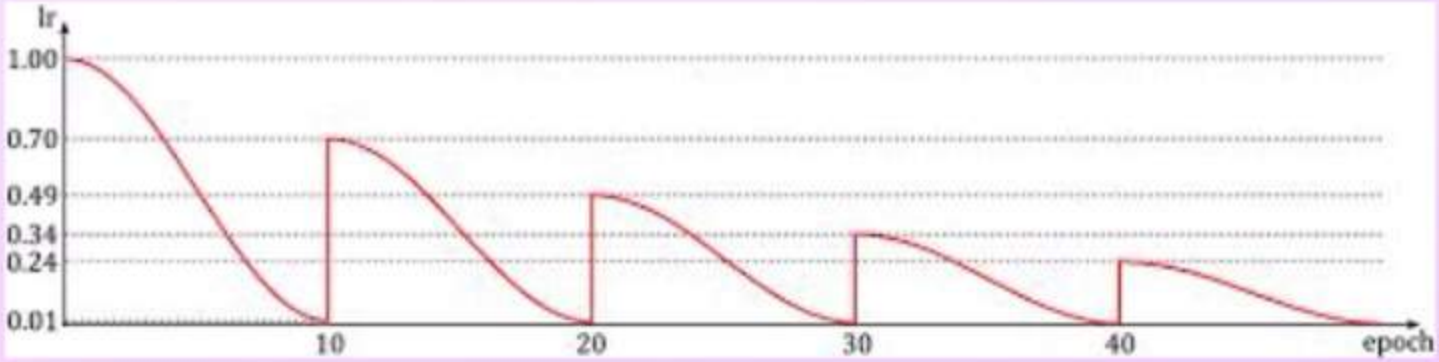

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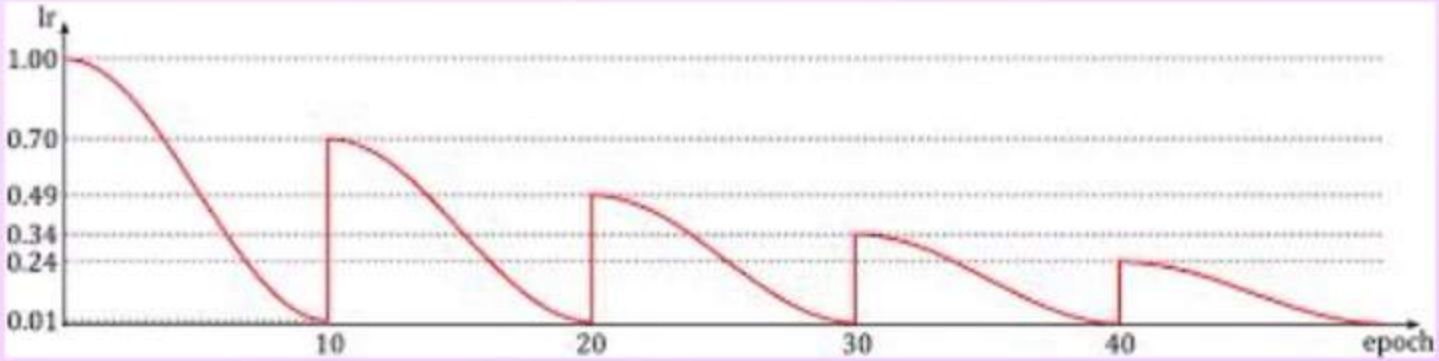

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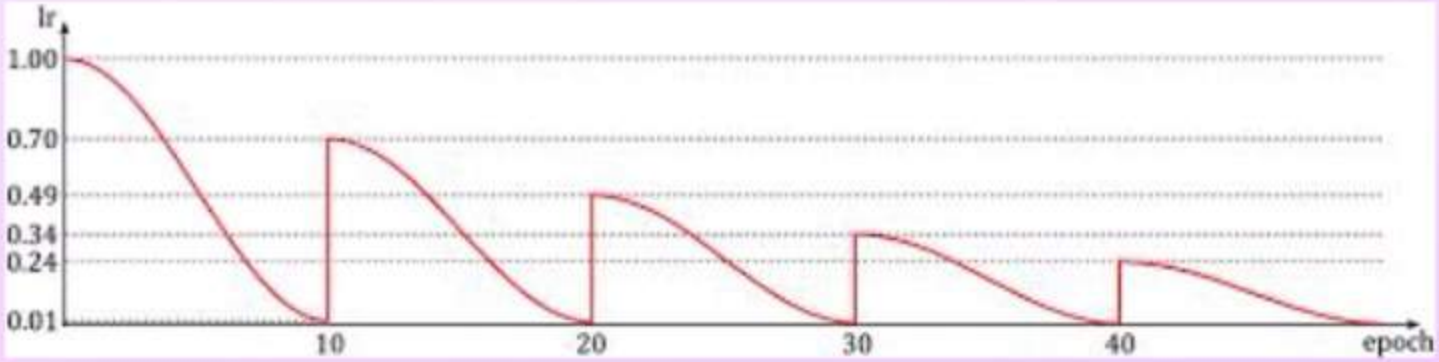

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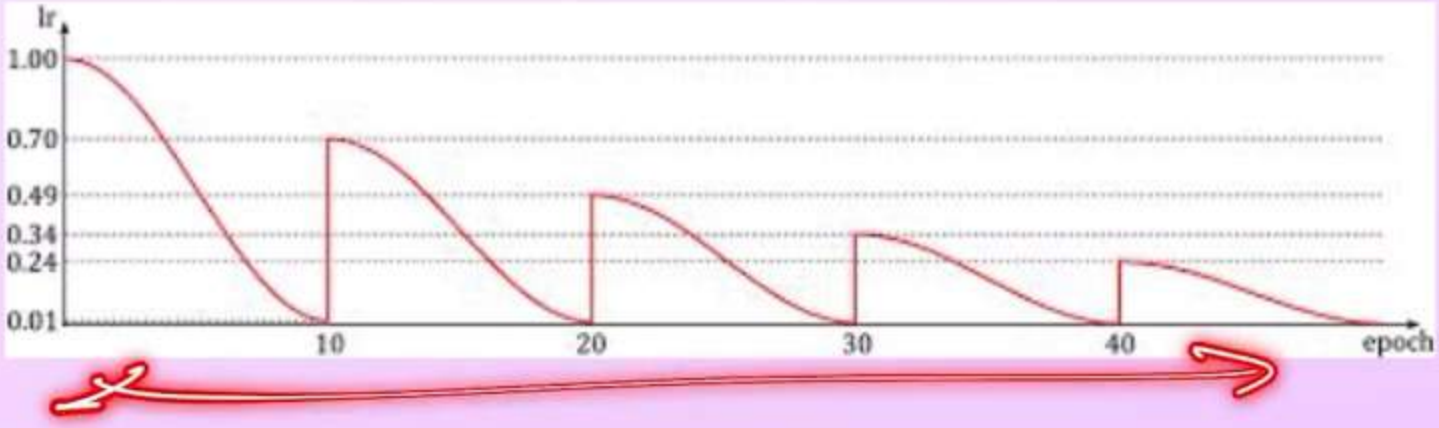

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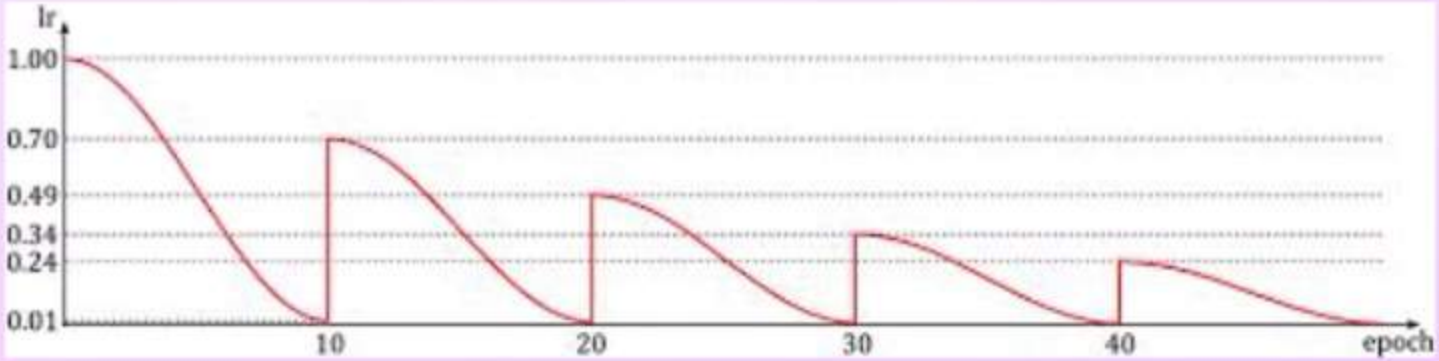

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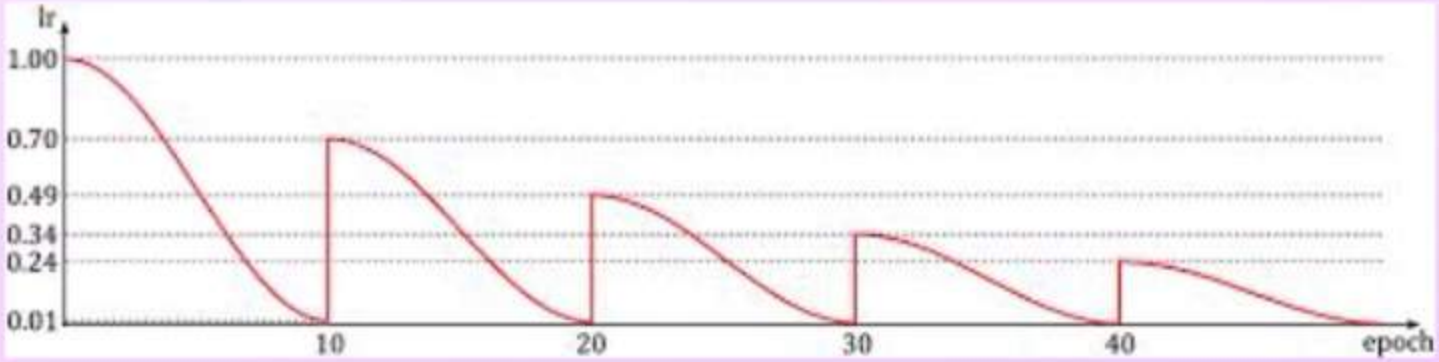

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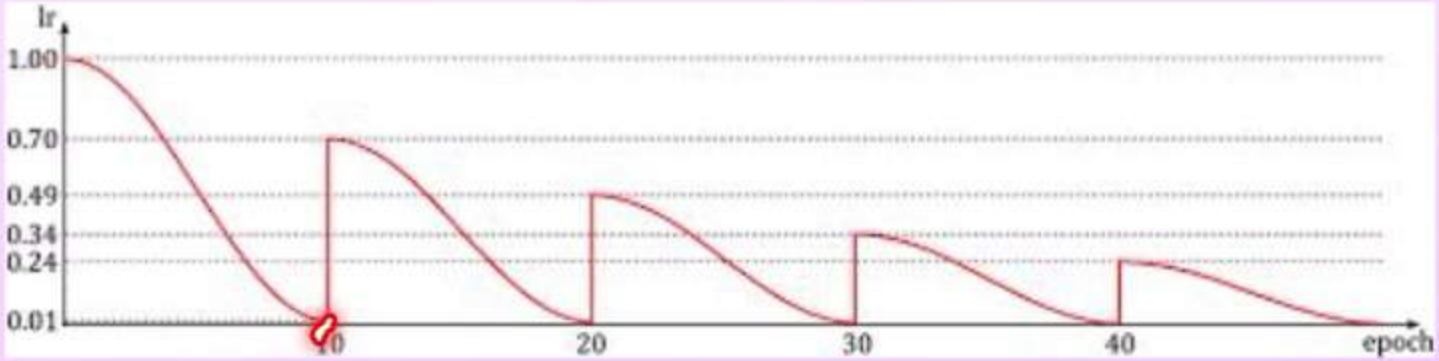

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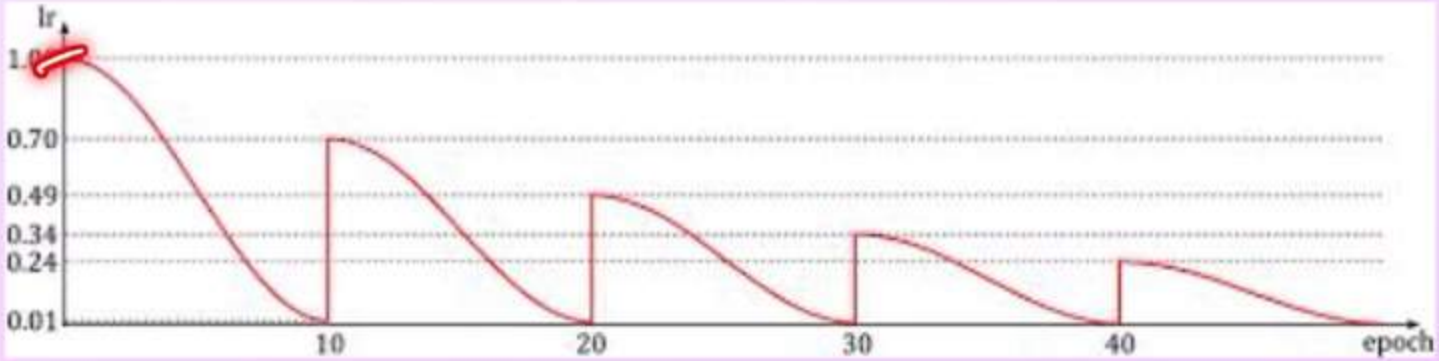

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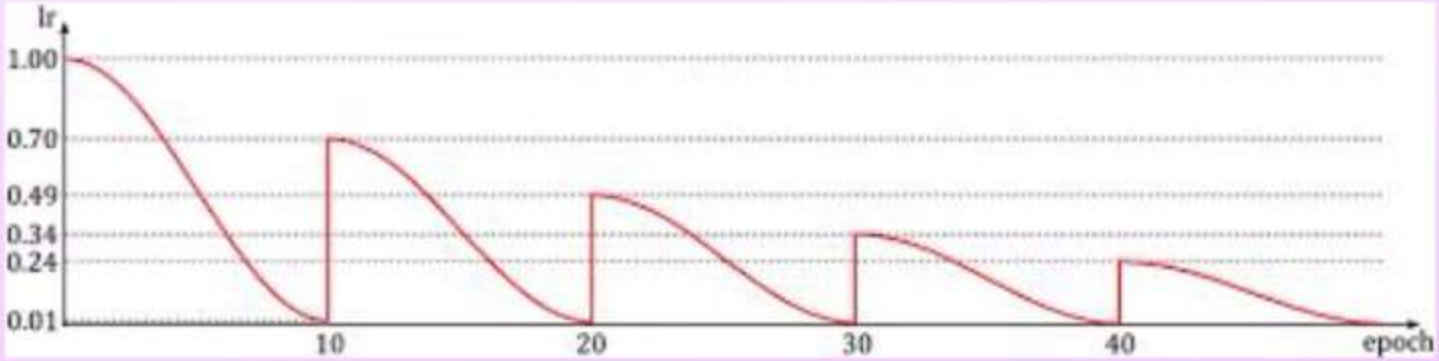

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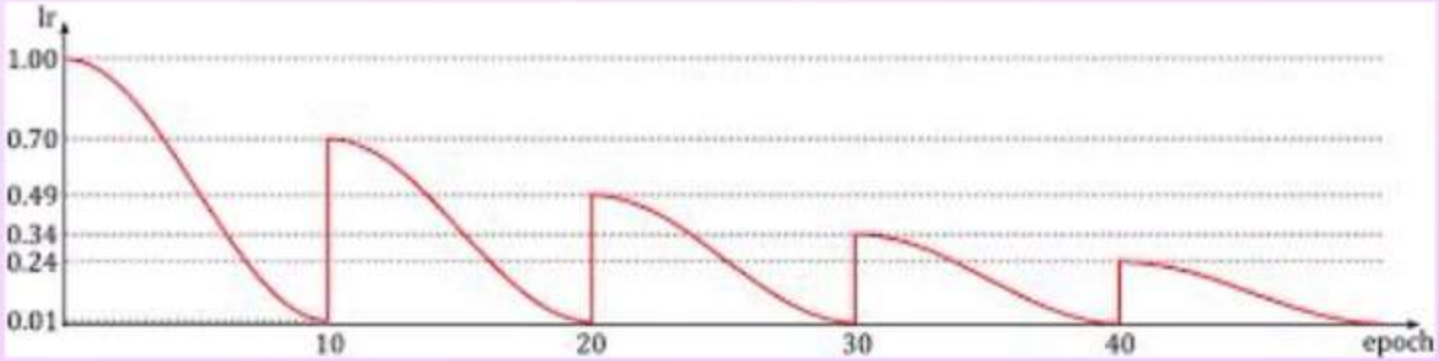

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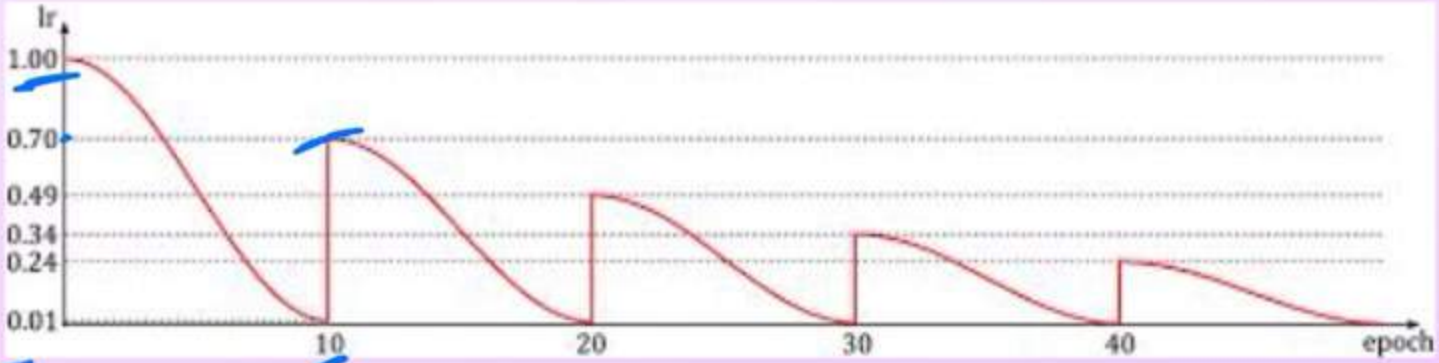
```
CosineAnnealingWarmupRestarts(optimizer, first_cycle_steps=10, cycle_mult=1.0, max_lr=0.1, min_lr=0.001, gamma=0.7)
```

Cosine Annealing Lr Scheduler

- Lr Scheduler - adjusts the learning rate during training
- Starts with high value and decreases over time
- Cosine Annealing scheduler

  - follows cosine wave pattern of reducing values

```
CosineAnnealingWarmupRestarts(optimizer, first_cycle_steps=10, cycle_mult=1.0, max_lr=0.1, min_lr=0.001, gamma=0.7)
```



1 × 0.7 ⇒ 0.7

Cosine Annealing Lr Scheduler

- Lr Scheduler - adjusts the learning rate during training
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  - follows cosine wave pattern of reducing values

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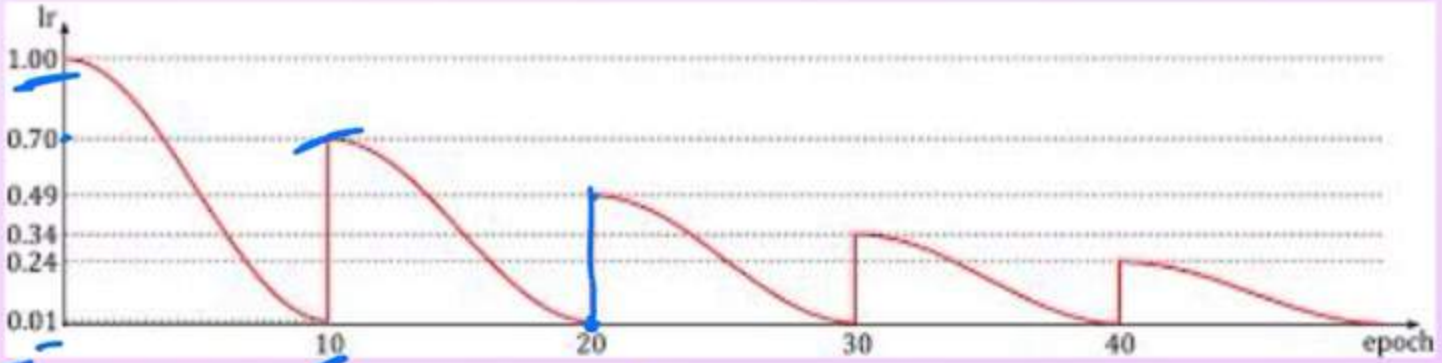
CosineAnnealingWarmupRestarts(optimizer, first_cycle_steps=10, cycle_mult=1.0, max_lr=0.1, min_lr=0.001, gamma=0.7)
```



1 × 0.7 ⇒ 0.7

0.7

Cosine Annealing Lr Scheduler

- Lr Scheduler - adjusts the learning rate during training
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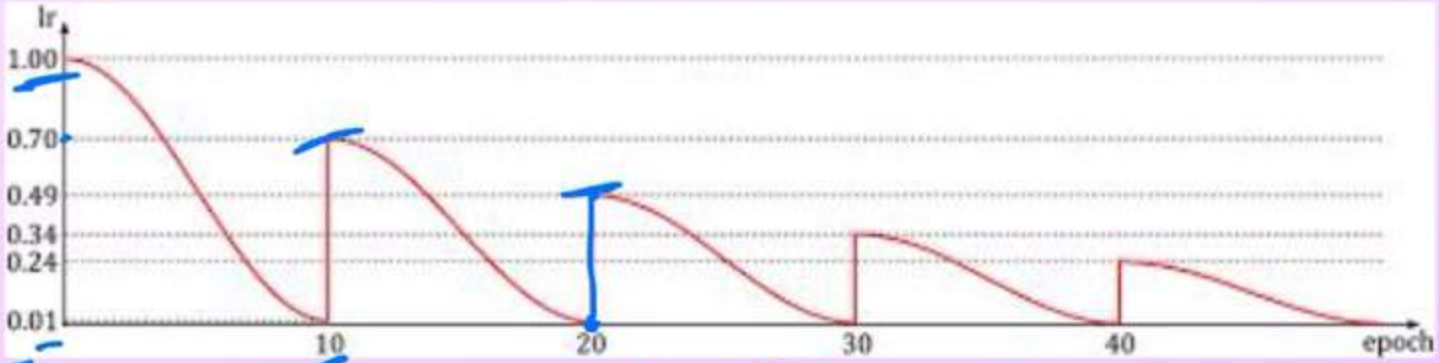


1 x 0.7 ⇒ 0.7

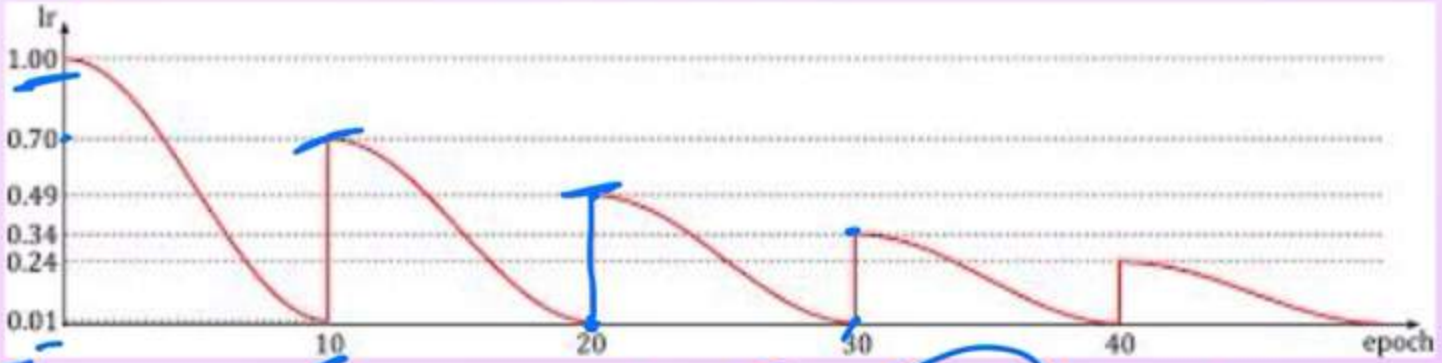
0.7 x 0.7 = 0.49

Cosine Annealing Lr Scheduler

- Lr Scheduler - adjusts the learning rate during training
- Starts with high value and decreases over time
- Cosine Annealing scheduler

  - follows cosine wave pattern of reducing values

```
CosineAnnealingWarmupRestarts(optimizer, first_cycle_steps=10, cycle_mult=1.0, max_lr=0.1,
min_lr=0.001, gamma=0.7)
```

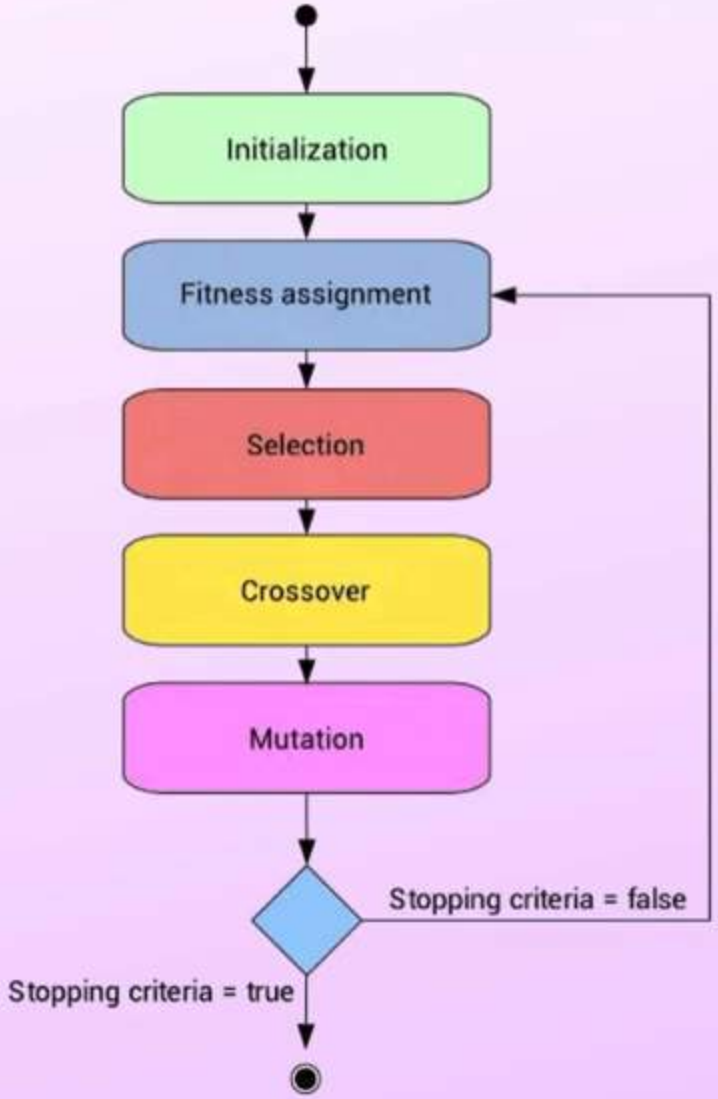


1 x 0.7 ⇒ 0.7

0.7 x 0.7 = 0.49 → gamma →

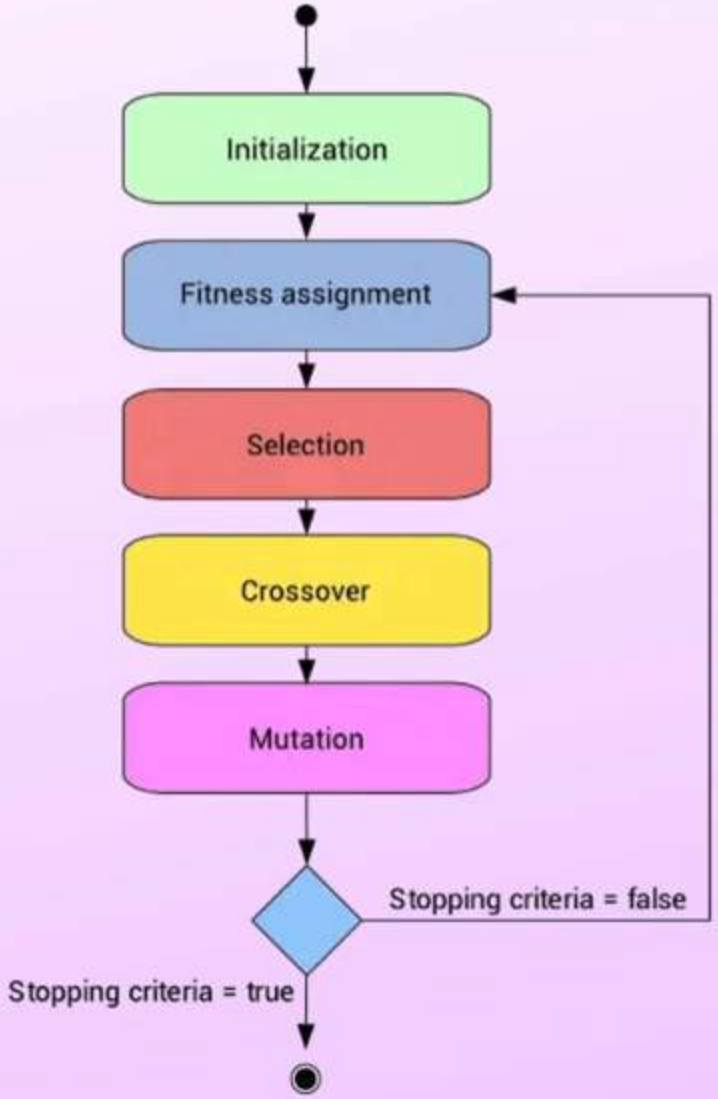
Genetic Algorithms

- Optimal Hyperparameters



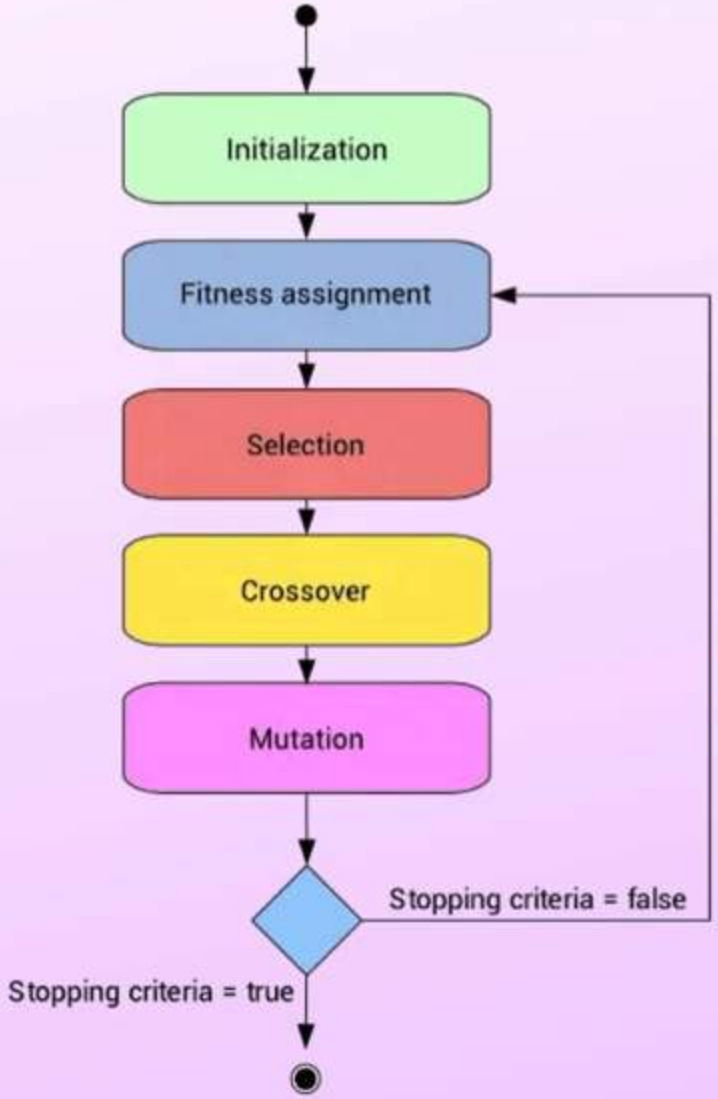
Genetic Algorithms

- Optimal Hyperparameters



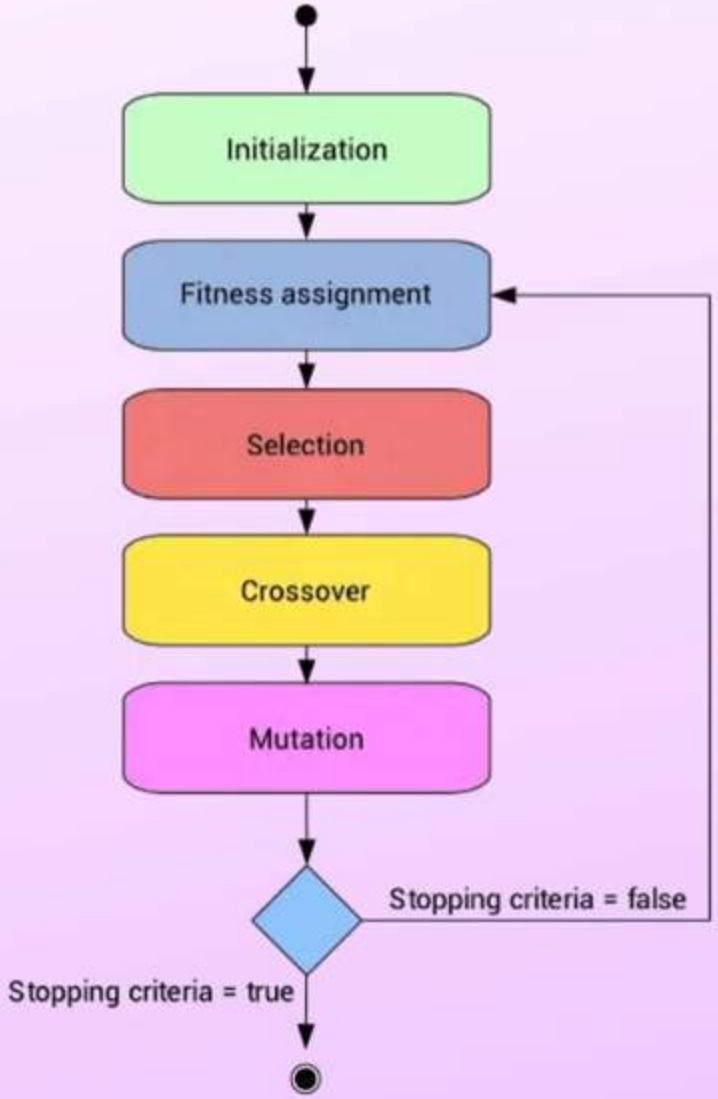
Genetic Algorithms

- Optimal Hyperparameters



Genetic Algorithms

- Optimal Hyperparameters



Genetic Algorithms

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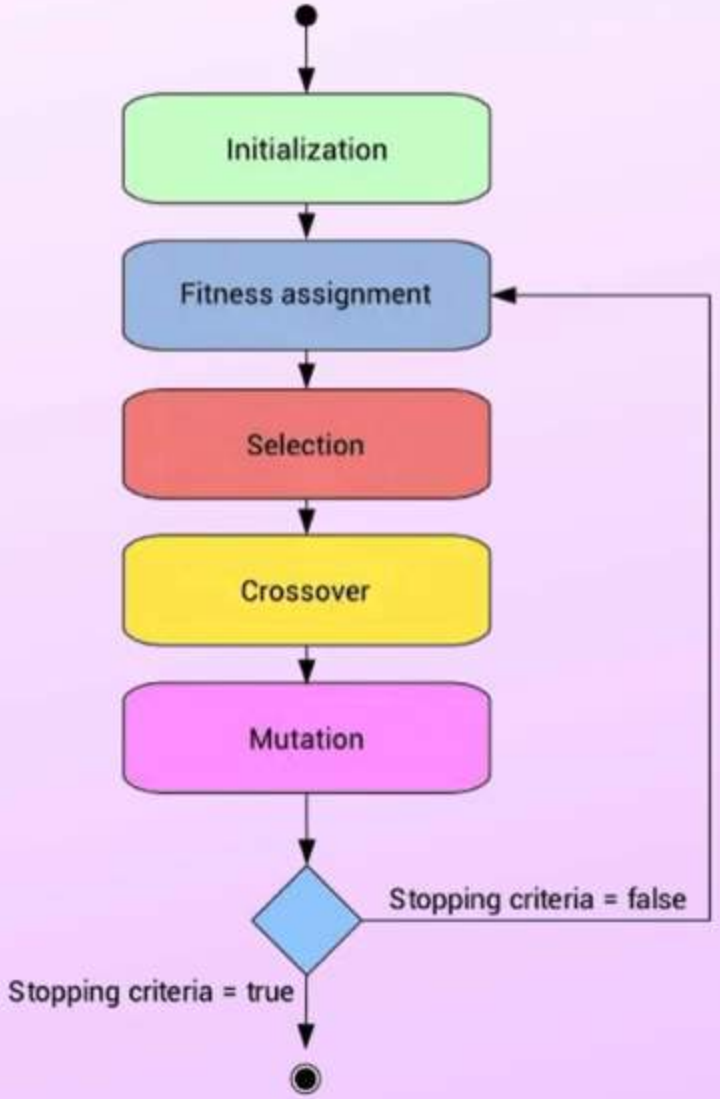

Genetic Algorithms

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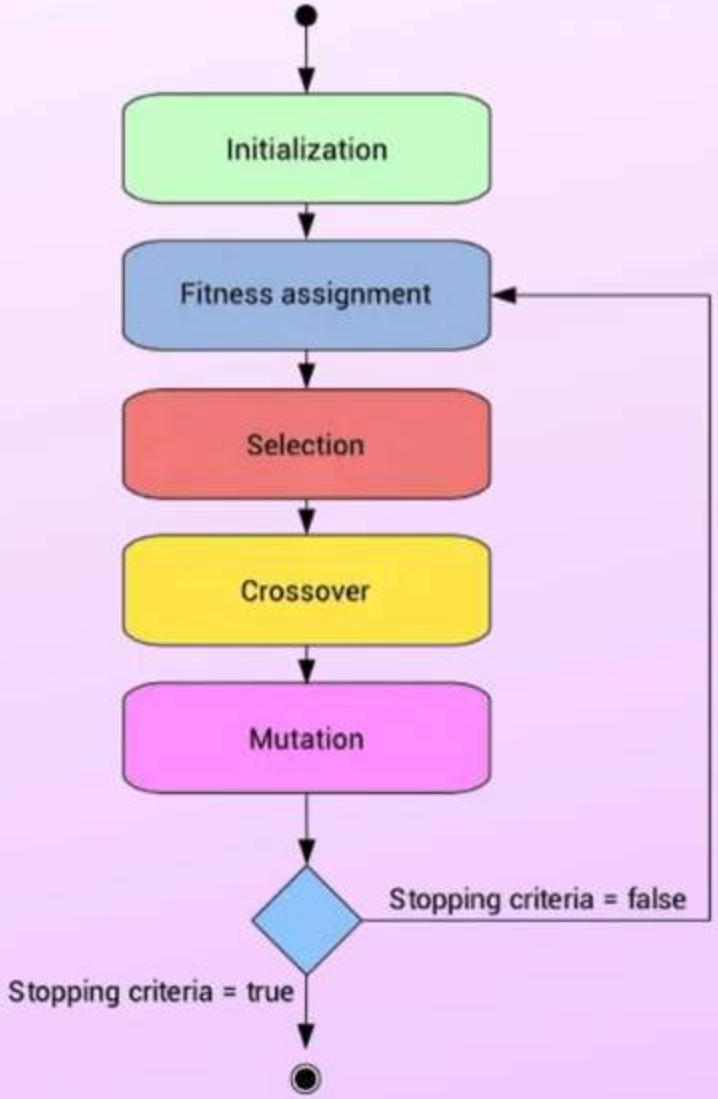
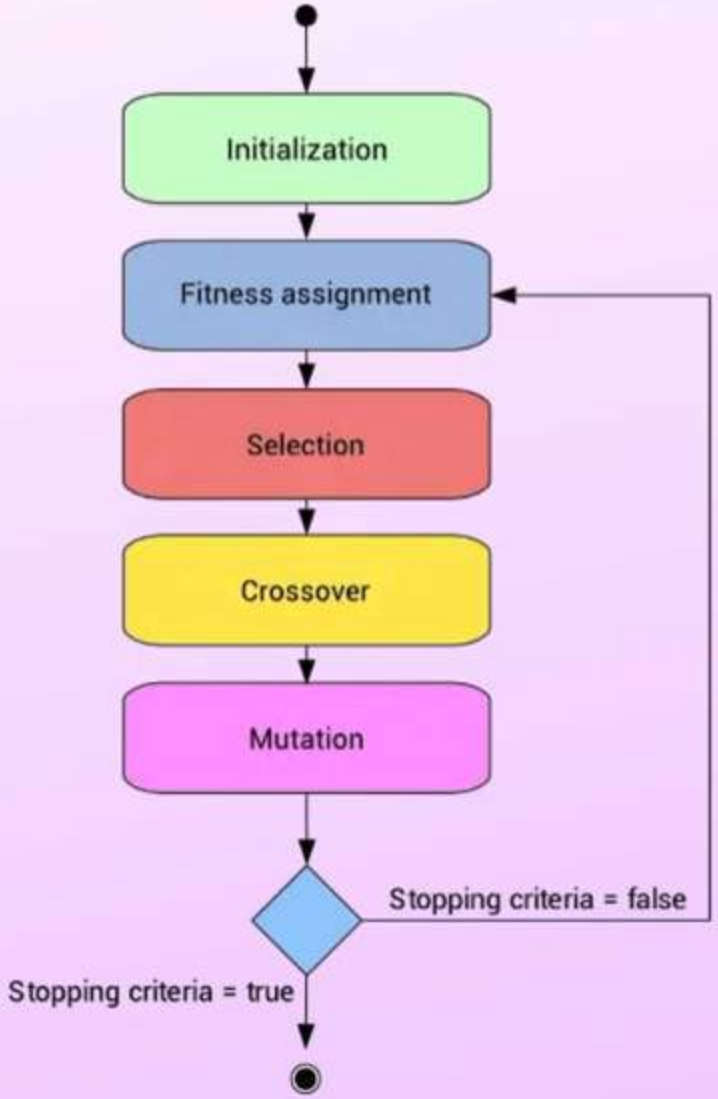


Genetic Algorithms

- Optimal Hyperparameters



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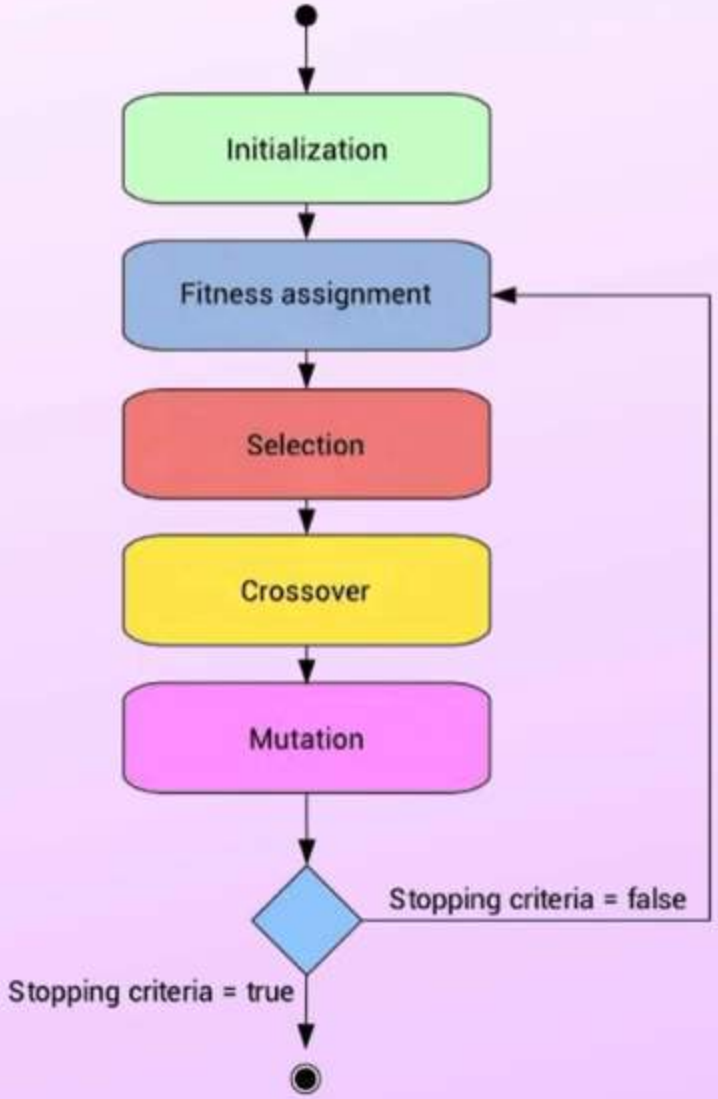
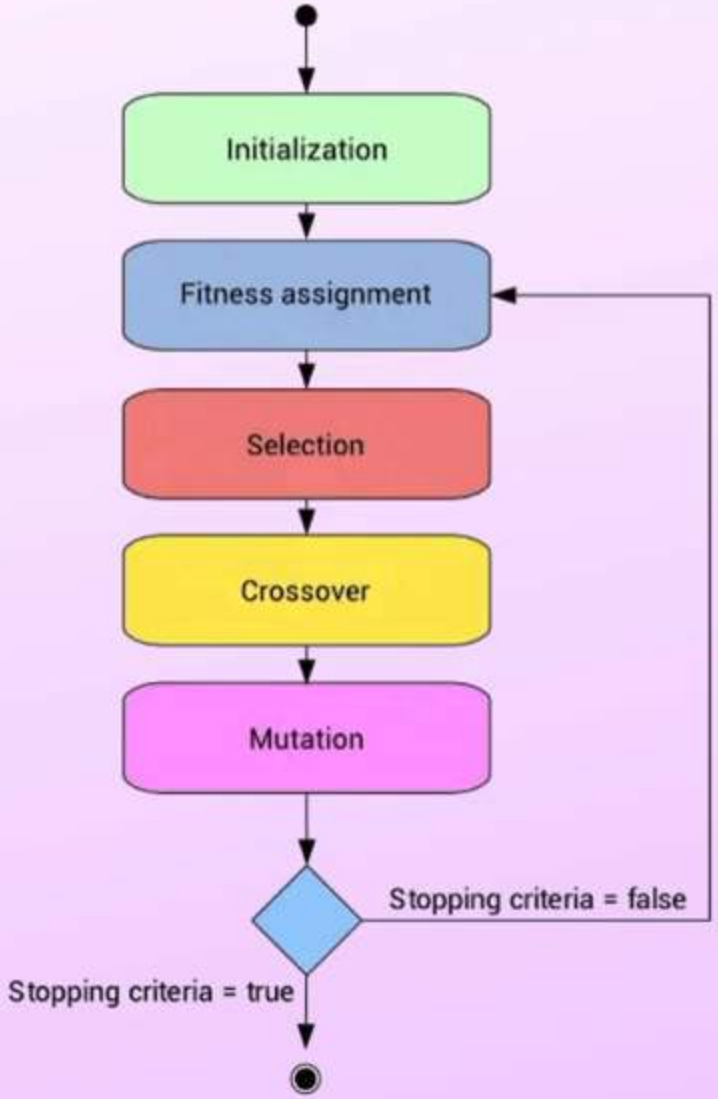


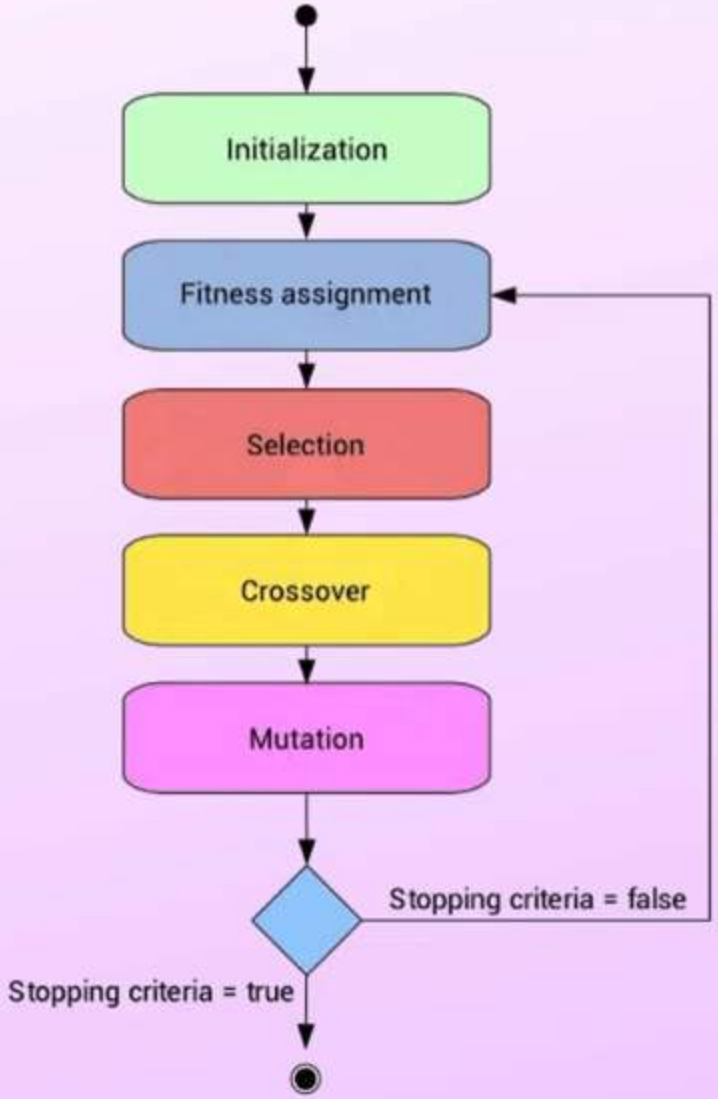
Genetic Algorithms

- Optimal Hyperparameters



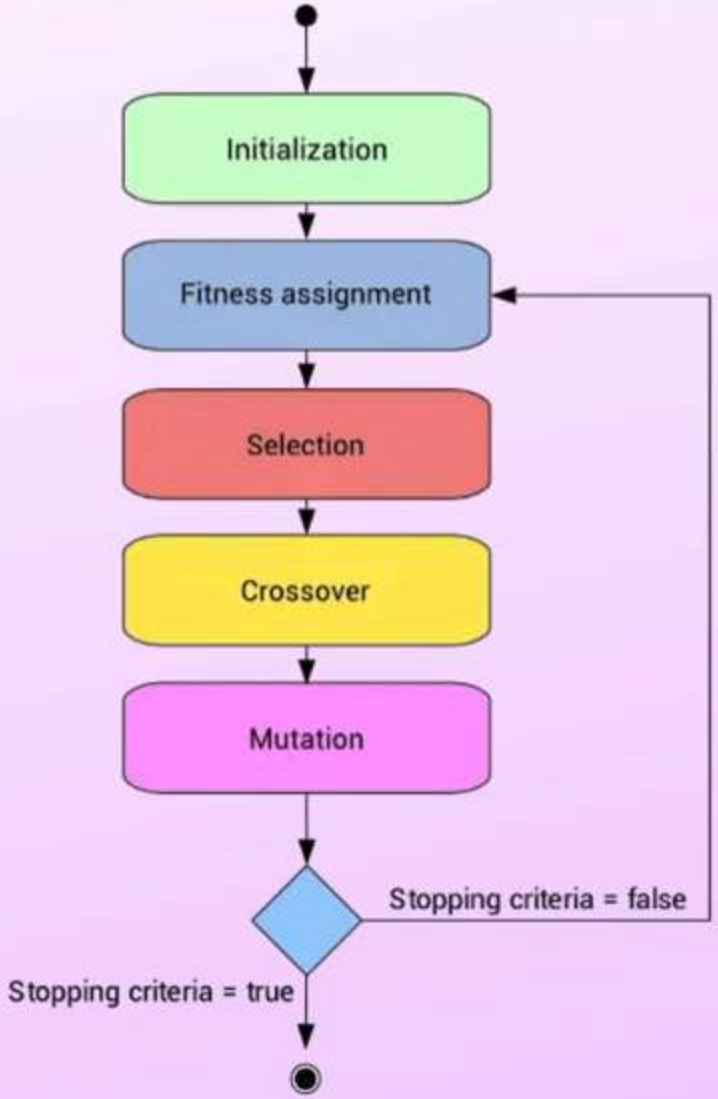
Genetic Algorithms

- Optimal Hyperparameters



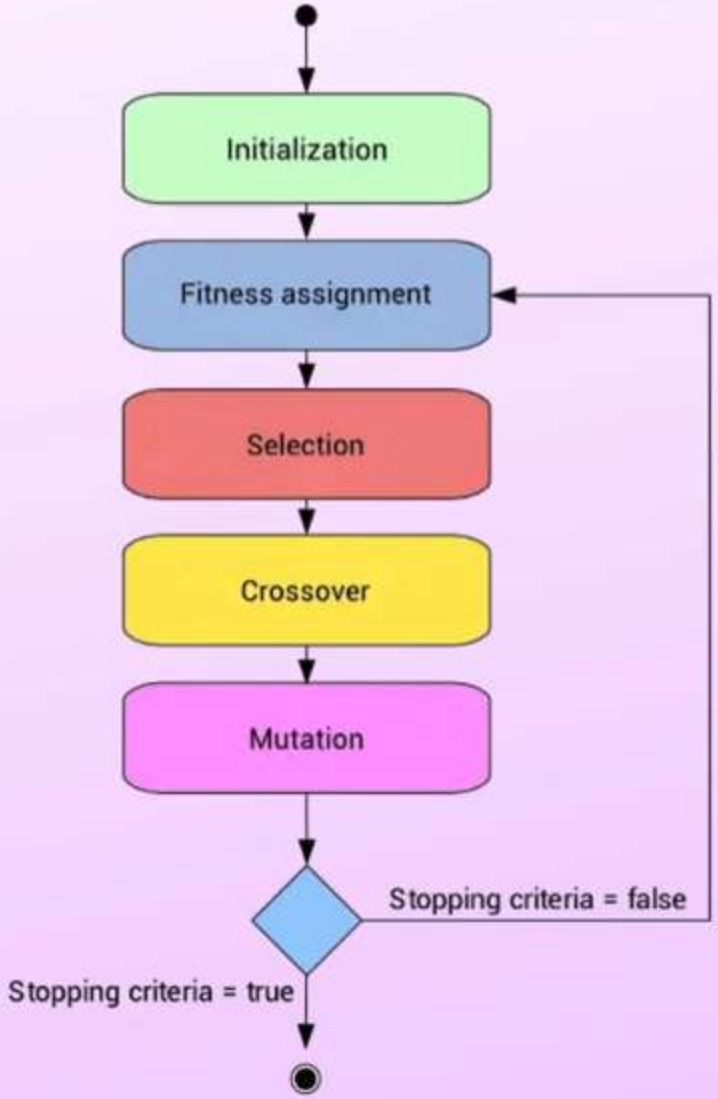
Genetic Algorithms

- Optimal Hyperparameters



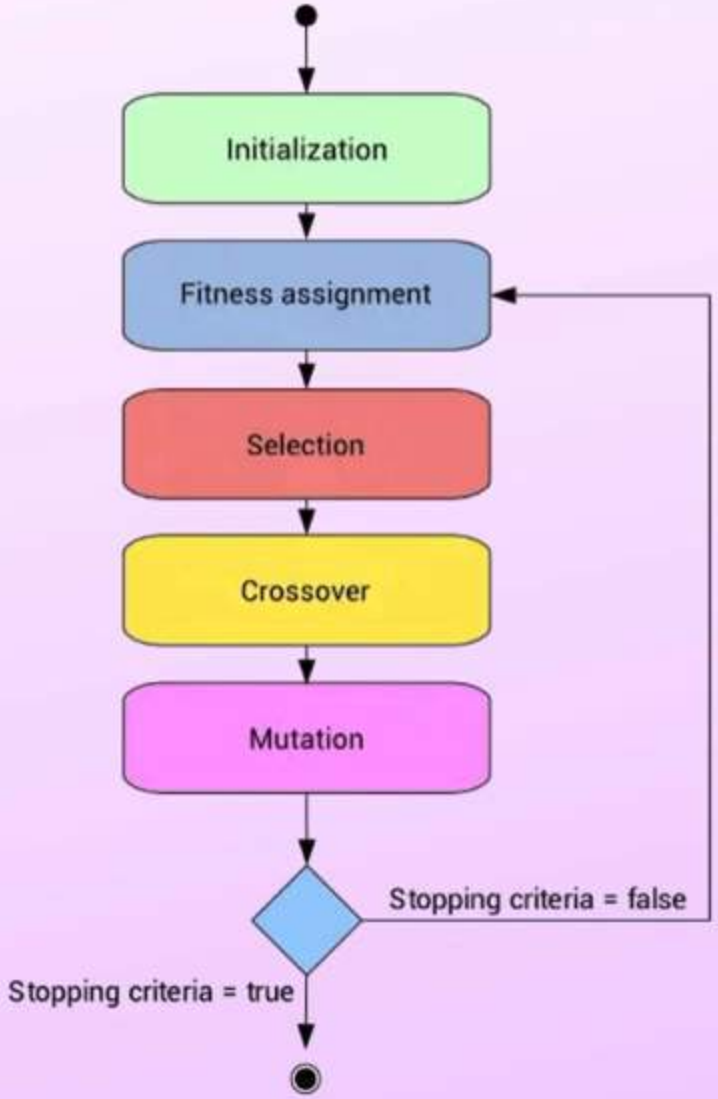
Genetic Algorithms

- Optimal Hyperparameters



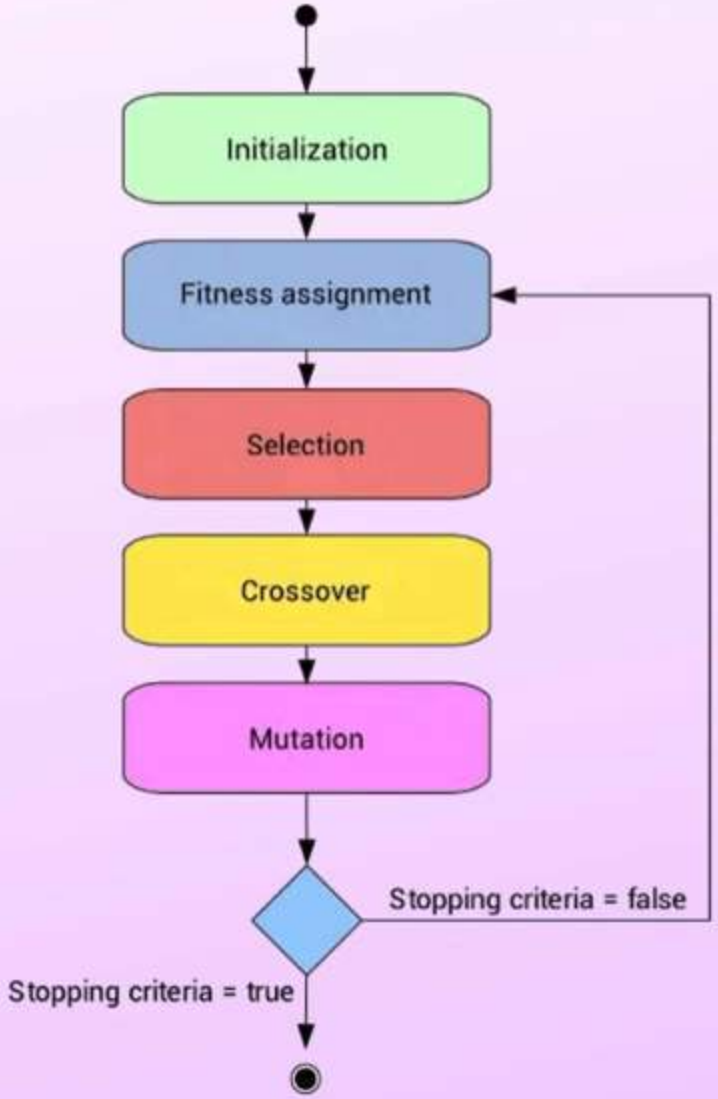
Genetic Algorithms

- Optimal Hyperparameters



Genetic Algorithms

- Optimal Hyperparameters



Genetic Algorithms

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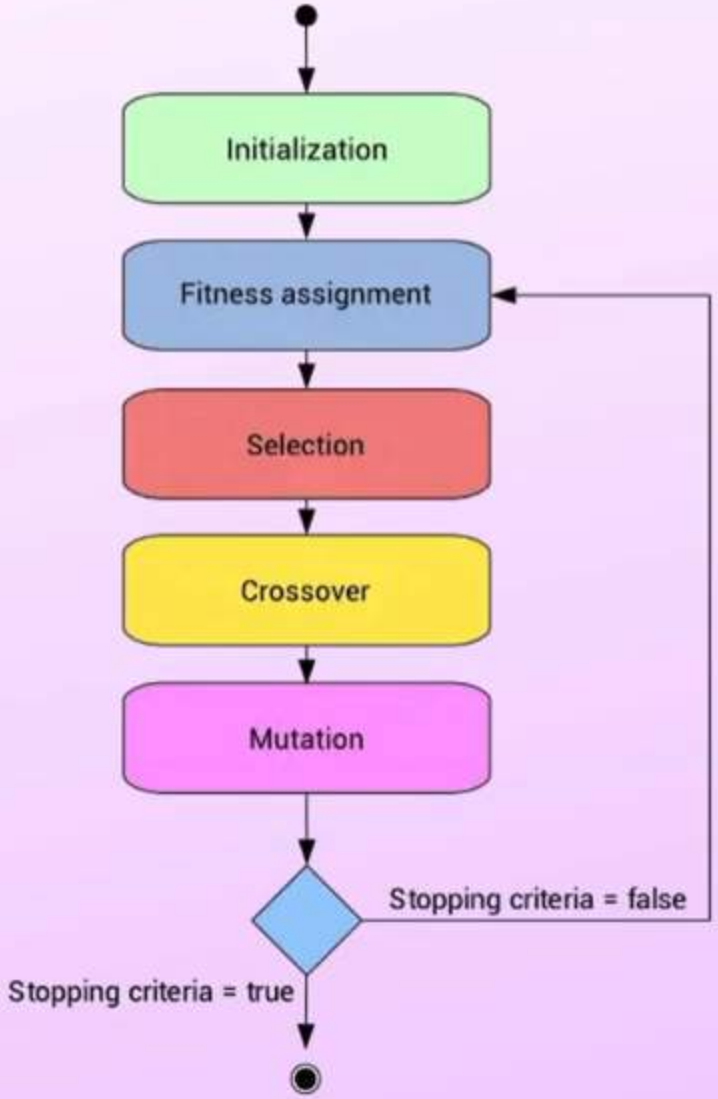


lr → [0.00001 , 0.1]

Batch

Decay

IOU

lr → [0.00001 , 0.1]

Batch → [4 , 64]

Decay → [0.

IOU

lr → [0.00001 , 0.1]

Batch → [4 , 64]

Decay → [0.0001 , 0.01]

IOU → [0.3 , 0.8]

lr → [0.00001 , 0.1]

Batch → [4 , 64]

Decay → [0.0001 , 0.01]

IOU → [0.3 , 0.8]

lr → [0.00001 , 0.1]

Batch → [4 , 64]

Decay → [0.0001 , 0.01]

IOU → [0.3 , 0.8]

lr → [0.00001 , 0.1]

Batch → [4 , 64]

Decay → [0.0001 , 0.01]

IOU → [0.3 , 0.8]

chromosome → [0.001 ,

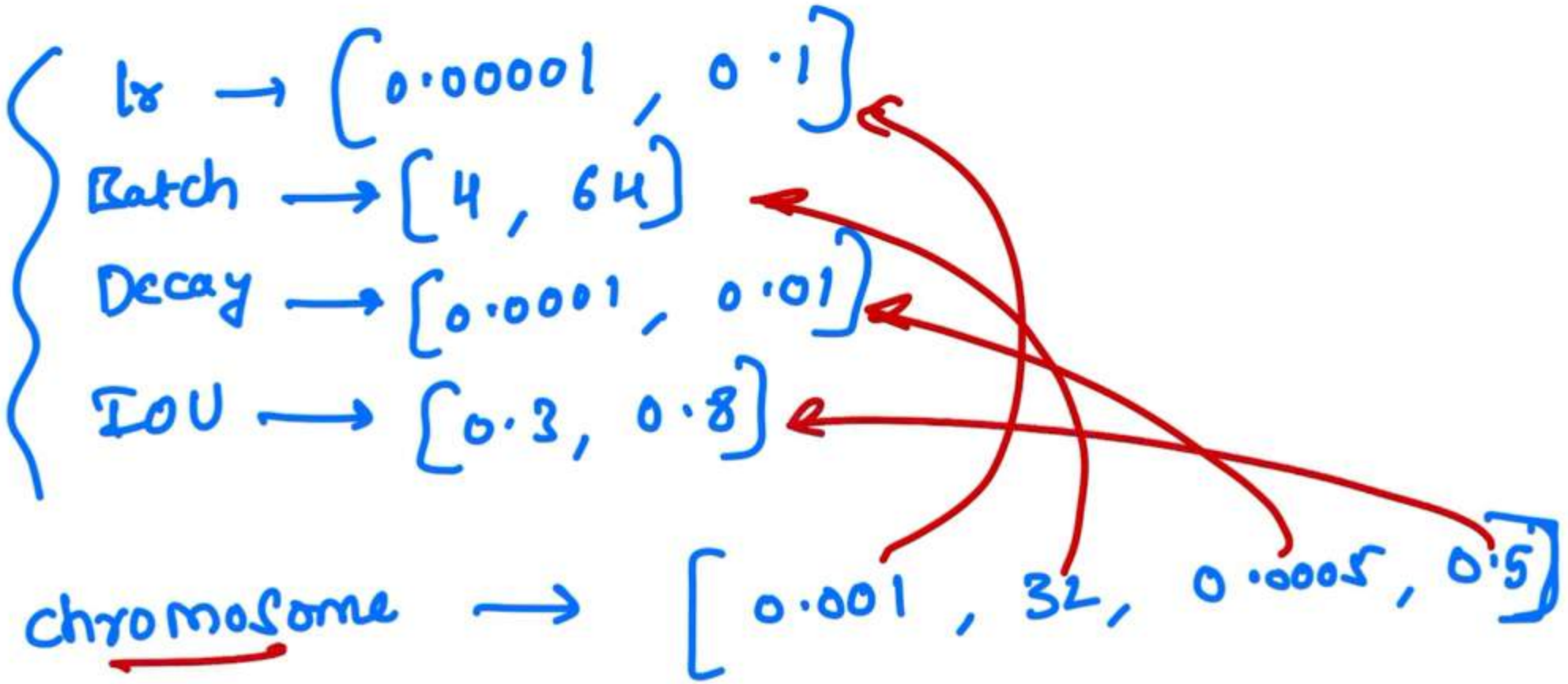
lr → [0.00001 , 0.1]

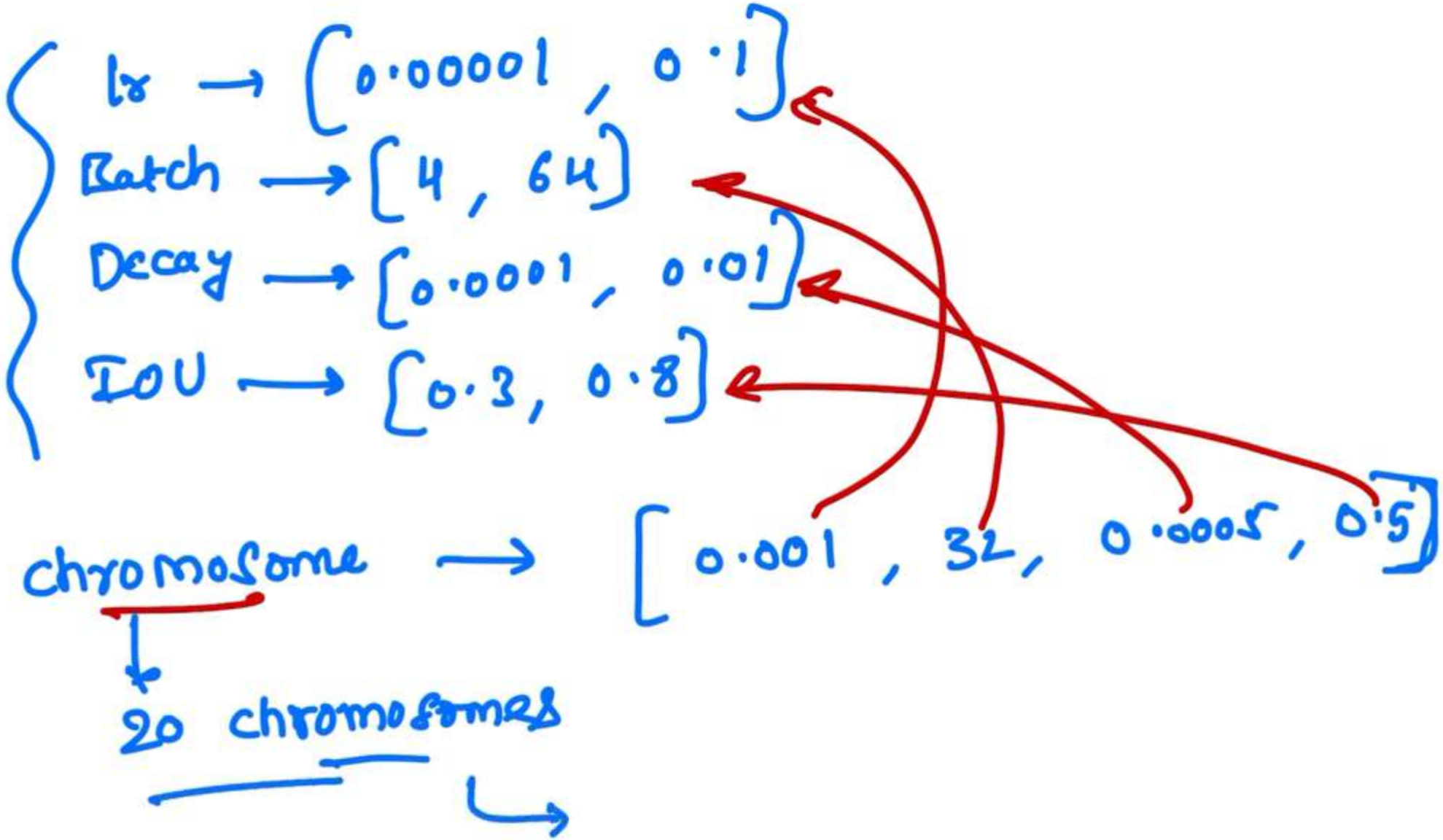
Batch → [4 , 64]

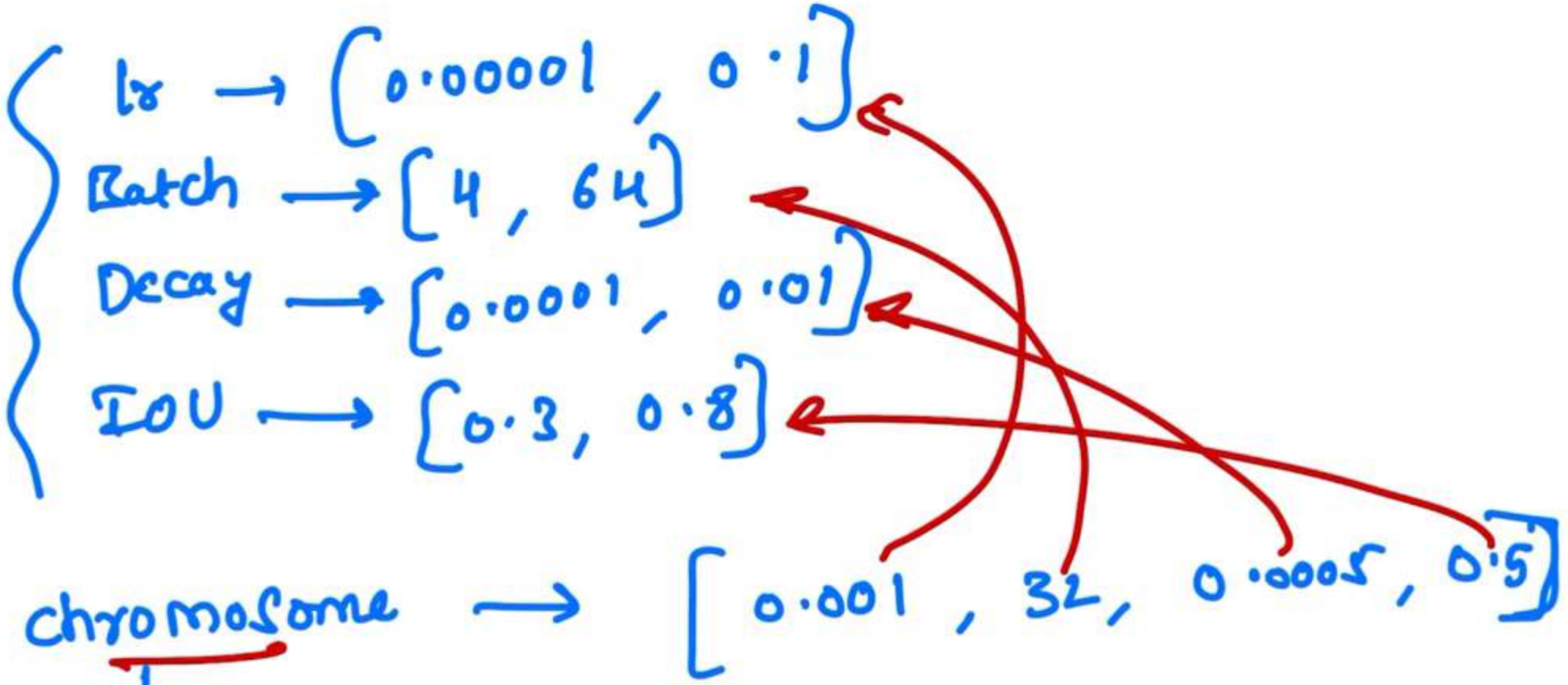
Decay → [0.0001 , 0.01]

IOU → [0.3 , 0.8]

chromosome → [0.001 , 32 , 0.0005 , 0.5]


lr → [0.00001 , 0.1]
Batch → [4 , 64]
Decay → [0.0001 , 0.01]
IOU → [0.3 , 0.8]
chromosome → [0.001 , 32 , 0.0005 , 0.5]

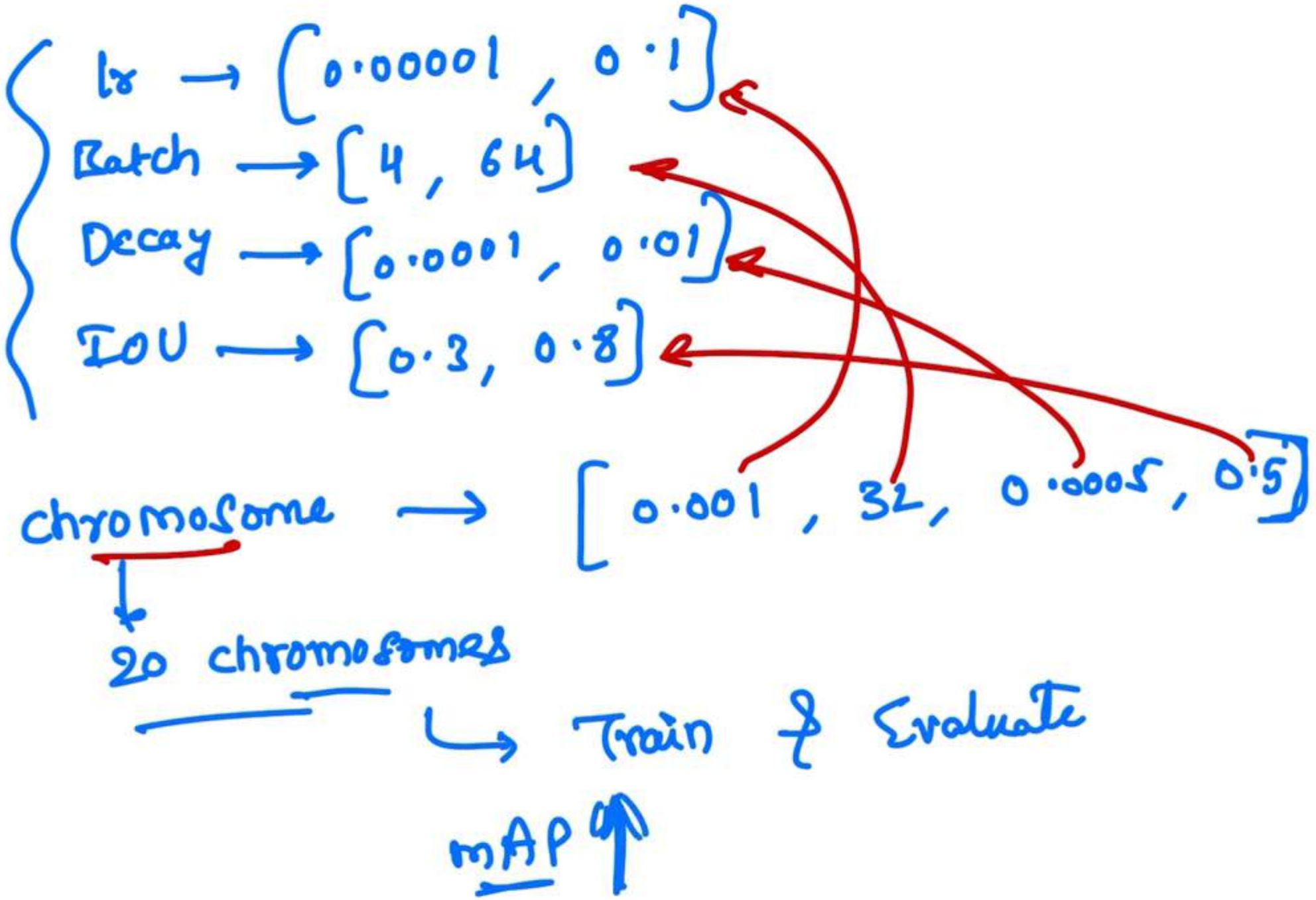

lr → [0.00001 , 0.1]
Batch → [4 , 64]
Decay → [0.0001 , 0.01]
IOU → [0.3 , 0.8]
chromosome → [0.001 , 32 , 0.0005 , 0.5]
20 chromosomes



20 chromosomes

↳ Train & Evaluate

mAP


lr → [0.00001 , 0.1]
Batch → [4 , 64]
Decay → [0.0001 , 0.01]
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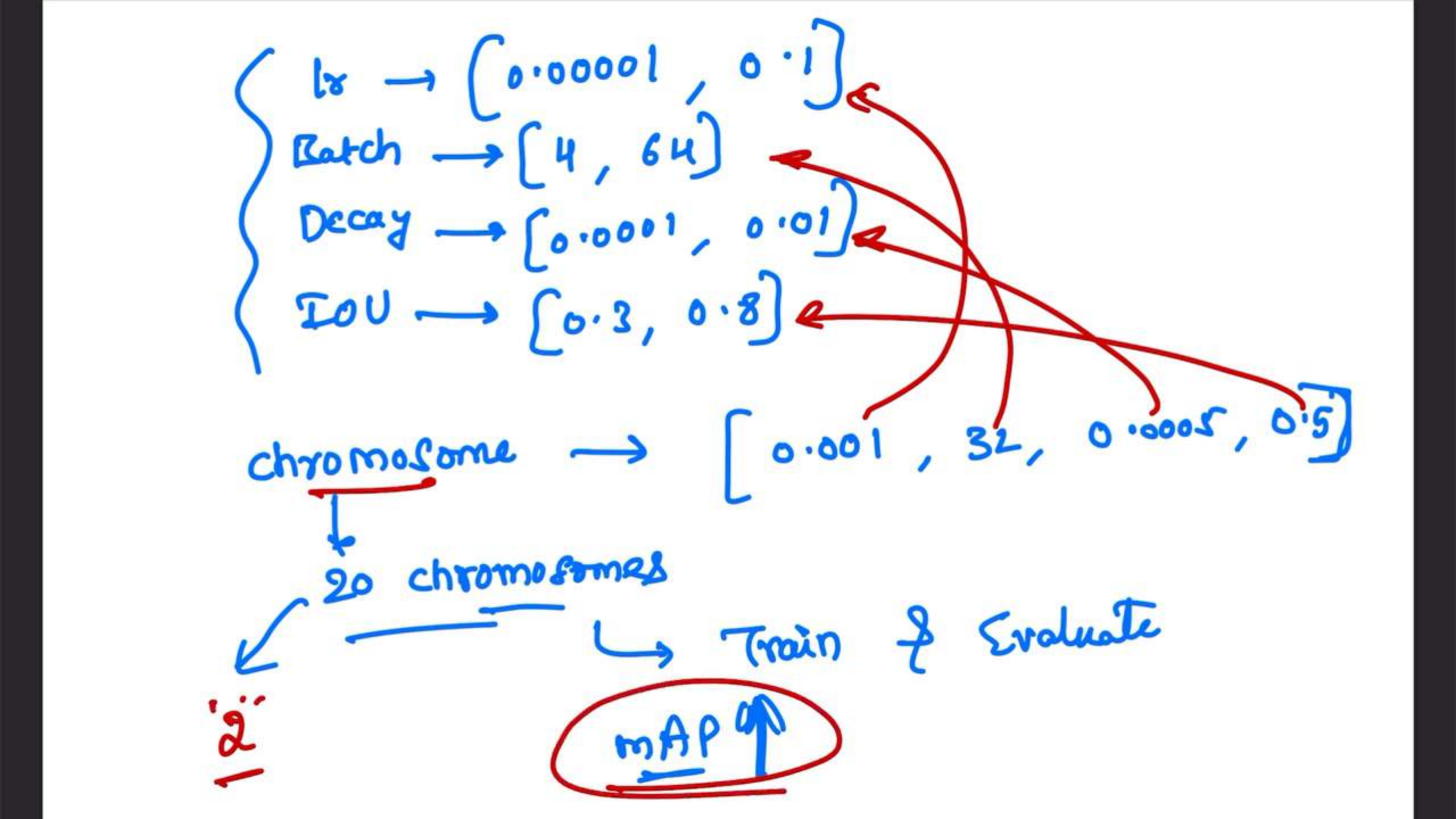
chromosome → [0.001 , 32 , 0.0005 , 0.5]
20 chromosomes
Train & Evaluate
mAP


lr → [0.00001 , 0.1]
Batch → [4 , 64]
Decay → [0.0001 , 0.01]
IOU → [0.3 , 0.8]
chromosome → [0.001 , 32, 0.0005 , 0.5]
20 chromosomes
Train & Evaluate
mAP
2

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { C1 = [0.001, 32, 0.0005, 0.7]
C2 = [0.005, 16, 0.0008, 0.6] }

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 {
C1 = [0.001, 32, 0.0005, 0.7]
C2 = [0.005, 16, 0.0008, 0.6]
}

||
child

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2

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lr → [0.00001, 0.1]
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→ 2

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||

child

[0.001, 16, 0.

lr → [0.00001, 0.1]

Batch → [4, 64]

Decay → [0.0001, 0.01]

IOU → [0.3, 0.8]

→ 2

C1 = [0.001, 32, 0.0005, 0.7]

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child

→ [0.001, 16, 0.0005, 0.6]

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
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→ 2 {
p1 = [0.001, 32, 0.0005, 0.7]
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}

||

child

c1 → [0.001, 16, 0.0005, 0.6]

|| mute

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
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child

C1 → [0.001, 16, 0.0005, 0.6]

mutation

o

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { p1 = [0.001, 32, 0.0005, 0.7]
→ p2 = [0.005, 16, 0.0008, 0.6]

child

c1 → [0.001, 16, 0.0005, 0.6]

mutation

→ [0.002, 16, 0.0005, 0.6]

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { p1 = [0.001, 32, 0.0005, 0.7]
p2 = [0.005, 16, 0.0008, 0.6]

child

c1 → [0.001, 16, 0.0005, 0.6]

mutation

[0.002, 16, 0.0005, 0.6]

10

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { p1 = [0.001, 32, 0.0005, 0.7]
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child

c1 → [0.001, 16, 0.0005, 0.6]

mutation

[0.002, 16, 0.0005, 0.6]

map

'10'

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { p1 = [0.001, 32, 0.0005, 0.7]
p2 = [0.005, 16, 0.0008, 0.6]

child

100 20

m

c1 → [0.001, 16, 0.0005, 0.6]

mutation

0.002, 16, 0.0005, 0.6

map

'10'

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

→ 2 { p1 = [0.001, 32, 0.0005, 0.7]
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child

100 20

mAP 0.9

C1 → [0.001, 16, 0.0005, 0.6]

mutation

[0.002, 16, 0.0005, 0.6]

map

'10'

lr → [0.00001, 0.1]
Batch → [4, 64]
Decay → [0.0001, 0.01]
IOU → [0.3, 0.8]

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p1 = [0.001, 32, 0.0005, 0.7]
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child

100 20

mAP 0.9

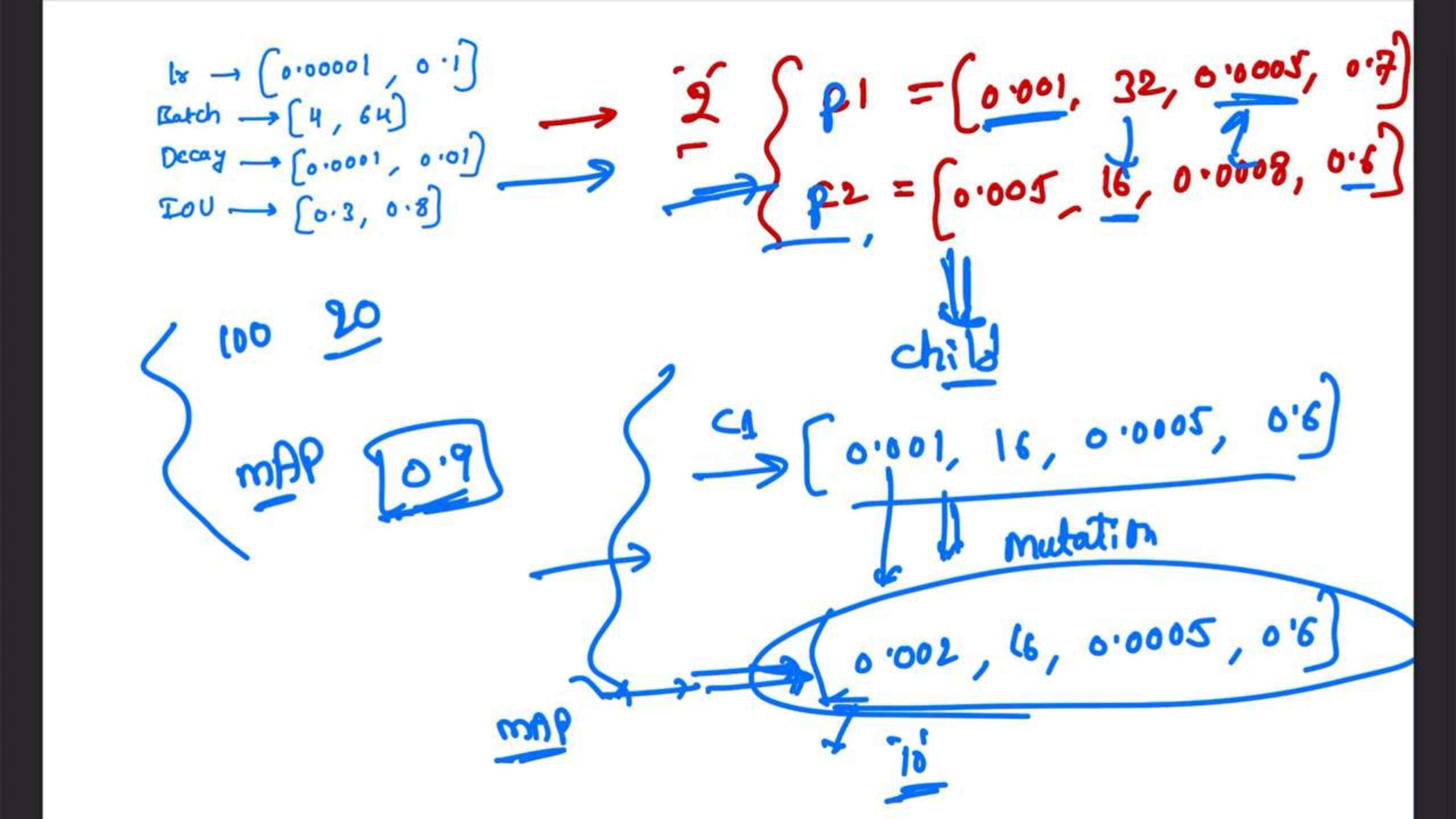
c1 → [0.001, 16, 0.0005, 0.6]

mutation

0.002, 16, 0.0005, 0.6

map

10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mutation
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map
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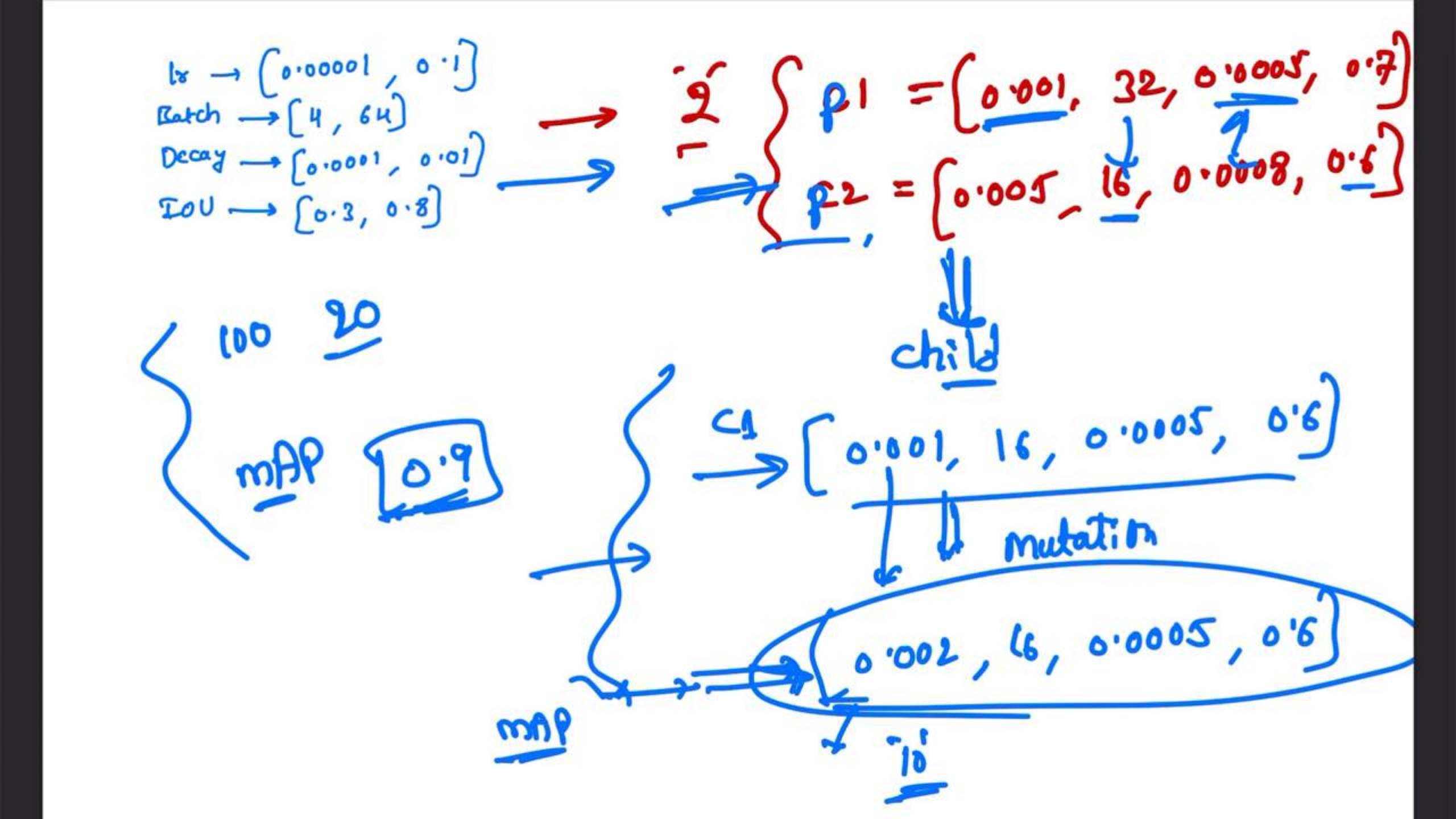
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mutation
0.002, 16, 0.0005, 0.6
map
10

Genetic Algorithms

- **Define Hyperparameters**: Learning rate, Batch size, Momentum, Weight decay etc.,
- **Encode Hyperparameters**: Chromosome - [learning_rate, batch_size, momentum].
- **Initial Population**: Generate an initial population of random hyperparameter sets.
- **Fitness Function**: Train the YOLOv4 model with each set of hyperparameters and evaluate its performance using a fitness function. This could be based on metrics like mAP on a validation set.
- **Selection**: Select the top-performing hyperparameter sets based on their fitness scores.
- **Crossover**: Combine pairs of selected hyperparameter sets to create new sets.
- **Mutation**: Introduce random changes to some hyperparameter sets to maintain diversity in the population and explore new areas of the hyperparameter space.
- **New Generation**: Create a new generation of hyperparameter sets using the selected, crossover, and mutated sets.
- **Repeat**: Repeat the process for a number of generations or until convergence, i.e., when the improvement in the fitness score plateaus.
- **Best Hyperparameters**: The best-performing hyperparameter set from the final generation is chosen as the optimal set.

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- **Encode Hyperparameters**: Chromosome - [learning_rate, batch_size, momentum].
- **Initial Population**: Generate an initial population of random hyperparameter sets.
- **Fitness Function**: Train the YOLOv4 model with each set of hyperparameters and evaluate its performance using a fitness function. This could be based on metrics like mAP on a validation set.
- **Selection**: Select the top-performing hyperparameter sets based on their fitness scores.
- **Crossover**: Combine pairs of selected hyperparameter sets to create new sets.
- **Mutation**: Introduce random changes to some hyperparameter sets to maintain diversity in the population and explore new areas of the hyperparameter space.
- **New Generation**: Create a new generation of hyperparameter sets using the selected, crossover, and mutated sets.
- **Repeat**: Repeat the process for a number of generations or until convergence, i.e., when the improvement in the fitness score plateaus.
- **Best Hyperparameters**: The best-performing hyperparameter set from the final generation is chosen as the optimal set.

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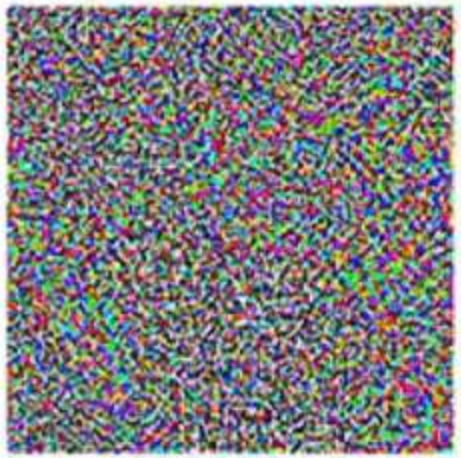
Adversarial Attacks

$\boldsymbol{x}$

"panda"
57.7% confidence

$+ .007 \times$



$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"nematode"
8.2% confidence

$=$

$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"gibbon"
99.3 % confidence

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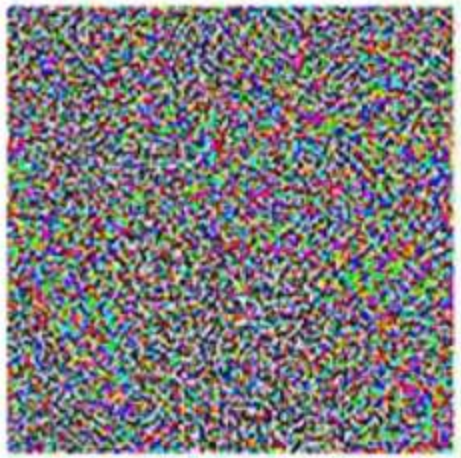

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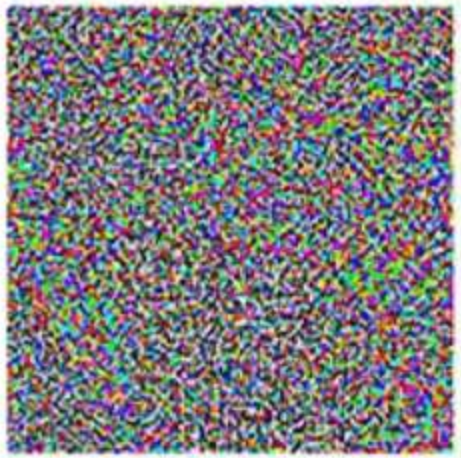

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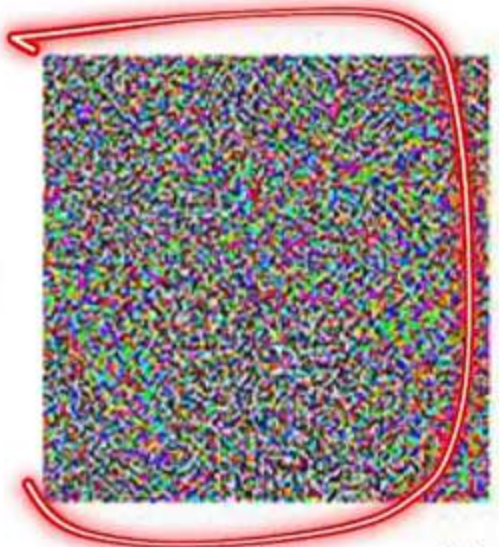

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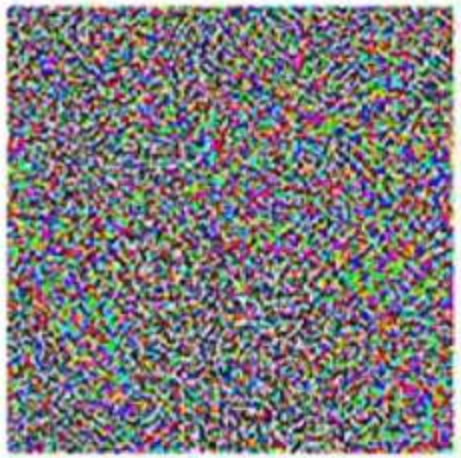

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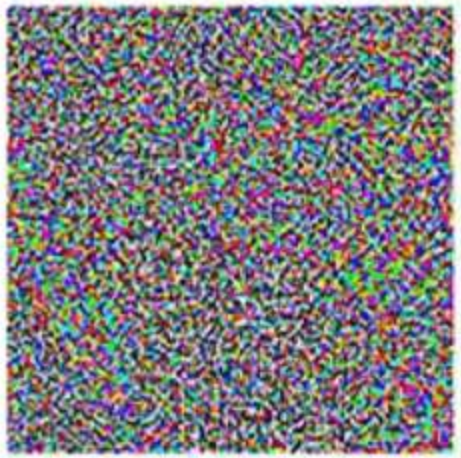

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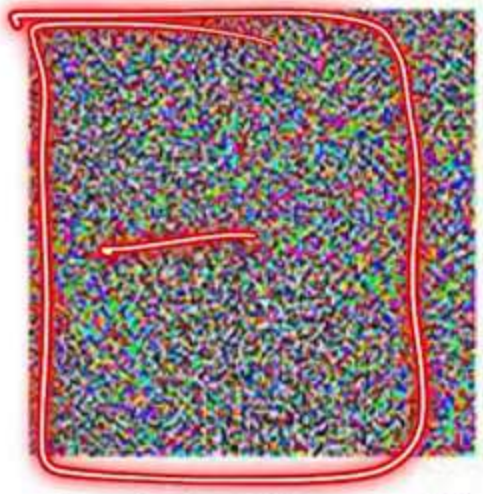

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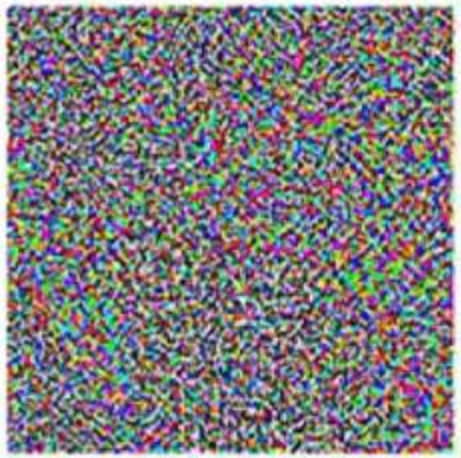

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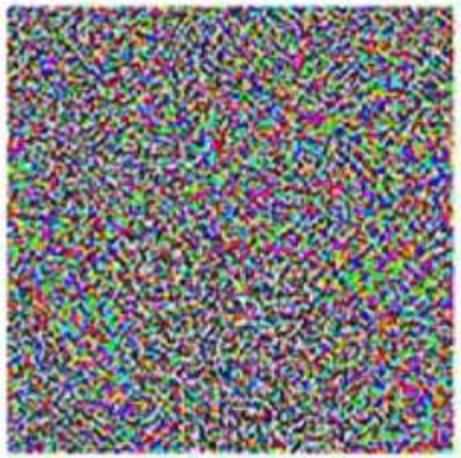

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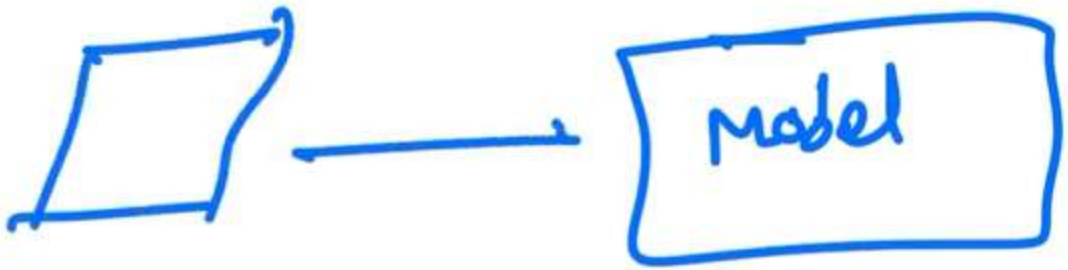
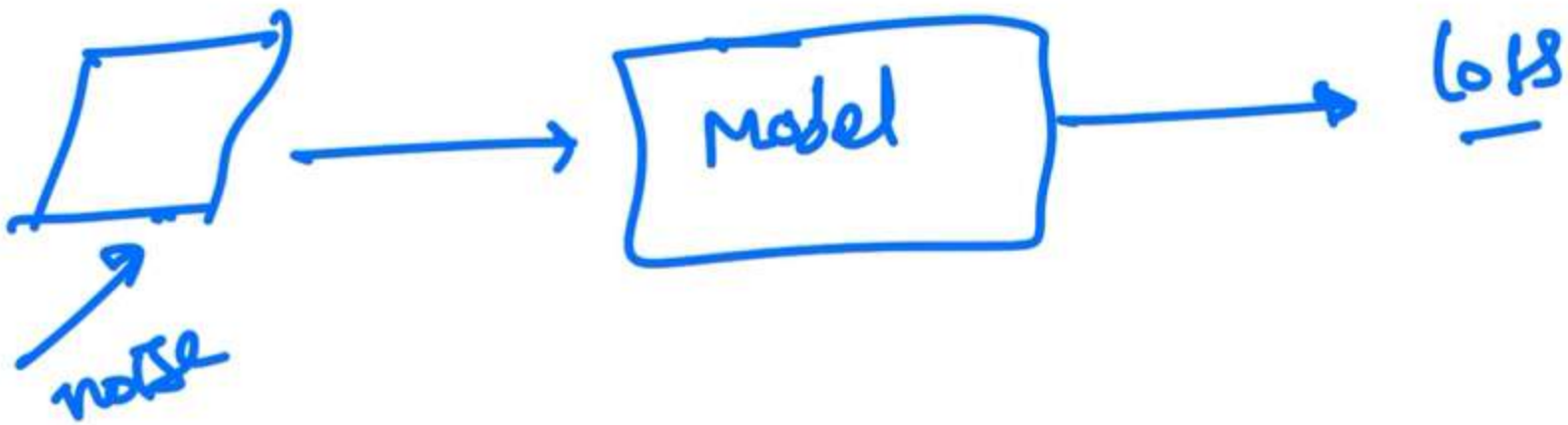
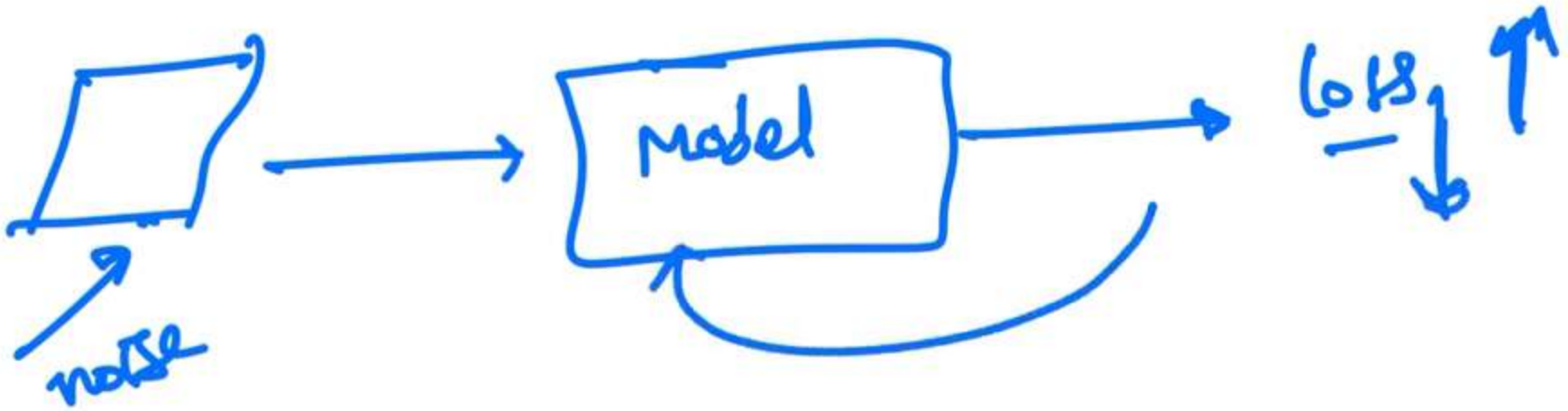
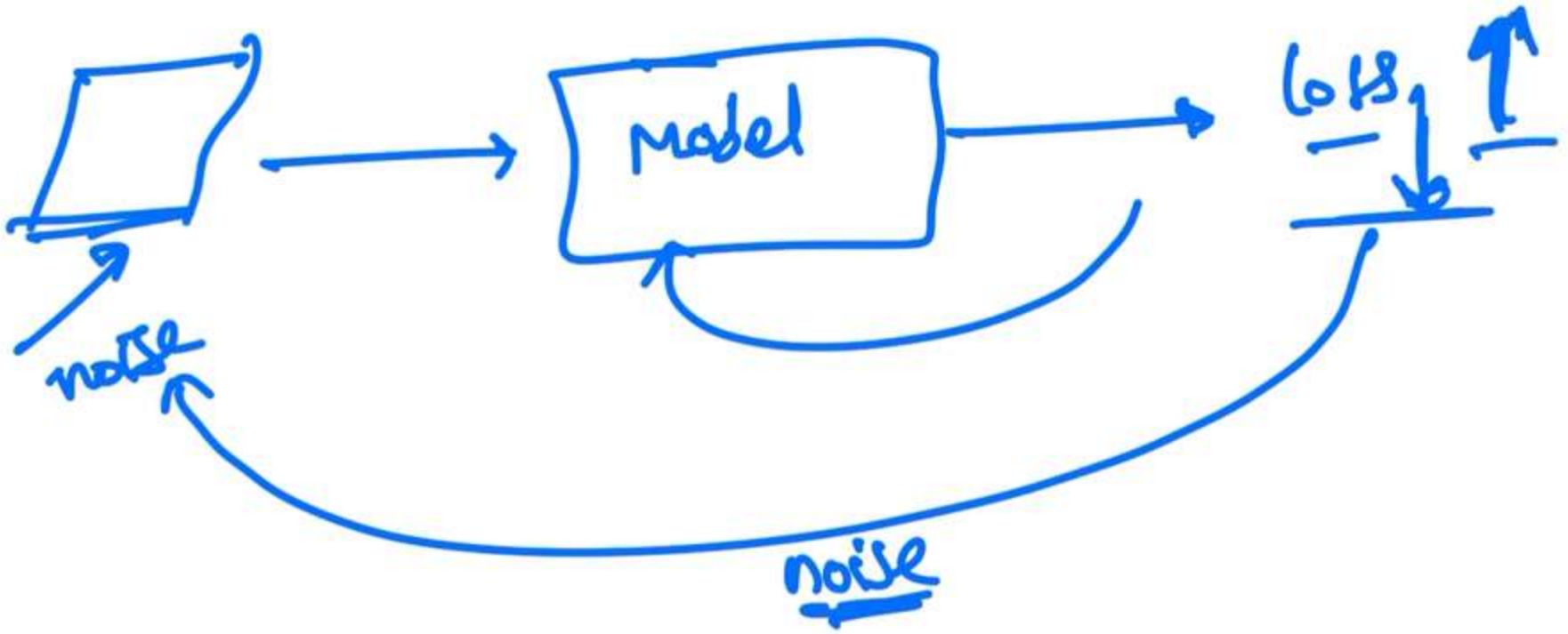

Model


model
noise


model
loss
noise


model
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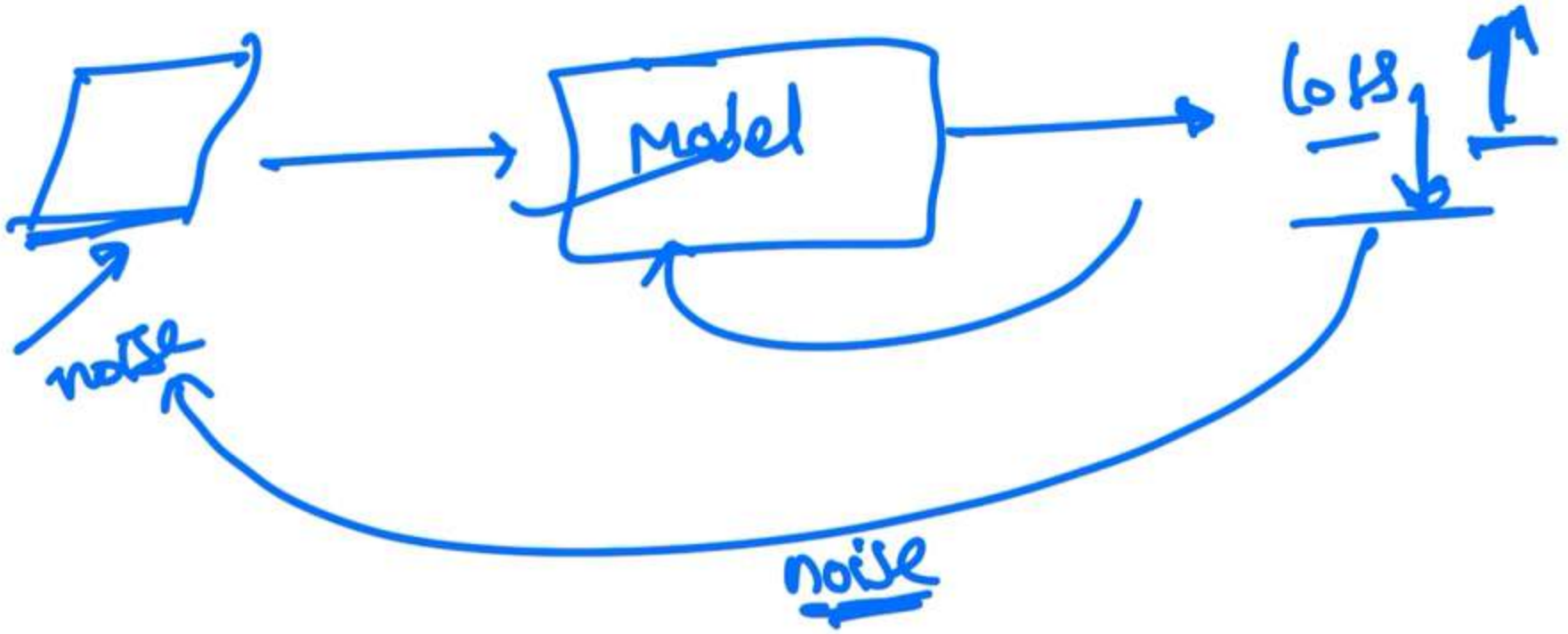
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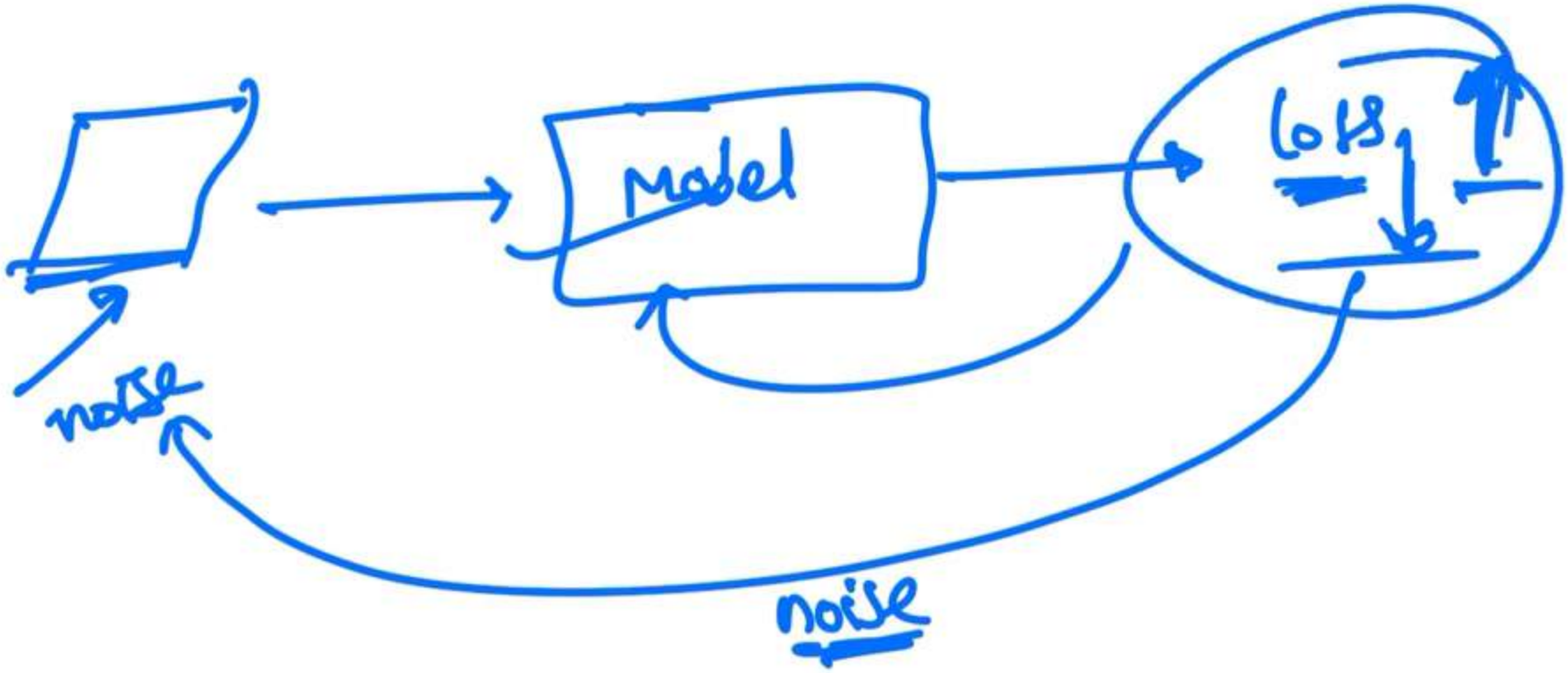
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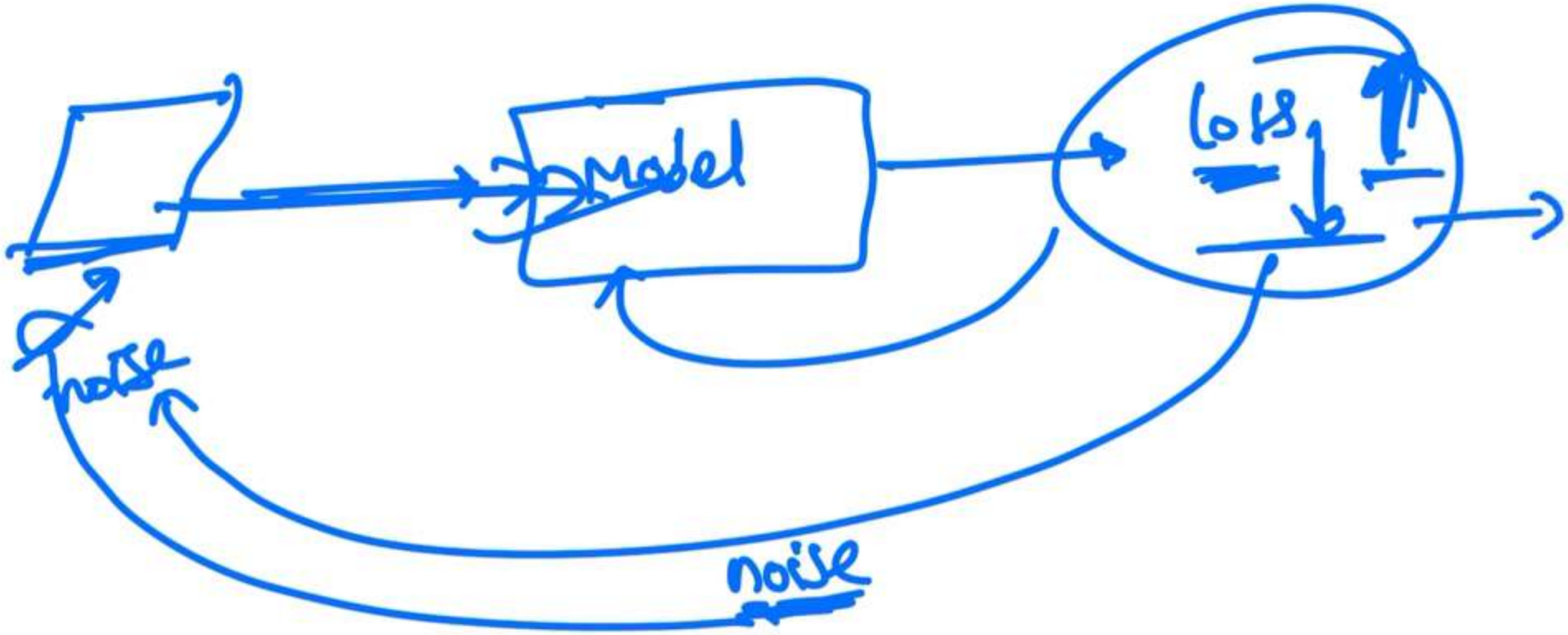
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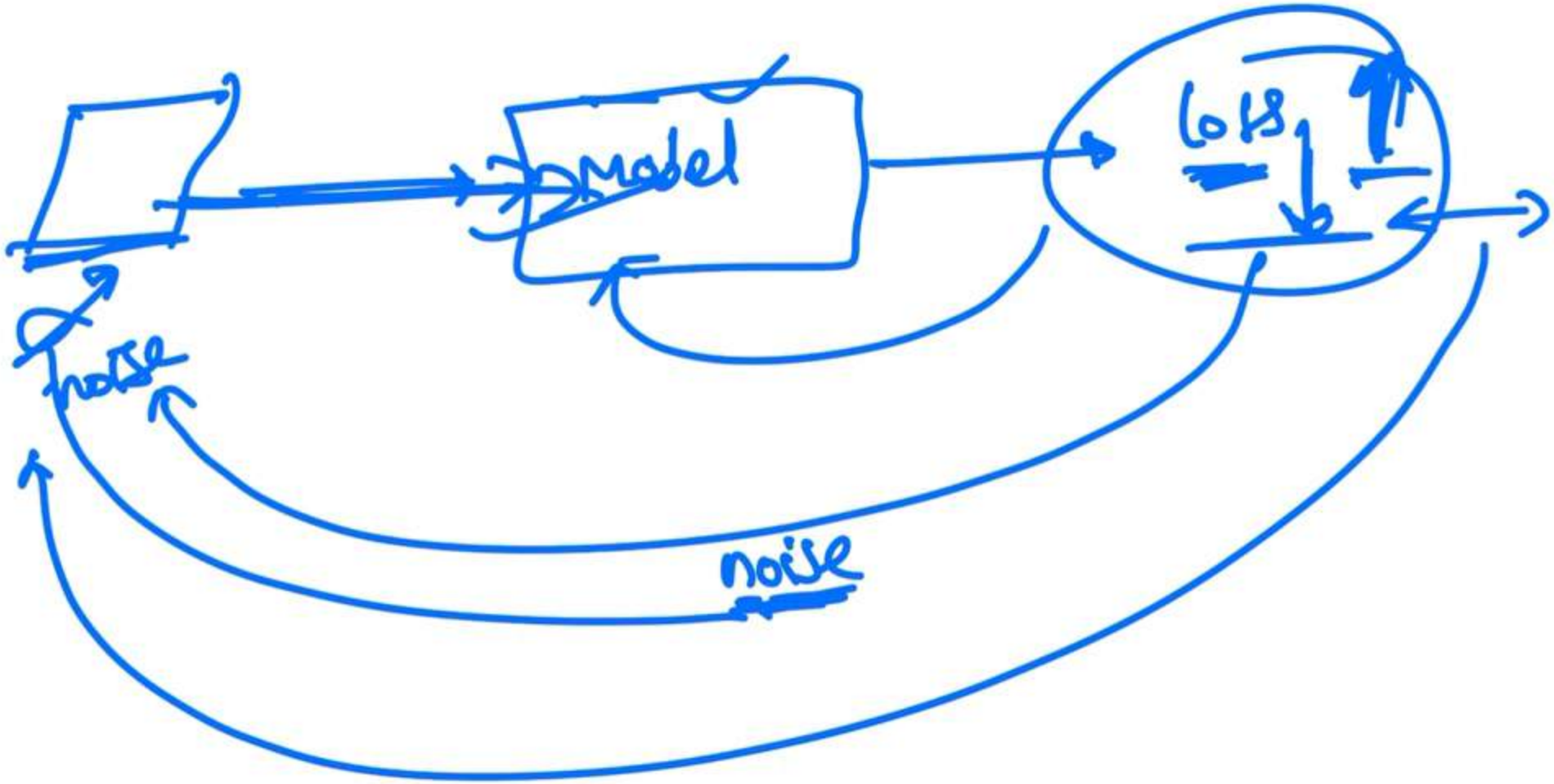
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