Journal Watch
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Matrix Completion With Column Manipulation: Near-Optimal Sample-Robustness-Rank Tradeoffs

Y. Chen, H. Xu, C. Caramanis, S. Sanghavi
(TIT, Jan. 2016)

- Goal: Matrix completion from partial observations when columns are adversarially corrupted
- Setup: $M, \ L_0, \ C_0 \in \mathbb{R}^{m\times(n+n_c)}$
  n: number of non-corrupted columns
  n_c: number of corrupted columns
  L_0 low-rank, S_0 column-sparse
  $I_0 \subset [n+n_c]$: indices of corrupted columns
  $\Omega \subseteq [m]\times[n+n_c]$
  P_Ω: projection onto space of matrices supported on Ω

$$M = L_0 + C_0$$

- Contributions:
  - an algorithm based on trimming+convex optimization
  - sufficient conditions under which algorithm provably recovers L_0 and identifies I_0

Algorithm 1 Manipulator Pursuit

Input: $\mathcal{P}_{\Omega}(M)$,Ω,λ, ρ.

Trimming: For $j = 1, \ldots, n + n_c$, if the number of observed entries h_j on the j-th column satisfies $h_j > \rho m$, then randomly select ρm entries (by sampling without replacement) from these h_j entries and set the rest as unobserved. Let $\hat{\Omega}$ be the set of remaining observed indices.

Solve for optimum (L^*, C^*):

$$\begin{aligned} \text{minimize}_{L,C} \quad & \|L\|_* + \lambda \|C\|_{1,2} \\ \text{subject to} \quad & \mathcal{P}_{\hat{\Omega}}(L + C) = \mathcal{P}_{\hat{\Omega}}(M) \end{aligned} \tag{2}$$

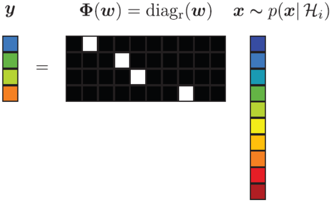
Set $I^* = \text{column-support}(C^*) := \{j : C^*_{ij} \neq 0 \text{ for some } i\}$.

Output: L^*, C^* and I^*.

Sparse Sensing for Distributed Detection

S. P. Chepuri and G. Leus
(TSP, Mar.15, 2016)

- Offline sampling technique for distributed detection
- Binary Hypothesis Testing setup, consider Bayesian and Neyman-Pearson frameworks
- Model: $\mathcal{H}_0 : x_m \sim p_m(x|\mathcal{H}_0),$
  $\mathcal{H}_1 : x_m \sim p_m(x|\mathcal{H}_1), \quad m = 1, \ldots, M.$



$$\text{P-B} : \underset{\boldsymbol{w}\in\{0,1\}^M}{\arg\min} \; \|\boldsymbol{w}\|_0 \quad \text{s.to } P_e(\boldsymbol{w}) \le e;$$

$$\text{P-N} : \underset{\boldsymbol{w}\in\{0,1\}^M}{\arg\min} \; \|\boldsymbol{w}\|_0 \quad \text{s.to } P_f(\boldsymbol{w}) \le \alpha, \text{ and } P_m(\boldsymbol{w}) \le \beta$$

$$\text{S-B} : \underset{\boldsymbol{w}\in\{0,1\}^M}{\arg\min} \; \|\boldsymbol{w}\|_0 \quad \text{s.to } f_{\mathrm{B}}(\boldsymbol{w}) \ge \lambda_{\mathrm{B}}$$

$$\text{S-N} : \underset{\boldsymbol{w}\in\{0,1\}^M}{\arg\min} \; \|\boldsymbol{w}\|_0 \quad \text{s.to } f_{\mathrm{N}}(\boldsymbol{w}) \ge \lambda_{\mathrm{N}}$$

- Use: $f_N(\mathbf{w}) = K(\mathcal{H}_1||\mathcal{H}_0) = \sum_{m=1}^{M} w_m K_m(\mathcal{H}_1||\mathcal{H}_0)$

Joint Covariance Estimation with Mutual Linear Structure

I. Soloveychik and A. Wiesel
(TSP, Mar.15, 2016)

- Goal: Joint estimation of structured covariance matrices.
  Given groups of measurements from populations with different covariance matrices (but with common structure),
  - estimate the common structure
  - estimate the covariance matrices
- Truncated SVD on sample covariances

$$\mathbf{S}_k = \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}_i^k \mathbf{x}_i^{kT}, \qquad \mathbf{S} = [\mathbf{s}_1, \ldots, \mathbf{s}_K]$$

$$\mathbf{S}' = \widehat{\mathbf{U}} \begin{pmatrix} \widehat{\boldsymbol{\Sigma}} & 0 \\ 0 & \widehat{\boldsymbol{\Sigma}}_n \end{pmatrix} \widehat{\mathbf{W}}^T = [\widehat{\mathbf{U}}_1 \widehat{\mathbf{U}}_2] \begin{pmatrix} \widehat{\boldsymbol{\Sigma}} & 0 \\ 0 & \widehat{\boldsymbol{\Sigma}}_n \end{pmatrix} [\widehat{\mathbf{W}}_1 \widehat{\mathbf{W}}_2]^T$$

- Estimator:
  $\widehat{\mathbf{Y}}' = \widehat{\mathbf{U}}_1 \widehat{\boldsymbol{\Sigma}} \widehat{\mathbf{W}}_1^T$

Poisson Matrix Recovery and Completion

Y. Cao and Y. Xie
(TSP, Mar.15, 2016)

- Goal: Matrix recovery/completion from compressive/incomplete measurements
- Assumption: Matrix M is low-rank, observations $y = [y_1, \ldots, y_m]$ are Poisson distributed

  Matrix recovery

  $y_i \sim \text{Poisson}(\text{Tr}(A_i^T M)), \quad i = 1, 2, \ldots, m.$

  Define $\mathcal{A} : \mathbb{R}_+^{d_1 \times d_2} \to \mathbb{R}^m$, with $[\mathcal{A}M]_i = \text{Tr}(A_i^T M)$.
- Formulation using maximum-likelihood:
  $L(X) = \sum_{i=1}^m (y_i \log[\mathcal{A}X]_i - [\mathcal{A}X]_i) - \lambda \text{pen}(X)$
- Contributions
  - Establish bounds on recovery error
  - Propose Penalized Maximum-Likelihood Singular Value Thresholding algorithm