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# Robust Linear Regression via $\ell_0$ Regularization

Jing Liu, Pamela C. Cosman, and Bhaskar D. Rao

- Goal: Outlier support identification in linear regression

- Background

- Linear regression: find  $\mathbf{x}$  given  $\{\mathbf{a}_i^\top\}, \mathbf{y}$

$$y_i = \mathbf{a}_i^\top x_i + \eta_i + e_i$$

- Overdetermined system, no freedom to design  $\{\mathbf{a}_i^\top\}$
  - Ordinary least squares sensitive to outliers
  - Dealing with outliers using sparse signal recovery methods  
“Projection method”

$$F\mathbf{y} = F\mathbf{e} + F\boldsymbol{\eta}$$

where rows of  $F$  form an orthobasis for  $\text{colsp}(A)$

- Model:

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \boldsymbol{\eta} + \mathbf{e},$$

where  $\mathbf{A} \in \mathbb{R}^{m \times n}$

$\boldsymbol{\eta}$ : inlier noise, small in magnitude

$\mathbf{e}$ : outliers, large in magnitude, sparse

- Proposed cost:

$$J(\mathbf{x}, \mathbf{e}) = \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{e}\|_1 + \alpha\|\mathbf{e}\|_0$$

- Contributions

- Algorithm for outlier identification
- Convergence analysis, theoretical guarantees for proposed algorithm

## ALGORITHM FOR ROBUST OUTLIER SUPPORT IDENTIFICATION (AROSI)

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**Input:**  $y, A, \alpha > 0$

**Initialization:**  $k = 0, e^{(0)} = 0, \mathcal{S}_0 = \{1, \dots, m\}$

**While**  $J(x, e)$  not converged **DO:**

**Iteration**  $k + 1$

**Step 1** (update  $x$ ):  $x^{(k+1)} = \arg \min_x \|y_{\mathcal{S}_k} - A_{\mathcal{S}_k} x\|_1;$

        If  $\|y_{\mathcal{S}_k} - A_{\mathcal{S}_k} x^{(k+1)}\|_1 = \|y_{\mathcal{S}_k} - A_{\mathcal{S}_k} x^{(k)}\|_1,$

        further update  $x^{(k+1)} = x^{(k)}.$

**Step 2** (update  $e$  and  $\mathcal{S}$ ):  $e_i^{(k+1)} = \begin{cases} 0, & |(y - Ax^{(k+1)})_i| \leq \alpha \\ (y - Ax^{(k+1)})_i, & \text{otherwise} \end{cases}$

$\mathcal{S}_{k+1} := \{i: e_i^{(k+1)} = 0\}$

$k := k + 1$

**End While**

**Output:** solution  $\tilde{x}$

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# Compressive Sensing-Based Detection With Multimodal Dependent Data

Thakshila Wimalajeewa, Pramod K. Varshney

- Goal: Solve detection problems using compressed data
- Background:
  - Obtain multimodal data from sensors, perform inference/detection tasks by fusing data
  - Challenging because of complex inter/intra modal dependencies
  - Two previously known approaches:
    - Copula theory
    - “Product approach”
- Contribution:
  - Detection schemes based on compressed data in the presence of inter modal dependencies

- Binary hypothesis testing problem; obtain compressed data:

$$\mathbf{y}_j = \mathbf{A}_j \mathbf{x}_j, \quad j \in [L]$$

Under  $\mathcal{H}_0$ : temporal and spatial independence

Under  $\mathcal{H}_1$ : temporal independence and spatial dependence

- Assumptions:
  - Observations are noiseless
  - Each  $\mathbf{A}_j$  is an orthoprojector

$$\mathbf{A}_j \mathbf{A}_j^\top = \mathbf{I}$$

## Two schemes

- LR based detection using compressed data:
  - Gaussian approximation-based
  - First and second order statistics of  $\mathbf{x}$  under the hypotheses is assumed to be known
- A covariance based test statistic in the compressed domain
  - Estimate statistics of  $\mathbf{x}$  from  $\mathbf{y}$ , then form test statistic
  - Test statistic  $T$

$$T = \frac{\sum_{i,j} |D_x(i,j)|}{\sum_i |D_x(i,i)|}$$

Tests for  $D_x$  diagonal ( $T = 1$ ) vs.  $D_x$  non diagonal ( $T > 1$ )

- $D_x$  estimated using  $\mathbf{y}_i$

# Sparse Bayesian Learning Approach for Outlier-Resistant Direction-of-Arrival Estimation

Jisheng Dai and Hing Cheung So

- Goal: DOA estimation in the presence of outliers
- Setup:  $K$  sources falling on an  $M$ -element array

$$\mathbf{Y} = \mathbf{A}_{\hat{\theta}}\mathbf{S} + \mathbf{E} + \mathbf{W}$$

$\{\hat{\theta}_1, \dots, \hat{\theta}_{\hat{K}}\}$ : fixed sampling grid

$\mathbf{Y} : M \times T$

$\mathbf{A}_{\hat{\theta}} : M \times \hat{K}$

$\mathbf{S} : \hat{K} \times T$

$\mathbf{E} : M \times T$  outlier matrix

$\mathbf{W} : M \times T$  dense noise matrix



- SBL formulation

$$p(\hat{\mathbf{S}}|\delta) = \prod_{t=1}^T \mathcal{CN}(\hat{\mathbf{s}}_t|\mathbf{0}, \text{diag}(\delta))$$
$$p(\mathbf{E}|\Gamma) = \prod_{i=1}^M \prod_{j=1}^T \mathcal{CN}(e_{i,j}|\mathbf{0}, \gamma_{i,j})$$

- Gamma prior on hyperparameters
- $(\hat{\mathbf{S}}, \mathbf{E})$  treated as hidden variable, and  $p(\delta, \Gamma|\mathbf{Y})$  maximized via EM
- Technique to handle off grid gap also mentioned

## Other interesting papers

- Fully Decomposable Compressive Sampling With Joint Optimization for Multidimensional Sparse Representation *W. Dai, Y. Li, J. Zou, H. Xiong, and Y. F. Zheng*
- Performance Analysis of Linear Receivers for Uplink Massive MIMO FBMC-OQAM Systems *F. Rottenberg, X. Mestre, F. Horlin, and J. Louveaux*
- Statistical Anomaly Detection via Composite Hypothesis Testing for Markov Models *J. Zhang and I. Ch. Paschalidis*
- Optimal Energy-Efficient Source and Relay Precoder Design for Cooperative MIMO-AF Systems *F. Heliot and R. Tafazolli*