Abstract

This thesis discusses three topics on econometrics.

Chapter 2 focuses on data sparsity issues and cold-start problems in personalized Point-Of-Interest (POI) recommendations. Firstly, most existing users only visit a small number of POIs, which results in severe data sparsity and makes most conventional methods unsuitable because they require adequate historical data from each user to learn the model. In addition, new users have little or no historical record. Existing ask-to-rate methods for cold start user scenarios treat user answers as historical data, which is inappropriate and causes difficulty in capturing user preferences. To tackle the data sparsity problem, we propose a user-experience model (UEM) to uncover user behaviors from several aspects. To handle the cold-start problem for new users, we propose a pseudo-rating mechanism (PRM) to capture new users' preferences and recommend POIs. Extensive experimental results demonstrate that the proposed method achieves better recommendation performance and fairness than the state-of-the-art methods.

Chapter 3 focuses on bias estimation and correction of Kernel Density Estimation (KDE). The smoothed bootstrap method is a useful method to approximate the bias of KDE. However, to conduct the smoothed bootstrap method, the kernel function should be positive, which makes this method inappropriate for higher order kernels. We generalize the smoothed bootstrap method to higher order kernels for estimating the bias and constructing a bias-corrected estimator based on it. Theoretical formulation and numerical simulation demonstrate that the proposed method achieves better performance compared to the traditional bias estimation. We also construct confidence bands/intervals based on the proposed bias correction method. Simulation studies reveal that our proposed bias correction estimator and confidence bands/intervals outperform the traditional bias correction method.

Chapter 4 focuses on bias estimation and correction of Local Polynomial Regression (LPR). LPR generally contains a bias that involves higher-order derivatives of the targeted function. The conventional bias correction method introduces another LPR estimator to estimate the derivatives of the underlying function and obtain a consistent bias correction estimator based on it. However, the conventional bias correction method could not handle the bias well. Inspired by the bias estimation and correction method proposed in Chapter 3, we propose a novel bias correction estimator for LPR. Theoretical formulation and numerical simulation demonstrate that the proposed method achieves better performance compared to the standard LPR and the conventional bias correction method.