Quickstart

February 19, 2025

1 Quickstart Guide to Pytorch

This section runs through the API for common tasks in machine learning.
Generally this section is for someone who is familir with other deep learning frameworks.

1.1 Working with Data

PyTorch has two primitives to work with data: `torch.utils.data.DataLoader` and `torch.utils.data.Dataset`. Dataset stores the samples and their corresponding labels, and DataLoader wraps an iterable around the Dataset.

[1]:
```
import torch
from torch import nn
from torch.utils.data import DataLoader
from torchvision import datasets
from torchvision.transforms import ToTensor
```

PyTorch offers domain-specific libraries such as TorchText, TorchVision, and TorchAudio, all of which include datasets. For this tutorial, we will be using a TorchVision dataset.

The `torchvision.datasets` module contains `Dataset` objects for many real-world vision data like CIFAR, COCO. In this tutorial, we use the FashionMNIST dataset. Every TorchVision `Dataset` includes two arguments: `transform` and `target_transform` to modify the samples and labels respectively.

[2]:
```
# Download training data from open datasets.
training_data = datasets.FashionMNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor(),
)

# Download test data from open datasets.
test_data = datasets.FashionMNIST(
    root="data",
    train=False,
    download=True,
    transform=ToTensor(),
```

```
)
```

We pass the Dataset as an argument to DataLoader. This wraps an iterable over our dataset, and supports automatic batching, sampling, shuffling and multiprocess data loading. Here we define a batch size of 64, i.e. each element in the dataloader iterable will return a batch of 64 features and labels.

[3]:
```
batch_size = 64

# Create data loaders.
train_dataloader = DataLoader(training_data, batch_size=batch_size)
test_dataloader = DataLoader(test_data, batch_size=batch_size)

for X, y in test_dataloader:
    print(f"Shape of X [N, C, H, W]: {X.shape}")
    print(f"Shape of y: {y.shape} {y.dtype}")

    # Time to introspect further
    print(f"dtype of X: {X.dtype}") # Tells us the type of data in the input␣
↪data
    print(f"The min and max values in X respectively: {X.min()}, {X.max()}")
    break
```

```
Shape of X [N, C, H, W]: torch.Size([64, 1, 28, 28])
Shape of y: torch.Size([64]) torch.int64
dtype of X: torch.float32
The min and max values in X respectively: 0.0, 1.0
```

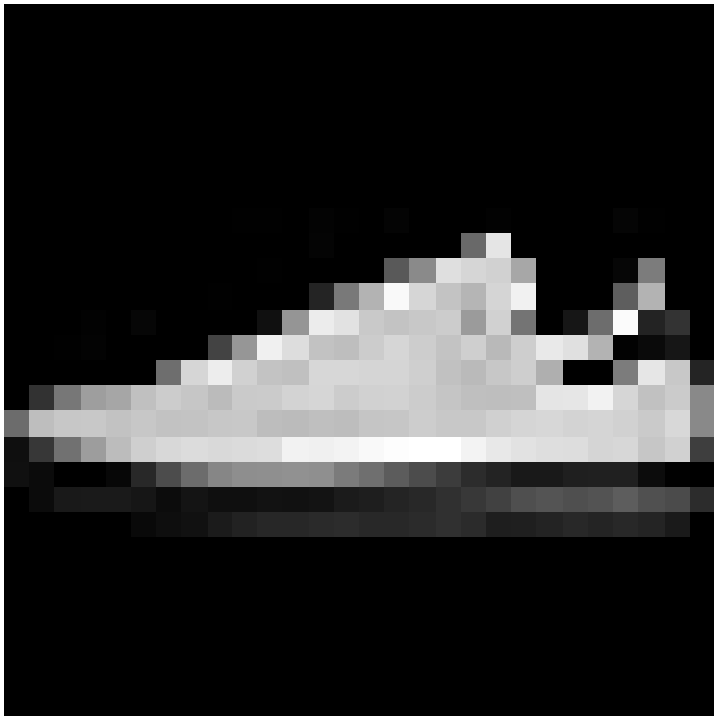
Furthermore I felt like extracting and looking at a single image so here is what I did

[4]:
```
import matplotlib.pyplot as plt
# import numpy as np

single_image, single_label = training_data[6]
single_image = single_image.squeeze().numpy() # Remove the batch dimension and␣
↪convert to NumPy
# single_image = (single_image * 255).astype(np.uint8)  # Scale to [0, 255] and␣
↪convert to uint8

plt.imshow(single_image, cmap='gray')
plt.title(f"Label: {single_label}")
plt.axis('off')  # Hide the axes
plt.show()
# plt.imsave('example.jpg', single_image, cmap='gray')
```

Label: 7



We can also inspect multiple images, for example create a grid of a batch in the input data

[5]:
```
import torchvision.utils as vutils

# Create a grid of images
grid = vutils.make_grid(X, nrow=8, normalize=True, scale_each=True)

# Convert the grid to a NumPy array and permute dimensions
grid = grid.permute(1, 2, 0).numpy()

# Display the grid
plt.imshow(grid)
plt.axis('off')
plt.show()
```

1.2 Creating Models

To define a neural network in PyTorch, we create a class that inherits from nn.Module. We define the layers of the network in the `__init__` function and specify how data will pass through the network in the `forward` function. To accelerate operations in the neural network, we move it to the accelerator such as CUDA, MPS, MTIA, or XPU. If the current accelerator is available, we will use it. Otherwise, we use the CPU.

EDIT: The above information regarding accelerators seems outdated as `torch.accelerator` only supports CUDA, MTIA, XPU.
For mac systems we will instead directly check MPS availability or use cpu instead.

[6]:
```python
# For CUDA, MTIA, or XPU
# device = torch.accelerator.current_accelerator().type if torch.accelerator.
↪is_available() else torch.device("cpu")
# print(f"Using {device} device")

# For MPS (Mac systems)
device = torch.device("mps") if torch.backends.mps.is_available() else torch.
↪device("cpu")
print(f"Using {device} device")
```

```
Using mps device
```

[7]:
```
# Define model
class NeuralNetwork(nn.Module):
    def __init__(self):
        super().__init__()
        self.flatten = nn.Flatten()
        self.linear_relu_stack = nn.Sequential(
            nn.Linear(28*28, 512),
            nn.ReLU(),
            nn.Linear(512, 512),
            nn.ReLU(),
            nn.Linear(512, 10)
        )

    def forward(self, x):
        x = self.flatten(x)
        logits = self.linear_relu_stack(x)
        return logits

model = NeuralNetwork().to(device)
print(model)
print(f"Model is on device: {next(model.parameters()).device}")  # Should print␣
↪'mps'
```

```
NeuralNetwork(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=784, out_features=512, bias=True)
    (1): ReLU()
    (2): Linear(in_features=512, out_features=512, bias=True)
    (3): ReLU()
    (4): Linear(in_features=512, out_features=10, bias=True)
  )
)
Model is on device: mps:0
```

1.3 Optimising the Model Parameters

To train a model, we need a loss function and and optimiser.

[8]:
```
loss_fn = nn.CrossEntropyLoss().to(device)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)
```

In a single training loop, the model makes predictions on the training dataset (fed to it in batches), and backpropagates the prediction error to adjust the model's parameters.

[9]:
```
def train(dataloader, model, loss_fn, optimizer):
    size = len(dataloader.dataset)
    model.train()
```

```
    for batch, (X, y) in enumerate(dataloader):
        X, y = X.to(device), y.to(device)

        # Compute prediction error
        pred = model(X)
        loss = loss_fn(pred, y)

        # Backpropagation
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()

        if batch % 100 == 0:
            loss, current = loss.item(), (batch + 1) * len(X)
            print(f"loss: {loss:>7f}  [{current:>5d}/{size:>5d}]")
```

We also check the model's performance against the test dataset to ensure it is learning.

[10]:
```
def test(dataloader, model, loss_fn):
    size = len(dataloader.dataset)
    num_batches = len(dataloader)
    model.eval()
    test_loss, correct = 0, 0
    with torch.no_grad():
        for X, y in dataloader:
            X, y = X.to(device), y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()
    test_loss /= num_batches
    correct /= size
    print(f"Test Error: \n Accuracy: {(100*correct):>0.1f}%, Avg loss:␣
↪{test_loss:>8f} \n")
```

The training process is conducted over several iterations (epochs). During each epoch, the model learns parameters to make better predictions. We print the model's accuracy and loss at each epoch; we'd like to see the accuracy increase and the loss decrease with every epoch.

[11]:
```
epochs = 5
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(train_dataloader, model, loss_fn, optimizer)
    test(test_dataloader, model, loss_fn)
print("Done!")
```

```
Epoch 1
-------------------------------
loss: 2.311492  [   64/60000]
loss: 2.293662  [ 6464/60000]
```

```
loss: 2.278553  [12864/60000]
loss: 2.269704  [19264/60000]
loss: 2.252427  [25664/60000]
loss: 2.227463  [32064/60000]
loss: 2.240565  [38464/60000]
loss: 2.201384  [44864/60000]
loss: 2.198047  [51264/60000]
loss: 2.173079  [57664/60000]
Test Error:
 Accuracy: 50.9%, Avg loss: 2.166078

Epoch 2
-------------------------------
loss: 2.174698  [   64/60000]
loss: 2.158323  [ 6464/60000]
loss: 2.109015  [12864/60000]
loss: 2.128747  [19264/60000]
loss: 2.073018  [25664/60000]
loss: 2.021720  [32064/60000]
loss: 2.061239  [38464/60000]
loss: 1.972798  [44864/60000]
loss: 1.973918  [51264/60000]
loss: 1.918002  [57664/60000]
Test Error:
 Accuracy: 54.5%, Avg loss: 1.907859

Epoch 3
-------------------------------
loss: 1.933078  [   64/60000]
loss: 1.898628  [ 6464/60000]
loss: 1.790941  [12864/60000]
loss: 1.838273  [19264/60000]
loss: 1.721255  [25664/60000]
loss: 1.676981  [32064/60000]
loss: 1.718241  [38464/60000]
loss: 1.602537  [44864/60000]
loss: 1.621176  [51264/60000]
loss: 1.528310  [57664/60000]
Test Error:
 Accuracy: 61.1%, Avg loss: 1.536844

Epoch 4
-------------------------------
loss: 1.598383  [   64/60000]
loss: 1.557854  [ 6464/60000]
loss: 1.412430  [12864/60000]
loss: 1.488797  [19264/60000]
loss: 1.359946  [25664/60000]
```

```
loss: 1.362863  [32064/60000]
loss: 1.395155  [38464/60000]
loss: 1.304919  [44864/60000]
loss: 1.333764  [51264/60000]
loss: 1.241617  [57664/60000]
Test Error:
 Accuracy: 63.5%, Avg loss: 1.262457

Epoch 5
-------------------------------
loss: 1.338601  [   64/60000]
loss: 1.313664  [ 6464/60000]
loss: 1.152314  [12864/60000]
loss: 1.257326  [19264/60000]
loss: 1.126186  [25664/60000]
loss: 1.161881  [32064/60000]
loss: 1.198766  [38464/60000]
loss: 1.122901  [44864/60000]
loss: 1.157875  [51264/60000]
loss: 1.077889  [57664/60000]
Test Error:
 Accuracy: 64.8%, Avg loss: 1.094102

Done!
```

More info on training your model.

1.4 Saving Models

A common way to save a model is to serialize the internal state dictionary (containing the model parameters).

[12]:
```
torch.save(model.state_dict(), "model.pth")
print("Saved PyTorch Model State to model.pth")
```

```
Saved PyTorch Model State to model.pth
```

1.5 Loading Models

The process for loading a model includes re-creating the model structure and loading the state dictionary into it.

[13]:
```
model = NeuralNetwork().to(device)
model.load_state_dict(torch.load("model.pth", weights_only=True))
```

[13]:
```
<All keys matched successfully>
```

This model can now be used to make predictions.

[14]:

```
classes = [
    "T-shirt/top",
    "Trouser",
    "Pullover",
    "Dress",
    "Coat",
    "Sandal",
    "Shirt",
    "Sneaker",
    "Bag",
    "Ankle boot",
]

model.eval()
x, y = test_data[0][0], test_data[0][1]
with torch.no_grad():
    x = x.to(device)
    pred = model(x)
    predicted, actual = classes[pred[0].argmax(0)], classes[y]
    print(f'Predicted: "{predicted}", Actual: "{actual}"')
```

```
Predicted: "Ankle boot", Actual: "Ankle boot"
```

More info on saving and loading your model.