Introduction to Tensorflow

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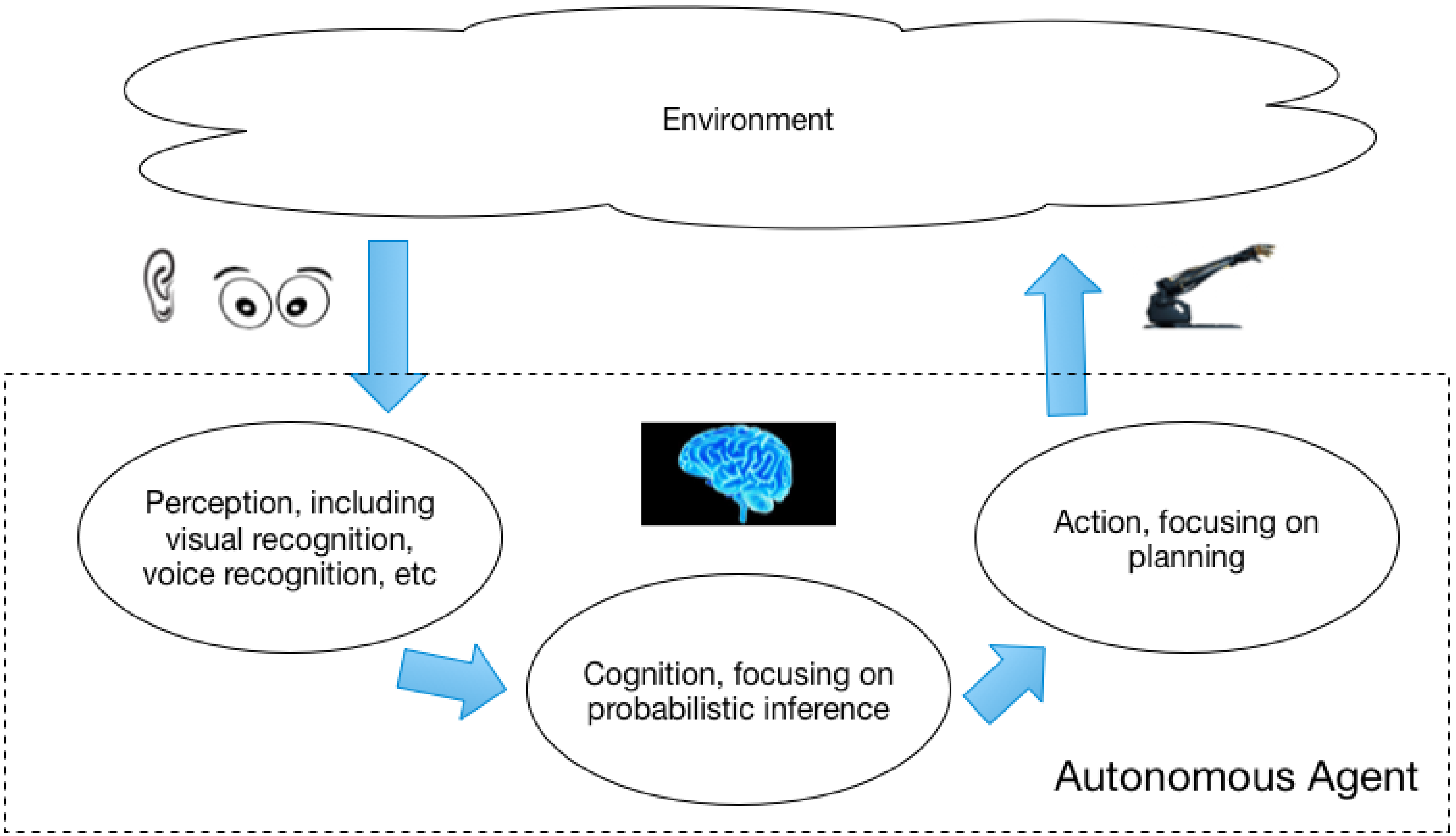
Up to now,

- Overview of Machine Learning
- Traditional Machine Learning Algorithms
- Deep Learning
  - Introduction
  - Functional view & features
  - Forward and backward computation
  - CNNs

Today's topic

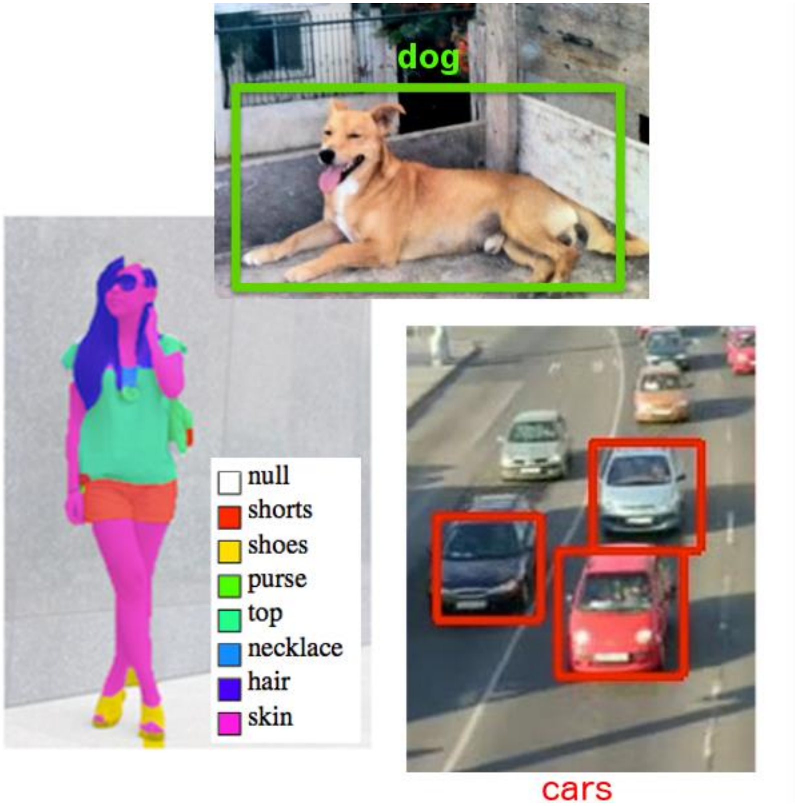
- Where learning is used?
- Introduction to Tensorflow
- Example: Linear Regression in TensorFlow

Perception-Cognition-Action Loop



Teaching content:
traditional learning,
deep learning

Perception



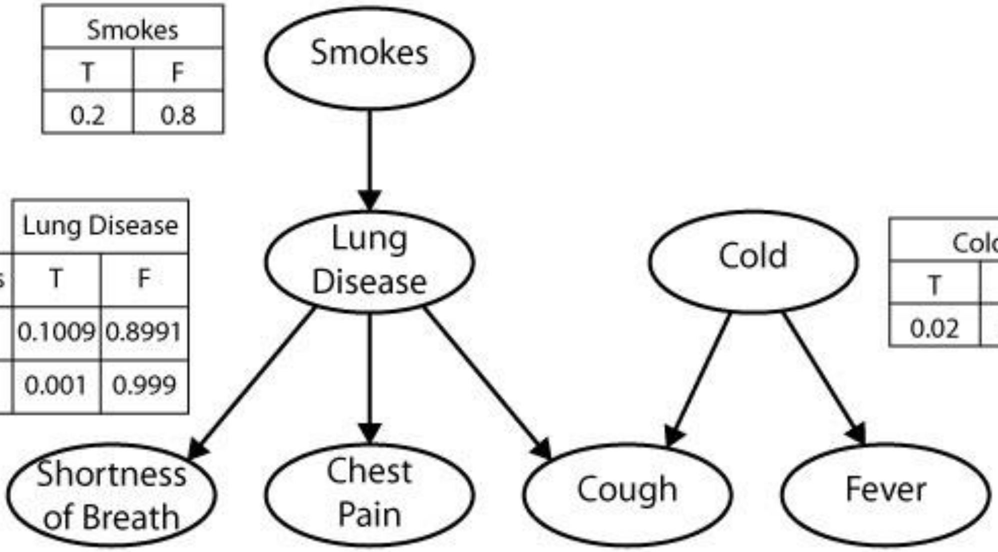
Visual Recognition

Voice Recognition

...

Teaching content:
Probabilistic graphical models

Cognition by Probabilistic Inference



Smokes	
T	F
0.2	0.8

	Lung Disease	
Smokes	T	F
T	0.1009	0.8991
F	0.001	0.999

Cold	
T	F
0.02	0.98

	Shortness of Breath	
Lung Disease	T	F
T	0.208	0.792
F	0.01	0.99

	Chest Pain	
Lung Disease	T	F
T	0.208	0.792
F	0.01	0.99

		Cough	
Lung Disease	Cold	T	F
T	T	0.7525	0.2475
T	F	0.505	0.495
F	T	0.505	0.495
F	F	0.01	0.99

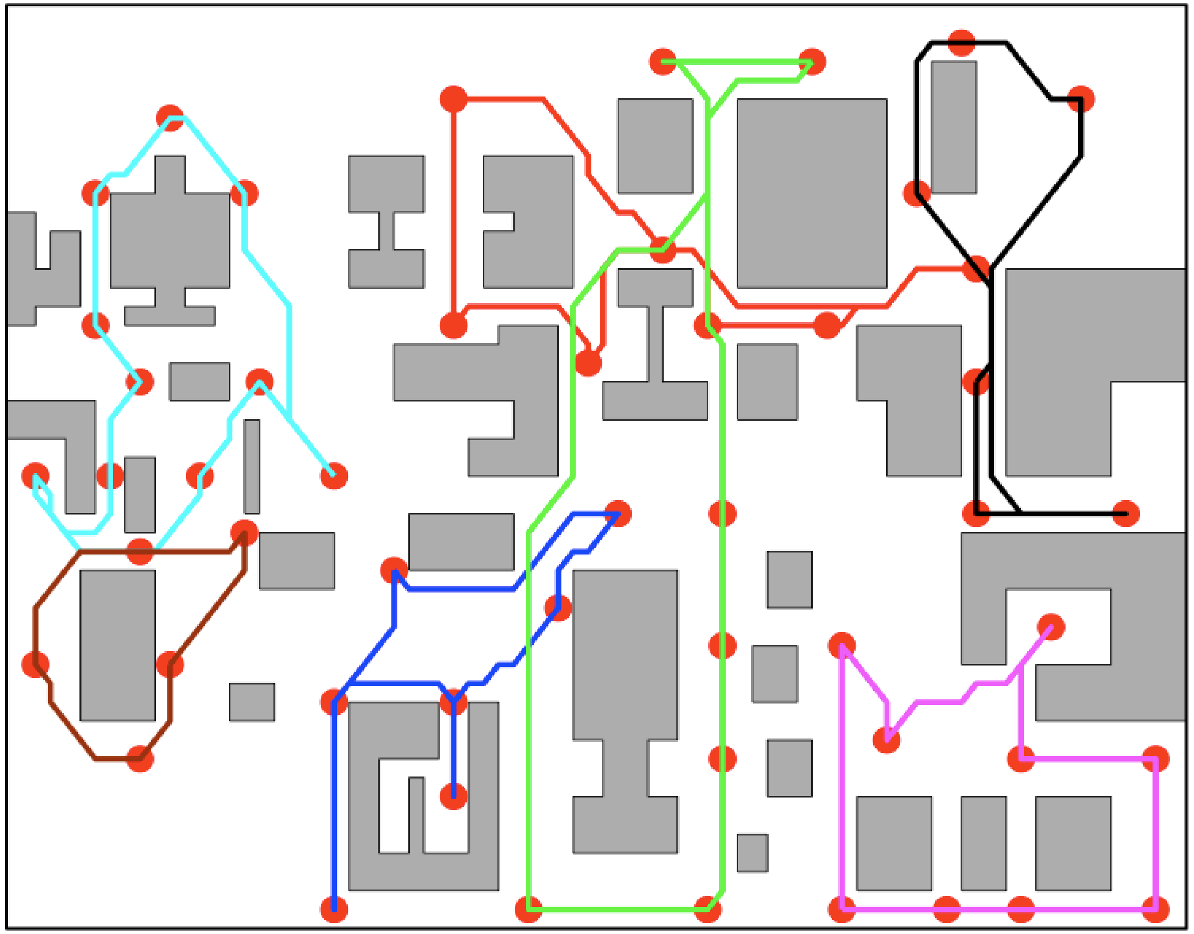
	Fever	
Cold	T	F
T	0.307	0.693
F	0.01	0.99

Q. how to automatically infer the disease (e.g., lung disease, cold, etc) from the symptoms (e.g., smokes, shortness of breath, chest pain, cough, fever, etc)?

Note: Symptoms obtained from perception.

Teaching content:
in other modules, e.g., COMP111, COMP222

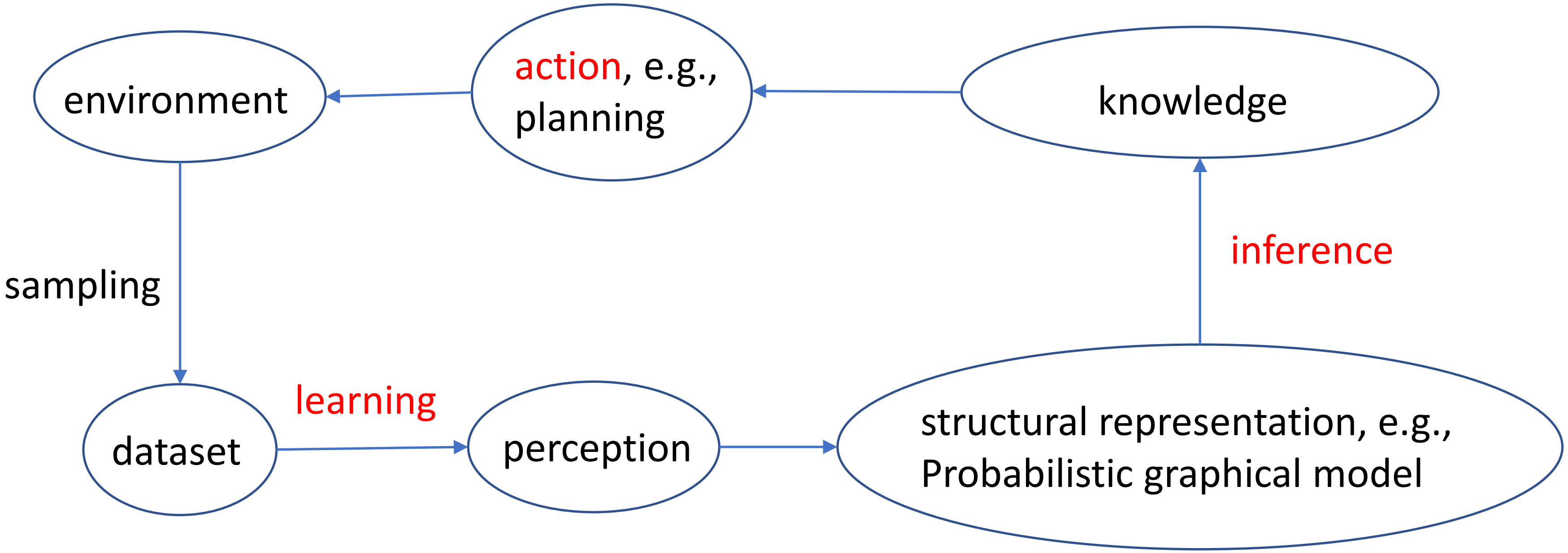
Action by Planning



After cognition, we may use the obtained knowledge to react to the environment

Q: in the factory floor as shown in the left diagram, how many robots is needed to patrol the area? and **how to plan** their activities?

What’s left?



environment
action, e.g.,
planning
knowledge
sampling
inference
dataset
learning
perception
structural representation, e.g.,
Probabilistic graphical model

Introduction to Tensorflow

Deep-Learning Package Design Choices

- Model specification:
  - Configuration file (e.g. Caffe, DistBelief, CNTK) versus
  - programmatic generation (e.g. Torch, Theano, Tensorflow)

I used these two

- For programmatic models, choice of high-level language:
  - Lua (Torch) vs. Python (Theano, Tensorflow) vs others.

- We chose to work with python because of rich community and library infrastructure.

What is TensorFlow?

- TensorFlow is a deep learning library open-sourced by Google.
- But what does it actually do?
  - TensorFlow provides primitives for defining functions on tensors and automatically computing their derivatives.

But what's a Tensor?

- Formally, tensors are multilinear maps from vector spaces to the real numbers (V vector space, and V* dual space)

$$f : \underbrace{V^* \times \cdots V^*}_{p \text{ copies}} \times \underbrace{V \times \cdots V}_{q \text{ copies}} \to \mathbb{R}$$

A scalar is a tensor ($f : \mathbb{R} \to \mathbb{R},\ f(e_1) = c$)

A vector is a tensor ($f : \mathbb{R}^n \to \mathbb{R},\ f(e_i) = v_i$)

A matrix is a tensor ($f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R},\ f(e_i, e_j) = A_{ij}$)

- Common to have fixed basis, so a tensor can be represented as a multidimensional array of numbers.

TensorFlow vs. Numpy

- Few people make this comparison, but TensorFlow and Numpy are quite similar. (Both are N-d array libraries!)
- Numpy has Ndarray support, but doesn't offer methods to create tensor functions and automatically compute derivatives (+ no GPU support).

VS

Simple Numpy Recap

```
In [23]: import numpy as np

In [24]: a = np.zeros((2,2)); b = np.ones((2,2))

In [25]: np.sum(b, axis=1)
Out[25]: array([ 2.,  2.])

In [26]: a.shape
Out[26]: (2, 2)

In [27]: np.reshape(a, (1,4))
Out[27]: array([[ 0.,  0.,  0.,  0.]])
```

Repeat in TensorFlow

More on Session soon

More on .eval() in a few slides

TensorShape behaves like a python tuple.

```
In [31]: import tensorflow as tf

In [32]: tf.InteractiveSession()

In [33]: a = tf.zeros((2,2)); b = tf.ones((2,2))

In [34]: tf.reduce_sum(b, reduction_indices=1).eval()
Out[34]: array([ 2.,  2.], dtype=float32)

In [35]: a.get_shape()
Out[35]: TensorShape([Dimension(2), Dimension(2)])

In [36]: tf.reshape(a, (1, 4)).eval()
Out[36]: array([[ 0.,  0.,  0.,  0.]], dtype=float32)
```

Numpy to TensorFlow Dictionary

Numpy	TensorFlow
`a = np.zeros((2,2)); b = np.ones((2,2))`	`a = tf.zeros((2,2)), b = tf.ones((2,2))`
`np.sum(b, axis=1)`	`tf.reduce_sum(a,reduction_indices=[1])`
`a.shape`	`a.get_shape()`
`np.reshape(a, (1,4))`	`tf.reshape(a, (1,4))`
`b * 5 + 1`	`b * 5 + 1`
`np.dot(a,b)`	`tf.matmul(a, b)`
`a[0,0], a[:,0], a[0,:]`	`a[0,0], a[:,0], a[0,:]`

TensorFlow requires explicit evaluation!

```
In [37]: a = np.zeros((2,2))

In [38]: ta = tf.zeros((2,2))

In [39]: print(a)
[[ 0.  0.]
 [ 0.  0.]]

In [40]: print(ta)
Tensor("zeros_1:0", shape=(2, 2), dtype=float32)

In [41]: print(ta.eval())
[[ 0.  0.]
 [ 0.  0.]]
```

TensorFlow computations define a ***computation graph*** *that has no numerical value until evaluated!*

TensorFlow Session Object (1)

- "A Session object encapsulates the environment in which Tensor objects are evaluated"

```
In [20]: a = tf.constant(5.0)

In [21]: b = tf.constant(6.0)

In [22]: c = a * b

In [23]: with tf.Session() as sess:
    ....:     print(sess.run(c))
    ....:     print(c.eval())
    ....:
30.0
30.0
```

c.eval() is just syntactic sugar for sess.run(c) in the currently active session!

TensorFlow Session Object (2)

- tf.InteractiveSession() is just convenient syntactic sugar for keeping a default session open in ipython.
- sess.run(c) is an example of a TensorFlow Fetch. Will say more on this soon

Tensorflow Computation Graph

- “TensorFlow programs are usually structured into
  - a construction phase, that assembles a graph, and
  - an execution phase that uses a session to execute ops in the graph.”
- All computations add nodes to global default graph

TensorFlow Variables (1)

- "When you train a model you use variables to hold and update parameters. Variables are in-memory buffers containing tensors"
- All tensors we've used previously have been constant tensors, not variables

TensorFlow Variables (2)

```
In [32]: W1 = tf.ones((2,2))

In [33]: W2 = tf.Variable(tf.zeros((2,2)), name="weights")

In [34]: with tf.Session() as sess:
             print(sess.run(W1))
             sess.run(tf.initialize_all_variables())
             print(sess.run(W2))
   ....:
[[ 1.  1.]
 [ 1.  1.]]
[[ 0.  0.]
 [ 0.  0.]]
```

Note the initialization step `tf.initialize_all_variables()`

TensorFlow Variables (3)

- TensorFlow variables must be initialized before they have values! Contrast with constant tensors

```
In [38]: W = tf.Variable(tf.zeros((2,2)), name="weights")

In [39]: R = tf.Variable(tf.random_normal((2,2)), name="random_weights")

In [40]: with tf.Session() as sess:
   ....:     sess.run(tf.initialize_all_variables())
   ....:     print(sess.run(W))
   ....:     print(sess.run(R))
   ....:
```

`Variable` objects can be initialized from constants or random values

Initializes all variables with specified values.

Updating Variable State

```
In [63]: state = tf.Variable(0, name="counter")

In [64]: new_value = tf.add(state, tf.constant(1))

In [65]: update = tf.assign(state, new_value)

In [66]: with tf.Session() as sess:
   ....:     sess.run(tf.initialize_all_variables())
   ....:     print(sess.run(state))
   ....:     for _ in range(3):
   ....:         sess.run(update)
   ....:         print(sess.run(state))
   ....:
0
1
2
3
```

Roughly `new_value = state + 1`

Roughly `state = new_value`

Roughly

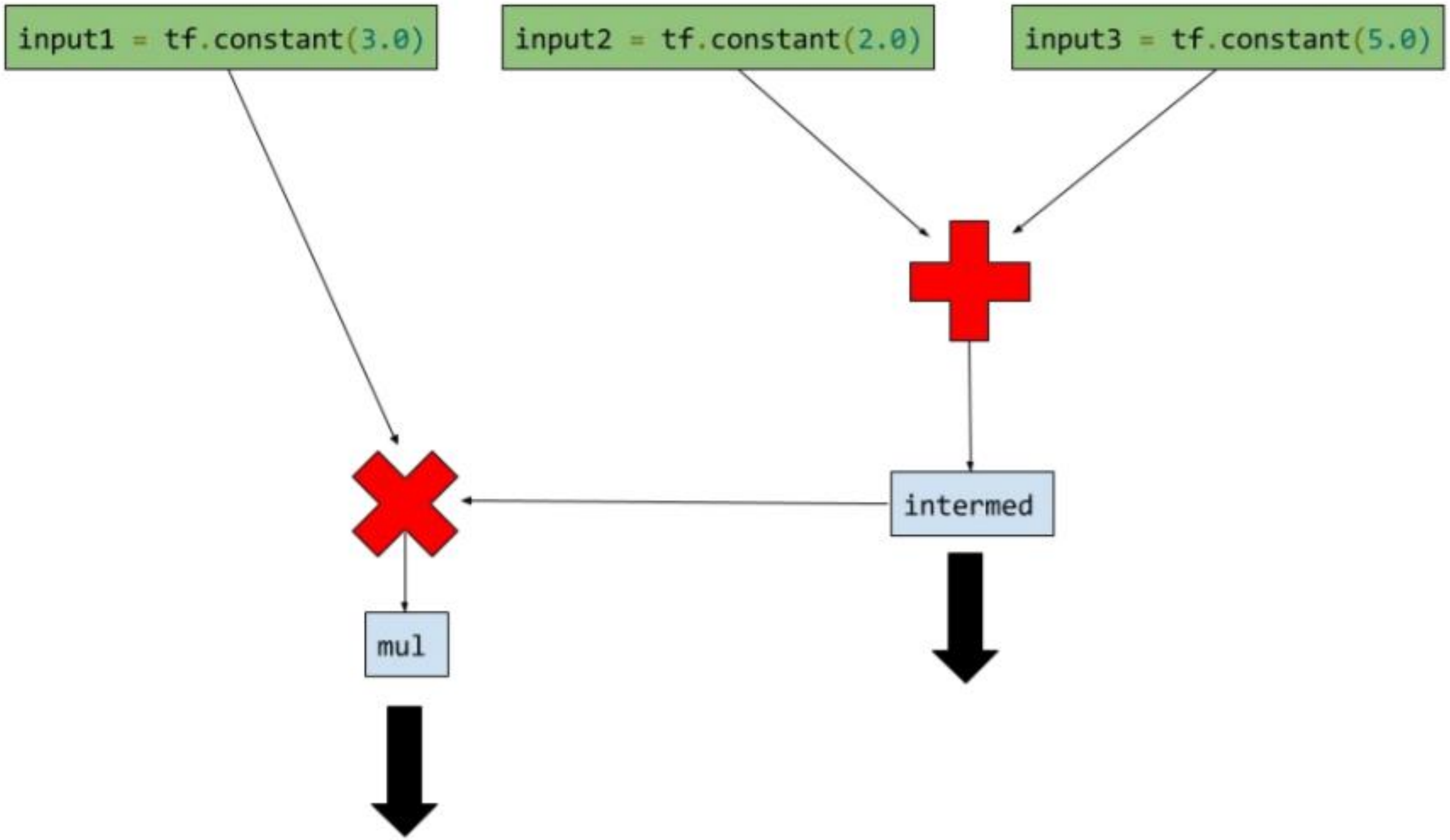
```
state = 0
print(state)
for _ in range(3):
  state = state + 1
  print(state)
```

Fetching Variable State (1)

```
In [82]: input1 = tf.constant(3.0)
In [83]: input2 = tf.constant(2.0)
In [84]: input3 = tf.constant(5.0)
In [85]: intermed = tf.add(input2, input3)
In [86]: mul = tf.mul(input1, intermed)
In [87]: with tf.Session() as sess:
   ....:     result = sess.run([mul, intermed])
   ....:     print(result)
   ....:
[21.0, 7.0]
```

Calling `sess.run(var)` on a `tf.Session()` object retrieves its value. Can retrieve multiple variables simultaneously with `sess.run([var1, var2])` (See *Fetches* in TF docs)

Fetching Variable State (2)



Inputting Data

- All previous examples have manually defined tensors. How can we input external data into TensorFlow?
- Simple solution: Import from Numpy:

```
In [93]: a = np.zeros((3,3))
In [94]: ta = tf.convert_to_tensor(a)
In [95]: with tf.Session() as sess:
    ....:     print(sess.run(ta))
    ....:
[[ 0.  0.  0.]
 [ 0.  0.  0.]
 [ 0.  0.  0.]]
```

Placeholders and Feed Dictionaries (1)

- Inputting data with tf.convert_to_tensor() is convenient, but doesn't scale.
- Use tf.placeholder variables (dummy nodes that provide entry points for data to computational graph).
- A feed_dict is a python dictionary mapping from tf. placeholder vars (or their names) to data (numpy arrays, lists, etc.).

Placeholders and Feed Dictionaries (2)

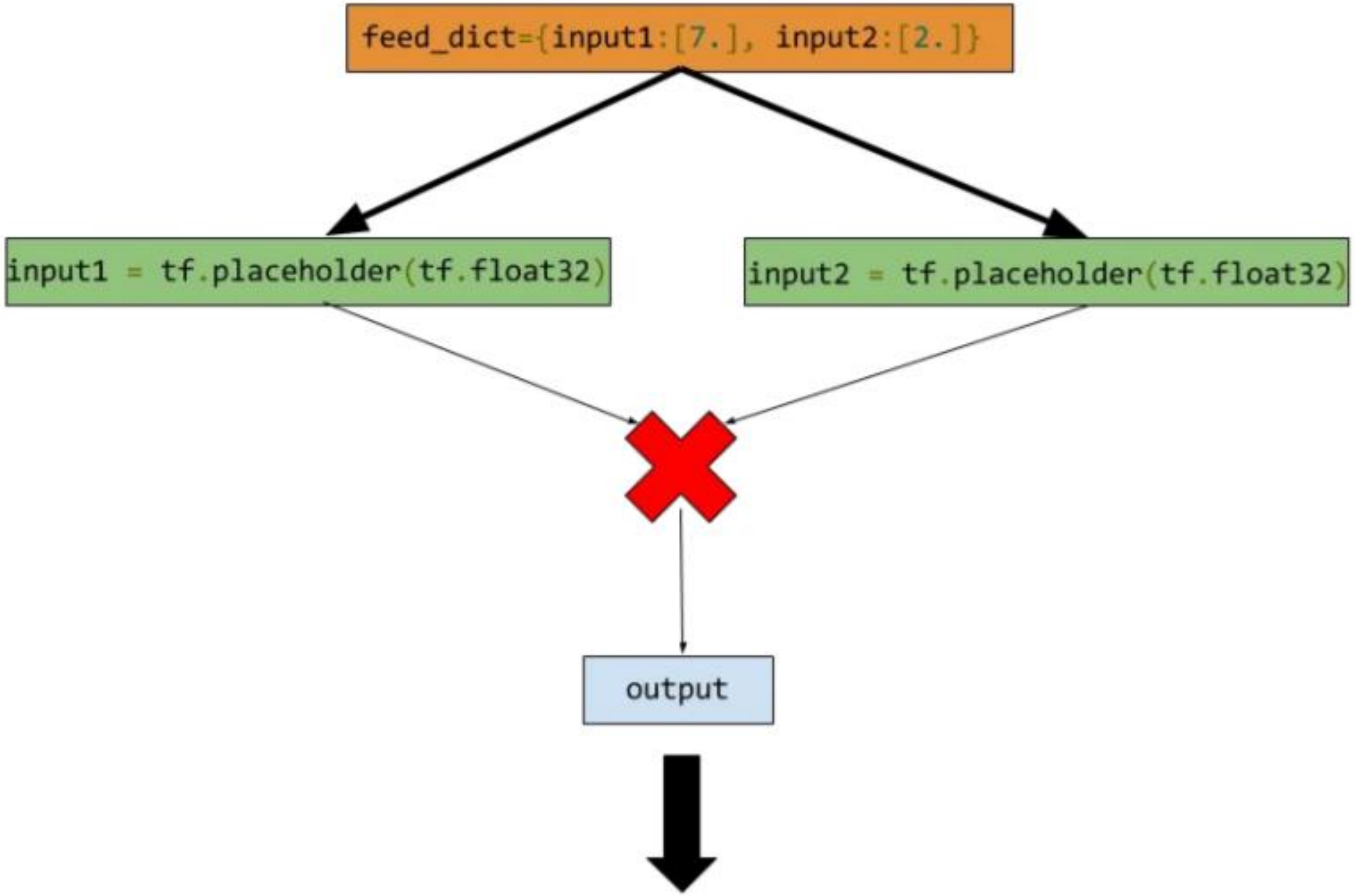
```
In [96]: input1 = tf.placeholder(tf.float32)

In [97]: input2 = tf.placeholder(tf.float32)

In [98]: output = tf.mul(input1, input2)

In [99]: with tf.Session() as sess:
   ....:       print(sess.run([output], feed_dict={input1:[7.], input2:[2.]}))
   ....:

[array([ 14.], dtype=float32)]
```

Define `tf.placeholder` *objects for data entry.*

Fetch value of output from computation graph.

Feed data into computation graph.

Placeholders and Feed Dictionaries (3)



Variable Scope (1)

- Complicated TensorFlow models can have hundreds of variables.
  - tf.variable_scope() provides simple name-spacing to avoid clashes.
  - tf.get_variable() creates/accesses variables from within a variable scope.

Variable Scope (2)

- Variable scope is a simple type of namespacing that adds prefixes to variable names within scope

```
with tf.variable_scope("foo"):
    with tf.variable_scope("bar"):
        v = tf.get_variable("v", [1])
assert v.name == "foo/bar/v:0"
```

Variable Scope (3)

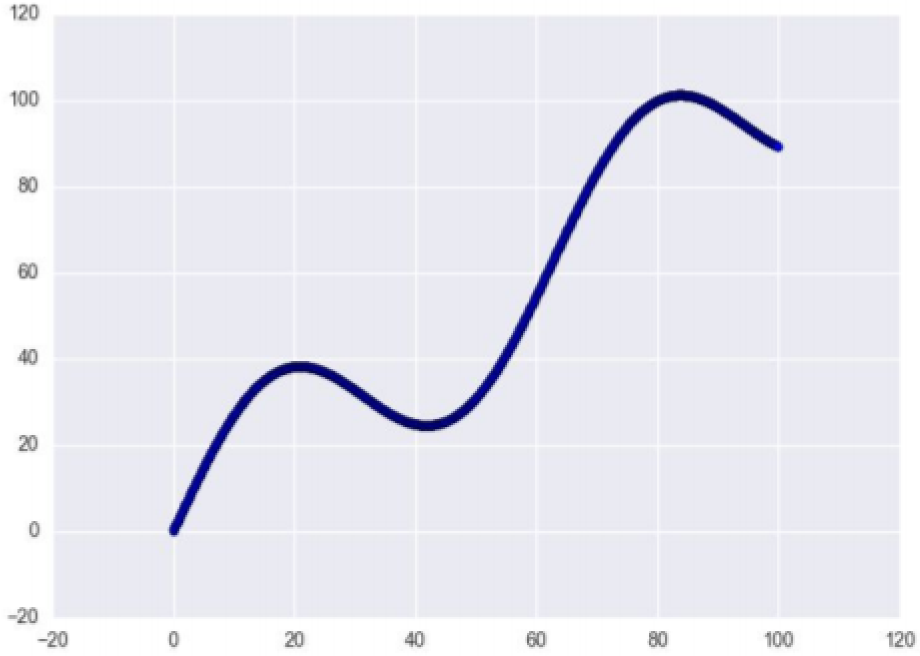
- Variable scopes control variable (re)use

```
with tf.variable_scope("foo"):
    v = tf.get_variable("v", [1])
    tf.get_variable_scope().reuse_variables()
    v1 = tf.get_variable("v", [1])
assert v1 == v
```

- You'll need to use reuse_variables() to implement RNNs in homework

Ex: Linear Regression in TensorFlow (1)

```
import numpy as np
import seaborn

# Define input data
X_data = np.arange(100, step=.1)
y_data = X_data + 20 * np.sin(X_data/10)

# Plot input data
plt.scatter(X_data, y_data)
```



Ex: Linear Regression in TensorFlow (2)

```
# Define data size and batch size
n_samples = 1000
batch_size = 100

# Tensorflow is finicky about shapes, so resize
X_data = np.reshape(X_data, (n_samples,1))
y_data = np.reshape(y_data, (n_samples,1))

# Define placeholders for input
X = tf.placeholder(tf.float32, shape=(batch_size, 1))
y = tf.placeholder(tf.float32, shape=(batch_size, 1))
```

Ex: Linear Regression in TensorFlow (3)

```
# Define variables to be learned
with tf.variable_scope("linear-regression"):
  W = tf.get_variable("weights", (1, 1),
                      initializer=tf.random_normal_initializer())
  b = tf.get_variable("bias", (1,),
                      initializer=tf.constant_initializer(0.0))
  y_pred = tf.matmul(X, W) + b
  loss = tf.reduce_sum((y - y_pred)**2/n_samples)
```

*Note **reuse=False** so these tensors are created anew*

$$J(W,b) = \frac{1}{N}\sum_{i=1}^{N}(y_i - (Wx_i + b))^2$$

Ex: Linear Regression in TensorFlow (4)

```
# Sample code to run one step of gradient descent
In [136]: opt = tf.train.AdamOptimizer()

In [137]: opt_operation = opt.minimize(loss)

In [138]: with tf.Session() as sess:
   .....:     sess.run(tf.initialize_all_variables())
   .....:     sess.run([opt_operation], feed_dict={X: X_data, y: y_data})
   .....:
```

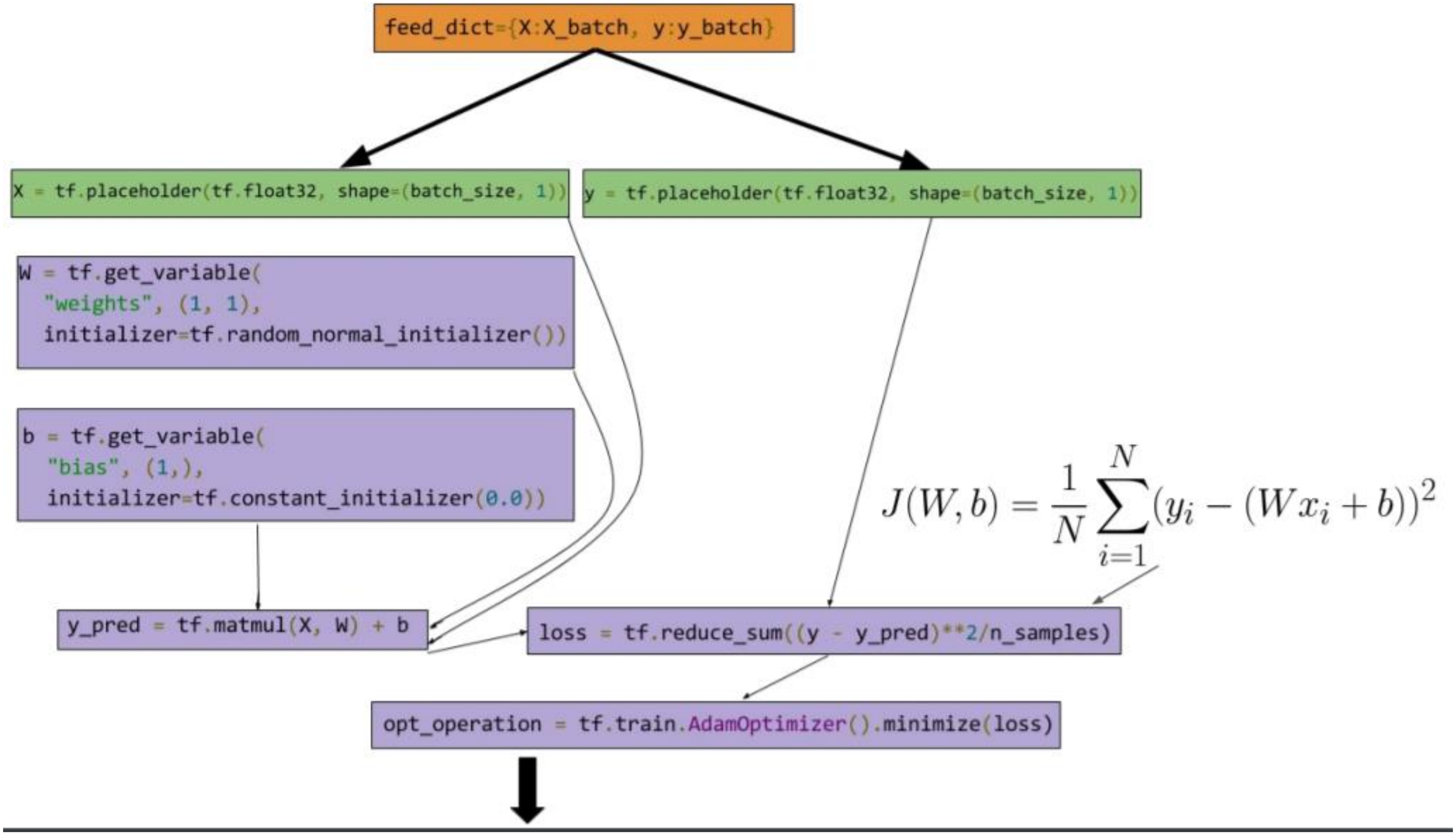
Note TensorFlow scope is not python scope! Python variable `loss` is still visible.

But how does this actually work under the hood? Will return to TensorFlow computation graphs and explain.

Ex: Linear Regression in TensorFlow (4)

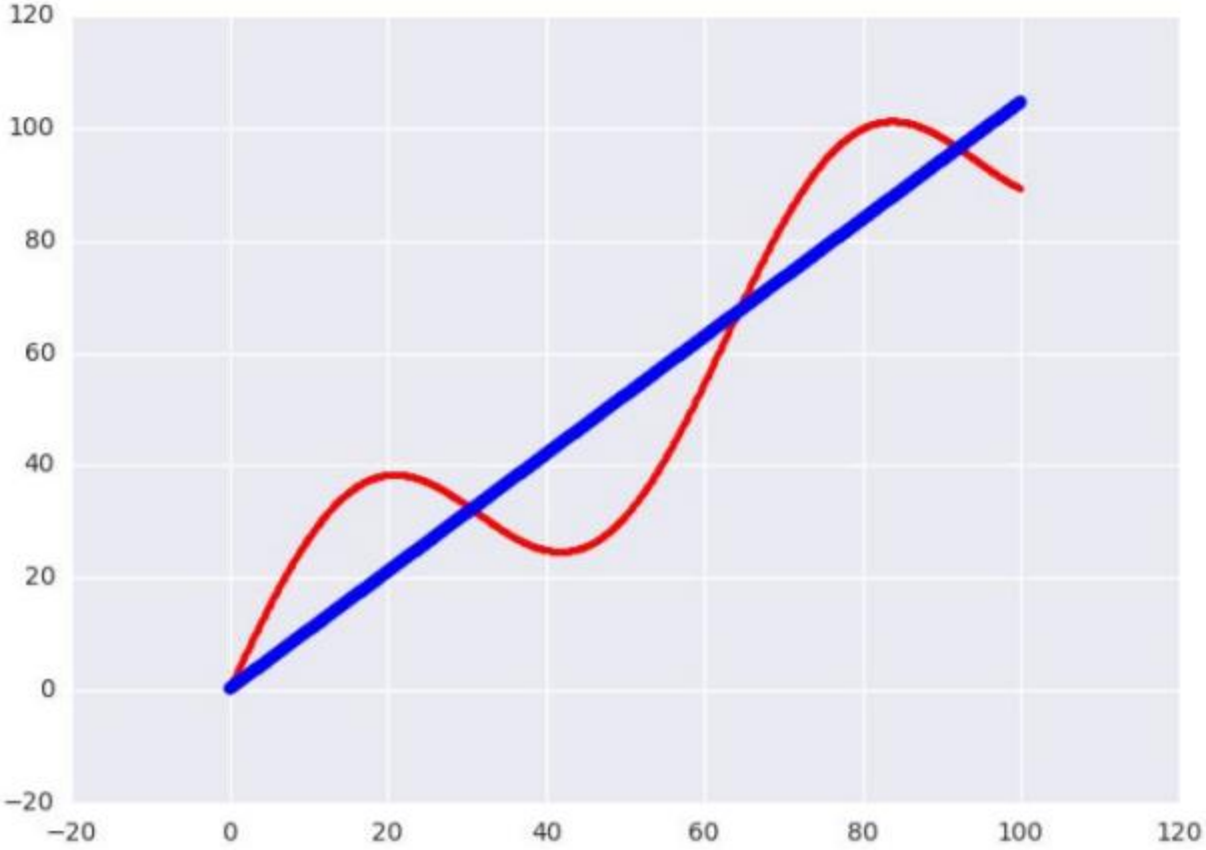
```
# Sample code to run full gradient descent:
# Define optimizer operation
opt_operation = tf.train.AdamOptimizer().minimize(loss)

with tf.Session() as sess:
  # Initialize Variables in graph
  sess.run(tf.initialize_all_variables())
  # Gradient descent loop for 500 steps
  for _ in range(500):
    # Select random minibatch
    indices = np.random.choice(n_samples, batch_size)
    X_batch, y_batch = X_data[indices], y_data[indices]
    # Do gradient descent step
    _, loss_val = sess.run([opt_operation, loss], feed_dict={X: X_batch, y: y_batch})
```

Let's do a deeper. graphical dive into this operation



feed_dict={X:X_batch, y:y_batch}
X = tf.placeholder(tf.float32, shape=(batch_size, 1))
y = tf.placeholder(tf.float32, shape=(batch_size, 1))
W = tf.get_variable(
"weights", (1, 1),
initializer=tf.random_normal_initializer())
b = tf.get_variable(
"bias", (1,),
initializer=tf.constant_initializer(0.0))
$J(W,b) = \frac{1}{N}\sum_{i=1}^{N}(y_i - (Wx_i + b))^2$
y_pred = tf.matmul(X, W) + b
loss = tf.reduce_sum((y - y_pred)**2/n_samples)
opt_operation = tf.train.AdamOptimizer().minimize(loss)

Ex: Linear Regression in TensorFlow (6)



Learned model offers nice fit to data.

Concept: Auto-Differentiation

- Linear regression example computed L^2 loss for a linear regression system. How can we fit model to data?
  - tf.train.Optimizer creates an optimizer.
  - tf.train.Optimizer.minimize(loss, var_list) adds optimization operation to computation graph.
- Automatic differentiation computes gradients without user input!

TensorFlow Gradient Computation

- TensorFlow nodes in computation graph have attached gradient operations.
- Use backpropagation (using node-specific gradient ops) to compute required gradients for all variables in graph.

TensorBoard

- TensorFlow has some neat built-in visualization tools (TensorBoard).
- We won't use TensorBoard for assignments, but encourage you to check it out for your projects.