TENSOR BASICS

```
1 import torch
2 import numpy as np
```

NumPy Arrays to PyTorch Tensors

```
1 \text{ arr} = \text{np.array}([1,2,3,4,5])
2 print(arr)
3 print(arr.dtype)
4 print(type(arr))
   [1 2 3 4 5]
   int64
   <class 'numpy.ndarray'>
1 \times = \text{torch.from numpy(arr)}
2 \# Equivalent to x = torch.as tensor(arr)
3 print(x)
4 # Print the type of data held by the tensor
5 print(x.dtype)
6 # Print the tensor object type
7 print(type(x))
8 print(x.type()) # this is more specific!
   tensor([1, 2, 3, 4, 5])
   torch.int64
   <class 'torch.Tensor'>
   torch.LongTensor
1 \operatorname{arr2} = \operatorname{np.arange}(0., 12.).\operatorname{reshape}(4,3)
2 print(arr2)
    [[ 0. 1. 2.]
    [ 3. 4. 5.]
     [ 6. 7. 8.]
     [ 9. 10. 11.]]
1 x2 = torch.from_numpy(arr2)
2 print(x2)
3 print(x2.type())
   tensor([[ 0., 1., 2.],
            [ 3., 4., 5.],
             [ 6., 7., 8.],
            [ 9., 10., 11.]], dtype=torch.float64)
   torch.DoubleTensor
```

Copying vs Sharing

torch.from_numpy(),torch.as_tensor() vs torch.tensor()

```
1 # Using torch.from numpy()
2 \operatorname{arr} = \operatorname{np.arange}(0,5)
3 t = torch.from numpy(arr)
4 print(t)
    tensor([0, 1, 2, 3, 4])
1 arr[2]=77
2 print(t)
    tensor([ 0, 1, 77, 3, 4])
1 # Using torch.tensor()
2 \operatorname{arr} = \operatorname{np.arange}(0,5)
3 t = torch.tensor(arr)
4 print(t)
    tensor([0, 1, 2, 3, 4])
1 arr[2]=77
2 print(t)
    tensor([0, 1, 2, 3, 4])
```

Class Constructors

torch.Tensor() torch.FloatTensor() torch.LongTensor()

```
1 data = np.array([1,2,3])

1 a = torch.Tensor(data)  # Equivalent to cc = torch.FloatTensor(data)
2 print(a, a.type())
    tensor([1., 2., 3.]) torch.FloatTensor

1 b = torch.tensor(data)
2 print(b, b.type())
    tensor([1, 2, 3]) torch.LongTensor

1 c = torch.tensor(data, dtype=torch.long)
2 print(c, c.type())
    tensor([1, 2, 3]) torch.LongTensor
```

Uninitialized tensors with .empty() torch.empty()

Initialized tensors with .zeros() and .ones() torch.zeros(size),torch.ones(size)

Tensors from ranges torch.arange(start,end,step), torch.linspace(start,end,steps)

Tensors from data torch.tensor()

```
1 x = torch.tensor([1, 2, 3, 4])
2 print(x)
3 print(x.dtype)
4 print(x.type())

tensor([1, 2, 3, 4])
torch.int64
```

 $1 \times = torch.FloatTensor([5.6.71)$

```
2 print(x)
3 print(x.dtype)
4 print(x.type())

   tensor([5., 6., 7.])
   torch.float32
   torch.FloatTensor

1 x = torch.tensor([8,9,-3], dtype=torch.int)
2 print(x)
3 print(x.dtype)
4 print(x.type())

   tensor([ 8,  9, -3], dtype=torch.int32)
   torch.int32
   torch.IntTensor
```

Random number tensors torch.rand(size),torch.randn(size),torch.randint(low,high,size)

```
1 \times = torch.rand(4, 3)
2 print(x)
   tensor([[0.6625, 0.2297, 0.9545],
            [0.6099, 0.5643, 0.0594],
            [0.7099, 0.4250, 0.2709],
            [0.9295, 0.6115, 0.2234]])
1 \times = torch.randn(4, 3)
2 print(x)
   tensor([[ 0.7205, -0.1121, -0.0309],
            [-0.1503, 1.8928, 1.3067],
            [-0.0662, -0.4235, -2.3768],
            [ 0.0641, -0.3435, 1.2287]])
1 \times = \text{torch.randint}(0, 5, (4, 3))
2 print(x)
   tensor([[2, 3, 3],
            [1, 1, 4],
            [1, 4, 4],
            [3, 4, 2]])
```

Random number tensors that follow the input size torch.rand_like(input), torch.randn_like(input), torch.randint_like(input,low,high)

Setting the random seed torch.manual_seed(int)

```
1 torch.manual_seed(42)
2 x = torch.rand(2, 3)
3 print(x)

   tensor([[0.8823, 0.9150, 0.3829],
        [0.9593, 0.3904, 0.6009]])

1 torch.manual_seed(42)
2 x = torch.rand(2, 3)
3 print(x)

   tensor([[0.8823, 0.9150, 0.3829],
        [0.9593, 0.3904, 0.6009]])
```

Tensor attributes

```
1 x.shape
     torch.Size([2, 3])

1 x.size()
     torch.Size([2, 3])

1 x.device
     device(type='cpu')

1 x.layout
     torch.strided
```

TENSOR OPERATIONS

Reshape tensors with .view()

Views reflect the most current data

```
1 z = x.view(2,5)

2 x[0]=234

3 print(z)
```

```
tensor([[234, 1, 2, 3, 4], [5, 6, 7, 8, 9]])
```

Views can infer the correct size

```
1 x.view(2,-1)
  tensor([[234,    1,    2,    3,    4],
       [ 5,    6,    7,    8,    9]])

1 x.view(-1,5)
  tensor([[234,    1,    2,    3,    4],
       [ 5,    6,    7,    8,    9]])
```

Adopt another tensor's shape with .view_as()

Tensor Arithmetic

```
1 a = torch.tensor([1,2,3], dtype=torch.float)
2 b = torch.tensor([4,5,6], dtype=torch.float)
3 print(a + b)
    tensor([5., 7., 9.])

1 print(torch.add(a, b))
    tensor([5., 7., 9.])

1 result = torch.empty(3)
2 torch.add(a, b, out=result) # equivalent to result=torch.add(a,b)
3 print(result)
    tensor([5., 7., 9.])

1 a.add_(b) # equivalent to a=torch.add(a,b)
2 print(a)
    tensor([5., 7., 9.])
```

Basic Tensor Operations

Arithmetic OPERATION FUNCTION DESCRIPTION

- a + b a.add(b) element wise addition
- a b a.sub(b) subtraction
- a * b a.mul(b) multiplication
- a / b a.div(b) division
- a % b a.fmod(b) modulo (remainder after division)
- ab a.pow(b) power

Monomial Operations OPERATION FUNCTION DESCRIPTION

- |a| torch.abs(a) absolute value
- 1/a torch.reciprocal(a) reciprocal
- a___√ torch.sqrt(a) square root
- log(a) torch.log(a) natural log
- e^a torch.exp(a) exponential
- 12.34 ==> 12. torch.trunc(a) truncated integer
- 12.34 ==> 0.34 torch.frac(a) fractional component

Trigonometry OPERATION FUNCTION DESCRIPTION

- sin(a) torch.sin(a) sine
- cos(a) torch.sin(a) cosine
- tan(a) torch.sin(a) tangent
- arcsin(a) torch.asin(a) arc sine
- arccos(a) torch.acos(a) arc cosine
- arctan(a) torch.atan(a) arc tangent
- sinh(a) torch.sinh(a) hyperbolic sine
- cosh(a) torch.cosh(a) hyperbolic cosine
- tanh(a) torch.tanh(a) hyperbolic tangent

Summary Statistics OPERATION FUNCTION DESCRIPTION

- $\sum a \operatorname{torch.sum}(a) \operatorname{sum}$
- a torch.mean(a) mean
- amax torch.max(a) maximum
- amin torch.min(a) minimum
- torch.max(a,b) returns a tensor of size a containing the element wise max between a and b

```
1 a = torch.tensor([1,2,3], dtype=torch.float)
2 b = torch.tensor([4,5,6], dtype=torch.float)
3 print(torch.add(a,b).sum())
    tensor(21.)
```

Dot products

```
1 #torch.dot(a,b) or a.dot(b) or b.dot(a)
2 a = torch.tensor([1,2,3], dtype=torch.float)
3 b = torch.tensor([4,5,6], dtype=torch.float)
4 print(a.mul(b)) # for reference
5 print()
6 print(a.dot(b))
  tensor([ 4., 10., 18.])
  tensor(32.)
```

Matrix multiplication

```
1 #torch.mm(a,b) or a.mm(b) or a @ b
2 = torch.tensor([[0,2,4],[1,3,5]], dtype=torch.float)
3 b = torch.tensor([[6,7],[8,9],[10,11]], dtype=torch.float)
5 print('a: ',a.size())
6 print('b: ',b.size())
7 print('a x b: ',torch.mm(a,b).size())
   a: torch.Size([2, 3])
   b: torch.Size([3, 2])
   a x b: torch.Size([2, 2])
1 print(torch.mm(a,b))
   tensor([[56., 62.],
           [80., 89.]])
1 print(a.mm(b))
   tensor([[56., 62.],
           [80., 89.]])
1 print(a @ b)
   tensor([[56., 62.],
           [80., 89.]])
```

Matrix multiplication with broadcasting

```
1 #torch.matmul(a,b) or a.matmul(b) or a @ b
2 t1 = torch.randn(2, 3, 4)
3 t2 = torch.randn(4, 5)
4
5 print(torch.matmul(t1, t2).size())
    torch.Size([2, 3, 5])
1 print(torch.mm(t1, t2).size())
```

L2 or Euclidian Norm torch.norm()

The Euclidian Norm gives the vector norm of x where x=(x1,x2,...,xn). It is calculated as ||x|| base $2:=\sqrt{x^2}$ base $1+\cdots+x^2$ base n. When applied to a matrix, torch.norm() returns the Frobenius norm by default.

```
1 x = torch.tensor([2.,5.,8.,14.])
2 x.norm()
```

Number of elements torch.numel()

```
1 x = torch.ones(3,7)
2 x.numel()

1 ##Mean Squared Error:
2 def mse(t1, t2):
3     diff = t1 - t2
4     return torch.sum(diff * diff) / diff.numel()
```