

SPUS - $\hat{\theta}$
& bijedan

1. TOČNOSTI PROCESURALNEGA ($\hat{\theta}$) NEVZPLJIVIH ESTIMATORJEV:
 $\hat{\theta}$ je funkcija slučajnih velikosti optimizirana po (x_1, \dots, x_n)

TOČNOST $\hat{\theta}$ - dobro rezultat daje estimacijo od $\hat{\theta}$

NEPOTVRDOST $\hat{\theta}$ - tako isto samo da je $E[\hat{\theta}] = 0$

KONVERGENCIOST - estimacija je konvergencija događaja krv. raspodelja

NEVZPLJIVOST: na vseh uporabah:

$$\lim_{n \rightarrow \infty} E[\hat{\theta}_n^2] = \lim_{n \rightarrow \infty} E[(\hat{\theta}_n - \theta)^2] = 0$$

NEVZPLJIVI PROCESURALNI - omijestimajoči vrednosti minimalne variancije $\hat{\theta}_{\text{MV}} = f(x_1, \dots, x_n)$

je njeniščenji napovednički pomen $\hat{\theta}$ ali je:

$$\text{Var}[\hat{\theta}_{\text{MV}}] \leq \text{Var}[\hat{\theta}_n] \text{ in ne potrebita } \hat{\theta}_n$$

2. a) $\hat{\theta}_1 = 1.1523, \hat{\theta}_2 = 2.242$

$$X(t) \rightarrow \text{GAUSS}, \text{var.} \approx 0$$

$$\leq 0.5\%$$
 shr. vr.

$$\hat{\theta}_M = \frac{1}{n} \sum_{i=1}^n x_i$$

pravilnost:

$$\hat{\sigma}_{\text{MSE}}^2 = E[(\hat{\theta}_M - \theta)^2] = E[\hat{\theta}_M^2] - E[\hat{\theta}_M]^2$$

$$E[\hat{\theta}_M^2] = E\left[\frac{1}{n} \sum_{i=1}^n x_i^2\right] = \frac{1}{n} \sum_{i=1}^n E[x_i^2] = \frac{1}{n} M_n^2, \text{var.} = \frac{1}{n} \sum_{i=1}^n \text{var}[x_i^2], \text{pa je } \hat{\sigma}_{\text{MSE}}^2 = E[\hat{\theta}_M^2] - \theta^2$$

NEPOTVRDAN

$$E[(\hat{\theta}_M - \theta)^2] = E\left[\left(\frac{1}{n} \sum_{i=1}^n x_i^2\right) - \theta\right]^2 = \frac{1}{n^2} \sum_{i=1}^n E[x_i^2] - 2\theta E[x_i] + \theta^2$$

x_1, x_2, \dots, x_n imajo N(0, 1), x_1, x_2, \dots, x_n so nezvezni, $N(0, 1)$, x_1, x_2, \dots, x_n

$$\text{var}[x_i] = E[x_i^2] - E[x_i]^2 = E[x_i^2] - \theta^2$$

CAUSALNO PREDIKCIJA:

$$E[(\hat{\theta}_M - \theta)^2] = \frac{1}{n^2} \left[n \cdot \text{var}[x_i] + (n - 1) \cdot \text{var}[x_i] \right] = \frac{n}{n} \cdot \text{var}[x_i] = \hat{\sigma}_{\text{MSE}}^2$$

Negocios

$$\rightarrow E[\bar{G}_k(x)] = \bar{G}_k(x)$$

$$W_k^2 = \frac{\partial^2}{\partial x^2} \bar{G}_k(x) = \frac{\partial^2}{\partial x^2} E[\bar{G}_k(x)]$$

$$= W_k^2 - 2W_k^2 E[\bar{x}_k] + W_k^2 E[\bar{x}_k^2]$$

$$E[\bar{x}_k^2] = \frac{1}{N} \sum_{i=1}^N (\bar{x}_k(i))^2 = \frac{1}{N} \sum_{i=1}^N [W_k^2 \bar{x}_k(i) + W_k^2 \bar{x}_k(i) - 2W_k^2 E[\bar{x}_k(i)] + W_k^2 E[\bar{x}_k(i)^2]]$$

$$\text{Porcentaje de variación} = \frac{E[\bar{x}_k^2] - W_k^2}{W_k^2} = \frac{2W_k^2 E[\bar{x}_k] - 2W_k^2}{W_k^2} = 2 \frac{E[\bar{x}_k] - 1}{1}$$

$$E[\bar{x}_k] = \bar{x}_k$$

Ad. 15.6., ch. 26.

$$\text{Porcentaje de variación} = \frac{E[\bar{x}_k^2] - W_k^2}{W_k^2} = \frac{2W_k^2 E[\bar{x}_k] - 2W_k^2}{W_k^2} = 2 \frac{E[\bar{x}_k] - 1}{1}$$

$$0.5\% \text{ de variación}$$

$$\Rightarrow \frac{1}{N} \sum_{i=1}^N \left[W_k^2 \bar{x}_k(i) + W_k^2 \bar{x}_k(i) - 2W_k^2 E[\bar{x}_k(i)] + W_k^2 E[\bar{x}_k(i)^2] \right] = 2 \cdot 10^{-5} \text{ GPa}$$

$$\Rightarrow \frac{1}{N} \sum_{i=1}^N \left[W_k^2 \bar{x}_k(i) + W_k^2 \bar{x}_k(i) - 2W_k^2 E[\bar{x}_k(i)] + W_k^2 E[\bar{x}_k(i)^2] \right] = 0.005 \text{ GPa}$$

c) $\mu = 15, \text{var} = 20$

$x_1, \dots, x_N \sim \text{indep. Poisson dist. with var. } X \text{ & exp. val. } \lambda$

$$\lambda_1 = \frac{1}{N} \sum_{i=1}^N x_i, \quad \lambda_2 = \frac{1}{2} (x_1 + x_2)$$

PRAESUMMEN, was ist estimator?

$$E[\lambda_1] = E\left[\frac{1}{N} \sum_{i=1}^N x_i\right] = \frac{1}{N} \sum_{i=1}^N E[x_i] = \lambda$$

NEUERSTEIN

$$E[\lambda_2] = E\left[\frac{1}{2}(x_1 + x_2)\right] = \frac{1}{2}(E[x_1] + E[x_2]) = \frac{1}{2}(\lambda + \lambda) = \lambda$$

NEUERSTEIN

$$\begin{aligned}\sigma_{\lambda_1}^2 &= E[\lambda_1^2] - E^2[\lambda_1] = E\left[\left(\frac{1}{N} \sum_{i=1}^N x_i\right)^2\right] - \lambda^2 \\ &= \frac{1}{N^2} \sum_{i=1}^N E[x_i^2] - \lambda^2 + \frac{1}{N^2} [N(\lambda^2 + \lambda) + (N^2 - N)\lambda^2] - \lambda^2 \\ &= \lambda^2 + \frac{\lambda^2}{N} - \lambda^2 = \frac{\lambda^2}{N}\end{aligned}$$

$$\begin{aligned}\sigma_{\lambda_2}^2 &= E[\lambda_2^2] - E^2[\lambda_2] = E\left[\frac{1}{4}(x_1 + x_2)^2\right] - \lambda^2 \\ &= \frac{1}{4} \left[E[x_1^2] + E[x_2^2] + 2E[x_1]E[x_2] \right] - \lambda^2 \\ &= \frac{1}{4} \left[(\lambda^2 + \lambda + \lambda^2) + \lambda + 2\lambda \cdot \lambda \right] - \lambda^2 = \frac{\lambda^2}{2}\end{aligned}$$

BOLZI JG ESTIMATOR ist UNBIAS UND HAT MINIMUM VARIANZ

$\Rightarrow \lambda_1$ ESTIMATOR \rightarrow bsp: $\lambda \neq N \geq 2$

[2] FUNKCIJE VEROJATNOSTI $L(\theta)$ \rightarrow jedinica za gubitke $\theta_1, \theta_2, \dots, \theta_n$.

$$L(\theta) = \delta_{\theta}(x_1, \dots, x_n) = \Theta(x_1, \dots, x_n)$$

vezadživačka $L(\theta) = \Theta(x_1, \dots, x_n)$ \rightarrow ML (maximum likelihood) estimacija je $\hat{\theta}_{ML}$.

$$\Theta = \Theta(x_1, \dots, x_n)$$

ML ESTIMATOR PREDUGAČKI $\hat{\theta}$

$(x_1, \dots, x_n) \rightarrow$ glavne varijable normalnosti X

ML ESTIMATOR $\hat{\mu}$ i $\hat{\sigma}^2$

$$L(\mu) = \log L(\mu, \sigma^2) = \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2}$$

$$\frac{\partial L(\mu)}{\partial \mu} = \frac{1}{\sigma^2} \sum (x_i - \mu) = \frac{1}{\sigma^2} \cdot \frac{1}{n} \sum (x_i - \mu) = \frac{1}{\sigma^2} \cdot \frac{1}{n} \cdot \sum (x_i - \bar{x}) = \frac{1}{\sigma^2} \cdot \frac{1}{n} \cdot n(\bar{x} - \mu) = \frac{n(\bar{x} - \mu)}{\sigma^2}$$

$$\log(L(\mu)) = \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2} = \frac{1}{2} \log(n) + \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum (x_i - \mu)^2$$

$$\frac{\partial \log(L(\mu))}{\partial \mu} = \frac{1}{\sigma^2} \cdot \frac{1}{n} \cdot \sum (x_i - \mu) = \frac{1}{\sigma^2} \cdot \frac{1}{n} \cdot n(\bar{x} - \mu) = \frac{n(\bar{x} - \mu)}{\sigma^2} = 0$$

$$\begin{aligned} \bar{x} &= \mu \\ \bar{x} - \mu &= 0 \\ \frac{1}{\sigma^2} \cdot \bar{x} - \frac{1}{\sigma^2} \cdot \mu &= 0 \\ \frac{1}{\sigma^2} \cdot (\bar{x} - \mu) &= 0 \\ \bar{x} - \mu &= 0 \\ \bar{x} &= \mu \end{aligned}$$

ML ESTIMATOR

$$\mathbb{E}[\bar{x}] = \mathbb{E}\left[\frac{1}{n} \sum x_i\right] = \frac{1}{n} \sum \mathbb{E}[x_i] = \frac{1}{n} \sum \mu = \mu$$

5)

$$f_X(x) = \begin{cases} a & 0 \leq x \leq a \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{a}{2} \leq x_i \leq a \quad 0.001 \leq a$$

$$\lim_{n \rightarrow \infty} E[\hat{a}] = a$$

$$\lim_{n \rightarrow \infty} \text{Var}[\hat{a}] = \lim_{n \rightarrow \infty} [E[\hat{a}^2] - E[\hat{a}]^2] = 0$$

Naherungsweise, konditioniert auf

$$E[\hat{a}] = E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} E[X_i]$$

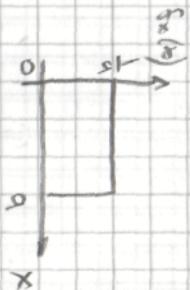
$$E[X_i] = \int_0^a x \cdot \frac{1}{a} da = \frac{1}{a} \cdot \frac{x^2}{2} \Big|_0^a = \frac{1}{a} \cdot \frac{a^2}{2} = \frac{a}{2}$$

$$\Rightarrow E[\hat{a}] = \frac{1}{n} \cdot \frac{a}{2} = \frac{a}{n}$$

$$\Rightarrow E[\hat{a}] = \frac{2}{3} M \cdot \frac{a}{2} = 0$$

\parallel

Konvergenz
gesichert



6)

$$\lim_{n \rightarrow \infty} [E[\hat{a}^2] - E[\hat{a}]^2] = \lim_{n \rightarrow \infty} [E[\hat{a}^2]] - a^2$$

$$E[\hat{a}^2] = E\left[\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2\right] = \frac{1}{n^2} E\left[\sum_{i=1}^n X_i^2 + 2 \sum_{i \neq j} X_i X_j\right]$$

$$\left\{ \begin{array}{l} E[X_i^2] = \int_0^a x^2 \cdot \frac{1}{a} dx = \frac{1}{a} \int_0^a x^2 dx = \frac{1}{a} \cdot \frac{x^3}{3} \Big|_0^a = \frac{a^2}{3} \\ E[X_i X_j] = \int_0^a x_i x_j \cdot \frac{1}{a} dx = \frac{1}{a} \int_0^a x_i x_j dx = \frac{1}{a} \cdot \frac{x_i x_j}{2} \Big|_0^a = \frac{a^2}{2} \end{array} \right.$$

$$\Rightarrow E[\hat{a}^2] = \frac{1}{n^2} \left[n \cdot \frac{a^2}{3} + (n^2 - n) \cdot \frac{a^2}{2} \right] = \frac{1}{n^2} \left[\frac{n a^2}{3} + \frac{(n^2 - n) a^2}{2} \right] = \frac{a^2}{n} + a^2$$

$$\lim_{n \rightarrow \infty} [E[\hat{a}^2] - E[\hat{a}]^2] = \lim_{n \rightarrow \infty} \left[\frac{a^2}{n} + a^2 - a^2 \right] = 0$$

Konvergenz gesichert

$$\hat{a}^2 = E[\hat{a}^2] - E[\hat{a}]^2 = \frac{a^2}{n}$$

$$\frac{\hat{a}^2}{n} = \frac{a^2}{n} = 0.001 \cdot a$$

$$3n = 10^6$$

$$n = 3.333.333$$

$$\boxed{n = 3.333.333}$$

5)