EE-559 – Deep learning

1.5. High dimension tensors

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https://fleuret.org/ee559/

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A tensor can be of several types:

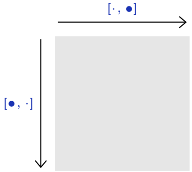
- `torch.float16`, `torch.float32`, `torch.float64`,
- `torch.uint8`,
- `torch.int8`, `torch.int16`, `torch.int32`, `torch.int64`

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

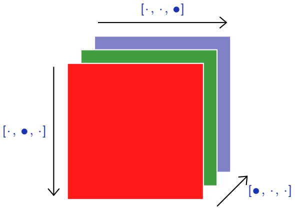
Operations with tensors stored in a certain device's memory are done by that device. We will come back to that later.

```
>>> 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))
```

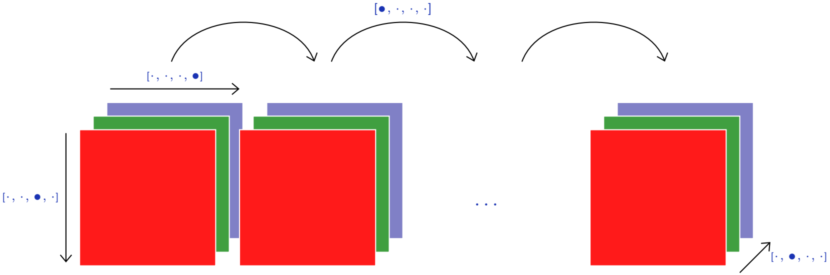
2d tensor (*e.g.* grayscale image)



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, nb_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_([mu, [std]])`

Pointwise math

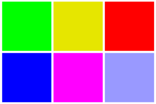
- `torch.abs(input, out=None)`
- `torch.add()`
- `torch.cos(input, out=None)`
- `torch.sigmoid(input, out=None)`
- `(+ many operators)`

Math reduction

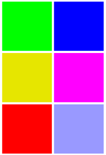
- `torch.dist(input, other, p=2, out=None)`
- `torch.mean()`
- `torch.norm()`
- `torch.std()`
- `torch.sum()`

BLAS and LAPACK Operations

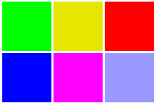
- `torch.eig(a, eigenvectors=False, out=None)`
- `torch.lstsq(B, A, out=None)`
- `torch.inverse(input, out=None)`
- `torch.mm(mat1, mat2, out=None)`
- `torch.mv(mat, vec, out=None)`



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



```
x.t()
```



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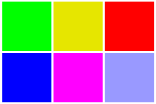
```
x.view(-1)
```



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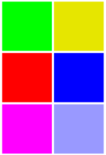
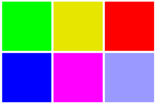


```
x.view(3, -1)
```



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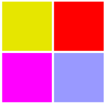
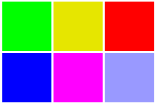


```
x[:, 1:3]
```



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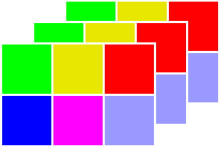
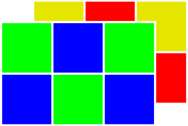
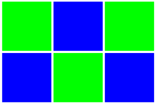


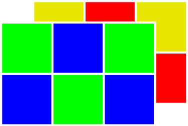
```
x.view(1, 2, 3).expand(3, 2, 3)
```



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



```
x[0:1, :, :]
```



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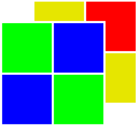
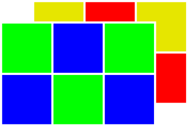


```
x[:, :, 0:2]
```



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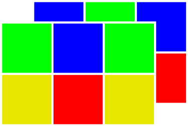
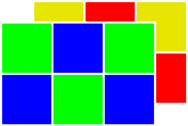


```
x.transpose(0, 1)
```



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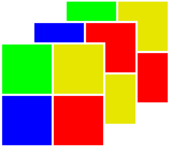
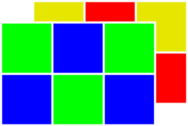


```
x.transpose(0, 2)
```



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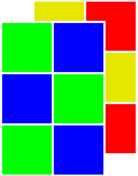

```
x.transpose(1, 2)
```

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() / 255
print(x.dtype, x.size(), x.min().item(), x.max().item())
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torch.float32 torch.Size([50000, 3, 32, 32]) 0.0 1.0
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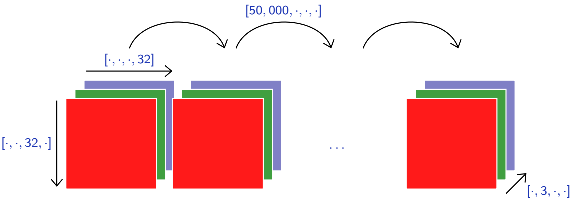
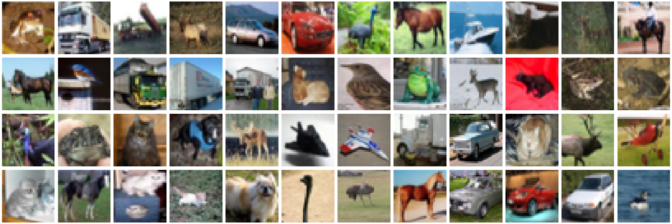
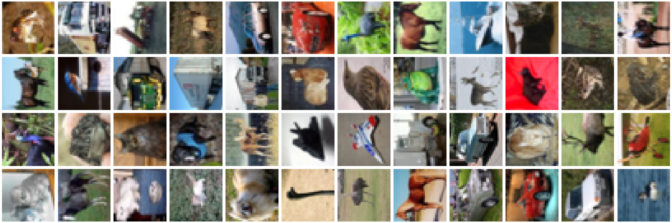


```
# Narrows to the first images, converts to float
x = x[:48]

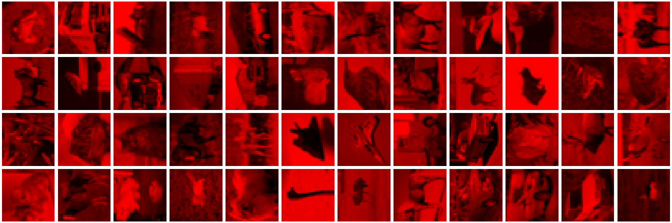
# Saves these samples as a single image
torchvision.utils.save_image(x, 'cifar-4x12.png',
                             nrow = 12, pad_value = 1.0)
```



```
# Switches the row and column indexes
x.transpose_(2, 3)
torchvision.utils.save_image(x, 'cifar-4x12-rotated.png',
                             nrow = 12, pad_value = 1.0)
```



```
# Kills the green and blue channels
x[:, 1:3].fill_(0)
torchvision.utils.save_image(x, 'cifar-4x12-rotated-and-red.png',
                             nrow = 12, pad_value = 1.0)
```



Broadcasting and dimension naming

Broadcasting automagically expands dimensions by replicating coefficients, when it is necessary to perform operations that are "intuitively reasonable".

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For instance:

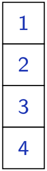
```
>>> x = torch.empty(100, 4).normal_(2)
>>> x.mean(0)
tensor([2.0476, 2.0133, 1.9109, 1.8588])
>>> x -= x.mean(0) # This should not work!
>>> x.mean(0)
tensor([-4.0531e-08, -4.4703e-07, -1.3471e-07,  3.5763e-09])
```

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
```



A

B

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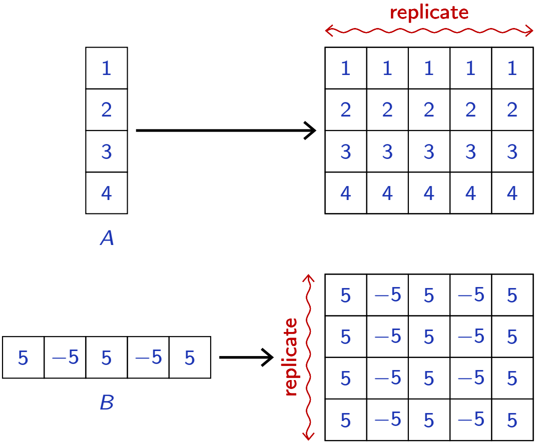

Broadcasted

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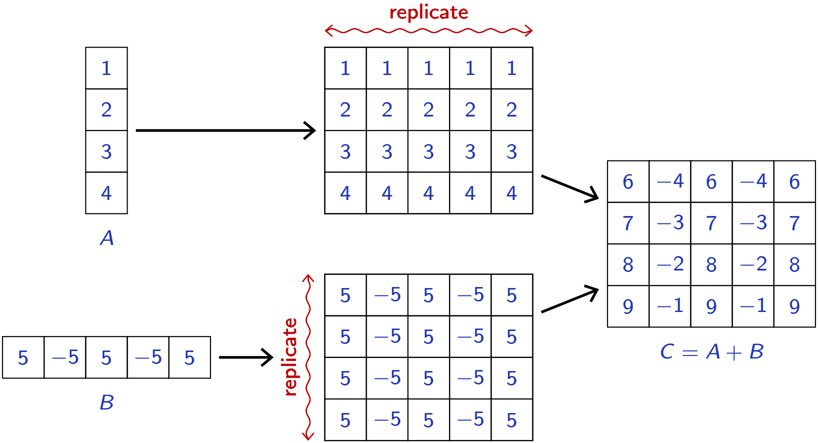

Broadcasted

To deal with complex operations, PyTorch provides a dimension naming mechanism:

```
>>> seq = torch.empty(100, 3, 1024, names = [ 'n', 'c', 't' ]).normal_()
>>> seq.mean('t').size()
torch.Size([100, 3])
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>>> time_first.size()
torch.Size([100, 1024, 3])
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>>> time_first = seq.align_to('n', 't', 'c')
>>> time_first.size()
torch.Size([100, 1024, 3])
>>> array = seq.flatten([ 'c', 't' ], 'i')
>>> array.size()
torch.Size([100, 3072])
>>> array.names
('n', 'i')
```

The end