

# 深度学习实践-实验六

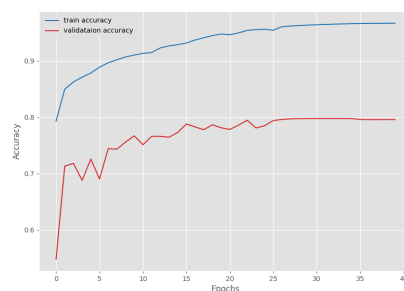
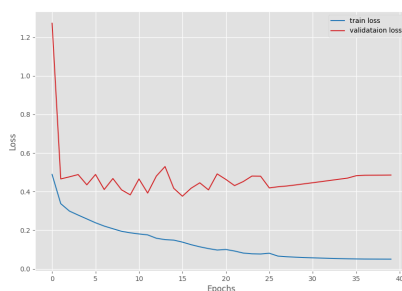
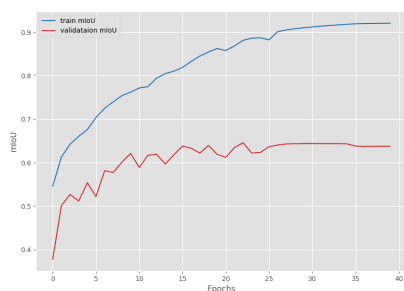
PB22151796-莫环欣

1.了解一下整段代码的结构(/work/code/src/), 将代码跑通 (跑通后, 见 outputs 文件夹), 解释说明分割任务的评价标准。

移除了 train.py 里调度器的 verbose 参数 (这个已经废弃了, 会报警告), 还有 utils 里 imwrite 提示格式不匹配自动转为 uint8

```
scheduler = MultiStepLR(optimizer, milestones=[25, 35], gamma=0.1)
```

使用默认参数运行, 网络为 UNet5()



评价标准有:

- **miou**
  - 平均交并比
  - **iou**: 对每个类别: 预测分割结果与真实分割结果的交集面积/并集面积
    - 对所有 **iou** 取平均即为 **miou**
- **pa**
  - 像素准确率
  - 预测正确的像素占总像素的比例
  - 也可以对每个类分别计算然后取平均
- **loss**
  - 通用指标, 损失
  - 预测结果与真实标签的差距, 越小越好

**2.用 torchsummary 或者 torchinfo 输出代码中提供的 UNet3() 和 UNet5()这两个模型的每一层的网络详细信息、参数数量和参数总量。**

这里使用 `torchinfo` ，代码放置在 `model` 中

## UNet3 Summary:

Layer (type:depth-idx)	Output Shape	Param #
UNet3	[1, 10, 512, 512]	--
└─Bottleneck: 1-1	[1, 64, 512, 512]	--
└─BaseConv: 2-1	[1, 32, 512, 512]	--
└─Conv2d: 3-1	[1, 32, 512, 512]	96
└─BatchNorm2d: 3-2	[1, 32, 512, 512]	64
└─SiLU: 3-3	[1, 32, 512, 512]	--
└─BaseConv: 2-2	[1, 64, 512, 512]	--
└─Conv2d: 3-4	[1, 64, 512, 512]	18,432
└─BatchNorm2d: 3-5	[1, 64, 512, 512]	128
└─SiLU: 3-6	[1, 64, 512, 512]	--
└─MaxPool2d: 1-2	[1, 64, 256, 256]	--
└─Bottleneck: 1-3	[1, 128, 256, 256]	--
└─BaseConv: 2-3	[1, 64, 256, 256]	--
└─Conv2d: 3-7	[1, 64, 256, 256]	4,096
└─BatchNorm2d: 3-8	[1, 64, 256, 256]	128
└─SiLU: 3-9	[1, 64, 256, 256]	--
└─BaseConv: 2-4	[1, 128, 256, 256]	--
└─Conv2d: 3-10	[1, 128, 256, 256]	73,728
└─BatchNorm2d: 3-11	[1, 128, 256, 256]	256
└─SiLU: 3-12	[1, 128, 256, 256]	--
└─MaxPool2d: 1-4	[1, 128, 128, 128]	--
└─Bottleneck: 1-5	[1, 256, 128, 128]	--
└─BaseConv: 2-5	[1, 128, 128, 128]	--
└─Conv2d: 3-13	[1, 128, 128, 128]	16,384
└─BatchNorm2d: 3-14	[1, 128, 128, 128]	256
└─SiLU: 3-15	[1, 128, 128, 128]	--
└─BaseConv: 2-6	[1, 256, 128, 128]	--
└─Conv2d: 3-16	[1, 256, 128, 128]	294,912
└─BatchNorm2d: 3-17	[1, 256, 128, 128]	512
└─SiLU: 3-18	[1, 256, 128, 128]	--
└─ConvTranspose2d: 1-6	[1, 128, 256, 256]	131,200
└─Bottleneck: 1-7	[1, 128, 256, 256]	--
└─BaseConv: 2-7	[1, 64, 256, 256]	--
└─Conv2d: 3-19	[1, 64, 256, 256]	16,384
└─BatchNorm2d: 3-20	[1, 64, 256, 256]	128
└─SiLU: 3-21	[1, 64, 256, 256]	--
└─BaseConv: 2-8	[1, 128, 256, 256]	--
└─Conv2d: 3-22	[1, 128, 256, 256]	73,728
└─BatchNorm2d: 3-23	[1, 128, 256, 256]	256
└─SiLU: 3-24	[1, 128, 256, 256]	--
└─ConvTranspose2d: 1-8	[1, 64, 512, 512]	32,832
└─Bottleneck: 1-9	[1, 64, 512, 512]	--

└─BaseConv: 2-9	[1, 32, 512, 512]	--
└─Conv2d: 3-25	[1, 32, 512, 512]	4,096
└─BatchNorm2d: 3-26	[1, 32, 512, 512]	64
└─SiLU: 3-27	[1, 32, 512, 512]	--
└─BaseConv: 2-10	[1, 64, 512, 512]	--
└─Conv2d: 3-28	[1, 64, 512, 512]	18,432
└─BatchNorm2d: 3-29	[1, 64, 512, 512]	128
└─SiLU: 3-30	[1, 64, 512, 512]	--
─Conv2d: 1-10	[1, 10, 512, 512]	650

Total params: 686,890

Trainable params: 686,890

Non-trainable params: 0

Total mult-adds (G): 44.24

Input size (MB): 3.15

Forward/backward pass size (MB): 1530.92

Params size (MB): 2.75

Estimated Total Size (MB): 1536.81

UNet5 Summary:

Layer (type:depth-idx)	Output Shape	Param #
UNet5	[1, 10, 512, 512]	--
─Bottleneck: 1-1	[1, 64, 512, 512]	--
└─BaseConv: 2-1	[1, 32, 512, 512]	--
└─Conv2d: 3-1	[1, 32, 512, 512]	96
└─BatchNorm2d: 3-2	[1, 32, 512, 512]	64
└─SiLU: 3-3	[1, 32, 512, 512]	--
└─BaseConv: 2-2	[1, 64, 512, 512]	--
└─Conv2d: 3-4	[1, 64, 512, 512]	18,432
└─BatchNorm2d: 3-5	[1, 64, 512, 512]	128
└─SiLU: 3-6	[1, 64, 512, 512]	--
─MaxPool2d: 1-2	[1, 64, 256, 256]	--
─Bottleneck: 1-3	[1, 128, 256, 256]	--
└─BaseConv: 2-3	[1, 64, 256, 256]	--
└─Conv2d: 3-7	[1, 64, 256, 256]	4,096
└─BatchNorm2d: 3-8	[1, 64, 256, 256]	128
└─SiLU: 3-9	[1, 64, 256, 256]	--
└─BaseConv: 2-4	[1, 128, 256, 256]	--
└─Conv2d: 3-10	[1, 128, 256, 256]	73,728
└─BatchNorm2d: 3-11	[1, 128, 256, 256]	256
└─SiLU: 3-12	[1, 128, 256, 256]	--
─MaxPool2d: 1-4	[1, 128, 128, 128]	--

└─Bottleneck: 1-5	[1, 256, 128, 128]	--
└─BaseConv: 2-5	[1, 128, 128, 128]	--
└─Conv2d: 3-13	[1, 128, 128, 128]	16,384
└─BatchNorm2d: 3-14	[1, 128, 128, 128]	256
└─SiLU: 3-15	[1, 128, 128, 128]	--
└─BaseConv: 2-6	[1, 256, 128, 128]	--
└─Conv2d: 3-16	[1, 256, 128, 128]	294,912
└─BatchNorm2d: 3-17	[1, 256, 128, 128]	512
└─SiLU: 3-18	[1, 256, 128, 128]	--
└─MaxPool2d: 1-6	[1, 256, 64, 64]	--
└─Bottleneck: 1-7	[1, 512, 64, 64]	--
└─BaseConv: 2-7	[1, 256, 64, 64]	--
└─Conv2d: 3-19	[1, 256, 64, 64]	65,536
└─BatchNorm2d: 3-20	[1, 256, 64, 64]	512
└─SiLU: 3-21	[1, 256, 64, 64]	--
└─BaseConv: 2-8	[1, 512, 64, 64]	--
└─Conv2d: 3-22	[1, 512, 64, 64]	1,179,648
└─BatchNorm2d: 3-23	[1, 512, 64, 64]	1,024
└─SiLU: 3-24	[1, 512, 64, 64]	--
└─MaxPool2d: 1-8	[1, 512, 32, 32]	--
└─Bottleneck: 1-9	[1, 1024, 32, 32]	--
└─BaseConv: 2-9	[1, 512, 32, 32]	--
└─Conv2d: 3-25	[1, 512, 32, 32]	262,144
└─BatchNorm2d: 3-26	[1, 512, 32, 32]	1,024
└─SiLU: 3-27	[1, 512, 32, 32]	--
└─BaseConv: 2-10	[1, 1024, 32, 32]	--
└─Conv2d: 3-28	[1, 1024, 32, 32]	4,718,592
└─BatchNorm2d: 3-29	[1, 1024, 32, 32]	2,048
└─SiLU: 3-30	[1, 1024, 32, 32]	--
└─ConvTranspose2d: 1-10	[1, 512, 64, 64]	2,097,664
└─Bottleneck: 1-11	[1, 512, 64, 64]	--
└─BaseConv: 2-11	[1, 256, 64, 64]	--
└─Conv2d: 3-31	[1, 256, 64, 64]	262,144
└─BatchNorm2d: 3-32	[1, 256, 64, 64]	512
└─SiLU: 3-33	[1, 256, 64, 64]	--
└─BaseConv: 2-12	[1, 512, 64, 64]	--
└─Conv2d: 3-34	[1, 512, 64, 64]	1,179,648
└─BatchNorm2d: 3-35	[1, 512, 64, 64]	1,024
└─SiLU: 3-36	[1, 512, 64, 64]	--
└─ConvTranspose2d: 1-12	[1, 256, 128, 128]	524,544
└─Bottleneck: 1-13	[1, 256, 128, 128]	--
└─BaseConv: 2-13	[1, 128, 128, 128]	--
└─Conv2d: 3-37	[1, 128, 128, 128]	65,536
└─BatchNorm2d: 3-38	[1, 128, 128, 128]	256
└─SiLU: 3-39	[1, 128, 128, 128]	--
└─BaseConv: 2-14	[1, 256, 128, 128]	--

		└─Conv2d: 3-40	[1, 256, 128, 128]	294,912
		└─BatchNorm2d: 3-41	[1, 256, 128, 128]	512
		└─SiLU: 3-42	[1, 256, 128, 128]	--
	└─ConvTranspose2d: 1-14		[1, 128, 256, 256]	131,200
	└─Bottleneck: 1-15		[1, 128, 256, 256]	--
	└─BaseConv: 2-15		[1, 64, 256, 256]	--
		└─Conv2d: 3-43	[1, 64, 256, 256]	16,384
		└─BatchNorm2d: 3-44	[1, 64, 256, 256]	128
		└─SiLU: 3-45	[1, 64, 256, 256]	--
	└─BaseConv: 2-16		[1, 128, 256, 256]	--
		└─Conv2d: 3-46	[1, 128, 256, 256]	73,728
		└─BatchNorm2d: 3-47	[1, 128, 256, 256]	256
		└─SiLU: 3-48	[1, 128, 256, 256]	--
	└─ConvTranspose2d: 1-16		[1, 64, 512, 512]	32,832
	└─Bottleneck: 1-17		[1, 64, 512, 512]	--
	└─BaseConv: 2-17		[1, 32, 512, 512]	--
		└─Conv2d: 3-49	[1, 32, 512, 512]	4,096
		└─BatchNorm2d: 3-50	[1, 32, 512, 512]	64
		└─SiLU: 3-51	[1, 32, 512, 512]	--
	└─BaseConv: 2-18		[1, 64, 512, 512]	--
		└─Conv2d: 3-52	[1, 64, 512, 512]	18,432
		└─BatchNorm2d: 3-53	[1, 64, 512, 512]	128
		└─SiLU: 3-54	[1, 64, 512, 512]	--
	└─Conv2d: 1-18		[1, 10, 512, 512]	650

=====  
Total params: 11,344,170

Trainable params: 11,344,170

Non-trainable params: 0

Total mult-adds (G): 83.44  
=====

Input size (MB): 3.15

Forward/backward pass size (MB): 1807.75

Params size (MB): 45.38

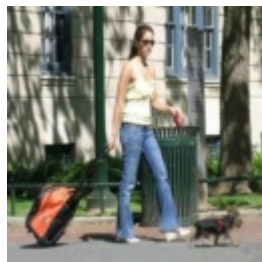
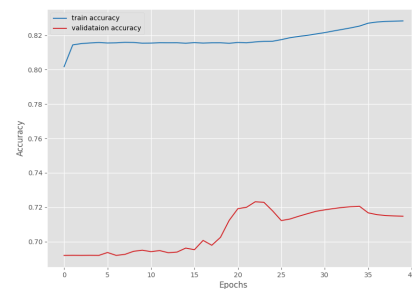
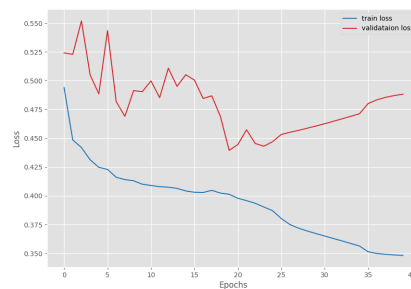
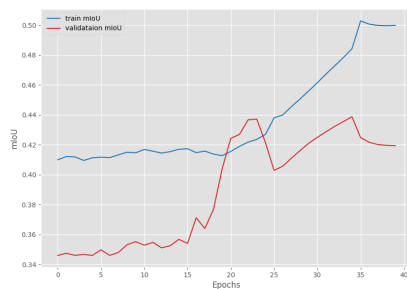
Estimated Total Size (MB): 1856.27  
=====

### 3.加入多个数据增广函数（旋转，翻转等），试一试效果。

这里引入水平翻转、垂直翻转、旋转，并使用 `UNet3()` 进行训练

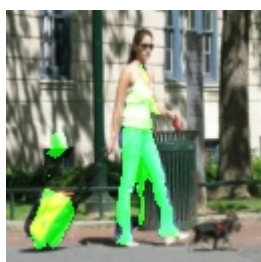
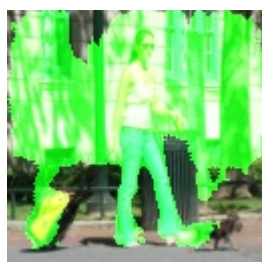
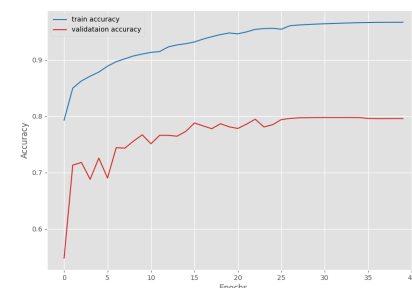
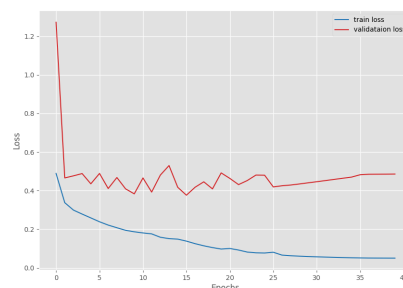
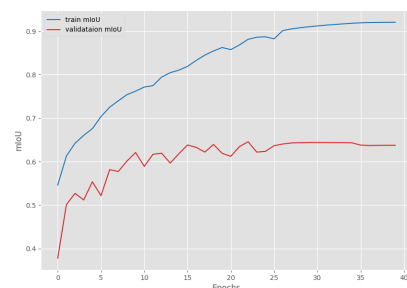
```
train_image_transform = transforms.Compose(
    [
        transforms.Resize([img_size, img_size]),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomRotation(degrees=30),
        transforms.RandomVerticalFlip(p=0.5),
        transforms.ToTensor(),
    ]
)
```

这里发现引入数据增强后性能略有下降，且训练过程震荡较大

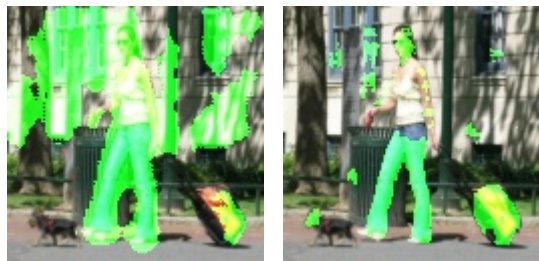
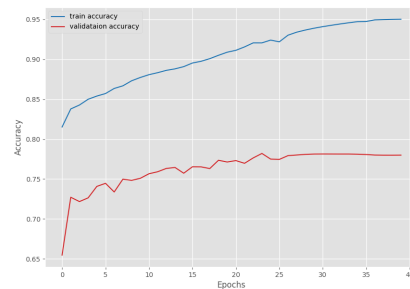
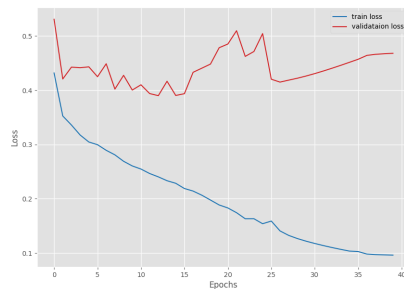
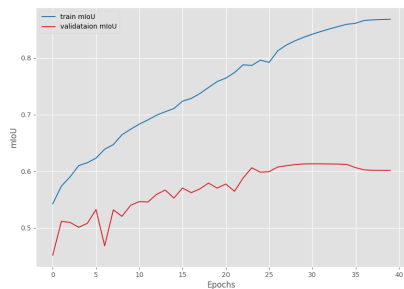


## 4.用 UNet3() 和 UNet5(), 分别试验一下分割效果，并分析结果。

### UNet5()



### UNet3()



可以看到模型在经过训练后专注于目标的能力有了一些提升，不过由于本身性能较低，训练后人物的上半身完全没有被识别到，并且 `UNet5()` 的性能较 `UNet3()` 更好（网络深度影响）。

## 5.附加：将 UNet5 改造成 UNet++，试一下效果

搓了一个“假冒伪劣”的小玩具，似乎不太符合 `UNet++` 的标准做法，在训练集上的效果似乎略有提升，但验证集依然过拟合，且性能没有太大提升

