Learning Robust Decision Rules for Censored and Confounded Data

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ABSTRACT

In this talk, we propose two robust criteria for learning optimal treatment rules with censored survival outcomes. The first one aims to identify a treatment rule that maximizes the restricted mean survival time, where the restriction is specified by a given quantile such as the median; the second one focuses on maximizing buffered survival probabilities, with the threshold adaptively adjusted to account for the restricted mean survival time. Moreover, we develop robust treatment rules that enable reliable policy recommendations when unmeasured confounding is present, using the proximal causal inference framework. Simulation studies and real-world applications demonstrate the superior performance of the proposed methods.

Keywords: Causal Inference, Decision-making, Survival analysis

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Causal Inference for All: Marginal Causal Effects for Outcomes Truncated by Death

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ABSTRACT

In longitudinal studies where outcomes may be truncated by death, standard causal estimands often fail to capture meaningful treatment effects, particularly when survival is affected by treatment. Traditional survivor average causal effects (SACEs), which condition on post-treatment survival, are challenging to interpret and identify without strong assumptions, and their direct extension to longitudinal settings poses additional difficulties. We propose a flexible class of marginal causal estimands that aggregate potential outcomes over time among individuals who would survive under both treatment and control. These estimands support a range of clinically relevant summaries, such as cumulative or last-observed outcomes, and can be tailored using weighting schemes to align with different decision-making goals. We illustrate these ideas through a reanalysis of a prostate cancer clinical trial, highlighting how different estimands may lead to different treatment conclusions.

Keywords: Local average effects, Longitudinal data analysis, Missing data, Selection bias

Quantum Speedups for Multiproposal MCMC

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ABSTRACT

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Multiproposal MCMC algorithms choose from multiple proposals to generate their next chain step in order to sample from challenging target distributions more efficiently. However, on classical machines, these algorithms require O(P) target evaluations for each Markov chain step when choosing from P proposals. Recent work demonstrates the possibility of quadratic quantum speedups for one such multiproposal MCMC algorithm. After generating P proposals, this quantum parallel MCMC (QPMCMC) algorithm requires only O(\sqrt{P}) target evaluations at each step, outperforming its classical counterpart. Here, I present a new, faster quantum multiproposal MCMC strategy, QPMCMC2. With a specially designed proposal distribution, QPMCMC2 requires only O(1) target evaluations and O(log P) qubits when computing over a large number of proposals P. Unlike its slower predecessor, the QPMCMC2 Markov kernel (1) maintains detailed balance exactly and (2) is fully explicit for a large class of graphical models. I demonstrate this flexibility by applying QPMCMC2 to novel Ising-type models built on bacterial evolutionary networks and obtain significant speedups for Bayesian ancestral trait reconstruction for 248 observed salmonella bacteria.

Keywords: Multiproposal MCMC; Quantum Computing; Ising models

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Indirect Statistical Inference with Guaranteed Necessity and Sufficiency

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ABSTRACT

This paper develops a new framework for indirect statistical inference with guaranteed necessity and sufficiency, applicable to continuous random variables. We prove that when comparing exponentially transformed order statistics from an assumed distribution with those from simulated unit exponential samples, the ranked quotients exhibit distinct asymptotics: the left segment converges to a non-degenerate distribution, while the middle and right segments degenerate to one. This yields a necessary and sufficient condition in probability for two sequences of continuous random variables to follow the same distribution. Building on this, we propose an optimization criterion based on relative errors between ordered samples. The criterion achieves its minimum if and only if the assumed and true distributions coincide, providing a second necessary and sufficient condition in optimization. These dual NS properties, rare in the literature, establish a fundamentally stronger inference framework than existing methods. Unlike classical approaches based on absolute errors (e.g., Kolmogorov–Smirnov), NSE exploits relative errors to ensure faster convergence, requires only mild approximability of the cumulative distribution function, and provides both point and interval estimates. Simulations and real-data applications confirm NSE's superior performance in preserving distributional assumptions where traditional methods fail.

Keywords: combinatorial mathematics, indirect inference, relative errors, simulated order statistics.