Deep Learning

Lesson 5—Introduction to TensorFlow

Learning Objectives

- ✓ Explore the meaning of TensorFlow
- ✓ Create computational and default graph in TensorFlow
- ✓ Demonstrate reshaping of a tensor with tf.reshape
- ✓ Implement Linear Regression and Gradient Descent in TensorFlow
- ✓ Discuss the meaning and application of Layers and Keras in TensorFlow
- ✓ Demonstrate the use of TensorBoard

Introduction to TensorFlow

Topic 1: Meaning of TensorFlow and Tensor Ranks

What is TensorFlow?

A popular Machine Learning library, particularly well suited for large scale Machine Learning

A product by Google Brain team that is used in Google Photos, Google Search and Google Cloud Speech.

An open source software library for numerical computation using data flow or computational graphs

A distributed computing tool that enables colossus neural networks to be trained across distributed servers. Google has also launched a cloud service to run TensorFlow graphs.

TensorFlow At A Glance

High level APIs like TF Layers, Keras and Pretty Tensor can run on top of TensorFlow. It provides simple API TF-Slim (tensorflow.contrib.slim) for simple training routines.

It provides a visualization tool called TensorBoard, in which one can view the computation graph, learning curves etc.

It runs on Operating Systems like Windows, Linux, and macOS, and mobile operating systems like iOS and Android.

It automatically computes gradients of the cost functions. This is called automatic differentiating (Autodiff).

It provides a simple Python API called TF.Learn (tensorflow.contrib.learn) for training neural networks in few lines of code.

It provides several optimization nodes to search for parameters that minimize a cost function.

It includes highly efficient C++ implementations of Machine Learning and custom C++ operations.

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Types of APIs

TensorFlow Core API

Low level Machine Learning development

1

Two Main APIs that TensorFlow provides

2

Higher Level APIs

More compact APIs such as tf.contrib.learn, or tf.layers

Types of APIs (Contd.)

1 **TensorFlow Core API**

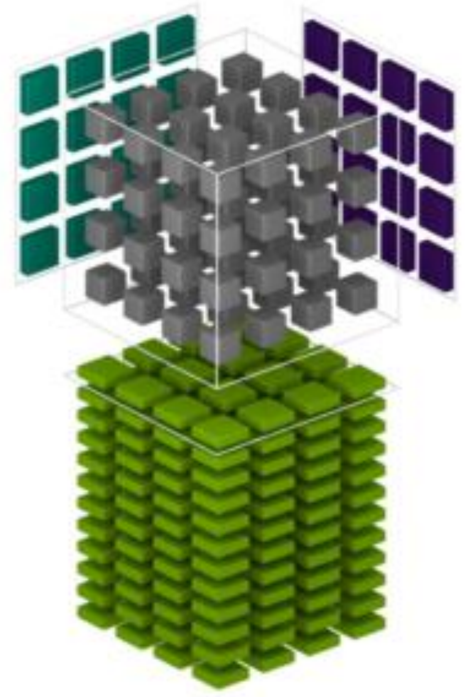
- TensorFlow Core provides complete programming control.
- It is more suitable for machine learning researchers and others who require fine levels of control over their models.

Types of APIs (Contd.)

2 Higher Level APIs

- Higher level APIs are built on top of TensorFlow Core.
- These are easier to learn and use than TensorFlow Core.
- They make repetitive tasks easier and more consistent between different users.
- Higher level API such as ***tf.contrib.learn*** helps you manage data sets, estimators, training and inference.

What are Tensors?



Tensors are multidimensional data arrays or inputs and outputs of TensorFlow.

They are a set of values shaped into an n-dimensional array with static and dynamic type dimensions.

They typically contain floats but can carry strings too in form of byte arrays.

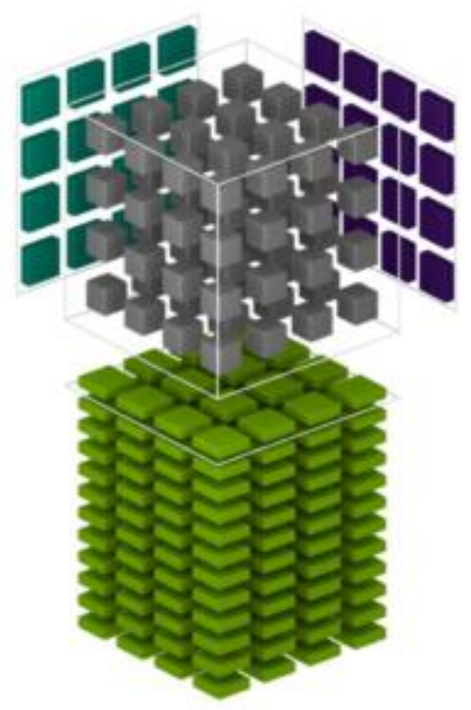
They mathematically represent a physical entity, characterized by magnitude and multiple directions.

They may be passed between the nodes of a computation graph and have a data type.

NumPy is a Python API used for numerical computations.

Tensor Ranks

The rank of a tf.tensor object is its number of dimensions.



A tensor's dimensionality can be described using rank, shape and dimension number.

Tensor's shape and dimensions determines its rank.

Tensor Ranks (Contd.)

Number of Dimensions + Shape determines Tensor Rank

3#a + Scalar shape with [ ]	Tensor Rank 0
[1. ,2., 3.] # a + vector with shape [3]	Tensor Rank 1
[[1., 2., 3.], [4., 5., 6.]] # a + a matrix with shape [2, 3]	Tensor Rank 2
[[[1., 2., 3.]], [[7., 8., 9.]]] # a + with shape [2, 1, 3]	Tensor Rank 3

Installation of TensorFlow

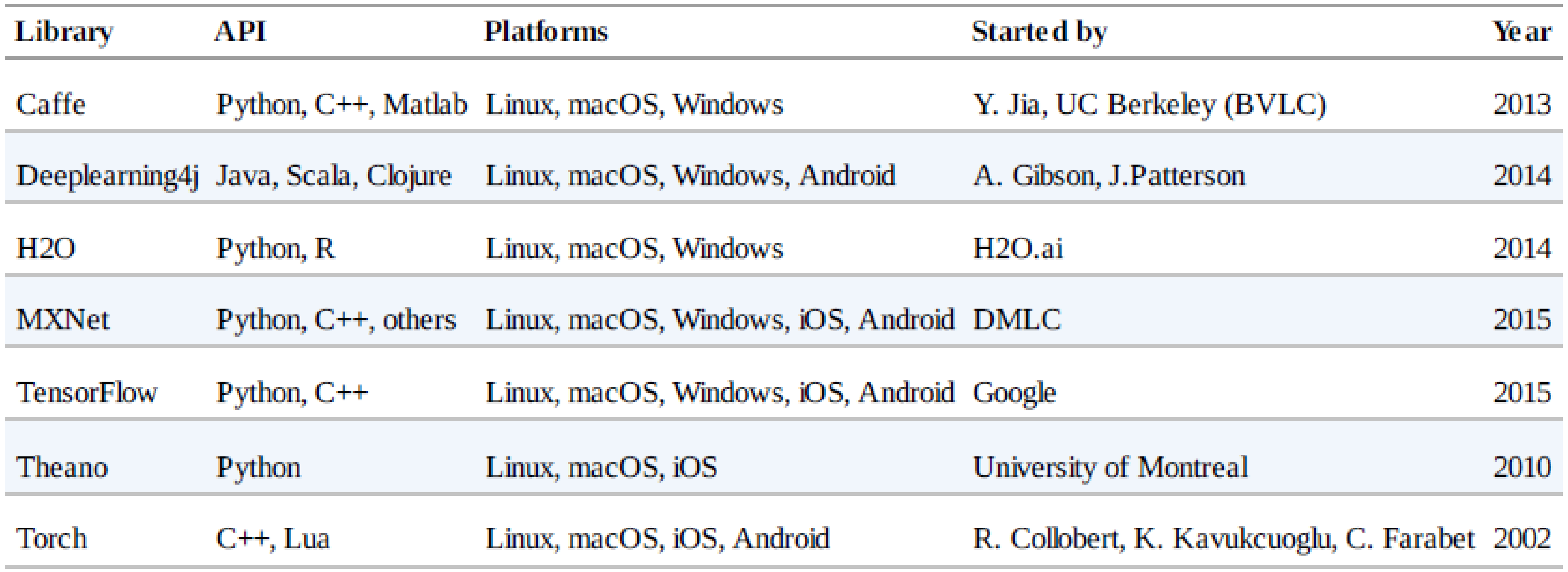
- Install TensorFlow:
  - $ pip3 install - upgrade tensorflow

- For GPU installation of TF:
  - $ pip3 install – upgrade tensorflow-gpu

- Test the installation:
  - $ python3 -c 'import tensorflow; print(tensorflow.__version__)‘
  - 1.0.0

Open Source Deep Learning Libraries

- There are other libraries that perform deep learning with almost similar capabilities.
- However, Google's TensorFlow has proven to be scalable, clean, flexible, and efficient library.
- The reason that it is backed by Google, has caused it to catapult to the top of developer's choice.

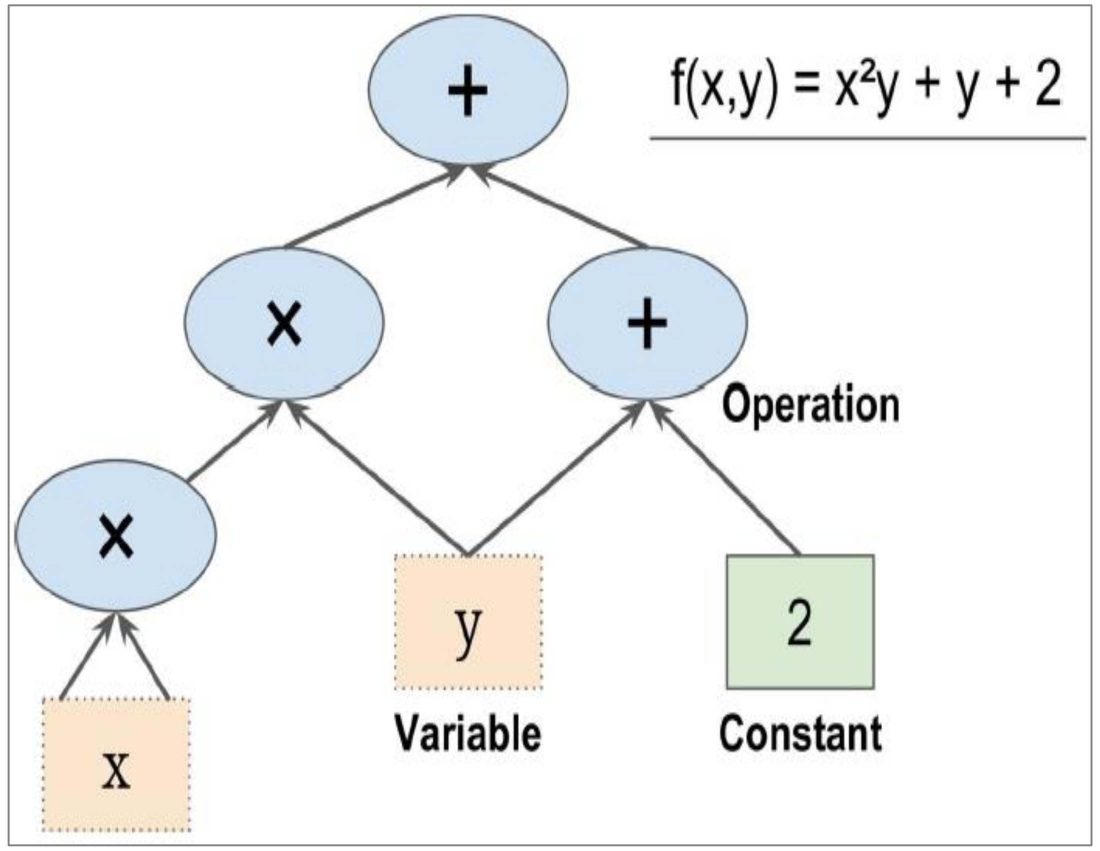


Library	API	Platforms	Started by	Year
Caffe	Python, C++, Matlab	Linux, macOS, Windows	Y. Jia, UC Berkeley (BVLC)	2013
Deeplearning4j	Java, Scala, Clojure	Linux, macOS, Windows, Android	A. Gibson, J.Patterson	2014
H2O	Python, R	Linux, macOS, Windows	H2O.ai	2014
MXNet	Python, C++, others	Linux, macOS, Windows, iOS, Android	DMLC	2015
TensorFlow	Python, C++	Linux, macOS, Windows, iOS, Android	Google	2015
Theano	Python	Linux, macOS, iOS	University of Montreal	2010
Torch	C++, Lua	Linux, macOS, iOS, Android	R. Collobert, K. Kavukcuoglu, C. Farabet	2002

Introduction to TensorFlow

Topic 2: Computational Graph

Computational Graph

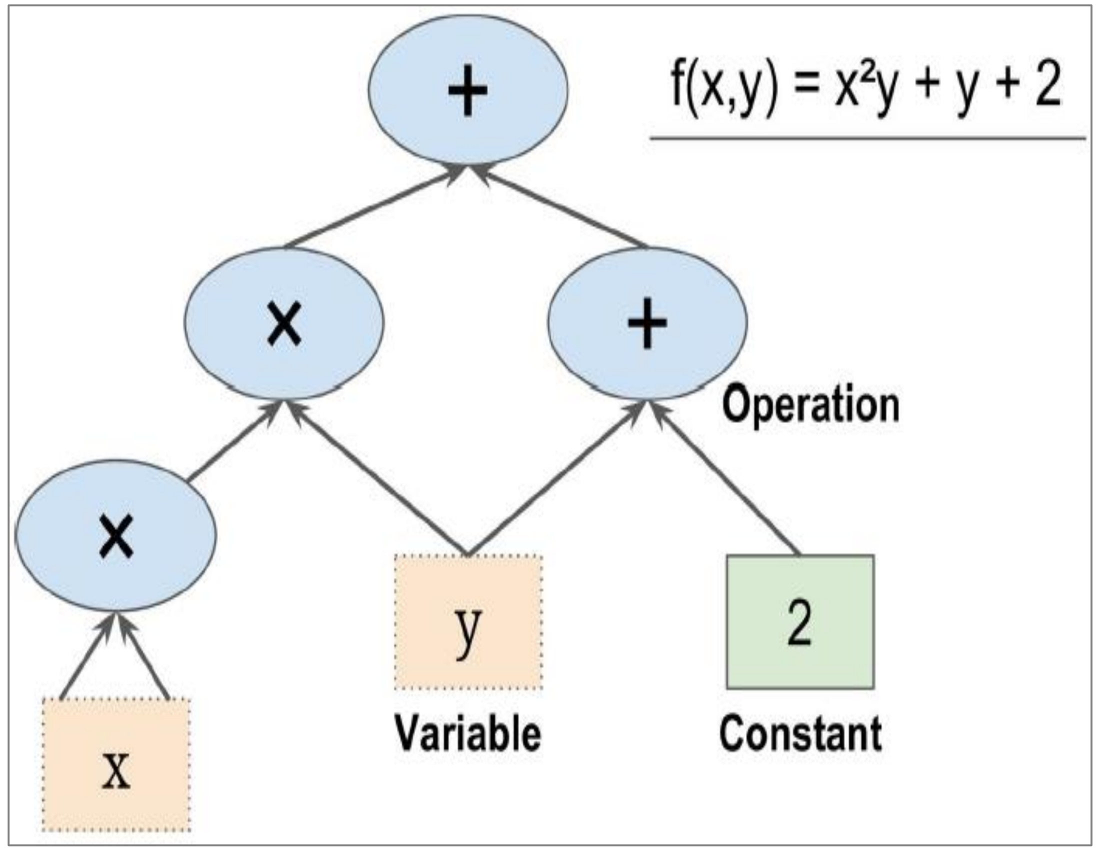


TensorFlow operations can be arranged into a graph termed as computational graph.

It enables creating very large scale neural networks as computing can be distributed across several CPUs or GPUs in a similar fashion.

Computational Graph is the graph of program logic which TensorFlow builds in the memory.

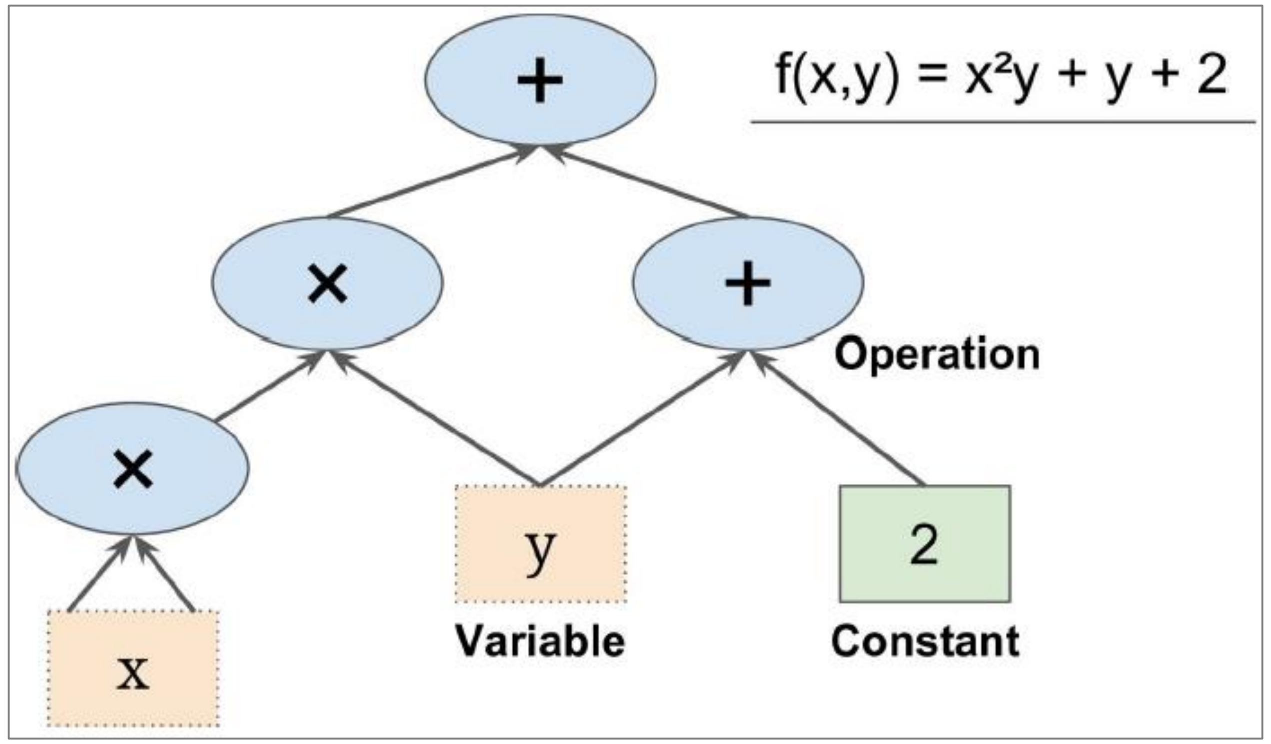
Computational Graph (Contd.)

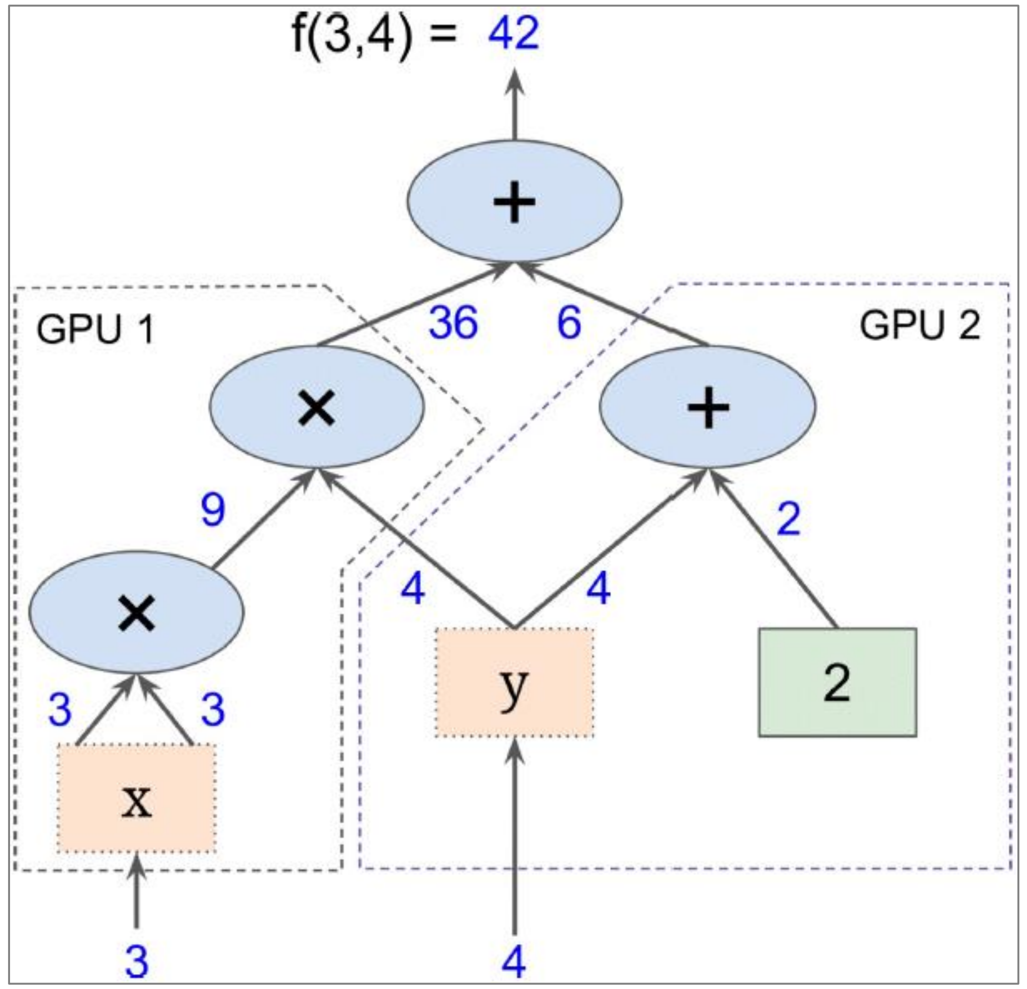


It demonstrates how variables are defined and operations are performed on them to solve a desired function.

The actual execution of the graph comes in the steps that follow later.

Computational Graph (Contd.)





- The computational graph can be broken into chunks and can run across many different CPUs or GPUs parallelly. This is called parallel computation.

TensorFlow Program Elements

Constant	• A parameter whose value never changes
Placeholder	• Permits a value to be assigned later • a = tf.placeholder(tf.float32)
feed_dict parameter	• Specifies Tensors that provide concrete values to the placeholders
Variable	• Allows addition of new trainable parameters to a graph • W = tf.Variable([.3], dtype=tf.float32) • b = tf.Variable([-.3], dtype=tf.float32) • x = tf.placeholder(tf.float32) • linear_model = W * x + b
Session	• A session is run to evaluate the nodes • This is called as the TensorFlow runtime

Creating Computational Graph

CONSTRUCTION PHASE

```
import tensorflow as tf

x = tf.Variable(3, name="x")
y = tf.Variable(4, name="y")
f = x*x*y + y + 2
```

- The code given here creates a graph in memory.
- It declares variables and function.
- This creates TF graph in memory corresponding to the objects created by the code (the actual execution of this logic does not happen yet).

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Creating Computational Graph

EXECUTION PHASE

```
>>> sess = tf.Session()
>>> sess.run(x.initializer)
>>> sess.run(y.initializer)
>>> result = sess.run(f)
>>> print(result)
42
>>> sess.close()
```

- To evaluate the graph, open TensorFlow session and run it.
- The above set of code runs a TF session to execute the three graph nodes (one each for x, y, and f) and print the result of the entire operation.

Creating Computational Graph

EXECUTION PHASE

```
with tf.Session() as sess:
    x.initializer.run()
    y.initializer.run()
    result = f.eval()
```

- To avoid calling sess.run multiple times, you can run the above code.
- The above given set of code encapsulates the running of three graph nodes under one session run.

Creating Computational Graph

INITIALIZATION PHASE

```
init = tf.global_variables_initializer()  # prepare an init node

with tf.Session() as sess:
    init.run()  # actually initialize all the variables
    result = f.eval()
```

- In the previous code, you initialized x and y separately.
- In the given code, you initialize it in one shot using a global initializer.
- So, instead of initializing each variable separately, ***global_variables_initializer*** can be used to initialize all the variables together:

Creating Computational Graph

INITIALIZATION AND EXECUTION PHASE

```
>>> sess = tf.InteractiveSession()
>>> init.run()
>>> result = f.eval()
>>> print(result)
42
>>> sess.close()
```

- The above code removes the need to encapsulate the session execution in a "with" block.
- An ***InteractiveSession*** (instead of Session) sets up a default session therefore a “*with*” block is no longer required.

Default Graph

- In Jupyter (or in a Python shell), it is common to run the same commands more than once while you are experimenting.
- As a result, you may end up with a default graph containing many duplicate nodes.
- One solution is to restart the Jupyter kernel (or the Python shell), but a more convenient solution is to just reset the default graph by running ***tf.reset_default_graph()***.
- For example, if you have a line of code x = tf.variable (3, name="x") and you run the program more than once or twice within the same Python shell, it would create multiple duplicate copies of the node pertaining to the variable x.
- This can be avoided by a number of techniques like resetting a graph.

Default Graph (Contd.)

- The default graph is the graph that is produced by default for a TensorFlow program.
- You can create other graphs programmatically (apart from the default graph) in certain situations, if required.
- Any new node gets added to default graph, unless the newly created graph is set as the default graph, for example, the case of variable x2 as shown in the next set of code.
- To use a new graph, create a Graph and use a "with" block to temporarily make it the default graph.

```
>>> x1 = tf.Variable(1)
>>> x1.graph is tf.get_default_graph()
True
```

```
>>> graph = tf.Graph()
>>> with graph.as_default():
...     x2 = tf.Variable(2)
...
>>> x2.graph is graph
True
>>> x2.graph is tf.get_default_graph()
False
```

Lifecycle of a Node Value

- A Node refers to an object in the computation graph.
- It can be a variable or constant or an operation.

- *y* is evaluated after the session starts, but it depends on x, which in turn depends on *w*.
- So computation order is *w*, *x*, and then *y*.
- When z is evaluated, it does not reuse computed value of x and w but re-computes them instead.
- Variables however maintain their value between graph executions.
- *y* and *z* get computed in one graph run, thus avoiding two different computations for *x* and *w*.

```
w = tf.constant(3)
x = w + 2
y = x + 5
z = x * 3

with tf.Session() as sess:
    print(y.eval())  # 10
    print(z.eval())  # 15
```

```
with tf.Session() as sess:
    y_val, z_val = sess.run([y, z])
    print(y_val)  # 10
    print(z_val)  # 15
```

Introduction to TensorFlow

Topic 3: Reshaping a Tensor

Shape of a Tensor

- TensorFlow provides several operations that you can use to determine the shape of a tensor and change the shape of a tensor.
- The following code returns the shape of a tensor:

```
tf.shape(input, name=None, out_type=tf.int32)
```

Tensor or SparseTensor

name for the operation

specified output type of the operation
(int32 or int64)
Defaults to tf.int32

- It returns the shapes of a tensor using 1D integer tensor of type out_type.

Source: https://www.tensorflow.org/api_docs/python

Size of a Tensor

- The following code returns the size of a tensor:

```
tf.size(input, name=None, out_type=tf.int32)
```

Tensor or SparseTensor

name for the operation

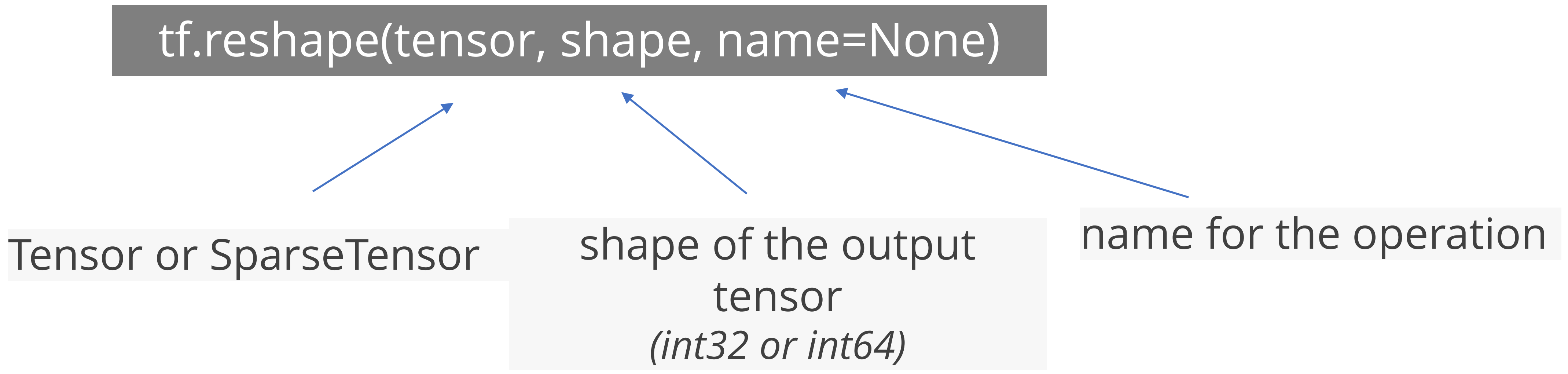
specified output type of the operation
(int32 or int64)
Defaults to tf.int32

- It returns the size of a tensor representing the number of elements in input.

Source: https://www.tensorflow.org/api_docs/python

Reshaping a Tensor

- The following code reshapes a tensor.



```
tf.reshape(tensor, shape, name=None)
```

- If a tensor is given, this operation returns a tensor that has the same values as "*tensor*" with shape "*shape.*"
- If one component of shape is the special value -1, the size of that dimension is computed so that the total size remains constant.
- In particular, a shape of [-1] flattens into 1-D.
- At most one component of shape can be -1.

Source: https://www.tensorflow.org/api_docs/python

Reshaping a Tensor

EXAMPLE

```
# tensor 't' is [1, 2, 3, 4, 5, 6, 7, 8, 9]
# tensor 't' has shape [9]
reshape(t, [3, 3]) ==> [[1, 2, 3],
                        [4, 5, 6],
                        [7, 8, 9]]
```

In the code given above:

- A tensor t is declared with shape [9].
- It is then reshaped to [3,3] shape and output is checked.
- Tensor t has shape [x, y, z] where,
  - x is no of rows
  - y is no of columns
  - z is depth

Reshaping a Tensor (Contd.)

EXAMPLE

```
# tensor 't' is [[[1, 1], [2, 2]],
#                [[3, 3], [4, 4]]]
# tensor 't' has shape [2, 2, 2]
reshape(t, [2, 4]) ==> [[1, 1, 2, 2],
                        [3, 3, 4, 4]]
```

In the code given above:

- A tensor "t" is declared with shape [2,2,2].
- It is then reshaped to [2,4] shape and output is checked.

Reshaping a Tensor (Contd.)

EXAMPLE

Create a tensor of shape [3,2,3] and flatten it to 1D with [-1] notation in the reshape command.

```
# tensor 't' is [[[1, 1, 1],
#                 [2, 2, 2]],
#                [[3, 3, 3],
#                 [4, 4, 4]],
#                [[5, 5, 5],
#                 [6, 6, 6]]]
# tensor 't' has shape [3, 2, 3]
# pass '[-1]' to flatten 't'
reshape(t, [-1]) ==> [1, 1, 1, 2, 2, 2, 3, 3, 3, 4, 4, 4, 5, 5, 5, 6, 6, 6]
```

```
# -1 can also be used to infer the shape
# -1 is inferred to be 9:
reshape(t, [2, -1]) ==> [[1, 1, 1, 2, 2, 2, 3, 3, 3],
                         [4, 4, 4, 5, 5, 5, 6, 6, 6]]
# -1 is inferred to be 2:
reshape(t, [-1, 9]) ==> [[1, 1, 1, 2, 2, 2, 3, 3, 3],
                         [4, 4, 4, 5, 5, 5, 6, 6, 6]]
# -1 is inferred to be 3:
reshape(t, [ 2, -1, 3]) ==> [[[1, 1, 1],
                              [2, 2, 2],
                              [3, 3, 3]],
                             [[4, 4, 4],
                              [5, 5, 5],
                              [6, 6, 6]]]
# tensor 't' is [7]
# shape `[]` reshapes to a scalar
reshape(t, []) ==> 7
```

Introduction to TensorFlow

Topic 4: Linear Regression and Gradient Descent

Linear Regression

RECAP

- Linear regression is a linear approach for modeling the relationship between a scalar dependent variable y and an independent variable x.

$$\hat{y} = \boldsymbol{w}^\top \boldsymbol{x}$$

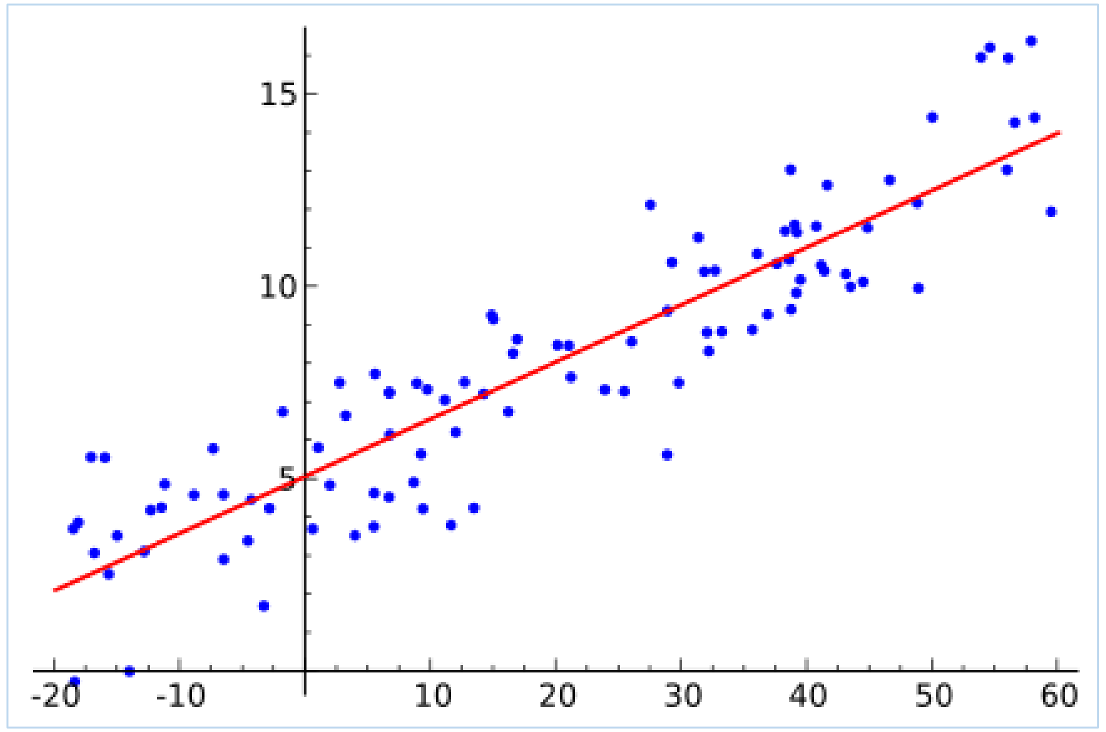
x and y are vectors of real numbers and w is a vector of weight parameters.

- The equation is also written as:

$$y = wx + b$$

where b is the bias or the value of output for zero input

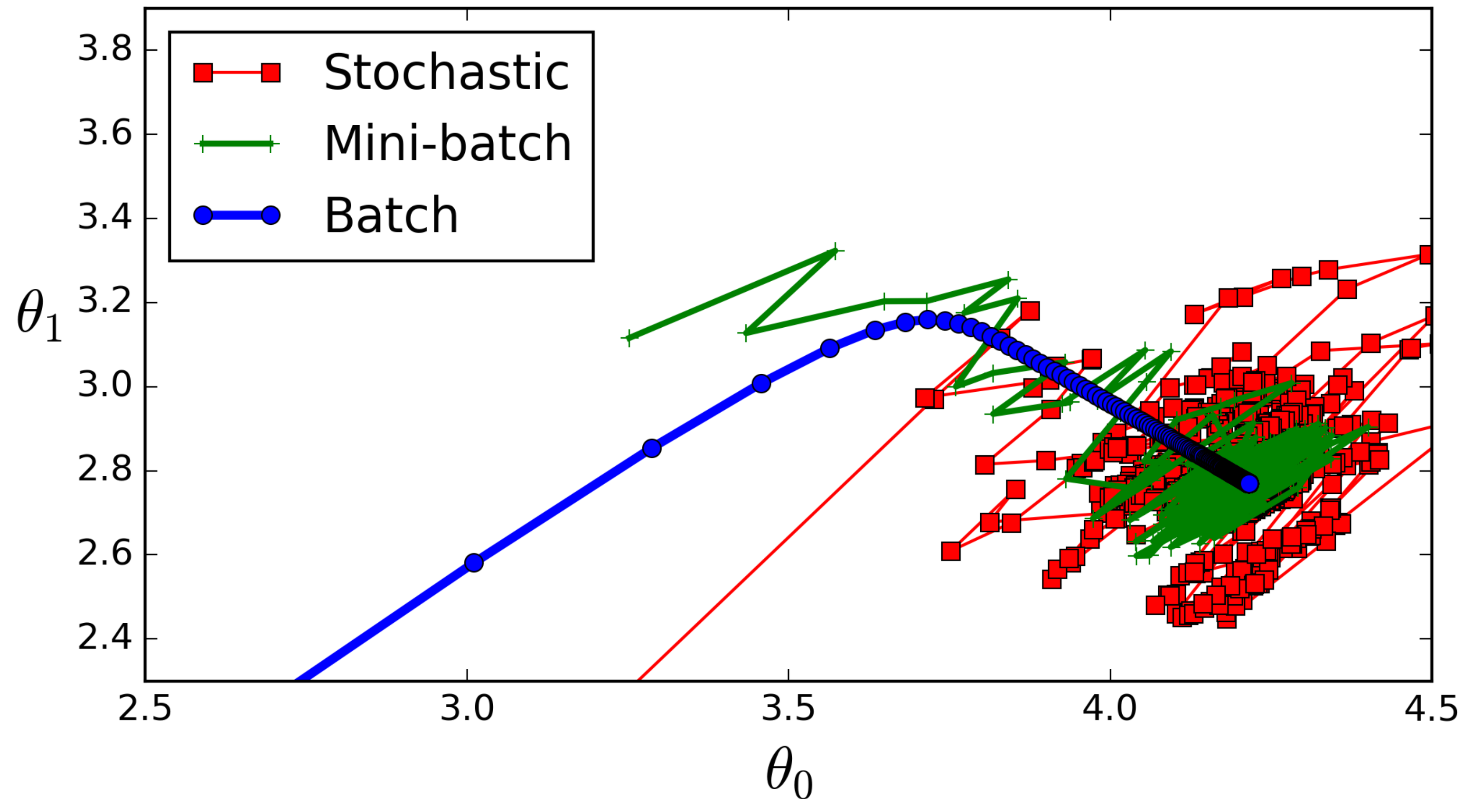
- Linear Regression can be of two types:
  - Simple Linear Regression
  - Multiple Linear Regression



Gradient Descent

RECAP

- Gradient descent is an optimization algorithm used for finding the weights or coefficients of machine learning algorithms.
- The goal of algorithm is to find model parameters like coefficients or weights that minimize the error of the model on the training dataset.
- This is done by making changes to the model that move it along a gradient or slope of errors down toward a minimum error value. This gives the algorithm the name ***gradient descent***.

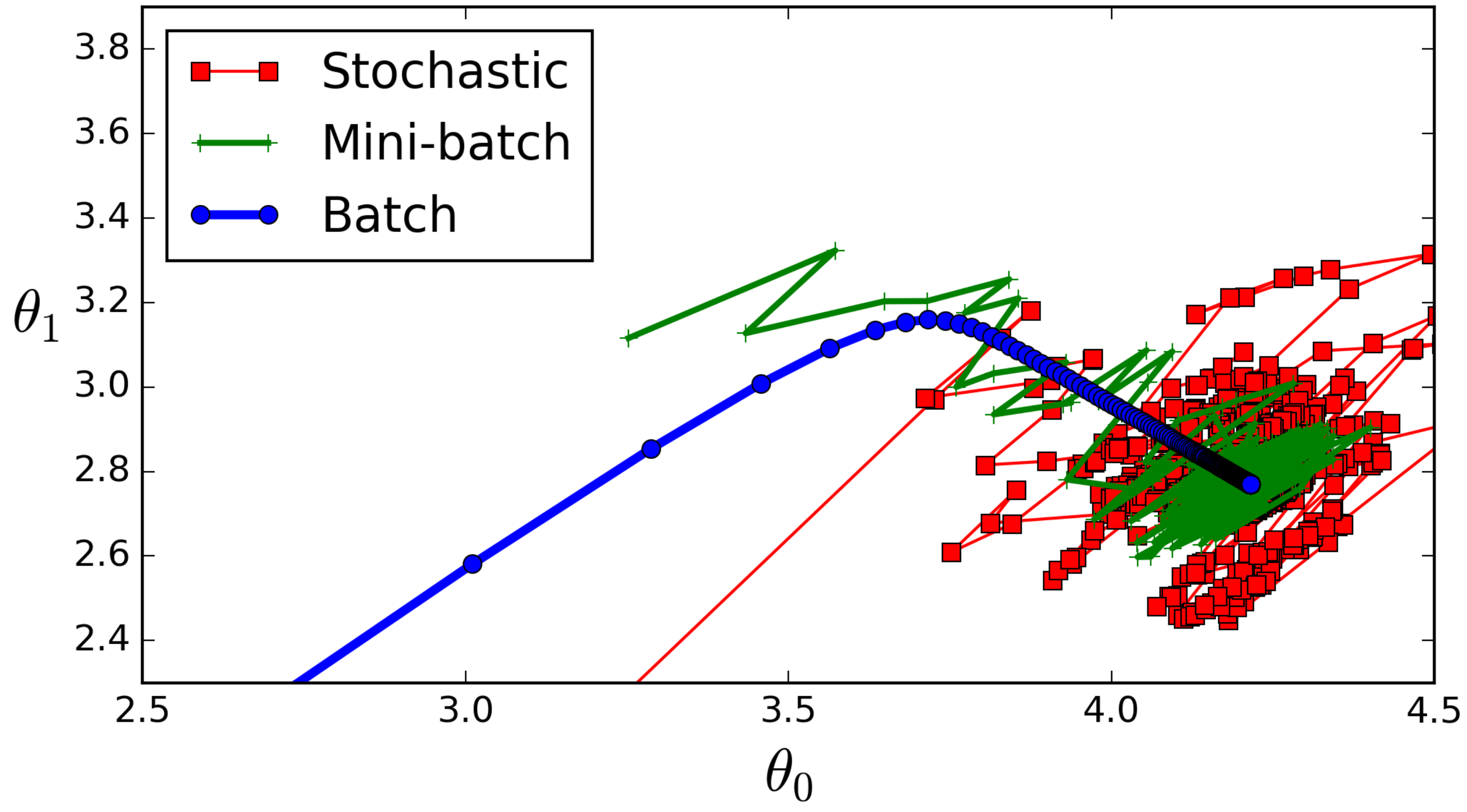


Source: https://stats.stackexchange.com

Gradient Descent

RECAP

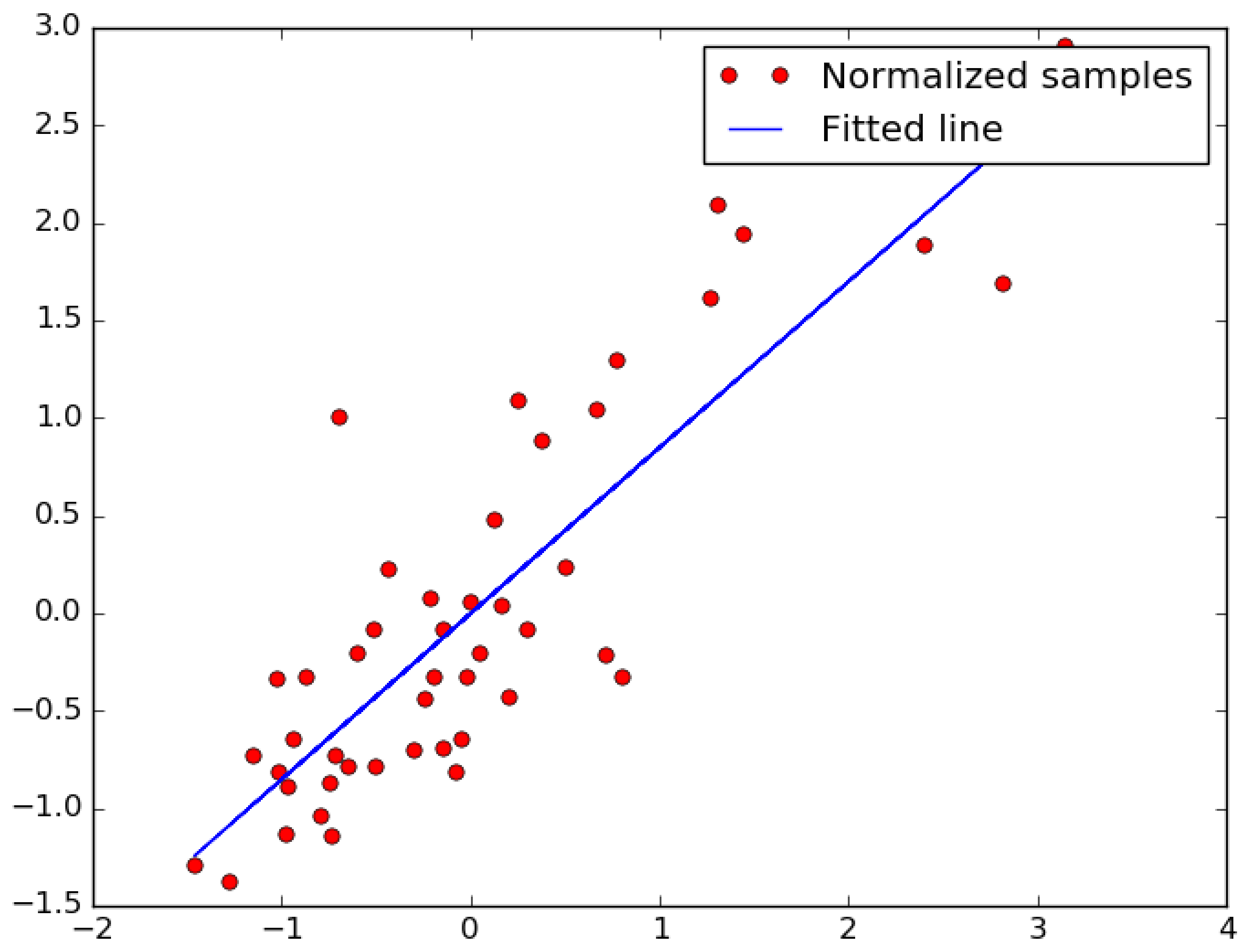
- The three types of gradient descent are:
  - Batch
  - Stochastic
  - Mini-batch
- Mini-batch gradient descent splits the training dataset into small batches that are used to calculate model error and update model coefficients.



Source: https://stats.stackexchange.com

Linear Regression in TensorFlow

- In order to train a data model, TensorFlow loops through the data and finds optimal line that fits the data.
- The linear relationship between two variables X and Y is estimated by designing an appropriate optimization problem.
- tf.estimator API in TensorFlow can be used to solve a binary classification problem



Linear Regression in TensorFlow

EXAMPLE

The following code is a Linear Regression model with TensorFlow, with a given a set of training data x_train and y_train.

```
import numpy as np
import tensorflow as tf

# Model parameters
W = tf.Variable([.3], tf.float32)
b = tf.Variable([-.3], tf.float32)
# Model input and output
x = tf.placeholder(tf.float32)
linear_model = W * x + b
y = tf.placeholder(tf.float32)
# loss
loss = tf.reduce_sum(tf.square(linear_model - y))
# sum of the squares
```

```
# optimizer
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)
# training data
x_train = [1,2,3,4]
y_train = [0,-1,-2,-3]
# training loop
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init) # reset values to wrong
for i in range(1000):
  sess.run(train, {x:x_train, y:y_train})

# evaluate training accuracy
curr_W, curr_b, curr_loss  = sess.run([W, b, loss], {x:x_train, y:y_train})
print("W: %s b: %s loss: %s"%(curr_W, curr_b, curr_loss))
```

Linear Regression in TensorFlow

OUTPUT

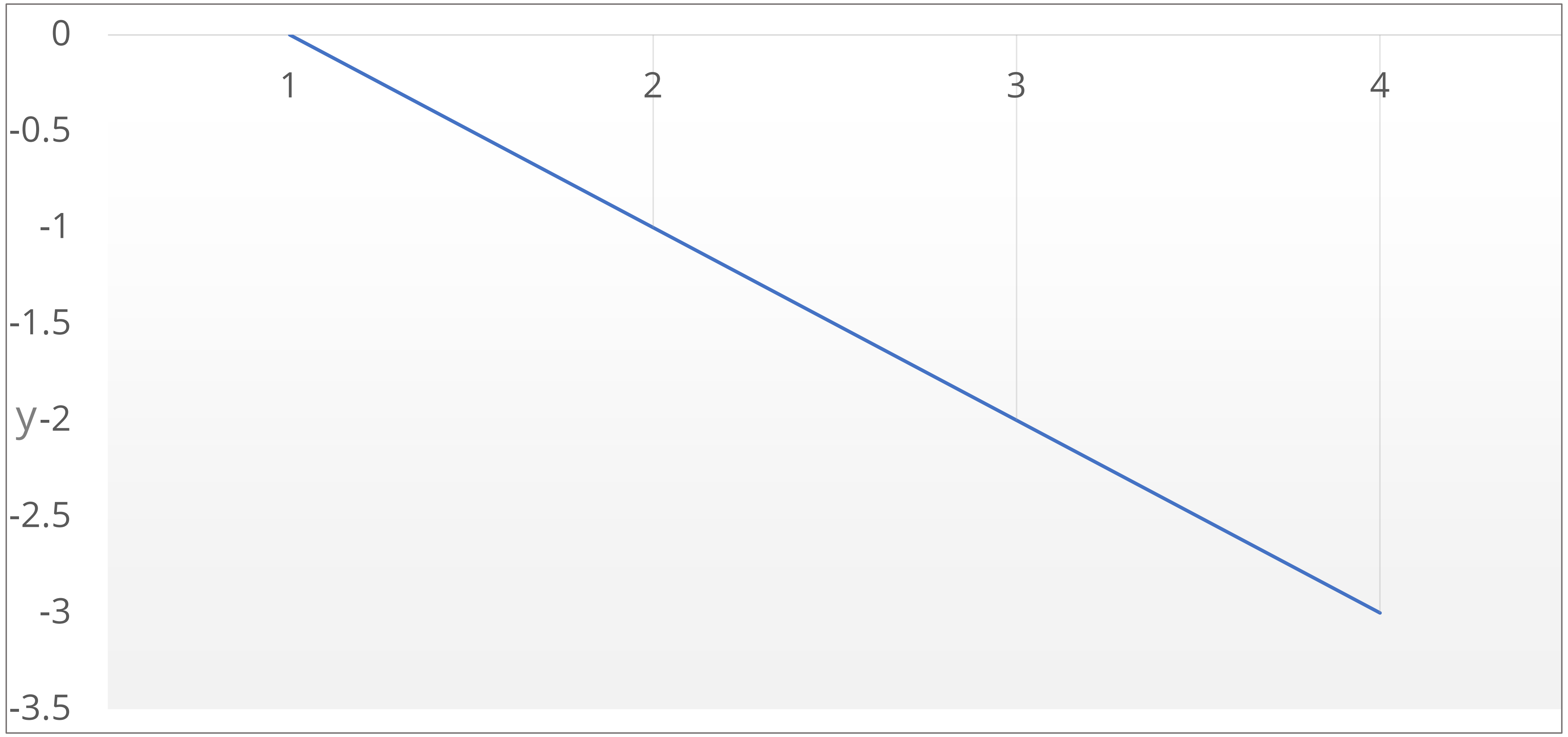
- In this model, you first declare placeholders for x, y, weights w and bias b.
- Then use MSE error as cost function and minimize it using GradientDescent optimizer.
- Run the session to find ideal weights and then print the training accuracy.
- The output produced after the execution is as follows:

```
W: [-0.9999969]
b: [ 0.99999082]
loss: 5.69997e-11
```

Linear Regression in TensorFlow

OUTPUT

The graph shows the fitted regression line after the model training.



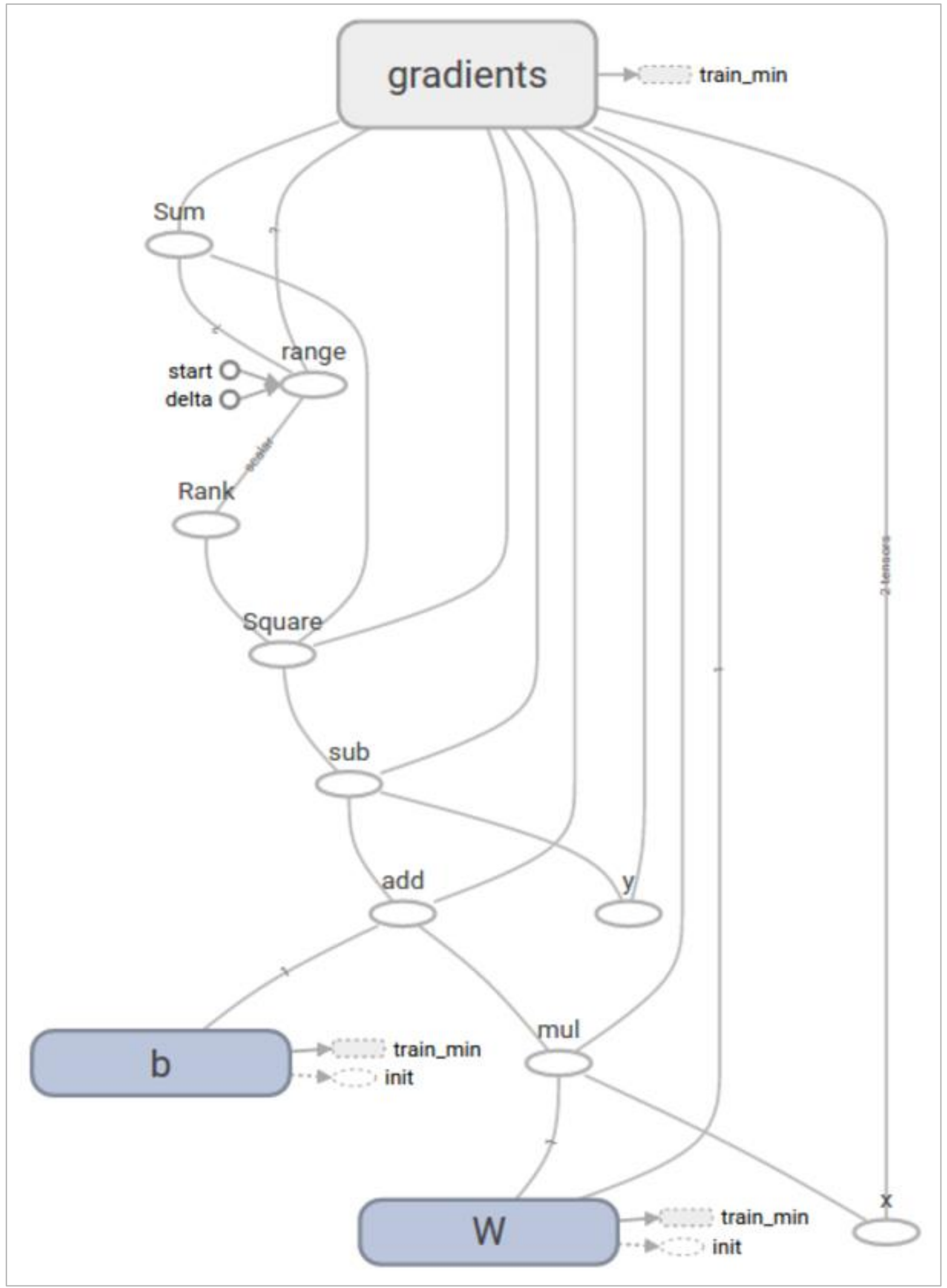
Algorithm learned:

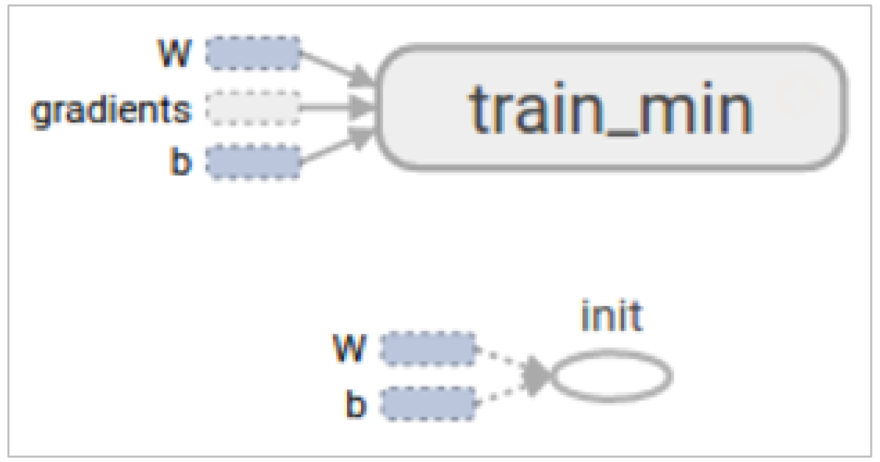
y = (-0.9999969) * x + 0.99999082

Linear Regression in TensorFlow

Visualization using TensorBoard

- The image shows the Computation Graph for Linear Regression code shown on previous slides.
- The various nodes correspond to weights, biases etc, as well as various operations from that code.





Linear Regression in TensorFlow

Linear Regression for the California housing dataset using Normal Equation method

- The code shows Linear Regression for the California housing dataset. Here weights are calculated using the Normal Equation:

$$\theta = (X^T.X)^{-1}.X^T.y$$

- One could have used normal NumPy to run the Normal Equation, but it would not run on GPU, whereas TensorFlow can (if GPU-version of TF is installed).

```python
import numpy as np
from sklearn.datasets import fetch_california_housing

housing = fetch_california_housing()
m, n = housing.data.shape
housing_data_plus_bias = np.c_[np.ones((m, 1)), housing.data]

X = tf.constant(housing_data_plus_bias, dtype=tf.float32, name="X")
y = tf.constant(housing.target.reshape(-1, 1), dtype=tf.float32, name="y")
XT = tf.transpose(X)
theta = tf.matmul(tf.matmul(tf.matrix_inverse(tf.matmul(XT, X)), XT), y)

with tf.Session() as sess:
    theta_value = theta.eval()
```

Gradient Descent in TensorFlow

Linear Regression for the California housing dataset using Gradient Descent Optimizer

- This code uses Batch Gradient Descent optimizer as opposed to Normal Equation in the prior slide.
- Here, you compute the gradients manually.
- This code assumes that normalization has been done previously.
- The random_uniform function creates random array for theta.

```
n_epochs = 1000
learning_rate = 0.01

X = tf.constant(scaled_housing_data_plus_bias, dtype=tf.float32, name="X")
y = tf.constant(housing.target.reshape(-1, 1), dtype=tf.float32, name="y")
theta = tf.Variable(tf.random_uniform([n + 1, 1], -1.0, 1.0), name="theta")
y_pred = tf.matmul(X, theta, name="predictions")
error = y_pred - y
mse = tf.reduce_mean(tf.square(error), name="mse")
gradients = 2/m * tf.matmul(tf.transpose(X), error)
training_op = tf.assign(theta, theta - learning_rate * gradients)

init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)

    for epoch in range(n_epochs):
        if epoch % 100 == 0:
            print("Epoch", epoch, "MSE =", mse.eval())
        sess.run(training_op)

    best_theta = theta.eval()
```

Gradient Descent in TensorFlow

Linear Regression for the California housing dataset using Gradient Descent Optimizer

- The weight (theta) adjustment logic is:

  $\boldsymbol{\theta}^{(\text{next step})} = \boldsymbol{\theta} - \eta \nabla_{\theta} \text{MSE}(\boldsymbol{\theta})$
- The gradient ∇_{θ}MSE(θ) is equivalent to:

  (2/m)*(y_pred-y)*X^T
- The main loop executes the training step over and over again (n_epochs times), and at every 100 iterations it prints out the current Mean Squared Error (mse).
- One should see the MSE go down at every iteration.

```
n_epochs = 1000
learning_rate = 0.01

X = tf.constant(scaled_housing_data_plus_bias, dtype=tf.float32, name="X")
y = tf.constant(housing.target.reshape(-1, 1), dtype=tf.float32, name="y")
theta = tf.Variable(tf.random_uniform([n + 1, 1], -1.0, 1.0), name="theta")
y_pred = tf.matmul(X, theta, name="predictions")
error = y_pred - y
mse = tf.reduce_mean(tf.square(error), name="mse")
gradients = 2/m * tf.matmul(tf.transpose(X), error)
training_op = tf.assign(theta, theta - learning_rate * gradients)

init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)

    for epoch in range(n_epochs):
        if epoch % 100 == 0:
            print("Epoch", epoch, "MSE =", mse.eval())
        sess.run(training_op)

    best_theta = theta.eval()
```

Important Features and Libraries

tf.contrib.learn

- **tf.contrib.learn** is a high-level TensorFlow library that simplifies the mechanics of machine learning including:
  - running training loops
  - running evaluation loops
  - managing data sets
  - managing feeding
- tf.contrib.learn defines many common models.

Important Features and Libraries

Autodiff

- Calculating gradients manually works for Linear Regression, but for neural networks, it can be tedious.
- TensorFlow has autodiff feature to automatically compute gradients.
- Simply replace the *gradients* = … line in the previous block of code with:

```
gradients = tf.gradients(mse, [theta])[0]
```

- Here the gradients node will compute the gradient vector of the MSE with regard to theta.

Important Features and Libraries

Optimizers

- The optimizers of TensorFlow provide variations on Gradient Descent.
- Optimizer APIs from TensorFlow abstract out the complexity of defining many of the training concepts with low level code.
- The optimizer base class provides methods to compute gradients for a loss and apply gradients to variables.
- A collection of subclasses implement classic optimization algorithms such as Gradient Descent.
- The Optimizer class itself need not be instantiated, but subclasses have to be.
- The base class for optimizers is:

class tf.train.Optimizer

- This class defines the API to add Ops to train a model.
- You need not use this class directly, but instead instantiate one of its subclasses such as GradientDescentOptimizer.

Important Features and Libraries

Optimizers

- To use optimizers, replace the *gradients = … and training_op = …* lines in the previous block of code with:

```
optimizer = tf.train.GradientDescentOptimizer(learning_rate=learning_rate)
training_op = optimizer.minimize(mse)
```

- Or with a different Optimizer as in:

```
optimizer = tf.train.MomentumOptimizer(learning_rate=learning_rate,
                                       momentum=0.9)
```

Mini-Batch Gradient Descent in TensorFlow

Implementation

- Here, you use mini-batch gradient descent for the same problem.
- For Mini-batch Gradient Descent, we need a way to replace X and y at every iteration with the next mini-batch.
- The simplest way to do this is to use placeholder nodes.

```
X = tf.placeholder(tf.float32, shape=(None, n + 1), name="X")
y = tf.placeholder(tf.float32, shape=(None, 1), name="y")
```

```
>>> A = tf.placeholder(tf.float32, shape=(None, 3))
>>> B = A + 5
>>> with tf.Session() as sess:
...     B_val_1 = B.eval(feed_dict={A: [[1, 2, 3]]})
...     B_val_2 = B.eval(feed_dict={A: [[4, 5, 6], [7, 8, 9]]})
...
>>> print(B_val_1)
[[ 6.  7.  8.]]
>>> print(B_val_2)
[[  9.  10.  11.]
 [ 12.  13.  14.]]
```

Mini-Batch Gradient Descent in TensorFlow

Execution

- To implement mini-batch gradient descent, define batch size and total number of batches:

```
batch_size = 100
n_batches = int(np.ceil(m / batch_size))
```

- In the execution phase, fetch the batches one by one and use them to run the training operations:

```
def fetch_batch(epoch, batch_index, batch_size):
    [...] # load the data from disk
    return X_batch, y_batch

with tf.Session() as sess:
    sess.run(init)

    for epoch in range(n_epochs):
        for batch_index in range(n_batches):
            X_batch, y_batch = fetch_batch(epoch, batch_index, batch_size)
            sess.run(training_op, feed_dict={X: X_batch, y: y_batch})

    best_theta = theta.eval()
```

Mini-Batch Gradient Descent in TensorFlow

Saving and Restoring Models

- A trained model can be saved to disk or restored.
- Checkpoints can be stored as well in long training cycles.
- Saving happens via a Saver node. During execution, call save() on the Saver node to actually save the model.

```
[...]
theta = tf.Variable(tf.random_uniform([n + 1, 1], -1.0, 1.0), name="theta")
[...]
init = tf.global_variables_initializer()
saver = tf.train.Saver()

with tf.Session() as sess:
    sess.run(init)

    for epoch in range(n_epochs):
        if epoch % 100 == 0:  # checkpoint every 100 epochs
            save_path = saver.save(sess, "/tmp/my_model.ckpt")

        sess.run(training_op)

    best_theta = theta.eval()
    save_path = saver.save(sess, "/tmp/my_model_final.ckpt")
```

Mini-Batch Gradient Descent in TensorFlow

Saving and Restoring Models

- Restore happens with a call to restore function:

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

- In case one wants to save only certain variables under new names:

```
saver = tf.train.Saver({"weights": theta})
```

Demo 1

TensorFlow Features

- **Objective**: Demonstrate various features of TensorFlow
- **Steps:**
    1) Write code to evaluate default computation graph of TensorFlow
    2) Demonstrate how placeholders are used in TensorFlow
    3) Write code to check use of arrays (tensors) and how they can be reshaped
    4) Demonstrate OLS (ordinary least squares) regression using TensorFlow
    5) Plot the cost function as number of Epochs increases
    6) Plot the regression fit line
- **Dataset used:** The code creates a sample dataset containing 10 numerical data samples.
- **Skills required:** Key aspects of TensorFlow such as computation graph, placeholders, tensors, reshape function, cost function, optimizers, etc.
- **Components of the code to be executed:** First steps with TensorFlow, working with array structures, and developing a simple model with low-level TensorFlow API Dataset used

Introduction to TensorFlow

Topic 6: TensorFlow APIs – Layers and Keras

Types of APIs

Recap

Two Main APIs that TensorFlow provides

1

TensorFlow Core API

Low level Machine Learning development

2

Higher Level APIs

More compact APIs such as tf.contrib.learn or tf.layers

Types of APIs

2 Higher Level APIs

- Higher level APIs are built on top of TensorFlow Core.
- These are easier to learn and use than TensorFlow Core.
- They make repetitive tasks easier and more consistent between different users.
- Higher level API such as ***tf.contrib.learn*** helps you manage data sets, estimators, training and inference.

Types of APIs

2 **Higher Level APIs**

Development of neural network programs can be simplified with two of the high-level TensorFlow APIs:

01 Layers API (tensorflow.layers or tf.layers)

02 Keras API (tensorflow.contrib.keras)

Using Layers to Build Neural Networks

- You can define neural networks layer with *tf.layers* API with simple code as given on the next slide.
- After defining the neural layers graph with *tf.layers*, the logic to define the cost function and optimizer like GradientDescentOptimizer needs to follow which is same as a normal neural network model.
- After which the model training session can be executed with mini batches of training data.
- Later, you can test the accuracy of the model with predictions on the test data.
- Thus, TF.layers can prove to be a high-level TensorFlow API to simplify the neural network development via simpler code.

Using Layers to Build Neural Networks

Example

- This code creates a four layer neural network using tf.layers API.
- Initially, two hidden layers use tanh activation function.
- The third layer is a fully connected layer with 10 outputs.
- The fourth layer is the Softmax layer to predict one of the 10 classes.

```
h1 = tf.layers.dense(inputs=tf_x, units=50,
                    activation=tf.tanh,
                    name='layer1')
h2 = tf.layers.dense(inputs=h1, units=50,
                    activation=tf.tanh,
                    name='layer2')

#fully connected third layer
logits = tf.layers.dense(inputs=h2,
                        units=10,
                        activation=None,
                        name='layer3')
#define predictions object for predicting the final output for test data later
predictions = {
    'classes' : tf.argmax(logits, axis=1,
                          name='predicted_classes'),
    'probabilities' : tf.nn.softmax(logits,
                          name='softmax_tensor')
}
```

Demo 2

Neural Network with TensorFlow

- **Objective**: Develop a 3-layer neural network code using high-level TensorFlow Layers API to classify the MNIST dataset.
- **Steps:**
    1) Use hyperbolic tangent activation function and softmax classification
    2) Print the training loss value as subsequent Epochs get completed.
    3) Print final test accuracy
- **Dataset used:** We use MNIST dataset to write code with Layers API.
- **Skills required:** TensorFlow Layers API, which are used to develop multi-layer neural networks using high-level coding.
- **Components of the code to be executed:** Building multilayer neural networks using TensorFlow's Layers API

Using Keras to Build Neural Networks

- Keras is a high level API used to simplify the neural network development via simple code.
- It is often used as a frontend with a TensorFlow backend.
- Keras can be installed as a separate package.
- However, after the release of TensorFlow 1.1.0, Keras has been added to the TensorFlow contrib sub-module.

Using Keras to Build Neural Networks

Example

- For the MNIST handwritten digit classification, you can classify the digit image to one of the 10 classes from zero to nine.
- This data is then converted into one hot vector, which is a way to convert categorical data into numerical data as shown in the bottom of the code.
- First, you need to convert the class labels (integers 0-9) into the one hot format.

```
y_train_onehot = keras.utils.to_categorical(y_train)
print('First 3 labels: ', y_train[:3])
print('\nFirst 3 labels (one-hot):\n', y_train_onehot[:3])
```

- The output of this code would be:

```
First 3 labels:  [5 0 4]
First 3 labels (one-hot):
 [[ 0.  0.  0.  0.  0.  1.  0.  0.  0.  0.]
 [ 1.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  1.  0.  0.  0.  0.  0.]]
```

Using Keras to Build Neural Networks

Example

One can define neural networks layer with tensorflow.contrib.keras API with simple code like this:

- This code defines the three layers of a neural network using Keras API for MNIST digit classification problem.
- The third layer is a classification layer to classify the digit image to one of the 10 classes.

```
model = keras.models.Sequential()
model.add(keras.layers.Dense(
        units=50,
        input_dim=X_train_centered.shape[1],
        kernel_initializer='glorot_uniform',
        bias_initializer='zeros',
        activation='tanh'))
model.add(keras.layers.Dense(
        units=50,
        input_dim=50,
        kernel_initializer='glorot_uniform',
        bias_initializer='zeros',
        activation='tanh'))
model.add(keras.layers.Dense(
        units=y_train_onehot.shape[1],        #10 units corresponding to 10 class labels
        input_dim=50,
        kernel_initializer='glorot_uniform',
        bias_initializer='zeros',
        activation='softmax'))
```

Using Keras to Build Neural Networks

- As seen in the code given on the previous slide, you can initialize a new model using the ***sequential class*** of Keras to implement a feedforward neural network.
- Then, you can add as many layers to it as we like.
- We used a new initialization algorithm for weight matrices by setting ***kernel_initializer='glorot_uniform'.***
- Glorot initialization, also known as Xavier initialization is a more robust way of initialization for deep neural networks.

Using Keras to Build Neural Networks

Example

- Compile the model with SGD optimizer and cross-entropy loss function:

```
sgd_optimizer = keras.optimizers.SGD(
      lr=0.001, decay=1e-7, momentum=.9)

model.compile(optimizer=sgd_optimizer,
           loss='categorical_crossentropy')
```

- You now have set values for the weight decay constant and momentum learning to adjust the learning rate at each epoch.
- Decay the weights and moderate the learning rate with subsequent training epochs to prevent vanishing gradients.
- The binary cross-entropy is just a technical term for the cost function in the logistic regression, and the categorical cross-entropy is its generalization for multiclass predictions via softmax.

Using Keras to Build Neural Networks

Example

- Later, run model.fit to train the model:

```
history = model.fit(X_train_centered, y_train_onehot,
        batch_size=64, epochs=50,
        verbose=1,
        validation_split=0.1)
```

- The line verbose=1 prints the optimization process over subsequent epochs.
- The validation_split=0.1 reserves 10% of the training data for validation after each epoch.

Using Keras to Build Neural Networks

Output

- The output looks like this:

```
Train on 54000 samples, validate on 6000 samples
Epoch 1/50
54000/54000 [==============================] - 3s - loss: 0.7247 -
val_loss: 0.3616
Epoch 2/50
54000/54000 [==============================] - 3s - loss: 0.3718 -
val_loss: 0.2815
Epoch 3/50
54000/54000 [==============================] - 3s - loss: 0.3087 -
val_loss: 0.2447
[...]
Epoch 50/50
54000/54000 [==============================] - 3s - loss: 0.0485 -
val_loss: 0.1174
```

Demo 3

Neural Network with TensorFlow and Keras

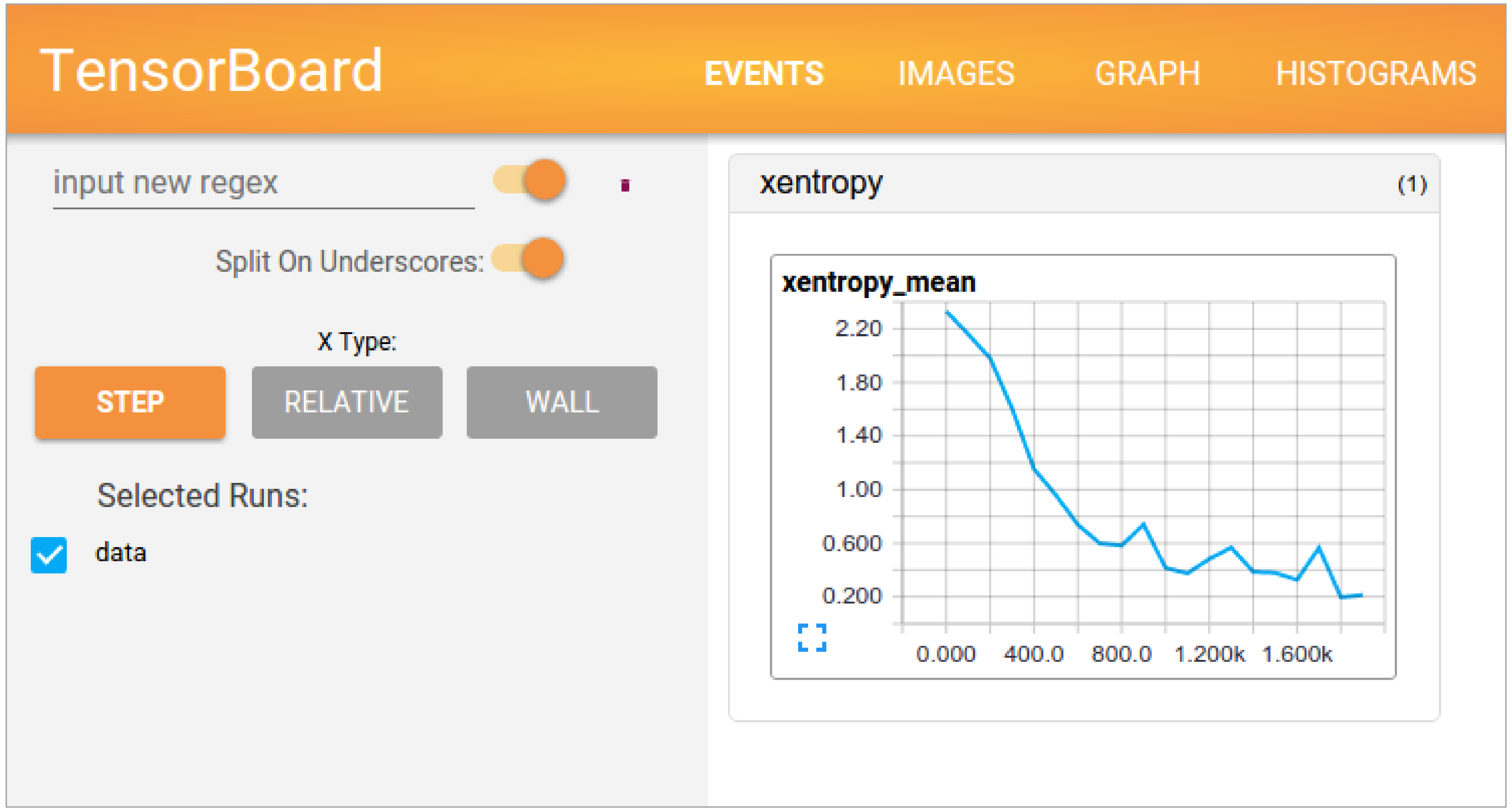
- **Objective**: Develop a 3-layer neural network code using high-level Keras API
- **Steps:**
  1) Use mini-batch stochastic gradient descent
  2) Print the training loss and validation loss as subsequent mini-batches get processed
  3) Predict some values using the trained model
  4) Print final training and test accuracy
- **Dataset used:** We use MNIST dataset to write code with Keras API.
- **Skills required:** TensorFlow Keras API, which are used to develop multi-layer neural networks using high-level coding.
- **Components of the code to be executed:** Developing multilayer neural networks with Keras

Introduction to TensorFlow

Topic 7: Tensorboard

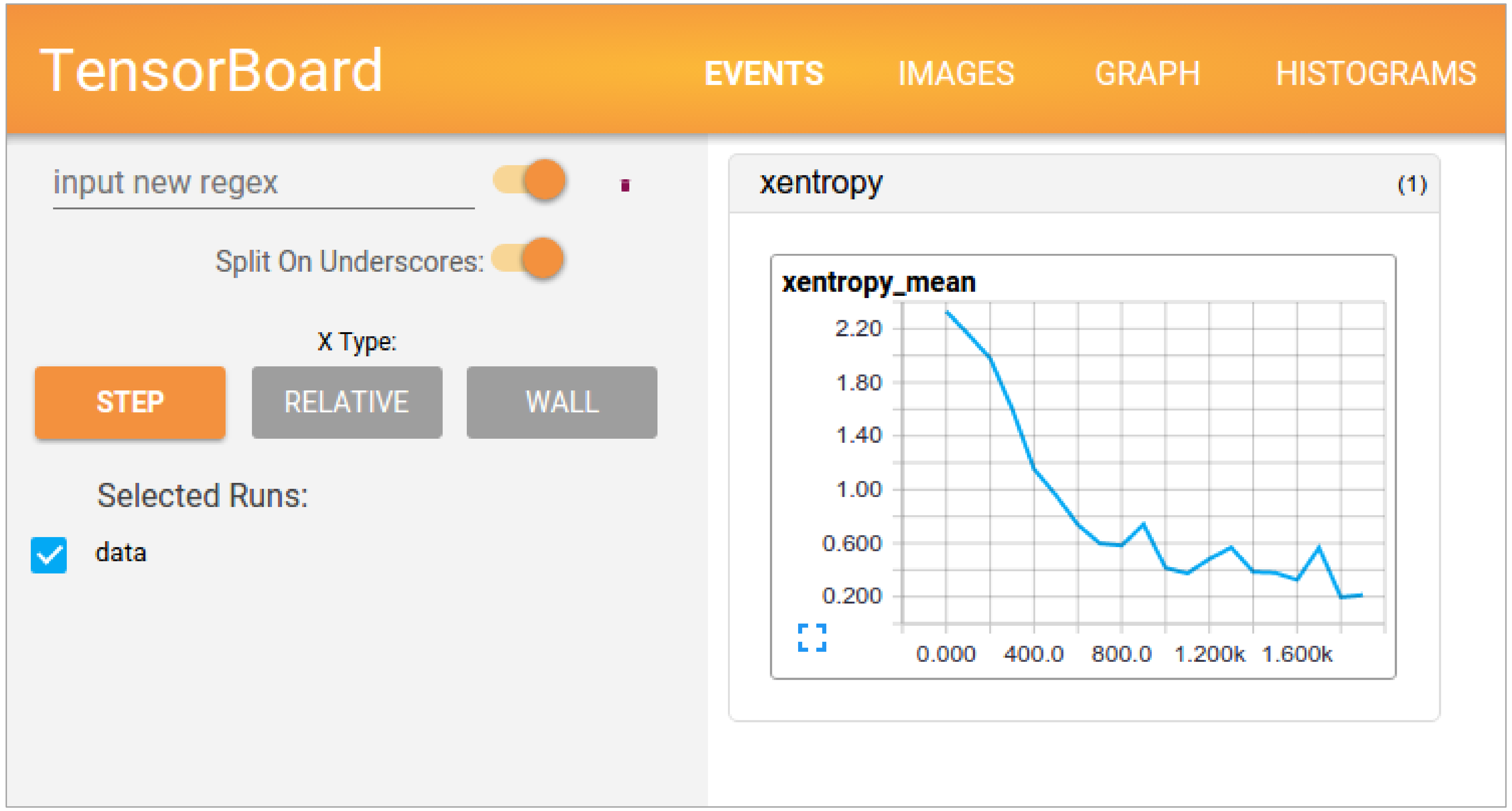
What Is TensorBoard?

- TensorBoard allows one to understand, debug, and optimize TensorFlow programs.
- TensorBoard operates by reading TensorFlow event files.
- Serialized data is entered in these event files when one annotates the nodes of TensorFlow with “summary operations”.

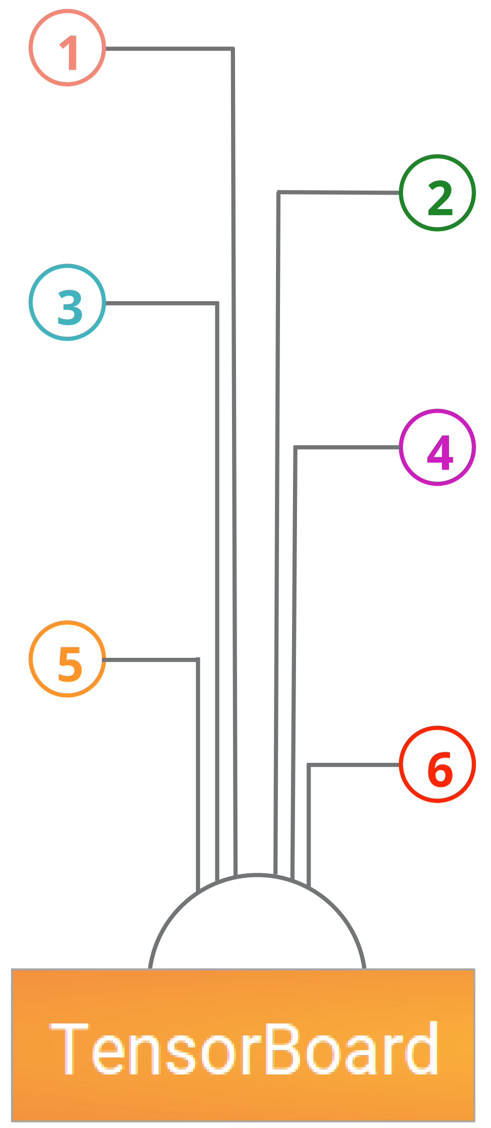


What Is TensorBoard?

- This tool allows:
  - Visualization of TensorFlow graph
  - Plotting quantitative metrics about the execution of the graph
  - Showing additional data like images that pass through it



Steps to Use TensorBoard



1. Attach the *“tf.summary.scalar”* ops to nodes whose output you wish to serialize. Each such scalar_summary is given a tag like “learning rate” or “loss function.”

2. Attach the *“tf.summary.histogram”* ops to the relevant nodes to visualize distributions of values

3. Use *“tf.summary.merge_all” to* merge all summary nodes ops

4. Run this to generate *“Summary”* protobuf object containing all summary

5. Write this object to disk using *“tf.summary.FileWriter”*

6. Enter *“tensorboard --logdir=/tmp/tensorflow/mnist”* on command prompt to start TensorBoard
TensorBoard is available at URL:localhost:6006

Using Timestamp in TensorBoard

- TensorBoard is an interactive visualization tool that shows learning curves and lots of other plots in web browser.
- It requires the code to log the stats and graph details to a log directory.
- One needs to use a different log directory in each run of the program, else log data from multiple runs will get merged and mess up TensorBoard.
- The simplest solution for this is to include a timestamp in the log directory name.

```
from datetime import datetime

now = datetime.utcnow().strftime("%Y%m%d%H%M%S")
root_logdir = "tf_logs"
logdir = "{}/run-{}/".format(root_logdir, now)
```

- Add the following code at end of construction phase:

```
mse_summary = tf.summary.scalar('MSE', mse)
file_writer = tf.summary.FileWriter(logdir, tf.get_default_graph())
```

Visualization with TensorBoard

- TensorBoard helps to understand the learning process and its results.
- Next, update the execution phase to evaluate the *mse_summary node* regularly during training (For example, every 10 mini batches).
- This will output a summary that one can then write to the events file using the *file_writer*.

```
[...]
for batch_index in range(n_batches):
    X_batch, y_batch = fetch_batch(epoch, batch_index, batch_size)
    if batch_index % 10 == 0:
        summary_str = mse_summary.eval(feed_dict={X: X_batch, y: y_batch})
        step = epoch * n_batches + batch_index
        file_writer.add_summary(summary_str, step)
    sess.run(training_op, feed_dict={X: X_batch, y: y_batch})
[...]
```

- Finally, close the file writer at the end of the program.

```
file_writer.close()
```

Visualization with TensorBoard (Contd.)

- Check the working directory:

```
$ cd $ML_PATH                # Your ML working directory (e.g., $HOME/ml)
$ ls -l tf_logs/run*
total 40
-rw-r--r-- 1 ageron staff 18620 Sep 6 11:10 events.out.tfevents.1472553182.mymac
```

- After a second run:

```
$ ls -l tf_logs/
total 0
drwxr-xr-x  3 ageron  staff  102 Sep  6 10:07 run-20160906091959
drwxr-xr-x  3 ageron  staff  102 Sep  6 10:22 run-20160906092202
```

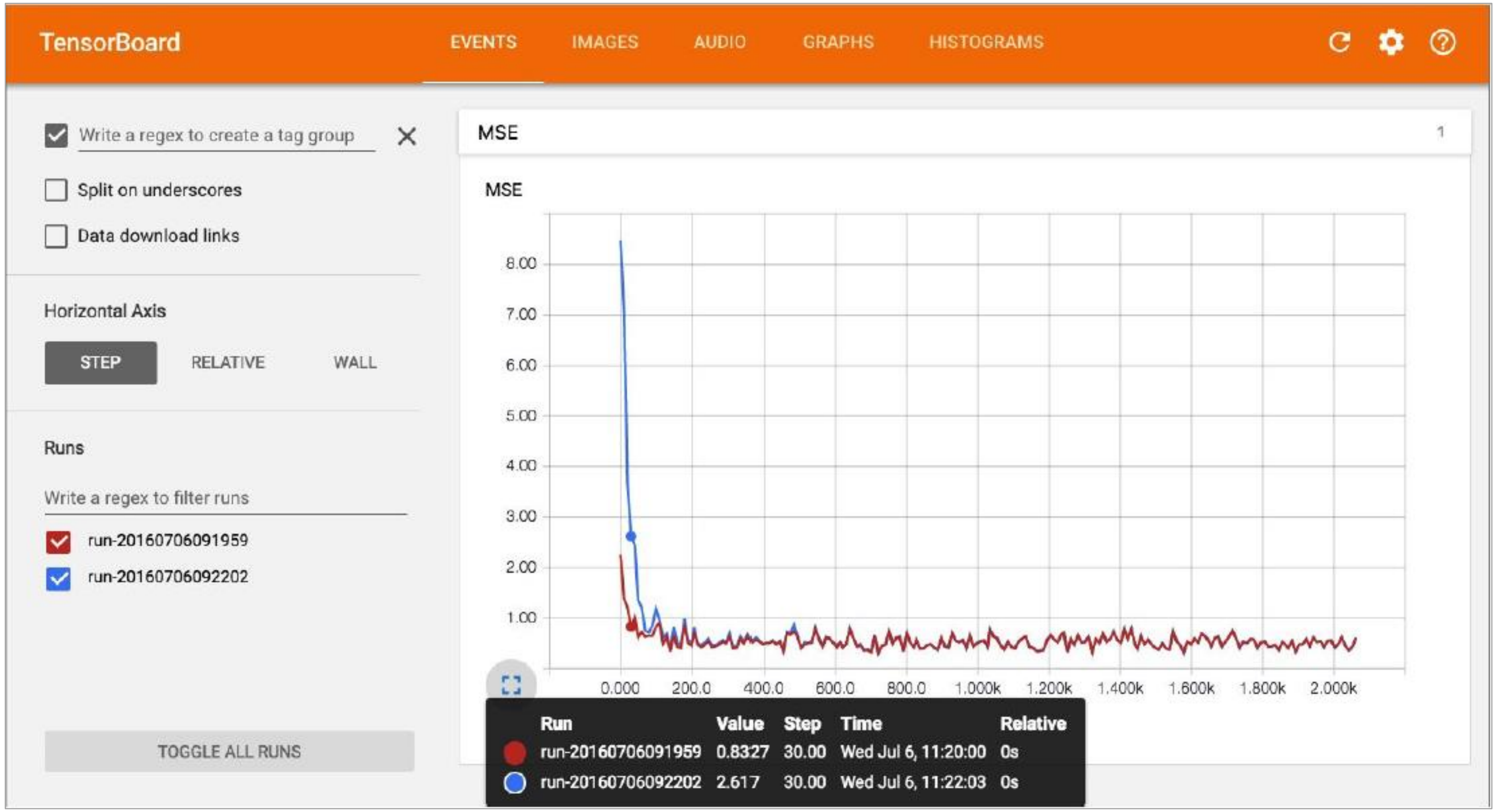
- Now start the TensorBoard server:

```
$ source env/bin/activate
$ tensorboard --logdir tf_logs/
Starting TensorBoard  on port 6006
(You can navigate to http://0.0.0.0:6006)
```

- Next open a browser and go to *http://0.0.0.0:6006/* (or *http://localhost:6006/*)

Events Tab on TensorBoard

- TensorBoard shows a lot of useful information around MSE, gradients, computation graph, variances, standard deviation etc.
- In the chart given below, you can see the MSE and how it declines over subsequent Epochs:

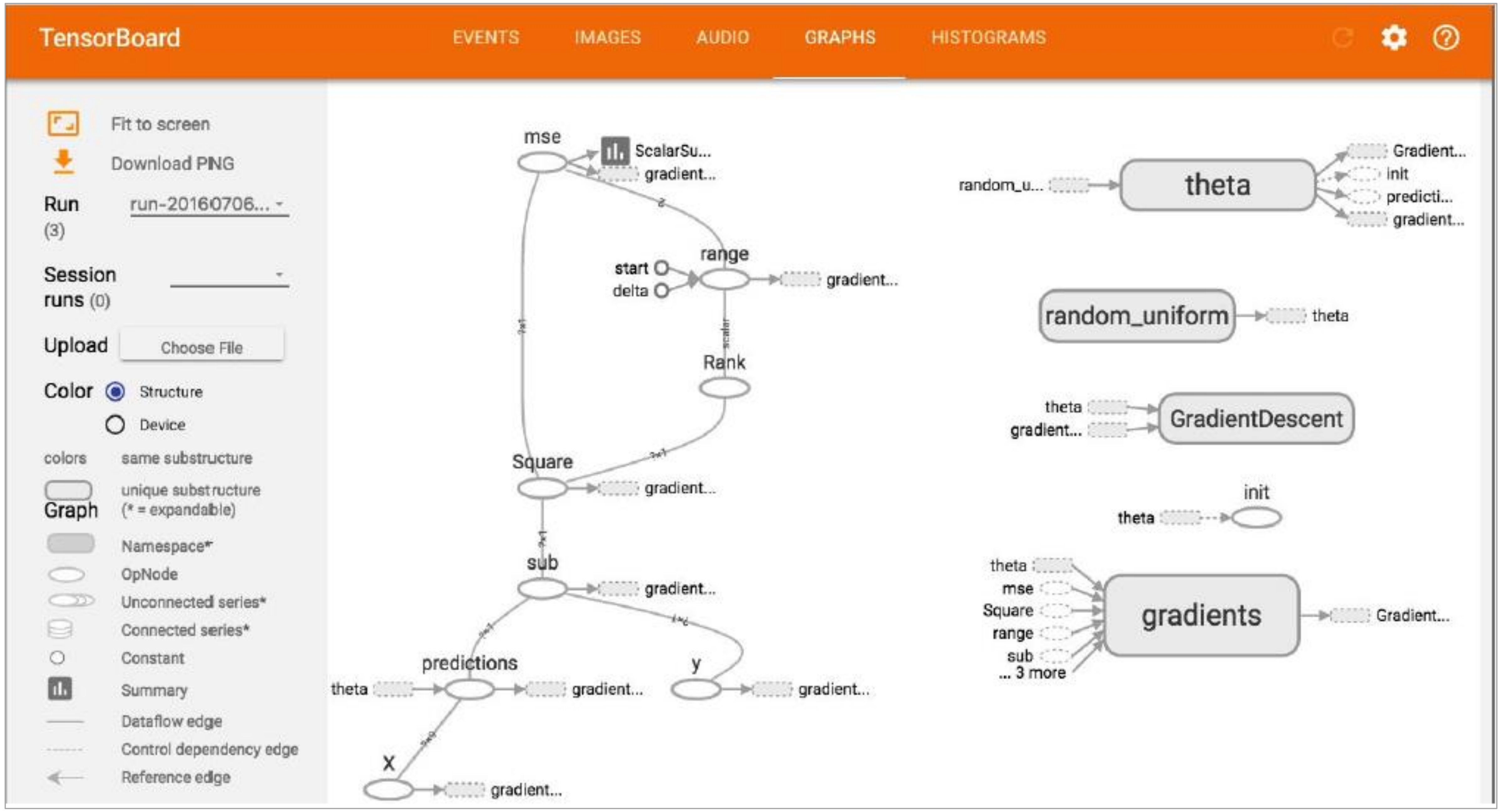


	Run	Value	Step	Time	Relative
🔴	run-20160706091959	0.8327	30.00	Wed Jul 6, 11:20:00	0s
🔵	run-20160706092202	2.617	30.00	Wed Jul 6, 11:22:03	0s

The blue and red line show two different instances of the program being run.

Graphs Tab on TensorBoard

- TensorBoard Graphs section shows the actual computation graph built by TensorFlow for the program.



Demo 4

Demonstration of TensorBoard

- **Objective**: Demonstrate various features of TensorBoard
- **Skills required:** TensorFlow and TensorBoard

Key Takeaways

- ✓ TensorFlow is one of the most popular Deep Learning libraries.
- ✓ It allows parallel computation over high-performance GPU processors.
- ✓ It works by first creating a Computation Graph of the program logic, before the actual execution is done.
- ✓ TensorFlow Core API allows low level programming for machine learning.
- ✓ Keras and TF.Layers are higher level APIs in TensorFlow, which make development of neural networks simpler.
- ✓ Trained models can be serialized to disk and restored again in code.
- ✓ TensorFlow includes TensorBoard, a powerful visualization tool to understand the machine learning process.

This concludes “Introduction to TensorFlow.”

The next lesson is “Training Deep Neural Networks.”