A unified imputation framework for interval-censored data: comparing AFT, RSF, and DeepSurv models

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Interval-censored data are common in longitudinal studies and pose challenges for time-to-event analysis. This work proposes a unified imputation-based framework for handling interval-censored data, where latent event times are iteratively generated within the observed censoring intervals and the censoring mechanism is handled externally through a scaled redistribution procedure. Within this framework, different predictive models—including AFT, Random Survival Forests, and DeepSurv—can be consistently compared through an iterative imputation scheme based on pseudo-event times within the observed intervals, followed by a common scaled redistribution procedure. Performance is assessed through simulations under varying censoring levels, interval widths, and hazard distributions, with extensions to nonlinear effects and high-dimensional covariates. Results are further validated using real-world clinical datasets.

Keywords: Interval-censored data, imputation-based framework, DeepSurv, random survival forests.

Interval-censored data represent a common challenge in biostatistics, reliability engineering, and longitudinal clinical trials. Unlike right-censoring, where the event is only known to occur after a given time, interval censoring arises when the event is only known to have occurred within a time window $[L, R]$. This setting is common in medical studies with periodic follow-up assessments, such as asymptomatic disease progression or dental health studies, where the exact transition time remains unobserved.

Let T denote a non-negative random variable representing the time to event. Under interval censoring, T is not directly observed; instead, one observes a pair (L_i, R_i) such that $T_i \in [L_i, R_i]$. Among the available approaches for estimating the survival function, the Turnbull estimator [1] is a widely used nonparametric extension of the Kaplan–Meier method. However, it cannot incorporate covariates or estimate hazard ratios, limiting its use in regression settings. Imputation offers a practical alternative by replacing incomplete observations with plausible event times $\hat{t}_i$ within $[L_i, R_i]$, enabling the use of standard survival workflows.

Within the proposed framework, Accelerated Failure Time (AFT) models are used as predictive tools to guide event-time imputation. These models assume that covariates act multiplicatively on survival time and are commonly written as

$$\log(T) = X\beta + \epsilon,$$

where ϵ follows a specified distribution (e.g., Gumbel for Weibull models). Although interpretable, AFT models may be limited in capturing complex nonlinear relationships.

Recent developments in machine learning (ML) and deep learning (DL) provide greater flexibility for modeling intricate patterns while treating censoring intervals as constraints within an imputation framework. Random Survival Forests (RSF) construct ensembles of trees using survival-based splitting rules such as the log-rank criterion [3]. DeepSurv is a Cox-based deep neural network that replaces the linear predictor $\beta^T X$ with a nonlinear function $h_\theta(X)$ learned from the data [4].

The Scaled Redistribution method is a semi-parametric adjustment that reallocates predicted event times within the observed interval $[L, R]$, ensuring coherence with censoring bounds while preserving relative variability. It avoids strong distributional assumptions and remains computationally efficient for small-to-medium datasets.

Despite the growing number of available methods, a unified benchmarking framework for comparing classical imputation approaches, AFT models, and modern predictive methods such as RSF and DeepSurv is still lacking. Building on previous research [5], this work addresses this gap through a comprehensive comparative evaluation of imputation strategies based on simulation studies and applications to real-world datasets.

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