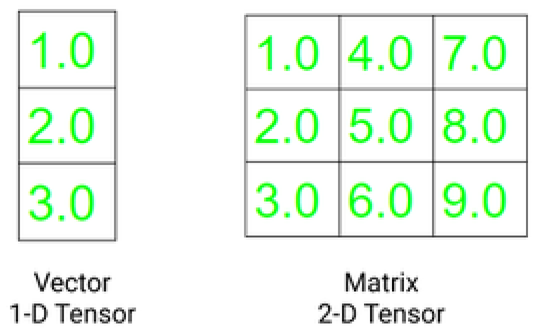
PyTorch

Pytorch is an open-source deep learning framework available with a Python and C++ interface. Pytorch resides inside the torch module. In PyTorch, the data that has to be processed is input in the form of a tensor.

PyTorch tensors:

The Pytorch is used to process the tensors. Tensors are multidimensional arrays like n-dimensional NumPy array. However, tensors can be used in GPUs as well, which is not in the case of NumPy array. PyTorch accelerates the scientific computation of tensors as it has various inbuilt functions.
A vector is a one-dimensional tensor, and a matrix is a two-dimensional tensor. One significant difference between the Tensor and multidimensional array used in C, C++, and Java is tensors should have the same size of columns in all dimensions. Also, the tensors can contain only numeric data types.



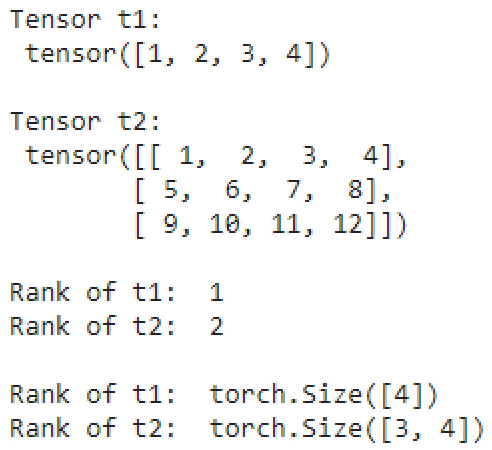
The two fundamental attributes of a tensor are:

- **Shape:** refers to the dimensionality of array or matrix
- **Rank:** refers to the number of dimensions present in tensor

```
# importing torch
import torch

# creating a tensors
t1=torch.tensor([1, 2, 3, 4])
t2=torch.tensor([[1, 2, 3, 4],
                                        [5, 6, 7, 8],
                                        [9, 10, 11, 12]])

# printing the tensors:
print("Tensor t1: \n", t1)
print("\nTensor t2: \n", t2)
```

```
# rank of tensors
print("\nRank of t1: ", len(t1.shape))
print("Rank of t2: ", len(t2.shape))

# shape of tensors
print("\nRank of t1: ", t1.shape)
print("Rank of t2: ", t2.shape)
```

Output:



```
Tensor t1:
 tensor([1, 2, 3, 4])

Tensor t2:
 tensor([[ 1,  2,  3,  4],
        [ 5,  6,  7,  8],
        [ 9, 10, 11, 12]])

Rank of t1:  1
Rank of t2:  2

Rank of t1:  torch.Size([4])
Rank of t2:  torch.Size([3, 4])
```

Creating Tensor in PyTorch

There are various methods to create a tensor in PyTorch. A tensor can contain elements of a single data type. We can create a tensor using a python list or NumPy array. The torch has 10 variants of tensors for both GPU and CPU. Below are different ways of defining a tensor.

torch.Tensor() : *It copies the data and creates its tensor. It is an alias for torch.FloatTensor.*
torch.tensor() : *It also copies the data to create a tensor; however, it infers the data type automatically.*
torch.as_tensor() : *The data is shared and not copied in this case while creating the data and accepts any type of array for tensor creation.*
torch.from_numpy() : *It is similar to tensor.as_tensor() however it accepts only numpy array.*

```
# importing torch module
import torch
import numpy as np

# list of values to be stored as tensor
data1 = [1, 2, 3, 4, 5, 6]
data2 = np.array([1.5, 3.4, 6.8,
                                  9.3, 7.0, 2.8])
```

```
# creating tensors and printing
t1 = torch.tensor(data1)
t2 = torch.Tensor(data1)
t3 = torch.as_tensor(data2)
t4 = torch.from_numpy(data2)

print("Tensor: ",t1, "Data type: ", t1.dtype,"\n")
print("Tensor: ",t2, "Data type: ", t2.dtype,"\n")
print("Tensor: ",t3, "Data type: ", t3.dtype,"\n")
print("Tensor: ",t4, "Data type: ", t4.dtype,"\n")
```

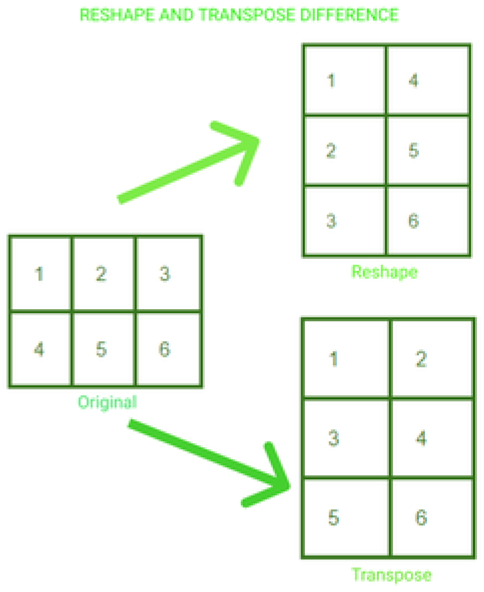
Output:

```
Tensor:  tensor([1, 2, 3, 4, 5, 6]) Data type:  torch.int64

Tensor:  tensor([1., 2., 3., 4., 5., 6.]) Data type:  torch.float32

Tensor:  tensor([1.5000, 3.4000, 6.8000, 9.3000, 7.0000, 2.8000], dtype=torch.float64) Data type:  torch.float64

Tensor:  tensor([1.5000, 3.4000, 6.8000, 9.3000, 7.0000, 2.8000], dtype=torch.float64) Data type:  torch.float64
```

Restructuring Tensors in Pytorch

We can modify the shape and size of a tensor as desired in PyTorch. We can also create a transpose of an n-d tensor. Below are three common ways to change the structure of your tensor as desired:

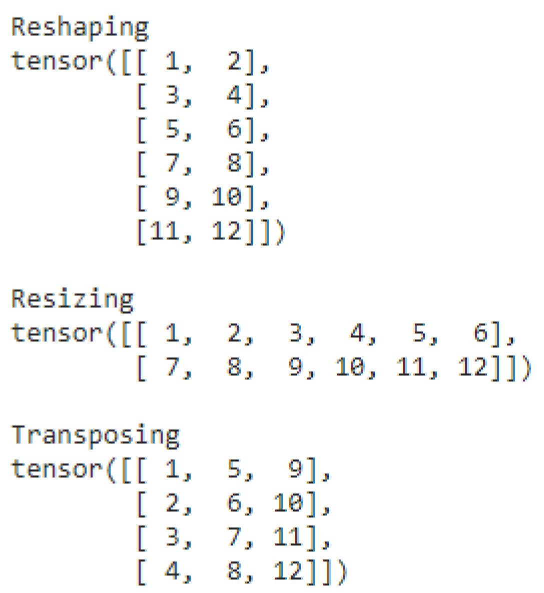
.reshape(a, b) : *returns a new tensor with size a,b*
.resize(a, b) : *returns the same tensor with the size a,b*
.transpose(a, b) : *returns a tensor transposed in a and b dimension*



A 2*3 matrix has been reshaped and transposed to 3*2. We can visualize the change in the arrangement of the elements in the tensor in both cases.

```
# import torch module

import torch


# defining tensor

t = torch.tensor([[1, 2, 3, 4],

                                   [5, 6, 7, 8],

                                   [9, 10, 11, 12]])


# reshaping the tensor

print("Reshaping")

print(t.reshape(6, 2))


# resizing the tensor

print("\nResizing")

print(t.resize(2, 6))


# transposing the tensor

print("\nTransposing")

print(t.transpose(1, 0))
```

Output :



```
Reshaping
tensor([[ 1,  2],
        [ 3,  4],
        [ 5,  6],
        [ 7,  8],
        [ 9, 10],
        [11, 12]])

Resizing
tensor([[ 1,  2,  3,  4,  5,  6],
        [ 7,  8,  9, 10, 11, 12]])

Transposing
tensor([[ 1,  5,  9],
        [ 2,  6, 10],
        [ 3,  7, 11],
        [ 4,  8, 12]])
```

Mathematical Operations on Tensors in PyTorch

We can perform various mathematical operations on tensors using Pytorch. The code for performing Mathematical operations is the same as in the case with NumPy arrays. Below is the code for performing the four basic operations in tensors.

```
# import torch module

import torch



# defining two tensors

t1 = torch.tensor([1, 2, 3, 4])

t2 = torch.tensor([5, 6, 7, 8])



# adding two tensors

print("tensor2 + tensor1")

print(torch.add(t2, t1))



# subtracting two tensor
```

print("\ntensor2 - tensor1")

print(torch.sub(t2, t1))

# multiplying two tensors

print("\ntensor2 * tensor1")

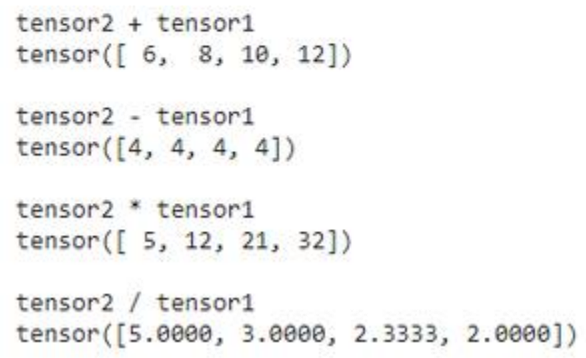
print(torch.mul(t2, t1))

# diving two tensors

print("\ntensor2 / tensor1")

print(torch.div(t2, t1))

Output:



```
tensor2 + tensor1
tensor([ 6,  8, 10, 12])

tensor2 - tensor1
tensor([4, 4, 4, 4])

tensor2 * tensor1
tensor([ 5, 12, 21, 32])

tensor2 / tensor1
tensor([5.0000, 3.0000, 2.3333, 2.0000])
```

Pytorch Modules

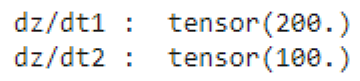
The PyTorch library modules are essential to create and train neural networks. The three main library modules are Autograd, Optim, and nn.

# 1. Autograd Module: The autograd provides the functionality of easy calculation of gradients without the explicitly manual implementation of forward and backward pass for all layers.
For training any neural network we perform backpropagation to calculate the gradient. By calling the .backward() function we can calculate every gradient from the root to the leaf.

# importing torch

```
import torch


# creating a tensor

t1=torch.tensor(1.0, requires_grad = True)

t2=torch.tensor(2.0, requires_grad = True)


# creating a variable and gradient

z=100 * t1 * t2

z.backward()


# printing gradient

print("dz/dt1 : ", t1.grad.data)

print("dz/dt2 : ", t2.grad.data)
```

Output:



```
dz/dt1 :  tensor(200.)
dz/dt2 :  tensor(100.)
```

2. Optim Module: PyTorch Optium Module which helps in the implementation of various optimization algorithms. This package contains the most commonly used algorithms like Adam, SGD, and RMS-Prop. To use torch.optim we first need to construct an Optimizer object which will keep the parameters and update it accordingly. First, we define the Optimizer by providing the optimizer algorithm we want to use. We set the gradients to zero before backpropagation. Then for updation of parameters the optimizer.step() is called.

optimizer = torch.optim.Adam(model.parameters(), lr=0.01) #defining optimizer

optimizer.zero_grad() #setting gradients to zero

optimizer.step() #parameter updation

# **3. nn Module:** This package helps in the construction of neural networks. It is used to build layers.

For creating a model with a single layer we can simply define it by using nn.Sequential().

```
model = nn.Sequential( nn.Linear(in, out), nn.Sigmoid(), nn.Linear(_in, _out), nn.Sigmoid() )

class Model (nn.Module) :

        def __init__(self):

            super(Model, self).__init__()

            self.linear = torch.nn.Linear(1, 1)

    def forward(self, x):

            y_pred = self.linear(x)

            return y_pred
```