Robust scatter regularization

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Introduction

Let $X = (X_1, \dots, X_p)^T$ be a p-dimensional random vector with $X_i \sim N_p(\mu, \Sigma)$

where μ is the mean and Σ is the nonsingular covariance matrix.

<u>Aim</u>: Estimate, in a robust way, μ and $\Theta = \Sigma^{-1}$ (concentration matrix) using a sample of size *n*.

Maximum Likelihood estimator

The ML estimator of (μ, Θ) maximizes

$$\log(\det(\Theta)) - \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^T \Theta(x_i - \mu).$$

When the sample covariance matrix S is nonsingular,

$$(\hat{\mu}_{ML}, \hat{\Theta}_{ML}) = (\bar{x}, S^{-1}).$$

When S is singular (e.g. when n < p), the ML estimator does not exist.

Regularized Maximum Likelihood estimator

The Regularized ML estimator of (μ, Θ) maximizes

$$\log(\det(\Theta)) - \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^T \Theta(x_i - \mu) - \lambda J(\Theta),$$

where $\lambda \ge 0$ is the penalty parameter and J is a penalty function.

Typical choices:

•
$$L_1$$
-norm: $J(\Theta) = \sum_{i,j=1}^{p} |\Theta_{ij}|$
• L_2 -norm: $J(\Theta) = \sum_{i,j=1}^{p} \Theta_{ij}^2$
• ...

Breakdown Point

Roughly speaking, the breakdown point is the smallest fraction of contamination that can drive the estimator over all bounds.

For a scatter estimator, breakdown can occur due to

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explosion: \lambda_1(\Theta) \to \infty
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or

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implosion: \lambda_p(\Theta) \rightarrow 0
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with $\lambda_{\rho}(\Theta) \leq \ldots \leq \lambda_1(\Theta)$.

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Breakdown of the Regularized ML procedure $\mu = 0, \Sigma = I_p$ and $x'_n = x_n + xe_1$



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Breakdown of the Regularized ML procedure $\mu = 0, \Sigma = I_p$ and $x'_n = x_n + xe_1$



Robust alternatives are needed!

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Minimum Covariance Determinant estimator

Find a subsample H of size h (with ⁿ/₂ ≤ h ≤ n) minimizing the generalized variance

 $\log(\det(\Sigma_H))$

(where Σ_H is the covariance matrix based on the *h* points).

• The location and scatter MCD estimates are given by the mean and covariance matrix of the optimal subsample.

Regularized MCD estimator

• Find a subsample *H* of size *h* maximizing

$$\log(\det(\Theta_H)) - \frac{1}{h} \sum_{i \in H} (x_i - \mu_H)^T \Theta_H(x_i - \mu_H) - \lambda J(\Theta_H)$$

• The regularized MCD estimator is given by the regularized ML estimator computed on the optimal subsample.

Properties of the Regularized MCD estimator

A. Robustness

The finite-sample breakdown point for joint location and scatter of the Regularized MCD estimator is equal to

$$arepsilon^*((\hat{\mu}_{ ext{MCD}},\hat{\Sigma}_{ ext{MCD}});X) = rac{\min(h,n-h+1)}{n}$$

where $\frac{n}{2} \le h \le n$ is the number of observations selected in the MCD solution.

In particular, for h = n/2, $\varepsilon^*((\hat{\mu}_{\mathrm{MCD}}, \hat{\Sigma}_{\mathrm{MCD}}); X) = 1/2$.

Properties of the Regularized MCD estimator

B. Computation

Iterative algorithm:

$$(\hat{\mu}_0, \hat{\Theta}_0) \rightarrow \ldots \rightarrow (\hat{\mu}_k, \hat{\Theta}_k) \rightarrow (\hat{\mu}_{k+1}, \hat{\Theta}_{k+1}) \rightarrow \ldots$$

- (μ̂₀, Θ̂₀) : Regularized ML estimator based on a random subset of 2 observations
- iteration k to k + 1 by means of a C-step
- works for n < p

Simulations

Clean setting: n = p = 50, $\Sigma_{ii} = 1$ and $\Sigma_{ij} = 0.5I(i, j \le 9)$ for all $i \ne j$. Contaminated setting: 5% of shift and correlation outliers (intermediate or extreme)

L_1 penalty	ML		MCD	
	$MSE(\hat{\mu})$	$KL(\widehat{\Theta})$	$MSE(\hat{\mu})$	$KL(\widehat{\Theta})$
Clean	0.98	6.94	1.43	6.46
5% Intermediate	1.70	9.76	1.42	6.53
5% Extreme	200.89	17.58	1.41	6.53

where

$${\it KL}(\widehat{\Theta}) = -\log(\det(\widehat{\Theta})) + {\it tr}(\widehat{\Theta}\Sigma) - (-\log(\det(\Sigma^{-1})) +
ho)$$

Applications

- Detection of outliers in high dimensional data (with n
- Robust graphical modelling
- Robust regularized regression

Detection of outliers

n = p = 50, $\Sigma_{ii} = 1$ and $\Sigma_{ij} = 0.5I(i, j \le 9)$ for all $i \ne j$, 5% of shift and correlation outliers



Regularized ML Mahalanobis distances

Conclusions

- Robust regularized scatter estimation is available.
- Other robust multivariate estimators can also be adapted to the penalized setting (e.g. *M* estimator,...).
- Still room for further research.