# Caspian Journal of Mathematical Sciences (CJMS)

University of Mazandaran, Iran

http://cjms.journals.umz.ac.ir ISSN: 1735-0611

CJMS. 1(2)(2012), 104-108

## Comments on Multiparameter Estimation in Truncated Power Series Distributions under the Stein's Loss

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ABSTRACT. This comment is to show that Theorem 3.3 of Dey and Chung (1991) (Multiparameter estimation in truncated power series distributions under the Stein's loss. *Commun. Statist.-Theory Meth.*, **20**, 309-326) may give us misleading results. Analytically and through simulation, we show that the Theorem does not improve the given estimator.

Keywords: Left-Truncated power series distributions, Stein loss function.

#### 1. Introduction

Let  $X=(X_1,\cdots,X_p)$  where  $X_1,\cdots,X_p$  are p independent random variables,  $X_i$  having the following left-truncated power series distribution

$$P_{\theta_i}(x_i) = \begin{cases} g_i(\theta_i)t_i(x_i)\theta_i^{x_i}, & x_i = a_i, a_i + 1, \dots; \\ 0, & \text{otherwise,} \end{cases}$$

where  $a_i$  is nonzero positive integer and  $g_i(\theta_i)$  is a normalizing constant, given as

$$g_i^{-1}(\theta_i) = \sum_{x_i = a_i}^{\infty} t_i(x_i)\theta_i^{x_i}, \ \theta_i > 0, i = 1, \dots, p.$$

<sup>&</sup>lt;sup>1</sup> Received: 15 May 2012 Revised: 12 June 2012 Accepted: 20 June 2012

Consider the loss function (Stein loss) is given by

$$L(\theta, \delta) = \sum_{i=1}^{p} \left( \frac{\delta_i}{\theta_i} - \log \left( \frac{\delta_i}{\theta_i} \right) - 1 \right)$$
 (1.1)

where  $\delta = (\delta_1, \dots, \delta_p)$  is an estimate of  $\theta = (\theta_1, \dots, \theta_p)$  and  $\log$  denotes the natural logarithm. For the loss function (1.1), the best multiple estimator of  $\theta$  (which is also the best unbiased estimator) is given by  $\delta^0(X) = (\delta_1^0(X), \dots, \delta_p^0(X))$  where

$$\delta_i^0(X) = \begin{cases} \frac{t_i(X_i - 1)}{t_i(X_i)}, & X_i = a_i + 1, a_i + 1, \cdots; \\ 0, & \text{elsewhere.} \end{cases}$$

and  $t_i(a_i - 1)$  is defined zero.

Suppose the rival estimator of  $\theta$  as

$$\delta(X) = \delta(X) + \phi(X)$$
  
=  $(\delta_1^0(X) + \phi_1(X), \dots, \delta_p^0(X) + \phi_p(X))$ 

where  $\phi(X) = (\phi_1(X), \dots, \phi_p(X)), \phi_i(X) > 0$  and  $\phi_i(X) = 0$  if  $X_i < a_i + 1, i = 1, \dots, p$ . Assume  $\delta_i^0(X), i = 1, \dots, p$ , be an increasing function of X.

The following theorem and corollary are from Dey and Chung (1991).

**Theorem 1.1.** Suppose that  $\delta(X) = \delta^0(X)(1 + \psi(X))$  where  $\psi(X) = (\psi_1(X), \dots, \psi_p(X))$  and  $\psi_i(X) = \phi_i(X)/\delta_i^0(X)$ ,  $i = 1, \dots, p$  with

$$\psi_i(X) = \frac{d(X)e^{-X_i}}{b+s_2}, \ s_2 = \sum_{j=1}^p e^{-2X_j}, i = 1, \dots, p$$

and the following additional conditions hold

- $(1) \ b \ge 1/4$
- (2) 0 < d(X) < 1/2
- (3) d(X) is a decreasing function in each coordinate
- (4)  $d(X + e_i) \le e^{-2}d(X), i = 1, \dots, p.$

Then  $\delta(X)$  will dominate  $\delta^0(X)$  in terms of risk if p > 2.

Corollary 1.2. Suppose that  $\delta(X) = \delta^0(X)(1 + \psi(X))$  where  $\psi(X) = (\psi_1(X), \dots, \psi_p(X))$  with

$$\psi_i(X) = \frac{0.5e^{-2s}e^{-X_i}}{b + s_2}$$

where  $s = \sum_{j=1}^{p} X_j$ ,  $s_2 = \sum_{j=1}^{p} e^{-2X_j}$  and  $b \ge 1/4$ . Then for  $p \ge 2$ ,  $\delta(X)$  dominates  $\delta^0(X)$  in terms of risk.

Now borrowing an idea of Liang (2009), we show that  $\delta$  given in corollary

3.3.1 in fact is not better than  $\delta^0$  in terms of risk. For simplicity, consider  $a_i=1$  for all  $i=1,\cdots,p$  and let  $\alpha=\min(\delta_1^0(2),\cdots,\delta_p^0(2))$ . Suppose that the parameter space is given by  $\Omega=\{\theta;\theta_i>0,i=1,\cdots,p\}$  and define the subspace  $\Omega_0\subset\Omega$  such that  $\Omega_0=\{\theta;\theta_i<\alpha,i=1,\cdots,p\}$ . The risk difference of  $\delta(X)$  and  $\delta^0(X)$  is given by

$$\begin{split} \Delta(\theta) = & R(\theta, \delta) - R(\theta, \delta^0) \\ = & R(\theta, \delta^0 + \phi) - R(\theta, \delta^0) \\ = & \sum_{i=1}^p E\bigg(\frac{\phi_i(X)}{\theta_i} - \log\bigg(1 + \frac{\phi_i(X)}{\delta_i^0(X)}\bigg)\bigg). \end{split}$$

Since  $\phi_i > 0$  and  $\theta_i < \alpha$  for  $i = 1, \dots, p$  and  $\theta \in \Omega_0$  and also for all x such that  $x_i \geq 2, i = 1, \dots, p$  we have

$$\delta_i^0(X) \ge \min(\delta_1^0(X), \cdots, \delta_p^0(X))$$

$$\ge \min(\delta_1^0(2), \cdots, \delta_p^0(2))$$

$$= \alpha,$$

then we get

$$\Delta(\theta) \ge \sum_{i=1}^{p} E\left(\frac{\phi_i(X)}{\alpha} - \log\left(1 + \frac{\phi_i(X)}{\alpha}\right)\right)$$
$$= \sum_{i=1}^{p} E\left(\eta_i(X) - \log(1 + \eta_i(X))\right),$$

where  $\eta_i(X) = \phi_i(X)/\alpha$ . It is known that  $\eta_i(X) - \log(1 + \eta_i(X)) > 0$  for X such that  $X_i \geq 2$  so that  $\Delta(\theta) > 0$  for  $\theta \in \Omega_0$ .

Another way to show that the estimator  $\delta$  is not better than  $\delta^0$  is by simulation. A Monti Carlo simulation is carried out to generate random variables from zero-truncated Poisson distribution using Matlab 7.4. For a particular set of parameters, the risks of the estimators  $\delta^0$  and  $\delta$  are computed and reported in Table 1. From Table 1, we observe that the risk of  $\delta$  is slightly higher than the risk of  $\delta^0$  for the a specific set of parameters and hence  $\delta$  is not an improved estimator of  $\delta^0$ .

Table 1.  $R_1$  is the risk of  $\delta^0$  and  $R_2$  is the risk of  $\delta$ .

p	Parameters							$R_1$	$R_2$			
2	.01	.07									5.5768	5.5782
3	.01	.07	.003								5.6621	5.6634
4	.01	.07	.003	.05							5.4648	5.4662
5	.01	.07	.003	.05	.00001						5.6188	5.6202
10	.01	.07	.003	.05	.00001	.001	.000015	.002	.001	.04	5.0567	5.0580

#### 2. Main results

The following is an example of a definition.

**Definition 2.1.** Let X be a real Banach space. A non-empty closed set  $P \subset X$  is called a cone of X if it satisfies the following conditions:

- (1)  $x \in P, \mu \geq 0$  implies  $\mu x \in P$ ,
- (2)  $x \in P, -x \in P$  implies x = 0.

Here is an example of a table.

Table 2.

1	2	3		
f(x)	g(x)	h(x)		
a	b	c		

The following is an example of an example.

**Example 2.2.** Consider the following boundary value problem system:

$$\begin{cases} u^{(4)}(t) = f(t, u(t), u''(t)) & 0 \le t \le 1, \\ u(0) = u(1) = 0, & u''(0) - u'''(0) = 0, & u''(1) - \frac{1}{2}u''(\frac{1}{2}) = 0, \end{cases}$$
where  $f(t, u(t), u''(t)) = \frac{1}{2}u''(t) = \frac{1}{2}u''(t) = \frac{1}{2}u''(t) = \frac{1}{2}u''(t) = 0,$  (2.1)

where  $f(t, u(t), u''(t)) = \frac{1}{\sqrt{1+u}} - (u'')^{-3} + \sin \pi t$ . Clearly,

$$0 < \int_0^1 (s + \frac{1}{2})(1 - s)ds < +\infty, \quad \min f_0 = +\infty, \quad \max f_\infty = 0.$$

System (2.1) has at least one positive solution.

The following is an example of a theorem and a proof [?, ?].

**Theorem 2.3.** If B is an open ball of a real inner product space  $\mathcal{X}$  of dimension greater than ...

*Proof.* First note that if f is a generalized Jensen mapping with parameters t = s > r, then

$$f(\lambda(x+y)) = \lambda f(x) + \lambda f(y)$$

$$\leq \lambda (f(x) + f(y))$$

$$= f(x) + f(y)$$
(2.2)

for some  $\lambda \geq 1$  ... in the proof of Theorem 2.3, one can show that  $f(x) = f(y_0) \dots$ 

The following is an example of a remark.

Remark 2.4. One can easily conclude that q is continuous by using Theorem 2.3.

### ACKNOWLEDGMENTS

The author is very grateful to the referee for his/her valuable suggestions and comments.

## References

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