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Nonparametric deconvolution problem for dependent sequences

Rafał Kulik, University of Ottawa

Abstract

We consider the nonparametric estimation of the density function of weakly and strongly dependent processes with noisy observations. We show that in the ordinary smooth case the optimal bandwidth choice can be influenced by long range dependence, as opposite to the standard case, when no noise is present. In particular, if the dependence is moderate the bandwidth, the rates of mean-square convergence and, additionally, central limit theorem are the same as in the i.i.d. case. If the dependence is strong enough, then the bandwidth choice is influenced by the strength of dependence, which is different when compared to the non-noisy case. Also, central limit theorem are influenced by the strength of dependence. On the other hand, if the density is supersmooth, then long range dependence has no effect at all on the optimal bandwidth choice.

AMS 2000 subject classifications: Primary 62G05; secondary 62G07, 60F05.

Keywords: long range dependence, linear processes, error-in-variables models, deconvolution.



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