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Bagging-enhanced sampling schedule for functional quadratic regression. (English)

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Summary: Establishing an optimal sampling schedule is a crucial step toward a precise inference of the underlying functional mechanism of a process, especially when data collection is expensive/difficult. This work is concerned with optimal sampling plans for predicting a scalar response using a functional predictor when a quadratic regression relationship is present. An optimality criterion for selecting the best sampling schedules is derived, and some important properties of the criterion are provided. In addition, a bootstrap aggregating (bagging) strategy is proposed to enhance the quality of the obtained sampling schedule.

MSC:

62H25 Factor analysis and principal components; correspondence analysis
62G08 Nonparametric regression and quantile regression
62H12 Estimation in multivariate analysis
62R10 Functional data analysis
62P10 Applications of statistics to biology and medical sciences; meta analysis

Keywords:

functional data analysis; functional principal component; functional regression model; bagging

Software:

fdapace; PACE; PACE; fda (R)

Full Text: DOI

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