

EE-559 – Deep learning

1.5. High dimension tensors

François Fleuret

<https://fleuret.org/ee559/>

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A tensor can be of several types:

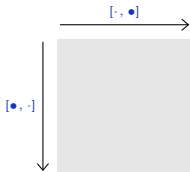
- `torch.float16`, `torch.float32`, `torch.float64`,
- `torch.uint8`,
- `torch.int8`, `torch.int16`, `torch.int32`, `torch.int64`

and can be located either in the CPU's or in a GPU's memory.

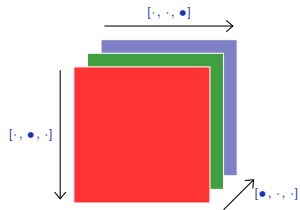
Operations with tensors stored in a certain device's memory are done by that device. We will come back to that later.

```
>>> x = torch.zeros(1, 3)
>>> x.dtype, x.device
(torch.float32, device(type='cpu'))
>>> x = x.long()
>>> x.dtype, x.device
(torch.int64, device(type='cpu'))
>>> x = x.to('cuda')
>>> x.dtype, x.device
(torch.int64, device(type='cuda', index=0))
```

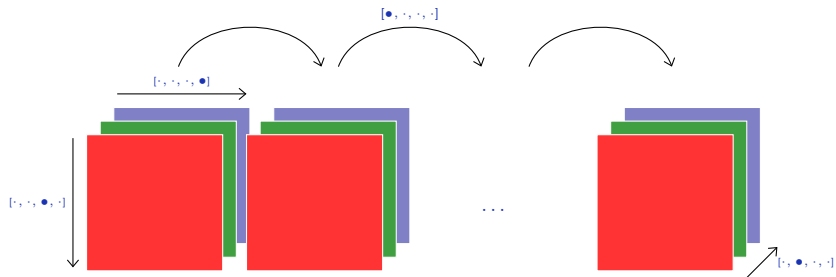
2d tensor (e.g. grayscale image)



3d tensor (e.g. rgb image)



4d tensor (e.g. sequence of rgb images)



Here are some examples from the vast library of tensor operations:

Creation

- `torch.empty(*size, ...)`
- `torch.zeros(*size, ...)`
- `torch.full(size, value, ...)`
- `torch.tensor(sequence, ...)`
- `torch.eye(n, ...)`
- `torch.from_numpy(ndarray)`

Indexing, Slicing, Joining, Mutating

- `torch.Tensor.view(*size)`
- `torch.cat(inputs, dimension=0)`
- `torch.chunk(tensor, chunks, dim=0)[source]`
- `torch.split(tensor, split_size, dim=0)[source]`
- `torch.index_select(input, dim, index, out=None)`
- `torch.t(input, out=None)`
- `torch.transpose(input, dim0, dim1, out=None)`

Filling

- `Tensor.fill_(value)`
- `torch.bernoulli_(proba)`
- `torch.normal_(μ , σ)`

Pointwise math

- `torch.abs(input, out=None)`
- `torch.add()`
- `torch.cos(input, out=None)`
- `torch.sigmoid(input, out=None)`
- (+ many operators)

Math reduction

- `torch.dist(input, other, p=2, out=None)`
- `torch.mean()`
- `torch.norm()`
- `torch.std()`
- `torch.sum()`

BLAS and LAPACK Operations

- `torch.eig(a, eigenvectors=False, out=None)`
- `torch.gels(B, A, out=None)`
- `torch.inverse(input, out=None)`
- `torch.mm(mat1, mat2, out=None)`
- `torch.mv(mat, vec, out=None)`



```
x = torch.tensor([ [ 1, 3, 0 ],  
                  [ 2, 4, 6 ] ])
```



x.t()



```
x = torch.tensor([ [ 1, 3, 0 ],  
                  [ 2, 4, 6 ] ])
```



```
x.view(-1)
```



```
x = torch.tensor([ [ 1, 3, 0 ],  
                  [ 2, 4, 6 ] ])
```



```
x.view(3, -1)
```



```
x = torch.tensor([ [ 1, 3, 0 ],  
                  [ 2, 4, 6 ] ])
```



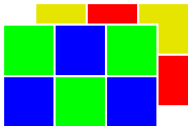
```
x.narrow(1, 1, 2)
```



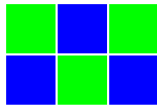
```
x = torch.tensor([ [ 1, 3, 0 ],  
                  [ 2, 4, 6 ] ])
```



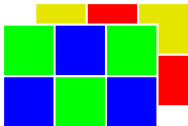
```
x.view(1, 2, 3).expand(3, 2, 3)
```



```
x = torch.tensor([ [ [ 1, 2, 1 ],  
                    [ 2, 1, 2 ] ],  
                  [ [ 3, 0, 3 ],  
                    [ 0, 3, 0 ] ] ])
```



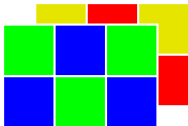
```
x.narrow(0, 0, 1)
```



```
x = torch.tensor([ [ [ 1, 2, 1 ],  
                    [ 2, 1, 2 ] ],  
                  [ [ 3, 0, 3 ],  
                    [ 0, 3, 0 ] ] ])
```



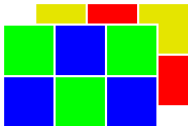
```
x.narrow(2, 0, 2)
```



```
x = torch.tensor([ [ [ 1, 2, 1 ],
                    [ 2, 1, 2 ] ],
                  [ [ 3, 0, 3 ],
                    [ 0, 3, 0 ] ] ])
```



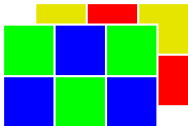
```
x.transpose(0, 1)
```

```
x = torch.tensor([ [ [ 1, 2, 1 ],
                    [ 2, 1, 2 ] ],
                  [ [ 3, 0, 3 ],
                    [ 0, 3, 0 ] ] ])
```



```
x.transpose(0, 2)
```



```
x = torch.tensor([ [ [ 1, 2, 1 ],
                    [ 2, 1, 2 ] ],
                  [ [ 3, 0, 3 ],
                    [ 0, 3, 0 ] ] ])
```



```
x.transpose(1, 2)
```

PyTorch offers simple interfaces to standard image data-bases.

```
import torch, torchvision
cifar = torchvision.datasets.CIFAR10('./cifar10/', train = True, download = True)
x = torch.from_numpy(cifar.data).permute(0, 3, 1, 2).float()
x = x / 255
print(x.type(), x.size(), x.min().item(), x.max().item())
```

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```

prints

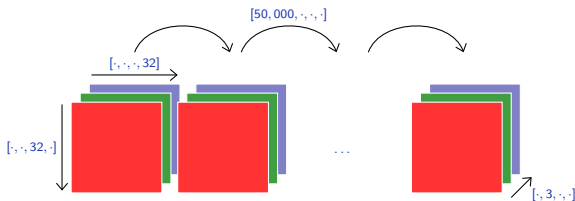
```
Files already downloaded and verified
torch.FloatTensor torch.Size([50000, 3, 32, 32]) 0.0 1.0
```

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```
import torch, torchvision
cifar = torchvision.datasets.CIFAR10('./cifar10/', train = True, download = True)
x = torch.from_numpy(cifar.data).permute(0, 3, 1, 2).float()
x = x / 255
print(x.type(), x.size(), x.min().item(), x.max().item())
```

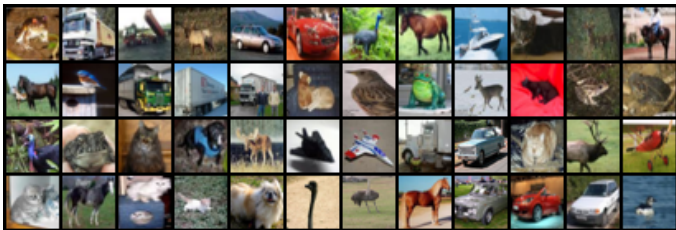
prints

```
Files already downloaded and verified
torch.FloatTensor torch.Size([50000, 3, 32, 32]) 0.0 1.0
```

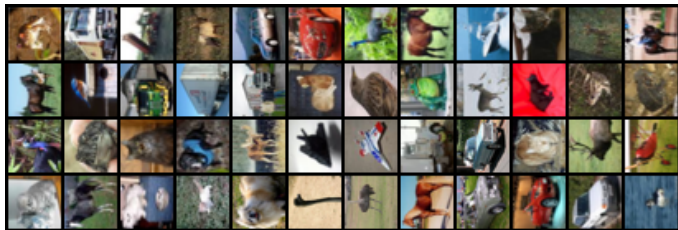


```
# Narrows to the first images, converts to float
x = x.narrow(0, 0, 48).float()

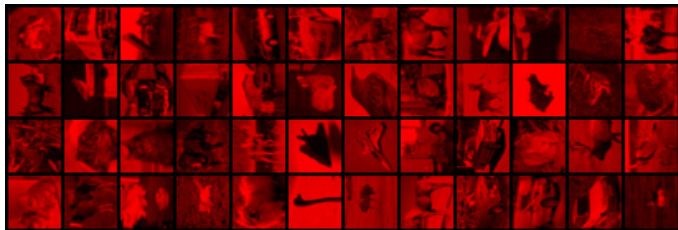
# Saves these samples as a single image
torchvision.utils.save_image(x, 'cifar-4x12.png', nrow = 12)
```



```
# Switches the row and column indexes
x.transpose_(2, 3)
torchvision.utils.save_image(x, 'cifar-4x12-rotated.png', nrow = 12)
```



```
# Kills the green and blue channels
x.narrow(1, 1, 2).fill_(0)
torchvision.utils.save_image(x, 'cifar-4x12-rotated-and-red.png', nrow = 12)
```



Broadcasting

Broadcasting automatically expands dimensions by replicating coefficients, when it is necessary to perform operations that are “intuitively reasonable”.

Broadcasting automatically expands dimensions by replicating coefficients, when it is necessary to perform operations that are “intuitively reasonable”.

For instance:

```
>>> x = torch.empty(100, 4).normal_(2)
>>> x.mean(0)
tensor([2.0476, 2.0133, 1.9109, 1.8588])
>>> x -= x.mean(0) # This should not work!
>>> x.mean(0)
tensor([-4.0531e-08, -4.4703e-07, -1.3471e-07,  3.5763e-09])
```

Precisely, broadcasting proceeds as follows:

1. If one of the tensors has fewer dimensions than the other, it is reshaped by adding as many dimensions of size 1 as necessary in the front; then
2. for every dimension mismatch, **if one of the two tensors is of size one**, it is expanded along this axis by replicating coefficients.

If there is a tensor size mismatch for one of the dimension and neither of them is one, the operation fails.

```
A = torch.tensor([[1.], [2.], [3.], [4.]])
B = torch.tensor([[5., -5., 5., -5., 5.]])
C = A + B
```

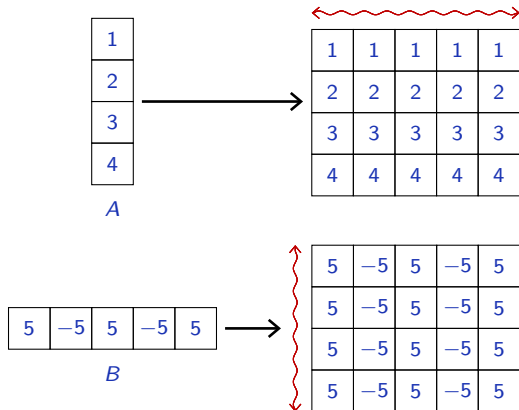
1
2
3
4

A

5	-5	5	-5	5
---	----	---	----	---

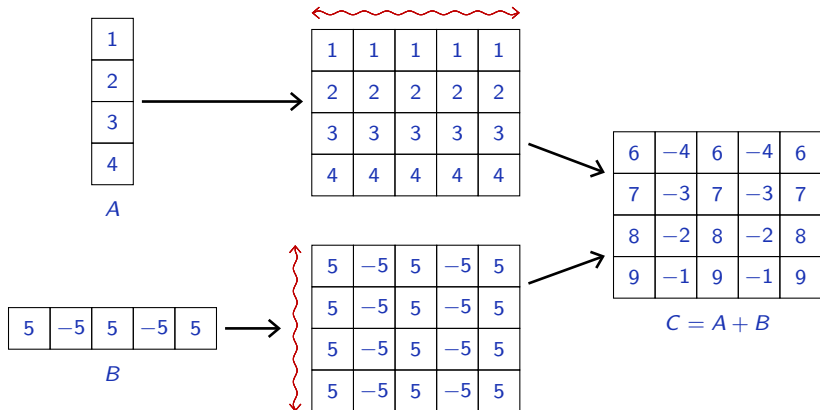
B

```
A = torch.tensor([[1.], [2.], [3.], [4.]])
B = torch.tensor([[5., -5., 5., -5., 5.]])
C = A + B
```



Broadcasted

```
A = torch.tensor([[1.], [2.], [3.], [4.]])
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C = A + B
```



Broadcasted

The end