

Introduction to PyTorch

<https://advancedinstitute.ai>

References and Resources

- ☐ [PyTorch Official Documentation](#)
- ☐ [PyTorch Tutorials](#)
- ☐ [Deep Learning Book \(Goodfellow et al.\)](#)
- ☐ [Dive into Deep Learning \(Interactive Book\)](#)
- ☐ [PyTorch Examples Repository](#)
- ☐ [Fast.ai - Practical Deep Learning](#)



Part 1

What is PyTorch?

What is PyTorch?

Introduction

- ❑ Open-source **deep learning framework** developed by Meta AI (Facebook)
- ❑ Released in 2016, now one of the **most popular** frameworks
- ❑ Key features:
 - **Dynamic computational graphs** (define-by-run)
 - **GPU acceleration** for fast computation
 - **Pythonic** - feels natural for Python developers
 - **Automatic differentiation** (autograd)
 - Strong **research community** and industry adoption
- ❑ Used by: Meta, Tesla, Uber, Microsoft, OpenAI, and many others

Why PyTorch?

Advantages

- **Ease of use:**
 - Pythonic API - natural for Python developers
 - Intuitive and flexible
 - Easy debugging (standard Python debugging tools)
- **Dynamic graphs:**
 - Build graphs on-the-fly
 - Different computation for each input
 - Ideal for research and experimentation
- **Performance:**
 - GPU acceleration
 - Optimized operations
 - Production-ready with TorchScript
- **Ecosystem:**
 - Rich libraries: TorchVision, TorchText, TorchAudio

Main Competitors

☐ **PyTorch:**

- Dynamic computational graphs (eager execution)
- More Pythonic, easier to debug
- Preferred in research community
- Gaining in production deployments

☐ **TensorFlow:**

- Static graphs (historically), now also eager with TF 2.x
- Stronger production/deployment tools
- TensorFlow Lite for mobile
- Preferred in industry (historically)

☐ **Trend:** Both are converging - PyTorch adding production tools, TensorFlow becoming more Pythonic

☐ **For today:** We focus on PyTorch!

Related Libraries

- ❑ **Core PyTorch:** torch
- ❑ **Computer Vision:** torchvision
 - Pre-trained models, datasets, transforms
- ❑ **Natural Language Processing:** torchtext
 - Text processing, datasets, vocabulary
- ❑ **Audio Processing:** torchaudio
 - Audio transforms, datasets
- ❑ **Higher-level APIs:**
 - **PyTorch Lightning:** high-level wrapper
 - **Fast.ai:** even higher-level, for practitioners
- ❑ **Deployment:**
 - **TorchServe:** model serving
 - **TorchScript:** production optimization



Part 2

Tensors - The Foundation

What are Tensors?

Fundamental Data Structure

- ❑ **Tensor:** Multi-dimensional array (generalization of matrices)
- ❑ **Dimensions:**
 - 0D tensor: scalar (single number)
 - 1D tensor: vector (array)
 - 2D tensor: matrix
 - 3D tensor: cube of numbers
 - 4D+ tensor: higher dimensions
- ❑ **Similar to NumPy arrays, but:**
 - Can run on GPU
 - Track gradients for automatic differentiation
 - Optimized for deep learning
- ❑ **Everything in PyTorch is a tensor!**

Creating Tensors

Basic Operations

```
1  import torch
2
3  # From Python list
4  x = torch.tensor([1, 2, 3])  # 1D tensor
5
6  # From NumPy array
7  import numpy as np
8  arr = np.array([[1, 2], [3, 4]])
9  x = torch.from_numpy(arr)  # 2D tensor
10
11 # Special tensors
12 zeros = torch.zeros(3, 4)      # 3x4 tensor of zeros
13 ones = torch.ones(2, 3)       # 2x3 tensor of ones
14 random = torch.randn(2, 3)    # Random normal distribution
15 identity = torch.eye(3)       # 3x3 identity matrix
```

Understanding Tensor Properties

```
1  x = torch.randn(3, 4, 5)
2
3  # Check shape
4  print(x.shape)          # torch.Size([3, 4, 5])
5  print(x.size())         # torch.Size([3, 4, 5]) - same
6
7  # Check data type
8  print(x.dtype)          # torch.float32 (default)
9
10 # Check device (CPU or GPU)
11 print(x.device)         # cpu or cuda:0
12
13 # Number of elements
14 print(x.numel())        # 60 (3 * 4 * 5)
```

Basic Arithmetic

□ Element-wise operations:

- Addition: $a + b$ or `torch.add(a, b)`
- Subtraction: $a - b$
- Multiplication: $a * b$
- Division: a / b

□ Matrix operations:

- Matrix multiplication: $a @ b$ or `torch.matmul(a, b)`
- Transpose: `a.T` or `a.transpose(0, 1)`

□ In-place operations: (modify tensor directly)

- `a.add_(b)`, `a.mul_(2)`
- Note the underscore suffix!

Tensor Operations Example

Common Operations

```
1  # Create tensors
2  a = torch.tensor([[1, 2], [3, 4]])
3  b = torch.tensor([[5, 6], [7, 8]])
4  # Element-wise operations
5  c = a + b          # [[6, 8], [10, 12]]
6  d = a * 2          # [[2, 4], [6, 8]]
7
8  # Matrix multiplication
9  e = a @ b          # [[19, 22], [43, 50]]
10
11 # Reshaping
12 f = a.view(4)       # [1, 2, 3, 4] - flatten
13 g = a.reshape(1, 4) # [[1, 2, 3, 4]]
14
15 # Indexing (like NumPy)
16 print(a[0, 1])      # 2
17 print(a[:, 1])      # [2, 4] - second column
```

Moving Tensors to GPU

□ Why GPU?

- Massive parallelization
- 10-100x faster for large operations
- Essential for training deep networks

□ Check GPU availability:

- `torch.cuda.is_available()`

□ Move tensors to GPU:

- `x = x.to('cuda')`
- `x = x.cuda()`

□ Move back to CPU:

- `x = x.to('cpu')`
- `x = x.cpu()`

□ Important: All tensors in an operation must be on same device!

GPU Example

Using CUDA

```
1  # Check if GPU is available
2  device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
3
4  # Create tensor on GPU directly
5  x = torch.randn(1000, 1000, device=device)
6
7  # Or move existing tensor to GPU
8  y = torch.randn(1000, 1000)
9  y = y.to(device)
10
11 # Perform operations (much faster on GPU!)
12 z = x @ y  # Matrix multiplication on GPU
13
14 # Move back to CPU for NumPy conversion
15 z_cpu = z.cpu()
16 z_numpy = z_cpu.numpy()
```



Part 3

Automatic Differentiation

What is Autograd?

Automatic Differentiation

- ❑ **Autograd:** PyTorch's automatic differentiation engine
- ❑ **Why do we need it?**
 - Deep learning = optimizing functions
 - Optimization requires **gradients** (derivatives)
 - Manual gradient calculation is error-prone and tedious
- ❑ **How it works:**
 - PyTorch tracks all operations on tensors
 - Builds a **computational graph**
 - Automatically computes gradients via **backpropagation**
- ❑ **Enable gradient tracking:**
 - `x = torch.randn(3, requires_grad=True)`
- ❑ **Compute gradients:**
 - `loss.backward()`

Autograd Example

Computing Gradients

```
1  # Create tensor with gradient tracking
2  x = torch.tensor([2.0], requires_grad=True)
3  # Forward pass: compute function
4  y = x ** 2 + 3 * x + 1  #  $y = x^2 + 3x + 1$ 
5  # Backward pass: compute gradient  $dy/dx$ 
6  y.backward()
7  # Access gradient
8  print(x.grad)  #  $dy/dx = 2x + 3 = 2(2) + 3 = 7$ 
9
10 # For multiple steps, remember to zero gradients
11 x.grad.zero_()  # Important!
12
13 # Another computation
14 z = x ** 3
15 z.backward()
16 print(x.grad)  #  $dz/dx = 3x^2 = 3(4) = 12$ 
```

How Autograd Tracks Operations

- **Dynamic computational graph:**
 - Built on-the-fly during forward pass
 - Each operation creates a node
 - Tracks dependencies between tensors
- **Example:** $z = (x + y) * w$
 - Node 1: $a = x + y$
 - Node 2: $z = a * w$
 - Graph: $x, y, w \rightarrow a \rightarrow z$
- **Backward pass:**
 - Traverse graph in reverse
 - Apply chain rule automatically
 - Accumulate gradients
- **After backward():** Graph is destroyed (for memory efficiency)

Gradient Accumulation

Important Concept

```
1  x = torch.tensor([2.0], requires_grad=True)
2
3  # First computation
4  y = x ** 2
5  y.backward()
6  print(x.grad)    # 4.0
7
8  # Second computation (without zeroing!)
9  z = x ** 3
10 z.backward()
11 print(x.grad)    # 16.0 = 4.0 + 12.0 (accumulated!)
12 # Always zero gradients before new backward pass
13 x.grad.zero_()
14 w = x ** 4
15 w.backward()
16 print(x.grad)    # 32.0 (fresh gradient)
```

Important Concept

- ❑ **Key point:** Gradients accumulate by default!
- ❑ **Always** `zero_grad()` in training loops



Part 4

Training with PyTorch: Linear Regression

Why Start with Linear Regression?

Simple but Complete Example

- **Linear regression:** Fitting a line to data
 - Simple: $y = wx + b$
 - But uses ALL PyTorch training concepts!
- **Advantages for learning:**
 - Easy to visualize
 - Fast to train
 - Shows complete workflow
 - Same patterns apply to complex models
- **You'll learn:** Model definition, Loss functions, Optimizers, Training loop
- **Then:** Apply same concepts to neural networks!

Problem Setup

Linear Regression Task

- **Goal:** Predict house prices based on size
- **Model:** $\text{price} = w \times \text{size} + b$
 - w = weight (slope)
 - b = bias (intercept)
- **Training data:**
 - Multiple (size, price) pairs
 - Example: (50m², R\$200k), (80m², R\$320k), ...
- **Task:** Find best w and b
 - Minimize error between predictions and actual prices
- **Loss function:** Mean Squared Error (MSE)
 - $$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Generate Synthetic Data

Creating Training Data

```
1  import torch
2  import matplotlib.pyplot as plt
3  # Set random seed for reproducibility
4  torch.manual_seed(42)
5
6  # Generate synthetic data:  $y = 2x + 3 + \text{noise}$ 
7  n_samples = 100
8  X = torch.randn(n_samples, 1) * 10 # House sizes (random)
9  y = 2 * X + 3 + torch.randn(n_samples, 1) * 2 # Prices with noise
10
11 # Visualize data
12 plt.scatter(X.numpy(), y.numpy(), alpha=0.5)
13 plt.xlabel('House Size (m2)')
14 plt.ylabel('Price (R\$ thousands)')
15 plt.title('Training Data')
16 plt.show()
17 print(f"Data shape: X={X.shape}, y={y.shape}")
```

Method 1: Manual Implementation

Understanding the Basics

□ Define model manually:

- Create weight and bias as tensors
- Enable gradient tracking

□ Training components:

- 1. **Forward pass:** compute predictions
- 2. **Compute loss:** how far off are we?
- 3. **Backward pass:** compute gradients
- 4. **Update weights:** gradient descent

□ Learning rate:

- Controls step size: $w_{new} = w_{old} - lr \times \frac{\partial L}{\partial w}$
- Too large: unstable, too small: slow

Manual Training Loop

Step-by-Step Implementation

```
1  # Initialize parameters randomly
2  w = torch.randn(1, 1, requires_grad=True)
3  b = torch.randn(1, requires_grad=True)
4
5  # Hyperparameters
6  learning_rate = 0.01
7  num_epochs = 100
8
9  # Training loop
10 for epoch in range(num_epochs):
11     # 1. Forward pass: compute predictions
12     y_pred = X @ w + b  # Matrix multiplication + bias
13
14     # 2. Compute loss (Mean Squared Error)
15     loss = torch.mean((y_pred - y) ** 2)
16     ...
```

Manual Training Loop

Step-by-Step Implementation

```
1  ...
2  # Training loop
3  for epoch in range(num_epochs):
4      ...
5      # 3. Backward pass: compute gradients
6      loss.backward()
7
8      # 4. Update weights (gradient descent)
9      with torch.no_grad():
10         w -= learning_rate * w.grad
11         b -= learning_rate * b.grad
12     # 5. Zero gradients for next iteration
13     w.grad.zero_()
14     b.grad.zero_()
15     if (epoch + 1) % 10 == 0: print(f'Epoch {epoch+1}, Loss: {loss.item()
        :.4f}')
```

Understanding the Training Loop

Key Steps Explained

□ Step 1: Forward Pass

- $y_pred = X @ w + b$
- Compute predictions using current weights

□ Step 2: Compute Loss

- $loss = \text{mean}((y_pred - y) ** 2)$
- Measure error between predictions and true values

□ Step 3: Backward Pass

- `loss.backward()`
- Automatically compute gradients: $\frac{\partial L}{\partial w}, \frac{\partial L}{\partial b}$

Key Steps Explained

□ Step 4: Update Weights

- `w -= lr * w.grad`
- Move in direction that reduces loss

□ Step 5: Zero Gradients

- `w.grad.zero_()`
- Clear for next iteration (gradients accumulate!)

Method 2: Using nn.Module

PyTorch's Standard Way

- ❑ **nn.Module:** Base class for all models
- ❑ **Advantages:**
 - Cleaner, more organized code
 - Automatic parameter management
 - Easy to extend to complex models
 - Same pattern for all models
- ❑ **Two methods to implement:**
 - `__init__`: define layers/parameters
 - `forward`: define computation
- ❑ **This is the standard approach!**
 - Manual method was for understanding
 - Always use nn.Module in practice

Define Model with nn.Module

Creating a Model Class

```
1  import torch.nn as nn
2
3  class LinearRegressionModel(nn.Module):
4      def __init__(self, input_dim, output_dim):
5          super(LinearRegressionModel, self).__init__()
6          # Define a linear layer:  $y = Wx + b$ 
7          self.linear = nn.Linear(input_dim, output_dim)
8
9      def forward(self, x):
10         # Define forward pass
11         return self.linear(x)
12
13 # Create model instance
14 model = LinearRegressionModel(input_dim=1, output_dim=1)
15
16 # Check model parameters
17 print(model)
```


Measuring Error

□ For regression:

- `nn.MSELoss()` - Mean Squared Error (most common)

- $$\text{MSE} = \frac{1}{n} \sum (y - \hat{y})^2$$

- `nn.L1Loss()` - Mean Absolute Error

- $$\text{MAE} = \frac{1}{n} \sum |y - \hat{y}|$$

- `nn.SmoothL1Loss()` - Huber loss

□ Usage:

- `criterion = nn.MSELoss()`
- `loss = criterion(predictions, targets)`

□ Why MSE for linear regression?

- Penalizes large errors more
- Differentiable everywhere
- Has nice mathematical properties

Optimizers in PyTorch

Weight Update Algorithms

- ❑ **Optimizer:** Updates model parameters to minimize loss
- ❑ **Common optimizers:**
 - **SGD:** `torch.optim.SGD(params, lr=0.01)`
 - Classic gradient descent
 - **Adam:** `torch.optim.Adam(params, lr=0.001)`
 - Adaptive learning rates, most popular
 - **RMSprop, AdamW, Adagrad...**
- ❑ **For linear regression:** SGD is fine
- ❑ **For neural networks:** Adam often works better
- ❑ **Usage:**
 - `optimizer.zero_grad()` - clear gradients
 - `loss.backward()` - compute gradients
 - `optimizer.step()` - update weights

Complete Training with nn.Module

The Standard Pattern

```
1  # 1. Create model
2  model = LinearRegressionModel(input_dim=1, output_dim=1)
3
4  # 2. Define loss function
5  criterion = nn.MSELoss()
6
7  # 3. Define optimizer
8  optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
9
10 # 4. Training loop
11 num_epochs = 100
12 losses = []
13 ...
```

Complete Training with nn.Module

The Standard Pattern

```
1  ...
2  # 4. Training loop
3  for epoch in range(num_epochs):
4      # Forward pass
5      y_pred = model(X)
6      loss = criterion(y_pred, y)
7
8      # Backward pass and optimization
9      optimizer.zero_grad() # Clear gradients
10     loss.backward()        # Compute gradients
11     optimizer.step()       # Update weights
12
13     # Record loss
14     losses.append(loss.item())
15     if (epoch + 1) % 10 == 0:
16         print(f'Epoch [{epoch+1}/{num_epochs}], Loss:{loss.item():.4f}')
```

The Training Loop Pattern

Remember This!

- This pattern is universal in PyTorch:

Step	Code
1. Forward pass	<code>outputs = model(inputs)</code>
2. Compute loss	<code>loss = criterion(outputs, targets)</code>
3. Zero gradients	<code>optimizer.zero_grad()</code>
4. Backward pass	<code>loss.backward()</code>
5. Update weights	<code>optimizer.step()</code>

The Training Loop Pattern

Remember This!

- **Works for:**
 - Linear regression (what we just did)
 - Neural networks
 - CNNs, RNNs, Transformers...
 - Any differentiable model!
- **Critical:** Never forget `optimizer.zero_grad()`!

Visualizing Training Progress

Monitoring the Loss

```
1  import matplotlib.pyplot as plt
2
3  # Plot training loss
4  plt.figure(figsize=(10, 5))
5  plt.plot(losses)
6  plt.xlabel('Epoch')
7  plt.ylabel('Loss')
8  plt.title('Training Loss Over Time')
9  plt.grid(True, alpha=0.3)
10 plt.show()
11
12 # Plot predictions vs actual
13 model.eval() # Set to evaluation mode
14 with torch.no_grad():
15     predictions = model(X)
16
17 plt.figure(figsize=(10, 5))
```

Evaluating the Model

Making Predictions

□ **After training, use the model:**

- Set to evaluation mode: `model.eval()`
- Disable gradients: `with torch.no_grad():`

□ **Why evaluation mode?**

- For linear regression: no difference
- For neural networks: disables dropout, changes batchnorm
- **Good habit to always use it!**

□ **Why no_grad?**

- Saves memory (don't need gradients for inference)
- Speeds up computation

□ **Get model parameters:**

- `w = model.linear.weight.item()`
- `b = model.linear.bias.item()`

Inference Example

Using the Trained Model

```
1  # Set to evaluation mode
2  model.eval()
3
4  # Create new data points
5  new_sizes = torch.tensor([[30.0], [50.0], [100.0]])
6
7  # Make predictions (no gradients needed)
8  with torch.no_grad():
9      predicted_prices = model(new_sizes)
10
11 # Print results
12 print("House Size → Predicted Price")
13 for size, price in zip(new_sizes, predicted_prices):
14     print(f"{size.item():.0f} m2 → R\${price.item():.1f}k")
15
16 # Extract learned parameters
17 w = model.linear.weight.item()
```

Preserving Your Work

□ **Save model:**

- `torch.save(model.state_dict(), 'linear_model.pth')`
- Saves only parameters (recommended)

□ **Load model:**

- Create model instance first
- `model = LinearRegressionModel(1, 1)`
- `model.load_state_dict(torch.load('linear_model.pth'))`
- `model.eval()`

□ **Why state_dict?**

- More flexible
- Portable across code changes
- Smaller file size

□ **File extension:** Usually `.pth` or `.pt`

Save and Load Example

Complete Workflow

```
1  # Save the trained model
2  torch.save(model.state_dict(), 'linear_regression_model.pth')
3  print("Model saved!")
4
5  # Later... load the model
6  # 1. Create the same model architecture
7  loaded_model = LinearRegressionModel(input_dim=1, output_dim=1)
8
9  # 2. Load the saved parameters
10 loaded_model.load_state_dict(torch.load('linear_regression_model.pth'))
11
12 # 3. Set to evaluation mode
13 loaded_model.eval()
14 ...
```

Complete Workflow

```
1  ...
2  # 4. Use it for predictions
3  with torch.no_grad():
4      test_input = torch.tensor([[75.0]])
5      prediction = loaded_model(test_input)
6      print(f"Prediction for 75 m2: R\${prediction.item():.1f}k")
```

The Same Patterns Apply!

☐ **What we learned:**

- Define model with `nn.Module`
- Choose loss function
- Choose optimizer
- Training loop: forward \rightarrow loss \rightarrow backward \rightarrow update
- Evaluation mode and inference
- Saving and loading

☐ **For neural networks:**

- **Same training loop!**
- Just change: model architecture (add layers, activations)
- Maybe: different loss function
- Maybe: different optimizer (Adam instead of SGD)

☐ **Next:** See a complete neural network example (MNIST)

Troubleshooting Training

- ❑ **Loss not decreasing:**
 - Learning rate too small → increase it
 - Learning rate too large → decrease it
 - Check if gradients are being computed
- ❑ **Loss is NaN:**
 - Learning rate too large
 - Numerical instability (gradient explosion)
- ❑ **Slow convergence:**
 - Try different optimizer (Adam vs SGD)
 - Normalize your input data
- ❑ **Forgot to zero gradients:**
 - Gradients accumulate → wrong updates
 - Always call `optimizer.zero_grad()`

Summary

- ❑ **Linear regression = simplest ML model**
 - But shows ALL PyTorch training concepts!
- ❑ **Training components:**
 - Model (`nn.Module`)
 - Loss function (`nn.MSELoss`)
 - Optimizer (`torch.optim.SGD` or `Adam`)
 - Training loop (the 5-step pattern)
- ❑ **Critical steps:**
 - Always `zero_grad()` before backward
 - Use `model.eval()` for inference
 - Use `torch.no_grad()` to save memory
- ❑ **This same pattern works for ANY model!**
 - Neural networks, CNNs, RNNs, Transformers...



Part 5

Building Neural Networks

torch.nn Module

- **torch.nn:** Building blocks for neural networks
- **Key components:**
 - **nn.Module:** Base class for all models
 - **Layers:** Linear, Conv2d, LSTM, etc.
 - **Activation functions:** ReLU, Sigmoid, Tanh
 - **Loss functions:** MSELoss, CrossEntropyLoss
- **Two ways to build networks:**
 - **Sequential:** simple linear stack of layers
 - **Module class:** more flexibility, custom forward pass
- We'll focus on the **Module class** approach

Simple Neural Network

Defining a Model

```
1  import torch.nn as nn
2
3  class SimpleNet(nn.Module):
4      def __init__(self, input_size, hidden_size, output_size):
5          super(SimpleNet, self).__init__()
6          # Define layers
7          self.fc1 = nn.Linear(input_size, hidden_size)
8          self.relu = nn.ReLU()
9          self.fc2 = nn.Linear(hidden_size, output_size)
10
11     def forward(self, x):
12         # Define forward pass
13         x = self.fc1(x)          # First linear layer
14         x = self.relu(x)         # Activation
15         x = self.fc2(x)          # Second linear layer
16         return x
17
```

Building Blocks

□ Fully Connected (Linear):

- `nn.Linear(in_features, out_features)`
- Standard dense layer: $y = Wx + b$

□ Convolutional:

- `nn.Conv2d(in_channels, out_channels, kernel_size)`
- For images and spatial data

□ Recurrent:

- `nn.LSTM(input_size, hidden_size)`
- `nn.GRU(input_size, hidden_size)`
- For sequences (text, time series)

□ Normalization:

- `nn.BatchNorm1d/2d`, `nn.LayerNorm`

□ Dropout:

- `nn.Dropout(p=0.5)` - regularization

Non-linearity

□ Why activations?

- Without them, network is just linear regression
- Activations add **non-linearity**

□ Common activations:

- **ReLU:** `nn.ReLU()` - most common
 - $f(x) = \max(0, x)$
- **Sigmoid:** `nn.Sigmoid()` - outputs in $[0,1]$
 - $f(x) = 1/(1 + e^{-x})$
- **Tanh:** `nn.Tanh()` - outputs in $[-1,1]$
- **Softmax:** `nn.Softmax()` - for classification
 - Converts logits to probabilities

□ Modern variants: LeakyReLU, ELU, GELU, Swish



Part 7

Best Practices & Tips

Preserving Your Work

□ **Save model:**

- `torch.save(model.state_dict(), 'model.pth')`
- Saves only weights (recommended)

□ **Load model:**

- `model = MNISTNet()`
- `model.load_state_dict(torch.load('model.pth'))`
- `model.eval()`

□ **Save entire model:** (not recommended)

- `torch.save(model, 'model.pth')`
- Can break if code changes

□ **Save checkpoint** (for resuming training):

- Save: model state, optimizer state, epoch, loss

Checkpoint Example

Saving Everything

```
1  # Save checkpoint
2  checkpoint = {
3      'epoch': epoch,
4      'model_state_dict': model.state_dict(),
5      'optimizer_state_dict': optimizer.state_dict(),
6      'loss': loss,
7  }
8  torch.save(checkpoint, 'checkpoint.pth')
9
10 # Load checkpoint
11 checkpoint = torch.load('checkpoint.pth')
12 model.load_state_dict(checkpoint['model_state_dict'])
13 optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
14 epoch = checkpoint['epoch']
15 loss = checkpoint['loss']
16 model.train() # or model.eval()
```

Avoid These Mistakes

- ❑ **Forgetting to zero gradients:**
 - Always call `optimizer.zero_grad()`
- ❑ **Not setting eval mode:**
 - Use `model.eval()` for inference
- ❑ **Mixing CPU and GPU tensors:**
 - All tensors must be on same device
- ❑ **Not using `torch.no_grad()`:**
 - Wastes memory during inference
- ❑ **Wrong tensor shapes:**
 - Check shapes with `.shape`
 - Use `.view()` or `.reshape()` carefully
- ❑ **Learning rate too high:**
 - Start with 0.001 for Adam, tune if needed

Finding Problems

- ❑ **Check tensor shapes:**
 - Print `x.shape` at each step
 - Use `torchinfo` or `torchsummary`
- ❑ **Verify gradients:**
 - Check if `requires_grad=True`
 - Print gradients: `param.grad`
- ❑ **Start simple:**
 - Overfit on small batch first
 - If model can't overfit, architecture issue

Finding Problems

☐ **Monitor training:**

- Plot loss curves
- Use TensorBoard for visualization

☐ **Use debugger:**

- PyTorch works with standard Python debuggers (pdb, ipdb)

Making Training Faster

- ❑ **Use GPU:**
 - Essential for large models/datasets
 - Move model and data to CUDA
- ❑ **Larger batch sizes:**
 - Better GPU utilization
 - But: need more memory, may need lower LR
- ❑ **Mixed precision training:**
 - `torch.cuda.amp` for automatic mixed precision - Faster and uses less memory
- ❑ **Data loading:**
 - Use multiple workers: `num_workers > 0`
 - Pin memory: `pin_memory=True`
- ❑ **Compile your model: (PyTorch 2.0+)**
 - `model = torch.compile(model)`

Advanced Topics

- ❑ **Transfer Learning:**
 - Use pre-trained models from `torchvision.models`
 - Fine-tune on your data
- ❑ **Learning Rate Scheduling:**
 - `torch.optim.lr_scheduler`
 - Adjust learning rate during training
- ❑ **Regularization:**
 - Dropout, BatchNorm, weight decay
- ❑ **Custom Datasets:**
 - Extend `torch.utils.data.Dataset`
- ❑ **Distributed Training:**
 - `torch.nn.DataParallel`
 - `torch.distributed`

Where to Go Next

❑ Official Resources:

- PyTorch Tutorials: pytorch.org/tutorials
- Documentation: pytorch.org/docs
- Examples: github.com/pytorch/examples

❑ Courses:

- Fast.ai: Practical Deep Learning
- Deep Learning Specialization (Coursera)
- Stanford CS231n (Computer Vision)

❑ Books:

- Deep Learning with PyTorch (Stevens et al.)
- Programming PyTorch for Deep Learning (Subramanian)

❑ Community:

- PyTorch Forums, Stack Overflow, Reddit r/MachineLearning

Summary

□ **PyTorch is:**

- Flexible, Pythonic deep learning framework
- Dynamic graphs, easy debugging
- Strong ecosystem and community

□ **Core concepts:**

- Tensors - multi-dimensional arrays
- Autograd - automatic differentiation
- nn.Module - building blocks for models

□ **Training workflow:**

- Define model → Loss + Optimizer → Training loop
- Forward → Loss → Backward → Update

□ **Remember:**

- Zero gradients before backward
- Set train/eval mode appropriately
- Start simple, add complexity gradually

Questions?