Tensors are the fundamental building blocks for performing mathematical operations in deep learning models.

Today, I will provide a comprehensive explanation with illustrative code examples.

Let's go! 🚀

Tensors are multi-dimensional arrays that form the backbone of numerical computing!

In PyTorch, creating tensors is a breeze!

You can initialize tensors from lists, zeros, ones, or even random values!

Initializing a Tensor

```
import numpy as np
# From data stored in list
data = [[1, 2], [3, 4]]
x_data = torch.tensor(data)
# From a NumPy array
np_array = np.array(data)
x_np = torch.from_numpy(np_array)
# With random or constant values:
shape=(2, 2)
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}")
```



```
Random Tensor:
tensor([[0.5689, 0.9375],
         [0.5977, 0.9958]])
  Ones Tensor:
> tensor([[1., 1.],
         [1., 1.]])
   Zeros Tensor:
   tensor([[0., 0.],
           [o., o.]])
```



Every tensor has attributes like `dtype`, `shape`, and `device` which tells us about the nature of the tensor.

Tensors can live on CPU or GPU, and PyTorch makes it seamless to perform operations between them!

Check this out 👇

Attributes of a tensor

```
• •
```

```
import numpy as np
import torch

tensor = torch.rand(2,3)

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

Tensor is stored on: cpu
```

Moving tensors to GPU

```
#  We move our tensor to the GPU if available
tensor = torch.rand(2, 3)
if torch.cuda.is_available():
    tensor = tensor.to("cuda")
```



You can perform a variety of operations on tensors, like addition, element-wise multiplication, and matrix multiplication!

Operations on tensors

```
import numpy as np
import torch
                                                            > First row: tensor([1., 1., 1., 1.])
# 
Standard indexing and slicing just like NumPy
tensor = torch.ones(4, 4)
print(f"First row: {tensor[0]}")-
                                                          → First column: tensor([1., 1., 1., 1.])
print(f"First column: {tensor[:, 0]}") -
print(f"Last column: {tensor[..., -1]}")-
                                                              Last column: tensor([1., 1., 1., 1.])
tensor[:,1] = 0
print(tensor)—
                                                                > tensor([[1., 0., 1., 1.],
                                                                           [1., 0., 1., 1.]
# Arithmetic Ops
# Matrix multiplication
                                                                           [1., 0., 1., 1.]
v1 = tensor.matmul(tensor.T)
                                                                          [1., 0., 1., 1.]])
# Element-wise product.
z1 = tensor * tensor
                                                                           tensor([[6., 5., 6., 6.]
# Inplace Ops
                                                                                  [6., 5., 6., 6.],
# Notive the underscore(_) after add
tensor.add_(5)
                                                                                   [6., 5., 6., 6.]
print(tensor).
                                                                                  [6., 5., 6., 6.]])
```





Bridge with NumPy!

Tensors in PyTorch have a close relationship with NumPy arrays.

They share a lot of similarities, making transitioning between them a breeze!

Bridge with NumPy

Tensors on the CPU and NumPy arrays can share their underlying memory locations, and changing one will change the other.

```
import torch
import numpy as np
# e Let's define a tensor 't' and
# and numpy array 'n' using the same tensor
                                                         > tensor: tensor([1., 1., 1., 1., 1.])
t = torch.ones(5)
print(f"tensor: {t}") --
n = t.numpy()
                                                         → numpy array: ([1., 1., 1., 1., 1.])
print(f"numpy array: {n}") —
# O Let's add one to t and check how it
# affects n; check this out -
                                                         > tensor: tensor([2., 2., 2., 2., 2.])
t.add_{-}(1)
print(f"tensor: {t}")
print(f"numpy array: {n}") -
                                                        > numpy array: ([2., 2., 2., 2., 2.])
```



Bridge with NumPy

Tensors on the CPU and NumPy arrays can share their underlying memory locations, and changing one will change the other.

```
import torch
import numpy as np
# e Let's define a tensor 't' and
# and numpy array 'n' using the same tensor
                                                          > tensor: tensor([1., 1., 1., 1., 1.])
t = torch.ones(5)
print(f"tensor: {t}") --
n = t.numpy()
                                                         → numpy array: ([1., 1., 1., 1., 1.])
print(f"numpy array: {n}") —
# O Let's add one to t and check how it
# affects n; check this out -
                                                          > tensor: tensor([2., 2., 2., 2., 2.])
t.add_{-}(1)
print(f"tensor: {t}")
print(f"numpy array: {n}") -
                                                        > numpy array: ([2., 2., 2., 2., 2.])
```

