Study Material - Youtube

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Video Overview

This video serves as a practical, hands-on tutorial introducing the fundamentals of the PyTorch library, with a specific focus on its core data structure: the **Tensor**. It is the second tutorial in a course on Deep Generative Models, bridging the gap between the mathematical theory of neural networks and their practical implementation. The instructor walks through the official PyTorch documentation and a Google Colab notebook to demonstrate how to create, manipulate, and perform operations on tensors, which are the building blocks for all models in PyTorch.

Learning Objectives

Upon completing this tutorial, students will be able to: - Understand the role of PyTorch and Google Colab in deep learning development. - Define what a Tensor is and explain its similarity and key differences with NumPy arrays. - Initialize Tensors in various ways: from Python lists, NumPy arrays, and by specifying shape and data type. - Identify and interpret the fundamental attributes of a Tensor: `shape`, `dtype`, and `device`. - Perform essential arithmetic operations on Tensors, distinguishing between matrix multiplication and element-wise multiplication. - Join multiple tensors together using concatenation. - Understand how to run computations on different hardware like CPUs and GPUs.

Prerequisites

To fully benefit from this tutorial, students should have a foundational understanding of: - **Python Programming**: Familiarity with basic syntax, data structures (especially lists), and the concept of libraries. - **NumPy**: Basic knowledge of NumPy arrays is helpful, as PyTorch Tensors are conceptually similar. - **Neural Network Fundamentals**: A basic understanding of Multi-Layer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), forward propagation, and backpropagation is assumed, as mentioned by the instructor (01:39, 02:18). - **Previous Lecture Concepts**: Familiarity with the concepts of forward and backward propagation, gradient computation, and the overall training procedure discussed in the previous tutorial (01:41).

Key Concepts Covered in This Video

- **PyTorch**: A deep learning framework for building and training neural networks.
- **Google Colab**: A cloud-based platform providing free access to computing resources, including GPUs, for running code notebooks.
- **Tensors**: The fundamental, specialized data structure in PyTorch, similar to multi-dimensional arrays, used to encode model inputs, outputs, and parameters.
- **Tensor Initialization**: Methods for creating tensors, including `torch.tensor()`, `torch.from_numpy()`, `torch.ones()`, `torch.rand()`, and `torch.zeros()`.
- **Tensor Attributes**: Properties of a tensor, such as its dimensions (`shape`), data type (`dtype`), and the device it's stored on (`device`).
- **Tensor Operations**: Arithmetic and manipulation functions like matrix multiplication (`@` or `matmul`), element-wise product (`*` or `mul`), and concatenation (`torch.cat`).

Introduction to PyTorch and Course Logistics

The Role of PyTorch in the Course

(00:20) The instructor begins by positioning this tutorial within the broader context of the Deep Generative Models (DGM) course. While much of the course focuses on the **mathematical theory** behind generative models, these tutorials are designed to provide the practical skills needed to **implement** those models.

(00:25) **PyTorch** is introduced as the primary tool for this implementation. It is a powerful open-source machine learning library that simplifies the process of building and training complex neural networks.

The course follows a dual-track approach, which can be visualized as follows:

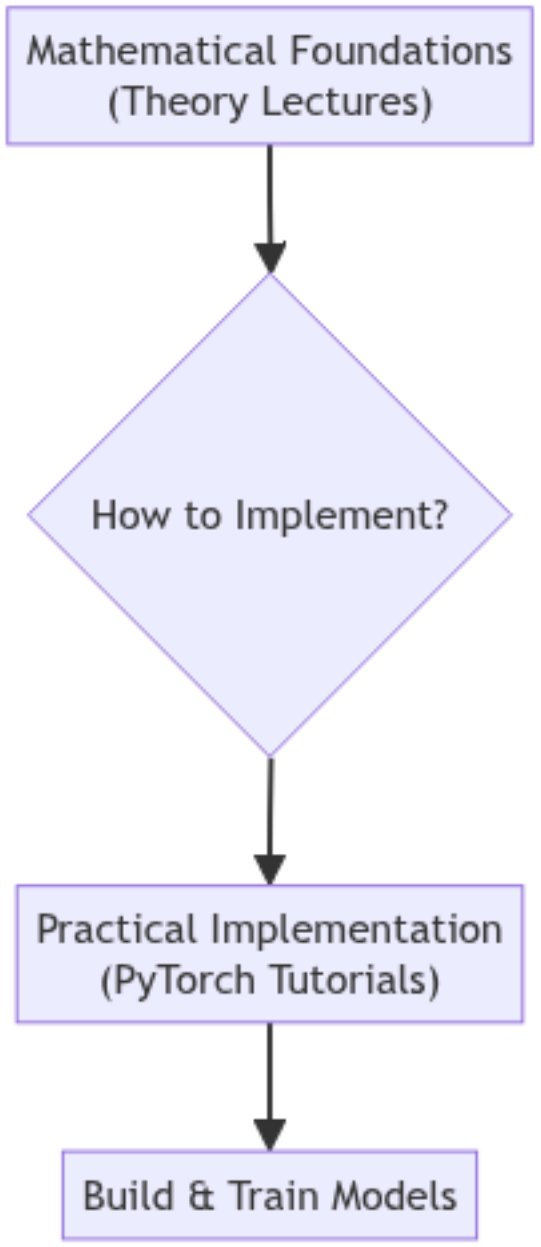


Figure 1: The learning path, combining theoretical knowledge with practical implementation using PyTorch.

The Coding Environment: Google Colab

(00:54) The instructor specifies that all coding exercises in the course will be conducted using **Google Colab**.

> **What is Google Colab?** Google Colaboratory, or "Colab," is a free, cloud-based Jupyter notebook environment. It allows you to write and execute Python code directly in your browser. Crucially for deep learning, it provides access to powerful hardware accelerators like **GPUs (Graphics Processing Units)** and TPUs (Tensor Processing Units) at no cost.

(01:00) The instructor highlights a key benefit: Google Colab provides access to a simple GPU (e.g., a 12GB GPU), which is sufficient for the models that will be built in this course. This removes the need for students to

have powerful, expensive hardware locally. All necessary libraries and packages are pre-installed, eliminating complex setup procedures.

Deep Dive into PyTorch Tensors

The core of this tutorial is understanding **Tensors**, the fundamental building block of PyTorch. The instructor uses the official PyTorch tutorials and a Google Colab notebook to demonstrate these concepts.

What are Tensors? An Intuitive Foundation

(08:13) Tensors are introduced as specialized data structures that are conceptually very similar to **arrays and matrices**. If you are familiar with NumPy's `ndarray`, you will find Tensors intuitive.

- **Purpose**: In PyTorch, tensors are used to encode all numerical data associated with a model. This includes:
  - **Inputs**: The data you feed into the model (e.g., images, text).
  - **Outputs**: The predictions made by the model.
  - **Model's Parameters**: The weights and biases that the model learns during training.
- **Key Advantage over NumPy**: The most significant advantage of PyTorch Tensors is their ability to run on **GPUs and other hardware accelerators** (08:43). This dramatically speeds up the massive parallel computations required for training deep neural networks. NumPy arrays, in contrast, are limited to CPU computations.

Initializing a Tensor

(09:26) Tensors can be created in several ways. The instructor demonstrates the most common methods using a Google Colab notebook.

1. Directly from Data

You can create a tensor directly from a Python list. The data type is automatically inferred.

Code Example (10:36):

```
# Import the necessary libraries
import torch
import numpy as np

# Create a tensor from a Python list
data = [[1, 2], [3, 4]]
x_data = torch.tensor(data)

print(x_data)
```

Explanation: - `data` is a standard 2x2 Python list. - `torch.tensor(data)` converts this list into a PyTorch tensor. The resulting `x_data` will have the same structure and values.

2. From a NumPy Array

PyTorch provides seamless interoperability with NumPy. You can create a tensor from a NumPy array and vice-versa.

> **Important Note:** When converting a NumPy array to a PyTorch tensor (and vice-versa), they can share the same underlying memory location. This means that changing the NumPy array

will change the tensor, and vice-versa. This is a powerful feature for efficiency but requires careful handling.

Code Example (11:43):

```
# Create a NumPy array from the 'data' list
np_array = np.array(data)

# Create a tensor from the NumPy array
x_np = torch.from_numpy(np_array)

print(x_np)
```

Explanation: - `np.array(data)` first creates a standard NumPy array. - `torch.from_numpy(np_array)` creates a tensor that shares its memory with `np_array`.

3. From Another Tensor

You can create a new tensor that inherits the properties (like shape and data type) of an existing tensor. This is useful when you need a tensor of the same dimensions but with different values.

Code Example (13:25):

```
# Create a tensor of all ones with the same properties as x_data
x_ones = torch.ones_like(x_data) # retains the properties of x_data
print(f"Ones Tensor: \n {x_ones} \n")

# Create a tensor with random values, overriding the datatype to float
x_rand = torch.rand_like(x_data, dtype=torch.float) # overrides the datatype of x_data
print(f"Random Tensor: \n {x_rand} \n")
```

Explanation: - `torch.ones_like(x_data)` creates a new tensor `x_ones` with the same shape (2x2) and data type (integer) as `x_data`, but filled with the value 1. - `torch.rand_like(x_data, dtype=torch.float)` creates a tensor `x_rand` with the same shape but fills it with random numbers between 0 and 1. The `dtype` argument explicitly overrides the original integer type to `torch.float`.

4. With Random or Constant Values (Specifying Shape)

You can also create tensors by directly specifying their shape (dimensions).

Code Example (15:05):

```
# Define the shape as a tuple
shape = (2, 3,)

# Create tensors with the specified shape
rand_tensor = torch.rand(shape)
ones_tensor = torch.ones(shape)
zeros_tensor = torch.zeros(shape)

print(f"Random Tensor: \n {rand_tensor} \n")
print(f"Ones Tensor: \n {ones_tensor} \n")
print(f"Zeros Tensor: \n {zeros_tensor} \n")
```

Explanation: - `shape = (2, 3,)` defines the desired dimensions: 2 rows and 3 columns. - `torch.rand(shape)` creates a 2x3 tensor with random values. - `torch.ones(shape)` creates a 2x3 tensor filled with 1s. - `torch.zeros(shape)` creates a 2x3 tensor filled with 0s.

Attributes of a Tensor

(16:31) Every tensor has attributes that describe its structure and where it is stored.

Code Example:

```
tensor = torch.rand(3, 4)

print(f"Shape of tensor: {tensor.shape}")
print(f"Datatype of tensor: {tensor.dtype}")
print(f"Device tensor is stored on: {tensor.device}")
```

Output:

```
Shape of tensor: torch.Size([3, 4])
Datatype of tensor: torch.float32
Device tensor is stored on: cpu
```

Explanation: - `tensor.shape`: Returns a tuple representing the dimensions of the tensor. Here, it's a 3x4 matrix. - `tensor.dtype`: Specifies the data type of the elements in the tensor (e.g., `float32`, `int64`). - `tensor.device`: Indicates the hardware where the tensor is stored. By default, it's the `cpu`. To move it to a GPU, you would use `tensor.to('cuda')`.

Operations on Tensors

PyTorch supports a vast library of over 1200 operations. The tutorial covers the most essential ones.

Joining Tensors

(18:32) You can concatenate a sequence of tensors along a given dimension using `torch.cat`.

Code Example (19:03):

```
# Create a 4x4 tensor of ones
tensor = torch.ones(4, 4)

# Concatenate three copies of the tensor along dimension 1 (columns)
t1 = torch.cat([tensor, tensor, tensor], dim=1)
print(t1)
```

Explanation: - `dim=1` specifies that the concatenation should happen along the columns. The original 4x4 tensor is repeated three times side-by-side, resulting in a 4x12 tensor. - If `dim=0` were used, the tensors would be stacked vertically (along rows), resulting in a 12x4 tensor.

Arithmetic Operations

This is a critical part of deep learning, and the instructor distinguishes between two types of multiplication.

1. Matrix Multiplication (22:42) This is the standard matrix product from linear algebra. - **How to perform it**: 1. Using the `@` symbol: `y1 = tensor @ tensor.T` 2. Using the `tensor.matmul()` method: `y2 = tensor.matmul(tensor.T)` 3. Using the `torch.matmul()` function: `y3 = torch.matmul(tensor, tensor.T)`

Code Example:

```
# This computes the matrix multiplication between two tensors.
tensor = torch.ones(4, 4)
y1 = tensor @ tensor.T
y2 = tensor.matmul(tensor.T)
```

Mathematical Intuition (21:32): For two matrices A of size $m \times n$ and B of size $n \times p$ to be multiplied, the number of columns in A must equal the number of rows in B. The resulting matrix $C = A \times B$ will have the size $m \times p$.

$$A_{m \times n} \times B_{n \times p} = C_{m \times p}$$

2. Element-wise Product (Hadamard Product) (25:08) This operation multiplies corresponding elements of two tensors. The tensors must have the same shape.

- **How to perform it**:
  1. Using the `*` symbol: `z1 = tensor * tensor`
  2. Using the `tensor.mul()` method: `z2 = tensor.mul(tensor)`
  3. Using the `torch.mul()` function: `z3 = torch.mul(tensor, tensor)`

Mathematical Intuition (25:32): If you have two matrices A and B of the same size $m \times n$, their element-wise product $C = A \odot B$ is a matrix where each element C_{ij} is the product of the corresponding elements A_{ij} and B_{ij}.

$$\text{If } A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \text{ and } B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, \text{ then } C = A \odot B = \begin{pmatrix} a_{11}b_{11} & a_{12}b_{12} \\ a_{21}b_{21} & a_{22}b_{22} \end{pmatrix}$$

This operation is fundamental in many neural network layers, especially in attention mechanisms and gating.

Visual Elements from the Video

- **PyTorch Tutorials Page (00:11)**: The instructor starts by showing the main landing page for PyTorch tutorials, highlighting the "Learn the Basics" section which forms the basis of the lecture.
- **Stanford CS231n Course Notes (02:53)**: The instructor recommends the Stanford CS231n course notes as an excellent resource for understanding the fundamentals of CNNs. A visual of the course page is shown.
- **CNN Convolution Diagram (03:30)**: A detailed diagram from the CS231n notes is shown, illustrating how a convolutional layer works. It depicts an input volume, a filter (kernel) sliding across it, and the resulting output volume (activation map). This visual is crucial for understanding the mechanics of convolution.
- **Google Colab Notebook (06:46)**: The majority of the tutorial takes place within a Google Colab notebook, where the instructor executes code snippets live to demonstrate tensor creation and operations.
- **Handwritten Matrix Multiplication Rules (21:27)**: The instructor uses a digital whiteboard to quickly sketch the rules for matrix multiplication, emphasizing that the inner dimensions must match.

Self-Assessment for This Video

1. **Question**: What is the primary advantage of using PyTorch Tensors over NumPy arrays for deep learning?
2. **Question**: Explain the difference between `torch.ones_like(x)` and `torch.ones(x.shape)`.
3. **Exercise**: Write the code to create a 5x5 tensor initialized with random numbers. Then, convert this tensor into a NumPy array.
4. **Question**: What are the three main attributes of a tensor discussed in the video? Describe each one.
5. **Exercise**: You have two tensors, `A` and `B`, both of shape (10, 20). Write three different lines of code that would compute their element-wise product.

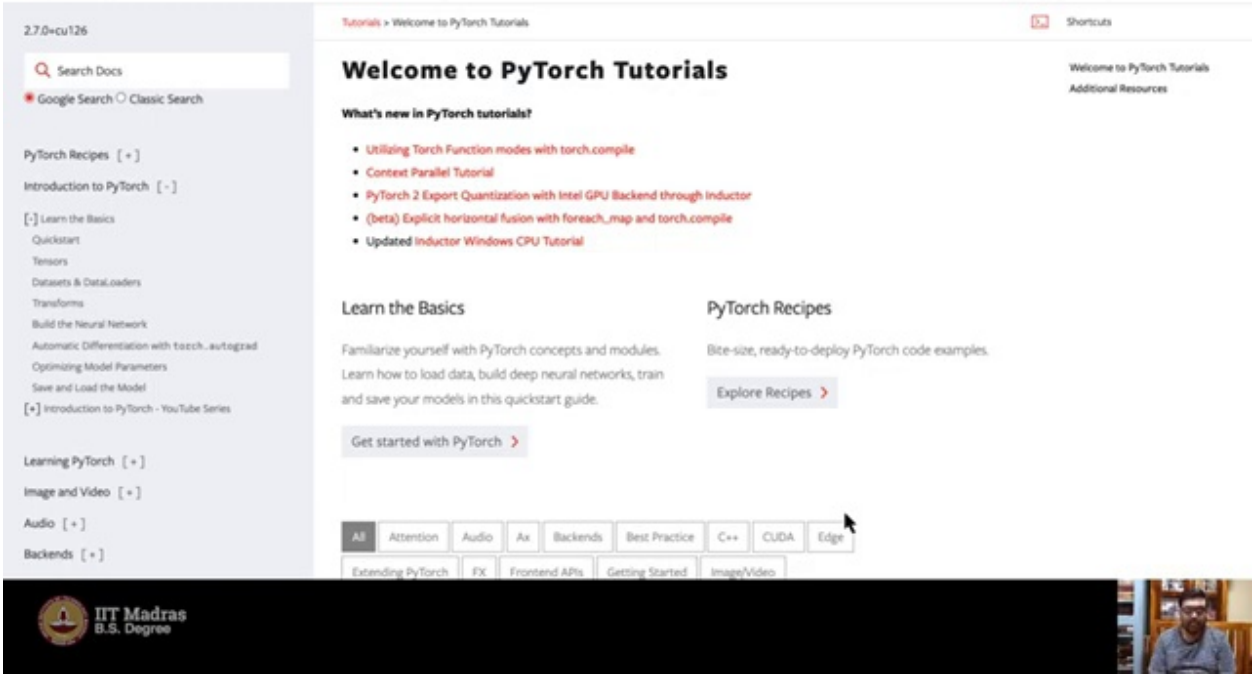
6. **Question**: You have a tensor `T` with `shape=(4, 4)`. What is the shape of `T @ T.T`? What is the shape of `torch.cat([T, T], dim=0)`?
7. **Application**: Why is it useful to run code on a GPU using a platform like Google Colab?

Key Takeaways from This Video

- **PyTorch is the Practical Tool for Theory**: PyTorch allows you to translate the mathematical concepts of deep learning into working code.
- **Tensors are Fundamental**: Everything in PyTorch revolves around the Tensor data structure. Mastering its creation and manipulation is the first step to becoming proficient.
- **GPU Acceleration is Key**: The ability of Tensors to leverage GPUs is what makes training large deep learning models feasible.
- **Google Colab Democratizes Access**: Platforms like Google Colab provide the necessary computational resources for free, making deep learning accessible to everyone.
- **Operations are Specific**: It is crucial to distinguish between matrix multiplication (`matmul` or `@`) and element-wise product (`mul` or `*`), as they serve different purposes and are used in different contexts within neural networks.

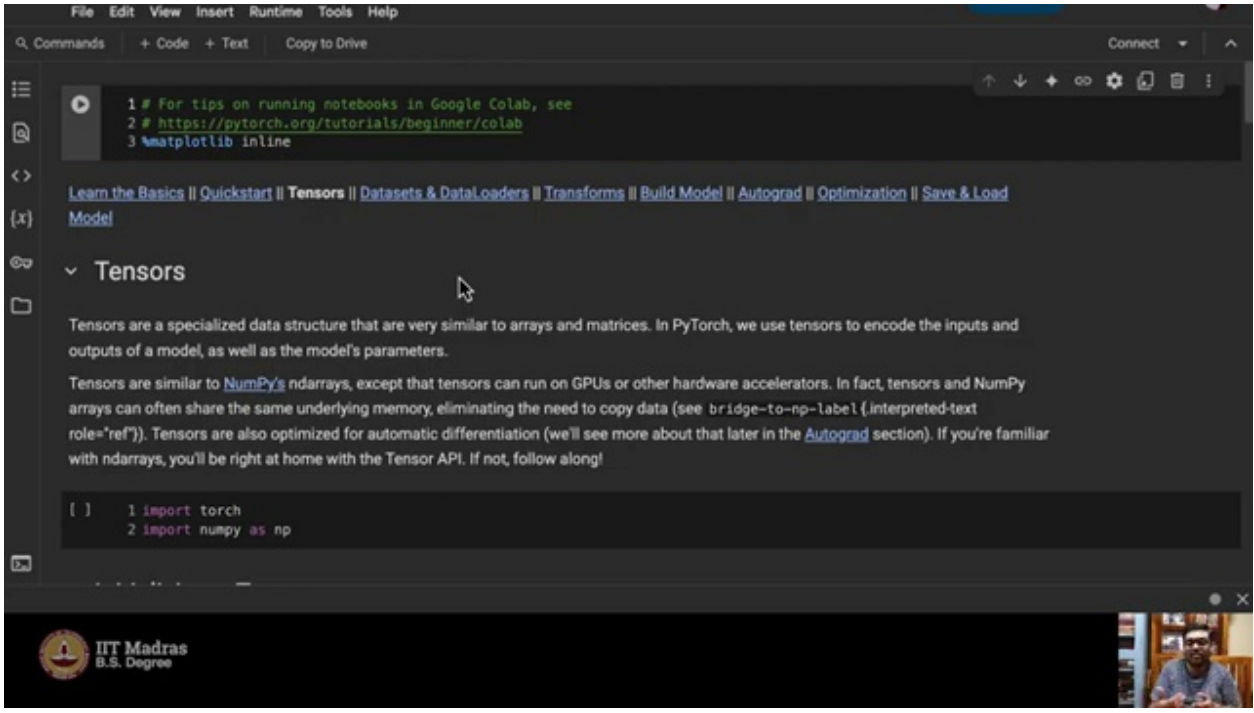
Visual References

Code example showing the creation of a PyTorch Tensor directly from a NumPy array. This is a key concept that visually demonstrates the interoperability between the two libraries. (at 04:45):

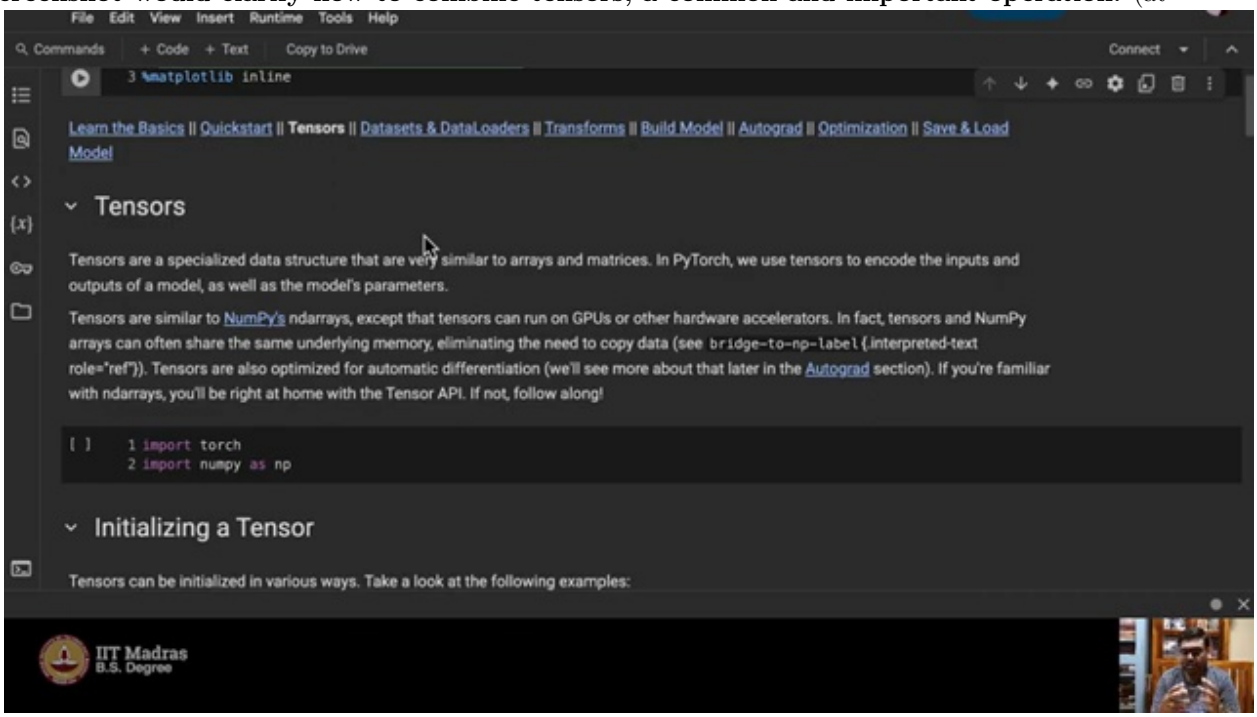


A screenshot displaying a tensor's fundamental attributes (`shape`, `dtype`, `device`) being accessed and printed in the code notebook. This is crucial for understanding and debugging tensor proper-

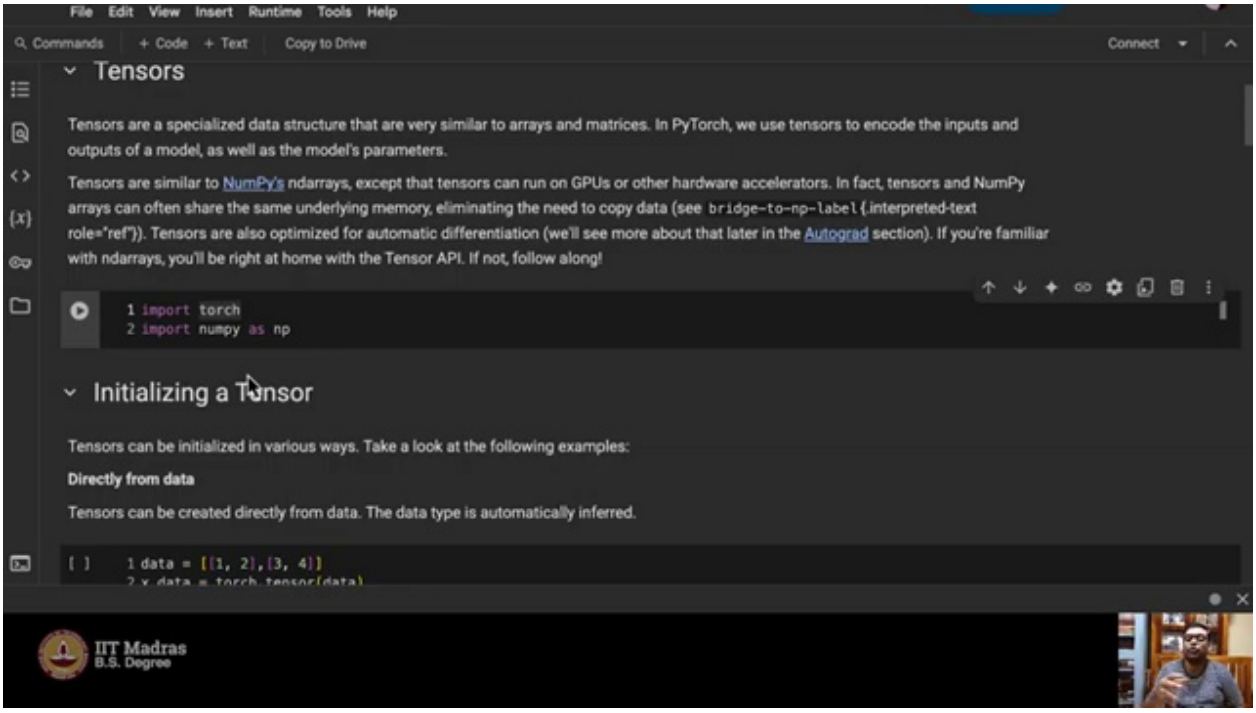
ties. (at 07:15):



A visual demonstration of `torch.cat` joining multiple tensors along a specific dimension (dim=1). This screenshot would clarify how to combine tensors, a common and important operation. (at 09:00):



Code and output comparing element-wise multiplication (`*`) with matrix multiplication (`@`). This highlights a critical operational difference that is a common point of confusion for beginners. (at

09:45): 
File Edit View Insert Runtime Tools Help
Commands + Code + Text Copy to Drive Connect
Tensors
Tensors are a specialized data structure that are very similar to arrays and matrices. In PyTorch, we use tensors to encode the inputs and outputs of a model, as well as the model's parameters.
Tensors are similar to NumPy's ndarrays, except that tensors can run on GPUs or other hardware accelerators. In fact, tensors and NumPy arrays can often share the same underlying memory, eliminating the need to copy data (see bridge-to-np-label{.interpreted-text role="ref"}). Tensors are also optimized for automatic differentiation (we'll see more about that later in the Autograd section). If you're familiar with ndarrays, you'll be right at home with the Tensor API. If not, follow along!
1 import torch
2 import numpy as np
Initializing a Tensor
Tensors can be initialized in various ways. Take a look at the following examples:
Directly from data
Tensors can be created directly from data. The data type is automatically inferred.
[ ] 1 data = [[1, 2],[3, 4]]
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