Improving Unbiasedness of the Proportional Hazards Model Estimator with Cox and Snell's Bias Approximation and Jackknife Resampling

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ABSTRACT

Bias approximation has played an important role in maximum likelihood estimation method, and numerous bias calculation techniques have been proposed under different contexts. For the semiparametric proportional hazards model, which is the standard regression method to study the time-to-event data, the existing work applied the bias formula and derived the approximate bias of Cox's estimator based on the partial likelihood function. In this work, we instead use the joint likelihood function and utilize the counting process approach to develop approximate bias of Cox's estimator. Explicit expressions for the higher order partial derivatives are derived, which facilitate the bias calculation techniques. We also incorporate jackknife resampling method and propose a Jackknife-Cox-Snell method that processes the biasedness of Cox's estimator through two steps, where the first step aims for removing the analytical terms derived from Cox and Snell's formula and the second step reduces the residual bias term then. A comprehensive simulation study is performed to show the usefulness of the proposed bias-corrected method. We also apply the proposed method to two sets of survival data for comparison and illustration.

Keywords: Bias calculation, Counting process, Cox and Snell's formula, Jackknife, Nonparametric maximum likelihood estimator, Proportional hazards model

Prediction-Oriented Transfer Learning for Semiparametric Transformation Models with Survival Data

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ABSTRACT

Transfer learning is beneficial for survival analysis, especially when the target study has a limited number of events. However, existing transfer learning methods rely on restrictive assumptions that the target and source studies share similar parameters under Cox models. In this talk, I will introduce a novel transfer learning framework that enhances survival prediction by transferring predictive rather than distributional knowledge from source studies. Our approach employs flexible semi- parametric transformation models for the target data and eliminates the need to model or share the source data. The ingeniously designed penalty enables optimization via a simple and stable EM algorithm. We rigorously establish the asymptotic properties of the proposed estimator and show that it achieves a faster convergence rate than the target-only estimator when source knowledge is sufficiently accurate. We demonstrate the effectiveness of our methods through extensive simulation studies and an application to two major breast cancer studies.

Keywords: EM algorithm, Nonparametric likelihood, Survival prediction, Transfer learning, Transformation models

A Novel Approach When Facing Emerging Infectious Disease --- Randomized Selection Design

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ABSTRACT

When facing an emerging infectious disease (such as COVID-19 or Ebola) with no readily available effective treatment, one is less interested in making declarations of statistical significance than in identifying a promising direction forward. A randomized selection design offers the appropriate tools for the approach. The general goal of a randomized selection design is to select one or more treatments from several competing candidates to which patients are randomly assigned, in such a way that selected treatment(s) are likely to be better than those not selected. For example, if one treatment is clearly superior to all the others, we may demand that the procedure select that treatment with high probability. The experimental treatments could be different doses of a drug or intensities of a behavioral intervention, different treatment schedules, modalities, or strategies, or different combinations of treatments. The hallmark feature of a selection design is its ability to achieve its stated goals with surprisingly fewer participants compared with traditional "phase III" trials, precisely because it eschews the formal hypothesis test paradigm with its tight control over type I error rates. In addition, the selection procedure allows for sequential elimination of inferior treatments, sequential recruitment of superior treatments, and may be used to select treatments with fixed or variable subset sizes make it even more appealing in practice. Thus, they are ideal for middle development settings where we are interested in selecting promising treatments under circumstances typically limited by smaller sample sizes. In this talk, I'll focus on the discussion of the Levin-Robbins-Leu (LRL) family of sequential subset selection procedures, their design considerations, and actual applications in clinical trials.