pract5

May 23, 2017

1 Practica 5 - Redes neuronales

1.0.1 Miguel Angel Carvajal

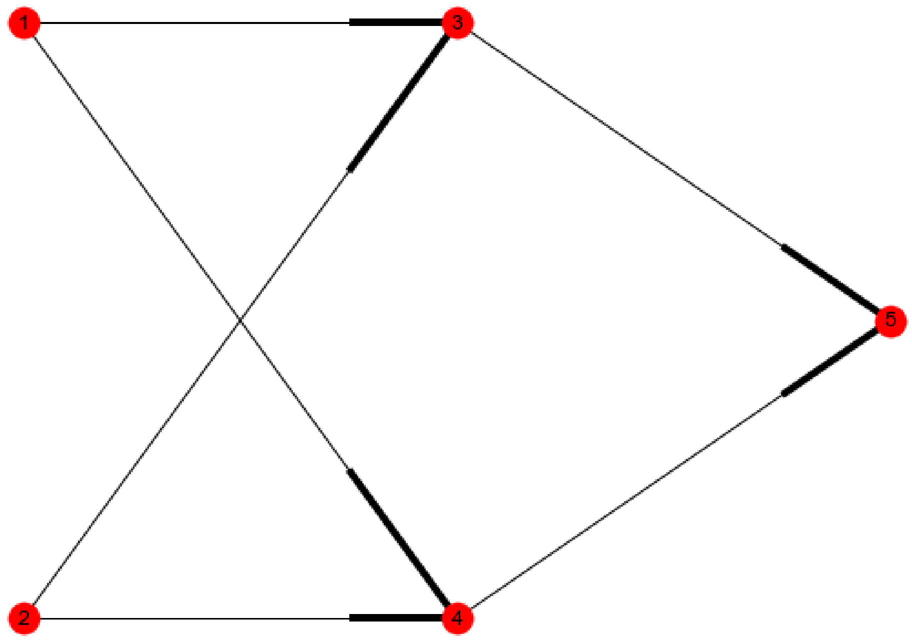
```
In [2]: import networkx as nx
        import matplotlib.pyplot as plt
        import seaborn
        import numpy as np
```

Ejercicio 1 La regla XOR tiene dos entradas (+1 o -1) y la salida es -1 si ambas son diferentes y +1 si ambas son iguales. Utilizar el algoritmo de retropropagación de errores para aprender el XOR en las siguientes arquitecturas (incluir unidades de entrada adicional para simular los umbrales). Comparar el tiempo de convergencia.

1.0.2 Item a

Se propone una red neuronal con la arquitectura siguiente

```
In [159]: G1 = nx.DiGraph()
          layers = ['1','2','3']
          G1.add_nodes_from([1,2],layer='1')
          G1.add_nodes_from([3,4],layer='2')
          G1.add_nodes_from([5],layer='3')
          G1.add_edges_from([(1,3),(2,3),(1,4),(2,4),(3,5),(4,5)])
          pos = {1:(0,1),2:(0,-1),3:(1,1),4:(1,-1),5:(2,0)} # dictionary with posit
          nx.draw(G1, pos= pos)
          nx.draw_networkx_labels(G1,pos)
          plt.show()
```

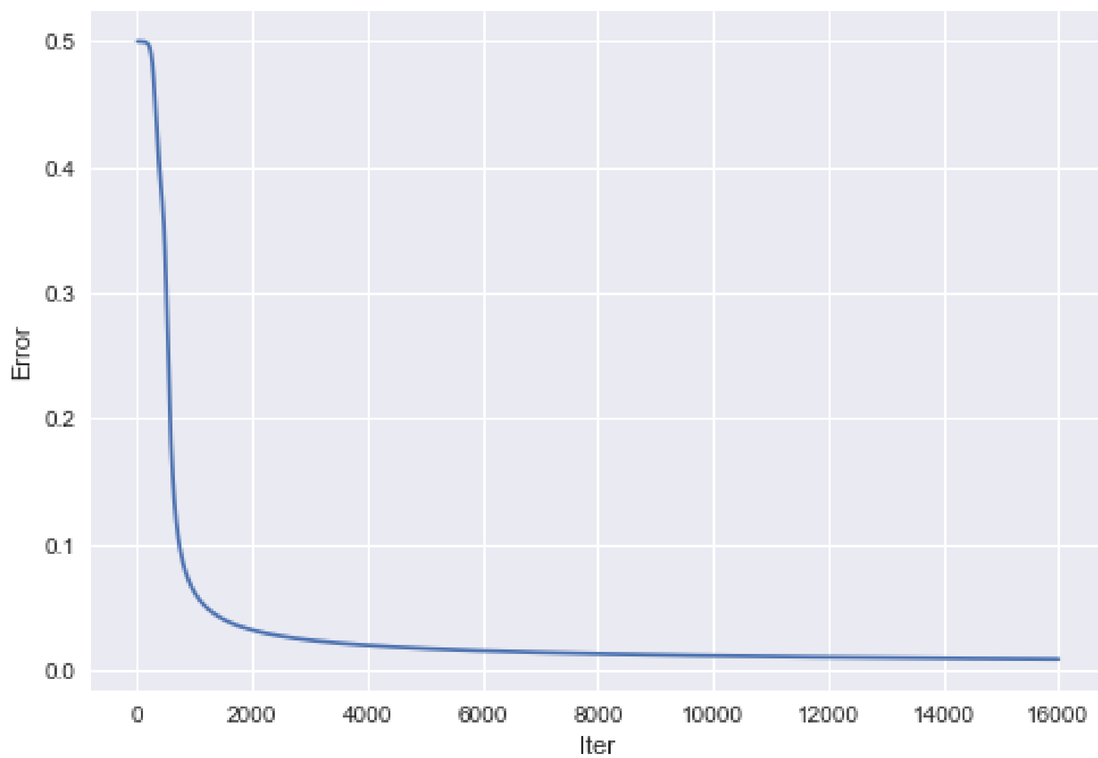


A continuación esta el codigo que construye la arquitectura dada en el item a y aplica el algoritmo de backpropagation para obtener los pesos finales

```
In [75]: def sigmoid(x, deriv = False):
             if deriv:
                 return x*(1-x)
             return 1/(1 + np.exp(-x))


         # input data, first and last are the bias
         D_in  = np.array([[0,0,1],
                          [0,1,1],
                          [1,0,1],
                          [1,1,1]])
         D_out = np.array([[1],[0],[0],[1]])

         np.random.seed(2)

         syn0 = 2*np.random.random((3,3)) - 1
         syn1 = 2*np.random.random((3,1)) - 1

         errors = []
         # training step
         for j in range(16000):
```

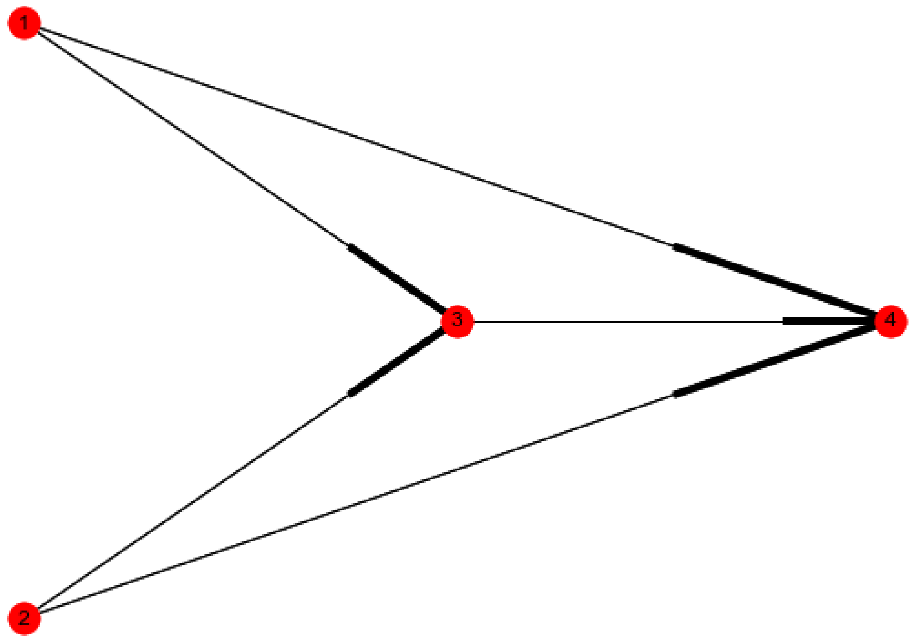
```
        l0 = D_in
        l1 = sigmoid(np.dot(l0, syn0))
        l1[:,2] = l0[:,2]
        l2 = sigmoid(np.dot(l1, syn1))

        l2_error = D_out - l2
        err = str(np.mean(np.abs(l2_error)))
#       if(j % 100) == 0:

#           print ("Error: " + str(err))
        errors.append(err)
        l2_delta = l2_error * sigmoid(l2, deriv = True)
        l1_error = l2_delta.dot(syn1.T)
        l1_delta = l1_error * sigmoid(l1, deriv = True)

        # update weights
        syn1 += l1.T.dot(l2_delta)
        syn0 += l0.T.dot(l1_delta)

    print(l1)
    print(l2)
    print ("weights")
    print (syn0)
    print  (syn1)
    n =  len(errors)
    plt.plot(np.linspace(0,1,n)*n, errors)
    plt.xlabel("Iter")
    plt.ylabel("Error")
    plt.show()
    errors_a = errors
```

```
[[  9.99589432e-01   9.42195616e-01   1.00000000e+00]
 [  9.29048739e-01   2.00316952e-02   1.00000000e+00]
 [  9.28904268e-01   1.98324557e-02   1.00000000e+00]
 [  6.56561897e-02   2.53740931e-05   1.00000000e+00]]
[[ 0.99168132]
 [ 0.00865052]
 [ 0.00864508]
 [ 0.98939733]]
weights
[[-5.22760186 -6.69156809  0.09932496]
 [-5.22541224 -6.68136897 -0.33933036]
 [ 7.79759126  2.79115771 -0.40069065]]
[[-11.00416978]
 [ 11.16790549]
 [  5.25822583]]
```



Item b
La arquitectura del item b esta aparece a continuacion

```
In [155]: G= nx.DiGraph()
          layers = ['1','2','3']
          G.add_nodes_from([1,2],layer='1')
          G.add_nodes_from([3],layer='2')
          G.add_nodes_from([4],layer='3')
          G.add_edges_from([(1,3),(2,3),(3,4),(1,4),(2,4)])
          pos= {1:(0,1),2:(0,-1),3:(1,0),4:(2,0)}
          nx.draw(G, pos= pos)
          nx.draw_networkx_labels(G,pos)
          plt.show()
```



A continuación esta el codigo que construye una red con dicha arquitectura

```
In [74]: # input data
         D_in  = np.array([[0,1,0],
                           [0,1,1],
                           [1,1,0],
                           [1,1,1]])
         D_out = np.array([[0],[1],[1],[0]])

         np.random.seed(1)

         syn0 = 2*np.random.random((3,4)) - 1
         syn1 = 2*np.random.random((4,1)) - 1

         errors = []
         # training step
         for j in range(16000):
             l0 = D_in
             l1 = sigmoid(np.dot(l0, syn0))
             l1[:,0] = l0[:,0]
             l1[:,2] = l0[:,2]
             l1[:,3] = l0[:,1]
             l2 = sigmoid(np.dot(l1, syn1))
             l2_error = D_out - l2
```

```
        if(j % 100) == 0:
            err = np.mean(np.abs(l2_error))
            print "Error: " + str(err)
        errors.append(err)
        l2_delta = l2_error * sigmoid(l2, deriv = True)
        l1_error = l2_delta.dot(syn1.T)
        l1_delta = l1_error* sigmoid(l1, deriv = True)


        # update weights
        syn1 += l1.T.dot(l2_delta)
        #print "l1", l1.shape
        # print "l1_error",l1_error[:,2:3].shape
        # quit()
        #print "sig", sigmoid(l1,de`riv = True).shape
        # print "l1_delta", l1_delta.shape
        #print "shape",l0.shape
        syn0 += l0.T.dot(l1_delta)


    print l2
    print "weights"
    print "Layer1",syn0
    print "Layer2",syn1
    n = len(errors)

    plt.plot(np.linspace(0,1,n)*n, errors)
    plt.xlabel("Iteraciones")
    plt.ylabel("Erorr")
    plt.show()
    errors_b = errors
```

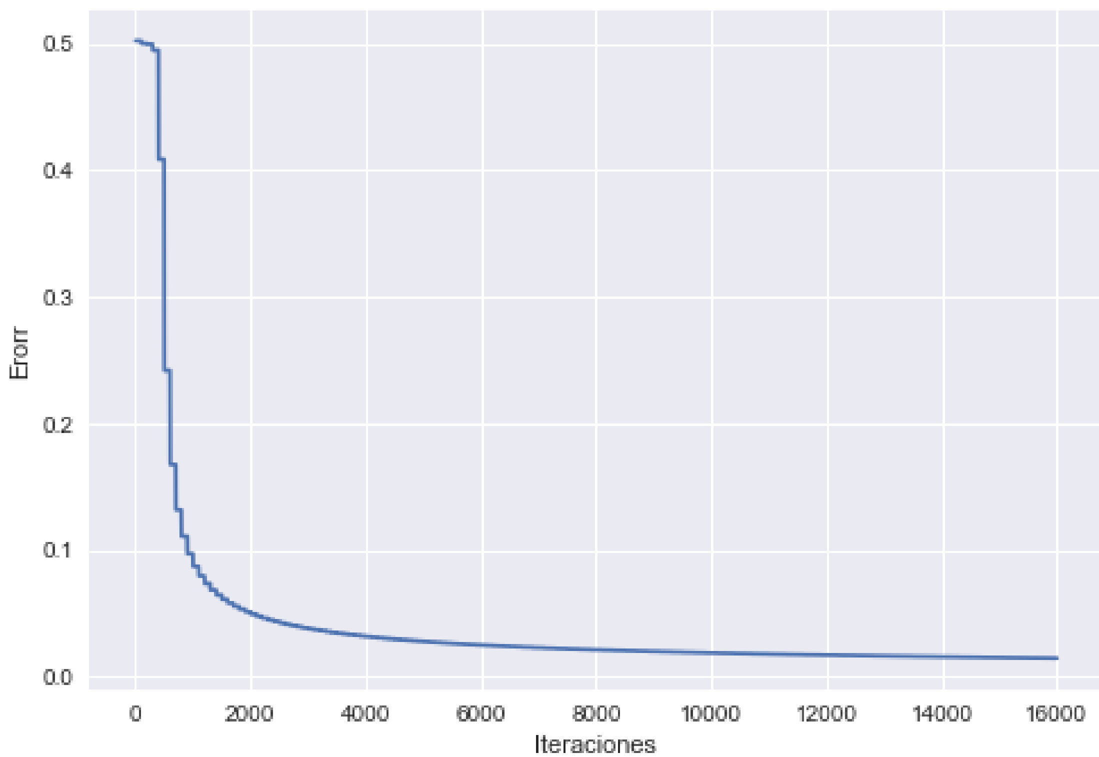
```
Error: 0.502133859242
Error: 0.500014718334
Error: 0.499436851038
Error: 0.494782885212
Error: 0.408672856488
Error: 0.241817242618
Error: 0.167654103848
Error: 0.13191740648
Error: 0.11096993037
Error: 0.0970720265824
Error: 0.0870847471174
Error: 0.0795033241588
Error: 0.0735152615328
Error: 0.068641932285
Error: 0.064582129657
```

```
Error: 0.0611362460942
Error: 0.0581664022481
Error: 0.0555740656466
Error: 0.0532867983923
Error: 0.0512500540225
Error: 0.0494219057095
Error: 0.0477695477913
Error: 0.0462669087241
Error: 0.0448929823564
Error: 0.0436306361444
Error: 0.0424657436767
Error: 0.0413865424489
Error: 0.0403831510902
Error: 0.0394472014124
Error: 0.0385715544384
Error: 0.0377500787233
Error: 0.0369774754835
Error: 0.0362491393164
Error: 0.0355610462781
Error: 0.034909663204
Error: 0.0342918736783
Error: 0.0337049171653
Error: 0.0331463386313
Error: 0.0326139465895
Error: 0.0321057779571
Error: 0.031620068458
Error: 0.0311552275679
Error: 0.0307098172023
Error: 0.0302825335055
Error: 0.0298721912226
Error: 0.0294777102323
Error: 0.0290981038985
Error: 0.0287324689565
Error: 0.0283799767018
Error: 0.0280398652876
Error: 0.0277114329707
Error: 0.0273940321711
Error: 0.0270870642312
Error: 0.0267899747812
Error: 0.0265022496275
Error: 0.026223411098
Error: 0.0259530147845
Error: 0.0256906466321
Error: 0.0254359203335
Error: 0.0251884749907
Error: 0.0249479730132
Error: 0.0247140982232
Error: 0.0244865541463
```

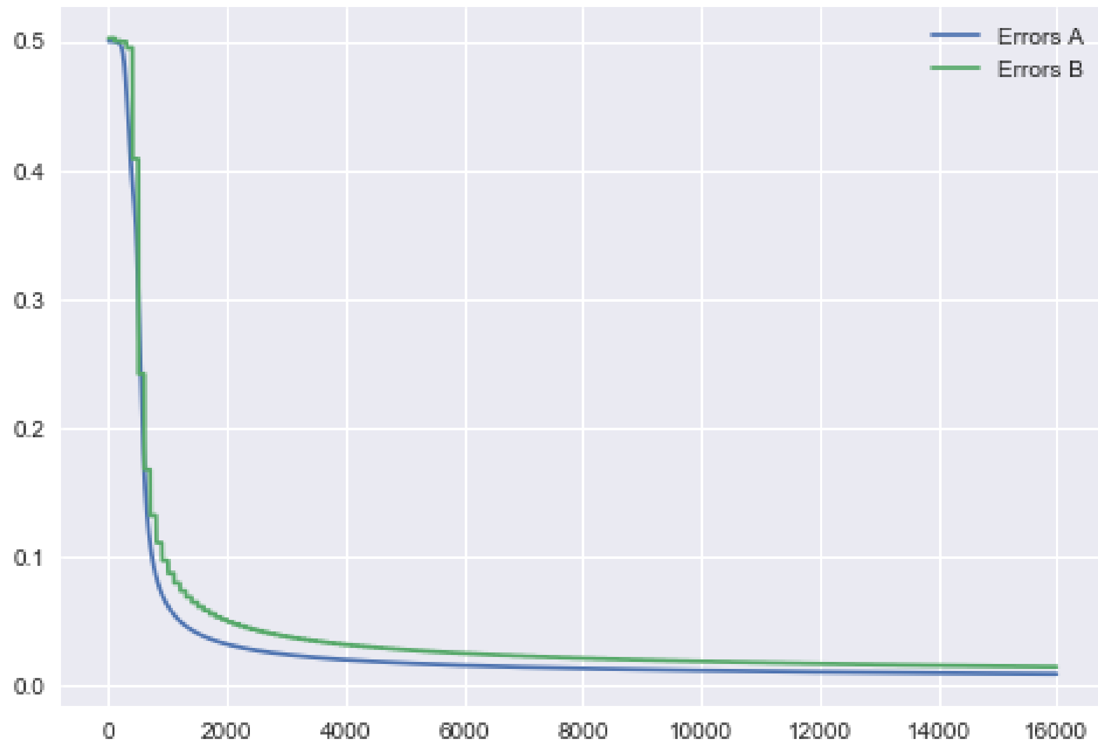
```
Error: 0.0242650624654
Error: 0.0240493616196
Error: 0.0238392055334
Error: 0.023634362461
Error: 0.0234346139339
Error: 0.0232397538021
Error: 0.0230495873574
Error: 0.0228639305321
Error: 0.0226826091652
Error: 0.0225054583291
Error: 0.0223323217115
Error: 0.0221630510467
Error: 0.0219975055924
Error: 0.0218355516475
Error: 0.0216770621063
Error: 0.0215219160474
Error: 0.0213699983535
Error: 0.0212211993585
Error: 0.0210754145212
Error: 0.0209325441223
Error: 0.0207924929829
Error: 0.0206551702026
Error: 0.0205204889163
Error: 0.0203883660673
Error: 0.0202587221955
Error: 0.0201314812407
Error: 0.0200065703577
Error: 0.0198839197447
Error: 0.0197634624816
Error: 0.0196451343795
Error: 0.0195288738394
Error: 0.0194146217195
Error: 0.0193023212114
Error: 0.0191919177227
Error: 0.0190833587676
Error: 0.0189765938641
Error: 0.0188715744366
Error: 0.0187682537244
Error: 0.018666586696
Error: 0.018566529968
Error: 0.0184680417279
Error: 0.0183710816628
Error: 0.0182756108901
Error: 0.0181815918941
Error: 0.0180889884641
Error: 0.0179977656372
Error: 0.0179078896437
Error: 0.017819327855
```

```
Error: 0.0177320487353
Error: 0.0176460217941
Error: 0.0175612175431
Error: 0.0174776074538
Error: 0.0173951639181
Error: 0.0173138602102
Error: 0.0172336704512
Error: 0.0171545695745
Error: 0.0170765332938
Error: 0.0169995380719
Error: 0.0169235610916
Error: 0.0168485802273
Error: 0.0167745740189
Error: 0.0167015216456
Error: 0.0166294029025
Error: 0.0165581981768
Error: 0.0164878884258
Error: 0.0164184551563
Error: 0.0163498804036
Error: 0.0162821467131
Error: 0.0162152371214
Error: 0.0161491351387
Error: 0.0160838247323
Error: 0.01601929031
Error: 0.0159555167051
Error: 0.0158924891615
Error: 0.0158301933193
Error: 0.0157686152017
Error: 0.0157077412016
Error: 0.0156475580692
Error: 0.0155880529003
Error: 0.0155292131247
Error: 0.015471026495
Error: 0.0154134810762
Error: 0.0153565652356
Error: 0.015300267633
Error: 0.0152445772112
Error: 0.0151894831873
Error: 0.0151349750435
Error: 0.0150810425196
Error: 0.0150276756041
Error: 0.014974864527
Error: 0.0149225997526
Error: 0.0148708719715
Error: 0.0148196720947
Error: 0.0147689912464
Error: 0.0147188207577
Error: 0.0146691521606
```

```
Error: 0.0146199771818
[[ 0.01550166]
 [ 0.9834097 ]
 [ 0.988201  ]
 [ 0.01439614]]
weights
Layer1 [[-0.16595599  8.29854581 -0.99977125 -0.39533485]
 [-0.70648822 -4.57663776 -0.62747958 -0.30887855]
 [-0.20646505 -8.56801613 -0.16161097  0.370439  ]]
Layer2 [[ -8.44593458]
 [ 17.62065808]
 [  8.41288618]
 [ -4.33067915]]
```




```
In [76]: n = len(errors_a)
         iterations = np.linspace(0,1,n)*n
         plt.plot(iterations, errors_a, label="Errors A")
         plt.plot(iterations, errors_b, label="Errors B" )
         plt.legend()
         plt.show()
```



1.0.3 Problema 2

El problema de paridad es una generalización del XOR para N entradas. La salida es +1 si el producto de las N entradas es +1 y -1 si el producto de las entradas es -1. Utilizando retropropagación aprender el problema en la siguiente arquitectura. Que pasa si $N' < N$?

In [87]:
```
N1 = 50
N2  = 60

p = 20 # number of test cases
np.random.seed(1)
# input data, first and last are the bias
D_in  = 2*np.random.randint(0,2,(p,N1)) - 1
D_out = np.empty((p,1))

for i in range(p):
    D_out[i] = (np.prod(D_in[i,:]) + 1)/2

syn0 = 2*np.random.random((N1,N2)) - 1
syn1 = 2*np.random.random((N2,1)) - 1

# training step
for j in range(3000):
```

```
        l0 = D_in
        l1 = sigmoid(np.dot(l0, syn0))
        l2 = sigmoid(np.dot(l1, syn1))
        l2_error = D_out - l2
        if(j % 100) == 0:
            print "Error: " + str(np.mean(np.abs(l2_error)))
        l2_delta = l2_error * sigmoid(l2, deriv = True)
        l1_error = l2_delta.dot(syn1.T)
        l1_delta = l1_error * sigmoid(l1, deriv = True)
        # update weights
        syn1 += l1.T.dot(l2_delta)
        syn0 += l0.T.dot(l1_delta)
    def cleanup(x):
        if (x < 0.1): return 0
        if (x > 0.9): return 1
    f= np.vectorize(cleanup)
    print(f(l2))
    print(D_out)
```

```
Error: 0.471123734219
Error: 0.00241236336049
Error: 0.00206176430508
Error: 0.00188884124559
Error: 0.00177151069056
Error: 0.00168306434654
Error: 0.0016126597167
Error: 0.00155459769209
Error: 0.00150546783753
Error: 0.00146306343261
Error: 0.00142587807335
Error: 0.00139284161106
Error: 0.00136316964244
Error: 0.0013362723589
Error: 0.00131169670176
Error: 0.00128908824999
Error: 0.00126816531922
Error: 0.00124870089318
Error: 0.00123050973318
Error: 0.00121343900027
Error: 0.00119736131471
Error: 0.00118216954017
Error: 0.00116777280998
Error: 0.00115409346206
Error: 0.00114106464796
Error: 0.00112862844847
Error: 0.00111673437448
Error: 0.00110533816373
Error: 0.00109440080729
```

```
Error: 0.00108388775596
[[0]
 [1]
 [0]
 [0]
 [1]
 [0]
 [1]
 [1]
 [0]
 [0]
 [0]
 [0]
 [1]
 [1]
 [0]
 [1]
 [1]
 [1]
 [1]
 [0]]
[[ 0.000]
 [ 1.000]
 [ 0.000]
 [ 0.000]
 [ 1.000]
 [ 0.000]
 [ 1.000]
 [ 1.000]
 [ 0.000]
 [ 0.000]
 [ 0.000]
 [ 0.000]
 [ 1.000]
 [ 1.000]
 [ 0.000]
 [ 1.000]
 [ 1.000]
 [ 1.000]
 [ 1.000]
 [ 0.000]]
```

Para N′ < N no se observó ningun cambio en la respuesta de la red.

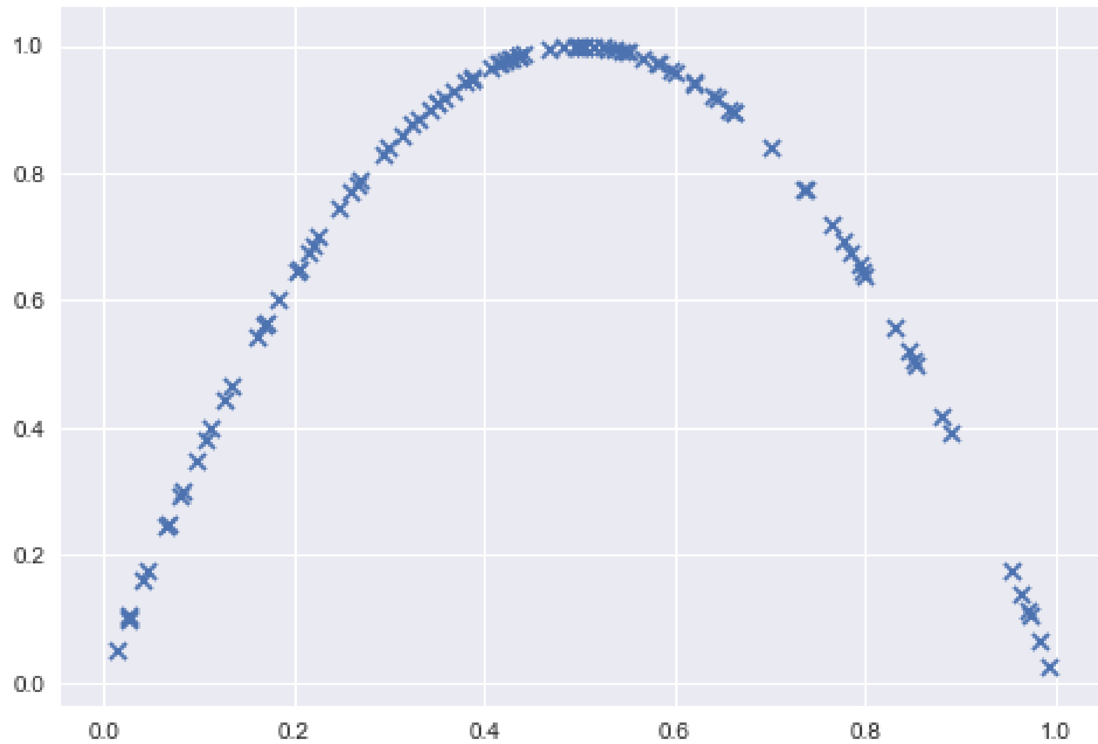
1.0.4 Problema 3

Aprender utilizando retropropagación el mapeo logítico $x(t+1) = 4x(t)(1-x(t))$ en la siguiente arquitectura. La función de activación. Presentar 100 ejemplos y luego testear para ejemplos no presentados. Comparar el error de entrenamiento con el error de generalización.

```
In [153]: def lineal(x, deriv = False):
              if deriv:
                  return 1
              return x


          N1 = 1
          N2  = 50

          p = 100 # number of test cases
          np.random.seed(2)


          # input data, first and last are the bias
          x   = np.random.rand(p,N1)
          print x.shape
          D_in = np.ones((p,2))
          D_in[:,-1:]= x

          # print (D_in)

          D_out = np.empty((p,1))
          D_out[:,0]  = 4*D_in[:,1]*(1-D_in[:,1] )

          plt.scatter(D_in[:,1],D_out[:,0], marker="x")
          plt.show()


          syn0  = 2*np.random.random((2,N2)) - 1
          syn1  = 2*np.random.random((N2,1))  - 1

          def evaluate(syn0, syn1, input):
              l0  = input
              l1  = sigmoid(np.dot(l0,syn0))
              l1[:,0]  = 1 # bias
              l1[:,1]  = l0[:,1]
              l2  = lineal(np.dot(l1,syn1))
              return l2

          eta = 0.001
          # training step
          for j in range(30000):
              l0  = D_in
```

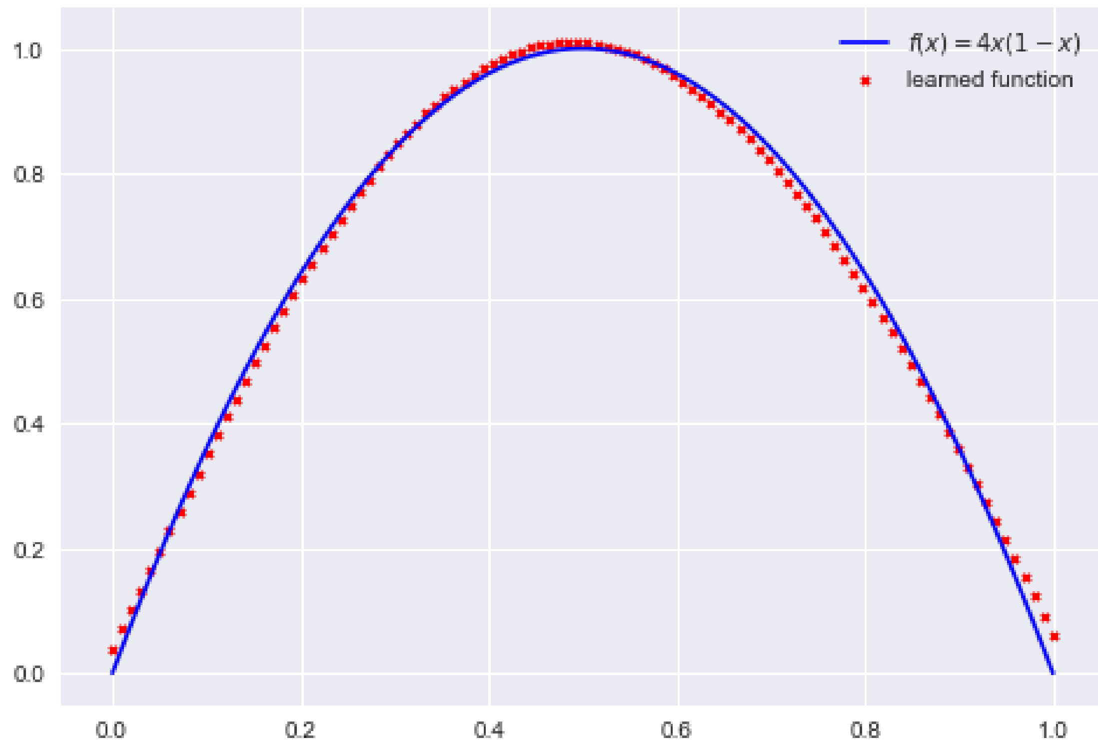
```
        l1 = sigmoid(np.dot(l0, syn0))

        l1[:,0] = 1 # bias
        l1[:,1] = l0[:,1]
        l2 = lineal(np.dot(l1, syn1))

        l2_error = D_out - l2
        if(j % 1000) == 0:
            print ("Error: " + str(np.mean(np.abs(l2_error))))
        l2_delta = l2_error * lineal(l2, deriv = True)

        l1_error = l2_delta.dot(syn1.T)

        l1_delta = l1_error * sigmoid(l1, deriv = True)

        # update weights
        syn1 += eta*l1.T.dot(l2_delta)
        syn0 += eta*l0.T.dot(l1_delta)
np.set_printoptions(formatter={'float': '{: 0.3f}'.format})
# print(l2)

x = np.linspace(0,1,100)
D_in = np.ones((100,2))
D_in[:,1]= x
plt.plot(x, 4*x*(1-x),'b',label=r"$f(x) = 4x(1-x)$")
plt.scatter(x, evaluate(syn0,syn1,D_in),marker='x',color='r',label="learr
plt.legend()
plt.show()
```

```
(100, 1)
```




```
Error: 2.39152852661
Error: 0.251520126163
Error: 0.244798999831
Error: 0.235004788992
Error: 0.219615825297
Error: 0.195467886205
Error: 0.160333344742
Error: 0.116837421351
Error: 0.0747219909244
Error: 0.0438498241693
Error: 0.0268365505417
Error: 0.0205664535642
Error: 0.0197992230816
Error: 0.0192532200528
Error: 0.0185719720081
Error: 0.0178103664749
Error: 0.0170609771325
Error: 0.0163682114245
Error: 0.0158649975496
Error: 0.0154590922963
Error: 0.015127163965
Error: 0.0148498441175
Error: 0.0146384356092
```

```
Error: 0.0144602762953
Error: 0.0143160564946
Error: 0.0142013188639
Error: 0.0141372068763
Error: 0.0140813189084
Error: 0.0140281645164
Error: 0.0139775150191
```



Arriba se muestra la funcion aprendida y por la red neuronal. Se ve que la capacidad de generalizacion es bastante buena con un error mas marcado para valores de x mayores

```
In [ ]:
```