Reference

This is from the coursera deep learning series of Andrew NG.

Convolutional Neural Networks: Application

Welcome to Course 4's second assignment! In this notebook, you will:

- Implement helper functions that you will use when implementing a TensorFlow model
- Implement a fully functioning ConvNet using TensorFlow

After this assignment you will be able to:

- Build and train a ConvNet in TensorFlow for a classification problem

We assume here that you are already familiar with TensorFlow. If you are not, please refer the *TensorFlow Tutorial* of the third week of Course 2 ("*Improving deep neural networks*").

Comments:

- This is a high level implementation of the code in "1. Convolution model-Step by Step - v1.pdf". Refer to the pdf file if not familiar the details here.
- Tensorflow details are in course 2.

1.0 - TensorFlow model

In the previous assignment, you built helper functions using numpy to understand the mechanics behind convolutional neural networks. Most practical applications of deep learning today are built using programming frameworks, which have many built-in functions you can simply call.

As usual, we will start by loading in the packages.

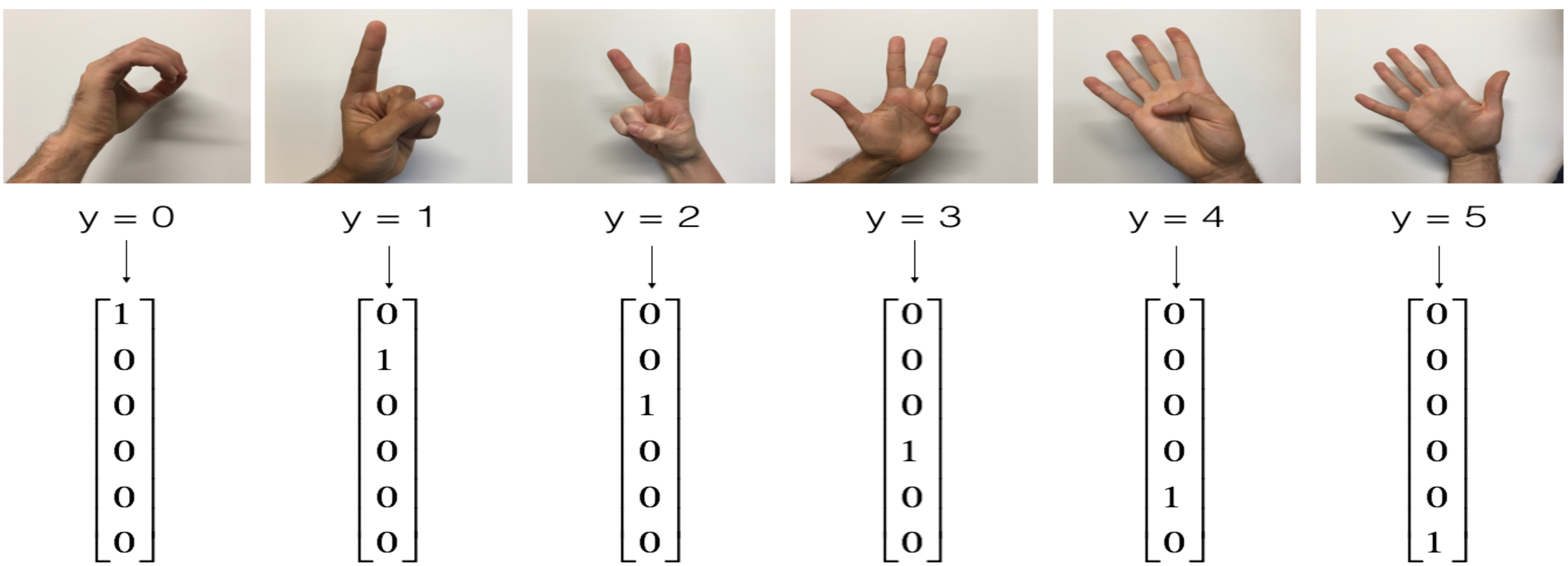
In [1]:
```python
import math
import numpy as np
import h5py
import matplotlib.pyplot as plt
import scipy
from PIL import Image
from scipy import ndimage
import tensorflow as tf
from tensorflow.python.framework import ops
from cnn_utils import *

%matplotlib inline
np.random.seed(1)
```

Run the next cell to load the "SIGNS" dataset you are going to use.

In [2]:
```python
# Loading the data (signs)
X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes = load_dataset()
```

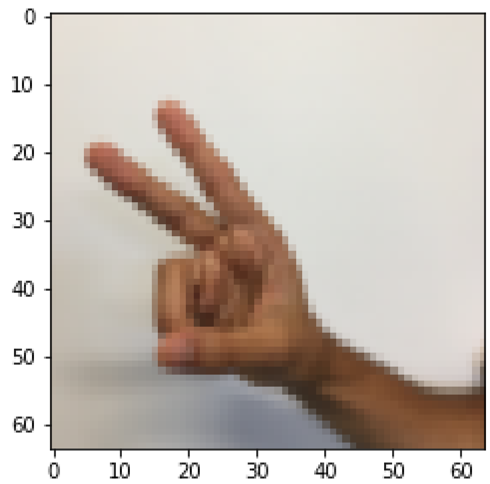
As a reminder, the SIGNS dataset is a collection of 6 signs representing numbers from 0 to 5.



The next cell will show you an example of a labelled image in the dataset. Feel free to change the value of `index` below and re-run to see different examples.

In [3]:
```
# Example of a picture
index = 6
plt.imshow(X_train_orig[index])
print ("y = " + str(np.squeeze(Y_train_orig[:, index])))
```

```
y = 2
```



In Course 2, you had built a fully-connected network for this dataset. But since this is an image dataset, it is more natural to apply a ConvNet to it.

To get started, let's examine the shapes of your data.

In [16]:
```
X_train = X_train_orig/255.
X_test = X_test_orig/255.
Y_train = convert_to_one_hot(Y_train_orig, 6).T
Y_test = convert_to_one_hot(Y_test_orig, 6).T
print ("number of training examples = " + str(X_train.shape[0]))
print ("number of test examples = " + str(X_test.shape[0]))
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))
conv_layers = {}
```

```
number of training examples = 1080
number of test examples = 120
X_train shape: (1080, 64, 64, 3)
Y_train shape: (1080, 6)
X_test shape: (120, 64, 64, 3)
Y_test shape: (120, 6)
```

1.1 - Create placeholders

TensorFlow requires that you create placeholders for the input data that will be fed into the model when running the session.

Exercise: Implement the function below to create placeholders for the input image X and the output Y. You should not define the number of training examples for the moment. To do so, you could use "None" as the batch size, it will give you the flexibility to choose it later. Hence X should be of dimension **[None, n_H0, n_W0, n_C0]** and Y should be of dimension **[None, n_y]**. Hint (https://www.tensorflow.org/api_docs/python/tf/placeholder).

In [17]:
```
def create_placeholders(n_H0, n_W0, n_C0, n_y):
    """
    Creates the placeholders for the tensorflow session.

    Arguments:
    n_H0 -- scalar, height of an input image
    n_W0 -- scalar, width of an input image
    n_C0 -- scalar, number of channels of the input
    n_y -- scalar, number of classes

    Returns:
    X -- placeholder for the data input, of shape [None, n_H0, n_W0, n_C0] and dtype "float"
    Y -- placeholder for the input labels, of shape [None, n_y] and dtype "float"
    """

    X = tf.placeholder(tf.float32, [None, n_H0, n_W0, n_C0])
    Y = tf.placeholder(tf.float32, [None, n_y])

    return X, Y
```

In [18]:
```
X, Y = create_placeholders(64, 64, 3, 6)
print ("X = " + str(X))
print ("Y = " + str(Y))
```

```
X = Tensor("Placeholder_2:0", shape=(?, 64, 64, 3), dtype=float32)
Y = Tensor("Placeholder_3:0", shape=(?, 6), dtype=float32)
```

1.2 - Initialize parameters

You will initialize weights/filters $W1$ and $W2$ using `tf.contrib.layers.xavier_initializer(seed = 0)` . **You don't need to worry about bias variables as you will soon see that TensorFlow functions take care of the bias**. Note also that you will **only initialize the weights/filters for the conv2d functions. TensorFlow initializes the layers for the fully connected part automatically**. We will talk more about that later in this assignment.

Exercise: Implement initialize_parameters(). The dimensions for each group of filters are provided below. Reminder - to initialize a parameter W of shape [1,2,3,4] in Tensorflow, use:

```
W = tf.get_variable("W", [1,2,3,4], initializer = ...)
```

[More Info (https://www.tensorflow.org/api_docs/python/tf/get_variable)](https://www.tensorflow.org/api_docs/python/tf/get_variable).

In [25]:
```
def initialize_parameters():
    """
    Initializes weight parameters to build a neural network with tensorflow. The shapes are:
                        W1 : [4, 4, 3, 8]
                        W2 : [2, 2, 8, 16]
    Returns:
    parameters -- a dictionary of tensors containing W1, W2
    """

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

    W1 = tf.get_variable("W1", [4, 4, 3, 8], initializer=tf.contrib.layers.xavier_initializer(seed=0))
    W2 = tf.get_variable("W2", [2, 2, 8, 16], initializer=tf.contrib.layers.xavier_initializer(seed=0))
    # Be familiar with what each dimension in W1/W2 describes. Note the two 8's should be consistent

    parameters = {"W1": W1,
                  "W2": W2}

    return parameters
```

In [26]:
```
tf.reset_default_graph()
with tf.Session() as sess_test:
    parameters = initialize_parameters()
    init = tf.global_variables_initializer()
    sess_test.run(init) #Without this sentence, the W1 will not be initiazed.
    print("W1 = " + str(parameters["W1"].eval()[1,1,1]))
    print("W2 = " + str(parameters["W2"].eval()[1,1,1]))
```

```
W1 = [ 0.00131723  0.1417614  -0.04434952  0.09197326  0.14984085 -0.03514394
 -0.06847463  0.05245192]
W2 = [-0.08566415  0.17750949  0.11974221  0.16773748 -0.0830943  -0.08058
 -0.00577033 -0.14643836  0.24162132 -0.05857408 -0.19055021  0.1345228
 -0.22779644 -0.1601823  -0.16117483 -0.10286498]
```

1.2 - Forward propagation

In TensorFlow, there are built-in functions that carry out the convolution steps for you.

- **tf.nn.conv2d(X,W1, strides = [1,s,s,1], padding = 'SAME'):** given an input X and a group of filters $W1$, this function convolves $W1$'s filters on X. The third input ([1,f,f,1]) represents the strides for each dimension of the input (m, n_H_prev, n_W_prev, n_C_prev). You can read the full documentation here (https://www.tensorflow.org/api_docs/python/tf/nn/conv2d)
- **tf.nn.max_pool(A, ksize = [1,f,f,1], strides = [1,s,s,1], padding = 'SAME'):** given an input A, this function uses a window of size (f, f) and strides of size (s, s) to carry out max pooling over each window. You can read the full documentation here (https://www.tensorflow.org/api_docs/python/tf/nn/max_pool)
- **tf.nn.relu(Z1):** computes the elementwise ReLU of Z1 (which can be any shape). You can read the full documentation here. (https://www.tensorflow.org/api_docs/python/tf/nn/relu)
- **tf.contrib.layers.flatten(P)**: given an input P, this function **flattens each example into a 1D vector it while maintaining the batch-size**. It returns a flattened tensor with shape [batch_size, k]. You can read the full documentation here. (https://www.tensorflow.org/api_docs/python/tf/contrib/layers/flatten) **Comments: Check the two print test code added to the following function, and see how this works**.
- Comments about FC see later.

Exercise:

Implement the `forward_propagation` function below to build the following model: `CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> FULLYCONNECTED`. You should use the functions above.

In detail, we will use the following parameters for all the steps:

```
- Conv2D: stride 1, padding is "SAME"
- ReLU
- Max pool: Use an 8 by 8 filter size and an 8 by 8 stride, padding is "SAME"
- Conv2D: stride 1, padding is "SAME"
- ReLU
- Max pool: Use a 4 by 4 filter size and a 4 by 4 stride, padding is "SAME"
- Flatten the previous output.
-
```

See "1. Convolution model-Step by Step - v1.pdf" to understand the details here.

In [ ]:
```
def forward_propagation(X, parameters):
    """
    Implements the forward propagation for the model:
    CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> FULLYCONNECTED

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

    Returns:
    Z3 -- the output of the last LINEAR unit
    """
    print(X.shape)
    # Retrieve the parameters from the dictionary "parameters"
    W1 = parameters['W1']
    W2 = parameters['W2']

    # CONV2D: stride of 1, padding 'SAME'
    Z1 = tf.nn.conv2d(X,W1,strides=[1,1,1,1],padding='SAME')
    # In the implementation from scratch case of "1. Convolution model-Step by Step - v1.pdf", the above sentence
    # with a nested for loops for indices such as number of samples m, image hight, width, chanels. Here just one
    # Thus with Tensorflow, we can easily implement multiple layers in CNN.

    # RELU
    A1 = tf.nn.relu(Z1)
    # MAXPOOL: window 8x8, sride 8, padding 'SAME'
    P1 = tf.nn.max_pool(A1,[1,8,8,1],strides=[1,8,8,1],padding='SAME')
    # CONV2D: filters W2, stride 1, padding 'SAME'
    Z2 = tf.nn.conv2d(P1,W2,strides=[1,1,1,1],padding='SAME')
    # RELU
    A2 = tf.nn.relu(Z2)

    # MAXPOOL: window 4x4, stride 4, padding 'SAME'
    P2 = tf.nn.max_pool(A2,[1,4,4,1],strides=[1,4,4,1],padding='SAME')
    print(P2.shape) #test code
    # FLATTEN
    P2 = tf.contrib.layers.flatten(P2)
    print(P2.shape) #test code. Note that P2 is not a purely 1D array after flatten. What is the purpose for this

    # FULLY-CONNECTED without non-linear activation function (not not call softmax).
    # 6 neurons in output layer. Hint: one of the arguments should be "activation_fn=None"
```

```python
    Z3 = tf.contrib.layers.fully_connected(P2,6,activation_fn=None)
    print(Z3.shape)
    return Z3
```

- **(See above)tf.contrib.layers.fully_connected(F, num_outputs):** given a the flattened input F, it returns the output computed using a fully connected layer. You can read the full documentation here. (https://www.tensorflow.org/api_docs/python/tf/contrib/layers/fully_connected)
- In the last function above (`tf.contrib.layers.fully_connected`), the fully connected layer automatically initializes weights in the graph and keeps on training them as you train the model. Hence, you did not need to initialize those weights when initializing the parameters. (See the C4M1 course slides of cs230.)
- **FULLYCONNECTED (FC) layer: Apply a fully connected layer without an non-linear activation function. Do not call the softmax here. This will result in 6 neurons in the output layer, which then get passed later to a softmax. In TensorFlow, the softmax and cost function are lumped together into a single function, which you'll call in a different function when computing the cost.**

In [57]:

```python
tf.reset_default_graph()

with tf.Session() as sess:
    np.random.seed(1)
    X, Y = create_placeholders(64, 64, 3, 6)
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    init = tf.global_variables_initializer()
    sess.run(init)
    a = sess.run(Z3, {X: np.random.randn(2,64,64,3), Y: np.random.randn(2,6)}) # consider only two pictures
    print("Z3 = " + str(a))
```

```
(?, 64, 64, 3)
(?, 2, 2, 16)
(?, 64)
(?, 6)
Z3 = [[ 1.4416984  -0.24909666  5.450499   -0.2618962  -0.20669907  1.3654671 ]
 [ 1.4070846  -0.02573211  5.08928    -0.48669922 -0.40940708  1.2624859 ]]
```

Expected Output:

Z3 = [[-0.44670227 -1.57208765 -1.53049231 -2.31013036 -1.29104376 0.46852064]
[-0.17601591 -1.57972014 -1.4737016 -2.61672091 -1.00810647 0.5747785]]

Comments: The output is different from the expected output. I used two versioins of other's correct code but still get different results as expected. This might be because I use a different dataset.

1.3 - Compute cost

Implement the compute cost function below. You might find these two functions helpful:

- **tf.nn.softmax_cross_entropy_with_logits(logits = Z3, labels = Y):** computes the softmax entropy loss. This function both computes the softmax activation function as well as the resulting loss. You can check the full documentation [here. (https://www.tensorflow.org/api_docs/python/tf/nn/softmax_cross_entropy_with_logits)](https://www.tensorflow.org/api_docs/python/tf/nn/softmax_cross_entropy_with_logits)
- **tf.reduce_mean:** computes the mean of elements across dimensions of a tensor. Use this to sum the losses over all the examples to get the overall cost. You can check the full documentation [here. (https://www.tensorflow.org/api_docs/python/tf/reduce_mean)](https://www.tensorflow.org/api_docs/python/tf/reduce_mean)

Exercise: Compute the cost below using the function above.

In [52]:
```
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
    """
    
    cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=Z3, labels=Y))
    
    return cost
```

In [53]:
```
tf.reset_default_graph()

with tf.Session() as sess:
    np.random.seed(1)
    X, Y = create_placeholders(64, 64, 3, 6)
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    cost = compute_cost(Z3, Y)
    init = tf.global_variables_initializer()
    sess.run(init)
    a = sess.run(cost, {X: np.random.randn(4,64,64,3), Y: np.random.randn(4,6)})
    print("cost = " + str(a))
```

```
(?, 64, 64, 3)
(?, 2, 2, 16)
(?, 64)
cost = 4.6648693
```

Expected Output:

cost =	2.91034

1.4 Model

Finally you will merge the helper functions you implemented above to build a model. You will train it on the SIGNS dataset.

You have implemented `random_mini_batches()` in the Optimization programming assignment of course 2. Remember that this function returns a list of mini-batches.

Exercise: Complete the function below.

The model below should:

- create placeholders
- initialize parameters
- forward propagate
- compute the cost
- create an optimizer

Finally you will create a session and run a for loop for num_epochs, get the mini-batches, and then for each mini-batch you will optimize the function. [Hint for initializing the variables (https://www.tensorflow.org/api_docs/python/tf/global_variables_initializer)](https://www.tensorflow.org/api_docs/python/tf/global_variables_initializer)

In [54]:
```python
def model(X_train, Y_train, X_test, Y_test, learning_rate=0.009,
          num_epochs=100, minibatch_size=64, print_cost=True):
    """
    Implements a three-layer ConvNet in Tensorflow:
    CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> FULLYCONNECTED

    Arguments:
    X_train -- training set, of shape (None, 64, 64, 3)
    Y_train -- test set, of shape (None, n_y = 6)
    X_test -- training set, of shape (None, 64, 64, 3)
    Y_test -- test set, of shape (None, n_y = 6)
    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:
    train_accuracy -- real number, accuracy on the train set (X_train)
    test_accuracy -- real number, testing accuracy on the test set (X_test)
    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 var
    tf.set_random_seed(1)                             # to keep results consistent (tensorflow seed)
    seed = 3                                          # to keep results consistent (numpy seed)
    (m, n_H0, n_W0, n_C0) = X_train.shape
    n_y = Y_train.shape[1]
    costs = []                                        # To keep track of the cost

    # Create Placeholders of the correct shape
    X, Y = create_placeholders(n_H0, n_W0, n_C0, 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)

    # *** The functions above will be run only once to construct the graph. When looping over epoch later, these
```

```
    # *** will not be called again and again as the 'graph' already there. So the print statements in those funct
    # *** not be run again and gain.

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

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

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

        # Run the initialization
        sess.run(init)

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

            minibatch_cost = 0.
            num_minibatches = int(m / minibatch_size) # number of minibatches of size minibatch_size in the trai
            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 minibatch f
                _ , temp_cost = sess.run([optimizer, cost], feed_dict={X:minibatch_X, Y:minibatch_Y})

                minibatch_cost += temp_cost / num_minibatches


            # Print the cost every epoch
            if print_cost == True and epoch % 5 == 0:
                print ("Cost after epoch %i: %f" % (epoch, minibatch_cost))
            if print_cost == True and epoch % 1 == 0:
                costs.append(minibatch_cost)


        # plot the cost
        plt.plot(np.squeeze(costs))
```

```python
        plt.ylabel('cost')
        plt.xlabel('iterations (per tens)')
        plt.title("Learning rate =" + str(learning_rate))
        plt.show()

        # Calculate the correct predictions
        predict_op = tf.argmax(Z3, 1)
        correct_prediction = tf.equal(predict_op, tf.argmax(Y, 1))

        # Calculate accuracy on the test set
        accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
        print(accuracy)
        train_accuracy = accuracy.eval({X: X_train, Y: Y_train})
        test_accuracy = accuracy.eval({X: X_test, Y: Y_test})
        print("Train Accuracy:", train_accuracy)
        print("Test Accuracy:", test_accuracy)

        return train_accuracy, test_accuracy, parameters
```

Run the following cell to train your model for 100 epochs. Check if your cost after epoch 0 and 5 matches our output. If not, stop the cell and go back to your code!

In [ ]:
```python
_, _, parameters = model(X_train, Y_train, X_test, Y_test)
```

Expected output: although it may not match perfectly, your expected output should be close to ours and your cost value should decrease.

Cost after epoch 0 =	1.917929
Cost after epoch 5 =	1.506757
Train Accuracy =	0.940741
Test Accuracy =	0.783333

You have finised the assignment and built a model that recognizes SIGN language with almost 80% accuracy on the test set. If you wish, feel free to play around with this dataset further. You can actually improve its accuracy by spending more time tuning the hyperparameters, or using regularization (as this model clearly has a high variance).

In [15]:
```
fname = "images/thumbs_up.jpg"
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(64,64))
plt.imshow(my_image)
```

Out[15]: <matplotlib.image.AxesImage at 0x7fa860df3588>