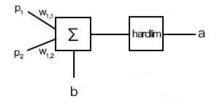
Homework 1

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1.1 单神经元感知机图: (其中, w_{1,1}=0; w_{1,2}=-1; b=-0.5)



求解过程:

- 1、将 P_1 , P_2 , P_3 , P_4 四个点放在平面直角坐标系中观察,则易看出判定边界为直线 y=-0.5;
- 2、确定一个与判定边界垂直的权值向量 w^T=[0,-1];
- 3、选择判定边界上一点(0,-0.5)代入判定式 $w^Tp+b=0$ 中,解得 b=-0.5.
- 1.2 由输入样例验证求解结果:

 a_1 = hardlim(w^Tp_1 +b) = hardlim($[0,-1]\cdot[1,-1]^T$ -0.5) = hardlim(0.5) = 1 = t_1 a_2 = hardlim(w^Tp_2 +b) = hardlim($[0,-1]\cdot[-1,-1]^T$ -0.5) = hardlim(0.5) = 1 = t_2 a_3 = hardlim(w^Tp_3 +b) = hardlim($[0,-1]\cdot[0,0]^T$ -0.5) = hardlim(-0.5) = 0 = t_3 a_4 = hardlim(w^Tp_4 +b) = hardlim($[0,-1]\cdot[1,0]^T$ -0.5) = hardlim(-0.5) = 0 = t_4 由以上验证知求解结果是正确的。

1.3 分类样本 p5, p6, p7, p8 如下:

 a_5 = hardlim(w^Tp_5 +b) = hardlim($[0,-1]\cdot[-2,0]^T$ -0.5) = hardlim(-0.5) = 0 a_6 = hardlim(w^Tp_6 +b) = hardlim($[0,-1]\cdot[1,1]^T$ -0.5) = hardlim(-1.5) = 0 a_7 = hardlim(w^Tp_7 +b) = hardlim($[0,-1]\cdot[0,1]^T$ -0.5) = hardlim(-1.5) = 0 a_8 = hardlim(w^Tp_8 +b) = hardlim($[0,-1]\cdot[-1,-2]^T$ -0.5) = hardlim(1.5) = 1 则有 p_5 , p_6 , p_7 为一类(p_3 , p_4), p_8 为另一类(p_1 , p_2)。

- 1.4 p_6 , p_7 , p_8 的分类与 w, b 的选择无关, p_5 的分类与 w, b 的选择有关。 因为 w, b 的选择所依赖的判定边界的斜率和偏移量都有一定的变化,而 p_5 在此变化范围之内, p_6 , p_7 , p_8 在此变化范围之外。
- 1.5 1、应用感知机学习规则修正 $w(0)^{T}$, b(0)值:

Iteration1: $a_1 = hardlim(w(0)^T p_1 + b(0)) = hardlim([0,0] \cdot [1,-1]^T + 0) = hardlim(0) = 1, t_1 = 1$ $w(1)^T = w(0)^T = [0,0]$ b(1) = b(0) = 0

Iteration2: $a_2 = hardlim(w(1)^Tp_2+b(1)) = hardlim([0,0]\cdot[-1,-1]^T+0) = hardlim(0) = 1, t_2=1$ $w(2)^T = w(1)^T = [0,0]$

b(2) = b(1) = 0 Iteration3: $a_3 = hardlim(w(2)^T p_3 + b(2)) = hardlim([0,0] \cdot [0,0]^T + 0) = hardlim(0) = 1, t_3 = 0$

 $w(3)^T = w(2)^T - p_3 = [0,0]$

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b(3) = b(2) + t_3 - a_3 = -1
Iteration4: a_4 = hardlim(w(3)^Tp_4 + b(3)) = hardlim([0,0] \cdot [1,0]^T - 1) = hardlim(-1) = 0, t_4 = 0
                w(4)^T = w(3)^T = [0,0]
                b(4) = b(3) = -1
Iteration5: a_1 = hardlim(w(4)^Tp_1+b(4)) = hardlim([0,0]\cdot[1,-1]^T-1) = hardlim(-1) = 0, t_1=1
                w(5)^T = w(4)^T + p_1 = [1,-1]
                b(5) = b(4) + t_1 - a_1 = 0
Iteration6: a_2 = hardlim(w(5)^Tp_2 + b(5)) = hardlim([1,-1]\cdot[-1,-1]^T + 0) = hardlim(0) = 1, t_2=1
                w(6)^T = w(5)^T = [1,-1]
                b(6) = b(5) = 0
Iteration7: a_3 = hardlim(w(6)^Tp_3 + b(6)) = hardlim([1,-1] \cdot [0,0]^T + 0) = hardlim(0) = 1, t_3 = 0
                w(7)^T = w(6)^T - p_3 = [1,-1]
                b(7) = b(6) + t_3 - a_3 = -1
Iteration8: a_4 = hardlim(w(7)^Tp_4 + b(7)) = hardlim([1,-1]\cdot[1,0]^T - 1) = hardlim(0) = 1, t_4 = 0
                w(8)^T = w(7)^T - p_4 = [0,-1]
                b(8) = b(7) - t_3 + a_3 = -2
Iteration9: a_1 = hardlim(w(8)^T p_1 + b(8)) = hardlim([0,-1] \cdot [1,-1]^T - 2) = hardlim(-1) = 0, t_1 = 1
                w(9)^T = w(8)^T + p_1 = [1,-2]
                b(9) = b(8) + t_1 - a_1 = -1
Iteration10: a_2 = hardlim(w(9)^Tp_2 + b(9)) = hardlim([1,-2]\cdot[-1,-1]^T-1) = hardlim(0) = 1, t_2=1
                w(10)^T = w(9)^T = [1,-2]
                b(10) = b(9) = -1
Iteration11:a<sub>3</sub> = hardlim(w(10)^Tp_3+b(10)) = hardlim([1,-2]·[0,0]<sup>T</sup>-1) = hardlim(-1) = 0, t<sub>3</sub>=0
                w(11)^T = w(10)^T = [1,-2]
                b(11) = b(10) = -1
Iteration12:a_4 = hardlim(w(11)^T p_4 + b(11)) = hardlim([1, -2] \cdot [1, 0]^T - 1) = hardlim([0, -1] \cdot [1, 0]^T - 1) = hardlim([0, -1] \cdot [1, 0] \cdot [1, 0]
                w(12)^T = w(11)^T - p_4 = [0,-2]
                b(12) = b(11) - t_3 + a_3 = -2
Iteration13~Iteration16: 结果都是正确的,不需要修正。
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即,经过修正得到 $w^{7}=[0,-2]$, b= -2.

2、验证(1.3)样本:

 $a_5 = hardlim(w^Tp_5 + b) = hardlim([0,-2] \cdot [-2,0]^T - 2) = hardlim(-2) = 0$ $a_6 = hardlim(w^Tp_6 + b) = hardlim([0,-2] \cdot [1,1]^T - 2) = hardlim(-4) = 0$ $a_7 = hardlim(w^T p_7 + b) = hardlim([0,-2] \cdot [0,1]^T - 2) = hardlim(-4) = 0$ $a_8 = hardlim(w^T p_8 + b) = hardlim([0,-2] \cdot [-1,-2]^T - 2) = hardlim(2) = 1$ 则有 p_5 , p_6 , p_7 为一类(p_3 , p_4), p_8 为另一类(p_1 , p_2)。(同(1.3))

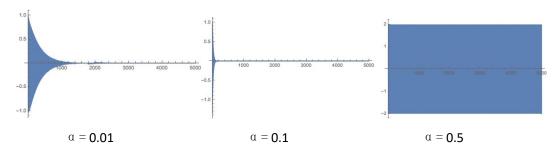
2.1

LMS 解题详细过程: 假设模型是线性的, $+h(x) = w_0 + w_1x_1 + w_2x_2$,

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损失函数 J(w) = \frac{1}{2} \sum_{i=1}^{m} \{h(x^{(i)}) - y^{(i)}\}^2 , 考虑随机梯度下降算法: w_i = w_i + \alpha(y^{(j)} - h(x^{(j)}))x_i^j。即: w(k+1) = w(k) + 2 \alpha e(k) p(k), b(k+1) = b(k) + 2 \alpha e(k)。在 python 上实现 w, b 计算及 e-i 的文件输出,通过 matlab 读取 e-i 文件并作图。
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```
import numpy as np
import time
p0 = np.matrix('1;-1')
p1 = np.matrix('-1;-1')
p2 = np.matrix('0;0')
p3 = np.matrix('1;0')
inputs = [p0, p1, p2, p3]
targets = [1, 1, -1, -1]
irritation = 5000 / 4
rates = [0.01, 0.1, 0.5]
deviation = []
def LMS(rate, index):
     file = open('deviations'+'%d'%index+'.txt', 'w')
     w = np.matrix('0,0')
    b = 0
     for i in range(irritation):
          for j in range(4):
               output = ((w * inputs[j]).tolist())[0][0] + b
               e = targets[j] - output
               if e != 0:
                    w = w + 2*rate*e*inputs[j].transpose()
                    b = b + 2*rate*e
               file.write('%.4f'%e+'\n')
     file.close()
     print w, b
for i in range(3):
     LMS(rates[i], i)
file = open('index', 'w')
for i in range(5000):
     file.write('%d'%(i+1)+'\n')
file.close()
```

迭代 5000 次之后的误差(e)-迭代次数(i)曲线:



2.2 最终的 w^T , b 结果:

$$\alpha = 0.01$$
: $w^T = [0,-2]$, $b = -1$

$$\alpha = 0.1$$
: $w^T = [0,-2]$, $b = -1$

$$\alpha = 0.5$$
: $w^T = [0,-3]$, $b = -3$

2.3 感知机和 ADALINE 都能处理题一中的分类问题。

感知机迭代到正确就会停止,而 ADALINE 会一直趋近于正确值。

当 ADALINE 的学习速率适当,且感知机与 ADALINE 都对 $w^T = [0, 0]$, b=0 的初始值进行修正时,它们都逐渐接近 $w^Tp+b=0$ 分界面。其中,感知机基于硬极限函数逐渐接近分类为 1 的点,ADALINE 基于线性函数逐渐接近分类为 0 的点。
