Journal Watch

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Minimax Optimal Sparse Signal Recovery With Poisson Statistics

M. H. Rohban, V. Saligrama, and D. M. Vaziri

- Goal: Derive bounds on the ℓ_2 recovery error of the sparse recovery problem with Poisson noise

- Setup: Observations $y_1, \ldots, y_n$ modeled as

$$y_i \sim \text{Poisson}(\lambda_{0,i} + \mathbf{a}_i^\top \mathbf{w}^*), \quad i \in [n],$$

where $\lambda_{0,i}$: rate of background Poisson noise

$$A = \begin{bmatrix} -\mathbf{a}_1^\top - \\ \vdots \\ -\mathbf{a}_n^\top - \end{bmatrix} : \ n \times p \text{ sensing matrix}$$

$\mathbf{w}^*$: parameter to be estimated, $k-$sparse.

- Contributions:
  - Upper bound: based on analysis of an ℓ_1-constrained Maximum-Likelihood estimator

$$\hat{\mathbf{w}} = \underset{\sum_i w_i \leq s;\ \forall i, w_i \geq 0}{\arg\min} Q(\mathbf{w}),$$

where

$$Q(\mathbf{w}) = \frac{1}{n} \sum_{i=1}^{n} -y_i \log(\lambda_{0,i} + \mathbf{a}_i^\top \mathbf{w}) + \lambda_{0,i} + \mathbf{a}_i^\top \mathbf{w}.$$

  - Lower bound: using Fano's method

Recursive Recovery of Sparse Signal Sequences from Compressive Measurements: A Review

N. Vaswani and J. Zhan

- Goal: Recursive dynamic recovery of sparse signal sequences
  Applications in MRI, audio reconstruction

- Setup:
  - MMV setting, support set of the signals varies with time

    $$y_t = A_t x_t + w_t,$$

    with $A_t \in \mathbb{R}^{n_t \times m}$ and noise w_t bounded.

  - Slow support change $\equiv$ Partial support knowledge

    $$\text{True support, } \mathcal{N} = \mathcal{T} \cup \Delta_u \backslash \Delta_e,$$

    where
    $\mathcal{T}$: erroneous support
    $\Delta_u = \mathcal{N} \backslash \mathcal{T}$: set of missing support entries
    $\Delta_e = \mathcal{T} \backslash \mathcal{N}$: set of extra entries in $\mathcal{T}$.

    Solution using Least-Squares CS-Residual, Modified-CS, Weighted-ℓ_1

- Contributions
  - Reformulation of the recursive recovery problem as recovery with partial support knowledge
  - Recursive dynamic versions of previously known algorithms

Type I and Type II Bayesian Methods for Sparse Signal Recovery Using Scale Mixtures

R. Giri and B. D. Rao

- Power Exponential Scale Mixture (PESM) family of distributions to model sparsity-inducing priors
- PESM family can be represented as

$$p(x) = \int p(x/\gamma)p(\gamma)d\gamma = \int PE(x; p, \gamma)p(\gamma)d\gamma,$$

where

$$PE(x; p, \gamma) = \frac{pe^{-\left(\frac{|x|}{\gamma}\right)^p}}{2\gamma\Gamma\left(\frac{1}{p}\right)}.$$

For example, $p = 1$ gives the Laplacian distribution.

- Contributions
  - Introduce the PESM family–can be used to represent several sparsity-promoting distributions.
  - Establish connections between SSR algorithms and PESM framework. In particular, Reweighted ℓ_1 minimization $\equiv$ MAP estimation using generalized t-distribution.
  - Derive EM inference procedure for PESM family.

Other interesting papers

- Iterative Bayesian Reconstruction of Non-IID Block-Sparse Signals. *M. Korki, J. Zhang, C. Zhang, and H. Zayyani*
- Distributed Recovery of Jointly Sparse Signals Under Communication Constraints. *S. M. Fosson, J. Matamoros, C. Anton-Haro, and E. Magli*
- Optimal Joint User Allocation and Multi-Pattern Resource Allocation in Heterogeneous Networks. *Q. Kuang, W. Utschick, and A. Dotzler*
- Compressed Sensing with Basis Mismatch: Performance Bounds and Sparse-Based Estimator. *S. Bernhardt, R. Boyer, S. Marcos, and P. Larzabal*