

AI Object Detection

Team members

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Speaker

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Contents

- 模型调优
- 数据集制作
- 预处理与数据增广
- 评估指标与可视化
- 训练策略
- 超参数调节
- 结果展示

Distribution of Work



朱昀玮

组长 超参数调优



万唯循

超参数调优



吕品灏

超参数调优



汪欣瑞

特征提取网络结构修改 评估指标与可视化



吴天骋

数据预处理与后处理 聚类分析与anchor计算



郑欣雨

数据集制作 超参数调优

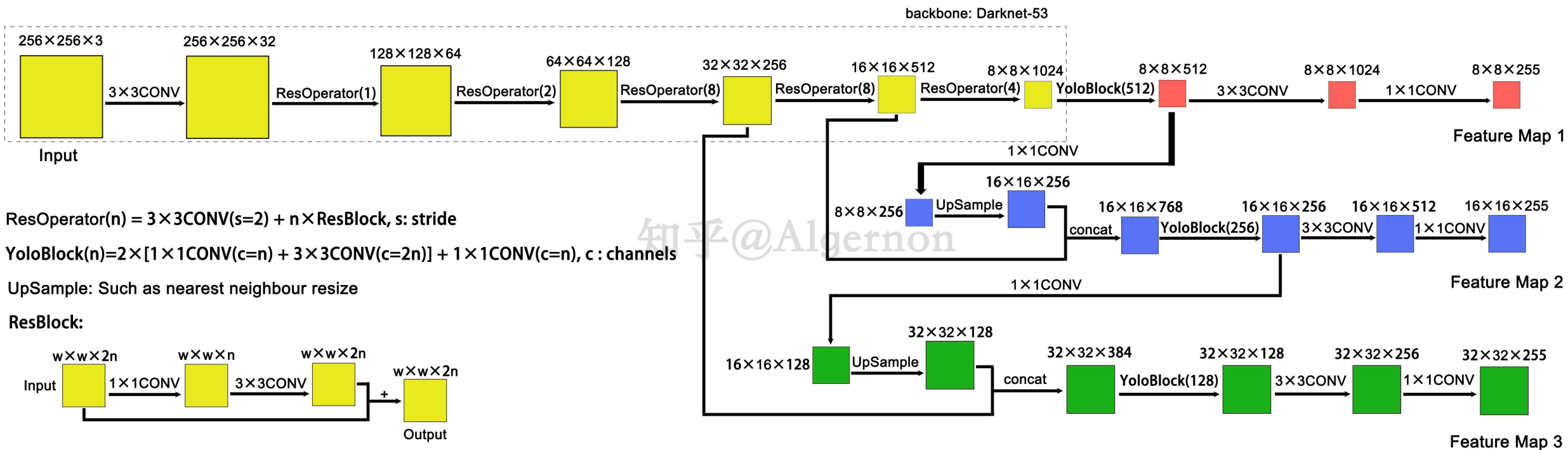


陆明奇

超参数调优 数据集制作

Model optimization

YOLOv3



Darknet-53

	Type	Filters	Size	Output
1x	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
2x	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
8x	Convolutional	256	3 × 3 / 2	32 × 32
	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
8x	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
4x	Convolutional	1024	3 × 3 / 2	8 × 8
	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

知乎 @Algernon

基本块：包含两个卷积/正则化层 --> 一个残差块 ResBlock

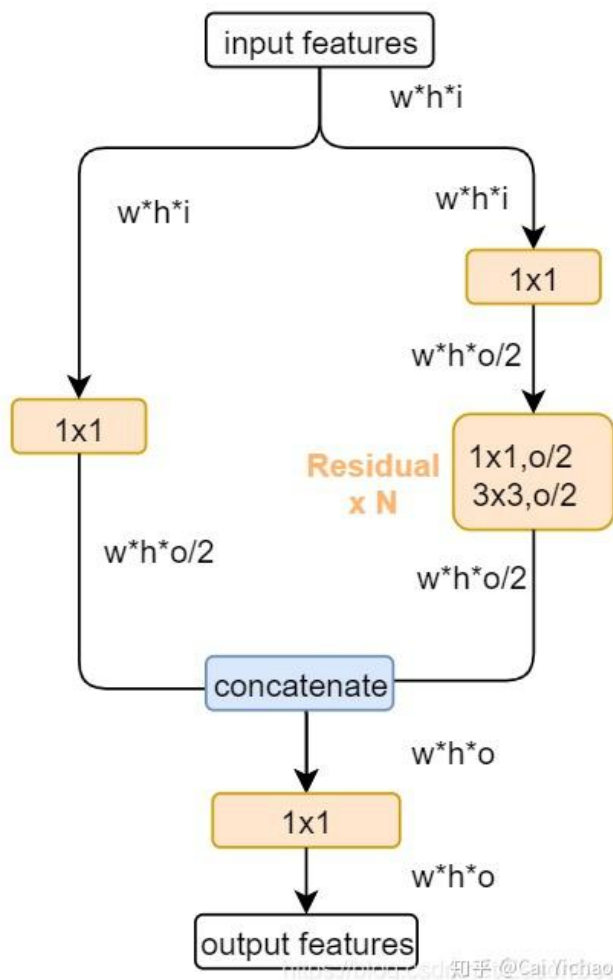
```
def basic_block(self, input, num_filters):
    conv1 = self.conv_bn(input, num_filters, filter_size=1, stride=1, padding=0)
    conv2 = self.conv_bn(conv1, num_filters * 2, filter_size=3, stride=1, padding=1)
    out = fluid.layers.elementwise_add(x=input, y=conv2, act=None) # 计算H(x)=F(x)+x
    return out
```

搭建网络模型 darknet-53

```
def net(self, img):
```

```
# 循环创建basic_block组
for i, stage_count in enumerate(stages):
    block = self.layer_warp(downsample_, # 输入数据
                            32 * (2 ** i), # 卷积核数量
                            stage_count) # 基本块数量
    blocks.append(block)
    if i < len(stages) - 1: # 如果不是最后一组，做降采样
        downsample_ = self.down_sample(block, block.shape[1] * 2)
blocks = blocks[-1:-4:-1] # 取倒数三层，并且逆序，后面跨层级联需要
```

CSPDarknet



➤ CSPNet (Cross Stage Partial Network)

- ✓ 增加梯度路径，避免不同的层学习到重复的梯度信息
- ✓ 平衡各层的计算量，减少内存流量

➤ Applying CSPNet to Darknet

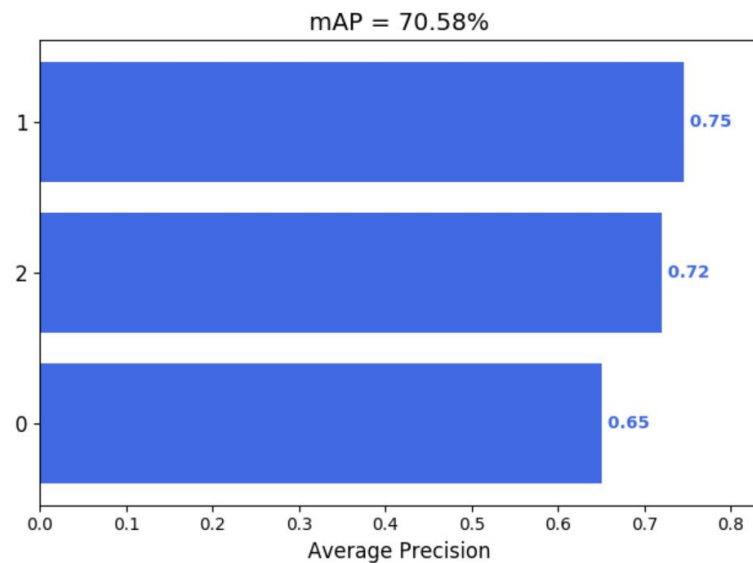
- ✓ YOLOv4与YOLOv5采用的特征提取网络结构
- ✓ 在初始代码残差块的连接中引入CSP结构，构建CSPDarknet

CSPDarknet

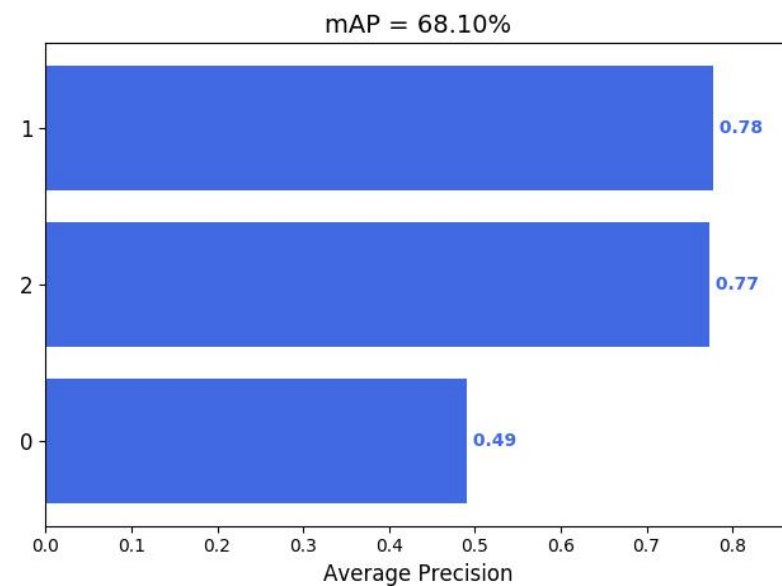
```
# 循环创建basic_block组
for i, stage_count in enumerate(stages):
    CSP_retain = self.conv_bn(downsample_, num_filters=downsample_.shape[1]//2, filter_size=1, stride=1, padding=0) # 第二个参数为卷积核数量
    CSP_conv = self.conv_bn(downsample_, num_filters=downsample_.shape[1]//2, filter_size=1, stride=1, padding=0) # 第二个参数为卷积核数量
    block = self.layer_warp(CSP_conv, # 输入数据
                            16 * (2 ** i), # 卷积核数量 32 * (2 ** i) -> 16 * (2 ** i)
                            stage_count) # 基本块数量
    block = fluid.layers.concat(input=[CSP_retain, block], axis=1)
    block = self.conv_bn(block, num_filters=block.shape[1], filter_size=1, stride=1, padding=0) # 第二个参数为卷积核数量
    blocks.append(block)
# 下一组ResOperator的3*3卷积部分
if i < len(stages) - 1: # 如果不是最后一组，做降采样
    downsample_ = self.down_sample(block, block.shape[1] * 2)
blocks = blocks[-1:-4:-1] # 取倒数三层，并且逆序，后面跨层级联需要
```

CSPDarknet

num_epochs=100, ignore_thresh=0.5, nms_thresh=0.45

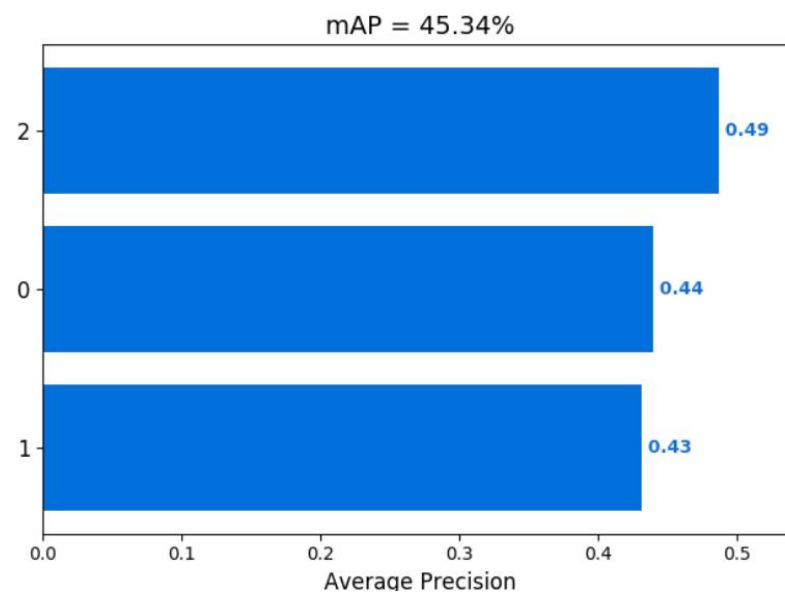
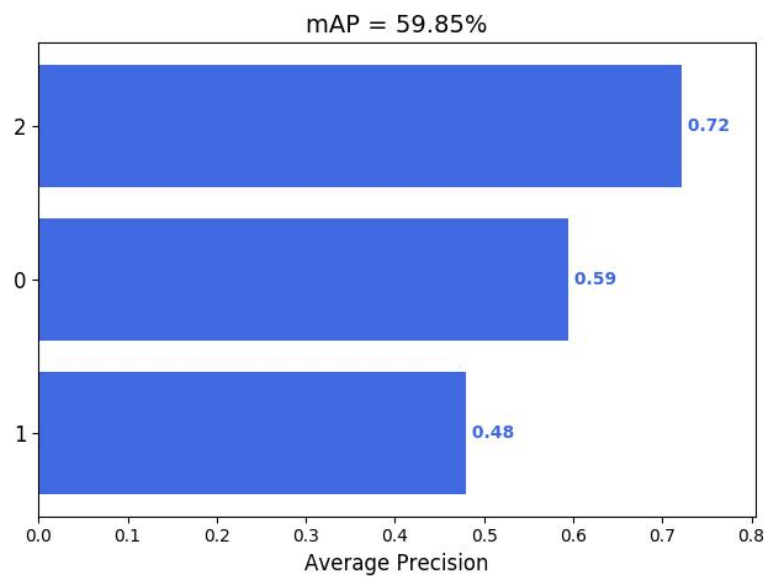


num_epochs=120, ignore_thresh=0.6, nms_thresh=0.407



CSPDarknet-53

Darknet-53



Dataset

Dataset

□ 校园采拍



□ 原始示例图片剪裁

□ 权威数据集下载

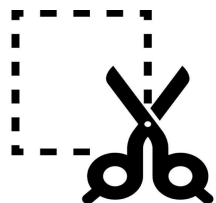


Dataset

□ 校园采拍

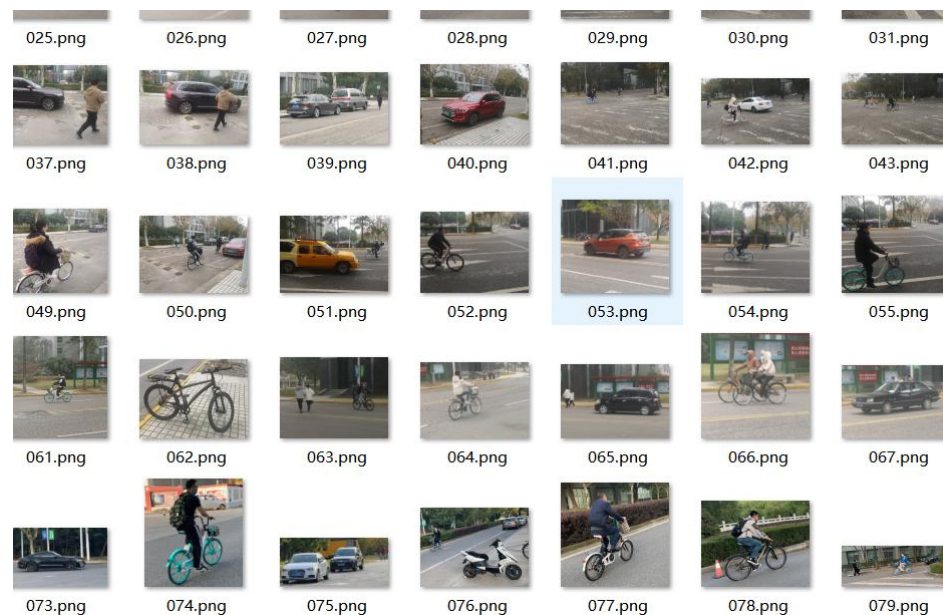
□ 原始示例图片剪裁

□ 权威数据集下载



 1.jpg (4.06MB, 4032x3024像素) - 1/101

101张原始图片, 训练1轮耗时5min



剪裁后加入其他图片, 训练1轮耗时2.5min

Dataset

□ 校园采拍

□ 原始示例图片剪裁

□ 权威数据集下载



• VOC

• COCO

• ImageNet

400张校园道路图片-->800张

Augmentation & Preprocessing

原始代码实现了：

- 色调、对比度、饱和度、亮度的随机改变
- 1:5的扩增与随机剪裁
- 图像各像素的中心化

增加：图像的水平翻转

```
# 预处理：图像样本增强，维度转换
def preprocess(img, bbox_labels, input_size, mode):
    img_width, img_height = img.size
    sample_labels = np.array(bbox_labels)

    if mode == 'train':
        if train_params['apply_distort']: # 是否扭曲增强
            img = distort_image(img)

        img, gtboxes = random_expand(img, sample_labels[:, 1:5]) # 扩展增强
        img, gtboxes, gtlables = random_crop(img, gtboxes, sample_labels[:, 0]) # 随机
        sample_labels[:, 0] = gtlables
        sample_labels[:, 1:5] = gtboxes

    img = resize_img(img, sample_labels, input_size)
    img = np.array(img).astype('float32')
    img -= train_params['mean_rgb']
    img = img.transpose((2, 0, 1)) # HWC to CHW
    img *= 0.007843
    return img, sample_labels
```

Training strategy

Learning rate

Warm-up

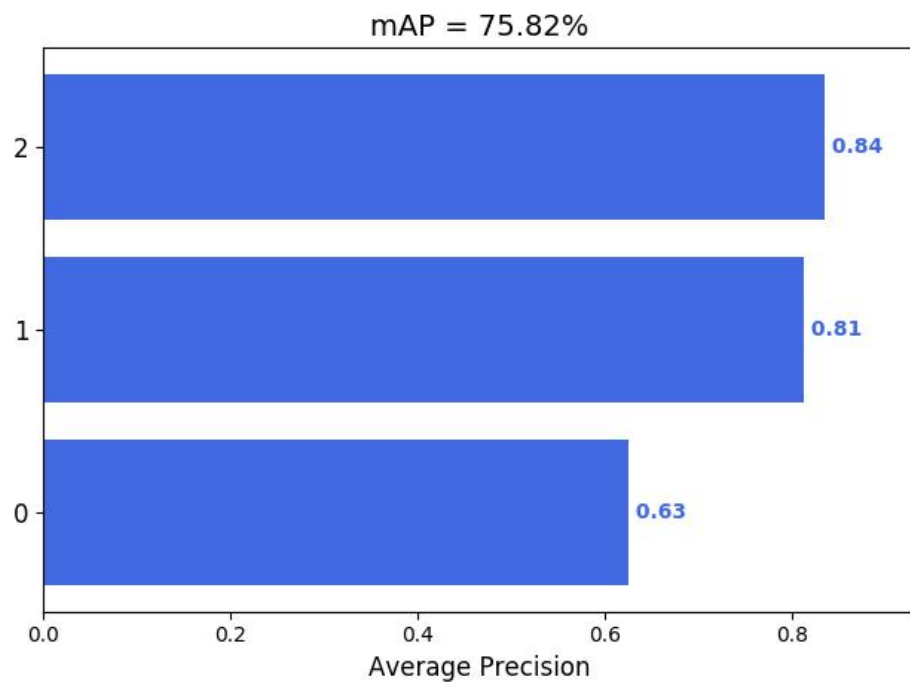
神经网络在刚开始训练的时候是非常不稳定的，因此刚开始的学习率应当设置得很低很低，这样可以保证网络能够具有良好的收敛性

Decay

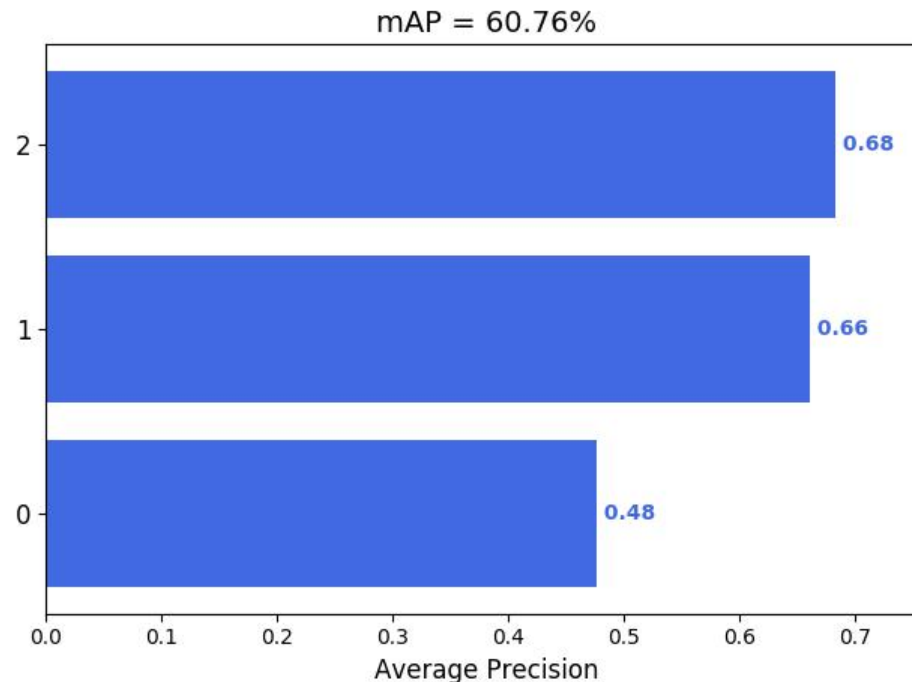
保证收敛到最优点附近时，以较小的学习率进行参数更新，以避免来回震荡

learning rate times: 0.5 --> 0.8 --> 1 --> 0.5 --> 0.25 --> 0.1

Optimizer



SGD, ignore_thresh=0.5,
num_epochs=100, nms_thresh=0.45
(num_epochs和nms_thresh均为条件最优)



Adam, ignore_thresh=0.5,
num_epochs=90, nms_thresh=0.45
(num_epochs和nms_thresh均为条件最优)

Hyperparameter adjustment

Evaluation index

➤ 迫切需要评价指标指引方向。。

➤ mAP

- mAP: mean Average Precision, 即各类别AP的平均值
- AP: Precision-Recall曲线下的面积
- Precision: $TP / (TP + FP)$
- Recall: $TP / (TP + FN)$
- TP: IoU>0.5的检测框数量 (同一Ground Truth只计算一次)
- FP: IoU≤0.5的检测框, 或者是检测到同一个Ground Truth的多余检测框的数量
- FN: 没有检测到的Ground Truth的数量
- IoU: “预测的边框” 和 “真实的边框” 的交集和并集的面积比值

➤ 修改GitHub开源代码, 配适本项目, 实现相关指标的计算与可视化

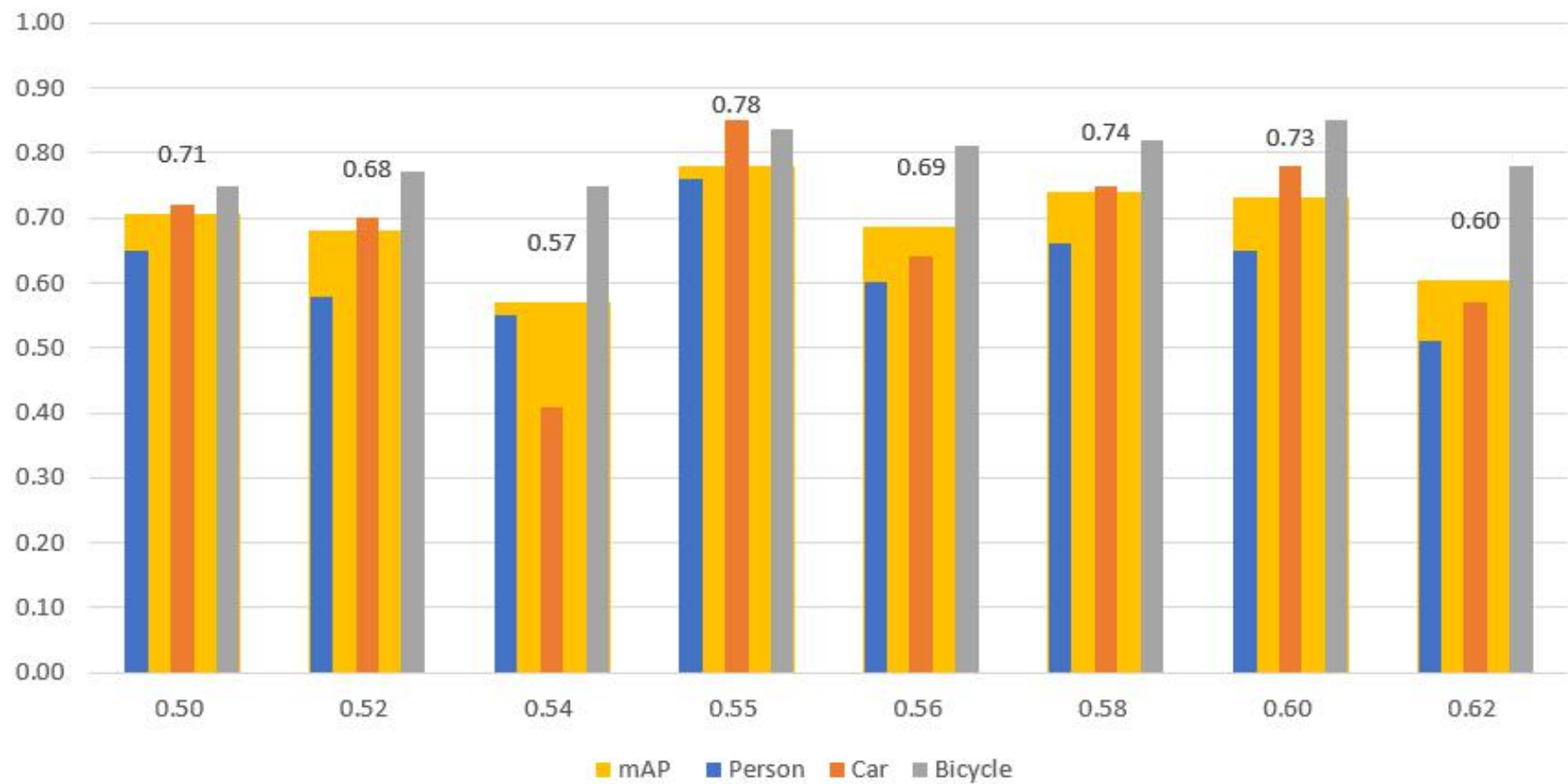
GitHub项目地址: <https://github.com/Cartucho/mAP>

参考资料: <https://www.zhihu.com/question/53405779/answer/419532990>

Parameters

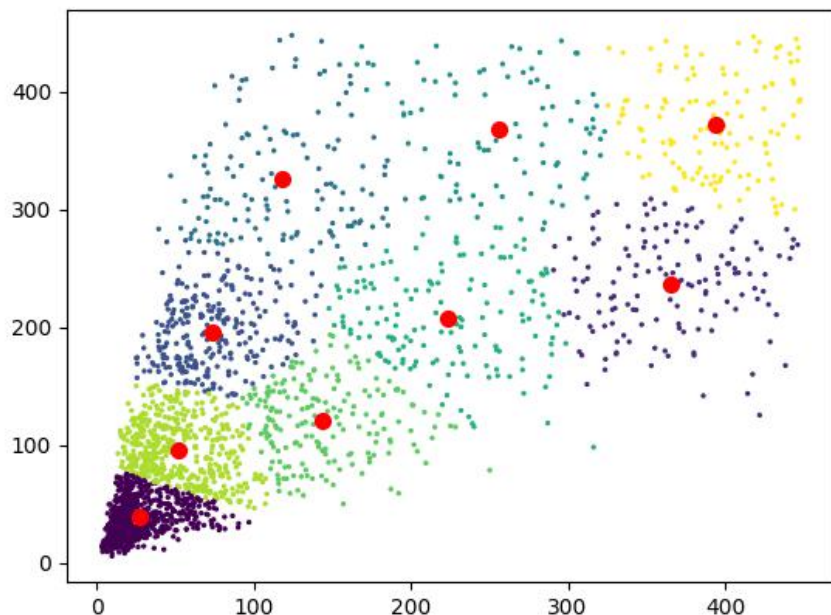
参数	含义
anchors	预设一组不同尺度不同、位置的固定参考框，将目标检测问题转换为"这个固定参考框中有没有认识的目标，目标框偏离参考框多远"
ignore_thresh	与训练过程中loss的计算有关，IoU超过该阈值的负样本不参与loss计算
nms_thresh	nms算法中使用的阈值，可通俗理解为"多大程度上允许同类型框的重叠"
valid_thresh	过滤掉置信度低的框

ignore_thresh

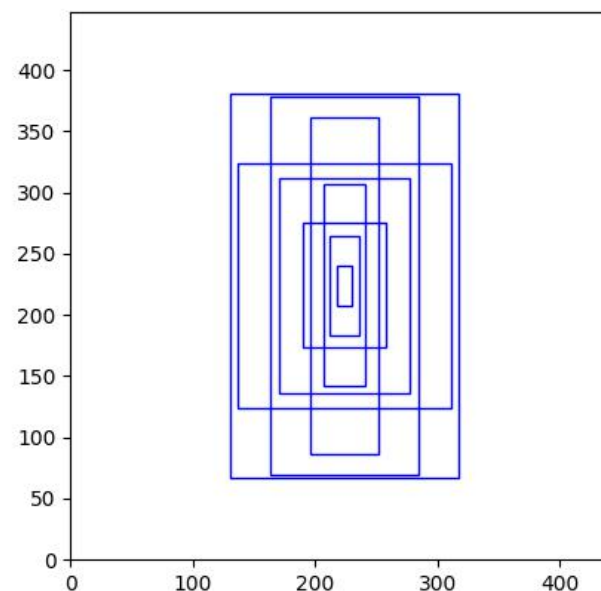


各`ignore_thresh`组，调节不同`epochs`、`nms_thresh`、`valid_thresh`取得的最大mAP

Anchors

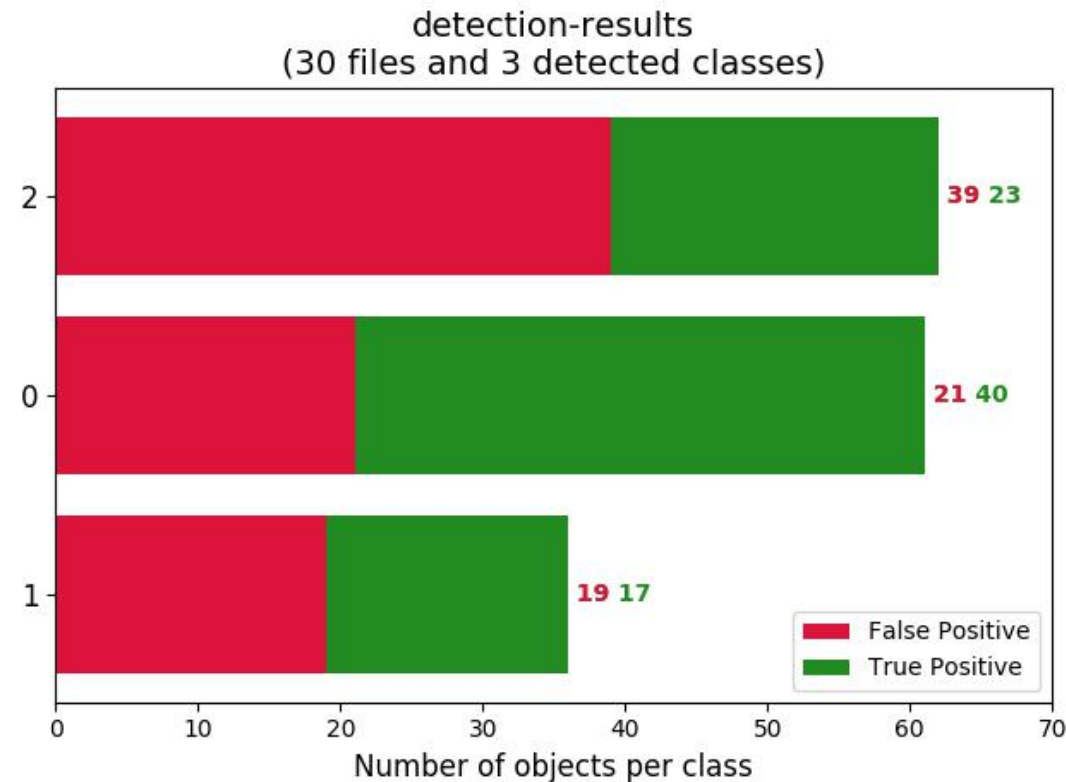
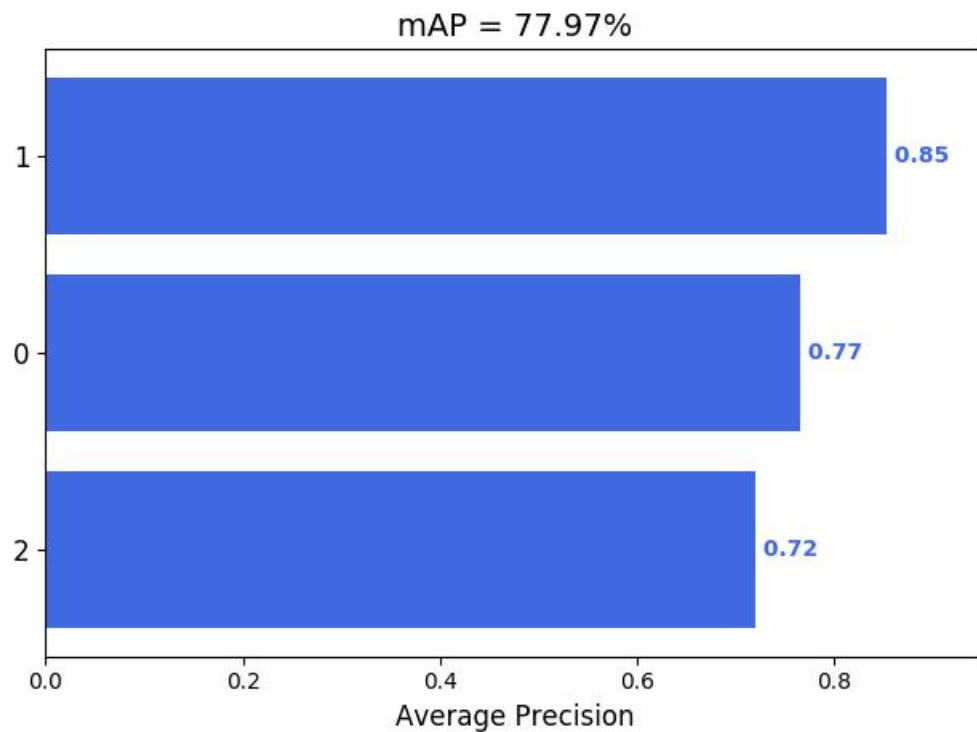


KMeans聚类结果中心点分布



anchor预测框大小可视化

Anchors



Our Best Result

800pics dataset, cspnet, sgd, custom_anchor, ignore0.55, 85 epochs

valid_thresh



valid_thresh = 0.01
FP占比极高



valid_thresh = **0.07**
精准干净的预测

Strategy

姓名缩写	模型(原始/CSP)	num_epochs	ignore_thresh	nms_thresh	valid_thresh	数据集 (400/800)	优化器	anchor(原始/重新)	class 0	class 1	class 2	map
wxr	CSP	140	0.60	0.407	0.010	400	SGD	原始	65.00%	69.00%	85.00%	73.04%
wxr	CSP	180	0.60	0.407	0.010	400	SGD	原始	58.00%	77.00%	80.00%	71.34%
wxr	CSP	120	0.60	0.407	0.010	400	SGD	原始	49.00%	78.00%	77.00%	68.10%
wxr	CSP	120	0.60	0.389	0.010	400	SGD	原始	48.00%	78.00%	77.00%	67.73%
lmq	CSP	80	0.58	0.450	0.010	400	SGD	原始	66.00%	74.00%	82.00%	74.00%
zyw	CSP	120	0.54	0.450	0.010	400	SGD	原始	55.00%	41.00%	75.00%	57.00%
wtc	CSP	85	0.55	0.450	0.070	800	SGD	重新计算	76.00%	85.00%	72.00%	78.00%
lmq	CSP	85	0.58	0.400	0.010	400	SGD	原始	61.00%	75.00%	81.00%	72.00%
wtc	CSP	90	0.55	0.450	0.010	400	Adam	原始	48.00%	66.00%	68.00%	61.00%
lmq	CSP	85	0.58	0.350	0.010	400	SGD	原始	61.00%	74.00%	81.00%	72.00%
zxy	CSP	100	0.50	0.450	0.010	400	SGD	原始	65.00%	72.00%	75.00%	70.58%
zxy	CSP	100	0.52	0.450	0.010	400	SGD	原始	58.00%	70.00%	77.00%	68.14%
wwx	CSP	145	0.62	0.407	0.010	400	SGD	原始	51.00%	52.00%	78.00%	60.42%
wwx	CSP	135	0.62	0.407	0.010	400	SGD	原始	50.00%	57.00%	74.00%	59.95%
wwx	原始	120	0.60	0.389	0.010	400	SGD	原始	42.00%	49.00%	69.00%	53.60%
wwx	原始	170	0.60	0.400	0.010	400	SGD	原始	59.00%	61.00%	73.00%	64.40%
lmq	原始	100	0.50	0.450	0.010	400	SGD	原始	59.00%	48.00%	72.00%	59.90%
lph	CSP	80	0.56	0.450	0.010	400	SGD	原始	60.00%	64.00%	81.00%	68.50%
lph	CSP	110	0.55	0.438	0.010	400	SGD	原始	62.59%	81.32%	83.55%	75.80%

部分训练成果概览

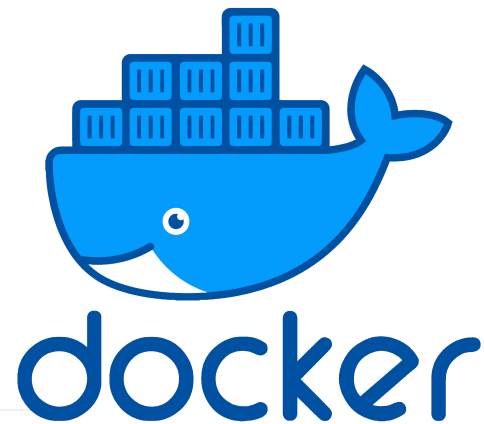
OutOfTimeErr

本周剩余0.0小时GPU环境使用时间

OutOfTimeErr



Docker Env



1.5

新手入门 使用指南 进阶使用 API 环境变量FLAGS FAQ

快速开始

> 安装说明

Ubuntu下安装

CentOS下安装

MacOS下安装

Windows下安装

使用conda安装

使用Docker安装

> 从源码编译

附录

> 深度学习基础教程

Fluid编程指南

文档 > 新手入门 > 安装说明 > 使用Docker安装

☆☆☆☆☆

使用Docker安装

Docker是一个开源的应用容器引擎。使用Docker，既可以将PaddlePaddle的安装&使用与系统环境隔离，也可以与主机共享GPU、网络等资源

I 环境准备

- 目前支持的系统类型，请见[安装说明](#)，请注意目前暂不支持在CentOS 6使用Docker
- 在本地主机上[安装Docker](#)
- 如需在Linux开启GPU支持，请[安装nvidia-docker](#)

I 安装步骤

1. 拉取PaddlePaddle镜像

- CPU版的PaddlePaddle: `docker pull hub.baidubce.com/paddlepaddle/paddle:[版本号]`
- GPU版的PaddlePaddle: `docker pull hub.baidubce.com/paddlepaddle/paddle:[版本号]-gpu-cuda9.0-cudnn7`

如果您的机器不在中国大陆地区，可以直接从DockerHub拉取镜像：

- CPU版的PaddlePaddle: `docker pull paddlepaddle/paddle:[版本号]`
- GPU版的PaddlePaddle: `docker pull paddlepaddle/paddle:[版本号]-gpu-cuda9.0-cudnn7`

Docker Env

The screenshot displays a Docker container environment. The main window is Visual Studio Code, showing a file explorer with 'CS_AI' and 'temp files' folders, and a terminal window running 'top' and 'nvidia-smi'. The terminal output shows system statistics and GPU information. The NVIDIA X Server Settings window is also visible, showing power and performance settings.

Visual Studio Code Interface:

- File Explorer: CS_AI, temp files
- Explorer: challenge.py 3, train.log
- Terminal: logs > train.log

Terminal Output (top):

```
top - 15:53:36 up 14:00, 1 user, load average: 1.51, 1.40, 1.14
任务: 424 total, 2 running, 422 sleeping, 0 stopped, 0 zombie
%Cpu(s): 6.4 us, 1.2 sy, 0.0 ni, 91.9 id, 0.5 wa, 0.0 hi, 0.0 si, 0.0 st
MiB Mem : 31921.1 total, 2777.8 free, 7226.5 used, 21916.8 buff/cache
MiB Swap: 2048.0 total, 2043.2 free, 4.8 used, 23047.5 avail Mem
```

Terminal Output (nvidia-smi):

```
NVIDIA-SMI 470.86 Driver Version: 470.86 CUDA Version: 11.4
```

GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile Uncorr. ECC
0	NVIDIA GeForce ...	Off	00000000:01:00.0	Off	N/A
N/A	53C P0	25W / N/A	7479MiB / 7982MiB	0%	Default

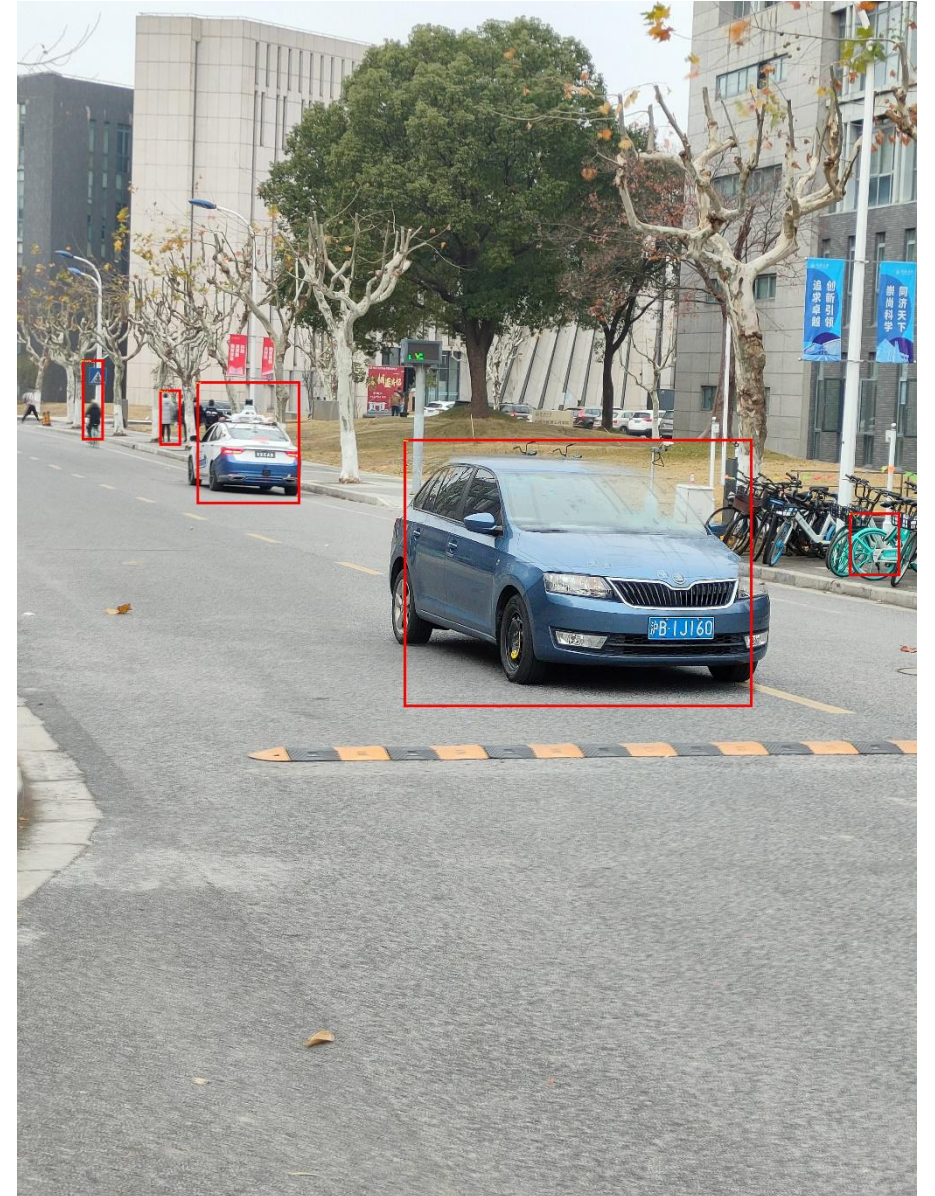
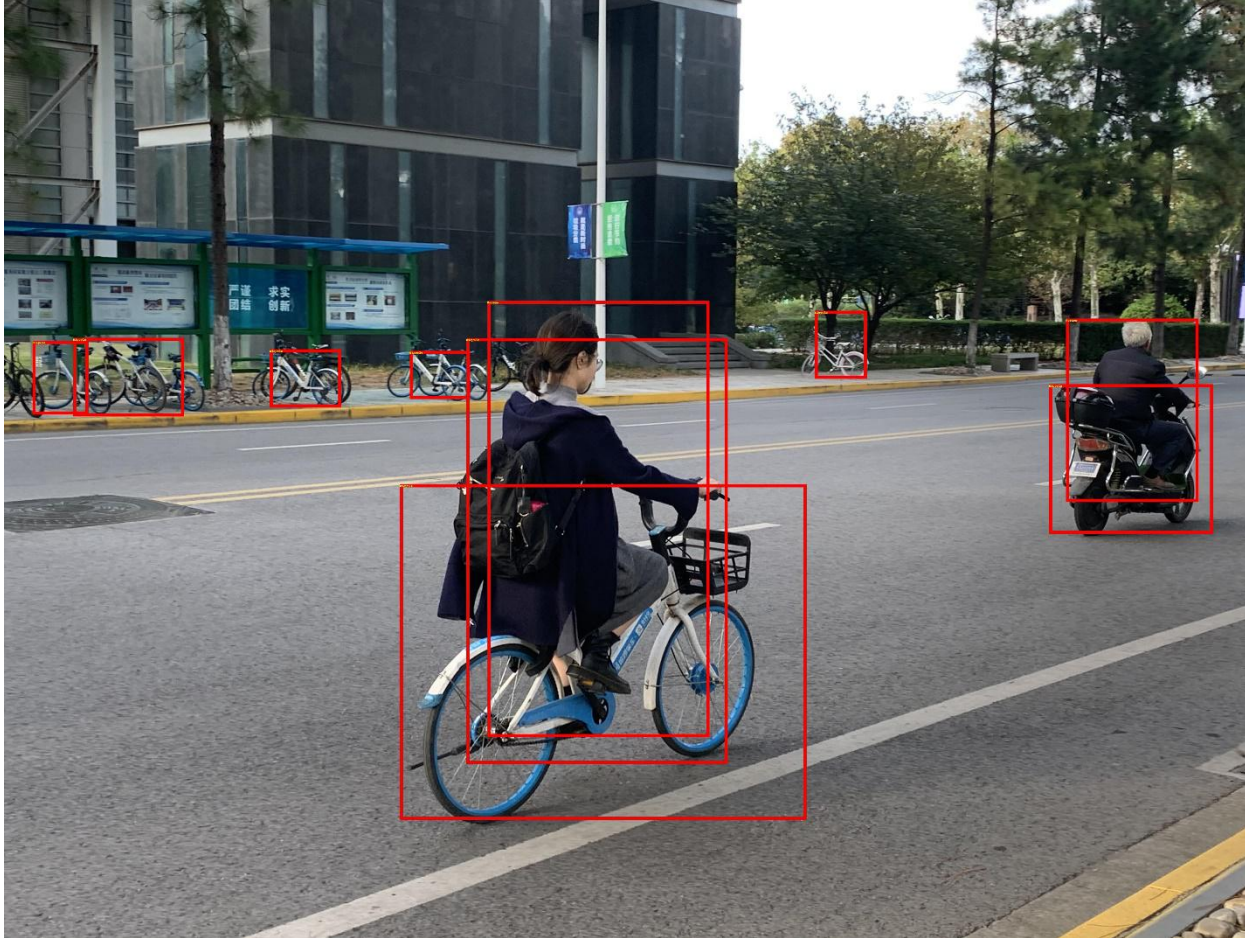
Terminal Output (Processes):

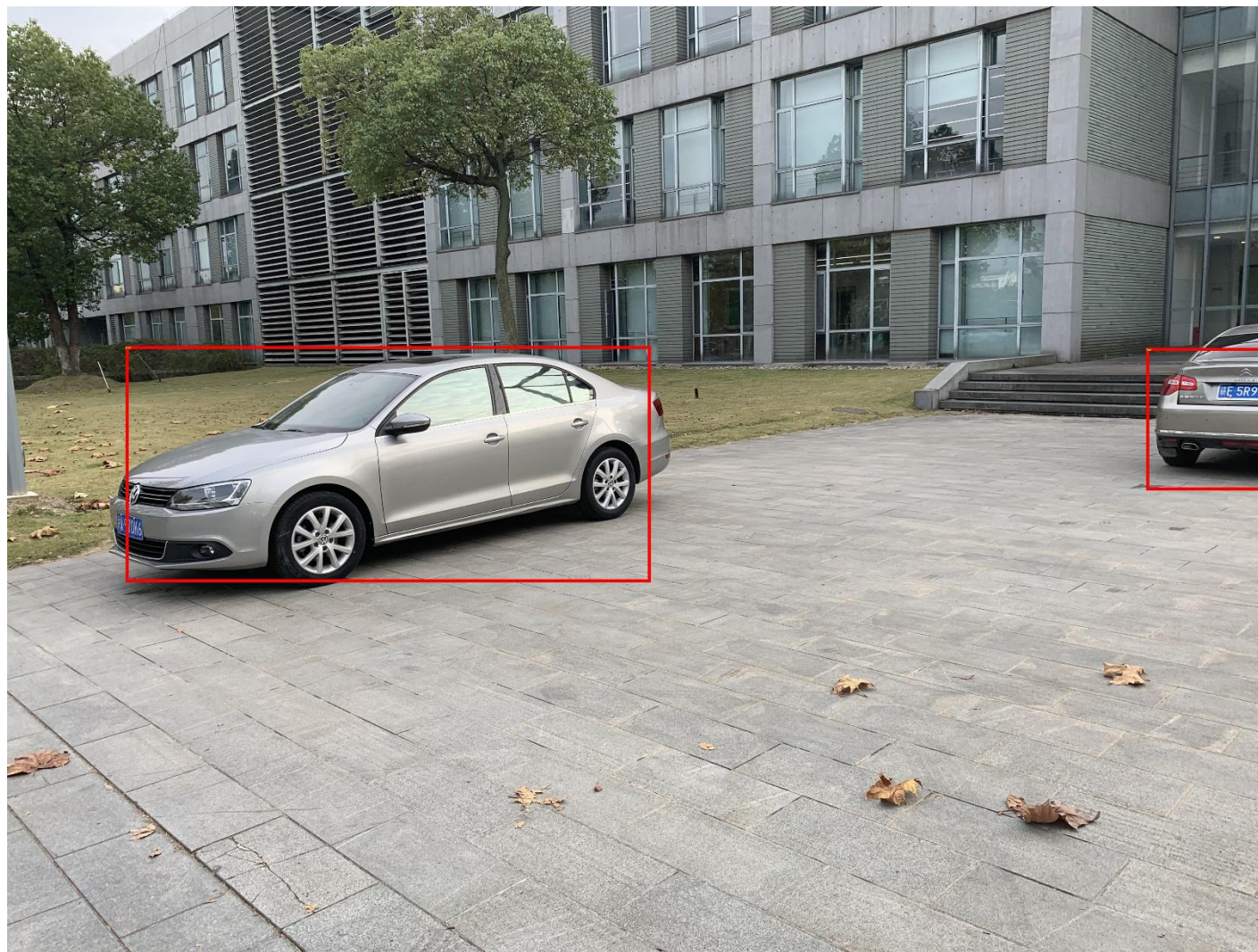
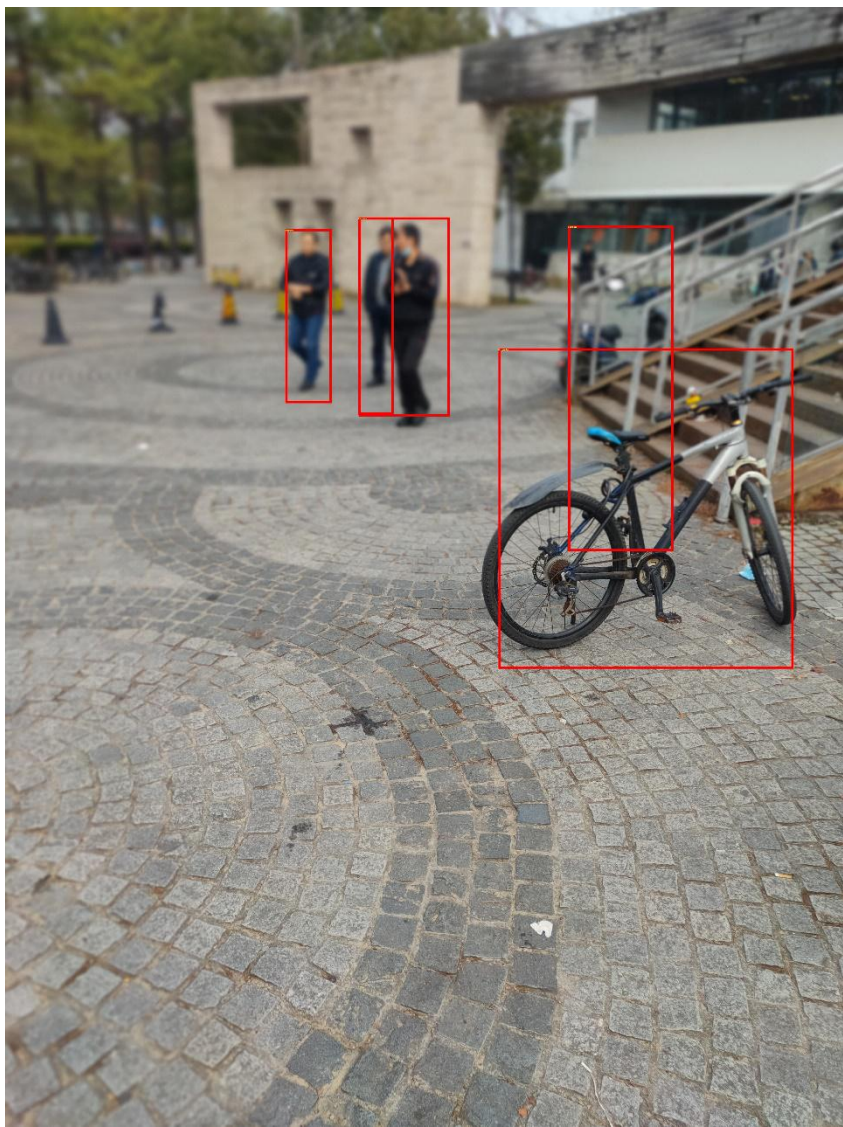
GPU	GI ID	CI ID	PID	Type	Process name	GPU Memory Usage
0	N/A	N/A	2739	G	/usr/lib/xorg/Xorg	4MiB
0	N/A	N/A	64816	C	python	7471MiB

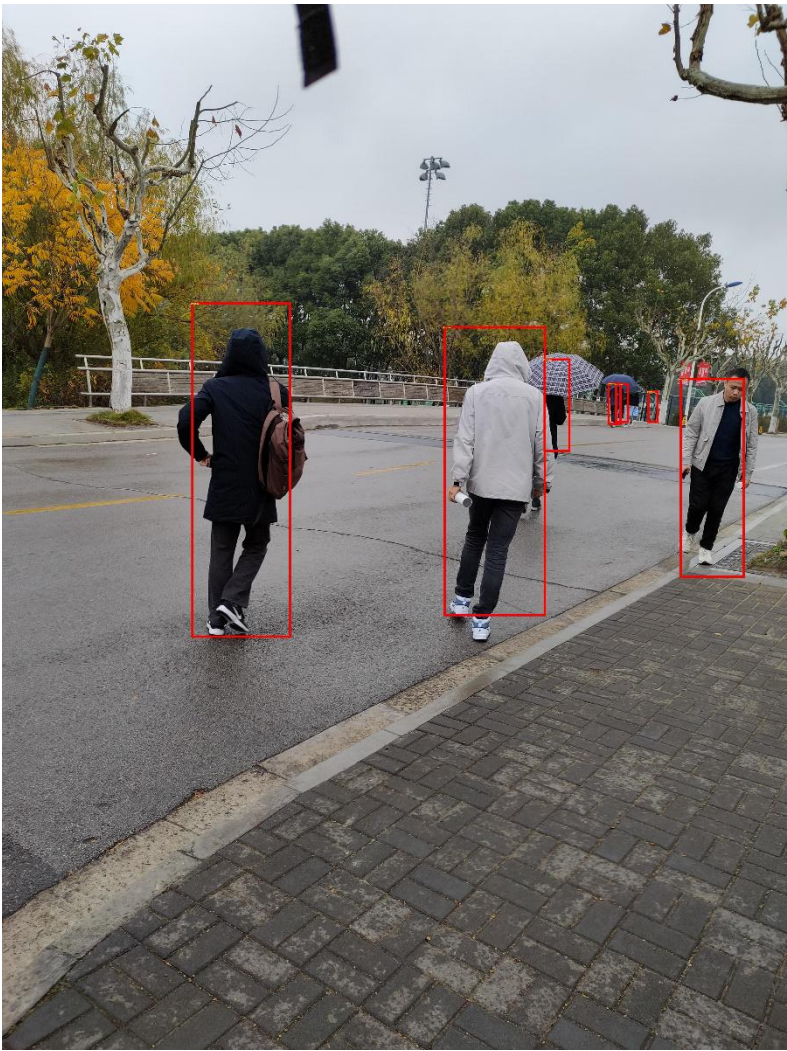
NVIDIA X Server Settings:

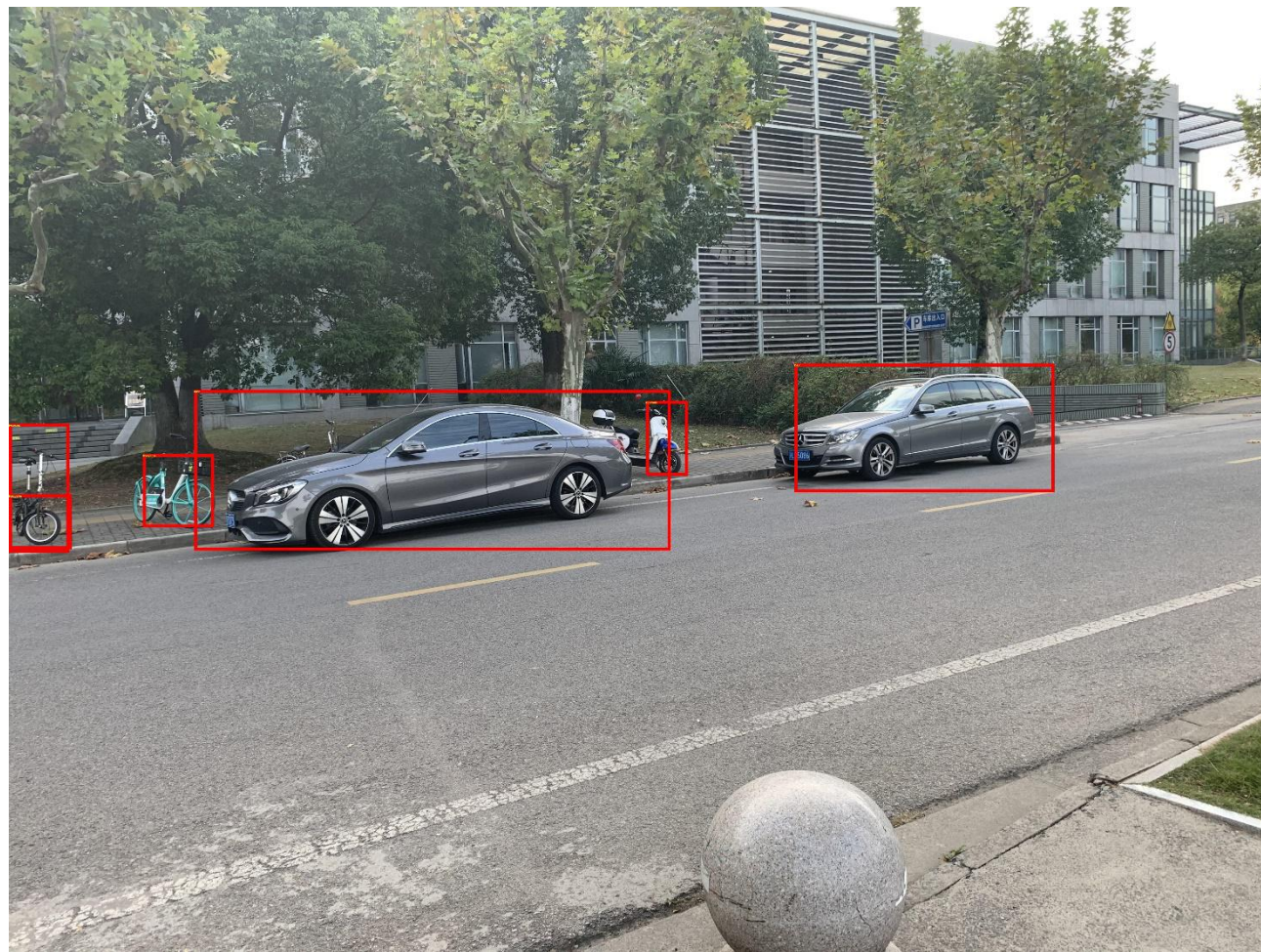
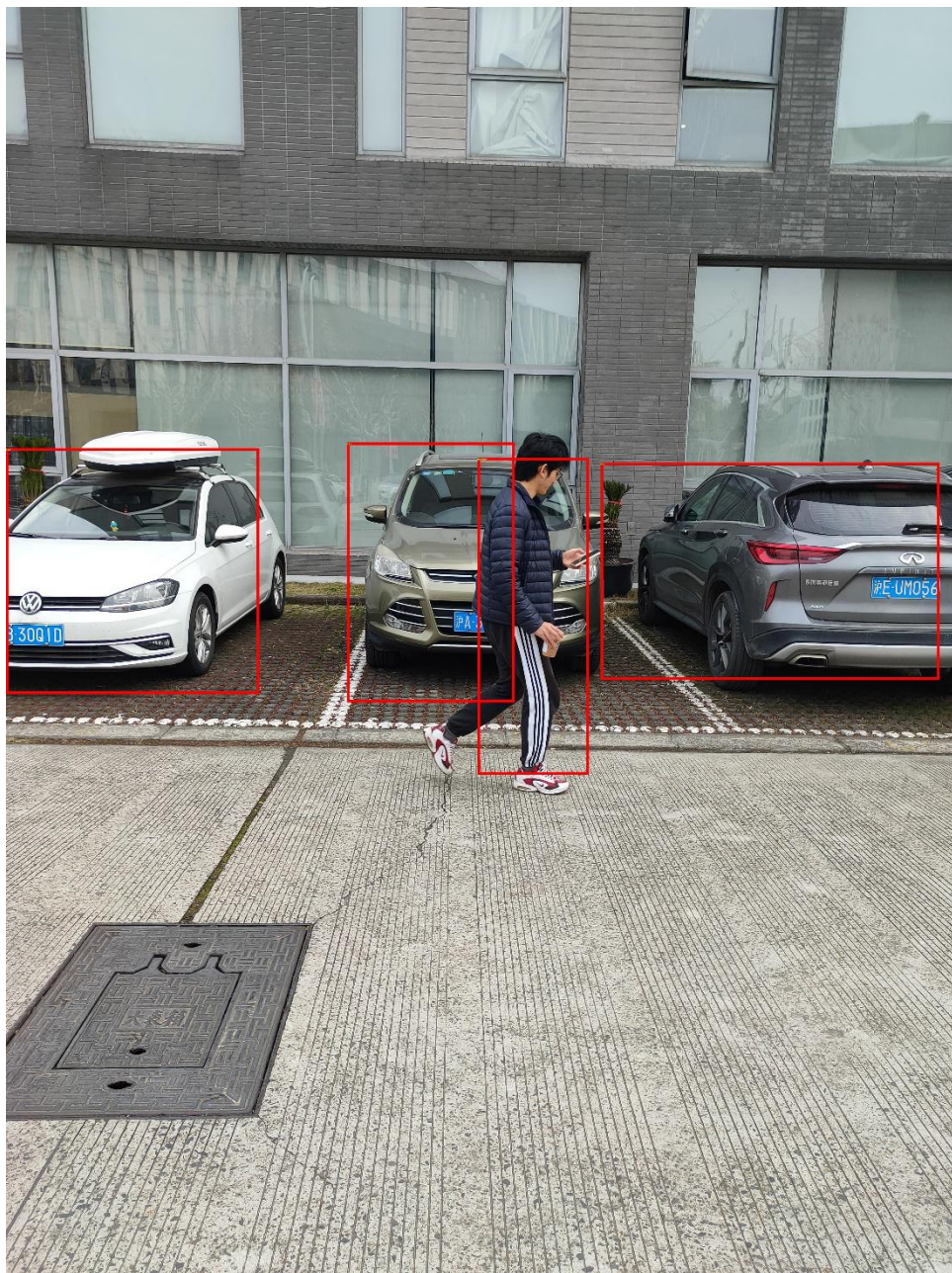
- PowerMizer Information: Adaptive Clocking: Enabled, Graphics Clock: 1365 Mhz, Memory Transfer Rate: 11000 Mhz, Power Source: AC, Current PCIe Link Width: x16, Current PCIe Link Speed: 8.0 GT/s, Performance Level: 3
- Performance Levels: Level 0 (300 MHz Graphics Clock, 645 MHz Memory Transfer Rate), Level 1 (300 MHz Graphics Clock, 2100 MHz Memory Transfer Rate), Level 2 (300 MHz Graphics Clock, 2100 MHz Memory Transfer Rate), Level 3 (300 MHz Graphics Clock, 2100 MHz Memory Transfer Rate)

Show Time









**Thanks For Listening
&
Thanks to my teammates**