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Change-point computation for large graphical models: a scalable algorithm for Gaussian graphical models with change-points. (English) Zbl 1444.62077

J. Mach. Learn. Res. 19, Paper No. 11, 38 p. (2018).

Summary: Graphical models with change-points are computationally challenging to fit, particularly in cases where the number of observation points and the number of nodes in the graph are large. Focusing on Gaussian graphical models, we introduce an approximate majorize-minimize (MM) algorithm that can be useful for computing change-points in large graphical models. The proposed algorithm is an order of magnitude faster than a brute force search. Under some regularity conditions on the data generating process, we show that with high probability, the algorithm converges to a value that is within statistical error of the true change-point. A fast implementation of the algorithm using Markov Chain Monte Carlo is also introduced. The performances of the proposed algorithms are evaluated on synthetic data sets and the algorithm is also used to analyze structural changes in the S&P 500 over the period 2000–2016.

MSC:

62H22 Probabilistic graphical models

62G10 Nonparametric hypothesis testing

62L20 Stochastic approximation

62P20 Applications of statistics to economics

Keywords:

change-points; Gaussian graphical models; proximal gradient; simulated annealing; stochastic optimization

Software:

changepointsHD; wbs

Full Text: arXiv Link

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