

第六章课后作业

5-2 设三个总体 G_1, G_2 和 G_3 的分布分别为: $N(2, 0.5^2)$, $N(0, 2^2)$ 和 $N(3, 1^2)$. 试问样品 $x=2.5$ 应判归哪一类?

(1) 按距离判别准则;

(2) 按贝叶斯判别准则 (取 $q_1=q_2=q_3=\frac{1}{3}$, $L(j|i)=\begin{cases} 1, i \neq j \\ 0, i = j \end{cases}$).

解: (1) 用样品到总体的相对平方距离作判别函数

$$\text{样品到 } G_1 \text{ 的距离: } d_1^2(x) = \frac{(2.5-2)^2}{0.5^2} = 1$$

$$\text{样品到 } G_2 \text{ 的距离: } d_2^2(x) = \frac{(2.5-0)^2}{2^2} = 1.5625$$

$$\text{样品到 } G_3 \text{ 的距离: } d_3^2(x) = \frac{(2.5-3)^2}{1^2} = 0.25$$

$$d_{\min} = d_3^2(x), \text{ 故 } x \in G_3$$

(2) 按贝叶斯判别准则, 判别函数为

$$Z_i(x) = -\frac{1}{2} \ln |Z_i| - \frac{1}{2} (x - \mu^{(i)})' Z_i^{-1} (x - \mu^{(i)}) \quad (q_1 = q_2 = q_3 = \frac{1}{3})$$

$$\text{则 } Z_1(x) = -\frac{1}{2} \ln 0.5^2 - \frac{(2.5-2)^2}{2 \times 0.5^2} = 0.1931$$

$$Z_2(x) = -\frac{1}{2} \ln 2^2 - \frac{(2.5-0)^2}{2 \times 2^2} = -1.4744$$

$$Z_3(x) = -\frac{1}{2} \ln 1^2 - \frac{(2.5-3)^2}{2 \times 1^2} = -0.125$$

$$\therefore \max_{1 \leq i \leq 3} Z_i(x) = Z_1(x), \text{ 故 } x \in G_1$$

5-10 已知某研究对象分为三类, 每个样品考察 4 项指标, 各类的观测样品数分别为 7, 4, 6; 另外还有 3 个待判样品 (所有观测数据见表 5.4). 假定样本均来自正态总体.

(1) 试用马氏距离判别法进行判别分析, 并对 3 个待判样品进行判别归类.

表 5.4 判别分类的数据

样品号	X_1	X_2	X_3	X_4	类别号
1	6.0	-11.5	19.0	90.0	1
2	-11.0	-18.5	25.0	-36.0	3
3	90.2	-17.0	17.0	3.0	2
4	-4.0	-15.0	13.0	54.0	1
5	0.0	-14.0	20.0	35.0	2
6	0.5	-11.5	19.0	37.0	3
7	-10.0	-19.0	21.0	-42.0	3
8	0.0	-23.0	5.0	-35.0	1
9	20.0	-22.0	8.0	-20.0	3
10	-100.0	-21.4	7.0	-15.0	1
11	-100.0	-21.5	15.0	-40.0	2
12	13.0	-17.2	18.0	2.0	2
13	-5.0	-18.5	15.0	18.0	1
14	10.0	-18.0	14.0	50.0	1
15	-8.0	-14.0	16.0	56.0	1
16	0.6	-13.0	26.0	21.0	3
17	-40.0	-20.0	22.0	-50.0	3
1	-8.0	-14.0	16.0	56.0	
2	92.2	-17.0	18.0	3.0	
3	-14.0	-18.5	25.0	-36.0	

解: (1) 通过提供的样本计算三类总体的样本均值和样本协方差矩阵, 通过 Python 程序计算得:

```

X_bar = [-14.42857143 -17.34285714 12.71428571 31.14285714]
Y_bar = [ 0.8 -17.425 17.5 0. ]
Z_bar = [ -6.65 -17.33333333 20.16666667 -15. ]
X_S =
[[1463.95238095 67.31190476 97.19047619 821.9047619 ]
 [ 67.31190476 16.83952381 18.61904762 174.12380952]
 [ 97.19047619 18.61904762 24.9047619 204.38095238]
 [ 821.9047619 174.12380952 204.38095238 1939.47619048]]
Y_S =
[[6.10082667e+03 1.49586667e+02 7.04666667e+01 1.43220000e+03]
 [1.49586667e+02 9.52250000e+00 6.21666667e+00 9.48666667e+01]
 [7.04666667e+01 6.21666667e+00 4.33333333e+00 6.23333333e+01]
 [1.43220000e+03 9.48666667e+01 6.23333333e+01 9.46000000e+02]]
Z_S =
[[ 391.255 9.67 -75.05 369.72 ]
 [ 9.67 17.16666667 12.66666667 129.1 ]
 [ -75.05 12.66666667 42.16666667 4.4 ]
 [ 369.72 129.1 4.4 1284. ]]

```

计算三个待判样品到三类总体的马氏距离：

$$D = (Y - \mu)' \Sigma^{-1} (Y - \mu)$$

计算结果为：

```
d1_X_square = 1.3945678050562498
d1_Y_square = 895973089446986.0
d1_Z_square = 39.87898930679415

d2_X_square = 35.63219086990604
d2_Y_square = 195708362558.17847
d2_Z_square = 68.70624559237007

d3_X_square = 123.06721325590334
d3_Y_square = 1219817336488197.5
d3_Z_square = 1.3961442455577868
```

根据计算结果，

待判样品1归为第1类；

待判样品2归为第1类；

待判样品3归为第3类；

代码如下：

```

1  import numpy as np
2
3  # 第一类观测值
4  X = np.array([[6.0, -11.5, 19.0, 90.0],
5                [-4.0, -15.0, 13.0, 54.0],
6                [0.0, -23.0, 5.0, -35.0],
7                [-100.0, -21.4, 7.0, -15.0],
8                [-5.0, -18.5, 15.0, 18.0],
9                [10.0, -18.0, 14.0, 50.0],
10               [-8.0, -14.0, 16.0, 56.0]
11               ])
12
13 # 第二类观测值
14 Y = np.array([[90.2, -17.0, 17.0, 3.0],
15               [0.0, -14.0, 20.0, 35.0],
16               [-100.0, -21.5, 15.0, -40.0],
17               [13.0, -17.2, 18.0, 2.0]
18               ])
19
20 # 第三类观测值
21 Z = np.array([[-11.0, -18.5, 25.0, -36.0],
22               [0.5, -11.5, 19.0, 37.0],
23               [-10.0, -19.0, 21.0, -42.0],
24               [20.0, -22.0, 8.0, -20.0],
25               [0.6, -13.0, 26.0, 21.0],
26               [-40.0, -20.0, 22.0, -50.0]
27               ])
28
29 # 三类样本均值
30 X_bar = np.mean(X, axis=0)
31 Y_bar = np.mean(Y, axis=0)
32 Z_bar = np.mean(Z, axis=0)
33 print(f'X_bar = {X_bar}\nY_bar = {Y_bar}\nZ_bar = {Z_bar}')
34
35 # 三类样本协方差
36 X_S = np.cov(X, rowvar=False)
37 Y_S = np.cov(Y, rowvar=False)
38 Z_S = np.cov(Z, rowvar=False)
39
40 # 方差求逆
41 X_S1 = np.linalg.inv(X_S)
42 Y_S1 = np.linalg.inv(Y_S)
43 Z_S1 = np.linalg.inv(Z_S)
44
45 # 待判样品1、2、3
46 P1 = np.array([-8.0, -14.0, 16.0, 56.0])
47 P2 = np.array([92.2, -17.0, 18.0, 3.0])
48 P3 = np.array([-14.0, -18.5, 25.0, -36.0])

```

```
51 # 计算待判样品与三类观测样品的马氏距离
52 # 待判样品1
53 tmp1 = np.dot(P1 - X_bar, X_S1)
54 d1_X_square = np.dot(tmp1, P1 - X_bar)
55
56 tmp1 = np.dot(P1 - Y_bar, Y_S1)
57 d1_Y_square = np.dot(tmp1, P1 - Y_bar)
58
59 tmp1 = np.dot(P1 - Z_bar, Z_S1)
60 d1_Z_square = np.dot(tmp1, P1 - Z_bar)
61
62 print(f'd1_X_square = {d1_X_square}\nd1_Y_square = {d1_Y_square}\nd1_Z_square = {d1_Z_square}\n')
63
64 # 待判样品2
65 tmp2 = np.dot(P2 - X_bar, X_S1)
66 d2_X_square = np.dot(tmp2, P2 - X_bar)
67
68 tmp2 = np.dot(P2 - Y_bar, Y_S1)
69 d2_Y_square = np.dot(tmp2, P2 - Y_bar)
70
71 tmp2 = np.dot(P2 - Z_bar, Z_S1)
72 d2_Z_square = np.dot(tmp2, P2 - Z_bar)
73
74 print(f'd2_X_square = {d2_X_square}\nd2_Y_square = {d2_Y_square}\nd2_Z_square = {d2_Z_square}\n')
75
76 # 待判样品3
77 tmp3 = np.dot(P3 - X_bar, X_S1)
78 d3_X_square = np.dot(tmp3, P3 - X_bar)
79
80 tmp3 = np.dot(P3 - Y_bar, Y_S1)
81 d3_Y_square = np.dot(tmp3, P3 - Y_bar)
82
83 tmp3 = np.dot(P3 - Z_bar, Z_S1)
84 d3_Z_square = np.dot(tmp3, P3 - Z_bar)
85
86 print(f'd3_X_square = {d3_X_square}\nd3_Y_square = {d3_Y_square}\nd3_Z_square = {d3_Z_square}\n')
```