

What about $\hat{\sigma}_2$?

$\hat{\sigma}_2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\theta}_1)^2$ is max-likelihood, but biased

$\hat{\sigma}'_2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \hat{\theta}_1)^2$ is unbiased, but the likelihood

of seeing the samples given $\hat{\sigma}'_2$ is slightly lower.

These estimators differ by a factor $\frac{n}{n-1}$, so for large n they are nearly the same.

Intuition for why $\hat{\sigma}_2$ is not unbiased: $n=2$



$$\hat{\sigma}_2 = \frac{1}{2} \left((x_1 - \hat{\theta}_1)^2 + (x_2 - \hat{\theta}_1)^2 \right)$$

$$\leq \frac{1}{2} \left((x_1 - \mu)^2 + (x_2 - \mu)^2 \right) \quad \sigma_x^2 = E[(X - \mu)^2]$$

So $\hat{\sigma}_2$ consistently underestimates σ^2 . *

In fact, $E(\hat{\sigma}_2) = \frac{n-1}{n} \sigma^2$

Confidence intervals

What is $P(\hat{\theta} = \theta)$? 0, assuming $\hat{\theta}$ is a continuous random variable.

Could we find a small Δ such that

θ is in $[\hat{\theta} - \Delta, \hat{\theta} + \Delta]$ with probability 95%, say.

This is called the 95% confidence interval.

* More precisely, $E[\hat{\sigma}_2] \leq E\left[\frac{1}{2}((x_1 - \mu)^2 + (x_2 - \mu)^2)\right]$

$$= \frac{1}{2} (E[(x_1 - \mu)^2] + E[(x_2 - \mu)^2])$$

$$= \frac{1}{2} (\text{Var}(x_1) + \text{Var}(x_2)) = \frac{1}{2} \cdot 2\sigma^2 = \sigma^2$$

Ex: Consider MLE of the Normal mean μ :

$$\hat{\theta}_1 = \frac{1}{n} \sum_{i=1}^n x_i, \text{ where } x_1, \dots, x_n \text{ are i.i.d. from } N(\mu, \sigma^2).$$

$\hat{\theta}_1$ is a r.v. with a mean and variance.

$$E[\hat{\theta}_1] = \mu$$

$$\begin{aligned} \text{Var}(\hat{\theta}_1) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n x_i\right) \\ &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 = \frac{1}{n^2} \cdot n\sigma^2 = \frac{1}{n} \sigma^2. \end{aligned}$$

By CLT,

$$\hat{\theta}_1 \rightarrow N\left(\mu, \frac{1}{n} \sigma^2\right)$$

$$\frac{\hat{\theta}_1 - \mu}{\sigma/\sqrt{n}} \rightarrow N(0, 1)$$

$$P(-z < \frac{\hat{\theta}_1 - \mu}{\sigma/\sqrt{n}} < +z) \approx \Phi(z) - \Phi(-z)$$

$$\Phi(z) - \Phi(-z) = 2\Phi(z) - 1$$

$$P(-z < \frac{\mu - \hat{\theta}_1}{\sigma/\sqrt{n}} < +z) \approx 2\Phi(z) - 1$$

$$P(\hat{\theta}_1 - z\sigma/\sqrt{n} < \mu < \hat{\theta}_1 + z\sigma/\sqrt{n}) \approx 2\Phi(z) - 1 = 0.95$$

(95% conf. int.)

$$\Phi(z) = 0.975$$

$z \approx 1.96$, from Φ table.

μ is within $1.96\sigma/\sqrt{n}$ of $\hat{\theta}_1$ with probability 95%
 The 95% confidence interval for μ is
 $[\hat{\theta}_1 - 1.96\sigma/\sqrt{n}, \hat{\theta}_1 + 1.96\sigma/\sqrt{n}]$.