Lab 7 - TensorFlow

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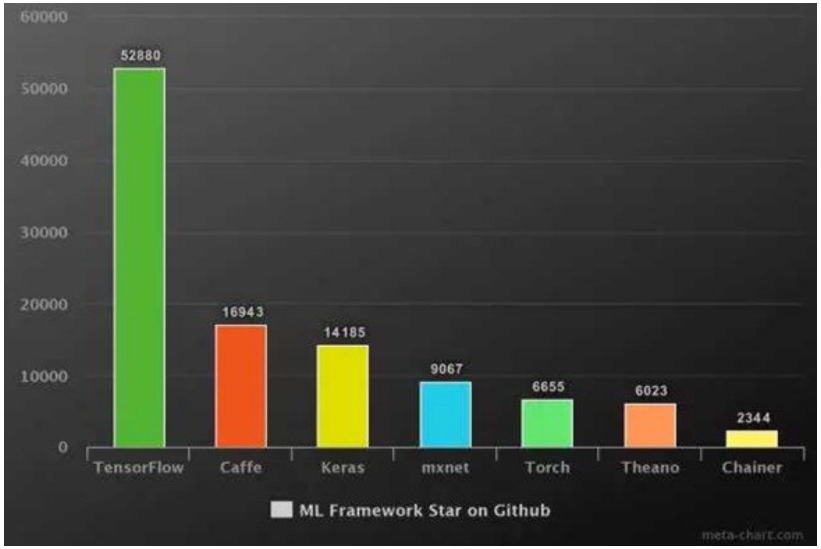
Content

What Is TensorFlow

- TensorFlow is Google's second-generation software library for dataflow programming.
- The TensorFlow framework supports various deep learning algorithms, as well as many computing platforms other than those for deep learning. The system stability is high.
- TensorFlow is open-source, which facilitates maintenance and update and improves the development efficiency.



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What Is TensorFlow

- TensorFlow can train and run the deep neural networks for
  - image recognition
  - handwritten digit classification
  - recurrent neural network
  - word embedding
  - natural language processing
  - video detection, and many more.
- TensorFlow is run on multiple CPUs or GPUs and also mobile operating systems.

TensorFlow Characteristics

Flexible and scalable

Multi-language

GPU

Cross-platform

Powerful computation

Distributed

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What Can We Do Using TensorFlow (1)

- Self-driving cars
- Music creation
- Image recognition
- Speech recognition
- Language models
- Human activity recognition
- Automated theorem proving
- Gaming (for example, play MarioKart racing games), etc.

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What Can We Do Using TensorFlow (2)

Artistic style transfer

Facial recognition

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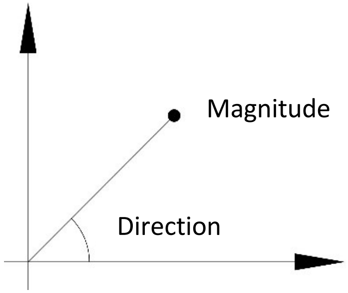
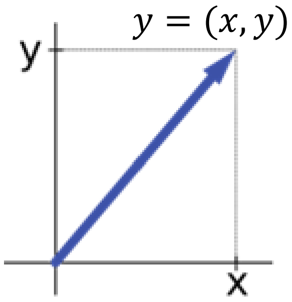
Basics of TensorFlow

- The word TensorFlow is made by two words:
  - Tensor: a multi-dimensional array
    - Tensor is the primary data structure in TensorFlow programs. Tensors are N-dimensional (where N could be 1, 2, 3, 4, or very large) data structures.
  - Flow: the flow of data in operation.
- In a running graph, tensors are the data that flows between nodes.

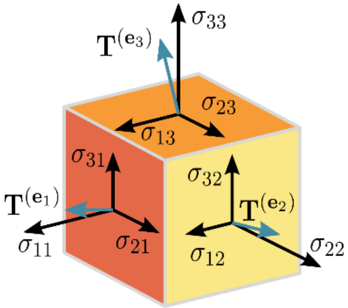
Basics of TensorFlow



Scalar



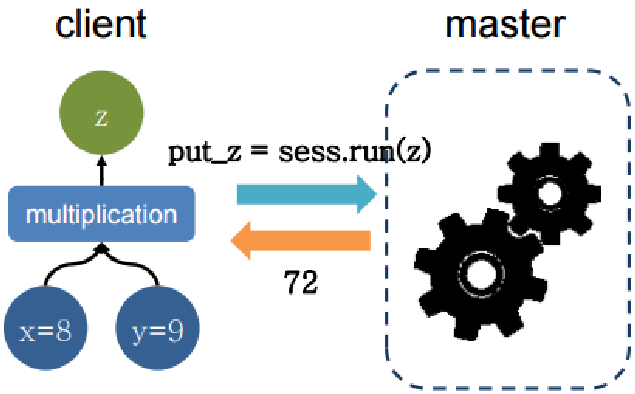
Vector



Tensor

Tensor

+



Data flow graph

Flow

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Tensor

- In TensorFlow, tensors are classified into constant tensors and variable tensors.
  - **A defined constant tensor** has an unchangeable value and dimension, and a defined variable tensor has a changeable value and an unchangeable dimension.
  - In neural networks, **variable tensors** are generally used as matrices for storing weights and other information, and are a type of trainable data.
    - Constant tensors can be used for storing hyperparameters or other structured data.

Constant Tensor Creation

- Constant Tensor: Common methods for creating a constant tensor include.
  - **tf.constant():** creates a constant tensor.
  - **tf.zeros(), tf.zeros_like(), tf.ones(), and tf.ones_like():** create an all-zero or all-one constant tensor.
  - **tf.fill():** creates a tensor with a user-defined value.
  - **tf.random:** creates a tensor with a known distribution.
  - Creating a list object by using NumPy, and then converting the list object into a tensor by using **tf.convert_to_tensor.**

Constant Tensor Creation

```
<tf.Tensor: shape=(2, 2), dtype=float32, numpy=
array([[1., 2.],
      [3., 4.]], dtype=float32)>
```

- tf.constant(value, dtype=None, shape=None, name='Const'):
  - value: A constant value (or list) of output type dtype.
  - dtype: The type of the elements of the resulting tensor.
  - shape: Optional dimensions of resulting tensor.
  - name: Optional name for the tensor.

```
import tensorflow as tf

const_a = tf.constant([[1, 2, 3, 4]],shape=[2,2], dtype=tf.float32)

# Create a 2x2 matrix with values 1, 2, 3, and 4.

Print(const_a)
```

Constant Tensor Creation

- View common attributes

```
print("value of the constant const_a:", const_a.numpy())

print("data type of the constant const_a:", const_a.dtype)

print("shape of the constant const_a:", const_a.shape)

print("name of the device that is to generate the constant const_a:", const_a.device)
```

```
Value of the constant const_a: [[1. 2.]
 [3. 4.]]
Data type of the constant const_a: <dtype: 'float32'>
Shape of the constant const_a: (2, 2)
Name of the device that is to generate the constant const_a:
/job:localhost/replica:0/task:0/device:CPU:0
```

Constant Tensor Creation

- tf.zeros(), tf.zeros_like(), tf.ones(), and tf.ones_like():
  - tf.zeros(): Create a constant with the value 0.
  - tf.zeros(shape, dtype=tf.float32, name=None):
    - shape: A list of integers, a tuple of integers, or a 1-D Tensor of type int32
    - dtype: The DType of an element in the resulting Tensor.
    - name: Optional string. A name for the operation.

```
zeros_b = tf.zeros(shape=[2, 3], dtype=tf.int32)
# Create a 2x3 matrix with all values being 0.
```

Constant Tensor Creation

- Create a tensor whose value is 0 based on the input tensor, with its shape being the same as that of the input tensor.
  - tf.zeros_like(input, dtype=None, name=None):
  - input_tensor: A Tensor or array-like object.
  - dtype: A type for the returned Tensor. Must be float16, float32, float64, int8, uint8, int16, uint16, int32, int64, complex64, complex128, bool or string (optional).
  - name: A name for the operation (optional).

```
zeros_like_c = tf.zeros_like(const_a)
#View generated data.
print( zeros_like_c.numpy() )
```

```
Output:
-----------
array([[0., 0.],
       [0., 0.]], dtype=float32)
```

Constant Tensor Creation

- tf.fill(): Create a tensor and fill it with a scalar value.
  - tf.fill(dims, value, name=None):
  - dims: A 1-D sequence of non-negative numbers. Represents the shape of the output tf.Tensor. Entries should be of type: int32, int64.
  - value: A value to fill the returned tf.Tensor.
  - name: Optional string. The name of the output tf.Tensor.

```
fill_d = tf.fill([3,3], 8)
# Create a 3x3 matrix with all values being 8.
#View data.
print( fill_d.numpy() )
```

```
Output:
------------
array([[8, 8, 8],
[8, 8, 8],
      [8, 8, 8]])
```

Constant Tensor Creation

- **tf.random():** This module is used to generate a tensor with a specific distribution.
  - Common methods in this module include:
    - tf.random.uniform(), tf.random.normal(), and tf.random.shuffle(). The following describes how to use tf.random.normal().
  - Create a tensor that conforms to a normal distribution.

```
random_e = tf.random.normal([5,5],mean=0,stddev=1.0, seed = 1)
#View the created data.
random_e.numpy()
```

```
Output:
-------------
array([[-0.8521641, 2.0672443, -0.94127315, 1.7840577, 2.9919195 ],
       [-0.8644102, 0.41812655, -0.85865736, 1.0617154, 1.0575105],
       [ 0.22457163, -0.02204755, 0.5084496, -0.09113179, -1.3036906 ],
       [-1.1108295, -0.24195422, 2.8516252, -0.7503834, 0.1267275 ],
       [0.9460202, 0.12648873, -2.6540542, 0.0853276, 0.01731399]],
      dtype=float32)
```

Constant Tensor Creation

- tf.random()

tf.random.normal(shape, mean=0.0, stddev=1.0, dtype=tf.float32, seed=None, name=None)

Parameter	Description
shape	A 1-D integer Tensor or Python array. The shape of the output tensor.
mean	A Tensor or Python value of type dtype, broadcastable with stddev. The mean of the normal distribution.
stddev	A Tensor or Python value of type dtype, broadcastable with mean. The standard deviation of the normal distribution.
dtype	The type of the output.
Seed	A Python integer. Used to create a random seed for the distribution. See tf.random.set_seed for behavior
Name	A name for the operation (optional).

Constant Tensor Creation

- Create a list object by using NumPy, and then convert the list object into a tensor by using tf.convert_to_tensor.
- **tf.convert_to_tensor** can be used to convert a Python data type into a tensor data type available to TensorFlow
- tf.convert_to_tensor(value, dtype=None, dtype_hint=None, name=None)

Parameter	Description
value	An object whose type has a registered Tensor conversion function.
dtype	Optional element type for the returned tensor. If missing, the type is inferred from the type of value.
dtype_hint	Optional element type for the returned tensor, used when dtype is None. In some cases, a caller may not have a dtype in mind when converting to a tensor, so dtype_hint can be used as a soft preference. If the conversion to dtype_hint is not possible, this argument has no effect.
name	Optional name to use if a new Tensor is created.

Constant Tensor Creation

- tf.convert_to_tensor()

```
#Create a list.
list_f = [1,2,3,4,5,6]
#View the data type.
print( type(list_f) )

tensor_f = tf.convert_to_tensor(list_f, dtype=tf.float32)
print( tensor_f )
```

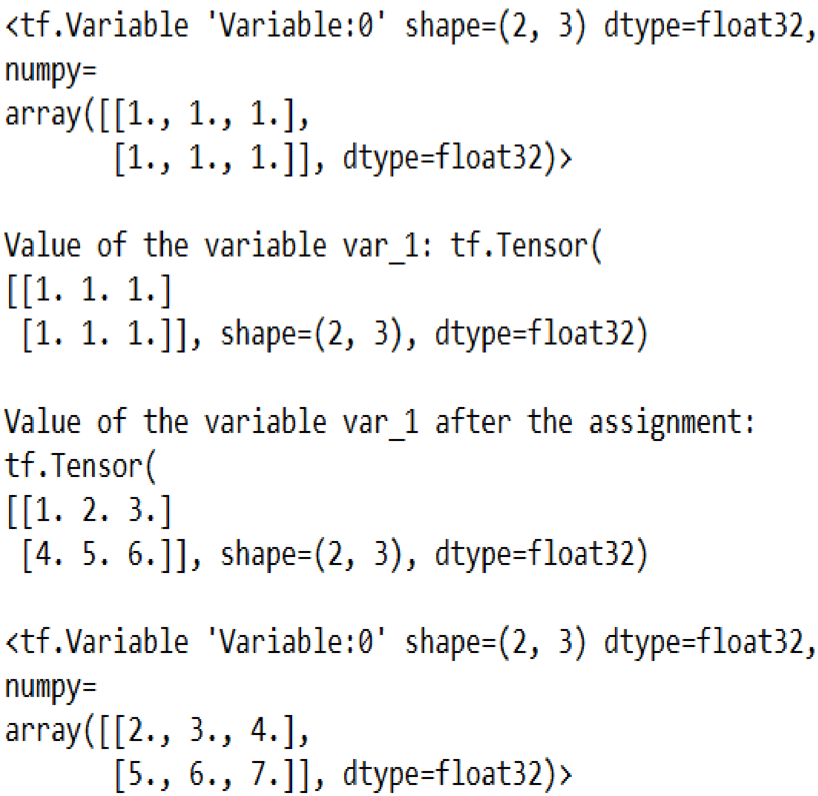
```
Output:
-----------
list

<tf.Tensor: shape=(6,), dtype=float32,
numpy=array([1., 2., 3., 4., 5., 6.],
dtype=float32)>
```

Variable Tensor Creation

- In TensorFlow, variables are operated using the **tf.Variable** class.
- tf.Variable indicates a tensor.
- The value of **tf.Variable can be changed by running an arithmetic operation** on tf.Variable.
- Variable values can be read and changed.

Variable Tensor Creation

```python
import tensorflow as tf
#Create a variable.
#Only the initial value needs to be provided
var_1 = tf.Variable(tf.ones([2,3]))
print( var_1 ,'\n')

#Read the variable value.
print("Value of the variable var_1:",
      var_1.read_value(),'\n')

#Assign a variable value.
var_value_1=[[1,2,3],[4,5,6]]

var_1.assign(var_value_1)
print("Value of the variable var_1 after the assignment:",
      var_1.read_value())

#Variable addition
var_1.assign_add(tf.ones([2,3]))
print(var_1)
```

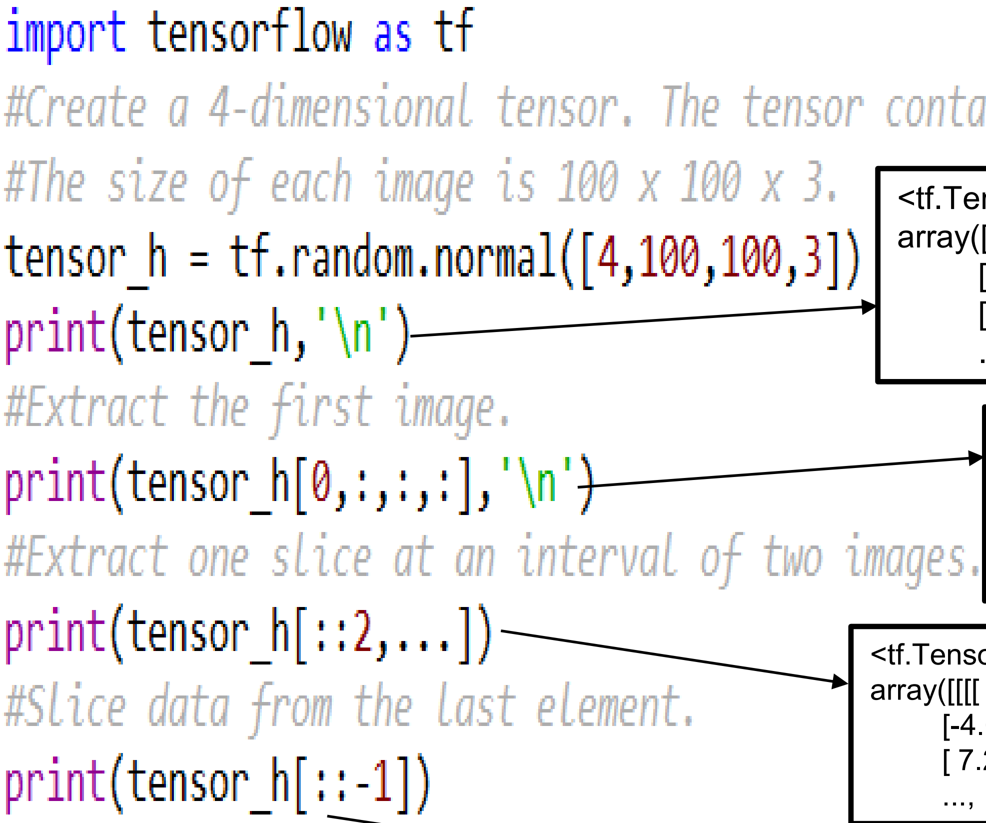


```
<tf.Variable 'Variable:0' shape=(2, 3) dtype=float32,
numpy=
array([[1., 1., 1.],
       [1., 1., 1.]], dtype=float32)>

Value of the variable var_1: tf.Tensor(
[[1. 1. 1.]
 [1. 1. 1.]], shape=(2, 3), dtype=float32)

Value of the variable var_1 after the assignment:
tf.Tensor(
[[1. 2. 3.]
 [4. 5. 6.]], shape=(2, 3), dtype=float32)

<tf.Variable 'Variable:0' shape=(2, 3) dtype=float32,
numpy=
array([[2., 3., 4.],
       [5., 6., 7.]], dtype=float32)>
```

Tensor Slicing and Indexing

- **Slicing:** Tensor slicing methods include:
  - **[start: end]:** extracts a data slice from the start position to the end position of the tensor.
  - **[start:end:step] or [::step]:** extracts a data slice at an interval of step from the start position to the end position of the tensor.
  - **[::-1]:** slices data from the last element.
  - **'...':** indicates a data slice of any length.

Tensor Slicing and Indexing



```python
import tensorflow as tf
#Create a 4-dimensional tensor. The tensor contains four images.
#The size of each image is 100 x 100 x 3.
tensor_h = tf.random.normal([4,100,100,3])
print(tensor_h,'\n')
#Extract the first image.
print(tensor_h[0,:,:,:],'\n')
#Extract one slice at an interval of two images.
print(tensor_h[::2,...])
#Slice data from the last element.
print(tensor_h[::-1])
```

```
<tf.Tensor: shape=(4, 100, 100, 3), dtype=float32, numpy=
array([[[[ 1.68444023e-01, -7.46562362e-01, -4.34964240e-01],
         [-4.69263226e-01, 6.26460612e-01, 1.21065331e+00],
         [ 7.21675277e-01, 4.61057723e-01, -9.20868576e-01],
         ...,
```

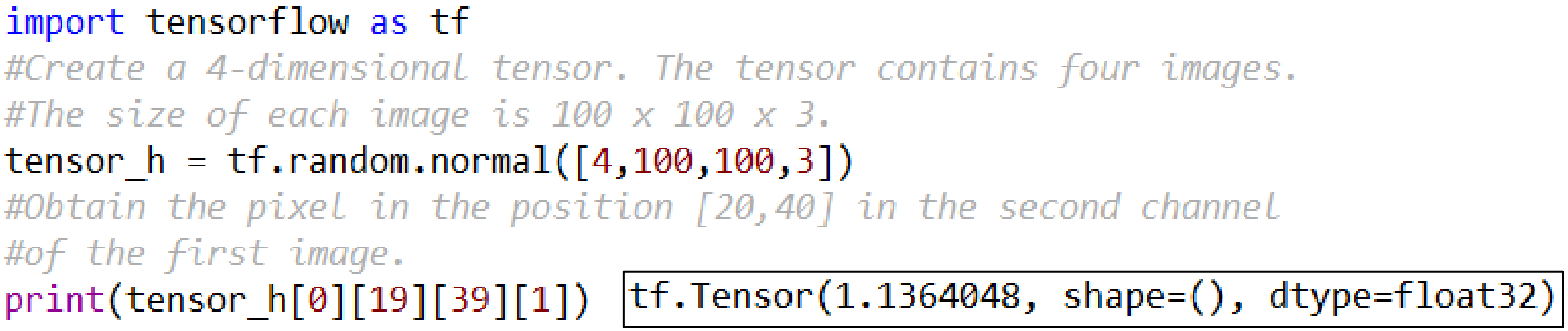
```
<tf.Tensor: shape=(100, 100, 3), dtype=float32, numpy=
array([[[ 1.68444023e-01, -7.46562362e-01, -4.34964240e-01],
        [-4.69263226e-01, 6.26460612e-01, 1.21065331e+00],
        [ 7.21675277e-01, 4.61057723e-01, -9.20868576e-01],
        ...,
```

```
<tf.Tensor: shape=(2, 100, 100, 3), dtype=float32, numpy=
array([[[[ 1.68444023e-01, -7.46562362e-01, -4.34964240e-01],
         [-4.69263226e-01, 6.26460612e-01, 1.21065331e+00],
         [ 7.21675277e-01, 4.61057723e-01, -9.20868576e-01],
         ...,
```

```
<tf.Tensor: shape=(4, 100, 100, 3), dtype=float32, numpy=
array([[[[-1.70684665e-01, 1.52386248e+00, -1.91677585e-01],
         [-1.78917408e+00, -7.48436213e-01, 6.10363662e-01],
         [ 7.64770031e-01, 6.06725179e-02, 1.32704067e+00],
         ...,
```

Tensor Slicing and Indexing

- **Indexing**: The basic format of an index is a[d1][d2][d3].



```
import tensorflow as tf
#Create a 4-dimensional tensor. The tensor contains four images.
#The size of each image is 100 x 100 x 3.
tensor_h = tf.random.normal([4,100,100,3])
#Obtain the pixel in the position [20,40] in the second channel
#of the first image.
print(tensor_h[0][19][39][1])
```

```
tf.Tensor(1.1364048, shape=(), dtype=float32)
```

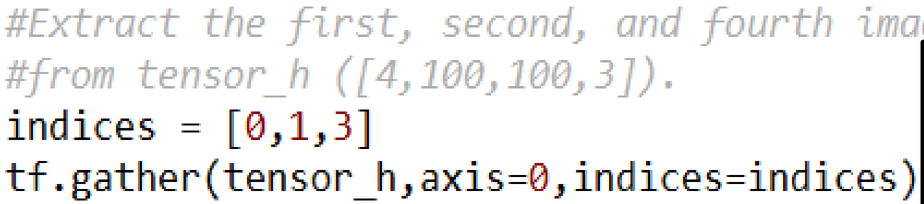
- If the indexes of data to be extracted are nonconsecutive, **tf.gather** and **tf.gather_nd** are commonly used for data extraction in TensorFlow.
- To extract data from a particular dimension:
- tf.gather(params, indices, axis=None)

params: input tensor

indices: index of the data to be extracted

axis: dimension of the data to be extracted

Tensor Slicing and Indexing

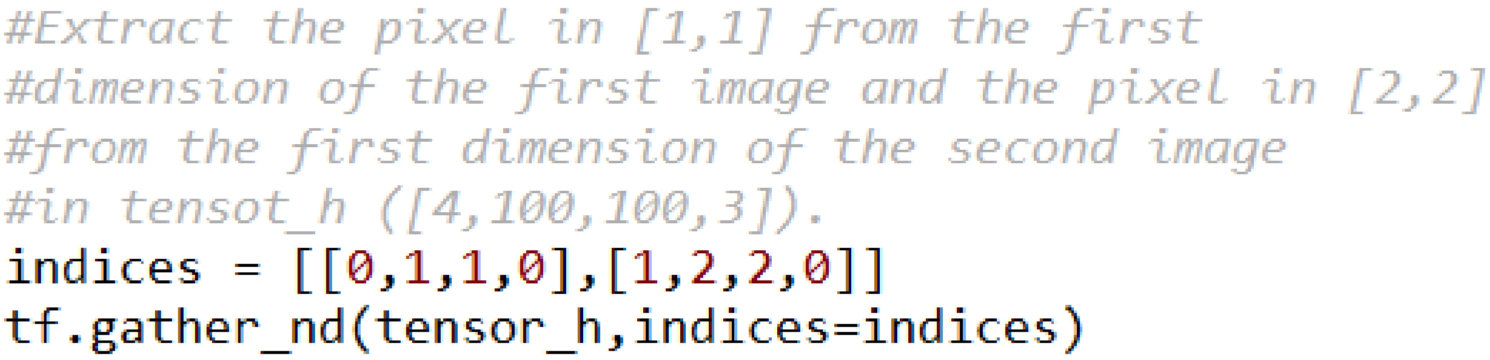


```
#Extract the first, second, and fourth images
#from tensor_h ([4,100,100,3]).
indices = [0,1,3]
tf.gather(tensor_h,axis=0,indices=indices)
```

```
Output:
-----------
<tf.Tensor: shape=(3, 100, 100, 3), dtype=float32, numpy=
array([[[[ 1.68444023e-01, -7.46562362e-01, -4.34964240e-01],
         [-4.69263226e-01, 6.26460612e-01, 1.21065331e+00],
         [ 7.21675277e-01, 4.61057723e-01, -9.20868576e-01],
         ...,
```

- **tf.gather_nd** allows data extraction from multiple dimensions:
- tf.gather_nd(params, indices, batch_dims=0, name=None):
    - params: The tensor from which to gather values.
    - indices: Must be one of the following types: int32, int64. Index tensor.
    - Name: A name for the operation (optional).
    - batch_dims: An integer or a scalar 'Tensor'. The number of batch dimensions.

Tensor Slicing and Indexing



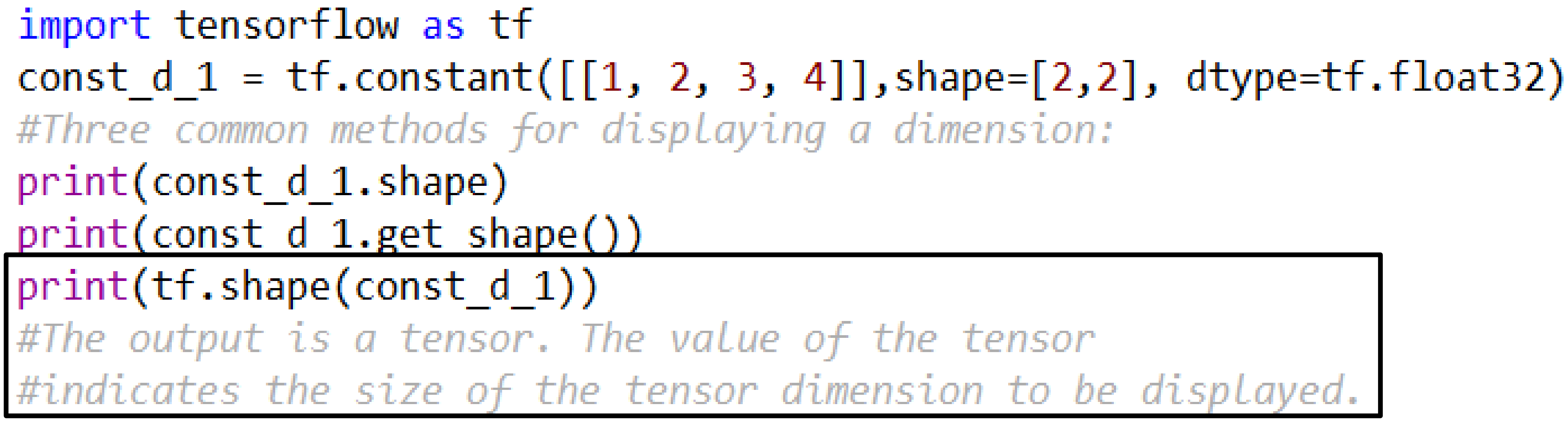
```
#Extract the pixel in [1,1] from the first
#dimension of the first image and the pixel in [2,2]
#from the first dimension of the second image
#in tensot_h ([4,100,100,3]).
indices = [[0,1,1,0],[1,2,2,0]]
tf.gather_nd(tensor_h,indices=indices)
```

```
Output:
----------
<tf.Tensor: shape=(2,), dtype=float32, numpy=array([0.5705869, 0.9735735], dtype=float32)>
```

Tensor Dimension Modification

```
Output:
-----------
(2, 2)
(2, 2)
tf.Tensor([2 2], shape=(2,), dtype=int32)
```

- Dimension display:

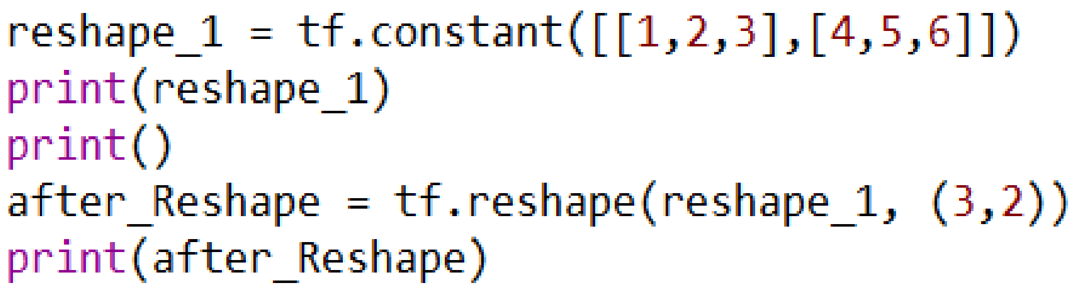


```python
import tensorflow as tf
const_d_1 = tf.constant([[1, 2, 3, 4]],shape=[2,2], dtype=tf.float32)
#Three common methods for displaying a dimension:
print(const_d_1.shape)
print(const_d_1.get_shape())
print(tf.shape(const_d_1))
#The output is a tensor. The value of the tensor
#indicates the size of the tensor dimension to be displayed.
```

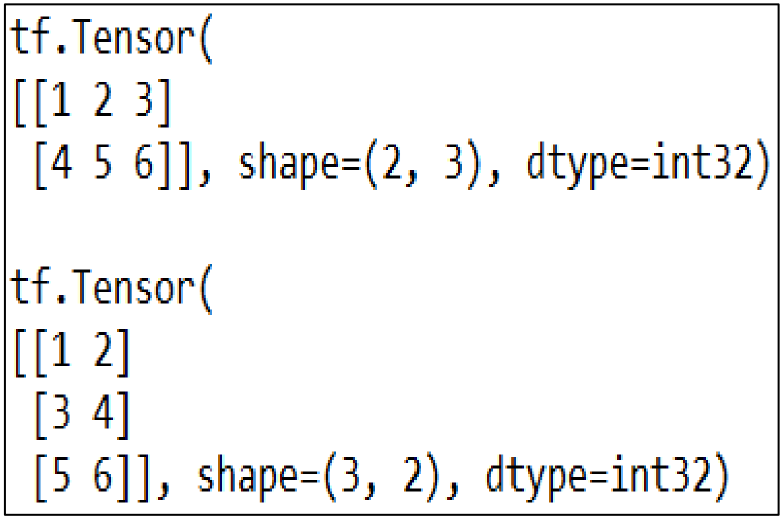
- **.shape** and **.get_shape()** return TensorShape objects,
- **tf.shape(x)** returns Tensor objects

Tensor Dimension Modification

- Dimension Reshaping:
- tf.reshape(tensor,shape,name=None):
  - tensor: input tensor
  - shape: dimension of the reshaped tensor



```
reshape_1 = tf.constant([[1,2,3],[4,5,6]])
print(reshape_1)
print()
after_Reshape = tf.reshape(reshape_1, (3,2))
print(after_Reshape)
```

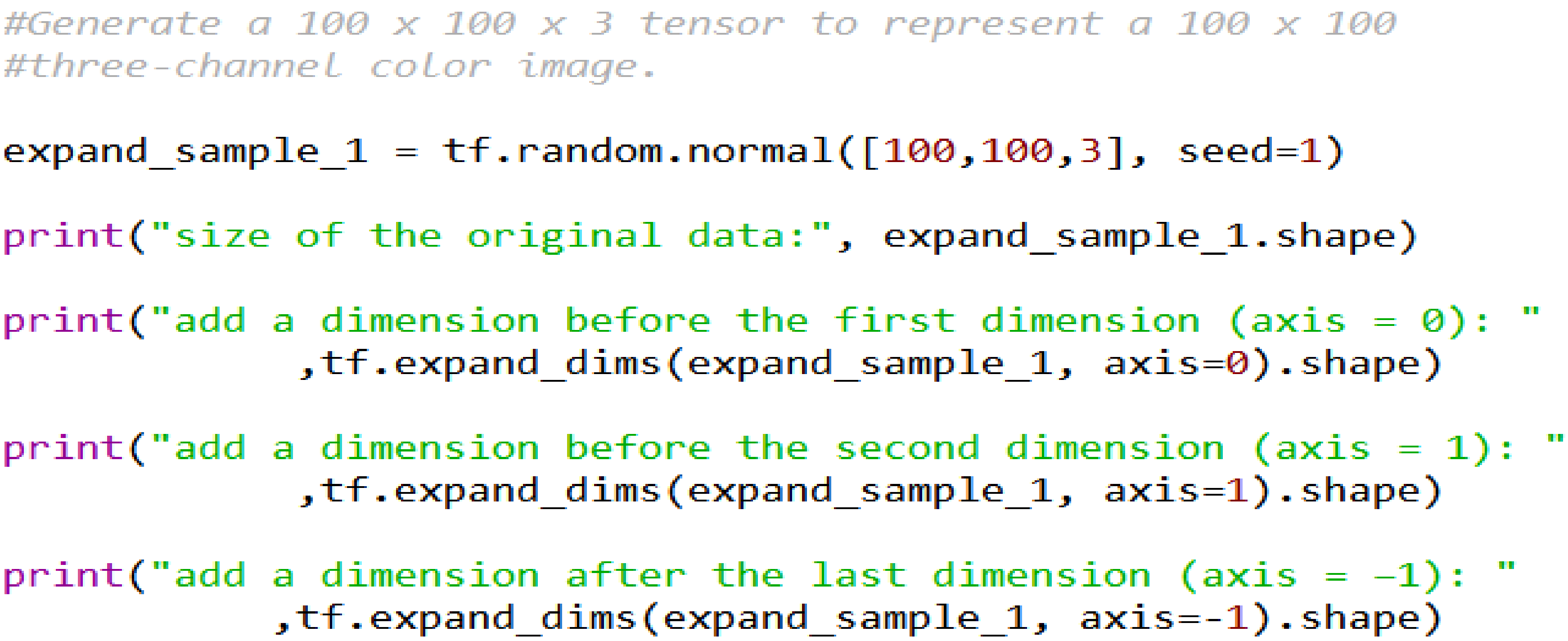


```
tf.Tensor(
[[1 2 3]
 [4 5 6]], shape=(2, 3), dtype=int32)

tf.Tensor(
[[1 2]
 [3 4]
 [5 6]], shape=(3, 2), dtype=int32)
```

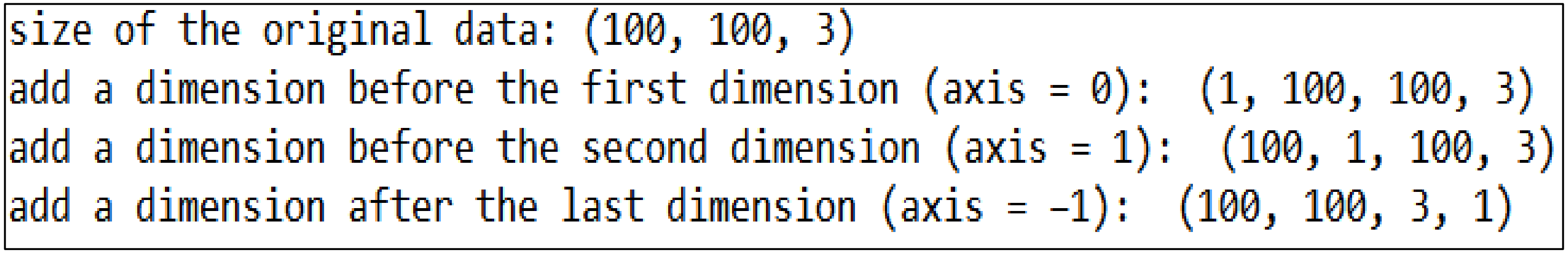
Tensor Dimension Modification

- **Dimension Expansion**
    - tf.expand_dims(input, axis, name=None):
        - input: input tensor
        - axis: adds a dimension after the axis dimension.
- When the number of dimensions of the input data is D, the axis must fall in the range of [–(D + 1), D] (included). A negative value indicates adding a dimension in reverse order.

Tensor Dimension Modification



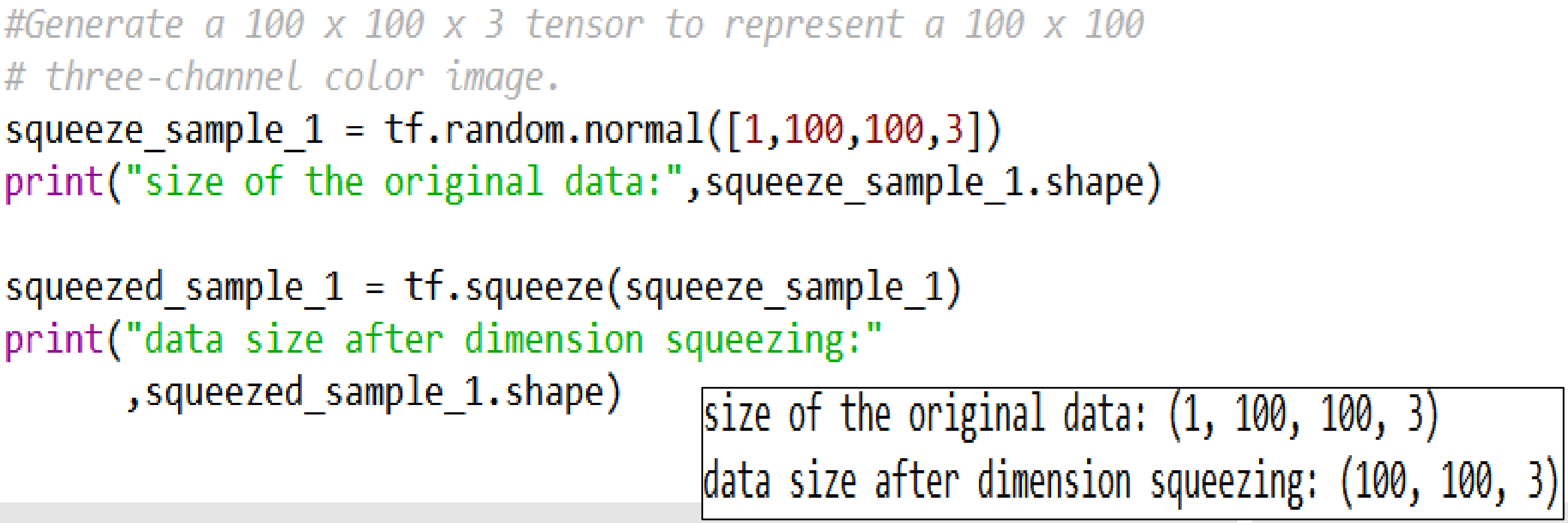
```
#Generate a 100 x 100 x 3 tensor to represent a 100 x 100
#three-channel color image.

expand_sample_1 = tf.random.normal([100,100,3], seed=1)

print("size of the original data:", expand_sample_1.shape)

print("add a dimension before the first dimension (axis = 0): "
            ,tf.expand_dims(expand_sample_1, axis=0).shape)

print("add a dimension before the second dimension (axis = 1): "
            ,tf.expand_dims(expand_sample_1, axis=1).shape)

print("add a dimension after the last dimension (axis = -1): "
           ,tf.expand_dims(expand_sample_1, axis=-1).shape)
```



```
size of the original data: (100, 100, 3)
add a dimension before the first dimension (axis = 0):  (1, 100, 100, 3)
add a dimension before the second dimension (axis = 1):  (100, 1, 100, 3)
add a dimension after the last dimension (axis = -1):  (100, 100, 3, 1)
```

Tensor Dimension Modification

- Dimension Squeeze: Remove dimension of size 1 from shape of tensor.
  - tf.squeeze(input, axis=None, name=None):
    - input: input tensor
    - axis: If axis is set to 1, dimension 1 needs to be deleted.

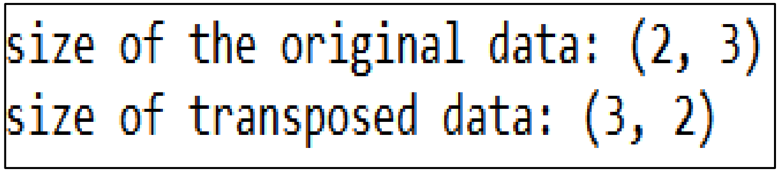


```
#Generate a 100 x 100 x 3 tensor to represent a 100 x 100
# three-channel color image.
squeeze_sample_1 = tf.random.normal([1,100,100,3])
print("size of the original data:",squeeze_sample_1.shape)

squeezed_sample_1 = tf.squeeze(squeeze_sample_1)
print("data size after dimension squeezing:"
      ,squeezed_sample_1.shape)
```

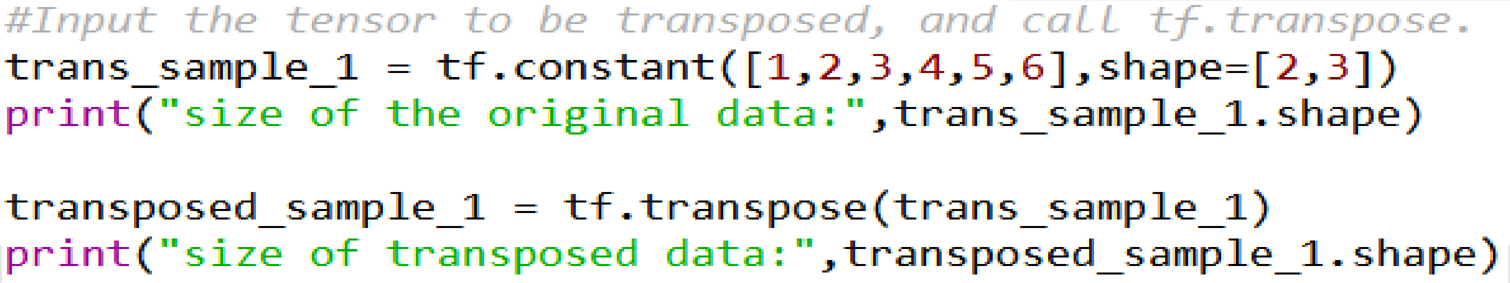
```
size of the original data: (1, 100, 100, 3)
data size after dimension squeezing: (100, 100, 3)
```

Tensor Dimension Modification

- Transpose:
  - tf.transpose(a, perm=None, conjugate=False, name='transpose'):
    - a: input tensor
    - perm: tensor size sequence, generally used to transpose high-dimensional arrays
    - conjugate: indicates complex number transpose.
    - name: tensor name



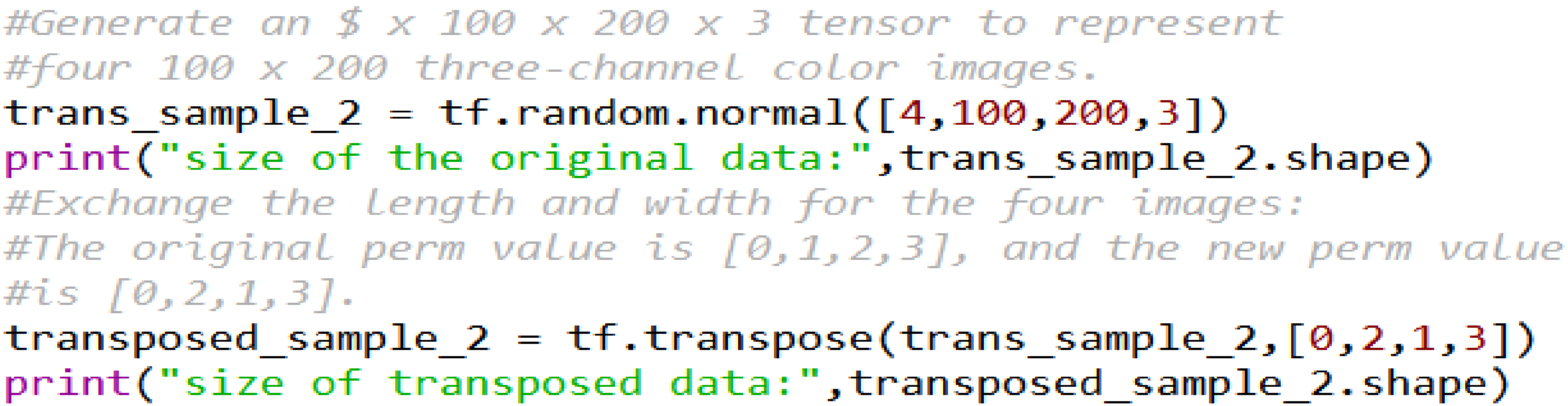
```
size of the original data: (2, 3)
size of transposed data: (3, 2)
```



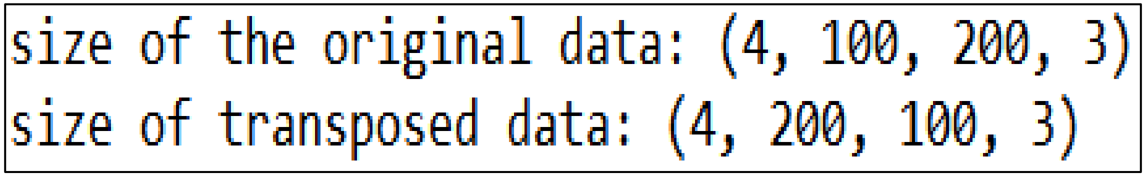
```
#Input the tensor to be transposed, and call tf.transpose.
trans_sample_1 = tf.constant([1,2,3,4,5,6],shape=[2,3])
print("size of the original data:",trans_sample_1.shape)

transposed_sample_1 = tf.transpose(trans_sample_1)
print("size of transposed data:",transposed_sample_1.shape)
```

Tensor Dimension Modification

- Data dimensions can be transposed by changing the sequence of values in perm.



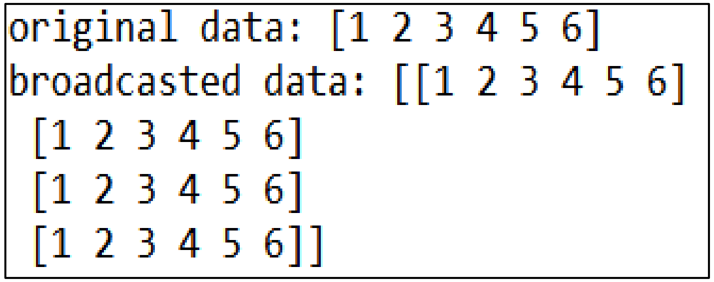
```
#Generate an $ x 100 x 200 x 3 tensor to represent
#four 100 x 200 three-channel color images.
trans_sample_2 = tf.random.normal([4,100,200,3])
print("size of the original data:",trans_sample_2.shape)
#Exchange the length and width for the four images:
#The original perm value is [0,1,2,3], and the new perm value
#is [0,2,1,3].
transposed_sample_2 = tf.transpose(trans_sample_2,[0,2,1,3])
print("size of transposed data:",transposed_sample_2.shape)
```



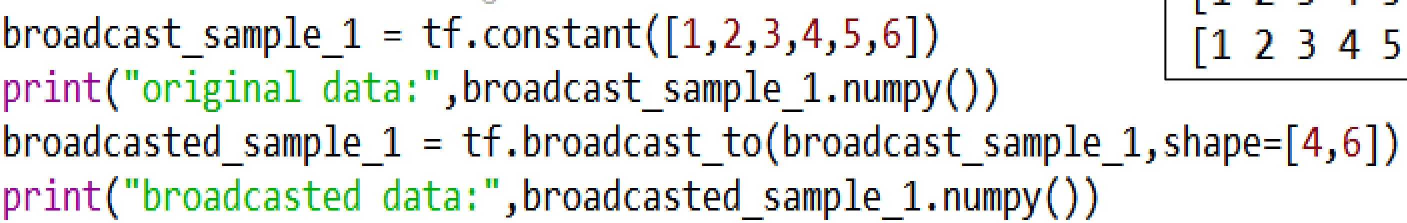
```
size of the original data: (4, 100, 200, 3)
size of transposed data: (4, 200, 100, 3)
```

Tensor Dimension Modification

- Broadcast (broadcast_to)
  - broadcast_to is used to broadcast data from a low dimension to a high dimension.
  - tf.broadcast_to(input, shape, name=None):
    - input: input tensor
    - shape: size of the output tensor

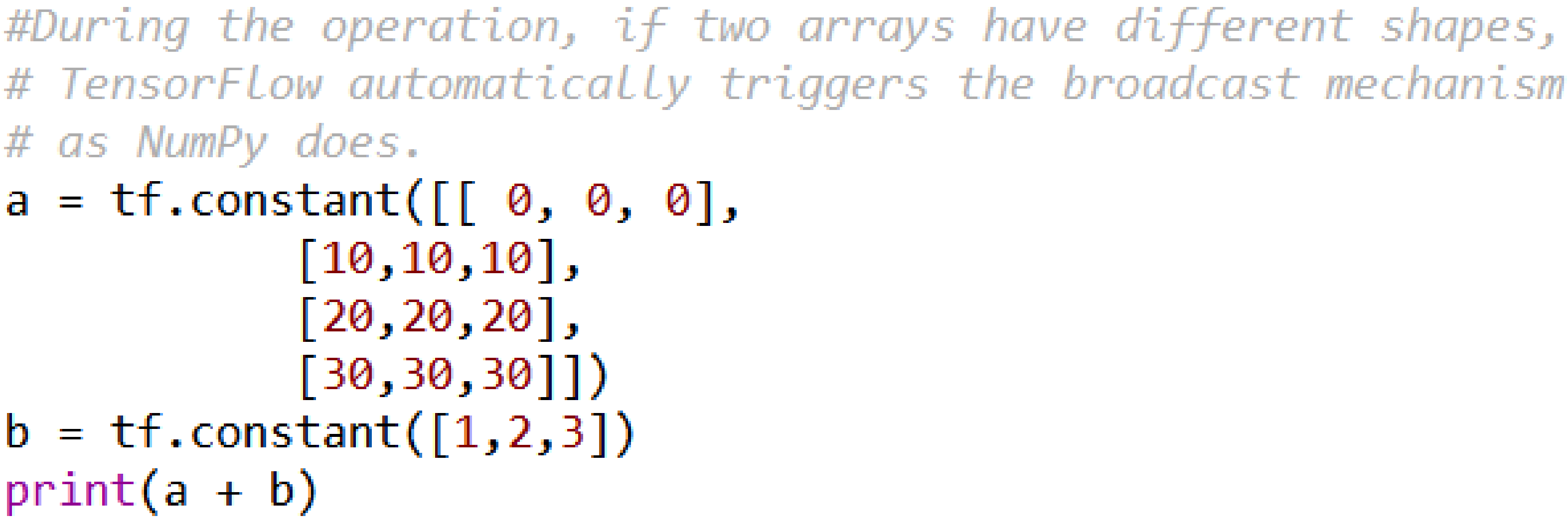


```
original data: [1 2 3 4 5 6]
broadcasted data: [[1 2 3 4 5 6]
 [1 2 3 4 5 6]
 [1 2 3 4 5 6]
 [1 2 3 4 5 6]]
```

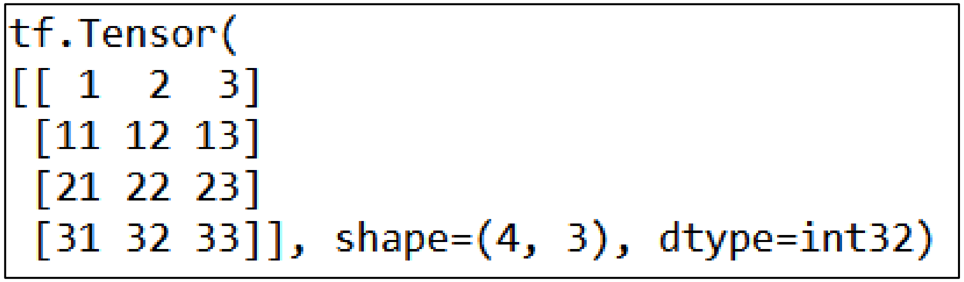


```
broadcast_sample_1 = tf.constant([1,2,3,4,5,6])
print("original data:",broadcast_sample_1.numpy())
broadcasted_sample_1 = tf.broadcast_to(broadcast_sample_1,shape=[4,6])
print("broadcasted data:",broadcasted_sample_1.numpy())
```

Tensor Dimension Modification



```
#During the operation, if two arrays have different shapes,
# TensorFlow automatically triggers the broadcast mechanism
# as NumPy does.
a = tf.constant([[ 0, 0, 0],
                 [10,10,10],
                 [20,20,20],
                 [30,30,30]])
b = tf.constant([1,2,3])
print(a + b)
```



```
tf.Tensor(
[[ 1  2  3]
 [11 12 13]
 [21 22 23]
 [31 32 33]], shape=(4, 3), dtype=int32)
```

Arithmetic Operations on Tensors

- Main arithmetic operations include:
  - addition (tf.add)
  - subtraction (tf.subtract)
  - multiplication (tf.multiply)
  - division (tf.divide)
  - logarithm (tf.math.log)
  - powers (tf.pow)

Arithmetic Operations on Tensors

- Add operation

```
a = tf.constant([[3, 5], [4, 8]])
b = tf.constant([[1, 6], [2, 9]])
print(tf.add(a, b))
```

```
Output:
-----------
tf.Tensor(
[[ 4 11]
 [ 6 17]], shape=(2, 2), dtype=int32)
```

- Matrix Multiplication

```
tf.matmul(a,b)
```

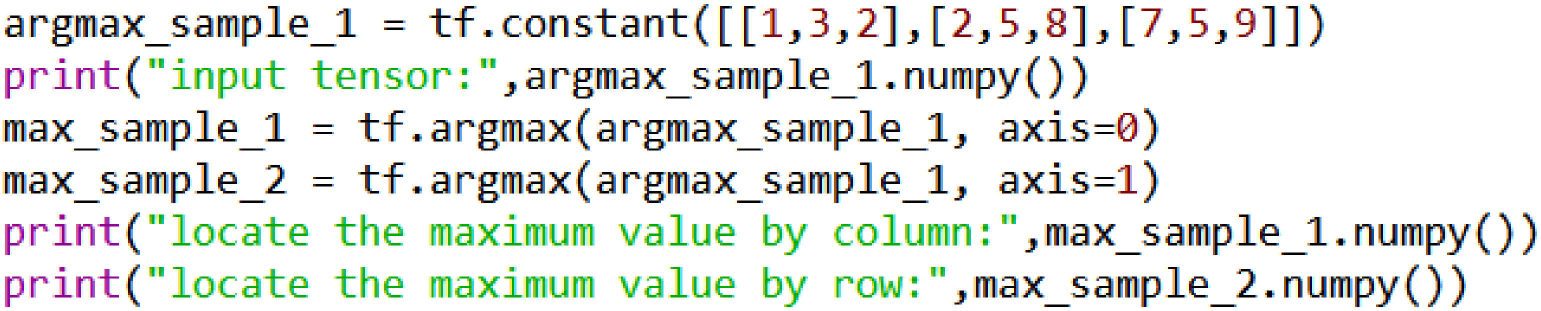
```
Output:
------------
tf.Tensor(
[[13 63]
 [20 96]], shape=(2, 2), dtype=int32)
```

Tensor Statistics Collection

- Methods for collecting tensor statistics include:
  - tf.reduce_min/max/mean(): calculates the minimum, maximum, and mean values.
  - tf.argmax()/tf.argmin(): calculates the positions of the maximum and minimum values.
  - tf.equal(): checks whether two tensors are equal by element.
  - tf.unique(): removes duplicate elements from tensors.
  - tf.nn.in_top_k(prediction, target, K): calculates whether the predicted value is equal to the actual value, and returns a Boolean tensor.

Tensor Statistics Collection

- tf.argmax(input,axis):
  - input: input tensor
  - axis: maximum output value in the axis dimension



```python
argmax_sample_1 = tf.constant([[1,3,2],[2,5,8],[7,5,9]])
print("input tensor:",argmax_sample_1.numpy())
max_sample_1 = tf.argmax(argmax_sample_1, axis=0)
max_sample_2 = tf.argmax(argmax_sample_1, axis=1)
print("locate the maximum value by column:",max_sample_1.numpy())
print("locate the maximum value by row:",max_sample_2.numpy())
```

```
Output:
--------------
input tensor: [[1 3 2]
 [2 5 8]
 [7 5 9]]
locate the maximum value by column: [2 1 2]
locate the maximum value by row: [1 2 2]
```

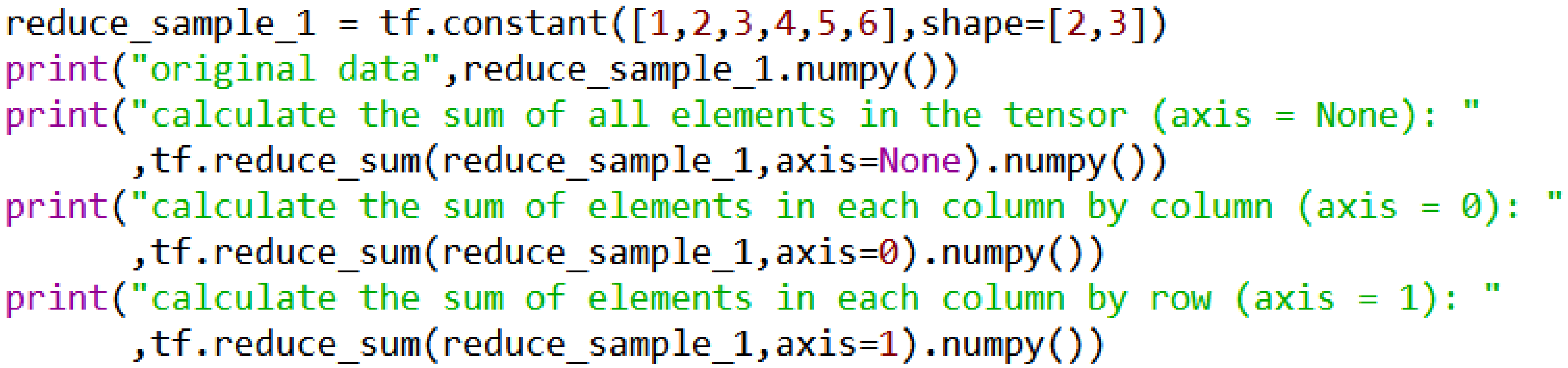
Dimension-based Arithmetic Operations

- In TensorFlow, a series of operations of tf.reduce_* reduce tensor dimensions.
- The series of operations can be performed on dimensional elements of a tensor, for example, calculating the mean value by row and calculating a product of all elements in the tensor.
- Common operations include:
  - tf.reduce_sum (addition),
    tf.reduce_min (minimum),
    tf.reduce_mean (mean value),
    tf.reduce_any (logical OR),
    tf.reduce_prod (multiplication),
    tf.reduce_max (maximum),
    tf.reduce_all (logical AND),
    tf.reduce_logsumexp (log(sum(exp)))

Tensor Statistics Collection

- Calculate the sum of elements in all dimensions of a tensor.
- tf.reduce_sum(input_tensor, axis=None, keepdims= False, name=None):
  - input_tensor: The tensor to reduce. Should have numeric type.
  - axis: The dimensions to reduce. If None (the default), reduces all dimensions. Must be in the range [-rank(input_tensor),rank(input_tensor)].
  - keepdims: If true, retains reduced dimensions with length 1.
  - name: A name for the operation (optional).

Tensor Statistics Collection



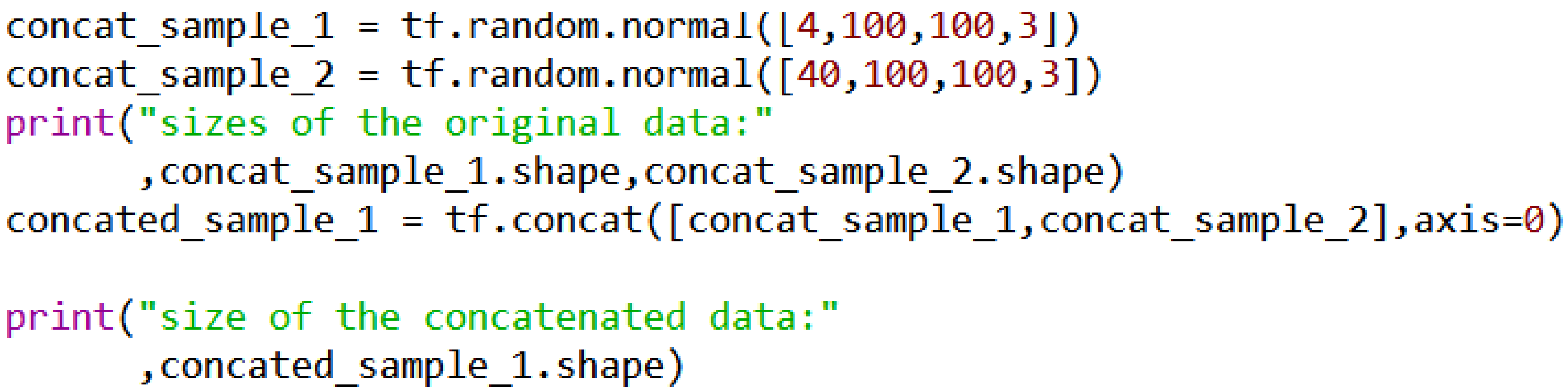
```
reduce_sample_1 = tf.constant([1,2,3,4,5,6],shape=[2,3])
print("original data",reduce_sample_1.numpy())
print("calculate the sum of all elements in the tensor (axis = None): "
      ,tf.reduce_sum(reduce_sample_1,axis=None).numpy())
print("calculate the sum of elements in each column by column (axis = 0): "
      ,tf.reduce_sum(reduce_sample_1,axis=0).numpy())
print("calculate the sum of elements in each column by row (axis = 1): "
      ,tf.reduce_sum(reduce_sample_1,axis=1).numpy())
```

```
Output:
----------
original data [[1 2 3]
 [4 5 6]]
calculate the sum of all elements in the tensor (axis = None):  21
calculate the sum of elements in each column by column (axis = 0):  [5 7 9]
calculate the sum of elements in each column by row (axis = 1):  [ 6 15]
```

Tensor Concatenation and Splitting

- Tensor Concatenation operations include:
  - tf.contact(): concatenates vectors based on the specified dimension, while keeping other dimensions unchanged.
  - tf.stack(): changes a group of R dimensional tensors to R+1 dimensional tensors, with the dimensions changed after the concatenation.
- tf.concat(values, axis, name='concat'):
  - values: input tensor
  - axis: dimension to concatenate
  - name: operation name

Tensor Concatenation

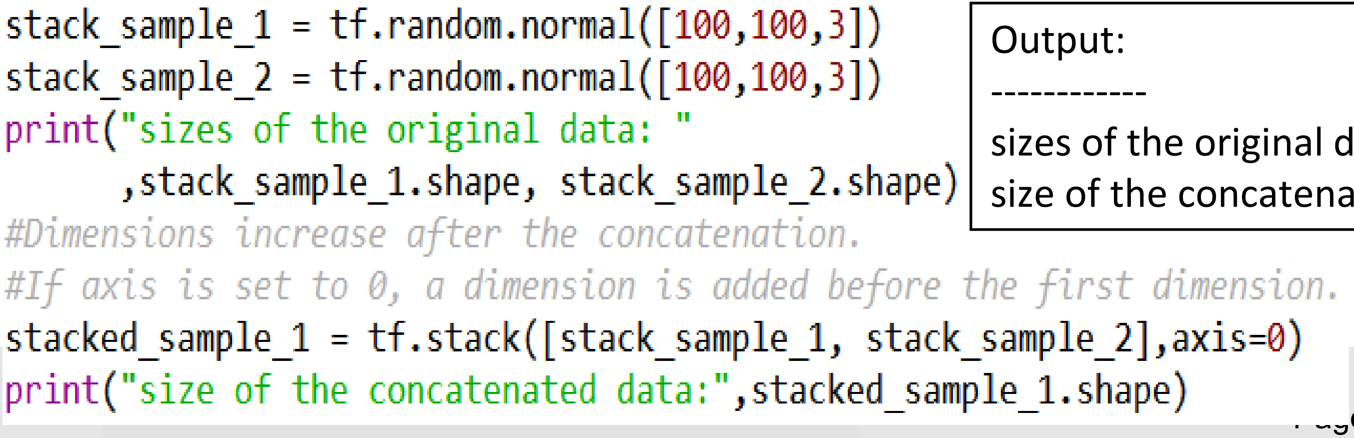


```
concat_sample_1 = tf.random.normal([4,100,100,3])
concat_sample_2 = tf.random.normal([40,100,100,3])
print("sizes of the original data:"
      ,concat_sample_1.shape,concat_sample_2.shape)
concated_sample_1 = tf.concat([concat_sample_1,concat_sample_2],axis=0)

print("size of the concatenated data:"
      ,concated_sample_1.shape)
```

```
Output:
------------
sizes of the original data: (4, 100, 100, 3) (40, 100, 100, 3)
size of the concatenated data: (44, 100, 100, 3)
```

Tensor Concatenation

- A dimension can be added to an original matrix in the same way. axis determines the position of the dimension.
- tf.stack(values, axis=0, name='stack'):
  - values: A list of Tensor objects with the same shape and type.
  - axis: The axis to stack along. Defaults to the first dimension. Negative values wrap around, so the valid range is [-(R+1), R+1).
  - name: A name for this operation (optional).



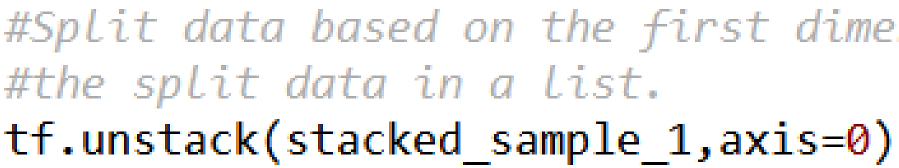
```
stack_sample_1 = tf.random.normal([100,100,3])
stack_sample_2 = tf.random.normal([100,100,3])
print("sizes of the original data: "
      ,stack_sample_1.shape, stack_sample_2.shape)
#Dimensions increase after the concatenation.
#If axis is set to 0, a dimension is added before the first dimension.
stacked_sample_1 = tf.stack([stack_sample_1, stack_sample_2],axis=0)
print("size of the concatenated data:",stacked_sample_1.shape)
```

```
Output:
------------
sizes of the original data:  (100, 100, 3) (100, 100, 3)
size of the concatenated data: (2, 100, 100, 3)
```

Tensor Splitting

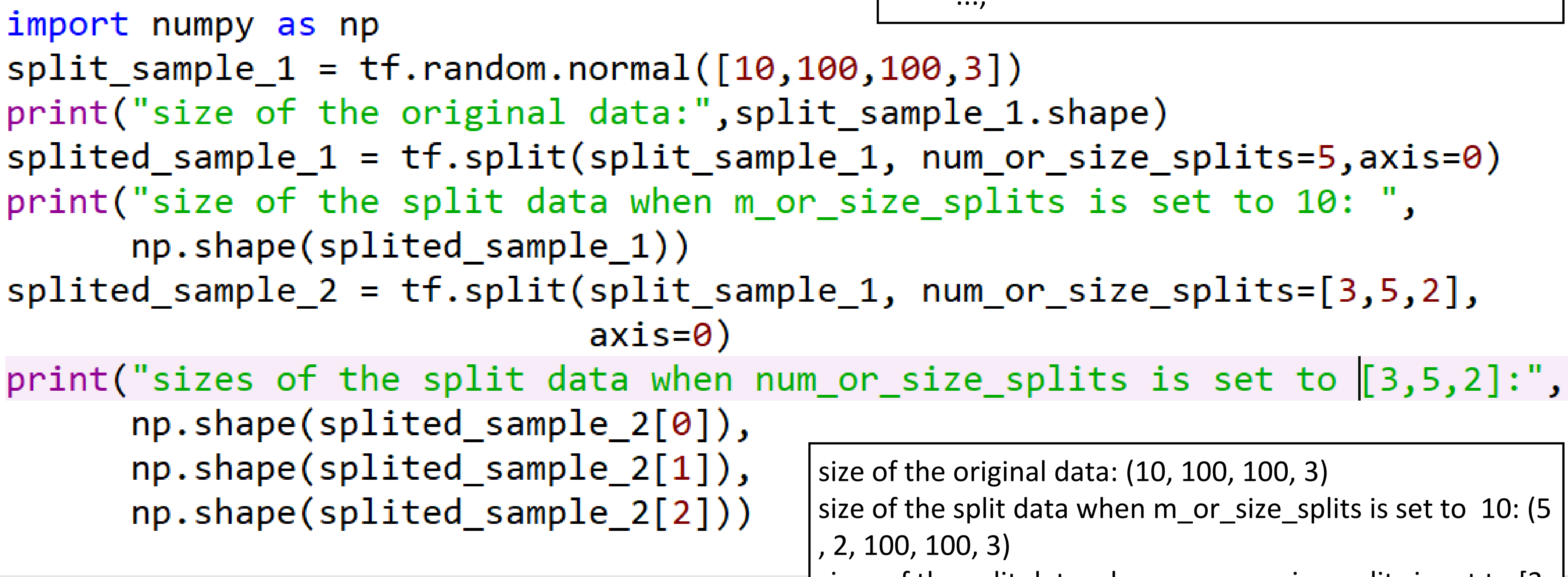
- tensor splitting operations include:
  - tf.unstack(): splits a tensor by a specific dimension.
  - tf.split(): splits a tensor into a specified number of sub tensors based on a specific dimension.
  - tf.split() is more flexible than tf.unstack().
- tf.unstack(value, num=None, axis=0,name='unstack'):
  - value: input tensor
  - num: indicates that a list containing num elements is output. The value of num must be the same as the number of elements in the specified dimension. This parameter can generally be ignored.
  - axis: specifies the dimension based on which the tensor is split.
  - name: operation name

Tensor Splitting



```
#Split data based on the first dimension and output
#the split data in a list.
tf.unstack(stacked_sample_1,axis=0)
```

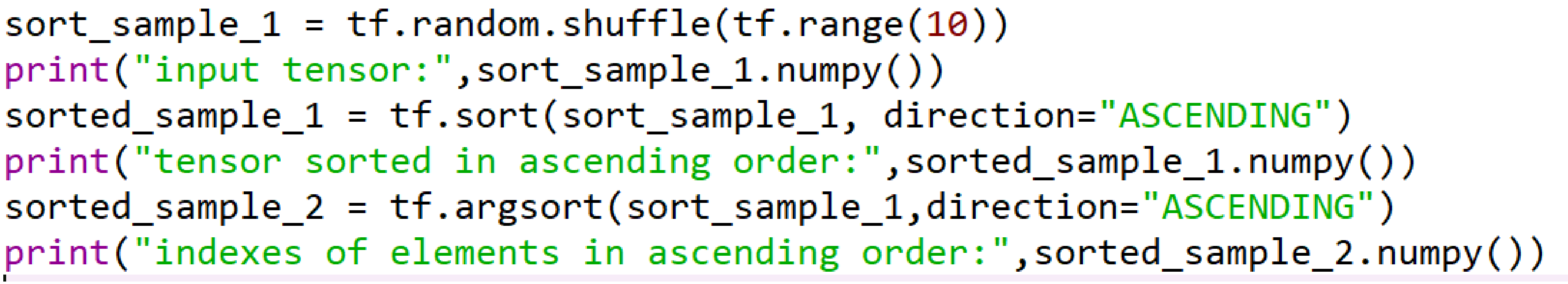
```
[<tf.Tensor: shape=(100, 100, 3), dtype=float32,
numpy=
 array([[[ 0.0665694 ,  0.7110351 ,  1.907618  ],
        [ 0.84416866,  1.5470593 , -0.5084871 ],
        [-1.9480026 , -0.9899087 , -0.09975405],
        ...,
```



```
import numpy as np
split_sample_1 = tf.random.normal([10,100,100,3])
print("size of the original data:",split_sample_1.shape)
splited_sample_1 = tf.split(split_sample_1, num_or_size_splits=5,axis=0)
print("size of the split data when m_or_size_splits is set to 10: ",
      np.shape(splited_sample_1))
splited_sample_2 = tf.split(split_sample_1, num_or_size_splits=[3,5,2],
                            axis=0)
print("sizes of the split data when num_or_size_splits is set to [3,5,2]:",
      np.shape(splited_sample_2[0]),
      np.shape(splited_sample_2[1]),
      np.shape(splited_sample_2[2]))
```

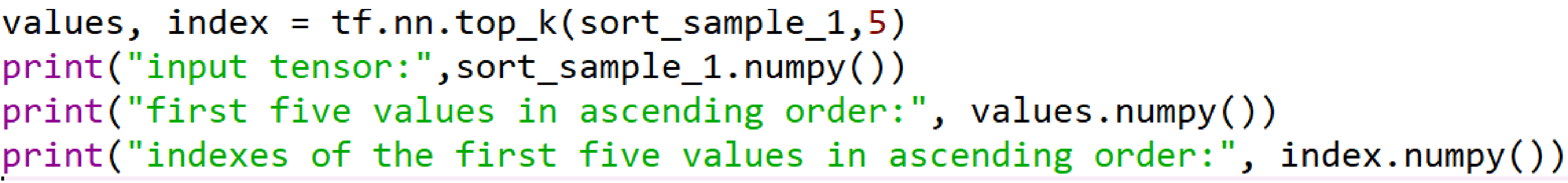
```
size of the original data: (10, 100, 100, 3)
size of the split data when m_or_size_splits is set to  10: (5
, 2, 100, 100, 3)
sizes of the split data when num_or_size_splits is set to [3,
5,2]: (3, 100, 100, 3) (5, 100, 100, 3) (2, 100, 100, 3)
```

Tensor Sorting



```python
sort_sample_1 = tf.random.shuffle(tf.range(10))
print("input tensor:",sort_sample_1.numpy())
sorted_sample_1 = tf.sort(sort_sample_1, direction="ASCENDING")
print("tensor sorted in ascending order:",sorted_sample_1.numpy())
sorted_sample_2 = tf.argsort(sort_sample_1,direction="ASCENDING")
print("indexes of elements in ascending order:",sorted_sample_2.numpy())
```

```
input tensor: [7 2 3 9 6 5 1 8 0 4]
tensor sorted in ascending order: [0 1 2 3 4 5 6 7 8 9]
indexes of elements in ascending order: [8 6 1 2 9 5 4 0 7 3]
```



```python
values, index = tf.nn.top_k(sort_sample_1,5)
print("input tensor:",sort_sample_1.numpy())
print("first five values in ascending order:", values.numpy())
print("indexes of the first five values in ascending order:", index.numpy())
```

```
input tensor: [7 2 3 9 6 5 1 8 0 4] first five values in
ascending order: [9 8 7 6 5] indexes of the first five
values in ascending order: [3 7 0 4 5]
```

Thanks

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