```
%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 comm
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')
```

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

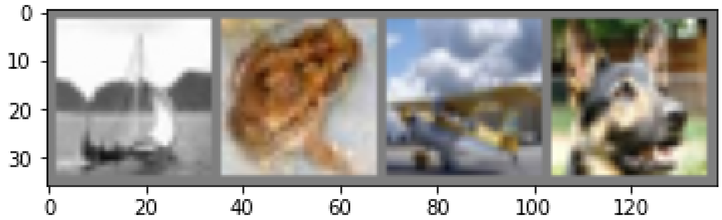
170500096/? [00:20<00:00, 68205847.04it/s]

```
Extracting ./data/cifar-10-python.tar.gz to ./data
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)))
```

```
ship  frog plane   dog
```



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: 2.153
[1,  4000] loss: 1.812
[1,  6000] loss: 1.656
[1,  8000] loss: 1.558
[1, 10000] loss: 1.507
[1, 12000] loss: 1.459
[2,  2000] loss: 1.404
[2,  4000] loss: 1.349
[2,  6000] loss: 1.324
[2,  8000] loss: 1.320
[2, 10000] loss: 1.300
[2, 12000] loss: 1.258
Finished Training
```

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

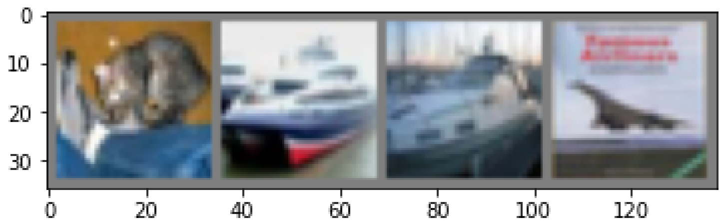
We have trained the network for 2 passes over the training dataset. But we need to check if the netwo

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:    cat   car  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 : 63 %
Accuracy of   car : 72 %
Accuracy of  bird : 47 %
Accuracy of   cat : 36 %
Accuracy of  deer : 35 %
Accuracy of   dog : 36 %
Accuracy of  frog : 78 %
Accuracy of horse : 54 %
Accuracy of  ship : 70 %
Accuracy of truck : 65 %
```

Okay, so what next?

How do we run these neural networks on the GPU?

Training on GPU

Just like how you transfer a Tensor on to the GPU, you transfer the neural net onto the GPU.

Let's first define our device as the first visible cuda device if we have CUDA available:

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

# Assume that we are on a CUDA machine, then this should print a CUDA device:

print(device)
```

```
cpu
```

The rest of this section assumes that `device` is a CUDA device.

Then these methods will recursively go over all modules and convert their parameters and buffers to

.. code:: python

```
net.to(device)
```

Remember that you will have to send the inputs and targets at every step to the GPU too:

.. code:: python

```
    inputs, labels = inputs.to(device), labels.to(device)
```

Why dont I notice MASSIVE speedup compared to CPU? Because your network is realllly small.

Exercise: Try increasing the width of your network (argument 2 of the first `nn.Conv2d`, and argument be the same number), see what kind of speedup you get.

Goals achieved:

- Understanding PyTorch's Tensor library and neural networks at a high level.
- Train a small neural network to classify images

Training on multiple GPUs

If you want to see even more MASSIVE speedup using all of your GPUs, please check out :doc: `data_p`

Where do I go next?

- :doc: `Train neural nets to play video games </intermediate/reinforcement_q_learning>`
- `Train a state-of-the-art ResNet network on imagenet`_
- `Train a face generator using Generative Adversarial Networks`_
- `Train a word-level language model using Recurrent LSTM networks`_
- `More examples`_
- `More tutorials`_
- `Discuss PyTorch on the Forums`_
- `Chat with other users on Slack`_

Multi layer perceptron from scratch

Reference: https://towardsdatascience.com/building-neural-network-from-scratch-9c88535bf8e9

A neural network needs a few building blocks

- Dense layer - a fully-connected layer, $f(X) = W \cdot X + \vec{b}$
- ReLU layer (or any other activation function to introduce non-linearity)
- Loss function - (crossentropy in case of multi-class classification problem)
- Backprop algorithm - a stochastic gradient descent with backpropageted gradients

Let's approach them one at a time.

Let's start by importing some libraires required for creating our neural network.

```
from __future__ import print_function
import numpy as np ## For numerical python
np.random.seed(42)
```

Every layer will have a forward pass and backpass implementation. Let's create a main class layer wh
Backward pass .backward().

```
class Layer:
    """
    A building block. Each layer is capable of performing two things:

    - Process input to get output:           output = layer.forward(input)

    - Propagate gradients through itself:    grad_input = layer.backward(input, grad_output)

    Some layers also have learnable parameters which they update during layer.backward.
    """
    def __init__(self):
        """Here we can initialize layer parameters (if any) and auxiliary stuff."""
        # A dummy layer does nothing
        pass

    def forward(self, input):
        """
        Takes input data of shape [batch, input_units], returns output data [batch, output_un
        """
        # A dummy layer just returns whatever it gets as input.
        return input

    def backward(self, input, grad_output):
        """
        Performs a backpropagation step through the layer, with respect to the given input.

        To compute loss gradients w.r.t input, we need to apply chain rule (backprop):

        d loss / d x  = (d loss / d layer) * (d layer / d x)
```

```
        Luckily, we already receive d loss / d layer as input, so you only need to multiply i

        If our layer has parameters (e.g. dense layer), we also need to update them here usin
        """
        # The gradient of a dummy layer is precisely grad_output, but we'll write it more exp
        num_units = input.shape[1]

        d_layer_d_input = np.eye(num_units)

        return np.dot(grad_output, d_layer_d_input) # chain rule
```

Nonlinearity ReLU layer

This is the simplest layer you can get: it simply applies a nonlinearity to each element of your network

```
class ReLU(Layer):
    def __init__(self):
        """ReLU layer simply applies elementwise rectified linear unit to all inputs"""
        pass

    def forward(self, input):
        """Apply elementwise ReLU to [batch, input_units] matrix"""
        relu_forward = np.maximum(0,input)
        return relu_forward

    def backward(self, input, grad_output):
        """Compute gradient of loss w.r.t. ReLU input"""
        relu_grad = input > 0
        return grad_output*relu_grad
```

Dense layer

Now let's build something more complicated. Unlike nonlinearity, a dense layer actually has somethin

A dense layer applies affine transformation. In a vectorized form, it can be described as:

$$f(X) = W \cdot X + \vec{b}$$

Where

- X is an object-feature matrix of shape [batch_size, num_features],
- W is a weight matrix [num_features, num_outputs]
- and b is a vector of num_outputs biases.

Both W and b are initialized during layer creation and updated each time backward is called. Note that a trick to train our model to converge faster [read more](). Instead of initializing our weights with small n initialize our weights with mean zero and variance of 2/(number of inputs + number of outputs)

```
class Dense(Layer):
    def __init__(self, input_units, output_units, learning_rate=0.1):
        """
        A dense layer is a layer which performs a learned affine transformation:
        f(x) = <W*x> + b
        """
        self.learning_rate = learning_rate
        self.weights = np.random.normal(loc=0.0,
                                        scale = np.sqrt(2/(input_units+output_units)),
                                        size = (input_units,output_units))
        self.biases = np.zeros(output_units)

    def forward(self,input):
        """
        Perform an affine transformation:
        f(x) = <W*x> + b

        input shape: [batch, input_units]
        output shape: [batch, output units]
        """
        return np.dot(input,self.weights) + self.biases

    def backward(self,input,grad_output):
        # compute d f / d x = d f / d dense * d dense / d x
        # where d dense/ d x = weights transposed
        grad_input = np.dot(grad_output, self.weights.T)

        # compute gradient w.r.t. weights and biases
        grad_weights = np.dot(input.T, grad_output)
        grad_biases = grad_output.mean(axis=0)*input.shape[0]

        assert grad_weights.shape == self.weights.shape and grad_biases.shape == self.biases.

        # Here we perform a stochastic gradient descent step.
        self.weights = self.weights - self.learning_rate * grad_weights
        self.biases = self.biases - self.learning_rate * grad_biases

        return grad_input
```

The loss function

Since we want to predict probabilities, it would be logical for us to define softmax nonlinearity on top predicted probabilities. However, there is a better way to do so.

If we write down the expression for crossentropy as a function of softmax logits (a), you'll see:

$$loss = -log \frac{e^{a_{correct}}}{\sum_i e^{a_i}}$$

If we take a closer look, we'll see that it can be rewritten as:

$$loss = -a_{correct} + log\sum_i e^{a_i}$$

It's called Log-softmax and it's better than naive log(softmax(a)) in all aspects:

- Better numerical stability
- Easier to get derivative right
- Marginally faster to compute

So why not just use log-softmax throughout our computation and never actually bother to estimate pr

```
def softmax_crossentropy_with_logits(logits,reference_answers):
    """Compute crossentropy from logits[batch,n_classes] and ids of correct answers"""
    logits_for_answers = logits[np.arange(len(logits)),reference_answers]

    xentropy = - logits_for_answers + np.log(np.sum(np.exp(logits),axis=-1))

    return xentropy

def grad_softmax_crossentropy_with_logits(logits,reference_answers):
    """Compute crossentropy gradient from logits[batch,n_classes] and ids of correct answers"
    ones_for_answers = np.zeros_like(logits)
    ones_for_answers[np.arange(len(logits)),reference_answers] = 1

    softmax = np.exp(logits) / np.exp(logits).sum(axis=-1,keepdims=True)

    return (- ones_for_answers + softmax) / logits.shape[0]
```

Full network

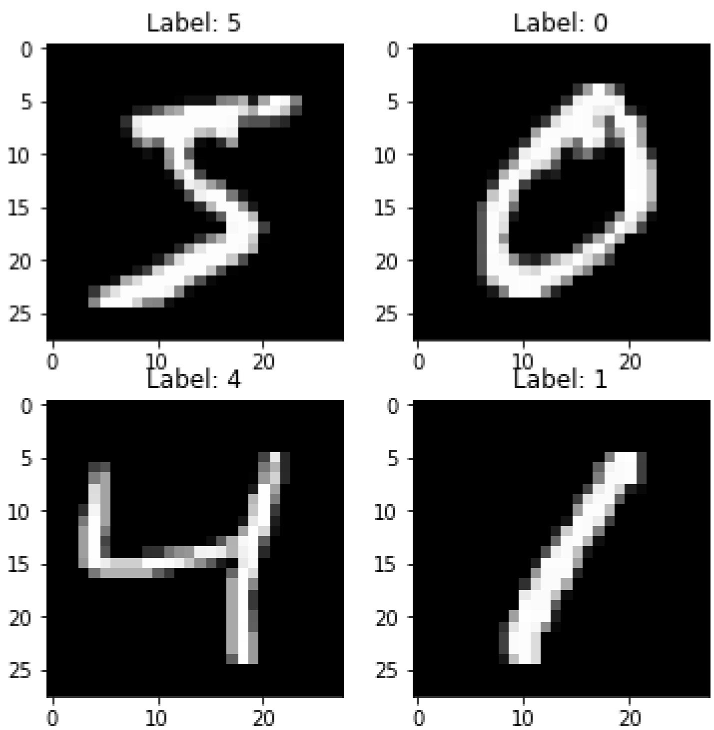
Now let's combine what we've just built into a working neural network. We are going to use MNIST da
Fortunately, Keras already have it in the numpy array format, so let's import it!.

TODO: USE PyTorch CIFAR10 dataset

```
import keras
import matplotlib.pyplot as plt
%matplotlib inline

def load_dataset(flatten=False):
    (X_train, y_train), (X_test, y_test) = keras.datasets.mnist.load_data()

    # normalize x
    X_train = X_train.astype(float) / 255.
    X_test = X_test.astype(float) / 255.

    # we reserve the last 10000 training examples for validation
    X_train, X_val = X_train[:-10000], X_train[-10000:]
    y_train, y_val = y_train[:-10000], y_train[-10000:]
```

```
    y_train, y_val = y_train[:-10000], y_train[-10000:]

    if flatten:
        X_train = X_train.reshape([X_train.shape[0], -1])
        X_val = X_val.reshape([X_val.shape[0], -1])
        X_test = X_test.reshape([X_test.shape[0], -1])

    return X_train, y_train, X_val, y_val, X_test, y_test

X_train, y_train, X_val, y_val, X_test, y_test = load_dataset(flatten=True)

## Let's look at some example
plt.figure(figsize=[6,6])
for i in range(4):
    plt.subplot(2,2,i+1)
    plt.title("Label: %i"%y_train[i])
    plt.imshow(X_train[i].reshape([28,28]),cmap='gray');
```

```
Using TensorFlow backend.
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 0s 0us/step
```



We'll define network as a list of layers, each applied on top of previous one. In this setting, computing

```
network = []
network.append(Dense(X_train.shape[1],100))
network.append(ReLU())
network.append(Dense(100,200))
network.append(ReLU())
network.append(Dense(200,10))
```

```
def forward(network, X):
    """
    Compute activations of all network layers by applying them sequentially.
    Return a list of activations for each layer.
    """
    activations = []
    input = X

    # Looping through each layer
    for l in network:
        activations.append(l.forward(input))
        # Updating input to last layer output
        input = activations[-1]

    assert len(activations) == len(network)
    return activations

def predict(network,X):
    """
    Compute network predictions. Returning indices of largest Logit probability
    """
    logits = forward(network,X)[-1]
    return logits.argmax(axis=-1)

def train(network,X,y):
    """
    Train our network on a given batch of X and y.
    We first need to run forward to get all layer activations.
    Then we can run layer.backward going from last to first layer.
    After we have called backward for all layers, all Dense layers have already made one grad
    """

    # Get the layer activations
    layer_activations = forward(network,X)
    layer_inputs = [X]+layer_activations  #layer_input[i] is an input for network[i]
    logits = layer_activations[-1]

    # Compute the loss and the initial gradient
    loss = softmax_crossentropy_with_logits(logits,y)
    loss_grad = grad_softmax_crossentropy_with_logits(logits,y)

    # Propagate gradients through the network
    # Reverse propogation as this is backprop
    for layer_index in range(len(network))[::-1]:
        layer = network[layer_index]

        loss_grad = layer.backward(layer_inputs[layer_index],loss_grad) #grad w.r.t. input, a

    return np.mean(loss)
```

Training loop

We split data into minibatches, feed each such minibatch into the network and update weights. This t stochastic gradient descent.

```
from tqdm import trange
def iterate_minibatches(inputs, targets, batchsize, shuffle=False):
    assert len(inputs) == len(targets)
    if shuffle:
        indices = np.random.permutation(len(inputs))
    for start_idx in trange(0, len(inputs) - batchsize + 1, batchsize):
        if shuffle:
            excerpt = indices[start_idx:start_idx + batchsize]
        else:
            excerpt = slice(start_idx, start_idx + batchsize)
        yield inputs[excerpt], targets[excerpt]
```

```
from IPython.display import clear_output
train_log = []
val_log = []


for epoch in range(25):

    for x_batch,y_batch in iterate_minibatches(X_train,y_train,batchsize=32,shuffle=True):
        train(network,x_batch,y_batch)

    train_log.append(np.mean(predict(network,X_train)==y_train))
    val_log.append(np.mean(predict(network,X_val)==y_val))

    clear_output()
    print("Epoch",epoch)
    print("Train accuracy:",train_log[-1])
    print("Val accuracy:",val_log[-1])
    plt.plot(train_log,label='train accuracy')
    plt.plot(val_log,label='val accuracy')
    plt.legend(loc='best')
    plt.grid()
    plt.show()
```

```
Epoch 24
Train accuracy: 1.0
Val accuracy: 0.9809
```