

$$4) \quad \text{LRT} : \frac{\prod_{i=1}^n \lambda_1 e^{-\lambda_1 x_i}}{\prod_{i=1}^n \lambda_0 e^{-\lambda_0 x_i}} \underset{H_0}{\overset{H_1}{>}} \tau$$

$$= \sum_{i=1}^n -\lambda_1 x_i \log \lambda_1 + \lambda_0 x_i \log \lambda_0 \underset{H_0}{\overset{H_1}{>}} \log \tau$$

$$\sum_{i=1}^n x_i [\lambda_0 \log \lambda_0 - \lambda_1 \log \lambda_1] \underset{H_0}{\overset{H_1}{>}} \log \tau$$

$$\lambda_1 > \lambda_0$$

$$\sum_{i=1}^n x_i \underset{H_0}{\overset{H_1}{>}} \log \tau [\lambda_0 \log \lambda_0 - \lambda_1 \log \lambda_1]^{-1}$$

our test statistic is $T(x_1, x_2, \dots, x_n) := \sum_{i=1}^n x_i$

we define the threshold $\gamma = \log \tau [\lambda_0 \log \lambda_0 - \lambda_1 \log \lambda_1]^{-1}$

$$P_{FP} = \int_{\gamma}^{\infty} \lambda e^{-\lambda x} dx$$

$$= -e^{-\lambda x} \Big|_{\gamma}^{\infty}$$

$$P_{FP} = e^{-\lambda \gamma}$$

a UMP does exist because for larger λ_1 , where $\lambda_1 > \lambda_0$, γ will become a smaller negative #, thus P_{FP} will decrease with increasing λ_1 .

$$5) \text{ LRT: } \frac{\prod_{i=1}^n \frac{\lambda_1}{2} e^{-\lambda_1 |x_i|}}{\prod_{i=1}^n \frac{\lambda_0}{2} e^{-\lambda_0 |x_i|}} \underset{H_0}{\overset{H_1}{>}} \tau$$

$$\sum_{i=1}^n -\lambda_1 |x_i| \log \lambda_1 + \lambda_0 |x_i| \log \lambda_0 \underset{H_0}{\overset{H_1}{>}} \log \tau$$

$$\sum_{i=1}^n |x_i| [\lambda_0 \log \lambda_0 - \lambda_1 \log \lambda_1] \underset{H_0}{\overset{H_1}{>}} \log \tau$$

$$\sum_{i=1}^n |x_i| \underset{H_0}{\overset{H_1}{>}} \log \tau [\lambda_0 \log \lambda_0 - \lambda_1 \log \lambda_1]^{-1}$$

$$t := \sum_{i=1}^n |x_i|$$

$$P_{FP} = \int_{-\infty}^{-\gamma} \frac{\lambda}{2} e^{\lambda x} dx + \int_{\gamma}^{\infty} \frac{\lambda}{2} e^{-\lambda x} dx$$

$$= \frac{1}{2} e^{\lambda x} \Big|_{-\infty}^{-\gamma} + \frac{1}{2} e^{-\lambda x} \Big|_{\gamma}^{\infty}$$

$$= \frac{1}{2} e^{-\lambda \gamma} + \frac{1}{2} e^{-\lambda \gamma}$$

$$\boxed{P_{FP} = e^{-\lambda \gamma}}$$

there is a UMP test given reasoning explained in 4

$$\begin{aligned}
 6) \quad \hat{\lambda}(x) &= \frac{\max_{\theta, \sigma_1^2} \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\theta_1)^2}{2\sigma_1^2}}}{\max_{\sigma_0^2} \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{x^2}{2\sigma_0^2}}} \quad \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \gamma \\
 &= \frac{\max_{\theta, \sigma_1^2} -\frac{(x-\theta_1)^2}{2\sigma_1^2} - \frac{1}{2} \log 2\pi\sigma_1^2}{\max_{\sigma_0^2} -\frac{x^2}{2\sigma_0^2} - \frac{1}{2} \log 2\pi\sigma_0^2} \quad \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \log \gamma
 \end{aligned}$$

$$\begin{aligned}
 &= \frac{\max_{\theta, \sigma_1^2} -\frac{1}{2\sigma_1^2} [x^T x - 2\theta^T s^T x + \theta^T s^T s \theta]}{\max_{\sigma_0^2} -\frac{1}{2\sigma_0^2} x^2 - \frac{1}{2} \log 2\pi\sigma_0^2}
 \end{aligned}$$

$$\begin{aligned}
 \max_{\theta} : \quad \frac{\partial}{\partial \theta} \left[-\frac{1}{2\sigma_1^2} [x^T x - 2\theta^T s^T x + \theta^T s^T s \theta] - \frac{1}{2} \log 2\pi\sigma_1^2 \right] &= 0 \\
 &= -\frac{1}{2\sigma_1^2} [-2s^T x + 2s^T s \theta] = 0
 \end{aligned}$$

$$\boxed{\hat{\theta} = \frac{s^T x}{s^T s}}$$

$$\max_{\sigma_1^2} : \quad \frac{\partial}{\partial \sigma_1^2} = \frac{1}{4\sigma_1^4} [x^T x - 2\theta^T s^T x + \theta^T s^T s \theta] - \frac{1}{2} \frac{1}{2\pi\sigma_1^2} = 0$$

$$\begin{aligned}
 \hat{\sigma}_1^2 &= [x^T x - 2\theta^T s^T x + \theta^T s^T s \theta] \\
 \boxed{\hat{\sigma}_1^2 &= (x - \hat{\theta} s)^2}
 \end{aligned}$$

$$\max_{\sigma_0^2} : \quad \frac{\partial}{\partial \sigma_0^2} \left[-\frac{1}{2\sigma_0^2} x^T x - \frac{1}{2} \log 2\pi\sigma_0^2 \right] = 0$$

$$= \frac{1}{4\sigma_0^4} x^T x - \frac{1}{2} \frac{1}{2\pi\sigma_0^2} = 0$$

$$\boxed{\hat{\sigma}_0^2 = x^T x}$$

$$6) \log \hat{\lambda}(x) = \log \frac{\frac{1}{\sqrt{2\pi\hat{\sigma}_1^2}} e^{-(x-\hat{\theta}_1)^2/2\hat{\sigma}_1^2}}{\frac{1}{\sqrt{2\pi\hat{\sigma}_0^2}} e^{-x^2/2\hat{\sigma}_0^2}} \quad \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \log \gamma$$

$$= \left[-(x-\hat{\theta}_1)^2/2\hat{\sigma}_1^2 - \frac{1}{2} \log[2\pi\hat{\sigma}_1^2] \right] - \left[-x^2/2\hat{\sigma}_0^2 - \frac{1}{2} \log[2\pi\hat{\sigma}_0^2] \right]$$

$$= \left[\left[x^T x + 2\hat{\theta}_1^T s^T x - \hat{\theta}_1^T s^T s \hat{\theta}_1 \right] / 2\hat{\sigma}_1^2 - 2\log \hat{\sigma}_1 + \frac{1}{2} \log 2\pi \right] - \left[x^T x / 2\hat{\sigma}_0^2 - \log \hat{\sigma}_0^2 + \frac{1}{2} \log 2\pi \right]$$

$$= \left[-\frac{1}{2} - \log \hat{\sigma}_1^2 \right] - \left[-\frac{1}{2} - \log \hat{\sigma}_0^2 \right]$$

$$= \log \hat{\sigma}_0^2 - \log \hat{\sigma}_1^2$$

$$= \log \frac{x^2}{(x-\hat{\theta}_1)^2}$$

$$= \log \frac{x^2}{\left(x - \frac{s^T x}{s^T s} s \right)^2} \quad \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \log \gamma$$

$$\hat{\lambda}(x) = e^{\left(\frac{x}{x - \frac{s^T x}{s^T s} s} \right)^2} \quad \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \gamma$$

$$7) \quad \sum x_i \sim N(0, n)$$

$$P_{FP} = \alpha = \int_{\delta}^{\infty} \frac{1}{\sqrt{2\pi n}} e^{-x^2/2n} dx \quad y = \frac{x}{\sqrt{n}} \quad dy = \frac{dx}{\sqrt{n}}$$

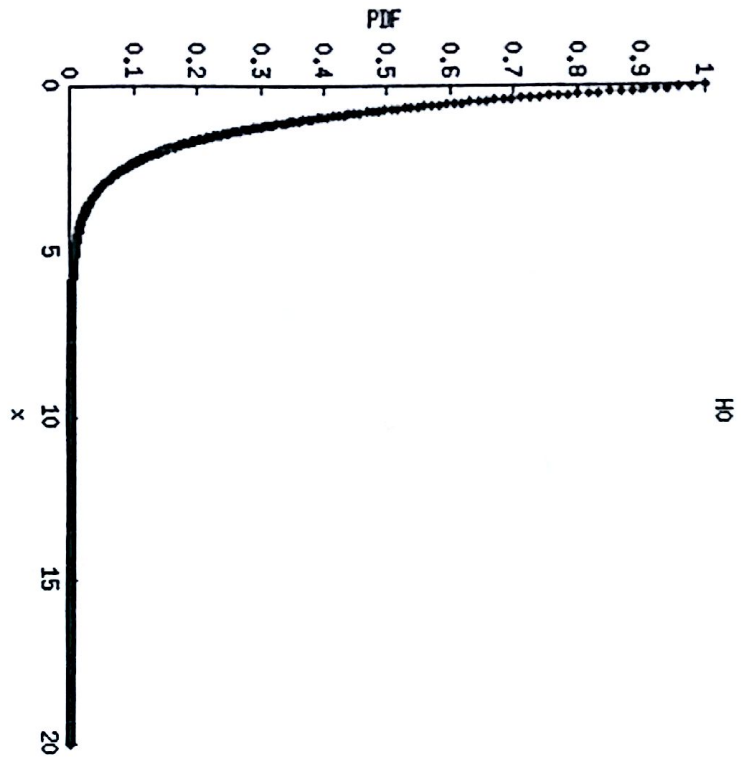
$$= \int_{\frac{\delta}{\sqrt{n}}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy$$

$$= Q\left(\frac{\delta}{\sqrt{n}}\right)$$

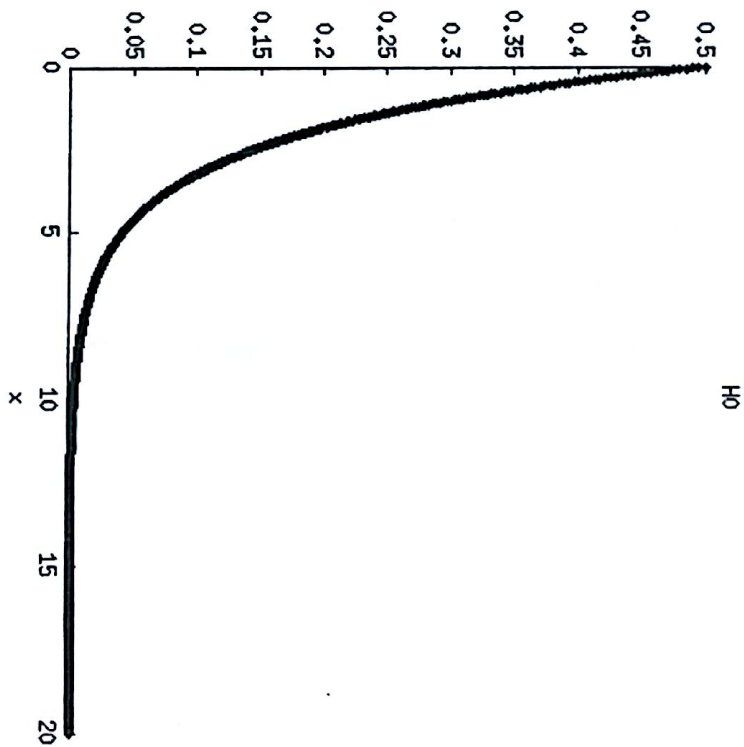
$$\alpha = Q\left(\frac{\delta}{\sqrt{n}}\right)$$

8a)

$$\langle p_0 \rangle = \cancel{0.5} \\ 0.5$$



$$\langle p_1 \rangle = \cancel{0.5} \\ 0.5$$



$$8b) P_{FP} = \int_{\gamma}^{\infty} e^{-x} dx$$

$$= -e^{-x} \Big|_{\gamma}^{\infty}$$

$$= e^{-\gamma}$$

$$P_{FP} \leq 0.05$$

$$e^{-\gamma} \leq 0.05$$

$$\gamma \geq -\log 0.05$$

$$P_D = \int_{\gamma}^{\infty} 0.5 e^{-x/2} dx$$

$$= -e^{-x/2} \Big|_{\gamma}^{\infty}$$

$$= e^{-\gamma/2}$$

SPRT :

$$\gamma_1 \leq \frac{e^{-\gamma/2}}{e^{-\gamma}}$$

$$\gamma_1 \leq \frac{1}{e^{-\gamma/2}}$$

$$\gamma_1 \leq e^{\gamma/2}$$

$$\gamma_0 \geq \frac{1 - e^{-\gamma/2}}{1 - e^{-\gamma}}$$

$$8c) \quad D(p_0 \| p_1) = \sum_{i=1}^n p_{0i} \log \frac{p_{0i}}{p_{1i}}$$

2

$$E_0[K^*] = \frac{(1 - P_{FA}) \log \left(\frac{1 - P_{FA}}{1 - P_D} \right) - P_{FA} \log \left(\frac{P_D}{P_{FA}} \right)}{D(p_0 \| p_1)}$$

$$E_1[K^*] = \frac{P_D \log \left(\frac{P_D}{P_{FA}} \right) - (1 - P_D) \log \left(\frac{1 - P_{FA}}{1 - P_D} \right)}{D(p_1 \| p_0)}$$

$$\gamma = -\log(0.05) = 2.99$$

$$\gamma_1 = e^{\gamma/2} = 4.47$$

$$\gamma_0 = \frac{1 - e^{-\gamma/2}}{1 - e^{-\gamma}} = 0.81$$

$$P_{FP} = 0.05 \quad P_D = e^{-\gamma/2} = 0.22$$

$$E_0 = 0.6 \rightarrow E_0 = 1$$

$$E_1 = 1$$