MACHINE LEARNING FRAMEWORK

The basics of PyTorch

Easy to learn, use, extend, and debug

Advantages

Tensorflow vs PyTorch

01 Easier to learn than Tensorflow

02 No more "add, compile, build". PyTorch's graph construction is dynamic

03 PyTorch also integrates with TensorBoard (visualization tool)

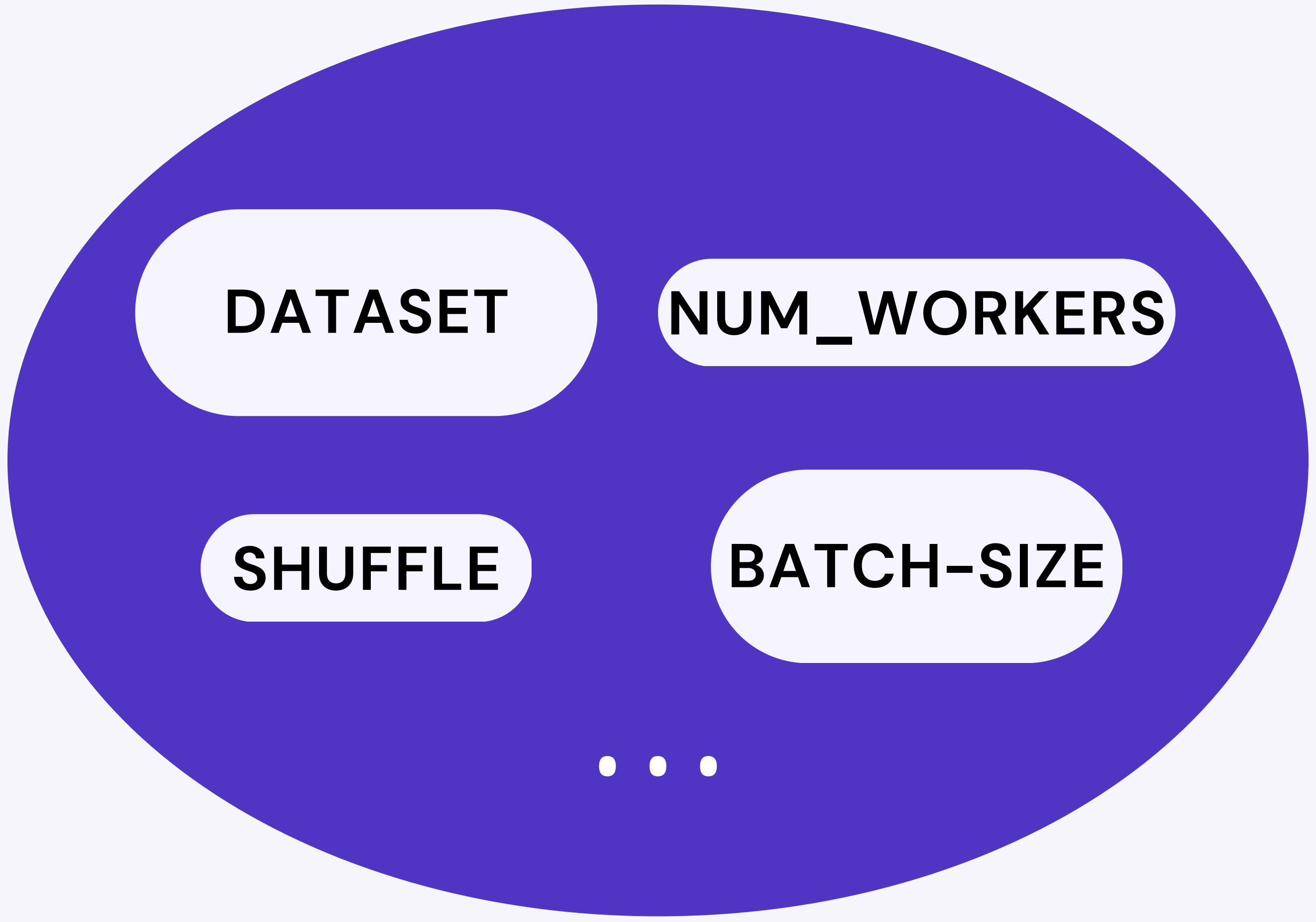
Quickstart

- Working with data
- Creating models
- Optimizing the Model Parameters
- Training steps
- Testing steps
- Saving and Loading a model

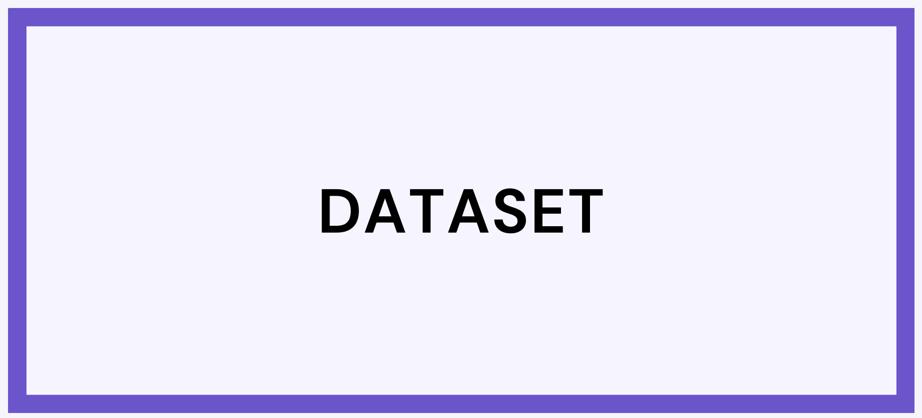
Working with data

- torch.utils.data.Dataloader
- torch.utils.data.Dataset

torch.utils.data.Dataloader



torch.utils.data.Dataset

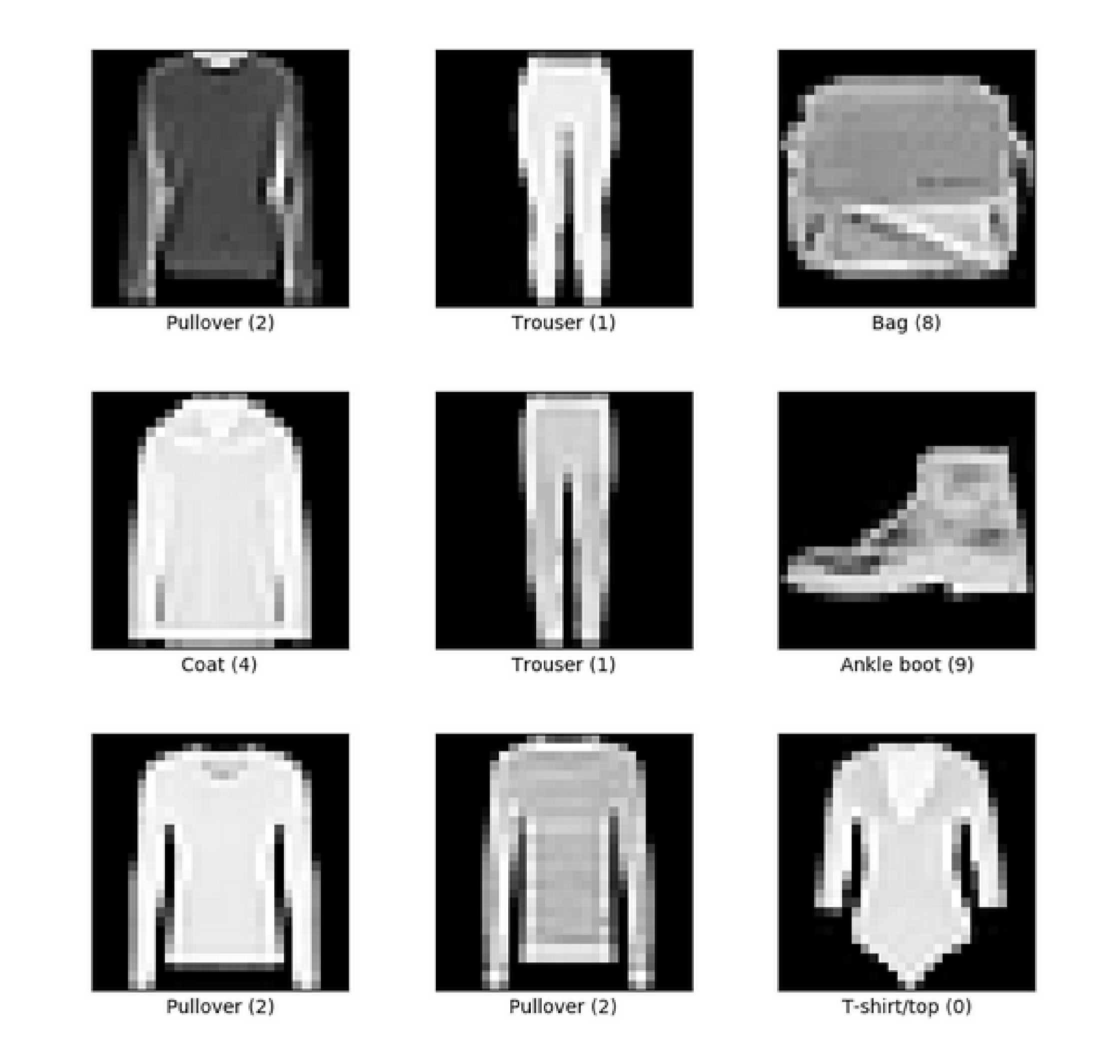


Working with data

Libraries **TorchText, TorchVision, TorchAudio** include datasets like COCO, FashionMNIST, ImageNet...

```
from torchvision import datasets
from torchvision.transforms import ToTensor
```

```
training_data = datasets.FashionMNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor(),
)
```



Working with data

Libraries **TorchText, TorchVision, TorchAudio** include datasets like COCO, FashionMNIST, ImageNet...

```
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}")
    break
```

out

```
Shape of X [N, C, H, W]: torch.Size([64, 1, 28, 28])
Shape of y: torch.Size([64]) torch.int64
```

Creating Models

1. **We create a class that inherits from nn.Module**
2. **We define the layers of the network in the __init__ function**
3. **We specify how data will pass through the network in the forward function**
4. To accelerate operations in the neural network, we move it to the GPU if available.

Creating Models

1. We create a class that inherits from nn.Module
2. We define the layers of the network in the __init__ function

```
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__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)
        )
```

Creating Models

3. We specify how data will pass through the network in the forward function

4. To accelerate operations in the neural network, we move it to the GPU if available.

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

```
device = "cuda" if torch.cuda.is_available() else "cpu"
model = NeuralNetwork().to(device)
```

Creating Models

```python
# Get cpu or gpu device for training.
device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Using {device} device")

# Define model
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__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)
```

Optimizing the Model Parameters

- Loss ??
- Optimizer ??

```
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)
```

Training steps

```
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
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

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

Make a simple prediction

Compute the error

Make the right adjustments

Testing steps

```
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")
```

Calculate the loss and correct %

Saving and Loading a model

- **Your own model**

```
model = torch.load('model.pth')

torch.save(model, 'model.pth')
```

- **A predefined architecture**

With the predefined pretrained model

```
model = models.vgg16(pretrained=True)
torch.save(model.state_dict(), 'model_weights.pth')
```

With another pretrained model

```
model = models.vgg16() # we do not specify pretrained=True, i.e. do not load default weights
model.load_state_dict(torch.load('model_weights.pth'))
```

Dive Deeper

- Tensors
- Autograd
- nn Module
- Optim

Tensors

- **What is it ?**

a Tensor is an n-dimensional array, and PyTorch provides many functions for operating on these Tensors.

- **Why ?**

Numpy is a great framework, but it cannot utilize GPUs to accelerate its numerical computations, but A PyTorch Tensor CAN!

- **How?**

```
import torch
dtype = torch.float
device = torch.device("cpu")
```

```
a = torch.randn((), device=device, dtype=dtype)
p = torch.tensor([1, 2, 3])
```

Autograd

When using autograd, the forward pass of your network will define a computational graph; nodes in the graph will be Tensors, and edges will be functions that produce output Tensors from input Tensors. Backpropagating through this graph then allows you to easily compute gradients.

Autograd

```python
learning_rate = 1e-6
for t in range(2000):
    # Forward pass: compute predicted y
    y_pred = a + b * x + c * x ** 2 + d * x ** 3

    # Compute and print loss
    loss = (y_pred - y).pow(2).sum().item()
    if t % 100 == 99:
        print(t, loss)

    # Backprop to compute gradients of a, b, c, d with respect to loss
    grad_y_pred = 2.0 * (y_pred - y)
    grad_a = grad_y_pred.sum()
    grad_b = (grad_y_pred * x).sum()
    grad_c = (grad_y_pred * x ** 2).sum()
    grad_d = (grad_y_pred * x ** 3).sum()

    # Update weights using gradient descent
    a -= learning_rate * grad_a
    b -= learning_rate * grad_b
    c -= learning_rate * grad_c
    d -= learning_rate * grad_d
```

Without Autograd

```python
learning_rate = 1e-6
for t in range(2000):
    # Forward pass: compute predicted y using operations on Tensors.
    y_pred = a + b * x + c * x ** 2 + d * x ** 3

    # Compute and print loss using operations on Tensors.
    # Now loss is a Tensor of shape (1,)
    # loss.item() gets the scalar value held in the loss.
    loss = (y_pred - y).pow(2).sum()
    if t % 100 == 99:
        print(t, loss.item())

    # Use autograd to compute the backward pass. This call will compute the
    # gradient of loss with respect to all Tensors with requires_grad=True.
    # After this call a.grad, b.grad. c.grad and d.grad will be Tensors holding
    # the gradient of the loss with respect to a, b, c, d respectively.
    loss.backward()

    # Manually update weights using gradient descent. Wrap in torch.no_grad()
    # because weights have requires_grad=True, but we don't need to track this
    # in autograd.
    with torch.no_grad():
        a -= learning_rate * a.grad
        b -= learning_rate * b.grad
        c -= learning_rate * c.grad
        d -= learning_rate * d.grad

        # Manually zero the gradients after updating weights
        a.grad = None
        b.grad = None
        c.grad = None
        d.grad = None
```

With Autograd

nn Module

- **What is it ?**

The nn package defines a set of Modules, which are roughly equivalent to neural network layers.

- **Why ?**

For large neural networks raw autograd can be a bit too low-level.

- **How?**

```
model = torch.nn.Sequential(
    torch.nn.Linear(3, 1),
    torch.nn.Flatten(0, 1)
)

# The nn package also contains definitions of popular loss functions; in this
# case we will use Mean Squared Error (MSE) as our loss function.
loss_fn = torch.nn.MSELoss(reduction='sum')
```

Optim

- **What is it ?**

Provides implementations of commonly used optimization algorithms.

- **How?**

```
learning_rate = 1e-3
optimizer = torch.optim.RMSprop(model.parameters(), lr=learning_rate)
```

```
optimizer = torch.optim.SGD(model.parameters(), lr=1e-6)
```

Conclusion

```python
# Get cpu or gpu device for training.
device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Using {device} device")

# Define model
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__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)
```

Conclusion

```
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
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

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

Conclusion

```
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")
```

Thank You