Deep Learning for Poets (Part I)

Amir H. Payberah
payberah@kth.se
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TensorFlow

Linear and Logistic regression

Deep Feedforward Networks

CNN, RNN, Autoencoders

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Deep Feedforward Networks

CNN, RNN, Autoencoders

Sheepdog or Mop

Chihuahua or Muffin

Barn Owl or Apple

Raw Chicken or Donald Trump

Artificial Intelligence Challenge

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- The challenge is to solve the tasks that are hard for people to describe formally.

- Let computers to learn from experience.

History of AI

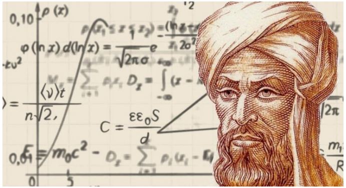
Greek Myths

- Hephaestus, the god of blacksmith, created a metal automaton, called Talos.

[the left figure: http://mythologian.net/hephaestus-the-blacksmith-of-gods]
[the right figure: http://elderscrolls.wikia.com/wiki/Talos]

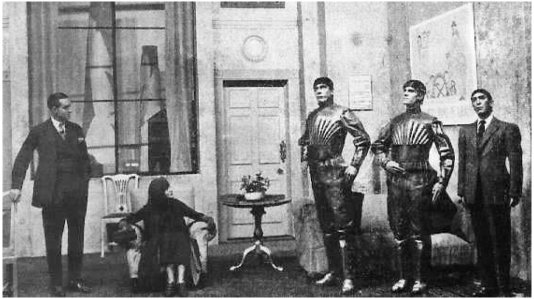
Formal Reasoning

- Mechanizing the process of human thought.



1920: Rossum's Universal Robots (R.U.R.)

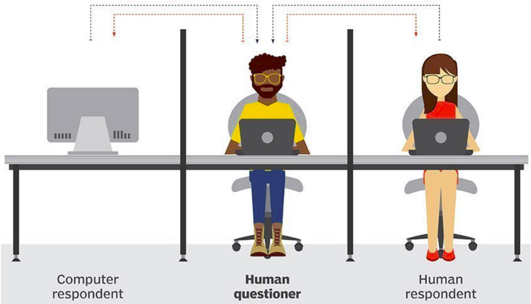
- A science fiction play by Karel Čapek, in 1920.
- A factory that creates artificial people named robots.



[https://dev.to/lschultebraucks/a-short-history-of-artificial-intelligence-7hm]

1950: Turing Test

- In 1950, Turing introduced the Turing test.
- An attempt to define machine intelligence.



[https://searchenterpriseai.techtarget.com/definition/Turing-test]

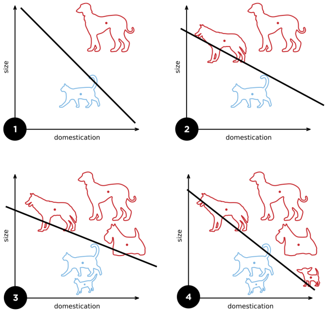
1956: The Dartmouth Workshop

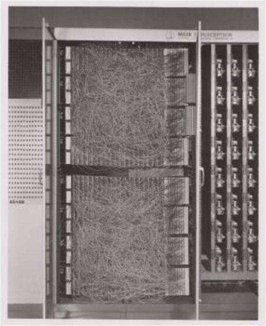
- Probably the first workshop of AI.
- Researchers from CMU, MIT, IBM met together and founded the AI research.

[https://twitter.com/lordsaicom/status/898139880441696257]

1958: Perceptron

- A supervised learning algorithm for binary classifiers.
- Implemented in custom-built hardware as the Mark 1 perceptron.

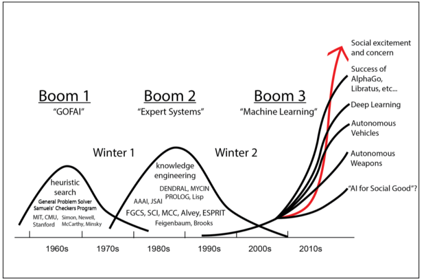




[https://en.wikipedia.org/wiki/Perceptron]

1974–1980: The First AI Winter

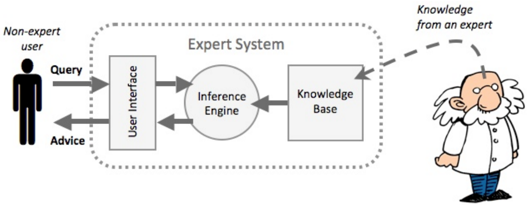
- The over optimistic settings, which were not occurred
- The problems:
  - Limited computer power
  - Lack of data
  - Intractability and the combinatorial explosion



[http://www.technologystories.org/ai-evolution]

1980's: Expert systems

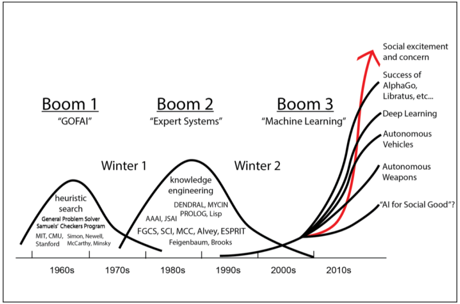
- The programs that solve problems in a specific domain.
- Two engines:
  - Knowledge engine: represents the facts and rules about a specific topic.
  - Inference engine: applies the facts and rules from the knowledge engine to new facts.



[https://www.igcseict.info/theory/7_2/expert]

1987–1993: The Second AI Winter

- After a series of financial setbacks.
- The fall of expert systems and hardware companies.



[http://www.technologystories.org/ai-evolution]

1997: IBM Deep Blue

- The first chess computer to beat a world chess champion Garry Kasparov.

[http://marksist.org/icerik/Tarihte-Bugun/1757/11-Mayis-1997-Deep-Blue-adli-bilgisayar]

2012: AlexNet - Image Recognition

- The ImageNet competition in image classification.
- The AlexNet Convolutional Neural Network (CNN) won the challenge by a large margin.

2016: DeepMind AlphaGo

- DeepMind AlphaGo won Lee Sedol, one of the best players at Go.
- In 2017, AlphaGo Zero that learned Go by playing against itself.

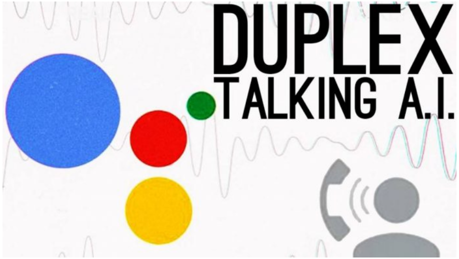
[https://www.zdnet.com/article/google-alphago-caps-victory-by-winning-final-historic-go-match]

2017: DeepStack

- A game of imperfect information.

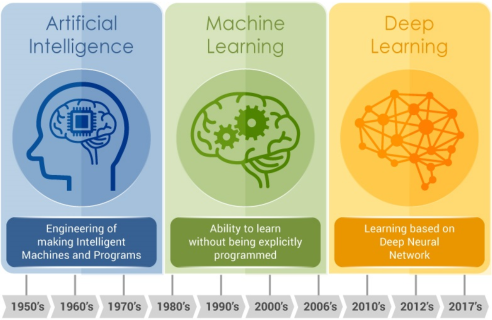
2018: Google Duplex

- An AI system for accomplishing real-world tasks over the phone.
- A Recurrent Neural Network (RNN) built using TensorFlow.



AI Generations

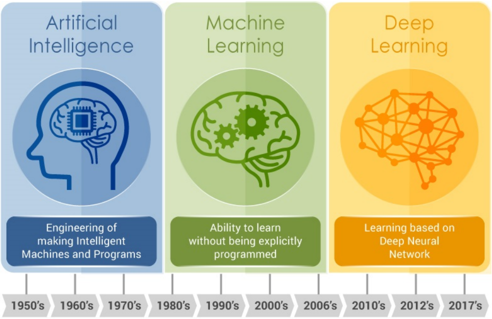
- Rule-based AI
- Machine learning
- Deep learning



[https://bit.ly/2woLEzs]

AI Generations - Rule-based AI

- Hard-code knowledge
- Computers reason using logical inference rules



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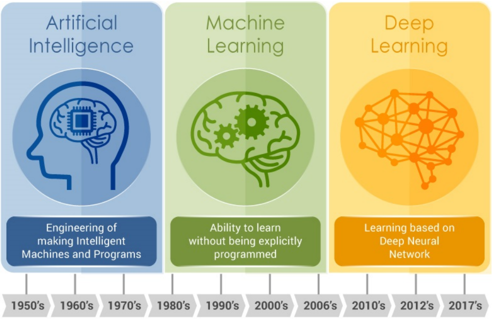
AI Generations - Machine Learning

- If AI systems acquire their own knowledge
- Learn from data without being explicitly programmed



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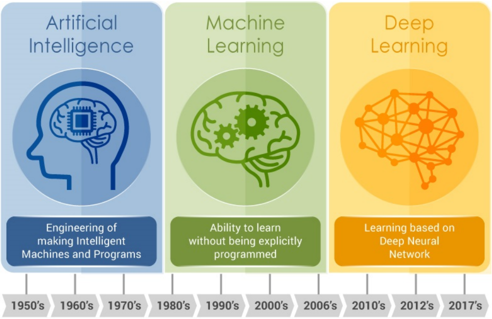
AI Generations - Deep Learning

- For many tasks, it is difficult to know what features should be extracted
- Use machine learning to discover the mapping from representation to output



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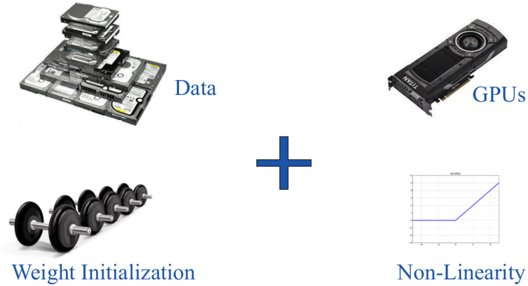
Why Does Deep Learning Work Now?

- Huge quantity of data
- Tremendous increase in computing power
- Better training algorithms



Machine Learning and Deep Learning

Learning Algorithms

- A ML algorithm is an algorithm that is able to learn from data.
- What is learning?

Learning Algorithms

- A ML algorithm is an algorithm that is able to learn from data.
- What is learning?
- A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. (Tom M. Mitchell)

Learning Algorithms - Example 1

- A spam filter that can learn to flag spam given examples of spam emails and examples of regular emails.

[https://bit.ly/2oiplYM]

Learning Algorithms - Example 1

- A spam filter that can learn to flag spam given examples of spam emails and examples of regular emails.
- Task T: flag spam for new emails
- Experience E: the training data
- Performance measure P: the ratio of correctly classified emails

[https://bit.ly/2oiplYM]

Learning Algorithms - Example 2

- Given dataset of prices of 500 houses, how can we learn to predict the prices of other houses, as a function of the size of their living areas?

[https://bit.ly/2MyiJUy]

Learning Algorithms - Example 2

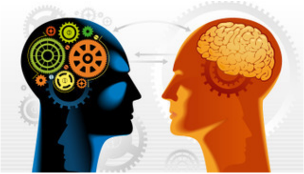
- Given dataset of prices of 500 houses, how can we learn to predict the prices of other houses, as a function of the size of their living areas?
- Task T: predict the price
- Experience E: the dataset of living areas and prices
- Performance measure P: the difference between the predicted price and the real price

[https://bit.ly/2MyiJUy]

Types of Machine Learning Algorithms

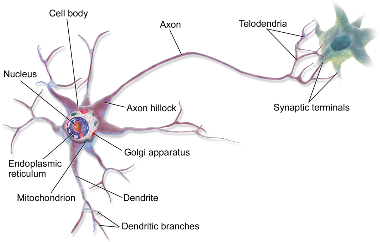
- Supervised learning
  - Input data is labeled, e.g., spam/not-spam or a stock price at a time.
  - Regression vs. classification

- Unsupervised learning
  - Input data is unlabeled.
  - Find hidden structures in data.



From Machine Learning to Deep Learning

- Deep Learning (DL) is part of ML methods based on learning data representations.
- Mimic the neural networks of our brain.



[A. Geron, O'Reilly Media, 2017]

Deep Learning Frameworks

Deep Learning Frameworks

- TensorFlow and Keras
- PyTorch
- Caffe
- ...

TensorFlow

Let's Start with an Example

Hello World

$$\mathtt{c} = \mathtt{a} \times \mathtt{b}$$

Hello World

$$c = a \times b$$

$$d = a + b$$

Hello World

$$c = a \times b$$

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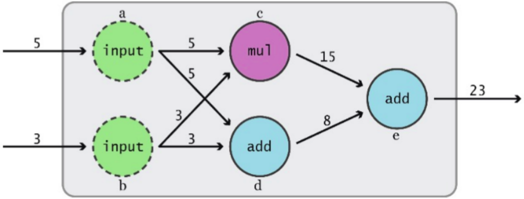
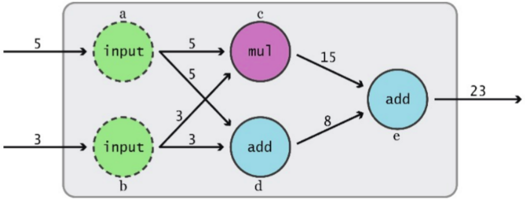


Two Phases of Tensorflow

- Working with TensorFlow involves two main phases.



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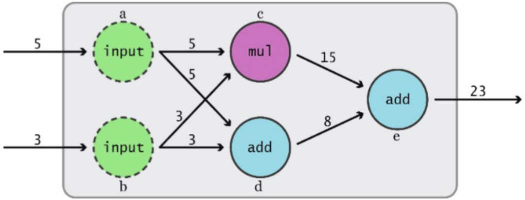
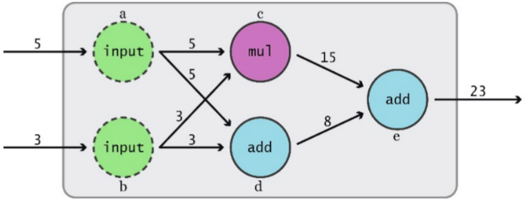
  1. Build a graph

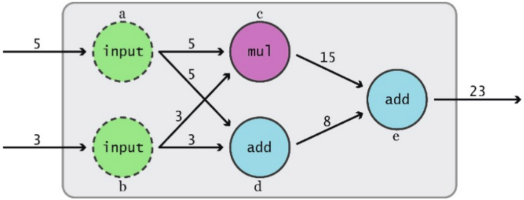


Two Phases of Tensorflow

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



Phase 1: Build a Graph



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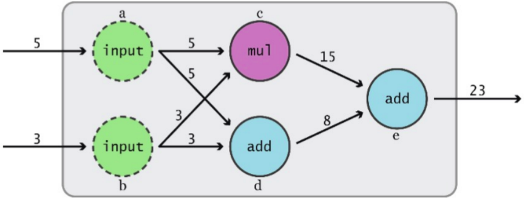

- `import tensorflow as tf`: it forms an empty default graph.

```
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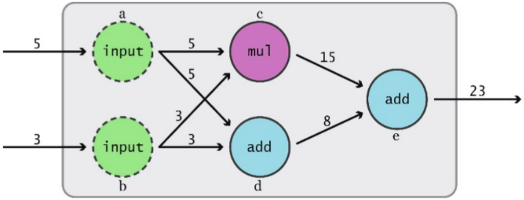

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a = tf.constant(5)
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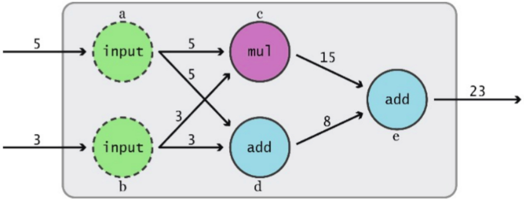

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a = tf.constant(5)
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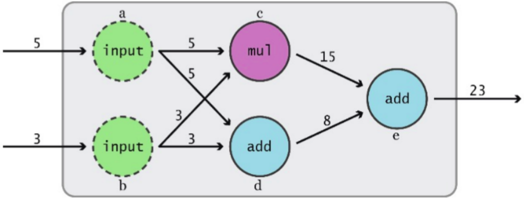
```
c = tf.multiply(a, b)
d = tf.add(a, b)
e = tf.add(c, d)
```

Phase 2: Execute a Graph



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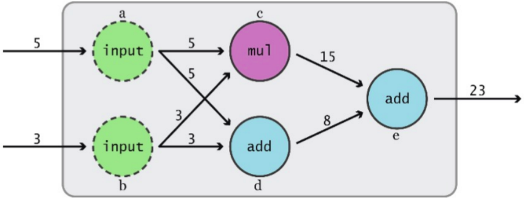
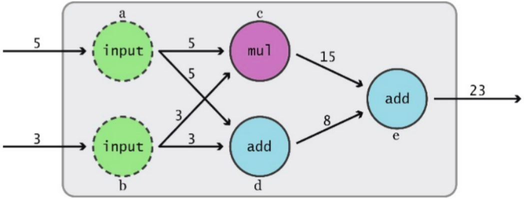


- Now run the computations: create and run a session.

Phase 2: Execute a Graph



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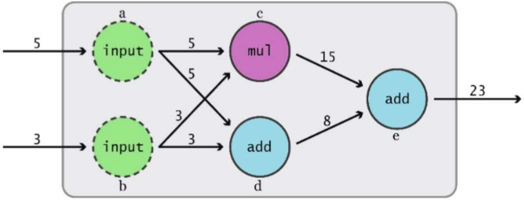

- Now run the computations: create and run a session.

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sess = tf.Session()
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```

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

The Complete Code

```python
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)
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Visualize the Code

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

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

Let's Give Name to Variables

```python
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:
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```

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

Tensor Objects

What is Tensor?

- The central unit of data in TensorFlow is the tensor.

What is Tensor?

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

Tensor Objects

- `tf.Tensor`

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- `tf.Tensor`
- Each Tensor object is specified by:
  - Rank
  - Shape
  - Datatype

Tensor Objects - Rank

- The number of dimensions.

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- `tf.rank` 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.

Tensor Objects - Shape

- The number of elements in each dimension.
- The `get_shape()` returns the shape of a `tf.Tensor` object.

```
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 `tf.Tensor` object.

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- We can explicitly choose the data type of a `tf.Tensor` object.
- `tf.cast()` changes the data type of a `tf.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.

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

Tensor Objects - Name Scopes

- Hierarchically group nodes by their names.

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```
with tf.name_scope("aut"):
  c1 = tf.constant(4, dtype=tf.int32, name="input1") # aut/intput1
  c2 = tf.constant(4.0, dtype=tf.float64, name="input2") # aut/inout2
```

Main Types of Tensors

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

Constants

Constants (1/3)

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

Constants (1/3)

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- 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)

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- 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

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- A variable is a Tensor whose value can be changed.

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- tf.get_variable creates a variable or returns it if it exists.

```
# 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

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- Initialize all variables at once.

```
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    sess.run(tf.global_variables_initializer())
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- Initialize only a subset of variables.

```
with tf.Session() as sess:
    sess.run(tf.variables_initializer([a, b]))
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Initialize Variables

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

- 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)

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```
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.

```
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

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```
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)

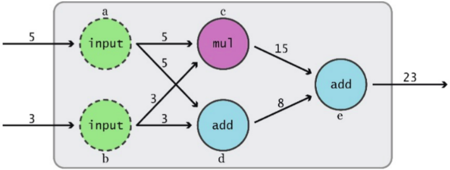
c = a + b

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

Dataflow Graphs

Graph

- A graph is composed of two types of objects:
    - Operations
    - Tensors



Common TensorFlow Operations)

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`.

Managing Multiple Graphs (1/2)

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Managing Multiple Graphs (1/2)

- Calling `import tensorflow` creates the default graph.
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- `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)

- Associate nodes to a right graph using `with` and `as_default()`.

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```
import tensorflow as tf

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

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

Managing Multiple Graphs (2/2)

- Associate nodes to a right graph using `with` and `as_default()`.

```
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.

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

```
# can be written as follows
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Feeding

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- To feed a placeholder, the input data is passed to the `session.run()`.

```
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]}))
```

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.

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

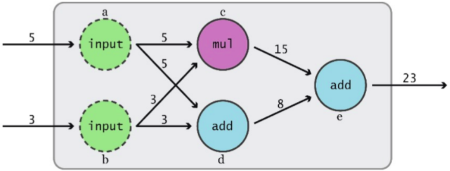
with tf.Session() as sess:
    print(sess.run(z, feed_dict={x: 3, y: 4.5}))
    print(sess.run(z, feed_dict={x: [1, 3], y: [2, 4]}))
```

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`.

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

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

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- You can use sess.run() to fetch the values of many tensors in the same step.

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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
```

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

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

Saving and Restoring Models

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- Save a model's parameters in disk.

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

Saving Models

- Save a model's parameters in disk.
- Create a Saver node at the end of the construction phase.
- 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)
  sess.run(train, {x: x_data, y_true: y_data})
  saver.save(sess, "/tmp/my_model_final.ckpt")
```

Restoring Models

- Create a `Saver` node at the end of the construction phase.

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- At the begining of the execution phase call its `restore()` method.

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  - Instead of initializing the variables using the `init` node.

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

TensorBoard

TensorBoard (1/2)

- TensorFlow provides a utility called TensorBoard.

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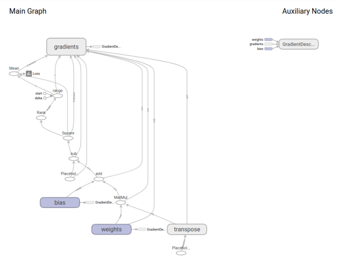
- TensorFlow provides a utility called TensorBoard.
- To visualize your model, you need to write the graph definition and some training stats to a log directory that TensorBoard will read from.

TensorBoard (2/2)

- Add the following code at the very end of the construction phase.

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



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- The first line writes the cost.

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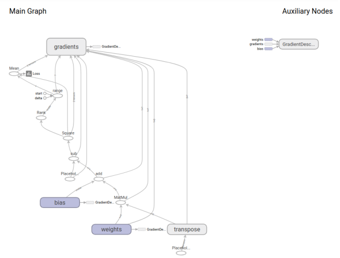
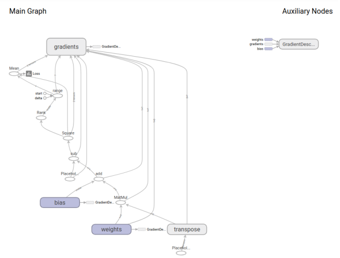


TensorBoard (2/2)

- 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.

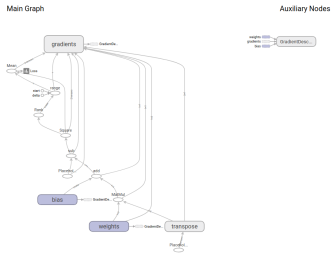
```
logdir = "."
mse_summary = tf.summary.scalar("MSE", cost)
file_writer = tf.summary.FileWriter(logdir, tf.get_default_graph())
file_writer.close()
```



TensorBoard (2/2)

- 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()
```



Summary

Summary

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

Questions?