

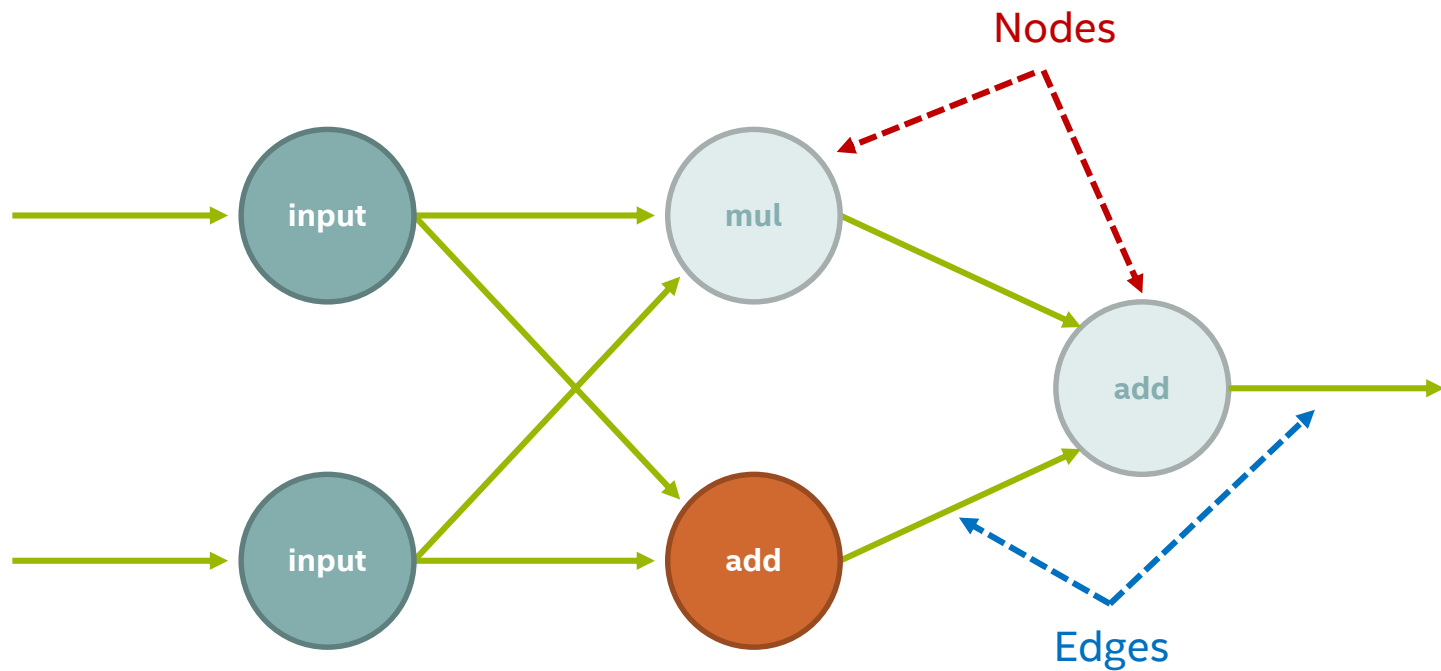
TENSORFLOW FUNDAMENTALS

WHAT IS TENSORFLOW?

- Framework for math using computation graphs
- Has features specifically for machine learning
- Primary interface is Python, integrates with NumPy
 - Implemented in C++ and CUDA
- Designed to be flexible, scalable, and deployable



COMPUTATION GRAPH

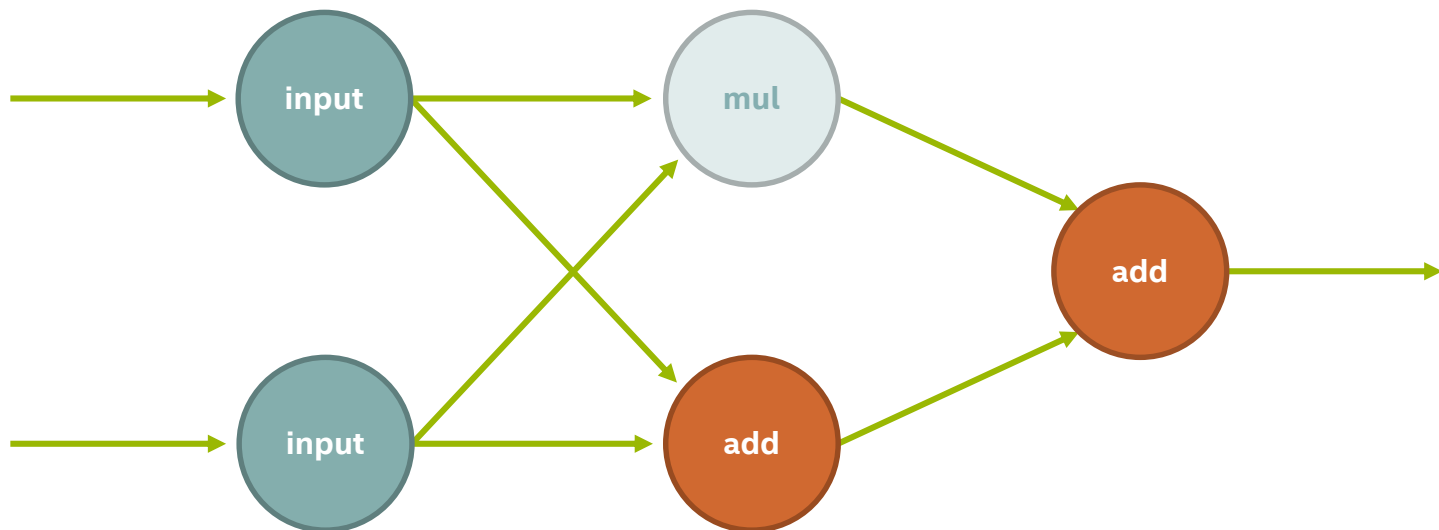


TENSORFLOW HISTORY

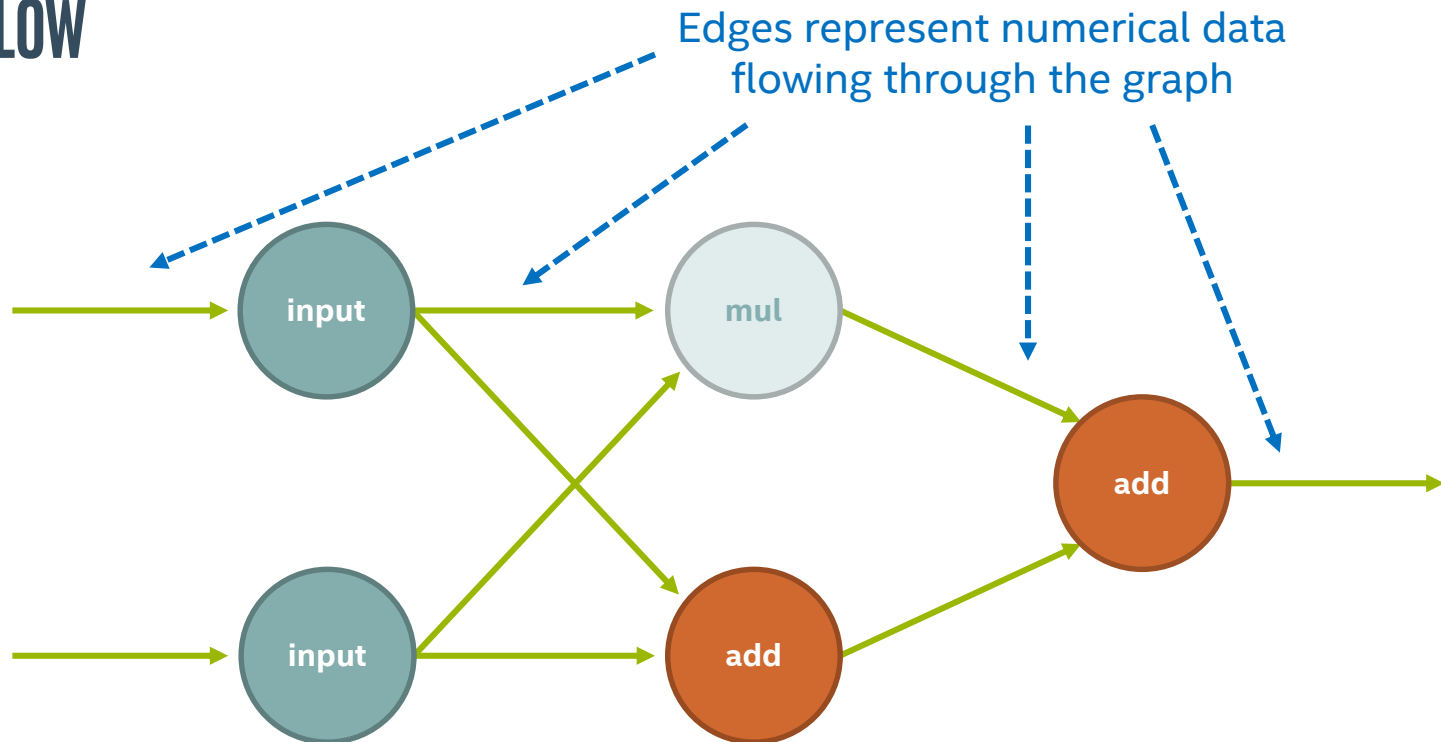
- Developed by Google, successor to DistBelief
- Open source implementation released in November 2015
- Key developments
 - **TensorFlow Serving**; Feb 2016
 - **Distributed runtime**; April 2016
 - **Accelerated Linear Algebra (XLA)**; January 2017
 - **TensorFlow Fold**; February 2017
- Current version is 1.0.0
 - Code guaranteed to be backwards-compatible until 2.0.0

COMPUTATION GRAPHS

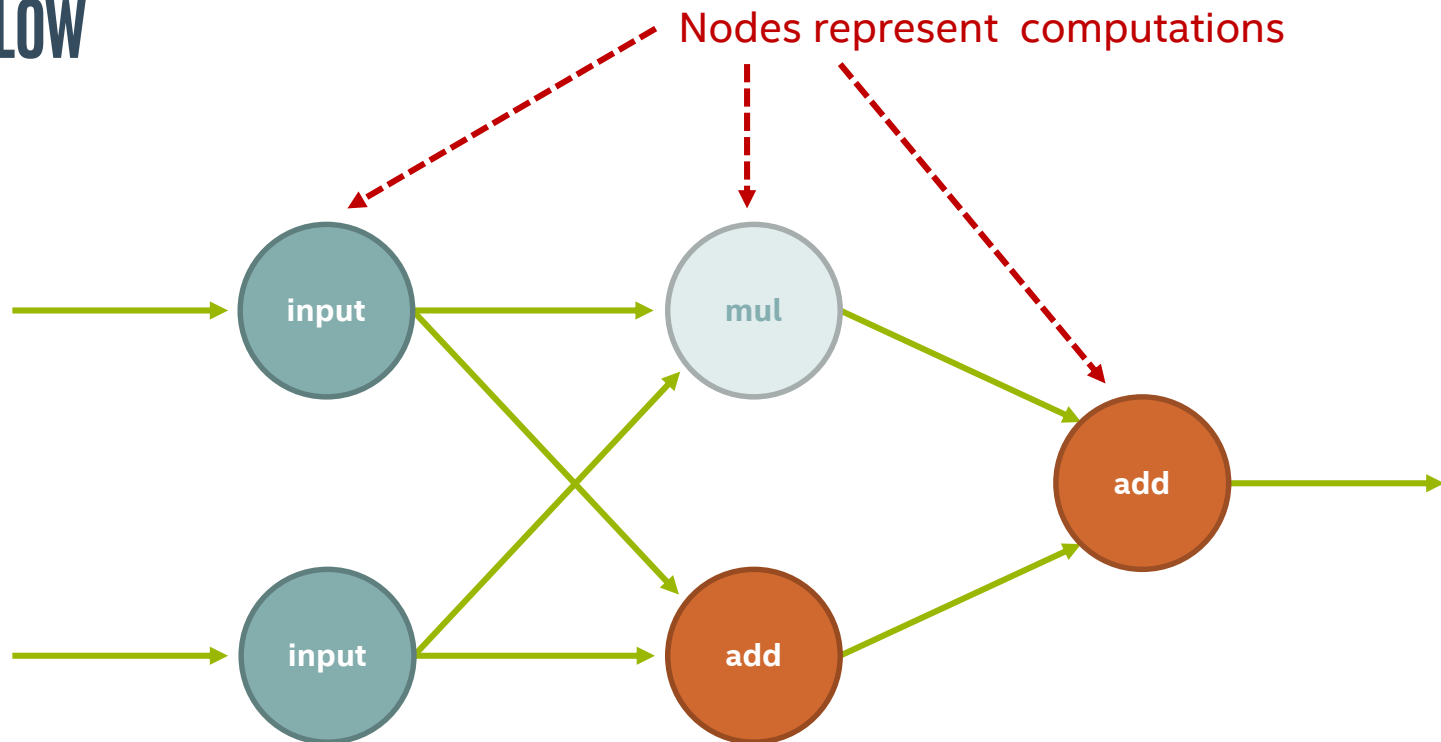
DATA FLOW



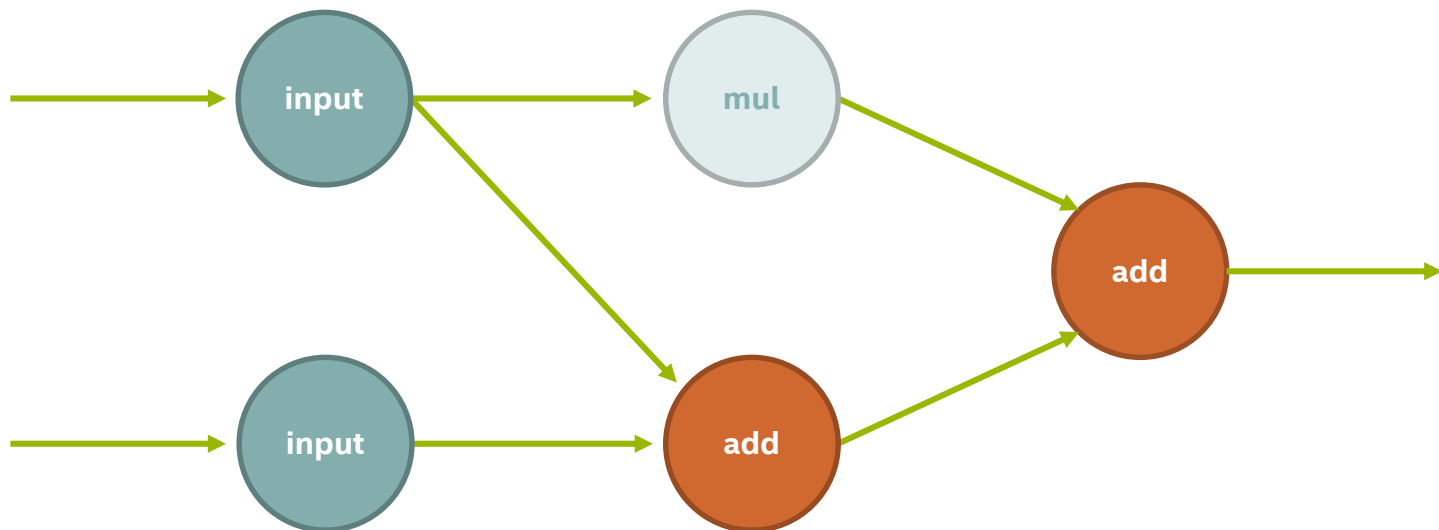
DATA FLOW



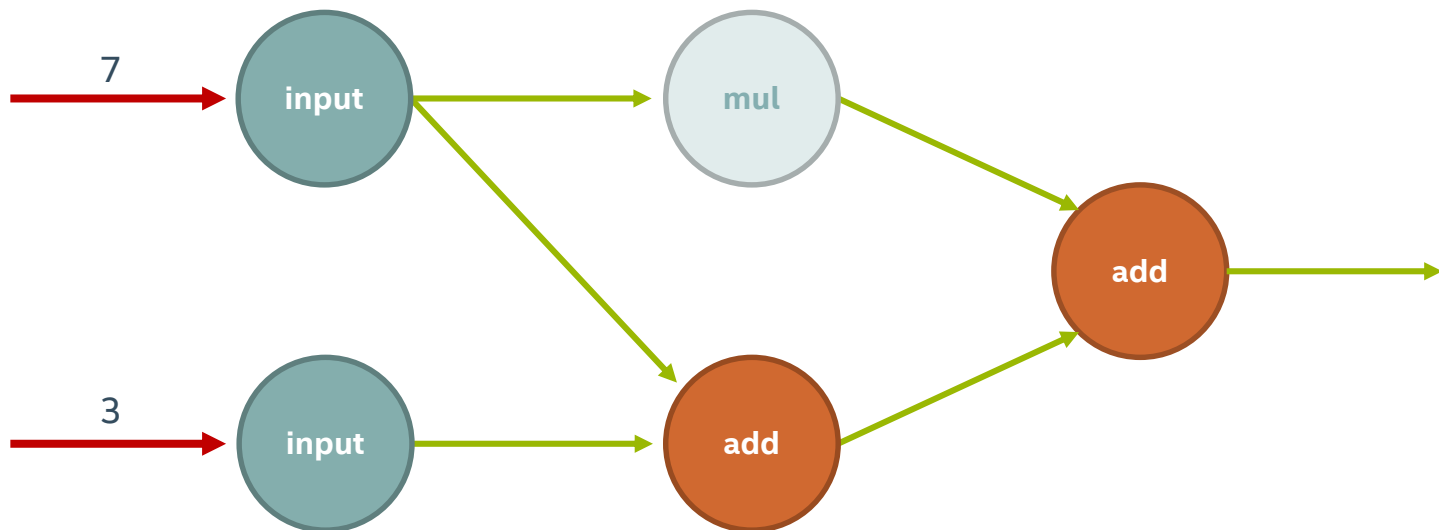
DATA FLOW



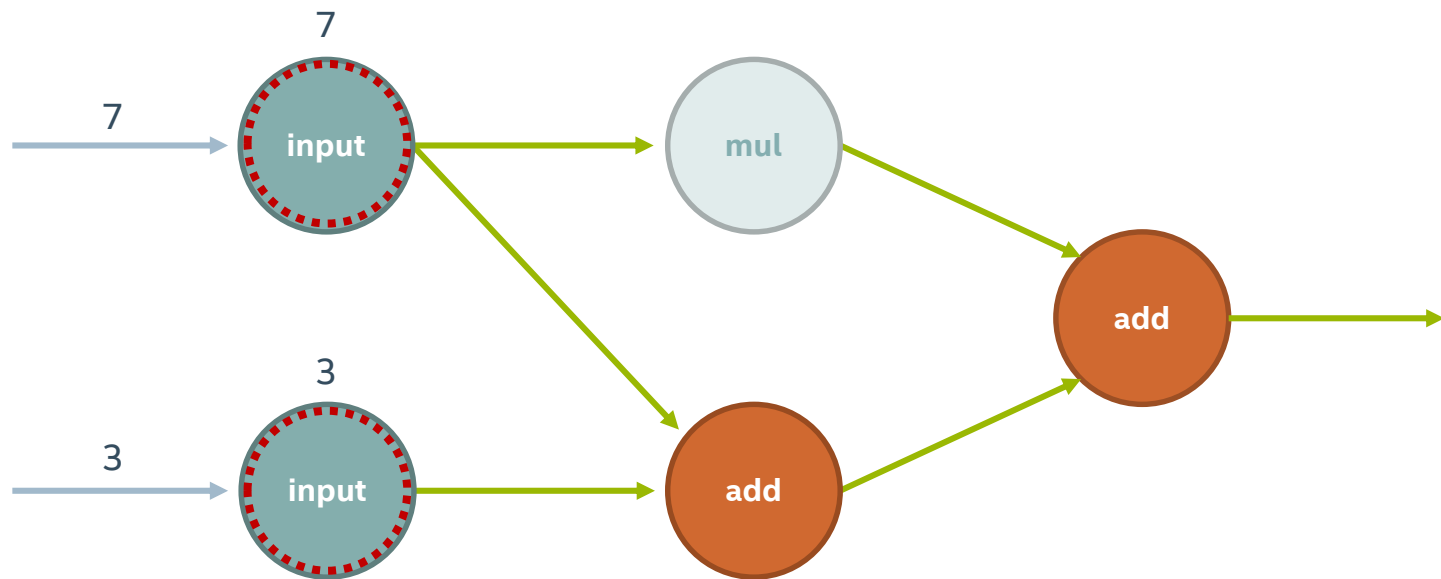
DATA FLOW



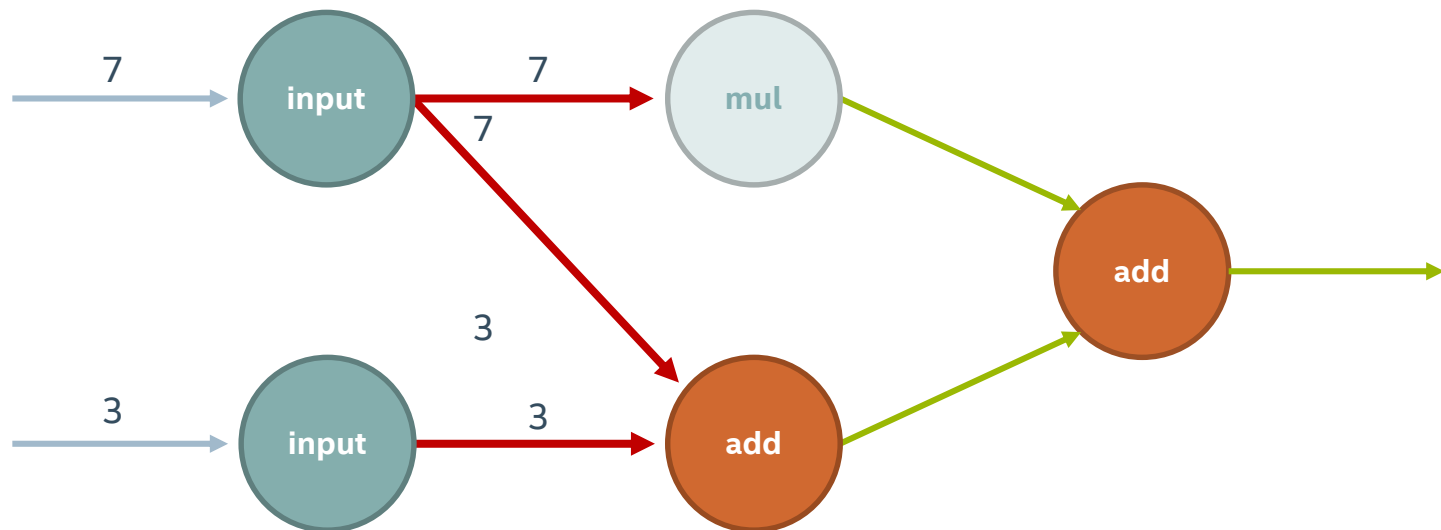
DATA FLOW



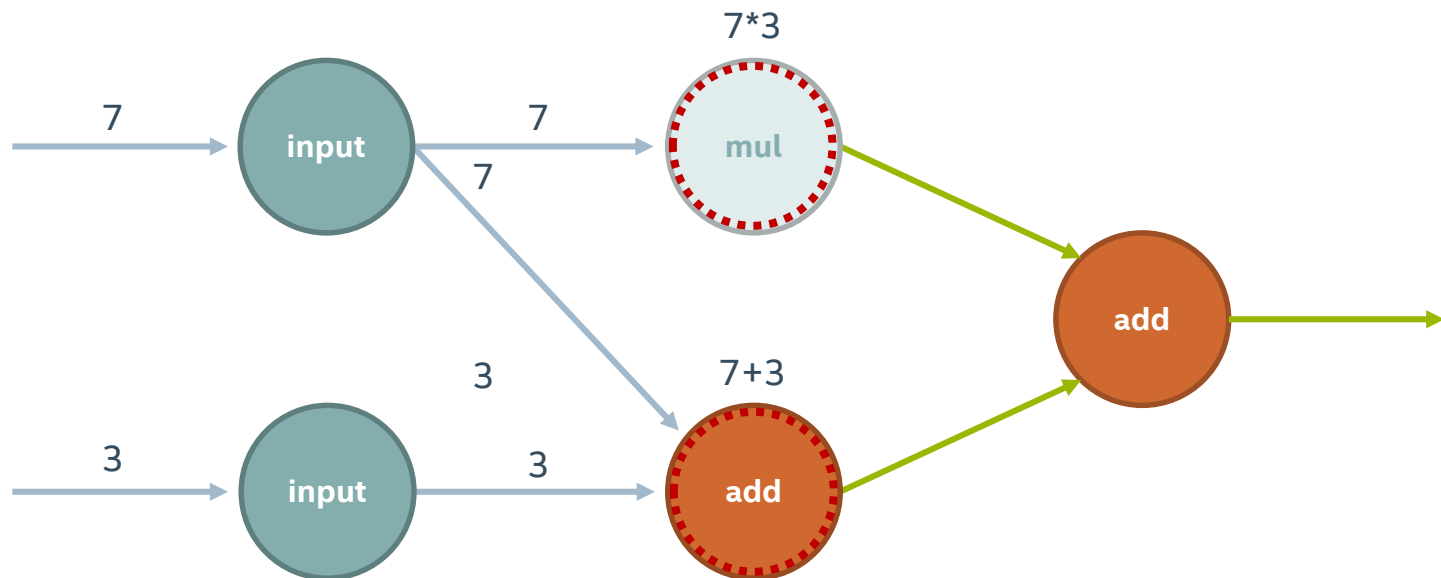
DATA FLOW



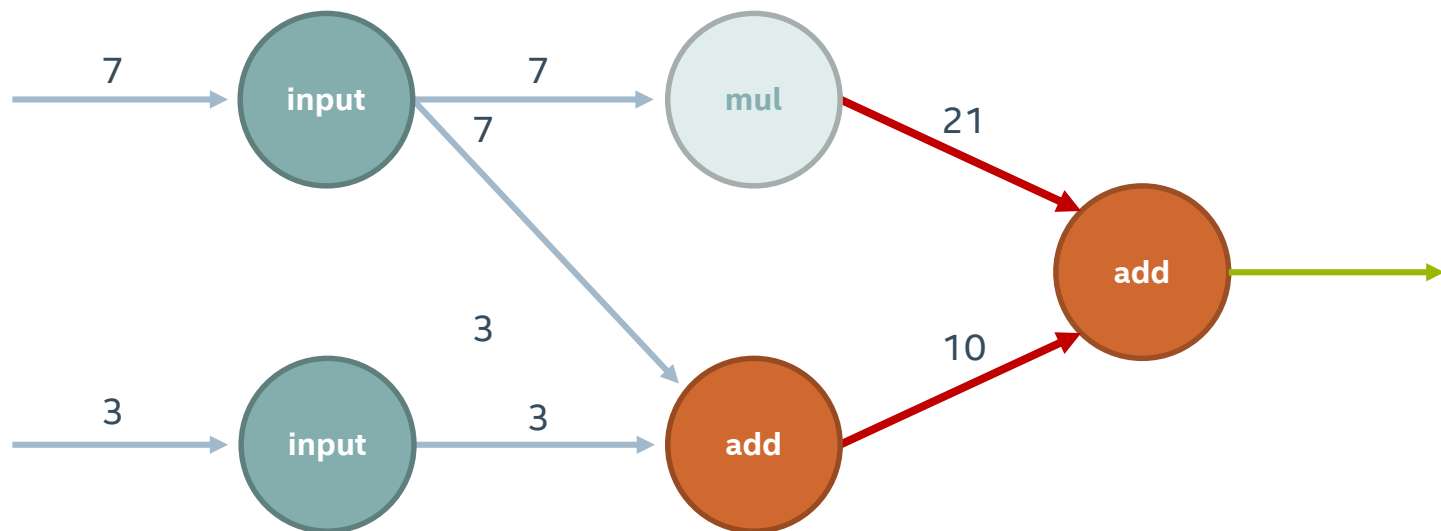
DATA FLOW



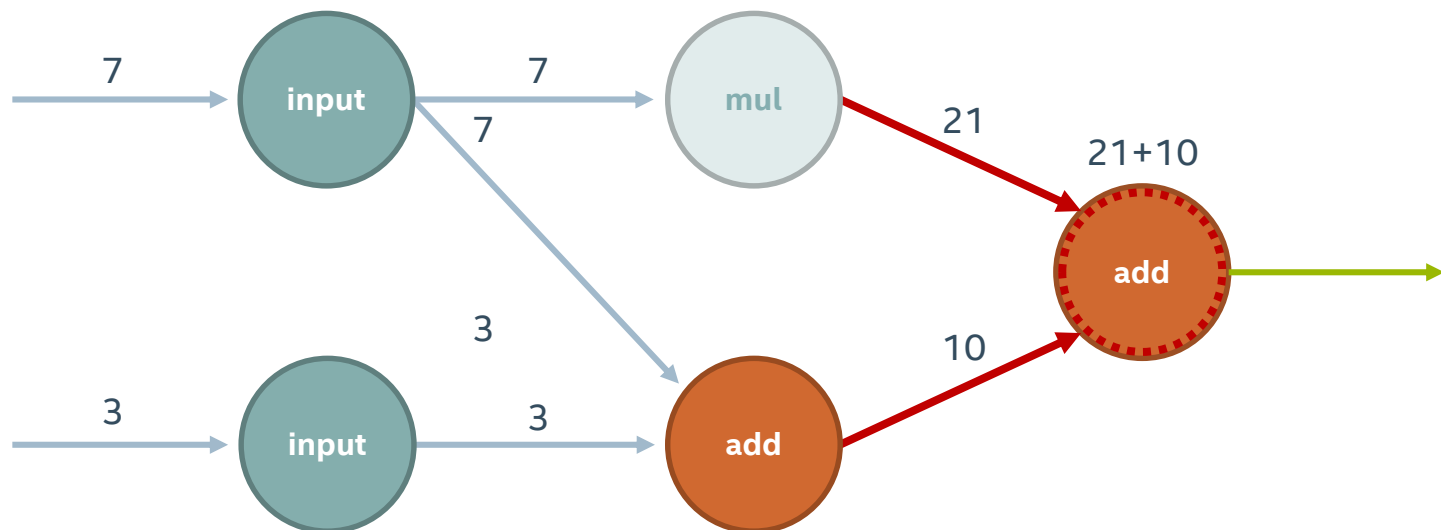
DATA FLOW



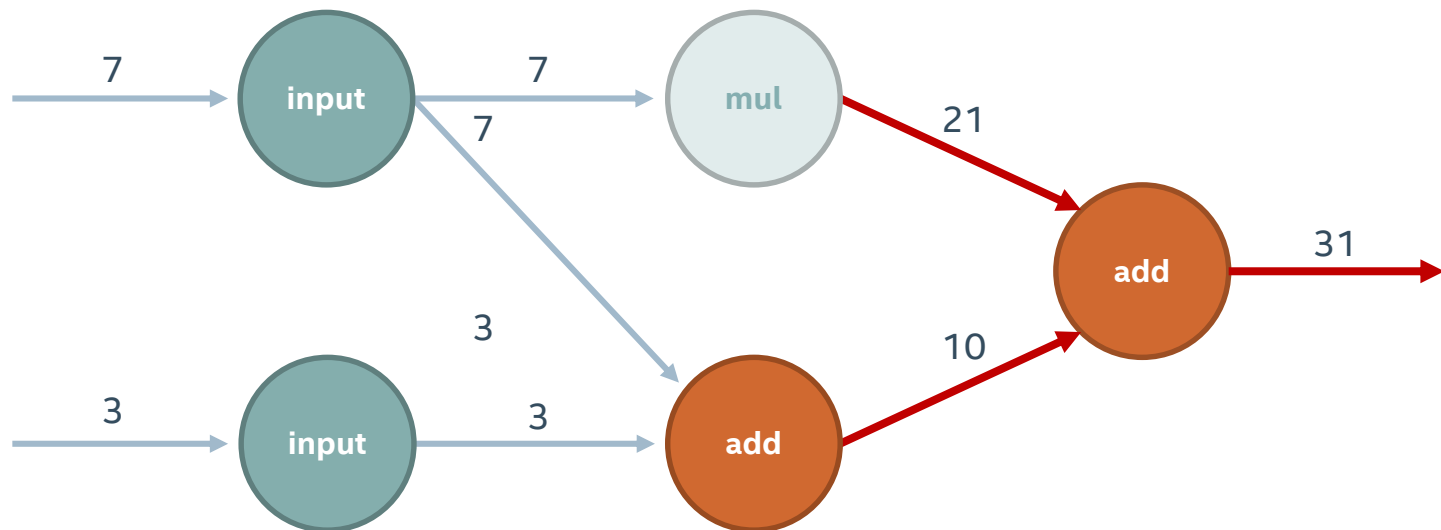
DATA FLOW



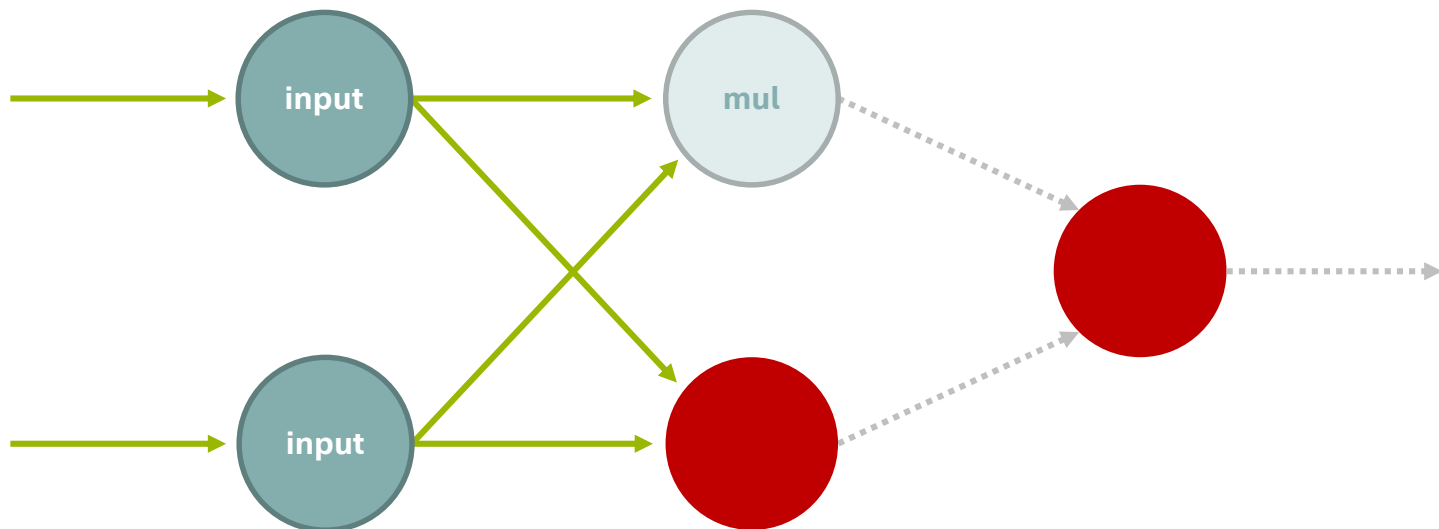
DATA FLOW



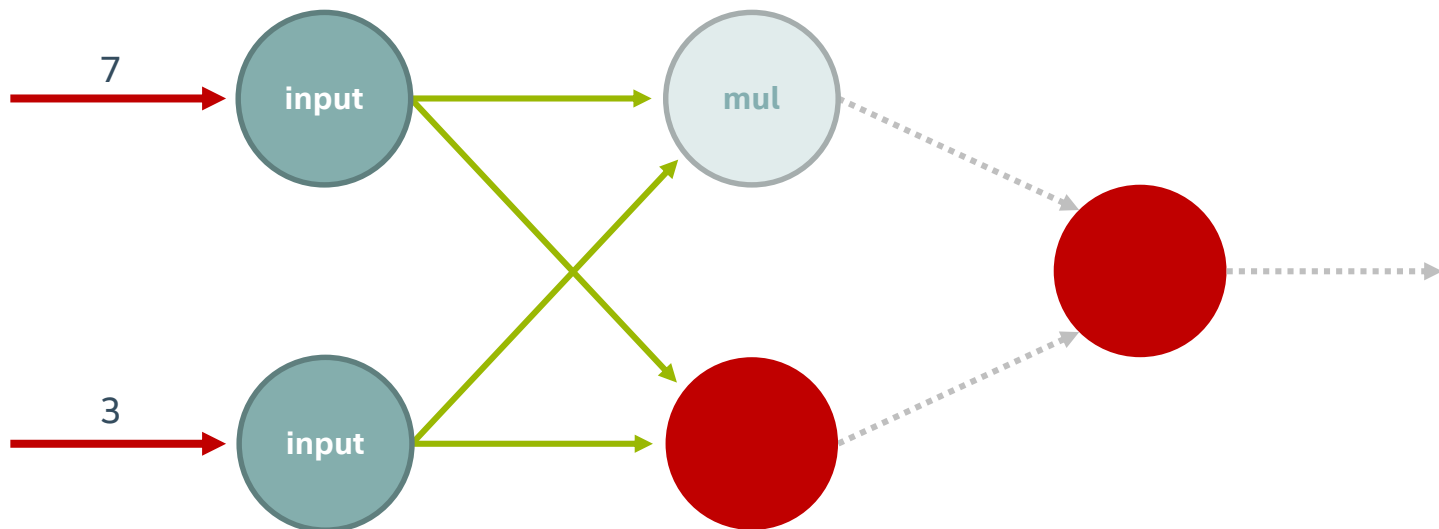
DATA FLOW



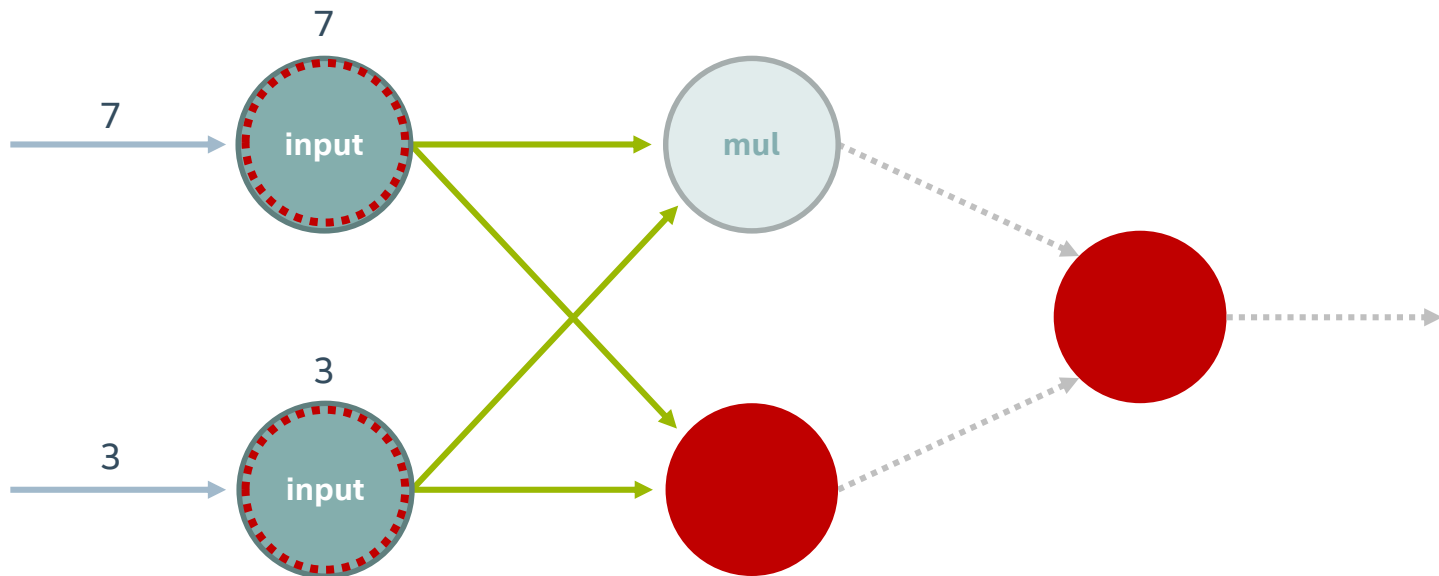
PARTIAL EXECUTION



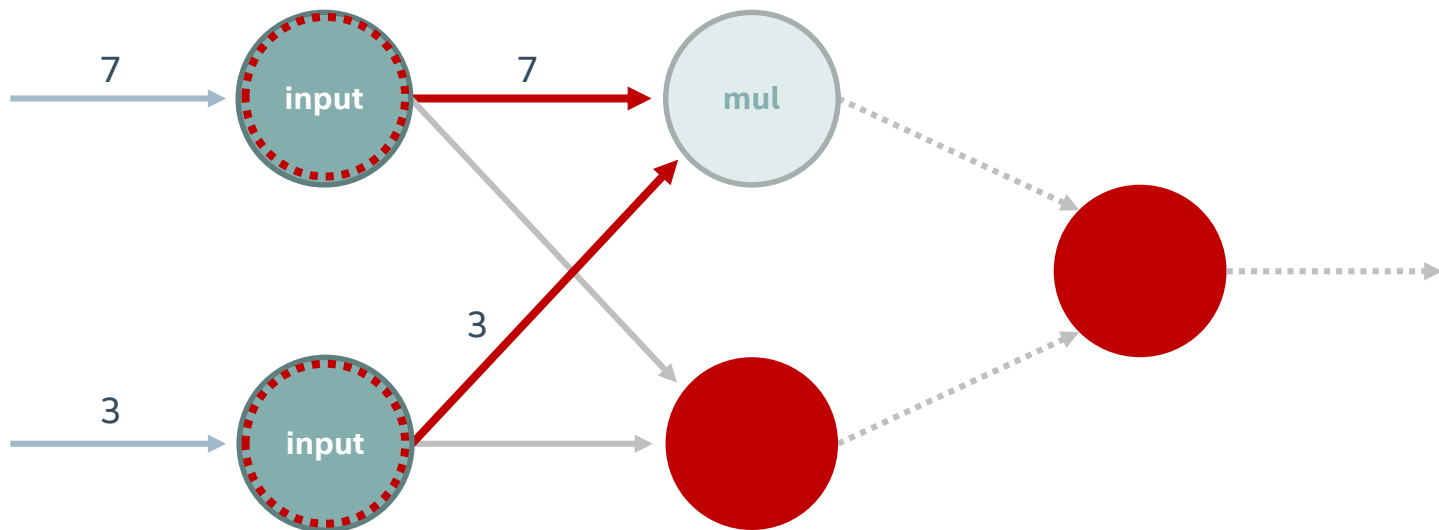
PARTIAL EXECUTION



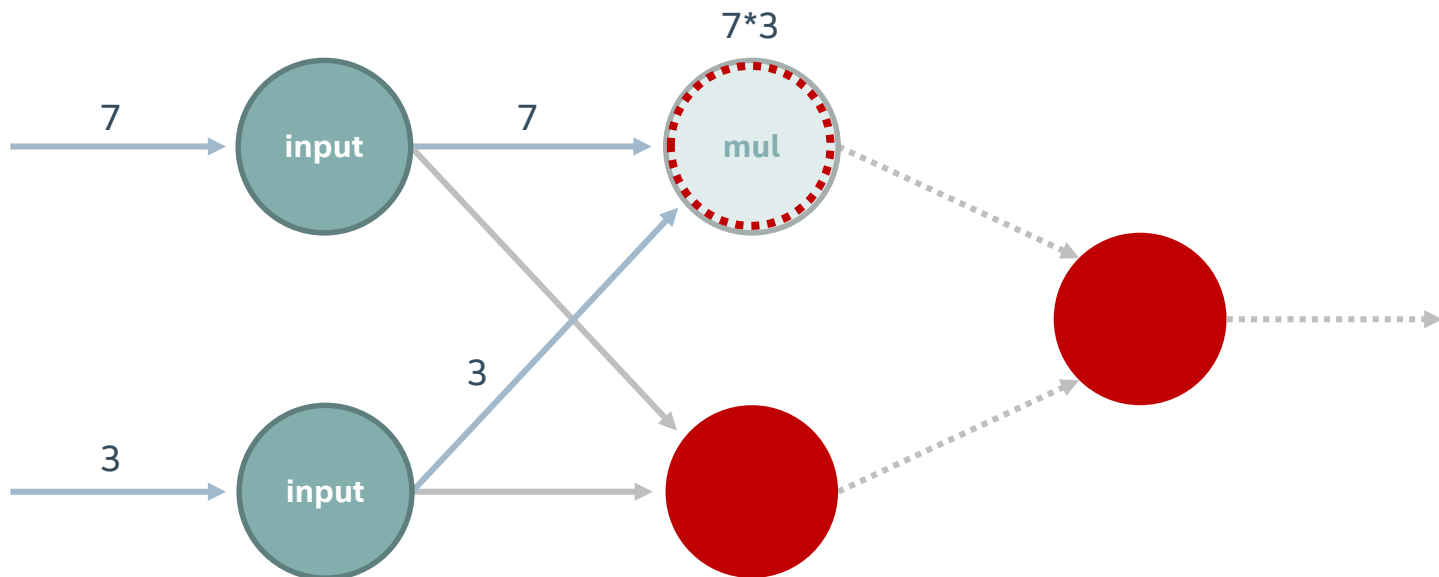
PARTIAL EXECUTION



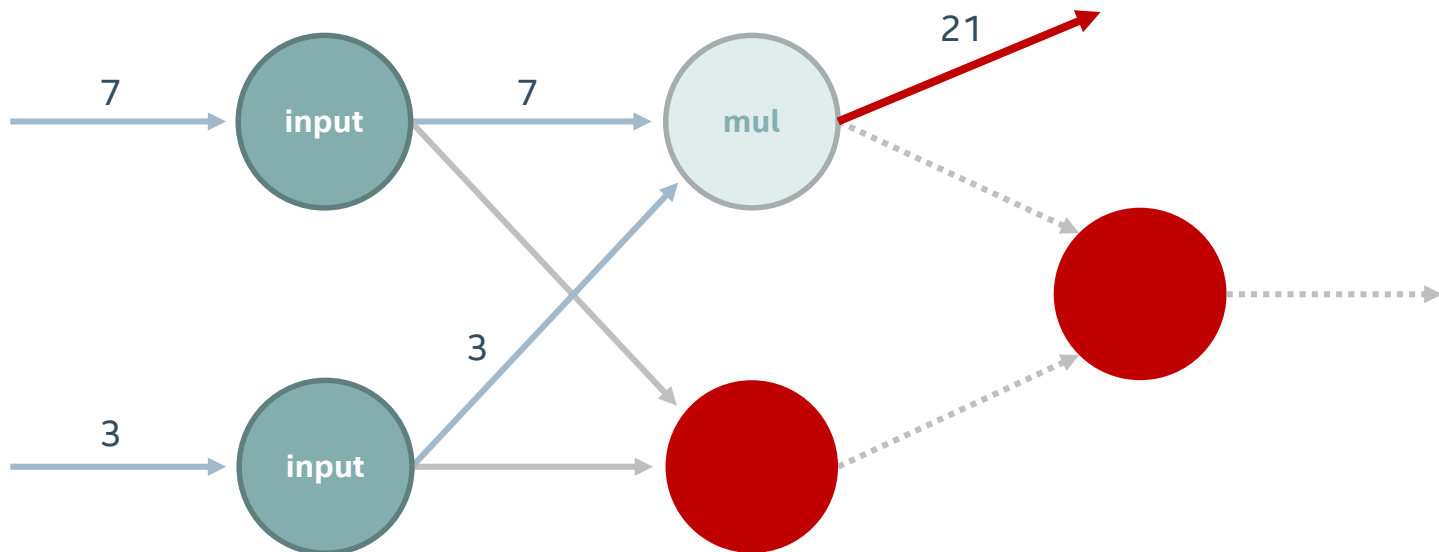
PARTIAL EXECUTION



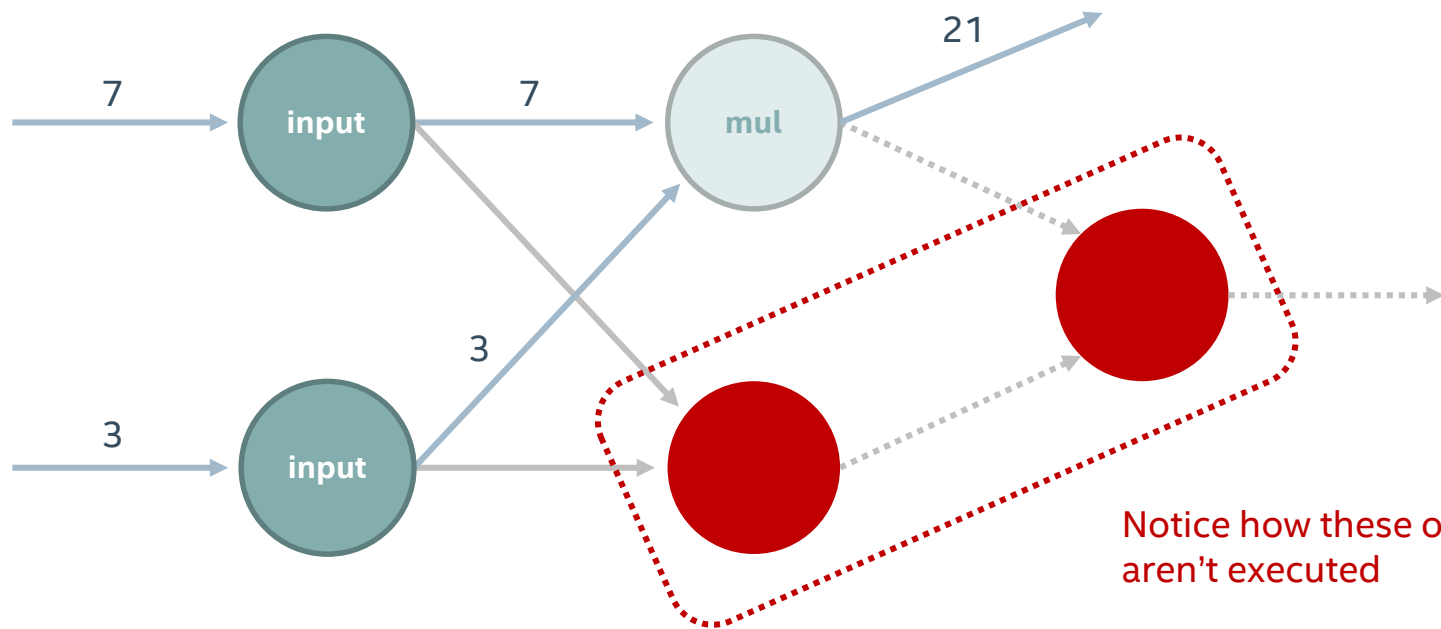
PARTIAL EXECUTION



PARTIAL EXECUTION



PARTIAL EXECUTION

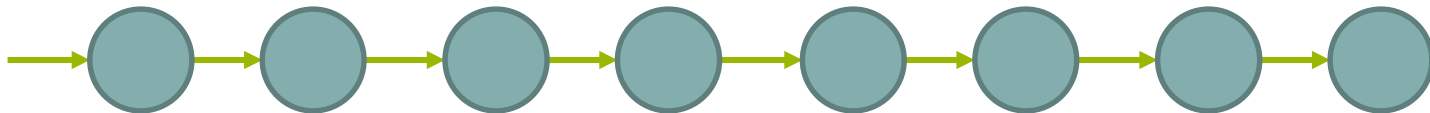


DEPENDENCIES

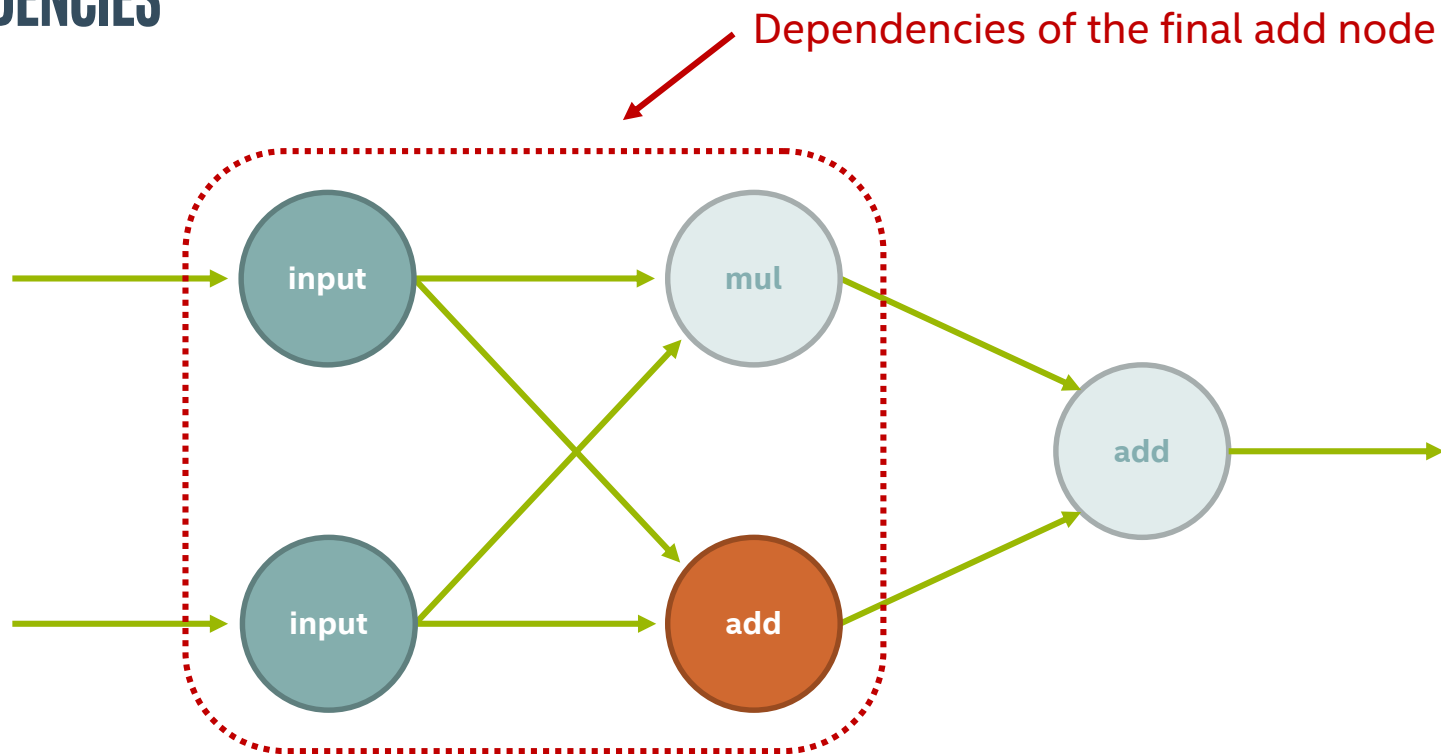
Nodes which are needed to compute another node

Different nodes have different dependencies

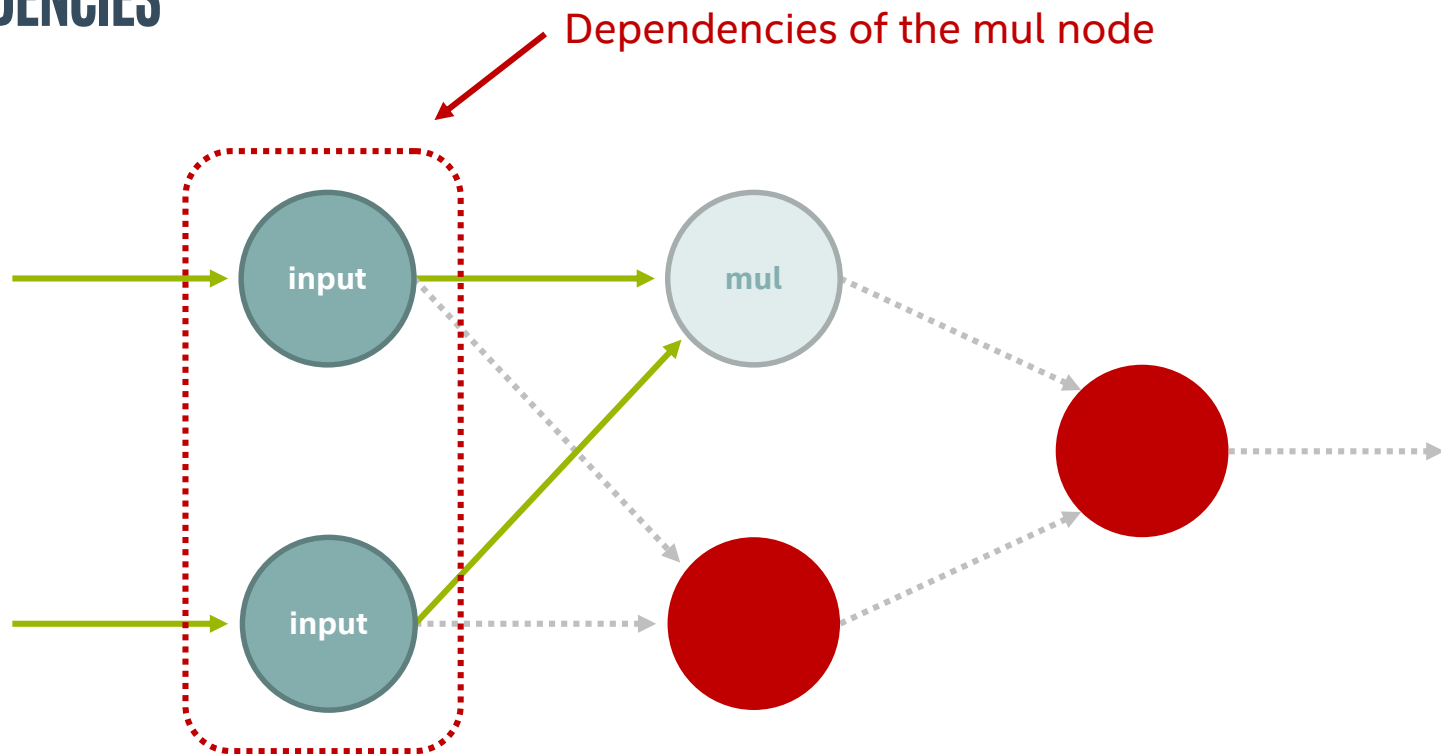
Nodes with *no* dependencies can run at any time



DEPENDENCIES



DEPENDENCIES



TENSORFLOW FUNDAMENTALS

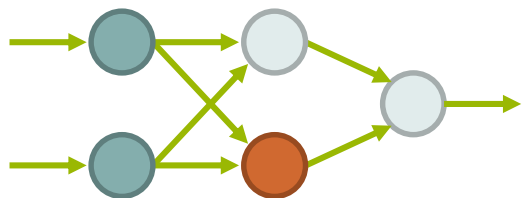
TODAY'S ITINERARY

Primary use-pattern: Define and Run

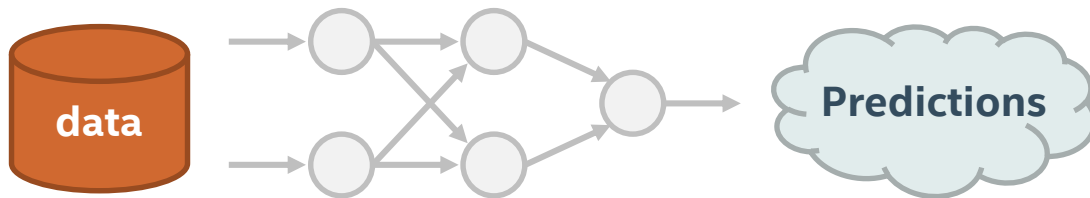
Quick example

TWO-STEP PROGRAMMING PATTERN

1. Define a computation graph



2. Run the graph



DEFINING GRAPHS

MAIN TENSORFLOW API CLASSES

Graph

- Container for operations and tensors

Operation

- Nodes in the graph
- Represent computations

Tensor

- Edges in the graph
- Represent data

When you import TensorFlow, it automatically creates a default graph

```
>>> import tensorflow as tf
```

default

This is the default location for model operations

```
>>> import tensorflow as tf
```

default

We can create constant data values with `tf.constant()`

```
>>> a = tf.constant(3.0)
```



a

default

`tf.constant()` creates an Operation that returns a fixed value

```
>>> a = tf.constant(3.0)
```



a

default

Operation functions can be given a `name` parameter, which gives the Operation a string name

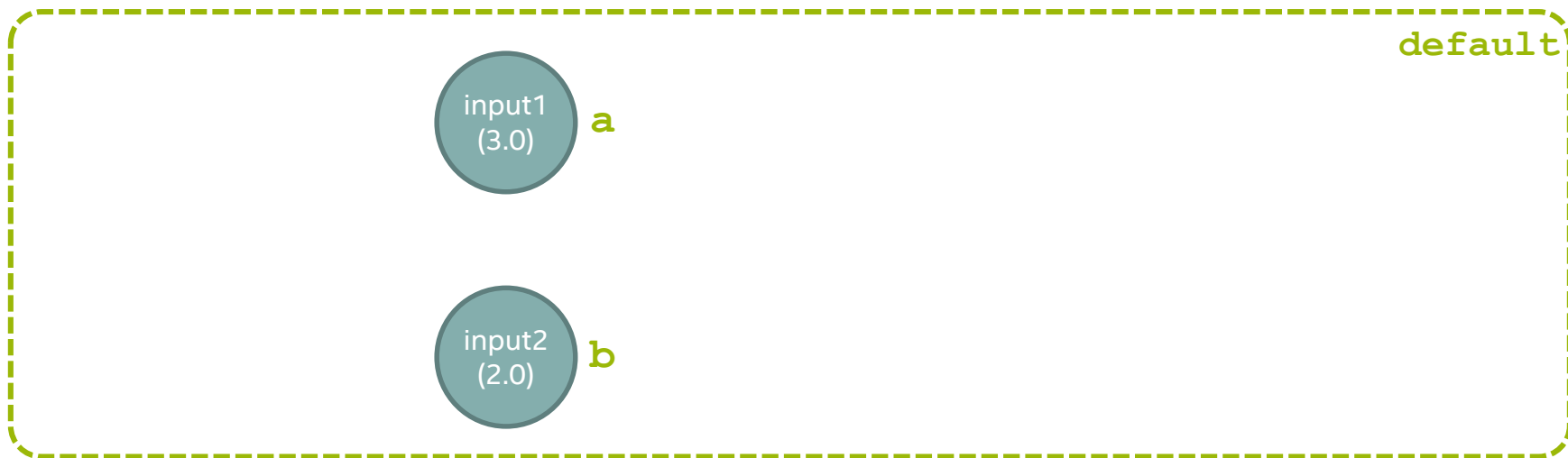
```
>>> a = tf.constant(3.0, name="input1")
```



default

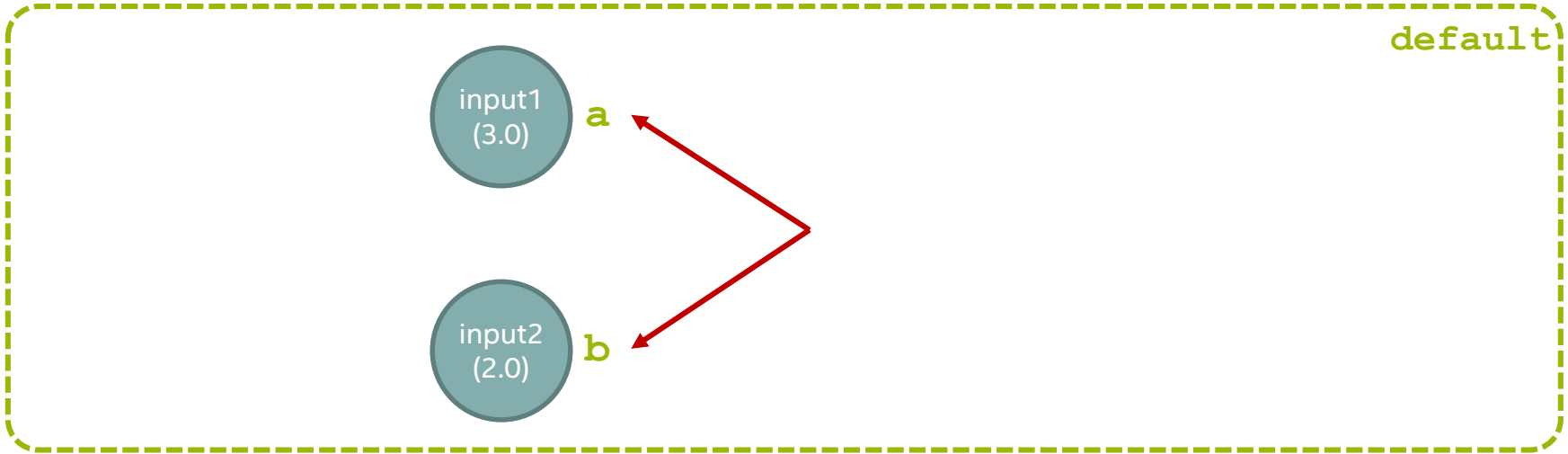
Additional Ops continue to populate the default graph

```
>>> b = tf.constant(2.0, name="input2")
```



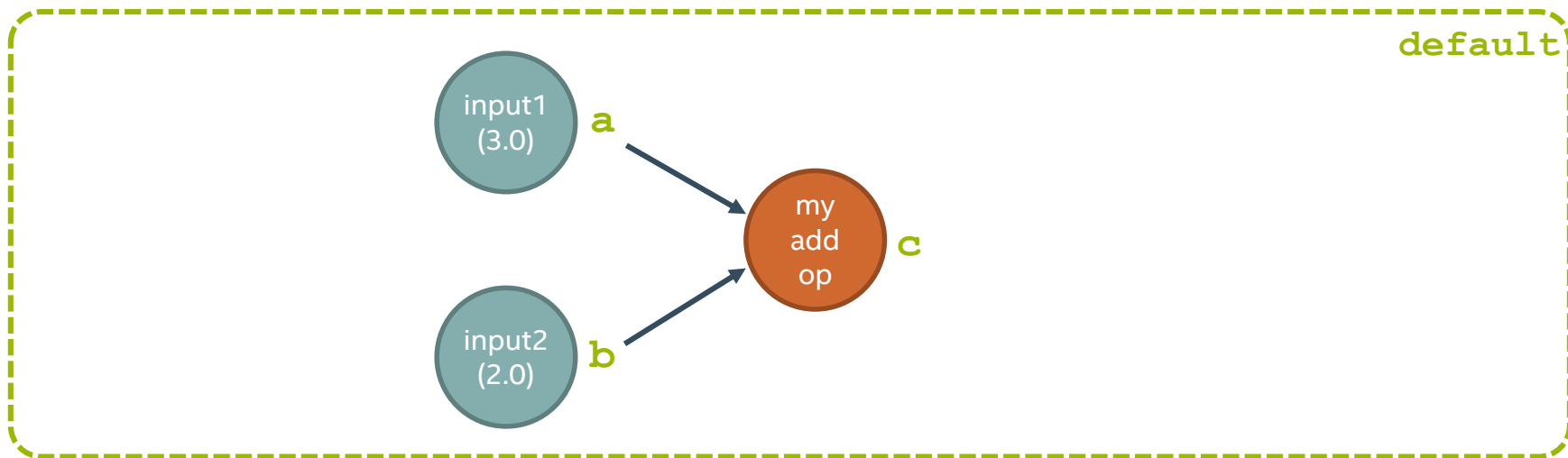
We have Python variable names which refer to the **Tensor** output of our two operations

```
>>> b = tf.constant(2.0, name="input2")
```



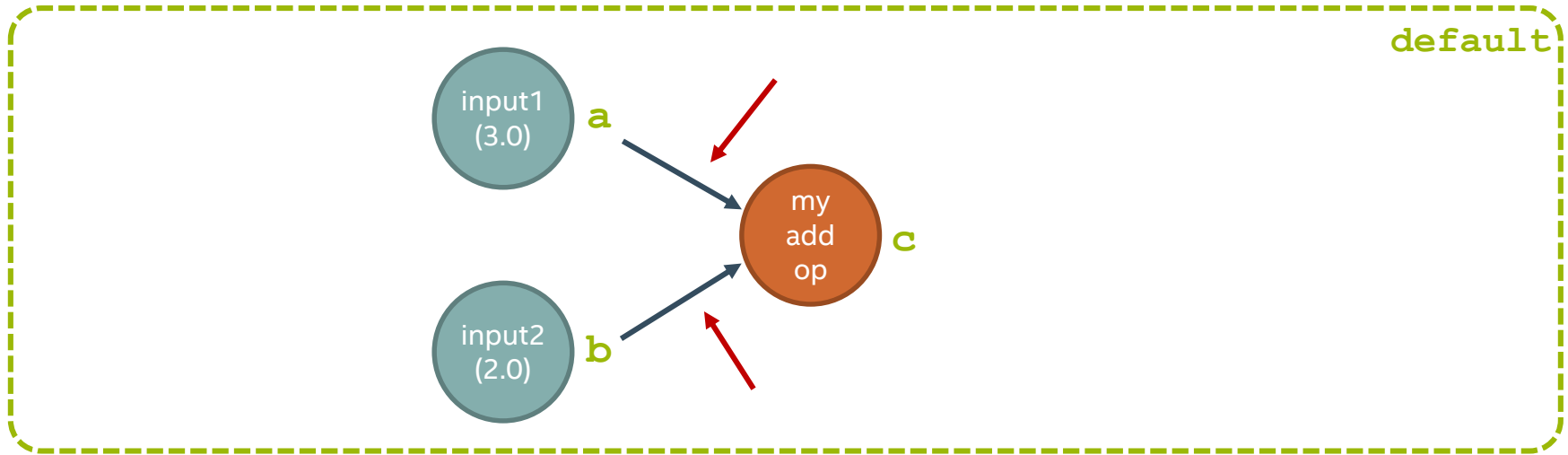
You can pass **Tensor** objects into other Ops

```
>>> c = tf.add(a, b, name="my_add_op")
```



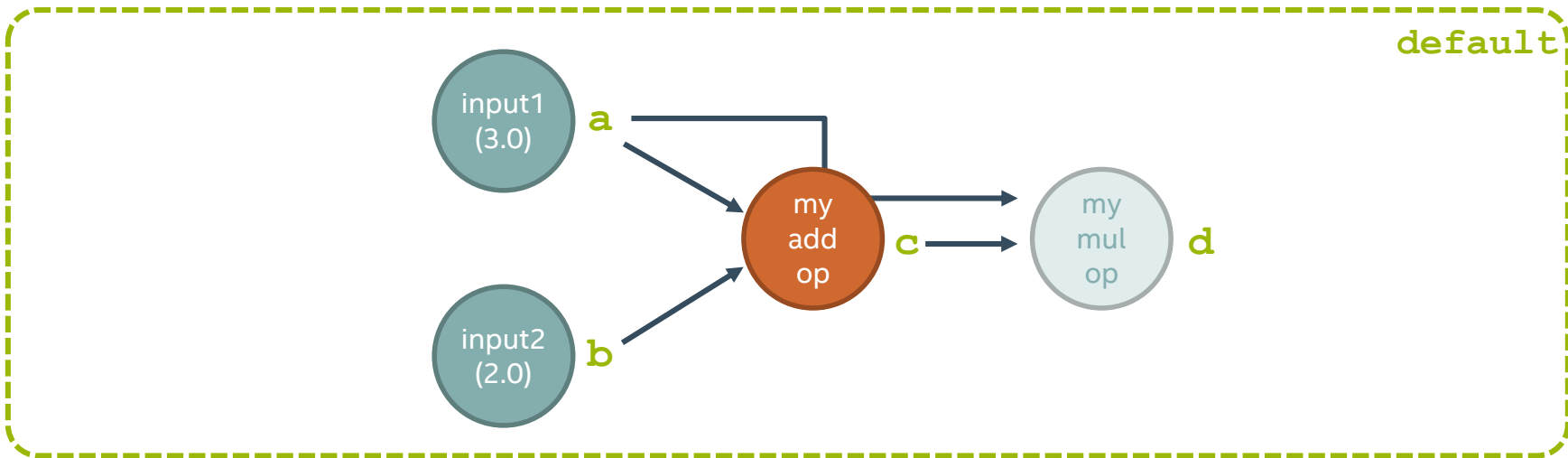
TensorFlow connects the referred Operations

```
>>> c = tf.add(a, b, name="my_add_op")
```



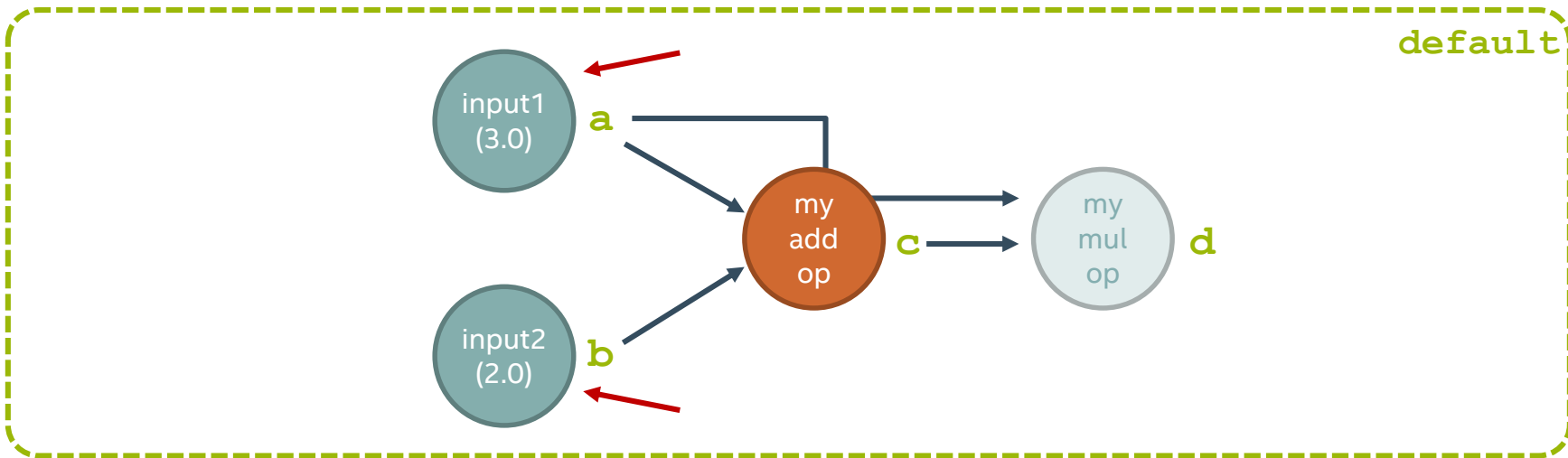
You can reuse the outputs of different Ops as much as you'd like

```
>>> c = tf.mul(a, c, name="my_mul_op")
```



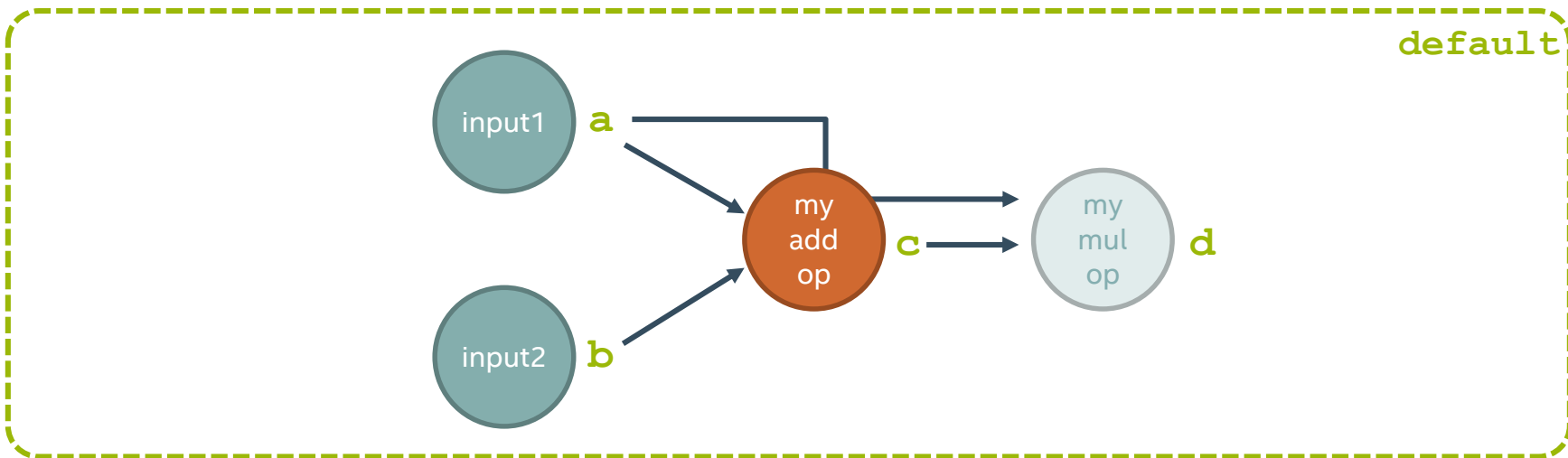
Recall: our inputs are fixed values (constant Ops)

>>>



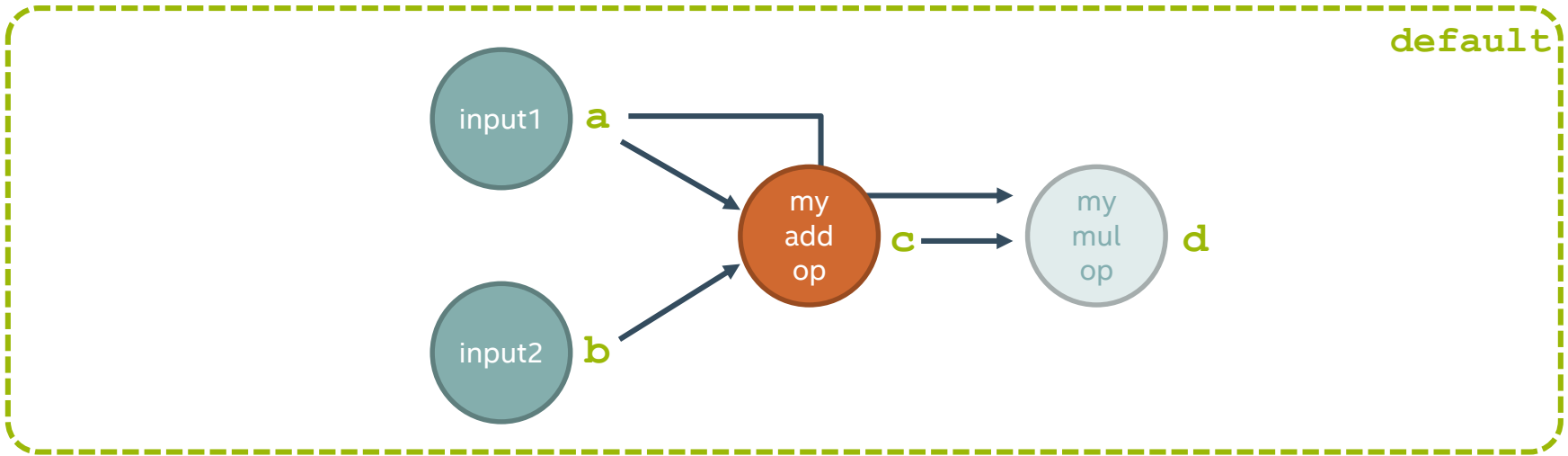
We could have used `tf.placeholder()`
to define explicit input that vary run-to-run

```
>>> a = tf.placeholder(tf.float32, name="input1")
```



Side note: we're passing in the data type `tf.float32` to `tf.placeholder`

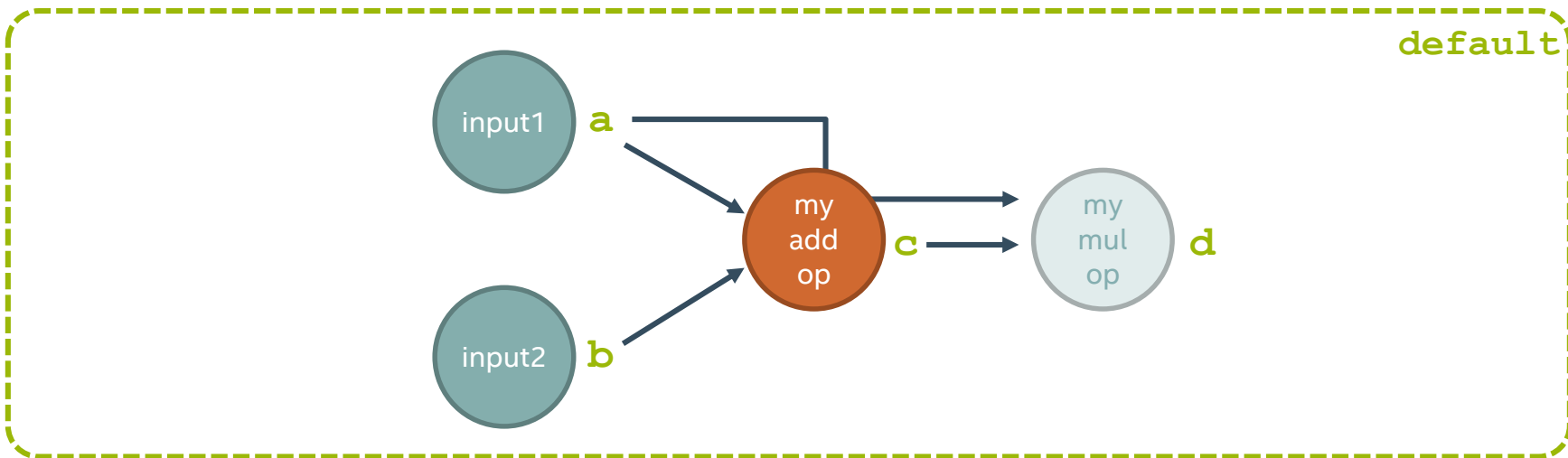
```
>>> a = tf.placeholder(tf.float32, name="input1")
```



RUNNING GRAPHS

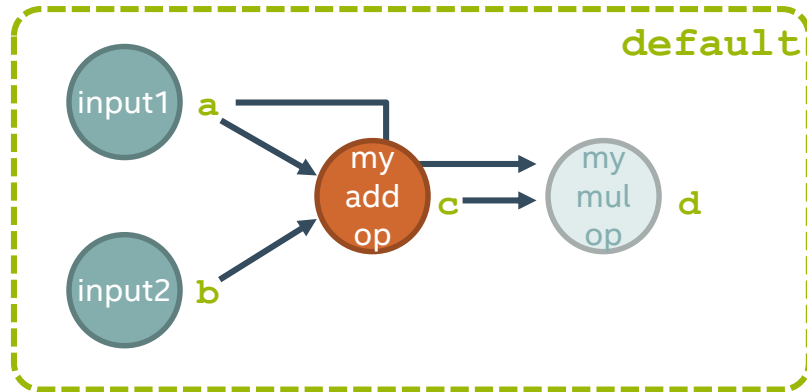
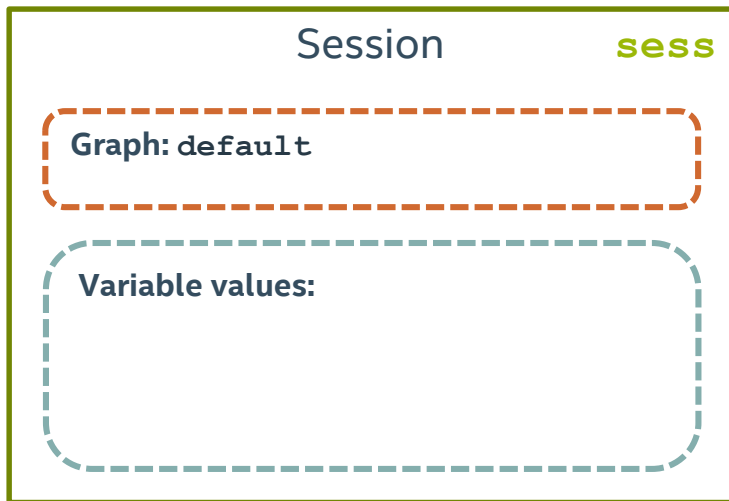
Now that we've created a graph, let's run it!

```
>>>
```



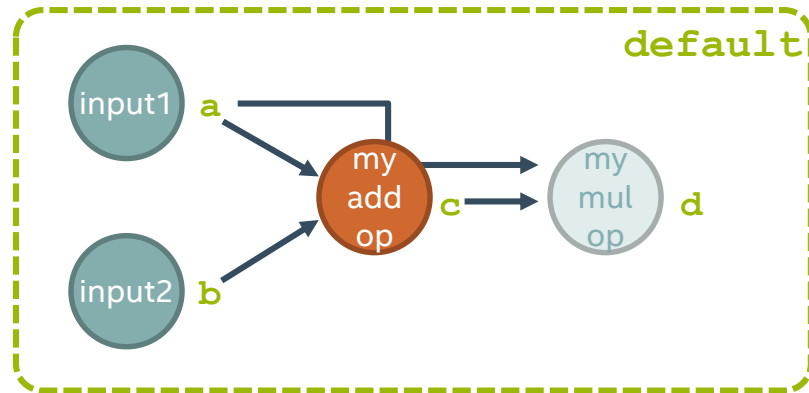
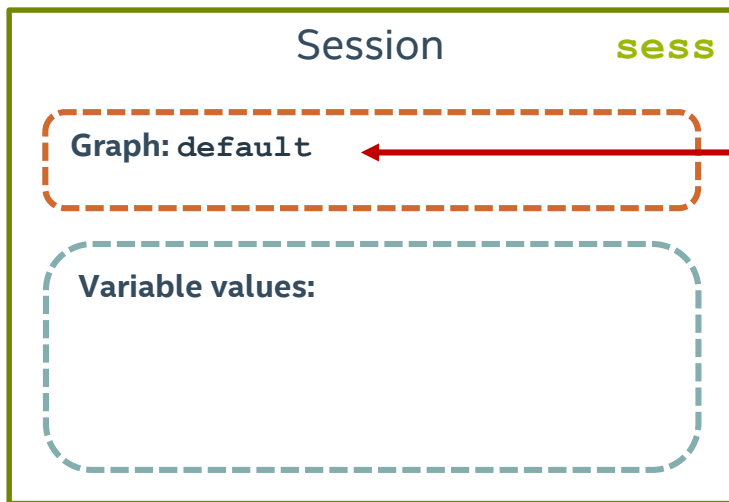
We use a **Session** object to execute graphs.
Each **Session** is dedicated to a single graph.

```
>>> sess = tf.Session()
```



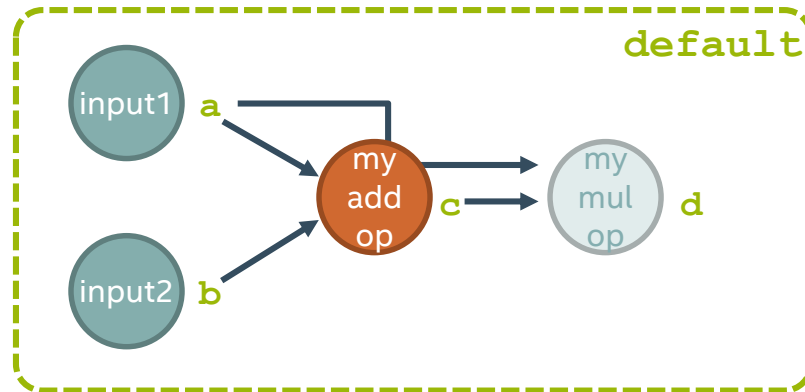
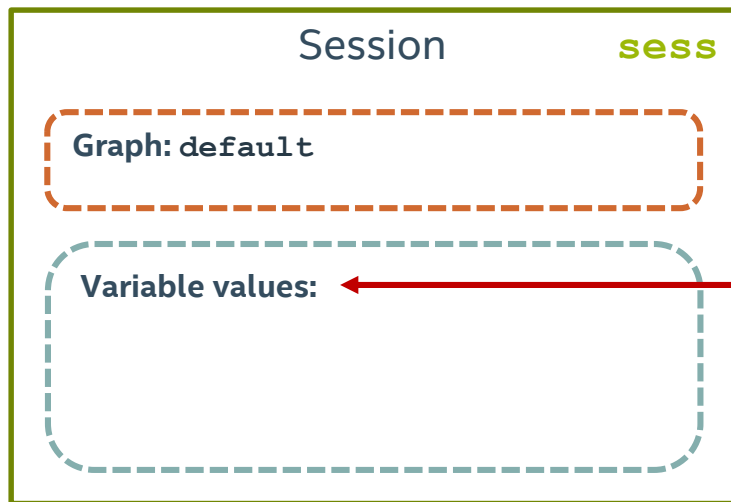
By default, a Session uses the current default graph

```
>>> sess = tf.Session()
```



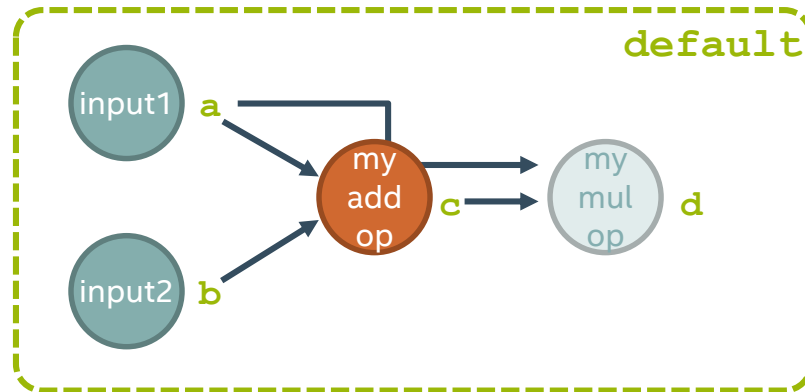
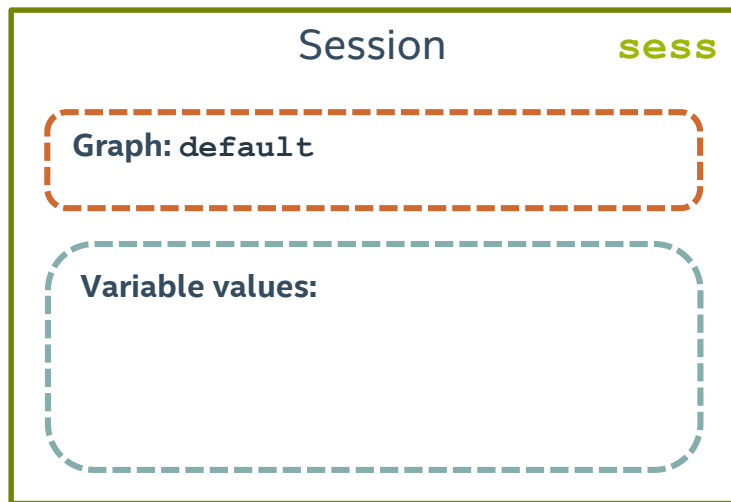
We'll discuss Variables shortly.

```
>>> sess = tf.Session()
```



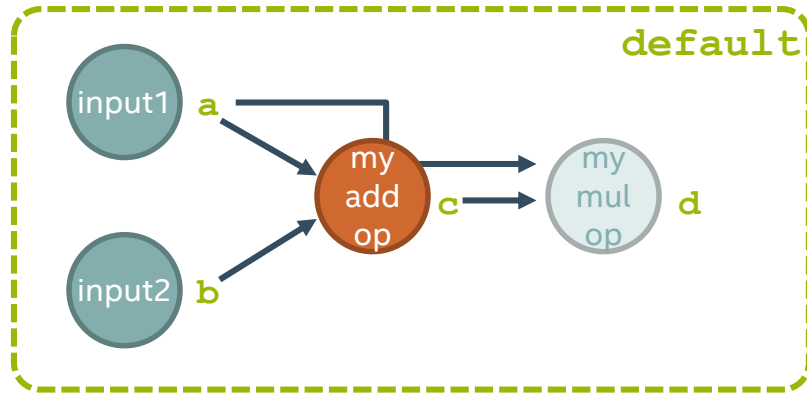
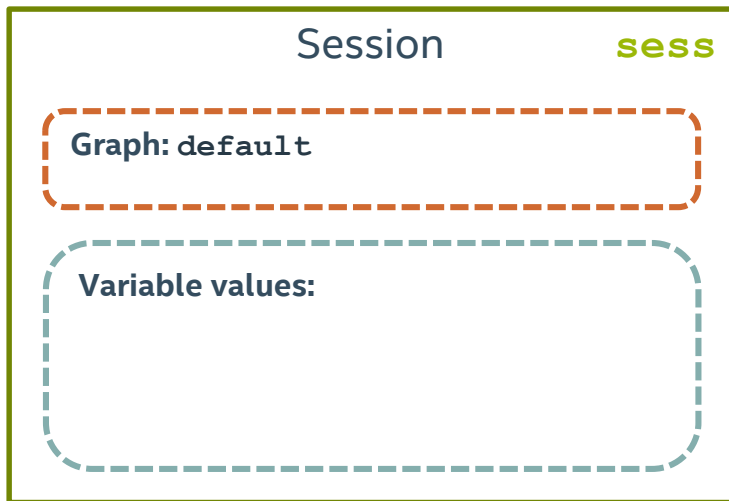
placeholders require data to fill them in when the graph is run

```
>>>
```



We do this by creating a dictionary mapping **Tensor** keys to numeric values

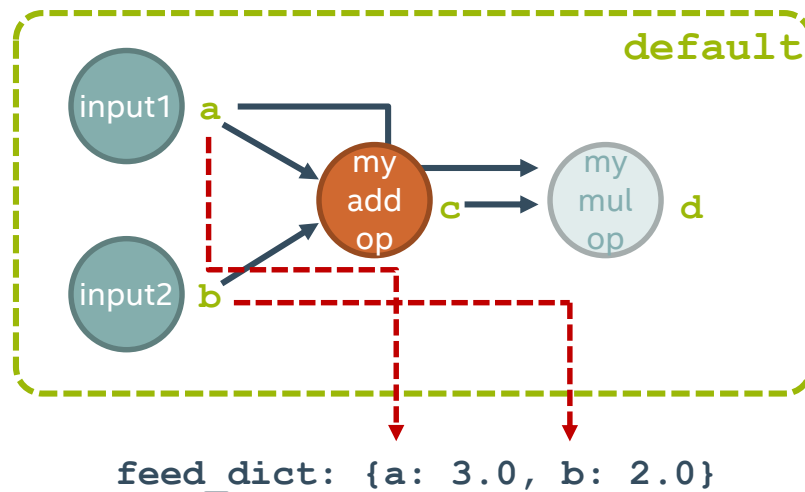
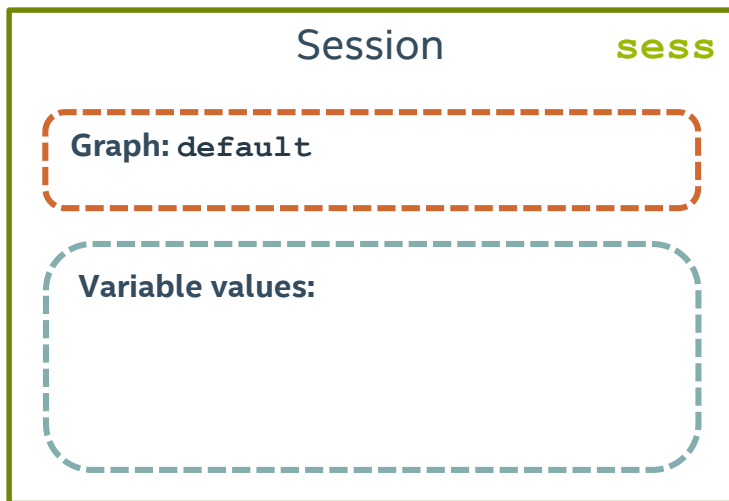
```
>>> feed_dict = {a: 3.0, b: 2.0}
```



```
feed_dict: {a: 3.0, b: 2.0}
```

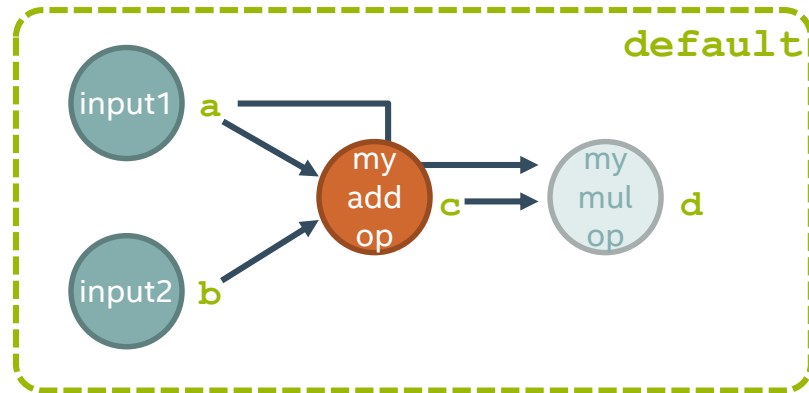
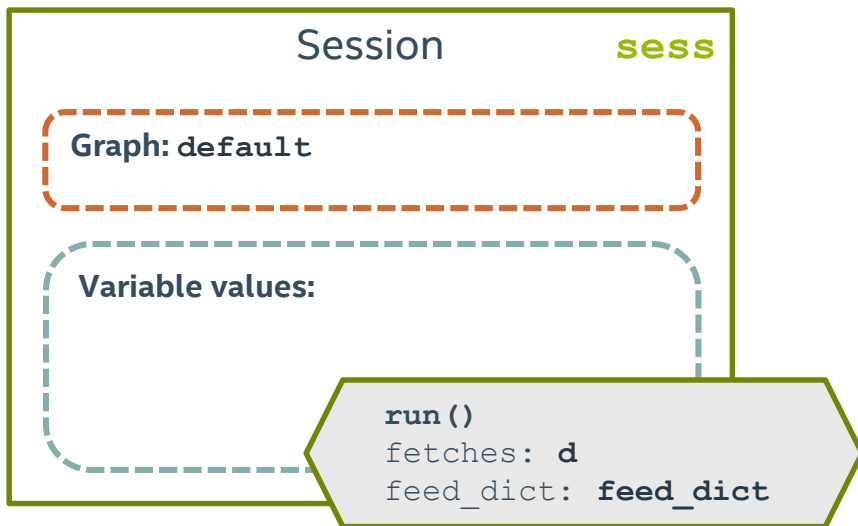
We pass in the same tensors as we used to create our graph

```
>>> feed_dict = {a: 3.0, b: 2.0}
```



We execute the graph with `sess.run(fetches, feed_dict)`

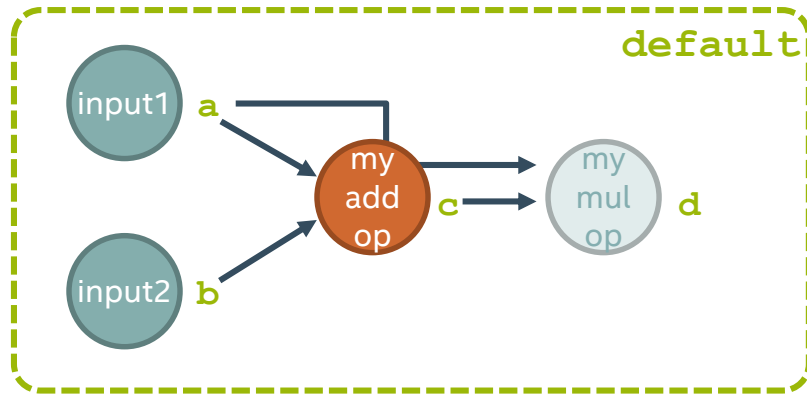
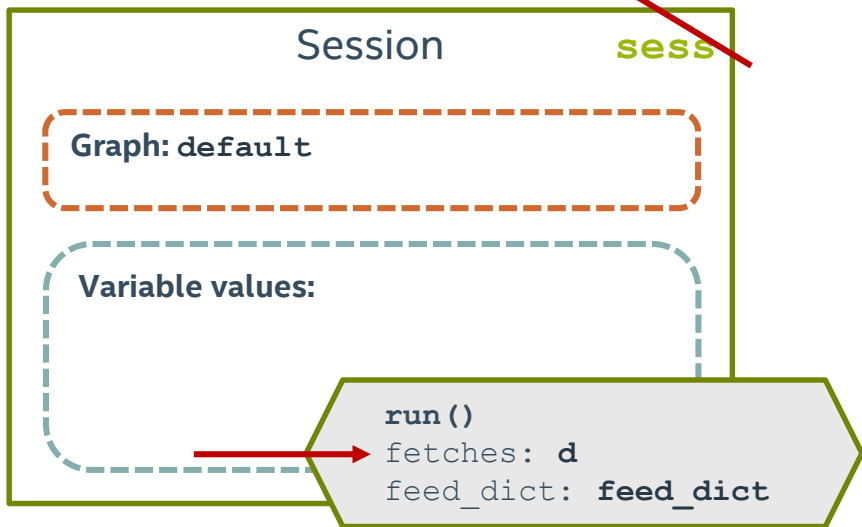
```
>>> out = sess.run(d, feed_dict=feed_dict)
```



`feed_dict: {a: 3.0, b: 2.0}`

Fetches (a Tensor, Operation, or list of these) tells TensorFlow what outputs we want

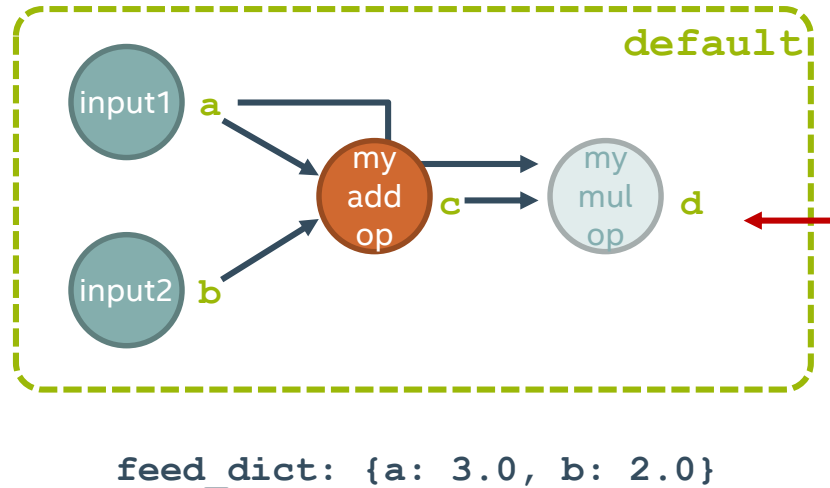
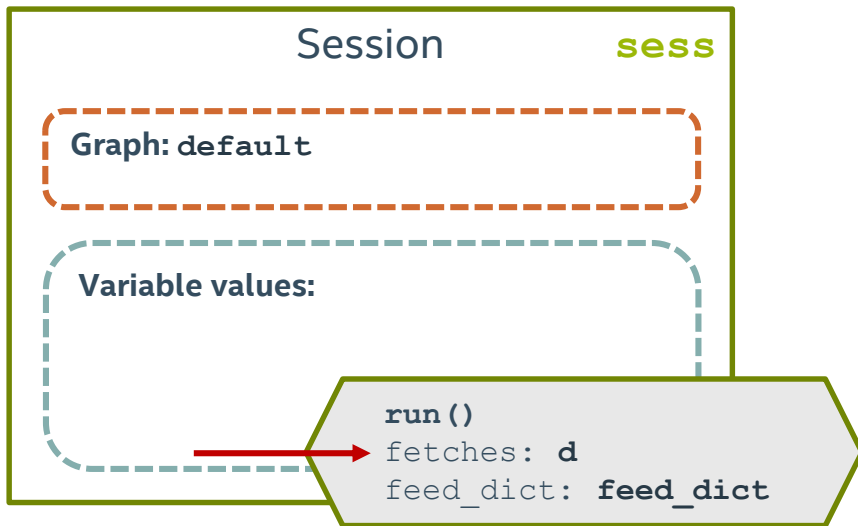
```
>>> out = sess.run(d, feed_dict=feed_dict)
```



`feed_dict: {a: 3.0, b: 2.0}`

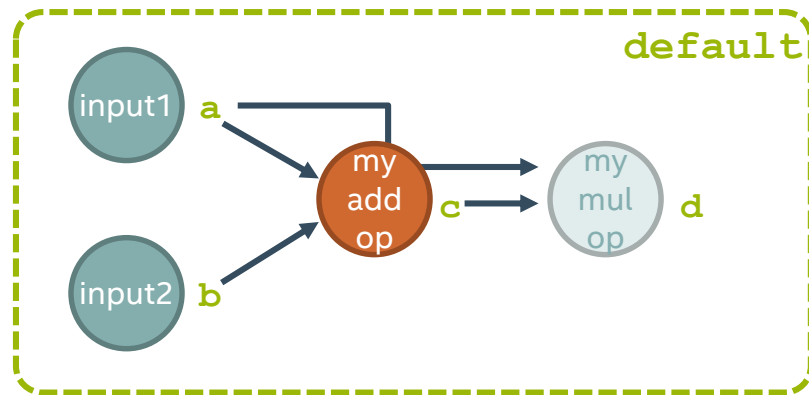
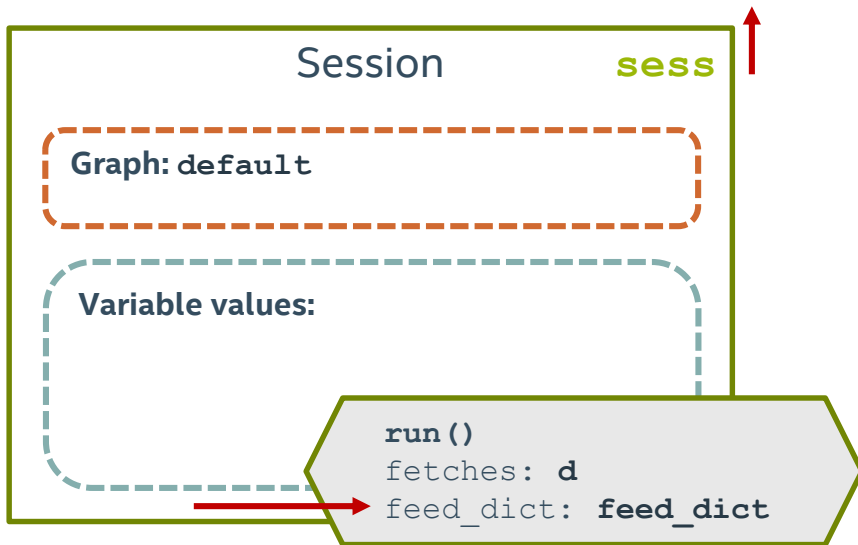
Here, we request `d`, the `Tensor` output of `my_mul_op`

```
>>> out = sess.run(d, feed_dict=feed_dict)
```



`feed_dict` tells the Session tensor substitutions

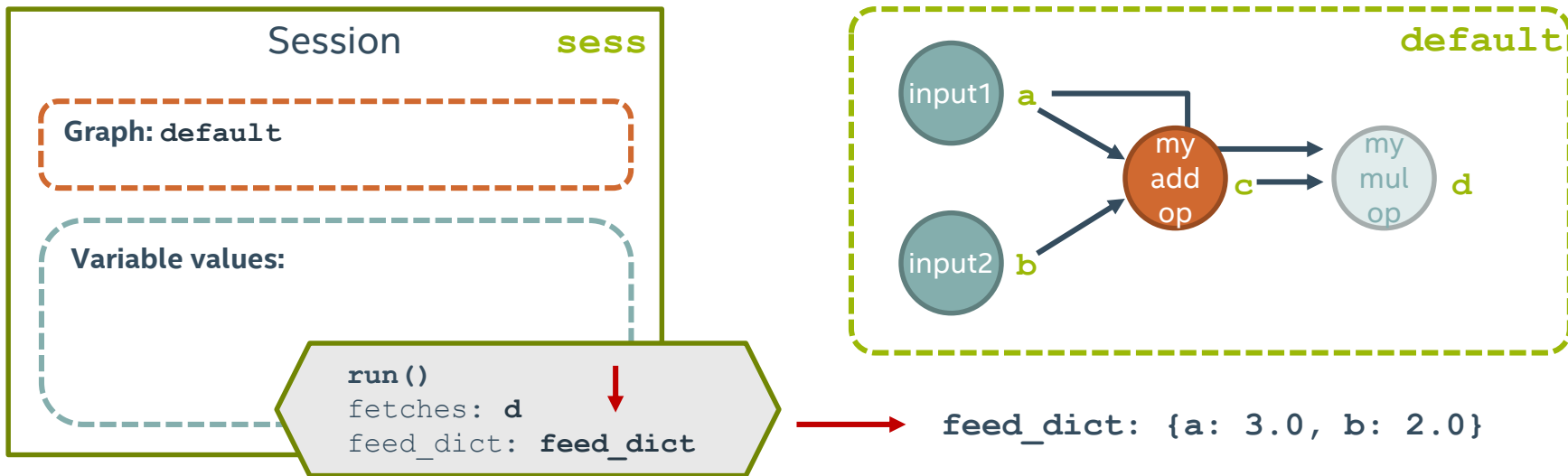
```
>>> out = sess.run(d, feed_dict=feed_dict)
```



`feed_dict: {a: 3.0, b: 2.0}`

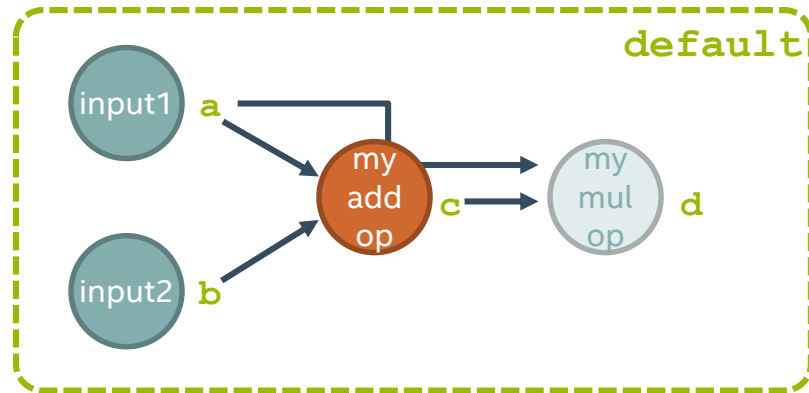
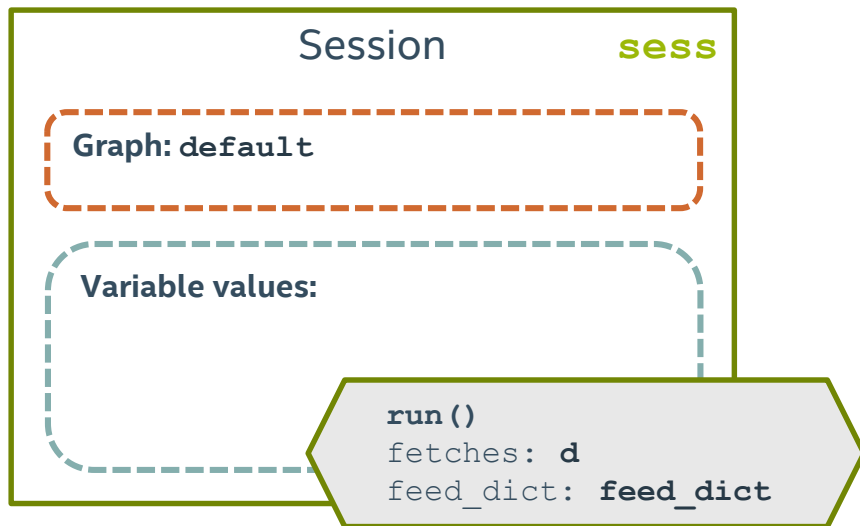
We created a `feed_dict`, in advance, which tells the Session to use 3.0 and 2.0 for `a` and `b`

```
>>> out = sess.run(d, feed_dict=feed_dict)
```



placeholder Ops must be feed a value

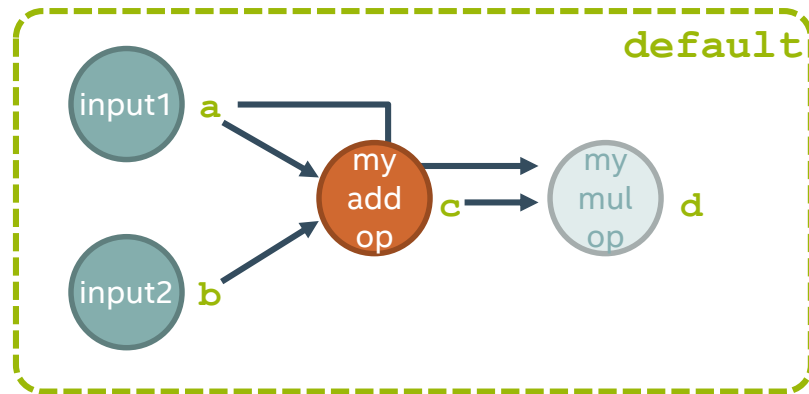
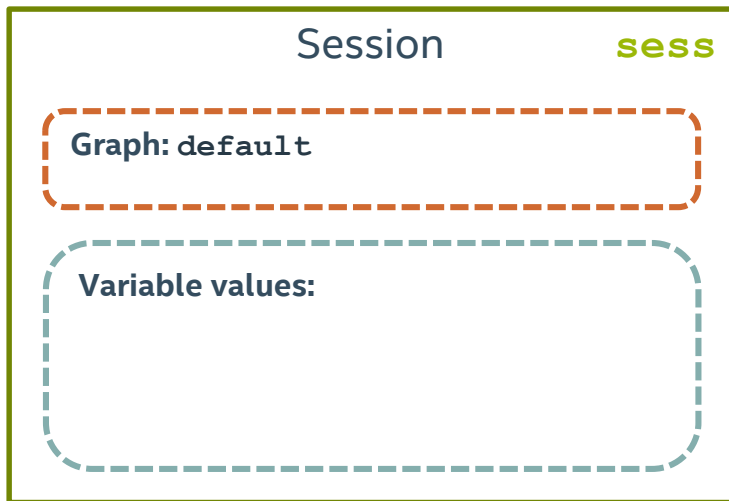
```
>>> out = sess.run(d, feed_dict=feed_dict)
```



`feed_dict: {a: 3.0, b: 2.0}`

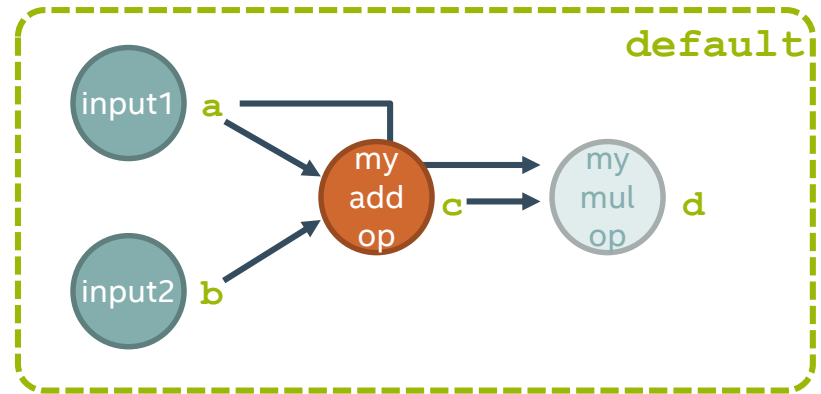
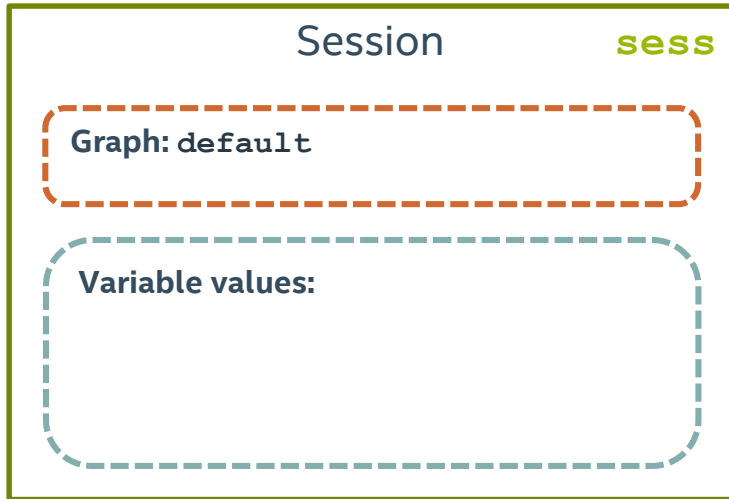
`sess.run` returns the fetched values as a NumPy array

```
>>>
```



```
feed_dict: {a: 3.0, b: 2.0}  
out = 15
```

```
>>> print(out) # prints the value 15
```

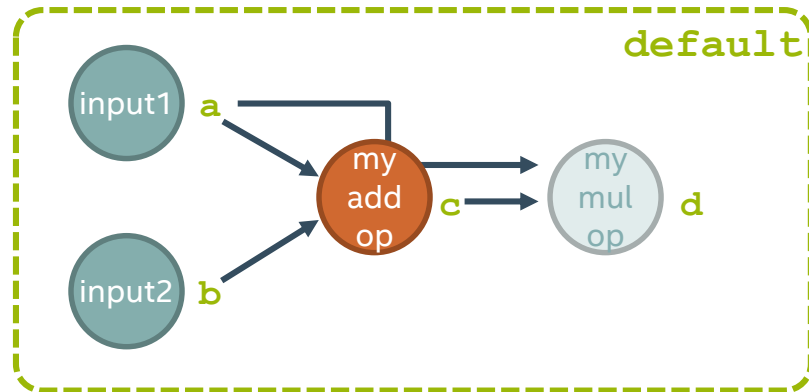
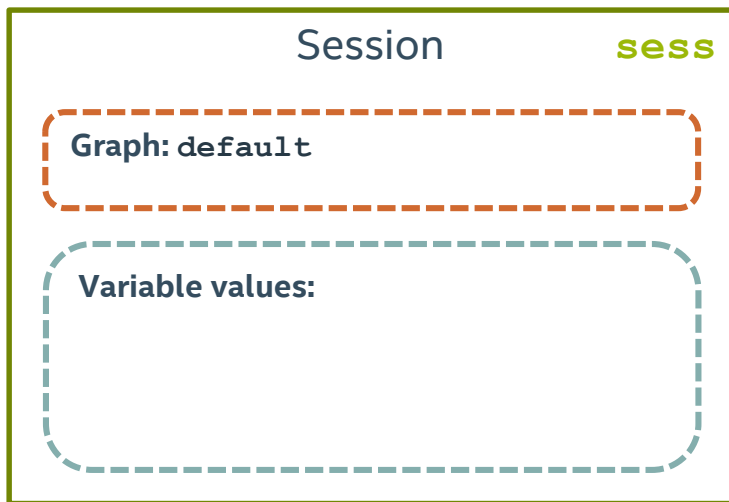


```
feed_dict: {a: 3.0, b: 2.0}  
out = 15
```

VARIABLES

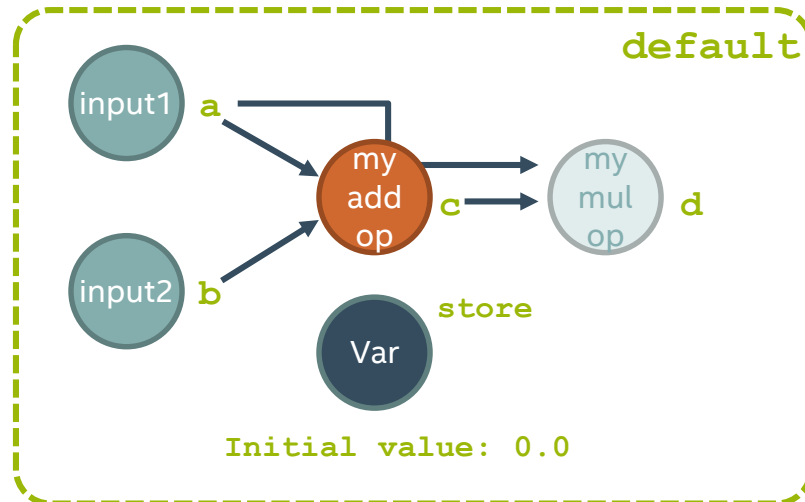
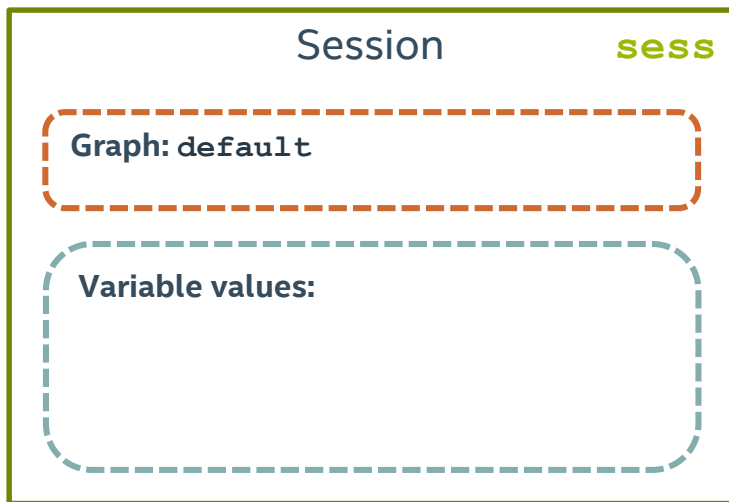
Our basic graph is well and good, but it would be nice to have stateful information. We can use `Variable` objects to accomplish this.

```
>>>
```



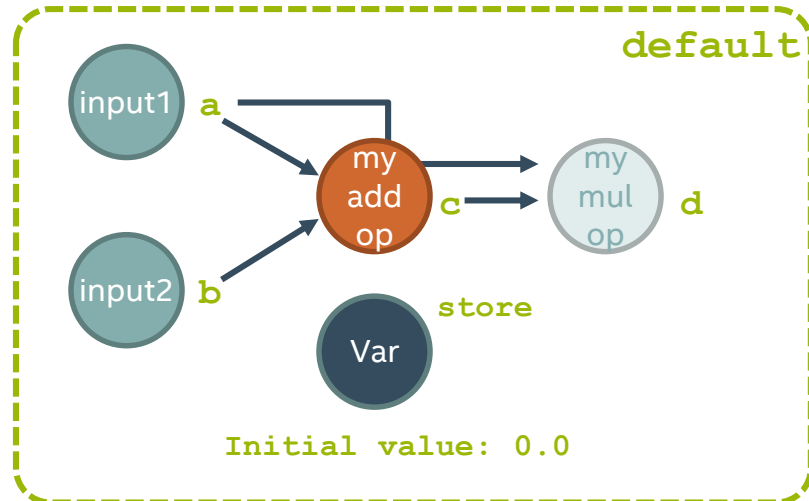
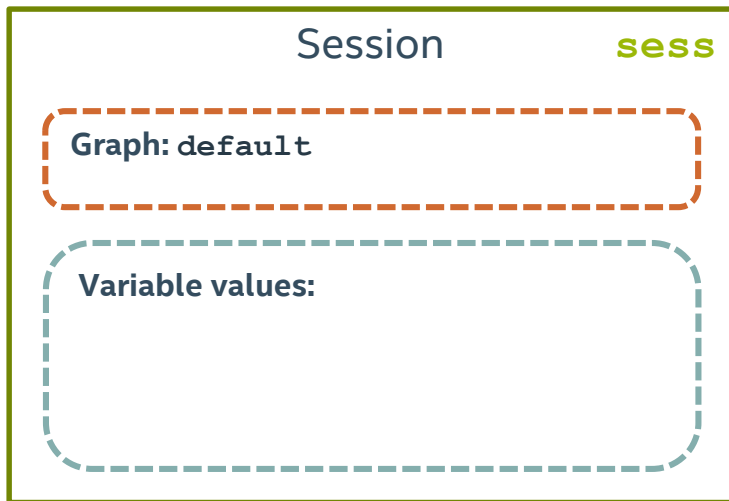
Our basic graph is well and good, but it would be nice to have stateful information. We can use `Variable` objects to accomplish this.

```
>>> store = tf.Variable(0.0, name="var")
```



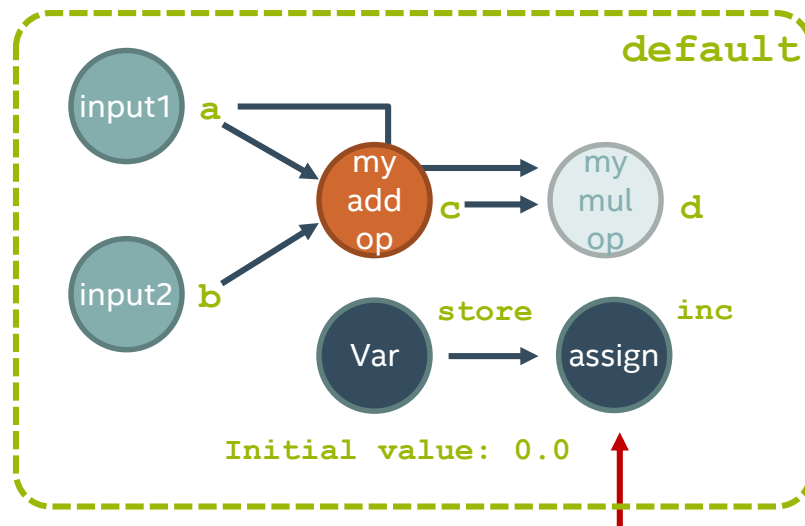
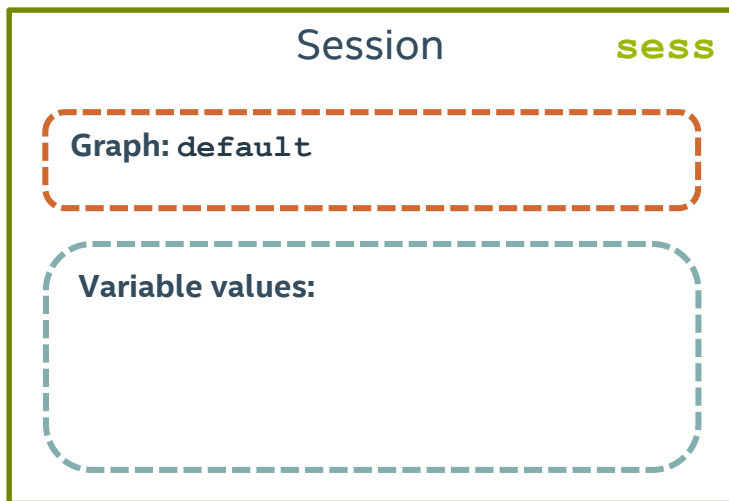
We need to pass in a initial value for our Variable, and we'll also give it a name.

```
>>> store = tf.Variable(0.0, name="var")
```



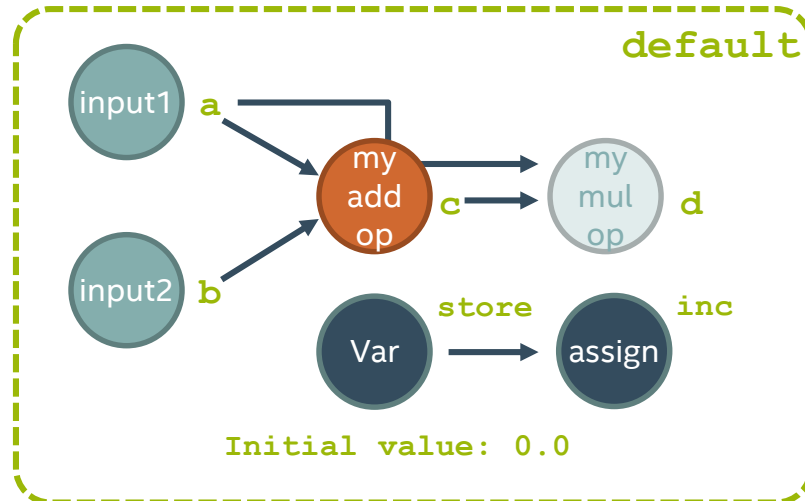
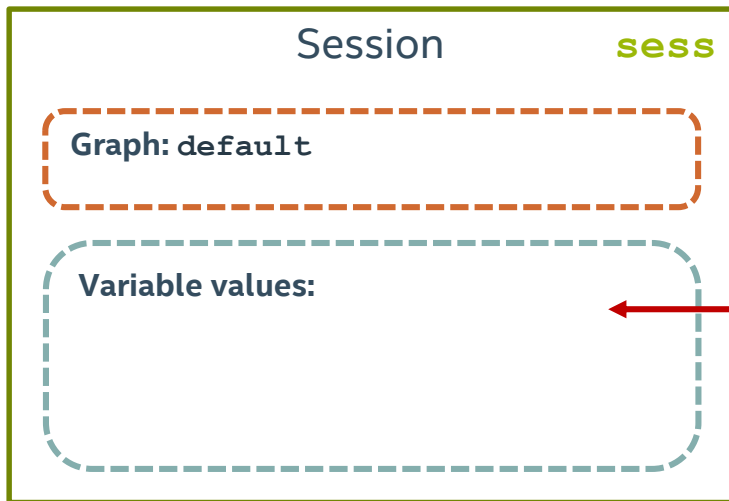
Let's also create an operation that allows us to increment the variable by 1

```
>>> inc = store.assign(store + 1)
```



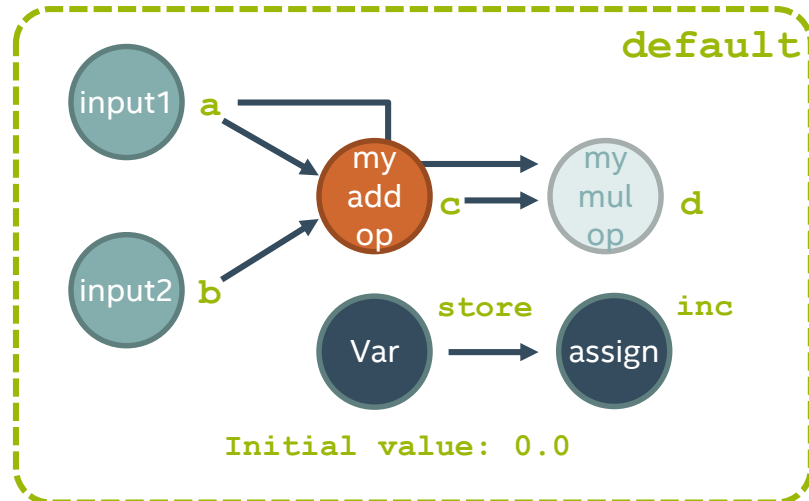
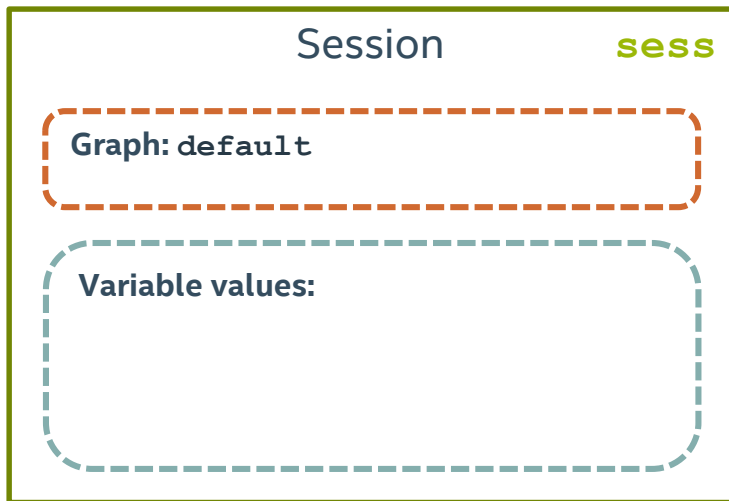
Note that our Session doesn't have any value for our Variable yet.

```
>>>
```



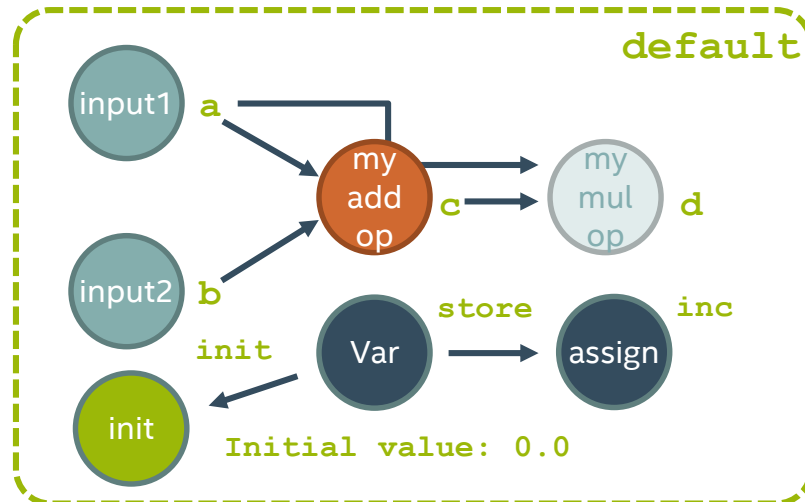
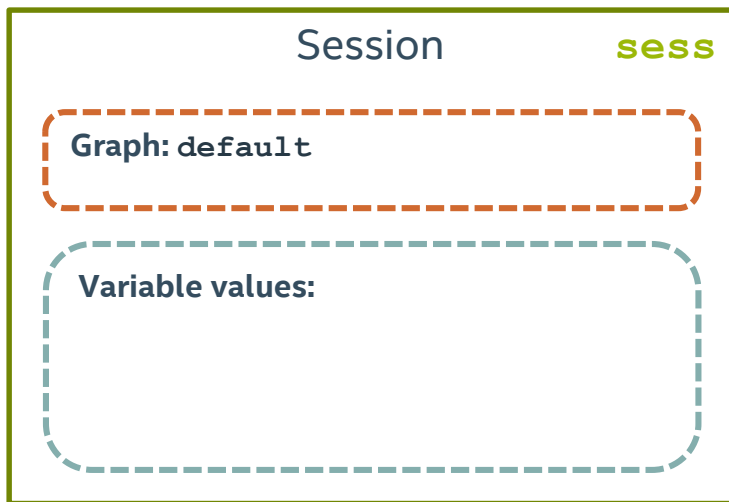
For our Session to use the Variable, we have to *initialize* it.

```
>>>
```



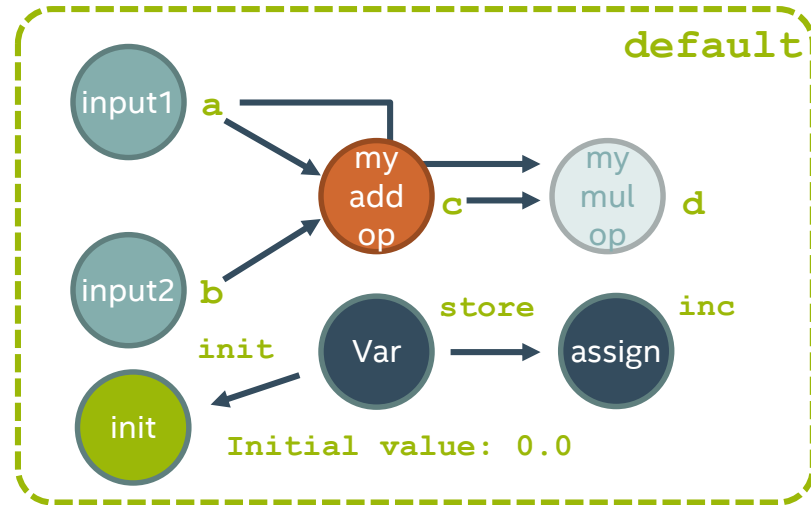
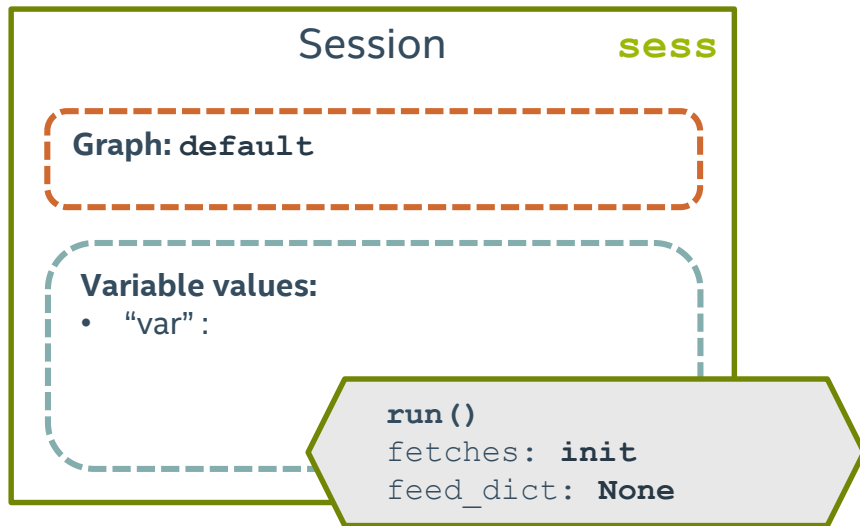
First, we'll create an initialization Op with
`tf.global_variables_initializer()`

```
>>> init = tf.global_variables_initializer()
```



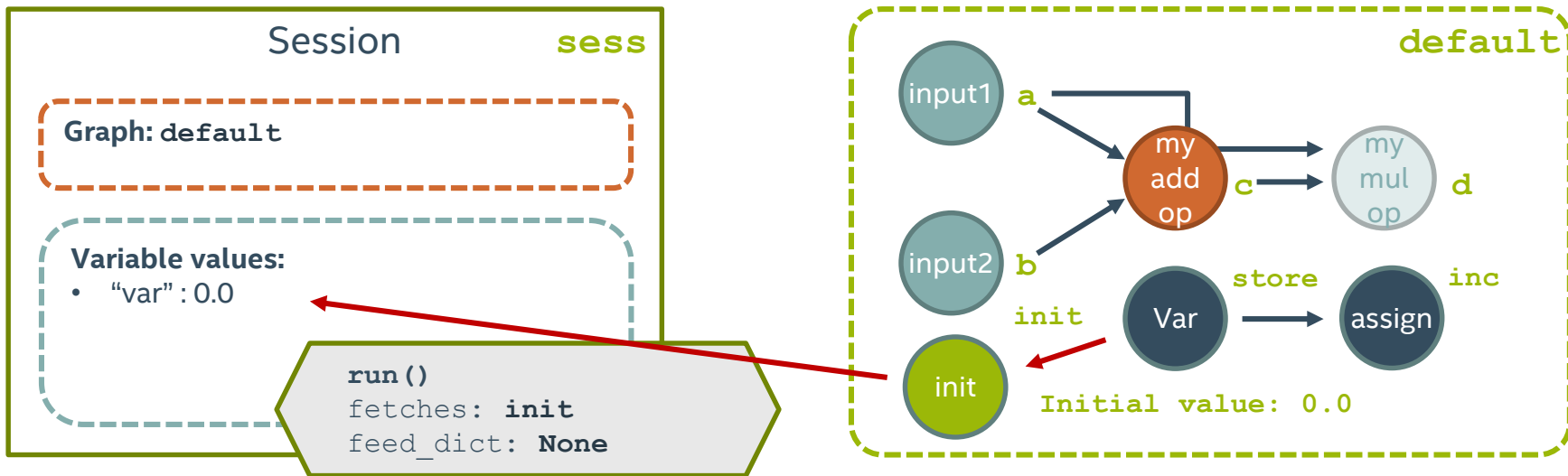
Then run the `init` Op in the Session we want to use the variables

```
>>> sess.run(init)
```



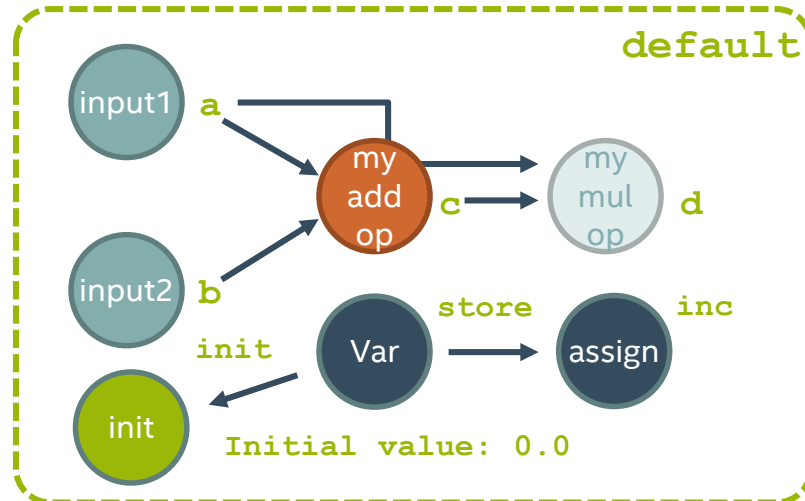
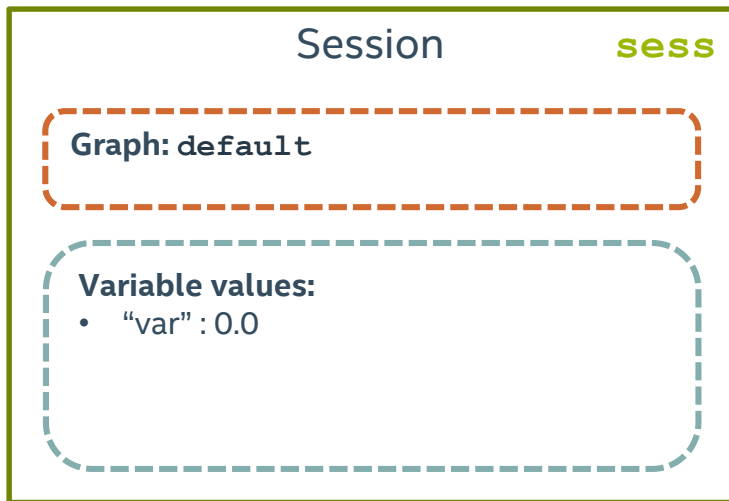
`init` reads the initial value from the variable and assigns it to the Session's store

```
>>> sess.run(init)
```



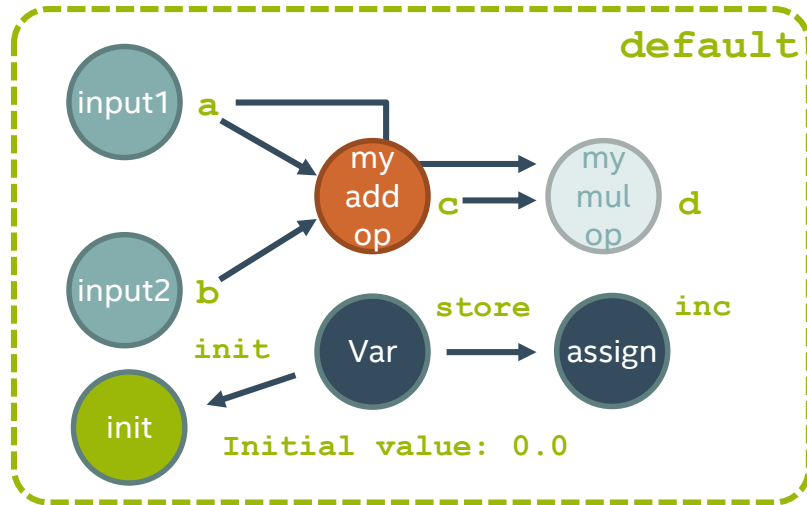
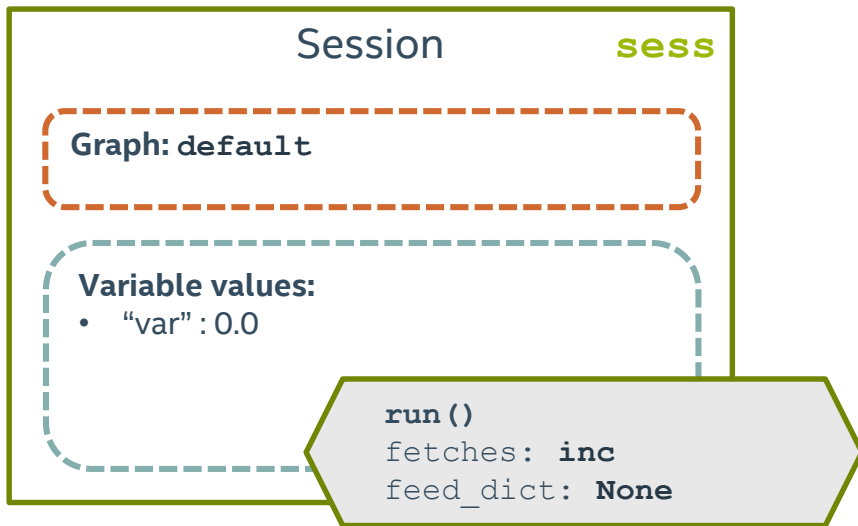
Now the `Session` will persist that value across multiple runs

```
>>>
```



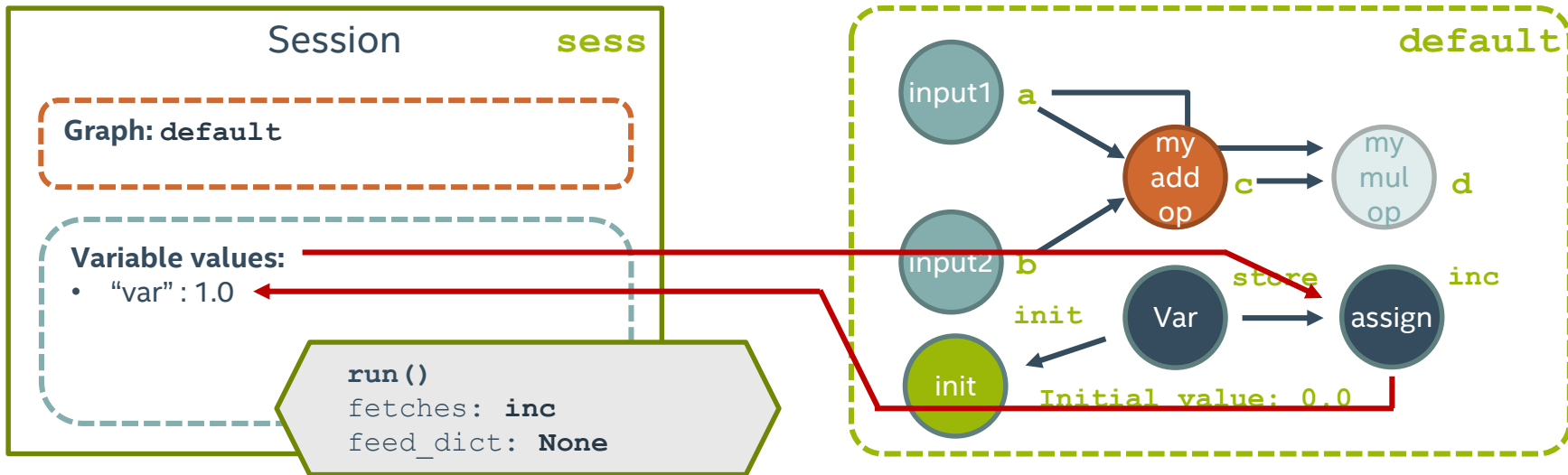
We can increment the value by one with our `inc` Op

```
>>> sess.run(inc)
```



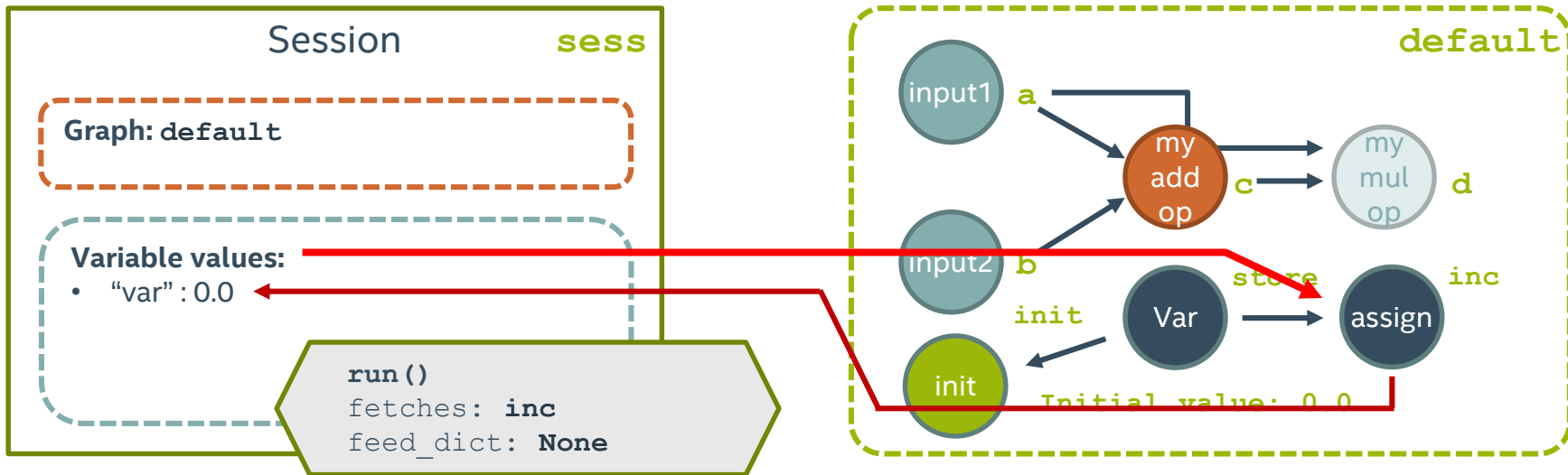
We can increment the value by one with `inc`

```
>>> sess.run(inc)
```



The assign Operation reads in the stored value from the Session

```
>>> sess.run(inc)
```



The Op calculates the new value ($0 + 1$) which is stored in the Session

```
>>> sess.run(inc)
```

