

# Getting Started with Tensorflow

Computing Lab II, Spring 2021



# Deep Learning Packages



Caffe

and others ...

# Deep Learning Frameworks

- Scale machine learning code
- **Compute gradients!**
- Standardize machine learning applications for sharing
- Plethora of deep learning packages available with different advantages, levels of abstraction, programming languages, etc.
- Provide an interface with GPU for parallel processing

# What is Tensorflow

tensorflow / tensorflow

Watch

8.5k

★ Star

142k

🍴 Fork

80.2k

<> Code

! Issues 3,173

🔗 Pull requests 258

🎬 Actions

📁 Projects 1

🛡 Security

📊 Insights

An Open Source Machine Learning Framework for Everyone <https://tensorflow.org>

tensorflow

machine-learning

python

deep-learning

deep-neural-networks

neural-network

ml

distributed

🕒 80,622 commits

🌿 42 branches

📦 0 packages

📦 103 releases

👤 2,421 contributors

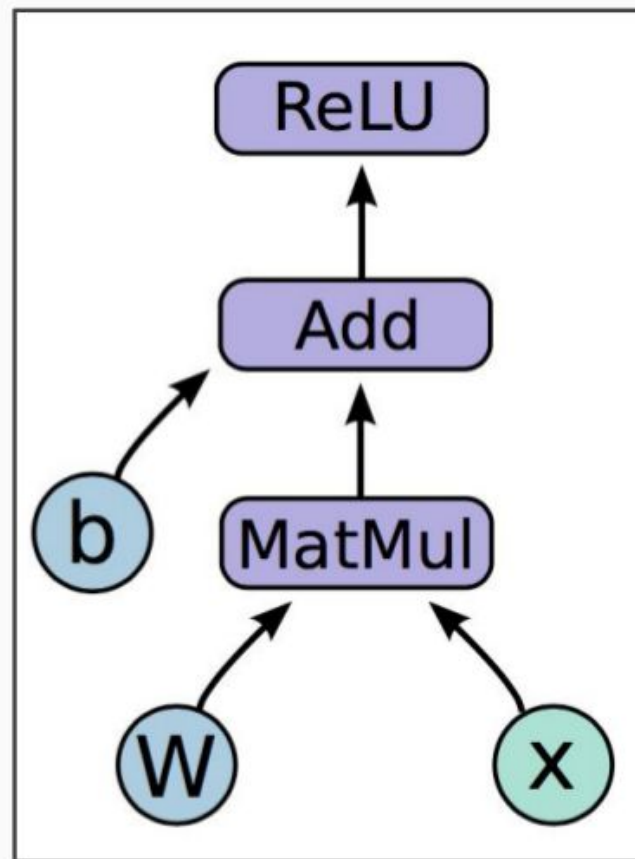
📄 Apache-2.0

# Programming Model

- **Idea:** Express numeric computation as a graph
- Graph nodes are operations that can have any number of inputs and exactly one output
- Graph edges are tensors that flow between nodes

Tensors are n-dimensional arrays

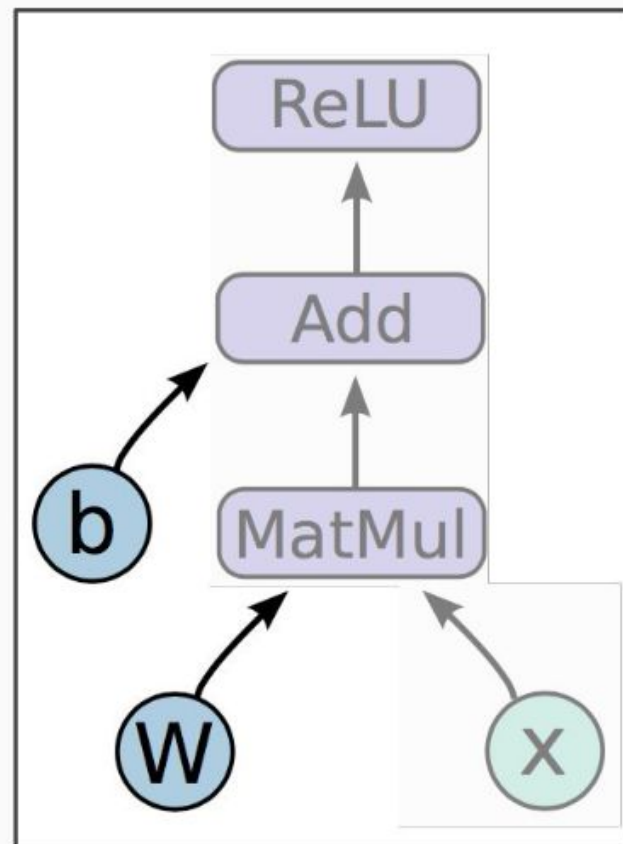
$$h = \text{ReLU}(Wx + b)$$



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

**Variables** are stateful nodes which output their current value.  
State is retained across multiple executions of a graph

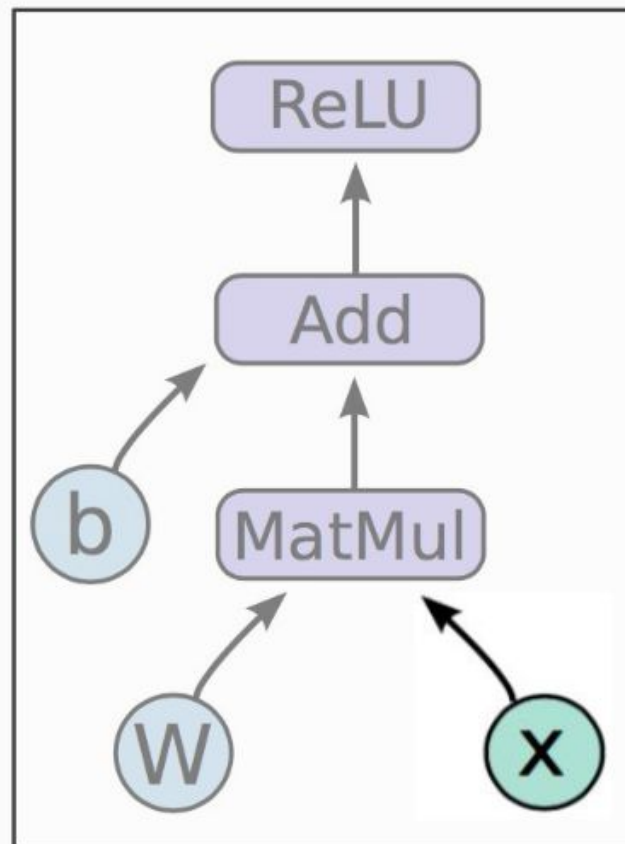
(mostly parameters)



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

**Placeholders** are nodes whose value is fed in at execution time

(inputs, labels, ...)





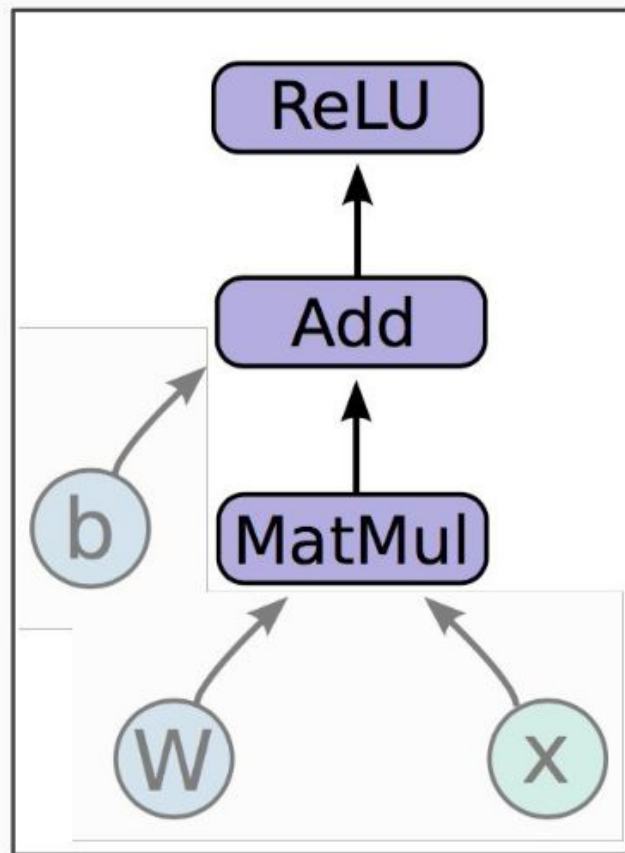
$$h = \text{ReLU}(Wx + b)$$

## Mathematical operations:

**MatMul:** Multiply two matrix values.

**Add:** Add elementwise (with broadcasting).

**ReLU:** Activate with elementwise rectified linear function.



## In code,

1. Create weights, including

Initialization

$W \sim \text{Uniform}(-1, 1); b = 0$

2. Create input placeholder  $x$

$m * 784$  input matrix

3. Build flow graph

```
import tensorflow as tf
```

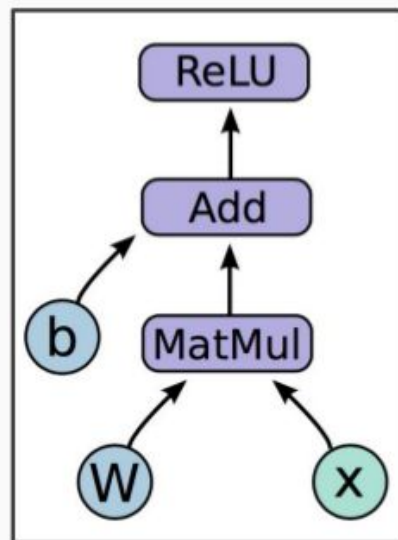
```
b = tf.Variable(tf.zeros((100,)))
```

```
W = tf.Variable(tf.random_uniform((784, 100), -1, 1))
```

```
x = tf.placeholder(tf.float32, (100, 784))
```

```
h = tf.nn.relu(tf.matmul(x, W) + b)
```

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



# But where is the graph?

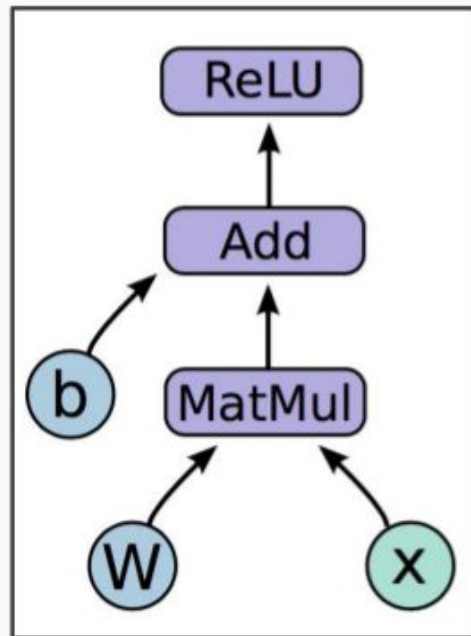
New nodes are automatically built into the underlying graph!

`tf.get_default_graph().get_operations():`

zeros/shape  
zeros/Const  
zeros  
Variable  
Variable/Assign  
Variable/read  
random\_uniform/shape  
random\_uniform/min  
random\_uniform/max  
random\_uniform/RandomUniform

random\_uniform/sub  
random\_uniform/mul  
random\_uniform  
Variable\_1  
Variable\_1/Assign  
Variable\_1/read  
Placeholder  
MatMul  
add  
**Relu** == h

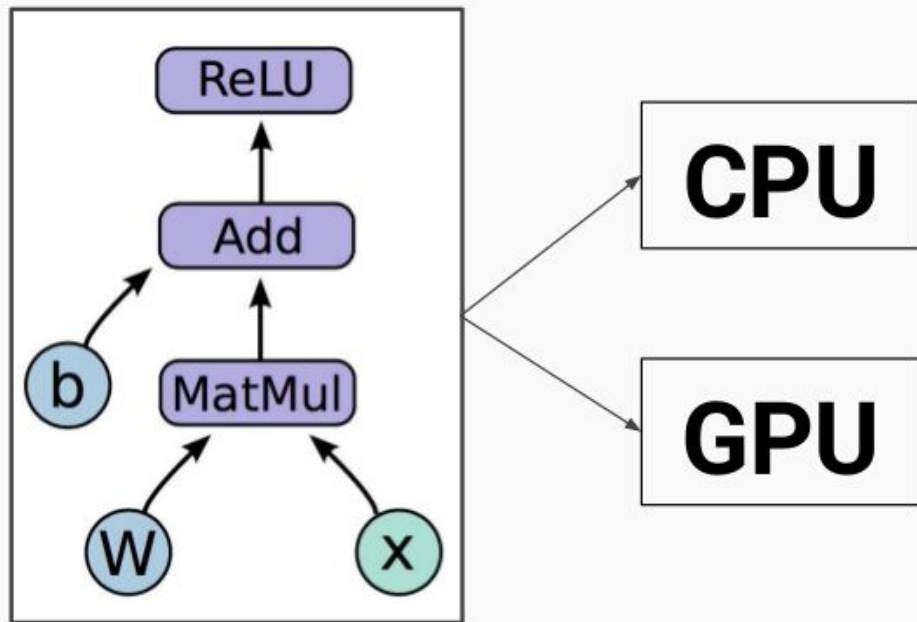
h refers to an op!



# How do we run it?

So far we have defined a **graph**.

We can deploy this graph with a **session**:  
a binding to a particular execution  
context (e.g. CPU, GPU)



# Getting output

```
sess.run(fetches, feeds)
```

**Fetches:** List of graph nodes.

Return the outputs of these nodes.

**Feeds:** Dictionary mapping from

graph nodes to concrete values.

Specifies the value of each graph

node given in the dictionary.

```
import numpy as np
import tensorflow as tf
```

```
b = tf.Variable(tf.zeros((100,)))
W = tf.Variable(tf.random_uniform((784, 100),
                                  -1, 1))
```

```
x = tf.placeholder(tf.float32, (100, 784))
h = tf.nn.relu(tf.matmul(x, W) + b)
```

```
sess = tf.Session()
sess.run(tf.initialize_all_variables())
sess.run(h, {x: np.random.random(100, 784)}))
```

# So what have we covered so far?

We first built a **graph** using **variables** and **placeholders**

We then deployed the graph onto a **session**, which is the **execution environment**

Next we will see how to **train** the model

# How do we define the loss?

Use **placeholders** for labels

Build loss node using labels and **predictions**

```
prediction = tf.nn.softmax(...) #Output of neural network
label = tf.placeholder(tf.float32, [100, 10])

cross_entropy = -tf.reduce_sum(label * tf.log(prediction), axis=1)
```

# How do we compute Gradients?

```
train_step = tf.train.GradientDescentOptimizer(0.5).minimize(cross_entropy)
```

`tf.train.GradientDescentOptimizer` is an **Optimizer** object

`tf.train.GradientDescentOptimizer(lr).minimize(cross_entropy)` adds optimization **operation** to computation graph

TensorFlow graph **nodes** have **attached gradient operations**

Gradient with respect to **parameters** computed with **backpropagation**

*...automatically*



# Creating the train\_step op

```
prediction = tf.nn.softmax(...)
label = tf.placeholder(tf.float32, [None, 10])

cross_entropy = tf.reduce_mean(-tf.reduce_sum(label * tf.log(prediction),
reduction_indices=[1]))

train_step = tf.train.GradientDescentOptimizer(0.5).minimize(cross_entropy)
```

# Other Optimizers

`class AdadeltaOptimizer` : Optimizer that implements the Adadelta algorithm.

`class AdagradDAOptimizer` : Adagrad Dual Averaging algorithm for sparse linear models.

`class AdagradOptimizer` : Optimizer that implements the Adagrad algorithm.

`class AdamOptimizer` : Optimizer that implements the Adam algorithm.

READ [tensorflow.org](https://www.tensorflow.org/api_guides/python/optimizers_v1)

These are other options

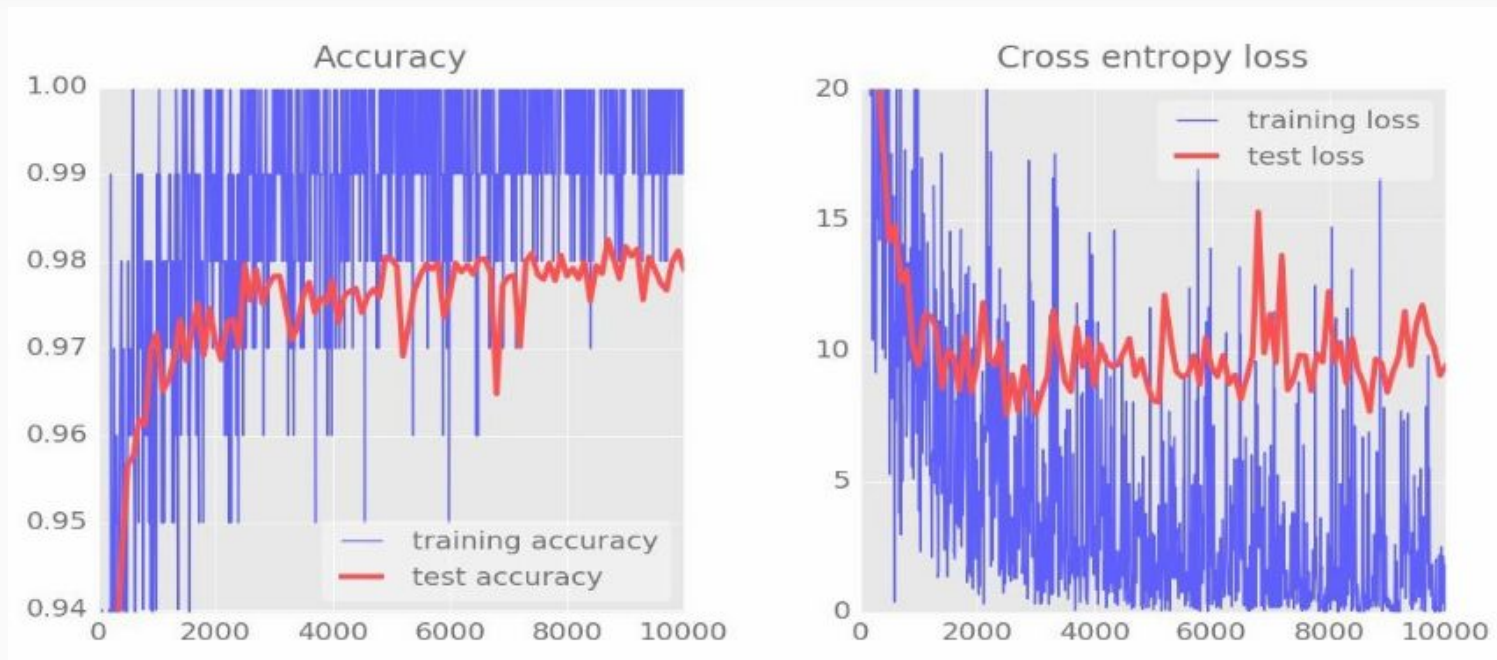


# Saving model weights

```
# Create a saver.  
  
saver = tf.train.Saver(...variables...)  
  
# Launch the graph and train, saving the model every 1,000 steps.  
  
sess = tf.Session()  
  
for step in xrange(1000000):  
    sess.run(..training_op..)   
  
    if step % 1000 == 0:  
        # Append the step number to the checkpoint name:  
        saver.save(sess, 'my-model', global_step=step)
```

READ [tensorflow.org](https://www.tensorflow.org)

# Noisy Accuracy Curve



# Thanks!

## References:

1. <http://cs231n.stanford.edu/>
2. <http://cs224n.stanford.edu/>
3. Martin Gorner's Slides on Tensorflow
4. Keras Tutorial on Fashion-MNIST:  
<https://www.tensorflow.org/tutorials/keras/classification>

