

Journal Watch
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Lekshmi Ramesh



Indian Institute of Science
Bangalore

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Learning Mixtures of Sparse Linear Regressions Using Sparse Graph Codes

D. Yin, R. Pedarsani, Y. Chen and K. Ramchandran

- Setup: Mixture of sparse linear regressions model
 - Unknown sparse vectors β^1, \dots, β^L of length n , with a total of k non zeros
 - Observe m linear measurements

$$y_i = x_i^\top \beta^{l_i} + w_i, \quad i \in [m]$$

with label $l_i \in [L]$ unknown
(l_i s chosen randomly according to a weight distribution)

- Goal is to estimate β^1, \dots, β^L
- Applications: speaker identification, background modeling

- When $L = 1$, this is the standard compressed sensing problem
- Contributions: An algorithm based on sparse graph codes; guarantees for $n, k \rightarrow \infty$ (under assumptions involving support overlap of β s)
 - Noiseless case: Sample and time complexity of $\Theta(k)$
 - Noisy case with $L = 2$: Sample complexity of $\Theta(k \text{polylog}(n))$

Provable Dynamic Robust PCA or Robust Subspace Tracking

Praneeth Narayanamurthy and Namrata Vaswani

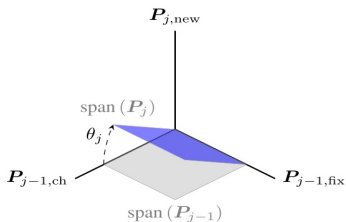
- Dynamic RPCA: track a slowly changing subspace in the presence of sparse outliers
- At time instant t , observe $y_t \in \mathbb{R}^n$ where

$$y_t = l_t + x_t + v_t, \quad t = 1, \dots, d.$$

l_t : true data lying in a slowly changing subspace of \mathbb{R}^n

x_t : sparse outlier

v_t : bounded noise



■ Contributions

- A recursive projected CS algorithm for subspace tracking that works under weaker assumptions on subspace change rate and outlier magnitude

Assuming previous subspace estimate \hat{P}_{t-1} is available, compute

$$\tilde{y}_t = \Psi x_t + b_t$$

where $\Psi = I - \hat{P}_{t-1} \hat{P}_{t-1}^\top$ and $b_t = \Psi(l_t + v_t)$, and use CS

- Improved outlier tolerance compared to previous RPCA algorithms

Limits on Sparse Data Acquisition: RIC Analysis of Finite Gaussian Matrices

Ahmed Elzanaty, Andrea Giorgetti and Marco Chiani

- Problem: Analysis of Restricted Isometry Constant (RIC) of Gaussian matrices
- Bounds on maximum sparsity level for CS algorithms usually obtained using
 - RIP based analysis
 - Coherence based analysis
 - Geometric methods

- Calculating the RIC is intractable; can be shown to be bounded for certain random designs
- RIP analysis usually done using concentration of measure arguments, this may be loose in some settings
- Contributions
 - New approach to deriving RIC based on distribution of extreme eigenvalues of Wishart matrices
 - Bound on maximum sparsity allowed for recovery algorithms like ℓ_1 minimization to guarantee a target reconstruction probability

Other interesting papers

- A Data-Dependent Weighted LASSO Under Poisson Noise. *X. J. Hunt, P. Reynaud-Bouret, V. Rivoirard, L. Sansonnet and R. Willett*
- Sharp Oracle Inequalities for Stationary Points of Nonconvex Penalized M-Estimators. *A. Elsenner and S. van de Geer*
- Estimation of a Density From an Imperfect Simulation Model. *M. Kohler and A. Krzyzak*
- Quickest Change Detection Under Transient Dynamics: Theory and Asymptotic Analysis *S. Zou, G. Fellouris and V. V. Veeravalli*