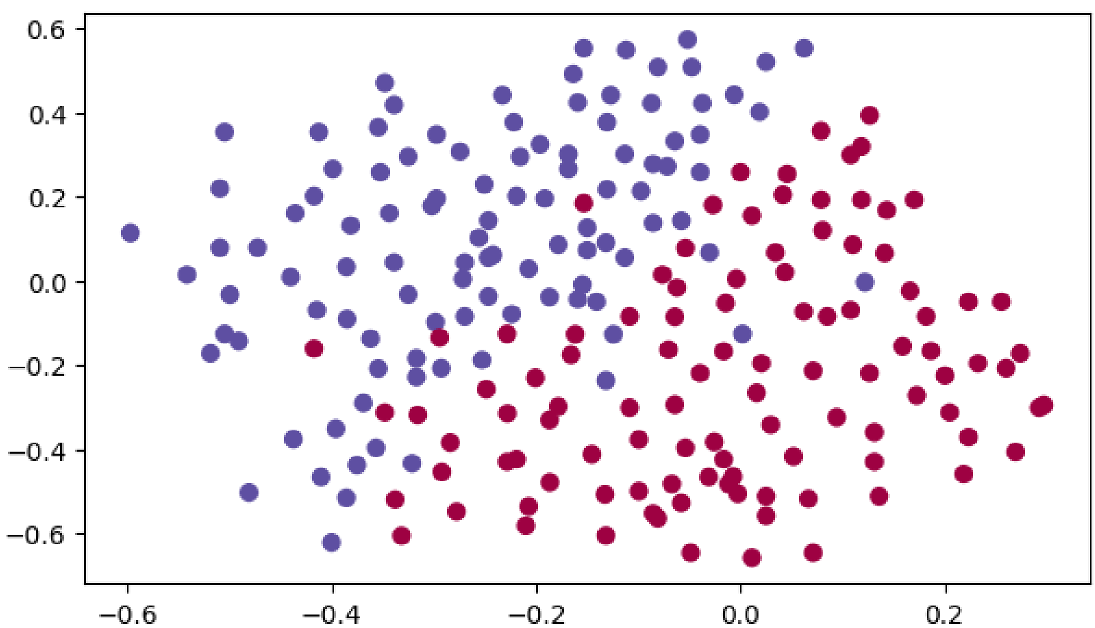
Regularization

```
# import packages
import numpy as np
import matplotlib.pyplot as plt
from reg_utils import sigmoid, relu, plot_decision_boundary, initialize_parameters, load_2D_dataset, predict_dec
from reg_utils import compute_cost, predict, forward_propagation, backward_propagation, update_parameters
import sklearn
import sklearn.datasets
import scipy.io
from testCases import *

%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()
```



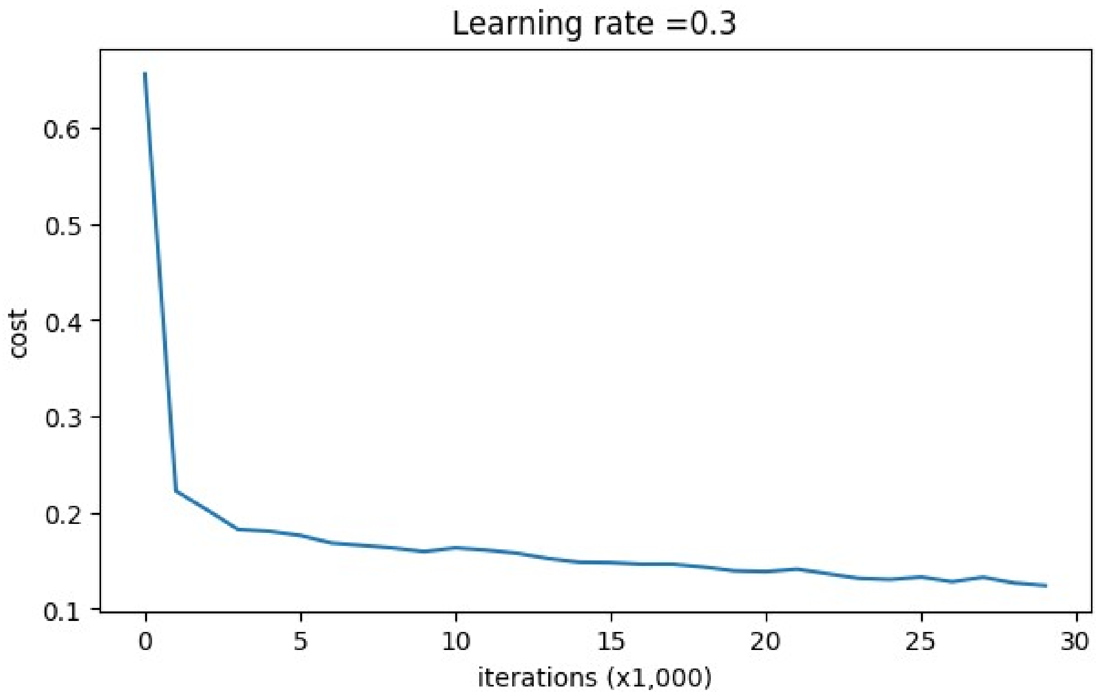
1 - Non-regularized model

```
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
    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)
```

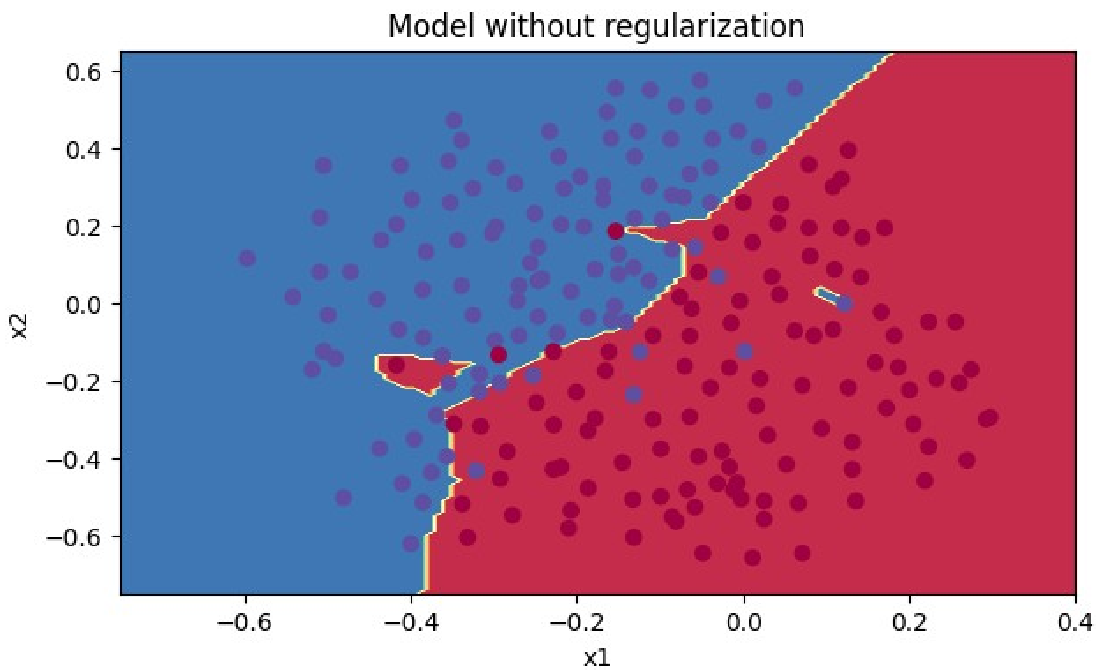
```
Cost after iteration 0: 0.6557412523481002
Cost after iteration 10000: 0.1632998752572417
Cost after iteration 20000: 0.138516424232598
```




```
On the training set:
Accuracy: 0.9478672985781991
On the test set:
Accuracy: 0.915
```

The train accuracy is 94.8% while the test accuracy is 91.5%.

```
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)
```



2 - L2 Regularization

```
# 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 = lambd * (np.sum(np.square(W1))+
np.sum(np.square(W2))+ np.sum(np.square(W3)))/(2*m)
```

```
    ### 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) + lambd*W3/m
    ### 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) + lambd*W2/m
    ### 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))
```

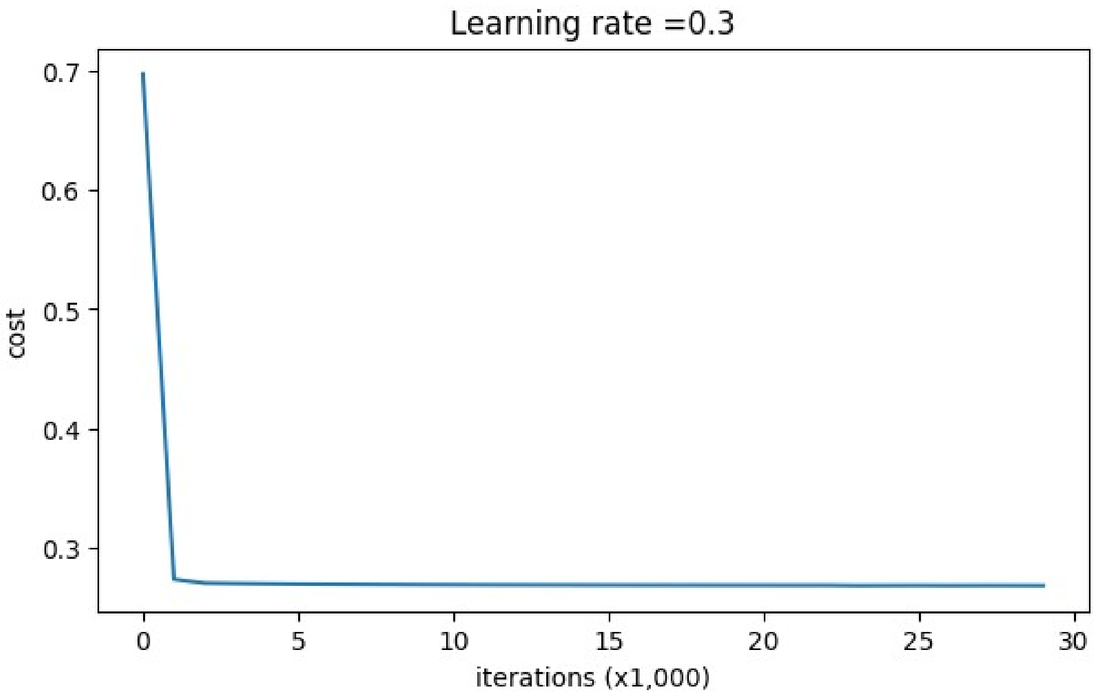
```python
    ### START CODE HERE ### (approx. 1 line)
    dW1 = 1./m * np.dot(dZ1, X.T) + lambd*W1/m
    ### END CODE HERE ###
    db1 = 1./m * np.sum(dZ1, axis=1, keepdims = True)

    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
```

```python
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 = "+ str(grads["dW1"]))
print ("dW2 = "+ str(grads["dW2"]))
print ("dW3 = "+ 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]]
```

```python
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)
```

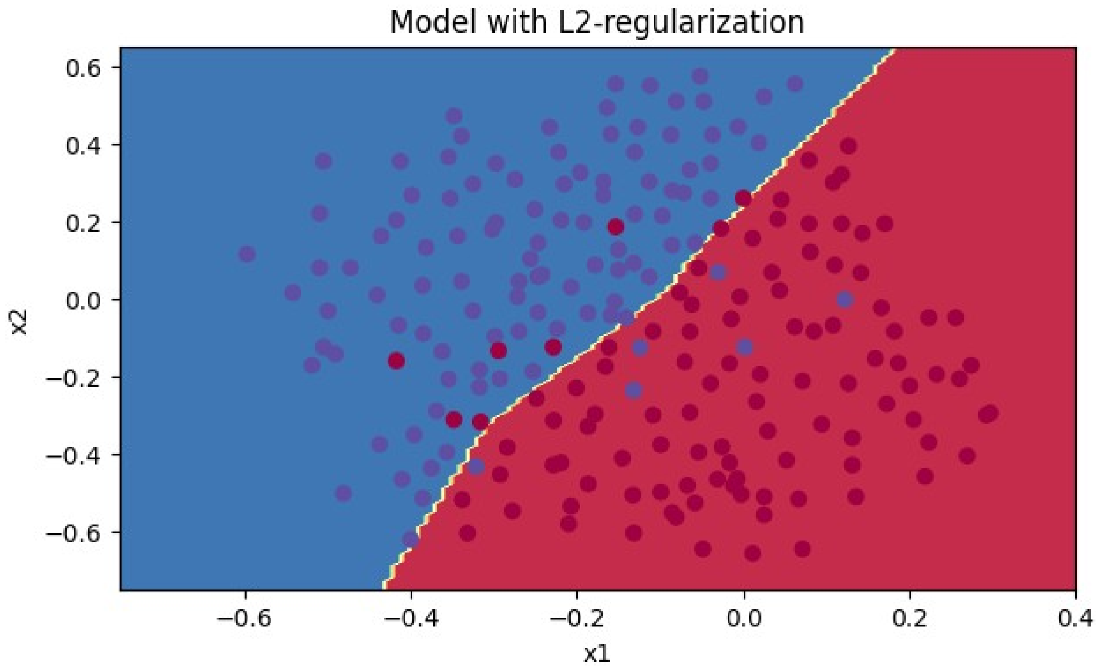
```
Cost after iteration 0: 0.6974484493131264
Cost after iteration 10000: 0.2684918873282238
Cost after iteration 20000: 0.26809163371273015
```




```
On the train set:
Accuracy: 0.9383886255924171
On the test set:
Accuracy: 0.93
```

the test set accuracy increased to 93%.

```
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)
```



3 - Dropout

```
# 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.rand(..., ...)
    D1 = ( D1 < keep_prob)                                          #
Step 2: convert entries of D1 to 0 or 1 (using keep_prob as the
threshold)
    A1 = 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.rand(..., ...)
    D2 = ( D2 < keep_prob )                                          #
Step 2: convert entries of D2 to 0 or 1 (using keep_prob as the
threshold)
    A2 = 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]]
```

3.2 - Backward propagation with dropout

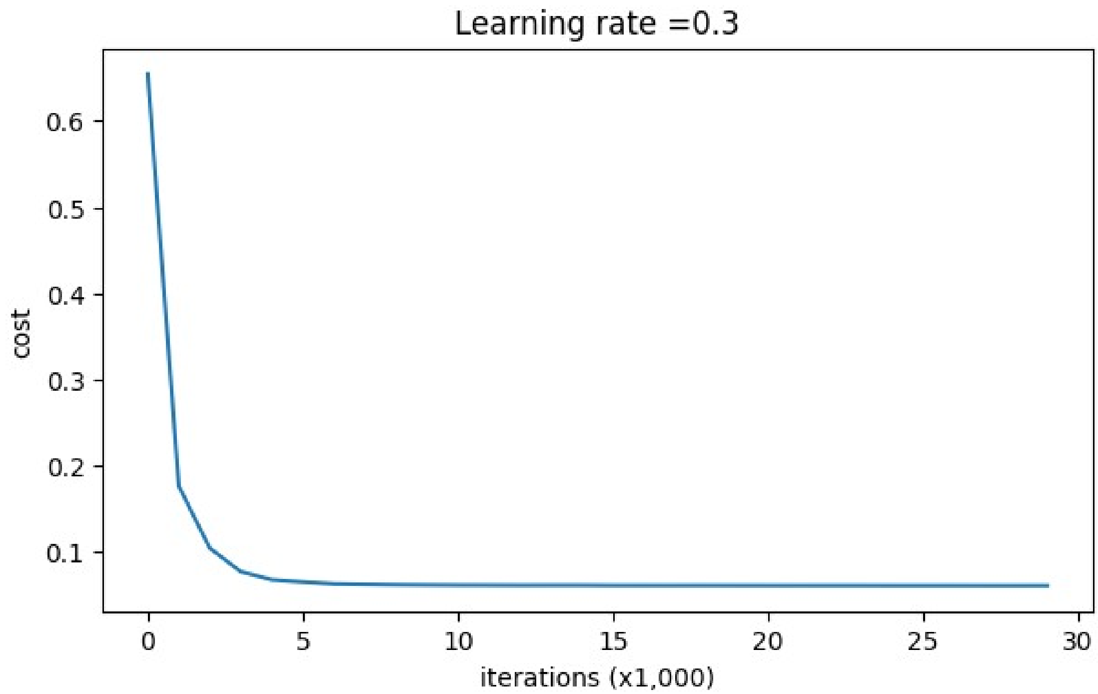
```
# GRADED FUNCTION: backward_propagation_with_dropout

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 = 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 = 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)
```

```python
    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 = " + str(gradients["dA1"]))
print ("dA2 = " + 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.        ]]
```

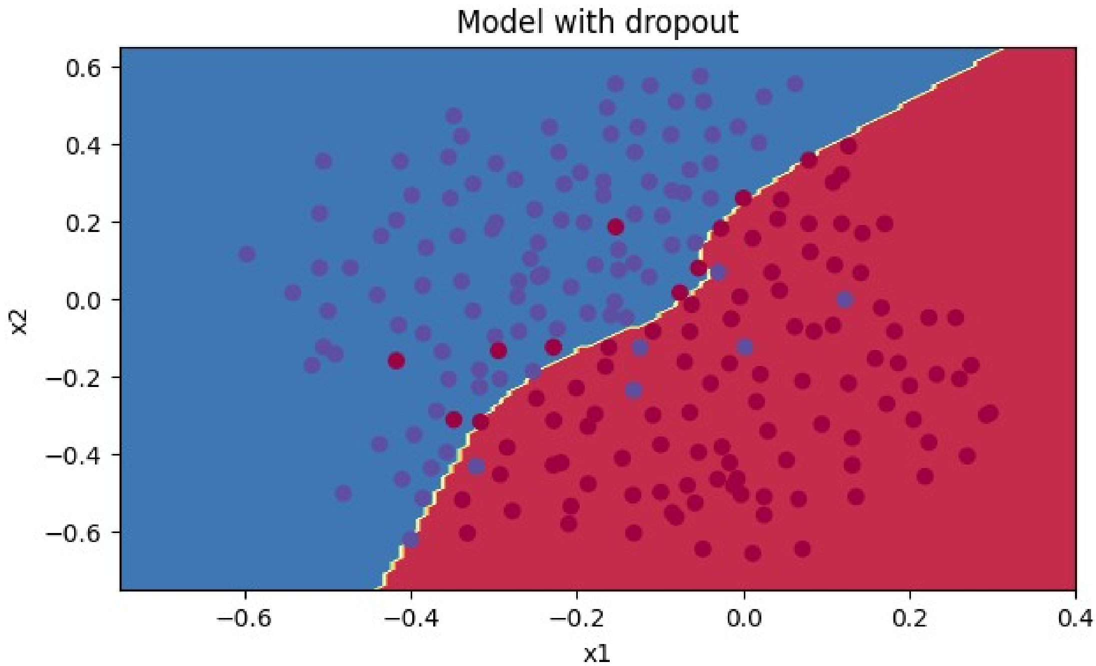
```python
parameters = model(train_X, train_Y, keep_prob = 0.86, learning_rate =
0.3)

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

c:\Users\dhava\Desktop\Deep Learrning Lab\Practical 5 -\2-
regularization\reg_utils.py:236: RuntimeWarning: divide by zero
encountered in log
  logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a3),
1 - Y)
c:\Users\dhava\Desktop\Deep Learrning Lab\Practical 5 -\2-
regularization\reg_utils.py:236: 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: 0.0610169865749056
Cost after iteration 20000: 0.060582435798513114
```




```
On the train set:
Accuracy: 0.9289099526066351
On the test set:
Accuracy: 0.95
```

```python
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)
```



Model with dropout
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
x2
−0.6
−0.4
−0.2
0.0
0.2
0.4
x1