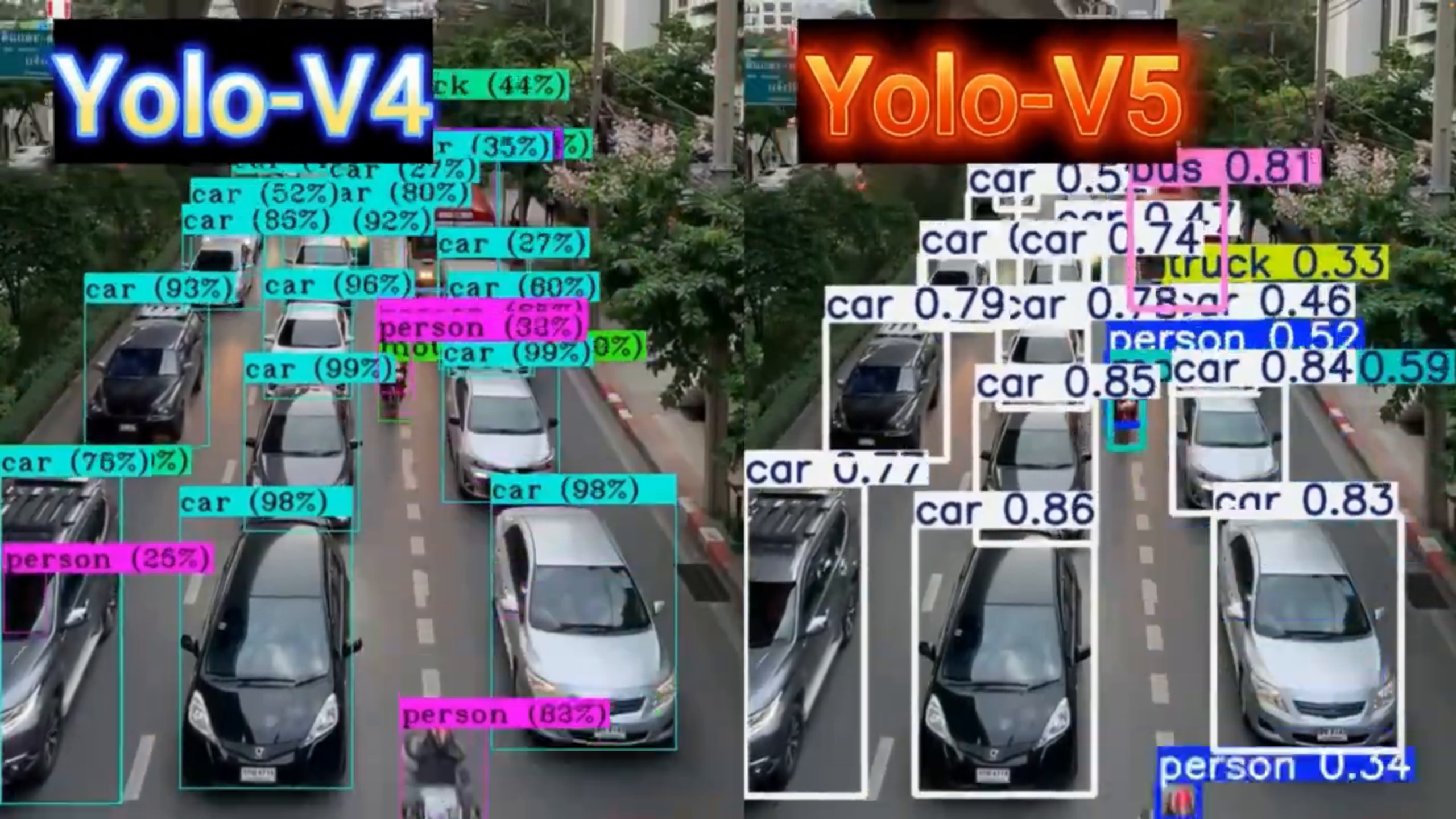
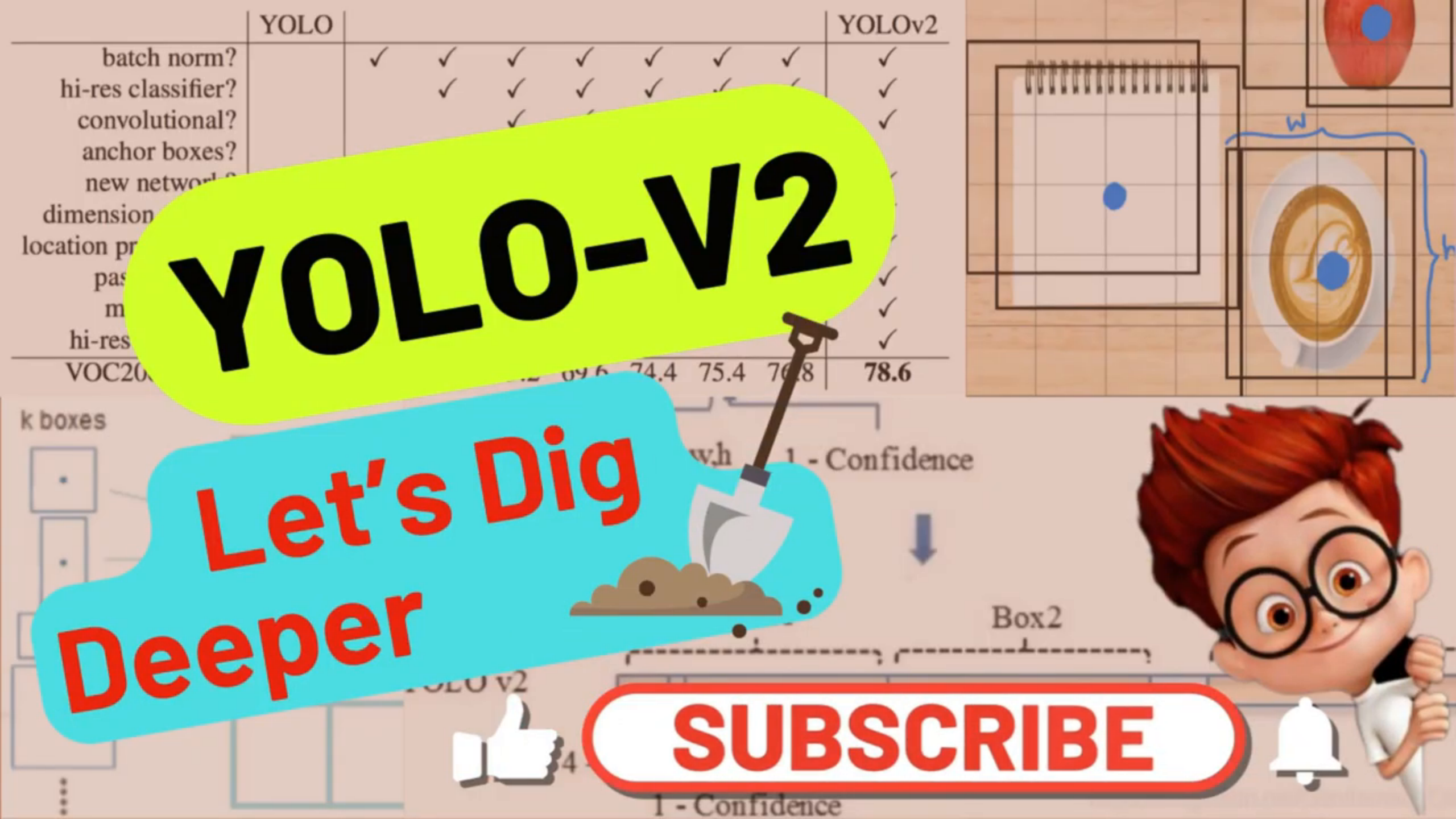

Yolo-V4
Yolo-V5
car (52%)
car (85%)
car (27%)
car (93%)
car (96%)
car (60%)
person (33%)
car (99%)
car (99%)
car (76%)
car (98%)
car (98%)
person (26%)
person (83%)
bus 0.81
car 0.74
truck 0.33
car 0.79
car 0.46
person 0.52
car 0.84
0.59
car 0.85
car 0.86
car 0.83
person 0.34


YOLO
YOLOv2
batch norm?
hi-res classifier?
convolutional?
anchor boxes?
78.6
YOLO-V2
Let's Dig Deeper
k boxes
1 - Confidence
Box2
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University of Washington*, Allen Institute for AI†
http://pjreddie.com/yolo9000/

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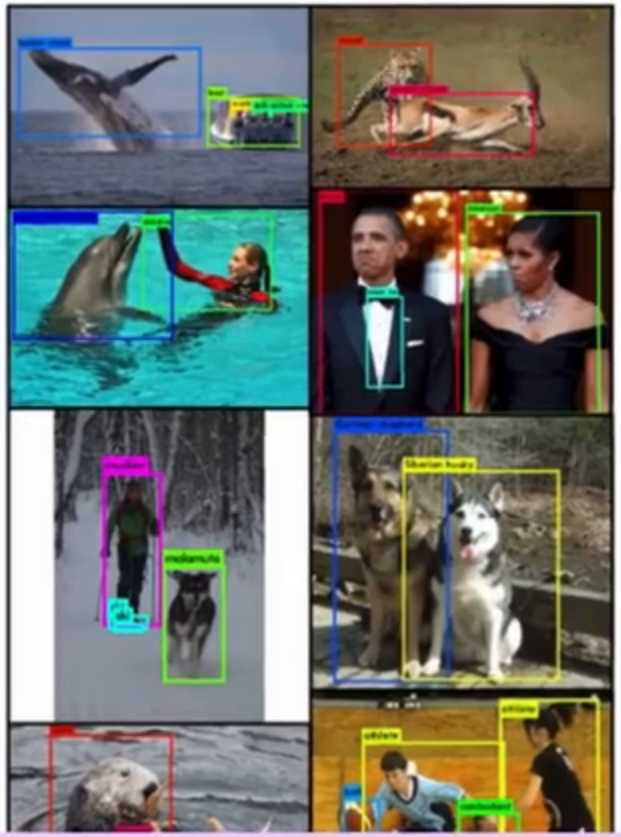

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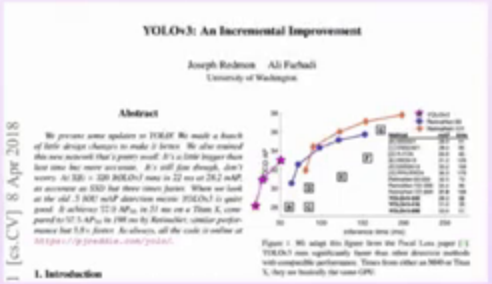
arXiv:1612.08242v1 [cs.CV] 25 Dec 2016



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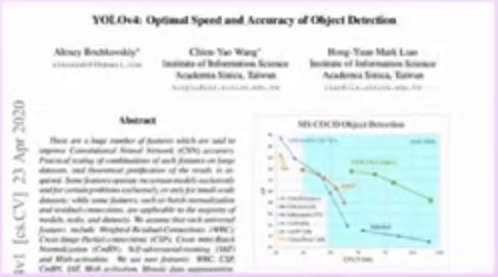
arXiv:1804.02767v1 [cs.CV] 8 Apr 2018



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arXiv:2004.10934v1 [cs.CV] 23 Apr 2020

YOLO-V5

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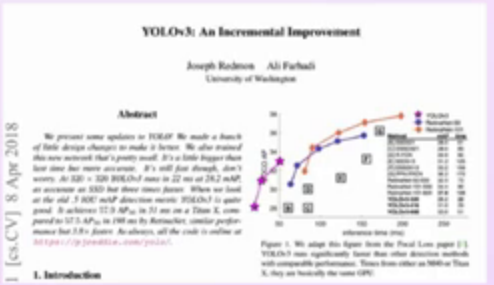

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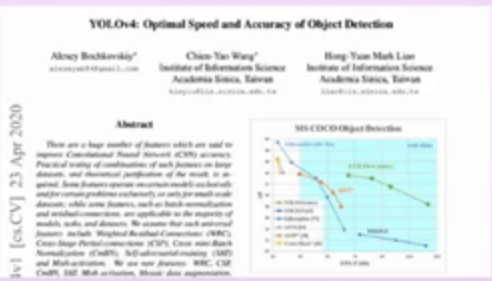
Figure 1. We adapt this figure from the Focal Loss paper [9]. YOLOv3 runs significantly faster than other detection methods with comparable performance. Times from either an M40 or Titan X, they are basically the same GPU.



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YOLO-V5

r/MachineLearning • 5 yr. ago
aloser

[News] YOLOv5 is Here: State-of-the-Art Object Detection at 140 FPS

News

YOLOv5 (PyTorch) was released by Ultralytics last night; early results show it runs inference extremely fast, weights can be exported to mobile, and it achieves state of the art on COCO.

It's insane how quickly SOTA for object detection is advancing. EfficientDet was just released in March. YOLOv4 in April. And now YOLOv5 in June.

- Ultralytics YOLOv5 Repo
- Writeup: YOLOv5 is Here: State-of-the-Art Object Detection at 140 FPS
- Tutorial: Training YOLOv5 on a Custom Dataset
- YOLOv5 Colab Notebook

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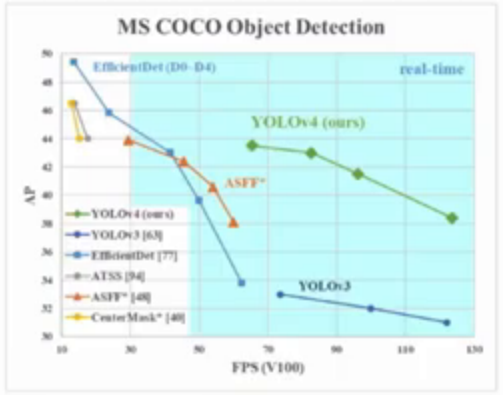

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YOLOv5
你只看一次v5

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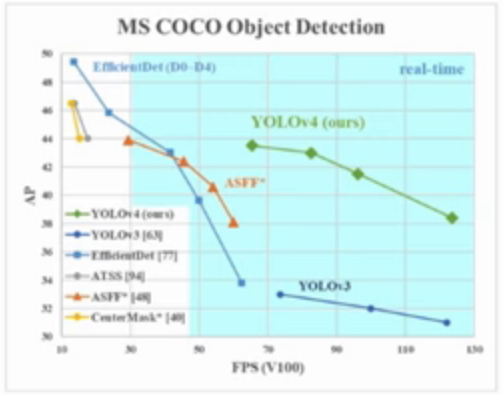

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AlexeyAB on Jun 11, 2020

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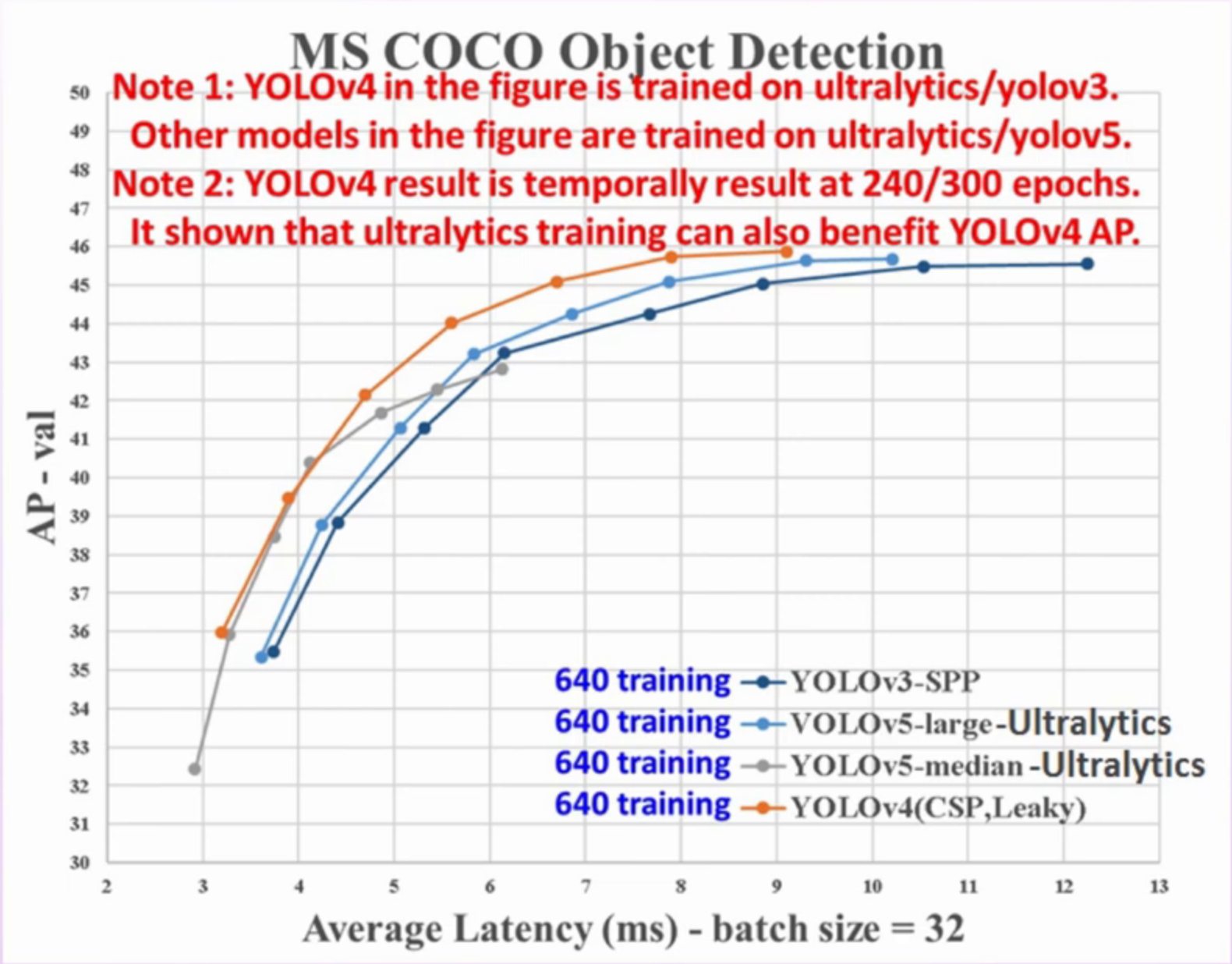
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Note 1: YOLOv4 in the figure is trained on ultralytics/yolov3.
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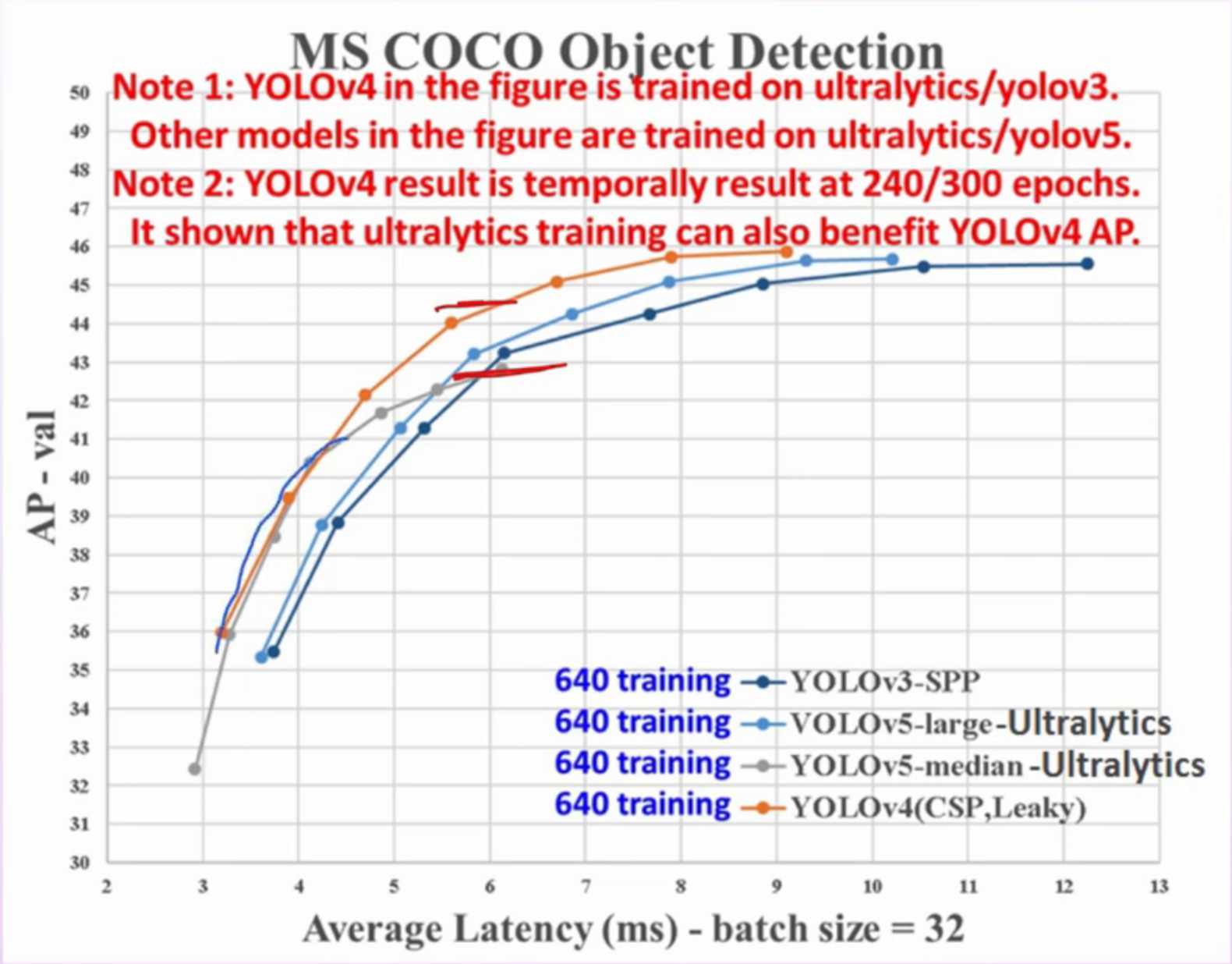
Note 2: YOLOv4 result is temporally result at 240/300 epochs.
It shown that ultralytics training can also benefit YOLOv4 AP.
AP - val
Average Latency (ms) - batch size = 32
640 training YOLOv3-SPP
640 training YOLOv5-large -Ultralytics
640 training YOLOv5-median -Ultralytics
640 training YOLOv4(CSP,Leaky)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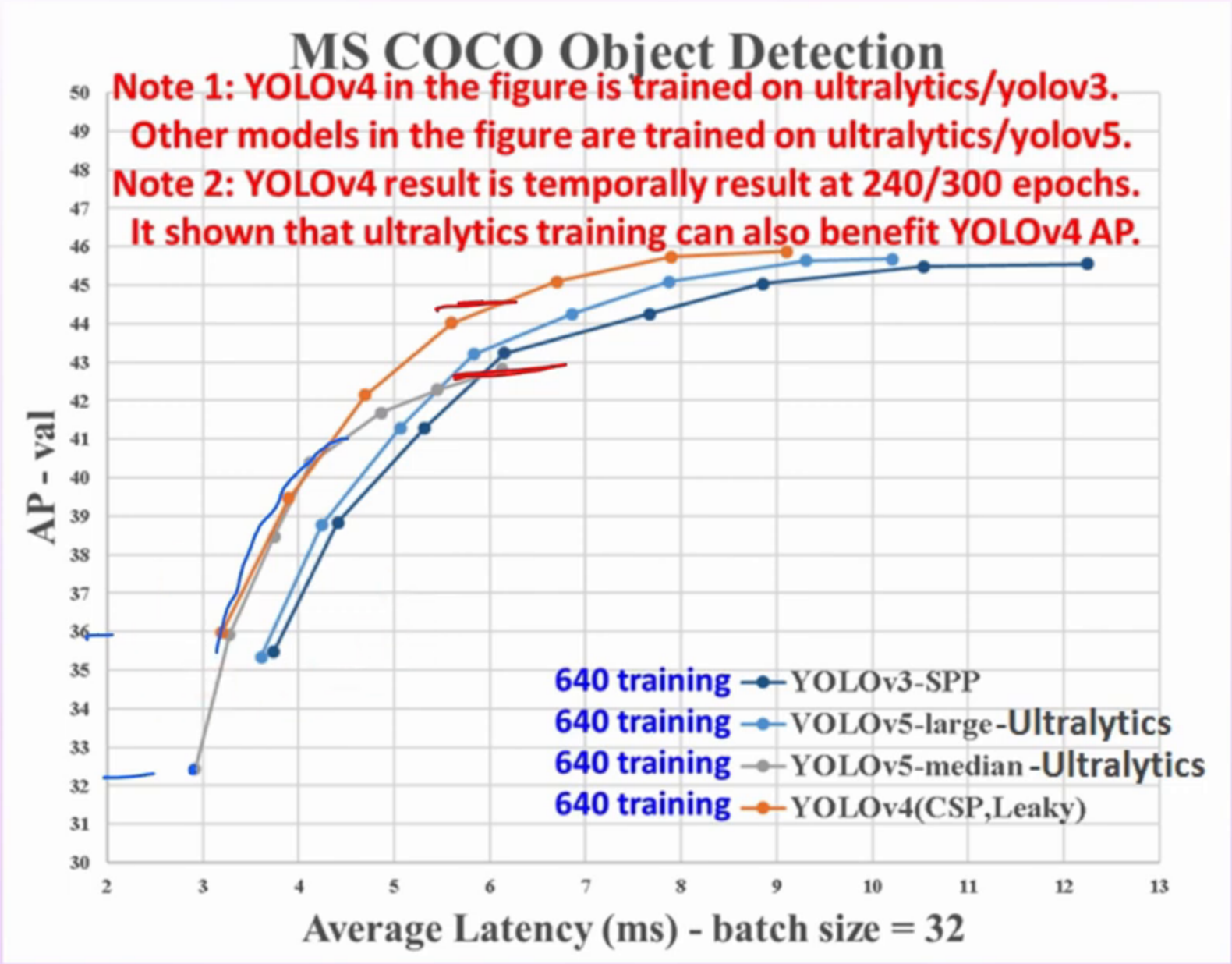
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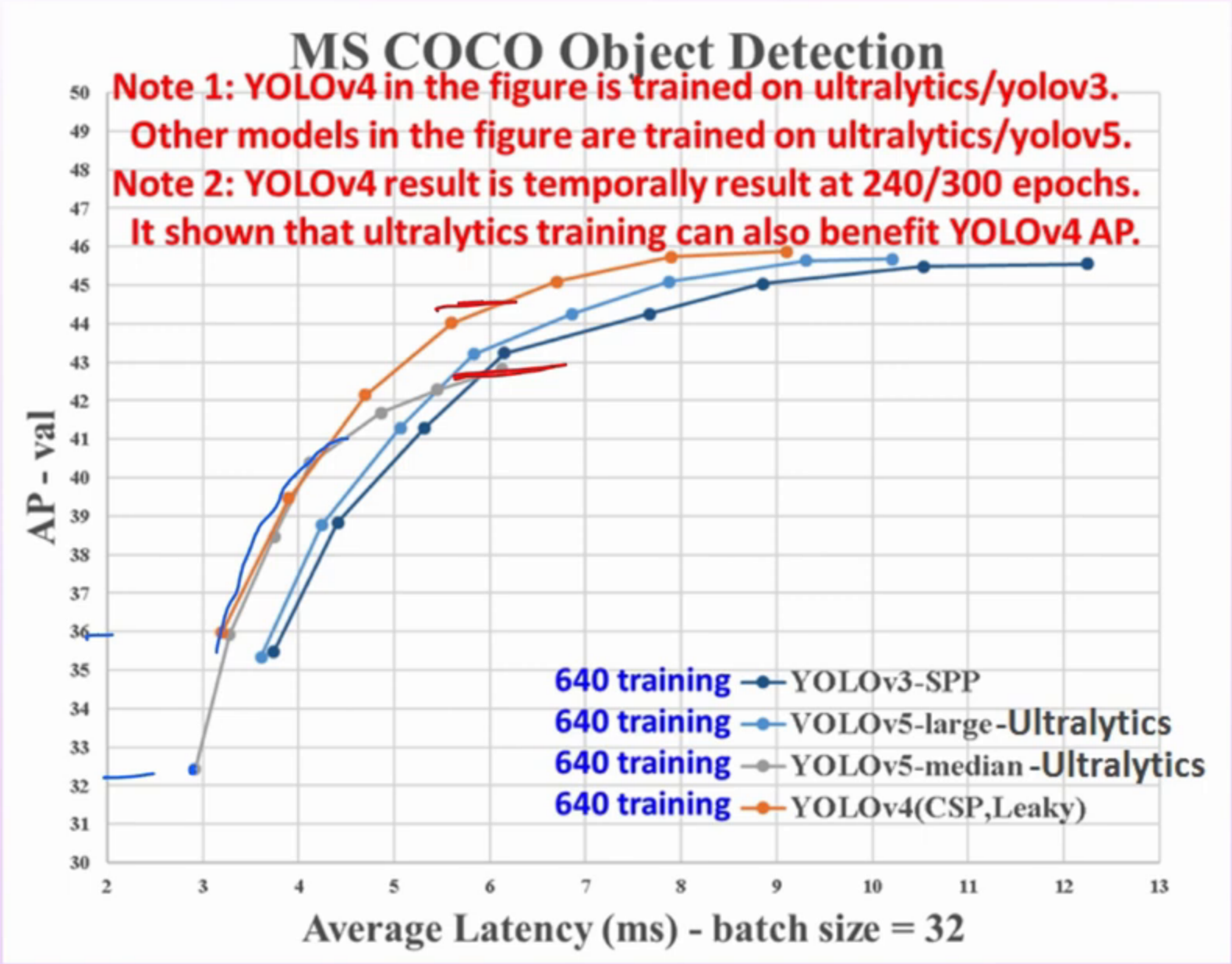
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glenn-jocher on Jun 11, 2020 · edited by glenn-jocher

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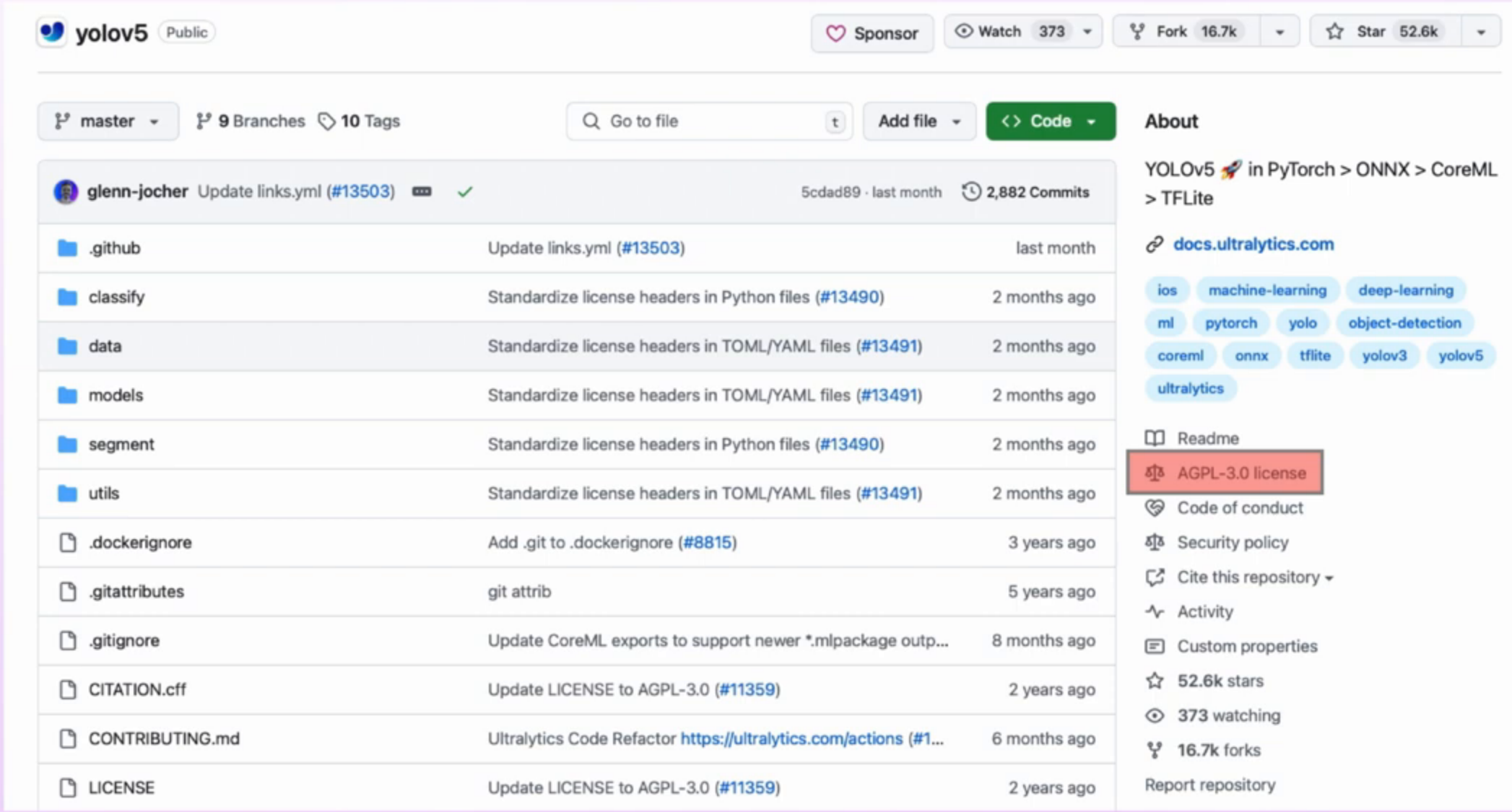

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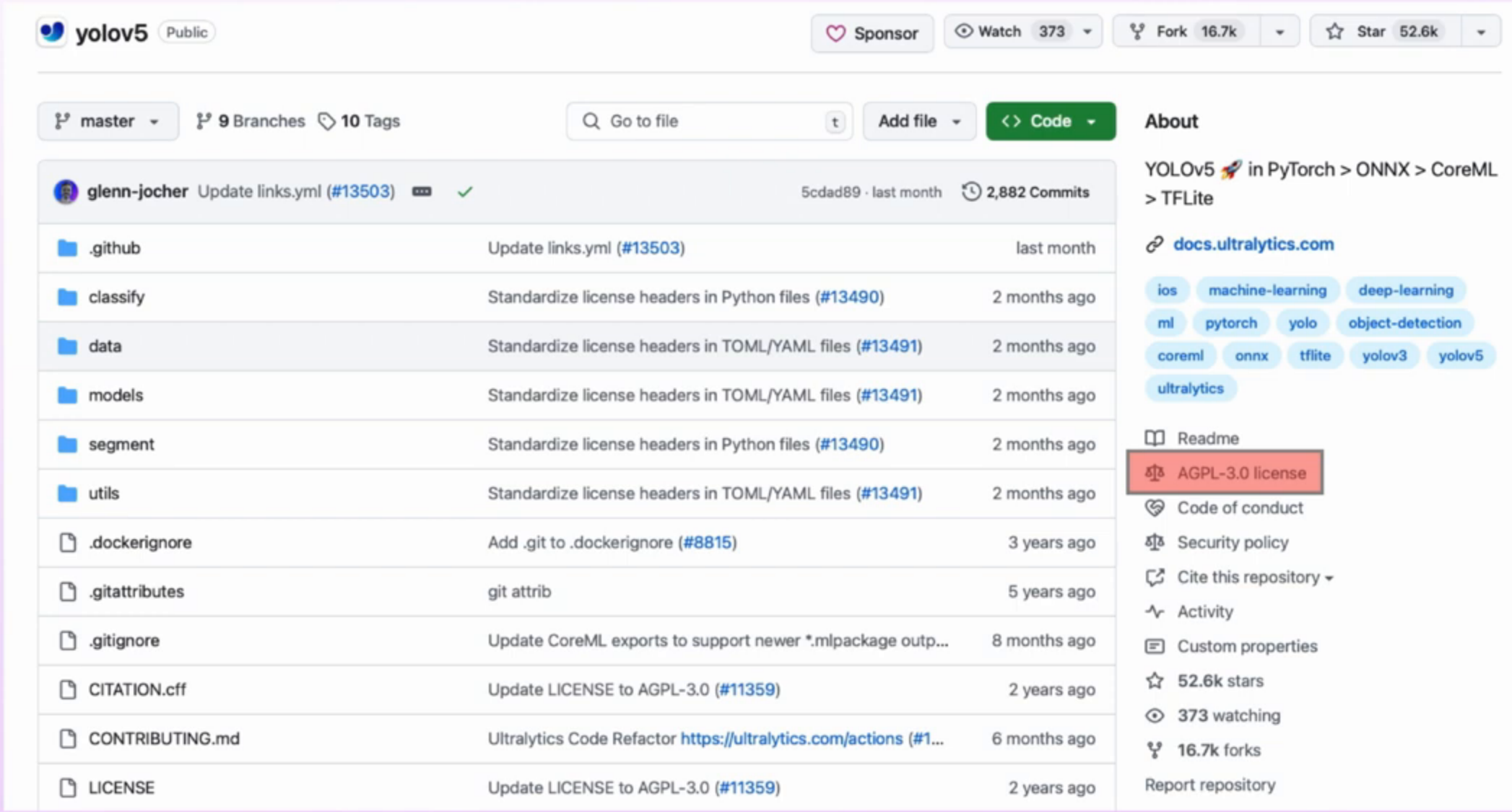


YOLO-V5

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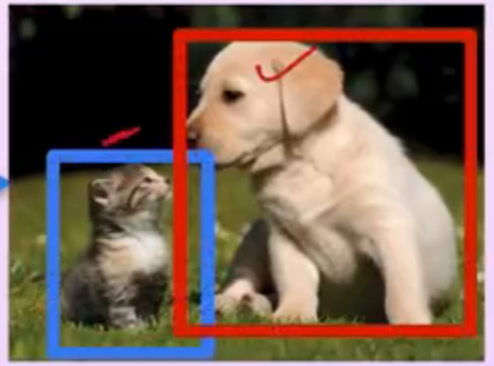

YOLO-V5

Backbone

CSP
Darknet53

Neck

SPP
+
PAN

Head

YOLOv3
Head

YOLO-V5

Backbone

CSP Darknet53

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YOLOv3 Head

YOLO-V5

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YOLOv3
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YOLO-V5

Backbone

3 x 3

6 x 6

Mish

Swish

YOLO-V5

Backbone

3 x 3 → 6 x 6

Mish → Swish

Add/Remove CSP blocks

YOLO-V5

Backbone

Modified
CSP
Darknet53

Neck

SPP
+
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YOLO-V5

Backbone

Modified
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SPP → SPPF

PAN → CSP-PAN

YOLO-V5

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Modified YOLOv3 Head

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- Cuda 14.6%
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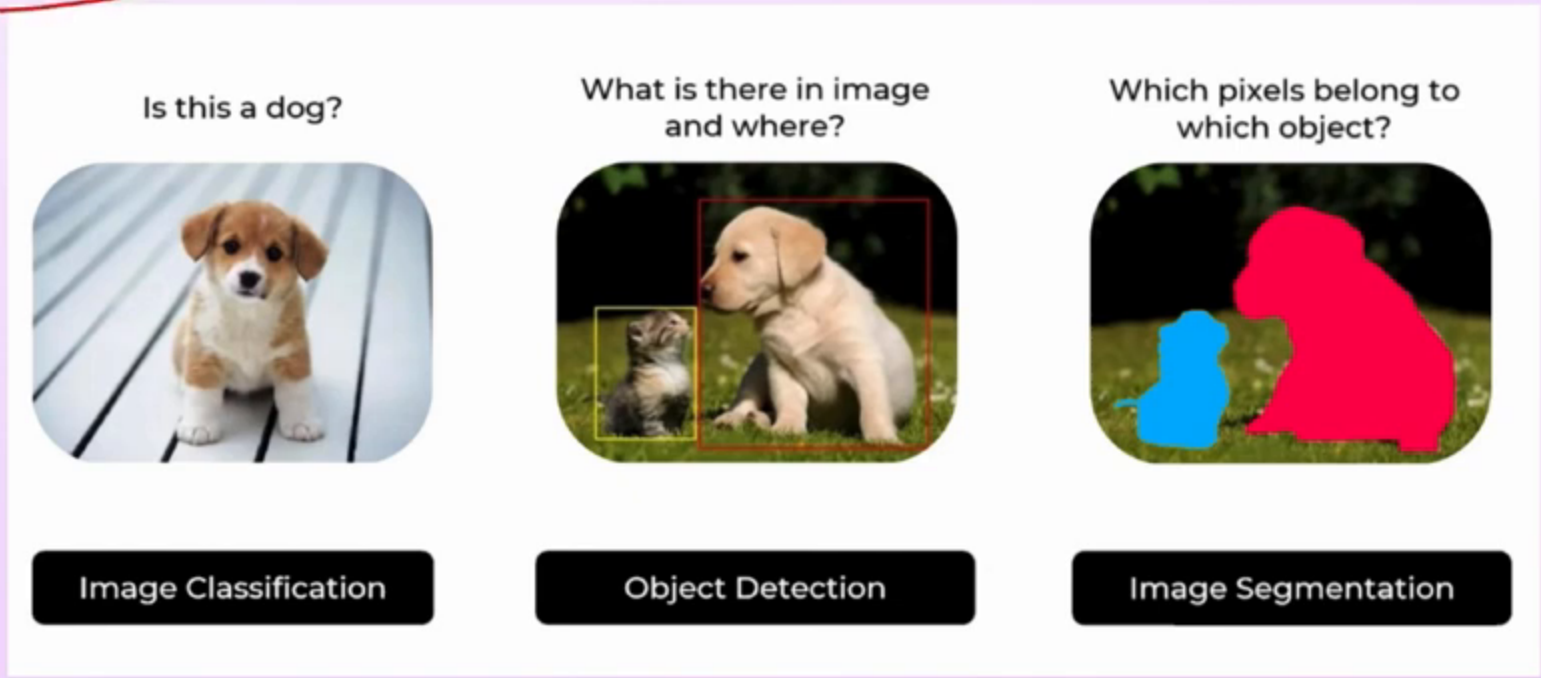
  * Object Detection
  * Classification
  * InstanceSegmentation



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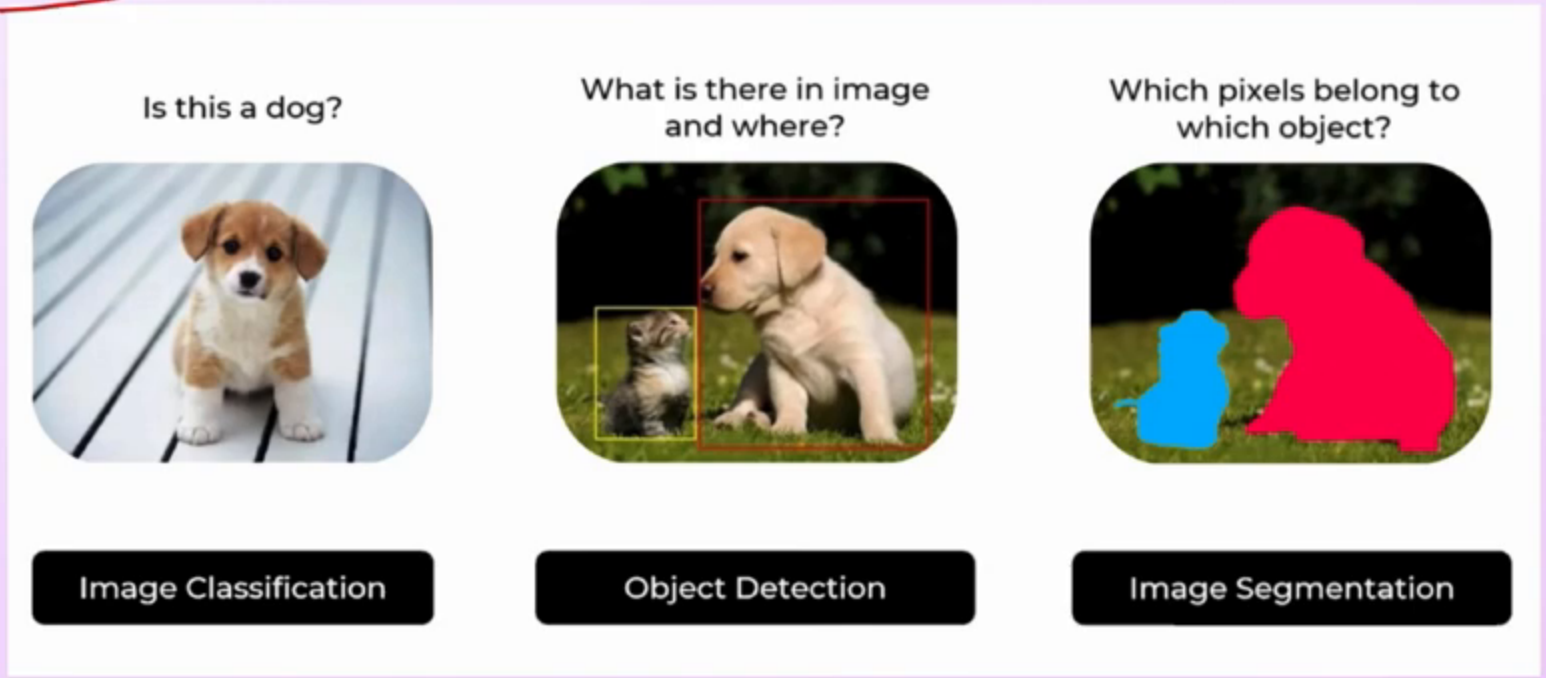

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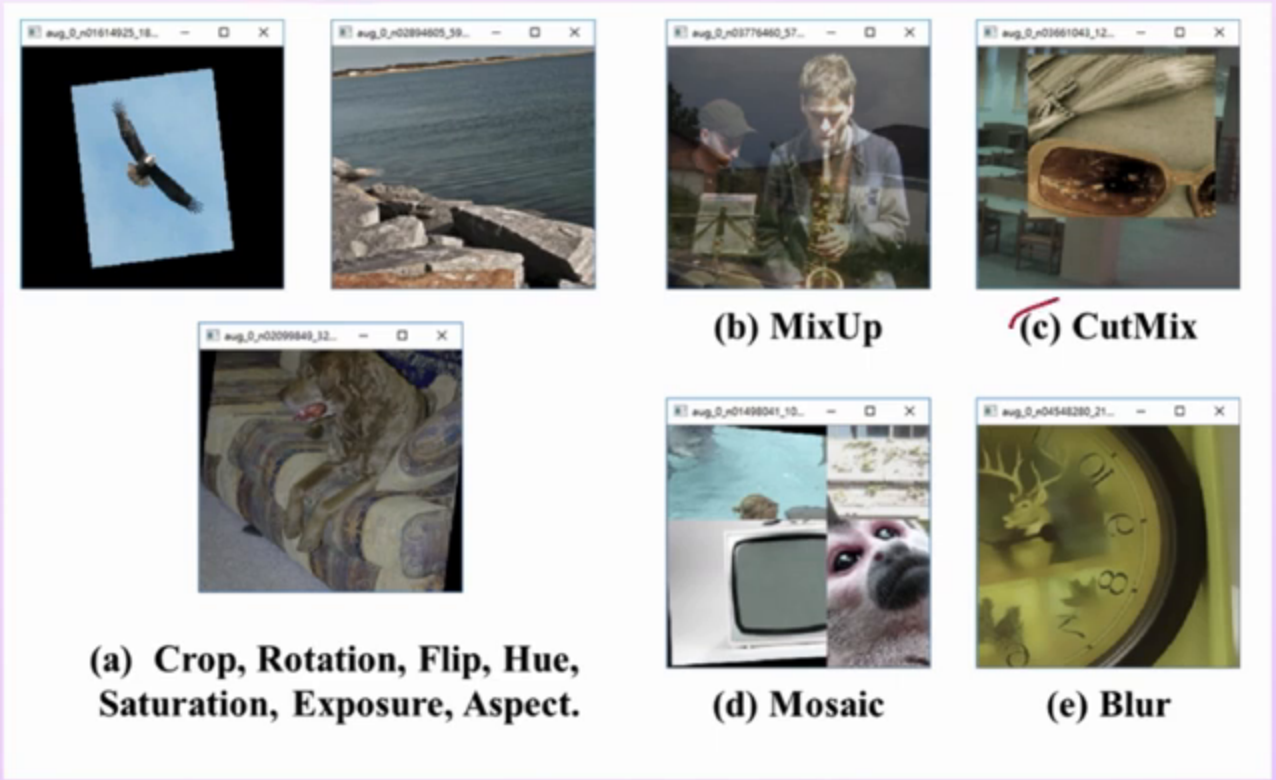

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* **Data Augmentations**
  * Mosaic
  * Mixup
  * Albumentations

* **Deployment**
  * ONNX
  * TensorRT
  * OpenVINO
  * CoreML
  * TF.js & TFLite
* **Ease of use**
  * One click prediction
    * Webcams, RTSP, Videos, Images
  * Easy Training & Deployment
* **Community**
  * Well documented & regularly updated
  * Frequent updates for Pretrained weights
  * Large community support

Features of Yolo-v5 Repo

* **Models**
  * Object Detection
  * Classification
  * InstanceSegmentation
* **Training & FineTuning**
  * Multi-Scale Training
  * Mixed Precision Training
  * GA for Hyperparameters
  * Experiment Tracking
  * AutoAnchor
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YOLO-V5

Backbone

Modified
CSP
Darknet53

Neck

SPPF
+
CSP-PAN

Head

Modified
YOLOv3
Head

YOLO-V5

Backbone

Modified
CSP
Darknet53

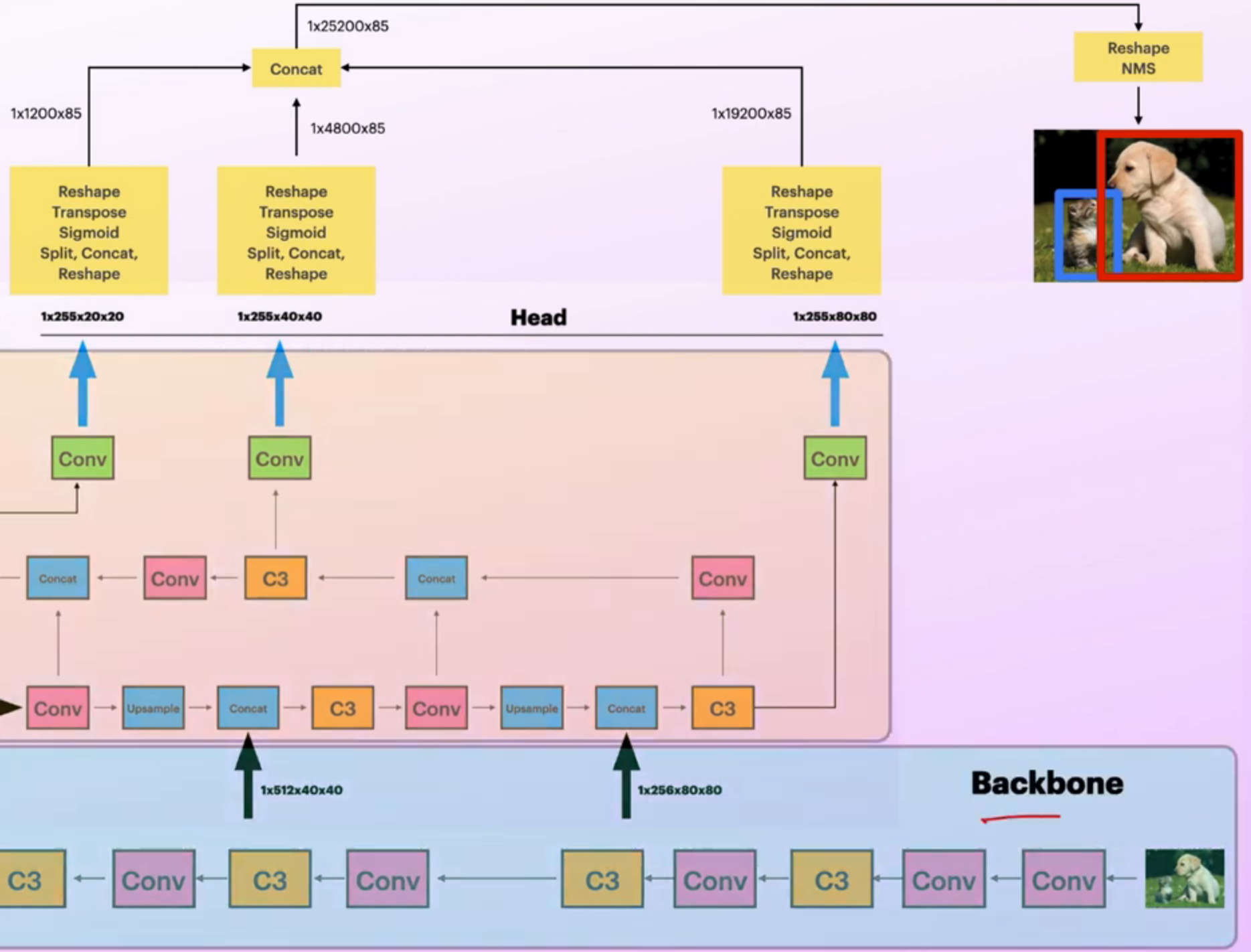
Neck

SPPF
+
CSP-PAN

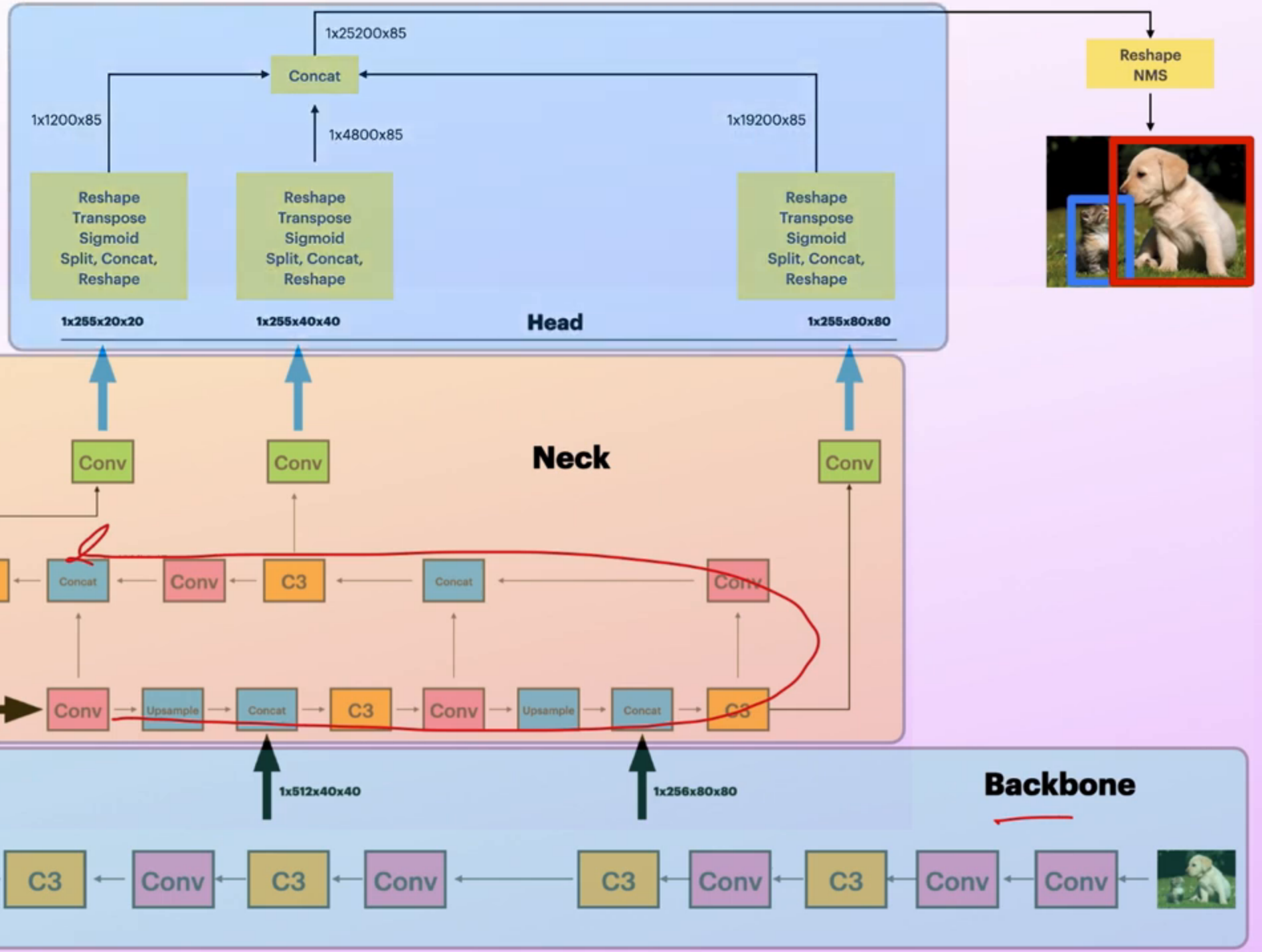
Head

Modified
YOLOv3
Head

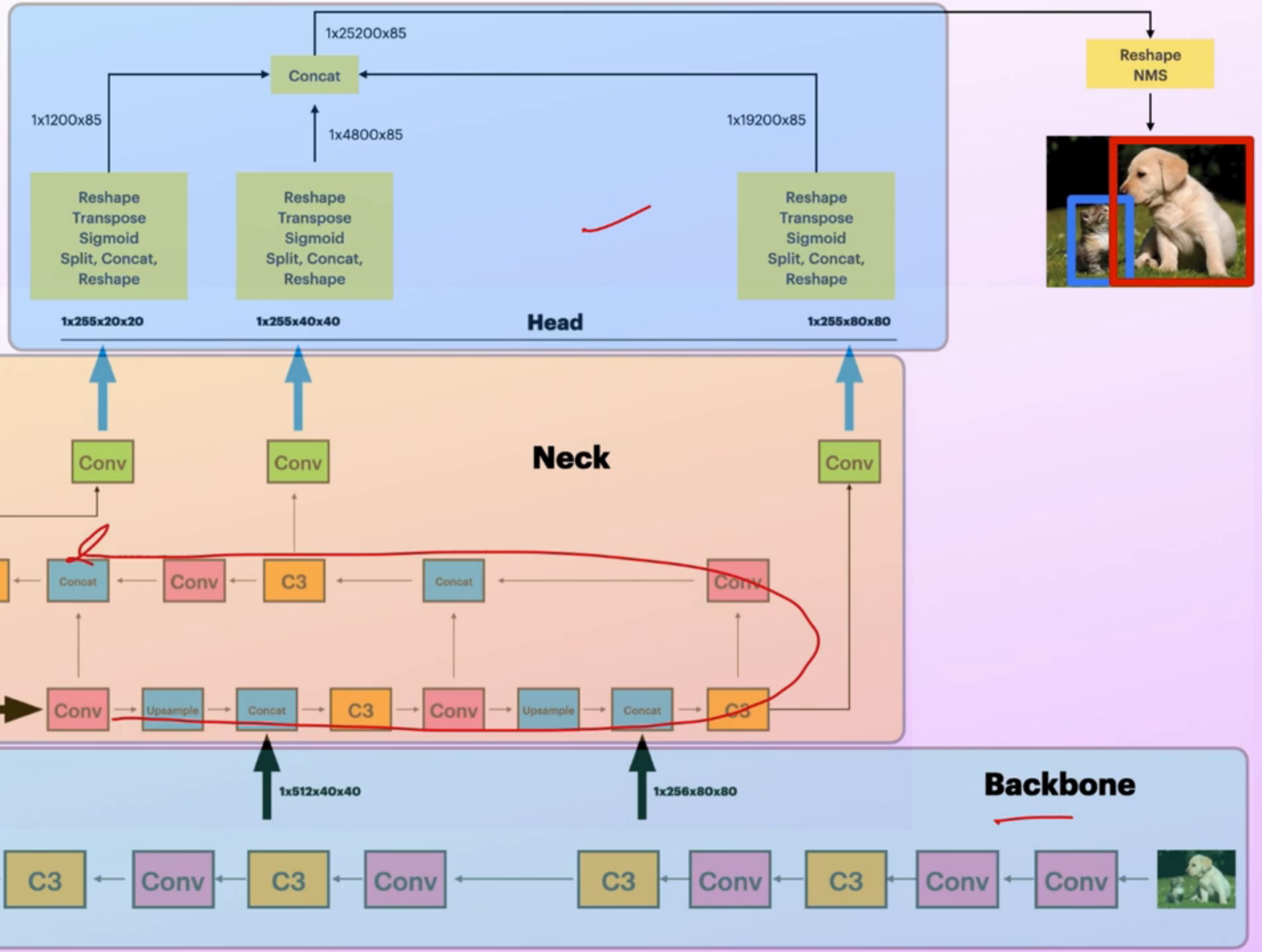
YOLO V5


1x25200x85
Concat
Reshape
NMS
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Conv
Conv
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv

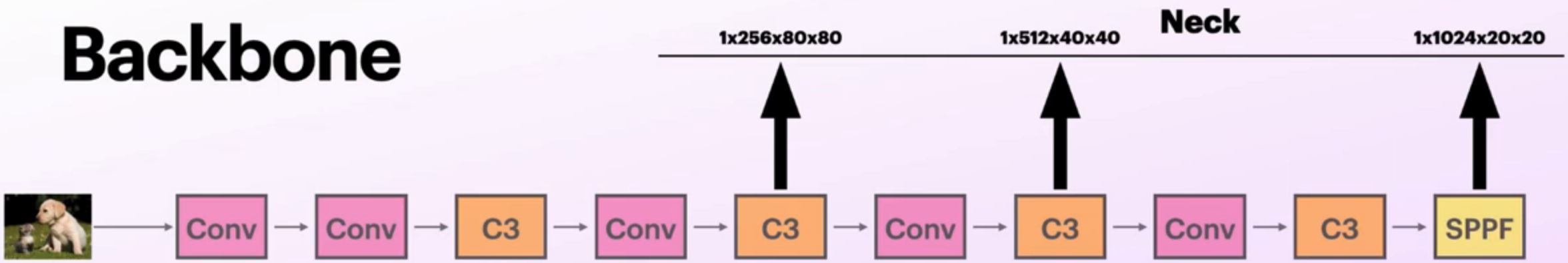
YOLO V5


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv

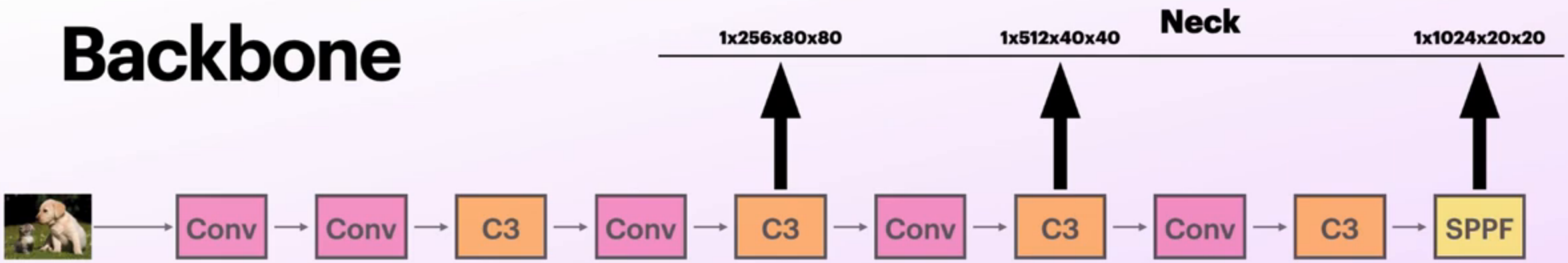
YOLO V5


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv

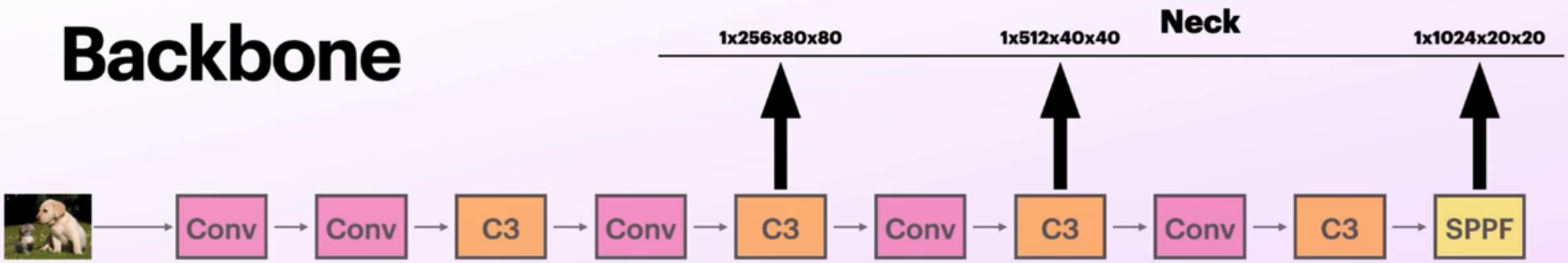
Backbone


Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
Conv
C3
Conv
C3
Conv
C3
Conv
C3
SPPF

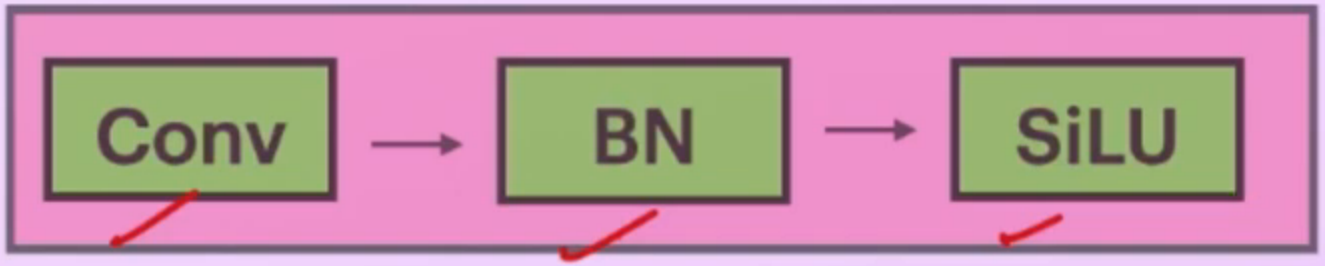
Backbone


Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
Conv
C3
Conv
C3
Conv
C3
Conv
C3
SPPF

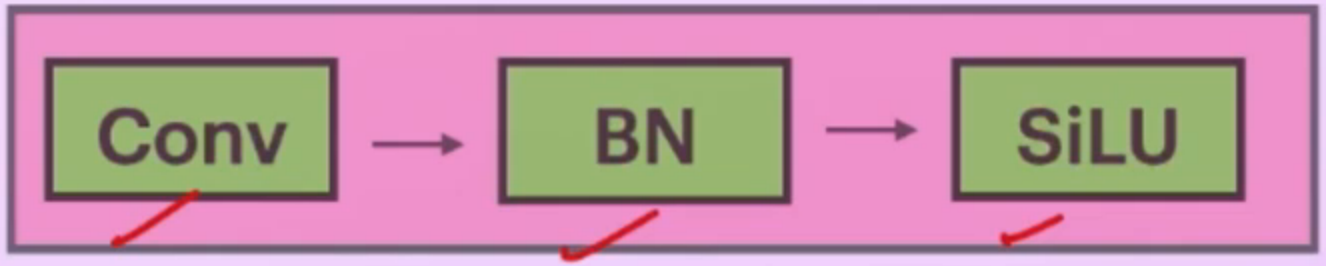
Backbone


Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
Conv
C3
Conv
C3
Conv
C3
Conv
C3
SPPF


Conv
BN
SiLU



$$SiLU = x * sigmoid(x)$$



$$SiLU = x * sigmoid(x)$$

Conv → Conv → C3 → Conv → C3 → Conv → C

Conv → Conv → C3 → Conv → C3 → Conv

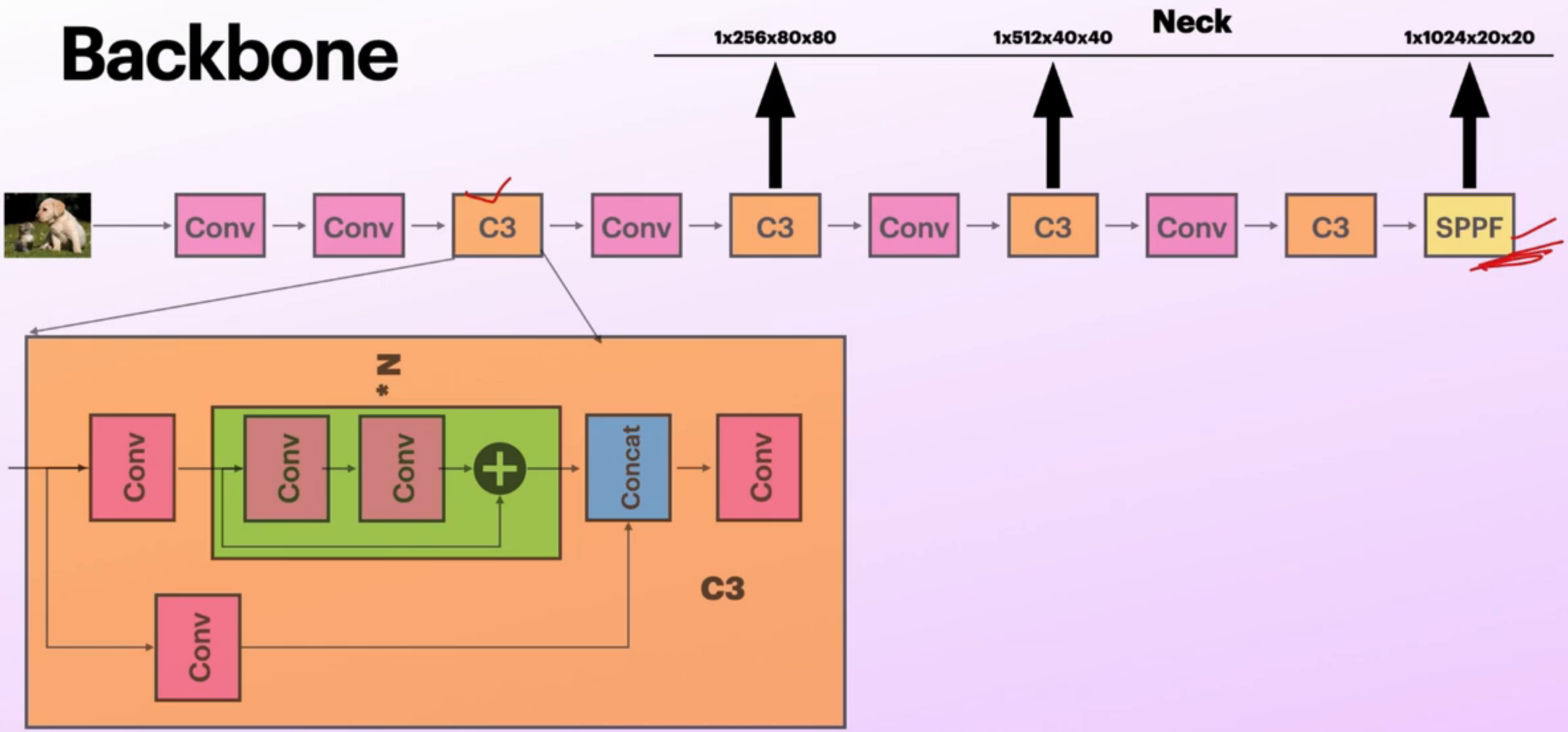
n *

Conv → Conv → Conv → (+) → Concat → Conv

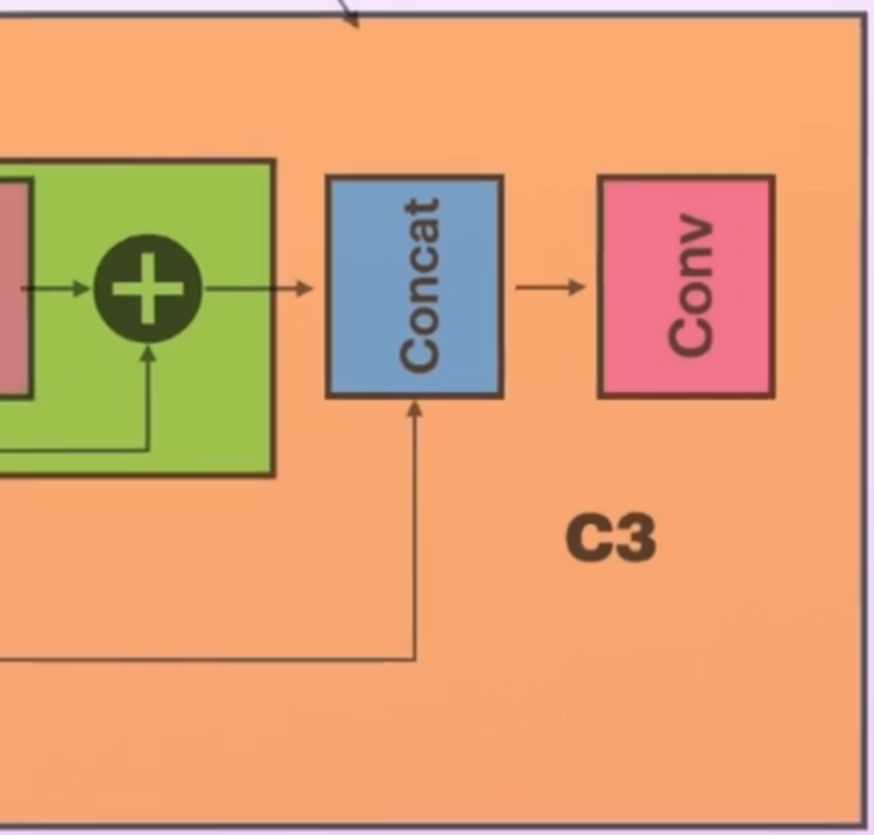
Conv

C3

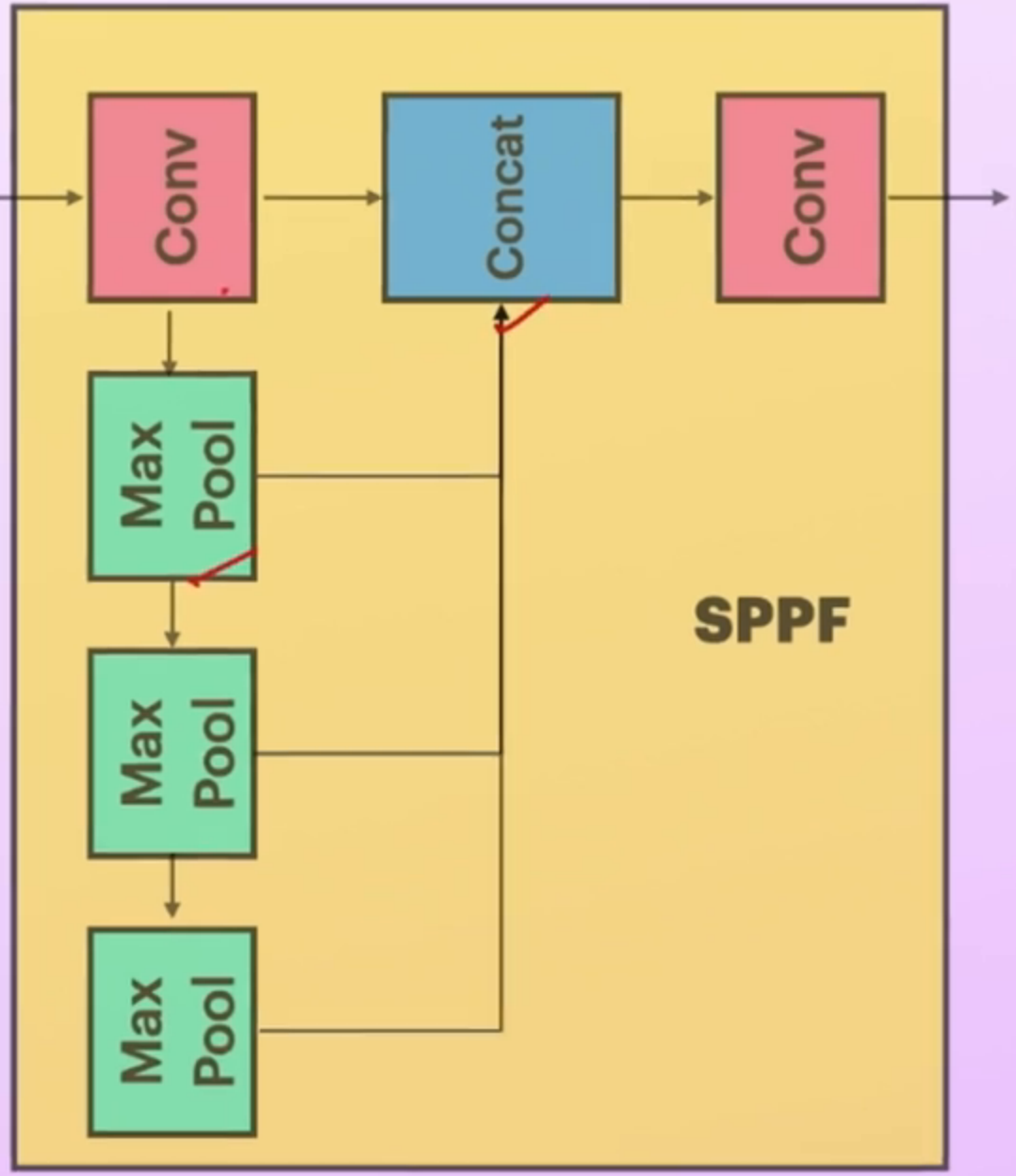
Backbone



$$SiLU = x * sigmoid(x)$$



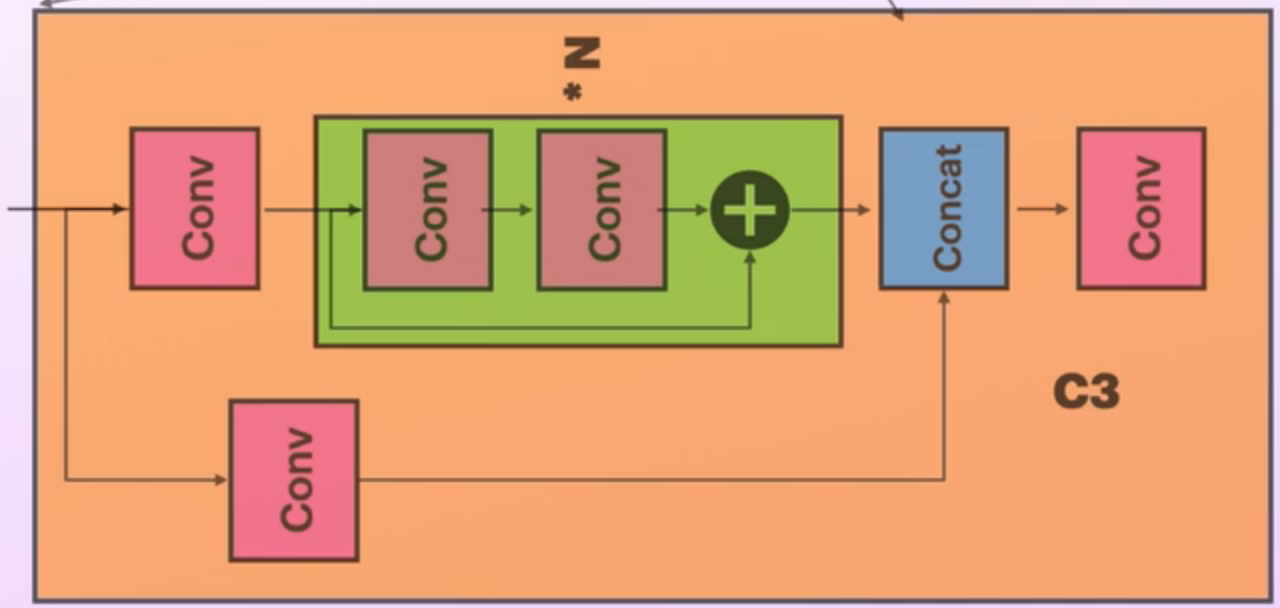
$$SiLU = x * sigmoid(x)$$

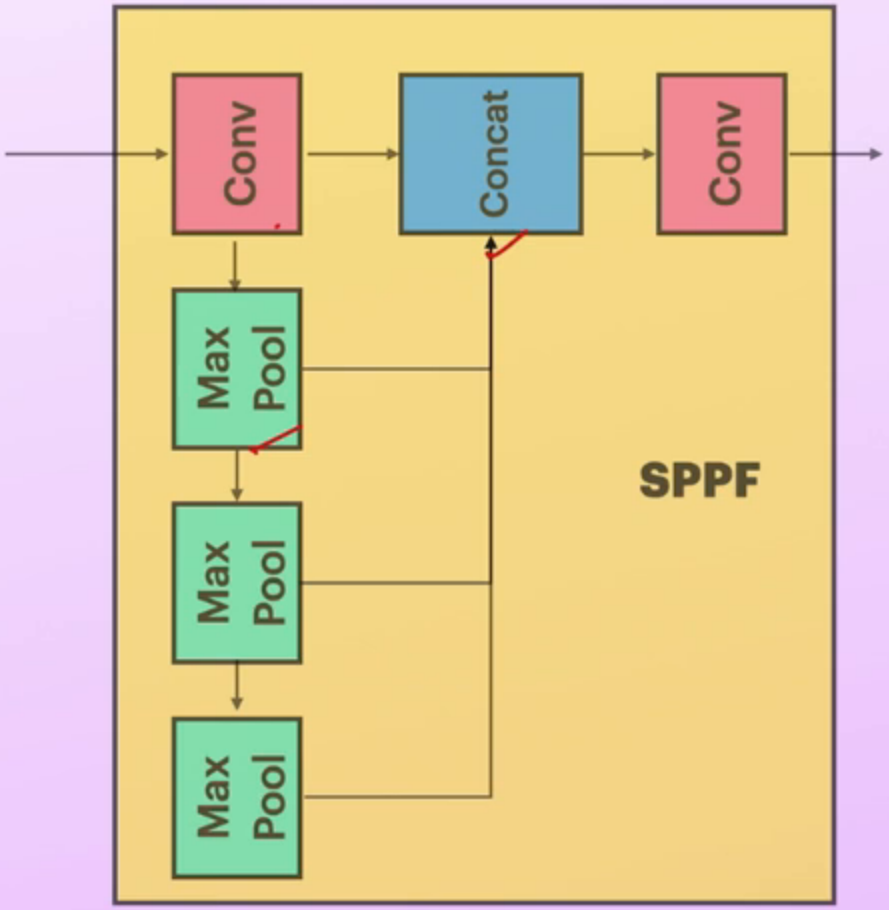


Backbone

Conv → Conv → C3 → Conv → C3 → Conv → C3 → Conv → C3 → SPPF

Neck: 1x256x80x80, 1x512x40x40, 1x1024x20x20





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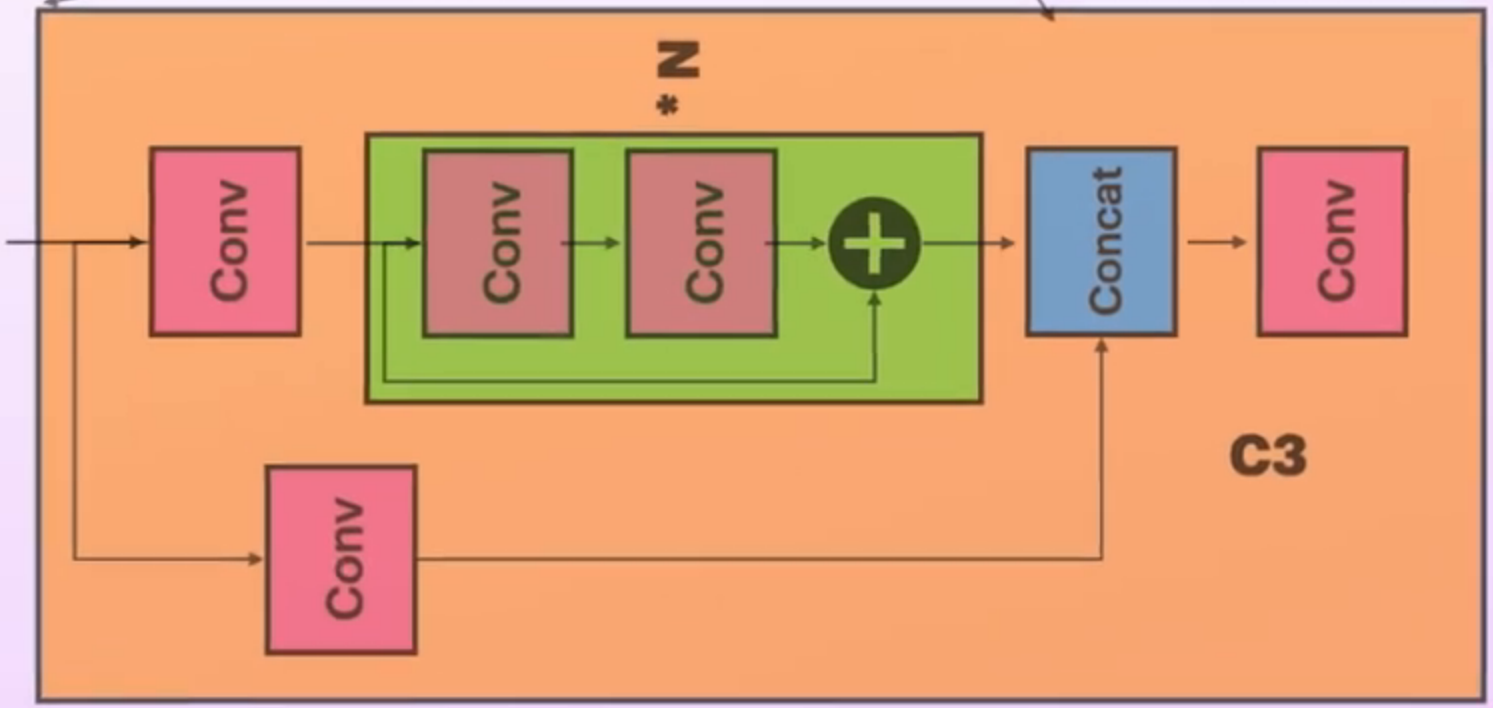
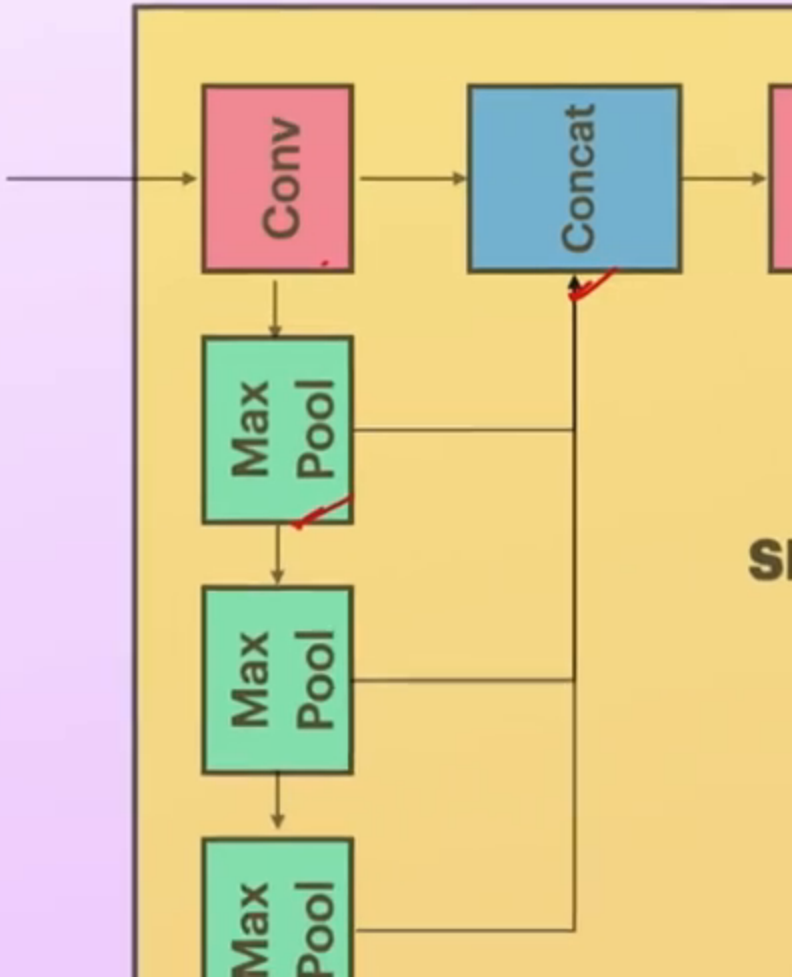
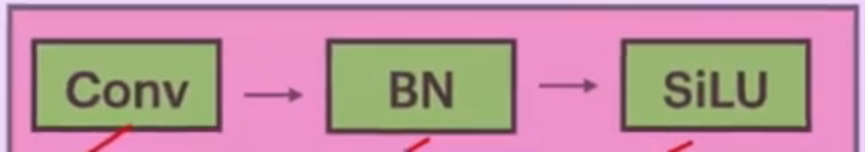
Backbone







$$SiLU = x * sigmoid(x)$$

Conv

Conv

C3

Conv

C3

Conv

N

*

Conv

Conv

Conv

Concat

Conv

Conv

C3

Conv

Conv

C3

Conv

C3

Conv

n

*

Conv

Conv

Conv

Concat

Conv

Conv

C3

Conv

Conv

C3

Conv

C3

Conv

N
*

Conv

Conv

Conv

Concat

Conv

Conv

C3

Conv

Conv

C3

Conv

C3

Conv

N
*

Conv

Conv

Conv

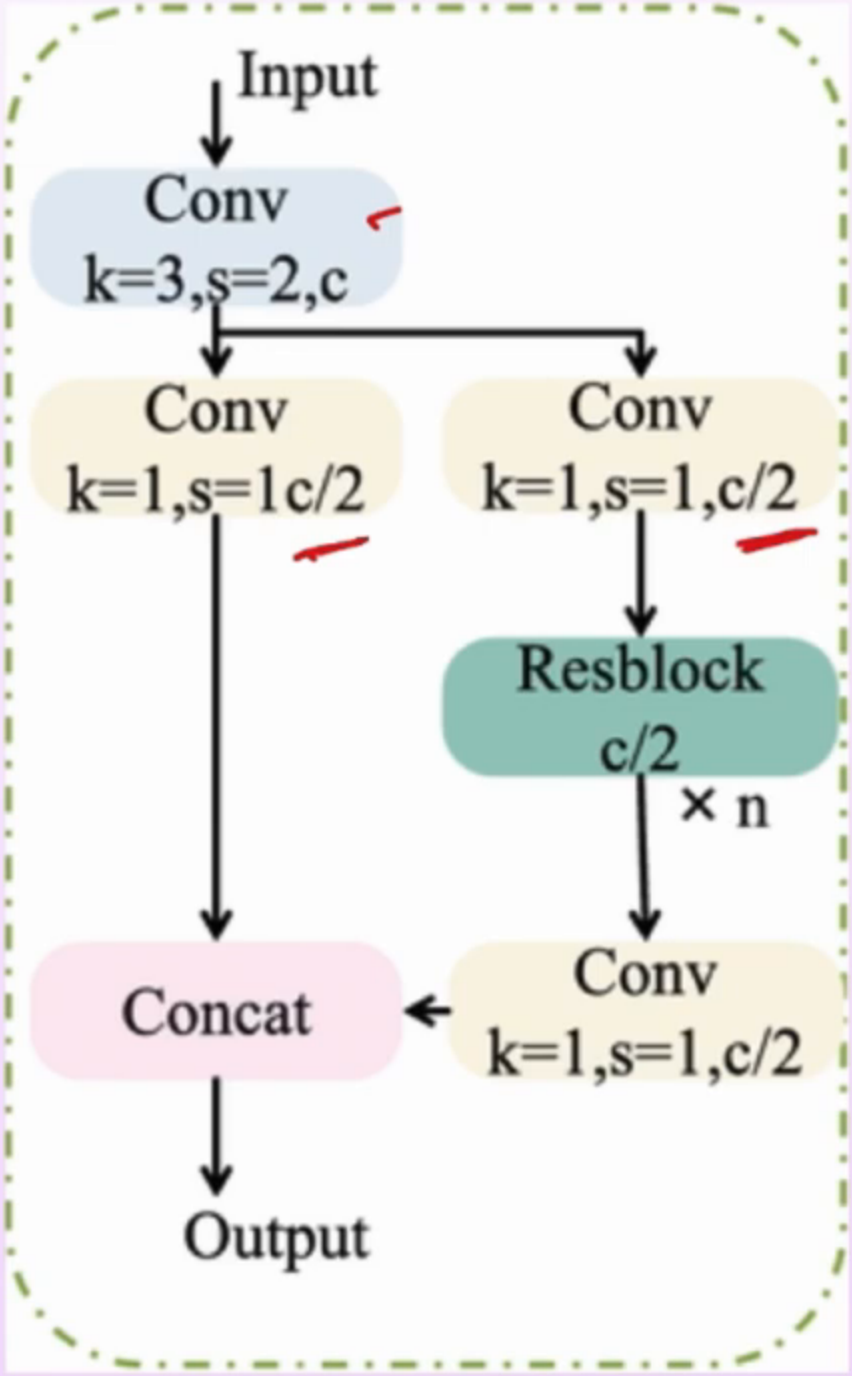
Concat

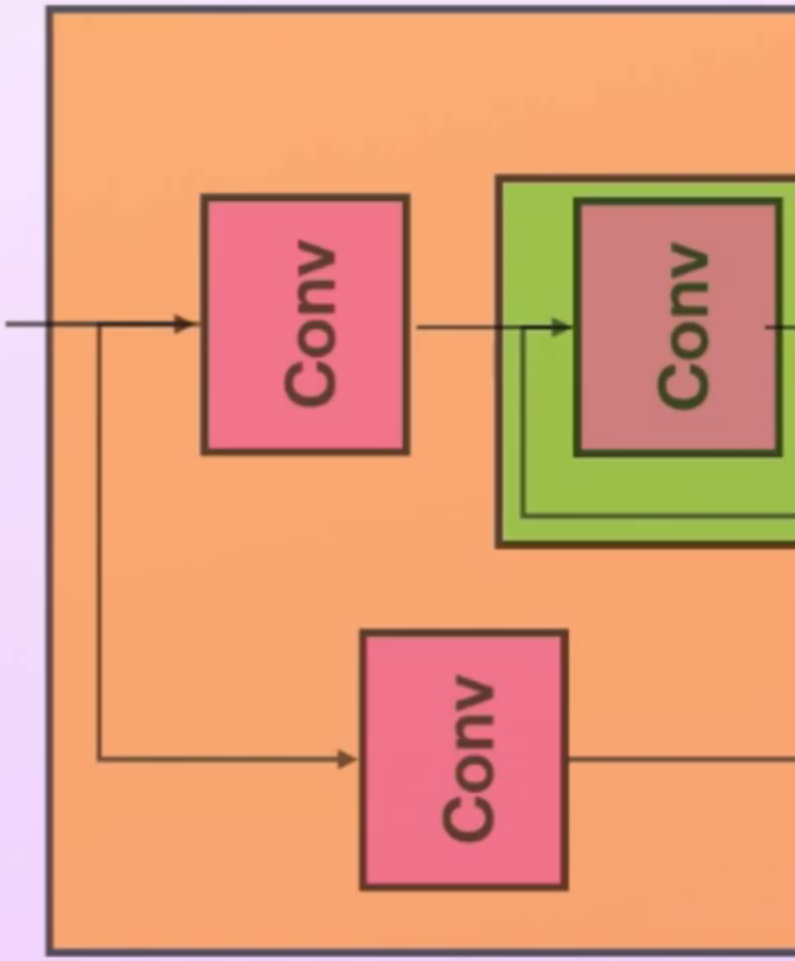
Conv

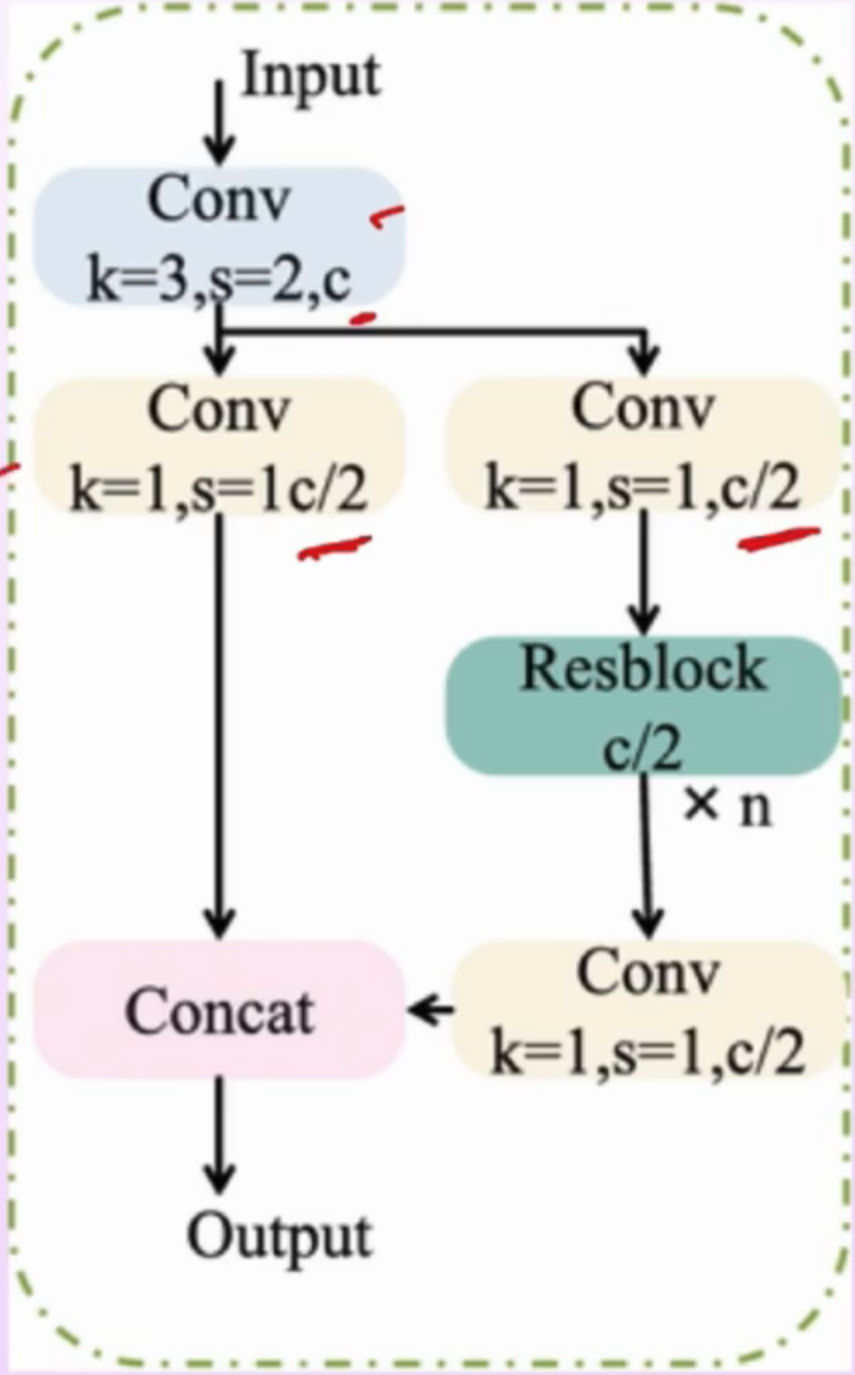
Conv

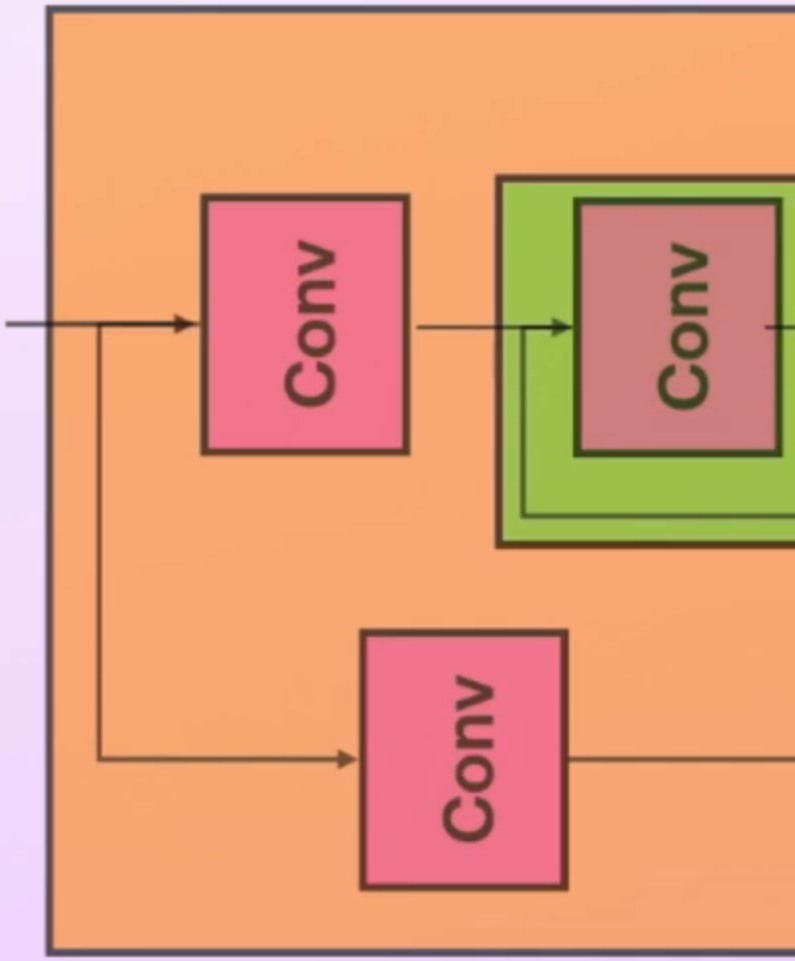
C3

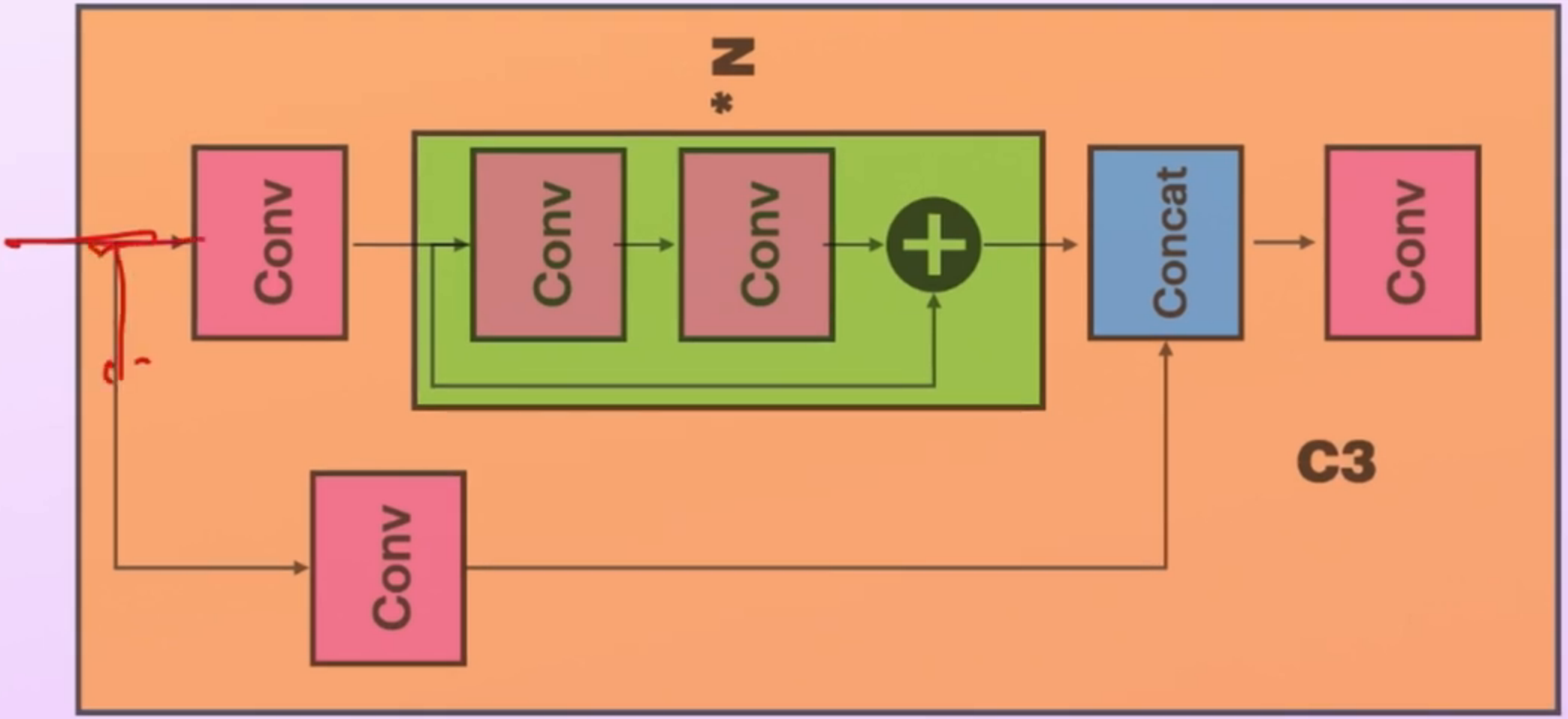
C3 Block


Input
Conv
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output

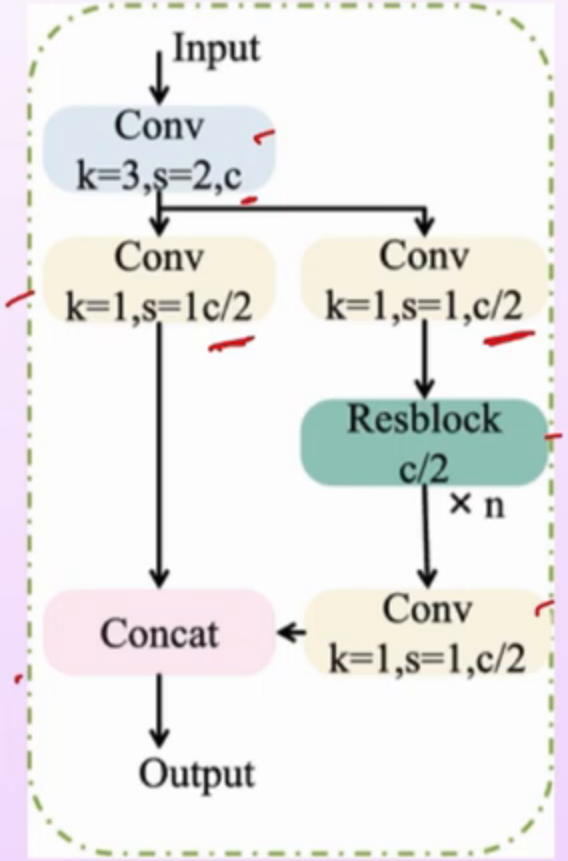

Conv
Conv
Conv

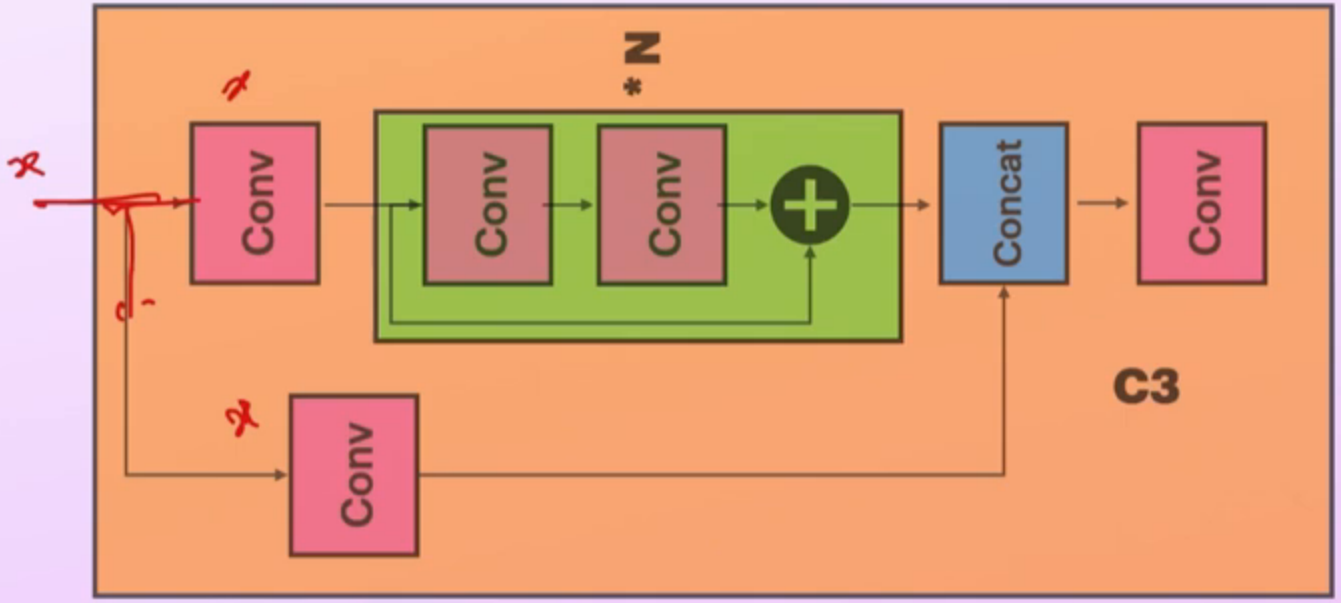

Input
Conv
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output


Conv
Conv
Conv

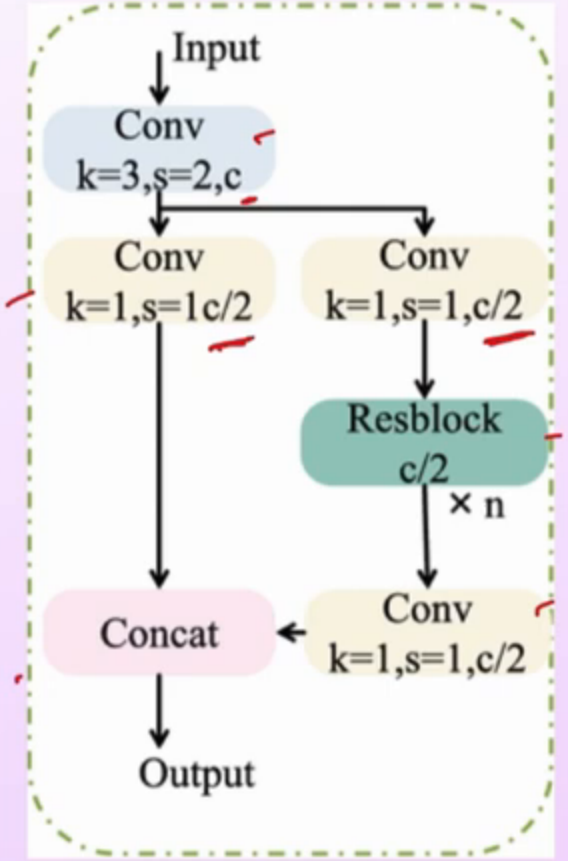

N
*
Conv
Conv
Conv
Concat
Conv
Conv
C3

C3 Block


Input
Conv
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output


* N
Conv
Conv
Conv
Concat
Conv
Conv
C3

C3 Block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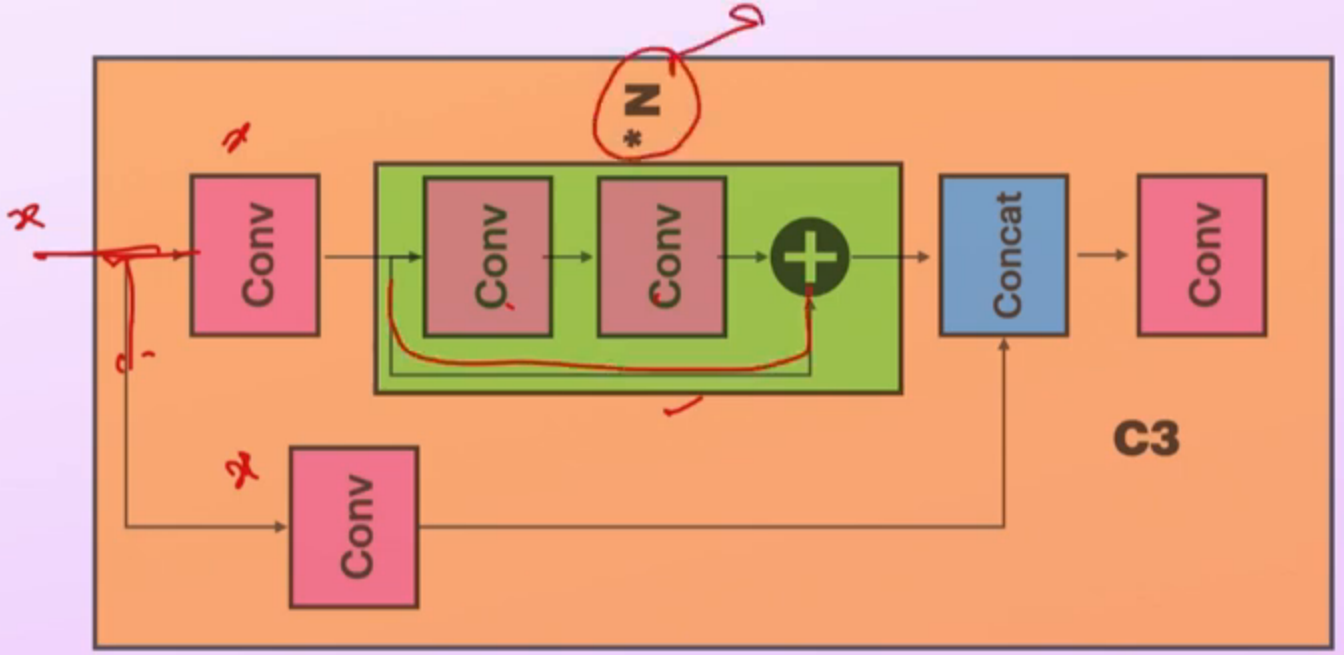
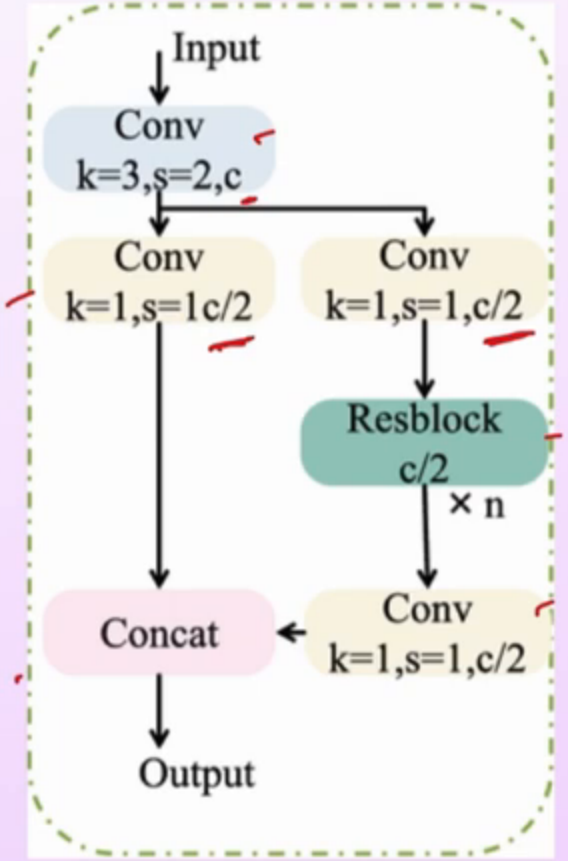
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output


N
*
Conv
Conv
Conv
Concat
Conv
Conv
C3

C3 Block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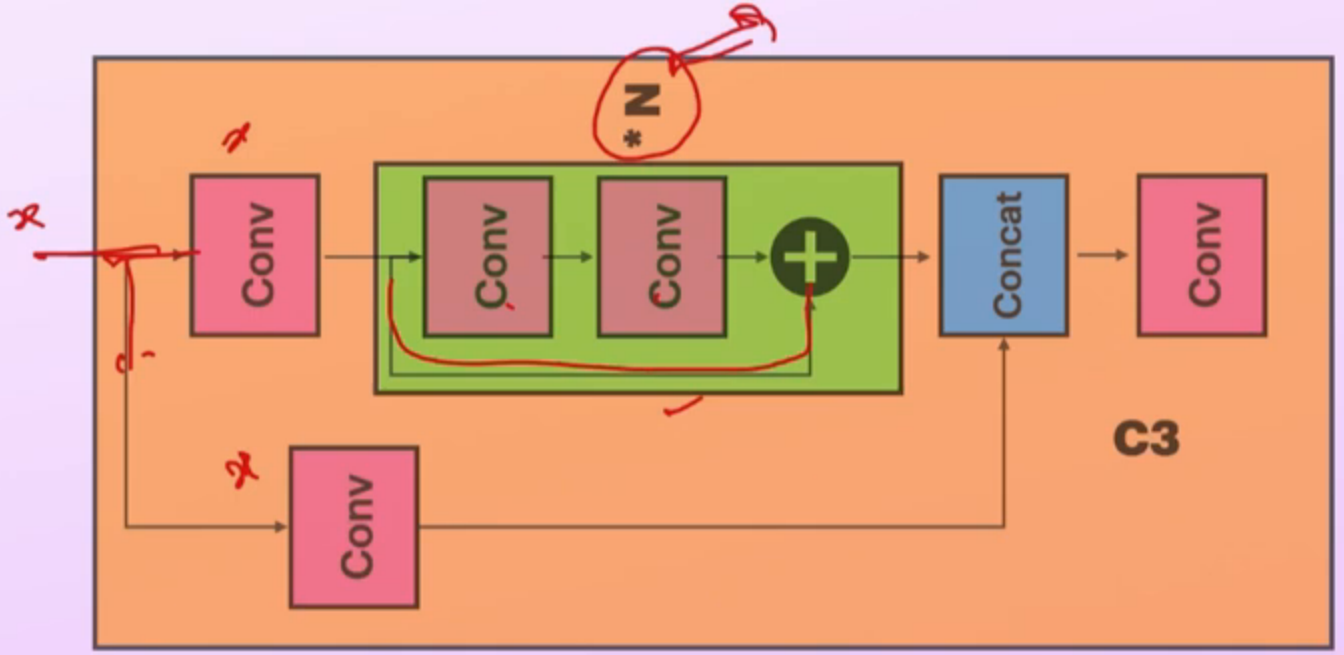
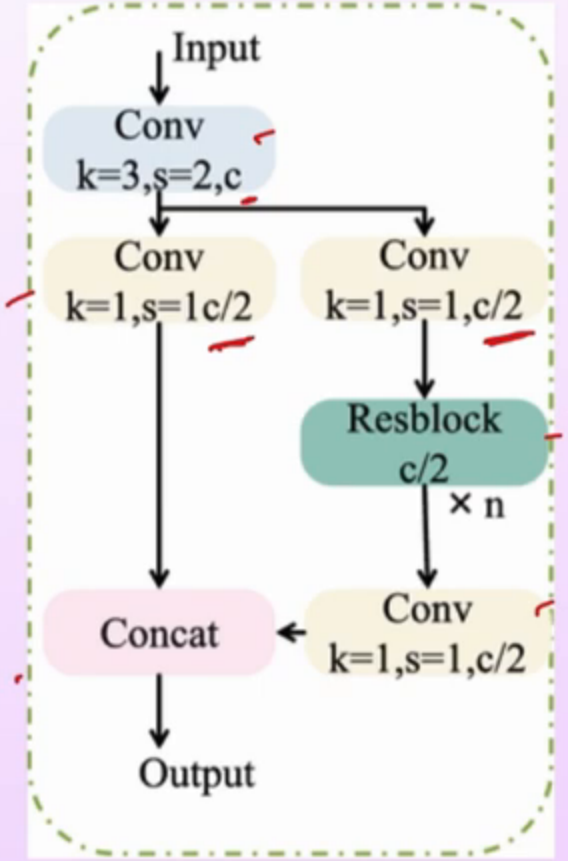
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output


* N
Conv
Conv
Conv
Concat
Conv
Conv
C3

C3 Block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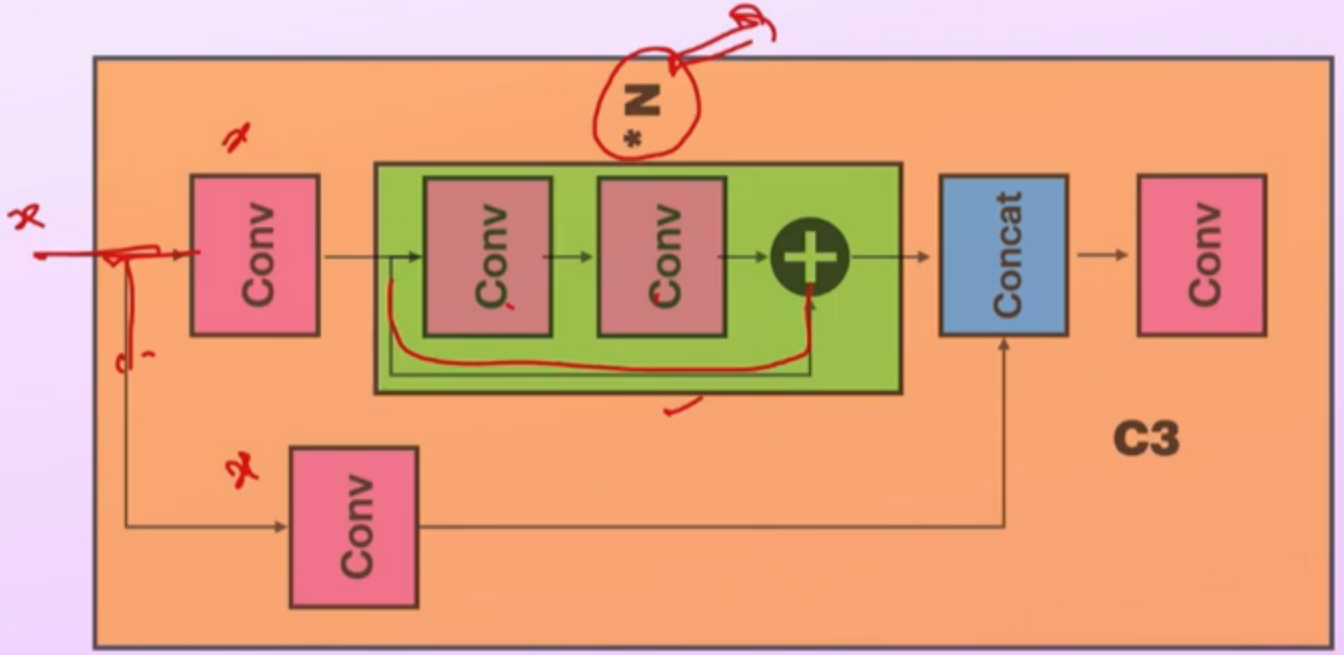
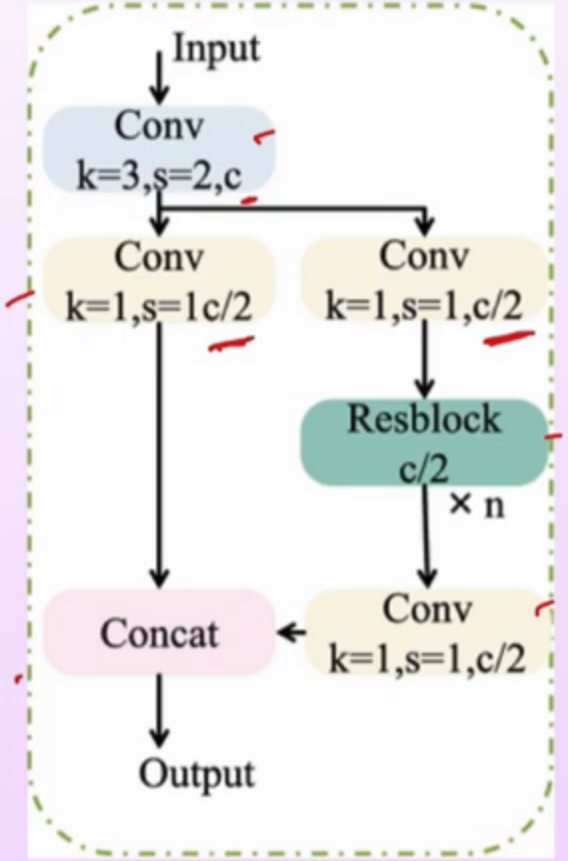
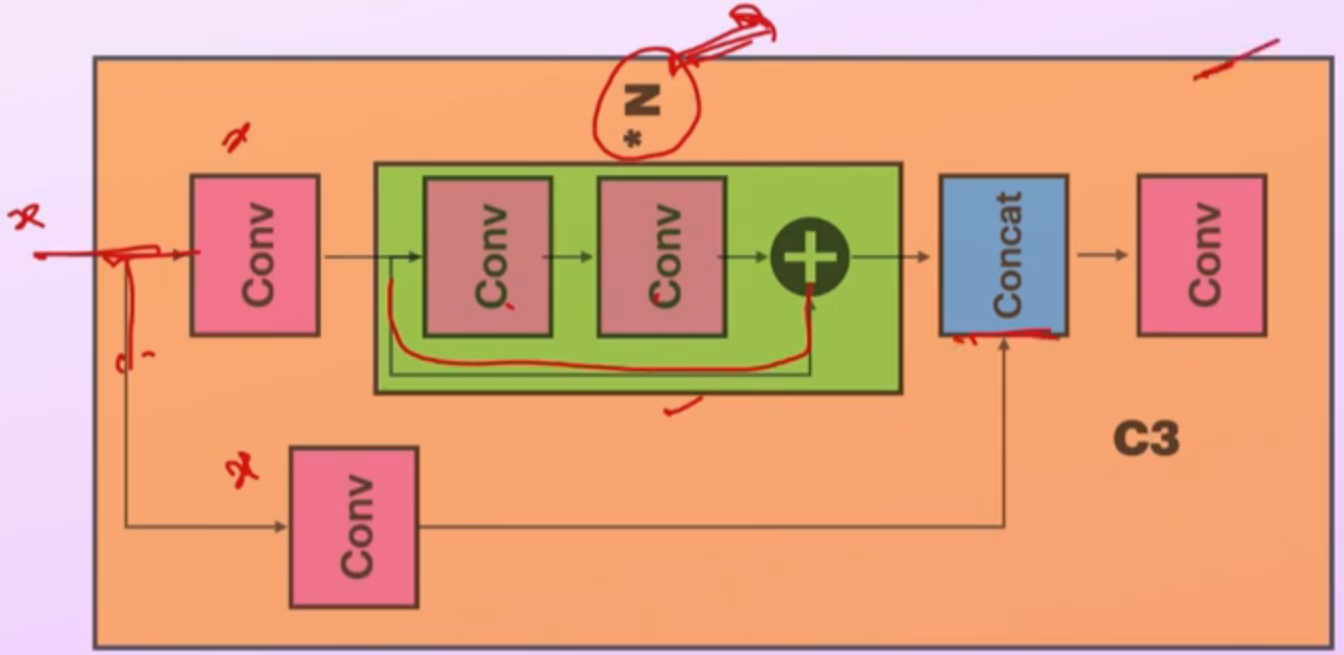
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output

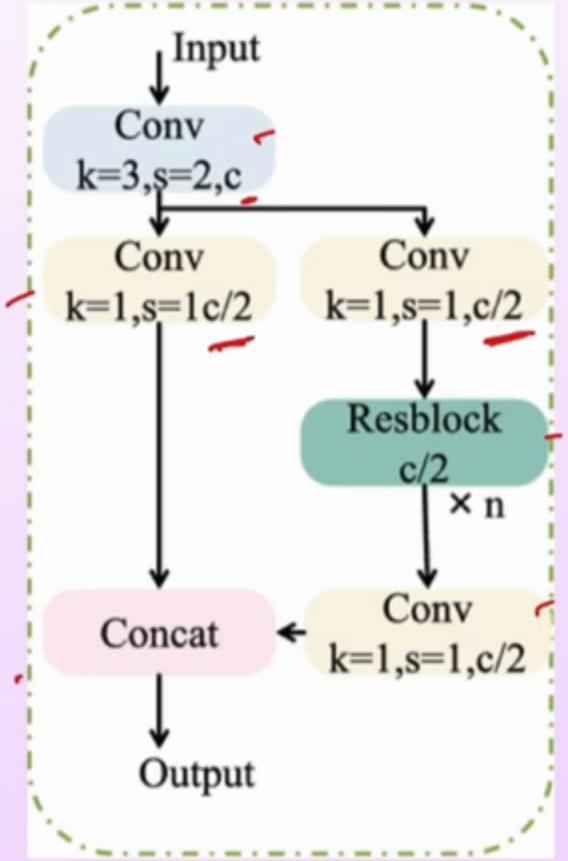

* N
Conv
Conv
Conv
Concat
Conv
Conv
C3

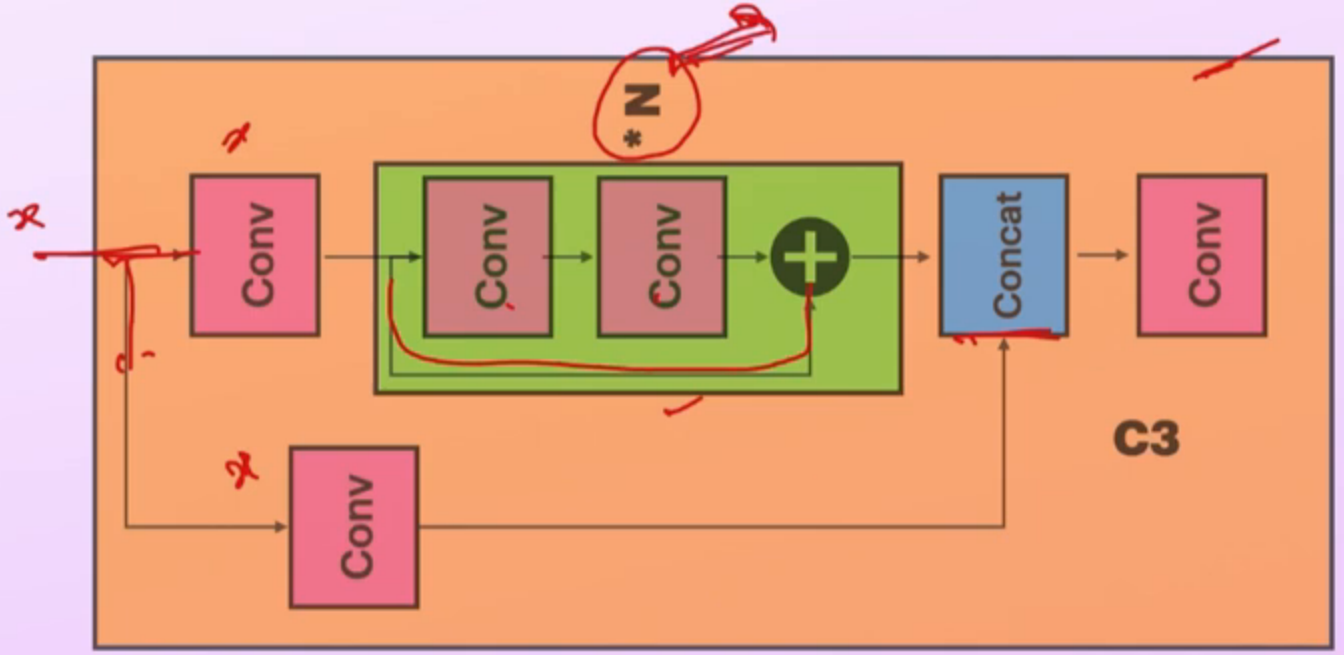
C3 Block


Input
Conv
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output

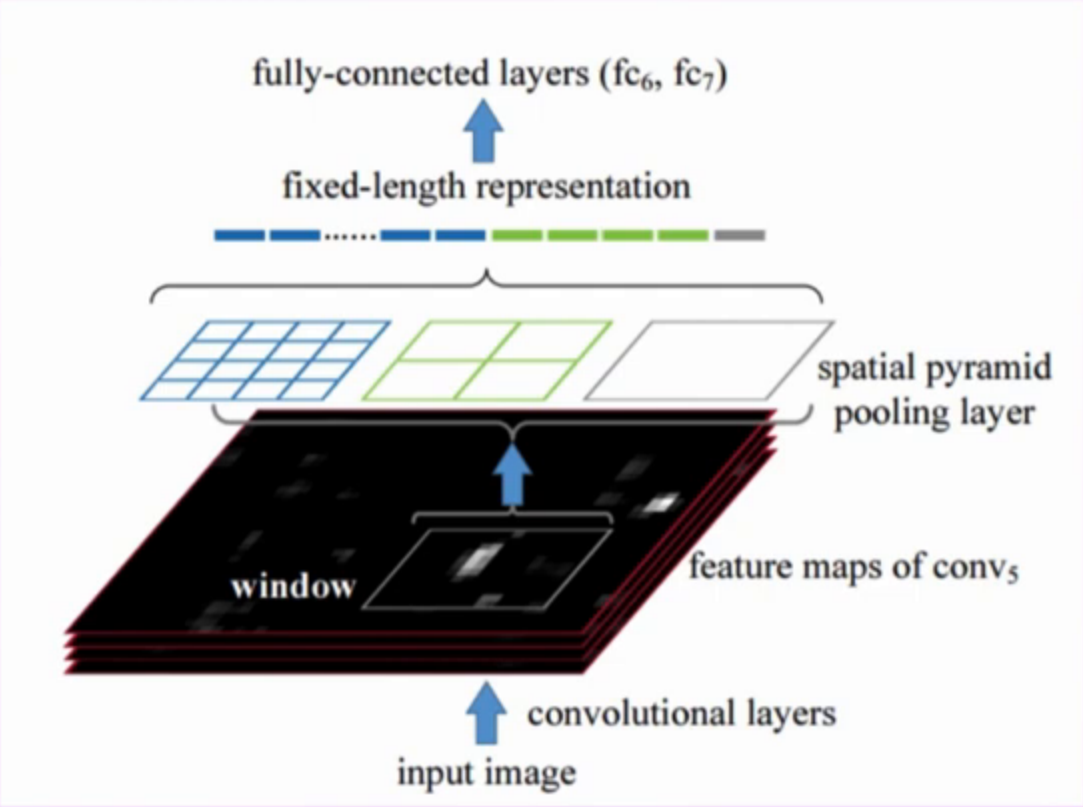

* N
Conv
Conv
Conv
Concat
Conv
Conv
C3

C3 Block

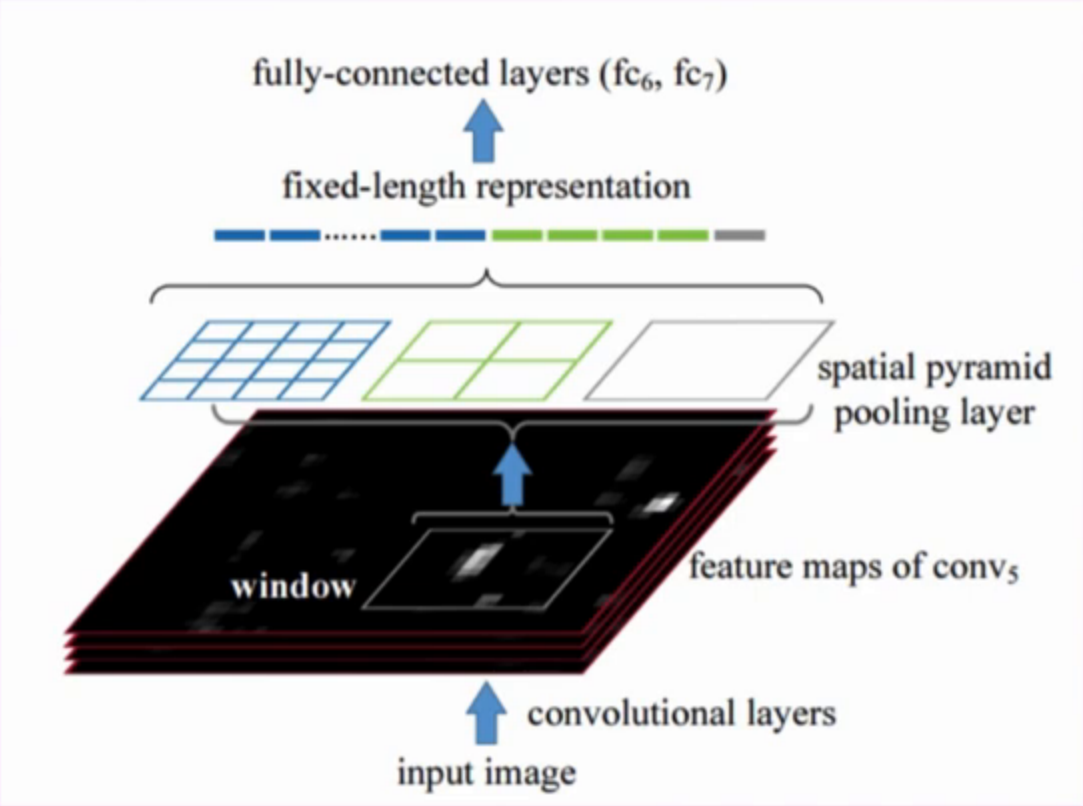

Input
Conv
k=3,s=2,c
Conv
k=1,s=1c/2
Conv
k=1,s=1,c/2
Resblock
c/2
× n
Concat
Conv
k=1,s=1,c/2
Output


* N
Conv
Conv
Conv
Concat
Conv
Conv
C3

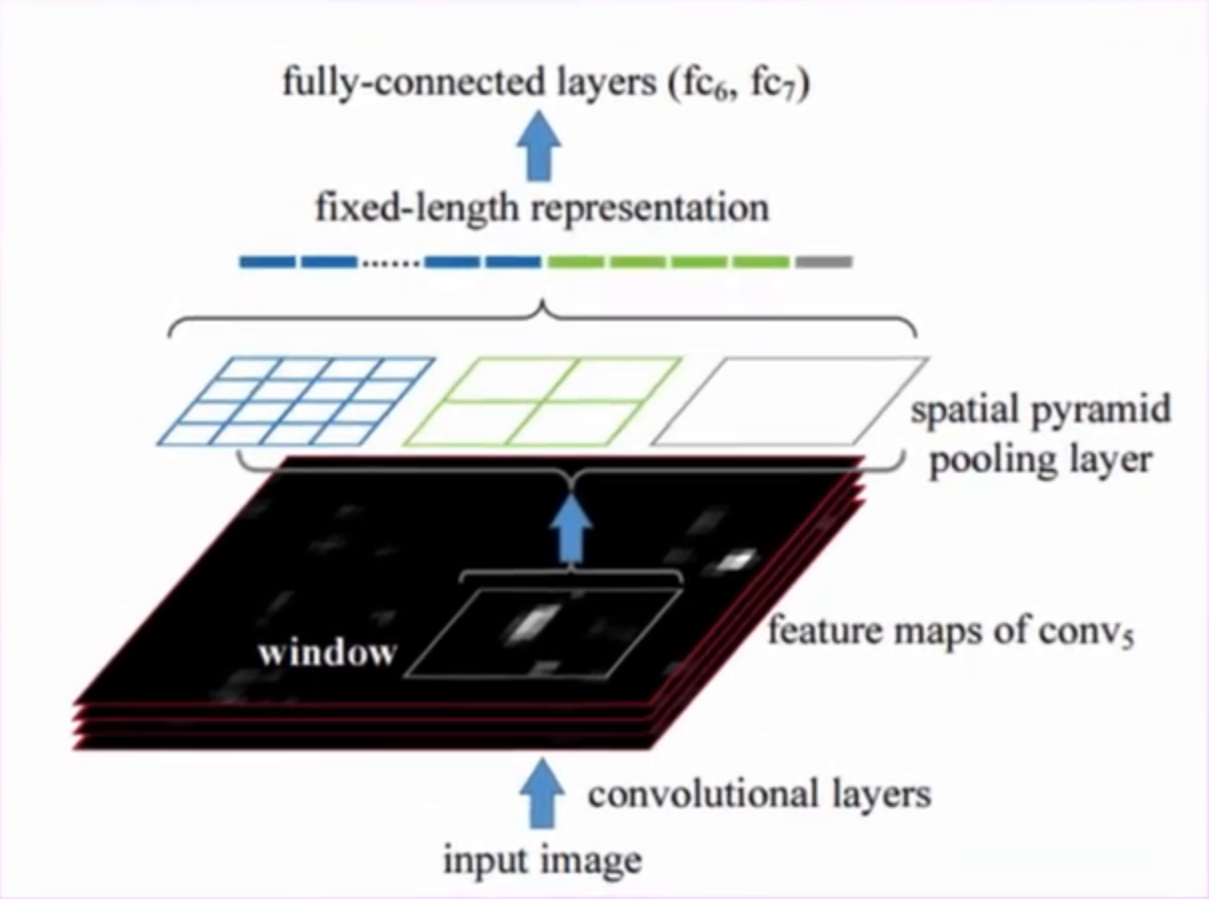
Spatial Pyramid Pooling Fast

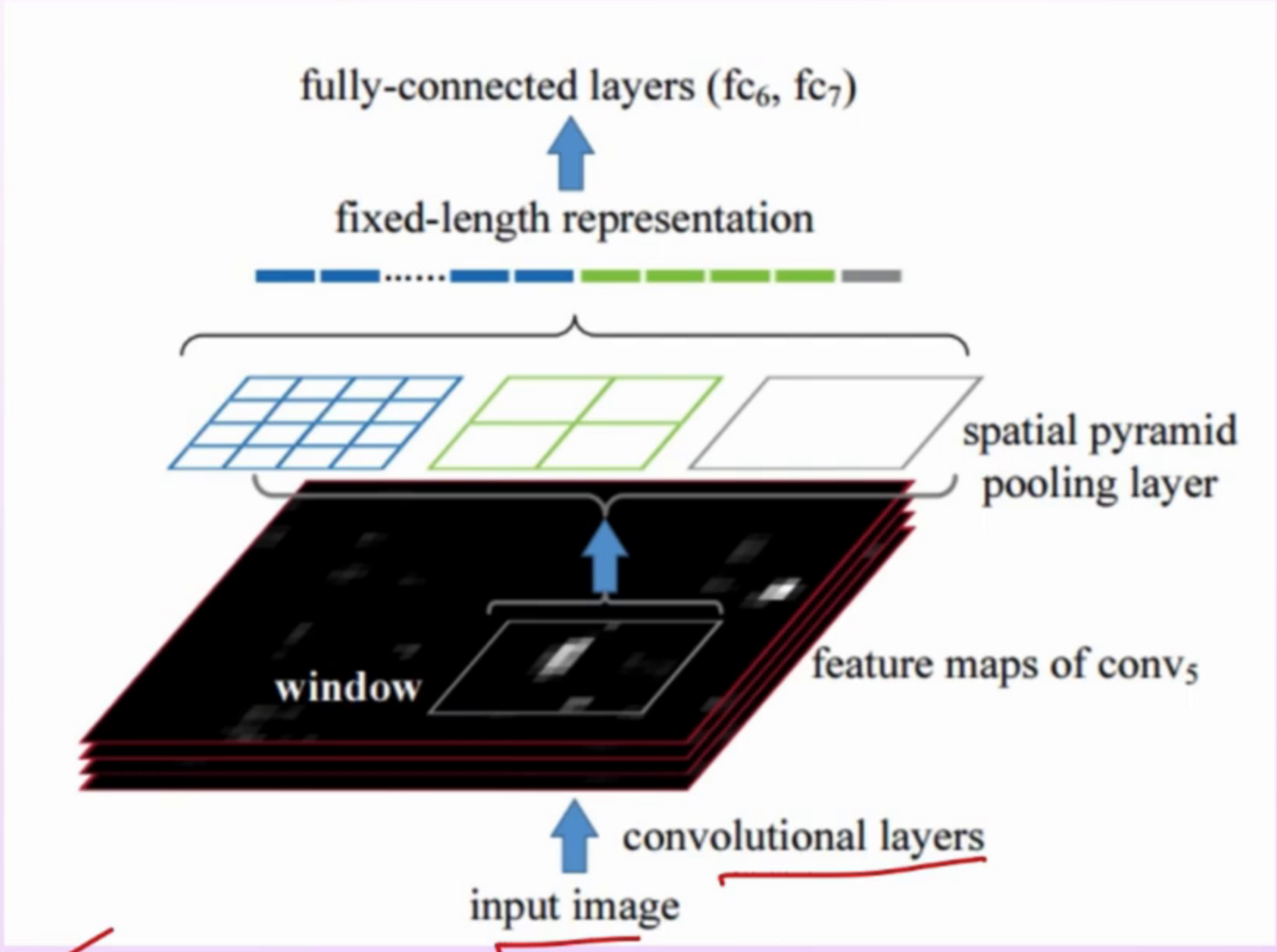


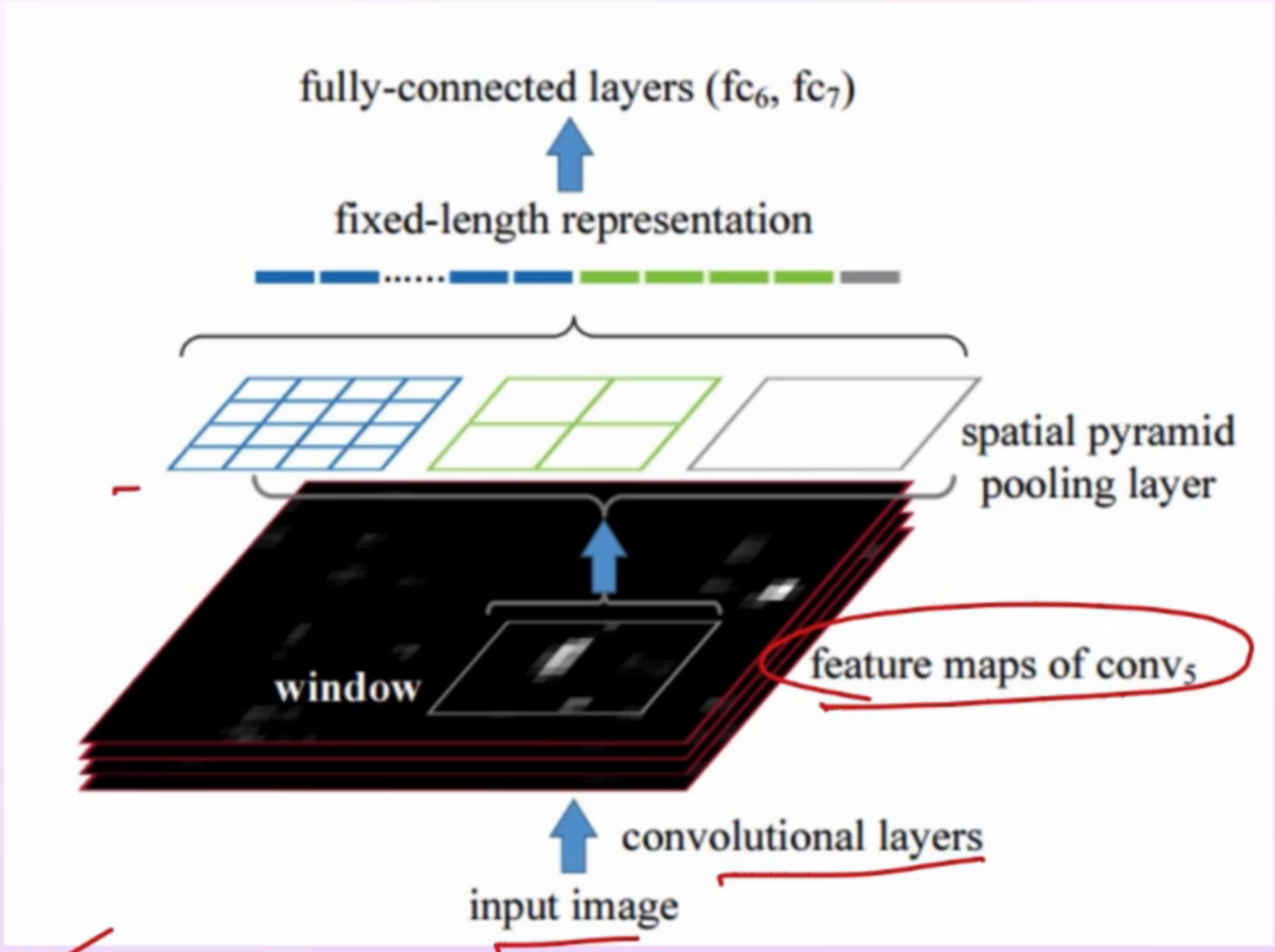
Spatial Pyramid Pooling Fast

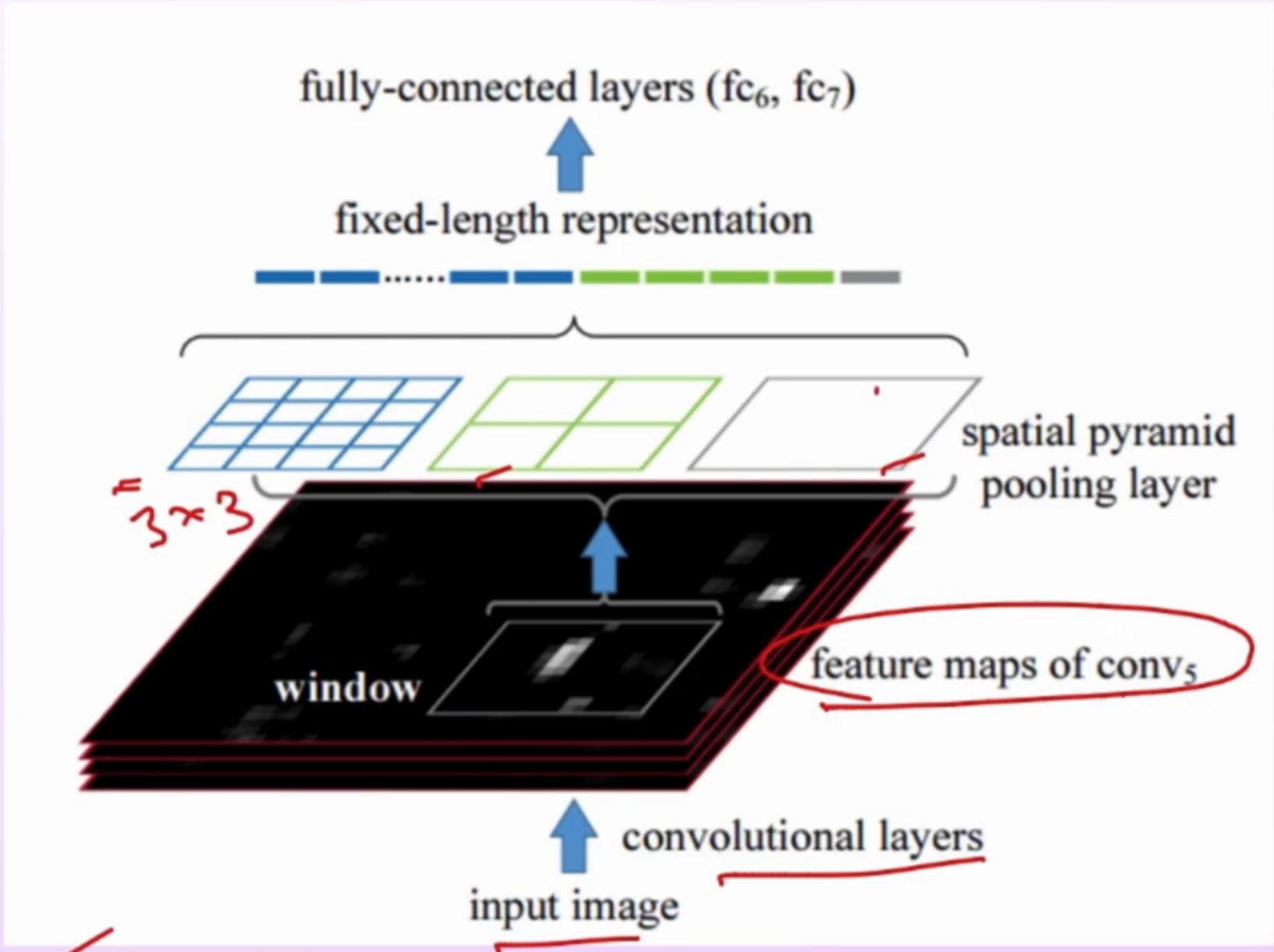


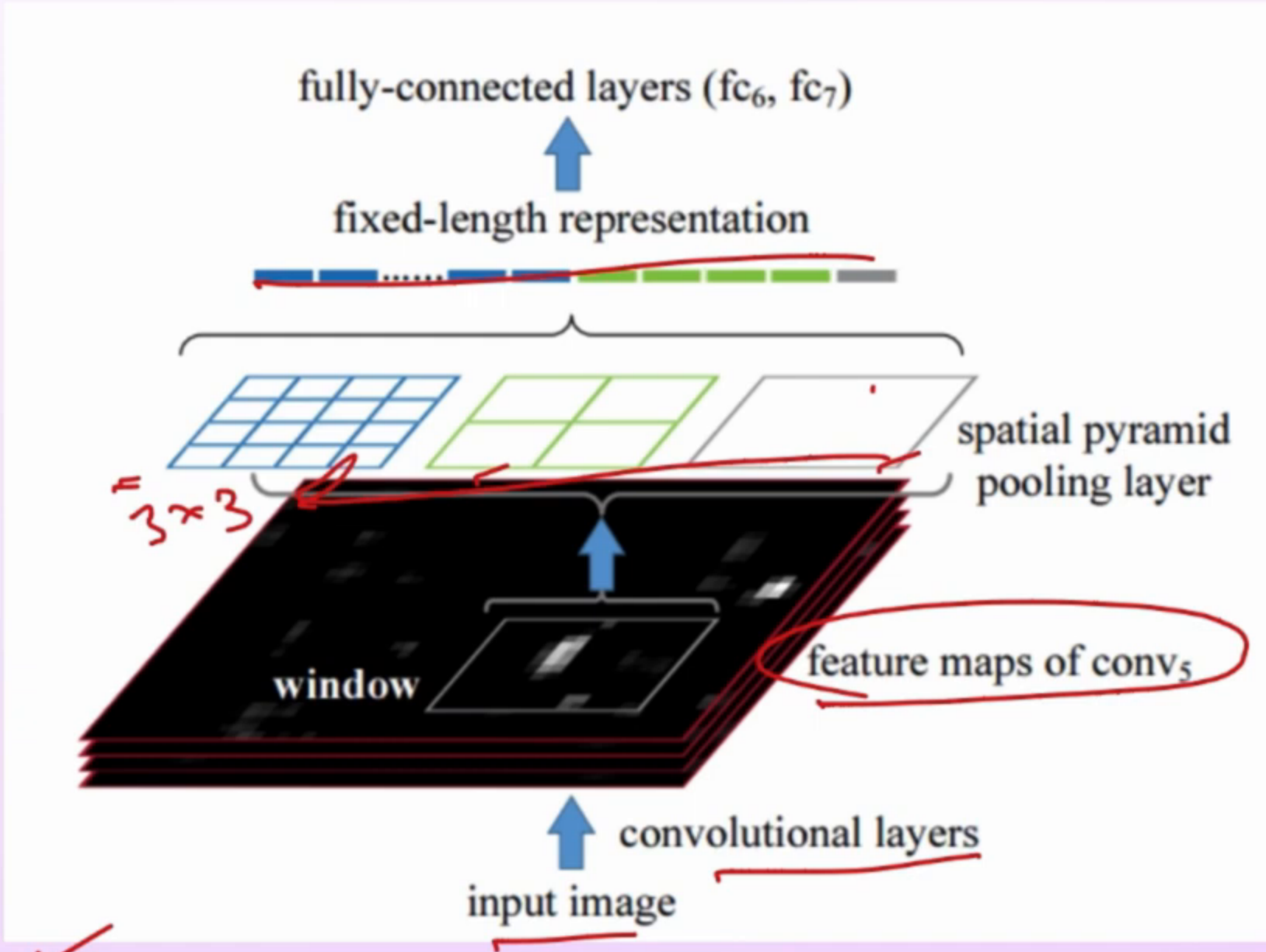
Spatial Pyramid Pooling Fast

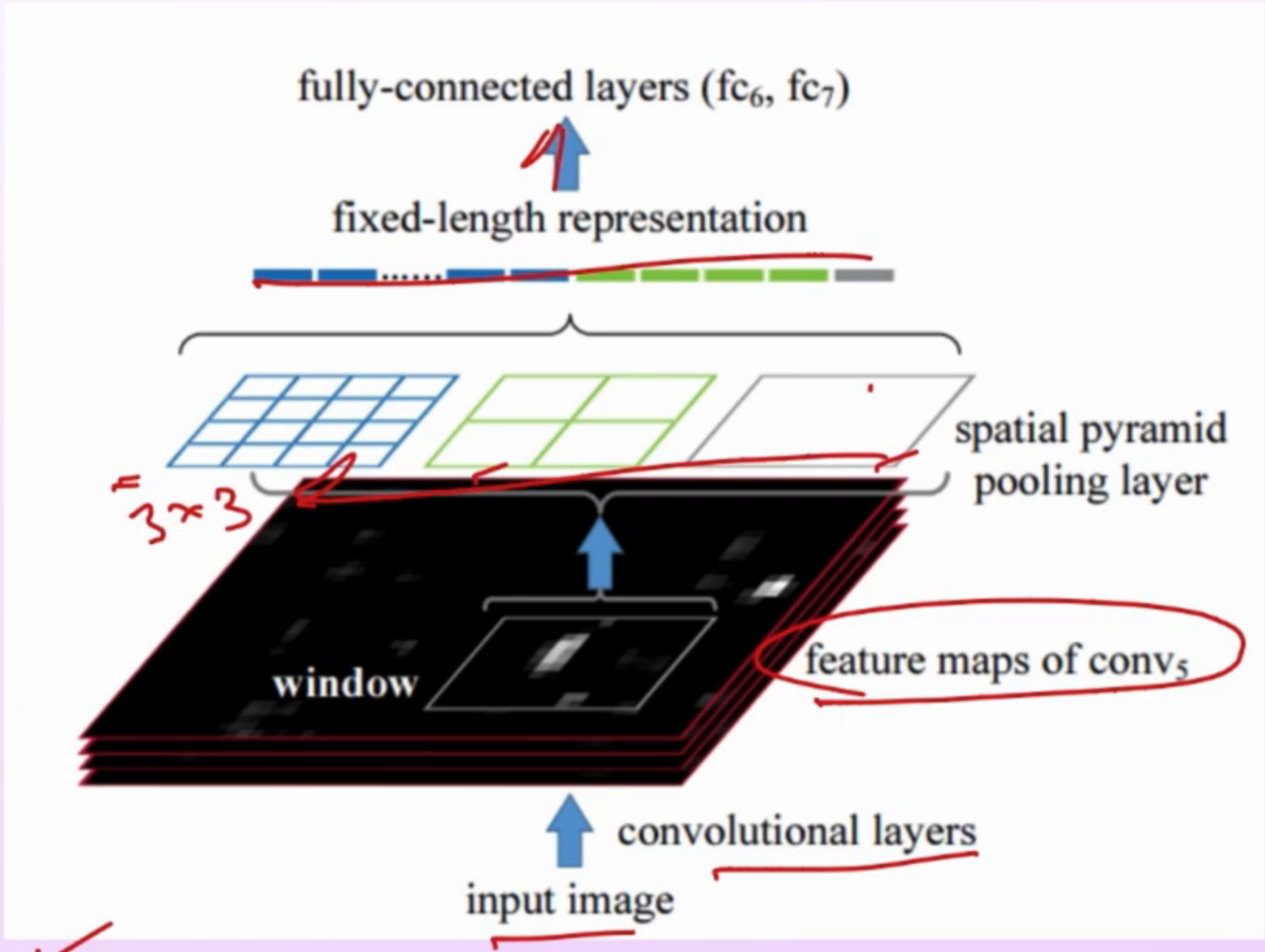


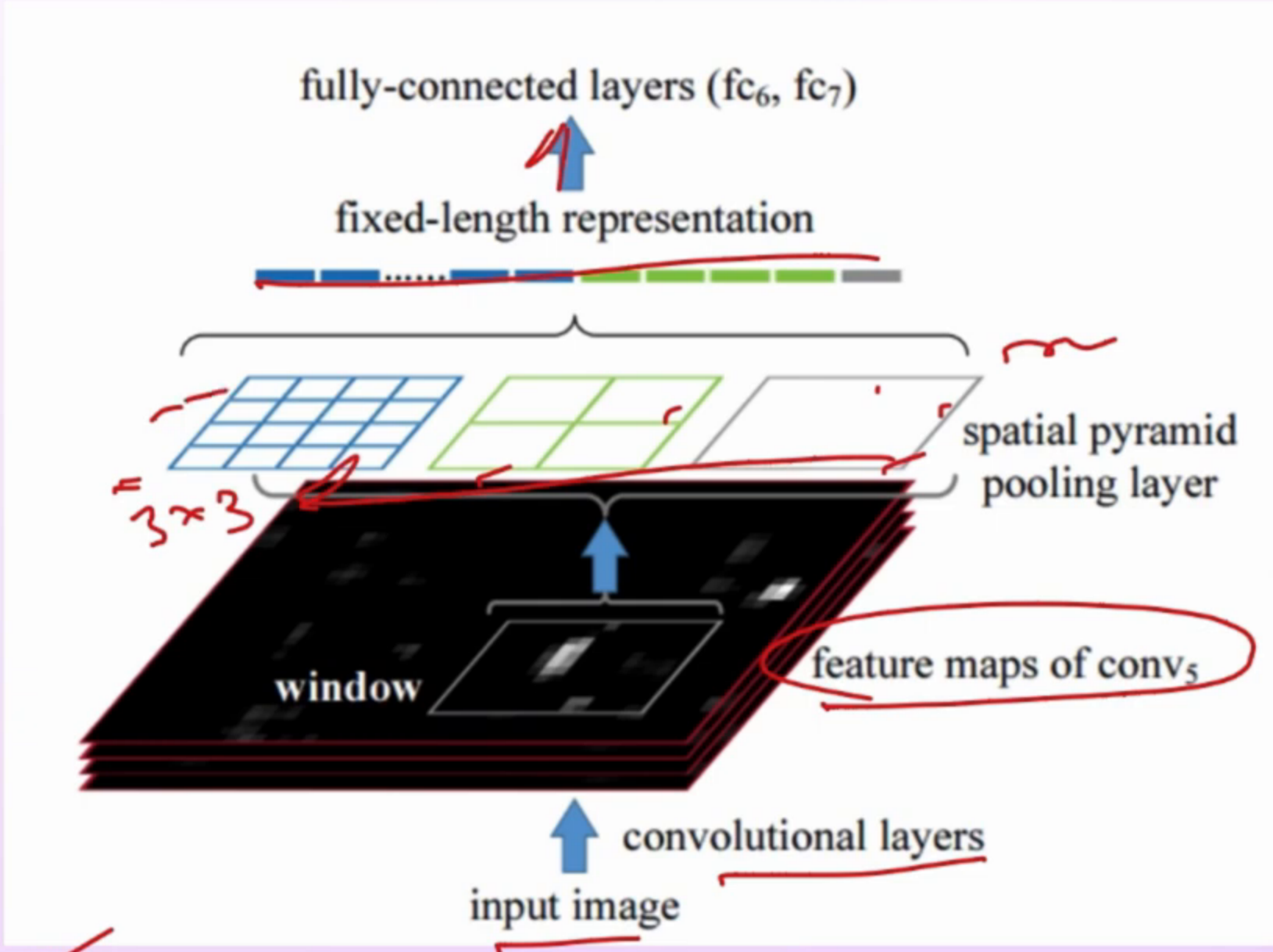

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
feature maps of $conv_5$
window
convolutional layers
input image

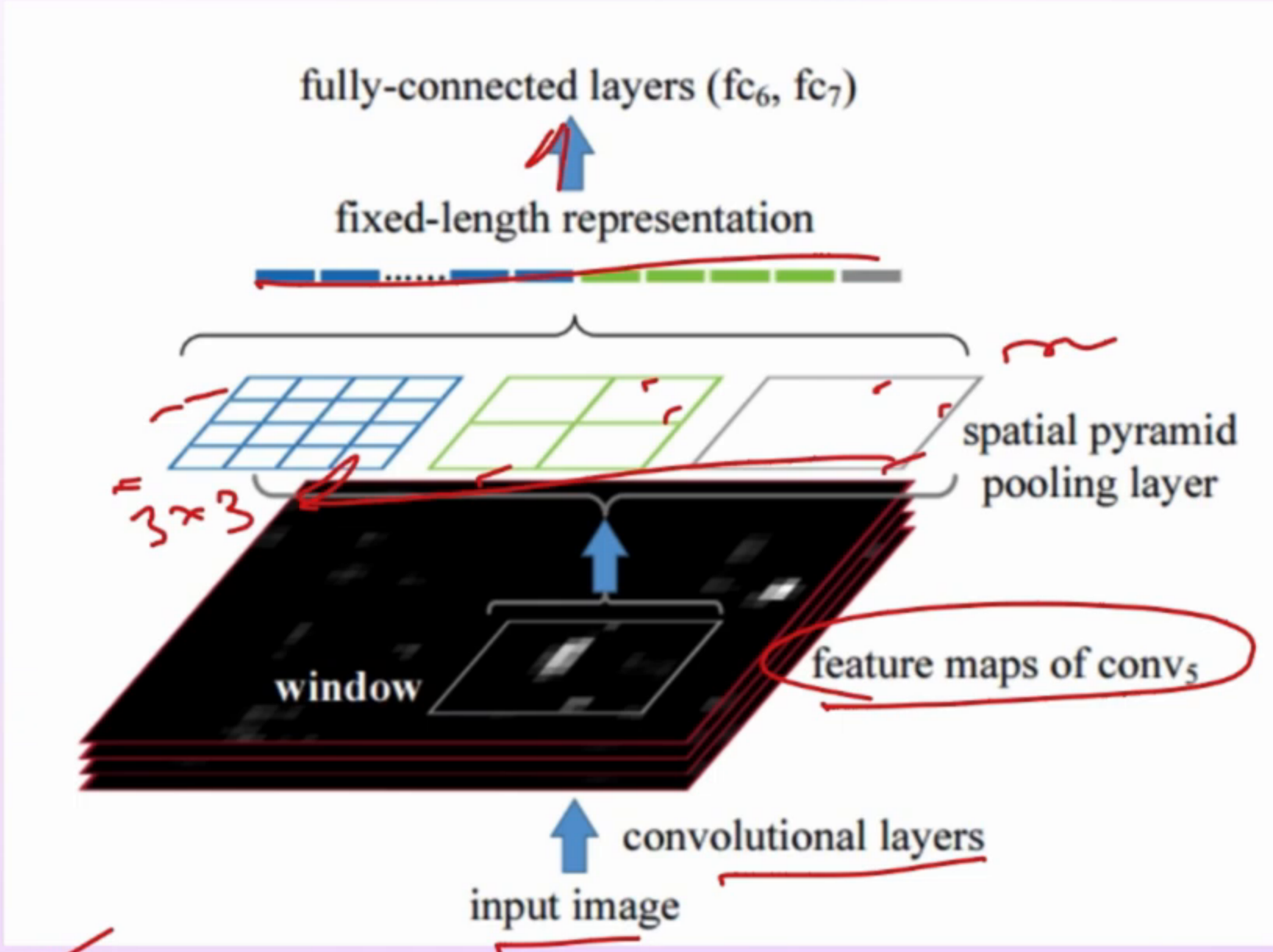

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
feature maps of $conv_5$
window
convolutional layers
input image

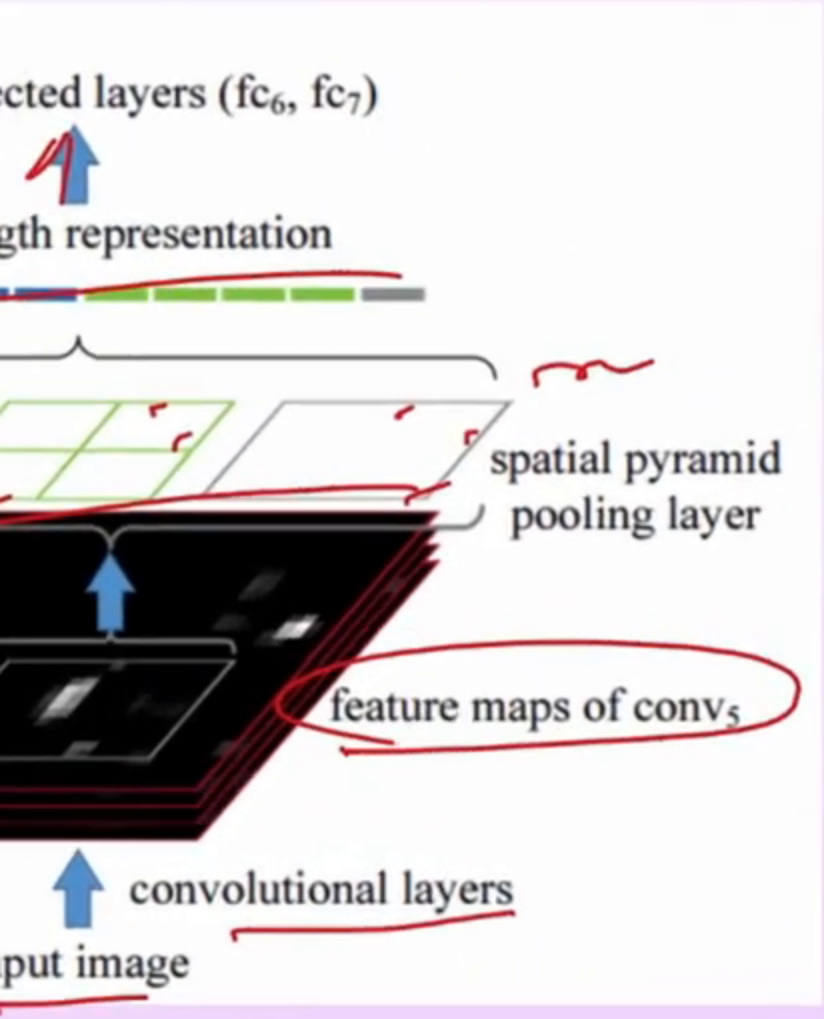

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
3x3
window
feature maps of $conv_5$
convolutional layers
input image

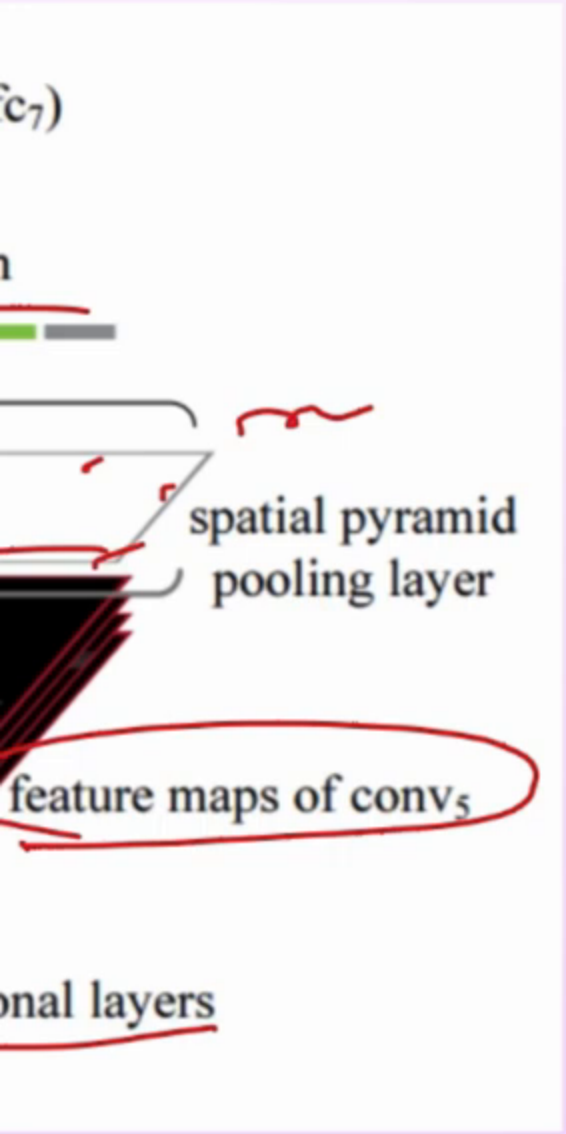

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
3×3
window
feature maps of $conv_5$
convolutional layers
input image

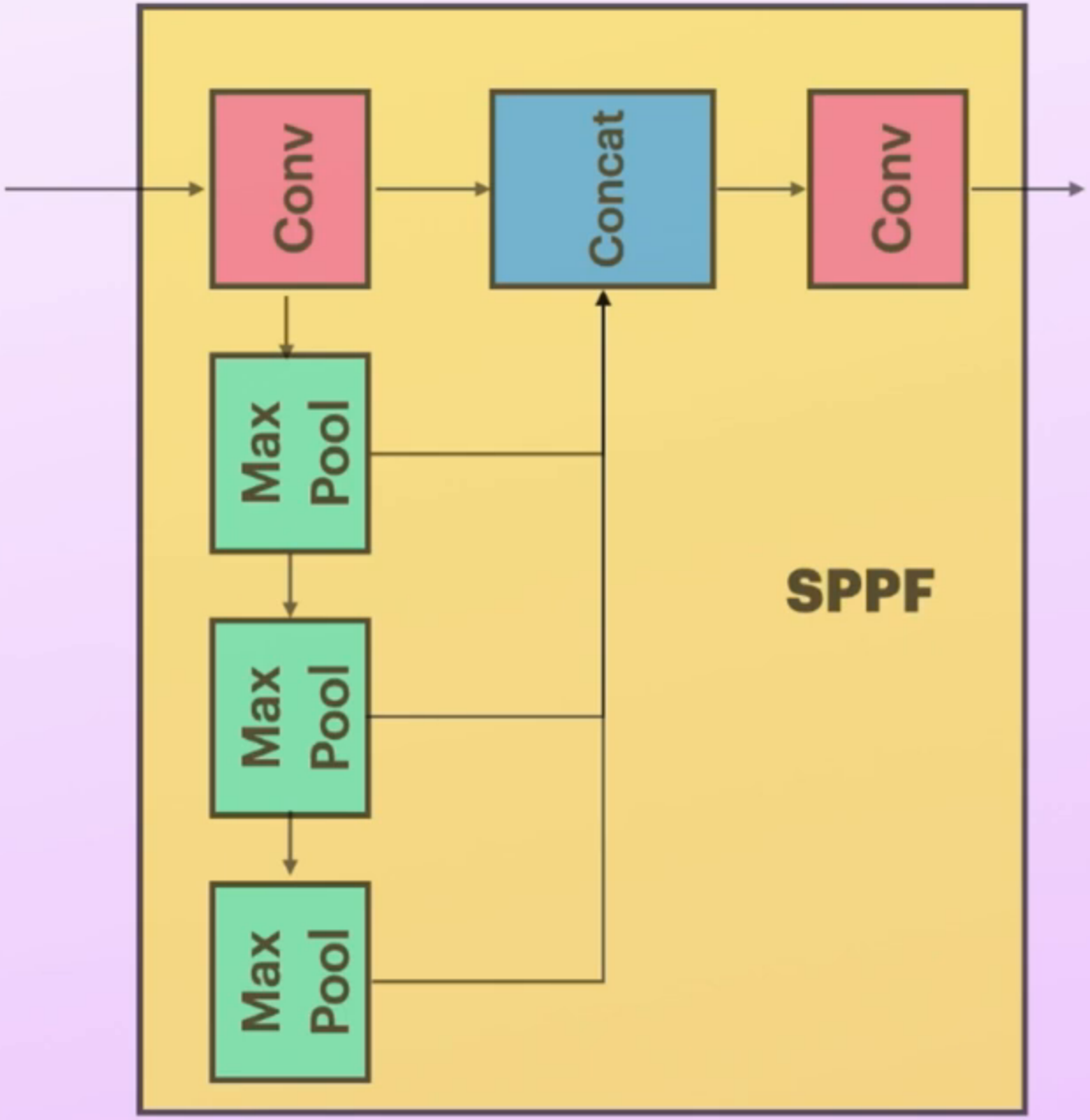

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
3x3
window
feature maps of $conv_5$
convolutional layers
input image


fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
window
feature maps of $conv_5$
convolutional layers
input image

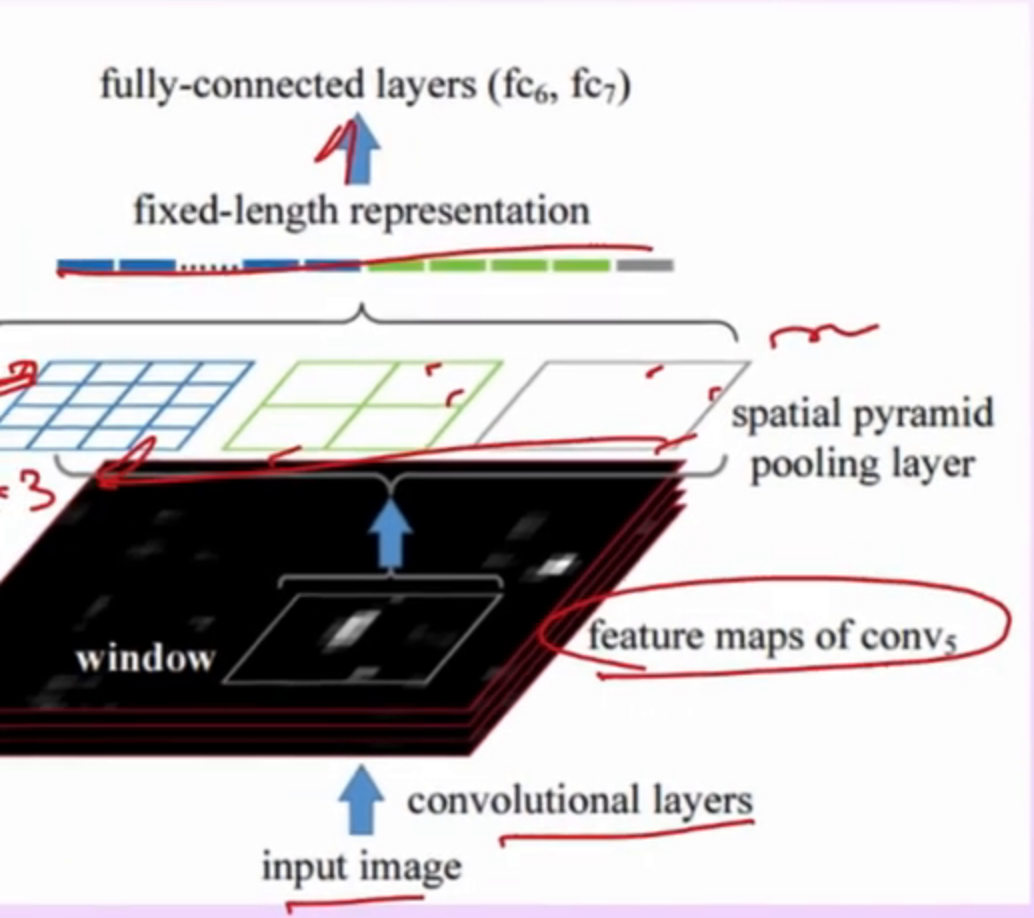

fully-connected layers (fc_6, fc_7)
fixed-length representation
spatial pyramid pooling layer
window
feature maps of $conv_5$
convolutional layers
input image

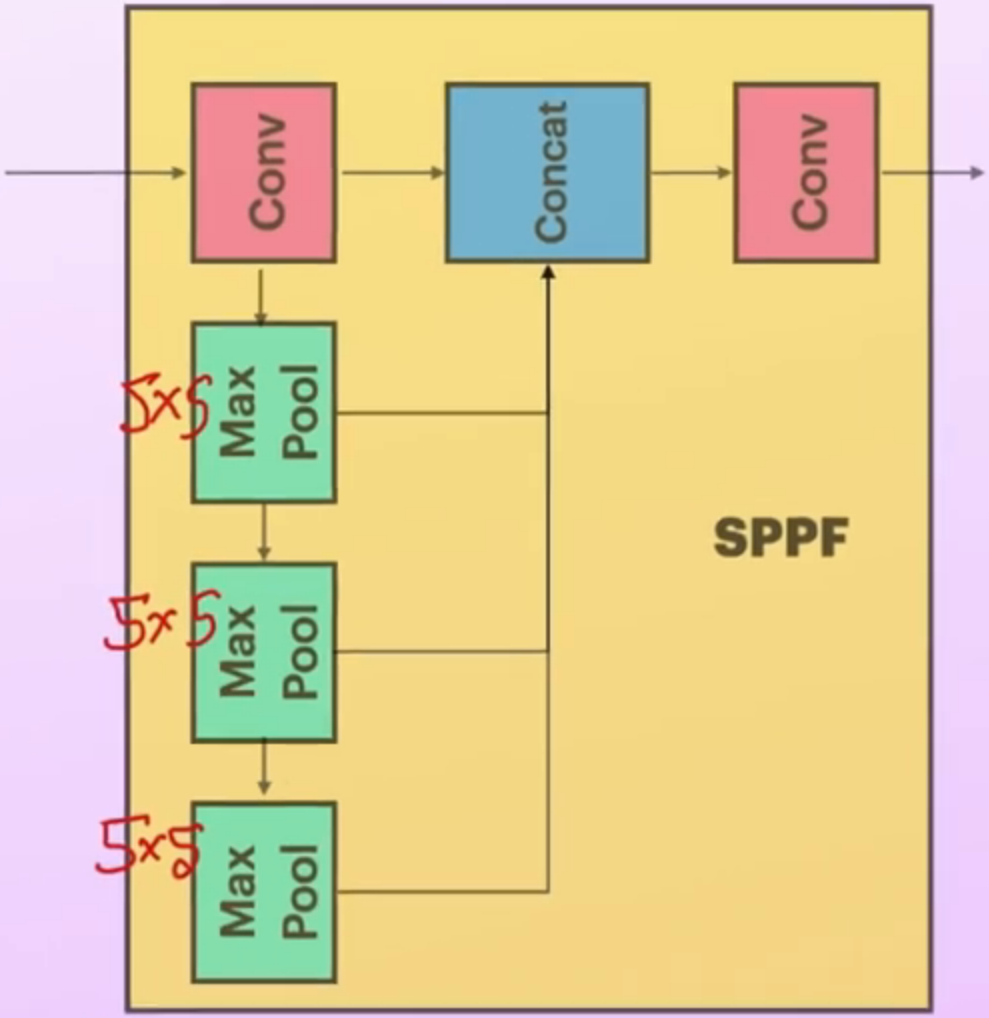

ected layers (fc6, fc7)
gth representation
spatial pyramid
pooling layer
feature maps of conv5
convolutional layers
put image


fc7)
n
spatial pyramid
pooling layer
feature maps of conv5
onal layers

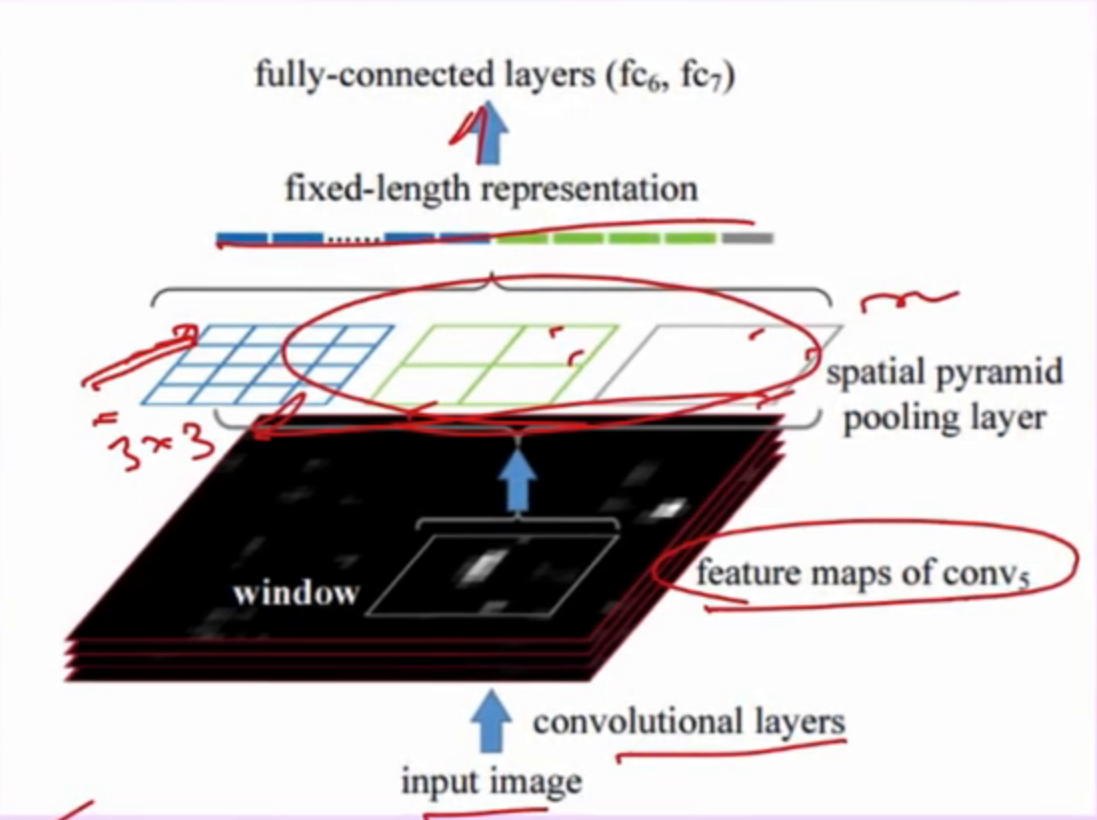

Conv
Concat
Conv
Max Pool
Max Pool
Max Pool
SPPF

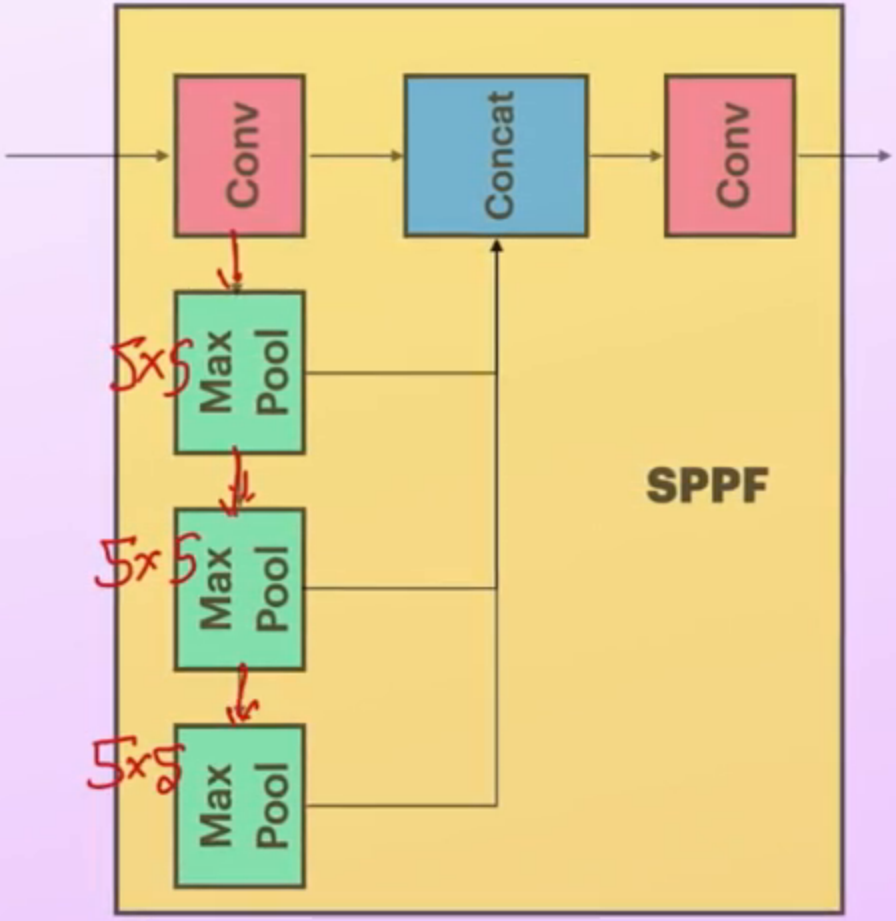
atial Pyramid Pooling Fast



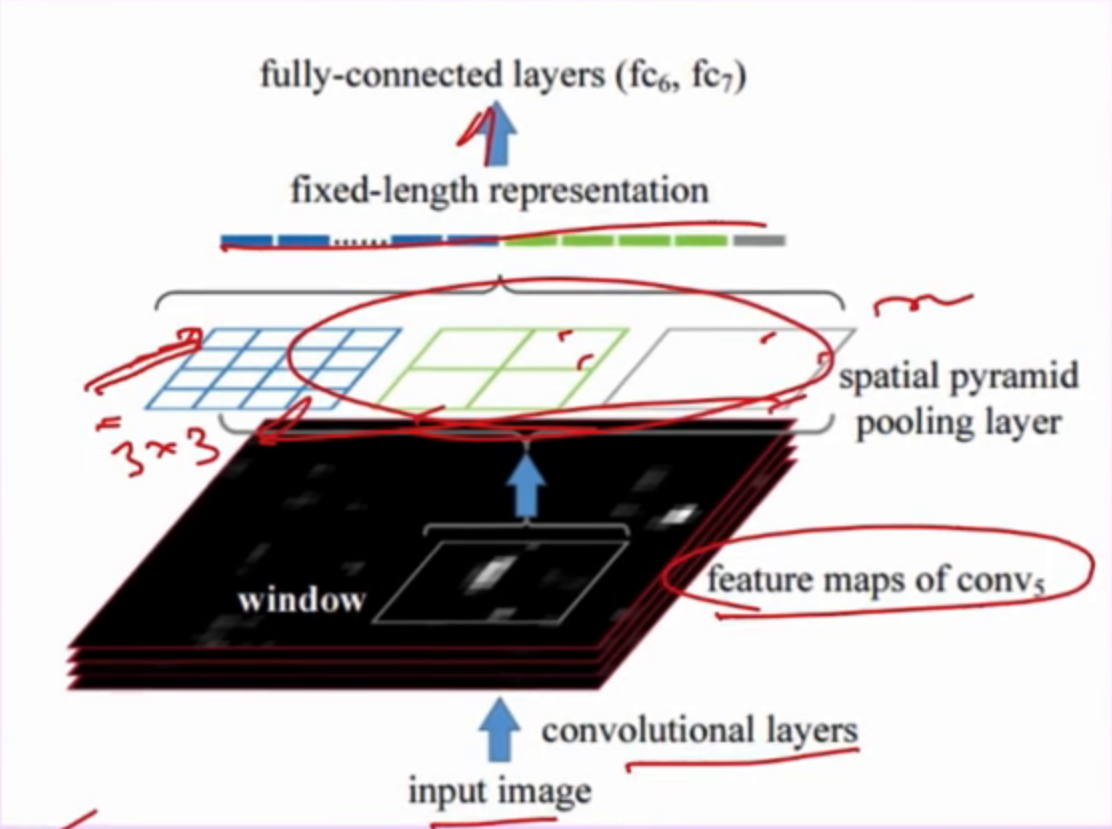


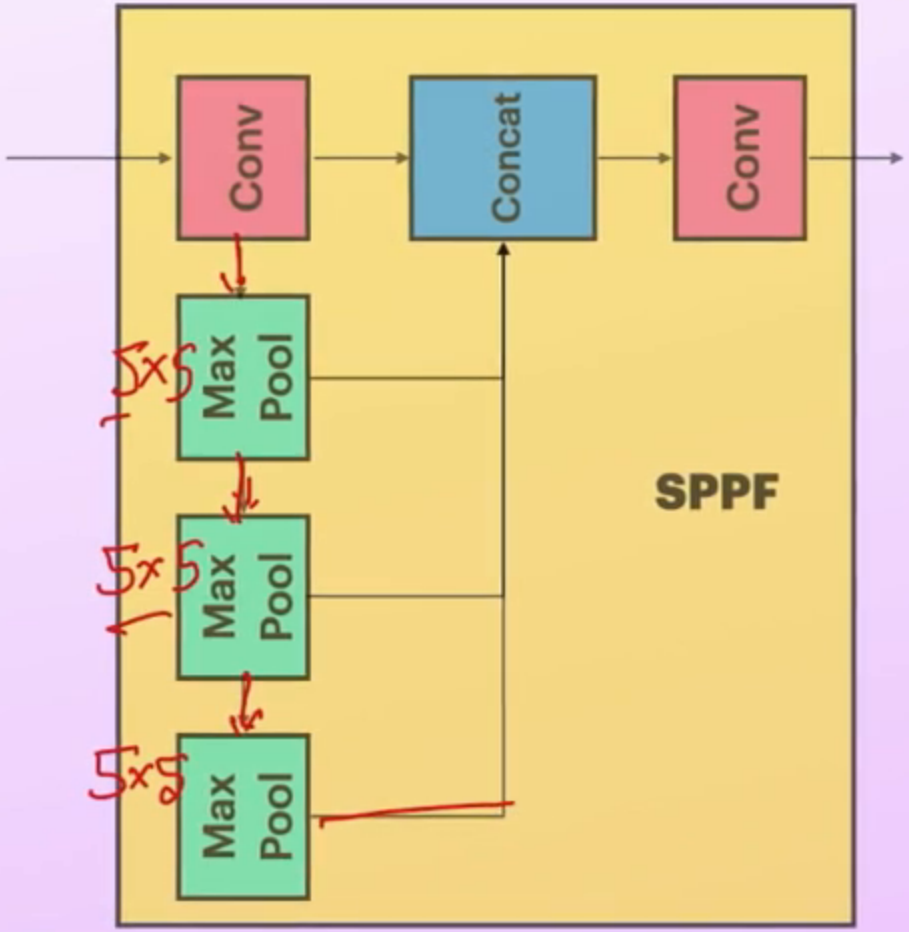
Spatial Pyramid Pooling Fast



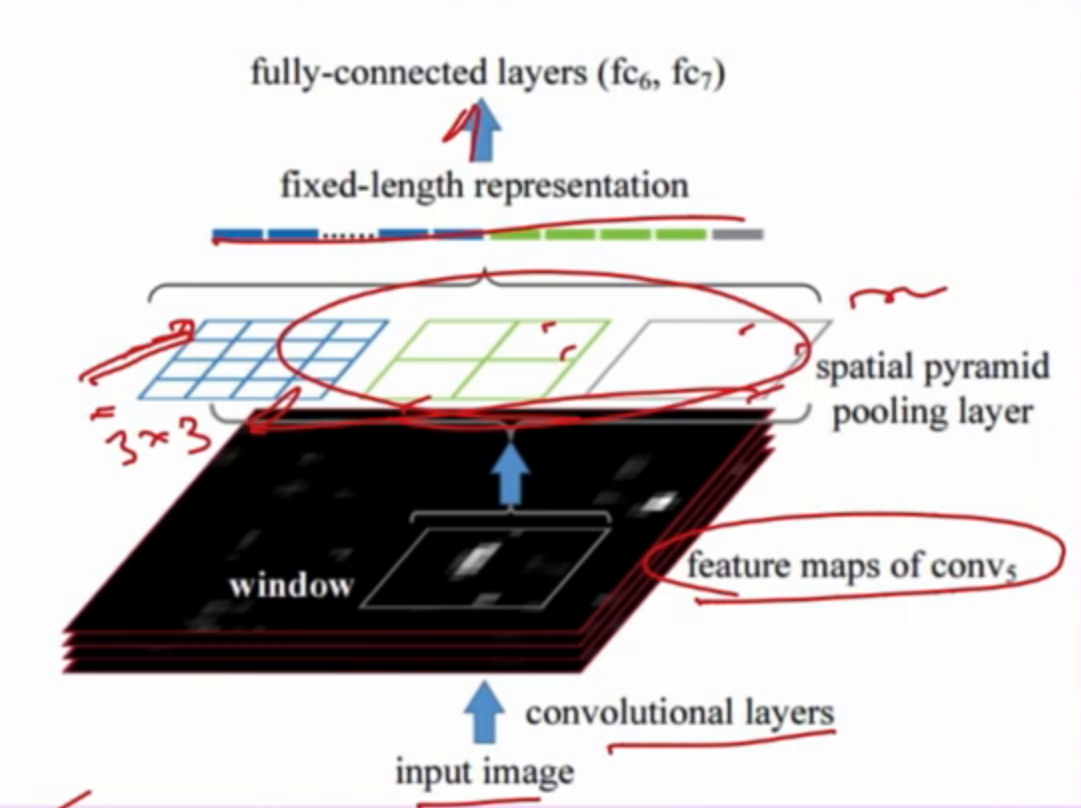


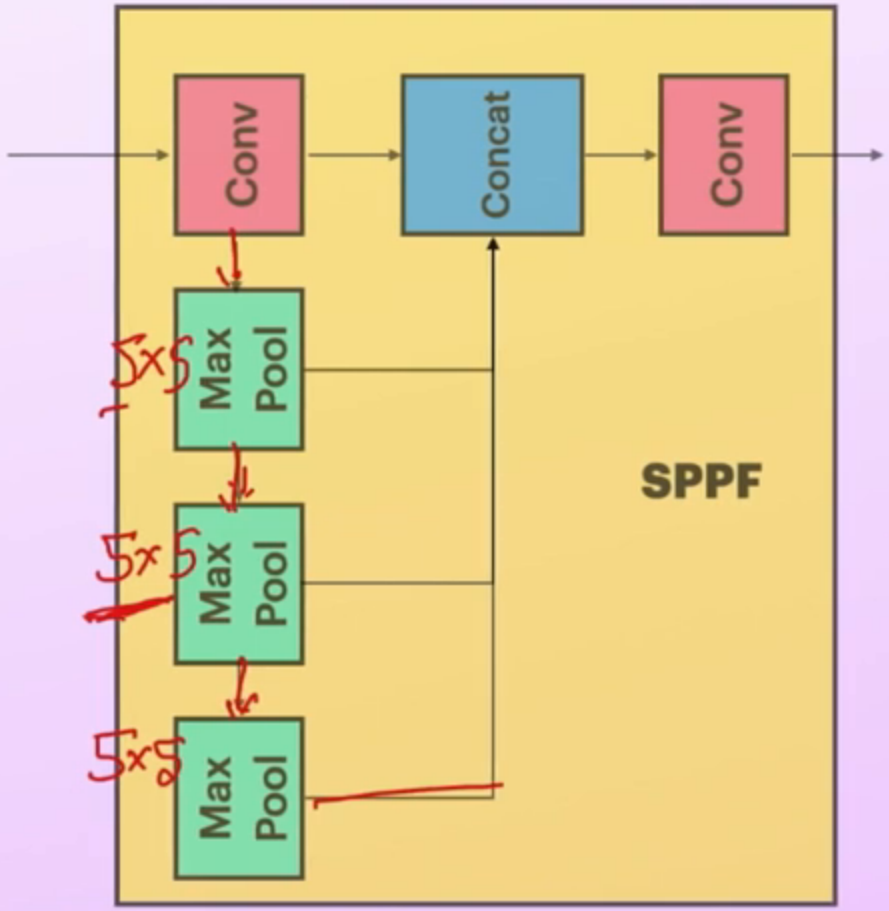
Spatial Pyramid Pooling Fast



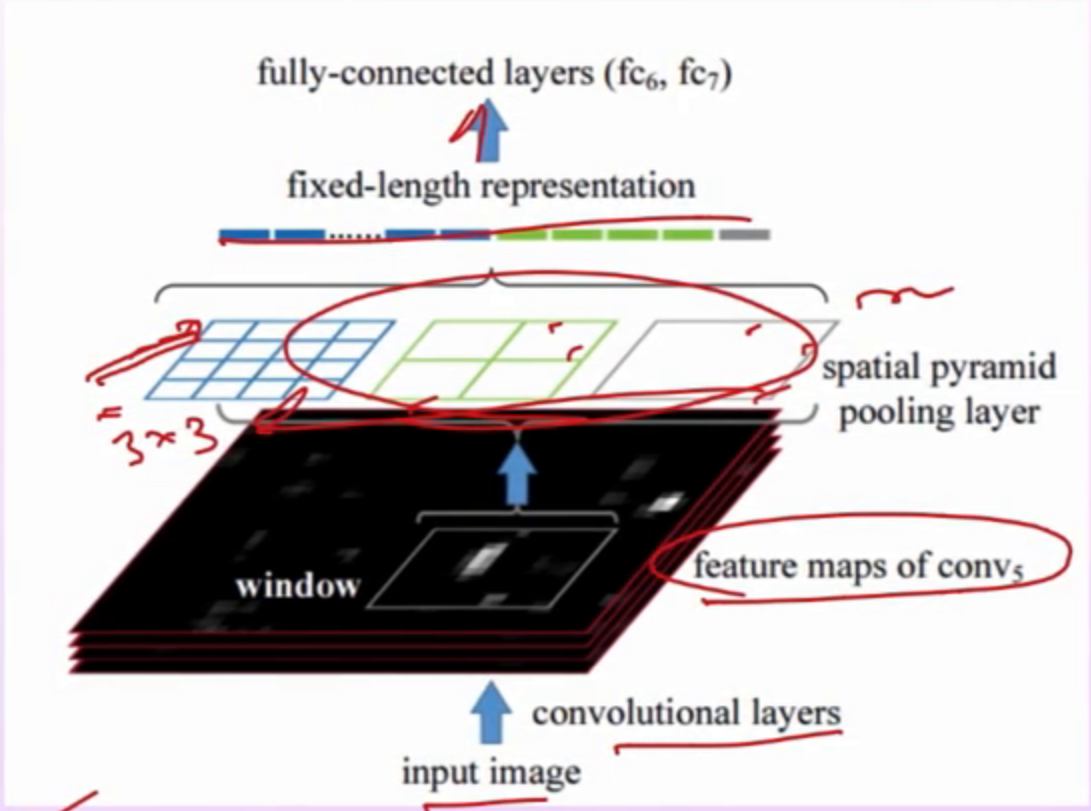


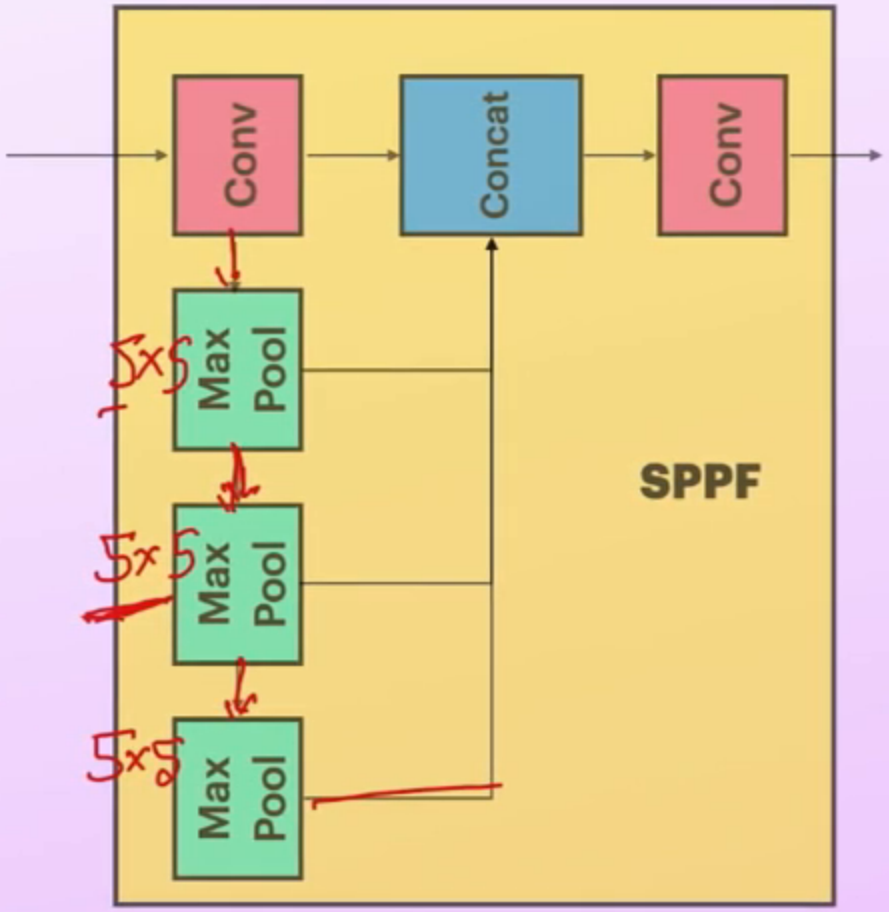
Spatial Pyramid Pooling Fast



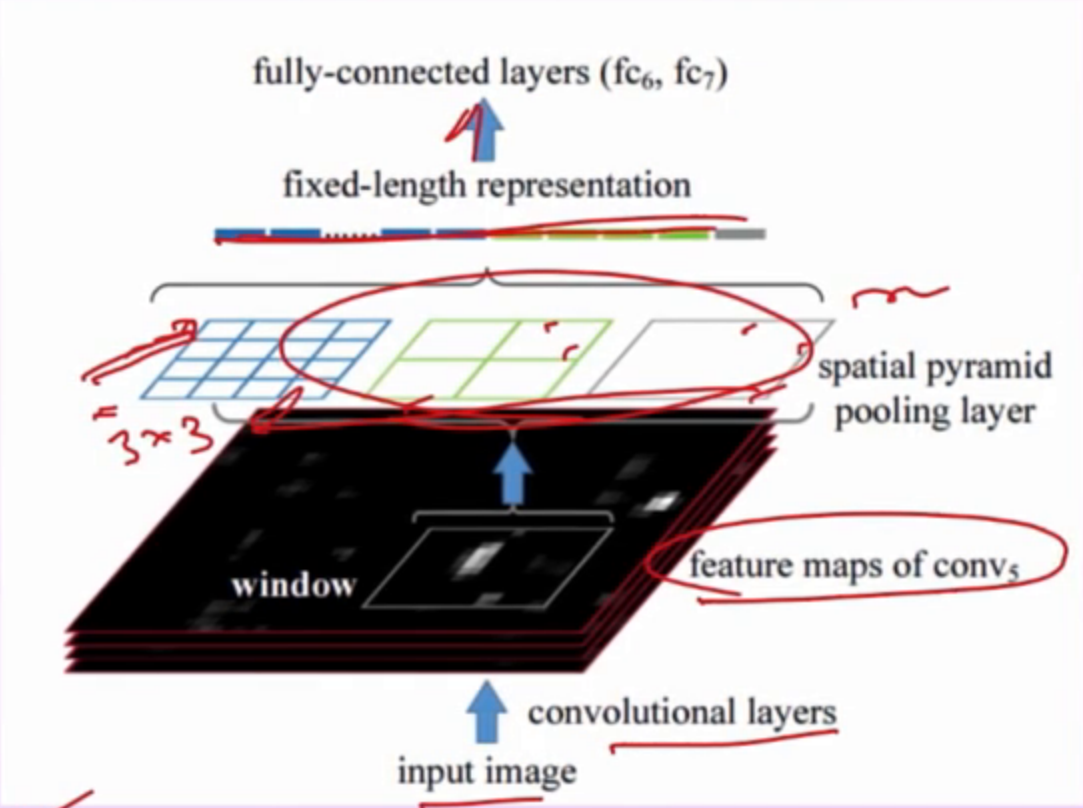


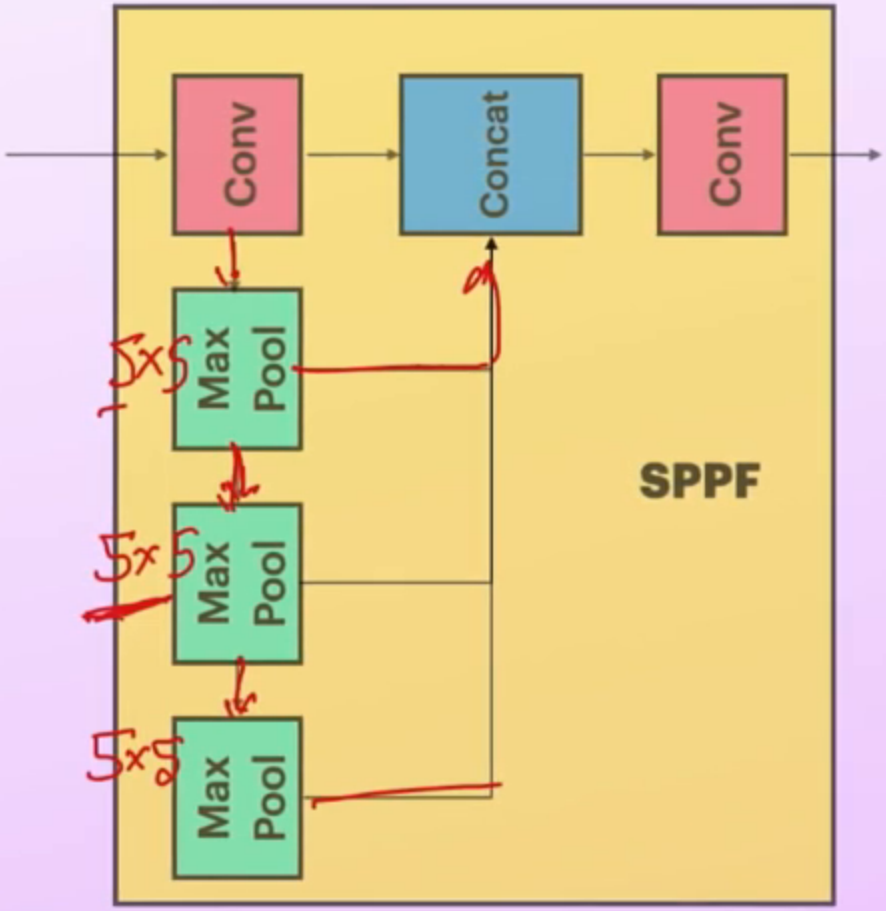
Spatial Pyramid Pooling Fast



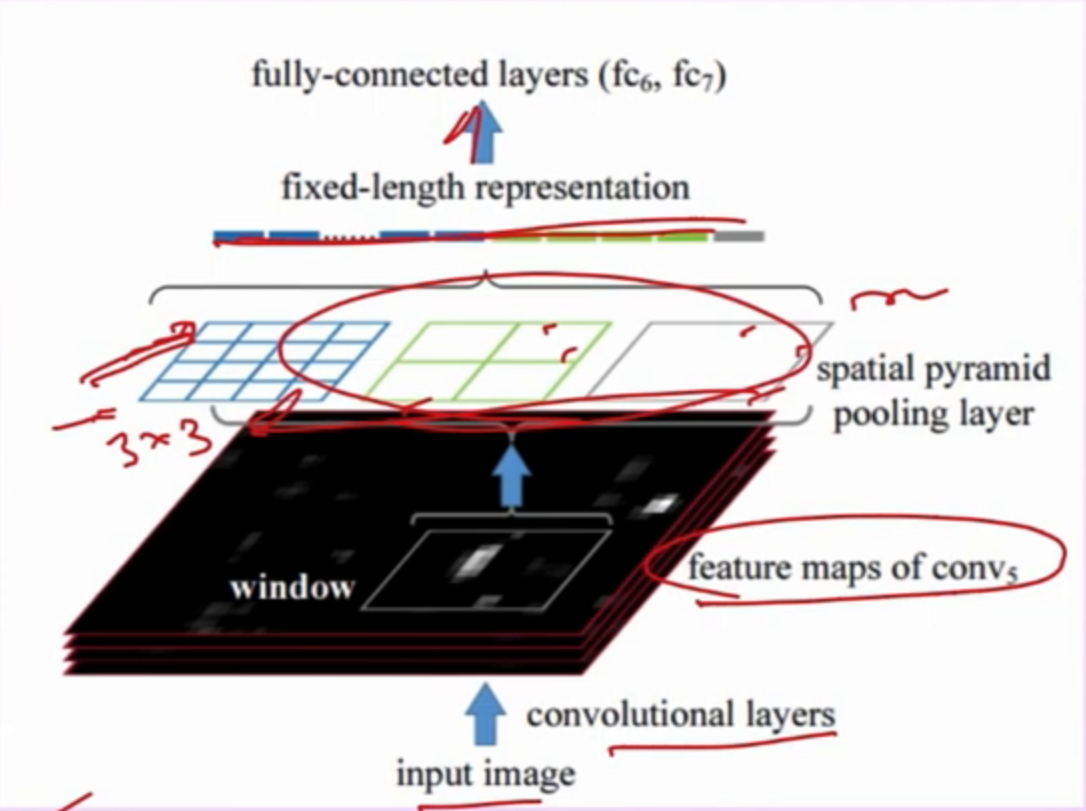


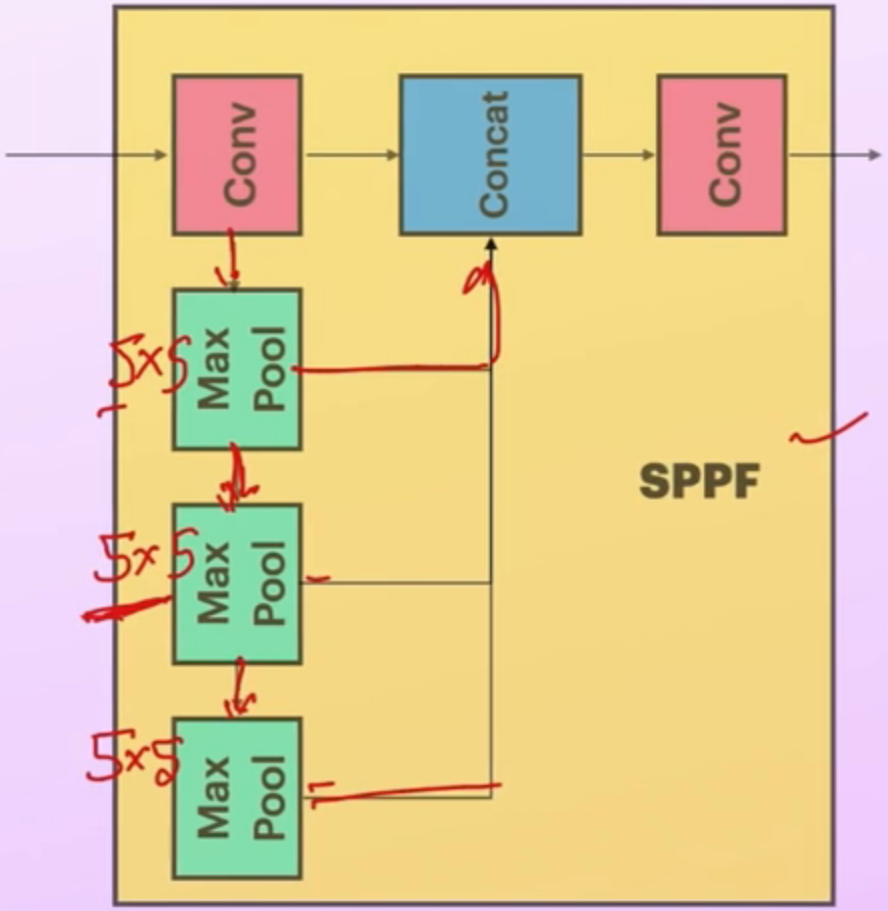
Spatial Pyramid Pooling Fast





Spatial Pyramid Pooling Fast





Path Aggregation Network

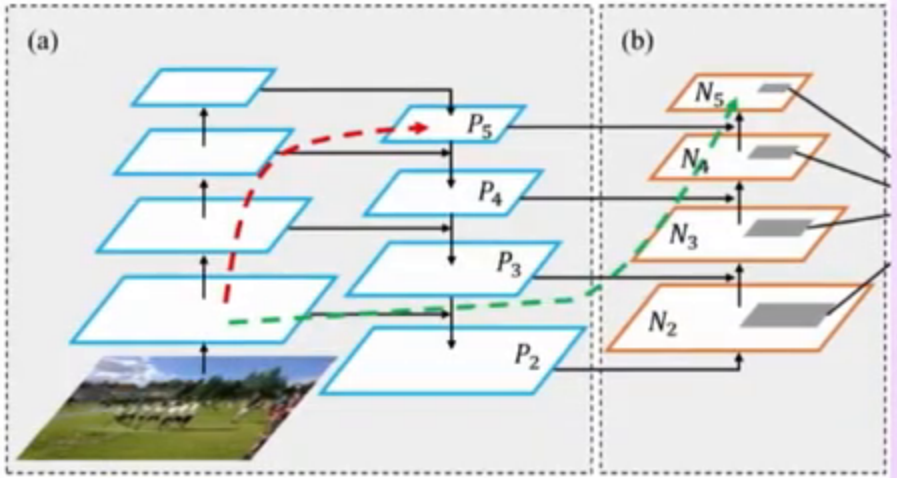
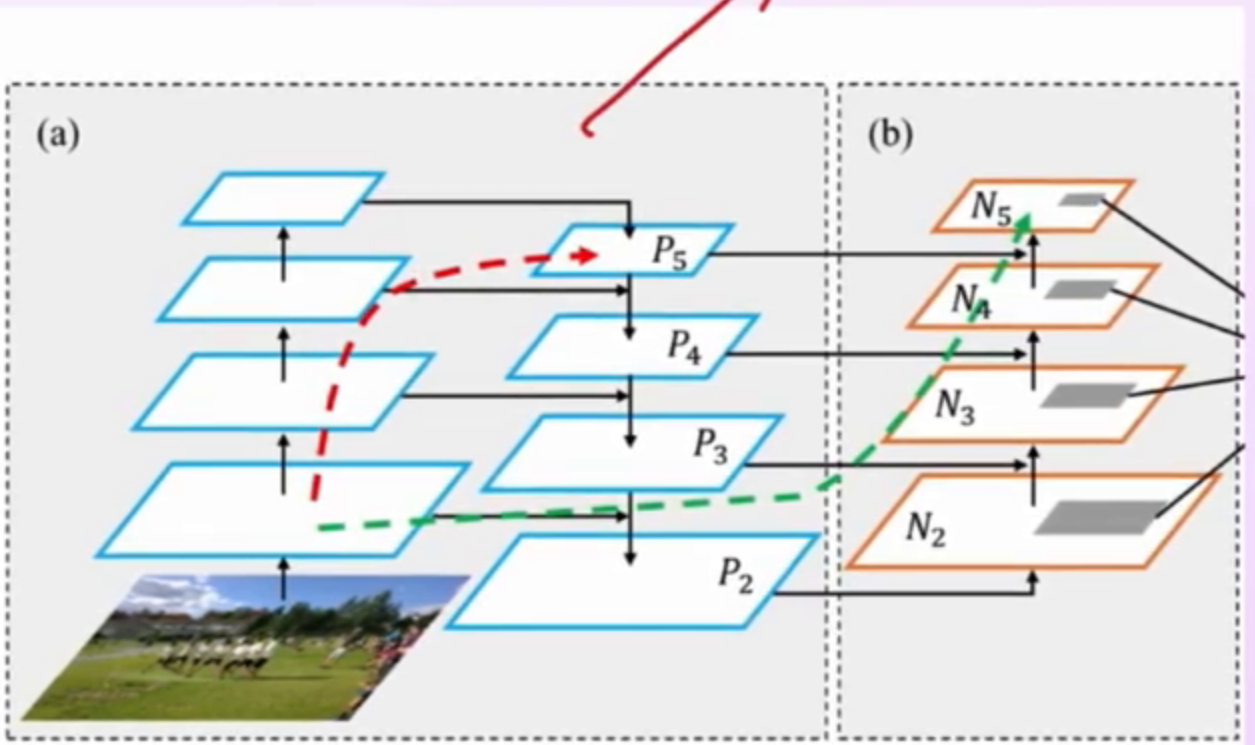


Figure 1. Illustration of our framework. (a) FPN backbone. (b) Bottom-up path branch. (e) Fully-connected fusion. Note that we omit channel dimension of feature



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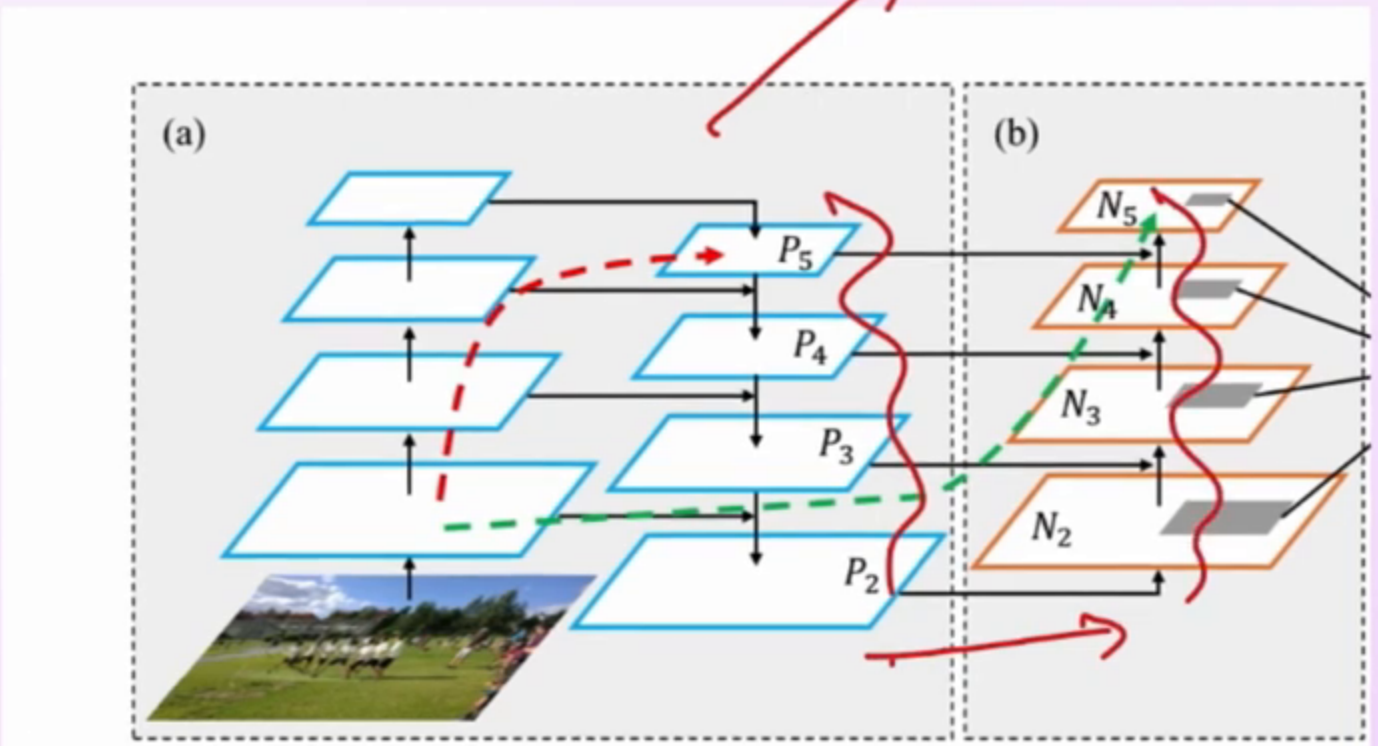
branch. (e) Fully-connected fusion. Note that we omit channel dimension of feature



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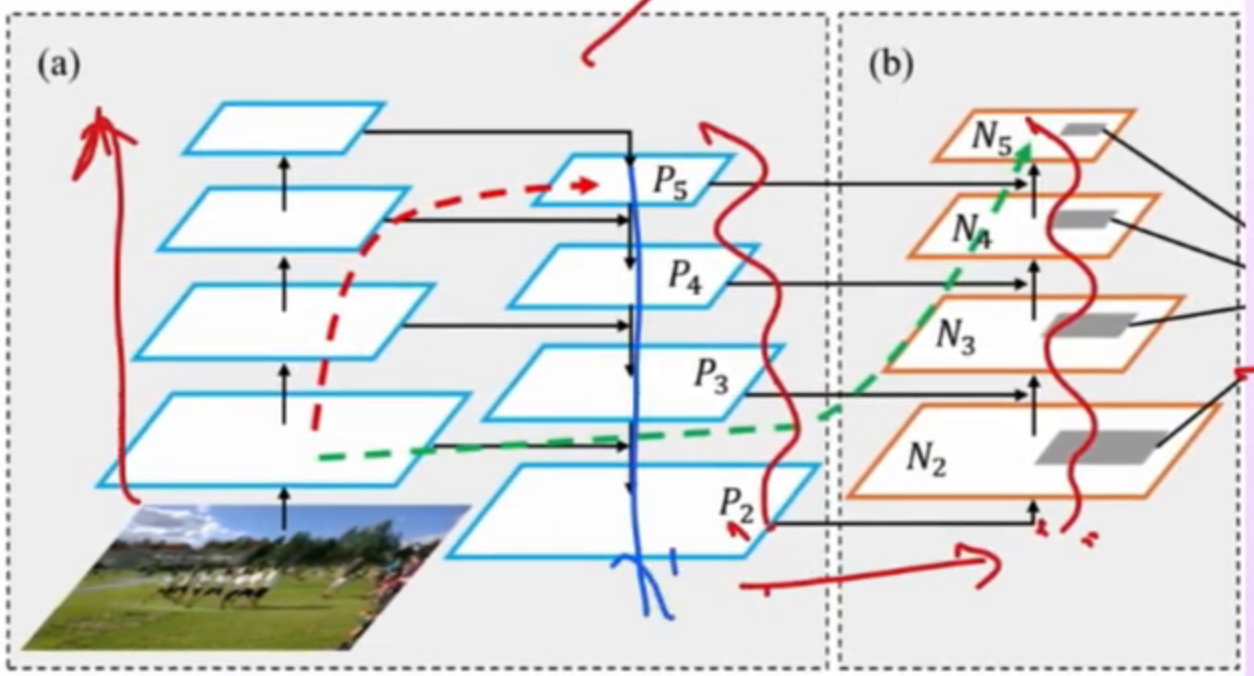

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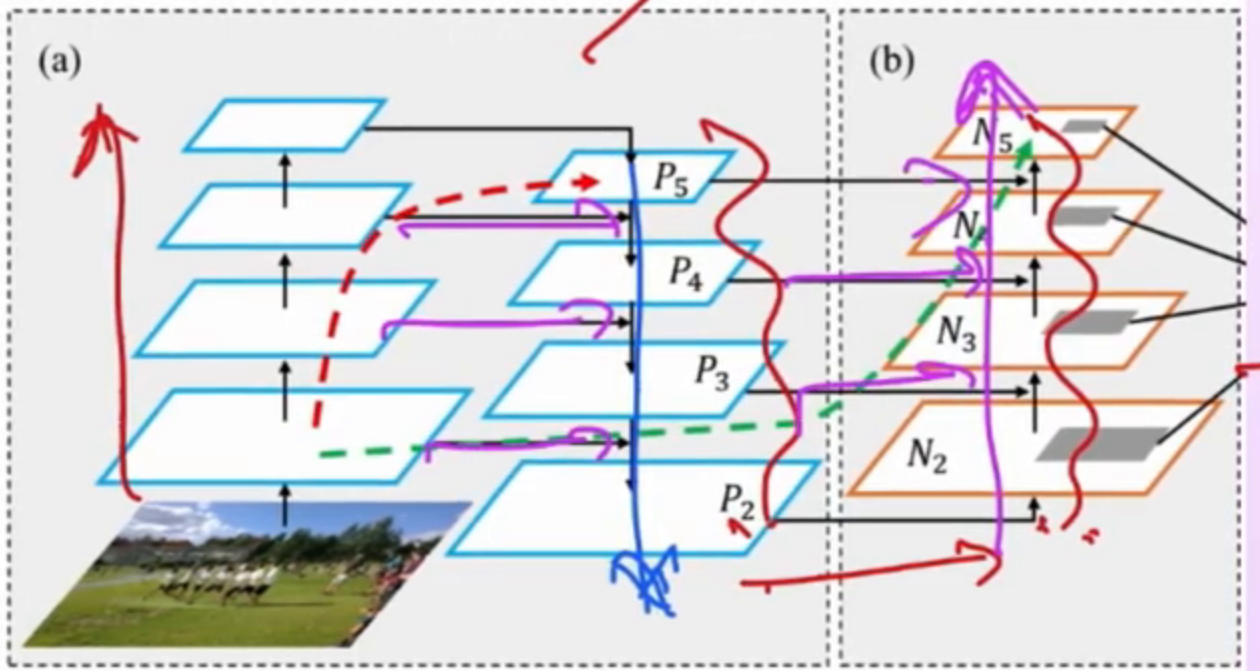

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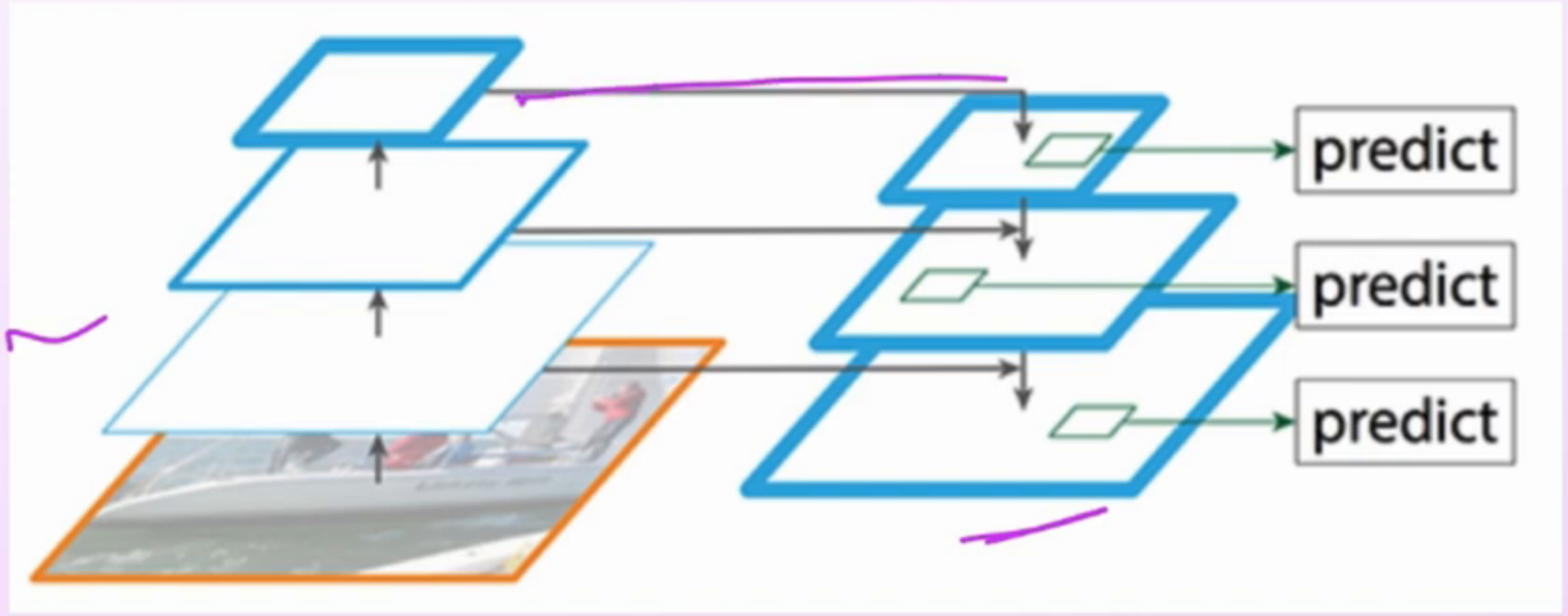
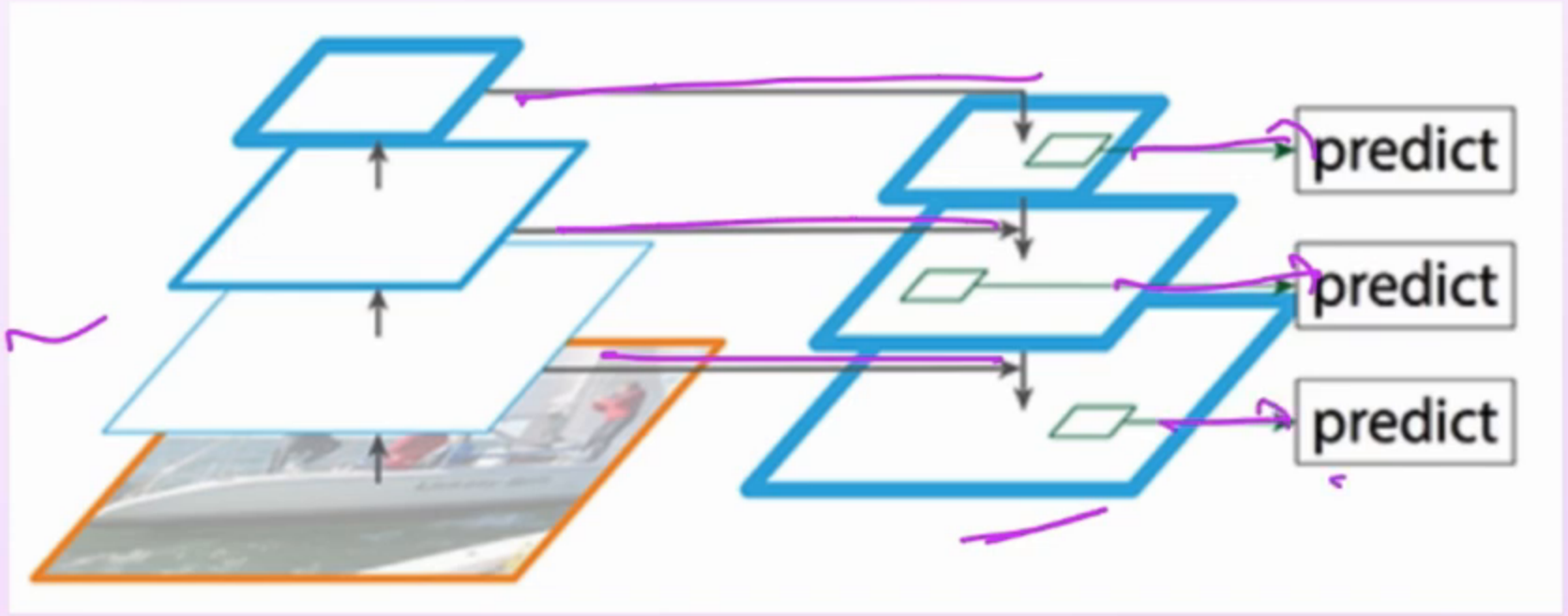


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.



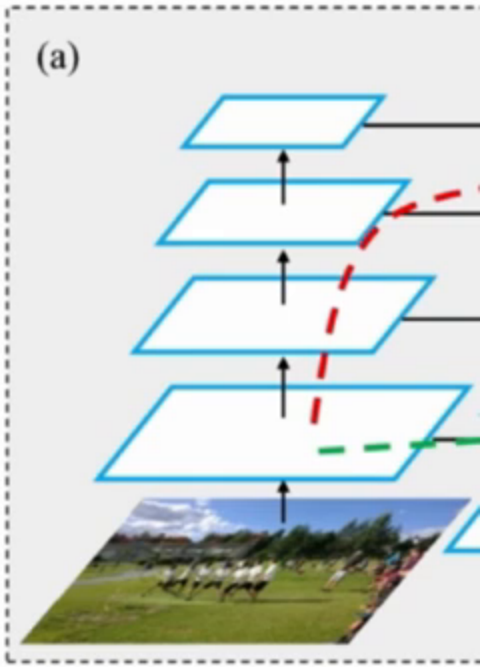


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

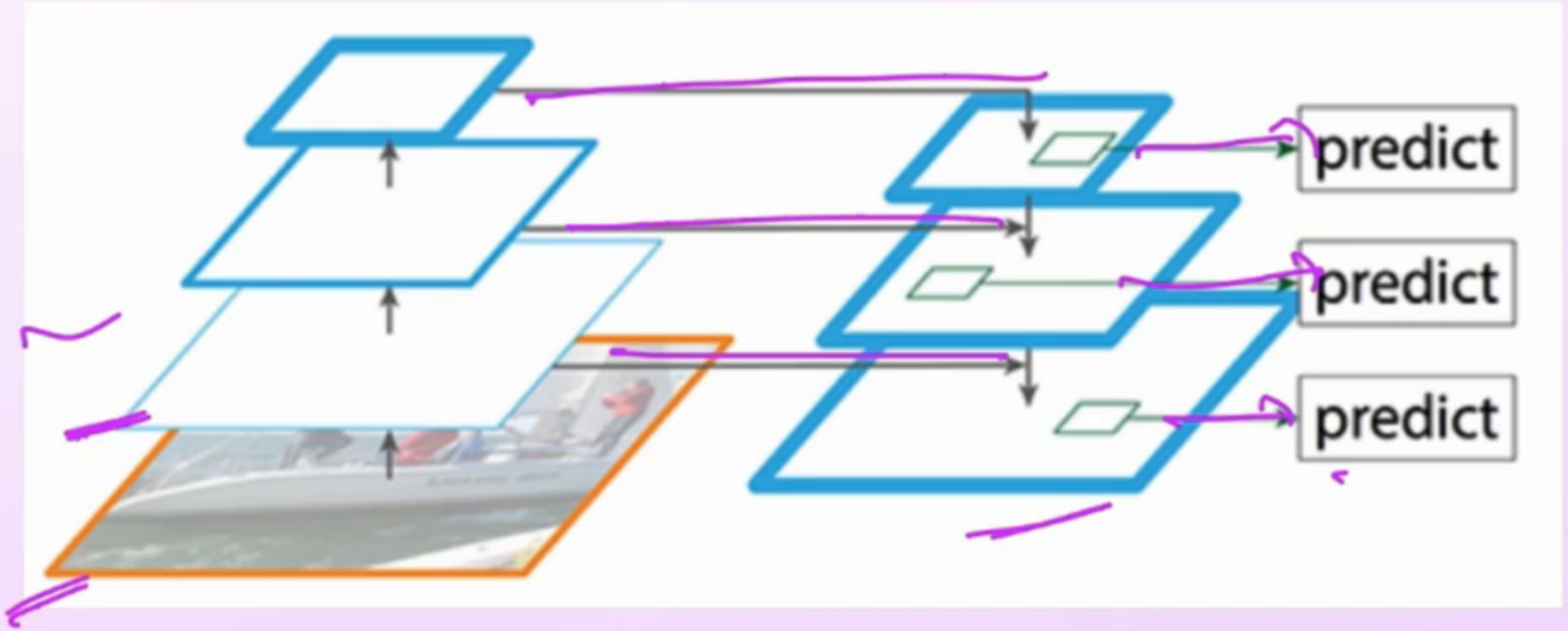
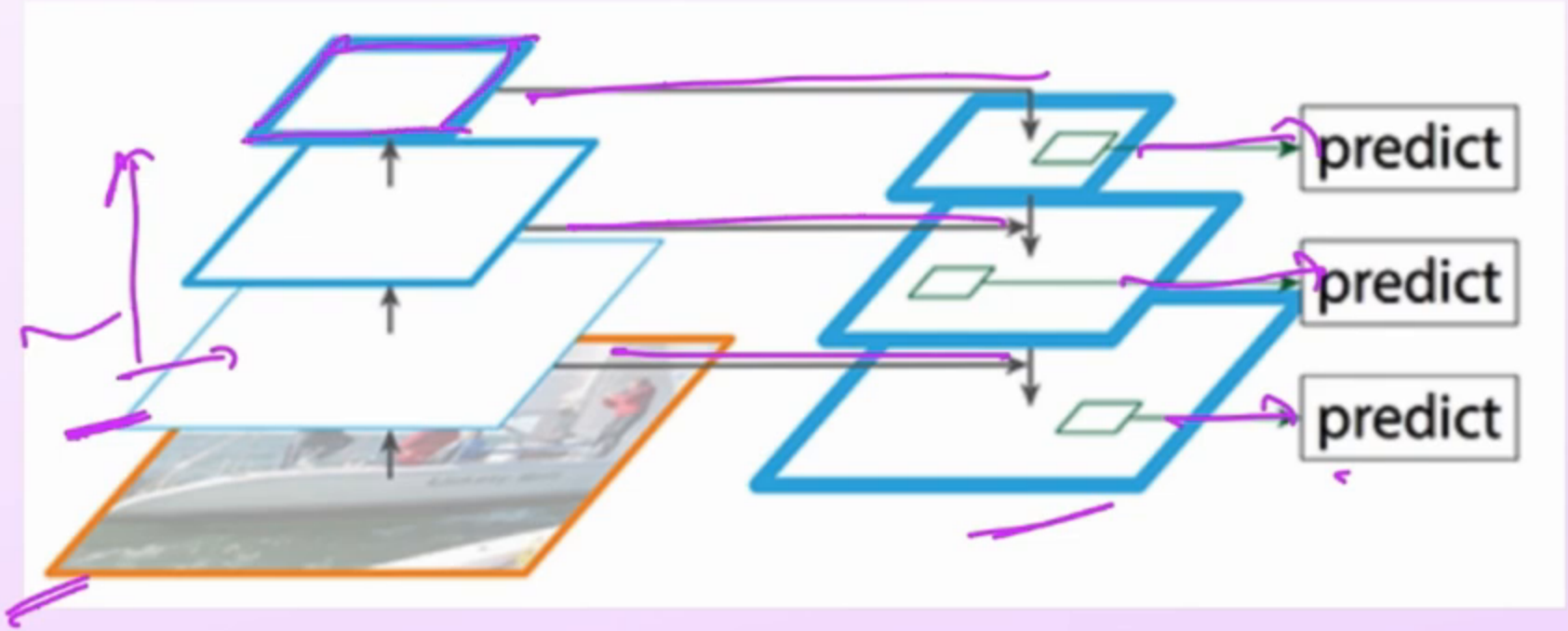


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.



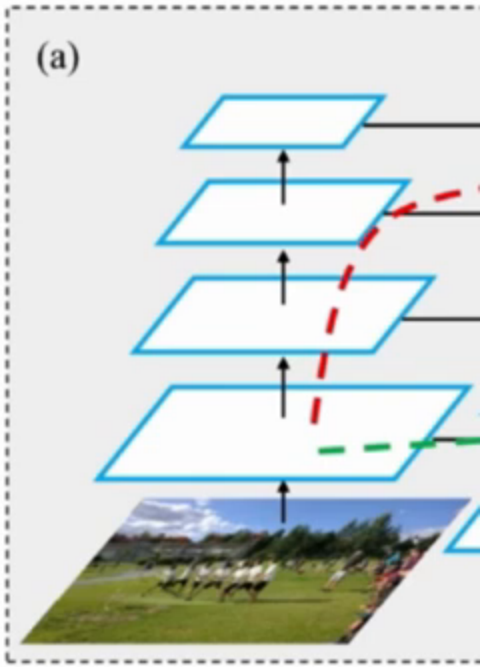


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

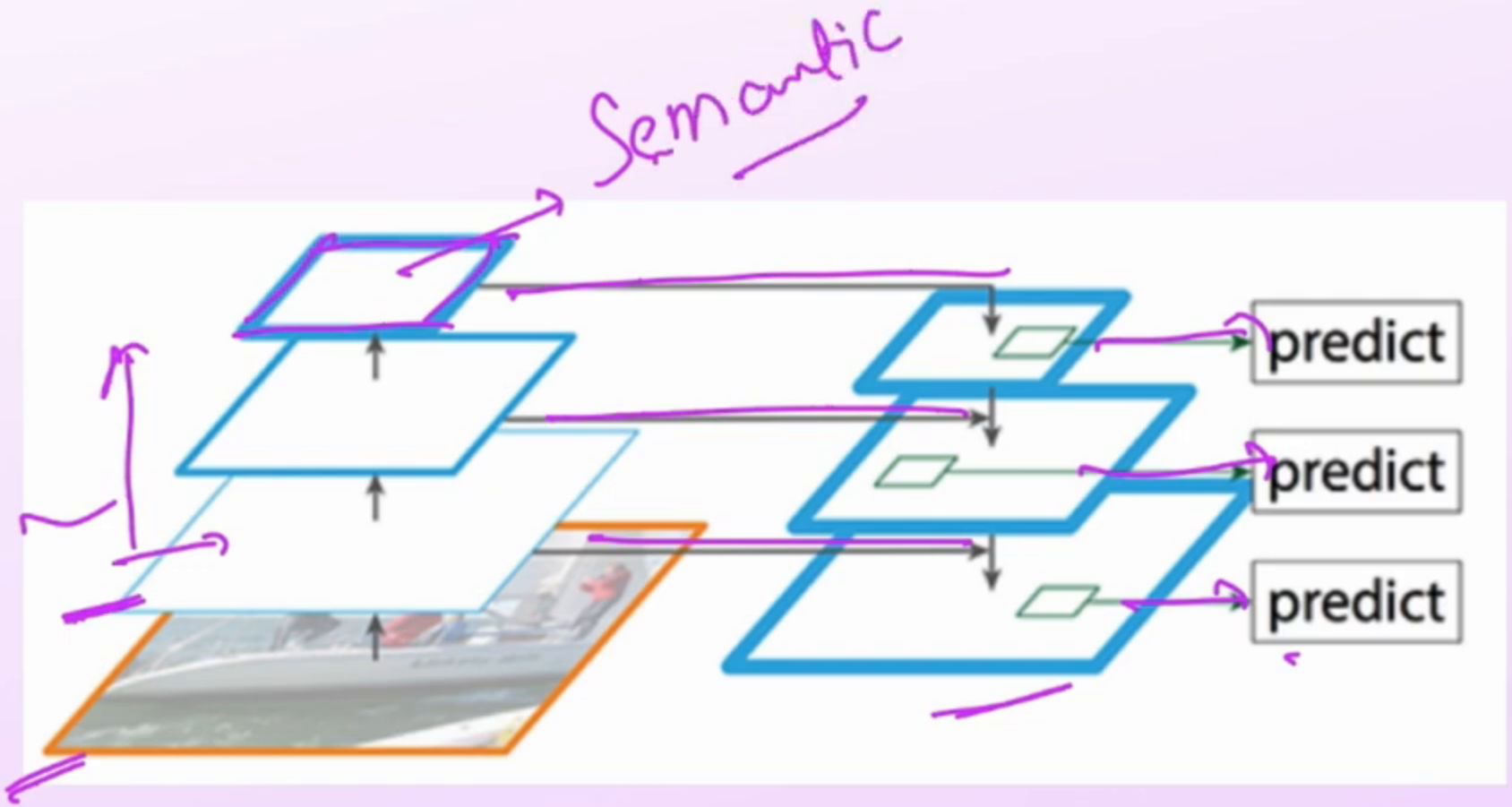


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

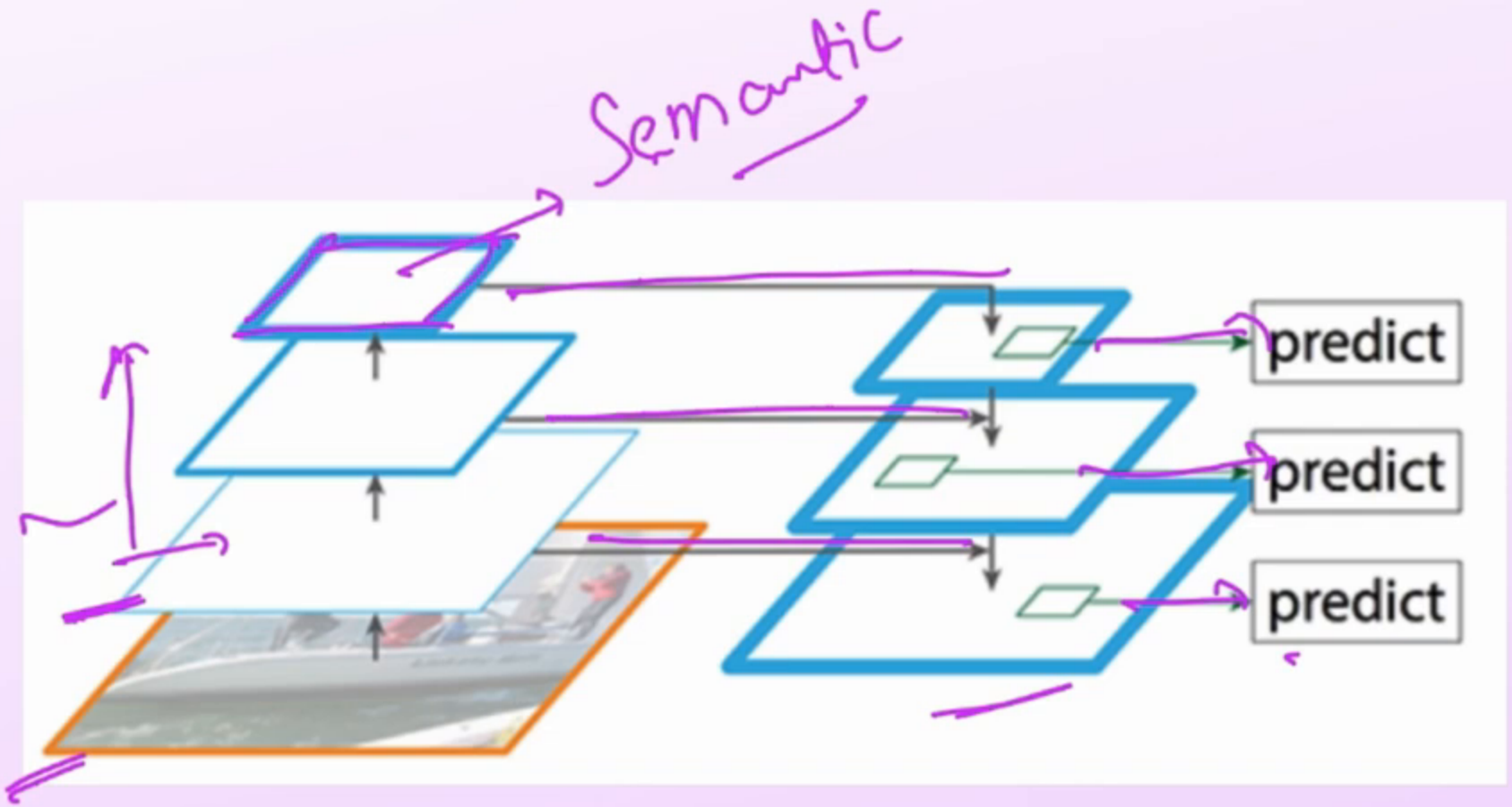


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

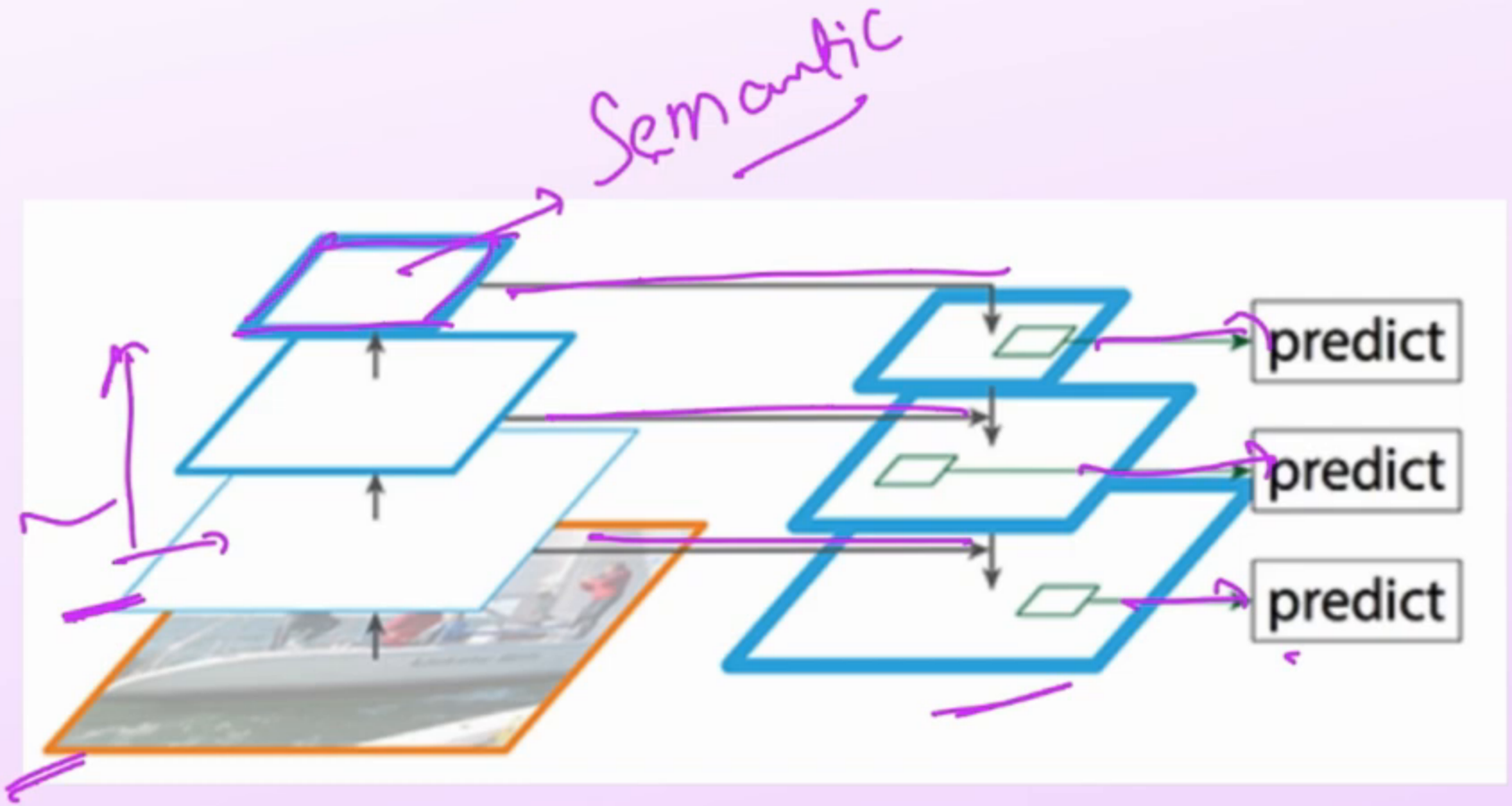


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

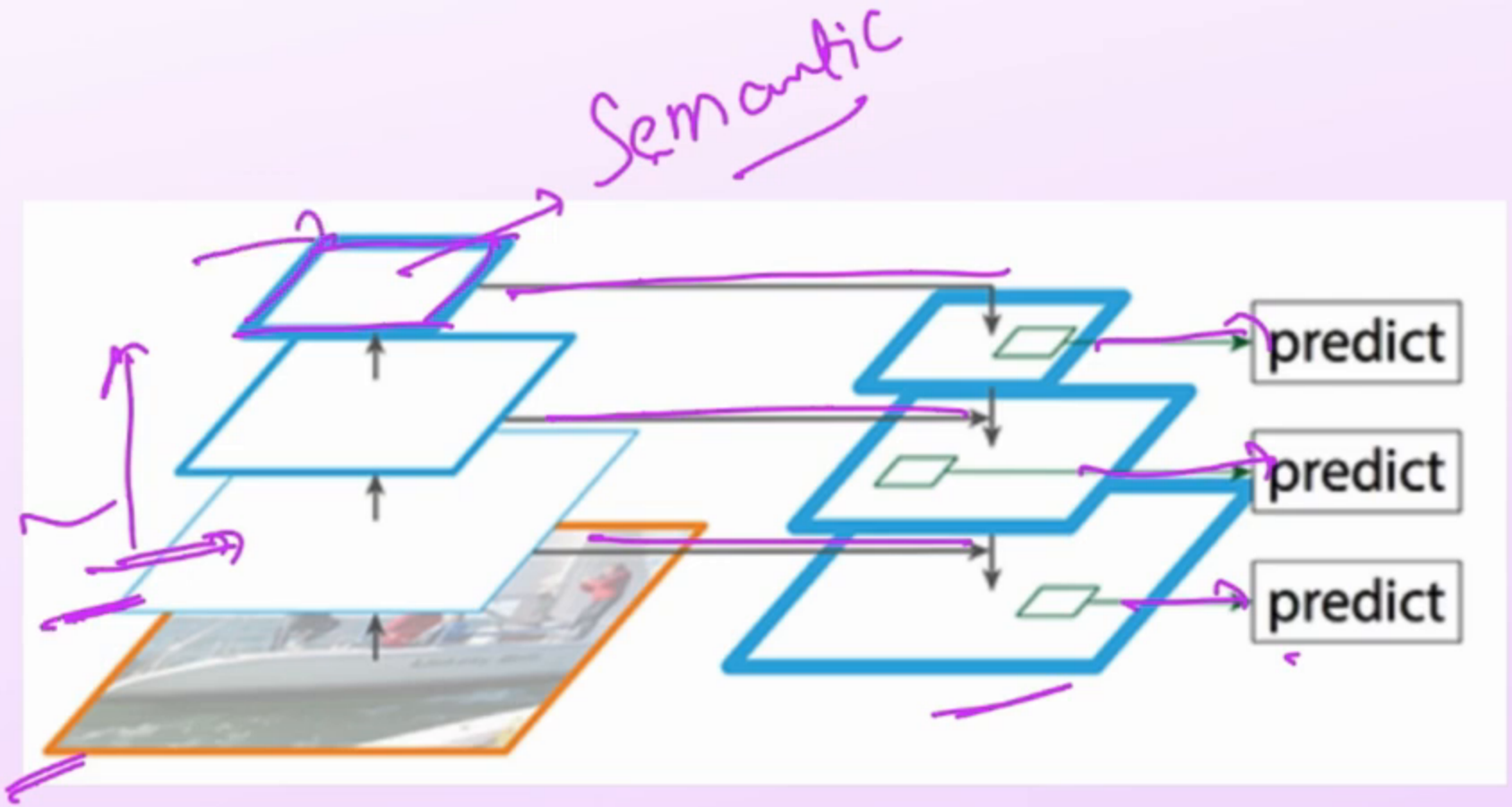


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.

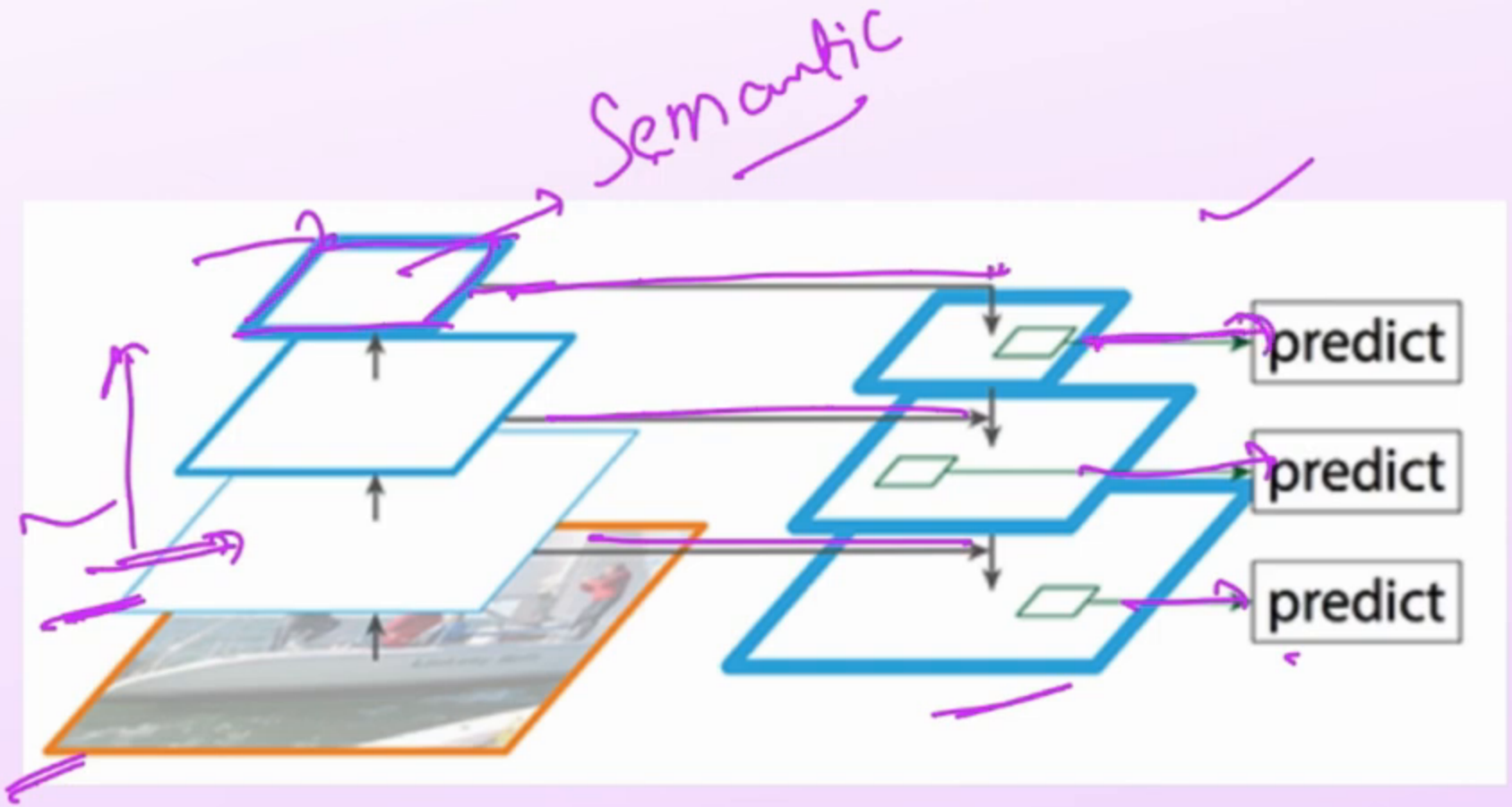
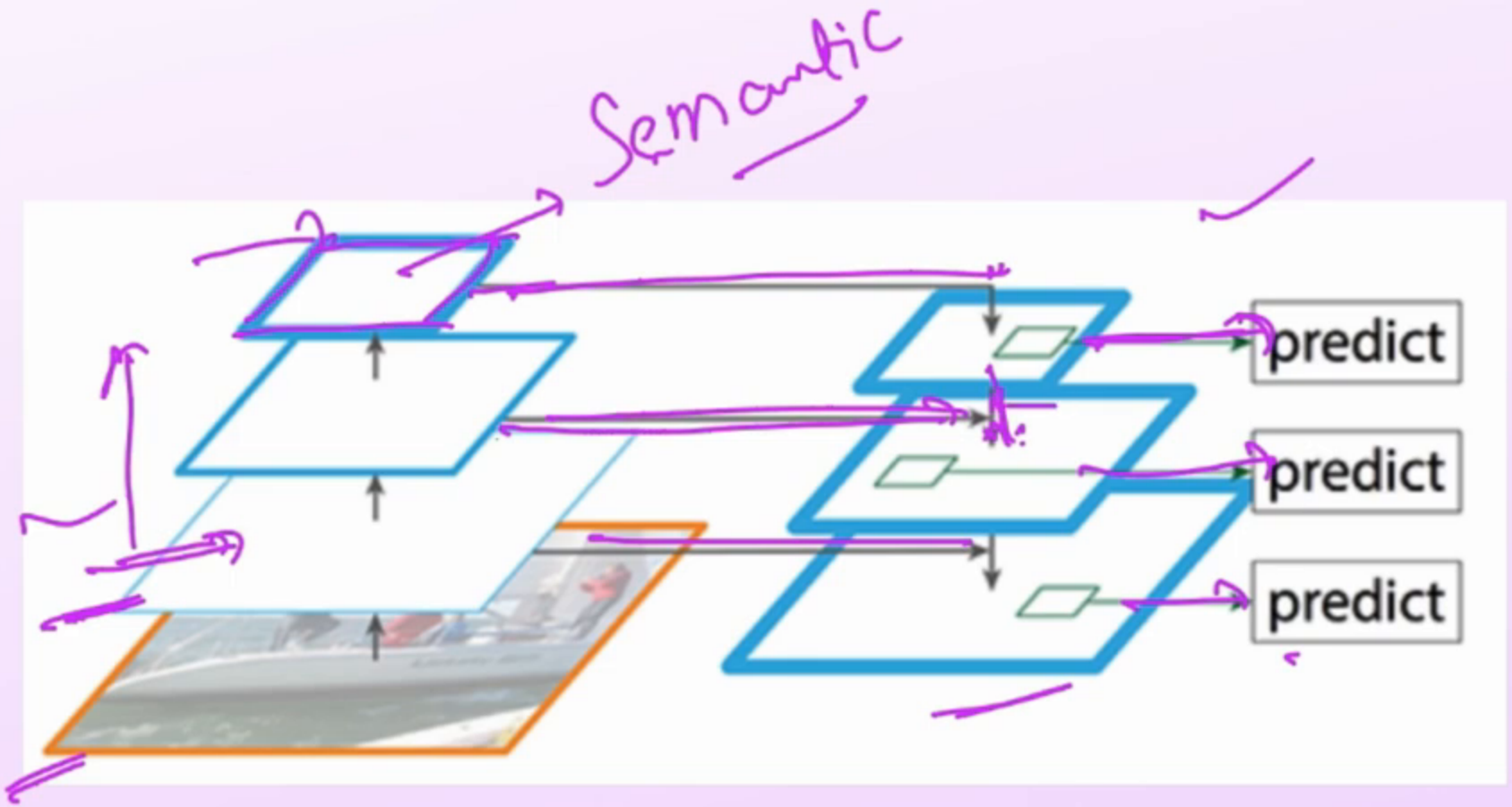
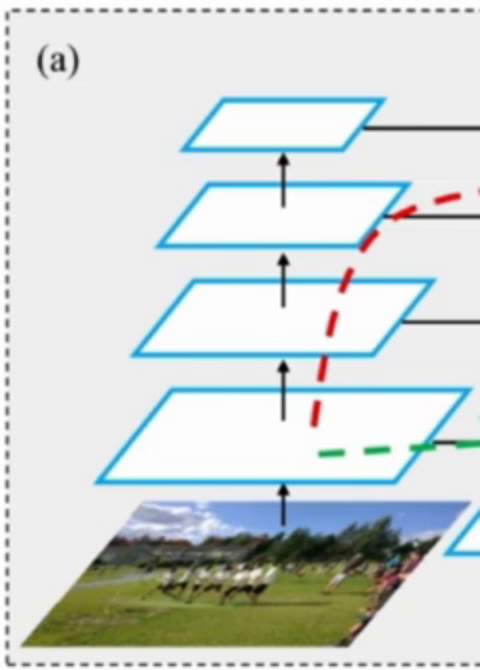


Figure 1. Illustration of our framev
branch. (e) Fully-connected fusion.





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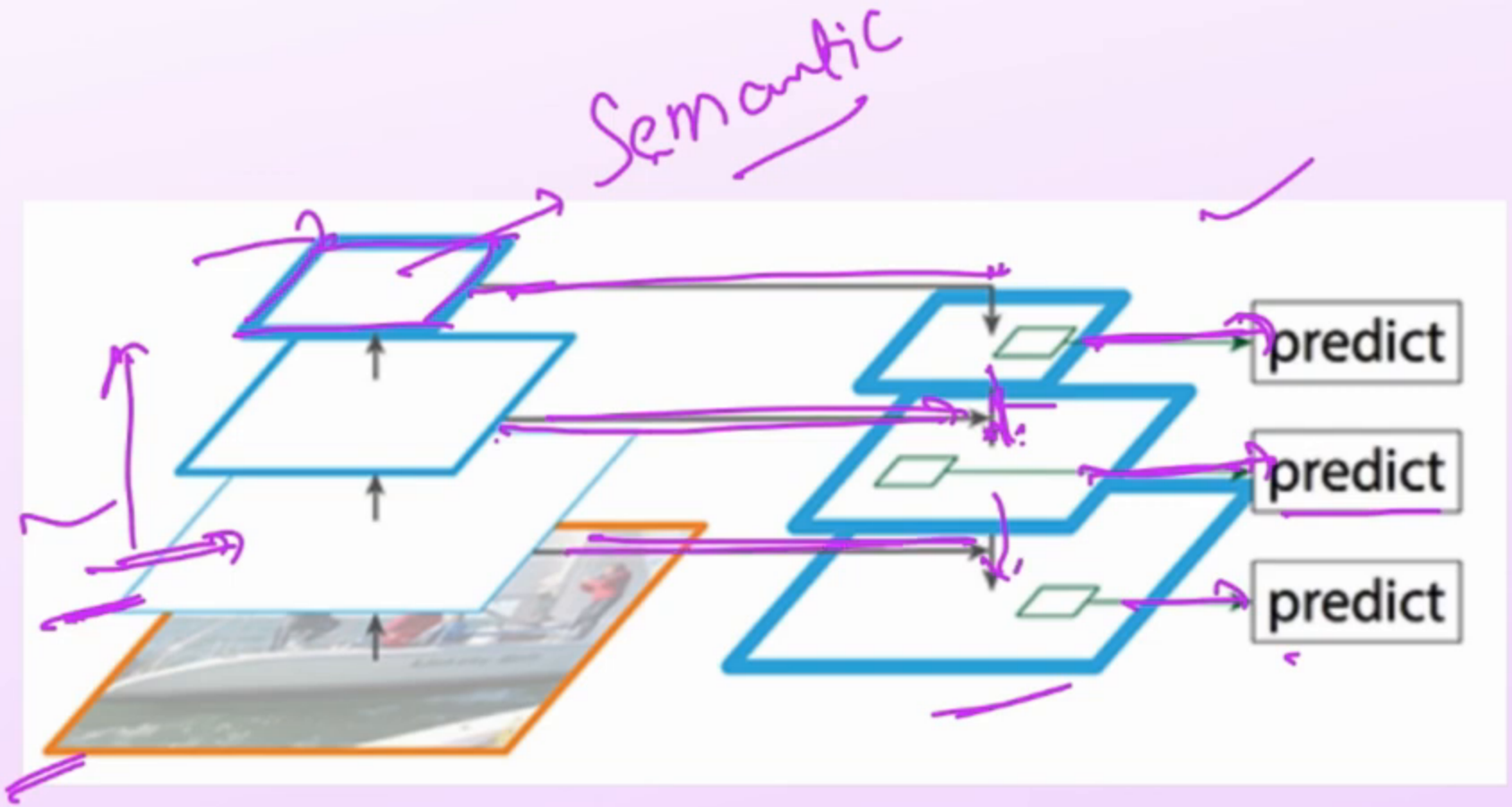

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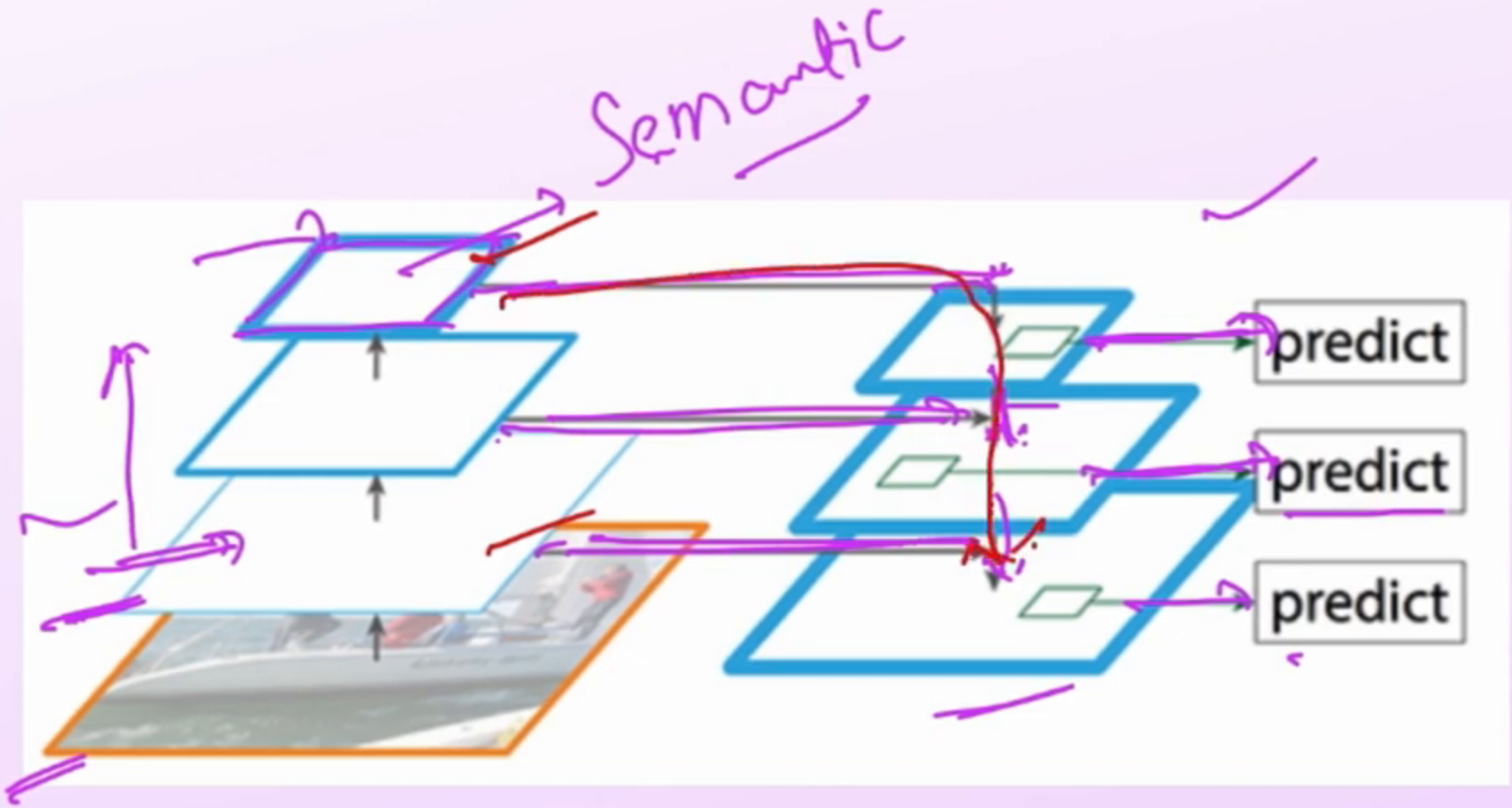

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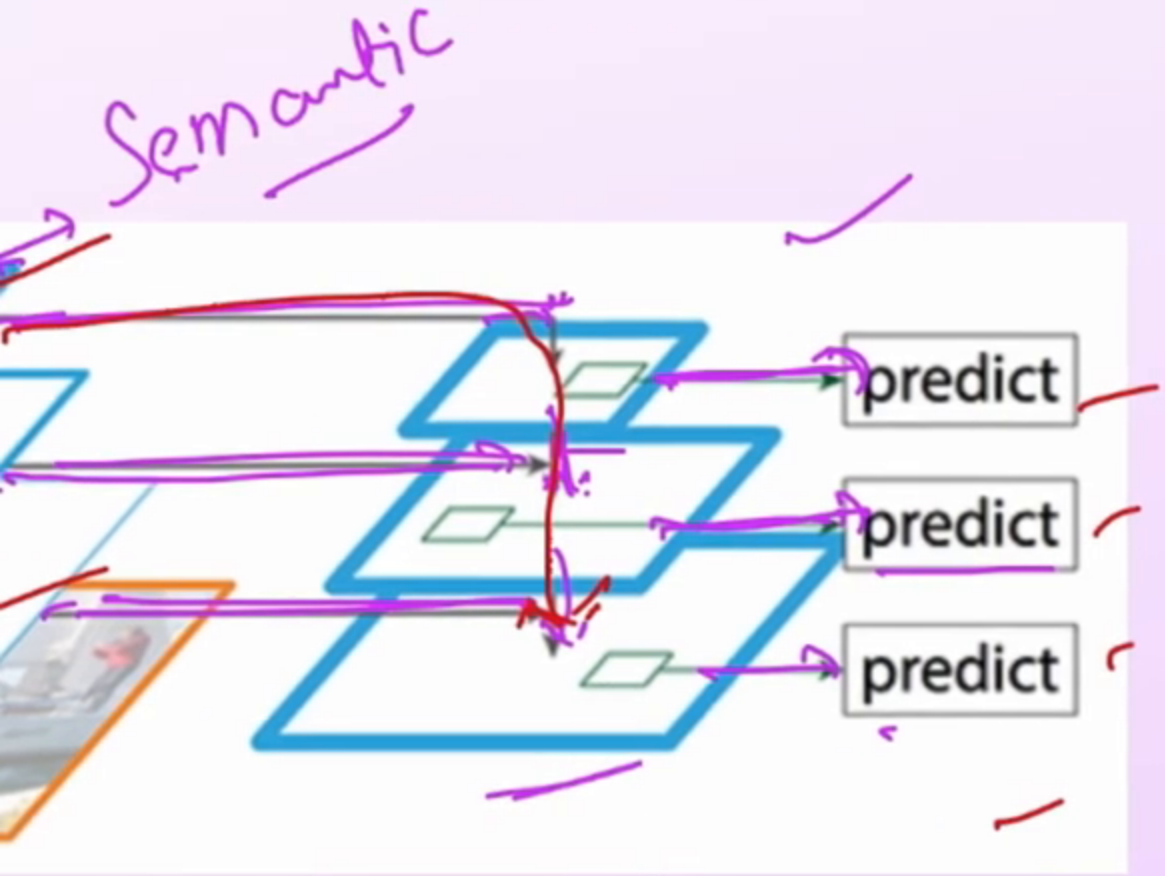


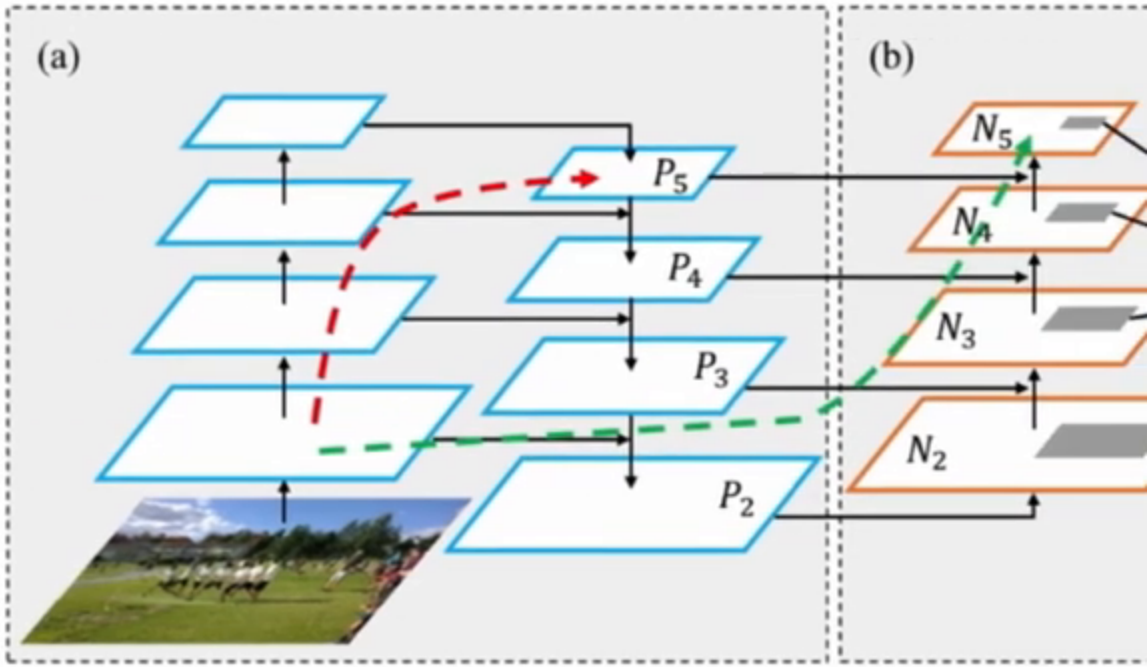
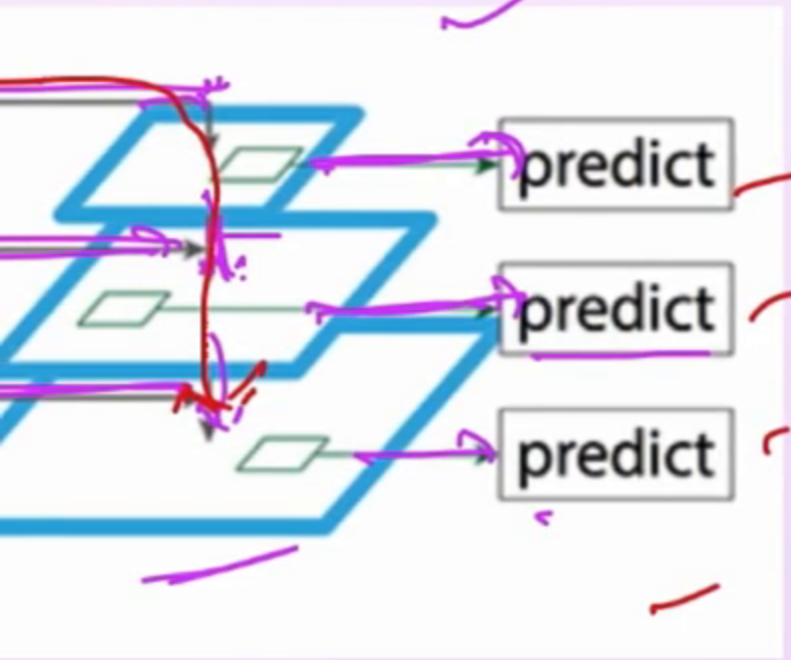
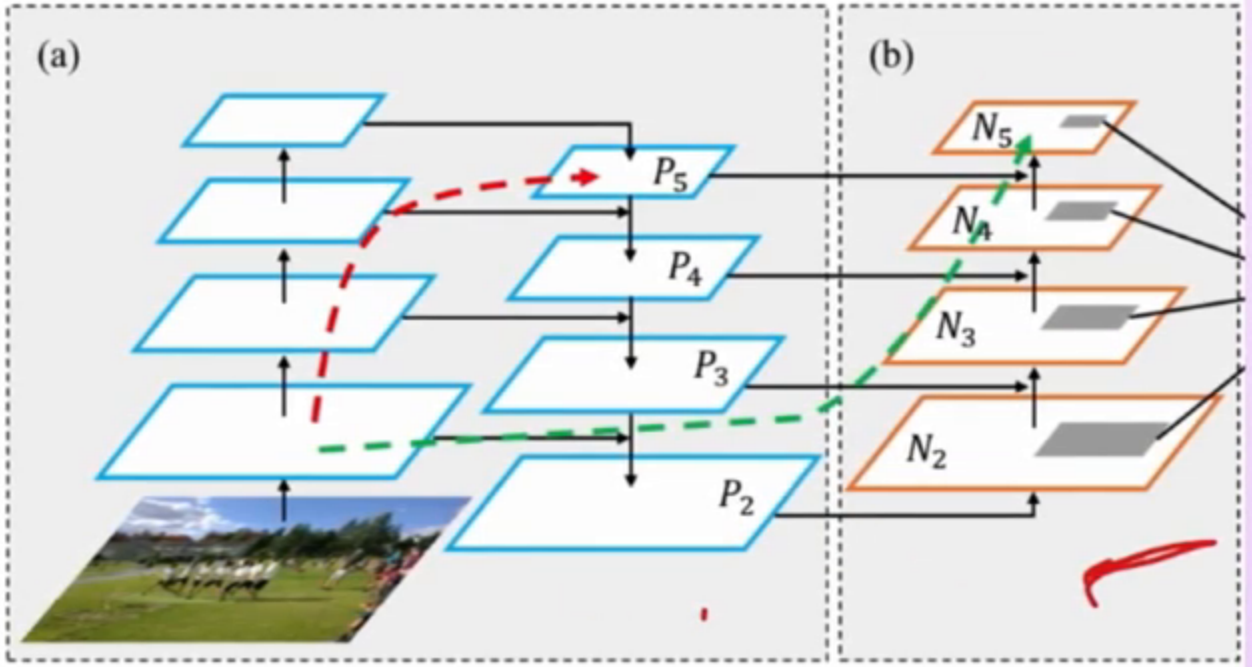


Figure 1. Illustration of our framework. (a) FPN backbone. (b) Bottom-up
branch. (e) Fully-connected fusion. Note that we omit channel dimension of





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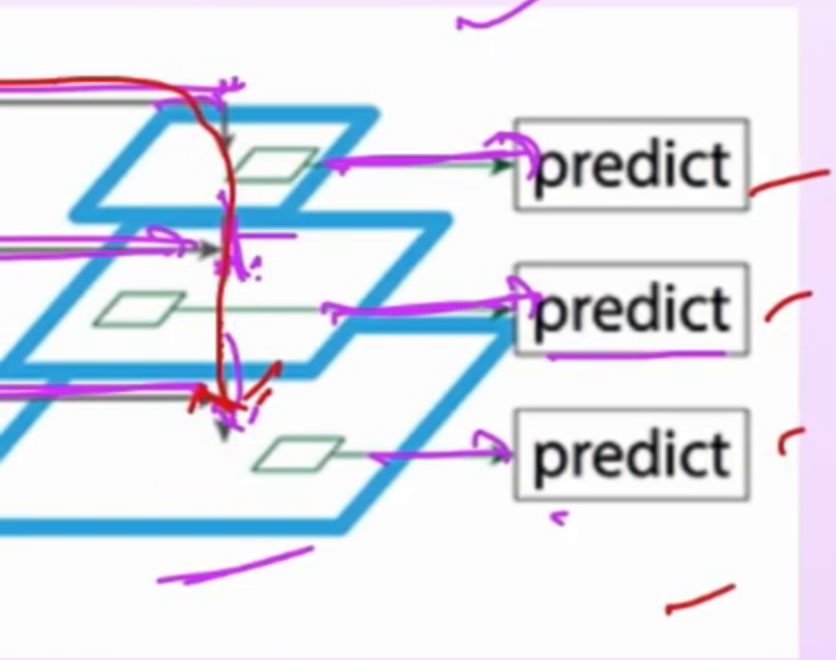

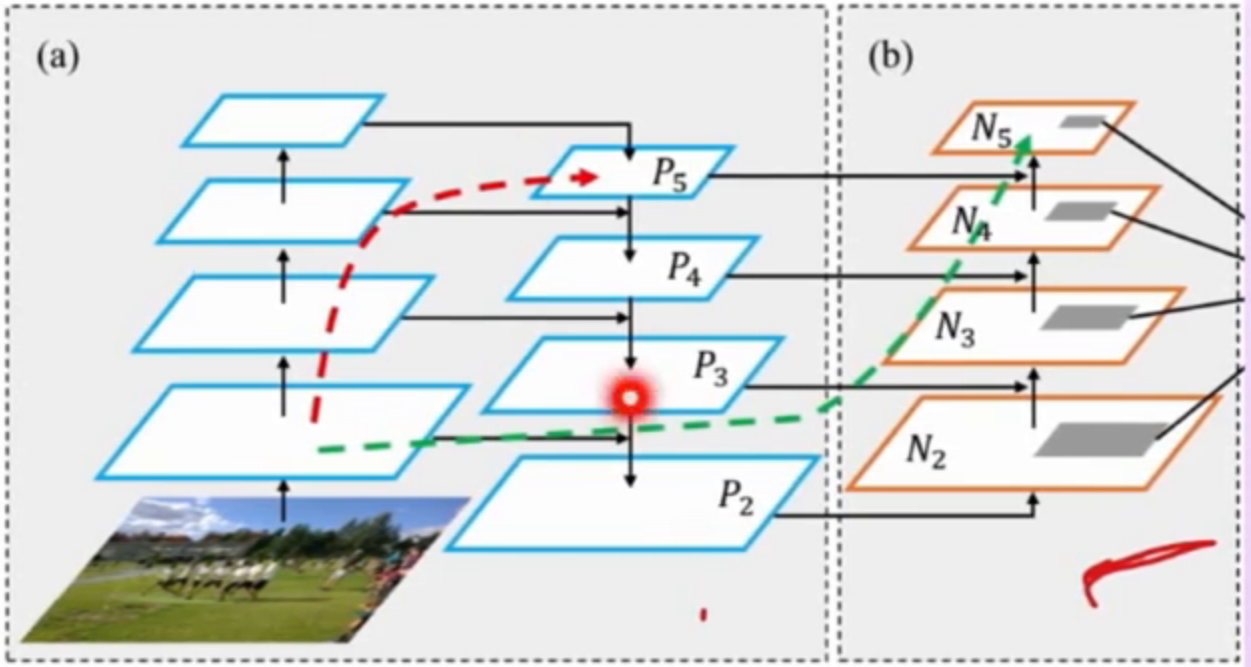

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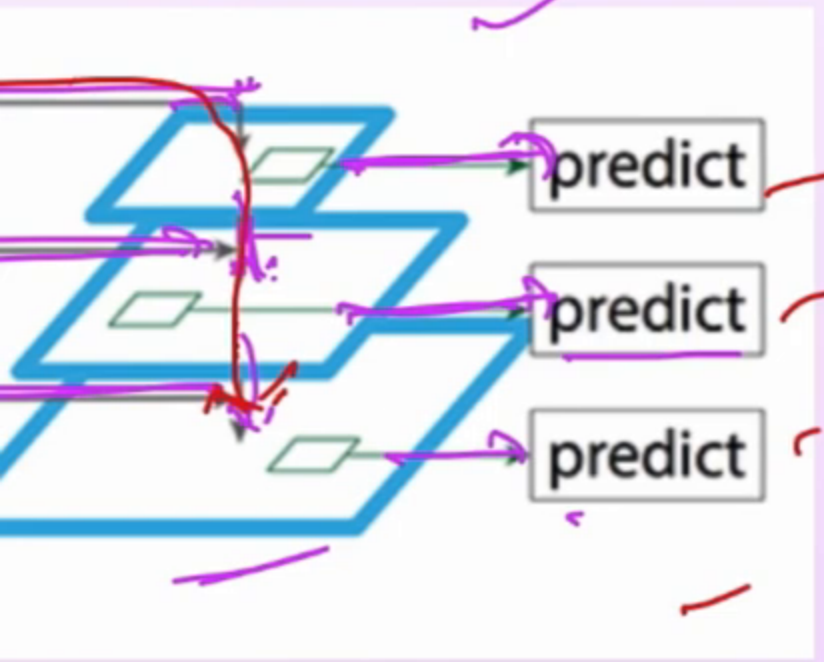

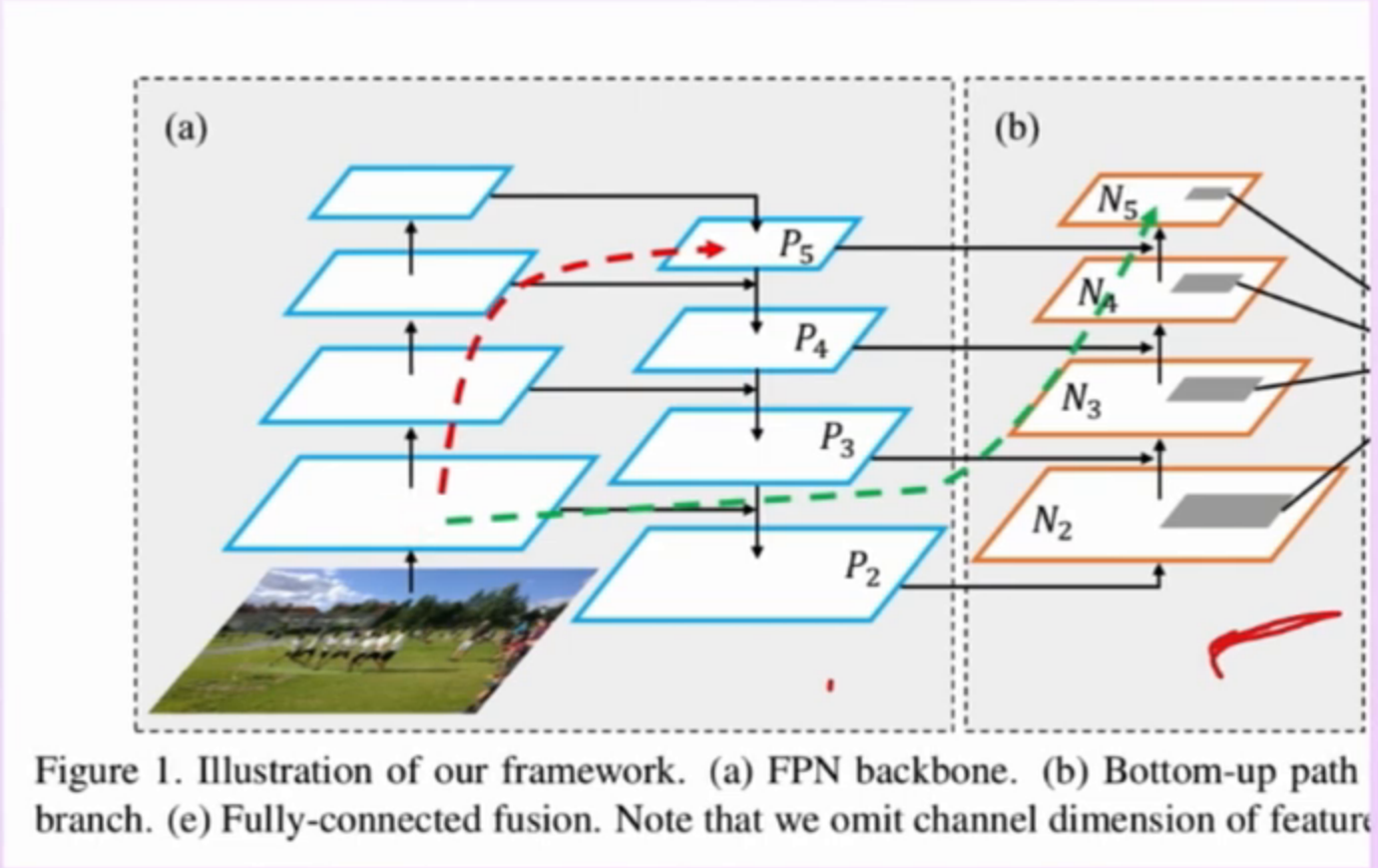

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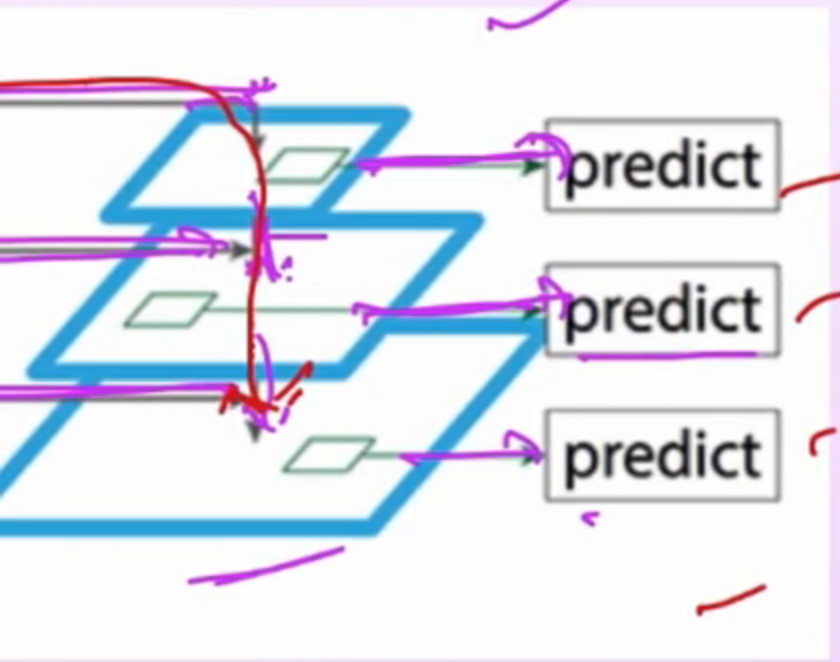

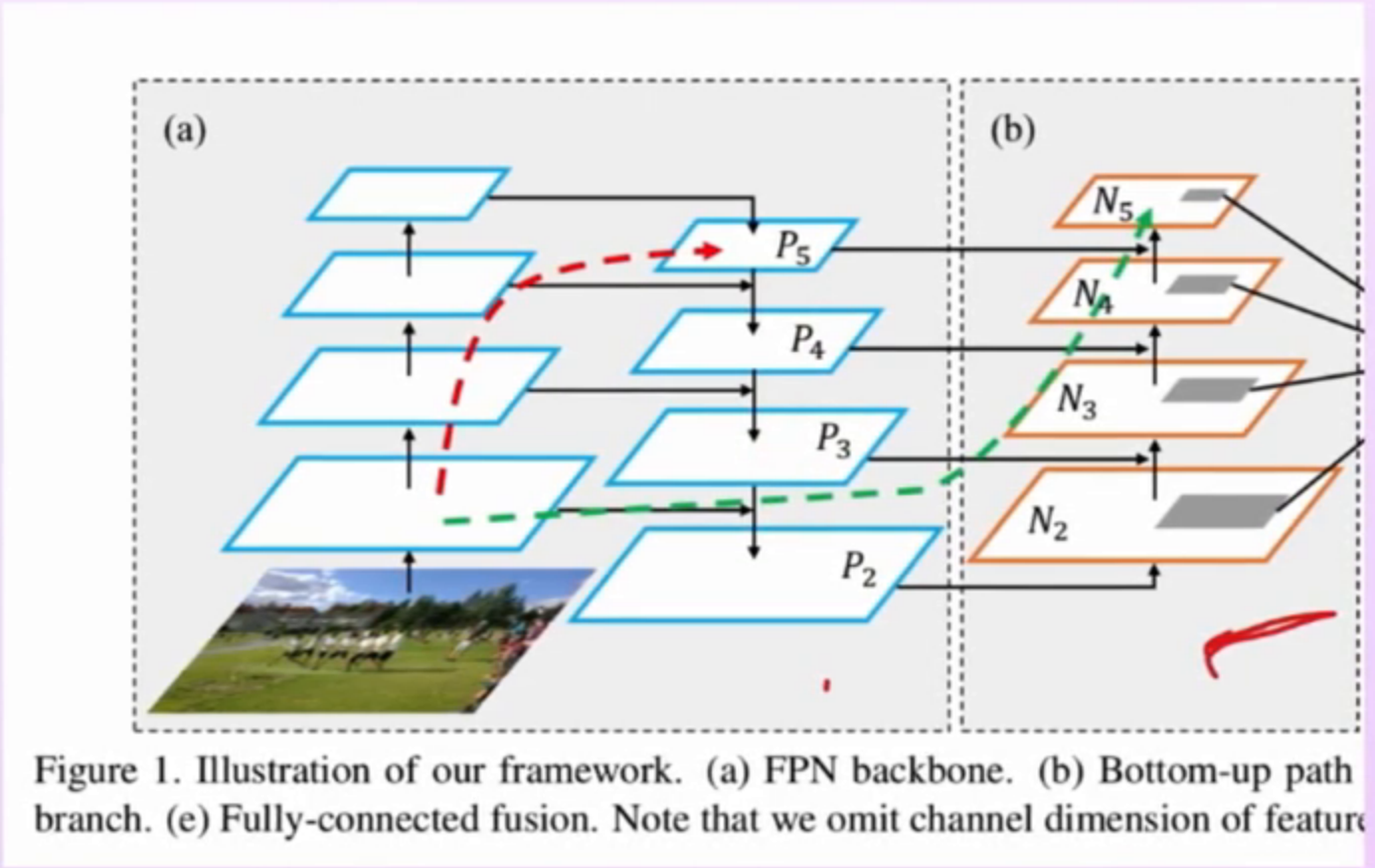

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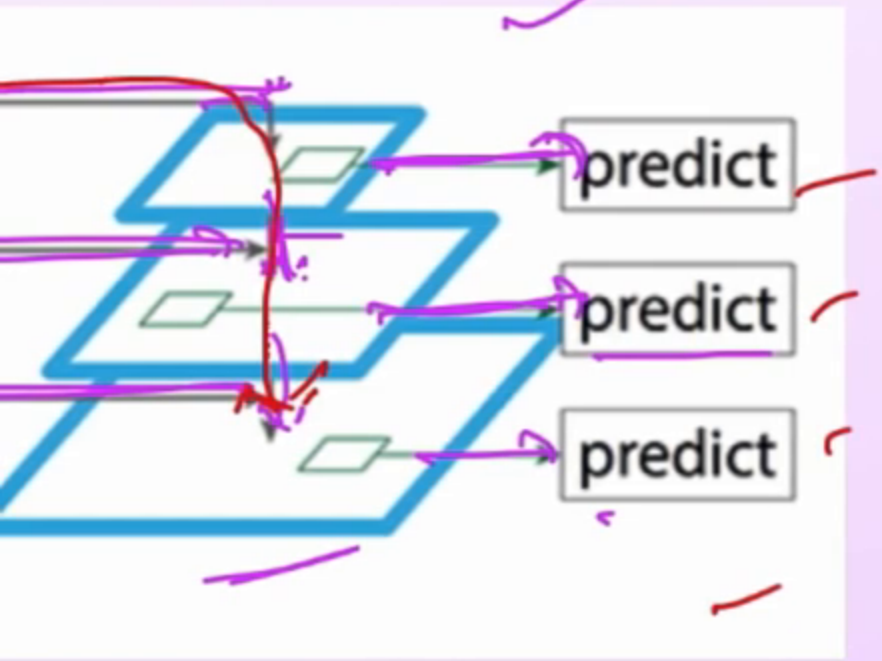

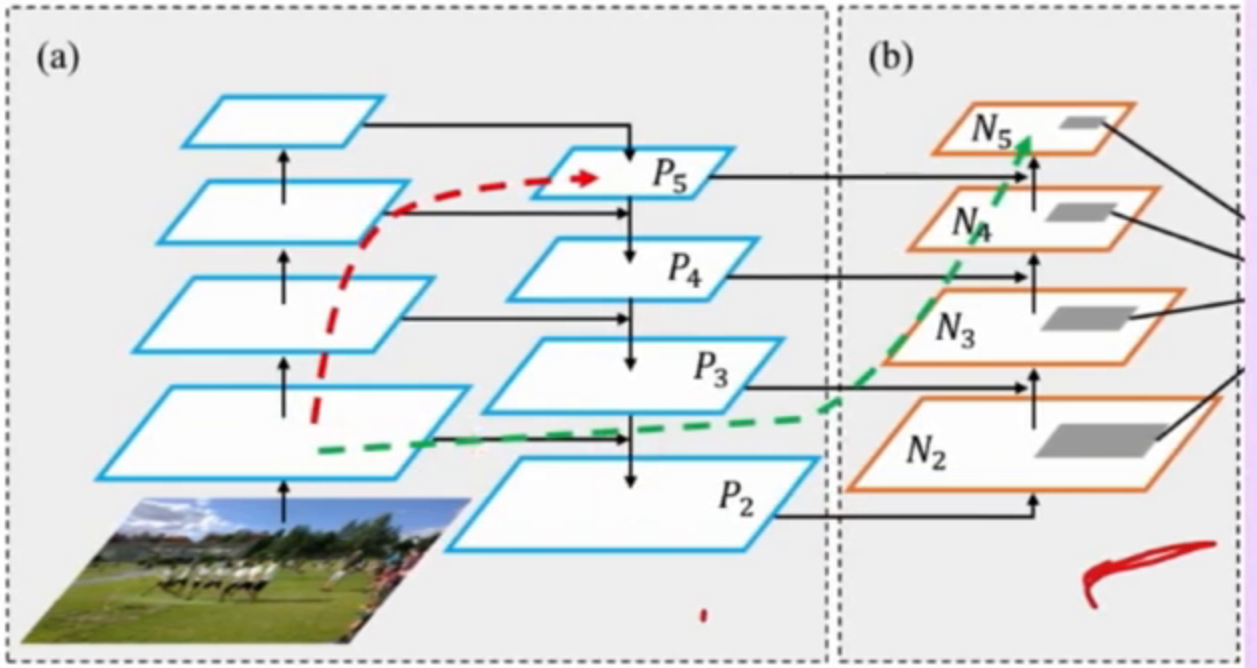

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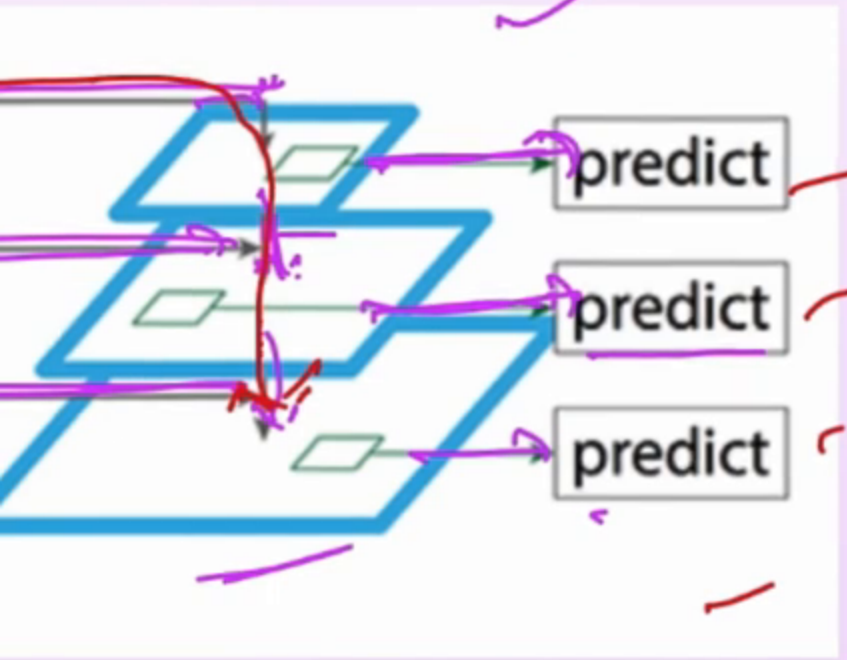

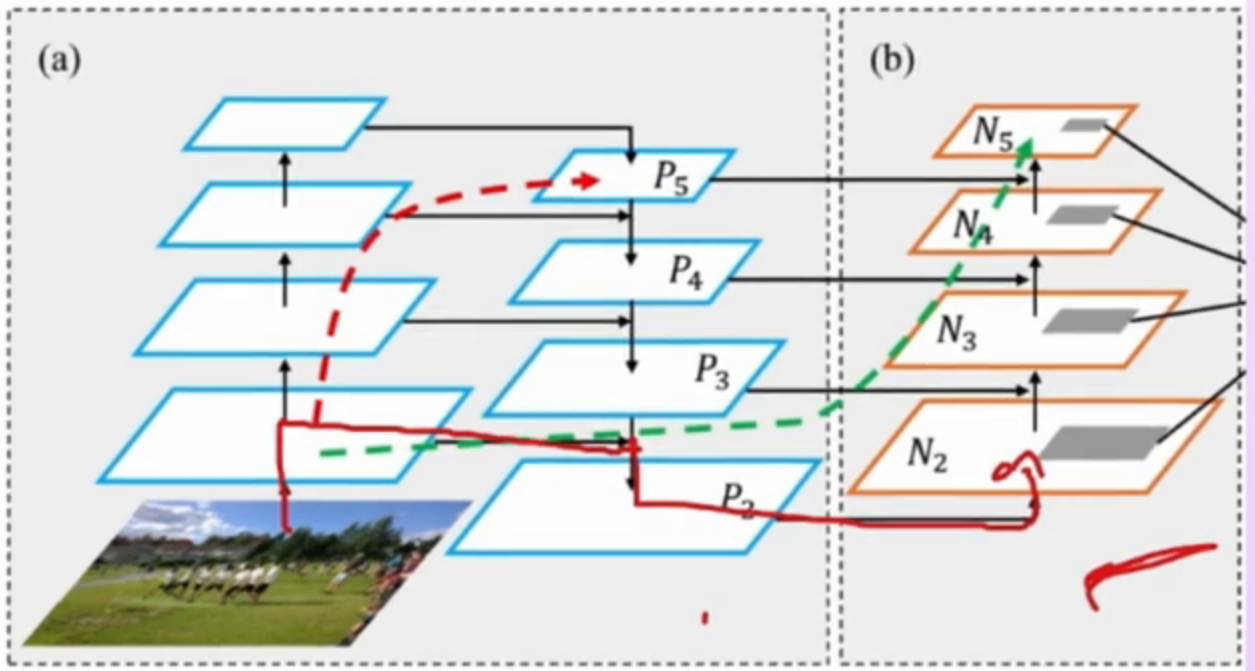

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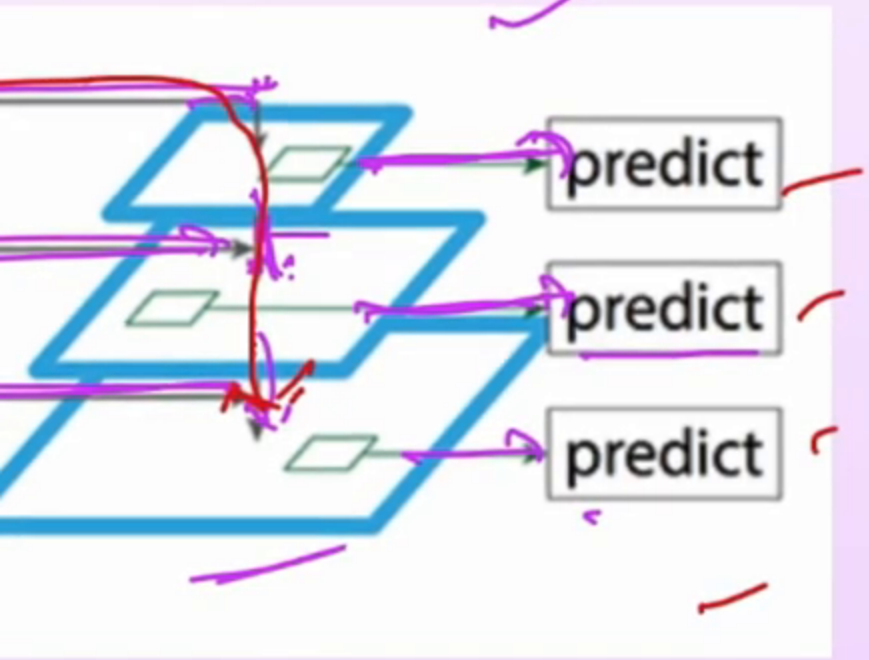

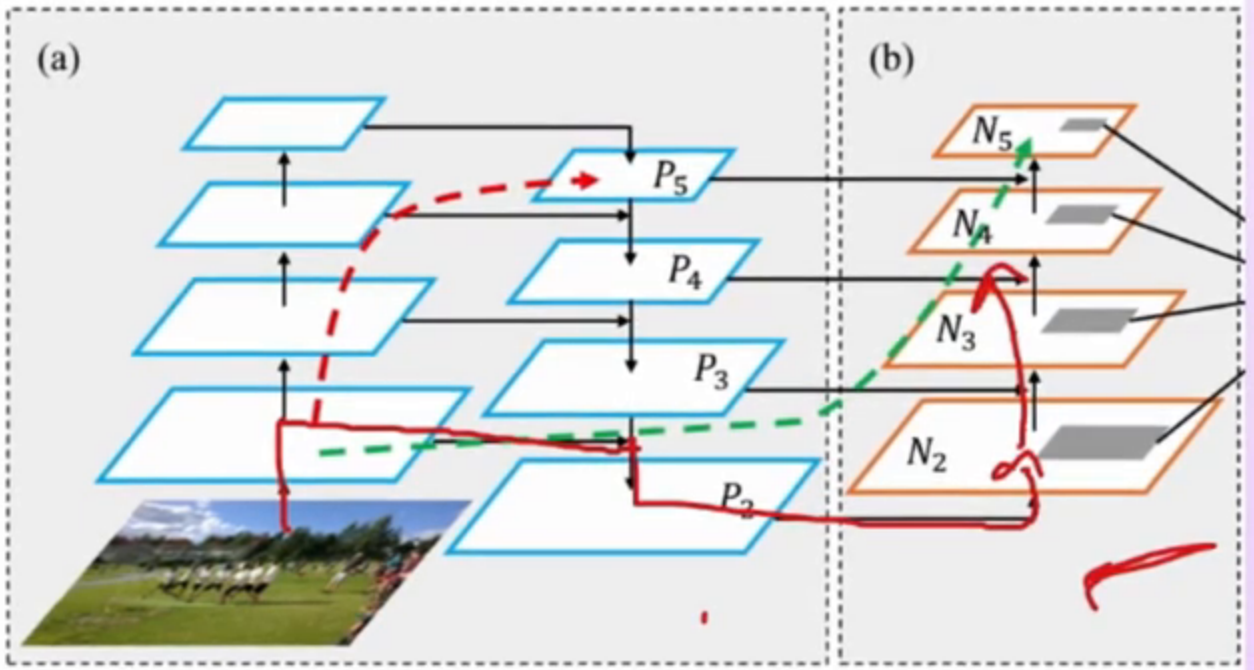

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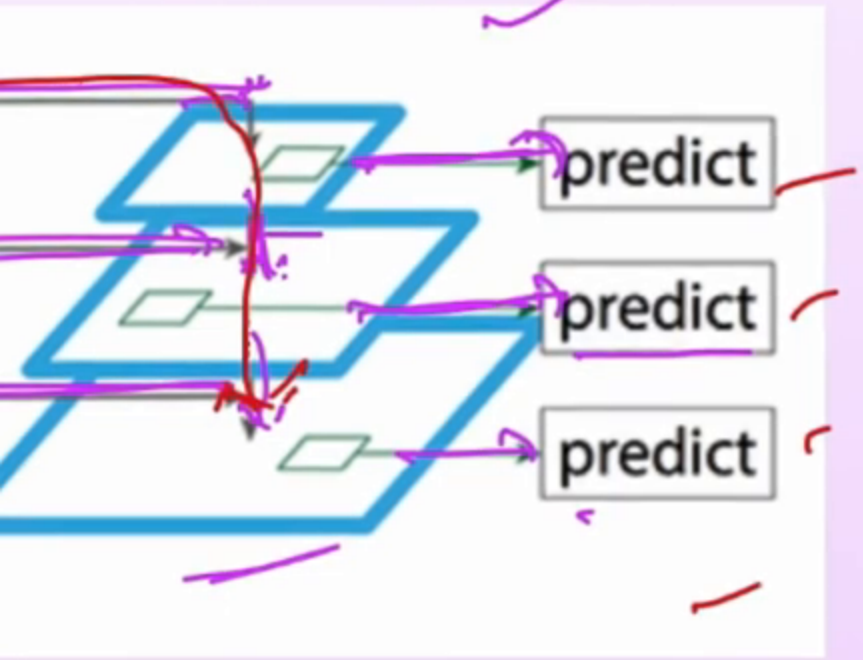

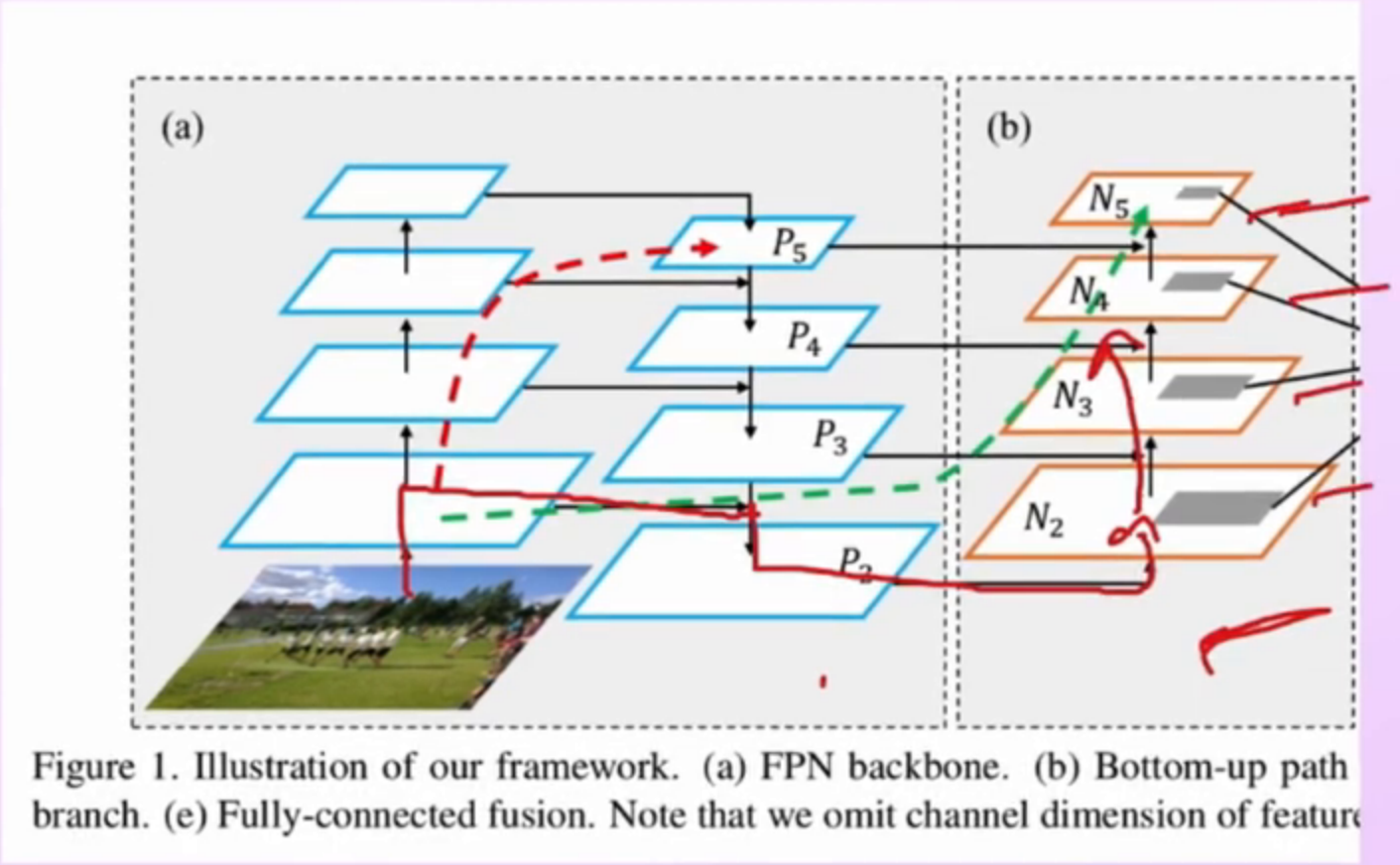

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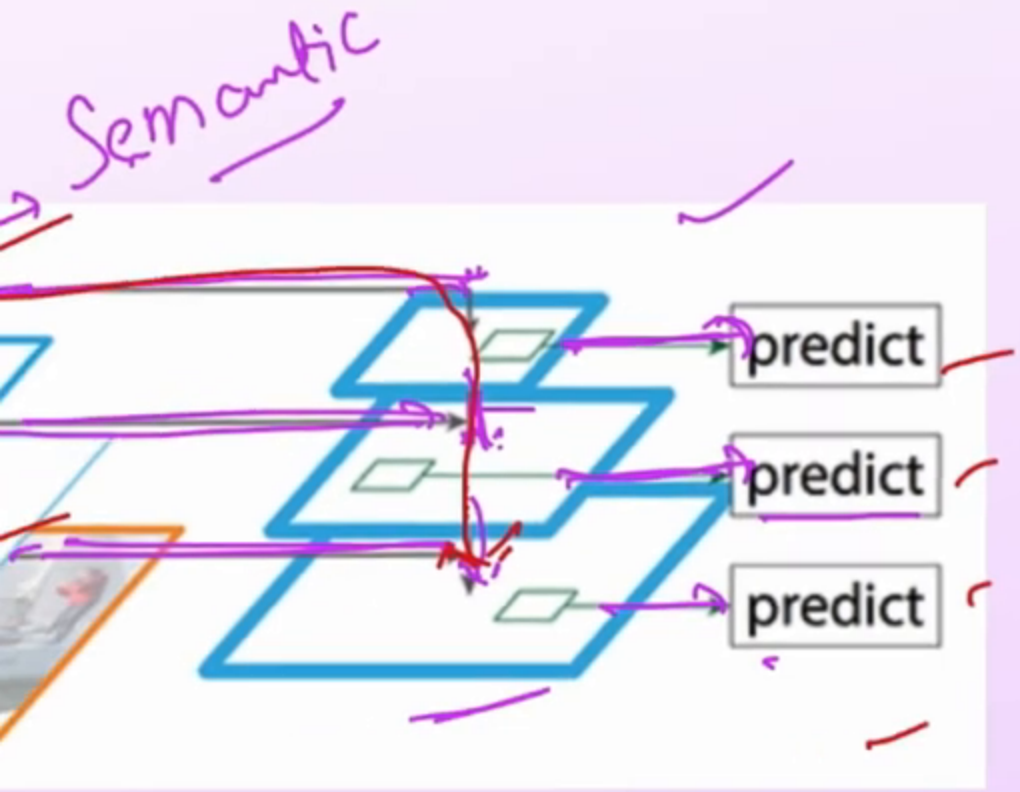

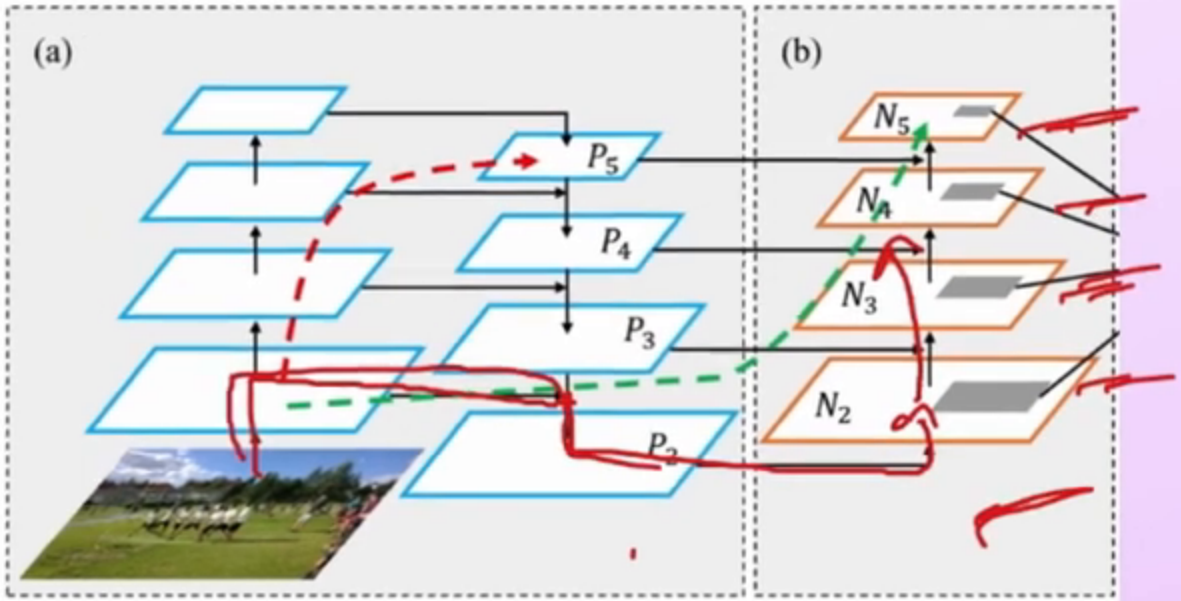

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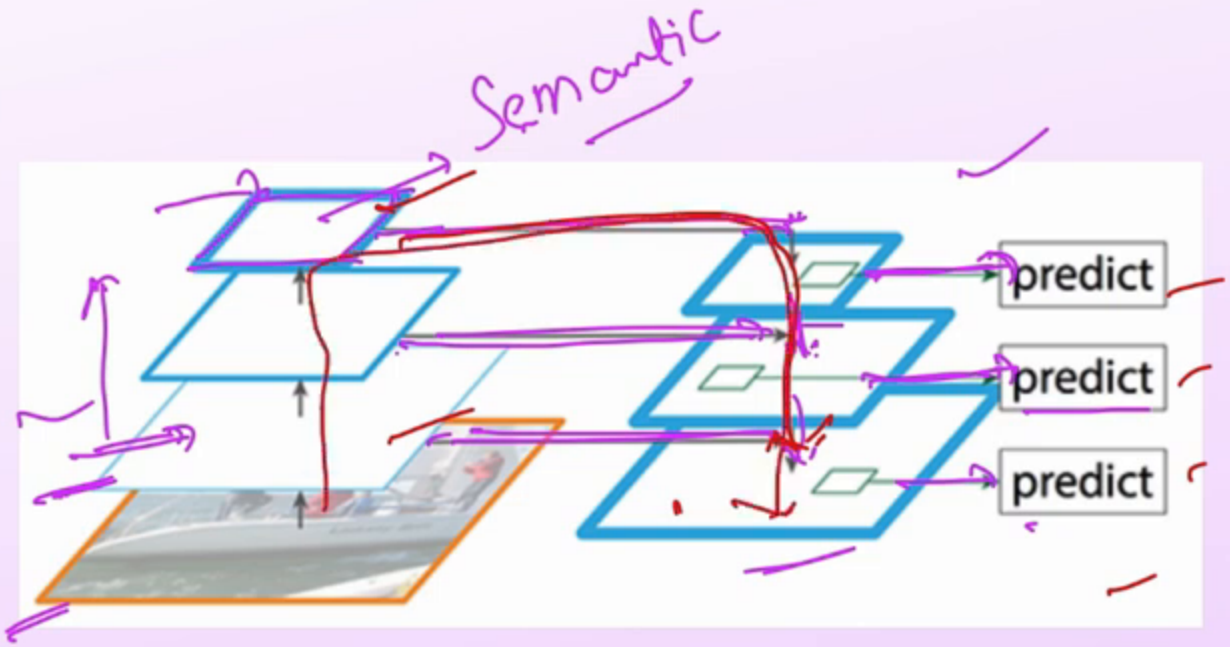
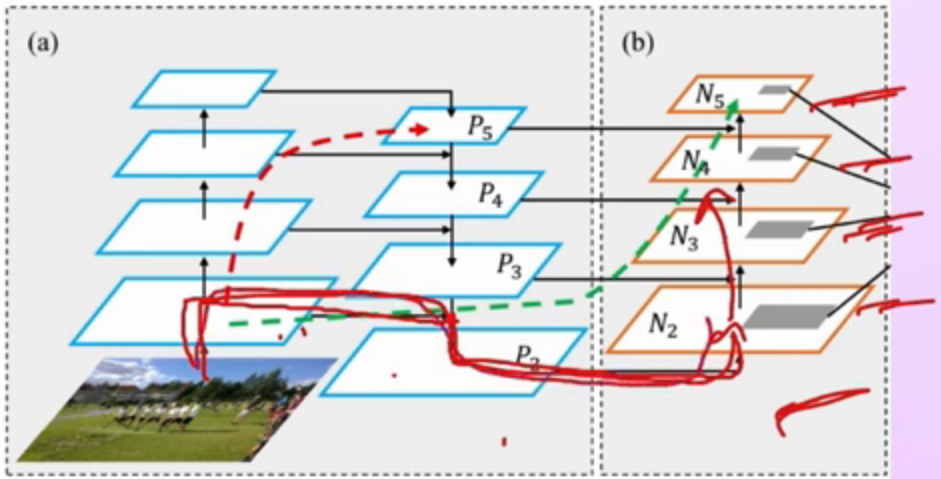
Path Aggregation Network





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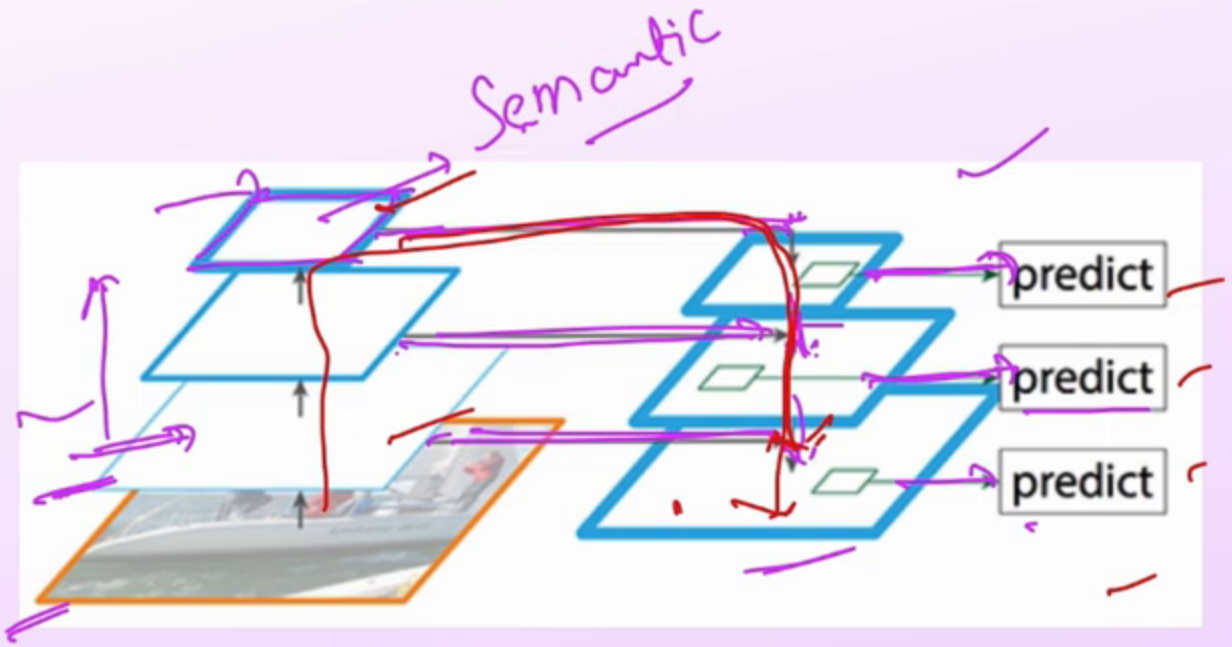

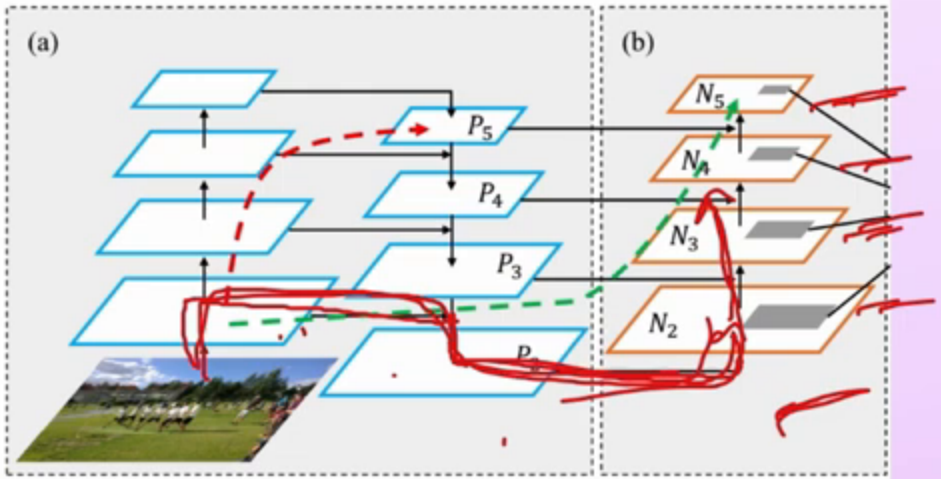

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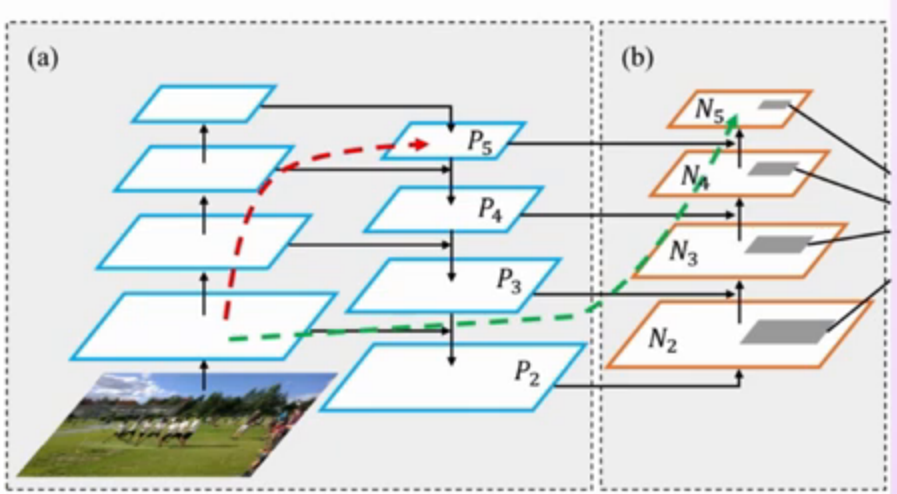

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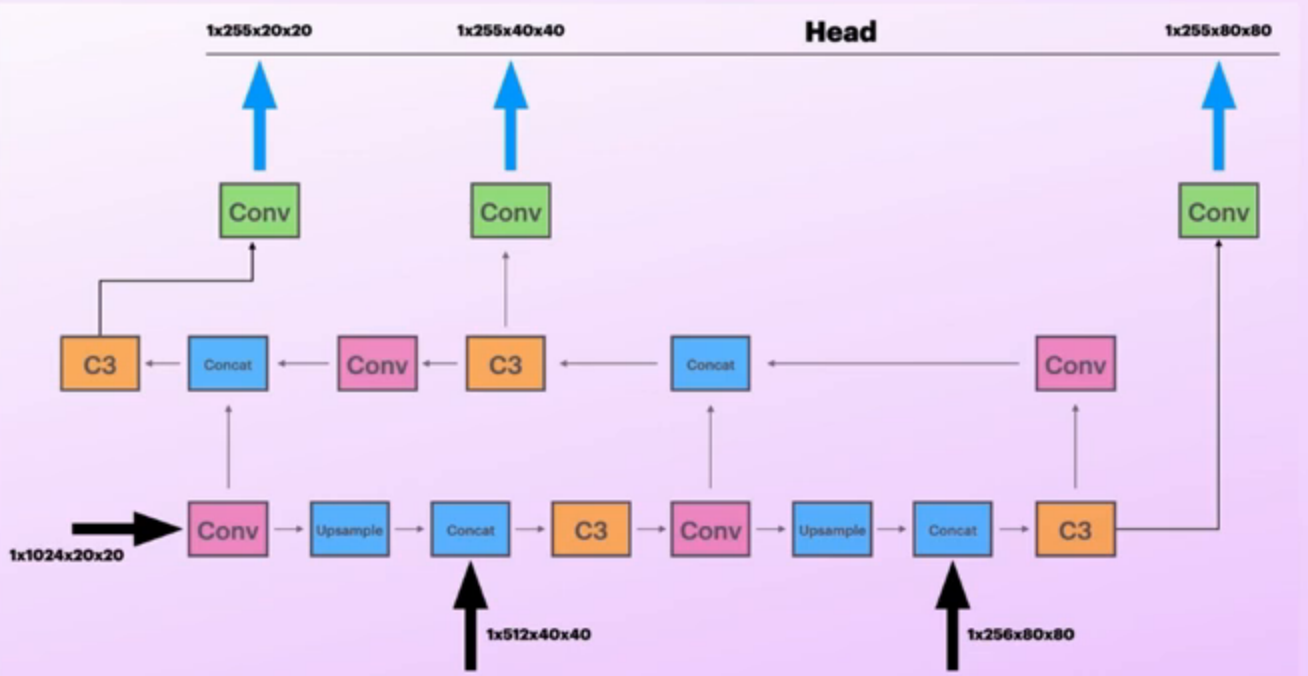
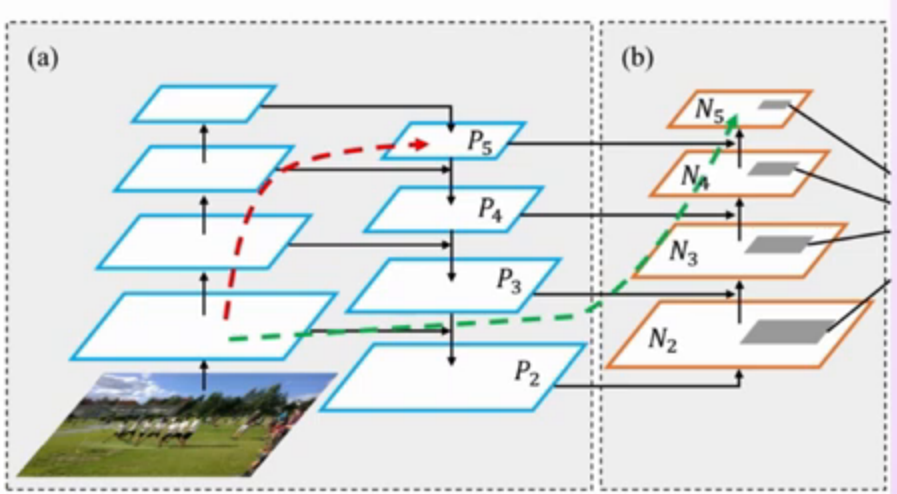


Path Aggregation Network



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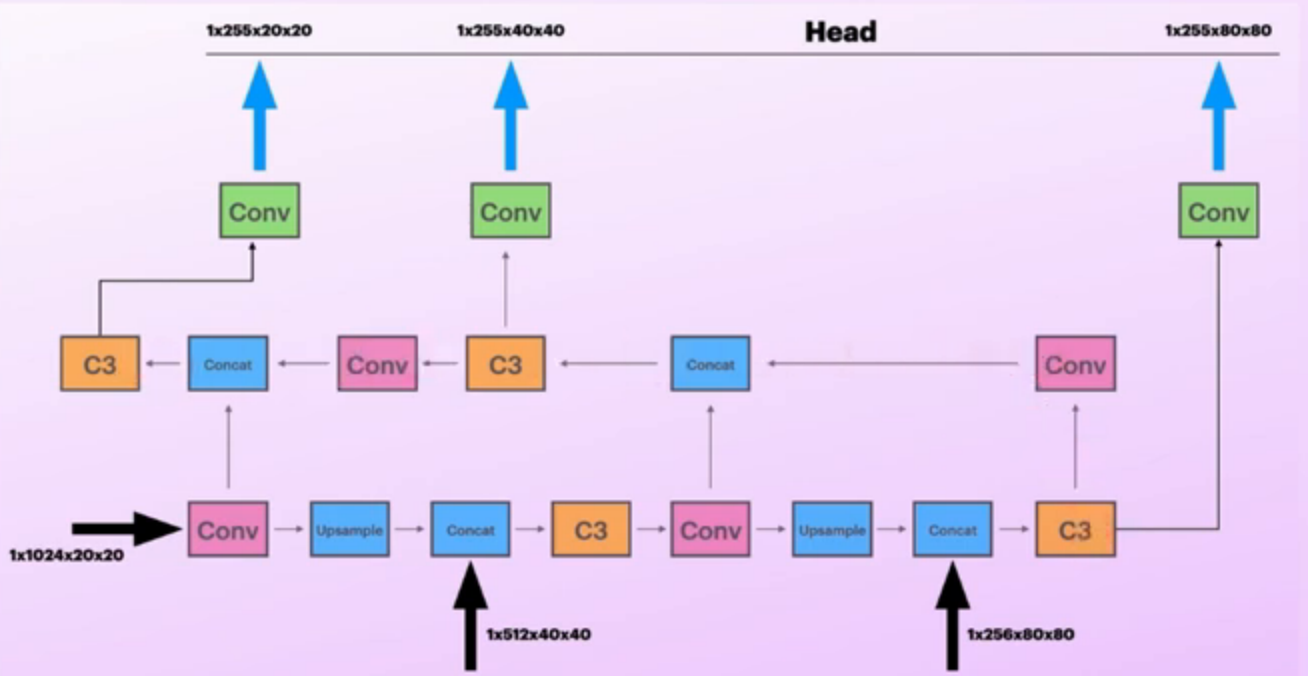
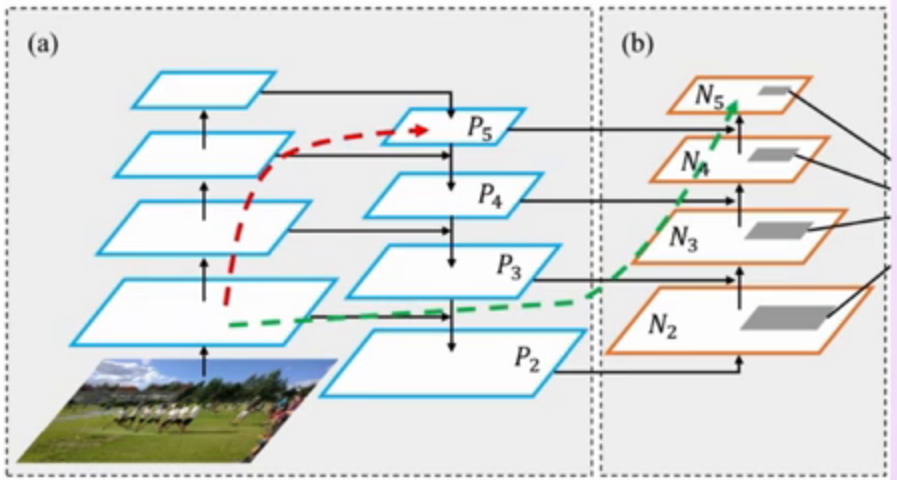


Path Aggregation Network



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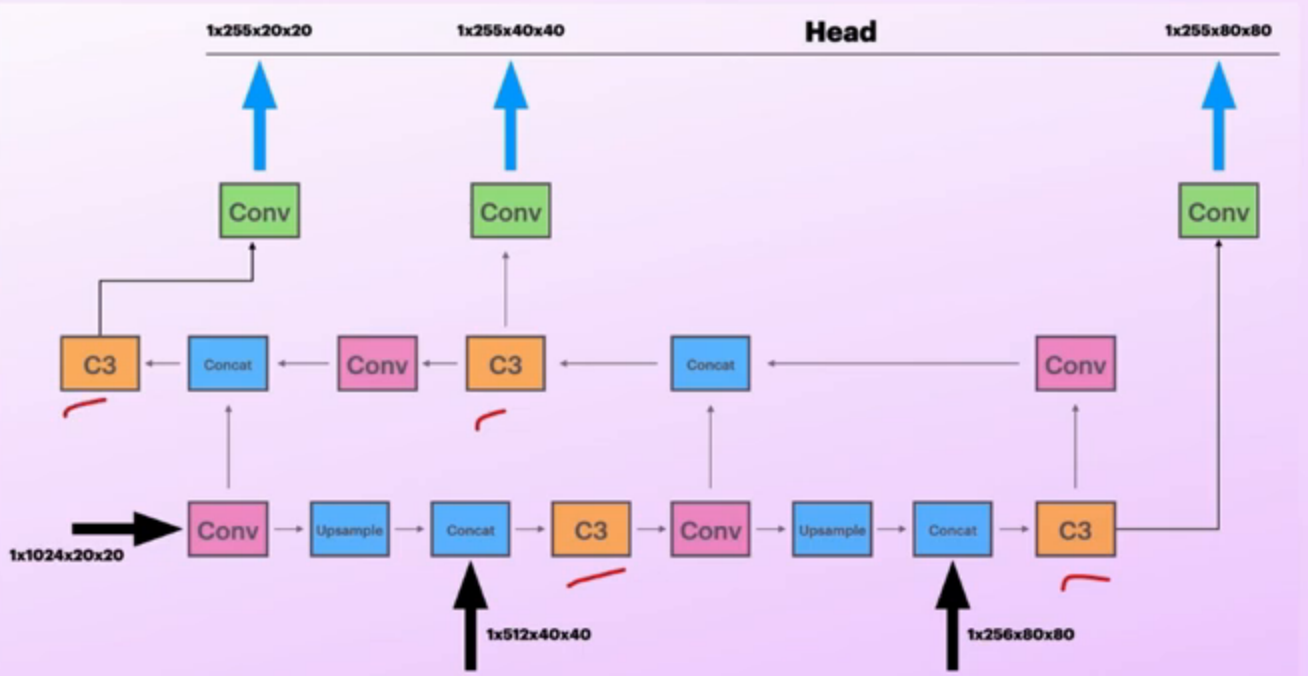
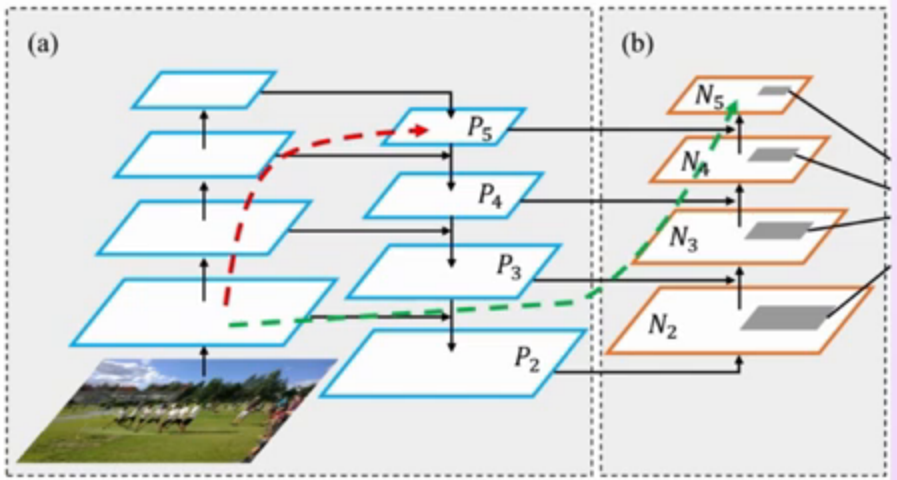


Path Aggregation Network



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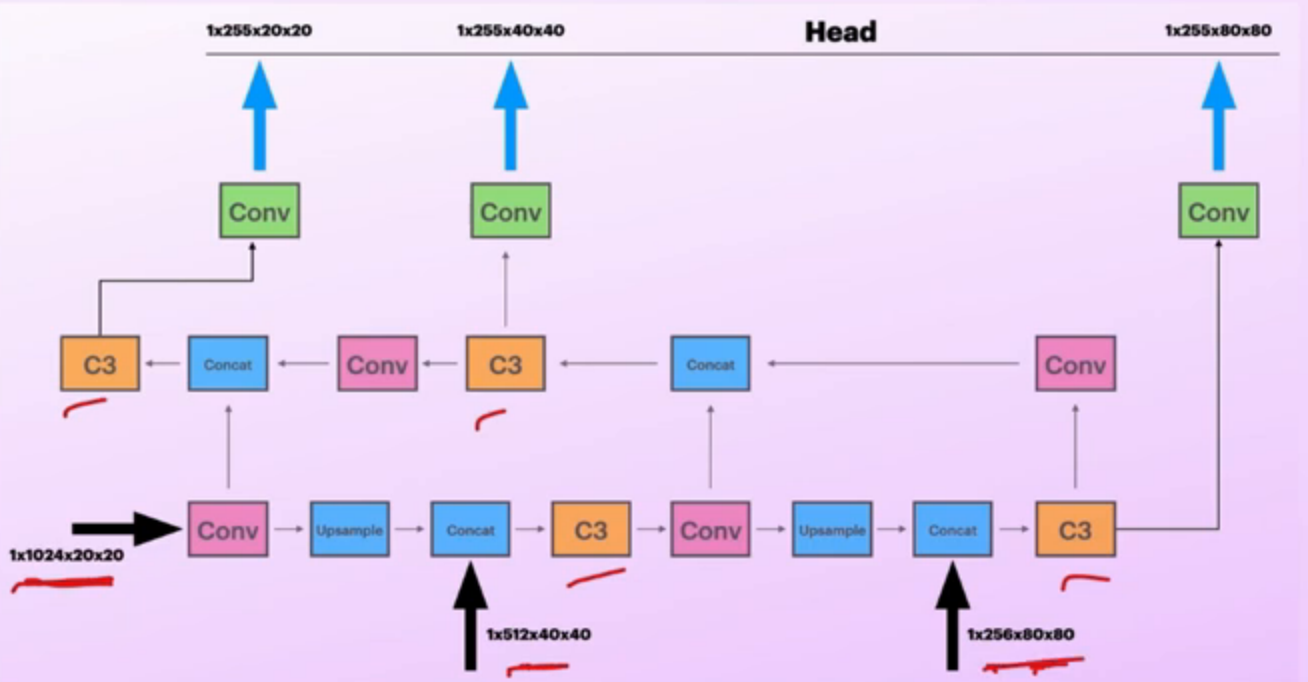

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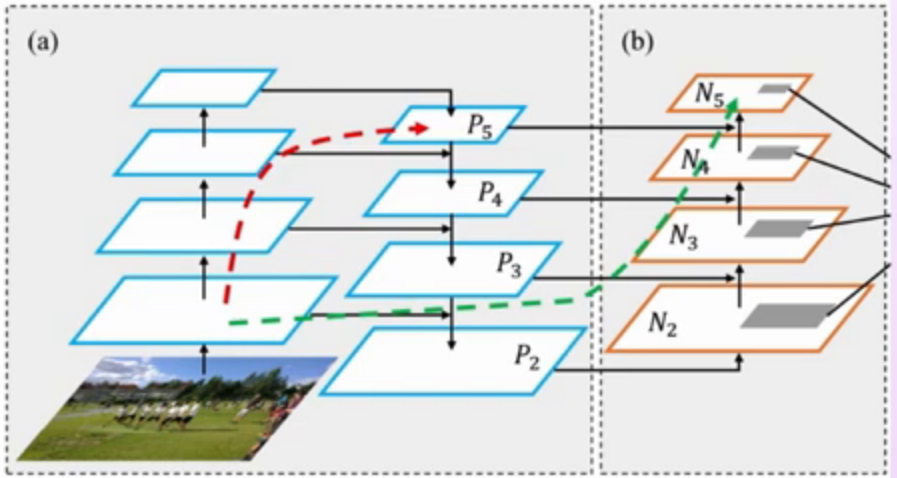

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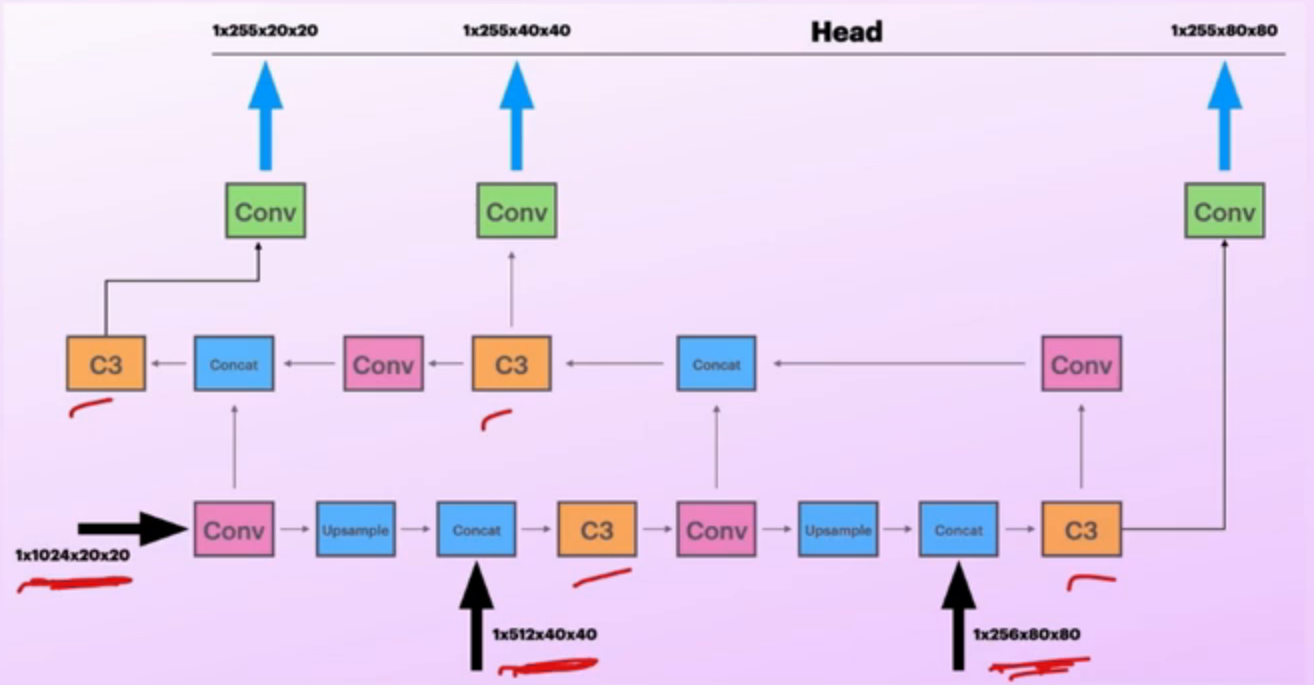
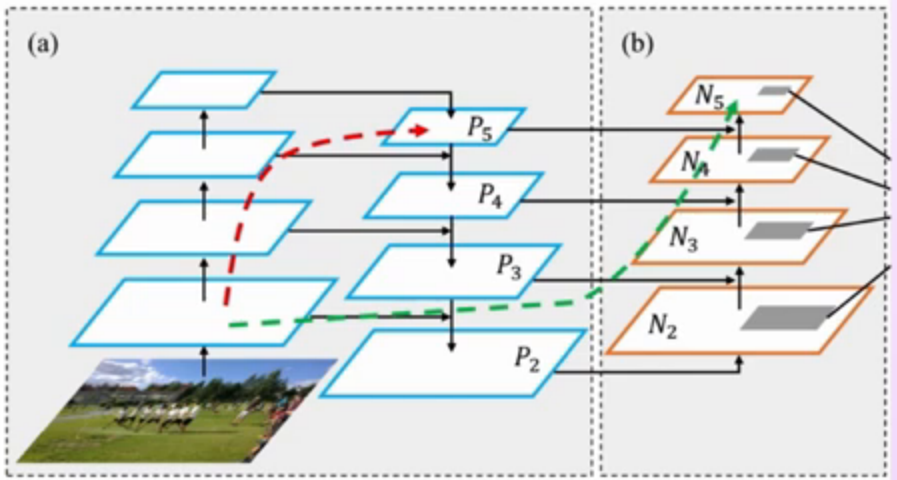


Path Aggregation Network



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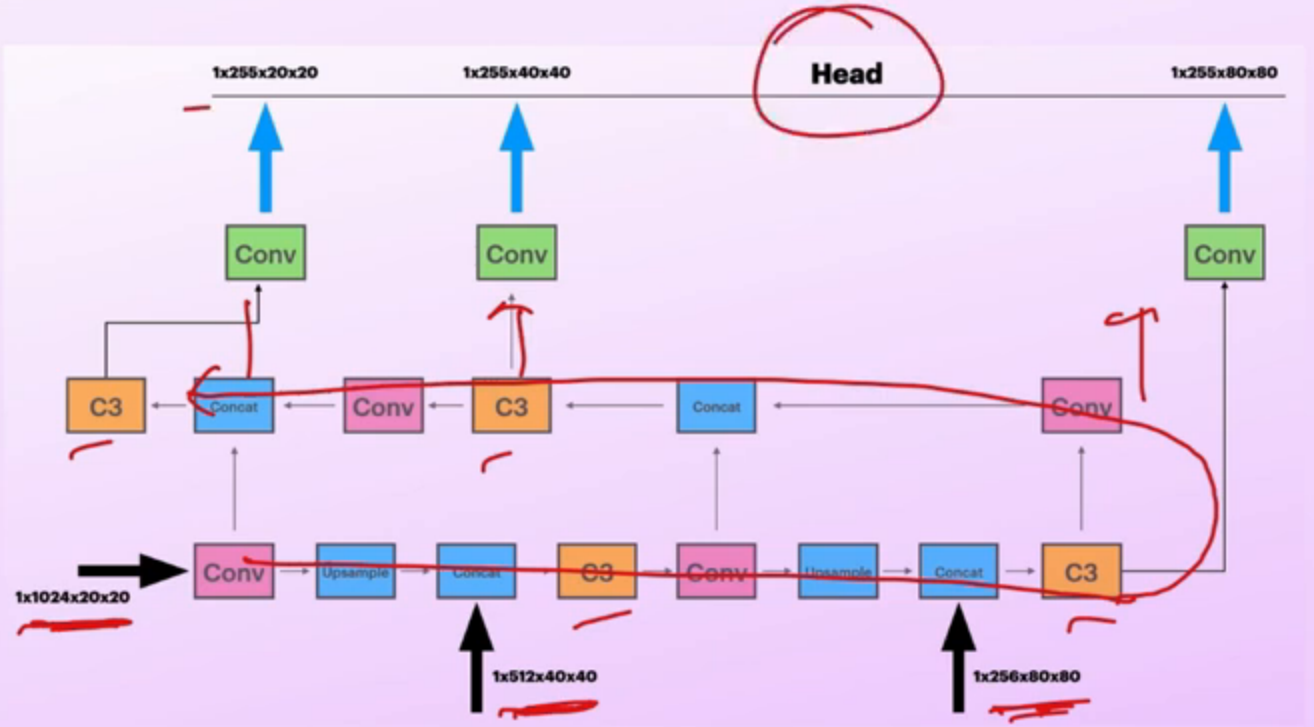
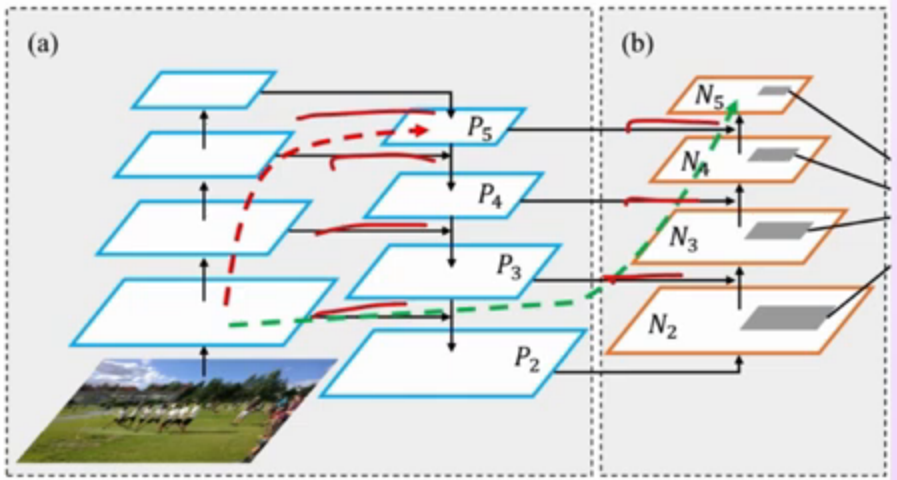


Path Aggregation Network



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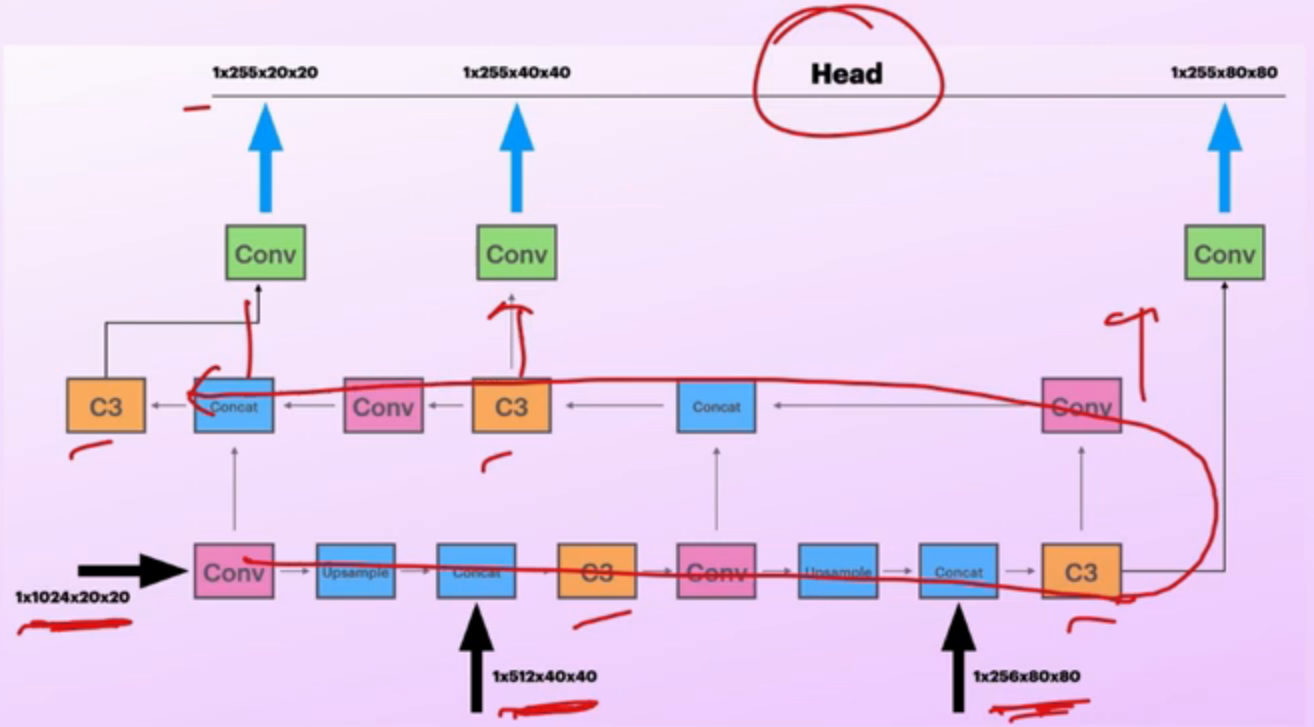

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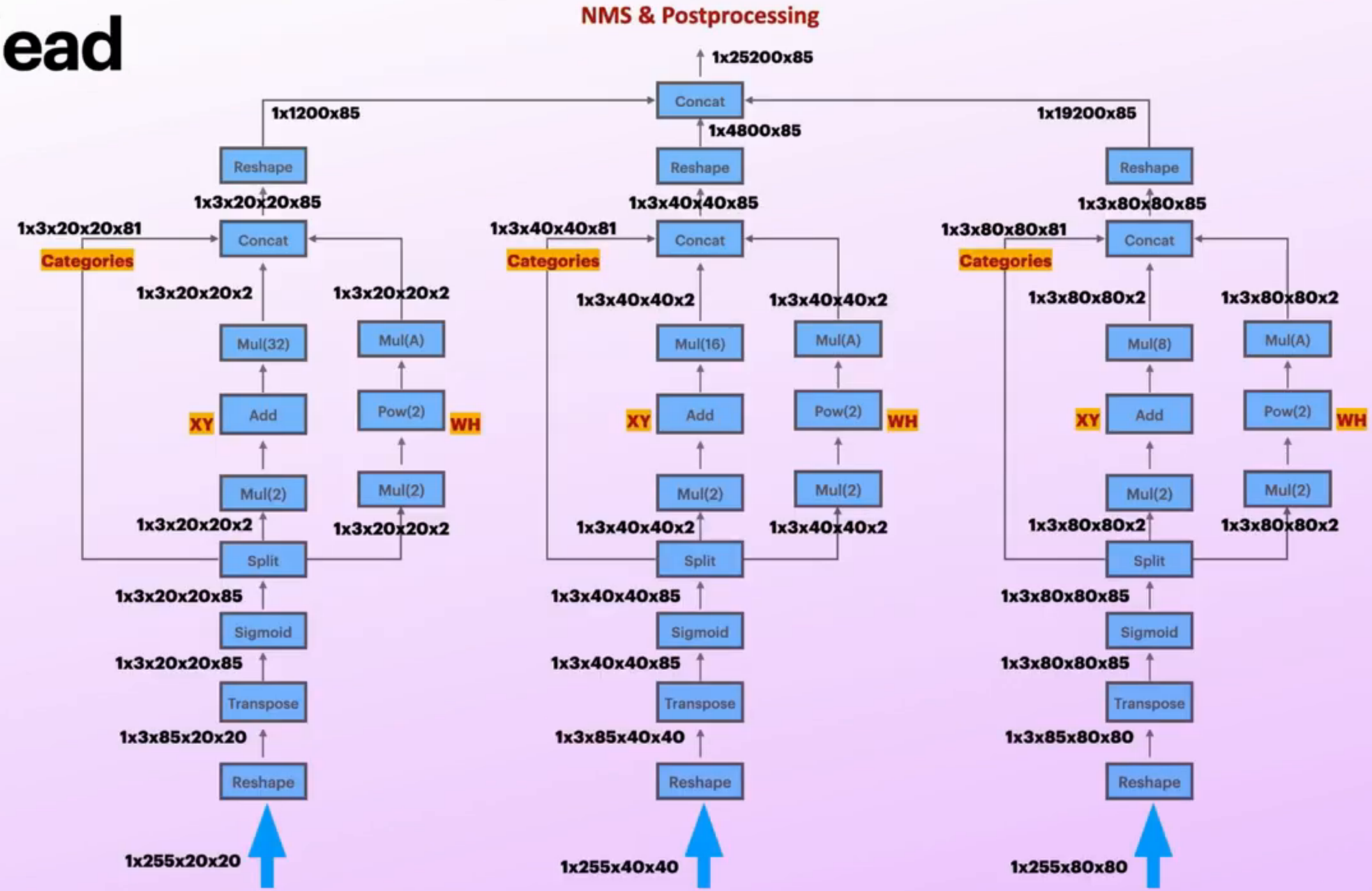
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Reshape
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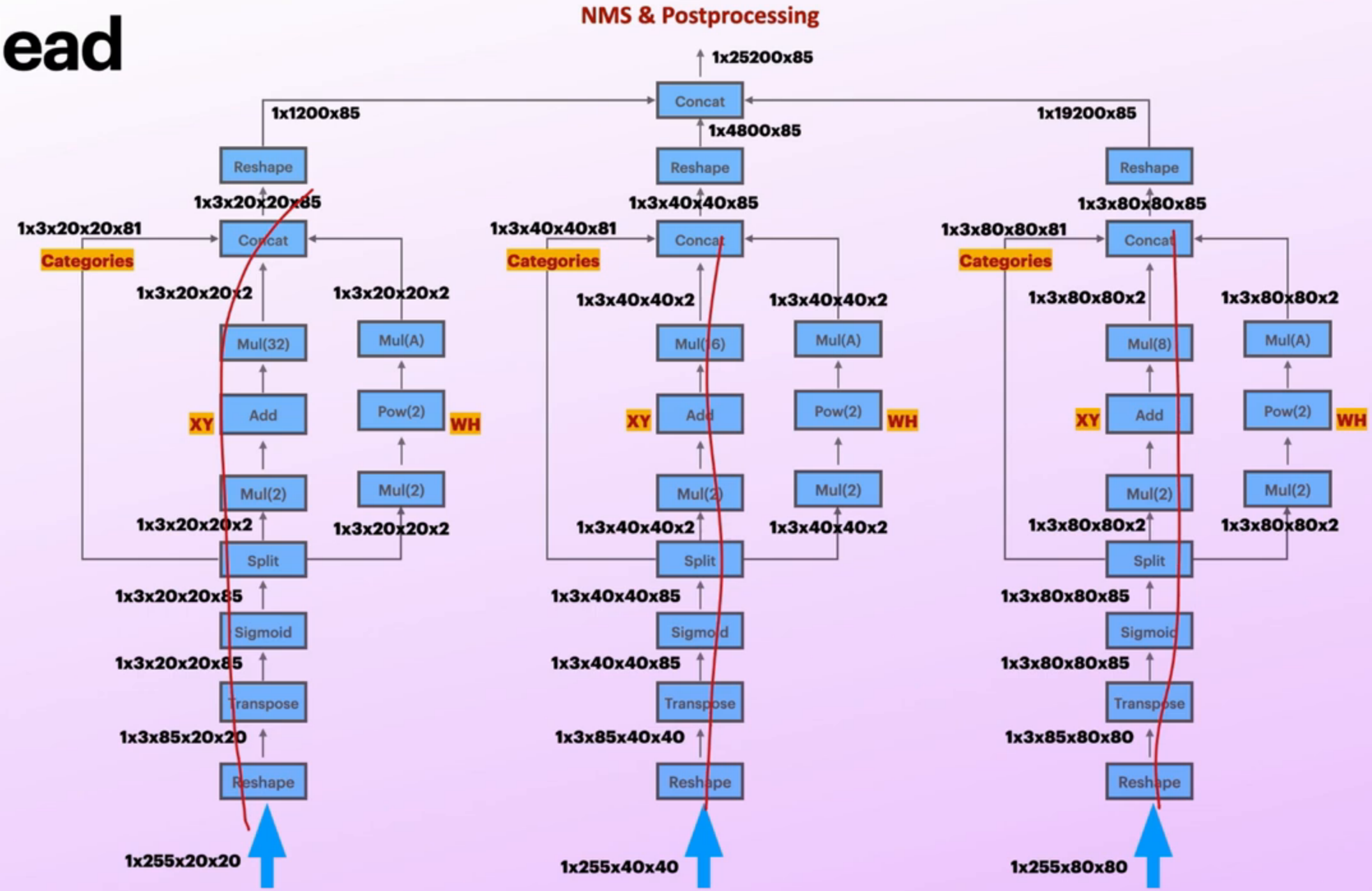
Head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1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
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1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
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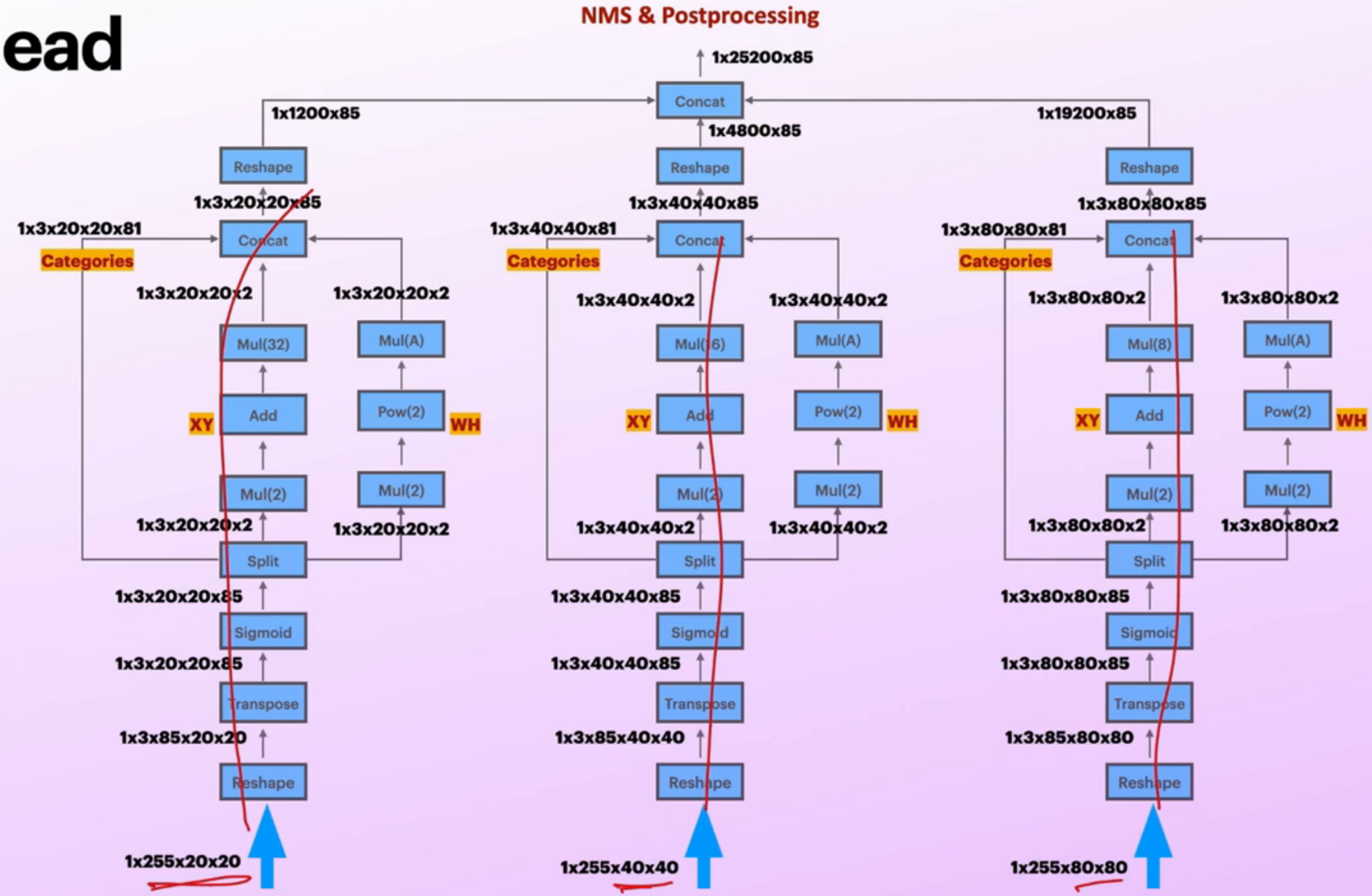
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80

Head


NMS & Postprocessing
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Reshape
Reshape
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1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
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1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
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Reshape
Reshape
Reshape
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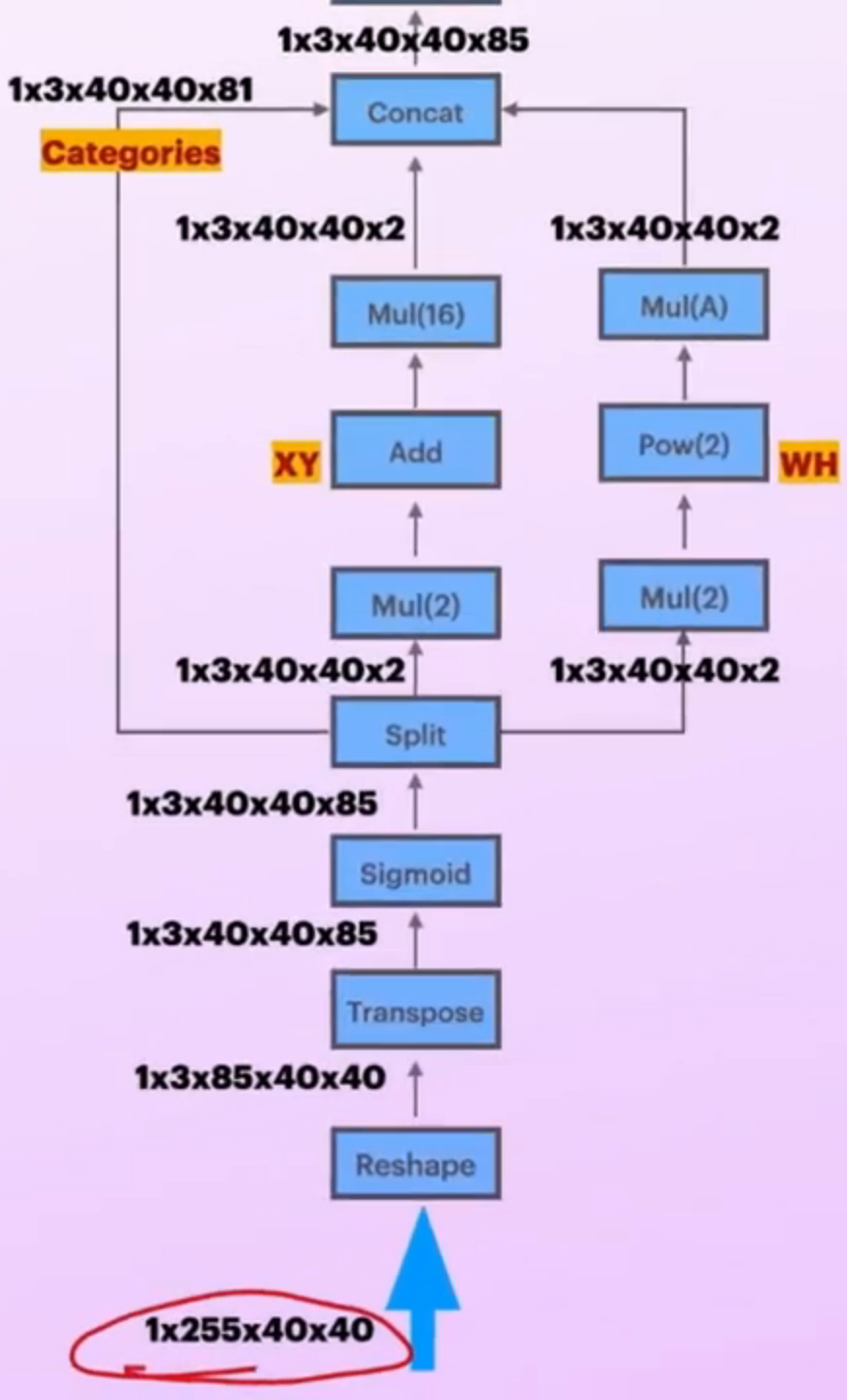
1x255x80x80


1x3x40x40x85
1x3x40x40x81
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1x3x40x40x2
1x3x40x40x2
Mul(16)
Mul(A)
Add
Pow(2)
XY
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
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Sigmoid
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Transpose
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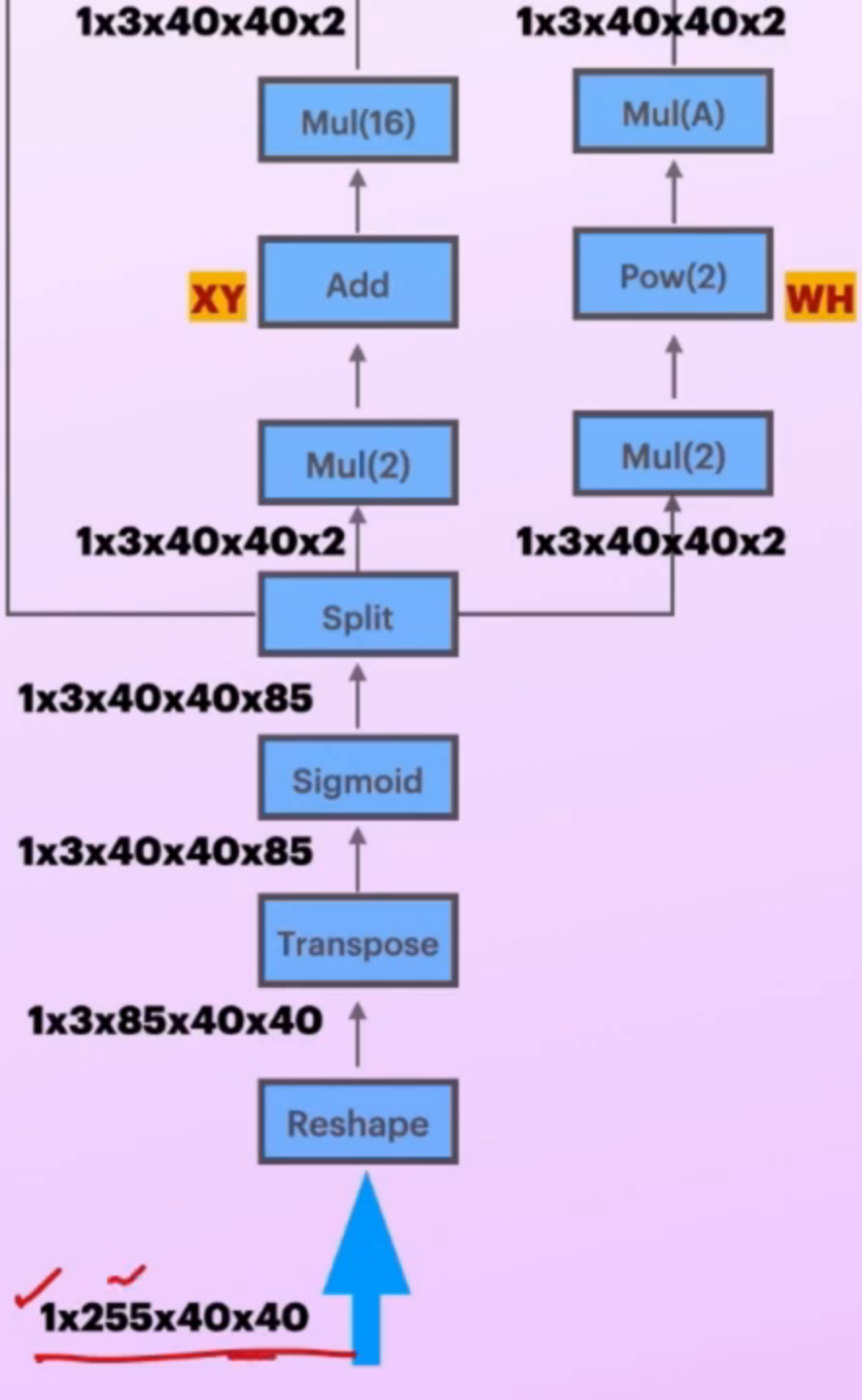
1x255x40x40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XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
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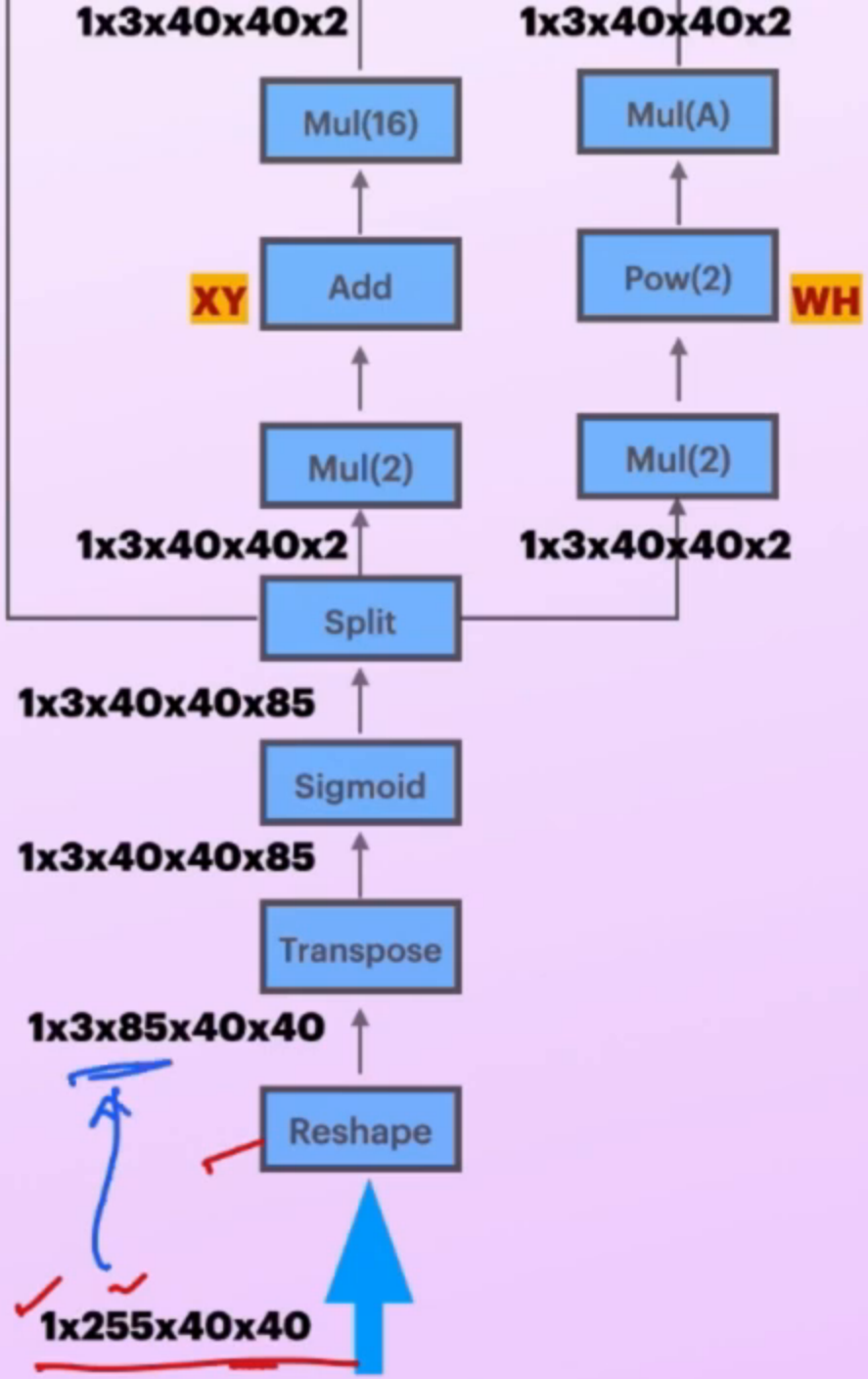
Sigmoid
1x3x40x40x85
Transpose
1x3x85x40x40
Reshape
1x255x40x40


1x3x40x40x2
1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
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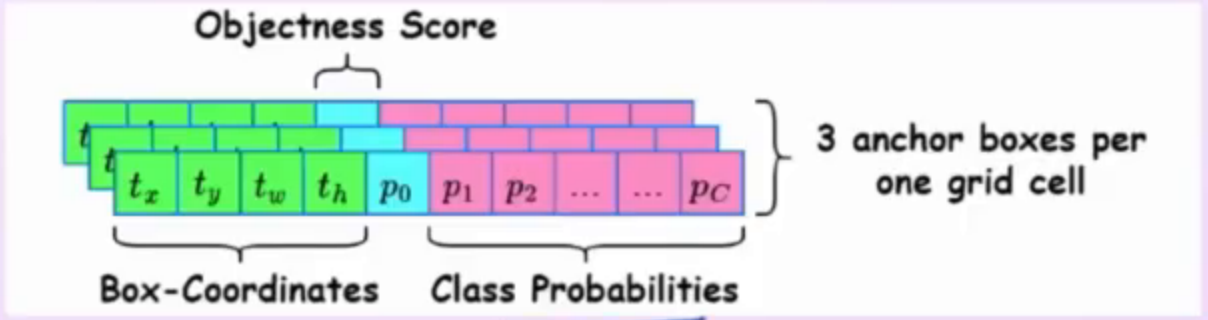
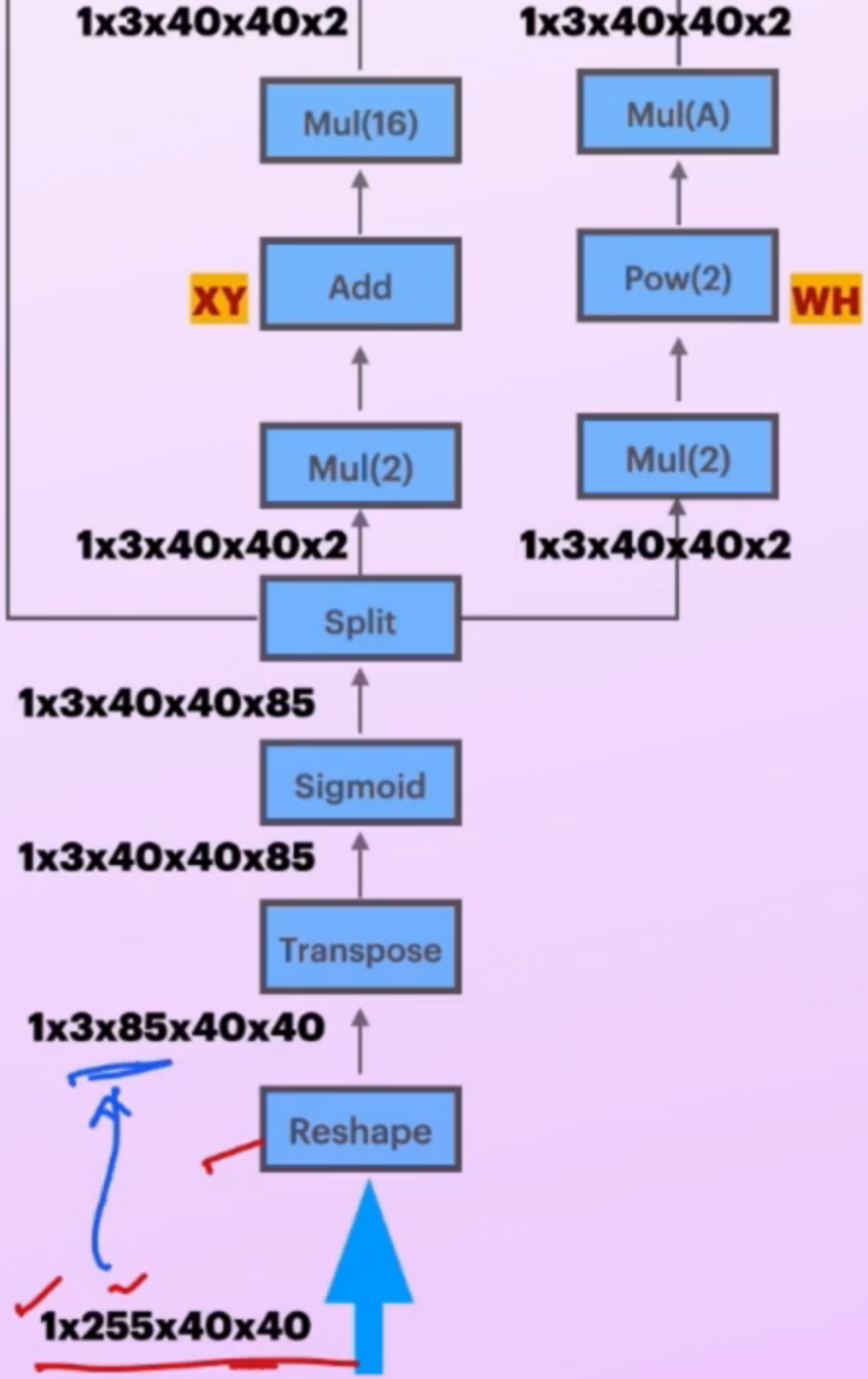
Sigmoid
1x3x40x40x85
Transpose
1x3x85x40x40
Reshape
1x255x40x40


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities
80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1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
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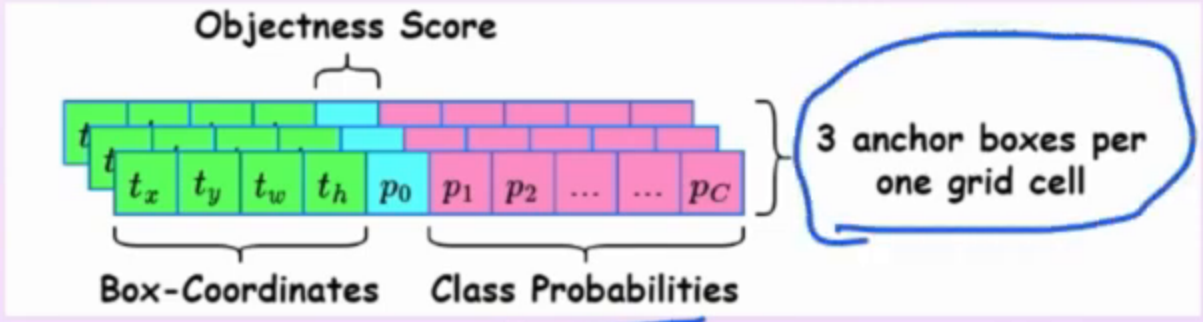
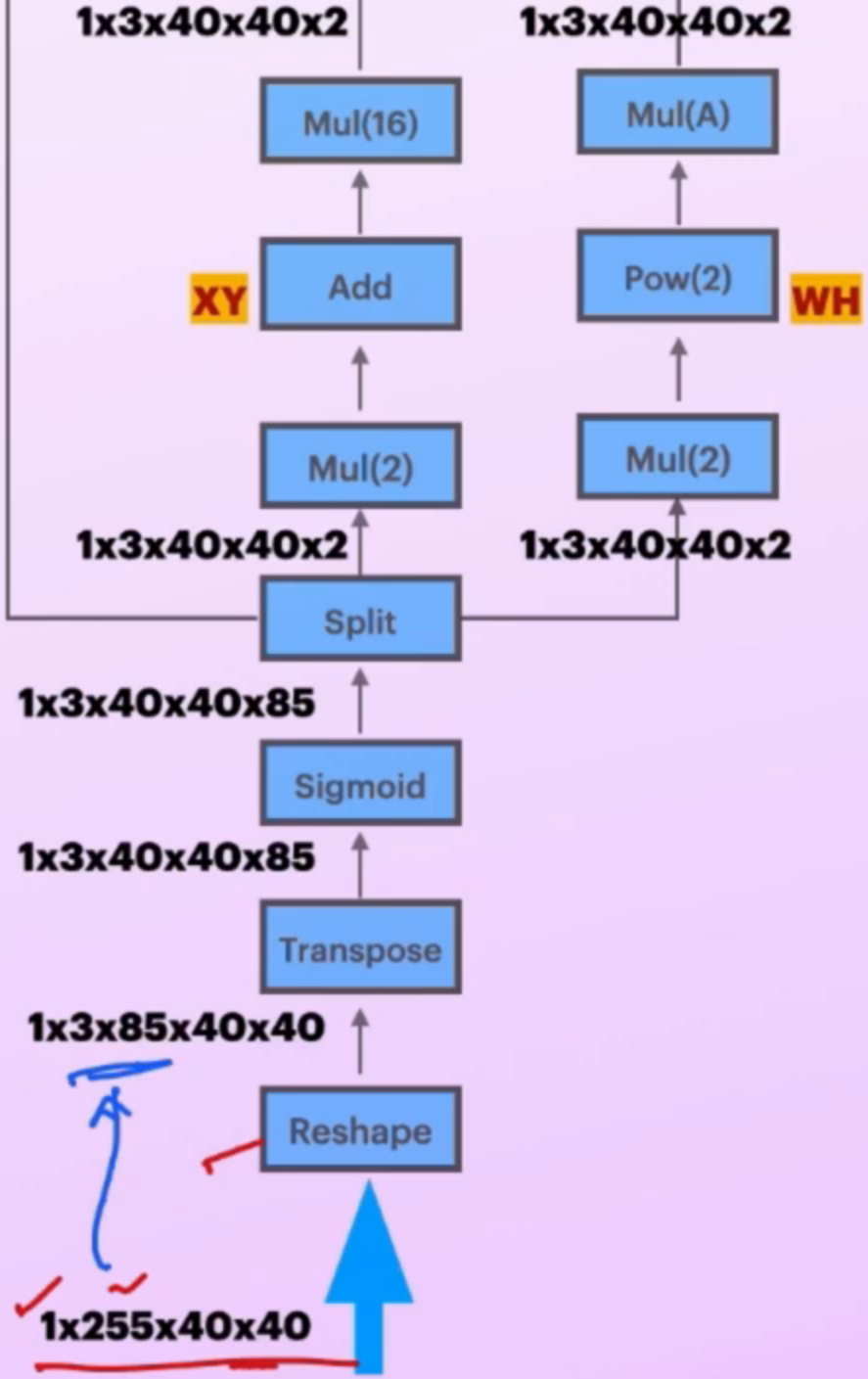
Transpose
1x3x85x40x40
Reshape
1x255x40x40


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities
4
80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1x3x40x40x2
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Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
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Sigmoid
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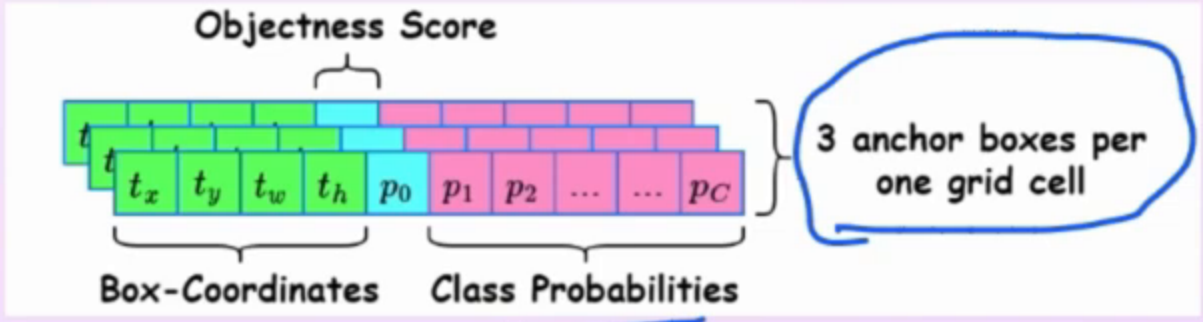
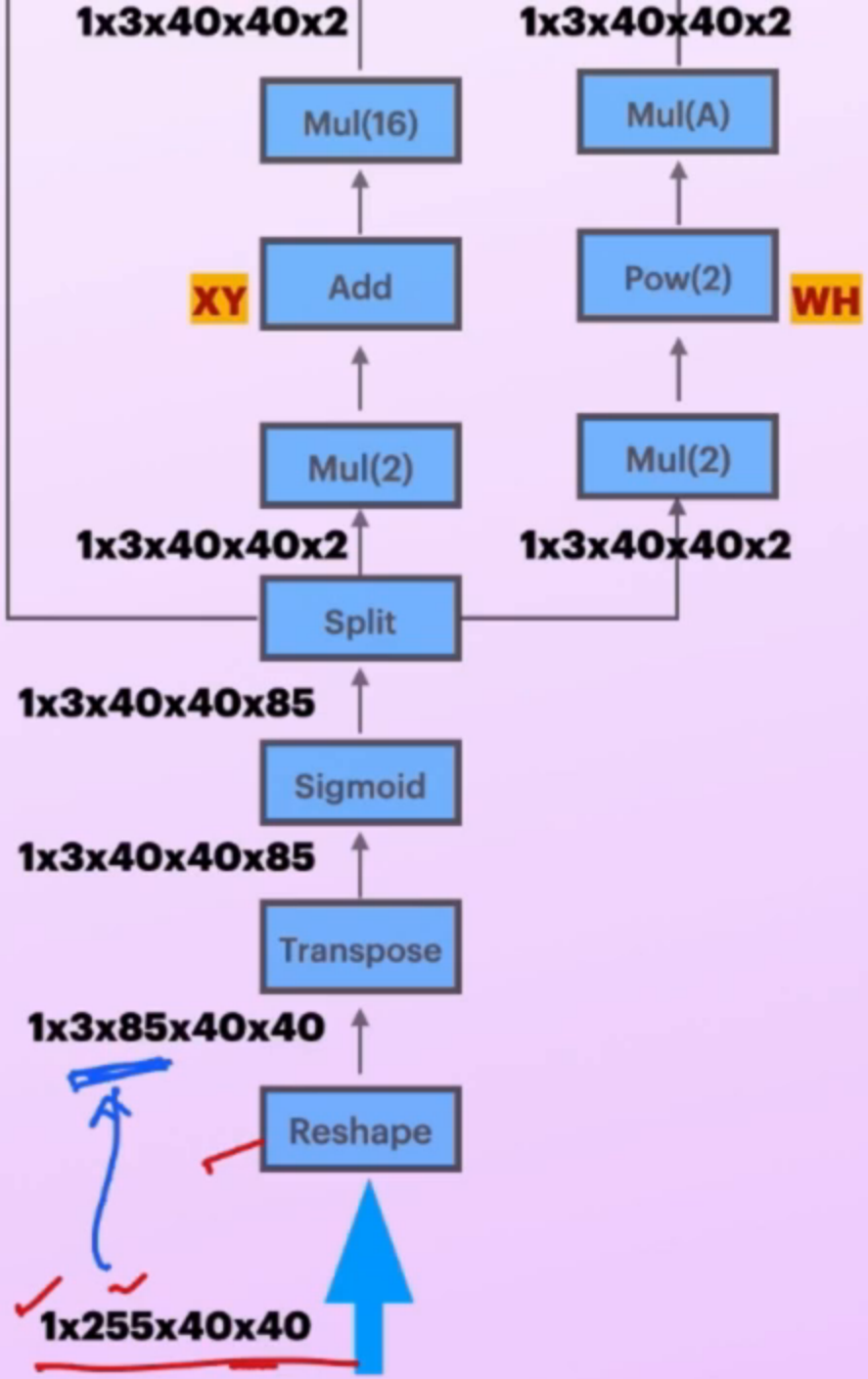
Transpose
1x3x85x40x40
Reshape
1x255x40x40


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities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1x3x40x40x2
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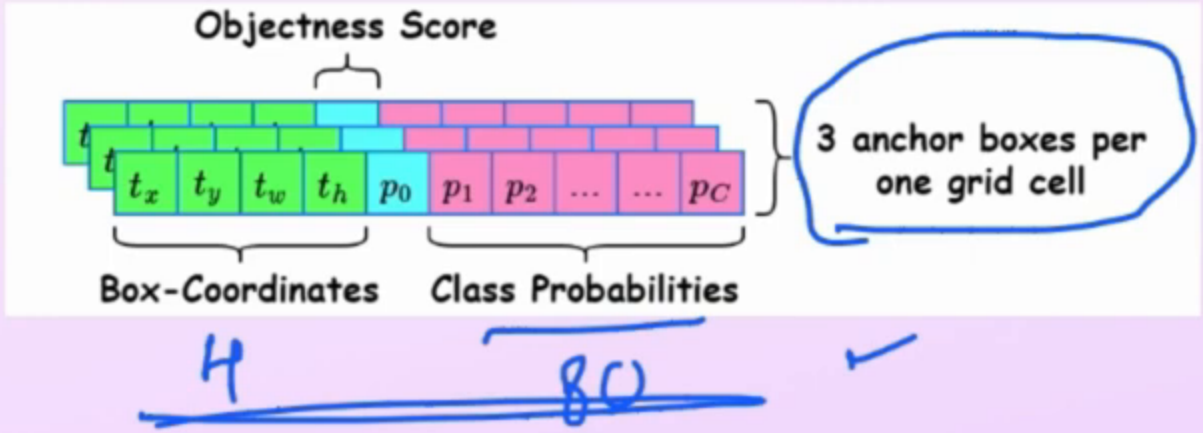
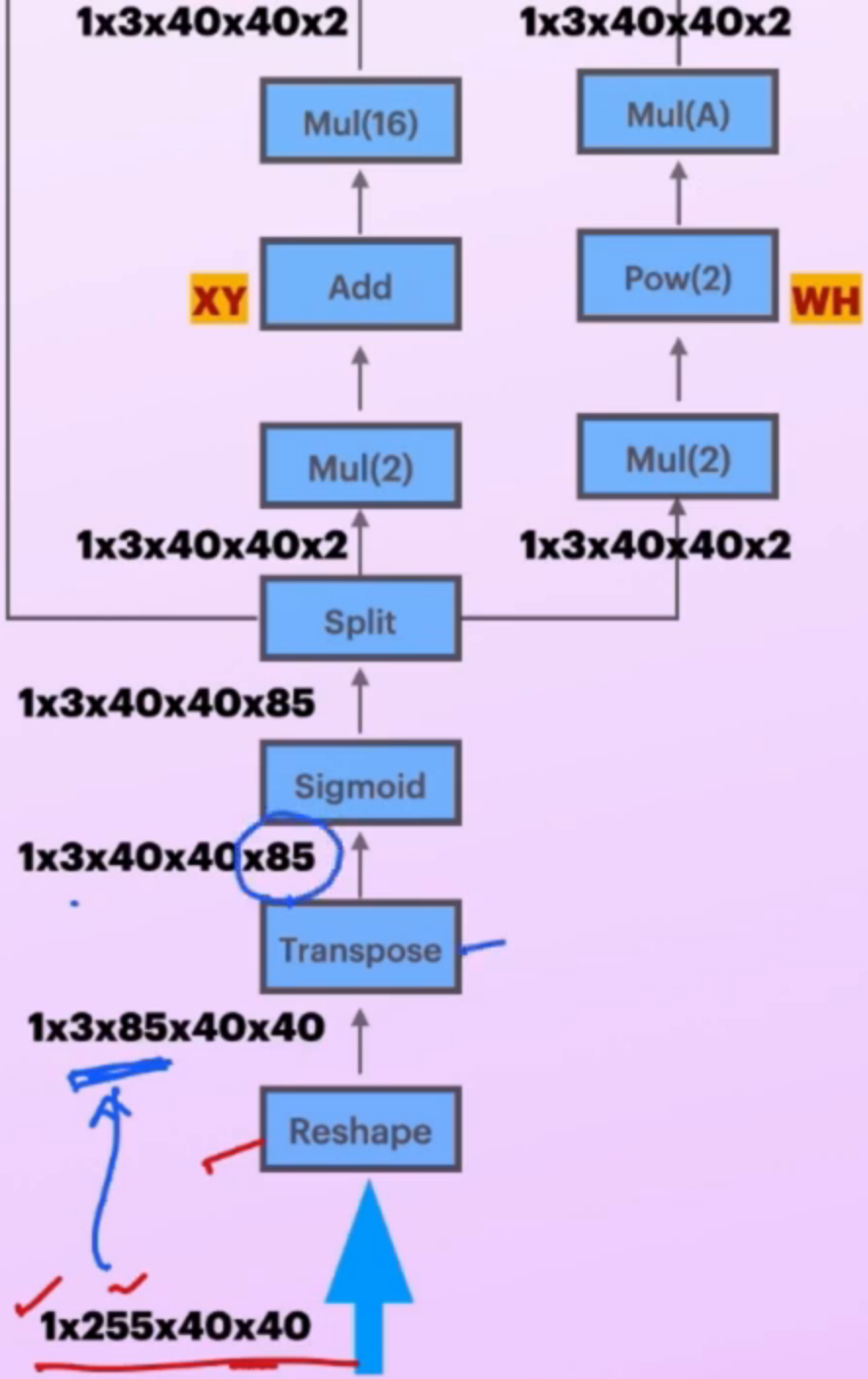
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose
1x3x85x40x40
Reshape
1x255x40x40


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities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1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
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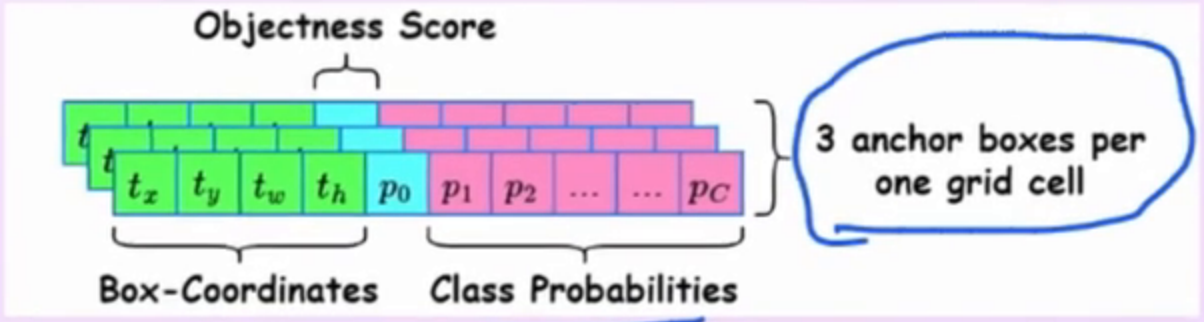
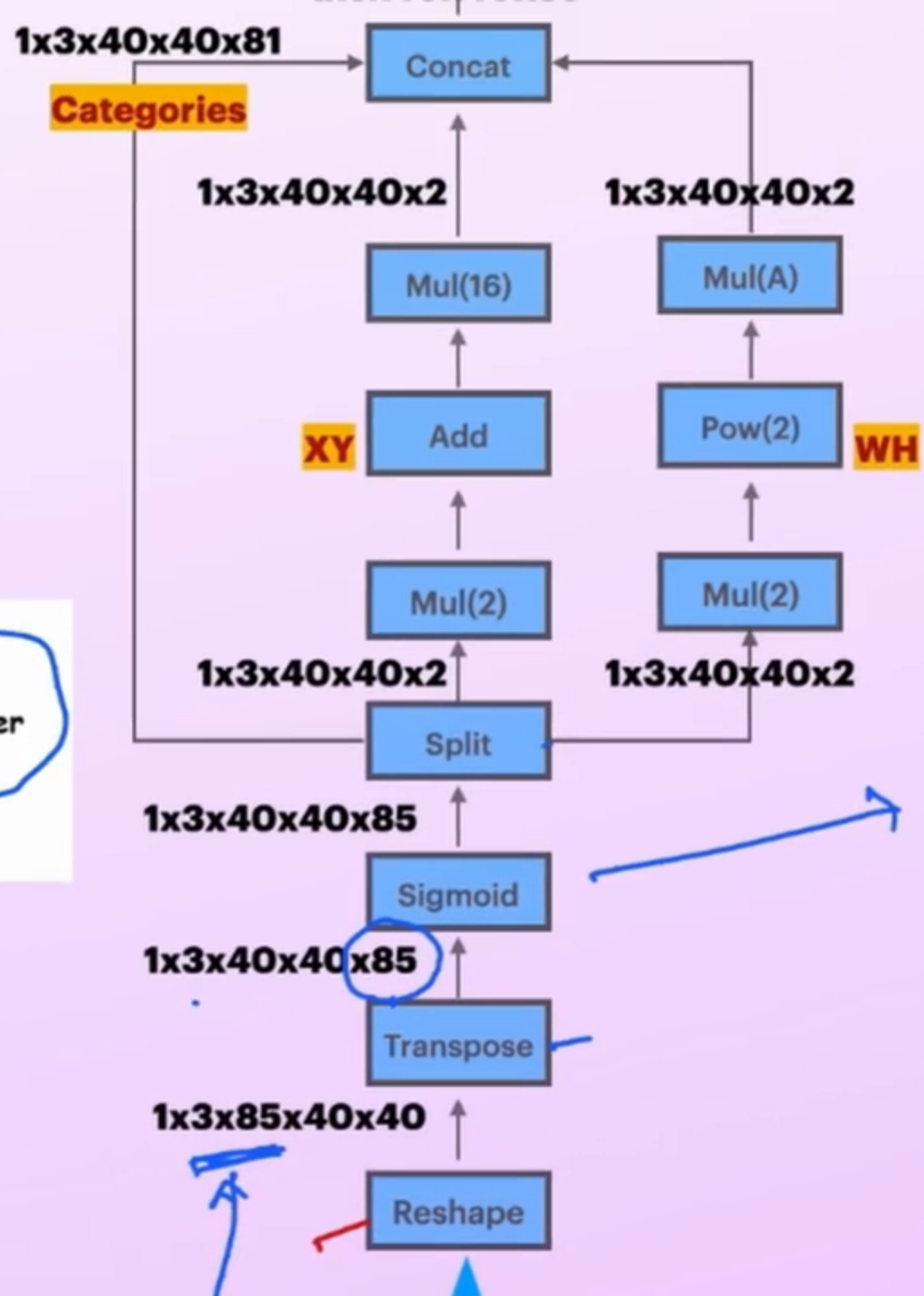
Transpose
1x3x85x40x40
Reshape
1x255x40x40


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 … … p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities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Categories
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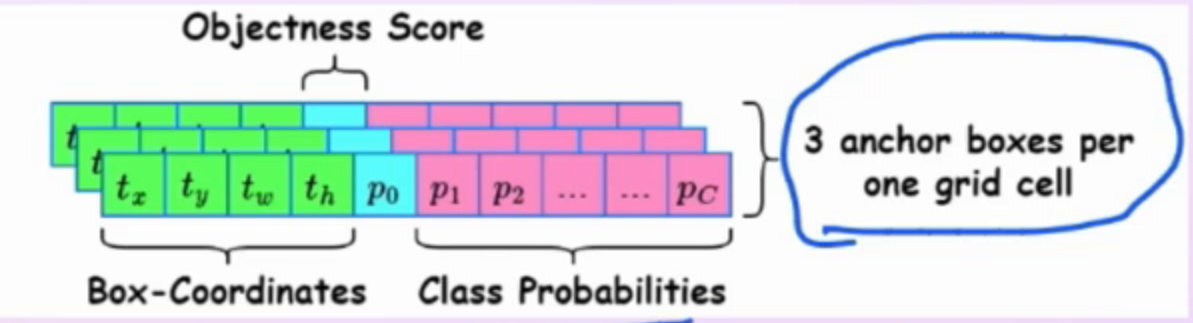
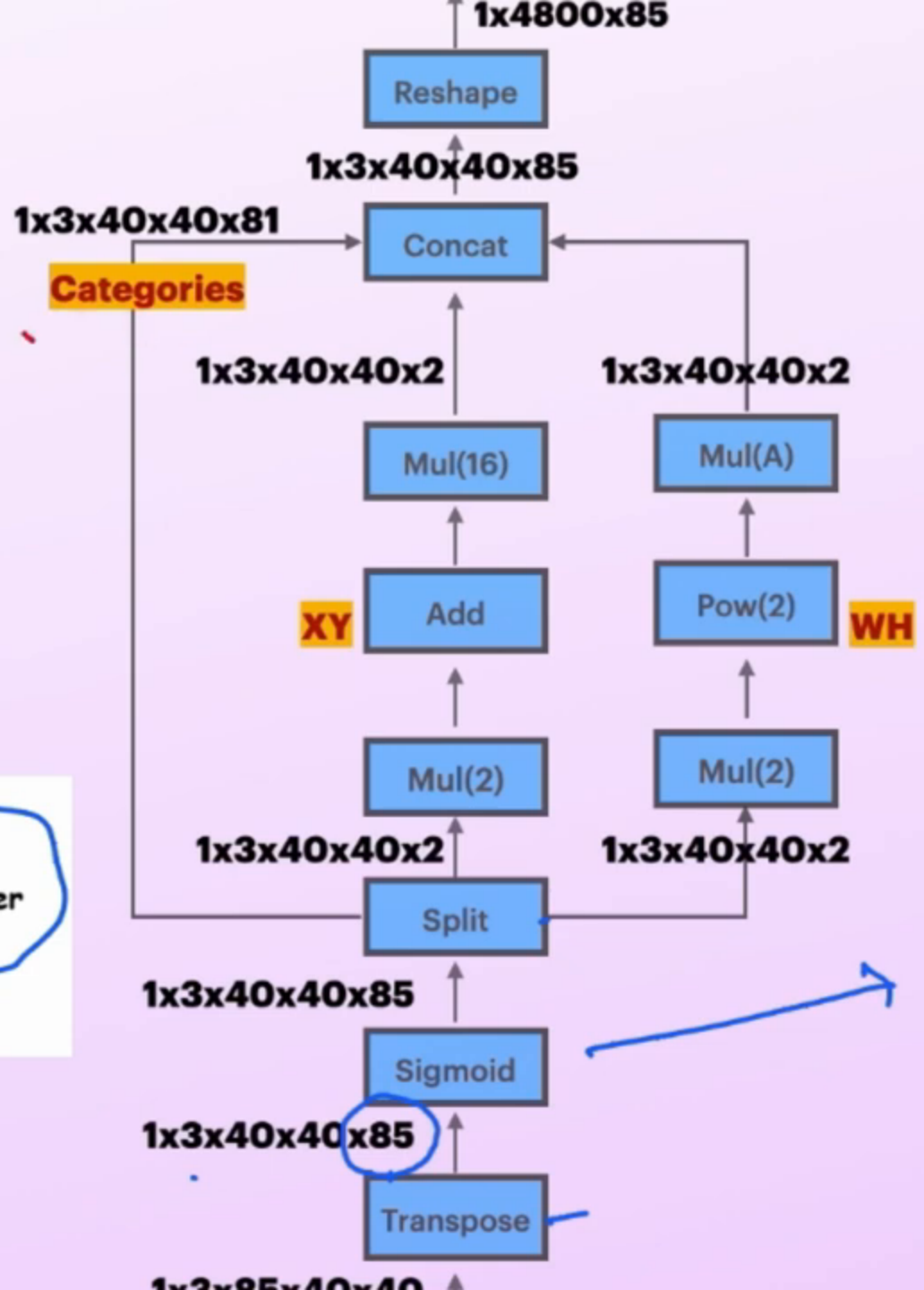
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose
1x3x85x40x40
Reshape


Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities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Reshape
1x3x40x40x85
1x3x40x40x81
Concat
Categories
1x3x40x40x2
1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
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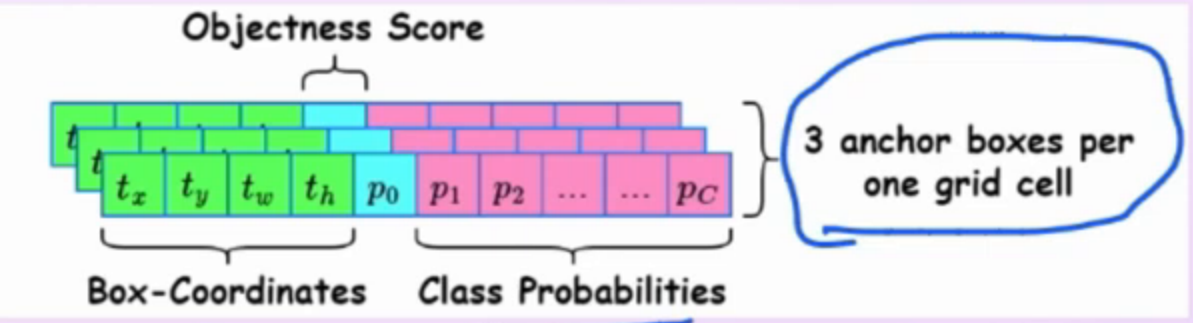
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose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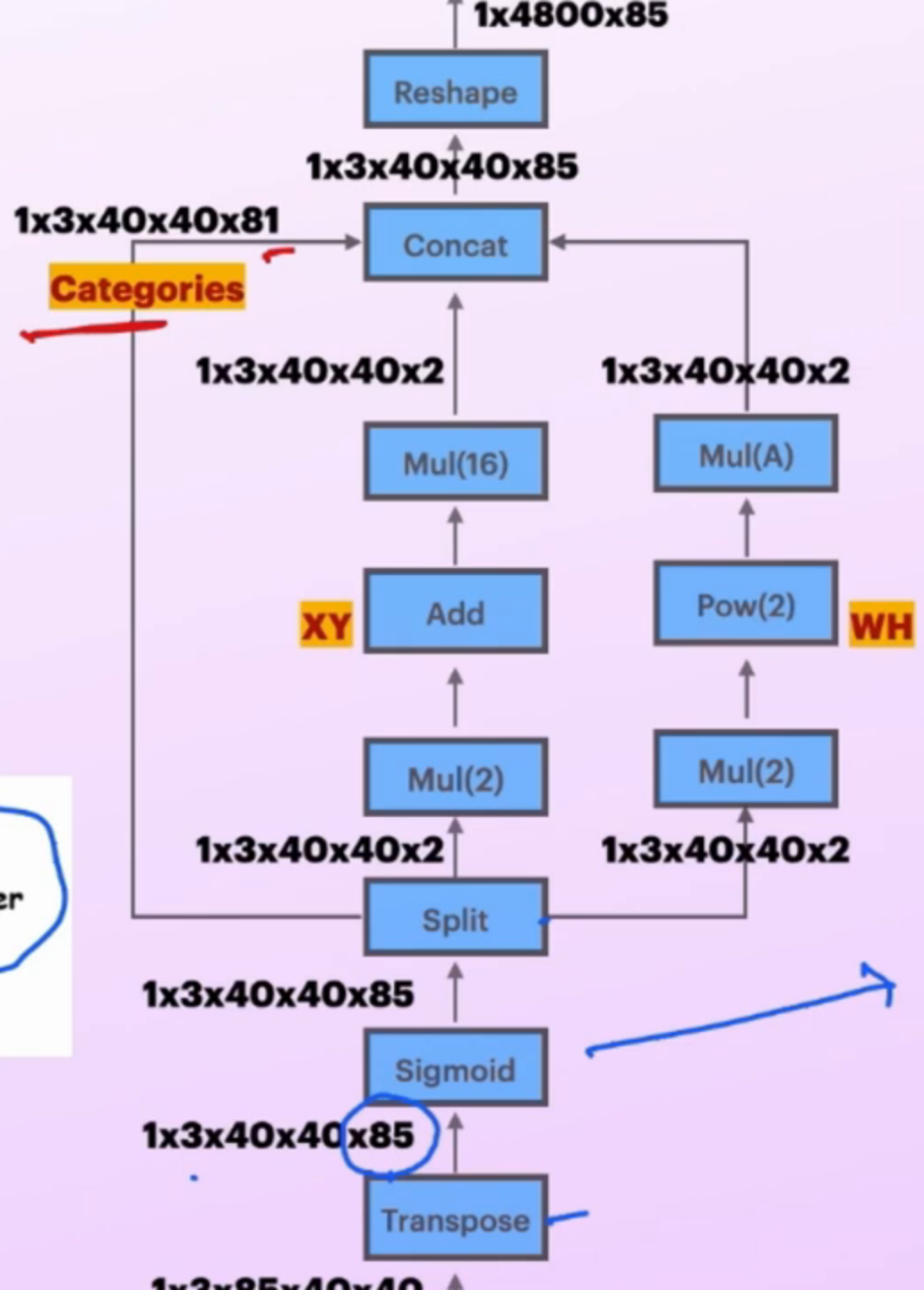
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities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Concat
Categories
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1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
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Sigmoid
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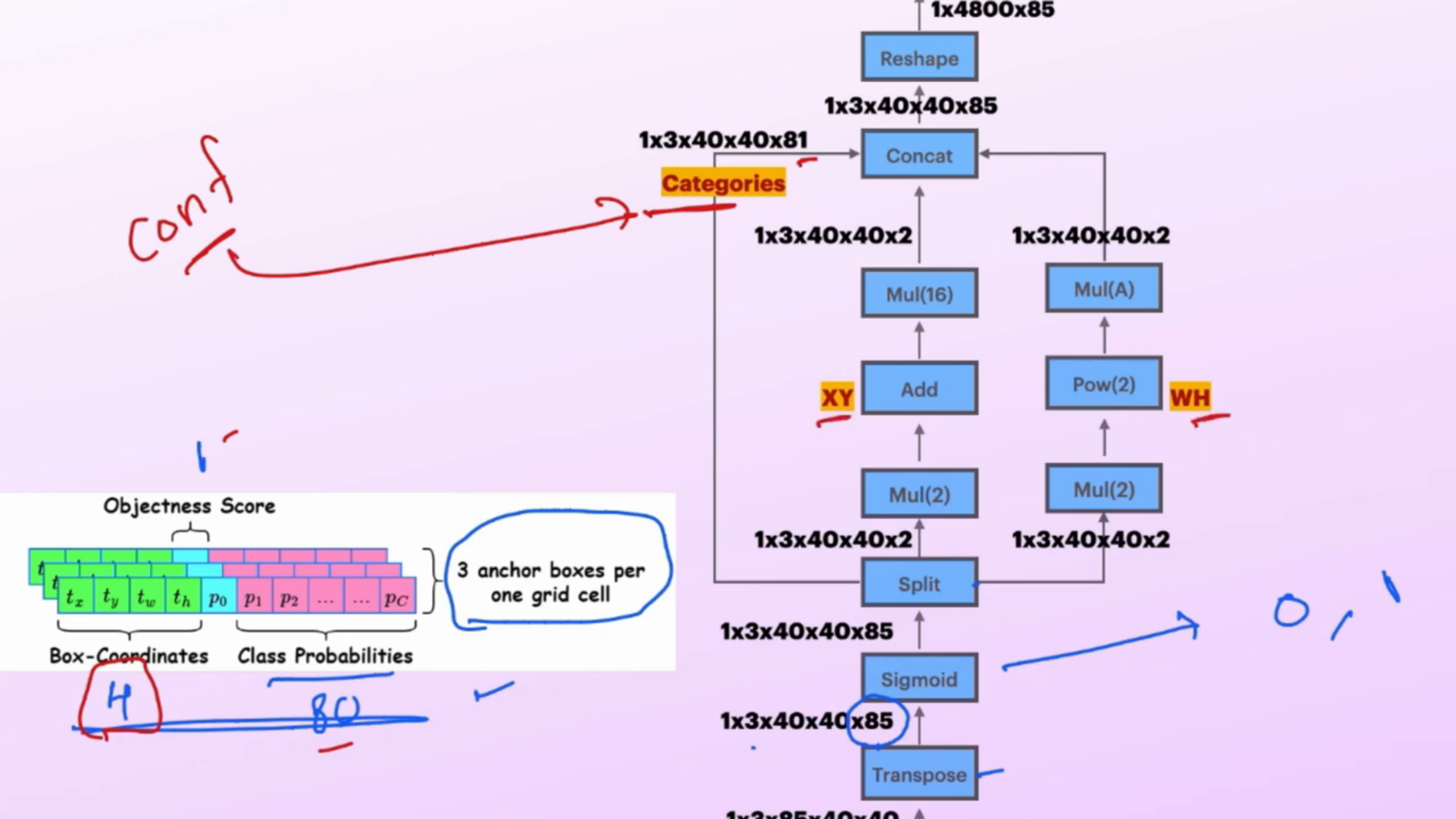
Transpose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Concat
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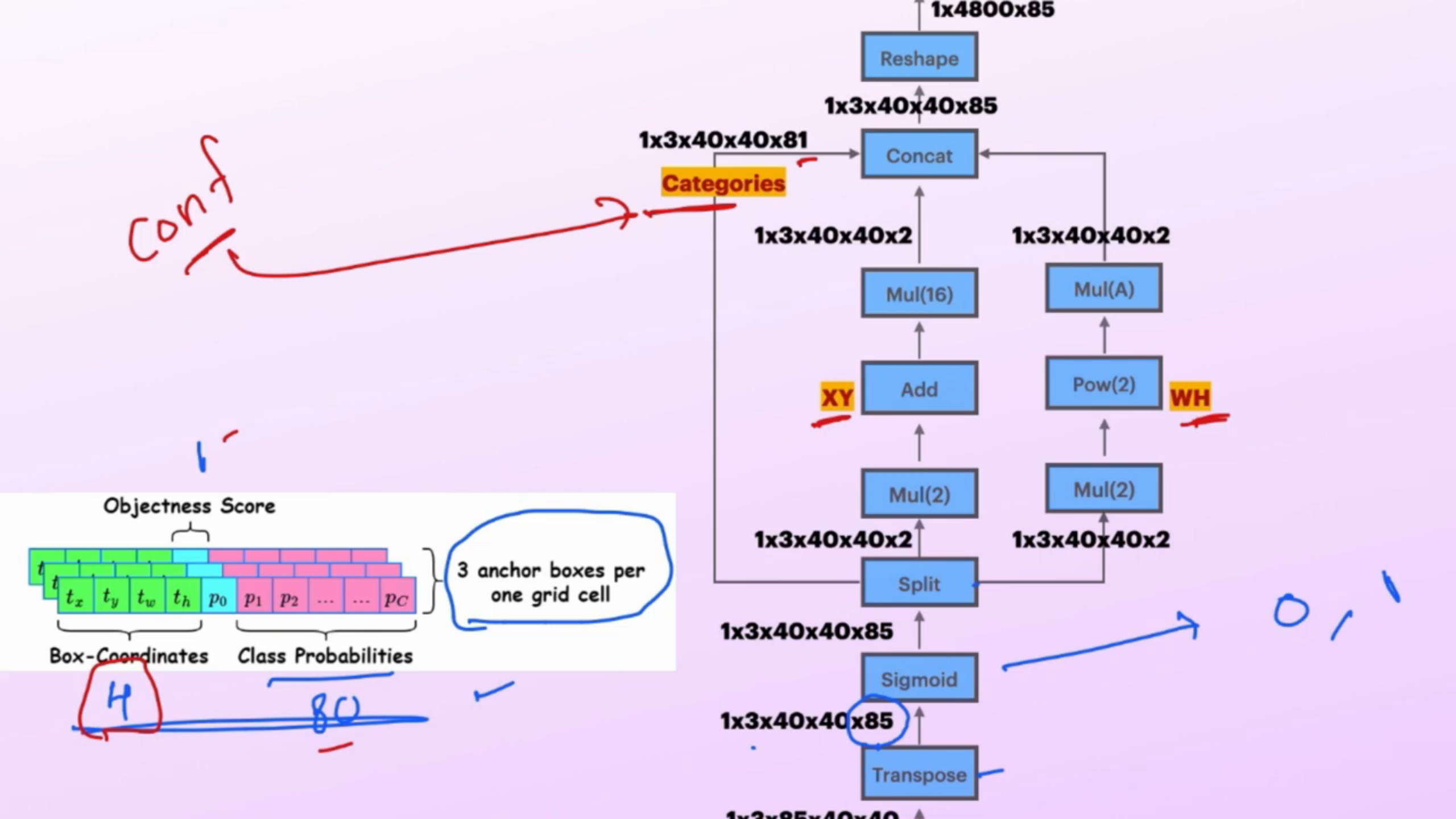
1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose
Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities
4
80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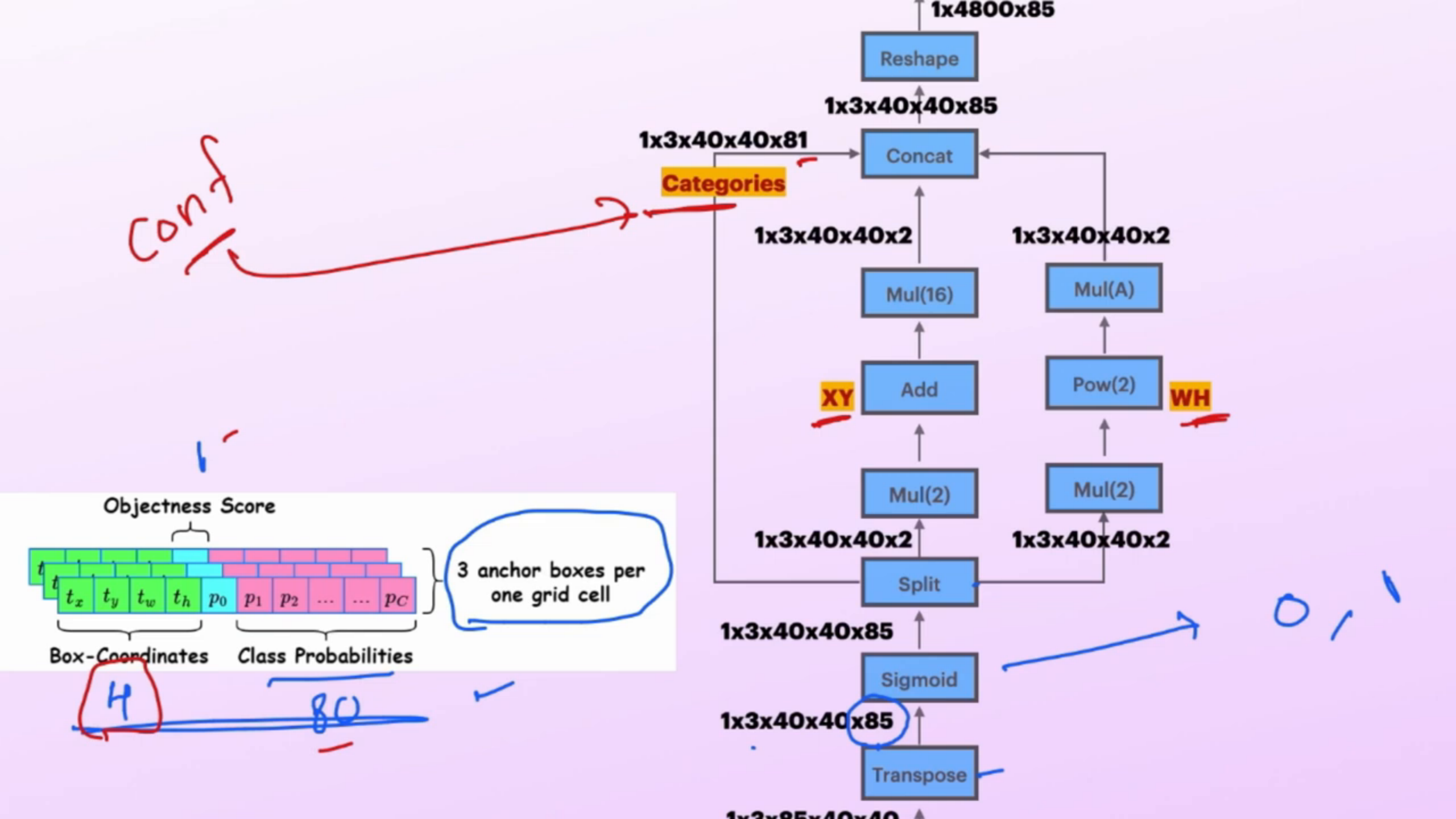
1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose
Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities
4
80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1x3x40x40x85
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Concat
Categories
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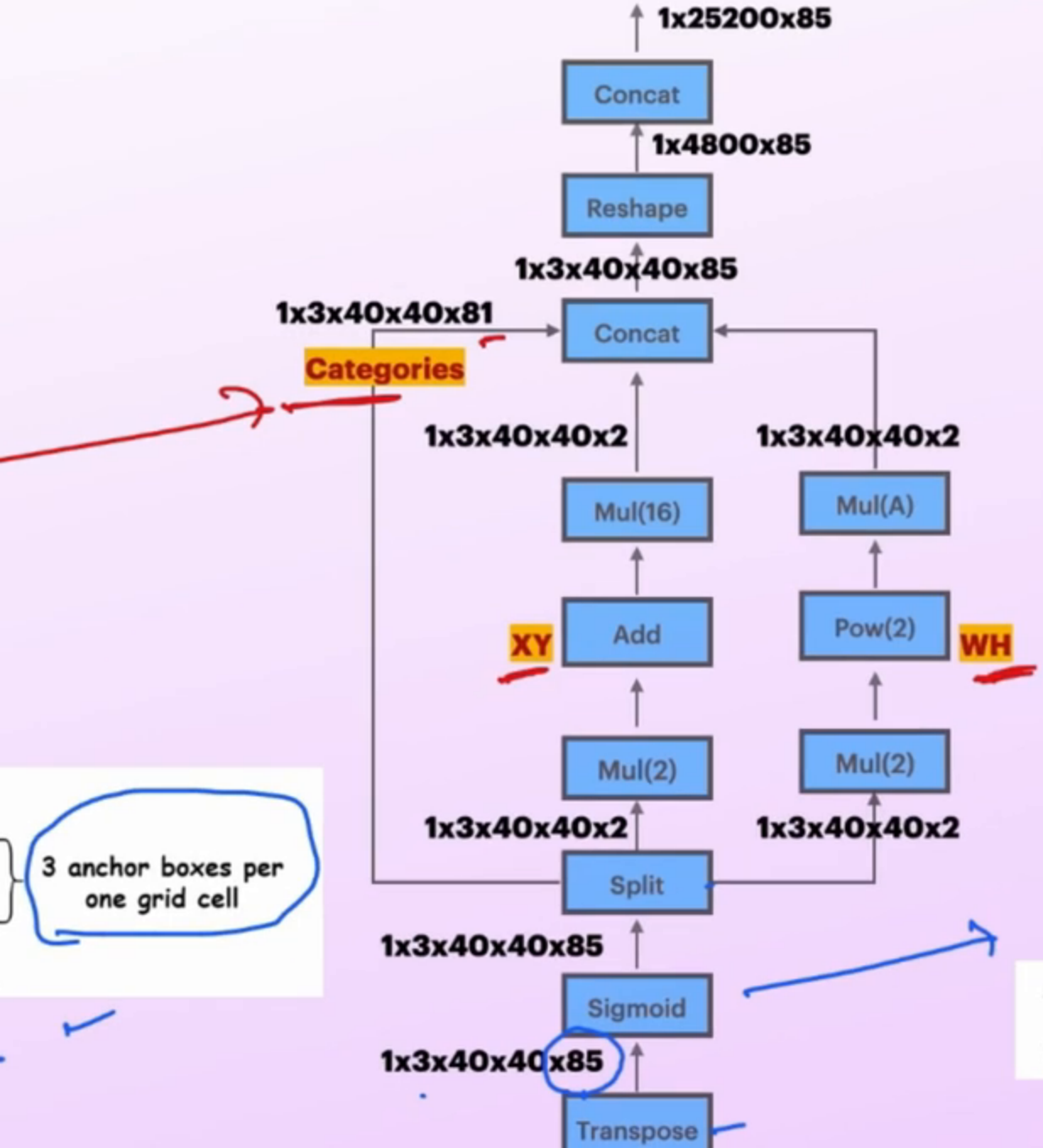
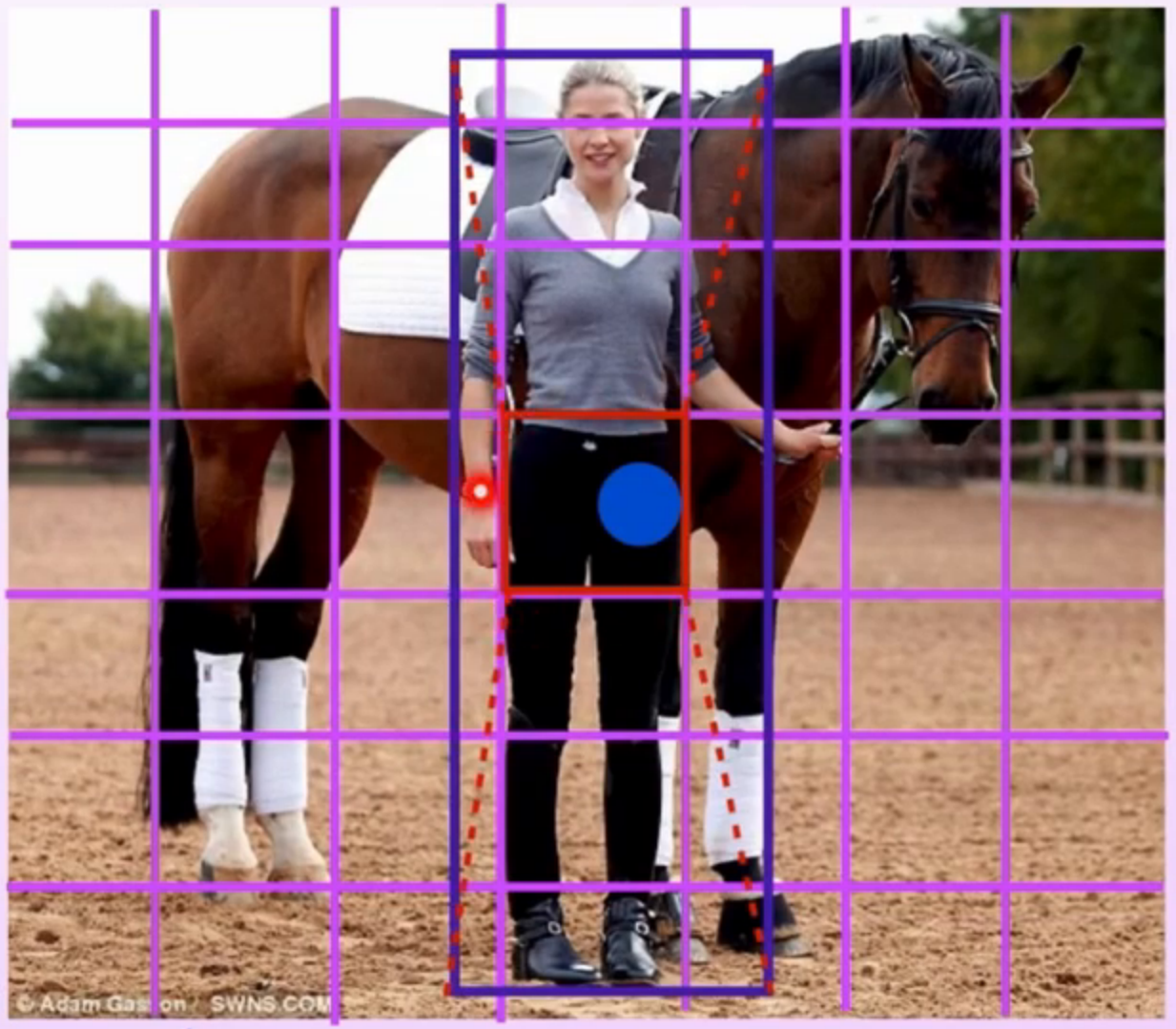
1x3x40x40x2
Mul(16)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
1x3x40x40x2
1x3x40x40x2
Split
1x3x40x40x85
Sigmoid
1x3x40x40x85
Transpose
Objectness Score
t_x t_y t_w t_h p_0 p_1 p_2 ... ... p_C
3 anchor boxes per one grid cell
Box-Coordinates
Class Probabilities

NMS & Postprocessing





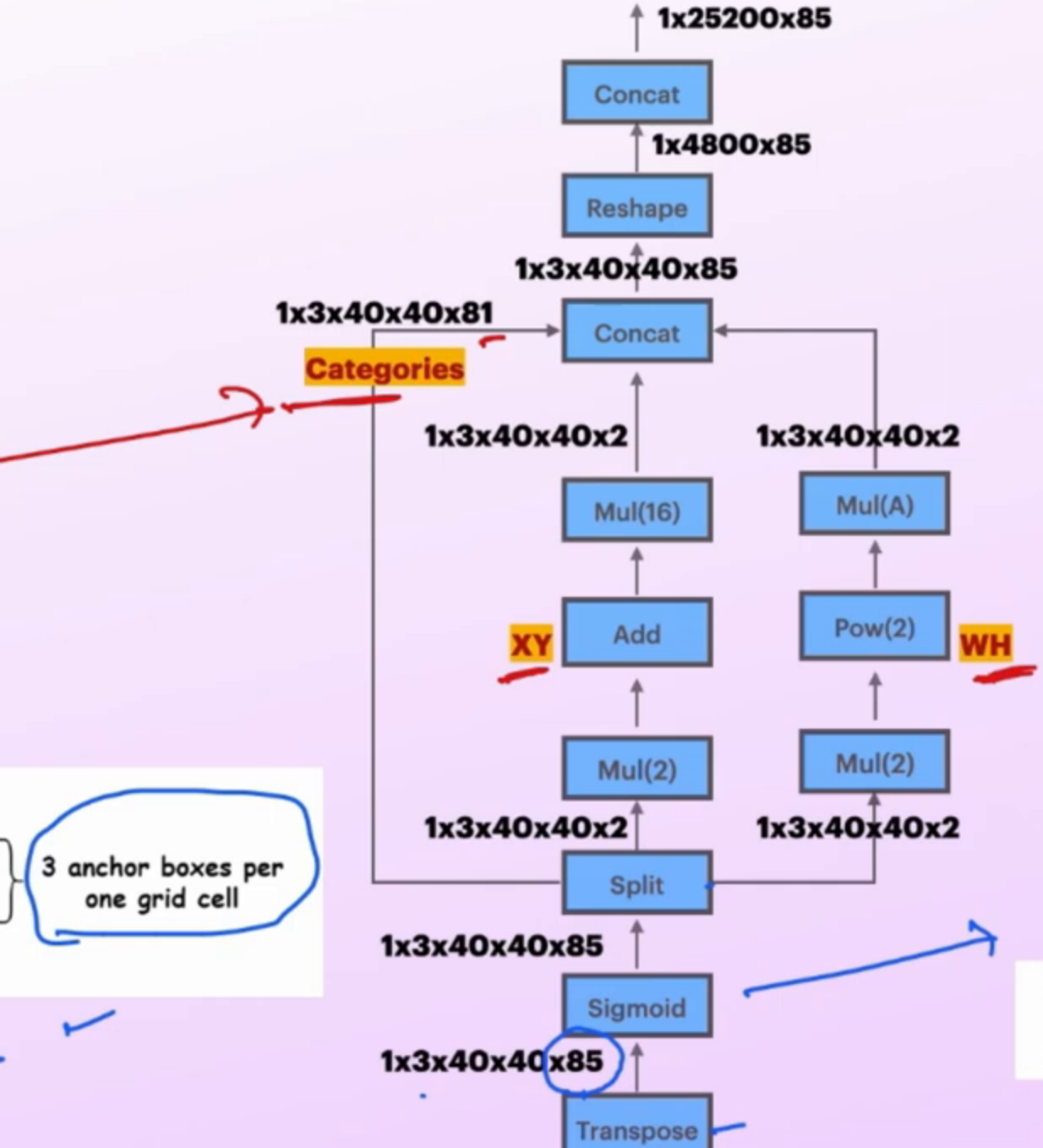
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$

$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

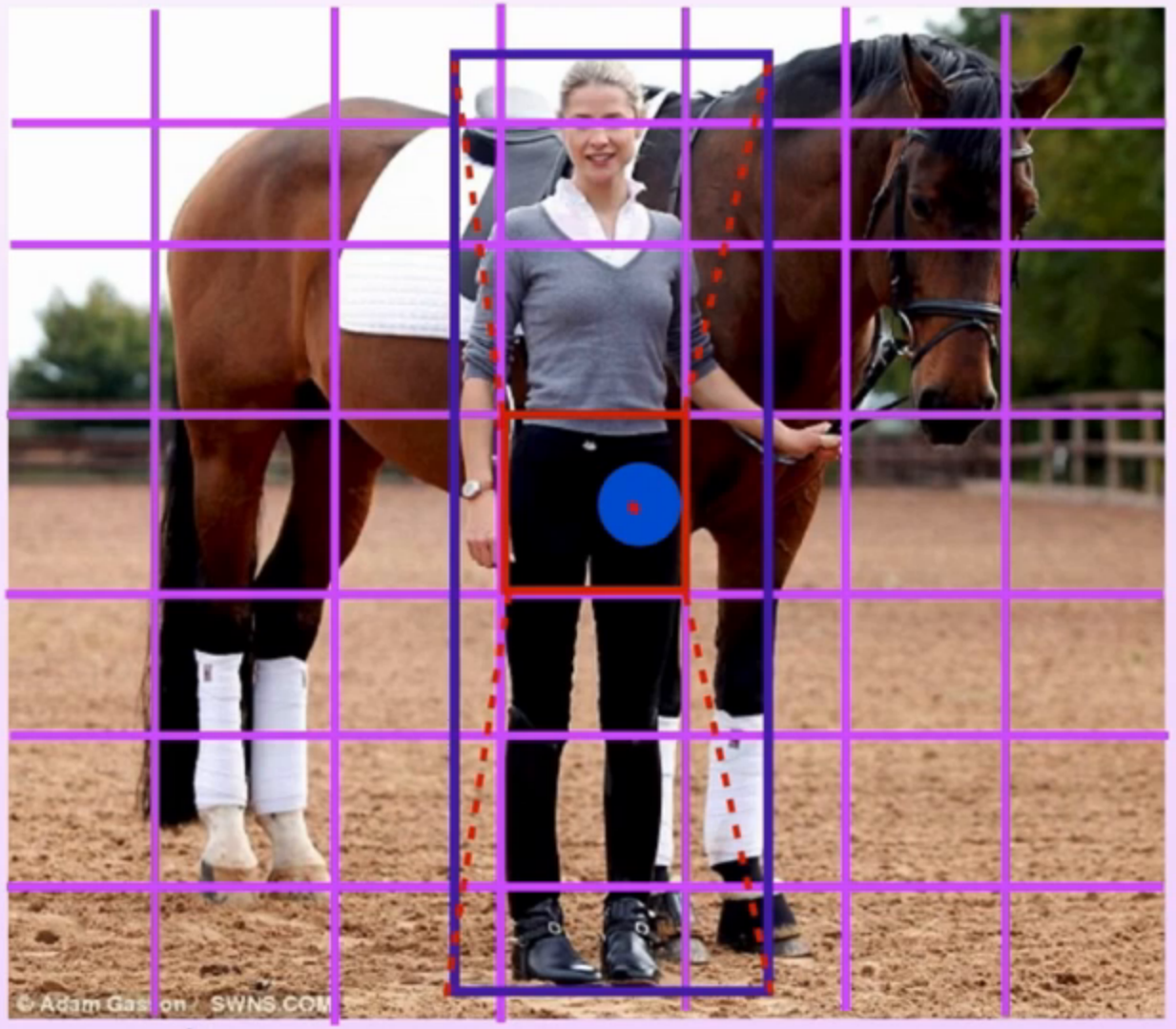
$$w = p_w \times (2 \cdot \sigma(t_w))^2$$

$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

NMS & Postprocessing



3 anchor boxes per one grid cell



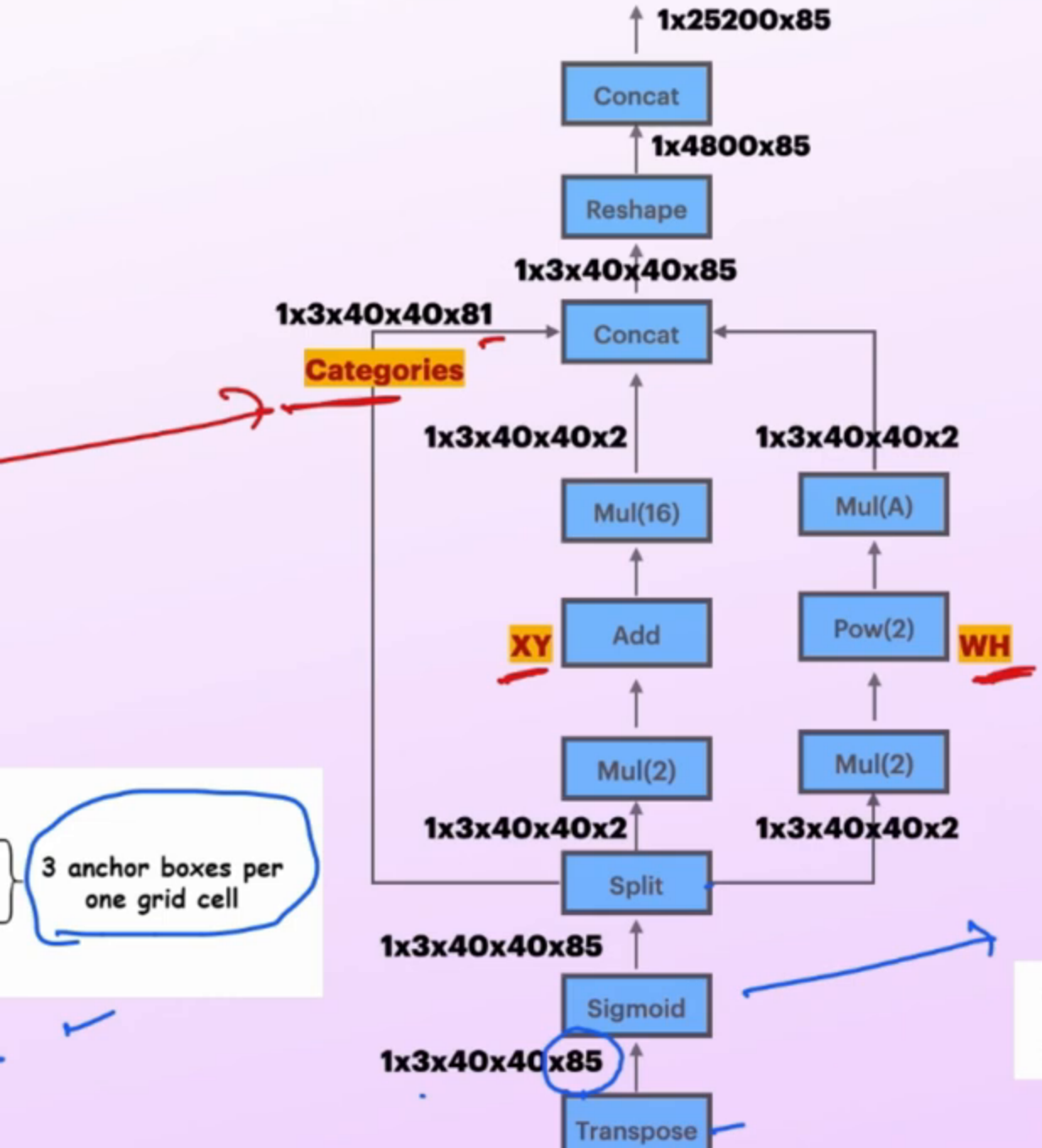
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$

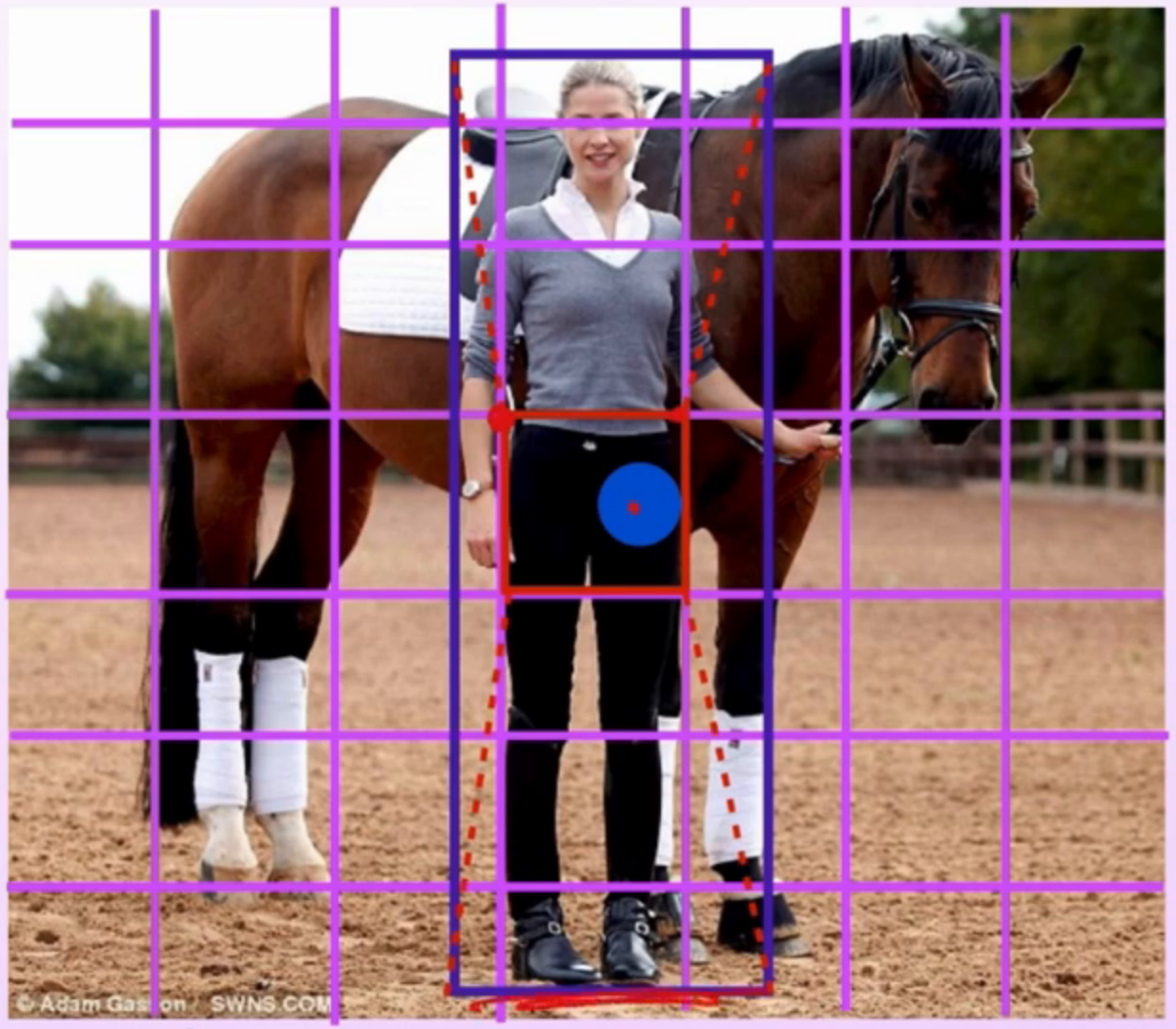
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

$$w = p_w \times (2 \cdot \sigma(t_w))^2$$

$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

NMS & Postprocessing





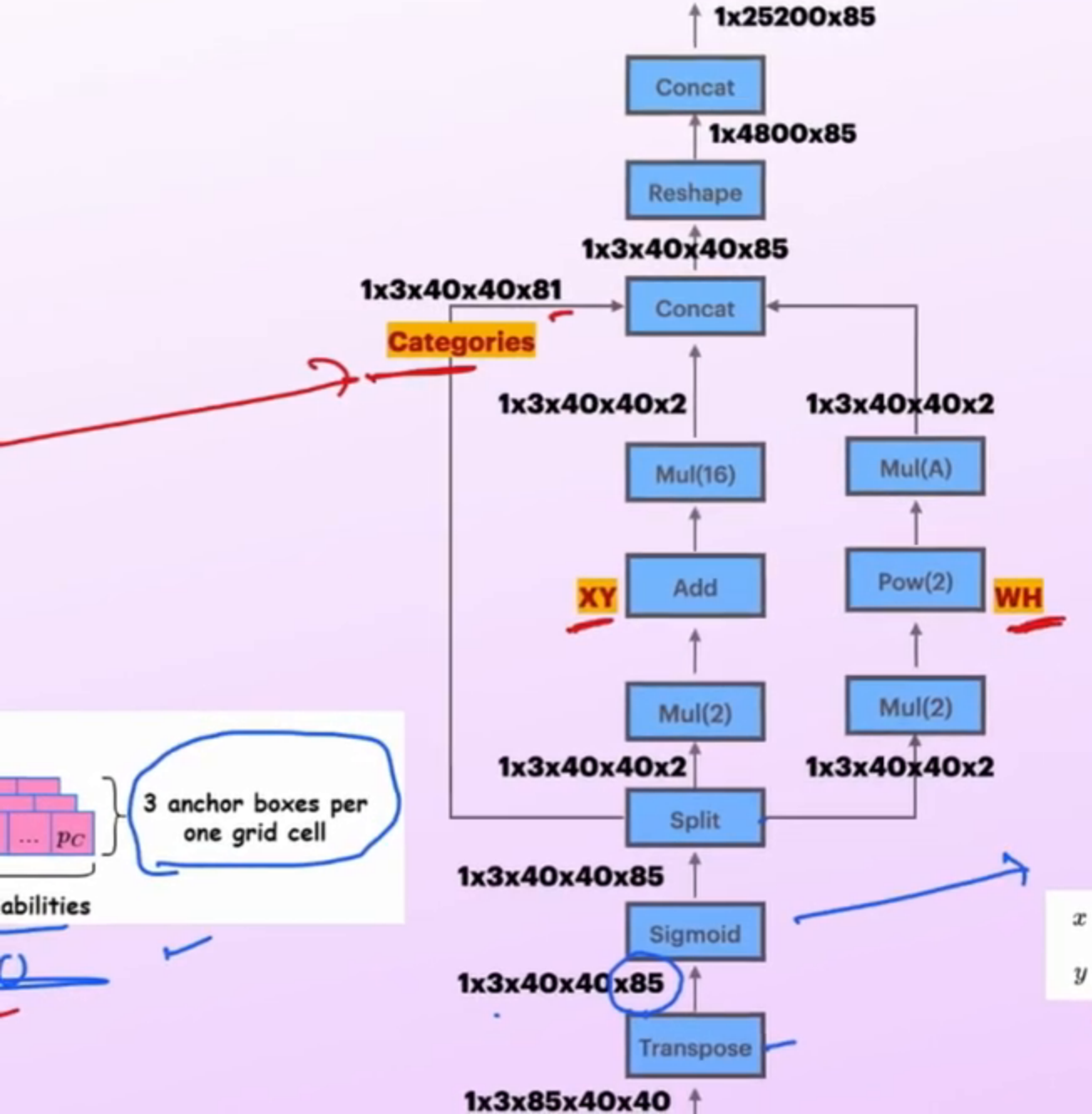
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$

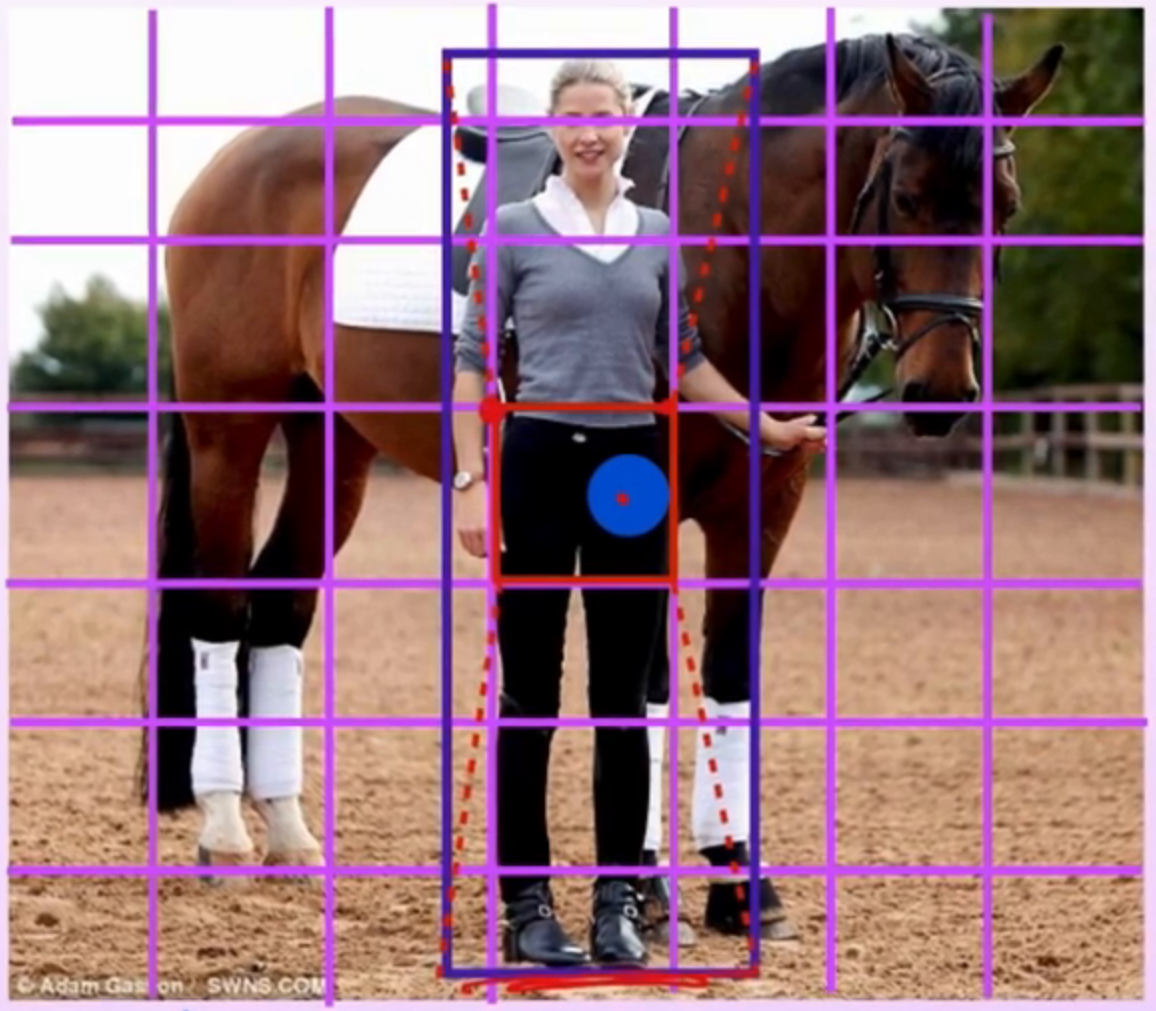
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

$$w = p_w \times (2 \cdot \sigma(t_w))^2$$

$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

NMS & Postprocessing





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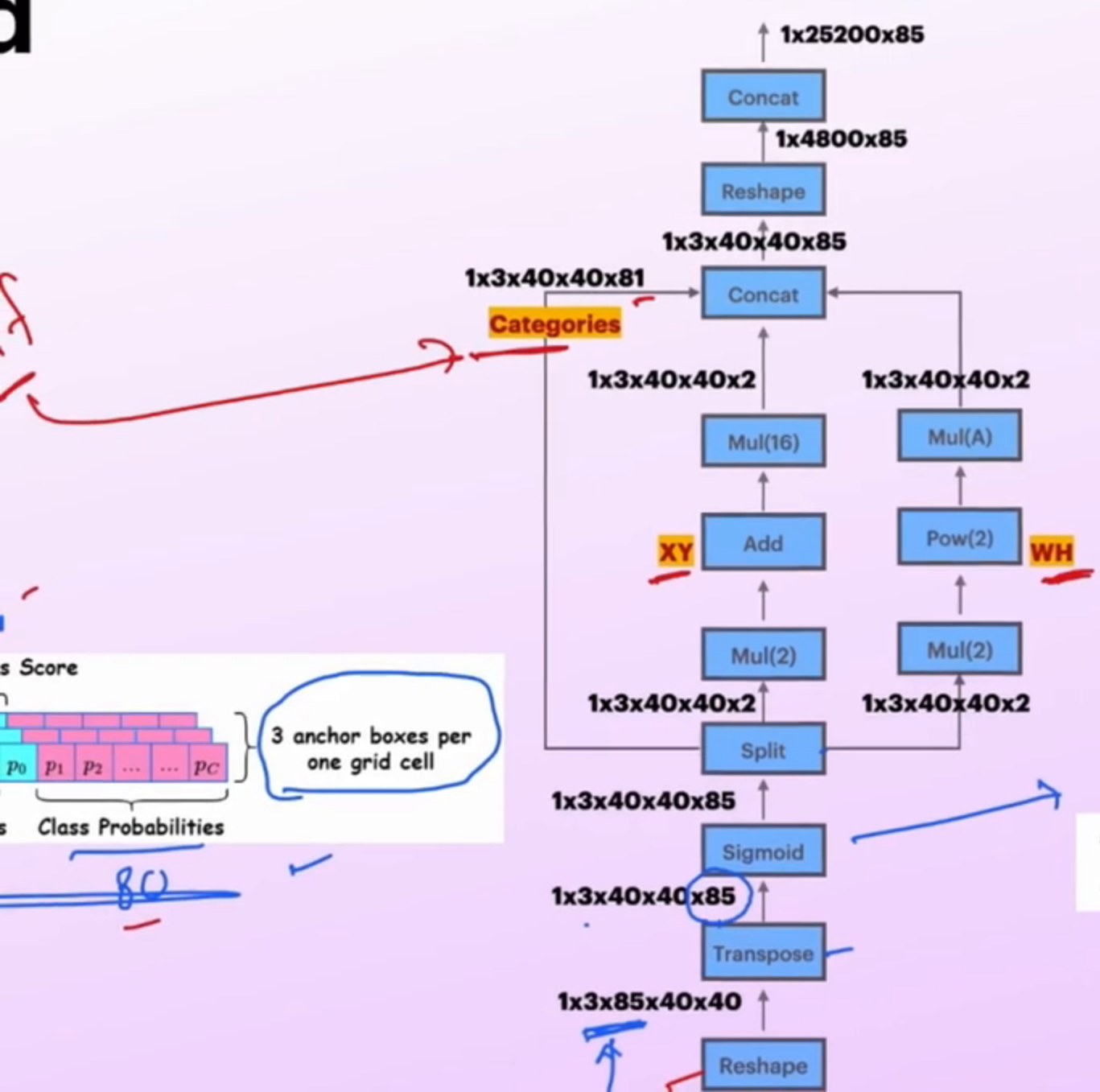

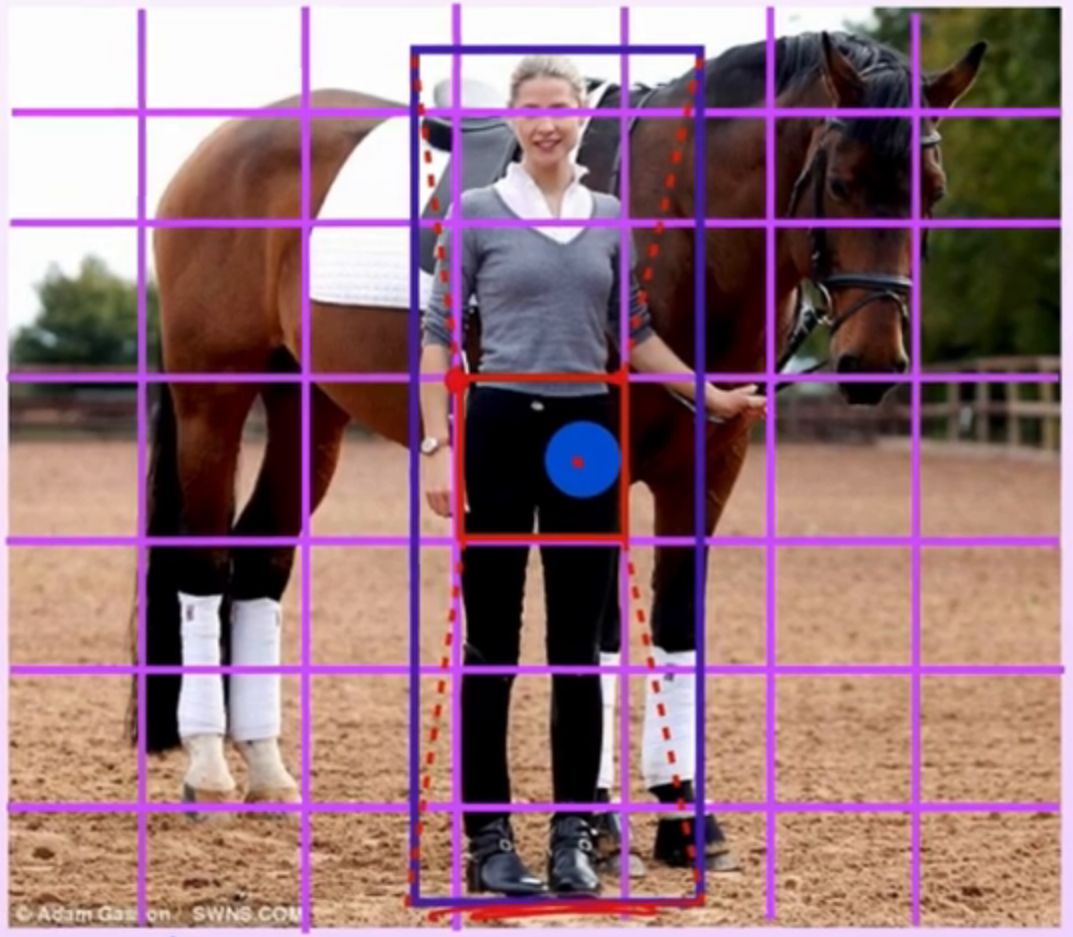

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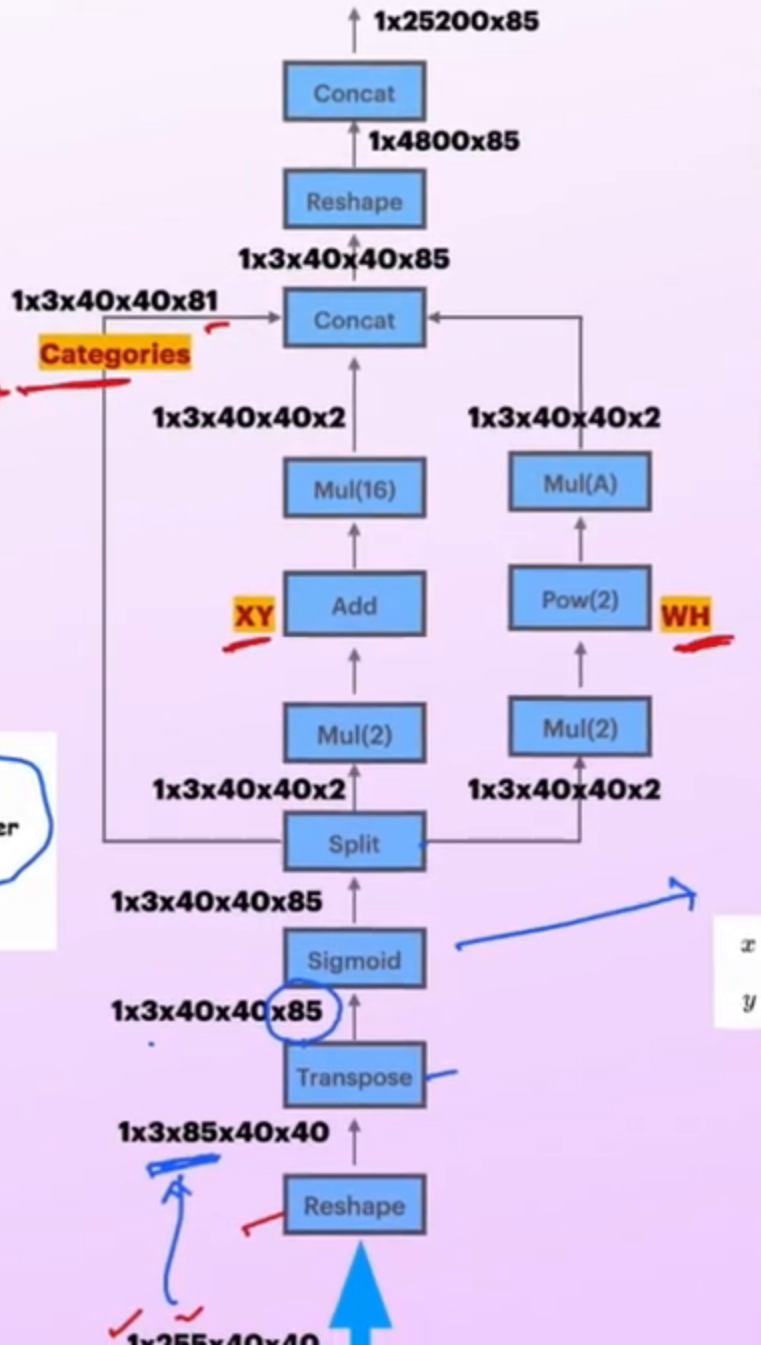

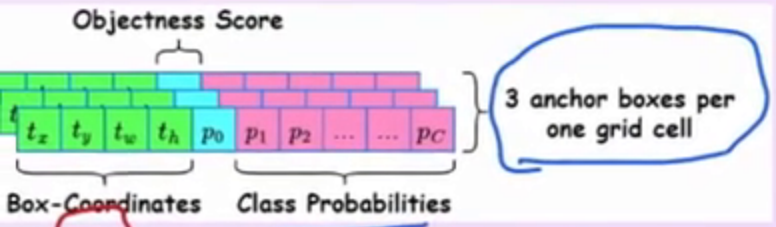

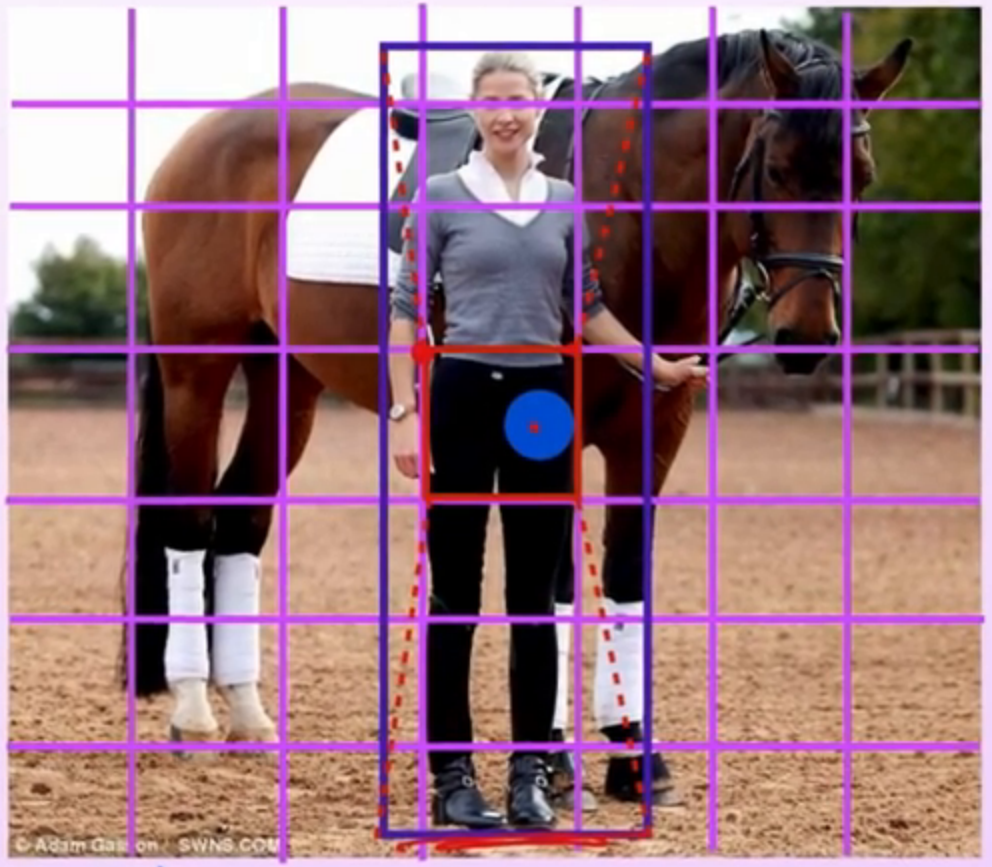

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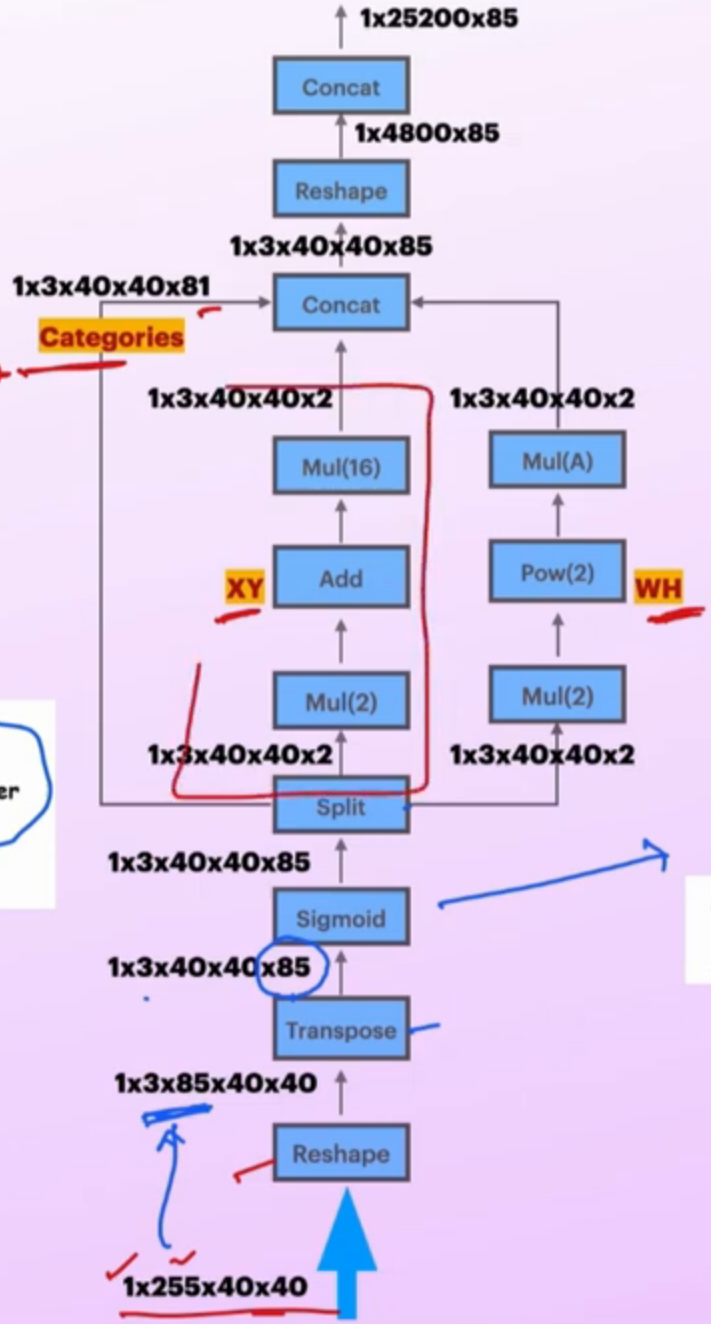

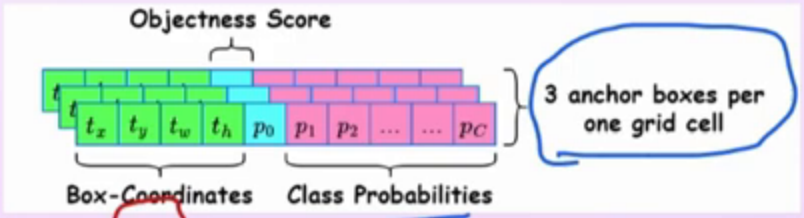

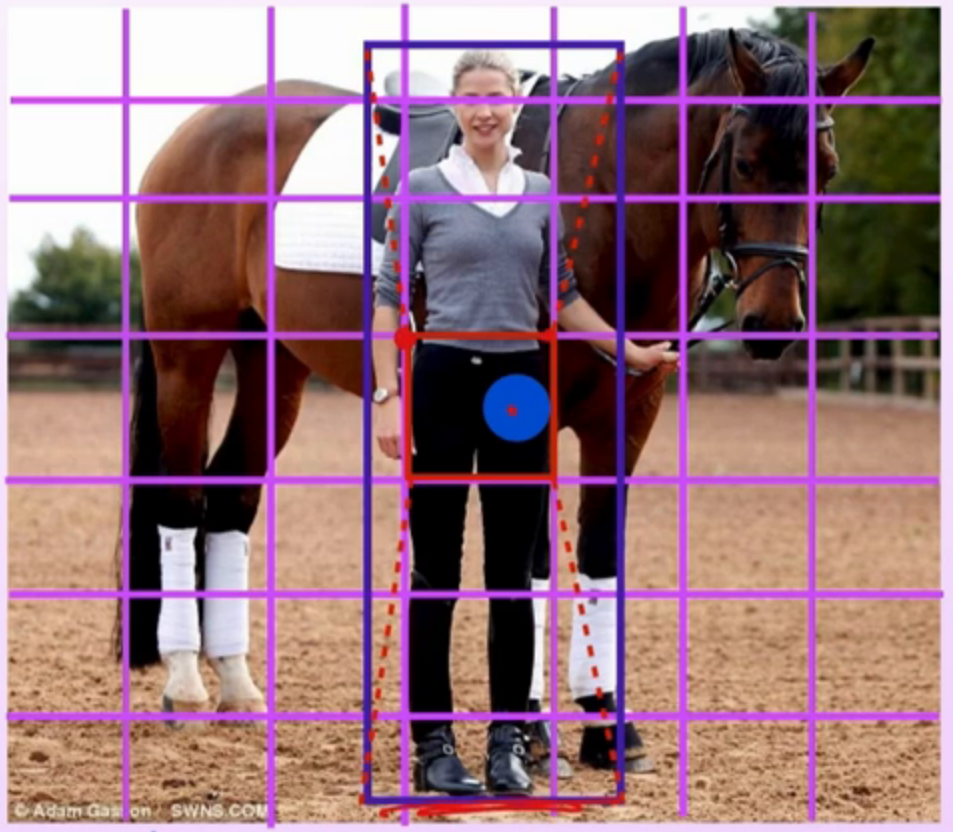

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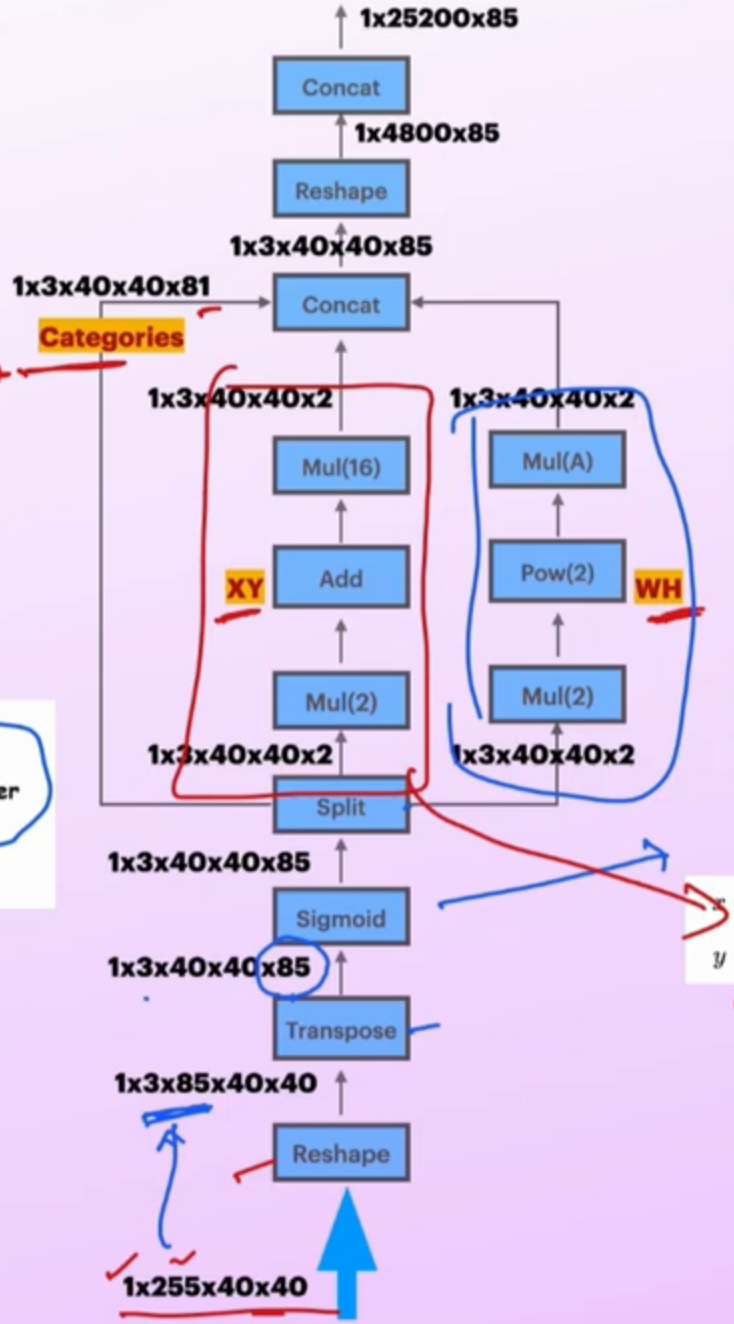

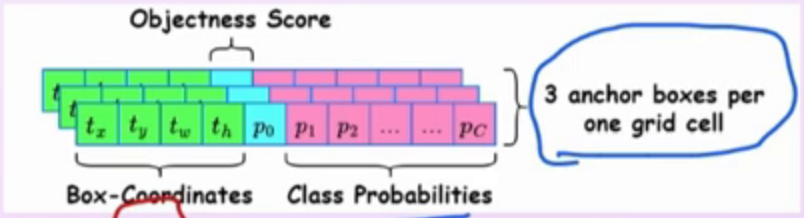

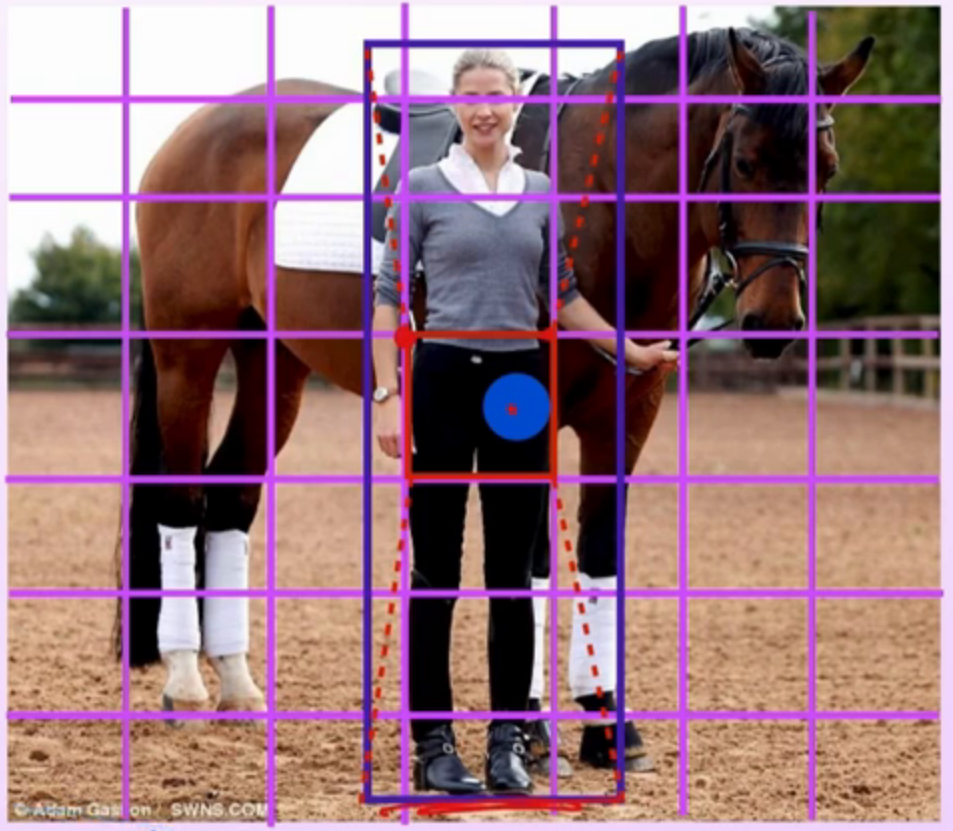

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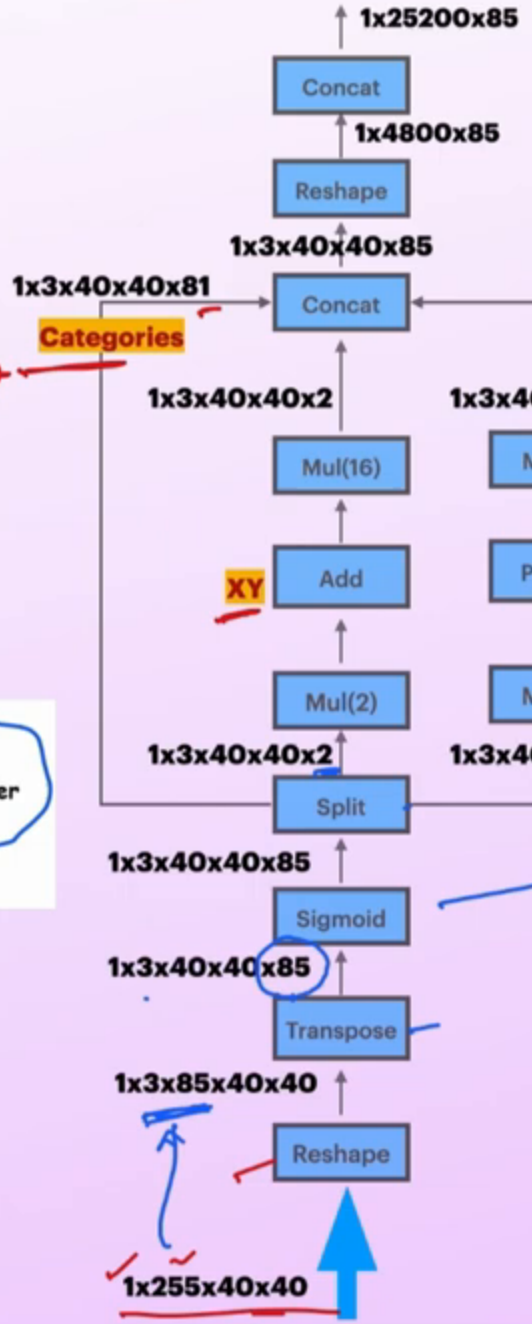

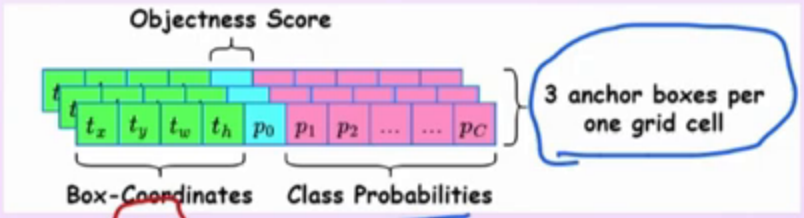

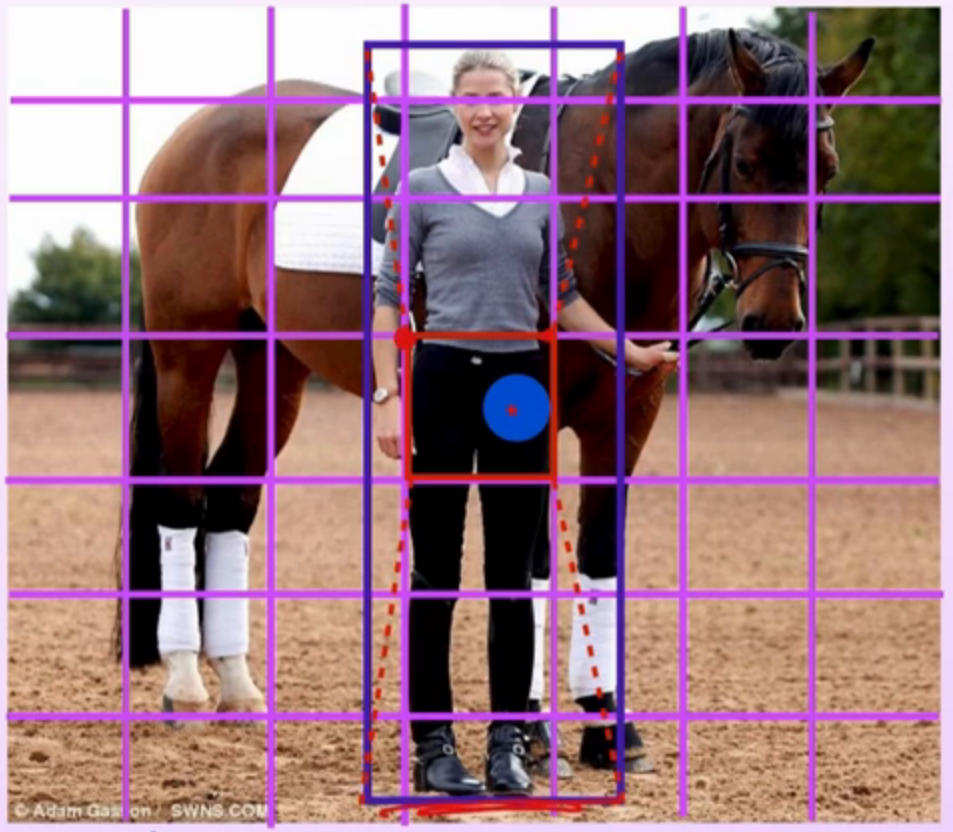

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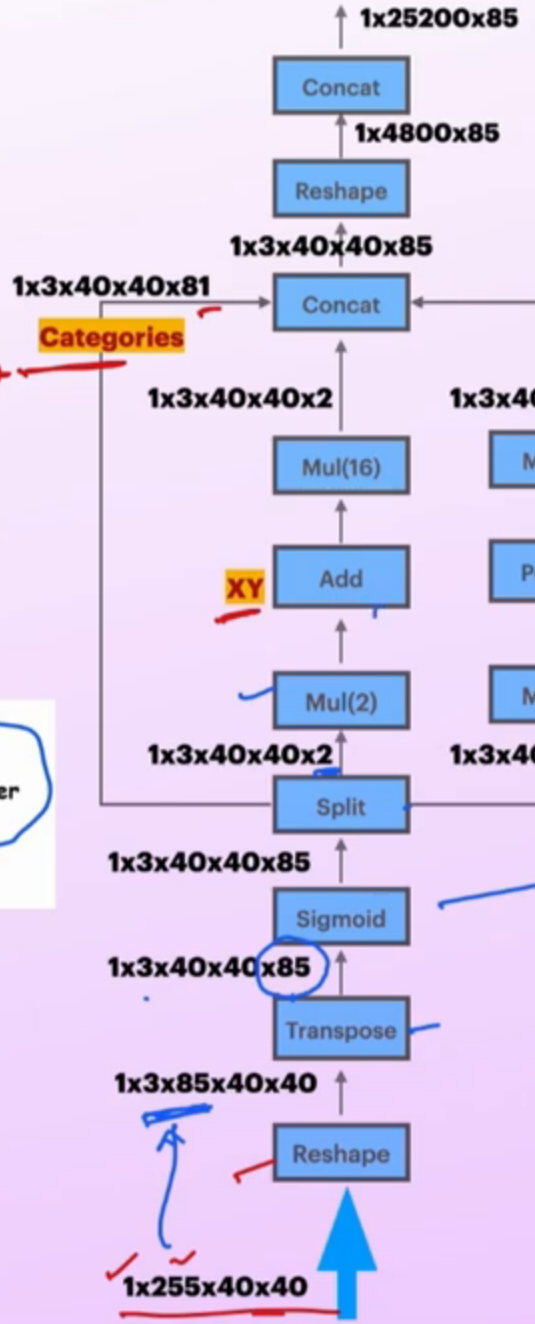

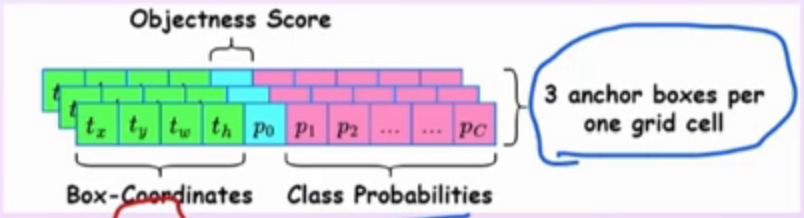

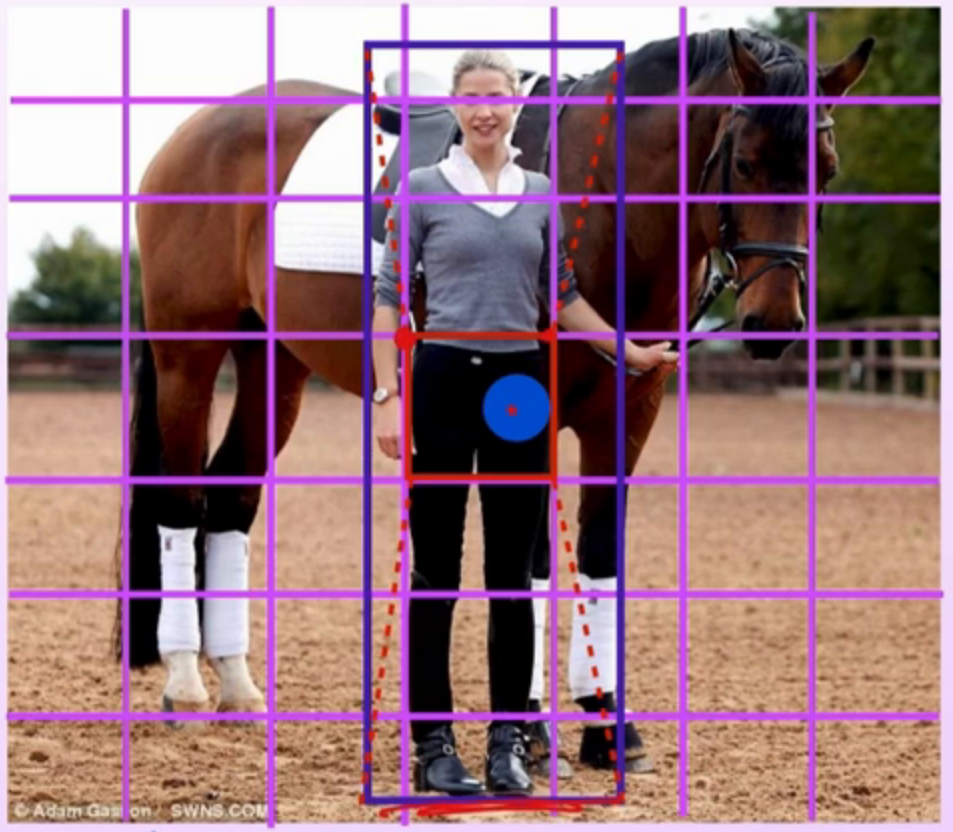

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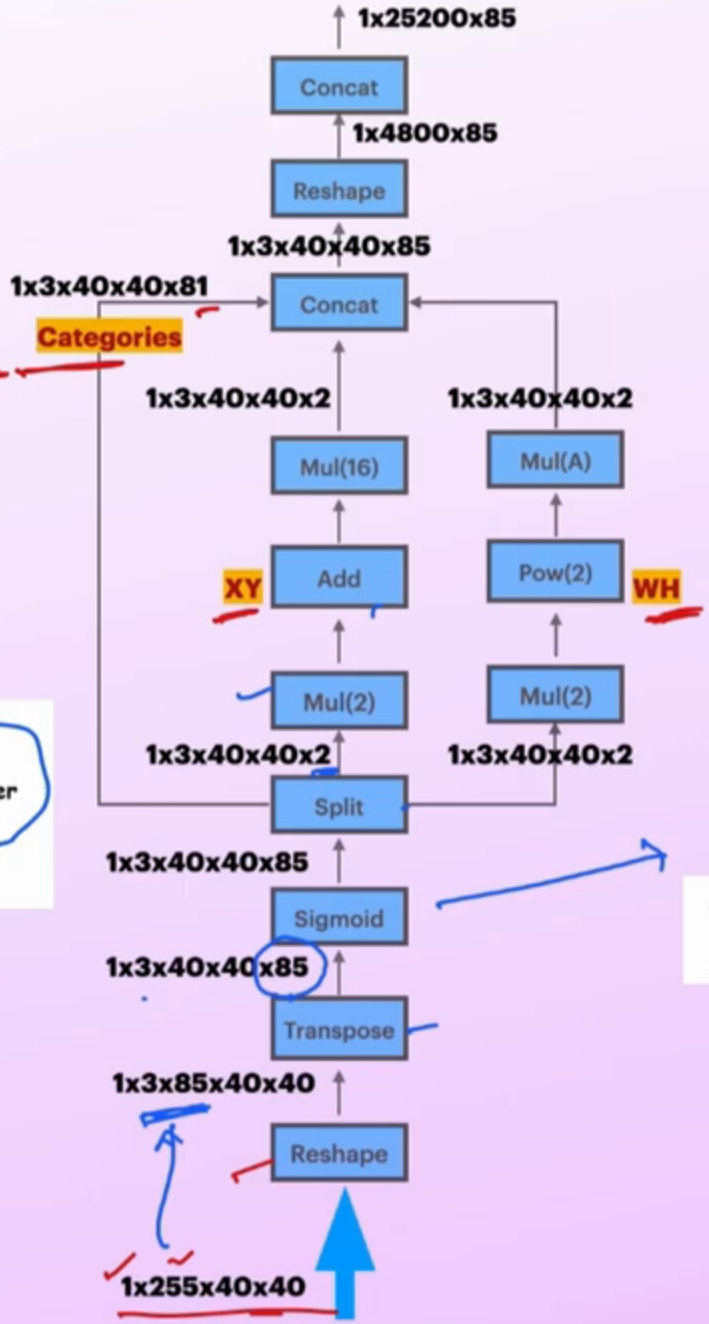

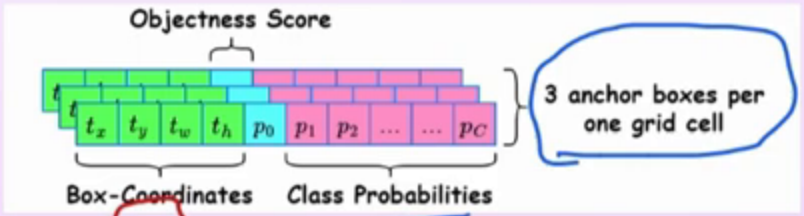

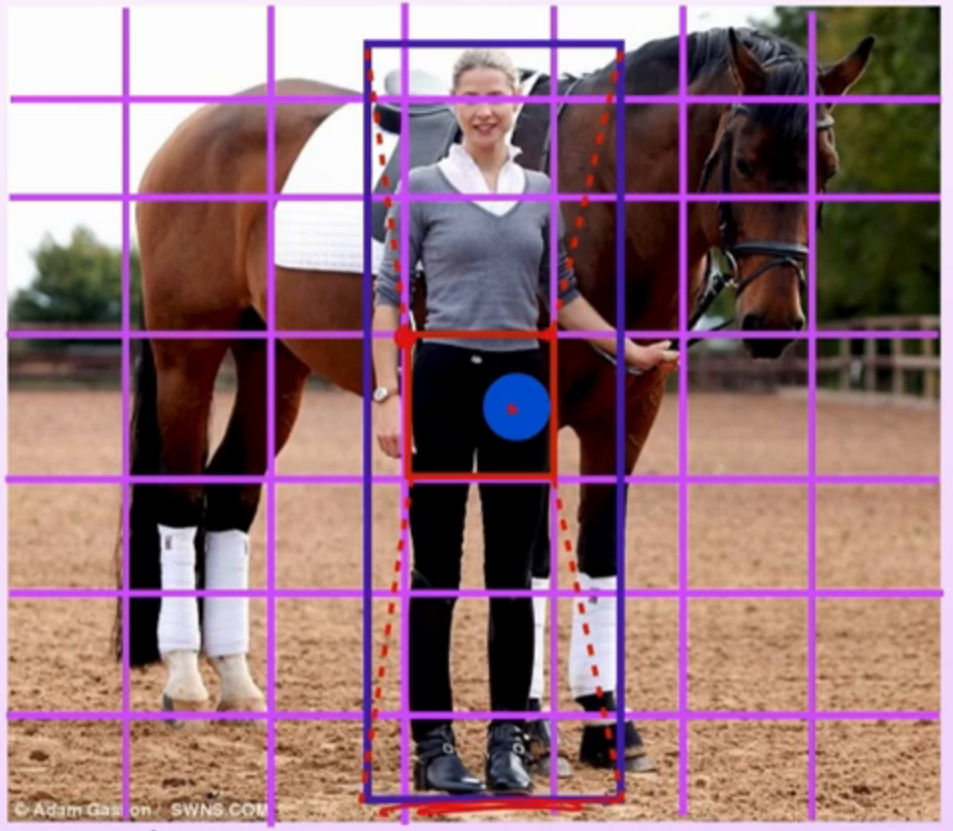

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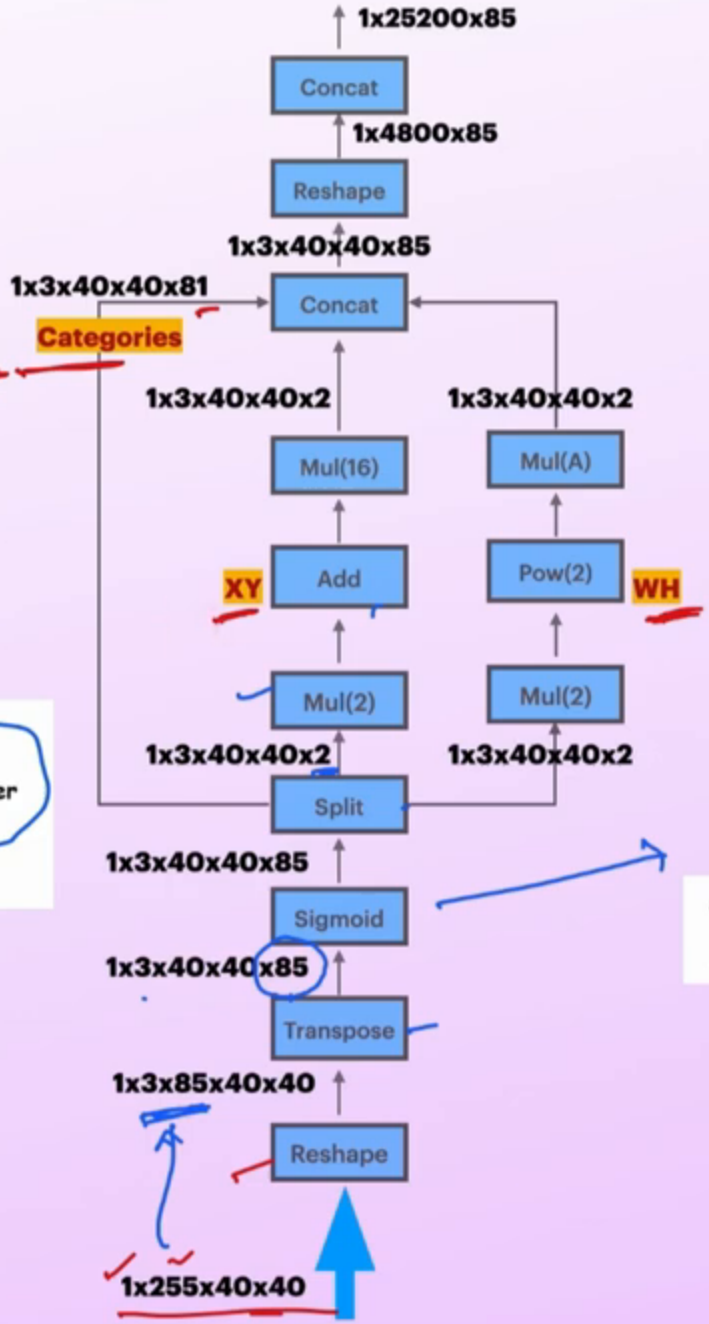

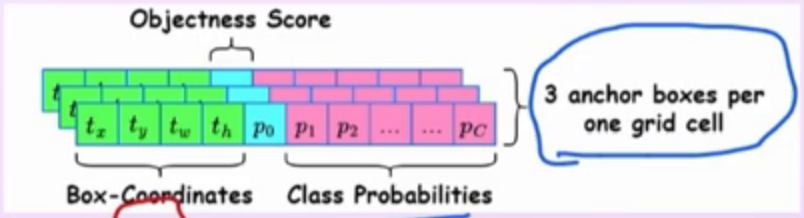

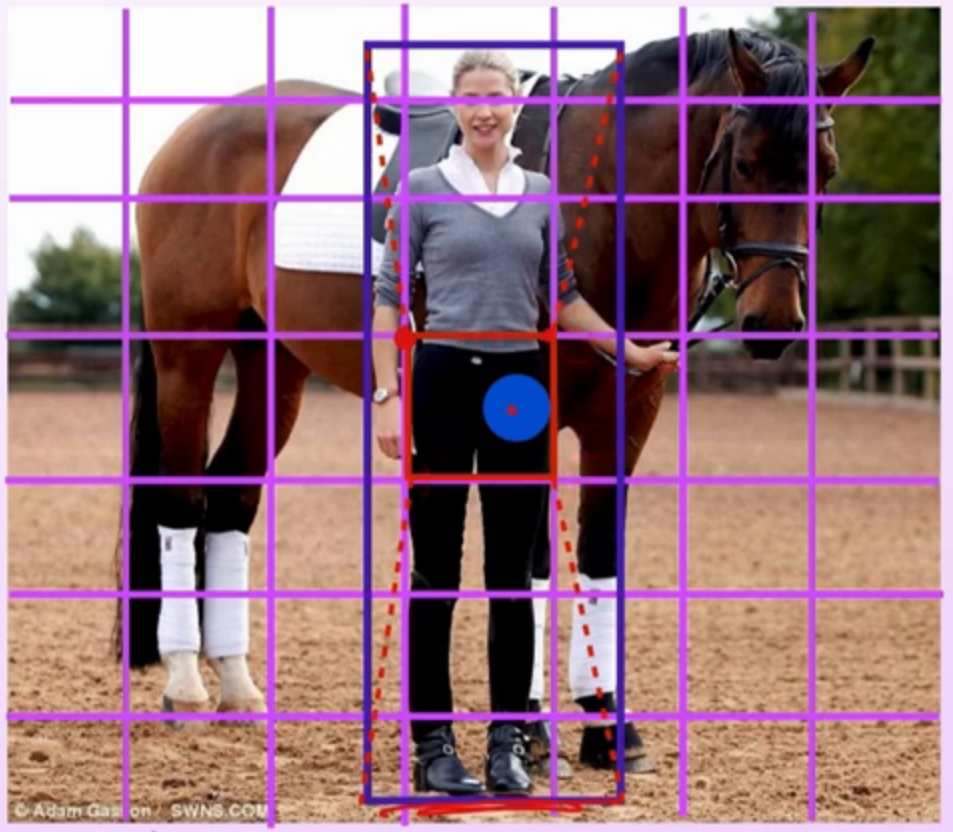

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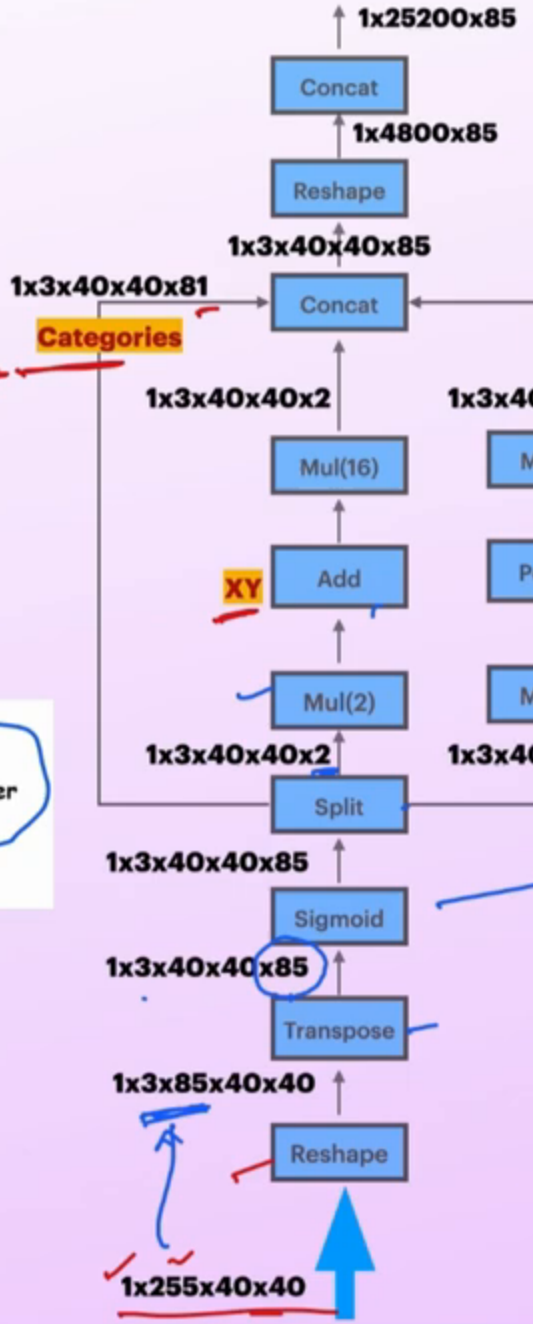

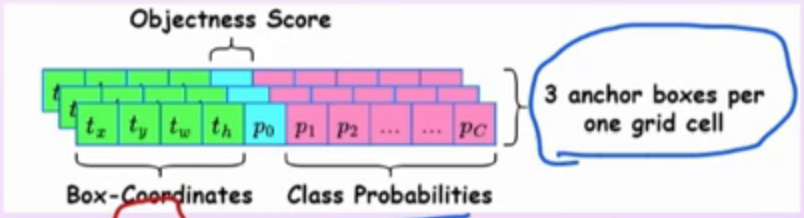

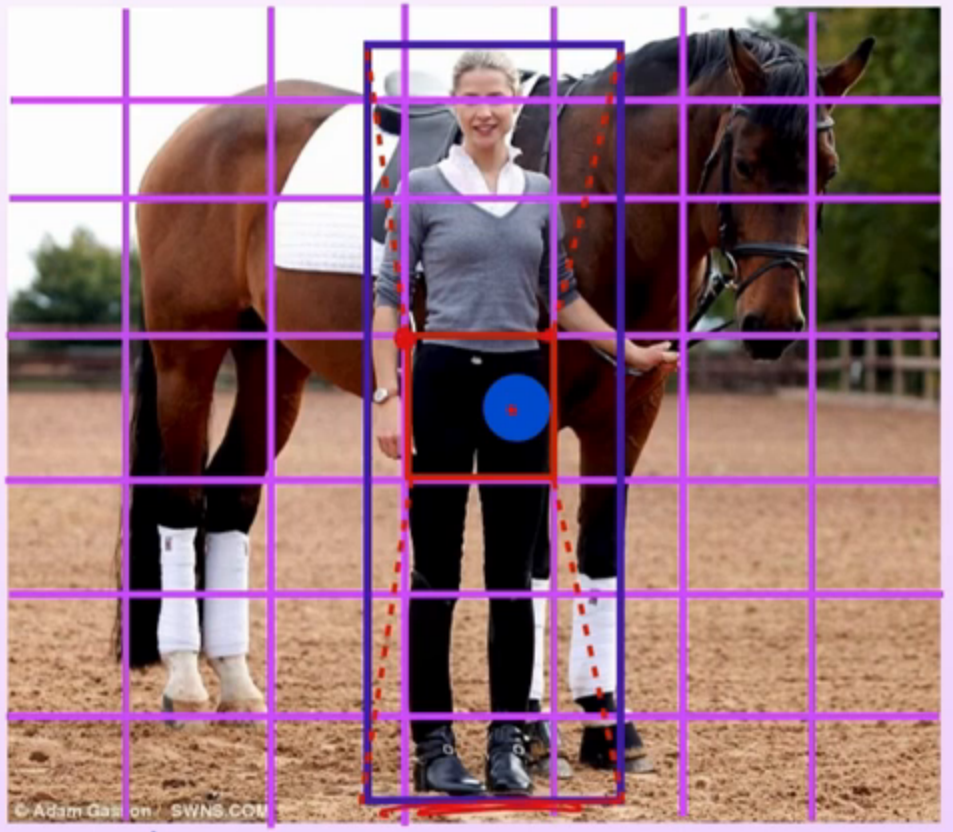

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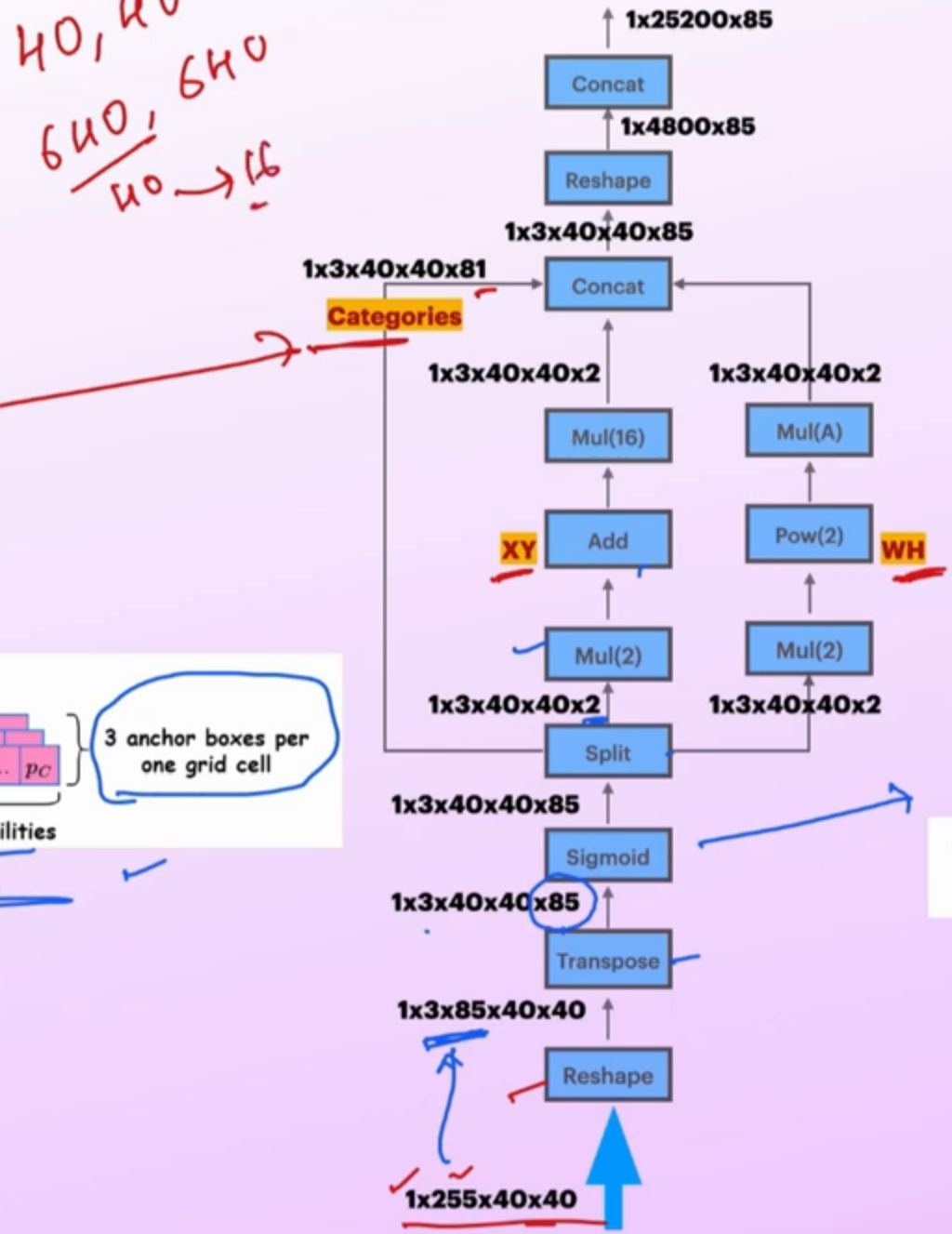

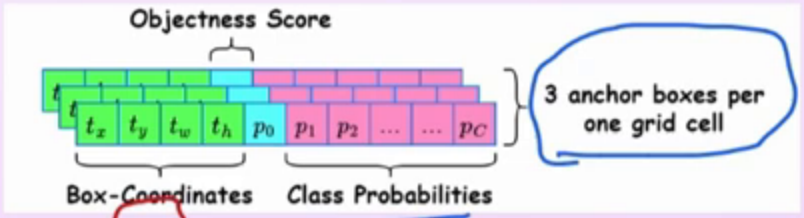

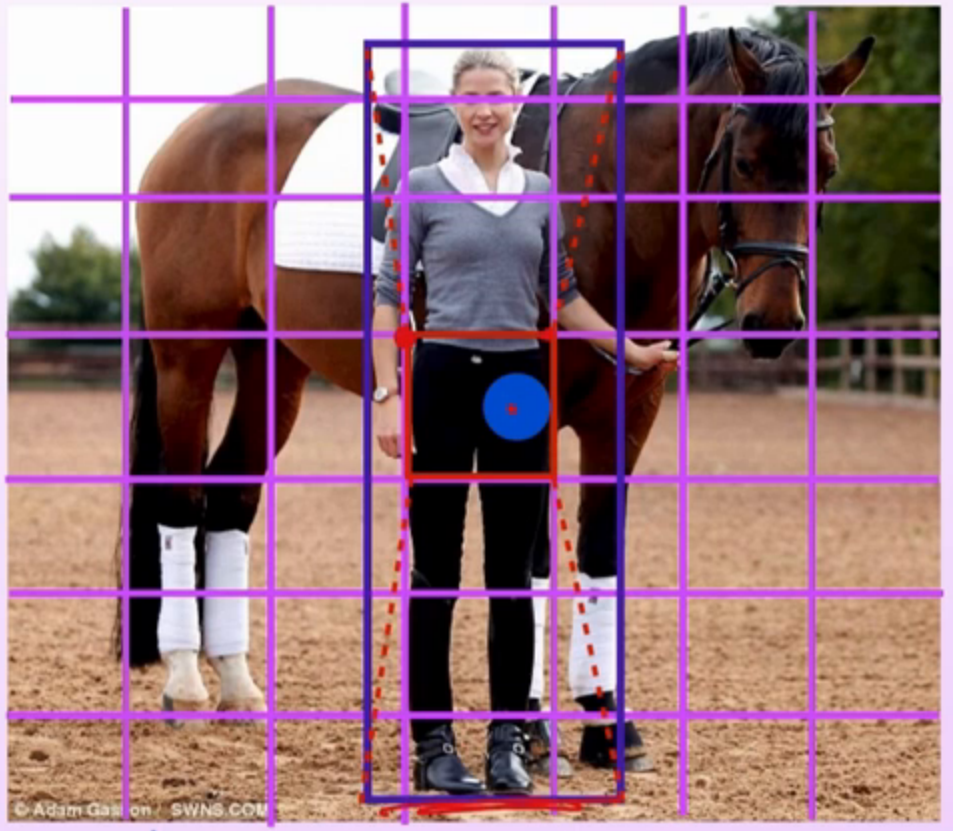

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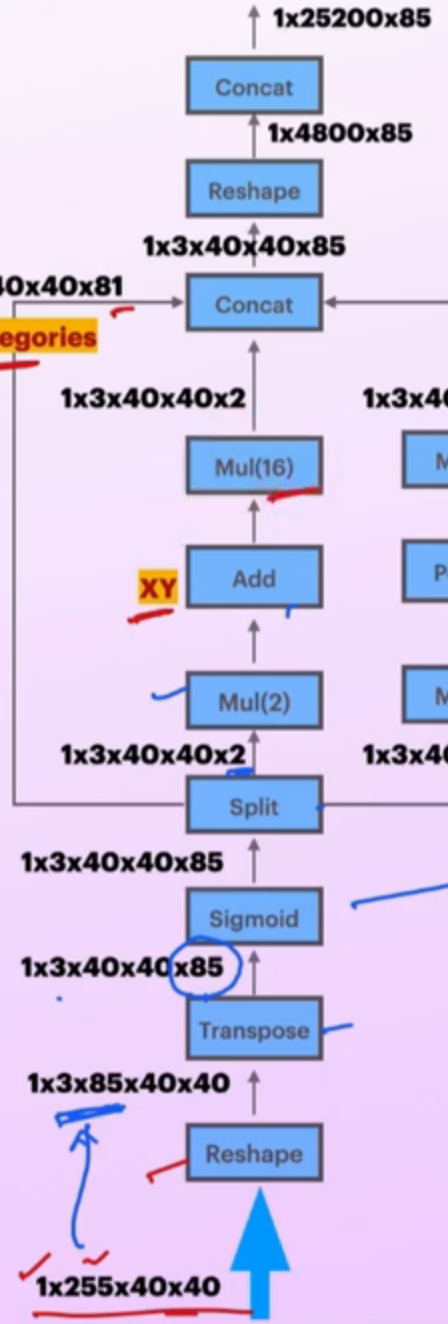

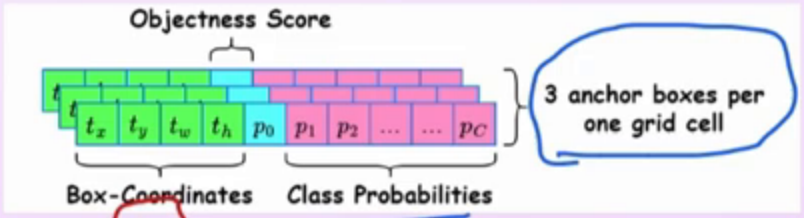

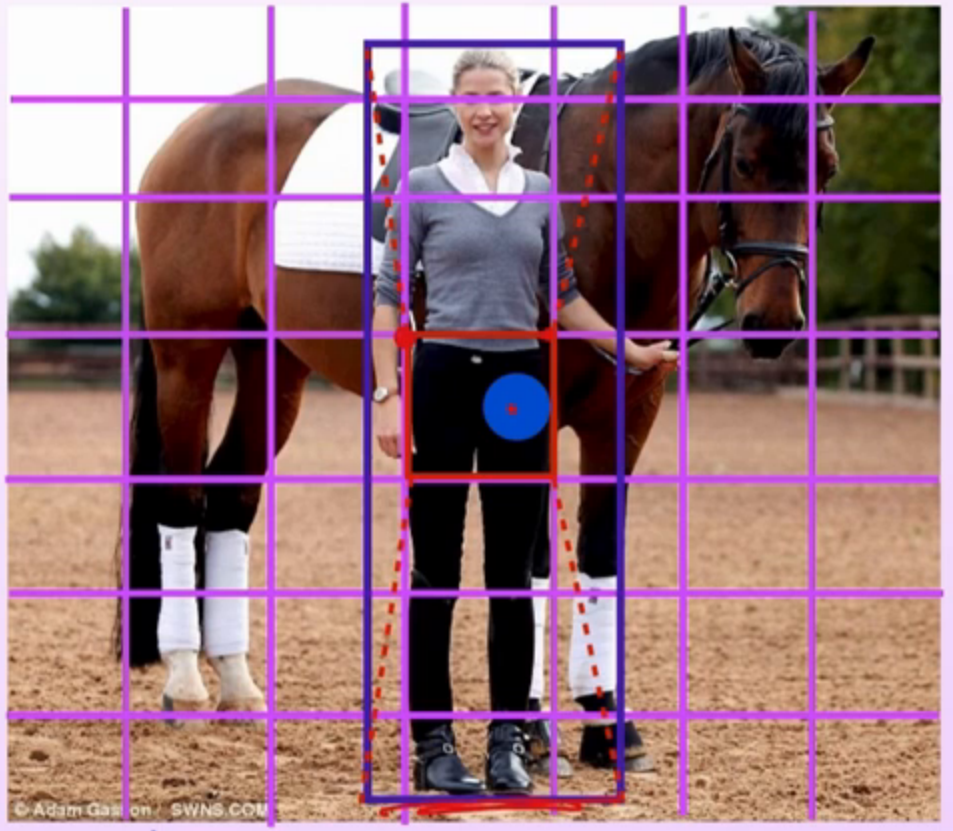

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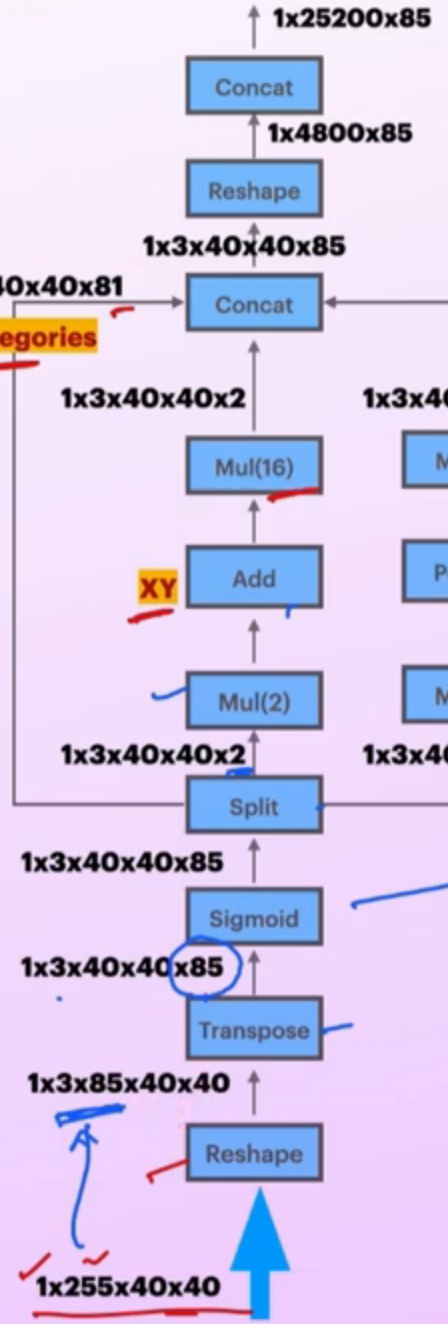

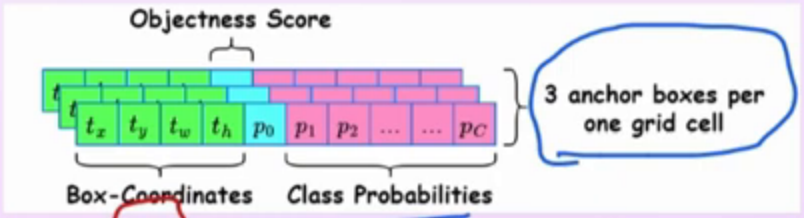

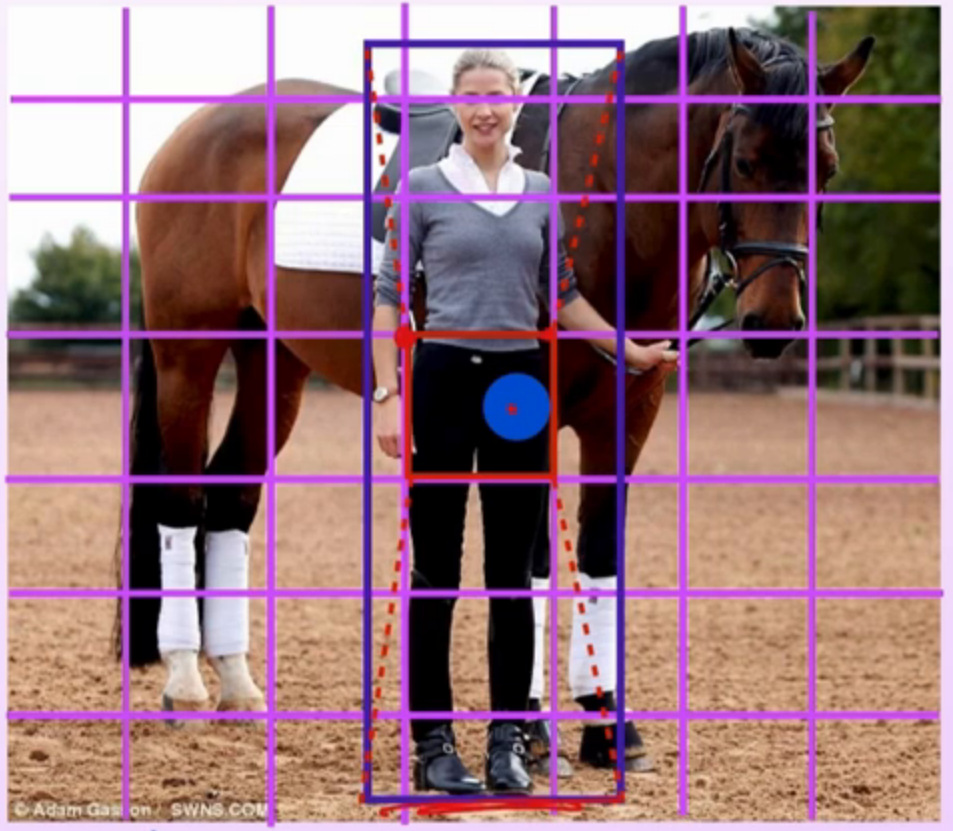

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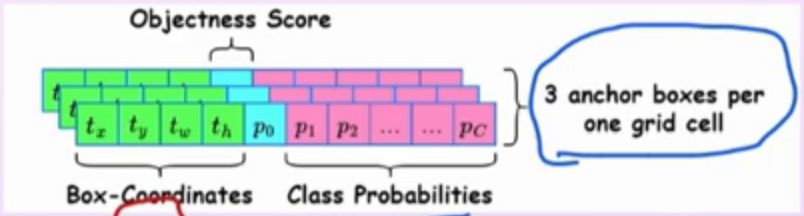

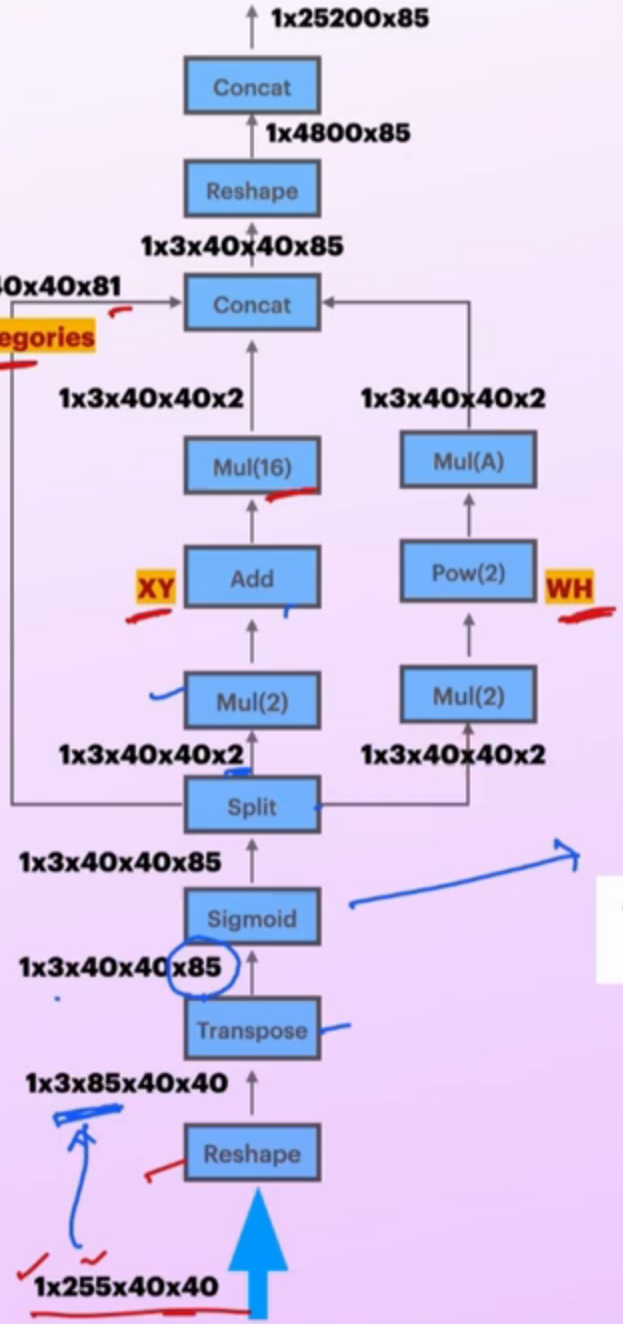

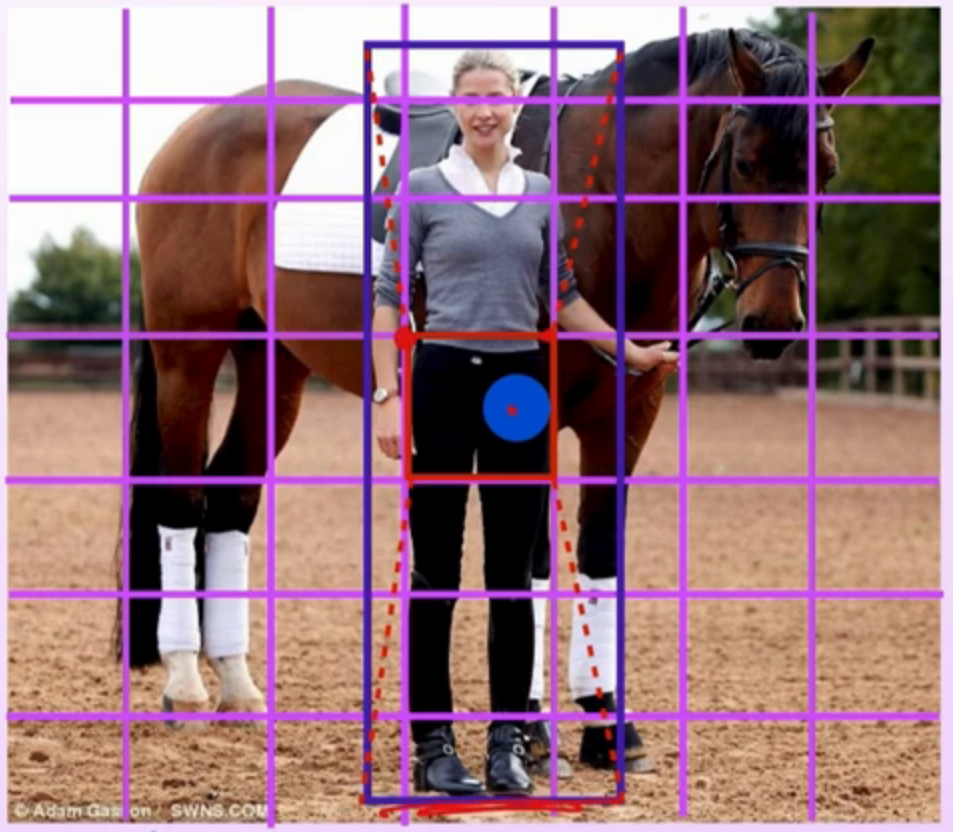

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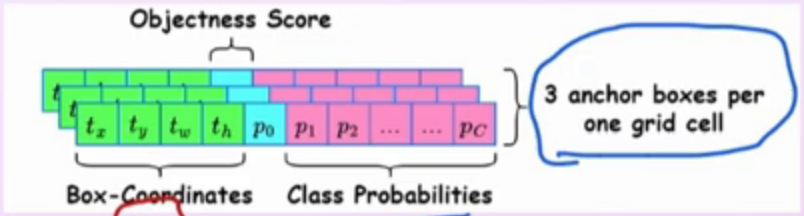
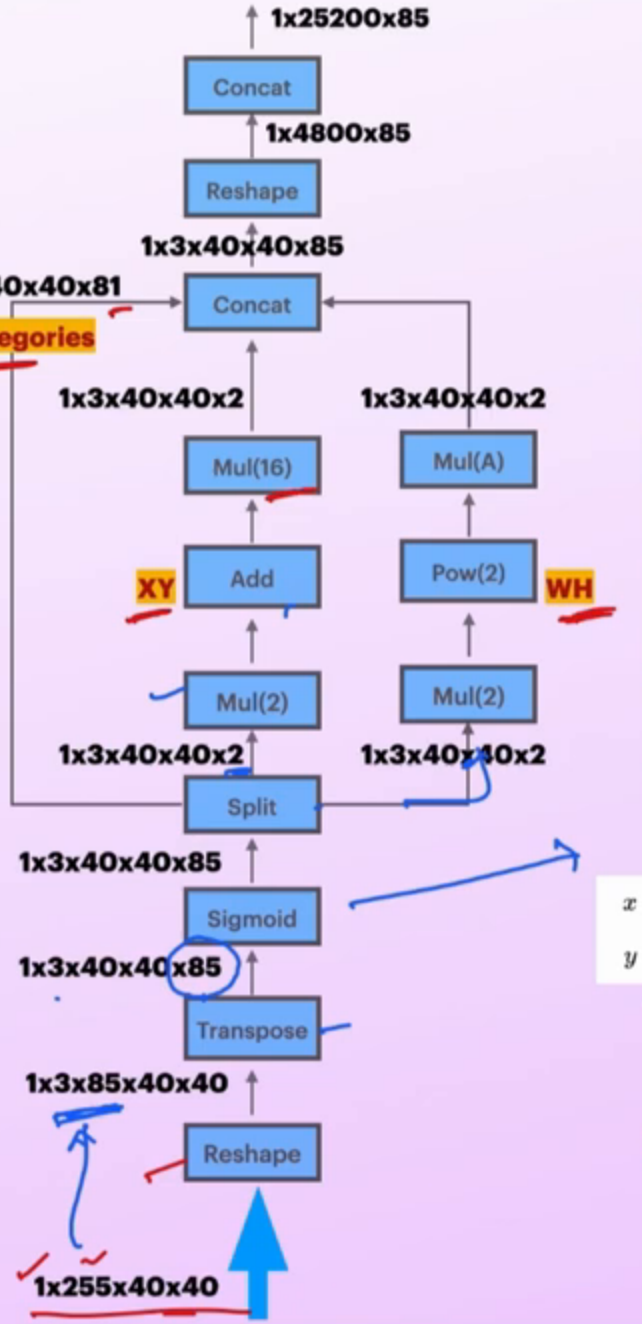
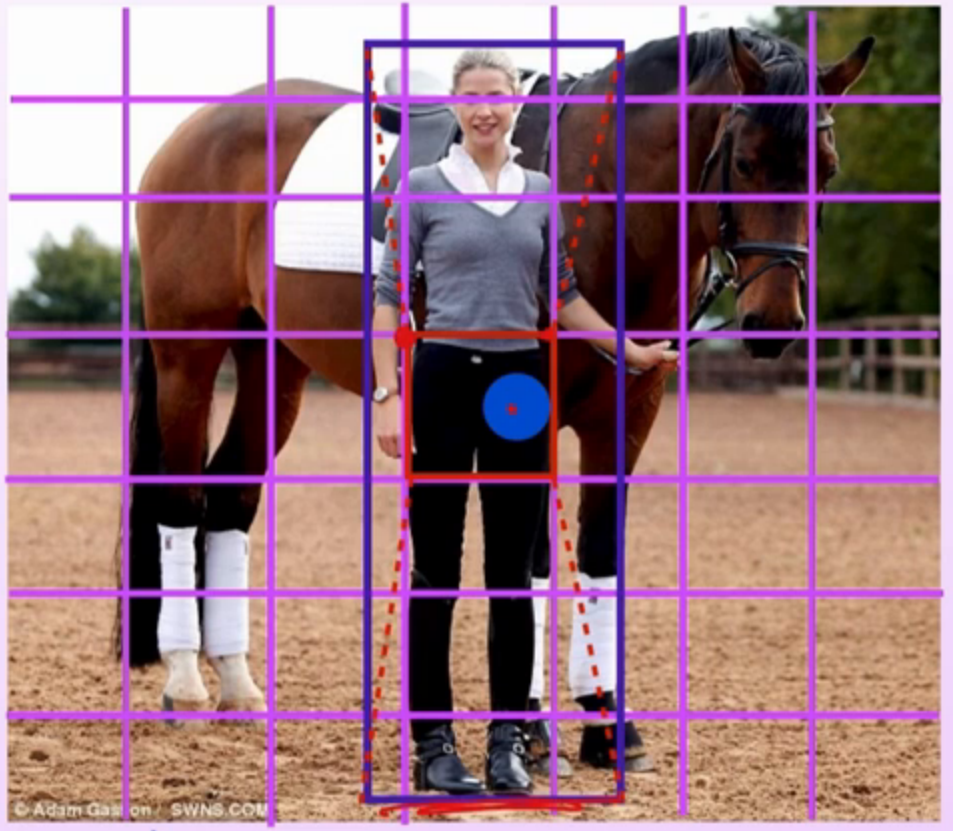




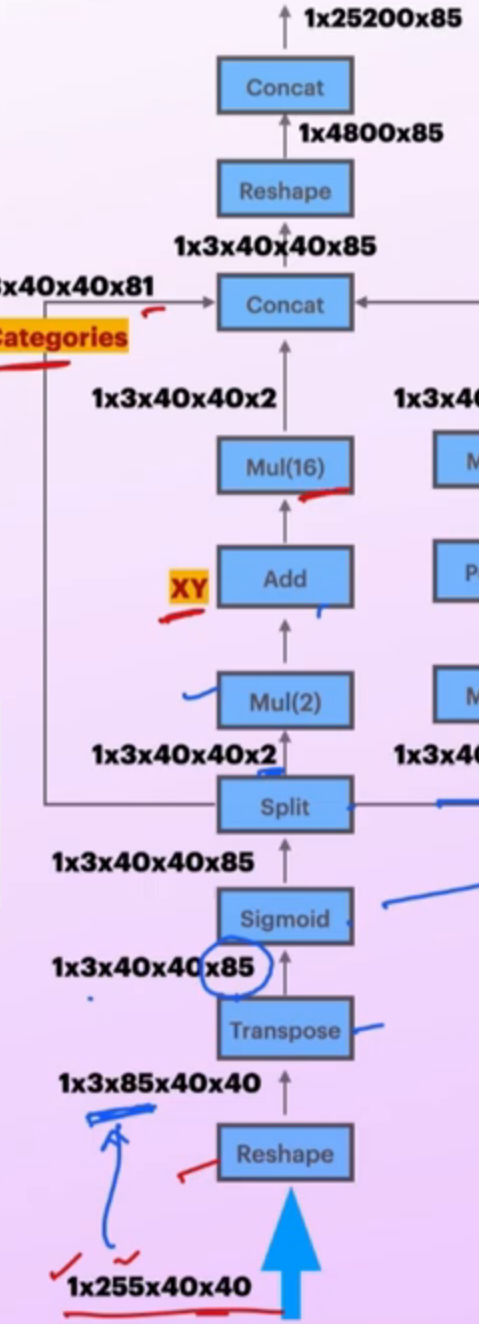


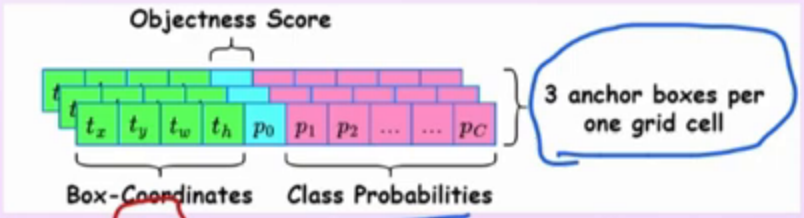
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

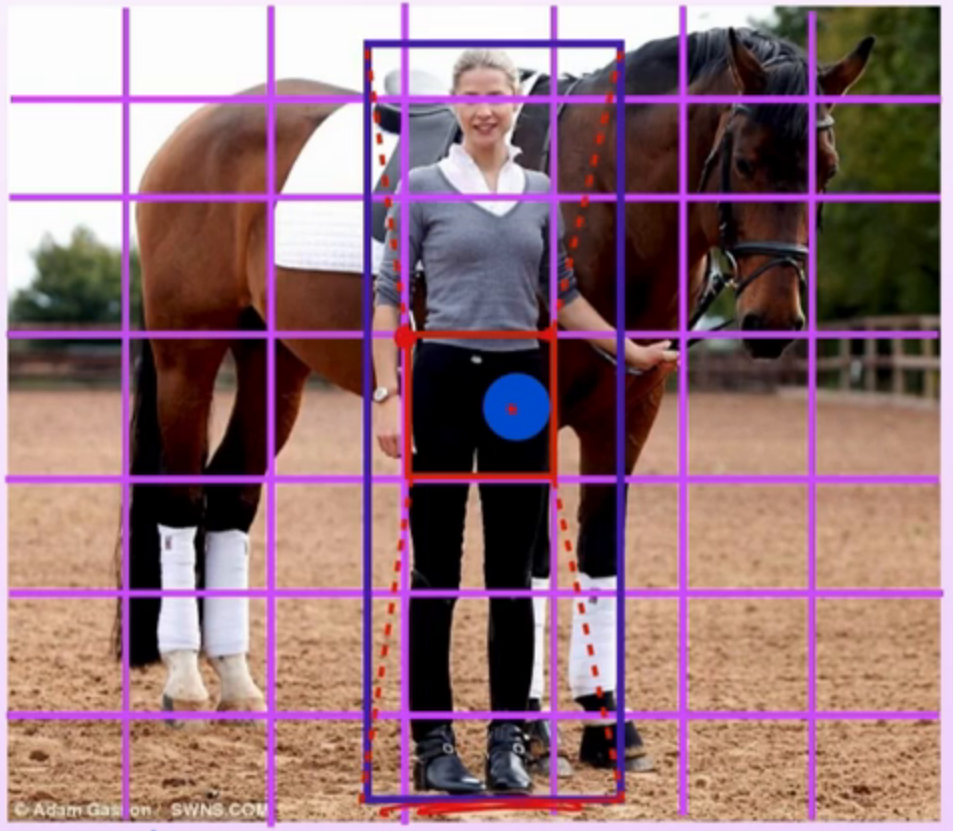
$$w = p_w \times (2 \cdot \sigma(t_w))^2$$
$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

Head

NMS & Postprocessing







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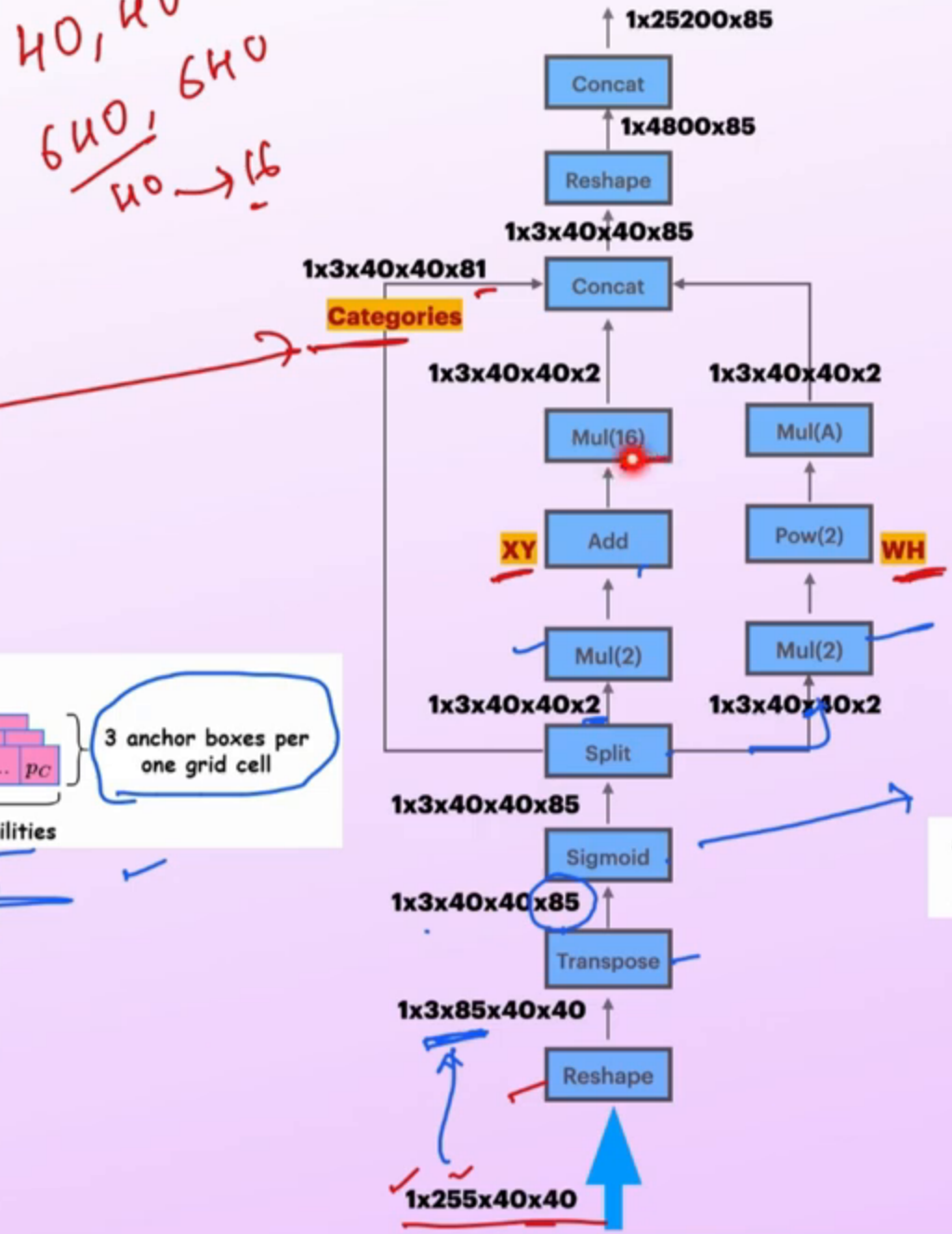

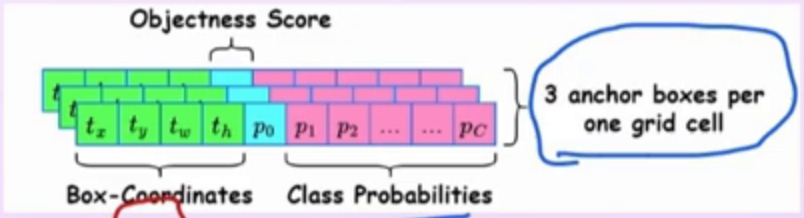

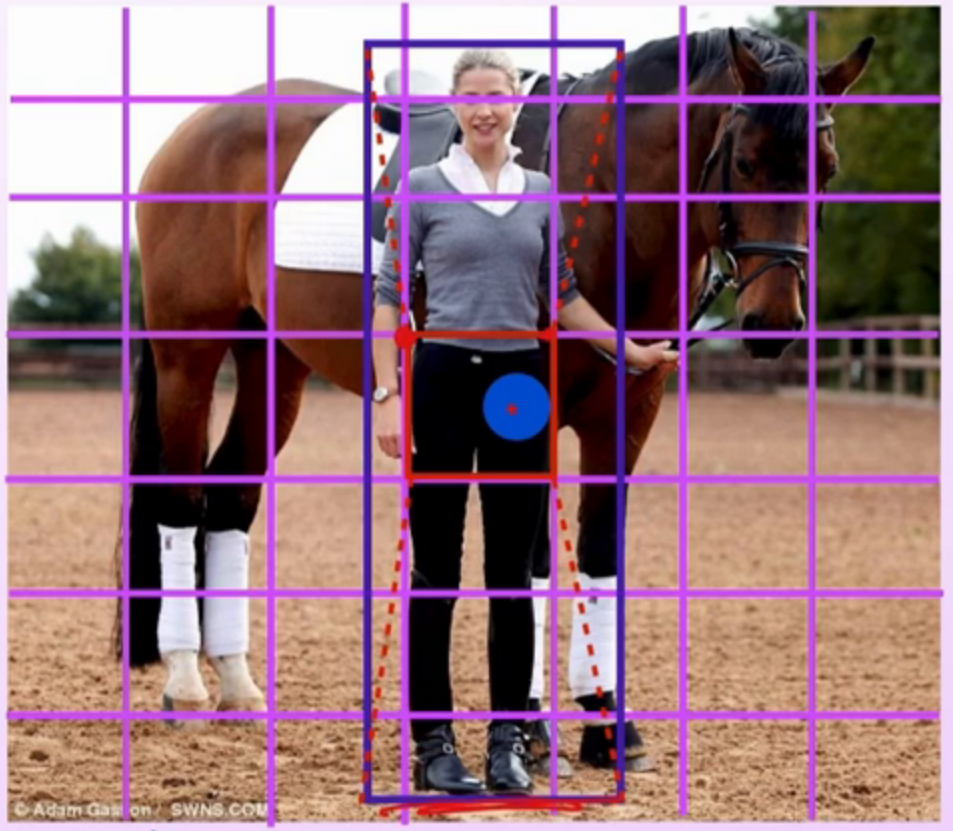

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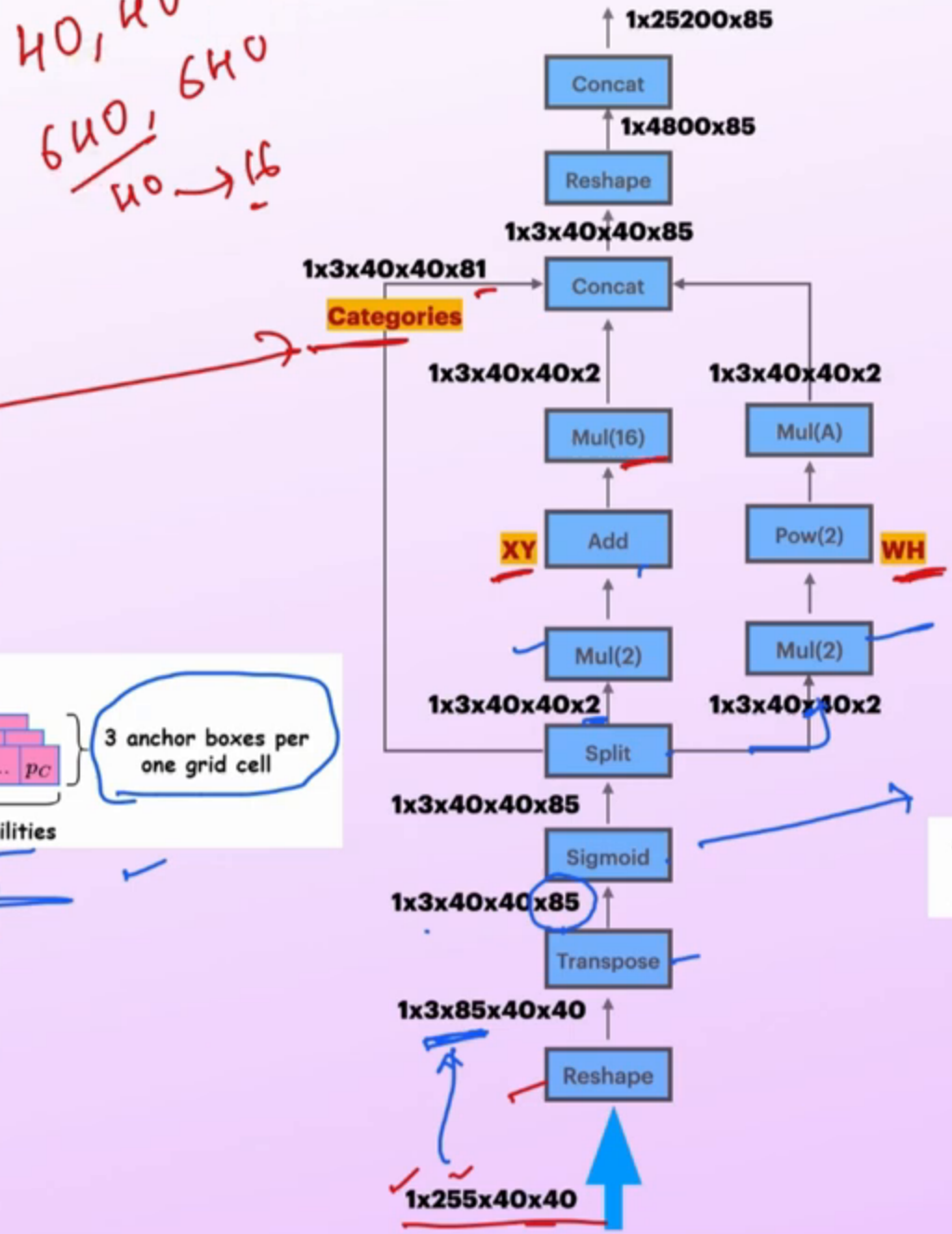

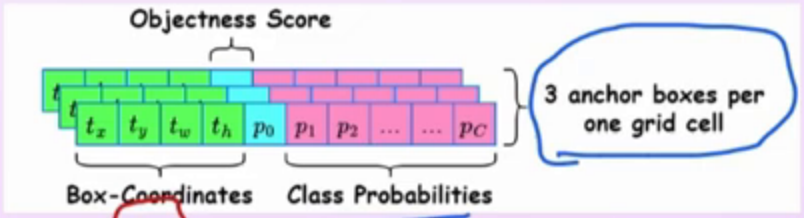

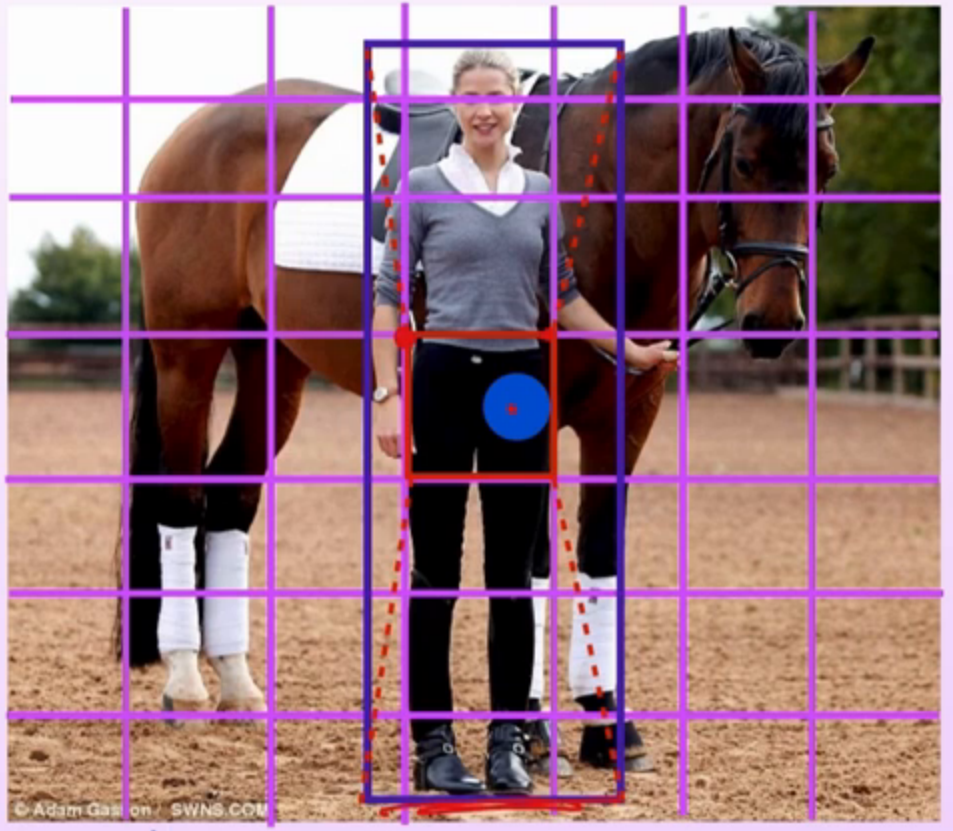

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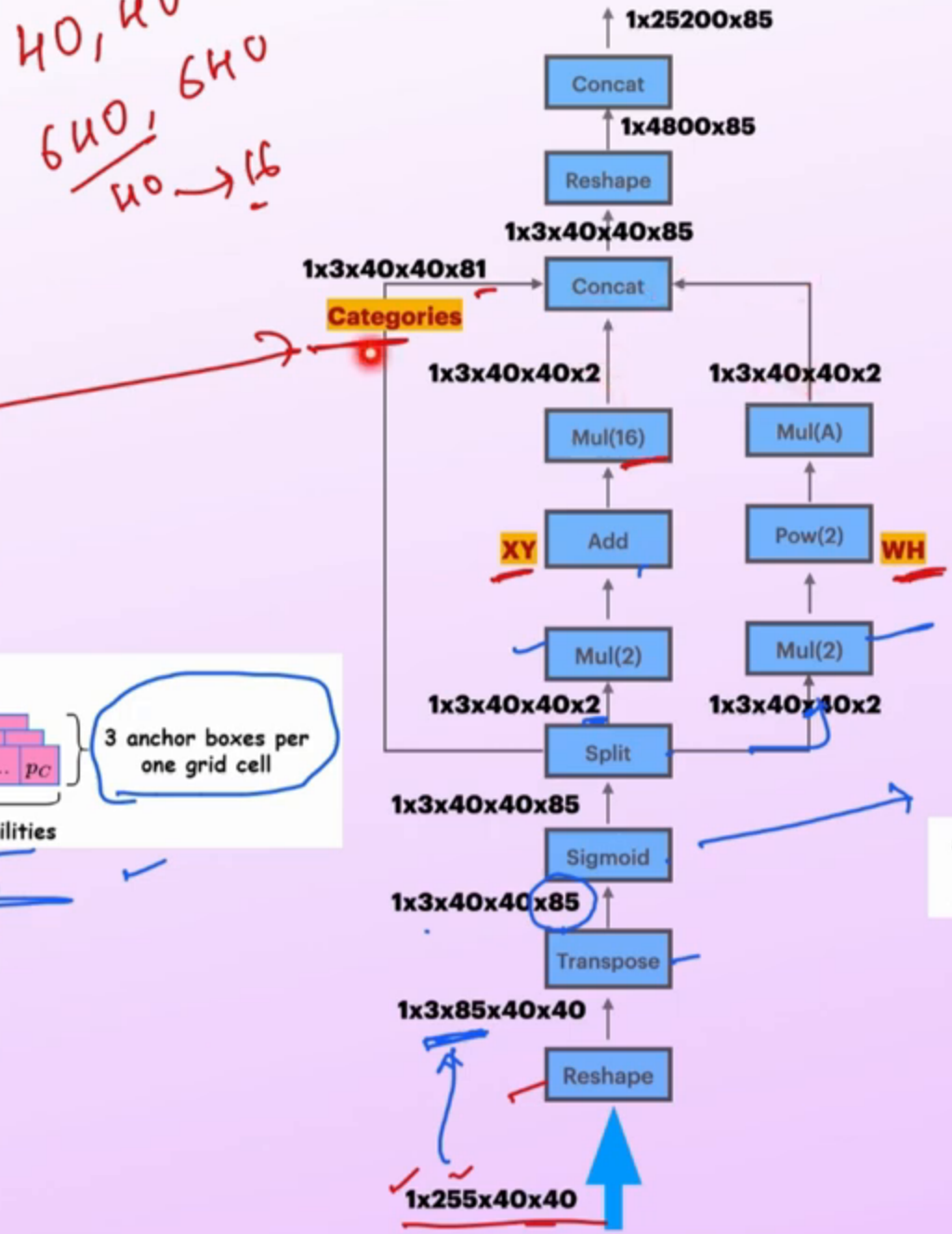

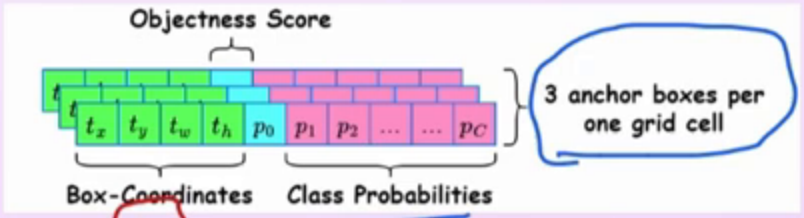

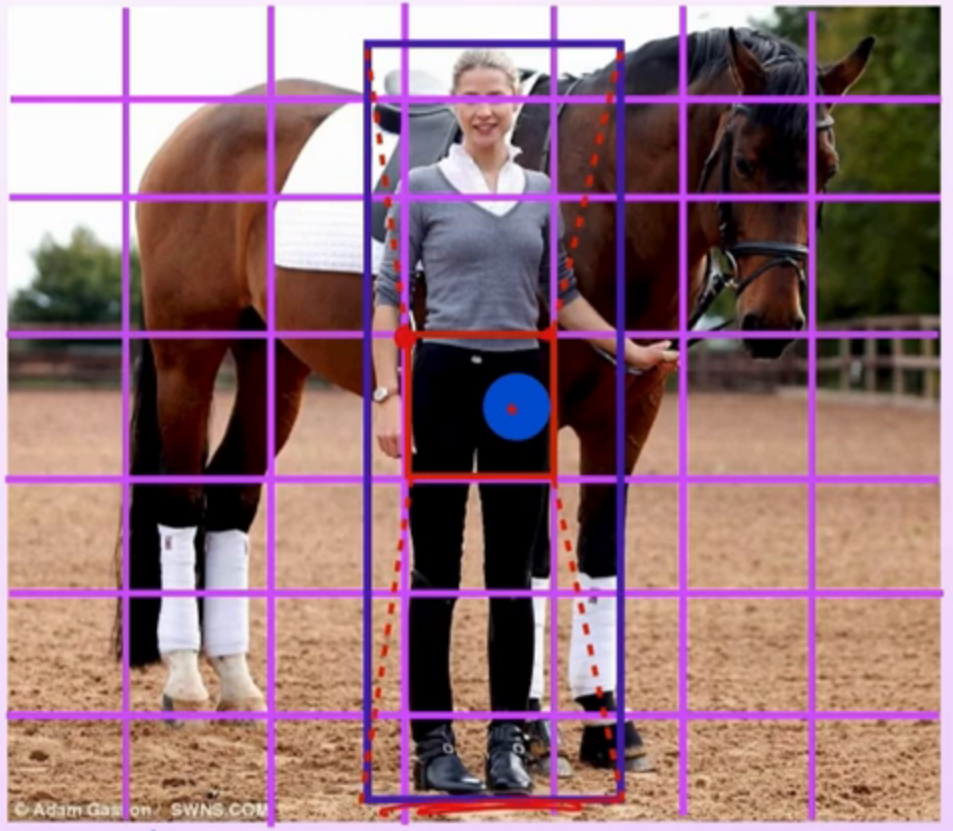

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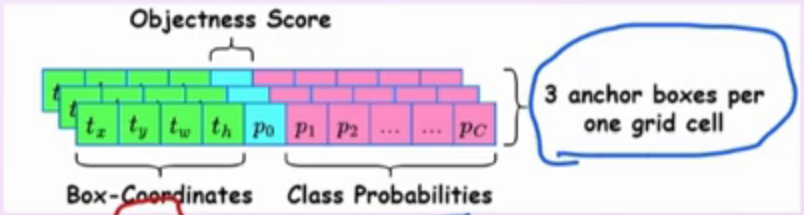

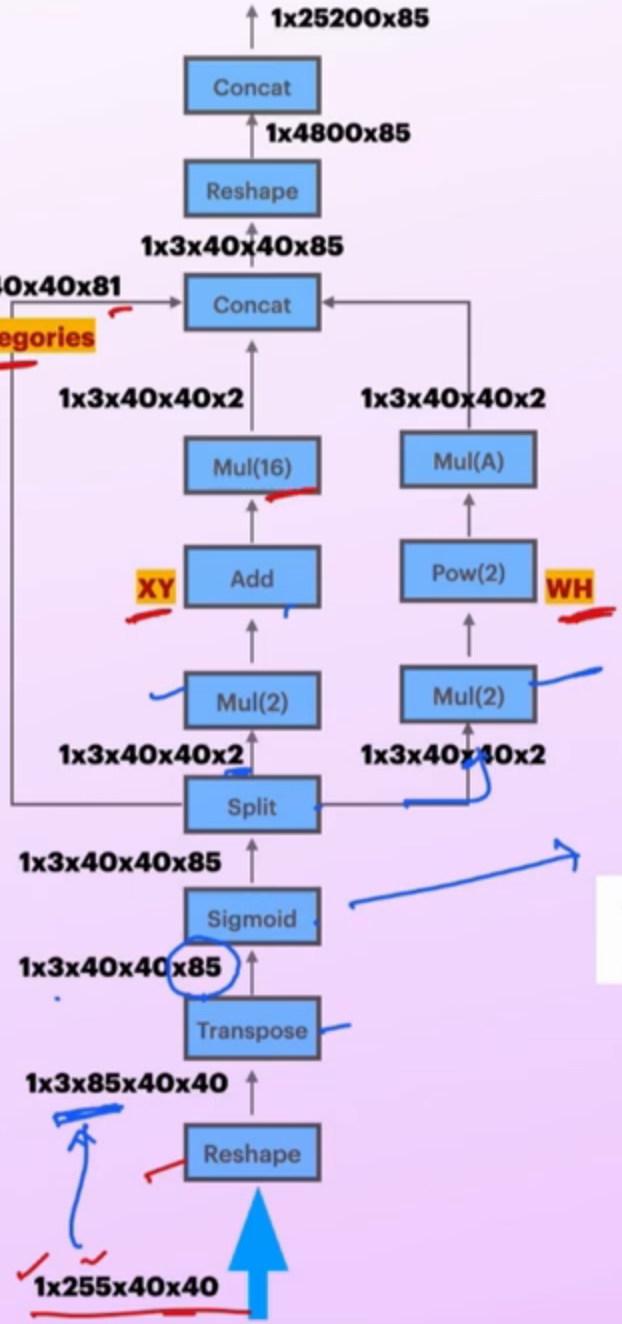

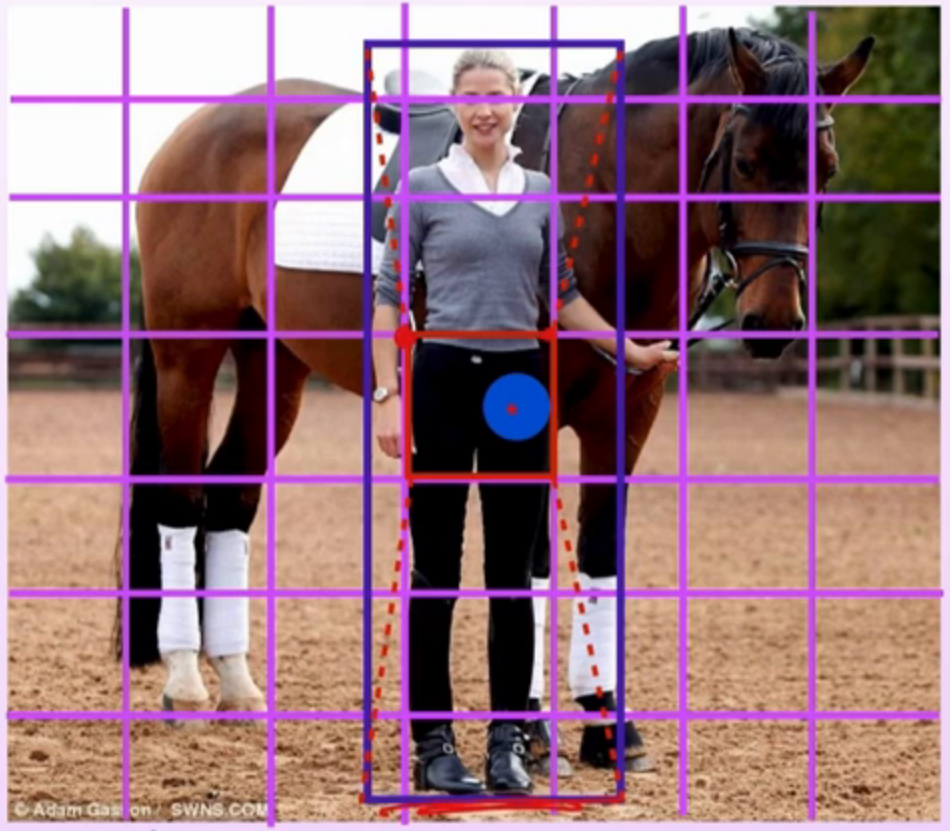

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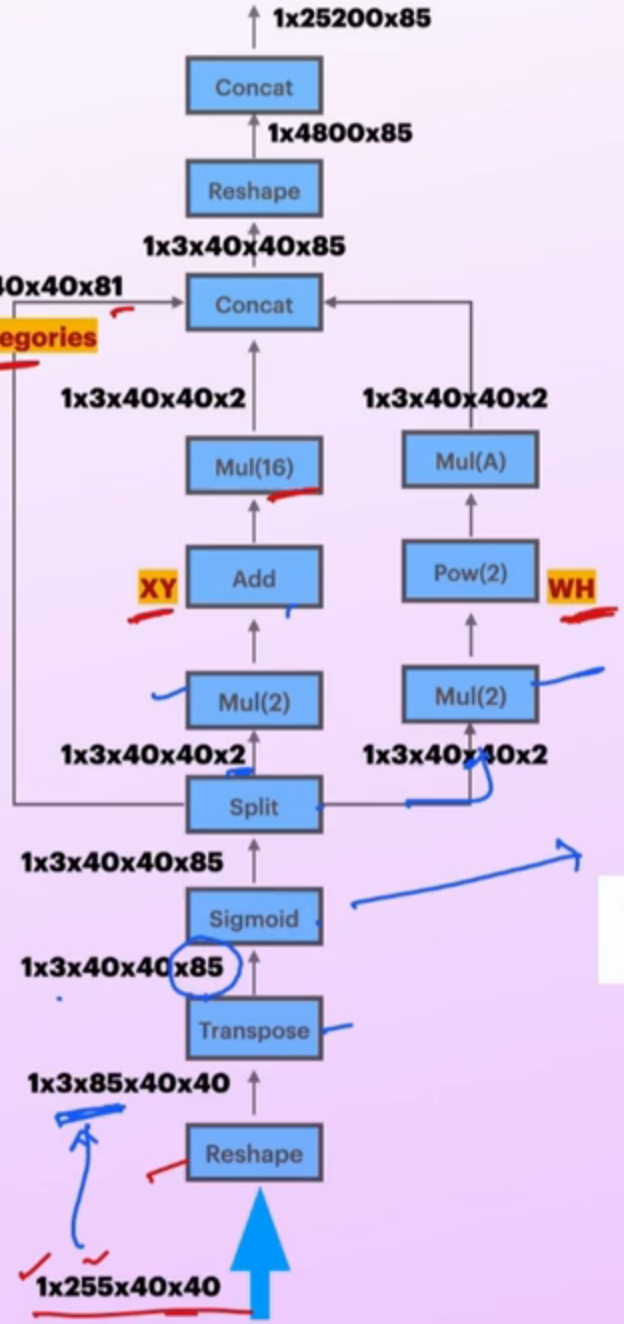

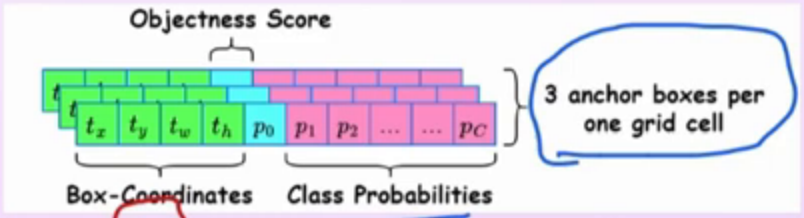

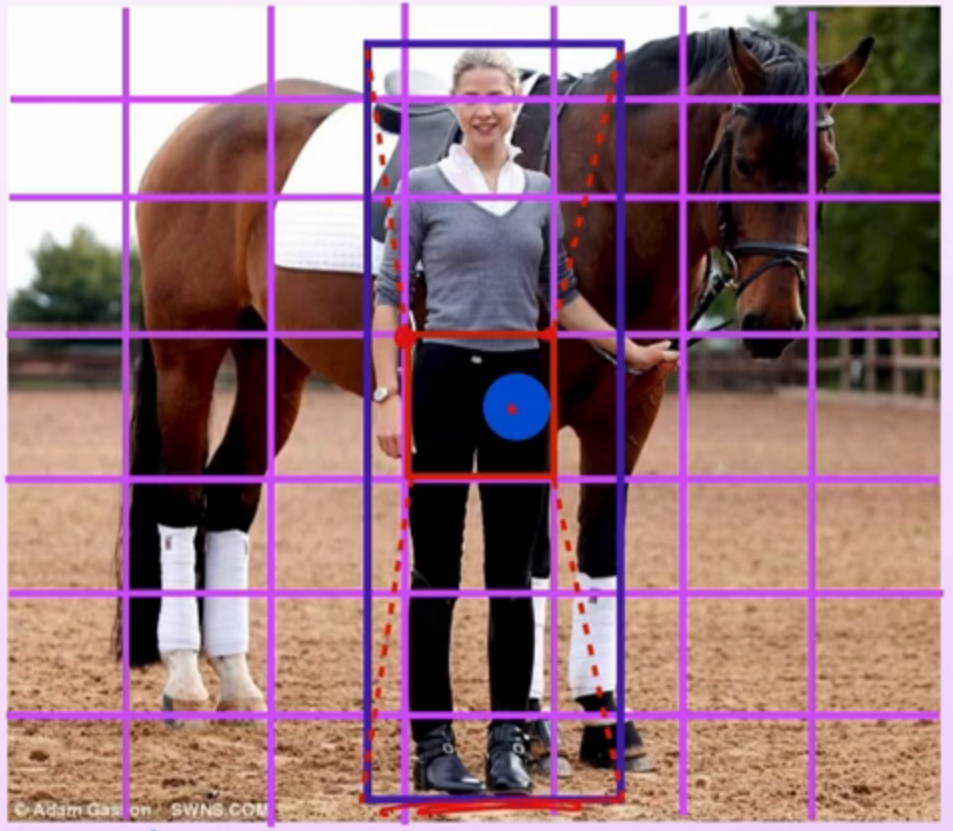

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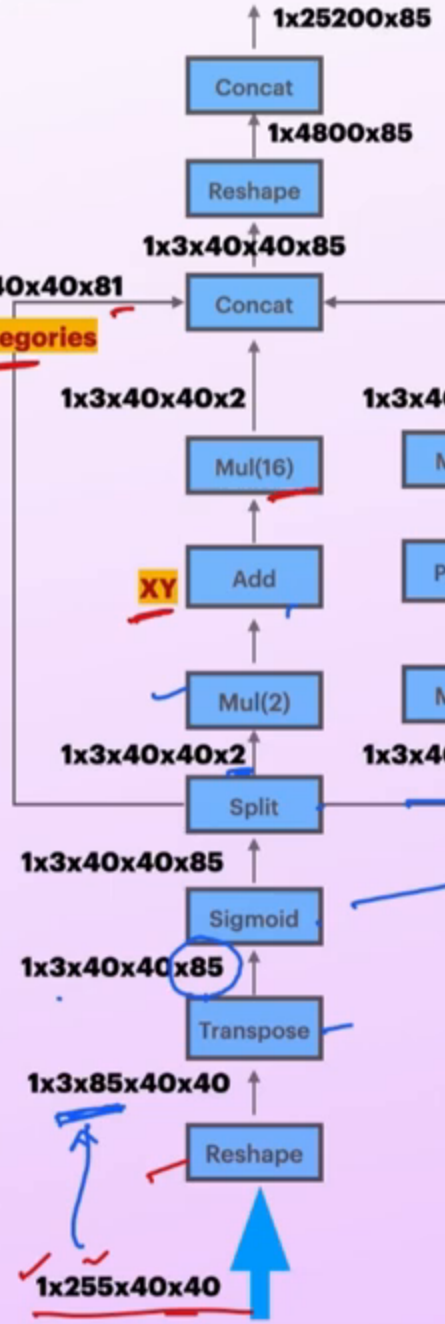

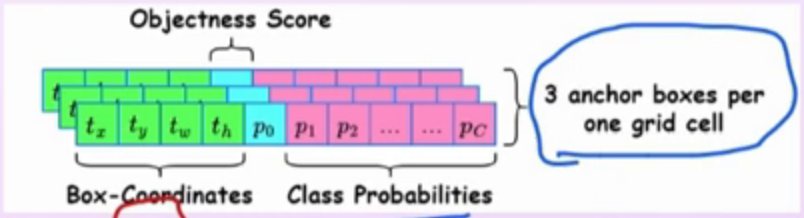

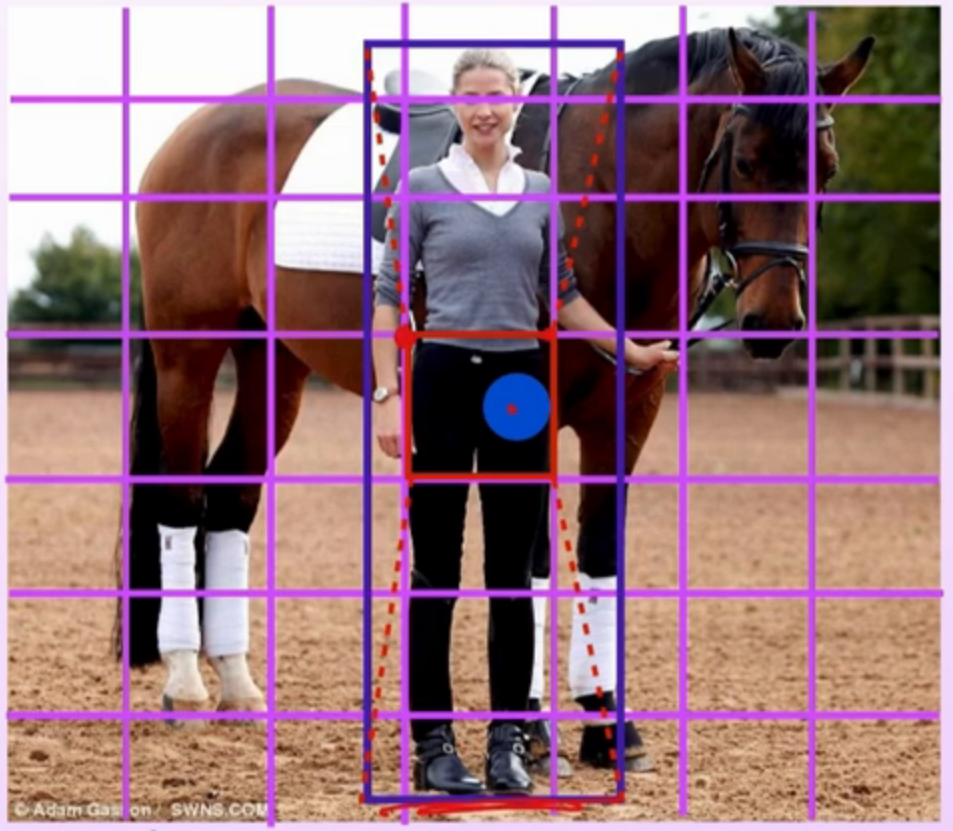

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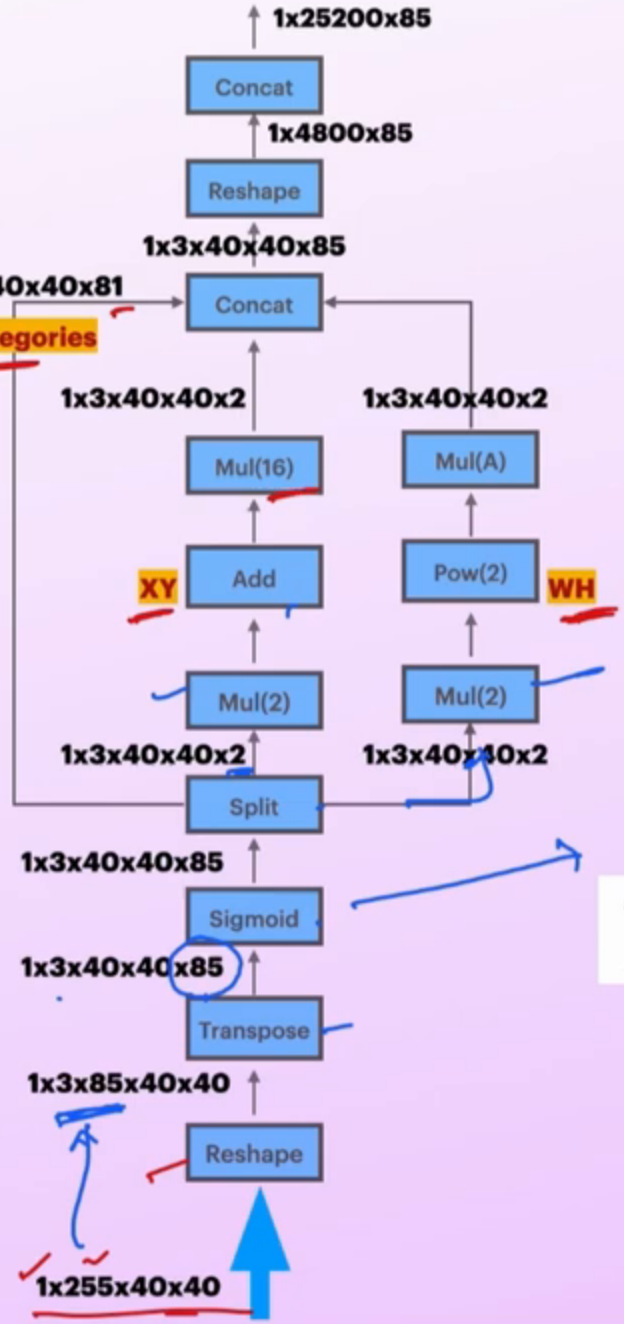

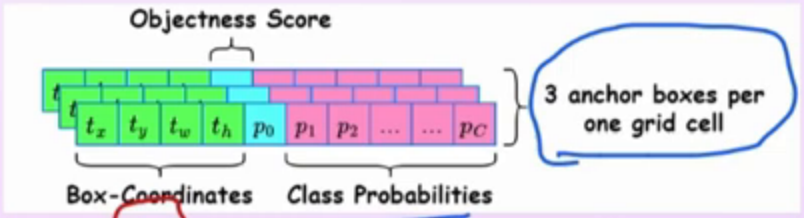

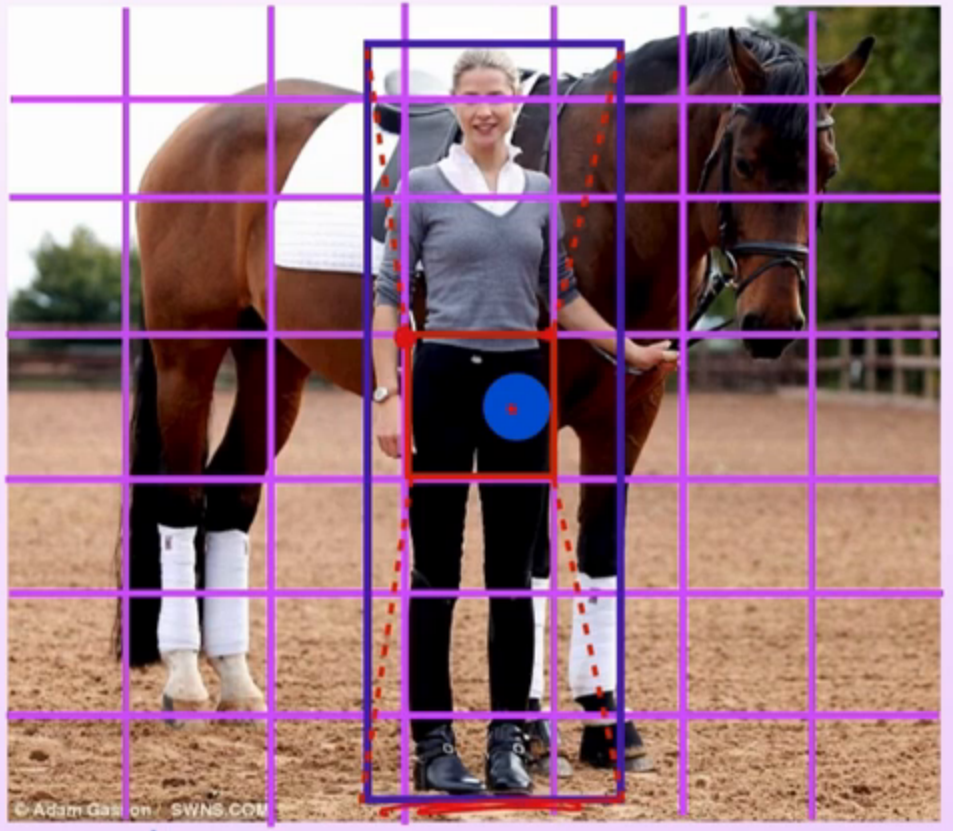

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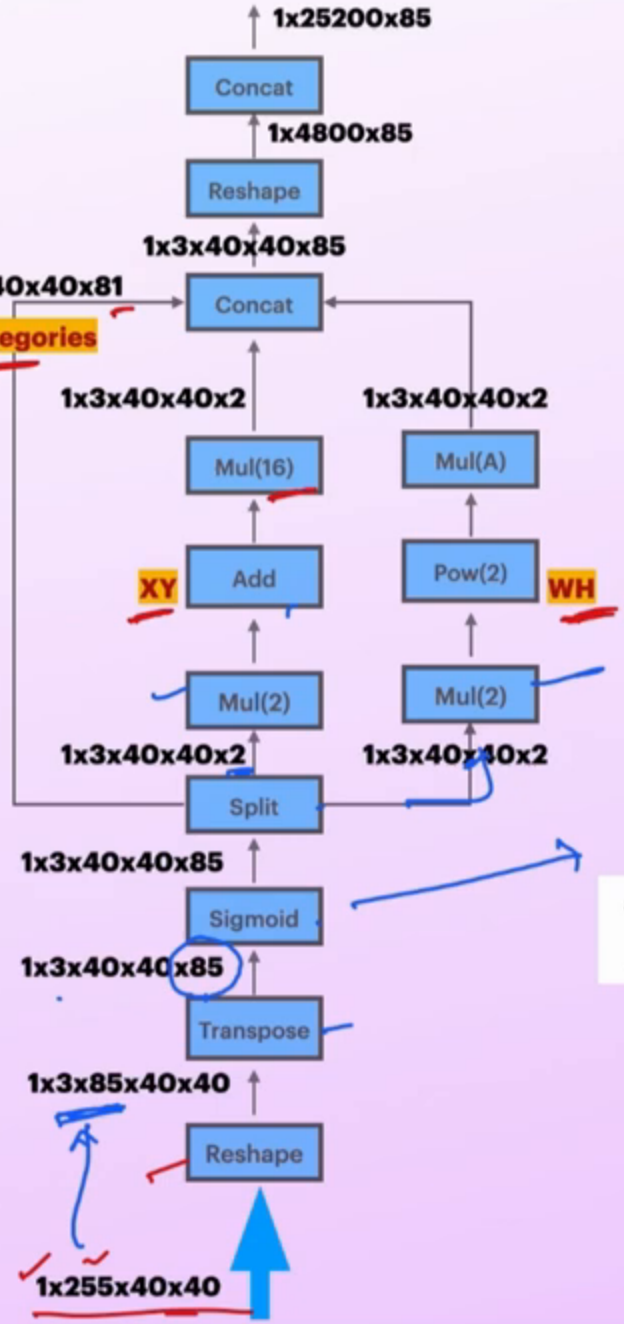
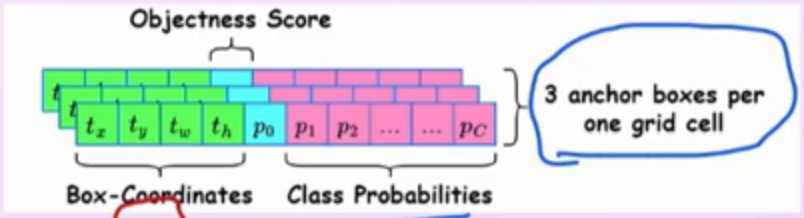
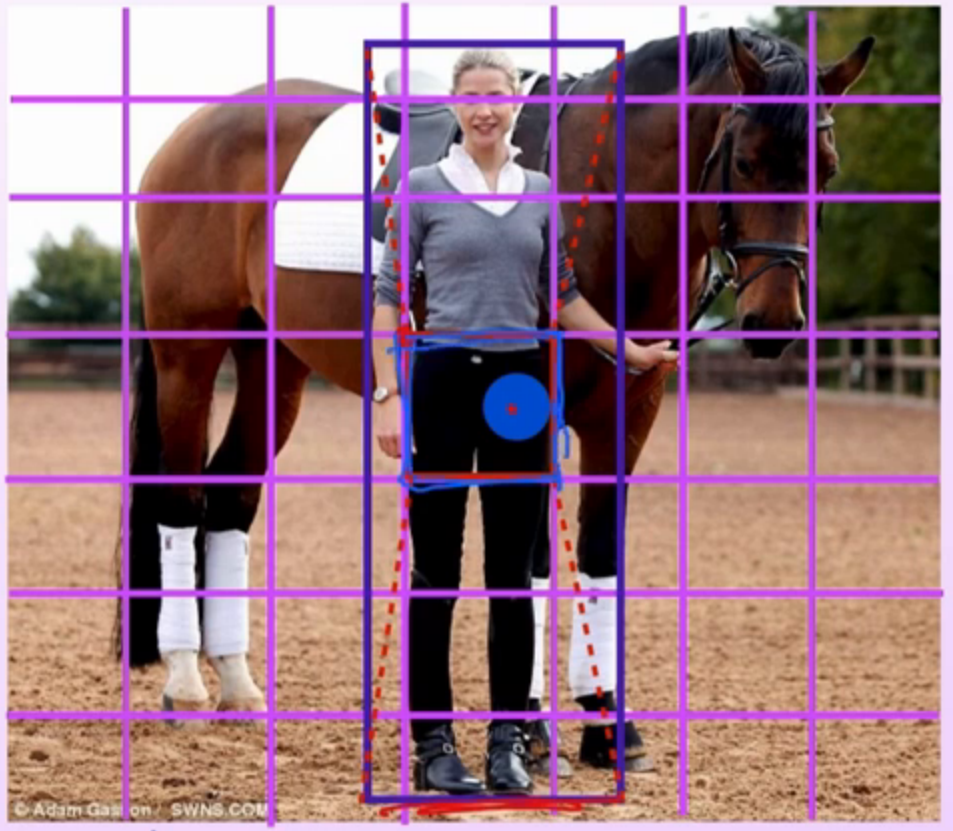
NMS & Postprocessing







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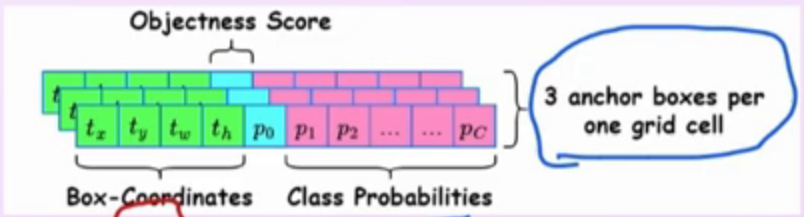

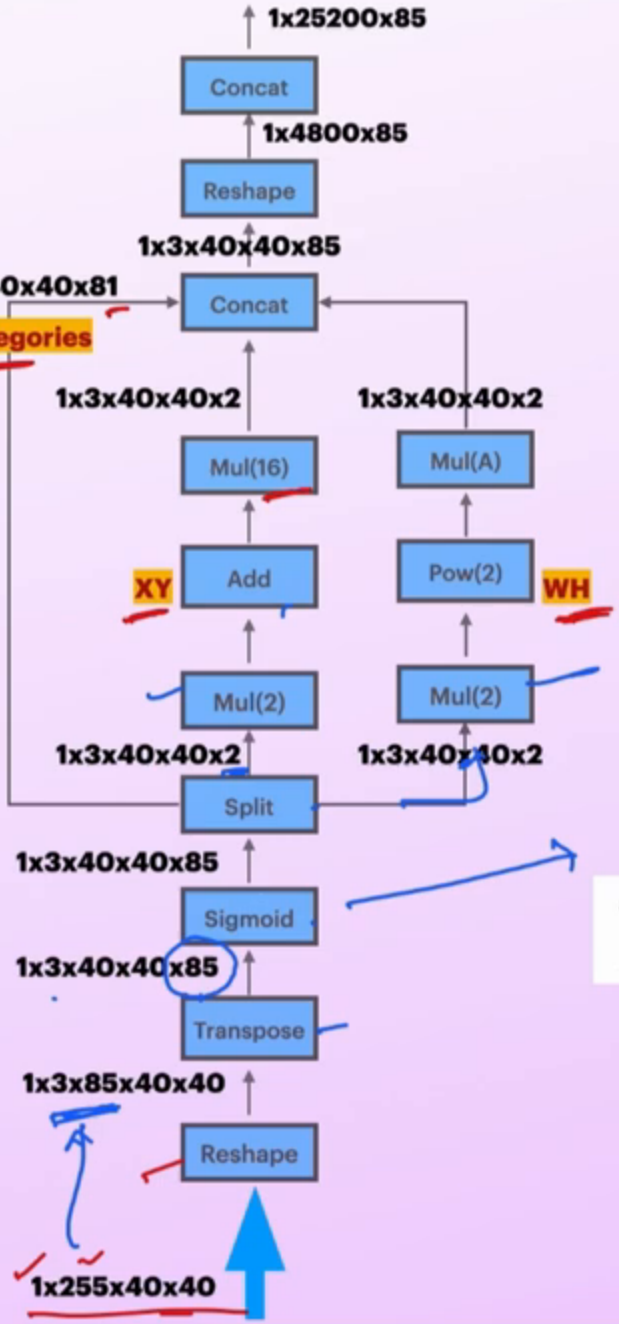

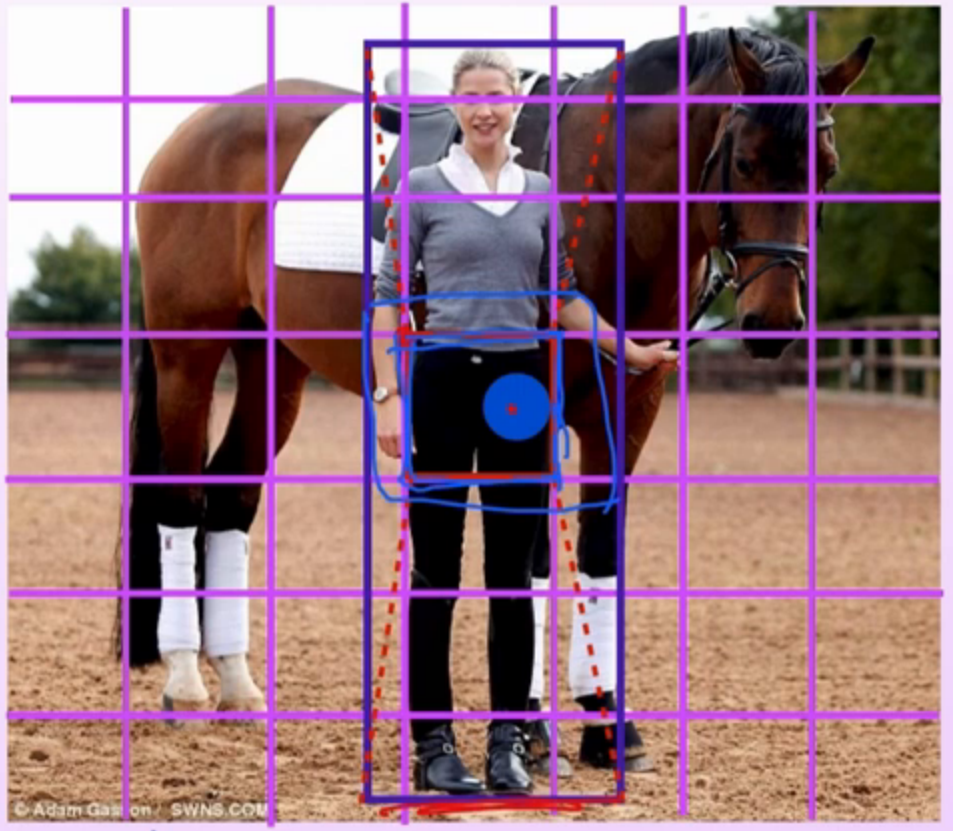

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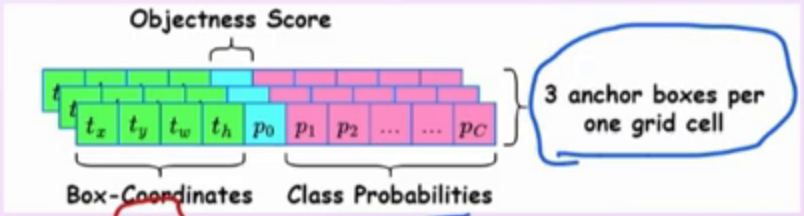

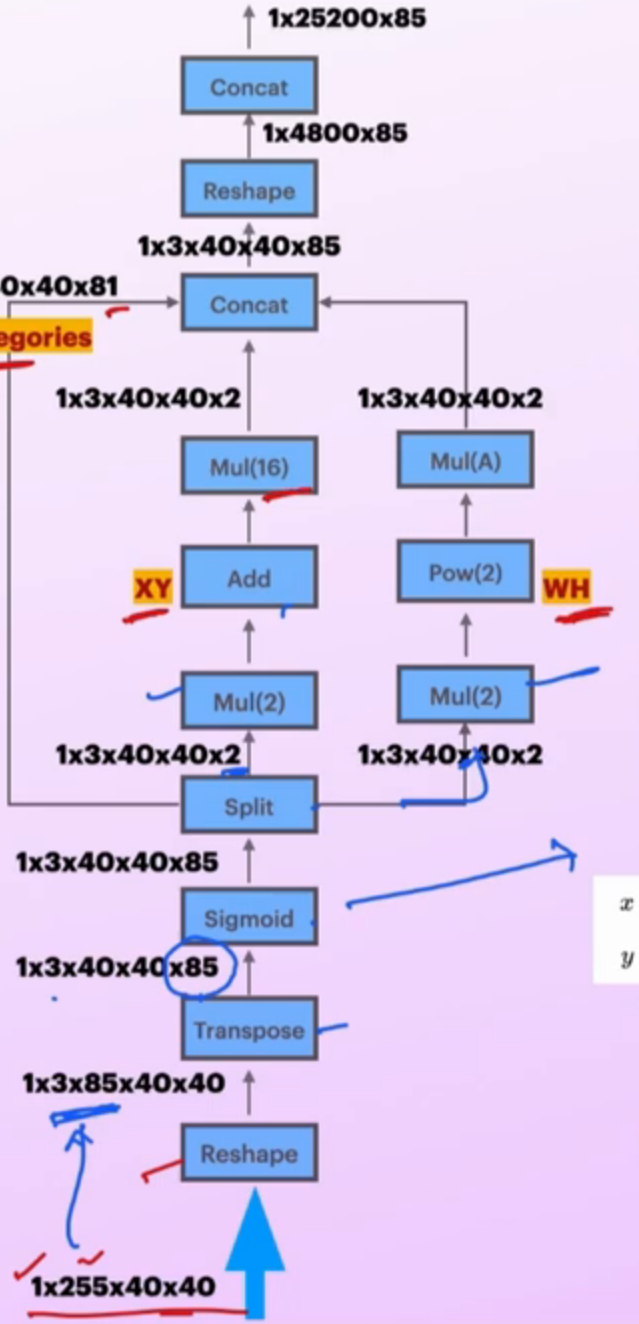

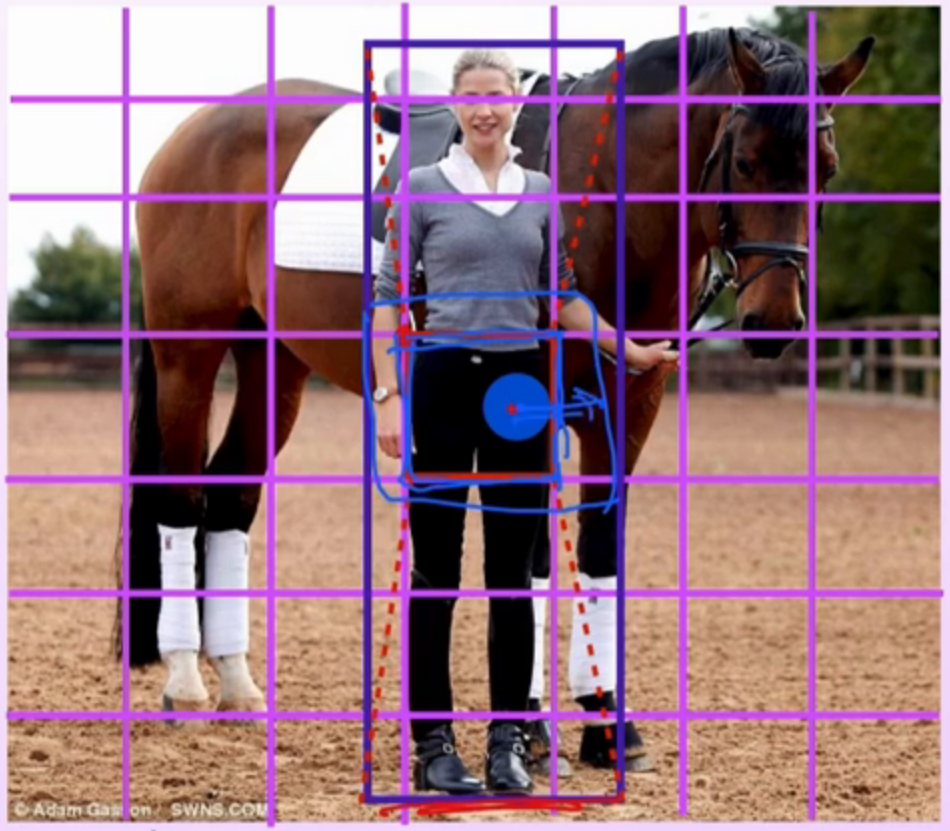

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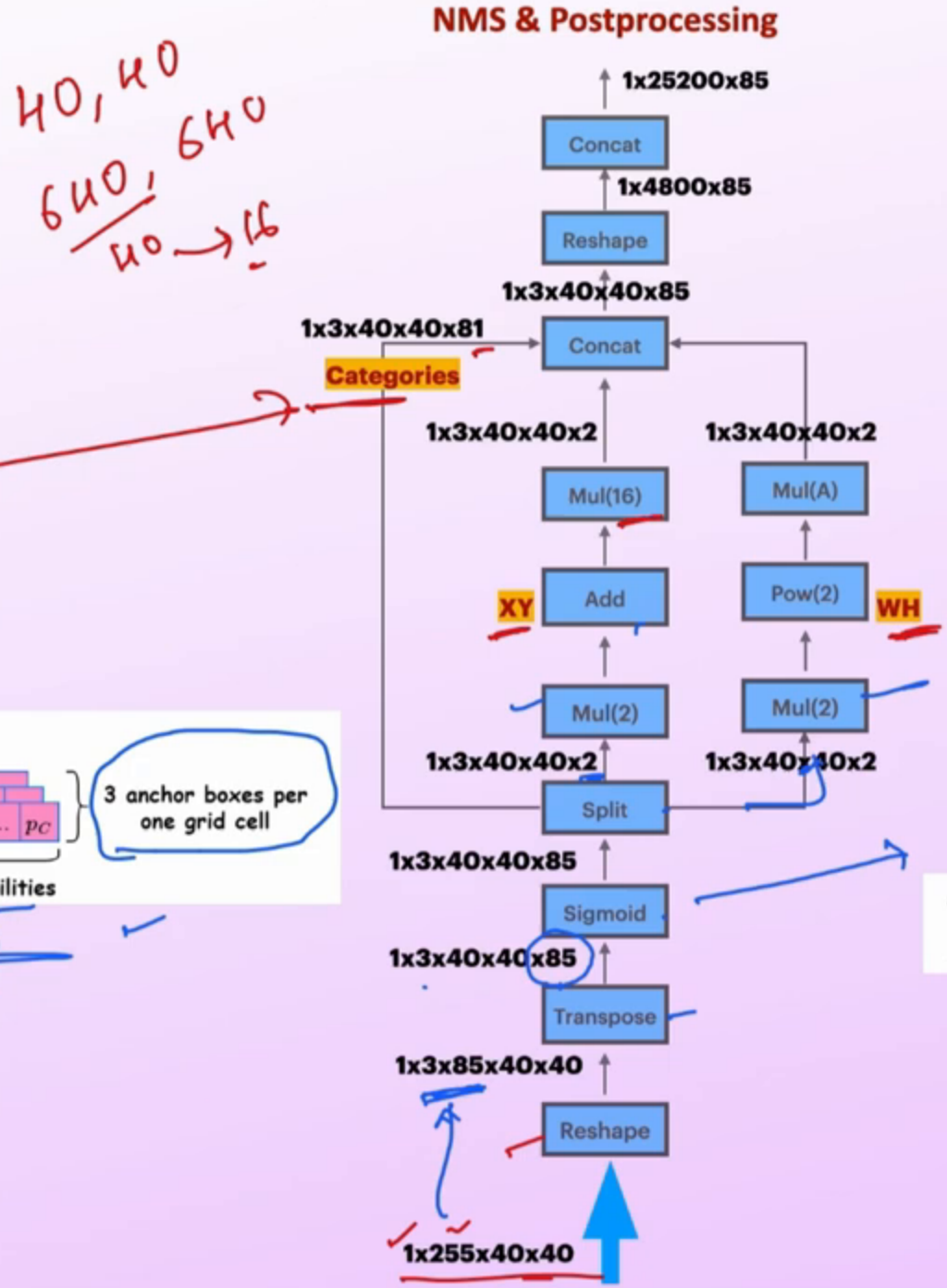

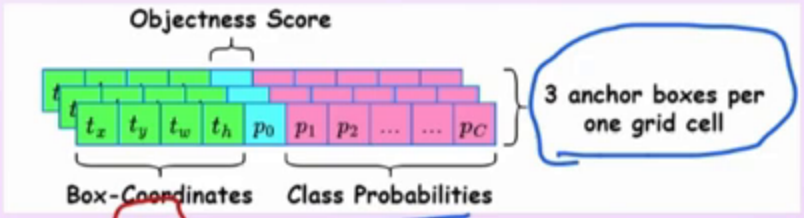

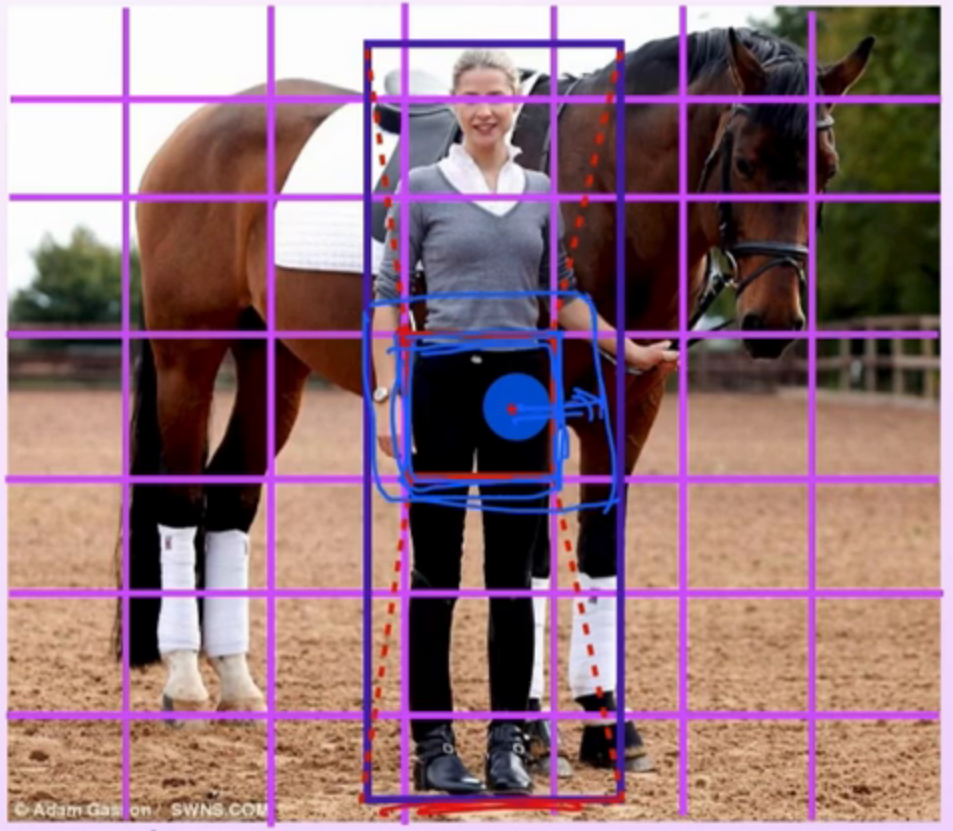

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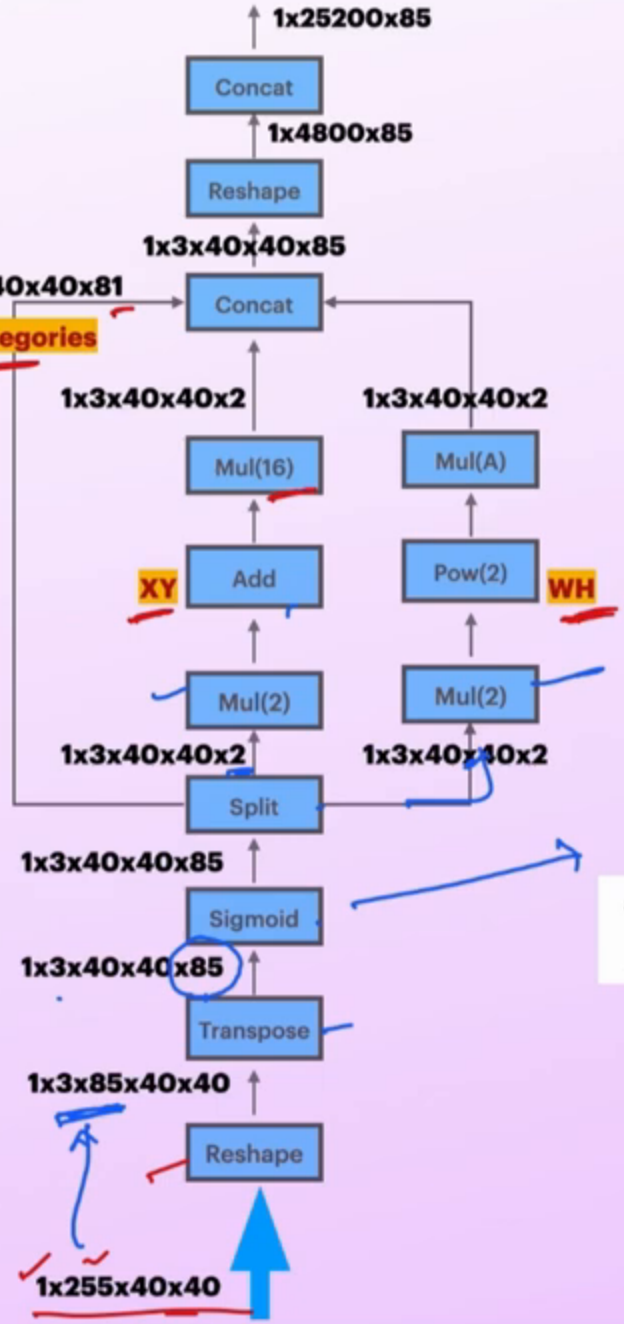

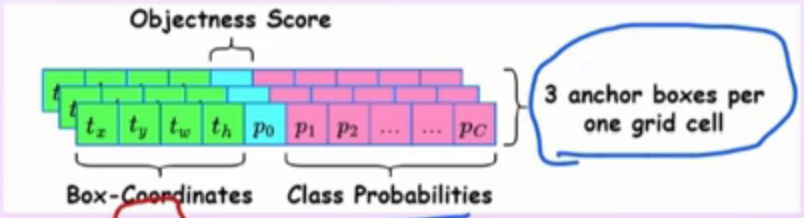

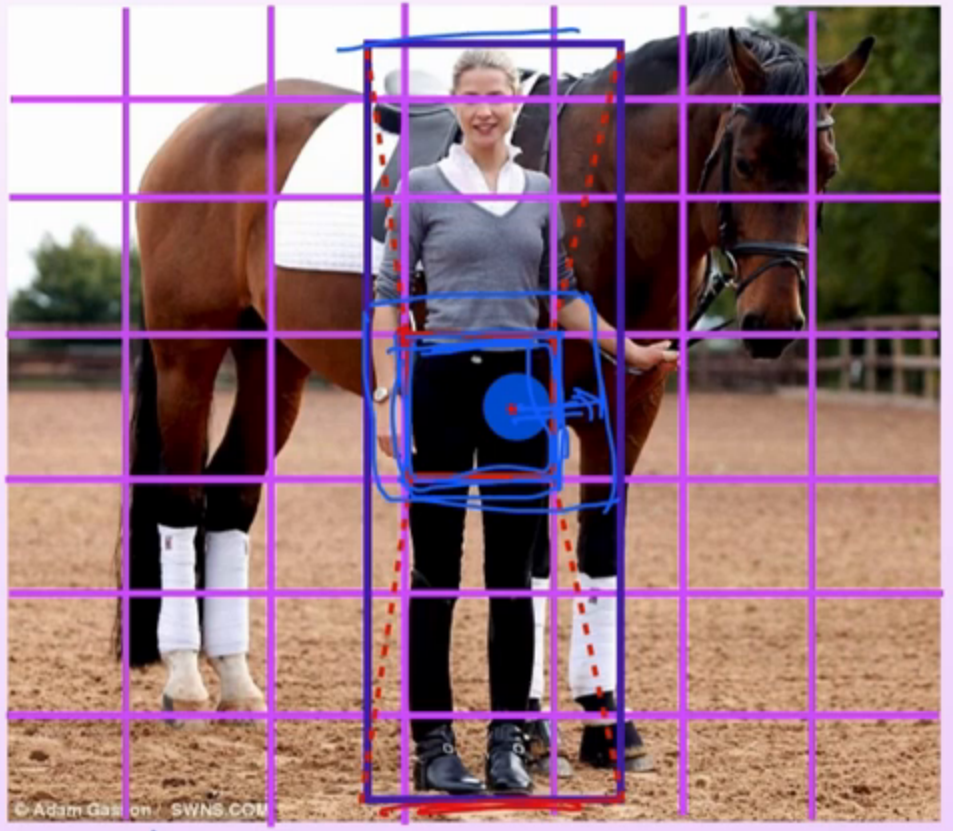

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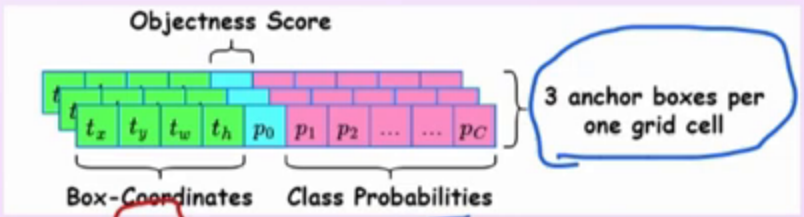
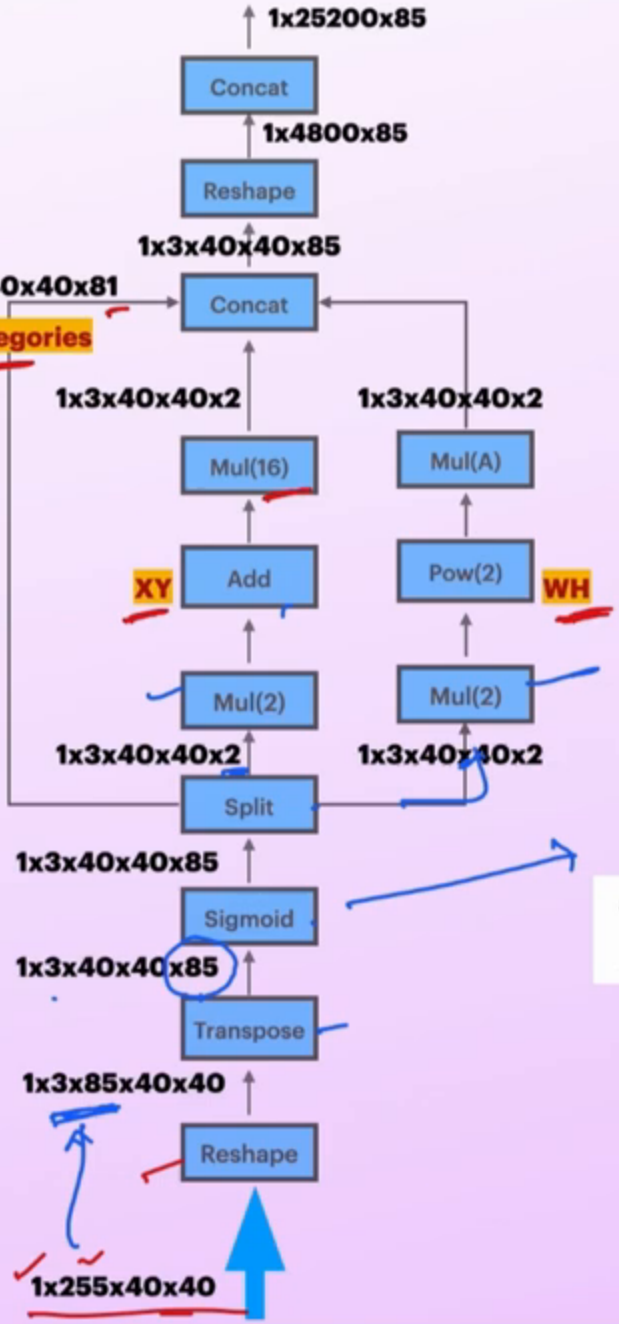
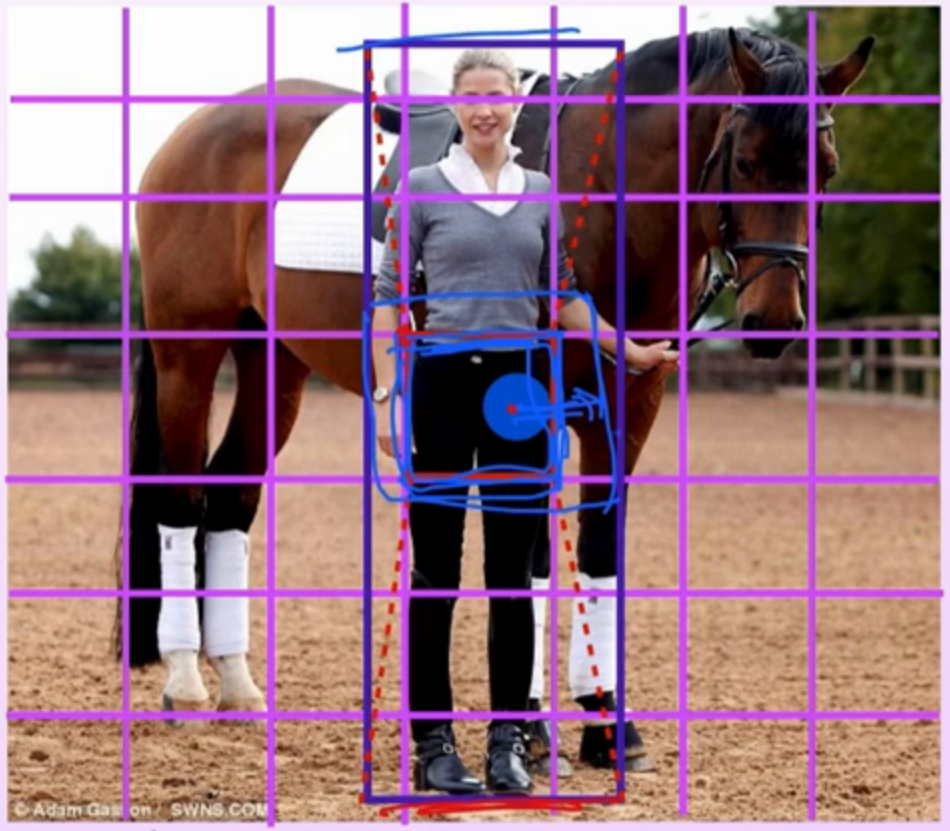
NMS & Postprocessing





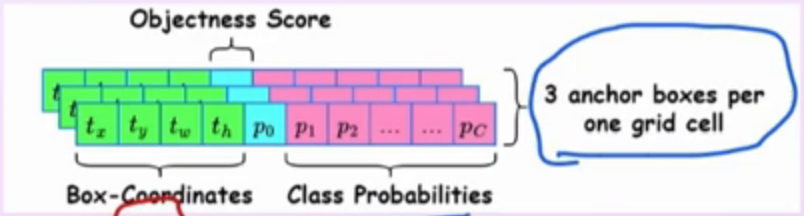


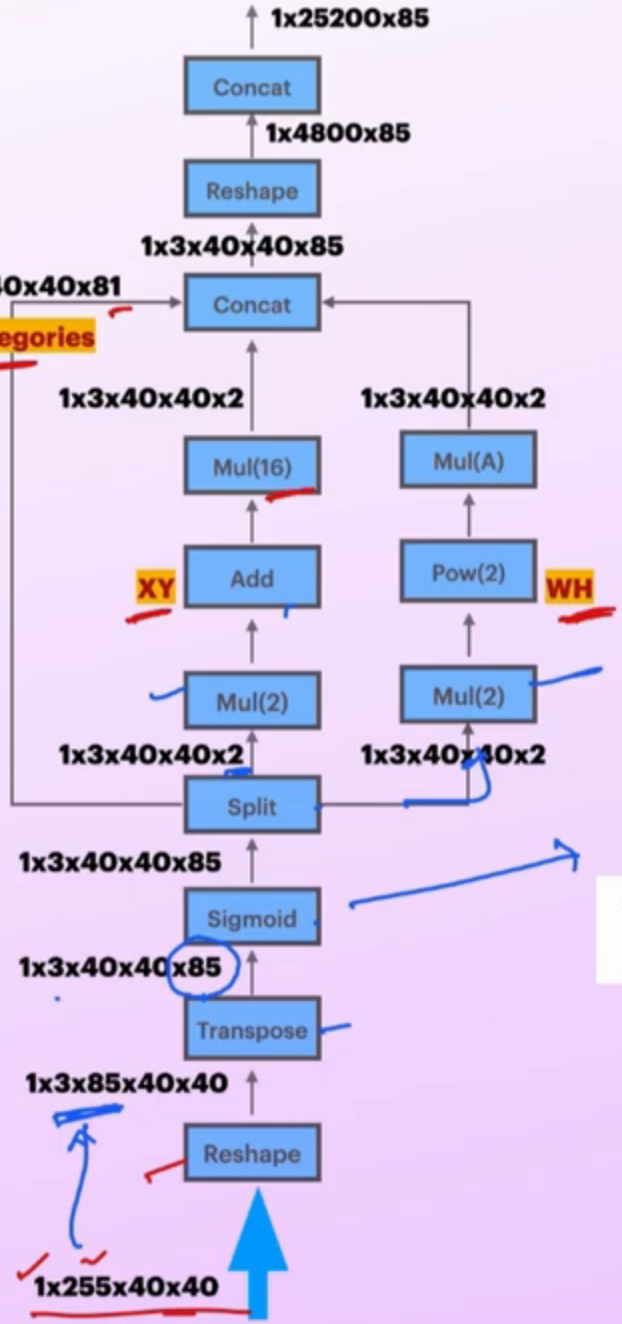
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

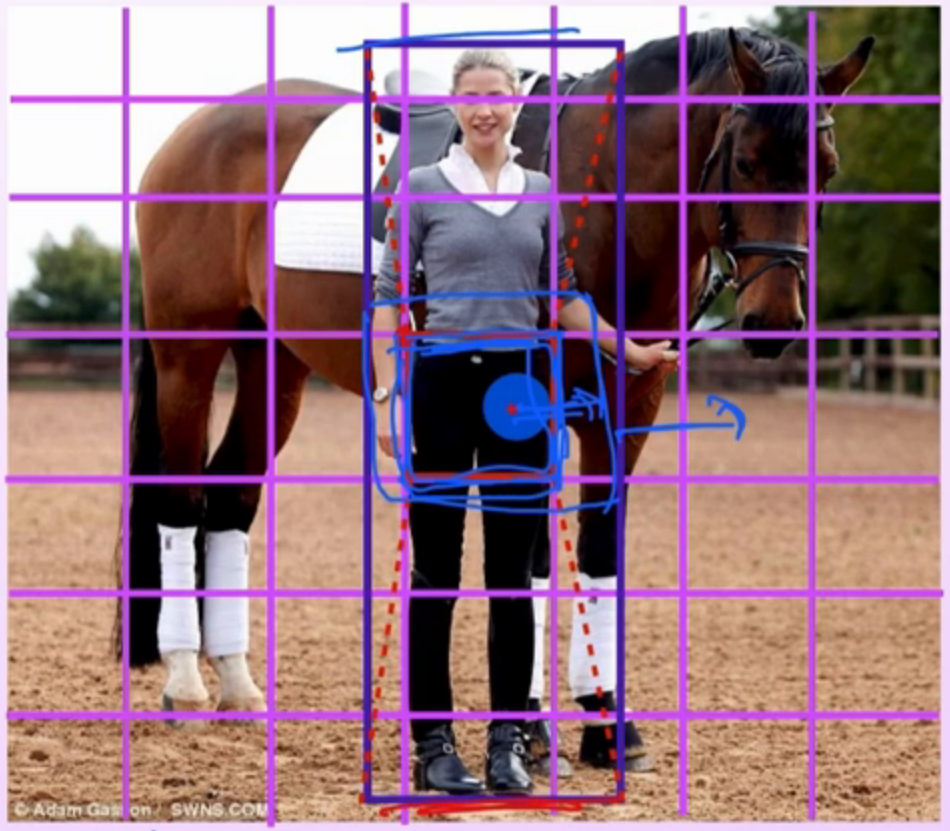
$$w = p_w \times (2 \cdot \sigma(t_w))^2$$
$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

Head

NMS & Postprocessing





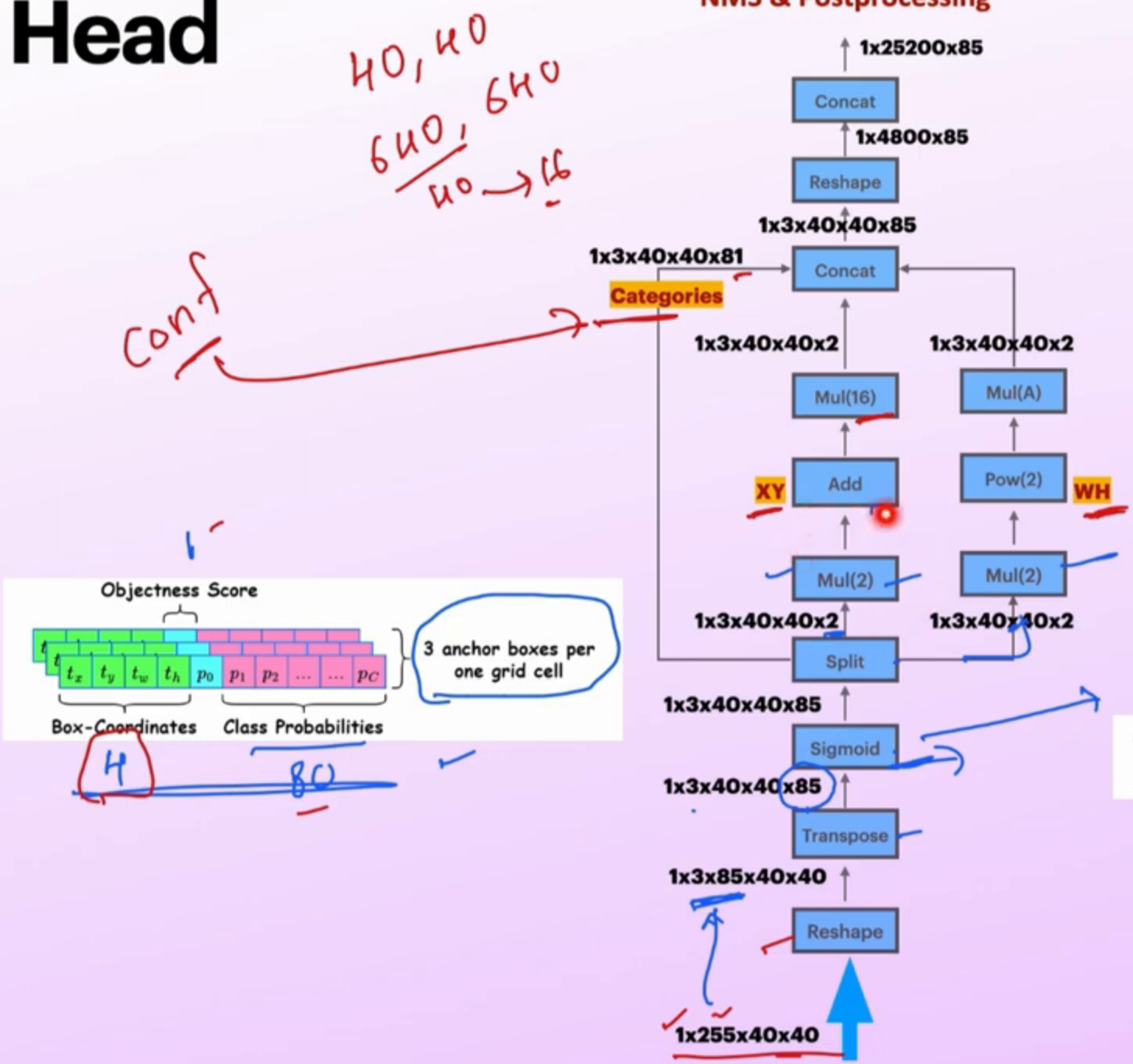


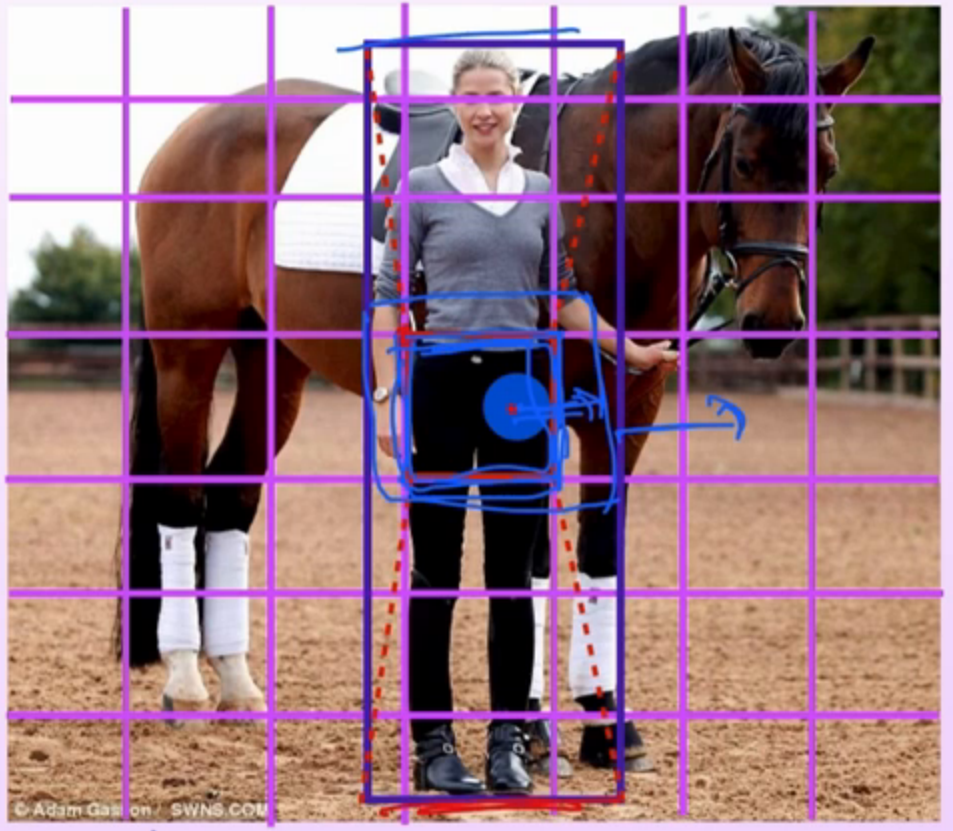
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

$$w = p_w \times (2 \cdot \sigma(t_w))^2$$
$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

Head

NMS & Postprocessing



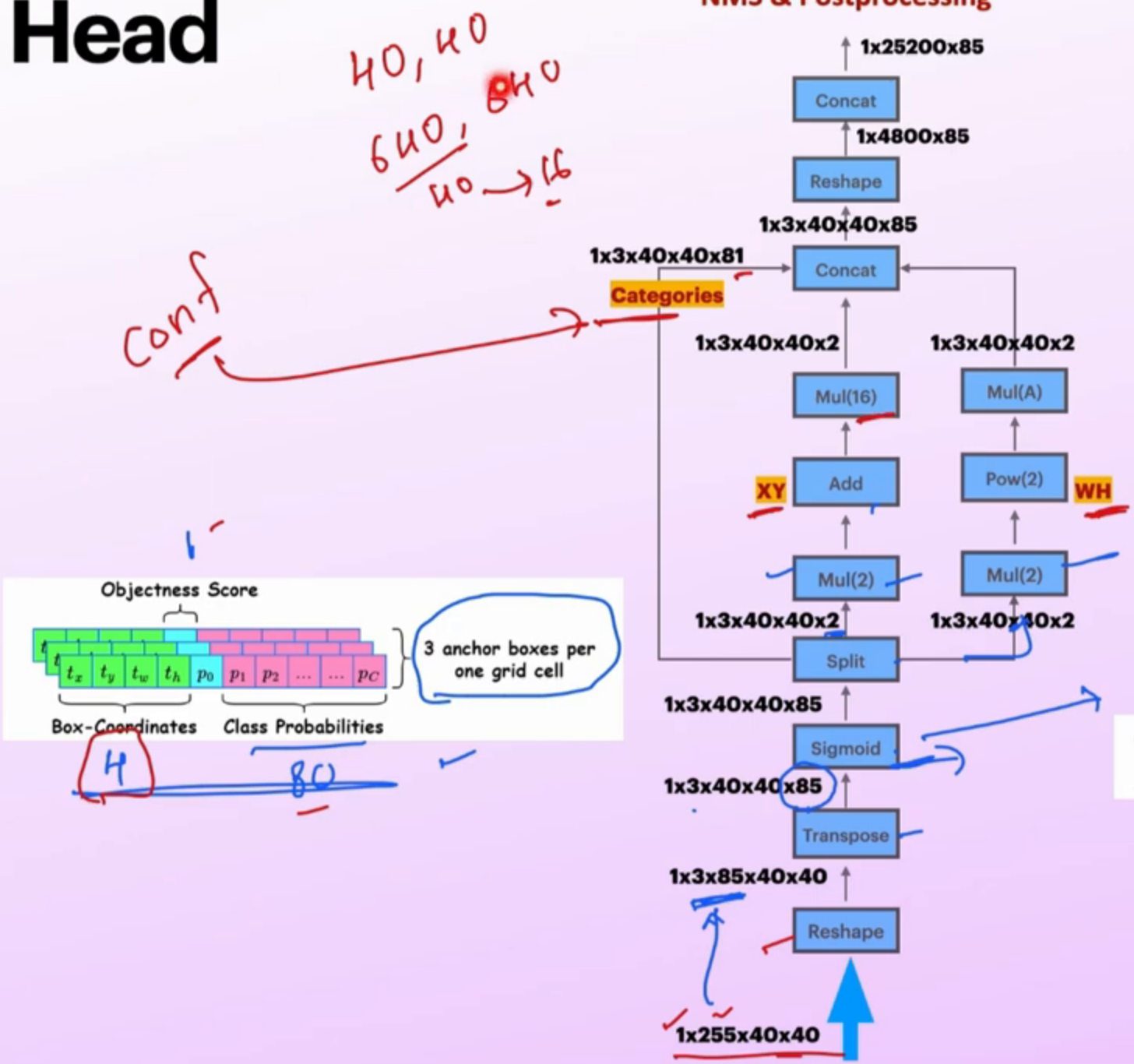


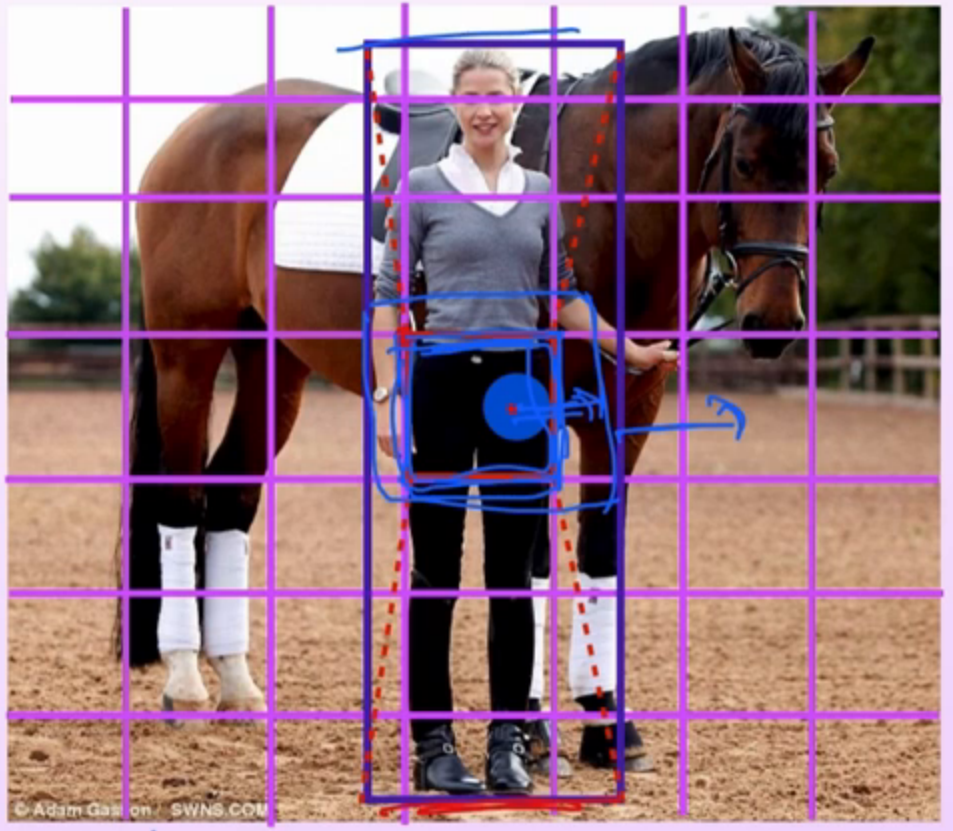
$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
$$y = ((2 \cdot \sigma(t_y)) - 0.5 + c_y) \times stride$$

$$w = p_w \times (2 \cdot \sigma(t_w))^2$$
$$h = p_h \times (2 \cdot \sigma(t_h))^2$$

Head

NMS & Postprocessing





$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
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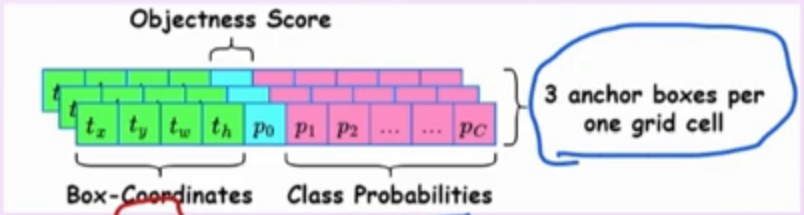
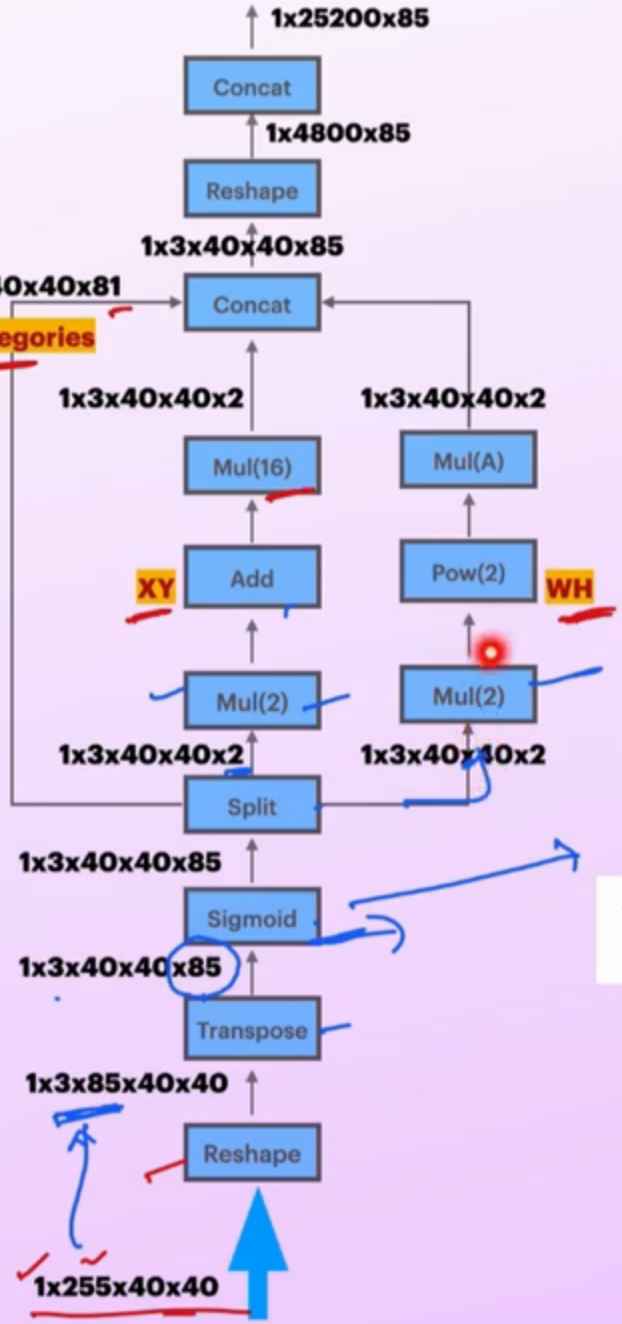
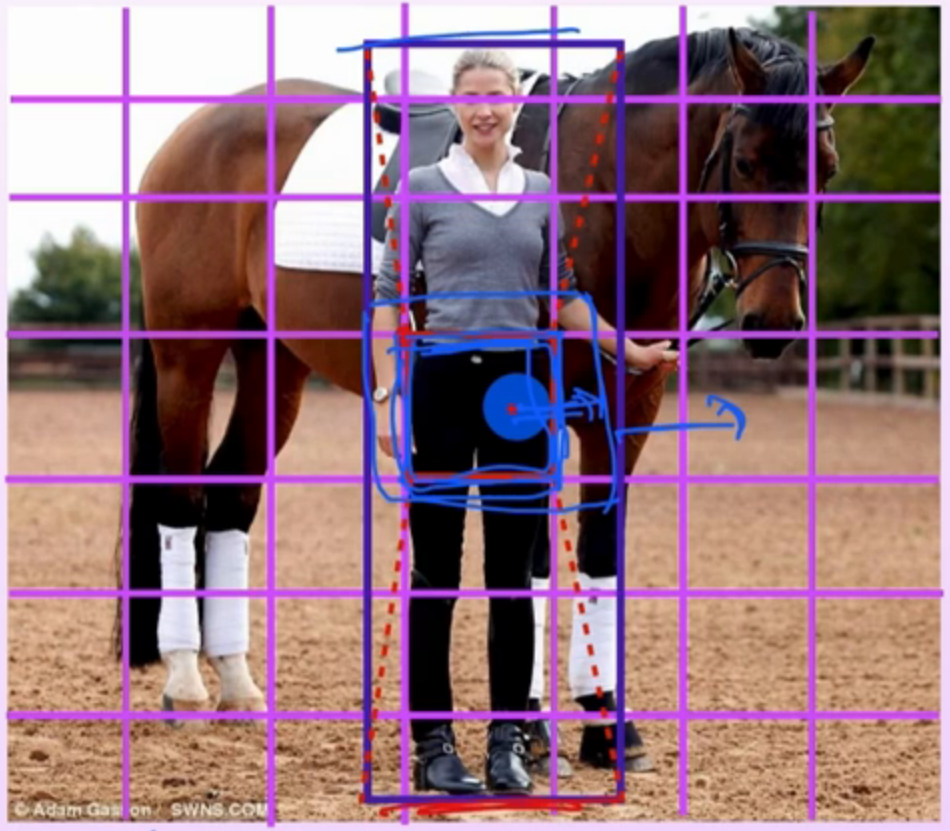
Head

NMS & Postprocessing







$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
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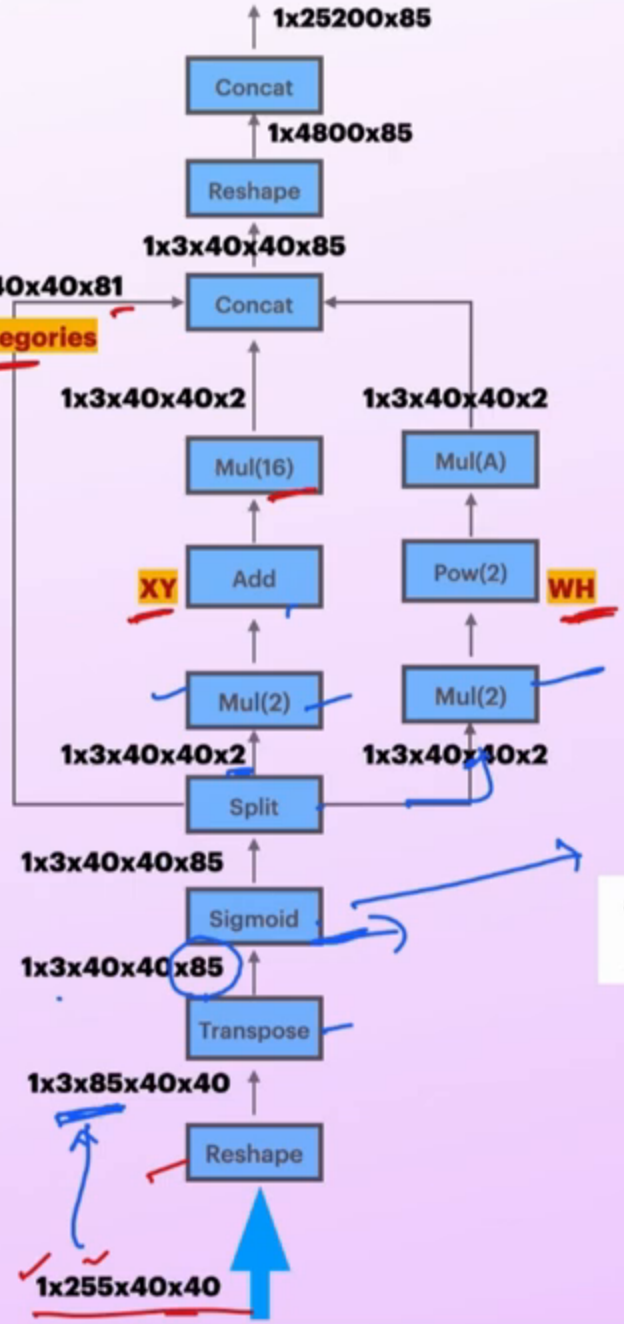
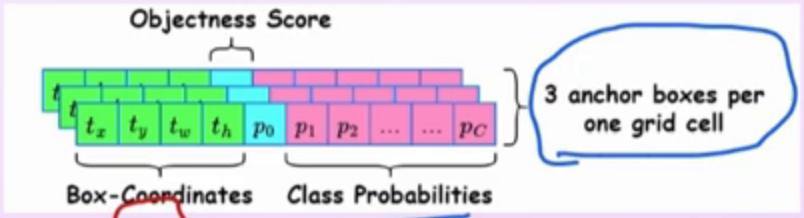
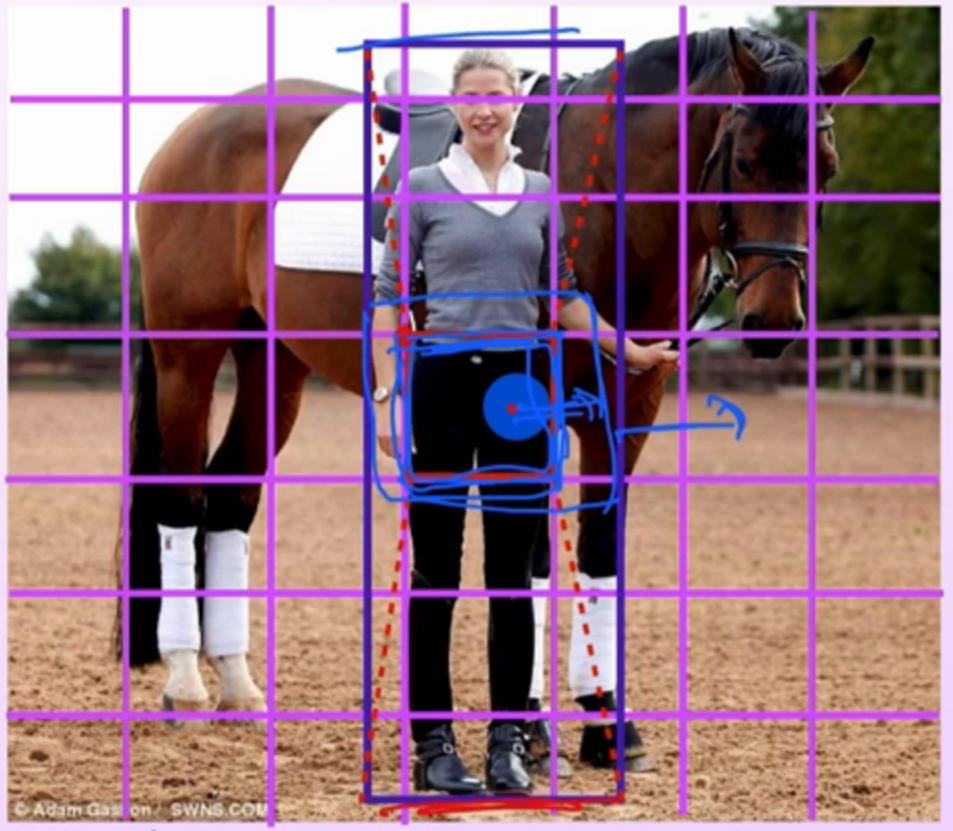
Head

NMS & Postprocessing







$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
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Head

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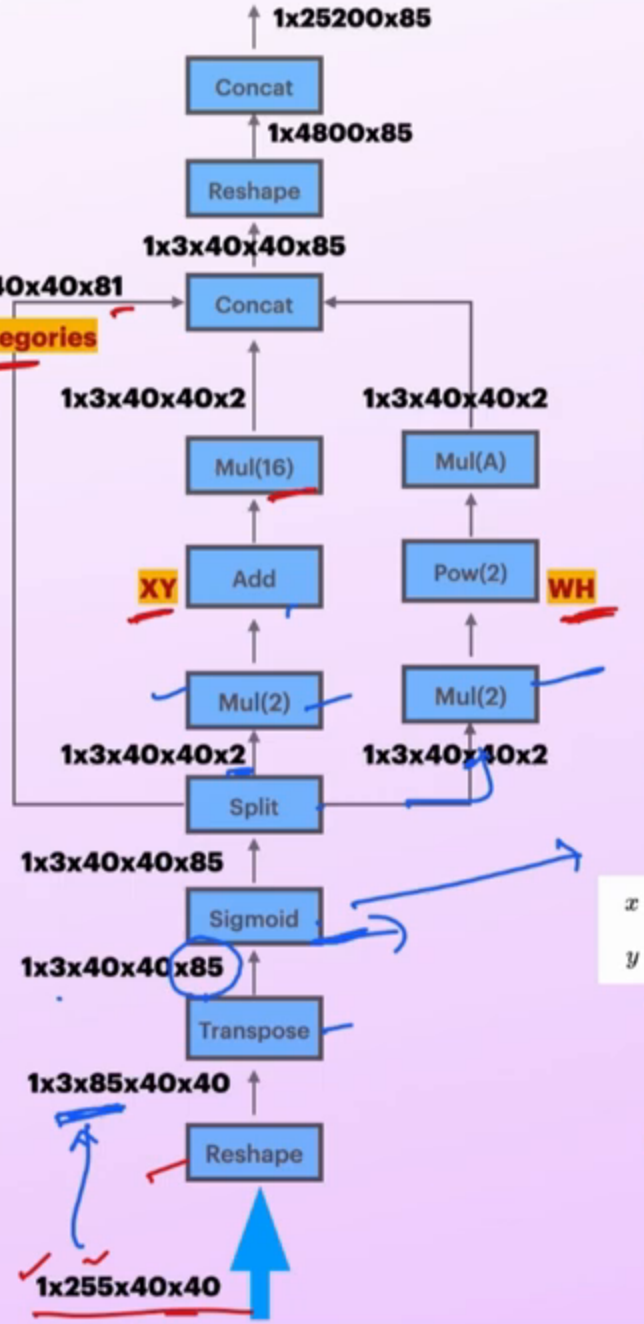

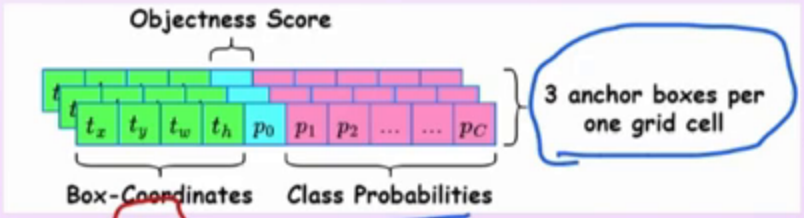

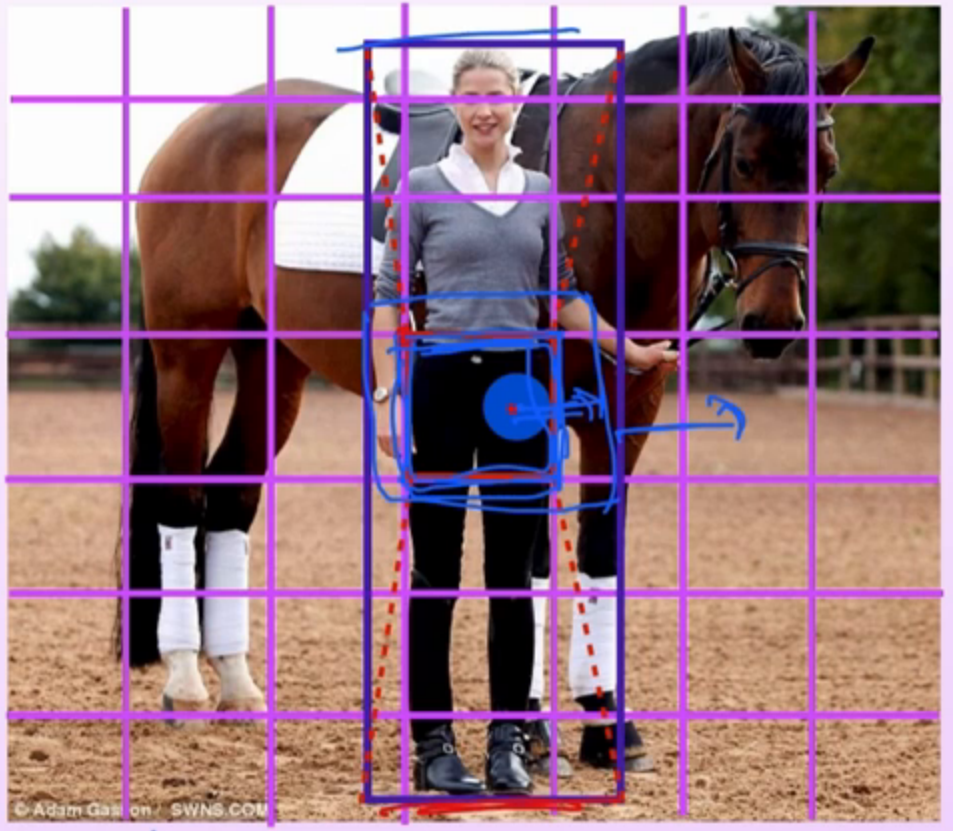

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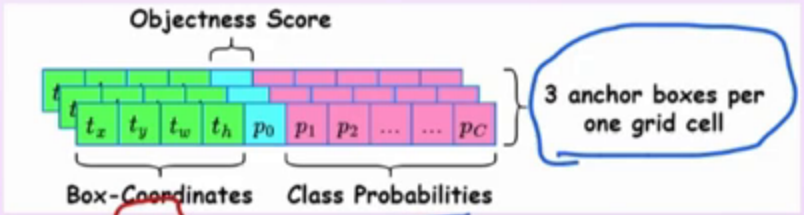

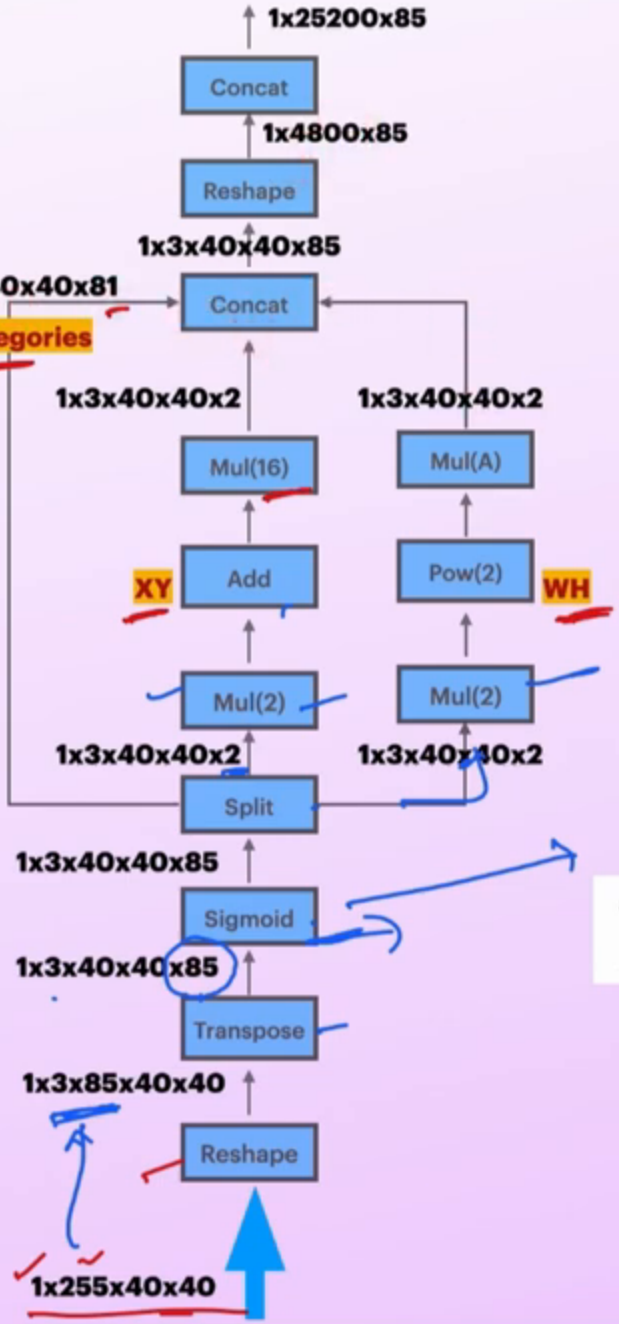

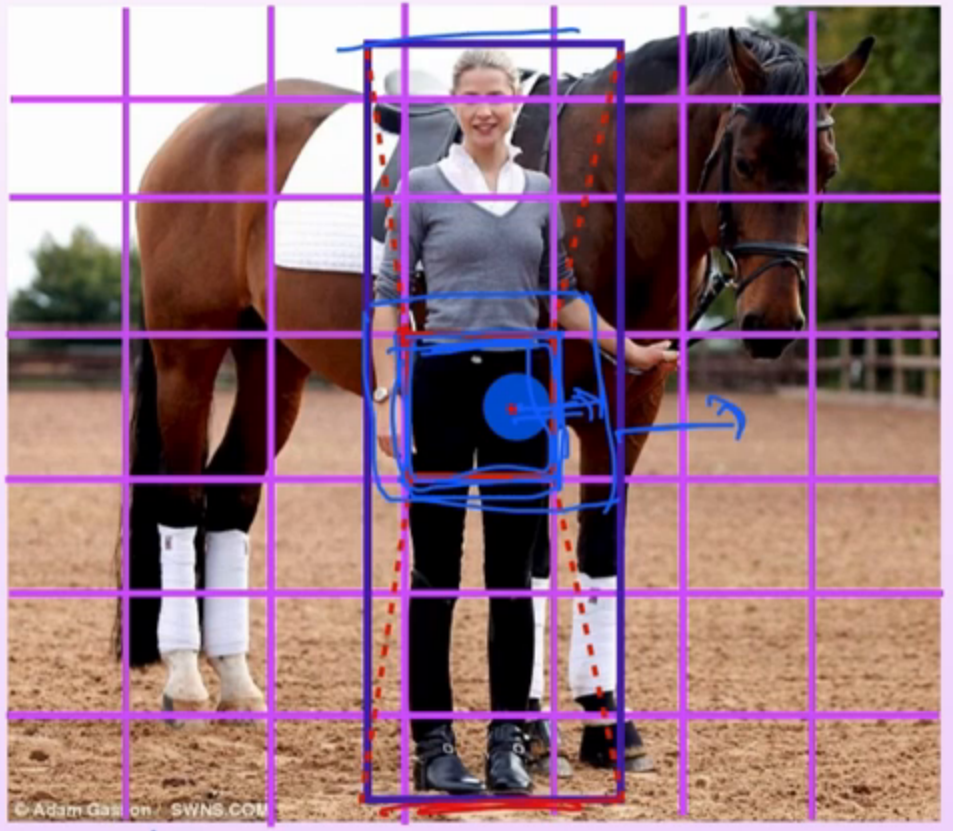

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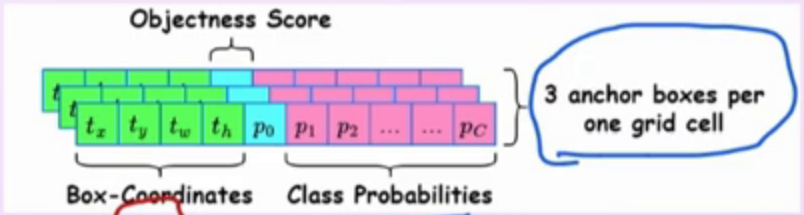

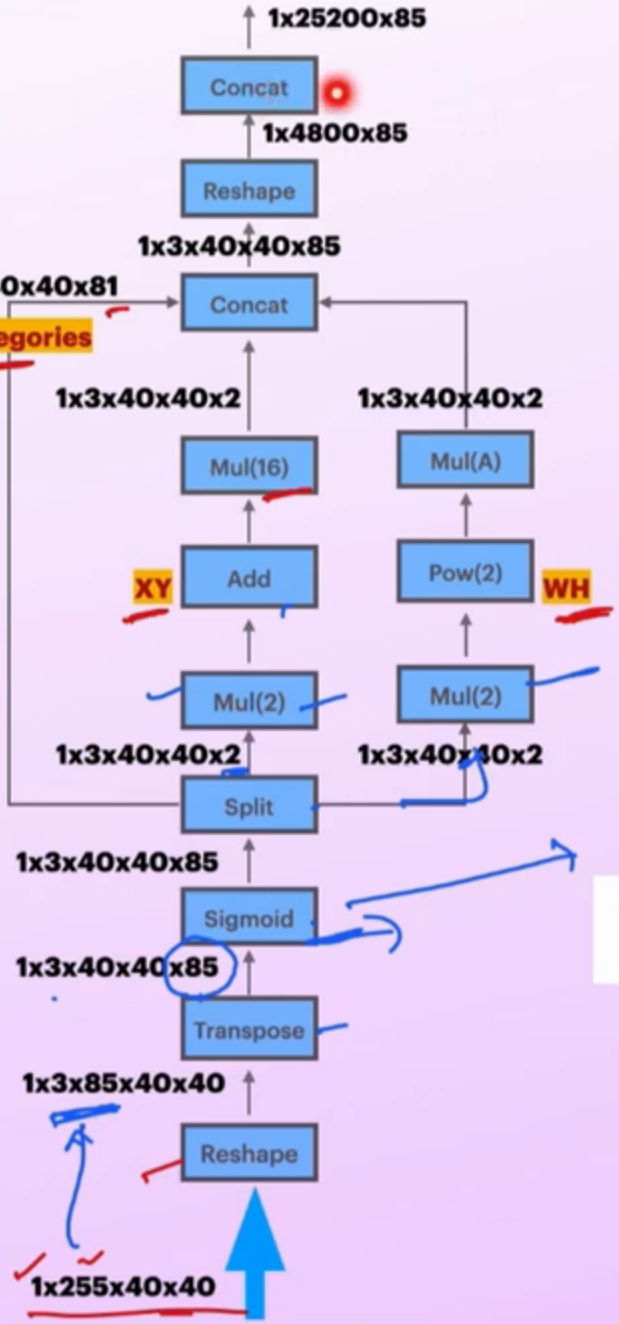

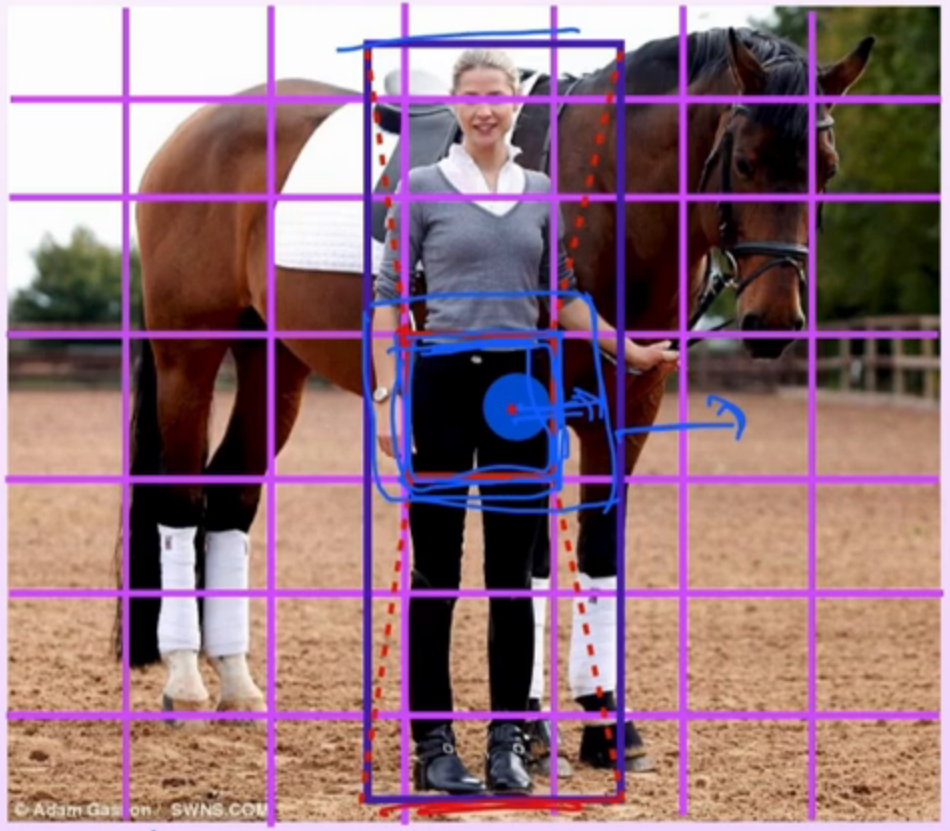

$$x = ((2 \cdot \sigma(t_x)) - 0.5 + c_x) \times stride$$
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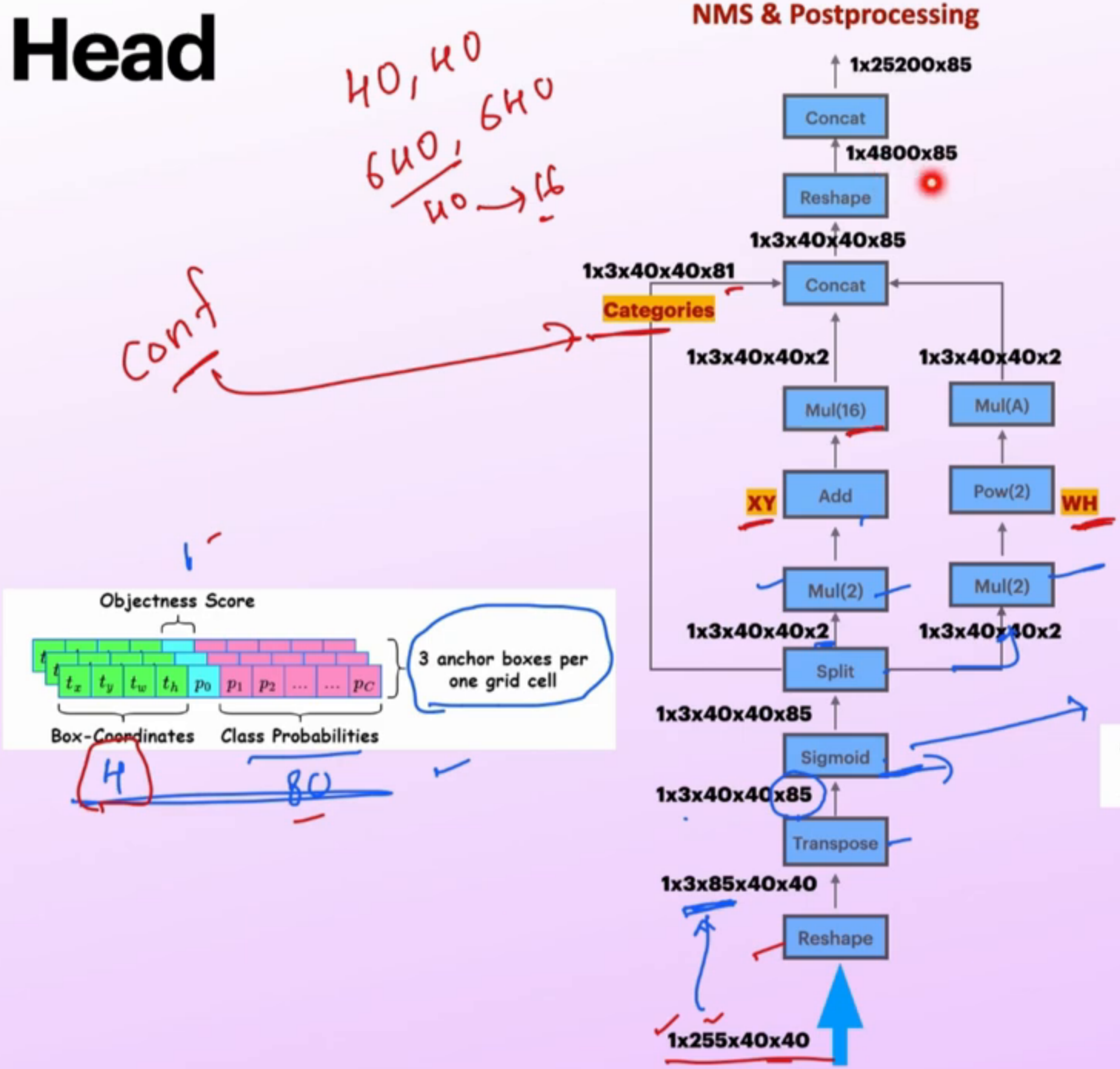
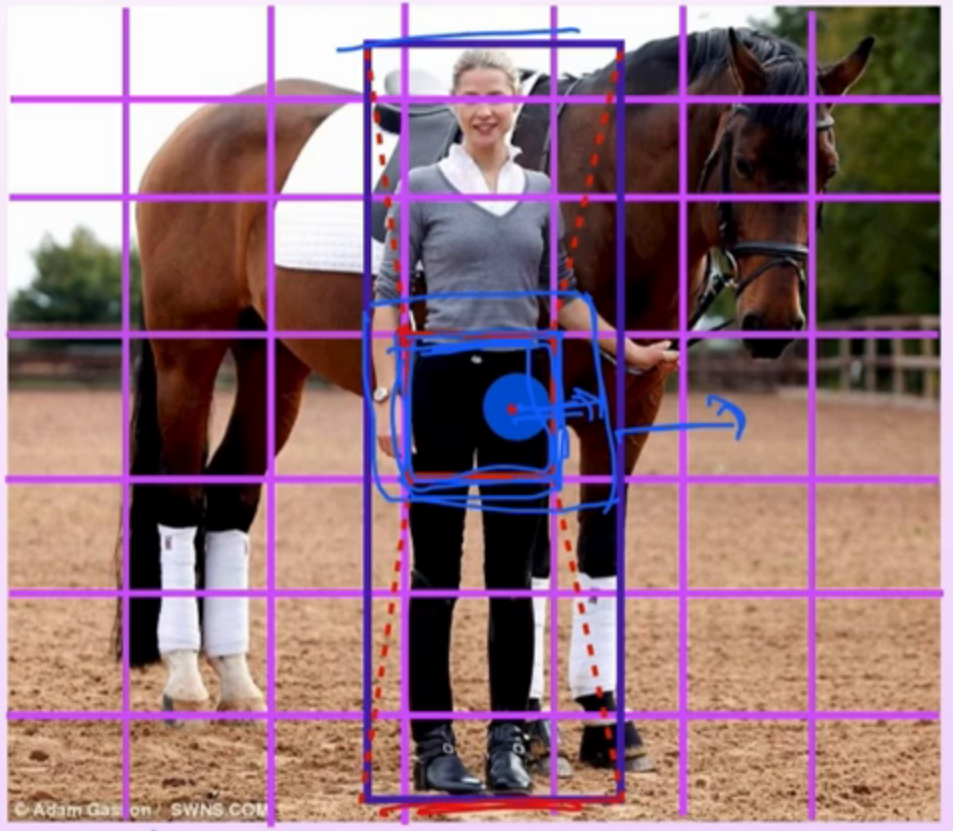
Head





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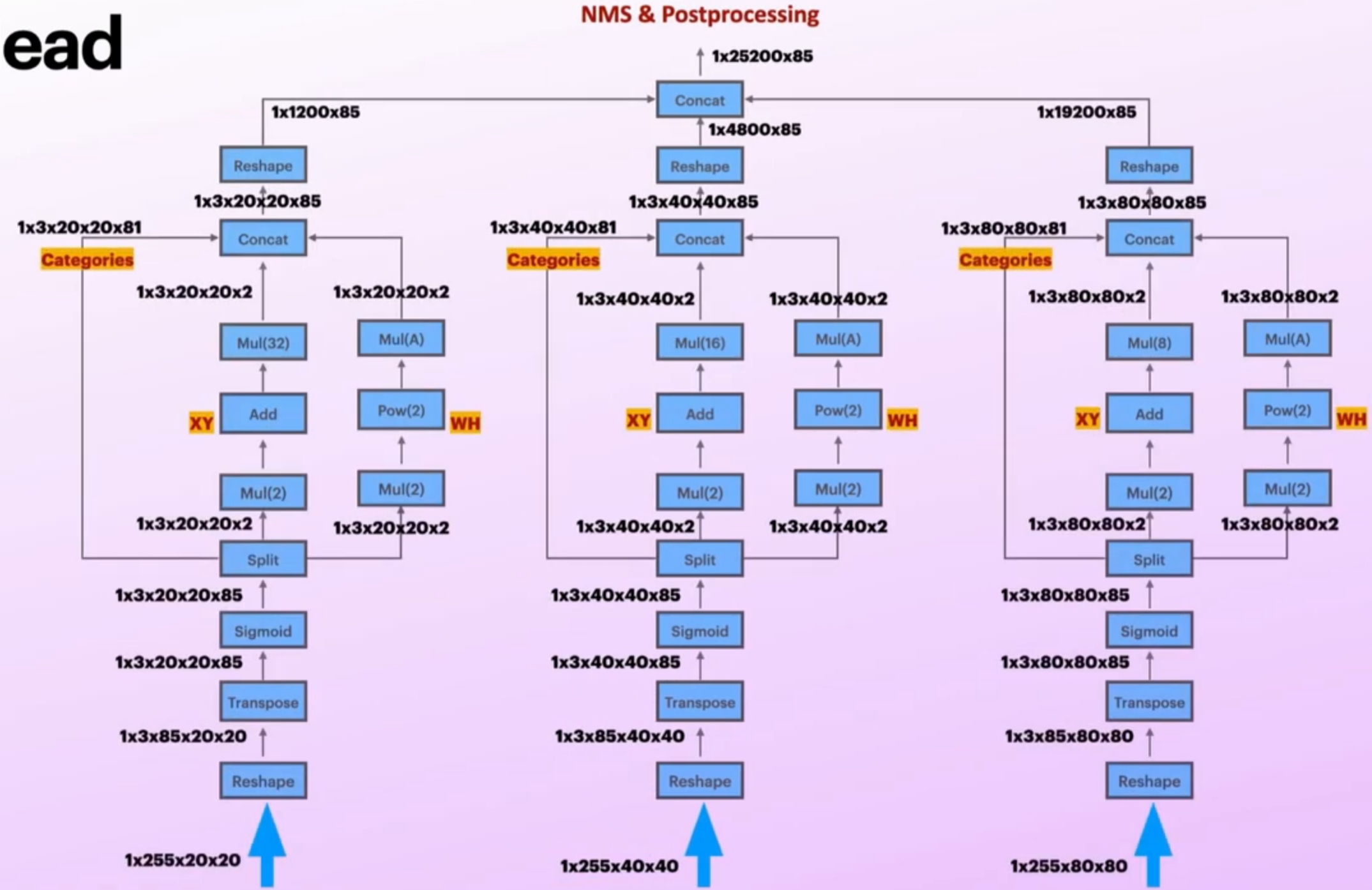
Head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XY
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XY
Add
Pow(2)
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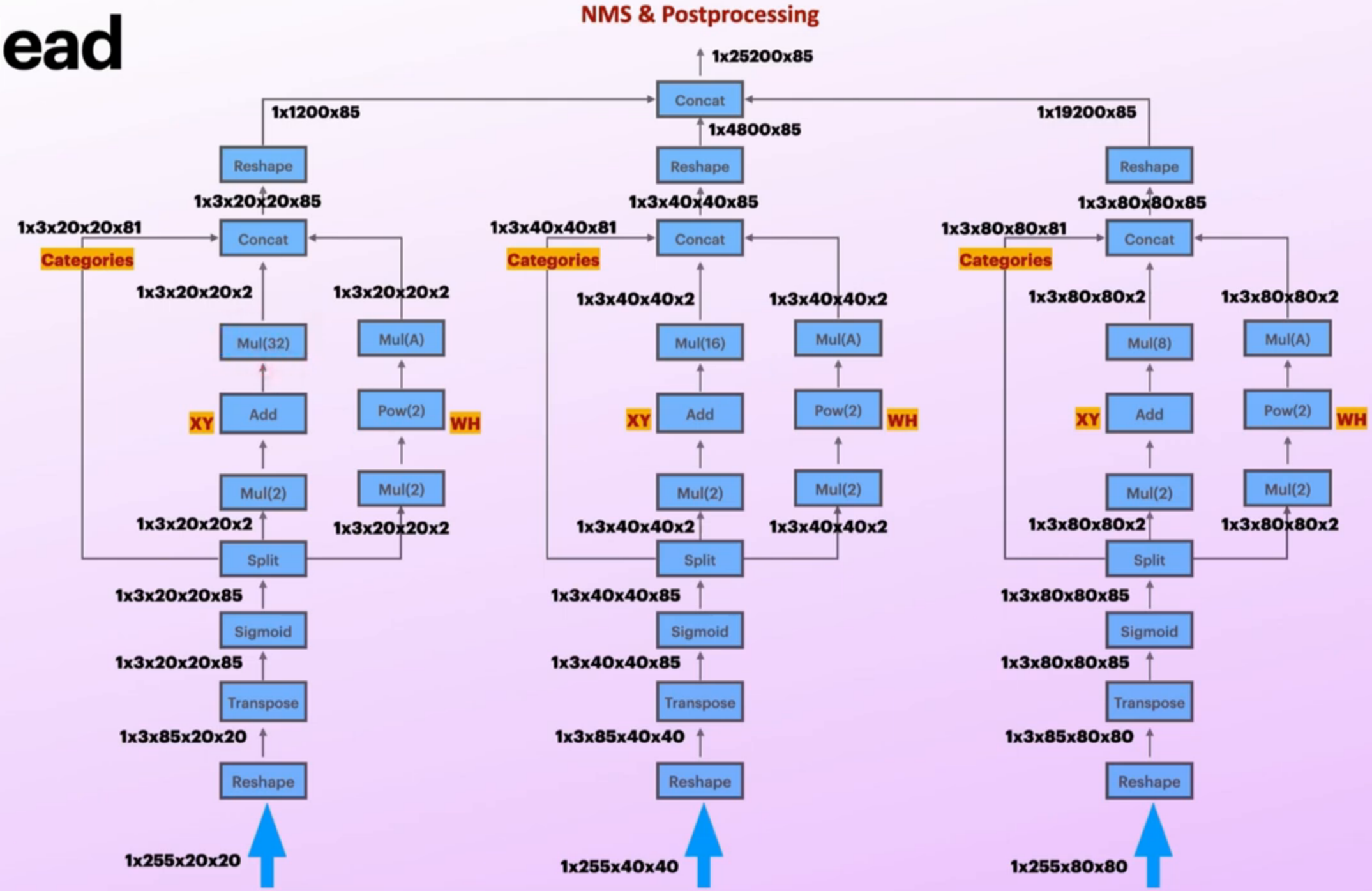
Head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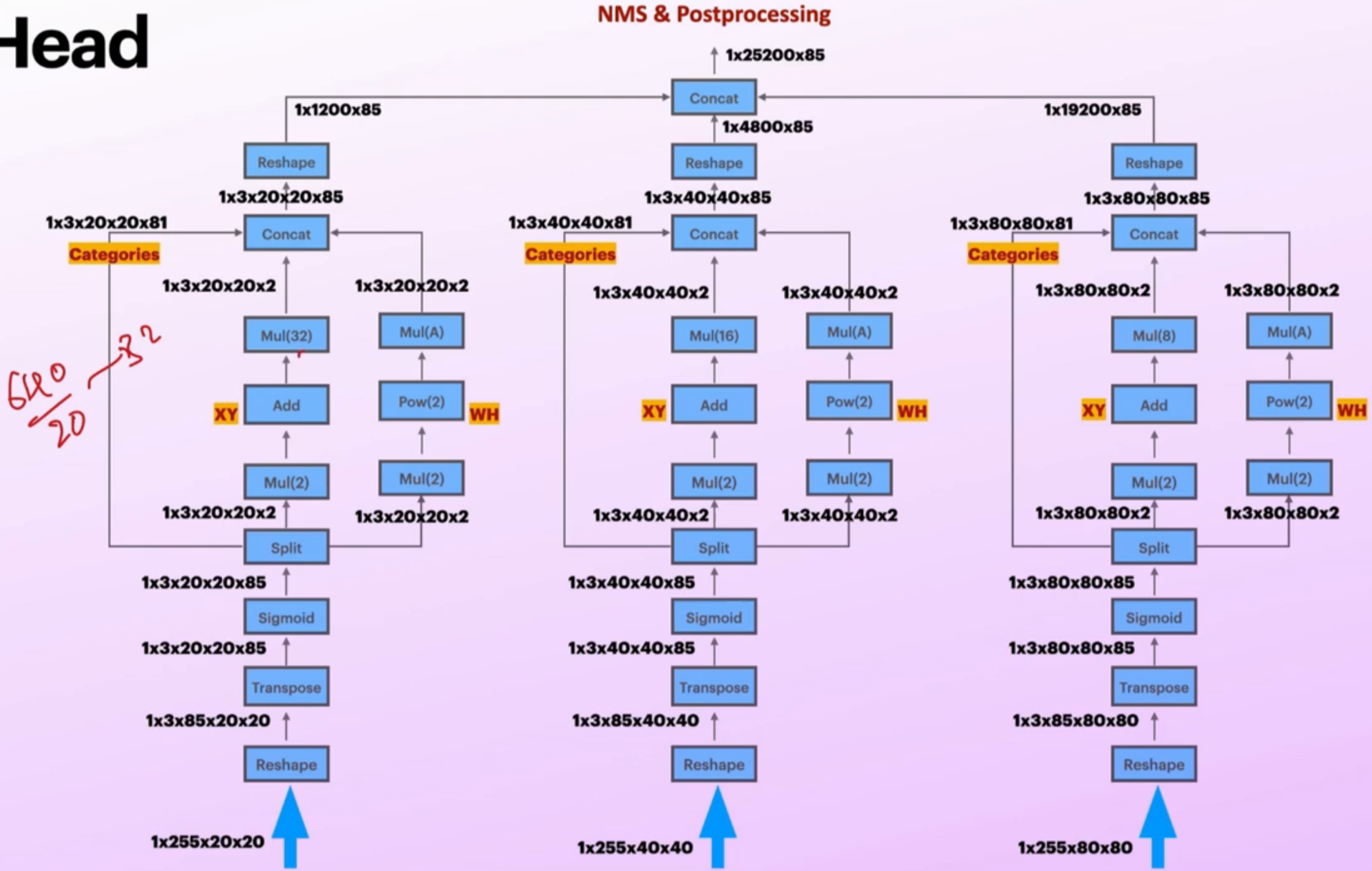
Head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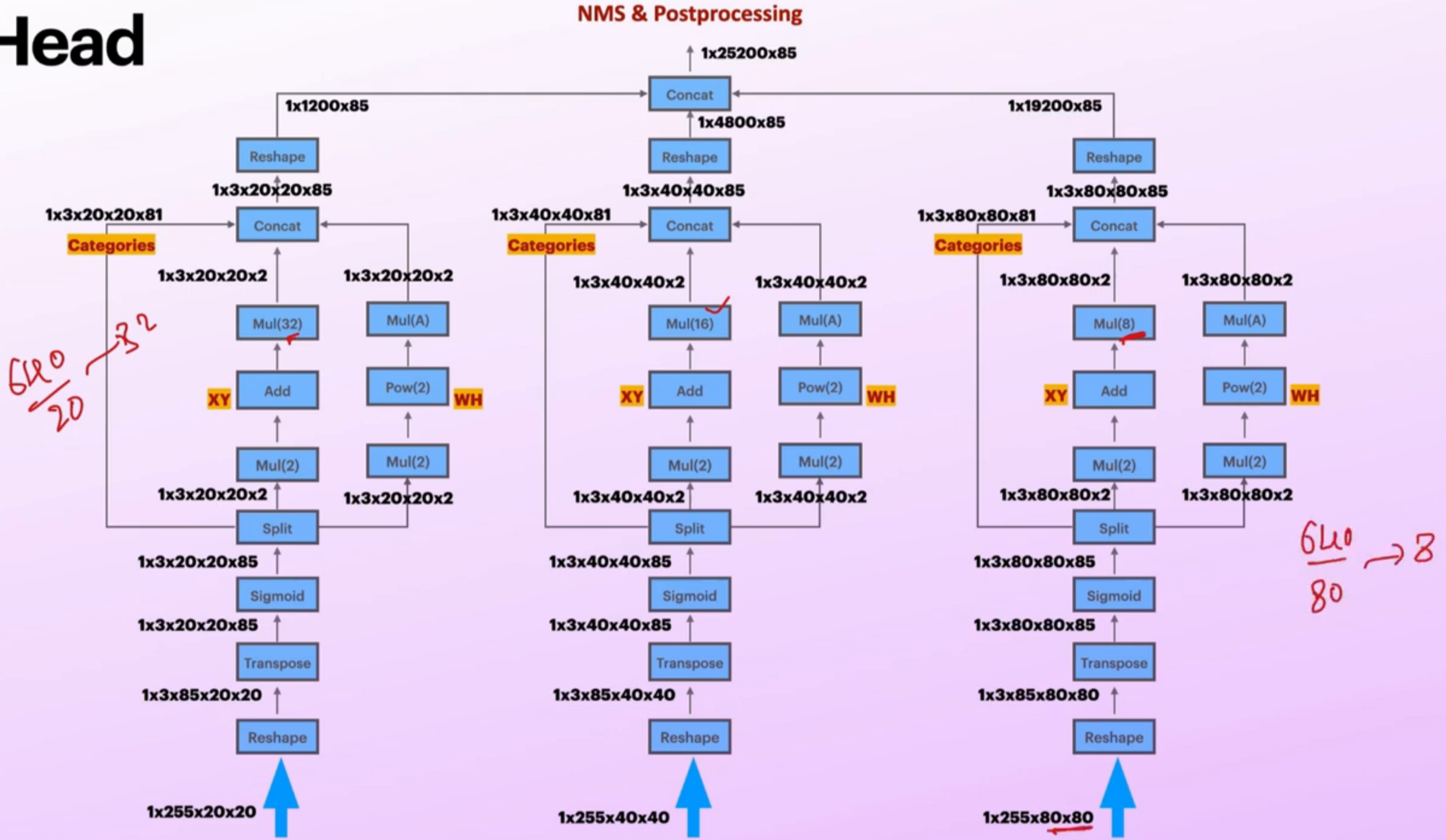
Head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Split
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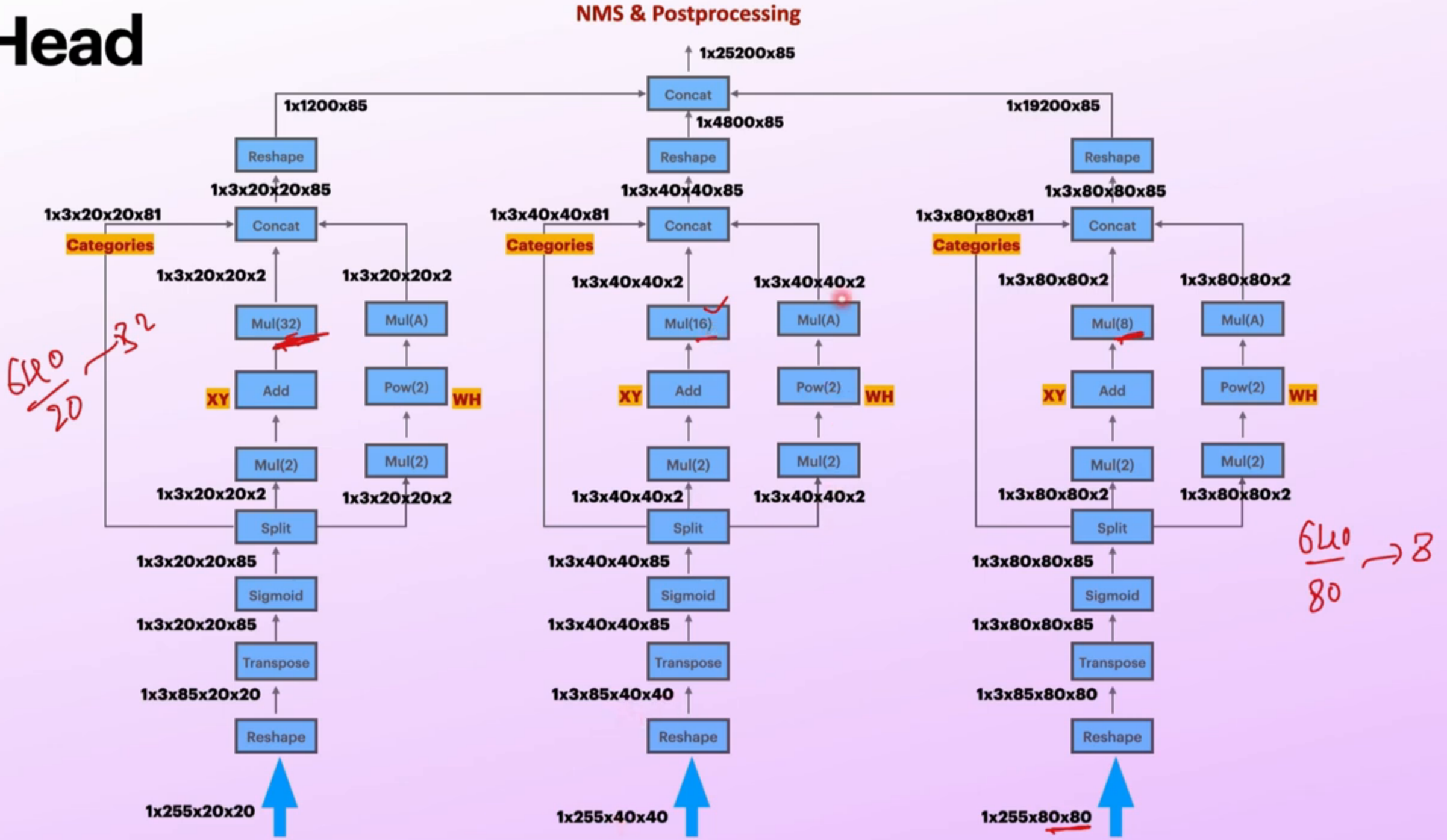
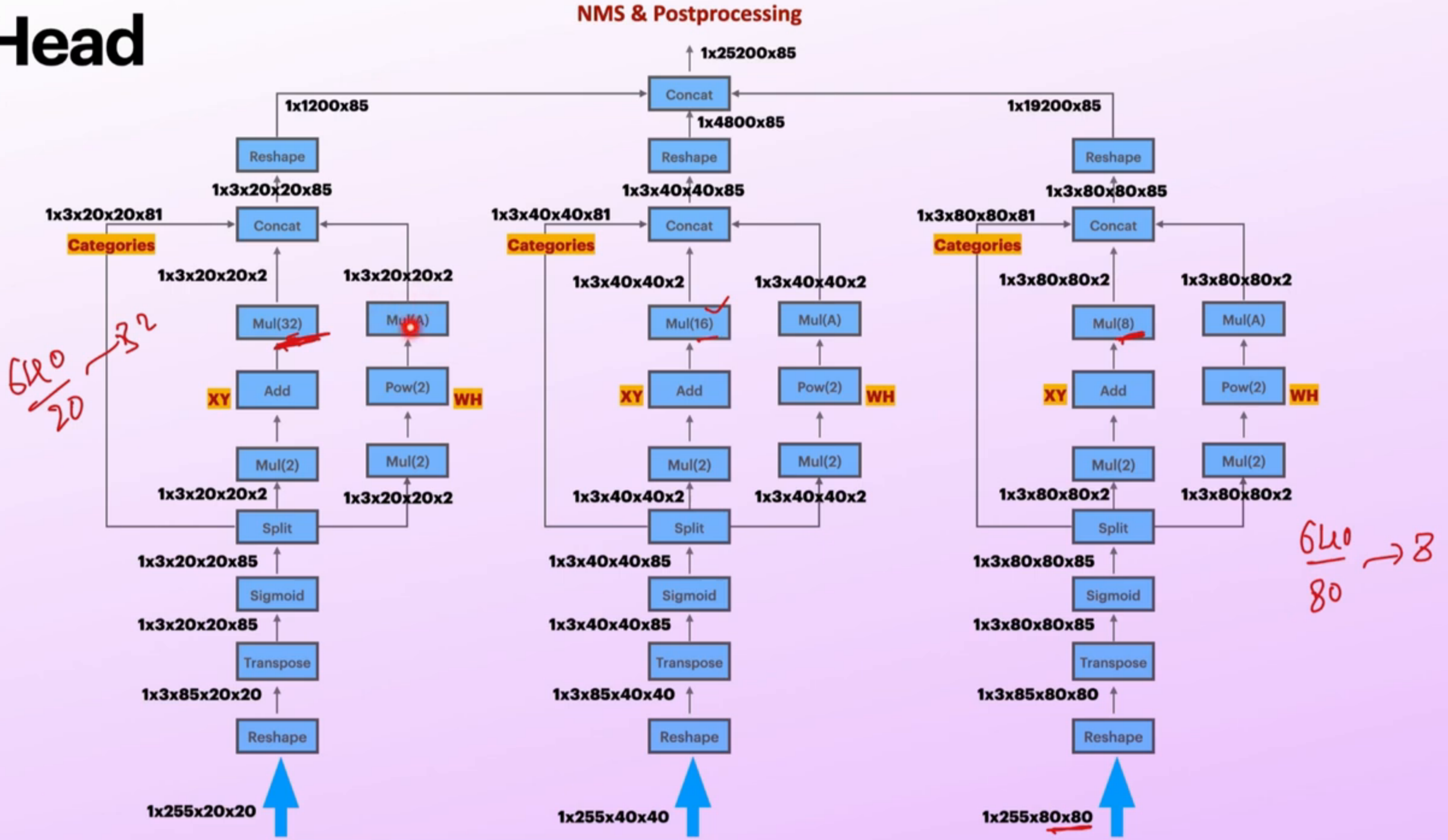
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80
640/20 → 32
640/80 → 8

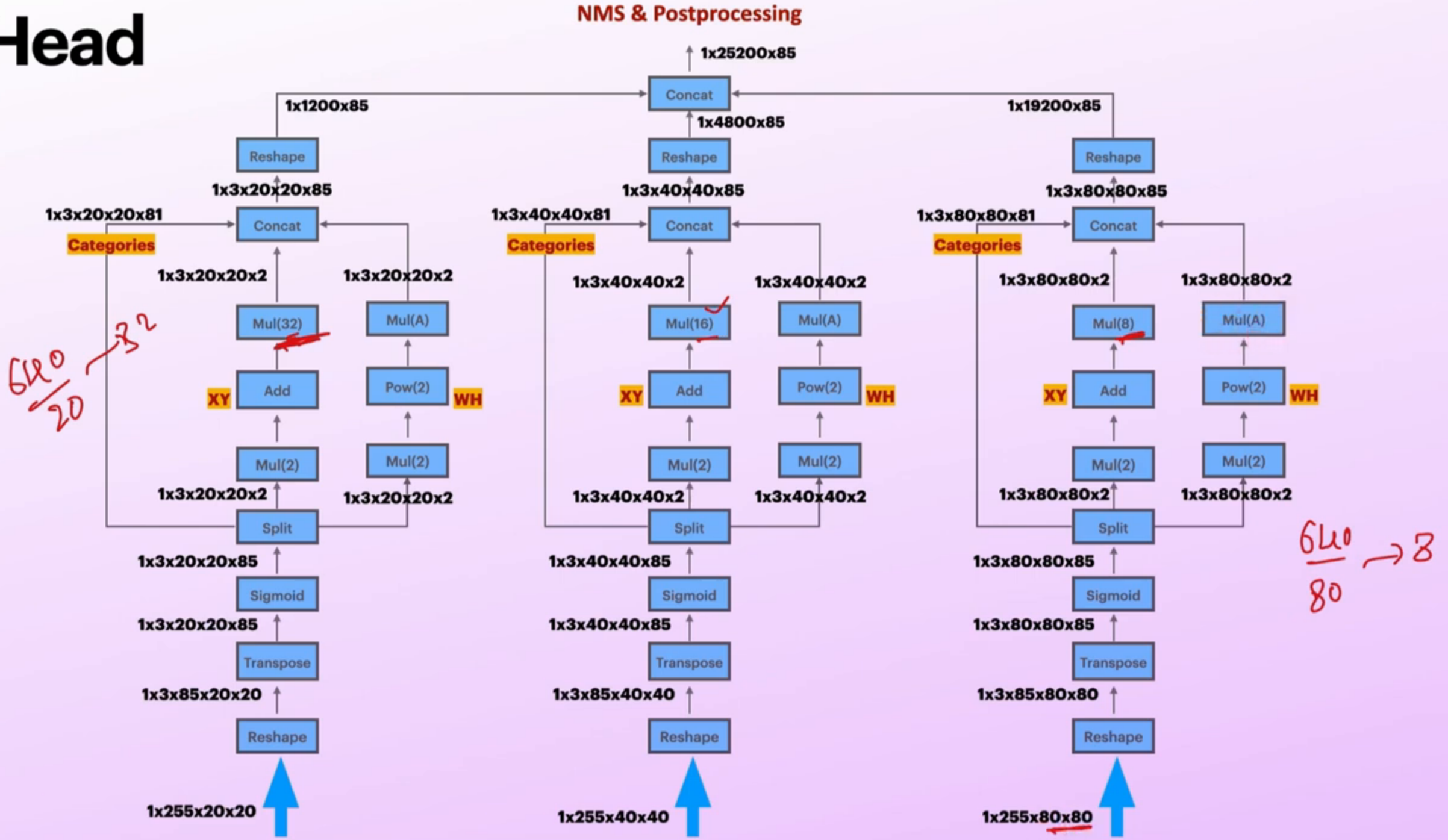
Head


NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80

Head


NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Categories
1x3x20x20x2
1x3x40x40x2
1x3x80x80x2
Mul(32)
Mul(16)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
Mul(2)
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Split
Sigmoid
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Transpose
Reshape
1x255x20x20
1x255x40x40
1x255x80x80

Head


NMS & Postprocessing
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Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
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1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
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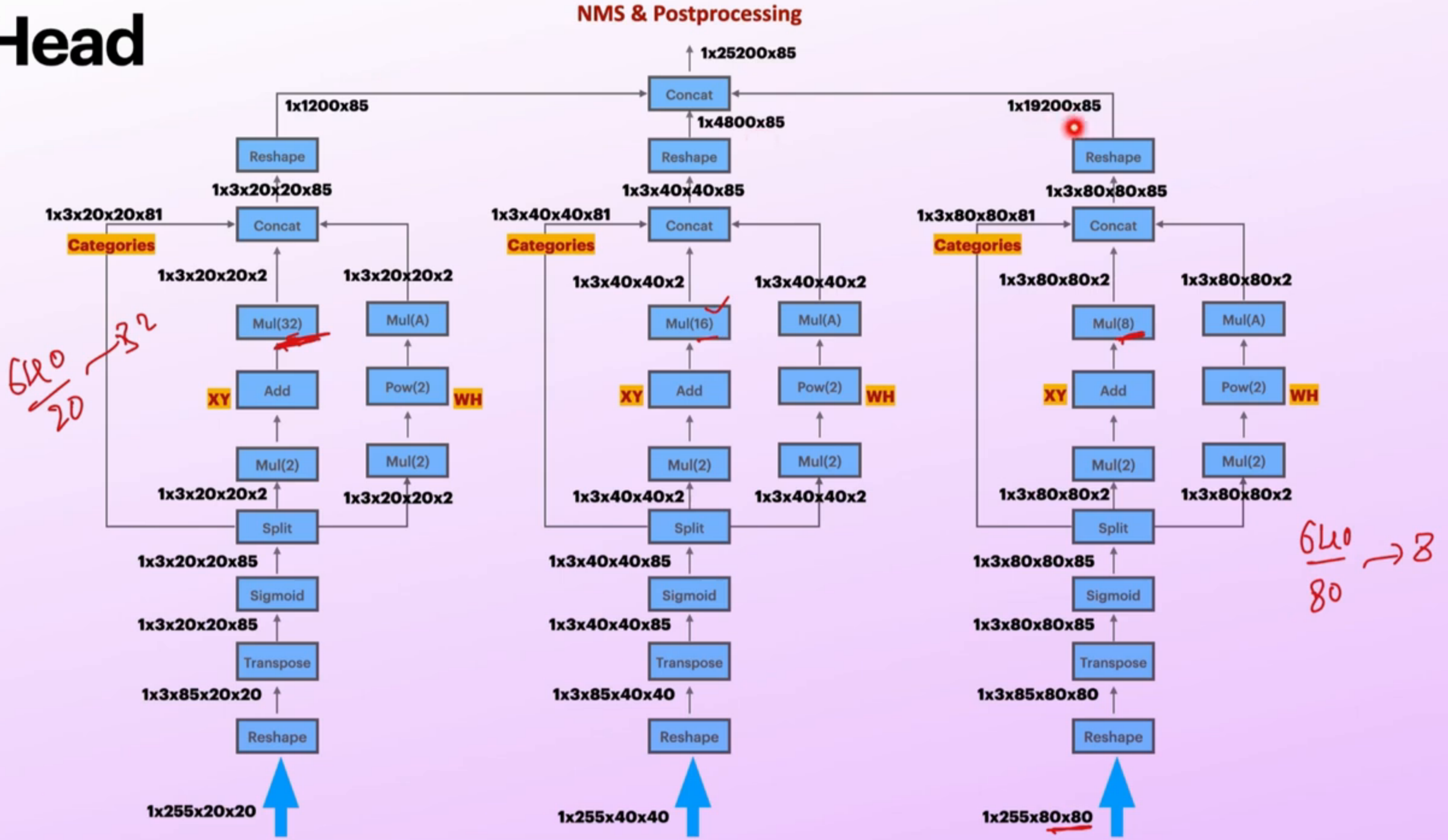
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80

Head


NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
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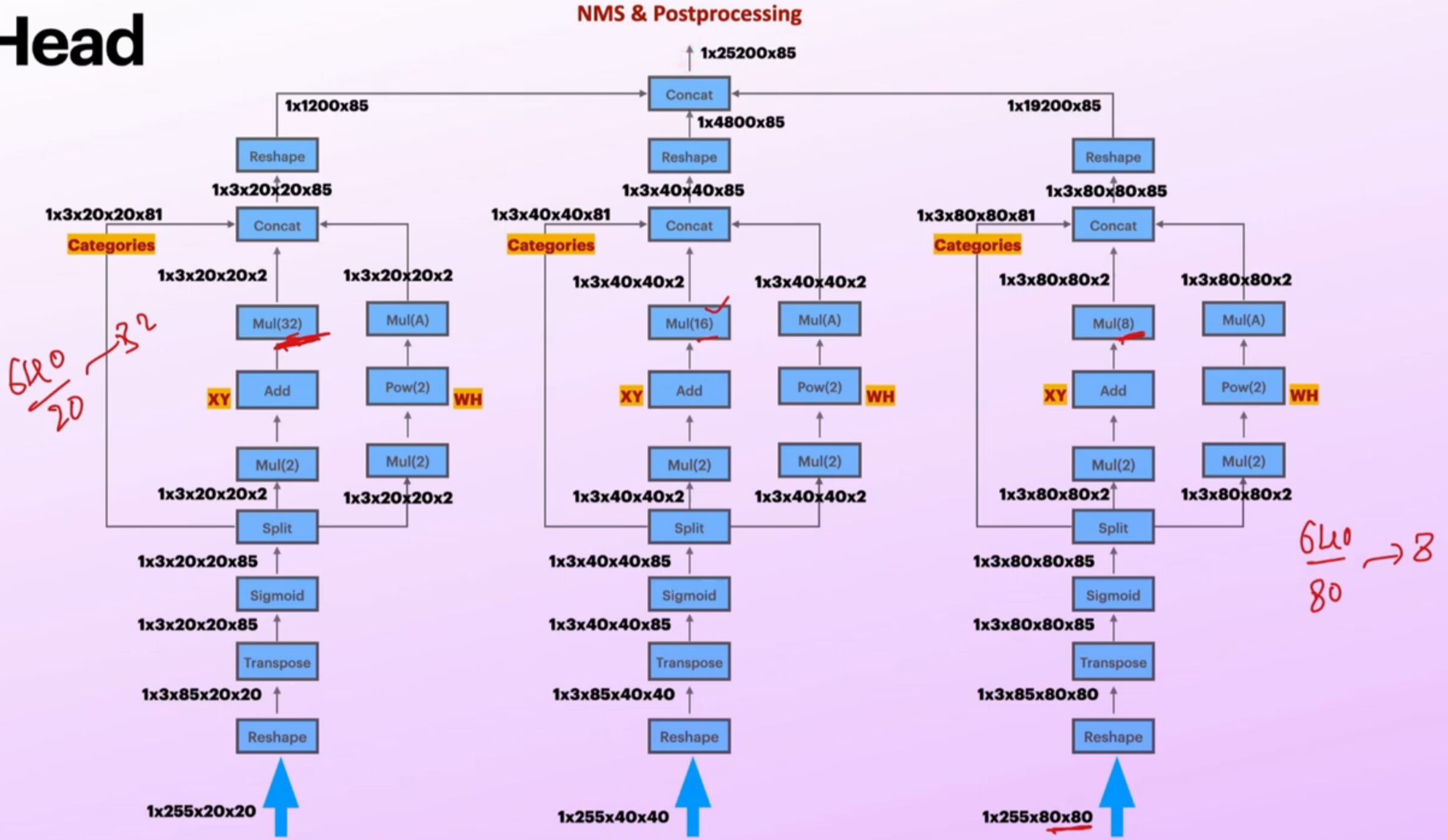
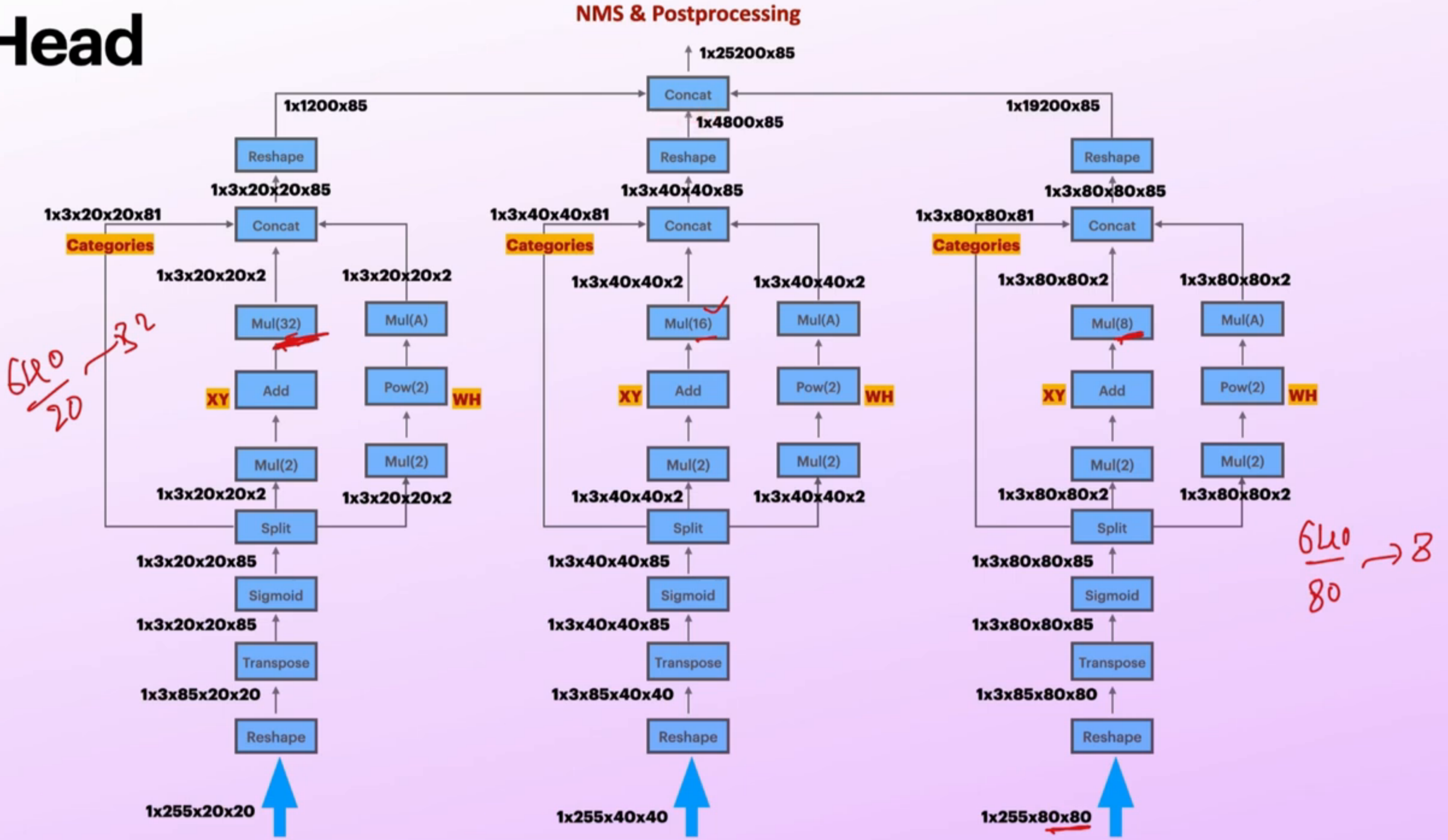
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80
640/20 → 32
640/80 → 8

Head


NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80
640/20 → 32
640/80 → 8

Head


NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
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XY
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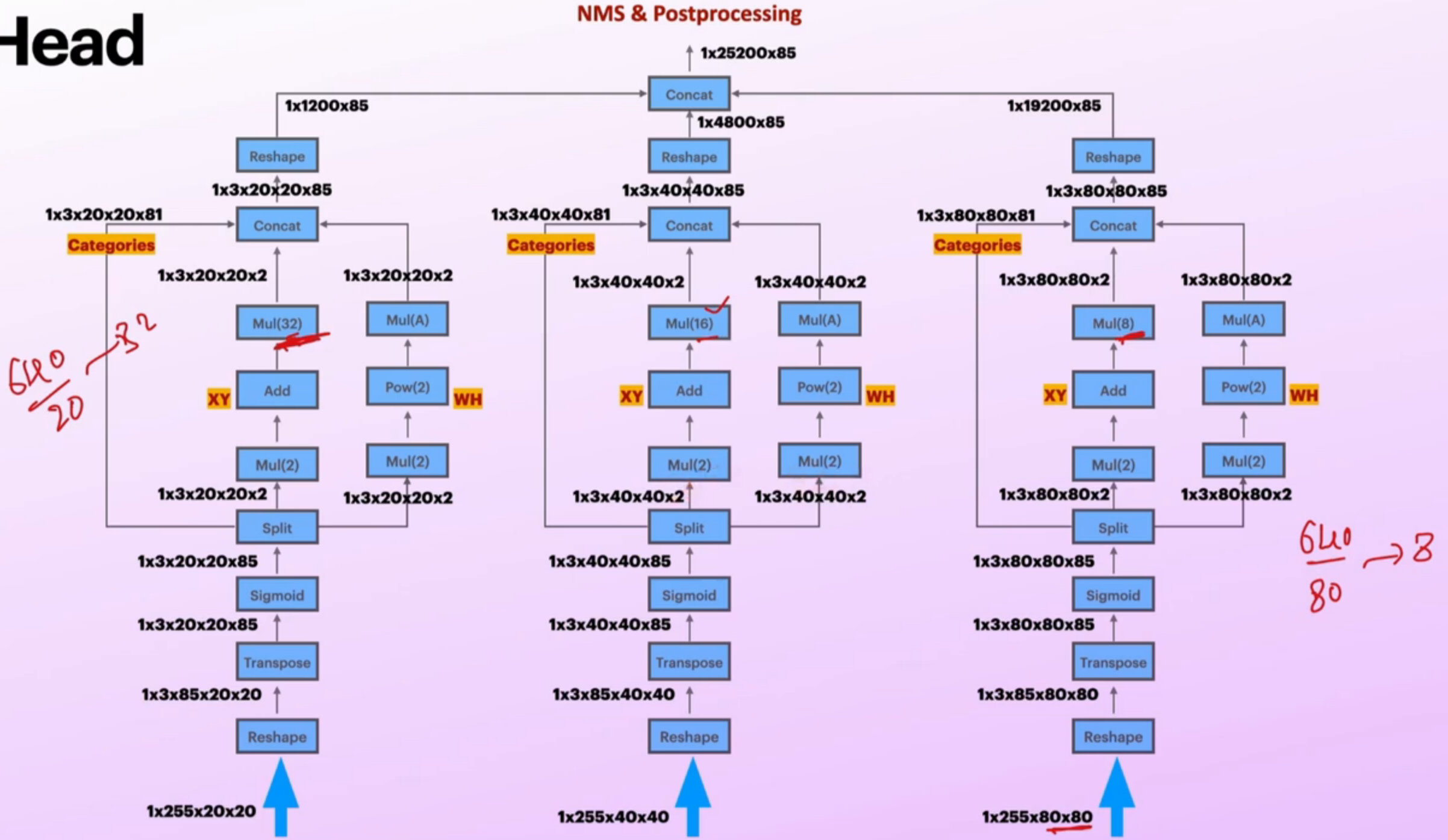
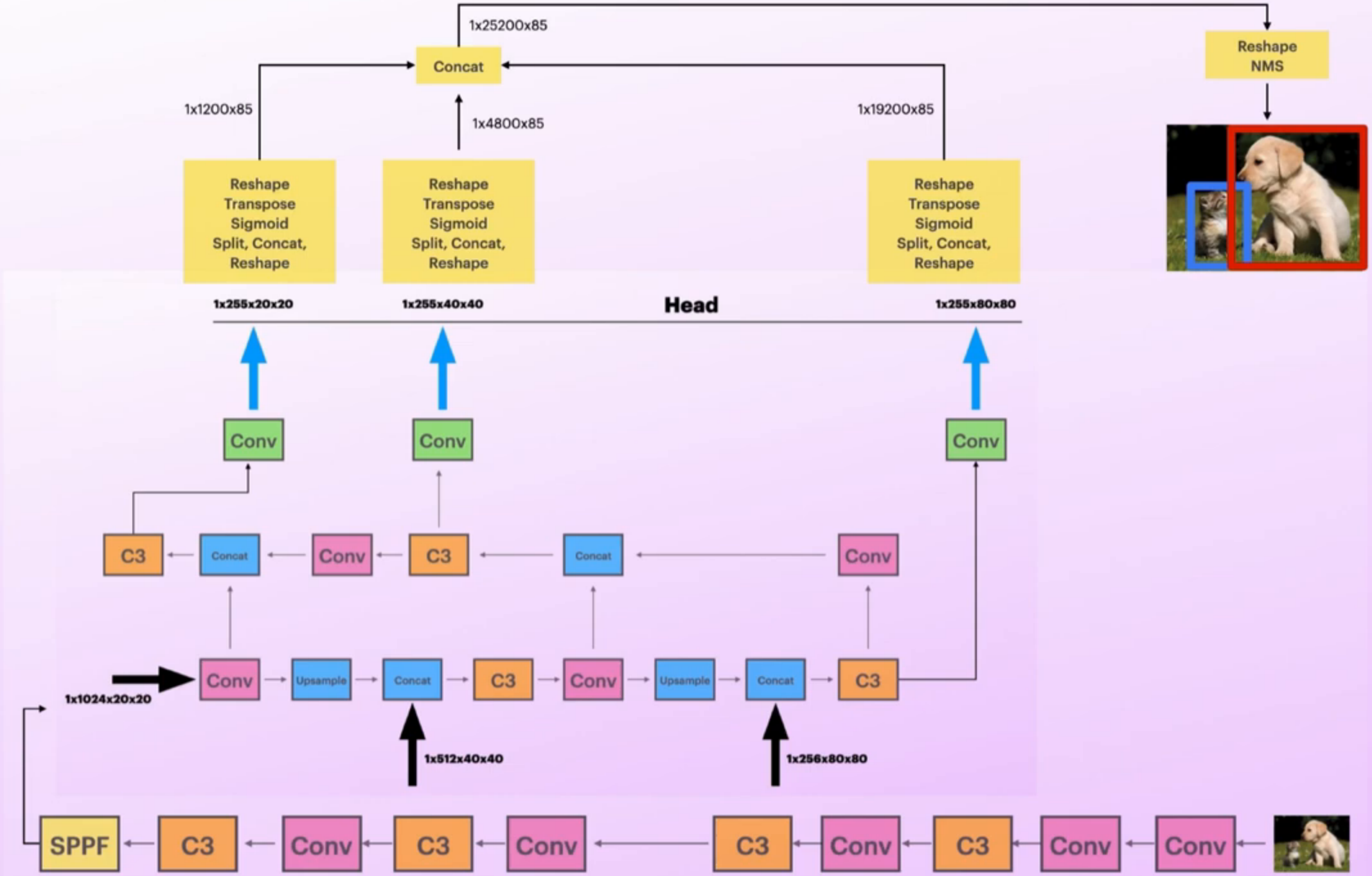
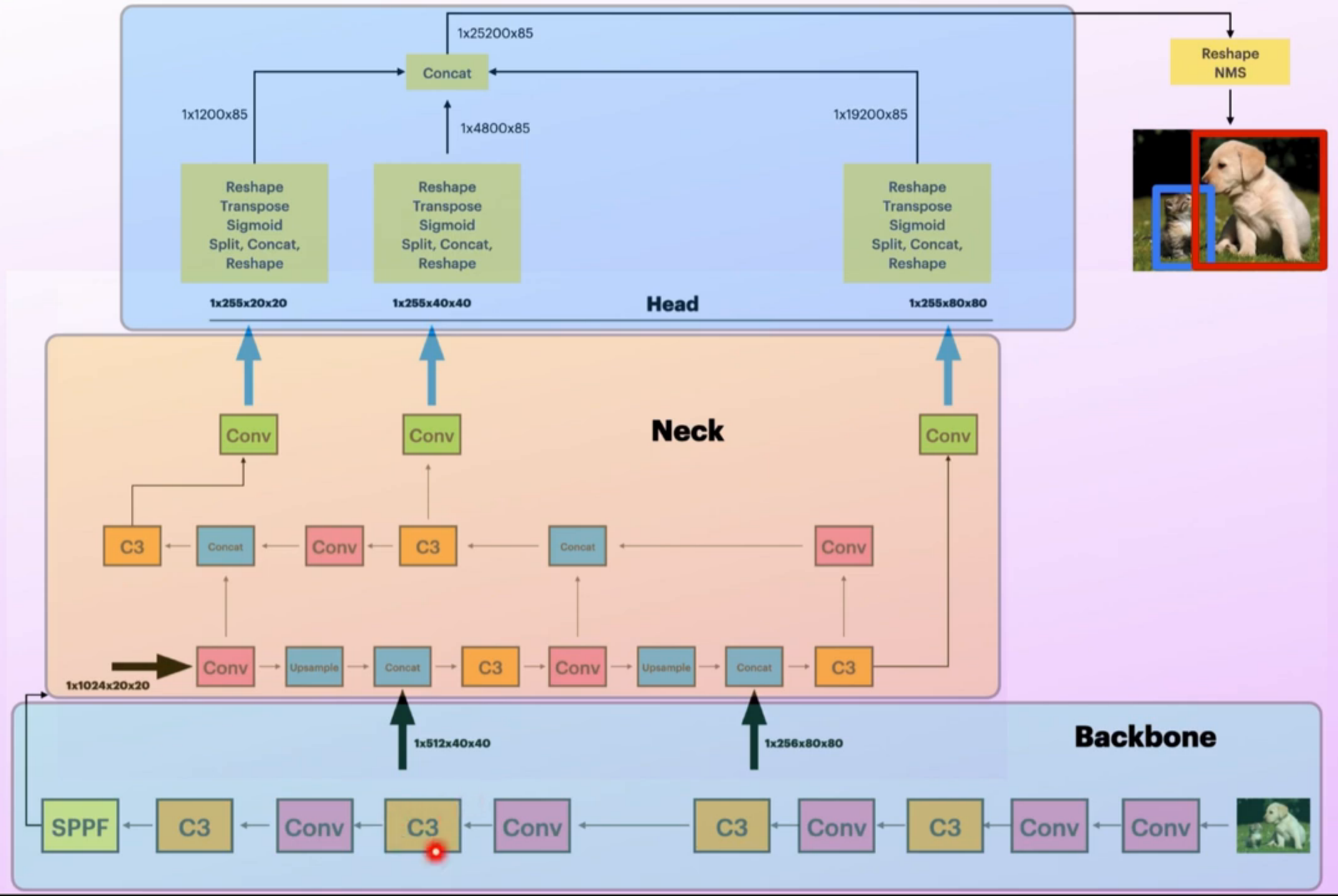
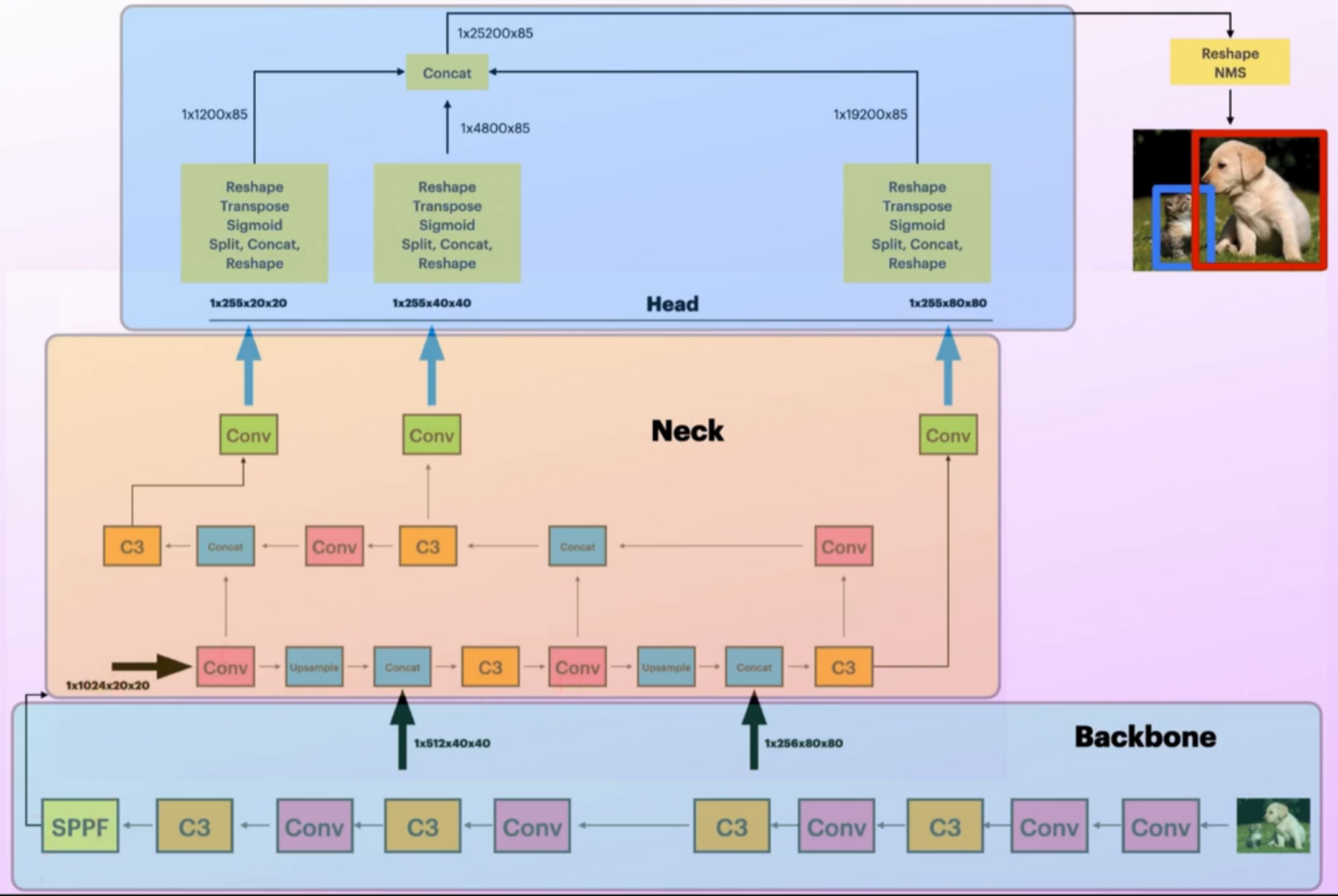
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80
640/20 → 32
640/80 → 8

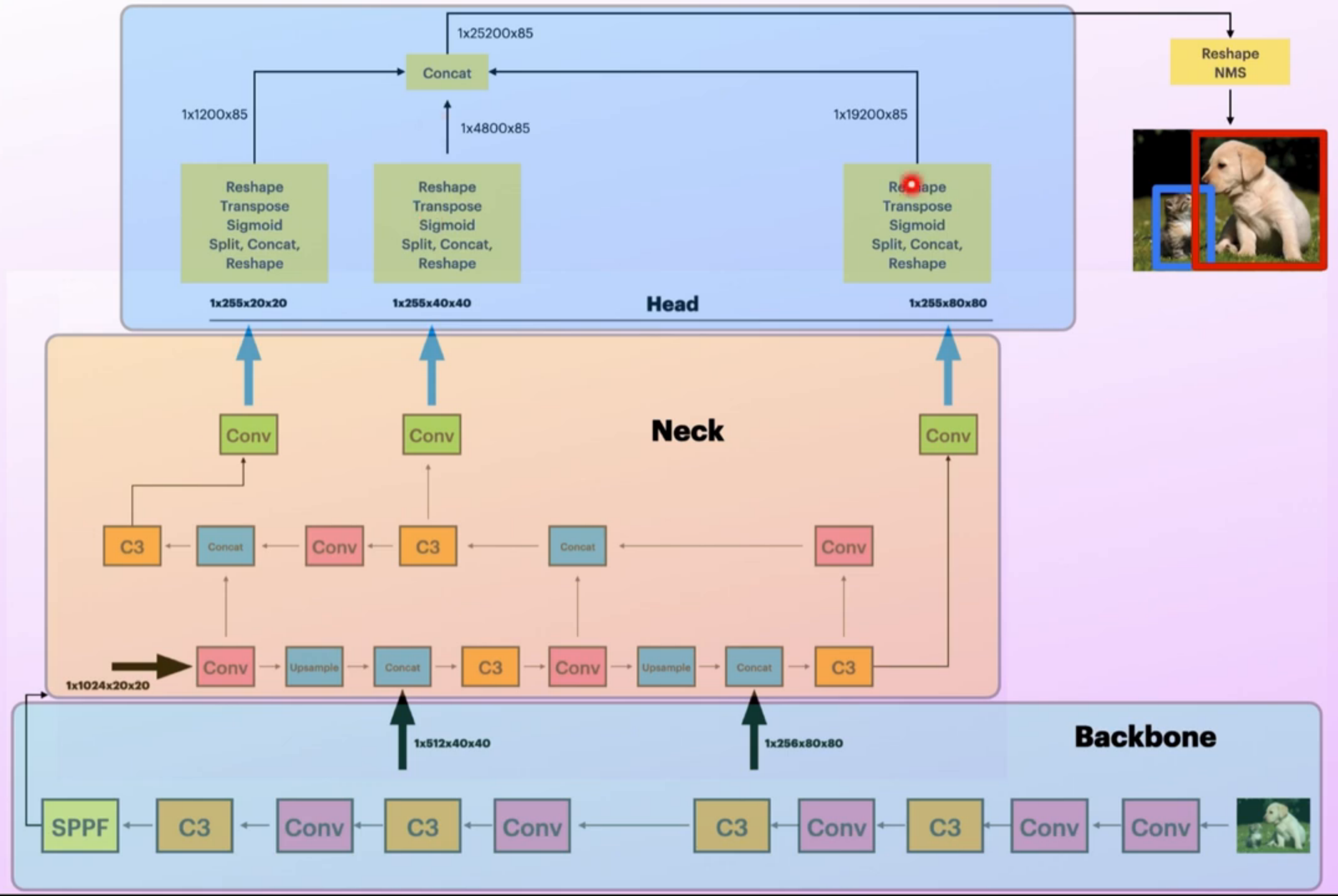
Head

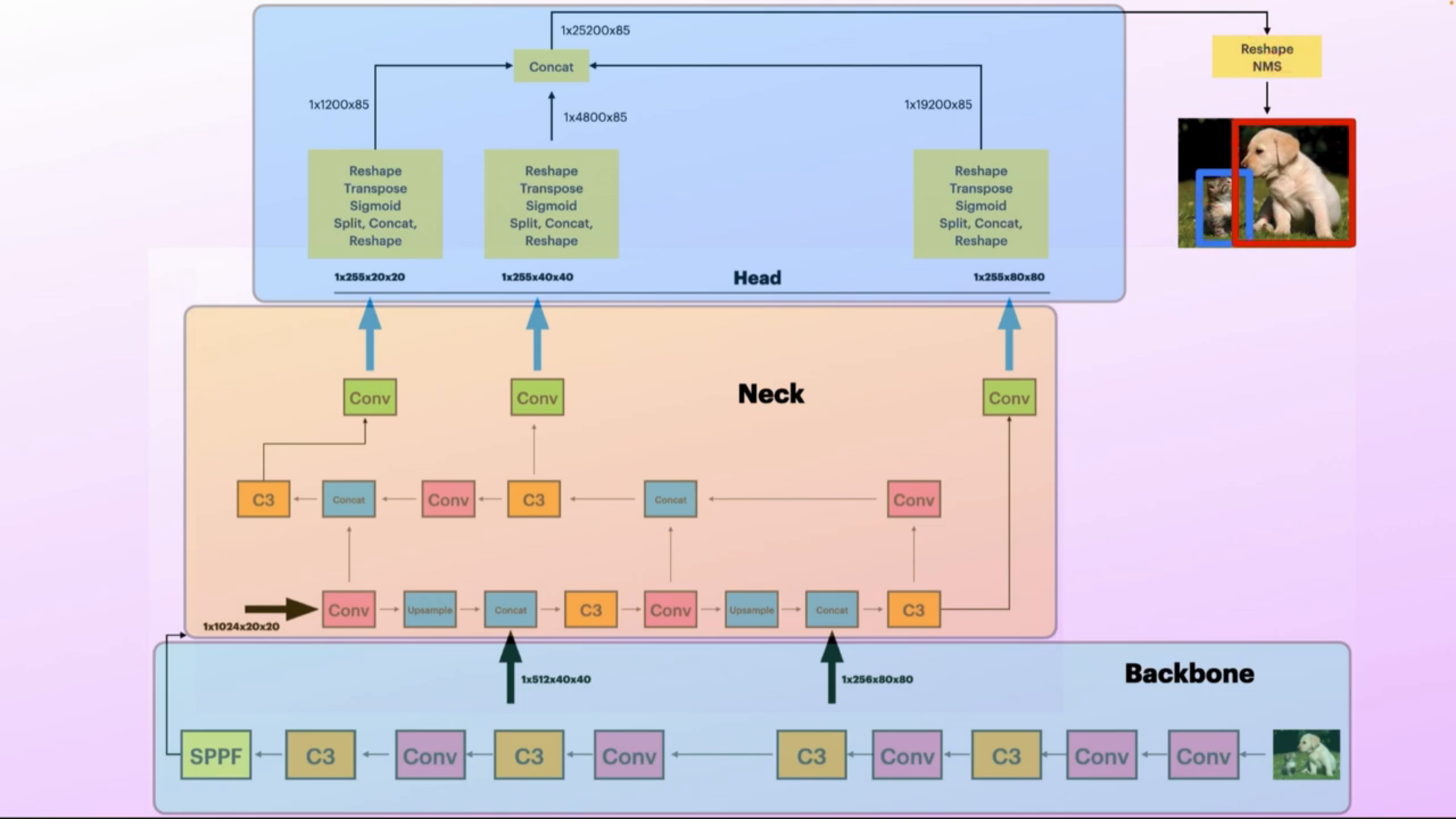

NMS & Postprocessing
1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Reshape
Reshape
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
1x3x20x20x81
1x3x40x40x81
1x3x80x80x81
Concat
Concat
Concat
Categories
Categories
Categories
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Mul(32)
Mul(A)
Mul(16)
Mul(A)
Mul(8)
Mul(A)
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
XY
Add
Pow(2)
WH
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
Mul(2)
1x3x20x20x2
1x3x20x20x2
1x3x40x40x2
1x3x40x40x2
1x3x80x80x2
1x3x80x80x2
Split
Split
Split
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Sigmoid
Sigmoid
Sigmoid
1x3x20x20x85
1x3x40x40x85
1x3x80x80x85
Transpose
Transpose
Transpose
1x3x85x20x20
1x3x85x40x40
1x3x85x80x80
Reshape
Reshape
Reshape
1x255x20x20
1x255x40x40
1x255x80x80
640/20 → 32
640/80 → 8

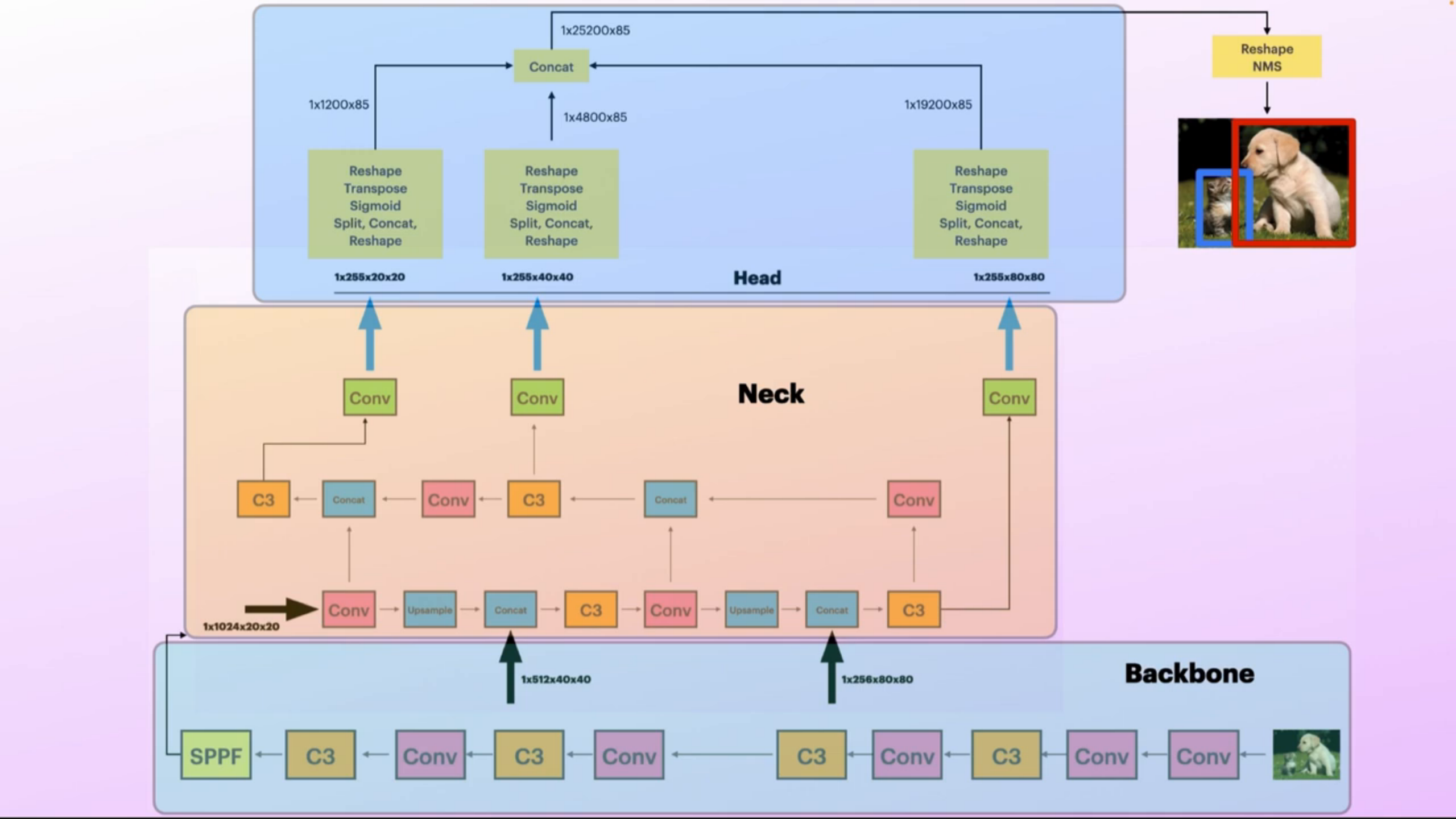

1x25200x85
Concat
Reshape
NMS
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Conv
Conv
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv

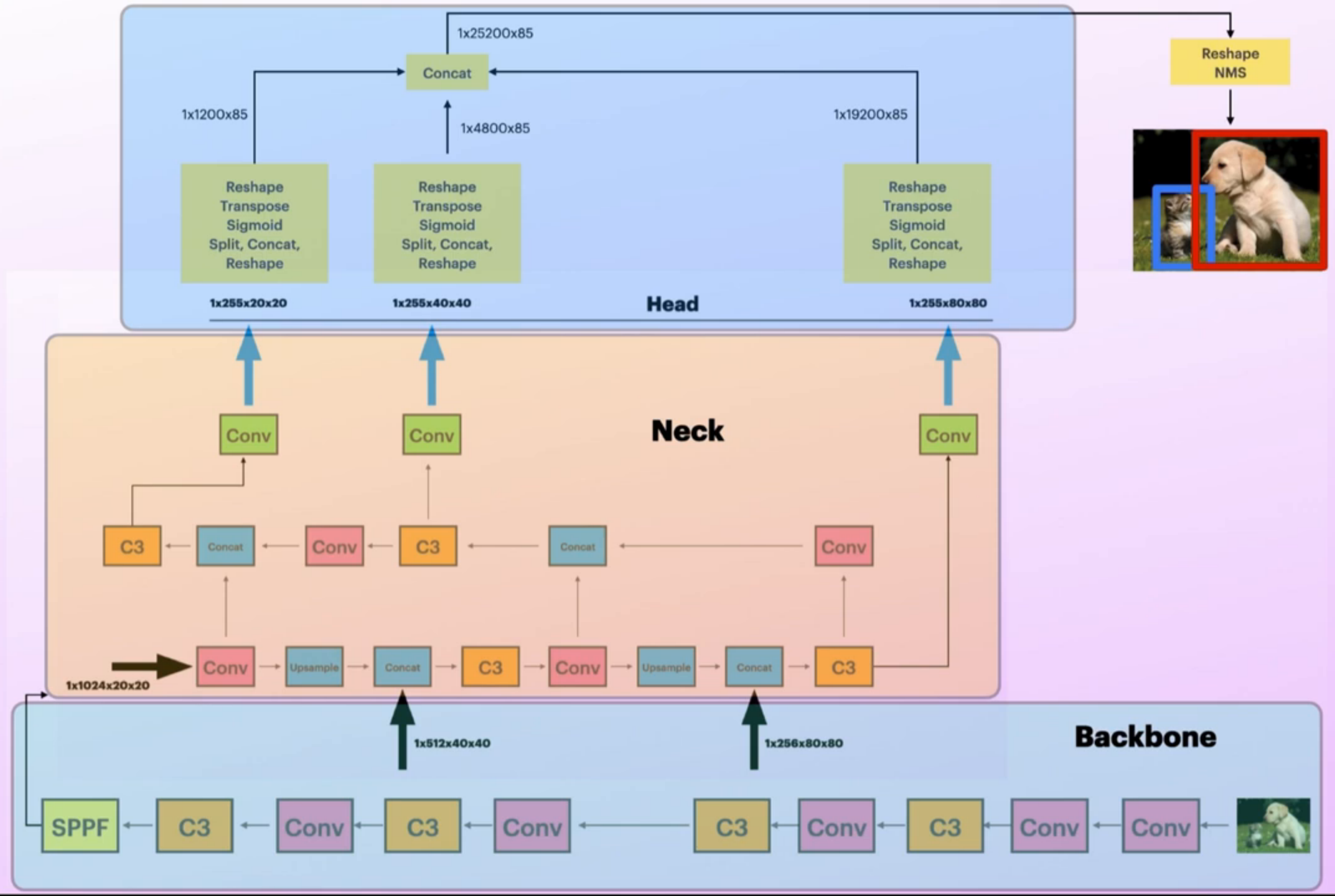

1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Neck
Conv
Conv
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv

```
2  print(x2.shape)
3  model.model[1]
```

[101] Python

```
torch.Size([1, 64, 160, 160])
```

```
Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
1  x3 = model.model[2](x2)
2  print(x3.shape)
3  model.model[2]
```

[102] Python

```
torch.Size([1, 64, 160, 160])
```

```
C3(
  (cv1): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv2): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
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  (cv3): Conv(
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    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
...
```

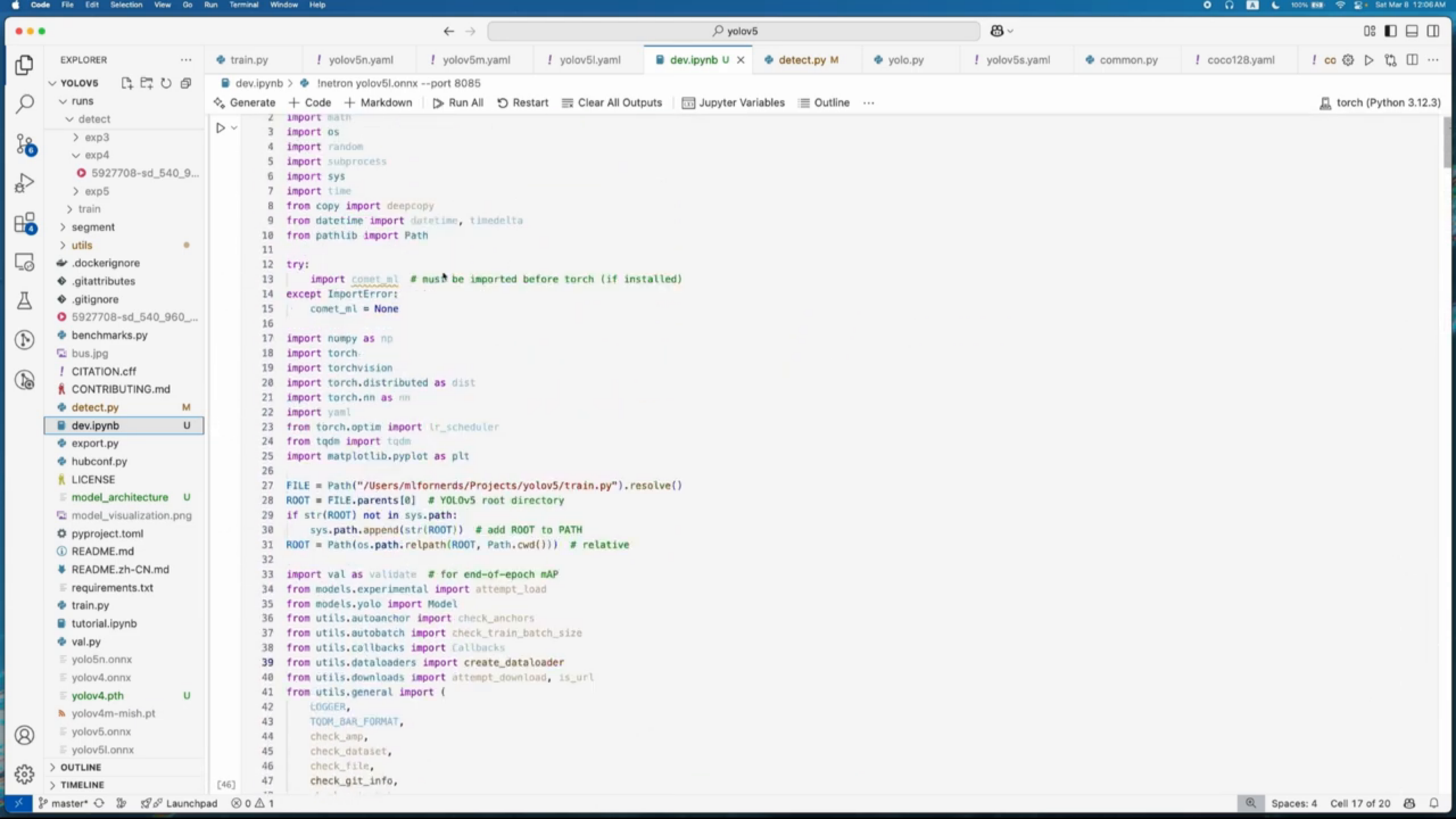
yolov5
train.py
yolov5n.yaml
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
detect.py M
yolo.py
yolov5s.yaml
common.py
coco128.yaml
EXPLORER
YOLOV5
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detect
exp3
exp4
5927708-sd_540_9...
exp5
train
segment
utils
.dockerignore
.gitattributes
.gitignore
5927708-sd_540_960_...
benchmarks.py
bus.jpg
CITATION.cff
CONTRIBUTING.md
detect.py M
dev.ipynb U
export.py
hubconf.py
LICENSE
model_architecture U
model_visualization.png
pyproject.toml
README.md
README.zh-CN.md
requirements.txt
train.py
tutorial.ipynb
val.py
yolo5n.onnx
yolov4.onnx
yolov4.pth U
yolov4m-mish.pt
yolov5.onnx
yolov5l.onnx
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dev.ipynb > !netron yolov5l.onnx --port 8085
Generate
Code
Markdown
Run All
Restart
Clear All Outputs
Jupyter Variables
Outline
torch (Python 3.12.3)
import math
import os
import random
import subprocess
import sys
import time
from copy import deepcopy
from datetime import datetime, timedelta
from pathlib import Path
try:
import comet_ml # must be imported before torch (if installed)
except ImportError:
comet_ml = None
import numpy as np
import torch
import torchvision
import torch.distributed as dist
import torch.nn as nn
import yaml
from torch.optim import lr_scheduler
from tqdm import tqdm
import matplotlib.pyplot as plt
FILE = Path("/Users/mlfornerds/Projects/yolov5/train.py").resolve()
ROOT = FILE.parents[0] # YOLOv5 root directory
if str(ROOT) not in sys.path:
sys.path.append(str(ROOT)) # add ROOT to PATH
ROOT = Path(os.path.relpath(ROOT, Path.cwd())) # relative
import val as validate # for end-of-epoch mAP
from models.experimental import attempt_load
from models.yolo import Model
from utils.autoanchor import check_anchors
from utils.autobatch import check_train_batch_size
from utils.callbacks import Callbacks
from utils.dataloaders import create_dataloader
from utils.downloads import attempt_download, is_url
from utils.general import (
LOGGER,
TQDM_BAR_FORMAT,
check_amp,
check_dataset,
check_file,
check_git_info,
[46]
master*
Launchpad
Spaces: 4
Cell 17 of 20

```
X = X.to(device).float() / 255 # image, converted to proper range
print(X.shape)
preds = model(X)
print(len(preds))
preds[0].shape, preds[1].shape, preds[2].shape
```

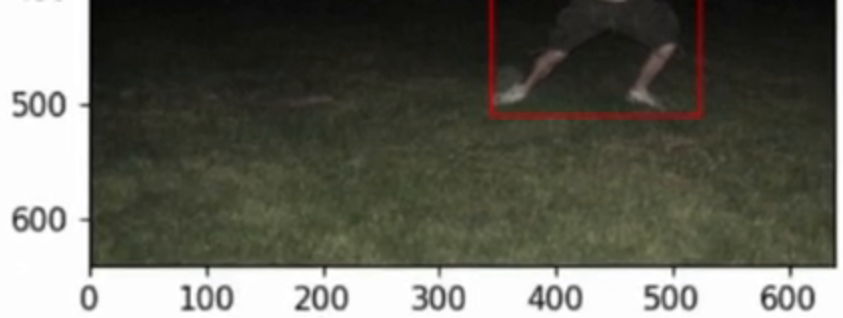
[99] Python

```
                 from  n    params  module                                  arguments
  0                -1  1      3520  models.common.Conv                      [3, 32, 6, 2, 2]
  1                -1  1     18560  models.common.Conv                      [32, 64, 3, 2]
  2                -1  1     18816  models.common.C3                        [64, 64, 1]
  3                -1  1     73984  models.common.Conv                      [64, 128, 3, 2]
  4                -1  2    115712  models.common.C3                        [128, 128, 2]
  5                -1  1    295424  models.common.Conv                      [128, 256, 3, 2]
  6                -1  3    625152  models.common.C3                        [256, 256, 3]
  7                -1  1   1180672  models.common.Conv                      [256, 512, 3, 2]
  8                -1  1   1182720  models.common.C3                        [512, 512, 1]
  9                -1  1    656896  models.common.SPPF                      [512, 512, 5]
 10                -1  1    131584  models.common.Conv                      [512, 256, 1, 1]
 11                -1  1         0  torch.nn.modules.upsampling.Upsample    [None, 2, 'nearest']
 12          [-1, 6]  1         0  models.common.Concat                    [1]
 13                -1  1    361984  models.common.C3                        [512, 256, 1, False]
 14                -1  1     33024  models.common.Conv                      [256, 128, 1, 1]
 15                -1  1         0  torch.nn.modules.upsampling.Upsample    [None, 2, 'nearest']
 16          [-1, 4]  1         0  models.common.Concat                    [1]
 17                -1  1     90880  models.common.C3                        [256, 128, 1, False]
 18                -1  1    147712  models.common.Conv                      [128, 128, 3, 2]
 19          [-1, 14]  1         0  models.common.Concat                    [1]
 20                -1  1    296448  models.common.C3                        [256, 256, 1, False]
 21                -1  1    590336  models.common.Conv                      [256, 256, 3, 2]
 22          [-1, 10]  1         0  models.common.Concat                    [1]
 23                -1  1   1182720  models.common.C3                        [512, 512, 1, False]
 24      [17, 20, 23]  1    229245  models.yolo.Detect                      [80, [[10, 13, 16, 30, 33, 23], [30, 61, 62, 45, 59, 119], [116, 90, 156, 198, 373, 326]], [128, 256, 512]]
YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

torch.Size([1, 3, 640, 640])
3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

```
x1 = model.model[0](X)
```




```
[ ]
1
```

(parameter) anchors: Any | None

```
[99]
1 model = Model(cfg, ch=3, nc=80, anchors=hyp.get('anchors')).to(device)
2 X = X.to(device).float() / 255 # image, converted to proper range
3 print(X.shape)
4 preds = model(X)
5 print(len(preds))
6 preds[0].shape, preds[1].shape, preds[2].shape
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  4                -1  2    115712  models.common.C3                        [128, 128, 2]
  5                -1  1    295424  models.common.Conv                      [128, 256, 3, 2]
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  8                -1  1   1182720  models.common.C3                        [512, 512, 1]
  9                -1  1    656896  models.common.SPPF                      [512, 512, 5]
 10                -1  1    131584  models.common.Conv                      [512, 256, 1, 1]
```

```
329                 math.log(0.6 / (m.nc - 0.99999)) if cf is None else torch.log(cf / cf.sum())
330             )  # cls
331             mi.bias = torch.nn.Parameter(b.view(-1), requires_grad=True)
332
333
334 Model = DetectionModel  # retain YOLOv5 'Model' class for backwards compatibility      Glenn Jocher, 3 years ago • New YOLOv5 Classification Models
335
336
    Glenn Jocher, 6 months ago | 3 authors (Glenn Jocher and others)
337 class SegmentationModel(DetectionModel):
338     """YOLOv5 segmentation model for object detection and segmentation tasks with configurable parameters."""
339
340     def __init__(self, cfg="yolov5s-seg.yaml", ch=3, nc=None, anchors=None):
341         """Initializes a YOLOv5 segmentation model with configurable params: cfg (str) for configuration, ch (int) for channels, nc (int) for num c
342         super().__init__(cfg, ch, nc, anchors)
343
344
    Glenn Jocher, 6 months ago | 2 authors (Glenn Jocher and one other)
345 class ClassificationModel(BaseModel):
346     """YOLOv5 classification model for image classification tasks, initialized with a config file or detection model."""
347
348     def __init__(self, cfg=None, model=None, nc=1000, cutoff=10):
349         """Initializes YOLOv5 model with config file `cfg`, input channels `ch`, number of classes `nc`, and `cuttoff`
350         index.
351         """
352         super().__init__()
353         self._from_detection_model(model, nc, cutoff) if model is not None else self._from_yaml(cfg)
354
355     def _from_detection_model(self, model, nc=1000, cutoff=10):
356         """Creates a classification model from a YOLOv5 detection model, slicing at `cutoff` and adding a classification
357         layer.
358         """
359         if isinstance(model, DetectMultiBackend):
360             model = model.model  # unwrap DetectMultiBackend
361         model.model = model.model[:cutoff]  # backbone
362         m = model.model[-1]  # last layer
363         ch = m.conv.in_channels if hasattr(m, "conv") else m.cv1.conv.in_channels  # ch into module
364         c = Classify(ch, nc)  # Classify()
365         c.i, c.f, c.type = m.i, m.f, "models.common.Classify"  # index, from, type
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217
        Glenn Jocher, 6 months ago | 5 authors (Glenn Jocher and others)
218     class DetectionModel(BaseModel):
219         """YOLOv5 detection model class for object detection tasks, supporting custom configurations and anchors."""
220
221         def __init__(self, cfg="yolov5s.yaml", ch=3, nc=None, anchors=None):      Glenn Jocher, 12 months ago • Replace inline comments with docstrings
222             """Initializes YOLOv5 model with configuration file, input channels, number of classes, and custom anchors."""
223             super().__init__()
224             if isinstance(cfg, dict):
225                 self.yaml = cfg  # model dict
226             else:  # is *.yaml
227                 import yaml  # for torch hub
228
229                 self.yaml_file = Path(cfg).name
230                 with open(cfg, encoding="ascii", errors="ignore") as f:
231                     self.yaml = yaml.safe_load(f)  # model dict
232
233             # Define model
234             ch = self.yaml["ch"] = self.yaml.get("ch", ch)  # input channels
235             if nc and nc != self.yaml["nc"]:
236                 LOGGER.info(f"Overriding model.yaml nc={self.yaml['nc']} with nc={nc}")
237                 self.yaml["nc"] = nc  # override yaml value
238             if anchors:
239                 LOGGER.info(f"Overriding model.yaml anchors with anchors={anchors}")
240                 self.yaml["anchors"] = round(anchors)  # override yaml value
241             self.model, self.save = parse_model(deepcopy(self.yaml), ch=[ch])  # model, savelist
242             self.names = [str(i) for i in range(self.yaml["nc"])]  # default names
243             self.inplace = self.yaml.get("inplace", True)
244
245             # Build strides, anchors
246             m = self.model[-1]  # Detect()
247             if isinstance(m, (Detect, Segment)):
248
249                 def _forward(x):
250                     """Passes the input 'x' through the model and returns the processed output."""
251                     return self.forward(x)[0] if isinstance(m, Segment) else self.forward(x)
252
253                 s = 256  # 2x min stride
```

```python
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[99]

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10	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
12	[-1, 6]	1	0	models.common.Concat	[1]
13	-1	1	361984	models.common.C3	[512, 256, 1, False]
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18	-1	1	147712	models.common.Conv	[128, 128, 3, 2]
19	[-1, 14]	1	0	models.common.Concat	[1]
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24	[17, 20, 23]	1	229245	models.yolo.Detect	[80, [[10, 13, 16, 30, 33, 23], [30, 61, 62, 45, 59, 119], [116, 90, 156,

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YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

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11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
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 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

[100]
```
x1 = model.model[0](X)
print(x1.shape)
model.model[0]
```

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

[101]
```
x2 = model.model[1](x1)
print(x2.shape)
model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
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YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

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3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
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  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
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print(x2.shape)
model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

torch.Size([1, 3, 640, 640])
3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

[100]

```
x1 = model.model[0](X)
print(x1.shape)
model.model[0]
```

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

[101]

```
x2 = model.model[1](x1)
print(x2.shape)
model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

torch.Size([1, 3, 640, 640])
3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

```
[100]
1 x1 = model.model[0](X)
2 print(x1.shape)
3 model.model[0]
```

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
[101]
1 x2 = model.model[1](x1)
2 print(x2.shape)
3 model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

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```
YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

torch.Size([1, 3, 640, 640])
3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

[100]

```
x1 = model.model[0](X)
print(x1.shape)
model.model[0]
```

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

[101]

```
x2 = model.model[1](x1)
print(x2.shape)
model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
YOLOv5s summary: 214 layers, 7235389 parameters, 7235389 gradients, 16.6 GFLOPs

torch.Size([1, 3, 640, 640])
3

(torch.Size([1, 3, 80, 80, 85]),
 torch.Size([1, 3, 40, 40, 85]),
 torch.Size([1, 3, 20, 20, 85]))
```

```
[100]
1  x1 = model.model[0](X)
2  print(x1.shape)
3  model.model[0]
```

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
[101]
1  x2 = model.model[1](x1)
2  print(x2.shape)
3  model.model[1]
```

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
torch.Size([1, 3, 20, 20, 85]))
```

```
x1 = model.model[0](X)
print(x1.shape)
model.model[0]
```

[100]

```
torch.Size([1, 32, 320, 320])

Conv(
  (conv): Conv2d(3, 32, kernel_size=(6, 6), stride=(2, 2), padding=(2, 2), bias=False)
  (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
x2 = model.model[1](x1)
print(x2.shape)
model.model[1]
```

[101]

```
torch.Size([1, 64, 160, 160])

Conv(
  (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
  (act): SiLU(inplace=True)
)
```

```
x3 = model.model[2](x2)
print(x3.shape)
model.model[2]
```

[102]

```
  (act): SiLU(inplace=True)
)
```

```
x3 = model.model[2](x2)
print(x3.shape)
model.model[2]
```

[102]

```
torch.Size([1, 64, 160, 160])

C3(
  (cv1): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv2): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv3): Conv(
    (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
...
```

```
    (act): SiLU(inplace=True)
  )
  (cv2): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv3): Conv(
    (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
)
```

```
[104]
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
```

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```
torch.Size([1, 64, 160, 160])
```

```
C3(
  (cv1): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv2): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv3): Conv(
    (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
```

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
```

```
torch.Size([1, 64, 160, 160])
```

```
C3(
  (cv1): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv2): Conv(
    (conv): Conv2d(64, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (cv3): Conv(
    (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
```

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
```

```
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
)
```

[104]

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
```

```
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
)
```

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[104]

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
```

```
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
)
```

[104]

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
```

```
    (bn): BatchNorm2d(64, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
    (act): SiLU(inplace=True)
  )
  (m): Sequential(
    (0): Bottleneck(
      (cv1): Conv(
        (conv): Conv2d(32, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
      (cv2): Conv(
        (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn): BatchNorm2d(32, eps=0.001, momentum=0.03, affine=True, track_running_stats=True)
        (act): SiLU(inplace=True)
      )
    )
  )
)
```

[104]

```python
# Create dummy input with correct shape
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
```

```
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

[104]

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:167: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if profile:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:101: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if self.dynamic or self.grid[i].shape[2:4] != x[i].shape[2:4]:
```

```
import onnx
path = "yolov5s
onnx.save(onnx.shape_inference.infer_shapes(onnx.load(path)), path)
```

(module) shape_inference

onnx shape inference. Shape inference is not guaranteed to be complete.

[105]

```
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```

[ ]

```
!netron yolov5l.onnx --port 8085
```

[5]

```
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

[104]

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:167: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if profile:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:101: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if self.dynamic or self.grid[i].shape[2:4] != x[i].shape[2:4]:
```

```
import onnx
path = "yolov5s.onnx"
onnx.save(onnx.shape_inference.infer_shapes(onnx.load(path)), path)
```

[105]

```
1
```

[ ]

```
!netron yolov5l.onnx --port 8085
```

[5]

```
dummy_input = torch.randn(1, 3, 640, 640)
dummy_input = dummy_input.to(device)
# Export to ONNX
torch.onnx.export(
    (parameter) opset_version: int | None

    opset_version (int, default 17): The version of the
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

[104]

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:167: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if profile:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:101: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if self.dynamic or self.grid[i].shape[2:4] != x[i].shape[2:4]:
```

```
import onnx
path = "yolov5s.onnx"
onnx.save(onnx.shape_inference.infer_shapes(onnx.load(path)), path)
```

[105]

```
1
```

[ ]

```
!netron yolov5l.onnx --port 8085
```

[5]

```
    dummy_input,
    "yolov5s.onnx",
    opset_version=12,
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```

[104]

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:167: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if profile:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:101: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if self.dynamic or self.grid[i].shape[2:4] != x[i].shape[2:4]:
```

```
import onnx
path = "yolov5s.onnx"
onnx.save(onnx.shape_inference.infer_shapes(onnx.load(path)), path)
```

[105]

```
1
```

[ ]

```
!netron yolov5l.onnx --port 8085
```

[5]

```
Serving 'yolov5l.onnx' at http://localhost:8085
^C
Traceback (most recent call last):
  File "/Users/mlfornerds/opt/miniconda3/envs/torch/lib/python3.12/site-packages/netron/server.py", line 265, in wait
    time.sleep(0.1)
```

```
    # do_constant_folding=False,  # Prevent folding
    input_names=['input'],
    output_names=['output']
)
```
[104]

```
/Users/mlfornerds/Projects/yolov5/models/yolo.py:268: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if augment:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:171: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if visualize:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:167: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if profile:
/Users/mlfornerds/Projects/yolov5/models/yolo.py:101: TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. W
  if self.dynamic or self.grid[i].shape[2:4] != x[i].shape[2:4]:
```

```
import onnx
path = "yolov5s.onnx"
onnx.save(onnx.shape_inference.infer_shapes(onnx.load(path)), path)
```
[105]

```
1
```
[ ]

```
!netron yolov5l.onnx --port 8085
```
[5]

```
Serving 'yolov5l.onnx' at http://localhost:8085
^C
Traceback (most recent call last):
  File "/Users/mlfornerds/opt/miniconda3/envs/torch/lib/python3.12/site-packages/netron/server.py", line 265, in wait
    time.sleep(0.1)
KeyboardInterrupt
```

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chmarks.py
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v5l.onnx
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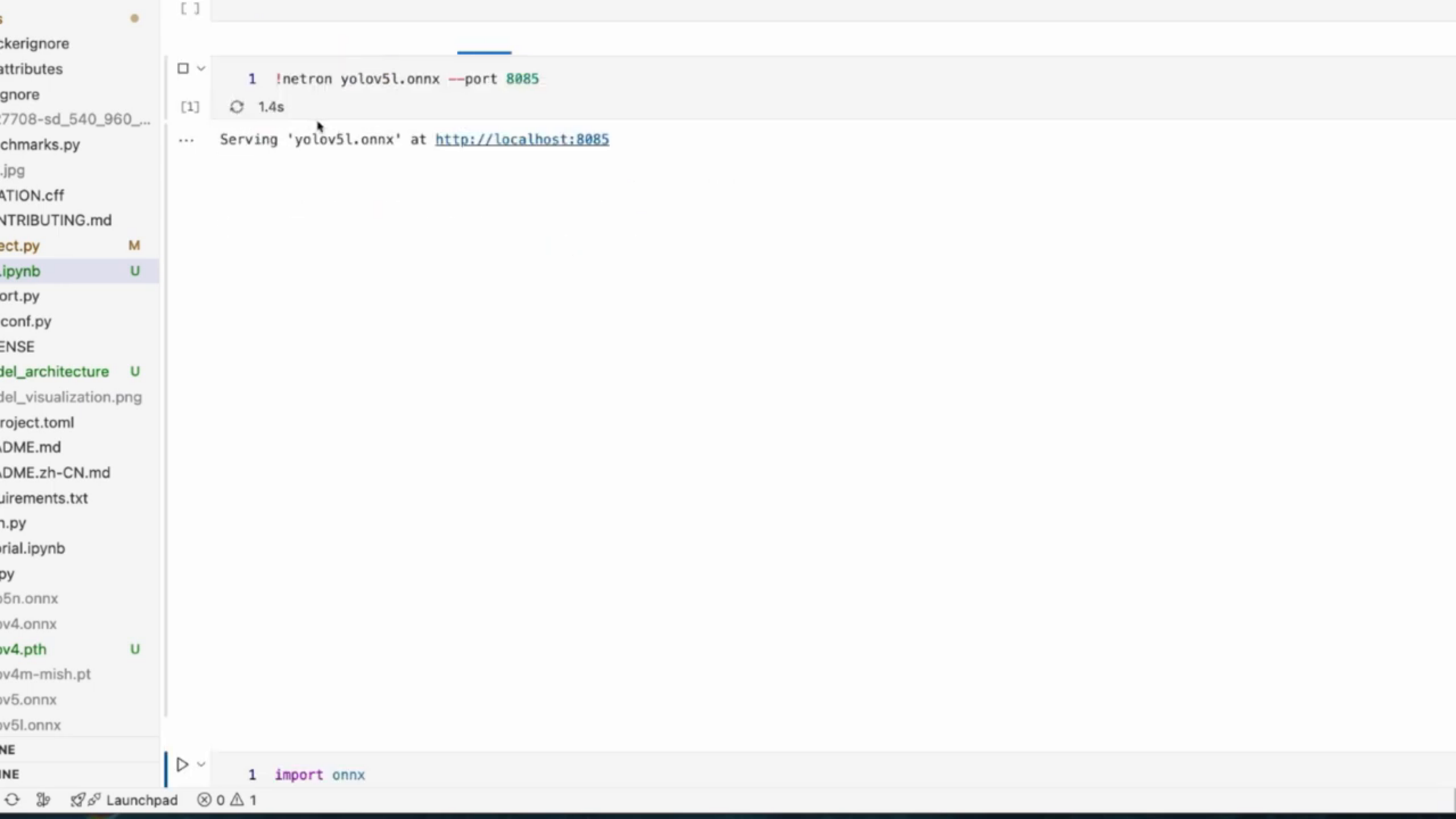
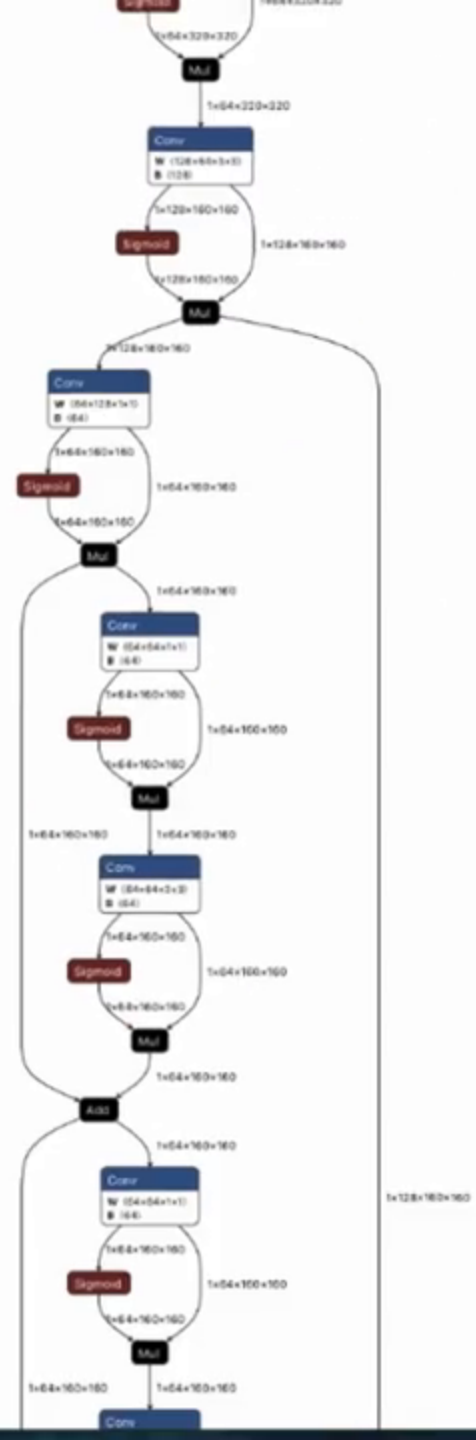
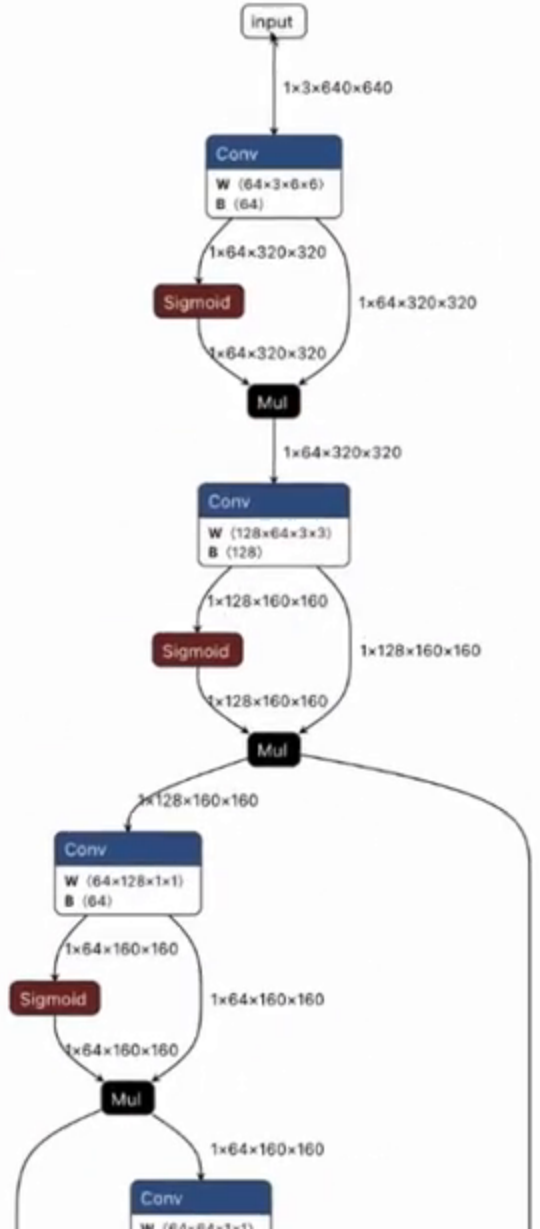
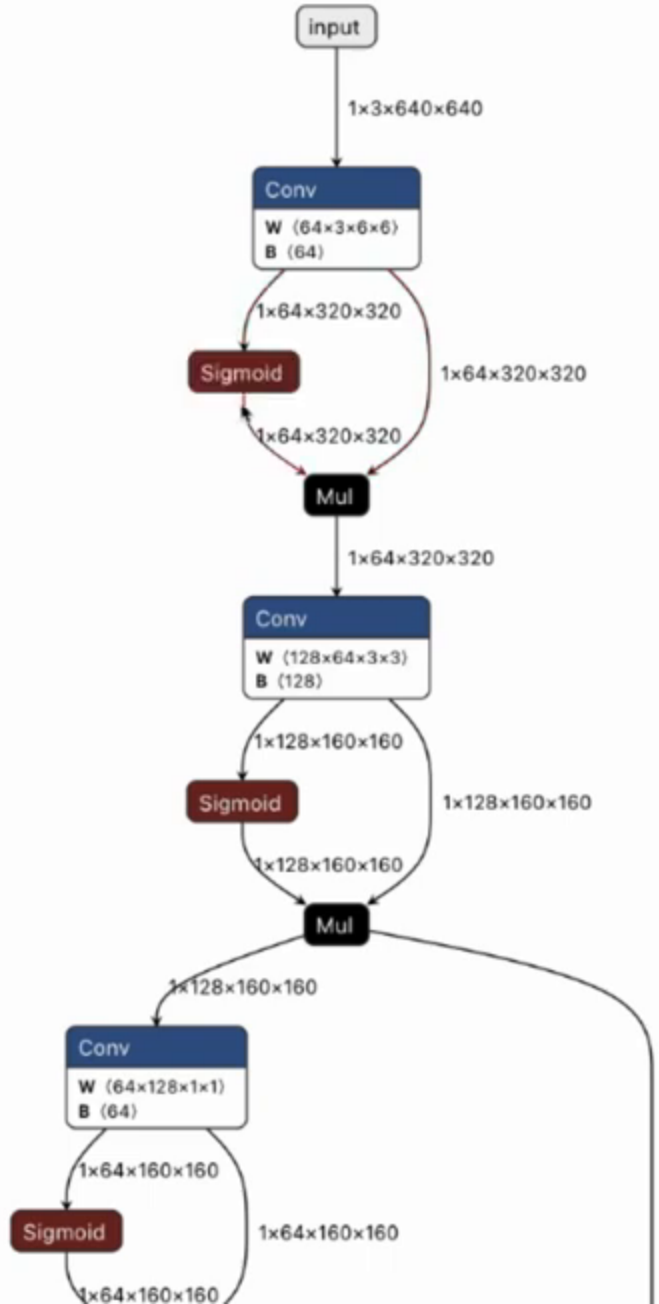
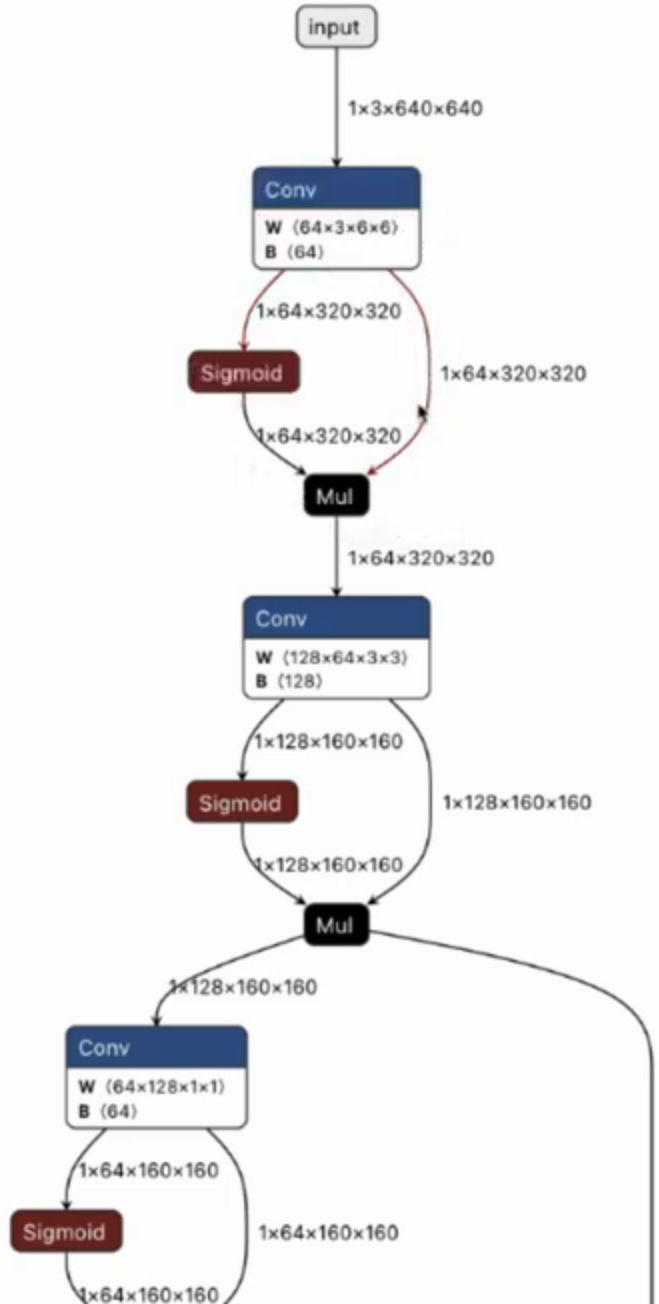
Launchpad ⊗ 0 ⚠ 1


[ ]
1 !netron yolov5l.onnx --port 8085
[1] 1.4s
Serving 'yolov5l.onnx' at http://localhost:8085
1 import onnx
Launchpad
0 1


Mul
1x64x220x220
Conv
W (128x64x3x3)
B (128)
1x128x160x160
Sigmoid
1x128x160x160
Mul
1x128x160x160
Conv
W (64x128x1x1)
B (64)
1x64x160x160
Sigmoid
1x64x160x160
Mul
1x64x160x160
Conv
W (64x64x1x1)
B (64)
1x64x160x160
Sigmoid
1x64x160x160
Mul
1x64x160x160
1x64x160x160
Conv
W (64x64x3x3)
B (64)
1x64x160x160
Sigmoid
1x64x160x160
Mul
1x64x160x160
Add
1x64x160x160
Conv
W (64x64x1x1)
B (64)
1x64x160x160
Sigmoid
1x64x160x160
Mul
1x64x160x160
1x64x160x160
Conv
1x128x160x160


input
1×3×640×640
Conv
W (64×3×6×6)
B (64)
1×64×320×320
Sigmoid
1×64×320×320
1×64×320×320
Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv


input
1×3×640×640
Conv
W (64×3×6×6)
B (64)
1×64×320×320
Sigmoid
1×64×320×320
1×64×320×320
Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160


input
1×3×640×640
Conv
W (64×3×6×6)
B (64)
1×64×320×320
Sigmoid
1×64×320×320
1×64×320×320
Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
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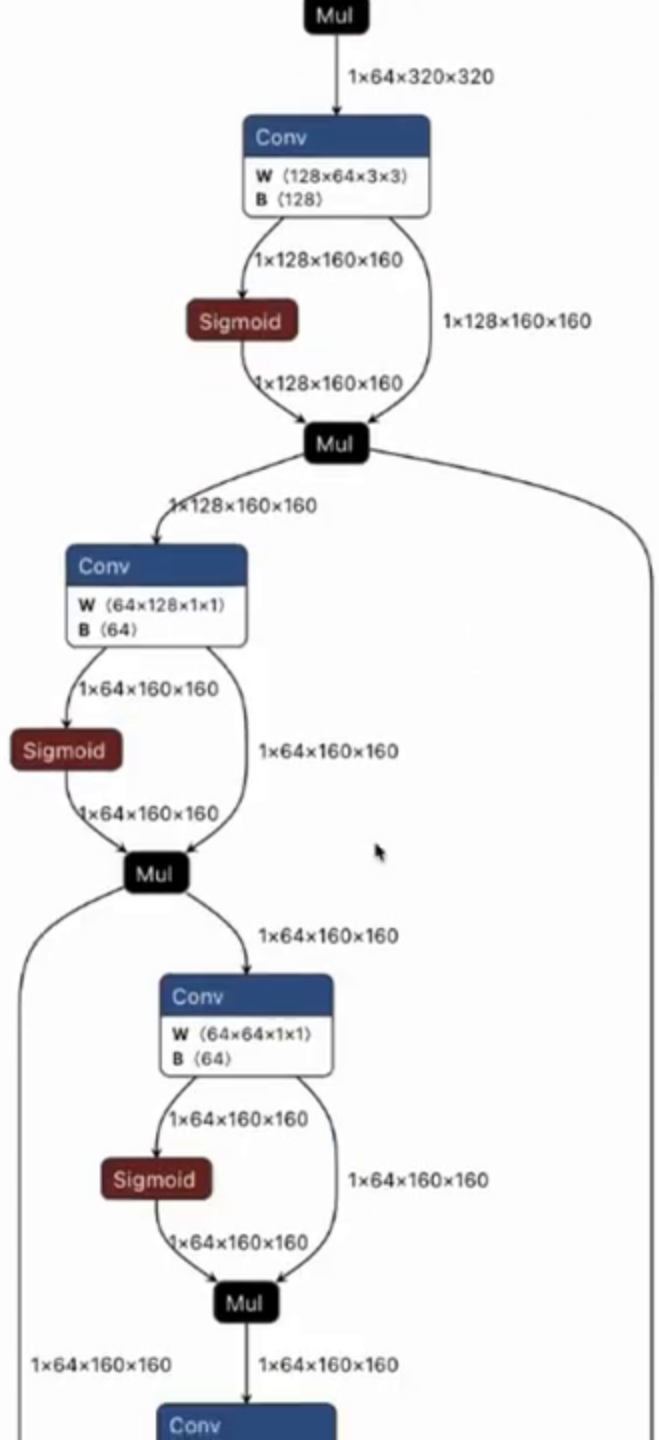
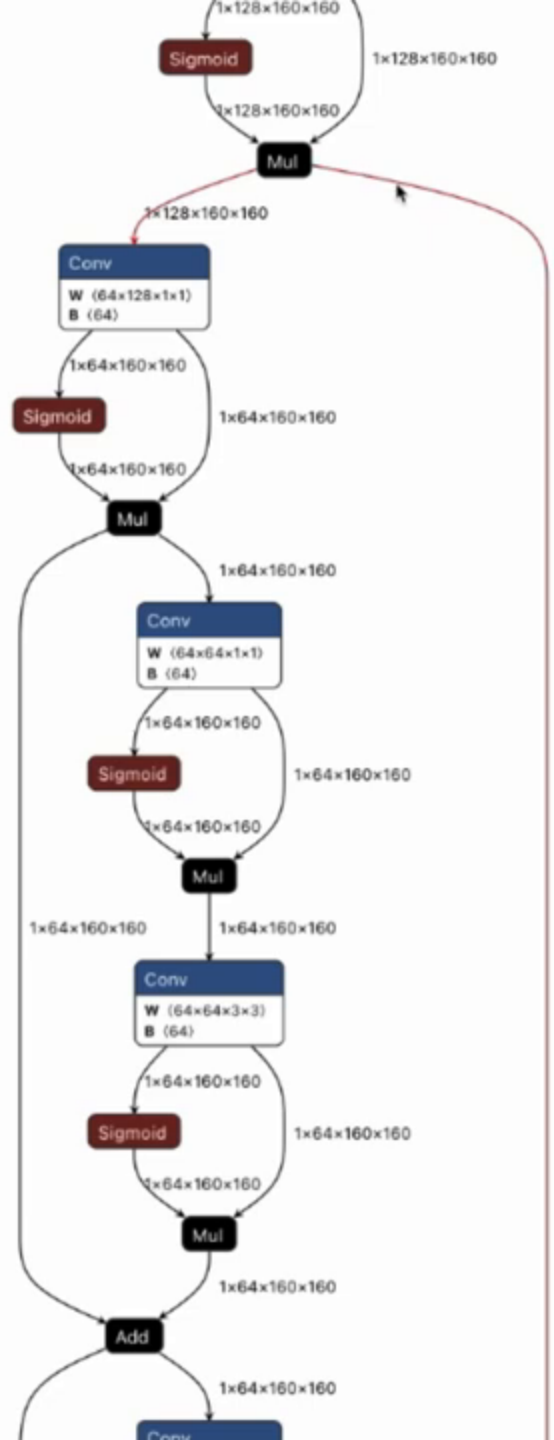
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160


Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
1×64×160×160
Conv


1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
1×64×160×160
Conv
W (64×64×3×3)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Add
1×64×160×160
Conv

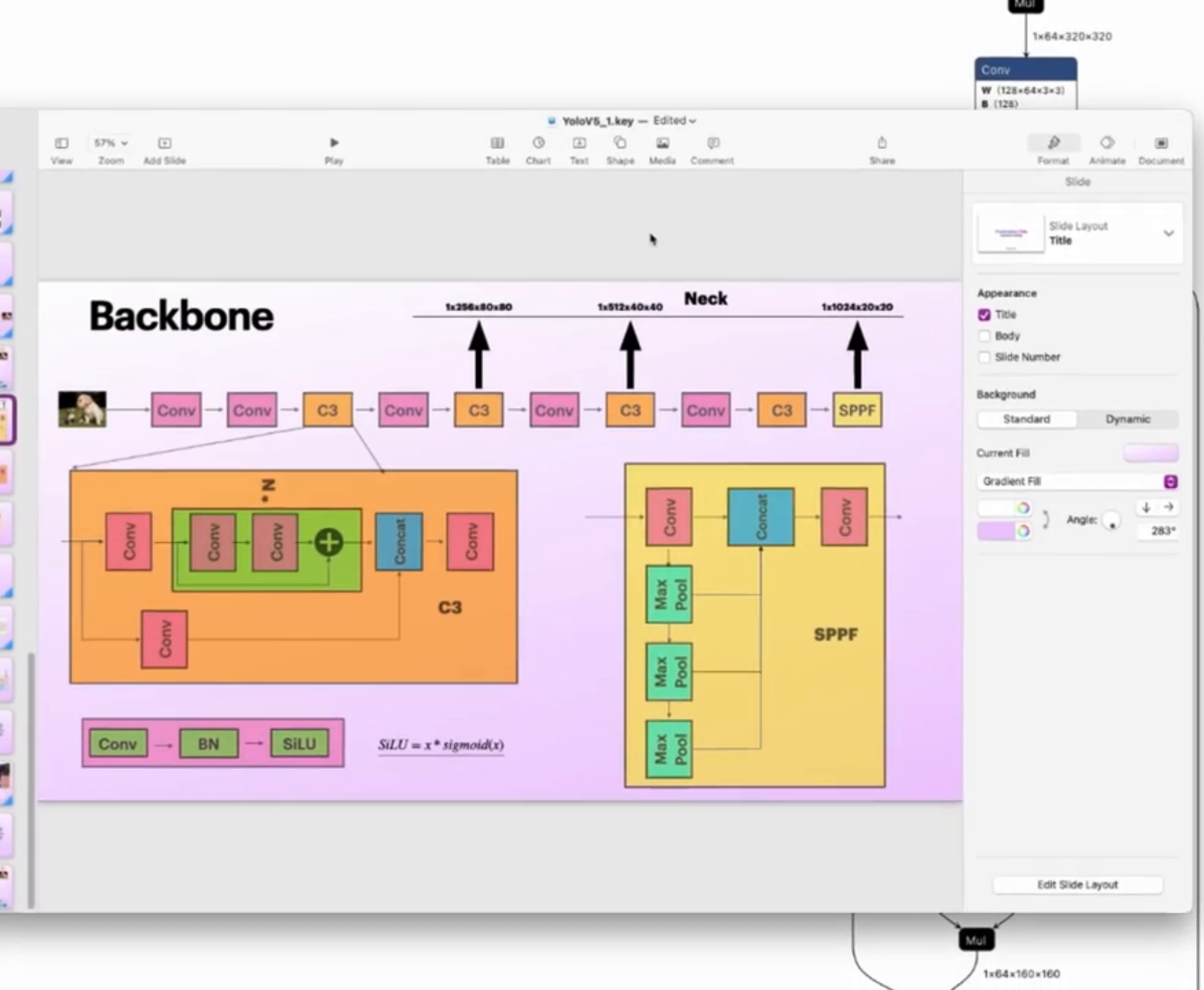

Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
YoloV5_1.key — Edited
View
Zoom
Add Slide
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Table
Chart
Text
Shape
Media
Comment
Share
Format
Animate
Document
Slide
Slide Layout
Title
Appearance
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Body
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Background
Standard
Dynamic
Current Fill
Gradient Fill
Angle:
283°
Edit Slide Layout
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
Conv
C3
Conv
C3
Conv
C3
Conv
C3
SPPF
N
Conv
Conv
Conv
Concat
Conv
Conv
C3
Conv
Concat
Conv
Max Pool
Max Pool
Max Pool
SPPF
Conv
BN
SiLU
SiLU = x * sigmoid(x)
Mul
1×64×160×160

YoloV5_1.key — Edited

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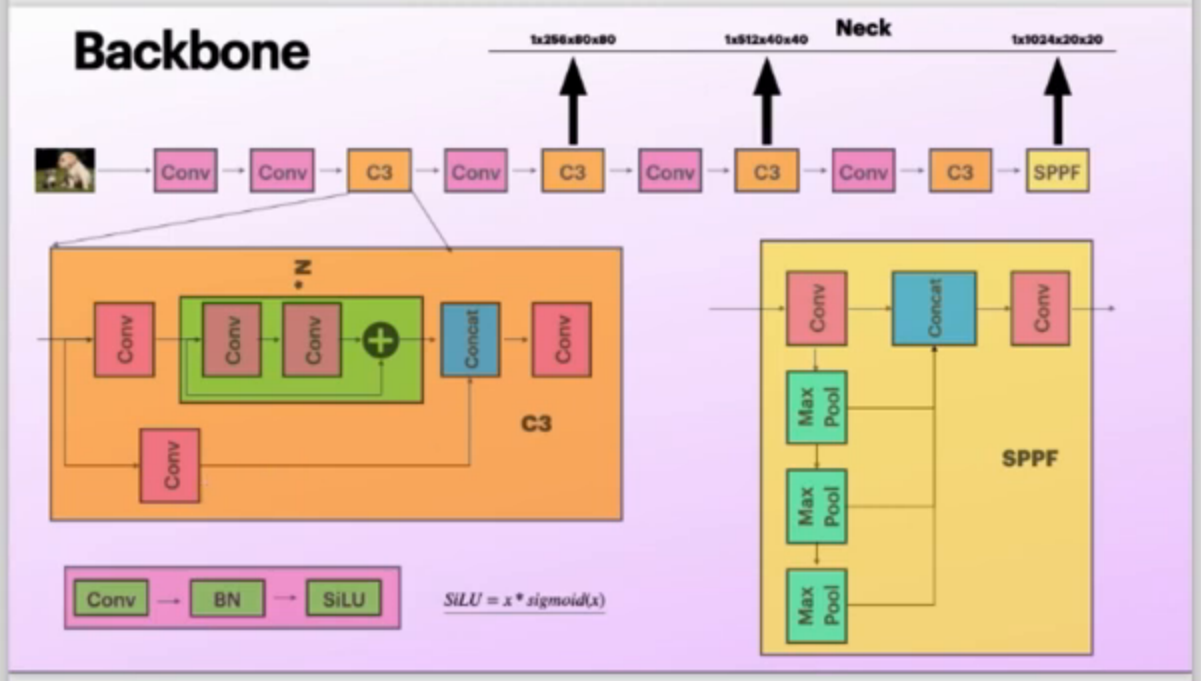

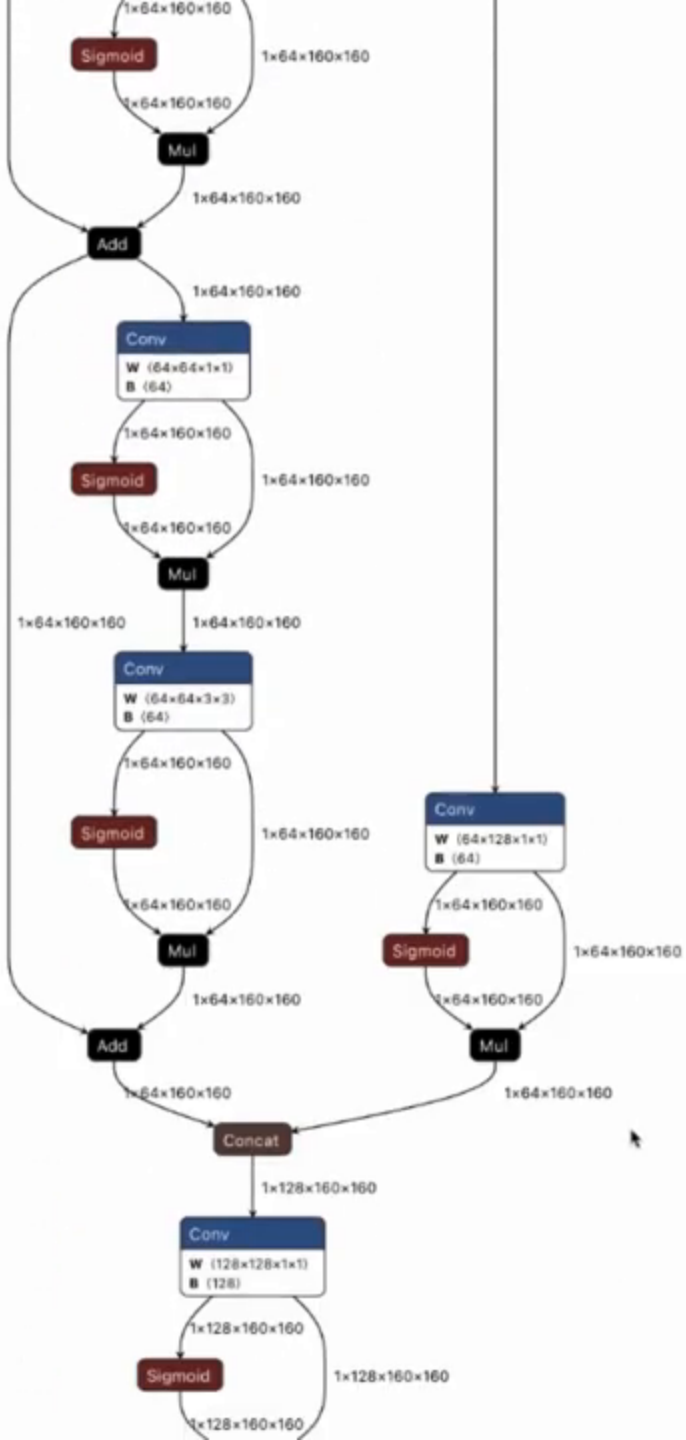

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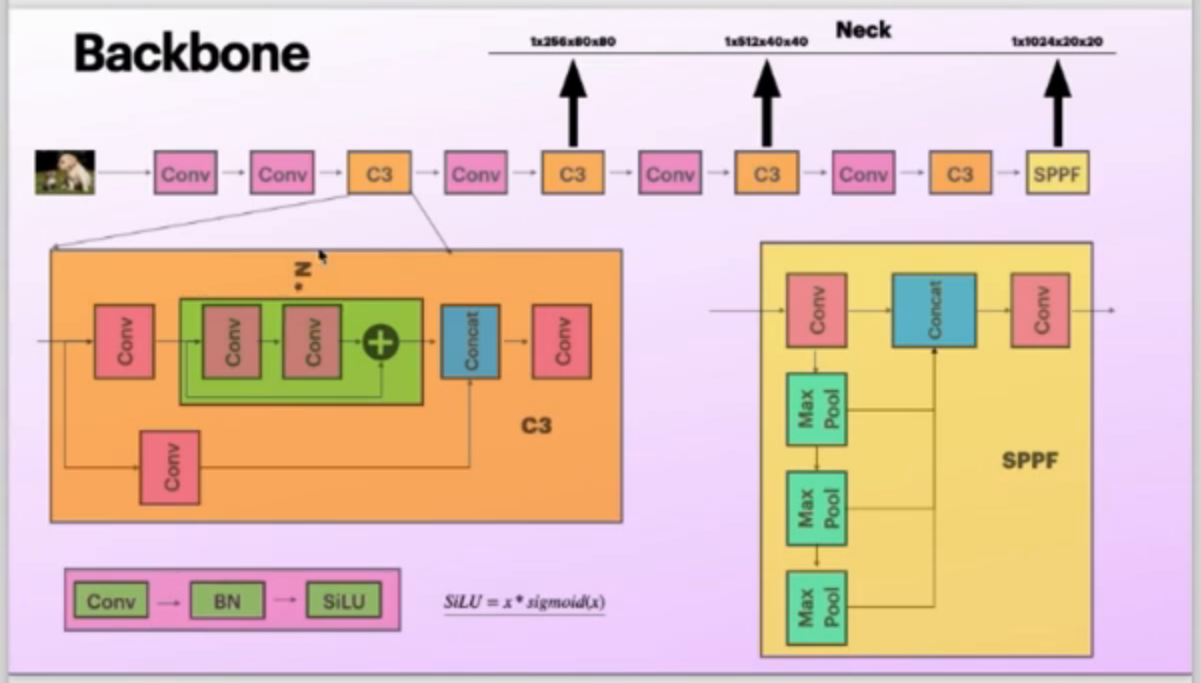

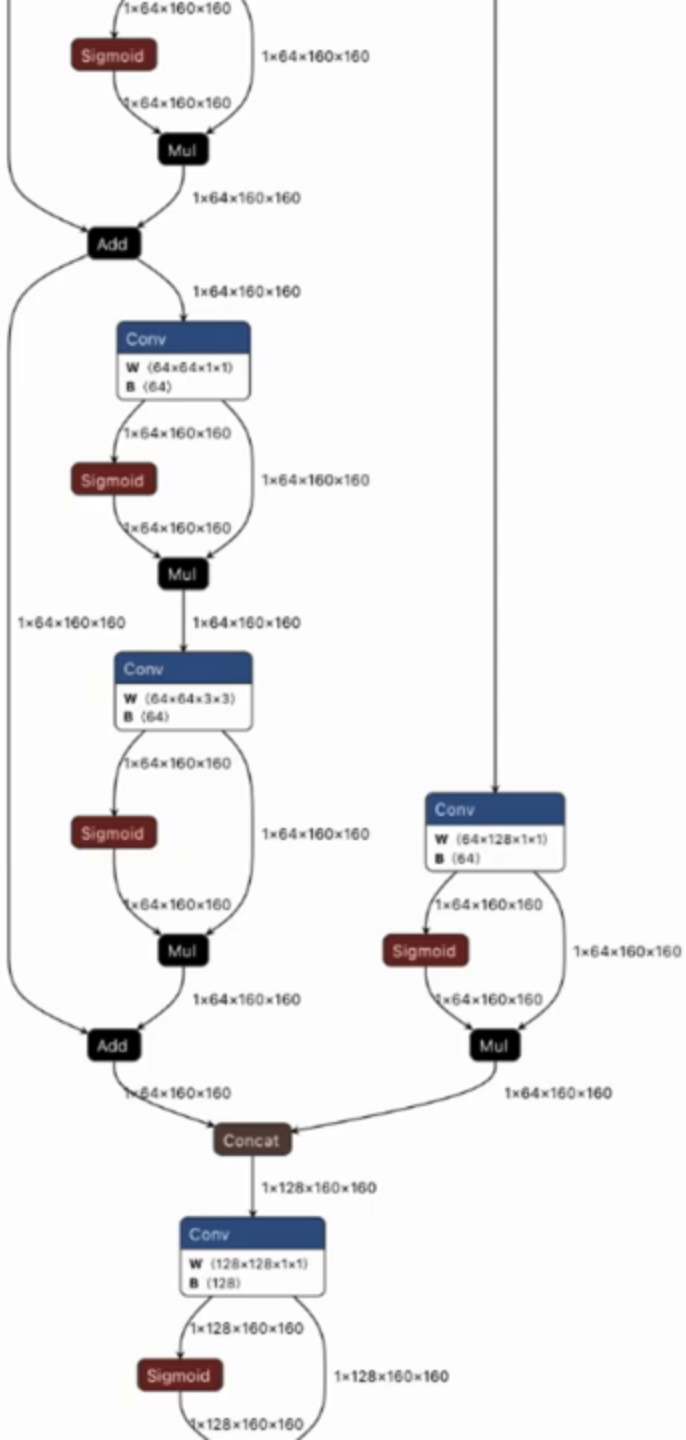

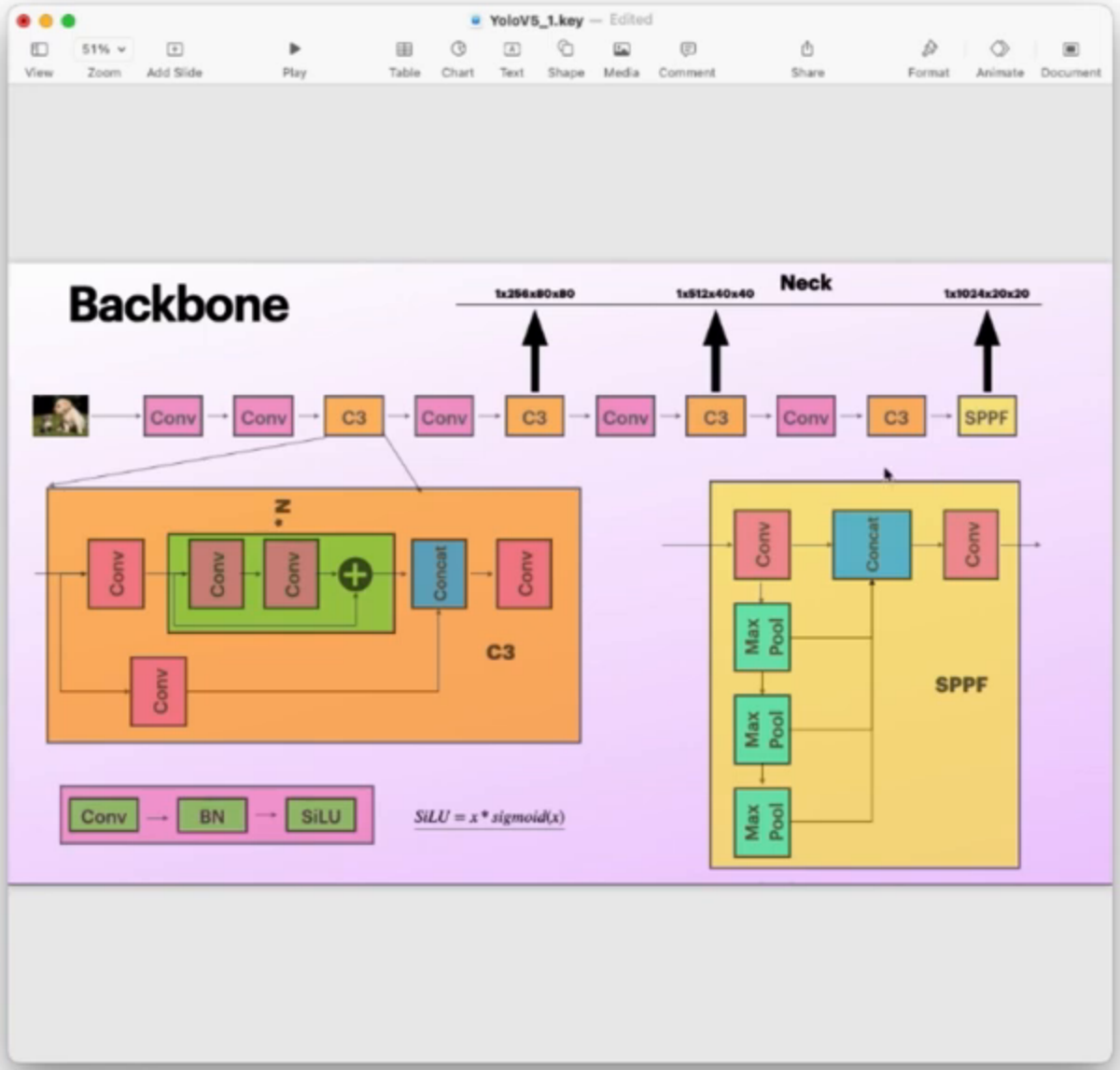
YoloV5_1.key — Edited
51%
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Shape
Media
Comment
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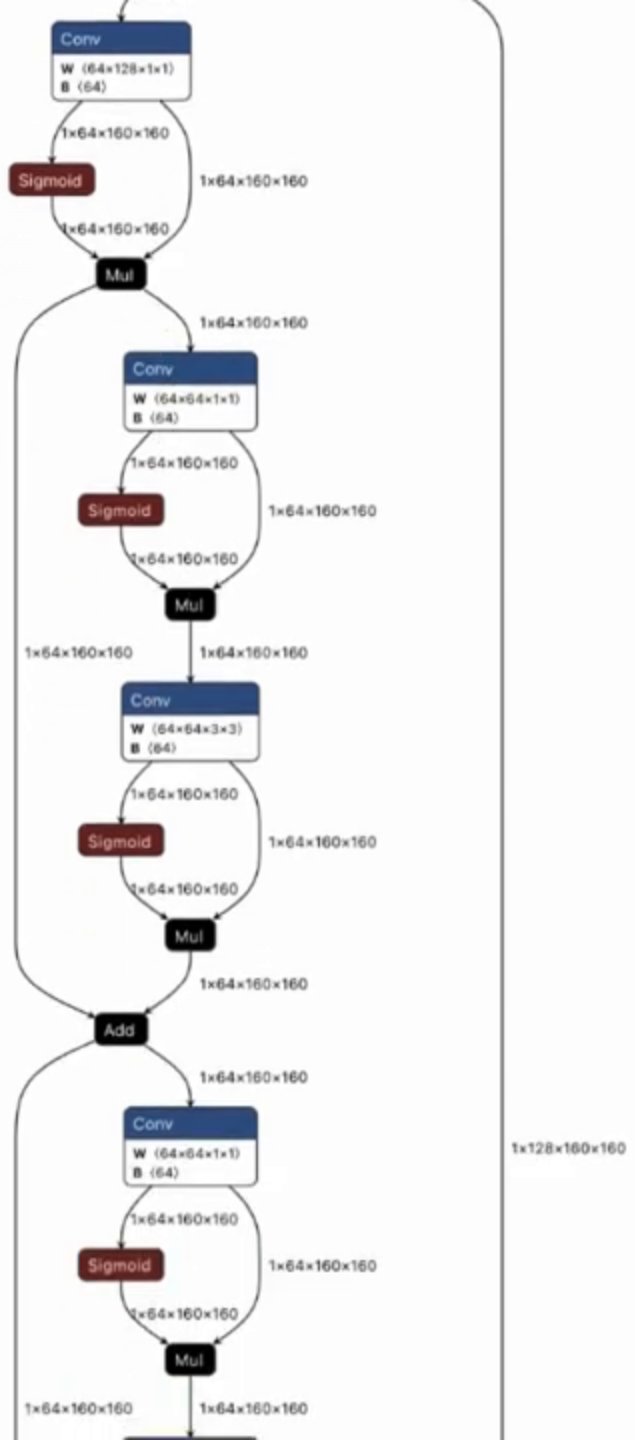
Document
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
Conv
C3
Conv
C3
Conv
C3
Conv
C3
SPPF
N
Conv
Conv
Conv
Concat
Conv
Conv
C3
Conv
Concat
Conv
Max Pool
Max Pool
Max Pool
SPPF
Conv
BN
SiLU
SiLU = x * sigmoid(x)


Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
1×64×160×160
Conv
W (64×64×3×3)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Add
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
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1×128×160×160

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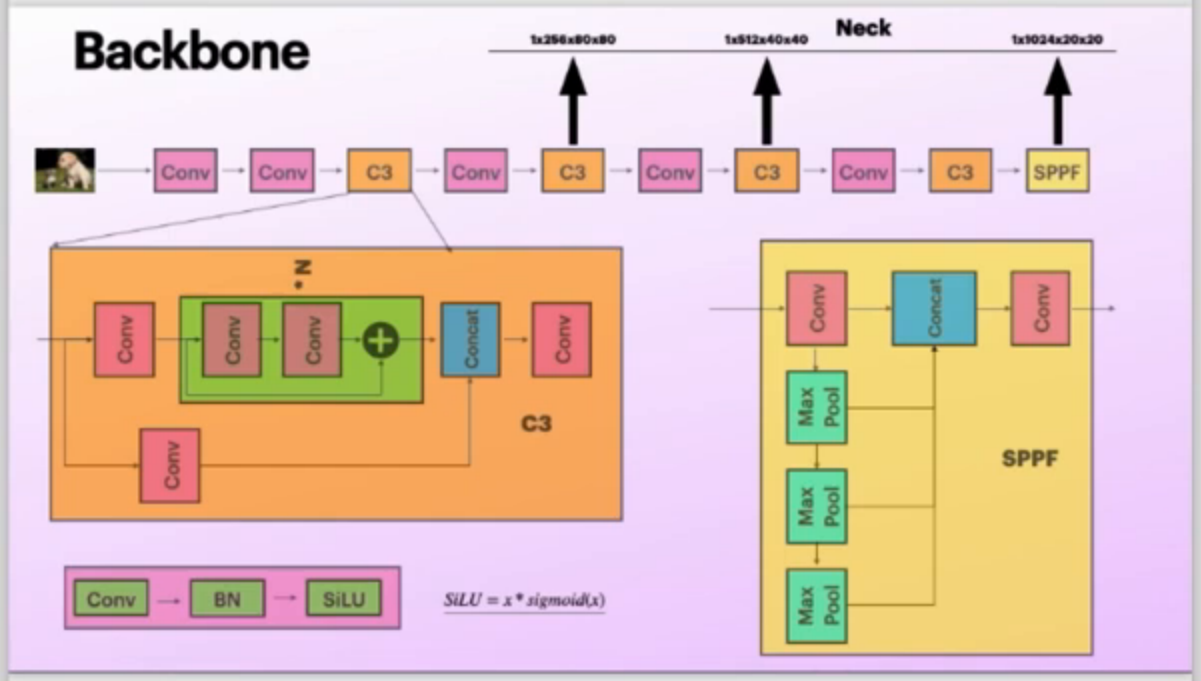

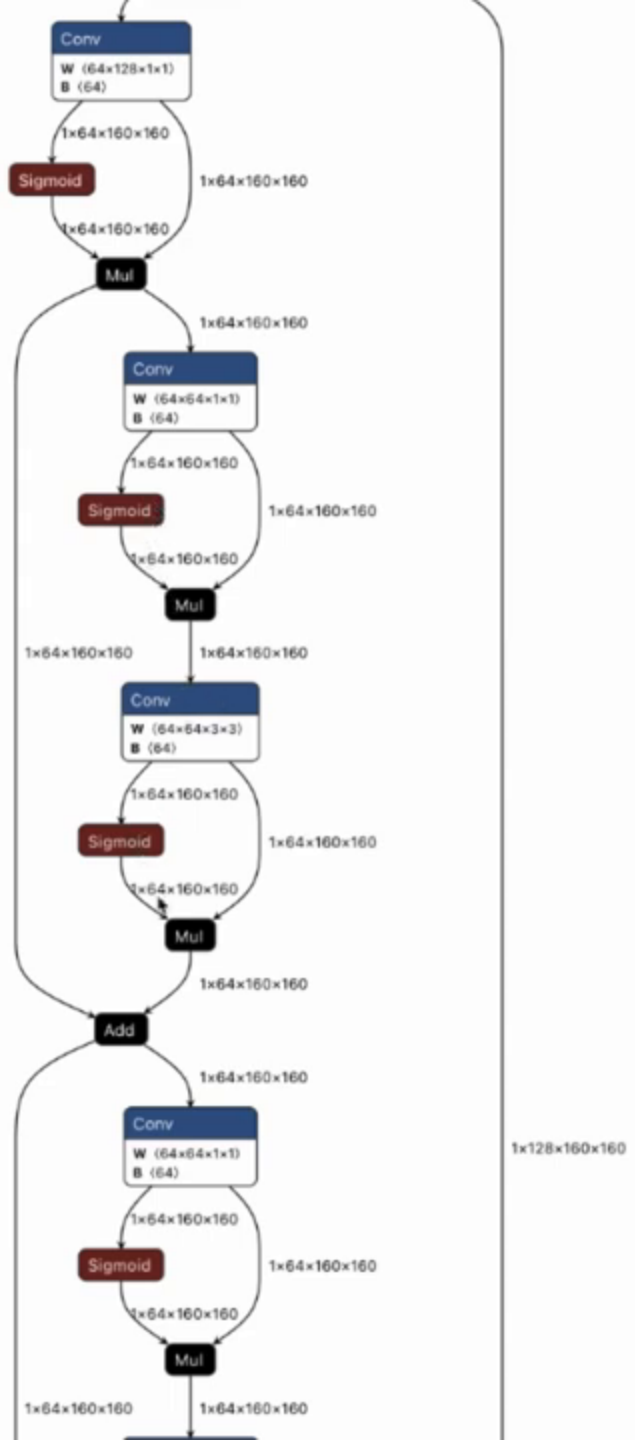

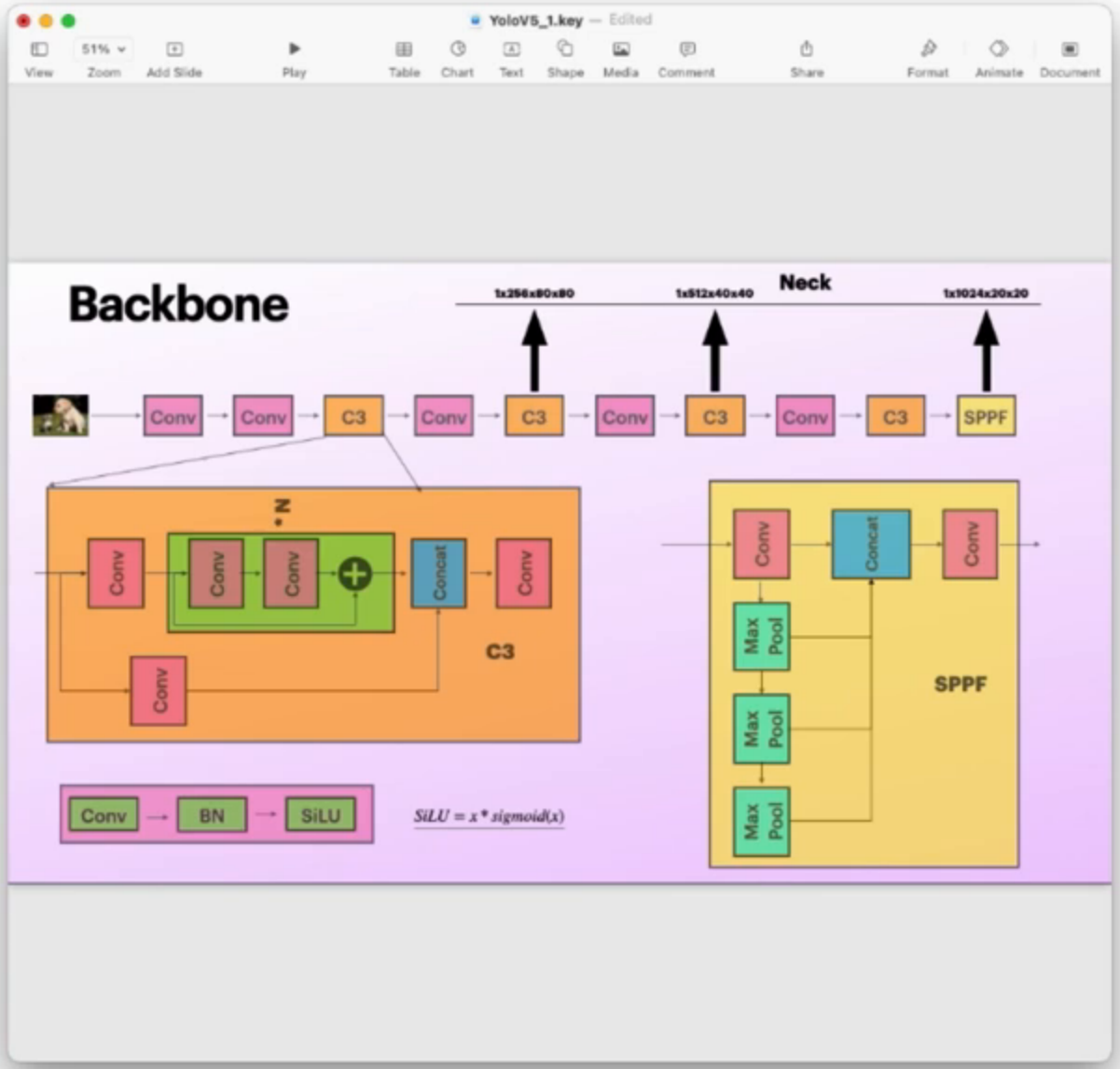
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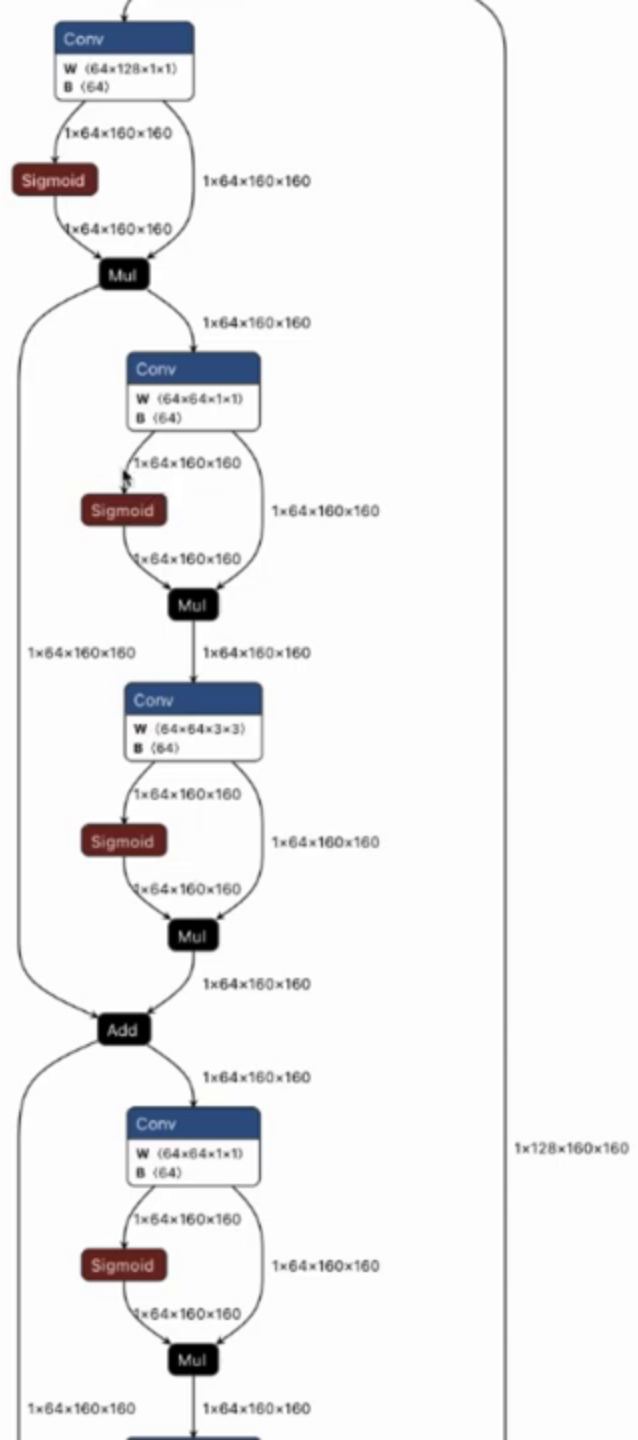
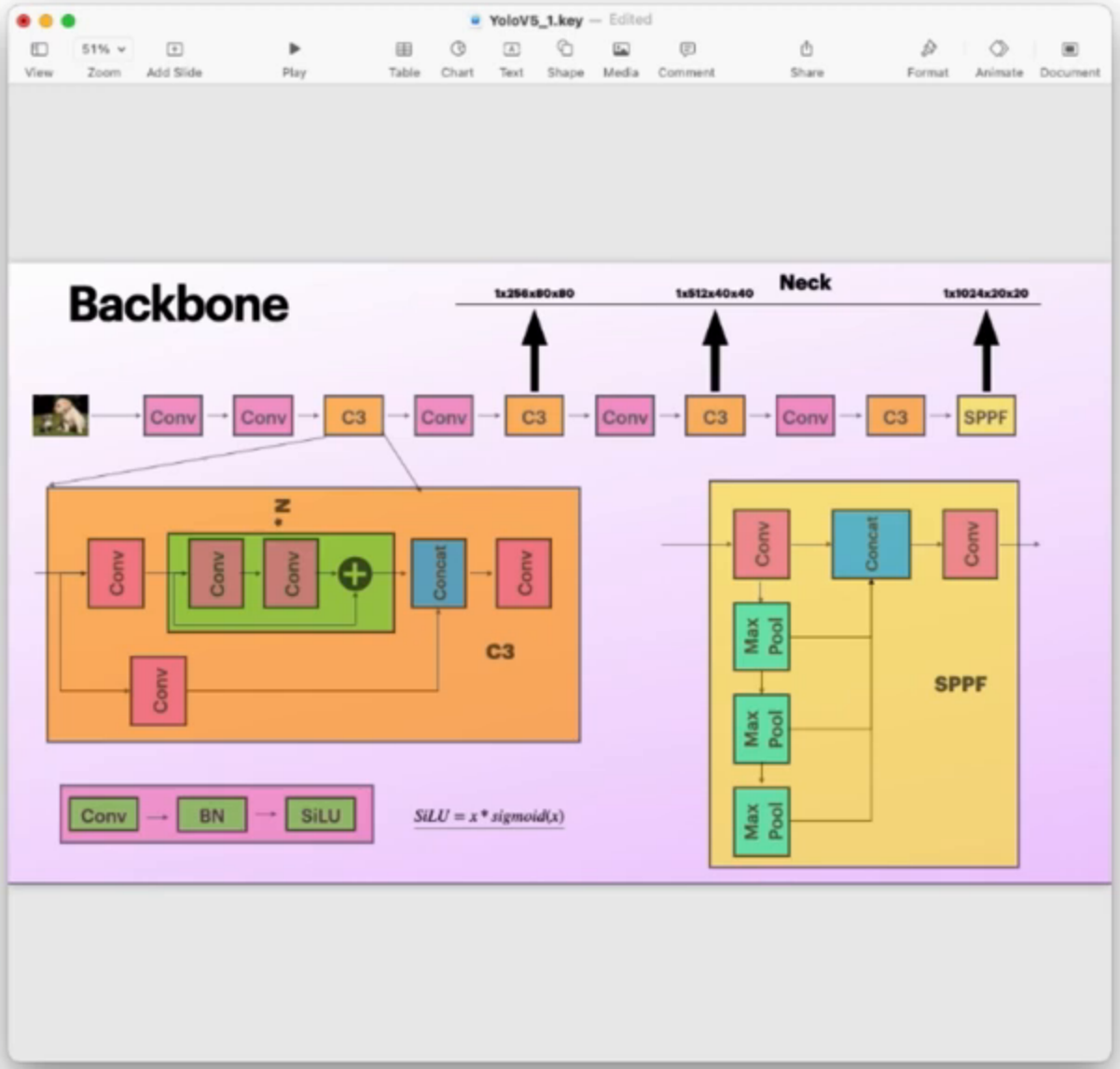
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
Concat
Max Pool
BN
SiLU
SiLU = x * sigmoid(x)


Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
Mul
Conv
W (64×64×1×1)
B (64)
Conv
W (64×64×3×3)
B (64)
Add
1×128×160×160


YoloV5_1.key — Edited
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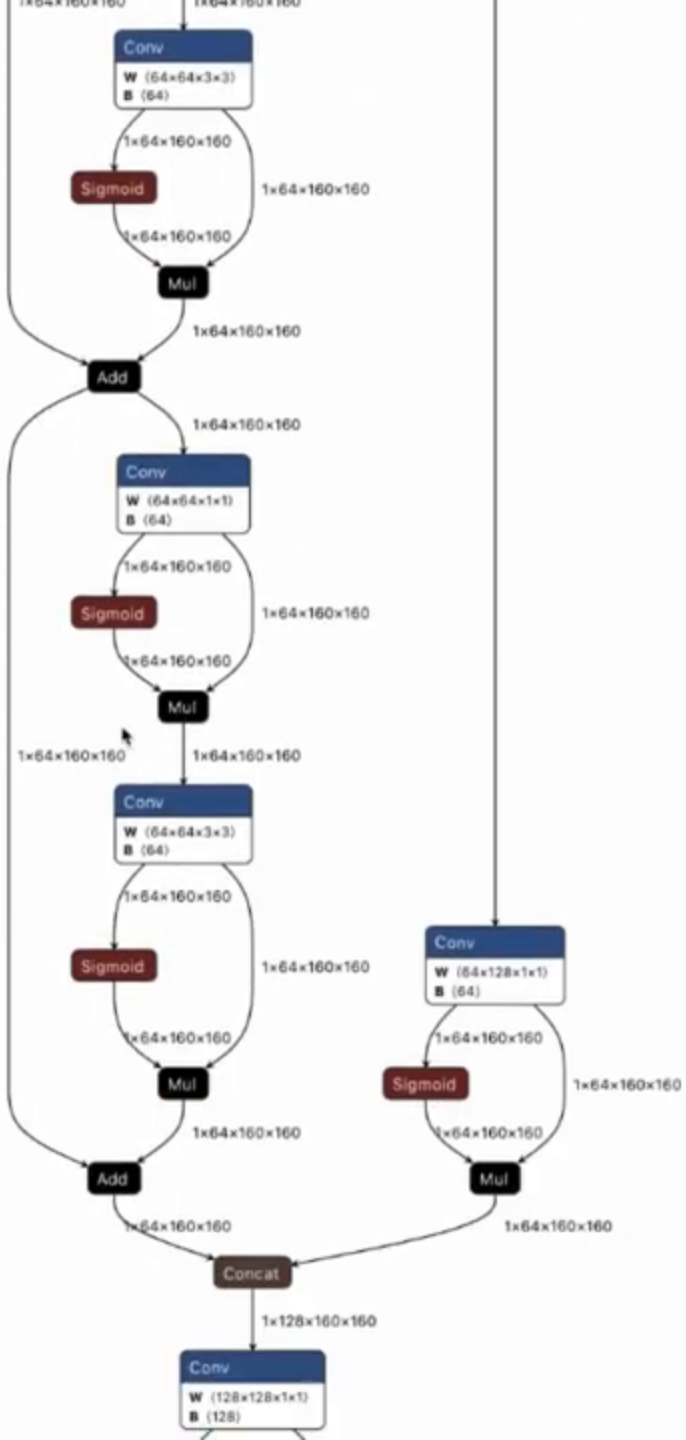
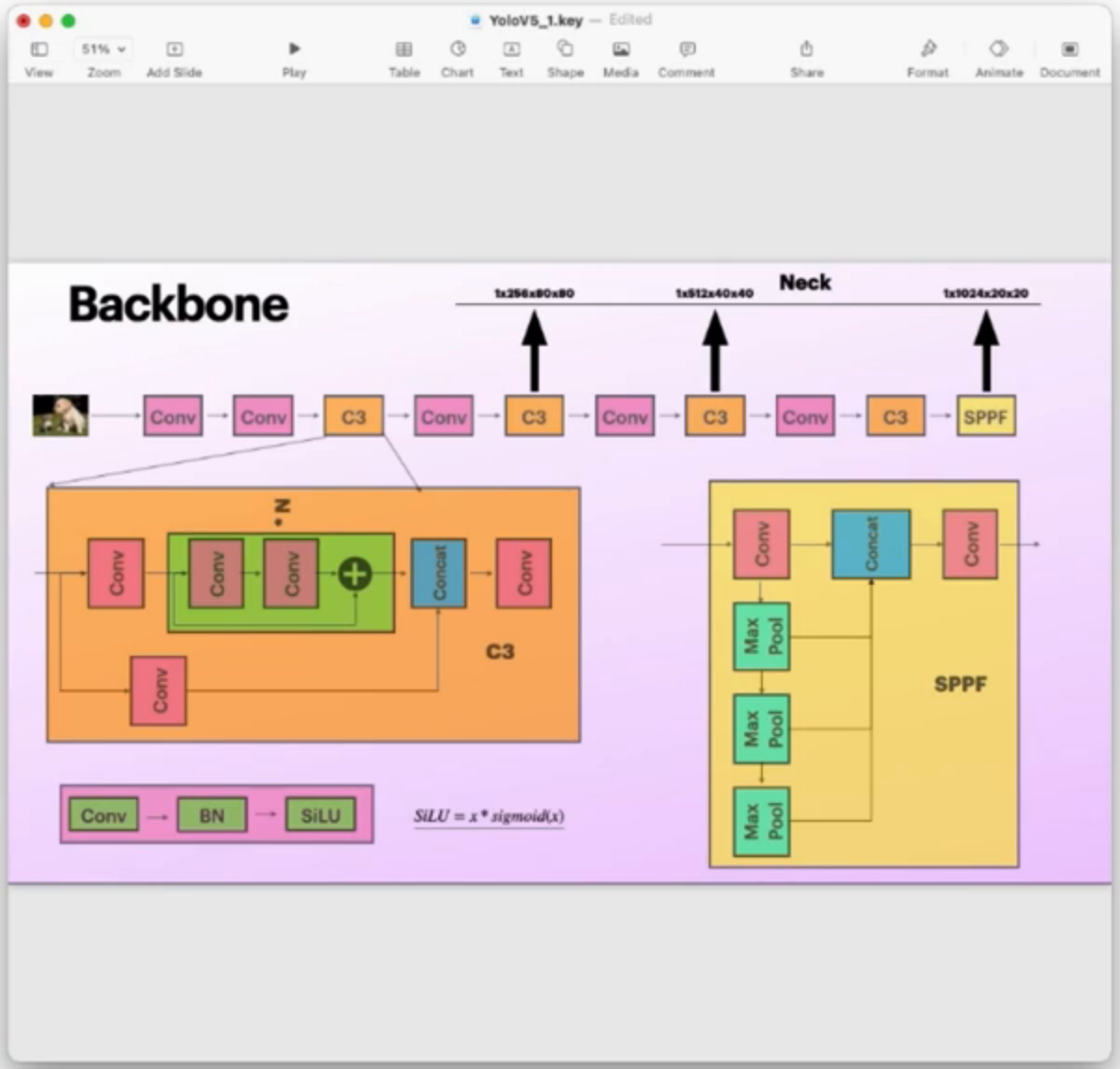
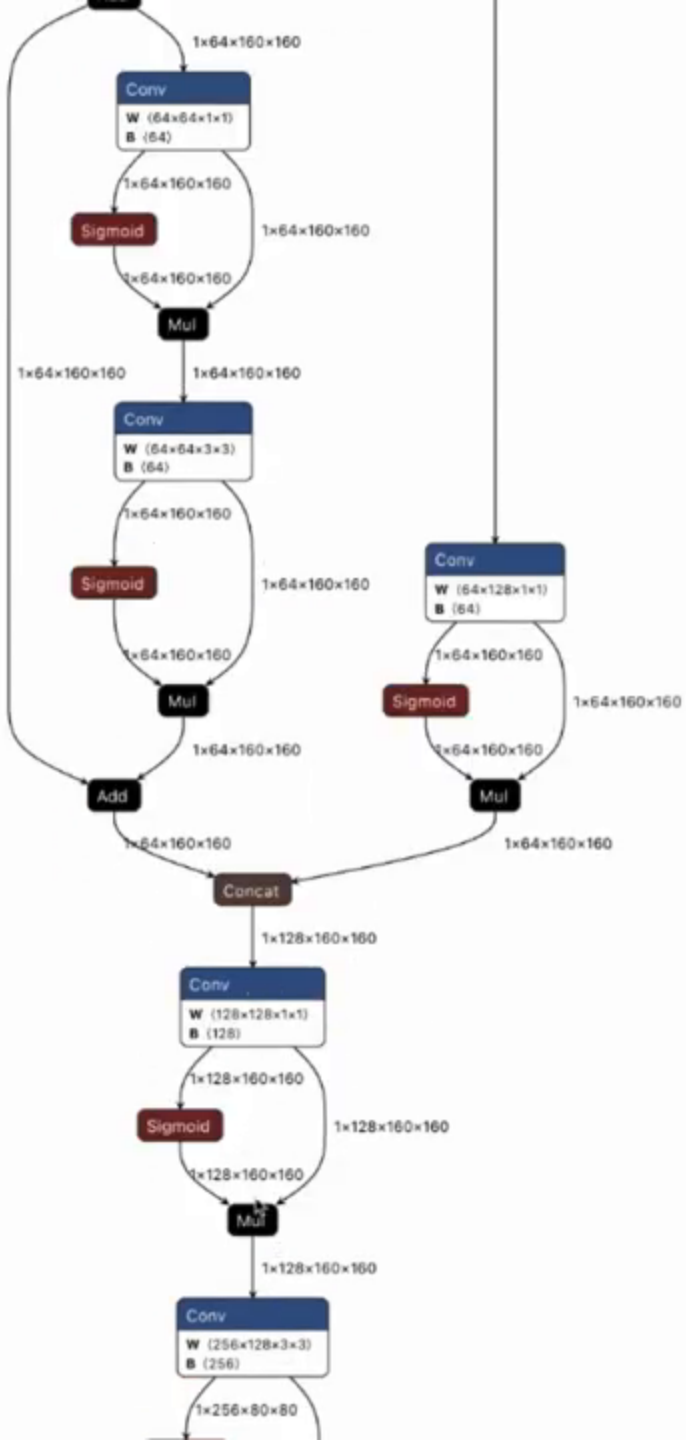
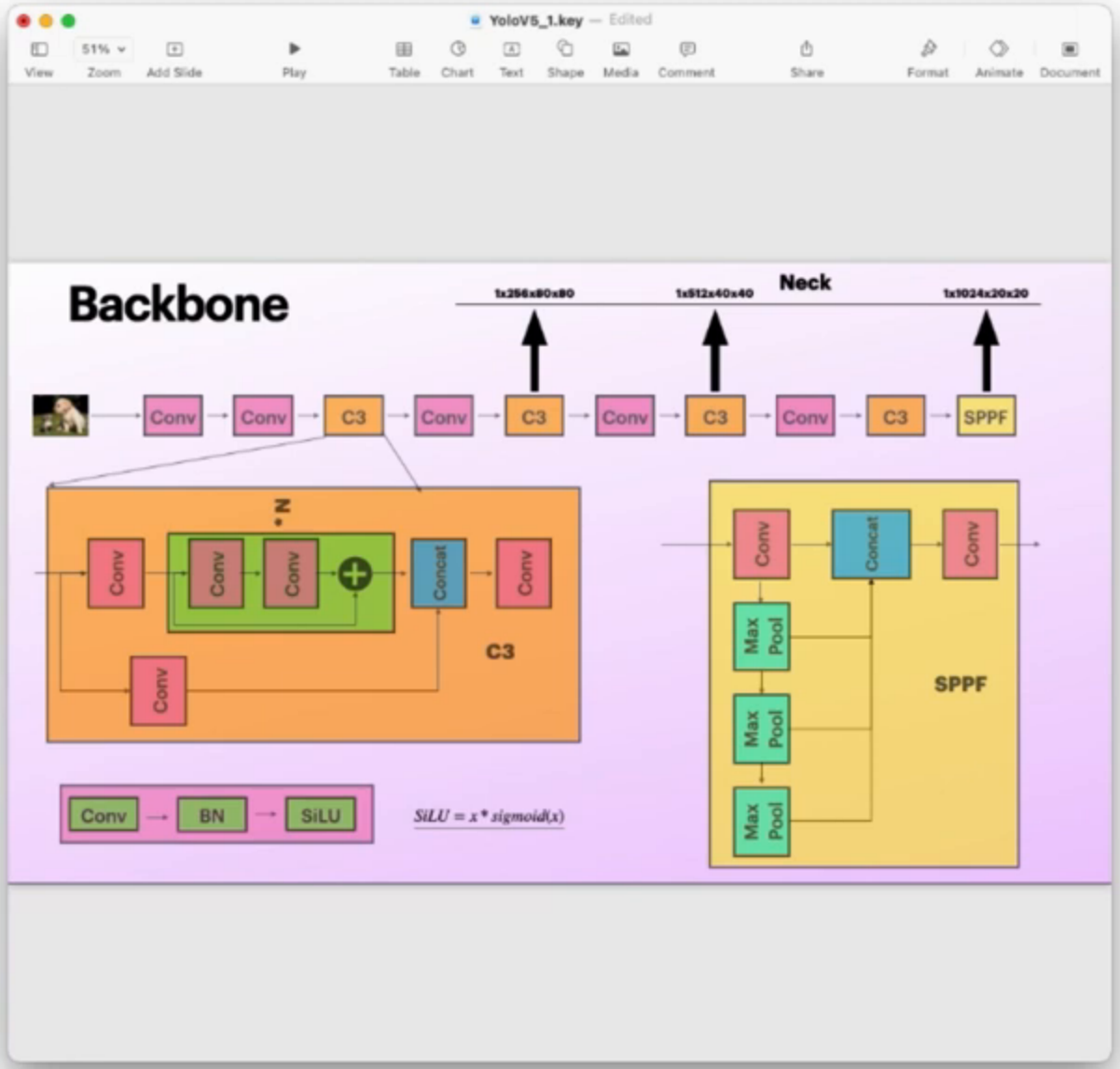
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
Concat
Max Pool
BN
SiLU
SiLU = x * sigmoid(x)


Conv
W (64×64×3×3)
B (64)
1×64×160×160
Sigmoid
Mul
Add
W (64×64×1×1)
W (64×128×1×1)
B (64)
W (128×128×1×1)
B (128)
Concat
1×128×160×160


YoloV5_1.key — Edited
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
N
Concat
Max Pool
Conv → BN → SiLU
SiLU = x * sigmoid(x)


1×64×160×160
Conv
W (64×64×1×1)
B (64)
Sigmoid
Mul
W (64×64×3×3)
W (64×128×1×1)
Add
Concat
W (128×128×1×1)
B (128)
W (256×128×3×3)
B (256)
1×256×80×80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Comment
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Format
Animate
Document
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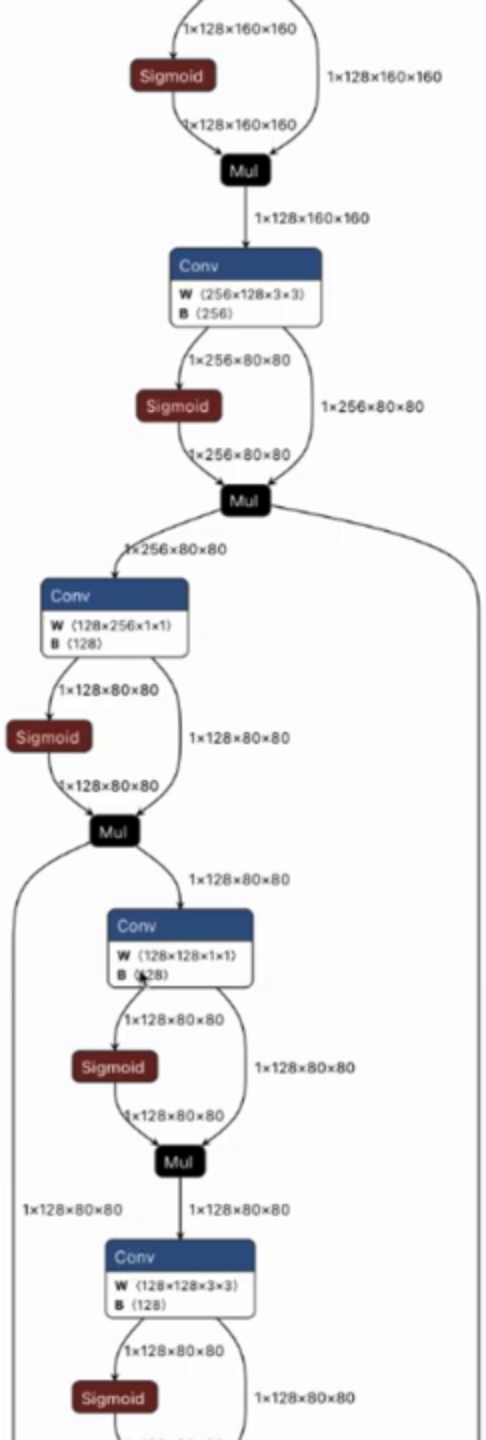
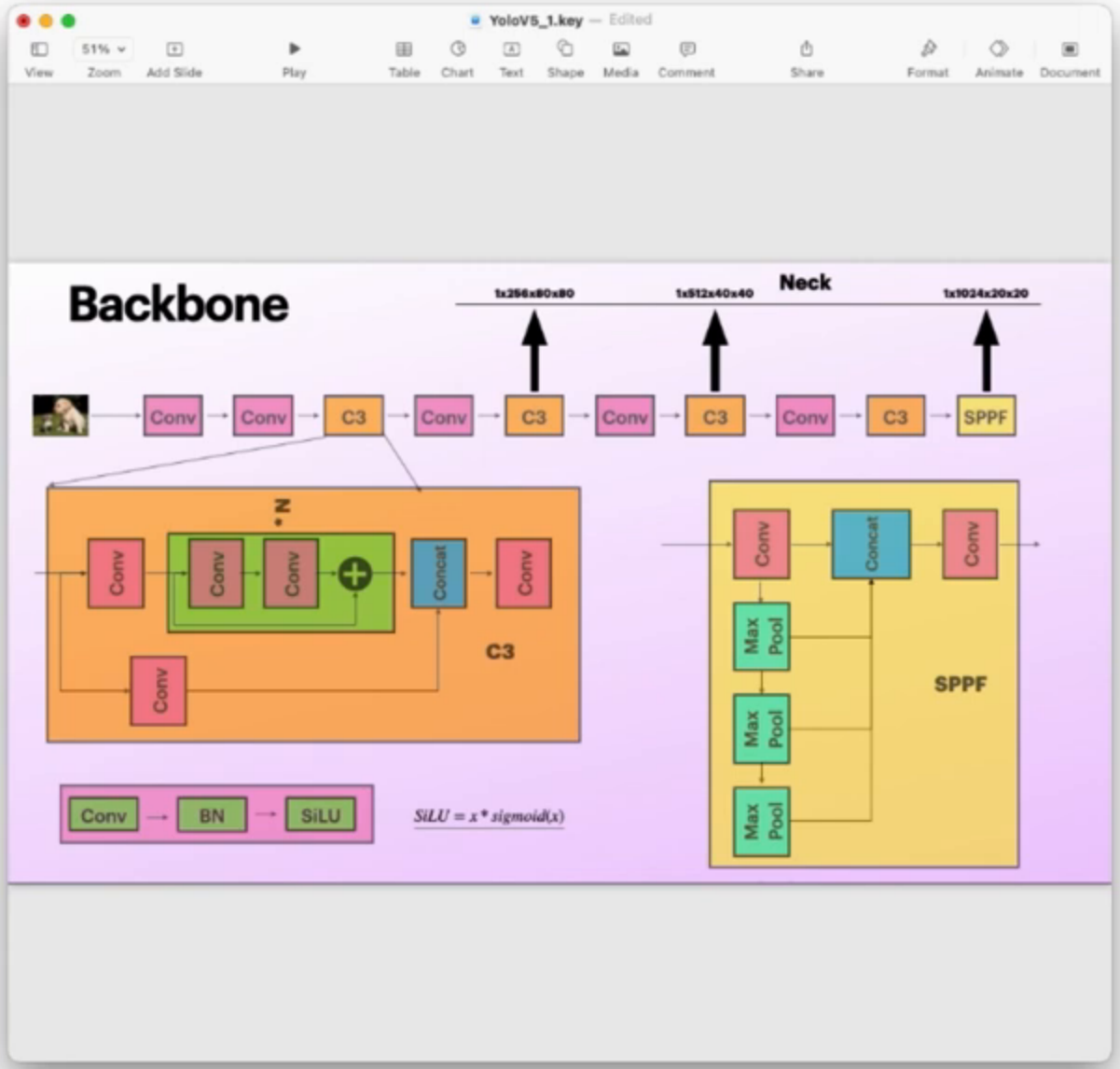
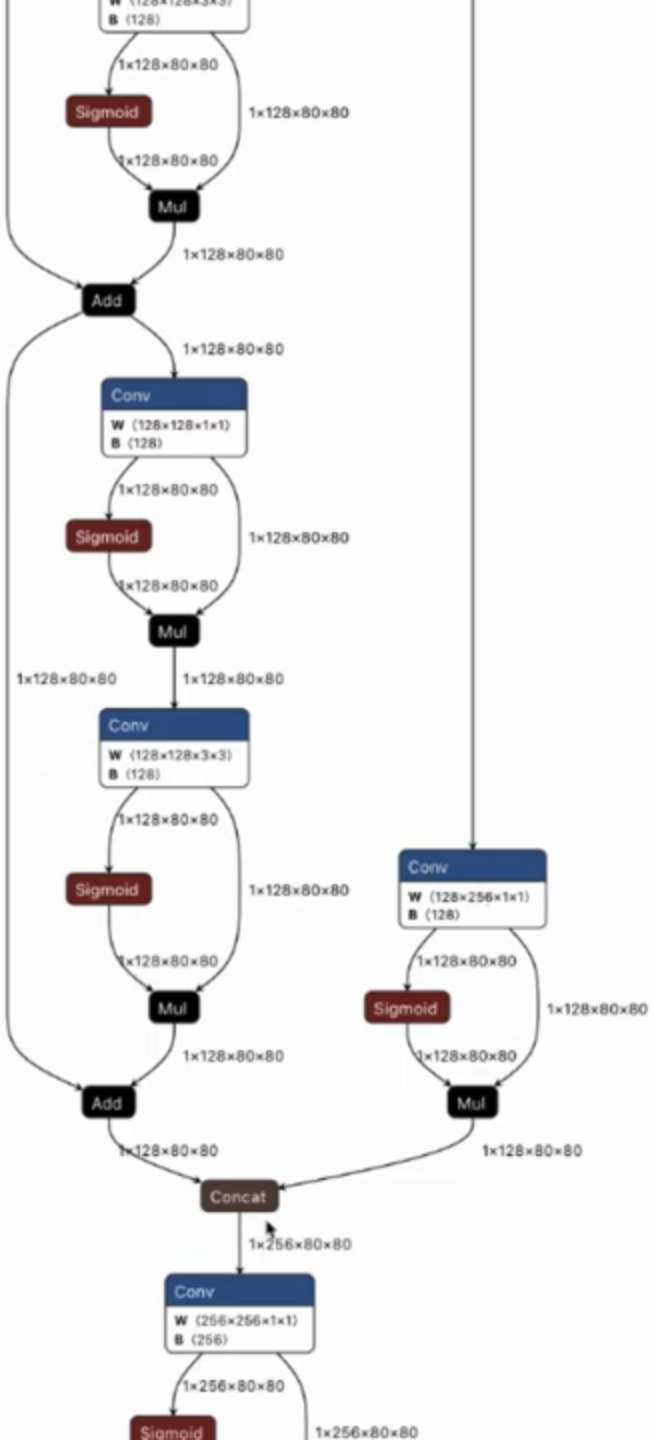
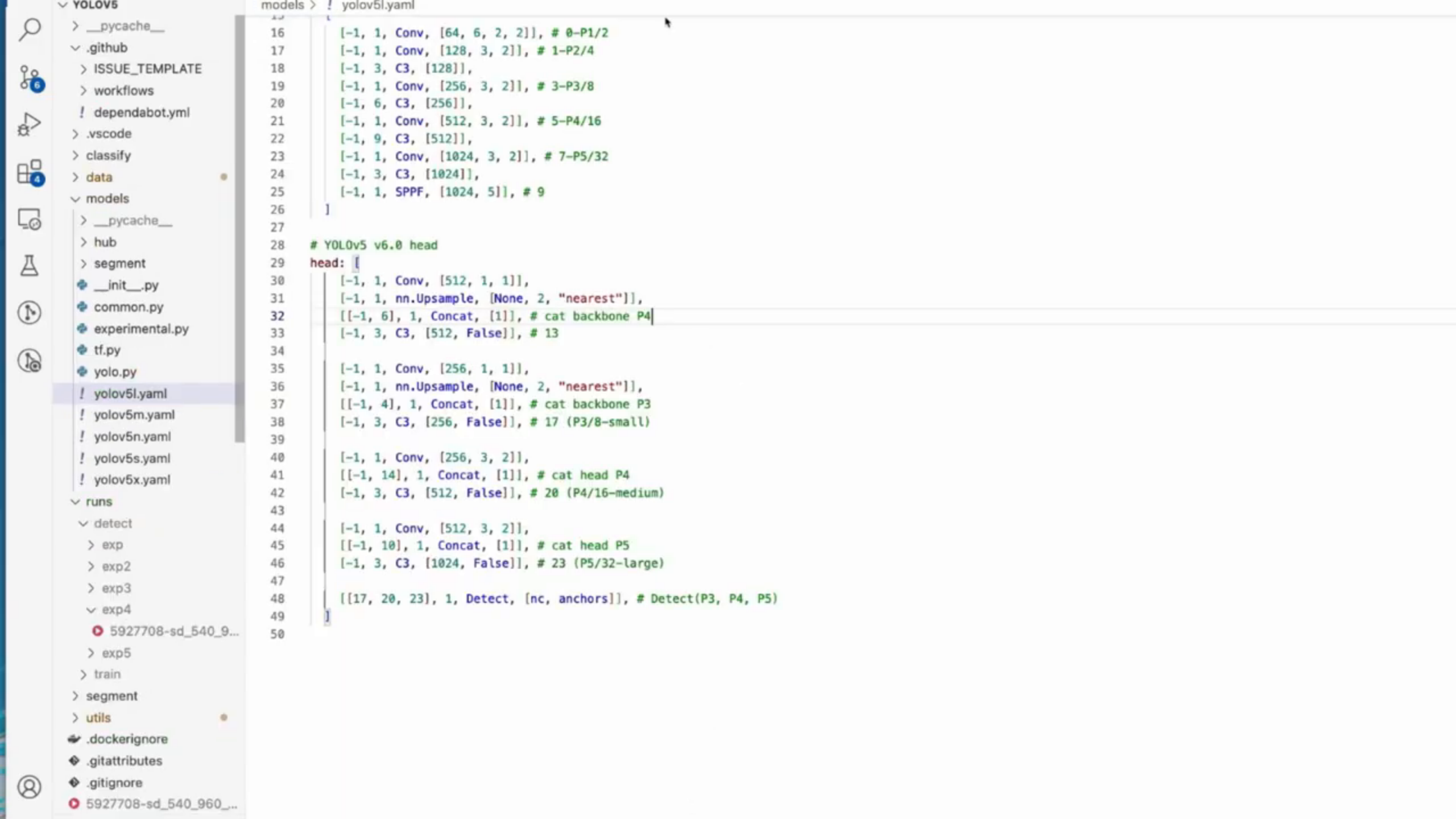
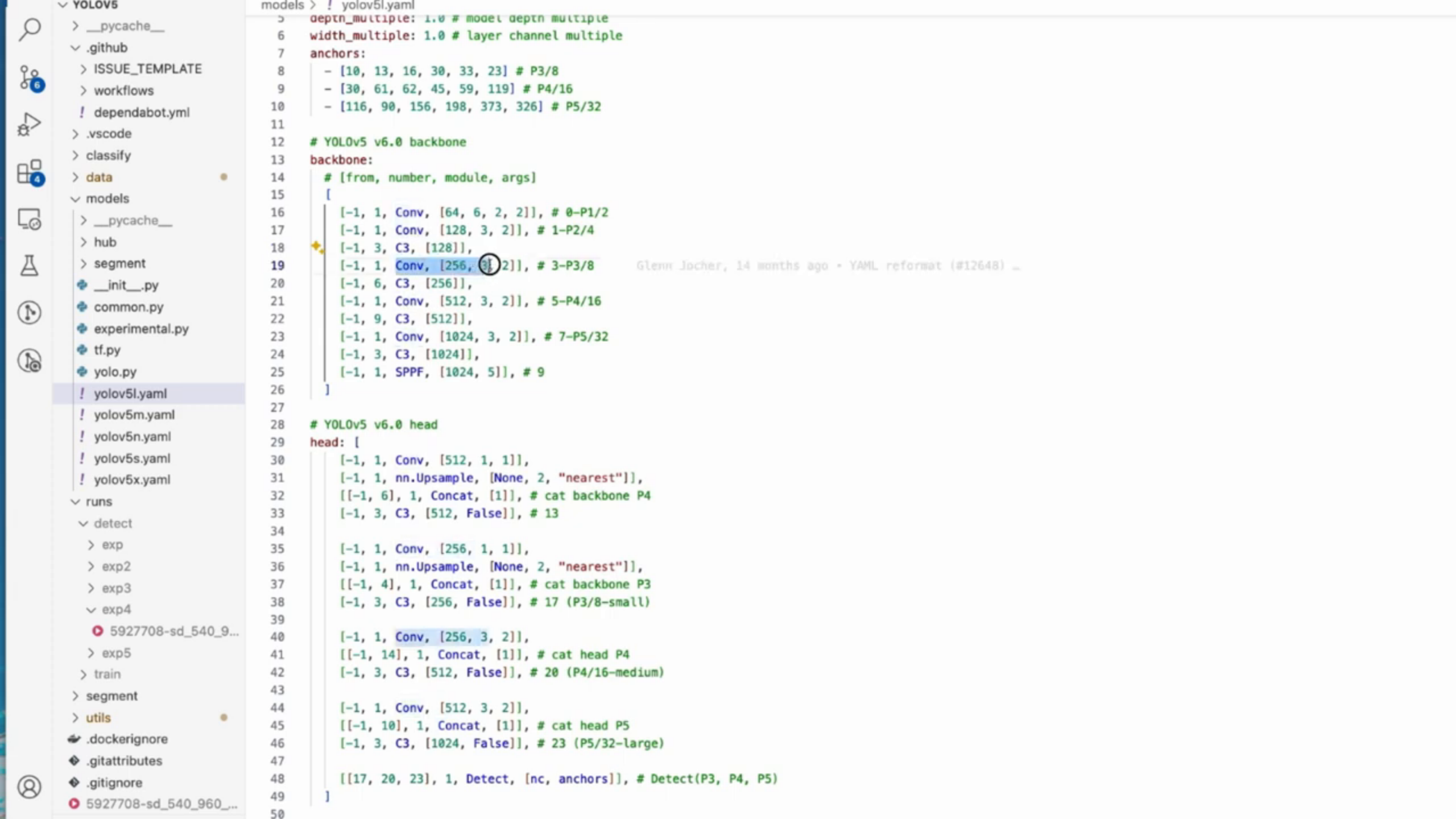
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
Concat
Max Pool
BN
SiLU
SiLU = x * sigmoid(x)

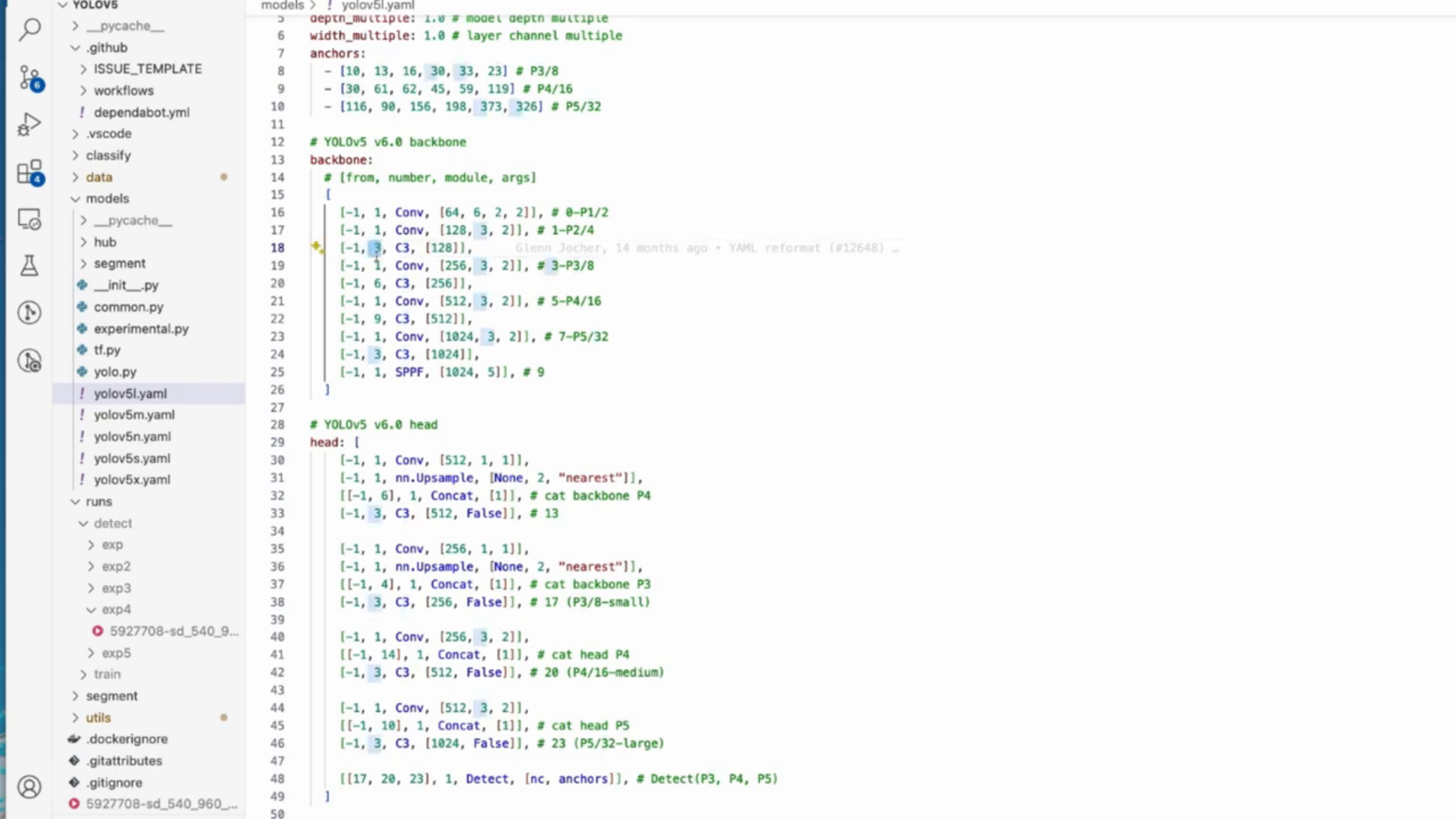

1×128×160×160
Sigmoid
Mul
Conv
W (256×128×3×3)
B (256)
1×256×80×80
1×128×80×80
W (128×256×1×1)
B (128)
W (128×128×1×1)
W (128×128×3×3)


YoloV5_1.key — Edited
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
N
Concat
Max Pool
Conv → BN → SiLU
SiLU = x * sigmoid(x)


W (128×128×3×3)
B (128)
1×128×80×80
Sigmoid
Mul
Add
W (128×128×1×1)
W (128×256×1×1)
W (256×256×1×1)
B (256)
Concat
1×256×80×80


YOLOV5
__pycache__
.github
ISSUE_TEMPLATE
workflows
dependabot.yml
.vscode
classify
data
models
__pycache__
hub
segment
__init__.py
common.py
experimental.py
tf.py
yolo.py
yolov5l.yaml
yolov5m.yaml
yolov5n.yaml
yolov5s.yaml
yolov5x.yaml
runs
detect
exp
exp2
exp3
exp4
5927708-sd_540_9...
exp5
train
segment
utils
.dockerignore
.gitattributes
.gitignore
5927708-sd_540_960_...
models > ! yolov5l.yaml
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
[-1, 1, Conv, [512, 3, 2]],
[[-1, 10], 1, Concat, [1]], # cat head P5
[-1, 3, C3, [1024, False]], # 23 (P5/32-large)
[[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
]


YOLOV5
__pycache__
.github
ISSUE_TEMPLATE
workflows
dependabot.yml
.vscode
classify
data
models
__pycache__
hub
segment
__init__.py
common.py
experimental.py
tf.py
yolo.py
yolov5l.yaml
yolov5m.yaml
yolov5n.yaml
yolov5s.yaml
yolov5x.yaml
runs
detect
exp
exp2
exp3
exp4
5927708-sd_540_9...
exp5
train
segment
utils
.dockerignore
.gitattributes
.gitignore
5927708-sd_540_960_...
models > ! yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
Glenn Jocher, 14 months ago • YAML reformat (#12648) …
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
[-1, 1, Conv, [512, 3, 2]],
[[-1, 10], 1, Concat, [1]], # cat head P5
[-1, 3, C3, [1024, False]], # 23 (P5/32-large)
[[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
]


YOLOV5
__pycache__
.github
ISSUE_TEMPLATE
workflows
dependabot.yml
.vscode
classify
data
models
__pycache__
hub
segment
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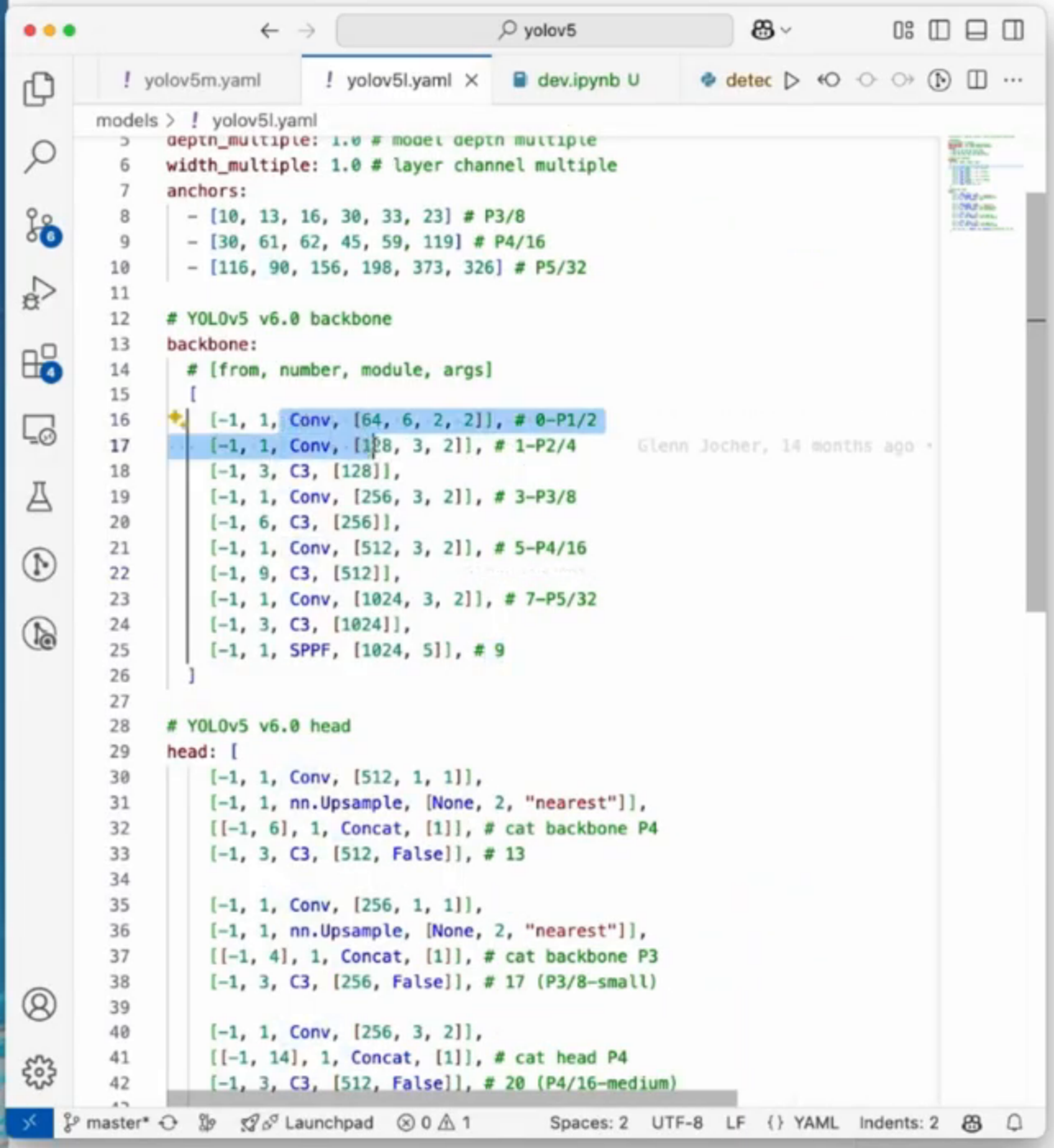
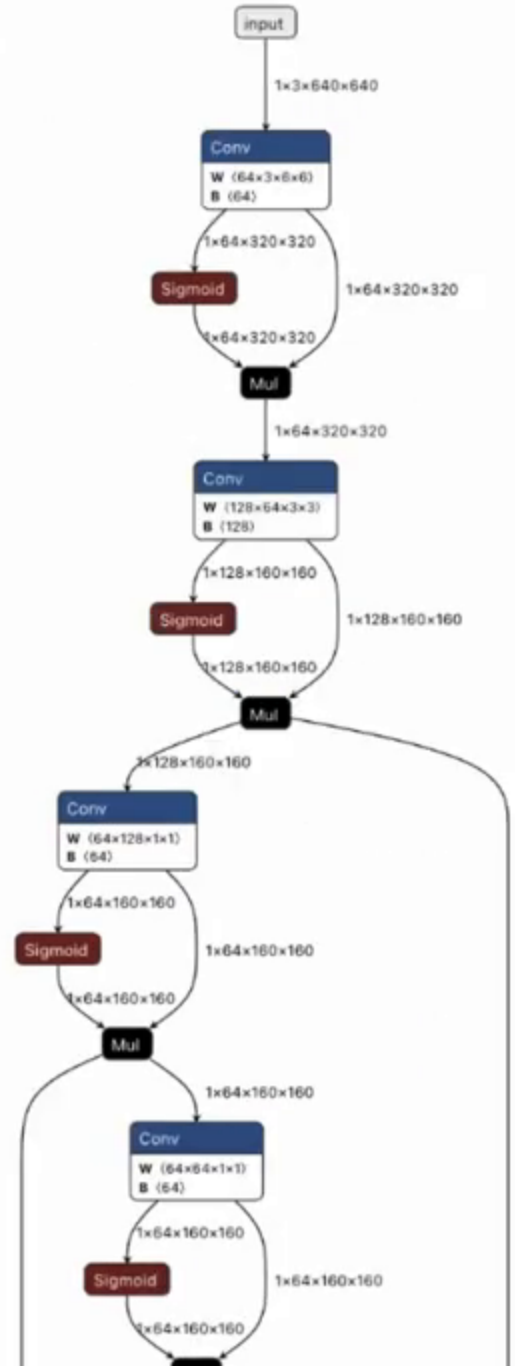
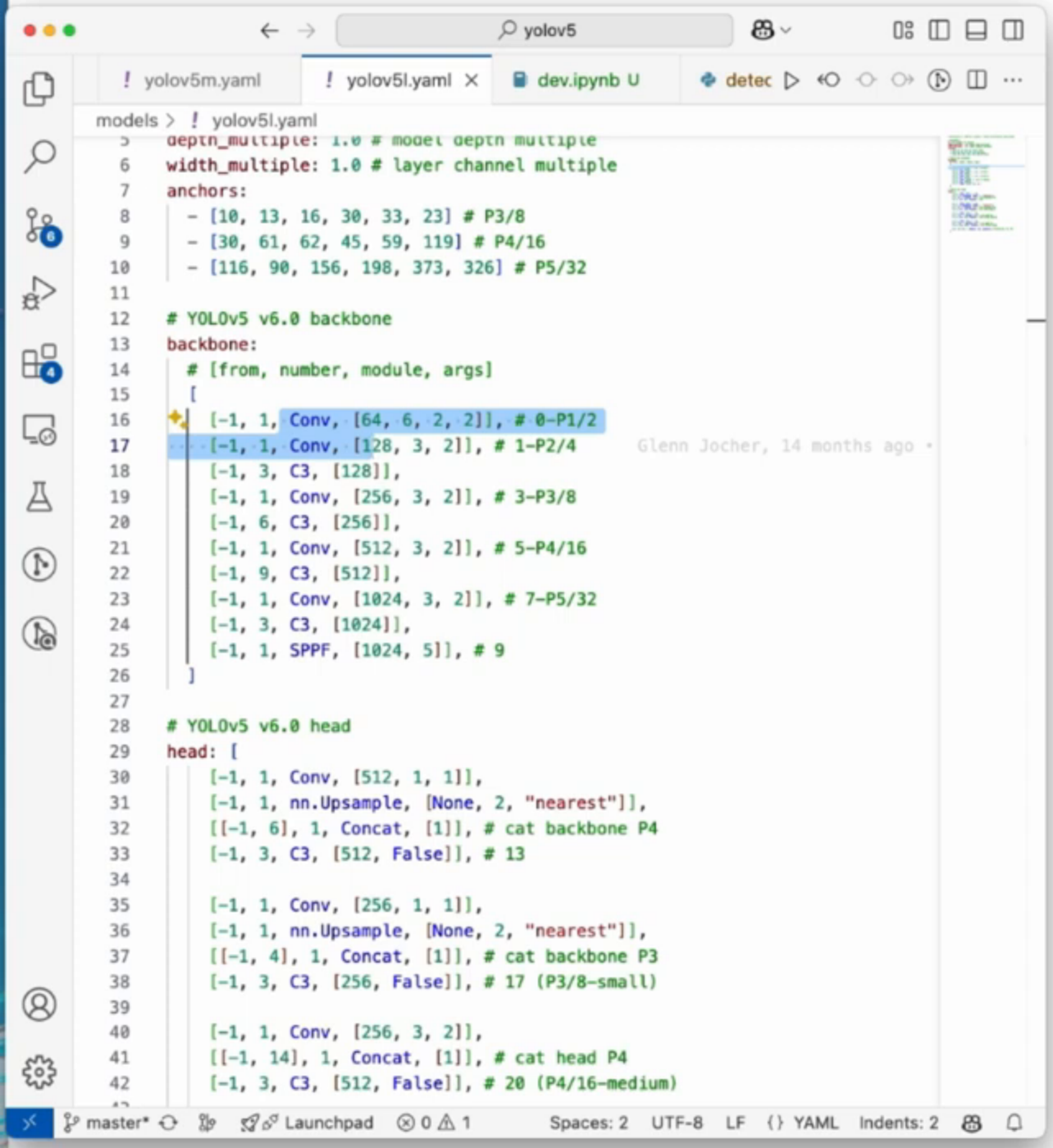
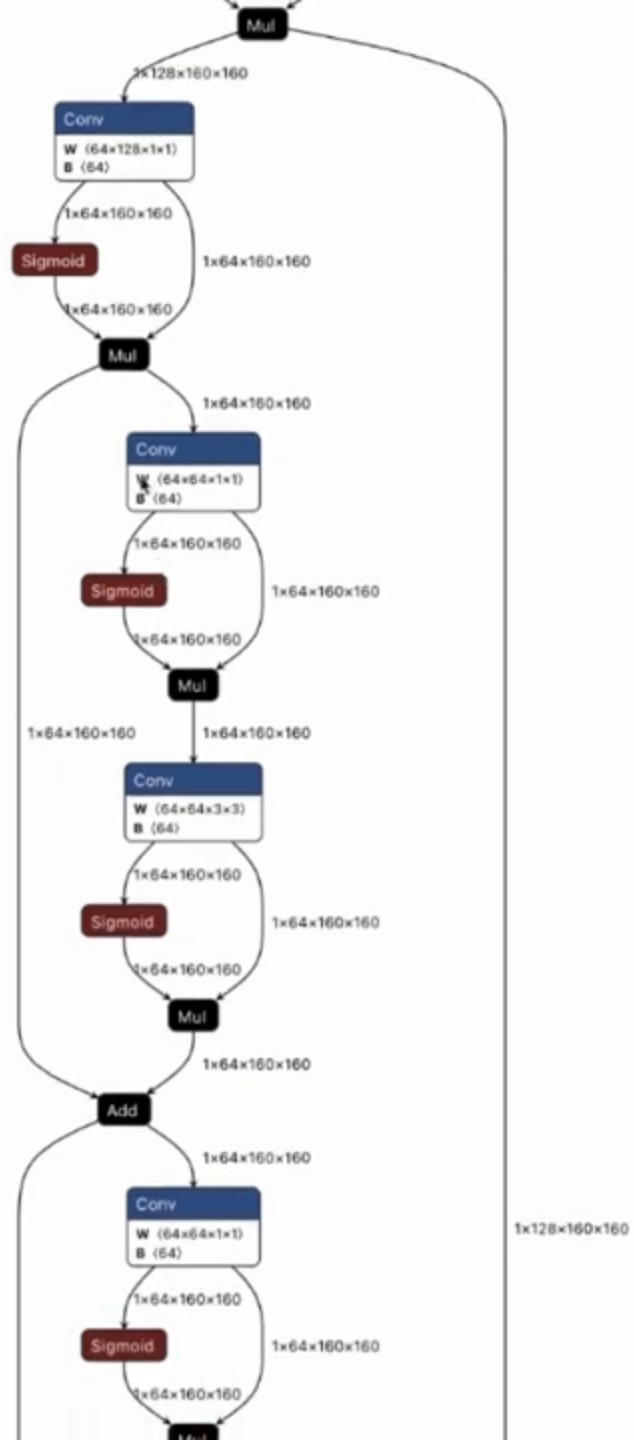
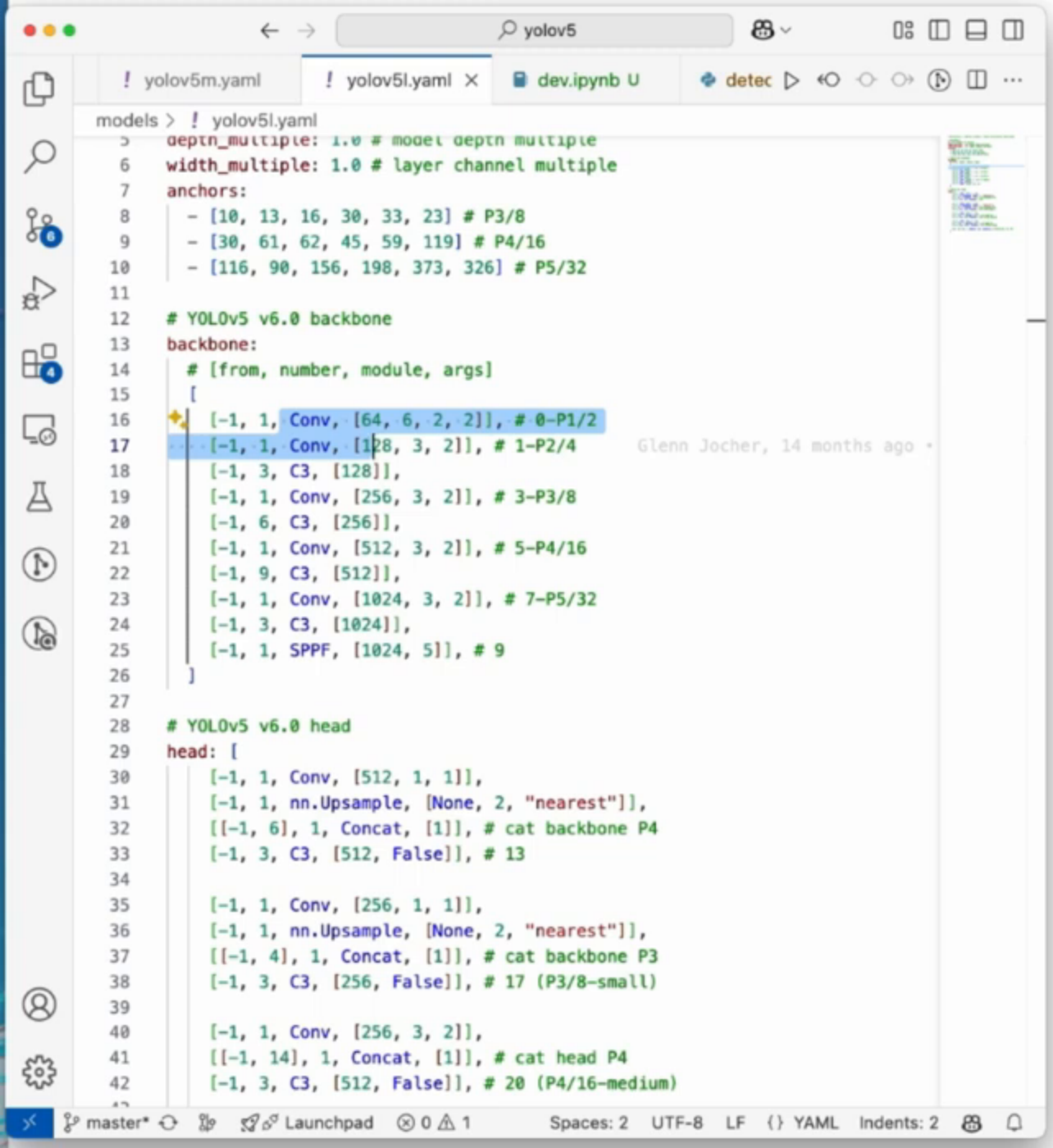
yolo.py
yolov5l.yaml
yolov5m.yaml
yolov5n.yaml
yolov5s.yaml
yolov5x.yaml
runs
detect
exp
exp2
exp3
exp4
5927708-sd_540_9...
exp5
train
segment
utils
.dockerignore
.gitattributes
.gitignore
5927708-sd_540_960_...
models > ! yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
[-1, 3, C3, [128]],
Glenn Jocher, 14 months ago • YAML reformat (#12648) …
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
[-1, 1, Conv, [512, 3, 2]],
[[-1, 10], 1, Concat, [1]], # cat head P5
[-1, 3, C3, [1024, False]], # 23 (P5/32-large)
[[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
]

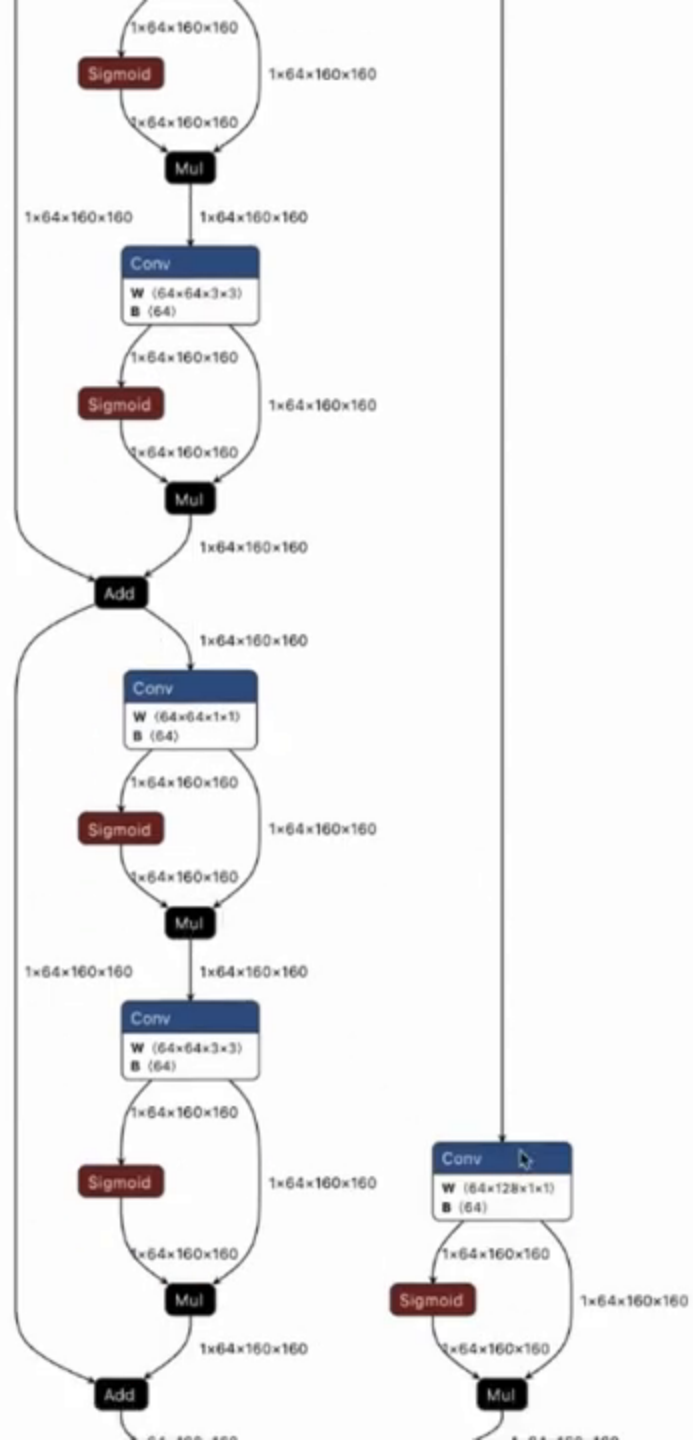

yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
models > yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
Glenn Jocher, 14 months ago
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
Spaces: 2
UTF-8
LF
YAML
Indents: 2

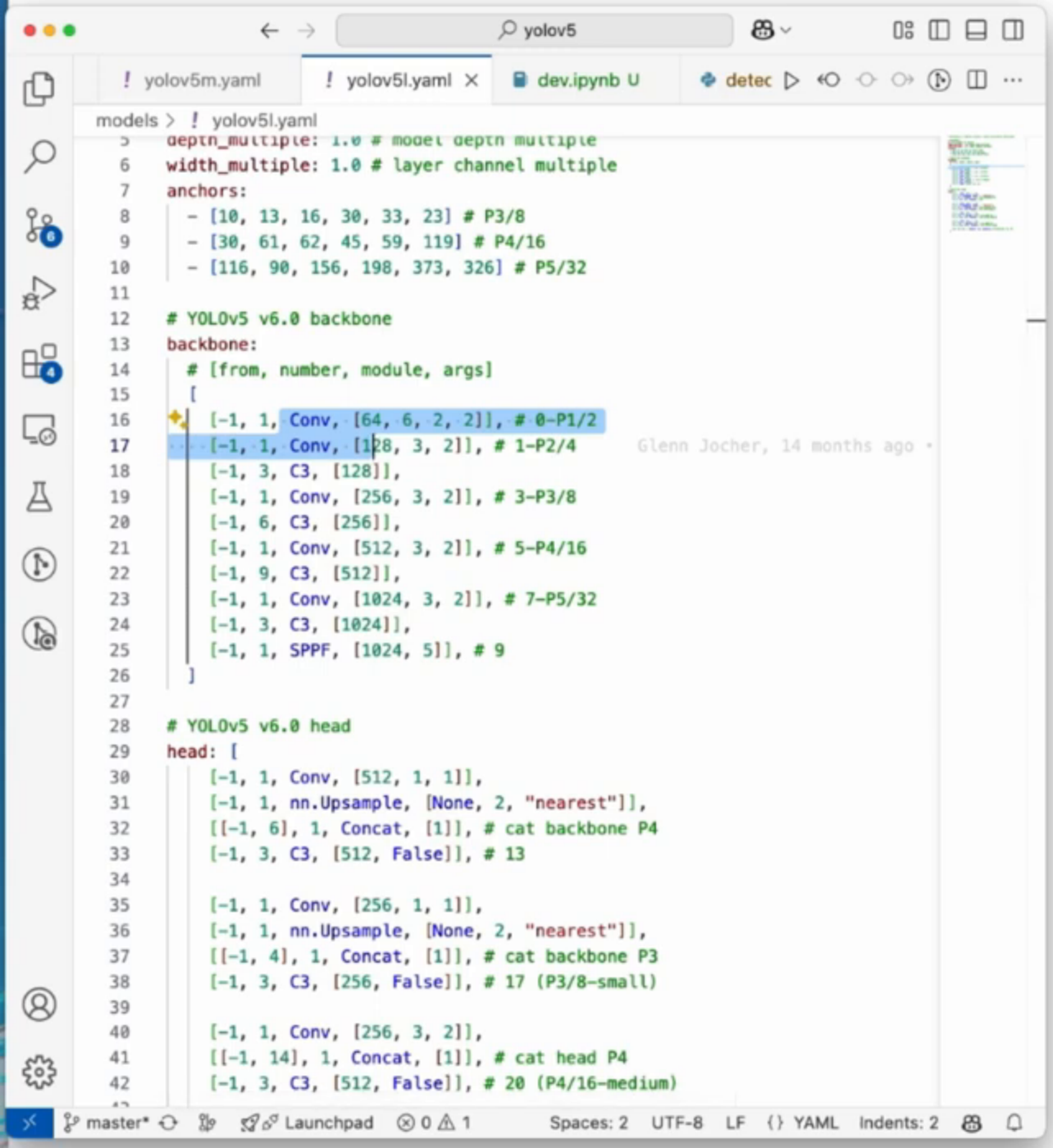

input
1×3×640×640
Conv
W (64×3×6×6)
B (64)
1×64×320×320
Sigmoid
1×64×320×320
1×64×320×320
Mul
1×64×320×320
Conv
W (128×64×3×3)
B (128)
1×128×160×160
Sigmoid
1×128×160×160
1×128×160×160
Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160

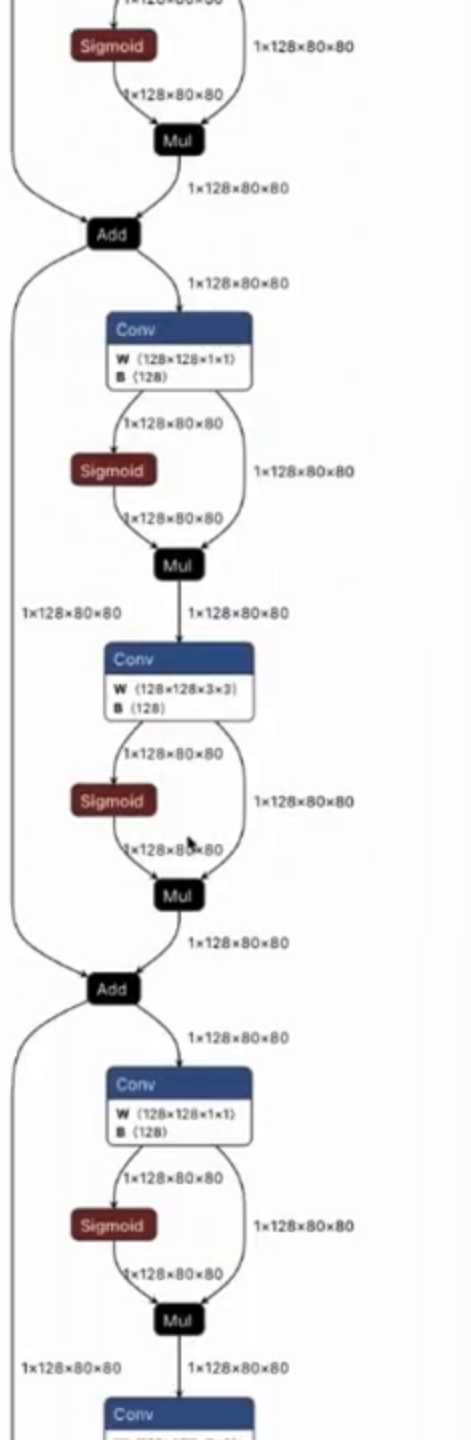

yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
detec
models > yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
Glenn Jocher, 14 months ago
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
0 1
Spaces: 2
UTF-8
LF
YAML
Indents: 2

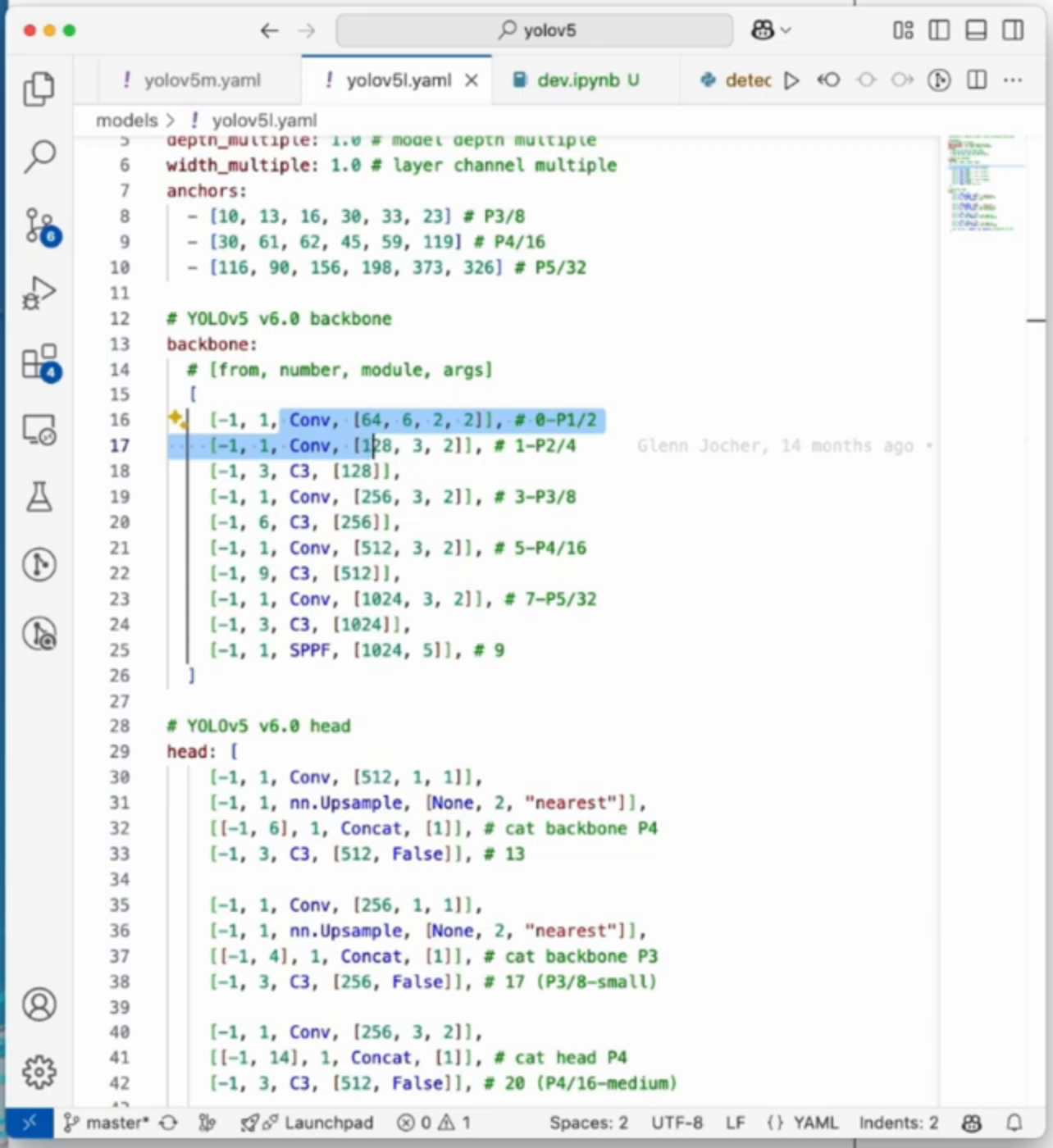

Mul
1×128×160×160
Conv
W (64×128×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
1×64×160×160
Conv
W (64×64×3×3)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×64×160×160
Add
1×64×160×160
Conv
W (64×64×1×1)
B (64)
1×64×160×160
Sigmoid
1×64×160×160
1×64×160×160
Mul
1×128×160×160

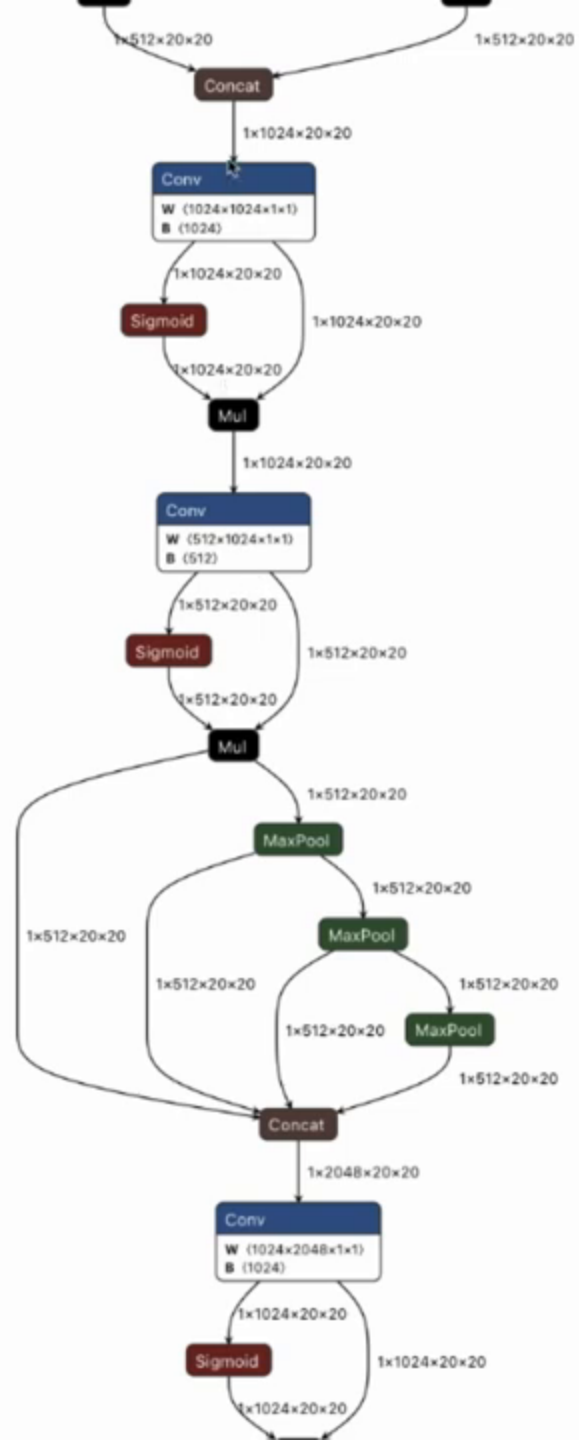

yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
detec
models > yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
Glenn Jocher, 14 months ago
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
0 1
Spaces: 2
UTF-8
LF
YAML
Indents: 2

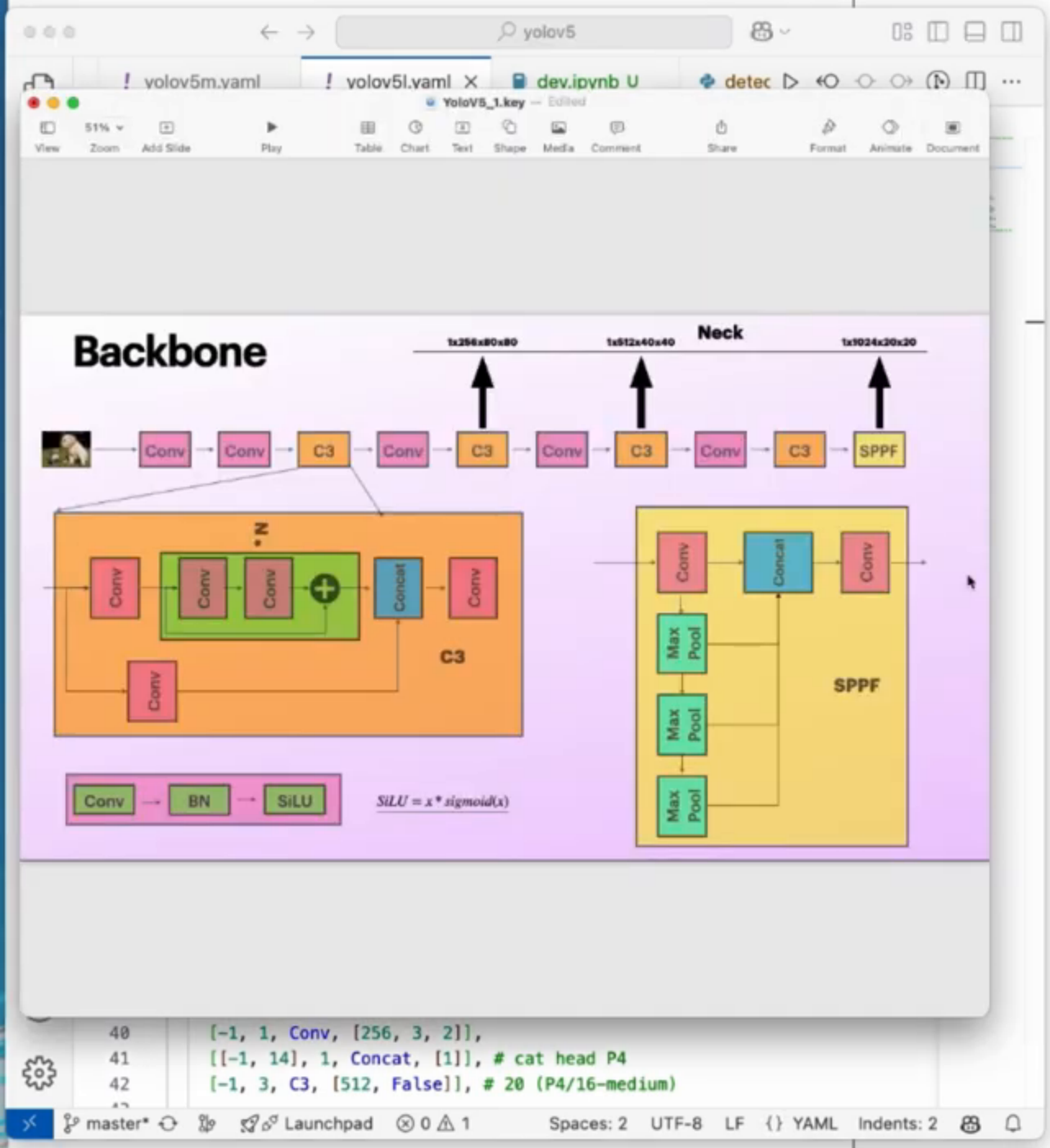

1×64×160×160
Sigmoid
Mul
Conv
W (64×64×3×3)
B (64)
Add
W (64×64×1×1)
W (64×128×1×1)


yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
detec
models > yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
Glenn Jocher, 14 months ago
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
0 1
Spaces: 2
UTF-8
LF
YAML
Indents: 2

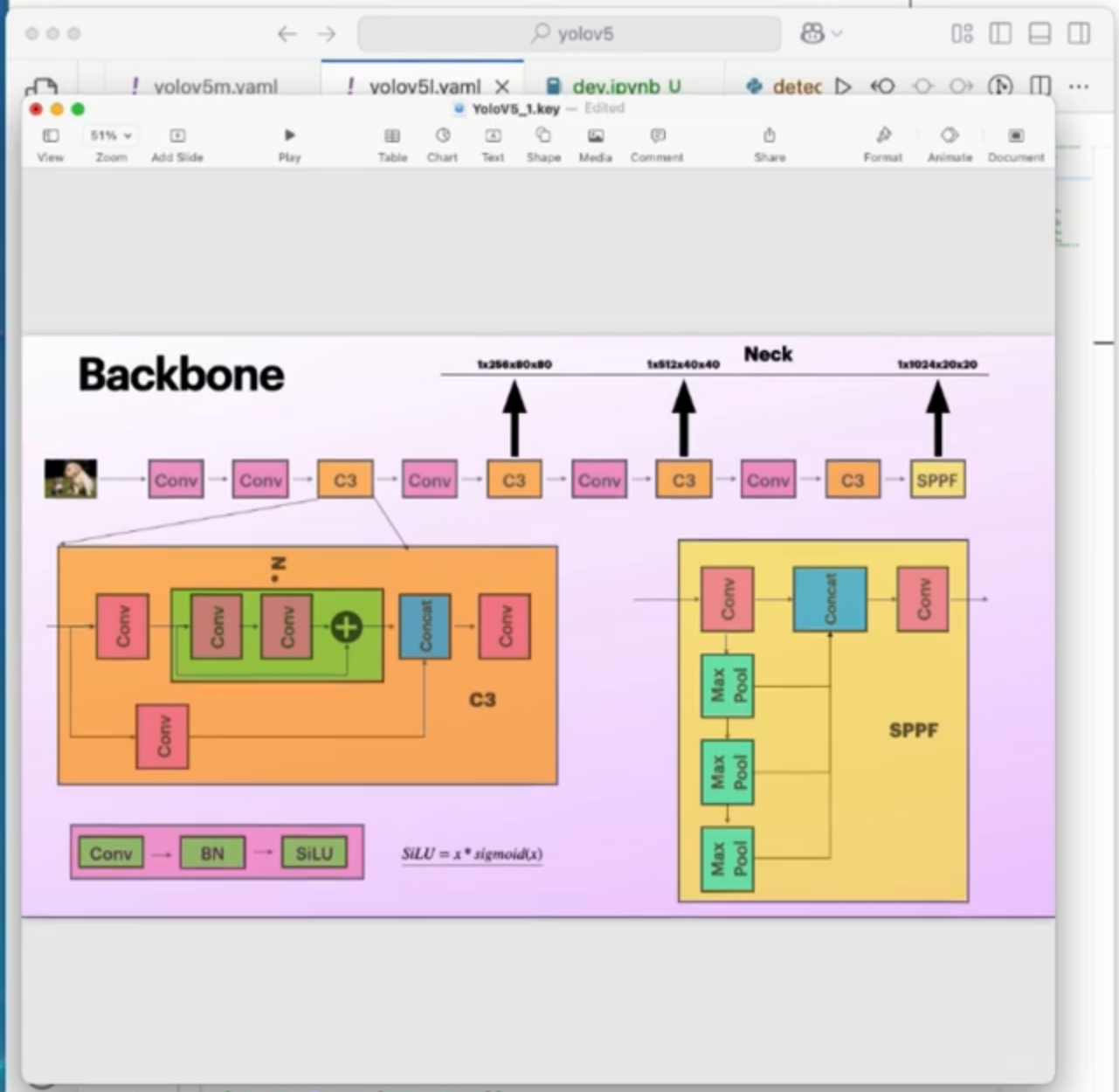

Sigmoid
1×128×80×80
Mul
Add
Conv
W (128×128×1×1)
B (128)
W (128×128×3×3)


yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
detec
models > yolov5l.yaml
depth_multiple: 1.0 # model depth multiple
width_multiple: 1.0 # layer channel multiple
anchors:
- [10, 13, 16, 30, 33, 23] # P3/8
- [30, 61, 62, 45, 59, 119] # P4/16
- [116, 90, 156, 198, 373, 326] # P5/32
YOLOv5 v6.0 backbone
backbone:
[from, number, module, args]
[
[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
[-1, 1, Conv, [128, 3, 2]], # 1-P2/4
Glenn Jocher, 14 months ago
[-1, 3, C3, [128]],
[-1, 1, Conv, [256, 3, 2]], # 3-P3/8
[-1, 6, C3, [256]],
[-1, 1, Conv, [512, 3, 2]], # 5-P4/16
[-1, 9, C3, [512]],
[-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
[-1, 3, C3, [1024]],
[-1, 1, SPPF, [1024, 5]], # 9
]
YOLOv5 v6.0 head
head: [
[-1, 1, Conv, [512, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 6], 1, Concat, [1]], # cat backbone P4
[-1, 3, C3, [512, False]], # 13
[-1, 1, Conv, [256, 1, 1]],
[-1, 1, nn.Upsample, [None, 2, "nearest"]],
[[-1, 4], 1, Concat, [1]], # cat backbone P3
[-1, 3, C3, [256, False]], # 17 (P3/8-small)
[-1, 1, Conv, [256, 3, 2]],
[[-1, 14], 1, Concat, [1]], # cat head P4
[-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
0 1
Spaces: 2
UTF-8
LF
YAML
Indents: 2

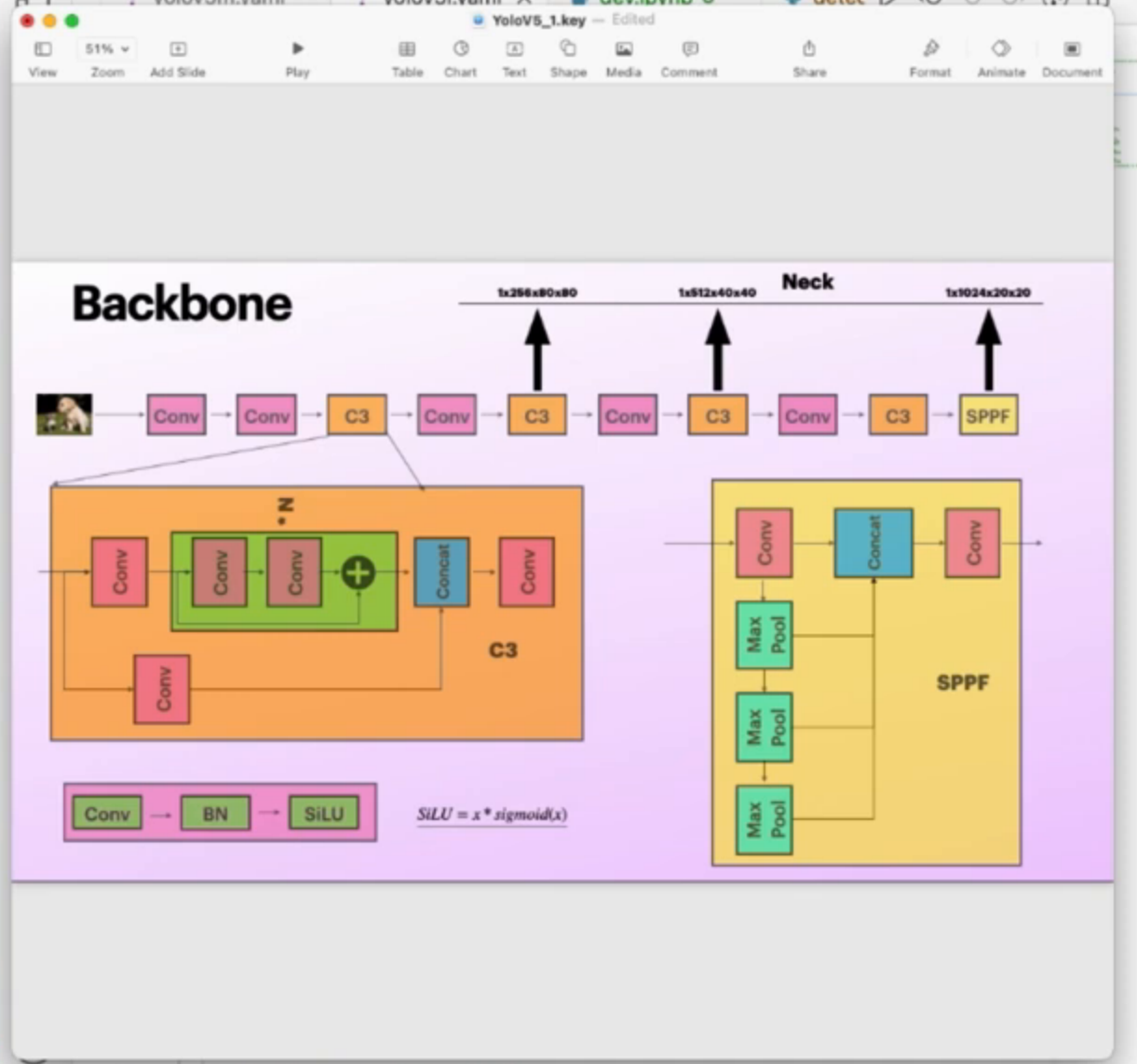

1×512×20×20
1×512×20×20
Concat
1×1024×20×20
Conv
W (1024×1024×1×1)
B (1024)
1×1024×20×20
Sigmoid
1×1024×20×20
1×1024×20×20
Mul
1×1024×20×20
Conv
W (512×1024×1×1)
B (512)
1×512×20×20
Sigmoid
1×512×20×20
1×512×20×20
Mul
1×512×20×20
MaxPool
1×512×20×20
1×512×20×20
MaxPool
1×512×20×20
1×512×20×20
1×512×20×20
MaxPool
1×512×20×20
Concat
1×2048×20×20
Conv
W (1024×2048×1×1)
B (1024)
1×1024×20×20
Sigmoid
1×1024×20×20
1×1024×20×20

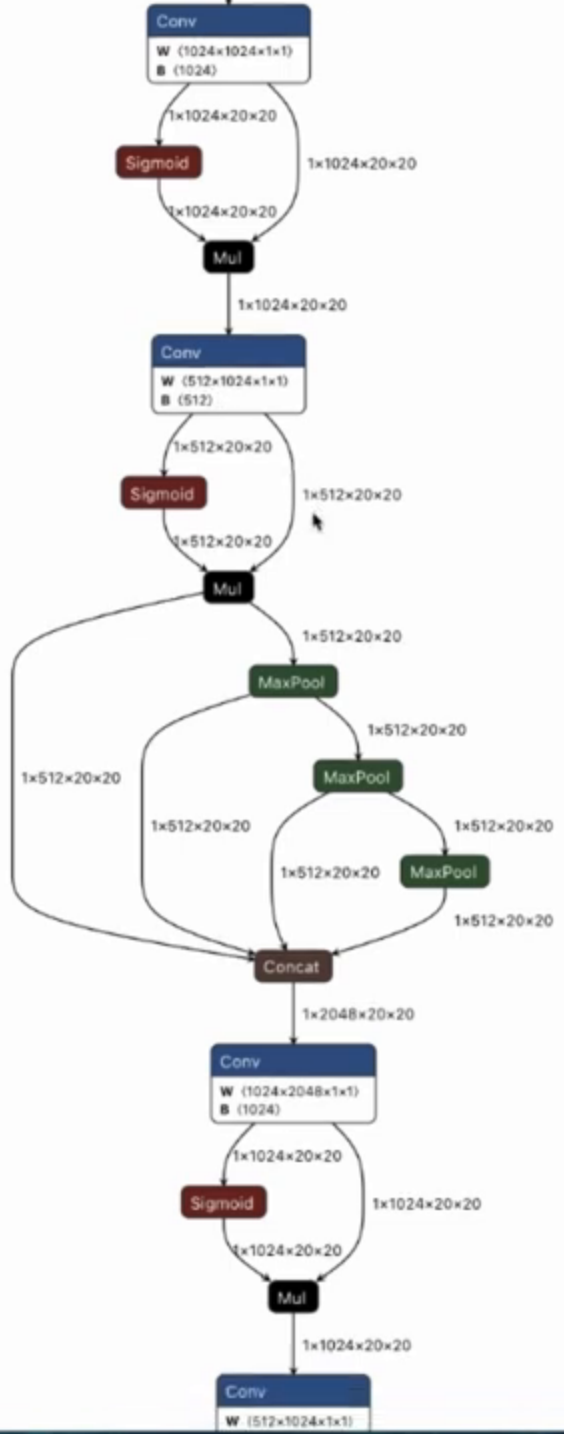

yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
YoloV5_1.key — Edited
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
Concat
Max Pool
BN
SiLU
SiLU = x * sigmoid(x)
40 [-1, 1, Conv, [256, 3, 2]],
41 [[-1, 14], 1, Concat, [1]], # cat head P4
42 [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
Spaces: 2
UTF-8
LF
YAML
Indents: 2


1×512×20×20
Concat
1×1024×20×20
Conv
W (1024×1024×1×1)
B (1024)
Sigmoid
Mul
W (512×1024×1×1)
B (512)
MaxPool
W (1024×2048×1×1)
B (1024)


yolov5
yolov5m.yaml
yolov5l.yaml
dev.ipynb U
YoloV5_1.key — Edited
Backbone
Neck
1x256x80x80
1x512x40x40
1x1024x20x20
Conv
C3
SPPF
N *
C3
SPPF
Max Pool
Concat
Conv → BN → SiLU
SiLU = x * sigmoid(x)
40 [-1, 1, Conv, [256, 3, 2]],
41 [[-1, 14], 1, Concat, [1]], # cat head P4
42 [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
master*
Launchpad
Spaces: 2
UTF-8
LF
YAML
Indents: 2

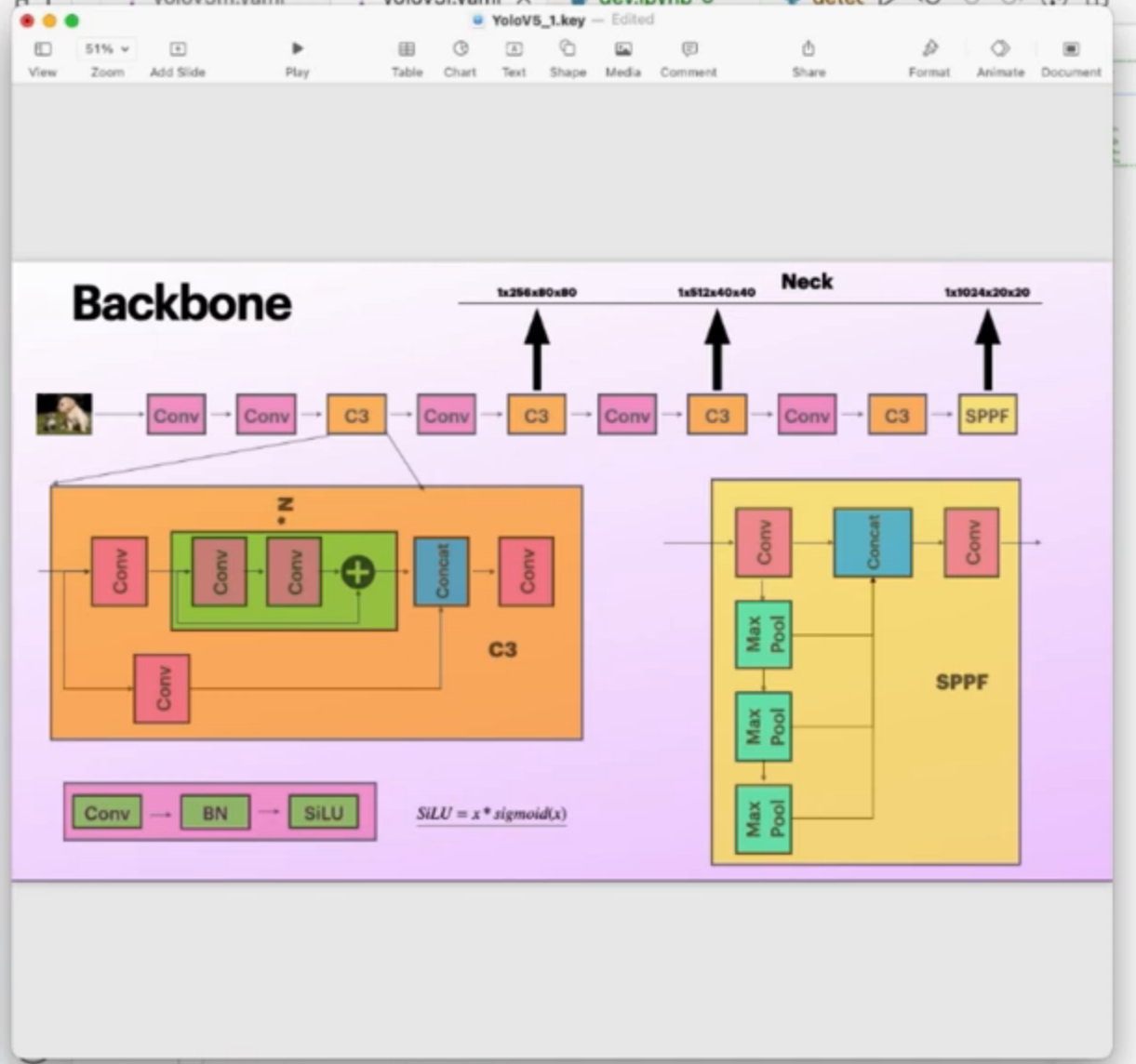

1×512×20×20
Concat
1×1024×20×20
Conv
W (1024×1024×1×1)
B (1024)
Sigmoid
Mul
W (512×1024×1×1)
B (512)
MaxPool
W (1024×2048×1×1)






```
40    [-1, 1, Conv, [256, 3, 2]],
41    [[-1, 14], 1, Concat, [1]], # cat head P4
42    [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
```

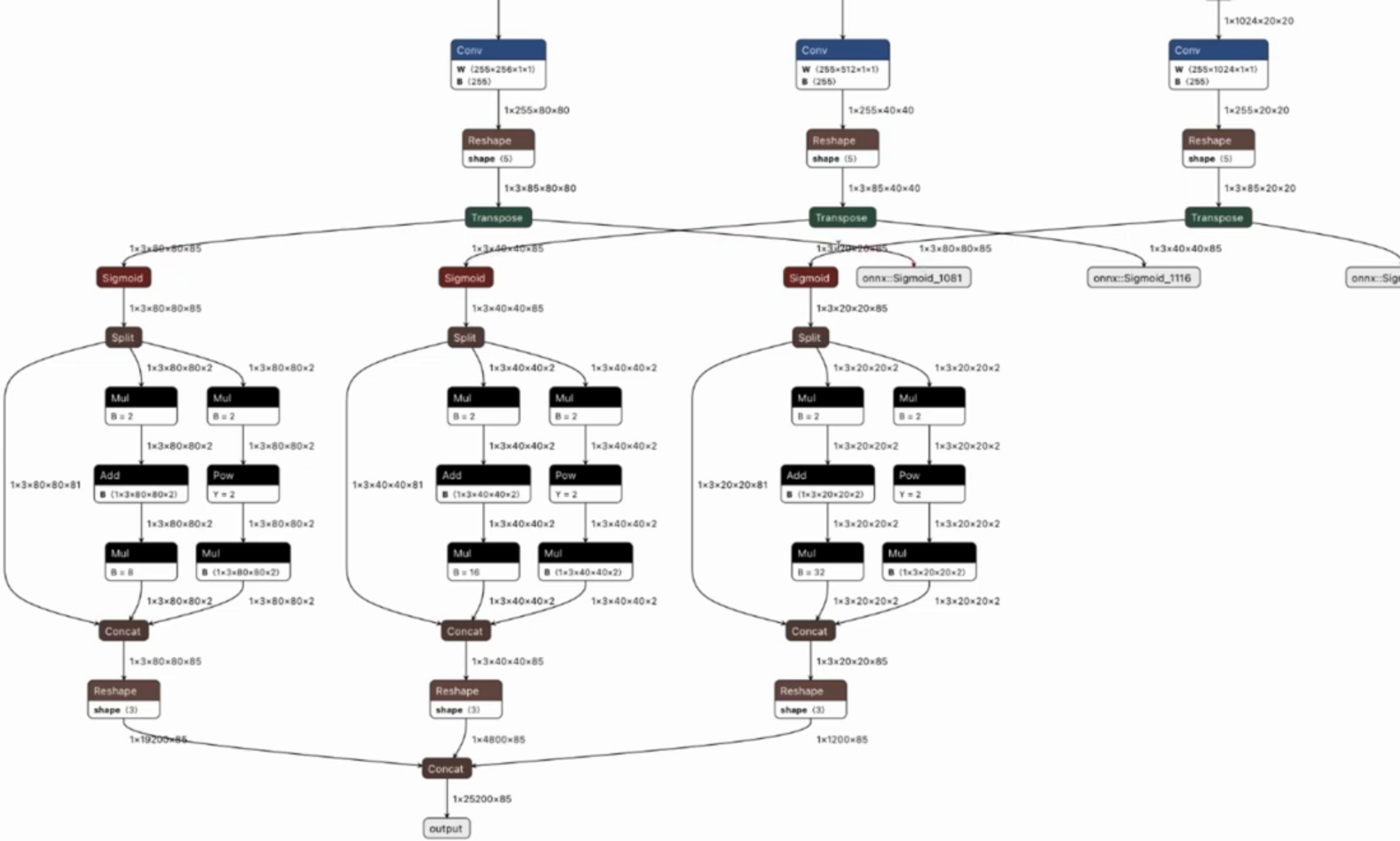
master* Launchpad 0 1 Spaces: 2 UTF-8 LF YAML Indents: 2

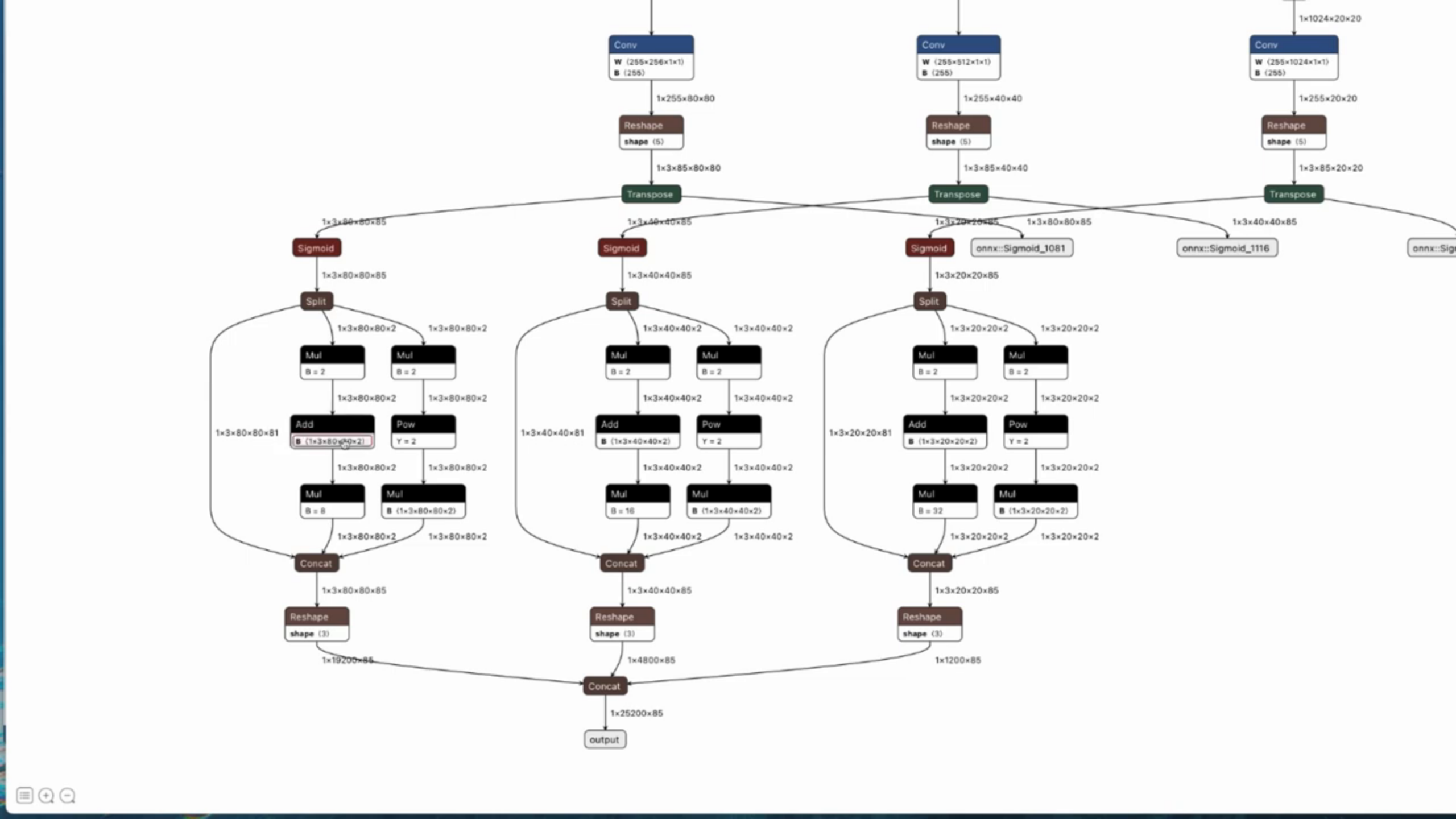


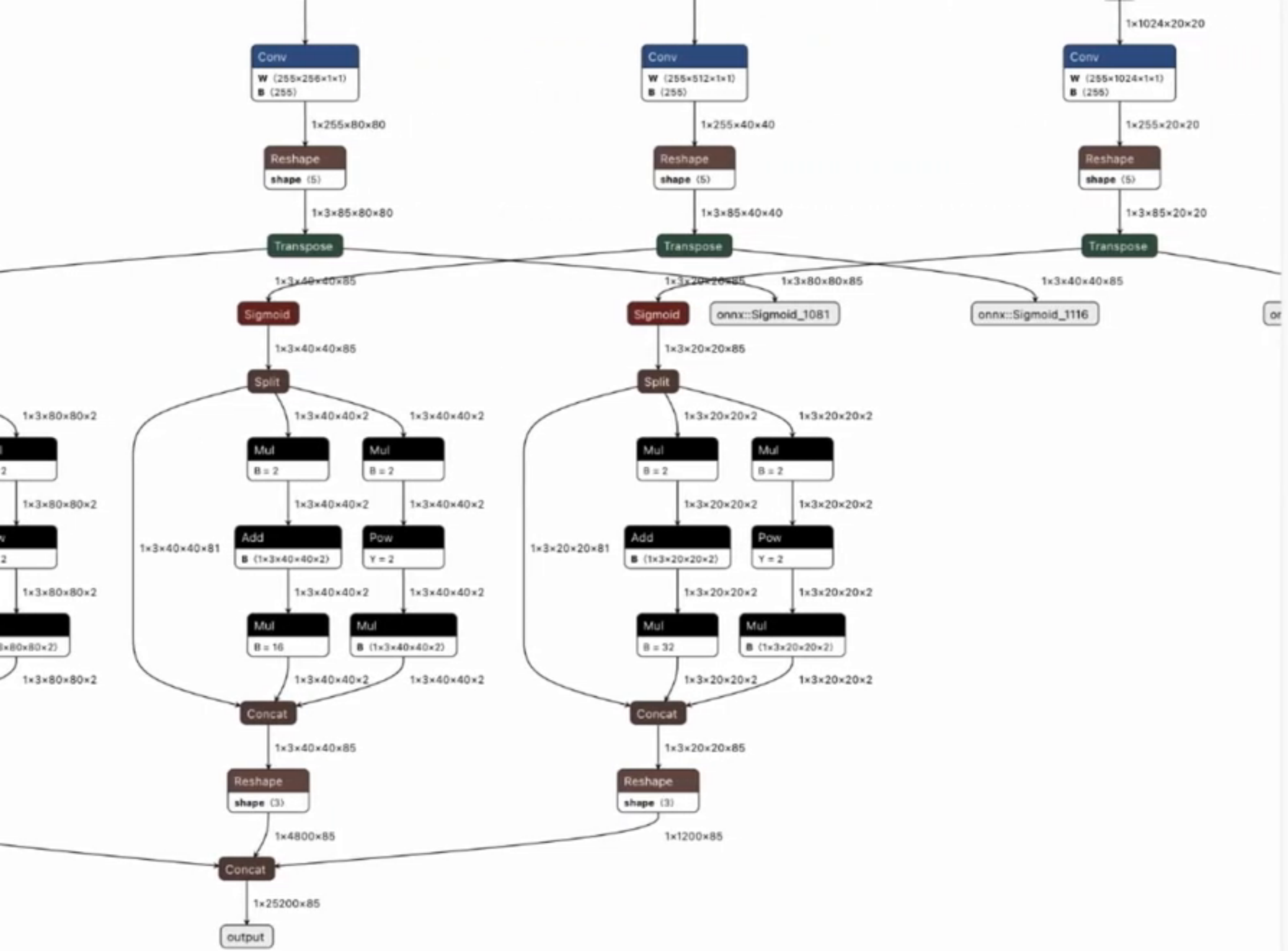

```
40    [-1, 1, Conv, [256, 3, 2]],
41    [[-1, 14], 1, Concat, [1]], # cat head P4
42    [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
```

master* Launchpad 0 1 Spaces: 2 UTF-8 LF YAML Indents: 2

1×256×40×40 Sigmoid 1×256×40×40
1×256×40×40 Mul
1×256×40×40 Concat
1×512×40×40 Conv
W (512×512×1×1) B (512)
1×512×40×40 Sigmoid 1×512×40×40
1×512×40×40 Mul
1×512×40×40 Conv
W (256×512×1×1) B (256)
1×256×40×40 Sigmoid 1×256×40×40
1×256×40×40 Mul
Sigmoid 1×128×80×80
1×128×80×80


Conv
W (255×256×1×1)
B (255)
1×255×80×80
Reshape
shape (5)
1×3×85×80×80
Transpose
1×3×80×80×85
Sigmoid
1×3×80×80×85
Split
1×3×80×80×2
1×3×80×80×2
Mul
B = 2
Mul
B = 2
1×3×80×80×2
1×3×80×80×2
1×3×80×80×81
Add
B (1×3×80×80×2)
Pow
Y = 2
1×3×80×80×2
1×3×80×80×2
Mul
B = 8
Mul
B (1×3×80×80×2)
1×3×80×80×2
1×3×80×80×2
Concat
1×3×80×80×85
Reshape
shape (3)
1×19200×85
Conv
W (255×512×1×1)
B (255)
1×255×40×40
Reshape
shape (5)
1×3×85×40×40
Transpose
1×3×40×40×85
Sigmoid
1×3×40×40×85
Split
1×3×40×40×2
1×3×40×40×2
Mul
B = 2
Mul
B = 2
1×3×40×40×2
1×3×40×40×2
1×3×40×40×81
Add
B (1×3×40×40×2)
Pow
Y = 2
1×3×40×40×2
1×3×40×40×2
Mul
B = 16
Mul
B (1×3×40×40×2)
1×3×40×40×2
1×3×40×40×2
Concat
1×3×40×40×85
Reshape
shape (3)
1×4800×85
Conv
W (255×1024×1×1)
B (255)
1×1024×20×20
1×255×20×20
Reshape
shape (5)
1×3×85×20×20
Transpose
1×3×20×20×85
Sigmoid
1×3×20×20×85
Split
1×3×20×20×2
1×3×20×20×2
Mul
B = 2
Mul
B = 2
1×3×20×20×2
1×3×20×20×2
1×3×20×20×81
Add
B (1×3×20×20×2)
Pow
Y = 2
1×3×20×20×2
1×3×20×20×2
Mul
B = 32
Mul
B (1×3×20×20×2)
1×3×20×20×2
1×3×20×20×2
Concat
1×3×20×20×85
Reshape
shape (3)
1×1200×85
1×3×80×80×85
onnx::Sigmoid_1081
1×3×40×40×85
onnx::Sigmoid_1116
Concat
1×25200×85
output


Conv
W (255×256×1×1)
B (255)
1×255×80×80
Reshape
shape (5)
1×3×85×80×80
Transpose
1×3×80×80×85
Sigmoid
1×3×80×80×85
Split
1×3×80×80×2
1×3×80×80×2
Mul
B = 2
Mul
B = 2
1×3×80×80×2
1×3×80×80×2
1×3×80×80×81
Add
B (1×3×80×80×2)
Pow
Y = 2
1×3×80×80×2
1×3×80×80×2
Mul
B = 8
Mul
B (1×3×80×80×2)
1×3×80×80×2
1×3×80×80×2
Concat
1×3×80×80×85
Reshape
shape (3)
1×19200×85
Conv
W (255×512×1×1)
B (255)
1×255×40×40
Reshape
shape (5)
1×3×85×40×40
Transpose
1×3×40×40×85
Sigmoid
1×3×40×40×85
Split
1×3×40×40×2
1×3×40×40×2
Mul
B = 2
Mul
B = 2
1×3×40×40×2
1×3×40×40×2
1×3×40×40×81
Add
B (1×3×40×40×2)
Pow
Y = 2
1×3×40×40×2
1×3×40×40×2
Mul
B = 16
Mul
B (1×3×40×40×2)
1×3×40×40×2
1×3×40×40×2
Concat
1×3×40×40×85
Reshape
shape (3)
1×4800×85
Conv
W (255×1024×1×1)
B (255)
1×1024×20×20
1×255×20×20
Reshape
shape (5)
1×3×85×20×20
Transpose
1×3×20×20×85
Sigmoid
1×3×20×20×85
Split
1×3×20×20×2
1×3×20×20×2
Mul
B = 2
Mul
B = 2
1×3×20×20×2
1×3×20×20×2
1×3×20×20×81
Add
B (1×3×20×20×2)
Pow
Y = 2
1×3×20×20×2
1×3×20×20×2
Mul
B = 32
Mul
B (1×3×20×20×2)
1×3×20×20×2
1×3×20×20×2
Concat
1×3×20×20×85
Reshape
shape (3)
1×1200×85
1×3×80×80×85
onnx::Sigmoid_1081
1×3×40×40×85
onnx::Sigmoid_1116
Concat
1×25200×85
output

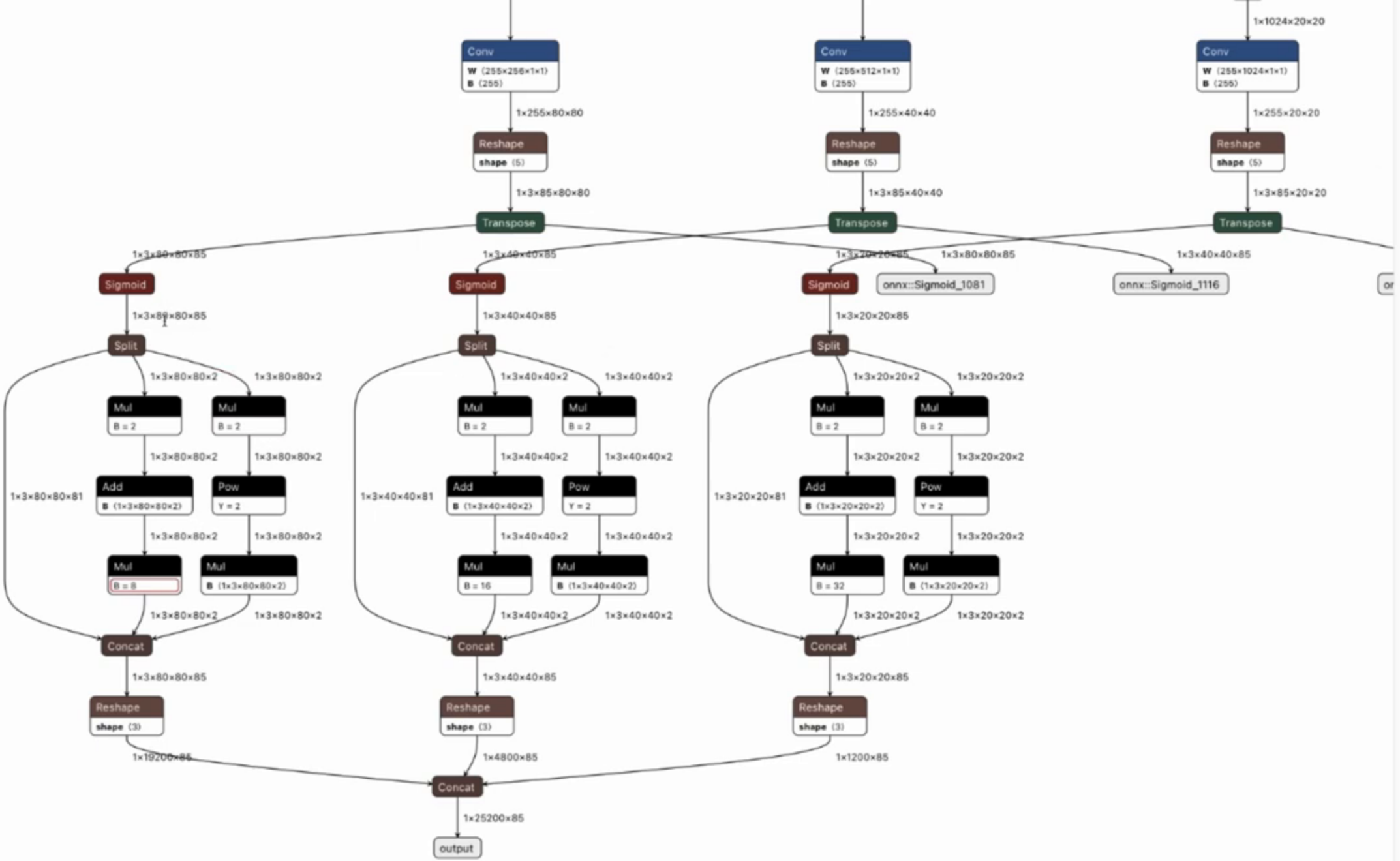


type float32

shape 1,3,80,80,2

value


```
[
    [
        [
            [
                [
                    -0.5,
                    -0.5
                ],
                [
                    0.5,
                    -0.5
                ],
                [
                    1.5,
                    -0.5
                ],
                [
                    2.5,
                    -0.5
                ],
                [
                    3.5,
                    -0.5
                ],
                [
                    4.5,
                    -0.5
                ],
                [
                    5.5,
                    -0.5
                ],
                [
                    6.5,
                    -0.5
                ],
                [
                    7.5,
                    -0.5
                ],
                [
                    8.5,
                    -0.5
                ],
                [
                    9.5,
                    -0.5
                ],
                [
                    10.5,
                    -0.5
                ],
                [
                    11.5,
                    -0.5
                ],
                [
                    12.5,
                    -0.5
                ],
                [
                    13.5,
                    -0.5
                ],
                [
                    14.5,
                    -0.5
                ],
```

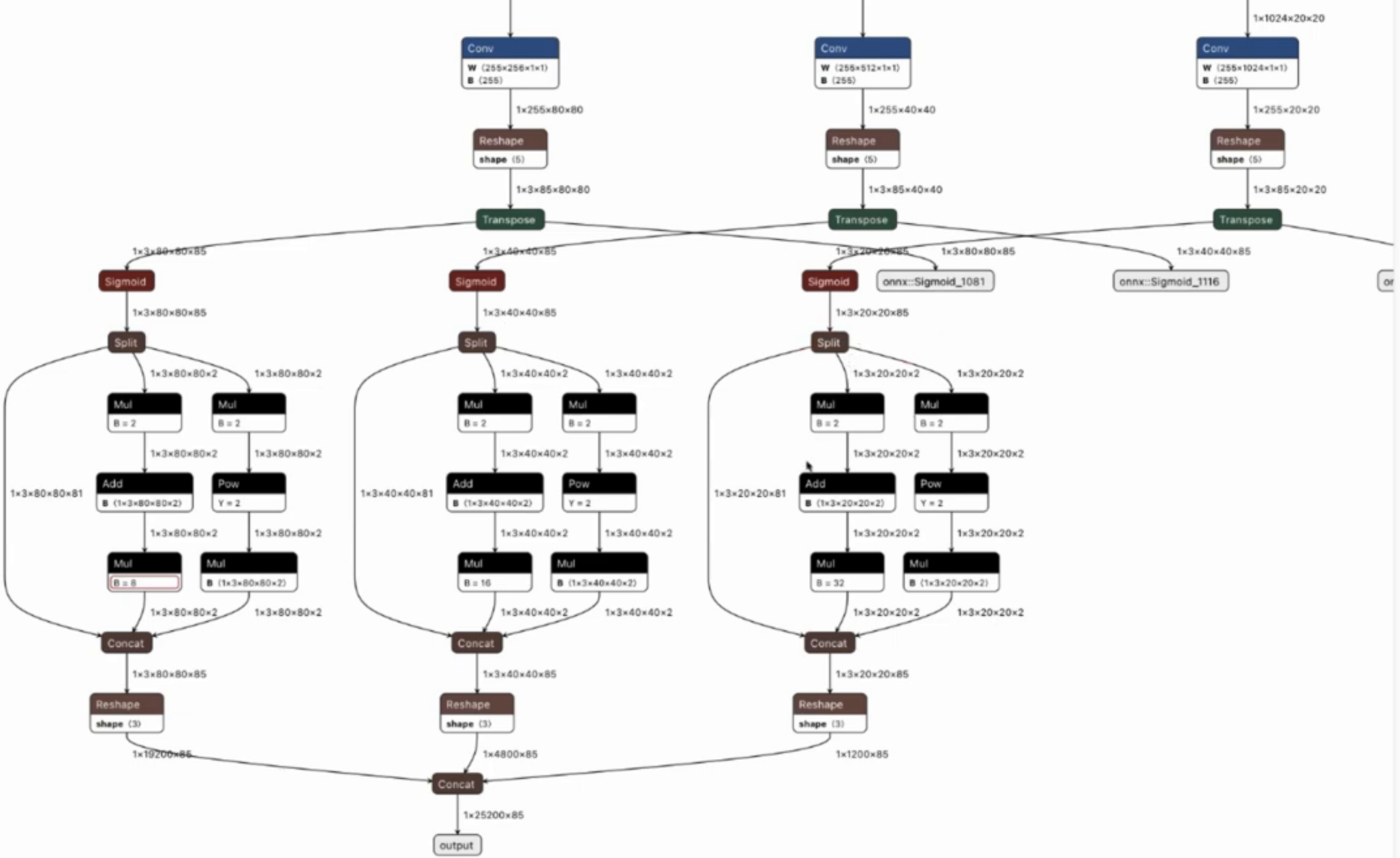


type float3

shape

METRICS

min	8
max	8
mean	8
std	0
sparsity	0.0%

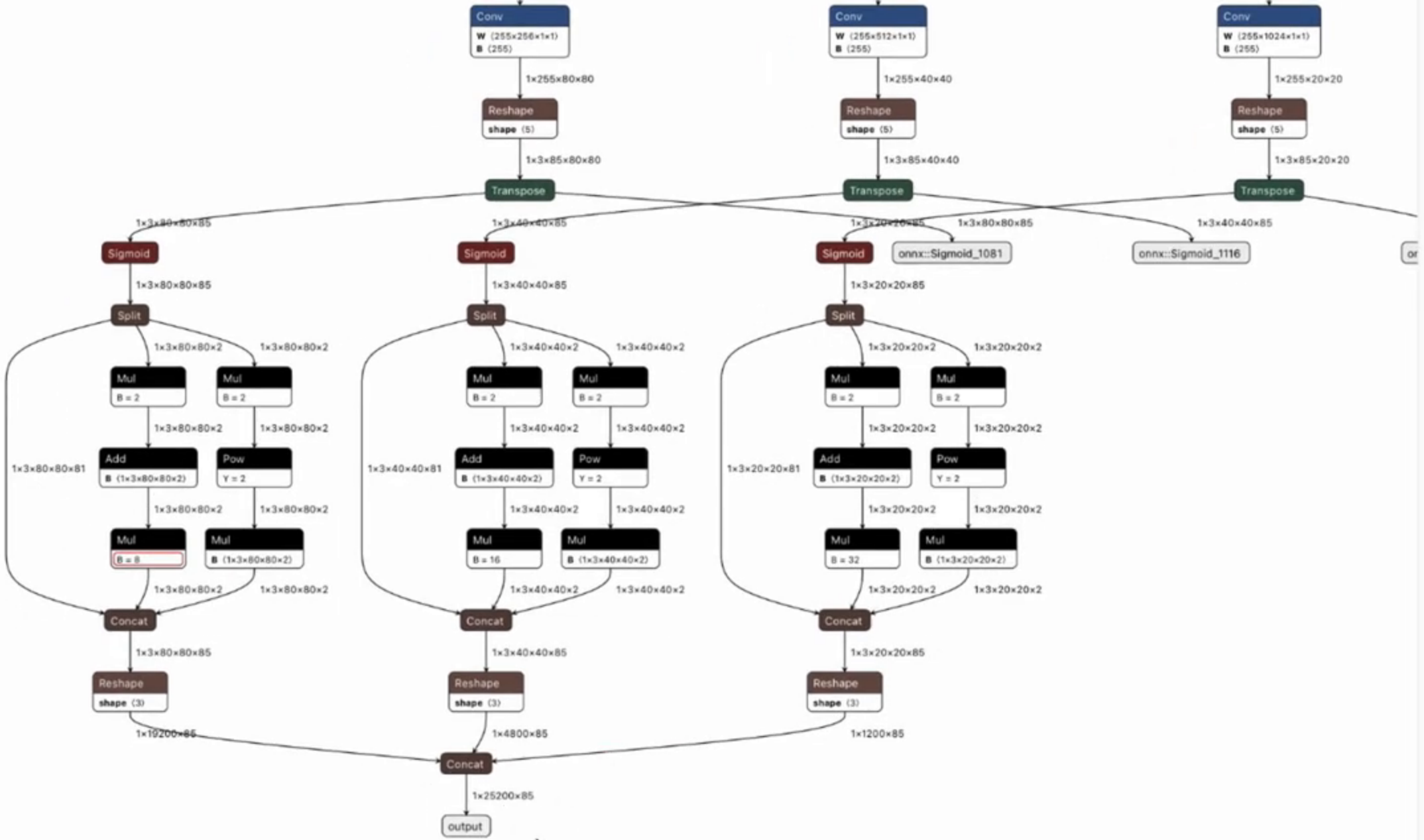


type float3

shape

METRICS

min	8
max	8
mean	8
std	0
sparsity	0.0%

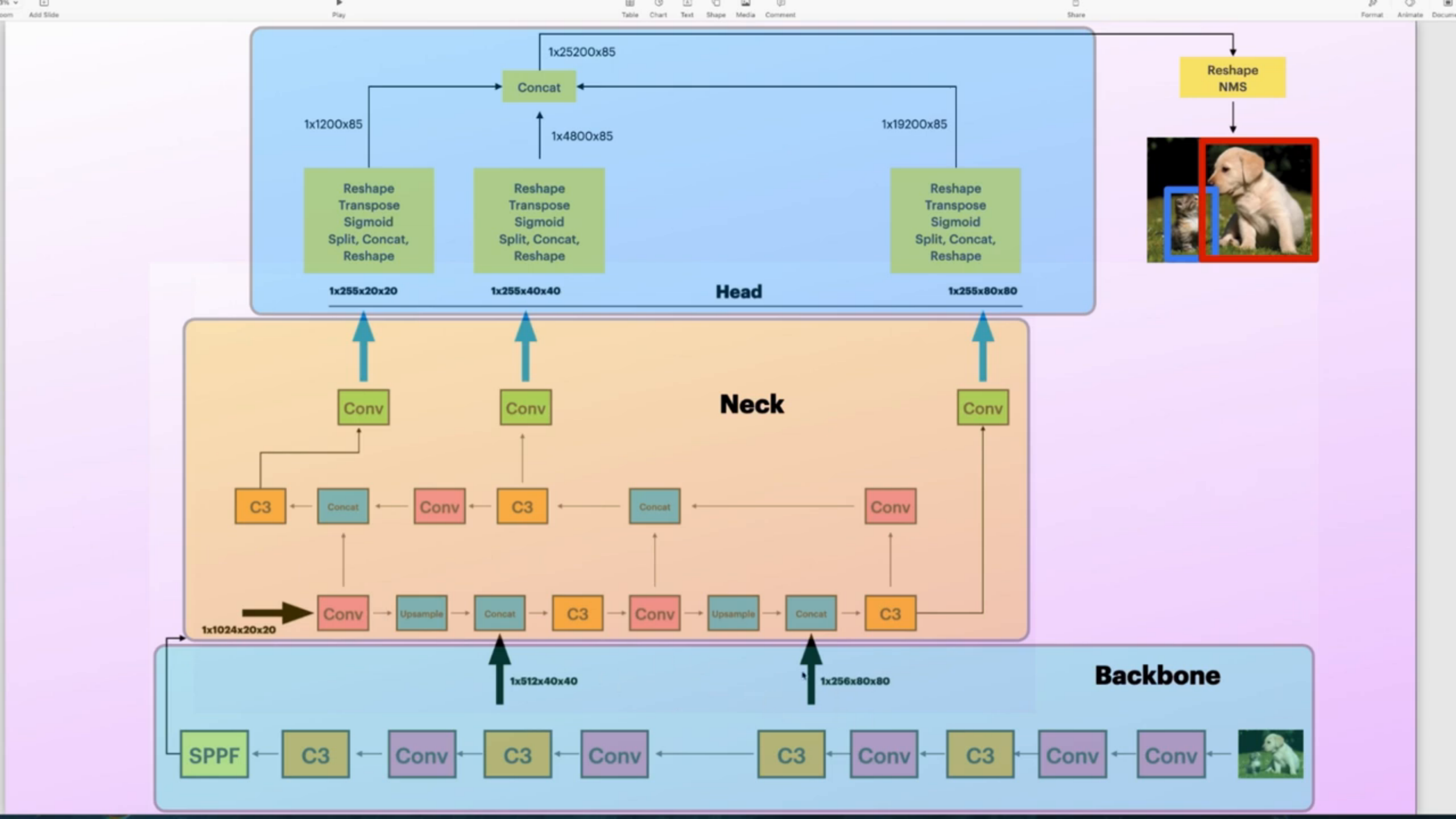


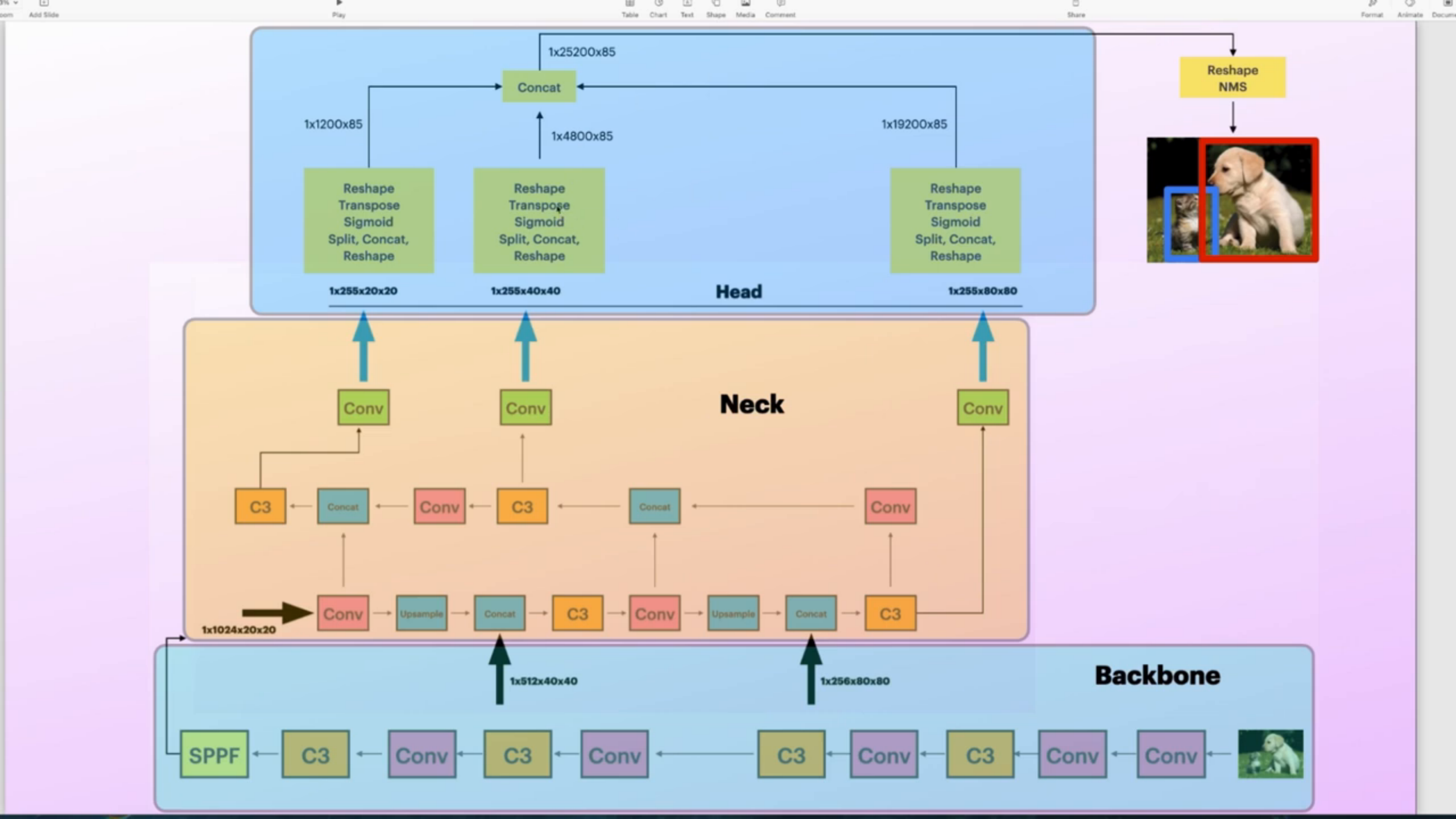
type float3

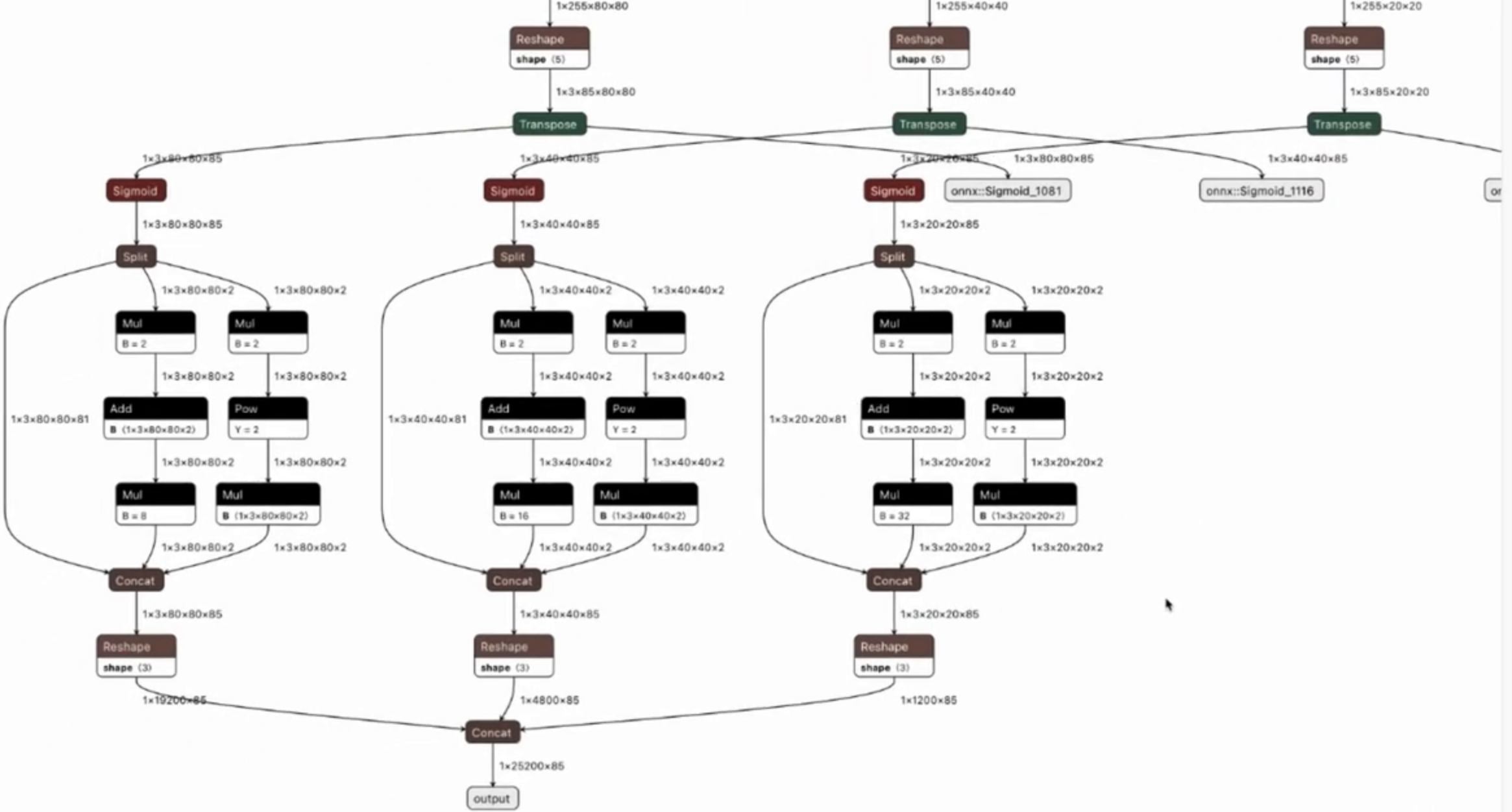
shape

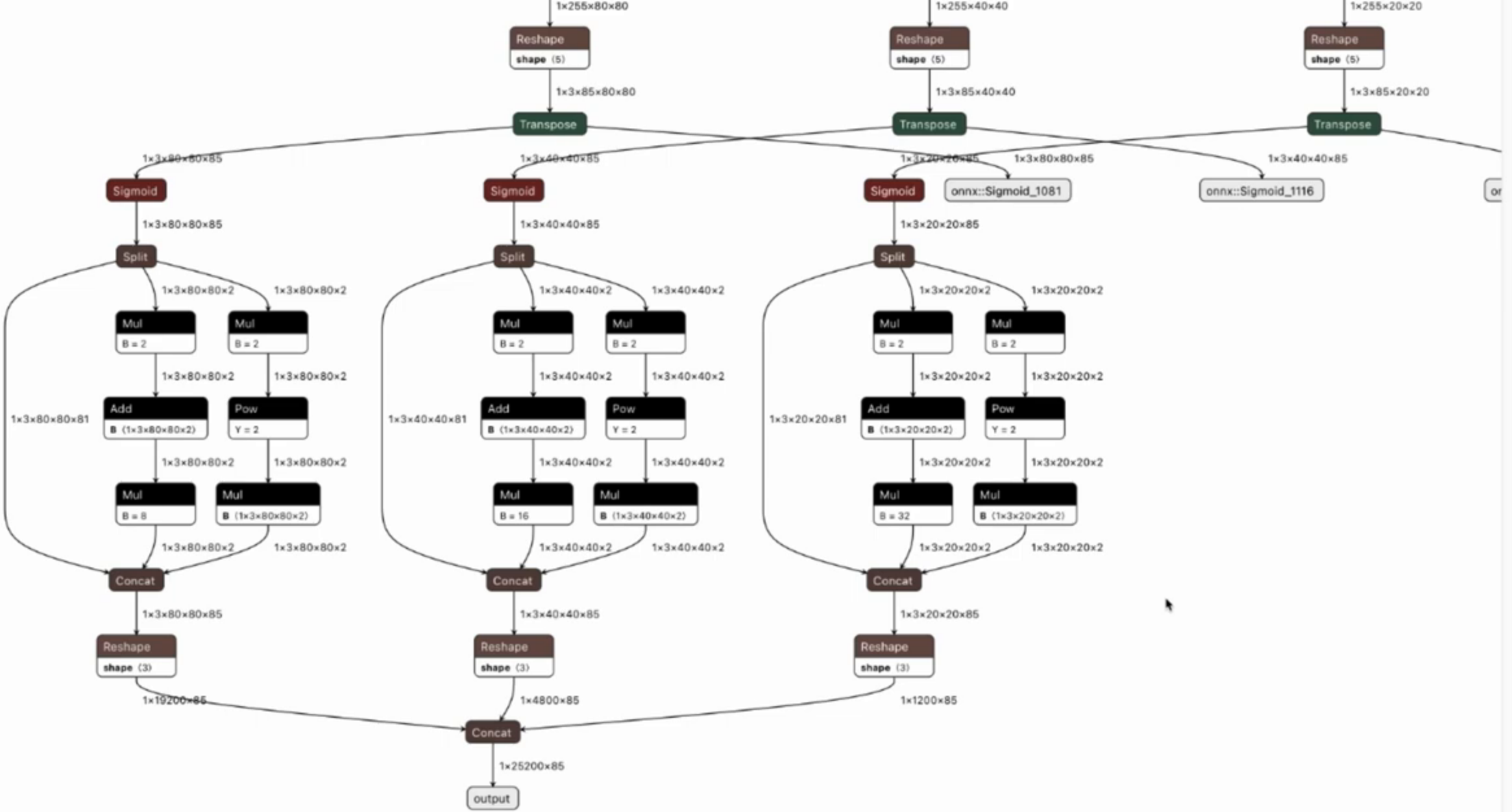
METRICS

min	8
max	8
mean	8
std	0
sparsity	0.0%


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1x25200x85
Concat
1x1200x85
1x4800x85
1x19200x85
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
Reshape
Transpose
Sigmoid
Split, Concat,
Reshape
1x255x20x20
1x255x40x40
Head
1x255x80x80
Reshape
NMS
Conv
Conv
Neck
Conv
C3
Concat
Conv
C3
Concat
Conv
Conv
Upsample
Concat
C3
Conv
Upsample
Concat
C3
1x1024x20x20
1x512x40x40
1x256x80x80
Backbone
SPPF
C3
Conv
C3
Conv
C3
Conv
C3
Conv
Conv


1×255×80×80
Reshape
shape (5)
1×3×85×80×80
Transpose
1×3×80×80×85
Sigmoid
1×3×80×80×85
Split
1×3×80×80×2
1×3×80×80×2
Mul
B = 2
Mul
B = 2
1×3×80×80×2
1×3×80×80×2
1×3×80×80×81
Add
B (1×3×80×80×2)
Pow
Y = 2
1×3×80×80×2
1×3×80×80×2
Mul
B = 8
Mul
B (1×3×80×80×2)
1×3×80×80×2
1×3×80×80×2
Concat
1×3×80×80×85
Reshape
shape (3)
1×19200×85
1×255×40×40
Reshape
shape (5)
1×3×85×40×40
Transpose
1×3×40×40×85
Sigmoid
1×3×40×40×85
Split
1×3×40×40×2
1×3×40×40×2
Mul
B = 2
Mul
B = 2
1×3×40×40×2
1×3×40×40×2
1×3×40×40×81
Add
B (1×3×40×40×2)
Pow
Y = 2
1×3×40×40×2
1×3×40×40×2
Mul
B = 16
Mul
B (1×3×40×40×2)
1×3×40×40×2
1×3×40×40×2
Concat
1×3×40×40×85
Reshape
shape (3)
1×4800×85
1×255×20×20
Reshape
shape (5)
1×3×85×20×20
Transpose
1×3×20×20×85
Sigmoid
1×3×20×20×85
Split
1×3×20×20×2
1×3×20×20×2
Mul
B = 2
Mul
B = 2
1×3×20×20×2
1×3×20×20×2
1×3×20×20×81
Add
B (1×3×20×20×2)
Pow
Y = 2
1×3×20×20×2
1×3×20×20×2
Mul
B = 32
Mul
B (1×3×20×20×2)
1×3×20×20×2
1×3×20×20×2
Concat
1×3×20×20×85
Reshape
shape (3)
1×1200×85
1×3×80×80×85
onnx::Sigmoid_1081
1×3×40×40×85
onnx::Sigmoid_1116
Concat
1×25200×85
output


1×255×80×80
Reshape
shape (5)
1×3×85×80×80
Transpose
1×3×80×80×85
Sigmoid
1×3×80×80×85
Split
1×3×80×80×2
1×3×80×80×2
Mul
B = 2
Mul
B = 2
1×3×80×80×2
1×3×80×80×2
1×3×80×80×81
Add
B (1×3×80×80×2)
Pow
Y = 2
1×3×80×80×2
1×3×80×80×2
Mul
B = 8
Mul
B (1×3×80×80×2)
1×3×80×80×2
1×3×80×80×2
Concat
1×3×80×80×85
Reshape
shape (3)
1×19200×85
1×255×40×40
Reshape
shape (5)
1×3×85×40×40
Transpose
1×3×40×40×85
Sigmoid
1×3×40×40×85
Split
1×3×40×40×2
1×3×40×40×2
Mul
B = 2
Mul
B = 2
1×3×40×40×2
1×3×40×40×2
1×3×40×40×81
Add
B (1×3×40×40×2)
Pow
Y = 2
1×3×40×40×2
1×3×40×40×2
Mul
B = 16
Mul
B (1×3×40×40×2)
1×3×40×40×2
1×3×40×40×2
Concat
1×3×40×40×85
Reshape
shape (3)
1×4800×85
1×255×20×20
Reshape
shape (5)
1×3×85×20×20
Transpose
1×3×20×20×85
Sigmoid
1×3×20×20×85
Split
1×3×20×20×2
1×3×20×20×2
Mul
B = 2
Mul
B = 2
1×3×20×20×2
1×3×20×20×2
1×3×20×20×81
Add
B (1×3×20×20×2)
Pow
Y = 2
1×3×20×20×2
1×3×20×20×2
Mul
B = 32
Mul
B (1×3×20×20×2)
1×3×20×20×2
1×3×20×20×2
Concat
1×3×20×20×85
Reshape
shape (3)
1×1200×85
1×3×80×80×85
onnx::Sigmoid_1081
1×3×40×40×85
onnx::Sigmoid_1116
Concat
1×25200×85
output