实验一

构建简单CNN实现Mnist手写数字数据集的分类

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import numpy

def get_params(model):
  np = 0
  for p in list(model.parameters()):
    np += p.nelement()
  return np

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

```
device(type='cuda')
```

加载数据

PyTorch里包含了 MNIST， CIFAR10 等常用数据集，调用 torchvision.datasets 即可把这些数据由远程下载到本地，下面给出MNIST的使用方法：

torchvision.datasets.MNIST(root, train=True, transform=None, target_transform=None, download=False)

root 为数据集下载到本地后的根目录，包括 training.pt 和 test.pt 文件

train，如果设置为True，从training.pt创建数据集，否则从test.pt创建。

download，如果设置为True, 从互联网下载数据并放到root文件夹下

transform, 一种函数或变换，输入PIL图片，返回变换之后的数据。

target_transform 一种函数或变换，输入目标，进行变换。

另外值得注意的是，DataLoader是一个比较重要的类，提供的常用操作有：batch_size(每个batch的大小), shuffle(是否进行随机打乱顺序的操作), num_workers(加载数据的时候使用几个子进程)

```
input_size = 28*28
output_size = 10

train_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=True, download=True,
                   transform=transforms.Compose([
                       transforms.ToTensor(),
```

```
                        transforms.Normalize((0.1307,), (0.3081,))
                    ])),
    batch_size=64, shuffle=True
)
test_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=False, transform=transforms.Compose([
                        transforms.ToTensor(),
                        transforms.Normalize((0.1307,), (0.3081,))
                    ])),
    batch_size=1000, shuffle=True
)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-
ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-
ubyte.gz to ../data/MNIST/raw/train-images-idx3-ubyte.gz
```

```
100%|██████████| 9912422/9912422 [00:05<00:00, 1905305.23it/s]
```

```
Extracting ../data/MNIST/raw/train-images-idx3-ubyte.gz to ../data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-
ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-
ubyte.gz to ../data/MNIST/raw/train-labels-idx1-ubyte.gz
```

```
100%|██████████| 28881/28881 [00:00<00:00, 804460.71it/s]
```

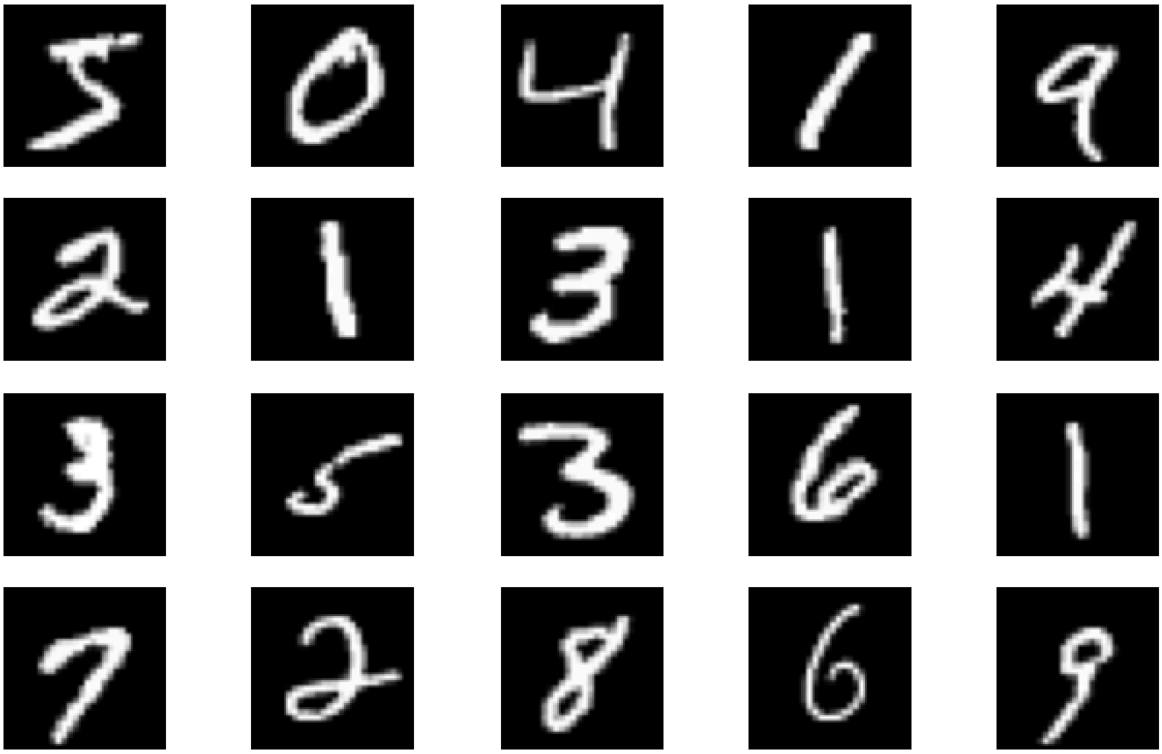
```
Extracting ../data/MNIST/raw/train-labels-idx1-ubyte.gz to ../data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-
ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-
ubyte.gz to ../data/MNIST/raw/t10k-images-idx3-ubyte.gz
```

```
100%|██████████| 1648877/1648877 [00:01<00:00, 1466150.68it/s]
```

```
Extracting ../data/MNIST/raw/t10k-images-idx3-ubyte.gz to ../data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz to ../data/MNIST/raw/t10k-labels-idx1-ubyte.gz
```

```
100%|██████████| 4542/4542 [00:00<00:00, 11928947.26it/s]

Extracting ../data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ../data/MNIST/raw
```

```
plt.figure(figsize = (8,5))
for i in range(20):
  plt.subplot(4,5,i+1)
  img, _ = train_loader.dataset.__getitem__(i)
  plt.imshow(img.squeeze().numpy(),cmap = 'gray')
  plt.axis('off')
```



2.创建网络

定义网络时，需要继承nn.Module，并实现它的forward方法，把网络中具有可学习参数的层放在构造函数**init**中。

只要在nn.Module的子类中定义了forward函数，backward函数就会自动被实现(利用autograd)。

```
class FC2Layer(nn.Module):
    def __init__(self, input_size, n_hidden, output_size):
        # nn.Module子类的函数必须在构造函数中执行父类的构造函数
        # 下式等价于nn.Module.__init__(self)
        super(FC2Layer, self).__init__()
        self.input_size = input_size
        # 这里直接用 Sequential 就定义了网络，注意要和下面 CNN 的代码区分开
        self.network = nn.Sequential(
            nn.Linear(input_size, n_hidden),
            nn.ReLU(),
            nn.Linear(n_hidden, n_hidden),
            nn.ReLU(),
            nn.Linear(n_hidden, output_size),
            nn.LogSoftmax(dim=1)
        )
    def forward(self, x):
        # view一般出现在model类的forward函数中，用于改变输入或输出的形状
        # x.view(-1, self.input_size) 的意思是多维的数据展成二维
        # 代码指定二维数据的列数为 input_size=784，行数 -1 表示我们不想算，电脑会自己计算对
应的数字
        # 在 DataLoader 部分，我们可以看到 batch_size 是64，所以得到 x 的行数是64
        # 大家可以加一行代码：print(x.cpu().numpy().shape)
        # 训练过程中，就会看到 (64, 784) 的输出，和我们的预期是一致的

        # forward 函数的作用是，指定网络的运行过程，这个全连接网络可能看不啥意义，
        # 下面的CNN网络可以看出 forward 的作用。
        x = x.view(-1, self.input_size)
        return self.network(x)



class CNN(nn.Module):
    def __init__(self, input_size, n_feature, output_size):
        # 执行父类的构造函数，所有的网络都要这么写
        super(CNN, self).__init__()
        # 下面是网络里典型结构的一些定义，一般就是卷积和全连接
        # 池化、ReLU一类的不用在这里定义
        self.n_feature = n_feature
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=n_feature,
kernel_size=5)
        self.conv2 = nn.Conv2d(n_feature, n_feature, kernel_size=5)
        self.fc1 = nn.Linear(n_feature*4*4, 50)
        self.fc2 = nn.Linear(50, 10)

    # 下面的 forward 函数，定义了网络的结构，按照一定顺序，把上面构建的一些结构组织起来
    # 意思就是，conv1, conv2 等等的，可以多次重用
    def forward(self, x, verbose=False):
        x = self.conv1(x)
```

```
        x = F.relu(x)
        x = F.max_pool2d(x, kernel_size=2)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, kernel_size=2)
        x = x.view(-1, self.n_feature*4*4)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.fc2(x)
        x = F.log_softmax(x, dim=1)
        return x
```

```
# 训练函数
def train(model):
    model.train()
    # 主里从train_loader里，64个样本一个batch为单位提取样本进行训练
    for batch_idx, (data, target) in enumerate(train_loader):
        # 把数据送到GPU中
        data, target = data.to(device), target.to(device)

        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % 100 == 0:
            print('Train: [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))


def test(model):
    model.eval()
    test_loss = 0
    correct = 0
    for data, target in test_loader:
        # 把数据送到GPU中
        data, target = data.to(device), target.to(device)
        # 把数据送入模型，得到预测结果
        output = model(data)
        # 计算本次batch的损失，并加到 test_loss 中
        test_loss += F.nll_loss(output, target, reduction='sum').item()
        # get the index of the max log-probability，最后一层输出10个数，
        # 值最大的那个即对应着分类结果，然后把分类结果保存在 pred 里
        pred = output.data.max(1, keepdim=True)[1]
        # 将 pred 与 target 相比，得到正确预测结果的数量，并加到 correct 中
        # 这里需要注意一下 view_as ，意思是把 target 变成维度和 pred 一样的意思
        correct += pred.eq(target.data.view_as(pred)).cpu().sum().item()

    test_loss /= len(test_loader.dataset)
    accuracy = 100. * correct / len(test_loader.dataset)
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        accuracy))
```

3.在小型全连接网络上训练

```
n_hidden = 8 # number of hidden units

model_fnn = FC2Layer(input_size, n_hidden, output_size)
model_fnn.to(device)
optimizer = optim.SGD(model_fnn.parameters(), lr=0.01, momentum=0.5)
print('Number of parameters: {}'.format(get_params(model_fnn)))

train(model_fnn)
test(model_fnn)
```

```
Number of parameters: 6442
Train: [0/60000 (0%)]	Loss: 2.267809
Train: [6400/60000 (11%)]	Loss: 1.667629
Train: [12800/60000 (21%)]	Loss: 1.133887
Train: [19200/60000 (32%)]	Loss: 0.789954
Train: [25600/60000 (43%)]	Loss: 0.667085
Train: [32000/60000 (53%)]	Loss: 0.578891
Train: [38400/60000 (64%)]	Loss: 0.404739
Train: [44800/60000 (75%)]	Loss: 0.406378
Train: [51200/60000 (85%)]	Loss: 0.340552
Train: [57600/60000 (96%)]	Loss: 0.495622

Test set: Average loss: 0.3989, Accuracy: 8834/10000 (88%)
```

4.在CNN上训练

```
# Training settings
n_features = 6 # number of feature maps

model_cnn = CNN(input_size, n_features, output_size)
model_cnn.to(device)
optimizer = optim.SGD(model_cnn.parameters(), lr=0.01, momentum=0.5)
print('Number of parameters: {}'.format(get_params(model_cnn)))

train(model_cnn)
test(model_cnn)
```

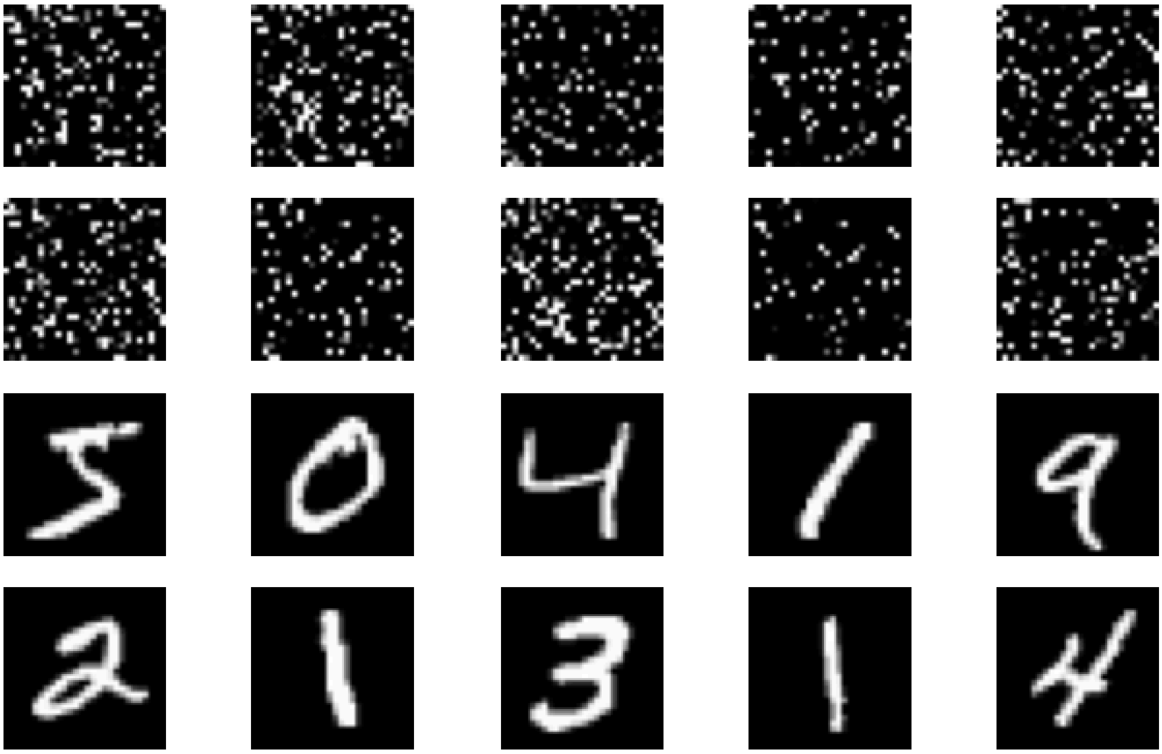
```
Number of parameters: 6422
Train: [0/60000 (0%)]	Loss: 2.313729
Train: [6400/60000 (11%)]	Loss: 1.540867
Train: [12800/60000 (21%)]	Loss: 0.659880
Train: [19200/60000 (32%)]	Loss: 0.253553
Train: [25600/60000 (43%)]	Loss: 0.368782
Train: [32000/60000 (53%)]	Loss: 0.468929
Train: [38400/60000 (64%)]	Loss: 0.207900
Train: [44800/60000 (75%)]	Loss: 0.218204
Train: [51200/60000 (85%)]	Loss: 0.276357
Train: [57600/60000 (96%)]	Loss: 0.123874

Test set: Average loss: 0.1568, Accuracy: 9533/10000 (95%)
```

5.打乱像素顺序，重新在两个网络上训练

考虑到CNN在卷积与池化上的优良特性，如果我们把图像中的像素打乱顺序，这样 卷积 和 池化 就难以发挥作用了，为了验证这个想法，我们把图像中的像素打乱顺序再试试。

首先下面代码展示随机打乱像素顺序后，图像的形态：

```
perm = torch.randperm(784)
plt.figure(figsize = (8,5))
for i in range(10):
  img, _ = train_loader.dataset.__getitem__(i)

  img_perm = img.view(-1, 28*28).clone()
  img_perm = img_perm[:, perm]
  img_perm = img_perm.view(-1, 28, 28)
  plt.subplot(4,5,i+1)
  plt.imshow(img_perm.squeeze().numpy(),cmap = 'gray')
  plt.axis('off')
  plt.subplot(4,5,i+11)
  plt.imshow(img.squeeze().numpy(),cmap = 'gray')
  plt.axis('off')
```



```python
# 对每个 batch 里的数据，打乱像素顺序的函数
def perm_pixel(data, perm):
    # 转化为二维矩阵
    data_new = data.view(-1, 28*28)
    # 打乱像素顺序
    data_new = data_new[:, perm]
    # 恢复为原来4维的 tensor
    data_new = data_new.view(-1, 1, 28, 28)
    return data_new

# 训练函数
def train_perm(model, perm):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        # 像素打乱顺序
        data = perm_pixel(data, perm)

        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % 100 == 0:
            print('Train: [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))

# 测试函数
```

```python
def test_perm(model, perm):
    model.eval()
    test_loss = 0
    correct = 0
    for data, target in test_loader:
        data, target = data.to(device), target.to(device)

        # 像素打乱顺序
        data = perm_pixel(data, perm)

        output = model(data)
        test_loss += F.nll_loss(output, target, reduction='sum').item()
        pred = output.data.max(1, keepdim=True)[1]
        correct += pred.eq(target.data.view_as(pred)).cpu().sum().item()

    test_loss /= len(test_loader.dataset)
    accuracy = 100. * correct / len(test_loader.dataset)
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        accuracy))
```

```python
perm = torch.randperm(784)
n_hidden = 8 # number of hidden units

model_fnn = FC2Layer(input_size, n_hidden, output_size)
model_fnn.to(device)
optimizer = optim.SGD(model_fnn.parameters(), lr=0.01, momentum=0.5)
print('Number of parameters: {}'.format(get_params(model_fnn)))

train_perm(model_fnn, perm)
test_perm(model_fnn, perm)
```

```
Number of parameters: 6442
Train: [0/60000 (0%)]	Loss: 2.276114
Train: [6400/60000 (11%)]	Loss: 1.977035
Train: [12800/60000 (21%)]	Loss: 1.208702
Train: [19200/60000 (32%)]	Loss: 0.766204
Train: [25600/60000 (43%)]	Loss: 0.572204
Train: [32000/60000 (53%)]	Loss: 0.502192
Train: [38400/60000 (64%)]	Loss: 0.519949
Train: [44800/60000 (75%)]	Loss: 0.381867
Train: [51200/60000 (85%)]	Loss: 0.450572
Train: [57600/60000 (96%)]	Loss: 0.397750

Test set: Average loss: 0.3996, Accuracy: 8857/10000 (89%)
```

```
perm = torch.randperm(784)
n_features = 6 # number of feature maps

model_cnn = CNN(input_size, n_features, output_size)
model_cnn.to(device)
optimizer = optim.SGD(model_cnn.parameters(), lr=0.01, momentum=0.5)
print('Number of parameters: {}'.format(get_params(model_cnn)))

train_perm(model_cnn, perm)
test_perm(model_cnn, perm)
```

```
Number of parameters: 6422
Train: [0/60000 (0%)]	Loss: 2.353731
Train: [6400/60000 (11%)]	Loss: 2.274198
Train: [12800/60000 (21%)]	Loss: 2.217433
Train: [19200/60000 (32%)]	Loss: 1.983218
Train: [25600/60000 (43%)]	Loss: 1.231610
Train: [32000/60000 (53%)]	Loss: 0.853280
Train: [38400/60000 (64%)]	Loss: 0.832802
Train: [44800/60000 (75%)]	Loss: 0.872526
Train: [51200/60000 (85%)]	Loss: 0.609364
Train: [57600/60000 (96%)]	Loss: 0.527641

Test set: Average loss: 0.5491, Accuracy: 8283/10000 (83%)
```

从打乱像素顺序的实验结果来看，全连接网络的性能基本上没有发生变化，但是 卷积神经网络的性能明显下降。

这是因为对于卷积神经网络，会利用像素的局部关系，但是打乱顺序以后，这些像素间的关系将无法得到利用。

实验二 搭建CNN完成CIFAR10分类

```
import torch
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64,
                                          shuffle=True, num_workers=2)
```

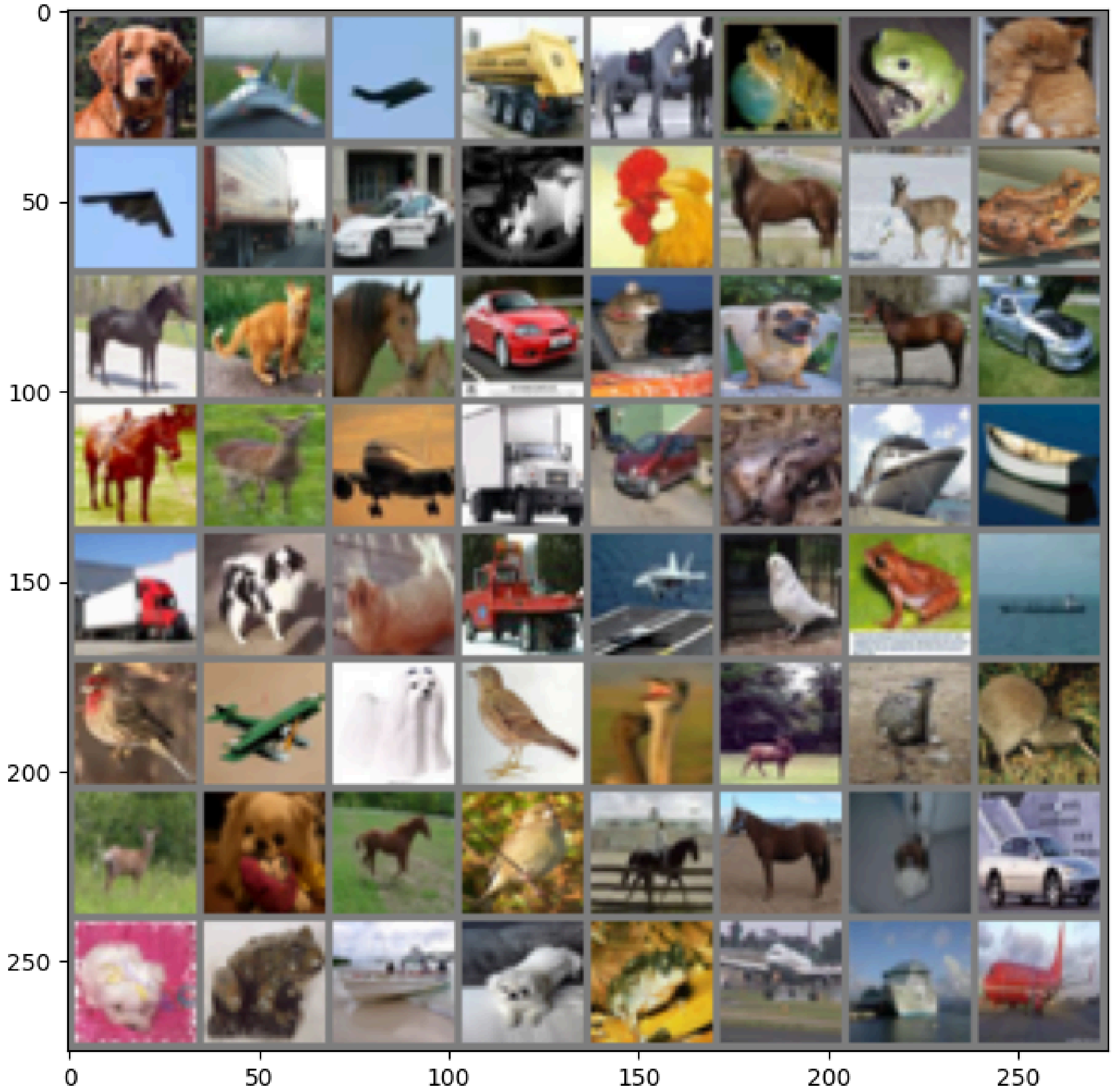
```
testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=8,
                                         shuffle=False, num_workers=2)

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

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data/cifar-10-python.tar.gz
```

```
100%|██████████| 170498071/170498071 [00:04<00:00, 42350767.25it/s]
```

```
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

```
def imshow(img):
    plt.figure(figsize=(8,8))
    img = img / 2 + 0.5     # 转换到 [0,1] 之间
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# 得到一组图像
images, labels = next(iter(trainloader))
# 展示图像
imshow(torchvision.utils.make_grid(images))
# 展示第一行图像的标签
for j in range(8):
    print(classes[labels[j]])
```




```
dog
plane
plane
truck
horse
frog
frog
cat
```

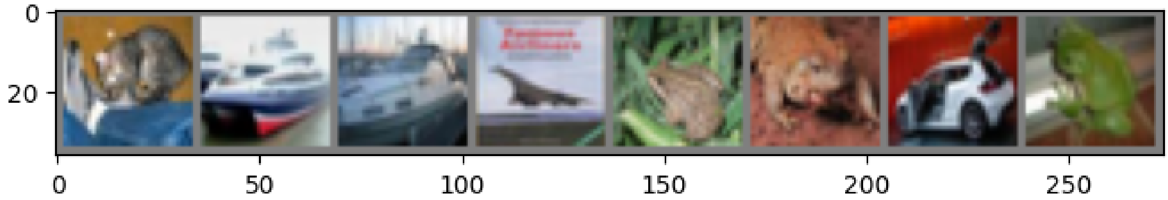
```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool  = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
```

```python
    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

# 网络放到GPU上
net = Net().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(net.parameters(), lr=0.001)
```

```python
for epoch in range(10):  # 重复多轮训练
    for i, (inputs, labels) in enumerate(trainloader):
        inputs = inputs.to(device)
        labels = labels.to(device)
        # 优化器梯度归零
        optimizer.zero_grad()
        # 正向传播 +  反向传播 + 优化
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        # 输出统计信息
    print('Epoch: %d Minibatch: %5d loss: %.3f' %(epoch + 1, i + 1, loss.item()))

print('Finished Training')
```

```
Epoch: 1 Minibatch:   782 loss: 0.661
Epoch: 2 Minibatch:   782 loss: 0.946
Epoch: 3 Minibatch:   782 loss: 0.685
Epoch: 4 Minibatch:   782 loss: 0.936
Epoch: 5 Minibatch:   782 loss: 0.623
Epoch: 6 Minibatch:   782 loss: 0.757
Epoch: 7 Minibatch:   782 loss: 0.744
Epoch: 8 Minibatch:   782 loss: 1.036
Epoch: 9 Minibatch:   782 loss: 0.991
Epoch: 10 Minibatch:   782 loss: 0.649
Finished Training
```

```python
# 得到一组图像
images, labels = next(iter(testloader))
# 展示图像
imshow(torchvision.utils.make_grid(images))
# 展示图像的标签
for j in range(8):
    print(classes[labels[j]])
```




```
cat
ship
ship
plane
frog
frog
car
frog
```

```
outputs = net(images.to(device))
_, predicted = torch.max(outputs, 1)

# 展示预测的结果
for j in range(8):
    print(classes[predicted[j]])
```

```
cat
ship
ship
plane
deer
frog
car
frog
```

```
correct = 0
total = 0

for data in testloader:
    images, labels = data
    images, labels = images.to(device), labels.to(device)
    outputs = net(images)
    _, predicted = torch.max(outputs.data, 1)
    total += labels.size(0)
    correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

```
Accuracy of the network on the 10000 test images: 63 %
```

实验三 VGG16对CIFAR10进行分类

VGG是由Simonyan 和Zisserman在文献《Very Deep Convolutional Networks for Large Scale Image Recognition》中提出卷积神经网络模型，其名称来源于作者所在的牛津大学视觉几何组(Visual Geometry Group)的缩写。
16层网络的结节信息如下：

- 01：Convolution using 64 filters
- 02: Convolution using 64 filters + Max pooling
- 03: Convolution using 128 filters
- 04: Convolution using 128 filters + Max pooling
- 05: Convolution using 256 filters
- 06: Convolution using 256 filters
- 07: Convolution using 256 filters + Max pooling
- 08: Convolution using 512 filters
- 09: Convolution using 512 filters
- 10: Convolution using 512 filters + Max pooling
- 11: Convolution using 512 filters
- 12: Convolution using 512 filters
- 13: Convolution using 512 filters + Max pooling
- 14: Fully connected with 4096 nodes
- 15: Fully connected with 4096 nodes
- 16: Softmax

1.定义dataloader

```
import torch
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

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)
testset  = torchvision.datasets.CIFAR10(root='./data', train=False,
download=True, transform=transform_test)

trainloader = torch.utils.data.DataLoader(trainset, batch_size=128, shuffle=True,
num_workers=2)
testloader = torch.utils.data.DataLoader(testset, batch_size=128, shuffle=False,
num_workers=2)

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

```
Files already downloaded and verified
Files already downloaded and verified
```

```
device(type='cuda', index=0)
```

定义VGG网络结构

```
class VGG(nn.Module):
    def __init__(self):
        super(VGG, self).__init__()
        self.cfg = [64, 'M', 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512,
'M']
        self.features = self._make_layers(self.cfg)
        self.classifier = nn.Linear(512, 10)

    def forward(self, x):
        out = self.features(x)
        out = out.view(out.size(0), -1)
        out = self.classifier(out)
        return out

    def _make_layers(self, cfg):
        layers = []
        in_channels = 3
        for x in cfg:
            if x == 'M':
                layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
            else:
                layers += [nn.Conv2d(in_channels, x, kernel_size=3, padding=1),
                           nn.BatchNorm2d(x),
                           nn.ReLU(inplace=True)]
                in_channels = x
```

```
        layers += [nn.AvgPool2d(kernel_size=1, stride=1)]
        return nn.Sequential(*layers)
```

```
net = VGG().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(net.parameters(), lr=0.001)
```

```
for epoch in range(10):  # 重复多轮训练
    for i, (inputs, labels) in enumerate(trainloader):
        inputs = inputs.to(device)
        labels = labels.to(device)
        # 优化器梯度归零
        optimizer.zero_grad()
        # 正向传播 +  反向传播 + 优化
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        # 输出统计信息
        if i % 100 == 0:
            print('Epoch: %d Minibatch: %5d loss: %.3f' %(epoch + 1, i + 1, 
loss.item()))

print('Finished Training')
```

```
Epoch: 1 Minibatch:     1 loss: 2.621
Epoch: 1 Minibatch:   101 loss: 1.599
Epoch: 1 Minibatch:   201 loss: 1.181
Epoch: 1 Minibatch:   301 loss: 1.007
Epoch: 2 Minibatch:     1 loss: 1.008
Epoch: 2 Minibatch:   101 loss: 1.230
Epoch: 2 Minibatch:   201 loss: 0.873
Epoch: 2 Minibatch:   301 loss: 0.875
Epoch: 3 Minibatch:     1 loss: 0.961
Epoch: 3 Minibatch:   101 loss: 0.716
Epoch: 3 Minibatch:   201 loss: 0.831
Epoch: 3 Minibatch:   301 loss: 0.794
Epoch: 4 Minibatch:     1 loss: 0.670
Epoch: 4 Minibatch:   101 loss: 0.819
Epoch: 4 Minibatch:   201 loss: 0.770
Epoch: 4 Minibatch:   301 loss: 0.718
Epoch: 5 Minibatch:     1 loss: 0.587
Epoch: 5 Minibatch:   101 loss: 0.524
Epoch: 5 Minibatch:   201 loss: 0.593
Epoch: 5 Minibatch:   301 loss: 0.588
Epoch: 6 Minibatch:     1 loss: 0.457
Epoch: 6 Minibatch:   101 loss: 0.615
Epoch: 6 Minibatch:   201 loss: 0.647
Epoch: 6 Minibatch:   301 loss: 0.657
Epoch: 7 Minibatch:     1 loss: 0.681
Epoch: 7 Minibatch:   101 loss: 0.607
Epoch: 7 Minibatch:   201 loss: 0.465
Epoch: 7 Minibatch:   301 loss: 0.533
Epoch: 8 Minibatch:     1 loss: 0.588
```

```
Epoch: 8 Minibatch:   101 loss: 0.584
Epoch: 8 Minibatch:   201 loss: 0.463
Epoch: 8 Minibatch:   301 loss: 0.448
Epoch: 9 Minibatch:     1 loss: 0.407
Epoch: 9 Minibatch:   101 loss: 0.465
Epoch: 9 Minibatch:   201 loss: 0.417
Epoch: 9 Minibatch:   301 loss: 0.423
Epoch: 10 Minibatch:     1 loss: 0.448
Epoch: 10 Minibatch:   101 loss: 0.285
Epoch: 10 Minibatch:   201 loss: 0.507
Epoch: 10 Minibatch:   301 loss: 0.371
Finished Training
```

```python
correct = 0
total = 0

for data in testloader:
    images, labels = data
    images, labels = images.to(device), labels.to(device)
    outputs = net(images)
    _, predicted = torch.max(outputs.data, 1)
    total += labels.size(0)
    correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %.2f %%' % (
    100 * correct / total))
```

```
Accuracy of the network on the 10000 test images: 82.94 %
```

思考

- dataloader 里面 shuffle 取不同值有什么区别?

  答：`shuffle=True`: 每次 epoch 开始时，数据集都会被重新打乱。这可以帮助模型避免记忆训练数据的顺序，从而提高模型的泛化能力，特别是对于小数据集或数据存在顺序依赖的情况。

  `shuffle=False`: 数据按照原始顺序进行处理，这在数据有特定顺序或需要按顺序处理时（例如时间序列数据）可能是必要的。

- transform 里，取了不同值，这个有什么区别?

  答：在数据预处理阶段， `transform` 能够对数据进行不同的转换，不同的 `transform` 设置可以显著的影响模型训练的效果，合适的取值能帮助模型在训练时学习到更多的特征，提升模型的泛化能力，并使模型在面对实际应用中的数据变化时更为鲁棒。在实际应用中，通常会根据具体任务和数据集的特性来选择合适的 `transform` 操作。

- epoch 和 batch 的区别?

  epoch是数据集被完整训练的轮次，batch是单次数据传播与误差反向传播是输入数据量的大小。

- 1x1的卷积和 FC 有什么区别？主要起什么作用?

1x1卷积是选用大小为1的卷积核，可以用来改变特征图的通道数。全连接层是一个每个神经元都与前一层的每个神经元连接的层，通常用于将卷积层或池化层的输出展平（flatten）后，进行进一步的分类或回归任务。

- residual leanring 为什么能够提升准确率?

  Residual Learning 通过引入残差块和快捷连接，解决了深层神经网络中常见的梯度消失、学习困难等问题，从而提高了网络的训练效果和准确率。它简化了学习目标，改善了梯度流动，允许设计更深的网络，并减少了训练误差，这些因素共同作用提升了模型的整体性能。

- 代码练习二里，网络和1989年 Lecun 提出的 LeNet 有什么区别?

  1. 激活函数不同，网络使用relu函数，lenet使用tanh函数
  2. 池化层不同，网络使用的是最大池化，lenet使用的是平均池化

- 代码练习二里，卷积以后feature map 尺寸会变小，如何应用 Residual Learning?

  在 Residual Learning 中，卷积操作后特征图尺寸的变化可以通过在快捷连接中调整尺寸来处理，确保残差块的输入和输出尺寸匹配。

- 有什么方法可以进一步提升准确率?

  数据增强、增加网络深度、优化网络结构、正则化、超参数的寻优、对数据进一步预处理