# TensorFlow Tutorial

Open Source Software

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Some material adapted from Olivier Poulin

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# Reading Material

- TensorFlow Guide (Reference Only) https://www.tensorflow.org/guide
  - \* Read TensorFlow Basics through "Training Loops"
  - \* Keras through "Training and evaluation ..."

# Introduction

What is TensorFlow?

 $TensorFlow^{TM}$  is:

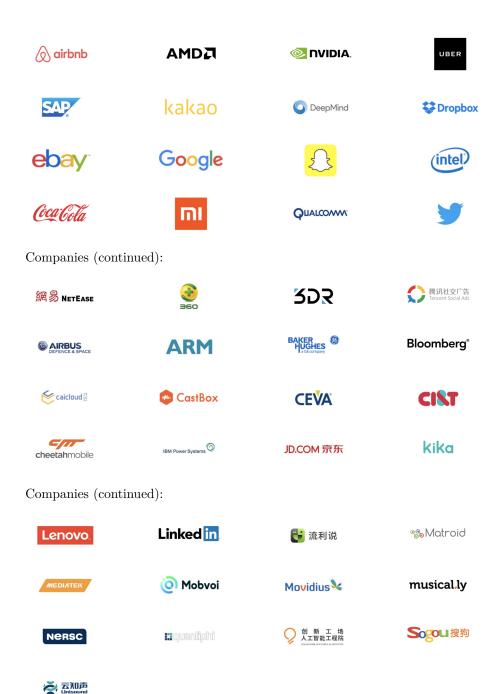
- Open source
- High performance numerical computation
- Deploys on CPUs, GPUs, TPU
- Desktops, clusters, mobile and edge devices
- Originally developed by Google Brain team within Google's AI organization

 $TensorFlow^{TM}$  has:

- Strong support for machine learning
- Strong support for deep learning
- Flexible numerical computation core

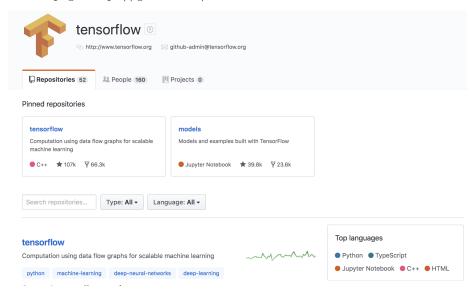
## Widely Used

Companies:



# By the Numbers

Github page: https://github.com/tensorflow



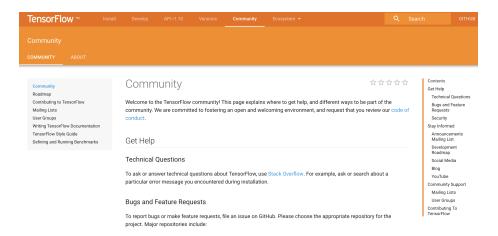
Main repository: https://github.com/tensorflow/tensorflow

- 53,075 commits (now 132,807)
- 27 branches (now 68)
- 1932 contributers (now 3155)
- 79 releases (now 169)
- 2021 Issues (now 2118 closed 33,110)
- Permissively licensed under Apache-2.0

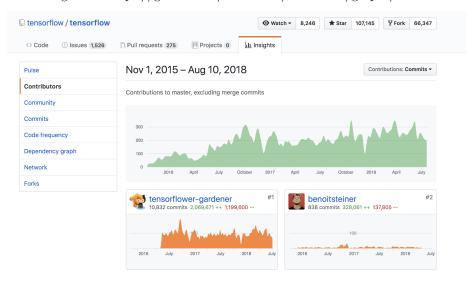


#### Active community

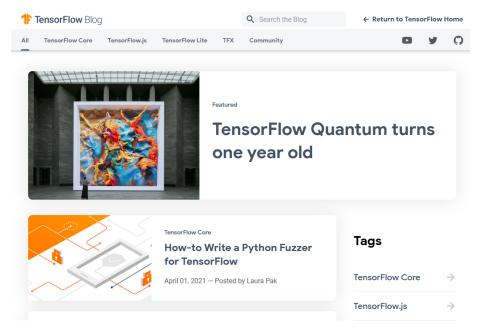
• Community overview: https://www.tensorflow.org/community/



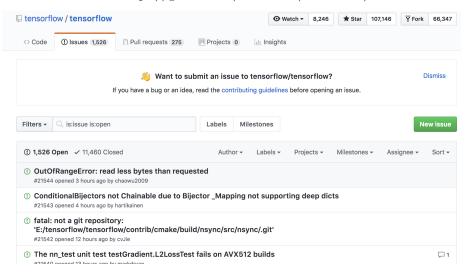
• Insights at: https://github.com/tensorflow/tensorflow/graphs/contributors



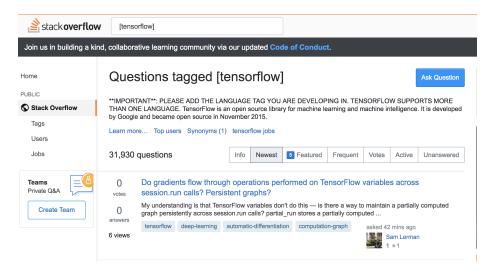
• Blog: https://blog.tensorflow.org/



• Issue Tracker: https://github.com/tensorflow/tensorflow/issues



• Questions: https://stackoverflow.com/questions/tagged/tensorflow



• User Models: https://github.com/tensorflow/models/tree/master/community



#### **TensorFlow Community Models**

This repository provides a curated list of the GitHub repositories with machine learning models and implementations powered by TensorFlow 2.

Note: Contributing companies or individuals are responsible for maintaining their repositories.

# **Computer Vision**

#### Image Recognition Model Features Maintaine DenseNet 169 • FP32 Inference Rethinking the Inception Architecture • Int8 Inference Inception V3 Intel Inception-v4, Inception-ResNet and the Impact • Int8 Inference Inception V4 Intel MobileNets: Efficient Convolutional Neural Networks Int8 Inference MobileNet V1 for Mobile Vision Applications • FP32 Inference Int8 Inference ResNet 101

#### Others:

- Twitter
- YouTube
- Release Notes

## The Basics

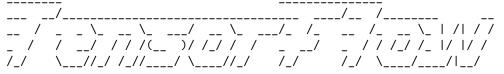
Much of this section courtesy of Olivier Poulin, one of our previous mentors.

#### **Multiple Installations**

- Virtualenv
- "native" pip
- Docker
- Source

For this class, we will use the Docker installation:

```
$ docker run -it -p 8888:8888 -e "DISPLAY"=host.docker.internal:0 \
tensorflow/tensorflow:latest
Unable to find image 'tensorflow/tensorflow:latest-devel' locally
latest-devel: Pulling from tensorflow/tensorflow
8ee29e426c26: Pull complete
...
9c2312dbc5d7: Pull complete
Digest: sha256:40844012558fe881ec58faf1627fd4bb3f64fe9d46a2fd8af70f139244cfb538
Status: Downloaded newer image for tensorflow/tensorflow:latest
```



#### Docker:

- Runs a TensorFLow Container
  - Bindings to Python
- Maps port 8888 on the Container to port 8888 outside the container
  - Allows you to run Jupyter Notebooks
- Starts up an interactive session
- Allows us to bring up windows on our native OS
  - Requires an X11 Server, but you should all have that from earlier

## Validate

From the Docker container:

```
# python
Python 3.8.10 (default, Nov 26 2021, 20:14:08)
[GCC 9.3.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
>>> import tensorflow as tf
>>> a = tf.constant(3)
>>> a
<tf.Tensor: shape=(), dtype=int32, numpy=3>
>>> b = tf.constant(5)
```

```
>>> c = a + b
>>> c
<tf.Tensor: shape=(), dtype=int32, numpy=8>
>>> print(c)
tf.Tensor(8, shape=(), dtype=int32)
```

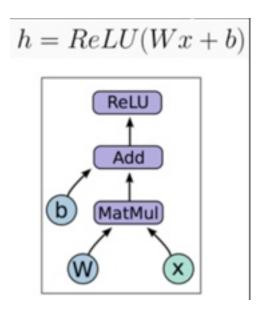
## What does TensorFlow do?

• Similar to Numpy, for n-dimensional arrays, but TensorFlow simplifies creation of tensor methods and computes derivatives.

Numpy	TensorFlow
a=np.zeros((2,2)); b=np.ones((2,2))	a=tf.zeros((2,2)); b=tf.ones((2,2))
np.sum(b,axis=1)	$tf.reduce\_sum(b,axis=[1])$
a.shape	$a.get\_shape()$
np.reshape(a, (1,4))	tf.reshape(a, (1,4))
b * 5 + 1	b * 5 + 1
np.dot(a, b)	tf.matmul(a, b)
a[0,0], a[:,0], a[0,:]	a[0,0], a[:,0], a[0,:]

## Base usage involves making execution graph

- TensorFlow uses a computation graph that has no numerical value until it's evaluated.
- Program structure has two phases: Construction phase and Execution phase.
- Construction phase assembles the computation graph.
- Execution phase runs the session object to execute all the operations in the graph.



## Base usage involves making execution graph

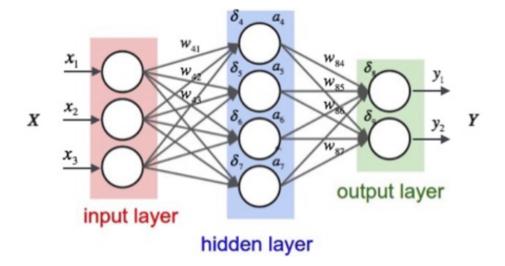
- Okay forget that ...
- This was Tensorflow 1.0
- In Tensorflow 2.0, the graph still exists but you can ignore it  $\dots$ 
  - Unless of course, you want to develop your algorithm in one place, and then run it later
  - Tensorflow allows you to save out the graph in a language independent file that can be migrated to another machine

#### What is Deep Learning?

- Deep learning is a machine learning method.
- More complex but has broader applications than classic task-specific algorithms.
- It bases the construction of its models on networks observed in biological nervous systems.
- Train Artificial Neural Networks to transform an input into a desired output.

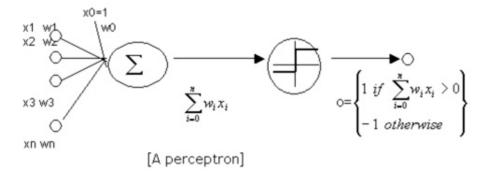
## Neural Network

- A collection of units or nodes (artificial neurons, hence neural network)
- Connected in layers to one another. Each node sends data to other nodes
- Train the "weights" and "biases" on each neuron to slowly inch the network towards a specific functionality.



# Simplest artificial neural network (ANN): Perceptron

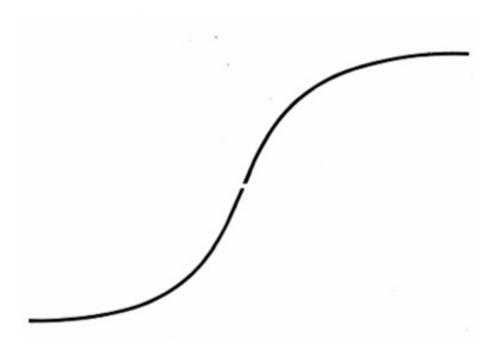
- Only binary inputs/outputs
- Binary output means the signals between neurons can only be binary as well
- Something either is, or isn't
- Limited in its functionality



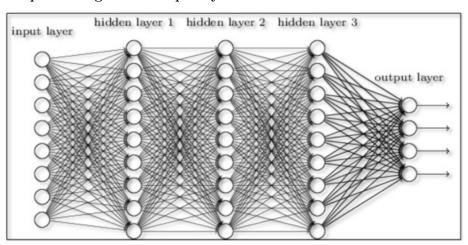
# Sigmoid Neurons

- Inputs/outputs are any values between 0 and 1
- Gives us much more nuanced outputs
- Can be used for % matches

$$f(t) = \frac{1}{1 + e^{-t}}$$

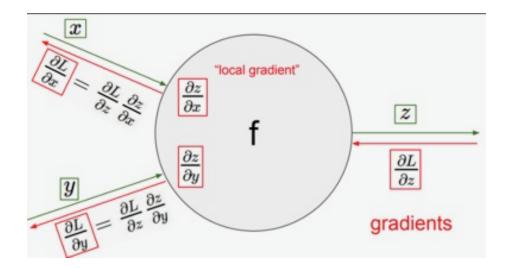


Deep Learning uses multiple layered networks



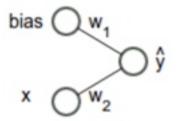
# How to train your dragon (network)

- Compare the output with training data
- Get a vector of all the errors and compute the downward slope of the error curve (derivative)
- Change the weights based on this "Gradient Descent"
- Complicated in huge networks



# A simple linear example

- Simplifies everything!
- Example: A simple linear regression!
- Linear function y = ab+c
- How do we train a simple network to mimic a linear function?
- Where bias = 1. This function becomes y = xw2 + w1



#### Get set up

For OSX, you will need to install a few packages on the host first to get the plots at the end to work:

brew install socat
socat TCP-LISTEN:6000,reuseaddr,fork UNIX-CLIENT:\"\$DISPLAY\" &
brew install --cask xquartz
open -a Xquartz

Then set Allow connections from network clients in the pop up if asked. Run a docker container and update it

```
docker run -it -p 8888:8888 -e "DISPLAY"=host.docker.internal:0 \
  tensorflow/tensorflow:latest
apt-get update
apt-get install -y python-tk xterm x11-apps qt5-default
xeyes & # Just a test to make sure our display is working
pip install matplotlib PyQt5
or use your own python installation
pip install tensorflow matplotlib PyQt5
Run a simple example
Imports:
import tensorflow as tf
from tensorflow.keras import Model
import matplotlib.pyplot as plt
Let's define some utilities:
def make_noisy_data(m=0.1, b=0.3, n=100):
 x = tf.random.uniform(shape=(n,))
 noise = tf.random.normal(shape=(len(x),), stddev=0.01)
 y = m * x + b + noise
 return x, y
def predict(x):
 y = m * x + b
 return y
def squared_error(y_pred, y_true):
 return tf.reduce_mean(tf.square(y_pred - y_true))
Set up the data:
x_train, y_train = make_noisy_data()
plt.plot(x_train, y_train, 'b.')
plt.show()
m = tf.Variable(0.)
b = tf.Variable(0.)
loss = squared_error(predict(x_train), y_train)
loss vec = []
print("Starting loss {:.6f}".format(loss.numpy()))
Training parameters:
```

```
learning_rate = 0.05
steps = 200
Execute the gradient descent:
for i in range(steps):
 with tf.GradientTape() as tape:
     predictions = predict(x_train)
     loss = squared_error(predictions, y_train)
 loss_vec.append(loss)
  gradients = tape.gradient(loss, [m, b])
 m.assign sub(gradients[0] * learning rate)
 b.assign_sub(gradients[1] * learning_rate)
 if i % 20 == 0:
     print("Step {:d}, Loss {:.6f}".format(i, loss.numpy()))
Report:
print("Solution: y = {:.6f} * x + {:.6f}".format(m.numpy(), b.numpy()))
plt.plot(list(range(steps)), loss_vec)
plt.show()
plt.plot(x_train, y_train, 'b.')
plt.plot(x_train, predict(x_train))
plt.show()
Using TensorFlow
Same Example in Keras
# MIT License
# This example is partially derived from the fashion example in Tensorflow.
# New code is copywritten by Wesley Turner (c) 2022
# The original code is copywritten below.
# Copyright (c) 2017 François Chollet
# TensorFlow and tf.keras
```

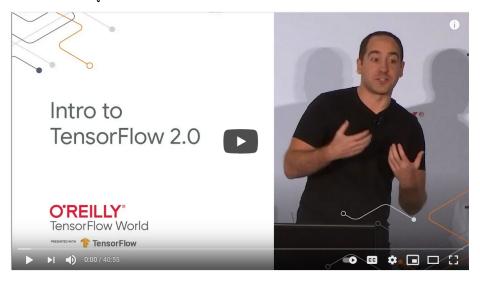
import tensorflow as tf

```
# Helper libraries
import numpy as np
import matplotlib.pyplot as plt
def make_noisy_data(m=0.1, b=0.3, n=100):
 x = 4*tf.random.uniform(shape=(n,1,1)) - 2
 noise = tf.random.normal(shape=(len(x),1,1), stddev=0.01)
 y = m * x + b + noise
 return x, y
def predict(m, b, x):
 y = m * x + b
 return y
def squared_error(y_pred, y_true):
 return tf.reduce_mean(tf.square(y_pred - y_true))
# Loading data
m = 0.1
b = 0.3
(train_x, train_y) = make_noisy_data(m=m, b=b, n=20000)
(test_x, test_y) = make_noisy_data(m=m, b=b, n=10000)
# 1. Create a model with a single neuron in 1 dense layer and 'relu' activation
# 2. Your model should use 'RMSprop' optimization, and mean squared error for
# both the loss function and the metric
# 3. Train your model on the 'train x' and 'train y' data from above.
model = tf.keras.Sequential([
    tf.keras.layers.Dense(1, activation='relu'),
])
model.compile(optimizer=tf.keras.optimizers.SGD(learning_rate=0.2),
              loss=tf.keras.losses.mean_squared_error,
              metrics=tf.keras.metrics.mean_squared_error)
model.fit(train_x, train_y, epochs=10)
# 4. Then evaluate the model against the test_x and test_y
test_loss, test_acc = model.evaluate(test_x, test_y, verbose=2)
#5 Finally, use your model to predict the correct output from the 'test_x'
predictions = model.predict(test_x)
# Calculate the actual values
actual = predict(m, b, test_x)
# Report
```

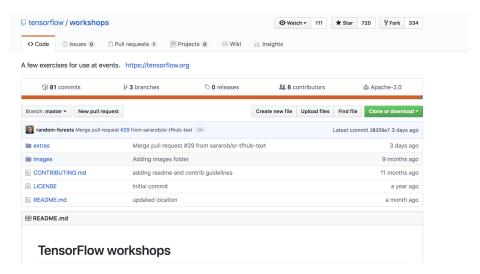
```
print('\nTest accuracy: ', test_acc, '\nTest Loss: ', test_loss)
print("Accuracy (MeanSquaredError): ", squared_error(predictions, actual).numpy())
# Plot
plt.plot(np.squeeze(train_x), np.squeeze(train_y), 'b.')
plt.plot(np.squeeze(test_x), np.squeeze(predictions), 'g*')
plt.plot(np.squeeze(test_x), np.squeeze(actual), 'r-')
plt.show()
```

#### **Tutorial**

Of course, Google has us covered: https://www.youtube.com/watch?v= 5 E C D 8 J 3 d v D Q



Website from the video: https://github.com/tensorflow/workshops



## Other links:

- Cats versus Dogs (longer version) https://bit.ly/2G0bWNe
- https://colab.research.google.com/
- https://js.tensorflow.org/
- https://ai.google/education/