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Online sparse identification for regression models. (English) Zbl 1447.93360

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Summary: In this paper, we propose an online alternating minimization (OAM) algorithm to estimate the sparse coefficients of stochastic regression models from time-series data. We apply the alternating minimization (AM) directly to the penalty function of the variant of the least absolute shrinkage and selection operator (Lasso), which leads to convex subproblems, and thereby can be solved efficiently. Moreover, under certain mild assumptions, we derive a convergence analysis framework and establish the strong consistency for the OAM estimator. Numerical experiments demonstrate the effectiveness of the proposed algorithm.

MSC:

93E12 Identification in stochastic control theory

68W27 Online algorithms; streaming algorithms

Keywords:

online alternating minimization (OAM); sparse identification; strong consistency

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