

# YOLOv3 Study Notes

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## 1 dataset.py

```
def parse_annotation(self, annotation):
    line = annotation.split()
    image_path = line[0]
    if not os.path.exists(image_path):
        raise KeyError("%s does not exist ... " % image_path)

    e_path)
    image = cv2.imread(image_path)
    bboxes = np.array([list(map(int, box.split(','))) for box in line[1:]])

    if self.data_aug:
        image, bboxes = self.random_horizontal_flip(np.copy(image), np.copy(bboxes))
        image, bboxes = self.random_crop(np.copy(image), np.copy(bboxes))
        image, bboxes = self.random_translate(np.copy(image), np.copy(bboxes))

    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image, bboxes = utils.image_preporcess(np.copy(image), [self.train_input_size, self.
    ↪ train_input_size], np.copy(bboxes))
    return image, bboxes
    line = annotation.split()
    image_path = line[0]
    if not os.path.exists(image_path):
        raise KeyError("%s does not exist ... " % image_path)
    image = cv2.imread(image_path)
    bboxes = np.array([list(map(int, box.split(','))) for box in line[1:]])

    if self.data_aug:
        image, bboxes = self.random_horizontal_flip(np.copy(image), np.copy(bboxes))
        image, bboxes = self.random_crop(np.copy(image), np.copy(bboxes))
        image, bboxes = self.random_translate(np.copy(image), np.copy(bboxes))

    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image, bboxes = utils.image_preporcess(np.copy(image), [self.train_input_size, self.
    ↪ train_input_size], np.copy(bboxes))
    return image, bboxes
```

This part is straightforward.

End of Function

To understand `preprocess_true_boxes`, we must first understand:

```
def bbox_iou(self, boxes1, boxes2):
    boxes1 = np.array(boxes1)
    boxes2 = np.array(boxes2)

    boxes1_area = boxes1[..., 2] * boxes1[..., 3]
    boxes2_area = boxes2[..., 2] * boxes2[..., 3]

    boxes1 = np.concatenate([boxes1[..., :2] - boxes1[..., 2:] * 0.5,
                              boxes1[..., :2] + boxes1[..., 2:] * 0.5], axis=-1)
    boxes2 = np.concatenate([boxes2[..., :2] - boxes2[..., 2:] * 0.5,
                              boxes2[..., :2] + boxes2[..., 2:] * 0.5], axis=-1)
```

From the function we can deduce that `box = (cx, cy, width, height)`, therefore

`boxes[..., :2] - boxes[..., 2:] * 0.5 = [all upper-left corners]`

and

```
boxes1[..., :2] + boxes1[..., 2:] * 0.5 = [all lower-right corners],
```

while concatenating (2,) `np`-array along the last axis simply means combining them into one (4,) `np`-array. Numerically in training `boxes1` and `boxes2` are like:

```
[[0.59375 3.78125 0.5      0.625  ]]
```

and

```
[[ 0.5      3.5      3.625     2.8125 ]
 [ 0.5      3.5      4.875     6.1875 ]
 [ 0.5      3.5     11.65625    10.1875 ]].
```

```
left_up = np.maximum(boxes1[..., :2], boxes2[..., :2])
right_down = np.minimum(boxes1[..., 2:], boxes2[..., 2:])
```

Think of the above as entrywise comparisons that give an array of maximum, which yields the coordinates of intersection rectangle for each fixed `boxes1` to boxes in `boxes2`.

```
inter_section = np.maximum(right_down - left_up, 0.0)
```

The entries in `inter_section` are the *width* and *height* of the intersection, the (broadcasted) `np.maximum` is just a tricky way to handle empty intersection.

```
inter_area = inter_section[..., 0] * inter_section[..., 1]
union_area = boxes1_area + boxes2_area - inter_area

return inter_area / union_area
```

**End of Function**

```
def preprocess_true_boxes(self, bboxes):
```

Here `bboxes` are the boxes from annotation file in which each line takes the form:

```
some/directory/hash.jpg 79,537,107,574,0 297,547,318,575,0
```

```
label = [np.zeros((self.train_output_sizes[i],
                  self.train_output_sizes[i],
                  self.anchor_per_scale,
                  5 + self.num_classes)) for i in range(3)]
bboxes_xywh = [np.zeros((self.max_bbox_per_scale, 4)) for _ in range(3)]
bbox_count = np.zeros((3,))

for bbox in bboxes:
    bbox_coor = bbox[:4]
    bbox_class_ind = bbox[4]

    onehot = np.zeros(self.num_classes, dtype=np.float)
    onehot[bbox_class_ind] = 1.0
    uniform_distribution = np.full(self.num_classes, 1.0 / self.num_classes)
    deta = 0.01
    smooth_onehot = onehot * (1 - deta) + deta * uniform_distribution
    # bbox_xywh is ground truth
    bbox_xywh = np.concatenate([(bbox_coor[2:] + bbox_coor[:2]) * 0.5, bbox_coor[2:] - bbox_coor
    ↪[:2]], axis=-1)
    # bbox_xywh_scaled is scaled ground truth relative to stride (13, 26, 52, as a unit)
    bbox_xywh_scaled = 1.0 * bbox_xywh[np.newaxis, :] / self.strides[:, np.newaxis]
```

Note that `bbox_xywh[np.newaxis, :]` is of shape (1, 4) and `1/self.strides[:, np.newaxis]` is of shape (3, 1), their multiplication will be conducted by “broadcasting” in `numpy`, which yields a (3, 4) dimensional `numpy` array. The product `bbox_xywh_scaled` consists of  $(c_x, c_y, w, h)$  which use “stride” as a unit, so 1 means “1 grid” (recall there are  $13 \times 13$ ,  $26 \times 26$ ,  $52 \times 52$  grids predictions from Darknet backbone).

```
iou = []
exist_positive = False
for i in range(3):
    anchors_xywh = np.zeros((self.anchor_per_scale, 4))
    anchors_xywh[:, 0:2] = np.floor(bbox_xywh_scaled[i, 0:2]).astype(np.int32) + 0.5
    anchors_xywh[:, 2:4] = self.anchors[i]
```

`anchors_xywh` essing boxes with objectiveneentially move centers of `bbox_xywh_scaled` to the middle of the grid that center lies in, then the anchor boxes' width and height are assigned, replacing the original width, height of `bbox_xywh_scaled`.

```
iou_scale = self.bbox_iou(bbox_xywh_scaled[i][np.newaxis, :], anchors_xywh)
```

The presence of `np.newaxis` is simply because multiplication between  $(4,)$  and  $(3, 4)$  array does not make sense. The additional dimension expand  $(4,)$  array into  $(1, 4)$  array, which is broadcasted and multiplied to  $(3, 4)$  array to give another  $(3, 4)$  array, and therefore, `iou_scale.shape = (3,)`.

```
iou.append(iou_scale)
iou_mask = iou_scale > 0.3 # a boolean list of length 3

if np.any(iou_mask): # if one of them is True
    xind, yind = np.floor(bbox_xywh_scaled[i, 0:2]).astype(np.int32)
    label[i][yind, xind, iou_mask, :] = 0
    label[i][yind, xind, iou_mask, 0:4] = bbox_xywh
    label[i][yind, xind, iou_mask, 4:5] = 1.0
    label[i][yind, xind, iou_mask, 5:] = smooth_onehot
```

`label[i]` is initialized at the beginning which is of size

$$\text{train\_output\_sizes} \times \text{train\_output\_sizes} \times 3 \times 85$$

for each `i`, where `train_output_sizes = 13, 26 or 52`.

```
bbox_ind = int(bbox_count[i] % self.max_bbox_per_scale)
bboxes_xywh[i][bbox_ind, :4] = bbox_xywh
```

`bboxes_xywh` is initialized (with zeros) at the beginning, `bboxes_xywh.shape = (3, 150, 4)`.

```
bbox_count[i] += 1

exist_positive = True

if not exist_positive:
    best_anchor_ind = np.argmax(np.array(iou).reshape(-1), axis=-1) # flatten and take max
    # best_detect belongs to which "i", namely, best "i"
    best_detect = int(best_anchor_ind / self.anchor_per_scale)
    # for this i, which index it is:
    best_anchor = int(best_anchor_ind % self.anchor_per_scale)
    # get the grid point in our 13x13, 26x26, 52x52 grid:
    xind, yind = np.floor(bbox_xywh_scaled[best_detect, 0:2]).astype(np.int32)

    label[best_detect][yind, xind, best_anchor, :] = 0
    label[best_detect][yind, xind, best_anchor, 0:4] = bbox_xywh
    label[best_detect][yind, xind, best_anchor, 4:5] = 1.0
    label[best_detect][yind, xind, best_anchor, 5:] = smooth_onehot

    bbox_ind = int(bbox_count[best_detect] % self.max_bbox_per_scale)
    bboxes_xywh[best_detect][bbox_ind, :4] = bbox_xywh
    # assign bbox_xywh into the list instead of append,
    # this is to make sure there are at most 150 boxes within all 3 scales.

    bbox_count[best_detect] += 1
label_sbbox, label_mbbox, label_lbbox = label
sbboxes, mbboxes, lbboxes = bboxes_xywh
return label_sbbox, label_mbbox, label_lbbox, sbboxes, mbboxes, lbboxes
```

In short,

`sbboxes, mbboxes, lbboxe`

are just ground truth bounding boxes (center, width and height), while

`label_sbbox, label_mbbox, label_lbbox`

are ground truth bounding boxes with objectiveness and probabilities of *each grid*.

**End of Function**

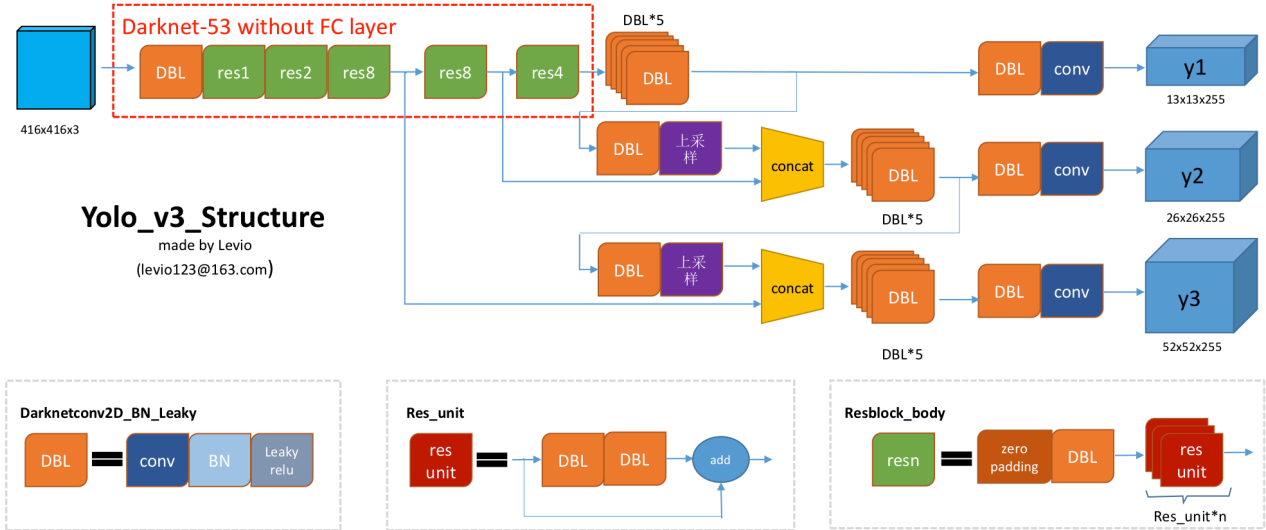


Figure 1: Structure of YOLOv3

## 2 yolov3.py

In darknet53 after a bunch of residue modules we get 3 branches `route_1`, `route_2` and `conv`, where

`route_1.shape = (-1, 52, 52, 256)`

`route_2.shape = (-1, 26, 26, 512)`

`conv.shape = (-1, 13, 13, 1024)`

Each branch then jumps into several stages of feature extractions, the whole process finally gives another 3 branches of undecoded/raw data of features, and they are endowed with the meaning of “grid-based detection” after reshaping into  $(-1, \text{output\_size}, \text{output\_size}, 3, 85)$  dimensional array.

```
def YOLOv3(input_layer):
    route_1, route_2, conv = backbone.darknet53(input_layer)

    conv = common.convolutional(conv, (1, 1, 1024, 512))
    conv = common.convolutional(conv, (3, 3, 512, 1024))
    conv = common.convolutional(conv, (1, 1, 1024, 512))
    conv = common.convolutional(conv, (3, 3, 512, 1024))
    conv = common.convolutional(conv, (1, 1, 1024, 512))
```

As `padding="same"` is being used along the chain of conv nets, there is no spatial dimension change.

```
conv_lobj_branch = common.convolutional(conv, (3, 3, 512, 1024))
conv_lbbox = common.convolutional(conv_lobj_branch, (1, 1, 1024, 3*(NUM_CLASS + 5)), activate=
    ↪ False, bn=False)

conv = common.convolutional(conv, (1, 1, 512, 256))
conv = common.upsample(conv)

conv = tf.concat([conv, route_2], axis=-1)

conv = common.convolutional(conv, (1, 1, 768, 256))
conv = common.convolutional(conv, (3, 3, 256, 512))
conv = common.convolutional(conv, (1, 1, 512, 256))
conv = common.convolutional(conv, (3, 3, 256, 512))
conv = common.convolutional(conv, (1, 1, 512, 256))

conv_mobj_branch = common.convolutional(conv, (3, 3, 256, 512))
conv_mbbox = common.convolutional(conv_mobj_branch, (1, 1, 512, 3*(NUM_CLASS + 5)), activate=
    ↪ False, bn=False)

conv = common.convolutional(conv, (1, 1, 256, 128))
```

```

conv = common.upsample(conv)

conv = tf.concat([conv, route_1], axis=-1)

conv = common.convolutional(conv, (1, 1, 384, 128))
conv = common.convolutional(conv, (3, 3, 128, 256))
conv = common.convolutional(conv, (1, 1, 256, 128))
conv = common.convolutional(conv, (3, 3, 128, 256))
conv = common.convolutional(conv, (1, 1, 256, 128))

conv_sobj_branch = common.convolutional(conv, (3, 3, 128, 256))
conv_sbbox = common.convolutional(conv_sobj_branch, (1, 1, 256, 3*(NUM_CLASS + 5)), activate=
↪ False, bn=False)

return [conv_sbbox, conv_mbbox, conv_lbbox]

```

**End of Function**

```

def decode(conv_output, i=0):
    """
    return tensor of shape [batch_size, output_size, output_size, anchor_per_scale, 5 + num_classes]
        contains (x, y, w, h, score, probability)
    """

```

conv\_output is the output of YOLOv3 (conv\_sbbox, conv\_mbbox or conv\_lbbox).

```

conv_shape      = tf.shape(conv_output)
batch_size      = conv_shape[0]
output_size     = conv_shape[1]

conv_output = tf.reshape(conv_output, (batch_size, output_size, output_size, 3, 5 + NUM_CLASS))

conv_raw_dxdy = conv_output[:, :, :, :, 0:2]
conv_raw_dwdh = conv_output[:, :, :, :, 2:4]
conv_raw_conf = conv_output[:, :, :, :, 4:5]
conv_raw_prob = conv_output[:, :, :, :, 5: ]

y = tf.tile(tf.range(output_size, dtype=tf.int32)[:, tf.newaxis], [1, output_size])
x = tf.tile(tf.range(output_size, dtype=tf.int32)[tf.newaxis, :], [output_size, 1])

```

For example, let's take output\_size = 13, then

```
y = np.tile(np.arange(13)[:, np.newaxis], [1, 13])
```

and

```
x = np.tile(np.arange(13)[np.newaxis, :], [13, 1])
```

are respectively:

```

[[ 0  0  0  0  0  0  0  0  0  0  0  0  0]  [[ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 1  1  1  1  1  1  1  1  1  1  1  1  1]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 2  2  2  2  2  2  2  2  2  2  2  2  2]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 3  3  3  3  3  3  3  3  3  3  3  3  3]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 4  4  4  4  4  4  4  4  4  4  4  4  4]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 5  5  5  5  5  5  5  5  5  5  5  5  5]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 6  6  6  6  6  6  6  6  6  6  6  6  6]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 7  7  7  7  7  7  7  7  7  7  7  7  7]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 8  8  8  8  8  8  8  8  8  8  8  8  8]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[ 9  9  9  9  9  9  9  9  9  9  9  9  9]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[10 10 10 10 10 10 10 10 10 10 10 10 10]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[11 11 11 11 11 11 11 11 11 11 11 11 11]  [ 0  1  2  3  4  5  6  7  8  9 10 11 12]
[12 12 12 12 12 12 12 12 12 12 12 12 12]] [ 0  1  2  3  4  5  6  7  8  9 10 11 12]]

```

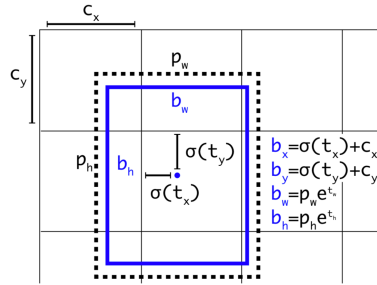
For x and y we expand dimension again along the last axis (break every single element into a bracketed element) before concatenation:

```
xy_grid = tf.concat([x[:, :, tf.newaxis], y[:, :, tf.newaxis]], axis=-1)
```

At this point, xy\_grid is (13,13,2) dimensional.

```
xy_grid = tf.tile(xy_grid[tf.newaxis, :, :, tf.newaxis, :], [batch_size, 1, 1, 3, 1])
xy_grid = tf.cast(xy_grid, tf.float32)
```

Now `xy_grid` is (batch\_size, 13, 13, 3, 2) dimensional. Recall that



```
pred_xy = (tf.sigmoid(conv_raw_dxdy) + xy_grid) * STRIDES[i]
pred_wh = (tf.exp(conv_raw_dwdh) * ANCHORS[i]) * STRIDES[i]
pred_xywh = tf.concat([pred_xy, pred_wh], axis=-1)

pred_conf = tf.sigmoid(conv_raw_conf)
pred_prob = tf.sigmoid(conv_raw_prob)

return tf.concat([pred_xywh, pred_conf, pred_prob], axis=-1)
```

Bear in mind that decoded `x, y` in `pred_xywh` denote the center of prediction rectangle, as is the output of the function `preprocess_true_boxes`.

**End of Function**

### 3 yolov3.compute\_loss

```
def bbox_giou(boxes1, boxes2):

    boxes1 = tf.concat([boxes1[..., :2] - boxes1[..., 2:] * 0.5,
                        boxes1[..., :2] + boxes1[..., 2:] * 0.5], axis=-1)
    boxes2 = tf.concat([boxes2[..., :2] - boxes2[..., 2:] * 0.5,
                        boxes2[..., :2] + boxes2[..., 2:] * 0.5], axis=-1)

    boxes1 = tf.concat([tf.minimum(boxes1[..., :2], boxes1[..., 2:]),
                        tf.maximum(boxes1[..., :2], boxes1[..., 2:])], axis=-1)
    boxes2 = tf.concat([tf.minimum(boxes2[..., :2], boxes2[..., 2:]),
                        tf.maximum(boxes2[..., :2], boxes2[..., 2:])], axis=-1)

    boxes1_area = (boxes1[..., 2] - boxes1[..., 0]) * (boxes1[..., 3] - boxes1[..., 1])
    boxes2_area = (boxes2[..., 2] - boxes2[..., 0]) * (boxes2[..., 3] - boxes2[..., 1])

    left_up = tf.maximum(boxes1[..., :2], boxes2[..., :2])
    right_down = tf.minimum(boxes1[..., 2:], boxes2[..., 2:])

    inter_section = tf.maximum(right_down - left_up, 0.0)
    inter_area = inter_section[..., 0] * inter_section[..., 1]
    union_area = boxes1_area + boxes2_area - inter_area
    iou = inter_area / union_area

    enclose_left_up = tf.minimum(boxes1[..., :2], boxes2[..., :2])
    enclose_right_down = tf.maximum(boxes1[..., 2:], boxes2[..., 2:])
    enclose = tf.maximum(enclose_right_down - enclose_left_up, 0.0)
    enclose_area = enclose[..., 0] * enclose[..., 1]
    giou = iou - 1.0 * (enclose_area - union_area) / enclose_area

    return giou
```

```
def compute_loss(pred, conv, label, bboxes, i=0):

    conv_shape = tf.shape(conv)
    batch_size = conv_shape[0]
    output_size = conv_shape[1]
    input_size = STRIDES[i] * output_size
```

```

conv = tf.reshape(conv, (batch_size, output_size, output_size, 3, 5 + NUM_CLASS))

conv_raw_conf = conv[:, :, :, :, 4:5]
conv_raw_prob = conv[:, :, :, :, 5:]

pred_xywh      = pred[:, :, :, :, 0:4]
pred_conf      = pred[:, :, :, :, 4:5]

label_xywh     = label[:, :, :, :, 0:4]
respond_bbox   = label[:, :, :, :, 4:5] # objectiveness
label_prob     = label[:, :, :, :, 5:]

giou = tf.expand_dims(bbox_giou(pred_xywh, label_xywh), axis=-1)
input_size = tf.cast(input_size, tf.float32)

bbox_loss_scale = 2.0 - 1.0 * label_xywh[:, :, :, :, 2:3] * label_xywh[:, :, :, :, 3:4] / (
    ↪ input_size ** 2)
giou_loss = respond_bbox * bbox_loss_scale * (1 - giou)

```

Note that for two sets  $U, V \in \mathcal{C}$ , where  $\mathcal{C} \in 2^{\mathbb{R}^2}$ , the function  $d(U, V) := 1 - \text{giou}(U, V)$  defines a metric, so `giou_loss` makes sense.

```

iou = bbox_iou(pred_xywh[:, :, :, :, np.newaxis, :], bboxes[:, np.newaxis, np.newaxis, np.
    ↪ newaxis, :, :])

```

`bboxes` are batched inside `Dataset("train").__next__` before passing into `compute_loss` (in a while loop until image count reaches batch size). Therefore `bboxes.shape = (16, 150, 4)`, where 150 is the maximal number of anchors (most of them are zeros due to initialization), so we see 3 ':'s in `bboxes`.

Finally

$$\text{pred\_xywh.shape} = (16, 13, 13, 3, 150, 4) = \text{bboxes.shape}$$

and

$$\text{iou.shape} = (16, 13, 13, 3, 150)$$

where computation gets rid of the last dimension. `bboxes` is copied to every grid for computation because from original paper:

*“the confidence prediction represents the IOU between the predicted box and any ground truth box”*

```

max_iou = tf.expand_dims(tf.reduce_max(iou, axis=-1), axis=-1)
respond_bgd = (1.0 - respond_bbox) * tf.cast( max_iou < IOU_LOSS_THRESH, tf.float32 )

```

In the internet some people call `IOU_LOSS_THRESH` as `ignore_thresh`. `respond_bgd` determines whether to penalize a prediction

- that overlaps too few with ground truth anchors (i.e., detected wrong location) **and**
- that makes false positive error.

```

conf_focal = tf.pow(respond_bbox - pred_conf, 2)

```

The concept of focal loss with  $\gamma = 2$  was introduced in [3], which down-weights the loss contributed by well-classified (high confidence) examples.

```

conf_loss = conf_focal *
(
    respond_bbox * tf.nn.sigmoid_cross_entropy_with_logits(labels=respond_bbox, logits=
    ↪ conv_raw_conf)
    +
    respond_bgd * tf.nn.sigmoid_cross_entropy_with_logits(labels=respond_bbox, logits=
    ↪ conv_raw_conf)
)

```

Where `tf.nn.sigmoid_cross_entropy_with_logits(labels=z, logits=x)` is

$$z * -\log(\text{sigmoid}(x)) + (1 - z) * -\log(1 - \text{sigmoid}(x)),$$

therefore `x` has to be a raw prediction data.

```

prob_loss = respond_bbox * tf.nn.sigmoid_cross_entropy_with_logits(labels=label_prob, logits=
↪ conv_raw_prob)

giou_loss = tf.reduce_mean(tf.reduce_sum(giou_loss, axis=[1,2,3,4]))
conf_loss = tf.reduce_mean(tf.reduce_sum(conf_loss, axis=[1,2,3,4]))
prob_loss = tf.reduce_mean(tf.reduce_sum(prob_loss, axis=[1,2,3,4]))

return giou_loss, conf_loss, prob_loss

```

**End of Function**

## 4 train.py

**Recap of Customized Training Loop with GradientTape.** Apart from predefined loss functions (such as `categorical_crossentropy` for classification, `mse` for regression, etc), it is occasional to come across non-standard loss functions from other repository with the use of `tf.GradientTape`.

Such implementation usually create 4 components:

**Component 1.** The model **architecture**

**Component 2.** The **loss function** used when computing the model loss

**Component 3.** The **optimizer** used to update the model weights

**Component 4.** The **step function** that encapsulates the forward and backward pass of the network

Now the code below is self-explanatory:

```

def train_step(image_data, target, epoch):

    # image_data = batch of images

    with tf.GradientTape() as tape:
        pred_result = model(image_data, training=True)
        giou_loss = conf_loss = prob_loss = 0

        # optimizing process
        for i in range(3):
            conv, pred = pred_result[i*2], pred_result[i*2+1]
            batch_label, batch_bboxes = target[i]
            loss_items = compute_loss(pred, conv, batch_label, batch_bboxes, i)
            giou_loss += loss_items[0]
            conf_loss += loss_items[1]
            prob_loss += loss_items[2]

        total_loss = giou_loss + conf_loss + prob_loss

        gradients = tape.gradient(total_loss, model.trainable_variables)
        optimizer.apply_gradients(zip(gradients, model.trainable_variables))

        # update learning rate
        global_steps.assign_add(1)
        if global_steps < warmup_steps:
            lr = global_steps / warmup_steps * cfg.TRAIN.LR_INIT
        else:
            lr = cfg.TRAIN.LR_END + 0.5 * (cfg.TRAIN.LR_INIT - cfg.TRAIN.LR_END) * (
                1 + tf.cos((global_steps - warmup_steps) / (total_steps - warmup_steps) * np.pi))
            )
        optimizer.lr.assign(lr.numpy())

        # writing summary data
        with writer.as_default():
            tf.summary.scalar("lr", optimizer.lr, step=global_steps)
            tf.summary.scalar("loss/total_loss", total_loss, step=global_steps)
            tf.summary.scalar("loss/giou_loss", giou_loss, step=global_steps)
            tf.summary.scalar("loss/conf_loss", conf_loss, step=global_steps)
            tf.summary.scalar("loss/prob_loss", prob_loss, step=global_steps)
        writer.flush()

```



```
for epoch in range(cfg.TRAIN.EPOCHS):
    for index, (image_data, target) in enumerate(trainset):
        train_step(image_data, target, epoch)

    model.save_weights("./checkpoints/yolov3-{}-{}.h5".format(cfg.WEIGHT_NAME_TO_SAVE, epoch))
```

## References

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- [3] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He and Piotr Dollar, *Focal Loss for Dense Object Detection*, [https://arxiv.org/pdf/1708.02002.pdf?fbclid=IwAR38T65chVOUNPhBDbaExH021\\_afCOL6o9PEztpBPBAzqY3dBR8v0Gy2qwg](https://arxiv.org/pdf/1708.02002.pdf?fbclid=IwAR38T65chVOUNPhBDbaExH021_afCOL6o9PEztpBPBAzqY3dBR8v0Gy2qwg).
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- [5] Adrian Rosebrock, *Using TensorFlow and GradientTape to train a Keras model*, <https://www.pyimagesearch.com/2020/03/23/using-tensorflow-and-gradienttape-to-train-a-keras-model/>