Initialization

Welcome to the first assignment of "Improving Deep Neural Networks".

Training your neural network requires specifying an initial value of the weights. A well chosen initialization method will help learning.

If you completed the previous course of this specialization, you probably followed our instructions for weight initialization, and it has worked out so far. But how do you choose the initialization for a new neural network? In this notebook, you will see how different initializations lead to different results.

A well chosen initialization can:

- Speed up the convergence of gradient descent
- Increase the odds of gradient descent converging to a lower training (and generalization) error

To get started, run the following cell to load the packages and the planar dataset you will try to classify.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import sklearn.datasets
from init_utils import sigmoid, relu, compute_loss, forward_propagation, backward_propagation
from init_utils import update_parameters, load_dataset, plot_decision_boundary, predict_dac

%matplotlib inline
plt.rcParams['figure.figure-size'] = (7.0, 4.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# load image dataset: blue/red dots in circles
train_X, train_Y, test_X, test_Y = load_dataset()
```

You should see a classifier to separate the blue dots from the red dots.

1 - Neural Network model

You will use a 3-layer neural network (already implemented for you). Here are the initialization methods you will experiment with:

- *Zeros initialization* -- setting `initialization = "zeros"` in the input argument.
- *Random initialization* -- setting `initialization = "random"` in the input argument. This initializes the weights to large random values.
- *He initialization* -- setting `initialization = "he"` in the input argument. This initializes the weights to random values scaled according to a paper by He et al., 2015.

Instructions: Please quickly read over the code below, and run it. In the next part you will implement the three initialization methods that this `model()` calls.

In [2]:
```
def model(X, Y, learning_rate = 0.01, num_iterations = 15000, print_cost = True, initialization = "he"):
    """
    Implements a three-layer neural network: LINEAR->RELU->LINEAR->RELU->LINEAR->SIGMOID.

    Arguments:
    X -- input data, of shape (2, number of examples)
    Y -- true "label" vector (containing 0 for red dots; 1 for blue dots), of shape (1, number of examples)
    learning_rate -- learning rate for gradient descent
    num_iterations -- number of iterations to run gradient descent
    print_cost -- if True, prints the cost every 1000 iterations
    initialization -- flag to choose which initialization to use ("zeros","random" or "he")

    Returns:
    parameters -- parameters learnt by the model
    """

    grads = {}
    costs = [] # to keep track of the loss
    m = X.shape[1] # number of examples
    layers_dims = [X.shape[0], 10, 5, 1]

    # Initialize parameters dictionary.
    if initialization == "zeros":
        parameters = initialize_parameters_zeros(layers_dims)
    elif initialization == "random":
        parameters = initialize_parameters_random(layers_dims)
    elif initialization == "he":
        parameters = initialize_parameters_he(layers_dims)

    # Loop (gradient descent)

    for i in range(0, num_iterations):

        # Forward propagation: LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -> SIGMOID.
        a3, cache = forward_propagation(X, parameters)

        # Loss
        cost = compute_loss(a3, Y)

        # Backward propagation.
        grads = backward_propagation(X, Y, cache)

        # Update parameters.
        parameters = update_parameters(parameters, grads, learning_rate)

        # Print the loss every 1000 iterations
        if print_cost and i % 1000 == 0:
            print("Cost after iteration {}: {}".format(i, cost))
            costs.append(cost)

    # plot the loss
    plt.plot(costs)
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate " + str(learning_rate))

    return parameters
```

2 - Zero initialization

There are two types of parameters to initialize in a neural network:

- the weight matrices $(W^{[1]}, W^{[2]}, W^{[3]}, ..., W^{[L-1]}, W^{[L]})$
- the bias vectors $(b^{[1]}, b^{[2]}, b^{[3]}, ..., b^{[L-1]}, b^{[L]})$

Exercise: Implement the following function to initialize all parameters to zeros. You'll see later that this does not work well since it fails to "break symmetry", but lets try it anyway and see what happens. Use np.zeros((..,..)) with the correct shapes.

In [3]:
```
# GRADED FUNCTION: initialize_parameters_zeros

def initialize_parameters_zeros(layers_dims):
    """
    Arguments:
    layer_dims -- python array (list) containing the size of each layer.

    Returns:
    parameters -- python dictionary containing your parameters "W1", "b1",..., "WL", "bL":
                    W1 -- weight matrix of shape (layers_dims[1], layers_dims[0])
                    b1 -- bias vector of shape (layers_dims[1], 1)
                    ...
                    WL -- weight matrix of shape (layers_dims[L], layers_dims[L-1])
                    bL -- bias vector of shape (layers_dims[L], 1)
    """

    parameters = {}
    L = len(layers_dims) # number of layers in the network

    for l in range(1, L):
        # This for-loop iterates over all the of layers of nodes
        parameters['W' + str(l)] = np.zeros((layers_dims[l], layers_dims[l-1]))
        parameters['b' + str(l)] = np.zeros((layers_dims[l], 1))
        assert(parameters['W' + str(l)].shape == (layers_dims[l], layers_dims[l-1]))
        assert(parameters['b' + str(l)].shape == (layers_dims[l], 1))

    return parameters
```

In [4]:
```
parameters = initialize_parameters_zeros([3,2,1])
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
```

```
W1 = [[ 0. 0. 0.]
 [ 0. 0. 0.]]
b1 = [[ 0.]
 [ 0.]]
W2 = [[ 0. 0.]]
b2 = [[ 0.]]
```

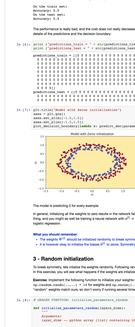
Expected Output:

W1	[[0 0 0] [0 0 0]]
b1	[[0.] [0.]]
W2	[[0 0]]
b2	[[0.]]

Run the following cells to train your model on 15,000 iterations using zeros initialization.

In [5]:
```
parameters = model(train_X, train_Y, initialization = "zeros")
print ("On the train set:")
predictions_train = predict(train_X, train_Y, parameters)
print ("On the test set:")
predictions_test = predict(test_X, test_Y, parameters)
```

```
Cost after iteration 0: 0.6931471805599453
Cost after iteration 1000: 0.6931471805599453
Cost after iteration 2000: 0.6931471805599453
Cost after iteration 3000: 0.6931471805599453
Cost after iteration 4000: 0.6931471805599453
Cost after iteration 5000: 0.6931471805599453
Cost after iteration 6000: 0.6931471805599453
Cost after iteration 7000: 0.6931471805599453
Cost after iteration 8000: 0.6931471805599453
Cost after iteration 9000: 0.6931471805599453
Cost after iteration 10000: 0.6931471805599453
Cost after iteration 11000: 0.6931471805599453
Cost after iteration 12000: 0.6931471805599453
Cost after iteration 13000: 0.6931471805599453
Cost after iteration 14000: 0.6931471805599453
```




```
On the train set:
Accuracy: 0.5
On the test set:
Accuracy: 0.5
```

The performance is really bad, and the cost does not really decrease, and the algorithm performs no better than random guessing. Why? Look look at the details of the predictions and the decision boundary:

In [6]:
```
print ("predictions_train = " + str(predictions_train))
print ("predictions_test = " + str(predictions_test))
```

```
predictions_train = [[0 0 0 
```