

# 数据缺失场合三参数 Weibull 分布的参数估计

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**摘要:** 给出了缺失数据场合三参数 Weibull 分布参数的近似极大似然估计, 通过 Monte-Carlo 模拟例子及实例证实了所给方法的可行性.

**关键词:** 缺失数据; 三参数 Weibull 分布; 近似极大似然估计

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## 0 引言

在可靠性统计分析中, 三参数 Weibull 分布是最为广泛使用的寿命分布之一. 在产品的寿命分析上, 如轴承的疲劳寿命<sup>[8]</sup>; 在生物医学上, 如实验动物的肿瘤出现时间<sup>[7]</sup>; 在气候分析上, 如年降水量和月降水量<sup>[14]</sup>, 风速的概率分布<sup>[9]</sup>, 河的最大流量<sup>[3]</sup>等. 关于三参数 Weibull 分布的统计分析已有许多文献作了研究, 可参阅文献[1]~[13]. 现考虑如下情况, 即由于某种原因, 使得试验中的某一些样本寿命数据丢失, 而只能知道其前后的寿命数据. 这种情况在现实中是经常发生的, 称其为数据丢失或数据缺失. 关于 Weibull 分布数据缺失场合下的统计分析, 可参阅文献[15]~[20], 这些文献仅针对两参数 Weibull 分布, 而三参数 Weibull 分布数据缺失场合下的统计分析, 至今未见有这方面的文献. 本文给出了参数的近似极大似然估计(AMLE), 当然, 这种方法可适用于三参数对数正态分布.

## 1 参数的近似极大似然估计(AMLE)

设产品的寿命  $t$  服从三参数 Weibull 分布, 其分布函数和密度函数分别为:

$$F(t; m, \eta, \theta) = 1 - e^{-(\frac{t-\theta}{\eta})^m}, \quad f(t; m, \eta, \theta) = \frac{m}{\eta} \left( \frac{t-\theta}{\eta} \right)^{m-1} e^{-(\frac{t-\theta}{\eta})^m}, \quad (1)$$

其中  $t > \theta, m > 0$  为形状参数,  $\eta > 0$  为尺度参数,  $\theta$  为位置参数. 现假定有  $n$  个产品进行寿命试验, 到有  $r$  个产品失效时停止试验, 其次序失效数据为:  $t_{(1)} \leq t_{(2)} \leq \dots \leq t_{(r)}$ . 现考虑如下情形: 上述  $r$  个失效数据由于某些原因而使得有若干个数据缺失, 设剩下  $k$  个数据, 剩下的失效数据为:  $0 \triangleq t_{(r_0)} \leq t_{(r_1)} \leq t_{(r_2)} \leq \dots \leq t_{(r_k)}, r_0 = 0$ .

令:  $Y = \ln(t - \theta)$ , 则  $Y$  服从位置参数为  $\mu = \ln \eta$ , 尺度参数  $= 1/m$  的极小值分布, 其分布函数和密度函数分别为:

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$$F(y; \mu, \sigma) = 1 - e^{-e^{\frac{y-\mu}{\sigma}}}, f(y; \mu, \sigma) = \frac{1}{\sigma} e^{\frac{y-\mu}{\sigma}} e^{-e^{\frac{y-\mu}{\sigma}}}, \quad (2)$$

令:  $Z = \frac{Y - \mu}{\sigma}$ , 则  $Z$  服从标准极小值分布, 其分布函数和密度函数分别为:

$$F(z) = 1 - e^{-e^z}, f(z) = e^z e^{-e^z}, \quad (3)$$

而  $Y_{(i)} = \ln(t_{(i)} - \theta)$ ,  $Z_{(i)} = \frac{Y_{(i)} - \mu}{\sigma}$ , 则  $Y_{(1)} \leq Y_{(2)} \leq \dots \leq Y_{(r)}$  为来自位置参数为  $\mu$ , 刻度参数为  $\sigma$  的极小值分布的样本容量为  $n$  的前  $r$  个次序统计量,  $Z_{(1)} \leq Z_{(2)} \leq \dots \leq Z_{(r)}$  为来自标准极小值分布的样本容量为  $n$  的前  $r$  个次序统计量, 考虑到数据有缺失场合, 则有:  $0 \triangleq Y_{(r_0)} \leq Y_{(r_1)} \leq Y_{(r_2)} \leq \dots \leq Y_{(r_k)}$  及  $0 \triangleq Z_{(r_0)} \leq Z_{(r_1)} \leq Z_{(r_2)} \leq \dots \leq Z_{(r_k)}$ .

易知似然函数  $L(\mu, \sigma, \theta)$  为 (其中  $C$  为正常数):

$$L(\mu, \sigma, \theta) = C \sigma^{-k} [F(Z_{(r_1)})]^{r_1-1} \prod_{i=1}^{k-1} [F(Z_{(r_{i+1})}) - F(Z_{(r_i)})]^{r_{i+1}-r_i-1} [1-F(Z_{(r_k)})]^{n-r_k} \prod_{i=1}^k f(Z_{(r_i)}), \quad (4)$$

考虑到  $\frac{\partial Z}{\partial \mu} = -\frac{1}{\sigma}$ ,  $\frac{\partial Z}{\partial \sigma} = -\frac{Z}{\sigma}$ ,  $\frac{\partial Z}{\partial \theta} = -\frac{1}{\sigma} \frac{1}{t-\theta} = -\frac{1}{\sigma} e^{-(\sigma Z + \mu)}$ ,  $\frac{\partial f(Z)}{\partial \mu} = -\frac{1}{\sigma} f'(Z)$ ,  $\frac{\partial f(Z)}{\partial \sigma} = -\frac{Z}{\sigma} f'(Z)$ ,  $\frac{\partial f(Z)}{\partial \theta} = -\frac{1}{\sigma} e^{-(\sigma Z + \mu)} f'(Z)$ ,  $f'(Z) = e^Z e^{-e^Z} - e^{2Z} e^{-e^Z}$ ,

$$\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \mu} = -\frac{1}{\sigma} \left\{ (r_1-1) \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{f(Z_{(r_{i+1})}) - f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} \right\}, \quad (5)$$

$$\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \sigma} = -\frac{1}{\sigma} \left\{ (r_1-1) \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{Z_{(r_{i+1})} f(Z_{(r_{i+1})}) - Z_{(r_i)} f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) Z_{(r_k)} \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k Z_{(r_i)} \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} + k \right\}, \quad (6)$$

$$\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \theta} = -\frac{1}{\sigma} \left\{ (r_1-1) e^{-(\sigma Z_{(r_1)} + \mu)} \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{e^{-(\sigma Z_{(r_{i+1})} + \mu)} f(Z_{(r_{i+1})}) - e^{-(\sigma Z_{(r_i)} + \mu)} f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) e^{-(\sigma Z_{(r_k)} + \mu)} \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k e^{-(\sigma Z_{(r_i)} + \mu)} \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} \right\}, \quad (7)$$

令  $\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \mu} = 0$ ,  $\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \sigma} = 0$ ,  $\frac{\partial \ln L(\mu, \sigma, \theta)}{\partial \theta} = 0$ , 得如下三个方程:

$$(r_1-1) \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{f(Z_{(r_{i+1})}) - f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} = 0, \quad (8)$$

$$k + (r_1-1) \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{Z_{(r_{i+1})} f(Z_{(r_{i+1})}) - Z_{(r_i)} f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) Z_{(r_k)} \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k Z_{(r_i)} \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} = 0, \quad (9)$$

$$(r_1-1) e^{-(\sigma Z_{(r_1)} + \mu)} \frac{f(Z_{(r_1)})}{F(Z_{(r_1)})} + \sum_{i=1}^{k-1} (r_{i+1}-r_i-1) \frac{e^{-(\sigma Z_{(r_{i+1})} + \mu)} f(Z_{(r_{i+1})}) - e^{-(\sigma Z_{(r_i)} + \mu)} f(Z_{(r_i)})}{F(Z_{(r_{i+1})}) - F(Z_{(r_i)})} - (n-r_k) e^{-(\sigma Z_{(r_k)} + \mu)} \frac{f(Z_{(r_k)})}{1-F(Z_{(r_k)})} + \sum_{i=1}^k e^{-(\sigma Z_{(r_i)} + \mu)} \frac{f'(Z_{(r_i)})}{f(Z_{(r_i)})} = 0, \quad (10)$$

令:  $p_r = \frac{r_i}{n+1}$ ,  $q_r = 1 - p_r$ ,  $F(\zeta_r) = p_r$ ,  $\zeta_r = \ln(-\ln q_r)$ . 将函数  $\frac{f(Z_{(r)})}{F(Z_{(r)})}$  在点  $\zeta_r$  处泰勒展开得:

$$\frac{f(Z_{(r)})}{F(Z_{(r)})} \approx \alpha_0 - \beta_0 Z_{(r)}, \quad (11)$$

其中:  $\frac{f(Z_{(r)})}{F(Z_{(r)})} \approx \frac{f(\zeta_r)}{F(\zeta_r)} + (Z_{(r)} - \zeta_r) \frac{f'(\zeta_r)F(\zeta_r) - f^2(\zeta_r)}{F^2(\zeta_r)} =$

$$\left\{ \frac{f(\zeta_r)}{F(\zeta_r)} - \zeta_r \frac{f'(\zeta_r)F(\zeta_r) - f^2(\zeta_r)}{F^2(\zeta_r)} \right\} - \frac{f^2(\zeta_r) - f'(\zeta_r)F(\zeta_r)}{F^2(\zeta_r)} Z_{(r)},$$

$$\alpha_0 = \frac{f(\zeta_r)}{F(\zeta_r)} - \zeta_r \frac{f'(\zeta_r)F(\zeta_r) - f^2(\zeta_r)}{F^2(\zeta_r)}, \quad (12)$$

$$\beta_0 = \frac{f^2(\zeta_r) - f'(\zeta_r)F(\zeta_r)}{F^2(\zeta_r)}. \quad (13)$$

易见  $\beta_0 > 0$ , 事实上

$$\begin{aligned} f^2(\zeta_r) - f'(\zeta_r)F(\zeta_r) &= e^{\zeta_r} e^{-\zeta_r} - [e^{\zeta_r} e^{-\zeta_r} - e^{2\zeta_r} e^{-\zeta_r}] [1 - e^{-\zeta_r}] = \\ &= e^{\zeta_r} e^{-\zeta_r} [1 - (1 - e^{\zeta_r})(1 - e^{-\zeta_r})] = \\ &= e^{\zeta_r} e^{-\zeta_r} [e^{\zeta_r} + e^{-\zeta_r} - e^{\zeta_r} e^{-\zeta_r}] = \\ &= e^{\zeta_r} e^{-\zeta_r} [e^{\zeta_r} (1 - e^{-\zeta_r}) + e^{-\zeta_r}] > 0 \end{aligned}$$

将函数  $\frac{f(Z_{(r)})}{1 - F(Z_{(r)})}$  在点  $\zeta_k$  处泰勒展开得:

$$\frac{f(Z_{(r)})}{1 - F(Z_{(r)})} \approx \alpha_k + \beta_k Z_{(r)}, \quad (14)$$

其中:  $\frac{f(Z_{(r)})}{1 - F(Z_{(r)})} \approx \frac{f(\zeta_k)}{1 - F(\zeta_k)} + (Z_{(r)} - \zeta_k) \frac{f'(\zeta_k)[1 - F(\zeta_k)] + f^2(\zeta_k)}{[1 - F(\zeta_k)]^2},$

$$\alpha_k = \frac{f(\zeta_k)}{1 - F(\zeta_k)} - \zeta_k \frac{f'(\zeta_k)[1 - F(\zeta_k)] + f^2(\zeta_k)}{[1 - F(\zeta_k)]^2}, \quad (15)$$

$$\beta_k = \frac{f'(\zeta_k)[1 - F(\zeta_k)] + f^2(\zeta_k)}{[1 - F(\zeta_k)]^2}. \quad (16)$$

易见  $\beta_k > 0$ , 事实上

$$\begin{aligned} f'(\zeta_k)[1 - F(\zeta_k)] + f^2(\zeta_k) &= (e^{\zeta_k} e^{-\zeta_k} - e^{2\zeta_k} e^{-\zeta_k}) e^{-\zeta_k} + e^{2\zeta_k} e^{-2\zeta_k} = \\ &= e^{\zeta_k} e^{-2\zeta_k} [e^{\zeta_k} + 1 - e^{\zeta_k}] = e^{\zeta_k} e^{-2\zeta_k} > 0 \end{aligned}$$

将二元函数  $\frac{f(Z_{(r+1)}) - f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})}$  在点  $(\zeta_{r+1}, \zeta_r)$  处泰勒展开得:

$$f \left( \frac{Z_{(r+1)} - f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \right) \approx \epsilon_i + \omega_i Z_{(r)} - \delta_i Z_{(r+1)}, \quad (17)$$

其中:  $\frac{f(Z_{(r+1)}) - f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \approx \frac{f(\zeta_{r+1}) - f(\zeta_r)}{F(\zeta_{r+1}) - F(\zeta_r)} +$

$$(Z_{(r+1)} - \zeta_{r+1}) \frac{f'(\zeta_{r+1})[F(\zeta_{r+1}) - F(\zeta_r)] - [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2} +$$

$$(Z_{(r)} - \zeta_r) \frac{-f'(\zeta_r)[F(\zeta_{r+1}) - F(\zeta_r)] + [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}$$

$$\epsilon_i = \frac{f(\zeta_{r+1}) - f(\zeta_r)}{F(\zeta_{r+1}) - F(\zeta_r)} - \zeta_{r+1} \frac{f'(\zeta_{r+1})[F(\zeta_{r+1}) - F(\zeta_r)] - [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2} -$$

$$\zeta_r \frac{-f'(\zeta_r)[F(\zeta_{r+1}) - F(\zeta_r)] + [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}, \quad (18)$$

$$\omega_i = \frac{-f'(\zeta_r)[F(\zeta_{r+1}) - F(\zeta_r)] + [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}, \quad (19)$$

$$\delta_i = -\frac{f'(\zeta_{r+1})[F(\zeta_{r+1}) - F(\zeta_r)] - [f(\zeta_{r+1}) - f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}. \quad (20)$$

将二元函数  $\frac{Z_{(r+1)}f(Z_{(r+1)}) - Z_{(r)}f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})}$  在点  $(\zeta_{r+1}, \zeta_r)$  处泰勒展开得:

$$\frac{Z_{(r+1)}f(Z_{(r+1)}) - Z_{(r)}f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \approx a_i + b_i Z_{(r)} - c_i Z_{(r+1)}, \quad (21)$$

其中:  $\frac{Z_{(r+1)}f(Z_{(r+1)}) - Z_{(r)}f(Z_{(r)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \approx \frac{\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)}{F(\zeta_{r+1}) - F(\zeta_r)} +$   
 $(Z_{(r+1)} - \zeta_{r+1}) \frac{[f(\zeta_{r+1}) + \zeta_{r+1}f'(\zeta_{r+1})][F(\zeta_{r+1}) - F(\zeta_r)] - [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2} +$   
 $(Z_{(r)} - \zeta_r) \frac{[-f(\zeta_r) - \zeta_r f'(\zeta_r)][F(\zeta_{r+1}) - F(\zeta_r)] + [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2},$

$$a_i = \frac{\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)}{F(\zeta_{r+1}) - F(\zeta_r)} - \zeta_{r+1} \frac{[f(\zeta_{r+1}) + \zeta_{r+1}f'(\zeta_{r+1})][F(\zeta_{r+1}) - F(\zeta_r)] - [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2} - \zeta_r \frac{[-f(\zeta_r) - \zeta_r f'(\zeta_r)][F(\zeta_{r+1}) - F(\zeta_r)] + [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}, \quad (22)$$

$$b_i = \frac{[-f(\zeta_r) - \zeta_r f'(\zeta_r)][F(\zeta_{r+1}) - F(\zeta_r)] + [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}, \quad (23)$$

$$c_i = -\frac{[f(\zeta_{r+1}) + \zeta_{r+1}f'(\zeta_{r+1})][F(\zeta_{r+1}) - F(\zeta_r)] - [\zeta_{r+1}f(\zeta_{r+1}) - \zeta_r f(\zeta_r)]f(\zeta_{r+1})}{[F(\zeta_{r+1}) - F(\zeta_r)]^2}. \quad (24)$$

将函数  $\frac{f'(Z_{(r)})}{f(Z_{(r)})}$  在点  $\zeta_r$  处泰勒展开得:

$$\frac{f'(Z_{(r)})}{f(Z_{(r)})} \approx d_i - e_i Z_{(r)}, \quad (25)$$

其中:  $\frac{f'(Z_{(r)})}{f(Z_{(r)})} \approx \frac{f'(\zeta_r)}{f(\zeta_r)} + (Z_{(r)} - \zeta_r) \frac{f''(\zeta_r)f(\zeta_r) - [f'(\zeta_r)]^2}{f^2(\zeta_r)},$

$$d_i = \frac{f'(\zeta_r)}{f(\zeta_r)} - \zeta_r \frac{f''(\zeta_r)f(\zeta_r) - [f'(\zeta_r)]^2}{f^2(\zeta_r)}, \quad (26)$$

$$e_i = -\frac{f''(\zeta_r)f(\zeta_r) - [f'(\zeta_r)]^2}{f^2(\zeta_r)}, \quad (27)$$

将二元函数  $\frac{f(Z_{(r+1)})}{F(Z_{(r+1)}) - F(Z_{(r)})}$  在点  $(\zeta_{r+1}, \zeta_r)$  处泰勒展开得:

$$\frac{f(Z_{(r+1)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \approx g_i + h_i Z_{(r)} - l_i Z_{(r+1)}, \quad (28)$$

其中:  $\frac{f(Z_{(r+1)})}{F(Z_{(r+1)}) - F(Z_{(r)})} \approx \frac{f(\zeta_{r+1})}{F(\zeta_{r+1}) - F(\zeta_r)} + (Z_{(r)} - \zeta_r) \frac{f(\zeta_{r+1})f(\zeta_r)}{[F(\zeta_{r+1}) - F(\zeta_r)]^2} +$

$$g_i = \frac{f(\zeta_{r_{i+1}})}{F(\zeta_{r_{i+1}}) - F(\zeta_r)} - \zeta_{r_{i+1}} \frac{f'(\zeta_{r_{i+1}})[F(\zeta_{r_{i+1}}) - F(\zeta_r)] - f^2(\zeta_{r_{i+1}})}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2} - \zeta_r \frac{f(\zeta_{r_{i+1}})f(\zeta_r)}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2} \quad (29)$$

$$h_i = \frac{f(\zeta_{r_{i+1}})f(\zeta_r)}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2}, \quad (30)$$

$$l_i = - \frac{f'(\zeta_{r_{i+1}})[F(\zeta_{r_{i+1}}) - F(\zeta_r)] - f^2(\zeta_{r_{i+1}})}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2}. \quad (31)$$

将二元函数  $\frac{f(Z_{(r_i)})}{F(Z_{(r_{i+1}}) - F(Z_{(r_i)}))}$  在点  $(\zeta_{r_{i+1}}, \zeta_r)$  处泰勒展开得:

$$\frac{f(Z_{(r_i)})}{F(Z_{(r_{i+1}}) - F(Z_{(r_i)}))} \approx s_i + u_i Z_{(r_i)} - v_i Z_{(r_{i+1})}, \quad (32)$$

其中 
$$\frac{f(Z_{(r_i)})}{F(Z_{(r_{i+1}}) - F(Z_{(r_i)}))} \approx \frac{f(\zeta_r)}{F(\zeta_{r_{i+1}}) - F(\zeta_r)} + (Z_{(r_{i+1})} - \zeta_{r_{i+1}}) \frac{-f(\zeta_r)f(\zeta_{r_{i+1}})}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2} + (Z_{(r_i)} - \zeta_r) \frac{f'(\zeta_r)[F(\zeta_{r_{i+1}}) - F(\zeta_r)] - f^2(\zeta_r)}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2},$$

$$s_i = \frac{f(\zeta_r)}{F(\zeta_{r_{i+1}}) - F(\zeta_r)} + \zeta_{r_{i+1}} \frac{f(\zeta_r)f(\zeta_{r_{i+1}})}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2} - \zeta_r \frac{f'(\zeta_r)[F(\zeta_{r_{i+1}}) - F(\zeta_r)] - f^2(\zeta_r)}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2}, \quad (33)$$

$$u_i = \frac{f'(\zeta_r)[F(\zeta_{r_{i+1}}) - F(\zeta_r)] - f^2(\zeta_r)}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2}, \quad (34)$$

$$v_i = \frac{f(\zeta_r)f(\zeta_{r_{i+1}})}{[F(\zeta_{r_{i+1}}) - F(\zeta_r)]^2}. \quad (35)$$

将(11), (14), (17), (25)代入方程(8)化简得:

$$\begin{aligned} & \left[ (r_1 - 1)\alpha_0 + \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)\epsilon_i - (n - r_k)\alpha_k + \sum_{i=1}^k d_i \right] \sigma + \left[ - (r_1 - 1)\beta_0 Y_{(r_1)} + \right. \\ & \left. \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)(\omega_i Y_{(r_i)} - \delta_i Y_{(r_{i+1})}) + (n - r_k)\beta_k Y_{(r_k)} - \sum_{i=1}^k e_i Y_{(r_i)} \right] + \\ & \left[ (r_1 - 1)\beta_0 - \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)(\omega_i - \delta_i) + (n - r_k)\beta_k + \sum_{i=1}^k e_i \right] \mu = 0, \end{aligned} \quad (36)$$

$$\hat{\mu} = B(\theta) - \hat{\sigma}C, \quad (37)$$

其中:

$$M = (r_1 - 1)\beta_0 - \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)(\omega_i - \delta_i) + (n - r_k)\beta_k + \sum_{i=1}^k e_i, \quad (38)$$

$$B(\theta) = \frac{1}{M} \left[ (r_1 - 1)\beta_0 \ln(t_{(r_1)} - \theta) - \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1) (\omega_i \ln(t_{(r_i)} - \theta) - \delta_i \ln(t_{(r_{i+1})} - \theta)) + (n - r_k)\beta_k \ln(t_{(r_k)} - \theta) + \sum_{i=1}^k e_i \ln(t_{(r_i)} - \theta) \right], \quad (39)$$

$$C = \frac{1}{M} \left[ (r_1 - 1)\alpha_0 + \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)\epsilon_i - (n - r_k)\alpha_k + \sum_{i=1}^k d_i \right], \quad (40)$$

将(11), (14), (21), (25)代入方程(9)化简得:

$$\left\{ k + (r_1 - 1)C(\alpha_0 - \beta_0 C) + \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)(a_i + b_i C - c_i C) - (n - r_k)C(\alpha_k + \beta_k C) + \sum_{i=1}^k C(d_i - e_i C) \right\} \sigma^2 + \left\{ (r_1 - 1)(Y_{(r_1)} - B(\theta))(\alpha_0 - \beta_0 C) - (r_1 - 1)C\beta_0(Y_{(r_1)} - B(\theta)) + \right.$$

$$\sum_{i=1}^{k-1} (r_{i+1} - r_i - 1) [b_i(Y_{(r_i)} - B(\theta)) - c_i(Y_{(r_{i+1})} - B(\theta))] - (n - r_k)C\beta_k(Y_{(r_k)} - B(\theta)) - (n - r_k)(\alpha_k + \beta_k C)(Y_{(r_k)} - B(\theta)) - \sum_{i=1}^k C e_i(Y_{(r_i)} - B(\theta)) + \sum_{i=1}^k (Y_{(r_i)} - B(\theta))(d_i - e_i C) \Big\} \sigma - \left\{ (r_1 - 1)\beta_0(Y_{(r_1)} - B(\theta))^2 + (n - r_k)\beta_k(Y_{(r_k)} - B(\theta))^2 + \sum_{i=1}^k e_i(Y_{(r_i)} - B(\theta))^2 \right\} = 0. \quad (41)$$

即: 
$$A\sigma^2 + D(\theta)\sigma - E(\theta) = 0, \quad (42)$$

其中: 
$$A = k + (r_1 - 1)C(\alpha_0 - \beta_0 C) + \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1)(a_i + b_i C - c_i C) - (n - r_k)C(\alpha_k + \beta_k C) + \sum_{i=1}^k C(d_i - e_i C), \quad (43)$$

$$D(\theta) = (r_1 - 1)(\ln(t_{(r_1)} - \theta) - B(\theta))(\alpha_0 - \beta_0 C) - (r_1 - 1)C\beta_0(\ln(t_{(r_1)} - \theta) - B(\theta)) + \sum_{i=1}^{k-1} (r_{i+1} - r_i - 1) [b_i(\ln(t_{(r_i)} - \theta) - B(\theta)) - c_i(\ln(t_{(r_{i+1})} - \theta) - B(\theta))] - (n - r_k)C\beta_k(\ln(t_{(r_k)} - \theta) - B(\theta)) - (n - r_k)(\alpha_k + \beta_k C)(\ln(t_{(r_k)} - \theta) - B(\theta)) - \sum_{i=1}^k C e_i(\ln(t_{(r_i)} - \theta) - B(\theta)) \sum_{i=1}^k (\ln(t_{(r_i)} - \theta) - B(\theta))(d_i - e_i C), \quad (44)$$

$$E(\theta) = (r_1 - 1)\beta_0(\ln(t_{(r_1)} - \theta) - B(\theta))^2 + (n - r_k)\beta_k(\ln(t_{(r_k)} - \theta) - B(\theta))^2 + \sum_{i=1}^k e_i(\ln(t_{(r_i)} - \theta) - B(\theta))^2. \quad (45)$$

由此得: 
$$\hat{\sigma} = \frac{-D(\theta) + \sqrt{D^2(\theta) + 4AE(\theta)}}{2A}, \quad (46)$$

代入(35)得: 
$$\hat{\mu}(\theta) = B(\theta) - \hat{\sigma}(\theta)C. \quad (47)$$

将(11), (14), (25), (28), (32)代入方程(10), 同时注意到:  $e^{-(\sigma z + \mu)} = e^{-\sigma \frac{\ln(t - \theta) - \mu}{\sigma} + \mu} = \frac{1}{t - \theta}$ , 化简方程(10)得:

$$\frac{r_1 - 1}{t_{(r_1)} - \theta} \left[ \alpha_0 - \beta_0 \frac{\ln(t_{(r_1)} - \theta) - \mu}{\sigma} \right] + \sum_{i=1}^{k-1} \frac{r_{i+1} - r_i - 1}{t_{(r_{i+1})} - \theta} \left[ g_i + h_i \frac{\ln(t_{(r_i)} - \theta) - \mu}{\sigma} - l_i \frac{\ln(t_{(r_{i+1})} - \theta) - \mu}{\sigma} \right] - \sum_{i=1}^{k-1} \frac{r_{i+1} - r_i - 1}{t_{(r_i)} - \theta} \left[ s_i + u_i \frac{\ln(t_{(r_i)} - \theta) - \mu}{\sigma} - v_i \frac{\ln(t_{(r_{i+1})} - \theta) - \mu}{\sigma} \right] - \frac{n - r_k}{t_{(r_k)} - \theta} \left[ \alpha_k + \beta_k \frac{\ln(t_{(r_k)} - \theta) - \mu}{\sigma} \right] + \sum_{i=1}^k \frac{1}{t_{(r_i)} - \theta} \left[ d_i - e_i \frac{\ln(t_{(r_i)} - \theta) - \mu}{\sigma} \right] = 0. \quad (48)$$

将(46), (47)代入(48)得:

$$\frac{r_1 - 1}{t_{(r_1)} - \theta} \left[ \alpha_0 - \beta_0 \frac{(\ln t_{(r_1)} - \theta) - \mu(\theta)}{\sigma(\theta)} \right] + \sum_{i=1}^{k-1} \frac{r_{i+1} - r_i - 1}{t_{(r_{i+1})} - \theta} \left[ g_i + h_i \frac{(\ln t_{(r_i)} - \theta) - \mu(\theta)}{\sigma(\theta)} - l_i \frac{\ln(t_{(r_{i+1})} - \theta) - \mu(\theta)}{\sigma(\theta)} \right] - \sum_{i=1}^{k-1} \frac{r_{i+1} - r_i - 1}{t_{(r_i)} - \theta} \left[ s_i + u_i \frac{\ln(t_{(r_i)} - \theta) - \mu(\theta)}{\sigma(\theta)} - v_i \frac{\ln(t_{(r_{i+1})} - \theta) - \mu(\theta)}{\sigma(\theta)} \right] - \frac{n - r_k}{t_{(r_k)} - \theta} \left[ \alpha_k + \beta_k \frac{\ln(t_{(r_k)} - \theta) - \mu(\theta)}{\sigma(\theta)} \right] + \sum_{i=1}^k \frac{1}{t_{(r_i)} - \theta} \left[ d_i - e_i \frac{\ln(t_{(r_i)} - \theta) - \mu(\theta)}{\sigma(\theta)} \right] = 0. \quad (49)$$

方程(49)仅含有位置参数  $\theta$ , 故可解超越方程(49)得参数  $\theta$  的近似极大似然估计(AMLE)  $\hat{\theta}$ . 代入(46), (47)得参数  $\sigma, \mu$  的近似极大似然估计(AMLE)分别为  $\hat{\sigma}, \hat{\mu}$ :

$$\hat{\sigma} = \frac{-D(\hat{\theta}) + \sqrt{D^2(\hat{\theta}) + 4AE(\hat{\theta})}}{2A}, \quad \hat{\mu} = B(\hat{\theta}) - \hat{\sigma}C. \quad (50)$$

由此形状参数  $m$  和尺度参数  $\eta$  的近似极大似然估计(AMLE)分别为  $\hat{m}$  和  $\hat{\eta}$ :

$$\hat{m} = \frac{1}{\sigma}, \hat{\eta} = e^{\mu}. \quad (51)$$

### 3 Monte-Carlo 模拟及实例

例1:我们对  $n=10$ , 参数真值取为:  $\theta=10, \eta=10, m=0.5(0.5)1.5$ , 通过 Monte-Carlo 模拟的方法产生10个服从三参数 Weibull 分布的随机数共三组. 利用本文方法可得参数  $\mu, m, \eta$  的近似极大似然估计列于下表.

表1 Monte-Carlo 模拟表

参数真值	模拟数据	缺失情况	近似极大似然估计(AMLE) $\hat{\theta}, \hat{m}, \hat{\eta}$
$\theta=10$ $m=0.5$ $\eta=10$	10.0425	$k=10$ 无缺失	9.4500, 0.5121, 10.1060
	10.0456		
	10.1148		
	10.7127	$k=8$ $t_{(1)}, t_{(2)}$ 缺失	9.1500, 0.4783, 9.9413
	10.9414		
	11.1614		
	18.3008	$k=5$ $t_{(1)}, t_{(2)}, t_{(3)}, t_{(9)}, t_{(10)}$ 缺失	9.0500, 0.3768, 11.6902
	58.2557		
	83.1450		
98.7374			
$\theta=10$ $m=1.0$ $\eta=10$	10.5041	$k=10$ 无缺失	10.3500, 1.0903, 10.0522
	12.2163		
	13.5298		
	15.1095	$k=8$ $t_{(1)}, t_{(2)}$ 缺失	10.3500, 1.0655, 9.8622
	18.0447		
	19.8137		
	20.5013	$k=5$ $t_{(1)}, t_{(2)}, t_{(3)}, t_{(9)}, t_{(10)}$ 缺失	10.1500, 1.0262, 9.9205
	21.8150		
	23.2187		
50.7382			
$\theta=10$ $m=1.5$ $\eta=10$	11.4449	$k=10$ 无缺失	9.7500, 1.5432, 10.0603
	11.7751		
	14.9218		
	15.5109	$k=8$ $t_{(1)}, t_{(2)}$ 缺失	10.1500, 1.6730, 10.0491
	16.7013		
	18.6616		
	20.9133	$k=5$ $t_{(1)}, t_{(2)}, t_{(3)}, t_{(9)}, t_{(10)}$ 缺失	9.5500, 1.5130, 10.0288
	22.0284		
	25.6172		
31.9577			

例2<sup>[1]</sup>:从1890年到1969年间,宾夕法尼亚州 Harrisburrq 的 Susquehanna 河20个每四年的最大流量( $10^6 ft^3/s$ )为:0.654, 0.613, 0.315, 0.449, 0.297, 0.402, 0.379, 0.423, 0.379, 0.3235, 0.269, 0.740, 0.418, 0.412, 0.494, 0.416, 0.338, 0.392, 0.414, 0.265 这些数据起先由 Dumonceaux 和 Autle(1973)用作说明极限分布的例子的, 利用本文方法可得  $\theta, m, \eta$  的近似极大似然估计, 同时列出这一问题的一些参数估计见下表.

表2 Susquehanna 河20个每年最大流量的参数估计

METHOD	$\hat{\theta}$	$\hat{m}$	$\hat{\eta}$
MME	0.2409	1.4790	0.2015
ME	0.2302	1.5750	0.2149
Zanakis	0.2650	1.3280	0.2020
WBE	0.2465	1.3960	0.1386
AMLE( $k=20$ ) 无缺失	0.2530	1.3846	0.1786
AMLE( $k=17$ ) $t_{(2)}, t_{(8)}, t_{(10)}$ 缺失	0.2475	1.1184	0.1746

例3<sup>[3]</sup>:本例由 MCCOSL(1974)提供的,数据包括同种型号的10个轴承的依小时计的疲劳寿命,依小到大排序为:152.7,172.0,172.5,173.3,193.0,204.7,216.5,234.9,262.6,422.6,利用本文方法可得  $\theta, m, \eta$  的近似极大似然估计,同时列出这一问题的一些参数估计见下表.

表3 轴承疲劳寿命的参数估计

METHOD	$\hat{\theta}$	$\hat{m}$	$\hat{\eta}$
MME	146.14	0.949	72.59
ME	129.43	1.165	96.02
Zanakis	151.09	1.170	65.41
WBE	142.48	1.112	56.64
AMLE( $k=10$ ) 无缺失	147.7500	1.0908	71.7147
AMLE( $k=8$ ), 缺失	152.3000	1.1039	65.8200

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## Statistical Inference for Incomplete Data Three-parameter WEIBULL Distribution

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**Abstract:** We derive an approximate maximum likelihood estimation of the parameters of the three-parameter Weibull distribution under a TYPE- I censored sample. In addition, we show the feasibility of this method by using two Monte-Carlo simulated samples.

**Key words:** TYPE- I censored data; three-parameter Weibull distribution; approximate maximum likelihood