

神经网络实验报告

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一、实验目的

学习神经网络图像分类方法。

二、实验内容

训练 CNN, 来对 CIFAR-10 数据集进行图像分类。

三、实验平台

Pytorch, torchvision, matplotlib

四、代码 (对核心代码进行详细说明。如调用库函数, 详细分析参数及返回值)

```
'''Train CIFAR10 with PyTorch.'''
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import torch.backends.cudnn as cudnn

import torchvision
import torchvision.transforms as transforms

import os
import argparse

from models import *
from utils import progress_bar

parser =
argparse.ArgumentParser(description='PyTorch CIFAR10 Training')
parser.add_argument('--lr', default=0.1,
type=float, help='learning rate')
parser.add_argument('--resume', '-r',
action='store_true',
help='resume from
checkpoint')
args = parser.parse_args()

device = 'cuda' if
torch.cuda.is_available() else 'cpu'
best_acc = 0 # best test accuracy
start_epoch = 0 # start from epoch 0 or
```

```
last_checkpoint_epoch

# Data
print('==> Preparing data..')
transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822,
0.4465), (0.2023, 0.1994, 0.2010)),
])

transform_test = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822,
0.4465), (0.2023, 0.1994, 0.2010)),
])

trainset = torchvision.datasets.CIFAR10(
    root='./data', train=True,
download=True,
transform=transform_train)
trainloader =
torch.utils.data.DataLoader(
    trainset, batch_size=128,
shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(
    root='./data', train=False,
download=True, transform=transform_test)
testloader =
torch.utils.data.DataLoader(
    testset, batch_size=100,
```

```

shuffle=False, num_workers=2)

classes = ('plane', 'car', 'bird',
           'cat', 'deer',
           'dog', 'frog', 'horse', 'ship',
           'truck')

# Model
print('==> Building model..')
net = ResNet18()
net = net.to(device)
if device == 'cuda':
    net = torch.nn.DataParallel(net)
    cudnn.benchmark = True

if args.resume:
    # Load checkpoint.
    print('==> Resuming from
checkpoint..')
    assert os.path.isdir('checkpoint'),
    'Error: no checkpoint directory found!'
    checkpoint =
torch.load('./checkpoint/ckpt.pth')

net.load_state_dict(checkpoint['net'])
best_acc = checkpoint['acc']
start_epoch = checkpoint['epoch']

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(),
lr=args.lr,
                        momentum=0.9,
weight_decay=5e-4)
scheduler =
torch.optim.lr_scheduler.CosineAnnealing
LR(optimizer, T_max=200)

# Training
def train(epoch):
    print('\nEpoch: %d' % epoch)
    net.train()
    train_loss = 0
    correct = 0

```

```

total = 0
    for batch_idx, (inputs, targets) in
enumerate(trainloader):
        inputs, targets =
inputs.to(device), targets.to(device)
        optimizer.zero_grad()
        outputs = net(inputs)
        loss = criterion(outputs, targets)
        loss.backward()
        optimizer.step()

        train_loss += loss.item()
        _, predicted = outputs.max(1)
        total += targets.size(0)
        correct +=
predicted.eq(targets).sum().item()

        progress_bar(batch_idx,
len(trainloader), 'Loss: %.3f |
Acc: %.3f%% (%d/%d)'
                        %
(train_loss/(batch_idx+1),
100.*correct/total, correct, total))

def test(epoch):
    global best_acc
    net.eval()
    test_loss = 0
    correct = 0
    total = 0
    with torch.no_grad():
        for batch_idx, (inputs, targets)
in enumerate(testloader):
            inputs, targets =
inputs.to(device), targets.to(device)
            outputs = net(inputs)
            loss = criterion(outputs,
targets)

            test_loss += loss.item()
            _, predicted = outputs.max(1)
            total += targets.size(0)
            correct +=

```

<pre> predicted.eq(targets).sum().item() progress_bar(batch_idx, len(testloader), 'Loss: %.3f Acc: %.3f%% (%d/%d)' % (test_loss/(batch_idx+1), 100.*correct/total, correct, total)) # Save checkpoint. acc = 100.*correct/total if acc > best_acc: print('Saving..') state = { 'net': net.state_dict(), 'acc': acc, </pre>	<pre> 'epoch': epoch, } if not os.path.isdir('checkpoint'): os.mkdir('checkpoint') torch.save(state, './checkpoint/ckpt.pth') best_acc = acc for epoch in range(start_epoch, start_epoch+200): train(epoch) test(epoch) scheduler.step() </pre>
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五、实验结果与分析

1. 前期准备

```
parser = argparse.ArgumentParser(description='PyTorch CIFAR10 Training')
```

```
parser.add_argument('--lr', default=0.1, type=float, help='learning rate') # 学习率默认 0.1
```

```
parser.add_argument('--resume', '-r', action='store_true', help='resume from checkpoint') # 断点续训
```

通过上述内容实现对学习率的预先设置。

```
device = 'cuda' if torch.cuda.is_available() else 'cpu' # 自动检测 GPU
```

```
cuda_device = -1
if torch.cuda.is_available():
    cuda_device = torch.cuda.device_count() - 1
device = torch.device('cuda:{}'.format(cuda_device) if cuda_device > -1 else 'cpu')
```

配置硬件。

```

transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4), # 随机裁剪
    transforms.RandomHorizontalFlip(),    # 水平翻转
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)) # CIFAR10 标准归一化
])

```

通过 transforms 进行数据增强。

```
net = ResNet18() # 默认使用 ResNet-18
```

```
net = net.to(device)
```

```
if device == 'cuda':
```

```
    net = torch.nn.DataParallel(net) # 多 GPU 支持
```

启用 ResNet-18，启用数据并行（多 GPU 训练）

```
if args.resume:
```

```
    checkpoint = torch.load('./checkpoint/ckpt.pth')
```

```
    net.load_state_dict(checkpoint['net']) # 加载模型参数
```

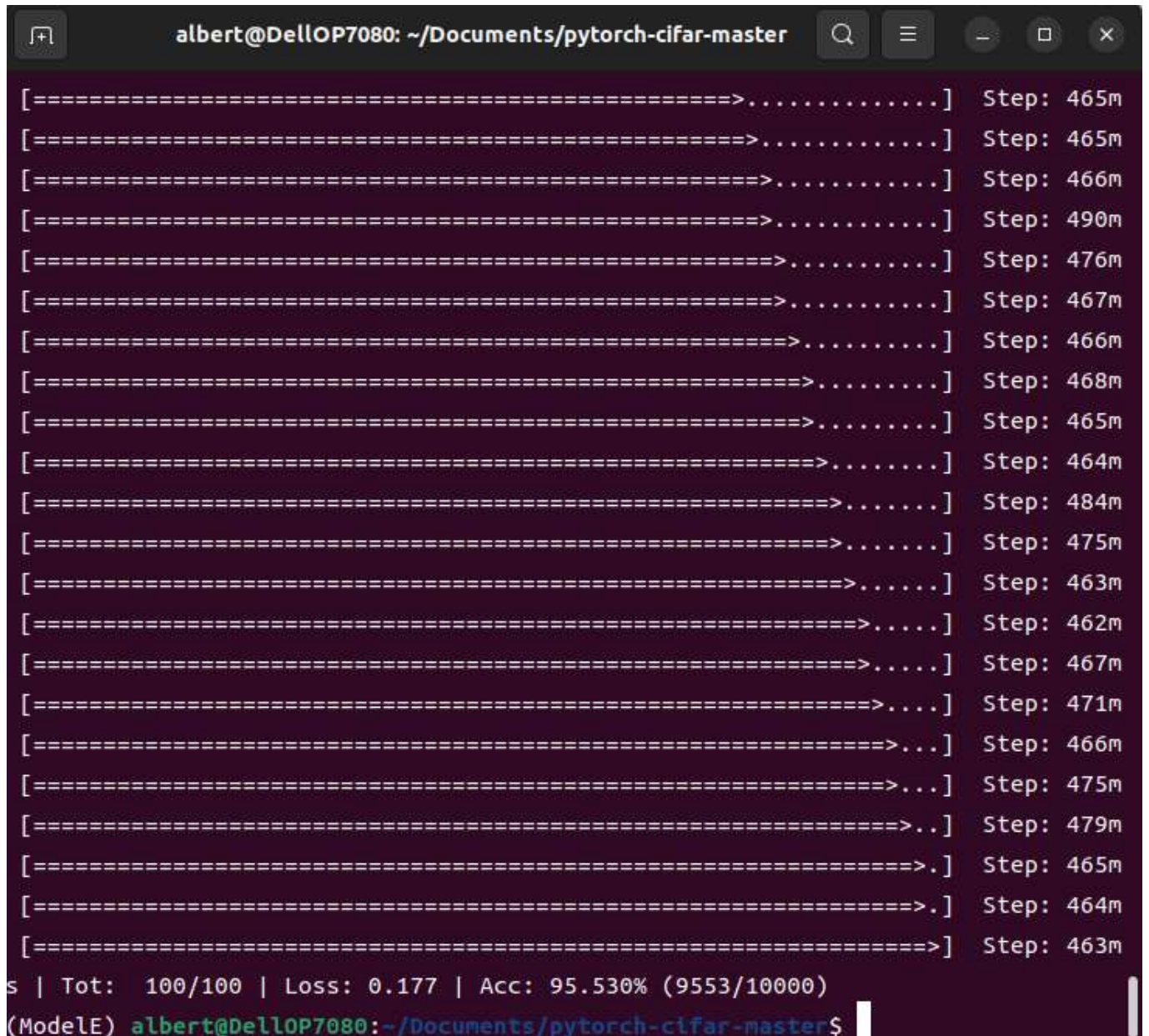
```
    best_acc = checkpoint['acc'] # 历史最佳准确率
```

```
    start_epoch = checkpoint['epoch'] # 恢复训练轮次
```

断点恢复机制。

```
criterion = nn.CrossEntropyLoss() # 交叉熵损失
```

```
optimizer = optim.SGD(net.parameters(), lr=args.lr,
                      momentum=0.9, weight_decay=5e-4) # 带动量与 L2 正则
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=200) # 余弦退火学习率
SGD + 动量 + 权重衰减, 200 个 epoch 的余弦退火策略
for epoch in range(start_epoch, start_epoch+200):
    train(epoch)
    test(epoch)
    scheduler.step() # 更新学习率
进行训练循环。
```



```
albert@DellOP7080: ~/Documents/pytorch-cifar-master

[=====>.....] Step: 465m
[=====>.....] Step: 465m
[=====>.....] Step: 466m
[=====>.....] Step: 490m
[=====>.....] Step: 476m
[=====>.....] Step: 467m
[=====>.....] Step: 466m
[=====>.....] Step: 468m
[=====>.....] Step: 465m
[=====>.....] Step: 464m
[=====>.....] Step: 484m
[=====>.....] Step: 475m
[=====>.....] Step: 463m
[=====>.....] Step: 462m
[=====>.....] Step: 467m
[=====>.....] Step: 471m
[=====>...] Step: 466m
[=====>...] Step: 475m
[=====>..] Step: 479m
[=====>.] Step: 465m
[=====>.] Step: 464m
[=====>] Step: 463m

s | Tot: 100/100 | Loss: 0.177 | Acc: 95.530% (9553/10000)
(ModelE) albert@DellOP7080:~/Documents/pytorch-cifar-master$
```

图 5-1 训练结果

六、总结

使用 CIFAR-10 数据集进行训练，直接采用 ResNet-18 网络结构，训练轮次 200 轮，最终正确率达到 95.53%。