

Functional Analysis of Classical Contractile Estimation in Riley and Exponential Distribution under Different Loss Functions Based on Censored Data

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Abstract: They usually estimate the unknown parameter by observing a random sample and using conventional estimation methods such as the maximum likelihood method. Sometimes we have information about the actual parameter as a guess. In such cases, the maximum likelihood estimator or any other estimator can be contracted in the guise of a conjectural value, and construct contraction estimators. The parameters studied will be compared with my methods, their anchors and their disadvantages. Then End-of-life test and estimator behavior of the estimator Based on their performance, they are computed.

Keywords: Riley distribution, entropy loss function, contraction estimator

1. Introduction

Let X_1, \dots, X_n be a simple example of the distribution with the non-parameter θ . In the statistical methods, based on the sample available in the sample and by using product estimators such as our monthly estimators (θ), the parameter estimator is used [1]. On the other hand, in binary methods, they improve the existing estimators by considering the distribution parameter for the parameter studied [2]. In the application brackets I have the insights about the non-parameter θ parameter θ_0 which the states can derive from logs or more. In the case of the parameter, it is referred to as the name of any specimen or name. Here, the final estimators are denoted by θ_0 and the sample size of the truck (1) with the form $k\theta + (1-k)\theta_0, k \in [0,1]$ where k . Returns to the value θ_0 . If $k = 1$, then the sample pellets if $k = 1$ are created from the value [4]. The calculations show that when the value of θ_0 is close to the value of the parameter θ , the end-of-line estimators have a more efficient computational estimator. The fruit is tested for 1 near θ_0 to θ , $H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$, which is then tested. Based on the rejection or expansion of node H, one can obtain the test of their estimators for the parameter θ and compute its behavior with the conventional estimators [5]

Runner-up and Run (1) [11] tested their end-to-end estimation in the Rayleigh distribution on the basis of record-breaking second power loss data. Hazor and Nizadeh (1) [12] made the estimation test article in the Distribution and Polling Classes based on the record and censored data. Bobby and Karen (1) [13] routinely damage the Rayleigh domain and the bifurcation point and based on the record and converter data extracted. Zadeh (1) [14] estimates the endpoints of the permissible distribution parameter based on the censored loss data and the asymmetric loss time

In the field of two-stage end-to-end testing in the Rayleigh area, Owa and Cheruvawa (1) and Cana and Cheruvawa (uninitiated), both methods were studied. Peruvianawa and

Cana (1) studied the two-stage estimation test in exponential distribution using the two-way ANOVA function.

2. Research Methodology

Suppose X_1, \dots, X_n be a simple example of a waypoint and exponential with the parameter σ with the function cables

$$f(x|\theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}}, x > 0, \theta > 0,$$

$$f(x;\sigma) = \frac{x}{\sigma} \exp\left(-\frac{x}{\sigma}\right), x > 0, \sigma > 0, (1)$$

And the fire is burning

$$F(x;\sigma) = 1 - \exp\left(-\frac{x}{\sigma}\right), x > 0, \sigma > 0, (2)$$

Should be. The rate of each ballot box is as follows:

$$r(t) = \frac{f(t;\sigma)}{1 - F(t;\sigma)} = \frac{t}{\sigma},$$

is also a function of t . The polling station has one that has its own rate of return, whereas the last one has a fixed rate. Occasionally I have bases on the non-parameter σ parameter as sx . Then the concept tells me that the data has been extracted from the path domain with the parameter σ . For a while.

The value σ is close to σ_0 or higher, from one test to another.

$$\begin{cases} H_0: \sigma = \sigma_0, \\ H_1: \sigma \neq \sigma_0, \end{cases} (3)$$

It is done. Based on the rejections or trends given in (3) at a given value, it is possible to test the end estimators and examine their behavior. In this paper, testing of end-of-line estimators for anomalous loss rate parameter

$$L(\sigma, \tilde{\sigma}) = \Delta - \ln(\Delta) - 1, \Delta = \frac{\tilde{\sigma}}{\sigma} (4)$$

It is examined, in which σ is the desired estimator for σ . The time-dependent anthropogenic function is a convex and non-

symmetric singularity in Δ and, as a function of Δ , has the mean at the point $\Delta = 1$. The loss function in situations where low estimate more important than the above estimate is used. Due to the fact that a loss function of scale-invariant, well can be used to estimate the scale parameter Rayleigh distribution used.

In Fig. 2, the estimator yield is calculated based on the monthly estimator (σ c) in the form of the covariance loss curve and its computation. In the third section, the tester forms the end of the tester and calculates its end-to-end damage. Its behavior is evaluated by the estimator for its endpoints and the sample is computed by computing its likelihood. Finally, the end-of-life tester code was evaluated using simple end-user methods, antennae, their expressions, and their behavior. At the end of the second type of data is used.

3. Estimated value in the form $c\sigma^{\wedge}$

Assume ..., X_n , $\backslash X$ is a simple example of the path distribution and exponential with the parameter σ with the functions given in (1). In this case, the estimator of the month σ is equal to $\sigma^{\wedge} = \frac{1}{2n} \sum_{i=1}^n X_i^2$ can be expressed as $U = 2n\sigma^{\wedge} / \sigma \sim X_{2n}^2$. Which I used to do throughout. Then consider the estimators in the form $c\sigma$. The sum of the estimators of the cosine loss equation is equal to

$$E[L(\sigma, \tilde{\sigma})] - E[L(\sigma', \tilde{\sigma})] = E\left[\frac{\tilde{\sigma}}{\sigma} - \ln\left(\frac{\tilde{\sigma}}{\sigma}\right) - 1\right] - E\left[\frac{\tilde{\sigma}}{\sigma'} - \ln\left(\frac{\tilde{\sigma}}{\sigma'}\right) - 1\right] \\ = \left(\frac{1}{\sigma} - \frac{1}{\sigma'}\right)E[\tilde{\sigma}] + \ln\left(\frac{\sigma}{\sigma'}\right).$$

If you place $E(\tilde{\sigma}) = \sigma$ in the well

$$E[L(\sigma, \tilde{\sigma})] - E[L(\sigma', \tilde{\sigma})] = \ln\left(\frac{\sigma}{\sigma'}\right) - \frac{\sigma}{\sigma'} + 1 \leq 0.$$

Therefore the estimator σ for σ is exponential if $E(\tilde{\sigma}) = \sigma$ given that $E(\tilde{\sigma}) = \sigma$, $\tilde{\sigma}$ for σ is exponential, so the estimator is estimated Dispute) in the estimators of the form $c\sigma$

$$B(\sigma, \hat{\sigma}_S) = E(\hat{\sigma}_S) - \sigma = k\sigma + (1-k)\sigma_0 - \sigma = (k-1)(\sigma - \sigma_0).$$

Indeed, it is equal to 1 for $k = 0$ or $\sigma = \sigma_0$. To check the approximated value of σ , we can test the holes given in (3) in the α value. The test statistic can be made from the test statistic $2n = \sigma^{\wedge} / \sigma$ which has a distribution of two with n degrees of freedom. Objective 2, instead of estimators based on rejections or assumptions, $H_0: \sigma = \sigma_0$ in (3) is a value of α . Ends the estimators called the tester, denoted by (σ_{ST}) . Types $(\sigma_{ST})^{\wedge}$ are such that if each chain $H_0: \sigma = \sigma_0$ its curve is then $(\sigma_{ST})^{\wedge} = k\sigma^{\wedge} + (1-k)\sigma_0$ and if $H_0: \sigma = \sigma_0 = \sigma^{\wedge}$. If the value σ is close to σ it must be obtained from the exponential estimator (σ_S) ; and if the value is not

$$R(\sigma, c\hat{\sigma}) = E\left[\frac{c\hat{\sigma}}{\sigma}\right] - E\left[\ln\left(\frac{c\hat{\sigma}}{\sigma}\right)\right] - 1 \\ = \frac{c}{\sigma} E[U] - E[\ln(U)] - \ln c + \ln(\sigma) - 1$$

I know. $E[U] = n$ For $E[\ln(U)]$, consider the subclass as follows:

$$\Gamma(\alpha) = \int_0^{\infty} t^{\alpha-1} e^{-t} dt. \quad (\Delta)$$

By measuring the angle (1) to α , the angle to (α) , and each angle $y = t$

$$\Psi(\alpha) = \frac{\Gamma'(\alpha)}{\Gamma(\alpha)} = \int_0^{\infty} [\ln(y) - \ln \alpha] \frac{y^{\alpha-1} e^{-y}}{\Gamma(\alpha) \alpha^{\alpha}} dy \\ = E[\ln Y] - \ln \alpha,$$

In which $Y \sim \text{Gamma}(\alpha, 2)$ is called $\psi(\alpha)$, the dia function is called integer which is equivalent to digamma (ψ) In R software. Given $\alpha = n$, we have $E[\ln(U)] = \ln 2 + \psi(n)$ at a fixed point equal to $c\sigma$

$$R(\sigma, c\hat{\sigma}) = c - \ln c + \ln n - \Psi(n) - 1. \quad (\phi)$$

Fig. (6) is a convex constellation of c and has a point at $c = c$. Therefore, the estimator σ^{\wedge} , the estimator has the opposite sum in the estimators with the $c\sigma$ form. Σ The estimator angle σ

$$R(\sigma, \hat{\sigma}) = \ln n - \Psi(n). \quad (\nu)$$

$$E[L(\sigma, \hat{\sigma})] \leq E[L(\sigma', \hat{\sigma})], \sigma \neq \sigma'. \quad (\lambda)$$

At present, cost estimators have a considerable loss. With respect to Kabul you have a loss

4. Test analysis of their end estimators

Assume that the value of σ is the value for the parameter σ , End estimator to the form

$$\hat{\sigma}_S = k\hat{\sigma} + (1-k)\sigma_0, \quad k \in [0, 1],$$

Consider σ , where the value of k is the so-called end of the coil with respect to its coefficient σ . The idea behind simple estimators is to improve the body of nonlinear estimators with the use of linear estimators. The estimator (σ_S) has the following dimensions

close to σ_0 , the exponential estimator is obtained. For the visual point of $(\sigma_{ST})^{\wedge}$, it was assumed.

Let H be the mean α . In that case

$$Pr(q_1 \leq \frac{\chi_{2n}^2}{\sigma_0} \leq q_2) = 1 - \alpha, \quad (9)$$

Where $q_1 = X_{(2n, \alpha)}^2$ and $q_2 = X_{(2n, 1-\alpha)}^2$ are multi-distributive quantiles with $2n$ degrees of freedom. That

is, $PrX_{2n2} < X_{2n.v2} = v$ in the contraction estimator test σ_{ST} can be written as follows.

$$\hat{\sigma}_{ST} = \begin{cases} k\hat{\sigma} + (1-k)\sigma, & a_1 \leq \hat{\sigma} \leq a_r \\ \hat{\sigma} & \hat{\sigma} < a_1 \text{ or } \hat{\sigma} > a_r \end{cases} \quad (10)$$

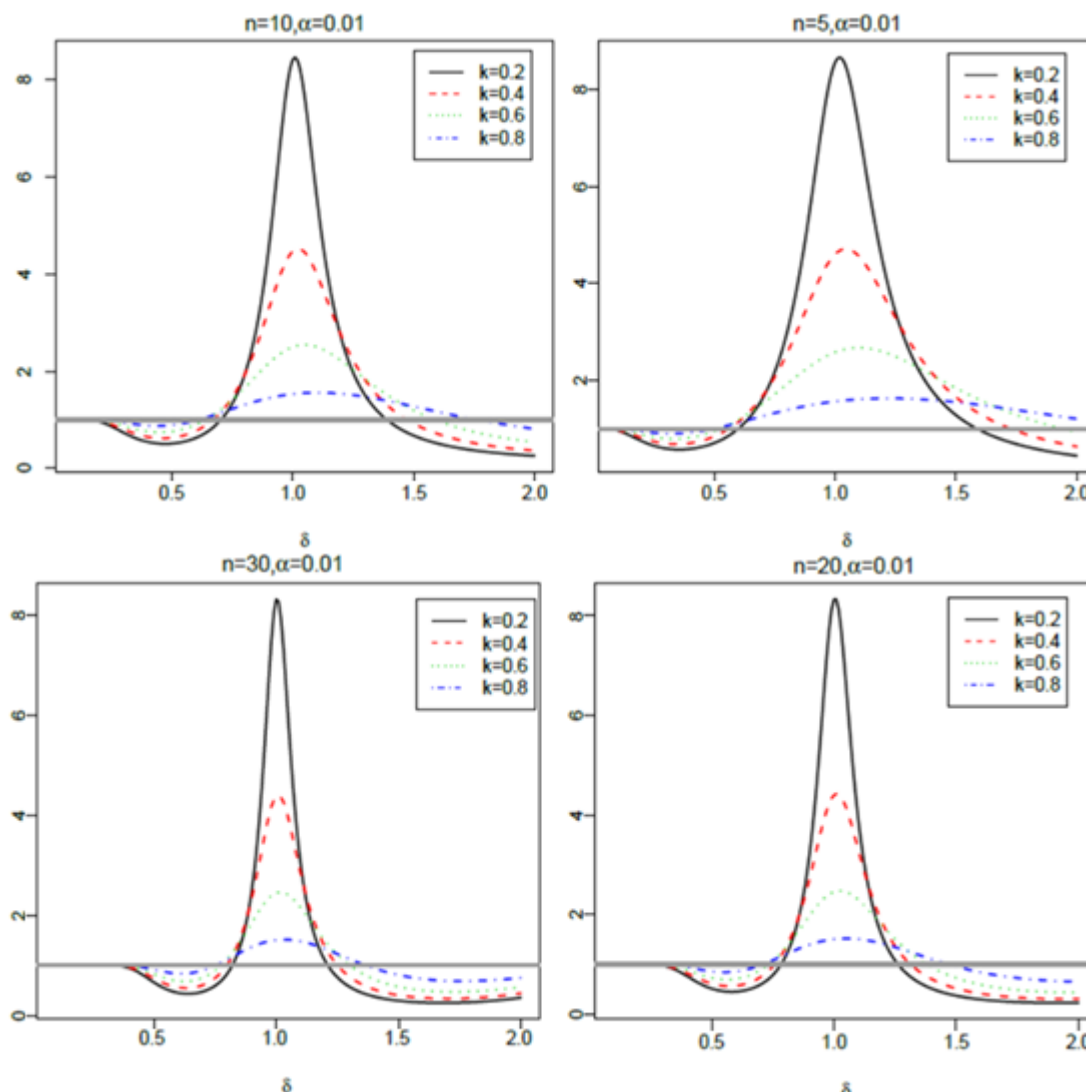
Then the exponent of the test of the end estimator (σ_{ST});

$$\begin{aligned} R(\sigma, \hat{\sigma}_{ST}) &= E \left[\frac{\hat{\sigma}_{ST}}{\sigma} \right] - E \left[\ln \left(\frac{\hat{\sigma}_{ST}}{\sigma} \right) \right] - 1 \\ &= E \left[\left\{ \frac{k\hat{\sigma} + (1-k)\sigma}{\sigma} \ln \left(\frac{k\hat{\sigma} + (1-k)\sigma}{\sigma} \right) - 1 \right\} I(A) \right] + E \left[\left\{ \frac{\hat{\sigma}}{\sigma} - \ln \left(\frac{\hat{\sigma}}{\sigma} \right) - 1 \right\} I(A^c) \right] \\ &= E \left[\left\{ \frac{kU}{\sqrt{n}} + (1-k)\delta - \ln \left(\frac{kU}{\sqrt{n}} + (1-k)\delta \right) - 1 \right\} I(B) \right] - E \left[\left\{ \frac{U}{\sqrt{n}} - \ln \left(\frac{U}{\sqrt{n}} \right) - 1 \right\} I(B) \right] + E \left[\frac{U}{\sqrt{n}} - \ln \left(\frac{U}{\sqrt{n}} \right) - 1 \right] \\ &= \int_{a_1}^{a_r} \left\{ (1-k)\delta + \frac{ku}{\sqrt{n}} - \ln \left((1-k)\delta + \frac{ku}{\sqrt{n}} \right) \right\} h(u) du \\ &\quad - \int_{a_1}^{a_r} \left[\frac{u}{\sqrt{n}} - \ln \left(\frac{u}{\sqrt{n}} \right) \right] h(u) du + \ln n - \Psi(n), \end{aligned} \quad (11)$$

Fig. (11) is computed using numerical methods in R software for selected values of n, k, α and δ . For the endpoint estimator test (σ_{ST}) and the endpoint estimator tester, their endpoint tester (σ_{ST}) is set as follows:

$$RE(\hat{\sigma}_{TS}, \hat{\sigma}) = \frac{R(\sigma, \hat{\sigma})}{R(\sigma, \hat{\sigma}_{ST})} \quad (12)$$

Figures 4.1 and 4.1 show the effect of n (12) on δ for values $n = 5, 10, 20, 30, k = 0.2, 0.4, 0.6, 0.8$, and $\alpha = 0.01$. Fixed for article. Figure 1 shows that the test shrinkage estimators for the values of δ close to a have lower risks (relative efficiency of greater than one) of the estimator σ and for n and α constant, with an increase in shrinkage coefficient k of the relative efficiency of $Z_{mnbvrdgrhay}$ contractility decreases Yourself. It is shown in Fig. 6 that, for k and α , for δ values close to, with the sample n , the performance of the testers of the end estimators is obtained. Therefore for the values of δ near to (values near σ to σ), and for each of the smaller samples and the faster endpoints, test the end-of-end estimators.



1. Diagrams of oil efficiency for $n = 5, 10, 20, 30, k = 0.2, 0.4, 0.6, 0.8$ and $\alpha = 0.01$ for k behavior.

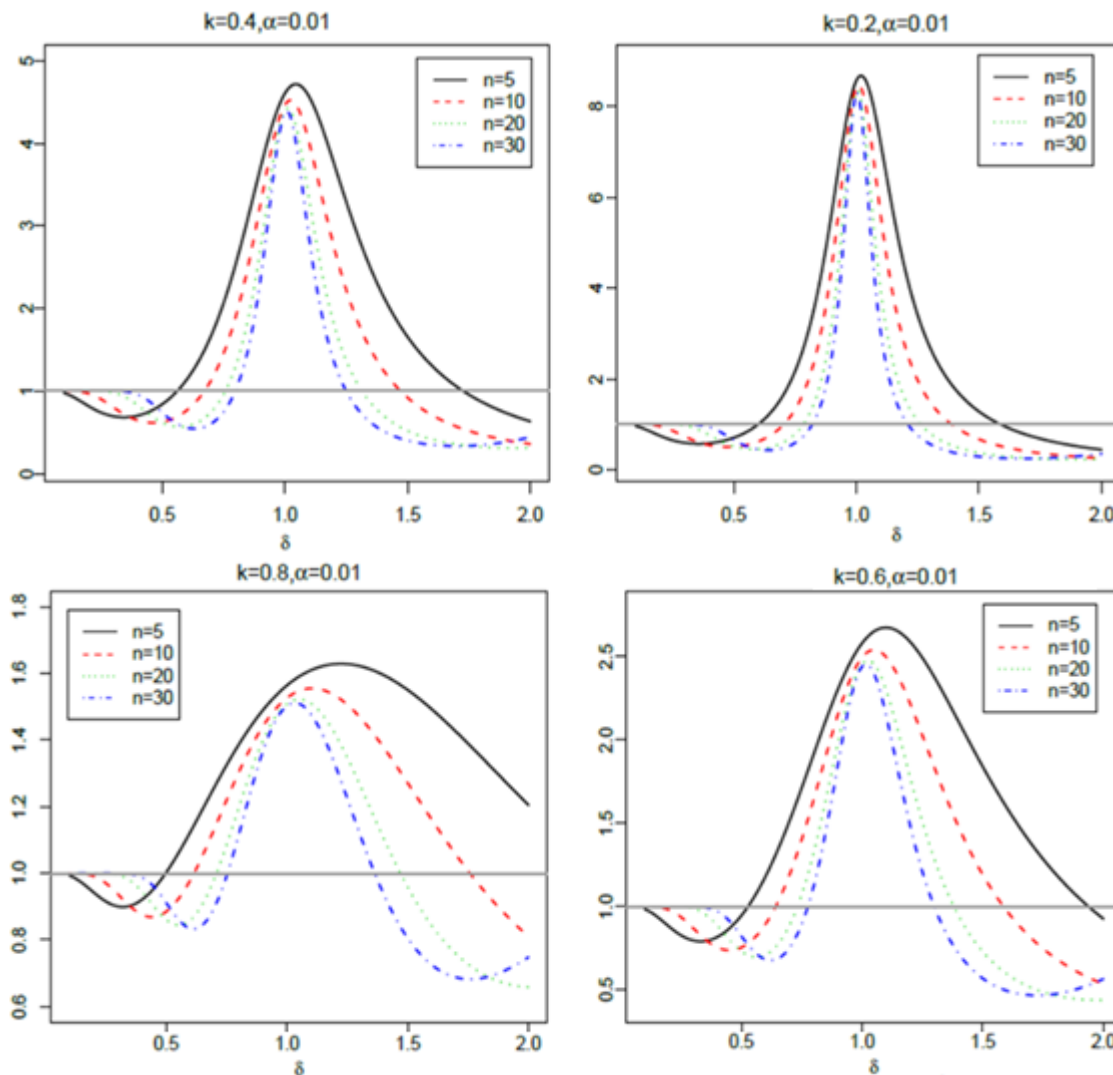


Figure 2: Diagrams of fuel efficiency for n = 5.10.20.30, k = 0.2 (2.0) 0.8, and alpha = 0.01

5. Analyze my endpoints and test their endpoint estimators

In this section, the endpoints are introduced, using my methods and testing the endpoint estimators. Their viscosity is estimated by the anthropogenic damage and their behavior to the sigma estimator is estimated by computing their likelihood. The endpoint estimator (sigma_S)^ under the entropy function is:

$$R(\sigma, \hat{\sigma}_S) = E\left[\frac{\hat{\sigma}_S}{\sigma}\right] - E\left[\ln\left(\frac{\hat{\sigma}_S}{\sigma}\right)\right] - 1$$

$$= E\left[\frac{k\hat{\sigma} + (1-k)\sigma_*}{\sigma}\right] - E\left[\ln\left(\frac{k\hat{\sigma} + (1-k)\sigma_*}{\sigma}\right)\right] - 1$$

$$= k + (1-k)\delta - \int_0^\infty \ln\left[(1-k)\delta + \frac{ku}{\gamma n}\right] h(u) du - 1 \quad (13)$$

The conversion function (13) is also converted to k using numerical methods. Consider the value of k = k, which can be obtained from the displacement of the exponential, as the endpoint of the endpoint. The test of the estimator shows the endpoint of the endpoint with k with (sigma_ST1)^. The end of the tester is end of the tester (sigma_ST1)^ is obtained by placing k = k in relation (11). Consider H_0: sigma = sigma_0. The curve is expressed in alpha (with alpha - 1) if

$$q_1 \leq \frac{\gamma n \hat{\sigma}}{\sigma_*} \leq q_\gamma \Leftrightarrow 0 \leq \frac{U}{\delta} - q_1 \leq 1.$$

Therefore, another choice for the end of the form would be the following form.

$$k_\gamma = \frac{U}{\delta} - q_1.$$

The tester shows the endpoint of the endpoint with k_2 with (sigma_ST2); If the chain of each relation (11) is obtained. If H_0: sigma = sigma_0, then, then, with a transcendence,

$$q_1 \leq \frac{\gamma n \hat{\sigma}}{\sigma_*} \leq q_\gamma \Rightarrow q_1 \leq E\left[\frac{\gamma n \hat{\sigma}}{\sigma_*}\right] \leq q_\gamma \Rightarrow q_1 \leq \gamma n \leq q_\gamma.$$

So if q_1 / 2n approx 1 if you want a lighter end, assuming q_1 / 2n approx 1 you have

$$\gamma n \frac{U}{\gamma n \delta} - \frac{q_1}{\gamma n} \approx \frac{\gamma n}{q_\gamma - q_1} \left(\frac{U}{\gamma n \delta} - 1\right),$$

Which is me. So the end of k_3 is as follows:

$$k_\gamma = \frac{\gamma n}{q_\gamma - q_1} \left|\frac{U}{\gamma n \delta} - 1\right|$$

The test of the endpoint estimator with endpoint k (σ_{ST3}) will have an exponent (11) with $k_3 = k$. To calculate the end-of-life testers (σ_{STi}), $i = 1, 2, 3, \dots$ using the exponential estimator, $\sigma_{STi} = 5.10.20.30$ and $\alpha = 0.01$ are shown. What is seen from Fig. 2 is that the efficiency for each tester reaches its value at $\delta = \delta$. For δ values close to (σ_0 close to σ), each tester having a visual function of zero, each value with n , is given by the value of i . Estimator (σ_{ST1}) which yields the same value for δ by using the end of k_{min} to eliminate the exponent of the exponent (σ_S).

6. Test analysis of end-of-run estimation based on second-order cantilevered data

A second type converter is used to perform longer test runs. In the second type cantilevered sample set, the observational graphs of 2 simple samples are observed. In other words, the n sample is put to the test, but instead of performing the test until the sample agents have finished, it is time to do it. This will do a great job at the test times and stages. It should be noted that in this type of converter, the number of observations is required to be constant and that the test is initiated, but during the test period of about 6 ms, Assuming the specimen concealed $x(1), \dots, x(r)$ of the sampling area, the gate is equal to

$$L(\theta | x_{1:n}, \dots, x_{r:n}) = \frac{n! \prod_{i=1}^r x_i}{(n-r)! \sigma^r} \exp \left\{ -\frac{\sum_{i=1}^r x_{i:n} + (n-r)x_{r:n}}{\gamma \sigma} \right\}, \quad (14)$$

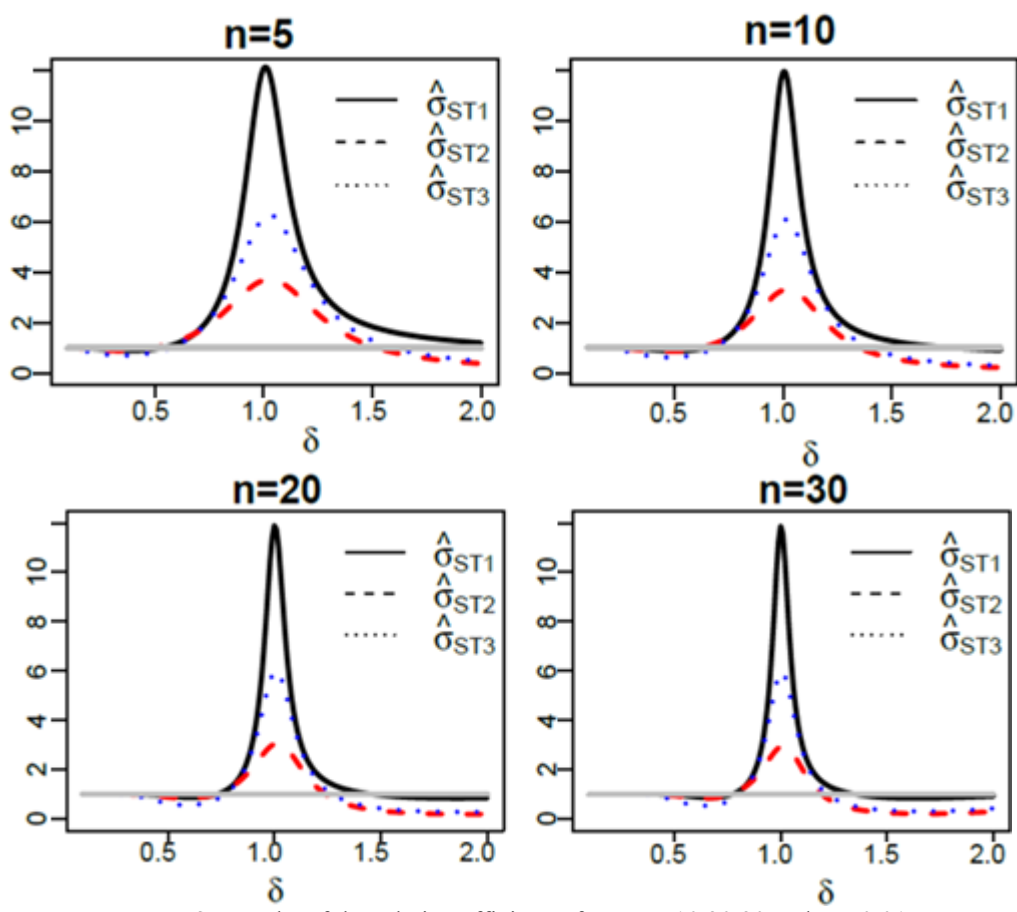


Image 3: Graphs of the relative efficiency for $n = 5.10.20.30$ and $\alpha = 0.01$

Instead, the month estimator of σ is equal to

$$T_r = \frac{\sum_{i=1}^r X_{i:n} + (n-r)X_{r:n}}{\gamma r} \quad (15)$$

1/4, 5/1, 6/3, 10/8, 12/1, 18/5, 19/7, 22/2
23, 30/6, 37/3, 46/3, 53/9, 59/8, 66/2.

7. Conclusion

A practical example must be analyzed to conclude the research.

The following data, The timescales (per minute) for the most specimens of the long hair in the test are longer.

Using the Chiropractor test with a test statistic value $D = 0.2341$ and a p -value = 0.3304, one can calculate the ratio distribution with parameter $\sigma = 580.59$. The assumption that the experiments will continue is $r = 4$. In relation to Equation (15), the estimation of the sea-month σ which is, in fact, an estimator of equilibrium is equal to $T4 = 1757.09$. According to Relation (7), the risk of this estimator is 0.1302. If the researcher has prior knowledge of the assumption $\sigma = 1700$, then the test statistic to test the

assumption $H_0: \sigma = 1700$ vs. $H_0: \sigma \neq 1700$ is $X^2 = [2rT]_{r/\sigma_0} = 8.27$. Assuming $\alpha = 0.05$ we have $q_1 = X_{8.0.975}^2 = 2.18$ and $q_2 = X_{8.0.975}^2 = 17.53$ in the more hypothetical node, the value is 0.05. The k_1 endpoint obtained by subtracting the endpoint estimator (13) is equal to 0.004. Since the value of k_1 depends on $\delta = \sigma_0 / \sigma$. We have an estimate of δ

$$\hat{\delta} = \frac{\sigma_0}{T_f} = \frac{1700}{1757/0.9} = 0.968$$

It is designed to estimate k_1 . The endpoints of k_2 and k_3 are also calculated as follows:

Table 1: Summary of estimators and performance of end-of-life testers and T_4

$\hat{\sigma}_{STr}$	$\hat{\sigma}_{ST2}$	$\hat{\sigma}_{ST3}$	T_f	
0.3664	0.4966	0.3665	0.1302	مخاطره
3/55191	2/62099	3/55183	—	کارایی نسبی

$$k_r = \frac{U/\delta - q_1}{q_2 - q_1} = \frac{rT_r/\sigma_0 - q_1}{q_2 - q_1}$$

$$= \frac{1}{17/53 - 2/18} \left\{ \frac{2(4)(1757/0.9)}{1700} - 2/18 \right\} = 0.39,$$

$$k_r = \frac{r}{q_2 - q_1} \left| \frac{T_r}{\sigma_0} - 1 \right| = \frac{2(4)}{17/53 - 2/18} \left| \frac{1757/0.9}{1700} - 1 \right| = 0.002.$$

Table 1 shows the computations of the computation estimators and the performance of the non-computation estimators and the estimation of T_4 . As it can be seen, the tester of the estimator had a higher likelihood than the estimator of T_4 . Σ tester (σ_{ST3}) has more computing power than other tester.

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