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Kulbear Tensorflow Tutorial History

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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 - Exploring the Tensorflow Library

To start, you will import the library:

In [1]:
```
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_mi
ni_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.

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

In [2]:
```
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='los
s')  # Create a variable for the loss

init = tf.global_variables_initializer()
# When init is run later (session.run(ini
```

```
# when init is run later (session.run(ini
t)),

# the loss variable will be initialized and
 ready to be computed
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.

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

In [3]:
```
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 [4]:
```
sess = tf.Session()
print(sess.run(c))
```

```
20
```

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

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]:
```
# 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 [6]:
```
# GRADED FUNCTION: linear_function

def linear_function():
    """
    Implements a linear function:
            Initializes W to be a random ten
sor of shape (4,3)
            Initializes X to be a random ten
```

```
sor of shape (3,1)
                Initializes b to be a random ten
sor of shape (4,1)
    Returns:
    result -- runs the session for Y = WX +
 b
    """

    np.random.seed(1)

    ### START CODE HERE ### (4 lines of cod
e)
    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 variab
le you want to calculate

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

    # close the session
    sess.close()

    return result
```

In [7]:
```
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]]

1.2 - 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 lets 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 need
ed), run the operations
    result = sess.run(..., feed_dict = {...})
    # This takes care of closing the session fo
r you :)
```

In [8]:

```
# 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 line
s 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 u
se the method 2 explained above.
    # You should use a feed_dict to pass z's
```

```
    # You should use a feed_dict to pass z's
value to x.
    with tf.Session() as sess:
        # Run session and call the output "r
esult"
        result = result = sess.run(sigmoid,
feed_dict = {x: z})

    ### END CODE HERE ###

    return result
```

In [9]:
```
print ("sigmoid(0) = " + str(sigmoid(0)))
print ("sigmoid(12) = " + str(sigmoid(12)))
```

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

Expected Output :

sigmoid(0)	0.5
sigmoid(12)	0.999994

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.

1.3 - 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:

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

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]:
```
# GRADED FUNCTION: cost

def cost(logits, labels):
    """
    Computes the cost using the sigmoid cros
s entropy
    
    Arguments:
    logits -- vector containing z, output of
the last linear unit (before the final sigmo
id activation)
    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 logi
ts will feed into z, and labels into y.
    
    Returns:
    cost -- runs the session of the cost (fo
rmula (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: logi
ts, y: labels})
    
    # Close the session (approx. 1 line). Se
e method 1 above.
    sess.close()
    
    ### END CODE HERE ###
    
    return cost
```

In [11]:
```
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 = [ 1.00538719  1.03664088  0.41385433
```

```
 0.39956614]
```

Expected Output :

cost	[1.00538719 1.03664088 0.41385433 0.39956614]

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:

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

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)

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]:
```
# GRADED FUNCTION: one_hot_matrix

def one_hot_matrix(labels, C):
    """
    Creates a matrix where the i-th row corr
esponds to the ith class number and the jth
 column
                     corresponds to the jth
 training example. So if example j had a lab
el 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 (dept
h), name it 'C'. (approx. 1 line)
    C = tf.constant(C, name='C')

    # Use tf.one_hot, be careful with the ax
is (approx. 1 line)
    one_hot_matrix = tf.one_hot(indices=labe
ls, 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). Se
e method 1 above.
    sess.close()

    ### END CODE HERE ###

    return one_hot
```

In [13]:

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

1.5 - 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 [14]:

```
# GRADED FUNCTION: ones

def ones(shape):
    """
```

```
    Creates an array of ones of dimension sh
ape

    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' (app
rox. 1 line)
    ones = sess.run(ones)

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

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

In [15]:
```
print ("ones = " + str(ones([3])))
```

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

Expected Output:

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

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

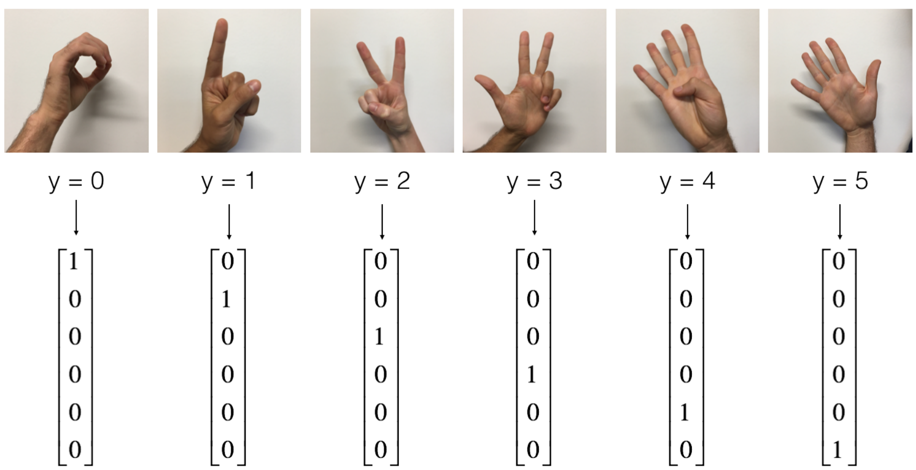
2.0 - Problem statement: SIGNS Dataset

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.

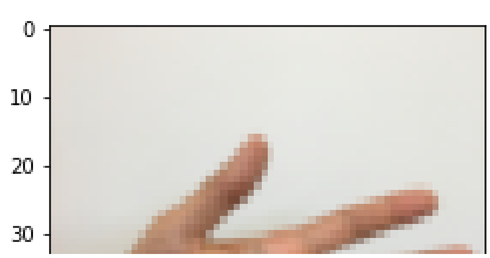


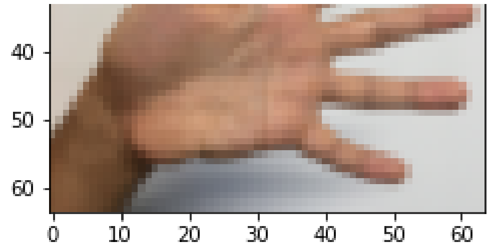
In [16]:
```
# Loading the dataset
X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes = load_dataset()
```

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

In [17]:
```
# Example of a picture
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 [18]:
```
# 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.

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

In [19]:
```
# GRADED FUNCTION: create_placeholders

def create_placeholders(n_x, n_y):
    """
    Creates the placeholders for the tensorf
low 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, o
f 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 w
ill for the placeholders.
      In fact, the number of examples during
test/train is different.
    """

    ### START CODE HERE ### (approx. 2 line
s)
    X = tf.placeholder(tf.float32, [n_x, Non
e], name="X")
    Y = tf.placeholder(tf.float32, [n_y, Non
e], name="Y")
    ### END CODE HERE ###
    
    return X, Y
```

In [20]:
```
X, Y = create_placeholders(12288, 6)
print("X = " + str(X))
print("Y = " + str(Y))
```

```
X = Tensor("X:0", shape=(12288, ?), dtype=fl
oat32)
Y = Tensor("Y:0", shape=(6, ?), dtype=float3
2)
```

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], initiali
zer = 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]:
```
# 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 co
ntaining 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_initi
alizer(seed=1))
    b1 = tf.get_variable("b1", [25, 1], init
ializer = tf.zeros_initializer())
    W2 = tf.get_variable("W2", [12, 25], ini
tializer = tf.contrib.layers.xavier_initiali
zer(seed=1))
    b2 = tf.get_variable("b2", [12, 1], init
ializer = tf.zeros_initializer())
    W3 = tf.get_variable("W3", [6, 12], init
ializer = tf.contrib.layers.xavier_initializ
er(seed=1))
    b3 = tf.get_variable("b3", [6, 1], initi
alizer = tf.zeros_initializer())
    ### END CODE HERE ###

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

    return parameters
```

In [22]:
```
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"]))
```

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

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]:
```
# GRADED FUNCTION: forward_propagation

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

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

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

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

    ### START CODE HERE ### (approx. 5 line
s)              # 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
```

In [24]:
```
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=f
loat32)
```

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.

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]:
```
# GRADED FUNCTION: compute_cost

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

    Arguments:
    Z3 -- output of forward propagation (out
put of the last LINEAR unit), of shape (6, n
umber of examples)
    Y -- "true" labels vector placeholder, s
```

```
    Y -- "true" labels vector placeholder, s
ame 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_cros
s_entropy_with_logits(logits=logits, labels=
labels))
    ### END CODE HERE ###

    return cost
```

In [26]:
```
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=floa
t32)
```

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(l
earning_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 [27]:
```
def model(X_train, Y_train, X_test, Y_test,
learning_rate = 0.0001,
          num_epochs = 1500, minibatch_size
```