

AlexNet 应用于 cifar 数据集实验报告

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目录

1. 修改的 AlexNet 结构	2
1) AlexNet 详细结构	2
2) 参数初始化	2
3) 测试及网络参数调整	3
(1) 增强数据集	3
(2) 修改学习率	3
4) 结果对比展示	3
(1) 无数据增强, 无学习率调整	3
(2) 无数据增强, 有学习率调整	4
(3) 有数据增强, 无学习率调整	6
(4) 有数据增强, 有学习率调整	7
2. 全连接层结构调整	9
1) AlexNet 详细结构	9
2) 参数初始化	9
3) 测试及网络参数调整	9
(1) 增强数据集	9
(2) 修改学习率	10
4) 结果对比展示	10
(1) 无数据增强, 无学习率调整	10
(2) 无数据增强, 有学习率调整	11
(3) 有数据增强, 无学习率调整	12
(4) 有数据增强, 有学习率调整	14

1. 修改的 AlexNet 结构

1) AlexNet 详细结构

Modified AlexNet for Cifar(3FC)					
input	32*32*3				
layer1	Conv2d	kernel	channel	padding	stride
		11*11*3	64	5	4
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
layer2	Conv2d	kernel	channel	padding	stride
		5*5*64	192	2	default
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
layer3	Conv2d	kernel	channel	padding	stride
		3*3*192	384	1	default
	Relu	inplace=True			
layer4	Conv2d	kernel	channel	padding	stride
		3*3*384	256	1	default
	Relu	inplace=True			
layer5	Conv2d	kernel	channel	padding	stride
		3*3*256	256	1	default
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
fully-connected	Dropout				
	Linear	256->4096			
	Relu	inplace=True			
	Dropout				
	Linear	4096->4096			
	Relu	inplace=True			
	Linear	4096->10			

2) 参数初始化

learning_rate = 0.1

momentum = 0.9

weight_decay = 0.0005

损失函数使用交叉熵，训练过程使用带动量的随机梯度下降法。

```

230 # 交叉熵损失函数
231 criterion = nn.CrossEntropyLoss()
232 # 随机梯度下降
233 optimizer = optim.SGD(model.parameters(), lr=0.1, momentum=0.9, weight_decay=5e-4)

```

3) 测试及网络参数调整

(1) 增强数据集

```
#### 数据预处理
transform = transforms.Compose([
    transforms.RandomCrop(32, padding=4), # 随机剪裁
    transforms.RandomHorizontalFlip(), # 随机水平翻转
    transforms.ToTensor(),# 转为tensor
    transforms.Normalize((0.5,0.5,0.5),(0.5,0.5,0.5)),# 归一化
])
```

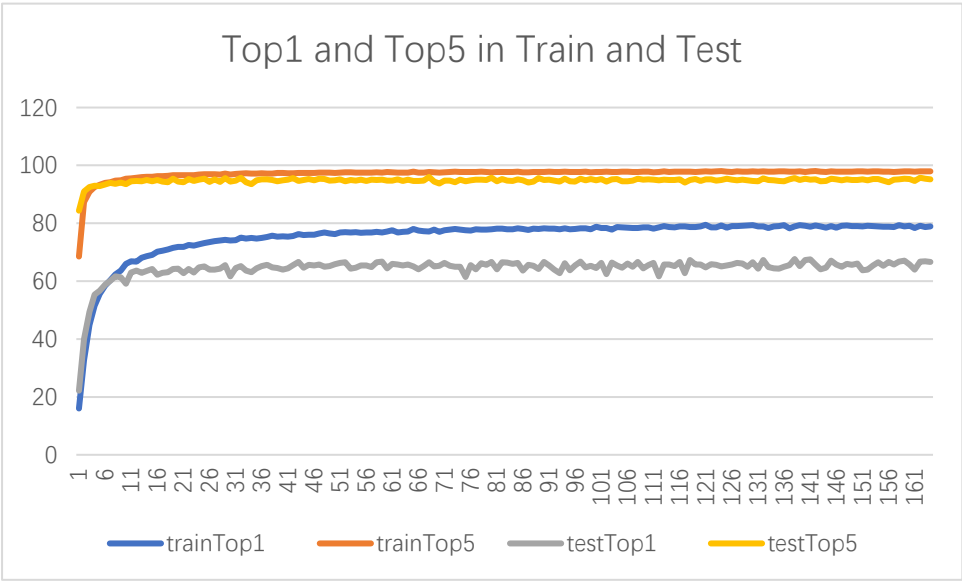
(2) 修改学习率

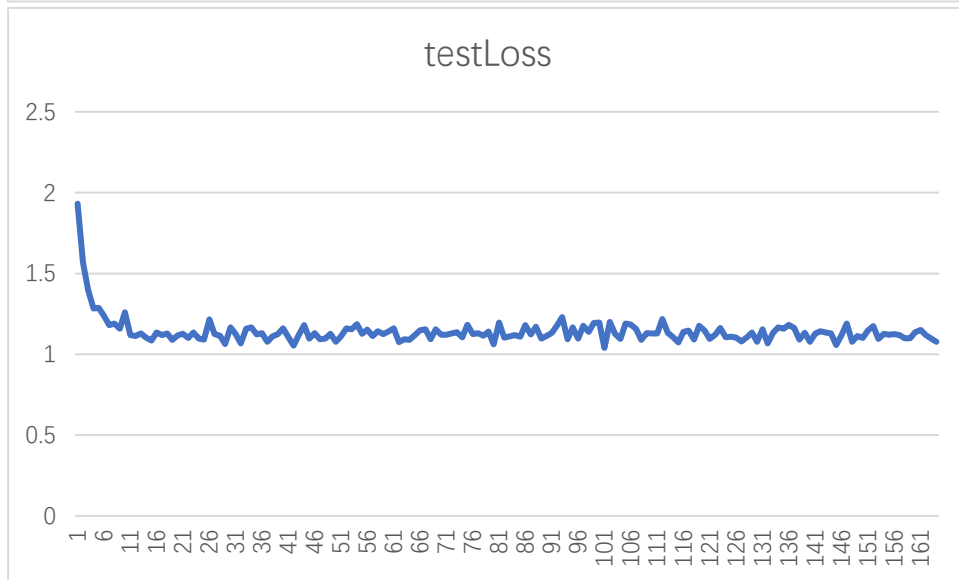
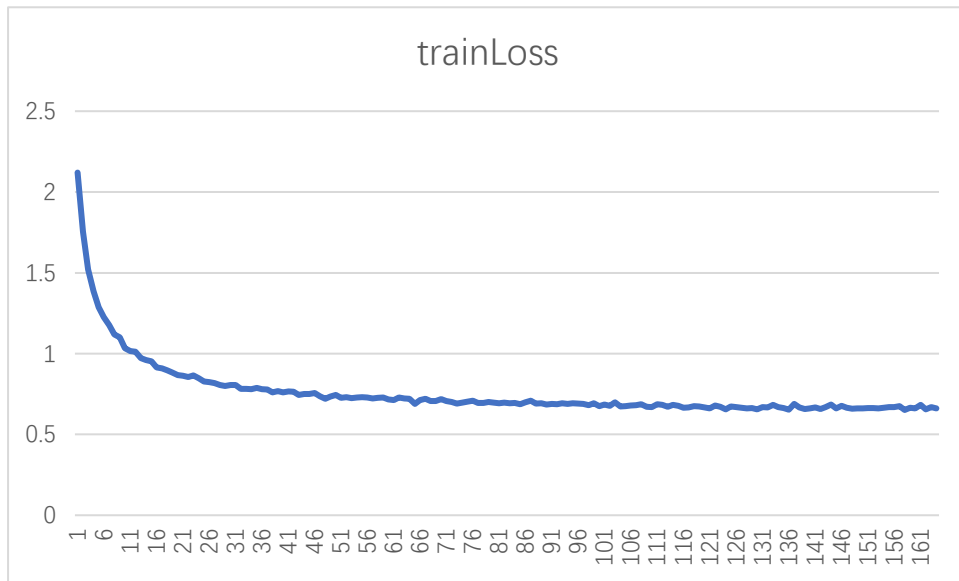
```
def adjust_learning_rate(optimizer, epoch):
    if epoch in [81, 122]:
        for param_group in optimizer.param_groups:
            param_group['lr'] = param_group['lr'] * 0.1
```

4) 结果对比展示

(1) 无数据增强，无学习率调整

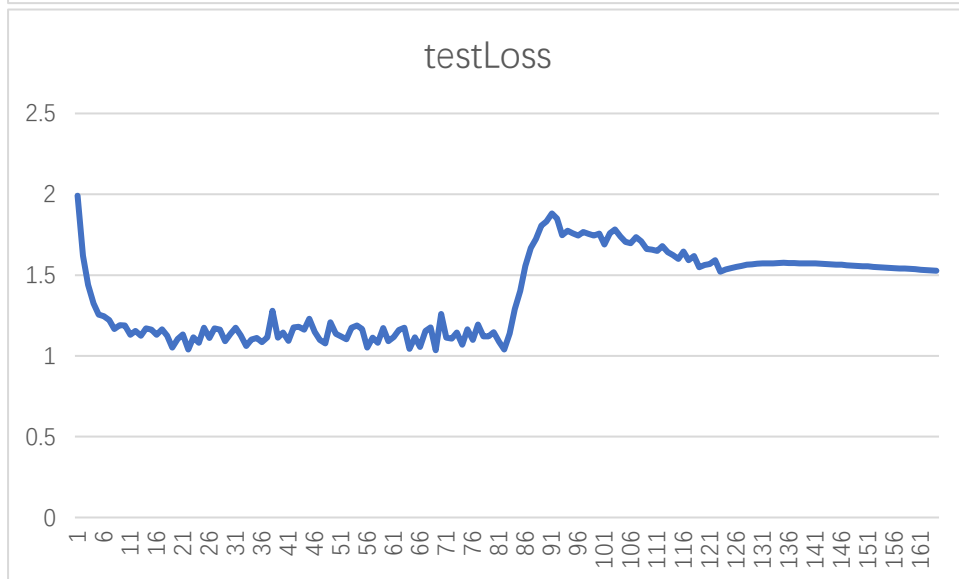
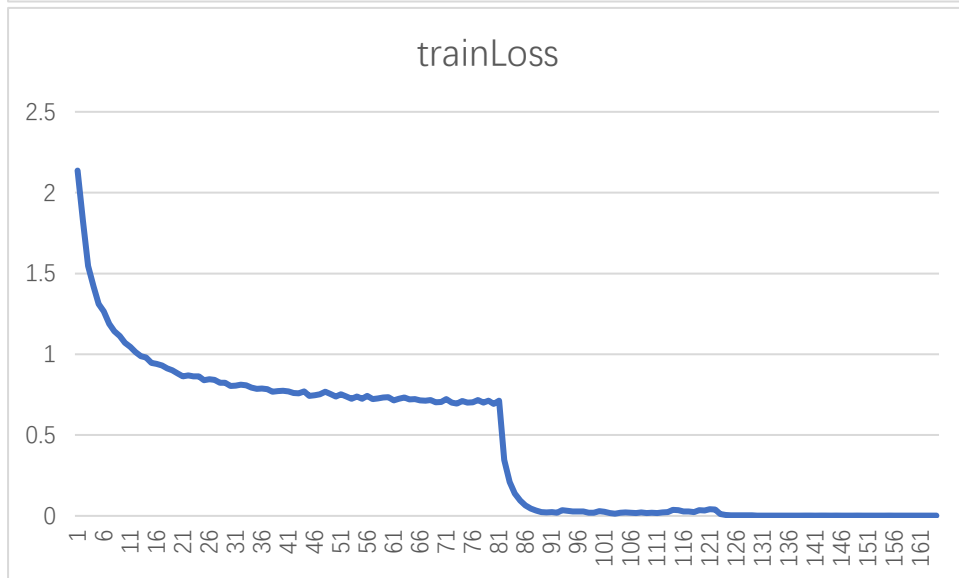
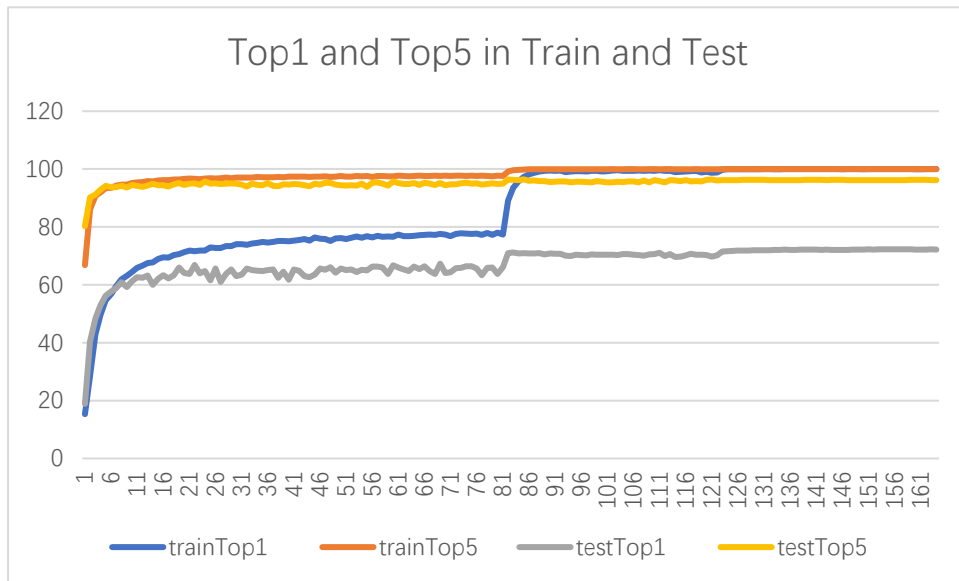
Best Accuracy		
train	Top-1	79.48
	Top-5	98.044
test	Top-1	67.65
	Top-5	96.01





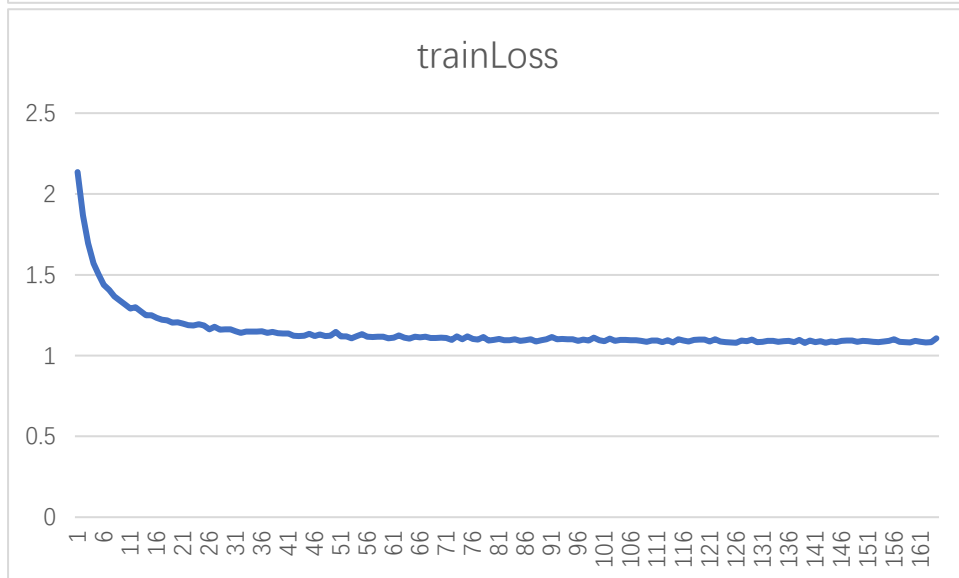
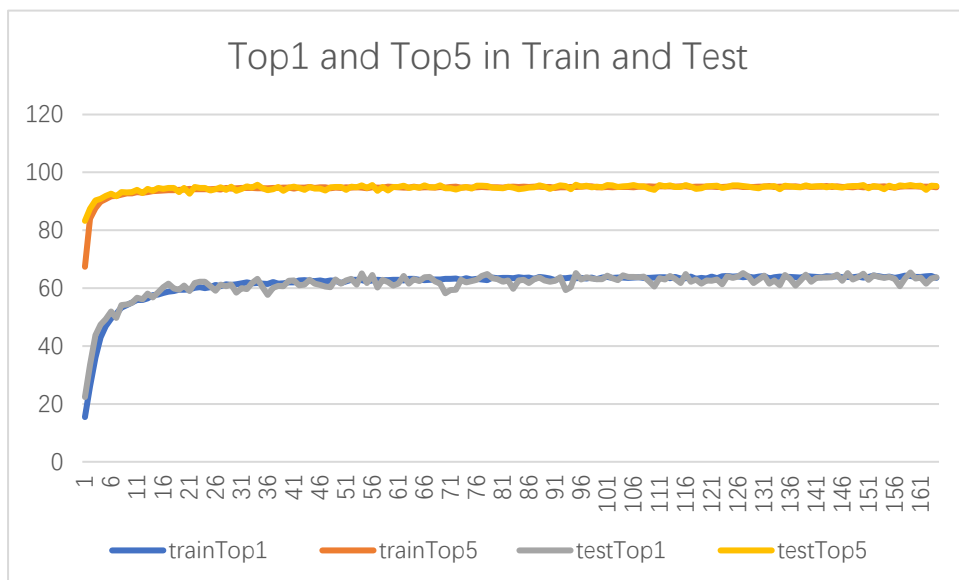
(2) 无数据增强，有学习率调整

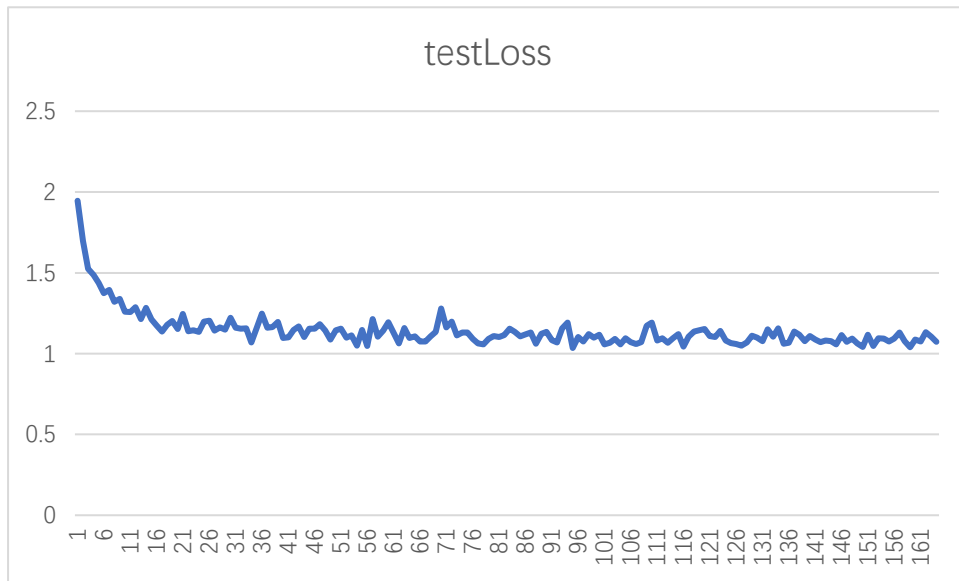
Best Accuracy		
train	Top-1	100
	Top-5	100
test	Top-1	72.17
	Top-5	96.46



(3) 有数据增强, 无学习率调整

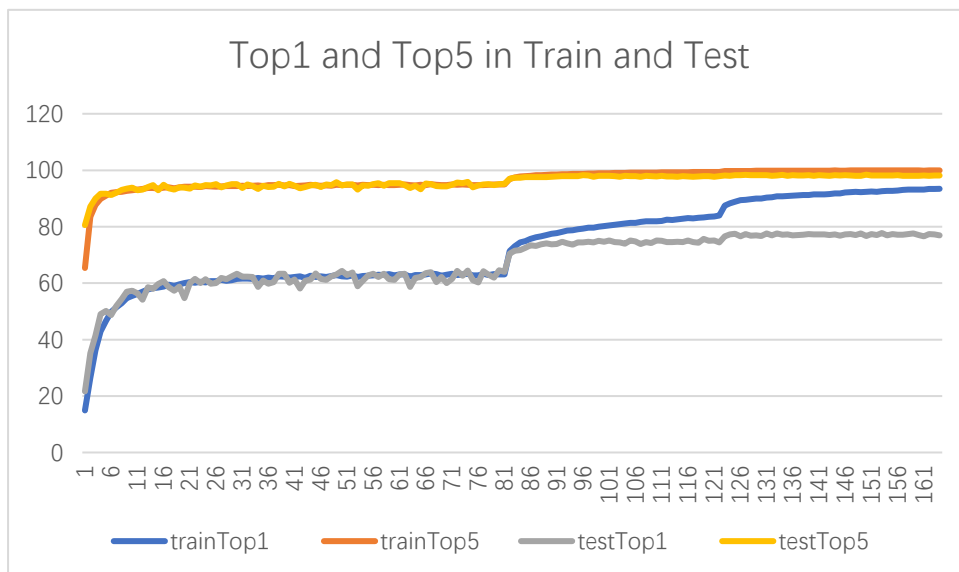
Best Accuracy		
train	Top-1	64.344
	Top-5	95.28
test	Top-1	65.25
	Top-5	95.73

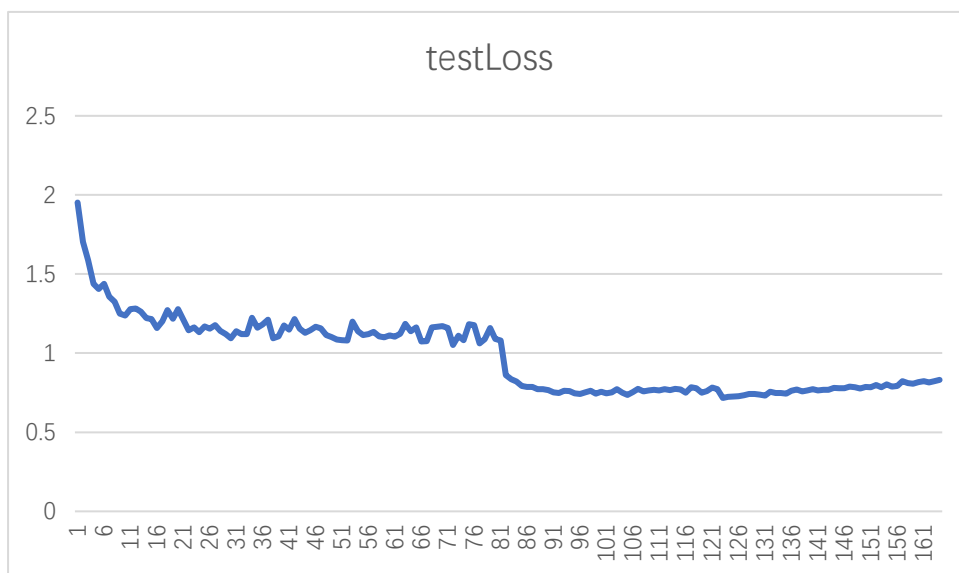
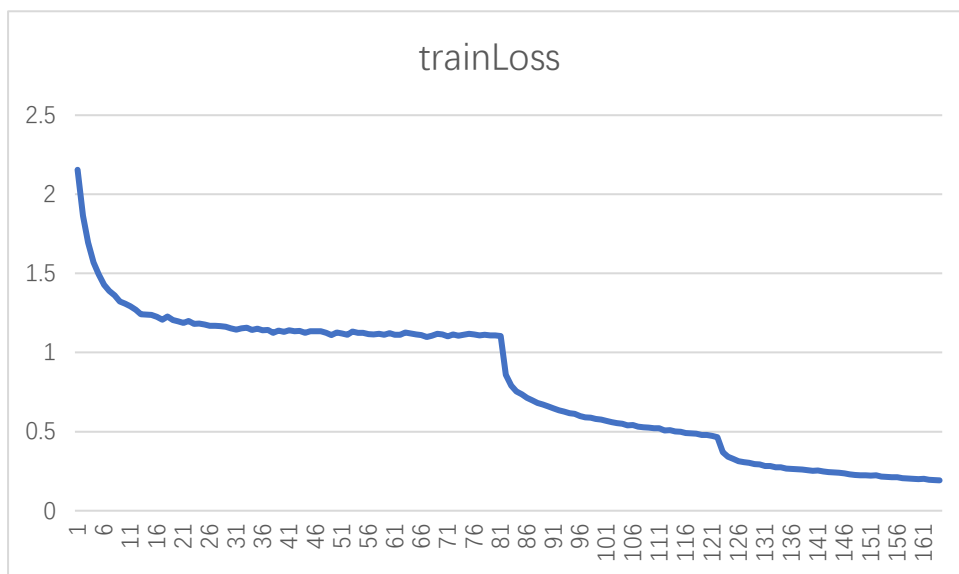




(4) 有数据增强, 有学习率调整

Best Accuracy		
train	Top-1	92.35
	Top-5	99.904
test	Top-1	77.61
	Top-5	98.43





2. 全连接层结构调整

1) AlexNet 详细结构

Modified AlexNet for Cifar(1FC)					
input	32*32*3				
layer1	Conv2d	kernel	channel	padding	stride
		11*11*3	64	5	4
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
layer2	Conv2d	kernel	channel	padding	stride
		5*5*64	192	2	default
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
layer3	Conv2d	kernel	channel	padding	stride
		3*3*192	384	1	default
	Relu	inplace=True			
layer4	Conv2d	kernel	channel	padding	stride
		3*3*384	256	1	default
	Relu	inplace=True			
layer5	Conv2d	kernel	channel	padding	stride
		3*3*256	256	1	default
	Relu	inplace=True			
	MaxPool2d	kernel_size		stride	
2*2		2			
fully-connected	256 -> 10				

2) 参数初始化

learning_rate = 0.1

momentum = 0.9

weight_decay = 0.0005

损失函数使用交叉熵，训练过程使用带动量的随机梯度下降法。

```

230 # 交叉熵损失函数
231 criterion = nn.CrossEntropyLoss()
232 # 随机梯度下降
233 optimizer = optim.SGD(model.parameters(), lr=0.1, momentum=0.9, weight_decay=5e-4)

```

3) 测试及网络参数调整

(1) 增强数据集

```

#### 数据预处理
transform = transforms.Compose([
    transforms.RandomCrop(32, padding=4), # 随机剪裁
    transforms.RandomHorizontalFlip(), # 随机水平翻转
    transforms.ToTensor(), # 转为tensor
    transforms.Normalize((0.5,0.5,0.5),(0.5,0.5,0.5)), # 归一化
])

```

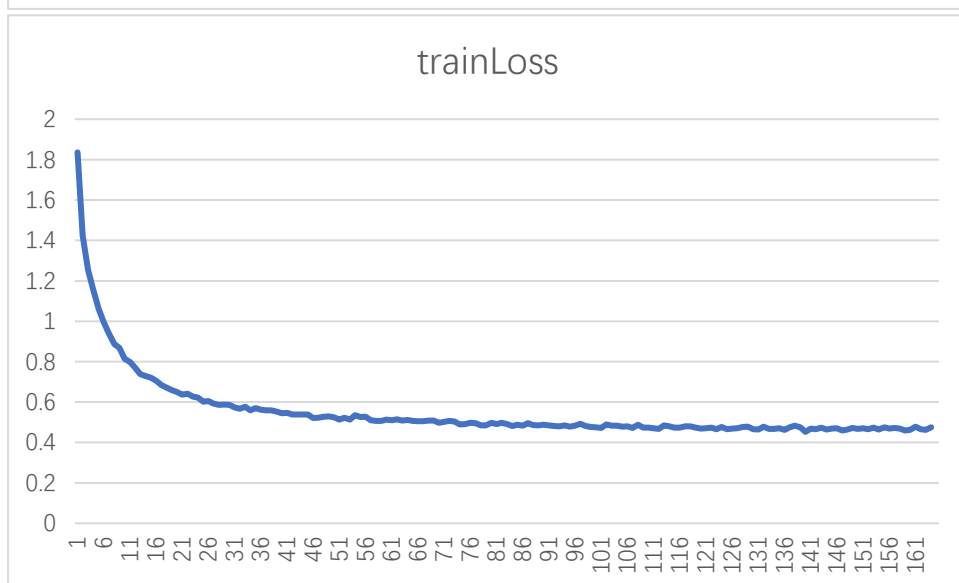
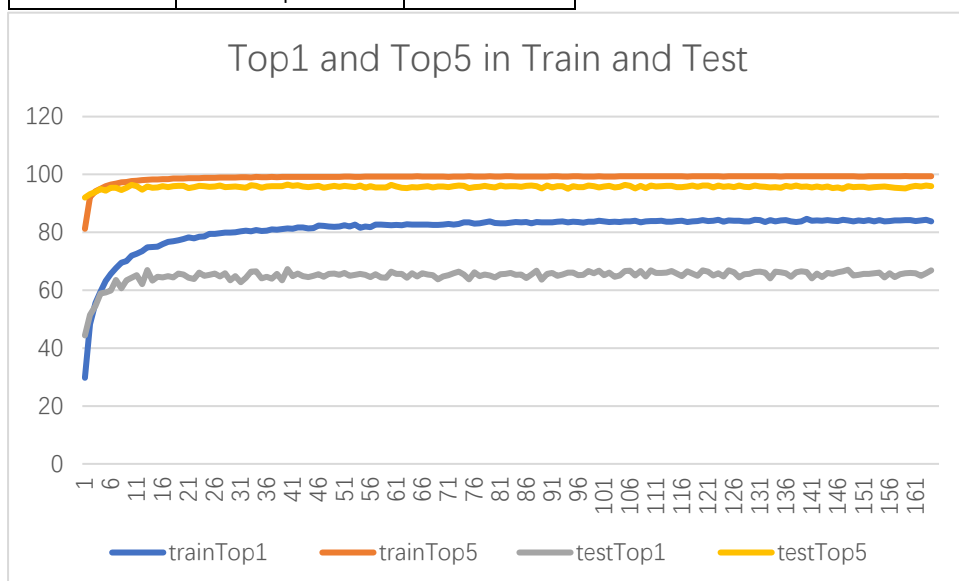
(2) 修改学习率

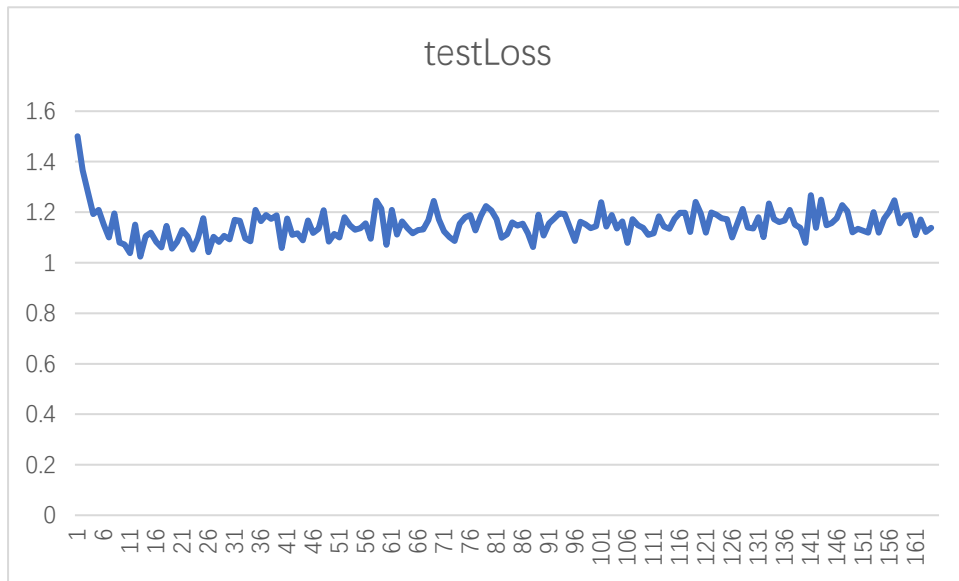
```
def adjust_learning_rate(optimizer, epoch):  
    if epoch in [81, 122]:  
        for param_group in optimizer.param_groups:  
            param_group['lr'] = param_group['lr'] * 0.1
```

4) 结果对比展示

(1) 无数据增强，无学习率调整

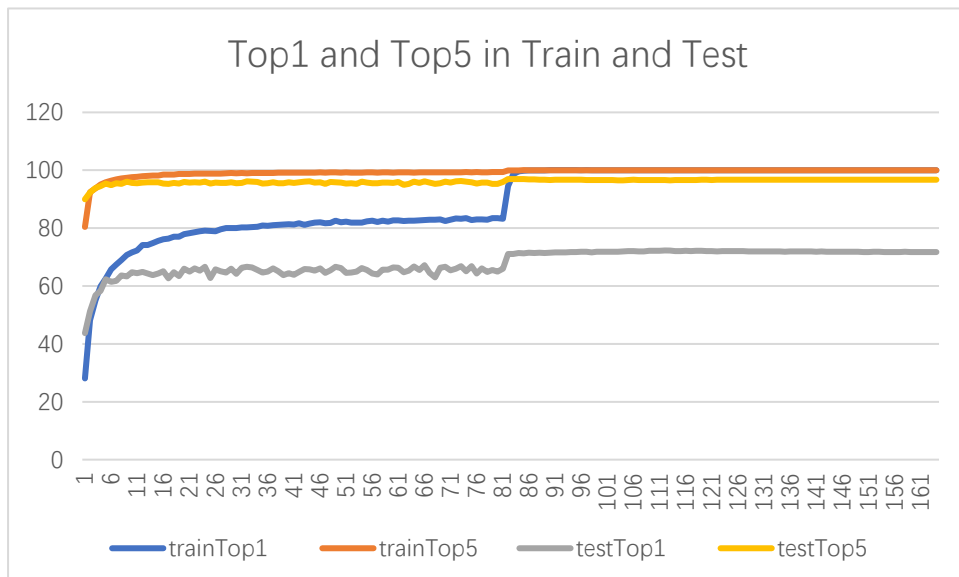
Best Accuracy		
train	Top-1	84.674
	Top-5	99.444
test	Top-1	67.31
	Top-5	96.51

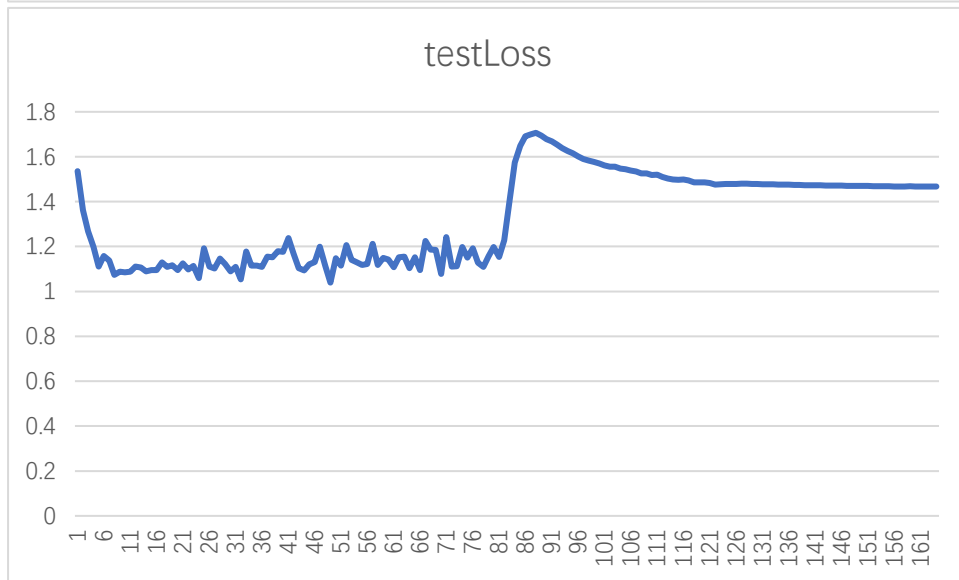
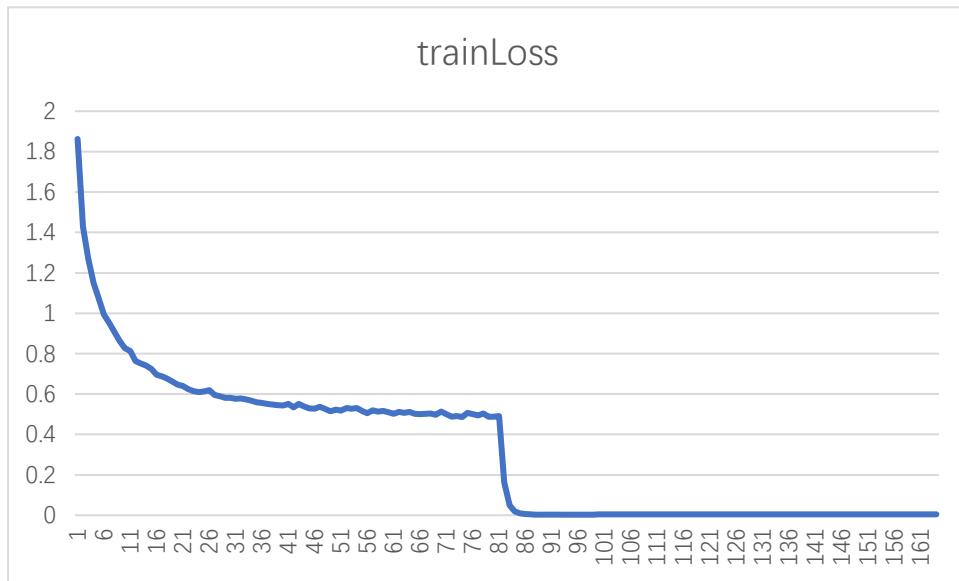




(2) 无数据增强, 有学习率调整

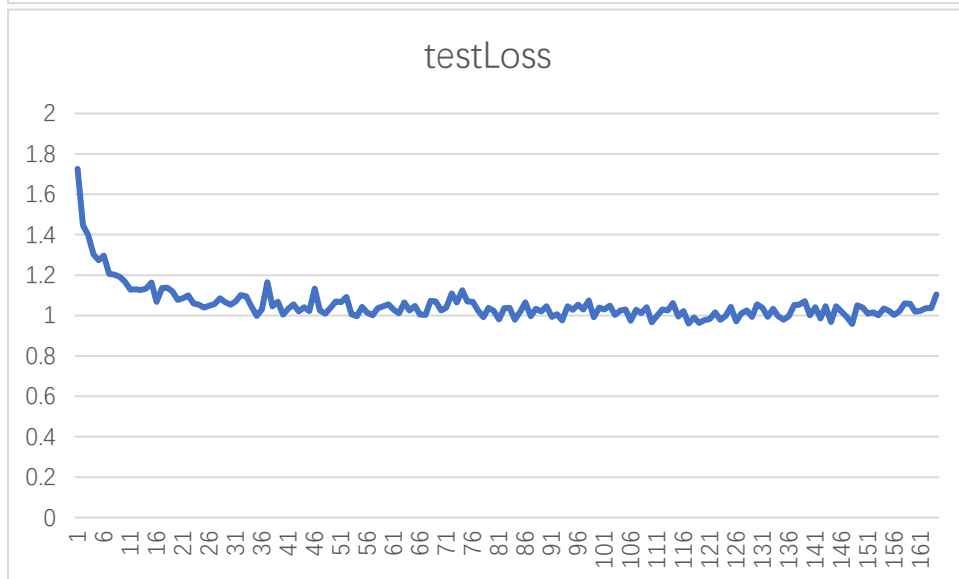
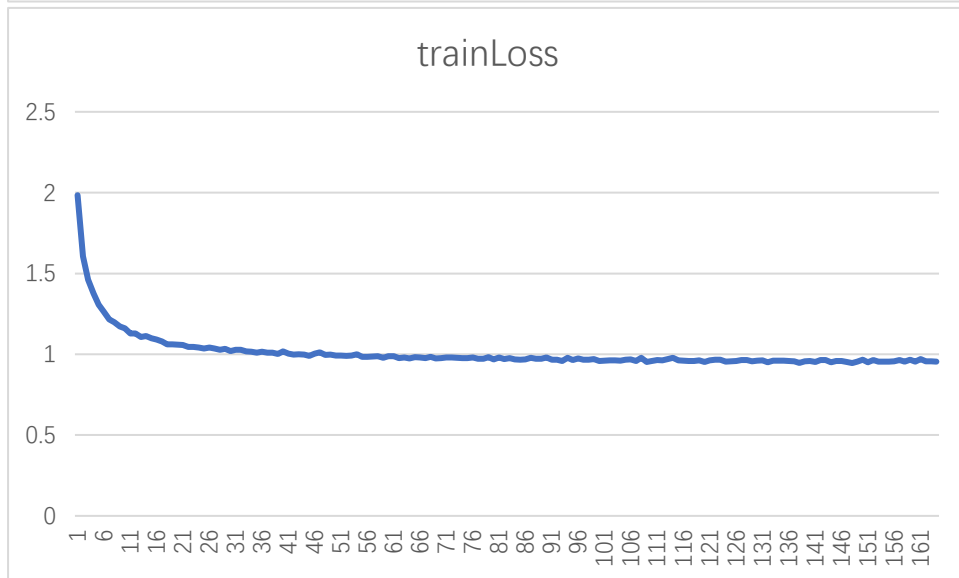
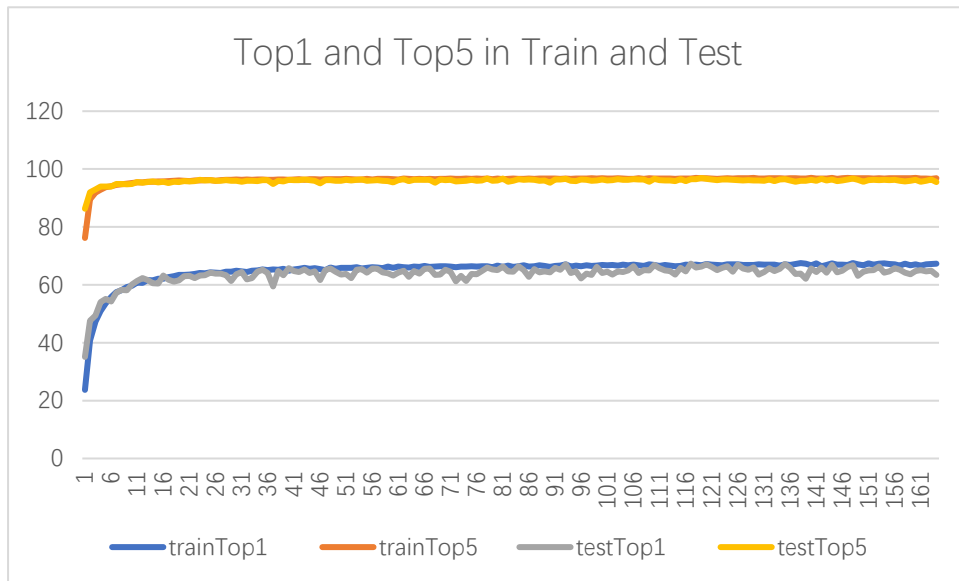
Best Accuracy		
train	Top-1	100
	Top-5	100
test	Top-1	72.26
	Top-5	96.96





(3) 有数据增强，无学习率调整

Best Accuracy		
train	Top-1	67.524
	Top-5	96.974
test	Top-1	67.33
	Top-5	96.9



(4) 有数据增强, 有学习率调整

Best Accuracy		
train	Top-1	95.164
	Top-5	99.984
test	Top-1	78.2
	Top-5	98.56

