Welcome to TensorFlow!

CS 20:
TensorFlow for Deep Learning Research
Lecture 1
1/12/2018

Thanks Danijar Hafner for the logo!

Agenda

Welcome

Overview of TensorFlow

Graphs and Sessions

What’s TensorFlow™?

“Open source software library for
numerical computation using data flow graphs”

Launched Nov 2015

Why TensorFlow?

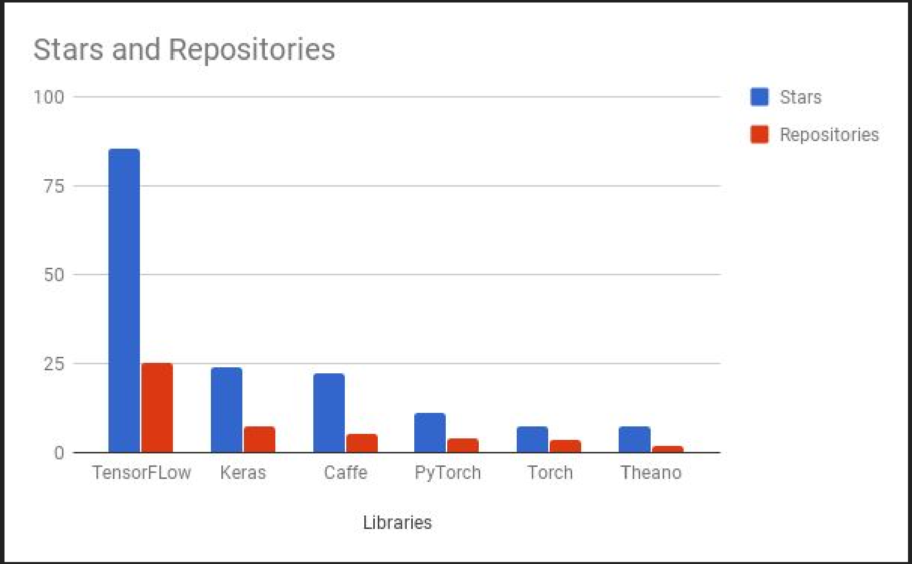
- Many machine learning libraries

Why TensorFlow?

- Flexibility + Scalability
  Originally developed by Google as a single infrastructure for machine learning in both production and research

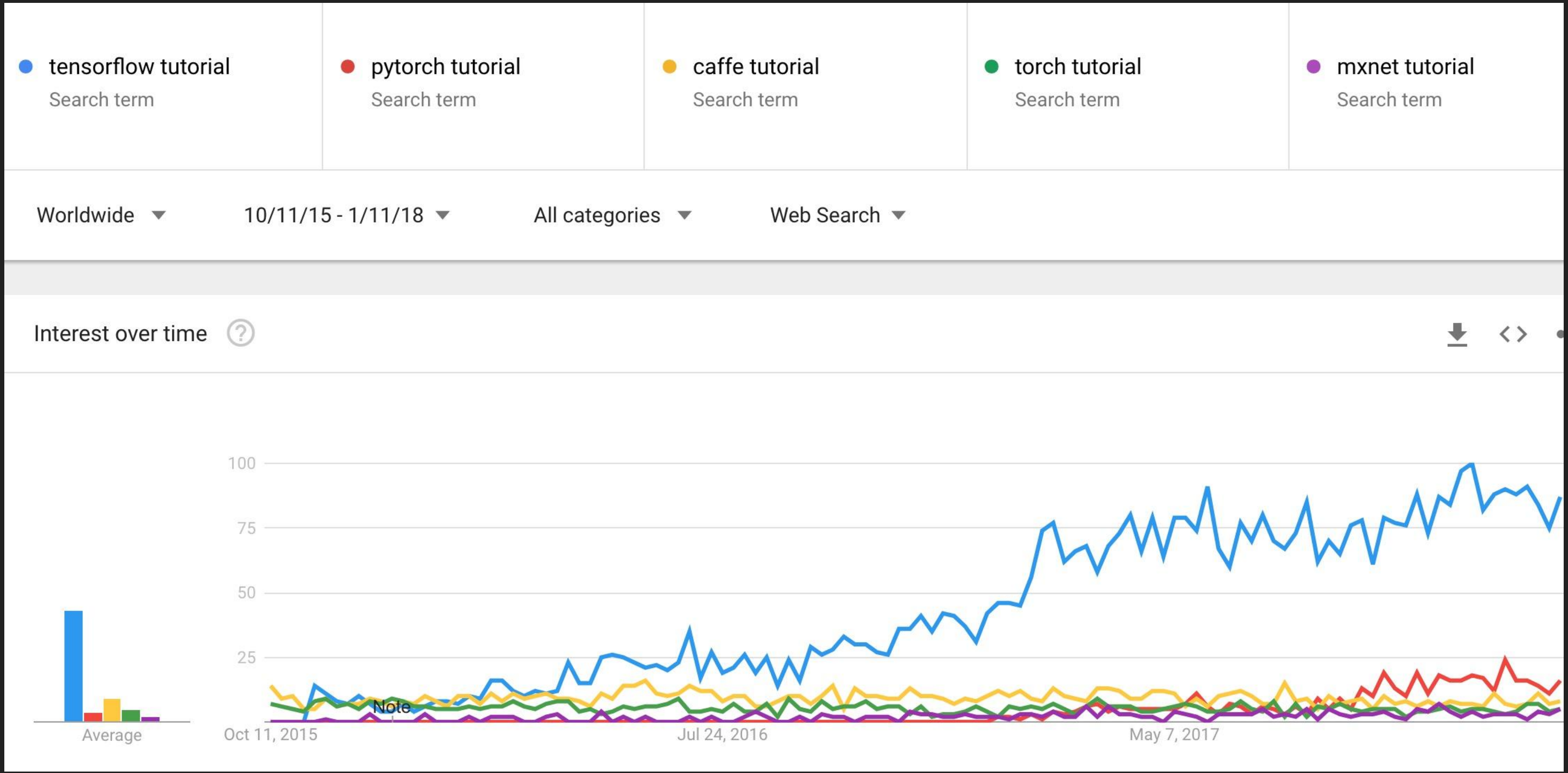
Why TensorFlow?

- Flexibility + Scalability
- Popularity



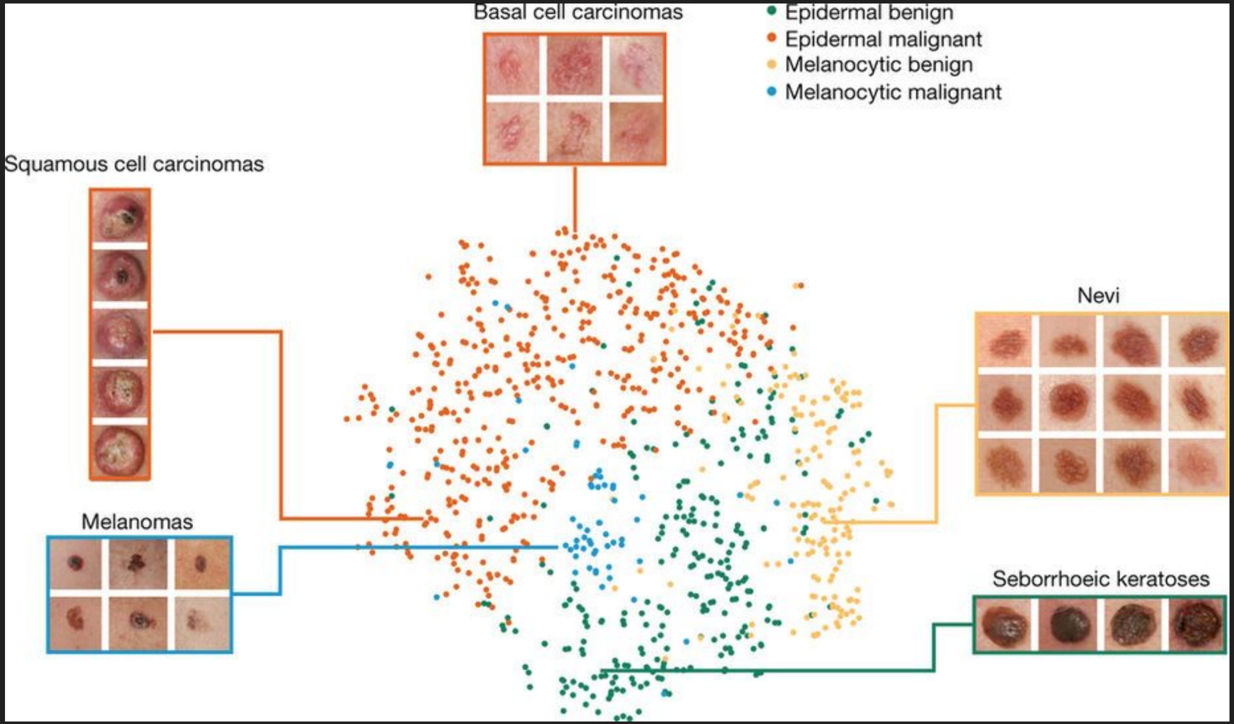
Companies using TensorFlow

Demand for tutorials on TensorFlow



Some cool projects using TensorFlow

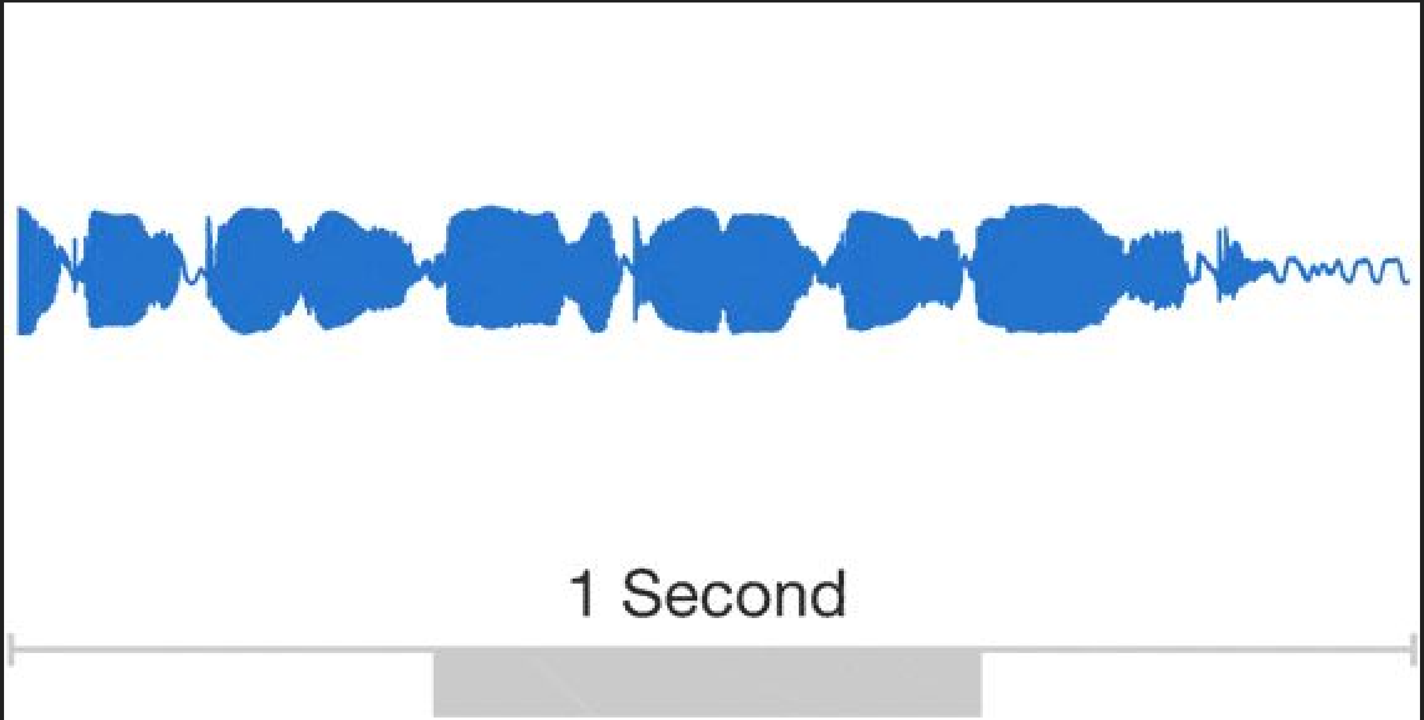
Classify skin cancer



Dermatologist-level classification of skin cancer with deep neural networks (Esteva et al., Nature 2017)

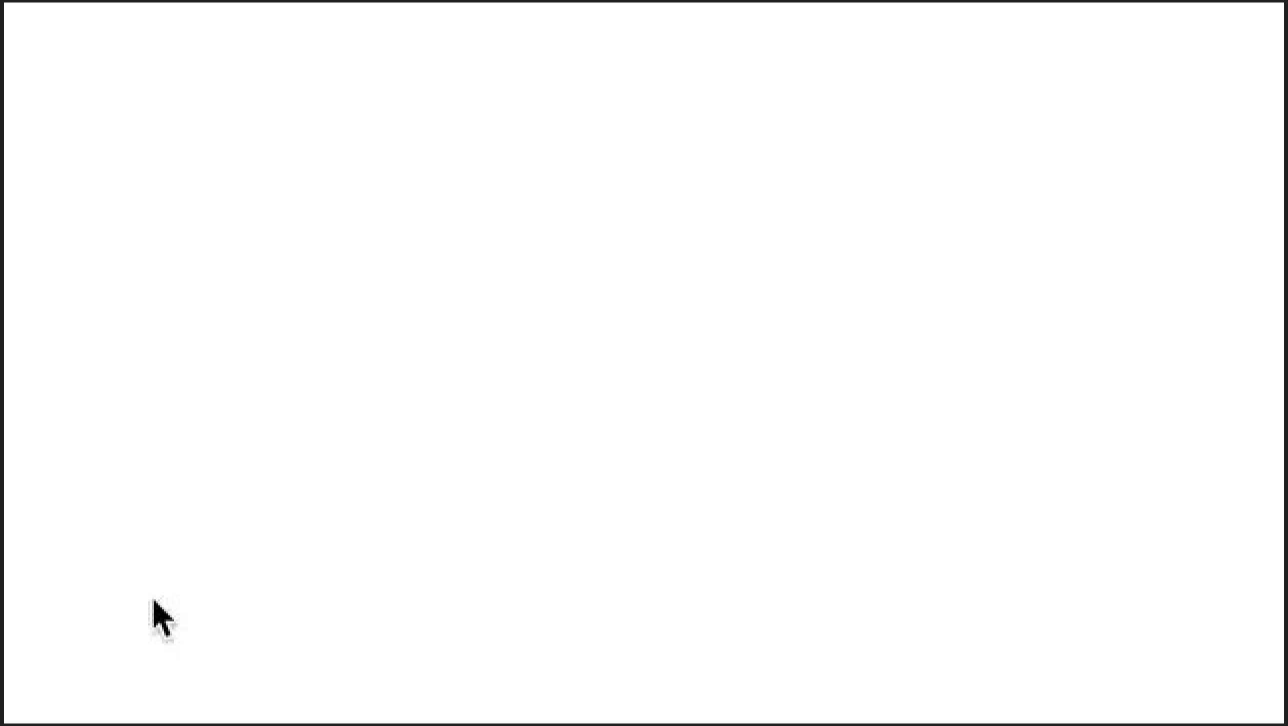
WaveNet: Text to Speech

It takes several hours to synthesize 1 second!



Wavenet: A generative model for raw audio (Oord et al., 2016)

Drawing



Draw Together with a Neural Network (Ha et al., 2017)

Neural Style Translation

Image Style Transfer Using Convolutional Neural Networks (Gatys et al., 2016)
Tensorflow adaptation by Cameroon Smith (cysmith@github)

I hope that this class will give you the tool to build cool projects like those!

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

CS20

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Logistics

- Piazza: piazza.com/stanford/winter2018/cs20
- Staff email: cs20-win1718-staff@lists.stanford.edu
- Students mailing list: cs20-win1718-students
- Guests mailing list: cs20-win1718-guests

Grading

- Assignments (3)
- Participation
- Check in

Resources

- The official documentations
- TensorFlow's official sample models
- StackOverflow should be your first port of call in case of bug
- Books
    - Aurélien Géron's Hands-On Machine Learning with Scikit-Learn and TensorFlow (O'Reilly, March 2017)
    - François Chollet's Deep Learning with Python (Manning Publications, November 2017)
    - Nishant Shukla's Machine Learning with TensorFlow (Manning Publications, January 2018)
    - Lieder et al.'s Learning TensorFlow A Guide to Building Deep Learning Systems (O'Reilly, August 2017)

Permission Number

[Link]

Many of you are ahead of me in academia so I probably need more of your help than you do mine

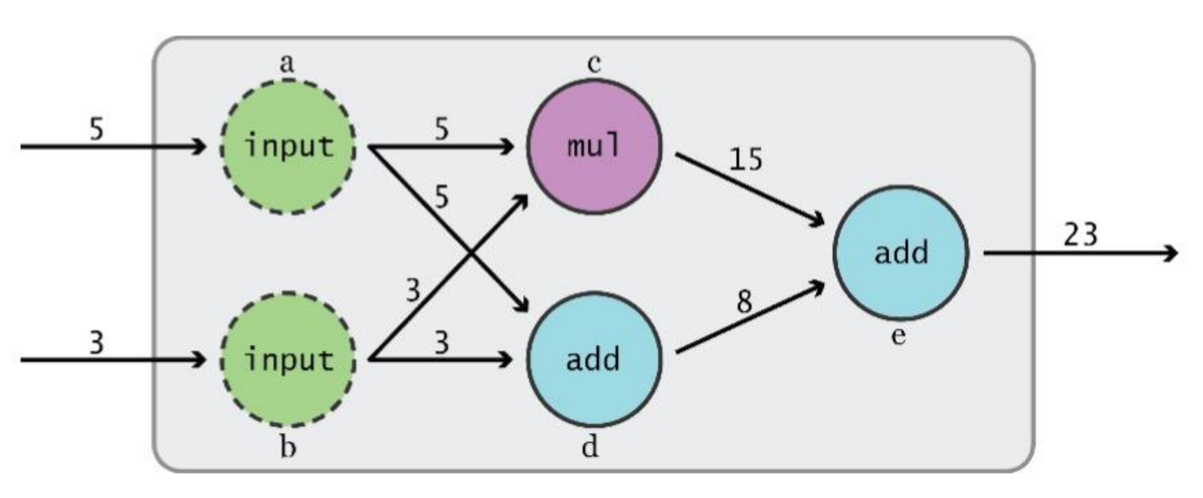
Getting Started

```
import tensorflow as tf
```

Graphs and Sessions

Data Flow Graphs

TensorFlow separates definition of computations from their execution

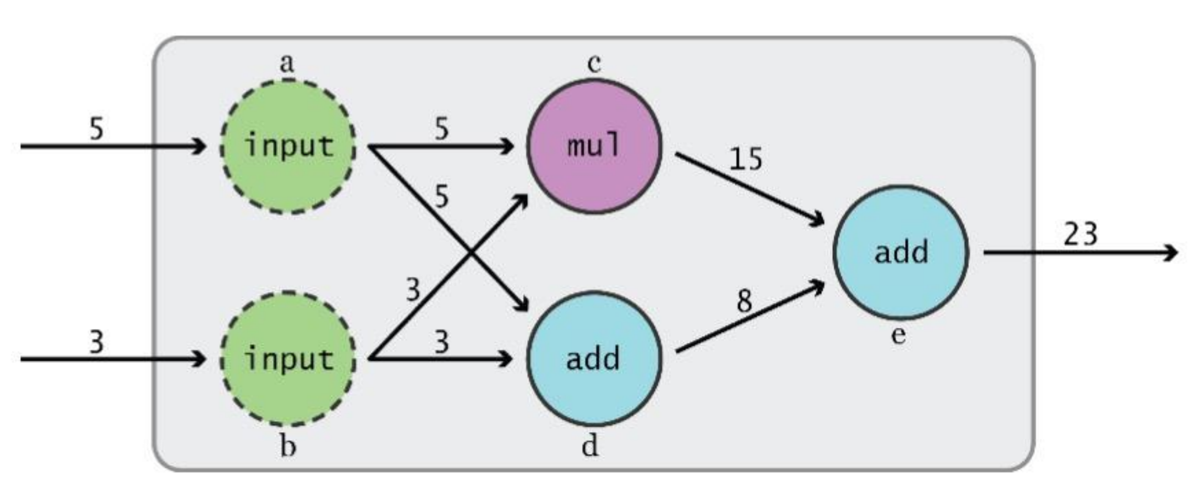


Graph from *TensorFlow for Machine Intelligence*

Data Flow Graphs

Phase 1: assemble a graph

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



Graph from *TensorFlow for Machine Intelligence*

Data Flow Graphs

This might change in the future with eager mode!!

Phase 1: assemble a graph

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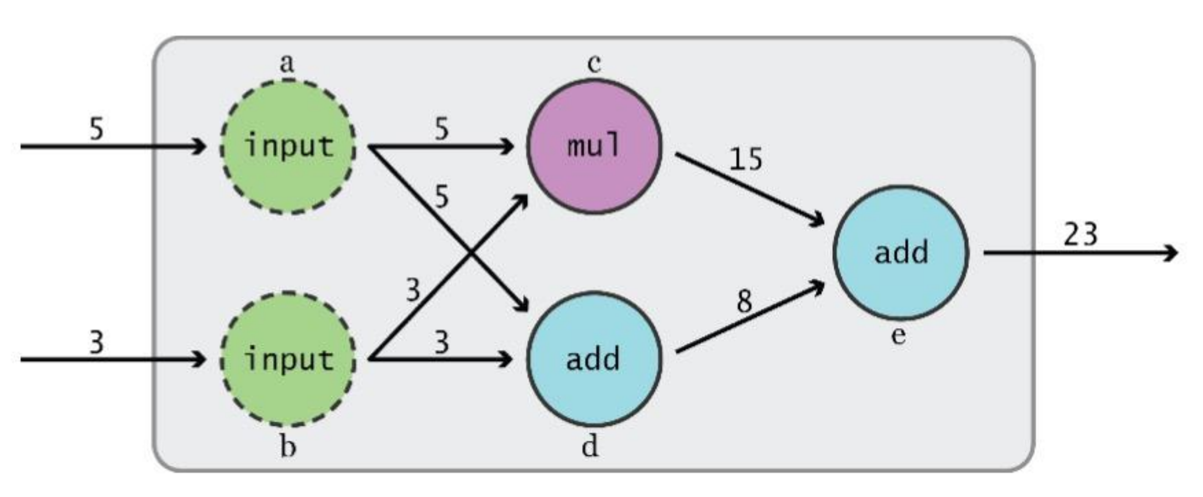


Graph from *TensorFlow for Machine Intelligence*

What’s a tensor?

What’s a tensor?

An n-dimensional array

0-d tensor: scalar (number)

1-d tensor: vector

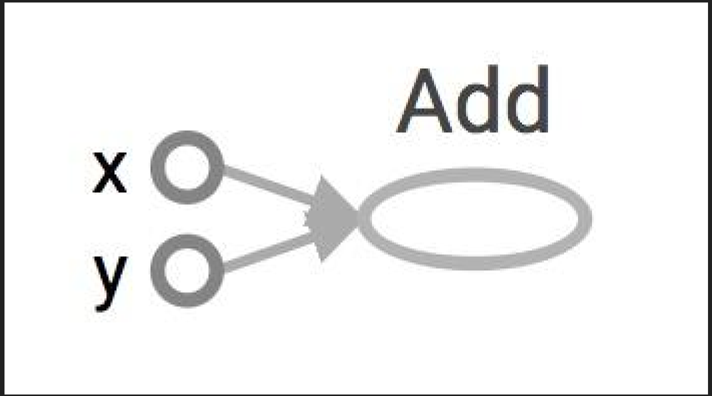
2-d tensor: matrix

and so on

Data Flow Graphs

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

Visualized by TensorBoard



Data Flow Graphs

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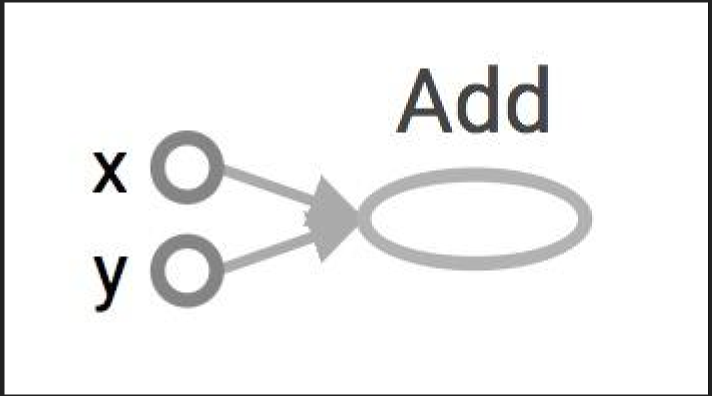


Why x, y?

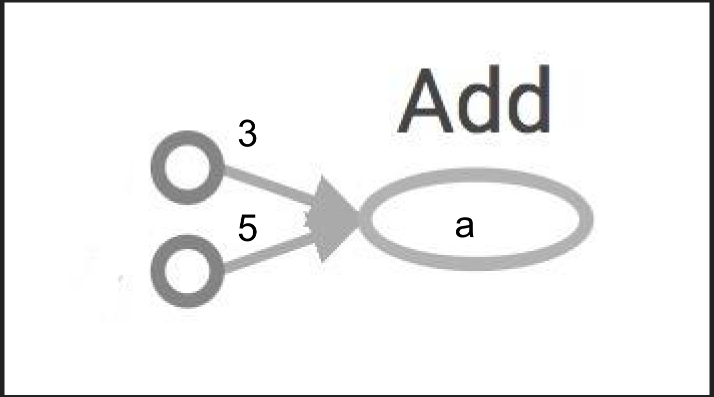
TF automatically names the nodes when you don't explicitly name them.
x = 3
y = 5

Data Flow Graphs

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

Nodes: operators, variables, and constants
Edges: tensors

Interpreted?



Data Flow Graphs

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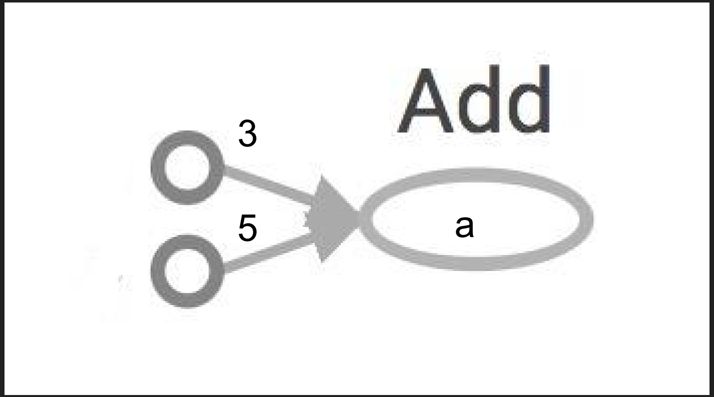
Interpreted?

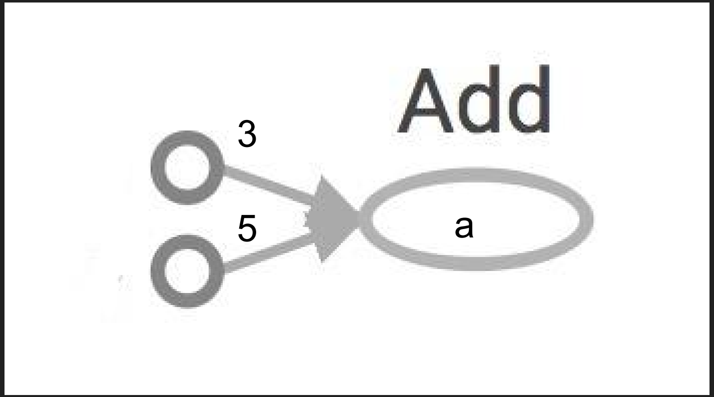


Nodes: operators, variables, and constants
Edges: tensors

Tensors are data.
TensorFlow = tensor + flow = data + flow
(I know, mind=blown)

Data Flow Graphs

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




```
>> Tensor("Add:0", shape=(), dtype=int32)
```

(Not 8)

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

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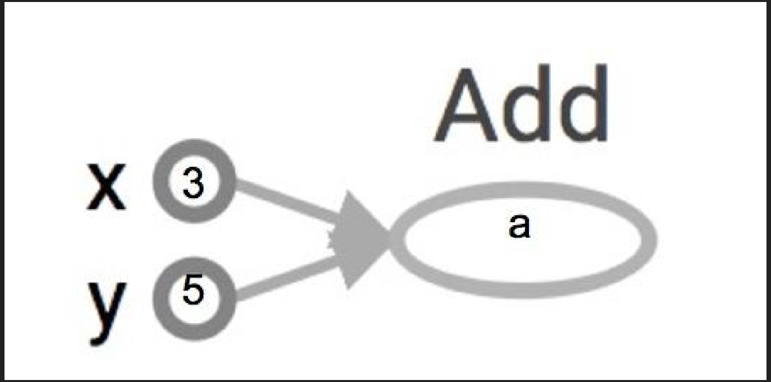
```
import tensorflow as tf
a = tf.add(3, 5)
sess = tf.Session()
print(sess.run(a))
sess.close()
```



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.

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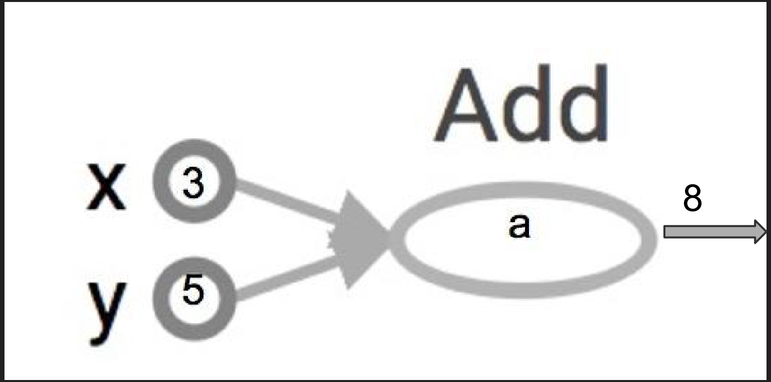
```
>> 8
```



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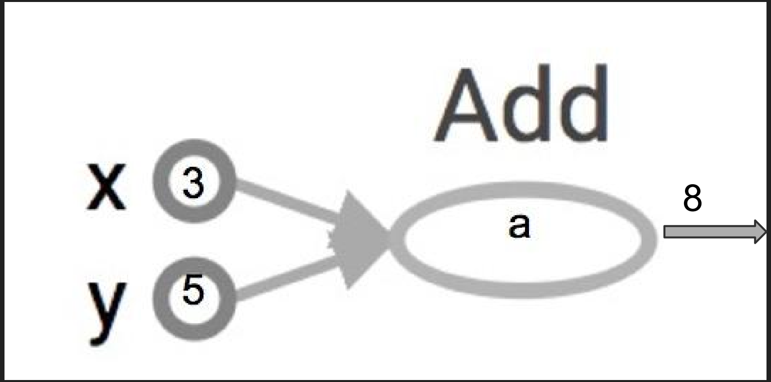
How to get the value of a?

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

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



tf.Session()

A Session object encapsulates the environment in which Operation objects are executed, and Tensor objects are evaluated.

tf.Session()

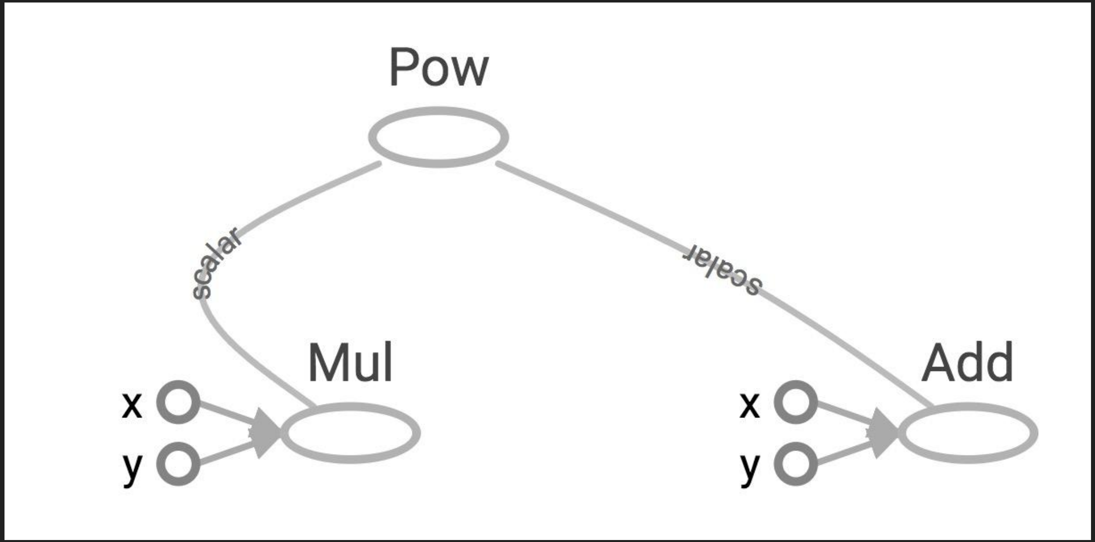
A Session object encapsulates the environment in which Operation objects are executed, and Tensor objects are evaluated.

Session will also allocate memory to store the current values of variables.

More graph

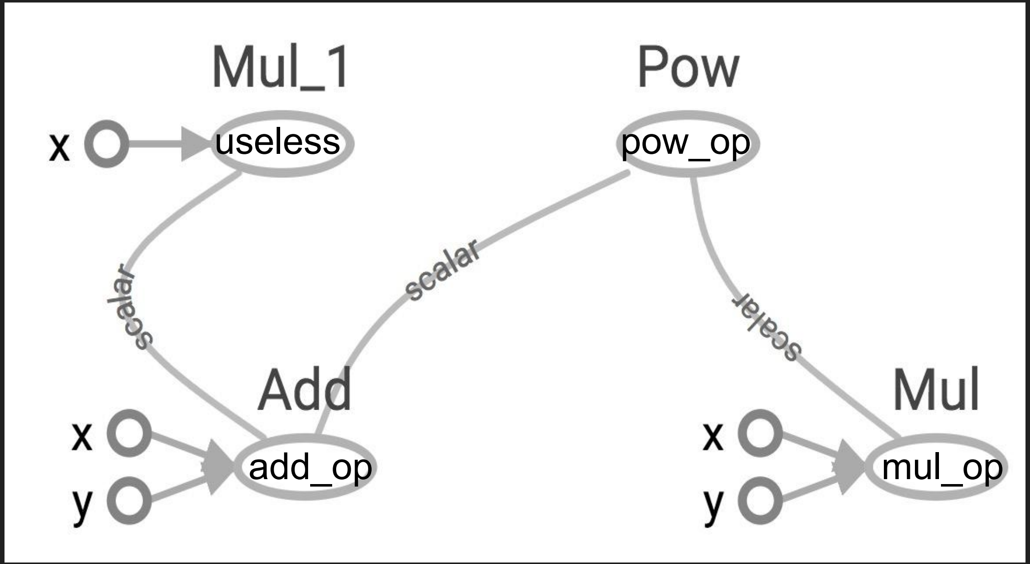
Visualized by TensorBoard

```
x = 2
y = 3
op1 = tf.add(x, y)
op2 = tf.mul(x, y)
op3 = tf.pow(op2, op1)
with tf.Session() as sess:
      op3 = sess.run(op3)
```



Subgraphs

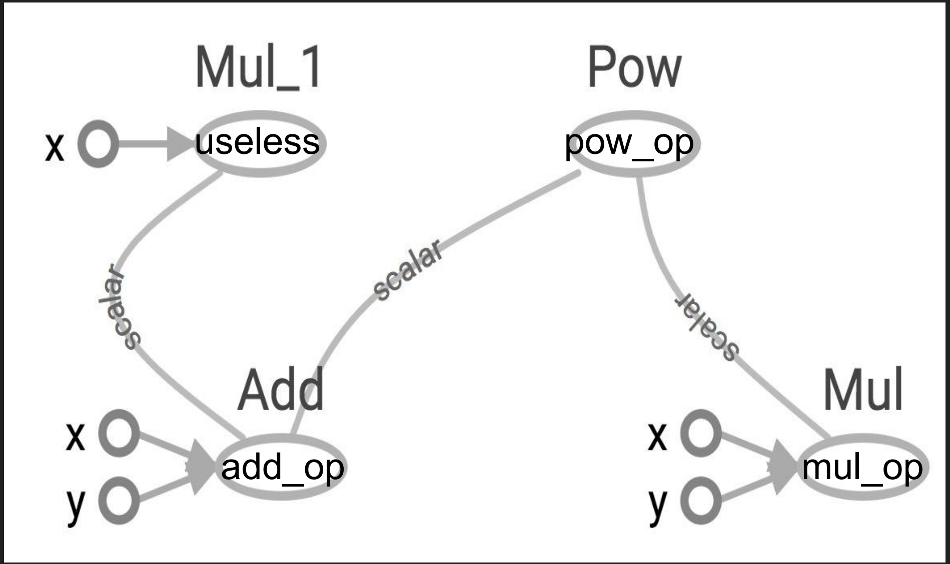
```
x = 2
y = 3
add_op = tf.add(x, y)
mul_op = tf.mul(x, y)
useless = tf.mul(x, add_op)
pow_op = tf.pow(add_op, mul_op)
with tf.Session() as sess:
      z = sess.run(pow_op)
```



Because we only want the value of pow_op and pow_op doesn’t depend on useless, session won’t compute value of useless
→ save computation

Subgraphs

```
x = 2
y = 3
add_op = tf.add(x, y)
mul_op = tf.mul(x, y)
useless = tf.mul(x, add_op)
pow_op = tf.pow(add_op, mul_op)
with tf.Session() as sess:
      z, not_useless = sess.run([pow_op, useless])
```



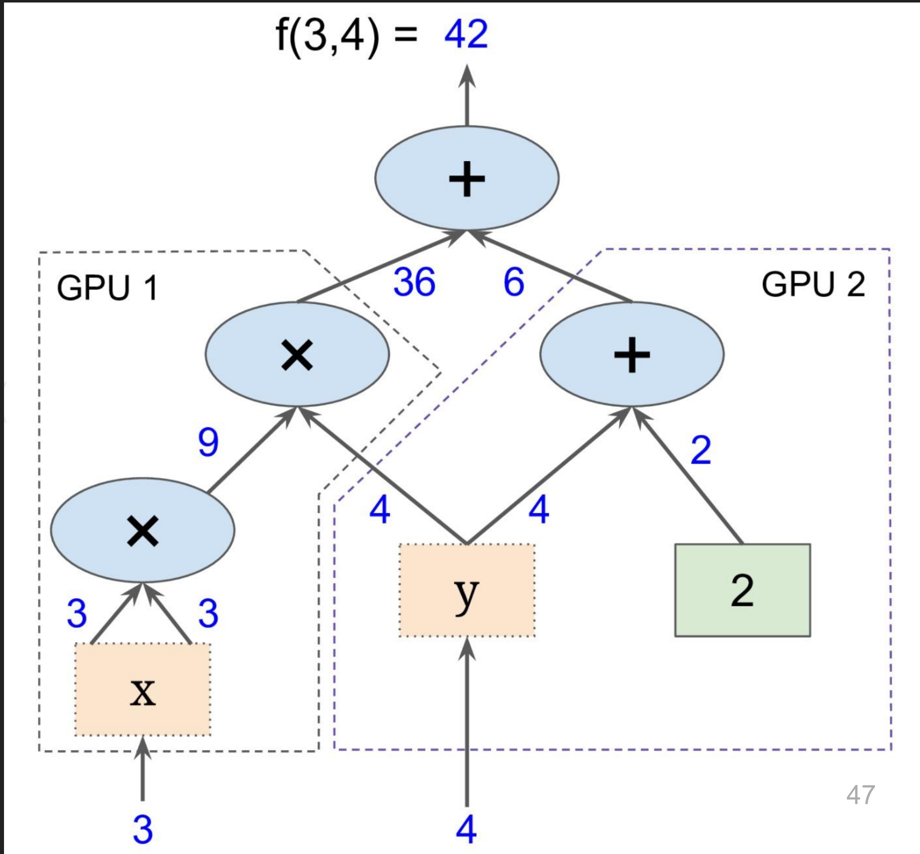

```
tf.Session.run(fetches,
               feed_dict=None,
               options=None,
               run_metadata=None)
```

fetches is a list of tensors whose values you want

Subgraphs

Possible to break graphs into several chunks and run them parallelly across multiple CPUs, GPUs, TPUs, or other devices

Example: AlexNet



Graph from *Hands-On Machine Learning with Scikit-Learn and TensorFlow*

Distributed Computation

To put part of a graph on a specific CPU or GPU:

```
# Creates a graph.
with tf.device('/gpu:2'):
  a = tf.constant([1.0, 2.0, 3.0, 4.0, 5.0, 6.0], name='a')
  b = tf.constant([1.0, 2.0, 3.0, 4.0, 5.0, 6.0], name='b')
  c = tf.multiply(a, b)

# Creates a session with log_device_placement set to True.
sess = tf.Session(config=tf.ConfigProto(log_device_placement=True))

# Runs the op.
print(sess.run(c))
```

What if I want to build more than one graph?

You can
but you don’t need more than one graph
The session runs the default graph

But what if I really want to?

URGH, NO

BUG ALERT!

- Multiple graphs require multiple sessions, each will try to use all available resources by default
- Can't pass data between them without passing them through python/numpy, which doesn't work in distributed
- It’s better to have disconnected subgraphs within one graph

I insist …

tf.Graph()

create a graph:

```
g = tf.Graph()
```

tf.Graph()

to add operators to a graph, set it as default:

```
g = tf.Graph()
with g.as_default():
      x = tf.add(3, 5)
sess = tf.Session(graph=g)
with tf.Session() as sess:
      sess.run(x)
```

tf.Graph()

To handle the default graph:

```
g = tf.get_default_graph()
```

tf.Graph()

Do not mix default graph and user created graphs

```
g = tf.Graph()

# add ops to the default graph
a = tf.constant(3)

# add ops to the user created graph
with g.as_default():
      b = tf.constant(5)
```

Prone to errors

tf.Graph()

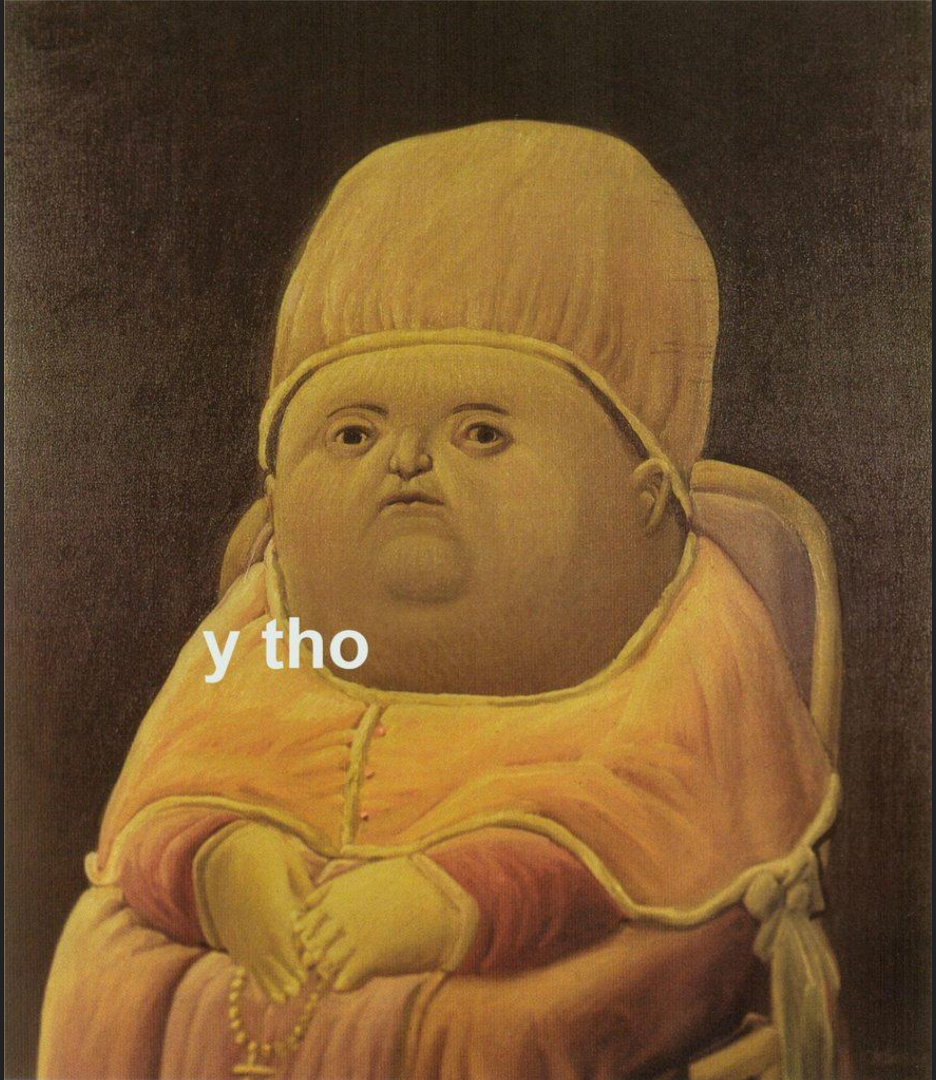
Do not mix default graph and user created graphs

```
g1 = tf.get_default_graph()
g2 = tf.Graph()

# add ops to the default graph
with g1.as_default():
      a = tf.Constant(3)

# add ops to the user created graph
with g2.as_default():
      b = tf.Constant(5)
```

Better
But still not good enough because no more than one graph!


y tho

Why graphs

1. Save computation. Only run subgraphs that lead to the values you want to fetch.

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Why graphs

1. Save computation. Only run subgraphs that lead to the values you want to fetch.
2. Break computation into small, differential pieces to facilitate auto-differentiation
3. Facilitate distributed computation, spread the work across multiple CPUs, GPUs, TPUs, or other devices
4. Many common machine learning models are taught and visualized as directed graphs

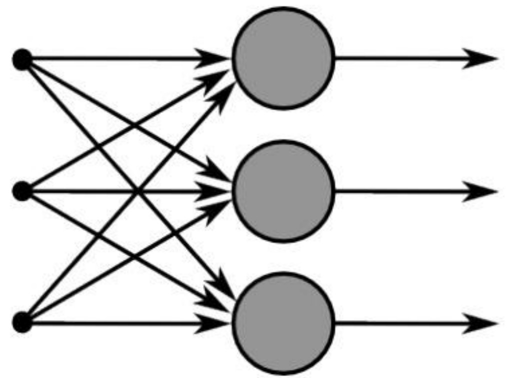

Figure 3: This image captures how multiple sigmoid units are stacked on the right, all of which receive the same input x.

A neural net graph from Stanford's CS224N course

Next class

Basic operations

Constants and variables

Data pipeline

Fun with TensorBoard

Feedback: huyenn@stanford.edu

Thanks!