03_Deep_Learning_Development_with_PyTorch

October 7, 2023

1 Chapter 3 - Deep Learning Development with PyTorch

[ ]:
```
import torch
import torchvision
```

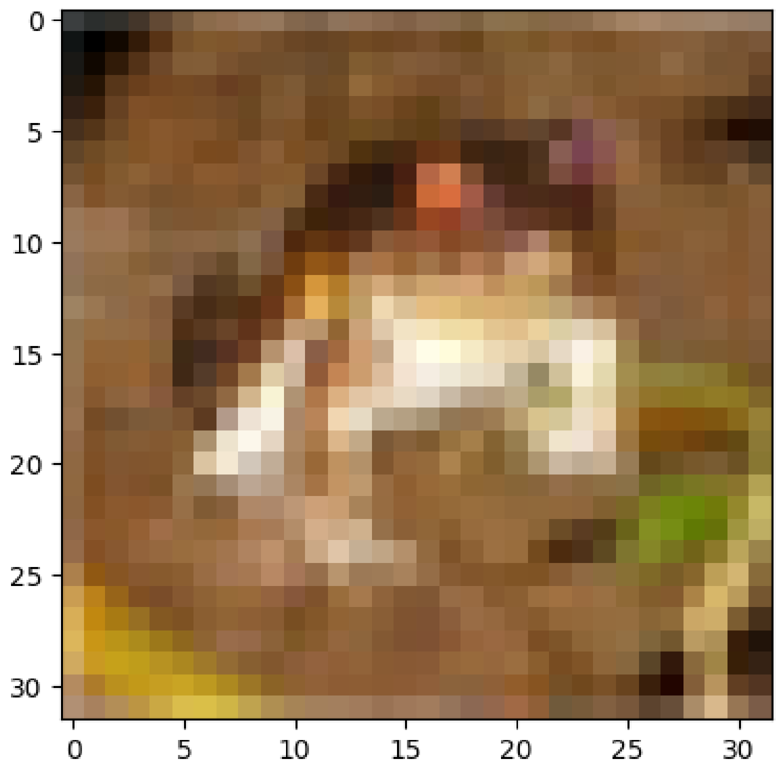
1.1 Data Loading

[ ]:
```
from torchvision.datasets import CIFAR10

train_data = CIFAR10(root="./train/",
                     train=True,
                     download=True)
```

```
Files already downloaded and verified
```

[ ]:
```
# Accessing the Data
import matplotlib.pyplot as plt
plt.imshow(train_data[0][0])

#Accessing the label
print(train_data[0][1])
```

```
6
```



```
[ ]: test_data = CIFAR10(root="./test/",
                         train=False,
                         download=True)


     print(len(test_data))

     print(test_data.data.shape)
```

```
Files already downloaded and verified
10000
(10000, 32, 32, 3)
```

1.2 Data Transforms

```
[ ]: from torchvision import transforms

     train_transforms = 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))])

train_data_transforms = CIFAR10(root="./train/",
                    train=True,
                    download=True,
                    transform=train_transforms)
```

```
Files already downloaded and verified
```

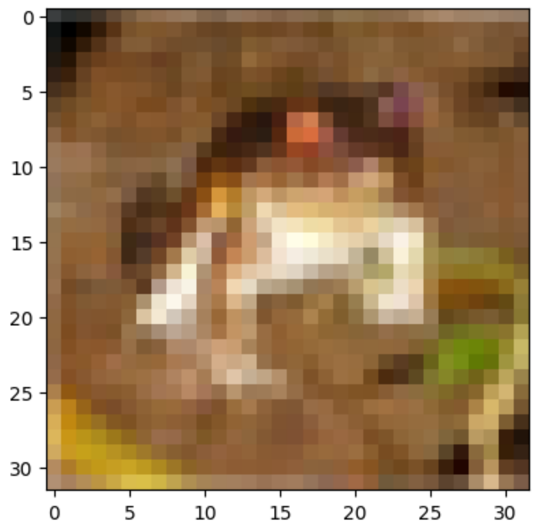
[ ]:
```
data,label = train_data[0]
print(type(data))
print(data)



data_transforms,label_transforms = train_data_transforms[0]
print(type(data_transforms))
print(data_transforms.size())
print(data_transforms)


fig = plt.figure(figsize=(10,5))
fig.add_subplot(1,2,1)
plt.imshow(data)
fig.add_subplot(1,2,2)
plt.imshow(data_transforms.permute(1, 2, 0))
```

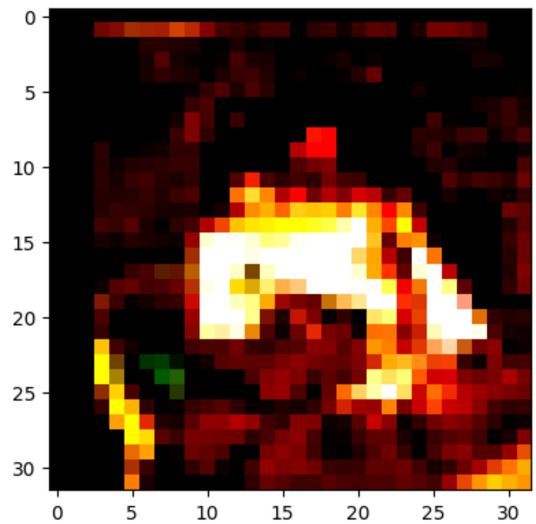
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```

```
<class 'PIL.Image.Image'>
<PIL.Image.Image image mode=RGB size=32x32 at 0x14F3FDD23B0>
<class 'torch.Tensor'>
torch.Size([3, 32, 32])
tensor([[[-2.4291, -2.4291, -2.4291,  …, -2.4291, -2.4291, -2.4291],
         [-2.4291, -2.4291, -2.4291,  …, -0.1223, -0.5293, -1.1109],
         [-2.4291, -2.4291, -2.4291,  …, -0.1029, -0.7232, -1.4404],
         …,
         [-2.4291, -2.4291, -2.4291,  …,  0.3236,  0.5950,  0.9051],
         [-2.4291, -2.4291, -2.4291,  …,  0.8858,  1.1184,  1.2735],
         [-2.4291, -2.4291, -2.4291,  …,  1.4673,  1.4091,  1.3316]],

        [[-2.4183, -2.4183, -2.4183,  …, -2.4183, -2.4183, -2.4183],
         [-2.4183, -2.4183, -2.4183,  …, -0.6286, -0.9826, -1.3562],
         [-2.4183, -2.4183, -2.4183,  …, -0.8056, -1.4152, -1.8873],
         …,
         [-2.4183, -2.4183, -2.4183,  …, -0.3926, -0.0582,  0.3154],
         [-2.4183, -2.4183, -2.4183,  …,  0.2368,  0.4531,  0.6694],
```

```
         [-2.4183, -2.4183, -2.4183,  …,  0.8071,  0.6891,  0.5908]],

        [[-2.2214, -2.2214, -2.2214,  …, -2.2214, -2.2214, -2.2214],
         [-2.2214, -2.2214, -2.2214,  …, -0.9922, -1.2069, -1.4020],
         [-2.2214, -2.2214, -2.2214,  …, -1.3825, -1.8117, -2.0653],
         …,
         [-2.2214, -2.2214, -2.2214,  …, -1.6361, -1.7141, -1.6751],
         [-2.2214, -2.2214, -2.2214,  …, -1.5971, -1.5580, -1.6946],
         [-2.2214, -2.2214, -2.2214,  …, -1.5190, -1.5580, -1.7336]]])
```

[ ]: <matplotlib.image.AxesImage at 0x14f3fdd36a0>





[ ]:
```python
test_transforms = transforms.Compose([
  transforms.ToTensor(),
  transforms.Normalize(
      (0.4914, 0.4822, 0.4465),
      (0.2023, 0.1994, 0.2010))])

test_data_transforms = torchvision.datasets.CIFAR10(
      root="./test/",
      train=False,
      transform=test_transforms)

print(test_data)
```

```
Dataset CIFAR10
    Number of datapoints: 10000
    Root location: ./test/
    Split: Test
```

1.3 Data Batching

[ ]:
```
trainloader = torch.utils.data.DataLoader(
                    train_data_transforms,
                    batch_size=16,
                    shuffle=True)
```

[ ]:
```
data_batch, labels_batch = next(iter(trainloader))
print(data_batch.size())

print(labels_batch.size())
```

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

[ ]:
```
testloader = torch.utils.data.DataLoader(
                    test_data_transforms,
                    batch_size=16,
                    shuffle=False)
```

1.4 Model Design

1.4.1 Using Existing & Pre-trained models

[ ]:
```
from torchvision import models

vgg16 = models.vgg16(pretrained=True)
```

```
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-
packages\torchvision\models\_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-
packages\torchvision\models\_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=VGG16_Weights.IMAGENET1K_V1`. You can also use
`weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

[ ]:
```
print(vgg16.features)

print(vgg16.avgpool)

print(vgg16.classifier)
```

```
Sequential(
  (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (1): ReLU(inplace=True)
```

```
  (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (3): ReLU(inplace=True)
  (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (6): ReLU(inplace=True)
  (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (8): ReLU(inplace=True)
  (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (11): ReLU(inplace=True)
  (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (13): ReLU(inplace=True)
  (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (15): ReLU(inplace=True)
  (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (18): ReLU(inplace=True)
  (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (20): ReLU(inplace=True)
  (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (22): ReLU(inplace=True)
  (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (25): ReLU(inplace=True)
  (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (27): ReLU(inplace=True)
  (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (29): ReLU(inplace=True)
  (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
)
AdaptiveAvgPool2d(output_size=(7, 7))
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```

[ ]:
```python
import torch.nn as nn
vgg16.classifier[-1] = nn.Linear(4096,10)

print(vgg16.classifier)

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

vgg_model = vgg16.to(device = device)
```

```
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=10, bias=True)
)
```

1.5 The PyTorch NN Module (torch.nn)

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

class SimpleNet(nn.Module):

    def __init__(self):
        super(SimpleNet, self).__init__()
        self.fc1 = nn.Linear(2048, 256)
        self.fc2 = nn.Linear(256, 64)
        self.fc3 = nn.Linear(64,2)

    def forward(self, x):
        x = x.view(-1, 2048)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.softmax(self.fc3(x),dim=1)
        return x
```

[ ]:
```python
simplenet = SimpleNet()
print(simplenet)

input = torch.rand(2048)
output = simplenet(input)
```

```
SimpleNet(
  (fc1): Linear(in_features=2048, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=64, bias=True)
```

```
  (fc3): Linear(in_features=64, out_features=2, bias=True)
)
```

1.6 Training

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

     class LeNet5(nn.Module):
         def __init__(self):
             super(LeNet5, self).__init__()
             self.conv1 = nn.Conv2d(3, 6, 5) # <1>
             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 = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
             x = F.max_pool2d(F.relu(self.conv2(x)), 2)
             x = x.view(-1, int(x.nelement() / x.shape[0]))
             x = F.relu(self.fc1(x))
             x = F.relu(self.fc2(x))
             x = self.fc3(x)
             return x

     device = "cuda" if torch.cuda.is_available() else "cpu"
     LeNet_model = LeNet5().to(device=device)
```

1.6.1 Fundamental Training Loop

Code Annotations:

<1> Our training loop

<2> Need to move inputs and labels to GPU is avail.

<3> Zero out gradients before each backprop or they'll accumulate

<4> Forward pass

<5> Compute loss

<6> Backpropagation, compute gradients

<7> Adjust parameters based on gradients

<8> accumulate batch loss so we can average over epoch

```
[ ]: from torch import optim
     from torch import nn
```

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(vgg_model.parameters(), # <1>
                      lr=0.001,
                      momentum=0.9)
```

[ ]:
```
N_EPOCHS = 10
for epoch in range(N_EPOCHS): # <1>

    epoch_loss = 0.0
    for inputs, labels in trainloader:
        inputs = inputs.to(device) # <2>
        labels = labels.to(device)

        optimizer.zero_grad() # <3>

        outputs = vgg_model(inputs) # <4>
        loss = criterion(outputs, labels) # <5>
        loss.backward() # <6>
        optimizer.step() # <7>

        epoch_loss += loss.item() # <8>
    print("Epoch: {} Loss: {}".format(epoch,
                  epoch_loss/len(trainloader)))
```

```
Epoch: 0 Loss: 0.8118732511878014
Epoch: 1 Loss: 0.5086276560378075
Epoch: 2 Loss: 0.4192588477998972
Epoch: 3 Loss: 0.36131201485037806
Epoch: 4 Loss: 0.3123959180480242
Epoch: 5 Loss: 0.2794492025240511
Epoch: 6 Loss: 0.25302029708057644
Epoch: 7 Loss: 0.23161081992231308
Epoch: 8 Loss: 0.20988165496785194
Epoch: 9 Loss: 0.19169600319910796
```

[ ]:
```
num_correct = 0.0

for x_test_batch, y_test_batch in testloader:

    vgg_model.eval()

    y_test_batch = y_test_batch.to(device)

    x_test_batch = x_test_batch.to(device)

    y_pred_batch = vgg_model(x_test_batch)

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

```
    num_correct += (predicted == y_test_batch).float().sum()



accuracy = num_correct/(len(testloader)*testloader.batch_size)



print(len(testloader), testloader.batch_size)

print("Test Accuracy: {}".format(accuracy))
```

```
625 16
Test Accuracy: 0.899899959564209
```

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

class LeNet5(nn.Module):
    def __init__(self):
        super(LeNet5, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5) # <1>
        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 = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, int(x.nelement() / x.shape[0]))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

device = "cuda" if torch.cuda.is_available() else "cpu"
LeNet_model = LeNet5().to(device=device)
```

[ ]:
```
from torch import optim
from torch import nn

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(LeNet_model.parameters(), # <1>
                      lr=0.001,
                      momentum=0.9)
```

[ ]:

```
N_EPOCHS = 10
for epoch in range(N_EPOCHS): # <1>

    epoch_loss = 0.0
    for inputs, labels in trainloader:
        inputs = inputs.to(device) # <2>
        labels = labels.to(device)

        optimizer.zero_grad() # <3>

        outputs = LeNet_model(inputs) # <4>
        loss = criterion(outputs, labels) # <5>
        loss.backward() # <6>
        optimizer.step() # <7>

        epoch_loss += loss.item() # <8>
    print("Epoch: {} Loss: {}".format(epoch,
                    epoch_loss/len(trainloader)))
```

```
Epoch: 0 Loss: 1.910171902961731
Epoch: 1 Loss: 1.5982797781372071
Epoch: 2 Loss: 1.4726939439201354
Epoch: 3 Loss: 1.3984185062599181
Epoch: 4 Loss: 1.335036766834259
Epoch: 5 Loss: 1.2921974471855164
Epoch: 6 Loss: 1.2550513487911223
Epoch: 7 Loss: 1.2278237766170501
Epoch: 8 Loss: 1.206542158164978
Epoch: 9 Loss: 1.188108439283371
```

[ ]:

```
num_correct = 0.0

for x_test_batch, y_test_batch in testloader:

    LeNet_model.eval()

    y_test_batch = y_test_batch.to(device)

    x_test_batch = x_test_batch.to(device)

    y_pred_batch = LeNet_model(x_test_batch)

    _, predicted = torch.max(y_pred_batch, 1)

    num_correct += (predicted == y_test_batch).float().sum()
```

```
accuracy = num_correct/(len(testloader)*testloader.batch_size)



print(len(testloader), testloader.batch_size)

print("Test Accuracy: {}".format(accuracy))
```

```
625 16
Test Accuracy: 0.616100013256073
```

[ ]:
```
print(LeNet_model)
print(vgg_model)
```

```
LeNet5(
  (conv1): Conv2d(3, 6, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=400, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=10, bias=True)
  )
)
```