

The Ultimate PyTorch Lock-In Guide

From Zero to Tensor Hero: Math Notation + PyTorch Fundamentals

3-Hour Masterclass Session

PART 1: MATH FOUNDATION (30 minutes)

Master these symbols before touching PyTorch code.

1.1 Essential Math Notation Crash Course

Symbol	Name	What It Means	Simple Example
x, y, z	Variables	Unknown numbers we want to find	$x = 5$
\mathbb{R}	Real Numbers	All numbers on number line	$3, -2.5, 0, \pi \in \mathbb{R}$
\in	Belongs to	Shows membership in a set	$x \in \mathbb{R}$ (x is a real number)
\mathbb{R}^n	n -dimensional space	List of n real numbers	$\mathbb{R}^3 = (x, y, z)$ (3D coords)
\sum	Summation	Add up a series of numbers	$\sum_{i=1}^5 i = 1 + 2 + 3 + 4 + 5 = 15$
\prod	Product	Multiply a series of numbers	$\prod_{i=1}^3 i = 1 \times 2 \times 3 = 6$
∂	Partial derivative	Rate of change while others stay constant	$\frac{\partial y}{\partial x}$
∇	Gradient	Vector of all partial derivatives	$\nabla f = [\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}]$
$\ \mathbf{x}\ $	Norm/Magnitude	Length of a vector	$\ [3, 4]\ = \sqrt{3^2 + 4^2} = 5$
\mathbf{x}^T	Transpose	Flip rows and columns	$[1, 2, 3]^T$ becomes vertical
\cdot	Dot product	Multiply corresponding elements and sum	$[1, 2] \cdot [3, 4] = (1)(3) + (2)(4) = 11$

1.2 Breaking Down the Scary Symbols

Sigma Notation (\sum) - The Loop of Math

Read as: "Sum from $i = 1$ to n of $f(i)$ "

$$\sum_{i=1}^4 i^2 = 1^2 + 2^2 + 3^2 + 4^2 = 30$$

Python equivalent: `sum([i**2 for i in range(1, 5)])`

Partial Derivatives (∂) - The Slope Finder

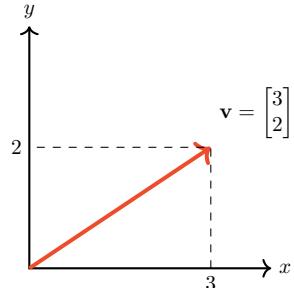
Regular derivative (dy/dx): Slope walking straight east.

Partial ($\partial y/\partial x$): Slope walking east, keeping north constant.

If $z = x^2 + 3xy + y^2$

$$\frac{\partial z}{\partial x} = 2x + 3y \quad (\text{Treat } y \text{ as constant})$$

1.3 Matrix & Vector Basics



1-D Tensor (Vector)

Represents magnitude and direction in space.

PART 2: PYTORCH CORE CONCEPTS (90 minutes)

2.1 TENSOR - The Fundamental Object

A tensor is a multi-dimensional array that can run on a GPU.

- **Scalar (0-D):** $a \in \mathbb{R} \rightarrow \text{torch.tensor}(5)$
- **Vector (1-D):** $\mathbf{v} \in \mathbb{R}^n \rightarrow \text{torch.tensor}([1, 2, 3])$
- **Matrix (2-D):** $\mathbf{M} \in \mathbb{R}^{m \times n} \rightarrow \text{torch.tensor}([[1, 2], [3, 4]])$
- **Tensor (n-D):** $\mathcal{T} \in \mathbb{R}^{d_1 \times \dots \times d_n} \rightarrow$ e.g., Batch of RGB Images: (Batch, Channels, Height, Width)

2.2 Tensor Operations & Broadcasting

Element-wise (Hadamard Product) @

```
A = torch.tensor([[1, 2], [3, 4]])
B = torch.tensor([[5, 6], [7, 8]])
C = A * B
# Result: [[5, 12], [21, 32]]
```

Visualizing Broadcasting

PyTorch automatically expands smaller tensors.

$$\begin{array}{|c|c|} \hline 1 & 2 \\ \hline 3 & 4 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 10 & 20 \\ \hline 10 & 20 \\ \hline \end{array} = \begin{array}{|c|c|} \hline 11 & 22 \\ \hline 13 & 24 \\ \hline \end{array}$$

$A_{(2 \times 2)}$ $b_{(1 \times 2)}$ $C_{(2 \times 2)}$

Matrix Multiplication (Dot Product) @

Inner dimensions must match! $\mathbb{R}^{m \times n} \times \mathbb{R}^{n \times p} = \mathbb{R}^{m \times p}$

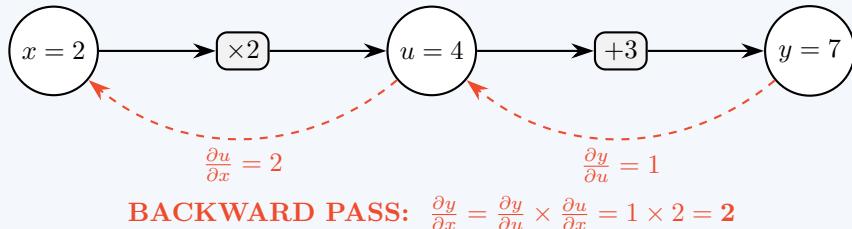
```
E = A @ B # or torch.matmul(A, B)
# E[0,0] = (1*5) + (2*7) = 19
```

2.3 AUTOGRAD & The Computation Graph

The Chain Rule: If $y = f(g(x))$, then $\frac{dy}{dx} = \frac{dy}{dg} \times \frac{dg}{dx}$. PyTorch tracks this dynamically!

Visualizing the Computational Graph (Forward & Backward Pass)

FORWARD PASS (Compute y)

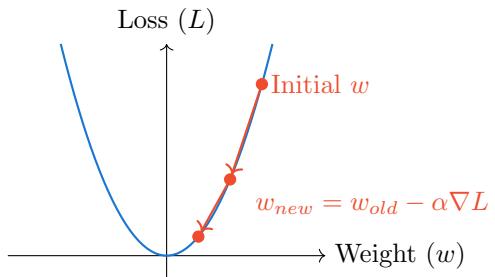


PyTorch Autograd Code:

```
import torch
x = torch.tensor(2.0, requires_grad=True)
y = (x * 2) + 3

y.backward() # Output: tensor(2.)
```

Gradient Descent Visualized



PART 3: MEMORY TABLES & CHEAT SHEETS

Table 1: Tensor Creation

Math / Concept	PyTorch Code	Operation	Change
Scalar $5 \in \mathbb{R}$	<code>torch.tensor(5)</code>	Reshape	$(2, 3) \rightarrow (3, 2)$
Vector $\mathbf{v} \in \mathbb{R}^3$	<code>torch.tensor([1, 2, 3])</code>	Transpose	$(2, 3) \rightarrow (3, 2)$
Zeros $0^{2 \times 3}$	<code>torch.zeros(2, 3)</code>	Add dim	$(3, 4) \rightarrow (1, 3, 4)$
Identity I_3	<code>torch.eye(3)</code>	Drop dim	$(1, 3, 1) \rightarrow (3)$
Uniform $\mathcal{U}(0, 1)$	<code>torch.rand(2, 2)</code>	Flatten	$(2, 3) \rightarrow (6,)$
Normal $\mathcal{N}(0, 1)$	<code>torch.randn(2, 2)</code>	Permute	$(H, W, C) \rightarrow (C, H, W)$
Range $\{0..9\}$	<code>torch.arange(10)</code>		
5 points 0 to 1	<code>torch.linspace(0, 1, 5)</code>		

Table 2: Operations Symbols

Sym	PyTorch	Action	PyTorch Code
<code>+</code>	<code>a + b</code>	Compute Grad	<code>y.backward()</code>
<code>*</code>	<code>a * b</code>	Access Grad	<code>x.grad</code>
<code>@</code>	<code>a @ b</code>		<code>optimizer.zero_grad</code>
<code>**</code>	<code>a ** 2</code>		<code>with torch.no_grad</code>

PART 4: PRACTICE QUESTION SET

Level 1: Tensor Basics

- Q1.** Create a tensor representing this matrix: $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$
- Q2.** What is the shape of `torch.tensor([[[1, 2], [3, 4]], [[5, 6], [7, 8]]])`? Draw it.
- Q3.** Create a 3×3 identity matrix I_3 . Verify $I_3 \cdot A = A$.
- Q4.** Generate 100 random numbers from $\mathcal{N}(0, 1)$, find mean and std.
- Q5.** Create a tensor with values 0 to 100, step 5 using `arange` and `linspace`.

Level 2: Operations & Broadcast

- Q6.** Given $\mathbf{u} = [1, 2, 3]^T, \mathbf{v} = [4, 5, 6]^T$. Compute: element-wise product, dot product, and outer product $\mathbf{u}\mathbf{v}^T$.
- Q7.** Explain why `A = torch.ones(3, 4); b = torch.arange(4); C = A + b` works. What is the shape of C?
- Q8.** Matrix multiply puzzle: Can you multiply $A_{(3 \times 4)}$ and $B_{(4 \times 2)}$? Output shape?
- Q9.** Reshape challenge: Tensor shape '(2,3,4)'. What are all possible 2D shapes?
- Q10.** Prove $(A^T)^T = A$ via PyTorch code.

Level 3: Autograd

- Q11.** Find derivative of $f(x) = x^3 - 2x^2 + 5x - 7$ at $x = 2$ using autograd.
- Q12.** For $f(x, y) = x^2y + y^3$, compute ∇f at $(2, 3)$. Verify manually.
- Q13.** Let $u = 2x + 1, y = u^2$. Find dy/dx at $x = 1$ via Chain Rule and Autograd.
- Q14.** What happens if you run `.backward()` twice without zeroing gradients?
- Q15.** Compute $\frac{\partial L}{\partial w}$ for MSE Loss $L = \frac{1}{n} \sum (y_i - (wx_i + b))^2$.

Level 4: Applied Math

- Q16.** Implement Softmax: $\frac{e^{x_i}}{\sum e^{x_j}}$ for $\mathbf{x} = [1, 2, 3]$.
- Q17.** Implement MSE Loss function manually.
- Q18.** Batch multiply: Tensors '(32, 10, 20)' and '(32, 20, 30)'. What is the shape?
- Q19.** Image shape '(3, 224, 224)'. How to convert to '(224, 224, 3)'?
- Q20.** If $\nabla L = [2, -3]$, $\alpha = 0.1$. What is the update direction? Why subtract?

PART 5: SOLUTIONS & EXPLANATIONS

Level 1 Solutions

- A1.** `A = torch.tensor([[1,2,3],[4,5,6]])`
(Shape: 2x3)
- A2.** Shape is (2, 2, 2). It is a 3D Cube (2 layers of 2x2 matrices).
- A3.** `I = torch.eye(3); result = I @ A`
- A4.** `x = torch.randn(100); x.mean(); x.std()`
- A5.** `torch.arange(0,101,5)` and `torch.linspace(0,100,21)`

Level 2 Solutions

- A6.** Hadamard: `u * v → [4, 10, 18]`. Dot: `torch.dot(u, v) → 32`. Outer: `torch.outer(u, v) → 3 × 3 matrix`.
- A7.** Broadcasting expands `b` from '(4,' to '(1,4)' to '(3,4)'. Shape is '(3,4)'.
- A8.** Yes. Inner dims match (4 = 4). Output is '(3, 2)'.
- A9.** Total elements = 24. 2D shapes: (2,12), (3,8), (4,6), (6,4), (8,3), etc.
- A10.** `double_t = A.t().t(); torch.equal(A, double_t) → True`.

Level 3 Solutions

- A11.** $f'(x) = 3x^2 - 4x + 5 \rightarrow f'(2) = 9$. `x.grad` returns 9.
- A12.** $\partial f / \partial x = 2xy = 12$. $\partial f / \partial y = x^2 + 3y^2 = 31$.
- A13.** $dy/dx = (dy/du)(du/dx) = (2u)(2) = 4(3) = 12$.
- A14.** Gradients accumulate! PyTorch adds new gradients to existing ones. Call `optimizer.zero_grad()` to reset.
- A15.** Uses Autograd. Chain rule computes $-2x_i(y_i - \hat{y}_i)/n$.

Level 4 Solutions

- A16.** `exp_x = torch.exp(x); probs = exp_x / exp_x.sum()`
- A17.** `loss = ((y_true - y_pred)**2).mean()`
- A18.** `torch.bmm(A,B)`. Output: '(32, 10, 30)'.
- A19.** `image.permute(1, 2, 0)`. Converts Channel-First to Channel-Last.
- A20.** $\theta_{new} = \theta_{old} - 0.1[2, -3] = \theta_{old} + [-0.2, 0.3]$. Subtract to go against gradient (descent).

Speed Hacks & Memory Techniques

Mental Models

- Tensor:** Just a fancy multi-dimensional array on steroids (GPU + Grads).
- BCHW:** Image dimensions are always Batch, Channel, Height, Width.
- Autograd Pipes:** Imagine water flowing backward through pipes. Gradients are valves.

Coding Speed Hacks

- Use `torch.zeros_like(x)` to copy shape and device simultaneously.
- Use `with torch.no_grad():` during inference to prevent memory explosion.
- Never do `x += 1` if tracking grads. Do `x = x + 1`.

Final Exam: Check Your Intuition

Question	Quick Answer
What does $\mathbb{R}^{3 \times 4}$ mean?	A matrix with 3 rows and 4 columns of real numbers.
Shape of $(AB)^T$ if $A_{(2 \times 3)}, B_{(3 \times 4)}$?	(4×2) . The matrix multiplication yields (2×4) , transpose flips it.
Why write <code>loss.backward()</code> ?	Triggers the computation graph to calculate $\partial L / \partial w$ for all weights.
How to fix device errors?	Ensure data <code>x</code> and <code>model</code> are both on <code>.to('cuda')</code> or <code>'cpu'</code> .

Lock-In Complete. $\nabla L \rightarrow 0$

You now have the mathematical and practical foundation to build neural networks.