Predictive Density Estimation in Nonparametric Statistical Models

論 文 の 内 容 の 要 旨
Abstract

論文題目 Predictive Density Estimation in Nonparametric Statistical Models
（ノンパラメトリック統計モデルにおける予測密度推定）

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This thesis investigates predictive density estimation in nonparametric statistical models. In applications, the purpose of statistical analysis is often prediction. Prediction in parametric models has been widely investigated. However, there exists a setting where parametric models impose stringent assumptions. In such a setting, nonparametric models provide more flexible modeling. Estimation using nonparametric statistical models has been widely used in application and has been investigated theoretically. In this thesis, we focus on prediction in nonparametric statistical model and present four new contributions to the literature.

First, we study asymptotically minimax predictive distributions in an infinite-dimensional function model. By attributing the predictive density estimation to predictive density estimation in a Gaussian infinite sequence model, we construct asymptotically minimax predictive distributions.

Second, we present refinements of estimators in nonparametric models focusing on the scale ratio. We show that typical Bayes estimators satisfying asymptotic minimaxity up to a constant multiple as a sample size grows to infinity has excess risk. To resolve this issue, we define scale-ratio minimaxity and propose a Bayes

estimator. We theoretically investigate the proposed Bayes estimator from the viewpoints of scale-ratio minimaxity and weak admissibility.

Third, we discuss exact minimaxity and weak admissibility in estimation of an intensity function of inhomogeneous Poisson point process. We use the risk related to prediction. By attributing the estimation to estimation in a Poisson sequence model, we give an exact minimax estimator and give bounds related to weak admissibility of the Bayes estimator based on a scale mixture of Gamma distributions.

Finally, we discuss model selection for prediction when distributions of current and future observations might differ. Such a predictive setting arises from extrapolation. Though the final contribution is discussed through parametric models, we show through numerical experiments that the result is extensible to prediction in a high-dimensional parametric model related to prediction in a nonparametric model. We propose a novel model selection criterion for such a prediction and provide numerical experiments to show that our criterion works better than existing model selection criteria.