

Guidebook to Exercise 2 (Tensors)

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2025-10-22

1 Tensors: The Fundamental PyTorch Data Structure

A **tensor** is a generalization of vectors and matrices to an arbitrary number of dimensions.

- A **0-D tensor** is a scalar (`torch.tensor(5)`)
- A **1-D tensor** is a vector (`torch.tensor([1,2,3])`)
- A **2-D tensor** is a matrix
- A **3-D tensor** or higher is used for structured data (e.g., images, batches)

Tensors hold numerical data and are the foundation of all computations in PyTorch, from deep learning to numerical simulation.

2 Creating Tensors

Use `torch.tensor()` to create tensors directly from Python lists:

```
tensor = torch.tensor([1, 2, 3, 4, 5, 6])
```

Shape and Size

Each tensor has a **shape**, which defines its dimensionality:

```
tensor.shape      # torch.Size([6])
```

You can reshape tensors using:

```
torch.reshape(tensor, (rows, cols))
```

Example transformations:

- $(2, 3) \rightarrow 2$ rows, 3 columns
- $(3, 2) \rightarrow 3$ rows, 2 columns
- $(3, 2, 1) \rightarrow$ a 3-D tensor with 3 “blocks”

3 Tensor Initialization

PyTorch provides convenience functions for creating constant or random tensors:

Function	Description	Example
<code>torch.full(size, value)</code>	Tensor filled with a constant	<code>torch.full([2,3], 9)</code>
<code>torch.ones(size)</code>	Tensor of ones	<code>torch.ones([3,3])</code>
<code>torch.zeros(size)</code>	Tensor of zeros	<code>torch.zeros([3,3])</code>
<code>torch.arange(start, end)</code>	Sequence of numbers	<code>torch.arange(0,5)</code>

4 Stacking and Concatenation

`torch.stack()` joins multiple tensors along a new dimension.

```
x = torch.tensor([1, 4])
y = torch.tensor([2, 5])
z = torch.tensor([3, 6])
torch.stack([x, y, z])          # shape: (3, 2)
torch.stack([x, y, z], dim=1)  # shape: (2, 3)
```

- `dim=0` adds a new row dimension
- `dim=1` stacks along columns

5 Indexing and Slicing

You can access elements or slices of tensors using Python indexing syntax. Examples:

Operation	Description	Output
<code>tensor[2:-2]</code>	Elements between indices 2 and -2	<code>[3, 4]</code>
<code>tensor[:, :2]</code>	Every other element	e.g., <code>[1, 3, 5]</code>
<code>tensor[torch.tensor(0)]</code>	First row	<code>[1, 2, 3]</code>
<code>tensor[:, torch.tensor(0)]</code>	First column	<code>[1, 4, 7]</code>

Equivalent forms:

```
tensor[0]
tensor[0, :]  
tensor[0, ...]
```

6 Broadcasting

Broadcasting allows operations between tensors of different shapes by expanding one to match the other without copying data.

Expression	Description	Output shape
$a + b$ (both scalars)	Simple addition	scalar
$a=[1,2]$, $b=4$	b is broadcast to match a	$[5,6]$
$a=[[1,2,3],[4,5,6]]$, $b=[10,20,30]$	b broadcast across rows	$(2,3)$
$a=[[1,2,3],[4,5,6]]$, $b=[[1],[2]]$	b broadcast across columns	$(2,3)$

Broadcasting rules:

1. Start comparing shapes from the rightmost dimension
2. Dimensions must be equal, or one must be 1
3. Missing dimensions are treated as 1

7 Arithmetic and Matrix Operations

PyTorch supports all standard arithmetic operators:

Operation	Description
$+$, $-$, $*$, $/$, $\%$, $//$	Element-wise operations
@ or <code>torch.matmul()</code>	Matrix multiplication

Example:

```
a = torch.tensor([[1, 2]])  
b = torch.tensor([[3], [4]])  
a @ b  # matrix multiplication → tensor([[11]])
```

8 Reduction Operations

Reduction operations collapse tensor dimensions by applying an aggregation function:

Function	Description	Example
<code>torch.max(t)</code>	Maximum element overall	<code>tensor(6)</code>
<code>torch.max(t, dim=0)</code>	Max along the first axis	values + indices
<code>torch.mean(t, dim=1)</code>	Mean along the second axis	<code>[0.33, 4.00]</code>
<code>torch.sum(x, dim=1, keepdim=True)</code>	Keeps reduced dimension	<code>[[3],[3]]</code>

9 Norms and Vector Lengths

The **L2 norm** (Euclidean length) of a vector measures its distance from the origin:

```
torch.linalg.vector_norm(x, ord=2, dim=1)
```

- With `dim`: computes per-row norm
- Without `dim`: reduces the entire tensor

10 Type Inference and Dtypes

Tensors can have different data types (`dtype`), such as:

- `torch.float32`, `torch.float64` (floating point)
- `torch.int32`, `torch.int64` (integers)

Be cautious: if you create a tensor from integers, operations like `torch.mean()` may produce integer outputs unless you specify `dtype=torch.float`.

Example:

```
torch.mean(torch.tensor([1, 0, 0], dtype=torch.float))
```