

Standard Error & the δ -method

Usual setup: X_1, \dots, X_n iid $f(x; \theta)$

$T = T(X_1, \dots, X_n)$ is an estimator of θ

$$\text{Bias}(T; \theta) = E[T] - \theta$$

T is unbiased if $\text{Bias}(T; \theta) = 0$

$$MSE(T; \theta) = E[(T - \theta)^2]$$

if T is unbiased for θ (σ_T^2)

$$\text{then } MSE(T; \theta) = V[T] = E[T^2] - E[T]^2$$

$$\text{Standard Error } (T) = SE(T) = \sqrt{V[T]} = \sigma_T$$

$$\text{If } E[X_i] = \mu \text{ ; } V[X_i] = \sigma^2 \text{ then } SE(\bar{X}) = \sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$$

If we have n iid $X_i \sim N(\mu, \sigma^2)$

$$\text{then } S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2, \frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}, [\mu = n-1, \sigma^2 = 2(n-1)]$$

$$V\left(\frac{(n-1)S^2}{\sigma^2}\right) = 2(n-1) = \frac{(n-1)^2}{\sigma^4} V(S^2) ; V(S^2) = \frac{2\sigma^4}{(n-1)}$$

$$\text{so } SE(S^2) = \frac{\sigma^2 \sqrt{2}}{\sqrt{n-1}}$$

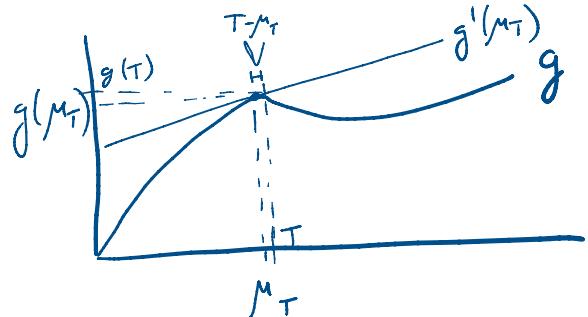
Introduction to the δ -method

Given $SE(T)$ and a function g :

Consider $g(T) \dots \nexists g(T) \approx g(\mu_T) + g'(\mu_T)(T - \mu_T)$

To estimate $SE(g(T))$

$$SE(g(T)) \approx |g'(\mu_T)| \cdot SE(T)$$



Example: $SE(S^2) = \frac{\sigma^2\sqrt{2}}{\sqrt{n-1}}$ — from above

estimate $SE(g(S^2))$ where $g(x) = \sqrt{x} \nexists g(S^2) = S$

$$g'(x) = \frac{1}{2\sqrt{x}}$$

$$\text{So } SE(g(S^2)) = \frac{1}{2\sqrt{\mathbb{E}(S^2)}} \cdot SE(S^2)$$

$$= \frac{1}{2\sqrt{\sigma^2}} \cdot \frac{\sigma^2\sqrt{2}}{\sqrt{n-1}} = \frac{\sigma}{\sqrt{2(n-1)}}$$

The notion of Sufficient Statistics

Consider an estimator T of θ with $T(X_1, \dots, X_n)$ w/ X_i i.i.d. $\sim f(x_i; \theta)$

Consider x_1, \dots, x_n

iid $\sim f(x_i; \theta)$

We say that T is sufficient for $\theta \in \Theta$

if $f_{(x_1, \dots, x_n | T)}(x_1, \dots, x_n | T)$ does not depend on θ .

Example: Let $f(x_i; \theta) \sim \text{Binomial}(k=1, \rho)$

$$[P(X_i=1) = \rho, P(X_i=0) = 1-\rho]$$

Consider $T = \sum_{i=1}^n x_i$, is it sufficient for $\theta = \rho$?

$$\text{the pmf } f_{(x_1, \dots, x_n | T)}(x_1, \dots, x_n | T = \sum_{i=1}^n x_i) = \frac{P(X_1=x_1, \dots, X_n=x_n)}{P(T = \sum_{i=1}^n x_i)}$$

$$= \frac{\rho^{x_1} (1-\rho)^{(1-x_1)} \cdots \rho^{x_n} (1-\rho)^{(1-x_n)}}{\binom{n}{x_1, \dots, x_n} \rho^{x_1 + \dots + x_n} (1-\rho)^{n - (x_1 + \dots + x_n)}}$$

$$= \frac{1}{\binom{n}{x_1, \dots, x_n}} \quad * \text{which does not depend on } \rho *$$

Thus T is sufficient for ρ .

Note Here *

We can only compute the Conditional pmf/pdf if our statistic is sufficient.

Otherwise, we would need to know θ & our analysis would be circular.

As a result, the conditional pmf/pdf is a measure of the accuracy of our estimation

Likelihood function $L(\theta | x_1, \dots, x_n)$

generally cannot compute as we generally do not know θ

statistical notation: x_1, \dots, x_n given

probability notation; think θ given

this is purely
notational or
psychological

$$L(\theta | x_1, \dots, x_n) = f(x_1, \dots, x_n; \theta)$$

note, not a conditional, think of as "such that", or "given"