Task3 字符识别模型——CNN模型构建

在Pytorch中构建CNN模型非常简单，只需要定义好模型的参数和正向传播即可，Pytorch会根据正向传播自动计算反向传播。

在本章我们会构建一个非常简单的CNN，然后进行训练。这个CNN模型包括两个卷积层，最后并联6个全连接层进行分类。

构建代码：

```python
import torch
torch.manual_seed(0)
torch.backends.cudnn.deterministic = False
torch.backends.cudnn.benchmark = True

import torchvision.models as models
import torchvision.transforms as transforms
import torchvision.datasets as datasets
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.autograd import Variable
from torch.utils.data.dataset import Dataset

# 定义模型
class SVHN_Model1(nn.Module):
    def __init__(self):
        super(SVHN_Model1, self).__init__()
        # CNN提取特征模块
        self.cnn = nn.Sequential(
            nn.Conv2d(3, 16, kernel_size=(3, 3), stride=(2, 2)),
            nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2)),
            nn.ReLU(),
            nn.MaxPool2d(2),
        )
        #
        self.fc1 = nn.Linear(32*3*7, 11)
        self.fc2 = nn.Linear(32*3*7, 11)
        self.fc3 = nn.Linear(32*3*7, 11)
        self.fc4 = nn.Linear(32*3*7, 11)
        self.fc5 = nn.Linear(32*3*7, 11)
        self.fc6 = nn.Linear(32*3*7, 11)

    def forward(self, img):
        feat = self.cnn(img)
        feat = feat.view(feat.shape[0], -1)
        c1 = self.fc1(feat)
        c2 = self.fc2(feat)
        c3 = self.fc3(feat)
        c4 = self.fc4(feat)
        c5 = self.fc5(feat)
        c6 = self.fc6(feat)
```

```
        return c1, c2, c3, c4, c5, c6

model = SVHN_Model1()
```

训练代码：

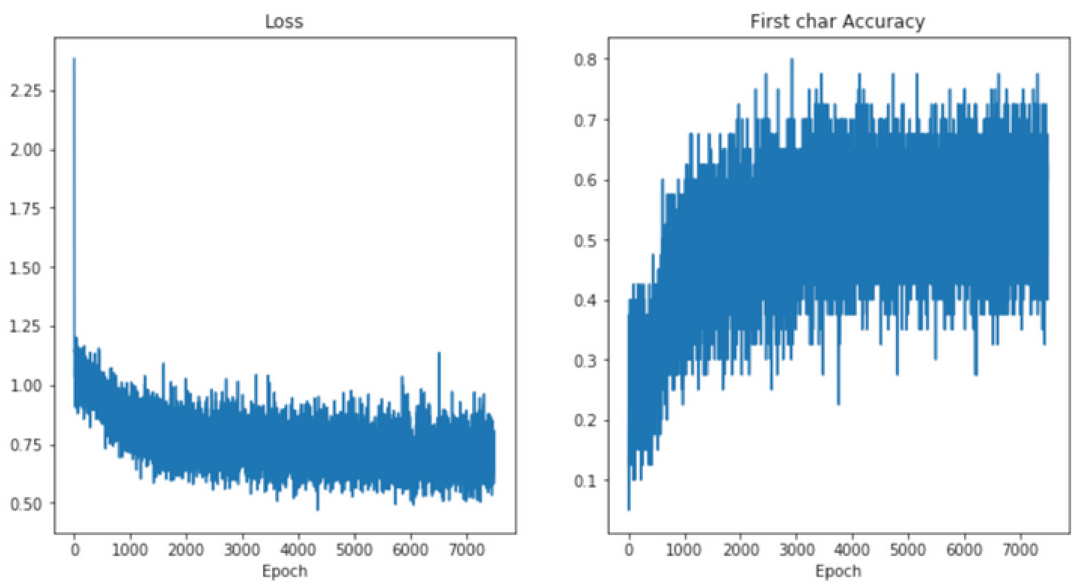
```
# 损失函数
criterion = nn.CrossEntropyLoss()
# 优化器
optimizer = torch.optim.Adam(model.parameters(), 0.005)

loss_plot, c0_plot = [], []
# 迭代10个Epoch
for epoch in range(10):
    for data in train_loader:
        c0, c1, c2, c3, c4, c5 = model(data[0])
        loss = criterion(c0, data[1][:, 0]) + \
                criterion(c1, data[1][:, 1]) + \
                criterion(c2, data[1][:, 2]) + \
                criterion(c3, data[1][:, 3]) + \
                criterion(c4, data[1][:, 4]) + \
                criterion(c5, data[1][:, 5])
        loss /= 6
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        loss_plot.append(loss.item())
        c0_plot.append((c0.argmax(1) == data[1][:, 0]).sum().item()*1.0 / c0.shape[0])

    print(epoch)
```

在训练完成后我们可以将训练过程中的损失和准确率进行绘制，如下图所示。从图中可以看出模型的损失在迭代过程中逐渐减小，字符预测的准确率逐渐升高。



当然为了追求精度，也可以使用在ImageNet数据集上的预训练模型，具体方法如下：

```python
class SVHN_Model2(nn.Module):
    def __init__(self):
        super(SVHN_Model1, self).__init__()

        model_conv = models.resnet18(pretrained=True)
        model_conv.avgpool = nn.AdaptiveAvgPool2d(1)
        model_conv = nn.Sequential(*list(model_conv.children())[:-1])
        self.cnn = model_conv

        self.fc1 = nn.Linear(512, 11)
        self.fc2 = nn.Linear(512, 11)
        self.fc3 = nn.Linear(512, 11)
        self.fc4 = nn.Linear(512, 11)
        self.fc5 = nn.Linear(512, 11)

    def forward(self, img):
        feat = self.cnn(img)
        # print(feat.shape)
        feat = feat.view(feat.shape[0], -1)
        c1 = self.fc1(feat)
        c2 = self.fc2(feat)
        c3 = self.fc3(feat)
        c4 = self.fc4(feat)
        c5 = self.fc5(feat)
        return c1, c2, c3, c4, c5
```