Reference

Coursera Deep learning series by Andrew NG

TensorFlow Tutorial

Machine learning frameworks like **TensorFlow, PaddlePaddle, Torch, Caffe, Keras,** and many others can speed up your machine learning development significantly. 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.

What you should remember about the Tensorflow:

- Tensorflow is a programming framework used in deep learning
- The two main object classes in tensorflow are Tensors and Operators.
- When you code in tensorflow you have to take the following steps:
    - Create a graph containing Tensors (Variables, Placeholders ...) and Operations (tf.matmul, tf.add, ...)
    - Create a session
    - Initialize the session
    - Run the session to execute the graph
- You can execute the graph multiple times as you've seen in model()
- The backpropagation and optimization is automatically done when running the session on the "optimizer" object.

First check a simple example:

```
import numpy as np
import tensorflow as tf
```

```
coefficients = np.array([[1.], [-20.], [100.]])

w = tf.Variable(0,dtype=tf.float32)
x = tf.placeholder(tf.float32, [3,1])
#cost = tf.add(tf.add(w**2,tf.multiply(-10.,w)),25)
#cost = w**2 - 10*w + 25
cost = x[0][0]*w**2 + x[1][0]*w + x[2][0]
train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)

init = tf.global_variables_initializer()
session = tf.Session()
session.run(init)
print(session.run(w))
```

```
0.0
```

```
session.run(train, feed_dict={x:coefficients})
print(session.run(w))
```

```
0.2
```

1 - Exploring the Tensorflow Library

To start, you will import the library:

In [2]:
```
import math
import numpy as np
import h5py
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.python.framework import ops
from tf_utils import load_dataset, random_mini_batches, convert_to_one_hot, predict

%matplotlib inline
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.

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

In [3]:

```
y_hat = tf.constant(36, name='y_hat')            # Define y_hat constant. Set to 36.
y = tf.constant(39, name='y')                    # Define y. Set to 39

loss = tf.Variable((y - y_hat)**2, name='loss')  # Create a variable for the loss

init = tf.global_variables_initializer()         # When init is run later (session.run(init)),
                                                 # the loss variable will be initialized and ready to computed
                                                 # Loss is initialized what? Only initialize the loss? Is this "
                                                 # the session" in the guideline before? Next cell it says "init

with tf.Session() as session:                    # Create a session and print the output
    session.run(init)                            # Initializes the variables
    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. **Compare to the running process of Flask framework.**

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

In [4]:
```
a = tf.constant(2)
b = tf.constant(10)
c = tf.multiply(a,b)
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 [5]:
```
sess = tf.Session()
print(sess.run(c))
```

```
20
```

Why we don't run initialization process in the above simple example?

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 [6]:
```
# Change the value of x in the feed_dict
x = tf.placeholder(tf.int64, name = 'x')
print(sess.run(2 * x, feed_dict = {x: 3}))
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 - 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 [7]:
```
def linear_function():

    np.random.seed(1)

    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)

    sess = tf.Session()
    result = sess.run(Y)

    sess.close()

    return result
```

In [8]:
```
print( "result = " + str(linear_function()))
```

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

1.2 - Computing the sigmoid

Tensorflow offers a variety of commonly used neural network functions like `tf.sigmoid` and `tf.softmax`.
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()
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 [9]:

```
def sigmoid(z):
    x = tf.placeholder(tf.float32, name="x")
    sigmoid = tf.sigmoid(x)

    with tf.Session() as sess:
        result =  sess.run(sigmoid, feed_dict = {x: z})

    return result
```

In [10]:
```python
print ("sigmoid(0) = " + str(sigmoid(0)))
print ("sigmoid(12) = " + str(sigmoid(12)))
```

```
sigmoid(0) = 0.5
sigmoid(12) = 0.9999938
```

Whenever using the code like

```python
with tf.Session() as sess:
    result = sess.run(sigmoid,feed_dict = {x:z})
```
Be aware that the session is closed thereafter.

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...m:

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

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

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

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.

In [11]:
```python
def cost(logits, labels):

    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)

    sess = tf.Session()
    cost = sess.run(cost, feed_dict={z: logits, y: labels})

    sess.close()

    return cost
```

In [12]:
```python
logits = sigmoid(np.array([0.2, 0.4, 0.7, 0.9]))
cost = cost(logits, np.array([0, 0, 1, 1]))
print ("cost = " + str(cost))
```

```
cost = [1.0053872  1.0366408  0.41385433 0.39956617]
```

1.4 - 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:

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

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)

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.

The one_hot_matrix() below 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.

In [13]:
```
def one_hot_matrix(labels, C):
    """

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

    Returns:
    one_hot -- one hot matrix
    """

    # 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)

    sess = tf.Session()

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


    return one_hot
```

In [14]:
```
labels = np.array([1,2,3,0,2,1])
one_hot = one_hot_matrix(labels, C=4)
print ("one_hot = " + "\n" + 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.]]
```

Note the '0' is encoded as (1,0,0,0). There is no more independent or dependent issue here.

1.5 - Initialize with zeros and ones

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 [15]:
```
def ones(shape):

    ones = tf.ones(shape)
    sess = tf.Session()
    ones = sess.run(ones)
    sess.close()
    return ones
```

In [16]:
```
print ("ones = " + str(ones([3])))
```

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

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 implement a tensorflow model:

- Create the computation graph
- Run the graph

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 resolutoion to 64 by 64 pixels.

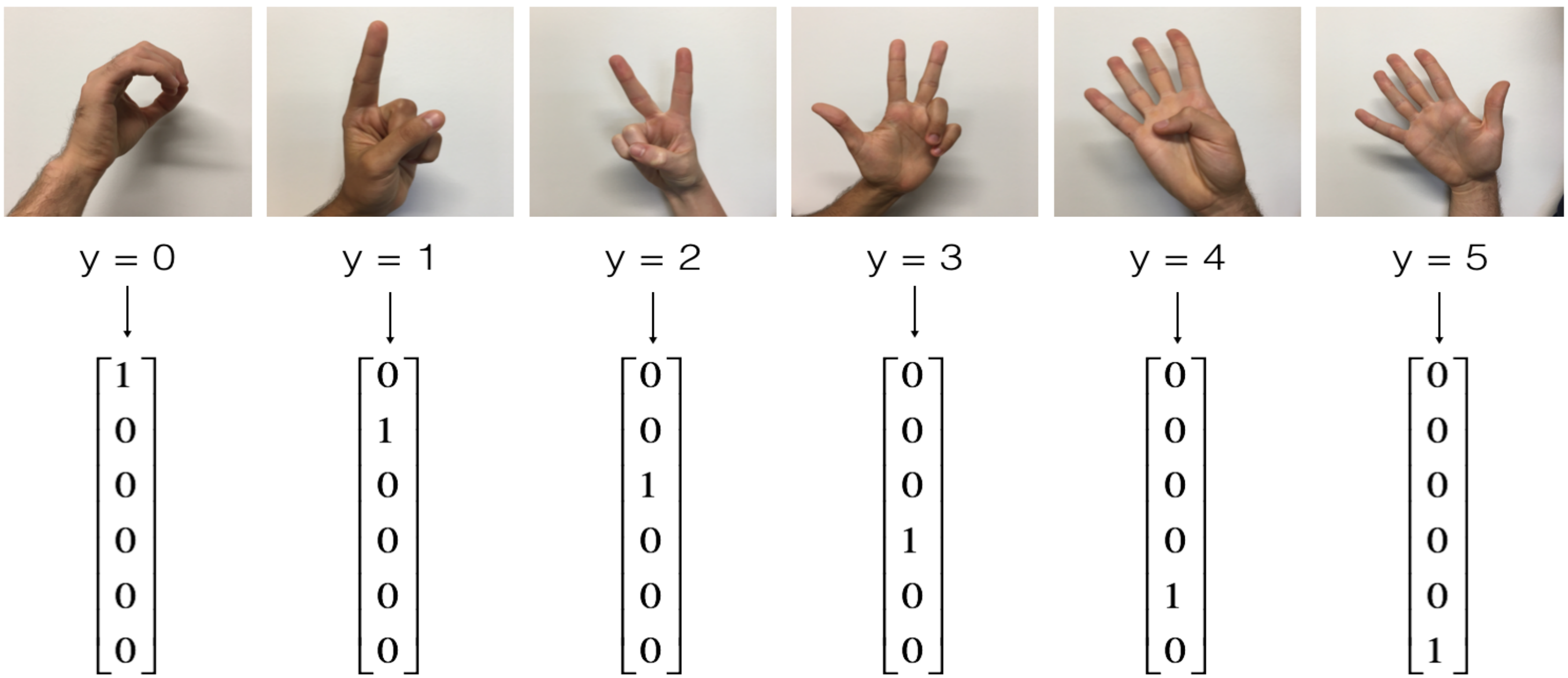


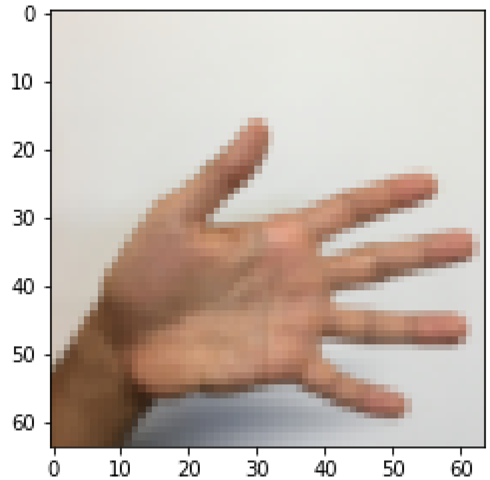
Figure 1: SIGNS dataset

In [17]:
```
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 [18]:
```
index = 0
plt.imshow(X_train_orig[index])
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 [19]:
```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)
```

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.

2.1 - 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.

Note the use of 'None' in the code below and the explanation in the comments.

In [20]:
```python
def create_placeholders(n_x, n_y):
    """

    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.
    """

    X = tf.placeholder(tf.float32, [n_x, None], name="X")
    Y = tf.placeholder(tf.float32, [n_y, None], name="Y")
    # Compare to x = tf.placeholder(tf.int64, name = 'x'). Earlier is for scalar, and here is for vector?

    return X, Y
```

Be familiar with the use of None in `tf.placeholder(tf.float32, [n_x, None], name="X")` . How that None will be populated? Is it the placeholder? Seems not, though it behaves like a place holder as it will be populated only later.

In [21]:
```python
X, Y = create_placeholders(12288, 6)
print("X = " + str(X))
print("Y = " + str(Y))
```

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

Expected Output:

X	Tensor("Placeholder_1:0", shape=(12288, ?), dtype=float32) (not necessarily Placeholder_1)
Y	Tensor("Placeholder_2:0", shape=(6, ?), dtype=float32) (not necessarily Placeholder_2)

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 [22]:
```
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

    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())
    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())

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

    return parameters
```

Note the use of tf.reset_default_graph() in many place below, while it is not when running `X, Y = create_placeholders(12288, 6)` before

In [25]:
```python
tf.reset_default_graph()
with tf.Session() as sess:
    parameters = initialize_parameters()
    print("W1 = " + str(parameters["W1"]))
    print("b1 = " + str(parameters["b1"]))
    print("W2 = " + str(parameters["W2"]))
    print("b2 = " + str(parameters["b2"]))
```

```
WARNING:tensorflow:From C:\Users\ljyan\Anaconda3\lib\site-packages\tensorflow\contrib\learn\python\learn\datase
ts\base.py:198: retry (from tensorflow.contrib.learn.python.learn.datasets.base) is deprecated and will be remo
ved in a future version.
Instructions for updating:
Use the retry module or similar alternatives.
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:

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.

In the code above, what is the purpose of adding `with tf.Session() as sess:` in the beginning? We did not run the code anyway. However, without the sentence (as below), we still can run.

In [ ]:
```
tf.reset_default_graph()

parameters = initialize_parameters()
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
```

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 [26]:
```python
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']

    # 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

    return Z3
```

In [38]:
```python
tf.reset_default_graph()

with tf.Session() as sess:
    X, Y = create_placeholders(12288, 6)
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    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 brackpropagation.

Comments:
The `with tf.Session() as sess:` is not necessary here as we are not running the graph yet. It should be useful when there is running code below those code.

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 [ ]:
```
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 examples)
    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)

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

    return cost
```

What does the .reduce_mean do?
https://stackoverflow.com/questions/34236252/what-is-the-difference-between-np-mean-and-tf-reduce-mean (https://stackoverflow.com/questions/34236252/what-is-the-difference-between-np-mean-and-tf-reduce-mean)

In [36]:
```
tf.reset_default_graph()

with tf.Session() as sess:
    X, Y = create_placeholders(12288, 6)
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    cost = compute_cost(Z3, Y)
    print("cost = " + str(cost))
```

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

Expected Output:

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

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).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).

2.6 - 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 [33]:
```
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->SOFTMAX.

    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
                                                      # overwriting tf variables
                                                      # compare to tf.reset_default_graph() used earlier

    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 in the train se
    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)
    X, Y = create_placeholders(n_x, n_y)

    # Initialize parameters
    parameters = initialize_parameters()

    # Forward propagation: Build the forward propagation in the tensorflow graph

    Z3 = forward_propagation(X, parameters)

    # Cost function: Add cost function to tensorflow graph
    cost = compute_cost(Z3, Y)
```

```python
    # 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()
    # Need make sure what variables to initialize. There is already initialize_parameters().

    # 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_size in the trair
            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 contain a minibat
                _ , minibatch_cost = sess.run([optimizer, cost], feed_dict={X: minibatch_X, Y: minibatch_Y})

                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
```

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 [ ]:
```
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.

2.7 - 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!
```

In [32]:

```
import scipy
from PIL import Image
from scipy import ndimage

my_image = "thumbs_up.jpg"

# We preprocess your image to fit your algorithm.
fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(64, 64)).reshape((1, 64 * 64 * 3)).T
my_image_prediction = predict(my_image, parameters)

plt.imshow(image)
print("Your algorithm predicts: y = " + str(np.squeeze(my_image_prediction)))
```

```
C:\Users\ljyan\Anaconda3\lib\site-packages\ipykernel_launcher.py:9: DeprecationWarning: `imread` is deprecat
ed!
`imread` is deprecated in SciPy 1.0.0.
Use ``matplotlib.pyplot.imread`` instead.
  if __name__ == '__main__':
C:\Users\ljyan\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: DeprecationWarning: `imresize` is depre
cated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  # Remove the CWD from sys.path while we load stuff.

Your algorithm predicts: y = 3
```

You indeed deserved a "thumbs-up" although as you can see the algorithm seems to classify it incorrectly. The reason is that the training set doesn't contain any "thumbs-up", so the model doesn't know how to deal with it! We call that a "mismatched data distribution" and it is one of the various of the next course on "Structuring Machine Learning Projects".