

$\chi^2$  Test.

Statistical model:

$$y_i = \mu_i + z_i, \quad z_i \sim N(0, 1), \quad 1 \leq i \leq n$$

$$\Leftrightarrow y \sim N(\mu, I), \quad \mu = (\mu_1, \dots, \mu_n)$$

$$H_0: \mu = 0 \quad \textcircled{\text{vs}} \quad H_1: \text{at least one } \mu_i \neq 0$$

Test statistic for  $\chi^2$  test:

$$T = \sum_{i=1}^n y_i^2 = \|y\|^2$$

Under  $H_0$ :  $T = \sum_{i=1}^n z_i^2 \Rightarrow$

 $\nwarrow \text{i.i.d. } \sim N(0, 1)$ 

$$\Rightarrow T \sim \chi_n^2 \Rightarrow$$

 $\Rightarrow$  we reject  $H_0$  on significance level:

$$T > \chi_n^2(1-\alpha)$$

Note: 1)  $E z_i^2 = 1$   $\text{var } z_i^2 = 2 \Rightarrow$   
 $\Rightarrow ET = n; \text{var } T = 2n \Rightarrow \text{CLT}$

$$\frac{T-n}{\sqrt{2n}} \xrightarrow{D} N(0, 1)$$

2)  $P_0(T > \chi_n^2(1-\alpha)) = 1-\alpha \Rightarrow$  for large  $n$

$$\Rightarrow P_0 \left( \frac{T-n}{\sqrt{2n}} > \frac{\chi_n^2(1-\alpha) - n}{\sqrt{2n}} \right) = 1-\alpha$$

$\sim N(0, 1) \qquad \sim Z(1-\alpha)$

$$\Rightarrow \chi_n^2(1-\alpha) \approx n + \sqrt{2n} Z(1-\alpha)$$

Under  $H_1$ :  $T \sim \chi^2(n, \lambda)$  - non-central  $\chi^2$

$\nwarrow$  non-centrality parameter

$$E(z_i + \mu_i)^2 = E z_i^2 + 2\mu_i E z_i + \mu_i^2 = \mu_i^2 + 1$$

$$\text{var}(z_i + \mu_i)^2 = E^2(z_i + \mu_i)^4 - (\mu_i^2 + 1)^2 =$$

$$= E z_i^4 + 4\mu_i E z_i^3 + 6\mu_i^2 E z_i^2 + 4\mu_i^3 E z_i + \mu_i^4 - (\mu_i^4 + 2\mu_i^2 + 1) = \left[ E z_i^k = \begin{cases} (k-1)!! & , k = \text{even} \\ 0 & , k = \text{odd} \end{cases} \right] =$$

$$= 3 + 6\mu_i^2 - 2\mu_i^2 - 1 = 4\mu_i^2 + 2$$

$$\Rightarrow ET = \| \mu \|^2 + n; \quad \text{var} T = 4\| \mu \|^2 + 2n$$

$$\xrightarrow{\text{CLT}} \frac{T - (n + \| \mu \|^2)}{\sqrt{2n + 4\| \mu \|^2}} \sim N(0, 1)$$

$$Z = \frac{T - n}{\sqrt{2n}} = \text{test Statistic}$$

$$\theta = \frac{\| \mu \|^2}{\sqrt{2n}} \propto \text{SNR} = \frac{\text{signal}}{\text{noise}} - \text{a measure that shows how strong is a signal with respect to noise}$$

$$H_0: Z \sim N(0, 1) \quad \text{vs} \quad H_1: Z \sim N\left(\theta, 1 + \frac{\theta}{\sqrt{n/8}}\right)$$

$$\Gamma \frac{T - (n + \| \mu \|^2)}{\sqrt{2n + 4\| \mu \|^2}} = \frac{\frac{T - n}{\sqrt{2n}} - \frac{\| \mu \|^2}{\sqrt{2n}}}{\sqrt{1 + \frac{2\| \mu \|^2}{n}}} = \frac{Z - \theta}{\sqrt{1 + \frac{\theta}{\sqrt{n/8}}}} \sim N(\theta, 1)$$

$\Rightarrow$  test statistic  $Z$  can distinguish hypotheses when  $\theta$  is large enough.

$\Leftrightarrow$  the power of the  $\chi^2$  test is not determined by the length of the largest needle but the  $\| \mu \|^2$  compared to  $\sqrt{n}$ .

### Definition of SNR

$$y_i = \mu_i + \sigma z_i; \quad i = 1, \dots, n \quad z_i \text{ iid } \sim N(0, 1)$$

the detection power depends on

$$\theta = \sqrt{\frac{n}{2}} \frac{\| \mu \|^2}{\sigma^2 n}$$



$$SNR \stackrel{df}{=} \frac{\|\mu\|^2}{\sigma^2 n} = \frac{\text{total signal power}}{\text{total expected noise power}}$$

$$\Rightarrow \Theta \propto SNR. \quad \Leftrightarrow \Theta = \sqrt{\frac{n}{2}} SNR$$

### Comparison between Bonferroni's and $\chi^2$ tests

- when the signal is more or less uniformly distributed there is no test better than the  $\chi^2$  test.
- when we have "needle in the haystack" problem there is no test better than Bonferroni test.

### Example 1.

$$\Theta = \frac{\|\mu\|^2}{\sqrt{2n}}, \quad \text{when } \Theta \rightarrow \infty \text{ } \chi^2 \text{ test can identify } H_1.$$

$$\text{Let } \mu_1 = \dots = \mu_n = \delta_n \Rightarrow \|\mu\|^2 = n \delta_n^2$$

$$\Rightarrow \Theta = \frac{n \delta_n^2}{\sqrt{2n}} = \frac{1}{\sqrt{2}} \sqrt{n} \delta_n^2$$

$$\text{If } \delta_n \rightarrow 0 \text{ s.t. } \sqrt{n} \delta_n^2 \rightarrow \infty, n \rightarrow \infty$$

$$(\text{for example, } \delta_n = n^{-(\frac{1}{2} + \varepsilon)}, \varepsilon > 0)$$

$$\text{if } \delta_n = \text{const}$$

then  $H_1$  can be detected by  $\chi^2$  test.

But Bonferroni can identify  $\mu^{(n)} > (1 + \varepsilon) \sqrt{2 \log n}$

### Example 2

$$\mu_1 = (1 + \varepsilon) \sqrt{2 \log n}; \mu_2 = \dots = \mu_n = 0. \quad (\text{Bonf can identify } H_1)$$

$$\|\mu\|^2 = (1 + \varepsilon)^2 \cdot 2 \log n \Rightarrow$$

$$\Theta = \frac{\|\mu\|^2}{\sqrt{2n}} = 2(1 + \varepsilon)^2 \frac{\log n}{\sqrt{2n}} \rightarrow 0, n \rightarrow \infty$$

$\Rightarrow \chi^2$  test can not identify Bonferroni needle.

Is there a test that does better than  $\chi^2$ -test when  $\theta \ll 1$ ? -4-

(signal is  $\approx$  uniformly distributed)

We show that the optimal test given by the Neyman-Pearson Lemma is powerless

Bayesian Problem:

$$H_0: \mu = 0 \quad (\text{VS}) \quad H_1: \mu \sim \pi_S,$$

here  $S^{n-1} = \{u \in \mathbb{R}^n : \|u\| = 1\}$  - sphere of radius 1  
 $\pi = \text{Unif}(S^{n-1})$

$$S_p^{n-1} = \{pu : u \in S^{n-1}\}; \quad \pi_p = \text{Unif}(S_p^{n-1})$$

$$f_1(y/u) = \frac{1}{(2\pi)^{n/2}} e^{-\frac{\|y - pu\|^2}{2}} \quad \Rightarrow \quad \text{Law of Total Probability}$$

$$f_1(y) = \int_{S^{n-1}} f_1(y/u) d\pi(u)$$

$$f_0(y) = \frac{1}{(2\pi)^{n/2}} e^{-\frac{\|y\|^2}{2}}$$

$$\Rightarrow L = \frac{f_1(y)}{f_0(y)} = \int_{S^{n-1}} \frac{e^{-\frac{\|y - pu\|^2}{2}}}{e^{-\frac{\|y\|^2}{2}}} d\pi(u) \quad (\text{E})$$

$$\begin{aligned} -\|y - pu\|^2 + \|y\|^2 &= -\|y\|^2 + 2p\langle y, u \rangle - p^2\|u\|^2 + \|y\|^2 \\ &= 2p\langle y, u \rangle - p^2 \\ &\quad \quad \quad u^T y \end{aligned}$$

$$\text{(E)} \quad \int_{S^{n-1}} e^{-\frac{1}{2}p^2 + pu^T y} \pi(du)$$

We show that optimal test cannot identify  $H_1$

when  $\theta_n = \frac{p^2}{\sqrt{2n}} \rightarrow 0, n \rightarrow \infty$ .

Scheme proof:



(1)  $E_0 L = 1$  (property of likelihood ratio) -5-

$$L = \frac{dP_1}{dP_0} \Rightarrow E_0 L = \int \frac{dP_1}{dP_0} dP_0 = \int dP_1 = 1$$

(2)  $\text{Var}_0 L \rightarrow 0$  ??

$\xrightarrow{(1)+(2)}$   $L \xrightarrow{P} 1$   
like in previous lecture

$P_1(\text{Type II Error}) \rightarrow 1 - \alpha$

prop  $\text{Var}_0 L \rightarrow 0$ ,  $\Theta_n = \frac{\rho^2}{\sqrt{2n}} \rightarrow 0, n \rightarrow \infty$

$\left\{ \begin{array}{l} y \sim N(0, I) \\ E e^{a^T y} = e^{\frac{1}{2} \|a\|^2} \end{array} \right.$  - mgf of Gaussian random vector

$$E_0 L^2 = E_0 \int \int_{\mathbb{R}^n \times \mathbb{R}^n} e^{-\frac{\rho^2}{2} + \rho \langle u, y \rangle} \cdot e^{-\frac{\rho^2}{2} + \rho \langle v, y \rangle} \pi(du) \pi(dv)$$

$$= e^{-\rho^2} E_0 \int \int e^{\rho \langle u+v, y \rangle} \pi(du) \pi(dv) =$$

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$$= e^{-\rho^2} \int \int e^{\frac{1}{2} \rho^2 \|u+v\|^2} \pi(du) \pi(dv) =$$

$$= \int \|u+v\|^2 = \|u\|^2 + \|v\|^2 + 2\langle u, v \rangle = 2 + 2\langle u, v \rangle \int =$$

$$= e^{-\rho^2} \int \int e^{\rho^2 + \rho^2 \langle u, v \rangle} \pi(du) \pi(dv) = \int \int e^{\rho^2 \langle u, v \rangle} \pi(du) \pi(dv)$$

$w = Sv$ , where  $S$  is rotation operator  $\Leftrightarrow S$  is orthogonal matrix:  $S^T S = I$

$$\Rightarrow \|v\|^2 = 1 \Rightarrow \|w\|^2 = \|Sv\|^2 = \langle Sv, Sv \rangle = \langle S^T S v, v \rangle = \langle v, v \rangle = \|v\|^2$$

$|\det S| = 1 \Rightarrow$  Jacobian of this transformation = 1

$$\Rightarrow v = S^T w$$

$$S(S_{n-1}) = S_{n-1}$$

$$\int_{S_{n-1}} e^{\rho^2 \langle u, v \rangle} \pi(du) = \int_{S_{n-1}} e^{\rho^2 \langle u, S^T w \rangle} \pi(du) =$$

$$= \int_{S_{n-1}} e^{\rho^2 \langle Su, w \rangle} \pi(du) = \int_{S_{n-1}} e^{\rho^2 \langle z, w \rangle} \pi(dz) =$$

$$= \int_{S_{n-1}} e^{\rho^2 \langle u, w \rangle} \pi(du)$$

$$w = (1 \ 0 \ \dots \ 0) \Rightarrow$$

$$\Rightarrow \iint_{S_{n-1} \times S_{n-1}} e^{\rho^2 \langle u, v \rangle} \pi(du) \pi(dv) = \int_{S_{n-1}} \int_{S_{n-1}} e^{\rho^2 \langle u, w \rangle} \pi(du) \pi(dv) =$$

$$= \iint_{S_{n-1} \times S_{n-1}} e^{\rho^2 u_1} \pi(du) \pi(dv) = \int_{S_{n-1}} \pi(dv) = 1 =$$

$$= \int_{S_{n-1}} e^{\rho^2 u_1} \pi(du)$$

$$e^{\rho^2 u_1} = 1 + \rho^2 u_1 + \frac{\rho^4 u_1^2}{2} + \dots$$

$$E e^{\rho^2 u_1} =$$

$$\left\{ \begin{array}{l} E u_1 = 0 \quad \text{--- due to symmetry} \\ u_1^2 + \dots + u_n^2 = 1 \Rightarrow E u_1^2 = \frac{1}{n} \\ \quad \nwarrow \nearrow \\ \quad \text{ident distributed} \end{array} \right.$$

$$\ominus 1 + \frac{\rho^4}{2n} + o\left(\frac{\rho^4}{2n}\right) = 1 + \theta_n^2 + o(\theta_n^2) \rightarrow 1, \quad \text{when } \theta_n \rightarrow 0$$

$$\text{We have that } E_0 L^2 \rightarrow 1, \quad E_0 L = 1$$

$$\Rightarrow \text{var } L \rightarrow 0, \quad \theta_n \rightarrow 0 \quad \perp$$