

Probabilistic Programming

Marius Popescu

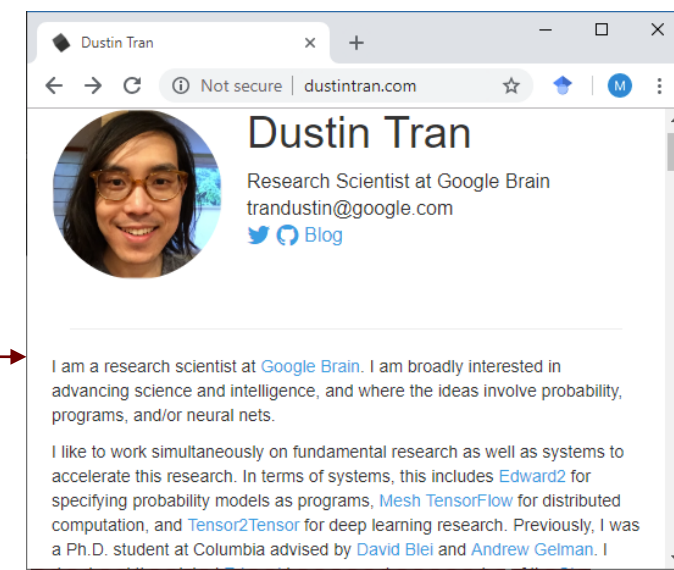
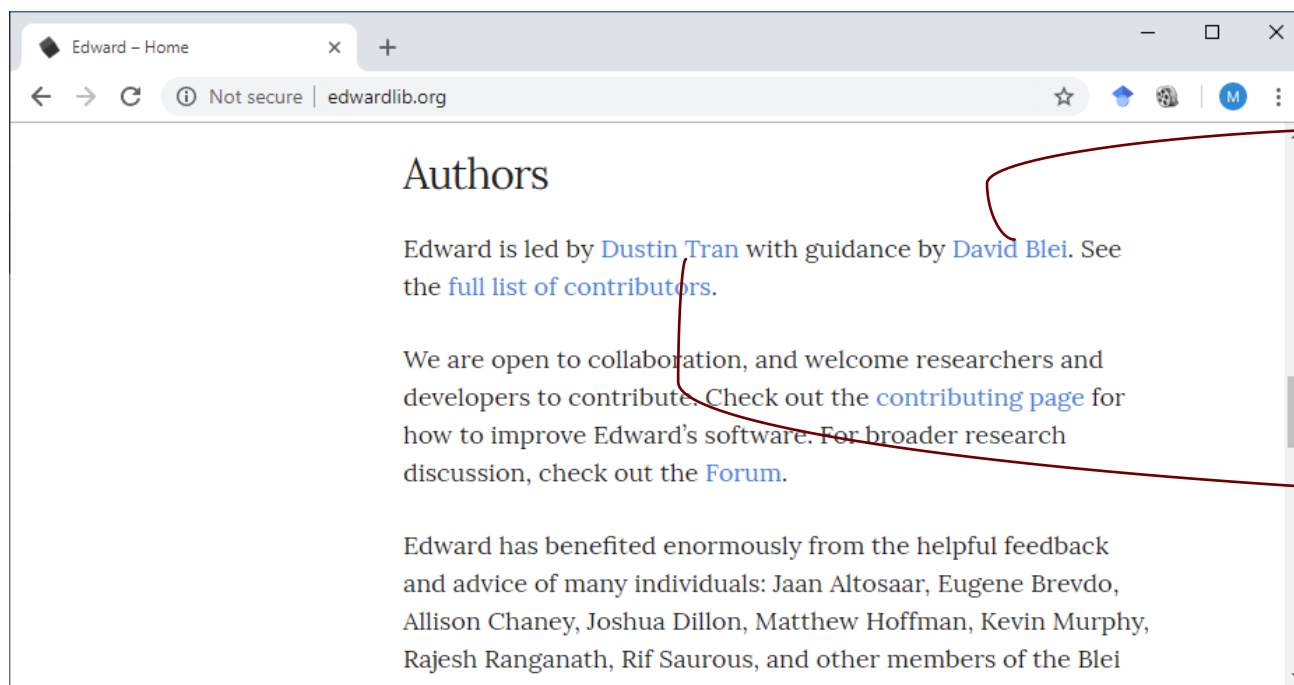
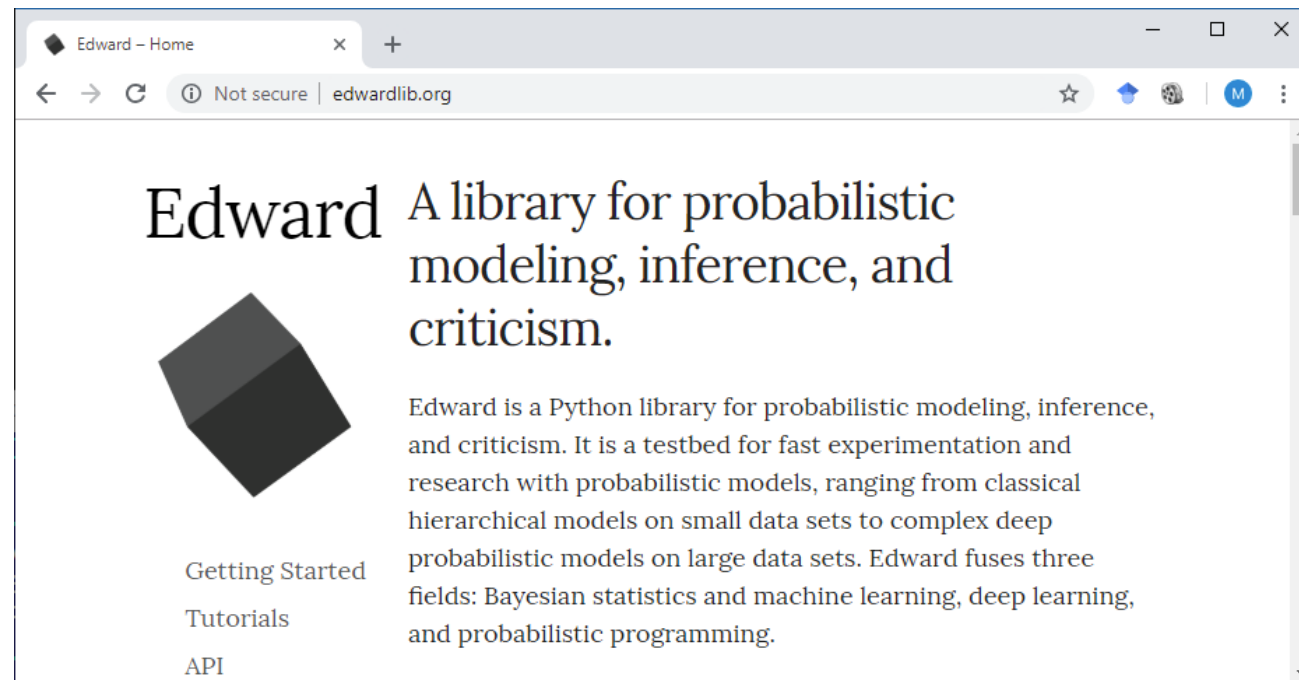
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2019 - 2020

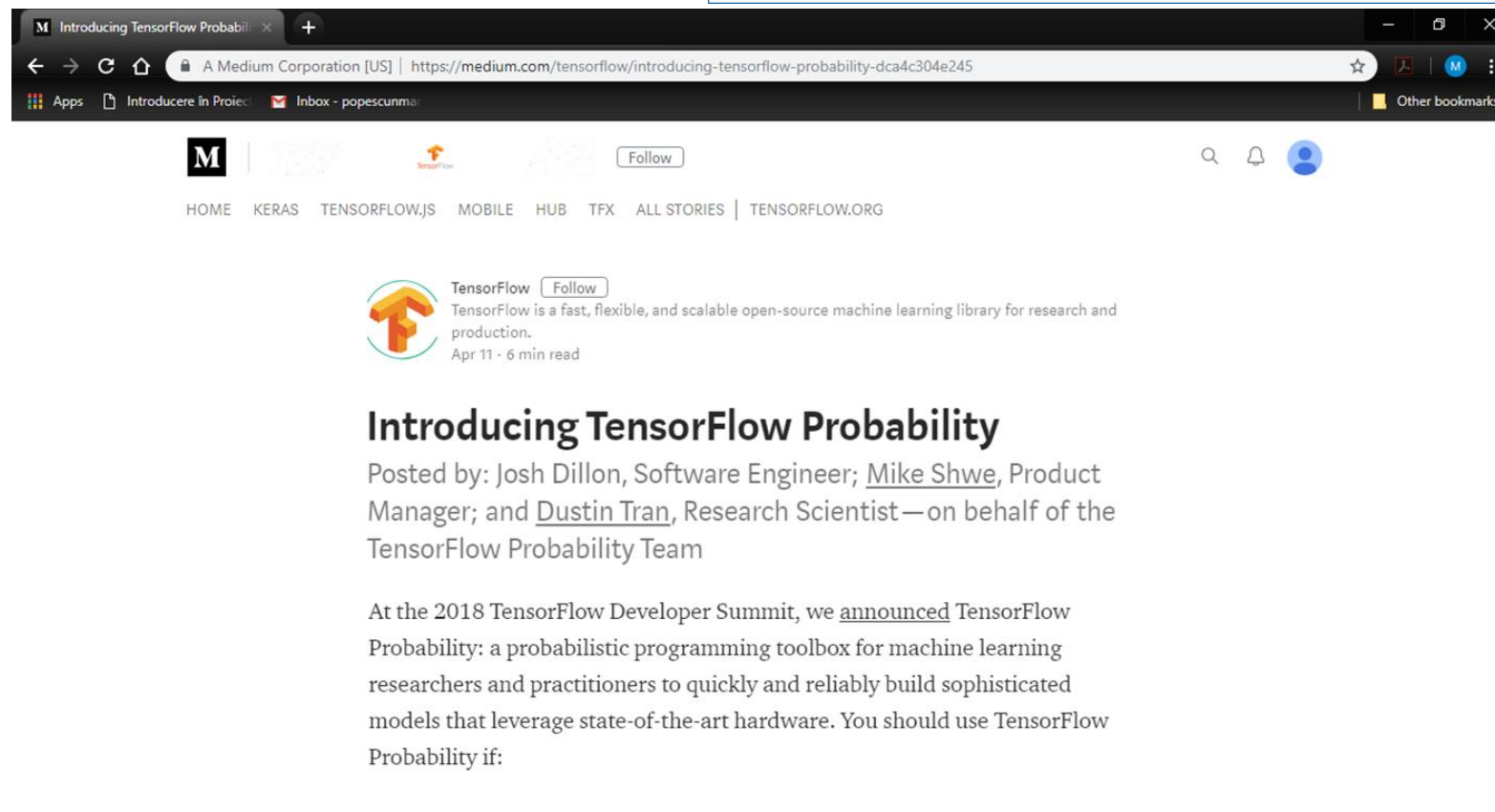
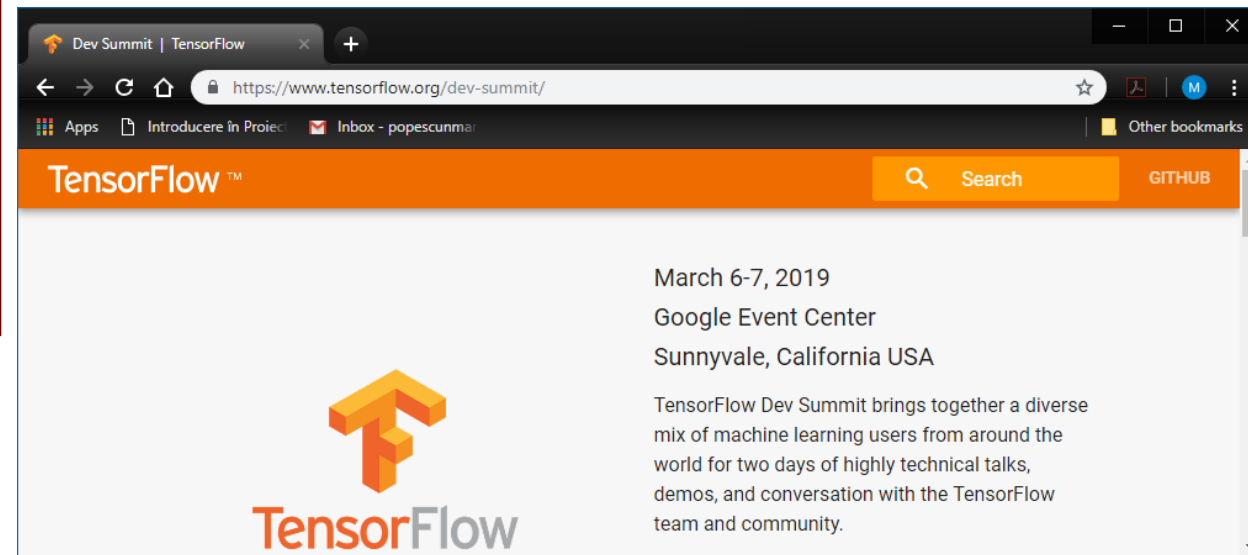
TensorFlow Probability / Edward2



Some History



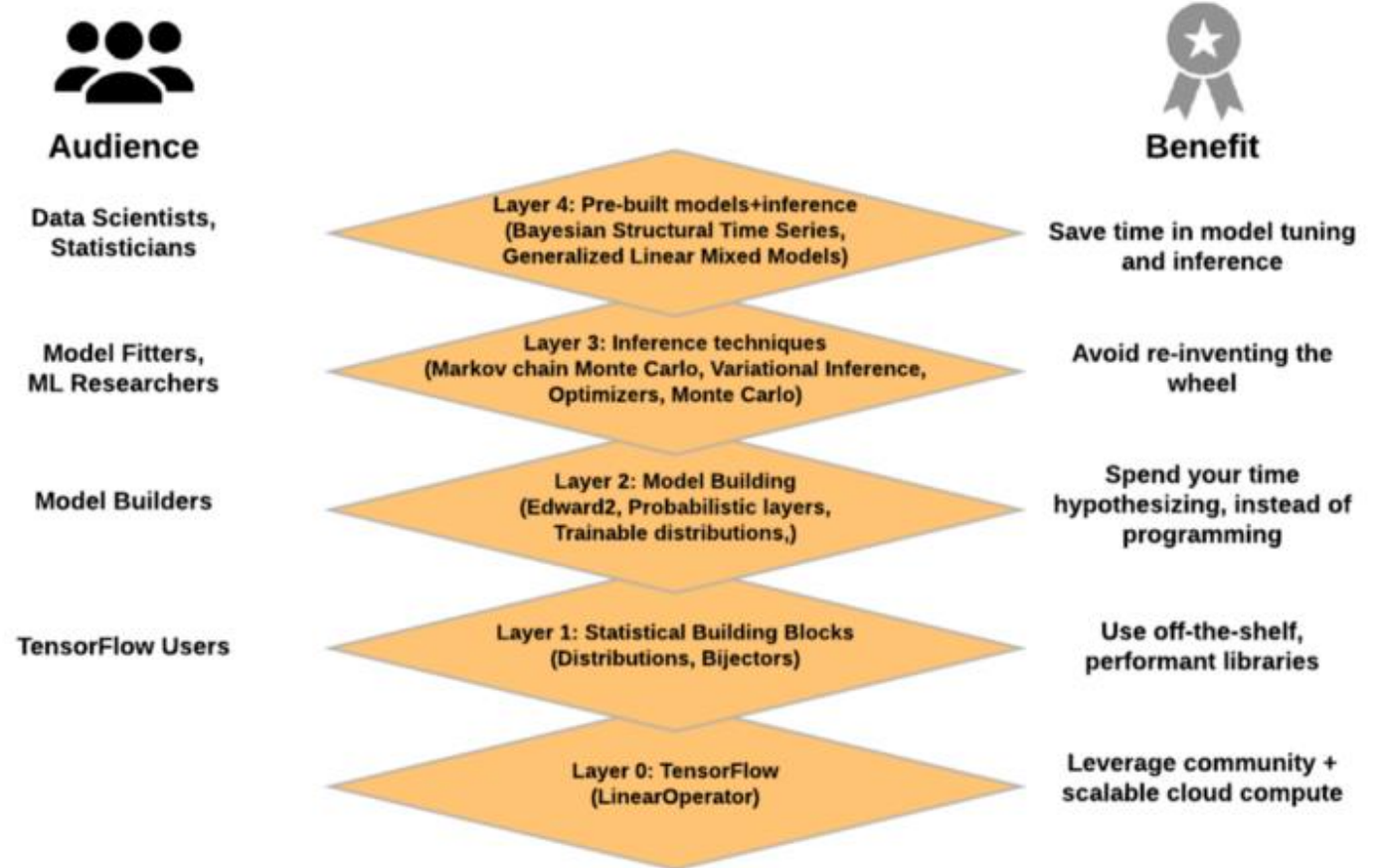
Some History



TFP

TensorFlow Probability (TFP) is a Python library built on TensorFlow that makes it easy to combine probabilistic models and deep learning on modern hardware (TPU, GPU).

It is a probabilistic programming toolbox for machine learning researchers and practitioners provides modular abstractions for probabilistic reasoning and statistical analysis in the TensorFlow ecosystem.



TFP Layer 1: Statistical Building Blocks

- Distributions (`tf.contrib.distributions`, `tf.distributions`): A large collection of probability distributions and related statistics with batch and broadcasting semantics.
- Bijectors (`tf.contrib.distributions.bijectors`): Reversible and composable transformations of random variables. Bijectors provide a rich class of transformed distributions, from classical examples like the log-normal distribution to sophisticated deep learning models such as masked autoregressive flows.

TFP Layer 2: Model Building

- Edward2 (`tfp.edward2`): A probabilistic programming language for specifying flexible probabilistic models as programs.
- Probabilistic Layers (`tfp.layers`): Neural network layers with uncertainty over the functions they represent, extending TensorFlow Layers.
- Trainable Distributions (`tfp.trainable_distributions`): Probability distributions parameterized by a single Tensor, making it easy to build neural nets that output probability distributions.

TFP Layer 3: Probabilistic Inference

- Markov chain Monte Carlo (tfp.mcmc): Algorithms for approximating integrals via sampling. Includes Hamiltonian Monte Carlo, random-walk Metropolis-Hastings, and the ability to build custom transition kernels.
- Variational Inference (tfp.vi): Algorithms for approximating integrals via optimization.
- Optimizers (tfp.optimizer): Stochastic optimization methods, extending TensorFlow Optimizers. Includes Stochastic Gradient Langevin Dynamics.
- Monte Carlo (tfp.monte_carlo): Tools for computing Monte Carlo expectations.

TFP Layer 4: Pre-made Models and Inference

- Bayesian structural time series: High-level interface for fitting time-series models (i.e., similar to R's BSTS package).
- Generalized Linear Mixed Models: High-level interface for fitting mixed-effects regression models (i.e., similar to R's lme4 package).

TensorFlow Basics



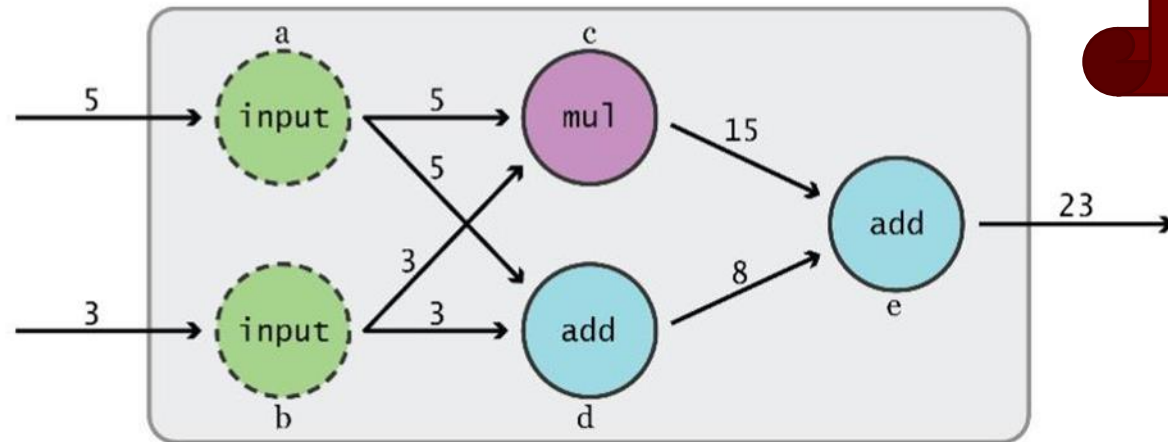
```
import tensorflow as tf
```



Data Flow Graphs

TensorFlow separates definition of computations from their execution

- Phase 1: assemble a graph
- Phase 2: use a session to execute operations in the graph.

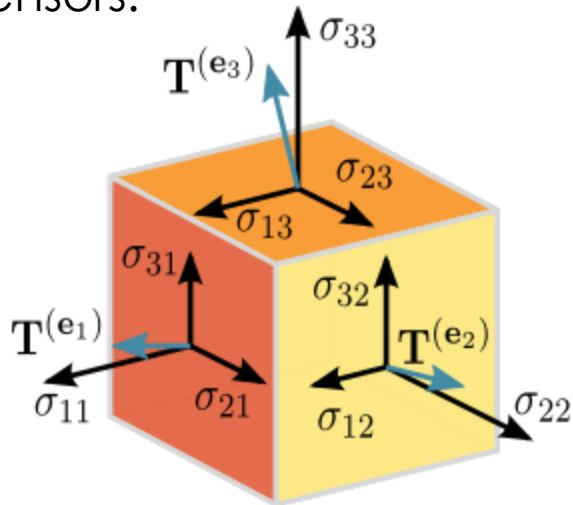


This might change in the future; in TensorFlow 2.0 the Eager execution will be the standard execution mode.

What's a tensor?

In Mathematics

A tensor is an arbitrarily complex geometric object that maps in a (multi-)linear manner geometric vectors, scalars, and other tensors to a resulting tensor. Thereby, vectors and scalars themselves are considered as the simplest tensors.



In TensorFlow

An n-dimensional array{

- 0-d / rank 0 tensor: scalar (number)
- 1-d / rank 1 tensor: vector
- 2-d / rank 2 tensor: matrix
- ...



Data Flow Graphs

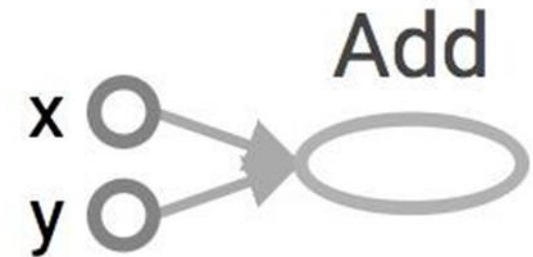
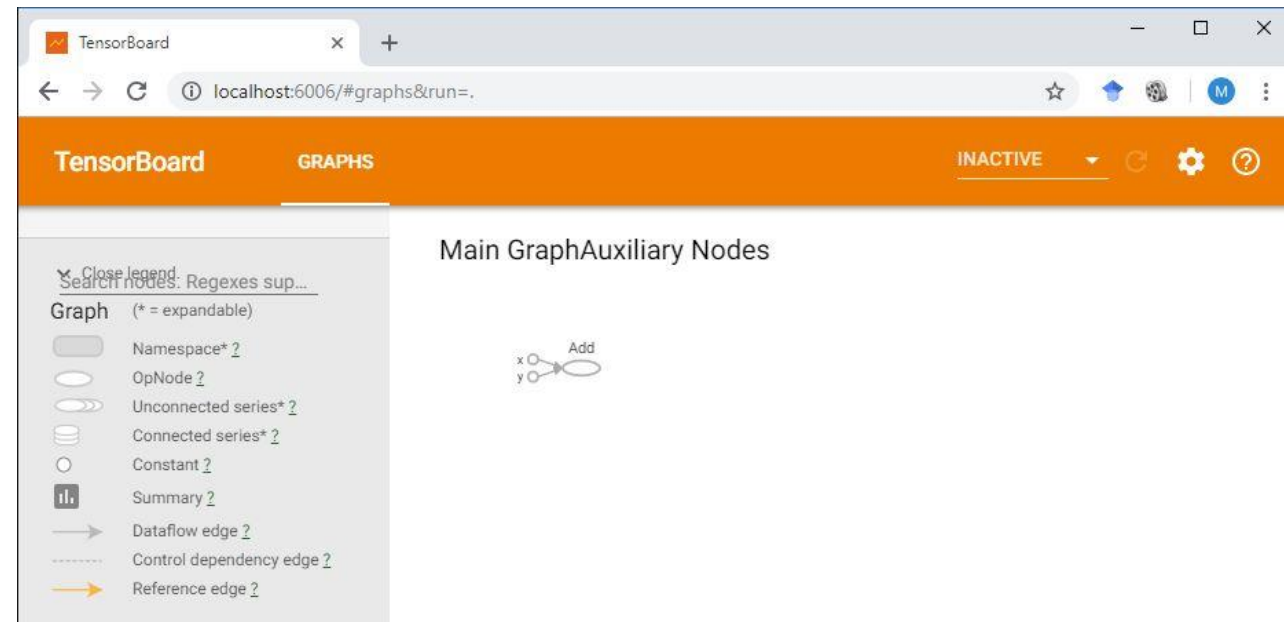
```
>>>import tensorflow as tf  
>>>a = tf.add(3, 5)
```

Why x, y?

TF automatically names the nodes when you don't explicitly name them.

x = 3

y = 5



Data Flow Graphs

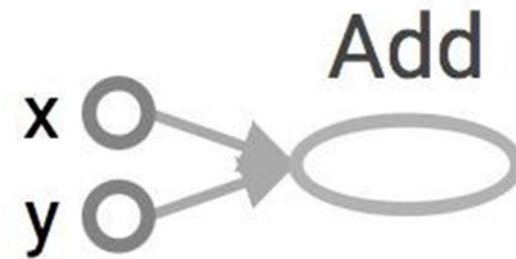
```
>>>import tensorflow as tf  
>>>a = tf.add(3, 5)
```

Nodes: operators, variables, and constants

Edges: tensors

Tensors are data.

TensorFlow = tensor + flow = data + flow

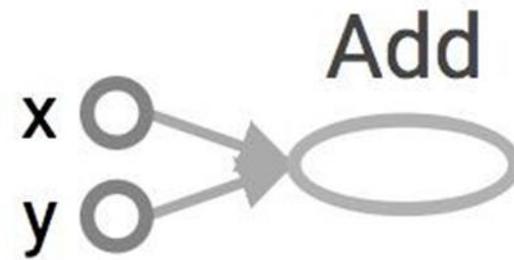


Interpretation?

Data Flow Graphs

```
>>>import tensorflow as tf  
>>>a = tf.add(3, 5)  
>>>print(a)  
Tensor("Add:0", shape=(), dtype=int32)
```

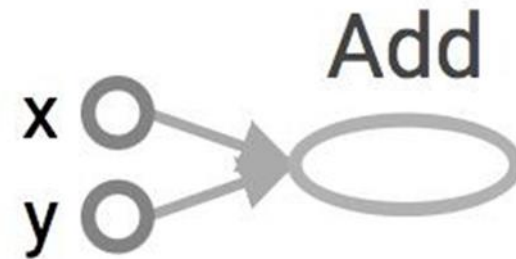
Not 8



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`

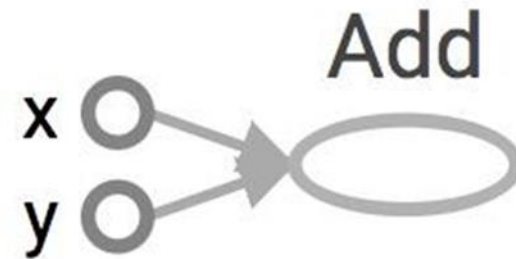
```
import tensorflow as tf
a = tf.add(3, 5)
sess = tf.Session()
print(sess.run(a))
sess.close()
```



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()
```

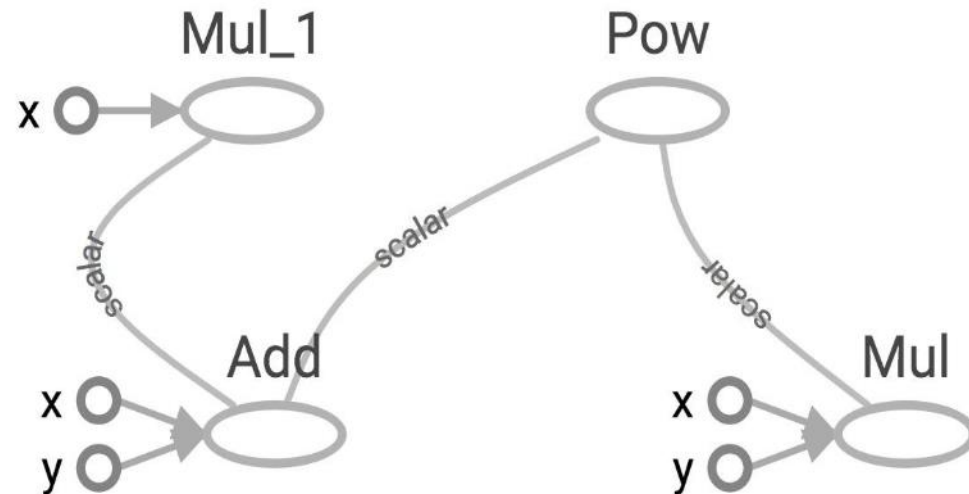


tf.Session()

- A Session object encapsulates the environment in which Operation objects are executed, and Tensor objects are evaluated.
- A TensorFlow session is used to run parts of the graph to get the variables we want.

Subgraphs

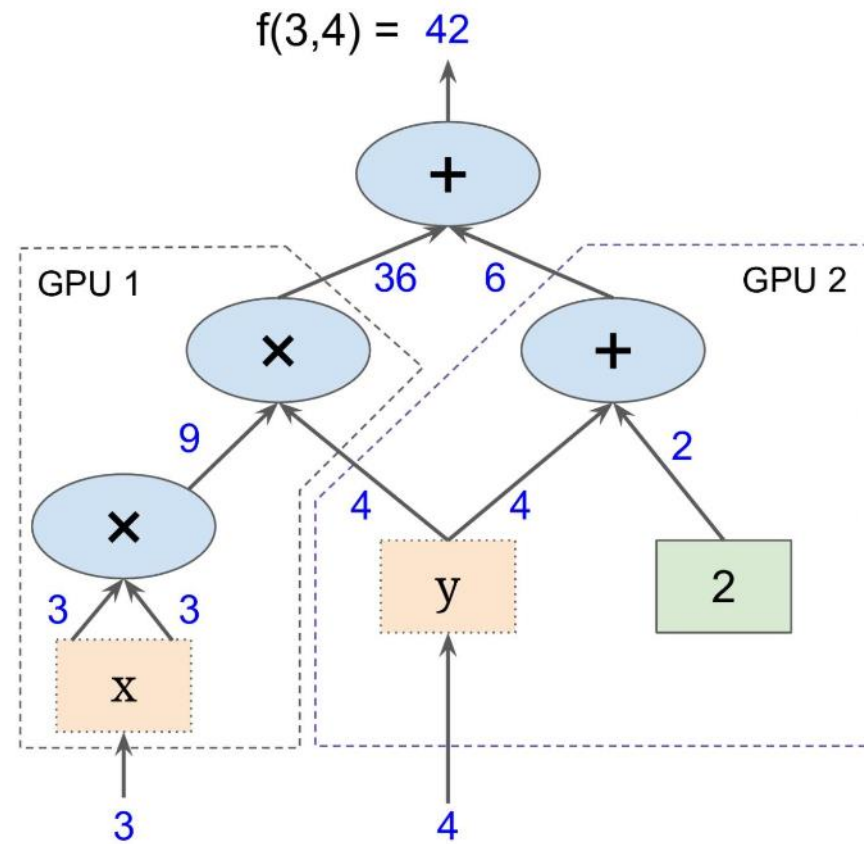
```
x = 2
y = 3
add_op = tf.add(x, y)
mul_op = tf.multiply(x, y)
useless = tf.multiply(x, add_op)
pow_op = tf.pow(add_op, mul_op)
with tf.Session() as sess:
    z = sess.run(pow_op)
```



Because we only want the value of `pow_op` and `pow_op` doesn't depend on `useless`, session won't compute value of `useless`

Subgraphs

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



Visualization with TensorBoard

```
import tensorflow as tf

a = tf.constant(2, name = 'a')
b = tf.constant(3, name = 'b')
x = tf.add(a, b, name = 'x')

writer = tf.summary.FileWriter('./graphs', tf.get_default_graph())
with tf.Session() as sess:
    # writer = tf.summary.FileWriter('./graphs', sess.graph)
    print(sess.run(x))
writer.close()
```


Visualization with TensorBoard

Run:

```
python yourprogram.py  
tensorboard --logdir="./graphs" --port 6006
```

Then open your browser and go to:

<http://localhost:6006/>


Visualization with TensorBoard


TensorBoard

GRAPHPS

INACTIVE

Search nodes. Regexes sup...

 Fit to screen

 Download PNG










Run (1)

Session runs (0)


Upload

Close legend.

Graph (* = expandable)

-  Namespace* [?](#)
-  OpNode [?](#)
-  Unconnected series* [?](#)
-  Connected series* [?](#)
-  Constant [?](#)
-  Summary [?](#)
-  Dataflow edge [?](#)
-  Control dependency edge [?](#)
-  Reference edge [?](#)

Main GraphAuxiliary Nodes



Tensors

tf.Tensor

Internally, TensorFlow represents tensors as n-dimensional arrays of base datatypes.

A `tf.Tensor` has the following properties:

- a data type (`float32`, `int32`, or `string`, for example)
- a shape

Shape

The TensorFlow documentation uses three notational conventions to describe tensor dimensionality: rank, shape, and dimension number.

Rank	Shape	Dimension number	Example
0	[]	0-D	A 0-D tensor. A scalar.
1	[D0]	1-D	A 1-D tensor with shape [5].
2	[D0, D1]	2-D	A 2-D tensor with shape [3, 4].
3	[D0, D1, D2]	3-D	A 3-D tensor with shape [1, 4, 3].
n	[D0, D1, ... Dn-1]	n-D	A tensor with shape [D0, D1, ... Dn-1].

Shapes can be represented via Python lists / tuples of ints, or with the `tf.TensorShape`.

Shape

- Getting a `tf.Tensor` object's shape:

```
zeros = tf.zeros(my_matrix.shape[1]) # makes a vector of zeros with the same size  
                                     # as the number of columns in a given matrix
```

- Changing the shape of a `tf.Tensor`:

```
rank_three_tensor = tf.ones([3, 4, 5])  
matrix = tf.reshape(rank_three_tensor, [6, 10]) # Reshape existing content into  
# a 6x10 matrix
```

Data Type

- To inspect a `tf.Tensor`'s data type use the `Tensor.dtype` property.
- It is possible to cast `tf.Tensors` from one datatype to another using `tf.cast`:

```
# Cast a constant integer tensor into floating point.
```

```
float_tensor = tf.cast(tf.constant([1, 2, 3]), dtype=tf.float32)
```


Creating Tensors: Constants

Constants

```
a = tf.constant(3, name='a')
```

```
a = tf.constant([2, 2], name='a')
```

```
a = tf.constant([[0, 1], [2, 3]], name='a')
```

Tensors filled with a specific value

```
tf.zeros(shape, dtype=tf.float32, name=None)
```

Creates a tensor of shape and all elements will be zeros

```
tf.zeros([2, 3], tf.int32) ==> [[0, 0, 0], [0, 0, 0]]
```

Tensors filled with a specific value

```
tf.zeros_like(input_tensor, dtype=None, name=None, optimize=True)
```

Creates a tensor of shape and type (unless type is specified) as the `input_tensor` but all elements are zeros.

```
# input_tensor is [[0, 1], [2, 3], [4, 5]]  
tf.zeros_like(input_tensor) ==> [[0, 0], [0, 0], [0, 0]]
```

Tensors filled with a specific value

```
tf.ones(shape, dtype=tf.float32, name=None)
```

```
tf.ones_like(input_tensor, dtype=None, name=None, optimize=True)
```

Tensors filled with a specific value

```
tf.fill(dims, value, name=None)
```

Creates a tensor filled with a scalar value.

```
tf.fill([2, 3], 8) ==> [[8, 8, 8], [8, 8, 8]]
```

Constants as Sequences

```
tf.lin_space(start, stop, num, name=None)  
tf.lin_space(10.0, 13.0, 4) ==> [10. 11. 12. 13.]
```

```
tf.range(start, limit=None, delta=1, dtype=None, name='range')  
tf.range(3, 18, 3) ==> [3 6 9 12 15]  
tf.range(5) ==> [0 1 2 3 4]
```


Randomly Generated Constants

`tf.random_normal`

`tf.truncated_normal`

`tf.random_uniform`

`tf.random_shuffle`

`tf.random_crop`

`tf.multinomial`

`tf.random_gamma`

Creating Tensors: Operations

Subtract

Classes

tensorflow::ops::Abs	Computes the absolute value of a tensor.
tensorflow::ops::AccumulateNV2	Returns the element-wise sum of a list of tensors.
tensorflow::ops::Acos	Computes acos of x element-wise.
tensorflow::ops::Acosh	Computes inverse hyperbolic cosine of x element-wise.
tensorflow::ops::Add	Returns x + y element-wise.
tensorflow::ops::AddN	Add all input tensors element wise.
tensorflow::ops::AddV2	Returns x + y element-wise.
tensorflow::ops::All	Computes the "logical and" of elements across dimensions of a tensor.
tensorflow::ops::Angle	Returns the argument of a complex number.
tensorflow::ops::Any	Computes the "logical or" of elements across dimensions of a tensor.
tensorflow::ops::ApproximateEqual	Returns the truth value of $\text{abs}(x-y) < \text{tolerance}$ element-wise.
tensorflow::ops::ArgMax	Returns the index with the largest value across dimensions of a tensor.

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- ▶ [candidate_sampling_ops](#)
- ▶ [control_flow_ops](#)
- ▶ [core](#)
- ▶ [data_flow_ops](#)
- ▶ [image_ops](#)
- ▶ [io_ops](#)
- ▶ [logging_ops](#)
- ▼ [math_ops](#)

[Overview](#)

[tensorflow::ops::Abs](#)
[tensorflow::ops::AccumulateNV2](#)
[tensorflow::ops::Acos](#)
[tensorflow::ops::Acosh](#)
[tensorflow::ops::Add](#)
[tensorflow::ops::AddN](#)
[tensorflow::ops::AddV2](#)
[tensorflow::ops::All](#)
[tensorflow::ops::Angle](#)

`tensor_diag_part(...)`: Returns the diagonal part of the tensor.

Functions

C++

array_ops

Overview

[tensorflow::ops::BatchToSpace](#)[tensorflow::ops::BatchToSpaceND](#)[tensorflow::ops::Bitcast](#)[tensorflow::ops::BroadcastDynamicShape](#)[tensorflow::ops::BroadcastTo](#)[tensorflow::ops::CheckNumerics](#)[tensorflow::ops::Concat](#)[tensorflow::ops::ConjugateTranspose](#)[tensorflow::ops::DebugGradientIdentity](#)[tensorflow::ops::DebugGradientRefIdentity](#)[tensorflow::ops::DeepCopy](#)[tensorflow::ops::DepthToSpace](#)[tensorflow::ops::DepthToSpace::Attrs](#)[tensorflow::ops::StopGradient](#)

Stops gradient computation.

[tensorflow::ops::StridedSlice](#)Return a strided slice from **input**.[tensorflow::ops::StridedSliceAssign](#)**Assign** **value** to the sliced l-value reference of **ref**.[tensorflow::ops::StridedSliceGrad](#)Returns the gradient of **StridedSlice**.[tensorflow::ops::Tile](#)

Constructs a tensor by tiling a given tensor.

[tensorflow::ops::Transpose](#)

Shuffle dimensions of x according to a permutation.

[tensorflow::ops::Unique](#)

Finds unique elements in a 1-D tensor.

[tensorflow::ops::UniqueV2](#)

Finds unique elements along an axis of a tensor.

[tensorflow::ops::UniqueWithCounts](#)

Finds unique elements in a 1-D tensor.

[tensorflow::ops::UniqueWithCountsV2](#)

Finds unique elements along an axis of a tensor.

[tensorflow::ops::UnravelIndex](#)

Converts a flat index or array of flat indices into a tuple of.

[tensorflow::ops::Unstack](#)Unpacks a given dimension of a rank-R tensor into **num** rank-(R-1) tensors.[tensorflow::ops::Where](#)

Returns locations of nonzero / true values in a tensor.

[tensorflow::ops::ZerosLike](#)

Returns a tensor of zeros with the same shape and type as x.

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Summary

Classes

C++

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- ▶ candidate_sampling_ops
- ▼ control_flow_ops
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 - tensorflow::ops::Abort
 - tensorflow::ops::Abort::Attrs
 - tensorflow::ops::ControlTrigger
 - tensorflow::ops::LoopCond
 - tensorflow::ops::Merge
 - tensorflow::ops::NextIteration
 - tensorflow::ops::RefNextIteration
 - tensorflow::ops::RefSelect
 - tensorflow::ops::RefSwitch
 - tensorflow::ops::Switch
- ▶ core

Control Flow Ops



Contents

- Summary
- Classes

Summary

Classes	
tensorflow::ops::Abort	Raise a exception to abort the process when called.
tensorflow::ops::ControlTrigger	Does nothing.
tensorflow::ops::LoopCond	Forwards the input to the output.
tensorflow::ops::Merge	Forwards the value of an available tensor from inputs to output .
tensorflow::ops::NextIteration	Makes its input available to the next iteration.
tensorflow::ops::RefNextIteration	Makes its input available to the next iteration.
tensorflow::ops::RefSelect	Forwards the indexth element of inputs to output .

Variables

tf.Variable class

```
# create variables with tf.Variable
s = tf.Variable(2, name="scalar")
m = tf.Variable([[0, 1], [2, 3]], name="matrix")
W = tf.Variable(tf.zeros([784,10]))
```

```
# create variables with tf.get_variable
s = tf.get_variable("scalar", initializer=tf.constant(2))
m = tf.get_variable("matrix", initializer=tf.constant([[0, 1], [2, 3]]))
W = tf.get_variable("big_matrix", shape=(784, 10), initializer=tf.zeros_initializer())
```


tf.Variable holds several ops

```
x = tf.Variable(...)
```

```
x.initializer # init op
```

```
x.value() # read op
```

```
x.assign(...) # write op
```

```
x.assign_add(...) # and more
```

You have to initialize your variables

```
import tensorflow as tf
```

```
W = tf.get_variable("big_matrix", shape=(784, 10), initializer=tf.zeros_initializer())
```

```
with tf.Session() as sess:  
    print(sess.run(W))
```

Initializer is an op. You need to execute it within the context of a session

FailedPreconditionError: Attempting to use uninitialized value Variable

You have to initialize your variables

The easiest way is initializing all variables at once:

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

Initialize only a subset of variables:

```
with tf.Session() as sess:  
    sess.run(tf.variables_initializer([a, b]))
```

Initialize a single variable

```
W = tf.Variable(tf.zeros([784,10]))  
with tf.Session() as sess:  
    sess.run(W.initializer)
```

Eval() a variable

```
# W is a random 700 x 10 variable object
W = tf.Variable(tf.truncated_normal([700, 10]))
with tf.Session() as sess:
    sess.run(W.initializer)
print(W)
    print(W.eval())

Tensor("Variable/read:0", shape=(700, 10), dtype=float32)
[[-0.76781619 -0.67020458  1.15333688 ..., -0.98434633 -1.25692499
  -0.90904623]
 [-0.36763489 -0.65037876 -1.52936983 ...,  0.19320194 -0.38379928
   0.44387451]
 [ 0.12510735 -0.82649058  0.4321366 ..., -0.3816964  0.70466036
   1.33211911]
 ...,
```

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
    sess.run(W.initializer)
    print(W.eval())
```

10



W.assign(100) creates an assign op. That op needs to be executed in a session to take effect.

```
W = tf.Variable(10)
assign_op = W.assign(100)
with tf.Session() as sess:
    sess.run(W.initializer)
    sess.run(assign_op)
    print(W.eval())
```

100



tf.Variable.assign()

```
# create a variable whose original value is 2
```

```
my_var = tf.Variable(2, name="my_var")
```

```
# assign a * 2 to a and call that op a_times_two
```

```
my_var_times_two = my_var.assign(2 * my_var)
```

```
with tf.Session() as sess:
```

```
    sess.run(my_var.initializer)
```

```
    sess.run(my_var_times_two)
```

```
    sess.run(my_var_times_two)
```

```
    sess.run(my_var_times_two)
```

```
# the value of my_var now is 4
```

```
# the value of my_var now is 8
```

```
# the value of my_var now is 16
```

“Hello World!”

Monty Hall Problem



Suppose you're on a game show, and you're given the choice of three doors: Behind one door is a car; behind the others, goats. You pick a door, say No. 1, and the host, who knows what's behind the doors, opens another door, say No. 3, which has a goat. He then says to you, "Do you want to pick door No. 2?" Is it to your advantage to switch your choice?

TFP Solution

```
import tensorflow as tf
from tensorflow_probability import edward2 as ed

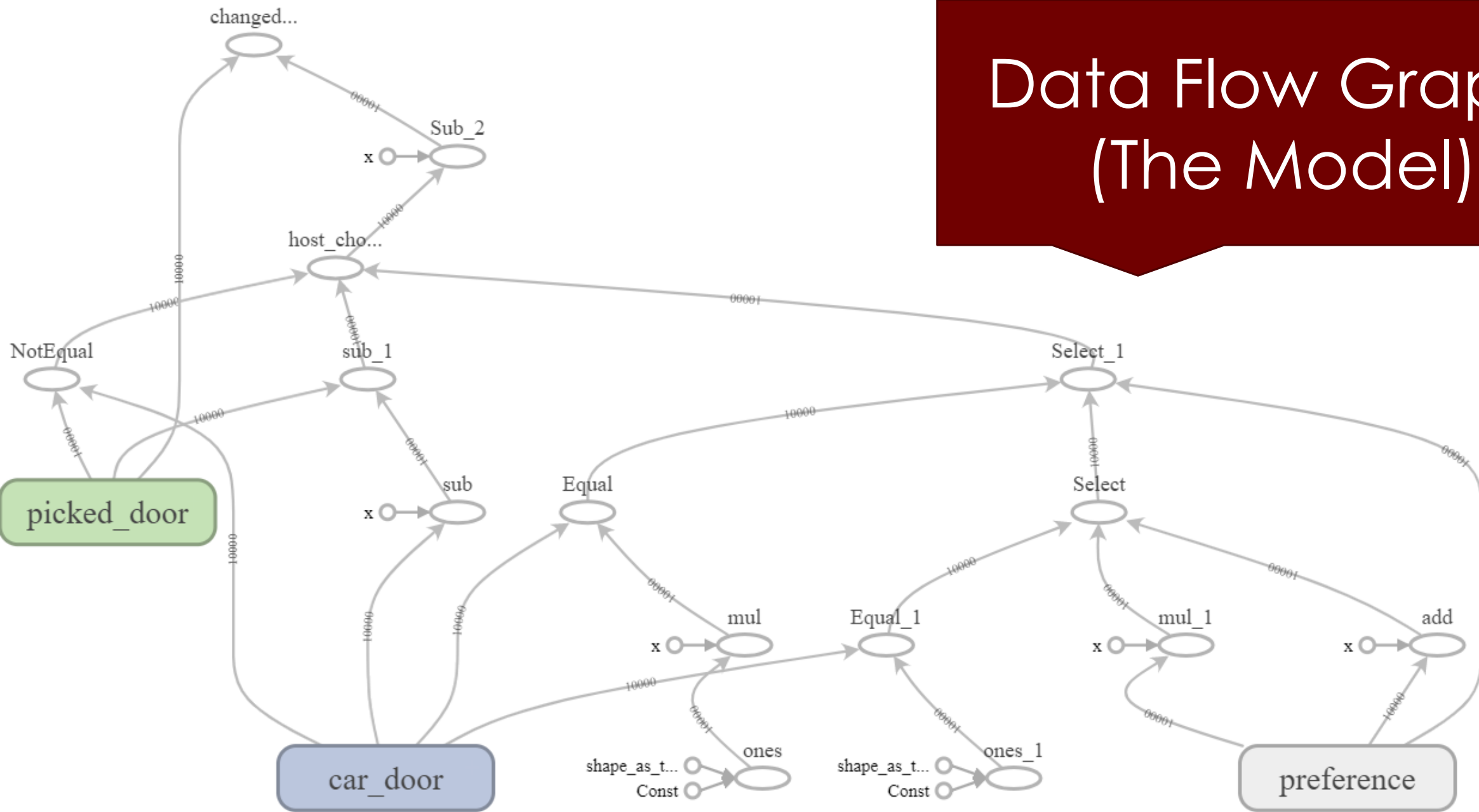
N = 10000

car_door = ed.Categorical(probs=tf.constant([1. / 3., 1. / 3., 1. / 3.]), sample_shape = N, name = 'car_door')
picked_door = ed.Categorical(probs=tf.constant([1. / 3., 1. / 3., 1. / 3.]), sample_shape = N, name = 'picked_door')
preference = ed.Bernoulli(probs=tf.constant(0.5), sample_shape = N, name = 'preference')

host_choice = tf.where(tf.not_equal(car_door, picked_door),
                        3 - car_door - picked_door,
                        tf.where(tf.equal(car_door, 2 * tf.ones(N, dtype=tf.int32)),
                                preference,
                                tf.where(tf.equal(car_door, tf.ones(N, dtype=tf.int32)),
                                        2 * preference,
                                        1 + preference))), name = 'host_choice')

#changed_door = 3 - host_choice - picked_door
changed_door = tf.subtract(tf.subtract(3, host_choice), picked_door, name = 'changed_door')
```

Data Flow Graphs (The Model)



Running

```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    car_door_samples, picked_door_samples, changed_door_samples = sess.run([car_door, picked_door, changed_door])

print("probability to win of a player who stays with the initial choice:", (car_door_samples == picked_door_samples).mean())
print("probability to win of a player who switches:", (car_door_samples == changed_door_samples).mean())
```

The Results

```
[C:\My\ProbabilisticProgrammingCourse\TFPandEdward2\11] - Far 3.0.5225 x64 Administrator
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>
C:\...\ogrammingCourse\TFPandEdward2\11>python monty_hall.py
2018-12-10 11:06:39.311511: I tensorflow/core/platform/cpu_feature_guard.cc:141]
Your CPU supports instructions that this TensorFlow binary was not compiled to
use: AVX2
probability to win of a player who stays with the initial choice: 0.3335
probability to win of a player who switches: 0.6665

C:\...\ogrammingCourse\TFPandEdward2\11>python monty_hall.py
2018-12-10 11:06:50.328939: I tensorflow/core/platform/cpu_feature_guard.cc:141]
Your CPU supports instructions that this TensorFlow binary was not compiled to
use: AVX2
probability to win of a player who stays with the initial choice: 0.3331
probability to win of a player who switches: 0.6669

C:\...\ogrammingCourse\TFPandEdward2\11>
1Left 2Right 3View.. 4Edit.. 5Print 6MkLink 7Find 8Histry 9Video 10
```