



— TensorFlow —

Introduction and Python Tutorial

Outlines

- Introduction To TensorFlow
- Installing TensorFlow
- TensorFlow Basic Operations
- Basic Training with TensorFlow

Part One

TensorFlow Basic Usage

What is TensorFlow?

- TensorFlow is a deep learning library was open-sourced by Google in Nov 2015.
- It is a multipurpose open source library for numerical computation using data flow graphs (networks).

What is TensorFlow?

- It has been designed with deep learning in mind it is written in C++ but can be used from many other programming language.
- It runs on many platforms (not windows friendly)

What is TensorFlow?

- The core of TensorFlow is the **dataflow graph** representing computations.
- The entire dataflow graph is a complete description of computations, and are executed on *devices* (**CPUs** or **GPUs**).

What is TensorFlow?

- Graph nodes are **operations** which have any number of inputs and outputs
- Graph edges are **tensors** which flow between nodes.
- TensorFlow provides primitives for defining functions on tensors and automatically computing their derivatives.

What is a Tensor

- A mathematical object analogous to but more general than a vector, represented by an array of components that are functions of the coordinates of a space
- A **scalar** is a tensor, a **vector** is a tensor, a **matrix** is a tensor.
- Simply a **multidimensional array of numbers**

TensorFlow vs Numpy

- TensorFlow and Numpy are very similar. They are N-d array libraries!
- Numpy has Ndarray support, but does not offer methods to create **tensor functions** and automatically **compute derivatives**.
- Numpy does not have **no GPU support**.

TensorFlow vs Numpy

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- Numpy does not have no GPU support.

TensorFlow vs Theano

- The Grand-daddy of deep-learning frameworks, which is written in Python
- Numerous open-source deep-libraries have been built on top of Theano, including Keras, Lasagne and Blocks. These libs attempt to layer an easier to use API on top of Theano's occasionally non-intuitive interface.

TensorFlow vs Theano

- Theano is an open source project primarily developed by a machine learning group at the [Université de Montréal](#).
- Tensorflow was inspired by Theano. Tensorflow has better support for distributed systems and more developer friendly.

Installing TensorFlow

- You must choose one of the following types of TensorFlow to install:
 - **TensorFlow with CPU support only.**
 - **TensorFlow with GPU support.**
- Platform options are Ubuntu, Mac OS X, and Windows

Installing TesnsorFlow

- On Ubuntu and Mac OS X, you have the following options:
 - Virtualenv
 - Native using pip
 - Docker
 - Anaconda
- On Windows you have native "using pip: or Anaconda. For other languages (Java, C++ and Go) check documentations

Installing TensorFlow

- On [Ubuntu 16.04 LTS](#) using the [virtualenv](#) option
- [Virtualenv](#) is a virtual Python environment isolated from other Python development, incapable of interfering with or being affected by other Python programs on the same machine

Installing TensorFlow

- Installing pip, python dev and virtualenv

```
sudo apt-get install python3-pip python3-dev python-virtualenv
```

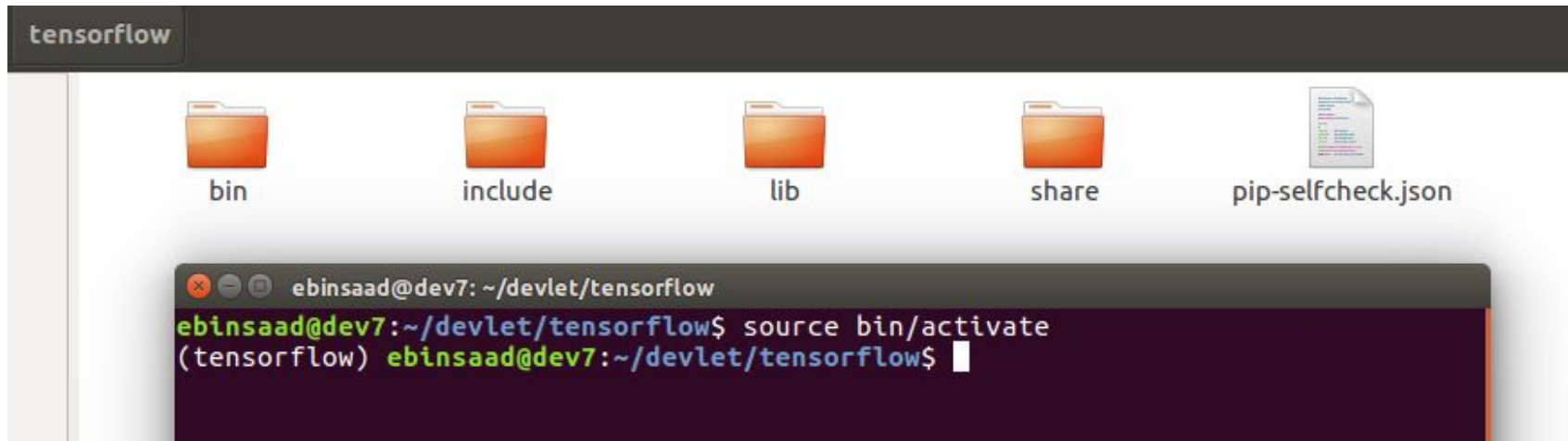
- Create a virtualenv environment

```
virtualenv --system-site-packages -p python3 tensorflow
```

- Activate the virtualenv

```
source -/tensorflow/bin/activate
```


Installing TensorFlow



- The preceding source command should change your prompt to **(tensorflow)\$**
- Note that you must activate the virtualenv environment each time you use TensorFlow.

Installing TensorFlow

- Install TensorFlow with pip

```
pip3 install --upgrade tensorflow
```

- Run the following code to test your installation

```
2  import tensorflow as tf
3
4  hello = tf.constant('Hello, TensorFlow!')
5
6  sess = tf.Session()
7
8  print(sess.run(hello))
```

Installing TensorFlow

- You should see the following if your installation was successful

```
Time Line # Log Message
3.6s      0  2017-07-24 22:03:46.086291: W tensorflow/core/platform/cpu_feature_guard.cc:45] The
                TensorFlow library wasn't compiled to use SSE4.1 instructions, but these are available on
                your machine and could speed up CPU computations.
                2017-07-24 22:03:46.086339: W tensorflow/core/platform/cpu_feature_guard.cc:45] The
                TensorFlow library wasn't compiled to use SSE4.2 instructions, but these are available on
                your machine and could speed up CPU computations.
                2017-07-24 22:03:46.086350: W tensorflow/core/platform/cpu_feature_guard.cc:45] The
                TensorFlow library wasn't compiled to use AVX instructions, but these are available on
                your machine and could speed up CPU computations.
                2017-07-24 22:03:46.086366: W tensorflow/core/platform/cpu_feature_guard.cc:45] The
                TensorFlow library wasn't compiled to use AVX2 instructions, but these are available on
                your machine and could speed up CPU computations.
                2017-07-24 22:03:46.086375: W tensorflow/core/platform/cpu_feature_guard.cc:45] The
                TensorFlow library wasn't compiled to use FMA instructions, but these are available on
                your machine and could speed up CPU computations.
3.7s      1  b'Hello, TensorFlow!'
```

Tensors

- The central unit of data in TensorFlow is the **tensor**.
- A tensor consists of a set of primitive values shaped into an array of any number of dimensions. A tensor's **rank** is its number of dimensions

```
2 3 'a rank 0 tensor; this is a scalar with shape []'  
3  
4 [1., 2., 3.] 'a rank 1 tensor; this is a vector with shape [3]'  
5  
6 [[1., 2., 3.], [4., 5., 6.]] 'a rank 2 tensor; a matrix with shape [2, 3]'  
7  
8 [[[1., 2., 3.]], [[7., 8., 9.]]] 'a rank 3 tensor with shape [2, 1, 3]'
```

Examples

Using TensorFlow

- Think of TensorFlow Core programs as consisting of :
 1. Building the computational graph.
 2. Running the computational graph.

Using TensorFlow

- What is a computational graph?
 - A series of TensorFlow operations arranged into a graph of nodes.
 - Each node takes zero or more tensors as inputs and produces a tensor as an output. One type of node is a constant. Like all TensorFlow constants, it takes no inputs, and it outputs a value it stores internally.

Using TensorFlow

```
1
2 import tensorflow as tf
3
4 # create two floating point Tensors node1 and node2
5
6 node1 = tf.constant(3.0, dtype=tf.float32)
7
8 node2 = tf.constant(4.0) # also tf.float32 implicitly
9
10 print(node1, node2)
```

| Time | Line # | Log Message |
|------|--------|--|
| 2.5s | 0 | Tensor("Const:0", shape=(), dtype=float32) |
| | | Tensor("Const_1:0", shape=(), dtype=float32) |

Using TensorFlow

The previous code only prints the node object not the values. To actually evaluate the nodes, we must run the computational graph within a **session**

```
11 # Create a session object to execute the computational graph
12 sess = tf.Session()
13
14 print(sess.run([node1, node2]))
15
```


Using TensorFlow

```
2 import tensorflow as tf
3
4 # Create two floating point Tensors node1 and node2
5 node1 = tf.constant(3.0, dtype=tf.float32)
6
7 node2 = tf.constant(4.0) # also tf.float32 implicitly
8 |
9 print(node1, node2)
10
11 # Create a session object to execute the computational graph
12 sess = tf.Session()
13
14 print(sess.run([node1, node2]))
```

| Time | Line # | Log Message |
|------|--------|---|
| 2.8s | 0 | Tensor("Const:0", shape=(), dtype=float32) Tensor("Const_1:0", shape=(), dtype=float32) [3.0, 4.0] |

What is a TensorFlow Session?

- A session allows to **execute graphs or part of graphs**. It **allocates resources** (on one or more machines) for that and holds the actual values of intermediate results and variables.
- In the graph we define the structure and the operations.

What is TensorFlow Graph?

- A graph defines the computation. It doesn't compute anything, it doesn't hold any values, it just defines the operations that you specified in your code.
- The **TensorFlow** Python library has a **default graph** to which ops constructors add nodes

Using TensorFlow

We can build more complicated computations by combining **Tensor** nodes with operations (Operations are also nodes.). For example, we can add our two constant nodes and produce a new graph as follows:

```
15  
16 node3 = tf.add(node1, node2)  
17  
18 print("node3: ", node3)  
19 print("sess.run(node3): ", sess.run(node3))
```

Using TensorFlow

```
2 import tensorflow as tf
3
4 # Create two floating point Tensors node1 and node2
5 node1 = tf.constant(3.0, dtype=tf.float32)
6 node2 = tf.constant(4.0) # also tf.float32 implicitly
7 print(node1, node2)
8
9 # Create a session object to execute the computational graph
10 sess = tf.Session()
11 print(sess.run([node1, node2]))
12
13 node3 = tf.add(node1, node2)
14
15 print("node3: ", node3)
16 print("sess.run(node3): ", sess.run(node3))
```

```
3.3s      3 node3: Tensor("Add:0", shape=(), dtype=float32)
          sess.run(node3): 7.0
```

Using TensorFlow

TensorFlow provides a utility called [TensorBoard](#) that can display a picture of the computational graph. Here is a screenshot showing how [TensorBoard](#) visualizes the graph:



How could we add input to the graph?

A graph can be parameterized to accept external inputs, known as **placeholders**. A **placeholder** is a promise to provide a value later.

```
6 a = tf.placeholder(tf.float32)
7 b = tf.placeholder(tf.float32)
8
9 adder_node = a + b # + provides a shortcut for tf.add(a, b)
```

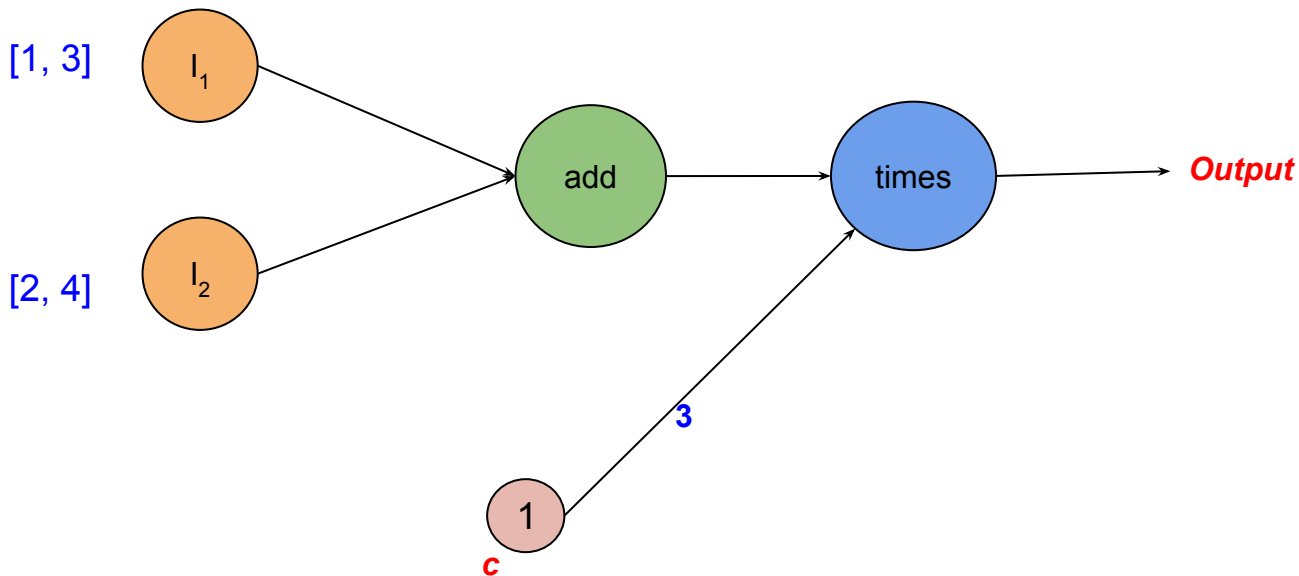
```
print(sess.run(adder_node, {a: 3, b:4.5}))
print(sess.run(adder_node, {a: [1,3], b: [2, 4]}))
```

How could we add input to the graph?

```
2  import tensorflow as tf
3
4  # Create two placeholders to hold floating point Tensors
5
6  a = tf.placeholder(tf.float32)
7  b = tf.placeholder(tf.float32)
8
9  adder_node = a + b  # + provides a shortcut for tf.add(a, b)
10
11 # Create a session object to execute the computational graph
12 sess = tf.Session()
13
14 print(sess.run(adder_node, {a: 3, b:4.5}))
15 print(sess.run(adder_node, {a: [1,3], b: [2, 4]}))
```


Using TensorFlow

Implement the following computational graph



Using TensorFlow

```
2  import tensorflow as tf
3
4  # Create two placeholders to hold floating point Tensors
5
6  a = tf.placeholder(tf.float32)
7  b = tf.placeholder(tf.float32)
8
9  c = tf.constant(3.0, dtype=tf.float32)
10 adder_node = a + b # + provides a shortcut for tf.add(a, b)
11
12 times_node = adder_node * c
13
14 # Create a session object to execute the computational graph
15 sess = tf.Session()
16
17 print(sess.run(times_node, {a: [1,3], b: [2, 4]}))
```

Basic Training with TensorFlow

- In machine learning we will typically want a model that can take arbitrary inputs, such as the one above.
- To make the model trainable, we need to be able to modify the graph to get new outputs with the same input.
- **Variables** allow us to add trainable parameters to a graph. They are constructed with a type and initial value

Training a Linear Model

$$\text{linear_model} = W * x + b$$

```
6  W = tf.Variable([0.3], dtype=tf.float32)
7  b = tf.Variable([-0.3], dtype=tf.float32)
8  x = tf.placeholder(tf.float32)
9
10 linear_model = W * x + b
11
```

Training a Linear Model

```
2 import tensorflow as tf
3
4 # linear_model = W * x + b
5
6 W = tf.Variable([0.3], dtype=tf.float32)
7 b = tf.Variable([-0.3], dtype=tf.float32)
8 x = tf.placeholder(tf.float32)
9
10 linear_model = W * x + b
11
12 ''' To initialize all the variables in a TensorFlow program,
13     you must explicitly call a special operation as follows: '''
14
15 sess = tf.Session()
16
17 init = tf.global_variables_initializer()
18
19 sess.run(init)
20
21 # apply the model with the inputs x
22 print(sess.run(linear_model, {x:[1,2,3,4]}))
```

Training a Linear Model

```
6  W = tf.Variable([0.3], dtype=tf.float32)
7  b = tf.Variable([-0.3], dtype=tf.float32)
8
9  x = tf.placeholder(tf.float32)
10 y = tf.placeholder(tf.float32)
11
12 linear_model = W * x + b
13
14 squared_deltas = tf.square(linear_model - y)
15
16 loss = tf.reduce_sum(squared_deltas)
```

```
27 # apply the mode with the inputs x with target y and print the sum square error
28 print(sess.run(loss, {x:[1,2,3,4], y:[0,-1,-2,-3]}))
```

Training a Linear Model

```
2 import tensorflow as tf
3
4 # linear_model = W * x + b
5
6 W = tf.Variable([0.3], dtype=tf.float32)
7 b = tf.Variable([-0.3], dtype=tf.float32)
8
9 x = tf.placeholder(tf.float32)
10 y = tf.placeholder(tf.float32)
11
12 linear_model = W * x + b
13
14 squared_deltas = tf.square(linear_model - y)
15
16 loss = tf.reduce_sum(squared_deltas)
17 |
18 ''' To initialize all the variables in a TensorFlow program,
19     you must explicitly call a special operation as follows: '''
20
21 sess = tf.Session()
22
23 init = tf.global_variables_initializer()
24
25 sess.run(init)
26
27 # apply the model with the inputs x with target y and print the sum square error
28 print(sess.run(loss, {x:[1,2,3,4], y:[0,-1,-2,-3]}))
29
```

The Result is

1 23.66

Training a Linear Model

- We want to learn the best values for W and b to minimize the loss.
- The simplest optimizer is **gradient descent**. It modifies each variable according to the magnitude of the derivative of loss with respect to that variable
- TensorFlow can automatically produce derivatives given only a description of the model using the function `tf.gradients`

Training a Linear Model

```
2  # loss
3  loss = tf.reduce_sum(tf.square(linear_model - y)) # sum of the squares
4
5  # optimizer
6  optimizer = tf.train.GradientDescentOptimizer(0.01)
7  train = optimizer.minimize(loss)
8
9  sess.run(init) # reset values to incorrect defaults.
10 for i in range(1000):
11     sess.run(train, {x:[1,2,3,4], y:[0,-1,-2,-3]})
12
13 print(sess.run([W, b]))
```

Training a Linear Model

```
1 import numpy as np
2 import tensorflow as tf
3
4 # Model parameters
5 W = tf.Variable([.3], dtype=tf.float32)
6 b = tf.Variable([-.3], dtype=tf.float32)
7 # Model input and output
8 x = tf.placeholder(tf.float32)
9 linear_model = W * x + b
10 y = tf.placeholder(tf.float32)
11 # loss
12 loss = tf.reduce_sum(tf.square(linear_model - y)) # sum of the squares
13 # optimizer
14 optimizer = tf.train.GradientDescentOptimizer(0.01)
15 train = optimizer.minimize(loss)
16 # training data
17 x_train = [1,2,3,4]
18 y_train = [0,-1,-2,-3]
19 # training loop
20 init = tf.global_variables_initializer()
21 sess = tf.Session()
22 sess.run(init) # reset values to wrong
23 for i in range(1000):
24     sess.run(train, {x:x_train, y:y_train})
25
26 # evaluate training accuracy
27 curr_W, curr_b, curr_loss = sess.run([W, b, loss], {x:x_train, y:y_train})
28 print("W: %s b: %s loss: %s"%(curr_W, curr_b, curr_loss))
```

Training a Linear Model

The optimal parameters of the is linear model with respect to x and y are $W = -1$ and $b = 1$

```
2017-07-25 21:37:02.915150: W tensorflow/core/platform/cpu_features.cc:117 TensorFlow library wasn't compiled to use SSE4.2 instructions, but your machine and could speed up CPU computations.
2017-07-25 21:37:02.915159: W tensorflow/core/platform/cpu_features.cc:117 TensorFlow library wasn't compiled to use AVX instructions, but your machine and could speed up CPU computations.
2017-07-25 21:37:02.915174: W tensorflow/core/platform/cpu_features.cc:117 TensorFlow library wasn't compiled to use AVX2 instructions, but your machine and could speed up CPU computations.
2017-07-25 21:37:02.915181: W tensorflow/core/platform/cpu_features.cc:117 TensorFlow library wasn't compiled to use FMA instructions, but your machine and could speed up CPU computations.
```

4.2s

1 W: [-0.9999969] b: [0.99999082] loss: 5.69997e-11

Questions