Module 2 - Session 1: Data and Model Building

Module 2 Overview

What will we learn?

- Data Pipeline → handle large datasets
- Beyond Sequential → custom architectures
- Optimizers
- Device Management
- Building an image classifier

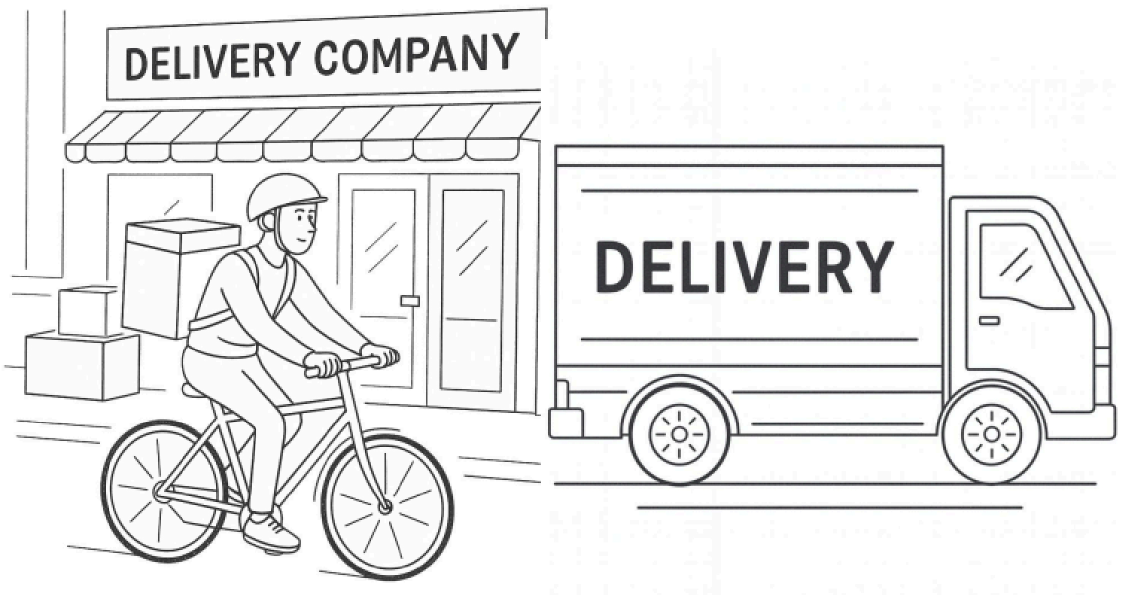
Session 1: Data and Model Building

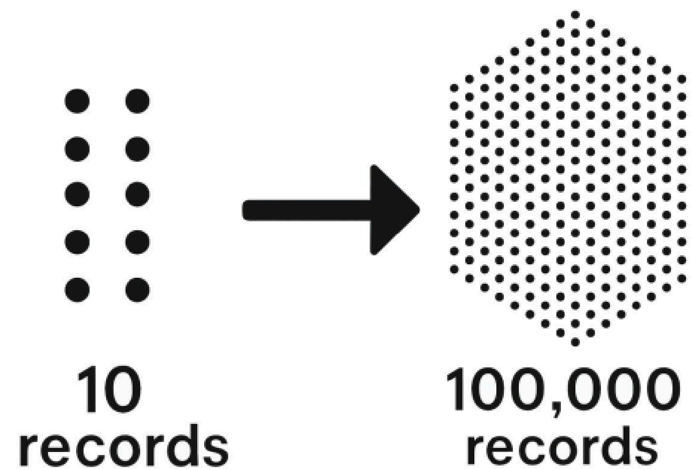
- Revisit the ML pipeline with a focus on PyTorch’s data handling tools
- Learn about data management at scale
- Explore building custom model architectures beyond the Sequential API

The Challenge: Large Datasets

100,000 delivery records

Problem: Loading all at once → runs out of memory





Solution: Work with data in batches

PyTorch Data Utilities

Three core tools:

1. **Transforms** - operations on each data point
2. **Dataset** - fetches samples from disk on demand
3. **DataLoader** - serves data in batches

1. Transforms

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

ToTensor: converts to tensors, scales 0-255 → 0-1

Normalize: centers around 0, scales using standard deviation

2. Dataset

```
dataset = MNIST(root='./data', train=True,
                download=True, transform=transform)
```

Key features:

- Fetches samples from disk when asked
- Doesn’t preload everything
- Handles where data lives, how to load samples, total count

3. DataLoader

```
dataloader = DataLoader(dataset, batch_size=64, shuffle=True)
```

Batch size: how many samples per batch

Shuffle: randomize order each epoch

Makes training on large datasets possible

Complete Data Pipeline

```python
# 1. Define transforms
transform = transforms.Compose([...])

# 2. Create dataset
train_dataset = MNIST(..., transform=transform)

# 3. Create dataloader
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)

# 4. Use in training loop
for batch in train_loader:
    images, labels = batch
    # train model
```

Beyond Sequential: Custom Models

`nn.Sequential`

```python
model = nn.Sequential(
        nn.Linear(1, 20),
        nn.ReLU(),
        nn.Linear(20, 1)
)
```

`nn.Module`

```python
class MyModel(nn.Module):
    # defines layers
    def __init__(self):
        super().__init__()
        self.layer1 = nn.Linear(1, 20)
        self.layer2 = nn.Linear(20, 1)

    # describes data flow
    def forward(self, x):
        x = self.layer1(x)
        x = F.relu(x)
        x = self.layer2(x)
        return x
```

More control, same functionality

Calling the Model

Don’t call `model.forward()` directly

Do call `model(input)`

PyTorch handles the forward call and essential bookkeeping

Why `super().__init__()`?

Necessary for parameter tracking

PyTorch needs to set up a system to track all learnable parameters (weights and biases)

Without it, PyTorch has nowhere to register your layers

Training Loop Pattern

```
for batch in dataloader:
    optimizer.zero_grad()    # Clear old calculations
    outputs = model(inputs)  # Forward pass
    loss = loss_fn(outputs, targets)  # Measure error
    loss.backward()          # Calculate gradients
    optimizer.step()         # Update weights
```

Order matters! Don’t swap these steps.

Evaluation

```
model.eval()  # Set to evaluation mode
with torch.no_grad():  # Disable gradient tracking
    for batch in test_loader:
        outputs = model(inputs)
        # Calculate accuracy
```

Two critical things:

- `model.eval()` - sets evaluation mode
- `torch.no_grad()` - disables gradient tracking

Measuring Performance

For classification: Accuracy

```
correct = (predictions == labels).sum().item()
total = labels.size(0)
accuracy = correct / total
```

Count correct predictions / total predictions

To sum up

- Data pipeline: Dataset, DataLoader, Transforms
- Model building: `nn.Module`
- Training loop: `for batch in dataloader:`
- Evaluation: `model.eval()`, `torch.no_grad()`, `accuracy`

What's Next?

In **Session 2: Loss Functions and Optimizers**, you learn:

- How loss functions measure error
- Cross-entropy loss for classification
- How optimizers use gradients to update weights
- Understanding backpropagation