

An Improved Preliminary Test Estimator for the Variance of a Normal Distribution

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(Received : July, 1990)

Summary

A preliminary test estimator (PTE) for the variance of a normal population has been proposed when a prior information about the variance is available. Empirical results of bias and relative efficiency reveal that the proposed estimator is better than the similar estimator constructed by Srivastava [2].

Key Words : Minimum Mean Square Error Estimator. Preliminary Test Estimator. Relative Bias. Relative Efficiency.

Introduction

Let x_1, x_2, \dots, x_n be a random, sample drawn from a normal population $N(\mu, \sigma^2)$, where μ and σ^2 both are not known. It is desired to estimate σ^2 . Goodman [1] showed that the minimum mean square error estimator among the class of estimators of the form Cs^2 is $T = (n-1)s^2/(n+1)$, where s^2 is the usual unbiased estimator of σ^2 .

Let σ_0^2 be available as a prior information on σ^2 besides the sample information in the form of T . These informations are used in the construction of the estimator $\hat{\sigma}^2$ proposed here. This estimator is obtained as a consequence of the preliminary test of the hypothesis $\sigma^2 = \sigma_0^2$ and is called Preliminary test estimator (PTE). It is defined as follows :

$$\hat{\sigma}^2 = \begin{cases} \sigma_0^2 & \text{if } H_0 : \sigma^2 = \sigma_0^2 \text{ is accepted,} \\ T & \text{otherwise.} \end{cases}$$

The expressions of bias and mean square error of $\hat{\sigma}^2$ are derived. Srivastava [2] has proposed a similar PTE of σ^2 as defined by

$$\hat{\sigma}_{PT}^2 = \begin{cases} \sigma_0^2 & \text{if } H_0 : \sigma^2 = \sigma_0^2 \text{ is accepted,} \\ s^2 & \text{otherwise.} \end{cases}$$

We have investigated gain in the relative efficiency of $\hat{\sigma}^2$ over $\hat{\sigma}_{PT}^2$.

2. Bias and mean square error of $\hat{\sigma}^2$

We know that ms^2/σ^2 is distributed as χ^2 with $m = (n-1)$ degrees of freedom. Hence the hypothesis $H_0: \sigma^2 = \sigma_0^2$ is tested using the statistic $w = ms^2/\sigma_0^2$ which has the density given by

$$f(w, k) = \frac{k^{m/2}}{2^{m/2} \Gamma(m/2)} e^{-kw/2} w^{(m/2)-1} \quad (k = \sigma_0^2/\sigma^2, k > 0) \quad (2.1)$$

If we denote by $\chi^2(m, \alpha)$ the upper $100\alpha\%$ point of Chi-square distribution with m degree of freedom, then the estimator $\hat{\sigma}^2$ may be written as

$$\hat{\sigma}^2 = \begin{cases} \sigma_0^2 & \text{if } w \leq \chi^2(m, \alpha), \\ T & \text{otherwise.} \end{cases} \quad (2.2)$$

The expected value of $\hat{\sigma}^2$ is given by

$$E(\hat{\sigma}^2) = E[\sigma_0^2 \mid w \leq \chi^2(m, \alpha)] P[w \leq \chi^2(m, \alpha)] + E[T \mid w \geq \chi^2(m, \alpha)] P[w \geq \chi^2(m, \alpha)] \quad (2.3)$$

$$= \frac{\sigma_0^2 k^{m/2}}{2^{m/2} \Gamma(m/2)} \left[\int_0^{\chi^2(m, \alpha)} e^{-kw/2} w^{(m/2)-1} dw + \frac{1}{n+1} \int_{\chi^2(m, \alpha)}^{\infty} e^{-kw/2} w^{m/2} dw \right] \quad (2.4)$$

On evaluating the integrals in (2.4) and simplifying we get

$$E(\hat{\sigma}^2) = \sigma_0^2 I(C, m/2) + \frac{m\sigma_0^2}{k(n+1)} \left\{ 1 - I\left(C, \frac{m}{2} + 1\right) \right\}, \quad (2.5)$$

where $C = \frac{1}{2} k\chi^2(m, \alpha)$ and $I(y, n) = \int_0^y e^{-x} x^{n-1} \frac{dx}{\Gamma(n)}$

Therefore

$$\frac{E(\hat{\sigma}^2)}{\sigma^2} = k I\left(C, \frac{m}{2}\right) + \frac{m}{(n+1)} \left\{ 1 - I\left(C, \frac{m}{2} + 1\right) \right\}. \quad (2.6)$$

The relative bias (Bias/σ^2) can be easily obtained from (2.6) and is given by

$$\text{Relative Bias} = k I\left(C, \frac{m}{2}\right) - \frac{m}{(n+1)} I\left(C, \frac{m}{2} + 1\right) - \frac{2}{(n+1)}. \quad (2.7)$$

The mean square error (MSE) of $\hat{\sigma}^2$ is defined as

$$\text{MSE}(\hat{\sigma}^2) = E[(\hat{\sigma}^2)]^2 - 2\sigma^2 E(\hat{\sigma}^2) + \sigma^4. \quad (2.8)$$

where

$$E(\hat{\sigma}^2)^2 = E[\sigma_0^4 \mid w \leq \chi^2(m, \alpha)] P[w \leq \chi^2(m, \alpha)] \\ + E[T^2 \mid w \geq \chi^2(m, \alpha)] P[w \geq \chi^2(m, \alpha)] \quad (2.9)$$

and $E(\hat{\sigma}^2)$ is given by (2.5). It is easy to evaluate (2.9) on substituting the values of $E(\hat{\sigma}^2)^2$ and $E(\hat{\sigma}^2)$ in (2.8) we obtain

$$\frac{\text{MSE}(\hat{\sigma}^2)}{\sigma^4} = \frac{2}{(n+1)} + k(k-2) I\left(C, \frac{m}{2}\right) + \frac{2m}{(n+1)} I\left(C, \frac{m}{2} + 1\right) \\ - \frac{m}{(n+1)} I\left(C, \frac{m}{2} + 2\right). \quad (2.10)$$

3. Relative efficiency of $\hat{\sigma}^2$

It is known that the variance of the unbiased estimator s^2 is $2\sigma^4/m$. Hence the relative efficiency of $\hat{\sigma}^2$ with respect to s^2 will be given by the ratio,

$$\text{RE}(\hat{\sigma}^2) = \frac{V(s^2)}{\text{MSE}(\hat{\sigma}^2)} \\ = \left[\frac{m}{(n+1)} + \frac{m k(k-2)}{2} I\left(C, \frac{m}{2}\right) \right. \\ \left. + \frac{m^2}{(n+1)} I\left(C, \frac{m}{2} + 1\right) - \frac{m^2}{2(n+1)} I\left(C, \frac{m}{2} + 2\right) \right]^{-1} \quad (3.1)$$

which is less than 1 for $k \geq 2$.

Table 1. Relative Bias : Bias / σ^2

n	k	0.4	0.6	0.8	1.0	1.2	1.6
5		-0.304	-0.228	-0.106	0.049	0.224	0.606
		-0.286	-0.202	-0.081	0.070	0.240	0.612
7		-0.250	-0.205	-0.102	0.045	0.220	0.602
		-0.232	-0.176	-0.074	0.067	0.234	0.608
9		-0.212	-0.188	-0.100	0.042	0.216	0.602
		-0.194	-0.157	-0.070	0.063	0.229	0.605

Table 2. Relative Efficiency of σ^2 with Respect to s^2

n	k	0.4	0.6	0.8	1.0	1.2	1.6
5		1.771	2.623	4.988	9.154	6.306	1.334
		1.896	2.826	5.048	7.822	5.345	1.292
7		1.383	1.894	3.607	7.324	4.820	0.906
		1.500	2.057	3.648	6.016	4.039	0.886
9		1.254	1.540	2.925	6.497	4.012	0.686
		1.315	1.711	2.971	5.208	3.374	0.676

Table 3 : Gain in Relative Efficiency

n	k	0.4	0.6	0.8	1.0	1.2	1.6
5		0.849	1.519	3.404	6.748	3.498	0.110
		0.908	1.712	3.629	5.989	3.373	0.210
7		0.513	0.881	2.070	4.684	1.935	0.036
		0.550	0.999	2.240	4.044	1.956	0.136
9		0.345	0.598	1.439	3.701	1.220	0.008
		0.389	0.703	1.546	3.126	1.299	0.012

4. Discussion of the numerical results

We have calculated values of the relative bias and relative efficiency $RE(\hat{\sigma}^2)$ for $n = 5, 7, 9$, level of significance $\alpha = .05, 0.10$ and $k = 0.4, 0.6, 0.8, 1.0, 1.2$ and 1.6 . These results are assembled in Table 1 and 2. Results of the gain in relative efficiency $[RE(\hat{\sigma}^2) - RE(\hat{\sigma}_{PT}^2)]$ are assembled in Table 3. In these tables the values in the first row correspond to the level of significance $\alpha = .05$ and those in the second row refer to $\alpha = .10$.

From Table 1, we observe that the relative bias of the proposed estimator increases as we increase the level of significance α . The estimator is positively biased for $k \geq 1$ and negatively biased for $k < 1$.

From Table 2, we observe that the proposed estimator $\hat{\sigma}^2$ is more efficient than the unbiased estimator s^2 for all values of k lying between 0.4 to 1.2 . We also observe that the relative efficiency increases with k and reaches its maximum at $k=1$ and then decreases.

We have compared the relative efficiency of the estimator $\hat{\sigma}^2$ defined by (2.2) with the relative efficiency of a similar estimator $\hat{\sigma}_{PT}^2$ proposed by Srivastava [2]. From Table 3 it is observed that the gain increases as k increases and reaches its maximum at $k = 1$. For $k > 1$ gain decreases rapidly. The values of relative bias of $\hat{\sigma}^2$ shown in Table 1 can be easily compared with the relative bias of $\hat{\sigma}_{PT}^2$ obtained by Srivastava [2]. It is found that $\hat{\sigma}^2$ is always less biased. Therefore, the estimator $\hat{\sigma}^2$ is not only less biased but more efficient than $\hat{\sigma}_{PT}^2$.

ACKNOWLEDGEMENT

The authors express their thanks to the referee for his helpful comments:

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