Introduction of TensorFlow (Basic Concept)

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Start Up

- **Google Machine Learning Tools**

1st Generation : *DistBelief*

- *Dean et al. 2011*
- *Major Output Products*
  - *Inception (Image Categorization)*
  - *Google Search*
  - *Google Translate*
  - *Google Photos*

2nd Generation : *TensorFlow*

- *Dean et al. 2015 (November, 1st)*
- *Most of DistBelief users at Google have already switched to TensorFlow*

Start Up

- **Main Developers of *DistBelief* and *TensorFlow***

Jeffrey Adgate "Jeff" Dean (born 1968) is an American computer scientist and software engineer. He is currently a Google Senior Fellow in the Systems and Infrastructure Group.

- Advertising / Crawling / Indexing / Query Systems
- ...

→ *Google Core*

- BigTable a large-scale semi-structured storage system.
- MapReduce a system for large-scale data processing applications.

→ *Hadoop*

- Google Brain a system for large-scale artificial neural networks
- LevelDB an open source on-disk key-value store.
- TensorFlow an open source machine learning software library.
- ...

→ *Large ML*

Start Up

❖ Features

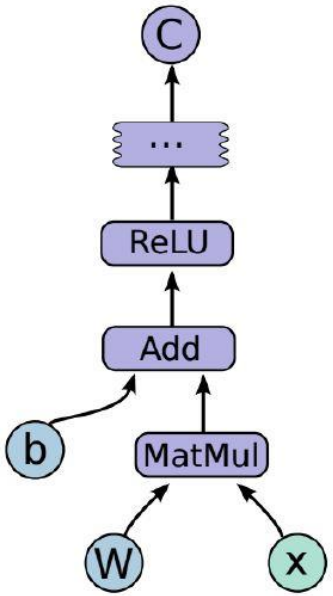
Programming Model	• Dataflow-like model	A directed Computational Graph 를 통해 모든 계산을 표현
Language	• Python • C++	현재는 Python, C++ 만 지원되나 FrontEnd 언어를 각 개발자가 만들면 되는 형태
Deployment	• Code once, Run everywhere	하나의 코드를 구현하면, 단-복수의 기계에서 똑같이 작동함
Computing Resource	• CPU • GPU	CPU 와 GPU 를 동시에 활용가능한 형태의 계산 Infra
Distribution Process	• Local Implementation • Distributed Implementation	Local, Distribution 2가지 모드에 대해 구현되어 있음. 옵션만 바꿔주면 TensorFlow가 알아서 작동됨
Math Expressions	• Math Graph Expression • Auto Differentiation	수식 및 계산 방식을 graph 형태로 표현. 따라서 자동으로 미분가능. 특히 Gradient 계산에 최적화해서 개발
Optimization	• Auto Elimination • Kernel Optimization • Communication Optimization • Support model, data parallelism • …	다양한 형태의 최적화를 TF가 알아서 진행함

Start Up

- **Computational Graph**

```
import tensorflow as tf

b = tf.Variable(tf.zeros([100]))                    # 100-d vector, init to zeroes
W = tf.Variable(tf.random_uniform([784,100],-1,1)) # 784x100 matrix w/rnd vals
x = tf.placeholder(name="x")                        # Placeholder for input
relu = tf.nn.relu(tf.matmul(W, x) + b)              # Relu(Wx+b)
C = [...]                                           # Cost computed as a function
                                                    # of Relu
```



$$C = ReLU(W \cdot x + b)$$

Start Up

- **Let's peek at what TensorFlow code looks like**
  - The first part of this code builds the data flow graph.

```
import tensorflow as tf
import numpy as np

# Create 100 phony x, y data points in NumPy, y = x * 0.1 + 0.3
x_data = np.random.rand(100).astype("float32")
y_data = x_data * 0.1 + 0.3

# Try to find values for W and b that compute y_data = W * x_data + b
# (We know that W should be 0.1 and b 0.3, but Tensorflow will
# figure that out for us.)
W = tf.Variable(tf.random_uniform([1], -1.0, 1.0))
b = tf.Variable(tf.zeros([1]))
y = W * x_data + b

# Minimize the mean squared errors.
loss = tf.reduce_mean(tf.square(y - y_data))
optimizer = tf.train.GradientDescentOptimizer(0.5)
train = optimizer.minimize(loss)
```

Start Up

- **Let's peek at what TensorFlow code looks like**
  - TensorFlow does not actually run any computation until the session is created and the *run* function is called.

```
# Before starting, initialize the variables.  We will 'run' this first.
init = tf.initialize_all_variables()

# Launch the graph.
sess = tf.Session()
sess.run(init)

# Fit the line.
for step in xrange(201):
    sess.run(train)
    if step % 20 == 0:
        print step, sess.run(W), sess.run(b)

# Learns best fit is W: [0.1], b: [0.3]
```

- **Download and set up Tensorflow**
  - https://www.tensorflow.org/versions/0.6.0/get_started/os_setup.html

Overview of TensorFlow

- **To use TensorFlow, you need to understand how TensorFlow:**
  - Represents computations as graphs.
  - Executes graphs in the context of Sessions.
  - Represents data as tensors.
  - Maintains state with Variables.
  - Uses feeds and fetches to get data into and out of arbitrary operations.

- **Overview of TensorFlow**
  - A programming system in which you represent computations as graphs
  - Nodes in the graph
    - Operation (op): to perform some computations
    - Input: one or more tensor, Output: one or more tensor
    - Tensor: a typed multi-dimensional array
      - ✓ EX) a mini-batch of images as a 4-D array of floating,

        [batch, height, width, channels]

Two Computation Phrases

- **To compute anything in TensorFlow**
  - A graph must be launched in a **Session**.
  - A Session
    - Place the graph ops onto Devices, such as **CPU**s or **GPU**s
    - Provide methods to execute them
    - Return tensors produced by ops as numpy ndarray objects in Python, and as tensorflow::Tensor instances in C and C++.

- **Two Computation Phrases of a Graph**
  - Construction phrase
    - Assemble a graph
    - ***ex)*** create a graph to represent and train a neural network
  - Execution phrase
    - Use a session to execute ops in the graph
    - ***ex)*** repeatedly execute a set of training ops in the graph

Two Computation Phrases

- **Building the Graph**
  - Start with ops that do not need any input (source ops), **Constant**
  - Pass their output to other ops that do computation
  - Ops constructors return objects
    - Stand for the output of the constructed ops
    - Pass these to other ops constructors to use as inputs

- **Default Graph**
  - Ops constructors add node to that graph

```
import tensorflow as tf

# Create a Constant op that produces a 1x2 matrix.  The op is
# added as a node to the default graph.
#
# The value returned by the constructor represents the output
# of the Constant op.
matrix1 = tf.constant([[3., 3.]])

# Create another Constant that produces a 2x1 matrix.
matrix2 = tf.constant([[2.],[2.]])
```

Two Computation Phrases

- **Default Graph**
  - Has three nodes: two constant() ops and one matmul() op

```
# Create a Matmul op that takes 'matrix1' and 'matrix2' as inputs.
# The returned value, 'product', represents the result of the matrix
# multiplication.
product = tf.matmul(matrix1, matrix2)
```

- **Launching the graph in a session**
  - Create a **Session** Object: should be closed to release resources
  - Without arguments, session constructor launches the default graph

```
# Launch the default graph.
sess = tf.Session()

# To run the matmul op we call the session 'run()' method, passing 'product'
# which represents the output of the matmul op.  This indicates to the call
# that we want to get the output of the matmul op back.
```

```
# The output of the op is returned in 'result' as a numpy `ndarray` object.
result = sess.run(product)
print result
# ==> [[ 12.]]

# Close the Session when we're done.
sess.close()
```

Two Computation Phrases

- **Session launches the graph, Session.run() method executes operations**

- **A Session with *Block***
  - Close automatically at the end of the with block

```
with tf.Session() as sess:
  result = sess.run([product])
  print result
```

- **GPU Usage**
  - Translate the graph definition into executable operations distributed across available compute resources, such as CPU or GPU
  - If you have GPU, TensorFlow uses your first GPU

Two Computation Phrases

❖ Interactive Usage

- In Python environments, such as Ipython, the InteractiveSession class is used.
- Tensor.eval() and Operation.run()
- This avoids having to keep a variable holding the session

```
# Enter an interactive TensorFlow Session.
import tensorflow as tf
sess = tf.InteractiveSession()

x = tf.Variable([1.0, 2.0])
a = tf.constant([3.0, 3.0])

# Initialize 'x' using the run() method of its initializer op.
x.initializer.run()

# Add an op to subtract 'a' from 'x'.  Run it and print the result
sub = tf.sub(x, a)
print sub.eval()
# ==> [-2. -1.]

# Close the Session when we're done.
sess.close()
```

Tensors

Tensors

- Tensor data structure to represent all data
- Only tensors are passed between operations in the computation graph
- n-dimensional array or list
  - Static type, a rank, and a shape

Rank	Math entity	Python example
0	Scalar (magnitude only)	`s = 483`
1	Vector (magnitude and direction)	`v = [1.1, 2.2, 3.3]`
2	Matrix (table of numbers)	`m = [[1, 2, 3], [4, 5, 6], [7, 8, 9]]`
3	3-Tensor (cube of numbers)	`t = [[[2], [4], [6]], [[8], [10], [12]], [[14], [16], [18]]]`
n	n-Tensor (you get the idea)	`....`

Tensors

❖ Tensors

➢ Shape

Rank	Shape	Dimension number	Example
0	[]	0-D	A 0-D tensor. A scalar.
1	[D0]	1-D	A 1-D tensor with shape [5].
2	[D0, D1]	2-D	A 2-D tensor with shape [3, 4].
3	[D0, D1, D2]	3-D	A 3-D tensor with shape [1, 4, 3].
n	[D0, D1, ... Dn]	n-D	A tensor with shape [D0, D1, ... Dn].

➢ Data Types

Data type	Python type	Description
DT_FLOAT	tf.float32	32 bits floating point.
DT_DOUBLE	tf.float64	64 bits floating point.
DT_INT64	tf.int64	64 bits signed integer.
DT_INT32	tf.int32	32 bits signed integer.
DT_INT16	tf.int16	16 bits signed integer.

Tensors

❖ Tensors

➢ Data Types

DT_INT8	tf.int8	8 bits signed integer.
DT_UINT8	tf.uint8	8 bits unsigned integer.
DT_STRING	tf.string	Variable length byte arrays. Each element of a Tensor is a byte array.
DT_BOOL	tf.bool	Boolean.
DT_COMPLEX64	tf.complex64	Complex number made of two 32 bits floating points: real and imaginary parts.
DT_QINT32	tf.qint32	32 bits signed integer used in quantized Ops.
DT_QINT8	tf.qint8	8 bits signed integer used in quantized Ops.
DT_QUINT8	tf.quint8	8 bits unsigned integer used in quantized Ops.

Variables

- **Variables: Creation, Initialization, Saving and Loading**
  - To hold and update parameters, maintain state in the graph across calls to ***run()***
  - In-memory buffers containing tensors
  - Must be explicitly initialized and can be saved to disk during and after training
  - Class ***tf.Variable***
    - Constructor: an initial value for the variable, a Tensor of any type and shape
    - After construction, the type and shape are fixed
    - **assign** Op with validate_shape=False

Variables

- **Creation**
  - Pass a Tensor as its initial value to the Variable() constructor
  - Initial value: constants, sequences and random values
    - *tf.zeros()*, *tf.linspace()*, *tf.random_normal()*
  - Fixed shape: the same shape as ops' shape

```
# Create two variables.
weights = tf.Variable(tf.random_normal([784, 200], stddev=0.35),
                      name="weights")
biases = tf.Variable(tf.zeros([200]), name="biases")
```

  - Calling *tf.Variable()* adds several ops to the graph

- **Initialization**
  - Add an op and run it
  - *tf.initialize_all_variables()*

```
# Create two variables.
weights = tf.Variable(tf.random_normal([784, 200], stddev=0.35),
                      name="weights")
biases = tf.Variable(tf.zeros([200]), name="biases")
...
# Add an op to initialize the variables.
init_op = tf.initialize_all_variables()

# Later, when launching the model
with tf.Session() as sess:
  # Run the init operation.
  sess.run(init_op)
```

Variables

- **Saving and Restoring**
  - *tf.train.saver*
  - Checkpoint Files: Variables are saved in binary files that contain a map from variable names to tensor values

```
# Create some variables.
v1 = tf.Variable(..., name="v1")
v2 = tf.Variable(..., name="v2")
...
# Add an op to initialize the variables.
init_op = tf.initialize_all_variables()

# Add ops to save and restore all the variables.
saver = tf.train.Saver()

# Later, launch the model, initialize the variables, do some work, save the
# variables to disk.
with tf.Session() as sess:
  sess.run(init_op)
  # Do some work with the model.
  ..
  # Save the variables to disk.
  save_path = saver.save(sess, "/tmp/model.ckpt")
  print("Model saved in file: %s" % save_path)
```

Variables

- **Saving and Restoring**
  - Restore

```
# Create some variables.
v1 = tf.Variable(..., name="v1")
v2 = tf.Variable(..., name="v2")
...
# Add ops to save and restore all the variables.
saver = tf.train.Saver()

# Later, launch the model, use the saver to restore variables from disk, and
# do some work with the model.
with tf.Session() as sess:
  # Restore variables from disk.
  saver.restore(sess, "/tmp/model.ckpt")
  print("Model restored.")
  # Do some work with the model
  ...
```

Variables

- **Choosing which Variables to Save and Restore**
  - No arguments to *tf.train.Saver()* ➔ handle all variables in the graph
    - *Each one of them is saved under the name*
  - Save and restore a subset of the variables
    - Ex) trained neural net with 5 layers ➔ want to train a new model with 6 layers, restoring the parameters from the 5 layers
  - Passing to the *tf.train.Saver()* constructor a Python dictionary: keys

```
# Create some variables.
v1 = tf.Variable(..., name="v1")
v2 = tf.Variable(..., name="v2")
...
# Add ops to save and restore only 'v2' using the name "my_v2"
saver = tf.train.Saver({"my_v2": v2})
# Use the saver object normally after that.
...
```

Variables

- **Example code serving a simple counter**

```
# Create a Variable, that will be initialized to the scalar value 0.
state = tf.Variable(0, name="counter")

# Create an Op to add one to `state`.

one = tf.constant(1)
new_value = tf.add(state, one)
update = tf.assign(state, new_value)

# Variables must be initialized by running an `init` Op after having
# launched the graph.  We first have to add the `init` Op to the graph.
init_op = tf.initialize_all_variables()

# Launch the graph and run the ops.
with tf.Session() as sess:
  # Run the 'init' op
  sess.run(init_op)
  # Print the initial value of 'state'
  print(sess.run(state))
  # Run the op that updates 'state' and print 'state'.
  for _ in range(3):
    sess.run(update)
    print(sess.run(state))

# output:

# 0
# 1
# 2
# 3
```

Variables

- **Fetches**
  - Execute the graph with a *run()* call on the *Session* object and pass in the tensors to retrieve

```
input1 = tf.constant(3.0)
input2 = tf.constant(2.0)
input3 = tf.constant(5.0)
intermed = tf.add(input2, input3)
mul = tf.mul(input1, intermed)

with tf.Session() as sess:
  result = sess.run([mul, intermed])
  print(result)

# output:
# [array([ 21.], dtype=float32), array([ 7.], dtype=float32)]
```

Variables

- **Feeds**
  - Patching a tensor directly into any operation in the graph
  - Temporarily replaces the output of an operation with a tensor value
  - Feed data as an argument to a run() call
  - Only used for the run call to which it is passed
  - *tf.placeholder()*

```
input1 = tf.placeholder(tf.float32)
input2 = tf.placeholder(tf.float32)
output = tf.mul(input1, input2)

with tf.Session() as sess:
  print(sess.run([output], feed_dict={input1:[7.], input2:[2.]}))

# output:
# [array([ 14.], dtype=float32)]
```

Operations

- **Operations**

Operations

Category	Examples
Element-wise mathematical operations	Add, Sub, Mul, Div, Exp, Log, Greater, Less, Equal, ...
Array operations	Concat, Slice, Split, Constant, Rank, Shape, Shuffle, ...
Matrix operations	MatMul, MatrixInverse, MatrixDeterminant, ...
Stateful operations	Variable, Assign, AssignAdd, ...
Neural-net building blocks	SoftMax, Sigmoid, ReLU, Convolution2D, MaxPool, ...
Checkpointing operations	Save, Restore
Queue and synchronization operations	Enqueue, Dequeue, MutexAcquire, MutexRelease, ...
Control flow operations	Merge, Switch, Enter, Leave, NextIteration

References

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- **Sangkeun Jung.** “Deep Learning Tutorial with Tensorflow.” *Natural Language Processing Tutorial*, 2016.

- www.tensorflow.org

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Thank you for your attention!

http://web.donga.ac.kr/yjko/

고 영 중