

# 计算机视觉第六次作业

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code:[https://github.com/NICHOLASFATHER/dongxu\\_master\\_degree/blob/master/W6\\_MNIST\\_FC.ipynb](https://github.com/NICHOLASFATHER/dongxu_master_degree/blob/master/W6_MNIST_FC.ipynb)

## 1.问题描述

在W6\_MNIST\_FC.ipynb基础上，增加卷积层结构/增加 dropout或者BN技术等，训练出尽可能高的MNIST分类效果。

## 2.超参数设置与数据集构建

```
torch.manual_seed(1)

EPOCH = 8
LR = 0.001
batch_size = 128
DOWNLOAD_MNIST = True
Device = 'cuda' if torch.cuda.is_available() else 'cpu'

train_data = torchvision.datasets.MNIST(root='./mnist/', train=True,
                                       transform=torchvision.transforms.ToTensor(),
                                       download=DOWNLOAD_MNIST)
test_data = torchvision.datasets.MNIST(root='./mnist/', train=False,
                                       transform=torchvision.transforms.ToTensor(),
                                       download=DOWNLOAD_MNIST)

train_dataloader = DataLoader(train_data, batch_size=batch_size, shuffle=True,
                              pin_memory=True)
test_dataloader = DataLoader(test_data, batch_size=batch_size, shuffle=False,
                              pin_memory=True)
```

## 3.模型搭建

```
# baseline
class FC_1(nn.Module):
    def __init__(self):
        super(FC_1, self).__init__()
        self.fc1 = nn.Linear(784, 256)
        self.fc2 = nn.Linear(256, 10)
        # self.fc3 = nn.Linear(10, 10)

    def forward(self, x):
        x = x.view(x.size(0), -1) # 调整数据维度
        x = self.fc1(x)
        x = F.relu(x)
```

```

        x = self.fc2(x)
#         x = F.relu(x)
#         x = self.fc3(x)

    output = x
    return output

# baseline plus
class FC_2(nn.Module):
    def __init__(self):
        super(FC_2, self).__init__()
        self.fc1 = nn.Linear(784, 256)
        self.fc2 = nn.Linear(256, 10)
        self.fc3 = nn.Linear(10, 10)

    def forward(self, x):
        x = x.view(x.size(0), -1) # 调整数据维度
        x = self.fc1(x)
        x = F.relu(x)
        x = self.fc2(x)
        x = F.relu(x)
        x = self.fc3(x)

    output = x
    return output

class Conv_net_base(nn.Module):
    def __init__(self):
        super(Conv_net_base, self).__init__()
        self.net = nn.Sequential(
            nn.Conv2d(1, 32, 5, padding=2), # h,w保持不变
            nn.MaxPool2d(2),
            nn.ReLU(),
            nn.Conv2d(32, 64, 5, padding=2),
            nn.MaxPool2d(2),
            nn.ReLU(),
            nn.Flatten(),
            nn.Linear(64*7*7, 10)
        )

    def forward(self, x):
        x = self.net(x)
        return x

class Conv_net_plus(nn.Module):
    def __init__(self):
        super(Conv_net_plus, self).__init__()
        self.net = nn.Sequential(
            nn.Conv2d(1, 16, 5, padding=2), # h,w保持不变
            nn.MaxPool2d(2),
            nn.ReLU(),
            nn.Conv2d(16, 32, 5, padding=2), # h,w保持不变
            nn.MaxPool2d(2),

```

```

        nn.ReLU(),
        nn.Conv2d(32, 64, 5, padding=2),
        nn.Flatten(),
        nn.ReLU(),
        nn.Linear(64*7*7, 512),
        nn.ReLU(),
        nn.Linear(512, 10)
    )

```

```

def forward(self, x):
    x = self.net(x)
    return x

```

```

class Conv_net_plus_bn(nn.Module):
    def __init__(self):
        super(Conv_net_plus_bn, self).__init__()
        self.net = nn.Sequential(
            nn.Conv2d(1, 16, 5, padding=2), # h,w保持不变
            nn.BatchNorm2d(16),
            nn.MaxPool2d(2),
            nn.ReLU(),

            nn.Conv2d(16, 32, 5, padding=2), # h,w保持不变
            nn.BatchNorm2d(32),
            nn.MaxPool2d(2),
            nn.ReLU(),

            nn.Conv2d(32, 64, 5, padding=2),
            nn.BatchNorm2d(64),
            nn.ReLU(),

            nn.Flatten(),
            nn.Linear(64*7*7, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(),
            nn.Linear(512, 10)
        )

```

```

def forward(self, x):
    x = self.net(x)
    return x

```

```

class Conv_net_plus_bn_dropout(nn.Module):
    def __init__(self):
        super(Conv_net_plus_bn_dropout, self).__init__()
        self.net = nn.Sequential(
            nn.Conv2d(1, 16, 5, padding=2), # h,w保持不变
            nn.BatchNorm2d(16),
            nn.MaxPool2d(2),
            torch.nn.Dropout2d(p=0.1),
            nn.ReLU(),

```

```

        nn.Conv2d(16, 32, 5, padding=2), # h,w保持不变
        nn.BatchNorm2d(32),
        nn.MaxPool2d(2),
        torch.nn.Dropout2d(p=0.1),
        nn.ReLU(),

        nn.Conv2d(32, 64, 5, padding=2),
        nn.BatchNorm2d(64),
        torch.nn.Dropout2d(p=0.1),
        nn.ReLU(),

        nn.Flatten(),
        nn.Linear(64*7*7, 512),
        nn.BatchNorm1d(512),
        torch.nn.Dropout(0.2),
        nn.ReLU(),
        nn.Linear(512, 10)
    )

    def forward(self, x):
        x = self.net(x)
        return x

```

## 4.训练与可视化

```

def train(network, save_name):

    optimizer = torch.optim.Adam(network.parameters(), lr=LR)
    # loss_func = nn.MSELoss()
    loss_func = nn.CrossEntropyLoss()
    best_val_acc = 0
    train_loss = []
    train_acc = []
    val_loss = []
    val_acc = []

    for epoch in range(EPOCH):
        loss_sum = 0
        acc_sum = 0
        print(f'EPOCH{epoch}\n-----')
        size = len(train_data_loader.dataset)

        network.train()
        for batch, item in enumerate(train_data_loader):

            # if batch == 4: # 删除
            #     break

            pics, labels = item
            pics = pics.to(Device)
            labels = labels.to(Device)

            output = network(pics)
            loss = loss_func(output, labels)

```

```

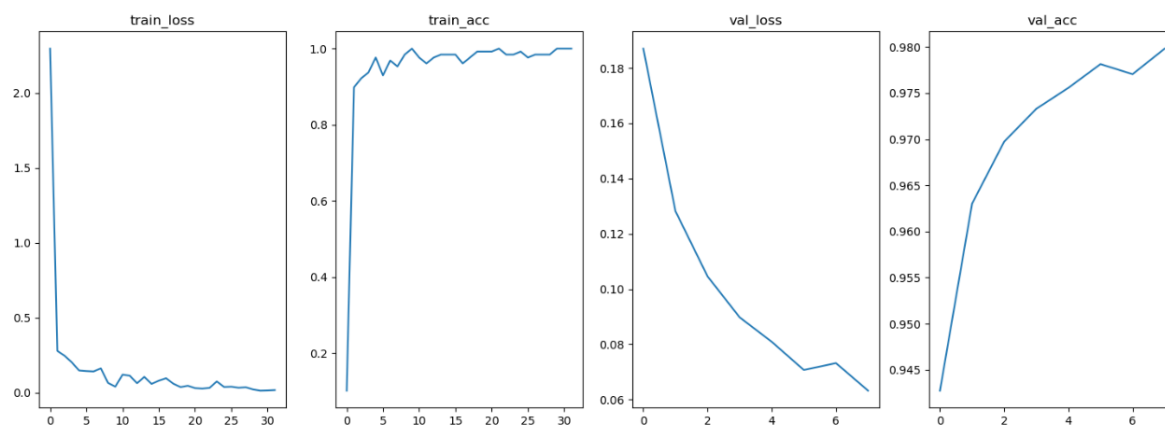
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
        if batch % 150 == 0:
            loss_value, current = loss.item(), batch*len(pics)
            train_loss.append(loss_value)
            acc = (output.argmax(dim=1) == labels).sum().item() / len(pics)
            train_acc.append(acc)
            print(f'loss:{loss_value:>7f}  accuracy:{acc:>7f}
[{{current:>5d}}/{{size:>5d}}]')

    with torch.no_grad():
        network.eval()
        for item in test_data_loader:
            pics, labels = item
            pics = pics.to(Device)
            labels = labels.to(Device)
            output = network(pics)  # (bs, 10)
            loss = loss_func(output, labels)
            loss_sum += loss.item()
            acc = (output.argmax(dim=1) == labels).sum().item() / len(pics)
            acc_sum += acc
        current_val_acc = acc_sum/len(test_data_loader)
        val_loss.append(loss_sum/len(test_data_loader))
        val_acc.append(current_val_acc)
        if current_val_acc > best_val_acc:
            best_val_acc = current_val_acc
            torch.save(network.state_dict(), f'{save_name}_model.pth')
        print(f'Test\nloss:{loss_sum/len(test_data_loader):>7f}  accuracy:
{{current_val_acc:>5f}}')

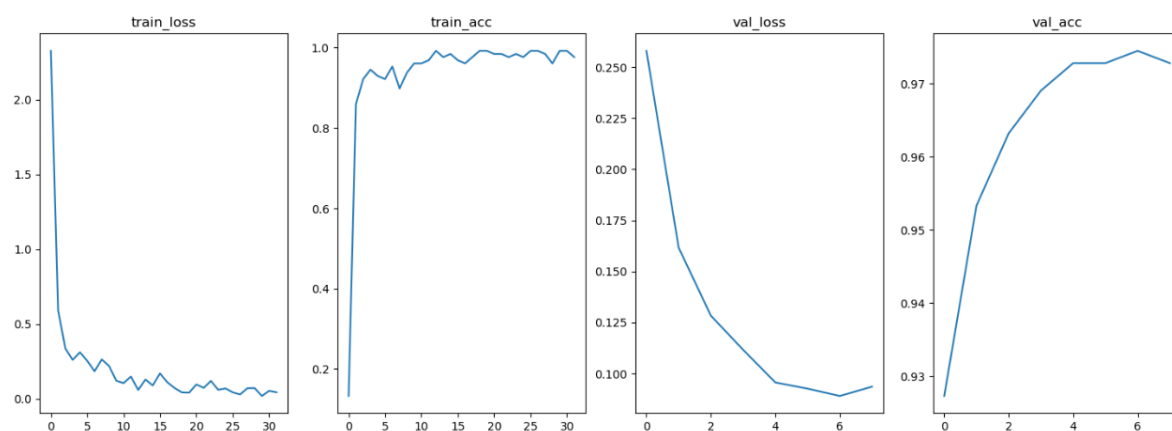
    names = ['train_loss', 'train_acc', 'val_loss', 'val_acc']
    plt.figure(figsize=(18, 6))
    plt.subplot(141)
    plt.plot(train_loss)
    plt.title(names[0])
    plt.subplot(142)
    plt.plot(train_acc)
    plt.title(names[1])
    plt.subplot(143)
    plt.plot(val_loss)
    plt.title(names[2])
    plt.subplot(144)
    plt.plot(val_acc)
    plt.title(names[3])
    plt.figure(figsize=(18, 6))
    plt.plot(val_acc)
    plt.title(names[3])
    return best_val_acc

```

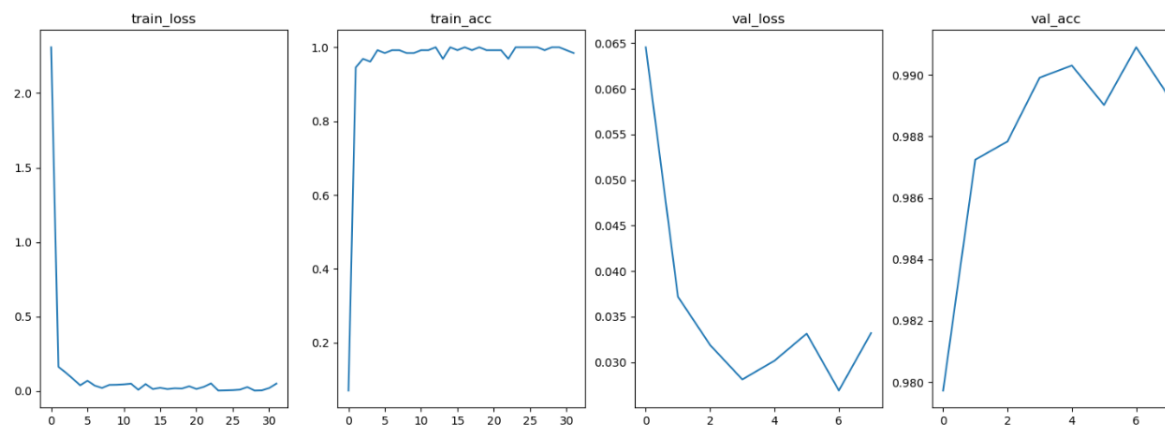
## 第一组：



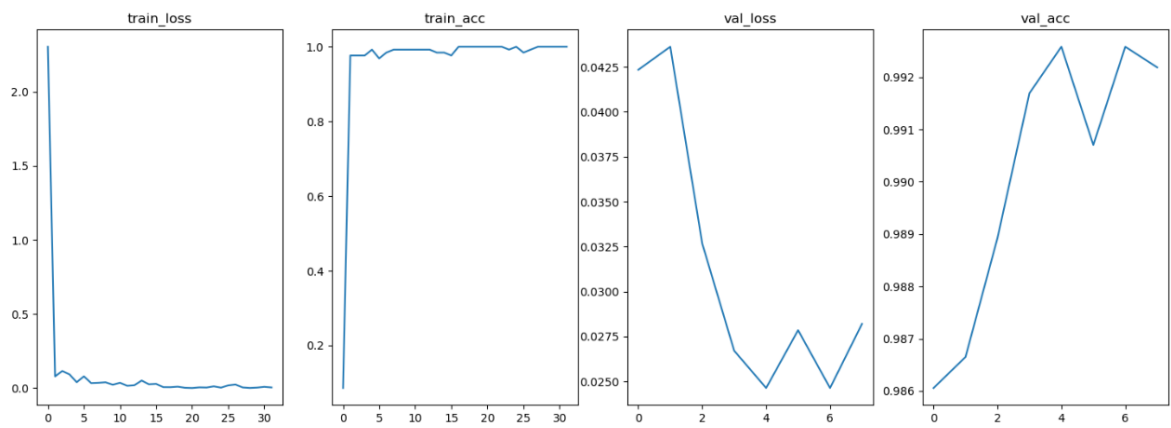
## 第二组：



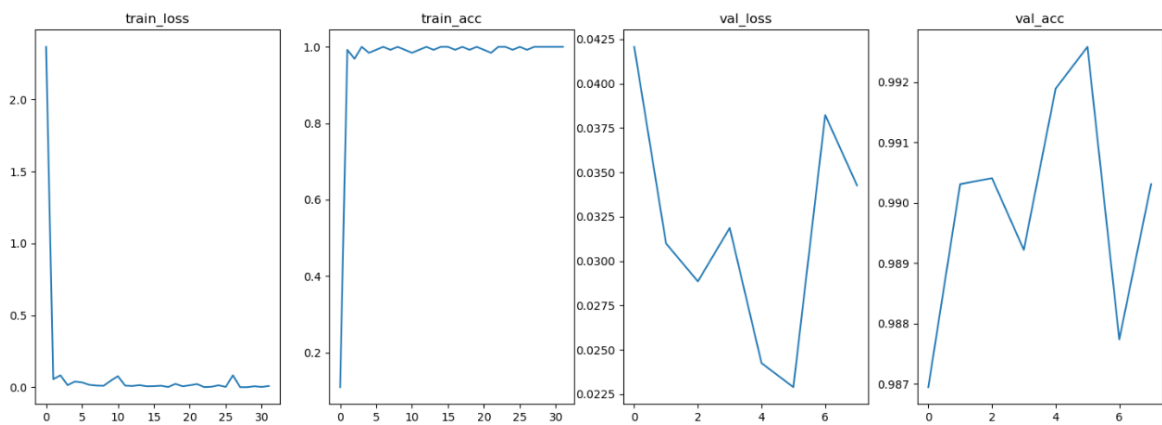
## 第三组：



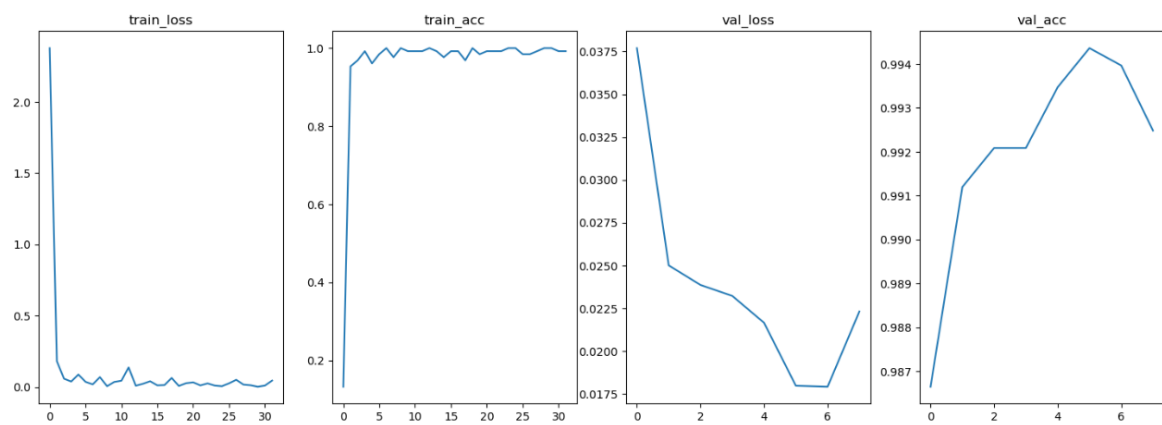
## 第四组：



## 第五组：



## 第六组：



## 5.实验结果及分析

网络架构	测试准确率
base_fc (两层全连接)	0.9798
plus_fc (三层全连接)	0.9744
conv_base (两层CNN)	0.9909
conv_plus (三层CNN)	0.9925
conv_plus_bn (增加batch_norm)	0.9925

网络架构	测试准确率
conv_plus_bn_dropout (增加dropout)	0.9943

可见，通过加深网络层数、加入batch\_norm技术和dropout正则化，可以有效地提高准确率。

## 6.思考与改进

- 受限于时间和计算资源，本次作业设置epoch为8，而且使用了较大的batch\_size（为了节省时间）。这样做可能使得模型没有被充分训练，因此可以从这两个超参入手改进。
- 可以考虑加入动态学习率调节，如余弦衰减，可能会让模型在更短的时间内收敛。