BIML 2017 Feb. 16, 2017

TENSOR FLOW TUTORIAL

Contents and examples extended from **Udacity Deep Learning** by Google
https://classroom.udacity.com/courses/ud730/

OFF-THE-SHELF DEEP LEARNING TOOLS

4x slower than competitors
but it's expected to be improved.

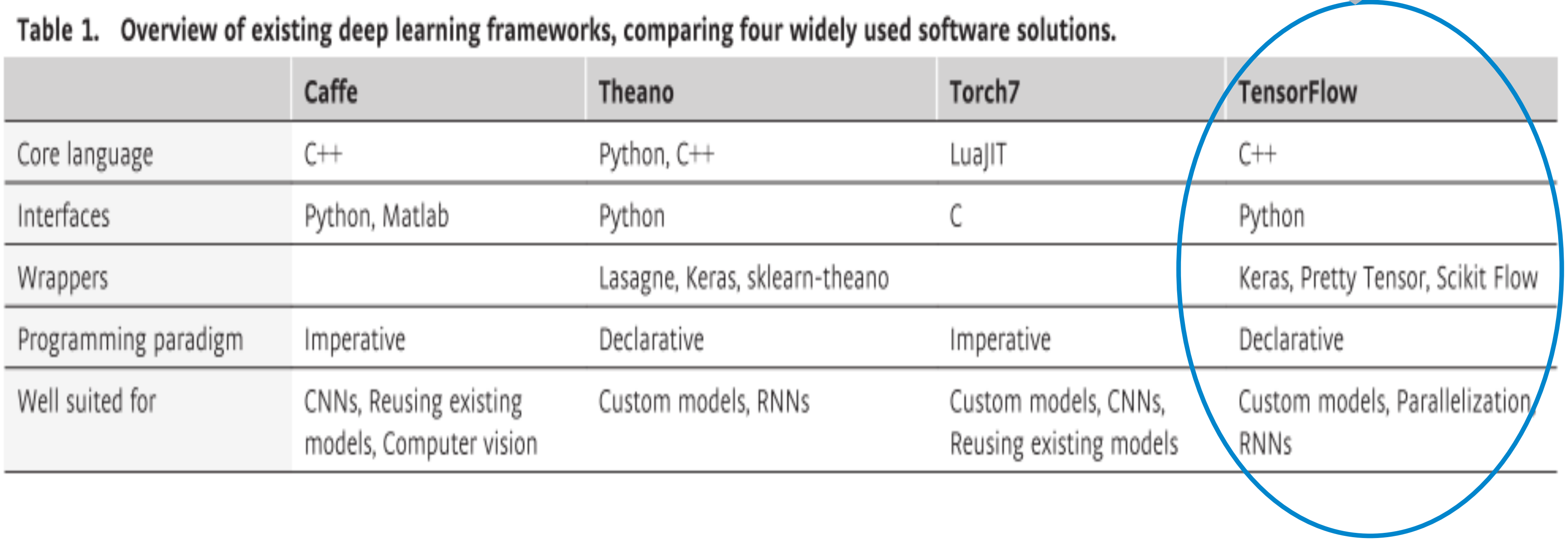


Table 1. Overview of existing deep learning frameworks, comparing four widely used software solutions.

	Caffe	Theano	Torch7	TensorFlow
Core language	C++	Python, C++	LuaJIT	C++
Interfaces	Python, Matlab	Python	C	Python
Wrappers		Lasagne, Keras, sklearn-theano		Keras, Pretty Tensor, Scikit Flow
Programming paradigm	Imperative	Declarative	Imperative	Declarative
Well suited for	CNNs, Reusing existing models, Computer vision	Custom models, RNNs	Custom models, CNNs, Reusing existing models	Custom models, Parallelization, RNNs

Table 1 in Angermueller et al. (2016) *Molecular Systems Biology*, (12), 878.

INSTALLING

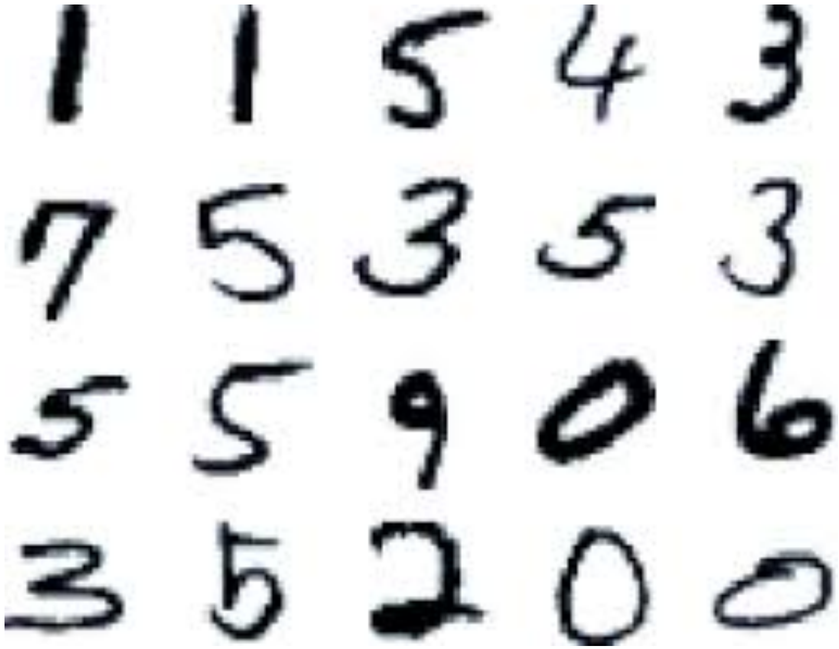
- **Install 64-bit Python 3.5 & pip (or** Anaconda3-4.2.0-Windows-x86_64)
- **Install virtualenv:**
  - CMD: pip install virtualenv
  - CMD: pip install virtualenvwrapper-win
- Create virtual environment
  - CMD: mkvirtualenv tensorflowCPU
- Install the CPU-only version of TensorFlow in the virtual environment
  - (TENSOR~) C:\Users\Name> pip install --upgrade https://storage.googleapis.com/tensorflow/windows/cpu/tensorflow-0.12.1-cp35-cp35m-win_amd64.whl

- The role of the Python code in TensorFlow is to build this external computation graph, and to dictate which parts of the computation graph should be run.

- Other heavy lifting such as numerical computations are don outside Python.

MNIST DATA

- 10 labels
- 1 channel
- 28x28 images



TRYING OUT MNIST TUTORIALS IN TENSORFLOW.ORG

GOTO: https://www.tensorflow.org/tutorials/mnist/pros/

Load MNIST Data

```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets('MNIST_data', one_hot=True)
```

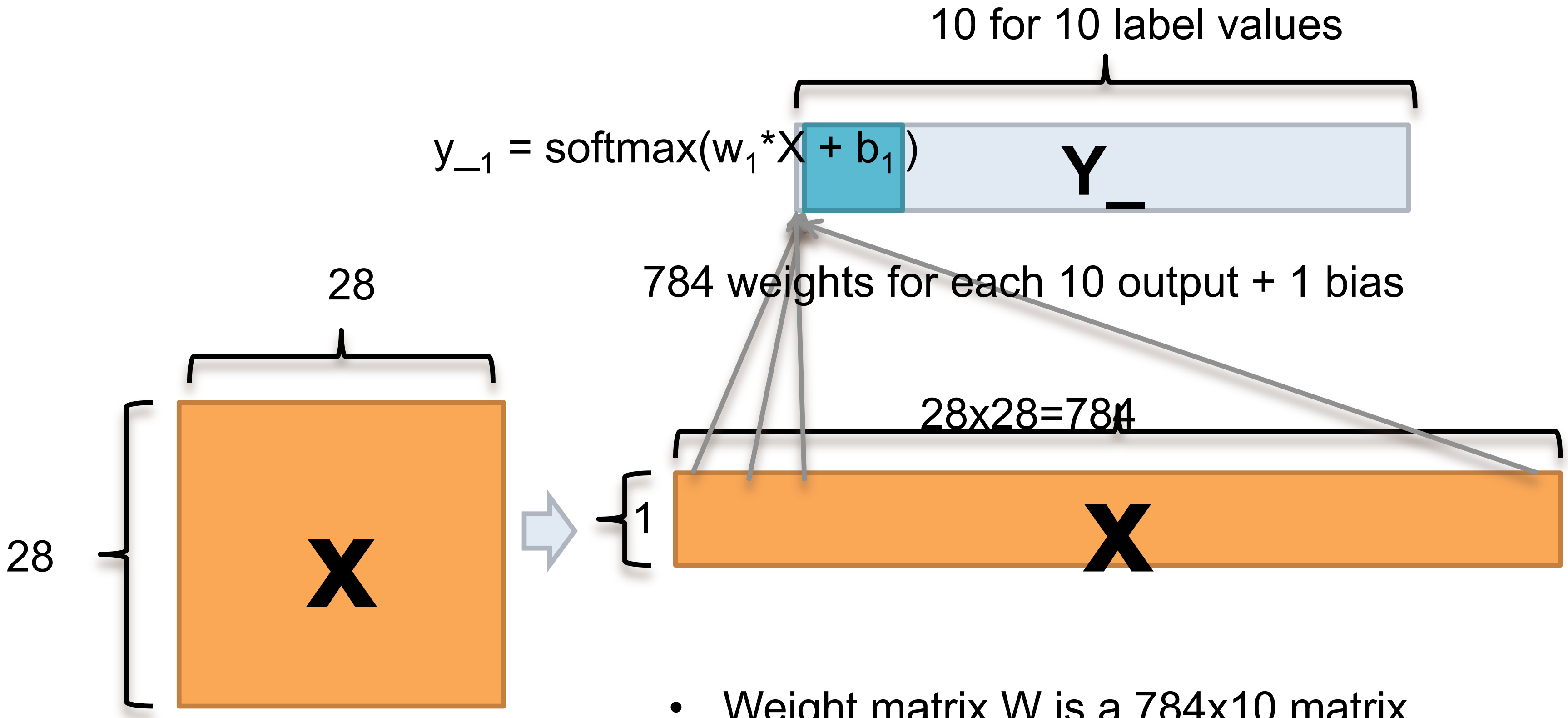
stores the training, validation,
and testing sets

Start TensorFlow InteractiveSession

```
import tensorflow as tf
sess = tf.InteractiveSession()
```

It allows you to interleave operations which build a computation graph with ones that run the graph.

MODEL1: Build a Softmax Regression Model


10 for 10 label values
$y\_1 = \text{softmax}(w_1 * X + b_1)$
Y_
784 weights for each 10 output + 1 bias
28
28
X
28x28=784
1
X

- Weight matrix W is a 784x10 matrix
  - we have 784 input features fully connected to 10 outputs
- Bias vector b is a 10-dimensional vector
  - we have 10 classes

Placeholders: create nodes for the input images and target output classes.

```
x = tf.placeholder(tf.float32, shape=[None, 784])
y_ = tf.placeholder(tf.float32, shape=[None, 10])
```

Variables: define & initalize weights W and bias b variables

```
W = tf.Variable(tf.zeros([784,10]))
b = tf.Variable(tf.zeros([10]))

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

Define the regression model.

```
z = tf.matmul(x,W) + b
```

Define the loss function : one used to update W and bias

```
cross_entropy =
tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(z, y_))
```

Applies the softmax on the model's unnormalized model prediction (z) and sums across all classes

Takes average over the sums across 10 classes

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

Training Step

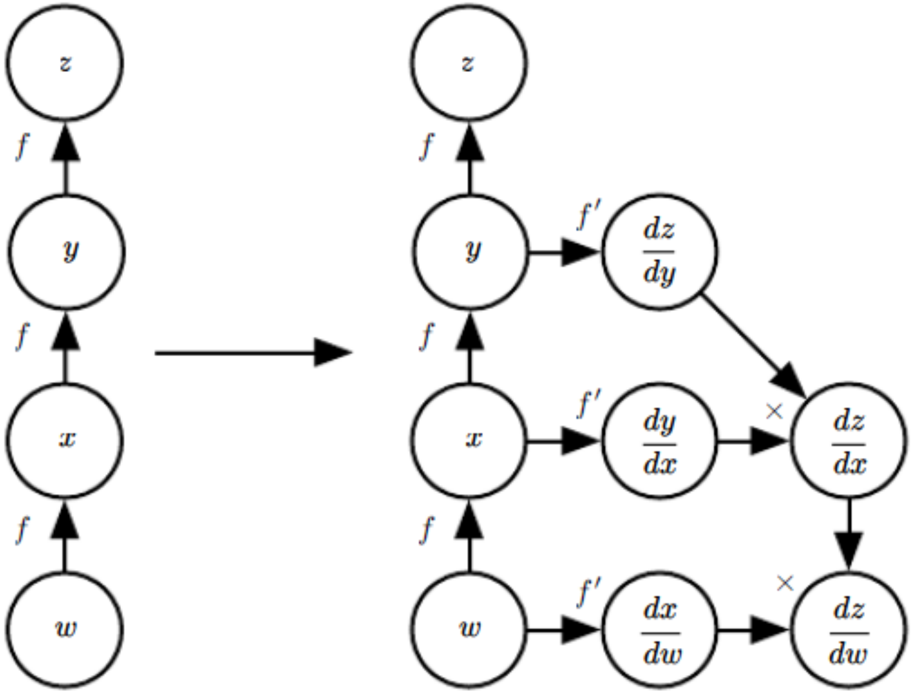
```
train_step =
tf.train.GradientDescentOptimizer(0.5).minimize(cross_entropy)
```

Steepest gradient descent, with a step length of 0.5, to descend the cross entropy.
Other built-in optimization functions: https://www.tensorflow.org/api_docs/python/train/#optimizers

- TensorFlow actually added set of new operations to the computation graph.
    - Ones to compute gradients,
    - Ones to compute parameter update steps, and
    - Ones apply update steps to the parameters.

TENSORFLOW BACK-PROPAGATION APPROACH

TensorFlow take a computational graph and add additional nodes to the graph that provide a symbolic description of the desired derivatives.



symbol-to-symbol approach to computing derivatives

Training iteration

```
for i in range(1000):
  batch = mnist.train.next_batch(100)
  train_step.run(feed_dict={x: batch[0], y_: batch[1]})
```

Evaluate model

Predicted label

true label

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
```

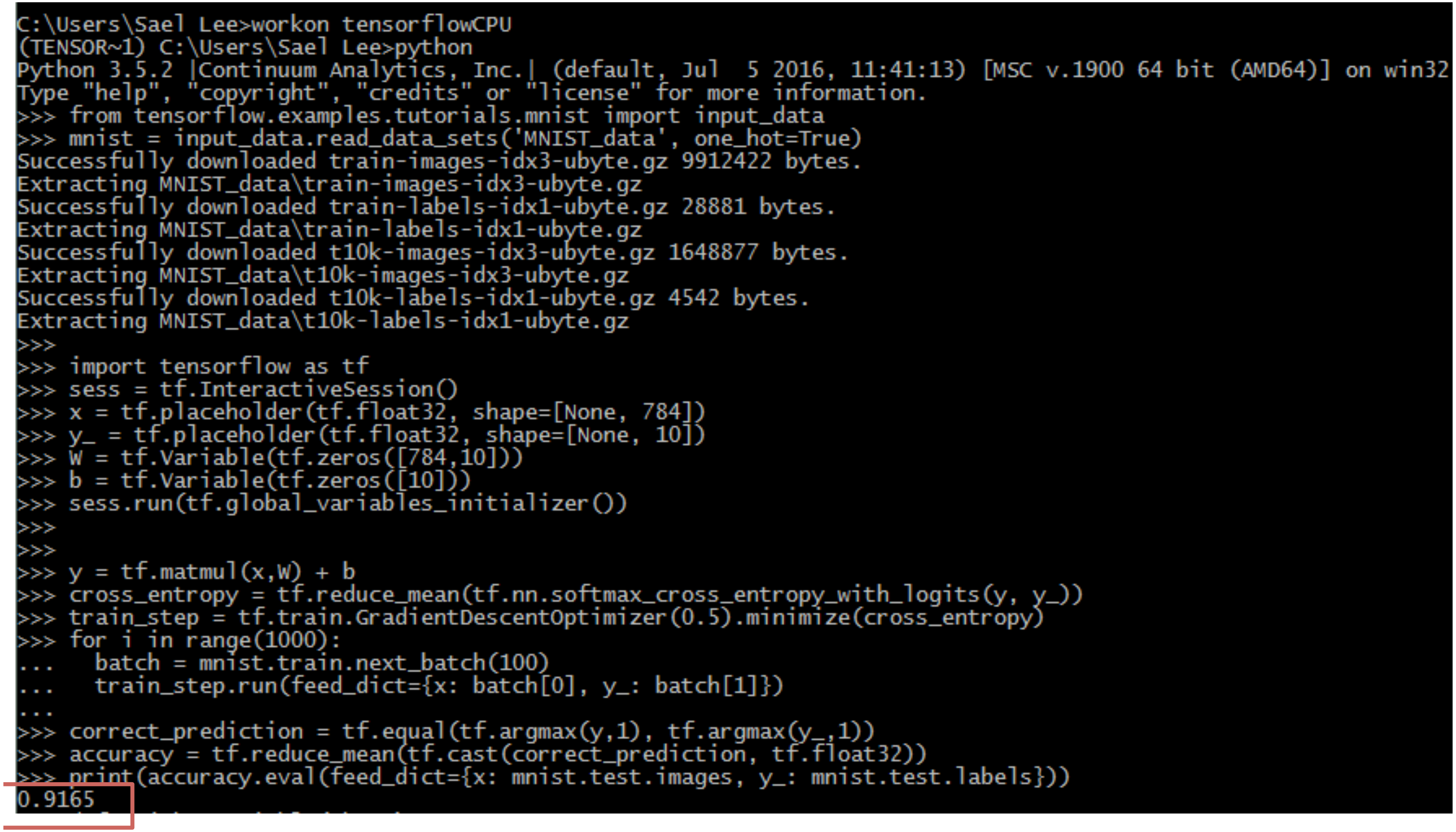
Take the avg.

Change Bool to float

```
accuracy = tf.reduce_mean(tf.cast(correct_prediction,
tf.float32))
```

evaluate our accuracy on the test data

```
print(accuracy.eval(feed_dict={x: mnist.test.images, y_:
mnist.test.labels}))
```



```
C:\Users\Sael Lee>workon tensorflowCPU
(TENSOR~1) C:\Users\Sael Lee>python
Python 3.5.2 |Continuum Analytics, Inc.| (default, Jul  5 2016, 11:41:13) [MSC v.1900 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license" for more information.
>>> from tensorflow.examples.tutorials.mnist import input_data
>>> mnist = input_data.read_data_sets('MNIST_data', one_hot=True)
Successfully downloaded train-images-idx3-ubyte.gz 9912422 bytes.
Extracting MNIST_data\train-images-idx3-ubyte.gz
Successfully downloaded train-labels-idx1-ubyte.gz 28881 bytes.
Extracting MNIST_data\train-labels-idx1-ubyte.gz
Successfully downloaded t10k-images-idx3-ubyte.gz 1648877 bytes.
Extracting MNIST_data\t10k-images-idx3-ubyte.gz
Successfully downloaded t10k-labels-idx1-ubyte.gz 4542 bytes.
Extracting MNIST_data\t10k-labels-idx1-ubyte.gz
>>>
>>> import tensorflow as tf
>>> sess = tf.InteractiveSession()
>>> x = tf.placeholder(tf.float32, shape=[None, 784])
>>> y_ = tf.placeholder(tf.float32, shape=[None, 10])
>>> W = tf.Variable(tf.zeros([784,10]))
>>> b = tf.Variable(tf.zeros([10]))
>>> sess.run(tf.global_variables_initializer())
>>>
>>>
>>> y = tf.matmul(x,W) + b
>>> cross_entropy = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y, y_))
>>> train_step = tf.train.GradientDescentOptimizer(0.5).minimize(cross_entropy)
>>> for i in range(1000):
...   batch = mnist.train.next_batch(100)
...   train_step.run(feed_dict={x: batch[0], y_: batch[1]})
...
>>> correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
>>> accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
>>> print(accuracy.eval(feed_dict={x: mnist.test.images, y_: mnist.test.labels}))
0.9165
```

Get 92% accuracy => very bad for MNIST

MODEL2: Build a Multilayer Convolutional Network

Weight Initialization

One way to randomize. initialize weights with a small amount of noise for symmetry breaking, and to prevent 0 gradients.

```
def weight_variable(shape):
  initial = tf.truncated_normal(shape, stddev=0.1)
  return tf.Variable(initial)

def bias_variable(shape):
  initial = tf.constant(0.1, shape=shape)
  return tf.Variable(initial)
```

Since we're using ReLU neurons, we should initialize them with a slightly positive initial bias to avoid "dead neurons"

Define Convolution and Pooling function

Model:

- Convolution stride of 1 and are zero padded so that the output is the same size as the input (same padding).
- Pooling: max pooling over 2x2 blocks.

```
def conv2d(x, W):
  return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2x2(x):
  return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                        strides=[1, 2, 2, 1], padding='SAME')
```

```
def conv2d(x, W):
  return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')
```

*Computes a 2-D convolution given 4-D input and filter tensors.

```
tf.nn.conv2d(input, filter, strides, padding,
        use_cudnn_on_gpu=None, data_format=None, name=None)
```

1. Flattens the filter to a 2-D matrix with shape [filter_height * filter_width * in_channels, output_channels].
2. Extracts image patches from the input tensor to form a *virtual* tensor of shape [batch, out_height, out_width, filter_height * filter_width * in_channels].
3. For each patch, right-multiplies the filter matrix and the image patch vector.

https://www.tensorflow.org/api_docs/python/nn/convolution#conv2d

```
def max_pool_2x2(x):
 return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                       strides=[1, 2, 2, 1], padding='SAME')
```

```
tf.nn.max_pool(value, ksize, strides, padding,
                              data_format='NHWC', name=None)
```

ARGUMENTS:

- **value**: A 4-D Tensor with shape [batch, height, width, channels] and type tf.float32.
- **ksize**: A list of ints that has length >= 4. The size of the window for each dimension of the input tensor.
- **strides**: A list of ints that has length >= 4. The stride of the sliding window for each dimension of the input tensor.
- **padding**: A string, either 'VALID' or 'SAME'. The padding algorithm.
- **data_format**: A string. 'NHWC' and 'NCHW' are supported.
- **name**: Optional name for the operation.

1st Convolutional Layer

patch size, #input channel, # output channel

```
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])
```

convolution will compute 32 features for each 5x5 patch

Bias per each 32 output channel

```
x_image = tf.reshape(x, [-1,28,28,1])
```

Reshape x to 4d tensor 2nd&3rd 2d image dim. 4th #of input channel

```
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
```

Convolve X_image with the weight tensor, add the bias, apply the ReLU function

reduce the image size to 14x14.

2nd Convolutional Layer

```
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])

h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
```

image size has been reduced to 7x7

Densely Connected Layer

```
W_fc1 = weight_variable([7 * 7 * 64, 1024])
b_fc1 = bias_variable([1024])

h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)
```

fully-connected layer with 1024 neurons to allow processing on the entire image.

Add Dropout

To reduce overfitting, apply **dropout** before the readout layer.

```
keep_prob = tf.placeholder(tf.float32)
h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)
```

Create placeholder for probability that a neuron's output is kept during dropout.

tf.nn.dropout op automatically handles scaling neuron outputs in addition to masking them

Readout Layer

```
W_fc2 = weight_variable([1024, 10])
b_fc2 = bias_variable([10])

y_conv = tf.matmul(h_fc1_drop, W_fc2) + b_fc2
```

Train and Evaluate the Model

Almost similar the SoftMax example with the following differences:

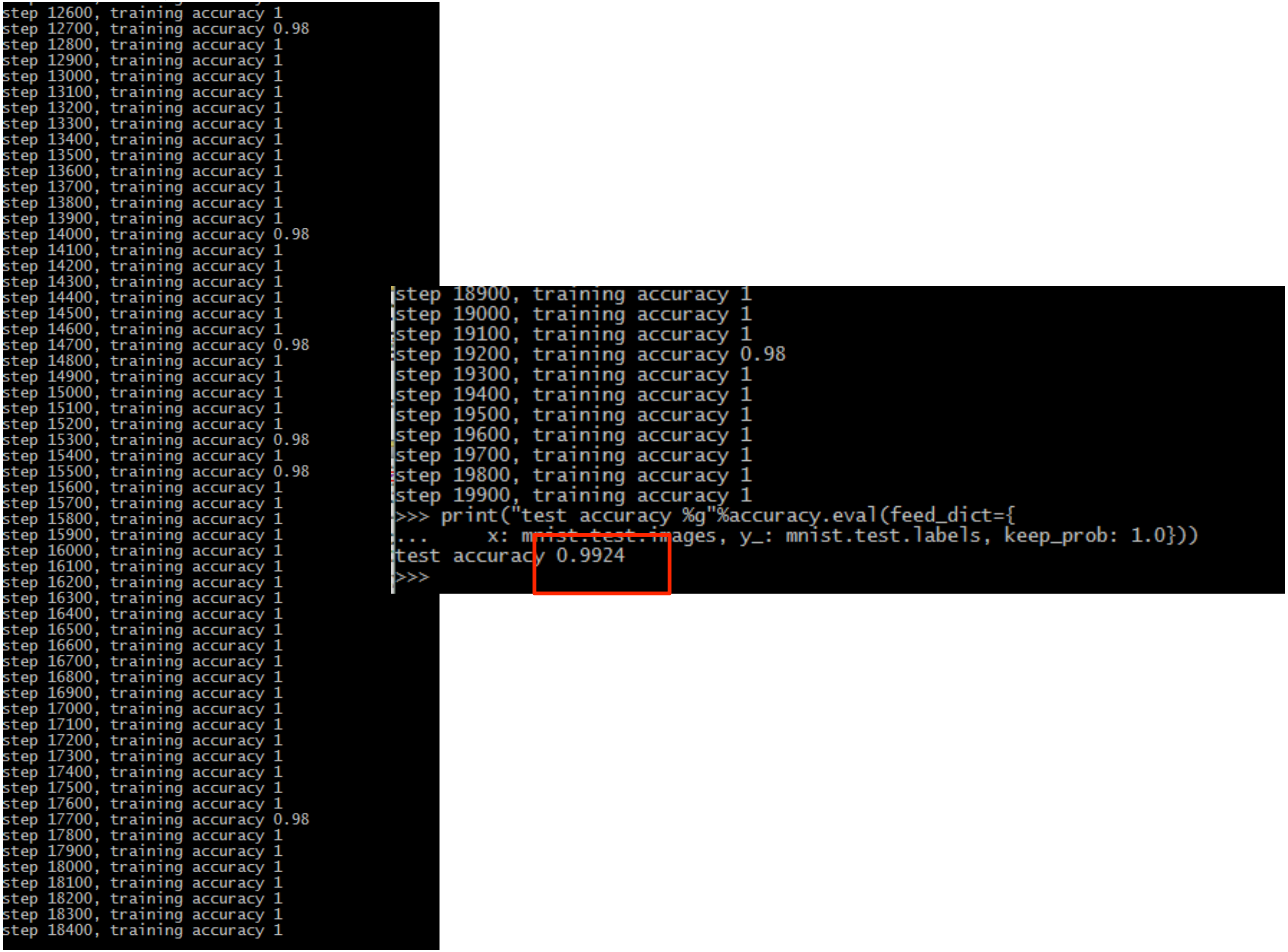
- Replace the steepest gradient descent optimizer with the more sophisticated ADAM optimizer.
- Include the additional parameter keep_prob in feed_dict to control the dropout rate.
- Add logging to every 100th iteration in the training process.

WARNING but it does 20,000 training iterations and may take a while (possibly up to half an hour), depending on your processor.

```
cross_entropy = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y_conv, y_))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
correct_prediction = tf.equal(tf.argmax(y_conv,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
sess.run(tf.global_variables_initializer())
for i in range(20000):
  batch = mnist.train.next_batch(50)
  if i%100 == 0:
    train_accuracy = accuracy.eval(feed_dict={
        x:batch[0], y_: batch[1], keep_prob: 1.0})
    print("step %d, training accuracy %g"%(i, train_accuracy))
  train_step.run(feed_dict={x: batch[0], y_: batch[1], keep_prob: 0.5})

print("test accuracy %g"%accuracy.eval(feed_dict={
    x: mnist.test.images, y_: mnist.test.labels, keep_prob: 1.0}))
```

Let’s change this to 2000 not to crush your laptop

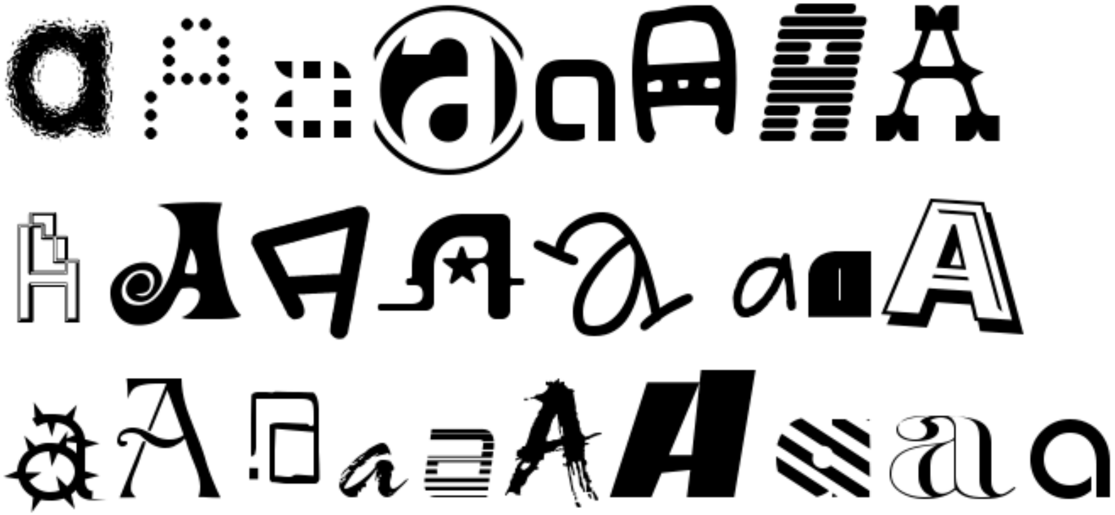


```
step 12600, training accuracy 1
step 12700, training accuracy 0.98
step 12800, training accuracy 1
step 12900, training accuracy 1
step 13000, training accuracy 1
step 13100, training accuracy 1
step 13200, training accuracy 1
step 13300, training accuracy 1
step 13400, training accuracy 1
step 13500, training accuracy 1
step 13600, training accuracy 1
step 13700, training accuracy 1
step 13800, training accuracy 1
step 13900, training accuracy 1
step 14000, training accuracy 0.98
step 14100, training accuracy 1
step 14200, training accuracy 1
step 14300, training accuracy 1
step 14400, training accuracy 1
step 14500, training accuracy 1
step 14600, training accuracy 1
step 14700, training accuracy 0.98
step 14800, training accuracy 1
step 14900, training accuracy 1
step 15000, training accuracy 1
step 15100, training accuracy 1
step 15200, training accuracy 1
step 15300, training accuracy 0.98
step 15400, training accuracy 1
step 15500, training accuracy 0.98
step 15600, training accuracy 1
step 15700, training accuracy 1
step 15800, training accuracy 1
step 15900, training accuracy 1
step 16000, training accuracy 1
step 16100, training accuracy 1
step 16200, training accuracy 1
step 16300, training accuracy 1
step 16400, training accuracy 1
step 16500, training accuracy 1
step 16600, training accuracy 1
step 16700, training accuracy 1
step 16800, training accuracy 1
step 16900, training accuracy 1
step 17000, training accuracy 1
step 17100, training accuracy 1
step 17200, training accuracy 1
step 17300, training accuracy 1
step 17400, training accuracy 1
step 17500, training accuracy 1
step 17600, training accuracy 1
step 17700, training accuracy 0.98
step 17800, training accuracy 1
step 17900, training accuracy 1
step 18000, training accuracy 1
step 18100, training accuracy 1
step 18200, training accuracy 1
step 18300, training accuracy 1
step 18400, training accuracy 1
```

```
step 18900, training accuracy 1
step 19000, training accuracy 1
step 19100, training accuracy 1
step 19200, training accuracy 0.98
step 19300, training accuracy 1
step 19400, training accuracy 1
step 19500, training accuracy 1
step 19600, training accuracy 1
step 19700, training accuracy 1
step 19800, training accuracy 1
step 19900, training accuracy 1
>>> print("test accuracy %g"%accuracy.eval(feed_dict={
...     x: mnist.test.images, y_: mnist.test.labels, keep_prob: 1.0}))
test accuracy 0.9924
>>>
```

NOTMNIST DATASET

examples of letter "A" in the notMNIST dataset



http://yaroslavvb.blogspot.kr/2011/09/notmnist-dataset.html

Multimodal classification problem (10 labels)
Single channel (gray image)
harder task than MNIST dataset

NOTMNIST DATA SET

- Download data and script at
- Store the data and script under
  - C:\Users\NAME\Envs\tensorflowCPU\myscripts
- Open command prompt by typing “cmd” on Windows search
- Assuming **pip, virtualenv, python, tensorflow** is installed type
  - > ‘mkvirtualenv tensorflowCPU’ to create new virtual environment
  - or
  - > ‘workon tensorflowCPU’ to resume working on project ‘tensorflowCPU’

SO WHAT WOULD YOU NEED TO GET STARTED?

- GPU cluster ?
  - Still need high computing power
- Good modeling of DNN
  - Input / Output design
  - Selection of Model Architecture (Deep Feedforward/ Conv olution NN/ Autoencoder/ etc.)
  - Selecting Model Training Choices
  - Model Selection - # of neurons in each layer; # of layers

- Data preparation
  - Sufficient number of data
    - (< # of model parameters)
  - Processing raw data
    - Categorical data need to change to numerical
      - One-hot code
    - Numerical features are typically normalization
      - z-score; log transformations;