Training YOLO v3 for Objects Detection with Custom Data

Lecture organization

Content

- What is YOLO?
- Architecture of YOLO v3
- Input
- Detections at 3 Scales
- Detection Kernels
- Grid Cells
- Anchor Boxes
- Predicted Bounding Boxes
- Objectness Score
- Conclusion

Simple definition

YOLO:

"You Only Look Once"

uses

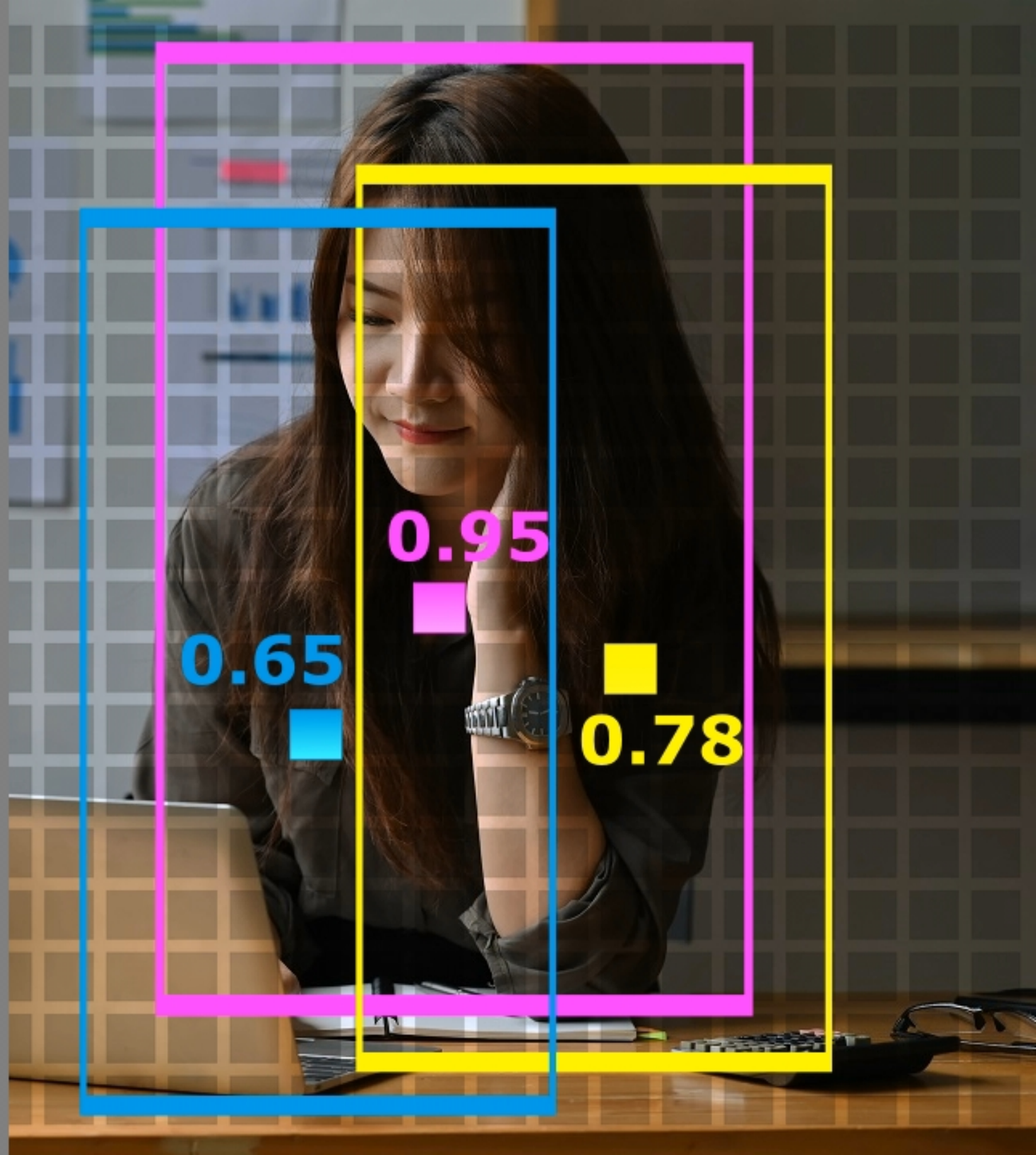
Convolutional Neural Networks

YOLO v3 can:

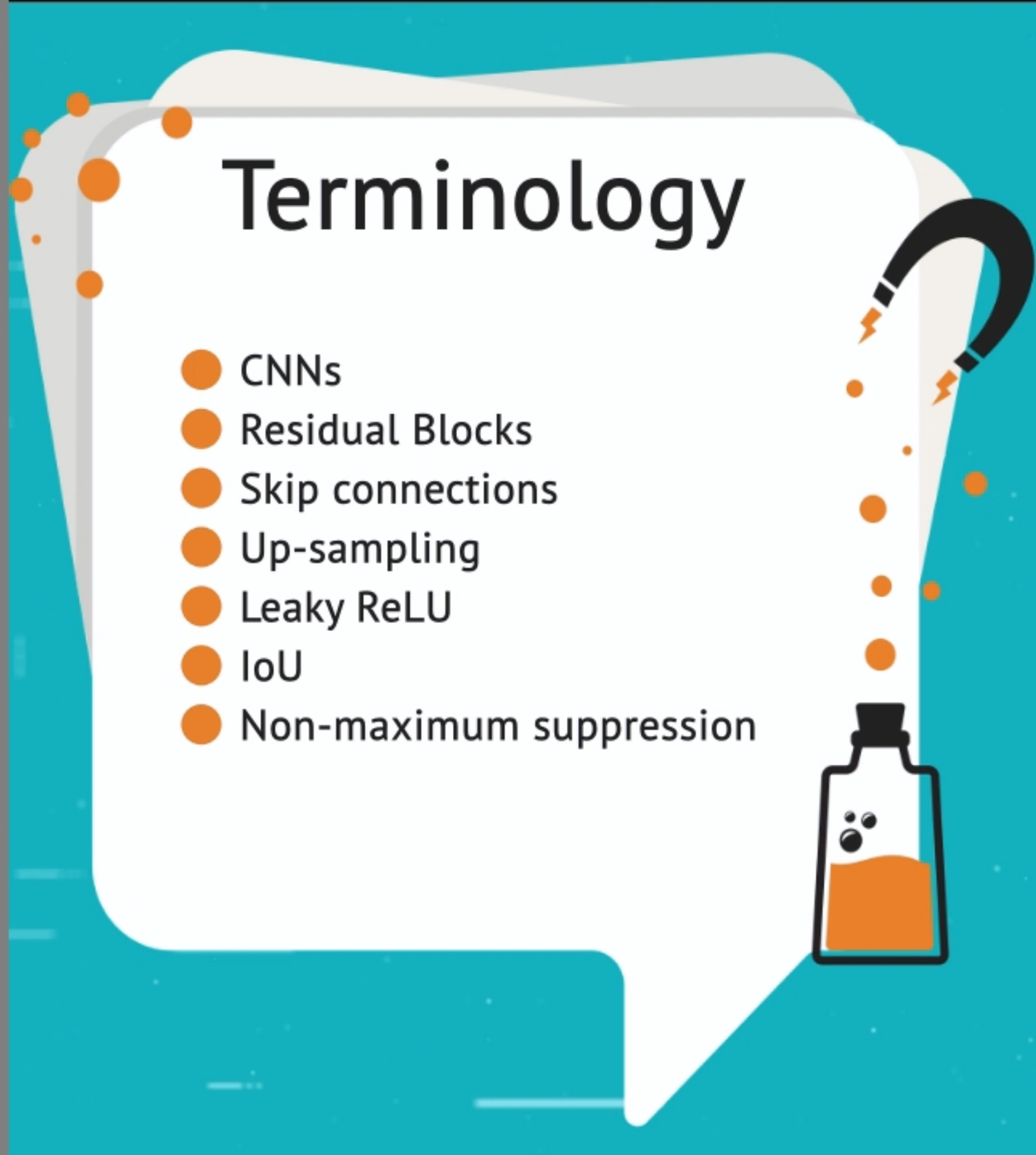
- ✓ detect multiple objects
- ✓ predict classes
- ✓ identify locations

YOLO v3:

- ✓ applies single NN
- ✓ divides image into grid cells
- ✓ produces cells' probabilities
- ✓ predicts Boxes



Prerequisites



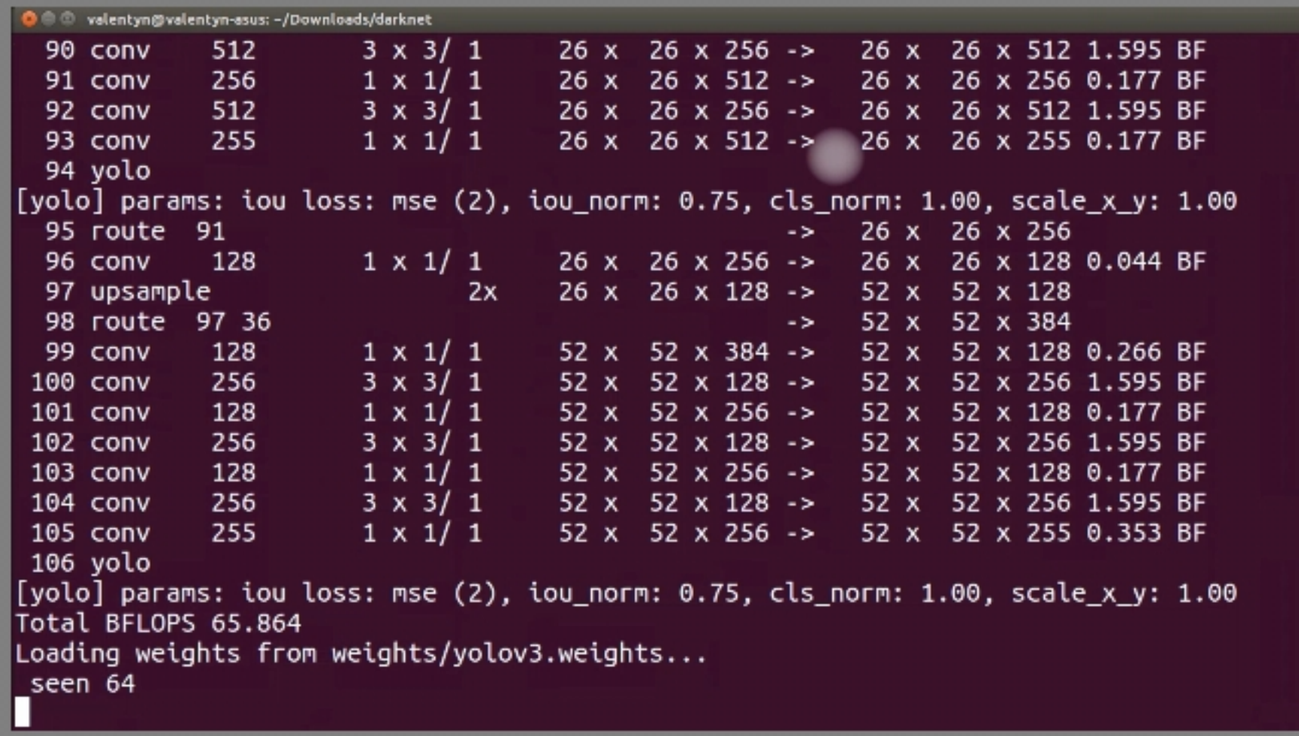
Layers' Structure

YOLO v3

- 53 CNNs layers (Darknet-53)
  stacked with
- 53 more layers
  producing
- 106 layers for YOLO v3

Darknet framework:

- ✓ loads 106 layers
- ✓ detections at layers: 82, 94 and 106



Improvements

Essential elements:

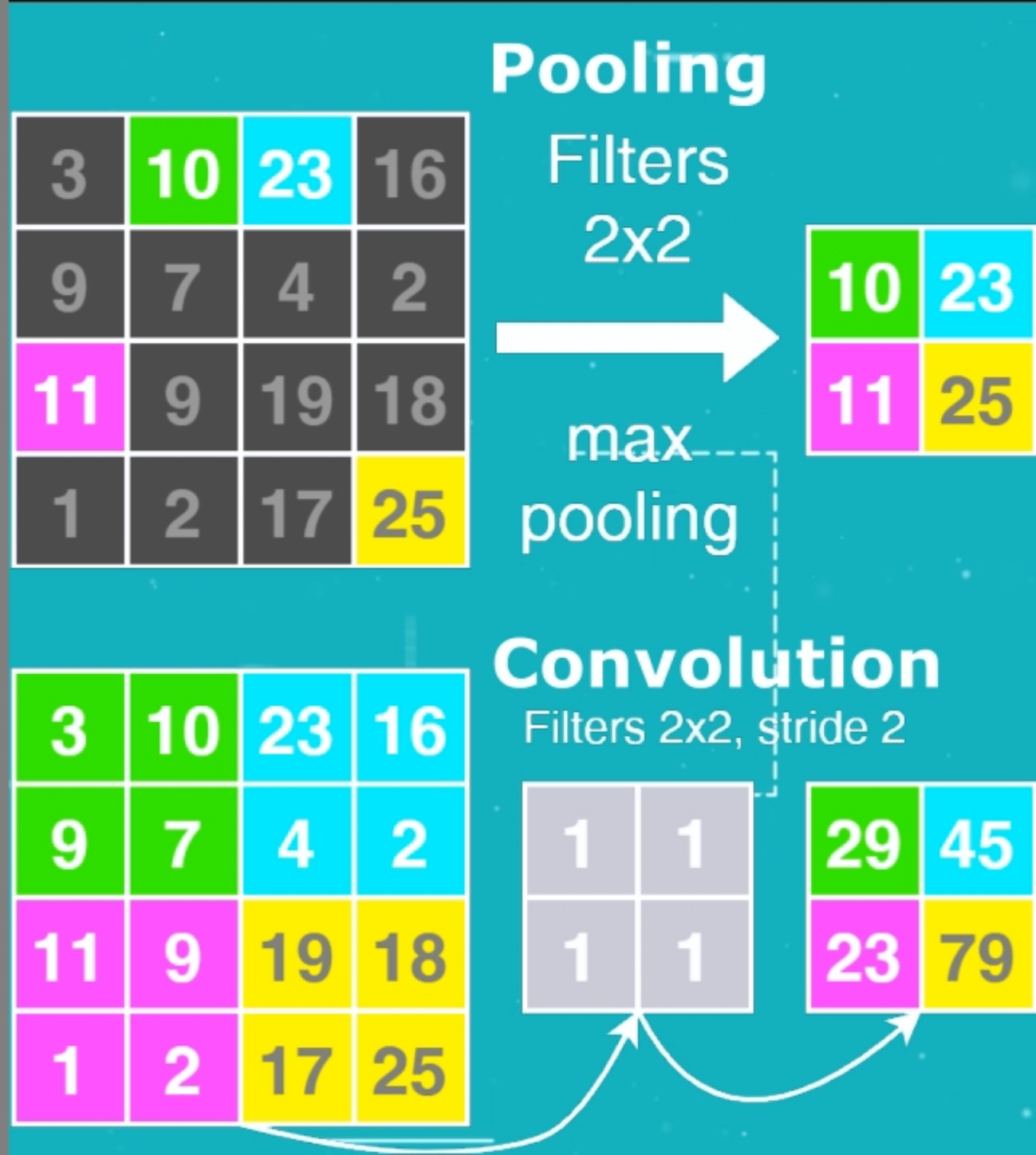
* Residual Blocks
* Skip Connections
* Up-Sampling

CNN Layers followed by

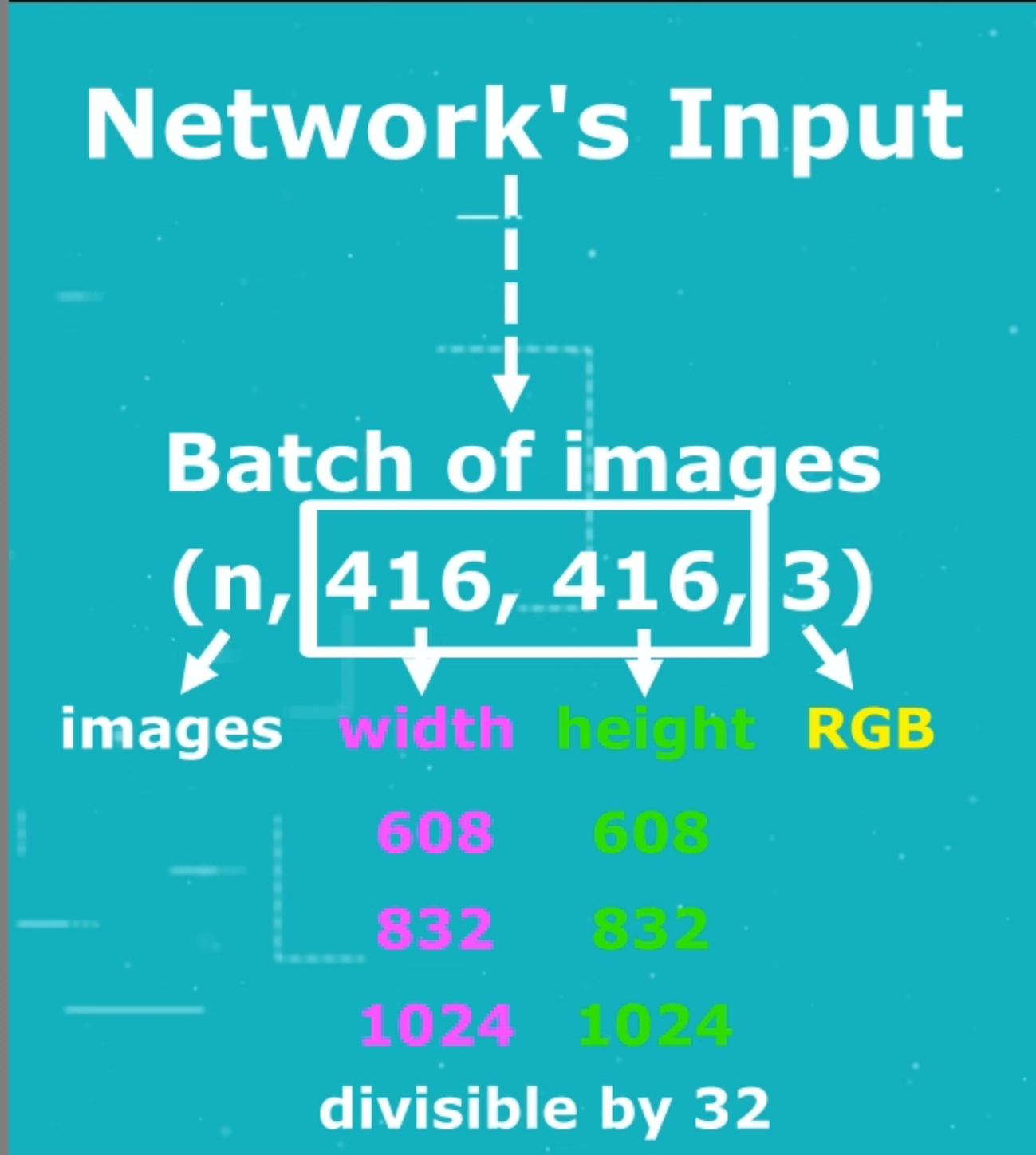
* Batch Normalization
* Leaky ReLU

YOLO v3:

- ✓ No Pooling layers
- ✓ Convolutional layers instead
- ✓ Prevents loss of low-level features
- ✓ Ability to detect small objects



Input's shape



Input images:

- ✓ Can be of any size
- ✓ Will be resized to network size

Aspect ratio:

- ✓ Can be kept or not
- ✓ Compare and choose best approach

608 x 608

not keeping aspect ratio

Layers of detection

Detections at:

82, 94, 106 layers

Downsamples input:

8

16

32

Network strides:

32, 16, 8

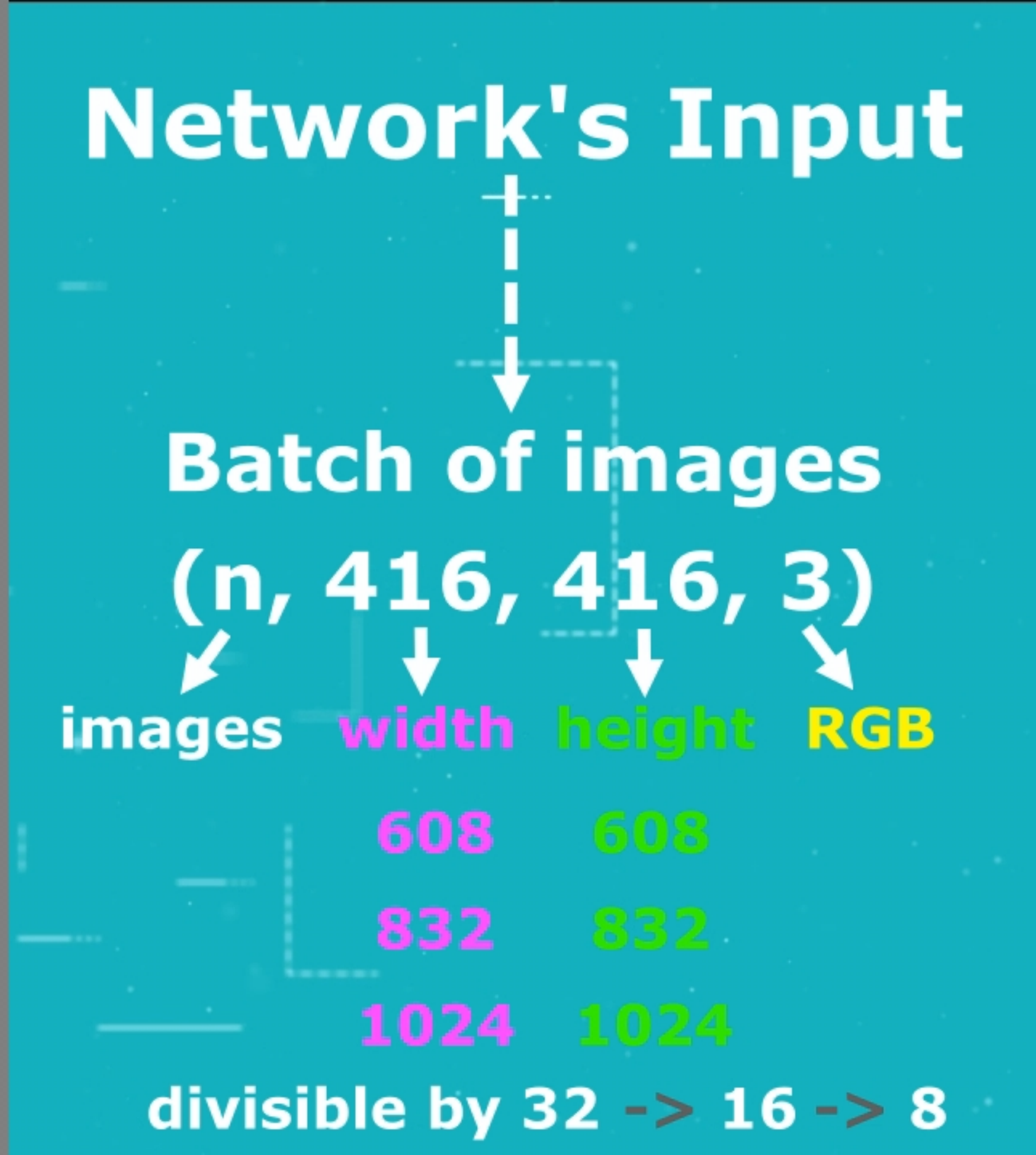
at layers
82, 94, 106

Size of outputs:

13x13, 26x26, 52x52
large medium small

Network's input
416 x 416

Possible inputs



Filters to be trained

Detections at:

82, 94, 106 layers

By 1x1 kernels

applied to

↓

Downsampled images:

52x52

26x26

13x13

Equation:

- (b * (5 + c)),

where:

- b = 3, number of BB
- (5 + c), BB attributes
- c = 80, COCO classes

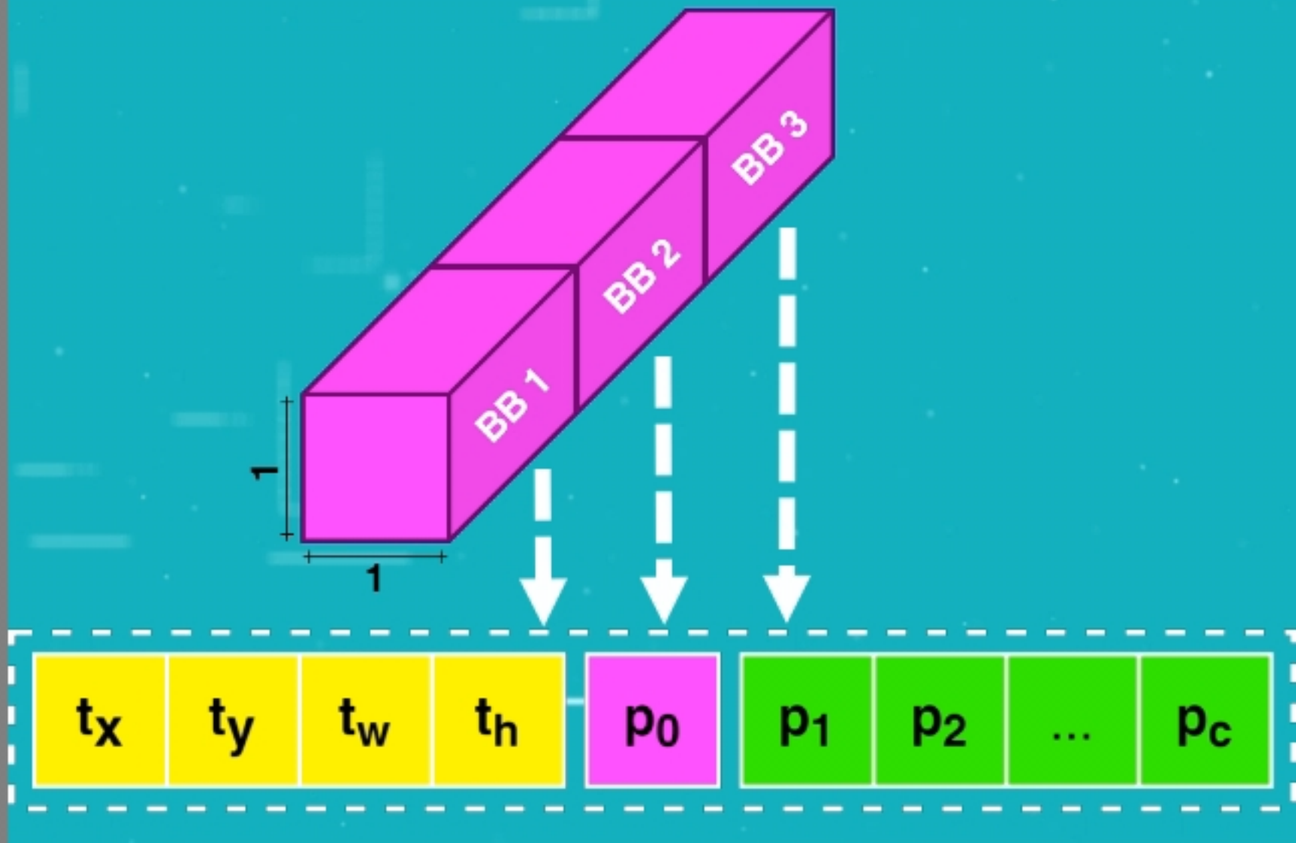
Result:

- (3 * (5 + 80)) = 255

Feature maps:

(13x13), (26x26), (52x52)

1x1 kernels' shape:



Maps' Shapes

Detections at:

82, 94, 106 layers

1x1 kernels

produce

Feature maps:

(13, 13, 255)

(26, 26, 255)

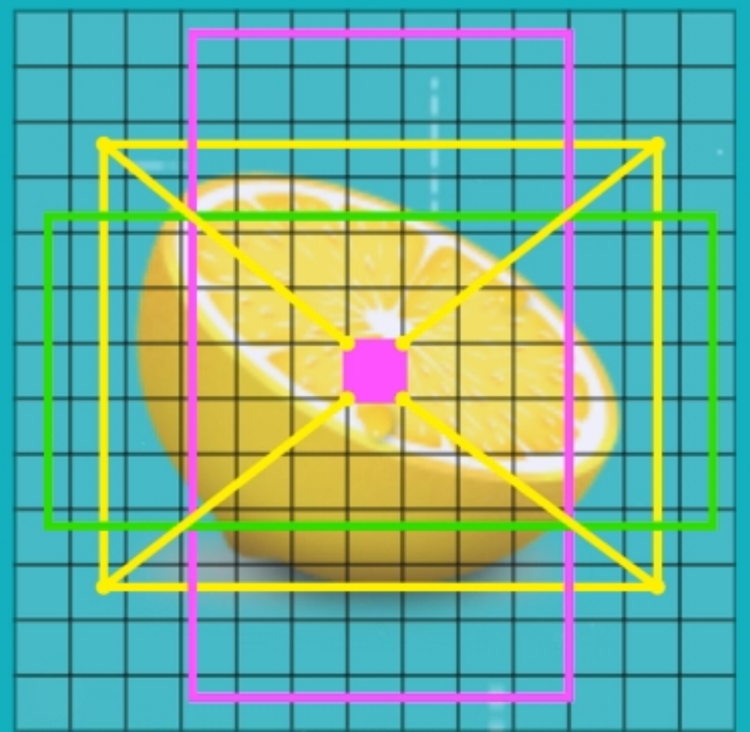
(52, 52, 255)

Detection cells

Feature maps:

(13, 13, 255), (26, 26, 255), (52, 52, 255)

3 BB for each cell



Training YOLO v3:

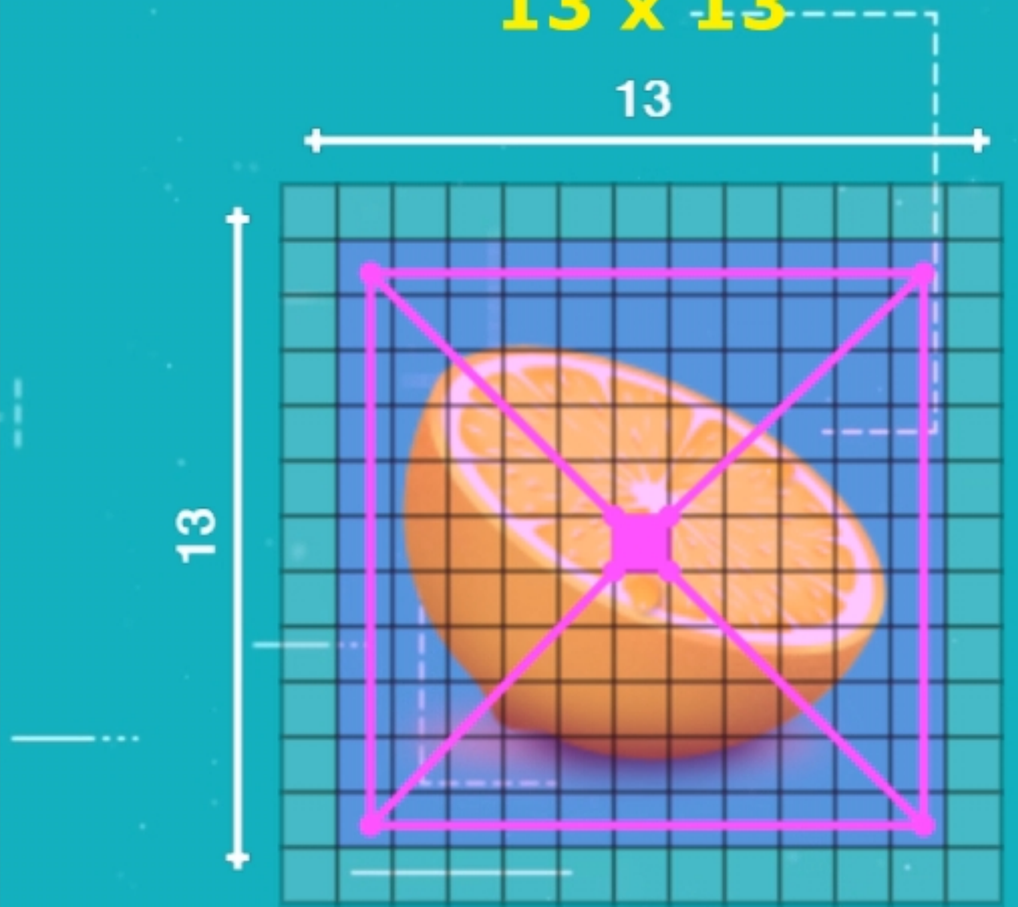
- ✓ One ground truth BB for one object
- ✓ Centre cell is assigned to predict this object
- ✓ Cell's objectness = 1

Input image:

416 x 416

Scale 1, stride 32:

13 x 13



Predictions by Anchor Boxes

Detections at layers:

82, 94, 106

3 anchors	3 anchors	3 anchors

9

Anchors (priors)

used to calculate

Predicted BB

real width and height

Calculations of Anchors

k-means clustering

applied to calculate

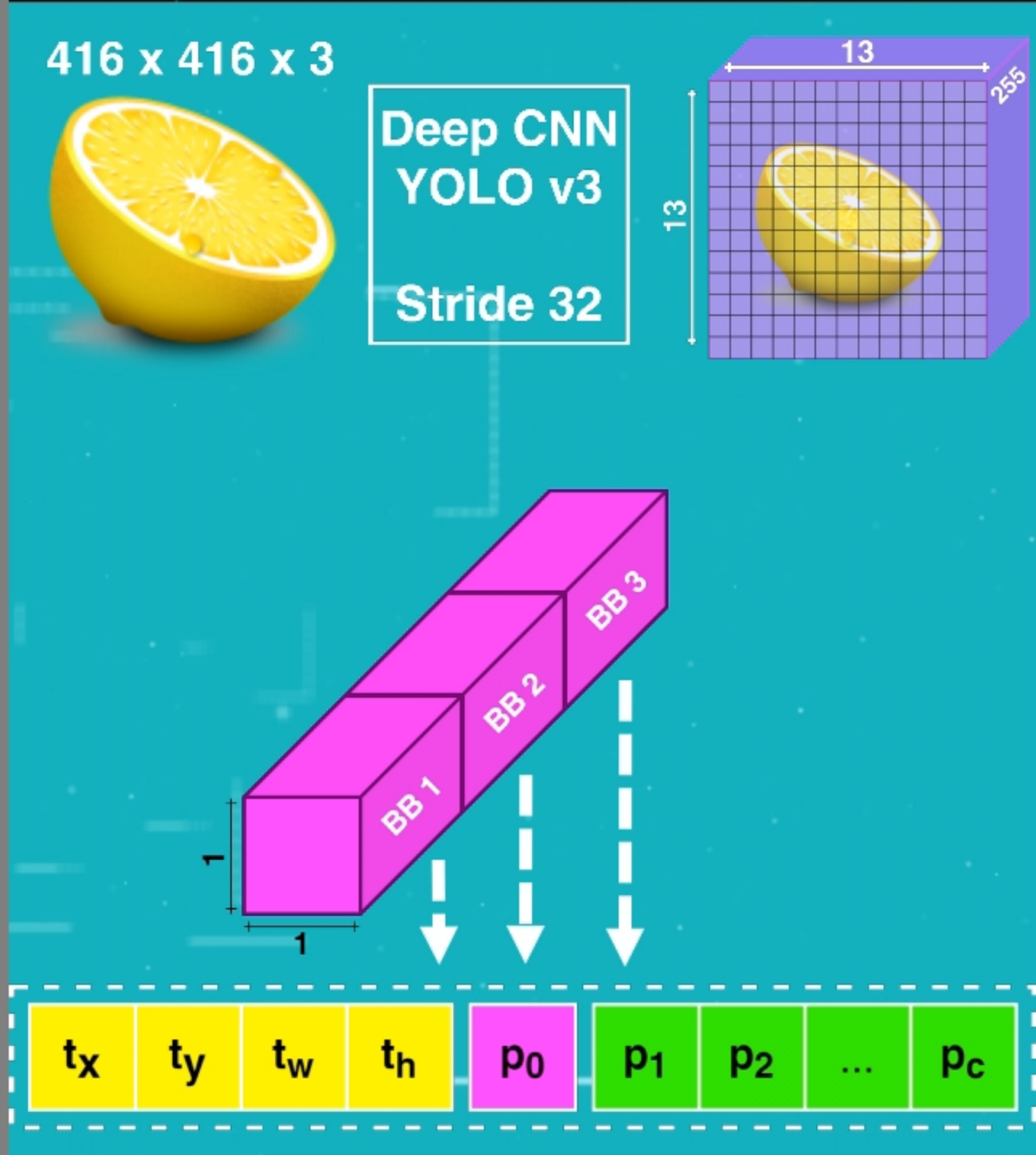
Anchors (priors)

for COCO dataset

Scale-1	Scale-2	Scale-3
(116×90)	(30×61)	(10×13)
(156×198)	(62×45)	(16×30)
(373×326)	(59×119)	(33×23)

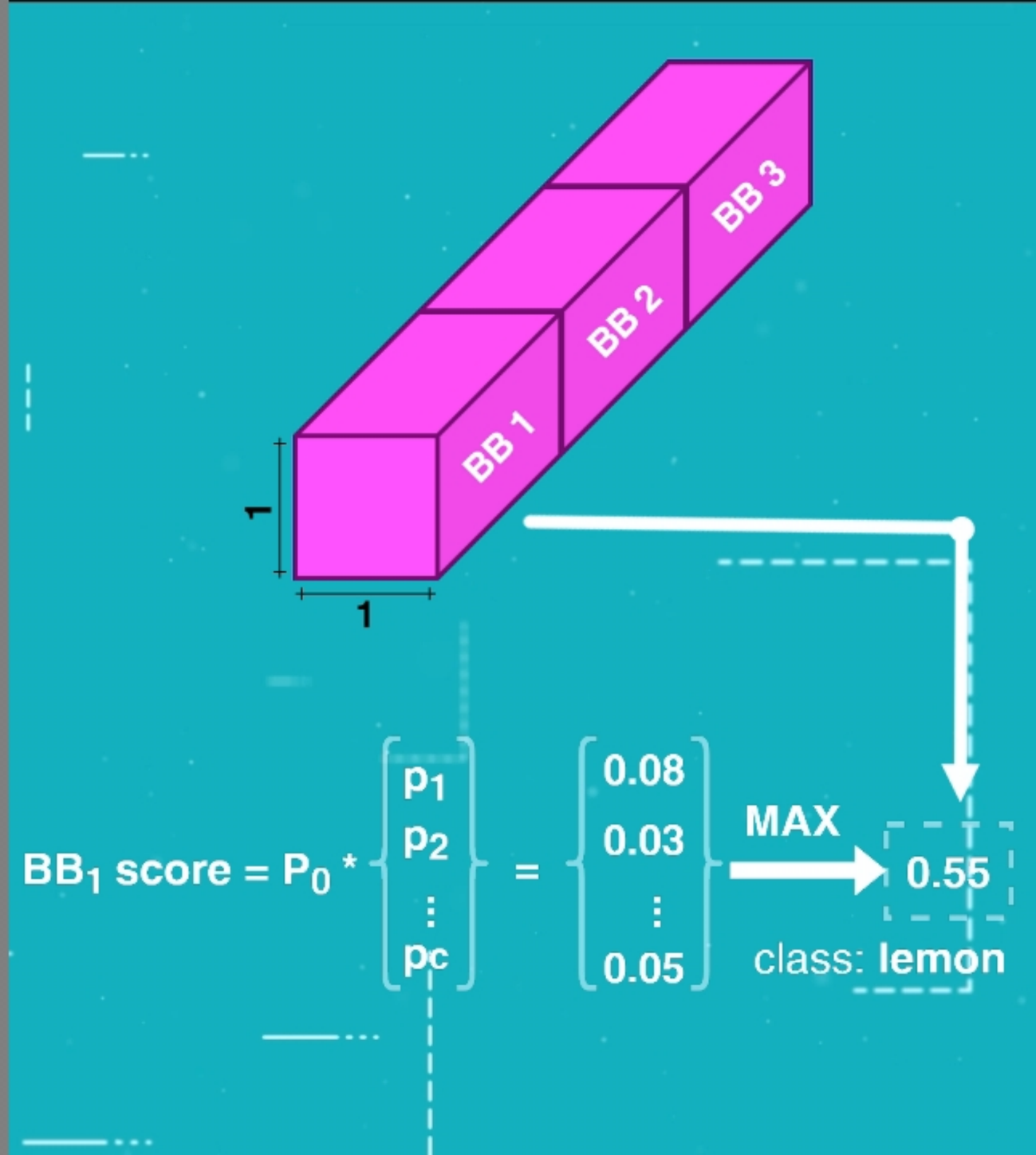
BB attributes obtained by:

- ✓ **Input** (416, 416, 3)
- ✓ **Deep CNN of YOLO v3**
- ✓ **Downsampled input image by stride 32**
- ✓ **(13, 13, 255) feature map at Scale-1**

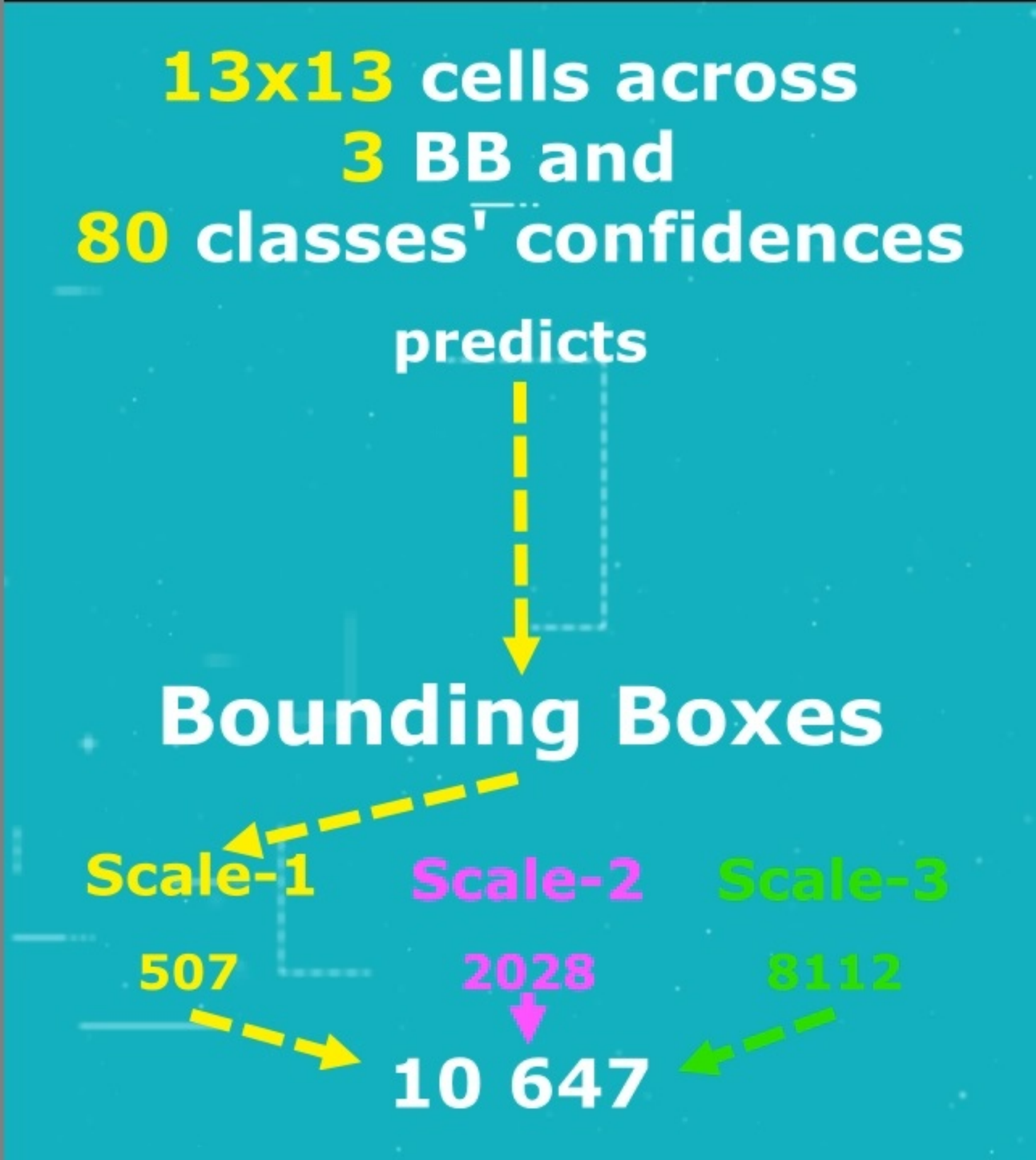


BB probabilities:

- ✓ Extract probabilities of BB
- ✓ Compute elementwise product
- ✓ Find maximum probability



Number of Bounding Boxes



Dimensions of Anchors

Anchors are

Bounding Boxes' priors calculated by K-means clustering

COCO dataset:

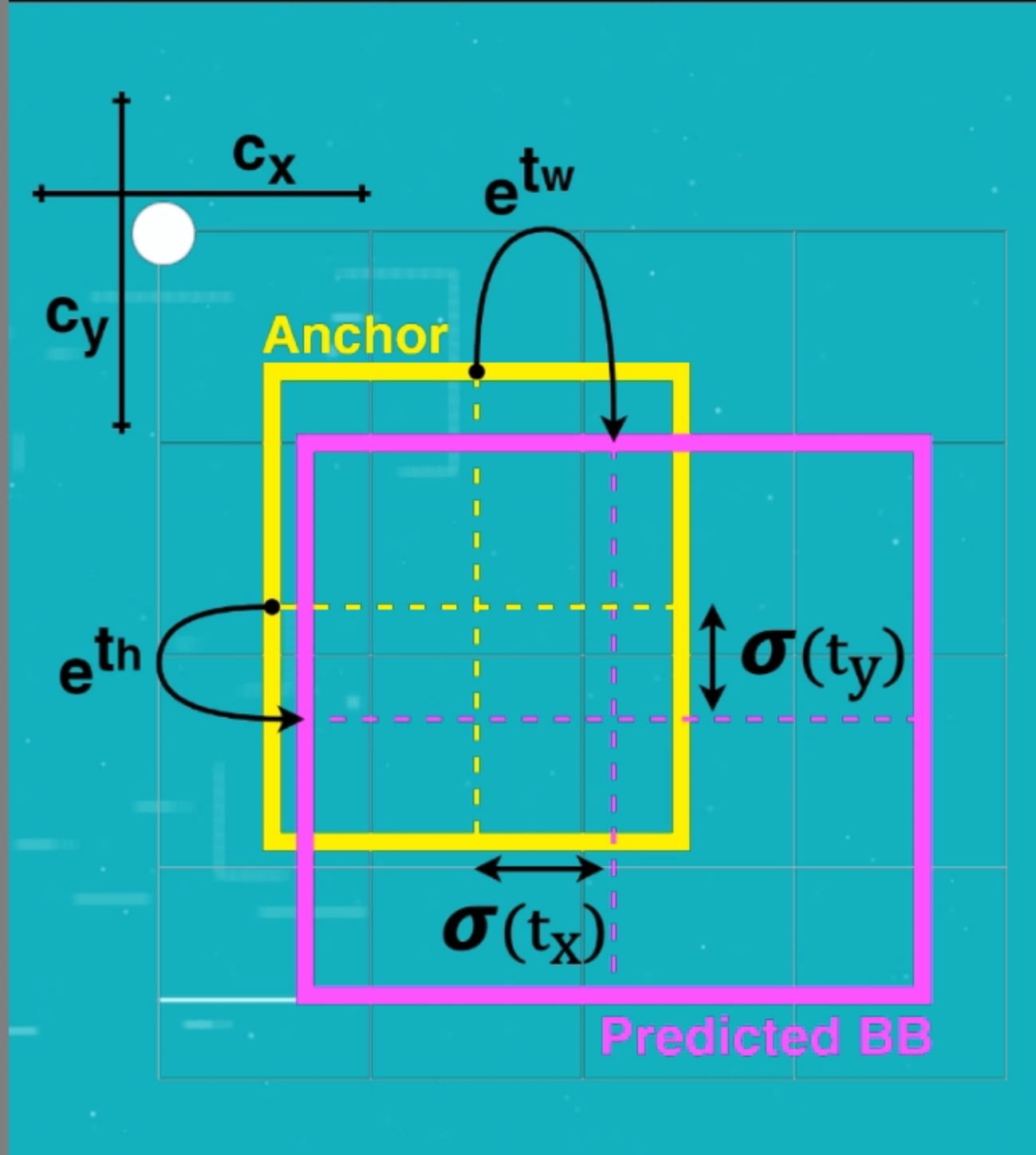
Scale-1	Scale-2	Scale-3
(116×90)	(30×61)	(10×13)
(156×198)	(62×45)	(16×30)
(373×326)	(59×119)	(33×23)

To predict BB:

- Calculate offset to anchor

also called as:

- Log-space transform
- Pass centre through sigmoid function

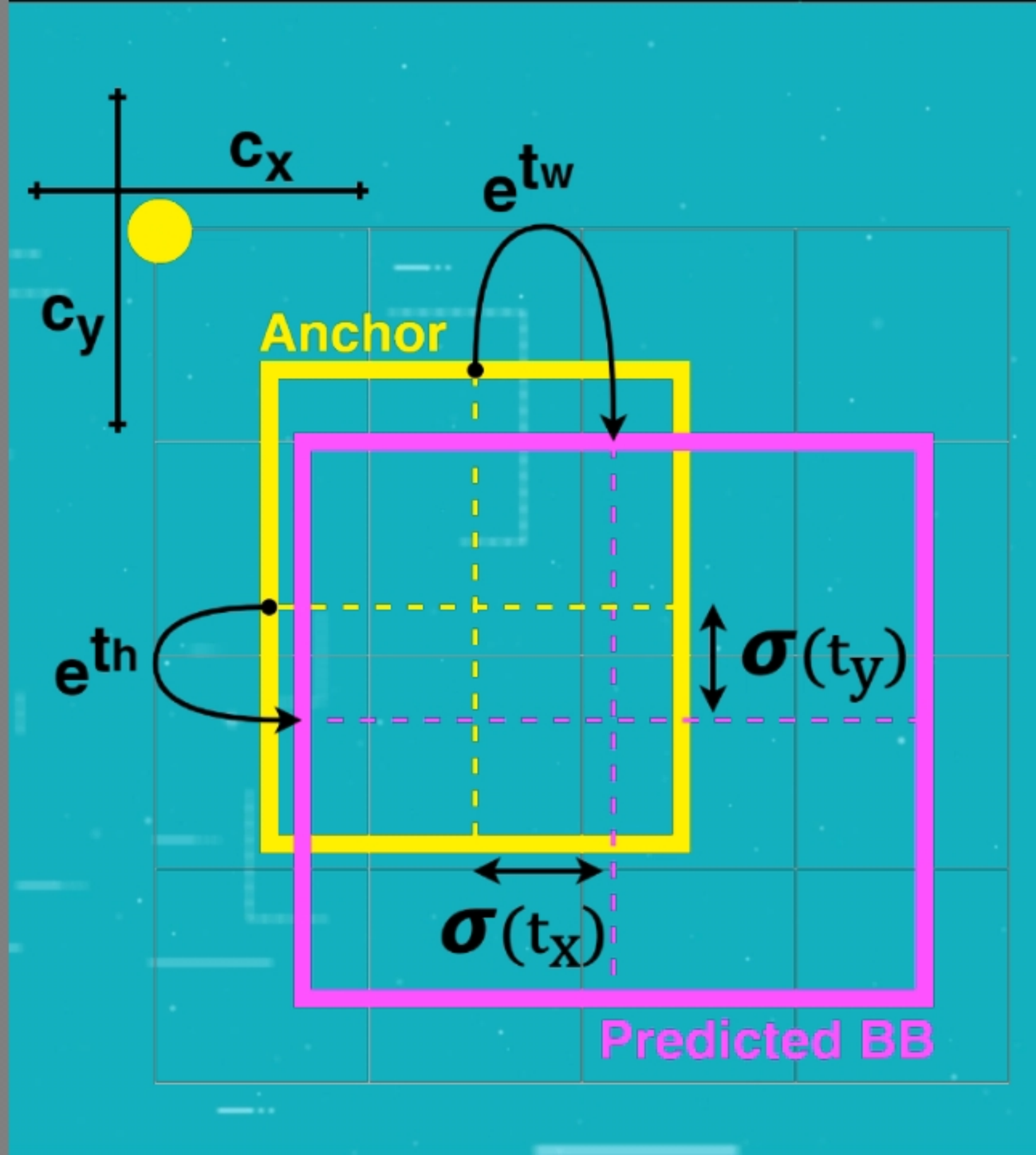


Equations:

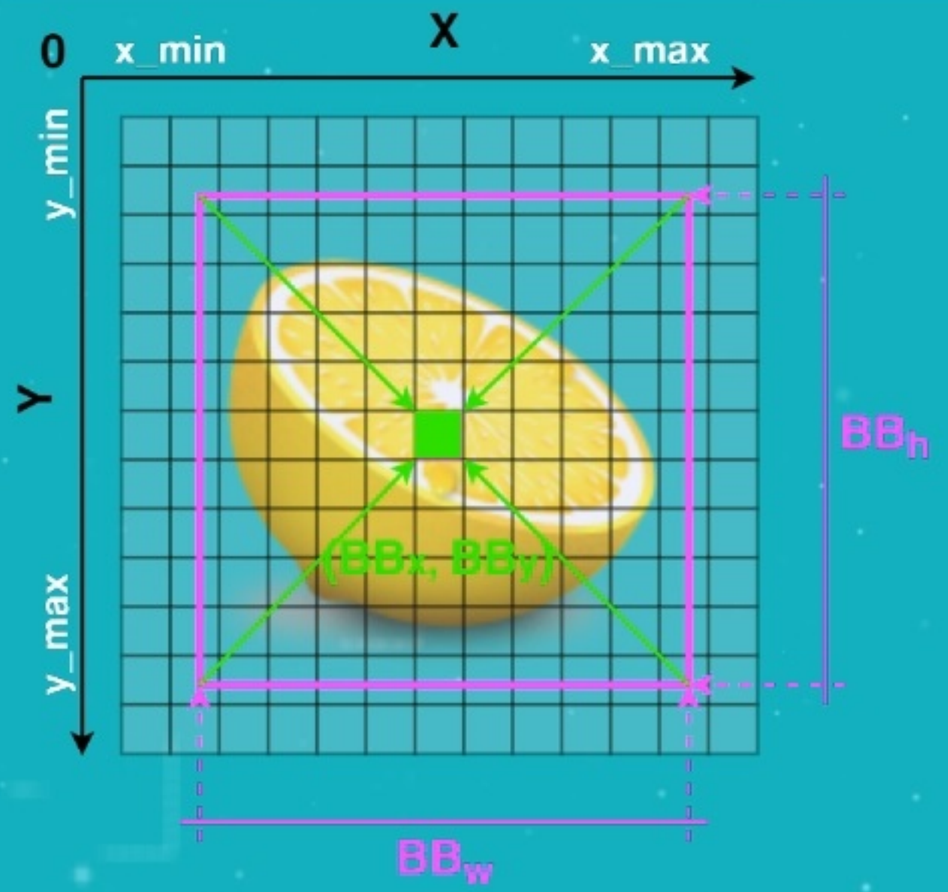
$$
\begin{cases}
b_x = \sigma(t_x) + c_x \\
b_y = \sigma(t_y) + c_y \\
b_w = p_w * e^{t_w} \\
b_h = p_h * e^{t_h}
\end{cases}
$$

where:

- ✓ b_x, b_y, b_w, b_h - centre, width, height of predicted BB
- ✓ t_x, t_y, t_w, t_h - outputs of NN
- ✓ c_x, c_y - cell's top left corner of the anchor box
- ✓ p_w, p_h - anchor's width, height



Coordinates of Bounding Boxes



$BB_x = b_x$ * width of image

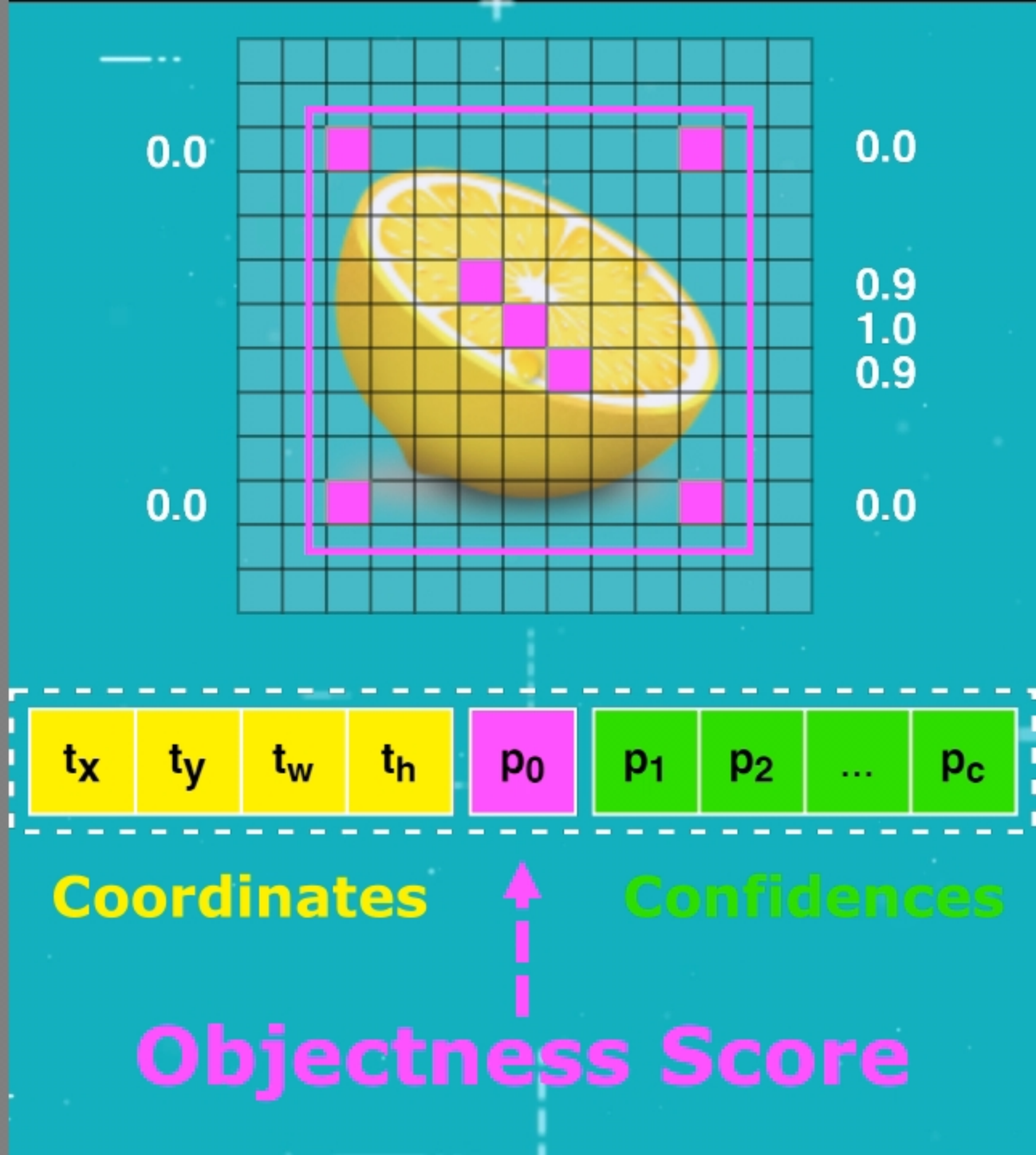
$BB_y = b_y$ * height of image

$BB_w = b_w$ * width of image

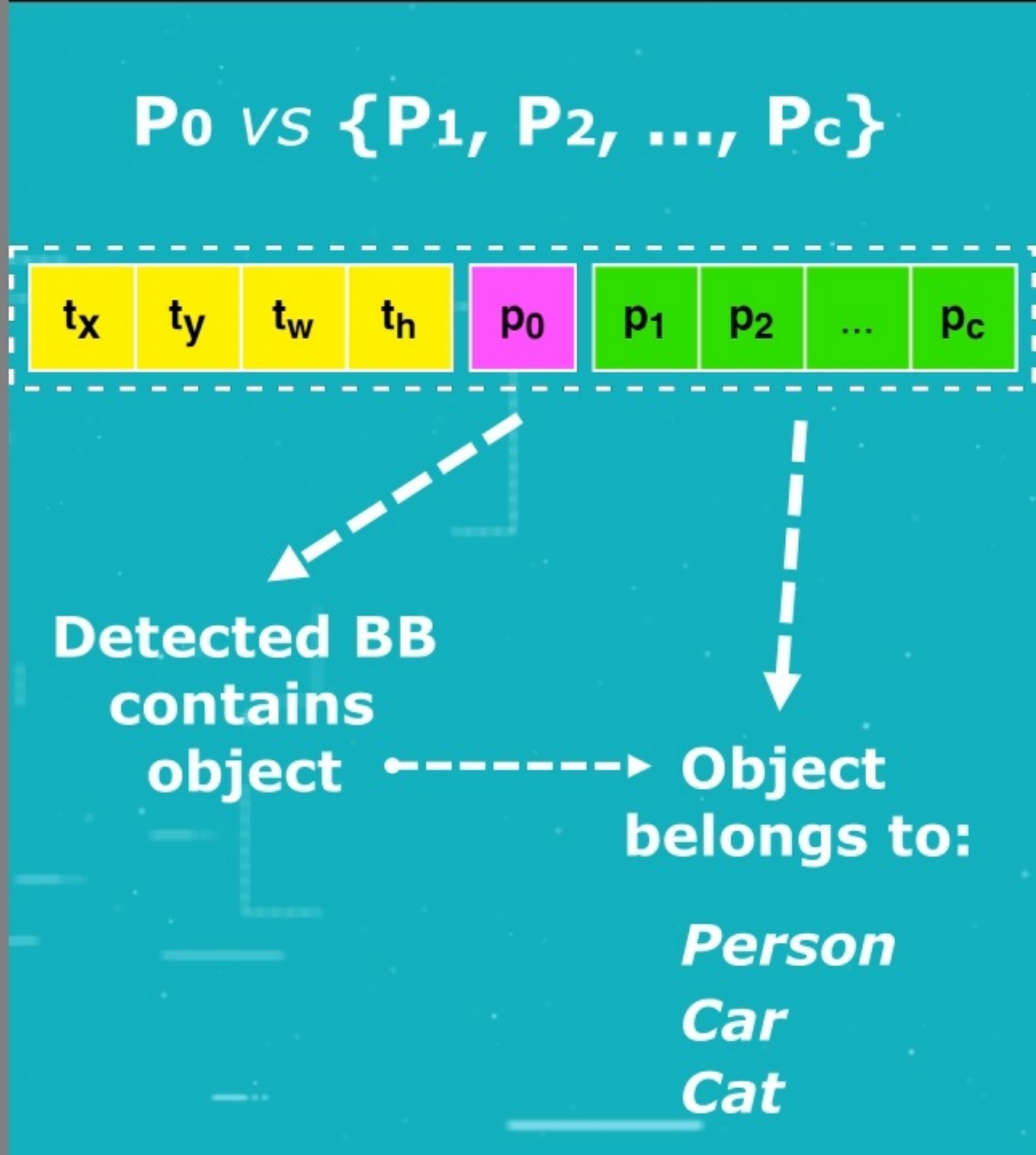
$BB_h = b_h$ * height of image

BB's attribute:

- p0 is Objectness Score
- Centre cell of ground truth BB has p0 = 1
- Corner cells of ground truth BB has p0 = 0
- p0 is a probability that BB contains object



Objectness Score



Calculating Objectness Score

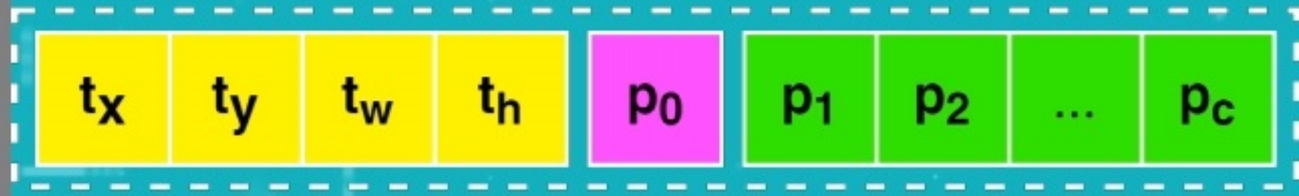
Equation for objectness score:

$$P_{object} * IoU = \sigma(t_0) = P_0$$

where

P_{object} - predicted probability

IoU - between predicted BB2 and ground truth BB1



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