Faster ML Development with TensorFlow

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How are machine learning models represented?

Model is a Data Structure
e.g. A Graph

aka

“Symbolic” | “Deferred Execution” |
“Define-and-run”

Model is a Program
e.g. Python Code

aka

“Imperative” | “Eager Execution” |
“Define-by-run”

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TensorFlow: Symbolic Mode

By default, TensorFlow is a **symbolic** engine.

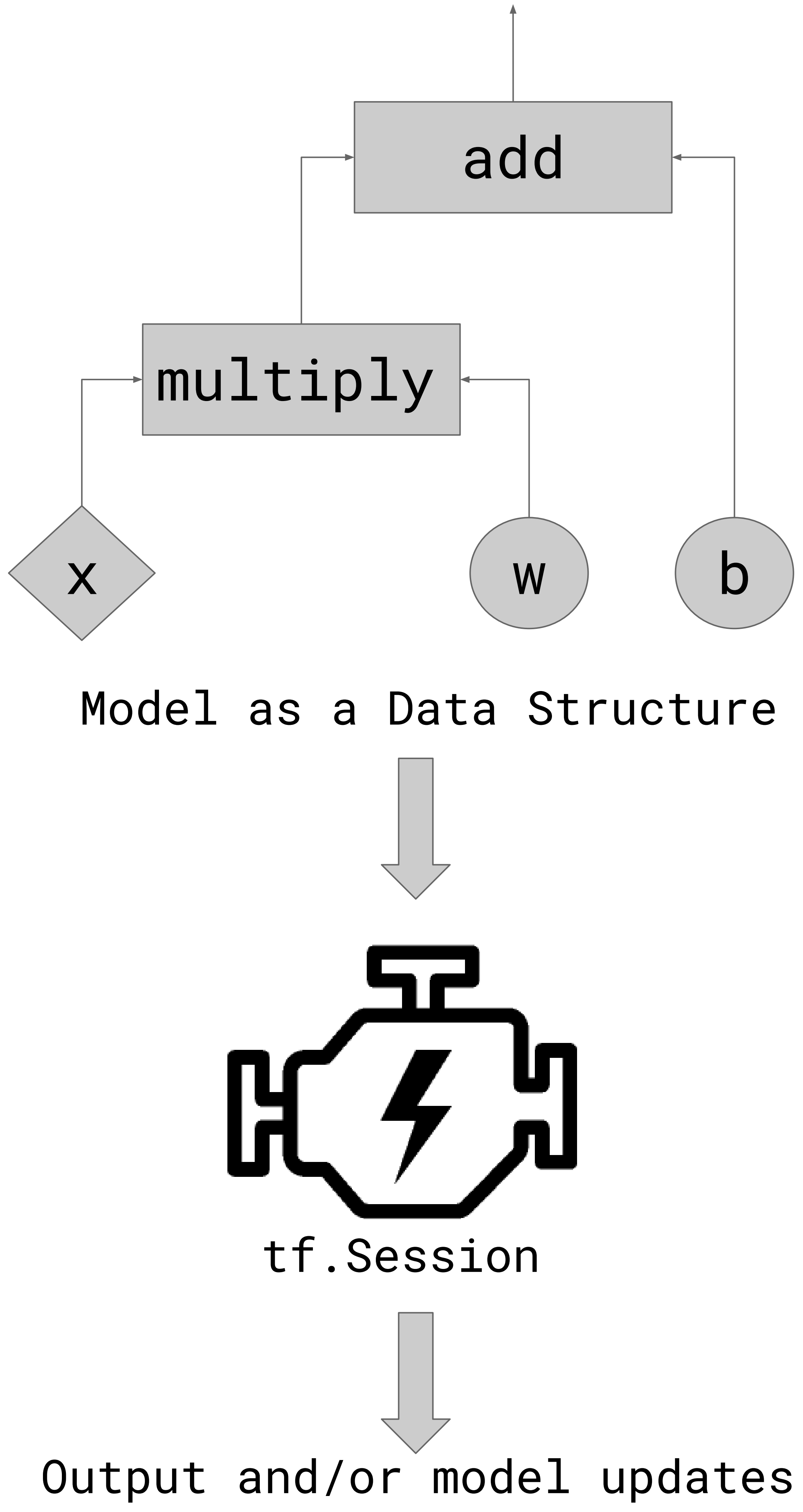
```
import tensorflow as tf

x = tf.constant(10.0)
w = tf.constant(4.0)
b = tf.constant(2.0)

y = tf.multiply(x, w)
print(y)
# You get: Tensor("Mul:0",shape=(), dtype=float32)

z = tf.add(y, b)
print(z)
# You get: Tensor("Add:0",shape=(), dtype=float32)
```

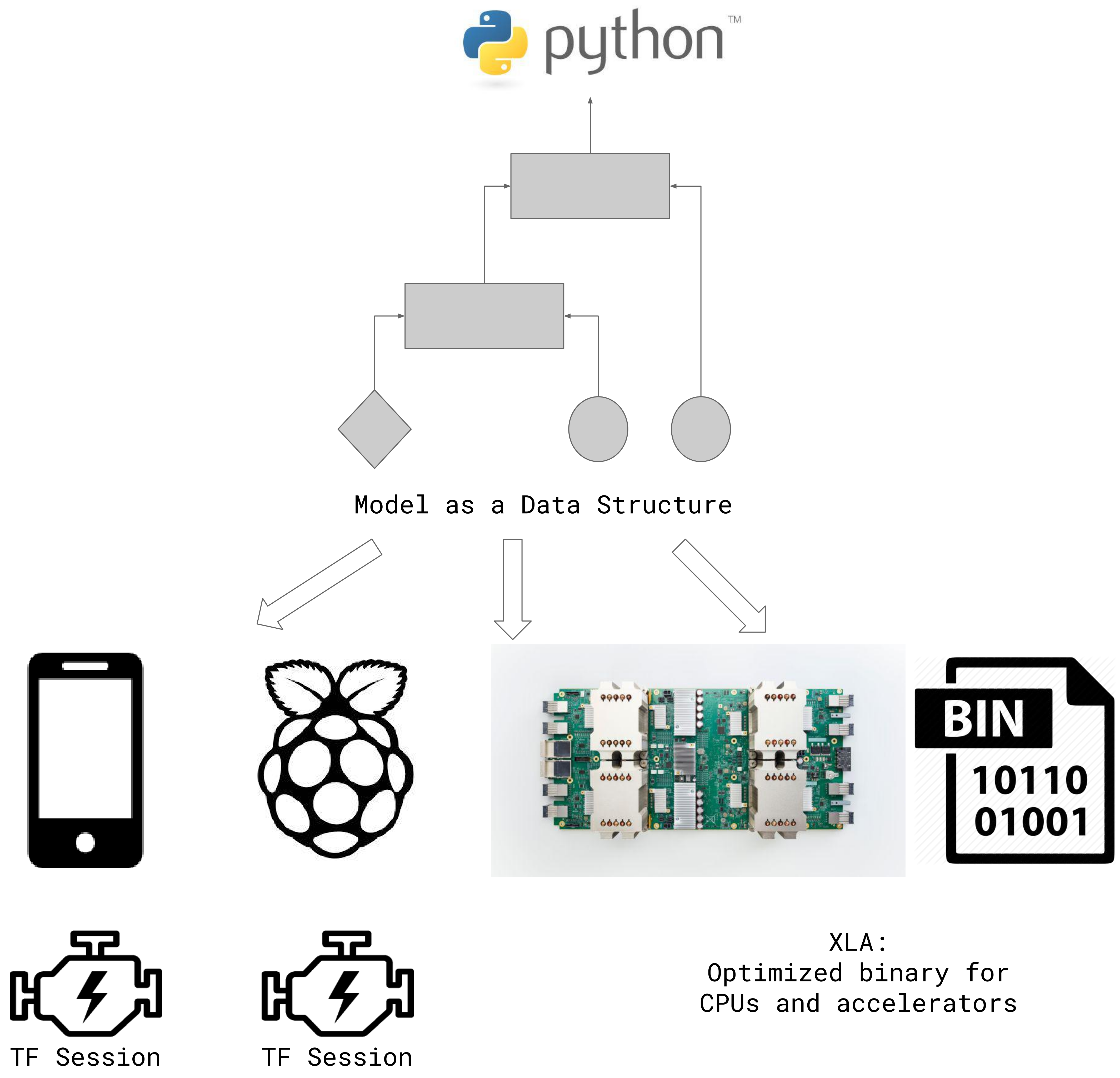
```
# You need to create a “session” to perform the
# actual computation.
sess = tf.Session()
print(sess.run(z))
# You get: 42.0.
```



Symbolic Execution in TensorFlow

Pros:

+ makes (de)serialization easier
  + **deployment on devices**
    (e.g., [mobile](), [TPU](), [XLA]())



Symbolic Execution in TensorFlow

Pros:

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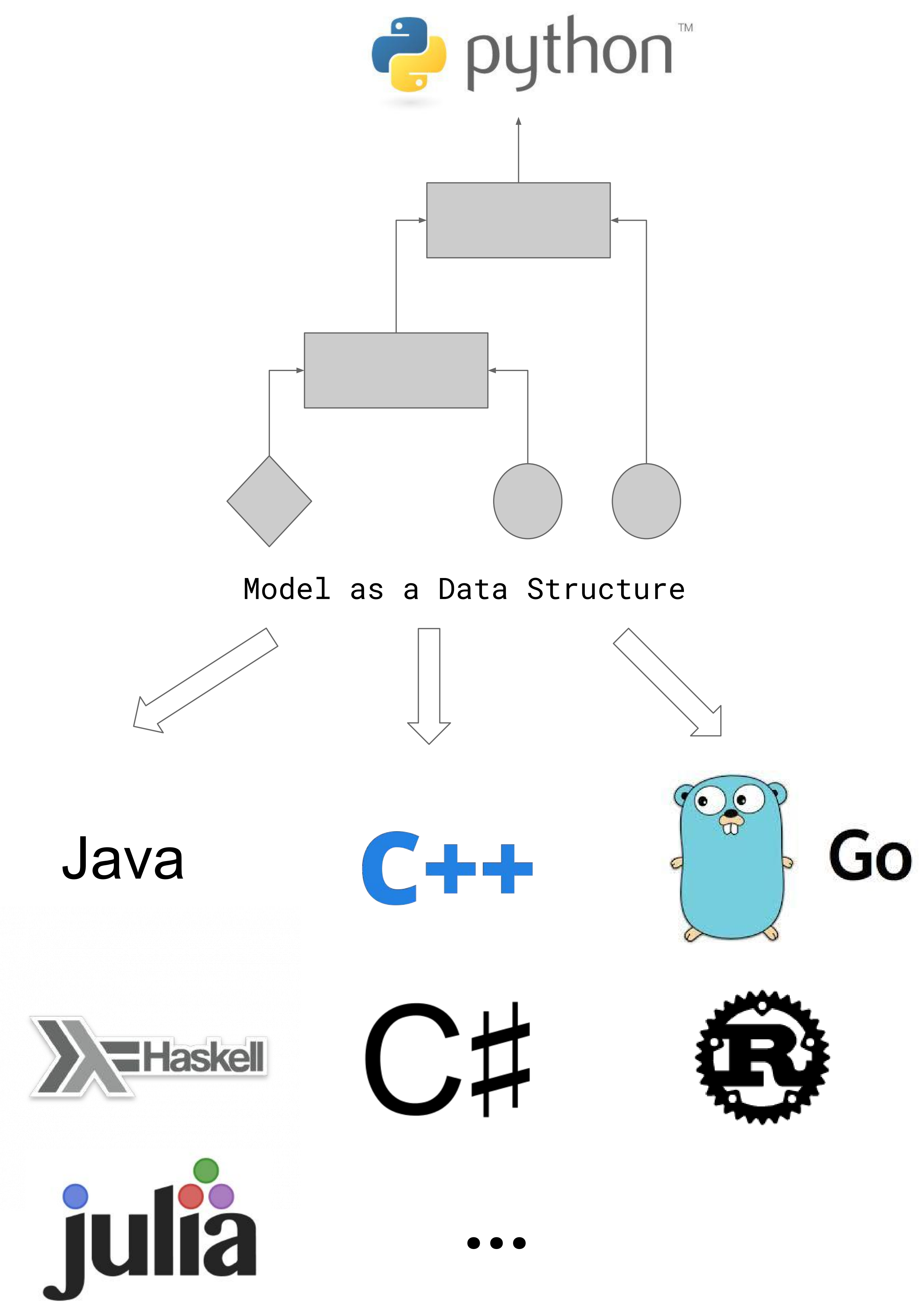
  + **interoperability between languages**



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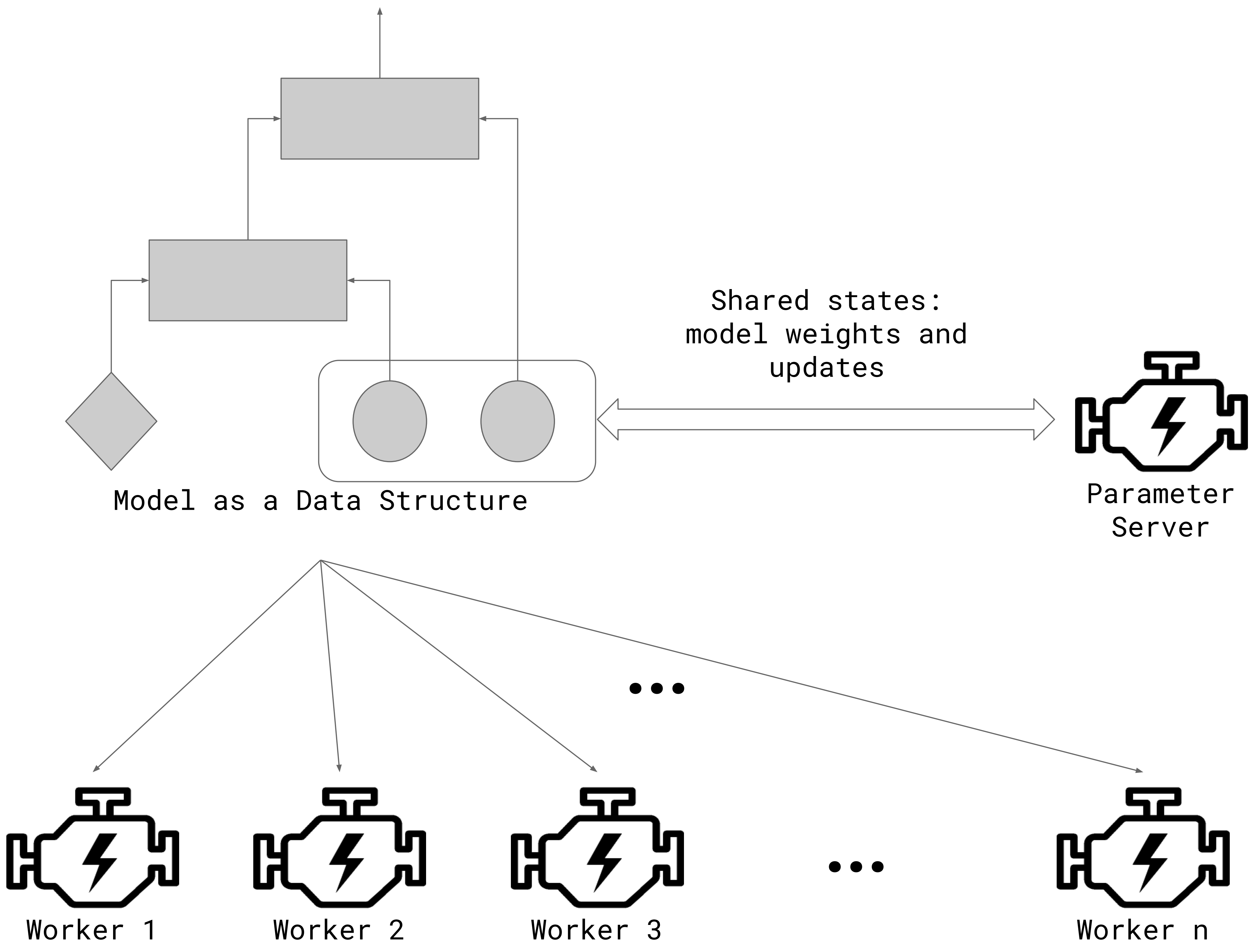
  + interoperability between languages
  + **distributed training**



Symbolic Execution in TensorFlow

Pros:

+ makes (de)serialization easier
  + deployment on devices
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  + interoperability between languages
  + distributed training
+ **speed and concurrency not limited by language**
  (e.g., Python global interpreter lock)

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Symbolic Execution in TensorFlow

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Cons:

- less intuitive
- harder to debug (*but see later slides)
- harder to write control flow structures
- harder to write dynamic models

Eager Execution in TensorFlow

- **+ easier to learn ("Pythonic")**
- **+ easier to debug**
- + makes dynamic (data-dependent) neural structures easier to write

Model is a Program
e.g. Python Code

aka
"Imperative" | "Eager Execution"

Eager Execution in TensorFlow

By default, TensorFlow is a **symbolic** engine.

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x = tf.constant(10.0)
w = tf.constant(4.0)
b = tf.constant(2.0)

y = tf.multiply(x, w)
print(y)
# You get: Tensor("Mul:0",shape=(), dtype=float32)

z = tf.add(y, b)
print(z)
# You get: Tensor("Add:0",shape=(), dtype=float32)
```

But since version1.5, you can switch to the **imperative (eager)** mode.

```
import tensorflow as tf

import tensorflow.contrib.eager as tfe
tfe.enable_eager_execution()

x = tf.constant(10.0)
w = tf.constant(4.0)
b = tf.constant(2.0)

y = tf.multiply(x, w)
print(y)
# You get: tf.Tensor(40.0,shape=(), dtype=float32)

z = tf.add(y, b)
print(z)
# You get: tf.Tensor(42.0,shape=(), dtype=float32)
```

See eager-mode examples and notebooks.

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Symbolic vs. Eager Mode

+ easier to learn (“Pythonic”)
+ easier to debug
+ **makes dynamic (data-dependent) neural structures easier to write**

Model is a Program
e.g. Python Code

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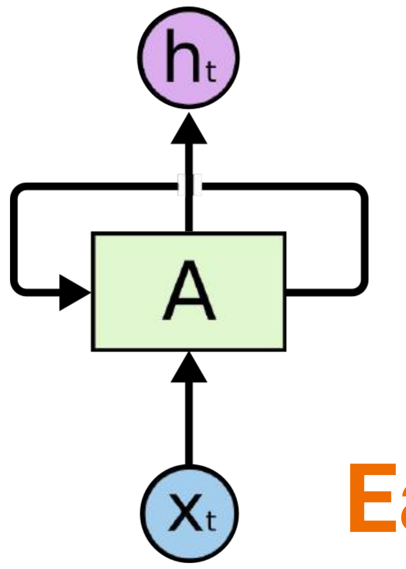
TensorFlow: Control Flow in Symbolic vs. Eager

Writing a basic RNN:



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Symbolic

```
dense1 = tf.layers.Dense(state_size, activation='tanh')
dense2 = tf.layers.Dense(state_size)

def loop_cond(i, state, output):
  return i < max_sequence_len

def loop_body(i, state, output):
  input_slice = input_array.read(i)
  combined = tf.concat([input_slice, state], axis=1)
  state_updated = dense1(combined)
  state = tf.where(i >= sequence_lengths, state, state_updated)
  output_updated = dense2(state)
  output = tf.where(
      i >= sequence_lengths, output, output_updated)
  return i + 1, state, output

_, final_state, final_output = tf.while_loop(
    loop_cond, loop_body,
    [i, initial_state, dummy_initial_output])

sess.run([final_state, final_output])
```

Eager

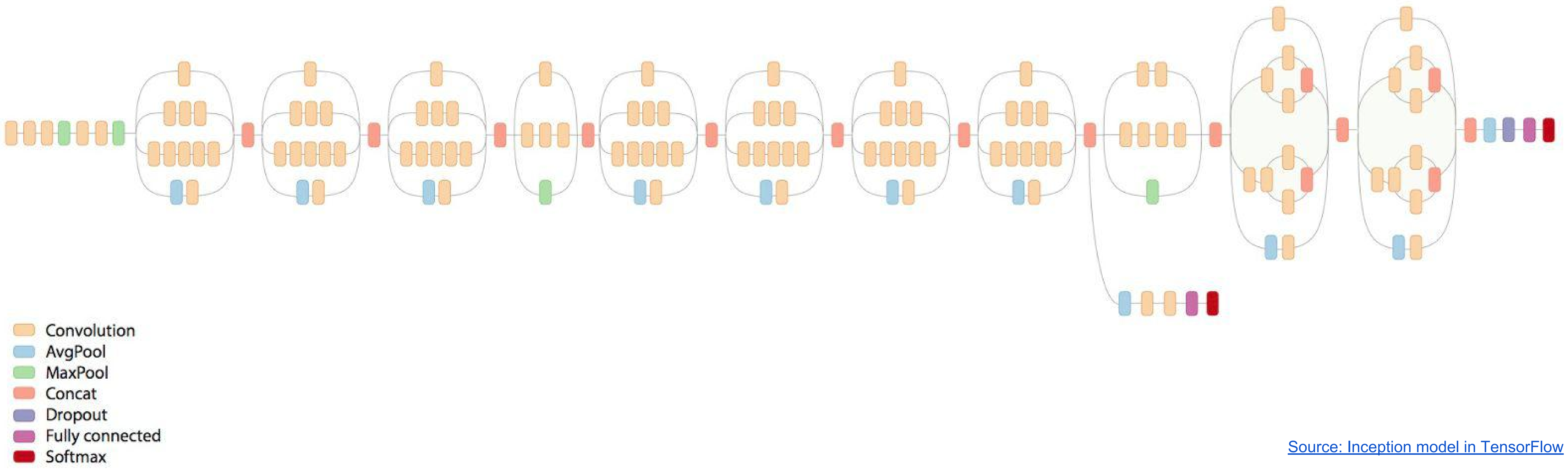
```
dense1 = tf.layers.Dense(state_size, activation='tanh')
dense2 = tf.layers.Dense(state_size)

for i in xrange(max_sequence_len):
  input_slice = input_array.read(i)
  combined = tf.concat([input_slice, state], axis=1)
  state_updated = dense1(combined)
  state = tf.where(i >= sequence_lengths, state, state_updated)
  output_updated = dense2(state)
  output = tf.where(
      i >= sequence_lengths, output, output_updated)

final_state, final_output = state, output
```

Model Structures: Static vs. Dynamic

Static models

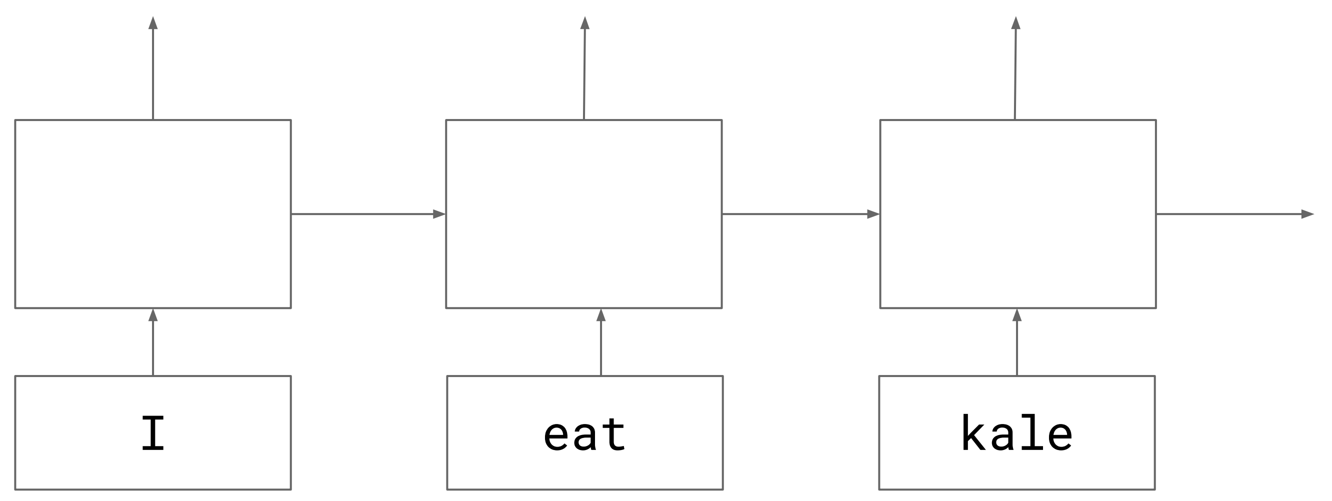


Source: Inception model in TensorFlow

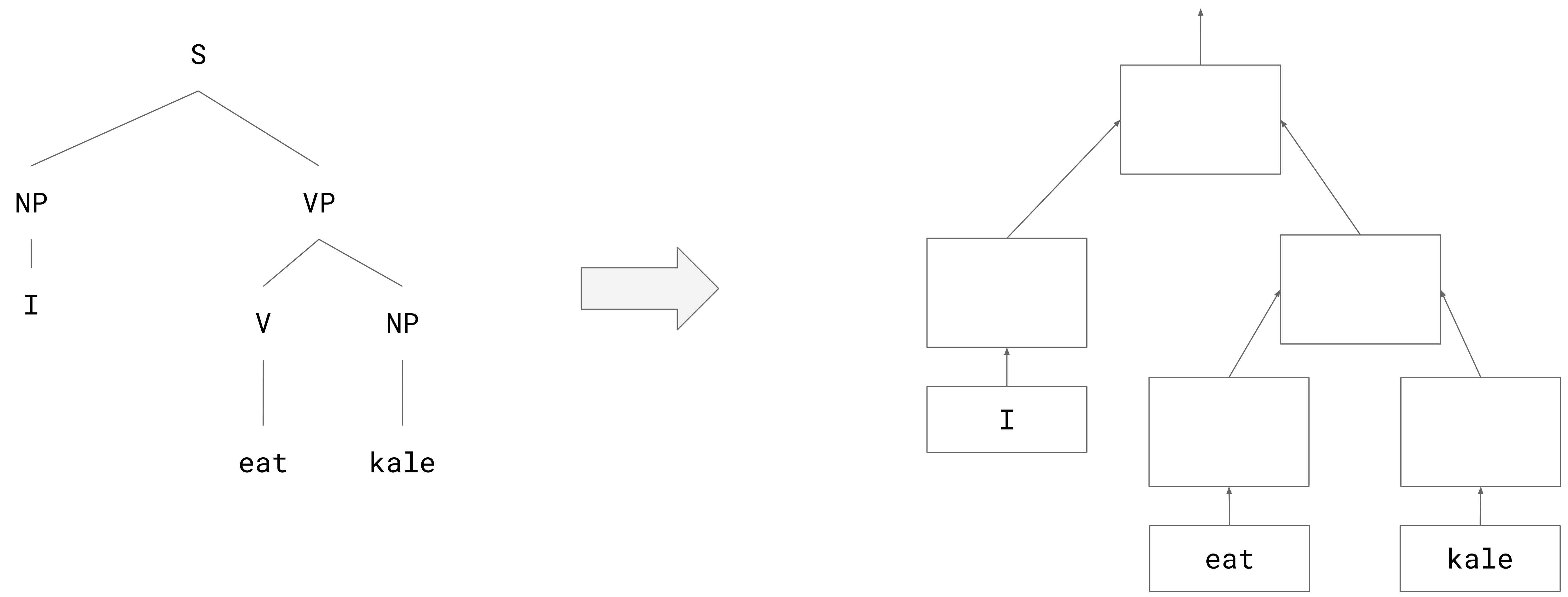
+ Model structure is fixed regardless of input data.
+ The majority of DL models for image, audio and numerical data.

Model Structures: Static vs. Dynamic

Traditional RNN



Dynamic Models, e.g., Tree RNN



+ Models whose structure cannot be easily described as a graph, i.e., changes a lot with input data.
+ Used by some state-of-the-art models that deal with hierarchical structures in natural language.
+ Difficult to write in the symbolic way (using `tf.cond` and `tf.while_loop`)
+ Straightforward with Eager: using the native Python control flow. See the SPINN example.

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What if you want to debug symbolic execution?

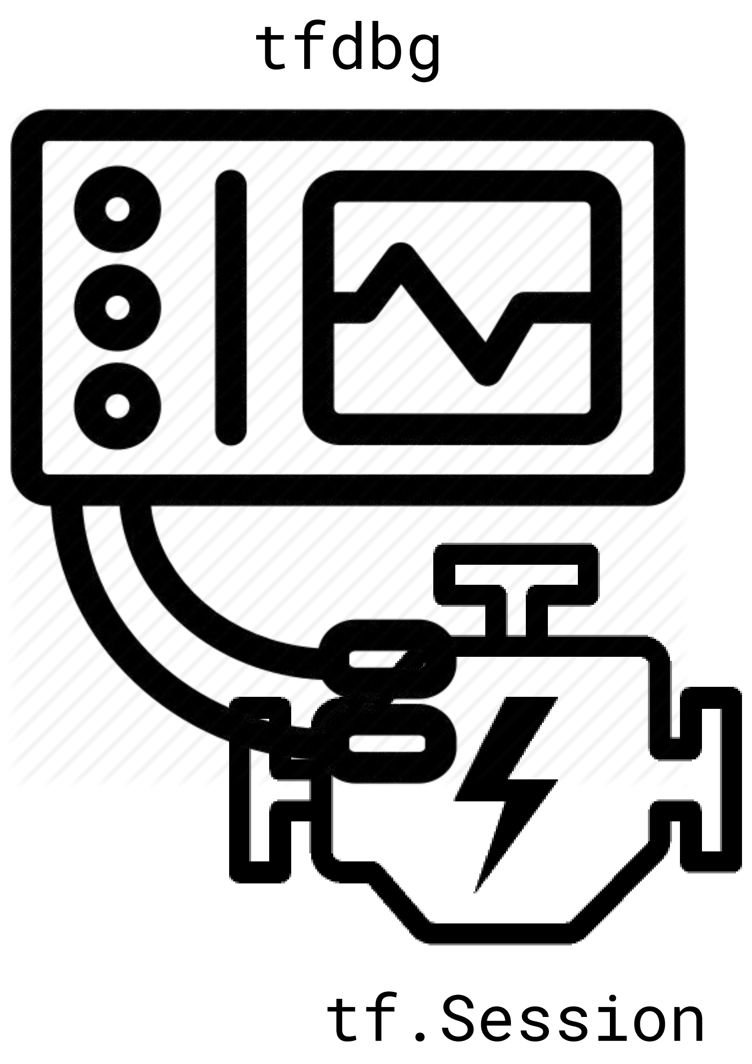
TensorFlow Debugger (tfdbg): Command Line Interface

```python
import tensorflow as tf
from tensorflow.python import debug as tfdbg

a = tf.constant(10.0)
b = tf.Variable(4.0)
c = tf.Variable(2.0)

x = tf.multiply(a, b)
y = tf.add(c, x)

sess = tf.Session()
sess = tfdbg.LocalCLIDebugWrapperSession(sess)
sess.run(tf.global_variables_initializer())
sess.run(y)
```



What if you want to debug symbolic execution?

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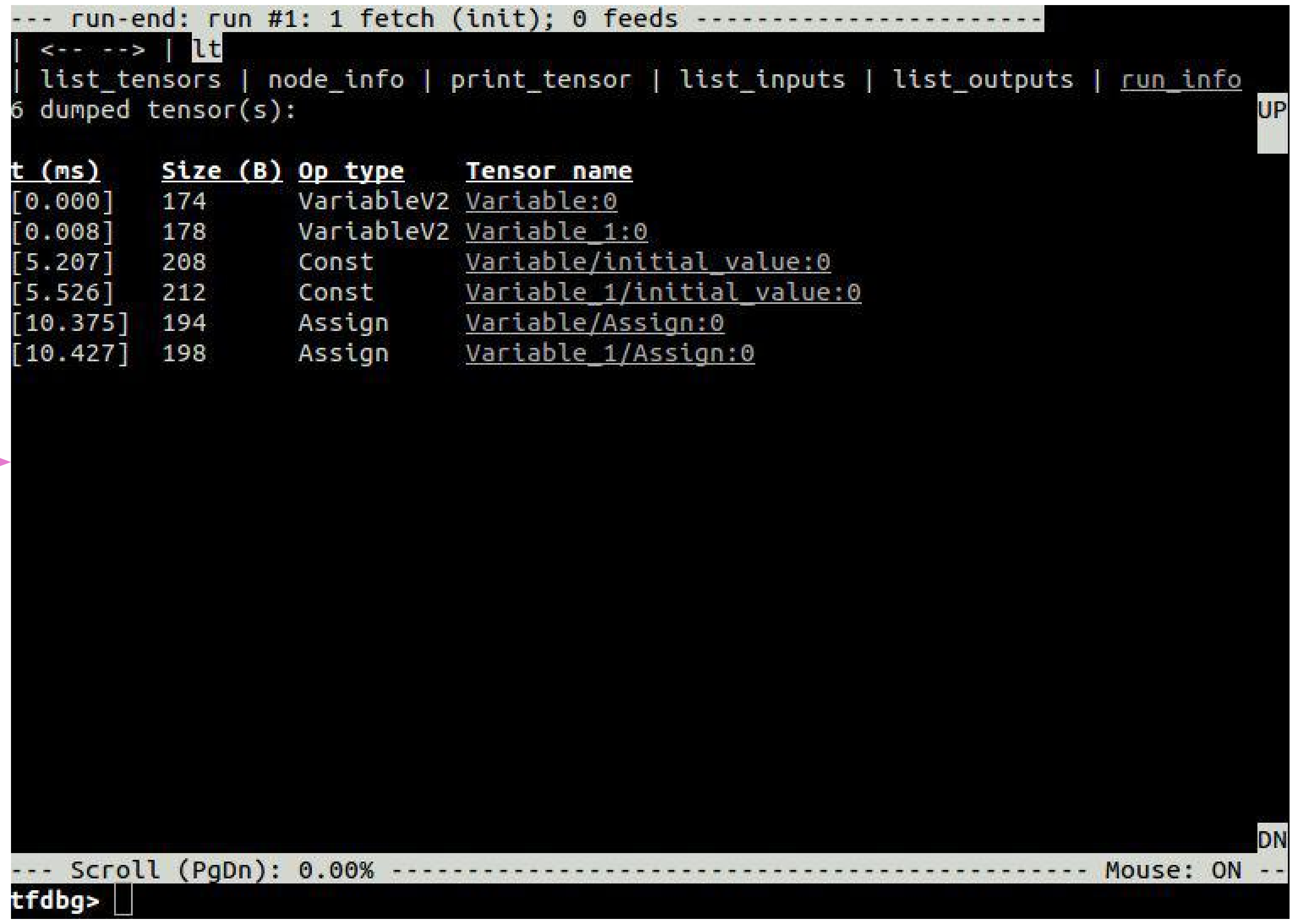
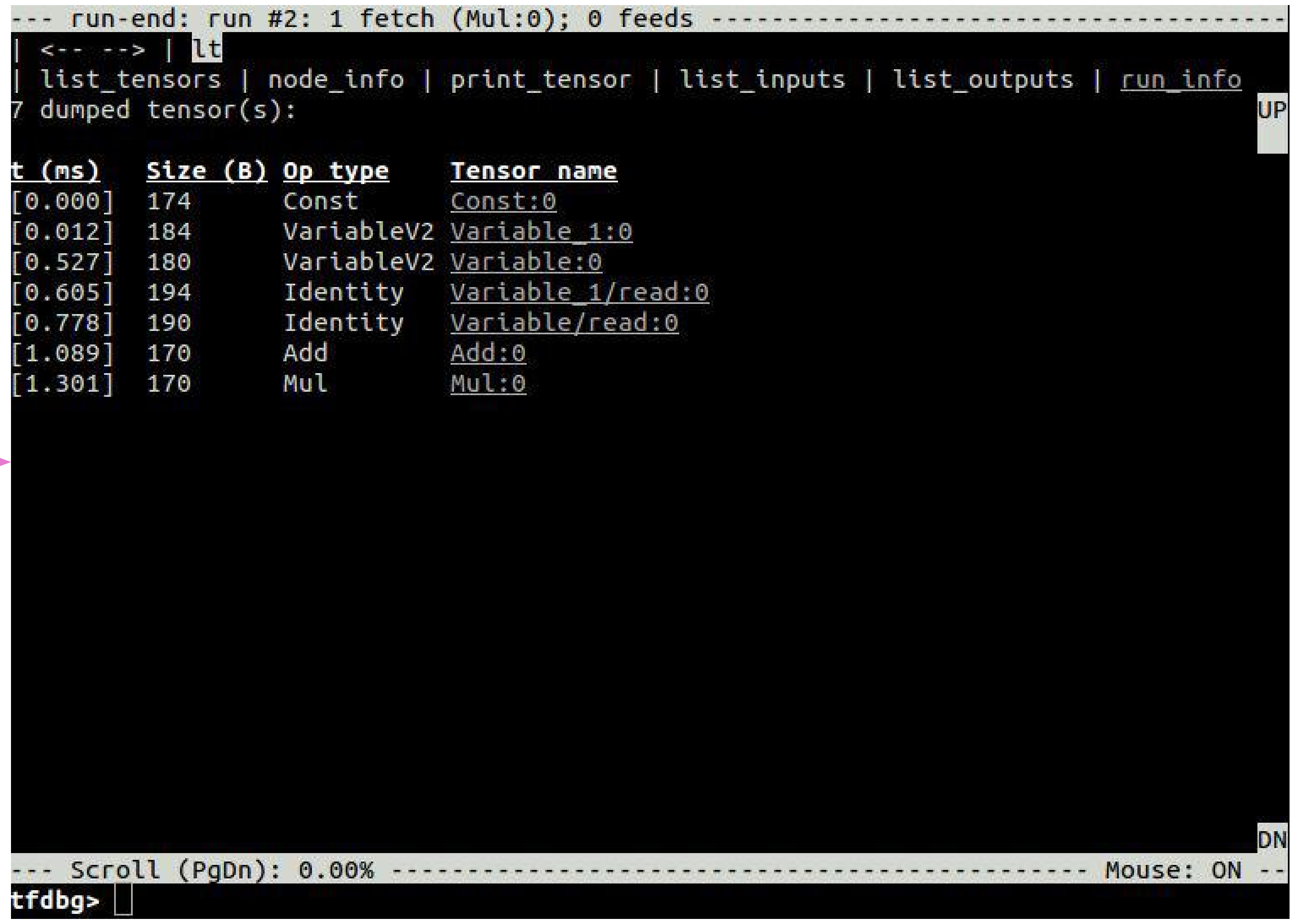
```





- Presents after each Session.run:
  - All tensor values in the computation graph
  - Graph structure

… in an interactive, mouse-clickable CLI.

TensorFlow: Debugging Numerical Instability
(NaNs and Infinities)

```
--- run-end: run #4: 1 fetch (train/Adam); 2 feeds ----------------------------
| <-- --> | lt -f has_inf_or_nan
| list_tensors | node_info | print_tensor | list_inputs | list_outputs | run_i
36 dumped tensor(s) passing filter "has_inf_or_nan":

t (ms)   Size    Op type     Tensor name
[14.385] 3.97k   Log         cross_entropy/Log:0
[14.490] 3.97k   Mul         cross_entropy/mul:0
[14.862] 4.00k   Mul         train/gradients/cross_entropy/mul_grad/mul:0
[14.935] 4.00k   Sum         train/gradients/cross_entropy/mul_grad/Sum:0
[14.995] 4.00k   Reshape     train/gradients/cross_entropy/mul_grad/Reshape:0
```

`tfdbg> run -f has_inf_or_nan`

See walkthrough at
https://www.tensorflow.org/programmers_guide/debugger

Common causes of NaNs and infinities in DL models:

- **underflow** followed by:
  - division by zero
  - logarithm of zero
- **overflow** caused by:
  - learning rate too high
  - bad training examples

New Tool: Graphical Debugger for TensorFlow

(TensorBoard Debugger Plugin)

```
# Do the following in a terminal.

# Install nightly builds.
pip install --upgrade --force-reinstall \
    tf-nightly tb-nightly grpcio

# Start tensorboard with debugger enabled.
tensorboard \
    --logdir /tmp/logdir \
    --port 6006 \
    --debugger_port 7007

# Open a browser and navigate to:
#   http://localhost:6006/#debugger

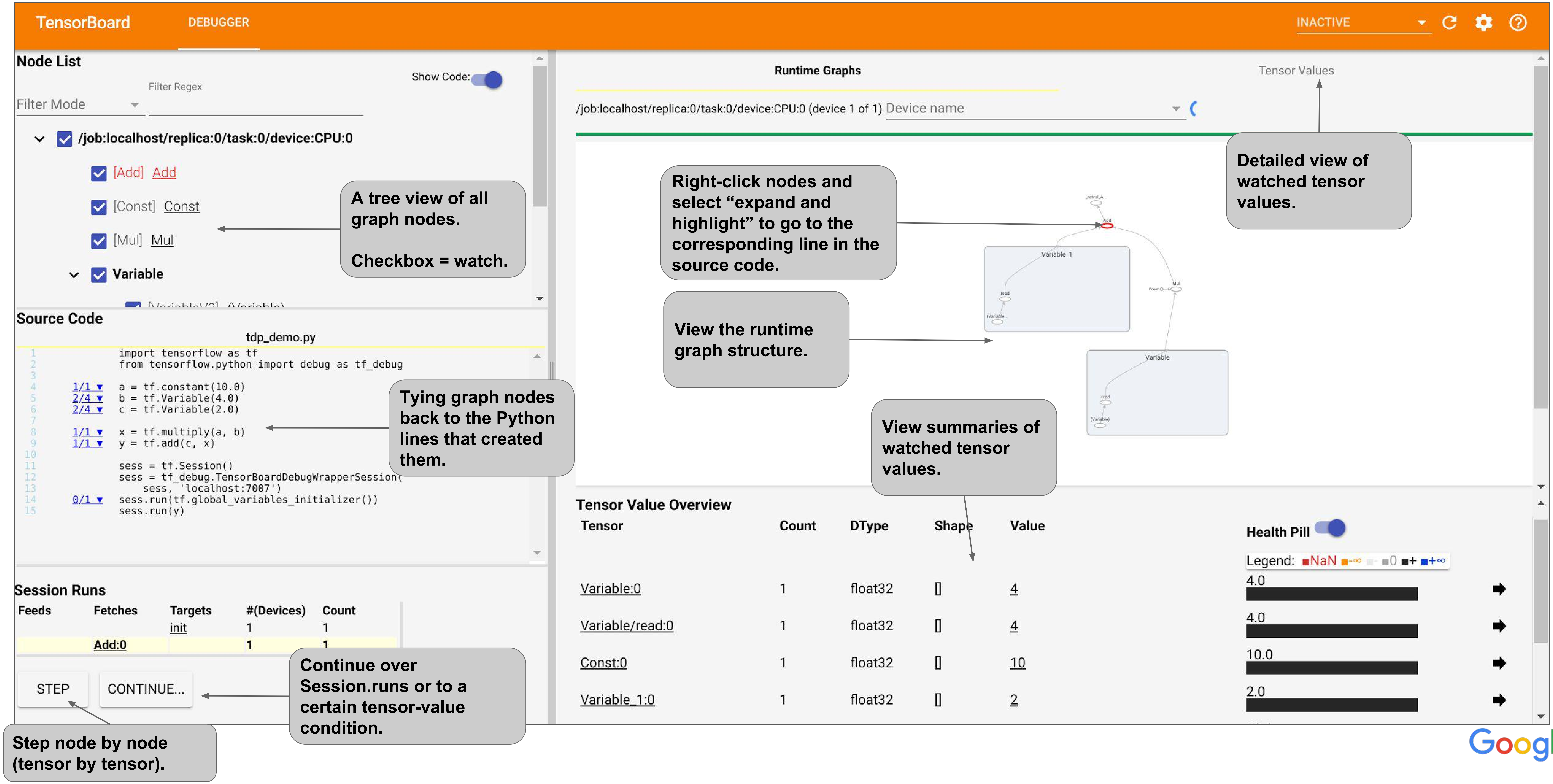
# Then save the code in a file and run it. -->
```

```python
import tensorflow as tf
from tensorflow.python import debug as tf_debug

a = tf.random_normal([10, 1])
b = tf.random_normal([10, 10])
c = tf.random_normal([10, 1])

x = tf.matmul(b, a)
y = tf.add(c, x)

sess = tf.Session()
sess = tf_debug.TensorBoardDebugWrapperSession(
   sess, 'localhost:7007')
for _ in xrange(100):
  sess.run(y)
```

- Not publicly announced yet (coming in TensorFlow 1.6)
- But available for preview in nightly builds of tensorflow and tensorboard

Try it yourself!

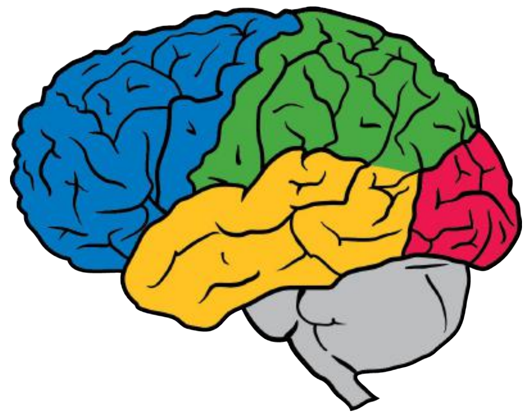
New Tool: Visual Debugger for TensorFlow



Summary

- ML/DL models can be represented in two ways:
  - as a **data structure** → **Symbolic Execution**:
    good for **deployment, distribution, and optimization**
  - as a **program** → **Eager Execution**:
    good for **prototyping, debugging and dynamic models; easier to learn**
- TensorFlow supports both modes
- TensorFlow Debugger (tfdbg) provides visibility into symbolically-executing models and help you debug/understand them in:
  - command line
  - browser

Acknowledgements



Google Brain Team in Mountain View, CA and Cambridge, MA.

Chi Zeng and Mahima Pushkarna: Collaborators on the visual tfdbg project.

Open-source contributors to TensorFlow.

Thank you!

For questions, email cais@google.com

For TensorFlow issues, go to https://github.com/tensorflow/tensorflow/issues

For TensorBoard issues, go to https://github.com/tensorflow/tensorboard/issues

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TensorFlow
OP 1
OP 2
OP 1
A
A
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