Improved estimator of the entropy and goodness of fit tests in ranked set sampling

Morteza Amini, M. Mehdizadeh and N. R. Arghami
Department of statistics, School of Mathematical Sciences, Ferdowsi University of Mashhad, P.O. Box 91775-1159, Mashhad, Iran

January 28, 2013

Abstract

The entropy is one of the most applicable uncertainty measures in many statistical and engineering problems. In statistical literature, the entropy is used in calculation of the Kullback-Leibler (KL) information which is a powerful mean for performing goodness of fit tests. Ranked Set Sampling (RSS) seems to provide improved estimators of many parameters of the population in the huge studied problems in the literature. It is developed for situations where the variable of interest is difficult or expensive to measure, but where ranking in small sub-samples is easy. In This paper, we introduced two estimators for the entropy and compare them with each other and the estimator of the entropy in Simple Random Sampling (SRS) in the sense of bias and Root of Mean Square Errors (RMSE). It is observed that the RSS scheme would improve this estimator. The best estimator of the entropy is used along with the estimator of the mean and two biased and unbiased estimators of variance based on RSS scheme, to estimate the KL information and perform goodness of fit tests for exponentiality and normality. The desired critical values and powers are calculated. It is also observed that RSS estimators would increase powers.

Keywords: Ordered Ranked set sampling; Judgement ranking; Order statistic; Information theory; Exponential; Normal; Uniform

1 Introduction

Suppose a continuous random variable $X$ has cumulative distribution function (cdf) $F(x)$ and a probability density function (pdf) $f(x)$. The differential entropy $H(f)$ of the random variable $X$ is defined to be

$$H(f) = -\int_{-\infty}^{\infty} f(x) \log f(x) dx.$$ (1)
The entropy is one of the most applicable uncertainty measures in many statistical and engineering problems. In statistical literature, the entropy is used in calculation of the Kullback-Leibler (KL) information which is a powerful mean for performing goodness of fit tests. The Kullback-Leibler (K-L) information of \( f(x) \) against \( f_0(x) \) is defined in [7] to be

\[
I(f; f_0) = \int_{-\infty}^{\infty} f(x) \log \frac{f(x)}{f_0(x)} \, dx. 
\]  

Since \( I(f; f_0) \) has the property that \( I(f; f_0) \geq 0 \), and the equality holds if only if \( f = f_0 \), the estimate of the K-L information has also been considered as a goodness of fit test statistic by some authors including [2] and [5]. It has been shown in the aforementioned papers that the test statistics based on the K-L information perform very well for testing exponentiality [5] as compared, in terms of power, with some leading test statistics.

Ranked Set Sampling (RSS) has been developed by McIntyre (1952). This method is applied for situations in which measuring a variable is costly or difficult, but where ranking in small subsets is easy. In this method, we first subdivide a sample of size \( n = k^2 \) randomly into \( k \) subsamples of size \( k \), rank each subsample visually or using any simple or cheap method and then in the \( r^{th} \) subsample, measure and record only the unit of rank \( r \) which is denoted by \( X_{r,k}^{(r)} \) \((r = 1, \ldots, k)\). Since the subsamples are independent, \( X_{r,k}^{(r)} \)'s are independent random variables. Also the marginal distribution of \( X_{r,k}^{(r)} \) is the same as that of \( r^{th} \) order statistic from a sample of size \( k \) of \( X \), i.e. \( X_{r,k} \). As it was proved by McIntyre, mean of this sample is an unbiased estimator of the mean of \( Y \) with an efficiency slightly less than \( \frac{1}{2}(k + 1) \), relative to the mean of a Simple Random Sample (SRS) of size \( k \). Thus “ranked set sampling should be useful when the quantification of an element is difficult but the elements of a set are easily drawn and ranked by judgment.” (Dell and Chutter 1972).

This method was also extended to estimating variance (Stokes 1980a), correlation coefficient (Stokes 1980b) and the situations in which the sample is subdivided into subsamples of different sizes.

In this paper, we introduced two estimators for the entropy and compare them with each other and the estimator of the entropy in Simple Random Sampling (SRS) in the sense of bias and Root of Mean Square Errors (RMSE). It is observed that the RSS scheme would improve this estimator. The best estimator of the entropy is used along with the estimator of the mean and two biased and unbiased estimators of variance based on RSS scheme, to estimate the KL information and perform goodness of fit tests for exponentiality and normality. The desired critical values and powers are calculated. It is also observed that RSS estimators would increase powers.

## 2 Entropy estimation

The nonparametric estimation of the entropy

\[
H = \int_0^1 \log \left( \frac{dF^{-1}(p)}{dp} \right) \, dp.
\]  

(3)
Table 1: Simulated Minimum RMSE (MRMSE) and Minimum Absolute Bias (MAB) of \( H_{1mn} \) and \( H_{2mn} \) and optimal \( m \) for \( k = 10 \) and three distributions with different values of \( r \).

| \( r \) | \( H_{1mn} \) | \( H_{2mn} \) | \( H_{1mn} \) | \( H_{2mn} \) |
|------|------|------|------|------|
| U(0,1) | \( \text{MRMSE (optimal } m^* \) | 0.062(8) | 0.081(5) | 0.045(11-13) | 0.073(5) |
|       | \( \text{MAB (optimal } m^* \) | 0.030(10) | 0.047(5) | 0.021(15) | 0.048(5) |
| e(1)  | \( \text{MRMSE (optimal } m^* \) | 0.157(5) | 0.168(4) | 0.125(6) | 0.140(4) |
|       | \( \text{MAB (optimal } m^* \) | 0.001(6) | 0.0137(5) | 0.004(7) | 0.014(5) |
| N(0,1)| \( \text{MRMSE (optimal } m^* \) | 0.184(5,10) | 0.246(5) | 0.138(7,8) | 0.233(5) |
|       | \( \text{MAB (optimal } m^* \) | 0.113(10) | 0.205(5) | 0.062(12) | 0.206(5) |

*\( m = 1(1)k/2 \) for \( H_{2mn} \) and \( m = 1(1)rk/2 \) for \( H_{1mn} \).

An estimate of (3) can be constructed by replacing the distribution function \( F \) by the empirical distribution \( F_n \). The derivative of \( F^{-1}(i/n) \) is estimated by \( (x_{i+w:n} - x_{i-w:n})n/(2w) \). The estimate of \( H \) is then

\[
H(m,n) = \frac{1}{n} \sum_{i=1}^{n} \log \left( \frac{n}{2m} (x_{i+m:n} - x_{i-m:n}) \right),
\]

where the window size \( m \) is a positive integer, which is less than \( n/2 \), and \( x_{i:n} = x_{i:n} \) for \( i < 1 \), and \( x_{i:n} = x_{n:n} \) for \( i > n \).

Ebrahimi et al. (1994) proposed a modified sample entropy as

\[
H_c(n,m) = n^{-1} \sum_{i=1}^{n} \log \left( \frac{n}{c_i m} (X_{(i+m)} - X_{(i-m)}) \right)
\]

where

\[
c_i = \begin{cases} 
1 + \frac{1}{m} & \text{if } 1 \leq i \leq m \\
2 & \text{if } m + 1 \leq i \leq n - m \\
1 + \frac{n-m}{m} & \text{if } n - m + 1 \leq i \leq n
\end{cases}
\]

To estimate the entropy in RSS scheme, we may note that the estimator of \( F^{-1}(i/n) \) must be positive for log function to be well-defined. So we have to order the ranked set sample. There are two ways to order this sample. First way is to order each replication, derive the estimator and then take the average as the main estimator. The second way is to order the whole sample of size \( rk \). This two methods yield two estimators as follows

\[
H_{1mn}^1 = \frac{1}{n} \sum_{i=1}^{n} \log \left( \frac{n}{c_i m} (X_{[i+m]} - X_{[i-m]}) \right)
\]

and

\[
H_{2mn}^2 = \frac{1}{n} \sum_{j=1}^{r} \sum_{i=1}^{k} \log \left( \frac{k}{d_i m} (X_{[i+m]_j} - X_{[i-m]_j}) \right),
\]
| SRS | RSS | SRS | RSS | SRS | RSS |
|-----|-----|-----|-----|-----|-----|
| 10  | 1   | -0.381 0.451 -0.259 0.326 | -0.392 0.561 -0.298 0.398 | -0.452 0.458 -0.342 0.428 |
| 2   | -0.222 0.293 -0.108 0.168 | -0.222 0.436 -0.142 0.266 | -0.342 0.441 -0.227 0.311 |
| 3   | -0.159 0.228 -0.070 0.124 | -0.174 0.405 -0.078 0.241 | -0.301 0.408 -0.207 0.289 |
| 4   | -0.140 0.224 -0.056 0.110 | -0.114 0.382 -0.031 0.236 | -0.305 0.394 -0.209 0.285 |
| 5   | -0.131 0.212 -0.050 0.107 | -0.064 0.371 0.012 0.249 | -0.289 0.389 -0.204 0.279 |
| 20* | 1   | -0.328 0.358 -0.274 0.302 | -0.335 0.424 -0.290 0.340 | -0.373 0.427 -0.313 0.358 |
| 2   | -0.176 0.203 -0.121 0.147 | -0.179 0.299 -0.139 0.206 | -0.221 0.288 -0.178 0.232 |
| 3   | -0.125 0.155 -0.076 0.103 | -0.151 0.280 -0.083 0.169 | -0.179 0.252 -0.141 0.200 |
| 4   | -0.104 0.134 -0.056 0.084 | -0.098 0.264 -0.052 0.161 | -0.176 0.255 -0.124 0.189 |
| 5   | -0.088 0.119 -0.046 0.074 | -0.062 0.253 -0.024 0.157 | -0.167 0.245 -0.117 0.184 |
| 6   | -0.079 0.117 -0.040 0.067 | -0.047 0.244 0.001 0.165 | -0.156 0.232 -0.116 0.185 |
| 7   | -0.076 0.111 -0.035 0.063 | -0.020 0.263 0.025 0.173 | -0.150 0.231 -0.116 0.185 |
| 8   | -0.068 0.109 -0.034 0.062 | 0.010 0.264 0.051 0.188 | -0.157 0.239 -0.114 0.185 |
| 9   | -0.064 0.108 -0.032 0.063 | 0.032 0.260 0.078 0.203 | -0.158 0.241 -0.116 0.188 |
| 10  | -0.061 0.106 -0.030 0.063 | 0.044 0.268 0.102 0.225 | -0.152 0.234 -0.113 0.184 |

*\(n = 10r\) cases are observed by RSS scheme with 10 samples and \(r\) replication.
Table 3: Monte Carlo biases and RMSE for $H_{mn}^1$ in three distributions for $n = 30$

| $n$ | $m$ | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE |
|-----|-----|------|------|------|------|------|------|------|------|------|------|
| 30* | 1   | -0.312 | 0.337 | -0.273 | 0.290 | -0.293 | 0.363 | -0.286 | 0.318 | -0.328 | 0.370 | -0.300 | 0.331 |
| 2   | -0.158 | 0.174 | -0.125 | 0.141 | -0.156 | 0.248 | -0.136 | 0.181 | -0.198 | 0.245 | -0.160 | 0.199 |
| 3   | -0.110 | 0.129 | -0.080 | 0.096 | -0.115 | 0.219 | -0.084 | 0.145 | -0.158 | 0.209 | -0.118 | 0.164 |
| 4   | -0.090 | 0.110 | -0.058 | 0.075 | -0.078 | 0.206 | -0.052 | 0.129 | -0.135 | 0.196 | -0.099 | 0.150 |
| 5   | -0.071 | 0.092 | -0.046 | 0.065 | -0.059 | 0.202 | -0.034 | 0.126 | -0.113 | 0.184 | -0.088 | 0.144 |
| 6   | -0.069 | 0.090 | -0.039 | 0.058 | -0.045 | 0.198 | -0.013 | 0.125 | -0.106 | 0.181 | -0.082 | 0.142 |
| 7   | -0.061 | 0.083 | -0.034 | 0.054 | -0.023 | 0.206 | 0.004 | 0.129 | -0.098 | 0.174 | -0.073 | 0.138 |
| 8   | -0.056 | 0.079 | -0.030 | 0.050 | -0.007 | 0.194 | 0.021 | 0.135 | -0.106 | 0.175 | -0.069 | 0.138 |
| 9   | -0.052 | 0.076 | -0.028 | 0.048 | 0.015 | 0.192 | 0.039 | 0.145 | -0.086 | 0.174 | -0.067 | 0.140 |
| 10  | -0.050 | 0.075 | -0.027 | 0.046 | 0.027 | 0.195 | 0.057 | 0.155 | -0.091 | 0.175 | -0.067 | 0.141 |
| 11  | -0.048 | 0.075 | -0.025 | 0.045 | 0.050 | 0.211 | 0.073 | 0.167 | -0.091 | 0.171 | -0.065 | 0.141 |
| 12  | -0.041 | 0.071 | -0.024 | 0.045 | 0.075 | 0.225 | 0.098 | 0.185 | -0.090 | 0.171 | -0.062 | 0.141 |
| 13  | -0.042 | 0.074 | -0.023 | 0.045 | 0.089 | 0.231 | 0.117 | 0.201 | -0.089 | 0.175 | -0.065 | 0.144 |
| 14  | -0.043 | 0.073 | -0.022 | 0.046 | 0.100 | 0.248 | 0.132 | 0.214 | -0.090 | 0.174 | -0.066 | 0.143 |
| 15  | -0.037 | 0.069 | -0.021 | 0.046 | 0.124 | 0.255 | 0.150 | 0.231 | -0.094 | 0.177 | -0.064 | 0.143 |

* $n = 10r$ cases are observed by RSS scheme with 10 samples and $r$ replication.
where
\[ d_i = \begin{cases} 1 + \frac{i-1}{m} & \text{if } 1 \leq i \leq m \\ 2 & \text{if } m + 1 \leq i \leq k - m \\ 1 + \frac{k-i}{m} & \text{if } k - m + 1 \leq i \leq k \end{cases} \]

Table 1 shows the values of simulated Minimum RMSE (MRMSE) and Minimum Absolute Bias (MAB) of \( H_{mn}^1 \) and \( H_{mn}^2 \) and optimal \( m \) for \( k = 10 \) and three famous distributions with different values of \( r \). From this values one can conclude that \( H_{mn}^1 \) is better estimator in the sense of RMSE and bias. Tables 2 and 3 show the values of Monte Carlo biases and RMS E for \( H_{mn}^1 \) in three distributions for \( n = 10, 20 \) and 30. This values present a distinct improvement of the estimator in RSS scheme relative to SRS scheme.

3 Goodness of fit tests

Park, S. and D. (2003) derived the nonparametric distribution function of \( H_c(n, m) \) as
\[ g_c(x) = \begin{cases} 0 & \text{if } x < \eta_i \text{ or } x > \eta_{i+1} \\ n^{-1} \frac{1}{\eta_i - \eta_{i+1}} & \text{if } \eta_i < x \leq \eta_{i+1}, i = 1, \ldots, n \end{cases} \]
where
\[ \eta_i = \begin{cases} \xi_{m+1} - \sum_{k=i}^{m} \frac{1}{m+k-1} (x(m+k) - x(1)) & \text{if } 1 \leq i \leq m \\ \frac{1}{2m} (x(i-m) + \ldots + x(i+m-1)) & \text{if } m + 1 \leq i \leq n - m + 1 \\ \xi_{n-m+1} + \sum_{k=n-m+2}^{n-1} \frac{1}{n+m-k+1} (x(n) - x(k-m-1)) & \text{if } n - m + 2 \leq i \leq n + 1 \end{cases} \]
They used it to correct the moments of the distribution which are used in goodness of fit tests.

In the exponentiality test, the aforementioned nonparametric distribution is used to estimate the mean and \( \hat{\lambda}_c \).

\[ I(g : f) = \int_{-\infty}^{\infty} g(x) \ln \frac{g(x)}{f(x)} dx \] (8)

\[ T_c = 1 + \log \hat{\lambda}_c - H_c(n, m) \] (9)

The following alternatives of the exponentiality null hypothesis have been considered to estimate the powers.

1. Gamma distribution with pdf
\[ f(x; \alpha) = \frac{x^{\alpha-1} \exp(-x)}{\gamma(\alpha)} \quad \alpha > 0, x > 0 \] (10)

2. Weibull distribution with pdf
\[ f(x; \beta) = \beta x^{\beta-1} \exp(-x^\beta) \quad \beta > 0, x > 0 \] (11)
3. Log-normal distribution with pdf

\[ f(x; \alpha) = \frac{1}{\sigma \sqrt{2\pi x}} \exp\left(-\frac{1}{2\sigma^2} \log x^2\right) \quad \sigma > 0, x > 0 \quad (12) \]

4. Uniform distribution with pdf

\[ f(x) = 1 \quad 0 < x < 1 \quad (13) \]

As mentioned by Arizono and Ohta (1989), an estimate for \( I(f, f_0) \), when \( f_0 \) is the normal pdf with known parameters \( \mu \) and \( \sigma \) is obtained as

\[ I_{mn} = \log(\sqrt{2\pi \sigma^2}) + \frac{1}{2n} \sum_{i=1}^{n} \left( \frac{x_i - \mu}{\sigma} \right)^2 - H(n, m). \quad (14) \]

When both \( \mu \) and \( \sigma \) are unknown, we place their estimates, that is, \( \hat{\mu} = \bar{X} \) and \( \hat{\sigma} = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2 \) in \( (29) \) and derive the test statistic as

\[ T = \log(\sqrt{2\pi \hat{\sigma}^2}) + 0.5 - H(n, m) \quad (15) \]

Park, S. and D. replaced the estimates \( H(n, m) \) and \( \hat{\sigma} \) with their corrected estimators \( H_c(n, m) \) and \( \hat{\sigma}_c \) and derived the test statistic

\[ T_c = \log(\sqrt{2\pi \hat{\sigma}_c^2}) + 0.5 - H_c(n, m) \quad (16) \]

In the normality test the following alternatives are considered to estimate the powers

1. Uniform distribution with pdf

\[ f(x) = 1 \quad 0 < x < 1 \quad (17) \]

2. Chi-square distribution with pdf

\[ f(x; \alpha) = \frac{1}{\Gamma(\alpha/2)} \left( \frac{1}{2} \right)^{\alpha/2} x^{(\alpha/2)-1} \exp\left(-\frac{1}{2} x\right) \quad \alpha > 0, x > 0 \quad (18) \]

3. t-student distribution with pdf

\[ f(x; \nu) = \frac{\Gamma((\nu + 1)/2)}{\Gamma(\nu/2)} \frac{1}{\sqrt{\nu \pi}} \left( \frac{1}{1 + x^2(\nu+1)/2} \right)^{\nu/2} \quad \nu > 2, -\infty < x < \infty \quad (19) \]

4. Exponential distribution with pdf

\[ f(x; \lambda) = \lambda \exp(-\lambda x), \quad \lambda > 0, \quad x > 0. \quad (20) \]
Table 4: Critical values for different values of $n$, $m$ and $\alpha$

| $n$ | $m$ | $\alpha$   | $\alpha$   |
|-----|-----|------------|------------|
|     |     | 0.1        | 0.05       | 0.025      | 0.01       | 0.1        | 0.05       | 0.025      | 0.01       |
| 10  | 1   | 0.5357     | 0.6318     | 0.7297     | 0.8617     | 0.5898     | 0.7027     | 0.8034     | 0.9215     |
|     | 2   | 0.2898     | 0.3546     | 0.4213     | 0.5099     | 0.3765     | 0.4404     | 0.5113     | 0.6005     |
|     | 3   | 0.2095     | 0.2645     | 0.3243     | 0.3944     | 0.3214     | 0.3712     | 0.4182     | 0.4667     |
|     | 4   | 0.1619     | 0.2154     | 0.2596     | 0.3293     | 0.3001     | 0.3221     | 0.3593     | 0.3987     |
|     | 5   | 0.1416     | 0.1916     | 0.2487     | 0.3122     | 0.2903     | 0.3091     | 0.3311     | 0.3544     |
|     | 20* | 1   | 0.4455     | 0.5091     | 0.5695     | 0.6373     | 0.4775     | 0.5405     | 0.6025     | 0.6587     |
|     |     | 2   | 0.2391     | 0.2822     | 0.3305     | 0.3813     | 0.2824     | 0.3264     | 0.3621     | 0.4092     |
|     |     | 3   | 0.1707     | 0.2089     | 0.2450     | 0.2939     | 0.2296     | 0.2614     | 0.2940     | 0.3460     |
|     |     | 4   | 0.1389     | 0.1738     | 0.2064     | 0.2498     | 0.2073     | 0.2339     | 0.2671     | 0.3112     |
|     |     | 5   | 0.1117     | 0.1445     | 0.1772     | 0.2173     | 0.2000     | 0.2287     | 0.2549     | 0.2875     |
|     |     | 6   | 0.0964     | 0.1269     | 0.1569     | 0.1918     | 0.1977     | 0.2255     | 0.2501     | 0.2802     |
|     |     | 7   | 0.0779     | 0.1114     | 0.1441     | 0.1741     | 0.1968     | 0.2223     | 0.2463     | 0.2695     |
|     |     | 8   | 0.0643     | 0.0983     | 0.1250     | 0.1754     | 0.2013     | 0.2225     | 0.2407     | 0.2612     |
|     |     | 9   | 0.0495     | 0.0915     | 0.1188     | 0.1604     | 0.2023     | 0.2213     | 0.2375     | 0.2569     |
|     | 10  | 0.0368   | 0.0797     | 0.1167     | 0.1543     | 0.2008     | 0.2175     | 0.2391     | 0.2512     |
|     | 30* | 1   | 0.4100     | 0.4567     | 0.4961     | 0.5656     | 0.4273     | 0.4729     | 0.5155     | 0.5768     |
|     |     | 2   | 0.2171     | 0.2498     | 0.2796     | 0.3156     | 0.2443     | 0.2776     | 0.3028     | 0.3451     |
|     |     | 3   | 0.1516     | 0.1819     | 0.2122     | 0.2402     | 0.1891     | 0.2145     | 0.2408     | 0.2777     |
|     |     | 4   | 0.1202     | 0.1481     | 0.1693     | 0.2065     | 0.1649     | 0.1855     | 0.2099     | 0.2407     |
|     |     | 5   | 0.0979     | 0.1210     | 0.1503     | 0.1860     | 0.1498     | 0.1739     | 0.1912     | 0.2300     |
|     |     | 6   | 0.0825     | 0.1102     | 0.1361     | 0.1559     | 0.1454     | 0.1658     | 0.1879     | 0.2208     |
|     |     | 7   | 0.0722     | 0.0950     | 0.1212     | 0.1501     | 0.1433     | 0.1660     | 0.1891     | 0.2134     |
|     |     | 8   | 0.0574     | 0.0849     | 0.1061     | 0.1449     | 0.1425     | 0.1663     | 0.1848     | 0.2082     |
|     |     | 9   | 0.0574     | 0.0849     | 0.0960     | 0.1270     | 0.1453     | 0.1631     | 0.1833     | 0.2046     |
|     |     | 10  | 0.0379     | 0.0635     | 0.0878     | 0.1162     | 0.1428     | 0.1654     | 0.1838     | 0.2039     |
|     |     | 11  | 0.0280     | 0.0545     | 0.0760     | 0.1097     | 0.1468     | 0.1661     | 0.1838     | 0.2056     |
|     |     | 12  | 0.0151     | 0.0447     | 0.0706     | 0.1030     | 0.1489     | 0.1697     | 0.1875     | 0.2049     |
|     |     | 13  | 0.0043     | 0.0354     | 0.0640     | 0.0927     | 0.1502     | 0.1719     | 0.1891     | 0.2072     |
|     |     | 14  | -0.0046    | 0.0274     | 0.0612     | 0.0882     | 0.1527     | 0.1720     | 0.1857     | 0.2073     |
|     | 15  | -0.0190   | 0.0182     | 0.0505     | 0.0813     | 0.1492     | 0.1716     | 0.1871     | 0.2091     |

*$n = 10r$ cases are observed by RSS scheme with 10 samples and $r$ replication.
Stokes (1980) proposed the sample variance as an estimator of the population variance as follows

$$\hat{\sigma}^2 = \frac{1}{rk - 1} \sum_{i=1}^{r} \sum_{j=1}^{k} (X_{[j|i]} - \hat{\mu})^2$$

(21)

This estimator is asymptotically unbiased and asymptotically more efficient than the sample variance in SRS. MacEachern et al. (2002) proposed an unbiased estimator of the variance as follows

$$\tilde{\sigma}^2 = \frac{1}{rk} (k - 1)MST + (rk - k + 1)MSE,$$

(22)

where

$$MST = \frac{1}{k - 1} \sum_{i} \sum_{j} (X_{j|i} - \hat{\mu})^2 - \frac{1}{k - 1} \sum_{j} \sum_{i} (X_{j|i} - \bar{X}_{[j]} )^2,$$

(23)

$$MSE = \frac{1}{k(r - 1)} \sum_{j} \sum_{i} (X_{[j|i]} - \bar{X}_{[j]} )^2,$$

(24)

$$\bar{X}_{[j]} = \sum_{i} X_{[j|i]}/r.$$  

(25)

and

$$\hat{\mu} = \sum_{i} \sum_{j} X_{[j|i]}/rk.$$  

(26)

If we use our entropy estimator for estimation of Kullback-Leibler distance between an unknown pdf and the pdf of the normal distribution, we derive

$$K_{mn} = \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2n} \sum_{i=1}^{n} \left( \frac{x_i - \mu}{\sigma} \right)^2 - H_{mn}^2.$$  

(27)

In goodness of fit test of normality when $\mu$ and $\sigma$ are unknown we can place their estimators in the RSS scheme, i.e. $\hat{\mu}$ in (26) and the Stokes estimator, (21) to derive the test statistic as

$$KL_{mn}^1 = \log(\sqrt{2\pi\hat{\sigma}^2}) + 0.5 - H_{mn}^2.$$  

(28)

If we place the MacEachern et al. estimator of variance in (27), we derive another test statistic as

$$KL_{mn}^2 = \log(\sqrt{2\pi\tilde{\sigma}^2}) + \frac{1}{2n} \sum_{i=1}^{n} \left( \frac{x_i - \tilde{\mu}}{\tilde{\sigma}} \right)^2 - H_{mn}^2.$$  

(29)

Table 4 contains critical values of exponentiality and normality tests for different values of $n$, $m$ and $\alpha$.

Table 5 propose a comparison of powers in RSS and SRS schemes, for exponentiality and normality tests. The SRS values of powers are given from Park. S. and D. with the modified sample entropy of Ebrahimi et al. and their modified estimators of moments. We used the similar window size $m$ for the comparison although our maximum powers may be obtained for different
Table 5: Power comparison of 0.05 tests against some alternatives in SRS and RSS schemes

### Exponentiality

| Alternatives     | SRS ($m = 4$) | RSS ($m = 4$) | SRS ($m = 6$) | RSS ($m = 6$) |
|------------------|---------------|---------------|---------------|---------------|
| Gamma (1.5)      | 0.2176        | 0.2740        | 0.3480        | 0.4193        |
| Lognormal (1)    | 0.2685        | 0.1908        | 0.6613        | 0.4156        |
| Weibull (1.5)    | 0.4639        | 0.6199        | 0.7752        | 0.9056        |
| Gamma (2)        | 0.8816        | 0.9693        | 0.9993        | 0.9999        |
| Gamma (3)        | 0.8021        | 0.9979        | 0.9989        | 1.0000        |
| Uniform          | 0.9138        | 0.9896        | 0.9995        | 1.0000        |
| Weibull (2)      | 0.9967        | 0.9994        | 1.0000        | 1.0000        |
| Lognormal (0.5)  | 0.6288        | 0.7078        | 0.8263        | 0.8307        |

| Alternatives     | SRS ($m = 3$) | RSS ($m = 4$) | SRS ($m = 6$) | RSS ($m = 6$) |
|------------------|---------------|---------------|---------------|---------------|
| $t(5)$           | 0.1069        | 0.0847        | 0.2395        | 0.1515        |
| $t(3)$           | 0.1989        | 0.1761        | 0.5132        | 0.4009        |
| Uniform          | 0.3851        | 0.4801        | 0.8850        | 0.9843        |
| $\chi^2$        | 0.5058        | 0.5704        | 0.9326        | 0.9709        |
| $\chi^2$ (Exponential) | 0.8656 | 0.9574 | 0.9997 | 1.0000 |
| $\chi^1$        | 0.9934        | 0.9999        | 1.0000        | 1.0000        |

Average power: 0.6288, 0.7078, 0.8263, 0.8307

### Normality

| Alternatives     | SRS ($m = 3$) | RSS ($m = 4$) | SRS ($m = 6$) | RSS ($m = 6$) |
|------------------|---------------|---------------|---------------|---------------|
| $t(5)$           | 0.1069        | 0.0847        | 0.2395        | 0.1515        |
| $t(3)$           | 0.1989        | 0.1761        | 0.5132        | 0.4009        |
| Uniform          | 0.3851        | 0.4801        | 0.8850        | 0.9843        |
| $\chi^2$        | 0.5058        | 0.5704        | 0.9326        | 0.9709        |
| $\chi^2$ (Exponential) | 0.8656 | 0.9574 | 0.9997 | 1.0000 |
| $\chi^1$        | 0.9934        | 0.9999        | 1.0000        | 1.0000        |

Average power: 0.5093, 0.5448, 0.5483, 0.5713

* $n = 10r$ cases are observed by RSS scheme with 10 samples and $r$ replication.
Table 6: Maximum powers (maximal $m$) of 0.05 tests against some alternatives of the null hypothesis distributions

| Alternatives       | $n$ | 10   | 20*  | 30*  | 40*  | 50*  |
|--------------------|-----|------|------|------|------|------|
|                    |     |      |      |      |      |      |
| **Exponentiality** |     |      |      |      |      |      |
| Gamma (1.5)        |     | 0.5760(5) | 0.3761(8) | 0.4126(12) | 0.4371(14) | 0.4569(7) |
| Lognormal (1)      |     | 0.1333(2) | 0.2140(3) | 0.3133(3) | 0.4143(4) | 0.5174(3) |
| Weibull (1.5)      |     | 0.5999(5) | 0.7600(8) | 0.8365(15) | 0.8725(8) | 0.9099(7) |
| Gamma (2)          |     | 0.5638(4) | 0.7216(8) | 0.7939(7) | 0.8570(8) | 0.9153(7) |
| Gamma (3)          |     | 0.9023(5) | 0.9745(5) | 0.9956(5) | 0.9997(5) | 1.0000(3-5) |
| Uniform            |     | 0.9201(5) | 1.0000(8,10) | 1.0000(3-15) | 1.0000(2-20) | 1.0000(2-25) |
| Weibull (2)        |     | 0.9659(5) | 0.9963(8) | 0.9998(8,12) | 1.0000(4-12) | 1.0000(3-12) |
| Lognormal (0.5)    |     | 0.9815(4) | 0.9995(3) | 1.0000(2-6) | 1.0000(2-9) | 1.0000(2-12) |

| Alternatives       | $n$ | 10   | 20*  | 30*  | 40*  | 50*  |
|--------------------|-----|------|------|------|------|------|
|                    |     |      |      |      |      |      |
| **Normality**      |     |      |      |      |      |      |
| t(5)               |     | 0.0813(4) | 0.0865(3) | 0.1133(3) | 0.1427(2) | 0.1615(2) |
| t(3)               |     | 0.1335(4) | 0.1846(2) | 0.2820(2) | 0.3514(3) | 0.4260(3) |
| Uniform            |     | 0.1523(2) | 0.5805(10) | 0.9036(11) | 0.9875(16) | 0.9992(16,20) |
| $\chi^2_4$        |     | 0.3462(4) | 0.6164(4) | 0.8305(6) | 0.9334(6) | 0.9781(5) |
| $\chi^2_2$ (Exponential) |     | 0.6926(4) | 0.9670(4) | 0.9992(4) | 1.0000(3-8) | 1.0000(1-14) |
| $\chi^2_1$        |     | 0.9492(3) | 0.9999(3-5) | 1.0000(1-12) | 1.0000(1-17) | 1.0000(1-22) |

* $n = 10r$ cases are observed by RSS scheme with 10 samples and $r$ replication.

values of $m$. For normality test two test statistics $KL^1_{mn}$ and $KL^2_{mn}$ are compared in the sense of power. For $n = 20$, using the statistic $KL^2_{mn}$ cause less powers than $KL^1_{mn}$. Although the average of powers of $KL^2_{mn}$ gets larger than the average power of $KL^1_{mn}$ when $n$ increases to 50, but the difference between this powers is ignorable. Since obtaining the statistic $KL^2_{mn}$ is more complicated than $KL^1_{mn}$, we prefer to use $KL^1_{mn}$ for the remaining of the study.

Table 6 shows the maximum powers and the maximal window size, $m$ for $\alpha = 0.05$ of exponentiality and normality tests. Ebrahimi et al. (1992) used such maximality to obtain some optimal window size $m$ for each $n$. Table 6 shows that here this values of optimal $m$ differs distinctly for different alternatives. In fact choosing an optimal $m$ depends very closely to the alternative which is unknown. So in this paper we use the average of powers for considered alternatives as a measure to decide about the optimal $m$. The values of average powers are tabulated in Table 7. The authors believe that this values are more useful for the experimenter who wants to perform a test, since he is not aware about the alternative. Table 6 shows the optimal $m$ and the maximum average powers for different values of $n$ of exponentiality and normality tests.
Table 7: Average powers $\alpha = 0.05$ for different alternatives and different values of $n$ and $m$

**Exponentiality**

| $n$ | $m$ | AP  | $n$ | $m$ | AP  | $n$ | $m$ | AP  | $n$ | $m$ | AP  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 10  | 1   | 0.2905 | 30* | 1   | 0.5470 | 40* | 1   | 0.6156 | 40* | 1   | 0.7692 | 50* | 11   | 0.7997 |
| 2   | 0.5138 | 2   | 0.6851 | 2   | 0.7325 | 17  | 0.7643 | 12  | 0.7950 |
| 3   | 0.6281 | 3   | 0.7364 | 3   | 0.7786 | 18  | 0.7634 | 13  | 0.7872 |
| 4   | 0.6939 | 4   | 0.7564 | 4   | 0.8026 | 19  | 0.7647 | 14  | 0.7866 |
| 5   | 0.7009 | 5   | 0.7759 | 5   | 0.8067 | 20  | 0.7551 | 15  | 0.7836 |

20* 1 | 0.4477 | 6   | 0.7640 | 6   | 0.8056 | 50* | 1   | 0.6509 | 16  | 0.7802 |

**Normality**

| $n$ | $m$ | AP  | $n$ | $m$ | AP  | $n$ | $m$ | AP  | $n$ | $m$ | AP  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 10  | 1   | 0.2765 | 30* | 1   | 0.5229 | 40* | 1   | 0.5776 | 40* | 1   | 0.6098 | 50* | 11   | 0.6746 |
| 2   | 0.3470 | 2   | 0.6154 | 2   | 0.6811 | 17  | 0.5960 | 12  | 0.6702 |
| 3   | 0.3622 | 3   | 0.6547 | 3   | 0.7130 | 18  | 0.5808 | 13  | 0.6647 |
| 4   | 0.3876 | 4   | 0.6628 | 4   | 0.7173 | 19  | 0.5702 | 14  | 0.6583 |
| 5   | 0.3520 | 5   | 0.6559 | 5   | 0.7072 | 20  | 0.5540 | 15  | 0.6517 |

20* 1 | 0.4276 | 6   | 0.6518 | 6   | 0.6995 | 50* | 1   | 0.6375 | 16  | 0.6457 |

$n = 10r$ cases are observed by RSS scheme with 10 samples and $r$ replication.
Table 8: Values of the window size \( m \) with largest average of powers against alternatives

| Optimal \( m \) (max average power) | Exponentiality | Normality |
|------------------------------------|----------------|-----------|
| 10 \( 5(0.7009) \)               | 4(0.3876)      |
| 20 \( 8(0.7406) \)               | 4(0.5586)      |
| 30 \( 5(0.7759) \)               | 4(0.6628)      |
| 40 \( 5(0.8067) \)               | 4(0.7173)      |
| 50 \( 5(0.8392) \)               | 3(0.7482)      |

References

Ahmad, I. A. and Lin, P. E. “A nonparametric estimation of the entropy for absolutely continuous distributions,” *IEEE Trans. Inf. Theory*, vol. 22, 372–375, 1976.

[2] Arizono, I. and Ohta, H. “A test for normality based on Kullback-Leibler information,” *The American Statistician*, vol. 43, pp. 20–23, 1989.

[4] Dmitriev, Y. G. and Tarasenko, F. P. “On the estimation of functional of the probability density and its derivatives,” *Theory probab. Applic.*, vol. 18, 628–633, 1973.

[5] Ebrahimi, N. and Habibullah, M. “Testing exponentiality based on Kullback-Leibler information,” *J. Royal Statist. Soc. B*, vol. 54, pp. 739–748, 1992.

[7] Kullback, S. “*Information Theory and Statistics,*” New York: Wiley, 1959.

[8] Park, S. “The entropy of consecutive order statistics,” *IEEE Trans. Inform. Theory*, vol. 41, pp. 2003–2007, 1995.

[9] Park, S. “Testing exponentiality based on the Kullback-Leibler information with the type II censored data,” *IEEE Trans. on Rel.*, vol. 54, pp. 22–26, 2005.

[10] Shannon, C. E. “A mathematical theory of communications,” *Bell System Tech. J.*, vol. 27, pp. 379–423, 1948.

[11] Teitler, S., Rajagopal, A. K. and Ngai, K. L. “Maximum entropy and reliability distributions,” *IEEE Trans. on Rel.*, vol. 35, pp. 391–395, 1986.

[12] Vasicek, O. “A test for normality based on sample entropy,” *J. Royal Statist. Soc. B*, vol. 38, pp. 730–737, 1976.

Arnold, B. C.; Balakrishnan, N. and Nagaraja, H. N. (1992). *A First Course in Order Statistics*. Cochran, W. G. (1977). *Sampling Techniques*. Third edition, Wiley, New York.

Dell, T. R. and Clutter, J. L. (1972). Ranked set sampling theory with order statistics background. *Biometrics* **28**, 545 – 555.
McIntyre, G. A. (1952). A method of unbiased selective sampling, using ranked sets. *J. Agri. Res.* 3, 385–390.

Muttllack, H. A. and L. I. McDonald (1990a). Ranked set sampling with respect to concomitant variables and with size biased probability of selection. *Commun. Statist. – Theory Meth.*, 19, 205–219.

Pearson, E. S. and Hartley, H. O. (1972). *Biometrika Tables for Statisticians*, Vol. 2. Cambridge University Press.

Shorack, G. R. and Wellner, J. A. (1986). *Emperical Processes with Application to Statistics*, Wiley, New York.

Stokes, S. L. (1977). Ranked set sampling with concomitant variables. *Commun. Statist. – Theory Meth.*, 6, 1207–1212.

Stokes, S. L. (1980a). Estimation of variance using judgment ordered ranked set samples. *Biometrics*, 36, 35–42.

Stokes, S. L. (1980b). Inference on the correlation coefficient in bivariate normal populations from ranked set samples. *J. Amer. Statist. Assoc.*, 75, 989–995.

Watterson, G.A. (1959). Linear estimation in censored samples from multivariate normal populations. *Ann. Math. Statist.* 30, 814–824.

Yu, Philip, L. H. and Lam, K. (1997). Regression estimator in ranked set sampling. *Biometrics*, 53, 1070–1080.