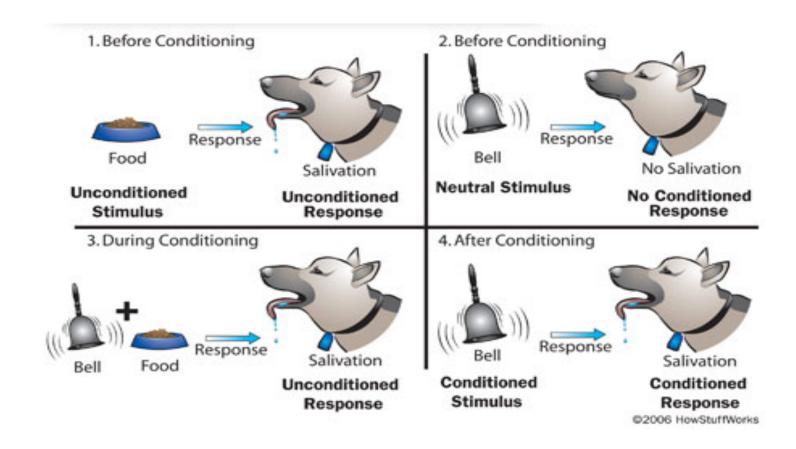


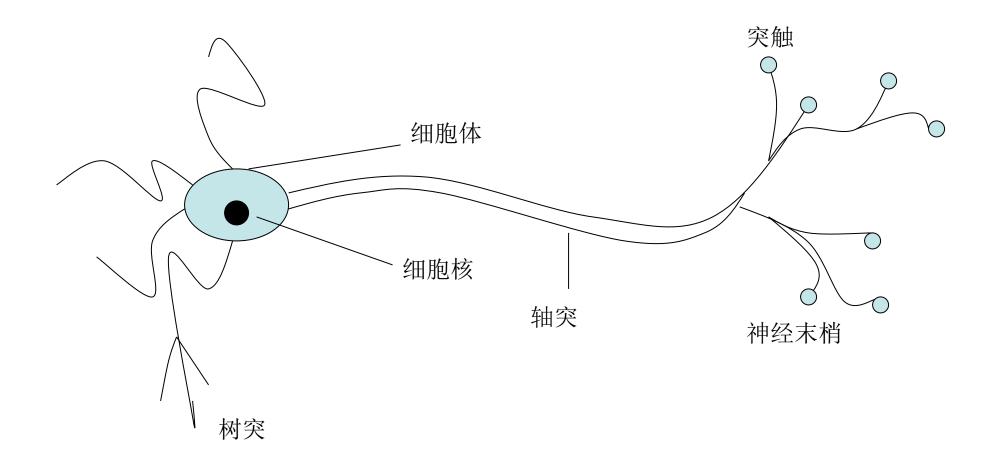
BP神经网络 张敏

18/1/2

巴普洛夫关于神经反射的实验

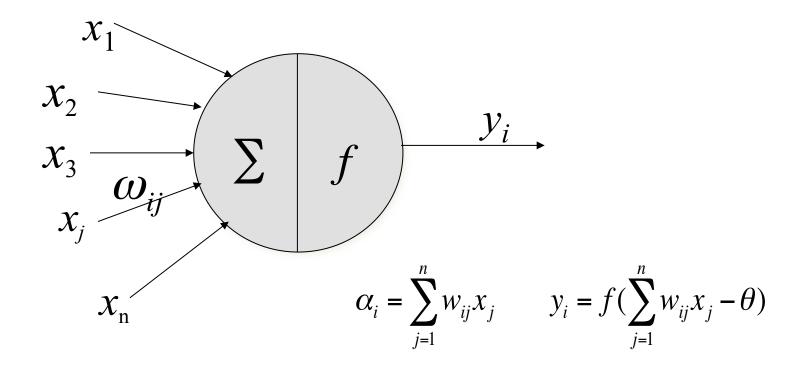


生物神经元结构



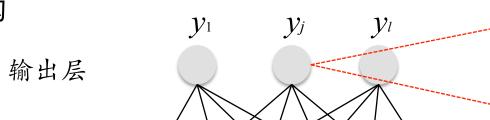


数学神经元结构



 x_j 为输入信号, f为传递函数, $w_{i,j}$ 表示与神经元 x_j 连接的权值, y_i 表示输出值, θ 表示阈值

BP网络结构



→第j个输出层神经元的输出:

$$\hat{\mathbf{y}}_j = f(\beta_j - \theta_j)$$

第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

隐层

 b_1

 W_{1j}

 b_2

 $b_{\scriptscriptstyle h}$

 $W_{\rm hi}$

 $\mathcal{W}_{ ext{qj}}$

 b_q

输入层

 χ_1 χ_i χ_d 第h个隐层神经元的输出:

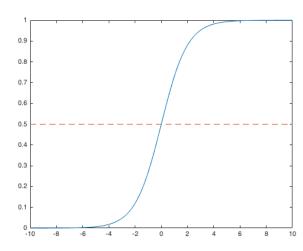
$$b_h = f(\alpha_h - \gamma_h)$$

第h个隐层神经元的输入:

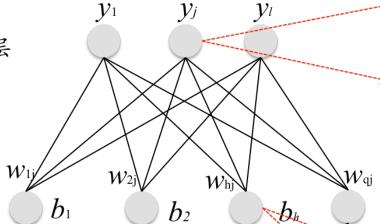
$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$

BP网络结构

$$E = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j - y_j)^2$$



输出层



→第j个输出层神经元的输出:

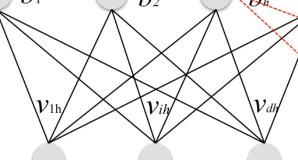
$$\hat{\mathbf{y}}_j = f(\beta_j - \theta_j)$$

第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

 b_q

 χ_d



 χ_i

输入层

 χ_1

→第h个隐层神经元的输出:

$$b_h = f(\alpha_h - \gamma_h)$$

第h个隐层神经元的输入:

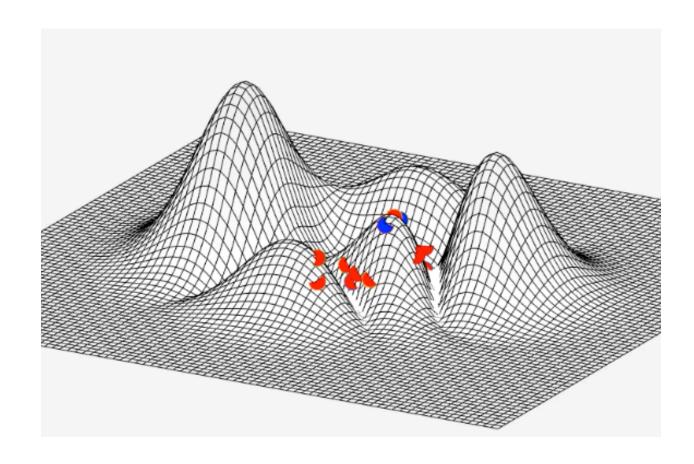
$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$

BP网络结构

$$E = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j - y_j)^2$$

网络训练目标:

找出合适的权值和阈值,使得误差 E 最小



BP网络结构

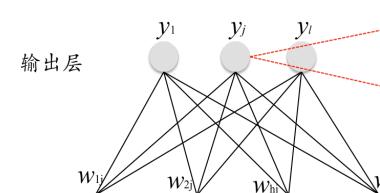
$$f(x) = sigmoid(x) = \frac{1}{1 + e^{-x}}$$

$$f'(x) = f(x)(1 - f(x))$$

$$\hat{y}_j = f(\beta_j - \theta_j)$$

$$E = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j - y_j)^2 \longrightarrow \frac{\partial E}{\partial \hat{y}_j} = \hat{y}_j - y_j^{\text{$\hat{\eta}$}}$$

$$\Delta w_{hj} = -\eta \frac{\partial E}{\partial w_{hj}} \qquad \frac{\partial E}{\partial w_{hj}} = \frac{\partial E}{\partial \hat{y}_{j}} \cdot \frac{\partial \hat{y}_{j}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial w_{hj}}$$



隐层

→第j个输出层神经元的输出:

$$\hat{\mathbf{y}}_j = f(\beta_j - \theta_j)$$

▶第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

 b_1 b_2 b_h

→第h个隐层神经元的输出:

$$b_h = f(\alpha_h - \gamma_h)$$

[→]第h个隐层神经元的输入:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$



BP网络结构

 $= \hat{y}_i (1 - \hat{y}_i)$

$$\frac{\partial E}{\partial w_{hj}} = \frac{\partial E}{\partial \hat{y}_{j}} \cdot \frac{\partial \hat{y}_{j}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial w_{hj}}$$

$$\frac{\partial \beta_{j}}{\partial w_{hj}} = b_{h} \quad \frac{\partial E}{\partial \hat{y}_{j}} = \hat{y}_{j} - y_{j}$$

$$\frac{\partial \hat{y}_{j}}{\partial \beta_{j}} = f'(\beta_{j} - \theta_{j}) \qquad f'(x) = f(x)(1 - f(x))$$

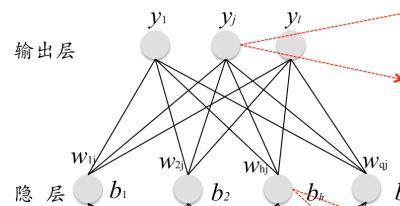
$$= f(\beta_{j} - \theta_{j})(1 - f(\beta_{j} - \theta_{j}))$$

 $\Delta w_{hj} = -\eta \frac{\partial E}{\partial w_{hj}}$

输入层

$$= -(\hat{y}_j - y_j)\hat{y}_j(1 - \hat{y}_j) \longrightarrow = -\eta \frac{\partial E}{\partial \hat{y}_j} \cdot \frac{\partial \hat{y}_j}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial w_{hj}}$$

$$= \hat{y}_i(1 - \hat{y}_i)(y_i - \hat{y}_i)$$



> 第i个输出层神经元的输出:

$$\hat{\mathbf{y}}_j = f(\boldsymbol{\beta}_j - \boldsymbol{\theta}_j)$$

▶第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

▶第h个隐层神经元的输出:

$$b_h = f(\alpha_h - \gamma_h)$$

→第h个隐层神经元的输入:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$





 $g_{j} = -\frac{\partial E}{\partial \hat{y}_{i}} \cdot \frac{\partial \hat{y}_{j}}{\partial \beta_{i}}$

BP网络结构

$$\Delta w_{hj} = -\eta \frac{\partial E}{\partial w_{hj}}$$

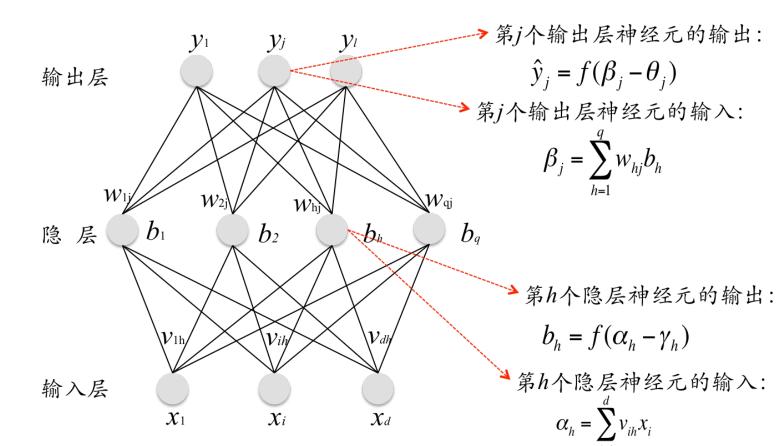
$$= -\eta \frac{\partial E}{\partial \hat{y}_{j}} \cdot \frac{\partial \hat{y}_{j}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial w_{hj}}$$

$$= \eta g_{j} b_{h}$$

$$= \eta \hat{y}_{j} (1 - \hat{y}_{j}) (y_{j} - \hat{y}_{j}) b_{h}$$

$$\Delta \theta_j = -\eta g_j$$

= $-\eta \hat{y}_i (1 - \hat{y}_i) (y_i - \hat{y}_i)$



BP网络结构

$$\Delta v_{ih} = \eta e_h x_i$$

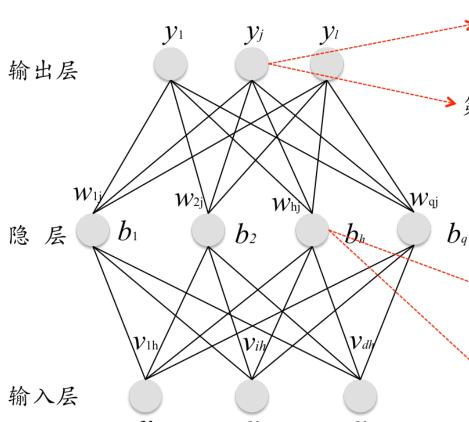
$$= -\eta \frac{\partial E}{\partial b_h} \cdot \frac{\partial b_h}{\partial \alpha_h} x_i$$

$$= \eta b_h (1 - b_h) \sum_{i=1}^{l} w_{hi} g_j x_i$$

$$\Delta \gamma_h = -\eta e_h$$

$$= \eta \frac{\partial E}{\partial b_h} \cdot \frac{\partial b_h}{\partial \alpha_h}$$

$$= -\eta b_h (1 - b_h) \sum_{i=1}^{l} w_{hi} g_i$$



→第j个输出层神经元的输出:

$$\hat{\mathbf{y}}_j = f(\beta_j - \theta_j)$$

▶第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

▶\$h个隐层神经元的输出:

$$b_h = f(\alpha_h - \gamma_h)$$

第h个隐层神经元的输入:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$

BP网络结构

$$\Delta w_{hj} = \eta \hat{y}_j (1 - \hat{y}_j) (y_j - \hat{y}_j) b_h$$

$$\Delta\theta_j = -\eta \hat{y}_j (1 - \hat{y}_j) (y_j - \hat{y}_j)$$

$$\Delta v_{ih} = \eta b_h (1 - b_h) \sum_{j=1}^{l} w_{hj} g_j x_i$$

$$\Delta \gamma_h = -\eta b_h (1 - b_h) \sum_{i=1}^l w_{hj} g_j$$

→第j个输出层神经元的输出:

$$\hat{\mathbf{y}}_j = f(\beta_j - \theta_j)$$

第j个输出层神经元的输入:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$

 b_q

→ 第h个隐层神经元的输出:

$$b_h = f(\alpha_h - \gamma_h)$$

第h个隐层神经元的输入:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$

输入层

网络训练过程

输入:训练集数据、学习速率yita

过程:

- 在(0,1)范围内随机初始化网络中所有连接权和阈值
- repeat
 - 根据网络输入和当前参数计算网络输出值y
 - 计算输出层神经元梯度项 g_i
 - 计算隐层神经元梯度项 e_h
 - 跟新连接权值和阈值
- until达到停止条件
- 输出:连接权值和阈值



代码实现

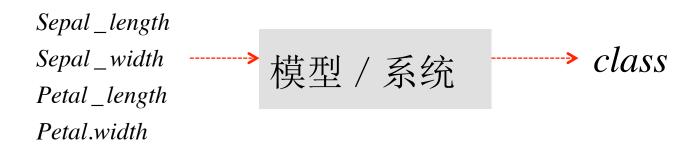
Python (sklearn)

- Net = MLPClassifier(hidden_layer_sizes=10,max_iter=1000).fit(tr_data.ix[:,0:6],tr_data.ix[:,6])
- res = Net.predict(te_data.ix[:,0:6])

R (nnet)

nnet(x, y, size, softmax = FALSE, maxit = 100)

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	class
5.1	3.5	1.4	0.2	setosa
4.9	3	1.4	0.2	setosa
7	3.2	4.7	1.4	versicolor
6.4	3.2	4.5	1.5	versicolor
6.3	3.3	6	2.5	virginica
5.8	2.7	5.1	1.9	virginica
6.5	3	5.8	2.2	?
6.2	2.9	4.3	1.3	?



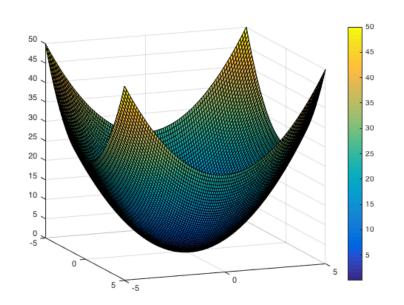


附录:BP神经网络自编代码

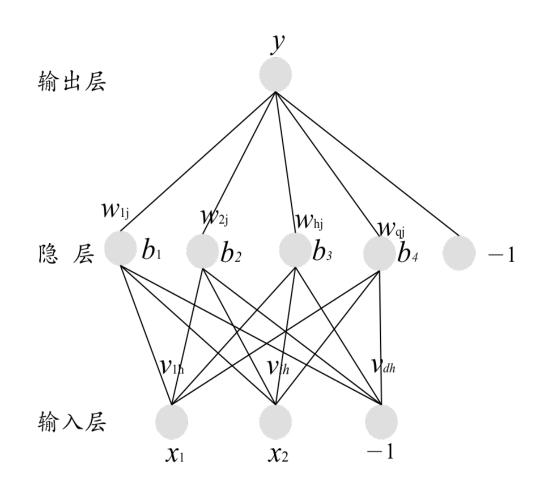
$$y = x_1^2 + x_2^2$$

训练集数据:BPdata_tr.txt

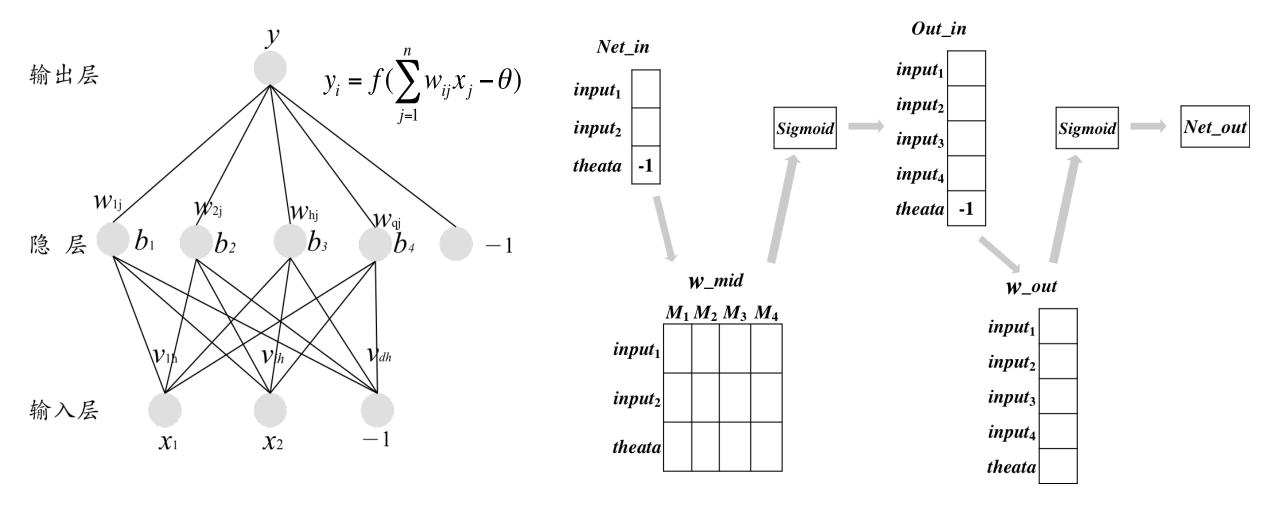
测试集数据:BPdata_te.txt



	x_1	x_2	У
0	0.29	0.23	0.14
1	0.50	0.62	0.64
2	0.00	0.53	0.28
3	0.21	0.53	0.33
4	0.10	0.33	0.12
5	0.06	0.15	0.03
6	0.13	0.03	0.02
7	0.24	0.23	0.11
8	0.28	0.03	0.08
9	0.38	0.49	?
10	0.29	0.47	?



附录:BP神经网络自编代码



附录:BP神经网络自编代码

$$f(x) = sigmoid(x) = \frac{1}{1 + e^{-x}}$$

def sigmoid(x): #映射函数

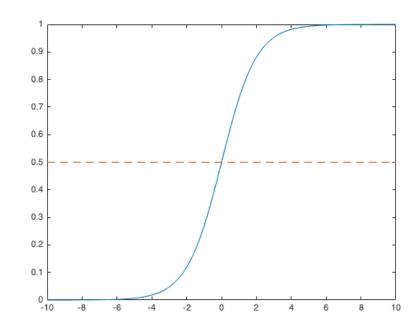
return 1/(1+math.exp(-x))

import math

import numpy as np

import pandas as pd

from pandas import DataFrame,Seres



附录:BP神经网络自编代码

#中间层神经元输入和输出层神经元输入

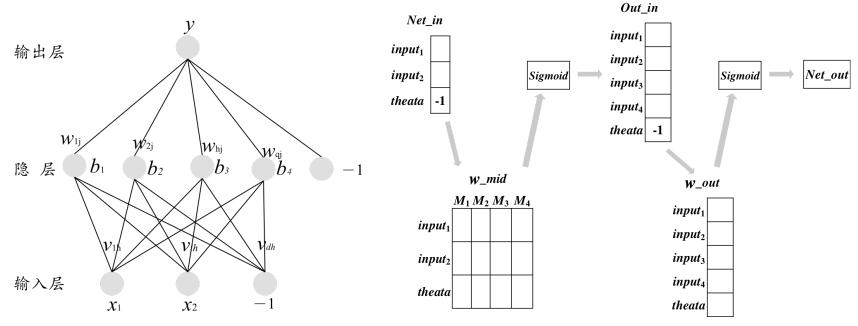
Net_in = DataFrame(0.6,index=['input1','input2','theata'],columns=['a'])

Out_in =

DataFrame(0,index=['input1','input2','input3','input4','theata'],columns=['a'])

Net in.ix[2,0] = -1

Out_in.ix[4,0] = -1





附录:BP神经网络自编代码

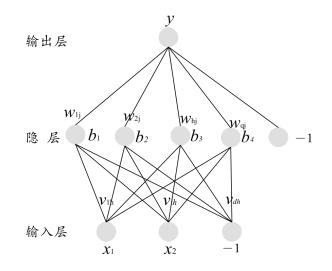
#中间层和输出层神经元权值

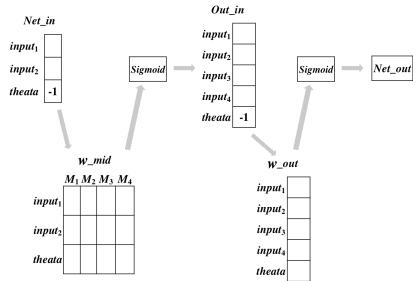
W_mid=DataFrame(0.5,index=['input1','input2','theata'], columns=['mid1','mid2','mid3','mid4'])

W_out=DataFrame(0.5,index=['input1','input2','input3','input4','theata'],columns=['a'])

W_mid_delta=DataFrame(0,index=['input1','input2','the ata'],columns=['mid1','mid2','mid3','mid4'])

W_out_delta=DataFrame(0,index=['input1','input2','input3','input4','theata'],columns=['a'])





附录:BP神经网络自编代码

#中间层的输出

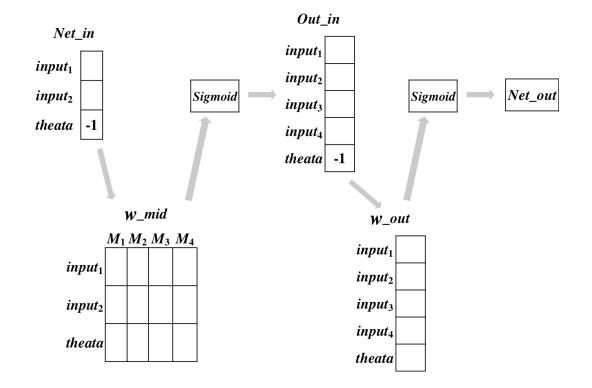
for i in range(0,4):

Out_in.ix[i,0] = sigmoid(sum(W_mid.ix[:,i]*Net_in.ix[:,0]))

#输出层的输出/网络输出

res = sigmoid(sum(Out_in.ix[:,0]*W_out.ix[:,0]))

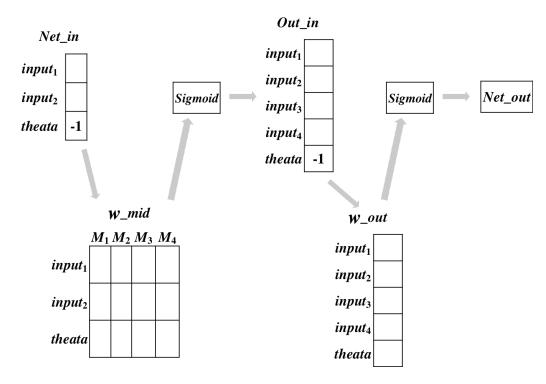
error = abs(res-real)



附录:BP神经网络自编代码

$$\Delta w_{hj} = \eta \hat{y}_j (1 - \hat{y}_j) (y_j - \hat{y}_j) b_h$$

$$\Delta\theta_j = -\eta \hat{y}_j (1 - \hat{y}_j) (y_j - \hat{y}_j)$$



#输出层权值变化量

W_out_delta.ix[:,0] = yita*res*(1-res)*(real-res)*Out_in.ix[:,0]

 $W_{out_delta.ix}[4,0] = -(yita*res*(1-res)*(real-res))$

W_out = W_out + W_out_delta #输出层权值更新

附录:BP神经网络自编代码

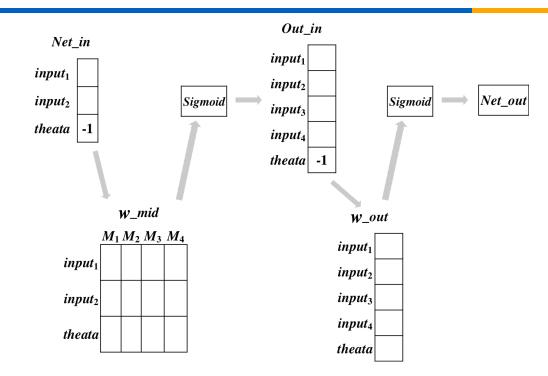
$$\Delta v_{ih} = \eta b_h (1 - b_h) \sum_{j=1}^l w_{hj} g_j x_i$$

$$\Delta v_{ih} = \eta b_h (1 - b_h) \sum_{j=1}^{l} w_{hj} g_j x_i$$

$$\Delta \gamma_h = -\eta b_h (1 - b_h) \sum_{j=1}^{l} w_{hj} g_j$$

#中间层权值变化量

for i in range(0,4):



 $W_{mid_delta.ix[:,i]} = yita*Out_{in.ix[i,0]}*(1-Out_{in.ix[i,0]})*W_{out.ix[i,0]}*res*(1-Out_{in.ix[i,0]})*W_{out.ix$ -res)*(real-res)*Net_in.ix[:,0]

 $W_{mid_delta.ix[2,i]} = -(yita*Out_{in.ix[i,0]}*(1-Out_{in.ix[i,0]})*W_{out.ix[i,0]}*res*(1-Out_{in.ix[i,0]})*W_{out.$ -res)*(real-res))

W mid = W mid + W mid delta #中间层权值更新





Thank you!

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热线电话:40068-40020

