

# Object Detection

Team 14

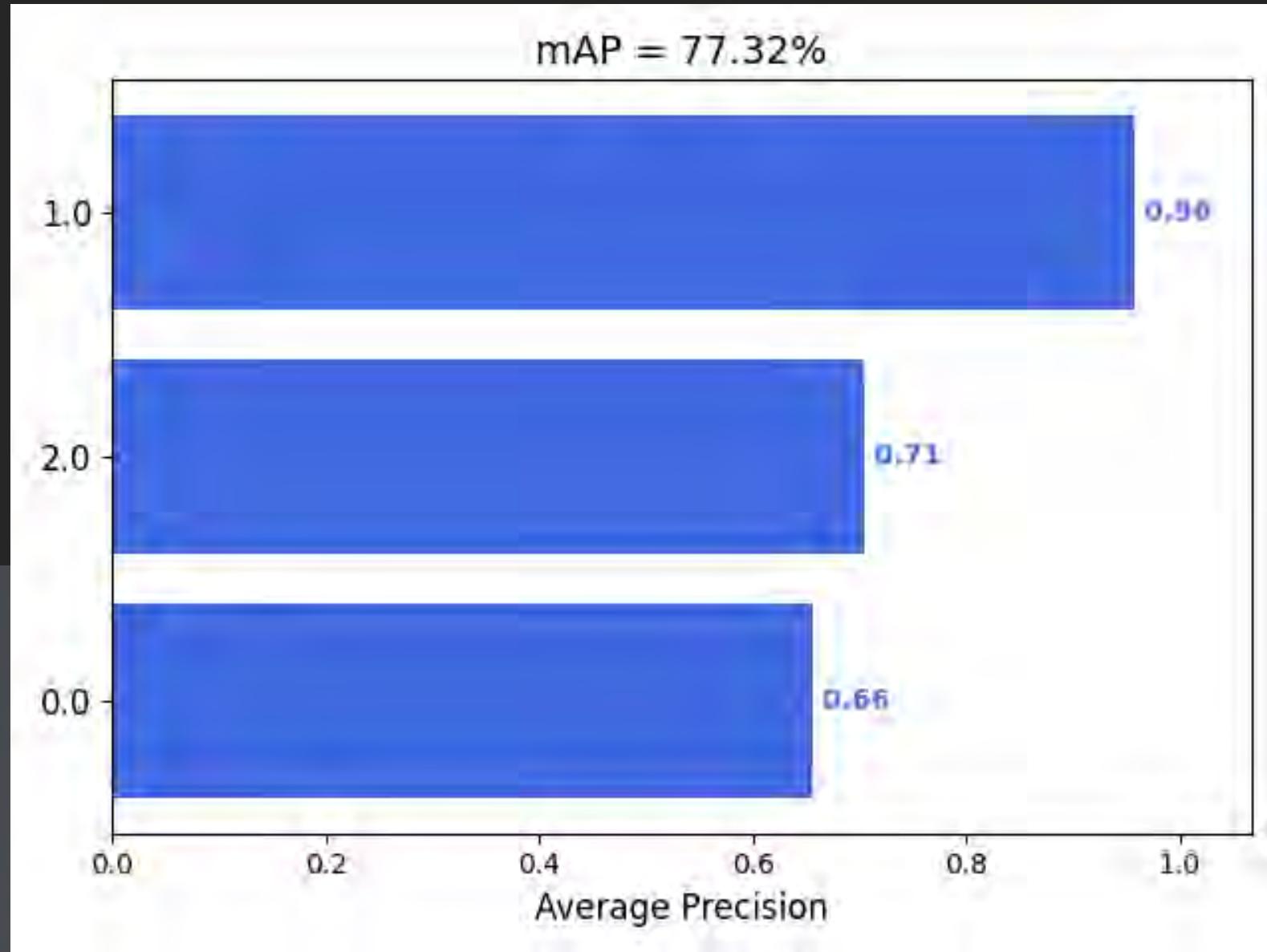
*PPT editor: Kong Yifei*

*respondent: Dai Liu*

Presentation

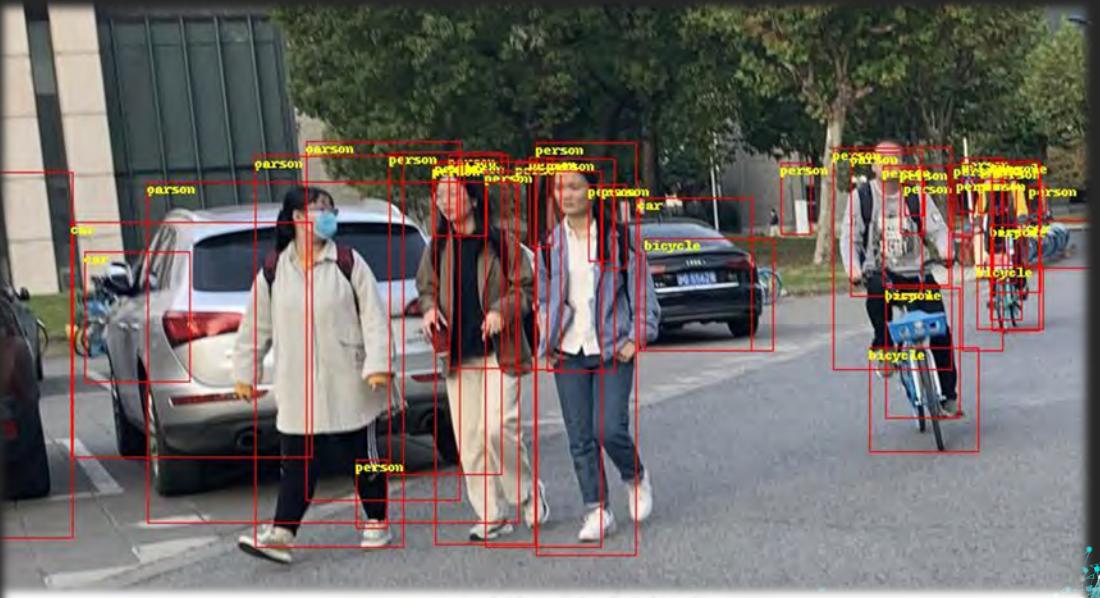
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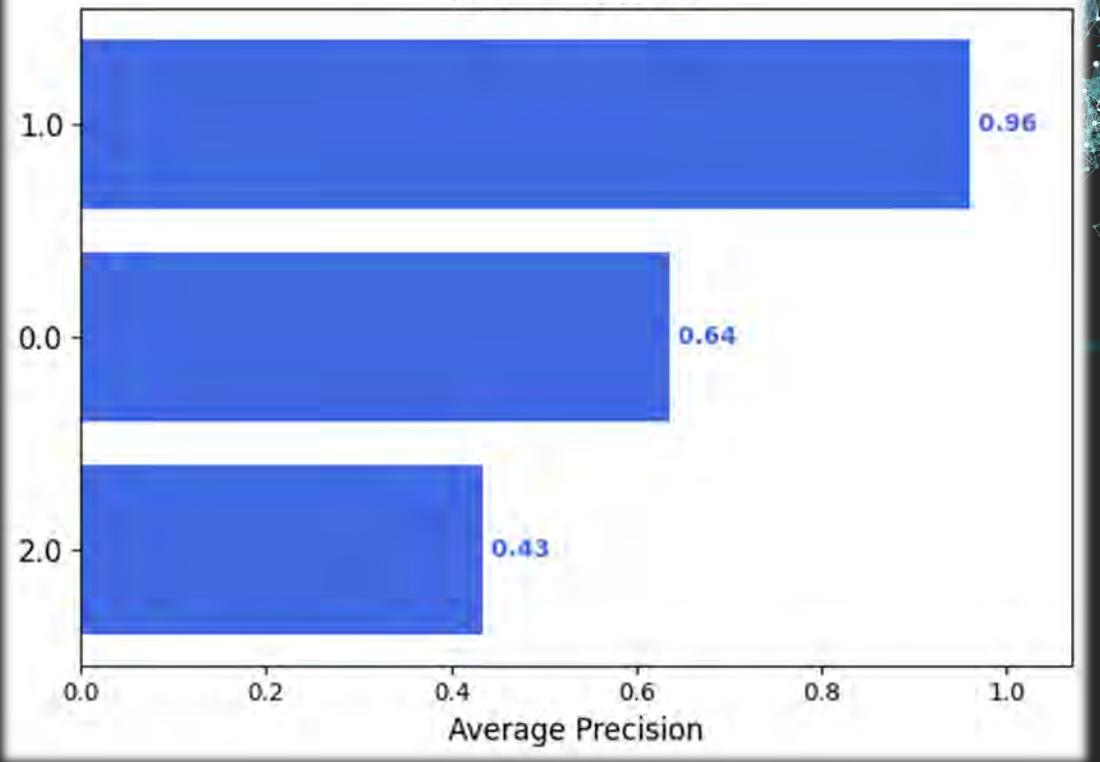


End

After about two week's  
hard work, we have  
achieved something  
amazing!



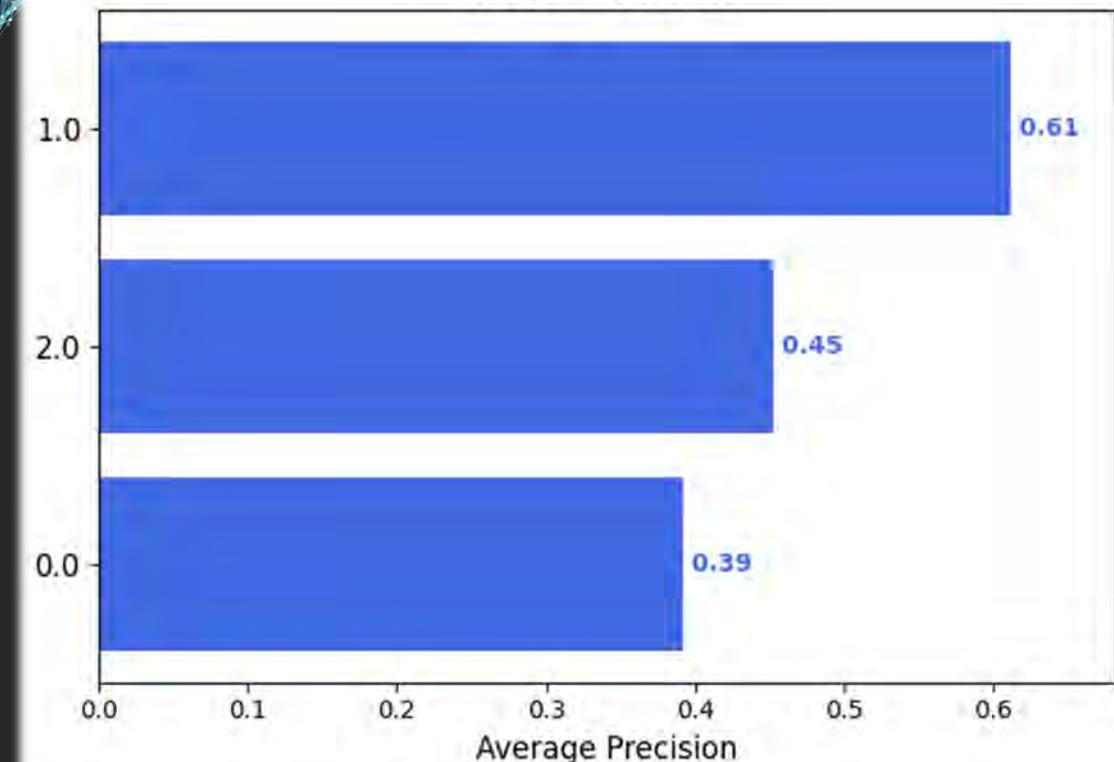
mAP = 67.69%



VS



mAP = 48.53%



Balance

# Division



- **Kong Yifei / Wang Shangyou / Jiang Xingyu:**
  - collecting and the produce of dataset
- **Tian Yu / Fan Qianhui:**
  - transformation of data formats and coding optimization
- **Gao Zhicheng:** algorithms optimization
- **Dai Liu:** algorithms optimization and co-ordination



# Optimization we have done

- Dataset
- Hyperparameter
- Structure
- Contrast

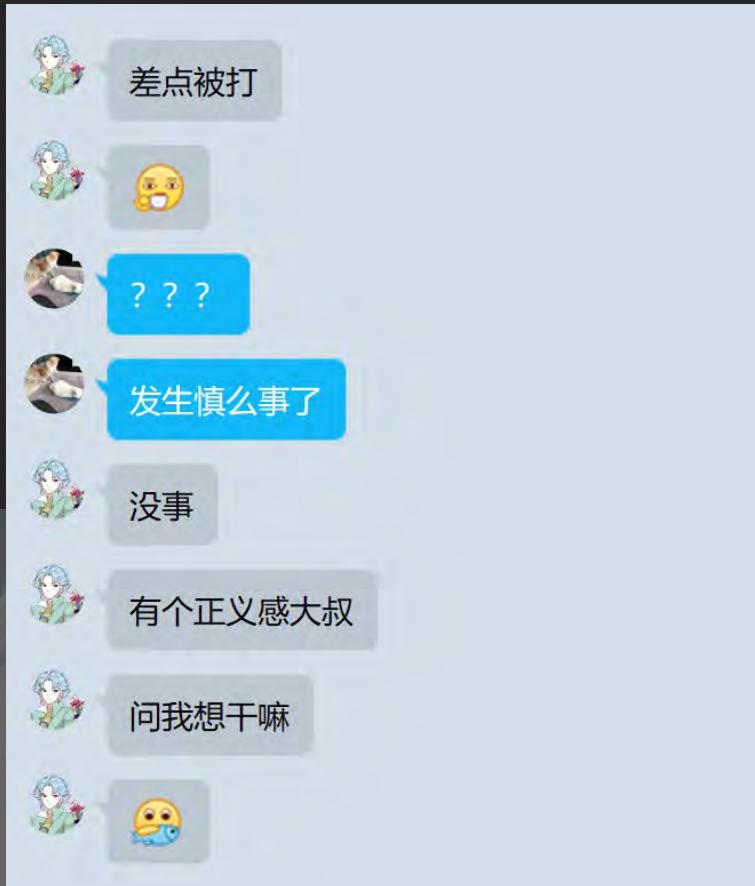


# Dataset Optimization

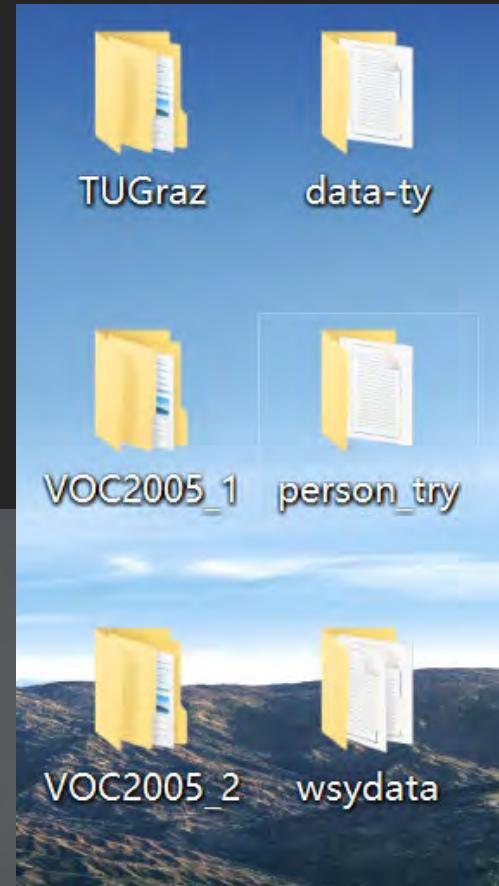
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## Part1

- Collect data in campus
- Pascal Voc
- Data cleaning



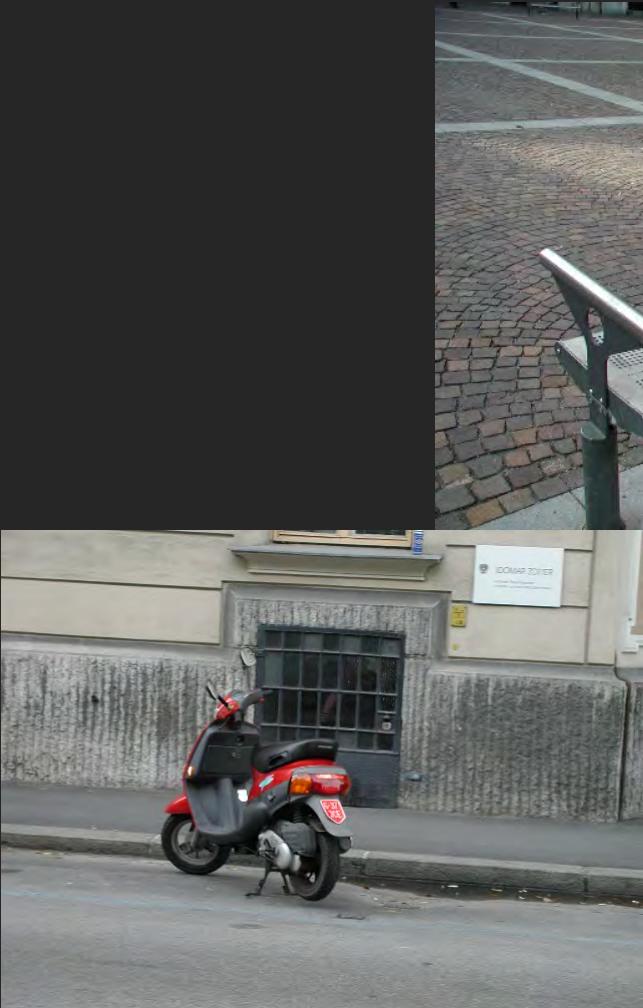
## Part2



# Dataset Optimization

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- To tackle the problem of misrecognition of the windows/trees/...
- we feed our model some ‘negative samples’

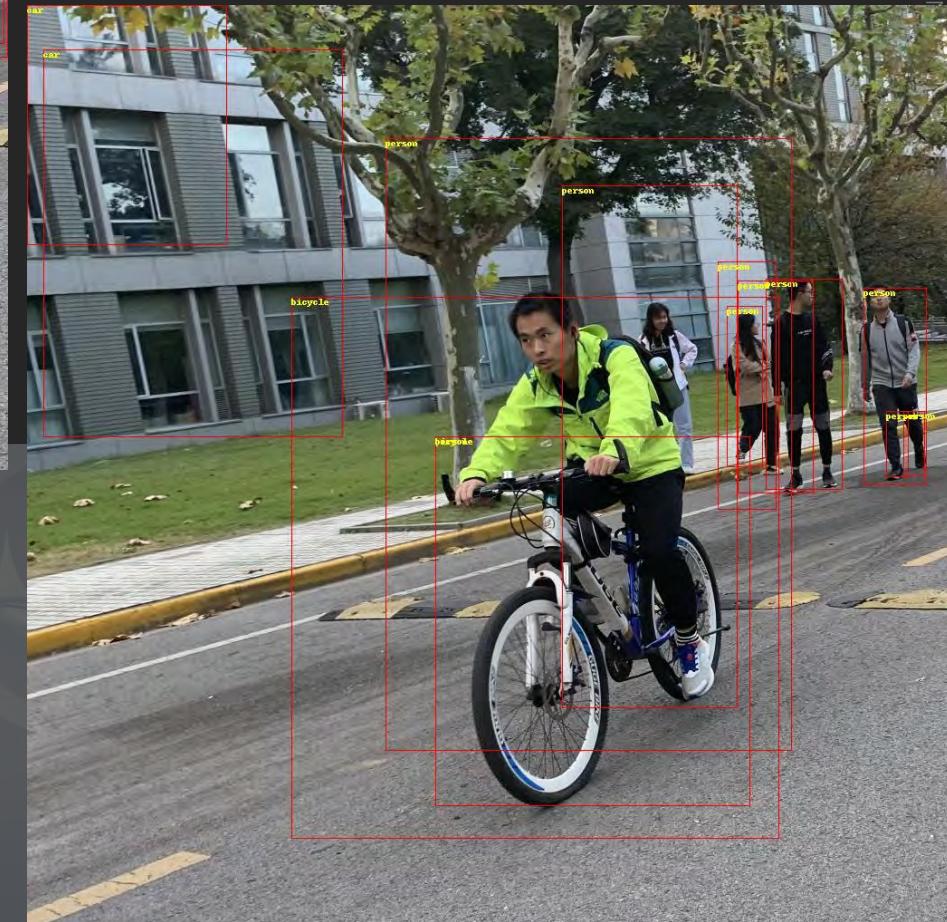


# Hyperparameter

- nms threshold  
(non-maximum suppression)

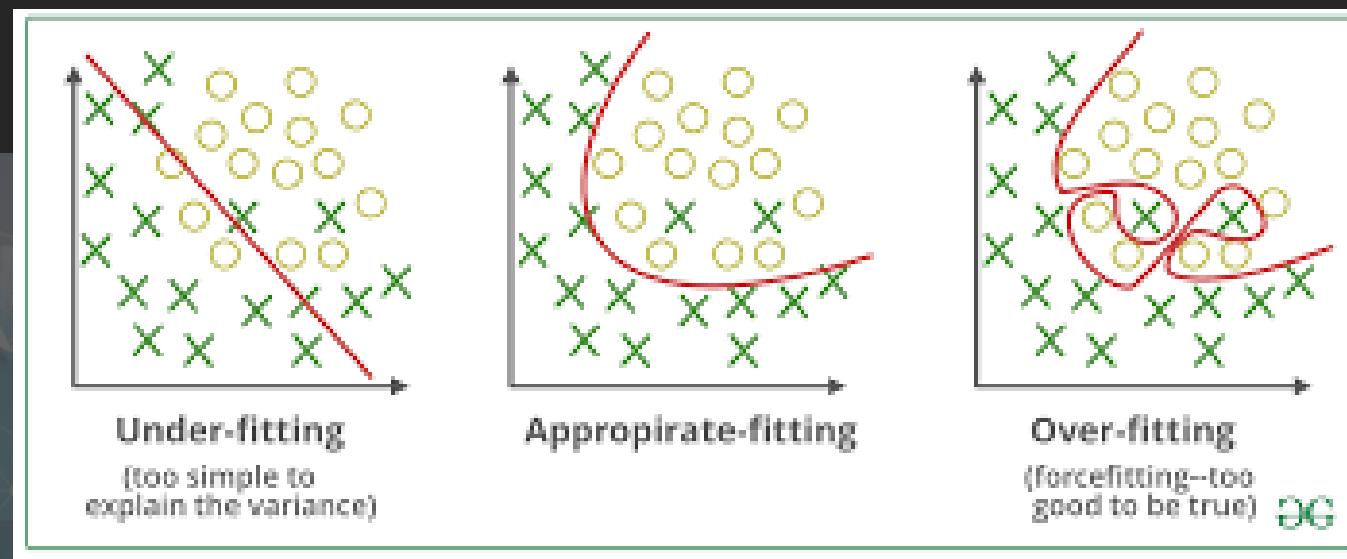
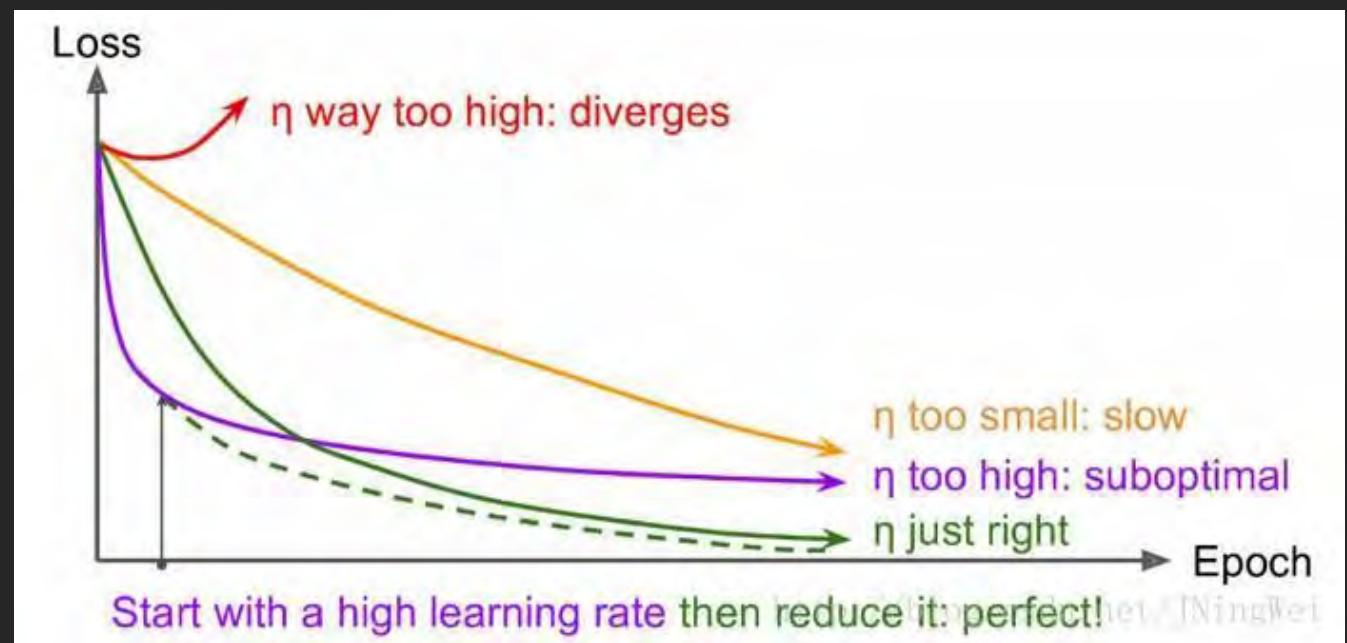


Low threshold



# Hyperparameter

- Learning rate
- Regularization



# Structure Optimization

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```
def cpu_soft_nms(np.ndarray[float, ndim=2] boxes, float sigma=0.5, float Nt=0.3, float threshold=0.001, unsigned int method=0):
    cdef unsigned int N = boxes.shape[0]
    cdef float iw, ih, box_area
    cdef float ua
    cdef int pos = 0
    cdef float maxscore = 0
    cdef int maxpos = 0
```

Method	AP	AP@0.5	area	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
[24]+NMS	37.7	70.0	37.8	44.6	34.7	24.4	23.4	50.6	50.1	45.1	25.1	42.6	36.5	40.7	46.8	39.8	38.2	17.0	37.8	36.4	43.7	<b>38.9</b>
[24]+S-NMS G	<b>39.4</b>	71.2	40.2	<b>46.6</b>	<b>36.7</b>	25.9	<b>24.9</b>	<b>51.9</b>	51.6	<b>48.0</b>	<b>25.3</b>	44.5	<b>37.3</b>	42.6	<b>49.0</b>	42.2	41.6	17.7	39.2	<b>39.3</b>	<b>45.9</b>	37.5
[24]+S-NMS L	<b>39.4</b>	71.2	<b>40.3</b>	<b>46.6</b>	36.3	<b>27.0</b>	24.2	51.2	<b>52.0</b>	47.2	<b>25.3</b>	<b>44.6</b>	37.2	<b>45.1</b>	48.3	<b>42.3</b>	<b>42.3</b>	<b>18.0</b>	<b>39.4</b>	37.1	45.0	38.7
[16]+NMS	49.8	79.4	52.8	54.4	47.1	37.6	38.1	63.4	59.4	62.0	35.3	56.0	38.9	59.0	54.5	50.5	47.6	24.8	53.3	52.2	57.4	52.7
[16]+S-NMS G	51.4	<b>80.0</b>	<b>53.8</b>	<b>56.0</b>	48.3	39.9	39.4	<b>64.7</b>	61.3	64.7	<b>36.3</b>	<b>57.0</b>	<b>40.2</b>	60.6	55.5	52.1	<b>50.7</b>	<b>26.5</b>	53.8	53.5	59.3	53.8
[16]+S-NMS L	<b>51.5</b>	<b>80.0</b>	53.2	55.8	<b>48.9</b>	<b>40.0</b>	<b>39.6</b>	64.6	<b>61.5</b>	<b>65.0</b>	<b>36.3</b>	56.5	<b>40.2</b>	<b>61.3</b>	<b>55.6</b>	<b>52.9</b>	50.3	26.2	<b>54.3</b>	<b>53.6</b>	<b>59.5</b>	<b>53.9</b>

Table 2. Results on Pascal VOC 2007 test set for off-the-shelf standard object detectors which use NMS as baseline and our proposed Soft-NMS method. Note that COCO-style evaluation is used.

```
tx2 = boxes[i,2]
ty2 = boxes[i,3]
ts = boxes[i,4]

pos = i + 1
# get max box
while pos < N:
    if maxscore < boxes[pos, 4]:
        maxscore = boxes[pos, 4]
        maxpos = pos
```

- Vertical
- Horizontal



## Vertical Contrast

During the whole process, we have totally train over 10 models with different hyperparameter setting or structure optimization. Finally, we got the best .



📁 V1-12.24 52%	2020/12/26 11:09	文件夹
📁 V2-12.24 48.53%	2020/12/26 11:08	文件夹
📁 V3-12.25 68.03%	2020/12/25 18:36	文件夹
📁 V4-12.25 71.33%	2020/12/26 21:07	文件夹
📁 V5-12.26 28.99%	2020/12/26 11:02	文件夹
📁 V5-TMP 30%	2020/12/26 11:04	文件夹
📁 V6-12.26 65%	2020/12/26 13:32	文件夹
📁 V7-12.26 67% 人增强, 自行车--	2020/12/26 18:55	文件夹
📁 V8-基于V4 人++, 自行车--	2020/12/26 19:14	文件夹
📁 V9-基于V8 70.4%	2020/12/26 19:24	文件夹
📁 V10-加入none数据 77.32%	2020/12/27 20:06	文件夹

# Contrast

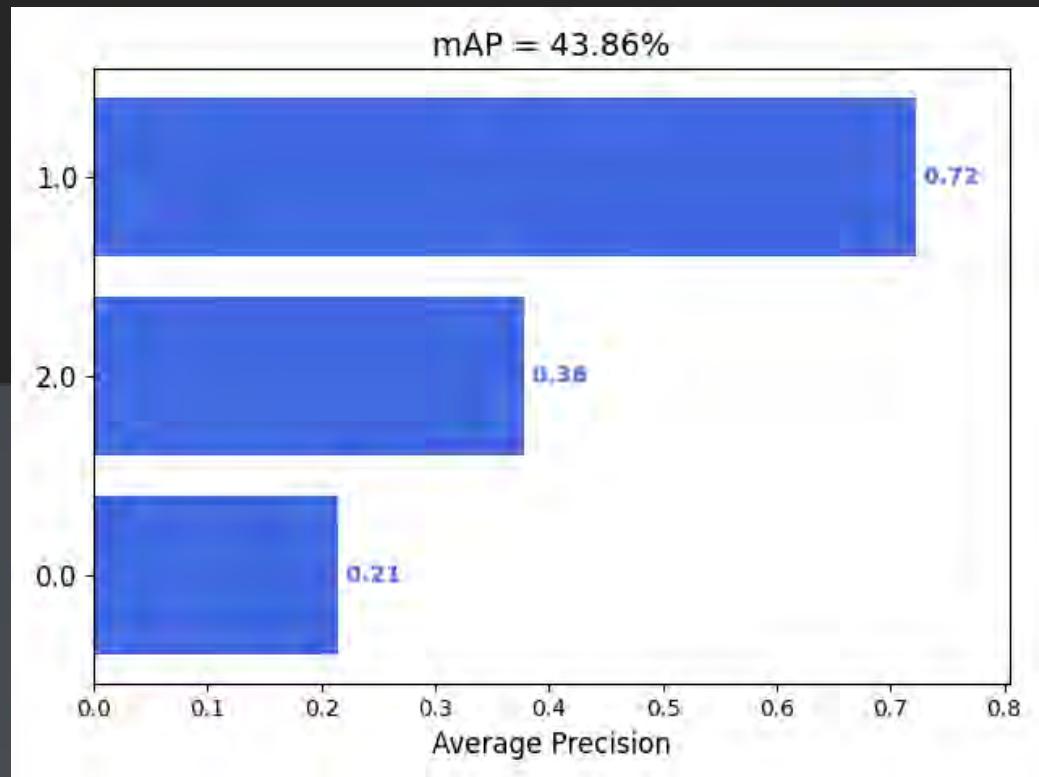
- Vertical
- Horizontal

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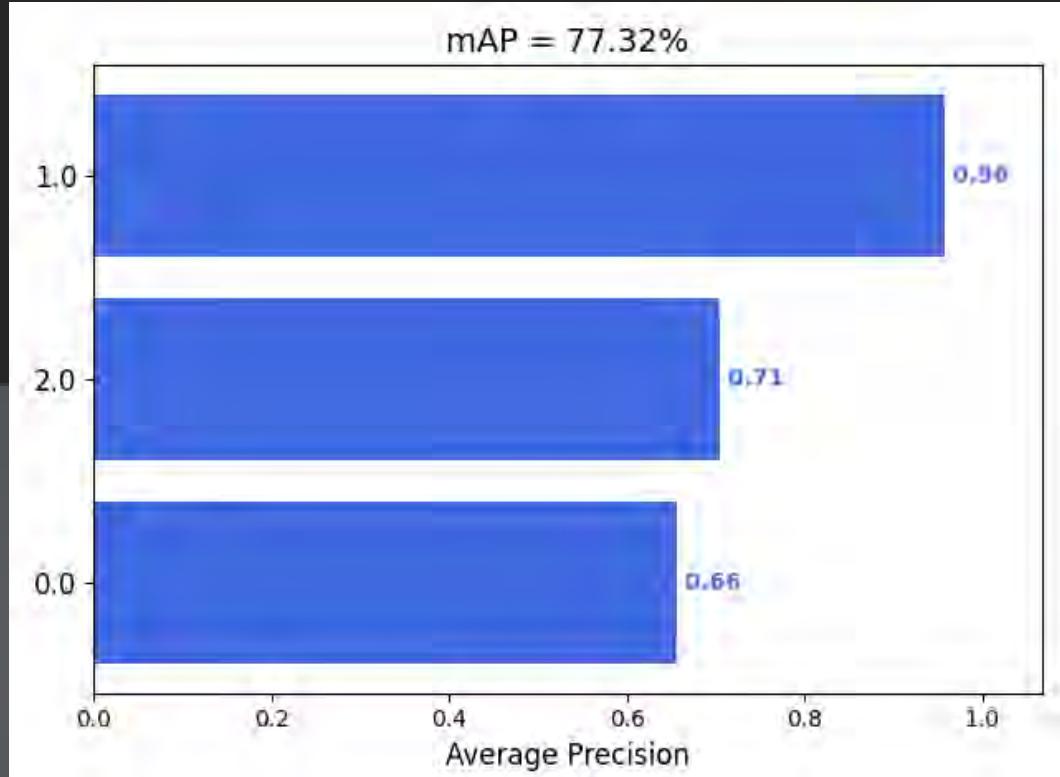
## Horizontal Contrast

Our team have trained two models synchronously . One is YoloV3 while the other is Tiny-Yolo

Tiny-yolo



yolov3



# Contrast

- Vertical
- Horizontal

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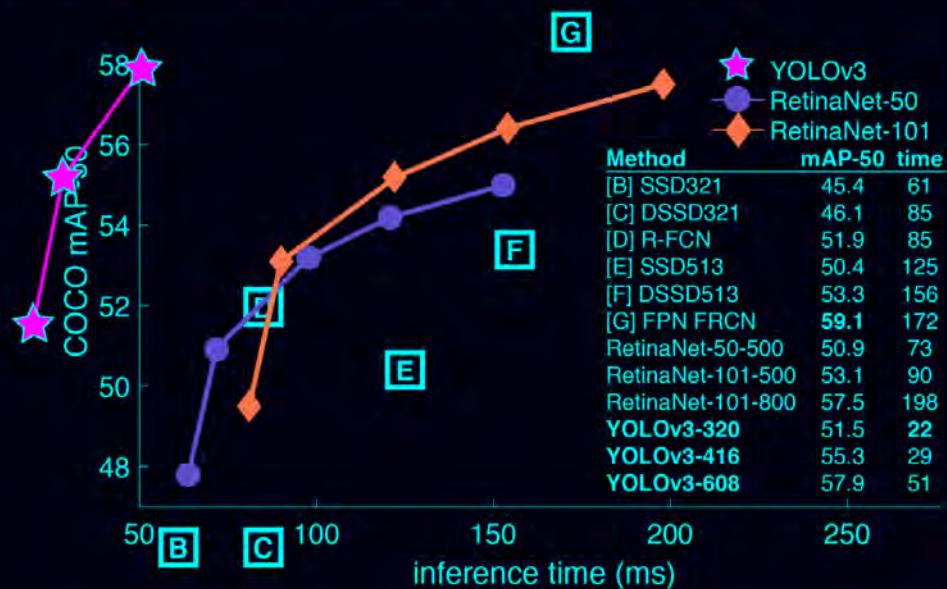


In addition, we have learnt the differences between various backbones through searching and reading literatures and papers.



## Comparison to Other Detectors

YOLOv3 is extremely fast and accurate. In mAP measured at .5 IOU YOLOv3 is on par with Focal Loss but about 4x faster. Moreover, you can easily tradeoff between speed and accuracy simply by changing the size of the model, no retraining required!



## Performance on the COCO Dataset

Model	Train	Test	mAP	FLOPS	FPS	Cfg	Weights
SSD300	COCO trainval	test-dev	41.2	-	46		link
SSD500	COCO trainval	test-dev	46.5	-	19		link
YOLOv2 608x608	COCO trainval	test-dev	48.1	62.94 Bn	40	cfg	weights
Tiny YOLO	COCO trainval	test-dev	23.7	5.41 Bn	244	cfg	weights
SSD321	COCO trainval	test-dev	45.4	-	16		link
DSSD321	COCO trainval	test-dev	46.1	-	12		link
R-FCN	COCO trainval	test-dev	51.9	-	12		link
SSD513	COCO trainval	test-dev	50.4	-	8		link
DSSD513	COCO trainval	test-dev	53.3	-	6		link
FPN FRCN	COCO trainval	test-dev	59.1	-	6		link
Retinanet-50-500	COCO trainval	test-dev	50.9	-	14		link
Retinanet-101-500	COCO trainval	test-dev	53.1	-	11		link
Retinanet-101-800	COCO trainval	test-dev	57.5	-	5		link
YOLOv3-320	COCO trainval	test-dev	51.5	38.97 Bn	45	cfg	weights
YOLOv3-416	COCO trainval	test-dev	55.3	65.86 Bn	35	cfg	weights
YOLOv3-608	COCO trainval	test-dev	57.9	140.69 Bn	20	cfg	weights
YOLOv3-tiny	COCO trainval	test-dev	33.1	5.56 Bn	220	cfg	weights
YOLOv3-spp	COCO trainval	test-dev	60.6	141.45 Bn	20	cfg	weights

# THANKS

