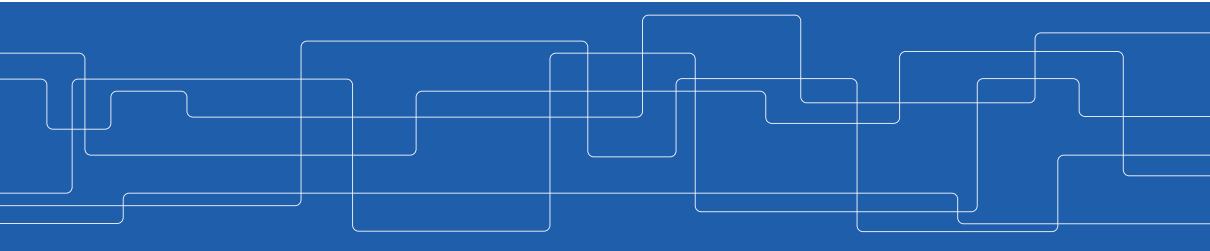
TensorFlow

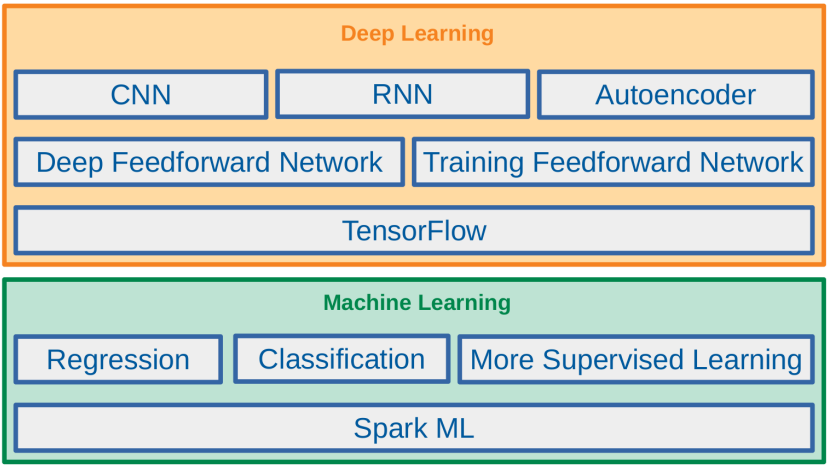
Amir H. Payberah
payberah@kth.se
23/11/2018



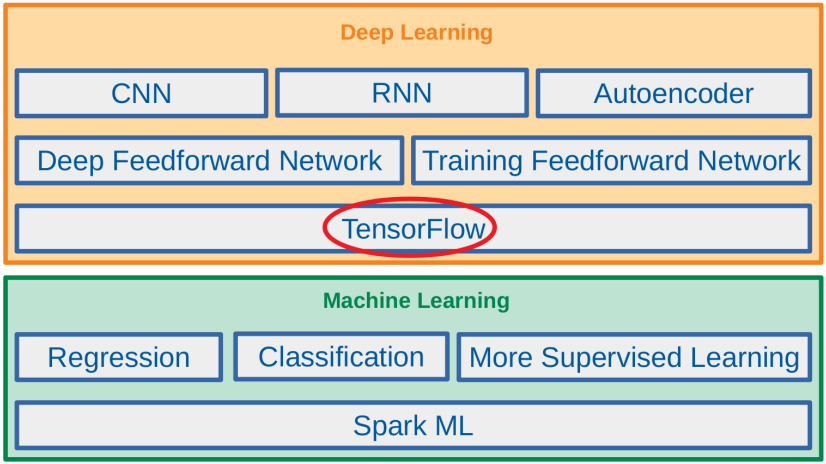
The Course Web Page

https://id2223kth.github.io

Where Are We?


Deep Learning
CNN
RNN
Autoencoder
Deep Feedforward Network
Training Feedforward Network
TensorFlow
Machine Learning
Regression
Classification
More Supervised Learning
Spark ML

Where Are We?


Deep Learning
CNN
RNN
Autoencoder
Deep Feedforward Network
Training Feedforward Network
TensorFlow
Machine Learning
Regression
Classification
More Supervised Learning
Spark ML

Introduction

- TensorFlow is an open source software library for numerical computation, particularly well suited and fine-tuned for large-scale Machine Learning.
- Was developed by the Google Brain team.

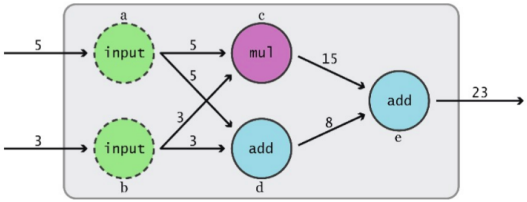
Hello World

- Implement machine learning algorithms by creating and computing operations that interact with one another.

$$e = c + d$$

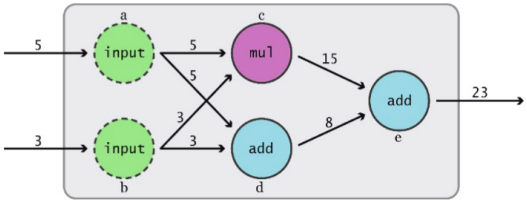
$$c = a \times b$$

$$d = a + b$$



Two Phases of Tensorflow

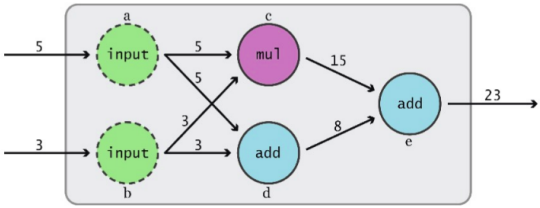
- Working with TensorFlow involves two main phases.
  1. Build a graph
  2. Execute it



Phase 1: Build a Graph

- `import tensorflow as tf`: it forms an empty default graph.

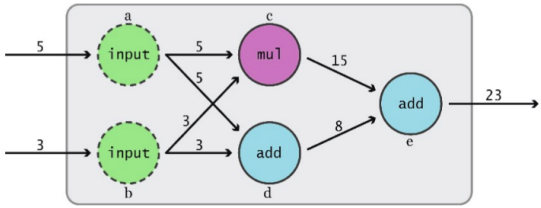
```
import tensorflow as tf

a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)
```



Phase 1: Build a Graph

- `import tensorflow as tf`: it forms an empty default graph.
- First, add two nodes to output a constant value

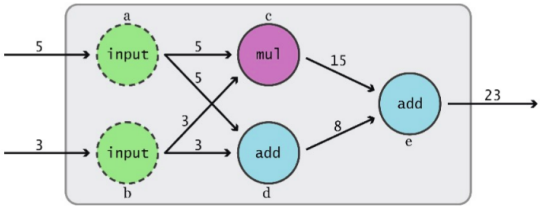
```
import tensorflow as tf

a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)
```



Phase 1: Build a Graph

- `import tensorflow as tf`: it forms an empty default graph.
- First, add two nodes to output a constant value
- Each of the next three nodes gets two existing variables as inputs, and performs simple arithmetic operations on them, and generates outputs.

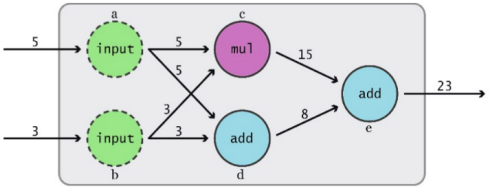
```
import tensorflow as tf

a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)
```



Phase 2: Execute a Graph

- Now, we are ready to run the computations.

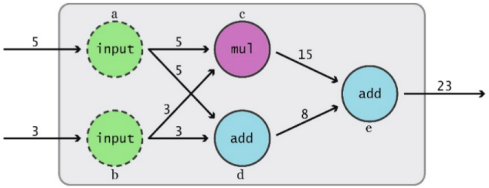
```
sess = tf.Session()
print(sess.run(e))
sess.close()

# Alternative way
with tf.Session() as sess:
  print(sess.run(e))
```



Phase 2: Execute a Graph

- Now, we are ready to run the computations.
- Create and run a session, by calling the `run()` method of the `Session` object.

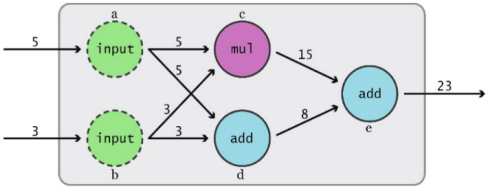
```
sess = tf.Session()
print(sess.run(e))
sess.close()

# Alternative way
with tf.Session() as sess:
  print(sess.run(e))
```



Phase 2: Execute a Graph

- Now, we are ready to run the computations.
- Create and run a session, by calling the `run()` method of the `Session` object.
- When `sess.run(e)` is called, it starts at the requested output `e`, and then works backward, computing nodes that must be executed.

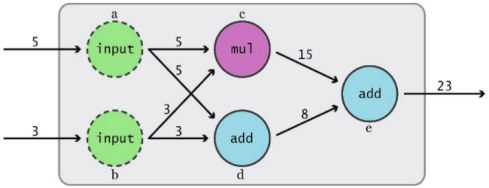
```
sess = tf.Session()
print(sess.run(e))
sess.close()

# Alternative way
with tf.Session() as sess:
  print(sess.run(e))
```



Phase 2: Execute a Graph

- Now, we are ready to run the computations.
- Create and run a session, by calling the `run()` method of the `Session` object.
- When `sess.run(e)` is called, it starts at the requested output `e`, and then works backward, computing nodes that must be executed.
- Close the session at the end of the computation, using the `sess.close()` command.

```
sess = tf.Session()
print(sess.run(e))
sess.close()

# Alternative way
with tf.Session() as sess:
  print(sess.run(e))
```



The Complete Code

```
import tensorflow as tf

# Building the Graph
a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)

# Executing the Graph
with tf.Session() as sess:
  print(sess.run(e))
```

Visualize the Code

```
import tensorflow as tf

# Building the Graph
a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)

writer = tf.summary.FileWriter("./graphs", tf.get_default_graph())

# Executing the Graph
with tf.Session() as sess:
  print(sess.run(e))
```

Visualize the Code

```
import tensorflow as tf

# Building the Graph
a = tf.constant(5)
b = tf.constant(3)

c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)

writer = tf.summary.FileWriter("./graphs", tf.get_default_graph())

# Executing the Graph
with tf.Session() as sess:
  print(sess.run(e))
```

```
tensorboard --logdir="./graphs" --port 6006
```

Let's Give Name to Variables

```
import tensorflow as tf

# Building the Graph
a = tf.constant(5, name="a")
b = tf.constant(3, name="b")

c = tf.multiply(a, b, name="c_mul")
d = tf.add(a, b, name="d_add")
e = tf.add(c, d, name="e_add")

writer = tf.summary.FileWriter("./graphs", tf.get_default_graph())

# Executing the Graph
with tf.Session() as sess:
  print(sess.run(e))
```

```
tensorboard --logdir="./graphs" --port 6006
```

Tensor Objects

What is Tensor?

- The central unit of data in TensorFlow is the tensor.
- An n-dimensional array of primitive values.

Tensor Objects

- The main object you manipulate and pass around is the `tf.Tensor`.
- TensorFlow programs work by building a graph of `tf.Tensor` objects, and running parts of this graph.
- Each Tensor object is specified by:
  - Rank
  - Shape
  - Datatype

Tensor Objects - Rank

- The number of dimensions.
  - rank 0: scalar (number), e.g., `5`
  - rank 1: vector, e.g., `[2, 5, 7]`
  - rank 2: matrix, e.g., `[[1, 2], [3, 4], [5, 6]]`
  - rank 3: 3-Tensor
  - rank n: n-Tensor
- The `tf.rank` method determines the rank of a `tf.Tensor` object.

```
c = tf.constant([[4], [9], [16], [25]])

r = tf.rank(c) # rank 2
```

Tensor Objects - Shape

- The number of elements in each dimension.
- The `get_shape()` returns the shape of the tensor as a tuple of integers.

```
c = tf.constant([[[1, 2, 3], [4, 5, 6]],
                 [[1, 1, 1], [2, 2, 2]]])

s = c.get_shape() # (2, 2, 3)
```

Tensor Objects - Data Types (1/2)

- We can explicitly choose the data type of a Tensor object.
- Make sure the data types match throughout the graph.
- We can use the `tf.cast()` method to change the data type of a Tensor object.

```
c = tf.constant(4.0, dtype=tf.float64)

x = tf.constant([1, 2, 3], dtype=tf.float32)
y = tf.cast(x, tf.int64)
```

Tensor Objects - Data Types (2/2)

Data type	Python type	Description
DT_FLOAT	tf.float32	32-bit floating point.
DT_DOUBLE	tf.float64	64-bit floating point.
DT_INT8	tf.int8	8-bit signed integer.
DT_INT16	tf.int16	16-bit signed integer.
DT_INT32	tf.int32	32-bit signed integer.
DT_INT64	tf.int64	64-bit signed integer.
DT_UINT8	tf.uint8	8-bit unsigned integer.
DT_UINT16	tf.uint16	16-bit unsigned integer.
DT_STRING	tf.string	Variable-length byte array. Each element of a Tensor is a byte array.
DT_BOOL	tf.bool	Boolean.
DT_COMPLEX64	tf.complex64	Complex number made of two 32-bit floating points: real and imaginary parts.
DT_COMPLEX128	tf.complex128	Complex number made of two 64-bit floating points: real and imaginary parts.
DT_QINT8	tf.qint8	8-bit signed integer used in quantized ops.
DT_QINT32	tf.qint32	32-bit signed integer used in quantized ops.
DT_QUINT8	tf.quint8	8-bit unsigned integer used in quantized ops.

Tensor Objects - Name

- Each Tensor object has an identifying name.
- This name is an intrinsic string name, not to be confused with the name of the variable.

```
c = tf.constant(4.0, dtype=tf.float64, name="input")
```

Tensor Objects - Name Scopes

- To deal with large graphs, we can use node grouping to make it easier to manage.

Tensor Objects - Name Scopes

- To deal with large graphs, we can use node grouping to make it easier to manage.
- Hierarchically group nodes by their names, using `tf.name_scope()` together with the `with` clause.

```
with tf.name_scope("myprefix"):
  c1 = tf.constant(4, dtype=tf.int32, name="input1")
  c2 = tf.constant(4.0, dtype=tf.float64, name="input2")
```

Tensor Objects - Name Scopes

- To deal with large graphs, we can use node grouping to make it easier to manage.
- Hierarchically group nodes by their names, using `tf.name_scope()` together with the `with` clause.
- Below, the name of each operation within the scope is prefixed with `myprefix/`, e.g., `myprefix/input1`.

```
with tf.name_scope("myprefix"):
  c1 = tf.constant(4, dtype=tf.int32, name="input1")
  c2 = tf.constant(4.0, dtype=tf.float64, name="input2")
```

Main Types of Tensors

- Constants `tf.constant`
- Variables `tf.Variable`
- Placeholders `tf.placeholder`

Constants

Constants (1/3)

- The value of a constant Tensor cannot be changed in the future.

```
tf.constant(<value>, dtype=None, shape=None, name="Const", verify_shape=False)

a = tf.constant([[0, 1], [2, 3]], name="b")
b = tf.constant([[4], [9], [16], [25]], name="c")
```

Constants (2/3)

- The initialization should be with a value, not with operation.

TensorFlow operation	Description
`tf.constant(value)`	Creates a tensor populated with the value or values specified by the argument *value*
`tf.fill(shape, value)`	Creates a tensor of shape *shape* and fills it with *value*
`tf.zeros(shape)`	Returns a tensor of shape *shape* with all elements set to 0
`tf.zeros_like(tensor)`	Returns a tensor of the same type and shape as *tensor* with all elements set to 0
`tf.ones(shape)`	Returns a tensor of shape *shape* with all elements set to 1
`tf.ones_like(tensor)`	Returns a tensor of the same type and shape as *tensor* with all elements set to 1
`tf.random_normal(shape, mean, stddev)`	Outputs random values from a normal distribution
`tf.truncated_normal(shape, mean, stddev)`	Outputs random values from a truncated normal distribution (values whose magnitude is more than two standard deviations from the mean are dropped and re-picked)
`tf.random_uniform(shape, minval, maxval)`	Generates values from a uniform distribution in the range [*minval*, *maxval*)
`tf.random_shuffle(tensor)`	Randomly shuffles a tensor along its first dimension

Constants (3/3)

- What's wrong with constants?

Constants (3/3)

- What's wrong with constants?
- Constants are stored in the graph definition.
- This makes loading graphs expensive when constants are big.

Constants (3/3)

- What's wrong with constants?
- Constants are stored in the graph definition.
- This makes loading graphs expensive when constants are big.
- Only use constants for primitive types.
- Use variables for data that requires more memory.

Variables

Variables

- A variable represents a Tensor whose value can be changed by running ops on it.

Variables

- A variable represents a Tensor whose value can be changed by running ops on it.
- `tf.Variable` is a class with several ops.

Variables

- A variable represents a Tensor whose value can be changed by running ops on it.
- `tf.Variable` is a class with several ops.
- Create variables with `tf.get_variable`.
- `tf.get_variable` returns an existing variable with the given parameters if it is available.

```
# not recommended way to make a variable
tf.Variable(<initial-value>, name=<optional-name>)

w = tf.Variable([[0, 1], [2, 3]], name="matrix")

# recommended
tf.get_variable(name, shape=None, dtype=tf.float32, initializer=None,
       regularizer=None, trainable=True, collections=None)

w = tf.get_variable("matrix", initializer=tf.constant([[0, 1], [2, 3]]))
```

Initialize Variables

- Variables should be initialized before being used.

Initialize Variables

- Variables should be initialized before being used.
- Initialize all variables at once.

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

Initialize Variables

- Variables should be initialized before being used.
- Initialize 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 Variables

- Variables should be initialized before being used.
- Initialize 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)
```

Assign Values to Variables (1/3)

- What does it print?

```
w = tf.get_variable("scalar", initializer=tf.constant(2))
w.assign(100)

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

Assign Values to Variables (1/3)

- What does it print?

```
w = tf.get_variable("scalar", initializer=tf.constant(2))
w.assign(100)

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

- Prints 2, because `w.assign(100)` creates an assign op.
- That op needs to be executed in a session to take effect.

```
w = tf.get_variable("scalar", initializer=tf.constant(2))
assign_op = w.assign(100)

with tf.Session() as sess:
    sess.run(w.initializer)
    sess.run(assign_op)
    print(sess.run(w))
```

Assign Values to Variables (2/3)

- What does it print?

```
w = tf.get_variable("scalar", initializer=tf.constant(2))
w_times_two = w.assign(2 * w)

with tf.Session() as sess:
    sess.run(w.initializer)
    print(sess.run(w_times_two))
    print(sess.run(w_times_two))
    print(sess.run(w_times_two))
```

Assign Values to Variables (3/3)

- `assign_add()` and `assign_sub()`

```
w = tf.get_variable("scalar", initializer=tf.constant(2))

with tf.Session() as sess:
    sess.run(w.initializer)

    # increment by 10
    print(sess.run(w.assign_add(10)))

    # decrement by 5
    print(sess.run(w.assign_sub(5)))
```

Placeholders

Placeholders

- Placeholders are built-in structures for feeding input values.
- Empty variables that will be filled with data later on.
- `shape=None` means that a tensor of any shape will be accepted.
  - E.g., `shape=[None, 10]`: a matrix with 10 columns and any number of rows.

```
tf.placeholder(dtype, shape=None, name=None)

x = tf.placeholder(tf.float32, shape=[None, 10])
```

Feeding Placeholders (1/2)

- What's wrong with this code?

```
a = tf.placeholder(tf.float32, shape=[3])

b = tf.constant([5, 5, 5], tf.float32)

c = a + b

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

Feeding Placeholders (2/2)

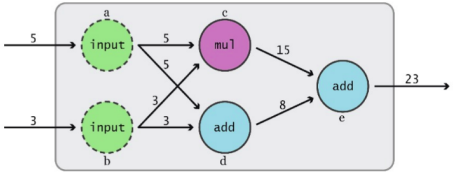
- Supplement the values to placeholders using a dictionary.

```
a = tf.placeholder(tf.float32, shape=[3])

b = tf.constant([5, 5, 5], tf.float32)

c = a + b

with tf.Session() as sess:
  print(sess.run(c, feed_dict={a: [1, 2, 3]}))
```

Dataflow Graphs

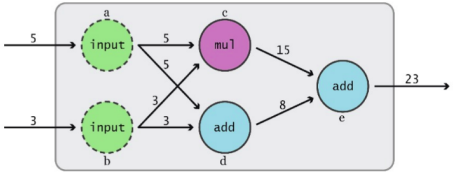
Graph

- A computational graph is a series of TensorFlow operations arranged into a graph.



Graph

- A computational graph is a series of TensorFlow operations arranged into a graph.
- The graph is composed of two types of objects:
  - Operations: the nodes of the graph that that consume and produce tensors.
  - Tensors: the edges in the graph that represent the flowing values through the graph.



Common TensorFlow Operations (1/2)

TensorFlow operator	Shortcut	Description
`tf.add()`	`a + b`	Adds a and b, element-wise.
`tf.multiply()`	`a * b`	Multiplies a and b, element-wise.
`tf.subtract()`	`a - b`	Subtracts a from b, element-wise.
`tf.divide()`	`a / b`	Computes Python-style division of a by b.
`tf.pow()`	`a ** b`	Returns the result of raising each element in a to its corresponding element b, element-wise.
`tf.mod()`	`a % b`	Returns the element-wise modulo.
`tf.logical_and()`	`a & b`	Returns the truth table of `a & b`, element-wise. `dtype` must be `tf.bool`.
`tf.greater()`	`a > b`	Returns the truth table of `a > b`, element-wise.
`tf.greater_equal()`	`a >= b`	Returns the truth table of `a >= b`, element-wise.
`tf.less_equal()`	`a <= b`	Returns the truth table of `a <= b`, element-wise.
`tf.less()`	`a < b`	Returns the truth table of `a < b`, element-wise.
`tf.negative()`	`-a`	Returns the negative value of each element in a.
`tf.logical_not()`	`~a`	Returns the logical NOT of each element in a. Only compatible with Tensor objects with `dtype` of `tf.bool`.
`tf.abs()`	`abs(a)`	Returns the absolute value of each element in a.
`tf.logical_or()`	`a | b`	Returns the truth table of `a | b`, element-wise. `dtype` must be `tf.bool`.

Common TensorFlow Operations (2/2)

- Matrix multiplication of two Tensor objects `A` and `B`: `tf.matmul(A, B)`
- Before using `matmul()`, we need to make sure both have the same number of dimensions and are aligned correctly.

```
a = tf.constant([[1, 2, 3], [4, 5, 6]])
print(a.get_shape())
# Out: (2, 3)

b = tf.constant([1, 0, 1])
print(b.get_shape())
# Out: (3,)

# In order to multiply them, we need to add a dimension to ‘b‘, transforming it from a
# 1D vector to a 2D single-column matrix.
b = tf.expand_dims(b, 1)
c = tf.matmul(a, b)
```

Managing Multiple Graphs (1/2)

- When we call `import tensorflow`, a default graph is automatically created.

Managing Multiple Graphs (1/2)

- When we call `import tensorflow`, a default graph is automatically created.
- We can also create additional graphs, by calling `tf.Graph()`.

Managing Multiple Graphs (1/2)

- When we call `import tensorflow`, a default graph is automatically created.
- We can also create additional graphs, by calling `tf.Graph()`.
- `tf.get_default_graph()` tells which graph is currently set as the default graph.

```
import tensorflow as tf

g = tf.Graph()
a = tf.constant(5)

print(a.graph is g)
# Out: False

print(a.graph is tf.get_default_graph())
# Out: True
```

Managing Multiple Graphs (2/2)

- Use `with` together with `as_default()` to associate your constructed nodes the a right graph.

```
import tensorflow as tf

g1 = tf.get_default_graph()
g2 = tf.Graph()

print(g1 is tf.get_default_graph())
# Out: True

with g2.as_default():
  print(g1 is tf.get_default_graph())
# Out: False
  print(g2 is tf.get_default_graph())
# Out: True
```

Session

Session

- A `Session` object encapsulates the environment.
- Operation objects are executed, and Tensor objects are evaluated.
- Session will also allocate memory to store the current values of variables.

Session

- A `Session` object encapsulates the environment.
- Operation objects are executed, and Tensor objects are evaluated.
- Session will also allocate memory to store the current values of variables.

```
sess = tf.Session()
outs = sess.run(e)
print("outs = {}".format(outs))
sess.close()
```

Session

- A `Session` object encapsulates the environment.
- Operation objects are executed, and Tensor objects are evaluated.
- Session will also allocate memory to store the current values of variables.

```
sess = tf.Session()
outs = sess.run(e)
print("outs = {}".format(outs))
sess.close()
```

```
# can be written as follows
with tf.Session() as sess:
    outs = sess.run(e)

print("outs = {}".format(outs))
```

Feeding

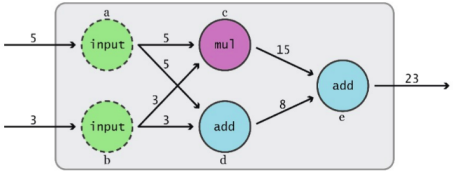
- A graph can be parameterized to accept external inputs via placeholders.
- To feed a placeholder, the input data is passed to the `session.run()`.
- Each key corresponds to a placeholder variable name, and the matching values are the data values.

```
x = tf.placeholder(tf.float32)
y = tf.placeholder(tf.float32)
z = x + y

with tf.Session() as sess:
    print(sess.run(z, feed_dict={x: 3, y: 4.5}))
    print(sess.run(z, feed_dict={x: [1, 3], y: [2, 4]}))
```

Fetches

- To fetch a list of outputs of nodes.

```
with tf.Session() as sess:
    fetches = [a, b, c, d, e]
    outs = sess.run(fetches)

print("outs = {}".format(outs))
```



Session.run() vs. Tensor.eval()

- Two ways to evaluate part of graph: `Session.run` and `Tensor.eval`.

Session.run() vs. Tensor.eval()

- Two ways to evaluate part of graph: `Session.run` and `Tensor.eval`.
- The most important difference is that you can use `sess.run()` to fetch the values of many tensors in the same step.

```
t = tf.constant(42.0)
u = tf.constant(37.0)
tu = tf.multiply(t, u)
ut = tf.multiply(u, t)

with sess.as_default():
   tu.eval()  # runs one step
   ut.eval()  # runs one step
   sess.run([tu, ut])  # evaluates both tensors in a single step
```

Linear Regression in TensorFlow

Linear Regression

- We want to find weights $\mathbf{w}$ and a bias term b.
- Assume our target value is a linear combination of some input vector $\mathbf{x}$: $\hat{y} = \mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathrm{b}$.

Linear Regression

- We want to find weights $\mathbf{w}$ and a bias term b.
- Assume our target value is a linear combination of some input vector $\mathbf{x}$: $\hat{\mathrm{y}} = \mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathrm{b}$.
- Let's generate synthetic data.

```
import numpy as np
import tensorflow as tf

x_data = np.random.randn(2000, 3)
w_real = [0.3, 0.5, 0.1]
b_real = -0.2
y_data = np.matmul(w_real, x_data.T) + b_real
```

Linear Regression - Placeholders and Variables

- Create placeholders for our input and output data.
- Create variables for our weights and intercept.

```
# placeholders
x = tf.placeholder(tf.float32, shape=[None, 3])
y_true = tf.placeholder(tf.float32, shape=None)

# variables
w = tf.get_variable("weights", dtype=tf.float32, initializer=tf.constant([[0., 0., 0.]]))
b = tf.get_variable("bias", dtype=tf.float32, initializer=tf.constant(0.))
```

Linear Regression - Defining a Cost Function

- We need a good measure to evaluate the model's performance.
- Let's define MSE (mean squared error).

```
# the cost function
y_hat = tf.matmul(w, tf.transpose(x)) + b

cost = tf.reduce_mean(tf.square(y_true - y_hat))
```

Linear Regression - The Gradient Descent Optimizer

- Next, we need to minimize the cost function.
- Let's use the gradient descent.
- First create an optimizer by using the `GradientDescentOptimizer()` function.
- Then, create a train operation by calling the `optimizer.minimize()` to update our variables.

```
# optimizer
learning_rate = 0.5

optimizer = tf.train.GradientDescentOptimizer(learning_rate)
train = optimizer.minimize(cost)
```

Linear Regression - Execute It

- At the end, we need to initialize the variables and execute the train operation.

```
num_steps = 10
init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)
    for step in range(num_steps):
        sess.run(train, {x: x_data, y_true: y_data})
    print(sess.run([w, b, cost], {x: x_data, y_true: y_data}))
```

Logistic Regression in TensorFlow

Logistic Regression

- We want to find weights $\mathbf{w}$ and a bias term $\mathtt{b}$ in a logisitc regression model:

$$\hat{\mathtt{y}} = \frac{1}{1 + \mathrm{e}^{-(\mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathtt{b})}}$$

- Let's generate synthetic data.

```
import numpy as np
import tensorflow as tf

x_data = np.random.randn(2000, 3)
w_real = [0.3, 0.5, 0.1]
b_real = -0.2
y_data = np.matmul(w_real, x_data.T) + b_real
```

Logistic Regression - Placeholders and Variables

- Create placeholders for our input and output data.
- Create variables for our weights and intercept.

```
# placeholders
x = tf.placeholder(tf.float32, shape=[None, 3])
y_true = tf.placeholder(tf.float32, shape=None)

# variables
w = tf.get_variable("weights", dtype=tf.float32, initializer=tf.constant([[0., 0., 0.]]))
b = tf.get_variable("bias", dtype=tf.float32, initializer=tf.constant(0.))
```

Logistic Regression - Defining a Loss Function

- For the cost function, we use the cross-entropy model.

```
z = tf.matmul(w, tf.transpose(x)) + b
y_hat = tf.sigmoid(z)

cost = -y_true * tf.log(y_hat) - (1 - y_true) * tf.log(1 - y_hat)
cost = tf.reduce_mean(cost)
```

Logistic Regression - Defining a Loss Function

- For the cost function, we use the cross-entropy model.

```
z = tf.matmul(w, tf.transpose(x)) + b
y_hat = tf.sigmoid(z)

cost = -y_true * tf.log(y_hat) - (1 - y_true) * tf.log(1 - y_hat)
cost = tf.reduce_mean(cost)
```

- Alternatively, we can use a designated function by TensorFlow.

```
cost = tf.nn.sigmoid_cross_entropy_with_logits(labels=y_true, logits=y_hat)
cost = tf.reduce_mean(cost)
```

Logistic Regression - The Gradient Descent Optimizer

- Similar to linear regression.

```
learning_rate = 0.5

optimizer = tf.train.GradientDescentOptimizer(learning_rate)
train = optimizer.minimize(cost)
```

Logistic Regression - Execute It

- Similar to linear regression.

```
num_steps = 10
init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)
    for step in range(num_steps):
        sess.run(train, {x: x_data, y_true: y_data})
    print(sess.run([w, b, cost], {x: x_data, y_true: y_data}))
```

Saving and Restoring Models

Saving Models

- Save a model's parameters in disk.
- Create a `Saver` node at the end of the construction phase.
- Then, in the execution phase, call its `save()` method whenever you want to save the model.

Saving Models

- Save a model's parameters in disk.
- Create a `Saver` node at the end of the construction phase.
- Then, in the execution phase, call its `save()` method whenever you want to save the model.

```
w = tf.Variable([[0, 0, 0]], dtype=tf.float32, name="weights")
[...]
init = tf.global_variables_initializer()
saver = tf.train.Saver()

with tf.Session() as sess:
  sess.run(init)
  for step in range(num_steps):
    if step % 100 == 0: # checkpoint every 100 epochs
      save_path = saver.save(sess, "/tmp/my_model.ckpt")
    sess.run(train, {x: x_data, y_true: y_data})
  best_w = sess.run(w)
  save_path = saver.save(sess, "/tmp/my_model_final.ckpt")
```

Restoring Models

- Create a `Saver` node at the end of the construction phase.
- Then, at the beginning of the execution phase call the `restore()` method of the `Saver` node.
  - Instead of initializing the variables using the `init` node.

```
with tf.Session() as sess:
  saver.restore(sess, "/tmp/my_model_final.ckpt")
  [...]
```

TensorBoard

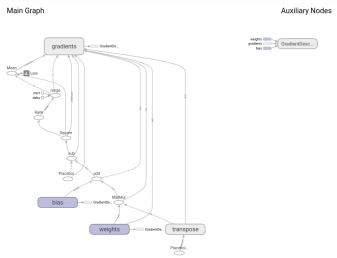
TensorBoard (1/3)

- TensorFlow provides a utility called TensorBoard.
- To visualize your model, you need to write the graph definition and some training stats to a log directory that TensorBoard will read from.
- Use a different log directory every time you run your program, or else TensorBoard will merge them.

TensorBoard (2/3)

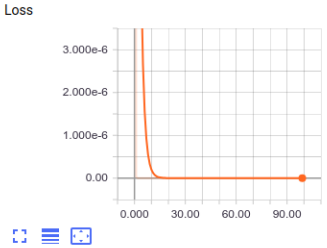
- Add the following code at the very end of the construction phase.
- The first line writes the `cost`.
- The second line creates a `FileWriter` that writes summaries of the graph.
- Start the TensorBoard web server (port 6006): `tensorboard --logdir .`

```
logdir = "."
mse_summary = tf.summary.scalar("MSE", cost)
file_writer = tf.summary.FileWriter(logdir, tf.get_default_graph())
file_writer.close()
```



TensorBoard (3/3)

```
cost_summary = tf.summary.scalar("Loss", cost)
file_writer = tf.summary.FileWriter('.', tf.get_default_graph())
[...]
for step in range(num_steps):
  sess.run(train, {x: x_data, y_true: y_data})
  summary_str = cost_summary.eval(feed_dict={x: x_data, y_true: y_data})
  file_writer.add_summary(summary_str, step)
```



Keras

Keras

- Keras is a high-level API to build and train deep learning models.
- To get started, import `tf.keras` to your program.

```
import tensorflow as tf
from tensorflow.keras import layers
```

Keras Layers (1/2)

- In Keras, you assemble layers `tf.keras.layers` to build models.
- A model is (usually) a graph of layers.
- There are many types of layers, e.g., `Dense`, `Conv2D`, `RNN`, ...

Keras Layers (2/2)

- Common constructor parameters:

```
layers.Dense(64, activation=tf.sigmoid, kernel_regularizer=tf.keras.regularizers.l1(0.01),
             bias_initializer=tf.keras.initializers.constant(2.0))
```

Keras Layers (2/2)

- Common constructor parameters:
  - `activation`: the activation function for the layer.

```
layers.Dense(64, activation=tf.sigmoid, kernel_regularizer=tf.keras.regularizers.l1(0.01),
             bias_initializer=tf.keras.initializers.constant(2.0))
```

Keras Layers (2/2)

- Common constructor parameters:
  - `activation`: the activation function for the layer.
  - `kernel_initializer` and `bias_initializer`: the initialization schemes of the layer's weights.

```
layers.Dense(64, activation=tf.sigmoid, kernel_regularizer=tf.keras.regularizers.l1(0.01),
             bias_initializer=tf.keras.initializers.constant(2.0))
```

Keras Layers (2/2)

- Common constructor parameters:
  - `activation`: the activation function for the layer.
  - `kernel_initializer` and `bias_initializer`: the initialization schemes of the layer's weights.
  - `kernel_regularizer` and `bias_regularizer`: the regularization schemes of the layer's weights, e.g., L1 or L2.

```
layers.Dense(64, activation=tf.sigmoid, kernel_regularizer=tf.keras.regularizers.l1(0.01),
             bias_initializer=tf.keras.initializers.constant(2.0))
```

Keras Models

- There are two ways to build Keras models: sequential and functional.

Keras Models

- There are two ways to build Keras models: sequential and functional.
- The sequential API allows you to create models layer-by-layer.

Keras Models

- There are two ways to build Keras models: sequential and functional.
- The sequential API allows you to create models layer-by-layer.
- The functional API allows you to create models that have a lot more flexibility.
  - You can define models where layers connect to more than just their previous and next layers.

Keras Models - Sequential Models

- You can use `tf.keras.Sequential` to build a sequential model.

```
from tensorflow.keras import layers

model = tf.keras.Sequential()

model.add(layers.Dense(64, activation="relu"))
model.add(layers.Dense(64, activation="relu"))
model.add(layers.Dense(10, activation="softmax"))
```

Keras Models - Functional Models

- You can use `tf.keras.Model` to build a functional model.

```
from tensorflow.keras import layers

inputs = tf.keras.Input(shape=(32,))
x = layers.Dense(64, activation="relu")(inputs)
x = layers.Dense(64, activation="relu")(x)
predictions = layers.Dense(10, activation="softmax")(x)

model = tf.keras.Model(inputs=inputs, outputs=predictions)
```

Training Keras Models

- Call the `compile` method to configure the learning process.
- `tf.keras.Model.compile` takes three important arguments.

```
model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001), loss="mse", metrics=["mae"])

model.fit(training_data, training_labels, epochs=10, batch_size=32)
```

Training Keras Models

- Call the `compile` method to configure the learning process.
- `tf.keras.Model.compile` takes three important arguments.
  - `optimizer`: specifies the training procedure.

```
model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001), loss="mse", metrics=["mae"])

model.fit(training_data, training_labels, epochs=10, batch_size=32)
```

Training Keras Models

- Call the `compile` method to configure the learning process.
- `tf.keras.Model.compile` takes three important arguments.
  - `optimizer`: specifies the training procedure.
  - `loss`: the cost function to minimize during optimization, e.g., mean squared error (`mse`), `categorical_crossentropy`, and `binary_crossentropy`.

```
model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001), loss="mse", metrics=["mae"])

model.fit(training_data, training_labels, epochs=10, batch_size=32)
```

Training Keras Models

- Call the `compile` method to configure the learning process.
- `tf.keras.Model.compile` takes three important arguments.
  - `optimizer`: specifies the training procedure.
  - `loss`: the cost function to minimize during optimization, e.g., mean squared error (`mse`), `categorical_crossentropy`, and `binary_crossentropy`.
  - `metrics`: used to monitor training.

```
model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001), loss="mse", metrics=["mae"])

model.fit(training_data, training_labels, epochs=10, batch_size=32)
```

Training Keras Models

- Call the `compile` method to configure the learning process.
- `tf.keras.Model.compile` takes three important arguments.
  - `optimizer`: specifies the training procedure.
  - `loss`: the cost function to minimize during optimization, e.g., mean squared error (`mse`), `categorical_crossentropy`, and `binary_crossentropy`.
  - `metrics`: used to monitor training.
- Call the `fit` method to fit the model the training data.

```
model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001), loss="mse", metrics=["mae"])

model.fit(training_data, training_labels, epochs=10, batch_size=32)
```

Evaluate and Predict

- `tf.keras.Model.evaluate`: evaluate the cost and metrics for the data provided.
- `tf.keras.Model.predict`: predict the output of the last layer for the data provided.

```
model.evaluate(test_data, test_labels, batch_size=32)

model.predict(test_data, batch_size=32)
```

Linear Regression in Keras

```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers

x_data = np.random.randn(2000, 3)
w_real = [0.3, 0.5, 0.1]
b_real = -0.2
y_data = np.matmul(w_real, x_data.T) + b_real

model = tf.keras.Sequential([layers.Dense(1, activation="linear")])

model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001),
              loss="mse", metrics=["mae"])

model.fit(x_data, y_data, epochs=100, batch_size=32)

print(model.get_weights())
```

Logistic Regression in Keras

```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers

x_data = ...
y_data = ...

model = tf.keras.Sequential([layers.Dense(1, activation="sigmoid")])

model.compile(optimizer=tf.train.GradientDescentOptimizer(0.001),
              loss="binary_crossentropy", metrics=["accuracy"])

model.fit(x_data, y_data, epochs=100, batch_size=32)

print(model.get_weights())
```

Summary

Summary

- Dataflow graph
- Tensors: constants, variables, placeholders
- Session
- Save and restore models
- TensorBoard
- Keras

Reference

- Aurélien Géron, Hands-On Machine Learning (Ch. 9, 12)
- Some slides were derived from Chip Huyen's slides:
  `http://web.stanford.edu/class/cs20si`

Questions?