

# Introduction to Tensorflow

8 May 2017, Nelson Liu



# What is TensorFlow?

- “An open-source software library for Machine Intelligence”
  - Think of it as NumPy, but with a computation graph and tuned for neural networks.
- Developed and maintained by Google Brain
- Very active community, used by hobbyists and corporations alike.

 tensorflow / tensorflow

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Computation using data flow graphs for scalable machine learning <http://tensorflow.org>

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 Apache-2.0

# Part I: Basics

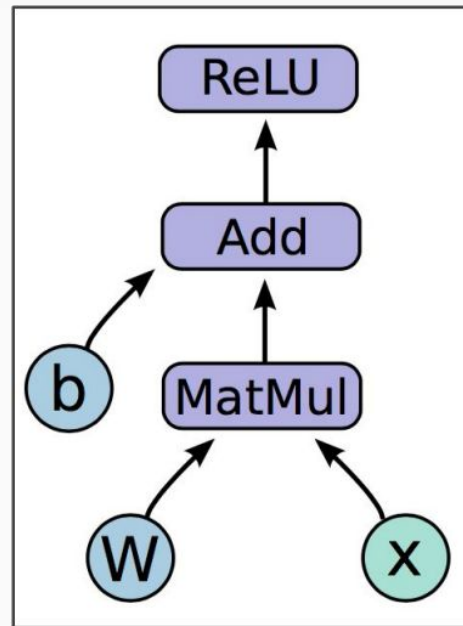
# Graph Computation

Core Idea: Express computations as a **graph**

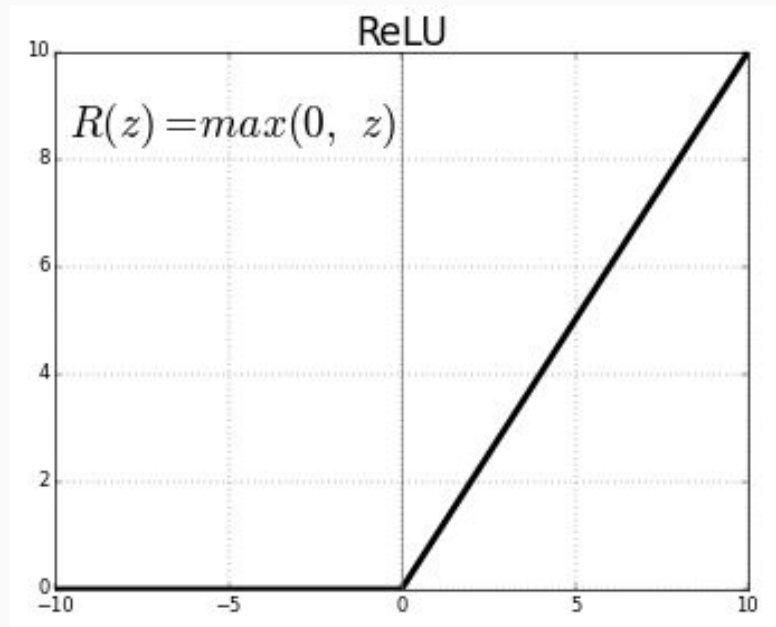
- **The graph nodes represent numeric operations** (e.g. +, -, average), and can have any number of inputs (edges leading into the node) and outputs (edges leading out of the node).
- **The graph edges represent tensors**, n-dimensional arrays that flow through the graph through the nodes.

# Example Graph: A one-layer neural net

$$h = \text{ReLU}(Wx + b)$$



# Reminder: ReLU



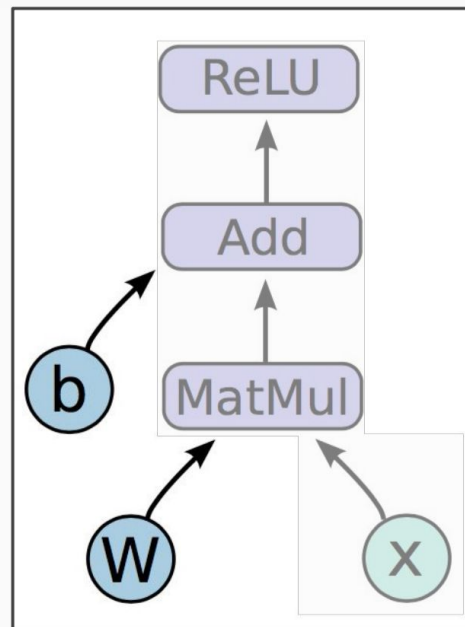
# Example Graph: A one-layer neural net

**Variables** are nodes that output their current value.

Their value is retained across multiple “executions” of the graph.

Generally used to represent the parameters (weights) of your model.

$$h = \text{ReLU}(Wx + b)$$



# Example Graph: A one-layer neural net

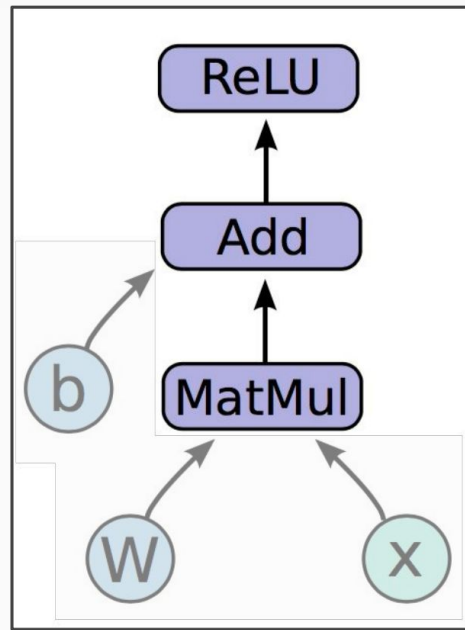
**Operations (ops)** are nodes that represent mathematical operations to be performed on the data.

**MatMul:** Multiply two matrices.

**Add:** Elementwise addition between two tensors.

**ReLU:** Apply the ReLU activation function to each element of the tensor.

$$h = \text{ReLU}(Wx + b)$$





## As code:

1. Create Variables  $W$  and  $b$  (the weights of the model), and initialize them.
2. Create an placeholder  $x$
3. Build the computation graph

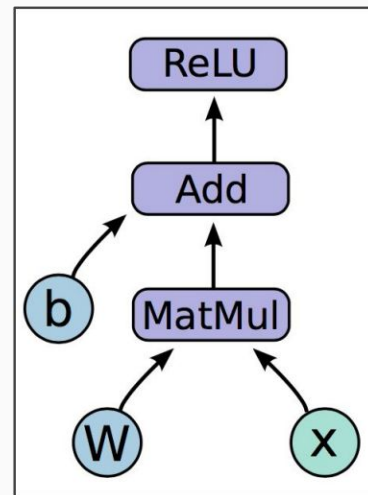
```
import tensorflow as tf

# Create Variables W and b
b = tf.Variable(tf.zeros((100,)))
W = tf.Variable(tf.random_uniform((784, 100), -1, 1))

# Create a placeholder that will take input matrices
# of size 100x784
x = tf.placeholder("float", (100, 784))

# String the placeholders and Variables together to
# build the graph
h = tf.nn.relu(tf.matmul(x, W) + b)
```

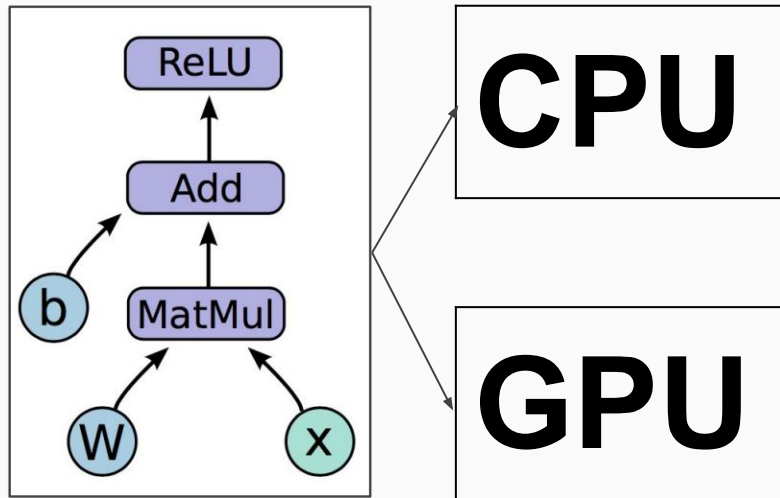
$$h = \text{ReLU}(Wx + b)$$



# Running the graph

In the last slide, we successfully defined a **graph**.

To run it, we need to create a **session**, which is essentially a binding to a particular “device” (execution environment, like a CPU or GPU or both!)



# Getting output

```
sess.run(to_fetch, feed_dict)
```

**to\_fetch:** A list of graph nodes. You're telling Tensorflow to run as much of the graph needed to return the output of these nodes.

**feed\_dict:** A dictionary used to "feed" values to the placeholders. The key is the placeholder object, and the value is the value you want to pass in.

```
import numpy as np
import tensorflow as tf

# Create Variables W and b
b = tf.Variable(tf.zeros((100,)))
W = tf.Variable(tf.random_uniform((784, 100), -1, 1))

# Create a placeholder that will take input matrices
# of size 100x784
x = tf.placeholder("float", (100, 784))

# String the placeholders and Variables together to
# build the graph
h = tf.nn.relu(tf.matmul(x, W) + b)

# Create a Tensorflow Session
with tf.Session() as sess:
    # Collect all the Variables in the graph and
    # returns an operation that will initialize them.
    sess.run(tf.global_variables_initializer())
    # Get the output of the op assigned to h
    sess.run(h, {x: np.random.random(100, 784)})
```

# Summary

- We started by building a graph, and defined **Variables** for our weights and **placeholders** for our inputs.
- We then created a **session** to run the graph, and got the output of the single layer neural network.
- Next, we'll **train the model** (change the weights to optimize the loss)

# Defining the loss

How do we pass in the correct **labels** to the graph? Use a **placeholder**!

Build a loss operation (node in the graph) that is a function of the **labels** and the model's **predictions**

```
predictions = tf.nn.softmax(...) # output of the neural net
labels = tf.placeholder("float", [100, 10])
# Categorical Cross-Entropy loss function
xentropy = tf.reduce_mean(
    -tf.reduce_sum(label * tf.log(prediction), axis=1))
```

# Categorical Cross-Entropy

$$H_{y'}(y) = - \sum_i (y'_i \cdot \log(y_i))$$

Standard loss function for multi-class classification. More details [here](#).

# Calculating the Gradients

```
# Creates an Optimizer object
optimizer = tf.train.GradientDescentOptimizer(0.5)
# Adds an optimization operation to the graph
train_op = optimizer.minimize(xentropy)
```

Tensorflow **graph nodes (operations)** have built-in **gradient operations**.

Tensorflow computes the gradient with respect to the **parameters/weights** with **backpropagation** automatically

# Using the train\_op in a model (example)

```
predictions = tf.nn.softmax(...)
labels = tf.placeholder("float", [None, 10])

xentropy = tf.reduce_mean(
    -tf.reduce_sum(label * tf.log(prediction)))

optimizer = tf.train.GradientDescentOptimizer(0.5)
train_op = optimizer.minimize(xentropy)
```



# Training the model

```
sess.run(train_op, feed_dict)
```

1. Create a session
2. Build a train loop over the data
3. Run the train\_op

```
with tf.Session() as sess:  
    sess.run(tf.global_variables_initializer())  
  
    # Loop 1000 times, so take 1000 "train steps"  
    for i in range(1000):  
        batch_x, batch_label = data_gen.next_batch()  
        train_loss, _ = sess.run(  
            [loss, train_op],  
            feed_dict={x: batch_x, label:batch_label})
```

# Summary

Steps for building a model in Tensorflow:

1. Construct the graph.
  - a. **Variables** for weights, **placeholders** for inputs / labels
  - b. Define the **loss function**.
  - c. Create the **training op**.
2. Initialize a session to run the graph in
3. Set up train loop, and train with `session.run(train_step, feed_dict)`

# Part II: Live Coding Example

# Part III: Using TensorBoard

# What's TensorBoard?

- A program bundled with Tensorflow to visualize the model's training curve, graph, and more.

Write a regex to create a tag group

☒ Show data download links☒ Ignore outliers in chart scaling

Tooltip sorting method: default

Smoothing



Horizontal Axis







STEP

RELATIVE

WALL

Runs

Write a regex to filter runs

- ☒  siamese\_bilstm/00/train
- ☒  siamese\_bilstm/00/val
- ☐  siamese\_bilstm\_keep\_0.75/00/train
- ☐  siamese\_bilstm\_keep\_0.75/00/val
- ☒  siamese\_matching\_bilstm/00/train
- ☒  siamese\_matching\_bilstm/00/val

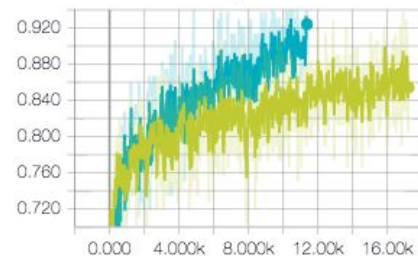
TOGGLE ALL RUNS

logs

train\_summaries

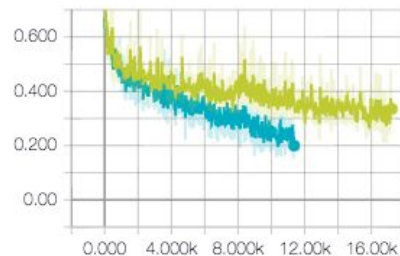
2

train\_summaries/accuracy



run to download CSV JSON

train\_summaries/loss

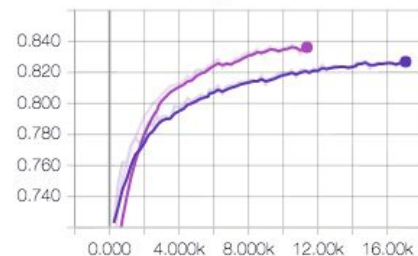


run to download CSV JSON

val\_summaries

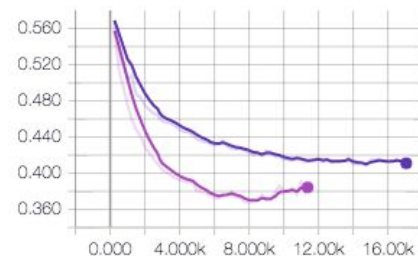
2

val\_summaries/accuracy

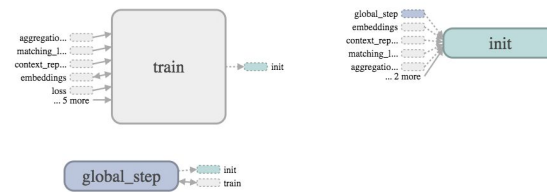
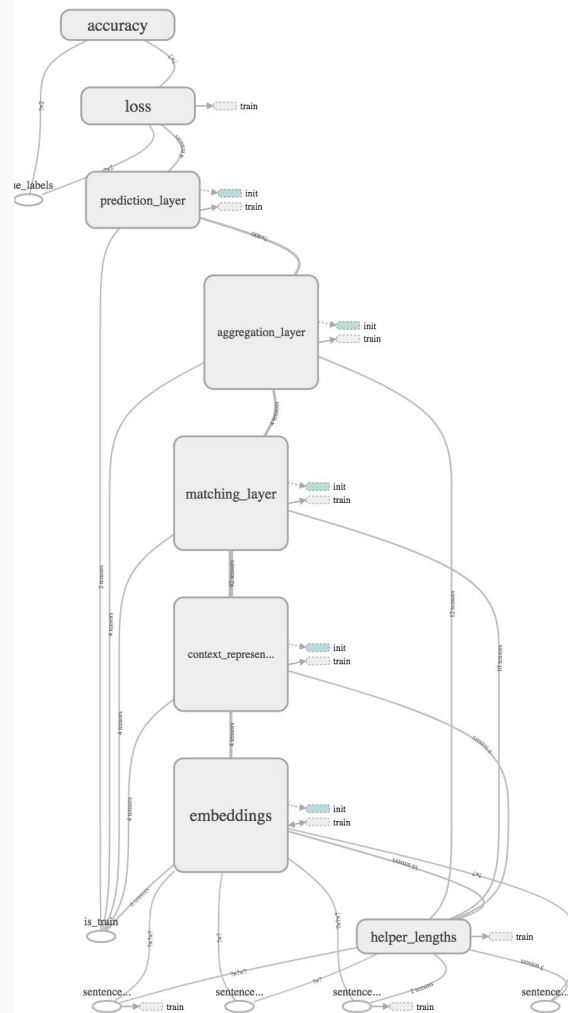


run to download CSV JSON

val\_summaries/loss



run to download CSV JSON



# Logging stats to Tensorboard (pt. 1): Summaries

```
tf.summary.scalar("name",value)
tf.summary.merge_all()
```

1. Create your graph
2. Add ops for statistics you want to log to tensorboard (e.g. loss, accuracy)
3. Create summary values for these ops, depending on their type (scalar for float)
4. Merge the various summary values into one summary op

```
# Statistics that we want to log
```

```
loss = ...
```

```
accuracy = ...
```

```
# Create summary values
```

```
tf.summary.scalar("loss", loss)
```

```
tf.summary.scalar("acc", accuracy)
```

```
summary_op = tf.summary.merge_all()
```



# The global\_step

Many Tensorflow programs have a `global_step` variable that is used to keep track of how many steps a model has seen.

Needs to be set to `trainable=False` -- why?

```
# Create the global_step variable, and make it untrainable
tf.Variable(0, name="global_step", trainable=False)
... build your graph here ...
# Pass the global_step variable to the Optimizer
# which will keep track of how many gradient updates it has done.
opt = tf.train.AdamOptimizer(global_step=global_step)
```

# Why is `global_step` useful?

Big Aspect: Keeping track of which Tensorboard summaries correspond to what step.

Think of the `global_step` as representing the time step that you're at. Tensorboard simply plots a point (the summary value) at that time step.

But what if you have to save a model, then load it back? How do you know how many gradient updates the model has done?

The `global_step` will tell you, and it enables you to keep plotting Tensorboard data right where you left off

# Logging stats to Tensorboard (pt. 2): global\_step

```
tf.Variable(  
    0, name="global_step",  
    trainable=False)
```

1. Set up an untrainable global\_step variable.
2. Pass it to the Optimizer, which will automatically handle incrementing it.
3. When you're running the model in the session, you can get it's value the same way you would evaluate any other op:  
`sess.run(global_step)`

```
# Create the global_step variable,  
# and make it untrainable  
tf.Variable(0, name="global_step", trainable=False)  
... build your graph here ...
```

```
# Pass the global_step variable to the Optimizer  
# which will keep track of how many gradient  
# updates it has done.  
opt = tf.train.AdamOptimizer(global_step=global_step)
```

```
# Set up a session  
with tf.Session() as sess:  
    sess.run(tf.global_variables_initializer())  
  
    for i in range(1000):  
        global_step_loop = sess.run(global_step)  
        train_loss, _ = sess.run(  
            [loss, train_op],  
            feed_dict={x: batch_x, label:batch_label})  
        ... etc ...
```

# Logging stats to Tensorboard (pt. 3): Writing the Summaries

```
writer = tf.summary.FileWriter(  
    summaries_dir,  
    session_variable.graph)  
writer.add_summary(  
    summary_output, global_step)
```

1. Set up a `tf.summary.FileWriter` object that will write the Tensorboard logs to a directory
2. Evaluate the summary op, and use `writer.add_summary` to write it to the disk

```
# Create the global_step variable  
# Build the graph  
# Set up summary op
```

```
log_period = 10  
# Set up a session  
with tf.Session() as sess:  
    sess.run(tf.global_variables_initializer())  
  
    for i in range(1000):  
        global_step_loop = sess.run(global_step)  
        train_loss, _ = sess.run(  
            train_op,  
            feed_dict={x: batch_x, label:batch_label})  
        if global_step_loop % log_period == 0:  
            summary = sess.run(  
                summary_op,  
                feed_dict={x: batch_x,  
                           label:batch_label})  
            writer.add_summary(summary, global_step_loop)
```

# Viewing the results

To start Tensorboard, run:

```
tensorboard --logdir=<summarywriter_output_directory>
```

And then navigate to <http://localhost:6006> in your browser.

# Organizing the graph layout

To group nodes of the graph with a similar function together in Tensorboard, you can surround them in:

```
with tf.name_scope("grouping_name"):  
    ...ops go here...
```

This makes the graph a lot more readable and functional.

Part IV:

Live Coding: Adding TensorBoard  
to our example model