

# TensorFlow Tutorials

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Slides compiled from  
CS 20: TensorFlow for Deep Learning Research  
Stanford University

# What's TensorFlow?

- Open source software library for numerical computation using data flow graphs
- Developed by Google Brain
- Provides primitives for defining functions on tensors and automatically computing their derivatives

# Companies using TensorFlow



kakao



QUALCOMM



# The programming stack

High-Level  
TensorFlow APIs

Estimators

Mid-Level  
TensorFlow APIs

Layers

Datasets

Metrics

Low-level  
TensorFlow APIs

Python

C++

Java

Go

TensorFlow  
Kernel

TensorFlow Distributed Execution Engine

# Goals

- Understand TF's computation graph approach
- Explore TF's built-in functions and classes
- Learn how to build and structure models best suited for a deep learning project

# Getting Started

```
import tensorflow as tf
```

# Tensor

- Generalization of vectors and matrices to higher dimensions
- TensorFlow represents tensors as n-dimensional arrays of base datatypes
- A [tf.Tensor](#) has the following properties:
  - a data type (float32, int32, or string, for example)
  - a shape
- Special tensors:  
[tf.Variable](#), [tf.constant](#), [tf.placeholder](#), [tf.SparseTensor](#)

# Variables

- the best way to represent shared, persistent state manipulated by your program
- Variables are manipulated via the `tf.Variable` class
- Variable is basically a wrapper on tensor that maintains states across multiple calls to run
- Example:

```
# create variables with tf.Variable
s = tf.Variable(2, name="scalar")
m = tf.Variable([[0, 1], [2, 3]], name="matrix")
W = tf.Variable(tf.zeros([784, 10]))  
  
# create variables with tf.get_variable
s = tf.get_variable("scalar", initializer=tf.constant(2))
m = tf.get_variable("matrix", initializer=tf.constant([[0, 1], [2, 3]]))
W = tf.get_variable("big_matrix", shape=(784, 10), initializer=tf.zeros_initializer())
```



# Initialize your variables

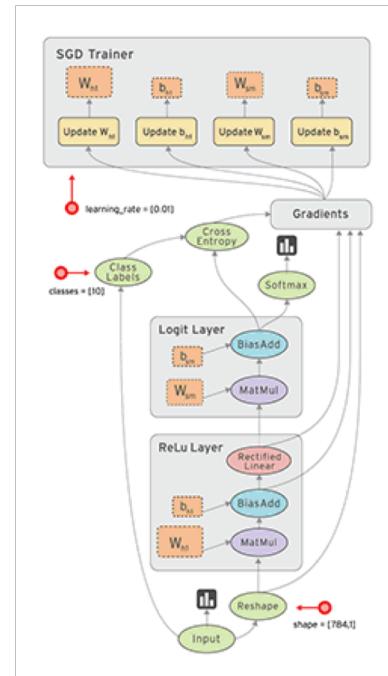
The easiest way is initializing **all variables at once**:

```
with tf.Session() as sess:  
    sess.run(tf.global_variables_initializer())
```

Initialize **only a subset** of variables:

```
with tf.Session() as sess:  
    sess.run(tf.variables_initializer([a, b]))
```

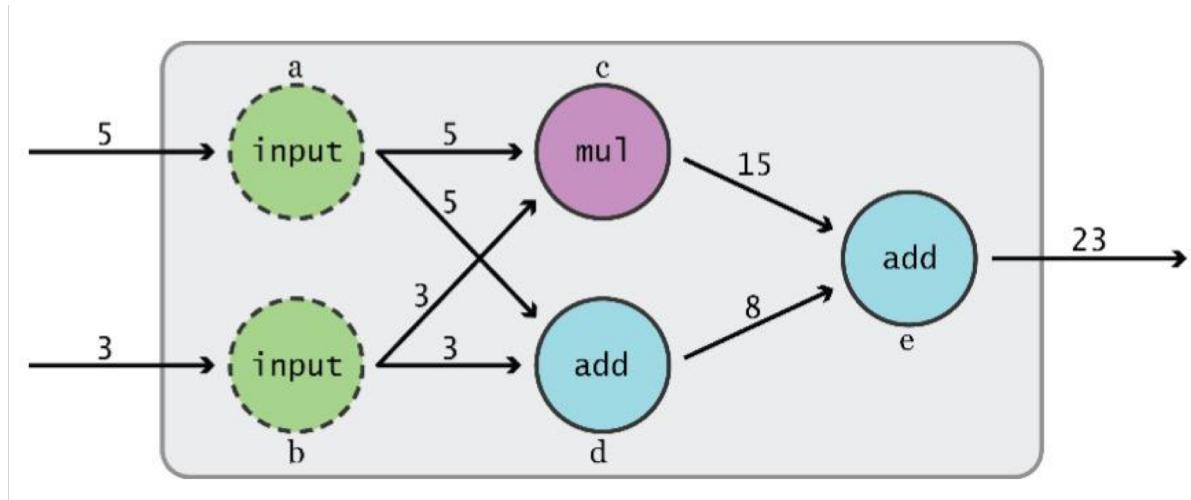
# Graphs and Sessions



From <https://www.tensorflow.org>

# Data Flow Graphs

- Dataflow: programming model for parallel programming
- TensorFlow **separates** definition of computations from their execution

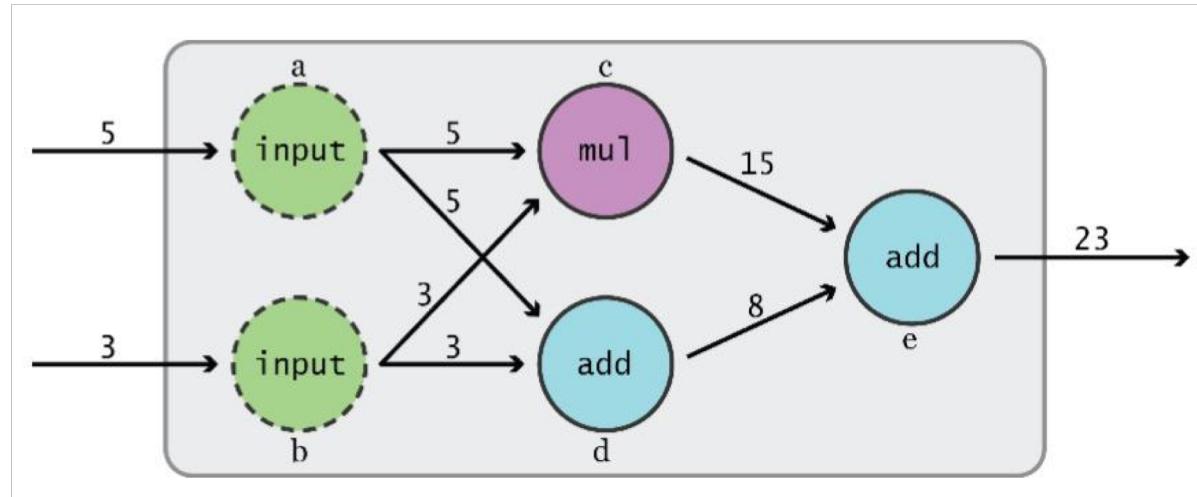


Graph from *TensorFlow for Machine Intelligence*

# Data Flow Graphs

Phase 1: assemble a graph

Phase 2: use a session to execute operations in the graph



# Data Flow Graphs

```
import tensorflow as tf  
a = tf.add(3, 5)  
print(a)
```

What will it print?

Not 8, why??

# How to get the value of a?

Create a **session**, assign it to variable sess so we can call it later

Within the session, evaluate the graph to fetch the value of **a**

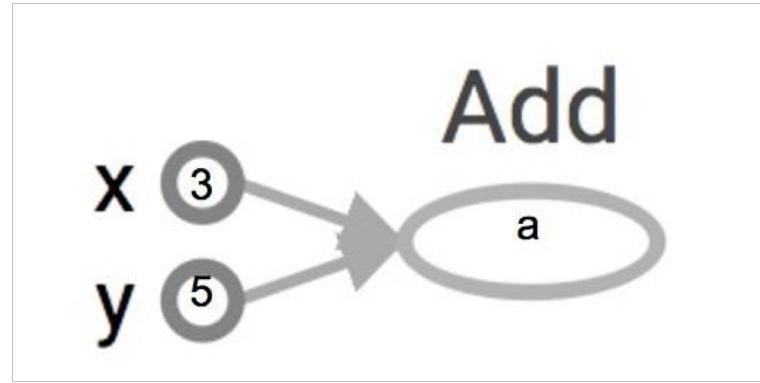
What is session?

# **tf.Session()**

- Encapsulates the environment in which Operation objects are executed, and Tensor objects are evaluated
- Allows to execute graphs or part of graphs
- Allocates resources (on one or more machines) for that and holds the actual values of intermediate results and variables

# How to get the value of a?

```
import tensorflow as tf  
a = tf.add(3, 5)  
sess = tf.Session()  
print(sess.run(a))  
sess.close()
```



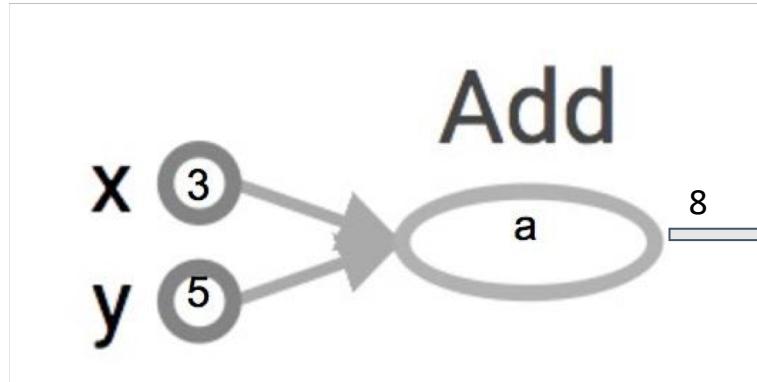
The session will look at the graph, trying to think: hmm, how can I get the value of a, then it computes all the nodes that leads to a.

# How to get the value of a?

```
import tensorflow as tf  
a = tf.add(3, 5)  
sess = tf.Session()  
print(sess.run(a))  >> 8  
sess.close()
```

Alternative approach:

```
import tensorflow as tf  
a = tf.add(3, 5)  
sess = tf.Session()  
with tf.Session() as sess:  
    print(sess.run(a))  
sess.close()
```



The session will look at the graph, trying to think: hmm, how can I get the value of a, then it computes all the nodes that leads to a.

# 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 network 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

# Arithmetic Ops

- `tf.abs`
- `tf.negative`
- `tf.sign`
- `tf.reciprocal`
- `tf.square`
- `tf.round`
- `tf.sqrt`
- `tf.rsqrt`
- `tf.pow`
- `tf.exp`

# TensorFlow Data Types

- `tf.float16` : 16-bit half-precision floating-point.
- `tf.float32` : 32-bit single-precision floating-point.
- `tf.float64` : 64-bit double-precision floating-point.
- `tf.bfloat16` : 16-bit truncated floating-point.
- `tf.complex64` : 64-bit single-precision complex.
- `tf.complex128` : 128-bit double-precision complex.
- `tf.int8` : 8-bit signed integer.
- `tf.uint8` : 8-bit unsigned integer.
- `tf.uint16` : 16-bit unsigned integer.
- `tf.int16` : 16-bit signed integer.
- `tf.int32` : 32-bit signed integer.
- `tf.int64` : 64-bit signed integer.
- `tf.bool` : Boolean.
- `tf.string` : String.
- `tf.qint8` : Quantized 8-bit signed integer.
- `tf.quint8` : Quantized 8-bit unsigned integer.
- `tf.qint16` : Quantized 16-bit signed integer.
- `tf.quint16` : Quantized 16-bit unsigned integer.
- `tf.qint32` : Quantized 32-bit signed integer.
- `tf.resource` : Handle to a mutable resource.

# Constants

```
import tensorflow as tf
a = tf.constant([2, 2], name='a')
b = tf.constant([[0, 1], [2, 3]], name='b')

tf.constant(
    value,
    dtype=None,
    shape=None,
    name='Const',
    verify_shape=False
)
```

# Randomly Generated Constants

- TF has several ops that create random tensors with different distributions
- the initialization of variables

- `tf.random_normal`
- `tf.truncated_normal`
- `tf.random_uniform`
- `tf.random_shuffle`
- `tf.random_crop`
- `tf.multinomial`
- `tf.random_gamma`
- `tf.set_random_seed`

# What's wrong with constants?

- Constants are stored in the graph definition

```
my_const = tf.constant([1.0, 2.0], name="my_const")
with tf.Session() as sess:
    print(sess.graph.as_graph_def())
```

```
attr {
  key: "value"
  value {
    tensor {
      dtype: DT_FLOAT
      tensor_shape {
        dim {
          size: 2
        }
      }
      tensor_content: "\000\000\200?\000\000\000@"
    }
  }
}
```

- This makes loading graphs expensive when constants are big
- Only use constants for primitive types.
- Use variables or readers for more data that requires more memory

# Placeholders

## A quick reminder:

A TF program often has 2 phases:

1. Assemble a graph
2. Use a session to execute operations in the graph

⇒ Assemble the graph first without knowing the values needed for computation

## Analogy:

Define the function  $f(x, y) = 2 * x + y$  without knowing value of x or y.  
x, y are placeholders for the actual values.

# Why placeholders?

We, or our clients, can later supply their own data when they need to execute the computation.

# Placeholders: Example

## Syntax

```
tf.placeholder(dtype, shape=None, name=None)

# create a placeholder for a vector of 3 elements, type tf.float32
a = tf.placeholder(tf.float32, shape=[3])

b = tf.constant([5, 5, 5], tf.float32)

# use the placeholder as you would a constant or a variable
c = a + b # short for tf.add(a, b)

with tf.Session() as sess:
    print(sess.run(c))          # >> Error (??)
```

# Placeholders: Example

**Solution:** Supplement the values to placeholders using a dictionary

## Syntax

```
tf.placeholder(dtype, shape=None, name=None)
# create a placeholder for a vector of 3 elements, type tf.float32
a = tf.placeholder(tf.float32, shape=[3])

b = tf.constant([5, 5, 5], tf.float32)

# use the placeholder as you would a constant or a variable
c = a + b # short for tf.add(a, b)

with tf.Session() as sess:
    print(sess.run(c, feed_dict={a: [1, 2, 3]}))
    # the tensor a is the key, not the string 'a'

# >> [6, 7, 8]
```

**You can feed\_dict any feedable tensor.  
Placeholder is just a way to indicate that something must be fed**

# Feeding values to TF ops

We can evaluate TF operations individually as well.

```
# create operations, tensors, etc (using the default graph)
a = tf.add(2, 5)
b = tf.multiply(a, 3)

with tf.Session() as sess:
    # compute the value of b given a is 15
    sess.run(b, feed_dict={a: 15})          # >> 45
```

# Extremely helpful for testing

Feed in dummy values to test parts of a large graph

# Putting it together

```
DATA_FILE = 'data/birth_life_2010.txt'

# Step 1: read in data from the .txt file
data, n_samples = utils.read_birth_life_data(DATA_FILE)

# Step 2: create placeholders for X (birth rate) and Y (life expectancy)
X = tf.placeholder(tf.float32, name='X')
Y = tf.placeholder(tf.float32, name='Y')

# Step 3: create weight and bias, initialized to 0
w = tf.get_variable('weights', initializer=tf.constant(0.0))
b = tf.get_variable('bias', initializer=tf.constant(0.0))

# Step 4: build model to predict Y
Y_predicted = w * X + b

# Step 5: use the squared error as the loss function
# you can use either mean squared error or Huber loss
loss = tf.square(Y - Y_predicted, name='loss')
```

How does TensorFlow know what variables to update?

# Optimizers

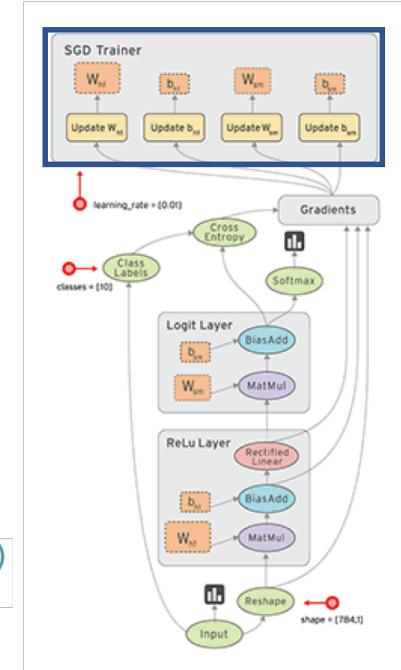
Session looks at all **trainable** variables that optimizer depends on and update them

Specify if a variable should be trained or not  
By default, all variables are trainable

```
tf.Variable(initial_value=None, trainable=True,...)
```

Add a **optimizer** to the program

```
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(loss)
_, l = sess.run([optimizer, loss], feed_dict={X: x, Y:y})
```



# Linear Regression

**Dataset** : World Development Indicators dataset

**Target**: Find a linear relationship between X and Y to predict Y from X

**Model**:

Inference:  $\hat{Y}_{predicted} = w * X + b$

Mean squared error:  $E[(y - \hat{y}_{predicted})^2]$

Lets execute the program

# Logistic Regression

**Dataset** : Mnist Dataset

**Target**: Recognize the digit in the image

**Model**:

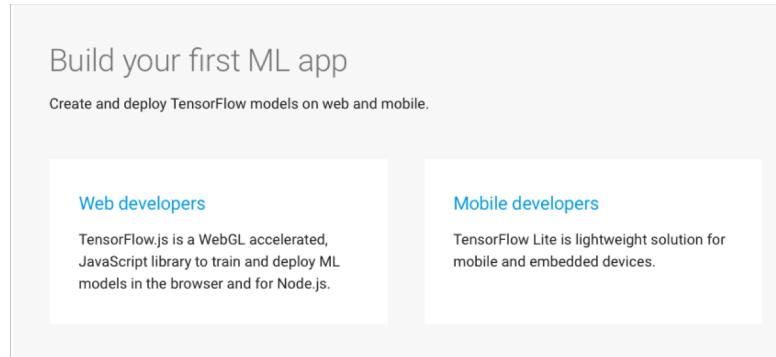
Inference:  $Y_{predicted} = \text{softmax}(X * w + b)$

Cross entropy loss :  $-\log(Y_{predicted})$

Lets execute the program

# Resources

- **Get Started with TensorFlow** (<https://www.tensorflow.org/tutorials/>)
- **Google Colab:** An easy way to learn and use TensorFlow
  - hosted Jupyter notebook environment that is free to use and requires no setup
- **CS 20: Tensorflow for Deep Learning Research** (<http://web.stanford.edu/class/cs20si/>)
- **Model Zoo Tensorflow** (<https://modelzoo.co/framework/tensorflow>)
- **For mobile and web developer**



# Questions

- Email me: [kk3671@rit.edu](mailto:kk3671@rit.edu)
- Visit me in my lab 74-1050

Thanks