**Assignment 5 : Implement the concept of regularization, gradient checking and optimization in convolutional model: step by step**

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.

import matplotlib.pyplot as plt
import h5py
import sklearn
import sklearn.datasets
import sklearn.linear_model
import scipy.io

def sigmoid(x):
    """
    Compute the sigmoid of x

    Arguments:
    x -- A scalar or numpy array of any size.

    Return:
    s -- sigmoid(x)
    """
    s = 1/(1+np.exp(-x))
    return s

def relu(x):
    """
    Compute the relu of x

    Arguments:
    x -- A scalar or numpy array of any size.

    Return:
    s -- relu(x)
    """
    s = np.maximum(0,x)

    return s

def load_planar_dataset(seed):

    np.random.seed(seed)

    m = 400 # number of examples
    N = int(m/2) # number of points per class
    D = 2 # dimensionality
    X = np.zeros((m,D)) # data matrix where each row is a single example
    Y = np.zeros((m,1), dtype='uint8') # labels vector (0 for red, 1 for blue)
    a = 4 # maximum ray of the flower

    for j in range(2):
        ix = range(N*j,N*(j+1))
        t = np.linspace(j*3.12,(j+1)*3.12,N) + np.random.randn(N)*0.2 # theta
        r = a*np.sin(4*t) + np.random.randn(N)*0.2 # radius
        X[ix] = np.c_[r*np.sin(t), r*np.cos(t)]
        Y[ix] = j

    X = X.T
    Y = Y.T

    return X, Y

def initialize_parameters(layer_dims):
    """
    Arguments:
    layer_dims -- python array (list) containing the dimensions of each layer in our network
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```
    Returns:
    parameters -- python dictionary containing your parameters "W1", "b1", ..., "WL", "bL":
                    W1 -- weight matrix of shape (layer_dims[l], layer_dims[l-1])
                    b1 -- bias vector of shape (layer_dims[l], 1)
                    Wl -- weight matrix of shape (layer_dims[l-1], layer_dims[l])
                    bl -- bias vector of shape (1, layer_dims[l])

    Tips:
    - For example: the layer_dims for the "Planar Data classification model" would have been [2,2,1].
    This means W1's shape was (2,2), b1 was (1,2), W2 was (2,1) and b2 was (1,1). Now you have to generalize it!
    - In the for loop, use parameters['W' + str(l)] to access Wl, where l is the iterative integer.
    """

    np.random.seed(3)
    parameters = {}
    L = len(layer_dims) # number of layers in the network

    for l in range(1, L):
        parameters['W' + str(l)] = np.random.randn(layer_dims[l], layer_dims[l-1]) / np.sqrt(layer_dims[l-1])
        parameters['b' + str(l)] = np.zeros((layer_dims[l], 1))

        assert(parameters['W' + str(l)].shape == (layer_dims[l], layer_dims[l-1]))
        assert(parameters['b' + str(l)].shape == (layer_dims[l], 1))


    return parameters

def forward_propagation(X, parameters):
    """
    Implements the forward propagation (and computes the loss) presented in Figure 2.

    Arguments:
    X -- input dataset, of shape (input size, number of examples)
    parameters -- python dictionary containing your parameters "W1", "b1", "W2", "b2", "W3", "b3":
                    W1 -- weight matrix of shape ()
                    b1 -- bias vector of shape ()
                    W2 -- weight matrix of shape ()
                    b2 -- bias vector of shape ()
                    W3 -- weight matrix of shape ()
                    b3 -- bias vector of shape ()

    Returns:
    loss -- the loss function (vanilla logistic loss)
    """

    # retrieve parameters
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    # LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -> SIGMOID
    Z1 = np.dot(W1, X) + b1
    A1 = relu(Z1)
    Z2 = np.dot(W2, A1) + b2
    A2 = relu(Z2)
    Z3 = np.dot(W3, A2) + b3
    A3 = sigmoid(Z3)

    cache = (Z1, A1, W1, b1, Z2, A2, W2, b2, Z3, A3, W3, b3)

    return A3, cache

def backward_propagation(X, Y, cache):
    """
    Implement the backward propagation presented in figure 2.

    Arguments:
    X -- input dataset, of shape (input size, number of examples)
    Y -- true "label" vector (containing 0 if cat, 1 if non-cat)
    cache -- cache output from forward_propagation()

    Returns:
    gradients -- A dictionary with the gradients with respect to each parameter, activation and pre-activation variables
    """
    m = X.shape[1]
    (Z1, A1, W1, b1, Z2, A2, W2, b2, Z3, A3, W3, b3) = cache

    dZ3 = A3 - Y
    dW3 = 1./m * np.dot(dZ3, A2.T)
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    dW3 = 1./m * np.dot(dZ3, A2.T)
    db3 = 1./m * np.sum(dZ3, axis=1, keepdims = True)

    dA2 = np.dot(W3.T, dZ3)
    dZ2 = np.multiply(dA2, np.int64(A2 > 0))
    dW2 = 1./m * np.dot(dZ2, A1.T)
    db2 = 1./m * np.sum(dZ2, axis=1, keepdims = True)

    dA1 = np.dot(W2.T, dZ2)
    dZ1 = np.multiply(dA1, np.int64(A1 > 0))
    dW1 = 1./m * np.dot(dZ1, X.T)
    db1 = 1./m * np.sum(dZ1, axis=1, keepdims = True)

    gradients = {"dZ3": dZ3, "dW3": dW3, "db3": db3,
                 "dA2": dA2, "dZ2": dZ2, "dW2": dW2, "db2": db2,
                 "dA1": dA1, "dZ1": dZ1, "dW1": dW1, "db1": db1}

    return gradients

def update_parameters(parameters, grads, learning_rate):
    """
    Update parameters using gradient descent

    Arguments:
    parameters -- python dictionary containing your parameters:
                    parameters['W' + str(i)] = Wi
                    parameters['b' + str(i)] = bi
    grads -- python dictionary containing your gradients for each parameters:
                    grads['dW' + str(i)] = dWi
                    grads['db' + str(i)] = dbi
    learning_rate -- the learning rate, scalar.

    Returns:
    parameters -- python dictionary containing your updated parameters
    """

    n = len(parameters) // 2 # number of layers in the neural networks

    # Update rule for each parameter
    for k in range(n):
        parameters["W" + str(k+1)] = parameters["W" + str(k+1)] - learning_rate * grads["dW" + str(k+1)]
        parameters["b" + str(k+1)] = parameters["b" + str(k+1)] - learning_rate * grads["db" + str(k+1)]

    return parameters

def predict(X, y, parameters):
    """
    This function is used to predict the results of a  n-layer neural network.

    Arguments:
    X -- data set of examples you would like to label
    parameters -- parameters of the trained model

    Returns:
    p -- predictions for the given dataset X
    """

    m = X.shape[1]
    p = np.zeros((1,m), dtype = np.int)

    # Forward propagation
    a3, caches = forward_propagation(X, parameters)

    # convert probas to 0/1 predictions
    for i in range(0, a3.shape[1]):
        if a3[0,i] > 0.5:
            p[0,i] = 1
        else:
            p[0,i] = 0

    # print results

    #print ("predictions: " + str(p[0,:]))
    #print ("true labels: " + str(y[0,:]))
    print("Accuracy: "  + str(np.mean((p[0,:] == y[0,:]))))

    return p

def compute_cost(a3, Y):
    """
    Implement the cost function

    Arguments:
```

```
    a3 -- post-activation, output of forward propagation
    Y -- "true" labels vector, same shape as a3

    Returns:
    cost - value of the cost function
    """
    m = Y.shape[1]

    logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a3), 1 - Y)
    cost = 1./m * np.nansum(logprobs)

    return cost

def load_dataset():
    train_dataset = h5py.File('datasets/train_catvnoncat.h5', "r")
    train_set_x_orig = np.array(train_dataset["train_set_x"][:]) # your train set features
    train_set_y_orig = np.array(train_dataset["train_set_y"][:]) # your train set labels

    test_dataset = h5py.File('datasets/test_catvnoncat.h5', "r")
    test_set_x_orig = np.array(test_dataset["test_set_x"][:]) # your test set features
    test_set_y_orig = np.array(test_dataset["test_set_y"][:]) # your test set labels

    classes = np.array(test_dataset["list_classes"][:]) # the list of classes

    train_set_y = train_set_y_orig.reshape((1, train_set_y_orig.shape[0]))
    test_set_y = test_set_y_orig.reshape((1, test_set_y_orig.shape[0]))

    train_set_x_orig = train_set_x_orig.reshape(train_set_x_orig.shape[0], -1).T
    test_set_x_orig = test_set_x_orig.reshape(test_set_x_orig.shape[0], -1).T

    train_set_x = train_set_x_orig/255
    test_set_x = test_set_x_orig/255

    return train_set_x, train_set_y, test_set_x, test_set_y, classes


def predict_dec(parameters, X):
    """
    Used for plotting decision boundary.

    Arguments:
    parameters -- python dictionary containing your parameters
    X -- input data of size (m, K)

    Returns
    predictions -- vector of predictions of our model (red: 0 / blue: 1)
    """

    # Predict using forward propagation and a classification threshold of 0.5
    a3, cache = forward_propagation(X, parameters)
    predictions = (a3>0.5)
    return predictions

def load_planar_dataset(randomness, seed):

    np.random.seed(seed)

    m = 50
    N = int(m/2) # number of points per class
    D = 2 # dimensionality
    X = np.zeros((m,D)) # data matrix where each row is a single example
    Y = np.zeros((m,1), dtype='uint8') # labels vector (0 for red, 1 for blue)
    a = 2 # maximum ray of the flower

    for j in range(2):

        ix = range(N*j,N*(j+1))
        if j == 0:
            t = np.linspace(j, 4*3.1415*(j+1),N) #+ np.random.randn(N)*randomness # theta
            r = 0.3*np.square(t) + np.random.randn(N)*randomness # radius
        if j == 1:
            t = np.linspace(j, 2*3.1415*(j+1),N) #+ np.random.randn(N)*randomness # theta
            r = 0.2*np.square(t) + np.random.randn(N)*randomness # radius

        X[ix] = np.c_[r*np.cos(t), r*np.sin(t)]
        Y[ix] = j

    X = X.T
    Y = Y.T

    return X, Y

def plot_decision_boundary(model, X, y):
```

```
    # Set min and max values and give it some padding
    x_min, x_max = X[0, :].min() - 1, X[0, :].max() + 1
    y_min, y_max = X[1, :].min() - 1, X[1, :].max() + 1
    h = 0.01
    # Generate a grid of points with distance h between them
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    # Predict the function value for the whole grid
    Z = model(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    # Plot the contour and training examples
    plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral)
    plt.ylabel('x2')
    plt.xlabel('x1')
    plt.scatter(X[0, :], X[1, :], c=y[0], cmap=plt.cm.Spectral)
    plt.show()

def load_2D_dataset():
    data = scipy.io.loadmat('/content/data.mat')
    train_X = data['X'].T
    train_Y = data['y'].T
    test_X = data['Xval'].T
    test_Y = data['yval'].T

    plt.scatter(train_X[0, :], train_X[1, :], c=train_Y[0], s=40, cmap=plt.cm.Spectral);

    return train_X, train_Y, test_X, test_Y


def compute_cost_with_regularization_test_case():
    np.random.seed(1)
    Y_assess = np.array([[1, 1, 0, 1, 0]])
    W1 = np.random.randn(2, 3)
    b1 = np.random.randn(2, 1)
    W2 = np.random.randn(3, 2)
    b2 = np.random.randn(3, 1)
    W3 = np.random.randn(1, 3)
    b3 = np.random.randn(1, 1)
    parameters = {"W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
    a3 = np.array([[ 0.40682402,  0.01629284,  0.16722898,  0.10118111,  0.40682402]])
    return a3, Y_assess, parameters

def backward_propagation_with_regularization_test_case():
    np.random.seed(1)
    X_assess = np.random.randn(3, 5)
    Y_assess = np.array([[1, 1, 0, 1, 0]])
    cache = (np.array([[-1.52855314,  3.32524635,  2.13994541,  2.60700654, -0.75942115],
         [-1.98043538,  4.1600994 ,  0.79051021,  1.46493512, -0.45506242]]),
  np.array([[ 0.        ,  3.32524635,  2.13994541,  2.60700654,  0.        ],
         [ 0.        ,  4.1600994 ,  0.79051021,  1.46493512,  0.        ]]),
  np.array([[-1.09989127, -0.17242821, -0.87785842],
         [ 0.04221375,  0.58281521, -1.10061918]]),
  np.array([[ 1.14472371],
         [ 0.90159072]]),
  np.array([[ 0.53035547,  5.94892323,  2.31780174,  3.16005701,  0.53035547],
         [-0.69166075, -3.47645987, -2.25194702, -2.65416996, -0.69166075],
         [-0.39675353, -4.62285846, -2.61101729, -3.22874921, -0.39675353]]),
  np.array([[ 0.53035547,  5.94892323,  2.31780174,  3.16005701,  0.53035547],
         [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ],
         [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ]]),
  np.array([[ 0.50249434,  0.90085595],
         [-0.68372786, -0.12289023],
         [-0.93576943, -0.26788808]]),
  np.array([[ 0.53035547],
         [-0.69166075],
         [-0.39675353]]),
  np.array([[-0.3771104 , -4.10060224, -1.60539468, -2.18416951, -0.3771104 ]]),
  np.array([[ 0.40682402,  0.01629284,  0.16722898,  0.10118111,  0.40682402]]),
  np.array([[-0.6871727 , -0.84520564, -0.67124613]]),
  np.array([[-0.0126646]]))
    return X_assess, Y_assess, cache

def forward_propagation_with_dropout_test_case():
    np.random.seed(1)
    X_assess = np.random.randn(3, 5)
    W1 = np.random.randn(2, 3)
    b1 = np.random.randn(2, 1)
    W2 = np.random.randn(3, 2)
    b2 = np.random.randn(3, 1)
    W3 = np.random.randn(1, 3)
    b3 = np.random.randn(1, 1)
    parameters = {"W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
```

```
    return X_assess, parameters

def backward_propagation_with_dropout_test_case():
    np.random.seed(1)
    X_assess = np.random.randn(3, 5)
    Y_assess = np.array([[1, 1, 0, 1, 0]])
    cache = (np.array([[-1.52855314,  3.32524635,  2.13994541,  2.60700654, -0.75942115],
           [-1.98043538,  4.1600994 ,  0.79051021,  1.46493512, -0.45506242]]), np.array([[ True, False,  True,  True,  True],
           [ True,  True,  True,  True, False]], dtype=bool), np.array([[ 0.        ,  0.        ,  4.27989081,  5.21401307,  0.
           [ 0.        ,  8.32019881,  1.58102041,  2.92987024,  0.        ]]), np.array([[-1.09989127, -0.17242821, -0.87785842],
           [ 0.04221375,  0.58281521, -1.10061918]]), np.array([[ 1.14472371],
           [ 0.90159072]]), np.array([[ 0.53035547,  8.02565606,  4.10524802,  5.78975856,  0.53035547],
           [-0.69166075, -1.71413186, -3.81223329, -4.61667916, -0.69166075],
           [-0.39675353, -2.62563561, -4.82528105, -6.0607449 , -0.39675353]]), np.array([[ True, False,  True, False,  True],
           [False,  True, False,  True,  True],
           [False, False,  True, False, False]], dtype=bool), np.array([[ 1.06071093,  0.        ,  8.21049603,  0.        ,  1.06071093]
           [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ],
           [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ]]), np.array([[ 0.50249434,  0.90085595],
           [-0.68372786, -0.12289023],
           [-0.93576943, -0.26788808]]), np.array([[ 0.53035547],
           [-0.69166075],
           [-0.39675353]]), np.array([[-0.7415562 , -0.0126646 , -5.65469333, -0.0126646 , -0.7415562 ]]), np.array([[ 0.32266394,  0.496

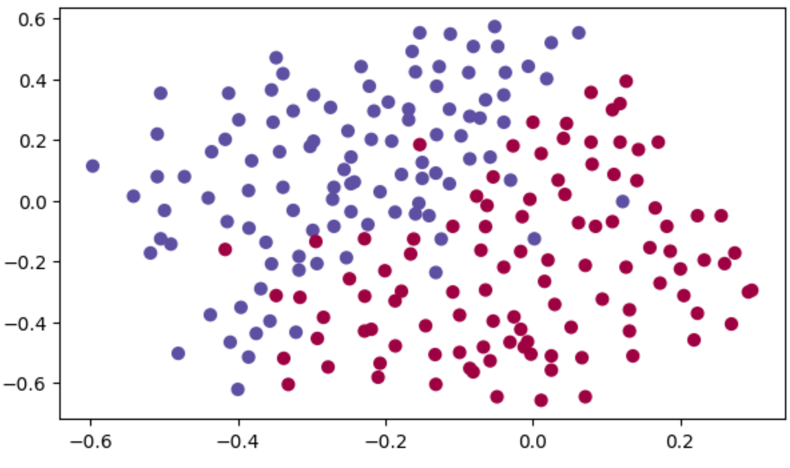

    return X_assess, Y_assess, cache



# import packages
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import sklearn.datasets
import scipy.io

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


train_X, train_Y, test_X, test_Y = load_2D_dataset()
```




```
def model(X, Y, learning_rate = 0.3, num_iterations = 30000, print_cost = True, lambd = 0, keep_prob = 1):
    """
    Implements a three-layer neural network: LINEAR->RELU->LINEAR->RELU->LINEAR->SIGMOID.

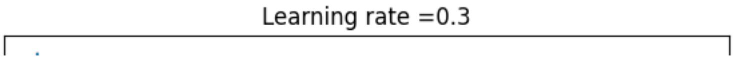
    Arguments:
    X -- input data, of shape (input size, number of examples)
    Y -- true "label" vector (1 for blue dot / 0 for red dot), of shape (output size, number of examples)
    learning_rate -- learning rate of the optimization
    num_iterations -- number of iterations of the optimization loop
    print_cost -- If True, print the cost every 10000 iterations
    lambd -- regularization hyperparameter, scalar
    keep_prob - probability of keeping a neuron active during drop-out, scalar.

    Returns:
    parameters -- parameters learned by the model. They can then be used to predict.
    """

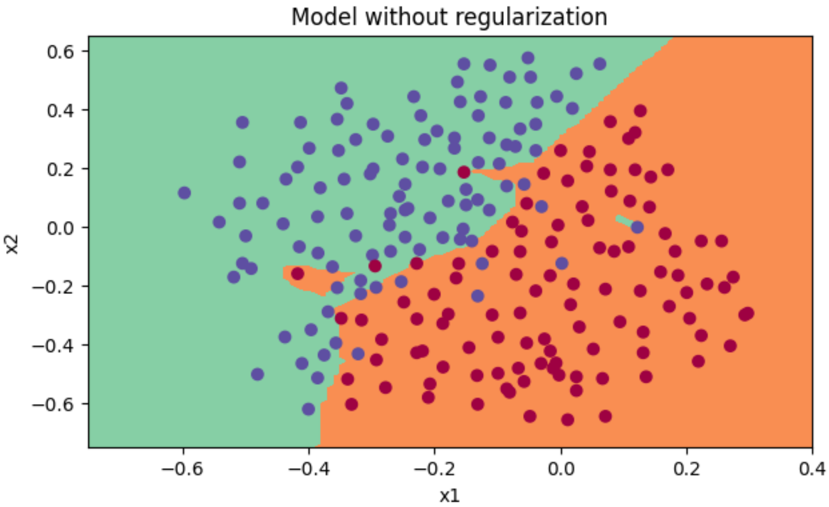
    grads = {}
    costs = []                            # to keep track of the cost
    m = X.shape[1]                        # number of examples
```

```python
    layers_dims = [X.shape[0], 20, 3, 1]

    # Initialize parameters dictionary.
    parameters = initialize_parameters(layers_dims)

    # Loop (gradient descent)

    for i in range(0, num_iterations):

        # Forward propagation: LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -> SIGMOID.
        if keep_prob == 1:
            a3, cache = forward_propagation(X, parameters)
        elif keep_prob < 1:
            a3, cache = forward_propagation_with_dropout(X, parameters, keep_prob)

        # Cost function
        if lambd == 0:
            cost = compute_cost(a3, Y)
        else:
            cost = compute_cost_with_regularization(a3, Y, parameters, lambd)

        # Backward propagation.
        assert(lambd==0 or keep_prob==1)    # it is possible to use both L2 regularization and dropout,
                                            # but this assignment will only explore one at a time
        if lambd == 0 and keep_prob == 1:
            grads = backward_propagation(X, Y, cache)
        elif lambd != 0:
            grads = backward_propagation_with_regularization(X, Y, cache, lambd)
        elif keep_prob < 1:
            grads = backward_propagation_with_dropout(X, Y, cache, keep_prob)

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

        # Print the loss every 10000 iterations
        if print_cost and i % 10000 == 0:
            print("Cost after iteration {}: {}".format(i, cost))
        if print_cost and i % 1000 == 0:
            costs.append(cost)

    # plot the cost
    plt.plot(costs)
    plt.ylabel('cost')
    plt.xlabel('iterations (x1,000)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters


parameters = model(train_X, train_Y)
print ("On the training 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: 0.6557412523481002
Cost after iteration 10000: 0.16329987525724216
Cost after iteration 20000: 0.13851642423254343
```




```
plt.title("Model without regularization")
axes = plt.gca()
axes.set_xlim([-0.75,0.40])
axes.set_ylim([-0.75,0.65])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```




```
# GRADED FUNCTION: compute_cost_with_regularization

def compute_cost_with_regularization(A3, Y, parameters, lambd):
    """
    Implement the cost function with L2 regularization. See formula (2) above.

    Arguments:
    A3 -- post-activation, output of forward propagation, of shape (output size, number of examples)
    Y -- "true" labels vector, of shape (output size, number of examples)
    parameters -- python dictionary containing parameters of the model

    Returns:
    cost - value of the regularized loss function (formula (2))
    """
    m = Y.shape[1]
    W1 = parameters["W1"]
    W2 = parameters["W2"]
    W3 = parameters["W3"]

    cross_entropy_cost = compute_cost(A3, Y) # This gives you the cross-entropy part of the cost

    ### START CODE HERE ### (approx. 1 line)
    L2_regularization_cost = np.divide(lambd,(2*m)) * (np.sum(np.square(W1)) + np.sum(np.square(W2)) + np.sum(np.square(W3)))
    ### END CODER HERE ###

    cost = cross_entropy_cost + L2_regularization_cost

    return cost


A3, Y_assess, parameters = compute_cost_with_regularization_test_case()

print("cost = " + str(compute_cost_with_regularization(A3, Y_assess, parameters, lambd = 0.1)))
```

```
cost = 1.7864859451590758
```

```
# GRADED FUNCTION: backward_propagation_with_regularization

def backward_propagation_with_regularization(X, Y, cache, lambd):
    """
    Implements the backward propagation of our baseline model to which we added an L2 regularization.

    Arguments:
    X -- input dataset, of shape (input size, number of examples)
    Y -- "true" labels vector, of shape (output size, number of examples)
    cache -- cache output from forward_propagation()
    lambd -- regularization hyperparameter, scalar
```

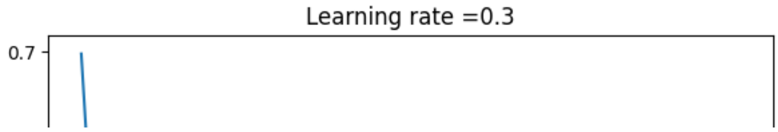
```
    Returns:
    gradients -- A dictionary with the gradients with respect to each parameter, activation and pre-activation variables
    """

    m = X.shape[1]
    (Z1, A1, W1, b1, Z2, A2, W2, b2, Z3, A3, W3, b3) = cache

    dZ3 = A3 - Y

    ### START CODE HERE ### (approx. 1 line)
    dW3 = 1./m * np.dot(dZ3, A2.T) + np.multiply((lambd/m),W3)
    ### END CODE HERE ###
    db3 = 1./m * np.sum(dZ3, axis=1, keepdims = True)

    dA2 = np.dot(W3.T, dZ3)
    dZ2 = np.multiply(dA2, np.int64(A2 > 0))
    ### START CODE HERE ### (approx. 1 line)
    dW2 = 1./m * np.dot(dZ2, A1.T) + np.multiply((lambd/m),W2)
    ### END CODE HERE ###
    db2 = 1./m * np.sum(dZ2, axis=1, keepdims = True)

    dA1 = np.dot(W2.T, dZ2)
    dZ1 = np.multiply(dA1, np.int64(A1 > 0))
    ### START CODE HERE ### (approx. 1 line)
    dW1 = 1./m * np.dot(dZ1, X.T) + np.multiply((lambd/m),W1)
    ### END CODE HERE ###
    db1 = 1./m * np.sum(dZ1, axis=1, keepdims = True)

    gradients = {"dZ3": dZ3, "dW3": dW3, "db3": db3,"dA2": dA2,
                 "dZ2": dZ2, "dW2": dW2, "db2": db2, "dA1": dA1,
                 "dZ1": dZ1, "dW1": dW1, "db1": db1}

    return gradients
```

```
X_assess, Y_assess, cache = backward_propagation_with_regularization_test_case()

grads = backward_propagation_with_regularization(X_assess, Y_assess, cache, lambd = 0.7)
print ("dW1 = \n"+ str(grads["dW1"]))
print ("dW2 = \n"+ str(grads["dW2"]))
print ("dW3 = \n"+ str(grads["dW3"]))
```

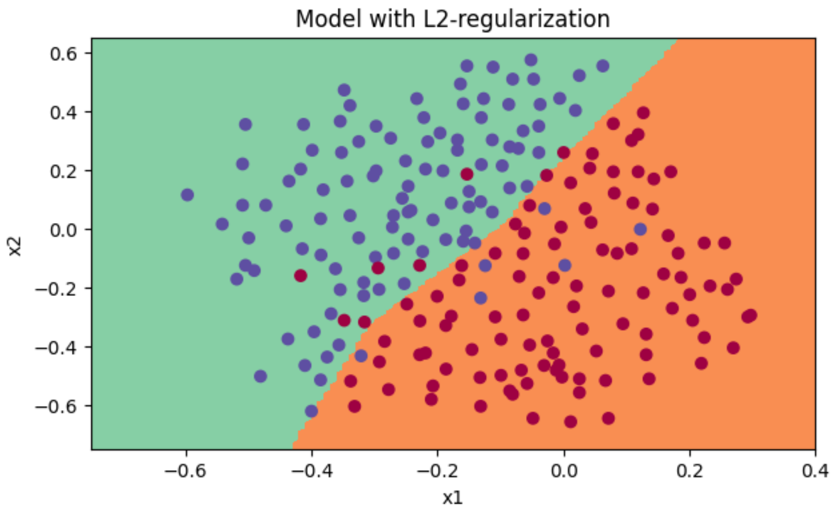
```
dW1 =
[[-0.25604646  0.12298827 -0.28297129]
 [-0.17706303  0.34536094 -0.4410571 ]]
dW2 =
[[ 0.79276486  0.85133918]
 [-0.0957219  -0.01720463]
 [-0.13100772 -0.03750433]]
dW3 =
[[-1.77691347 -0.11832879 -0.09397446]]
```

```
parameters = model(train_X, train_Y, lambd = 0.7)
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: 0.6974484493131264
Cost after iteration 10000: 0.2684918873282239
Cost after iteration 20000: 0.268091633712730
```




```
plt.title("Model with L2-regularization")
axes = plt.gca()
axes.set_xlim([-0.75,0.40])
axes.set_ylim([-0.75,0.65])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```




```
# GRADED FUNCTION: forward_propagation_with_dropout

def forward_propagation_with_dropout(X, parameters, keep_prob = 0.5):
    """
    Implements the forward propagation: LINEAR -> RELU + DROPOUT -> LINEAR -> RELU + DROPOUT -> LINEAR -> SIGMOID.

    Arguments:
    X -- input dataset, of shape (2, number of examples)
    parameters -- python dictionary containing your parameters "W1", "b1", "W2", "b2", "W3", "b3":
                    W1 -- weight matrix of shape (20, 2)
                    b1 -- bias vector of shape (20, 1)
                    W2 -- weight matrix of shape (3, 20)
                    b2 -- bias vector of shape (3, 1)
                    W3 -- weight matrix of shape (1, 3)
                    b3 -- bias vector of shape (1, 1)
    keep_prob - probability of keeping a neuron active during drop-out, scalar

    Returns:
    A3 -- last activation value, output of the forward propagation, of shape (1,1)
    cache -- tuple, information stored for computing the backward propagation
    """

    np.random.seed(1)

    # retrieve parameters
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    # LINEAR -> RELU -> LINEAR -> RELU -> LINEAR -> SIGMOID
    Z1 = np.dot(W1, X) + b1
    A1 = relu(Z1)
    ### START CODE HERE ### (approx. 4 lines)         # Steps 1-4 below correspond to the Steps 1-4 described above.
    D1 = np.random.rand(A1.shape[0], A1.shape[1])                                      # Step 1: initialize matrix D1 = np.random.ranc
    D1 = (D1<keep_prob)                                          # Step 2: convert entries of D1 to 0 or 1 (using keep_prob as the threshc
    A1 = np.multiply(A1, D1)                                          # Step 3: shut down some neurons of A1
    A1 = A1/keep_prob                                         # Step 4: scale the value of neurons that haven't been shut down
    ### END CODE HERE ###
    Z2 = np.dot(W2, A1) + b2
    A2 = relu(Z2)
    ### START CODE HERE ### (approx. 4 lines)
    D2 = np.random.rand(A2.shape[0], A2.shape[1])                                      # Step 1: initialize matrix D2 = np.random.ranc
```

```
    D2 = (D2<keep_prob)                                          # Step 2: convert entries of D2 to 0 or 1 (using keep_prob as the thresho
    A2 = np.multiply(A2, D2)                                          # Step 3: shut down some neurons of A2
    A2 = A2/keep_prob                                          # Step 4: scale the value of neurons that haven't been shut down
    ### END CODE HERE ###
    Z3 = np.dot(W3, A2) + b3
    A3 = sigmoid(Z3)

    cache = (Z1, D1, A1, W1, b1, Z2, D2, A2, W2, b2, Z3, A3, W3, b3)

    return A3, cache


X_assess, parameters = forward_propagation_with_dropout_test_case()

A3, cache = forward_propagation_with_dropout(X_assess, parameters, keep_prob = 0.7)
print ("A3 = " + str(A3))
```

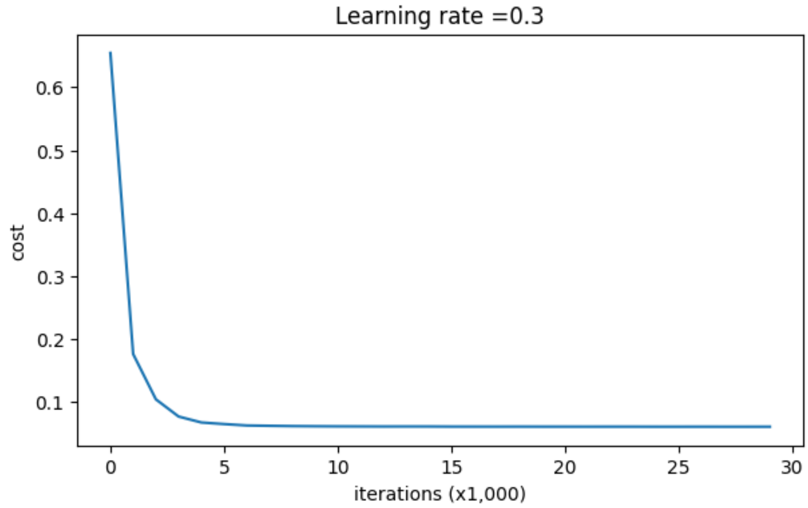
```
     A3 = [[0.36974721 0.00305176 0.04565099 0.49683389 0.36974721]]
```

```
# GRADED FUNCTION: backward_propagation_with_dropout

def backward_propagation_with_dropout(X, Y, cache, keep_prob):
    """
    Implements the backward propagation of our baseline model to which we added dropout.

    Arguments:
    X -- input dataset, of shape (2, number of examples)
    Y -- "true" labels vector, of shape (output size, number of examples)
    cache -- cache output from forward_propagation_with_dropout()
    keep_prob - probability of keeping a neuron active during drop-out, scalar

    Returns:
    gradients -- A dictionary with the gradients with respect to each parameter, activation and pre-activation variables
    """

    m = X.shape[1]
    (Z1, D1, A1, W1, b1, Z2, D2, A2, W2, b2, Z3, A3, W3, b3) = cache

    dZ3 = A3 - Y
    dW3 = 1./m * np.dot(dZ3, A2.T)
    db3 = 1./m * np.sum(dZ3, axis=1, keepdims = True)
    dA2 = np.dot(W3.T, dZ3)
    ### START CODE HERE ### (≈ 2 lines of code)
    dA2 = np.multiply(dA2, D2)              # Step 1: Apply mask D2 to shut down the same neurons as during the forward propagation
    dA2 = dA2/keep_prob              # Step 2: Scale the value of neurons that haven't been shut down
    ### END CODE HERE ###
    dZ2 = np.multiply(dA2, np.int64(A2 > 0))
    dW2 = 1./m * np.dot(dZ2, A1.T)
    db2 = 1./m * np.sum(dZ2, axis=1, keepdims = True)

    dA1 = np.dot(W2.T, dZ2)
    ### START CODE HERE ### (≈ 2 lines of code)
    dA1 = np.multiply(dA1, D1)              # Step 1: Apply mask D1 to shut down the same neurons as during the forward propagation
    dA1 = dA1/keep_prob              # Step 2: Scale the value of neurons that haven't been shut down
    ### END CODE HERE ###
    dZ1 = np.multiply(dA1, np.int64(A1 > 0))
    dW1 = 1./m * np.dot(dZ1, X.T)
    db1 = 1./m * np.sum(dZ1, axis=1, keepdims = True)

    gradients = {"dZ3": dZ3, "dW3": dW3, "db3": db3,"dA2": dA2,
                 "dZ2": dZ2, "dW2": dW2, "db2": db2, "dA1": dA1,
                 "dZ1": dZ1, "dW1": dW1, "db1": db1}

    return gradients


X_assess, Y_assess, cache = backward_propagation_with_dropout_test_case()

gradients = backward_propagation_with_dropout(X_assess, Y_assess, cache, keep_prob = 0.8)

print ("dA1 = \n" + str(gradients["dA1"]))
print ("dA2 = \n" + str(gradients["dA2"]))
```

```
     dA1 =
     [[ 0.36544439  0.         -0.00188233  0.         -0.17408748]
      [ 0.65515713  0.         -0.00337459  0.         -0.        ]]
     dA2 =
     [[ 0.58180856  0.         -0.00299679  0.         -0.27715731]
      [ 0.          0.53159854 -0.          0.53159854 -0.34089673]
      [ 0.          0.         -0.00292733  0.         -0.        ]]
```

```
parameters = model(train_X, train_Y, keep_prob = 0.86, learning_rate = 0.3)

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: 0.6543912405149825
<ipython-input-5-184c4132b3bc>:252: RuntimeWarning: divide by zero encountered in log
  logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a3), 1 - Y)
<ipython-input-5-184c4132b3bc>:252: RuntimeWarning: invalid value encountered in multiply
  logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a3), 1 - Y)
Cost after iteration 10000: 0.061016986574905605
Cost after iteration 20000: 0.060582435798513114
```




```
On the train set:
Accuracy: 0.9289099526066351
On the test set:
Accuracy: 0.95
<ipython-input-5-184c4132b3bc>:219: DeprecationWarning: `np.int` is a deprecated alias for the builtin `int`. To silence this warni
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  p = np.zeros((1,m), dtype = np.int)
```

```
plt.title("Model with dropout")
axes = plt.gca()
axes.set_xlim([-0.75,0.40])
axes.set_ylim([-0.75,0.65])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```