[1]:
```
# For tips on running notebooks in Google Colab, see
# https://pytorch.org/tutorials/beginner/colab
%matplotlib inline
```

Training a Classifier

We will use the MNIST dataset.

Training an image classifier

We will do the following steps in order:

1. Load and normalize the training and test datasets
2. Define a Convolutional Neural Network
3. Define a loss function
4. Train the network on the training data
5. Test the network on the test data

1. Load and normalize the dataset

[2]:
```
import torch
import torchvision
import torchvision.transforms as transforms
```

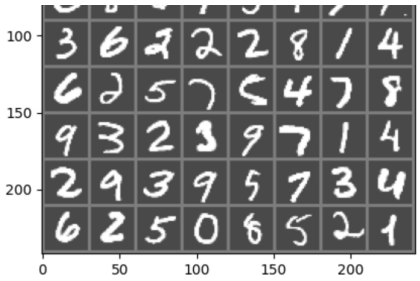
The output of torchvision datasets are PILImage images of range [0, 1]. We transform them to Tensors of normalized range [-1, 1].

[14]:
```
# transform = transforms.Compose(
#     [transforms.ToTensor(),
#      transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

# batch_size = 4

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

# testset = torchvision.datasets.MNIST(root='./data', train=False,
#                                      download=True, transform=transform)
# testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,
#                                          shuffle=False, num_workers=2)
# classes = ('plane', 'car', 'bird', 'cat',
#            'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
# classes = tuple(str(i) for i in range(10))
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.1307,), (0.3081,))])  # MNIST mean and std

batch_size = 64   # You can choose 4 or bigger, 64 is common

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

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

classes = tuple(str(i) for i in range(10))
```

Let us show some of the training images, for fun.

[15]:
```
import matplotlib.pyplot as plt
import numpy as np

# functions to show an image


def imshow(img):
    img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()


# get some random training images
dataiter = iter(trainloader)
images, labels = next(dataiter)

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join(f'{classes[labels[j]]:5s}' for j in range(batch_size)))
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [0.28789353..1.910743
4].
```




```
4    1    6    6    2    2    7    8    9    7    1    4    0    8    7    7    0    8    6    4    3    1    7    4
3    6    2    2    2    8    1    4    6    2    5    7    5    4    7    8    9    3    2    3    9    7    1    4
2    9    3    9    5    7    3    4    6    2    5    0    8    5    2    1
```

2. Define a Convolutional Neural Network

[17]:
```
import torch.nn as nn
import torch.nn.functional as F


class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)           # 1 channel for MNIST
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 4 * 4, 120)      # 28x28 -> conv1(5x5)->24x24->pool->12x12->conv2(5x5)->8x8->pool->4x4
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = torch.flatten(x, 1) # flatten all dimensions except batch
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x


net = Net()
```

3. Define a Loss function and optimizer

Let's use a Classification Cross-Entropy loss and SGD with momentum.

[18]:
```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

4. Train the network

This is when things start to get interesting. We simply have to loop over our data iterator, and feed the inputs to the network and optimize.

[26]:
```
for epoch in range(3):  # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999:    # print every 2000 mini-batches
            print(f'[{epoch + 1}, {i + 1:5d}] loss: {running_loss / 2000:.3f}')
            running_loss = 0.0

print('Finished Training')
```

```
Finished Training
```

Let's quickly save our trained model:

[27]:
```
PATH = './mnist_net.pth'
torch.save(net.state_dict(), PATH)
```

See here for more details on saving PyTorch models.

5. Test the network on the test data

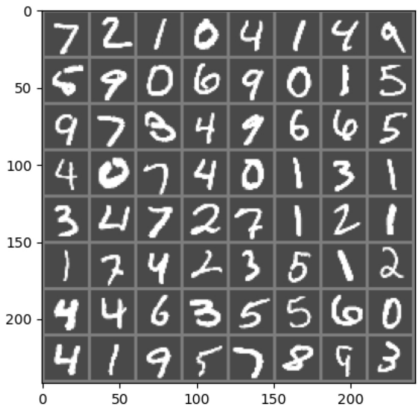
We have trained the network over the training dataset.

We will predict the class label that the neural network outputs, and check it against the ground-truth.

[28]:
```
dataiter = iter(testloader)
images, labels = next(dataiter)

# print images
```

```
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join(f'{classes[labels[j]]:5s}' for j in range(4)))
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [0.28789353..1.910743
4].
```




```
GroundTruth:  7     2     1     0
```

Next, let's load back in our saved model (note: saving and re-loading the model wasn't necessary here, we only did it to illustrate how to do so):

[29]:
```
net = Net()
net.load_state_dict(torch.load(PATH))
```

[29]:
```
<All keys matched successfully>
```

Okay, now let us see what the neural network thinks these examples above are:

[30]:
```
outputs = net(images)
```

The outputs are energies for the 10 classes. The higher the energy for a class, the more the network thinks that the image is of the particular class. So, let's get the index of the highest energy:

[31]:
```
_, predicted = torch.max(outputs, 1)

print('Predicted: ', ' '.join(f'{classes[predicted[j]]:5s}'
                              for j in range(4)))
```

```
Predicted:  7     2     1     0
```

Let us look at how the network performs on the whole dataset.

[32]:
```
correct = 0
total = 0
# since we're not training, we don't need to calculate the gradients for our outputs
with torch.no_grad():
    for data in testloader:
        images, labels = data
        # calculate outputs by running images through the network
        outputs = net(images)
        # the class with the highest energy is what we choose as prediction
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

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

```
Accuracy of the network on the 10000 test images: 97 %
```

That looks way better than chance, which is 10% accuracy (randomly picking a class out of 10 classes). Seems like the network learnt something.

Hmmm, what are the classes that performed well, and the classes that did not perform well:

[33]:
```
# prepare to count predictions for each class
correct_pred = {classname: 0 for classname in classes}
total_pred = {classname: 0 for classname in classes}

# again no gradients needed
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predictions = torch.max(outputs, 1)
        # collect the correct predictions for each class
        for label, prediction in zip(labels, predictions):
            if label == prediction:
                correct_pred[classes[label]] += 1
            total_pred[classes[label]] += 1


# print accuracy for each class
for classname, correct_count in correct_pred.items():
    accuracy = 100 * float(correct_count) / total_pred[classname]
    print(f'Accuracy for class: {classname:5s} is {accuracy:.1f} %')
```

```
Accuracy for class: 0     is 99.4 %
Accuracy for class: 1     is 99.2 %
Accuracy for class: 2     is 96.5 %
Accuracy for class: 3     is 96.2 %
Accuracy for class: 4     is 99.4 %
Accuracy for class: 5     is 98.1 %
Accuracy for class: 6     is 98.9 %
Accuracy for class: 7     is 96.5 %
Accuracy for class: 8     is 97.4 %
Accuracy for class: 9     is 95.5 %
```