



PRÁCTICA 4: ENTRENAMIENTO DE REDES NEURONALES

Aprendizaje Automático y Big Data



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1. Código

```
import numpy as np
import scipy.io
import scipy.optimize as opt

def debugInitializeWeights(fan_in, fan_out):
    """
    Initializes the weights of a layer with fan_in incoming connections and
    fan_out outgoing connections using a fixed set of values.
    """

    # Set W to zero matrix
    W = np.zeros((fan_out, fan_in + 1))

    # Initialize W using "sin". This ensures that W is always of the same
    # values and will be useful in debugging.
    W = np.array([np.sin(w) for w in
                   range(np.size(W))]).reshape((np.size(W, 0), np.size(W, 1)))

    return W

def computeNumericalGradient(J, theta):
    """
    Computes the gradient of J around theta using finite differences and
    yields a numerical estimate of the gradient.
    """

    numgrad = np.zeros_like(theta)
```

```
perturb = np.zeros_like(theta)
```

```
tol = 1e-4
```

```
for p in range(len(theta)):
```

```
    # Set perturbation vector
```

```
    perturb[p] = tol
```

```
    loss1 = J(theta - perturb)
```

```
    loss2 = J(theta + perturb)
```

```
    # Compute numerical gradient
```

```
    numgrad[p] = (loss2 - loss1) / (2 * tol)
```

```
    perturb[p] = 0
```

```
return numgrad
```

```
def checkNNGradients(costNN, reg_param):
```

```
    """
```

```
    Creates a small neural network to check the back propogation gradients.
```

```
    Outputs the analytical gradients produced by the back prop code and the
```

```
    numerical gradients computed using the computeNumericalGradient function.
```

```
    These should result in very similar values.
```

```
    """
```

```
    # Set up small NN
```

```
    input_layer_size = 3
```

```
    hidden_layer_size = 5
```

```
    num_labels = 3
```

```
    m = 5
```

```
    # Generate some random test data
```

```

Theta1 = debugInitializeWeights(hidden_layer_size, input_layer_size)
Theta2 = debugInitializeWeights(num_labels, hidden_layer_size)

# Reusing debugInitializeWeights to get random X
X = debugInitializeWeights(input_layer_size - 1, m)

# Set each element of y to be in [0,num_labels]
y = [(i % num_labels) for i in range(m)]

# Unroll parameters
nn_params = np.append(Theta1, Theta2).reshape(-1)

# Compute Cost
cost, grad = costNN(nn_params, input_layer_size, hidden_layer_size, num_labels, X, y,
reg_param)

def reduced_cost_func(p):
    """ Cheaply decorated nnCostFunction """
    return costNN(p, input_layer_size, hidden_layer_size, num_labels,
        X, y, reg_param)[0]

numgrad = computeNumericalGradient(reduced_cost_func, nn_params)

# Check two gradients
np.testing.assert_almost_equal(grad, numgrad)
return (grad - numgrad)

def sigmoide(x):
    return 1/(1+ np.exp(np.negative(x)))

def pesosAleatorios(L_in,L_out):

```

```
ini =0.12
```

```
pesos = np.random.rand((L_in+1)*L_out)*(2*ini) - ini
```

```
pesos = np.reshape(pesos, (L_out,1+L_in))
```

```
return pesos
```

```
def sigmoideDerivada(z):
```

```
    sd = sigmoide(z) * (1 - sigmoide(z));
```

```
    return sd
```

```
def backprop(params_rn, num_entradas, num_ocultas, num_etiquetas, X, y, reg):
```

```
    Theta1 = np.reshape(params_rn[:num_ocultas*(num_entradas+1)],(num_ocultas,  
(num_entradas+1)))
```

```
    Theta2 = np.reshape(params_rn[num_ocultas*(num_entradas+1):],(num_etiquetas,  
(num_ocultas+1)))
```

```
    m = X.shape[0]
```

```
    #Propagacion hacia delante
```

```
    a1 = np.vstack((np.ones(X.shape[0]),X.T))
```

```
    z2=np.matmul(Theta1,a1)
```

```
    a2=sigmoide(z2)
```

```
    a2 = np.vstack((np.ones(a2.shape[1]),a2))
```

```
    z3=np.matmul(Theta2,a2)
```

```
    a3=sigmoide(z3)
```

```
    h = a3
```

```
    etiqueta = np.identity(num_etiquetas)
```

```
    aux = np.array(y)-1
```

```
    ycod = etiqueta[aux,:]
```

```
    J = np.sum((-ycod) *np.log(h).T - (1 - ycod) * np.log(1 - h).T)/m
```

```
    #Regularizacion
```

```
regular = (reg/(2*m))*(np.sum(np.square(Theta1[:,1:]))+np.sum(np.square(Theta2[:,1:])))
```

```
final = J+regular
```

```
#Retro propagacion
```

```
d3 = h.T - ycod
```

```
d2 = np.matmul(Theta2.T,d3.T)[1:,:] *sigmoideDerivada(z2)
```

```
grad1 = np.matmul(d2,a1.T)/m
```

```
grad2 = np.matmul(d3.T,a2.T)/m
```

```
#Regularizacion del gradiente
```

```
reg1= (reg/m) * Theta1[:,1:]
```

```
reg2= (reg/m) * Theta2[:,1:]
```

```
#Regularizacion del gradiente
```

```
fingrad1 = grad1
```

```
fingrad1[:,1:] += reg1
```

```
fingrad2 = grad2
```

```
fingrad2[:,1:] += reg2
```

```
#Fin del gradiente
```

```
aux = np.reshape(fingrad1,fingrad1.shape[0]*fingrad1.shape[1])
```

```
aux2 = np.reshape(fingrad2, fingrad2.shape[0]*fingrad2.shape[1])
```

```
grad =np.concatenate((aux,aux2))
```

```
return final,grad
```

```
def main():
```

```
weights = scipy.io.loadmat('ex4weights.mat')
```

```
data = scipy.io.loadmat('ex4data1.mat')
```

```
theta1, theta2 = weights['Theta1'], weights['Theta2']
```

```

y= data['y']
y= np.reshape(y,y.shape[0])
X= data['X']
num_entradas=400
num_ocultas=25
num_etiquetas=10

aux = np.reshape(theta1,(num_entradas+1)*num_ocultas)
aux2 = np.reshape(theta2,(num_ocultas+1)*num_etiquetas)
aux3 = np.concatenate((aux,aux2))
params_rn=aux3
print("Coste sin regularizar:(lambda=0)")
J=backprop(params_rn,num_entradas,num_ocultas,num_etiquetas,X,y,0)
print(J)
print("Chequeo del gradiente")
print(np.sum(np.abs(checkNNGradients(backprop, 0))))
print("Coste con regularizacion:(lambda=1)")
J=backprop(params_rn,num_entradas,num_ocultas,num_etiquetas,X,y,1)
print(J)
print(np.sum(np.abs(checkNNGradients(backprop,1))))

#Prueba de minimizacion
aleatheta1=pesosAleatorios(num_entradas,num_ocultas)
aleatheta2=pesosAleatorios(num_ocultas,num_etiquetas)
aleat =
np.concatenate((np.reshape(aleatheta1,(num_entradas+1)*num_ocultas),np.reshape(aleatheta
2,(num_ocultas+1)*num_etiquetas)))

sol=opt.minimize(backprop,aleat,args=(400,25,10,X,y,1),jac=True)

print(sol)
main()

```

2. Ejemplo de ejecución

```
Coste sin regularizar:(lambda=0)
(0.2876291651613189, array([ 6.18712766e-05,  0.00000000e+00,
 0.00000000e+00, ...,
        9.66104721e-05, -7.57736846e-04,  7.73329872e-04]))
Chequeo del gradiente
1.058905681888822e-09
Coste con regularizacion:(lambda=1)
(0.38376985909092365, array([ 6.18712766e-05, -2.11248326e-12,
 4.38829369e-13, ...,
        4.70513145e-05, -5.01718610e-04,  5.07825789e-04]))
1.0641309430847734e-09
```