```
%matplotlib inline
```

Training a Classifier

This is it. You have seen how to define neural networks, compute loss and make updates to the weigh

Now you might be thinking,

What about data?

Generally, when you have to deal with image, text, audio or video data, you can use standard python pa
Then you can convert this array into a `torch.*Tensor`.

- For images, packages such as Pillow, OpenCV are useful
- For audio, packages such as scipy and librosa
- For text, either raw Python or Cython based loading, or NLTK and SpaCy are useful

Specifically for vision, we have created a package called `torchvision`, that has data loaders for comr
MNIST, etc. and data transformers for images, viz., `torchvision.datasets` and `torch.utils.data.Da`

This provides a huge convenience and avoids writing boilerplate code.

For this tutorial, we will use the CIFAR10 dataset. It has the classes: ‘airplane’, ‘automobile’, ‘bird’, ‘cat’,
The images in CIFAR-10 are of size 3x32x32, i.e. 3-channel color images of 32x32 pixels in size.

.. figure:: /_static/img/cifar10.png :alt: cifar10

cifar10

Training an image classifier

We will do the following steps in order:

1. Load and normalizing the CIFAR10 training and test datasets using `torchvision`
2. Define a Convolution Neural Network
3. Define a loss function
4. Train the network on the training data
5. Test the network on the test data
6. Loading and normalizing CIFAR10 ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

Using `torchvision`, it’s extremely easy to load CIFAR10.

```
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 Tensor

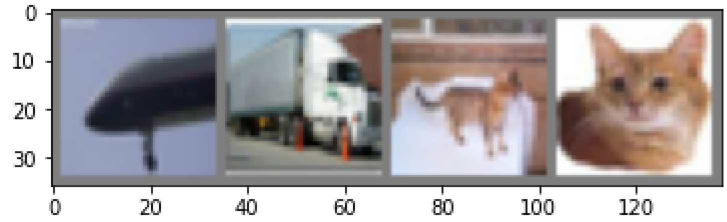
```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                          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=4,
                                         shuffle=False, num_workers=2)

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

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

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

```
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)))


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

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```

```
plane truck   cat   cat
```



2. Define a Convolution Neural Network ^^ Copy the neural netw
   before and modify it to take 3-channel images (instead of 1-channel images as it was defined).

```
import torch.nn as nn
import torch.nn.functional as F


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)

    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


net = Net()
```

3. Define a Loss function and optimizer ^^ Let's use a Classifica
   momentum.

```
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

```
for epoch in range(2):  # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs
        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('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

```
[1,  2000] loss: 2.162
[1,  4000] loss: 1.844
[1,  6000] loss: 1.664
[1,  8000] loss: 1.539
[1, 10000] loss: 1.519
[1, 12000] loss: 1.463
[2,  2000] loss: 1.391
[2,  4000] loss: 1.367
[2,  6000] loss: 1.329
[2,  8000] loss: 1.334
[2, 10000] loss: 1.305
[2, 12000] loss: 1.268
Finished Training
```

5. Test the network on the test data ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

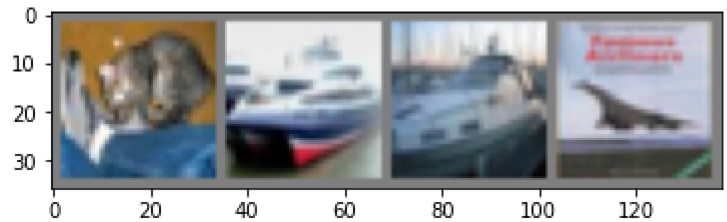
We have trained the network for 2 passes over the training dataset. But we need to check if the netwo

We will check this by predicting the class label that the neural network outputs, and checking it agains correct, we add the sample to the list of correct predictions.

Okay, first step. Let us display an image from the test set to get familiar.

```
dataiter = iter(testloader)
images, labels = dataiter.next()

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

```
GroundTruth:    cat  ship  ship plane
```



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

```
outputs = net(images)
```

The outputs are energies for the 10 classes. Higher the energy for a class, the more the network think
So, let's get the index of the highest energy:

```
_, predicted = torch.max(outputs, 1)

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

```
Predicted:   frog  ship  ship plane
```

The results seem pretty good.

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

```
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        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: 56 %
```

That looks waaay better than chance, which is 10% accuracy (randomly picking a class out of 10 clas something.

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

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1


for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of plane : 47 %
Accuracy of   car : 64 %
Accuracy of  bird : 49 %
Accuracy of   cat : 35 %
Accuracy of  deer : 44 %
Accuracy of   dog : 47 %
Accuracy of  frog : 68 %
Accuracy of horse : 63 %
Accuracy of  ship : 80 %
Accuracy of truck : 59 %
```