Regularization - v2

July 20, 2019

1 Regularization

Welcome to the second assignment of this week. Deep Learning models have so much flexibility and capacity that **overfitting can be a serious problem**, if the training dataset is not big enough. Sure it does well on the training set, but the learned network **doesn't generalize to new examples** that it has never seen!

You will learn to: Use regularization in your deep learning models.

Let's first import the packages you are going to use.

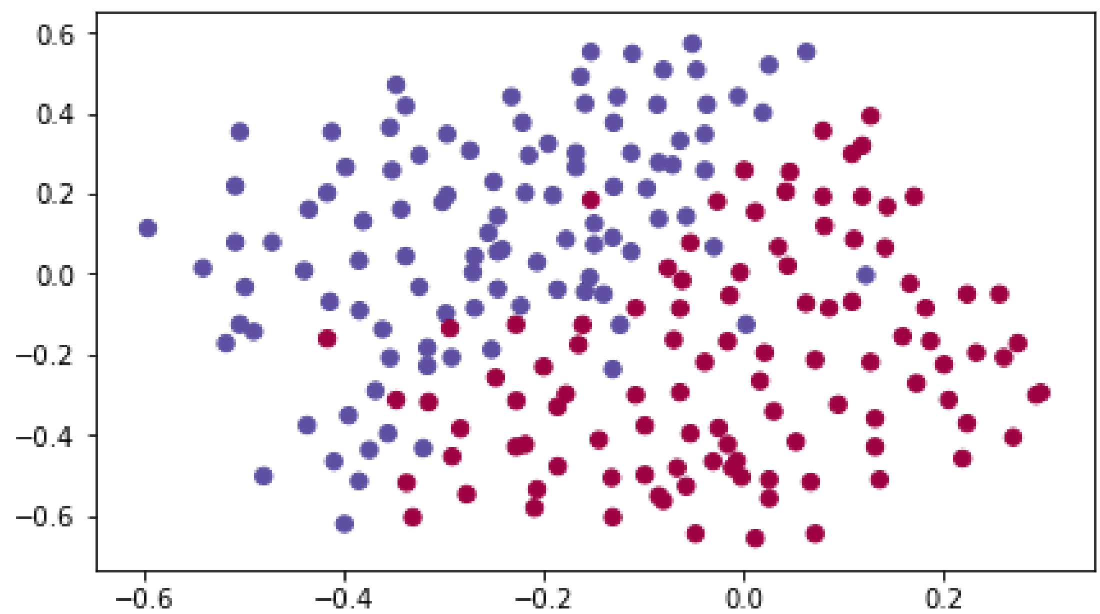
In [1]:
```
# import packages
import numpy as np
import matplotlib.pyplot as plt
from reg_utils import sigmoid, relu, plot_decision_boundary, initialize_parameters, load
from reg_utils import compute_cost, predict, forward_propagation, backward_propagation,
import sklearn
import sklearn.datasets
import 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'
```

Problem Statement: You have just been hired as an AI expert by the French Football Corporation. They would like you to recommend positions where France's goal keeper should kick the ball so that the French team's players can then hit it with their head.

Figure 1 : **Football field** The goal keeper kicks the ball in the air, the players of each team are fighting to hit the ball with their head

They give you the following 2D dataset from France's past 10 games.

In [2]:
```
train_X, train_Y, test_X, test_Y = load_2D_dataset()
```



Each dot corresponds to a position on the football field where a football player has hit the ball with his/her head after the French goal keeper has shot the ball from the left side of the football field. - If the dot is blue, it means the French player managed to hit the ball with his/her head - If the dot is red, it means the other team's player hit the ball with their head

Your goal: Use a deep learning model to find the positions on the field where the goalkeeper should kick the ball.

Analysis of the dataset: This dataset is a little noisy, but it looks like a diagonal line separating the upper left half (blue) from the lower right half (red) would work well.

You will first try a non-regularized model. Then you'll learn how to regularize it and decide which model you will choose to solve the French Football Corporation's problem.

1.1 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 [3]: def model(X, Y, learning_rate = 0.3, num_iterations = 30000, print_cost = True, lambd =
            """
            Implements a three-layer neural network: LINEAR->RELU->LINEAR->RELU->LINEAR->SIGMOID
```

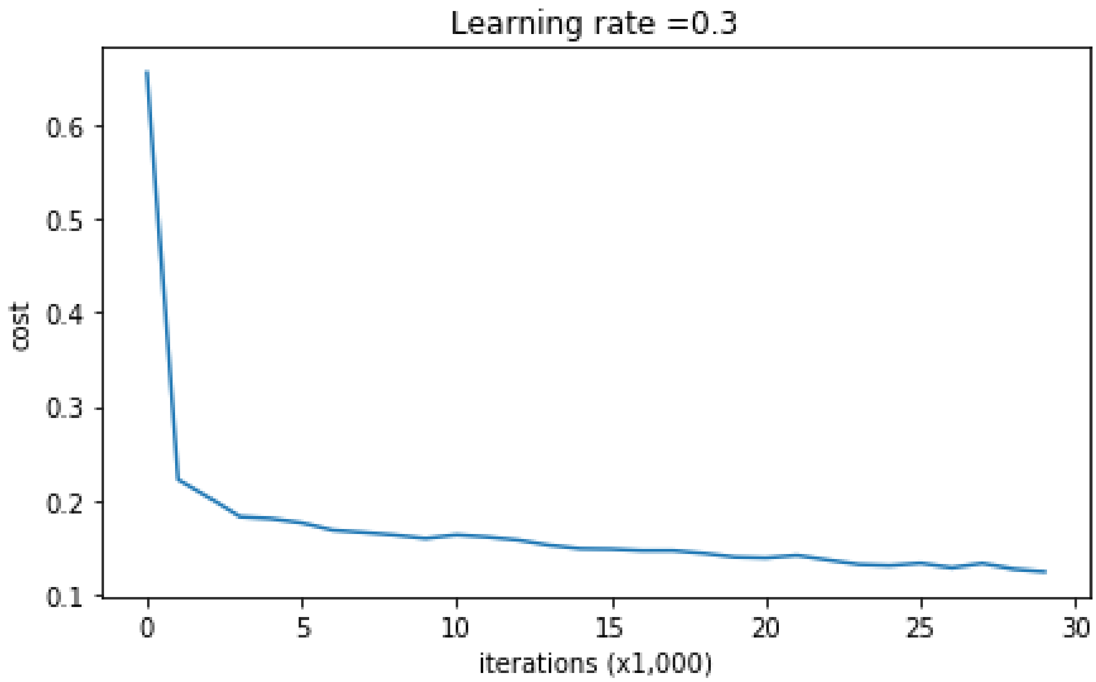
```python
    Arguments:
    X -- input data, of shape (input size, number of examples)
    Y -- true "label" vector (1 for blue dot / 0 for red dot), of shape (output size, nu
    learning_rate -- learning rate of the optimization
    num_iterations -- number of iterations of the optimization loop
    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 regularizati
                                            # but this assignment will only explore one
        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 [4]: 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: 0.16329987525724213
Cost after iteration 20000: 0.13851642423253263
```




```
On the training set:
Accuracy: 0.947867298578
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 [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)
```