

# AIDL: PROJECTS

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Session 2 (2019/05/07): Deep dive into Tensorflow

# Instructors



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# Projects

# Specs

Evaluation:

- Project report: 40%
- Presentation: 30%
- Advisor qualification: 30%

Requirements:

- Program a model
- Train a model
- Inference pipeline up & running! (even if the results are bull\*\*\*\*)

# Classes

# Note on previous labs

- This will NOT assume any tech skill learned from them
- Starting from scratch
- Forget about them (during these sessions :P)

# In-class exercises

- Not tests
- Meant to force you to think & apply what has been taught
- Difficult to finish in-class. Finish them at home if you want to get all the juice out of it
- Accumulative
- Not a single solution

A possible solution will be pushed to the repo after class

# Personal motivation: why am I here?

- I hated all the way through college
- Dislike current education system
- Refactor my own skills
- You should be able to pass a DL interview!

Can I do something BETTER?



# Personal motivation: edu system



I:N

XIV century



XXI century

# Personal motivation: edu system



How to get there:

- Provide feedback
- Ask questions

# The DL engineer quadrant

Programmers that understand DL as lego blocks

Random people



Implementation

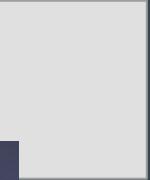
Follow the gradient!



Theoretical



The  
PhD



# The 5 minute recap



A digital timer with a black background and white digits, showing the time as 04:59:59. The digits are large and bold, with a slight shadow effect. There are small horizontal tick marks between the colons.

- The content of each class will be based on all the previous lessons
- 5 min recap at the beginning of each class

Previously on *AIDL: Projects...*

**“Give them the tools to  
apply DL in the industry”**



# Subject goals

**Product development**

**Ready to prod model**

**Implement DL model**



DEEPMLEARNING4J



theano



TensorLayer



TensorFlow

PYTORCH

Caffe



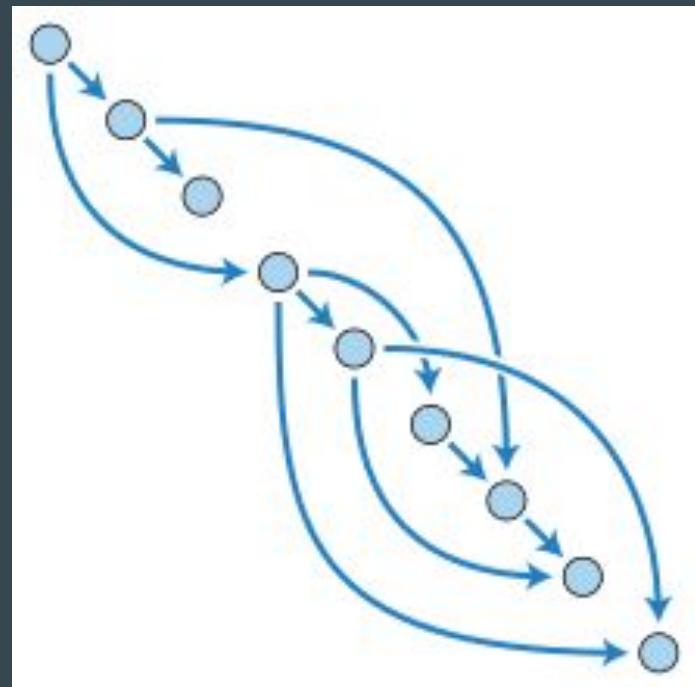
Lasagne



mxnet

# Directed Acyclic Graph (DAG)

- Edged are directed from one node to another
- Nodes have a topological ordering
- No closed loops!



# Computational graph

Static computational graph: Define-and-Run methodology.

Pros:

- Speed: can spend a long time optimizing the graph
- Memory: can predict and allocate all mem ahead of time

Cons:

- Inflexible: once compiled, it cannot be modified at run time
- Debugging: graph representation doesn't match code
- Static: more difficult to support flexible sized inputs

Dynamic computational graph: Define-by-Run strategy

Pros:

- Can change structure of NN at runtime (add layers, change shape, etc.)
- Support flexible sized inputs
- Easier to debug
- More natural to code

Cons:

- Compile at runtime, can be slower
- Dynamic batching more difficult

# Surprise test!

# Learning

Learning step:

1. Forward pass the inputs through the model
2. Compute loss / objective function
3. Use optimization algorithm to update trainable variables:
  - a. Compute the gradients using BACKPROPAGATION
  - b. Use the gradients to update the model

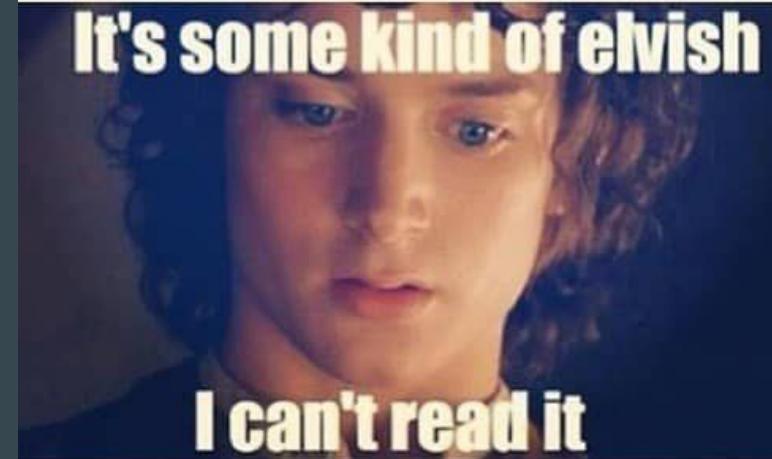
Example: Linear regression

# Understanding backprop

- Key ingredient: chain rule
- Local derivatives do not depend on final loss
- The local derivatives tell us what is going to be held in memory!

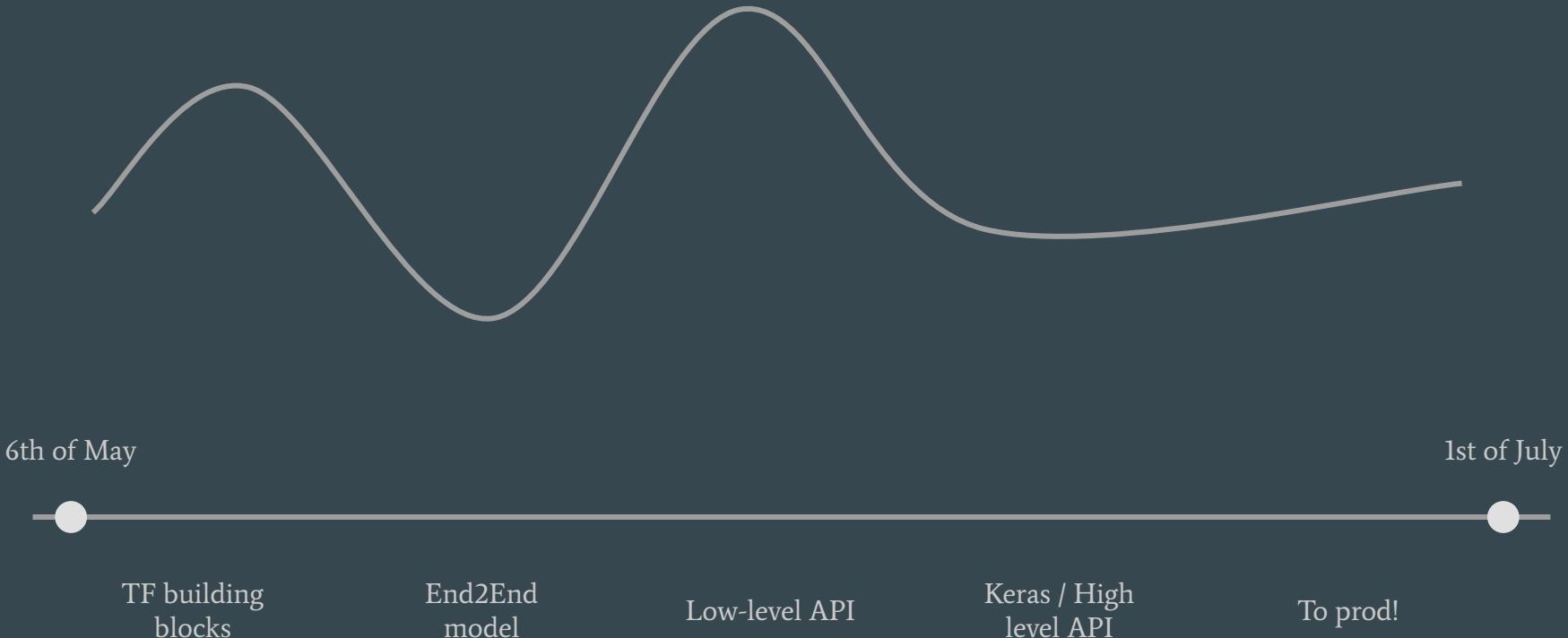
$$h(x) = g(f(x))$$

$$h'(x) = g'(f(x)) \cdot f'(x)$$



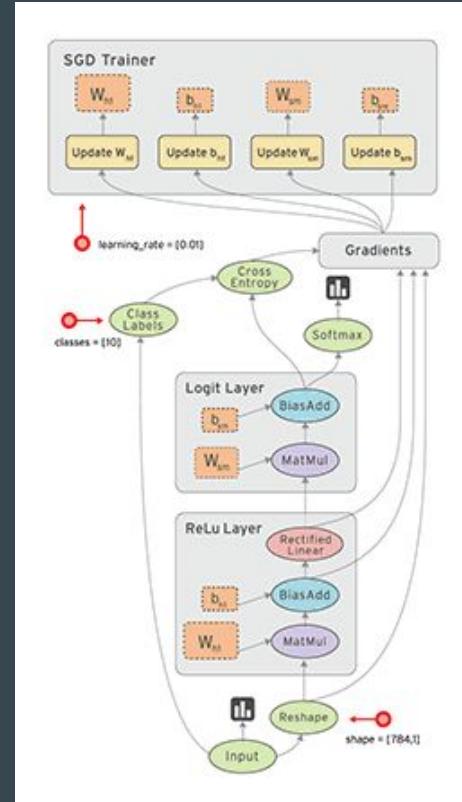
# Tensorflow: a gentle introduction

# Tensorflow



# It's all about graphs

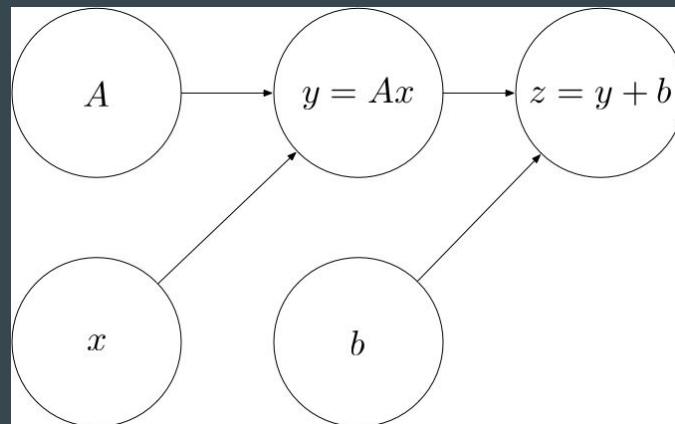
Tensorflow is a symbolic computational library that uses **static computational graphs** (define-and-run) to represent the models



# Computational graph & Dataflow

Programs are represented as directed graphs with data flowing through them where:

- **Nodes:** Operations of the program → **tf.Operation**
- **Edges:** Data flowing through the graph → **tf.Tensor**

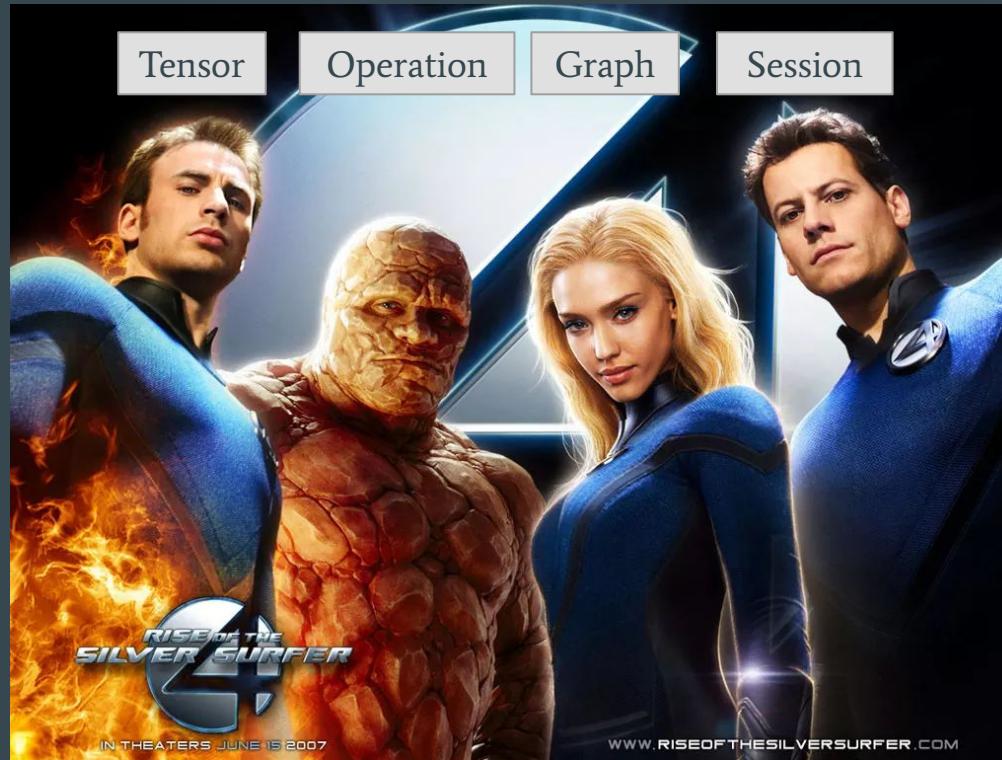


# From symbolic to real numbers

Two phases:

- **Definition phase**: build the computational graph → `tf.Graph`
- **Execution phase**: interact with the graph feeding data and fetching results.  
Run a subgraph of the original graph & change its state → `tf.Session`

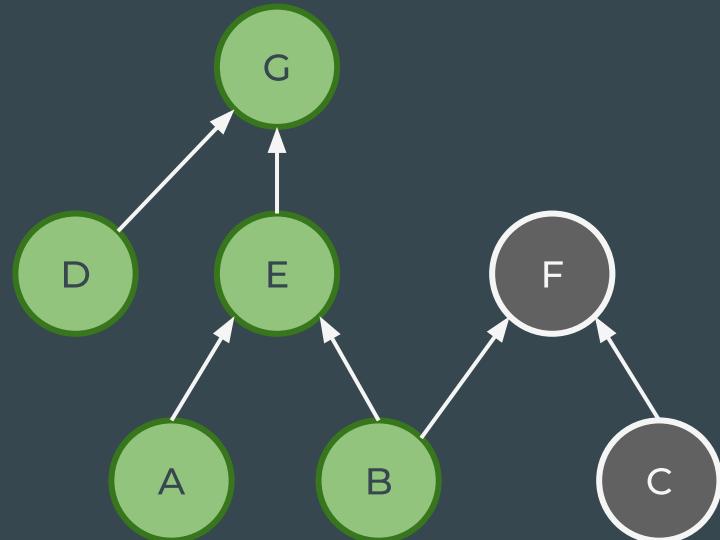
# Fantastic four



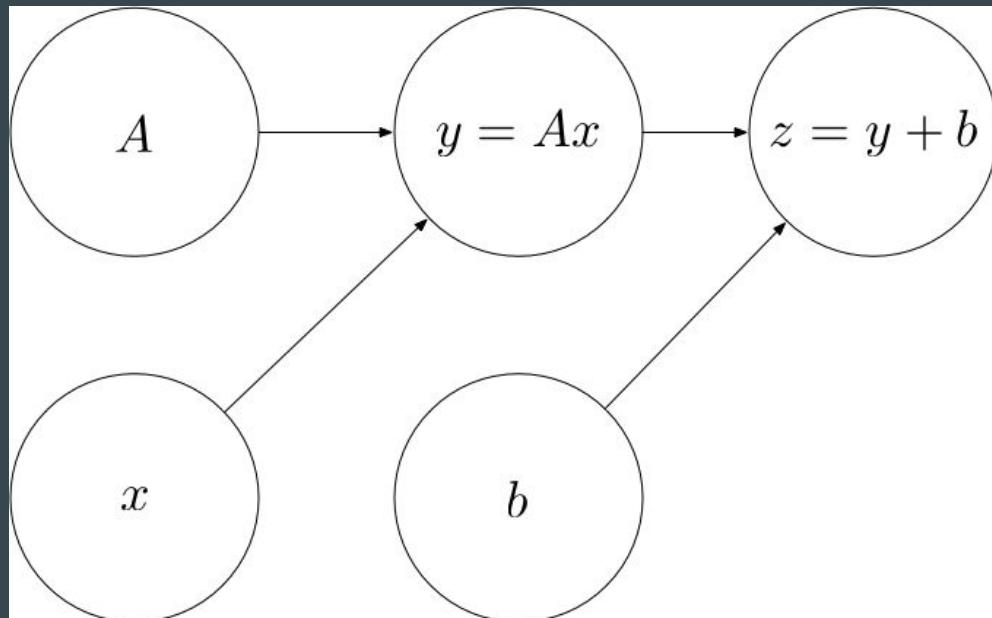
# Computation paths

Data goes in/out in the graph through:

- IN: feeding → feed\_dict
- OUT: fetching



# Micro example I: the graph



# Micro example II: the code

```
import tensorflow as tf
import random

graph = tf.Graph()
with graph.as_default():
    x = tf.placeholder(tf.float32, shape=[], name='x')
    A = tf.get_variable('A', shape=[], dtype=tf.float32,
initializer=tf.initializers.random_normal())
    b = tf.random_normal(shape=[], dtype=tf.float32, name='b')
    y = A * x
    z = y + b

with tf.Session(graph=graph) as sess:
    sess.run(tf.global_variables_initializer())
    result = sess.run(z, feed_dict={x: random.random()})
```

The diagram illustrates the execution flow of the provided TensorFlow code. It is divided into four main phases:

- Fetching**: This phase is represented by the first red box containing the imports and the start of the graph definition.
- Feeding**: This phase is represented by the second red box containing the placeholder and variable definitions.
- Definition phase**: This phase is represented by the third red box containing the operations (y and z).
- Execution phase**: This phase is represented by the fourth red box containing the session creation, initializer run, and final result retrieval.

Specific code elements are highlighted with red boxes and arrows:

- The imports (`import tensorflow as tf` and `import random`) are in the **Fetching** phase.
- The `graph` definition and the start of the `with graph.as_default():` block are in the **Feeding** phase.
- The `x` placeholder and the `A` variable are defined in the **Definition phase**.
- The `y` and `z` operations are also defined in the **Definition phase**.
- The `sess` creation, `tf.global_variables_initializer()`, and `result = sess.run(z, feed_dict={x: random.random()})` are in the **Execution phase**.

# Micro example III: line by line

```
import tensorflow as tf
import random

graph = tf.Graph()
with graph.as_default():
    x = tf.placeholder(tf.float32, shape=[], name='x')
    A = tf.get_variable('A', shape=[], dtype=tf.float32,
initializer=tf.initializers.random_normal())
    b = tf.random_normal(shape=[], dtype=tf.float32, name='b')
    y = A * x
    z = y + b

with tf.Session(graph=graph) as sess:
    sess.run(tf.global_variables_initializer())
    result = sess.run(z, feed_dict={x: random.random()})
```

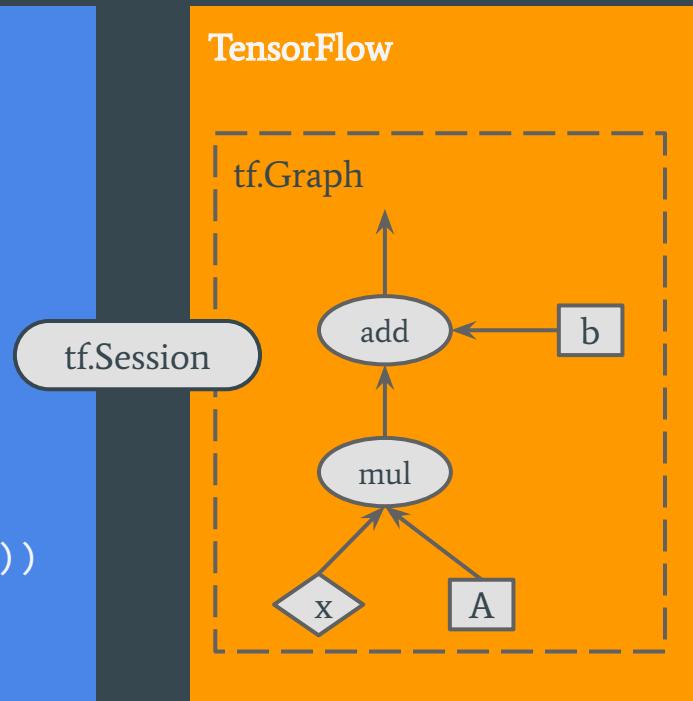
# Python & TF

## Python

```
graph = tf.Graph()
with graph.as_default():
    x = tf.placeholder(..., name='x')
    A = tf.get_variable('A', ...)
    b = tf.random_normal(..., name='b')
    y = A * x
    z = y + b

with tf.Session(graph=graph) as sess:
    sess.run(tf.global_variables_initializer())
    result = sess.run(z, feed_dict={x:
random.random()})
```

## TensorFlow



# New family members

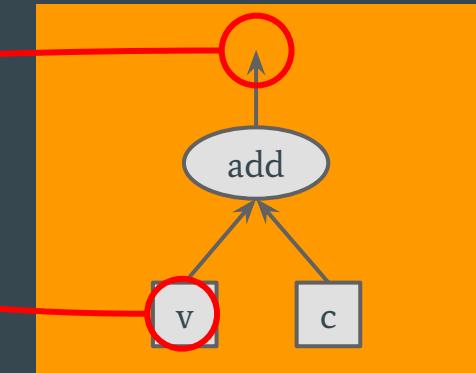
Special instances of tf.Tensor:

- **Variables** (tf.get\_variable): holds values that can change from one session run to another
- **Placeholders** (tf.placeholder): represents a “data shell”, doesn’t know its value, only the shape and type. The real values are fed through the session (*feed\_dict*)
- **Constants** (tf.constant): immutable value

# Sanity check

```
v = tf.get_variable('v', shape=[], initializer=1)
c = tf.constant(4)
v = tf.add(v, c) # same as 'v + c'
```

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



Q: What's the value of *result*?

A:  $\text{result} = 5$

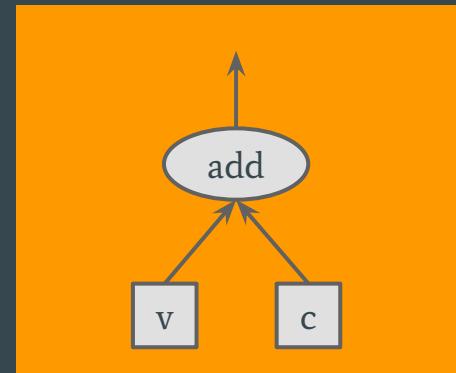
Q: And what about the *graph variable* *v*?

A:  $v = 1$

# Sanity check II

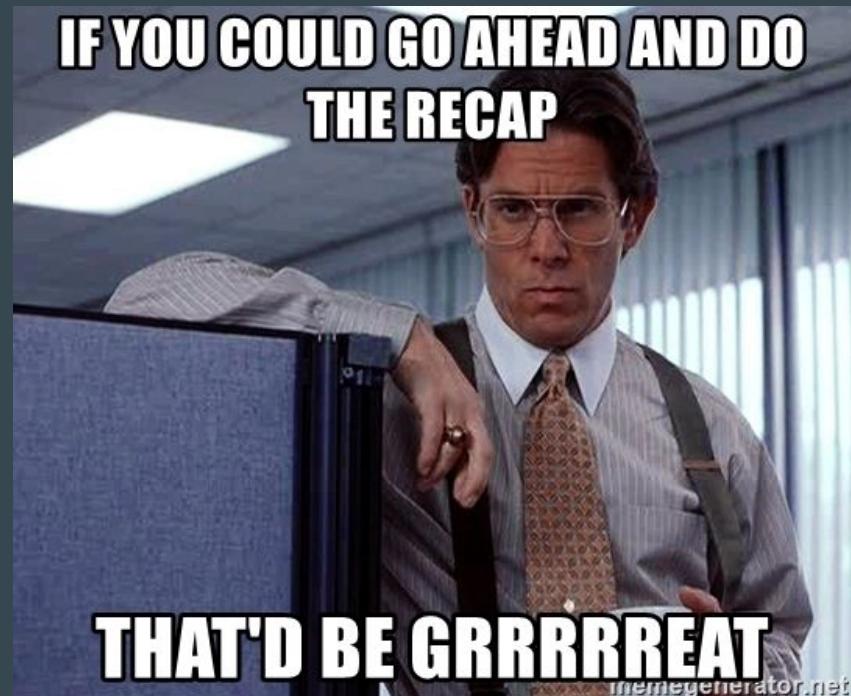
```
v = tf.get_variable('v', shape=[], initializer=1)
c = tf.constant(4)
v_update = v.assign_add(c)

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



# Recap!

- tf.Session
  - sess.run()
- tf.Graph
  - graph.as\_default()
- tf.placeholder
- tf.get\_variable
  - assign, assign\_add, assign\_sub
- tf.constant
- Python operations overridden. TF provides custom functions too...
  - + == tf.add
  - x == tf.mul



# Questions?

