

1 TensorFlow Tutorial

Welcome to this week's programming assignment. Until now, you've always used numpy to build neural networks. Now we will step you through a deep learning framework that will allow you to build neural networks more easily. Machine learning frameworks like TensorFlow, PaddlePaddle, Torch, Caffe, Keras, and many others can speed up your machine learning development significantly. All of these frameworks also have a lot of documentation, which you should feel free to read. In this assignment, you will learn to do the following in TensorFlow:

- Initialize variables
- Start your own session
- Train algorithms
- Implement a Neural Network

Programing frameworks can not only shorten your coding time, but sometimes also perform optimizations that speed up your code.

1.1 1 - Exploring the Tensorflow Library

To start, you will import the library:

In [1]:

```
1 import math
2 import numpy as np
3 import h5py
4 import matplotlib.pyplot as plt
5 import tensorflow as tf
6 from tensorflow.python.framework import ops
7 from tf_utils import load_dataset, random_mini_batches, convert_to_one_hot,
  predict
8
9 %matplotlib inline
10 np.random.seed(1)
```

Now that you have imported the library, we will walk you through its different applications. You will start with an example, where we compute for you the loss of one training example.

$$loss = \mathcal{L}(\hat{y}, y) = (\hat{y}^{(i)} - y^{(i)})^2 \quad (1)$$

In [2]:

```
1 y_hat = tf.constant(36, name='y_hat')           # Define y_hat constant. Set
  to 36.
2 y = tf.constant(39, name='y')                   # Define y. Set to 39
3
4 loss = tf.Variable((y - y_hat)**2, name='loss')  # Create a variable for the
  loss
5
6 init = tf.global_variables_initializer()         # When init is run later
  (session.run(init)),
7
  initialized and ready to be computed
8 ▼ with tf.Session() as session:                 # Create a session and print
  the output
9     session.run(init)                           # Initializes the variables
10    print(session.run(loss))                     # Prints the loss
```

9

Writing and running programs in TensorFlow has the following steps:

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 the Session. This will run the operations you'd written above.

Therefore, when we created a variable for the loss, we simply defined the loss as a function of other quantities, but did not evaluate its value. To evaluate it, we had to run

`init=tf.global_variables_initializer()` . That initialized the loss variable, and in the last line we were finally able to evaluate the value of `loss` and print its value.

Now let us look at an easy example. Run the cell below:

In [3]:

```
1 a = tf.constant(2)
2 b = tf.constant(10)
3 c = tf.multiply(a,b)
4 print(c)
```

Tensor("Mul:0", shape=(), dtype=int32)

As expected, you will not see 20! You got a tensor saying that the result is a tensor that does not have the shape attribute, and is of type "int32". All you did was put in the 'computation graph', but you have not run this computation yet. In order to actually multiply the two numbers, you will have to create a session and run it.

In [4]:

```
1 sess = tf.Session()
2 print(sess.run(c))
```

20

Great! To summarize, **remember to initialize your variables, create a session and run the operations inside the session**

Progress: 100%

Next, you'll also have to know about placeholders. A placeholder is an object whose value you can specify only later. To specify values for a placeholder, you can pass in values by using a "feed dictionary" (`feed_dict` variable). Below, we created a placeholder for `x`. This allows us to pass in a number later when we run the session.

In [5]:

```
1  # Change the value of x in the feed_dict
2
3  x = tf.placeholder(tf.int64, name = 'x')
4  print(sess.run(2 * x, feed_dict = {x: 3}))
5  sess.close()
```

6

When you first defined `x` you did not have to specify a value for it. A placeholder is simply a variable that you will assign data to only later, when running the session. We say that you **feed data** to these placeholders when running the session.

Here's what's happening: When you specify the operations needed for a computation, you are telling TensorFlow how to construct a computation graph. The computation graph can have some placeholders whose values you will specify only later. Finally, when you run the session, you are telling TensorFlow to execute the computation graph.

1.1.1 1.1 - Linear function

Lets start this programming exercise by computing the following equation: $Y = WX + b$, where W and X are random matrices and b is a random vector.

Exercise: Compute $WX + b$ where W , X , and b are drawn from a random normal distribution. W is of shape (4, 3), X is (3,1) and b is (4,1). As an example, here is how you would define a constant X that has shape (3,1):

```
x = tf.constant(np.random.randn(3,1), name = "X")
```

You might find the following functions helpful:

- `tf.matmul(..., ...)` to do a matrix multiplication
- `tf.add(..., ...)` to do an addition
- `np.random.randn(...)` to initialize randomly

In [6]:

```
1  # GRADED FUNCTION: linear_function
2
3  def linear_function():
4      """
5      Implements a linear function:
6          Initializes W to be a random tensor of shape (4,3)
7          Initializes X to be a random tensor of shape (3,1)
8          Initializes b to be a random tensor of shape (4,1)
9
10     Returns:
11     result -- runs the session for Y = WX + b
12     """
13
14     np.random.seed(1)
15
16     ### START CODE HERE ### (4 lines of code)
17     X = np.random.randn(3, 1)
18     W = np.random.randn(4, 3)
19     b = np.random.randn(4, 1)
20     Y = tf.add(tf.matmul(W, X), b)
21     ### END CODE HERE ###
22
23     # Create the session using tf.Session() and run it with sess.run(...) on
24     the variable you want to calculate
25
26     ### START CODE HERE ###
27     sess = tf.Session()
28     result = sess.run(Y)
29     ### END CODE HERE ###
30
31     # close the session
32     sess.close()
33
34     return result
```

In [7]:

```
1 print( "result = " + str(linear_function()))
```

```
result = [[-2.15657382]
 [ 2.95891446]
 [-1.08926781]
 [-0.84538042]]
```

Expected Output :

```
result [[-2.15657382] [ 2.95891446] [-1.08926781] [-0.84538042]]
```

1.1.2 1.2 - Computing the sigmoid

Great! You just implemented a linear function. Tensorflow offers a variety of commonly used neural network functions like `tf.sigmoid` and `tf.softmax`. For this exercise let's compute the sigmoid function of an input.

You will do this exercise using a placeholder variable `x`. When running the session, you should use the feed dictionary to pass in the input `z`. In this exercise, you will have to (i) create a placeholder `x`, (ii) define the operations needed to compute the sigmoid using `tf.sigmoid`, and then (iii) run the session.

Exercise : Implement the sigmoid function below. You should use the following:

- `tf.placeholder(tf.float32, name = "...")`
- `tf.sigmoid(...)`
- `sess.run(..., feed_dict = {x: z})`

Note that there are two typical ways to create and use sessions in tensorflow:

Method 1:

```
sess = tf.Session()
# Run the variables initialization (if needed), run the operations
result = sess.run(..., feed_dict = {...})
sess.close() # Close the session
```

Method 2:

```
with tf.Session() as sess:
    # run the variables initialization (if needed), run the operations
    result = sess.run(..., feed_dict = {...})
    # This takes care of closing the session for you :)
```

In [8]:

```
1  ▼ # GRADED FUNCTION: sigmoid
2
3  ▼ def sigmoid(z):
4      """
5          Computes the sigmoid of z
6
7          Arguments:
8          z -- input value, scalar or vector
9
10         Returns:
11         results -- the sigmoid of z
12         """
13
14         ### START CODE HERE ### ( approx. 4 lines of code)
15         # Create a placeholder for x. Name it 'x'.
16         x = tf.placeholder(tf.float32, name="x")
17
18         # compute sigmoid(x)
19         sigmoid = tf.sigmoid(x)
20
21         # Create a session, and run it. Please use the method 2 explained above.
22         # You should use a feed_dict to pass z's value to x.
23  ▼ with tf.Session() as sess:
24         # Run session and call the output "result"
25         result = sess.run(sigmoid, feed_dict = {x: z})
26
27         ### END CODE HERE ###
28
29     return result
```

In [9]:

```
1 print ("sigmoid(0) = " + str(sigmoid(0)))
2 print ("sigmoid(12) = " + str(sigmoid(12)))
```

```
sigmoid(0) = 0.5
sigmoid(12) = 0.999994
```

Expected Output :

```
sigmoid(0)      0.5
sigmoid(12)     0.999994
```

To summarize, you now know how to:

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.

1.1.3 1.3 - Computing the Cost

You can also use a built-in function to compute the cost of your neural network. So instead of needing to write code to compute this as a function of $a^{[2](i)}$ and $y^{(i)}$ for $i=1\dots m$: $J = -\frac{1}{m} \sum_{i=1}^m \left(y^{(i)} \log a^{[2](i)} + (1-y^{(i)}) \log (1-a^{[2](i)}) \right)$

you can do it in one line of code in tensorflow!

Exercise: Implement the cross entropy loss. The function you will use is:

- `tf.nn.sigmoid_cross_entropy_with_logits(logits = ..., labels = ...)`

Your code should input z , compute the sigmoid (to get a) and then compute the cross entropy cost J . All this can be done using one call to `tf.nn.sigmoid_cross_entropy_with_logits`, which computes

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

In [10]:

```
1  ▾ # GRADED FUNCTION: cost
2
3  ▾ def cost(logits, labels):
4      """
5          Computes the cost using the sigmoid cross entropy
6
7          Arguments:
8              logits -- vector containing z, output of the last linear unit (before the
final sigmoid activation)
9              labels -- vector of labels y (1 or 0)
10
11          Note: What we've been calling "z" and "y" in this class are respectively
called "logits" and "labels"
12          in the TensorFlow documentation. So logits will feed into z, and labels
into y.
13
14          Returns:
15          cost -- runs the session of the cost (formula (2))
16      """
17
18      ### START CODE HERE ###
19
20      # Create the placeholders for "logits" (z) and "labels" (y) (approx. 2
lines)
21      z = tf.placeholder(tf.float32, name="z")
22      y = tf.placeholder(tf.float32, name="y")
23
24      # Use the loss function (approx. 1 line)
25      cost = tf.nn.sigmoid_cross_entropy_with_logits(logits=z, labels=y)
26
27      # Create a session (approx. 1 line). See method 1 above.
28      sess = tf.Session()
29
30      # Run the session (approx. 1 line).
31      cost = sess.run(cost, feed_dict={z: logits, y: labels})
32
33      # Close the session (approx. 1 line). See method 1 above.
34      sess.close()
35
36      ### END CODE HERE ###
37
38      return cost
```

In [11]:

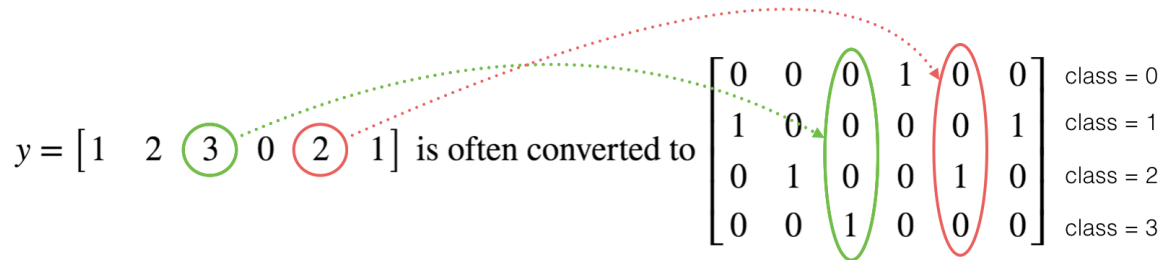
```
1  logits = sigmoid(np.array([0.2,0.4,0.7,0.9]))
2  cost = cost(logits, np.array([0,0,1,1]))
3  print ("cost = " + str(cost))
```

```
cost = [ 1.00538719  1.03664088  0.41385433  0.39956614]
```

Expected Output :

```
cost [1.00538719 1.03664088 0.41385433 0.39956614]
```

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:



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)`

Exercise: Implement the function below to take one vector of labels and the total number of classes C , and return the one hot encoding. Use `tf.one_hot()` to do this.

In [12]:

```
1  ▾ # GRADED FUNCTION: one_hot_matrix
2
3  ▾ def one_hot_matrix(labels, C):
4      """
5  ▾     Creates a matrix where the i-th row corresponds to the ith class number
        and the jth column
6          corresponds to the jth training example. So if example j
        had a label i. Then entry (i,j)
7          will be 1.
8
9      Arguments:
10     labels -- vector containing the labels
11     C -- number of classes, the depth of the one hot dimension
12
13     Returns:
14     one_hot -- one hot matrix
15     """
16
17     ### START CODE HERE ###
18
19     # Create a tf.constant equal to C (depth), name it 'C'. (approx. 1 line)
20     C = tf.constant(C, name='C')
21
22     # Use tf.one_hot, be careful with the axis (approx. 1 line)
23     one_hot_matrix = tf.one_hot(indices=labels, depth=C, axis=0)
24
25     # Create the session (approx. 1 line)
26     sess = tf.Session()
27
28     # Run the session (approx. 1 line)
29     one_hot = sess.run(one_hot_matrix)
30
31     # Close the session (approx. 1 line). See method 1 above.
32     sess.close()
33
34     ### END CODE HERE ###
35
36     return one_hot
```

In [13]:

```
1  labels = np.array([1,2,3,0,2,1])
2  one_hot = one_hot_matrix(labels, C = 4)
3  print ("one_hot = " + str(one_hot))
```

```
one_hot = [[ 0.  0.  0.  1.  0.  0.]
 [ 1.  0.  0.  0.  0.  1.]
 [ 0.  1.  0.  0.  1.  0.]
 [ 0.  0.  1.  0.  0.  0.]
```

Expected Output:

```
one_hot [[ 0. 0. 0. 1. 0. 0.] [ 1. 0. 0. 0. 0. 1.] [ 0. 1. 0. 0. 1. 0.] [ 0. 0. 1. 0. 0. 0.]
```

1.1.5 1.5 - Initialize with zeros and ones

Typesetting math: 100%

Now you will learn how to initialize a vector of zeros and ones. The function you will be calling is `tf.ones()`. To initialize with zeros you could use `tf.zeros()` instead. These functions take in a shape and return an array of dimension shape full of zeros and ones respectively.

Exercise: Implement the function below to take in a shape and to return an array (of the shape's dimension of ones).

- `tf.ones(shape)`

In [14]:

```
1  ▼ # GRADED FUNCTION: ones
2
3  ▼ def ones(shape):
4      """
5      Creates an array of ones of dimension shape
6
7      Arguments:
8      shape -- shape of the array you want to create
9
10     Returns:
11     ones -- array containing only ones
12     """
13
14     ### START CODE HERE ###
15
16     # Create "ones" tensor using tf.ones(...). (approx. 1 line)
17     ones = tf.ones(shape)
18
19     # Create the session (approx. 1 line)
20     sess = tf.Session()
21
22     # Run the session to compute 'ones' (approx. 1 line)
23     ones = sess.run(ones)
24
25     # Close the session (approx. 1 line). See method 1 above.
26     sess.close()
27
28     ### END CODE HERE ###
29     return ones
```

In [15]:

```
1  print ("ones = " + str(ones([3])))
```

```
ones = [ 1.  1.  1.]
```

Expected Output:

```
ones [1. 1. 1.]
```

2 2 - Building your first neural network in tensorflow

In this part of the assignment you will build a neural network using tensorflow. Remember that there are two parts to implementing a tensorflow model:

- Create the computation graph
- Run the graph

Let's delve into the problem you'd like to solve!

2.0.1 2.0 - Problem statement: SIGNS 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 resolution to 64 by 64 pixels.

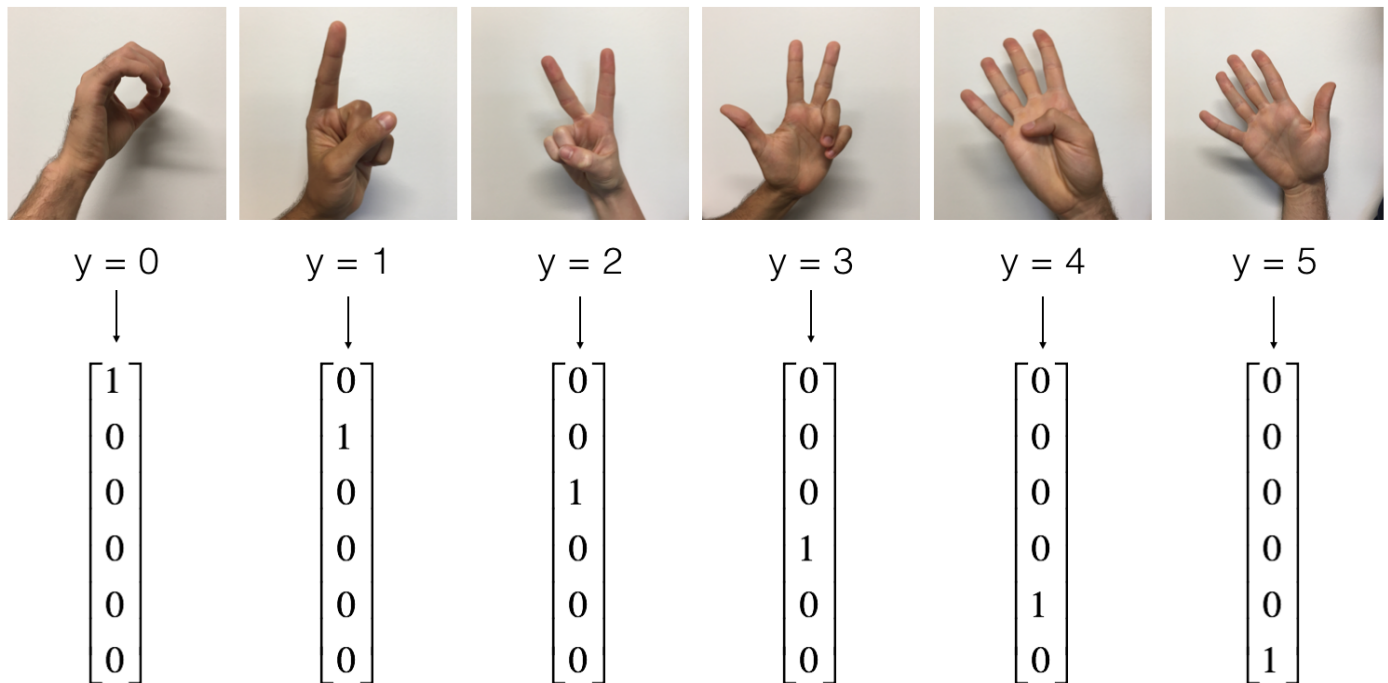


Figure 1: SIGNS dataset

Run the following code to load the dataset.

In [16]:

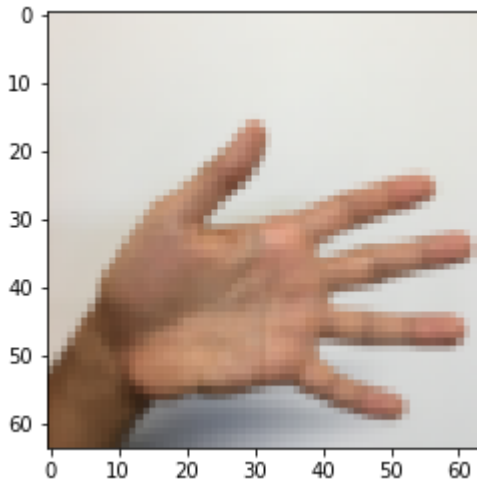
```
1 # Loading the dataset
2 X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes =
  load_dataset()
```

Change the index below and run the cell to visualize some examples in the dataset.

In [17]:

```
1 # Example of a picture
2 index = 0
3 plt.imshow(X_train_orig[index])
4 print ("y = " + str(np.squeeze(Y_train_orig[:, index])))
```

y = 5



As usual you flatten the image dataset, then normalize it by dividing by 255. On top of that, you will convert each label to a one-hot vector as shown in Figure 1. Run the cell below to do so.

In [18]:

```
1 # Flatten the training and test images
2 X_train_flatten = X_train_orig.reshape(X_train_orig.shape[0], -1).T
3 X_test_flatten = X_test_orig.reshape(X_test_orig.shape[0], -1).T
4 # Normalize image vectors
5 X_train = X_train_flatten/255.
6 X_test = X_test_flatten/255.
7 # Convert training and test labels to one hot matrices
8 Y_train = convert_to_one_hot(Y_train_orig, 6)
9 Y_test = convert_to_one_hot(Y_test_orig, 6)
10
11 print ("number of training examples = " + str(X_train.shape[1]))
12 print ("number of test examples = " + str(X_test.shape[1]))
13 print ("X_train shape: " + str(X_train.shape))
14 print ("Y_train shape: " + str(Y_train.shape))
15 print ("X_test shape: " + str(X_test.shape))
16 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)

Note that 12288 comes from $64 \times 64 \times 3$. Each image is square, 64 by 64 pixels, and 3 is for the RGB colors. Please make sure all these shapes make sense to you before continuing.

Your goal is to build an algorithm capable of recognizing a sign with high accuracy. To do so, you are going to build a tensorflow model that is almost the same as one you have previously built in numpy for cat recognition

(but now using a softmax output). It is a great occasion to compare your numpy implementation to the tensorflow one.

The model is *LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -> SOFTMAX*. The SIGMOID output layer has been converted to a SOFTMAX. A SOFTMAX layer generalizes SIGMOID to when there are more than two classes.

2.0.2 2.1 - Create placeholders

Your first task is to create placeholders for x and y . This will allow you to later pass your training data in when you run your session.

Exercise: Implement the function below to create the placeholders in tensorflow.

In [19]:

```
1  # GRADED FUNCTION: create_placeholders
2
3  def create_placeholders(n_x, n_y):
4      """
5      Creates the placeholders for the tensorflow session.
6
7      Arguments:
8      n_x -- scalar, size of an image vector (num_px * num_px = 64 * 64 * 3 =
12288)
9      n_y -- scalar, number of classes (from 0 to 5, so -> 6)
10
11      Returns:
12      X -- placeholder for the data input, of shape [n_x, None] and dtype
"float"
13      Y -- placeholder for the input labels, of shape [n_y, None] and dtype
"float"
14
15      Tips:
16  - You will use None because it let's us be flexible on the number of
examples you will for the placeholders.
17      In fact, the number of examples during test/train is different.
18      """
19
20      ### START CODE HERE ### (approx. 2 lines)
21      X = tf.placeholder(tf.float32, [n_x, None], name="X")
22      Y = tf.placeholder(tf.float32, [n_y, None], name="Y")
23      ### END CODE HERE ###
24
25      return X, Y
```

In [20]:

```
1  X, Y = create_placeholders(12288, 6)
2  print ("X = " + str(X))
3  print ("Y = " + str(Y))
```

```
X = Tensor("X:0", shape=(12288, ?), dtype=float32)
Y = Tensor("Y:0", shape=(6, ?), dtype=float32)
```

Expected Output:

Typesetting math: 100%
X = Tensor("Placeholder_1:0", shape=(12288, ?), dtype=float32) (not necessarily Placeholder_1)

Y Tensor("Placeholder_2:0", shape=(10, ?), dtype=float32) (not necessarily Placeholder_2)

2.0.3 2.2 - Initializing the parameters

Your second task is to initialize the parameters in tensorflow.

Exercise: Implement the function below to initialize the parameters in tensorflow. You are going use Xavier Initialization for weights and Zero Initialization for biases. The shapes are given below. As an example, to help you, for W1 and b1 you could use:

```
W1 = tf.get_variable("W1", [25,12288], initializer = tf.contrib.layers.xavier_initializer(seed = 1))
b1 = tf.get_variable("b1", [25,1], initializer = tf.zeros_initializer())
```

Please use `seed = 1` to make sure your results match ours.

In [21]:

```
1  ▼ # GRADED FUNCTION: initialize_parameters
2
3  ▼ def initialize_parameters():
4      """
5  ▼     Initializes parameters to build a neural network with tensorflow. The
        shapes are:
6
7             W1 : [25, 12288]
8             b1 : [25, 1]
9             W2 : [12, 25]
10            b2 : [12, 1]
11            W3 : [6, 12]
12            b3 : [6, 1]
13
14            Returns:
15            parameters -- a dictionary of tensors containing W1, b1, W2, b2, W3, b3
16            """
17
18            tf.set_random_seed(1)                                # so that your "random" numbers
match ours
19
20            ### START CODE HERE ### (approx. 6 lines of code)
21            W1 = tf.get_variable("W1", [25, 12288], initializer =
tf.contrib.layers.xavier_initializer(seed=1))
22            b1 = tf.get_variable("b1", [25, 1], initializer = tf.zeros_initializer())
23            W2 = tf.get_variable("W2", [12, 25], initializer =
tf.contrib.layers.xavier_initializer(seed=1))
24            b2 = tf.get_variable("b2", [12, 1], initializer = tf.zeros_initializer())
25            W3 = tf.get_variable("W3", [6, 12], initializer =
tf.contrib.layers.xavier_initializer(seed=1))
26            b3 = tf.get_variable("b3", [6, 1], initializer = tf.zeros_initializer())
27            ### END CODE HERE ###
28  ▼     parameters = {"W1": W1,
29                     "b1": b1,
30                     "W2": W2,
31                     "b2": b2,
32                     "W3": W3,
33                     "b3": b3}
34
35     return parameters
```

In [22]:

```
1  tf.reset_default_graph()
2  ▼ with tf.Session() as sess:
3      parameters = initialize_parameters()
4      print("W1 = " + str(parameters["W1"]))
5      print("b1 = " + str(parameters["b1"]))
6      print("W2 = " + str(parameters["W2"]))
7      print("b2 = " + str(parameters["b2"]))
```

```
W1 = <tf.Variable 'W1:0' shape=(25, 12288) dtype=float32_ref>
b1 = <tf.Variable 'b1:0' shape=(25, 1) dtype=float32_ref>
W2 = <tf.Variable 'W2:0' shape=(12, 25) dtype=float32_ref>
b2 = <tf.Variable 'b2:0' shape=(12, 1) dtype=float32_ref>
```

Expected Output:

Typesetting math: 100%

```
W1 < tf.Variable 'W1:0' shape=(25, 12288) dtype=float32_ref >
b1 < tf.Variable 'b1:0' shape=(25, 1) dtype=float32_ref >
W2 < tf.Variable 'W2:0' shape=(12, 25) dtype=float32_ref >
b2 < tf.Variable 'b2:0' shape=(12, 1) dtype=float32_ref >
```

As expected, the parameters haven't been evaluated yet.

2.0.4 2.3 - Forward propagation in tensorflow

You will now implement the forward propagation module in tensorflow. The function will take in a dictionary of parameters and it will complete the forward pass. The functions you will be using are:

- `tf.add(..., ...)` to do an addition
- `tf.matmul(..., ...)` to do a matrix multiplication
- `tf.nn.relu(...)` to apply the ReLU activation

Question: Implement the forward pass of the neural network. We commented for you the numpy equivalents so that you can compare the tensorflow implementation to numpy. It is important to note that the forward propagation stops at `z3`. The reason is that in tensorflow the last linear layer output is given as input to the function computing the loss. Therefore, you don't need `a3` !

In [23]:

```
1  ▼ # GRADED FUNCTION: forward_propagation
2
3  ▼ def forward_propagation(X, parameters):
4      """
5      Implements the forward propagation for the model: LINEAR -> RELU ->
6      LINEAR -> RELU -> LINEAR -> SOFTMAX
7
8      Arguments:
9      X -- input dataset placeholder, of shape (input size, number of examples)
10     parameters -- python dictionary containing your parameters "W1", "b1",
11     "W2", "b2", "W3", "b3"
12     the shapes are given in initialize_parameters
13
14     Returns:
15     Z3 -- the output of the last LINEAR unit
16     """
17
18     # Retrieve the parameters from the dictionary "parameters"
19     W1 = parameters['W1']
20     b1 = parameters['b1']
21     W2 = parameters['W2']
22     b2 = parameters['b2']
23     W3 = parameters['W3']
24     b3 = parameters['b3']
25
26     ### START CODE HERE ### (approx. 5 lines)                                # Numpy
27     Equivalents:
28     Z1 = tf.add(tf.matmul(W1, X), b1)                                         # Z1 = np.dot(W1,
29     X) + b1                                                                    # Z1 = np.dot(W1,
30     A1 = tf.nn.relu(Z1)                                                        # A1 = relu(Z1)
31     Z2 = tf.add(tf.matmul(W2, A1), b2)                                         # Z2 = np.dot(W2,
32     a1) + b2                                                                    # Z2 = np.dot(W2,
33     A2 = tf.nn.relu(Z2)                                                        # A2 = relu(Z2)
34     Z3 = tf.add(tf.matmul(W3, A2), b3)                                         # Z3 =
35     np.dot(W3, Z2) + b3
36     ### END CODE HERE ###
37
38     return Z3
```

In [24]:

```
1  tf.reset_default_graph()
2
3  ▼ with tf.Session() as sess:
4      X, Y = create_placeholders(12288, 6)
5      parameters = initialize_parameters()
6      Z3 = forward_propagation(X, parameters)
7      print("Z3 = " + str(Z3))
```

Z3 = Tensor("Add_2:0", shape=(6, ?), dtype=float32)

Expected Output:

Z3 Tensor("Add_2:0", shape=(6, ?), dtype=float32)

You may have noticed that the forward propagation doesn't output any cache. You will understand why below, when we get to backpropagation.

2.0.5 2.4 Compute cost

As seen before, it is very easy to compute the cost using:

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

Question: Implement the cost function below.

- It is important to know that the " logits " and " labels " inputs of `tf.nn.softmax_cross_entropy_with_logits` are expected to be of shape (number of examples, num_classes). We have thus transposed Z3 and Y for you.
- Besides, `tf.reduce_mean` basically does the summation over the examples.

In [25]:

```
1  ▼ # GRADED FUNCTION: compute_cost
2
3  ▼ def compute_cost(Z3, Y):
4      """
5          Computes the cost
6
7          Arguments:
8          Z3 -- output of forward propagation (output of the last LINEAR unit), of
shape (6, number of examples)
9          Y -- "true" labels vector placeholder, same shape as Z3
10
11         Returns:
12         cost - Tensor of the cost function
13         """
14
15         # to fit the tensorflow requirement for
tf.nn.softmax_cross_entropy_with_logits(...,...)
16         logits = tf.transpose(Z3)
17         labels = tf.transpose(Y)
18
19         ### START CODE HERE ### (1 line of code)
20         cost =
tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=logits,
labels=labels))
21         ### END CODE HERE ###
22
23         return cost
```

In [26]:

```
1  tf.reset_default_graph()
2
3  ▼ with tf.Session() as sess:
4      X, Y = create_placeholders(12288, 6)
5      parameters = initialize_parameters()
6      Z3 = forward_propagation(X, parameters)
7      cost = compute_cost(Z3, Y)
8      print("cost = " + str(cost))
```

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

Expected Output:

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

2.0.6 2.5 - Backward propagation & parameter updates

This is where you become grateful to programming frameworks. All the backpropagation and the parameters update is taken care of in 1 line of code. It is very easy to incorporate this line in the model.

After you compute the cost function. You will create an "optimizer" object. You have to call this object along with the cost when running the `tf.session`. When called, it will perform an optimization on the given cost with the chosen method and learning rate.

For instance, for gradient descent the optimizer would be:

```
optimizer = tf.train.GradientDescentOptimizer(learning_rate = learning_rate)
optimizer.minimize(cost)
```

To make the optimization you would do:

```
_, c = sess.run([optimizer, cost], feed_dict={X: minibatch_X, Y: minibatch_Y})
```

This computes the backpropagation by passing through the tensorflow graph in the reverse order. From cost to inputs.

Note When coding, we often use `_` as a "throwaway" variable to store values that we won't need to use later. Here, `_` takes on the evaluated value of `optimizer`, which we don't need (and `c` takes the value of the `cost` variable).

2.0.7 2.6 - Building the model

Now, you will bring it all together!

Exercise: Implement the model. You will be calling the functions you had previously implemented.

In [27]:

```
1 def model(X_train, Y_train, X_test, Y_test, learning_rate = 0.0001,
2           num_epochs = 1500, minibatch_size = 32, print_cost = True):
3     """
4     Implements a three-layer tensorflow neural network: LINEAR->RELU-
5     >LINEAR->RELU->LINEAR->SOFTMAX.
6
7     Arguments:
8     X_train -- training set, of shape (input size = 12288, number of
9     training examples = 1080)
10    Y_train -- test set, of shape (output size = 6, number of training
11    examples = 1080)
12    X_test -- training set, of shape (input size = 12288, number of training
13    examples = 120)
14    Y_test -- test set, of shape (output size = 6, number of test examples =
15    120)
16    learning_rate -- learning rate of the optimization
17    num_epochs -- number of epochs of the optimization loop
18    minibatch_size -- size of a minibatch
19    print_cost -- True to print the cost every 100 epochs
20
21    Returns:
22    parameters -- parameters learnt by the model. They can then be used to
23    predict.
24    """
25
26    ops.reset_default_graph()                                # to be able to rerun
27    the model without overwriting tf variables
28    tf.set_random_seed(1)                                    # to keep consistent
29    results
30    seed = 3                                                  # to keep consistent
31    results
32    (n_x, m) = X_train.shape                                  # (n_x: input size, m
33    : number of examples in the train set)
34    n_y = Y_train.shape[0]                                    # n_y : output size
35    costs = []                                                # To keep track of the
36    cost
37
38    # Create Placeholders of shape (n_x, n_y)
39    ### START CODE HERE ### (1 line)
40    X, Y = create_placeholders(n_x, n_y)
41    ### END CODE HERE ###
42
43    # Initialize parameters
44    ### START CODE HERE ### (1 line)
45    parameters = initialize_parameters()
46    ### END CODE HERE ###
47
48    # Forward propagation: Build the forward propagation in the tensorflow
49    graph
50    ### START CODE HERE ### (1 line)
51    Z3 = forward_propagation(X, parameters)
52    ### END CODE HERE ###
53
54    # Cost function: Add cost function to tensorflow graph
55    ### START CODE HERE ### (1 line)
56    cost = compute_cost(Z3, Y)
57    ### END CODE HERE ###
58
59    # Backpropagation: Define the tensorflow optimizer. Use an
```


AdamOptimizer.

```
48     ### START CODE HERE ### (1 line)
49     optimizer =
tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)
50     ### END CODE HERE ###
51
52     # Initialize all the variables
53     init = tf.global_variables_initializer()
54
55     # Start the session to compute the tensorflow graph
56     with tf.Session() as sess:
57
58         # Run the initialization
59         sess.run(init)
60
61         # Do the training loop
62         for epoch in range(num_epochs):
63
64             epoch_cost = 0.                                # Defines a cost related
to an epoch
65             num_minibatches = int(m / minibatch_size) # number of
minibatches of size minibatch_size in the train set
66             seed = seed + 1
67             minibatches = random_mini_batches(X_train, Y_train,
minibatch_size, seed)
68
69             for minibatch in minibatches:
70
71                 # Select a minibatch
72                 (minibatch_X, minibatch_Y) = minibatch
73
74                 # IMPORTANT: The line that runs the graph on a minibatch.
75                 # Run the session to execute the "optimizer" and the "cost",
the feeddict should contain a minibatch for (X,Y).
76                 ### START CODE HERE ### (1 line)
77                 _, minibatch_cost = sess.run([optimizer, cost], feed_dict=
{X: minibatch_X, Y: minibatch_Y})
78                 ### END CODE HERE ###
79
80                 epoch_cost += minibatch_cost / num_minibatches
81
82                 # Print the cost every epoch
83                 if print_cost == True and epoch % 100 == 0:
84                     print ("Cost after epoch %i: %f" % (epoch, epoch_cost))
85                 if print_cost == True and epoch % 5 == 0:
86                     costs.append(epoch_cost)
87
88                 # plot the cost
89                 plt.plot(np.squeeze(costs))
90                 plt.ylabel('cost')
91                 plt.xlabel('iterations (per tens)')
92                 plt.title("Learning rate =" + str(learning_rate))
93                 plt.show()
94
95                 # lets save the parameters in a variable
96                 parameters = sess.run(parameters)
97                 print ("Parameters have been trained!")
98
99                 # Calculate the correct predictions
100                 correct_prediction = tf.equal(tf.argmax(Z3), tf.argmax(Y))
101
```

```

102         # Calculate accuracy on the test set
103         accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
104
105         print ("Train Accuracy:", accuracy.eval({X: X_train, Y: Y_train}))
106         print ("Test Accuracy:", accuracy.eval({X: X_test, Y: Y_test}))
107
108         return parameters

```

Run the following cell to train your model! On our machine it takes about 5 minutes. Your "Cost after epoch 100" should be 1.016458. If it's not, don't waste time; interrupt the training by clicking on the square  in the upper bar of the notebook, and try to correct your code. If it is the correct cost, take a break and come back in 5 minutes!

In []:

```

1 parameters = model(X_train, Y_train, X_test, Y_test)

```

Expected Output:

Train Accuracy 0.999074

Test Accuracy 0.716667

Amazing, your algorithm can recognize a sign representing a figure between 0 and 5 with 71.7% accuracy.

Insights:

- Your model seems big enough to fit the training set well. However, given the difference between train and test accuracy, you could try to add L2 or dropout regularization to reduce overfitting.
- Think about the session as a block of code to train the model. Each time you run the session on a minibatch, it trains the parameters. In total you have run the session a large number of times (1500 epochs) until you obtained well trained parameters.

2.0.8 2.7 - Test with your own image (optional / ungraded exercise)

Congratulations on finishing this assignment. You can now take a picture of your hand and see the output of your model. To do that:

1. Click on "File" in the upper bar of this notebook, then click "Open" to go on your Coursera Hub.
2. Add your image to this Jupyter Notebook's directory, in the "images" folder
3. Write your image's name in the following code
4. Run the code and check if the algorithm is right!