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**D-trace estimation of a precision matrix using adaptive lasso penalties.** (English)

Zbl 1414.62224

Adv. Data Anal. Classif., ADAC 12, No. 2, 425-447 (2018).

**Summary:** The accurate estimation of a precision matrix plays a crucial role in the current age of high-dimensional data explosion. To deal with this problem, one of the prominent and commonly used techniques is the  $\ell_1$  norm (Lasso) penalization for a given loss function. This approach guarantees the sparsity of the precision matrix estimate for properly selected penalty parameters. However, the  $\ell_1$  norm penalization often fails to control the bias of obtained estimator because of its overestimation behavior. In this paper, we introduce two adaptive extensions of the recently proposed  $\ell_1$  norm penalized D-trace loss minimization method. They aim at reducing the produced bias in the estimator. Extensive numerical results, using both simulated and real datasets, show the advantage of our proposed estimators.

**MSC:**

**62H30** Classification and discrimination; cluster analysis (statistical aspects)

Cited in **3** Documents

**62J10** Analysis of variance and covariance (ANOVA)

**65S05** Graphical methods in numerical analysis

**Keywords:**

adaptive thresholding; D-trace loss; Gaussian graphical model; gene expression data; high-dimensionality

**Software:**

glasso

**Full Text:** [DOI](#)

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