

9 - parameter estimation

method of moments

k^{th} population moment = $\mu_k = E(X^k)$

k^{th} sample moment = $m_k = \frac{1}{n} \sum_{i=1}^n x_i^k$ (estimates from the sample X_1, X_2, \dots, X_n)

central moments

k^{th} population central moment = $\mu'_k = E(X - \mu_1)^k$ ($k \geq 2$) ($k=1 \rightarrow 0$)

k^{th} sample central moment = $m'_k = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^k$

↳ first sample moment = the sample mean $\rightarrow \bar{x}$

↳ second population central moment = variance, $V(x)$ ($\frac{1}{n-1}$ instead of $\frac{1}{n}$)
unbiased

• simply matching the first k parameters of population and sample.

ex: in poisson \rightarrow one parameter $\mu_1 = E(x) = \lambda$

↳ thus, one equation: $\mu_1 = \lambda = m_1 = \bar{x}$

ex: in gamma $\rightarrow \alpha$ and λ ,

$m_1 = \bar{x} = 48.233$ $m'_2 = S^2 = 679.122$

2 equations

$\mu_1 = E(x) = \frac{\alpha}{\lambda} = m_1$

$\hat{\alpha} = m_1^2 / m'_2 = 3.4227$

$\mu_2 = \text{Var}(x) = \frac{\alpha}{\lambda^2} = m'_2$

$\hat{\lambda} = m_1 / m'_2 = 0.0710$

ex: cdf $F(x) = 1 - \left(\frac{x}{\sigma}\right)^{-\theta}$ two parameters

↳ pdf $f(x) = F'(x) = \theta \cdot \sigma^{-\theta} \cdot x^{-\theta-1}$

$$\left. \begin{aligned} \mu_1 = E(x) &= \int_0^{\infty} x f(x) dx = \frac{\theta \sigma}{\theta-1} = m_1 \\ \mu_2 = E(x^2) &= \int_0^{\infty} x^2 f(x) dx = \frac{\theta \sigma^2}{\theta-2} = m_2 \end{aligned} \right\} \begin{aligned} \hat{\theta}_{\text{mom}} &= \sqrt{\frac{m_2}{m_2 - m_1^2}} + 1 \\ \hat{\sigma}_{\text{mom}} &= \frac{m_1 \sqrt{\hat{\theta} - 1}}{\hat{\theta}} \end{aligned}$$

method of maximum likelihood

maximum likelihood estimator = the parameter value that maximize the likelihood of the observed sample

discrete distribution = maximize the joint pmf of data $P(X_1, \dots, X_n)$

continuous distribution = maximize the joint density $f(X_1, \dots, X_n)$

sample: 3 4 8 6 5 $\rightarrow P(x=3) \cdot P(x=4) \cdot P(x=8) \cdot P(x=6) \cdot P(x=5)$
 $\lambda = \text{unknown}$

(independent)
joint
distribution

$(x, y)' \rightarrow$ hard as product
 $z = xy \quad \ln z = \ln x + \ln y$
 $(\ln z)' = (\ln x)' + (\ln y)'$

$$P = \frac{e^{-\lambda} \lambda^3}{3!} \cdot \frac{e^{-\lambda} \lambda^4}{4!} \cdot \frac{e^{-\lambda} \lambda^8}{8!} \cdot \frac{e^{-\lambda} \lambda^6}{6!} \cdot \frac{e^{-\lambda} \lambda^5}{5!}$$

to take derivative take \ln of both side

Sum is easier

$$P\{X = (X_1, X_2, \dots, X_n)\} = P(X) = \prod_{i=1}^n P(X_i) \xrightarrow[\text{likelihood}]{\text{to maximize}} \text{derivative} \rightarrow \frac{\partial P(X)}{\partial \sigma} = 0$$

$$\ln \prod_{i=1}^n P(X_i) = \sum_{i=1}^n \ln P(X_i) \xrightarrow[\text{make}]{\text{take derivative}} = 0 \quad \text{find unknown parameter}$$

estimation of standard errors

$$\sigma(\hat{\lambda}) = \sqrt{\text{Var}(\hat{\lambda})} = \sqrt{E(\hat{\lambda}^2) - E^2(\hat{\lambda})}$$

\downarrow \downarrow
 $k=2$ $k=1$

$\text{var}(x) = E(x^2) - E(x)^2$
 \downarrow \downarrow
 second moment \downarrow first moment