§ Tensorflow

1. Exploring the Tensorflow Library

* writing and running programs in Tensorflow:
  1. Create Tensors (variables) that are not yet executed/evaluated
  2. write operations between those Tensors
  3. Initialize your Tensors
  4. Create a session
  5. Run session. This will run the operations you'd written above

Remember to initialize your variables, create a session and run the operations inside the session.

(1) Linear Function

```python
# GRADED FUNCTION: linear_function

def linear_function():
    """
    Implements a linear function:
            Initializes W to be a random tensor of shape (4,3)
            Initializes X to be a random tensor of shape (3,1)
            Initializes b to be a random tensor of shape (4,1)
    Returns:
    result -- runs the session for Y = WX + b
    """

    np.random.seed(1)

    ### START CODE HERE ### (4 lines of code)
    X = np.random.randn(3, 1)
    W = np.random.randn(4, 3)
    b = np.random.randn(4, 1)
    Y = tf.add(tf.matmul(W, X), b)
    ### END CODE HERE ###

    # Create the session using tf.Session() and run it with sess.run(...) on the variable you want
to calculate

    ### START CODE HERE ###
    sess = tf.Session()
    result = sess.run(Y)
    ### END CODE HERE ###

    # close the session
    sess.close()

    return result
```

$Y = WX + b$

(2) Computing the sigmoid

1. Create placeholders
2. Specify the computation graph corresponding to operations you want to compute
3. Create the session.

④ Run the session, using a feed dictionary if necessary to specify placeholder variables' values.

```python
# GRADED FUNCTION: sigmoid

def sigmoid(z):
    """
    Computes the sigmoid of z

    Arguments:
    z -- input value, scalar or vector

    Returns:
    results -- the sigmoid of z
    """

    ### START CODE HERE ### ( approx. 4 lines of code)
    # Create a placeholder for x. Name it 'x'.
    x = tf.placeholder(tf.float32, name="x")

    # compute sigmoid(x)
    sigmoid = tf.sigmoid(x)

    # Create a session, and run it. Please use the method 2 explained above.
    # You should use a feed_dict to pass z's value to x.
    with tf.Session() as sess:
        # Run session and call the output "result"
        result = result = sess.run(sigmoid, feed_dict = {x: z})

    ### END CODE HERE ###

    return result
```

(3) Computing the cost

$$J = -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log a^{[2](i)} + (1-y^{(i)})\log(1-a^{[2](i)})\right)$$

```python
# GRADED FUNCTION: cost

def cost(logits, labels):
    """
    Computes the cost using the sigmoid cross entropy

    Arguments:
    logits -- vector containing z, output of the last linear unit (before the final sigmoid activa
tion)
    labels -- vector of labels y (1 or 0)

    Note: What we've been calling "z" and "y" in this class are respectively called "logits" and "
labels"
    in the TensorFlow documentation. So logits will feed into z, and labels into y.

    Returns:
    cost -- runs the session of the cost (formula (2))
    """

    ### START CODE HERE ###

    # Create the placeholders for "logits" (z) and "labels" (y) (approx. 2 lines)
    z = tf.placeholder(tf.float32, name="z")
    y = tf.placeholder(tf.float32, name="y")

    # Use the loss function (approx. 1 line)
    cost = tf.nn.sigmoid_cross_entropy_with_logits(logits=z, labels=y)

    # Create a session (approx. 1 line). See method 1 above.
    sess = tf.Session()

    # Run the session (approx. 1 line).
    cost = sess.run(cost, feed_dict={z: logits, y: labels})

    # Close the session (approx. 1 line). See method 1 above.
    sess.close()

    ### END CODE HERE ###

    return cost
```

$$-\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\sigma(z^{[2](i)}) + (1-y^{(i)})\log(1-\sigma(z^{[2](i)}))\right)$$

(4) Using One-Hot encodings

Many times in deep learning you will have a y vector with numbers ranging from 0 to C-1, where C is the number of classes. If C is for example 4, then you might have the following y vector which you will need to convert as follows:

$$y = \begin{bmatrix}1 & 2 & 3 & 0 & 2 & 1\end{bmatrix} \text{ is often converted to } \begin{array}{cl} \begin{bmatrix} 0&0&0&1&0&0\\ 1&0&0&0&0&1\\ 0&1&0&0&1&0\\ 0&0&1&0&0&0 \end{bmatrix} & \begin{matrix} \text{class} = 0\\ \text{class} = 1\\ \text{class} = 2\\ \text{class} = 3 \end{matrix} \end{array}$$

This is called a "one hot" encoding, because in the converted representation exactly one element of each column is "hot" (meaning set to 1). To do this conversion in numpy, you might have to write a few lines of code. In tensorflow, you can use one line of code:

- tf.one_hot(labels, depth, axis)

```
# GRADED FUNCTION: one_hot_matrix

def one_hot_matrix(labels, C):
    """
    Creates a matrix where the i-th row corresponds to the ith class number and the jth column
                     corresponds to the jth training example. So if example j had a label i. Then
entry (i,j)
                     will be 1.

    Arguments:
    labels -- vector containing the labels
    C -- number of classes, the depth of the one hot dimension

    Returns:
    one_hot -- one hot matrix
    """

    ### START CODE HERE ###

    # Create a tf.constant equal to C (depth), name it 'C'. (approx. 1 line)
    C = tf.constant(C, name='C')

    # Use tf.one_hot, be careful with the axis (approx. 1 line)
    one_hot_matrix = tf.one_hot(indices=labels, depth=C, axis=0)

    # Create the session (approx. 1 line)
    sess = tf.Session()

    # Run the session (approx. 1 line)
    one_hot = sess.run(one_hot_matrix)

    # Close the session (approx. 1 line). See method 1 above.
    sess.close()

    ### END CODE HERE ###

    return one_hot
```

(5) Initialize with zeros and ones

```
# GRADED FUNCTION: ones

def ones(shape):
    """
    Creates an array of ones of dimension shape

    Arguments:
    shape -- shape of the array you want to create

    Returns:
    ones -- array containing only ones
    """

    ### START CODE HERE ###

    # Create "ones" tensor using tf.ones(...). (approx. 1 line)
    ones = tf.ones(shape)

    # Create the session (approx. 1 line)
    sess = tf.Session()

    # Run the session to compute 'ones' (approx. 1 line)
    ones = sess.run(ones)

    # Close the session (approx. 1 line). See method 1 above.
    sess.close()

    ### END CODE HERE ###
    return ones
```

2. Building the first NN in Tensorflow

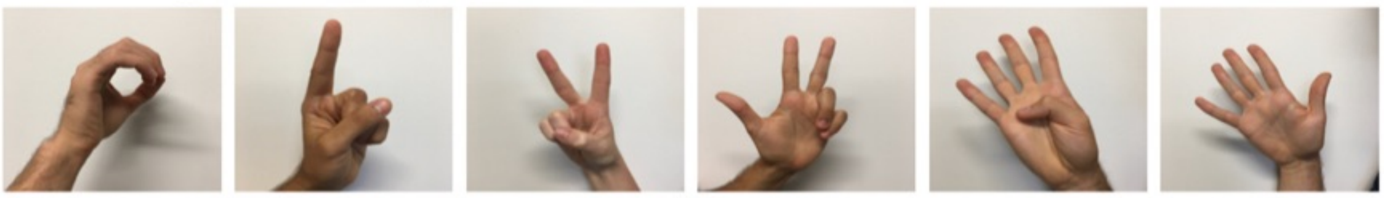
Dataset:

One afternoon, with some friends we decided to teach our computers to decipher sign language. We spent a few hours taking pictures in front of a white wall and came up with the following dataset. It's now your job to build an algorithm that would facilitate communications from a speech-impaired person to someone who doesn't understand sign language.

- **Training set**: 1080 pictures (64 by 64 pixels) of signs representing numbers from 0 to 5 (180 pictures per number).
- **Test set**: 120 pictures (64 by 64 pixels) of signs representing numbers from 0 to 5 (20 pictures per number).

Note that this is a subset of the SIGNS dataset. The complete dataset contains many more signs.

Here are examples for each number, and how an explanation of how we represent the labels. These are the original pictures, before we lowered the image resolutoion to 64 by 64 pixels.



$$y=0 \rightarrow \begin{bmatrix}1\\0\\0\\0\\0\\0\end{bmatrix} \quad y=1 \rightarrow \begin{bmatrix}0\\1\\0\\0\\0\\0\end{bmatrix} \quad y=2 \rightarrow \begin{bmatrix}0\\0\\1\\0\\0\\0\end{bmatrix} \quad y=3 \rightarrow \begin{bmatrix}0\\0\\0\\1\\0\\0\end{bmatrix} \quad y=4 \rightarrow \begin{bmatrix}0\\0\\0\\0\\1\\0\end{bmatrix} \quad y=5 \rightarrow \begin{bmatrix}0\\0\\0\\0\\0\\1\end{bmatrix}$$

```python
# Flatten the training and test images
X_train_flatten = X_train_orig.reshape(X_train_orig.shape[0], -1).T
X_test_flatten = X_test_orig.reshape(X_test_orig.shape[0], -1).T
# Normalize image vectors
X_train = X_train_flatten / 255.
X_test = X_test_flatten / 255.
# Convert training and test labels to one hot matrices
Y_train = convert_to_one_hot(Y_train_orig, 6)
Y_test = convert_to_one_hot(Y_test_orig, 6)

print("number of training examples = " + str(X_train.shape[1]))
print("number of test examples = " + str(X_test.shape[1]))
print("X_train shape: " + str(X_train.shape))
print("Y_train shape: " + str(Y_train.shape))
print("X_test shape: " + str(X_test.shape))
print("Y_test shape: " + str(Y_test.shape))
```

```
number of training examples = 1080
number of test examples = 120
X_train shape: (12288, 1080)
Y_train shape: (6, 1080)
X_test shape: (12288, 120)
Y_test shape: (6, 120)
```

$\underbrace{64 \times 64}_{\text{image}} \times 3 \rightarrow$ RGB

(1) Create placeholders

```python
# GRADED FUNCTION: create_placeholders

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 * 3 = 12288)
    n_y -- scalar, number of classes (from 0 to 5, so -> 6)

    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 will for the
placeholders.
      In fact, the number of examples during test/train is different.
    """
```

```
    ### START CODE HERE ### (approx. 2 lines)
    X = tf.placeholder(tf.float32, [n_x, None], name="X")
    Y = tf.placeholder(tf.float32, [n_y, None], name="Y")
    ### END CODE HERE ###

    return X, Y
```

(2) Initializing the parameters

```
# GRADED FUNCTION: initialize_parameters

def initialize_parameters():
    """
    Initializes parameters to build a neural network with tensorflow. The shapes are:
                        W1 : [25, 12288]
                        b1 : [25, 1]
                        W2 : [12, 25]
                        b2 : [12, 1]
                        W3 : [6, 12]
                        b3 : [6, 1]

    Returns:
    parameters -- a dictionary of tensors containing W1, b1, W2, b2, W3, b3
    """

    tf.set_random_seed(1)                          # so that your "random" numbers match ours

    ### START CODE HERE ### (approx. 6 lines of code)
    W1 = tf.get_variable("W1", [25, 12288], initializer = tf.contrib.layers.xavier_initializer(see
d=1))
    b1 = tf.get_variable("b1", [25, 1], initializer = tf.zeros_initializer())
    W2 = tf.get_variable("W2", [12, 25], initializer = tf.contrib.layers.xavier_initializer(seed=1
))
    b2 = tf.get_variable("b2", [12, 1], initializer = tf.zeros_initializer())
    W3 = tf.get_variable("W3", [6, 12], initializer = tf.contrib.layers.xavier_initializer(seed=1)
)
    b3 = tf.get_variable("b3", [6, 1], initializer = tf.zeros_initializer())
    ### END CODE HERE ###

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

    return parameters
```

(3) Forward Propagation in TensorFlow

```
# GRADED FUNCTION: forward_propagation

def forward_propagation(X, parameters):
    """
    Implements the forward propagation for the model: LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -
> SOFTMAX

    Arguments:
    X -- input dataset placeholder, of shape (input size, number of examples)
    parameters -- python dictionary containing your parameters "W1", "b1", "W2", "b2", "W3", "b3"
                  the shapes are given in initialize_parameters

    Returns:
    Z3 -- the output of the last LINEAR unit
    """

    # Retrieve the parameters from the dictionary "parameters"
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    W3 = parameters['W3']
    b3 = parameters['b3']

    ### START CODE HERE ### (approx. 5 lines)              # Numpy Equivalents:
    Z1 = tf.add(tf.matmul(W1, X), b1)                       # Z1 = np.dot(W1, X) + b1
    A1 = tf.nn.relu(Z1)                                     # A1 = relu(Z1)
    Z2 = tf.add(tf.matmul(W2, A1), b2)                      # Z2 = np.dot(W2, a1) + b2
    A2 = tf.nn.relu(Z2)                                     # A2 = relu(Z2)
    Z3 = tf.add(tf.matmul(W3, A2), b3)                      # Z3 = np.dot(W3,Z2) + b3
    ### END CODE HERE ###

    return Z3
```

(4) Compute cost

```python
# GRADED FUNCTION: compute_cost

def compute_cost(Z3, Y):
    """
    Computes the cost

    Arguments:
    Z3 -- output of forward propagation (output of the last LINEAR unit), of shape (6, number of e
xamples)
    Y -- "true" labels vector placeholder, same shape as Z3

    Returns:
    cost - Tensor of the cost function
    """

    # to fit the tensorflow requirement for tf.nn.softmax_cross_entropy_with_logits(...,...)
    logits = tf.transpose(Z3)
    labels = tf.transpose(Y)

    ### START CODE HERE ### (1 line of code)
    cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=logits, labels=labels))
    ### END CODE HERE ###

    return cost
```

the function to compute cost

(5) Build Model

```python
def model(X_train, Y_train, X_test, Y_test, learning_rate = 0.0001,
          num_epochs = 1500, minibatch_size = 32, print_cost = True):
    """
    Implements a three-layer tensorflow neural network: LINEAR->RELU->LINEAR->RELU->LINEAR->SOFTMA
X.

    Arguments:
    X_train -- training set, of shape (input size = 12288, number of training examples = 1080)
    Y_train -- test set, of shape (output size = 6, number of training examples = 1080)
    X_test -- training set, of shape (input size = 12288, number of training examples = 120)
    Y_test -- test set, of shape (output size = 6, number of test examples = 120)
    learning_rate -- learning rate of the optimization
    num_epochs -- number of epochs of the optimization loop
    minibatch_size -- size of a minibatch
    print_cost -- True to print the cost every 100 epochs

    Returns:
    parameters -- parameters learnt by the model. They can then be used to predict.
    """

    ops.reset_default_graph()                         # to be able to rerun the model without over
writing tf variables
    tf.set_random_seed(1)                             # to keep consistent results
    seed = 3                                          # to keep consistent results
    (n_x, m) = X_train.shape                          # (n_x: input size, m : number of examples i
n the train set)
    n_y = Y_train.shape[0]                            # n_y : output size
    costs = []                                        # To keep track of the cost

    # Create Placeholders of shape (n_x, n_y)
    ### START CODE HERE ### (1 line)
    X, Y = create_placeholders(n_x, n_y)
    ### END CODE HERE ###

    # Initialize parameters
    ### START CODE HERE ### (1 line)
    parameters = initialize_parameters()
    ### END CODE HERE ###

    # Forward propagation: Build the forward propagation in the tensorflow graph
    ### START CODE HERE ### (1 line)
    Z3 = forward_propagation(X, parameters)
    ### END CODE HERE ###

    # Cost function: Add cost function to tensorflow graph
    ### START CODE HERE ### (1 line)
    cost = compute_cost(Z3, Y)
    ### END CODE HERE ###

    # Backpropagation: Define the tensorflow optimizer. Use an AdamOptimizer.
    ### START CODE HERE ### (1 line)
    optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)
    ### END CODE HERE ###
```

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

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

        # Run the initialization
        sess.run(init)

        # Do the training loop
        for epoch in range(num_epochs):

            epoch_cost = 0.                       # Defines a cost related to an epoch
            num_minibatches = int(m / minibatch_size) # number of minibatches of size minibatch_si
ze in the train set
            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 feedict should co
ntain a minibatch for (X,Y).
                ### START CODE HERE ### (1 line)
                _ , minibatch_cost = sess.run([optimizer, cost], feed_dict={X: minibatch_X, Y: min
ibatch_Y})
                ### 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}))
```