

Module 1 - Session 2: The ML Pipeline and Building Your First Model

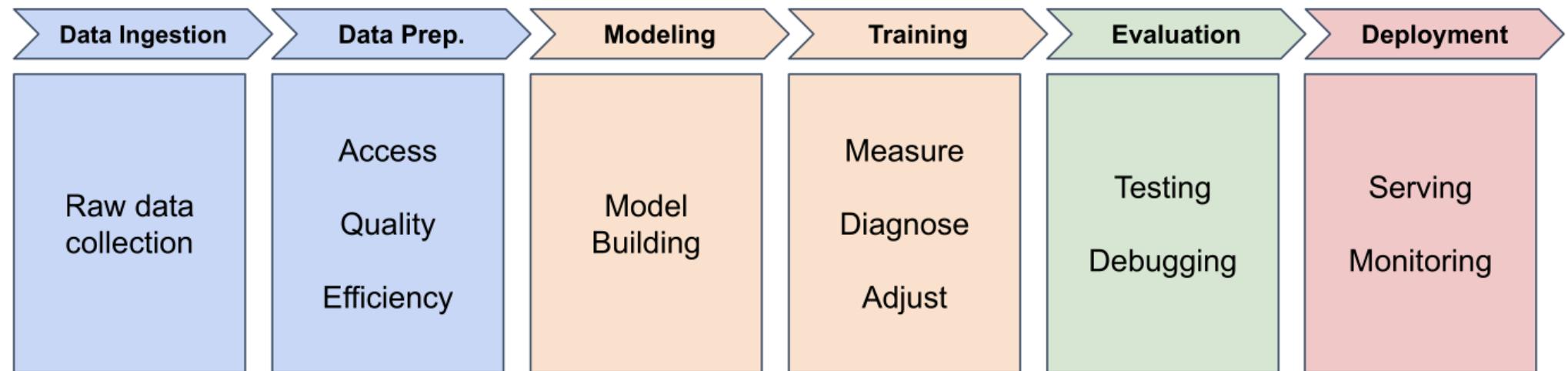


Session 2



The Machine Learning Pipeline

Six stages from data to deployed model



The Machine Learning Pipeline

Stage 1: Data Ingestion

Gathering and organizing raw data

- Delivery records from company database
- Messy data: inconsistent formats, missing values, errors
- Organize for PyTorch to work efficiently



Stage 2: Data Preparation

Cleaning, transforming, and organizing

- Fix errors (impossible times, duplicates)
- Handle missing values
- Engineer features (addresses → distances)

Most time-consuming stage in real projects

Stage 3: Model Building

Designing the architecture

- How many neurons?
- How are they connected?
- What types of layers?

For delivery predictor: one neuron (simplest architecture)

Stage 4: Training

Teaching the model to make predictions

- Feed examples (8.2 miles → 22 minutes)
- Measure prediction errors
- Adjust parameters to improve
- Repeat for many epochs

Stage 5: Evaluation

Testing on unseen data

- Use test set (held back during training)
- Measure performance (accuracy, error)
- Detect issues and debug

Key question: Does your model work well enough to trust it?

Stage 6: Deployment

Getting your model into the real world

(We'll cover this later in the course)



Building Your First Neural Network

Let's see it in PyTorch code

Imports

```
1 import torch  
2 import torch.nn as nn  
3 import torch.optim as optim
```



- `torch`: core functionality
- `nn`: neural network components
- `optim`: training tools

Preparing Data

```
1 distances = torch.tensor([[5.0], [6.0], [8.0], [10.0]],  
2                         dtype=torch.float32)  
3 times = torch.tensor([[22.2], [25.6], [31.2], [38.5]],  
4                      dtype=torch.float32)
```

Tensors: optimized containers for neural network math

Understanding Tensor Shapes

```
1 distances = torch.tensor([[5.0], [6.0], [8.0], [10.0]])  
2 distances.shape # torch.Size([4, 1])
```

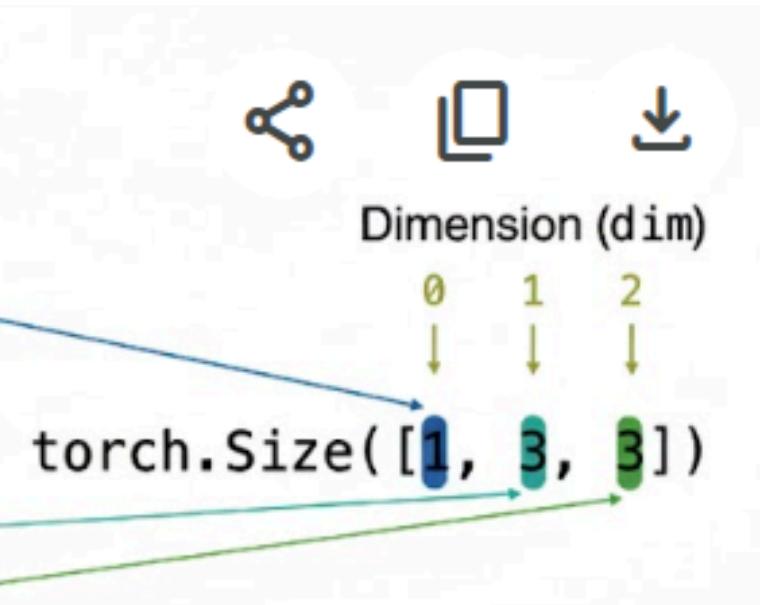
- First dimension: batch size (4 samples)
- Second dimension: features per sample (1 feature)

Tensor Dimensions: 3 dimensions

dim=0
`tensor([[1, 2, 3],
 [3, 6, 9],
 [2, 4, 5]])`

dim=1
`tensor([[1, 2, 3],
 [3, 6, 9],
 [2, 4, 5]])`

dim=2
`tensor([[[1, 2, 3],
 [3, 6, 9],
 [2, 4, 5]]])`



How to read brackets as dimensions

Creating the Model

```
1 model = nn.Sequential(  
2     nn.Linear(1, 1) # 1 input, 1 output  
3 )
```

Sequential: container that passes data through layers in order

Linear layer: single neuron ($\text{weight} \times \text{input} + \text{bias}$)

Loss Function

```
1 loss_function = nn.MSELoss()
```

Mean Squared Error: measures how wrong predictions are

- Bigger errors → bigger loss
- Perfect predictions → loss = 0

Optimizer

```
1 optimizer = optim.SGD(model.parameters(), lr=0.01)
```



SGD (Stochastic Gradient Descent):

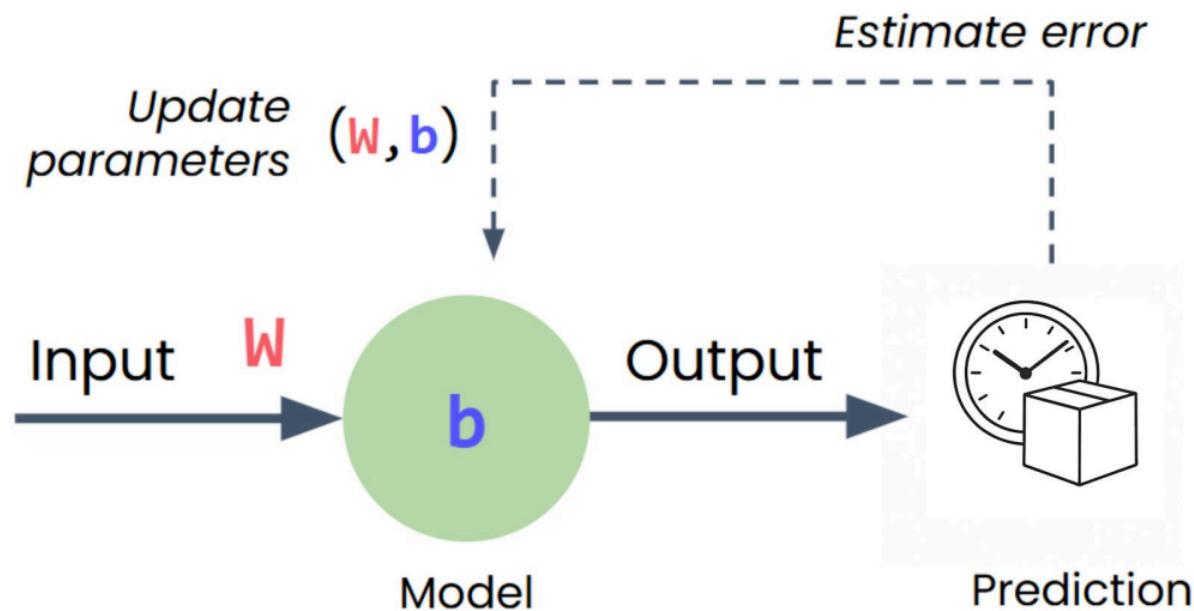
- Figures out which direction to adjust weights/bias
- `lr` (learning rate): controls step size

The Training Loop

```

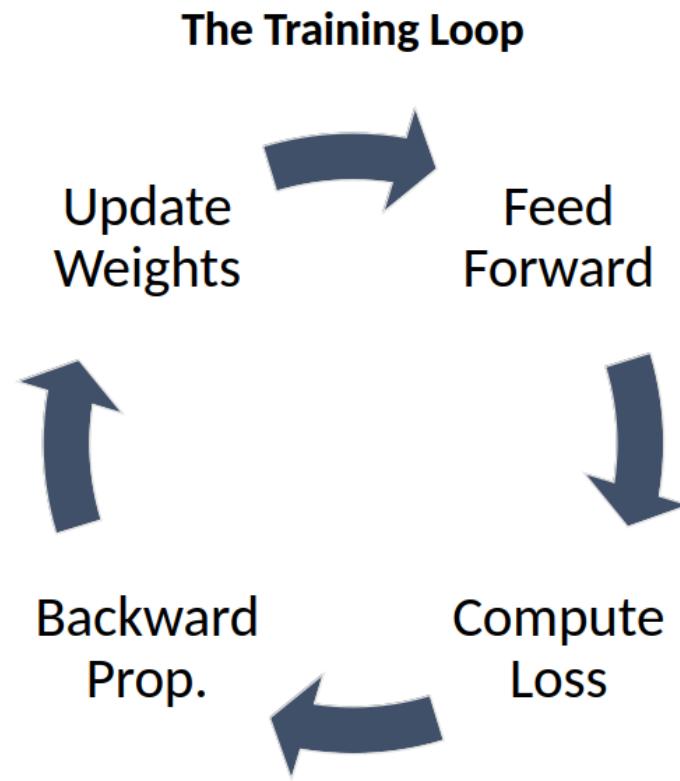
1 for epoch in range(500):
2     optimizer.zero_grad()          # Clear old calculations
3     outputs = model(distances)    # Make predictions
4     loss = loss_function(outputs, times) # Measure error
5     loss.backward()                # Calculate gradients
6     optimizer.step()              # Update weights/bias

```



Each epoch: one full pass through training data

Training Loop Breakdown



`outputs = model(distances)` - Model uses distance as input

`loss = loss_function(outputs, times)` - Compares predictions to real times

`loss.backward()` - Figures out how to adjust weight/bias (backpropagation)

`optimizer.step()` - Makes the adjustments

Making Predictions (Inference)

```
1 with torch.no_grad():
2     new_distance = torch.tensor([[7.0]])
3     prediction = model(new_distance)
4     print(prediction)
```

torch.no_grad(): skip training overhead for faster inference

Lab 1: Building a Simple Neural Network

“What I hear, I forget. What I see, I remember. What I do, I understand.”

START WITH LAB 1

What's Next?

In **Session 3: Activation Functions** we learn:

- Why linear models fail for complex patterns
- Introducing non-linearity with activation functions
- ReLU and other activation functions