Reference

Coursera Deep learning series by Andrew NG

Introduction

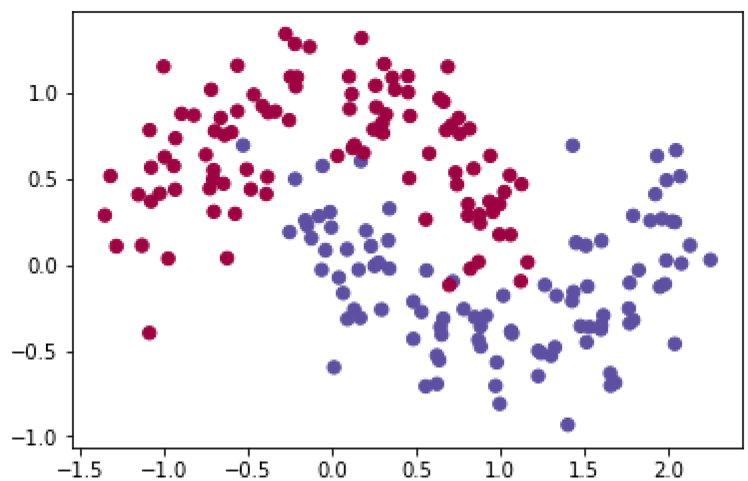
Welcome to the second assignment of this week. Deep Learning models have so much flexibility and capacity that overfitting can be a serious problem.

In [1]:
```
# 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_reg 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 [3]:
```python
# Generate a dataset to test the regularization
np.random.seed(0)
m = 200
X, Y = sklearn.datasets.make_moons(m, noise=0.20)

#To comply with the equations.
X = X.T
Y = Y.reshape(1,m)
print(X.shape, Y.shape)

plt.scatter(X[0,:], X[1,:], s=40, c=np.squeeze(Y), cmap=plt.cm.Spectral) #plt.cm.Spectral
```

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

Out[3]:
```
<matplotlib.collections.PathCollection at 0x21d1cc4d4a8>
```



In [4]:
```
import numpy as np
from sklearn.model_selection import train_test_split
X=X.T #To be consistent with train_test_split
Y=Y.T
print(X.shape,Y.shape)
train_X, test_X, train_Y, test_Y = train_test_split(X, Y, test_size=0.33, random_state=42)
print(train_X.shape, test_X.shape, train_Y.shape, test_Y.shape)

train_X = train_X.T #This is to be consistent to the model used below.
test_X = test_X.T
train_Y = train_Y.T
test_Y = test_Y.T
```

```
(200, 2) (200, 1)
(134, 2) (66, 2) (134, 1) (66, 1)
```

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. We use " `lambd` " instead of " `lambda` " because " `lambda` " is a reserved keyword in Python.
- in *dropout mode* -- by setting the `keep_prob` to a value less than one

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.

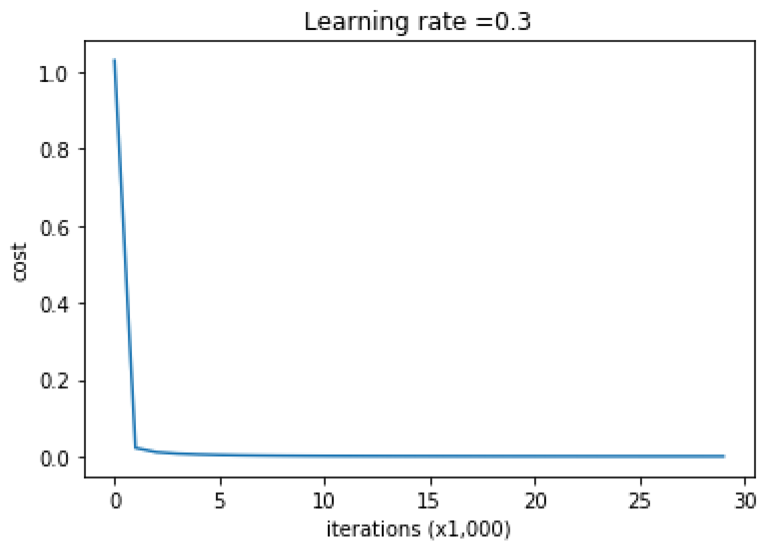
In [5]:
```python
def model(X, Y, learning_rate = 0.3, num_iterations = 30000, print_cost = True, lambd = 0, keep_prob = 1):
    """
    Implements a three-layer neural network: LINEAR->RELU->LINEAR->RELU->LINEAR->SIGMOID.

    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
```

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

In [6]:
```python
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)
```

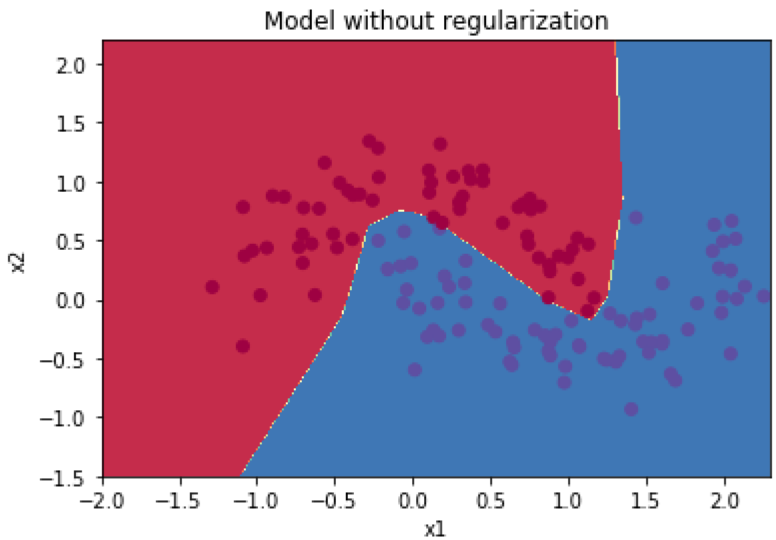
```
Cost after iteration 0: 1.030668564098119
Cost after iteration 10000: 0.0013096475336283563
Cost after iteration 20000: 0.00045300271498517185
```




```
On the training set:
Accuracy: 1.0
On the test set:
Accuracy: 0.9242424242424242
```

In [7]:
```
plt.title("Model without regularization")
axes = plt.gca()
axes.set_xlim([-2.0, 2.3])
axes.set_ylim([-1.5, 2.2])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```

```
(1, 134)
(134,)
```



2 - L2 Regularization

The standard way to avoid overfitting is called **L2 regularization**. It consists of appropriately modifying your cost function, from:

$$J = -\frac{1}{m} \sum\limits_{i = 1}^{m} \large{(}\small y^{(i)}\log\left(a^{[L](i)}\right) + (1-y^{(i)})\log\left(1- a^{[L](i)}\right) \large{)} \tag{1}$$

To:

$$J_{regularized} = \small \underbrace{-\frac{1}{m} \sum\limits_{i = 1}^{m} \large{(}\small y^{(i)}\log\left(a^{[L](i)}\right) + (1-y^{(i)})\log\left(1- a^{[L](i)}\right) \large{)} }_\text{cross-entropy cost} + \underbrace{\frac{1}{m} \frac{\lambda}{2} \sum\limits_l\sum\limits_k\sum\limits_j W_{k,j}^{[l]2} }_\text{L2 regularization cost} \tag{2}$$

Let's modify your cost and observe the consequences.

Exercise: Implement `compute_cost_with_regularization()` which computes the cost given by formula (2). To calculate $\sum\limits_k\sum\limits_j W_{k,j}^{[l]2}$, 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 $\frac{1}{m}\frac{\lambda}{2}$.

Extend this to the L-layer model.

In [8]:
```
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

    L2_regularization_cost = lambd * (np.sum(np.square(W1)) + np.sum(np.square(W2)) + np.sum(np.square(W3))) / (

    cost = cross_entropy_cost + L2_regularization_cost

    return cost
```

In [9]:
```
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
```

Because you changed the cost, you have to change backward propagation as well! All the gradients have to be computed with respect to this new cost.

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 [10]:
```
def backward_propagation_with_regularization(X, Y, cache, lambd):

    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) + (lambd * W3) / m
    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) + (lambd * W2) / m

    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) + (lambd * W1) / m
    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 [11]:
```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"]))
```

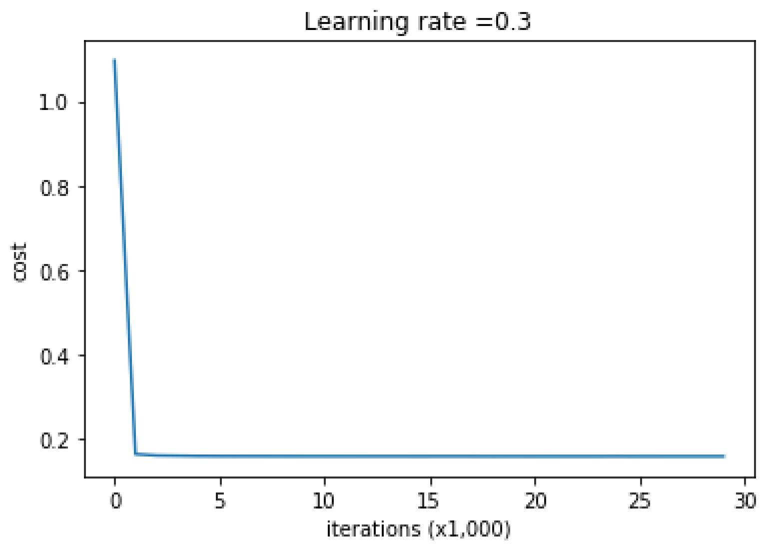
```
dW1 = [[-0.25604646  0.12298827 -0.28297129]
 [-0.17706303  0.34536094 -0.4410571 ]]
dW2 = [[ 0.79276486  0.85133918]
 [-0.0957219  -0.01720463]
 [-0.13100772 -0.03750433]]
dW3 = [[-1.77691347 -0.11832879 -0.09397446]]
```

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 [12]:
```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)
```

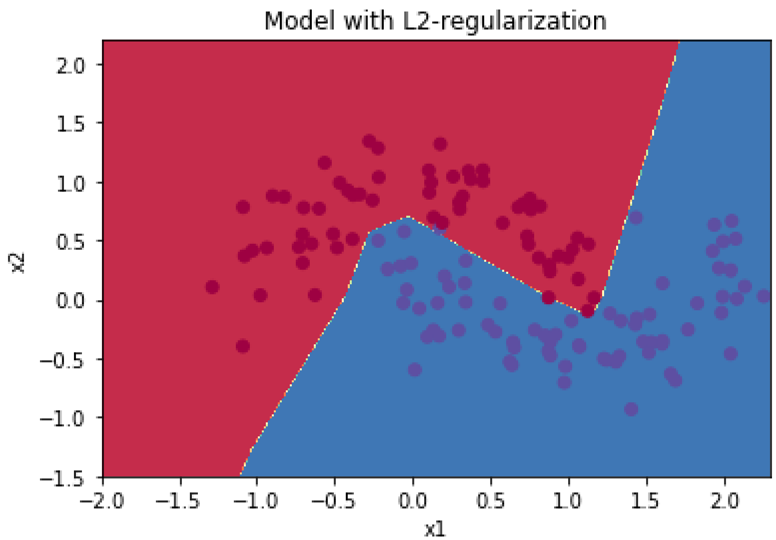
```
Cost after iteration 0: 1.0963418369311082
Cost after iteration 10000: 0.15812776244188406
Cost after iteration 20000: 0.15796526408237627
```




```
On the train set:
Accuracy: 0.9925373134328358
On the test set:
Accuracy: 0.9393939393939394
```

In [13]:
```
plt.title("Model with L2-regularization")
axes = plt.gca()
axes.set_xlim([-2.0, 2.3])
axes.set_ylim([-1.5, 2.2])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```

```
(1, 134)
(134,)
```



Observations:

- The value of λ is a hyperparameter that you can tune using a dev 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.

3 - Dropout

Finally, **dropout** is a widely used regularization technique that is specific to deep learning. **It randomly shuts down some neurons in each iteration.** Watch these two videos to see what this means!

0:00 / 0:08

Figure 2 : Drop-out on the second hidden layer.
At each iteration, you shut down (= set to zero) each neuron of a layer with probability $1 - keep\_prob$ or keep it with probability $keep\_prob$ (50% here). The dropped neurons don't contribute to the training in both the forward and backward propagations of the iteration.

0:00 / 0:08

Figure 3 : Drop-out on the first and third hidden layers.
1^{st} layer: we shut down on average 40% of the neurons. 3^{rd} layer: we shut down on average 20% of the neurons.

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.

Instructions: You would like to shut down some neurons in the first and second layers. To do that, you are going to carry out 4 Steps:

1. In lecture, we dicussed creating a variable $d^{[1]}$ with the same shape as $a^{[1]}$ using `np.random.rand()` to randomly get numbers between 0 and 1. Here, you will use a vectorized implementation, so create a random matrix $D^{[1]} = [d^{[1](1)} d^{[1](2)} \ldots d^{[1](m)}]$ of the same dimension as $A^{[1]}$.
2. Set each entry of $D^{[1]}$ to be 0 with probability (`1-keep_prob`) or 1 with probability (`keep_prob`), by thresholding values in $D^{[1]}$ appropriately. Hint: to set all the entries of a matrix X to 0 (if entry is less than 0.5) or 1 (if entry is more than 0.5) you would do: `X = (X < 0.5)`. Note that 0 and 1 are respectively equivalent to False and True.
3. 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.
4. 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 [14]:

```
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 abo
    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
    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
    ### 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 t
    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
    ### 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 [15]:
```
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 [16]:

```python
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 va
    """

    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 propa
    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 propa
    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}
```

```python
    return gradients
```

In [17]:
```python
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.        ]]
```

Expected Output:

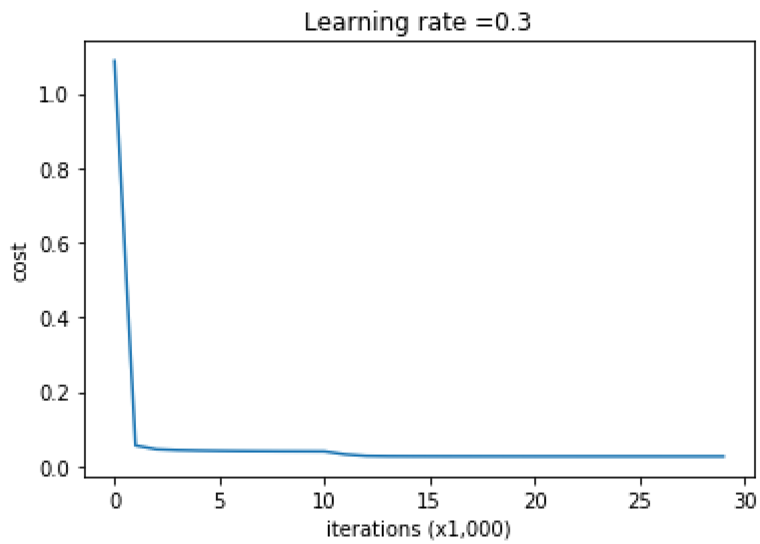
dA1	[[0.36544439 0. -0.00188233 0. -0.17408748] [0.65515713 0. -0.00337459 0. -0.]]
dA2	[[0.58180856 0. -0.00299679 0. -0.27715731] [0. 0.53159854 -0. 0.53159854 -0.34089673] [0. 0. -0.00292733 0. -0.]]

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 24% probability. The function `model()` will now call:

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

In [18]:
```
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)
```

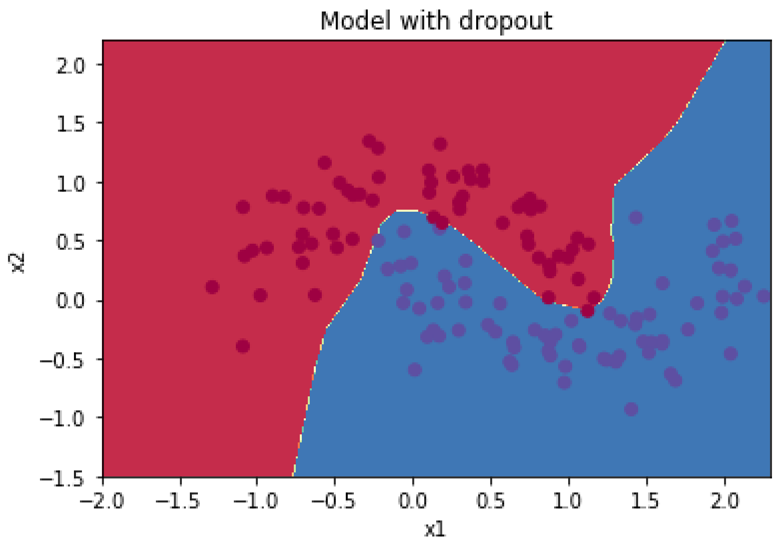
```
Cost after iteration 0: 1.087298398064148
Cost after iteration 10000: 0.039881393279895795
Cost after iteration 20000: 0.02647010624682434
```




```
On the train set:
Accuracy: 0.9925373134328358
On the test set:
Accuracy: 0.9090909090909091
```

In [19]:
```
plt.title("Model with dropout")
axes = plt.gca()
axes.set_xlim([-2.0, 2.3])
axes.set_ylim([-1.5, 2.2])
plot_decision_boundary(lambda x: predict_dec(parameters, x.T), train_X, train_Y)
```

```
(1, 134)
(134,)
```



Note:

- A **common mistake** when using dropout is to use it both in training and testing. You should use dropout (randomly eliminate nodes) only in training.
- Deep learning frameworks like [tensorflow (https://www.tensorflow.org/api_docs/python/tf/nn/dropout)](https://www.tensorflow.org/api_docs/python/tf/nn/dropout), [PaddlePaddle (http://doc.paddlepaddle.org/release_doc/0.9.0/doc/ui/api/trainer_config_helpers/attrs.html)](http://doc.paddlepaddle.org/release_doc/0.9.0/doc/ui/api/trainer_config_helpers/attrs.html), [keras (https://keras.io/layers/core/#dropout)](https://keras.io/layers/core/#dropout) or [caffe (http://caffe.berkeleyvision.org/tutorial/layers/dropout.html)](http://caffe.berkeleyvision.org/tutorial/layers/dropout.html) come with a dropout layer implementation. Don't stress - you will soon learn some of these frameworks.

What you should remember about dropout:

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

- During training time, divide each dropout layer by keep_prob to keep the same expected value for the activations. For example, if keep_prob is 0.5, then we will on average shut down half the nodes, so the output will be scaled by 0.5 since only the remaining half are contributing to the solution. Dividing by 0.5 is equivalent to multiplying by 2. Hence, the output now has the same expected value. You can check that this works even when keep_prob is other values than 0.5.

4 - Conclusions

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.

Congratulations for finishing this assignment! And also for revolutionizing French football. :-)

What we want you to remember from this notebook:

- Regularization will help you reduce overfitting.
- Regularization will drive your weights to lower values.
- L2 regularization and Dropout are two very effective regularization techniques.