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Title	Reliability Estimation from Left-Truncated and Right-Censored Data Using Splines
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- Condition 1: The maximum spacing of the knots satisfies

$$\Delta = \max_{l+1 \leq j \leq m_n+l+1} |t_j - t_{j-1}| = O(n^{-\nu}).$$

Moreover, there exists a constant $M > 0$ such that $\Delta/\delta \leq M$ uniformly in n , where $\delta = \min_{l+1 \leq j \leq m_n+l+1} |t_j - t_{j-1}|$.

- Condition 2: The interval $[a, b]$ satisfies $P(\{Y \in [a, b]\}) = 1$.
- Condition 3: there exists a constant $C_0 > 0$ such that $\lambda_0(t) \geq C_0$ for $t \in [a, b]$. In addition, the true failure rate λ_0 is differentiable up to order r and all the derivatives are uniformly bounded by a constant M in $[a, b]$, where $r \geq 1$.

Remark 1. Condition 1 is a weak restriction on the knot sequence, which is satisfied when equally-spaced knots are used. This condition is also adopted by Stone (1994). Condition 2 requires that $[L, \bar{C}] \subset [a, b]$. Condition 3 is needed in the proof of the asymptotic normality in Theorem 3. It usually holds in practice. Product lifetime data are generated from a continuous random variable. Continuous parametric lifetime distributions, such as Weibull, lognormal and inverse Gaussian distributions have been widely used to model the lifetime data. See Balakrishnan and Mitra (2011, 2012, 2013), among others. All these distributions have smooth hazard rate functions. As an extension from parametric to nonparametric estimation, the smoothness assumption in Condition 3 is natural and reasonable. This assumption is also used in Wang (2005) and Zhao and Zhang (2017).

Theorem 1 (Consistency) Suppose that Conditions 1-3 hold. Then the estimated failure rate $\hat{\lambda}_n$ converges to the true failure rate λ_0 in L_2 norm, that is,

$$\|\hat{\lambda}_n - \lambda_0\|_2 \rightarrow_p 0, \quad \text{as } n \rightarrow \infty.$$

Theorem 2 (Rate of convergence) Suppose that Conditions 1-3 hold. If ν is chosen to be $1/(2r+1)$, then

$$n^{\frac{r}{2r+1}} \|\hat{\lambda}_n - \lambda_0\|_2 = O_p(1).$$

Remark 2. Theorem 2 shows that the spline likelihood estimators have a convergence rate slower than $n^{-1/3}$ and faster than $n^{-1/3}$.

To discuss the asymptotic distributions of functions of $\hat{\lambda}_n$, define

$$\mathcal{H}_r = \left\{ h(\cdot) : |h^{(r-1)}(s) - h^{(r-1)}(t)| \leq c_0 |s - t| \text{ for all } a \leq s, t \leq b \right\},$$

where $h^{(r-1)}$ is the $(r-1)$ th derivative of h , and $c_0 > 0$ is a constant. Let \mathcal{U}_λ denote a neighborhood of the failure rate λ_0 . We also define a sequence of maps G_n , mapping \mathcal{U}_λ in the parameter space for λ into $\mathcal{L}^\infty(\mathcal{H}_r)$ as

$$G_n(\lambda)[h] = n^{-1} \sum_{i=1}^n \left\{ \delta_i \frac{h(Y_i)}{\lambda(Y_i)} - \int_{L_i}^{Y_i} h(t) dt \right\} = \mathbb{P}_n \phi(\lambda; X)[h].$$

