

# **MEM-264 Applied Statistics**

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## **Applications**

# 1st Example : Normal distribution with known variance

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\theta, \sigma^2)$  where  $\sigma^2$  is known.

$$H_0 : \theta \leq \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

$$\begin{aligned} f(x_1; \theta) &\propto \exp\left\{-\frac{1}{2\sigma^2}(x_1 - \theta)^2\right\} \\ &\propto \exp\left\{-\frac{1}{2\sigma^2}(x_1^2 - 2\theta x_1 + \theta^2)\right\} \end{aligned}$$

joint pdf :  $f(\underline{x}; \theta) \propto \exp\left\{-\frac{1}{2\sigma^2}\left(\sum_{j=1}^n x_j^2 - 2\theta \sum_{j=1}^n x_j + n\theta^2\right)\right\}$

$$\underline{x} = (x_1, x_2, \dots, x_n)^T$$

$$\underline{\theta}' > \theta \quad \Lambda(\underline{x}) = \frac{f(\underline{x}; \theta')}{f(\underline{x}; \theta)} \propto \exp\left\{-\frac{n}{2\sigma^2}\left[(\theta')^2 - \theta^2\right]\right\} \exp\left\{\frac{\sum x_i}{\sigma^2}(\theta' - \theta)\right\} = \exp\left\{-\frac{n}{2\sigma^2}\left[(\theta')^2 - \theta^2\right]\right\} \exp\left\{n \frac{\sum x_i}{\sigma^2}(\theta' - \theta)\right\}$$

$\underline{t}(\underline{x}) = \bar{X}_n$        $\Lambda(\underline{t}(x))$

the  $f(\underline{x}; \theta)$  has MLR in the statistics  $T = \underline{t}(X) = \bar{X}_n$

Given  $\alpha \in (0, 1]$ , there is  $t_\alpha$  s.t the test  $\phi_\alpha(\underline{x}) = \begin{cases} 1 & \text{if } \bar{X}_n > t_\alpha \\ 0 & \text{if } \bar{X}_n \leq t_\alpha \end{cases}$  has size exactly  $\alpha$ .

$\phi_\alpha$  is a uniformly most powerful (UMP) test of size  $\alpha$ .

## 1st Example : Normal distribution with known variance

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\theta, \sigma^2)$  where  $\sigma^2$  is known.

$$H_0 : \theta \leq \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

$$\bar{X}_n \sim \mathcal{N}(\theta_{\text{true}}, \frac{\sigma^2}{n})$$

$$\text{size } \alpha \Rightarrow \mathbb{E}_{\theta} \{ \phi_0(X) \} \leq \mathbb{E}_{\theta_0} \{ \phi_0(X) \} = \alpha$$

under the null hypothesis

$$\bar{X}_n \sim \mathcal{N}(\theta_0, \frac{\sigma^2}{n})$$

$$\mathbb{E}_{\theta_0} \{ \phi_0(X) \} = \mathbb{P}_{\theta_0} \{ \bar{X}_n > t_0 \} = \alpha$$

$$\mathbb{P} \left\{ \frac{\bar{X}_n - \theta_0}{\sigma} > z_0 \right\} = \alpha = 1 - \mathbb{P} \left\{ \frac{\bar{X}_n - \theta_0}{\sigma} \leq z_0 \right\}$$

$$z_0 = \frac{t_0 - \theta_0}{\sigma} \Leftrightarrow \boxed{t_0 = \sigma z_0 + \theta_0}$$

$$\mathbb{P} \left\{ \frac{\bar{X}_n - \theta_0}{\sigma} \leq z_0 \right\} = 1 - \alpha$$

## 2nd Example : Normal distribution with known mean value

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\mu, \theta)$ ,  $\theta > 0$  where  $\mu = \bar{\theta}$   <sup>$\sigma^2$</sup>   $(\cdot) = (0, +\infty)$

$$H_0 : \theta \leq \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

$$f(x; \theta) \propto \exp \left\{ -\frac{\sum x_j^2}{2\theta} \right\}$$

$$\theta' > \theta \quad \Lambda(x) = \frac{f(x; \theta')}{f(x; \theta)} \propto \exp \left\{ -\sum_{j=1}^n x_j^2 \frac{1}{2} \left( \frac{1}{\theta'} - \frac{1}{\theta} \right) \right\} = \exp \left\{ -\frac{\theta_0^{-1}}{\theta_0} \frac{1}{2} \left( \frac{1}{\theta'} - \frac{1}{\theta} \right) \right\}$$

$$\tilde{\Lambda}(t(x)) \quad , \quad t(x) = \theta_0^{-1} \sum_{j=1}^n x_j^2 \quad \text{MLR}$$

$$\phi_0(x) = \begin{cases} 1, & \theta_0^{-1} \sum x_j^2 > t_0 \\ 0, & \theta_0^{-1} \sum x_j^2 \leq t_0 \end{cases} \quad , \quad \text{UMP among all tests of size } \leq \mathbb{E}_{\theta_0} \{ \phi_0(X) \}$$

$$\sum_{j=1}^n \left( \frac{x_j}{\theta^{1/2}} \right)^2 \quad \frac{x_j}{\theta^{1/2}} \sim \mathcal{N}(0, 1)$$

$$t(x) = T \sim \chi_n^2 \quad , \quad n - \text{degrees of freedom.}$$

## 2nd Example : Normal distribution with known mean value

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\mu, \theta)$ ,  $\theta > 0$  where  $\mu$  is known.

$$H_0 : \theta \leq \underline{\theta_0} \quad \text{vs} \quad H_1 : \theta > \theta_0$$

$$\mathbb{P}_{\theta_0} \{ T > t_0 \} = \alpha = 1 - \mathbb{P}_{\theta_0} \{ T \leq t_0 \} \Rightarrow \mathbb{P}_{\theta_0} \{ T \leq t_0 \} = F_{\chi_n^2}(t_0; \theta_0) = 1 - \alpha$$

for example

$$H_0 : \theta \leq 2, \quad H_1 : \theta > 2$$

$$X_1, \dots, X_5 \sim \mathcal{N}(0, \frac{11}{\theta}) \quad \alpha = 0,05$$

$$t_0 = 11.07$$

$$\phi_0(x) = \begin{cases} 1, & \sum x_i^2 > \theta_0 t_0 = 2 \cdot 11.07 = 22.14 \\ 0, & \sum x_i^2 \leq 22.14. \end{cases}$$

Degrees of freedom (df)	$\chi^2$ value <sup>[19]</sup>										
1	0.004	0.02	0.06	0.15	0.46	1.07	1.64	2.71	3.84	6.63	10.83
2	0.10	0.21	0.45	0.71	1.39	2.41	3.22	4.61	5.99	9.21	13.82
3	0.35	0.58	1.01	1.42	2.37	3.66	4.64	6.25	7.81	11.34	16.27
4	0.71	1.06	1.65	2.20	3.36	4.88	5.99	7.78	9.49	13.28	18.47
5	1.14	1.61	2.34	3.00	4.35	6.06	7.29	9.24	11.07	15.09	20.52
6	1.63	2.20	3.07	3.83	5.35	7.23	8.56	10.64	12.59	16.81	22.46
7	2.17	2.83	3.82	4.67	6.35	8.38	9.80	12.02	14.07	18.48	24.32
8	2.73	3.49	4.59	5.53	7.34	9.52	11.03	13.36	15.51	20.09	26.12
9	3.32	4.17	5.38	6.39	8.34	10.66	12.24	14.68	16.92	21.67	27.88
10	3.94	4.87	6.18	7.27	9.34	11.78	13.44	15.99	18.31	23.21	29.59
<b>P value (Probability)</b>	0.95	0.90	0.80	0.70	0.50	0.30	0.20	0.10	0.05	0.01	0.001

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### 3rd Example : 2 normal distributions of known variances

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\theta, \sigma_1^2)$  and  $Y_1, \dots, Y_m$  be an i.i.d sample and  $Y_1 \sim \mathcal{N}(\alpha\theta, \sigma_2^2)$ , where  $\alpha, \sigma_1^2, \sigma_2^2$  are given.

$$H_0 : \theta \leq \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

$$\tilde{z} = (X_1, \dots, X_n, Y_1, \dots, Y_m)^T$$

$$f_{\tilde{z}}(\tilde{z}; \theta) \propto \exp \left\{ -\frac{1}{2\sigma_1^2} \sum_{j=1}^n (x_j - \theta)^2 - \frac{1}{2\sigma_2^2} \sum_{j=1}^m (y_j - \alpha\theta)^2 \right\} = \exp \left\{ -\frac{1}{2\sigma_1^2} \sum_{j=1}^n (x_j^2 - 2\theta x_j + \theta^2) - \frac{1}{2\sigma_2^2} \sum_{j=1}^m (y_j^2 - 2\alpha\theta y_j + \alpha^2 \theta^2) \right\}$$

$$\Lambda(\tilde{z}) \propto \exp \left\{ \frac{\sum x_j}{\sigma_1^2} (\theta' - \theta) + \frac{\alpha \sum y_j}{\sigma_2^2} (\theta' - \theta) \right\} = \exp \left\{ [\theta' - \theta] \left( \frac{n}{\sigma_1^2} \bar{X}_n + \frac{\alpha m}{\sigma_2^2} \bar{Y}_m \right) \right\}$$

MLR in the statistics  $t(\tilde{z}) = \frac{n}{\sigma_1^2} \bar{X}_n + \frac{\alpha m}{\sigma_2^2} \bar{Y}_m$

UMP 
$$f_0(\tilde{z}) = \begin{cases} 1, & t(\tilde{z}) > t_0 \\ 0, & t(\tilde{z}) \leq t_0 \end{cases}$$

### 3rd Example : 2 normal distributions of known variances

Let  $X_1, \dots, X_n$  be an i.i.d sample and  $X_1 \sim \mathcal{N}(\theta, \sigma_1^2)$  and  $Y_1, \dots, Y_m$  be an i.i.d sample and  $Y_1 \sim \mathcal{N}(\alpha\theta, \sigma_2^2)$ , where  $\alpha, \sigma_1^2, \sigma_2^2$  are given.

$$H_0 : \theta \leq \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

what is the distribution of  $T = t(\mathbf{Z})$ ?

$$\bar{X}_n \sim \mathcal{N}\left(\theta, \frac{\sigma_1^2}{n}\right), \quad \bar{Y}_m \sim \mathcal{N}\left(\alpha\theta, \frac{\sigma_2^2}{m}\right)$$

$$\frac{1}{\sigma_{1,2}} \bar{X}_n \sim \mathcal{N}\left(\theta \frac{n}{\sigma_1^2}, \frac{n}{\sigma_1^2}\right), \quad \frac{\alpha m}{\sigma_2^2} \bar{Y}_m \sim \mathcal{N}\left(\alpha^2 \theta \frac{m}{\sigma_2^2}, \alpha^2 \frac{m}{\sigma_2^2}\right)$$

$$T \sim \mathcal{N}\left(\left[\frac{n}{\sigma_1^2} + \alpha^2 \frac{m}{\sigma_2^2}\right] \theta, \frac{n}{\sigma_1^2} + \alpha^2 \frac{m}{\sigma_2^2}\right)$$

$$\xrightarrow{\text{z-score}} t_0$$