

1. (a) Begin with $T_1 = \bar{X}^2$ and apply δ -method

$$\bar{X}^2 = \mu^2 + 2\mu(\bar{X} - \mu) + (\bar{X} - \mu)^2$$

$$\sqrt{n}(\bar{X}^2 - \mu^2) = 2\mu\sqrt{n}(\bar{X} - \mu) + \sqrt{n}(\bar{X} - \mu)(\bar{X} - \mu)$$

We know $\sqrt{n}(\bar{X} - \mu) \sim N(0, \sigma^2)$ and $\bar{X} - \mu \xrightarrow{P} 0$
 so $\sqrt{n}(\bar{X}^2 - \mu^2) \xrightarrow{d} N(0, 4\mu^2\sigma^2)$

$$\sqrt{n}(T_1 - T_2) = \sqrt{n}(\sigma^2/n) \rightarrow 0$$

$$\sqrt{n}(T_2 - T_3) = \sqrt{n}(S^2 - \sigma^2)/n = (S^2 - \sigma^2)/\sqrt{n} \xrightarrow{P} 0$$

because $S^2 \xrightarrow{P} \sigma^2$. Therefore, according to Slutsky's Theorem, $\sqrt{n}(T_j - \theta)$ have the same limiting distribution

(b) Now we assume $\mu^2 = \theta = 0$. Therefore the linear term in ~~the~~ the Taylor expansion vanishes.

We know $n\bar{X}^2 \sim \sigma^2\chi_{n-1}^2$ (this is an exact result)

and $E(n\bar{X}^2) = \sigma^2$. Therefore $a(n) = n$ is the required normalizing constant.

$$n(T_2 - \theta) = n(\bar{X}^2 - \sigma^2/n) = n\bar{X}^2 - \sigma^2$$

and $n(T_2 - \theta) \sim \sigma^2(\chi_{n-1}^2 - 1)$, a location-scale transformed χ_{n-1}^2 variable

$$n(T_2 - T_3) = S^2 - \sigma^2 \xrightarrow{P} 0, \text{ so } \text{the same}$$

$n(T_2 - \theta)$ and $n(T_3 - \theta)$ have the same

limiting distributions

$$2(a) \quad L = \prod_{i=1}^n \left[e^{-\mu} \mu^{x_i} / x_i! \right] = \exp(n\bar{X} \log \mu - n\mu) / \prod_{i=1}^n x_i!$$

$$\frac{\partial \log L}{\partial \mu} = \frac{n\bar{X}}{\mu} - n = 0 \Rightarrow \hat{\mu} = \bar{X}$$

$$\frac{\partial^2 \log L}{\partial \mu^2} = -\frac{n\bar{X}}{\mu^2} \Rightarrow \mathcal{I}_n(\mu) = \frac{n}{\mu}$$

$$\begin{aligned} -2 \log \Lambda &= -2n \left\{ \bar{X} \log \mu_0 - \mu_0 - \bar{X} \log \bar{X} + \bar{X} \right\} \\ &= 2n \left[\bar{X} \log (\bar{X}/\mu_0) - (\bar{X} - \mu_0) \right] \end{aligned}$$

For large n , reject if $-2 \log \Lambda > \chi^2_{1, \alpha} = z_{\alpha/2}^2$

$$(b) \quad \text{Wald test} \quad \text{Reject if } \frac{[\hat{\mu} - \mu_0]^2}{\mathcal{I}_n^{-1}(\hat{\mu})} > z_{\alpha/2}^2$$

$$\text{if } \frac{n[\bar{X} - \mu_0]^2}{\bar{X}/n} > z_{\alpha/2}^2$$

Invert acceptance rule to get confidence interval

$$L_W = \bar{X} - z_{\alpha} \sqrt{\bar{X}/n} \quad U_W = \bar{X} + z_{\alpha/2} \sqrt{\bar{X}/n}$$

$$\text{Score test} \quad \text{Reject if } \frac{n^2(\bar{X}/\mu_0 - 1)^2}{\mathcal{I}_n(\mu_0)} > z_{\alpha/2}^2$$

$$\text{if } \frac{n(\bar{X} - \mu_0)^2}{\mu_0} > z_{\alpha/2}^2$$

Inverting acceptance rule means solving the quadratic inequality $n(\bar{X} - \mu)^2 \leq \mu z_{\alpha/2}^2$. Roots (in μ) are

$$\bar{X} - \frac{z_{\alpha/2}^2}{2n} \pm z_{\alpha/2} \sqrt{\bar{X}/n} \sqrt{1 + z_{\alpha/2}^2/(4n\bar{X})}$$

It is straightforward to verify $L_S - L_W \rightarrow 0$,

$U_S - U_W \rightarrow 0$. In fact $\sqrt{n}(L_S - L_W) \rightarrow 0$, $\sqrt{n}(U_S - U_W) \rightarrow 0$

3. Estimate θ using only X_1

(a) Method of moments: $E(X_1) = n\theta^2 \Rightarrow \hat{\theta}_M = \sqrt{X_1/n}$

(b) Likelihood $L(\theta|X_1) = \binom{n}{X_1} \theta^{2X_1} (1-\theta^2)^{n-X_1}$
 $\Rightarrow \hat{\theta}_M = \sqrt{X_1/n}$

Use Δ -method. Write $\eta = \theta^2$

$$\sqrt{n} [\sqrt{X_1/n} - \theta] = \sqrt{n} \left[\cancel{\theta} + (X_1/n - \theta^2)^{1/2} \eta^{1/2} + R \right] \doteq \sqrt{n} \left(\frac{X_1}{n} - \theta^2 \right)^{1/2} \frac{1}{2\theta}$$

$$\therefore \sqrt{n} (\hat{\theta}_M - \theta) \xrightarrow{d} N\left(0, \frac{1-\theta^2}{4\theta^2}\right) \text{ as } n \rightarrow \infty$$

Check asymptotic efficiency by finding Fisher's info.

$$L(\theta|X_1, X_2, X_3) = \log \left(\frac{n!}{X_1! X_2! X_3!} \right) + X_1 \log \theta^2 + X_2 \log (2\theta(1-\theta)) + X_3 \log ((1-\theta)^2)$$

$$\frac{\partial \log L}{\partial \theta} = \frac{2X_1 + X_2}{\theta} - \frac{X_2 + 2X_3}{1-\theta} \quad (*)$$

$$\frac{\partial^2 \log L}{\partial \theta^2} = -\frac{2X_1 + X_2}{\theta^2} - \frac{X_2 + 2X_3}{(1-\theta)^2}$$

$$J_n = \frac{2n}{\theta(1-\theta)}$$

Easy to see that $\frac{1-\theta^2}{4n} = \frac{(1-\theta)(1+\theta)}{4n} > \frac{\theta(1-\theta)}{2n}$

$\therefore \hat{\theta}_M$ is not asymptotically efficient.

MLE of θ based on (X_1, X_2, X_3) is $\hat{\theta}^* = \frac{2X_1 + X_2}{2n}$

as can be seen from (*). From ML theory

$$\sqrt{n} (\hat{\theta}^* - \theta) \xrightarrow{d} N(0, J_n^{-1}) = N\left(0, \frac{\theta(1-\theta)}{2}\right).$$

[In fact, the exact variance of $\hat{\theta}^*$ is $\theta(1-\theta)/(2n)$.]

(4) (a) $S = \sum_{i=1}^n I\{X_i > 0\}$ is binomial $(n, 1-F(0))$

$$\therefore \frac{S - n(1-F(0))}{\sqrt{nF(0)(1-F(0))}} \xrightarrow{d} N(0, 1). \quad (*)$$

Under H_0 , $F(0) = 1/2$ because 0 is the median

$$\therefore c_{n\alpha} = \frac{n}{2} + z_{\alpha} \sqrt{n/4}$$

(b) If $\theta = 1$, $F(1) = 1/2$ and $F(0) < 1/2$

$$P\left[S > \frac{n}{2} + z_{\alpha} \sqrt{n/4}\right]$$

$$= P\left[\frac{S - n(1-F(0))}{\sqrt{nF(0)(1-F(0))}} > \frac{n/2 - n + nF(0)}{\sqrt{nF(0)(1-F(0))}} + z_{\alpha} \sqrt{\frac{1/4}{F(0)(1-F(0))}}\right]$$

$$= P\left[Z > -\sqrt{n} \frac{1/2 - F(0)}{\sqrt{F(0)(1-F(0))}} + \frac{z_{\alpha}}{2} \frac{1}{\sqrt{F(0)(1-F(0))}}\right]$$

where $Z \sim N(0, 1)$.

Note that the power depends only on $F(0) < 1/2$ and not on θ .

(c) Let $n \rightarrow \infty$. Then $-\sqrt{n} \frac{1/2 - F(0)}{\sqrt{F(0)(1-F(0))}} \rightarrow -\infty$

and $\frac{z_{\alpha}}{2} \frac{1}{\sqrt{F(0)(1-F(0))}}$ is fixed.

$\therefore$ power $\rightarrow 1$