# A Test For Trend Change in Failure Rate Using Censored Data

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### **Abstract**

The problem of trend change in the failure rate is great interest in the reliability and survival analysis. In this paper we develop a test statistic for testing whether or not the failure rate changes its trend using random censored data. The asymptotic normality of the test statistic is established. The efficiency values of loss due to censoring are discussed.

#### 1. Introduction

Reliabilists find it useful to categorize life distributions (distributions such that F(x)=0 for x<0 according to different aging properties. These categories are useful for modeling situations where items improve or deteriorate with age. If distribution F has a density f, the failure rate is defined as

$$\mathbf{r}(\mathbf{x}) = \frac{f(\mathbf{x})}{\overline{F}(\mathbf{x})} ,$$

where  $\overline{F}(x) = 1-F(x)$  is the reliability function.

Based on the behavior of failure rate, various nonparametric classes of life distributions have been defined. One such class of distributions is called as the bathtub-shaped failure rate (BTR), if there

exists a change point  $\tau$  such that r(t) is decreasing in  $[0, \tau]$  and increasing in  $[\tau, \infty]$ .

The dual class is "upside-down bathtub-shaped failure rate" (UBR). If r(t) is constant for all t>0, it is said that the life distribution F is constant failure rate (CFR).

It is well known that F is CFR if and only if F is an exponential distribution (i.e.,  $F(t) = \exp(-t/\mu)$ ) for t>0,  $\mu$ >0. Due to this "no-aging" property of the exponential distribution, it is of practical interest to know whether a given life distribution F is CFR or BTR. Therefore, we consider the problem of testing

 $H_0$ : F is CFR

against

 $H_1: F \text{ is BTR (not CFR)}.$ 

When the dual model is proposed, we  $H_0$  test against

 $H'_1: F$  is UBR (not CFR).

Matthews and Farewell (1982) and Matthews, Farewell and Pyke (1985) considered the problem of testing for a CFR against the alternative with two constant failure rates involving a single change point.

Park (1988) proposed a test for CFR versus BTR (UBR), assuming that the proportion of the population that fails at or before the change point of failure rate is known.

The trend change in mean residual life has been discussed by Guess, Hollander and Proschan (1986), Aly (1990), Hawkins, Kochar and Loader (1992), Lim and Park (1998), and Na (1998).

In this paper we develop a test statistic for testing exponentiality against BTR (UBR) alternative using censored data. We assume that the change point is known. We derive the asymptotic null distribution of our test statistic. To establish the asymptotic distribution of our test statistic, we use the technique of Joe and Proschan (1982). We discuss the efficiency values of loss due to censoring.

Section 2 is devoted to develop a test statistic for testing exponentiality against BTR(UBR) alternative. The efficiency values of loss due to censoring are presented in Section 3.

# 2. A test for Trend Change in Failure Rate

In this section we develop a test statistic for testing exponentiality against BTR(UBR) alternative. We assume that the change point of failure rate is known or has been specified by the user. Motivated by Park (1988), we consider the parameter

$$T(F) = \int_{0}^{\tau} \int_{0}^{t} [r(s) - r(t)] \, \overline{F}(s) \, \overline{F}(t) \, ds dt +$$

$$\int_{-\tau}^{\infty} \int_{-\tau}^{t} [r(t) - r(s)] \, \overline{F}(s) \, \overline{F}(t) \, ds dt$$

as a measure of the deviation from  $H_0$  in favor of  $H_1$ . Straight calculations show that T(F) can be rewritten as

$$\begin{split} \mathbf{T}(\mathbf{F}) &= \int_0^{\tau} \{2 - F(\tau) \, \bar{F}(t) - 2 \bar{F}^{\,2}(t)\} \, dt \, + \\ &\int_{\tau}^{\infty} \{ (F(\tau) - 1) \, \bar{F}(t) - 2 \bar{F}^{\,2}(t) \} \, dt \\ &= \int_0^{\infty} B(F(x), \ F(\tau)) \, dx \end{split} \tag{2.1}$$

where

$$B(u,v) \equiv \begin{cases} B_1(u,v) \equiv -2(1-u)^2 + (2-v)(1-u) \\ & \text{if } 0 \le u \le v, \\ B_2(u,v) \equiv 2(1-u)^2 - (1-v)(1-u) \\ & \text{if } v < u \le 1 \end{cases}$$

We replace F in (2.1) by the Kaplan-Meier (KM) estimator defined in (2.2) below.

Let  $X_D$ ,  $X_2$ ,  $\cdots$   $X_n$  be independent and identically distributed (i.i.d.) according to a continuous life distribution function F and let  $C_D$ ,  $C_2$ ,  $\cdots$   $C_n$  be i.i.d. according to a continuous life distribution G where  $C_i$  is the

censoring time associated with  $T_i$ , i=1,  $2, \dots, n$ . In random censoring case we can only observe  $(Y_1, \delta_1) \dots (Y_n, \delta_n)$  where

$$Y_i = min(X_i, C_i), \delta_i = I(X_i \le C_i)$$
  
 $1 \le i \le n,$ 

It is assumed that Xs and Ys are mutually independent. The random variable  $Y_i$  is said to be uncensored or censored according as  $\delta_i = 1$  or  $\delta_i = 0$ . Therefore  $Y_1, \cdots Y_n$  are observations from a life distribution H with reliability function.  $\overline{H} = \overline{FG} = (1-F)(1-G)$ The Kaplan-Meier estimator is defined by

$$\overline{F_n}(x) = 1 - F_n(x) = \prod_{(i:X_m \le x)} \left(\frac{n \cdot i}{n \cdot i + 1}\right)^{\delta_{(n)}}, \quad (2.2)$$

where  $Y_{(a)}$ ,  $\cdots$ ,  $Y_{(a)}$  are the ordered Ys and  $\delta_{(i)}$  is the censoring status corresponding to  $Y_{(i)}$ . We treat  $Y_{(a)}$  as uncensored observation whether it is uncensored or not. When censored observations are tied with uncensored we treat the uncensored as preceding the censored.

As to the problem of testing  $H_0$  against,  $H_1$  we propose a test statistic

$$T_n^c = \frac{\sqrt{n}T(F_n)}{\widehat{u}_E}$$

where

$$\mu_{F} = \sum_{i=1}^{n} \left\{ \prod_{v=1}^{i-1} \left( \frac{n-v}{n-v+1} \right)^{\delta_{(i)}} \right\} (Y_{(i)} - Y_{(i-1)})$$

For computational purpose,  $T(F_n)$  may be written as

$$T(F_{\nu}) = \sum_{i=1}^{i^*} B_i \left( \prod_{v=1}^{i-1} c_v^{\delta_{(v)}} \right) (Y_{(i)} - Y_{(i-1)}) +$$

$$B_{I}\left(\prod_{v=1}^{i*} c_{v}^{\delta_{(v)}}\right) (\tau - Y_{G^{\bullet}}) \\ + B_{2}\left(\prod_{v=1}^{i*} c_{v}^{\delta_{(v)}}\right) (Y_{G^{\bullet}+I} - \tau) + \\ \sum_{i=i*+2}^{n} B_{2}\left(\prod_{v=1}^{i-1} c_{v}^{\delta_{(v)}}\right) (Y_{G} - Y_{G-I})$$

where  $c_v = (n-v) / (n-v+1)$ ,  $B_1(u) = (2 - F_n(\tau))$  $u - 2u^2$ ,  $B_2(u) = (F_n(\tau) - 1)u + 2u^2$ , and  $0 = Y_{(0)} < Y_{(1)} < \cdots < Y_{(i^2)} \le \tau < Y_{(i^2+1)} < \cdots < Y_{(n)}$ .

When there is no censoring, by replacing F in (2.1) with empirical distribution, this test statistic reduces to the one  $T_n^*$ .

$$T_{n}^{*} = \sum_{i=1}^{i^{*}} B_{1} \left( \frac{n-i+1}{n} \right) (Y_{(i)} - Y_{(i\cdot 1)}) + B_{1} \left( \frac{n-i^{*}}{n} \right) (\tau - Y_{(i^{*})}) + B_{2} \left( \frac{n-i^{*}}{n} \right) (Y_{(i^{*}+1)} - \tau) + \sum_{i=1^{*}+2}^{n} B_{2} \left( \frac{n-i+1}{n} \right) (Y_{(i)} - Y_{(i\cdot 1)})$$

To establish asymptotic normality of  $T_n^e$ , we assume the following conditions on the distributions F and G.

(i) 
$$\int_0^\infty \bar{F}^{\beta}(x) dx < \infty \text{ and}$$
$$\int_0^\infty \{ \bar{F}^{\beta}(x) \bar{G}(x) \}^{-1} dF(x) < \infty,$$

for some  $\beta \in (0, 1/2)$ , and

(ii)
$$\sqrt{n} \int_{\mathbf{Y}_{(n)}}^{\infty} \bar{F}(x) dx \xrightarrow{P} \mathbf{0}$$
.

The derivation of the asymptotic normality of  $T_n^c$  is similar to that of Guess (1984), using the techniques of Joe and Proschan (1982) and Gill (1983). The asymptotic distribution of  $T_n^c$  is summarized in Theorem 2.1.

**THEOREM 2.1** Suppose F and G are continuous distributions. Assume that F exists at  $\tau$  and  $F'(\tau)$  is positive. If conditions (i) and (ii) above are satisfied, then

$$\sqrt{n}(T(F_n) - T(F) \xrightarrow{d} \int_0^\infty J(F(t), F(\tau)) dt + \int_{\tau}^\infty J_2(F(t), F(\tau)) dt + \int_{\tau}^\infty J_2(F(t), F(\tau)) dt \Big) \triangle(t)$$

where  $J(u, v) = -\partial B(u, v) / \partial u$ ,  $J_1\sqrt{u}, v) = -\partial B_1(u, v) / \partial v$ ,  $J_2(u, v) = -\partial B_2(u, v) / \partial v$  and  $\triangle(t)$  denotes a mean zero Gaussian process with covariance

$$ar{F}(x)\,ar{F}(y)\,\int_0^{x\,\wedge\,y}\,rac{dF}{ar{F}^2ar{G}}\;.$$

Under  $H_0$ , i.e. F is exponential with mean  $\mu$ ,

$$T_n^c \xrightarrow{d} N(0, \sigma^2) \text{ as } n \to \infty$$
,

where

$$\sigma^{2} = \int_{0}^{1} \frac{4z^{3} - 4(1 - p)z^{2} + (1 - p)^{2}z}{\overline{H}(-\mu \log z)} dz + \int_{1-p}^{1} \frac{(3 - 2p)z - 4z^{2}}{\overline{H}(-\mu \log z)} dz, \qquad (2.3)$$

and  $p = 1 - \exp(-\tau / \mu)$ .

Since the asymptotic null variance  $\sigma^2$ 

depends on the nuisanse parameter H, we need a consistent estimator of  $\sigma^2$ . We can obtain a consistent estimator of  $\sigma^2$ ,  $\sigma^2$ , by replacing  $\bar{H}$  in (2.3) with  $\bar{H}_n$ , the empirical reliability function of  $Y_1, \dots, Y_n$ . For computational purpose, we have

$$\begin{split} \sigma_{n}^{2} &= \frac{1}{2} \, \, \hat{P}^{2} - \frac{2}{3} \, \hat{P} + \frac{1}{3} \\ &+ \sum_{i=1}^{n-1} \frac{n}{(n-i+1)(n-i)} \bigg( B_{i}(4) - \frac{4}{3} \, \hat{\vec{p}} B_{i}(3) \\ &+ \frac{1}{2} \, \hat{\vec{p}}^{2} B_{i}(2) \bigg) - n \bigg( B_{n}(4) - \frac{4}{3} \, \hat{\vec{p}} B_{n}(3) \\ &+ \frac{1}{2} \, \hat{\vec{p}}^{2} B_{n}(2) \bigg) \\ &+ \sum_{i=1}^{k} \frac{n}{(n-i+1)(n-i)} \bigg( -\frac{4}{3} \, B_{i}(3) \\ &+ \frac{3-2p}{2} \, B_{i}(2) \bigg) - \frac{n}{n-k} \bigg( \frac{(2\hat{p}+1)(1-\hat{p})^{2}}{6} \bigg) \end{split}$$

where  $\hat{p} = 1 - \exp(-\tau/\hat{\mu}_{F})$ ,  $B_{i}(a) = \exp(-a)$  $Y_{(i)}/\hat{\mu}_{F}$  and  $Y_{(k)} \leq -\hat{\mu}_{F}\log(1-\hat{p}) < Y_{(k+1)}$ .

The BTR test procedure rejects  $H_0$  in favor of  $H_1$  at the approximate level  $\alpha$  if ,  $T_n^c / \sigma_n \geq z_\alpha$ , where  $z_\alpha$  is the upper  $\alpha$ -quantile of standard normal distribution. Analogously, the approximate  $\alpha$  level test of  $H_0$  versus  $H_1$  reject  $H_0$  if  $T_n^c / \sigma_n \geq -z_\alpha$ .

# 3. The Efficiency Loss Due To Censoring

In this section we study the efficacy loss due to censoring by comparing the efficiency of a test based on  $T_n^*$  for uncensored model with the efficacy of our BTR test based on  $T_n^c$  for randomly censored model. Since  $T_n^c$  and  $T_n^*$  have the same asymptotic means we get the Pitman ARE of the test based on  $T_n^c$  relative to that based on  $T_n^*$  as  $ARE_r(T_n^c, T_n^c) = \sigma_0^2 / \sigma^2$  where  $\sigma_0^2$  is the asymptotic null variance of  $\sqrt{n}T_n^c$ . If in particular the censoring distribution is exponential,  $\bar{G}(x) = \exp(-px)$  for  $x \ge 0$  with p < 1. Then we get

$$ARE_{p}(T_{n}^{c}, T_{n}^{*}) = \left(P^{2} - P + \frac{1}{3}\right) / \left(\frac{(p+1)^{2} \rho^{2} - (5p+1)(p+1)\rho + 6p^{2} + 2}{(3-\rho)(2-\rho)(1-\rho)} + \frac{(2p+1+\overline{p}^{1\rho} - 2\overline{p}^{2\rho})\rho + 2 - 4p - 2\overline{p}^{1\rho}}{(2-\rho)(1-\rho)}\right)$$

$$(3.1)$$

where  $p = 1 - \exp(-\tau)$ .

Table 1 indicates  $ARE_F(T_n^c, T_n^*)$  for some different amount of censoring, where  $\bar{G}(x) = \exp{(-px)}$  when  $\tau = 0.1, 0.7, 2.3$ . From Table 1 we notice that the value of  $ARE_F(T_n^c, T_n^*)$  increases to 1 as  $\rho$  decreases. As expected from (3.1), it is obvious that the efficiency loss  $ARE_F(T_n^c, T_n^*)$  tends to 1 as  $\rho$  tends to 0 (corresponding to the case of no censoring). Also we notice that the efficiency loss due to censoring is large when  $\tau = 0.7$  and the smallest efficiency loss is obtained when  $\tau = 2.3$ .

Table 1 The Pitman ARE of T<sup>\*</sup><sub>n</sub> relative T<sup>\*</sup><sub>n</sub> for some τ and amount of censoring

τ	ρ			
	1/9	1/4	3/7	2/3
0.1	.841	. 647	.429	.181
0.7	.867	.695	.473	.212
2.3	.903	.786	.644	.475

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