

Tensorflow demo to train a neural network to classify digits

```
import tensorflow as tf
import math
import numpy as np
import h5py
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.python.framework import ops

mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
m = x_train.shape[0] # m is the total number of samples

print("m = " + str(m))

print("Shape of training data x_train: " + str(x_train.shape) + " y_train : " + str(y_
print("Shape of test data : " + str(x_test.shape)).
```

```
↳ m = 60000
Shape of training data x_train: (60000, 28, 28) y_train : (60000,)
Shape of test data : (10000, 28, 28)
```

Print some random digits


```
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

digit_index = 729
some_digit = x_train[digit_index]

plt.imshow(some_digit, cmap = matplotlib.cm.binary, interpolation="nearest")
#plt.axis("off")
plt.show()

print("Y Label : " + str(y_train[digit_index]))
```

```
↳ 0
```



Y Label : 4

Flatten the 2D images to 1D array

```
# Flatten the images from 2D to 1D
X_train_flatten = x_train.reshape(x_train.shape[0], -1).T
X_test_flatten = x_test.reshape(x_test.shape[0], -1).T
print("X_train_flatten shape = " + str(X_train_flatten.shape))
print("X_test_flatten shape = " + str(X_test_flatten.shape))
```

```
↳ X_train_flatten shape = (784, 60000)
   X_test_flatten shape = (784, 10000)
```

Convert class label y to one hot vectors

```
# Convert each label to a vector of total_classes where only one index that correspond
# Each label vector is a column vector
def one_hot_matrix(labels):

    # There are total 10 digits, thus, C that corresponds to total number of classes i
    C = tf.constant(10, name="C")
    one_hot_matrix = tf.one_hot(indices=labels, depth=C, axis=0)

    sess = tf.Session()
    one_hot = sess.run(one_hot_matrix)
    sess.close()

    return one_hot
```

Convert y-labels to 1 hot representation

```
y_train_onehot = one_hot_matrix(y_train)
y_test_onehot = one_hot_matrix(y_test)

print("Shape of y_train_onehot : " + str(y_train_onehot.shape))
print("Shape of y_test_onehot : " + str(y_test_onehot.shape))
```

```
↳ Shape of y_train_onehot : (10, 60000)
   Shape of y_test_onehot : (10, 10000)
```

```
def create_placeholders(n_x, n_y):
    """
    Creates the placeholders for the tensorflow session.

    Arguments:
    n_x -- scalar, size of an image vector (num_px * num_px = 64 * 64 = 784)
    n_y -- scalar, number of classes (from 0 to 9, so -> 10).

    Returns:
    X -- placeholder for the data input, of shape [n_x, None] and dtype "float"
    Y -- placeholder for the input labels, of shape [n_y, None] and dtype "float"

    Tips:
    - You will use None because it let's us be flexible on the number of examples you
      In fact, the number of examples during test/train is different.
    """

    ### START CODE HERE ### (approx. 2 lines)
    X = tf.placeholder(tf.float32, shape = (n_x, None))
    Y = tf.placeholder(tf.float32, shape = (n_y, None))
    ### END CODE HERE ###

    return X, Y
```

```

# Initializes the parameters for the Neural network
# The neural network has 2 hidden layers with 25 nodes in the first layer and 12 nodes
# The output layer has 10 nodes corresponding to the 10 output classes
def initialize_parameters():

    tf.set_random_seed(7)

    W1 = tf.get_variable("W1", shape=[25, 784], initializer = tf.contrib.layers.xavier
    b1 = tf.get_variable("b1", [25, 1], initializer=tf.zeros_initializer())
    W2 = tf.get_variable("W2", [12, 25], initializer=tf.contrib.layers.xavier_initiali
    b2 = tf.get_variable("b2", [12, 1], initializer=tf.zeros_initializer())
    W3 = tf.get_variable("W3", [10, 12], initializer = tf.contrib.layers.xavier_initia
    b3 = tf.get_variable("b3", [10,1], initializer = tf.zeros_initializer())

    parameters = {
        "W1": W1,
        "b1": b1,
        "W2": W2,
        "b2": b2,
        "W3": W3,
        "b3": b3
    }

    return parameters

```

Predict against a random sample

```

# Implements the forward propagation in the neural network.
# For the 2 hidden layers, RELU is the activation function.
# For the output layer, there's no activation function.
# Actually, there's sigmoid function, but taken care of in the cost calculation
def forward_propagation(X, parameters):

    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    W3 = parameters['W3']
    b3 = parameters['b3']

    Z1 = tf.add(tf.matmul(W1, X), b1)
    A1 = tf.nn.relu(Z1)
    Z2 = tf.add(tf.matmul(W2, Z1), b2)
    A2 = tf.nn.relu(Z2)
    Z3 = tf.add(tf.matmul(W3, Z2), b3)

    return Z3

# For the output layer, we use softmax activation function and calculate the overall c
# Z3 is the output from the last hidden layer
# Y is the "true" labels vector placeholder
def calculate_cost(Z3, Y):

    # Tensorflow expects the shape to be (num_examples, num_classes)
    # Hence, we need to transpose these two
    labels = tf.transpose(Y) # These correspond to y
    logits = tf.transpose(Z3) # These correspond to Z

    cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits = logits, labels = labels))

    return cost

tf.reset_default_graph()

```

```

with tf.Session() as sess:
    X, Y = create_placeholders(784, 10)
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    cost = calculate_cost(Z3, Y)
    print("cost = " + str(cost))

↳ cost = Tensor("Mean:0", shape=(), dtype=float32)

def random_mini_batches(X, Y, mini_batch_size = 64, seed = 0):
    """
    Creates a list of random minibatches from (X, Y)

    Arguments:
    X -- input data, of shape (input size, number of examples)
    Y -- true "label" vector (containing 0 if cat, 1 if non-cat), of shape (1, number
    mini_batch_size - size of the mini-batches, integer
    seed -- this is only for the purpose of grading, so that you're "random minibatches

    Returns:
    mini_batches -- list of synchronous (mini_batch_X, mini_batch_Y)
    """

    m = X.shape[1]                                # number of training examples
    mini_batches = []
    np.random.seed(seed)

    # Step 1: Shuffle (X, Y)
    permutation = list(np.random.permutation(m))
    shuffled_X = X[:, permutation]
    shuffled_Y = Y[:, permutation].reshape((Y.shape[0],m))

    # Step 2: Partition (shuffled_X, shuffled_Y). Minus the end case.
    num_complete_minibatches = math.floor(m/mini_batch_size) # number of mini batches
    for k in range(0, num_complete_minibatches):
        mini_batch_X = shuffled_X[:, k * mini_batch_size : k * mini_batch_size + mini_
        mini_batch_Y = shuffled_Y[:, k * mini_batch_size : k * mini_batch_size + mini_
        mini_batch = (mini_batch_X, mini_batch_Y)
        mini_batches.append(mini_batch)

    # Handling the end case (last mini-batch < mini_batch_size)
    if m % mini_batch_size != 0:
        mini_batch_X = shuffled_X[:, num_complete_minibatches * mini_batch_size : m]
        mini_batch_Y = shuffled_Y[:, num_complete_minibatches * mini_batch_size : m]
        mini_batch = (mini_batch_X, mini_batch_Y)
        mini_batches.append(mini_batch)

    return mini_batches

# Now we build the main neural network using the previously built functions

def model(X_train, Y_train, X_test, Y_test, learning_rate=0.0001,
          num_epochs = 200, minibatch_size=32, print_cost=True):

    ops.reset_default_graph()

    tf.set_random_seed(7)
    seed = 3
    (n_x, m) = X_train.shape # Get the number of features and training samples
    n_y = Y_train.shape[0]

    costs = [] # To keep track of the costs

    # Create placeholders for X and Y
    X, Y = create_placeholders(n_x, n_y)

```

```

# Initialize the W and b parameters for all the layers
parameters = initialize_parameters()

# Forward propagation
Z3 = forward_propagation(X, parameters)

# Calcualte the cost in forward propagation
cost = calculate_cost(Z3, Y)

# Backpropagation: Define the tensorflow optimizer. Use an AdamOptimizer.
optimizer = tf.train.AdamOptimizer(learning_rate = learning_rate).minimize(cost)

# Initialize all the variables
init = tf.global_variables_initializer()

# Start the tensorflow session
with tf.Session() as sess:

    # Run the initialization
    sess.run(init)

    for epoch in range(num_epochs):

        epoch_cost = 0
        num_minibatches = int(m / minibatch_size) # number of minibatches of size
        seed = seed + 1
        minibatches = random_mini_batches(X_train, Y_train, minibatch_size, seed)

        for minibatch in minibatches:

            # Select a minibatch
            (minibatch_X, minibatch_Y) = minibatch

            # IMPORTANT: The line that runs the graph on a minibatch.
            # Run the session to execute the "optimizer" and the "cost", the feedi
            ### START CODE HERE ### (1 line)
            _, minibatch_cost = sess.run([optimizer, cost], feed_dict={X: minibat
            ### END CODE HERE ###

            epoch_cost += minibatch_cost / num_minibatches

        # Print the cost every epoch
        if print_cost == True and epoch % 100 == 0:
            print ("Cost after epoch %i: %f" % (epoch, epoch_cost))
        if print_cost == True and epoch % 5 == 0:
            costs.append(epoch_cost)

    # plot the cost
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    # lets save the parameters in a variable
    parameters = sess.run(parameters)
    print ("Parameters have been trained!")

    # Calculate the correct predictions
    correct_prediction = tf.equal(tf.argmax(Z3), tf.argmax(Y))

    # Calculate accuracy on the test set
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))

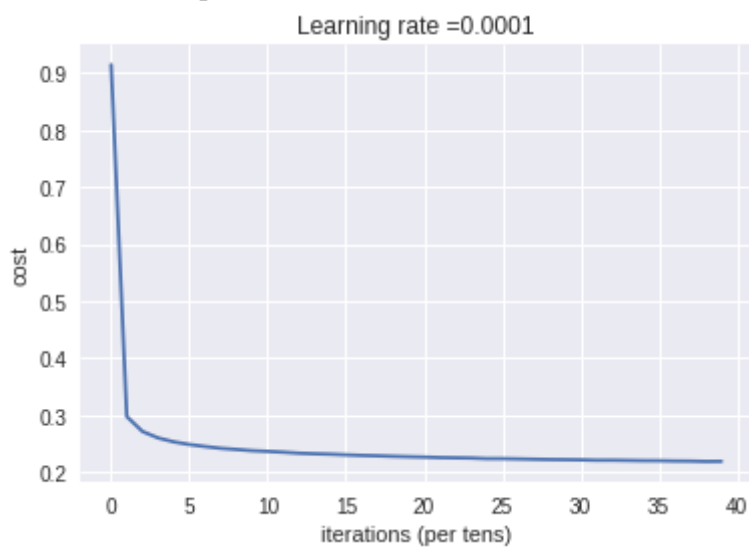
    print ("Train Accuracy:", accuracy.eval({X: X_train, Y: Y_train}))
    print ("Test Accuracy:", accuracy.eval({X: X_test, Y: Y_test}))

    return parameters

```

```
parameters = model(X_train_flatten, y_train_onehot, X_test_flatten, y_test_onehot)
```

```
↳ Cost after epoch 0: 0.914693  
Cost after epoch 100: 0.226118
```



Parameters have been trained!

Train Accuracy: 0.94088334

Test Accuracy: 0.9266