```
# Package imports
import numpy as np
import matplotlib.pyplot as plt
from testCases import *
import sklearn
import sklearn.datasets
import sklearn.linear_model
from planar_utils import plot_decision_boundary, sigmoid, load_planar_dataset, load_extra_datasets

%matplotlib inline

np.random.seed(1) # set a seed so that the results are consistent
```

```
X, Y = load_planar_dataset()
```

```
# Visualize the data:
#plt.scatter(X[0, :], X[1, :], c=Y, s=40, cmap=plt.cm.Spectral);
```

```
### START CODE HERE ### (≈ 3 lines of code)
shape_X = X.shape
shape_Y = Y.shape
m = shape_X[1]       # training set size
### END CODE HERE ###

#print ('The shape of X is: ' + str(shape_X))
#print ('The shape of Y is: ' + str(shape_Y))
#print ('I have m = %d training examples!' % (m))
```

Simple Logistic Regression

```
# Train the logistic regression classifier
#clf = sklearn.linear_model.LogisticRegressionCV();
#clf.fit(X.T, Y.T);
```

```
# Plot the decision boundary for logistic regression
#plot_decision_boundary(lambda x: clf.predict(x), X, Y)
#plt.title("Logistic Regression")

# Print accuracy
#LR_predictions = clf.predict(X.T)
#print ('Accuracy of logistic regression: %d ' % float((np.dot(Y,LR_predictions) + np.dot(1-Y,1-LR_prediction
#       '% ' + "(percentage of correctly labelled datapoints)")
```

Defining Neural Network Structure

```
# GRADED FUNCTION: layer_sizes

def layer_sizes(X, Y):
    """
    Arguments:
    X -- input dataset of shape (input size, number of examples)
    Y -- labels of shape (output size, number of examples)

    Returns:
    n_x -- the size of the input layer
    n_h -- the size of the hidden layer
    n_y -- the size of the output layer
    """
    ### START CODE HERE ### (≈ 3 lines of code)
    n_x = X.shape[0] # size of input layer
    n_h = 4
    n_y = Y.shape[0] # size of output layer
    ### END CODE HERE ###
    return (n_x, n_h, n_y)
```

```
#X_assess, Y_assess = layer_sizes_test_case()
#(n_x, n_h, n_y) = layer_sizes(X_assess, Y_assess)
#print("The size of the input layer is: n_x = " + str(n_x))
#print("The size of the hidden layer is: n_h = " + str(n_h))
#print("The size of the output layer is: n_y = " + str(n_y))
```

```
# GRADED FUNCTION: initialize_parameters

def initialize_parameters(n_x, n_h, n_y):
    """
    Argument:
    n_x -- size of the input layer
    n_h -- size of the hidden layer
    n_y -- size of the output layer

    Returns:
    params -- python dictionary containing your parameters:
                    W1 -- weight matrix of shape (n_h, n_x)
                    b1 -- bias vector of shape (n_h, 1)
                    W2 -- weight matrix of shape (n_y, n_h)
                    b2 -- bias vector of shape (n_y, 1)
    """

    np.random.seed(2) # we set up a seed so that your output matches ours although the initialization is rand

    ### START CODE HERE ### (≈ 4 lines of code)
    W1 = np.random.randn(n_h, n_x) * 0.01
    b1 = np.zeros(shape=(n_h, 1))
    W2 = np.random.randn(n_y, n_h) * 0.01
    b2 = np.zeros(shape=(n_y, 1))
    ### END CODE HERE ###

    assert (W1.shape == (n_h, n_x))
    assert (b1.shape == (n_h, 1))
    assert (W2.shape == (n_y, n_h))
    assert (b2.shape == (n_y, 1))

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

```
#n_x, n_h, n_y = initialize_parameters_test_case()

#parameters = initialize_parameters(n_x, n_h, n_y)
#print("W1 = " + str(parameters["W1"]))
#print("b1 = " + str(parameters["b1"]))
#print("W2 = " + str(parameters["W2"]))
#print("b2 = " + str(parameters["b2"]))
```

```
# GRADED FUNCTION: forward_propagation

def forward_propagation(X, parameters):
    """
    Argument:
    X -- input data of size (n_x, m)
    parameters -- python dictionary containing your parameters (output of initialization function)

    Returns:
    A2 -- The sigmoid output of the second activation
    cache -- a dictionary containing "Z1", "A1", "Z2" and "A2"
    """
    # Retrieve each parameter from the dictionary "parameters"
    ### START CODE HERE ### (≈ 4 lines of code)
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    ### END CODE HERE ###

    # Implement Forward Propagation to calculate A2 (probabilities)
    ### START CODE HERE ### (≈ 4 lines of code)
    Z1 = np.dot(W1, X) + b1
    A1 = np.tanh(Z1)
    Z2 = np.dot(W2, A1) + b2
    A2 = sigmoid(Z2)
    ### END CODE HERE ###

    assert(A2.shape == (1, X.shape[1]))

    cache = {"Z1": Z1,
             "A1": A1,
             "Z2": Z2,
             "A2": A2}

    return A2, cache
```

```
#X_assess, parameters = forward_propagation_test_case()

#A2, cache = forward_propagation(X_assess, parameters)

# Note: we use the mean here just to make sure that your output matches ours.
#print(np.mean(cache['Z1']) ,np.mean(cache['A1']),np.mean(cache['Z2']),np.mean(cache['A2']))
```

```
# GRADED FUNCTION: compute_cost

def compute_cost(A2, Y, parameters):
    """
    Computes the cross-entropy cost given in equation (13)
    Arguments:
    A2 -- The sigmoid output of the second activation, of shape (1, number of examples)
    Y -- "true" labels vector of shape (1, number of examples)
    parameters -- python dictionary containing your parameters W1, b1, W2 and b2

    Returns:
    cost -- cross-entropy cost given equation (13)
    """

    m = Y.shape[1] # number of example

    # Compute the cross-entropy cost
    ### START CODE HERE ### (≈ 2 lines of code)
    logprobs = np.dot(Y, np.log(A2).T) + np.dot(1 - Y, np.log(1 - A2).T)
    cost = np.float64(-logprobs / m)
    ### END CODE HERE ###
    # use directly np.dot())
    # cost=-(np.dot(Y,np.log(A2.T))+np.dot(np.log(1-A2),(1-Y).T))/m

    cost = np.squeeze(cost)     # makes sure cost is the dimension we expect.
                                # E.g., turns [[17]] into 17
    #assert(isinstance(cost, float))

    return cost
```

```
#A2, Y_assess, parameters = compute_cost_test_case()

#print("cost = " + str(compute_cost(A2, Y_assess, parameters)))
```

```
# GRADED FUNCTION: backward_propagation

def backward_propagation(parameters, cache, X, Y):
    """
    Implement the backward propagation using the instructions above.

    Arguments:
    parameters -- python dictionary containing our parameters
    cache -- a dictionary containing "Z1", "A1", "Z2" and "A2".
    X -- input data of shape (2, number of examples)
    Y -- "true" labels vector of shape (1, number of examples)

    Returns:
    grads -- python dictionary containing your gradients with respect to different parameters
    """
    m = X.shape[1]

    # First, retrieve W1 and W2 from the dictionary "parameters".
    ### START CODE HERE ### (≈ 2 lines of code)
    W1 = parameters['W1']
    W2 = parameters['W2']
    ### END CODE HERE ###

    # Retrieve also A1 and A2 from dictionary "cache".
    ### START CODE HERE ### (≈ 2 lines of code)
    A1 = cache['A1']
    A2 = cache['A2']
    ### END CODE HERE ###

    # Backward propagation: calculate dW1, db1, dW2, db2.
    ### START CODE HERE ### (≈ 6 lines of code, corresponding to 6 equations on slide above)
    dZ2 = A2 - Y
    dW2 = np.dot(dZ2, A1.T) / m
    db2 = np.sum(dZ2, axis=1, keepdims=True) / m
    dZ1 = np.dot(W2.T, dZ2) * (1 - np.power(A1, 2))
    dW1 = np.dot(dZ1, X.T) / m
    db1 = np.sum(dZ1, axis=1, keepdims=True) / m
    ### END CODE HERE ###

    grads = {"dW1": dW1,
             "db1": db1,
             "dW2": dW2,
             "db2": db2}

    return grads
```

```
#parameters, cache, X_assess, Y_assess = backward_propagation_test_case()

#grads = backward_propagation(parameters, cache, X_assess, Y_assess)
#print ("dW1 = "+ str(grads["dW1"]))
#print ("db1 = "+ str(grads["db1"]))
#print ("dW2 = "+ str(grads["dW2"]))
#print ("db2 = "+ str(grads["db2"]))
```

```
# GRADED FUNCTION: update_parameters

def update_parameters(parameters, grads, learning_rate = 1.2):
    """
    Updates parameters using the gradient descent update rule given above

    Arguments:
    parameters -- python dictionary containing your parameters
    grads -- python dictionary containing your gradients

    Returns:
    parameters -- python dictionary containing your updated parameters
    """
    # Retrieve each parameter from the dictionary "parameters"
    ### START CODE HERE ### (≈ 4 lines of code)
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    ### END CODE HERE ###

    # Retrieve each gradient from the dictionary "grads"
    ### START CODE HERE ### (≈ 4 lines of code)
    dW1 = grads['dW1']
    db1 = grads['db1']
    dW2 = grads['dW2']
    db2 = grads['db2']
    ## END CODE HERE ###

    # Update rule for each parameter
    ### START CODE HERE ### (≈ 4 lines of code)
    W1 = W1 - learning_rate * dW1
    b1 = b1 - learning_rate * db1
    W2 = W2 - learning_rate * dW2
    b2 = b2 - learning_rate * db2
    ### END CODE HERE ###

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

```
#parameters, grads = update_parameters_test_case()
#parameters = update_parameters(parameters, grads)

#print("W1 = " + str(parameters["W1"]))
#print("b1 = " + str(parameters["b1"]))
#print("W2 = " + str(parameters["W2"]))
#print("b2 = " + str(parameters["b2"]))
```

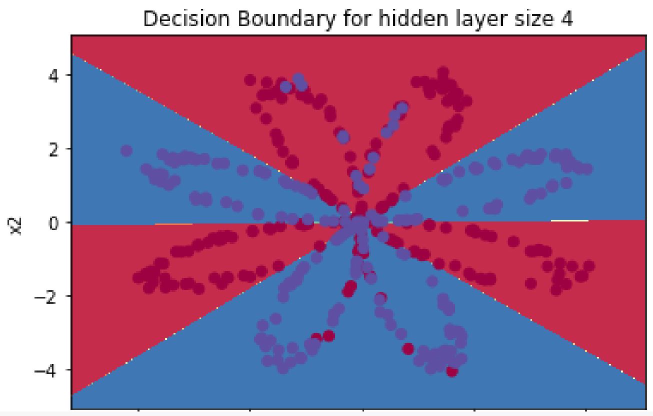
```
# GRADED FUNCTION: nn_model

def nn_model(X, Y, n_h, num_iterations = 10000, print_cost=False):
    """
    Arguments:
    X -- dataset of shape (2, number of examples)
    Y -- labels of shape (1, number of examples)
    n_h -- size of the hidden layer
    num_iterations -- Number of iterations in gradient descent loop
    print_cost -- if True, print the cost every 1000 iterations

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

    np.random.seed(3)
    n_x = layer_sizes(X, Y)[0]
    n_y = layer_sizes(X, Y)[2]

    # Initialize parameters, then retrieve W1, b1, W2, b2. Inputs: "n_x, n_h, n_y". Outputs = "W1, b1, W2, b2
    ### START CODE HERE ### (≈ 5 lines of code)
    parameters = initialize_parameters(n_x, n_h, n_y)
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    ### END CODE HERE ###

    # Loop (gradient descent)

    for i in range(0, num_iterations):

        ### START CODE HERE ### (≈ 4 lines of code)
        # Forward propagation. Inputs: "X, parameters". Outputs: "A2, cache".
        A2, cache = forward_propagation(X, parameters)

        # Cost function. Inputs: "A2, Y, parameters". Outputs: "cost".
        cost = compute_cost(A2, Y, parameters)

        # Backpropagation. Inputs: "parameters, cache, X, Y". Outputs: "grads".
        grads = backward_propagation(parameters, cache, X, Y)
        # Gradient descent parameter update. Inputs: "parameters, grads". Outputs: "parameters".
        parameters = update_parameters(parameters, grads)

        ### END CODE HERE ###

        # Print the cost every 1000 iterations
        if print_cost and i % 1000 == 0:
            print ("Cost after iteration %i: %f" %(i, cost))

    return parameters
```

```
#X_assess, Y_assess = nn_model_test_case()

#parameters = nn_model(X_assess, Y_assess, 4, num_iterations=10000, print_cost=False)
#print("W1 = " + str(parameters["W1"]))
#print("b1 = " + str(parameters["b1"]))
#print("W2 = " + str(parameters["W2"]))
#print("b2 = " + str(parameters["b2"]))
```

```
# GRADED FUNCTION: predict

def predict(parameters, X):
    """
    Using the learned parameters, predicts a class for each example in X

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

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

    # Computes probabilities using forward propagation, and classifies to 0/1 using 0.5 as the threshold.
    ### START CODE HERE ### (≈ 2 lines of code)
    A2, cache = forward_propagation(X, parameters)
    predictions = np.round(A2)
    ### END CODE HERE ###

    return predictions
```

```
#parameters, X_assess = predict_test_case()

#predictions = predict(parameters, X_assess)
#print("predictions mean = " + str(np.mean(predictions)))
```

```
# Build a model with a n_h-dimensional hidden layer
parameters = nn_model(X, Y, n_h = 4, num_iterations = 10000, print_cost=True)

# Plot the decision boundary
plot_decision_boundary(lambda x: predict(parameters, x.T), X, Y)
plt.title("Decision Boundary for hidden layer size " + str(4))
print ('Accuracy: %d' % float((np.dot(Y,predictions.T) + np.dot(1-Y,1-predictions.T))/float(Y.size)*100) + '%
     Cost after iteration 0: 0.693048
     Cost after iteration 1000: 0.288083
     Cost after iteration 2000: 0.254385
     Cost after iteration 3000: 0.233864
     Cost after iteration 4000: 0.226792
     Cost after iteration 5000: 0.222644
     Cost after iteration 6000: 0.219731
     Cost after iteration 7000: 0.217504
     Cost after iteration 8000: 0.219425
     Cost after iteration 9000: 0.218550
     Accuracy: 67%
```



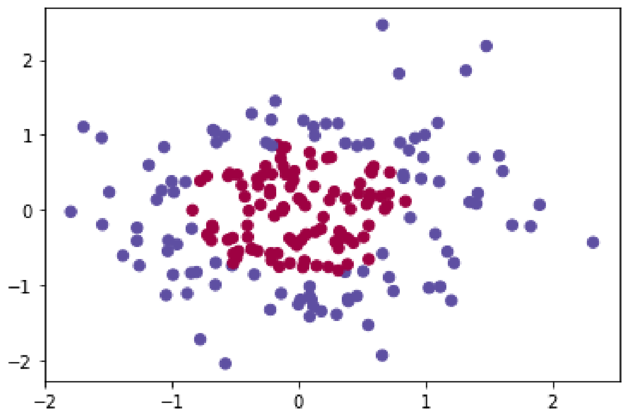
```
# Print accuracy
predictions = predict(parameters, X)
print ('Accuracy: %d' % float((np.dot(Y,predictions.T) + np.dot(1-Y,1-predictions.T))/float(Y.size)*100) + '%
```

```
Accuracy: 90%
```

```
# This may take about 2 minutes to run

plt.figure(figsize=(16, 32))
hidden_layer_sizes = [1]
for i, n_h in enumerate(hidden_layer_sizes):
    plt.subplot(5, 2, i+1)
    plt.title('Hidden Layer of size %d' % n_h)
    parameters = nn_model(X, Y, n_h, num_iterations = 5000)
    plot_decision_boundary(lambda x: predict(parameters, x.T), X, Y)
    predictions = predict(parameters, X)
    accuracy = float((np.dot(Y,predictions.T) + np.dot(1-Y,1-predictions.T))/float(Y.size)*100)
    print ("Accuracy for {} hidden units: {} %".format(n_h, accuracy))
```

```
Accuracy for 1 hidden units: 67.5 %
```

```
# Datasets
noisy_circles, noisy_moons, blobs, gaussian_quantiles, no_structure = load_extra_datasets()

datasets = {"noisy_circles": noisy_circles,
            "noisy_moons": noisy_moons,
            "blobs": blobs,
            "gaussian_quantiles": gaussian_quantiles}

### START CODE HERE ### (choose your dataset)
dataset = "gaussian_quantiles"
### END CODE HERE ###

X, Y = datasets[dataset]
X, Y = X.T, Y.reshape(1, Y.shape[0])

# make blobs binary
if dataset == "blobs":
    Y = Y%2

# Visualize the data
plt.scatter(X[0, :], X[1, :], c=Y, s=40, cmap=plt.cm.Spectral);
```



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