THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

DEPARTMENT OF APPLIED MATHEMATICS
應 用 數 學 系

Dr. JIANG Binyan

Research interests include:

- High dimensional data analysis
- Survival data analysis
- Mixture models
- Network data analysis

Start-up grant project

Outcome-dependent Logistic Learning for Optimal Dynamic Treatment Regimes

Abstract

Personalized medicine is of growing interest across clinical sciences since patients might have heterogeneous response to treatments in clinical practice. Comparing with the traditional "one size fits all" approach, significant improvement in patient outcome could be obtained using patient-level information. On the other hand, treatments in practice usually involve decisions made sequentially over time. A dynamic treatment regime based on the accruing observations on the patient is then needed for better clinical outcomes. In recent literatures, this is commonly formularized as an optimization problem where we want to search for a sequence of treatments (as functions of patient-level covariates) that maximized the total expected outcomes. When parametric methods such as A-learning and q-learning are used, the decision rules become functions of regression parameters. Parameter inference under these parametric methods has been an active research topic in the last decade. The main difficulty in parameter inference is caused by the non-smoothness of the objective functions. As a consequence, both Wald type confident interval and standard Bootstrap confident interval can perform very poorly.

In this project, we propose a novel learning approach called logistic learning to find optimal individualized treatment rules (ITRs) that maximize the expected clinical outcome for multi-stage treatments. By using the cross-entropy loss as the surrogate lose function, treatment variables (which take discrete values) are formularized as part of the weights of a weighted logistic-likelihood function. Consequently, unlike existing approaches such as q-learning and outcome weighted learning, the objective functions for estimating the parameters become continuous and parameter inference becomes feasible even without the regularity condition, which is commonly used in the literature. We plan to propose efficient estimation for the parameters in our model and establish their asymptotic distributions for parameter inference.