# STATS 507
# Data Analysis in Python

Lecture 24: TensorFlow

# TensorFlow

Open source symbolic math library
- Popular in ML, especially for neural networks

Developed by GoogleBrain
- Google's AI/Deep learning division
- You may recall their major computer vision triumph circa 2012:
  http://www.nytimes.com/2012/06/26/technology/in-a-big-network-of-computers-evidence-of-machine-learning.html

TensorFlow is **not** new, and **not** very special:
- Many other symbolic math programs predate it!
- **TensorFlow is unique in how quickly it gained so much market share**
- Open-sourced only in 2015…
- ...and almost immediately became the dominant framework for NNs

# TensorFlow: Installation

Easiest: `pip install tensorflow==1.14`

Also easy: install in anaconda

TensorFlow updated to version 2.0 over the summer, which introduces a few difficulties for us (more on this on the next slide). So we will use version 1.14.

More information: https://www.tensorflow.org/install/

**Note:** if you want to do fancier things (e.g., run on GPU instead of CPU), installation and setup gets a lot harder. For this course, we're not going to worry about it. In general, for running on a GPU, if you don't have access to a cluster with existing TF installation, you should consider paying for Amazon/GoogleCloud instances.

# Aside: TensorFlow, Versions and Upgrading

Over the summer, TensorFlow introduced version 2.0

This new version of TensorFlow made some fundamental changes

- Added built-in support for Keras https://en.wikipedia.org/wiki/Keras
- Added tricks for computational speedups such as eager execution
  - https://en.wikipedia.org/wiki/Eager_evaluation
- Streamlined code surrounding running models (more on this soon)

**But Google Cloud Platform has not yet implemented support for TensorFlow2.0**

- So we will continue to use 1.X

**Warning:** all our slides will be about TensorFlow v1.X. Be careful when you go to read the documentation, because most of the TensorFlow docs will default to 2.0. The TF version 1 documentation is archived here: https://github.com/tensorflow/docs/tree/master/site/en/r1

# Fundamental concepts of TensorFlow

**Tensor**

Recall that a tensor is really just an array of numbers
"Rank" of a tensor is the number of dimensions it has
So, a matrix is a rank-2 tensor, vector is rank 1, scalar rank 0
A cube of numbers is a 3-tensor, and so on

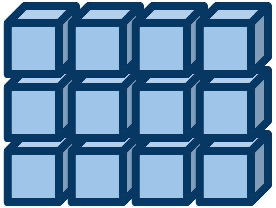
**Computational graph**

Directed graph that captures the "flow" of data through the program
Nodes are operations (i.e., computations)
Edges represent data sent between operations

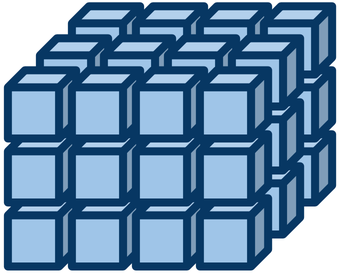
# Tensors

0-tensor (scalar)

1-tensor (vector)



2-tensor (matrix)



3-tensor

**Note:** most things you read will call this dimension the *rank* of the tensor, but you should know that some mathematicians use *rank* to mean the tensor generalization of linear algebraic rank. These people will usually use the term *order* instead.

# Tensors: `tf.Tensor` objects

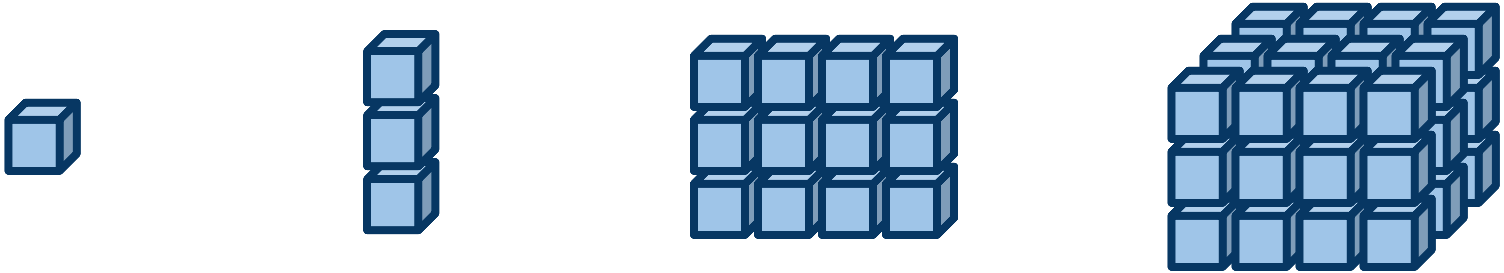
Tensors are represented in TensorFlow as `tf.Tensor` objects

Every `tf.Tensor` object has:

- data type (e.g., int, float, string, …)
- shape (e.g., 2-by-3-by-5, 5-by-5, 1-by-1, etc)
  - Shape encodes both rank **and** ‘length’ of each dimension

`tf.Tensor` objects are, in general, immutable

- with slight exceptions, which we’ll talk about soon



# Special `tf.Tensor()` objects

`tf.Constant`: will not change its value during your program.

Like an immutable tensor

`tf.Placeholder`: gets its value from elsewhere in your program

E.g., from training data or from results of other Tensor computations

`tf.Variable`: represents a tensor whose value may change during execution

Unlike above `tf.Tensor` types, `tf.Variables` are **mutable**

Useful for ML, because we want to update parameters during training

`tf.SparseTensor`: most entries of a `SparseTensor` will be zero

TF stores this differently; saves on memory

Useful for applications where data is sparse, such as networks

# Special `tf.Tensor()` objects

`tf.Constant`: will not change its value during your program.

- Like an immutable tensor

`tf.Placeholder`: gets its value from elsewhere in your program

- E.g., from training data or from results of other Tensor computations

`tf.Variable`: represents a tensor whose value may change during execution

- Unlike above `tf.Tensor` types, `tf.Variables` are **mutable**
- Useful for ML, because we want to update parameters during training

`tf.SparseTensor`: most entries of a `SparseTensor` will be zero

For now, these three are the important ones.

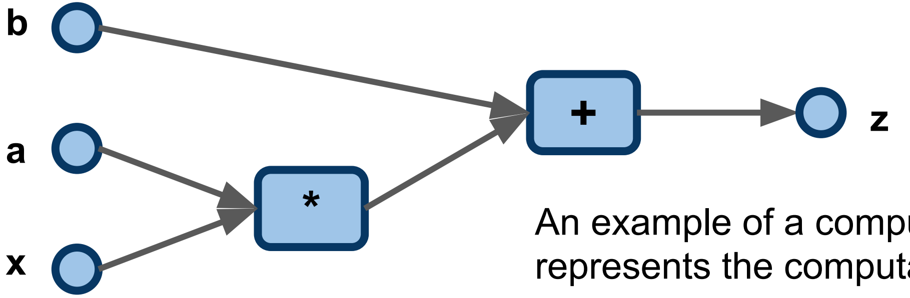
# Computational Graph

From the "Getting Started" guide: "A **computational graph** is a series of TensorFlow operations arranged into a graph of nodes."

Every node takes zero or more tensors as input and outputs one or more tensors.

A TensorFlow program consists, essentially, of two sections:

1) Building the computational graph
2) Running the computational graph




An example of a computational graph that represents the computation `z = a*x + b`.

# TF as Dataflow

**Dataflow** is a term for frameworks in which computation is concerned with the **pipeline** by which the data is processed

- Data transformed and combined via a series of operations
- This view makes it clear when parallelization is possible…
- ...because dependence between operations can be read off the graph
- https://en.wikipedia.org/wiki/Dataflow
- https://en.wikipedia.org/wiki/Stream_processing

This should sound familiar from PySpark!

# Building the Computational Graph

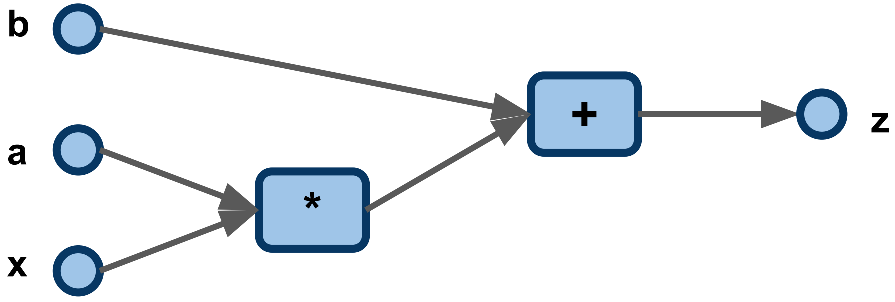
Here's a snippet of a TF program, in which we define a computational graph.

```
# Now we define some variables
a = tf.constant(2, dtype=tf.float32)
b = tf.constant(1, dtype=tf.float32)
x = tf.placeholder(tf.float32)

z = a*x + b
```

**Note:** depending on what version of numpy you are running, you may get warnings that "Passing (type, 1) or '1type' as a synonym of type is deprecated." You can safely ignore these warnings.

Equivalent computational graph:



# Building the Computational Graph

Here's a snippet of a TF program, in which we define a computational graph.

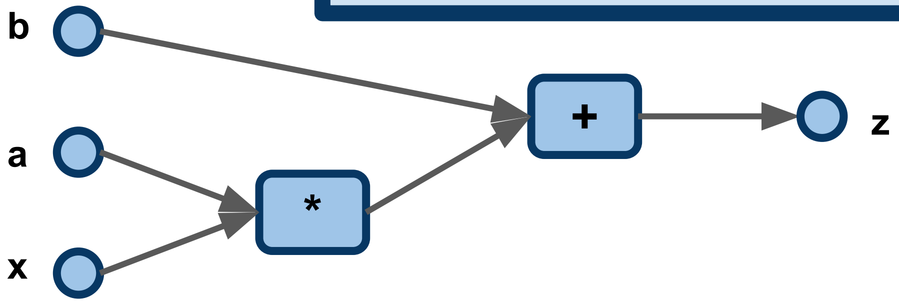
```
# Now we define some variables
a = tf.constant(2, dtype=tf.float32)
b = tf.constant(1, dtype=tf.float32)
x = tf.placeholder(tf.float32)

z = a*x + b
```

`tf.constant` is a TF tensor whose value will not change. This is the TF analogue of an immutable type.

`tf.placeholder` is a TF tensor whose value will be assigned at runtime, after building the graph.

Equivalent computational graph:



# Building the Computational Graph

```
sess = tf.Session()
a = tf.constant(2, dtype=tf.float32)
x = tf.placeholder(tf.float32)
adder_node1 = a + x
adder_node2 = tf.add(a,x)
print(adder_node1)
print(adder_node2)
```

```
Tensor("add_22:0", dtype=float32)
Tensor("Add_4:0", dtype=float32)
```

```
print(sess.run(adder_node1, {x:10}))
print(sess.run(adder_node2, {x:10}))
```

```
12.0
12.0
```

`+` Is just short for the `tf.add()` function.

Similarly, `*` is short for the `tf.multiply()` function.

# Building the Computational Graph

```
sess = tf.Session()

a = tf.constant(2, dtype=tf.float32)
b = tf.constant(1, dtype=tf.float32)
x = tf.placeholder(tf.float32)
z = a*x + b

print a
print x
print z
```

These are all `tf.Tensor` objects.

```
Tensor("Const_34:0", shape=(), dtype=float32)
Tensor("Placeholder_19:0", dtype=float32)
Tensor("add_17:0", dtype=float32)
```

```
print sess.run(z, {x: 4})
print sess.run(z, {x: 5})
```

```
9.0
11.0
```

Variables don't have values until you run the graph!

# Running TensorFlow

```python
import tensorflow as tf

# Before we can actually do anything,
# we have to start a session.
sess = tf.Session()

# Now we define some variables
a = tf.constant(2, dtype=tf.float32)
b = tf.constant(1, dtype=tf.float32)
x = tf.placeholder(tf.float32)

z = a*x + b

# Run the code, print the result.
print sess.run(z, {x: 4})

# Close the session
sess.close()
```

```
9.0
```

Operations are defined here, but we still haven't actually computed anything, yet...

Computation only carried out once we give a value to x and ask TF to run the graph.

# Data types in TensorFlow

Every `tf.Tensor()` object has a data type, accessed through the `dtype` attribute.

```
helloworld = tf.constant('hello world!')
print helloworld.dtype
ramanujan = tf.constant(1729, dtype=tf.int16)
print ramanujan.dtype
approxpi = tf.constant(3.14159, dtype=tf.float32)
print approxpi.dtype
imaginary = tf.constant((0.0,1.0), dtype=tf.complex64)
print imaginary.dtype
```

```
<dtype: 'string'>
<dtype: 'int16'>
<dtype: 'float32'>
<dtype: 'complex64'>
```

**Four basic data types:**

- Strings
- Integers
- Floats
- Complex numbers

Some flexibility in specifying precision

**Note:** if no `dtype` is specified, TF will do its best to figure it out from context, but this doesn't always go as expected, such as when you want a vector of complex numbers. When in doubt, specify!

# Creating Tensors

These are all rank-0 tensors. Yes, `tf.string` is a single item, and so is `tf.complex`.

```
helloworld = tf.constant('hello world!', dtype=tf.string)
ramanujan = tf.constant(1729, dtype=tf.int16)
approxpi = tf.constant(3.14159, dtype=tf.float32)
imaginary = tf.constant((0.0,1.0), dtype=tf.complex64)
```

To create a 1-tensor (i.e., a vector), just pass a list of scalars.

```
fibonacci = tf.constant([0,1,1,2,3,5,8,13,21], dtype=tf.int8)
animals = tf.constant(['dog','cat','bird','goat'], dtype=tf.string)
print animals
```

```
Tensor("Const_143:0", shape=(4,), dtype=string)
```

**Note:** all elements of a `tf.Tensor` must be of the same datatype. The one sneaky way around this is to serialize objects to strings and store them in a tensor with `dtype=tf.string`.

# Creating Tensors

```
onebyonemx = tf.constant([[3.1415]], dtype=tf.float32)
print onebyonemx
```

```
Tensor("Const_170:0", shape=(1, 1), dtype=float32)
```

```
onevec = tf.constant([3.1415], dtype=tf.float32)
print onevec
```

```
Tensor("Const_171:0", shape=(1,), dtype=float32)
```

```
scalar = tf.constant(3.1415, dtype=tf.float32)
print scalar
```

```
Tensor("Const_172:0", shape=(), dtype=float32)
```

We can create a 1-by-1 matrix, which is **different** from a 1-vector, which is different from a scalar.

# Creating Tensors

```
identity = tf.constant([[1,0,0],[0,1,0],[0,0,1]], dtype=tf.float32)
print identity
```

```
Tensor("Const_144:0", shape=(3, 3), dtype=float32)
```

To create a matrix, we can pass a list of its rows.

```
oneThruNine = tf.constant([[1,2,3],[4,5,6],[7,8,9]], dtype=tf.float32)
with sess.as_default():
    print oneThruNine.eval()
```

```
[[ 1.  2.  3.]
 [ 4.  5.  6.]
 [ 7.  8.  9.]]
```

Matrix populated in row-major order.

# Creating Tensors

```
identity = tf.constant([[1,0,0],[0,1,0],[0,0,1]], dtype=tf.float32)
print identity
```

```
Tensor("Const_144:0", shape=(3, 3), dtype=float32)
```

To create a matrix, we can pass a list of its rows.

```
oneThruNine = tf.constant([[1,2,3],[4,5,6],[7,8,9]], dtype=tf.float32)
with sess.as_default():
    print oneThruNine.eval()
```

```
[[ 1.  2.  3.]
 [ 4.  5.  6.]
 [ 7.  8.  9.]]
```

The `eval()` method actually computes a tensor's value and returns it as a numpy array. `eval()` has to be run within a given session designated as "default", so we specify `sess` as the default. More on this in a few slides.

# Creating Tensors

Create a 10-by-10 matrix of all ones

```
J = tf.ones([10,10])
print J
```

```
Tensor("ones_2:0", shape=(10, 10), dtype=float32)
```

Create a 4-tensor, which we could use to represent one second of 720p color video (27 frames per second, 1280x720 resolution, 3 colors)

```
video = tf.zeros([27,1280,720,3])
print video
```

```
Tensor("zeros_1:0", shape=(27, 1280, 720, 3), dtype=float32)
```

# Tensor shape

**Rank:** number of dimensions

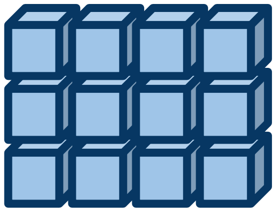
**Shape:** sizes of the dimensions

```
video = tf.zeros([27,1280,720,3])
print video
```

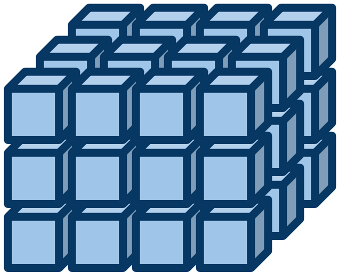
```
Tensor("zeros_3:0", shape=(27, 1280, 720, 3), dtype=float32)
```

```
print video.shape
```

```
(27, 1280, 720, 3)
```



Rank 2, shape 3-by-4



Rank 3, shape 3-by-4-by-3

**Note:** This looks like a tuple, but it is actually its own special type, `tf.TensorShape`

# More about tensor rank

```
video = tf.zeros([27,1280,720,3])
print video
```

```
Tensor("zeros_4:0", shape=(27, 1280, 720, 3), dtype=float32)
```

```
r = tf.rank(video)
```

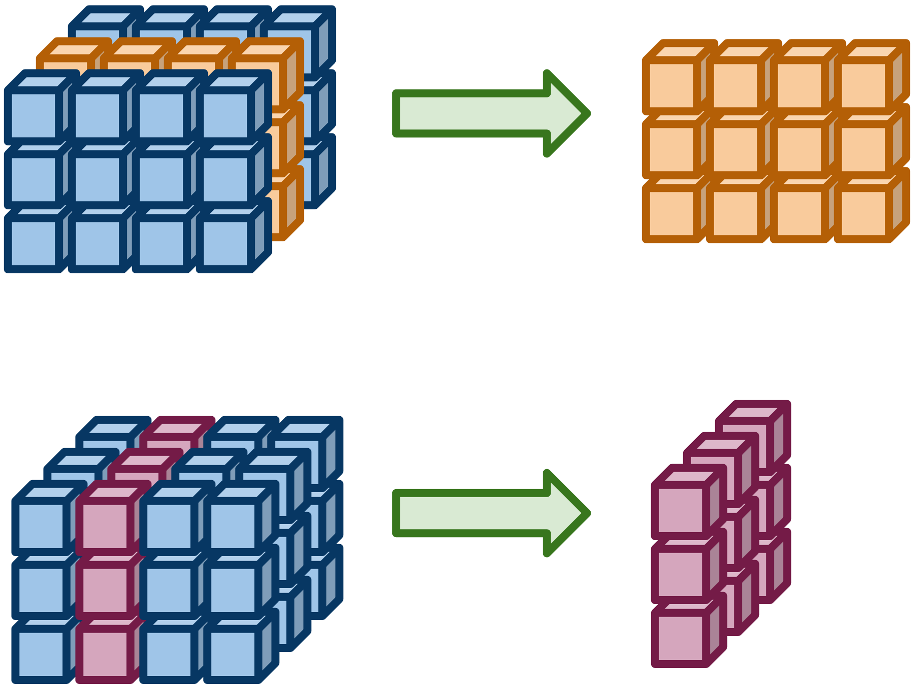
```
len(video.shape)
```

```
4
```

`r` will only get a value once we run the computational graph. There are good design reasons behind this: if the rank of our tensor depends on other inputs or variables, then we can't know the rank of the tensor until runtime!

If the tensor is already populated (so that its rank is already established), one can simply look at the length of its shape object to get the rank.

# Tensor slices



It is often natural to refer to certain subsets of the entries of a tensor. A “subtensor” of a tensor is often called a **slice**, and the operation of picking out a slice is called **slicing** the tensor.

# Tensor slices

```
fibovec = tf.constant([0,1,1,2,3,5,8,13,21], dtype=tf.int8)
print( fibovec )
```

```
Tensor("Const_3:0", shape=(9,), dtype=int8)
```

One index is enough to specify a number in a vector (i.e., a 1-tensor)

```
print( fibovec[0] )
```

```
Tensor("strided_slice:0", shape=(), dtype=int8)
```

Need two indices to pick out an entry of a matrix (i.e., a 2-tensor)

```
J = tf.ones([4,3], dtype=tf.float32)
print( J[1,2] )
```

```
Tensor("strided_slice_1:0", shape=(), dtype=float32)
```

# Tensor slices

Use `':'` to pick out all entries along a row or column.

```
J = tf.ones([4,3])
print J
```

```
Tensor("ones_3:0", shape=(4, 3), dtype=float32)
```

```
print J[1,2]
```

```
Tensor("strided_slice_13:0", shape=(), dtype=float32)
```

```
print J[1,:]
```

Create a vector from the second (zero-indexing!) row of the matrix.

```
Tensor("strided_slice_14:0", shape=(3,), dtype=float32)
```

```
print J[:,2]
```

Create a vector from the third column of the matrix.

```
Tensor("strided_slice_15:0", shape=(4,), dtype=float32)
```

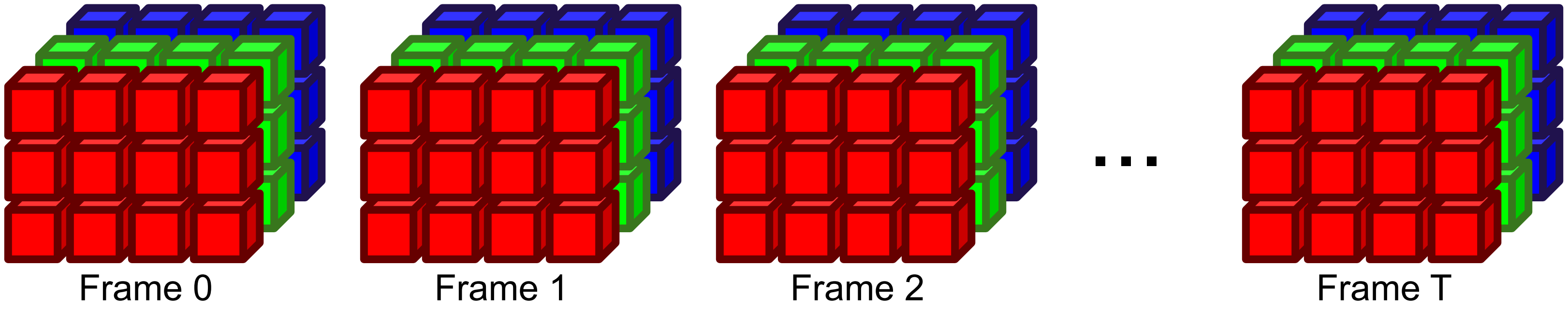
**Note:** result is a "column vector" regardless of whether we slice a row or a column!

# Tensor Slices

More complicated example: video processing

Four dimensions:

- Pixels (height-by-width)
- Three colors (RGB)
- Time index (multiple frames)



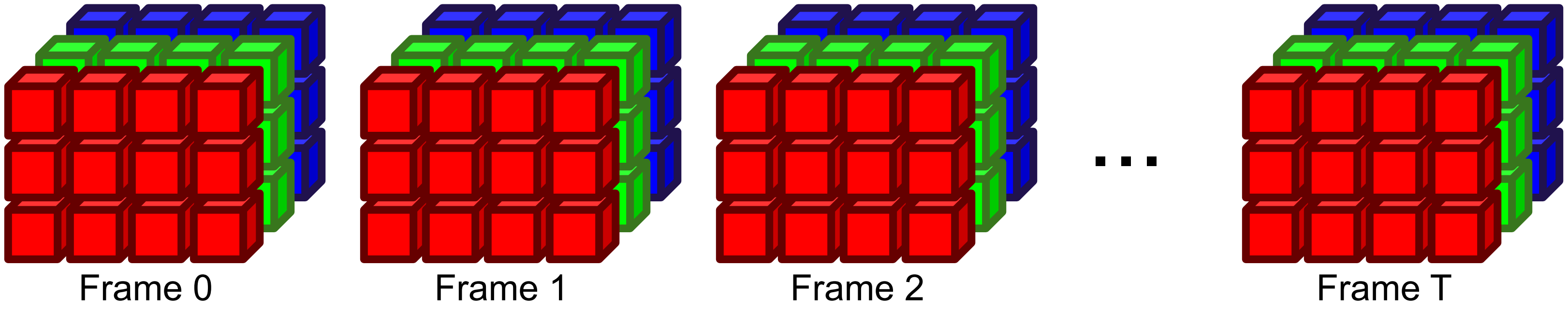
# Tensor Slices

More complicated example: video processing

Four dimensions:

- Pixels (height-by-width)
- Three colors (RGB)
- Time index (multiple frames)

**Test your understanding:**
What is the rank of the "video" tensor below?



# Tensor Slices

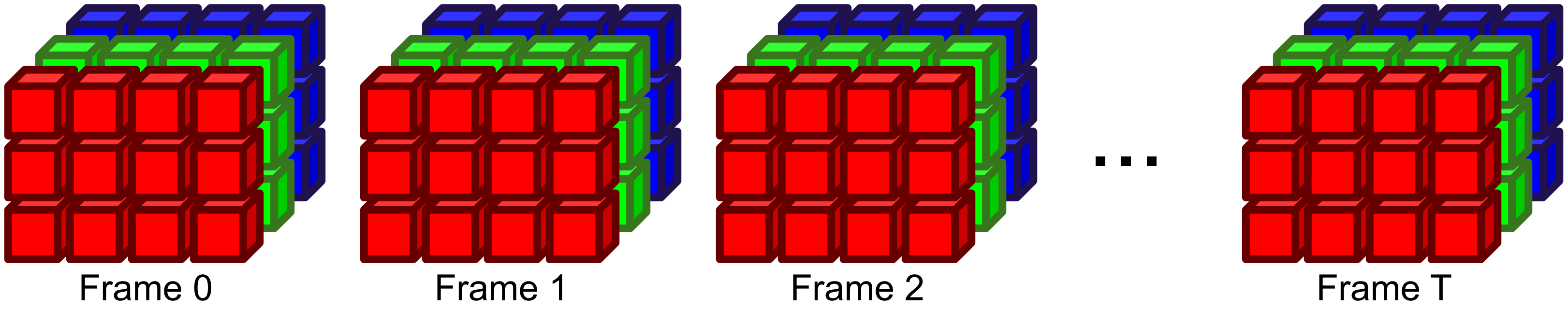
More complicated example: video processing

Four dimensions:

- Pixels (height-by-width)
- Three colors (RGB)
- Time index (multiple frames)

**Test your understanding:**
What is the rank of the "video" tensor below?

**Answer:** 4, since there are four dimensions; height, width, color and time.



# Tensor slices

Use ':' to pick out all entries along a row or column.

```
video = tf.zeros([27,1280,720,3])
print video
```

```
Tensor("zeros_5:0", shape=(27, 1280, 720, 3), dtype=float32)
```

```
firstframe = video[0,:,:,:]
print firstframe
```

Pick out the 3-color 1280-by-720 image that is the first frame of the video

```
Tensor("strided_slice_19:0", shape=(1280, 720, 3), dtype=float32)
```

```
bluevideo = video[:,:,:,2]
print bluevideo
```

Pick out only the blue channel of the video (see RGB on wikipedia)

```
Tensor("strided_slice_20:0", shape=(27, 1280, 720), dtype=float32)
```

```
redvideo = video[:,:,:,0]
print redvideo
```

Pick out only the red channel of the video

```
Tensor("strided_slice_21:0", shape=(27, 1280, 720), dtype=float32)
```

# Reshaping tensors

**Test your understanding:**

**Q:** I have an x-by-y-by-z tensor. What is its rank?

# Reshaping tensors

**Test your understanding:**

**Q:** I have an x-by-y-by-z tensor. What is its rank?

**A:** 3

**Q:** How many elements are in this x-by-y-by-z 3-tensor?

# Reshaping tensors

**Test your understanding:**

**Q:** I have an x-by-y-by-z tensor. What is its rank?

**A:** 3

**Q:** How many elements are in this x-by-y-by-z 3-tensor?

**A:** x*y*z

# Reshaping tensors

```
mytensor = tf.zeros([10,20,30])
print mytensor
```

```
Tensor("zeros_7:0", shape=(10, 20, 30), dtype=float32)
```

Reshape a 3-tensor into a 4-tensor. Note that the shapes are consistent with one another.

```
newtensor = tf.reshape(mytensor, [125,3,2,8])
print newtensor
```

```
Tensor("Reshape_2:0", shape=(125, 3, 2, 8), dtype=float32)
```

```
badtensor = tf.reshape(mytensor, [10,20,40])
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-187-e5c481ed6827> in <module>()
----> 1 badtensor = tf.reshape(mytensor, [10,20,40])
```

Reshaping to an inconsistent shape results in an error.

# Evaluating Tensors

```
sess = tf.Session()
fibonacci = tf.constant([0,1,1,2,3,5,8,13,21], dtype=tf.int8)
print fibonacci
```

```
Tensor("Const_165:0", shape=(9,), dtype=int8)
```

```
print fibonacci.eval(session=sess)
```

```
[ 0  1  1  2  3  5  8 13 21]
```

Evaluating the tensor lets us finally see the tensor's contents rather than only its shape and dtype.

Evaluation requires running a computational graph, so we have to give TF a session to run.

# Building a Simple Model: Linear Regression

```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=float32>
```

# Building a Simple Model: Linear Regression

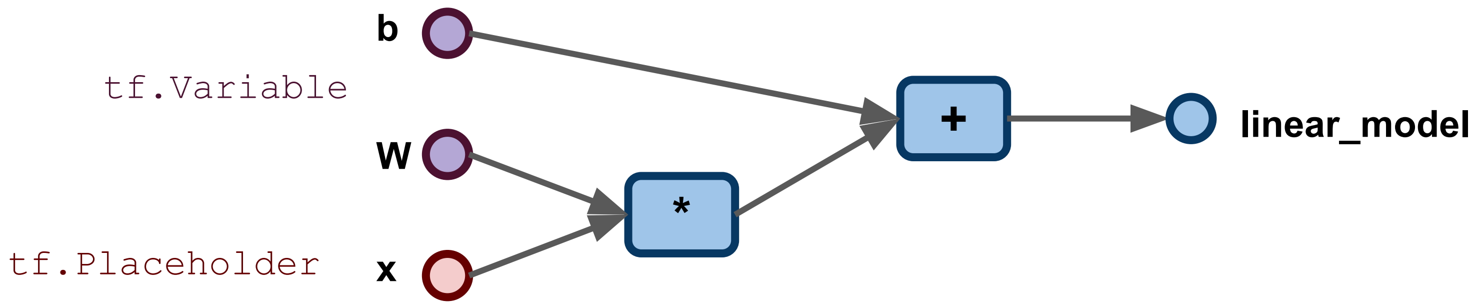
```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=float32>
```

`W` and `b` are both rank-1 tensors, with values 0.3 and -0.3, respectively.

**Model:** y = Wx + b



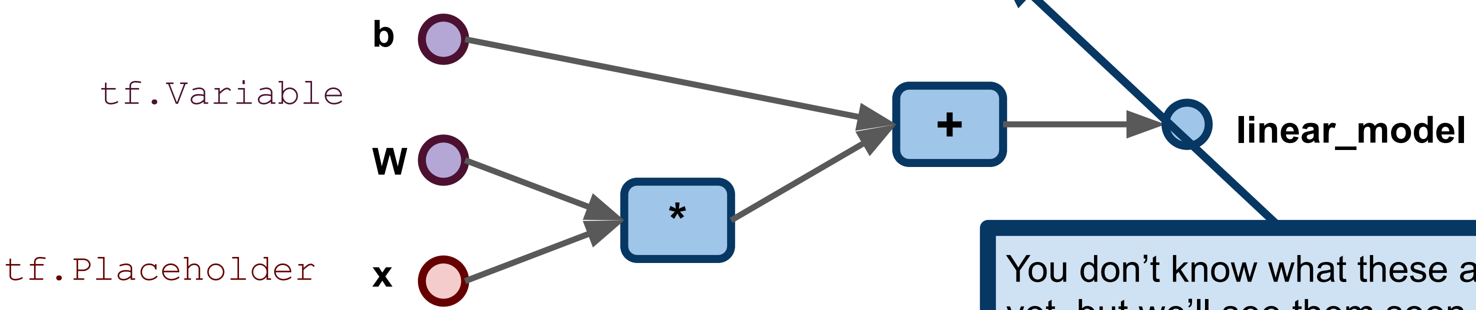
# Building a Simple Model: Linear Regression

```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=f
```

**From the documentation:** The `Variable()` constructor requires an initial value for the variable, which can be a Tensor of any type and shape. The initial value defines the type and shape. The initial value defines the type and shape of the variable. After construction, the type and shape of the variable are fixed, but the value can be changed using one of the **assign functions**.




You don't know what these are, yet, but we'll see them soon.

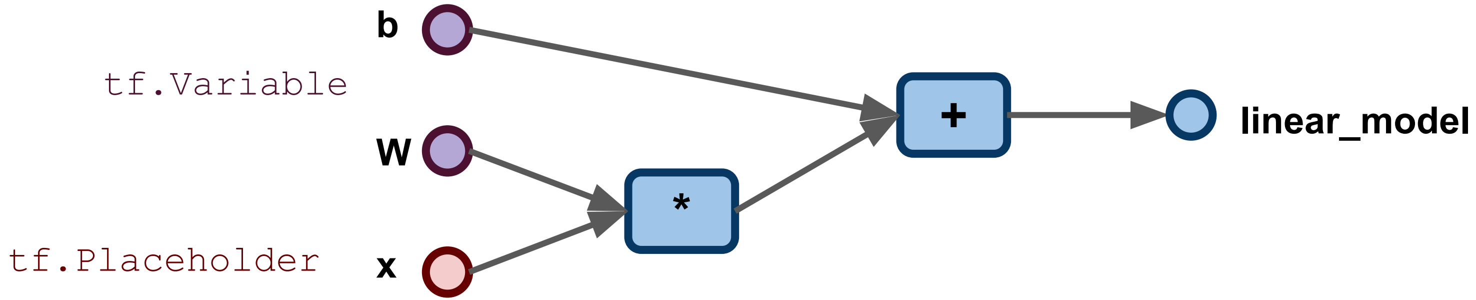
# Building a Simple Model: Linear Regression

```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=float32>
```

**Test your understanding:** why is the shape unknown, here?



# Building a Simple Model: Linear Regression

```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=float32>
```

**Model:** y = Wx + b

```
init = tf.global_variables_initializer()
sess.run(init)
```

```
print(sess.run(linear_model, {x: [1, 2, 3, 4]}))
```

```
[ 0.          0.30000001  0.60000002  0.90000004]
```

`tf.Constant` tensors are initialized immediately when we create them. On the other hand, `tf.Variable` Tensors need to be initialized before we can run the computational graph. `init` here becomes a pointer to a TF subgraph.

**More information:** https://www.tensorflow.org/api_docs/python/tf/global_variables_initializer

# Building a Simple Model: Linear Regression

```
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
x = tf.placeholder(tf.float32)
linear_model = W*x + b

linear_model
```

```
<tf.Tensor 'add_27:0' shape=<unknown> dtype=float32>
```

```
init = tf.global_variables_initializer()
sess.run(init)
```

```
print(sess.run(linear_model, {x: [1, 2, 3, 4]}))
```

```
[ 0.          0.30000001  0.60000002  0.90000004]
```

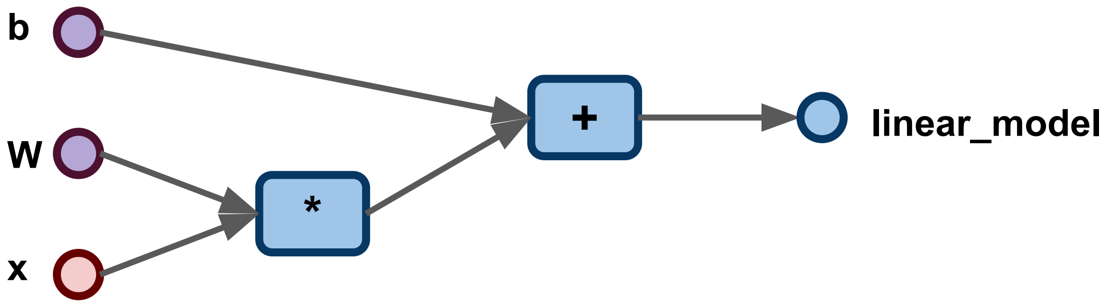
Evaluate the computational graph with `x` taking the values 1, 2, 3 and 4.

# Building a Simple Model: Linear Regression

So far, we have a circuit that computes a linear regression estimate

To train our model, we need:

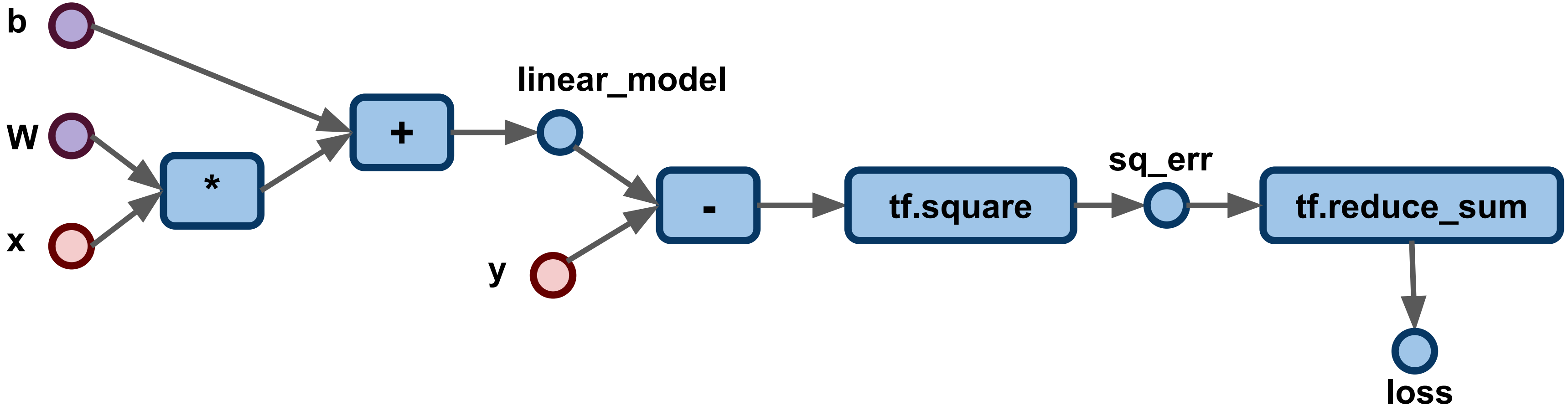
1) A loss function
2) A placeholder y for the training data dependent values



# Building a Simple Model: Linear Regression

```
y = tf.placeholder(tf.float32)
sq_err = tf.square(linear_model - y)
loss = tf.reduce_sum(sq_err)
print(sess.run(loss, {x: [1, 2, 3, 4], y: [0, -1, -2, -3]}))
```

```
23.66
```



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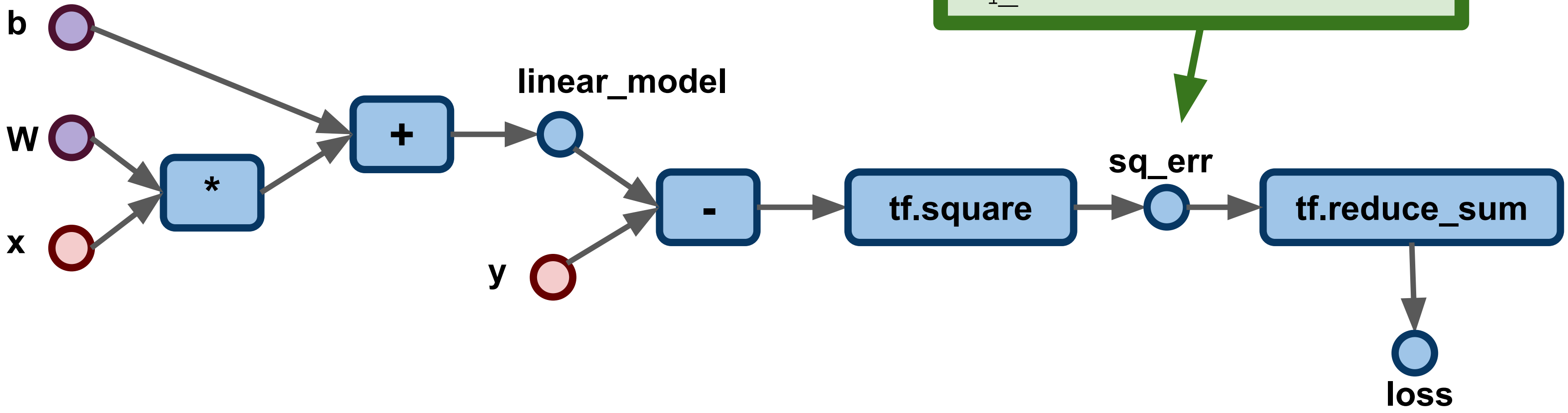
```

```
23.66
```

**Test your understanding:** is `sq_err` a vector or a scalar?



# Building a Simple Model: Linear Regression

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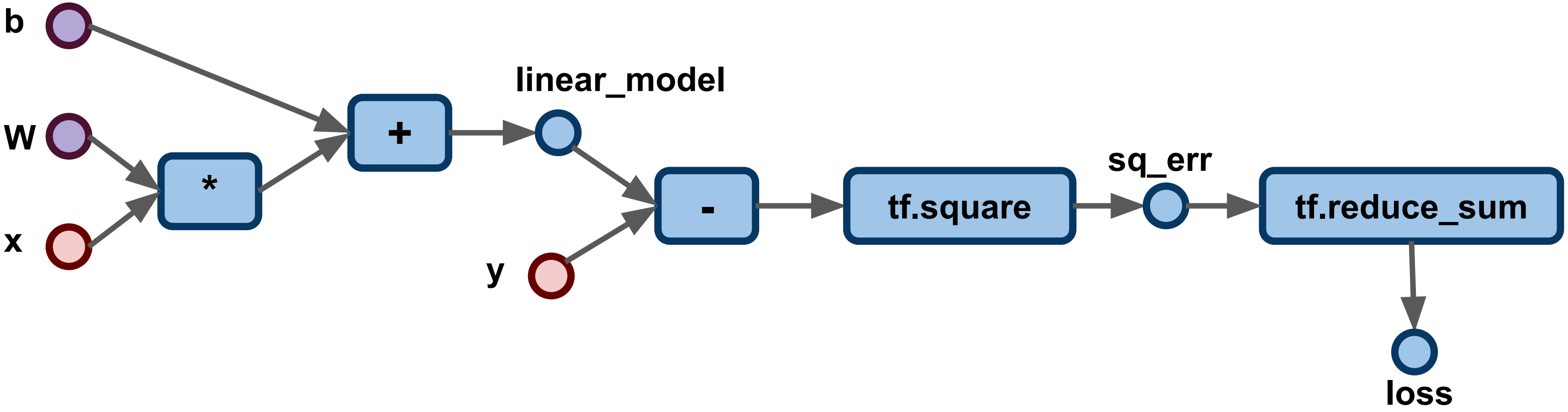
```

```
23.66
```

**Note:** `tf.reduce_sum` does just what you think it does!



# Building a Simple Model: Linear Regression

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```

```
23.66
```

**How can we improve (i.e., decrease) this loss?**

**Option 1:** set `w` and `b` manually.

We know `W=-1, b=1` is the correct answer

To change values of `tf.Variables`, use `tf.assign`

Need to tell TF to use the newly-updated variables instead of the old ones.

```
fixedW = tf.assign(W, [-1])
fixedb = tf.assign(b, [1])
sess.run([fixedW, fixedb])
print(sess.run(loss, {x: [1, 2, 3, 4], y: [0, -1, -2, -3]}))
```

```
0.0
```

# Building a Simple Model: Linear Regression

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```
23.66
```

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**Option 2:** use closed-form solution for loss-minimizing `W` and `b`.

  ...but then what happens when we have a model with no closed-form solution?

# Building a Simple Model: Linear Regression

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**Option 3:** use the built-in `tf.train` optimizer

Takes advantage of **symbolic differentiation**

Allows easy implementation of **gradient descent** and related techniques

# Building a Simple Model: Linear Regression

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```

```
23.66
```

**How can we improve (i.e., decrease) this loss?**

**Option 1:** set `W` and `b` manually.

We know `W=-1, b=1` is the correct answer

To change valu `sign`

**This is why we use TensorFlow!**

**Option 2:** use close `W` and `b`.

...but then what happens when we have a model with no closed-form solution?

**Option 3:** use the built-in `tf.train` optimizer

Takes advantage of **symbolic differentiation**

Allows easy implementation of **gradient descent** and related techniques

# Training a Simple Model: Linear Regression

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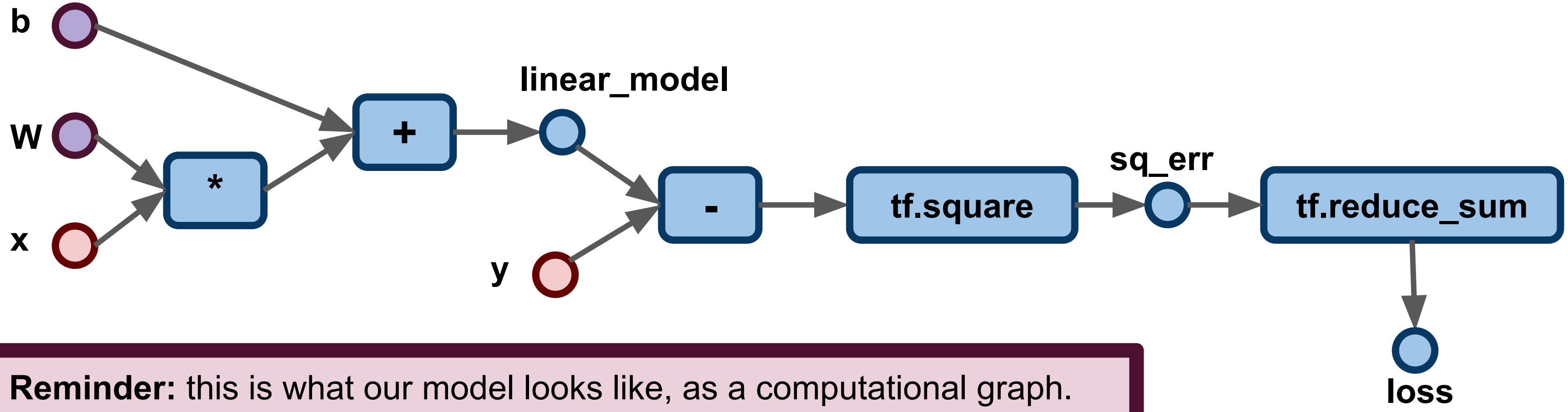
```
23.66
```




**Reminder:** this is what our model looks like, as a computational graph.

# Gradient Descent: Crash Course

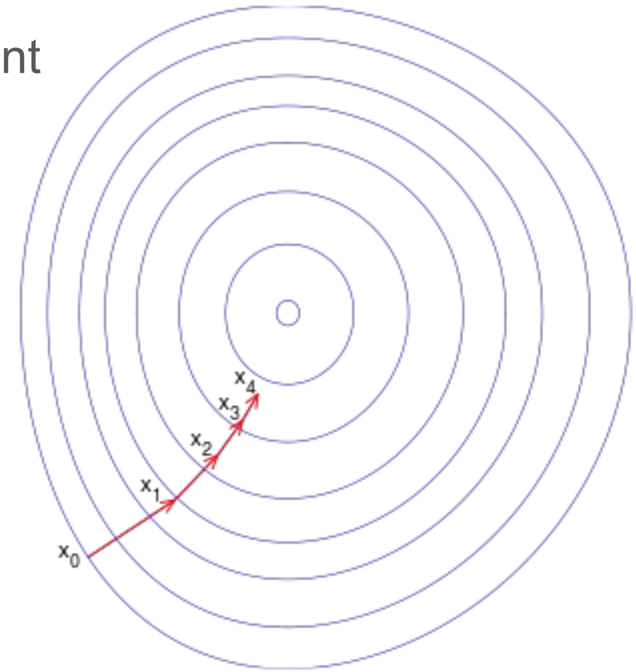
Iterative optimization method for minimizing a function

At location x, take gradient of loss function

Take a **gradient step** in the direction of the gradient

Size of step changes over time

according to **learning rate**



# Gradient Descent: Crash Course

Iterative optimization method for minimizing a function

- At location x, take gradient of loss function
- Take a **gradient step** in the direction of the gradient
- Size of step changes over time according to **learning rate**

In short, gradient descent is a method for minimizing a function, provided we can compute its gradient (i.e., derivative). It's enough for this course to treat this as a black box.

**For more information:**


S. P. Boyd and L. Vandenberghe (2004). *Convex Optimization*. Cambridge University Press.

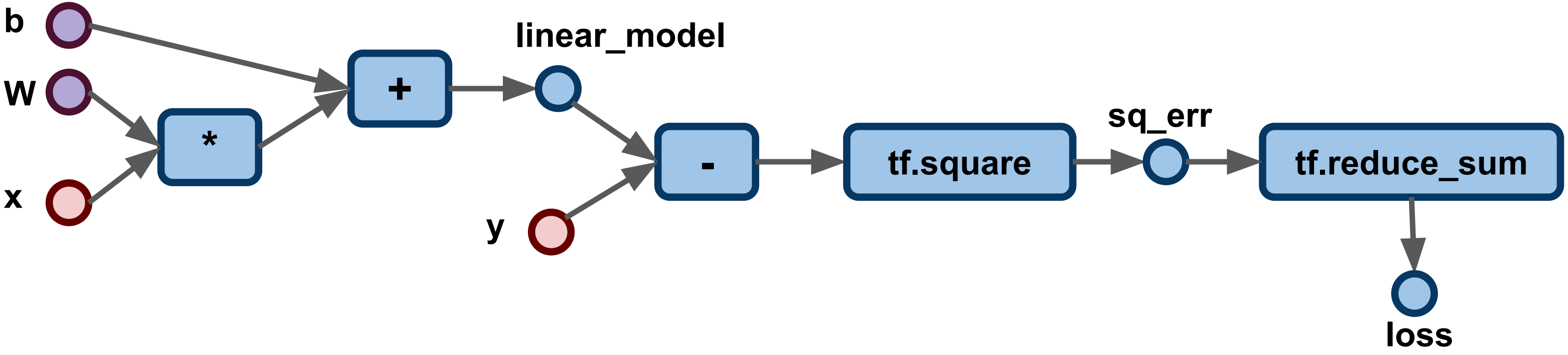
J. Nocedal and S. J. Wright (2006). *Numerical Optimization*. Springer.

# Training a Simple Model: Linear Regression

```
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)

sess.run(init) # reset values to incorrect defaults.
for i in range(1000):
    sess.run(train, {x: [1, 2, 3, 4], y: [0, -1, -2, -3]})
print(sess.run([W, b]))
```

```
[array([-0.9999969], dtype=float32), array([ 0.99999082], dtype=float32)]
```



# Training a Simple Model: Linear Regression

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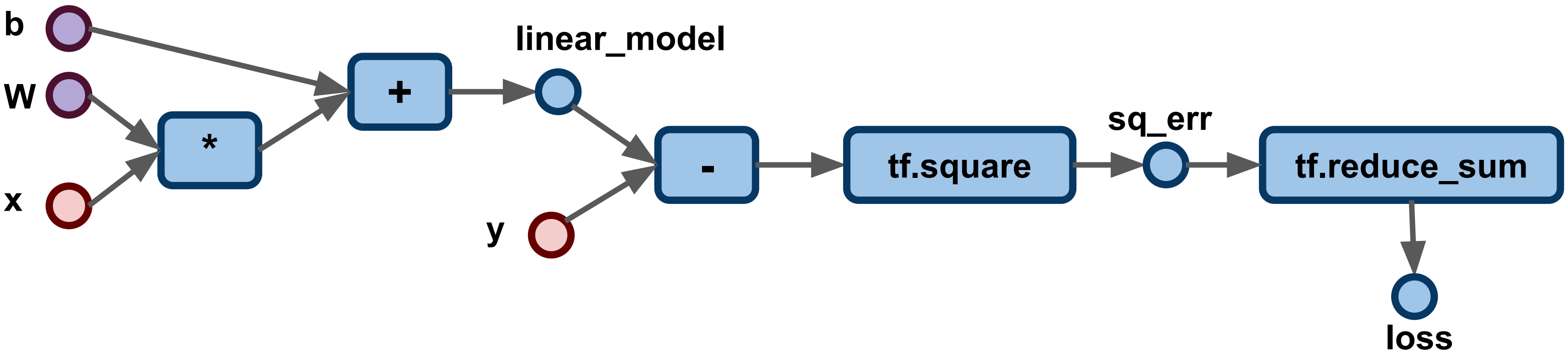
print(sess.run([W, b]))
```

```
[array([-0.9999969], dtype=float32), array([ 0.99999082], dtype=float32)]
```

Each iteration of this loop computes one gradient step and updates the variables accordingly.

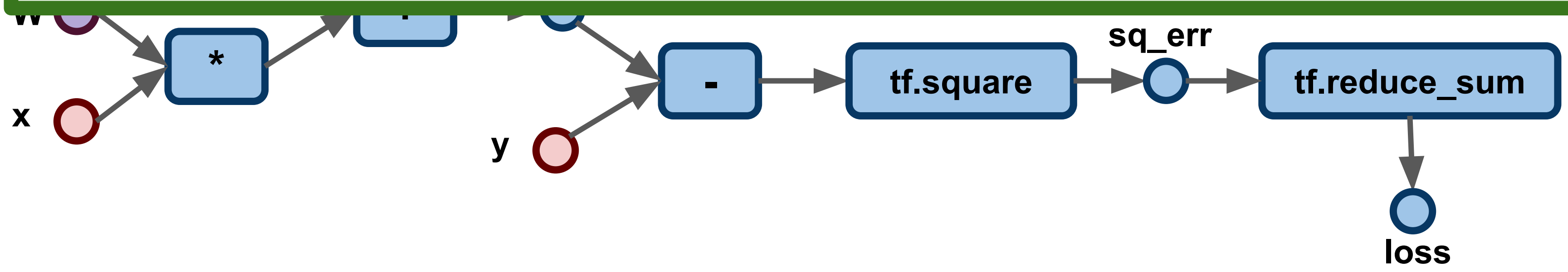


# Training a Simple Model: Linear Regression

```
optimizer = tf.train.GradientDescentOptimizer(0.01)
```

Each iteration of this loop

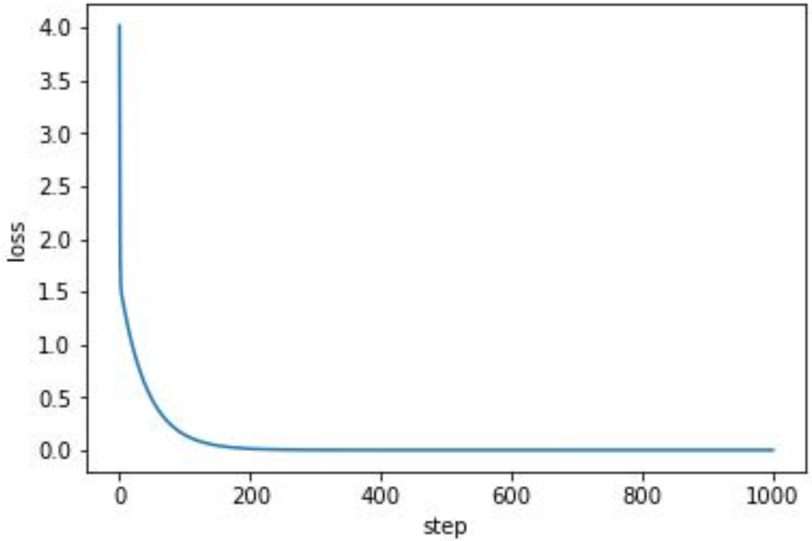
**Note:** As you can see below, the computational graph can get very complicated very quickly. TensorFlow has a set of built-in tools, collectively called **TensorBoard**, for handling some of this complexity: https://www.tensorflow.org/tensorboard/graphs
(these examples are for TF version 2. For TF version 1.X, see https://github.com/tensorflow/tensorboard/blob/master/docs/r1/overview.md)



# Training a Simple Model: Linear Regression

```
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)

sess.run(init) # reset values to incorrect defaults.
losses = range(1000)
for i in range(1000):
    sess.run(train, {x: [1, 2, 3, 4], y: [0, -1, -2, -3]})
    losses[i] = sess.run(loss, {x: [1, 2, 3, 4], y: [0, -1, -2, -3]})
plt.xlabel('step'); plt.ylabel('loss'); _ = plt.plot(losses);
```




**Note:** TensorBoard includes a set of tools for visualization, including for tracking loss, but the approach here is quicker and easier for our purposes.

# TensorFlow Estimators API: `tf.estimators`

`tf.estimators` is a TF module that simplifies model training and evaluation

Module allows one to run models on CPU or GPU, local or on cloud, etc

Simplifies much of the work of building the graph and estimating parameters

More information:

- https://github.com/tensorflow/docs/blob/master/site/en/r1/guide/estimators.md
- https://github.com/tensorflow/docs/blob/master/site/en/r1/guide/premade_estimators.md
- https://github.com/tensorflow/docs/blob/master/site/en/r1/tutorials/estimators/linear.ipynb

**Note:** Keras in TensorFlow v2 serves similar purpose for specifying neural nets

- https://www.tensorflow.org/guide/keras