

In [1]: # Seyun Kim  
# ECE472 Deep Learning Homework 2

In [2]: '''  
Number of samples: 1000  
iterations: 5000  
learning\_rate = 0.4  
layers = [2, 30, 40, 30, 1]  
  
First I used tanh as my activation function but changed to a sigmoid as I thought it might be easier for me to work on. Still,  
I could have used tanh as activation function and pass its outcome to sigmoid to get a result that ranges from 0 to 1.  
  
I first tried 1000 examples, 100 iterations, layers of [2 20 30 20 1] and 0.1 learning\_rate. The result was about 50-60%  
correct data labels. For better accuracy, I tried changing the layers, examples but the loss didn't decrease as much.  
Then, I figured that the number of iterations were too small so I increased it to 1000 and the layer to [2 20 30 40 30 1]. The  
result was better but not good enough so I increased the number of iterations to 5000. The result is shown below. Among anything else,  
the number of iterations affected the accuracy the most.  
'''

Out[2]: "\nNumber of samples: 1000\niterations: 5000\nlearning\_rate = 0.4\nlayers = [2, 30, 40, 30, 1]\n\nFirst I used tanh as my activation function but changed to a sigmoid as I thought it might be easier for me to work on. Still,\nI could have used tanh as activation function and pass its outcome to sigmoid to get a result that ranges from 0 to 1. \n\nI first tried 1000 examples, 100 iterations, layers of [2 20 30 20 1] and 0.1 learning\_rate. The result was about 50-60% \nincorrect data labels. For better accuracy, I tried changing the layers, examples but the loss didn't decrease as much. \nThen, I figured that the number of iterations were too small so I increased it to 1000 and the layer to [2 20 30 40 30 1]. The \nresult was better but not good enough so I increased the number of iterations to 5000. The result is shown below. Among anything else,\nthe number of iterations affected the accuracy the most.\n"

In [3]: import numpy as np  
import tensorflow as tf  
import matplotlib.pyplot as plt  
from matplotlib import cm

In [4]: # Parameters  
N = 500  
iterations = 5000  
learning\_rate = 0.4  
layers = [2, 30, 40, 30, 1]

In [5]: # Data generation  
def twospirals(n\_points):  
 n = np.sqrt(np.random.rand(n\_points,1)) \* 600 \* (2\*np.pi)/360  
 dlx = -np.cos(n)\*n + np.random.rand(n\_points,1) \* np.random.rand()  
 dly = np.sin(n)\*n + np.random.rand(n\_points,1) \* np.random.rand()  
 return (np.vstack((np.hstack((dlx,dly)),np.hstack((-dlx,-dly)))),  
 np.hstack((np.zeros(n\_points),np.ones(n\_points))))

In [6]: # Data generated  
# x: [2\*N, 2]  
# y: [2\*N, 1]  
x, y = twospirals(N)

In [7]: y\_target = y.reshape([-1,1])

In [8]: # Model parameter  
w = {}  
b = {}  
l2w = {}  
l2b = {}  
l2 = {}  
l2norm = 0  
#Initializing weights and biases according to the layers and computing their L2 norm  
for i in range(0, len(layers)-1):  
 w[i] = tf.Variable(tf.random.normal([layers[i], layers[i+1]], 0, 1, tf.float32))  
 l2w[i] = tf.reduce\_sum(tf.square(w[i]))  
 b[i] = tf.Variable(tf.zeros([layers[i+1], 1]))  
 l2b[i] = tf.reduce\_sum(tf.square(b[i]))  
#Merging L2 norm of weights and biases  
for j in range(0, len(layers)-1):  
 l2norm = l2norm + l2w[j] + l2b[j]  
 j=j+2

In [9]: # Multi-Layer Perceptron model (sigmoid function used)  
def f(inputs, w, b):  
 y\_hat = tf.sigmoid(tf.add(tf.matmul(tf.cast(inputs, tf.float32), w[0]), tf.transpose(b[0])))  
 for i in range(1, len(layers)-1):  
 outputs = tf.add(tf.matmul(tf.cast(y\_hat, tf.float32), w[i]), tf.transpose(b[i])) # z  
 y\_hat = tf.sigmoid(tf.cast(outputs, tf.float32)) # f  
 return y\_hat  
# f: probability of example belonging to spiral 1  
# (1000,1)

In [10]: # BCE loss for one example  
def loss(y\_i, y\_h):  
 return -tf.multiply(tf.cast(y\_i, tf.float32), tf.math.log(y\_h))-tf.multiply((1-tf.cast(y\_i, tf.float32)), tf.math.log(1-y\_h))

In [11]: # BCE average loss and L2 penalty for all examples  
def cost(y\_target, y\_hat, l2norm):  
 return tf.reduce\_mean(loss(tf.cast(y\_target, tf.float32), tf.cast(y\_hat, tf.float32)), 0)+l2norm

In [12]: # Computes derivatives of cost w.r.t to the model parameters and updates them  
# Returns updated weights and biases  
def gparam(x, w, b, y\_target, layers, l2norm, learning\_rate):  
 dC\_dw = {}  
 dC\_db = {}  
 with tf.GradientTape(persistent = True) as g:  
 g.watch(w)  
 g.watch(b)  
 y\_hat = f(x,w,b)  
 c = cost(y\_target, y\_hat, l2norm)  
 dC\_dw = g.gradient(c, w)  
 dC\_db = g.gradient(c, b)  
 W = {}  
 B = {}  
 W[0] = tf.math.subtract(w[0], learning\_rate \* dC\_dw[0])  
 B[0] = tf.math.subtract(b[0], learning\_rate \* dC\_db[0])  
  
 for i in range(1, len(layers)-1):  
 W[i] = tf.math.subtract(w[i], learning\_rate \* dC\_dw[i])  
 B[i] = tf.math.subtract(b[i], learning\_rate \* dC\_db[i])  
  
 '''  
 original function:  
 for i in range(0, len(layers)-1):  
 w[i] = tf.math.subtract(w[i], learning\_rate\*dC\_dw[i])  
 error -> function traced cannot alter the structure of input argument  
 '''  
  
 return W, B

In [13]: @tf.function  
def forward(x, w, b, iterations, y\_target, layers):  
 for i in range(0, iterations):  
 w, b = gparam(x, w, b, y\_target, layers, l2norm, learning\_rate)  
 W = w  
 B = b  
 p\_1 = f(x,w,b)  
 return p\_1, W, B

In [14]: p\_1, W, B = forward(x, w, b, iterations, y\_target, layers)

In [15]: # Data for generating contour  
# Returns true if the possibility of a point belonging to spiral 1 is greater than 0.5 and false otherwise  
@tf.function  
def boundary(new\_x, w, b):  
 return f(new\_x, w, b) > 0.5

In [16]: # Contour Setup  
n\_plot = 600  
xgrid = np.linspace(-3.2\*np.pi, 3.2\*np.pi, n\_plot, dtype = np.float32)  
ygrid = xgrid  
xplot, yplot = np.meshgrid(xgrid,ygrid)  
xx = np.reshape(xplot, (-1,1))  
yy = np.reshape(yplot, (-1,1))  
cont = np.concatenate((xx,yy),1)

In [17]: # Generate contour z-values  
contz = boundary(cont, W, B)

In [18]: #Plot spirals 1 and 2 and contour map  
#If p\_1 is greater than 0.5, mark it spiral 1  
  
plt.figure()  
plt.contourf(xgrid, ygrid, np.reshape(contz,(n\_plot,n\_plot)))  
for i in range(0, 2\*N):  
 if p\_1[i] > 0.5:  
 plt.plot(x[i,0], x[i,1], '.r')  
 else:  
 plt.plot(x[i,0], x[i,1], '.b')  
plt.title("Binary Classification of Spirals")  
plt.xlabel("x")  
plt.ylabel("y")  
plt.legend(("Spiral 1", "Spiral 2"))  
plt.show()

