Week 5: CNN-1

实验准备

- 熟悉python语言的使用和numpy,torch的基本用法
- 熟悉神经网络的训练过程与优化方法
- 结合理论课的内容,了解卷积与卷积神经网络(CNN)的内容和原理
- 了解常用的CNN模型的基本结构,如AlexNet,Vgg,ResNet

实验过程

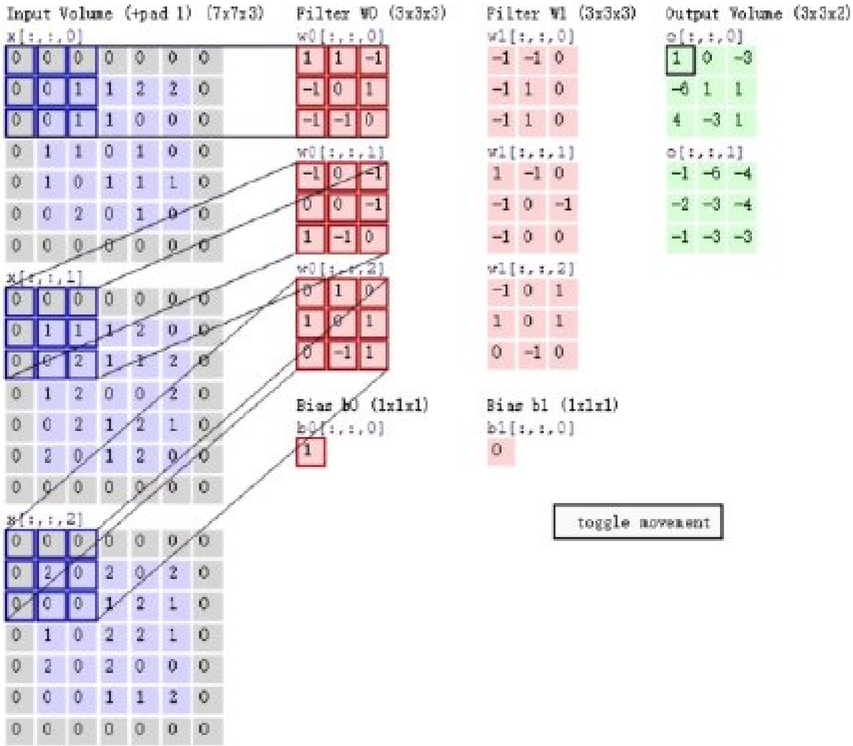
1. 卷积与卷积层

- numpy实现卷积
- pytorch中的卷积层和池化层

2. CNN

- 实现并训练一个基本的CNN网络
- ResNet
- VGG

卷积



在实验课上我们已经了解过卷积运算的操作当我们对一张二维的图像做卷积时,将卷积核沿着图像进行滑动乘加即可(如上图所示).

下面的conv函数实现了对二维**单通道**图像的卷积.考虑输入的卷积核kernel的长宽相同,padding为对图像的四个边缘补0,stride为卷积核窗口滑动的步长.

In [1]:

```
import numpy as np

def convolution(img, kernel, padding=1, stride=1):
    """
    img: input image with one channel
    kernel: convolution kernel
    """

    h, w = img.shape
    kernel_size = kernel.shape[0]

    # height and width of image with padding
    ph, pw = h + 2 * padding, w + 2 * padding
    padding_img = np.zeros((ph, pw))
    padding_img[padding:h + padding, padding:w + padding] = img

    # height and width of output image
    result_h = (h + 2 * padding - kernel_size) // stride + 1
    result_w = (w + 2 * padding - kernel_size) // stride + 1

    result = np.zeros((result_h, result_w))

    # convolution
    x, y = 0, 0
    for i in range(0, ph - kernel_size + 1, stride):
        for j in range(0, pw - kernel_size + 1, stride):
            roi = padding_img[i:i+kernel_size, j:j+kernel_size]
            result[x, y] = np.sum(roi * kernel)
            y += 1
        y = 0
        x += 1
    return result
```

下面在图像上简单一下测试我们的conv函数,这里使用3*3的高斯核对下面的图像进行滤波.
lena

In [2]:

```
from PIL import Image
import matplotlib.pyplot as plt
img = Image.open('pics/lena.jpg').convert('L')
plt.imshow(img, cmap='gray')
```

Out[2]:

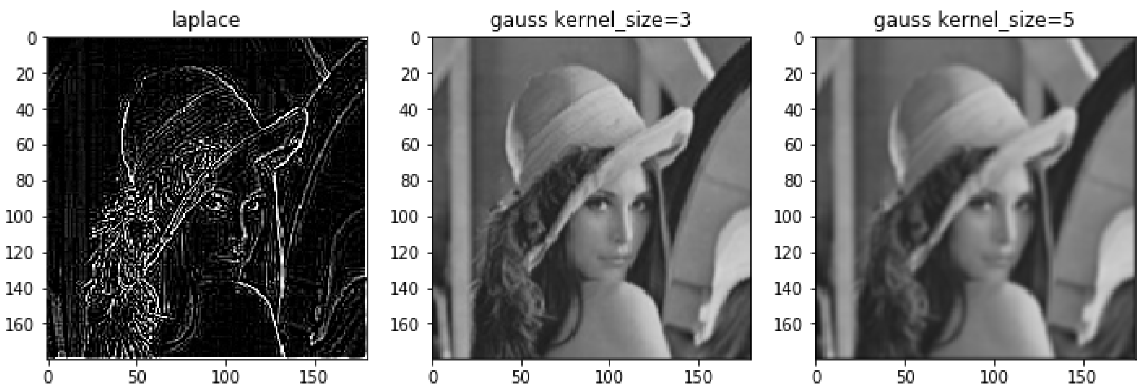
```
<matplotlib.image.AxesImage at 0x7f99ba7f75c0>
```

In [3]:

```
#  a Laplace kernel
laplace_kernel = np.array([[-1, -1, -1],
                           [-1, 8, -1],
                           [-1, -1, -1]])

# Gauss kernel with kernel_size=3
gauss_kernel3 = (1/ 16) * np.array([[1, 2, 1],
                                    [2, 4, 2],
                                    [1, 2, 1]])

# Gauss kernel with kernel_size=5
gauss_kernel5 = (1/ 84) * np.array([[1, 2, 3, 2, 1],
                                     [2, 5, 6, 5, 2],
                                     [3, 6, 8, 6, 3],
                                     [2, 5, 6, 5, 2],
                                     [1, 2, 3, 2, 1]])

fig, ax = plt.subplots(1, 3, figsize=(12, 8))

laplace_img = convolution(np.array(img), laplace_kernel, padding=1, stride=1)
ax[0].imshow(Image.fromarray(laplace_img), cmap='gray')
ax[0].set_title('laplace')

gauss3_img = convolution(np.array(img), gauss_kernel3, padding=1, stride=1)
ax[1].imshow(Image.fromarray(gauss3_img), cmap='gray')
ax[1].set_title('gauss kernel_size=3')

gauss5_img = convolution(np.array(img), gauss_kernel5, padding=2, stride=1)
ax[2].imshow(Image.fromarray(gauss5_img), cmap='gray')
ax[2].set_title('gauss kernel_size=5')
```

Out[3]:

```
Text(0.5,1,'gauss kernel_size=5')
```



上面我们实现了实现了对单通道输入单通道输出的卷积.在CNN中,一般使用到的都是多通道输入多通道输出的卷积,要实现多通道的卷积, 我们只需要对循环调用上面的conv函数即可.

In [4]:

```
def myconv2d(features, weights,  padding=0, stride=1):
    """
    features: input, in_channel * h * w
    weights: kernel, out_channel * in_channel * kernel_size * kernel_size
    return output with out_channel
    """
    in_channel, h, w = features.shape
    out_channel, _, kernel_size, _ = weights.shape

    # height and width of output image
    output_h = (h + 2 * padding - kernel_size) // stride + 1
    output_w = (w + 2 * padding - kernel_size) // stride + 1
    output = np.zeros((out_channel, output_h, output_w))

    # call convolution out_channel * in_channel times
    for i in range(out_channel):
        weight = weights[i]
        for j in range(in_channel):
            feature_map = features[j]
            kernel = weight[j]
            output[i] += convolution(feature_map, kernel, padding, stride)
    return output
```

接下来, 让我们测试我们写好的myconv2d函数.

In [5]:

```
input_data=[
           [[0,0,2,2,0,1],
            [0,2,2,0,0,2],
            [1,1,0,2,0,0],
            [2,2,1,1,0,0],
            [2,0,1,2,0,1],
            [2,0,2,1,0,1]],

           [[2,0,2,1,1,1],
            [0,1,0,0,2,2],
            [1,0,0,2,1,0],
            [1,1,1,1,1,1],
            [1,0,1,1,1,2],
            [2,1,2,1,0,2]]
            ]
weights_data=[[
               [[ 0, 1, 0],
                [ 1, 1, 1],
                [ 0, 1, 0]],

               [[-1, -1, -1],
                [ -1, 8, -1],
                [ -1, -1, -1]]
           ]]

# numpy array
input_data   = np.array(input_data)
weights_data = np.array(weights_data)

# show the result
print(myconv2d(input_data, weights_data, padding=3, stride=3))
```

```
[[[  0.   0.   0.   0.]
  [  0.   8.  10.   0.]
  [  0.  -5.   2.   0.]
  [  0.   0.   0.   0.]]]
```

在Pytorch中,已经为我们提供了卷积和卷积层的实现.使用同样的input和weights,以及stride,padding,pytorch的卷积的结果应该和我们的一样.可以在下面的代码中进行验证.

In [6]:

```
import torch
import torch.nn.functional as F
input_tensor = torch.tensor(input_data).unsqueeze(0).float()
F.conv2d(input_tensor, weight=torch.tensor(weights_data).float(), bias=None, str
ide=3, padding=3)
```

Out[6]:

```
tensor([[[[ 0.,  0.,  0.,  0.],
          [ 0.,  8., 10.,  0.],
          [ 0., -5.,  2.,  0.],
          [ 0.,  0.,  0.,  0.]]]])
```

作业:

上述代码中convolution的实现只考虑卷积核以及padding和stride长宽一致的情况,若输入的卷积核可能长宽不一致,padding与stride的输入可能为两个元素的元祖(代表两个维度上的padding与stride)并使用下面test input对你的convolutionV2进行测试.

In [7]:

```
def convolutionV2(img, kernel, padding=(0,0), stride=(1,1)):
    """
    img: input image with one channel
    kernel: convolution kernel
    """

    h, w = img.shape
    kernel_size_h, kernel_size_w = kernel.shape
    padding_h, padding_w = padding[0], padding[1]
    stride_h, stride_w = stride[0], stride[1]

    # height and width of image with padding
    ph, pw = h + 2 * padding_h, w + 2 * padding_w
    padding_img = np.zeros((ph, pw))
    padding_img[padding_h:h + padding_h, padding_w:w + padding_w] = img

    # height and width of output image
    result_h = (h + 2 * padding_h - kernel_size_h) // stride_h + 1
    result_w = (w + 2 * padding_w - kernel_size_w) // stride_w + 1

    result = np.zeros((result_h, result_w))

    # convolution
    x, y = 0, 0
    for i in range(0, ph - kernel_size_h + 1, stride_h):
        for j in range(0, pw - kernel_size_w + 1, stride_w):
            roi = padding_img[i:i+kernel_size_h, j:j+kernel_size_w]
            result[x, y] = np.sum(roi * kernel)
            y += 1
        y = 0
        x += 1
    return result
```

In [8]:

```
# test input
test_input = np.array([[1, 1, 2, 1],
                       [0, 1, 0, 2],
                       [2, 2, 0, 2],
                       [2, 2, 2, 1],
                       [2, 3, 2, 3]])

test_kernel = np.array([[1, 0], [0, 1], [0, 0]])

# output
print(convolutionV2(test_input, test_kernel, padding=(1, 0), stride=(1, 1)))
print('\n')
print(convolutionV2(test_input, test_kernel, padding=(2, 1), stride=(1, 2)))
print('\n')
```

```
[[ 1.  2.  1.]
 [ 2.  1.  4.]
 [ 2.  1.  2.]
 [ 4.  4.  1.]
 [ 5.  4.  5.]]


[[ 0.  0.  0.]
 [ 1.  2.  0.]
 [ 0.  1.  1.]
 [ 2.  1.  2.]
 [ 2.  4.  2.]
 [ 2.  4.  1.]
 [ 0.  3.  3.]]
```

卷积层

Pytorch提供了卷积层和池化层供我们使用.

卷积层与上面相似, 而池化层与卷积层相似,Pooling layer的主要目的是缩小features的size.常用的有MaxPool(滑动窗口取最大值)与AvgPool(滑动窗口取均值)

In [9]:

```
import torch
import torch.nn as nn


x = torch.randn(1, 1, 32, 32)

conv_layer = nn.Conv2d(in_channels=1, out_channels=3, kernel_size=3, stride=1, p
adding=0)
y = conv_layer(x)
print(x.shape)
print(y.shape)
```

```
torch.Size([1, 1, 32, 32])
torch.Size([1, 3, 30, 30])
```

请问:

1. 输入与输出的tensor的size分别是多少?该卷积层的参数量是多少?
2. 若kernel_size=5,stride=2,padding=2, 输出的tensor的size是多少?在上述代码中改变参数后试验后并回答.
3. 若输入的tensor size为N*C*H*W,若第5行中卷积层的参数为in_channels=C,out_channels=Cout,kernel_size=k,stride=s,padding=p,那么输出的tensor size是多少?

In [10]:

```
import torch
import torch.nn as nn


x = torch.randn(1, 1, 32, 32)

conv_layer = nn.Conv2d(in_channels=1, out_channels=3, kernel_size=5, stride=2, p
adding=2)
y = conv_layer(x)
print(x.shape)
print(y.shape)
```

```
torch.Size([1, 1, 32, 32])
torch.Size([1, 3, 16, 16])
```

答:

1. $size_{in}$ =32; $size_{out}$ =30; $F \times F \times C_{input} \times K + K = 3 * 3 * 1 * 3 + 3 = 30$ [Ref. (https://blog.csdn.net/gaishi_hero/article/details/81512404)](https://blog.csdn.net/gaishi_hero/article/details/81512404)
2. $size_{out}$ =16.
3. $min((h + 2 * p - k)//s + 1, (w + 2 * p - k)//s + 1)$

In [11]:

```
# input N * C * H * W
x = torch.randn(1, 1, 4, 4)

# maxpool
maxpool = nn.MaxPool2d(kernel_size=2, stride=2)
y = maxpool(x)

# avgpool
avgpool = nn.AvgPool2d(kernel_size=2, stride=2)
z = avgpool(x)

#avgpool
print(x)
print(y)
print(z)
```

```
tensor([[[[-0.7988, -0.6036,  1.0944,  1.0869],
          [ 1.1715, -1.8142, -0.5802,  1.5753],
          [ 1.3232,  0.6413, -0.5604,  0.9052],
          [-0.3123,  1.1715,  0.0411, -0.0606]]]])
tensor([[[[1.1715, 1.5753],
          [1.3232, 0.9052]]]])
tensor([[[[-0.5113,  0.7941],
          [ 0.7059,  0.0813]]]])
```

GPU

我们可以选择在cpu或gpu上来训练我们的模型.
实验室提供了4卡的gpu服务器,要查看各个gpu设备的使用情况,可以在服务器上的jupyter主页点击new->terminal,在terminal中输入nvidia-smi即可查看每张卡的使用情况.如下图.

nvidia-smi
上图左边一栏显示了他们的设备id(0,1,2,3),风扇转速,温度,性能状态,能耗等信息,中间一栏显示他们的bus-id和显存使用量,右边一栏是GPU使用率等信息.注意到中间一栏的显存使用量,在训练模型前我们可以根据空余的显存来选择我们使用的gpu设备.
在本次实验中我们将代码中的torch.device('cuda:0')的0更换成所需的设备id即可选择在相应的gpu设备上运行程序.

CNN(卷积神经网络)

一个简单的CNN

接下来,让我们建立一个简单的CNN分类器. 这个CNN的整体流程是
卷积(Conv2d) -> BN(batch normalization) -> 激励函数(ReLU) -> 池化(MaxPooling) ->
卷积(Conv2d) -> BN(batch normalization) -> 激励函数(ReLU) -> 池化(MaxPooling) ->
全连接层(Linear) -> 输出.

In [12]:

```
import torch
import torch.nn as nn
import torch.utils.data as Data
import torchvision


class MyCNN(nn.Module):

    def __init__(self, image_size, num_classes):
        super(MyCNN, self).__init__()
        # conv1: Conv2d -> BN -> ReLU -> MaxPool
        self.conv1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, stride=1, p
adding=1),
            nn.BatchNorm2d(16),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        # conv2: Conv2d -> BN -> ReLU -> MaxPool
        self.conv2 = nn.Sequential(
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, stride=1,
padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        # fully connected layer
        self.fc = nn.Linear(32 * (image_size // 4) * (image_size // 4), num_clas
ses)


    def forward(self, x):
        """
        input: N * 3 * image_size * image_size
        output: N * num_classes
        """
        x = self.conv1(x)
        x = self.conv2(x)
        # view(x.size(0), -1): change tensor size from (N ,H , W) to (N, H*W)
        x = x.view(x.size(0), -1)
        output = self.fc(x)
        return output
```

这样,一个简单的CNN模型就写好了.与前面的课堂内容相似,我们需要对完成网络进行训练与评估的代码.

In [13]:

```
def train(model, train_loader, loss_func, optimizer, device):
    """
    train model using loss_fn and optimizer in an epoch.
    model: CNN networks
    train_loader: a Dataloader object with training data
    loss_func: loss function
    device: train on cpu or gpu device
    """
    total_loss = 0
    # train the model using minibatch
    for i, (images, targets) in enumerate(train_loader):
        images = images.to(device)
        targets = targets.to(device)

        # forward
        outputs = model(images)
        loss = loss_func(outputs, targets)

        # backward and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

        # every 100 iteration, print loss
        if (i + 1) % 100 == 0:
            print ("Step [{}/{}] Train Loss: {:.4f}"
                   .format(i+1, len(train_loader), loss.item()))
    return total_loss / len(train_loader)
```

In [14]:

```python
def evaluate(model, val_loader, device):
    """
    model: CNN networks
    val_loader: a Dataloader object with validation data
    device: evaluate on cpu or gpu device
    return classification accuracy of the model on val dataset
    """
    # evaluate the model
    model.eval()
    # context-manager that disabled gradient computation
    with torch.no_grad():
        correct = 0
        total = 0

        for i, (images, targets) in enumerate(val_loader):
            # device: cpu or gpu
            images = images.to(device)
            targets = targets.to(device)


            outputs = model(images)

            # return the maximum value of each row of the input tensor in the
            # given dimension dim, the second return vale is the index location
            # of each maxium value found(argmax)
            _, predicted = torch.max(outputs.data, dim=1)


            correct += (predicted == targets).sum().item()

            total += targets.size(0)

        accuracy = correct / total
        print('Accuracy on Test Set: {:.4f} %'.format(100 * accuracy))
        return accuracy
```

In [15]:

```python
def save_model(model, save_path):
    # save model
    torch.save(model.state_dict(), save_path)
```

In [16]:

```
import matplotlib.pyplot as plt
def show_curve(ys, title):
    """
    plot curlve for Loss and Accuacy
    Args:
        ys: loss or acc list
        title: loss or accuracy
    """
    x = np.array(range(len(ys)))
    y = np.array(ys)
    plt.plot(x, y, c='b')
    plt.axis()
    plt.title('{} curve'.format(title))
    plt.xlabel('epoch')
    plt.ylabel('{}'.format(title))
    plt.show()
```

准备数据与训练模型

接下来，我们使用CIFAR10数据集来对我们的CNN模型进行训练.

CIFAR-10:该数据集共有60000张彩色图像,这些图像是32*32,分为10个类,每类6000张图.这里面有50000张用于训练,构成了5个训练批,每一批10000张图;另外10000用于测试,单独构成一批.在本次实验中,使用CIFAR-10数据集来训练我们的模型.我们可以用torchvision.datasets.CIFAR10来直接使用CIFAR10数据集.
cifar10

In [17]:

```
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms

# mean and std of cifar10 in 3 channels
cifar10_mean = (0.49, 0.48, 0.45)
cifar10_std = (0.25, 0.24, 0.26)

# define transform operations of train dataset
train_transform = transforms.Compose([
    # data augmentation
    transforms.Pad(4),
    transforms.RandomHorizontalFlip(),
    transforms.RandomCrop(32),

    transforms.ToTensor(),
    transforms.Normalize(cifar10_mean, cifar10_std)])

test_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(cifar10_mean, cifar10_std)])

# torchvision.datasets provide CIFAR-10 dataset for classification
train_dataset = torchvision.datasets.CIFAR10(root='./data/',
                                             train=True,
                                             transform=train_transform,
                                             download=True)

test_dataset = torchvision.datasets.CIFAR10(root='./data/',
                                            train=False,
                                            transform=test_transform)

# Data loader: provides single- or multi-process iterators over the dataset.
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=100,
                                           shuffle=True)

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=100,
                                          shuffle=False)
```

```
Files already downloaded and verified
```

训练过程中使用交叉熵(cross-entropy)损失函数与Adam优化器来训练我们的分类器网络. 阅读下面的代码并在To-Do处,根据之前所学的知识,补充前向传播和反向传播的代码来实现分类网络的训练.

In [18]:

```
def fit(model, num_epochs, optimizer, device):
    """
    train and evaluate an classifier num_epochs times.
    We use optimizer and cross entropy loss to train the model.
    Args:
        model: CNN network
        num_epochs: the number of training epochs
        optimizer: optimize the loss function
    """

    # loss and optimizer
    loss_func = nn.CrossEntropyLoss()

    model.to(device)
    loss_func.to(device)

    # log train loss and test accuracy
    losses = []
    accs = []

    for epoch in range(num_epochs):

        print('Epoch {}/{}:'.format(epoch + 1, num_epochs))
        # train step
        loss = train(model, train_loader, loss_func, optimizer, device)
        losses.append(loss)

        # evaluate step
        accuracy = evaluate(model, test_loader, device)
        accs.append(accuracy)


    # show curve
    show_curve(losses, "train loss")
    show_curve(accs, "test accuracy")
```

In [19]:

```
# hyper parameters
num_epochs = 10
lr = 0.01
image_size = 32
num_classes = 10
```

In [20]:

```python
# declare and define an objet of MyCNN
mycnn = MyCNN(image_size, num_classes)
print(mycnn)
```

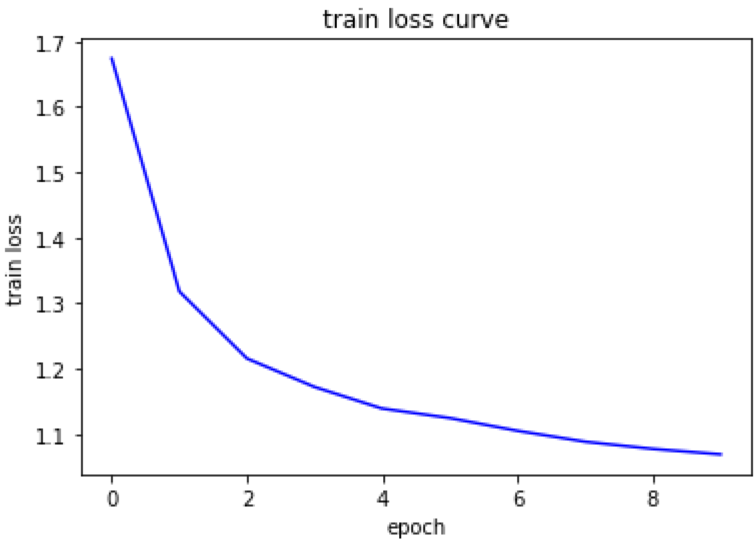
```
MyCNN(
  (conv1): Sequential(
    (0): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
    (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, c
eil_mode=False)
  )
  (conv2): Sequential(
    (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, c
eil_mode=False)
  )
  (fc): Linear(in_features=2048, out_features=10, bias=True)
)
```

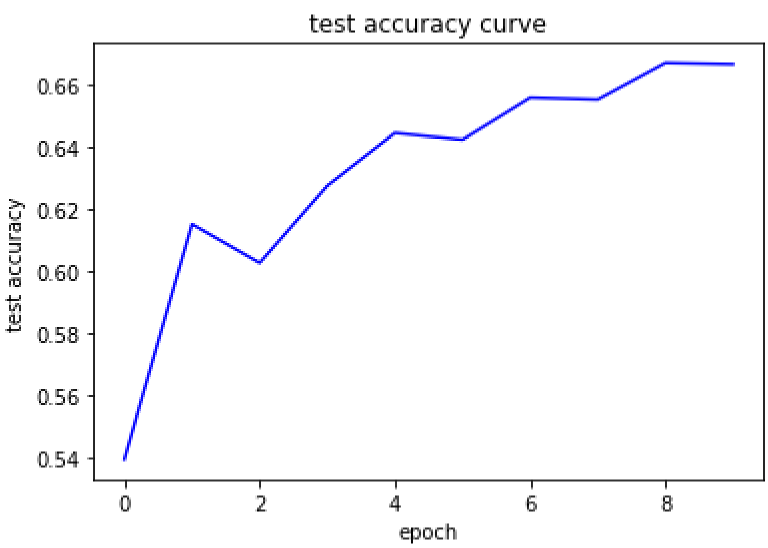
In [21]:

```
# Device configuration, cpu, cuda:0/1/2/3 available
device = torch.device('cuda:0')

optimizer = torch.optim.Adam(mycnn.parameters(), lr=lr)

# start training on cifar10 dataset
fit(mycnn, num_epochs, optimizer, device)
```

```
Epoch 1/10:
Step [100/500] Train Loss: 1.8075
Step [200/500] Train Loss: 1.6811
Step [300/500] Train Loss: 1.6177
Step [400/500] Train Loss: 1.3389
Step [500/500] Train Loss: 1.2736
Accuracy on Test Set: 53.9500 %
Epoch 2/10:
Step [100/500] Train Loss: 1.5978
Step [200/500] Train Loss: 1.2951
Step [300/500] Train Loss: 1.3162
Step [400/500] Train Loss: 1.2874
Step [500/500] Train Loss: 1.1236
Accuracy on Test Set: 61.5300 %
Epoch 3/10:
Step [100/500] Train Loss: 1.3468
Step [200/500] Train Loss: 1.3069
Step [300/500] Train Loss: 1.1912
Step [400/500] Train Loss: 1.2451
Step [500/500] Train Loss: 1.3067
Accuracy on Test Set: 60.2800 %
Epoch 4/10:
Step [100/500] Train Loss: 1.3471
Step [200/500] Train Loss: 1.2564
Step [300/500] Train Loss: 1.1971
Step [400/500] Train Loss: 1.1134
Step [500/500] Train Loss: 1.3163
Accuracy on Test Set: 62.7700 %
Epoch 5/10:
Step [100/500] Train Loss: 1.2081
Step [200/500] Train Loss: 1.0366
Step [300/500] Train Loss: 1.0514
Step [400/500] Train Loss: 1.1292
Step [500/500] Train Loss: 1.0381
Accuracy on Test Set: 64.4700 %
Epoch 6/10:
Step [100/500] Train Loss: 0.9613
Step [200/500] Train Loss: 0.9588
Step [300/500] Train Loss: 1.1643
Step [400/500] Train Loss: 0.9842
Step [500/500] Train Loss: 1.0876
Accuracy on Test Set: 64.2500 %
Epoch 7/10:
Step [100/500] Train Loss: 1.1227
Step [200/500] Train Loss: 1.1365
Step [300/500] Train Loss: 1.2146
Step [400/500] Train Loss: 1.0229
Step [500/500] Train Loss: 1.3981
Accuracy on Test Set: 65.6000 %
Epoch 8/10:
Step [100/500] Train Loss: 1.1427
Step [200/500] Train Loss: 0.9221
Step [300/500] Train Loss: 1.1509
Step [400/500] Train Loss: 0.9516
Step [500/500] Train Loss: 1.1159
Accuracy on Test Set: 65.5400 %
Epoch 9/10:
Step [100/500] Train Loss: 1.0614
Step [200/500] Train Loss: 1.0258
Step [300/500] Train Loss: 0.9749
Step [400/500] Train Loss: 0.9400
```

```
Step [500/500] Train Loss: 1.2101
Accuracy on Test Set: 66.7200 %
Epoch 10/10:
Step [100/500] Train Loss: 1.2158
Step [200/500] Train Loss: 1.1549
Step [300/500] Train Loss: 0.9802
Step [400/500] Train Loss: 0.9733
Step [500/500] Train Loss: 1.0673
Accuracy on Test Set: 66.6800 %
```





ResNet

接下来,让我们完成更复杂的CNN的实现.
ResNet又叫做残差网络.在ResNet网络结构中会用到两种残差模块，一种是以两个3*3的卷积网络串接在一起作为一个残差模块，另外一种是1*1、3*3、1*1的3个卷积网络串接在一起作为一个残差模块。他们如下图所示。

ResNet
我们以左边的模块为例实现一个ResidualBlock.注意到由于我们在两次卷积中可能会使输入的tensor的size与输出的tensor的size不相等,为了使它们能够相加,所以输出的tensor与输入的tensor size不同时,我们使用downsample(由外部传入)来使保持size相同

现在,试在**To-Do补充代码**完成下面的forward函数来完成ResidualBlock的实现,并运行它.

In [22]:

```
# 3x3 convolution
def conv3x3(in_channels, out_channels, stride=1):
    return nn.Conv2d(in_channels, out_channels, kernel_size=3,
                     stride=stride, padding=1, bias=False)

# Residual block
class ResidualBlock(nn.Module):
    def __init__(self, in_channels, out_channels, stride=1, downsample=None):
        super(ResidualBlock, self).__init__()
        self.conv1 = conv3x3(in_channels, out_channels, stride)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.relu = nn.ReLU(inplace=True)
        self.conv2 = conv3x3(out_channels, out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)
        self.downsample = downsample

    def forward(self, x):
        """
        Defines the computation performed at every call.
        x: N * C * H * W
        """
        residual = x
        # if the size of input x changes, using downsample to change the size of residual
        if self.downsample:
            residual = self.downsample(x)
        out = self.conv1(x)
        out = self.bn1(out)

        """
        To-Do: add code here
        """
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)

        out += residual
        out = self.relu(out)
        return out
```

下面是一份针对cifar10数据集的ResNet的实现.它先通过一个conv3x3,然后经过3个包含多个残差模块的layer(一个layer可能包括多个ResidualBlock, 由传入的layers列表中的数字决定), 然后经过一个全局平均池化层,最后通过一个线性层.

In [23]:

```
class ResNet(nn.Module):
    def __init__(self, block, layers, num_classes=10):
        """
        block: ResidualBlock or other block
        layers: a list with 3 positive num.
        """
        super(ResNet, self).__init__()
        self.in_channels = 16
        self.conv = conv3x3(3, 16)
        self.bn = nn.BatchNorm2d(16)
        self.relu = nn.ReLU(inplace=True)
        # layer1: image size 32
        self.layer1 = self.make_layer(block, 16, num_blocks=layers[0])
        # layer2: image size 32 -> 16
        self.layer2 = self.make_layer(block, 32, num_blocks=layers[1], stride=2)
        # layer1: image size 16 -> 8
        self.layer3 = self.make_layer(block, 64, num_blocks=layers[2], stride=2)
        # global avg pool: image size 8 -> 1
        self.avg_pool = nn.AvgPool2d(8)

        self.fc = nn.Linear(64, num_classes)

    def make_layer(self, block, out_channels, num_blocks, stride=1):
        """
        make a layer with num_blocks blocks.
        """

        downsample = None
        if (stride != 1) or (self.in_channels != out_channels):
            # use Conv2d with stride to downsample
            downsample = nn.Sequential(
                conv3x3(self.in_channels, out_channels, stride=stride),
                nn.BatchNorm2d(out_channels))

        # first block with downsample
        layers = []
        layers.append(block(self.in_channels, out_channels, stride, downsample))

        self.in_channels = out_channels
        # add num_blocks - 1 blocks
        for i in range(1, num_blocks):
            layers.append(block(out_channels, out_channels))

        # return a layer containing layers
        return nn.Sequential(*layers)

    def forward(self, x):
        out = self.conv(x)
        out = self.bn(out)
        out = self.relu(out)
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.avg_pool(out)
        # view: here change output size from 4 dimensions to 2 dimensions
        out = out.view(out.size(0), -1)
        out = self.fc(out)
        return out
```

In [24]:

```
resnet = ResNet(ResidualBlock, [2, 2, 2])
print(resnet)
```

```
ResNet(
  (conv): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
  (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (relu): ReLU(inplace)
  (layer1): Sequential(
    (0): ResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
    )
    (1): ResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): ResidualBlock(
      (conv1): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), paddi
ng=(1, 1), bias=False)
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      )
    )
    (1): ResidualBlock(
      (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
    )
  )
  (layer3): Sequential(
```

```
    (0): ResidualBlock(
      (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), paddi
ng=(1, 1), bias=False)
        (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      )
    )
    (1): ResidualBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
    )
  )
  (avg_pool): AvgPool2d(kernel_size=8, stride=8, padding=0)
  (fc): Linear(in_features=64, out_features=10, bias=True)
)
```

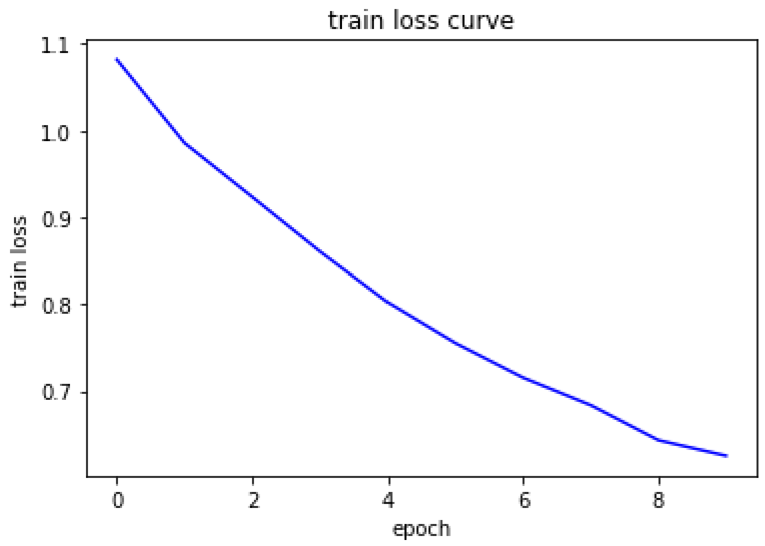
使用fit函数训练实现的ResNet,观察结果变化.

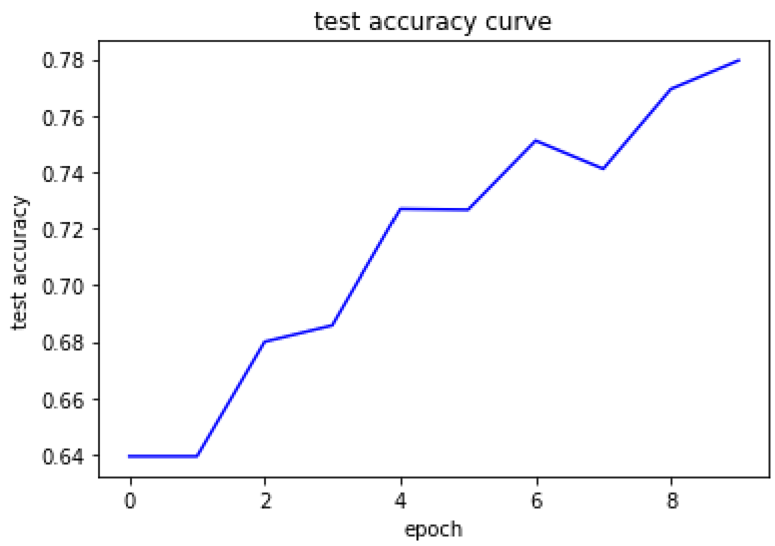
In [26]:

```
# Hyper-parameters
num_epochs = 10
lr = 0.001
# Device configuration
device = torch.device('cuda:0')
# optimizer
optimizer = torch.optim.Adam(resnet.parameters(), lr=lr)

fit(resnet, num_epochs, optimizer, device)
```

```
Epoch 1/10:
Step [100/500] Train Loss: 1.0425
Step [200/500] Train Loss: 1.2821
Step [300/500] Train Loss: 1.0189
Step [400/500] Train Loss: 1.0343
Step [500/500] Train Loss: 1.0760
Accuracy on Test Set: 63.9400 %
Epoch 2/10:
Step [100/500] Train Loss: 0.9691
Step [200/500] Train Loss: 0.9280
Step [300/500] Train Loss: 1.1253
Step [400/500] Train Loss: 1.0832
Step [500/500] Train Loss: 0.7534
Accuracy on Test Set: 63.9400 %
Epoch 3/10:
Step [100/500] Train Loss: 0.9576
Step [200/500] Train Loss: 0.8765
Step [300/500] Train Loss: 0.7416
Step [400/500] Train Loss: 0.8020
Step [500/500] Train Loss: 0.7128
Accuracy on Test Set: 68.0000 %
Epoch 4/10:
Step [100/500] Train Loss: 1.0099
Step [200/500] Train Loss: 0.9608
Step [300/500] Train Loss: 0.8774
Step [400/500] Train Loss: 0.7870
Step [500/500] Train Loss: 0.7058
Accuracy on Test Set: 68.5800 %
Epoch 5/10:
Step [100/500] Train Loss: 0.8077
Step [200/500] Train Loss: 0.5876
Step [300/500] Train Loss: 0.8926
Step [400/500] Train Loss: 0.8441
Step [500/500] Train Loss: 0.9973
Accuracy on Test Set: 72.6900 %
Epoch 6/10:
Step [100/500] Train Loss: 0.8229
Step [200/500] Train Loss: 0.7058
Step [300/500] Train Loss: 0.7750
Step [400/500] Train Loss: 0.7295
Step [500/500] Train Loss: 0.8246
Accuracy on Test Set: 72.6600 %
Epoch 7/10:
Step [100/500] Train Loss: 0.7068
Step [200/500] Train Loss: 0.6928
Step [300/500] Train Loss: 0.8502
Step [400/500] Train Loss: 0.7325
Step [500/500] Train Loss: 0.6583
Accuracy on Test Set: 75.1100 %
Epoch 8/10:
Step [100/500] Train Loss: 0.6834
Step [200/500] Train Loss: 0.8615
Step [300/500] Train Loss: 0.7363
Step [400/500] Train Loss: 0.8829
Step [500/500] Train Loss: 0.7208
Accuracy on Test Set: 74.1100 %
Epoch 9/10:
Step [100/500] Train Loss: 0.6611
Step [200/500] Train Loss: 0.5346
Step [300/500] Train Loss: 0.4550
Step [400/500] Train Loss: 0.7190
```

```
Step [500/500] Train Loss: 0.5672
Accuracy on Test Set: 76.9400 %
Epoch 10/10:
Step [100/500] Train Loss: 0.5207
Step [200/500] Train Loss: 0.6895
Step [300/500] Train Loss: 0.5880
Step [400/500] Train Loss: 0.6893
Step [500/500] Train Loss: 0.7157
Accuracy on Test Set: 77.9500 %
```





作业

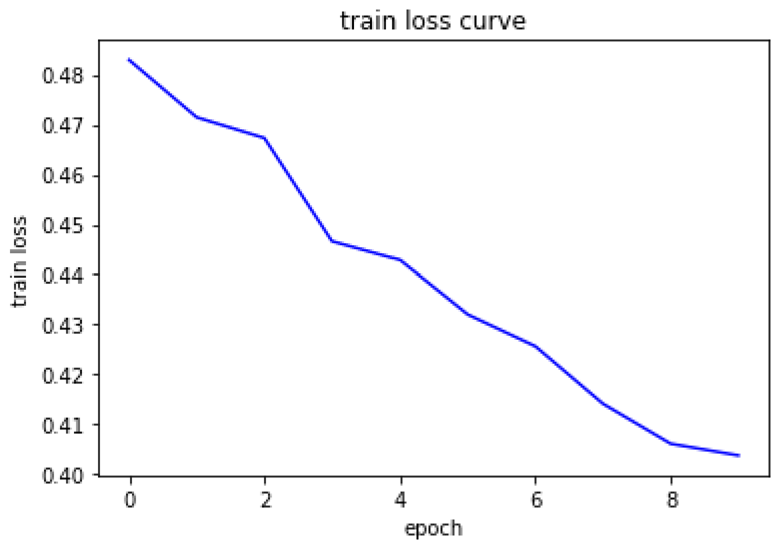
尝试改变学习率lr,使用SGD或Adam优化器,训练10个epoch,提高ResNet在测试集上的accuracy.

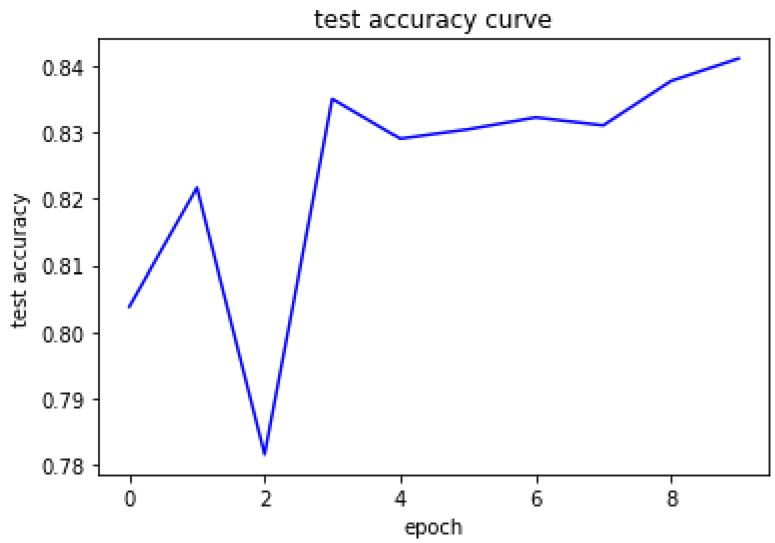
In [30]:

```
# Hyper-parameters
num_epochs = 10
lr = 0.0015
# Device configuration
device = torch.device('cuda:0')
# optimizer
optimizer = torch.optim.Adam(resnet.parameters(), lr=lr)

fit(resnet, num_epochs, optimizer, device)
```

```
Epoch 1/10:
Step [100/500] Train Loss: 0.7118
Step [200/500] Train Loss: 0.4573
Step [300/500] Train Loss: 0.4669
Step [400/500] Train Loss: 0.2568
Step [500/500] Train Loss: 0.4969
Accuracy on Test Set: 80.3800 %
Epoch 2/10:
Step [100/500] Train Loss: 0.4439
Step [200/500] Train Loss: 0.4941
Step [300/500] Train Loss: 0.5434
Step [400/500] Train Loss: 0.4898
Step [500/500] Train Loss: 0.4460
Accuracy on Test Set: 82.1700 %
Epoch 3/10:
Step [100/500] Train Loss: 0.4875
Step [200/500] Train Loss: 0.3971
Step [300/500] Train Loss: 0.5229
Step [400/500] Train Loss: 0.6836
Step [500/500] Train Loss: 0.4133
Accuracy on Test Set: 78.1500 %
Epoch 4/10:
Step [100/500] Train Loss: 0.3835
Step [200/500] Train Loss: 0.5045
Step [300/500] Train Loss: 0.4055
Step [400/500] Train Loss: 0.3561
Step [500/500] Train Loss: 0.4818
Accuracy on Test Set: 83.5100 %
Epoch 5/10:
Step [100/500] Train Loss: 0.3647
Step [200/500] Train Loss: 0.5745
Step [300/500] Train Loss: 0.2970
Step [400/500] Train Loss: 0.4631
Step [500/500] Train Loss: 0.3952
Accuracy on Test Set: 82.9100 %
Epoch 6/10:
Step [100/500] Train Loss: 0.4992
Step [200/500] Train Loss: 0.4990
Step [300/500] Train Loss: 0.4383
Step [400/500] Train Loss: 0.5731
Step [500/500] Train Loss: 0.3213
Accuracy on Test Set: 83.0500 %
Epoch 7/10:
Step [100/500] Train Loss: 0.3208
Step [200/500] Train Loss: 0.3100
Step [300/500] Train Loss: 0.4275
Step [400/500] Train Loss: 0.4537
Step [500/500] Train Loss: 0.4117
Accuracy on Test Set: 83.2300 %
Epoch 8/10:
Step [100/500] Train Loss: 0.4122
Step [200/500] Train Loss: 0.4852
Step [300/500] Train Loss: 0.4390
Step [400/500] Train Loss: 0.3829
Step [500/500] Train Loss: 0.3836
Accuracy on Test Set: 83.1100 %
Epoch 9/10:
Step [100/500] Train Loss: 0.3871
Step [200/500] Train Loss: 0.3587
Step [300/500] Train Loss: 0.2804
Step [400/500] Train Loss: 0.2926
```

```
Step [500/500] Train Loss: 0.4059
Accuracy on Test Set: 83.7800 %
Epoch 10/10:
Step [100/500] Train Loss: 0.3101
Step [200/500] Train Loss: 0.4478
Step [300/500] Train Loss: 0.3073
Step [400/500] Train Loss: 0.3947
Step [500/500] Train Loss: 0.3530
Accuracy on Test Set: 84.1200 %
```





作业

下图表示将SE模块嵌入到ResNet的残差模块.
SE-Resnet module
其中,global pooling表示全局池化层(将输入的size池化为1*1), 将c*h*w的输入变为c*1*1的输出.FC表示全连接层(线性层),两层FC之间使用ReLU作为激活函数.通过两层FC后使用sigmoid激活函数激活.最后将得到的c个值与原输入c*h*w按channel相乘,得到c*h*w的输出.

补充下方的代码完成SE-Resnet block的实现.

In [31]:

```
class SELayer(nn.Module):
    def __init__(self, channel, reduction=16):
        super(SELayer, self).__init__()
        # The output of AdaptiveAvgPool2d is of size H x W, for any input size.
        self.avg_pool = nn.AdaptiveAvgPool2d((1, 1))
        self.relu = nn.ReLU(inplace=True)
        self.fc1 = nn.Linear(channel, channel//reduction)
        self.fc2 = nn.Linear(channel//reduction, channel)
        self.sigmoid = nn.Sigmoid()


    def forward(self, x):
        out = self.avg_pool(x)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.relu(out)
        out = self.fc2(out)
        out = self.sigmoid(out)
        out = out.view(out.shape[0], -1, 1, 1)
        return x*out
```

In [32]:

```
class SEResidualBlock(nn.Module):
    def __init__(self, in_channels, out_channels, stride=1, downsample=None, red
uction=16):
        super(SEResidualBlock, self).__init__()
        """
        To-Do: add code here
        """
        self.conv1 = conv3x3(in_channels, out_channels, stride)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.relu = nn.ReLU(inplace=True)
        self.conv2 = conv3x3(out_channels, out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)
        self.se = SELayer(out_channels, reduction)
        self.downsample = downsample

    def forward(self, x):

        residual = x
        """
        To-Do: add code here
        """
        if self.downsample:
            residual = self.downsample(x)
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out = self.se(out)
        out = out + residual
        out = self.relu(out)
        return out
```

In [33]:

```
se_resnet = ResNet(SEResidualBlock, [2, 2, 2])
print(se_resnet)
```

```
ResNet(
  (conv): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
  (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (relu): ReLU(inplace)
  (layer1): Sequential(
    (0): SEResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (relu): ReLU(inplace)
        (fc1): Linear(in_features=16, out_features=1, bias=True)
        (fc2): Linear(in_features=1, out_features=16, bias=True)
        (sigmoid): Sigmoid()
      )
    )
    (1): SEResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (relu): ReLU(inplace)
        (fc1): Linear(in_features=16, out_features=1, bias=True)
        (fc2): Linear(in_features=1, out_features=16, bias=True)
        (sigmoid): Sigmoid()
      )
    )
  )
  (layer2): Sequential(
    (0): SEResidualBlock(
      (conv1): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), pad
ding=(1, 1), bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (relu): ReLU(inplace)
        (fc1): Linear(in_features=32, out_features=2, bias=True)
        (fc2): Linear(in_features=2, out_features=32, bias=True)
        (sigmoid): Sigmoid()
```

```
        )
        (downsample): Sequential(
          (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), paddi
ng=(1, 1), bias=False)
          (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        )
      )
      (1): SEResidualBlock(
        (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
        (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        (relu): ReLU(inplace)
        (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
        (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        (se): SELayer(
          (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
          (relu): ReLU(inplace)
          (fc1): Linear(in_features=32, out_features=2, bias=True)
          (fc2): Linear(in_features=2, out_features=32, bias=True)
          (sigmoid): Sigmoid()
        )
      )
    )
    (layer3): Sequential(
      (0): SEResidualBlock(
        (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), pad
ding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        (relu): ReLU(inplace)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        (se): SELayer(
          (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
          (relu): ReLU(inplace)
          (fc1): Linear(in_features=64, out_features=4, bias=True)
          (fc2): Linear(in_features=4, out_features=64, bias=True)
          (sigmoid): Sigmoid()
        )
        (downsample): Sequential(
          (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), paddi
ng=(1, 1), bias=False)
          (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        )
      )
      (1): SEResidualBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
rack_running_stats=True)
        (relu): ReLU(inplace)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), pad
ding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, t
```

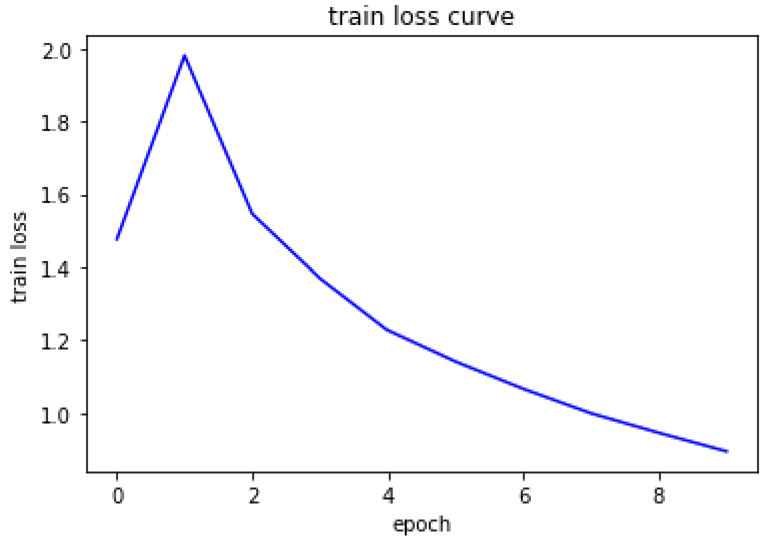
```
rack_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (relu): ReLU(inplace)
        (fc1): Linear(in_features=64, out_features=4, bias=True)
        (fc2): Linear(in_features=4, out_features=64, bias=True)
        (sigmoid): Sigmoid()
      )
    )
  )
  (avg_pool): AvgPool2d(kernel_size=8, stride=8, padding=0)
  (fc): Linear(in_features=64, out_features=10, bias=True)
)
```

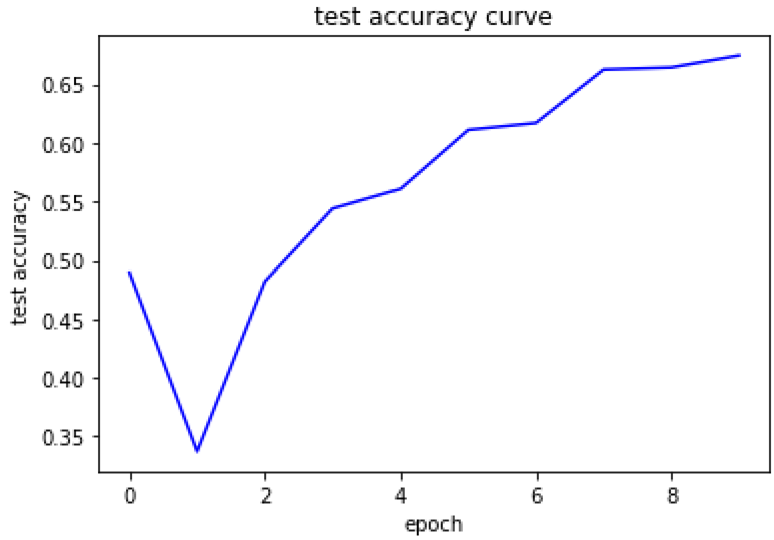
In [34]:

```
# Hyper-parameters
num_epochs = 10
lr = 0.001
# Device configuration
device = torch.device('cuda:0')
# optimizer
optimizer = torch.optim.Adam(se_resnet.parameters(), lr=lr)

fit(se_resnet, num_epochs, optimizer, device)
```

```
Epoch 1/10:
Step [100/500] Train Loss: 1.6276
Step [200/500] Train Loss: 1.4714
Step [300/500] Train Loss: 1.4851
Step [400/500] Train Loss: 1.2222
Step [500/500] Train Loss: 1.2060
Accuracy on Test Set: 48.9400 %
Epoch 2/10:
Step [100/500] Train Loss: 2.2510
Step [200/500] Train Loss: 2.0723
Step [300/500] Train Loss: 1.8598
Step [400/500] Train Loss: 2.0755
Step [500/500] Train Loss: 1.7243
Accuracy on Test Set: 33.7100 %
Epoch 3/10:
Step [100/500] Train Loss: 1.7078
Step [200/500] Train Loss: 1.5886
Step [300/500] Train Loss: 1.5629
Step [400/500] Train Loss: 1.5738
Step [500/500] Train Loss: 1.4202
Accuracy on Test Set: 48.1800 %
Epoch 4/10:
Step [100/500] Train Loss: 1.5383
Step [200/500] Train Loss: 1.4838
Step [300/500] Train Loss: 1.3516
Step [400/500] Train Loss: 1.4415
Step [500/500] Train Loss: 1.1955
Accuracy on Test Set: 54.4100 %
Epoch 5/10:
Step [100/500] Train Loss: 1.2495
Step [200/500] Train Loss: 1.2082
Step [300/500] Train Loss: 1.1445
Step [400/500] Train Loss: 1.0991
Step [500/500] Train Loss: 1.1674
Accuracy on Test Set: 56.0800 %
Epoch 6/10:
Step [100/500] Train Loss: 1.0126
Step [200/500] Train Loss: 1.1029
Step [300/500] Train Loss: 0.8674
Step [400/500] Train Loss: 0.9355
Step [500/500] Train Loss: 1.1729
Accuracy on Test Set: 61.1100 %
Epoch 7/10:
Step [100/500] Train Loss: 1.1173
Step [200/500] Train Loss: 1.2414
Step [300/500] Train Loss: 1.1263
Step [400/500] Train Loss: 1.0653
Step [500/500] Train Loss: 0.9470
Accuracy on Test Set: 61.7000 %
Epoch 8/10:
Step [100/500] Train Loss: 1.0067
Step [200/500] Train Loss: 0.9689
Step [300/500] Train Loss: 0.9487
Step [400/500] Train Loss: 1.1266
Step [500/500] Train Loss: 1.1523
Accuracy on Test Set: 66.2600 %
Epoch 9/10:
Step [100/500] Train Loss: 0.7574
Step [200/500] Train Loss: 0.7837
Step [300/500] Train Loss: 0.9518
Step [400/500] Train Loss: 0.9028
```

```
Step [500/500] Train Loss: 0.8175
Accuracy on Test Set: 66.4400 %
Epoch 10/10:
Step [100/500] Train Loss: 0.7346
Step [200/500] Train Loss: 0.7445
Step [300/500] Train Loss: 0.8594
Step [400/500] Train Loss: 0.9784
Step [500/500] Train Loss: 0.8334
Accuracy on Test Set: 67.4600 %
```





Vgg

接下来让我们阅读vgg网络的实现代码.VGGNet全部使用3*3的卷积核和2*2的池化核，通过不断加深网络结构来提升性能。Vgg表明了卷积神经网络的深度增加和小卷积核的使用对网络的最终分类识别效果有很大的作用.
vgg
下面是一份用于训练cifar10的简化版的vgg代码.
有时间的同学可以阅读并训练它.

In [35]:

```
import math

class VGG(nn.Module):
    def __init__(self, cfg):
        super(VGG, self).__init__()
        self.features = self._make_layers(cfg)
        # linear layer
        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):
        """
        cfg: a list define layers this layer contains
            'M': MaxPool, number: Conv2d(out_channels=number) -> BN -> ReLU
        """
        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)
```

In [36]:

```
cfg = {
    'VGG11': [64, 'M', 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512, 'M'],
    'VGG13': [64, 64, 'M', 128, 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512
, 'M'],
    'VGG16': [64, 64, 'M', 128, 128, 'M', 256, 256, 256, 'M', 512, 512, 512, 'M'
, 512, 512, 512, 'M'],
    'VGG19': [64, 64, 'M', 128, 128, 'M', 256, 256, 256, 256, 'M', 512, 512, 512
, 512, 'M', 512, 512, 512, 512, 'M'],
}
vggnet = VGG(cfg['VGG11'])
print(vggnet)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
    (2): ReLU(inplace)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, c
eil_mode=False)
    (4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
    (5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
    (6): ReLU(inplace)
    (7): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, c
eil_mode=False)
    (8): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1))
    (9): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
    (10): ReLU(inplace)
    (11): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (12): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
    (13): ReLU(inplace)
    (14): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (15): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (16): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
    (17): ReLU(inplace)
    (18): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (19): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
    (20): ReLU(inplace)
    (21): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (22): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (23): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
    (24): ReLU(inplace)
    (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (26): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
    (27): ReLU(inplace)
    (28): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (29): AvgPool2d(kernel_size=1, stride=1, padding=0)
  )
  (classifier): Linear(in_features=512, out_features=10, bias=True)
)
```

In [37]:

```
# Hyper-parameters
num_epochs = 10
lr = 1e-3
# Device configuration
device = torch.device('cuda:0')

# optimizer
optimizer = torch.optim.Adam(vggnet.parameters(), lr=lr)

fit(vggnet, num_epochs, optimizer, device)
```

```
Epoch 1/10:
Step [100/500] Train Loss: 1.6253
Step [200/500] Train Loss: 1.4231
Step [300/500] Train Loss: 1.3688
Step [400/500] Train Loss: 1.3814
Step [500/500] Train Loss: 0.9911
Accuracy on Test Set: 57.4000 %
Epoch 2/10:
Step [100/500] Train Loss: 1.8048
Step [200/500] Train Loss: 1.4972
Step [300/500] Train Loss: 1.3364
Step [400/500] Train Loss: 1.2925
Step [500/500] Train Loss: 1.1823
Accuracy on Test Set: 58.4400 %
Epoch 3/10:
Step [100/500] Train Loss: 1.1463
Step [200/500] Train Loss: 0.9488
Step [300/500] Train Loss: 1.1180
Step [400/500] Train Loss: 0.9506
Step [500/500] Train Loss: 0.8822
Accuracy on Test Set: 69.1200 %
Epoch 4/10:
Step [100/500] Train Loss: 0.9562
Step [200/500] Train Loss: 0.7132
Step [300/500] Train Loss: 0.7834
Step [400/500] Train Loss: 0.9923
Step [500/500] Train Loss: 0.6245
Accuracy on Test Set: 74.0900 %
Epoch 5/10:
Step [100/500] Train Loss: 0.6804
Step [200/500] Train Loss: 0.7942
Step [300/500] Train Loss: 0.6620
Step [400/500] Train Loss: 0.5886
Step [500/500] Train Loss: 0.6147
Accuracy on Test Set: 78.1000 %
Epoch 6/10:
Step [100/500] Train Loss: 0.4513
Step [200/500] Train Loss: 0.6562
Step [300/500] Train Loss: 0.5617
Step [400/500] Train Loss: 0.6486
Step [500/500] Train Loss: 0.6400
Accuracy on Test Set: 78.4500 %
Epoch 7/10:
Step [100/500] Train Loss: 0.6970
Step [200/500] Train Loss: 0.5626
Step [300/500] Train Loss: 0.4481
Step [400/500] Train Loss: 0.5924
Step [500/500] Train Loss: 0.5008
Accuracy on Test Set: 80.9900 %
Epoch 8/10:
Step [100/500] Train Loss: 0.5288
Step [200/500] Train Loss: 0.4491
Step [300/500] Train Loss: 0.5524
Step [400/500] Train Loss: 0.5024
Step [500/500] Train Loss: 0.4200
Accuracy on Test Set: 81.3000 %
Epoch 9/10:
Step [100/500] Train Loss: 0.5242
Step [200/500] Train Loss: 0.4221
Step [300/500] Train Loss: 0.4665
Step [400/500] Train Loss: 0.6280
```

```
Step [500/500] Train Loss: 0.5573
Accuracy on Test Set: 81.2000 %
Epoch 10/10:
Step [100/500] Train Loss: 0.3493
Step [200/500] Train Loss: 0.5310
Step [300/500] Train Loss: 0.6748
Step [400/500] Train Loss: 0.4147
Step [500/500] Train Loss: 0.4272
Accuracy on Test Set: 83.5300 %
```