NONPARAMETRIC BINARY REGRESSION USING A GAUSSIAN-PROCESS PRIOR

Abstract

The talk describes a nonparametric Bayesian approach to estimating the regression function for binary response data measured with multiple covariates. A multiparameter Gaussian process, after some transformation, is used as a prior on the regression function. Such a prior does not require any assumption such as monotonicity or additivity of the covariate effects. However, additional restrictions may be imposed through hyperprior specification. Conjugacy is achieved in the model through the introduction of some latent variables, and thus an efficient Gibbs sampler is described for the purpose of computing the posterior distribution. A hierarchical model is described to build the nonparametric prior around a parametric family without actually restricting to that parametric model. A major focus here is in studying the asymptotic property of the posterior distribution. Sufficient conditions on the prior and the true regression function are derived for posterior consistency. Simulation study results and analysis of some real data are also presented to illustrate and judge the performance of the estimator.

(This is joint work with Nidhan Choudhuri and Subhashis Ghosal.)