

$$E(s'^2) = \frac{n-1}{n} \sigma^2 \neq \sigma^2 \rightarrow \text{biase.}$$

$$E(s^2) = \frac{n-1}{n-1} \sigma^2 = \sigma^2 \rightarrow \text{unbiase.}$$

n is large enough if $n > 30$ ($n_+ > 10$ & $n_- > 10$)

The error of estimation: $\xi = |\hat{\theta} - \theta|$, $\hat{\theta}$ RV

Prob that $\mu - 2\sigma < Y < \mu + 2\sigma$.

Distribution

Probability.

Normal

0.9544

Uniform

1.0

Exponential

0.9502.

Given $b = 2\sigma_{\hat{p}} = 2\sqrt{\frac{pq}{n}}$ (\hat{p} unbiased $\rightarrow \sigma_{\hat{p}} = \sqrt{\frac{pq}{n}}$)
the prob that $b < 2\sqrt{\frac{pq}{n}} \Rightarrow 0.95$.

Interval estimator: A rule specifying the method to calculate two numbers that form the endpoints of the interval.

Confidence coefficient: the probability that a (random) ~~sample~~ confidence interval will enclose θ is called the confidence coefficient.

Confidence coefficient identifies the fraction of the time, in repeated sampling, that the intervals constructed will contain the target parameter θ .

if $P(\hat{\theta}_L \leq \theta \leq \hat{\theta}_U) = 1 - \alpha \rightarrow$ confidence coefficient.

Two side confidence interval: $P(\theta_L \leq \theta \leq \theta_U)$.

One side confidence interval: $P(\theta_L \leq \theta)$ or $P(\theta \leq \theta_U)$.

check pivotal method at this page. PY11 - PY14.

We use $\hat{\theta} \pm Z_{\frac{\alpha}{2}} \cdot \sigma_{\hat{\theta}}$ for large sample est.

e.g. $\hat{p}_1 - \hat{p}_2 \pm Z_{\frac{\alpha}{2}} \sqrt{\frac{p_1 q_1}{n_1} + \frac{p_2 q_2}{n_2}}$ ($q_2 = 1 - p_2$) maybe.

$$\bar{Y} \pm Z_{\frac{\alpha}{2}} \left(\frac{\sigma}{\sqrt{n}} \right) \approx \bar{Y} \pm Z_{\frac{\alpha}{2}} \left(\frac{s}{\sqrt{n}} \right).$$

For small interval: $P(-t_{\frac{\alpha}{2}} \leq T \leq t_{\frac{\alpha}{2}})$

two side: $\bar{Y} \pm t_{\frac{\alpha}{2}} \left(\frac{s}{\sqrt{n}} \right) \in (\theta)$

one side: $P(T \leq t_{\alpha}) = 1 - \alpha.$

$$\frac{Y - \mu}{\frac{s}{\sqrt{n}}} \leq t_{\alpha} \quad Y - \mu \leq \frac{s}{\sqrt{n}} t_{\alpha} \quad Y - \frac{s}{\sqrt{n}} t_{\alpha} \leq \mu.$$

$$\text{So } P\left(\bar{Y} - t_{\alpha}\left(\frac{s}{\sqrt{n}}\right) \leq \mu\right) = 1 - \alpha.$$

$$\text{large interval: } Z = \frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

Construct common variance s^2 :

Given $Y_{11}, Y_{12}, Y_{13}, \dots, Y_{1n}, Y_{21}, Y_{22}, Y_{23}, \dots, Y_{2n}$

$$\bar{Y}_1 = \frac{1}{n_1} \sum_{i=1}^{n_1} Y_{1i} \quad \bar{Y}_2 = \frac{1}{n_2} \sum_{i=1}^{n_2} Y_{2i}$$

Pooled square estimator:

$$s_p^2 = \frac{\sum_{i=1}^{n_1} (Y_{1i} - \bar{Y}_1)^2 + \sum_{i=1}^{n_2} (Y_{2i} - \bar{Y}_2)^2}{n_1 + n_2 - 2} = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$$

$$W = \frac{(n_1 + n_2 - 2) s_p^2}{\sigma^2} = \frac{\sum_{i=1}^{n_1} (Y_{1i} - \bar{Y}_1)^2}{\sigma^2} + \frac{\sum_{i=1}^{n_2} (Y_{2i} - \bar{Y}_2)^2}{\sigma^2}$$

is the sum of 2 independent χ^2 -dist RV with $(n_1 - 1), (n_2 - 1)$ df.

df of $W = n_1 + n_2 - 2$ So

$$T = \frac{Z}{\sqrt{\frac{W}{df}}} = \left[\frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{\sigma \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right] \cdot \sqrt{\frac{(n_1 + n_2 - 2) s_p^2}{\sigma^2 (n_1 + n_2 - 2)}}$$

$$= \frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \quad \text{with } (n_2 + n_1 - 2) \text{ df}$$

So for $\mu_1 - \mu_2$:

$$(\bar{y}_1 - \bar{y}_2) \pm t_{\frac{\alpha}{2}} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} \quad \left(\begin{array}{c} \text{independent} \\ \sigma_1 = \sigma_2 \end{array} \right)$$

Estimate confidence interval for σ^2

Given $s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$

then $\chi^2 \in \frac{(n-1)s^2}{\sigma^2}$

$$P \left[\chi_{\frac{\alpha}{2}}^2 \leq \frac{(n-1)s^2}{\sigma^2} \leq \chi_{1-\frac{\alpha}{2}}^2 \right] = 1-\alpha$$

$$P \left[\chi_{1-\frac{\alpha}{2}}^2 \leq \frac{(n-1)s^2}{\sigma^2} \leq \chi_{\frac{\alpha}{2}}^2 \right] = 1-\alpha$$

$$P \left[\frac{(n-1)s^2}{\chi_{\frac{\alpha}{2}}^2} < \sigma^2 < \frac{(n-1)s^2}{\chi_{1-\frac{\alpha}{2}}^2} \right] = 1-\alpha$$

So $100(1-\alpha)\%$ CI for σ^2 : $\sigma^2 \in \left[\frac{(n-1)s^2}{\chi_{\frac{\alpha}{2}}^2}, \frac{(n-1)s^2}{\chi_{1-\frac{\alpha}{2}}^2} \right]$

Sufficient statistic: an unbiased estimator with small variance is or can be made to be a function of a sufficient statistic.

Efficiency: Given two unbiased estimator, $\hat{\theta}_1, \hat{\theta}_2$ of θ , note Var of $\hat{\theta}_1, \hat{\theta}_2$ as $V(\hat{\theta}_1), V(\hat{\theta}_2)$, then efficiency of $\hat{\theta}_1$ relative to $\hat{\theta}_2$, $\text{eff}(\hat{\theta}_1, \hat{\theta}_2)$

$$\text{eff}(\hat{\theta}_1, \hat{\theta}_2) = \frac{V(\hat{\theta}_2)}{V(\hat{\theta}_1)}$$

if $\text{eff}(\theta_1^*, \theta_2^*) < 1 \rightarrow \text{Pick } \theta_2^*$
 else $> 1 \rightarrow \text{Pick } \theta_1^*$

Consistency: $P(|\frac{Y}{n} - p| \leq \varepsilon) = 1$ When $n \rightarrow +\infty$.

if true, $\frac{Y}{n}$ is a consistent estimator of p .
 $\frac{Y}{n}$ converges in probability to p .

经过大量实验结果 \rightarrow 某个 P 值

estimator $\hat{\theta}_n$ is consistent estimator if.

$$\lim_{n \rightarrow \infty} P(|\hat{\theta}_n - \theta| \leq \varepsilon) = 1$$

$$\text{or } \lim_{n \rightarrow \infty} P(|\hat{\theta}_n - \theta| > \varepsilon) = 0$$

$$\lim_{n \rightarrow \infty} V(\hat{\theta}_n) = 0 \leftarrow \text{unbiased } \hat{\theta}_n \text{ consistent.}$$

Proof: Let Y be any independent Var. with
 $E(Y) = \mu$ & $V(Y) = \sigma^2 < \infty$

By Chebyshev's theorem:

$$P(|Y - \mu| > k\sigma) \leq \frac{1}{k^2}$$

if θ unbiased $\rightarrow E(\hat{\theta}_n) = \theta$.

$$\text{So } P(|\hat{\theta}_n - \theta| > k\sigma_{\hat{\theta}_n}) \leq \frac{1}{k^2}$$

$$\text{let } k = \frac{\varepsilon}{\sigma_{\hat{\theta}_n}}$$

$$P(|\hat{\theta}_n - \theta| > \varepsilon) = P(|\hat{\theta}_n - \theta| > \left[\frac{\varepsilon}{\sigma_{\hat{\theta}_n}}\right] \sigma_{\hat{\theta}_n}) \leq \frac{1}{\left(\frac{\varepsilon}{\sigma_{\hat{\theta}_n}}\right)^2} = \frac{V(\hat{\theta}_n)}{\varepsilon^2}$$