Dynamic Prediction of Generalized Functional Data

Dynamic prediction, which typically refers to the problem of predicting future outcomes using the historical records from the same subject, is often of interest in biomedical research. For generalized function data, dynamic prediction turns out challenging due to the high density and complex correlation structure of repeated measures, which imposes heavy computational burden on traditional methods such as mixed models. Moreover, out-of-sample estimation of individual random effects is not feasible when the outcome value is not continuous. To address these issues, we developed a novel, fast, scalable method that combines the principals of mixed models and functional data analysis. This method, based on the fast Generalized Functional Principla Analysis (fGFPCA) model, is able to handle large-scale, high-density repeated measures much more efficiently. Its model structure can accommodate great flexibility and estimate the out-of-sample individual-specific random effects without refitting the model. We designed a simulation study and a case study on the National Health and Nutrition Examination study (NHANES) data to demonstrate the predictive performance and computational efficiency of the proposed method. Compared to existing methods that can achieve similar purposes, the proposed method can fit much more complex models with greater prediction accuracy, also spent a lot less computation time.