统计信号处理基础 第 01 次作业

许凌玮 2018011084

1. 设二元假设检验的观测信号模型为

$$\begin{cases} H_0\colon x=-1+n\\ H_1\colon x=1+n \end{cases} \qquad n \, \sim \, \mathcal{N}\left(0,\sigma_n^2=\frac{1}{2}\right)$$

若两种假设是等先验概率的,而代价因子为 $C_{00}=1, C_{01}=8, C_{10}=4, C_{11}=2$,试求贝叶斯(最佳)表达式和平均代价C。

【解答】

似然函数分别为

$$\begin{split} p_0(x) &= P(x|H_0) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{(x+1)^2}{2\sigma_n^2}\right) = \frac{1}{\sqrt{\pi}} \exp(-(x+1)^2) \\ p_1(x) &= P(x|H_1) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{(x-1)^2}{2\sigma_n^2}\right) = \frac{1}{\sqrt{\pi}} \exp(-(x-1)^2) \end{split}$$

则似然比为

$$\lambda(x) = \frac{p_1(x)}{p_0(x)} = \exp\Bigl(-((x-1)^2 - (x+1)^2)\Bigr) = \exp(4x)$$

侕

$$\xi = P(H_0) = \frac{1}{2}, \qquad \lambda_0 = \frac{\xi(C_{10} - C_{00})}{(1 - \xi)(C_{01} - C_{11})} = \frac{1}{2}$$

因此贝叶斯 (最佳) 表达式为

$$\begin{split} \lambda(x) \gtrless_{H_0}^{H_1} \lambda_0 & \Rightarrow \frac{p_1(x)}{p_0(x)} \gtrless_{H_0}^{H_1} \frac{\xi(C_{10} - C_{00})}{(1 - \xi)(C_{01} - C_{11})} & \Rightarrow \exp(4x) \gtrless_{H_0}^{H_1} \frac{1}{2} \\ & \Rightarrow x \gtrless_{H_0}^{H_1} \frac{1}{4} \ln\left(\frac{1}{2}\right) \end{split}$$

记 $V_T = \frac{1}{4}\ln(\frac{1}{2})$,则虚警概率和检测概率分别为

$$\begin{split} P_F &= \int_{D_1} p_0(x) dx = \int_{V_T}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{(x+1)^2}{2\sigma_n^2}\right) dx = Q\left(\frac{V_T+1}{\sigma_n}\right) = Q\left(\sqrt{2}\left[\frac{1}{4}\ln\left(\frac{1}{2}\right)+1\right]\right) \\ P_D &= \int_{D_1} p_1(x) dx = \int_{V_T}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{(x-1)^2}{2\sigma_n^2}\right) dx = Q\left(\frac{V_T-1}{\sigma_n}\right) = Q\left(\sqrt{2}\left[\frac{1}{4}\ln\left(\frac{1}{2}\right)-1\right]\right) \end{split}$$

总的平均代价为

$$\begin{split} C &= C_{00}P(H_0)(1-P_F) + C_{10}P(H_0)P_F + C_{01}P(H_1)(1-P_D) + C_{11}P(H_1)P_D \\ &= \frac{1}{2}[(1-P_F) + 4P_F + 8(1-P_D) + 2P_D] \\ &= \frac{9}{2} + \frac{3}{2}P_F - 3P_D \\ &= \frac{9}{2} + \frac{3}{2}Q\left(\sqrt{2}\left[\frac{1}{4}\ln\left(\frac{1}{2}\right) + 1\right]\right) - 3Q\left(\sqrt{2}\left[\frac{1}{4}\ln\left(\frac{1}{2}\right) - 1\right]\right) \end{split}$$

2. 什么假设下代价函数曲线是上凸的?

【解答】

平均代价函数

$$\begin{split} C &= C_{00}P(H_0)P(D_0 \mid H_0) + C_{10}P(H_0)P(D_1 \mid H_0) + C_{01}P(H_1)P(D_0 \mid H_1) + C_{11}P(H_1)P(D_1 \mid H_1) \\ &= \xi C_{00} \int_{D_0} p_0(r)dr + \xi C_{10} \int_{D_1} p_0(r)dr + (1-\xi)C_{01} \int_{D_0} p_1(r)dr + (1-\xi)C_{11} \int_{D_1} p_1(r)dr \\ &= \xi C_{10} + (1-\xi)C_{11} + \int_{D_0} \left[\xi p_0(r)(C_{00} - C_{10}) + (1-\xi)p_1(r)(C_{01} - C_{11})\right]dr \end{split}$$

猜测先验概率为 $P(H_0)=x$ 。假设正确判决的代价小于错误判决的代价,即 $C_{10}-C_{00}>0$ 且 $C_{01}-C_{11}>0$,则此时判决准则为

$$\lambda(r) = \frac{p_1(r)}{p_0(r)} \mathop{\gtrless}_{H_0}^{H_1} \frac{x(C_{10} - C_{00})}{(1 - x)(C_{01} - C_{11})} \triangleq \lambda_0(x)$$

则平均代价为

$$\begin{split} C(\xi,x) &= \xi C_{00}(1-P_F(x)) + \xi C_{10}P_F(x) + (1-\xi)C_{01}P_M(x) + (1-\xi)C_{11}(1-P_M(x)) \\ &= \xi C_{10} + (1-\xi)C_{11} + \int_{D_0(x)} [\xi p_0(r)(C_{00}-C_{10}) + (1-\xi)p_1(r)(C_{01}-C_{11})]dr \end{split}$$

其中 $D_0(x)=\{r|\lambda(r)<\lambda_0(x)\}$ 。注意 $D_0(x)$ 有可能是分段的,取决于 $\lambda(r)$ 的形式。

最小平均代价函数(对应贝叶斯准则的情形)为

$$C_{min}(\xi) = C(\xi,x)|_{x=\xi}$$

任意取定一个 $x = \xi_1$,此时 $C(\xi, \xi_1)$ 为一条直线(关于 ξ 的一次函数),且当 $\xi \neq \xi_1$,即猜测的先验概率不等于实际的先验概率时,平均代价更大,则

$$C(\xi,\xi_1) \geq C(\xi_1,\xi_1) = C_{min}(\xi_1)$$

上式在 $\xi = \xi_1$ 时取等。

又由于

$$\begin{split} \frac{\partial C_{min}(\xi)}{\partial \xi} &= C_{10} - C_{11} + \int_{D_0(\xi)} \left[p_0(r) (C_{00} - C_{10}) + p_1(r) (C_{11} - C_{01}) \right] dr \\ \frac{\partial C(\xi, \xi_1)}{\partial \xi} &= C_{10} - C_{11} + \int_{D_0(\xi_1)} \left[p_0(r) (C_{00} - C_{10}) + p_1(r) (C_{11} - C_{01}) \right] dr = \frac{\partial C_{min}(\xi)}{\partial \xi} \bigg|_{\xi = \xi_1} \end{split}$$

因此 $C(\xi, \xi_1)$ 为 $C_{min}(\xi)$ 在 $\xi = \xi_1$ 处的切线。

 $\label{eq:control_fit}$ 记 $f(r) = p_0(r)(C_{00} - C_{10}) + p_1(r)(C_{11} - C_{01})$,则f(r)在 $D_0(\xi)$ 上的积分可写为

$$\int_{D_0(\xi)} f(r)dr = \int_{-\infty}^{\lambda_0(\xi)} \int_{\lambda(r)=u} f(r)dr \, du$$

 $\label{eq:definition} \ensuremath{\gimel} g(u) = \int_{\lambda(r) = u} f(r) dr = \int_{\lambda(r) = u} [p_0(r)(C_{00} - C_{10}) + p_1(r)(C_{11} - C_{01})] dr, \quad \ensuremath{\gimel} | \frac{\partial C_{min}(\xi)}{\partial \xi} \ensuremath{\lnot} \ensuremath{\upsigma} \ensuremath{\psigma} \ens$

$$\frac{\partial C_{min}(\xi)}{\partial \xi} = C_{10} - C_{11} + \int_{-\infty}^{\lambda_0(\xi)} g(u) du$$

则 $C_{min}(\xi)$ 的二阶导为

$$\frac{\partial^2 C_{min}(\xi)}{\partial \xi^2} = \frac{\partial}{\partial \xi} \left(C_{10} - C_{11} + \int_{D_0(\xi)} f(r) dr \right) = \frac{\partial}{\partial \xi} \left(\int_{-\infty}^{\lambda_0(\xi)} g(u) du \right) = \lambda_0'(\xi) g(\lambda_0(\xi))$$

其中

$$\begin{split} \lambda_0'(\xi) &= \frac{d}{d\xi} \left(\frac{\xi(C_{10} - C_{00})}{(1 - \xi)(C_{01} - C_{11})} \right) = \frac{(C_{10} - C_{00})}{(1 - \xi)^2(C_{01} - C_{11})} > 0 \\ g(\lambda_0(\xi)) &= \int_{\lambda(r) = \lambda_0(\xi)} f(r) dr = \int_{\lambda(r) = \lambda_0(\xi)} [p_0(r)(C_{00} - C_{10}) + p_1(r)(C_{11} - C_{01})] dr \leq 0 \end{split}$$

(由于概率非负,即 $p_0(r)\geq 0$ 且 $p_1(r)\geq 0$,而 $C_{00}-C_{10}<0$ 且 $C_{11}-C_{01}<0$,因此恒有 $f(r)\leq 0$,因此对f(r)的积分也将不大于 0,故上式成立。)

因此有

$$\frac{\partial^2 C_{min}(\xi)}{\partial \xi^2} = \lambda_0'(\xi) g(\lambda_0(\xi)) \leq 0$$

此式即满足 $C_{min}(\xi)$ 上凸要求(上凸函数的二阶条件)。

综上所述,在正确判决的代价小于错误判决的代价的条件下(充分条件), $C_{min}(\xi)$ 恒为上凸函数。