YOLOv3 Study Notes

Ching-Cheong Lee

March 2, 2021

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 ... " % imagparse_annotation

        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 straightfoward. **_End_ of Function**

```
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 $= (c_x, c_y, \text{width}, \text{height})$, therefore

$$\texttt{boxes[...,:2]} - \texttt{boxes[...,2:]} * 0.5 = \texttt{[all upper-left corners]}$$

and

$$\texttt{boxes1[..., :2]} + \texttt{boxes1[..., 2:]} * 0.5 = \texttt{[all lower-right corners]},$$

while concatenating $(2,)$ np-array along the last axis simpliy means combing 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 13×13, 26×26, 52×52 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 anothoer $(3,4)$ array, and theirfore, 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

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

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**

2 yolov3.py

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

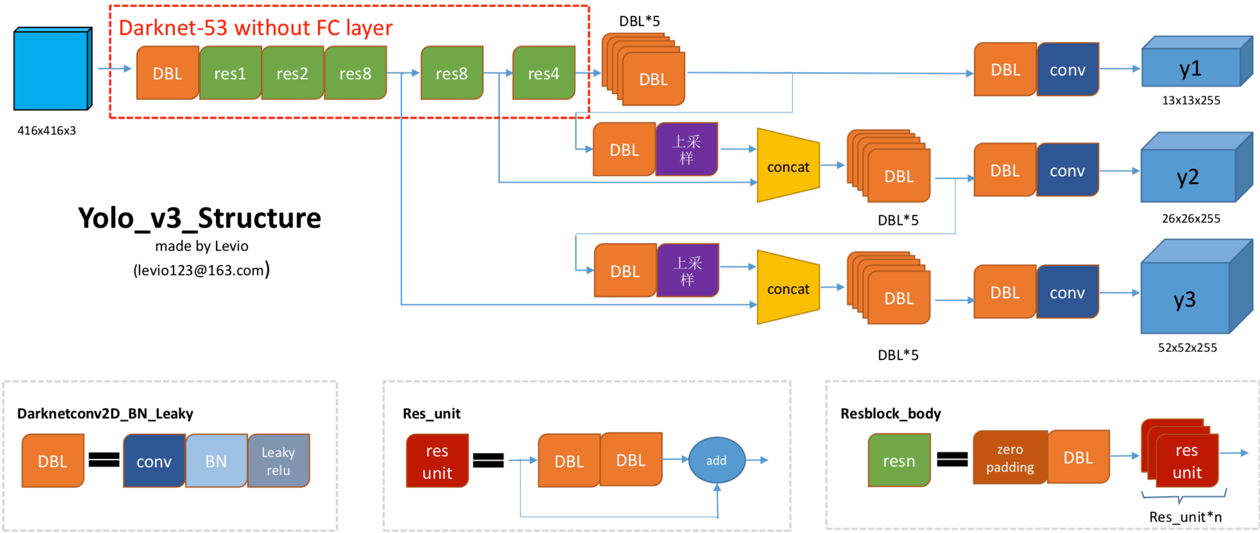


Figure 1: Structure of YOLOv3

$$\texttt{route\_1.shape} = (-1, 52, 52, 256)$$

$$\texttt{route\_2.shape} = (-1, 26, 26, 512)$$

$$\texttt{conv.shape} = (-1, 13, 13, 1024)$$

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 $(-1, \texttt{output\_size}, \texttt{output\_size}, 3, 85)$ 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]]
```

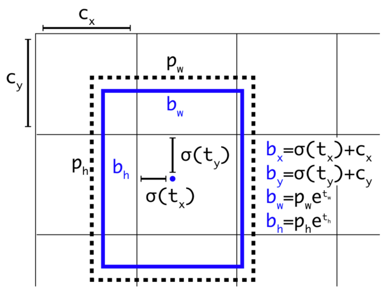
For x and y we expand dimension again along the last axis (break every single element into a bracketed element) before concatenation:

```
    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:]
```

```python
    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 $U, V \in \mathscr{C}$, where $\mathscr{C} \in 2^{\mathbb{R}^2}$, the function $d(U, V) := 1 - \mathrm{giou}(U, V)$ defines a metric, so `giou_loss` makes sense.

```python
    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

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

and

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

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"

```python
    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.

```python
    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-classificed (high confidence) examples.

```python
    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(sigmoid(x)) + (1 - z) * -log(1 - sigmoid(x)),`

therefore x has to be a raw prediction data.

```python
    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_crossentrop` for classfication, `mse` for regression, etc), it is ocassional 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

[1] *YOLOv3 源码解析 1-5*, `https://blog.csdn.net/sxlsxl119/article/details/103028021`.

[2] *YOLOv3 算法的一点理解*, `https://yunyang1994.gitee.io/2018/12/28/YOLOv3/`.

[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=IwAR38T65chV0UNPhBDbAExH021_afC0L6o9PEztpBPBAzqY3dBR8v0Gy2qwg.

[4] Joseph Redmon, Ali Farhadi, YOLOv3: *An Incremental Improvement*, https://arxiv.org/abs/1804.02767.

[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/