Anchor Free Single Stage 2D Object Detector

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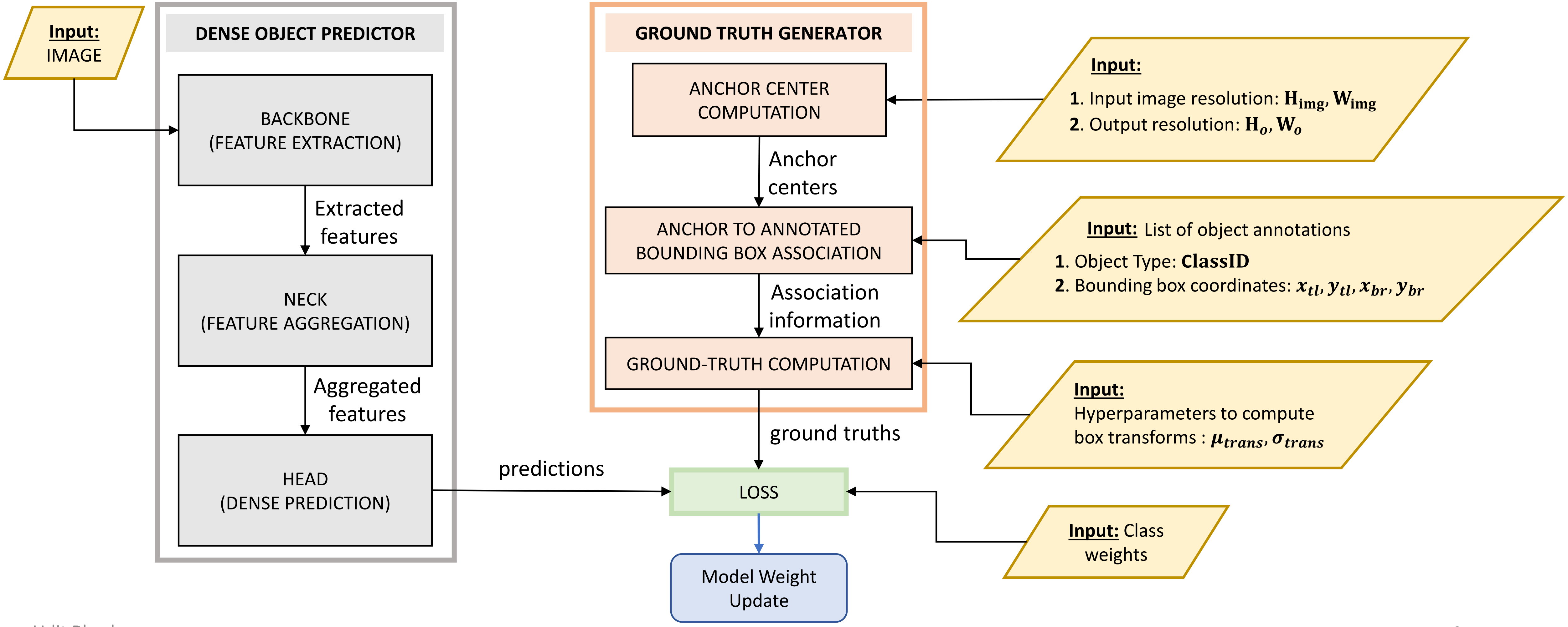
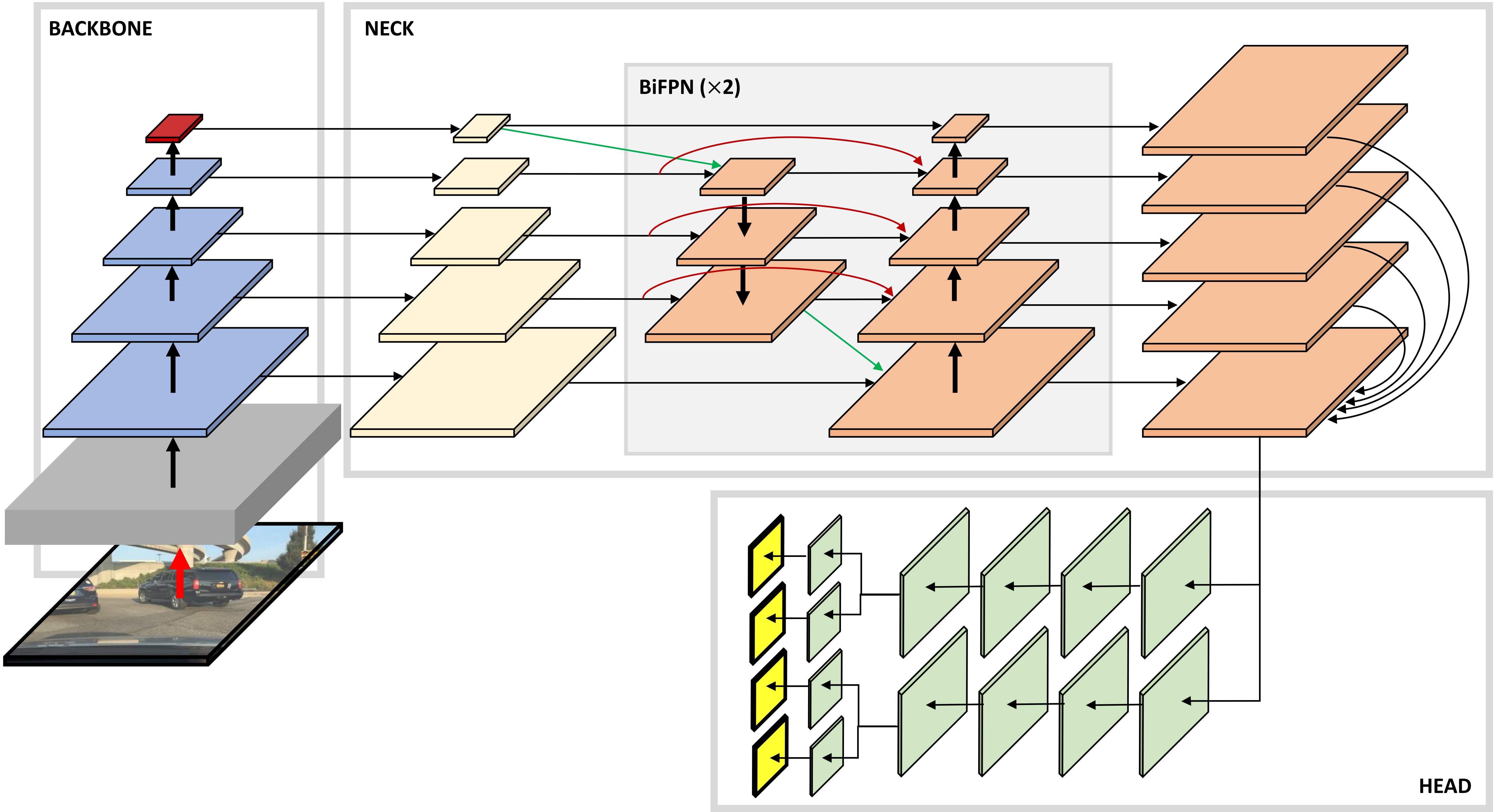
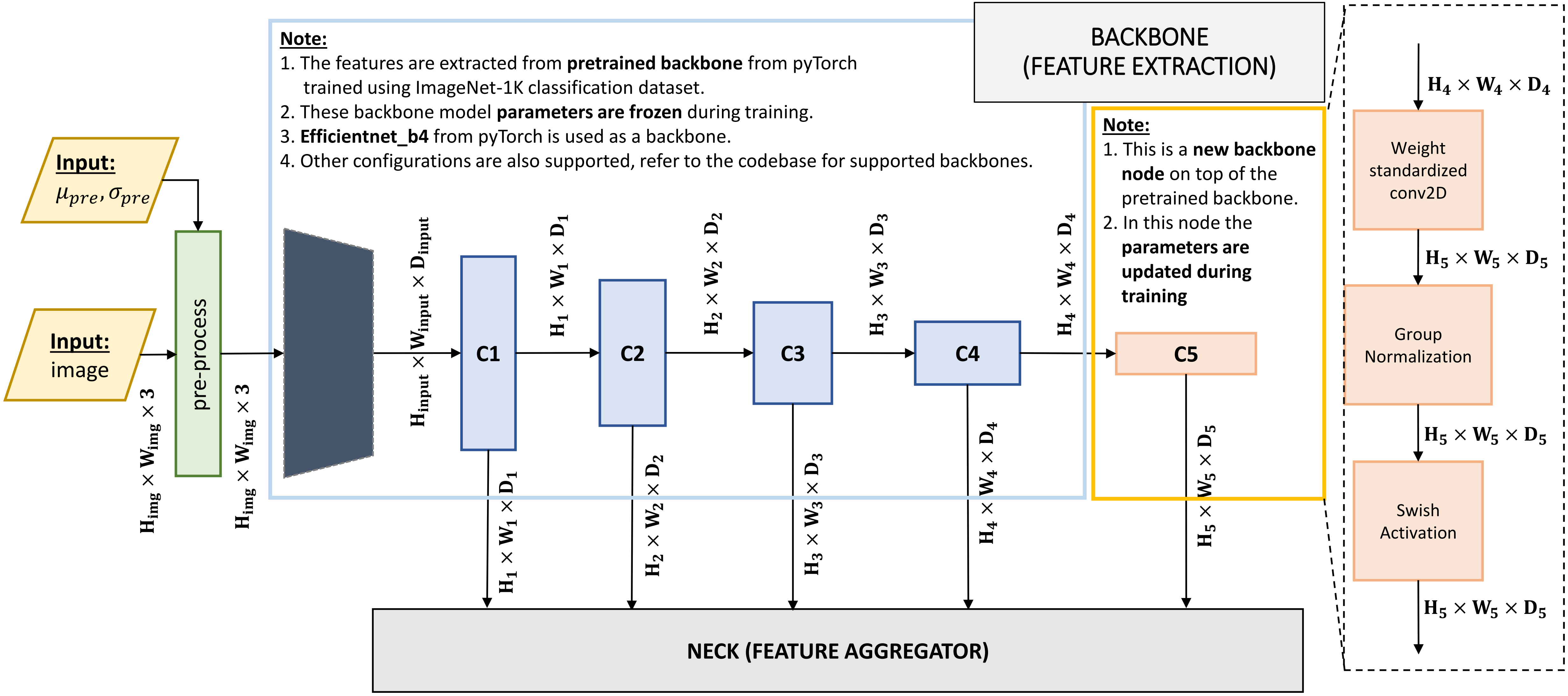
CONCEPT LEVEL ARCHITECTURE (DENSE PREDICTOR)

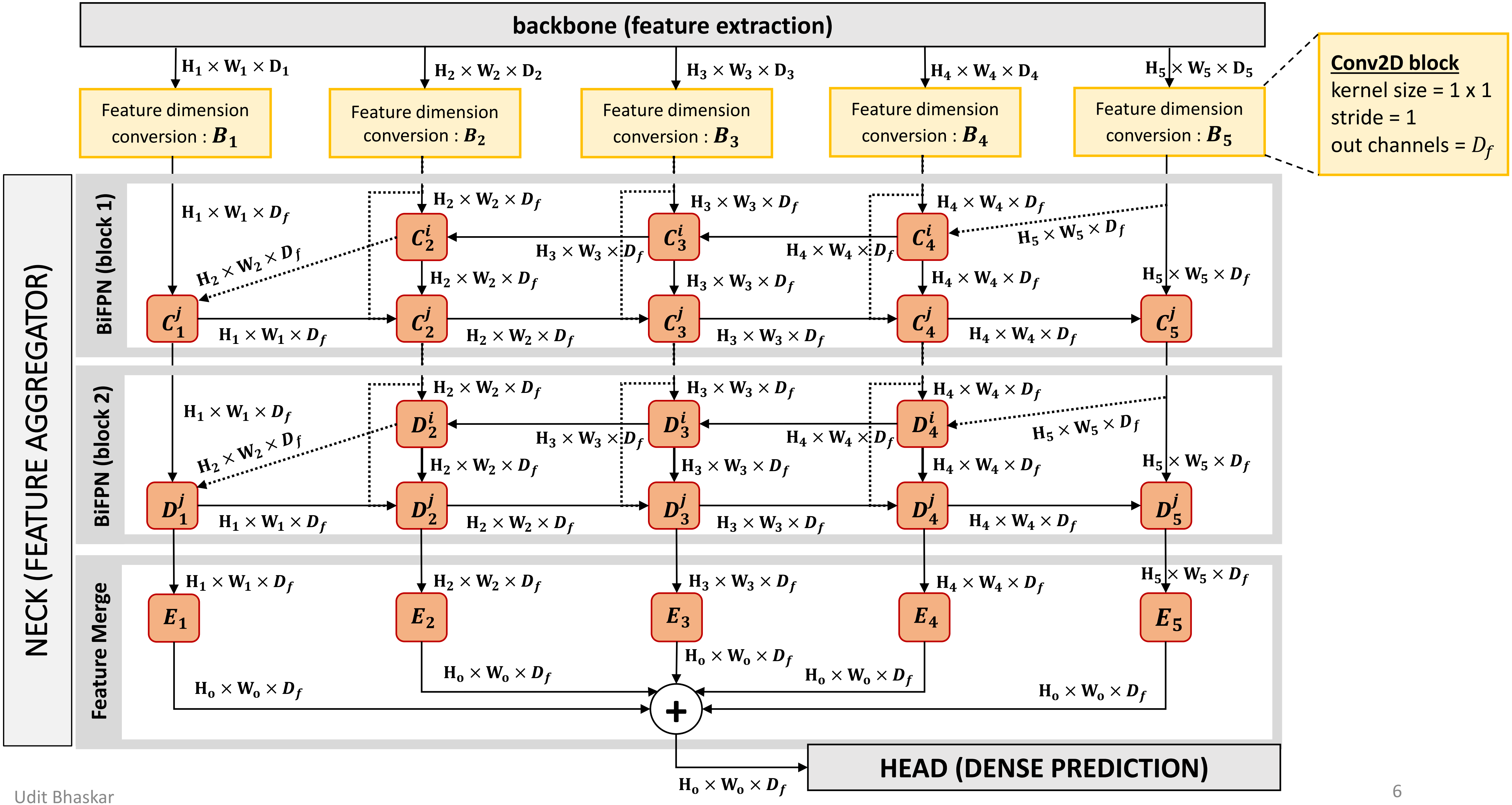




BACKBONE
NECK
BiFPN (×2)
HEAD



BACKBONE
(FEATURE EXTRACTION)
Note:
1. The features are extracted from pretrained backbone from pyTorch trained using ImageNet-1K classification dataset.
2. These backbone model parameters are frozen during training.
3. Efficientnet_b4 from pyTorch is used as a backbone.
4. Other configurations are also supported, refer to the codebase for supported backbones.
Input: μ_{pre}, σ_{pre}
Input: image
pre-process
$H_{img} \times W_{img} \times 3$
$H_{img} \times W_{img} \times 3$
$H_{input} \times W_{input} \times D_{input}$
C1
$H_1 \times W_1 \times D_1$
C2
$H_2 \times W_2 \times D_2$
C3
$H_3 \times W_3 \times D_3$
C4
$H_4 \times W_4 \times D_4$
Note:
1. This is a new backbone node on top of the pretrained backbone.
2. In this node the parameters are updated during training
C5
$H_5 \times W_5 \times D_5$
$H_4 \times W_4 \times D_4$
Weight standardized conv2D
$H_5 \times W_5 \times D_5$
Group Normalization
$H_5 \times W_5 \times D_5$
Swish Activation
$H_5 \times W_5 \times D_5$
NECK (FEATURE AGGREGATOR)



backbone (feature extraction)
H1 × W1 × D1
H2 × W2 × D2
H3 × W3 × D3
H4 × W4 × D4
H5 × W5 × D5
Feature dimension conversion : B1
Feature dimension conversion : B2
Feature dimension conversion : B3
Feature dimension conversion : B4
Feature dimension conversion : B5
Conv2D block
kernel size = 1 x 1
stride = 1
out channels = Df
NECK (FEATURE AGGREGATOR)
BiFPN (block 1)
H1 × W1 × Df
H2 × W2 × Df
H3 × W3 × Df
H4 × W4 × Df
H5 × W5 × Df
C2i
C3i
C4i
C1j
C2j
C3j
C4j
C5j
BiFPN (block 2)
D2i
D3i
D4i
D1j
D2j
D3j
D4j
D5j
Feature Merge
E1
E2
E3
E4
E5
Ho × Wo × Df
+
HEAD (DENSE PREDICTION)

Top down connections

$$c_4^i = f_4^i\left(w_1' B_4 + w_2' \mathrm{interp}(B_5)\right)$$

$$c_3^i = f_3^i\left(w_3' B_3 + w_4' \mathrm{interp}(c_4^i)\right)$$

$$c_2^i = f_2^i\left(w_5' B_2 + w_6' \mathrm{interp}(c_3^i)\right)$$

Bottom up connections

$$c_1^j = f_1^j\left(w_7' B_1 + w_8' \mathrm{interp}(c_2^i)\right)$$

$$c_2^j = f_2^j\left(w_9' B_2 + w_{10}' c_2^i + w_1' \mathrm{interp}(c_1^j)\right)$$

$$c_3^j = f_3^j\left(w_{11}' B_3 + w_{12}' c_3^i + w_{13}' \mathrm{interp}(c_2^j)\right)$$

$$c_4^j = f_4^j\left(w_{13}' B_4 + w_{14}' c_4^i + w_{16}' \mathrm{interp}(c_3^j)\right)$$

$$c_5^j = f_5^j\left(w_{15}' B_5 + w_{16}' \mathrm{interp}(c_4^j)\right)$$

Feature merge

$$E_1 = f_1^e\left(\mathrm{interp}(D_2^i)\right)$$

$$E_2 = f_2^e\left(\mathrm{interp}(D_1^j)\right)$$

$$E_3 = f_3^e\left(\mathrm{interp}(D_2^j)\right)$$

$$E_4 = f_4^e\left(\mathrm{interp}(D_3^j)\right)$$

$$E_5 = f_5^e\left(\mathrm{interp}(D_4^j)\right)$$

$$E = E_1 + E_2 + E_3 + E_4 + E_5$$

FEATURE AGGREGATOR FORMULAS

Weight Computation for merging three feature maps

$$w_i' = \frac{ReLU(w_i)}{ReLU(w_i) + ReLU(w_j) + ReLU(w_k) + \varepsilon}$$

$$w_j' = \frac{ReLU(w_j)}{ReLU(w_i) + ReLU(w_j) + ReLU(w_k) + \varepsilon}$$

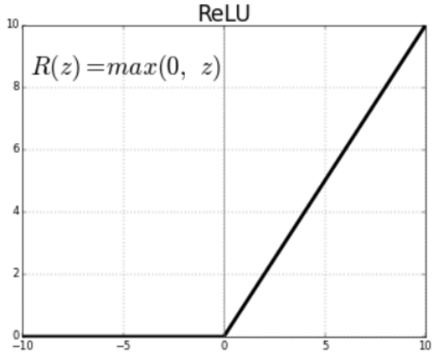
$$w_k' = \frac{ReLU(w_k)}{ReLU(w_i) + ReLU(w_j) + ReLU(w_k) + \varepsilon}$$

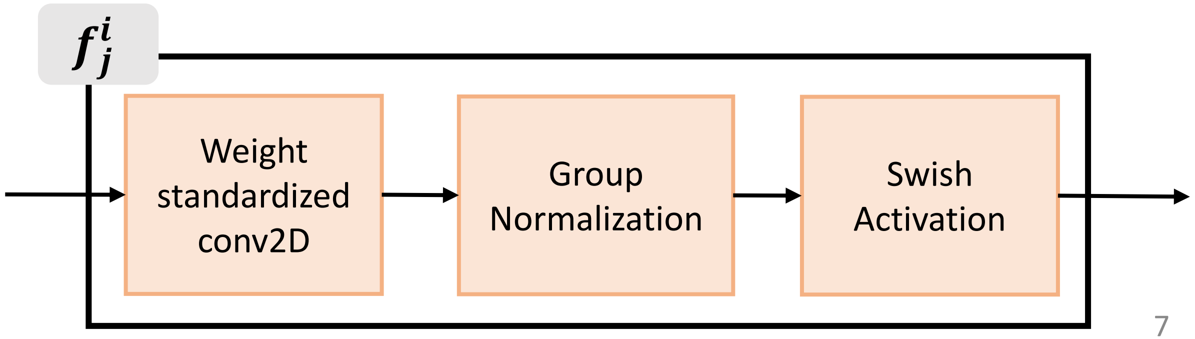
note:
$\boldsymbol{w_i, w_j, w_k}$ are **trainable** parameters

Weight Computation for merging two feature maps

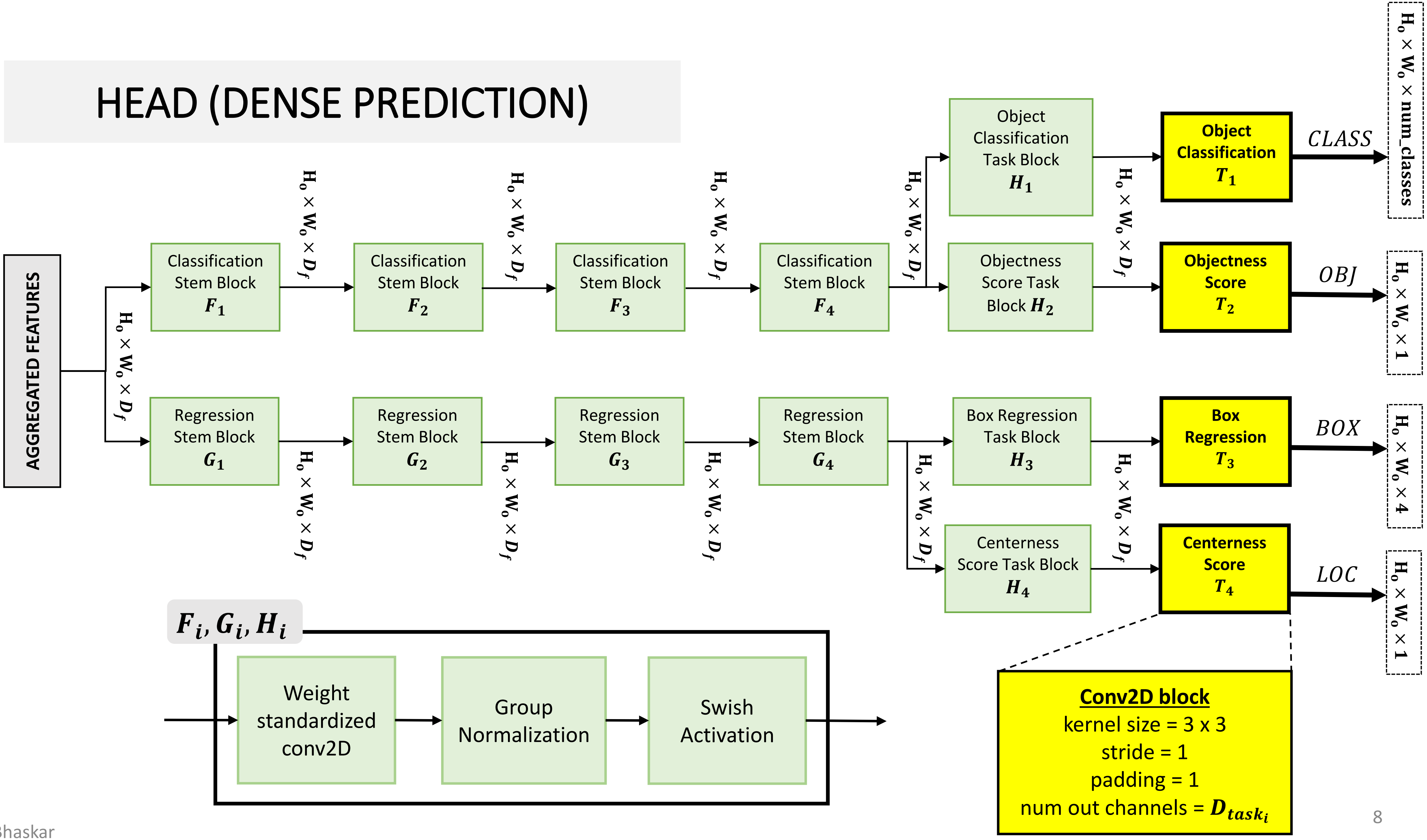
$$w_i' = \frac{ReLU(w_i)}{ReLU(w_i) + ReLU(w_j) + \varepsilon}$$

$$w_j' = \frac{ReLU(w_j)}{ReLU(w_i) + ReLU(w_j) + \varepsilon}$$

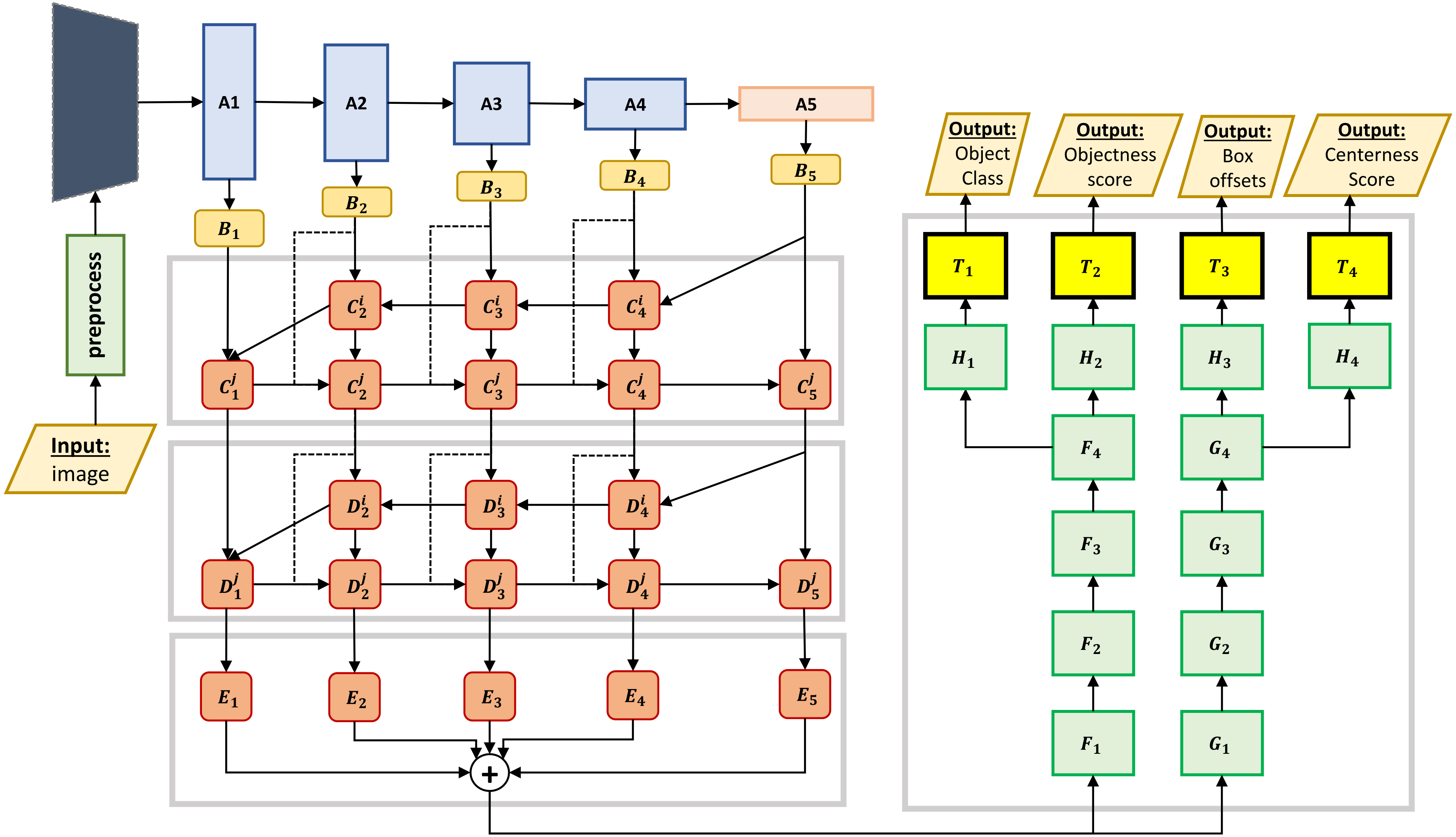




HEAD (DENSE PREDICTION)



ARCHITECTURE SUMMARY



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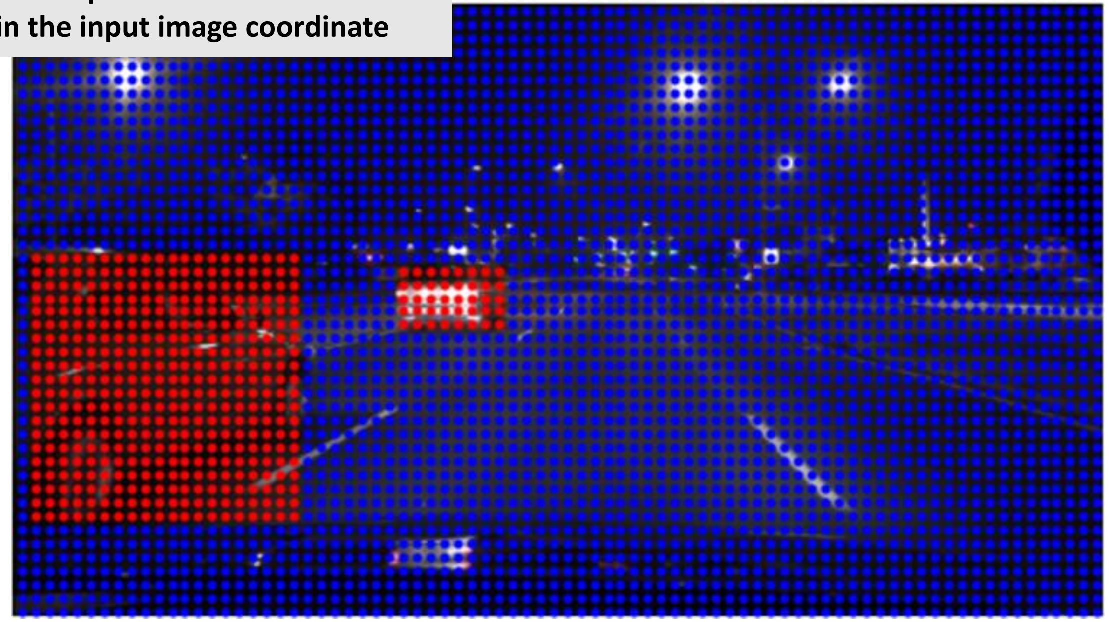
ANCHOR CENTER COMPUTATION

pytorch code snippet

```
xcoord = torch.arange(start=0, end=width,  step=1, dtype=torch.float32, device=device) + 0.5
ycoord = torch.arange(start=0, end=height, step=1, dtype=torch.float32, device=device) + 0.5
xcoord *= stride_width
ycoord *= stride_height
xcoord = xcoord.unsqueeze(0).repeat(height, 1)
ycoord = ycoord.unsqueeze(-1).repeat(1, width)
grid_coords = torch.stack((xcoord, ycoord), dim=-1).reshape(-1, 2)
```

Visual depiction of anchor centers in the input image coordinate



Input: $\mathbf{H_o, W_o}$

Generate a vector of x and y grid indexes in the output resolution $(\boldsymbol{H_o, W_o})$

$$x_{index} = (0,1,2,3,4, \dots, W_o - 1)$$
$$y_{index} = (0,1,2,3,4, \dots, H_o - 1)$$

Compute the grid center coordinates in the output resolution

$$x_{index} = x_{index} + 0.5$$
$$y_{index} = y_{index} + 0.5$$

Input : $\mathbf{H_{img}, W_{img}}$

Transform the grid coordinate from the output resolution to the input image resolution

$$s_w = \frac{W_{image}}{W_o}$$
$$s_h = \frac{H_{image}}{H_o}$$
$$x_{coord} = s_w * x_{index}$$
$$y_{coord} = s_h * y_{index}$$

Generate the whole grid by using tensor repeat and stack operations.

Output: *anchor center coordinates*

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ANCHOR TO ANNOTATED BOUNDING BOX ASSOCIATION

Input:
Thresholds
$T_w, T_h,$
T_r^{low}, T_r^{high}

Input: List of object annotations
1. Object Type: **ClassID**
2. Bounding box coordinates: $x_{tl}, y_{tl}, x_{br}, y_{br}$

Select prominent ground truth annotations. Some of the annotated bounding boxes are either **invalid** or are **too small**, such annotations are removed by thresholding on the box aspect ratio and box dimension

$$\mathbf{w^i = x_2 - x_1\ , h^i = y_2 - y_1\ , ratio^i = w^i/h^i}$$

$$\mathbf{flag = \left(w^i \geq T_w\right) \& \left(h^i \geq T_h\right) \& \left(ratio^i \geq T_r^{low}\right) \& \left(ratio^i \leq T_r^{high}\right)}$$

if the **flag** is true the annotations are selected for association

Input:
anchor center coordinates

Each of the anchor centres are associated with the ground truth box using the following rules:
1) The anchor centre coordinates shall **lie within the annotated bounding box**.
2) If an anchor is associated with multiple boxes from rule 1 then choose that box where the **distance between the center of the box and the associated anchor coordinate is smallest.**
3) The **unassociated anchor centres** are marked as **negative** or **background.**

Compute association of the anchor centre coordinates with **all** the annotated bounding boxes. Mark the **associated anchor** centres as **'ignored'** and the **unassociated anchors** as **'negative'** or background.

Optionally one can **ignore the associated anchor coordinates near the boundary of the groundtruth box** to avoid 'confusing' the detector during training. To do that shrink the associated box by a certain fraction and compute if the previously associated anchor coordinates are outside the box. **If outside then mark it as 'negative'.**

Extract the positive anchors

Overlay the extracted **'positive' anchors on top** of the **'ignored' anchors**

Output:
anchor to groundtruth associations

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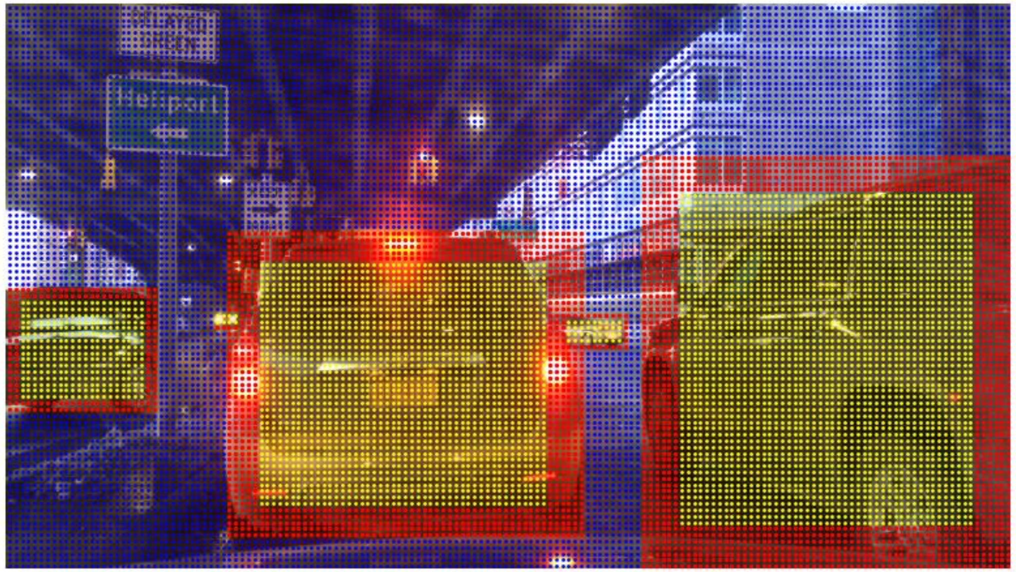
ASSOCIATION VISUALIZATION

../../..\../dataset/bdd/bdd100k_images_100k/bdd100k/images/100k/train\00091078-7cff8ea6.jpg



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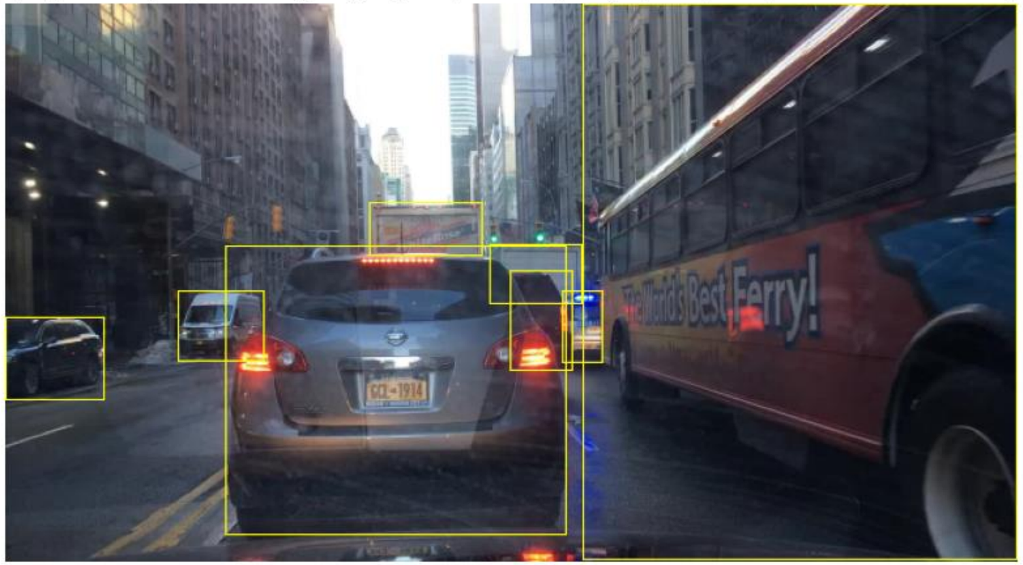
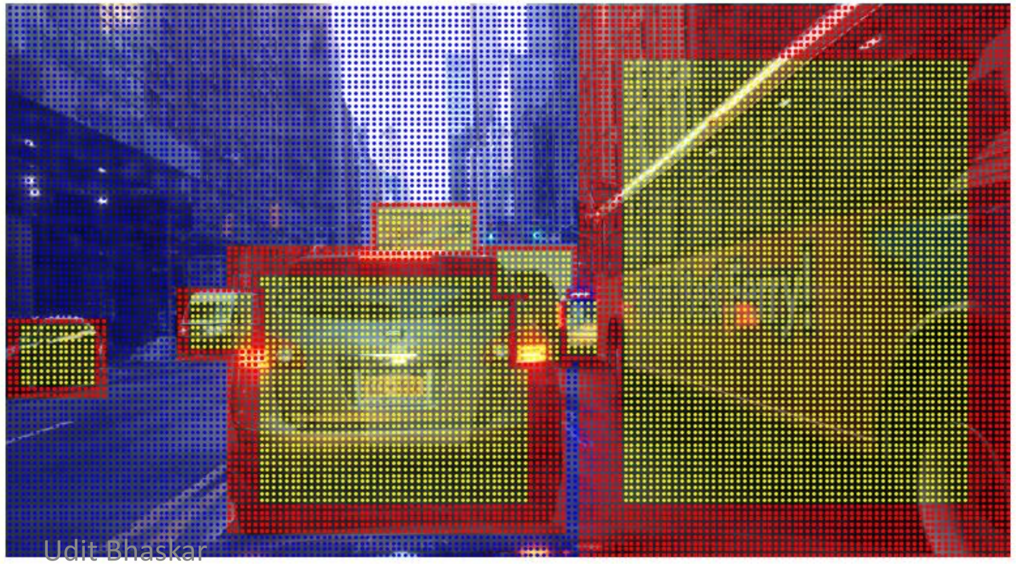




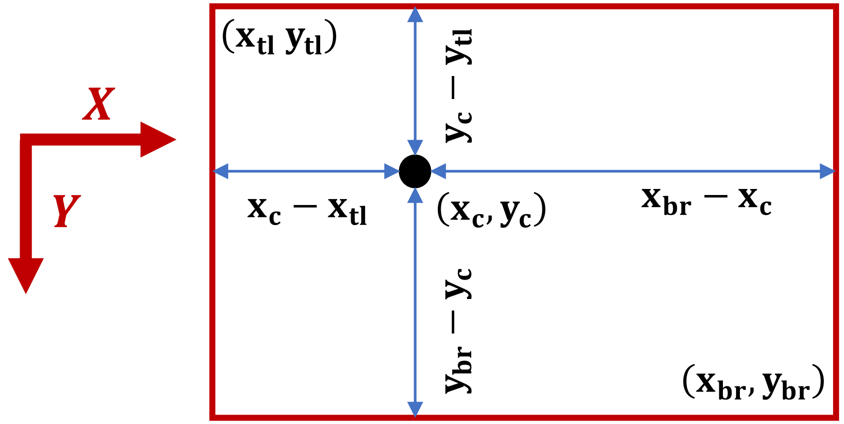
Positive

Ignored

Negative

BOX OFFSETS & BOX PROPOSALS

	Normalized Ground truth box offset	Proposal from predicted box offset
Box top left x coordinate	$t^x_{tl} = \dfrac{\log(x_c - x_{tl}) - \mu^x_{tl}}{\sigma^x_{tl}}$	$x_{tl} = x_c - \exp\left(\mu_{t^x_{tl}} + \sigma_{t^x_{tl}} * t^x_{tl}\right)$
Box top left y coordinate	$t^y_{tl} = \dfrac{\log(y_c - y_{tl}) - \mu^y_{tl}}{\sigma^y_{tl}}$	$y_{tl} = y_c - \exp\left(\mu_{t^y_{tl}} + \sigma_{t^y_{tl}} * t^y_{tl}\right)$
Box bottom right x coordinate	$t^x_{br} = \dfrac{\log(x_{br} - x_c) - \mu^x_{br}}{\sigma^x_{br}}$	$x_{br} = x_c + \exp\left(\mu_{t^x_{br}} + \sigma_{t^x_{br}} * t^x_{br}\right)$
Box bottom right y coordinate	$t^y_{br} = \dfrac{\log(y_{br} - y_c) - \mu^y_{br}}{\sigma^y_{br}}$	$y_{br} = y_c + \exp\left(\mu_{t^y_{br}} + \sigma_{t^y_{br}} * t^y_{br}\right)$



Note:

- The neural network **learns to predict** the offsets: $t^x_{tl}, t^y_{tl}, t^x_{br}, t^y_{br}$
- The **ground truth** for $t^x_{tl}, t^y_{tl}, t^x_{br}, t^y_{br}$ is computed from the assignment of ground truth bounding box to anchor centres
- $\mu_{t^x_{tl}}, \mu_{t^y_{tl}}, \mu_{t^w_{br}}, \mu_{t^h_{br}}$ and $\sigma_{t^x_{tl}}, \sigma_{t^x_{tl}}, \sigma_{t^w_{br}}, \sigma_{t^h_{br}}$ are the statistic of the **unnormalized** ground truth offsets
- The **ground truth** for $t^x_{tl}, t^y_{tl}, t^w_{br}, t^h_{br}$ is **normalized** such that the **ground truth offsets** have **zero mean** and **unit variance**
- $(x_c, y_c) \rightarrow$ anchor centre coordinates
- $(x_{tl}, y_{tl}, x_{br}, y_{br}) \rightarrow$ propoposal box corner coordinates computed from anchor centres and predicted offsets.

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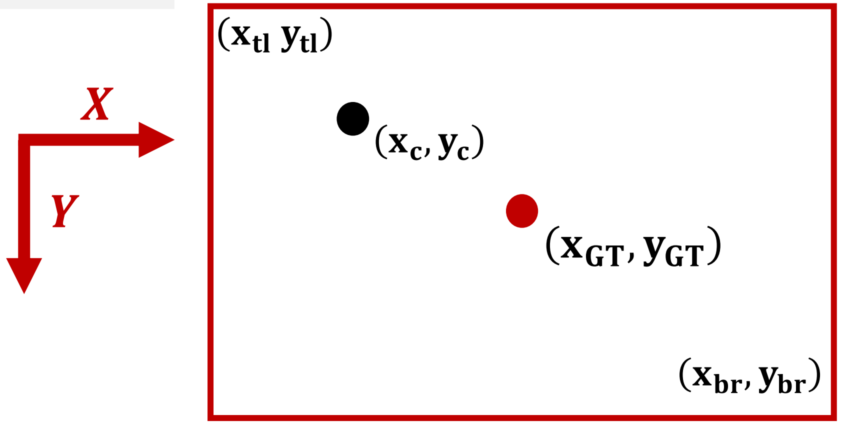
CENTERNESS SCORE

$$x_{GT} = \frac{x_{tl} + x_{br}}{2} \qquad y_{GT} = \frac{y_{tl} + y_{br}}{2}$$

$$W_{GT} = x_{br} - x_{tl} \qquad H_{GT} = y_{br} - y_{tl}$$

$$centerness_{GT} = \exp\left(-\frac{1}{2}\left(\left(\frac{x_c - x_{GT}}{s_w W_{GT}}\right)^2 + \left(\frac{y_c - y_{GT}}{s_h H_{GT}}\right)^2\right)\right)$$



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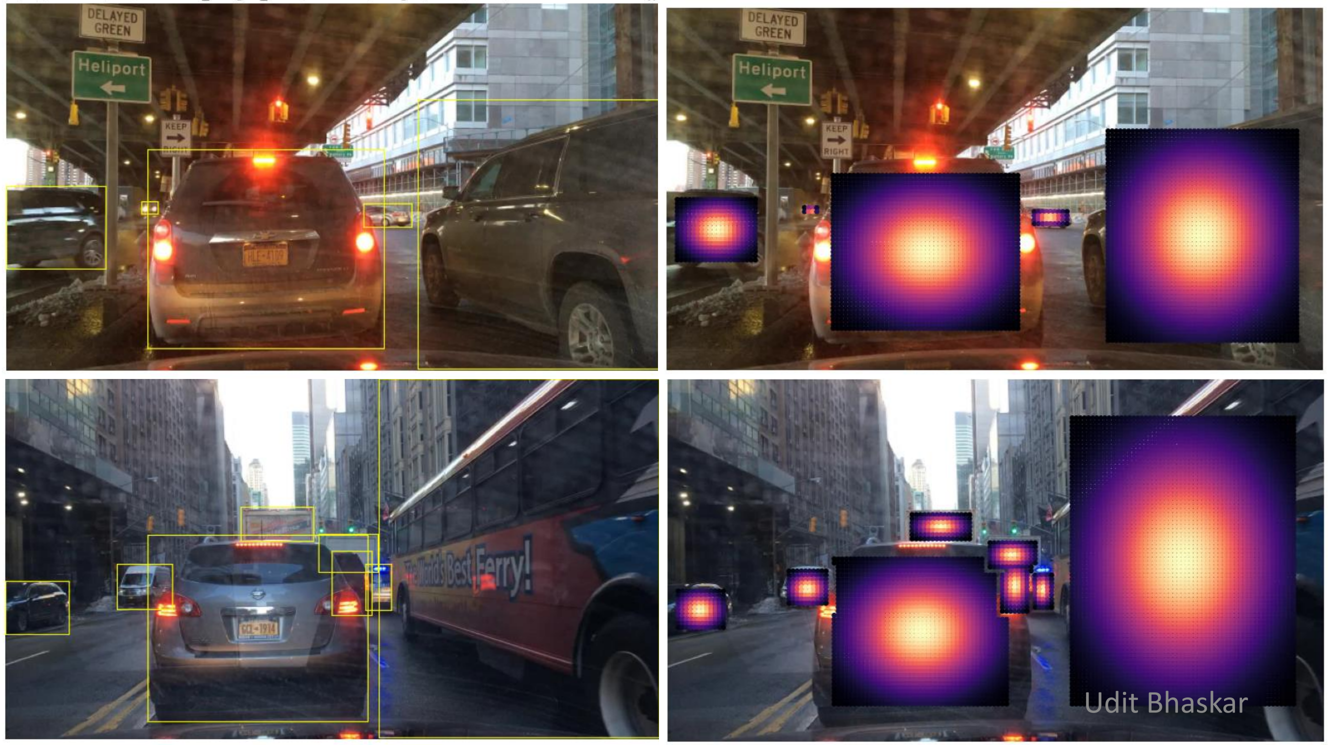

Note:

- The neural network **learns to predict** the centerness score which is in the range $[0, 1]$
- The **ground truth** for centerness is computed from the assignment of ground truth bounding box to anchor centres.
- It is hypothesised that the predicted outputs from the anchors that are more towards the centre of the object are more accurate.
- $(s_w, s_h) \rightarrow$ scaling factors to **adjust the spread** of the centerness ground-truth probability

OBJECTNESS & CLASSIFICATION SCORE

Input:
anchor to groundtruth associations

Compute Ground Truth for objectness score

Check if the anchor is associated with a ground truth object.

- If **associated** with the **ground truth**, objectness is set as **1**.
- If the anchor center is **associated** with the **background class**, set it as **0**.
- The **ignored anchors are not considered for training**

Output:
groundtruth objectness

Compute Ground Truth for classification score

Compute **one-hot** representation of the associated class label.
Anchors that are associated with **positive classes** are considered for **training**.

Output:
groundtruth class

LOSS FUNCTIONS

TASK	LOSS FUNCTION
Object Classification	Class Weighted Cross Entropy Loss
Objectness	Focal Loss
Box Offset Regression	Smooth L1 Loss
Centerness Score Regression	Binary Cross Entropy Loss

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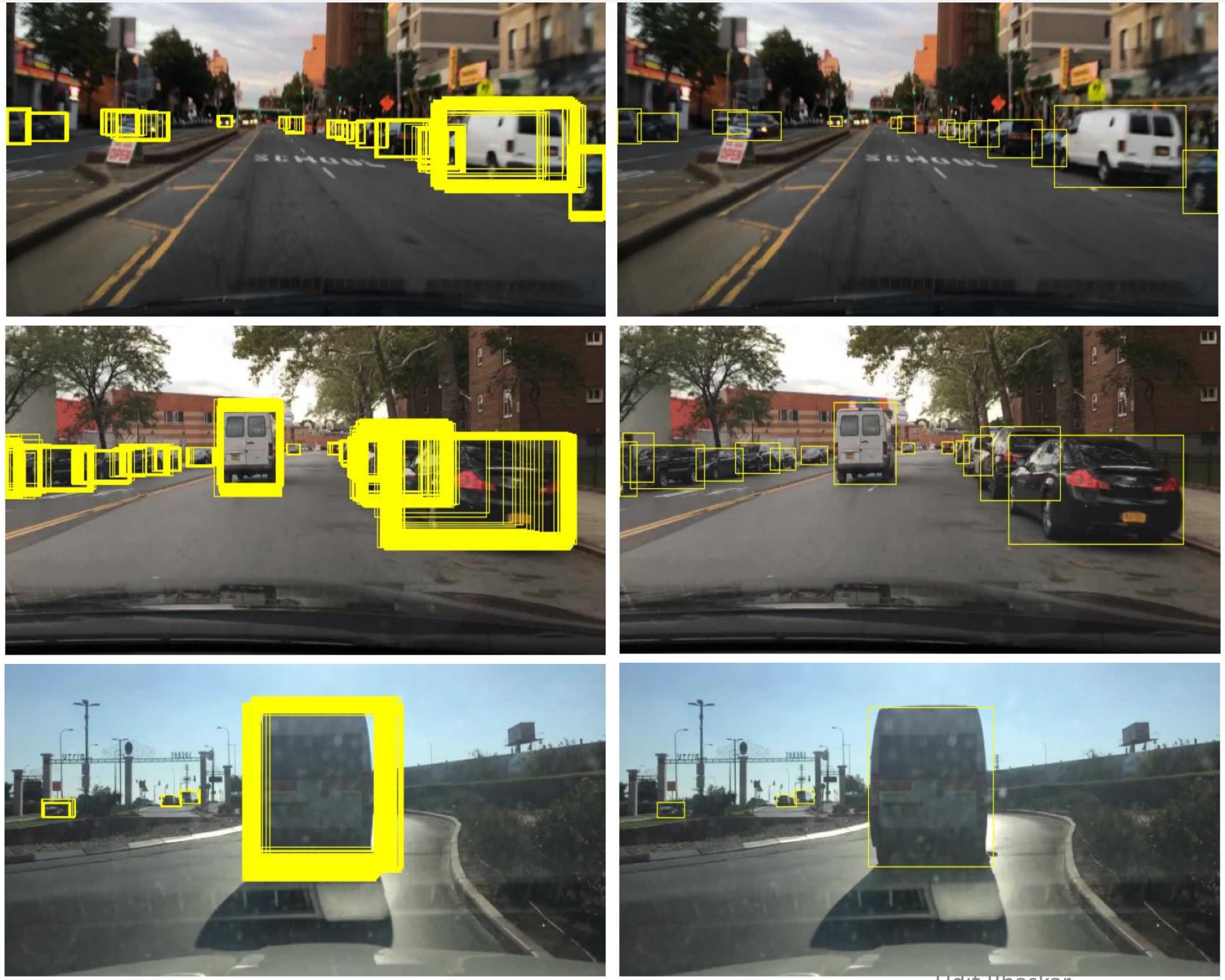
NON MAXIMAL SUPRESSION :

Use ROC plot to determine the threshold for non maximal suppression



NMS Threshold determination

Inputs: bounding box predictions from the positive anchors

Inputs: NMS threshold to be considered **[0.1, 0.2, ... 0.9, 0.99]**

compute a **list of predicted bounding** boxes after applying the nms. For each **NMS threshold** do the following

Inputs: ground truth bounding box (annotations)

Using **greedy association** perform a bipartite matching between the set the **predicted** and **ground truth box** coordinates

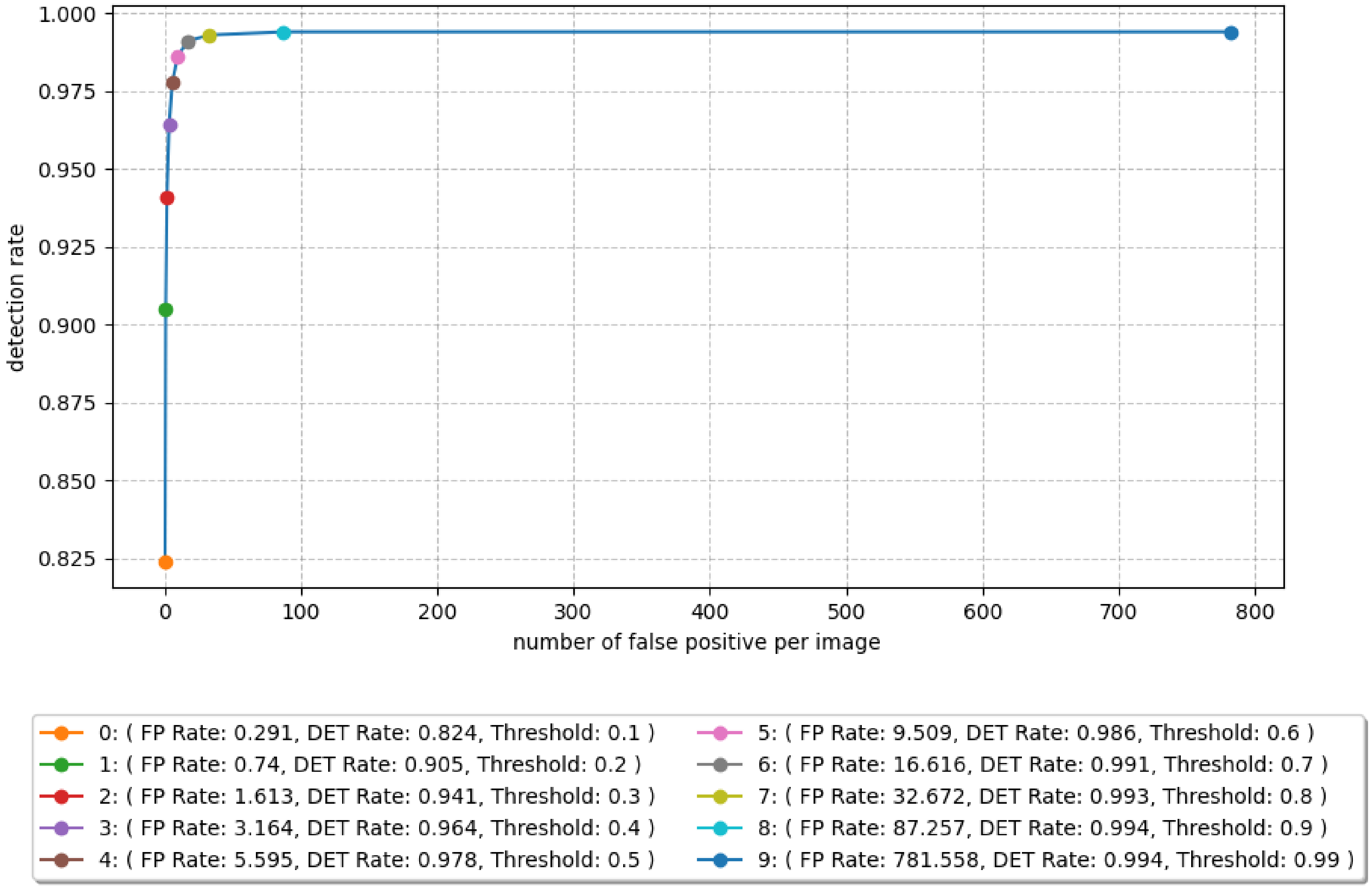
Compute **the total number of True positives and False Positives**. The predictions that are associated with the GT box are considered as true positives and the predictions that are not associated as False positives.

$$DetectionRate = \frac{total\ number\ of\ TPs}{tosl\ number\ of\ GT\ boxes}.$$

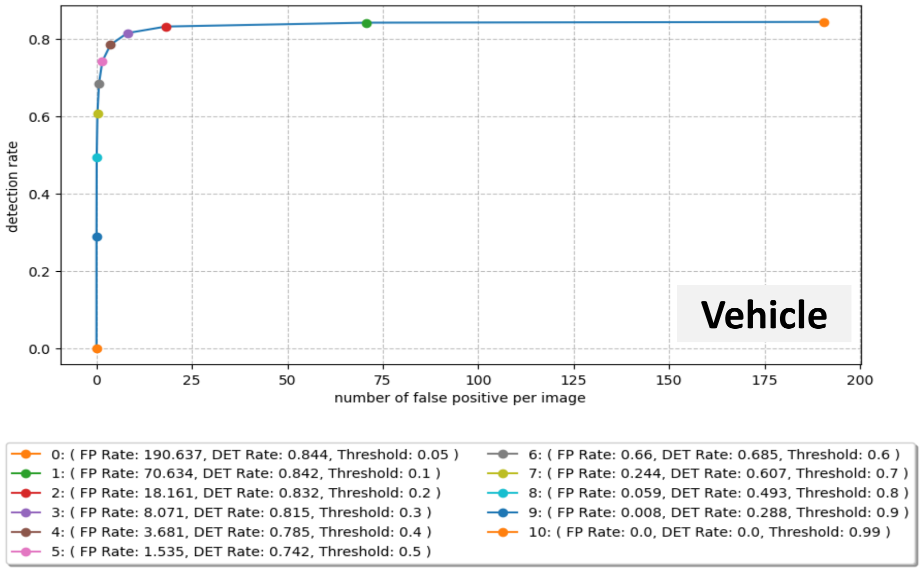
$$FalsePositiveRate = \frac{total\ number\ of\ FPs}{tosl\ number\ of\ images}.$$

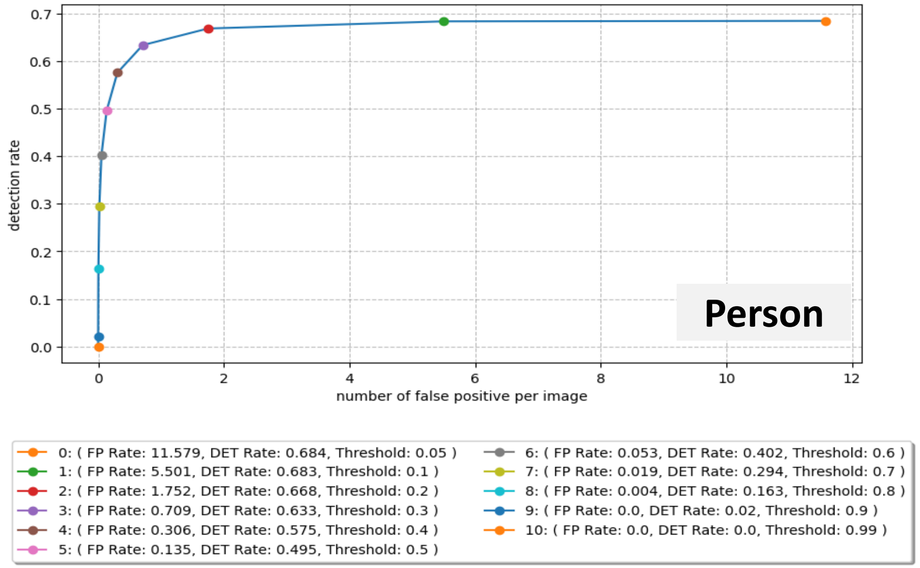
Output: ROC[thresholds]

ROC for NMS Threshold determination



ROC for Score Threshold determination





Inputs:
predicted bounding boxes from all anchors

Inputs:
1. detection thresholds to be considered
   [0.05, 0.1, 0.2, ... 0.9, 0.99]
2. Object class

compute a **list of predicted bounding** boxes after applying the nms.
For each **detection threshold** do the following

compute score for each prediction $score = \sqrt{prob_{cntr} * prob_{cls} * prob_{obj}}$
Select prediction **If** $score \geq Det_{thr}$

Using **greedy association** perform a bipartite matching between the set the **selected** and **ground truth box** coordinates

Inputs: ground truth bounding box (annotations)

Compute **the total number of True positives and False Positives**.
The predictions that are associated with the GT box are considered as true positives and the predictions that are not associated as False positives.

$$DetectionRate = \frac{total\ number\ of\ TPs}{tosl\ number\ of\ GT\ boxes}.$$

$$FalsePositiveRate = \frac{total\ number\ of\ FPs}{tosl\ number\ of\ images}.$$

Output: ROC[thresholds]