Task01- Regularization

It is highly pivotal for deep learning models to be trained in a fashion that prevents issues like over-fitting, especially when the dataset is small. When a model over-fits, it fails to generalize well to new samples (unseen during training).

To avoid over-fitting, you will implement two techniques:

- L2-Regularization
- Dropout

In [7]:

```
!git clone https://github.com/SanVik2000/EE5179-Final.git
```

```
fatal: destination path 'EE5179-Final' already exists and is not an
empty directory.
```

In [8]:

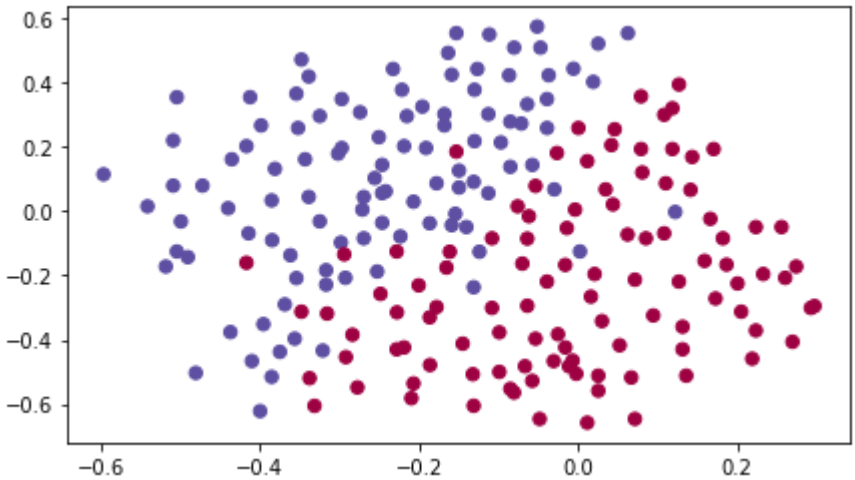
```
!cp /content/EE5179-Final/Tutorial-3/reg_utils.py /content
!cp /content/EE5179-Final/Tutorial-3/testCases.py /content
```

In [9]:

```
# import packages
import numpy as np
import matplotlib.pyplot as plt
from reg_utils import sigmoid, relu, plot_decision_boundary, initialize_paramete
rs, load_2D_dataset, predict_dec
from reg_utils import compute_cost, predict, forward_propagation, backward_propa
gation, 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'
```

In [10]:

```
def load_2D_dataset():
    data = scipy.io.loadmat('/content/EE5179-Final/Tutorial-3/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, s=40, cmap=plt.cm.Spect
ral);

    return train_X, train_Y, test_X, test_Y

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



In [11]:

```
print(train_X.shape,train_Y.shape,test_X.shape, test_Y.shape)
```

```
(2, 211) (1, 211) (2, 200) (1, 200)
```

Each dot corresponds to a data point, where

- blue dot represents class-1
- red dot represents class 2

Your goal: Use a deep learning model to classify the data points among two classes.

1 - Non-regularized model

You will use the following neural network (already implemented for you below). This model can be used:

- in *regularization mode* -- by setting the `lambd` input to a non-zero value.
- in *dropout mode* -- by setting the `keep_prob` to a value less than one and greater than zero.

You will first try the model without any regularization. Then, you will implement:

- *L2 regularization* -- functions: "`compute_cost_with_regularization()`" and "`backward_propagation_with_regularization()`"
- *Dropout* -- functions: "`forward_propagation_with_dropout()`" and "`backward_propagation_with_dropout()`"

In each part, you will run this model with the correct inputs so that it calls the functions you've implemented. Take a look at the code below to familiarize yourself with the model.

In [12]:

```
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 pred
ict.
    """

    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 -> SIG
MOID.
        if keep_prob == 1:
            a3, cache = forward_propagation(X, parameters)
        elif keep_prob < 1:
            a3, cache = forward_propagation_with_dropout(X, parameters, keep_pro
b)

        # 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 regu
larization and dropout,
                                            # but this assignment will only expl
ore 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)
```

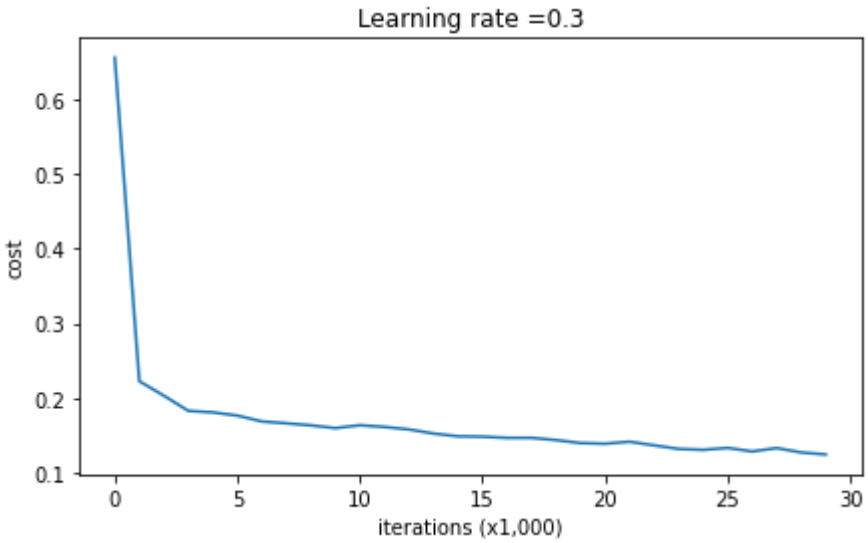
```
        # Update parameters.
        parameters = update_parameters(parameters, grads, learning_rate)

        # 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
```

Let's train the model without any regularization, and observe the accuracy on the train/test sets.

In [13]:

```
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: 0.13851642423284755
```

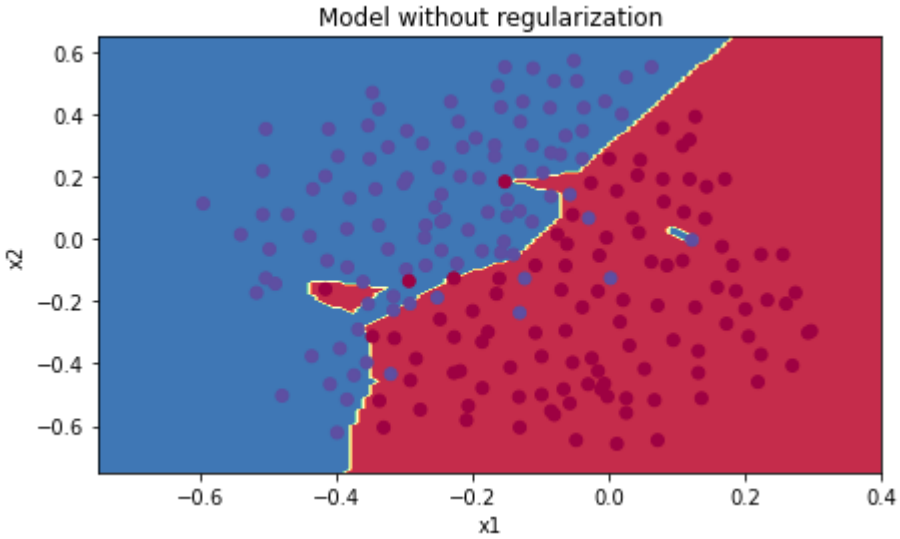



```
On the training set:
Accuracy: 0.9478672985781991
On the test set:
Accuracy: 0.915
```

The train accuracy is 94.8% while the test accuracy is 91.5%. This is the **baseline model** (you will observe the impact of regularization on this model). Run the following code to plot the decision boundary of your model.

In [14]:

```
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)
```



The non-regularized model is obviously overfitting the training set. It is fitting the noisy points! Lets now look at two techniques to reduce overfitting.

2 - L2 Regularization

The standard way to avoid overfitting is called **L2 regularization**. THe new modified cost function now becomes:

$$J_{regularized} = \underbrace{-\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\left(a^{[L](i)}\right)+(1-y^{(i)})\log\left(1-a^{[L](i)}\right)\right)}_{\text{cross-entropy cost}} + \underbrace{\frac{1}{m}\frac{\lambda}{2}\sum_{l}\sum_{k}\sum_{j}W_{k,j}^{[l]2}}_{\text{L2 regularization cost}} \quad (2)$$

Exercise: Implement `compute_cost_with_regularization()` which computes the cost given by formula (2). To calculate $\sum_k \sum_j W_{k,j}^{[l]2}$, use :

```
np.sum(np.square(Wl))
```

Note that you have to do this for $W^{[1]}$, $W^{[2]}$ and $W^{[3]}$, then sum the three terms and multiply by $\frac{1}{m}\frac{\lambda}{2}$.

In [15]:

```
# 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 = (1.0/m)* (0.5*lambd) * (np.sum(np.square(W1))+np.su
m(np.square(W2))+np.sum(np.square(W3)))
    ### END CODER HERE ###

    cost = cross_entropy_cost + L2_regularization_cost

    return cost
```

In [16]:

```
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
```

Expected Output:

cost	1.78648594516

Since the cost function is changed now, we have to also include the effects of the gradients of this additional term in our gradient descent algorithm.

Exercise: Implement the changes needed in backward propagation to take into account regularization. The changes only concern dW1, dW2 and dW3. For each, you have to add the regularization term's gradient ($\frac{d}{dW}(\frac{1}{2}\frac{\lambda}{m}W^2) = \frac{\lambda}{m}W$).

In [17]:

```
# 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 = 1.0/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 = 1.0/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))
    ### START CODE HERE ### (approx. 1 line)
    dW1 = 1.0/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
```

In [18]:

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

grads = backward_propagation_with_regularization(X_assess, Y_assess, cache, lamb
d = 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]]
```

Expected Output:

```
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]]
```

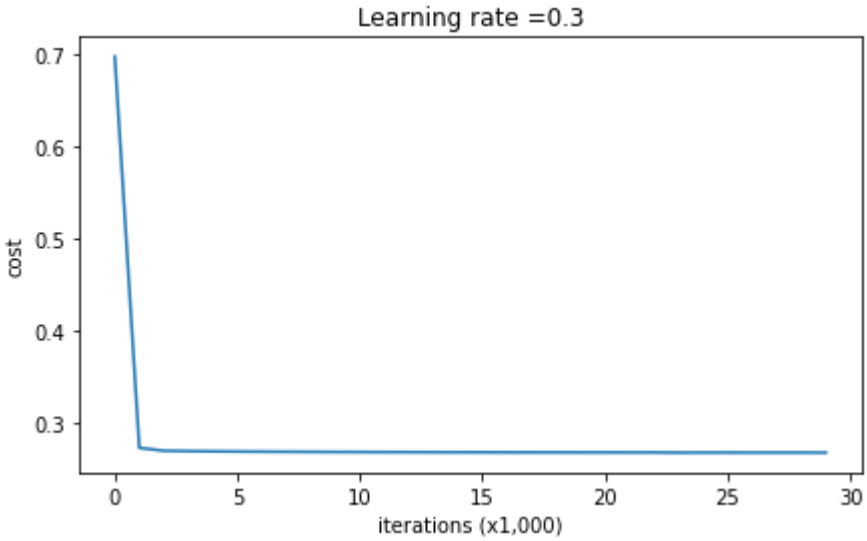
Let's now run the model with L2 regularization ($\lambda = 0.7$). The `model()` function will call:

- `compute_cost_with_regularization` instead of `compute_cost`
- `backward_propagation_with_regularization` instead of `backward_propagation`

In [19]:

```
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: 0.26849188732822393
Cost after iteration 20000: 0.2680916337127301
```



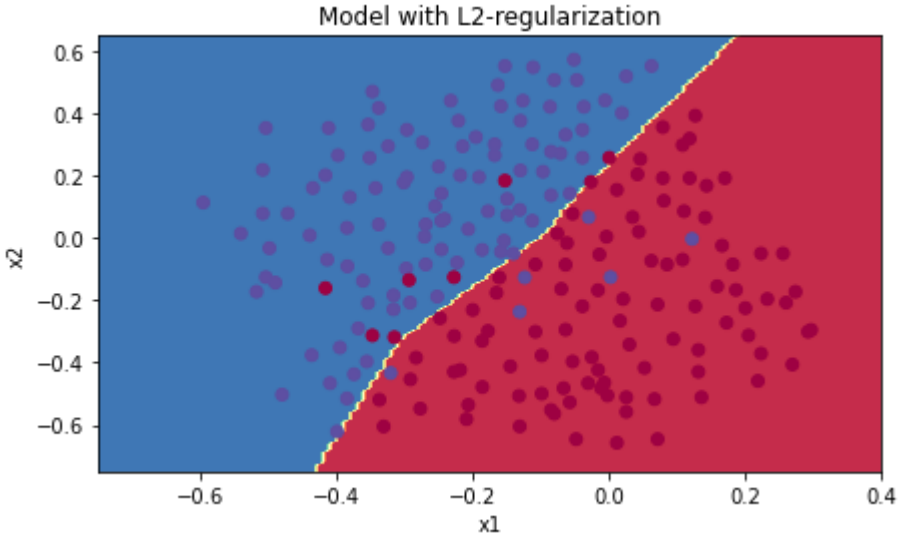

```
On the train set:
Accuracy: 0.9383886255924171
On the test set:
Accuracy: 0.93
```

The test set accuracy has now increased to 93%.

You are not overfitting the training data anymore. Let's plot the decision boundary.

In [20]:

```
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)
```



Observations:

- The value of λ is a hyperparameter that you can tune using a validation set.
- L2 regularization makes your decision boundary smoother. If λ is too large, it is also possible to "oversmooth", resulting in a model with high bias.

What is L2-regularization actually doing?:

L2-regularization relies on the assumption that a model with small weights is simpler than a model with large weights. Thus, by penalizing the square values of the weights in the cost function you drive all the weights to smaller values. It becomes too costly for the cost to have large weights! This leads to a smoother model in which the output changes more slowly as the input changes.

3 - Dropout

Dropout is a widely used regularization technique that is specific to deep learning. **It randomly shuts down some neurons in each iteration.**

When you shut some neurons down, you actually modify your model. The idea behind drop-out is that at each iteration, you train a different model that uses only a subset of your neurons. With dropout, your neurons thus become less sensitive to the activation of one other specific neuron, because that other neuron might be shut down at any time.

3.1 - Forward propagation with dropout

Exercise: Implement the forward propagation with dropout. You are using a 3 layer neural network, and will add dropout to the first and second hidden layers. We will not apply dropout to the input layer or output layer.

Hint: Let's say that keep_prob = 0.8, which means that we want to keep about 80% of the neurons and drop out about 20% of them. We want to generate a vector that has 1's and 0's, where about 80% of them are 1 and about 20% are 0. This python statement:
`X = (X < keep_prob).astype(int)`

is conceptually the same as this if-else statement (for the simple case of a one-dimensional array) :

```
for i,v in enumerate(x):
    if v < keep_prob:
        x[i] = 1
    else: # v >= keep_prob
        x[i] = 0
```

Note that the `X = (X < keep_prob).astype(int)` works with multi-dimensional arrays, and the resulting output preserves the dimensions of the input array.

Also note that without using `.astype(int)`, the result is an array of booleans `True` and `False`, which Python automatically converts to 1 and 0 if we multiply it with numbers. (However, it's better practice to convert data into the data type that we intend, so try using `.astype(int)`.)

Steps to be followed:

1. Set $A^{[1]}$ to $A^{[1]} * D^{[1]}$. (You are shutting down some neurons). You can think of $D^{[1]}$ as a mask, so that when it is multiplied with another matrix, it shuts down some of the values.
2. Divide $A^{[1]}$ by `keep_prob`. By doing this you are assuring that the result of the cost will still have the same expected value as without drop-out. (This technique is also called inverted dropout.)

In [21]:

```
# 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 -> RE
LU + 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 correspo
nd 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).astype(int)
# Step 2: convert entries of D1 to 0 or 1 (using keep_prob as the threshold)
    A1 = np.multiply(A1,D1)                                                 # Step 3:
shut down some neurons of A1
    A1 = np.multiply(1.0/keep_prob , A1)
# 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).astype(int)
# Step 2: convert entries of D2 to 0 or 1 (using keep_prob as the threshold)
    A2 = np.multiply(A2,D2)                                                  # Step
 3: shut down some neurons of A2
    A2 = np.multiply(1.0/keep_prob , A2)
```

```
    # 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
```

In [22]:

```
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]]
```

Expected Output:

A3 [[0.36974721 0.00305176 0.04565099 0.49683389 0.36974721]]

3.2 - Backward propagation with dropout

Exercise: Implement the backward propagation with dropout. As before, you are training a 3 layer network. Add dropout to the first and second hidden layers, using the masks $D^{[1]}$ and $D^{[2]}$ stored in the cache.

Instruction: Backpropagation with dropout is actually quite easy. You will have to carry out 2 Steps:

1. You had previously shut down some neurons during forward propagation, by applying a mask $D^{[1]}$ to `A1`. In backpropagation, you will have to shut down the same neurons, by reapplying the same mask $D^{[1]}$ to `dA1`.
2. During forward propagation, you had divided `A1` by `keep_prob`. In backpropagation, you'll therefore have to divide `dA1` by `keep_prob` again (the calculus interpretation is that if $A^{[1]}$ is scaled by `keep_prob`, then its derivative $dA^{[1]}$ is also scaled by the same `keep_prob`).

In [23]:

```
# 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(D2,dA2)                  # Step 1: Apply mask D2 to shut d
own the same neurons as during the forward propagation
    dA2 = np.multiply(1.0/keep_prob,dA2)                  # Step 2: Scale the va
lue 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(D1,dA1)                                      # Step 1: Apply
 mask D1 to shut down the same neurons as during the forward propagation
    dA1 = np.multiply(1.0/keep_prob,dA1)                  # Step 2: Scale the va
lue 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
```

In [24]:

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

gradients = backward_propagation_with_dropout(X_assess, Y_assess, cache, keep_pr
ob = 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.        ]]
```

Expected Output:

```
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.        ]]
```

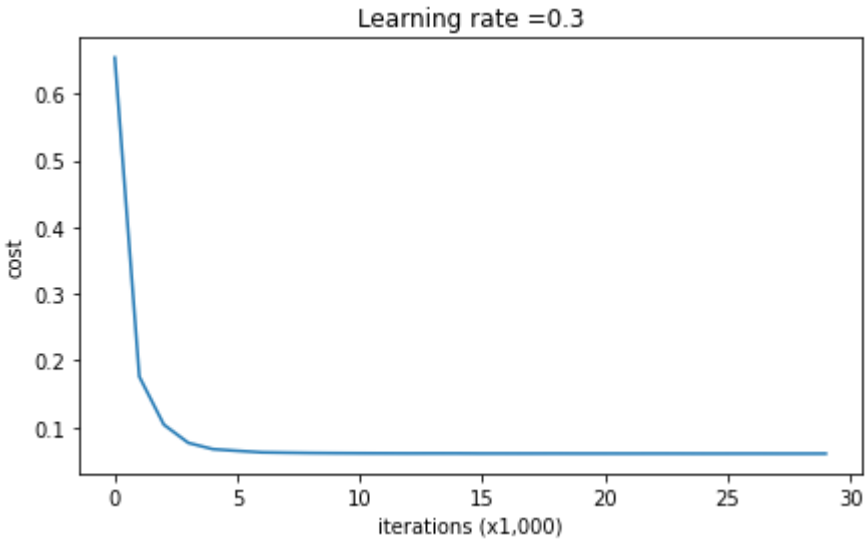
Let's now run the model with dropout (`keep_prob = 0.86`). It means at every iteration you shut down each neurons of layer 1 and 2 with 14% probability. The function `model()` will now call:

- `forward_propagation_with_dropout` instead of `forward_propagation` .
- `backward_propagation_with_dropout` instead of `backward_propagation` .

In [25]:

```
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

/content/reg_utils.py:236: RuntimeWarning: divide by zero encountere
d in log
  logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a
3), 1 - Y)
/content/reg_utils.py:236: RuntimeWarning: invalid value encountered
in multiply
  logprobs = np.multiply(-np.log(a3),Y) + np.multiply(-np.log(1 - a
3), 1 - Y)

Cost after iteration 10000: 0.0610169865749056
Cost after iteration 20000: 0.060582435798513114
```

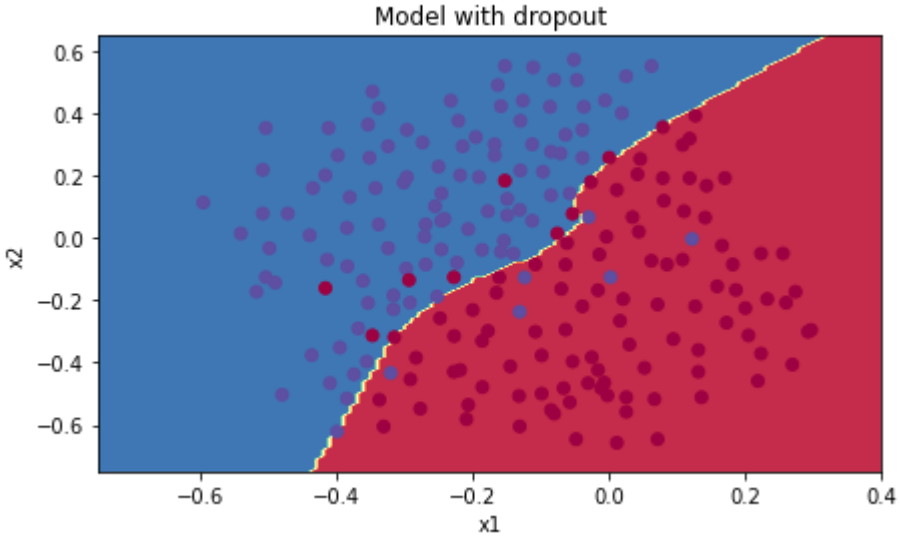



```
On the train set:
Accuracy: 0.9289099526066351
On the test set:
Accuracy: 0.95
```

The test accuracy has increased again (to 95%)! Your model is not overfitting the training set and performs well on the test set.

In [26]:

```
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)
```



Note:

- You only use dropout during training. Don't use dropout (randomly eliminate nodes) during test time.
- Apply dropout both during forward and backward propagation.

4 - Conclusions

Here are the results of our three models:

Model	**Train Accuracy**	**Test Accuracy**
3-layer NN without regularization	95	91.5
3-layer NN with L2-regularization	94	93
3-layer NN with Dropout regularization	93	95

Note that regularization hurts training set performance! This is because it limits the ability of the network to overfit to the training set. But since it ultimately gives better test accuracy, it is helping your system.

In [ ]:

```
!pip install nbconvert
!sudo apt-get install texlive-xetex texlive-fonts-recommended texlive-plain-gene
ric
!jupyter nbconvert --to html "/content/drive/MyDrive/Colab Notebooks/Task_01_Reg
ularization_EE21S060.ipynb"
```