CS 224S: TensorFlow Tutorial

Lecture and Live Demo

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Intro to Deep Learning Frameworks

- Scales machine learning code
- Computes gradients!
- Standardizes machine learning applications for sharing
- Zoo of Deep Learning frameworks available with different advantages, paradigms, levels of abstraction, programming languages, etc
- Interface with GPUs for parallel processing

In some ways, rightfully gives Deep Learning its name as a separate *practice*

What is TensorFlow?

- Open source software library for numerical computation using data flow graphs
- Originally developed by Google Brain Team to conduct machine learning research
- “Tensorflow is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms”

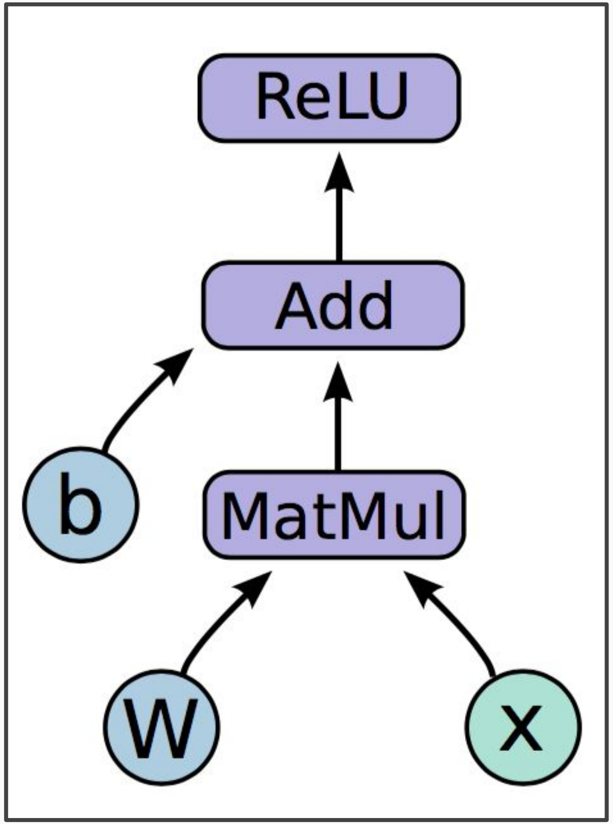
Programming model

Big idea: express a numeric computation as a **graph**.

- Graph nodes are **operations** which have any number of inputs and outputs
- Graph edges are **tensors** which flow between nodes

Programming model

$$h = ReLU(Wx + b)$$



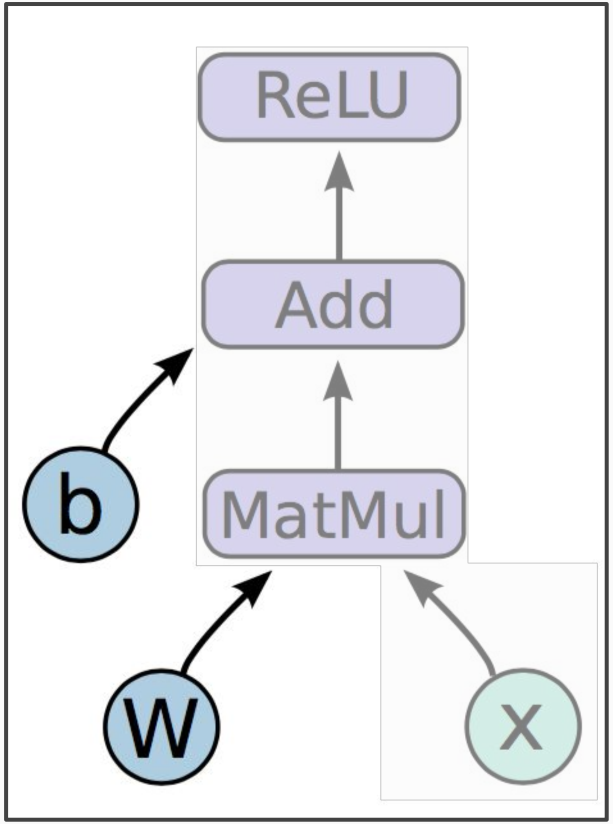
Programming model

$$h = ReLU(Wx + b)$$

Variables are stateful nodes which output their current value.

State is retained across multiple executions of a graph

(mostly parameters)

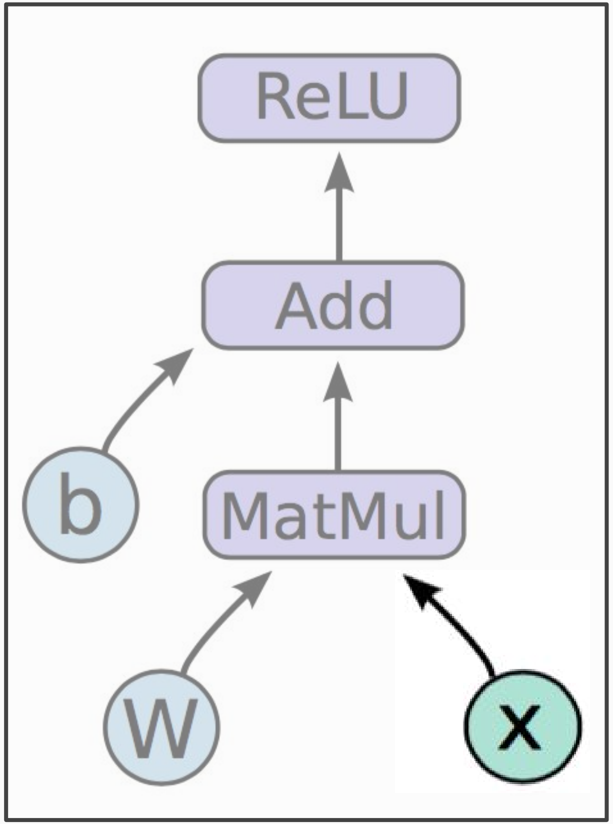


Programming model

$$h = ReLU(Wx + b)$$

Placeholders are nodes whose value is fed in at execution time

(inputs, labels, ...)

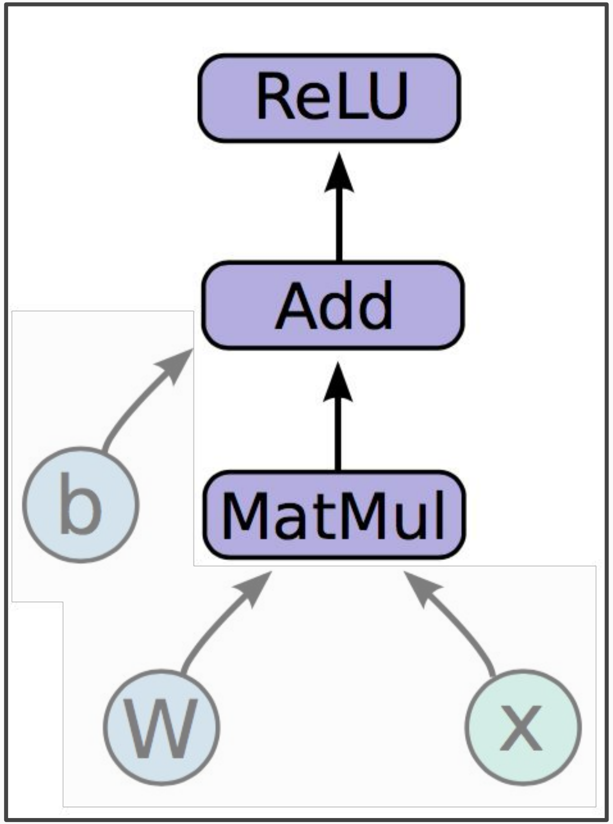


Programming model

$$h = ReLU(Wx + b)$$

Mathematical operations:

MatMul: Multiply two matrix values.
Add: Add elementwise (with broadcasting).
ReLU: Activate with elementwise rectified linear function.



In code,

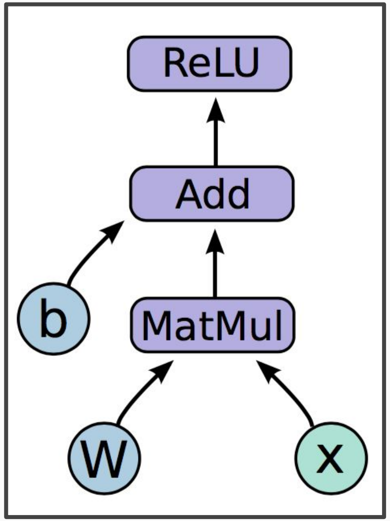
1. Create weights, including initialization
   W ~ *Uniform*(-1, 1); b = **0**

2. Create input placeholder x
   m * 784 input matrix

3. Build flow graph

```python
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)
```

$$h = ReLU(Wx + b)$$



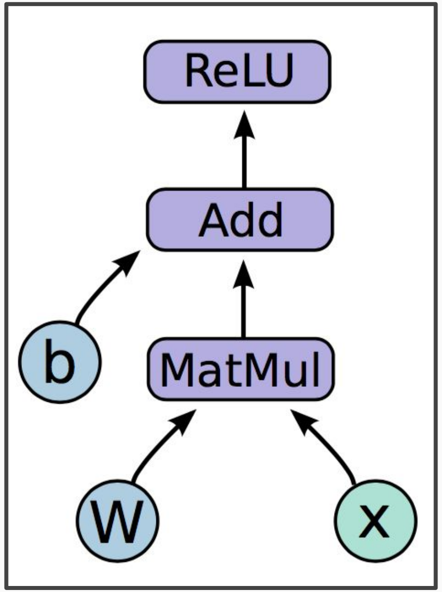
But where is the graph?

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

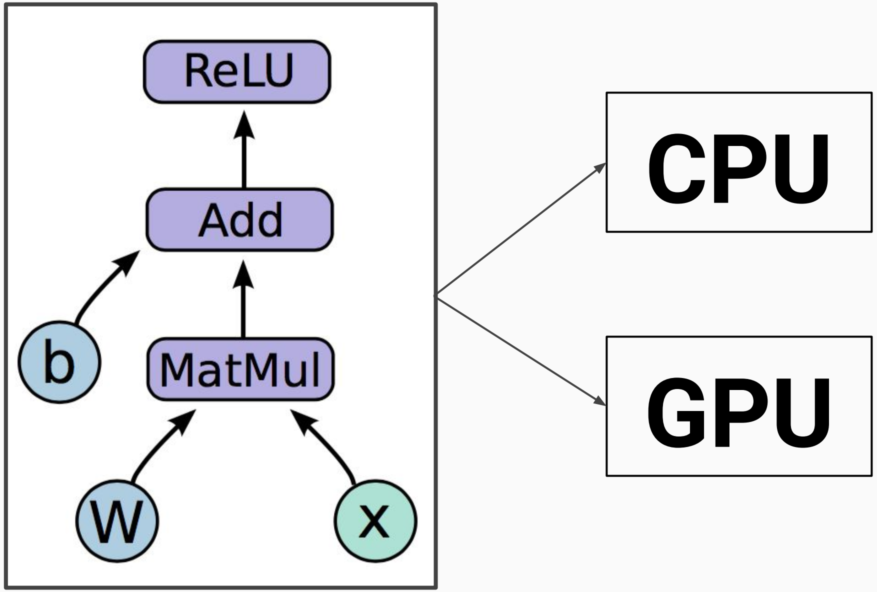
h refers to an op!



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.

```python
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 **placeholder** for **labels**

Build loss node using labels and **prediction**

```
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)
```

Training the Model

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

1. Create Session
2. Build training schedule
3. Run `train_step`

```
sess = tf.Session()
sess.run(tf.initialize_all_variables())

for i in range(1000):
    batch_x, batch_label = data.next_batch()
    sess.run(train_step, feed_dict={x: batch_x,
                                    label: batch_label}
```

Variable sharing: naive way

```
variables_dict = {
     "weights": tf.Variable(tf.random_normal([782, 100]),
                                    name="weights")
     "biases": tf.Variable(tf.zeros([100]), name="biases")
     }
```

Not good for encapsulation!

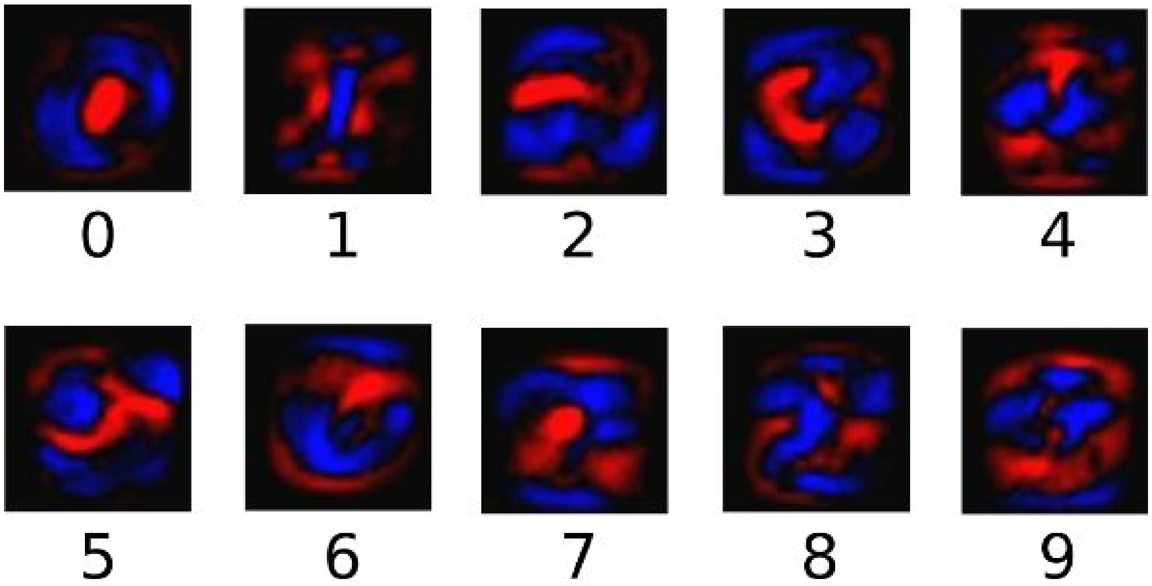
What’s in a Name?

`tf.variable_scope()` provides simple name-spacing to avoid clashes

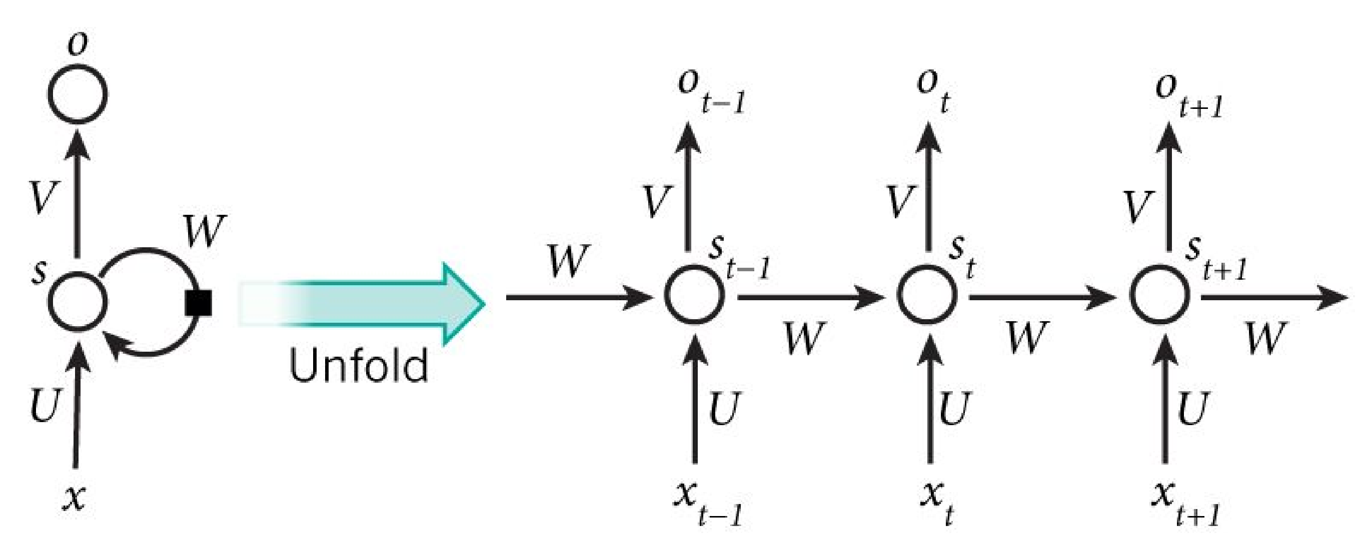
`tf.get_variable()` creates/accesses variables from within a variable scope

```
with tf.variable_scope("foo"):
    v = tf.get_variable("v", shape=[1])  # v.name == "foo/v:0"

with tf.variable_scope("foo", reuse=True):
    v1 = tf.get_variable("v")      # Shared variable found!

with tf.variable_scope("foo", reuse=False):
    v1 = tf.get_variable("v")      # CRASH foo/v:0 already exists!
```

Live Demo: Learning the MNIST dataset



RNNs

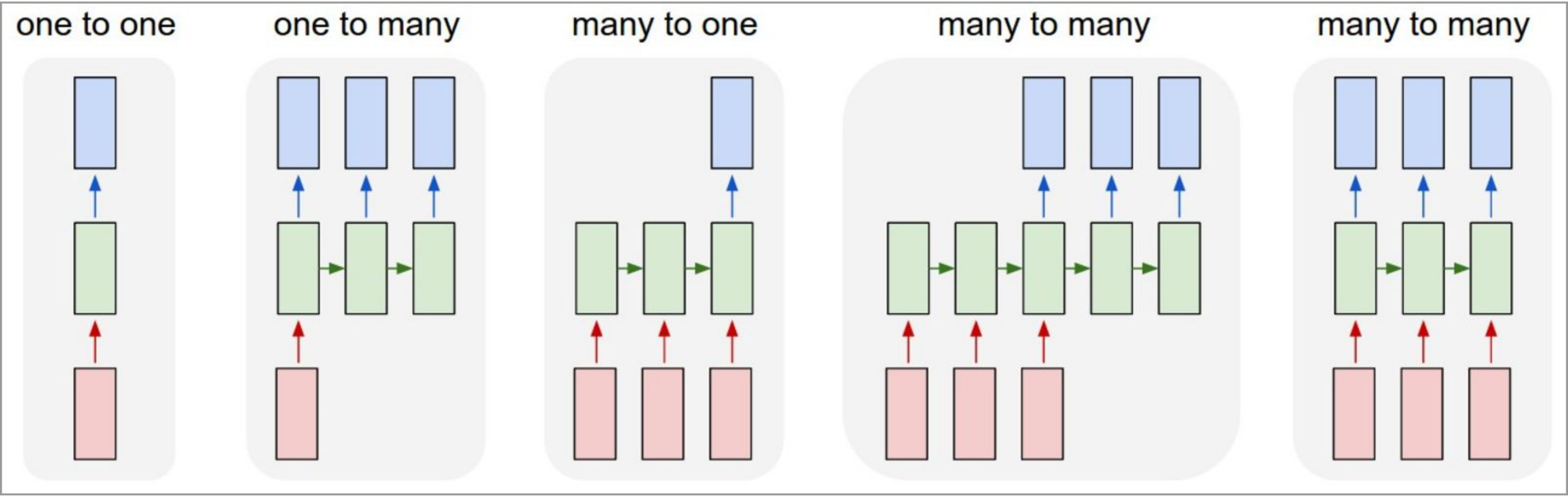


Cell types:

- Vanilla
- LSTM
- GRU

http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/

RNN sequences



http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN + Tensorflow

- Most calculations are performed on a per-batch basis
- RNNs expects tensors of shape [B, T, ..] as input, where B is batch size, T is length in time of each input.
- **What if each sequence is not the same length T?**

- Solution: **Batching and Padding**

Batching and Padding

- Imagine one of your sequences is of length 1000, but the average sequence length is 20.
  - Pad all sequences to length 1000 -- huge waste of memory and time!
  - Make batches of size 32, and pad all examples in the batch to maximum sequence length in batch. Only one batch suffers!
  - Padding: Appending 0’s to shorter sequences in a batch to make them equal length.
- Dynamically unroll the RNN (example on next slide)

dynamic_rnn

```
# Create input data
X = np.random.randn(2, 10, 8)

# The second example is of length 6
X[1,6:] = 0
X_lengths = [10, 6]

cell = tf.nn.rnn_cell.LSTMCell(num_units=64, state_is_tuple=True)

outputs, last_states = tf.nn.dynamic_rnn(
    cell=cell,
    dtype=tf.float64,
    sequence_length=X_lengths,
    inputs=X)
```

http://www.wildml.com/2016/08/rnns-in-tensorflow-a-practical-guide-and-undocumented-features/

In Summary:

1. Build a graph
    a. Feedforward / Prediction
    b. Optimization (gradients and train_step operation)

2. Initialize a session

3. Train with `session.run(train_step, feed_dict)`

Questions?

Acknowledgments

Barak Oshri, Nishith Khandwala, CS224N CAs last quarter

Jon Gauthier, Natural Language Processing Group, Symbolic Systems

Bharath Ramsundar, PhD Student, Drug Discovery Research

Chip Huyen, Undergraduate, teaching CS20SI: TensorFlow for Deep Learning Research last quarter

Live Demo: Tackling MNIST using Tensorflow

Insert link to the ipython notebook
Link to the github repo: https://github.com/pbhatnagar3/cs224s-tensorflow-tutorial