第2章作出:

ハ P(Y=1)=元、P(Y=+)=元

対方側 対解本 $X=(1,N)^{T}$, 由于戶 in 係数据中元 N. 放剂用 Laplace 平清: $Y_1 > 1,=3$. $S_2=9$. $\lambda=1$, $Y_2 = 2$ $\lambda=1$ $\lambda=1$

2.1.
$$P(Y=1) = \pi$$
. $P(Y=0) = 1 - \pi$.

$$P(X_{i} | Y=K) = \frac{1}{|x_{i}|} e^{x} p^{x} \left\{ \frac{(x-\mu_{i})^{2}}{p(x)} \right\}$$

$$P(X_{i} | Y=K) = \frac{1}{|x_{i}|} e^{x} p^{x} \left\{ \frac{(x-\mu_{i})^{2}}{p(x)} \right\}$$

$$P(X_{i} | Y=K) = \frac{P(X_{i} | Y=K)}{P(X_{i})} P(Y=K)$$

$$P(X_{i} | Y=K) P(Y=K)$$

$$= \frac{P(X_{i} | Y=K)}{x \cdot \frac{1}{|x_{i}|} e^{x} p^{x}} \frac{(x-\mu_{i})^{2}}{x^{x}} + (1-\pi) \frac{1}{|x_{i}|} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2}$$

$$= \frac{P(X_{i} | Y=K)}{x \cdot \frac{1}{|x_{i}|} e^{x} p^{x}} \frac{(x-\mu_{i})^{2}}{x^{x}} + (1-\pi) \frac{1}{|x_{i}|} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2}$$

$$= \frac{P(Y=1 | X) = \frac{(1-x)}{x \cdot p^{x}} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2} + (1-\pi) e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2}$$

$$= \frac{(1-x)}{x \cdot p^{x}} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2} + (1-\pi) e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2}$$

$$= \frac{(1-x)}{x \cdot p^{x}} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2} + (1-\pi) e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2}$$

$$= \frac{\pi}{(x-\mu_{i})^{2}} e^{x} p^{x} \frac{(x-\mu_{i})^{2}}{2\sigma_{i}} + \frac{\pi}{(x-\mu_{i})^{2}} e^{x} p^$$

 $P(y=o|x) = \frac{\frac{1-\pi}{6\tau_0} \exp\left\{\frac{(x-\mu_{i0})^2}{2\sigma_{i0}^2}\right\}}{\frac{\pi}{6\tau_0} \exp\left\{\frac{(x-\mu_{i0})^2}{2\sigma_{i0}}\right\} + \frac{1-\pi}{6\tau_0} \exp\left\{\frac{(x-\mu_{i0})^2}{2\sigma_{i0}^2}\right\}} \mathcal{R}_{i0}^{2} + 2\pi \frac{1}{2\sigma_{i0}^2} \left\{\frac{(x-\mu_{i0})^2}{2\sigma_{i0}^2}\right\}$

战百分 LR模型

$$\begin{split} P(\mathcal{Y} = | \mathcal{X}_{1}, \mathcal{X}_{0}) &= \frac{P(\mathcal{X}_{1}, \mathcal{X}_{0} | \mathcal{Y} = 1) P(\mathcal{Y} = 1)}{P(\mathcal{X}_{1}, \mathcal{X}_{0} | \mathcal{Y} = 0) P(\mathcal{Y} = 0) + P(\mathcal{X}_{1}, \mathcal{X}_{0} | \mathcal{Y}) P(\mathcal{Y} = 1)} = \frac{1}{1 + \frac{P(\mathcal{Y} = 0)}{P(\mathcal{Y} = 1)} \frac{P(\mathcal{X}_{0}, \mathcal{X}_{1} | \mathcal{Y} = 0)}{P(\mathcal{X}_{0}, \mathcal{X}_{1} | \mathcal{Y} = 0)}} \\ P(\mathcal{X}_{1}, \mathcal{X}_{2} | \mathcal{Y} = 0) &= \frac{N(\mu_{10}, \mu_{20}, \sigma_{1}, \sigma_{2}, \rho)}{N(\mu_{11}, \mu_{21}, \sigma_{1}, \sigma_{2}, \rho)} \\ &= e^{\chi \rho} \left\{ \frac{\sigma_{2}^{2}(2\chi_{1} - \mu_{10} - \mu_{11})(\mu_{11} - \mu_{10}) + \sigma_{2}^{2}(2\chi_{2} - \mu_{10} - \mu_{21}) - 2\rho\sigma_{1}\sigma_{2}(\mu_{10}\mu_{20} - \mu_{10}\mu_{20})\chi_{2} - (\mu_{11} - \mu_{21})\chi_{1}}{2(|-\rho^{2}|) \sigma_{1}^{2}\sigma_{2}^{2}} \right\} \\ P(\mathcal{X}_{1}, \mathcal{X}_{2} | \mathcal{X}_{2}) &= \frac{1}{P(\mathcal{X}_{1}, \mathcal{X}_{2} | \mathcal{X}_{2})} P(\mathcal{X}_{2}, \mathcal{X}_{3}) P(\mathcal{X}_{2}) P(\mathcal{X}_{2}) P(\mathcal{X}_{3}) P(\mathcal{X}_{3})$$