

# CS\_IOC5008\_0856043\_HW2 Report

[Github link](#)

## Brief introduction

### 1. Development environment

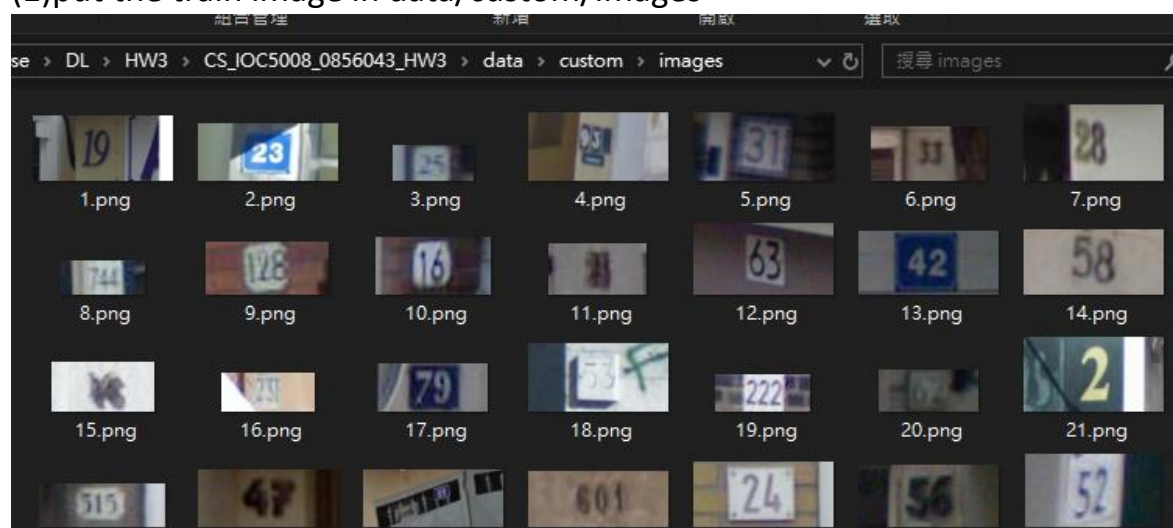
Python version : 3.7.4

Framework : Pytorch

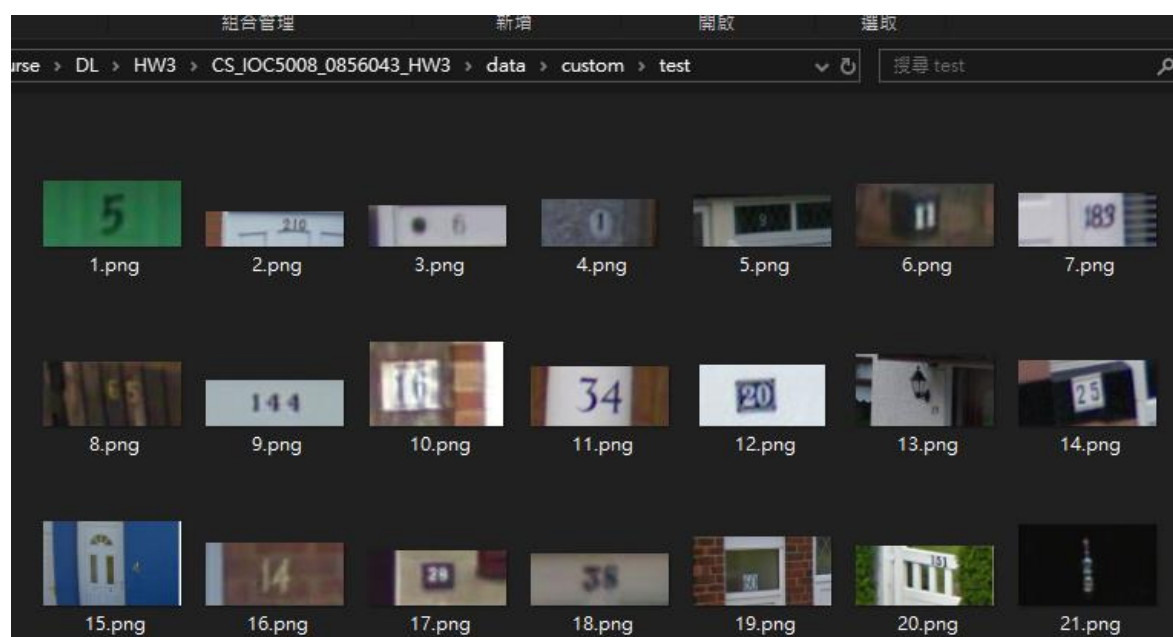
Hardware : NVIDIA GeForce GTX 1080 Ti 11GB

### 2. How to run the code.

(1)put the train image in data/custom/images



(2)put the test images in data/custom/test

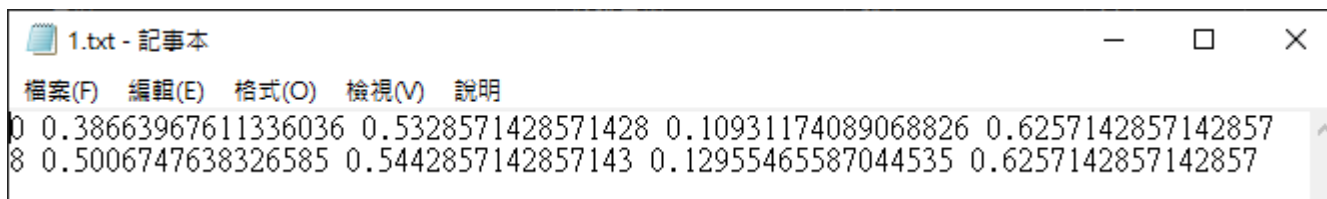
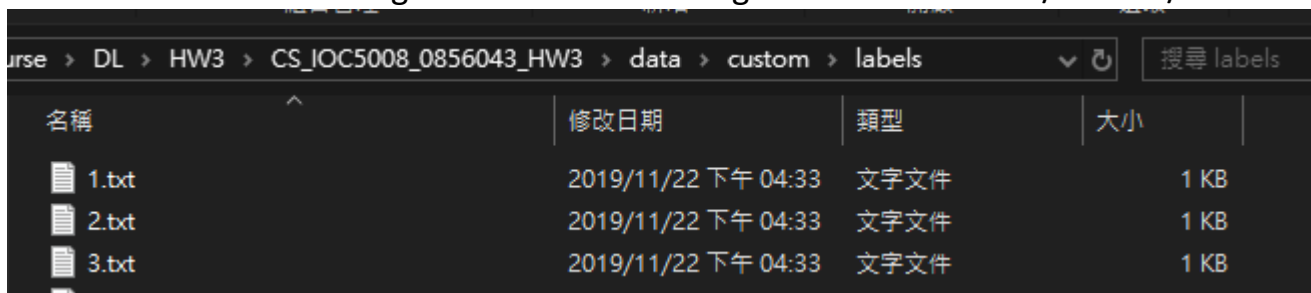


(3) analysis the digitStruct.mat file.

Run data/custom/parsedata.py

```
parsedata.py
128 def makeTxt():
129     dsFileName = './digitStruct.mat'
130     testCounter = 0
131     for dsObj in yieldNextDigitStruct(dsFileName):
132
133         fp = open("./labels/"+dsObj.name[:-4]+'.txt', "a")
134         im=Image.open('./images/'+dsObj.name)
135         x = im.size[0]
136         y = im.size[1]
137         for bbox in dsObj.bboxList:
138
139             fp.write("{} {} {} {} {}{}\n".format(
140                 bbox.label-1, bbox.left/x+bbox.width/(2*x), bbox.top/y+bbox.height/(2*y), bbox.width/x, bbox.height/y))
141         fp.close()
142         if testCounter >= 5:
143             break
144         print('done')
```

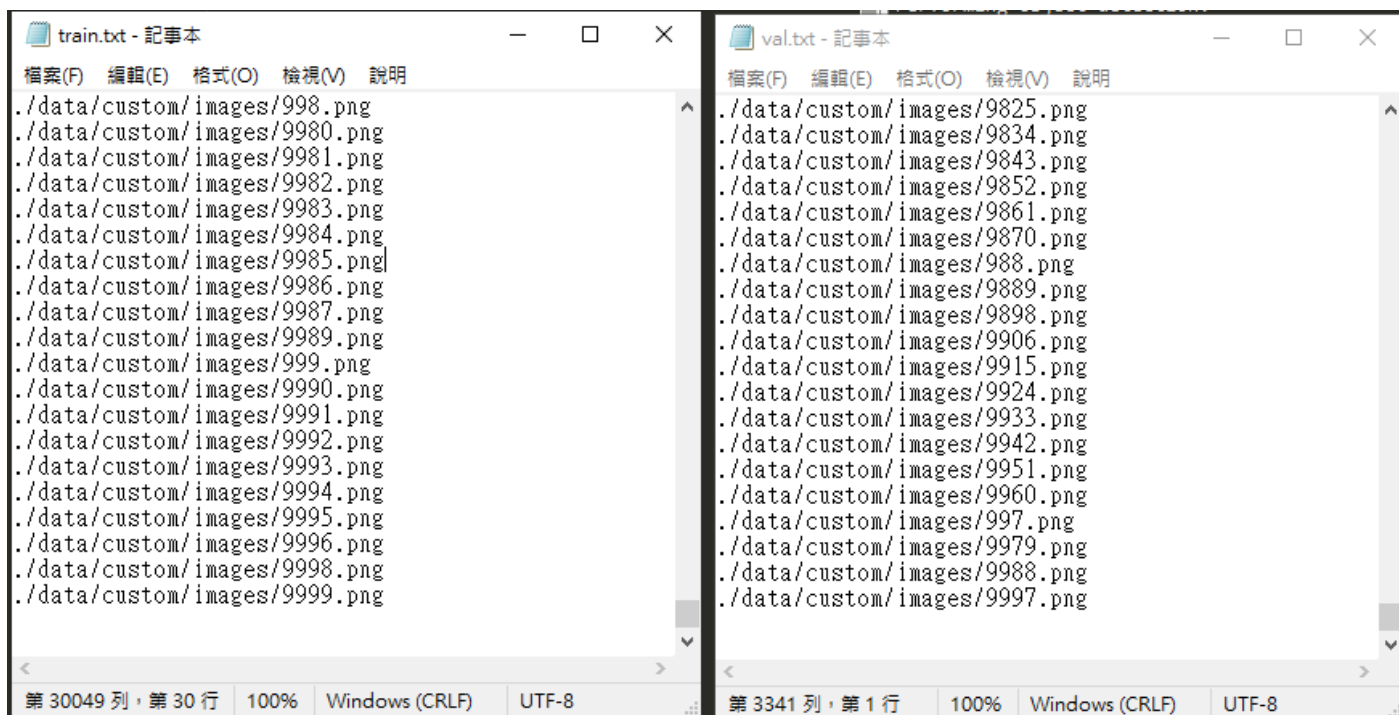
It will make each test images one txt file for the ground-truth in data/custom/labels.



(4)Spilt the train data using maketxt.py

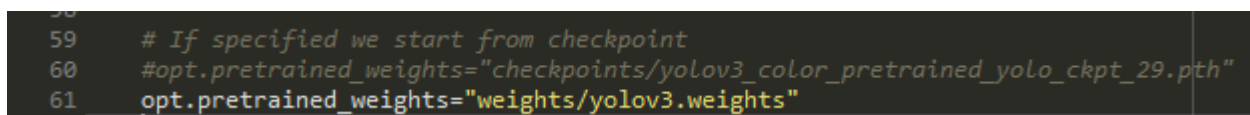
It will store 90% data in data/custom/train.txt for train-set and 10% in data/custom/val.txt for validation-set.

```
maketxt.py
1 import glob
2 import os
3 import numpy as np
4 import sys
5 current_dir = "./data/custom/images"
6 split_pct = 10 # 10% validation set
7 file_train = open("data/custom/train.txt", "w")
8 file_val = open("data/custom/val.txt", "w")
9 counter = 1
10 index_test = round(100 / split_pct)
11 for fullpath in glob.iglob(os.path.join(current_dir, "*.png")):
12     title, ext = os.path.splitext(os.path.basename(fullpath))
13     if counter == index_test:
14         counter = 1
15         file_val.write(current_dir + "/" + title + '.png' + "\n")
16     else:
17         file_train.write(current_dir + "/" + title + '.png' + "\n")
18         counter = counter + 1
19 file_train.close()
20 file_val.close()
```

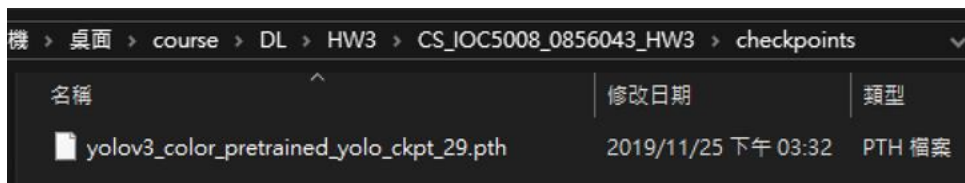


## (5)Run train.py

Change the pretrained\_weights to train from the pretrained network.



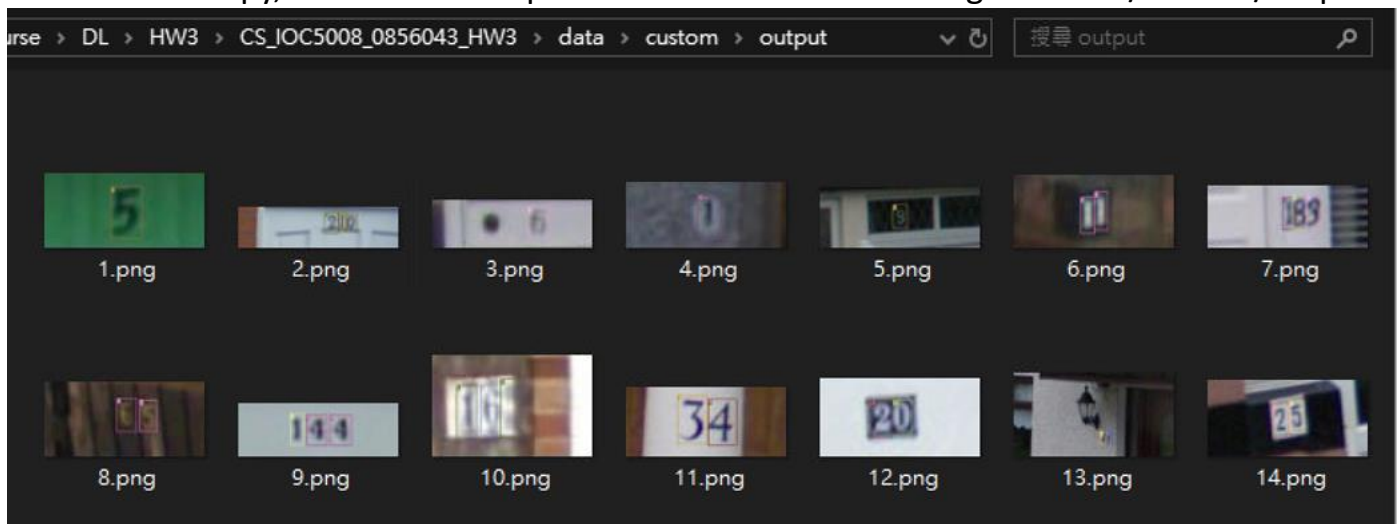
And then run this file

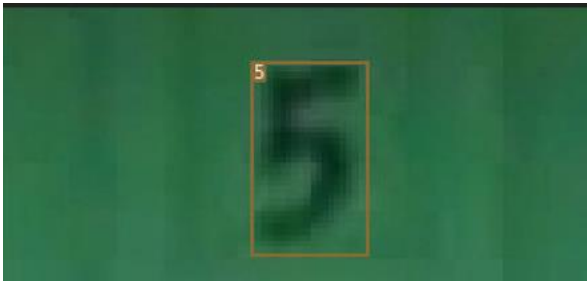


After train, it will create .pth file and we can do some test or predict the result.

## (6)detect

Run the detect.py, it will draw the predict result on the test images in data/custom/output





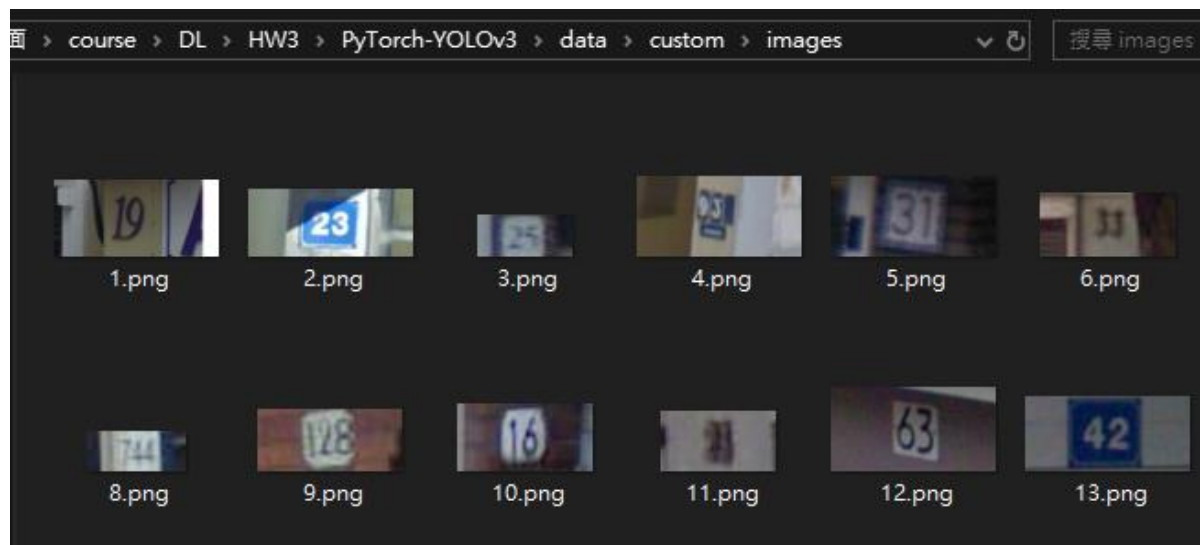
### (7)Print Json

Run printjson.py and it will create the result that dump into the json form in data/custom/0856043\_.json

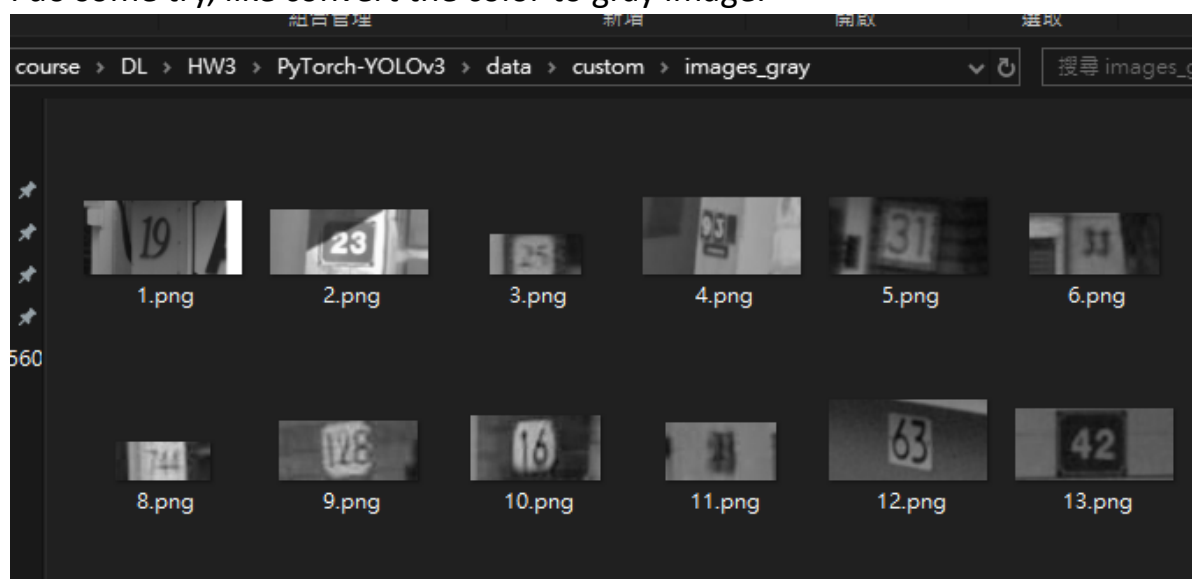
```
0856043_.json x
1 [
2   {
3     "bbox": [
4       [
5         9,
6         41,
7         41,
8         60
9       ]
10    ],
11    "label": [
12      5
13    ],
14    "score": [
15      0.998767614364624
16    ]
17  },
18 ]
```

# Methodology

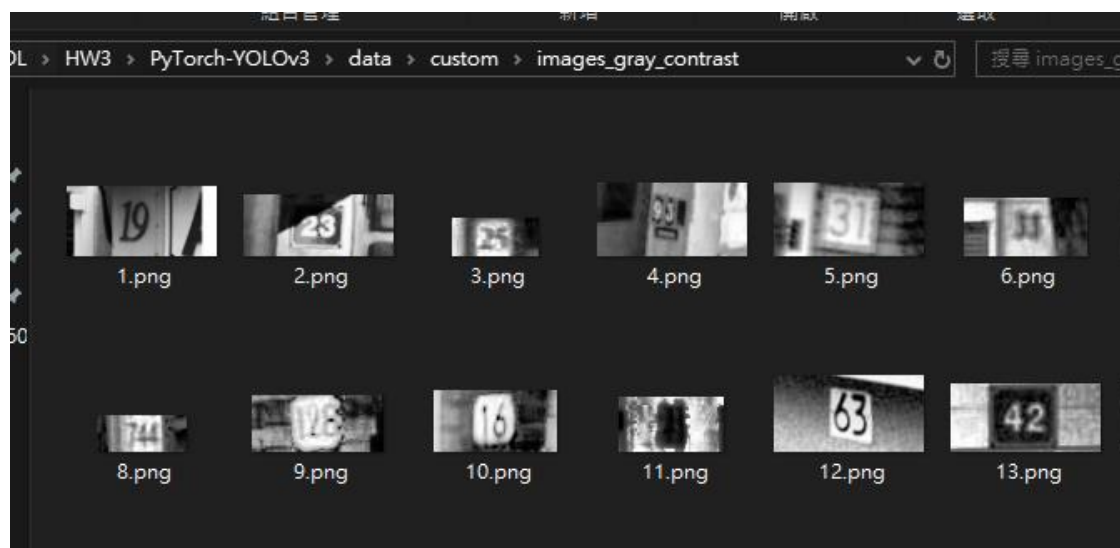
## 1. Data preprocess



I do some try, like convert the color to gray image.



And increase the contrast.





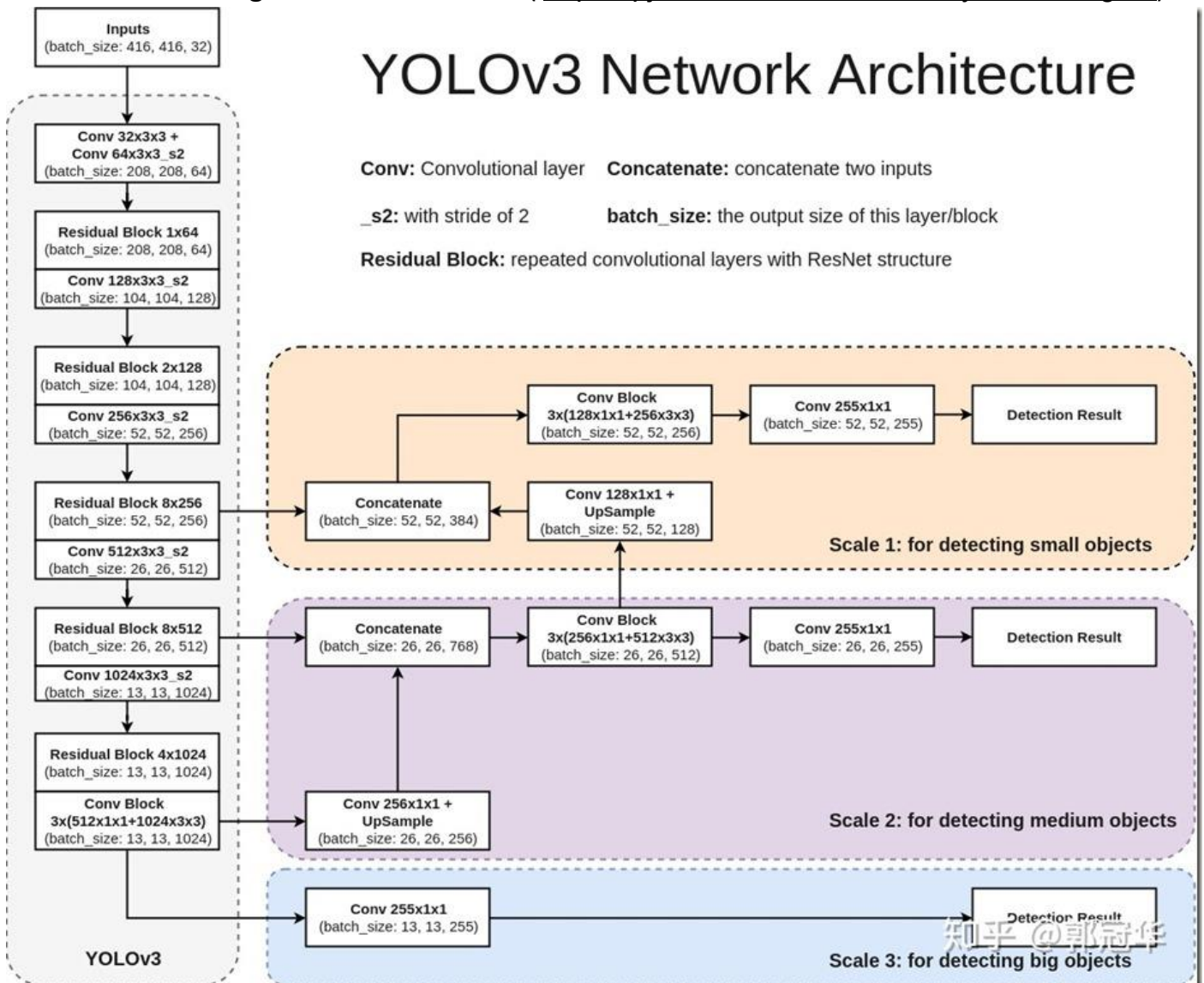
But they don't increase the mAP, so I just use the original images.  
And also use do some random flip.

```
# Apply augmentations
if self.augment:
    if np.random.random() < 0.5:
        img, targets = horizontal_flip(img, targets)
```

## 2. Models

I use yolov3 as my model.

Pre-trained on imagenet+Coco datasets.( <https://pjreddie.com/media/files/yolov3.weights>)



Compare to yolov2, version 3 use 3 different feature (13\*13, 26\*26, 52\*52) to detect big, medium, and small objects.

### 3. Hyperparameters

Image size: 416\*416

Loss function: binary cross-entropy loss

Output activation: Logistic loss

Base model: ResNet

Darknet model: darknet-53

learning\_rate: 0.001

batch\_size: 8

epochs: 30

## Model speed benchmark

Upload my weight and test code into Colab.

```
[32] imgs = [] # Stores image paths
img_detections = [] # Stores detections for each image index
total_times=0
print("\nPerforming object detection:")
prev_time = time.time()
for batch_i, (img_paths, input_imgs) in enumerate(dataloader):
    # Configure input
    input_imgs = Variable(input_imgs.type(Tensor))
    # Get detections
    with torch.no_grad():
        detections = model(input_imgs)
        detections = non_max_suppression(detections, conf_thres, nms_thres)
    # Log progress
    current_time = time.time()
    inference_time = datetime.timedelta(seconds=current_time - prev_time)
    time_v = current_time - prev_time
    prev_time = current_time
    print("\t+ Batch %d, Inference Time: %s" % (batch_i, inference_time))
    total_times += time_v

    # Save image and detections
    imgs.extend(img_paths)
    img_detections.extend(detections)

print("average time:", total_times/200)
```

Test for 200 images

```
+ Batch 189, Inference Time: 0:00:00.027554
+ Batch 190, Inference Time: 0:00:00.029346
+ Batch 191, Inference Time: 0:00:00.027081
+ Batch 192, Inference Time: 0:00:00.027916
+ Batch 193, Inference Time: 0:00:00.030166
+ Batch 194, Inference Time: 0:00:00.027901
+ Batch 195, Inference Time: 0:00:00.027860
+ Batch 196, Inference Time: 0:00:00.027483
+ Batch 197, Inference Time: 0:00:00.029546
+ Batch 198, Inference Time: 0:00:00.027969
+ Batch 199, Inference Time: 0:00:00.027547
average time: 0.029423400163650512
```

Average time=29.4ms

Test for 100 images

```
+ Batch 92, Inference Time: 0:00:00.028591
+ Batch 93, Inference Time: 0:00:00.030214
+ Batch 94, Inference Time: 0:00:00.028774
+ Batch 95, Inference Time: 0:00:00.028023
+ Batch 96, Inference Time: 0:00:00.028052
+ Batch 97, Inference Time: 0:00:00.028789
+ Batch 98, Inference Time: 0:00:00.026763
+ Batch 99, Inference Time: 0:00:00.028151
average time: 0.0297226619720459
```

Average time=29.7ms

Test for 1000 images

```
+ Batch 991, Inference Time: 0:00:00.033592
+ Batch 992, Inference Time: 0:00:00.028442
+ Batch 993, Inference Time: 0:00:00.027667
+ Batch 994, Inference Time: 0:00:00.027280
+ Batch 995, Inference Time: 0:00:00.027413
+ Batch 996, Inference Time: 0:00:00.028444
+ Batch 997, Inference Time: 0:00:00.027150
+ Batch 998, Inference Time: 0:00:00.028098
+ Batch 999, Inference Time: 0:00:00.028050
average time: 0.028286385536193847
```

Average time=28.2ms

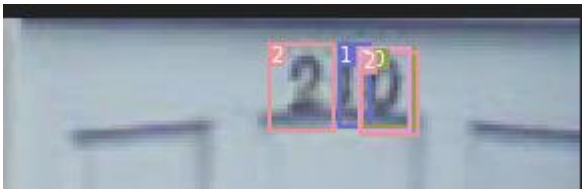


# Findings

I think this task is very difficult because the image has some many other things that we don't want to predict.

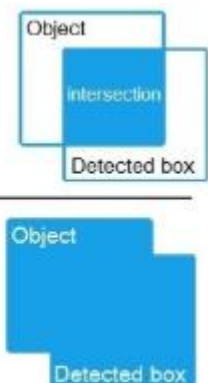


And it also very easy to predict overlapping.

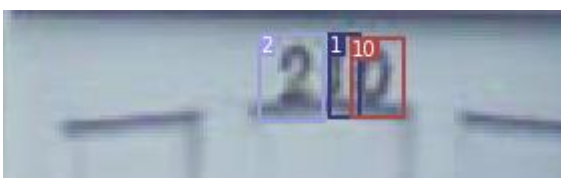


So I also do some work to prevent this thing happened.

I use the concept of IOU.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$


When the bounding-box that have a big confident, we can delete the other when IOU value greater than some threshold.



Here is the result.

But things got weird, when I use this idea in the whole prediction, the score of using IOU is always worse than not doing anything...

|                                      |            |
|--------------------------------------|------------|
| gray contrast                        | 0.38461    |
| gray contrast count iou              | 0.37262    |
| color pretrained_darknet iou         | 0.42054    |
| color pretrained_darknet             | 0.42929    |
| gray contrast pretrained_darknet     | 0.39479    |
| gray contrast pretrained_darknet iou | 0.38529    |
| color pretrained_yolov3 9            | 0.44315    |
| color pretrained_yolov3 9 iou        | 0.43667    |
| color pretrained_yolov3 19           | 0.45788    |
| color pretrained_yolov3 19 iou       | 0.45259    |
| color pretrained_yolov3 29           | (1)0.46305 |
| color pretrained_yolov3 29 iou       | 0.45732    |

Here is my grade records. The scores that using iou method to delete overlapping objects always get about 1% lower than original.

## Reference

[Yolov3-pytorch-implement](#)

[Train Yolo on my dataset\(Medium article\)](#)

[Yolov3 explain\(Chinese\)](#)

[Yolo website](#)